# **Appendix H**

# **Terrestrial Species Stressor Monitoring Reports**



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## **Evaluating mammalian diversity in the Mojave Desert and Great Valley ecoregions of California using camera trap surveys**

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## **Executive Summary**

- **1.** In response to the drought State of Emergency declared in 2014, California's Department of Fish and Wildlife (CDFW) prioritized monitoring of wildlife populations and their associations with drought stressors and habitat features. As part of this effort, CDFW initiated Terrestrial Species Stressor Monitoring (TSM) surveys in 2016 to collect baseline data on wildlife species in the Mojave Desert and Great Valley ecoregions. In this report, we present our analysis of camera trap data from the 2016-17 TSM surveys. For each ecoregion, our objectives were to estimate the occupancy and richness of terrestrial mammal species weighing >0.5kg and to evaluate community and speciesspecific responses to climate and habitat variables.
- **2.** We deployed camera traps at 320 and 265 sites across the Mojave Desert and Great Valley ecoregions, respectively, in the springs of 2016 and 2017. We used this camera trap data, in combination with multi-species hierarchical occupancy models, to estimate and evaluate mammal distributions.
- **3.** Sixteen and 22 species of terrestrial mammals (>0.5kg) were photographed in the Mojave Desert and Great Valley ecoregions, respectively, with camera-specific estimates of species richness ranging from  $0 - 13$ . Black-tailed jackrabbits ( $\psi = 0.73$ ) and kit foxes ( $\psi$  $= 0.34$ ) had the highest estimated occupancies in the Mojave, whereas coyotes ( $\psi = 0.49$ ) and raccoons ( $\psi$  = 0.45) had the highest estimated occupancies in the Great Valley. The mammal community in the Mojave tended to be positively associated with elevation and negatively associated with mean temperature and distance to pinyon juniper forest. The mammal community in the Great Valley, alternatively, tended to be positively associated with crop diversity and negatively associated with natural vegetative cover.
- **4.** Our results suggest projected increases in temperature will negatively influence the Mojave Desert's mammal community, and consequently, that the protection of climate refugia (e.g., high elevations, shaded areas, and permanent water sources) may be an increasingly important conservation strategy. This is particularly true for some species in the region, like deer, Audubon's cottontail, and bobcat, which appeared to be more vulnerable to projected climate changes than species like the kit fox.
- **5.** In the Great Valley, our results suggest that the remnant mammal community is adept at accessing resources and surviving in this human-modified, agricultural landscape. Working with landowners to diversify agricultural practices and maintain habitat heterogeneity is important, however, as heterogeneity within and among croplands positively influences the mammal community.

**6.** Biodiversity loss, climate change, and anthropogenic pressures on ecosystems are accelerating. The infrastructure required to monitor changes in biodiversity and species' vulnerability to stressors, however, is often lacking. Our analysis demonstrates the utility of camera traps and multi-species occupancy models for monitoring terrestrial mammals, including elusive species. Expanding beyond our snapshot in time however, requires long-term data. With longer-term data (e.g.,  $>$  5 years), we can develop an understanding of the processes occurring within these ecoregions including trends in species' occupancy and the influence of climate, environment, and humans on mammal communities. This information in turn, would allow managers to track, improve, and adapt management actions aimed at addressing the loss of wildlife populations.

#### **Introduction**

Following the drought State of Emergency declared in 2014, the California Department of Fish and Wildlife (CDFW) was tasked with implementing projects that respond to drought conditions. In order to effectively design and implement these projects, however, additional information on many wildlife populations is needed. Consequently, CDFW has prioritized monitoring wildlife populations including their distributions, abundances, vulnerability to drought stressors, and relationships to other habitat features.

The spatial distributions of wildlife are shaped by a diversity of biotic and abiotic factors. One such factor is water availability. In California, wildlife populations are generally positively associated with the presence of water (Schoenherr 1992). Bobcats (*Lynx rufus*), for example, are positively associated with stream density and riparian areas (Markovchick-Nicholls et al. 2008; Broman et al. 2014), the persistence of bighorn sheep (*Ovis canadensis*) is positively correlated with the presence of dependable springs (Epps et al. 2004), and striped skunks (*Mephitis mephitis*) often select for wetland habitat (Lariviére & Messier 2000). In southwestern USA, including the Mojave Desert, artificial water catchments (hereafter "guzzler") may also influence the distributions of wildlife because they provide permanent or semi-permanent surface water in areas where natural water is scarce (Bleich 1992; Cutler and Morrison 1998; Bleich et al. 2010; Larsen et al. 2012).

The influence of vegetative cover on the occurrence of wildlife, alternatively, is generally species-specific. Black-tailed jackrabbits (*Lepus californicus*) and kit foxes (*Vulpes macrotis*), for example, favor arid and semi-arid grasslands and shrublands (McGrew 1979; Wilson & Ruff 1999), whereas red foxes (*Vulpes vulpes*), California ground squirrels (*Otospermophilus beecheyi*), and opossums (*Didelphis virginiana*) are able to exploit a diversity of habitats (Whitaker 1980; Pérez-Hernandez et al. 2016). Landscape or habitat heterogeneity may also play a role in determining species' distributions. Species richness and landscape heterogeneity tend to be positively related, as heterogeneous landscapes provide more niches and resources (e.g., food, nest sites, den sites, and cover) than homogenous landscapes (MacArthur and MacArthur 1961; Rosenzweig 1995; Benton et al. 2003; Green et al. 2005).

Human disturbance fragments ecosystems, alters animal movements, and increases human activity and persecution, making it an additional driver of wildlife distributions (Forman & Alexander 1998; Crooks 2002; Ordeñana et al. 2010). In southern California, for example,

native carnivore richness was negatively associated with urban intensity (Ordeñana et al. 2010). In some instances, however, human disturbance can have a minimal or positive influence of species' distributions, as has been found with generalist carnivores like coyotes (*Canis latrans*), gray foxes (*Urocyon cinereoargenteus*), striped skunks, opossums, and raccoons (*Procyon lotor*; Crooks 2002; Ordeñana et al. 2010; Goad et al. 2014; Kowalski et al. 2015; Wang et al. 2015).

Lastly, climatic variables often influence species' distributions (Grinnell 1917). Warming temperatures over the past 30 years have influenced the function and composition of many ecological communities and, in turn, the distributions of many species (Walther et al. 2002). When climate change decreases habitat quality, the result may be local extinctions or a decrease in the number of available habitat patches, which in turn, may lead to the extirpation of a metapopulation (Hanski 1999). Bighorn sheep populations in hotter, drier environments, for example, are more likely to go extinct (Epps et al. 2004). Kit foxes, alternatively, have adaptations for reducing heat loads and conserving water (Cypher 2003), and consequently, may be more tolerant of increases in temperatures and decreases in precipitation. Climate may also influence a species' probability of detection. Increased movements of mule deer (*Odocoileus hemionus*), for example, were associated with decreased temperatures and increased weekly precipitation (Nicholson et al. 1997).

In 2016, CDFW began a coordinated monitoring process by initiating Terrestrial Species Stressor Monitoring (TSM) surveys. TSM surveys collected baseline data on a wide variety of common wildlife species throughout the drought-stricken Mojave Desert (MD) and Great Valley (GV) ecoregions of California. Survey methods included automated sound recordings, visual encounter surveys, rapid habitat assessments, and camera trap surveys. We began our analysis of the TSM surveys by focusing on data collected via camera traps, a non-invasive survey method that targets medium- to large-sized mammals. We had the specific objectives of: (1) estimating the occupancy and richness of terrestrial mammal species weighing >0.5kg in the MD and GV ecoregions; and (2) elucidating community and species-specific responses to ecological variables. Our overarching goal was to provide a better understanding of how ecological traits, including both climate and habitat features, are influencing mammal distributions and richness in the MD and GV ecoregions. This information will help guide the design and implementation of future drought-response projects.

#### **Methods**

#### *Camera trap survey and photo identification*

Personnel from CDFW deployed Reconyx PC900 cameras at 320 and 265 sites across the MD and GV ecoregions of California, respectively, between March – August 2016 and March – June 2017 (Fig. 1). To guide the placement of cameras, CDFW calculated the total cover of key lifeforms within each ecoregion (Table 1). For each ecoregion, they then selected a spatiallybalanced random sample of hexagons, stratified by lifeform, from the USDA Forest Inventory and Analysis program's hexagon grid (hexagon radius is  $\sim$  2.6 km) and deployed 1-3 cameras, spaced by 1-2 km, within each hexagon. Exact survey locations within the hexagon were also stratified by lifeform. To do this, CDFW created a finer scale grid of ~2400 points separated by 100m within each hexagon and calculated the lifeform at every point within the fine-scale grids.

Cameras were cable-locked onto T-posts that were securely placed in the ground. If Tpost mounting was not possible, cameras were secured to a tree or shrub bole. To maximize detection probabilities, a 1-kg salt lick, 500 ml of oatmeal-peanut butter mixture, and 150 g of fishy cat food were placed on the ground near the center of the camera's field of view. When possible, CDFW personnel positioned cameras to face north in order to avoid direct sunlight and potential false triggers. They programmed cameras to take three photos at each trigger event with a delay of one second between trigger events. Each camera was deployed for 20 to 66 days ( $\bar{x}$  = 34,  $SD = 7.6$ ) at sites in the MD ecoregion and  $9 - 37$  days ( $\bar{x} = 29$ ,  $SD = 3.5$ ) at sites in the GV ecoregion.

Two observers identified photographic detections to the species-level, unaware of how the other observer had classified photos. Observers only recorded a species once during each 24 hr period that a camera was deployed (e.g., a bobcat photographed 5 times over 24-hrs at camera *j* would result in a single data entry). We then determined when there were mismatches between observers in species identification, and had a third individual decide on the final classification (referred to as 'reconciled data'). We used the reconciled data for all analyses. To evaluate the influence that observer bias may have on estimates of occupancy (Table 4), we carried out a preliminary analysis where we compared occupancy estimates based on identifications by observer 1 vs. observer 2. Estimates did not differ between observers (i.e., estimates' 95% credible intervals overlapped), suggesting there were minimal discrepancies between observers in their classification of photos and in the future, the data entry process can be streamlined by using only a single observer.

#### *Covariates*

We hypothesized that climate, elevation, slope, water accessibility, vegetative cover, and human disturbance could influence the occupancy and detection patterns of terrestrial mammalian species. To represent climate, we downloaded 4-km resolution precipitation and temperature data from PRISM (Prism Climate Group 2018) for March – August 2016 and March – June 2017 (i.e., the study periods). We used ArcMAP 10.4.1 (ESRI, Redlands, CA, USA) to determine the mean precipitation, temperature, and maximum temperature at each camera location during the respective survey period. We then used the 30-m resolution National Elevation Dataset (USGS 2016) to calculate and extract slope and elevation values for each site location in ArcMAP.

To evaluate water accessibility in the GV, we used Point Blue's Automated Water Tracking System (http://data.pointblue.org/apps/autowater/), which provides up-to-date assessments of the distribution of open surface water in the Central Valley. Specifically, we downloaded data for the study periods and created a single layer for each year indicating whether water was present at some point during the sampling period or not. We then measured the distance from each camera location to the nearest water source. In the MD, we used Global Surface Water Explorer (Pekel et al. 2016) to identify permanent and seasonal water sources. Again, we measured the distances from each camera to the nearest water source. For the MD, we also included a categorical variable indicating whether the camera was located by a guzzler.

We then placed a buffer radius of 1km around the camera locations. A 1-km buffer size provides information on the general conditions surrounding the camera that is applicable to our suite of variably sized species. We used CDFW's Vegetation Classification and Mapping Program (vegCAMP; https://www.wildlife.ca.gov/Data/VegCAMP) data to calculate percent cover of natural vegetation at the GV sites, percent cover of desert scrub at the MD sites, and distance to the nearest forested area for all sites. In the Mojave where forest cover is limited, forested areas consisted solely of pinyon-juniper woodlands. We then used USDA's cropscape data (USDA CropScape 2016) to calculate the number of crop types within the buffered areas in the GV. Lastly, we estimated human disturbance by extracting values from the U.S. Geological Survey's human footprint model [\(https://sagemap.wr.usgs.gov/humanfootprint.aspx\)](https://sagemap.wr.usgs.gov/humanfootprint.aspx).

To account for variation in the probability of photographing mammals, we explored maximum temperature, precipitation, human disturbance, and bait status as covariates for detection. Bait status was a categorical variable indicating whether a camera station's bait was disturbed at the end of the sampling period (1) or not (0). In the MD, we also included a categorical variable indicating whether the camera was located by a guzzler (1) or not (0).

### *Multi-species occupancy modeling*

We used multi-species hierarchical occupancy models (Dorazio and Royle 2005), analyzed under a Bayesian framework, to estimate and evaluate the distributions and richness of terrestrial mammal species weighing >0.5kg. Multi-species models link species-specific detection and occupancy using community-level hyper-parameters (Zipkin et al. 2010; Iknayan et al. 2014). These hyper-parameters specify the mean response and variation among species within the community to a respective covariate, thus permitting composite analyses of both communities and individual species (Kéry and Royle 2008). The models also facilitate estimates of species richness (i.e., number of species in the community and at each camera).

To discern non-detection from true absence, we treated each trap day as a repeat survey at a particular camera. We assumed occurrence and detection probabilities differed by species and year (2016 = 1, 2017 = 0), and were influenced by ecological covariates. In the MD ecoregion, we assessed two model structures for occupancy  $(\psi)$  and detection  $(p)$ :



Model 2:  $\psi$ (water, scrub, elevation, pinyon-juniper, year),  $p$ (human disturbance, precipitation, bait status, year)

In the GV ecoregion, we also assessed two model structures for occupancy and detection:

- Model 1:  $\psi$ (water, precipitation, temperature, natural cover, year),  $p$ (crop diversity, maximum temperature, bait status, year)
- Model 2:  $\psi$ (forest, crop diversity, latitude, year), *p*(human disturbance, precipitation, bait status, year)

We incorporated covariates into the model linearly on the logit-probability scale (Zipkin et al. 2010) and ensured models did not include covariates that were correlated. We estimated posterior distributions of parameters using Markov Chain Monte Carlo implemented in JAGS (Plummer 2011) through program R. We generated three chains of 50,000 iterations thinned by 50 and used uninformative priors.

Next, we projected our model results across each of the ecoregions to estimate speciesspecific probabilities of occupancy and species richness. We used these model-based inferences, which rely on covariate associations, to ensure our estimates were representative of the ecoregions and not just sampled locations (Gregoire 1998; Furnas and McGrann 2018). To project our results, we overlaid a 1km x 1km grid onto the two ecoregions and calculated covariate values for each grid cell. Using these covariate values and the multi-species occupancy modeling output (e.g., community- and species-level beta values for the model covariates), we projected occupancy probabilities across the MD and GV ecoregions for each detected species. We also summed species' occupancy probabilities within each of the grid cells to generate estimates of species richness at the 1km x 1km scale.

#### **Results**

In the MD ecoregion, we photographed 16 and 13 species of mammals over 7,402 and 3,467 trap nights in 2016 and 2017, respectively (Table 2). Black-tailed jackrabbits and kit foxes were the most frequently detected species in both years (Table 2). Among the species photographed the least often were the California ground squirrel, opossum, raccoon, striped skunk, and spotted skunk (*Spilogale gracilis*; Table 2).

In the Great Valley (GV) ecoregion, we photographed 17 and 20 species of mammals over 2,570 and 5,171 trap nights in 2016 and 2017, respectively (Table 2). The most photographed species was the black-tailed jackrabbit in both years (Table 2). Conversely, we photographed gray fox the least often in 2016 and American mink and mountains lions the least often in 2017 (Table 2).

#### *Multi-species occupancy modeling*

Black-tailed jackrabbits ( $\psi$  = 0.72), kit foxes ( $\psi$  = 0.36), and coyotes ( $\psi$  = 0.33) had the highest estimated occupancies in the MD ecoregion (Fig. 2). Many species in the MD, conversely, had low estimates of occupancy due to their limited numbers of photographic detections (Table 2; Fig. 2, Appendix S2). Species' occupancy probabilities varied among the key lifeforms, but the majority of species (i.e., 75%) were most likely to occupy upper Mojave desert scrub (Appendix S1). Among the covariates, mean temperature had the greatest influence on community-level occupancy in the MD, with occupancy decreasing as mean temperature increased (Table 3). This negative relationship was most evident for species like deer, bobcat, and Audubon's cottontail (*Sylvilagus audubonii*; Fig. 3; Appendix S2). The kit fox was the only species positively associated with temperature (Fig. 3; Appendix S2). Community-level occupancy in the MD was also related to elevation and distance to pinyon-juniper woodlands, with occupancy tending to increase at higher elevations close to pinyon-juniper habitat (Table 3). The positive influence of elevation also held true for individual species like the badger (*Taxidea taxus*), Audubon's

cottontail, bobcat, gray fox, and deer (Fig. 3; Appendix S2). The presence of guzzlers had a weak effect at the community-level, but at the species-level was strongly and positively associated with the occupancy of Audubon's cottontail, bighorn sheep, bobcat, coyote, and gray fox (Fig. 3; Appendix S2). Species' detection probabilities also tended to be positively associated with the presence of a guzzler (Appendix S2). Lastly, precipitation also had a weak effect at the community-level, but was strongly and negatively related to coyote occupancy, and strongly and positively related to Audubon's cottontail and mule deer occupancy (Appendix S2).

Coyotes ( $\psi$  = 0.49) and raccoons ( $\psi$  = 0.45) had the highest estimated occupancies in the GV ecoregion (Fig. 2). Thirteen of the 22 photographed species, conversely, had occupancy probabilities  $< 0.10$  (Fig. 2). Similar to the MD, this result was a consequence of species having a limited number of photographic detections (Table 2). Among the key lifeforms, human-altered lifeforms like rice fields and orchards/vineyards had the highest mean estimated occupancies for over half of the species (Appendix S1). We note, however, that these lifeforms encompassed a limited number of sampling sites (Table 1). The 95% credible intervals overlapped zero for all community-level hyper-parameters in the GV except natural cover, where species' occupancy probabilities tended to decrease as natural cover increased (i.e., percent natural cover within a 1 km buffered area surrounding the camera trap; Table 3). This was particularly true for opportunistic mammals like California ground squirrel and red fox (Appendix S2). Among the remaining covariates, we found that community-level occupancy tended to increase with crop diversity in the GV and that community-level detection tended to decrease with human disturbance and again, increase with crop diversity (Table 3). Latitude had only a weak, positive influence on community-level occupancy, but at the species-level had a strong, negative influence on the occupancy of, for example, badger, kit fox, and Audubon's cottontail, and a strong, positive influence on the occupancy of, for example, deer, raccoon, and opossum (Fig. 4; Appendix S2). Similarly, precipitation only had a weak influence at the community-level, for both occupancy and detection, but often had a strong influence at the species-level (Fig. 4; Appendix S2).

The distributions of high and low occupancy value areas varied among species (examples shown in Fig. 5, 6). For example, areas with high occupancy values for badger were patchily distributed throughout the MD whereas areas with high occupancy values for kit fox were fairly contiguous in the central part of the ecoregion (Fig. 5). Projected estimates of mammal richness ranged from 0-9 in the MD with a mean of 2.4  $(SD = 1.13)$ , and 2-13 in the GV with a mean of 6.3 (*SD* = 2.39; Fig. 7). In the MD, estimated species richness appeared to be greatest in the mountainous regions where it was cooler, such as within the Mojave National Preserve. Over 70% of the area with the greatest estimated species richness fell within National Park Service boundaries (Fig. 7). In the GV, species richness appeared to be greatest at higher latitudes (Fig. 7).

#### **Discussion**

The California Department of Fish and Wildlife (CDFW) developed Terrestrial Species Stressor Monitoring (TSM) surveys with the goal of collecting baseline data on a wide variety of wildlife species throughout the Mojave Desert and Great Valley ecoregions of California. Having reliable estimates of wildlife populations and methods for detecting wildlife loss are vital in making

informed conservation and management decisions (Zipkin et al. 2010). Methods for directly or indirectly monitoring population abundance (e.g., mark-recapture), however, are often time and cost-intensive, particularly for large-scale or long-term monitoring (Bailey et al. 2004). Additionally, abundance estimation generally focuses on a single species. A viable alternative for managers involved in large-scale, multi-species monitoring programs is occupancy, or the probability that a landscape unit is occupied by a species of interest (Bailey et al. 2004; MacKenzie et al. 2005). By analyzing data from the camera trap surveys in an occupancymodeling framework, we were able to help achieve TSM goals by generating baseline estimates of occupancy for 16 and 22 mammalian species in the Mojave Desert and Great Valley ecoregions, respectively, and empirically evaluate how these estimates were influenced by climate and habitat features. These efforts could form the foundation of a long-term monitoring program and be used to more effectively design said program (e.g., power analyses to determine number of sampling locations and sampling duration). Long-term monitoring is vital as it would allow managers to quantify and detect trends in occupancy, changes in habitat use, and drivers of local colonization and extinction (MacKenzie et al. 2005). This information, in turn, would have innumerable applications including the design of effective and efficient wildlife management strategies, the mitigation of large-scale ecological stressors, and the development of land use plans that minimize adverse impacts on biodiversity.

In addition to estimating occupancy and species richness, we also evaluated potential drivers of these parameters. In the Mojave Desert ecoregion, our results elucidated the influence of artificial water catchments (i.e., guzzlers) and climate on mammal distributions. Water is a critical resource to wildlife populations, particularly in arid ecosystems around the world (Larsen et al. 2012). We found that the occupancy probabilities of close to half the detected species in the Mojave Desert, as well as the probability of photographing these species, was greater at guzzler sites. Some of these species include, for example, bighorn sheep, Audubon's cottontail, and gray fox. Previous research has also found that ungulates (e.g., deer and bighorn sheep) and mediumsized mammals use these artificial water sources, as well as avian species, small mammals, and a variety of herptofauna (Smith and Henry 1985; Bleich 1992; Cutler and Morrison 1998; Bleich et al. 2010). Our results suggest that guzzlers are a viable and important conservation option in the Mojave, and may become increasingly important as habitats continue to be modified by human development (i.e., where wildlife and humans must compete for water) and climate change (Krausman et al. 2006).

Temperatures in southern California deserts are projected to increase 2° C by 2050 (Snyder and Sloan 2005). Our results suggest this will negatively affect the occupancy of medium to large-sized mammals in the Mojave. We found mean temperature was negatively associated with community- and species-level  $(n = 6)$  occupancy, and that elevation, which was highly correlated with temperature  $(r = -0.82)$ , was positively associated with community- and species-level  $(n = 7)$  occupancy. There was only one species, the kit fox, which appeared to be well adapted for projected climate changes as their distributions were positively associated with temperature, negatively associated with elevation, and weakly and negatively associated to both precipitation and the presence of a guzzler. For other Mojave mammals, however, extreme heat and drought resulting from climate change may exceed survival thresholds (Bachelet et al. 2016). Deer, Audubon's cottontail, and bobcat, for example, tended to be negatively associated with temperature and positively associated with water (i.e., precipitation and guzzlers). These species

may be approaching their physiological thresholds in the Mojave, making them vulnerable to future climate change in the region (Serra-Diaz et al. 2014). Based on these results, we recommend protecting climate refugia including permanent water sources (e.g., guzzlers), shady valleys, high elevations, and north facing slopes in order to help mitigate hypothesized impacts of climate change (Bachelet et al. 2016). We also recommend protecting upper Mojave Desert scrub, which covers just 11.5% of the ecoregion, as 12 of the 16 detected mammals had their highest mean estimated occupancies within this lifeform.

In the Great Valley, one of the most intensely developed agricultural regions in the world (Nelson et al. 2003), heterogeneity within and among croplands had a larger influence on mammal occupancy than did climate. The generally positive influence of crop diversity on mammal occupancy and detection supports the heterogeneity hypothesis, which states that diversity is maximized in heterogeneous landscapes, both farmed and natural, as they provide more niches and complementary resources than homogenous landscapes (MacArthur and MacArthur 1961; Rosenzweig 1995; Benton et al. 2003). Thus, in the Great Valley, working with landowners to diversify agricultural practices (e.g., crop diversity, cultivation practices, rotation planning) may greatly benefit the mammal community. In addition to the influence of crop diversity, we also found that the mammal community was negatively related to natural vegetative cover (i.e., grasslands, shrublands, forests, riparian areas, and wetlands). Supporting this trend, we found 15 of the 22 detected species had their highest mean estimated occupancies in a human-altered lifeform (i.e., crop/fallow fields, orchards/vineyards, or rice fields). While this result may seem surprising, it is not unexpected. Many of the species detected in the Great Valley are opportunistic feeders often associated with humans, such as striped skunks, Virginia opossums, raccoons, and California ground squirrels, or they are species known to be behaviorally plastic and adaptable, like coyotes, bobcats, and mule deer (Crooks 2002; Markovchick-Nichols et al. 2008; Ordeñana et al. 2010; Goad et al. 2014; Kowalski et al. 2015; Wang et al. 2015). In such an intensely developed region, it is likely that mammals sensitive to human disturbance have become locally extinct or rare, leaving behind species adept at accessing resources (e.g., food, cover, den sites) and surviving in agricultural, human-modified landscapes.

Biodiversity loss, climate change, and anthropogenic pressures on ecosystems are accelerating (Walther et al. 2002; Alkemade et al. 2009; Butchart et al. 2010). The infrastructure required to monitor changes in biodiversity and species' vulnerability to stressors, however, is often lacking (Ahumada et al., 2013). Our research demonstrates the utility of camera traps for monitoring terrestrial mammals; they provide records of detections for a wide diversity of species, living in a broad range of ecosystems, at any time of day. We also demonstrate the strength of multi-species hierarchical occupancy models (Dorazio and Royle 2005; Iknayan et al. 2014). Unlike traditional community analyses, our multi-species approach allowed us to: (1) account for observation error (i.e., detection probability) so results can be comparable across species, sites, and, in the future, years; (2) retain species identity; and (3) share data across species, permitting comprehensive assessments of the mammal communities and individual species (Zipkin et al. 2010). Furthermore, many species in our study had low detection probabilities. By integrating data across species, we were able to estimate occupancy probabilities for these rare and elusive species and properly account for them in our estimates of species richness.

We encourage continued, systematic camera trap surveys in both the Mojave Desert and Great Valley ecoregions such that results will expand beyond this snapshot in time. With multiyear data, we can estimate trends in occupancy and evaluate how water availability, climate, vegetation, and human disturbance are influencing mammal communities (MacKenzie et al. 2005; Ahumada et al. 2013). This information would allow policy makers and managers to then track, improve, and adapt policies and management actions aimed at addressing the loss of wildlife populations at both local and landscape scales (Butchart et al., 2010).

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### **Supplementary Materials**

**Appendix S1.** Mammal species' mean occupancy, and 95% credible intervals, within each of the major habitat strata of the A) Mojave Desert and B) Great Valley ecoregions, 2016-17. The habitat with the largest estimated occupancy for each species is highlighted

**Appendix S2.** Species names and mean and 95% credible intervals (95% CI) for estimates of species-specific probabilities of occurrence, detection probability (for survey duration), and covariate effects on occupancy (PSI) and detection (P) in the Mojave Desert and Great Valley ecoregions of California, 2016-17. We present results from a) model 1 in the MD, b) model 2 in the MD, c) model 1 in the GV, and d) model 2 in the GV. We highlighted covariate effects that did not overlap 0.0.

**Table 1.** The number of cameras (*n*) deployed in each of the key lifeforms of the Mojave Desert (A) and Great Valley (B) ecoregions of California, 2016-2017, and the percent coverage (% cover) of each lifeform within the respective ecoregion.

# **A.**



# **B.**



	Scientific name	Mojave Desert					<b>Great Valley</b>				
Common name		$2016 (n = 217)$		$2017 (n = 103)$		<b>Both</b>	2016 $(n = 85)$		$2017 (n = 180)$		<b>Both</b>
		# det.	Naïve $\Psi$	# det.	Naïve $\Psi$	$\Psi$	#	Naïve		Naïve	
							det.	$\Psi$	# det.	$\mathbf{U}$	$\Psi$
Ringtail	<b>Bassariscus</b> astutus	$---$	---	$---$	$---$	---	---	$---$	$\overline{7}$	0.02	0.01
Coyote	Canis latrans	211	0.34	95	0.28	0.33	82	0.41	178	0.42	0.49
Elk	Cervus canadensis	---	---	---	---	---	14	0.02	$---$	$---$	0.01
Opossum	Didelphis virginiana	2	0.005	$---$	$---$	0.003	40	0.12	199	0.23	0.20
Wild Burro	Equus asinus	18	0.02	74	0.05	0.03	$---$	---	---	---	---
Common porcupine	Erethizon dorsatum	$---$	---	---	$---$	$---$	$---$	$---$	$\tau$	0.02	0.02
Black-tailed jackrabbit	Lepus californicus	1106	0.68	730	0.77	0.72	242	0.32	615	0.36	0.34
<b>Bobcat</b>	Lynx rufus	107	0.17	88	0.22	0.25	31	0.13	57	0.09	0.11
Striped skunk	Mephitis mephitis	$\overline{4}$	0.004	---	$---$	0.002	56	0.34	272	0.40	0.41
American mink	Mustela vison	---	---	---	---	---	$---$	---	1	0.01	0.02
Mule deer	Odocoileus hemionus	92	0.07	32	0.03	0.06	104	0.22	279	0.35	0.32
CA ground squirrel	Otospermophilus beecheyi	1	0.005	$---$	$---$	0.01	68	0.08	266	0.17	0.14
Rock squirrel	Otospermophilus variegatus	10	0.009	---	$---$	0.01	$---$	$---$	---	---	---
Bighorn sheep	Ovis canadensis	68	0.03	57	0.05	0.04	$---$	$---$	$---$	---	---
Raccoon	Procyon lotor	3	0.005	$---$	$---$	0.004	151	0.29	330	0.51	0.45
Mountain lion	Puma concolor	---	---	$- - -$	---	---	$---$	---	3	0.01	0.01
Western gray squirrel	Sciurus griseus	$---$	---	---	$---$	---	4	0.03	93	0.09	0.09
Fox squirrel	Sciurus niger	$---$	---	---	$---$	---	8	0.05	18	0.06	0.07
Spotted skunk	Spilogale gracilis	$\overline{7}$	0.03	3	0.01	0.03	---	$---$	$---$	---	$---$
Wild Boar	Sus scrofa	$---$	---	---	---	---	$---$	---	14	0.02	0.01
Audubon's cottontail	Sylvilagus audubonii	485	0.22	196	0.24	0.25	170	0.18	447	0.24	0.22
Brush rabbit	Sylvilagus bachmani	$---$	---	$---$	$---$	$---$	8	0.03	$---$	$---$	0.02
American badger	Taxidea taxus	45	0.12	28	0.17	0.24	$\overline{7}$	0.03	9	0.04	0.06
Gray fox	Urocyon cinereoargenteus	48	0.06	47	0.07	0.09	$\overline{2}$	0.01	40	0.03	0.03
Kit fox	Vulpes macrotis	380	0.45	226	0.34	0.36	11	0.03	20	0.02	0.02
Red fox	<i>Vulpes vulpes</i>	$---$	---	$---$	$---$	$---$	35	0.05	12	0.03	0.04

**Table 2**. Mammal species detected during TSM 2016-17 camera trap surveys in the Mojave Desert and Great Valley ecoregions, their numbers of detections (# det.), naïve occupancy estimates (naïve  $\psi$ ), and estimates of occupancy across both years.

**Table 3.** Mean  $(\bar{x})$  and 95% credible interval estimates of the community-level hyperparameters hypothesized to influence the probability of occupancy and detection of terrestrial mammal species in the (A) Mojave Desert and (B) Great Valley ecoregions of California, 2016-2017.



B.

A.



Table 4. The total number of detections, based on observer 1 vs. observer 2, of each mammal species photographed during TSM 2016 camera trap surveys in the Mojave Desert (A) and Great Valley (B), California, 2016. The total number of detections is the sum of the number of days during which the species was photographed at each camera. The number of differences is the number of discrepancies between observer 1 and observer 2 in their camera-specific recordings of detections (e.g., if observer 1 recorded a coyote on 5 days at camera X and 2 days at camera Y whereas observer 2 recorded a coyote on 2 days at camera X and 5 days at camera Y, the total number of observations would be 7 for both observers but the number of differences would be 6).





#### **B.**



Figure 1. Camera traps deployed in the Mojave Desert and Great Valley ecoregions of California, 2016 – 2017, as part of the Terrestrial Species Stressor Monitoring surveys.



**Figure 2.** Mean occupancy probabilities for mammal species (> 0.5kg) in the A) Mojave Desert  $(n = 320 \text{ sites})$  and B) Great Valley ( $n = 265 \text{ sites}$ ) ecoregions of California, 2016-17. A.



Mojave Desert Ecoregion





**Figure 3.** Standardized beta coefficients, and 95% credible intervals, for the influence of A) guzzler classification, B) mean temperature, C) slope, and D) elevation on species' probabilities of occupancy during camera trap surveys in the Mojave Desert ecoregion of California, 2016-17.





**Figure 4.** Standardized beta coefficients, and 95% credible intervals, for the influence of A) precipitation, B) crop diversity, and C) latitude on species' probabilities of occupancy during the TSM 2016-2017 camera trap surveys in the Great Valley ecoregion of California.



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**Figure 5.** Projected occupancy probabilities across the Mojave Desert ecoregion of California, 2017, for A) black-tailed jackrabbits (*Lepus californicus*), B) kit fox (*Vulpes macrotis*), C) coyote (*Canis latrans*), and D) American badger (*Taxidea taxus*). Note that the occupancy scales differ among species.



Figure 6. Projected occupancy probabilities across the Great Valley ecoregion of California, 2017, for A) coyotes (*Canis latrans*), B) raccoons (*Procyon lotor*), C) striped skunks (*Mephitis mephitis*), D) black-tailed jackrabbits (*Lepus californicus*), and E) mule deer (*Odocoileus hemionus*). Note that the occupancy scales differ among species.





**Figure 7.** Estimated mammal richness across the A) Mojave Desert and B) Great Valley ecoregions of California.



A.





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**Appendix S1a.** Mammal species' mean occupancy, and 95% credible intervals, within each of the major habitat strata of the Mojave Desert ecoregion, 2016-17. The habitat with the largest estimated occupancy for each species is highlighted





**Appendix S1b.** Mammal species' mean occupancy, and 95% credible intervals, within each of the major habitat strata of the Great Valley ecoregion, 2016-17. The habitat with the largest estimated occupancy for each species is highlighted.





**Appendix S2a.** Species names and mean and 95% credible intervals (95% CI) for estimates of species-specific probabilities of occurrence, detection probability (for survey duration), and covariate effects on occupancy (PSI) and detection (P) in the Mojave Desert ecoregion of California, 2016-17. Results are presented for model 1; covariate effects that did not overlap 0.0 are highlighted.






**Appendix S2b.** Species names and mean and 95% credible intervals (95% CI) for estimates of species-specific probabilities of occurrence, detection probability (for survey duration), and covariate effects on occupancy (PSI) and detection (P) in the Mojave Desert ecoregion of California, 2016-17. Results are presented for model 2; covariate effects that did not overlap 0.0 are highlighted.







**Appendix S2c.** Species names and mean and 95% credible intervals (95% CI) for estimates of species-specific probabilities of occurrence, detection probability (for survey duration), and covariate effects on occupancy (PSI) and detection (P) in the Great Valley ecoregion of California, 2016-17. Results are presented for model 1; covariate effects that did not overlap 0.0 are highlighted.







**Appendix S2d.** Species names and mean and 95% credible intervals (95% CI) for estimates of species-specific probabilities of occurrence, detection probability for survey duration, and covariate effects on occupancy (PSI) and detection (P) in the Great Valley ecoregion of California, 2016-17. Results are presented for model 2; covariate effects that did not overlap 0.0 are highlighted.







## **An evaluation of avifaunal diversity in California's Great Valley**

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# **Executive Summary**

- **1.** Reconciliation ecology focuses on modifying human-dominated landscapes to maximize their ability to support wildlife, recognizing that wildlife habitat can be improved and expanded without losing human habitat. This approach may be applicable to songbird management in the Great Valley ecoregion of California, an intensely modified agricultural area. Developing management actions aimed at reconciling the Great Valley for a specific songbird of interest or native songbird diversity, however, requires reliable estimates and evaluations of species distributions and richness. In this study, we aimed to help provide this information using songbird data collected as part of California Department of Fish and Wildlife's Terrestrial Species Stressor Monitoring surveys.
- **2.** We deployed automated recorders at 263 sites across the Great Valley ecoregion between March and July of 2016 and 2017. We identified recordings to the species-level, and used multi-species hierarchical occupancy models to estimate and evaluate the occupancy and richness of songbird species.
- **3.** We recorded 84 species of songbirds, with estimated occupancies ranging from 0.01 for the black-throated gray warbler to 0.65 for the red-winged blackbird. Mean estimated richness ranged from  $5 - 34$  songbird species ( $\bar{x} = 16.10$ ) and was greatest in mixed habitats. Overall, our results suggest Great Valley's songbird community was positively associated with heterogeneous landscapes, both natural and agricultural, that were close to a forested area.
- **4.** We used data collected by automated recorders to generate baseline estimates of occupancy for >80 songbird species in the Great Valley. Site-level detection probabilities were high for the majority of songbirds, providing support for the effectiveness of automated recorders as a monitoring tool. Further, our research highlights potential starting points for reconciling the Great Valley when the goal is to increase the distribution and richness of songbirds. These include increasing natural and agricultural heterogeneity, and conserving remnant forests and natural vegetation throughout the region. We encourage CDFW to use our estimates as baselines, thus setting the stage for long-term monitoring of songbird communities in the region. A long-term monitoring program would provide the agency with the empirical data needed to evaluate the processes driving the songbird populations, such as trends in occupancy and drivers of local colonization and extinction probabilities.

### **Introduction**

Reservation ecology, restoration ecology, and reconciliation ecology describe three approaches for addressing ecosystem change and potential, corresponding losses and degradation of natural habitat and wildlife populations. Reservation ecology focuses on protecting areas from further development by designating them as preserves (Rosenzweig 2003). If the size of protected areas is small, however, then long-term maintenance of a diversity of species is unlikely (Rosenzweig 2003). Restoration ecology, alternatively, focuses on restoring an area to its historic state including the biota and ecosystem conditions (Rosenzweig 2001; Jackson and Hobbs 2009; Bullock et al. 2011). Restoring ecosystems to their historical conditions, however, is unlikely when considered in the light of rapid environmental and human-mediated change (Choi et al. 2008; Seastedt et al. 2008; Hobbs et al. 2009). Lastly, reconciliation ecology focuses on modifying and diversifying human-dominated landscapes so they can harbor a wide variety of wildlife, recognizing that we can improve and expand wildlife habitat without having to lose human habitat (Rosenzweig 2003). Reconciliation ecology acknowledges the relevance of new and novel ecosystems, which have often been irreversibly changed by modifications to abiotic conditions or biotic compositions (Fox 2007; Seastedt et al. 2008; Hobbs et al. 2009).

Some of the most important cases of reconciliation ecology are agricultural landscapes (Daily et al. 2001). Croplands and pastures occupy approximately 40% of the world's land surface, a number that will likely surge given projected two- to threefold increases in food demand by 2050 (Foley et al. 2005; Green et al. 2005). Agricultural landscapes' ability to serve as wildlife habitat ranges widely depending on a multitude of factors such as land tenure, crop species, the size of crop fields, cultivation practices, agrochemical usage, and rotation planning (Benton et al. 2003; Fahrig et al. 2011). For example, areas with low to intermediate-intensity land use can positively impact native wildlife (Daily et al. 2001) while areas experiencing rapid agricultural intensification tend to negatively impact native wildlife (McKinney 2002; Benton et al. 2003; Green et al. 2005). The negative effects of rapid agricultural intensification are likely due to large-scale transitions from heterogeneous (i.e., in structure, time, and space) to homogeneous agricultural landscapes that provide fewer niches and resources, such as food, nest sites, den sites, and cover (MacArthur and MacArthur 1961; Rosenzweig 1995; Benton et al. 2003; Green et al. 2005). The positive relationship between the richness of wildlife populations and landscape heterogeneity is widely supported (Benton et al. 2003; Lee and Martin 2017). Our understanding of the degree to which heterogeneity in croplands and pastures benefits wildlife and specific taxa, however, is limited (Benton et al. 2003; Fahrig et al. 2011). Improving this understanding would not only inform the conservation and management of wildlife in farmlands, but also provide a potentially feasible method in which to reconcile these human-dominated landscapes (Benton et al. 2003; Foley et al. 2005; Fahrig et al. 2011; Lee and Martin 2017). Reconciling agricultural areas in a way that maximizes their potential as wildlife habitat is imperative, given their increasing coverage globally and because the fate of many species depends on their ability to use human-modified landscapes (Green et al. 2005; Ewers and Didham 2006; Fahrig et al. 2011).

In this study, we explored the ecological drivers of songbird distributions in a humanmodified, agricultural landscape. We focused on songbird species, specifically, as farming serves as one of the biggest threats to globally threatened and near-threatened birds (McKinney 2002; Green et al. 2005). We applied our question to the Great Valley of California, an area that has been transformed from seasonal wetlands and alkali scrub to one of the most intensely developed agricultural regions in the world (Frayer et al. 1989; Nelson et al. 2003). A better understanding of how to maximize the distributions of specific species of interest or overall songbird diversity in a landscape like the Great Valley, could have local to global relevance due to the loss of wildlife populations and increasing coverage of croplands and pastures worldwide (Alkemade et al. 2009; Fahrig et al. 2011). Additionally, our research was motivated by the lack of studies in areas of high-intensity agricultural land use (Haslem and Bennett 2008; Prevedello and Vieira 2010; Mendoza et al. 2014; Kennedy et al. 2017). Studies that sample outside of native habitats tend to take place in urban areas or areas of low-intensity land uses (Daily et al. 2001; Haslem and Bennett 2008; Prevedello and Vieira 2010; Mendoza et al. 2014).

Prioritizing management actions aimed at reconciling the Great Valley ecoregion for one or more bird species requires reliable estimates and evaluations of species richness and species distributions (Yoccoz et al. 2001; Lindenmayer and Hobbs 2007; Zipkin et al. 2009; Furnas and Callas 2015). Thus, our specific objectives for the Great Valley ecoregion and each of its major habitat strata were threefold. First, we determined baseline estimates of occupancy for songbird species. Species' estimates of occupancy are based on repeated detection-nondetection data, and are considered an informative index to population status (MacKenzie et al. 2002; Royle et al. 2005). Second, we identified habitats that support the greatest richness of songbirds. Third, to help determine which ecological variables should be targeted by reconciliation efforts, we evaluated community and species-specific responses to landscape heterogeneity, water, and land cover variables, all of which have been found to influence avian richness (Gill 1995; McKinney 2002; Benton et al. 2003; Billeter et al. 2008; Lee and Martin 2017). We considered anthropogenic-driven heterogeneity (e.g., different field crops, types of grazed lands, orchards) and natural heterogeneity (e.g., woodlands, wetlands, grasslands) separately, as the strength of their influences on avifaunal diversity may differ. We hypothesized that increasing water availability and landscape heterogeneity, both anthropogenic and natural, would have the greatest, positive influence on species-specific occupancy and overall songbird richness because of increased niche and resource availability (MacArthur and MacArthur 1961; Rosenzweig 1995).

### **Methods**

# *Automated recorder survey and bird call classifications*

In 2016, California Department of Fish and Wildlife (CDFW) initiated Terrestrial Species Stressor Monitoring (TSM) surveys in the Great Valley (GV) ecoregion of California. TSM surveys employ noninvasive survey techniques, including automated sound recordings, visual encounter surveys, and camera trap surveys, to collect baseline data on a wide variety of

common wildlife species. In this study, we focused on songbird data collected via automated recorders, an increasingly common tool for surveying bird communities (Furnas and Callas 2015; Shonfield and Bayne 2017).

We surveyed 263 sites across the GV ecoregion between March and July of 2016 and 2017 (Fig. 1). We identified survey locations by first selecting a spatially balanced random sample of hexagons, stratified by vegetative community, from the USDA Forest Inventory and Analysis program's hexagon grid (hexagon radius is  $\sim$  2.6 km). We then randomly selected 1-3 survey locations within each hexagon, which were spaced by 1-2 km and stratified by vegetative community. At each survey location, we deployed an SM3-BAT bioacoustic recorder with microphone (Wildlife Acoustics, Inc., Maynard, MA, USA, hereafter termed ARU). We cablelocked ARUs to securely placed T-posts 2-m above the ground and if T-post mounting was not possible, we secured devices to a tree or other vegetation. We programmed ARUs to record three, 5-min sessions on three consecutive days during the survey period. The first session was at 30 minutes before sunrise, the second at sunrise, and the third at 30 minutes after sunrise (Furnas & Callas, 2015).

After the field season, we reviewed the recordings and identified bird species by song or call. To aid in bird identification, we examined spectrograms in Raven Pro software (v. 1.5; Cornell Lab of Ornithology Bioacoustics Research Program, Ithaca, NY, USA). We omitted recordings that could not be identified to the species-level and in an effort to ensure species were similar ecologically, we restricted our analysis to songbirds (i.e., species in the order Passeriformes; Barker, Cibois, Schikler, Feinstein, & Cracraft, 2004). We also classified the level of background noise (e.g., wind, rain, vehicle and air traffic) during each recording using an ordinal variable ranging from zero, indicating no noise, to four, indicating loud noise.

#### *Covariates*

We expected that land cover, water accessibility, and landscape heterogeneity would influence songbird distributions in the GV. To represent land cover, we buffered each sampling location by 500m in ArcMAP 10.4.1 (ESRI, Redlands, CA, USA). We used this buffer size because in our preliminary analyses, we found that the direction of covariate relationships was consistent across buffer sizes (i.e., 1km, 500m, and 100m) but the strength of the relationships tended to be greatest when using the 500m buffer. We used data from CDFW's Vegetation Classification and Mapping Program (CDFW 2017)) to calculate percent cover of natural vegetation (i.e., within each 500m buffered area), percent cover of agricultural vegetation, and distances from each sampling location to the nearest forested area and urban area. We used data from Point Blue's Automated Water Tracking System (Point Blue 2017) to identify areas that had open surface water during the survey period, and then measured the distance from each ARU to the nearest available water source.

To represent landscape heterogeneity, we calculated the number of crop types and number of natural vegetation types within each 500m buffered area. To quantify crop types, we used USDA cropscape data (USDA 2017) and to quantify natural vegetation types, we used the regional dominance types identified in the vegCAMP data. We also represented landscape heterogeneity by calculating Simpson's measure of evenness, which accounts for the relative abundance of different species making up the richness of an area (Simpson 1949):

$$
-\sum_{i=0}^{n} P(i) \times lnP(i)
$$
  
In(*# vegetation types*) where  $P(i) = \frac{area covered by vegetation type i total area$ 

When estimating natural and agricultural evenness, vegetation types included each natural dominance type and each crop species, respectively, and total area included natural and agricultural cover within the buffered areas, respectively.

To account for the influence that temperature may have on the vocal activity of songbirds, we included maximum daily temperature as a covariate for species' detection probabilities (McGrann and Furnas 2016). To estimate maximum temperatures, we downloaded 4-km resolution temperature data from PRISM (Prism Climate Group 2017) for the survey period. We then determined the mean maximum temperature at each sampling location over the 3-day survey period. We also included background noise and Julian day and its quadratic term as covariates for detection. Background noise can impede the audibility and identification of bird species while the phenology of birds' vocal behaviors can change over the course of the breeding season (Slagsvold 1977; Strebel et al. 2014).

### *Multi-species occupancy modeling*

We used multispecies hierarchical occupancy models to estimate the probability songbird *i*  occurred within the area sampled by an ARU during our survey period (i.e., occurrence; Dorazio & Royle 2005; Iknayan et al. 2014). Multi-species models link species-specific detection and occupancy using community-level hyper-parameters, which specify the mean response and variation among species within the community to a respective covariate (Kéry and Royle 2008; Zipkin et al. 2010). Linking occurrence models for individual species together within a hierarchical model results in a more efficient use of data, increased precision in estimates of occupancy, and assessments of ecological variables at both the species- and community-level (Kéry and Royle 2008; Zipkin et al. 2009; Iknayan et al. 2014). The models also produces estimates of species richness (i.e., number of species in the community and at each sampling location). To produce estimates of songbird richness that accounted for songbird species that were not recorded during sampling but may have occupied areas of the GV, we augmented the dataset by adding ten all-zero observations.

Occupancy models distinguish the true absence of a species from the non-detection of a species (i.e., species present but not recorded) using spatially or temporally replicated survey data. For each sampling location, we treated each 5-minute acoustic recording (*n* = 9) as a repeat survey at that particular site. We assumed occurrence and detection probabilities differed between years and among species, and were influenced by ecological covariates. To avoid overparameterizing our models and ensure all parameters were estimable, we restricted the number of covariates included in each model. We assessed two model structures for occupancy  $(\psi)$  and detection (*p*):



We incorporated covariates into the model linearly on the logit-probability scale (Zipkin et al. 2010) and ensured models did not include covariates that were correlated. We then linked species-specific models using a mixed modelling approach where we assumed species-specific parameters were random effects derived from a normally distributed, community-level hyperparameter (Iknayan et al. 2014).

We estimated posterior distributions of parameters using Markov Chain Monte Carlo implemented in JAGS (Plummer 2011) through program R. We generated three chains of 50,000 iterations thinned by 50 and used uninformative priors. We assessed model convergence using the Gelman-Rubin statistic, where values < 1.1 indicated convergence (Gelman et al. 2004). During each model iteration, we summed the number of estimated species at recorder *j* to generate probability distributions representing site-specific estimates of species richness (Zipkin et al. 2010). We also used our model output to estimate mean, habitat-specific estimates of occupancy and songbird richness. To classify habitat, we used vegCAMP data to quantify the percent cover of (1) urban and agriculture, (2) grassland and oak savannah, (3) riparian and wetland, (4) forest, and (5) shrub within each 500m buffered sampling locations. We then categorized each sampling location based on the dominant habitat type. When a single habitat type did not cover >60% of the area, we categorized the habitat type as 'mixed'.

#### **Results**

We recorded 84 songbird species during our 2,367 sampling occasions (i.e., 5-minute recordings) in the Great Valley ecoregion (Table 1). Eight species were recorded on over 500 occasions, including western meadowlarks and red-winged blackbirds, whereas 20 species were recorded on less than 10 occasions (Table 1). Among the covariates, natural and agricultural cover were correlated  $(|r| > 0.6)$  as were measures of habitat heterogeneity, both natural (i.e., number of natural vegetation types and natural evenness) and agricultural (i.e., number of agricultural vegetation types and agricultural evenness).

Mean estimated richness ranged from  $5 - 34$  songbird species ( $\bar{x} = 16.10$ ) with redwinged blackbirds ( $\psi$  = 0.65), brown-headed cowbirds ( $\psi$  = 0.65), and western meadowlarks ( $\psi$  $= 0.65$ ) having the highest estimated occupancies (Table 1; Appendix S1). Many species, conversely, had low estimates of occupancy due to their limited numbers of detections (Table 1; Appendix S1). Site-level detection probabilities were  $> 0.3$  for every species but the Lincoln's sparrow, and > 0.6 for the majority of species (Table 1; Appendix S2). At the community-level, and for close to half of the songbird species, detection probability had a quadratic relationship with Julian day (Table 2; Appendix S3). We were also more likely to detect songbirds on cooler days and at sites with reduced levels of noise (Table 2; Appendix S3).

Overall, our results suggest Great Valley's songbird community was more likely to use heterogeneous landscapes, both natural and agricultural, that were close to a forested area (Table 2). Among the covariates, natural heterogeneity, as measured by Simpson's measure of evenness, had the largest positive influence on community-level occupancy while distance to forest had the largest negative influence (Table 2). At the species-level, natural evenness was positively related to the distributions of 25 songbirds, including Bewick's wren, song sparrow, and wrentit, and distance to forest was negatively related to the distributions (i.e., species more likely to occupy areas close to forest) of 29 songbirds, including the black-headed grosbeak, bushtit, and oak titmouse (Table 2; Appendix S3). Six and seven songbird species had the converse relationship with natural evenness and distance to forest, respectively (Table 2; Appendix S3). Our alternative measure of habitat heterogeneity, which was the number of natural and agricultural vegetation types, also tended to have a positive influence on songbird occupancy at both the community and species level (Table 2). Specifically, 13 and 11 songbird species were positively related to the number of natural and agricultural vegetation types, respectively, whereas only 3 and 2 species had a negative relationship with these variables (Table 2; Appendix S3). Lastly, in general, songbirds were more likely to occupy areas close to water but this relationship tended to be weak (Table 2; Appendix S3). Water availability appeared to be most important to common yellowthroat, marsh wren, song sparrow, and tree swallow (Appendix S3).

The greatest number of sampling locations fell within urban and agricultural habitat ( $n =$ 105), followed by mixed habitat (*n* = 60), grassland and oak savannah (*n* = 52), riparian areas and wetlands ( $n = 38$ ), and shrublands ( $n = 7$ ). At the community and species-levels, occupancy probabilities varied among the major habitat strata but tended to be greatest in mixed habitat (*n* = 27 species; Fig. 3; Appendix S1). We note, however, that among the various habitat strata, error estimates for mean and species-specific occupancy probabilities tended to overlap. This limits our ability to determine if the community or a particular species was more or less likely to occupy riparian and wetland habitat than mixed habitat, for example. Songbird richness also appeared to be greatest in mixed habitat ( $\bar{x}$  = 17.48), followed by urban and agricultural habitat  $({\bar x} = 17.13;$  Fig. 4). Error bars associated with our estimates of songbird richness also tended to overlap, however (Fig. 4).

#### **Discussion**

Effectively prioritizing actions aimed at conserving wildlife requires reliable estimates of species richness, species distributions, and an understanding of how these parameters are driven by ecological factors (Yoccoz et al. 2001; Lindenmayer and Hobbs 2007; Zipkin et al. 2009; Furnas and Callas 2015). The distribution and habitat requirements of species within an ecosystem are

rarely known, however, making it difficult to discern optimal management strategies (White et al. 2013). In this study, we applied a field technique that was developed in forested regions as part of the Ecoregion Biodiversity (EBM) surveys, and applied it in the Great Valley, an intensely modified agricultural region. Despite the dramatically different landscapes, similar to Furnas and Callas (2015), we found that detection probabilities using ARUs were high for most species. Further, because the ARUs collected data on a numerous species simultaneously, we were able to estimate the distributions and richness of over 80 songbird species in the Great Valley (Fig. 2; Appendix S1). Our research provides additional support for the effectiveness of automated recorders as a tool for collecting detection-nondetection data on multiple species (Furnas and Callas 2015).

It is challenging and often infeasible to create new protected areas or to implement major restoration efforts in intensely developed regions like the Great Valley (Rosenzweig 2003; Seastedt et al. 2008; Choi et al. 2008; Jackson and Hobbs 2009). Thus, efforts must focus on reconciling these ecosystems in a way that maximizes their ability to function as suitable habitat for both endemic wildlife species and humans (Rosenzweig 2003; Seastedt et al. 2008; Hobbs et al. 2009). In addition to providing baseline estimates of occupancy for songbirds, our research also produced a number of key findings relevant to prioritizing actions aimed at reconciling the Great Valley. Specifically, our evaluation of community and species-specific responses to ecological variables suggests that increasing natural and agricultural heterogeneity, and conserving remnant forests and natural vegetation throughout the region, offer potential starting points for reconciling the Great Valley when the goal is to increase the distribution and richness of songbirds.

We found that songbird richness was greatest in mixed habitat (i.e., areas encompassing multiple habitat types), that over 30% of the songbird species were most likely to occupy mixed habitat, and that songbirds, both the community and individual species, tended to be positively associated with natural and agricultural heterogeneity. Similar to prior studies, these results support that diversity is maximized in heterogeneous landscapes, likely because they provide more niches and complementary resources than homogeneous landscapes (MacArthur and MacArthur 1961; Benton et al. 2003; Haslem and Bennett 2008; Lee et al. 2017). Increasing landscape heterogeneity by actively managing natural areas and encouraging landowners to tailor their agricultural practices (e.g., crop diversity, cultivation practices, rotation planning) may therefore be a viable approach for reconciling the Great Valley. While the songbird community tended to be positively associated with both natural and agricultural heterogeneity, the strength of these relationships varied. Natural evenness, for example, had the largest positive influence on the songbird community (Table 4; Appendix S2). Thus, even in this intensely modified landscape, native vegetation played a vital role in maintaining songbird populations (Haslem and Bennett 2008). These results suggest actions aimed at increasing landscape heterogeneity should not be done in isolation, but rather in parallel with the protection of remnant natural habitats.

Our multi-species model also illustrated the importance of forested habitats, specifically, to songbirds in the Great Valley. Forest had the largest influence on the occupancy of avian

species, at both the community- and species-levels, where species were more likely to occupy areas close to forest cover (Table 2). Forested areas generally have high species diversity, including bird diversity, as they provide critical resources like foraging and roosting sites and help facilitate the movement of individuals (Gill 1995; Haslem and Bennett 2008; Mendoza et al. 2014). Despite their role in supporting terrestrial wildlife, however, forested landscapes continue to be converted into agricultural, mining, and urban areas (White et al. 2013). Our results highlight the importance of conserving forests within the Great Valley and that maximizing landscape heterogeneity should not be considered a replacement for reducing the loss and degradation of native forests (Kennedy et al. 2017).

Climate and land use change will continue to transform many of the world's ecosystems (Rosenzweig 2003; Millenium Ecosystem Assessment 2005; Seastedt et al. 2008; Hobbs et al. 2009; Walther et al. 2009; Bullock et al. 2011; Steffen et al. 2015). Methods for reconciling these novel landscapes in a way that maximizes their potential as wildlife habitat is imperative, as the fate of many species depends on their ability to utilize human-modified landscapes (Green et al. 2005; Ewers and Didham 2006; Fahrig et al. 2011). This is particularly true for agricultural landscapes given their increasing coverage globally (Daily et al. 2001; Foley et al. 2005; Green et al. 2005). Our research employed automated recorders and multispecies occupancy models to estimate and evaluate the distributions of 84 songbird species and to identify plausible ways in which the Great Valley, an intensely developed agricultural region, could be reconciled for the benefit of the songbird community. Our findings underscore the importance of conserving natural vegetation, forested areas in particular, and of promoting landscape heterogeneity in both natural and agricultural areas. If done in isolation, however, these results will represent only a snapshot in time. We encourage CDFW to use our estimates as baselines, thus setting the stage for long-term monitoring of songbird communities in the region. A long-term monitoring program would allow CDFW to develop an understanding of the processes driving the songbird populations, such as trends in occupancy, changes in habitat use, and drivers of local colonization and extinction probabilities (MacKenzie et al. 2005; Tingley and Beissinger 2013). Furthermore, this information would allow managers to test, track, improve, and adapt management actions aimed reconciling the Great Valley for the benefit of endemic songbird species.

# **Supplementary Material**

**Appendix S1.** Songbird species in the Great Valley ecoregion of California and their occupancy probabilities overall, and within each of the major habitat strata. The habitat strata in which each species had the highest occupancy probability is highlighted.

**Appendix S2**. Songbird species in the Great Valley ecoregion of California and their site-level detection probabilities  $(\pm 95 \text{ credible intervals}).$ 

**Appendix S3.** Mean and 95% credible interval estimates for covariate effects on occupancy (PSI) and detection (P) for 84 songbird species in the Great Valley ecoregion of California, 2016-17. Results are based on model 1 (3a) and model 2 (3b); covariate effects that do not overlap 0.0 are highlighted in yellow.

**Table 1**. Songbird species detected during TSM 2016-17 automated recorder surveys in the Great Valley ecoregion of California, numbers of detections (# det.), proportion of sites at which the species was detected (naïve  $\psi$ ), occupancy probabilities ( $\psi$ ), and site-level detection probabilities ( $p^*$ ).





**Table 2**. Mean  $(\bar{x})$  and 95% credible interval estimates for the community-level parameters hypothesized to influence songbird species' occupancy  $(\psi)$  and detection  $(p)$  probabilities in the Great Valley ecoregion, California, 2016-17. Bolded beta values have credible intervals that did not include zero.

	Covariate		Community-level		Species-level	
			$\bar{x}$	95% CI	$+$	
Model	$\Psi_1$	# natural vegetation types	0.09	$-0.007 - 0.195$	13	3
	$\Psi$ <sub>2</sub>	# agricultural vegetation types	0.11	$0.018 - 0.191$	11	$\overline{2}$
	$\Psi_3$	Distance to forest	$-0.57$	$-0.799 - 0.345$	7	29
	$\Psi_4$	Distance to water	$-0.04$	$-0.139 - 0.053$	$\overline{2}$	4
	$\Psi$ <sub>5</sub>	Year	0.24	$0.097 - 0.405$	12	$\overline{2}$
	$p_1$	Maximum temperature	$-0.10$	$-0.192 - 0.018$	3	11
	$p_2$	Julian day	0.88	$0.526 - 1.212$	34	$\overline{0}$
	$p_3$	Julian day <sup>2</sup>	$-0.93$	$-1.279 - 0.574$	$\Omega$	32
	$p_4$	Noise level	$-0.13$	$-0.214 - 0.050$	3	15
	$P_5$	Year	0.03	$-0.029 - 0.104$	7	3
$\mathcal{L}$ Model						
	$\Psi_1$	Crop cover $(\%)$	0.10	$-0.010 - 0.206$	14	3
	$\Psi$ <sub>2</sub>	Natural evenness	0.20	$0.080 - 0.322$	25	6
	$\Psi_3$	Agricultural evenness	0.14	$0.064 - 0.217$	11	1
	$\Psi_4$	Distance to urban	$-0.07$	$-0.153 - 0.003$	$\theta$	4
	$\Psi$ <sub>5</sub>	Year	0.24	$0.102 - 0.404$	12	$\overline{2}$
	$p_1$	Maximum temperature	0.17	$0.013 - 0.339$	$\overline{2}$	$\boldsymbol{0}$
	$p_2$	Julian day	0.32	$0.111 - 0.521$	21	$\boldsymbol{0}$
	$p_3$	Temperature * Julian day	$-0.58$	$-0.888 - 0.287$	$\Omega$	22
	$p_4$	Noise level	$-0.13$	$-0.215 - 0.049$	$\overline{2}$	15
	p <sub>5</sub>	Year	0.05	$-0.009 - 0.116$	9	$\overline{2}$

**Figure 1.** Automated recorder locations during Terrestrial Species Stressor Monitoring surveys in the Great Valley ecoregion of California, 2016-2017.



**Figure 2.** Mean occupancy probabilities  $(\pm 95\%$  credible intervals) for songbird species across the Great Valley ecoregion, California, 2016-17. We present species with occupancy estimates > 0.05.





**Figure 3.** Region-wide and habitat-specific mean estimated occupancy probabilities  $(\pm 1)$  standard deviation) for songbird species in the Great Valley ecoregion of California, 2016-17.

**Figure 4.** Overall and habitat-specific estimates ( $\pm$  95% credible interval) of songbird richness in the Great Valley ecoregion, California, 2016-17.



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**Appendix S1.** Songbird species in the Great Valley ecoregion of California and their occupancy probabilities overall, and within each of the major habitat strata . The habitat strata in which each species had the highest occupancy probability is highlighted.









**Appendix S2.** Songbird species in the Great Valley ecoregion of California and their site-level detection probabilities ( $\pm$  95 credible intervals).




**Appendix S3a.** Mean and 95% credible interval estimates for covariate effects on occupancy (PSI) and detection (P) for 84 songbird species in the Great Valley ecoregion of California, 2016-17. Results are based on model 1; covariate effects that do not overlap 0.0 are highlighted in yellow.



















**Appendix S3b.** Mean and 95% credible interval estimates for covariate effects on occupancy (PSI) and detection (P) for 84 songbird species in the Great Valley ecoregion of California, 2016-17. Results are based on model 2; covariate effects that do not overlap 0.0 are highlighted in yellow.







BRBL Brewer's Blackbird 0.03 -0.217 0.288 0.11 -0.180 0.380 0.05 -0.311 0.408







0.20 -0.239 0.629<br>0.28 -0.166 0.770

**P** (max temperature)

*95% CI 95% CI 95% CI*

-0.06 -0.528 0.372

0.17 -0.078 0.432  $0.05 -0.164 0.273$  $-0.58$   $-0.915$   $-0.268$ -0.08 -0.231 0.069  $-0.05$   $-0.197$  0.095

*95% CI 95% CI 95% CI*

 $0.06$   $-0.254$   $0.390$ BESP Bell's Sparrow 0.71 -0.028 1.488 -0.80 -1.710 0.078 -0.03 -0.465 0.437 BEWR Bewick's Wren 0.08 -0.310 0.476 -0.63 -1.271 -0.031 -0.46 -0.647 -0.277  $-0.13$   $-0.650$   $0.417$  $-BB - 0.314 - 0.074$ BHGR Black-headed Grosbeak 0.97 0.465 1.491 -0.51 -1.167 0.108 -0.55 -0.773 -0.331  $-0.09$   $-0.405$  0.203 -0.14 -0.303 0.014 0.04 -0.133 0.206 BTYW Black-throated Gray Warbler 0.24 -0.872 1.334 -0.48 -1.471 0.536 -0.21 -0.748 0.307 0.07 -0.078 0.223  $-0.38$   $-0.630$   $-0.138$ -0.07 -0.592 0.473  $-0.19 -0.356 -0.025$ 

-0.14 -0.664 0.376



