Occupancy of Riparian Birds in the Southern Central Valley: Applying Remote Sensing Methods to Understand Species Relationship with Vegetation

Christopher J. Orner

ABSTRACT

Bird species are often used as indicator species to assess ecosystem health, so understanding how birds respond to their environment can inform how landscape managers can support their populations. Bird species are often strongly related to vegetation, but the specific relationships vary between species, across scales, and between regions. Occupancy modeling is a powerful tool to analysis these relationships over a landscape, and remote sensing methods can provide meaningful metrics across entire landscapes that fields surveys cannot provide. This paper explores what factors are important for modeling individual bird species occupancy and detectability, and how can both be used to inform management decisions. First, a vegetation classification was performed to assess (1) how easily can best practice remote sensing methods be applied to publicly available imagery, (2) what vegetation taxonomic granularity can publicly available imagery provide. Second, an occupancy was run for 21 species using both remotely sensed vegetation and field survey data to assess (1) what factors impact detectability, (2) what factors impact occupancy, and (3) how do these factors vary among species. Species' detectability and occupancy were heterogeneously affected by nearly every variable. Observer was the most commonly shared variable for detectability (15 of 21), and vegetation was for occupancy (15 of 21). Most species occupancy was positively affected by vegetation, so landscape managers should broadly protect, restore, and support riparian vegetation to protect species.

KEYWORDS

annual grasslands, riparian vegetation, remote sensing, vegetation classification, multi-year occupancy modeling, detection probability

INTRODUCTION

Understanding where species currently live and why they live there is critical to inform landscape management decisions for conservation in a changing climate. When tested, classic ecological relationships have not uniformly stood up to empirical data across species. For example, as the climate warms, species are expected to move upslope to track cooler temperatures, but some species move downslope to track precipitation shifts (Tingley et al. 2012). Birds are often used as indicators of ecosystem health, although with caution, so understanding how they will respond can provide insight into how ecosystems will fare.

Where bird species live is often significantly impacted by vegetation. On a local scale, their occurrence can be influenced by total vegetation coverage (Mills et al. 1991), structure (Kus 1998, Nur et al. 2008, Seavy et al. 2009), individual plant species (Nur et al. 2008), species composition, volume, and the interaction of composition and volume (Seavy and Alexander 2011). On a habitat scale, bird species occurrence can be influenced by their proximity to suitable habitat (Kus 1998), proximity to other habitat patches, and the size of patches (Saab 1999). On a landscape level, bird species occupancies are influenced by human altered landscapes, like agriculture (Saab 1999, Lee and Rotenberry 2015), urban development (Lee and Rotenberry 2015), precipitation, and temperature (Tingley et al. 2012). Often, bird species respond more on landscape scales than local scales (Saab 1999, Lee and Rotenberry 2015).

Moreover, in all the previously cited studies, bird species were not related significantly to all the same vegetation variables. For the species that did share significant relationships, they did not respond uniformly; some were positively impacted while others were negatively. Some of the heterogeneous responses have been attributed to common life history traits, like feeding guild, habitat preference, and migratory status (Saab 1999, Tingley et al. 2012, Ocampo-Peñuela and Pimm 2015a). However, a species may also have different responses to the same variables in different regions of its range (Nur et al. 2008, Tingley et al. 2012). To better understand how birds will respond to a changing climate, the individual species must be better understood.

To overcome this challenge, individual species' occupancy can be modeled to analysis how their likelihood of occupying a site is impacted by different environmental variables. Occupancy modeling additional can account for imperfect detection of species during surveys because sometimes they were present, but not observed (MacKenzie et al. 2002). Treating false negatives as absences can seriously underestimate occupancy (MacKenzie et al. 2003), and for multi-year studies, overestimate local extinction and colonization rates at sites (Moilanen 2002, MacKenzie et al. 2003). Conducting multiple surveys each year enables modeling detection probability since observers are more likely to encounter the species if it does occupy a site. Including weather and time covariates while controlling for observers enables occupancy models to account of different detection probabilities under different conditions and refine occupancy estimates (MacKenzie et al. 2002).

I choose to focus on riparian bird species in annual grassland ecosystems in Southern California to study individual species responses because riparian forests are key habitat with most of the habitat variation concentrated locally within the riparian corridor. Riparian forests disproportionately provide ecosystem services (Sweeney et al. 2004), and upwards of 90% of original riparian ecosystems have disappeared California (Katibah 1984). Nearly 11% of California is annual grassland (Ford et al. 2017), and it is expected to be the most strongly impacted by a changing climate and human pressures with 37% lost by 2100 (Svoray et al. 2013, Byrd et al. 2015). Adding to the urgency is California's biodiversity with over 4,000 plant and 580 vertebrate species, over 340 of them bird species (Myers et al. 2000). California riparian forests provide critical habitat to species, especially birds, while they are under increasing threat. One of the regions expected to be hit the hardest is Southern California's Sierra foothills and Central Valley (Jongsomjit et al. 2013).

Fortunately, existing tools are available to provide landscape wide metrics on rangelands to help inform management decisions. Remote sensing has recently help landscape managers of annual grasslands assess rangeland composition (Shapero et al. 2017), biomass production (Potter 2014), more efficiently dispatch resources to key areas (Ford et al. 2017), and access how rangeland extent is changing (Shapero et al. 2017, Sawalhah et al. 2018). The results of vegetation coverage assessments also match field surveys (Boswell et al. 2017), so remote sensing has the potential to reliably provide information across the whole landscape. All of these are relatively new tools to help manage rangeland to monitor habitat degradation and meet conservation objectives (Svoray et al. 2013).

Riparian ecosystems within annual grasslands present an opportunity to supplement landscape scale assessments with targeted, local information around creeks that have large effects on the surrounding annual grassland. Riparian vegetation has been successfully classified with specialized, privately collected datasets (Jeong et al. 2016). However, not much has been made it the way of publicly available imagery. General remote sensing best practices apply to riparian habitats though. Because some bird species are influenced by individual plant species, classifying imagery down to the greatest taxonomic specificity is desired, and high-resolution imagery is best suited for that (Blaschke 2010). In high-resolution imagery, trees are comprised of multiple pixels, so object-based image analysis (OBIA) is preferred to smooth out variation between pixels making up one tree (Blaschke 2010, Dronova 2015). OBIA has performed better than pixel-based methods in riparian systems, which are prone to salt-and-pepper speckle in the classification (Jeong et al. 2016). Together, remotely sensed vegetation coverage products combined with occupancy models can further the understanding of individual species response vegetation variables and apply those relationships across an entire landscape.

The goal of this study was to ask what factors are important for modeling individual bird species occupancy and detectability, and how can both be used to inform management decisions? First, the importance of vegetation is well studied, so (1) how easily can best practice remote sensing methods be applied to publicly available imagery, (2) what taxonomic granularity can publicly available imagery distinguish between? Second, to understand where bird species live, (1) what factors impact detectability, (2) what factors impact occupancy, and (3) do these factors vary among species.

METHODS

Study area

Tejon Ranch is in the Southern Central Valley of California and is the largest contiguous piece of private property in California. The ranch sits at an ecological confluence with portions of the San Joaquin Valley, Sierra Nevada Mountains, Southern Coast Ranges, Mojave Desert, and all the Tehachapi Mountains within its boundaries (Ratcliff et al. 2018). The property dates to 1866 when the last parcels were purchased to form the boundaries the ranch has today; much of the land has been used for ranching since, so the riparian forests have remained largely connected and intact (Tejon Ranch Corporation 2017, Ratcliff et al. 2018).

The Tejon Ranch Corporation owns all the land, and in 2008, they stated their intentions to put 90% of the ranch (97,124 hectares) into conservation (Tejon Ranch Conservancy 2013). The Tejon Ranch Corporation formed a non-profit, the Tejon Ranch Conservancy, to jointly manage the landscape with a multitude of management goals. Several of the goals are aimed at supporting riparian corridors with the specific intention to support bird populations by promoting beneficial vegetation structure and composition (Tejon Ranch Conservancy 2013). The Tejon Ranch Conservancy has been studying several creeks for the past six years by conducting point transects.

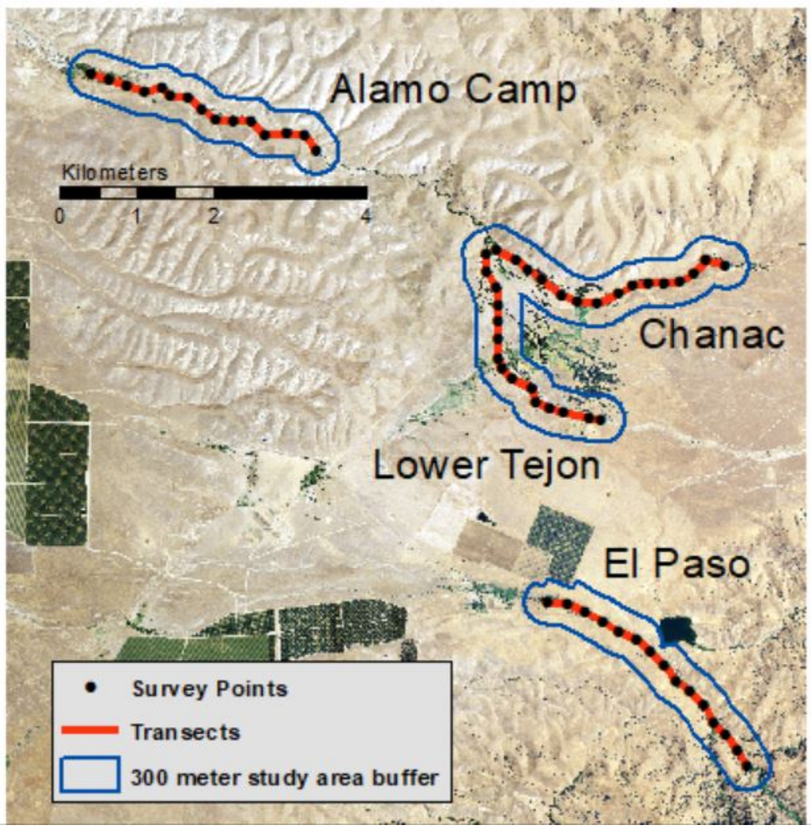

Figure 1. Study area on Tejon Ranch. The four creeks, their transects, all 60 survey points, and the 300-meter buffers are plotted against the 2012 NAIP imagery. The dominate landscape cover is annual grasslands with some agricultural fields nearby.

I selected the four creeks that had data collected all six years: Alamo Camp, Chanac, El Paso, and Lower Tejon. I buffered the four creeks by 300 meters to refine the study area to the riparian corridors. The final area covered 11.06 km^2 with an elevation range from 230 to 650 meters. (Fig. 1). Because of the its long history, old riparian forests, and conservation goals, Tejon Ranch provides an excellent site to study riparian birds' occupancy and supplement field data with vegetation data derived from remote sensing methods.

Vegetation classification

Data sources

I used the United States Department of Agriculture's (USDA) National Agriculture Imagery Program (NAIP) imagery. The USDA produces NAIP every two years on average for California (United States Department of Agriculture 2012). The United States Geological Survey (USGS) hosts the data for free public download on the USGS's EarthExplorer website (https://earthexplorer.usgs.gov/). I downloaded imagery from 2012, 2014, and 2016 (USGS EarthExplorer 2019). The 2014 and 2016 imagery were collected while the Tejon Ranch Conservancy conducted creek surveys, but 2014 and 2016 imagery both contained spectral or phenological boundaries. The USDA merged the 2016 imagery without having preprocessed the data to create a spectrally consistent dataset. The 2014 contains phenological boundaries with unclear causes. I chose 2012 imagery because 2012 contained no spectral or phenological boundaries and precedes the first creek surveys, so 2012 served as a baseline.

Image inspection

The cover types within the refined study area fell into three main classes: green vegetation, and grassland, and shadow. Within the green vegetation class were three main sub-classes: trees, shrubs, and annual herbaceous wetland. Trees could be further identified as buckeye, cottonwood/willow, and oak species. Shrubs could be further identified as California grapevine and mulefat. Within the grassland class were three main sub-classes: grassland, bare earth, and rock outcrops. The spectral similarity between sub-classes suggested the main classes could be reliably be classified but also that subsequent sub-classifications would be difficult. A hierarchical classification was developed to help accentuate separability as subsequent levels (Wu et al. 2019) (Fig. 2). Despite the challenges, two observations are of note. First, the refined study area encompasses annual grasslands, so riparian vegetation is the only green vegetation remaining on the landscape after the grassland plants senesce. Second, herbaceous wetland comprises a small percentage of the image, so green vegetation also well reflects the coverage of woody riparian vegetation (trees and shrubs).

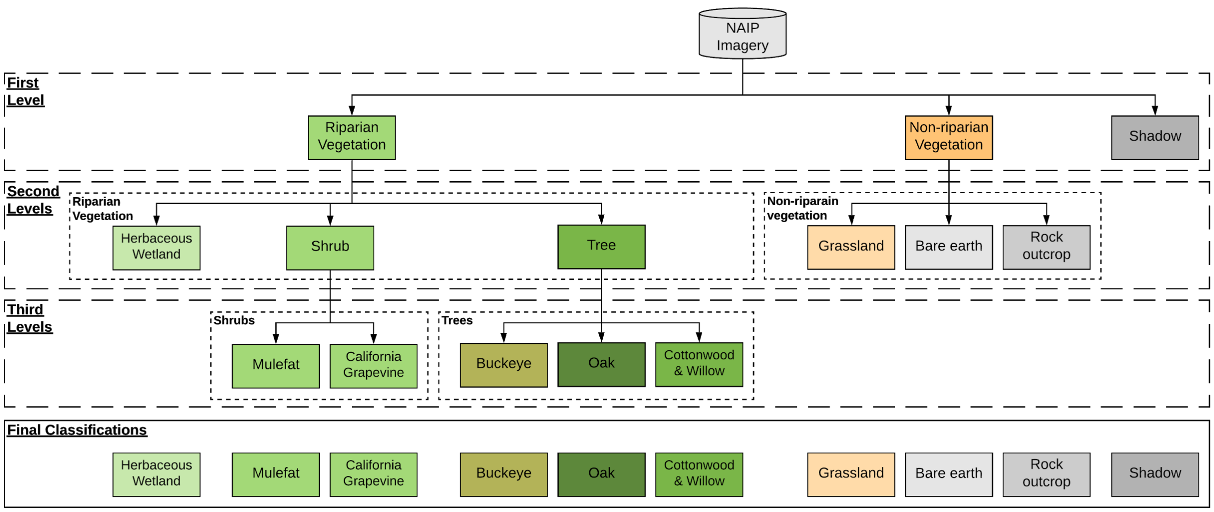

Figure 2. Conceptual framework for classification scheme. To successively classify vegetation with increasing taxonomic specificity, a hierarchical scheme was developed by spectral similarity and taxonomic grouping.

Training & test samples

Supervised classifications require samples to train a classification algorithm. To access the accuracy of a classification, test samples with identified classes are required to compare a classification's output against. I created training and test samples together to speed up the identification workflow. I aimed for 50 points for each class: 30 for training and 20 for testing. Stratified random sampling was best suited to the study area because most of the area was grassland, but most classes were in narrow riparian corridors. To create categories to stratify sampling along, I ran a two cluster iso-cluster analysis in ArcGIS (Esri Inc., version 10.6.1) with the RGB and NIR bands. To begin, I generated 350 random points in the cluster that aligned with green vegetation, for an average of 50 points per class for six vegetation classes plus shadow. I generated 200 points for the cluster that aligned with grassland, for an average of 50 for rock and bare earth and 100 for grassland to help capture its variability. I identified and labeled the points' classes using the 2012 NAIP imagery and a high-resolution base map in Google Earth Pro from August 2012 (Google, version 7.3.2.5776). For classes that were not adequately sampled from the stratified random sampling, I added additional points near randomly generated points until each class had at least 45 points. I randomly selected 20 training samples per class, exported those to create a separate test point dataset, and exported other the entries to create a training dataset (Table 1). I added columns to the training samples to reflect their first, second, and third level classes in the hierarchy.

Table 1. Final number of samples for training and test sample points. Stratified random samples were generated and then classified by their ideal final classification. Cottonwood and willow, oak, and grassland were common, and under-sampled classes, like herbaceous wetland and California grapevine required additional samples by add by hand.

Training and test sample points

	Number of points		
Class	Training	Test	Total
Riparian Vegetation			
Herbaceous wetland	27	20	47
California grapevine	25	20	45
Mulefat	60	20	80
Buckeye	31	20	51
Cottonwood and willow	147	20	167
Oak	94	20	114
Non-riparian Vegetation			
Grassland	116	20	136
Bare earth	63	20	83
Rock outcrop	38	20	58
Shadow			
Shadow	41	20	61

Classification methods

I performed an unsupervised iso-cluster classification with 30 clusters in ArcGIS using all four bands of the 2012 NAIP imagery. I assigned each cluster to a class: green vegetation, grassland, or shadow. Using the first level classifications, I masked the 2012 NAIP imagery and performed a second unsupervised classification. Due to poor separability, the classification was stopped after the second level and subsequent analyses were performed on the first level product (Fig. 3).

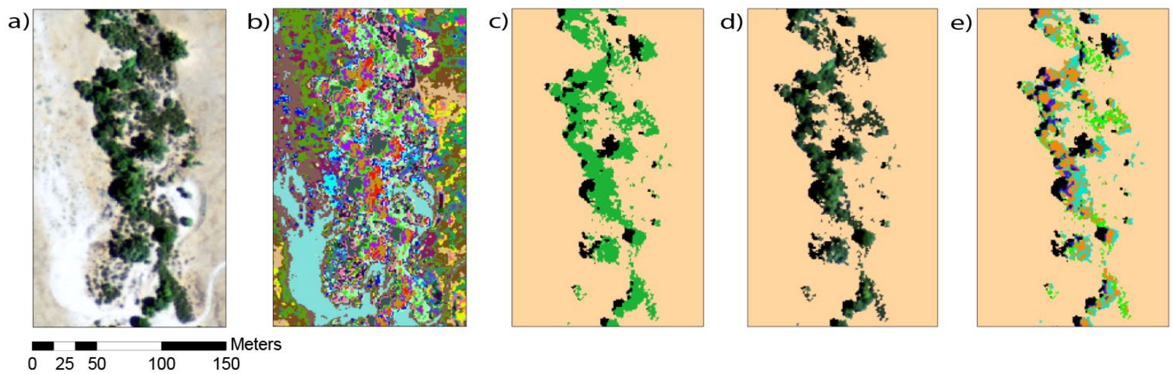

Figure 3. Classification process for the unsupervised classification. (a) First 2012 NAIP imagery was loaded into ArcGIS and pre-processed. (b) Then an unsupervised classification was run with 30 clusters. (c) The 30 clusters were reassigned to green vegetation, grassland, or shadow. (d) That classified was then used to mask the NAIP the second level of classifications, above is from green vegetation. (e) The second level unsupervised classification produced clusters that spanned both tree and shrub classes. Herbaceous wetland was not present in this area.

Then I performed an OBIA maximum likelihood classification in eCognition (Trimble Inc., version 9.4). To generate objects, I used a multi-resolution segmentation algorithm (Fig. 4). Like the unsupervised classification, I used the first level classifications as masks on the NAIP imagery to perform the second level classifications. Also like the unsupervised classification, class separability was poor, classifications were stopped after the second level. Because an OBIA analysis requires significantly more time and was unable to classify beyond the first level, I chose to move forward with only unsupervised classification for the accuracy assessment and further analysis.

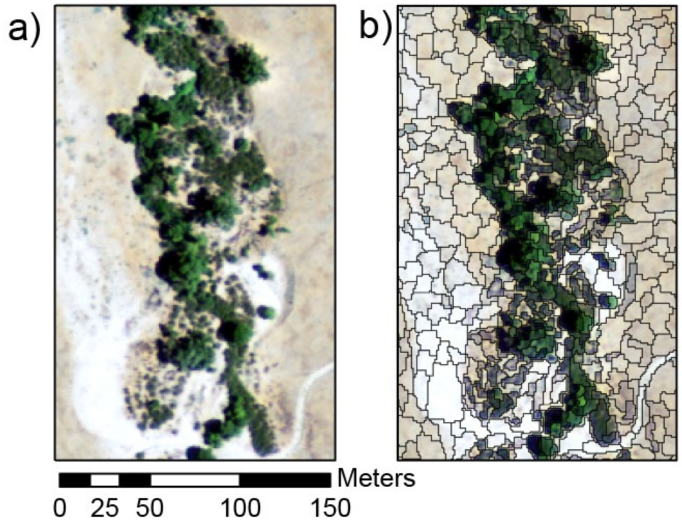

Figure 4. Image segmentation for the OBIA. (a) First, the 2012 NAIP imagery was loaded into eCognition after having been preprocessed in ArcGIS. (b) Segments produced with a scale parameter set at 10, shape at 0.3, and compactness at 0.8. The objects appear to follow the boundary of green vegetation, grassland, and shadows well. Of note, the segmentations produced crisp boundaries for bare earth in the lower right and left sides that will be useful in second level classifications.

Accuracy assessment

To evaluate the accuracy of the classification, I performed an accuracy assessment for each. Because the unsupervised classification required no training samples, I took 50 random samples points from each first level class (green vegetation, grassland, and shadow) from the full sample point dataset, so shadow had 50 samples too. I constructed a contingency matrix to calculate the unsupervised classification's overall accuracy, kappa statistic, and the user's and producer's accuracies of each class.

Occupancy modeling

Field methods

In the 2012, survey transects were established along four creeks with 15 points each by the Tejon Ranch Conservancy. They recorded the location of each point with a handheld GPS unit. Each transect was about three kilometers, and each point was located roughly 200 meters apart. From 2013-2018, Tejon Ranch Conservancy staff and volunteers conducted the surveys each year using point-count methodologies at each point. Three times each year between May and June, five-minute point-count transect surveys were conducted. Each transect began at sunrise and continued until completed, often ending before 10:00 PDT.

All 15 points along a transect were observed within one survey. Both ends of a transect could be used to start the survey. Observers picked one end of the transect and worked their way down to the other end. Sometimes points were moved several meters due to creeks' jumping their banks, and the new coordinates were recorded. If a point was moved, all observations associated with the point remained with it because the changes were small compared to the 200-meter distance between points.

At the start of each survey, observers recorded the date, temperature, wind, sky conditions, and the cloud cover. The cloud cover, sky conditions, and wind values came from a categorical list with higher numbers reflecting rougher or cloudier conditions (Table 2). Sky conditions include some measure of cloud cover, but cloud cover segments coverage into more categories. Sky conditions also include categories for fog, smoke, and precipitation that are not encompassed by cloud cover or wind categories.

Table 2. Categorical covariates and their values. Categorical variables were collected at the start of each transect and copied with everyone point in the transect for analysis. Cloud cover and sky conditions have similarities, but sky condition includes precipitation categories while cloud cover goes all the way up to 100% cover.

Categorical Covariates	
Covariate	Codes
Cloud Cover	1 = 0-25% 2 = 25-50% 3 = 50-75% 4 = 75-100%
Sky Conditions[1]	0 = clear or few clouds 1 = partly cloudy (scattered) or variable sky 2 = cloudy (broken) or overcast 4 = fog or smoke 5 = drizzle 6 = snow 7 = showers
Wind	0 = smoke rises vertically 1 = wind direction shown by smoke drift 2 = wind felt on face 3 = leaves/twigs in constant motion 4 = raises dust, moves small branches 5 = small trees sway, white caps

[1] The missing 3 code is not a mistake. A 3 code was missing from the field survey sheets, and none of the surveys had a 3 recorded.

At each point, observers recorded the start time, each bird detected and their species, sex, age, behavior, if they were flying over the point, detection method, distance from the point, if they were in a group, and if so, the number of birds in the group. For analysis, flyovers were excluded because they do not represent birds detected occupying the survey point's area. Birds detected greater than 100 meters away were also excluded to prevent double counting species across points and maintain independent sites. The remaining entries were condensed to the presence or absence of a species at a point.

Covariate preprocessing

Date and time field survey data required reprocessing for use in models. Date was transformed into Julian days, so it was a continuous variable. Point times were transformed into minutes after civil twilight to remove the effect of changing sunrise times because birds are most active at sunrise and less active as the morning progresses. Civil twilight times were obtained from the US Naval observatory using the mid-latitude and mid-longitude of all survey points.

In addition to field survey data, remotely sensed vegetation, elevation, and precipitation data were included for analysis. Vegetation and elevation data had one value for each survey point while precipitation was annual. Vegetation data came from the unsupervised classification's riparian vegetation class. Survey points were buffered 100 meters and the percent-area coverage of riparian vegetation was calculated. Elevation data come from the USGS's 10-meter resolution National Elevation Dataset, accessed through the USGS's The National Map website (https://viewer.nationalmap.gov/basic/). Survey points' elevation were extracted with a cubic convolution interpolation.

Precipitation data was incorporated from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Daly et al. 2002). I downloaded monthly precipitation 800m resolution raster datasets from October 2012 to September 2018. In ArcGIS, I extracted each point's monthly precipitation values with a bilinear interpolation. Monthly precipitation was summed to annual water-year precipitation by summing the months of October through September. For example, 2013's precipitation values came from summing October 2012 through September 2013. I chose water-year annual values instead of calendar-year annuals because the water-year better reflects the amount of water an ecosystem has received by summer. Lastly, to aid model convergence, all continuous covariates were scaled (MacKenzie et al. 2003).

Statistical analysis

I performed the analysis in the statistical program R (R Core Team 2018) with the RStudio interface (RStudio Team 2016) using the multi-season occupancy model in the unmarked package (Fiske and Chandler 2011). The occupancy modeling followed the multi-season methodology laid out in Mackenzie et al. (2003), following Fiske and Chandler's workflow (2011). The multi-season model builds out occupancy from the predicted first year occupancy and can perform poorly for species with low detection. I chose a 10% detectability threshold, after Tingley et al (2012), for 2013's survey data because the model builds out occupancy from the initial year.

The multi-season model estimates occupancy probability with four occupancy parameters: first year occupancy, colonization, extinction, and detectability. All parameters are derived from regressions, and all regressions accept continuous and categorical variables. First year occupancy covariates cannot vary between years. Colonization and extinction covariates can vary between years but not between surveys. Detectability covariates can vary between surveys.

An unrestricted model was run for each species to determine which covariates were significant (Fig. 5). Because several covariates were categorical, likelihood ratio tests (LRTs) were performed. An LRT assesses the factor wide-significance of categorical variables with a chi-squared statistic. To keep interpretation consistent, I performed LRTs for continuous variables as well. An LRT requires another model with a covariate excluded for comparison, so every iteration of the model with one covariate removed was run for all 21 species. A total of 15 models per species were run, for a total of 315 models across all species.

Species life history traits were compiled to summarize the results. The traits came from *The Birds of North America Online* (Rodewald 2015) and *The Birder's Handbook* (Ehrlich et al. 1988) with a primary focus on Passeriformes (songbirds), habitat preference, and seasonal status. Habitat was defined as where the species occurs in an annual grassland ecosystem (riparian, grassland, or both) as opposed to where it occurs throughout its entire range. Riparian species refers to species that occur predominantly in riparian habitats even though they may leave to forage in surrounding grassland. Both refers to species that occur in both riparian or grassland habitats without a predominance for one or the other.

Interpretation of model

The multi-season 'unmarked' model produces coefficients that are not readily interpreted without a further understanding of how the model handled the data and ran the regressions. The model transformed the scaled covariate values with a logit-link function, so the covariates were suitable for a binomial generalized linear model because occupancy is a binary variable. The model then regressed the covariates on their respective occupancy parameters: first year occupancy, colonization, extinction, and detectability. The resulting coefficients fit a binomial distribution, so the magnitude of the effects of the covariates cannot be interpreted as linear. Therefore, a coefficient does not represent the same effect across its covariate's range, so while it's tempting to interpret the estimate as a linear coefficient, doing so would mischaracterize the relationship. Hence, it's difficult to interpret the magnitude of a coefficient, and it's much more meaningful to interpret a coefficient's sign (positive or negative) and focus on the direction's meaning.

Additionally, my model used continuous and categorical covariates, and their interpretation is different. Continuous variables follow the interpretation outlined above, but categorical variables' produce a coefficient for each level (cloud cover = 1, 2, 3, or 4). Categorical variables' coefficients represent the difference from a baseline; in my models, the baseline is the first categorical element (e.g. a cloud cover of 1). Because the coefficients are relative to a baseline, they can result in non-linear and inconsistent relations that prevent generalization to the whole categorical variable.[1]

It is more meaningful treat categorical variables as fixed effects and interpret their significance. If a categorical variable is significant then it should be included in the model because it helps explain a meaningful amount of variation and provides a control for the covariate's effect and prevents omitted-variable bias that would confound other covariates. That's why I calculated factor-wide significance using a likelihood ratio test because it tests that all the levels of a covariate help capture a meaningful amount of variation if taken together. I also used the likelihood ratio test to evaluate the significance of continuous variables to keep significance evaluation and interpretation consistent across both categorical and continuous variables.

[1] For example, a cloud cover of 2 may have a coefficient of -0.5, a 3 may be -0.9, and a 4 may be -0.7. 1 through 3 suggest detectability decreases with increasing cloud cover, but the increase from 3 to 4 breaks the trend. The cloud cover factor coefficients can neither be interpreted to have a consistent nor linear effect.)

Dynamic Occupancy Model

Occupancy Parameter	Regression Equation
First Year Occupancy	= Creek† + Elevation* + Greenness*
Colonization	= Year† + Rain*
Extinction	= Year† + Rain*
Detectability	= Cloud† + Date* + Observer† + Sky† + Temperature* + Time* + Wind†

†Categorical variable
*Continuous variable

Figure 5. Unrestricted dynamic occupancy model. This model was run for all species to explore which variables significantly impact occupancy and detectability. Colonization and extinction parameters were included because they are integral to the model. They were not interpreted because they are of more interest for exploring how species change location each year while this study is more focused on factors across all years.

RESULTS

Classification algorithms

The object-based imagery analysis did not perform well because the objects suffered from high intra-class variability making classification extremely difficult (Fig. 6). Instead, the iso-cluster unsupervised classification with 30 clusters reliably classified green vegetation, grassland, and shadow; albeit, only the first level of the classification was obtainable. Despite the broad classes, green vegetation was a meaningful proxy for woody riparian vegetation in an annual grassland ecosystem. I used the green vegetation class as a proxy for woody riparian vegetation in the occupancy model and referred to it as “greenness.”

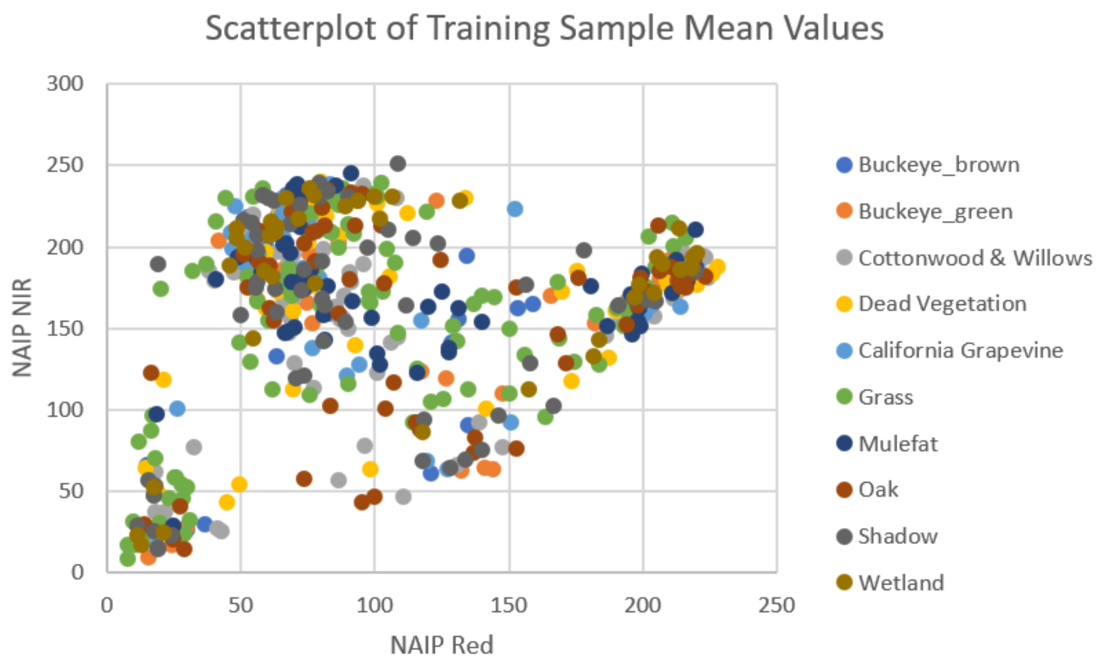

Figure 6. Scatterplot of object means across all classes. The overlap between classes displays high intra-class variable and low separability. The first level of the unsupervised classification was successful, but the low object separability even between first level classes means separability was reduced by the segmentation algorithm.

Accuracy assessment

The overall accuracy for the classification was 91% and a 0.86 kappa statistic (Table 3). In the final classification, shadow was 1.5% of the area, green was 6.8%, and grassland was 91.6%. Shadow and grass had the highest producer accuracies, both at 94%, meaning that 94% of the pixels identified as shadow in the training samples were classified correctly as shadow. However, shadow had the lowest user accuracy at 81%, meaning that 81% of the pixels classified as shadow were shadow pixels. A high producer accuracy and low user accuracy means the classification reliably classified shadows and shadows, but it also classified other classes as shadows that weren't shadows. Grass's user accuracy was 100%. Green had the lowest producer accuracy at 84%, but its user accuracy was 93%. A low producer accuracy and high user accuracy means the classification did not classify green as green as well as hoped, but the pixels that were classified as green are reliably green. The unsupervised algorithm most often confused green for shadow, reducing producer accuracy for green and reducing user accuracy for shadow. The unsupervised classification's tendency to classify green as shadow resulted in over-predicting shadow and under-predicting green. Green is likely under-represented as a result.

Table 3. Unsupervised classification contingency table. The contingency table assesses the accuracy of the classification and how well it preformed for each class. The overall accuracy was 91% and was found by summing the diagonal (the correct classifications) and dividing by the total number of points (150). An overall accuracy above 85% is considered a good classification. The kappa statistic was 86% which presents how likely the classification did not randomly assign classes. The kappa statistic is usually lower than the overall accuracy, and an acceptable kappa statistic is great then 80%.

Classification	Ground Truth			Total	User's Accuracy
	Shadow	Green Veg.	Grass		
Unclassified	0	0	0	0	—
Shadow	47	8	3	58	0.81
Green Veg.	3	42	0	45	0.93
Grass	0	0	47	47	1.00
Total	50	50	50		
Producer's Accuracies	0.94	0.84	0.94		
					Overall Accuracy: 0.91 Kappa: 0.86

Summary statistics

Across all years, creeks, and surveys, observers recorded 105 bird species (Appendix A). Only 45 species were detected at least once each year, and only 21 species were detected at 10% or more of points during the first year (Table 4). 16 of the 21 species were year-round residents and the remaining five were migratory species there for the breeding season. 14 of the 21 species were predominantly riparian species while the other seven occur in both riparian and grassland habitat. 16 of the 21 species were Passeriformes, two Piciformes, one Falconiformes, one Galliformes, and one Columbiformes.

Table 4. Species detected at least 10% of 2013 survey points and their habitat preference and seasonal status. Birds species are listed alphabetically by their alpha codes. The majority of species are riparian in annual grasslands (14) and most are year-round residents (16).

Species List

Common Name	Habitat*	Seasonal Status
Acorn Woodpecker	Riparian	Year-round
American Kestrel	Both	Breeding
Ash-throated Flycatcher	Riparian	Breeding
Bewick's Wren	Riparian	Year-round
Brown-headed Cowbird	Both	Year-round
Bullock's Oriole	Riparian	Year-round
Bushtit	Riparian	Year-round
California Towhee	Riparian	Year-round
California Quail	Both	Year-round
European Starling	Both	Breeding
House Finch	Both	Year-round
House Wren	Riparian	Year-round
Lawrence's Goldfinch	Riparian	Breeding
Mourning Dove	Both	Year-round
Nuttall's Woodpecker	Riparian	Breeding
Oak Titmouse	Riparian	Year-round
Phainopepla	Riparian	Year-round
Song Sparrow	Riparian	Year-round
White-breasted Nuthatch	Riparian	Year-round
Western Kingbird	Both	Year-round
Western Scrub-Jay	Riparian	Year-round

*Habitat is defined as the habitat the species predominately occupies. Both means the species inhabitants both riparian or grassland habitat.

Detectability

All but one species' detectability (Oak Titmouse) were significantly affected by at least one detection variable, and no species' detectability was significantly affected by all of them (Table 5). One species' detectability was significantly affected by six of the seven covariates (Acorn Woodpecker - all except wind), and only two species' detectability were only significantly affected by one covariate (Western Scrub-jay with date and Mourning Dove with observer).

Table 5. Significant occupancy and detectability variables by species. Each filled-in cell represents a significant relationship. Blue represents significant LRT for categorical variables. For continuous variables, the sign is included and filled-in green for positive, and red for negative. A full table of the chi-squared probabilities and coefficient values for continuous variables can be found in appendix B and C.

	First Year Occupancy			Detectability						
Species	Creek	Elevation	Greenness	Cloud	Sky	Wind	Temp	Date	Time	Obsvr
ACWO		+	+				+	-	+	
AMKE			-							
ATFL									-	
BEWR										
BHCO			+					-		
BUOR		-	+							
BUSH		-	+					+		
CALT		-	+						-	
CAQU			+				-		-	
EUST							-	-		
HOFI			+						+	
HOWR		-	+							
LAGO			+				-			
MODO			+							
NUWO		-	+					+		
OATI			+							
PHAI							-	+		
SOSP		-	-				+	-		
WBNU		+					-	+	+	
WEKI		-	-					-		
WESJ								+		

Weather covariates

Weather covariates (cloud, sky conditions, wind, and temperature) had 16 of 21 species' detectability significantly related to at least one of them. Cloud cover significantly affected the detectability of nine species, including four of five migratory species. Sky conditions significantly affected the detectability of eight species, including all five migratory species. Wind significantly affected six species' detectability, including only one migratory species. Temperature significantly impacted the detectability of seven species. Two species' detectability were positively affected by temperature, and five were negatively related. Both species whom temperature significantly and positively impacted their detectability were year-round residents, and the five species with significant negative detectability relationships were split between three year-round residents and two migratory species. Both species with significant positive detectability relationships were also riparian species while the five species with significant negative detectability relationships were two riparian species and three riparian and grassland species.

Time covariates

Time covariates (date and time) had 14 of 21 species' detectability significantly related to at least one of them. Species' detectability was often significantly related to date or time but not both. Only two species' detectability were significantly affected by both date and time (Acorn Woodpecker and White-breasted Nuthatch), but their responses were mixed. Time had a significant positive effect on both species' detectability, but date had a significant negative effect Acorn Woodpecker's detectability and a significant positive effect on White-breasted Nuthatch detectability.

Date was significantly related to the detectability of ten species. The relationship signs were split evenly with five significant positive relationships and five significant negative relationships. Both the positive and negative relationships had four year-round residents and one migratory species.

Time was significantly related to the detectability of six species, and they were split evenly between three positive and three negative relationships. Of the species' detectability significantly affected by time, one positive and one negative relationship were from non-Passerine birds (Acorn Woodpecker was positive and California Quail was negative), two Passerine species' detectability had positive relationships with time (House Finch and White-breasted Nuthatch), two Passerine species' detectability had negative relationships (Ash-throated Flycatcher and California Towhee).

All three species whose detectability was significantly and positively affected by time were year-round residents. The three species who had negatively affected detectability were split between two year-round residents and one migratory breeding resident. Both the three positive and three negative relationships were split between two riparian species and one species that occurs in both riparian and grassland habitat.

Observer

Observer was significantly related to the detectability of the greatest number of species (15 of 21), including all five migratory species. Of the 15 species, nine were riparian species and six occurred in both riparian and grassland habitat. 10 of the 15 species whose detectability was significantly affected by observer were Passeriformes, and five of those were year-round residents. The other five were migratory Passeriformes.

First year occupancy

First year occupancy covariates (creek, elevation, and greenness) had 18 of 21 species' first year occupancy significantly related to at least one of them. (Table 3). Four species' first year occupancy was significantly related to all of them (Acorn Woodpecker, House Wren, Song Sparrow, and Western Kingbird), and three species' first year occupancy were not significantly affected by any of them (Ash-throated Flycatcher, Bewick's Wren, and European Starling). All four of the species whose first-year occupancy probability was significantly related to all three covariates were riparian species. Two of the species whose occupancy probability was not significantly related to any occupancy covariate (Ash-throated Flycatchers and Bewick's Wrens) were also riparian species.

Eight species' first year occupancy was significantly related to creek segment. All eight were year-round residents. For elevation, nine species' first year occupancy were significantly affected. Of note, all nine species whose first-year occupancy was significantly related to elevation were significantly related to either creek (one), greenness (four), or both (four) with no species only related to solely elevation. Of the nine species whose elevation significantly affected their first-year occupancy, two had positive relationships while seven had negative relationships.

15 species' first year occupancy was significantly affected by greenness. Of the 15 species, nine were predominately riparian birds (60%) and six were species that occur in both riparian and grassland habitat (40%). Of the nine riparian birds, eight of were positively related to greenness (Fig 7), and only one was negatively related (Song Sparrow). Of the six species that occur in both

riparian and grassland habitat, four were positively related, and two were negatively related (American Kestrel and Western Kingbird).

Trends across both detectability and occupancy

Species had extremely heterogeneous responses to the detectability and occupancy covariates. None were related to all the covariates, but all were related to at least one. The species significantly related to the most covariates was Acorn Woodpecker (9 out of 10). The least related species was Oak Titmouse, which had a significant relationship only with greenness. The most commonly shared covariates were greenness and observer.

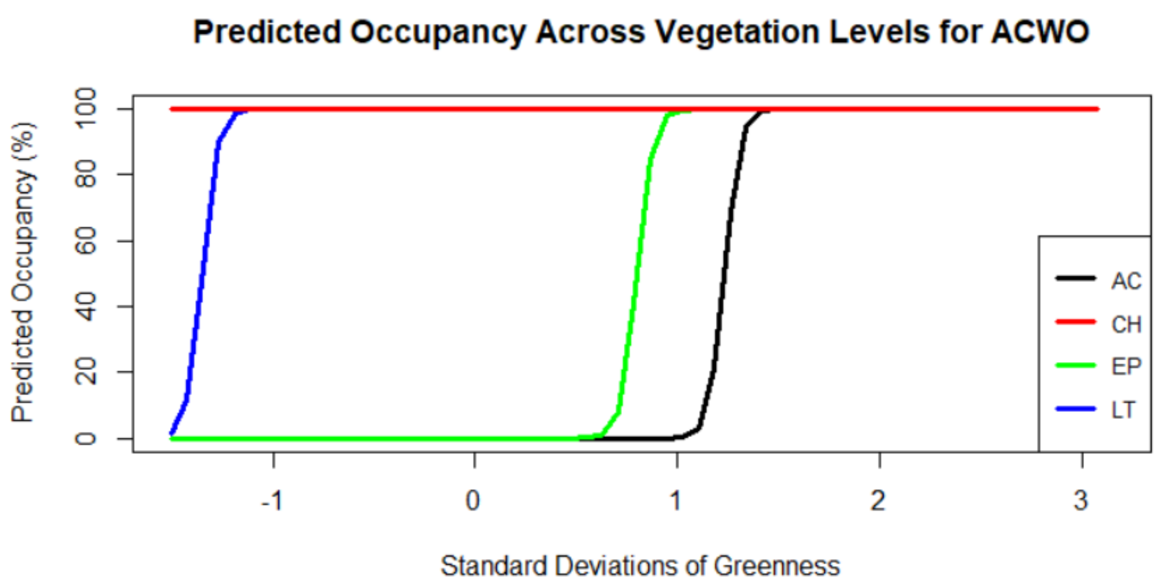

Figure 7. Example of greenness' impact on first year occupancy probability while controlling for Acorn Woodpeckers. The plot exemplifies how creek can be an important fixed effect for species while also highlighting the non-linearity of covariates relationship with occupancy. The non-linear relationship signifies a threshold exists for greenness past which Acorn Woodpeckers are very likely to occupy a site and controlling for creek emphasizes the thresholds are different for each creek due to other factors are not accounted for but would otherwise introduce more biased without a fixed effect to absorb them.

DISCUSSION

Classification algorithms

The consensus in the remote sensing community is object-based imagery analysis often works best for high resolution imagery (Blaschke 2010). However, OBIA did not perform well in this study. Objects became too homogeneous across classes such that classification became too difficult. However, the strengths of OBIA reside in its ability to smooth noise amongst pixels apart of the same object (Dronova 2015), suggesting the homogeneity of this study's objects are likely the result of under-segmentations, so more than one class was present within objects. Future riparian studies should segment images into smaller objects to avoid homogenizing them beyond use in classifications.

I shifted focus to simpler pixel-based classifications that are readily replicable and more accessible, and pixel-based approaches have succeeded in classify rangeland vegetation into tree, shrub, and herbaceous classes (Boswell et al. 2017). OBIA is still a promising approach to classify riparian vegetation to greater taxonomic granularity because other studies have succeeded with privately collected spectral data supplemented with LiDAR (Jeong et al. 2016). Shapero et al. (2017) successful classified rangeland vegetation with NAIP imagery using an OBIA. However, like this study, their analysis reduced all woody vegetation into one forest class, suggesting current publicly available imagery may lack the spatial or spectral resolution to reliably classifying riparian vegetation species and composition without supplemental data sources, especially LiDAR. Further advancements in hyperspectral imagery, lidar, and synthetic aperture radar are up and coming to help identify vegetation species, assess vegetation structure, and estimate biomass, respectively (Boswell et al. 2017) which all would serve as critical inputs for any classification algorithm to help identify species and vegetation composition.

Unsupervised classification performance

The 91% overall accuracy demonstrated riparian vegetation can be classified with simple methods and have meaningful interpretation as woody riparian vegetation in annual grassland ecosystems. The classification did produce mutual confusion between shadow and green vegetation and under-predict green vegetation, but these results are preferential for my analysis. Over-predicting shadow and under-predicting greens vegetation is preferred to under-predicting shadow and over-predicting green vegetation. Trees in the middle of riparian corridors cast shadows that conceal green vegetation underneath, but trees along the edge cast shadows concealing grassland underneath. The mutual confusion favors over-predicting shadows and reduces the likeliness that grassland underneath a shadow is misclassified as green vegetation. Because I used green vegetation as a proxy for woody riparian, under-predicting green vegetation also reduces the likeliness that woody riparian vegetation is overestimated since some of the green vegetation pixels are herbaceous wetland.

Furthermore, researchers are adopting machine learning algorithms that can improve unsupervised classifications on the pixel level with existing data products (Scheunders et al. 2018), and they often require marginally more time devoted to understanding the algorithm's parameters. As a result, remote sensing should be applied more often to rangeland and riparian vegetation studies because of their meaningful products that provide information across an entire landscape, even with simple unsupervised classifications.

Detectability

20 out of 21 (95%) species' detectability were significantly impacted by at least one detectability covariate. I expected the detectability would vary across weather and time covariates because the detectability of birds varies across environmental conditions and between species (MacKenzie et al. 2002), and results confirm this. However, the heterogeneous responses (positive or negative) among order, riparian, and migratory summary statistic groupings did not elucidate clear patterns.

I expected Passerine species would become harder to detect as the day progressed because many Passerine species sing most actively at dawn. However, two Passerines' detectability had positive significant relationships and two had negative, suggesting the response is mixed. Additionally, time may not be significant detectability factor for most Passerine species since 12 species' detectability were not significantly related.

I expected all species would become harder to detect as temperature increased because birds will rest to avoid the worst of the heat. For the species whose detectability were significantly affected by temperature, my expectation was confirmed. However, most species' detectability (14 of 21) were not significantly related to temperature.

Many species were also significantly related to observer, including all five migratory species, suggesting unless observer was already determined to be insignificant (Tingley et al. 2012), it is critically important to include observers in models to avoid omitted-variable bias and confounded results.

The responses appear to be species specific, so knowing what daily and hourly conditions that may impact a species' detectability is not readily evident without modeling. Furthermore, that all but one species was significantly related to at least one detectability covariate, suggest it's important to record and incorporate all detectability variables in models. Future analyses could be performed to look at species life history traits with generalized linear mixed models to evaluate if responses are less heterogeneous than they initially appear (Tingley et al. 2012, Ocampo-Peñuela and Pimm 2015a).

Occupancy

18 out of 21 (86%) species' first-year occupancy probably was significantly impacted by at least one covariate. I expected greenness would have the most significant positive impacts on species' first year occupancy, and specifically riparian species because successive studies have highlighted the importance of vegetation quantity whether its area (Saab 1999), height (Nur et al. 2008, Seavy et al. 2009), volume (Mills et al. 1991, Seavy and Alexander 2011), or structure (Kus 1998, Saab 1999). The results confirmed vegetation is significant for bird occupancy with 15 out of 18 (83%) species' first-year occupancy probability significantly impacted by greenness and 12 out of 15 (80%) with positively relationships. Additionally, the mixed responses from the three species that occur in both riparian and grassland habitat may indicate which species prefer riparian or grassland habitat of the two habitat types.

Greenness was the only occupancy covariate with a significant relationship with most species. However, all but three species were significantly related with at least one covariate, suggesting that recording and including all the covariates in occupancy models is important to not potentially miss an important relationship before evaluating covariate significance for a particular species.

Management recommendations

Remote sensing can provide insightful landscape-level products to evaluate rangeland productivity (Potter 2014), deploy resources more efficiently to key areas (Ford et al. 2017), and track how rangeland boundaries change over time (Sawalhah et al. 2018). Riparian ecosystems within rangelands possess unique challenges, but methods for publicly available data are improving (Shapero et al. 2017). Unfortunately, the effect of management actions on the annual grasslands that dominate rangelands is still difficult to separate from climatic variability (Wylie et al. 2012). However, riparian vegetation is perennial and more stable than its surrounding grasslands. On Tejon Ranch, riparian vegetation composition across different creeks is not significantly impacted by annual precipitation and almost all the difference was explained by abiotic factors (Ratcliff et al. 2018), so the impact of management decisions may more readily be inferred from remote sensing analysis (Wylie et al. 2012).

Most species' occupancy probability was positively impacted by increased woody vegetation cover, so managers should protect existing riparian trees and shrubs and promote their expansion. Species can survive equally as well as in replanted habitat that's reached the mature vegetation structure as natural habitat (Kus 1998). Years since a habitat was restored is a strong predictor of bird populations, and management methods that promote existing and restored habitat can support recovering populations (Gardali et al. 2006). However, abundance on restored plots often doesn't exceed natural plots than restored plots (Gardali et al. 2006), so protecting existing habitat is critical.

Protecting natural habitat in California is a priority as a biodiversity hotspot (Myers et al. 2000), and riparian forests in annual grassland is a key habitat since they perform disproportionately more ecosystem services to species (Sweeney et al. 2004). Fortunately, managers can get many birds with one stone by restoring habitat, putting areas into conservation, while also securing social benefits from ecosystem services, like stabilizing water supplies (Ocampo-Peñuela and Pimm

2015b). Several management goals can be meet by protecting, restoring, and supporting riparian habitat. The Tejon Ranch is uniquely situated to protect its riparian forests in the annual grasslands by putting 90% of its land into conservation. Remote sensing totals and occupancy models will be key tools to better understand how to manage the largest privately-owned conservation area.

ACKNOWLEDGEENTS

I would like to thank Felix Ratcliff, James Bartolome, Luke Macaulay, and Peter Hopkinson for welcoming me into the rangeland group. Peter Hopkinson introduced me to the research group; James Bartolome took me on as one of his honors students; and Luke Macaulay guided me on best practice to manage R scripts, sharing my code for review, and supplied me with lab space to work. Felix's mentorship was invaluable to my completing this project, and everything from data standardization to occupancy modeling to interpreting the results would not have been possible without him. Their constant support and advice made my thesis possible. I am indebted to the Tejon Ranch Conservancy for sharing their remarkable bird observation dataset spanning six years with over 12,000 entries. Without their partnership, I would not have had a project. I would also like to thank Professor Iryna Dronova of the Landscape Architecture department. She taught me almost all I know about remotes sensing and vegetation classification, and she patiently advised me through all the obstacles I faced. Rowen Peterson and Lindsey Schwartz compiled life history trait data and were kind enough to provide it for the species. I enjoyed the company of Veronica Yovovich and Yuling Gao who made long days in the lab better, and whose encouragement helped me persevere. Finally, I would like to thank Patina Mendez, Kurt Spreyer, Leslie McGinnis, and Ellen Plane for teaching the Environmental Sciences senior thesis class and having the patience me to tackle my project in ways that worked best for my workflow and that I work best.

REFERENCES

Blaschke, T. 2010. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing 65:2–16.

Block, W. M., L. A. Brennan, and R. J. Gutiérrez. 1987. Evaluation of guild-indicator species for use in resource management. Environmental Management 11:265–269.

Boswell, A., S. Petersen, B. Roundy, R. Jensen, D. Summers, A. Hulet, and 1 Natural Resource Conservation Service, Monticello, Utah, 84535, USA. 2017. Rangeland monitoring using remote sensing: comparison of cover estimates from field measurements and image analysis. AIMS Environmental Science 4:1–16.

Byrd, K. B., L. E. Flint, P. Alvarez, C. F. Casey, B. M. Sleeter, C. E. Soulard, A. L. Flint, and T. L. Sohl. 2015. Integrated climate and land use change scenarios for California rangeland ecosystem services: wildlife habitat, soil carbon, and water supply. Landscape Ecology 30:729–750.

Chase, M. K., W. B. Kristan III, A. J. Lynam, M. V. Price, and J. T. Rotenberry. 2000. Single Species as Indicators of Species Richness and Composition in California Coastal Sage Scrub Birds and Small Mammals. Conservation Biology 14:474–487.

Daly, C., W. P. Gibson, G. H. Taylor, G. L. Johnson, and P. Pasteris. 2002. A knowledge-based approach to the statistical mapping of climate. Climate Research 22:99–113.

Dronova, I. 2015. Object-Based Image Analysis in Wetland Research: A Review. Remote Sensing 7:6380–6413.

Ehrlich, P. R., D. S. Dobkin, and D. Wheye. 1988. The birder’s handbook: a field guide to the natural history of North American birds: including all species that regularly breed north of Mexico. Simon & Schuster, New York.

Fiske, I., and R. Chandler. 2011. Unmarked: An R package for fitting hierarchical models of wildlife occurrence and abundance. Journal of Statistical Software 43:1–23.

Ford, L. D., H. S. Butterfield, P. A. Van Hoorn, K. B. Allen, E. Inlander, C. Schloss, F. Schuetzenmeister, and M. Tsalyuk. 2017. Testing a Remote Sensing-Based Interactive System for Monitoring Grazed Conservation Lands. Rangelands 39:123–132.

Gardali, T., A. L. Holmes, S. L. Small, N. Nur, G. R. Geupel, and G. H. Golet. 2006. Abundance Patterns of Landbirds in Restored and Remnant Riparian Forests on the Sacramento River, California, U.S.A. Restoration Ecology 14:391–403.

Jeong, S. G., Y. Mo, H. G. Kim, C. H. Park, and D. K. Lee. 2016. Mapping riparian habitat using a combination of remote-sensing techniques. International Journal of Remote Sensing

37:1069–1088.

Katibah, E. F. 1984. A brief history of riparian forests in the Central Valley of California. Pages 23–29 *in* R. E. Warner and K. M. Hendrix, editors. California Riparian Systems: Ecology, Conservation, and Productive Management. University of California Press, California.

Kus, B. E. 1998. Use of Restored Riparian Habitat by the Endangered Least Bell's Vireo (Vireo bellii pusillus). Restoration Ecology 6:75–82.

Lee, M.-B., and J. T. Rotenberry. 2015. Effects of land use on riparian birds in a semiarid region. Journal of Arid Environments 119:61–69.

MacKenzie, D. I., J. D. Nichols, J. E. Hines, M. G. Knutson, and A. B. Franklin. 2003. Estimating site occupancy, colonization, and local extinction when a species in detected imperfectly. Ecology 84:2200–2207.

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. ESTIMATING SITE OCCUPANCY RATES WHEN DETECTION PROBABILITIES ARE LESS THAN ONE. Ecology 83:2248–2255.

Mills, G. S., J. B. Dunning, and J. M. Bates'. 1991. The Relationship between Breeding Bird Density and Vegetation Volume:13.

Moilanen, A. 2002. Implications of empirical data quality to metapopulation model parameter estimation and application. Oikos 96:516–530.

Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent. 2000. Biodiversity hotspots for conservation priorities. Nature 403:853–858.

Nur, N., G. Ballard, and G. r Geupel. 2008. Regional analysis of riparian bird species response to vegetation and local habitat features. The Wilson Journal of Ornithology 120:840–855.

Ocampo-Peñuela, N., and S. L. Pimm. 2015. Elevational Ranges of Montane Birds and Deforestation in the Western Andes of Colombia. PLOS ONE 10:e0143311.

Ocampo-Peñuela, N., and S. L. Pimm. 2015. Bird conservation would complement landslide prevention in the Central Andes of Colombia. PeerJ 3:e779.

Potter, C. 2014. Monitoring the production of Central California coastal rangelands using satellite remote sensing. Journal of Coastal Conservation 18:213–220.

R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Ratcliff, F., J. Bartolome, L. Macaulay, S. Spiegal, and M. D. White. 2018. Applying ecological site concepts and state-and-transition models to a grazed riparian rangeland. Ecology and Evolution 8:4907–4918.

Roberge, J.-M., and P. Angelstam. 2006. Indicator species among resident forest birds – A cross-regional evaluation in northern Europe. Biological Conservation 130:134–147.

Rodewald, P., editor. 2015. The Birds of North American. Ithaca: Cornell Laboratory of Ornithology.

RStudio Team. 2016. RStudio: Integrated Development Environment for R. RStudio, Inc., Boston, MA.

Saab, V. 1999. Importance of Spatial Scale to Habitat Use by Breeding Birds in Riparian Forests: A Hierarchical Analysis 9:18.

Sawalhah, M. N., S. D. Al-Kofahi, Y. A. Othman, and A. F. Cibils. 2018. Assessing rangeland cover conversion in Jordan after the Arab spring using a remote sensing approach. Journal of Arid Environments 157:97–102.

Scheunders, P., D. Tuia, and G. Moser. 2018. Contributions of Machine Learning to Remote Sensing Data Analysis. Pages 199–243 Comprehensive Remote Sensing. Elsevier.

Seavy, N. E., J. H. Viers, and J. K. Wood. 2009. Riparian bird response to vegetation structure: a multiscale analysis using LiDAR measurements of canopy height. Ecological Applications 19:1848–1857.

Seavy, N. E., and J. D. Alexander. 2011. Interactive Effects of Vegetation Structure and Composition Describe Bird Habitat Associations in Mixed Broadleaf–Conifer Forest. Journal of Wildlife Management 75:344–352.

Shapero, M., I. Dronova, and L. Macaulay. 2017. Implications of changing spatial dynamics of irrigated pasture, California's third largest agricultural water use. Science of The Total Environment 605–606:445–453.

Svoray, T., A. Perevolotsky, and P. M. Atkinson. 2013. Ecological sustainability in rangelands: the contribution of remote sensing. International Journal of Remote Sensing 34:6216–6242.

Sweeney, B. W., T. L. Bott, J. K. Jackson, L. A. Kaplan, J. D. Newbold, L. J. Standley, W. C.

Hession, and R. J. Horwitz. 2004. Riparian deforestation, stream narrowing, and loss of stream ecosystem services. Proceedings of the National Academy of Sciences 101:14132–14137.

Tejon Ranch Conservancy. 2013. Conservation Activities and Best Management Practices. Page 121. Tejon Ranch Conservancy, Frazier Park, CA.

Tejon Ranch Corporation. 2017. History: The historical timeline takes us through more than two centuries of highlights that helped shape the Tejon Ranch that we know today. http://tejonranch.com/the-company/corporate-values/history/.

Tingley, M. W., M. S. Koo, C. Moritz, A. C. Rush, and S. R. Beissinger. 2012. The push and pull of climate change causes heterogeneous shifts in avian elevational ranges. Global Change Biology 18:3279–3290.

United States Department of Agriculture. 2012. NAIP Digital Ortho Photo Image. United States Department of Agriculture Farm Service Agency Aerial Photography Field Office, Salt Lake City, Utah.

USGS EarthExplorer. 2019. NAIP Aerial Imagery. https://earthexplorer.usgs.gov/.

Wu, M., X. Zhao, Z. Sun, and H. Guo. 2019. A Hierarchical Multiscale Super-Pixel-Based Classification Method for Extracting Urban Impervious Surface Using Deep Residual Network From WorldView-2 and LiDAR Data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 12:210–222.

Wylie, B. K., S. P. Boyte, and D. J. Major. 2012. Ecosystem Performance Monitoring of Rangelands by Integrating Modeling and Remote Sensing. Rangeland Ecology & Management 65:241–252.