

ELUCIDATING PATTERNS OF BAT SPECIES OCCUPANCY ACROSS A  
DISTURBED LANDSCAPE IN CALIFORNIA'S CENTRAL VALLEY

By

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## ABSTRACT

### ELUCIDATING PATTERNS OF BAT SPECIES OCCUPANCY ACROSS A DISTURBED LANDSCAPE IN CALIFORNIA'S CENTRAL VALLEY

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California's Central Valley, one of the most productive agricultural regions in the world, is home to 14 species of resident and migratory bats. The Central Valley has been identified as a crisis ecoregion, and a high number of species are at risk due to anthropogenic land use. In addition, the Central Valley has faced severe drought, effects of which are intensified on the natural landscape by agricultural irrigation practices. In response to the historical drought of 2012-2015, California Department of Fish and Wildlife (CDFW) implemented the Terrestrial Species Stressor Monitoring (TSSM) project, which in part aimed to collect information on baseline occupancy data and habitat associations for bats. Bat surveys were conducted using SM3BAT acoustic detectors at 274 sites spanning the Central Valley in both the driest (2016) and wettest years on record (2017). The objectives of my thesis were to determine (1) Do anthropogenic land use and drought influence bat occupancy at a landscape level? If so, do bats use anthropogenic land types more during the drought? (2) Do anthropogenic land use and drought affect bat species differently based on habitat specialization? I hypothesized that bat occupancy would be greater in agricultural areas during the drought, anthropogenic land use would predict the distribution patterns of habitat

specialists, and occupancy for all species would be lower during the drought. This data collection effort resulted in the largest bat acoustic survey of the Central Valley with 14 species detected and over 3,300 species-site-night events. I fit single-species occupancy models in a Bayesian framework, using environmentally or biologically relevant covariates. Using these models, I generated range wide occupancy predictions for individual species and total species richness. Migratory species contracted their geographic range during the drought, while hibernating species did not. Further, arid-adapted species expanded from natural open areas into cultivated landscapes during the drought. The results of this thesis suggest that migratory species may more easily adapt to drought conditions, irrigated agricultural areas may act as drought refugia, and large-scale acoustic studies can serve as an alternative or supplement to capture for acoustically detectable bat species.

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## TABLE OF CONTENTS

ABSTRACT .....	ii
ACKNOWLEDGEMENTS .....	iv
TABLE OF CONTENTS.....	vi
LIST OF TABLES .....	viii
LIST OF FIGURES .....	ix
LIST OF APPENDICES.....	xii
INTRODUCTION.....	1
METHODS .....	7
Study Area.....	7
Site Selection.....	9
Acoustic Recording and Analysis .....	12
Occupancy and Detection Covariates .....	15
Occupancy .....	15
Detection .....	19
Distribution Modeling .....	22
Single-season occupancy modeling .....	22
Range-wide species distribution and richness .....	25
RESULTS .....	26
Occupancy Models .....	28
Detection covariate effects .....	30
Landscape characteristics and occupancy .....	31

Species richness .....	50
DISCUSSION .....	51
Drought .....	51
Human Land Use .....	53
Conservation Implications .....	57
LITERATURE CITED .....	60
Appendix A .....	71
Appendix B .....	74
Appendix C .....	77
Appendix D .....	82
Appendix E .....	83

## LIST OF TABLES

Table 1. Environmental covariates that may impact species occupancy for single-species occupancy models for ten bat species in the Central Valley. All variables were used at the finest available temporal and spatial resolutions.....	17
Table 2. Environmental covariates that were included to characterize imperfect detection for single-species occupancy models for ten bat species in the Central Valley. All variables were used at the finest available temporal and spatial resolution. ....	21
Table 3. Bat species detected with automated ultrasonic detectors placed at randomly selected sites in 2016 and 2017, and relative number of detections, given total detector nights in 2016 (n = 657) and 2017 (n = 1231) in the Central Valley, CA. ....	27
Table 4. Estimated detection and proportion of sites occupied within the sample for 10 bat species for 274 sites in the Central Valley, CA. See Table 3 for species code definitions.....	29
Table 5. Observed effects of environmental covariates on occupancy probability for ten bat species in Central Valley, CA. Highlighted cells denote covariates with indicator variable values greater than 0.5.....	32



## LIST OF FIGURES

Figure 1. Locations of 274 sites across California’s Central Valley, selected using a spatially stratified-random design. Sites were either sampled in 2016 (green, n = 90) or 2017 (black, n = 184).	10
Figure 2. Map depicting paired sampling design within 5 km USDA hexes in the Central Valley, California. Points denote sampling locations near the San Luis Wildlife Refuge complex.	11
Figure 3. Setup of SM3Bat recorder at site. Microphones were elevated above the ground using a 3 m metal conduit. The acoustic microphone (SMM-A2) was positioned 2 m above the ground, and the ultrasonic microphone (SMM-U1) was positioned 3 m above the ground.	13
Figure 4. Model predicted influence of log (number of auto-classified calls) on detection 10 species detected in the Central Valley, CA.	30
Figure 5. Posterior distributions of the occupancy estimates for tree roosting migrants <i>L. blossevillii</i> (LABL), <i>L. cinereus</i> (LACI), and <i>L. noctivagans</i> (LANO). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).	34
Figure 6. Model averaged posterior mean occupancy probability of western red bat (LABL), using 0.89 X 0.89 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). X denotes sites with no detections. Panels c/d denote 95% credible interval width.	35
Figure 7. Model averaged posterior mean occupancy probability of hoary bat (LACI), using 1.78 x 1.78 km square grid in (a) 2016 (drought, n=94) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). White x denotes sites with no detections. Panels c/d denote 95% credible interval width.	36
Figure 8. Model averaged posterior mean occupancy probability of silver-haired bat (LANO), using a 2.7 x 2.7 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). X denotes sites with	

no detections. Panels c/d denote 95% credible interval width. Crosshatch is CDFW species range. ....37

Figure 9. Posterior distributions of the occupancy estimates for myotis species *M. californicus* (MYCA), *M. lucifugus* (MYLU), and *M. yumanensis* (MYYU). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV). ....39

Figure 10. Model averaged (see text for details) posterior mean occupancy probability of California myotis (MYCA), using a 1.78 x 1.78 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184) for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote associated 95% credible interval width uncertainty in 2016 and 2017 respectively. ....40

Figure 11. Model averaged posterior mean occupancy probability of little brown bat (MYLU), using a 1.78 x 1.78 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. Crosshatch represents CDFW species range. ....41

Figure 12. Model averaged posterior mean occupancy probability of Yuma myotis (MYYU), using a 1.78 x 1.78 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. ....42

Figure 14. Posterior distributions of the occupancy estimates for human tolerant species *E. fuscus* (EPFU) and *T. brasiliensis* (TABR). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).....43

Figure 15. Model averaged posterior mean occupancy probability of big brown bat (EPFU), using 2.7 x 2.7 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. ....44

Figure 16. Model averaged posterior mean occupancy probability of Brazilian free-tailed bat (TABR), using a 3.5 x 3.5 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). White x denotes sites with no detections. Panels c/d denote 95% credible interval width. ....45

Figure 17. Posterior distributions of the occupancy estimates for arid-adapted species *E. perotis* (EUPE) and *P. hesperus* (PAHE). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).....47

Figure 18. Model averaged posterior mean occupancy probability of western mastiff bat (EUPE), using 3.5 x 3.5 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. Crosshatch pattern denotes CDFW species range.....48

Figure 19. Model averaged posterior mean occupancy probability of canyon bat (PAHE), using a 0.89 x 0.89 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. ....49

Figure 20. Projected species richness for 2016 (a) and 2017 (b) for acoustically detectable species in the Central Valley, CA, using a 3.5 km x 3.5 km grid. White circle size denotes number of species detected at a given acoustic detector location. Panel (c) illustrates the change in species richness between 2016 and 2017.....50

## LIST OF APPENDICES

Appendix A. Parameter estimates for single species occupancy models of 10 bat species in the California Central Valley from 2016 – 2017, with posterior means and upper and lower 95% Bayesian credible intervals. Effects with a Kuo and Mallick indicator variable > 0.5 were the only covariates included in the table. Effects are on the logit scale. The c-hat value obtained from posterior predictive checks is indicated for each model. Spatial scale used for model is indicated below species code. See Table 3 for species code definitions.....	71
Appendix B. Parameterization of the single-season occupancy model using Kuo and Malik (1998) indicator variables and a posterior-predictive check on aggregated detection histories, modified from Kery and Schaub (2012) and Jobin et al. (2018). Model is specified to be used in JAGS. This model was used to estimate occupancy and detection probabilities for bat species in the Central Valley. ....	74
Appendix C. Description of methods and results of pairwise comparison between SonoBat and Kaleidoscope Pro. ....	77
Appendix D. Metadata for acoustic deployment of sites using SM3BAT recorders in California, USA. ....	82
Appendix E. Posterior means and lower and upper bounds of the 95% Bayesian credible interval for detection covariates. The thicker, colored lines show the 50% CIs. The black points denote the posterior mean of each covariate. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV). ....	83

## INTRODUCTION

Two of the greatest threats to global biodiversity are human land use and climate change (Fahrig 2003, Thomas et al. 2004). Conversion of natural ecosystems for human use, primarily to agriculture and urban areas, is widespread, with the extent estimated at 50% for North America alone (Hoekstra et al. 2005, Watson et al. 2016). Combined with human land use, climate change is further impacting natural areas by increasing the frequency of extreme events including drought, flooding, and heat waves (Luber and McGeethin 2008, Trenberth et al. 2013). The combined stressors of climate change and human land use require species to disperse across disturbed landscapes, shift their phenology, use existing life history strategies to live in these newly created habitats, or decline (Parmesan 2006, Morrison et al. 2012, Newbold 2018). The response of individual species to anthropogenic stressors is highly variable; however, habitat specialists are often more adversely affected than generalists. Specialized species exhibit less plasticity and are often the first species to face local declines or extirpation (Travis 2003, Davies et al. 2004, but see Prugh et al. 2018). To prioritize conservation, we need to understand the effect of anthropogenic factors on species across the generalist to specialist continuum.

Bats represent a diverse taxonomic group, with over 1,400 named species (Simmons and Cirranello 2019), comprised of both generalist and specialist species that vary greatly in their response to anthropogenic factors (Jones et al. 2009, Russo and Ancillotto 2015). Bats exhibit a wide variety of habitat requirements and, unlike other

mammal species, can disperse using powered flight. However, their slow life history strategies make them particularly susceptible to anthropogenic factors including intensified drought, urbanization, and agricultural intensification (Kunz and Lumsden 2003, Jones et al. 2009, Voigt and Kingston 2016, Frick et al. 2019).

Urbanization is projected to increase globally, as more people move to urban centers. Bats are sensitive to landscape changes caused by urbanization including human development, increased urban noise, artificial light, and loss of corridors (Theobald et al. 1997, Threlfall et al. 2011, Voigt and Kingston 2016). As cities form, there is an increase in impervious surfaces and a decrease in the density of tree cover (Coleman and Barclay 2013). This transformation leads to conditions beneficial to habitat generalists, who are better able to exploit structural resources than tree, cave, and cliff roosting species (McKinney and Lockwood 1999, Duchamp et al. 2004, Loeb et al. 2009). Although roost availability and habitat for specialists is decreased in urban areas, surface water sources in these areas, such as swimming pools (Nystrom and Bennett 2019) and urban ponds (Gehrt and Chelsvig 2003), may provide resources that are otherwise unavailable at natural water sources depleted by drought (Lisón and Calvo 2011, Russo et al. 2012).

Bats are also impacted by agricultural intensification and development on the landscape; however these responses vary greatly depending on crop type, surrounding landscapes, and agricultural management strategy (e.g., organic versus conventional and magnitude of pesticide input; Williams-Guillen et al. 2016). As urban areas expand, new agricultural development has slowed in the United States; however output intensity has

increased dramatically (Matson 1997). Current high intensity practices require monocultures of crops, which homogenize the landscape. Annual row crops and rice have negative impacts on bat abundance and activity because they lack structural variability required by many species (Gehrt and Chelsvig 2003, Williams-Guillen et al. 2016, Toffoli and Rughetti 2017). This effect is not as clear in orchards, where bat activity is often greater because of structural variability and similarity to natural areas (Braun de Torrez 2014, Williams-Guillen et al. 2016). The negative impacts of structural loss are often lessened by proximity to natural areas, and the presence of riparian corridors and tree cover is one of the greatest predictors of bat diversity. Both habitat specialists and generalists use these areas for commuting and foraging (Lumsden and Bennett 2005, Harvey et al. 2006, Ober and Hayes 2008, Jones et al. 2009, Bailey et al. 2019).

In addition to modifying existing vegetation, agricultural development directly modifies surface water structure and availability (Elmqvist et al. 2016). Surface water in agricultural areas is transported from natural riparian systems to surrounding crop lands using levees, systems lacking the structural complexity of natural areas. Levees are not shaded and support different assemblages of aquatic invertebrates (Hodkinson and Jackson 2005, O'Brien et al. 2006, Razgour et al. 2011). Additionally, these diversions deplete water in natural areas, an effect that is intensified during drought years (Faunt et al. 2016). Experimental studies have observed that decreases in natural water surface area negatively impacts bats, especially larger, less maneuverable species (Tuttle et al. 2006, Hall et al. 2016). As a coping strategy, bats may shift to irrigated areas and manmade

water sources to find surface water suitable for drinking. In addition to providing a water source, irrigation can increase arthropod community abundance (Frampton et al. 2000) and may provide bat foraging resources adjacent to depleted natural areas. Drought decreases insect biodiversity in natural areas and increases crop pest abundance (Trumble and Butler 2009, Leschin-Hoar 2015), so as natural water sources are depleted by drought, bats may be able to exploit agricultural areas as drought refugia.

Current knowledge of the effects of anthropogenic land use on bat biodiversity largely focuses on examining the impacts at small spatial and/or temporal scales. As a host of factors are predicted to negatively affect bats, it is increasingly important to develop a baseline understanding of bat distributions in North America, and how individual bat species will respond to change (Weller et al. 2009, Frick et al. 2019). California's Central Valley is a prime location to observe the impacts of human land-use and drought on bats. The Central Valley is experiencing rapid growth in urban areas and is one of the most productive agricultural regions in the world (Faunt et al. 2016). Additionally, California has faced fluctuating water conditions and intense drought in recent years. The driest four consecutive years in California were from 2012 - 2015, a consequence of record high temperatures and the lowest four year cumulative precipitation on record (DWR 2016). The drought led to significantly depleted spring runoff during the 2016 water year. This extremely dry year was followed by 2017, which had atmospheric river storms and major flooding, leading to runoff conditions greater



than 150% of average (DWR 2017). As a result, the Central Valley represents a region where the effects of drought and human land-use can be studied in tandem.

California is home to 25 species of resident and migratory bats, richness resulting from mild year-round climates and high habitat complexity. Of the 25 species in California, 11 hold special conservation status (CDFW 2015). Studies in other regions have shown that bat species are differentially impacted by habitat change associated with anthropogenic land use (Braun de Torrez 2014, Starbuck et al. 2015, Neece et al. 2018, Olimpi and Philpott 2018); however, to date, there have not been any large scale studies to look at the impact of anthropogenic change on bats in California's Central Valley (Pierson et al. 2006). With the advent of bat acoustic monitoring and higher computer processing speeds, monitoring of acoustically detectable bat species is increasingly practical (Hayes et al. 2009) and can be implemented at a landscape scale to describe species distribution patterns (Rodhouse et al. 2012, Loeb et al. 2015, Neece et al. 2018, Bailey et al. 2019).

My objective was to examine the impacts of anthropogenic land cover on acoustically detectable bat species in the Central Valley. More specifically, I aimed to address the following questions: (1) Do anthropogenic land use and drought influence bat occupancy at a landscape level? If so, do bats use areas with anthropogenic land-cover more during drought? (2) Do anthropogenic land use and drought affect bat species differently based on their habitat specialization? I hypothesized that bat occupancy would be greater in agricultural areas during the drought, anthropogenic land use would

negatively impact the distribution patterns of most habitat specialists, and occupancy for all species would be lower during the drought.

## METHODS

### Study Area

California's Central Valley is 60-100 km wide and approximately 720 km long (total area 47,000 km<sup>2</sup>). Elevations range from 3m to 91m (WRCC 2016). Along the expanse of the Central Valley there is a gradient of climate conditions, ranging from a hot Mediterranean climate in the north, to a Mediterranean steppe climate/low latitude desert on the south end. Summers are hot and dry and winters cool and damp (WRCC 2016), with the majority of precipitation occurring between October and May (TWC 2017). Mean daily minimum temperature in January, the coldest month in the Central Valley, is 4°C (TWC 2017). Mean daily maximum temperature in July, the warmest month, is 35°C (TWC 2017). Mean annual precipitation is 12.7 to 63 cm (CDFW 2015). The dominant cover types in the Central Valley are row crops, orchards, rice, grassland, shrubland, wetlands, and wooded riparian corridors (Sleeter 2008). Historically, the Central Valley was a grassland/shrubland dominated ecoregion; however, large areas of natural grassland and wetland were converted for agricultural land use (Sleeter 2008, Soulard and Wilson 2015, Faunt et al. 2016). The human population of the Central Valley was 6.8 million in 2010 and it is projected to double by 2060 (Great Valley Center 2014). The Central Valley is a "crisis ecoregion", with a high biodiversity of species threatened by habitat conversion (Myers et al. 2000, Hoekstra et al. 2005).

The Central Valley is home to at least 14 bat species. Of these 14 species, 10 were detected acoustically at a high enough frequency for modeling. For the purposes of this analysis, I have grouped bats into the following four groups based on primary habitat specializations: human-tolerant, arid-adapted, crevice/cave roosting myotis, and tree-roosting migrants. Human-tolerant species, bats that have adapted to rely on human structures, were big brown bat (*Eptesicus fuscus*; EPFU) and Brazilian free-tailed bat (*Tadarida brasiliensis*; TABR). Arid-adapted bats, species that are common in open, arid environments were western mastiff bat (*Eumops perotis*; EUPE) and canyon bat (*Parastrellus hesperus*; PAHE). Crevice/cave roosting myotis were small myotis bat species that rely on crevices (buildings, caves, tree snags, or cliff faces) for roosting, typically exhibit social maternal behaviors, and display site fidelity. Species in this group were California myotis (*Myotis californicus*; MYCA), little brown bat (*Myotis lucifugus*; MYLU), and Yuma myotis (*Myotis yumanensis*; MYYU). Tree-roosting migrants are species that primarily roost in tree snags or foliage and exhibit latitudinal or long-distance migrations in part or all their range. Species in this group were western red bat (*Lasiurus blossevillii*; LABL), hoary bat (*Lasiurus cinereus*; LACI), and silver-haired bat (*Lasionycteris noctivagans*; LANO). Hereafter, I will refer to bat species using four-letter abbreviations using the first and last two letters of the scientific name of each species (found in Table 3).

## Site Selection

We surveyed 274 sites between 15 March and 15 July of 2016 and 2017 (Figure 1). Detectors were deployed for 7 nights; but equipment failure and logistics resulted in a range of successful nights deployed from 4-7 nights. This sampling period was chosen because it aligned with the breeding season of birds, another focal taxon of the CDFW monitoring program (Rich et al. 2019). Between March and July, sampling locations were spread throughout the CV and approximately 30 detectors were deployed at any given time on a rotating basis to capture latitudinal variation of bat distributions.

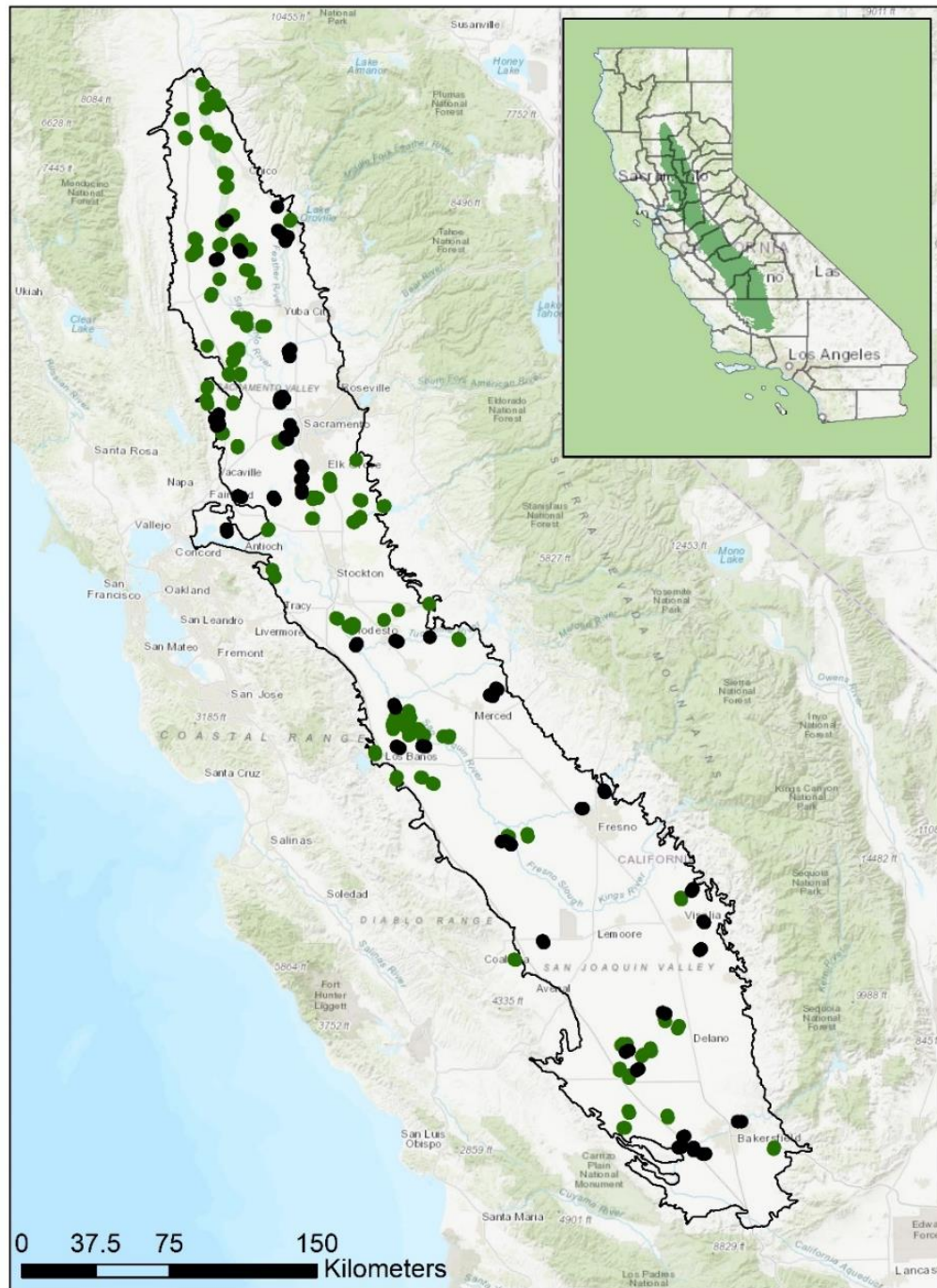


Figure 1. Locations of 274 sites across California's Central Valley, selected using a spatially stratified-random design. Sites were either sampled in 2016 (green,  $n = 90$ ) or 2017 (black,  $n = 184$ ).

Within this study area, we identified survey locations by selecting a spatially balanced random sample of hexagons, from the United States Department of Agriculture (USDA) Forest Inventory and Analysis program hexagonal grid (hexagon radius ~2.6 km). Points within the hexes were stratified by vegetative lifeform: crop, orchard, grassland, alfalfa, rice, wetlands, and riparian. Within each hexagon, 1-2 survey locations were chosen. Using the random sample, sites were opportunistically selected based on land ownership and access constraints and were placed at least 1000 m apart within the hexagon (Figure 2).

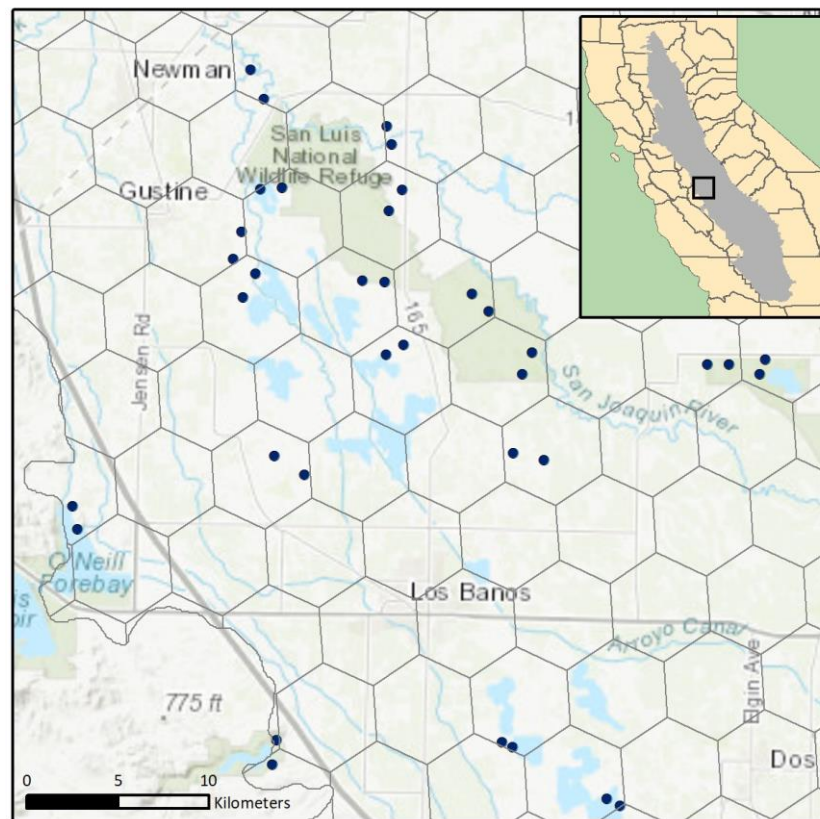


Figure 2. Map depicting paired sampling design within 5 km USDA hexes in the Central Valley, California. Points denote sampling locations near the San Luis Wildlife Refuge complex.

### Acoustic Recording and Analysis

At each site, we deployed an SM3BAT detector and wind baffled ultrasonic microphone (SMM-U1; Wildlife Acoustics, Inc., Maynard, MA). Recorders were affixed to a t-post, approximately 1 m above the ground, using a U-bolt assembly and cable lock. We elevated microphones above the ground using a 3 m metal conduit. Microphones were directed toward the flyway, when apparent, and pointed downward at a 45 degree angle to protect them from precipitation and to deter perching birds (Figure 3).





Figure 3. Setup of SM3Bat recorder at site. Microphones were elevated above the ground using a 3 m metal conduit. The acoustic microphone (SMM-A2) was positioned 2 m above the ground, and the ultrasonic microphone (SMM-U1) was positioned 3 m above the ground.

We deployed recorders to optimize recording quality and call classification. We programmed acoustic recorders to record full-spectrum triggered ultrasonic calls across the frequency range of bat species in the area (Appendix D). Recorders were active for 22 min 30 sec per half hour from 30 minutes before sunset until 0400 the following morning. All procedures were approved by HSU IACUC (protocol number 16/17.W.08-A, September 7, 2016).

Recorded calls were processed using Kaleidoscope Pro V4.3.2 (Wildlife Acoustics, Concord, MA). Noise filtering and auto-classification was conducted with the Kaleidoscope Pro species auto-classifier, selecting for bats present in California. Auto-classified output included species presence values (p) per night, per site. Any detections that had a value of  $p < 0.05$  (“match ratio,” high probability of positive species ID), were selected for further review. Up to 5 species events/site/night were manually vetted for accuracy by a trained observer using a species identification key, and classified as a confirmation (matches the auto-classifier, positive ID), rejection (does not match the auto-classifier, no ID), or given an alternative ID (does not match the auto-classifier, different species). Secondary vetting of the calls was conducted on 30 sites using full spectrum analysis in SonoBat V4.2.2 (Szewczak 2018). I completed a comparison between auto-classifier methods; however, the Kaleidoscope Pro detection histories were used in the final analysis (Appendix C) because secondary analysis suggested high agreement between SonoBat and Kaleidoscope Pro (78% - 98%), after manual vetting was completed.

## Occupancy and Detection Covariates

### Occupancy

I extracted land cover values for 2016 and 2017 from USDA CropScape Cropland Data Layer (Boryan et al. 2011). I reclassified the rasters into nine categories: row crops (all ground based crops), orchard/vineyard (all tree crops), semi-natural open habitat (grassland, shrubland, barren, and fallow), rice, herbaceous wetland, wooded wetland, developed, and forest using raster in R version 5.3.2 (Hijmans 2018).

For each site, I extracted percentage of the above land cover classes within buffered radii of 500m, 1000m, 1500m, and 2000m from the acoustic detector, for the corresponding deployment year. These buffers were chosen based on core habitat use areas for the focal species in the area. This information is not available for all species, so when not available, I included radii that have been found to be influential for similar species in the literature. Bats modeled at the 500m scale were: LABL and PAHE (Nicholls and Racey 2006, Walters et al. 2007). LACI, MYCA, MYLU, and MYYU were modeled at the 1000m radius (Henry and Thomas 2002, Evelyn et al. 2004). EPFU and LANO were modeled at 1500m (Campbell et al. 1996, Cryan et al. 2001). Lastly, EUPE and TABR were modeled at the 2000m scale (Vaughan 1959, Olimpi 2017).

In addition to proportion of land cover types, I calculated the Euclidian distance to wooded wetland features to account for distance to natural riparian edge habitat in the Central Valley, a feature that is beneficial to tree roosting bat species (Pierson et al. 2006).

In addition to remotely sensed data, I reviewed survey site photographs (taken in the four cardinal directions and primary intercardinals) to determine if water was present when the acoustic recorders were deployed. Water was defined as present when it was visible in at least one of the eight cardinal photos or absent if none of the photos had visible water. I included this categorical covariate of water presence at the survey location to account for irrigation ponds, standing water, and seasonal flooding that is not available as geospatial data. Finally, latitude was included in all models to control for spatial autocorrelation and account for heterogeneity that was unexplained by coarse scale habitat covariates. Longitude was excluded from analysis because of collinearity with latitude (Table 1).

Table 1. Environmental covariates that may impact species occupancy for single-species occupancy models for ten bat species in the Central Valley. All variables were used at the finest available temporal and spatial resolutions.

Name	Variable	Relevance	Spatial	Temporal
			Resolution	Resolution
<b>year</b>	2016 or 2017	2016 represents the driest year on record and 2017 represents one of the wettest years on record. Bats change their distributions on the landscape in water limited locations in drought years. Drought reduces the abundance of insects in temporal zones. (Tuttle et al. 2006, Trumble and Butler 2009, Hall et al. 2016)	-	-
<b>dist.ww</b>	Euclidian distance to wooded wetland cover class in CROPSCAPE	Represents natural edge features used by many species for movement. (Lumsden and Bennett 2005, Ober and Hayes 2008, Bailey et al. 2019)	30m	yearly
<b>row crops</b>	Proportion of row crops within buffered area (0-1)	Negatively impacts bat activity and richness for many species (Williams-Guillen et al. 2016)	30m	yearly
<b>orch</b>	Proportion of tree crops or vineyards within buffered area (0-1)	Positively impacts bat activity and use (Pierson et al. 2006, Braun de Torrez 2014)	30m	yearly
<b>open</b>	Proportion of habitat classified as grassland, shrubland, barren, or fallow within buffered area (0-1)	Represents naturalized open areas used by some species for commuting.	30m	yearly

Name	Variable	Relevance	Spatial	Temporal
			Resolution	Resolution
<b>rice</b>	Proportion of rice within buffered area (0-1)	Seasonally inundated and may provide increased forage for bats, but observed to decrease species richness in other growing regions (Sterling and Buttner 2011, Toffoli and Rughetti 2017).	30m	yearly
<b>dev</b>	Proportion of developed within buffered area (0-1)	Represents roads and human population centers. May negatively influence some bats. (Voigt and Kingston 2016)	30m	yearly
<b>site water</b>	Presence or absence of water at a site from digital cardinal photos	Represents water at site, which may attract bats that require pools for foraging or drinking. (Lisón and Calvo 2011, Heim et al. 2017)	~ 30 m	-
<b>latitude</b>	Latitude of acoustic detector	Accounts for site level spatial heterogeneity that was not accounted for with coarse scale habitat covariates	-	-

### Detection

Many factors can influence the detectability of bats on the landscape (Table 2). To test the effect of anthropogenic landcover on bat species, I accounted for factors that are known to influence detectability of bats (Russo et al. 2018).

Julian date was included as a detection covariate to account for nightly differences in activity caused by unmeasured variables, and differences in detectability based on temperature and season (Hayes 1997). I hypothesized that species that were only present in the northern latitudes of the valley would be more active in their known range later in the season, thus increasing detectability. Julian date was correlated with daily mean temperature (24 hour cycle) and precipitation, and thus reflects both of those variables.

Vegetation clutter was included as a covariate because sound transmission and call shape is influenced by the amount of and structure of clutter (Patriquin et al. 2003, Parsons and Szewczak 2009). Increasing clutter at a site leads to difficulty in auto-classifier discrimination and decreases detection confirmations for a species. I extracted 30 m resolution NLCD 2011 canopy cover layers and calculated the total percentage of canopy cover within a 100m radius buffer from the recorder (Homer et al. 2012). This layer was chosen because it included a measure of canopy cover tree species within natural and anthropogenic areas. This distance envelops the maximum radius of detectability (Stilz and Schnitzler 2012).

Increasing wind speed decreases the probability of detection of bat species, by reducing nightly activity and recording quality (Parsons and Szewczak 2009). To account

for these impacts, daily maximum wind-velocity was extracted for each recorder location for each deployment day from gridMET surface meteorological data (Abatzoglou 2013).

Because our vetting methods were biased toward high quality calls, it is possible that bats occupied sites but were not detected because of poor call quality. I hypothesized that the overall call quality would impact detection. Call quality is a function of a host of factors including distance to recorded subject, refraction, noise interference, and environmental variables at the microsite (Parsons and Szewczak 2009). Subsequently, number of automated IDs is a function of call quality, therefore the number of calls available for vetting increases our chances of a species confirmation. Following Banner et al. (2018), I included a natural log transformed variable of acoustic calls identified to species, by the auto-classifier at the  $i$ th site, on the  $j$ th occasion. This covariate serves as a proxy for fine scale microsite features that were not documented (i.e., site temperature, wind speed at recorder, surrounding habitat features).



Table 2. Environmental covariates that were included to characterize imperfect detection for single-species occupancy models for ten bat species in the Central Valley. All variables were used at the finest available temporal and spatial resolution.

<b>Name</b>	<b>Variable</b>	<b>Relevance</b>	<b>Spatial Resolution</b>	<b>Temporal Resolution</b>
<b>wind</b>	Daily maximum wind velocity at the acoustic detector location	Decreases bat activity and recording quality (Parsons and Szewczak 2009)	4 km	daily
<b>date</b>	Date of survey night	Explains unexplained nightly heterogeneity and greater bat activity in the late season (Hayes 1997)	-	-
<b>canopy</b>	Percent canopy cover within 100 m radius of detector	Canopy decreases sound attenuation distance and changes call shape (Parsons and Szewczak 2009)	30 m	2011
<b>files</b>	Number of calls identified to target species with 95% program confidence by auto-classification software	Acts as a proxy for fine scale microsite features that were not documented (i.e., site temperature, wind speed at recorder, surrounding habitat features) (Banner et al. 2018)	site	daily

## Distribution Modeling

### Single-season occupancy modeling

I used a single-season occupancy modeling approach, implemented in a Bayesian framework, to evaluate the effects of drought and human land use for 10 bat species. These models use detection/non-detection data to estimate the probability that the species of interest occupied a spatial unit during the survey period. In addition, detection and occupancy can be modeled as a linear function of covariates to explain heterogeneity (MacKenzie et al. 2002, Kery and Royle 2016). I treated each site as a sample unit and considered each night (30 minutes before sunset until 0400) as a separate survey occasion ( $n = 4 - 7$ ). Because bats are a highly mobile species, they can cover many sample units during a given survey night. As such, “occupancy” hereafter should be interpreted as the probability a bat used a given sampling unit at some point during the surveyed period (MacKenzie 2005). Detection and occupancy were modeled as a function of covariates. Prior to analysis, I standardized all continuous covariates to have a mean of 0 and a standard deviation of 1 and tested for collinearity using Pearson’s correlation coefficient. Because we did not re-survey the same sites each year, I was unable to calculate species turnover rates using a dynamic approach. Rather, year was included as a fixed effect to determine variation between the two survey periods.

To fit models, I used JAGS version 4.3.0 through package R2jags in program R version 5.3.2 (Su and Yajima 2015, R Core Team 2018). I used vague priors (Kery and Royle 2016, Northrup and Gerber 2018) and treated all terms as fixed effects. For the

intercept values, I used a *Uniform*(0, 1) prior on the probability scale. For all logit-scale parameters I used a Normal prior with a mean of 0 and variance of 2 [*Normal*(0, 0.5  $\tau$ )]. I evaluated sensitivity to priors by considering a *Uniform*(-10, 10) for all logit-scale parameters (beta terms), but found no difference in the posterior mean estimates when covariates had high influence in the model (indicator variable above 0.5). I ran 3 independent chains of 50,000 iterations, discarded an initial 5,000 iterations as burn-in, and retained every 10th iteration for a 13,500 iteration sample.

“Model selection” was completed using Kuo and Mallick indicator variables (Kuo and Mallick 1998). I did not have a set of *a priori* models, as required for an information-theoretic approach, because each habitat covariate represents a non-mutually exclusive hypothesis. The use of indicator variable selection allowed me to run a single model for each species, and provides a posterior mean that indicates the importance of each covariate within the model (Kuo and Mallick 1998, Hooten and Hobbs 2015). This latent variable (*w* or *v* in below model) has a specified prior of *Bernoulli*(0.5), with an equal likelihood of being included in each iteration. Covariate effects were considered when the mean of the posterior of the indicator variable was greater than 0.5; however covariate effects with an indicator variable value between 0.5 – 0.9 still had uncertainty in the direction of the effect, with 95% credible intervals overlapping zero.

I chose the habitat types for the model based on the different cover types in the Central Valley. Interaction terms were considered for different crop types to test whether

species were using irrigated areas as refugia during the drought (e.g., year:row crop). For all models I specified the model at the  $i$ th site on the  $j$ th occasion as follows:

$$\begin{aligned} \text{logit}(\Psi_i) = & \alpha + \beta_1 \text{Year}_i W_1 + \beta_2 \text{Distance to Riparian}_i W_2 + \beta_3 \text{Row Crops}_i W_3 \\ & + \beta_4 \text{Row Crops}_i : \text{Year}_i W_4 + \beta_5 \text{Orchard}_i W_5 + \beta_6 \text{Orchard}_i : \text{Year}_i \\ & W_6 + \beta_7 \text{Open}_i W_7 + \beta_8 \text{Site Water}_i W_8 + \beta_9 \text{Latitude}_i W_9 + \beta_{10} \\ & \text{Developed}_i W_{10} + \beta_{11} \text{Rice}_i W_{11} + \beta_{12} \text{Rice}_i : \text{Year}_i W_{12} \end{aligned}$$

$$\begin{aligned} \text{logit}(p) = & \alpha + \beta_1 \text{Wind}_{i,j} W_1 + \beta_2 \text{Julian Date}_{i,j} W_2 + \beta_3 \text{Canopy}_i W_3 + \\ & \beta_4 \log(\text{Autoclassified Files}_{i,j} + 1) W_4 \end{aligned}$$

For all models, I assessed convergence using the Brooks-Gelman-Rubin convergence diagnostic (r-hat) and convergence was assumed when the diagnostic was  $< 1.1$ . Additionally, I visually inspected chains for convergence.

I tested the goodness-of-fit for the models using a posterior predictive check on the aggregated site detection history (Kery and Royle 2016) and calculated a Bayesian P value for a chi-squared test statistic based on the aggregated detection history (number of detections/site). The ratio of the test statistic for the observed and expected datasets (c-hat) was also calculated (MacKenzie and Bailey 2004), with values closer to one indicating a well-fitting model.

### Range-wide species distribution and richness

Range-wide projections were estimated using spatially explicit occupancy predictions across the Central Valley ecoregion. I created grids by converting the buffered circle area to a square with the same area of each respective model scale (e.g., 1000m radius buffer = 1772.45 m side square). Percentage of each land cover covariate was included for each grid cell and extracted using raster in R version 5.3.2 (Hijmans 2018). Average Euclidian distance to riparian areas was averaged for each grid cell. Latitude was calculated as the centroid of the grid cell. Because site water was a survey-specific covariate, this was not included in species distribution projections, and all maps represent predicted occupancy at sites without water.

All predictive maps were created using the posterior mean estimates for each covariate. The posterior mean beta estimates were multiplied by each respective indicator variable to adjust the mean estimate (i.e., low IV, low covariate influence). Model uncertainty was mapped using the same methods for the upper and lower 95% credible intervals and is represented as the range of uncertainty.

Predicted richness maps were created using the aggregated results of species distribution maps. All predictions were coarsened to a 3.5 x 3.5 km. If a grid cell had a predicted occupancy of  $> 0.5$  it was considered “occupied” and the respective species was considered present in that cell. Occupied sites for all bat species were combined to estimate ecoregion-wide richness.

## RESULTS

One-thousand eight hundred and eighty-eight nights were surveyed at 90 sites in 2016 ( $n = 657$ ) and 184 sites in 2017 ( $n = 1231$ ), and I recorded a total of 401,501 auto-classified recording files identified to 17 bat species. After filtering there were 7,253 species-night-site events that were vetted manually. Less than 50% of these calls were confirmed for a total of 3,301 species-site-night events over the survey period. A total of 15 different species were confirmed after manual vetting (Table 3).

Table 3. Bat species detected with automated ultrasonic detectors placed at randomly selected sites in 2016 and 2017, and relative number of detections, given total detector nights in 2016 (n = 657) and 2017 (n = 1231) in the Central Valley, CA.

Species	Species Code	2016 Events	2017 Events	Total Events	2016 Relative Detections	2017 Relative Detections
<i>Tadarida brasiliensis</i>	TABR	350	894	1244	53%	73%
<i>Myotis yumanensis</i>	MYYU	167	287	454	25%	23%
<i>Lasiurus cinereus</i>	LACI	133	282	415	20%	23%
<i>Lasiurus blossevillii</i>	LABL	37	304	341	6%	25%
<i>Eumops perotis</i>	EUPE	72	95	167	11%	8%
<i>Myotis lucifugus</i>	MYLU	43	118	161	7%	10%
<i>Eptesicus fuscus</i>	EPFU	36	116	152	5%	9%
<i>Lasionycteris noctivagans</i>	LANO	6	139	145	1%	11%
<i>Myotis californicus</i>	MYCA	34	86	120	5%	7%
<i>Parastrellus hesperus</i>	PAHE	29	43	72	4%	3%
<i>Corynorhinus townsendii</i> *	COTO	1	11	12	0%	1%
<i>Antrozous pallidus</i> *	ANPA	1	8	9	0%	1%
<i>Euderma maculatum</i> *	EUMA	0	5	5	0%	0%
<i>Myotis evotis</i> *	MYEV	1	3	4	0%	0%
<b>Total</b>		910	2391	3301		

\* Too few detections for occupancy modeling.

## Occupancy Models

I completed single-season single-species occupancy modeling for ten bat species with an adequate number of detections (Table 3). All models converged after the initial iterations, with no  $\hat{r}$  values exceeding a threshold of 1.1. Posterior predictive checks indicated that the models fit relatively well, with  $\hat{c}$  values ranging from 0.3 to 1.7 for all species (Appendix A; with a  $\hat{c}$  value  $> 1$  indicating possible over dispersion and lack of fit to model assumptions). Mean detection probability calculated for each specific site ranged from 0.098 to 0.991 and the proportion of occupied sites within the sample ranged from 0.36 to 0.96 (Table 4).



Table 4. Estimated detection and proportion of sites occupied within the sample for 10 bat species for 274 sites in the Central Valley, CA. See Table 3 for species code definitions.

<b>Species</b>	<b>Detection Probability</b>	<b>Occupancy Probability</b>
EPFU	0.162	0.416
EUPE	0.258	0.354
LABL	0.436	0.796
LACI	0.306	0.832
LANO	0.098	0.526
MYCA	0.139	0.369
MYLU	0.170	0.449
MYYU	0.469	0.613
PAHE	0.111	0.241
TABR	0.991	0.967

### Detection covariate effects

As expected, log transformed number of auto-classified calls had an influence on all bat species. As number of files increased, the probability of detection also increased at varying rates (Figure 4). This effect was weak for EUPE, the lowest frequency bat in the survey effort. This is likely due to a high number of auto-classified misidentifications for this species in Kaleidoscope Pro.

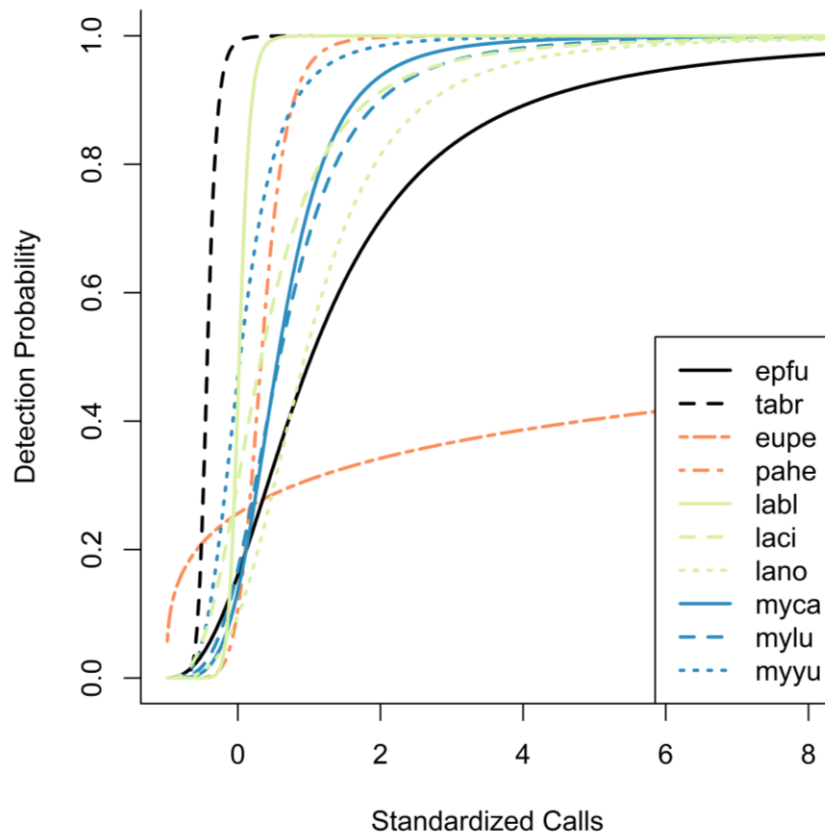


Figure 4. Model predicted influence of log (number of auto-classified calls) on detection 10 species detected in the Central Valley, CA.

Site-level habitat measurements and broad-scale weather measurements did not have a clear effect on detection for most species. Maximum wind speed had a clear negative impact on detection for MYYU and TABR and a 1 SD increase in wind (1.78 kph) decreased the odds of detection by 0.76 (CRI 0.64 – 0.90, IV = 0.97) and 0.71 (CRI 0.61 – 0.82, IV = 1), respectively. Canopy cover had a clear negative impact on detection for MYLU and TABR, and a 1 SD increase in canopy cover (7%), decreased the odds of detection by 0.55 (CRI 0.42 – 0.72, IV = 1) and 0.69 (CRI 0.60 – 0.79, IV = 1). Survey date did not have a clear directional impact on detection of any of the species.

#### Landscape characteristics and occupancy

I summarized the results from single-season occupancy models by creating maps of the range-wide predicted occupancy probability for each species. Some areas have high uncertainty in the predicted maps, because there is greater uncertainty in posterior means for some species. Additionally, interaction terms resulted in greater uncertainty in 2017.

Table 5. Observed effects of environmental covariates on occupancy probability for ten bat species in Central Valley, CA. Highlighted cells denote covariates with indicator variable values greater than 0.5.

Species	Year*	Dist. to WW	Row Crop	Row Crop : Year	Orchard	Orchard : Year	Open	Site Water	Dev.	Rice	Rice : Year	Lat.
<b>Tree roosting migrants</b>												
Western red bat - LABL ( <i>Lasiurus blossevillii</i> )	<b>+</b> <b>(0.99)</b>	- (0.42)	- (0.45)	<b>+</b> <b>(0.62)</b>	+	+	+	+	+	+	+	+
Hoary bat - LACI ( <i>Lasiurus cinereus</i> )	<b>+</b> <b>(0.97)</b>	+	- (0.39)	+	<b>+</b> <b>(0.96)</b>	- (0.39)	<b>+</b> <b>(0.60)</b>	<b>+</b> <b>(0.99)</b>	+	+	+	+
Silver-haired bat - LANO ( <i>Lasionycteris noctivagans</i> )	<b>+</b> <b>(1.0)</b>	<b>+</b> <b>(0.52)</b>	<b>+</b> <b>(0.83)</b>	+	- (0.33)	<b>+</b> <b>(0.54)</b>	- (0.33)	+	- (0.19)	+	- (0.29)	- (0.23)
<b>Crevice / cave roosting Myotis</b>												
California myotis - MYCA ( <i>Myotis californicus</i> )	+	+	+	- (0.22)	<b>+</b> <b>(0.82)</b>	- (0.41)	+	- (0.36)	<b>-</b> <b>(0.53)</b>	- (0.42)	- (0.49)	<b>+</b> <b>(0.98)</b>
Little brown bat - MYLU ( <i>Myotis lucifugus</i> )	+	<b>-</b> <b>(0.90)</b>	+	<b>+</b> <b>(0.57)</b>	- (0.30)	<b>+</b> <b>(0.53)</b>	- (0.48)	<b>+</b> <b>(0.65)</b>	<b>-</b> <b>(0.26)</b>	<b>+</b> <b>(0.85)</b>	+	<b>+</b> <b>(1.0)</b>
Yuma myotis - MYYU ( <i>Myotis yumanensis</i> )	<b>-</b> <b>(0.62)</b>	<b>-</b> <b>(0.63)</b>	+	+	<b>+</b> <b>(0.60)</b>	<b>-</b> <b>(0.62)</b>	- (0.24)	+	+	- (0.25)	+	<b>+</b> <b>(1.0)</b>
<b>Human-tolerant species</b>												
Big brown bat - EPFU ( <i>Eptesicus fuscus</i> )	<b>+</b> <b>(0.59)</b>	- (0.23)	- (0.23)	- (0.26)	+	- (0.19)	+	- (0.24)	- (0.37)	- (0.25)	+	<b>+</b> <b>(0.84)</b>
Brazilian free-tailed bat- TABR ( <i>Tadarida brasiliensis</i> )	<b>+</b> <b>(0.99)</b>	+	<b>+</b> <b>(0.69)</b>	- (0.46)	+	+	- (0.35)	+	+	+	+	+
<b>Arid-adapted species</b>												
Western mastiff bat - EUPE ( <i>Eumops perotis</i> )	<b>-</b> <b>(0.78)</b>	- (0.16)	- (0.31)	<b>-</b> <b>(0.73)</b>	<b>+</b> <b>(0.83)</b>	<b>-</b> <b>(0.73)</b>	<b>+</b> <b>(1.0)</b>	+	+	- (0.27)	+	- (0.35)
Canyon bat - PAHE ( <i>Parastrellus hesperus</i> )	- (0.47)	+	- (0.37)	<b>-</b> <b>(0.66)</b>	+	<b>-</b> <b>(0.71)</b>	+	<b>-</b> <b>(0.65)</b>	+	<b>-</b> <b>(0.59)</b>	<b>-</b> <b>(0.58)</b>	+

\*2017, the "wet year" is represented as year = 1, so a positive effect of year indicates greater occupancy in 2017.

### Tree roosting migrants

LABL and LACI had high predicted occupancy probability across the Central Valley in both years (Figures 5, 6, and 7), where LANO did not (Figure 8). All tree roosting migrants had a negative response to the drought and had greater predicted probability of occupancy in 2017. A change in year from 2016 (dry) to 2017 (wet) increased the odds of occupancy for LABL, LACI, and LANO 17.4 (CRI 3.8 – 102, IV = 0.998), 5.2 (CRI 1.3 - 22.1, IV = 0.965), and 15.6 (CRI 4.9 – 54.1, IV = 1) times, respectively (Figures 5, 6, 7, and 8).

There were no shared habitat features among the species for habitat covariates that influenced occupancy; however, all models provided at least marginal support for one or more habitat covariates (Figure 5). Notably, an increase in orchard cover by 1 SD (21%) increased the odds of use for LACI by 3.17 times (CRI 1.13 – 9.61, IV 0.961).

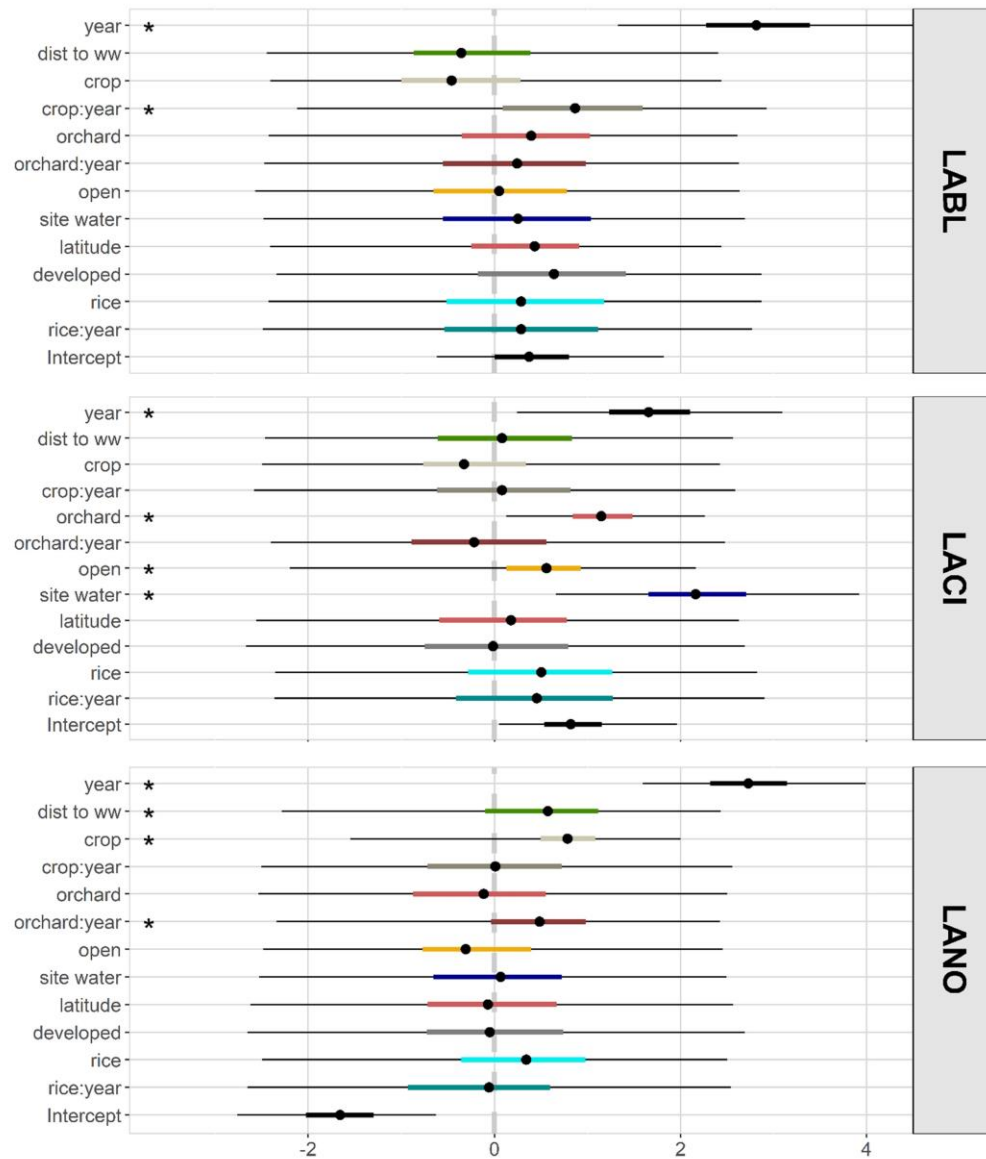


Figure 5. Posterior distributions of the occupancy estimates for tree roosting migrants *L. blossevillii* (LABL), *L. cinereus* (LACI), and *L. noctivagans* (LANO). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).

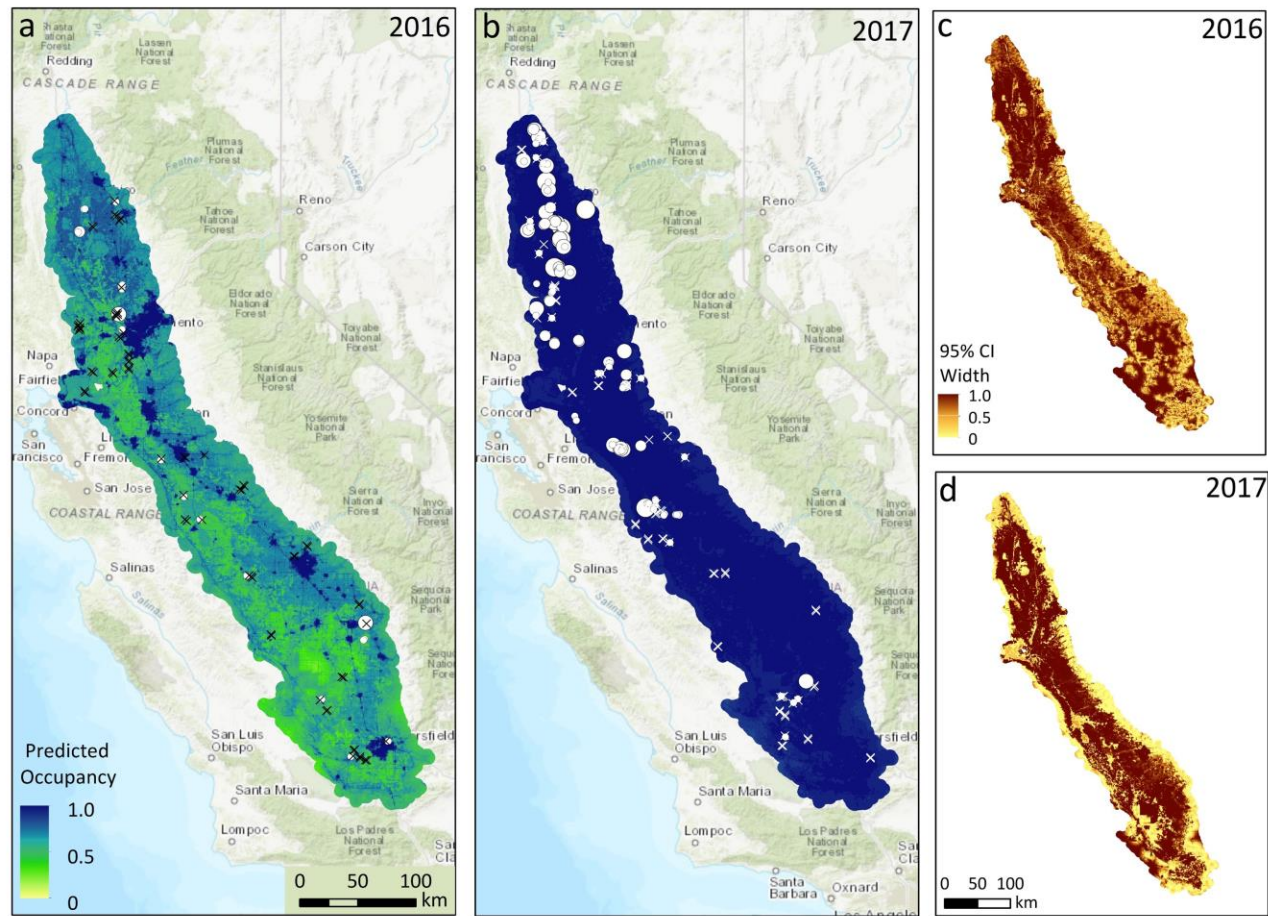


Figure 6. Model averaged posterior mean occupancy probability of western red bat (LABL), using 0.89 X 0.89 km square grid in (a) 2016 (drought,  $n=90$ ) and (b) 2017 (post-drought,  $n=184$ ), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). X denotes sites with no detections. Panels c/d denote 95% credible interval width.

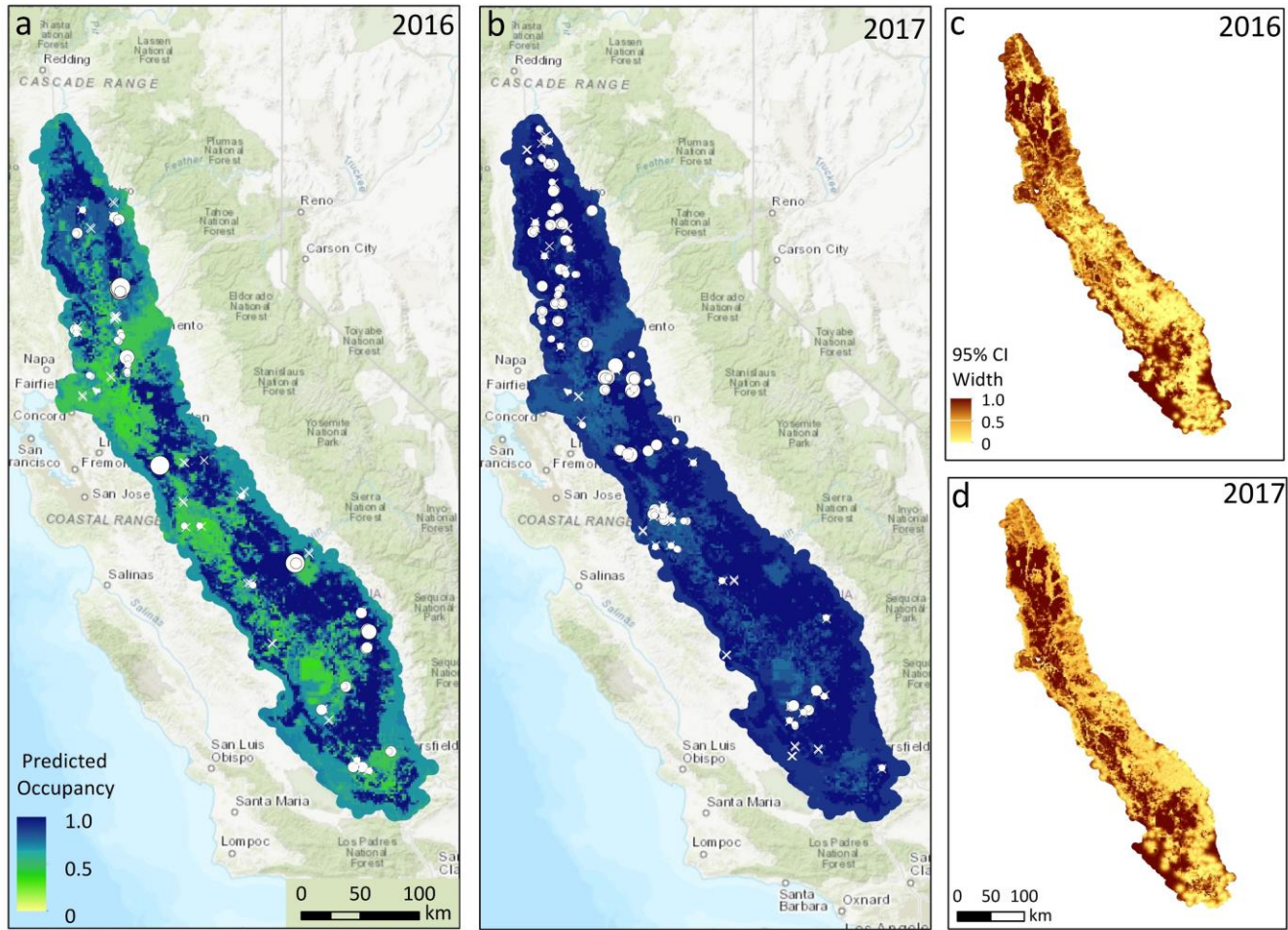


Figure 7. Model averaged posterior mean occupancy probability of hoary bat (LACI), using 1.78 x 1.78 km square grid in (a) 2016 (drought, n=94) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). White x denotes sites with no detections. Panels c/d denote 95% credible interval width.



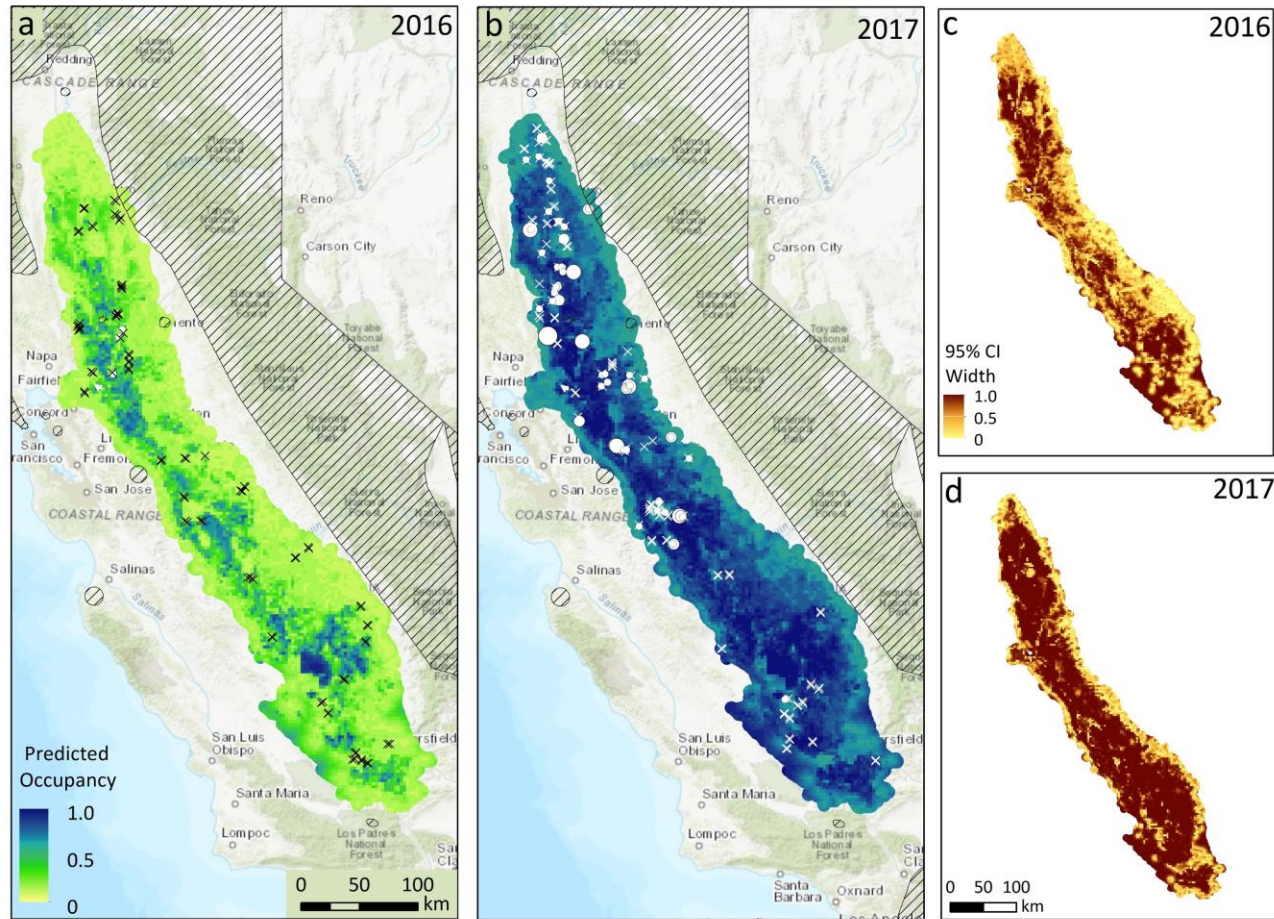


Figure 8. Model averaged posterior mean occupancy probability of silver-haired bat (LANO), using a 2.7 x 2.7 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). X denotes sites with no detections. Panels c/d denote 95% credible interval width. Crosshatch is CDFW species range.

Crevice/cave roosting myotis

MYCA, MYLU, and MYYU did not have strong differences in occupancy probability between 2016 and 2017 (Figures 9, 4010, 11, and 12). A change in year from 2016 (dry) to 2017 (wet) decreased the odds of occupancy for MYYU by 0.62 (CRI 0.11-8.4, IV=.62); however this relationship had high uncertainty (**Error! Reference source not found.**).

There were no landscape habitat covariates that had clear directional influence on species occupancy for these three species. Instead, all three species had greater predicted occupancy in the northern latitudes of the Central Valley. One SD increase in latitude (1.4°, approx. 155 km) increased the odds of occupancy for MYCA, MYLU, and MYYU by 3.01 (CRI 1.37 – 7.74, IV = 0.977), 10.69 (CRI 3.96 – 37.41, IV = 1), and 3.0 (CRI 1.91 – 4.94, IV = 1) times, respectively (Figures 9, 4010, 11, and 12).

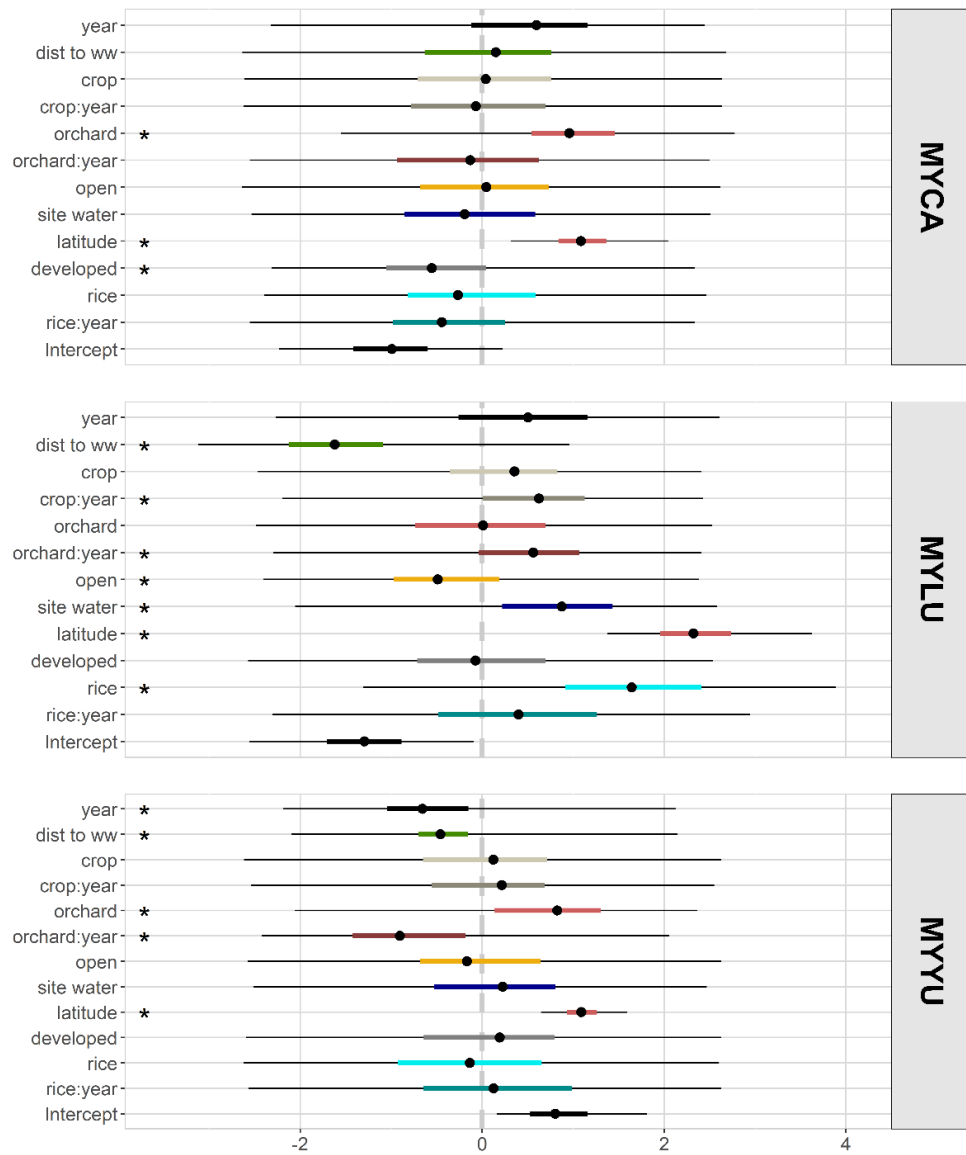


Figure 9. Posterior distributions of the occupancy estimates for myotis species *M. californicus* (MYCA), *M. lucifugus* (MYLU), and *M. yumanensis* (MYYU). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).

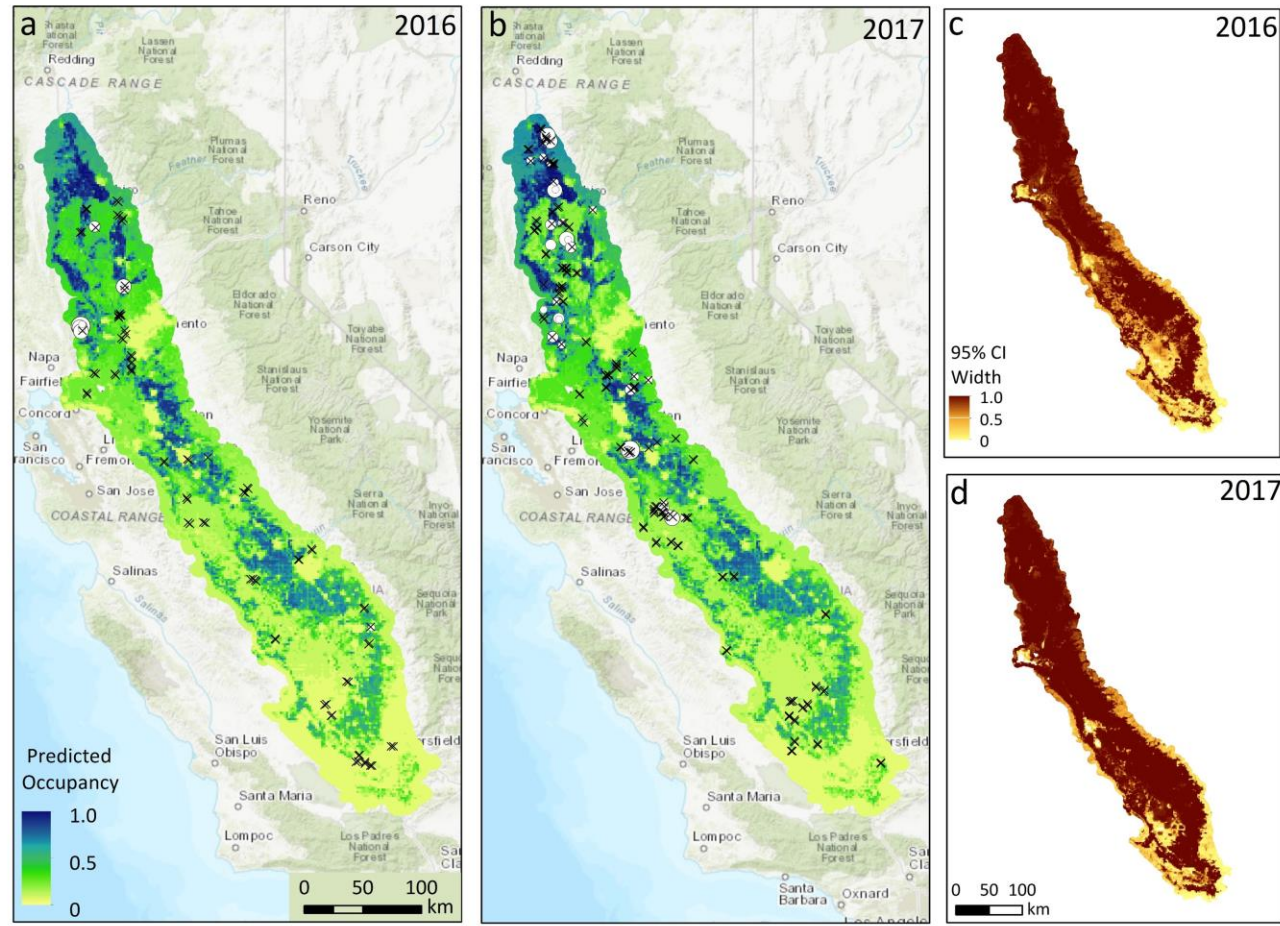


Figure 10. Model averaged (see text for details) posterior mean occupancy probability of California myotis (MYCA), using a 1.78 x 1.78 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184) for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote associated 95% credible interval width uncertainty in 2016 and 2017 respectively.



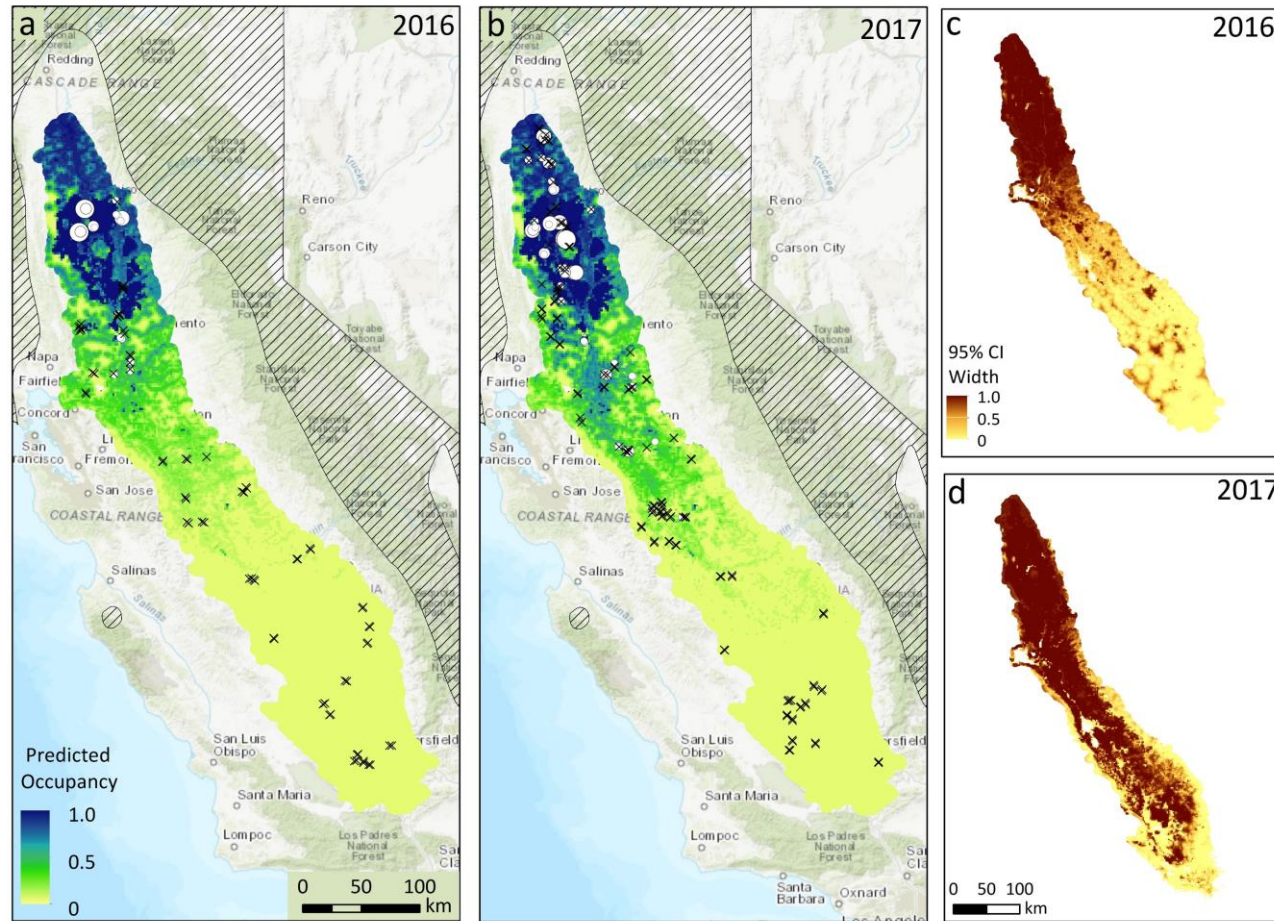


Figure 11. Model averaged posterior mean occupancy probability of little brown bat (MYLU), using a 1.78 x 1.78 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. Crosshatch represents CDFW species range.

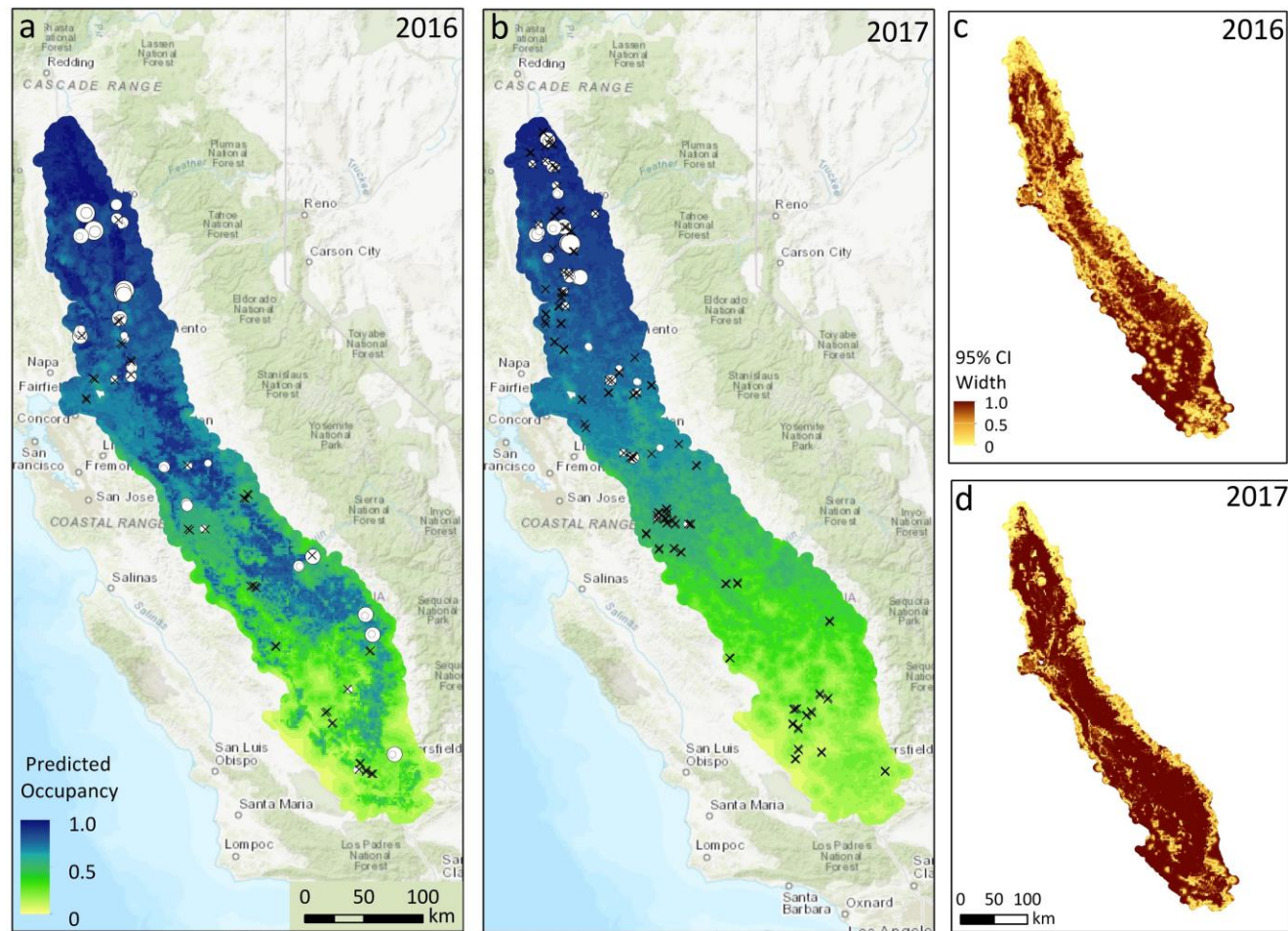


Figure 12. Model averaged posterior mean occupancy probability of Yuma myotis (MYU), using a 1.78 x 1.78 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width.

### Human-tolerant species

EPFU had relatively low predicted occupancy between the two years, where TABR was detected at virtually every site. EPFU did not have a strong difference in occupancy probability between 2016 and 2017 (Figures 13 and 14), however TABR was 13.4 times (CRI 2.13 – 92.76, IV = 0.99) more likely to occupy the Central Valley in 2017 (Figures 13 and 15). There was not a clear influence of habitat covariates for either species.

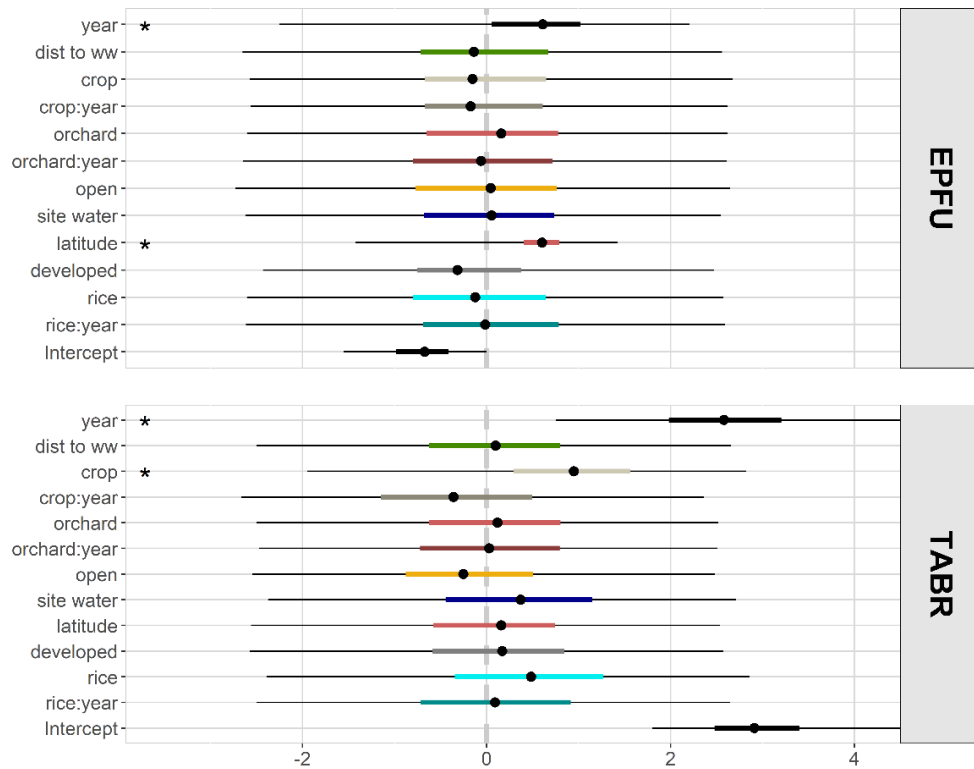


Figure 13. Posterior distributions of the occupancy estimates for human tolerant species *E. fuscus* (EPFU) and *T. brasiliensis* (TABR). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).



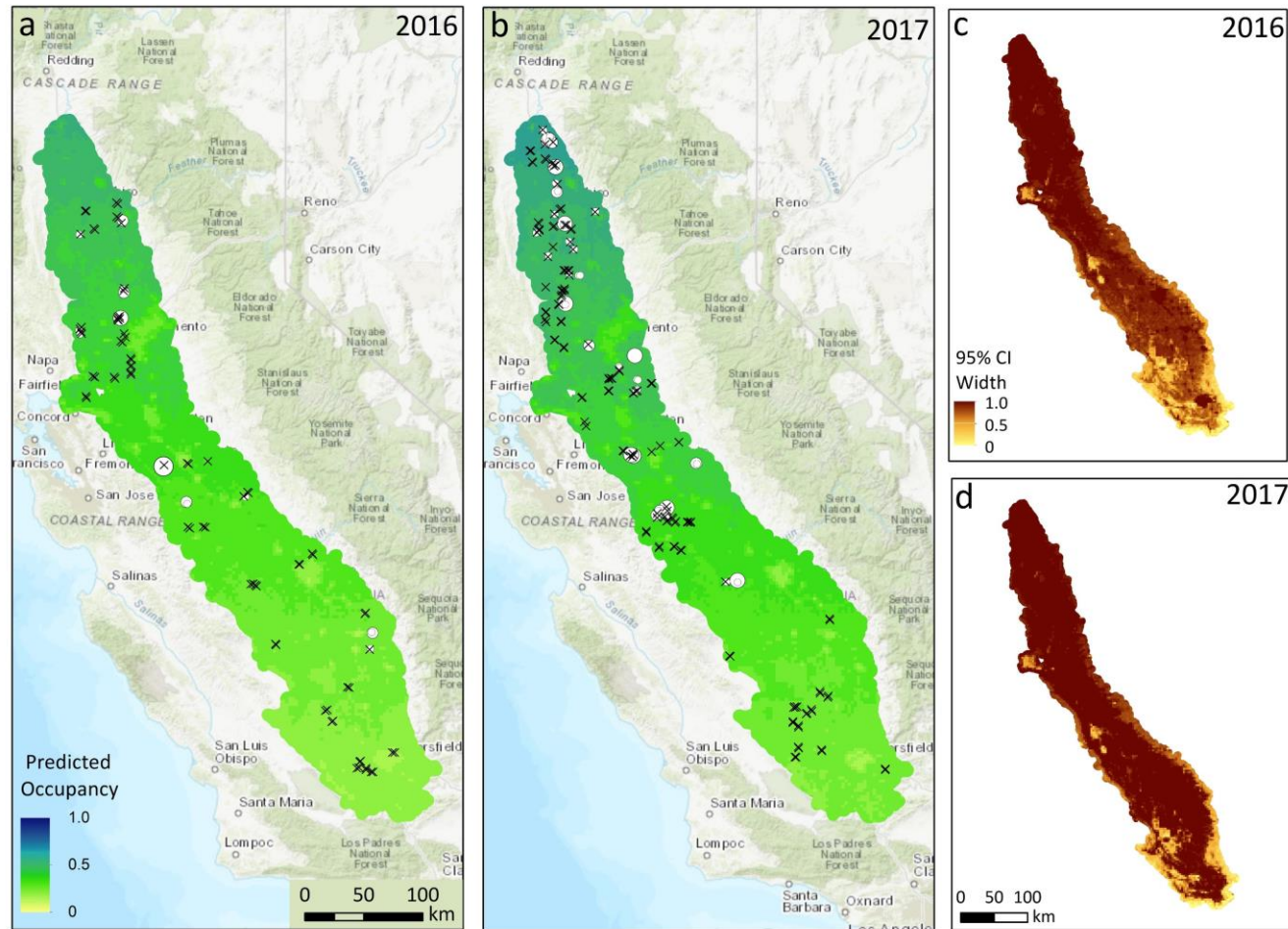


Figure 14. Model averaged posterior mean occupancy probability of big brown bat (EPFU), using 2.7 x 2.7 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width.



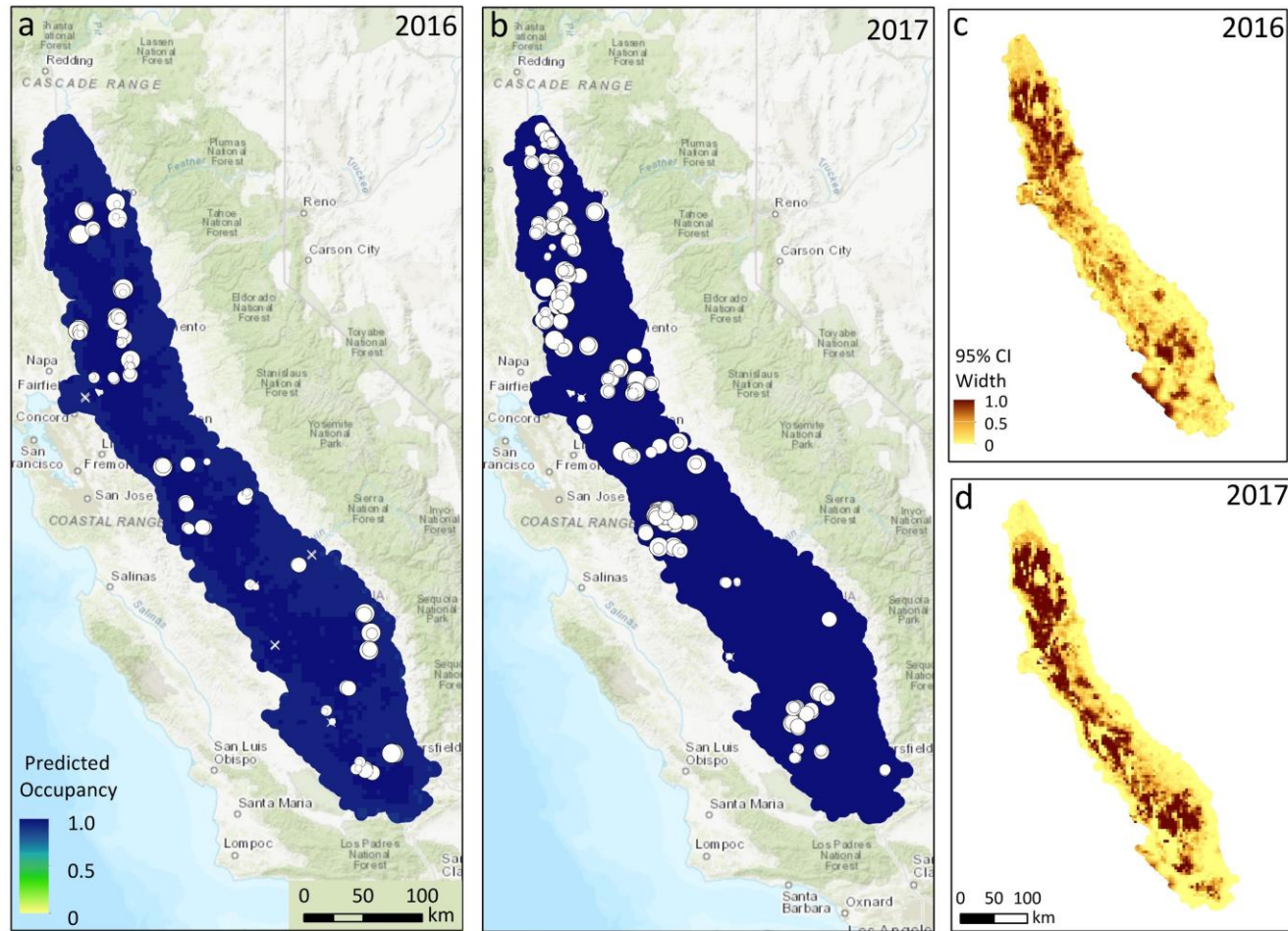


Figure 15. Model averaged posterior mean occupancy probability of Brazilian free-tailed bat (TABR), using a 3.5 x 3.5 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). White x denotes sites with no detections. Panels c/d denote 95% credible interval width.

### Arid-adapted species

EUPE and PAHE had generally high predicted occupancy probability in the open areas of the Central Valley in both years. There was not a clear directional response to drought for either species (Figures 16, 17, and 18).

For EUPE and PAHE, percentage of open cover was the only covariate that had a clear directional influence on occupancy probability. An increase in 1 SD led to an increase in odds of occupancy by 2.67 (CRI 1.59 – 4.83, IV = 0.99) and 6.44 (CRI 2.22 – 22.83, IV = 0.99) (Figure 16). There was model support for the interactive terms between orchard and year and crop and year. The models suggest that occupancy probability was greater in cultivated areas in 2016 for both EUPE and PAHE.

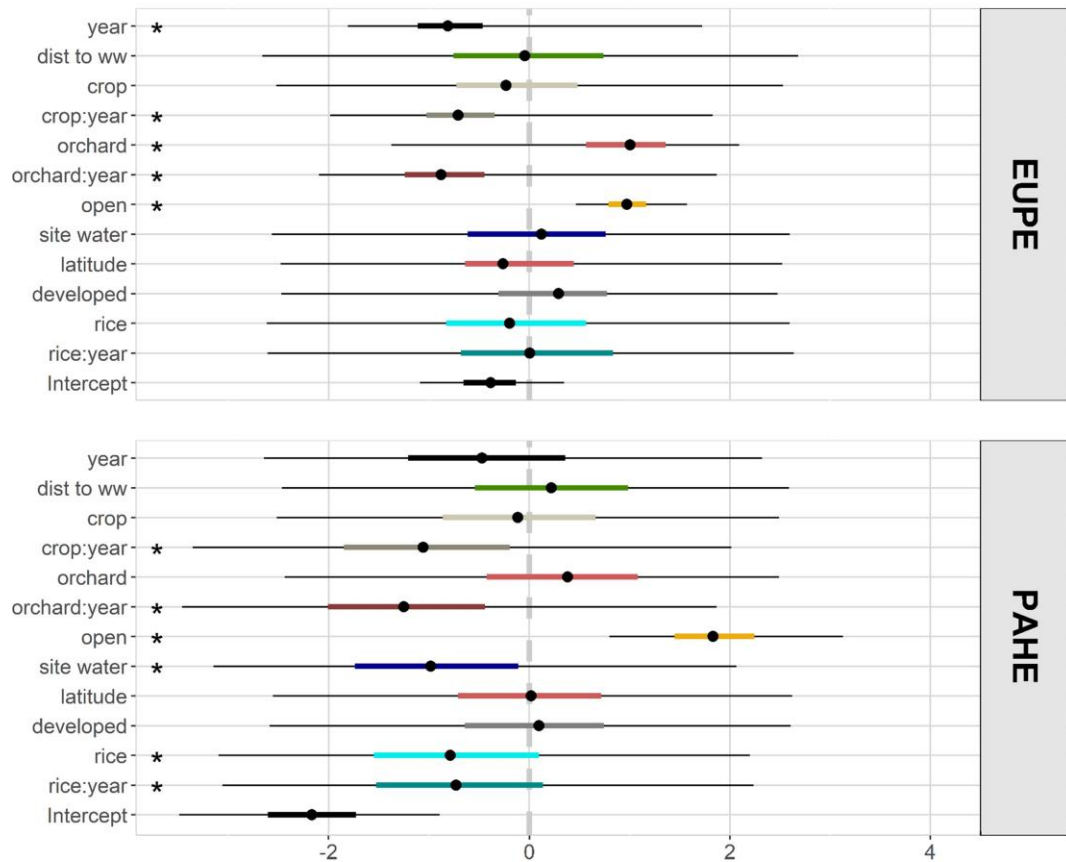


Figure 16. Posterior distributions of the occupancy estimates for arid-adapted species *E. perotis* (EUPE) and *P. hesperus* (PAHE). The thick, colored lines denote the 50% CIs and the thin, black lines denote the 95% CI. The black points denote the posterior mean of each covariate. 2017, the “wet year” is represented as year = 1. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).

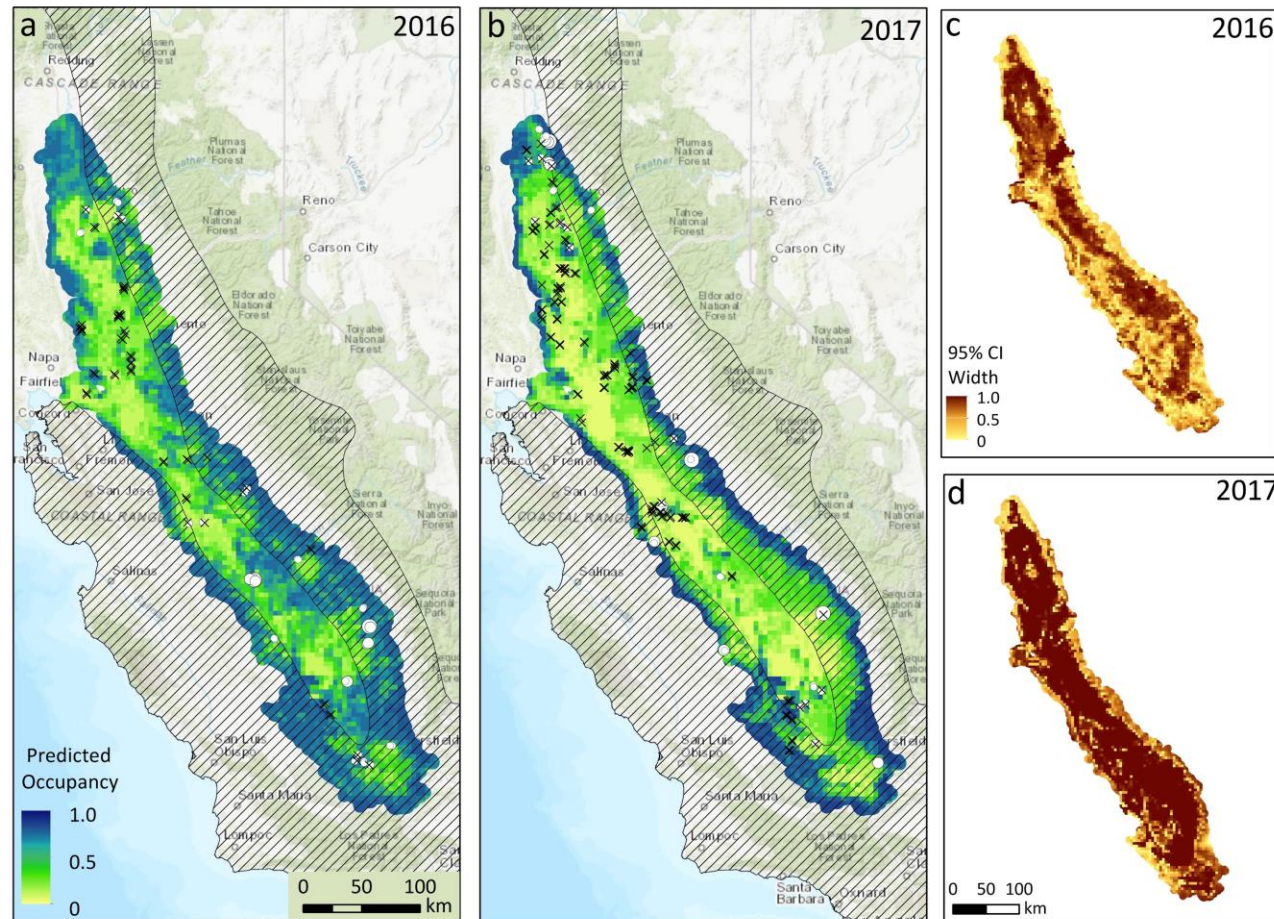


Figure 17. Model averaged posterior mean occupancy probability of western mastiff bat (EUPE), using 3.5 x 3.5 km square grid in (a) 2016 (drought, n=90) and (b) 2017 (post-drought, n=184), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width. Crosshatch pattern denotes CDFW species range.



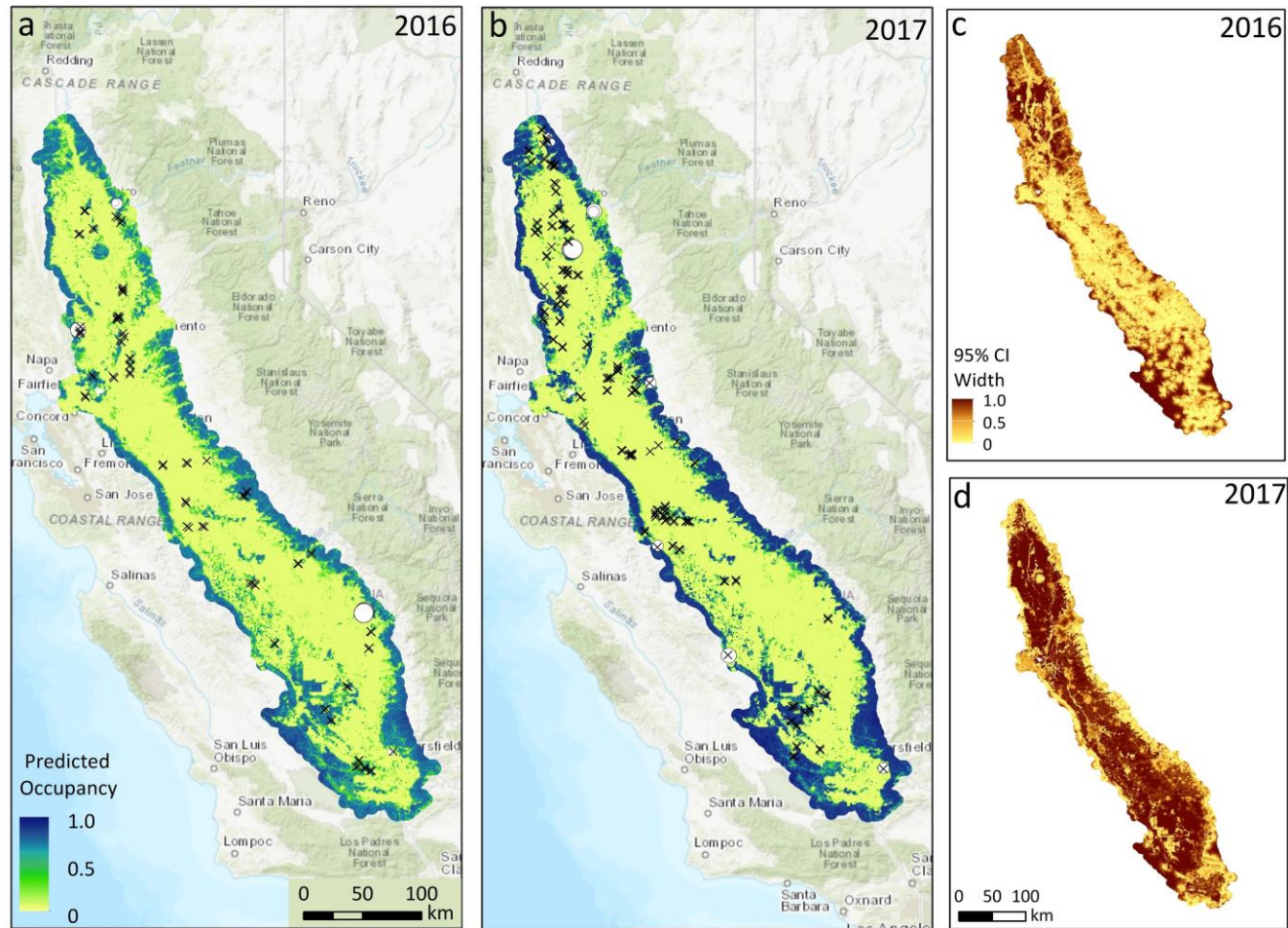


Figure 18. Model averaged posterior mean occupancy probability of canyon bat (PAHE), using a  $0.89 \times 0.89$  km square grid in (a) 2016 (drought,  $n=90$ ) and (b) 2017 (post-drought,  $n=184$ ), for habitat conditions in the Central Valley, CA. White circle size denotes number of nights the bat was detected at a site (range 1-7). Black x denotes sites with no detections. Panels c/d denote 95% credible interval width.

### Species richness

Species richness was greater in 2017 (wet) than 2016 (dry) in the Central Valley (Figure 19). From 2016 to 2017, there was a change in occupancy of up to five species. This pattern was largely driven by the migratory species LABL, LACI, LANO, and TABR which had greater range-wide occupancy in 2017.

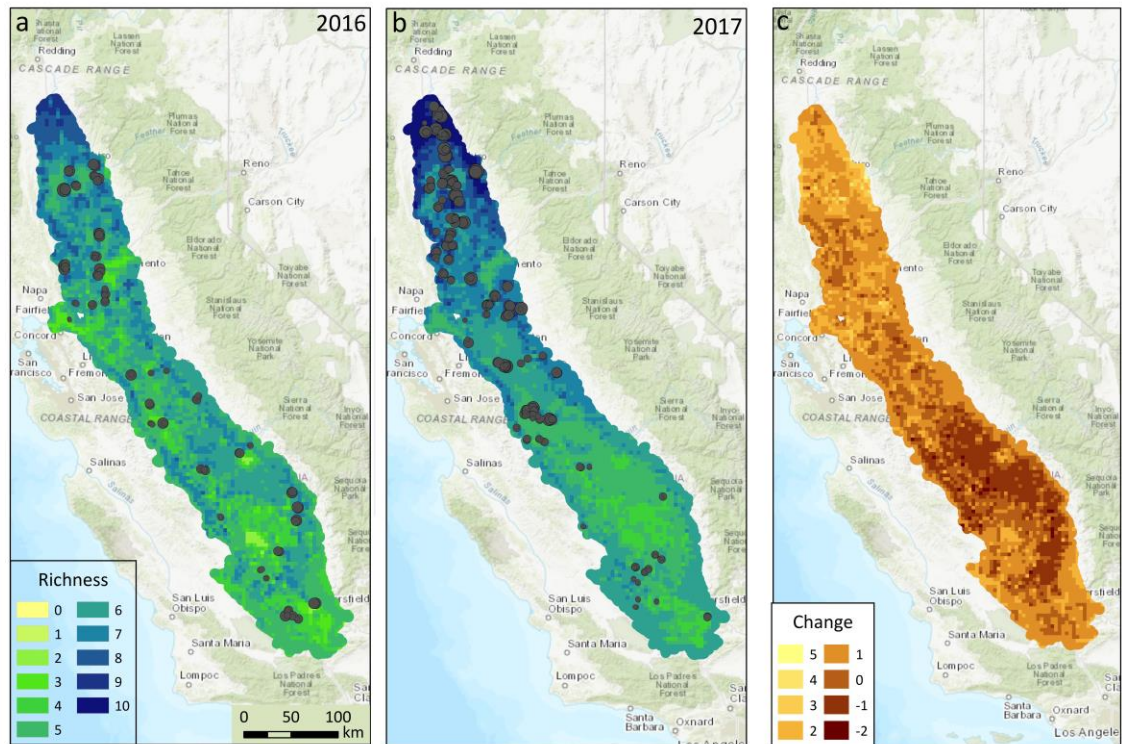


Figure 19. Projected species richness for 2016 (a) and 2017 (b) for acoustically detectable species in the Central Valley, CA, using a 3.5 km x 3.5 km grid. White circle size denotes number of species detected at a given acoustic detector location. Panel (c) illustrates the change in species richness between 2016 and 2017.

## DISCUSSION

Anthropogenic land-use and drought predicted bat species occupancy on the landscape scale, with varied effects based on species habitat specialization and movement strategy. Interestingly, predicted occupancy for migratory species (LABL, LACI, LANO, and TABR) was lower across the Central Valley during the drought, while hibernating species had similar predicted occupancy in both years (EPFU, MYCA, MYLU, MYYU, and PAHE). Arid-adapted species (PAHE and EUPE) expanded from natural open areas into orchard and crop habitat types during the drought, potentially to exploit food and water resources that were otherwise unavailable on the natural landscape. There was not a clear impact of landscape scale habitat features on all species; however, percentage of orchard cover was the most common anthropogenic predictor of greater species occupancy. Overall, these maps illustrate high variation in landscape scale bat occupancy in the Central Valley. These extrapolated maps provide the most complete look at bat landscape distributions in California's Central Valley.

### Drought

My results demonstrate that not all bat species expanded their range after the drought ended in 2017; however, species richness was greater across the majority of the valley in 2017 after the drought. During the drought (2016), occupancy of migratory species, LABL, LACI, LANO, and TABR was low, with patchy areas of high predicted occupancy. Migration is a function of unfavorable climate conditions or resource

availability (Fleming and Eby 2003, Popa-Lisseanu and Voigt 2009, Pettit and O’Keefe 2017) and long-distance migrants (LABL, LACI, LANO, TABR) may shift their range to follow available resources (Constantine 1959). These species may not employ long-distance seasonal migrations out of California, because of the Mediterranean climate, but rather seasonally shift their distribution (Grinnell 1918, Benson 1947, Cryan 2003, Pierson et al. 2006, Weller et al. 2016). My analysis supports shifted distribution, as migratory species appeared to use their dispersal abilities to exploit food and habitat resources after the drought. The lower observed occupancy during 2016 may represent restrictions in species distribution and/or abundance on the landscape; however, without measuring species activity, the mechanism driving these patterns is unclear.

Conversely, drought was not a predictor of occupancy (EPFU, MYCA, MYLU, and PAHE) or positively impacted (EUPE and MYYU) the occupancy of the rest of the bats considered. The commonality between these species is their ability to hibernate (except EUPE) and their preference for permanent roost structures (rock crevices, buildings, bridges, caves). Bats that roost in permanent structures have more roost fidelity than foliage roosting bats (Lewis 1995). The lack of change between the two years suggests that this site fidelity is detectable on a landscape scale. Fidelity is advantageous because bats do not have to expend energy learning new foraging areas; however, lack of plasticity in roost site location may indicate that these species may be more adversely impacted by future drought, if they do not shift to track resources.



Arid-adapted species (EUPE and PAHE) were more likely to be encountered in cultivated areas during the drought, an association that was not observed in 2017. Although arid adapted, these species still require occasional water, and PAHE will forage over water. These two species are most widespread in the San Joaquin Valley (CDFW 2015), a more arid region, where most of the water is in irrigation holdings. Over 80,000 acres (90% of total) were fallowed in the San Joaquin Valley in 2016 (Medellín-Azuara et al. 2016); however, production remained constant in orchards, leading to severely depleted groundwater stores. The reduced water table impacted natural open areas, so arid species may have shifted to irrigated areas to exploit food and water resources (Amorim et al. 2018). Additionally, the greater temperatures and drought conditions reportedly increased the amount of crop pests in this area, especially lepidopterans, which may have drawn EUPE and PAHE to agricultural areas (Trumble and Butler 2009, Leschin-Hoar 2015, California Department of Pesticide Regulation 2018).

#### Human Land Use

I did not identify a specific landscape feature that negatively impacted all bat species; rather, there were a variety of impacts with no clear, shared pattern. This may be partially due to the vast diversity of crops grown in the Central Valley, as demonstrated when reclassifying landcover in this study (61 different tree crop types and 53 types of row crops). This contrasts other growing regions where comparable studies have been

executed (Braun de Torrez 2014, Williams-Guillen et al. 2016, Amorim et al. 2018), which were completed in more homogeneous growing regions.

Row crop habitat alone did not predict occupancy for any of the bats, except TABR, which has a demonstrated adaptation for foraging over open habitats, and exploiting crop pest populations (McCracken et al. 2012). Although rice is often managed as wetland habitat for bird species in the Central Valley (Sterling and Buttner 2011), this crop did not impact occupancy for any bat species except MYLU. This result is similar to a European study, which found only one genus foraged in conventional rice lands (Toffoli and Rughetti 2017).

The most common cultivation type associated with positive occupancy in the Central Valley was orchard and vineyard crop types. Orchards positively impacted occupancy in at least one year for EUPE, MYCA, MYLU, MYYU, and LACI. These crops provide vertical structure, cover, foraging habitat, and water that is lacking across much of the current habitat in the Central Valley (Soulard and Wilson 2015). This observed pattern suggests that orchards may provide a suitable habitat source for bats. Over 28% of the Central Valley is represented by orchards and vineyards. As much of the native hardwood riparian forests have been converted to cropland, the positive association with orchards supports previous work that suggested that orchards may serve as alternative habitat for bats in this modified landscape (Pierson et al. 2006).

Notably, there was greater predicted species richness in the northern latitudes of the Central Valley, a pattern driven by EPFU, MYCA, MYLU, and MYYU. Although

contrary to typical latitudinal gradient patterns, this is consistent with prior knowledge of bats in California. This area, known as the Sacramento Basin, is characterized by more water, diverse roosting habitats, natural riparian forests, and a greater richness of crops (DWR 2003). Structure and natural areas as small as remnant trees in vineyards, or degraded riparian areas, have a demonstrated increase in bat activity (Olimpi and Philpott 2018, Polyakov et al. 2019). This analysis did not address these fine scale features; however more fine scale features in the Sacramento Basin, in conjunction with more water and foraging habitat, may have also driven the observed distributions.

Landscape features did not explain variation in bat occupancy for all species; however, the geospatial layers used are freely available on a yearly timescale, which will allow future analysis using this framework. I elected to use photographed site water instead of remotely sensed data because these layers did not capture fluctuations in surface water between the two years, or irrigated water sources. I used the same model for all bat species in this analysis so I could compare the relative effects between the considered species; however there was some evidence of overfitting for species with few detections. Depending on the goals of future work, there may be a benefit to modeling habitat features specific to the bat and employ model selection to remove covariates that do not influence each respective species.

Many aspects of acoustic surveys introduce uncertainty (Russo et al. 2018); however this modeling assumes that manual vetting accurately identifies the species in question. Given the extremely low detection probability (Table 4) and out of range

detections for LANO, it is likely that false detections were present for this species. For EPFU, MYCA, and MYLU the low detection probabilities were likely caused by conservative vetting because of high overlap in acoustic call shapes. The low detection probabilities for EUPE and PAHE likely represent the rarity of the species in the study area. All other species have distinct calls (LABL and MYYU) or are prolific on the landscape (TABR).

Using the automated classifier calls dramatically increased the fit of the models, but to tease out the specific features that impact species detectability, site specific wind, temperature, and other fine scale weather measurements would need to be collected. Finally, our study was limited to two years and serves as a snapshot in time and future surveys would help to determine if these occupancy patterns persist. Continuous monitoring at the same sites would allow wildlife agencies to measure ongoing population trends and employ a dynamic occupancy modeling framework to determine extinction and colonization probabilities (Rodhouse et al. 2015, Neece et al. 2018).

As suggested by previous studies, this thesis reinforces that the magnitude of habitat specialization impacts how bats respond to drought and human land use. Understanding where bats are likely to be on the landscape is especially important, because of the increasing human development in the Central Valley. In addition to human land conversion, *Pseudogymnoascus destructans* (Pd), the fungus that causes white-nose syndrome (WNS), was detected in California for the first time in 2018 (CDFW 2019). The results of this thesis reinforces the high variation in bat distributions and the need for

targeted survey efforts to further evaluate the impacts of anthropogenic land use and drought on bat species, especially as these factors continue to increase.

### Conservation Implications

The combined results of my thesis most clearly demonstrate the role of orchards as an important source of habitat for many bat species in the Central Valley and provides evidence that some bat species may exhibit more plasticity when facing drought stressors. Although the conversion of native vegetation to agroecosystems often results in negative impacts on bat activity and diversity (Williams-Guillen et al. 2016), in this instance orchards appear to provide habitat that is otherwise unavailable on this modified landscape.

In the Central Valley, 21% of the available habitat is orchards and vineyards. Comparatively, only 0.3% of this area is comprised of wooded riparian habitat. As such, orchards contribute disproportionately to available canopy cover. Historically, the Central Valley was dominated by riparian forest; however, less than 4% of this habitat remains (Katibah 1984). Instead, this habitat was largely replaced by tree nut crops, especially almonds, walnuts, and pistachios. Because of this, it seems likely that foliage dependent bats, LABL and LACI would be required to shift their habitat distribution to orchards. This was the case for LACI; however an effect was not apparent for LABL. Orchards had a positive effect on occupancy for all bat species, in at least one year. There was a significant effect for four species, LACI, MYCA, MYYU and EUPE. Due to the nature

of this study, I am unable to describe the exact role the orchards served for the bats; however previous studies have observed bats roosting, foraging, and moving through orchards (Pierson et al. 2006, Braun de Torrez 2014).

Although irrigated, orchard trees are not immune to the impacts of drought. Due to their perennial nature, these crops cannot be fallowed without loss of investment, which results in a high investment of water resources to these crops. Over 31% of crops irrigated during drought in California were orchards (Johnson and Cody 2015). During the drought of 2012-2016, many farms employed the use of irrigation management to withhold water. Trees subjected to water stress during the developmental phase often have less dense foliage and fruiting. To compound this issue, survival and biomass of riparian trees is decreased during drought (Garssen et al. 2014). This could have future implications for tree roosting bats, which all exhibited lower occupancy across the Central Valley in 2016. The loss of foliage density of all trees in the study area may have led to the observed year effect for the tree roosting species LABL, LACI, and LANO. My thesis suggests that despite the impacts of drought on agricultural landscapes, these areas buffer some bat species from the impacts of drought. In preparation for future drought, it would be beneficial for bats if we maintain crop types with vertical structure, and consider planting linear habitat features (e.g., hedgerows) to provide matrix connectivity for bats to exploit available anthropogenic resources (Heim et al. 2017, Olimpi 2017).

Overall, more orchards are being planted in the Central Valley, as farmers adapt to changing market demands (Fulton et al. 2019). Although these new orchards may

provide new habitat for bats in the area, they are often managed primarily to maximize profitability. Pesticides and intensive agriculture have negative impacts on bats in most cases (Williams-Guillen et al. 2016), so it is possible that orchards, although exhibiting greater bat occupancy, may actually serve as a population sink for bats. If conventional agricultural landscapes harm bats in the Central Valley, then they would likely have higher abundance or activity in organic landscapes; however this has not been investigated in the study area.

This study reinforces importance of large-scale acoustic efforts and their ability to detect change on the landscape. Large scale monitoring allows for the extrapolation of species occupancy patterns, which is unachievable at a smaller scale. Moreover, this study emphasizes the need to understand landscape scale decisions that are made during times of scarcity, especially if these decisions displace bats from their preferred habitats. As a highly mobile taxa, bats can move with relative ease across a matrix of private and public lands. Therefore, conservation strategies for bats will need to involve continued maintenance of public lands as well as supporting potential bat habitat on private land. This latter component will require working with agricultural managers to reinforce the benefits of having bats on the landscape. To achieve this goal, education about ecosystem services provided by bats, fine scale research on how bats are using these areas, and increased research on the effects of pesticides on bats is required to conserve bats in the Central Valley and other agricultural regions of the world.

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## APPENDIX A

Appendix A. Parameter estimates for single species occupancy models of 10 bat species in the California Central Valley from 2016 – 2017, with posterior means and upper and lower 95% Bayesian credible intervals. Effects with a Kuo and Mallick indicator variable  $> 0.5$  were the only covariates included in the table. Effects are on the logit scale. The c-hat value obtained from posterior predictive checks is indicated for each model. Spatial scale used for model is indicated below species code. See Table 3 for species code definitions.

Species	Parameter	B	Lower CI	Upper CI	Indicator Variable	c-hat
EPFU 1500	Detection	-1.653	-1.991	-1.329		1.47
	Julian date	0.484	-0.422	0.933	<b>0.935</b>	
	log (number of files)	2.336	1.913	2.777	<b>1.000</b>	
	Occupancy	-0.707	-1.552	0.001		
	Year	0.433	-2.251	2.210	<b>0.586</b>	
	Latitude	0.522	-1.427	1.425	<b>0.835</b>	
EUPE 2000	Detection	-1.065	-1.419	-0.774		1.71
	log (number of files)	0.502	-1.853	1.788	<b>0.747</b>	
	Occupancy	-0.388	-1.092	0.347		
	Year	-0.673	-1.810	1.724	<b>0.781</b>	
	Crop	-0.124	-2.523	2.532	0.312	
	crop:year	-0.575	-1.985	1.828	<b>0.734</b>	
	orchard	0.890	-1.376	2.093	<b>0.839</b>	
	orchard:year	-0.716	-2.098	1.872	<b>0.733</b>	
LABL 500	open	0.983	0.466	1.574	<b>0.999</b>	1.02
	Detection	-0.258	-0.491	-0.017		
	Julian date	-0.243	-1.821	1.684	<b>0.774</b>	
	log (number of files)	13.483	11.924	15.036	<b>1.000</b>	
	Occupancy	0.437	-0.619	-1.819		
	year	2.856	1.327	4.625	<b>0.998</b>	
	crop	-0.297	-2.408	2.443	<b>0.453</b>	
LACI 1000	crop:year	0.766	-2.122	2.925	<b>0.617</b>	1.21
	Detection	-0.820	-0.991	-0.644		
	wind	-0.120	-2.122	2.088	<b>0.657</b>	
	Julian date	-0.227	-1.195	1.368	<b>0.870</b>	
	log (number of files)	2.887	2.482	3.311	<b>1.000</b>	

Species	Parameter	B	Lower CI	Upper CI	Indicator Variable	c-hat
	Occupancy	0.871	0.049	1.963		
	year	1.657	0.241	3.094	<b>0.965</b>	
	orchard	1.154	0.126	2.263	<b>0.961</b>	
	open	0.406	-2.198	2.162	<b>0.603</b>	
	site water	2.190	0.660	3.923	<b>0.987</b>	
LANO 1500	Detection	-2.232	-2.603	-1.885		0.99
	log (number of files)	3.376	2.912	3.891	<b>1.000</b>	
	Occupancy	-1.668	-2.763	-0.629		
	year	2.745	1.598	3.991	<b>1.000</b>	
	distance to ww	0.422	-2.288	2.431	<b>0.515</b>	
	crop	0.712	-1.546	2.000	<b>0.826</b>	
	orchard	-0.110	-2.539	2.503	0.326	
	orchard:year	0.377	-2.344	2.426	<b>0.535</b>	
MYCA 1000	Detection	-1.848	-2.311	-1.320		1.49
	log (number of files)	4.145	3.172	5.143	<b>1.000</b>	
	Occupancy	-1.002	-2.231	0.224		
	orchard	0.942	-1.551	2.776	<b>0.818</b>	
	latitude	1.102	0.314	2.047	<b>0.977</b>	
	developed	-0.401	-2.313	2.338	<b>0.529</b>	
MYLU 1000	Detection	-1.596	-1.894	-1.305		1.45
	canopy	-0.591	-0.864	-0.326	<b>1.000</b>	
	log (number of files)	3.456	2.819	4.130	<b>1.000</b>	
	Occupancy	-1.304	-2.564	-0.095		
	distance to ww	-1.532	-3.125	0.959	<b>0.901</b>	
	crop	0.199	-2.469	2.414	0.409	
	crop:year	0.478	-2.197	2.428	<b>0.565</b>	
	orchard	-0.008	-2.487	2.528	0.296	
	orchard:year	0.428	-2.295	2.408	<b>0.534</b>	
	site water	0.725	-2.055	2.579	<b>0.653</b>	
	latitude	2.369	1.375	3.622	<b>1.000</b>	
	rice	1.606	-1.310	3.890	<b>0.852</b>	
MYYU 1000	Detection	-0.125	-0.300	0.053		1.61
	wind	-0.270	-0.447	-0.103	<b>0.974</b>	
	log (number of files)	3.892	3.219	4.608	<b>1.000</b>	
	Occupancy	0.860	0.164	1.813		
	year	-0.484	-2.186	2.129	<b>0.617</b>	

Species	Parameter	B	Lower CI	Upper CI	Indicator Variable	c-hat
	distance to ww	-0.314	-2.098	2.147	<b>0.630</b>	
	orchard	0.623	-2.062	2.368	<b>0.598</b>	
	orchard:year	-0.702	-2.421	2.056	<b>0.623</b>	
	latitude	1.100	0.647	1.597	<b>1.000</b>	
PAHE	Detection	-2.124	-2.854	-1.467		0.37
500	wind	-0.382	-2.022	2.057	<b>0.648</b>	
	log (number of files)	7.456	5.905	9.034	<b>1.000</b>	
	Occupancy	-2.172	-3.490	-0.893		
	crop	-0.091	-2.521	2.491	0.371	
	crop:year	-0.964	-3.359	2.016	<b>0.664</b>	
	orchard	0.285	-2.438	2.488	0.442	
	orchard:year	-1.155	-3.464	1.868	<b>0.719</b>	
	open	1.863	0.797	3.128	<b>0.997</b>	
	site water	-0.857	-3.150	2.064	<b>0.652</b>	
	rice	-0.682	-3.101	2.200	<b>0.592</b>	
	rice:year	-0.642	-3.061	2.236	<b>0.583</b>	
TABR	Detection	4.736	4.215	5.289		1.37
2000	wind	-0.343	-0.491	-0.200	<b>0.999</b>	
	canopy	-0.368	-0.506	-0.232	<b>1.000</b>	
	log (number of files)	8.480	7.555	9.438	<b>1.000</b>	
	Occupancy	2.982	1.804	4.534		
	year	2.594	0.756	4.530	<b>0.986</b>	
	crop	0.838	-1.950	2.827	<b>0.690</b>	

## APPENDIX B

Appendix B. Parameterization of the single-season occupancy model using Kuo and Malik (1998) indicator variables and a posterior-predictive check on aggregated detection histories, modified from Kery and Schaub (2012) and Jobin et al. (2018). Model is specified to be used in JAGS. This model was used to estimate occupancy and detection probabilities for bat species in the Central Valley.

```

sink("SingleSeasonOcc.jags")
cat("
  model {

    # Priors
    mean.psi ~ dunif(0,1)
    alpha.psi <- logit(mean.psi)

    #beta priors
    for (i in 1:12){
      beta.psi[i] ~ dnorm(0, 0.5)
    }

    mean.p ~ dunif(0,1)
    alpha.p <- logit(mean.p)

    for (i in 1:4) {
      beta.p[i] ~ dnorm(0, 0.5)
    }

    #priors for indicator variables
    for (i in 1:12){
      w[i] ~dbern(0.5)
    }

    for(i in 1:4){
      v[i] ~ dbern(0.5)
    }

    # State Process
    for (i in 1:R) {
      z[i] ~ dbern(psi[i])          # True occupancy z at site i
      logit(psi[i]) <- alpha.psi
    }
  }

```

```

+ beta.psi[1] * year[i] * w[1]
+ beta.psi[2] * distww[i] * w[2]
+ beta.psi[3] * crop[i] * w[3]
+ beta.psi[4] * crop[i] * year[i] * w[4]
+ beta.psi[5] * orch[i] * w[5]
+ beta.psi[6] * orch[i] * year[i] * w[6]
+ beta.psi[7] * open[i] * w[7]
+ beta.psi[8] * sitewater[i] * w[8]
+ beta.psi[9] * lat[i] * w[9]
+ beta.psi[10] * dev[i] * w[10]
+ beta.psi[11] * rice[i] * w[11]
+ beta.psi[12] * rice[i] * year[i] * w[12]
}

# Observation process
for (i in 1:R) {
  for (j in 1:sitedays[i]) {
    det[i,j] ~ dbern(eff.p[i,j])
    eff.p[i,j] <- (z[i] * p[i,j])      # Detection-nondetection at i and j
    y.new[i,j]~dbern(eff.p[i,j])      #replicate dataset under the same model
    logit(p[i,j]) <- alpha.p
    + beta.p[1] * wind[i,j] * v[1]
    + beta.p[2] * jdate[i,j] * v[2]
    + beta.p[3] * canopy[i] * v[3]
    + beta.p[4] * log(nf[i,j] + 1) * v[4]
  } #j
} #i

#Missing Events
for (i in missing7) {
  det[i,7] <- 0
  y.new[i,7]<-0
  eff.p[i,7]<-0
}

for (i in missing6){
  det[i,6] <- 0
  y.new[i,6]<-0
  eff.p[i,6]<-0
}

for (i in missing5){

```

```

    det[i,5] <- 0
    y.new[i,5]<-0
    eff.p[i,5]<-0
  }

  for (i in missing4){
    y.new[i,4]<-0
    eff.p[i,4]<-0
  }

  #computation of fit statistic
  for(p in 1:R){
    s.det[p]<-sum(det[p,])
    eval[p]<-max(0.01, sum(eff.p[p,]))
    E[p]<-pow((s.det[p]-eval[p]),2)/(eval[p]+0.01)
    sum.y.new[p]<-max(0.01, sum(y.new[p,]))
    E.new[p]<-pow((sum.y.new[p]-eval[p]), 2)/(eval[p] + 0.01)
  }

  fit<-sum(E[])
  fit.new<-sum(E.new[])

  # Derived quantities
  my.psi<-z[]
  occ.fs <- sum(z[]) # Number of occupied sites within sample
  my.p <- exp(alpha.p) / (1 + exp(alpha.p)) # Sort of average detection
}
", fill = TRUE)
sink()

```



## APPENDIX C

Appendix C. Description of methods and results of pairwise comparison between SonoBat and Kaleidoscope Pro.

### METHODS

We surveyed 274 sites between 15 March and 15 July of 2016 and 2017 (Figure 1). From these sites, I selected 30 sites for comparison in Kaleidoscope Pro and SonoBat. Ten species of bats were considered in this analysis, spanning the range of characteristic frequencies between 10 kHz and 50 kHz. These bats, sorted from low to high characteristic frequency were: *Eumops perotis* (EUPE), *Lasiurus cinereus* (LACI), *Tadarida brasiliensis* (TABR), *Lasionycteris noctivagans* (LANO), *Eptesicus fuscus* (EPFU), *Myotis lucifugus* (MYLU), *Lasiurus blossevillii* (LABL), *Parastreullus hesperus* (PAHE), *Myotis californicus* (MYCA), and *Myotis yumanensis* (MYYU).

#### Site Selection and Acoustic Monitoring

Recorded calls were first processed using Kaleidoscope Pro (K-Pro) 4.3.2 (Wildlife Acoustics, Concord, MA). Filtering of noise and auto-classification was conducted in zero-crossing using the Kaleidoscope Pro species auto-classifier, using a pool of species present in California. Auto-classified output included species presence values (p) per night, per site. Any detections that had a value of  $p < 0.05$  (“match ratio”, high probability of positive species ID), were selected for further review. As many calls as needed to confirm or reject species occupancy were manually vetted for each event

(species/site/night) for accuracy by a trained observer using a species identification key, and classified as a confirmation (matches the auto-classifier, positive ID), rejection (does not match the auto-classifier, no ID), or given an alternative ID (does not match the auto-classifier, different species).

I conducted independent vetting in SonoBat 4.2.2 (Szewczak 2018). Analysis was conducted using the “Central Valley” auto-classifier in SonoBat version 4.2.2 (Arcata, CA), which considers all ten species analyzed. Noise scrubbing was conducted prior to running calls through the auto-classifier. Auto-classifier call acceptance was set to 80% with 32 passes considered at a sequence decision threshold of 0.95 to closely match the K-Pro method of “high-grading” species decision (Reichert et al. 2018). I vetted as many species events as needed for each site for calls that did not have species confusion (i.e., SonoBat was confident in a single species ID). Vetting was conducted using the same species identification key used for the K-Pro analysis. Only calls that were vetted to one of the ten candidate species were vetted.

Comparisons between nightly detection histories were compiled as the percentage of agreement at the species level per nightly event.

## RESULTS

A total of 87,029 files were considered in this analysis. K-Pro identified 37,684 WAV files to one of the 10 species (43%) of the calls to one of the 10 species considered and SonoBat North America identified 13,500 (15%) of the calls to species. 410 of 894

events were confirmed by manual vetting in K-Pro (45%) and I confirmed 490 of 711 events in SB (69%). Species confirmation following manual vetting varied by species and classification software; however for all species except LABL the confirmation rate (number of events confirmed/total events per species) was greater when using SonoBat (Table C.1).

Event agreement was low between Kaleidoscope Pro and SonoBat in the absence of vetting (46% - 88%). Vetting improved event agreement to 78% - 98%, depending on species. Agreement between auto-classified calls for SonoBat (80% - 100%) was greater than Kaleidoscope Pro (50% - 96%, Table C.2).

Table C.1. Number of confirmed events and confirmation rates (confirmed by manual vetting/number of auto-classified events) for Kaleidoscope Pro and SonoBat North America. Calls were collected at 30 randomly selected sites in the Central Valley, CA. Bold represents which program had a greater number of confirmed events or confirmation rates. See table 3 for species code definitions.

Species	Kaleidoscope Pro Confirmed Events	SonoBat Confirmed Events	Kaleidoscope Pro Confirmation Rate	SonoBat Confirmation Rate
EPFU	19	<b>42</b>	0.31	<b>0.68</b>
EUPE	<b>20</b>	10	0.16	<b>0.38</b>
LABL	36	<b>38</b>	0.56	0.56
LACI	<b>52</b>	24	0.37	<b>0.65</b>
LANO	12	<b>32</b>	0.16	<b>0.52</b>
MYCA	19	<b>57</b>	0.34	<b>0.68</b>
MYLU	21	<b>33</b>	0.36	<b>0.63</b>
MYYU	61	<b>77</b>	0.58	<b>0.75</b>
PAHE	<b>25</b>	23	0.45	<b>0.96</b>
TABR	145	<b>154</b>	0.94	<b>0.79</b>
Overall	410	490	0.46	<b>0.69</b>

Table C.2. Percentage of agreement of acoustic call classification. Auto-ID and manual vetting columns denote a pairwise comparison between SonoBat and Kaleidoscope Pro for respective vetting strategies. Kaleidoscope Pro and SonoBat columns are a pairwise comparison between vetting strategies for each program. Calls were collected at 30 randomly selected sites in the Central Valley, CA. See table 3 for species code definitions.

	<b>Auto-ID KPro / SB</b>	<b>Manual Vetting KPro / SB</b>	<b>Kaleidoscope Pro Vetted / Unvetted</b>	<b>SonoBat Vetted / Unvetted</b>
EPFU	76	86	79	90
EUPE	48	93	50	92
LABL	75	85	86	85
LACI	46	78	56	94
LANO	71	80	69	85
MYCA	79	78	82	87
MYLU	82	85	85	91
MYYU	88	81	78	88
PAHE	83	98	85	100
TABR	79	89	96	80
Average				
Agreement	73	85	77	89

## APPENDIX D

## Appendix D. Metadata for acoustic deployment of sites using SM3BAT recorders in California, USA.

<b>Metadata Field</b>	<b>Setting</b>
Detector type	Wildlife Acoustics SM3Bat
Microphone type	Wildlife Acoustics SMM-U1
Microphone height	3 meters
Weather proofing	Yes
Format	WAV
Cable	Wildlife Acoustics SM3/SM4 Microphone Cable (10 meters) for SMM-U1/A1/A2
High pass filter	Off
Gain	Automatic (12 dB)
Sample Rate	256000 Hz
Format	WAV
Channels	1 (Mono)
Lower frequency bound	6 KHz
Upper frequency bound	192 kHz
Minimum duration	1.5 ms
Maximum duration	Off
Digital trigger level	Automatic (+12 dB)
Maximum recording duration – no signal	2.0 s
Maximum duration – triggered	5.0 s

## APPENDIX E

Appendix E. Posterior means and lower and upper bounds of the 95% Bayesian credible interval for detection covariates. The thicker, colored lines show the 50% CIs. The black points denote the posterior mean of each covariate. The asterisks denote any covariates that had greater than a 50% (0.5) inclusion ratio (IV).

