

BUILDING HABITAT SUITABILITY MODELS TO EXAMINE DISTRIBUTION
SHIFTS FOR THE BLACK-HEADED GROSBEAK, HAIRY WOODPECKER, AND
YELLOW-RUMPED WARBLER DUE TO DROUGHT, FIRE, AND BARK BEETLE
INFESTATION IN THE PACIFIC NORTHWEST

By

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GENERAL ABSTRACT

BUILDING HABITAT SUITABILITY MODELS TO EXAMINE DISTRIBUTION SHIFTS FOR THE BLACK-HEADED GROSBEAK, HAIRY WOODPECKER, AND YELLOW-RUMPED WARBLER IN THE PACIFIC NORTHWEST DUE TO DROUGHT, FIRE, AND BARK BEETLE INFESTATION

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Spatial models that describe species distributions are valuable in determining how environmental impacts, such as drought, fire, and bark beetle infestations, have shifted these distributions and guide management decisions. In this thesis, I begin by comparing the utility of two datasets by building habitat suitability models for Black-headed Grosbeak, Hairy Woodpecker, and Yellow-rumped Warbler. By combining the datasets, I created response curves that explain habitat associations I expected from each species. I expanded upon the methods section to compare pre- and post-drought data from the 2011 California multi-year drought and evaluate how the three avian species have shifted their habitat use due to drought, fire, and bark beetle infestation. I then related these changes back to vegetation productivity from remotely sensed data. I found that these three species have experienced large shifts in their suitable habitat due to drought, fire, and bark beetle infestation. Hairy Woodpeckers, which normally can use fire-impacted habitat, have shifted out these areas perhaps due to increased fire intensity and longevity that has mismatched with the lay periods of their food resource. Yellow-rumped Warblers and Black-headed Grosbeaks have tightened in around water sources and shifted out of

areas where vegetation has been severely impacted by the drought. I also found a weak correlation between vegetation productivity and these avian distribution shifts. As climate change continues to impact the intensity and longevity of drought with the cascading influences from fires and bark beetles, it is ever more critical to study how species are shifting in response and identify areas that continue to meet their biological needs.

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TABLE OF CONTENTS

GENERAL ABSTRACT	ii
ACKNOWLEDGEMENTS	iv
LIST OF TABLES	viii
LIST OF FIGURES	ix
LIST OF APPENDICES	xi
CHAPTER 1: COMBINED USE OF AVIAN SURVEYS ALONG THE PACIFIC CREST TRAIL WITH BIODIVERSITY REPOSITORIES TO MODEL HABITAT SUITABILITY THROUGHOUT NORTHERN CALIFORNIA	1
Abstract	1
Introduction	3
Methods	6
Study Region	6
Occurrence Data	8
Environmental Covariates	9
MaxEnt	12
Model Selection and Evaluation	13
Results	15
BKHGRO Habitat Suitability	17
HAIWOO Habitat Suitability	19
YERWAR Habitat Suitability	21
Model Evaluation	23
Discussion	24
Habitat Associations for BKHGRO, HAIWOO, and YERWAR	27

Conclusions.....	29
Literature Cited	31
Appendices.....	38
CHAPTER 2: DISTRIBUTION SHIFTS FOR BLACK-HEADED GROSBEAK, HAIRY WOODPECKER, AND YELLOW-RUMPED WARBLER IN THE PACIFIC NORTHWEST DUE TO DROUGHT, FIRE, AND BARK BEETLE INFESTATIONS	
Abstract	52
Introduction.....	54
Methods	57
Study Area	57
Occurrence Data.....	58
Environmental Covariates.....	59
Model Selection and Evaluation	60
Spatial Methods	62
NDVI.....	62
Comparison of Vegetation Productivity to Avian Habitat Suitability Models	63
Results.....	64
Black-headed Grosbeak	64
Hairy Woodpecker	67
Yellow-rumped Warbler	71
NDVI Change in Vegetation Productivity	75
Discussion.....	78
Model Limitations and Future Steps.....	83
Conclusion	84

Literature Cited	86
Appendices.....	92

LIST OF TABLES

Table 1. Environmental covariates selected for each species to build the habitat suitability models based on the MaxEnt Jackknife feature using the Combined Dataset.	15
Table 2. Model parameters run for each bird species and their resulting AIC, Δ AIC, and AUC.	16
Table 3. Results of models created with the two datasets and the Combined Dataset. Cross-validation was performed against each of the models along with their AUC. For the logistic threshold, the number of occurrences that fall within the area selected by the model divided by the number of occurrences available by the dataset is provided.....	16
Table 4. Monte Carlo results for injecting uncertainty into the three combined models..	24
Table 5. Environmental covariates selected for each species along with the final model's regularization multiplier and AUC for the years 2010 and 2016.....	61
Table 6. Percent contribution of each environmental covariate in the 2010 and 2016 BKHGRO models.	66
Table 7. Percent contribution of each environmental covariate in the 2010 and 2016 HAIWOO models.	69
Table 8. Percent contribution of each environmental covariate in the 2010 and 2016 YERWAR models.....	74
Table 9. Spearman's Correlation between Δ NDVI and bird suitability models.....	77

LIST OF FIGURES

Figure 1. The PCT route where data was collected in 2010 by McGrann and Furnas (2016).....	8
Figure 2. BKHGRO response curves from MaxEnt with a regularization multiplier of 1.5 for each of the environmental covariates using the Combined Dataset.....	18
Figure 3. Habitat suitability model for the BKHGRO built from the Combined Dataset with a regularization multiplier of 1.5.	19
Figure 4. HAIWOO response curves from MaxEnt with a regularization multiplier of one for each of the environmental covariates using the Combined Dataset.....	20
Figure 5. Habitat suitability model for the HAIWOO built from the Combined Dataset with a regularization multiplier of one.....	21
Figure 6. YERWAR response curves from MaxEnt with a regularization multiplier of one for each of the environmental covariates using the Combined Dataset.....	22
Figure 7. Habitat suitability model for the YERWAR built from the PCT Data and GBIF-BISON Data combined with a regularization multiplier of one.	23
Figure 8. Occurrences from HAIWOO and the zones of fire-impacted areas. Fire polygons from Monitoring Trends in Burn Severity (2009).....	27
Figure 9. Response curves for distance to bark beetle infestations with the covariate alone and combined in the full model. The covariate alone displays a bimodal response where the species is either very close to the infested area, or is further away. The covariate combined shows that areas near the infested habitat is more suitable.	28
Figure 10. Study region in northern California that extends from Buck’s Lake Wilderness to the Oregon border. Road data from the U.S. Census Bureau (2020) and the digital elevation map from the U.S. Geologic Survey (2013).....	58
Figure 11. Response curves in 2010 for the BKHGRO using a regularization multiplier of 1.5.....	65
Figure 12. Response curves in 2016 for the BKHGRO using a regularization multiplier of three.....	65
Figure 13. Increase in suitability for the Black-headed Grosbeak from the 2010 model to the 2016 model. Blue areas show an increase in suitability from 2010 to 2016.....	66

Figure 14. Decrease in suitability for the Black-headed Grosbeak from the 2010 model to the 2016 model. Red areas show a decrease in suitability from 2010 to 2016.	67
Figure 15. Response curves in 2010 for the HAIWOO using a regularization multiplier of one.	68
Figure 16. Response curves in 2016 for the HAIWOO using a regularization multiplier of one.	69
Figure 17. Increase in suitability for the Hairy Woodpecker from the 2010 model to the 2016 model. Blue areas show an increase in suitability from 2010 to 2016.	70
Figure 18. Decrease in suitability for the Hairy Woodpecker from the 2010 model to the 2016 model. Red areas show a decrease in suitability from 2010 to 2016.	71
Figure 19. Response curves in 2010 for the YERWAR using a regularization multiplier of one.	73
Figure 20. Response curves in 2016 for the YERWAR using a regularization multiplier of 2.5.	73
Figure 21. Increase in suitability for the Yellow-rumped Warbler from the 2010 model to the 2016 model. Blue areas show an increase in suitability from 2010 to 2016.	74
Figure 22. Decrease in suitability for the Yellow-rumped Warbler from the 2010 model to the 2016 model. Red areas show a decrease in suitability from 2010 to 2016.	75
Figure 23. Δ NDVI from 2010 to 2016 where blue areas show an increase in vegetation productivity and white is the combination of no change and negative change. Landsat-5 and Landsat-8 image courtesy of the U.S. Geological Survey (USGS, 2010; USGS 2016). Lake polygon layers provided by California Department of Fish and Wildlife (2012).	76
Figure 24. Δ NDVI from 2010 to 2016 where red areas show a decrease in vegetation productivity and white is the combination of no change and an increase in productivity. Landsat-5 and Landsat-8 image courtesy of the U.S. Geological Survey (USGS, 2010; USGS 2016). Lake polygon layers provided by California Department of Fish and Wildlife (2012).	77

LIST OF APPENDICES

Appendix A: Pearson correlation matrix produced in R (R code in the Appendix Section RCODE) of the correlation between environmental covariates. Covariates with a relationship above 0.7 were not used within the same model and prevent a potential reversal of the relationship within the model.....	38
Appendix B: BKHGRO response curves for the individual covariates.....	40
Appendix C: HAIWOO response curves for the individual covariates.....	41
Appendix D: YERWAR response curves for the individual covariates.	42
Appendix E: BKHGRO habitat suitability model built from GBIF-BISON Data with regularization multiplier of 1.5.	43
Appendix F: BKHGRO habitat suitability model built from PCT Data with a regularization multiplier of 1.5.	44
Appendix G: HAIWOO habitat suitability model built from the GBIF-BISON Dataset with a regularization multiplier of 5.5.	45
Appendix H: HAIWOO habitat suitability model built from the PCT Data with a regularization multiplier of 5.5.	46
Appendix I: YERWAR habitat suitability model built from the PCT Data with a regularization multiplier of 1.	47
Appendix J: YERWAR habitat suitability model built from the GBIF-BISON Data with a regularization multiplier of 1.	48
Appendix K: R-Script code to find the correlation between environmental covariates and find the mean value of suitability for each species.	49
Appendix L: Python script for calculating the standard error in the aspect and slope rasters.	49
Appendix M: Habitat suitability model for the BKHGRO built from the Combined Dataset with a regularization multiplier of 3.	92
Appendix N: Habitat suitability model for the YERWAR built from the Combined Dataset with a regularization multiplier of 2.5.	93

Appendix O: Habitat suitability model for the HAIWOO built from the Combined Dataset with a regularization multiplier of 3.5.	94
Appendix P: BKHGRO, YERWAR, and HAIWOO occurrences within tree communities for 2010 and 2016. The number associated with each tree community in the Fortypba layer is the community number selected by Oregon State University’s LEMMA program. The sections of codes are grouped by the dominant tree species followed by subdominant species within the community.....	94

CHAPTER 1: COMBINED USE OF AVIAN SURVEYS ALONG THE PACIFIC
CREST TRAIL WITH BIODIVERSITY REPOSITORIES TO MODEL HABITAT
SUITABILITY THROUGHOUT NORTHERN CALIFORNIA

Abstract

Models that describe species distributions are valuable in guiding management decisions. I compared and combined two avian datasets during the 2010 breeding season in northern California, USA. These datasets were a large-scale avian diversity survey from McGrann and Furnas and combined data from Biological Information Serving Our Nation (BISON) and Global Biodiversity Information Facility (GBIF). My objective was to compare the utility of these two datasets, that employ different field protocols, to model habitat use for Black-headed Grosbeak, Hairy Woodpecker, and Yellow-rumped Warbler, three common forest birds in my study area that occupy distinctive habitats. I also tested whether combining the datasets together would create a model with greater generality over the study area and determine if the data will create response curves that explain certain relationships between environmental characteristics and species occurrences. I found that fine-scale data along a single, albeit extensive, transect built models that predicted suitability well for the section of trail, but did not predict occurrences well for areas beyond the trail in two of the three species. I also found that data from Biological Information Serving Our Nation (BISON) and Global Biodiversity Information Facility (GBIF) did not have the sampling structure required for finer scale

modeling and lacked observations in areas that may be critical for sampling, such as fire-impacted areas. By combining these two datasets, I produced models that captured the range of these species throughout the study area and I created response curves that explained anticipated habitat associations for each species.

Introduction

Birds are excellent indicators of environmental change because they rely on plant communities and the overall structure of vegetation to provide food, shelter, and breeding and nesting sites. Their distributions, therefore, will shift as a result of human land use change (Lee et al., 2004) and other factors such as fire or drought (Zimmerman, 1997). In an effort to conserve bird habitat, managers require tools to aid their decision-making processes, including spatial modeling tools (Tingley et al., 2009; Turner et al., 2016). In this study, I use a spatial modeling tool, MaxEnt, in a habitat suitability modeling procedure to select environmental characteristics that determine what vegetation or land cover types are associated with specific avian species occurrences. It is important to create accurate habitat models to determine areas which may be crucial to establish as nature preserves that anticipate the effects of climate change and human land-use.

Habitat suitability models have been used to predict the spatial occurrence and distribution of a species based on measures of habitat (Peterson et al., 2011), such as elevation, topography, habitat type, precipitation, and temperature (MacArthur, 1965; Hedley & Buckland, 2004; Odion et al., 2010; McGrann & Thorne, 2014; Asner et al., 2015; Kadmon et al., 2016; McGrann & Furnas, 2016). It is important to note that habitat suitability models have been utilized to reveal patterns of species distribution and the actual quality or true suitability of habitats is more difficult to quantify because it also depends on abundance, reproduction, and survival (Johnson, 2019; Johnson & Wood, 2018). Nonetheless, habitat suitability models are very useful for conservation and

management because they are typically represented as grid-based maps of the spatial distribution of estimated habitat suitability (Kimble, 2016; Scott et al., 2002). Habitat models have been created for many avian species, such as the species that I include in this study: Hairy Woodpecker (*Picoides villosus*) (Russell et al., 2007), Yellow-rumped Warbler (*Dendroica coronata*) (Price, 2000), and Black-headed Grosbeak (*Pheucticus melanocephalus*) (St-Louis et al., 2014).

MaxEnt is a spatial modeling tool that has been utilized in a wide variety of species distribution applications, including the mapping of phenotypic diversity in Hairy Woodpeckers (Klicka et al., 2011), modeling climate-induced shifts in the distribution of Warbler species (Ralston & Kirchman, 2013), and it has been applied in conservation planning by modeling habitat suitability for migratory birds, including the Black-headed Grosbeak (Seavy et al., 2012).

Habitat suitability models use species occurrence data, which are typically geographic locations where the species has been detected in the field using a standardized survey protocol that typically employs some randomized sampling procedure. Ideally, data are collected via these same protocols across the entire study area of interest (Austin & Heyligers, 1989). However, in reality, most published species distribution studies employ very different survey protocols; it is uncommon to find that data are collected in exactly the same manner across more than one study. It is for this reason that most biodiversity databanks and clearinghouses, such as Biological Information Serving Our Nation (BISON) and Global Biodiversity Information Facility (GBIF), offer a collection of existing datasets that may be variably biased due to the original purpose of the study

(Barry & Elith, 2006). Additionally, data from these clearinghouses may not contain points with confirmed species absence, nor do they typically include replicated visits allowing for calculating detection probability of species that may have been undetected by the observer, so presence-only methods were developed to find patterns in the data to determine habitat that is unsuitable and the model reflects this pattern (Elith et al., 2010).

Using a single modeling approach, I compared two datasets of avian species distributions that were collected using varying sampling designs and spatial coverage in northern California. My analysis compared data collected using a large-scale avian diversity survey along the Pacific Crest National Scenic Trail in northern California (McGrann & Furnas, 2016; Furnas & McGrann, 2018), which I will, henceforth, call the PCT Data, and combined data from Biological Information Serving Our Nation (BISON) and Global Biodiversity Information Facility (GBIF), which I will call the GBIF-BISON Data. The PCT Data represents a study with a standardized methodology for point counts and automated recording units, while the GBIF-BISON Data obtains their data from contributors who have varying methods and data quality.

My objectives were to test the generality of model predictions derived from each dataset and use these predictions to evaluate three hypotheses. My hypotheses were: (1) the PCT Data will perform well for modeling the habitat associations of the species for areas near the trail but will decrease in performance with distance from the trail. (2) The GBIF-BISON Data, although composed of observations dispersed throughout the entire study area, will not be detailed enough to transfer to a finer scale analysis. (3) By combining these two datasets, which I will call the Combined Dataset, I can create a

model that is fine-tuned to the scale of the analysis but that also generalizes well across my entire study area and creates parsimonious response curves by associating species occurrences with environmental characteristics. In order to test these hypotheses on the generality of model predictions, I felt it was best to compare model predictions for three relatively common and widespread species that also have distinctive niches, habitat associations, and life histories. I reference these species using a six-letter alpha coding system (Pyle & DeSante, 2003): (1) Black-headed Grosbeak (BKHGRO) is a neotropical migrant. The species prefers a complex vegetation composition and structure with a mixture of hardwood and conifer trees (Williams & Koenig, 1980). (2) Yellow-rumped Warbler (YERWAR) is a year-round resident and elevation migrant and considered a habitat generalist, found in all elevations but with a preference for coniferous forests. Both BKHGRO and YERWAR also have close habitat associations with water (Kirkpatrick et al., 2009; Becker, 2013). (3) Also a resident, Hairy Woodpeckers (HAIWOO) occur at higher elevations, and although abundant in green forests, they are particularly associated with recently burned areas. In burned forests, there is an abundance of snags, which yield wood-boring insects (Parker et al., 2006), an important food resource (Saab et al., 2019).

Methods

Study Region

I studied a region along the northern California portion of the PCT that extended from Bucks Lake Wilderness (39.907°N, -121.127°W) to the Oregon Border (42.005°N, -

122.913°W) (Figure 1. The PCT route where data was collected in 2010 by McGrann and Furnas (2016).). Much of the southern and eastern portion of this section of the PCT lies within the rain shadow of the Cascade Mountains, exhibiting drier conditions. The trail then turns west into the moister Klamath Mountains (McGrann et al., 2014). These conditions create a diverse climate that is predominantly forested, ranging from mixed hardwood/conifer forests at lower elevations to mixed conifer and subalpine forests at mid- to upper-elevations. Some portions of this section of the PCT, particularly further to the south and to the east, consist of semiarid sagebrush (*Artemisia tridentata*) and montane chaparral (Schoenherr, 1992).

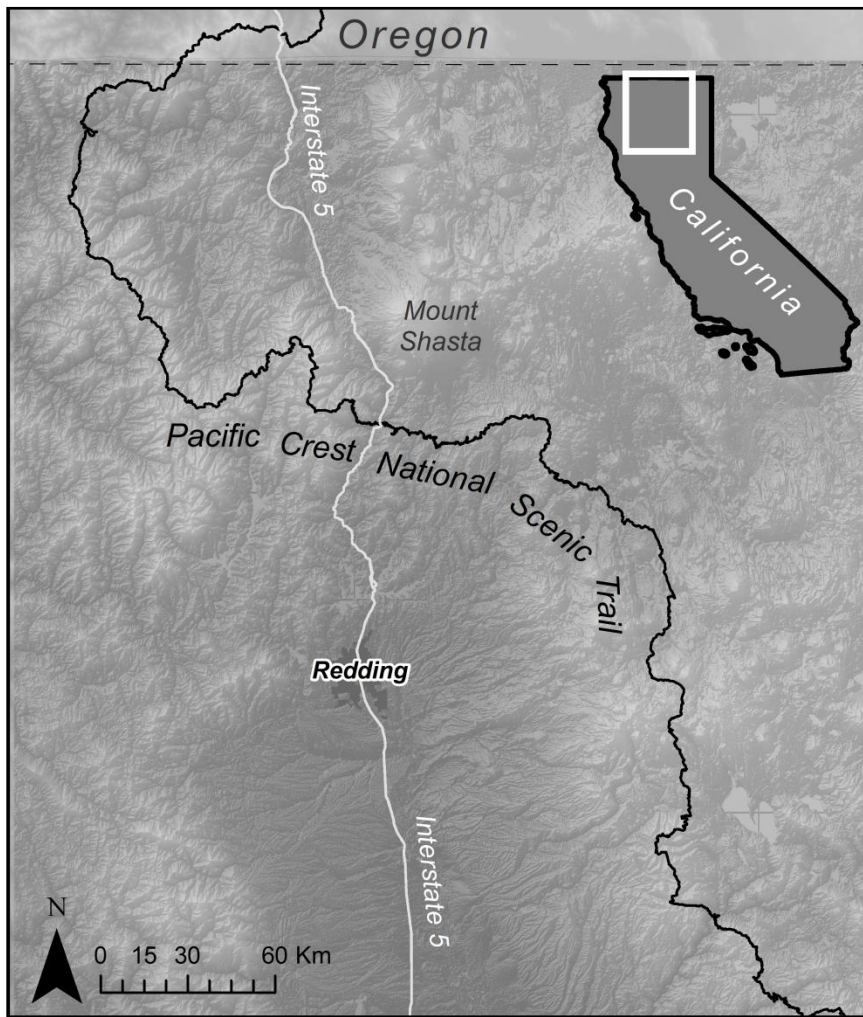


Figure 1. The PCT route where data was collected in 2010 by McGrann and Furnas (2016).

Occurrence Data

The PCT Data contains avian occurrence data for the year 2010 and was acquired from McGrann and Furnas (2016). The PCT Data was collected along the trail via fixed-radius (50 m) point-counts and automated recorders in a standardized method as described in detail in Furnas & Callas (2015), McGrann and Furnas (2016), and Furnas and McGrann (2018). The large number of replicates at each survey site combined with

the amount of surveys conducted provides high quality data concentrated on this transect.

BKHGRO was detected at 83 sites, YERWAR, 206 sites, and HAIWOO, 29 sites.

I downloaded data from GBIF and BISON for the year 2010 in the months of May, June, and July to match the timeframe of when surveys were completed for the PCT Data. These two databases both obtain occurrence data from data contributors such as Cornell lab of Ornithology, the eBird Observation Dataset, and the Great Backyard Bird Count. These two datasets were combined into a single dataset, which I call GBIF-BISON Data. For each species, the number of individual detections extracted from the GBIF-BISON Data for the study area included 84 for BKHGRO, 195 for YERWAR, and 101 for HAIWOO. The GBIF-BISON Data contains spatial bias due to an uneven method of sampling and may distort spatial models (Beck et al., 2014). Modeling was completed using the GBIF-BISON Data and the PCT Data separately and combined to cover a larger area for each species in the study area, which I call the Combined Dataset.

Environmental Covariates

I tested 14 environmental covariates that I thought would be associated with occurrence of the three avian species based upon their natural history and habitat requirements as described in Sousa (1987) and DeGraaf & Rappole (1995). I downloaded 8 variables from the Oregon State University's Landscape Ecology, Modelling, Mapping and Analysis (LEMMA) program, which obtain their data by integrating vegetation measurements from field surveys, mapped environmental data, and Landsat Thematic Mapper (TM) imagery (30 m resolution) (Ohmann & Gregory, 2002; Landscape Ecology, Modeling, Mapping, 2020). The variables I selected were hardwood and conifer

canopy cover, total canopy cover, quadratic mean diameter of all dominant and codominant trees (qmd_dom), forest type based on the basal area of dominant tree species (Fortypba), vegetation class based on the canopy cover and basal area (vegetation class), and density of live trees and snags. The Fortypba layer contained 983 categorical values, but some modeling software, such as the Hyper-Envelope Modeling Interface Version 2 (HEMI2), require less than 255 categories, so I did the following process to reduce the amount into coarser scale. First, I extracted the Fortypba values to the survey sites and classified these as values from 1-98. The remaining values in the Fortypba layer were combined into coarser classifications based on the dominant tree species. At the end of this process, 141 categories were represented in the new Fortypba layer.

The remaining six covariates included in my models were distance from fire, distance from water, distance from bark beetle infestation, elevation (as surrogate for temperature), aspect, and slope. Distance from fire, water, and bark beetle infestations help measure habitat resources (e.g., food, cover, and nesting habitat) that may be important to a species. Elevation, aspect, and slope are characteristics of the terrain which can be associated with temperature or light exposure, which also influences vegetation. All covariates were converted to rasters of grid cells that represent the value of the covariate at on location in the landscape. I calculated a distance to fire raster (i.e., a grid of cells where the value assigned to each cell represents a distance value) by downloading fire polygons of mapped burned areas from the Monitoring Trends in Burn Severity data set (Eidenshink et al., 2009) and applying the Euclidian distance function in ArcGIS (version 10.7.1, Environmental Systems Research Institute, Redlands, CA). This resulted

in a raster that calculated distance to the edge of the polygon where everything within the polygon was assigned a value of zero. Stream and river polylines were downloaded from the National Hydrography Dataset (1:24,000; Terziotti & Archuleta, 2020). Bark beetle infestation polygons were downloaded from the USDA Forest Service and were obtained via aerial “sketchmapping” (Schrader-Patton & Pywell, 2003). I used a similar approach to convert streams and rivers polylines into a distance to water raster and to convert bark beetle infestation polygons into a distance raster. Digital elevation maps (DEMs) were downloaded from the U.S. Geologic Survey (30 m resolution). Temperature decreases with increasing elevation according to a known rate (i.e., the adiabatic lapse rate). Therefore, I considered elevation to be a surrogate covariate for temperature. From the DEMs, I also derived aspect and slope rasters, which represent a surrogate covariate for precipitation (Geroy et al., 2011; Phillips & Schümm, 1987). I converted the linear aspect raster into categorical values after determining which covariates were critical to each of the avian species. All rasters were scaled to 30 m to match the vegetation covariate raster cell size, clipped to the study area, and converted into ASCII files using ArcGIS.

I reduced the number of variables used to create the model by performing several steps. First, I analyzed the correlation between all the environmental variables using the Pearson correlation statistic (Appendix: R Script). Next, I used MaxEnt’s jackknife feature to evaluate each environmental variables contribution to each model (Elith et al., 2010). I removed variables that had less than 2% contribution and were highly correlated (i.e., a correlation coefficient > 0.7), or did not impact the jackknife’s regularization training gain when removed. The regularization training gain is a measure between a

random sample of the entire study area the species could inhabit and the environmental covariates correlated to the species occurrence (Elith et al., 2010).

MaxEnt

I performed MaxEnt within the software BlueSpray (beta version 42, SchoonerTurtles, Arcata, CA), which calculates area under the curve (AUC) and the Akaike information criterion (AIC). AUC measured model performance by measuring a model's discriminatory ability and represents the proportion of times the actual sample of presence locations has a larger estimated suitability than a random sample (Fielding & Bell, 1997). AUC is generally used in presence-absence modeling, but when used in presence-only modeling is prevalence-dependent where it serves to tell us if the model is significantly better than a random prediction (van Proosdij et al., 2016). Using AUC with presence-only data, a larger sample size spread over the study area will typically result in more accurate models. Models with small sample sizes should be treated with caution as small sample sizes often inflate the AUC value in presence-only modeling (van Proosdij et al., 2016). AIC attempts to balance predictive ability of the model with model complexity by providing an estimate of the relative "quality" among a series of competing models (Plant, 2012). Additionally, BlueSpray can perform Monte Carlo simulations within MaxEnt (Graham & Kimble, 2018). Monte Carlo simulations are a statistical method where the model is replicated a large amount of times with aspects of the model randomized with each replicate (Plant, 2012). Using the spatial coordinates of the bird occurrences and the set of covariates that I selected, which were selected based upon the criterion of at least 2% contribution to the model, I increased the regularization

multiplier in the combined model by increments of 0.5 until I achieved the lowest AIC. A higher regularization multiplier smooths out the response curves to reduce the complexity of the models produced. To create the most parsimonious model and to be able to evaluate how the two datasets models compare for each species, I used the best regularization parameter from the Combined Dataset to create models with only the PCT Data and only the GBIF-BISON Data.

Model Selection and Evaluation

Models were evaluated based on their AIC (Muscarella et al., 2014), delta Akaike information criteria (Δ AIC), and AUC. In order to assess whether the models are accurately predicting suitable habitat, I calculated the number of observed occurrences that fell within the predicted habitat suitability grid cells using the 10% logistic threshold MaxEnt calculated for each species. This 10% logistic threshold indicates probability value that is the minimum value for suitable habitat and it can assist in determining the generality of my models between datasets.

I also employed cross-validation to test the generality of my models across datasets and to evaluate model performance on the best model for each species with the lowest AIC. Cross-validation can be performed in MaxEnt. This process involves splitting a designated percent of occurrence locations into a training dataset, which is used to fit the model, and a testing dataset, which is used to test against the rest of the occurrence locations (Merow et al., 2013). A robust model would have little variation of predicted habitat among iterations (Kimble, 2016) and generally, models that over fit the data perform well on the training data and poorly on the test data. For the Combined

Dataset, 70% of the data was used for training and 30% was used for testing. I performed cross-validation on the PCT Data where 100% of the data was used for training and used the GBIF-BISON Data for testing. I then reversed the process using 100% of the GBIF-BISON for training and used the PCT Data for testing. To assess whether the models are accurately predicting suitable habitat, I calculated how many of these occurrences fall within the 10% logistic threshold.

To further validate model robustness, I used Monte Carlo simulations to check for spatial uncertainty in the occurrence points and covariates. I injected error into each of the species models with the Combined Datasets using the Monte Carlo feature in BlueSpray (Graham & Kimble, 2018). I ran 80 iterations and evaluated the mean AIC, standard deviation of the AIC, mean AUC and standard deviation of the AUC. The DEM is noted to vary vertically up to 2.42 meters in the conterminous United States (Gesch et al., 2014). In the programming language Python, I calculated the standard deviation of error in the slope raster by varying the amount of error in the DEM and taking the average standard deviation over 10 runs (Appendix: Python Script). I found that slope had an average standard error of 0.728 degrees. Data from OSU LEMMA underestimates values (Bell et al., 2015), with most rasters seen to have reductions by 0.05. Bark beetle infestations had patch areas combined into a larger polygon (USDA, 2010), so there may be an overestimation. LEMMA also notes that their overall classification accuracy for 10 categories was 45% and that most misclassification errors were minor (Ohmann & Gregory, 2002). Monitoring Trends in Burn Severity map fires accurately that are greater

than 1000 acres (Eidenshink et al., 2009). GPS average error is 0.715 meters (U.S. Department Of Defense, 2007).

Results

Six environmental covariates for BKHGRO, six for HAIWOO, and five for YERWAR each contributed to explaining more than 2% of the variation in the MaxEnt model initially made for each species and were included in building these individual models for each species using the Combined Dataset (the habitat suitability models.

Table 1). These covariates appear to have a significant correlation with the occurrence locations of the species and were determined to be valuable in creating the habitat suitability models.

Table 1. Environmental covariates selected for each species to build the habitat suitability models based on the MaxEnt Jackknife feature using the Combined Dataset.

Species	Environmental Covariates
BKHGRO	1) Fortypba 2) elevation 3) distance to bark beetle infestations 4) distance to fires 5) slope 6) distance to streams
HAIWOO	1) Fortypba 2) distance to bark beetle infestations 3) slope 4) hardwood canopy cover 5) distance to fires 6) aspect
YERWAR	1) Fortypba 2) slope 3) hardwood canopy cover 4) distance to fires 5) distance to streams

The best model for BKHGRO, based on the lowest AIC, had a regularization multiplier of 1.5 to produce smooth response curves that did not over fit the data. For HAIWOO and YERWAR, the best regularization multiplier was one. In the best model of the Combined Dataset for each species, the 10% logistic threshold MaxEnt calculated for each species was 0.33 for BKHGRO, 0.38 for HAIWOO, and 0.28 for YERWAR ().

Table 2).

Table 2. Model parameters run for each bird species and their resulting AIC, Δ AIC, and AUC.

Data	Bird Species	Regularization multiplier	AIC	Δ AIC	AUC
Combined	BKHGRO	1.5	10157	0	0.88
Combined	BKHGRO	2	10159	2	0.87
Combined	BKHGRO	1	10201	44	0.89
Combined	HAIWOO	1	4973	0	0.83
Combined	HAIWOO	1.5	4991	18	0.82
Combined	YERWAR	1	29863	0	0.80
Combined	YERWAR	1.5	29866	3	0.79

The PCT Data and the GBIF-BISON Data had higher AUC values than the Combined Dataset for BKHGRO and YERWAR (

Table 3). For the HAIWOO data, the AUC value of the Combined Dataset was just as high as the GBIF-BISON model validated against the PCT data. The Combined Dataset when cross-validated against itself dropped five units for BKHGRO, 13 units for HAIWOO, and two units for YERWAR. When I performed cross-validation on the PCT Data or the GBIF-BISON Data, the AUC decreased to just over the random prediction line. When I performed cross-validation on the Combined Dataset, the AUC decreased slightly.

Table 3. Results of models created with the two datasets and the Combined Dataset. Cross-validation was performed against each of the models along with their AUC. For the logistic threshold, the number of occurrences that fall within the area selected by the model divided by the number of occurrences available by the dataset is provided.

Bird Species	Data Used to Create Model	AUC	Data used for Cross-validation	Cross-validation AUC	Logistic Threshold for the PCT Data	Logistic Threshold for the GBIF-BISON Data
BKHGRO	PCT	0.95	GBIF-BISON	0.55	0.88	0.12
BKHGRO	PCT	0.91	PCT	0.85	0.85	0.30

Bird Species	Data Used to Create Model	AUC	Data used for Cross-validation	Cross-validation AUC	Logistic Threshold for the PCT Data	Logistic Threshold for the GBIF-BISON Data
BKHGRO	GBIF-BISON	0.91	PCT	0.56	0.23	0.88
BKHGRO	GBIF-BISON	0.90	GBIF-BISON	0.78	0.28	0.87
BKHGRO	Combined	0.88	Combined	0.83	0.93	0.88
HAIWOO	PCT	0.94	GBIF-BISON	0.55	0.86	0.11
HAIWOO	PCT	0.95	PCT	0.73	0.62	0.07
HAIWOO	GBIF/BISON	0.85	PCT	0.54	0.21	0.81
HAIWOO	GBIF-BISON	0.87	GBIF-BISON	0.74	0.24	0.76
HAIWOO	Combined	0.85	Combined	0.72	0.69	0.72
YERWAR	PCT	0.91	GBIF-BISON	0.51	0.85	0.24
YERWAR	PCT	0.91	PCT	0.88	0.83	0.25
YERWAR	GBIF-BISON	0.81	PCT	0.54	0.56	0.92
YERWAR	GBIF-BISON	0.82	GBIF-BISON	0.72	0.52	0.89
YERWAR	Combined	0.79	Combined	0.77	0.94	0.87

BKHGRO Habitat Suitability

I found that covariates elevation, Fortypba, distance to bark beetle infestations, slope, stream distance, and fires contributed significantly to my model for BKHGRO habitat suitability (Figure 2Figure 3). BKHGRO appears to find close proximity to bark beetle infestations as more suitable; this species has been observed to prefer forests impacted by beetle impacts (Fair et al., 2018; Mosher, 2011). The species appears to favor elevations above 800 meters but below 1,100 meters, but my models indicate some suitability in lower elevations where occurrences were recorded in isolated forested

habitats in the central valley as indicated by the Fortypba layer. I found higher suitability closer to burned areas. Suitability also peaks close to streams. BKHGRO has been noted to have a preference for a mixed hardwood/conifer plant community (Airola & Barrett, 1985) and Fortypba did confirm these preferences showing a high affinity for white fir (*Abies concolor*), ponderosa pine (*Pinus ponderosa*), California incense cedar (*Calocedrus decurrens*), sugar pine (*Pinus lambertiana*), Douglas fir (*Pseudotsuga menziesii*), California black oak (*Quercus kelloggii*), and canyon live oak (*Quercus chrysolepis*). This species appears to find slopes less than 30 degrees as more suitable.

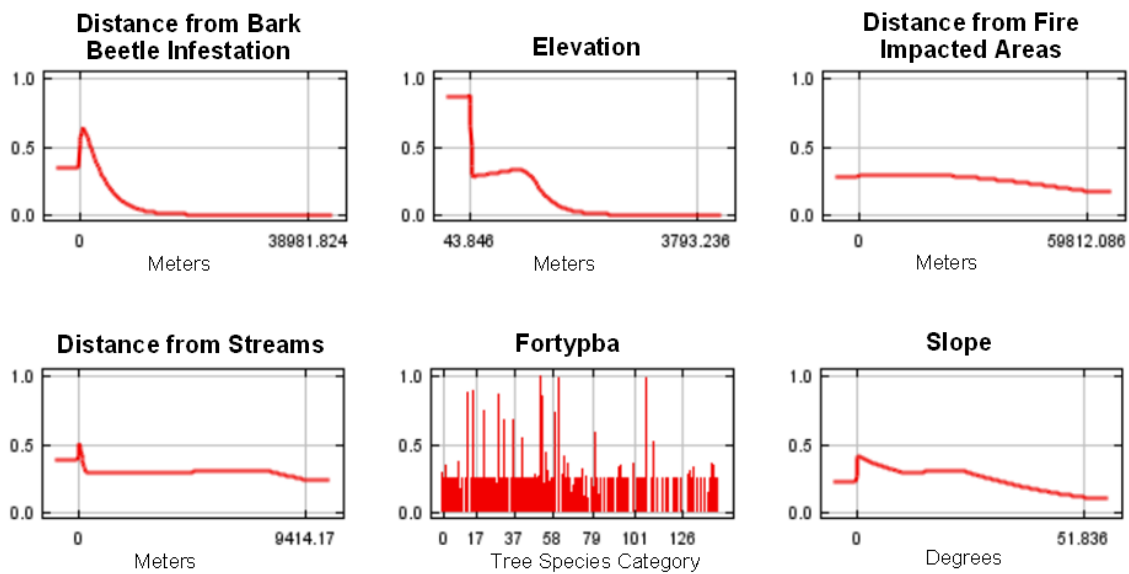


Figure 2. BKHGRO response curves from MaxEnt with a regularization multiplier of 1.5 for each of the environmental covariates using the Combined Dataset.

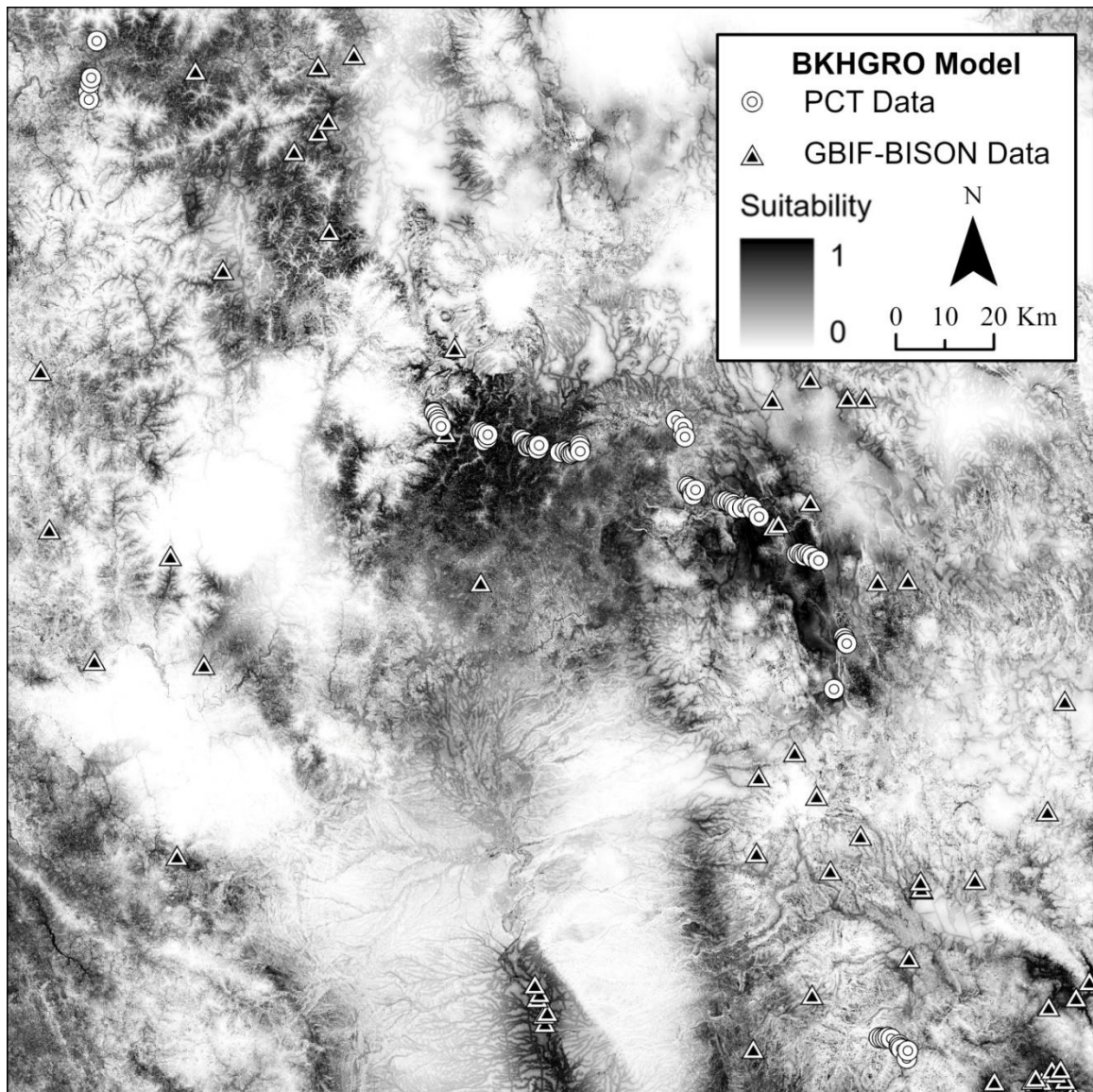


Figure 3. Habitat suitability model for the BKHGRO built from the Combined Dataset with a regularization multiplier of 1.5.

HAIWOO Habitat Suitability

For HAIWOO, I found that the covariates of aspect, distance from bark beetle infestations, distance from fires, hardwood canopy cover, Fortypba, and slope contributed significantly to my model of habitat suitability (Figure 4 & Figure 5), where areas closer to bark beetle infestations and fire-impacted habitat are considered more suitable. HAIWOO

appears to prefer south facing slopes that are less than 15 degrees. Areas with lower percentages of hardwood canopy, but greater percentages of conifer species, had higher suitability, including red fir (*Abies procera*), white fir, Jeffrey pine (*Pinus jeffreyi*), ponderosa pine, white oak (*Quercus garryana*), and California black oak.

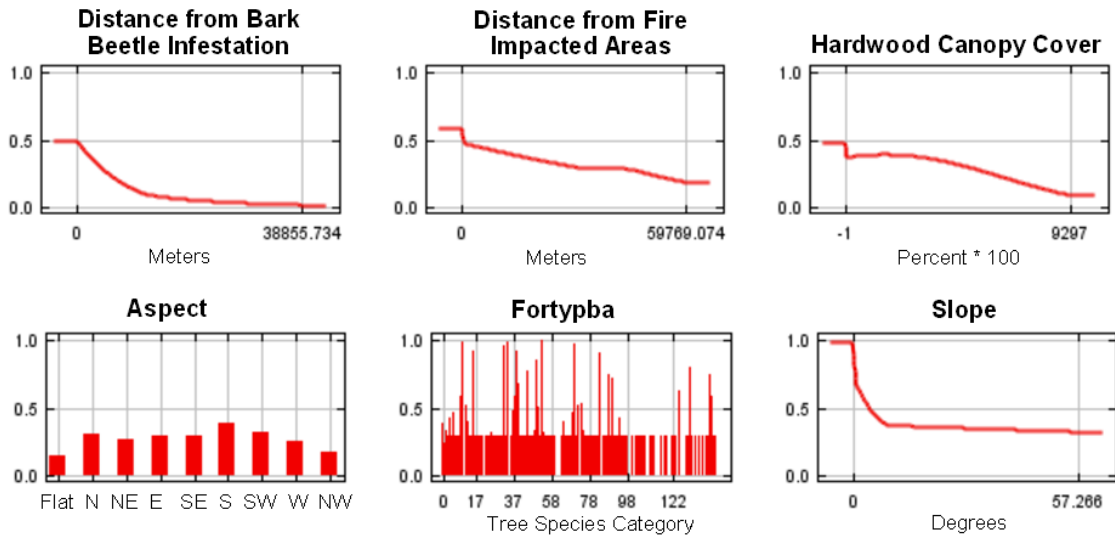


Figure 4. HAIWOO response curves from MaxEnt with a regularization multiplier of one for each of the environmental covariates using the Combined Dataset.

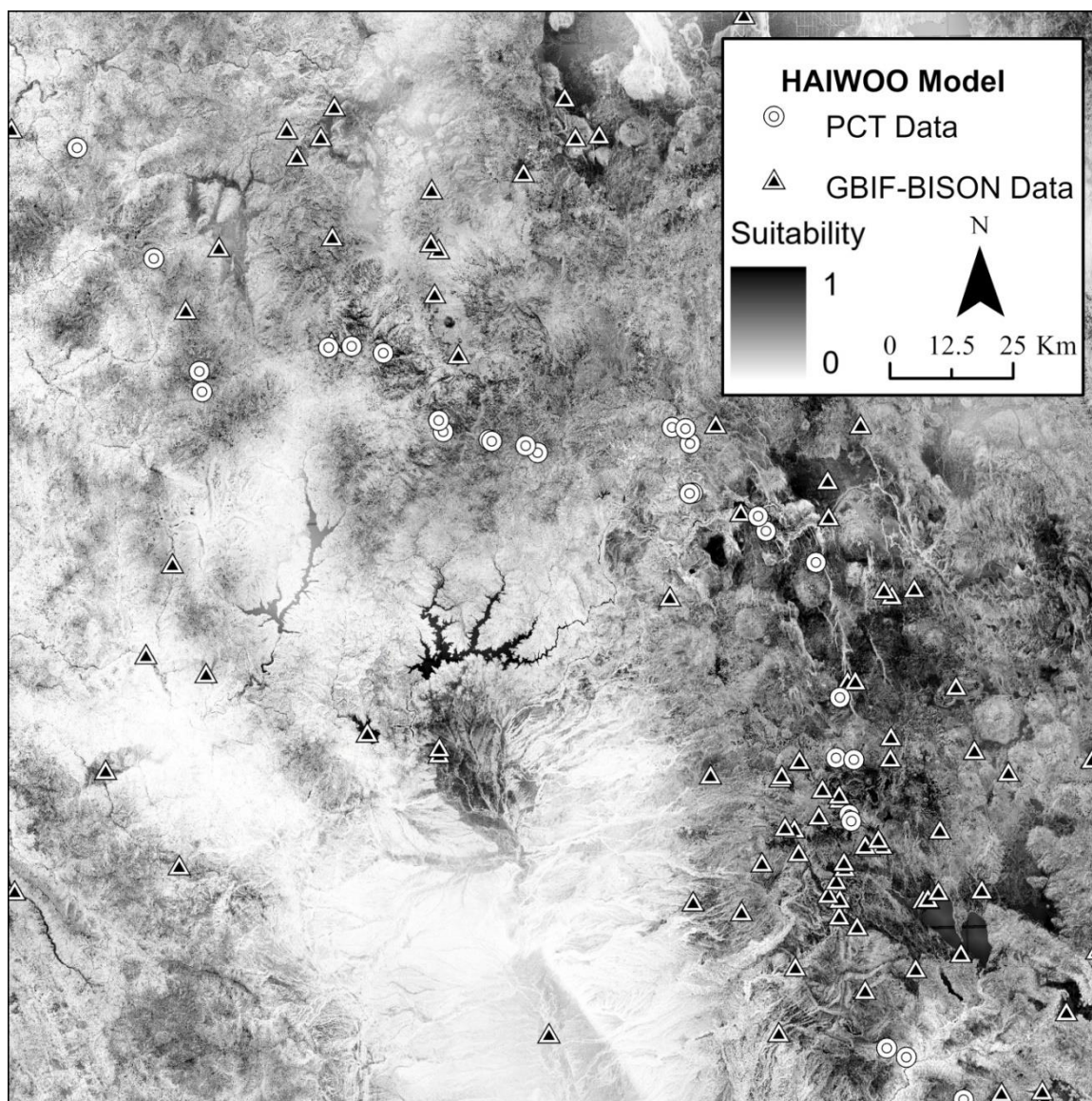


Figure 5. Habitat suitability model for the HAIWOO built from the Combined Dataset with a regularization multiplier of one.

YERWAR Habitat Suitability

For YERWAR, I found that the covariates of distance from fire impacted areas, hardwood canopy cover, distance from streams, Fortypba, and slope contributed significantly to my model of habitat suitability (Figure 6 & Figure 7). My model also

indicated higher suitability nearer to areas impacted by fire. I found that suitability was greatest with little to no hardwood canopy cover. Areas nearer to streams have greater suitability than areas away from streams. Suitability was greatest in habitats dominated by coniferous trees, including white fir, red fir, California incense cedar, Jeffrey pine, sugar pine, Western white pine (*Pinus monticola*), ponderosa pine, Douglas fir, mountain hemlock (*Tsuga mertensiana*), knobcone pine (*Pinus attenuate*), Brewer spruce (*Picea breweriana*), Lodgepole pine (*Pinus contorta*), live oak, subalpine fir (*Abies lasiocarpa*), white oak, bitter cherry (*Prunus emarginata*), blue oak (*Quercus douglasii*), and Pacific silver fir (*Abies amabilis*). YERWAR appears to find slopes less than 30 degrees as more suitable.

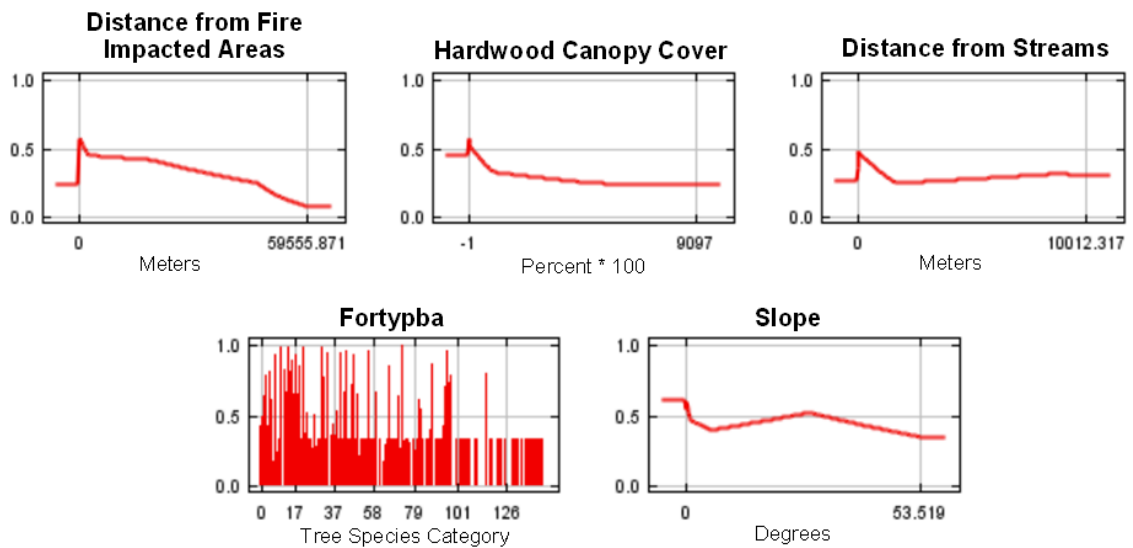


Figure 6. YERWAR response curves from MaxEnt with a regularization multiplier of one for each of the environmental covariates using the Combined Dataset.

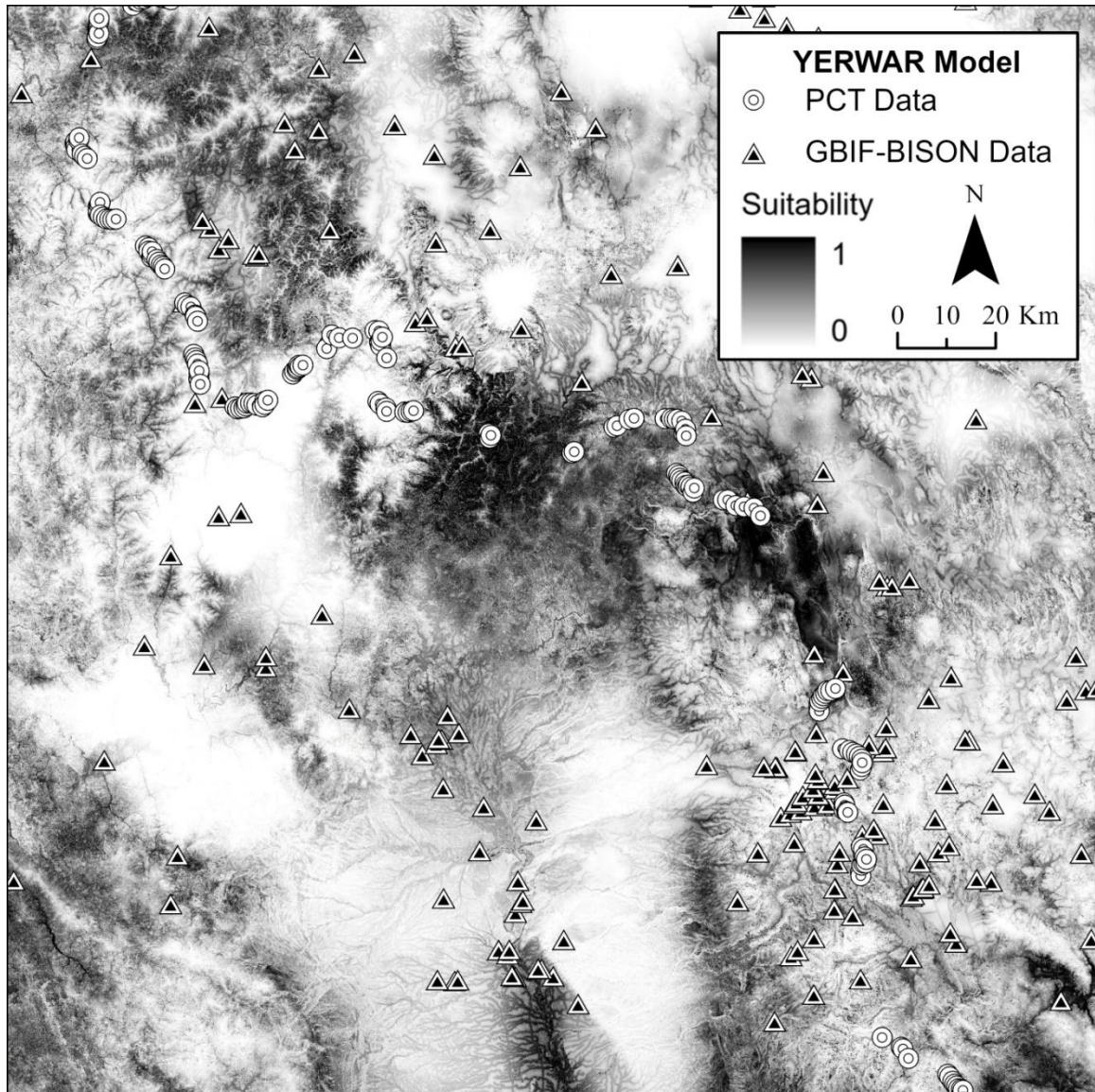


Figure 7. Habitat suitability model for the YERWAR built from the PCT Data and GBIF-BISON Data combined with a regularization multiplier of one.

Model Evaluation

With injected uncertainty into the best MaxEnt combined models (Table 4. Monte Carlo results for injecting uncertainty into the three combined models.) for BKHGRO, the AIC increased by 58 and the AUC decreased by 0.03 from the original model. For HAIWOO,

the AIC increased by 97 and the AUC decreased by 0.03. For YERWAR model, the AIC increased by 135 and the AUC decreased by 0.02.

Table 4. Monte Carlo results for injecting uncertainty into the three combined models.

Species	\overline{AIC}	AIC Deviation	\overline{AUC}	AUC Deviation
BKHGRO	10215	63.99	0.85	0.01
HAIWOO	5070	27.1	0.80	0.01
YERWAR	29998	84.20	0.78	0.01

Discussion

My approach of combining complementary datasets derived from different methods in the field has resulted in habitat suitability models that are generalizable across my entire study area. Previous studies have also combined this PCT Data with data from another large-scale biodiversity monitoring program throughout northern California to model bird diversity-climate relationships (McGrann & Furnas, 2016; Furnas & McGrann 2018). In these studies, the PCT Data served to strengthen the multi-species occupancy models used for the analysis and to improve the representation of the remote, high-elevation habitats that were poorly sampled by the more extensive region-wide monitoring program. The models created with the Combined Dataset performed at predicting the occurrences in all but one case with HAIWOO. In a similar approach, I used MaxEnt to create response curves that represent the expected habitat associations for each species across the entire study area beyond only the PCT. Further, I determined that

my models were robust after injecting error into the observed data and the covariates and found the AUC only decreased by 0.02 to 0.04 points. Altogether, this indicates that my models are predictive of the actual spatial distribution of these species and of where these species might find suitable habitat across my entire study area. My future research direction will include the use of these models to study how these species' habitats might be shifting due to drought, fire, or climate change, thus making my modeling approach useful to management decisions.

By combining the two datasets, I created a model that increased the ability to predict locations that included occurrences with a small reduction in AUC values. Although the AUC for the PCT Data was high, it did not predict occurrences well beyond the trail for the three species, indicating that the PCT Data may be suitable for fine-scale analysis on species distributions along this specific region of the trail. The PCT survey sites, due to the trail's design and the route chosen for the trail, may be biased towards higher elevations and other habitats disproportionately occurring along the trail, which was also reported by Furnas & McGrann (2018). It appears, from my analysis, that the PCT Data does not have enough predictive power to project to a larger area and requires additional data covering the broader range of environmental covariates throughout the study area. Yet, it would be cost prohibitive to apply more widely, across the entire study area, the intensive survey methods designed for application along this transect.

The GBIF-BISON Data has wider coverage of the study area but also has its own inherent biases. The AUC for the GBIF-BISON Data was slightly lower than the PCT Data overall, and it did not project well to the PCT Data. This can indicate that although

GBIF-BISON Data may cover a larger area, it may not have the consistent and structured sampling design required for fine scale modeling. Additionally, data from these sources are generally biased towards roads (Ronen Kadmon, 2004) and contain surveyor bias as observers favor habitats that are easier to access from roads or that are considered favorable for observing greater numbers of birds (Tulloch & Szabo, 2012). For example, I noticed that HAIWOO, which was expected to benefit from foraging in fire-impacted areas, was observed to have few occurrences within these areas (Figure 8). I suspect that observers who collected GBIF-BISON Data, chose to avoid burned forests. The GBIF-BISON Data, however, included some sampled areas at lower elevations, such as in the Sacramento Valley, where the PCT Data did not have any survey sites. The GBIF-BISON Data also had gaps, particularly in the remote and high-elevation wilderness areas, where the PCT Data was able fill in. Inclusion of the occurrences in the Sacramento Valley influenced the shape of the response curves, and the full range of the species was represented more appropriately.

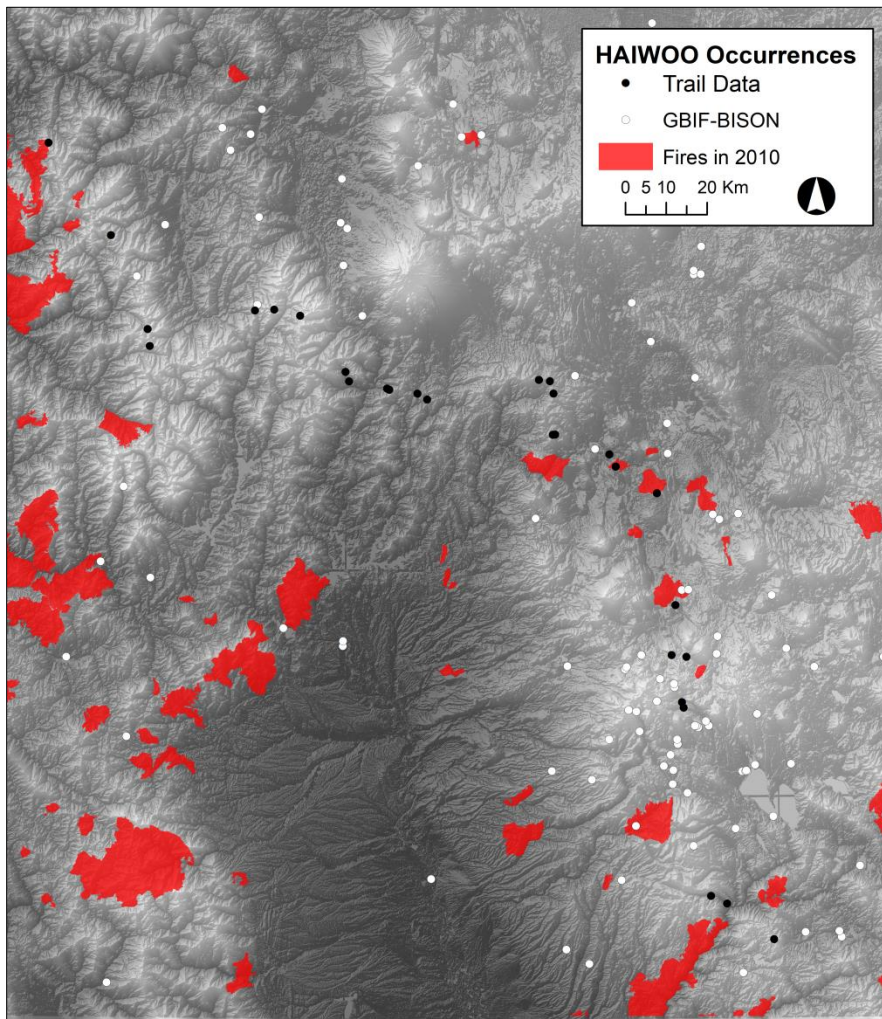


Figure 8. Occurrences from HAIWOO and the zones of fire-impacted areas. Fire polygons from Monitoring Trends in Burn Severity (2009).

Habitat Associations for BKHGRO, HAIWOO, and YERWAR

Response curves described well my anticipated habitat associations for BKHGRO, HAIWOO, and YERWAR. Previous studies have documented BKHGRO in disturbed habitat near fires (Bagne & Purcell, 2011) and, more rarely, in high-elevation habitats (Wilson, 2013). As a canopy nester, it prefers nesting in close proximity to streams, which can act to moderate temperatures for the nest site (Becker, 2013).

BKHGRO forage in a variety of habitats (Airola & Barrett, 1985) but within 2 km of a water source and readily use shrubs in early successional habitats (Gardali & Holmes, 2011). BKHGRO's affinity for shrubs may also lead to an affinity for a specific tree cover from the Fortypba layer (Pase, 1982), particularly at lower- to mid-elevation montane forests where a distinct shrub layer is commonplace in the understory. The response curves for the BKHGRO, when run with individual covariates, may suggest a bimodal response with distance to bark beetle infestations (Figure 9). They are found in bark beetle infested habitats (Mosher, 2011) where they most likely do not forage on the boring beetles, but instead may consume arthropods that follow a bark beetle infestation (Weslien & Schroeder, 1999), since BKHGRO glean insects (Airola & Barrett, 1985) rather than drill for boring beetles. The species also forage away from these infestations on other insects or seeds. When the distance to bark beetle infestations covariate is combined into the full model, it takes on a curve where close proximity to bark beetles is very suitable.

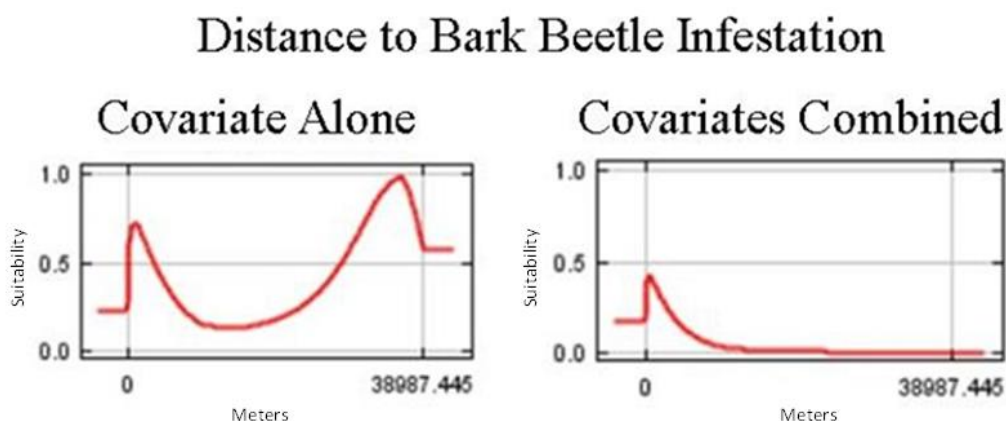


Figure 9. Response curves for distance to bark beetle infestations with the covariate alone and combined in the full model. The covariate alone displays a bimodal response where the species is either very close to the infested area, or is further away. The covariate combined shows that areas near the infested habitat is more suitable.

HAIWOO utilizes fire-impacted areas and forages on bark beetles (Saab et al., 2019), and I observed these habitats to have higher suitability. Since HAIWOO nest and forage in both snags or live conifer trees that may show signs of defoliation from bark beetles (Bull et al., 1986), lower amounts of hardwood canopy cover would have higher suitability. Slope and aspect may influence the woodpecker's choice of nest site, preferring areas with lower moisture gradients (Bull et al., 1986). A mixture of hardwood and conifer tree species showed signs of high suitability. This could indicate that HAIWOO is a generalist, preferring many tree species for foraging and nesting.

For YERWAR, high suitability was evident near, but not *within*, fire-impacted habitat, as the edge of this habitat may provide good foraging for insects that are abundant on the edges of burned forests. I documented higher suitability in close proximity to streams; which is also documented by others (Kirkpatrick et al., 2009).

Conclusions

I found that first identifying the trade-offs of each dataset, and deciding on whether to select the appropriate dataset, or combine both, was crucial in creating the best model to address my research questions and hypotheses. The PCT Data, derived from a transect survey protocol, may be suitable for intensive sampling along environmental gradients and in describing climate-diversity relationship (the original purpose of the data) but not necessarily for extrapolation far beyond the trail itself. The intent of the original biodiversity study along the PCT was *not* to describe species distributions across

a broader study area. Data from BISON or GBIF is beneficial for broad scale analysis but may leave out areas for fine scale analysis and these data may poorly represent more remote and high-elevation habitats. Also, the GBIF-BISON Data may not include the full range of the species and their habitats. If I use these models to generate fine-scale maps, I need to find additional datasets that capture more of the covariates required to model those areas, and combining datasets, habitat suitability models can be built that fill in spatial gaps and can more adequately inform management (Turner et al., 2016). Additionally, I found that GBIF-BISON underrepresented fire-impacted areas and throughout the region.

A future study should look into building models for the PCT Data that is limited to the elevations in which the PCT Data encompasses. This would create fine scale models for this section of remote montane wilderness in which the PCT Data is well suited for. Additionally, by using only the PCT Data, users can account for detection probability due to the high number of revisits to each sample site. This will help account for species that may have been present at the site, but went undetected by the surveyor. I did not account for detection probability in this study due to my large study area and the additional datasets that comprise of a mix of survey methods and did not allow for presence-absence data to be downloaded. A future study could limit the research to focus only on the PCT Data and use the presence-absence data to account for this imperfect detection.

Another future study should look into alternatives for the Fortypba covariate. This is because the Fortypba layer is very complex and a simpler layer may make more sense

to the phenomena of the species. For these models, the Fortypba layer served to improve the models and the avian species seemed to be associated with certain tree species in the layer. Potentially, other layers may better represent a simpler expectation of the species responses would be only using the canopy cover or finding a tree layer that focuses on guilds of trees.

In the end, I provide a useful approach to modeling habitat suitability by combining an intensive transect survey with data sources from repositories such as BISON and GBIF. Overall, my models well characterized the suitability of habitat for these three bird species and demonstrated their utility. With well-developed models, managers can determine which habitats in their area are suitable and also track the overall response of avian diversity to drought, fire, climate change, or human land-use change. Future research directions should examine whether this modeling approach can track the response of birds, and their habitats, to these environmental changes.

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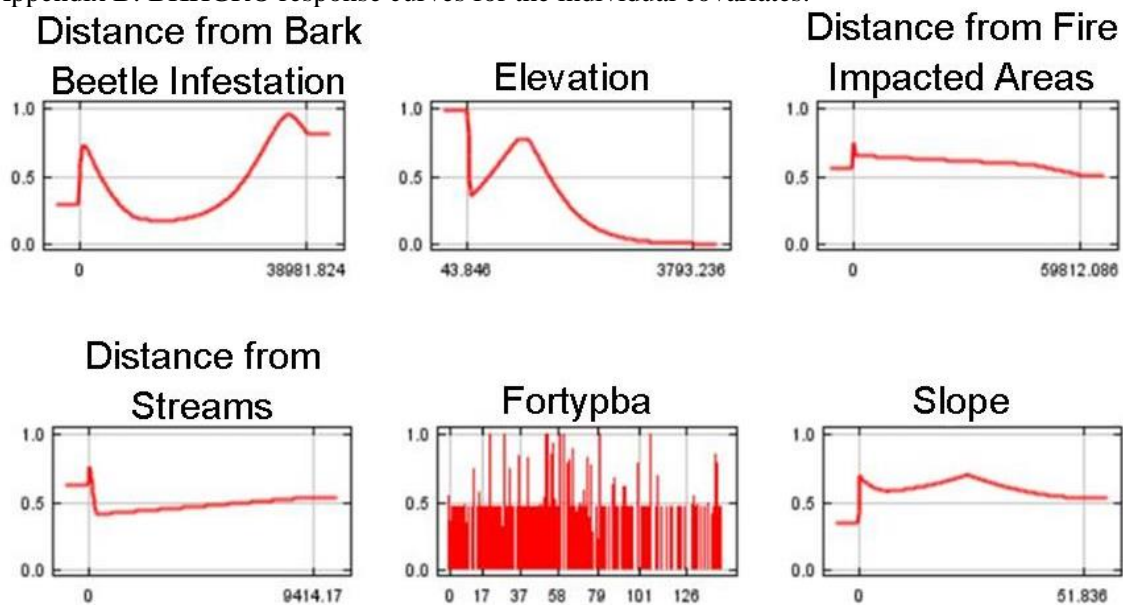
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Appendices

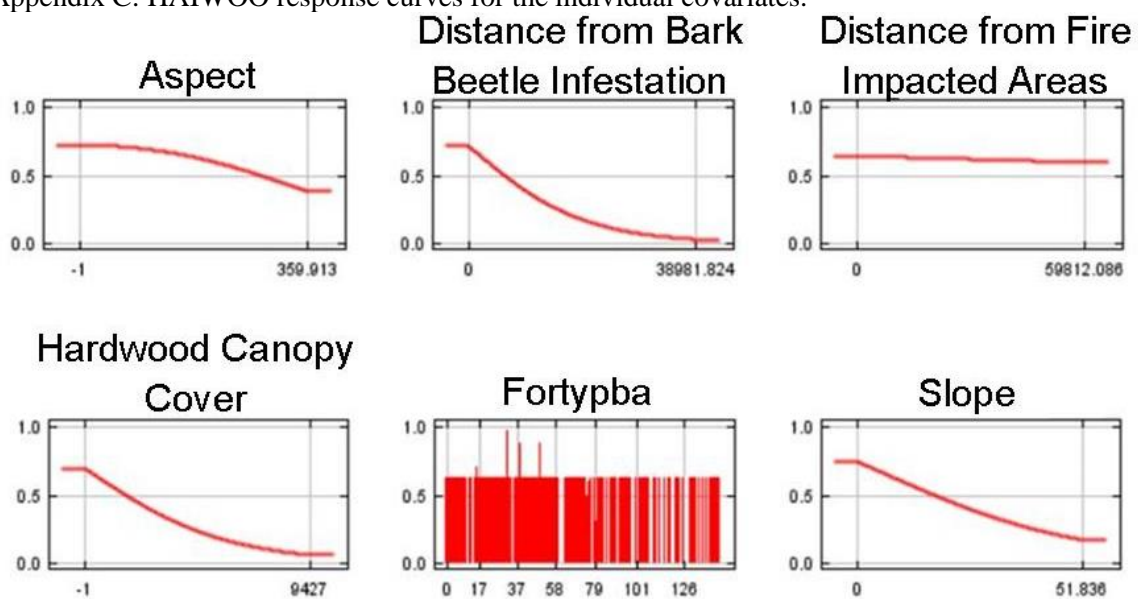
Appendix A: Pearson correlation matrix produced in R (R code in the Appendix Section RCODE) of the correlation between environmental covariates. Covariates with a relationship above 0.7 were not used within the same model and prevent a potential reversal of the relationship within the model.

	Vegetation Class	Live Tree Density	Distance from Streams	Snag Density	Quadratic Mean Diameter of Dominant Tree Species	Hardwood Canopy Cover	Distance from Fires	Elevation	Conifer Canopy Cover	Total Canopy Cover	Distance from Bark Beetle Infestation	Slope
Vegetation Class	1.000	0.643	-0.315	0.157	0.638	-0.125	0.074	0.135	0.863	0.763	-0.039	0.001
Live Tree Density		1.000	-0.285	0.086	0.419	0.119	0.032	-0.017	0.758	0.780	-0.049	0.038
Distance from Streams			1.000	-0.152	-0.263	-0.100	-0.248	-0.050	-0.354	-0.363	0.078	-0.143
Snag Density				1.000	0.178	-0.122	-0.020	0.248	0.150	0.071	-0.087	0.143
Quadratic Mean Diameter of Dominant Tree Species					1.000	-0.162	0.117	0.223	0.624	0.503	-0.051	0.096
Hardwood Canopy Cover						1.000	-0.031	-0.653	-0.130	0.368	-0.014	0.262
Distance from Fires							1.000	0.203	0.070	0.040	0.436	0.328
Elevation								1.000	0.074	-0.220	0.071	-0.046
Conifer Canopy Cover									1.000	0.858	-0.080	0.021

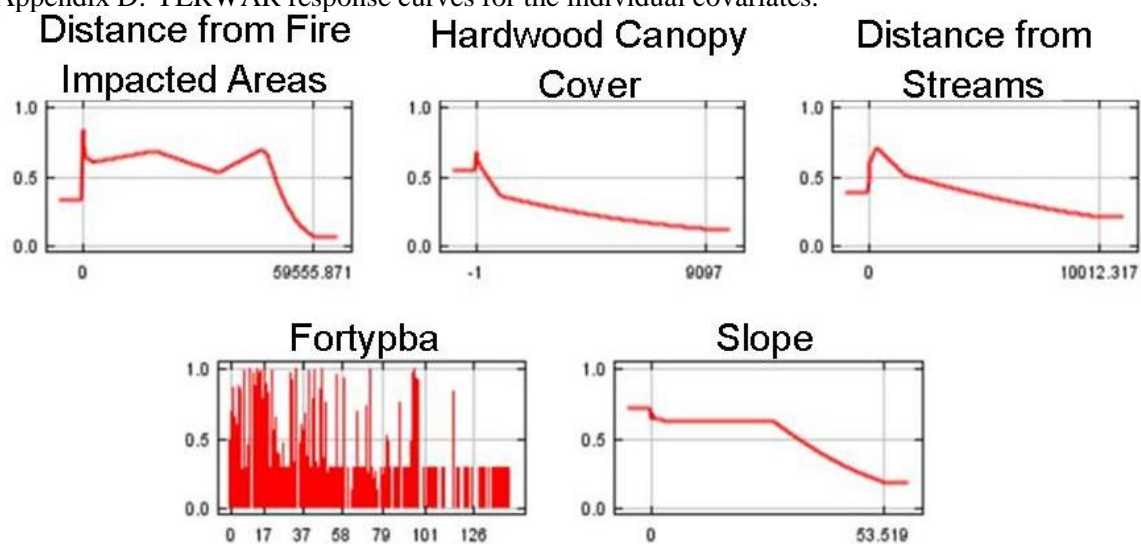
Appendix B: BKHGRO response curves for the individual covariates.



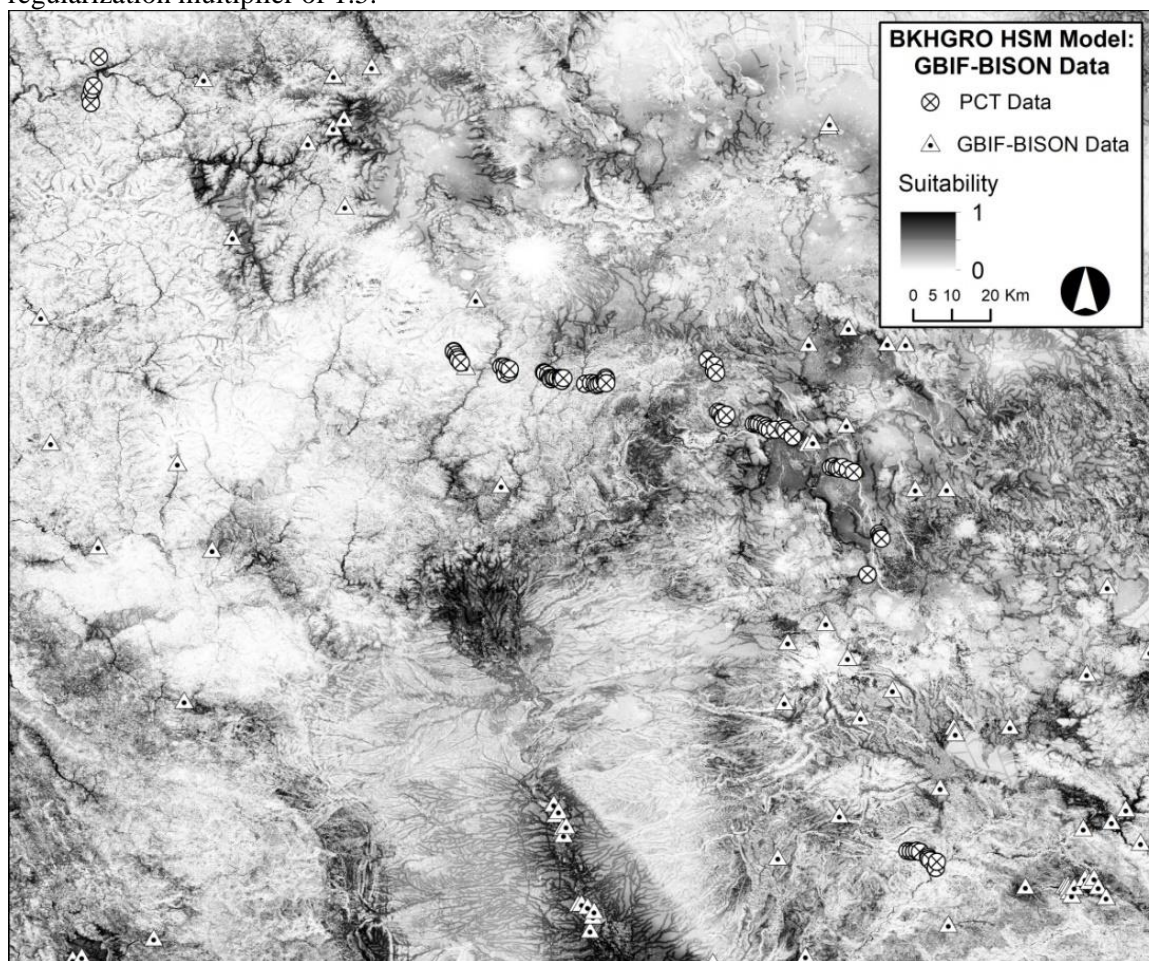
Appendix C: HAIWOO response curves for the individual covariates.



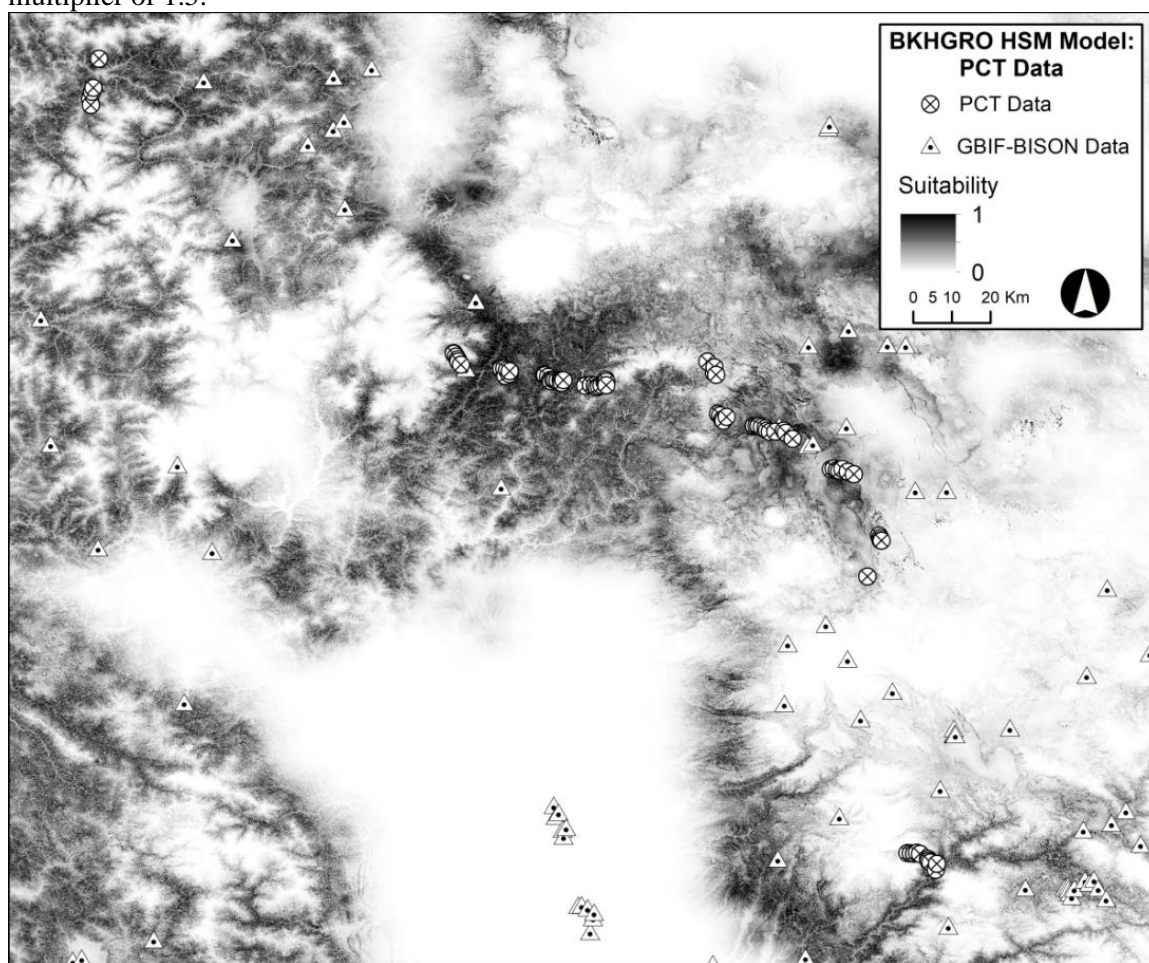
Appendix D: YERWAR response curves for the individual covariates.



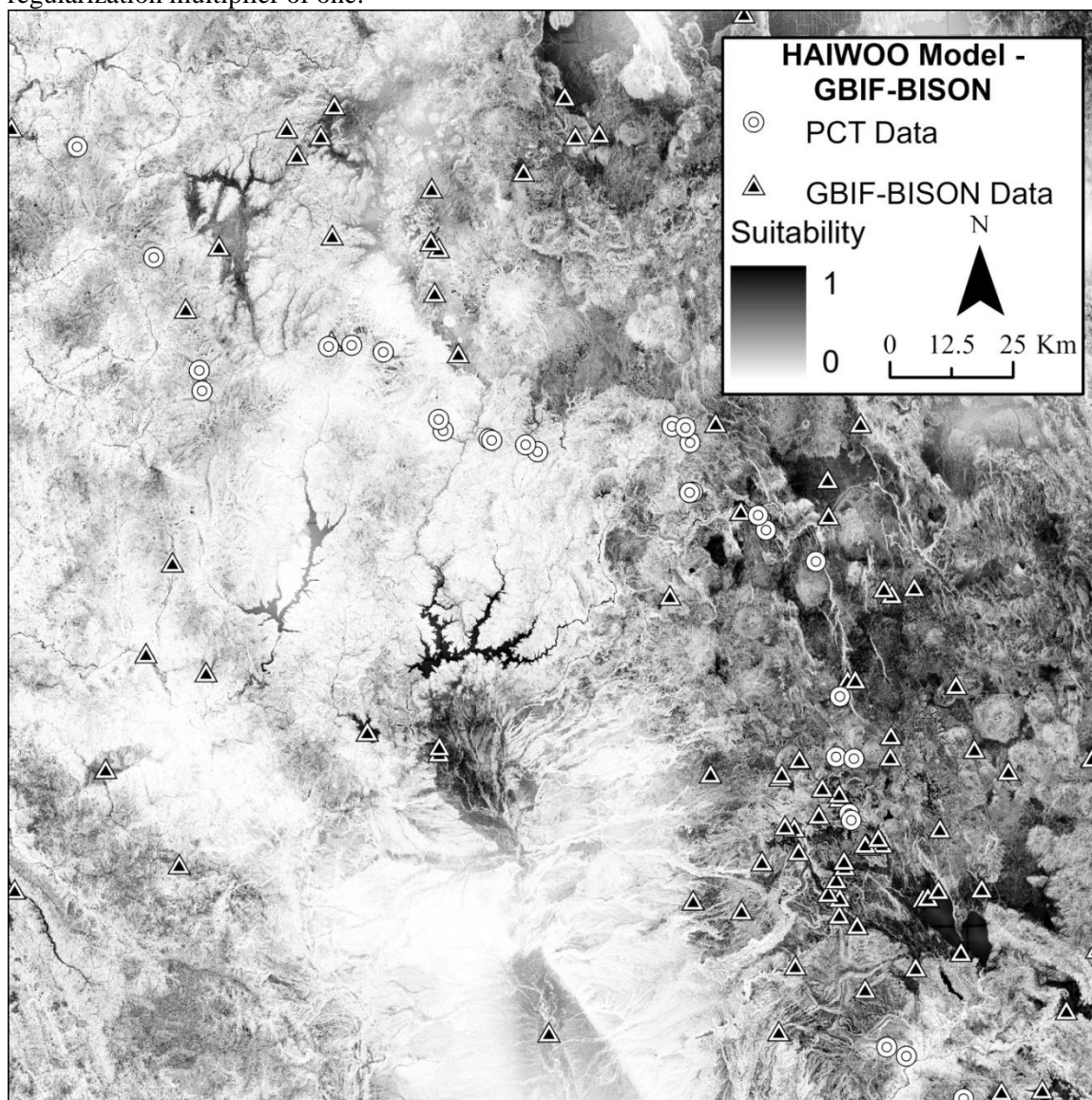
Appendix E: BKHGRO habitat suitability model built from GBIF-BISON Data with regularization multiplier of 1.5.



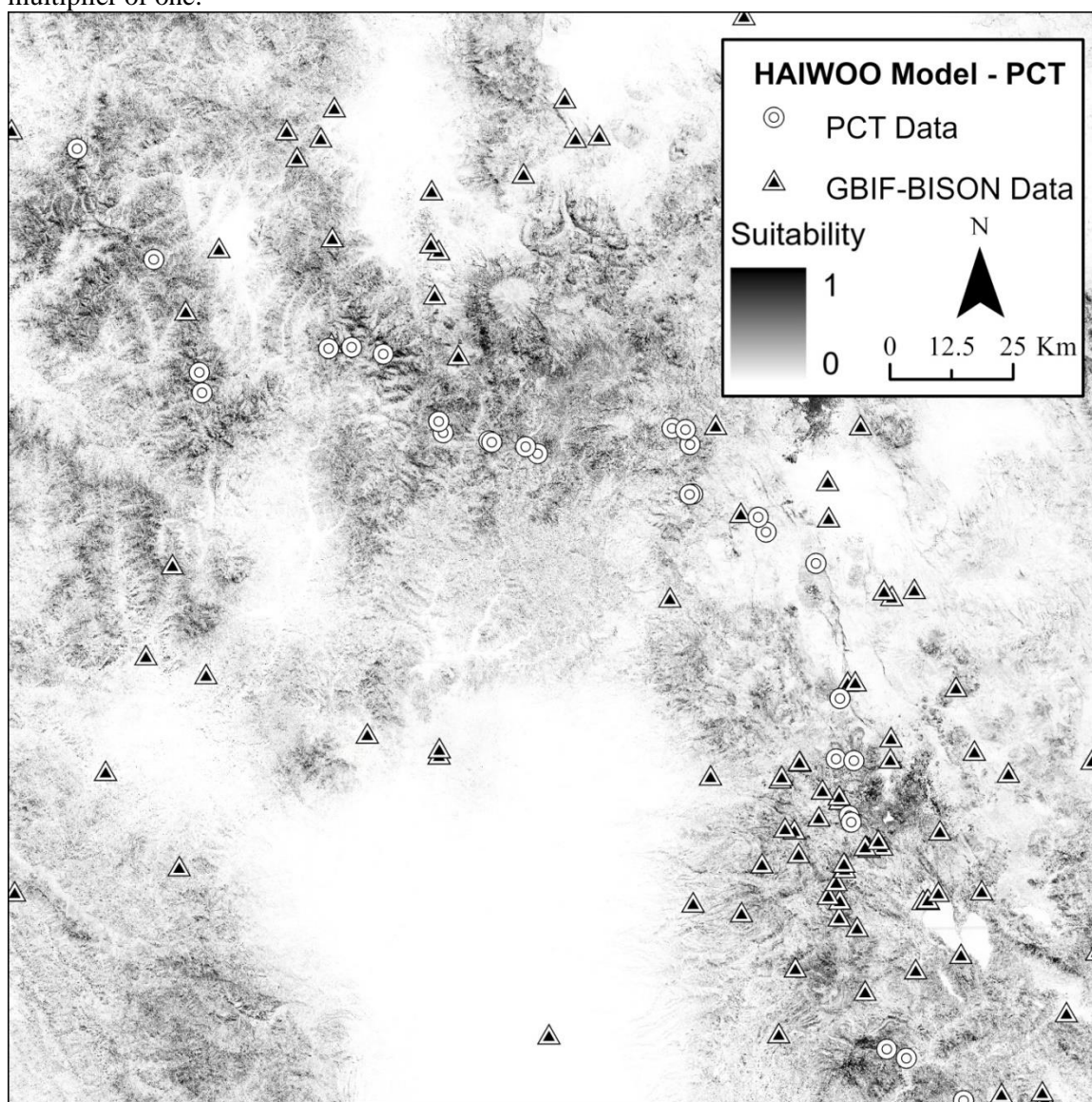
Appendix F: BKHGRO habitat suitability model built from PCT Data with a regularization multiplier of 1.5.



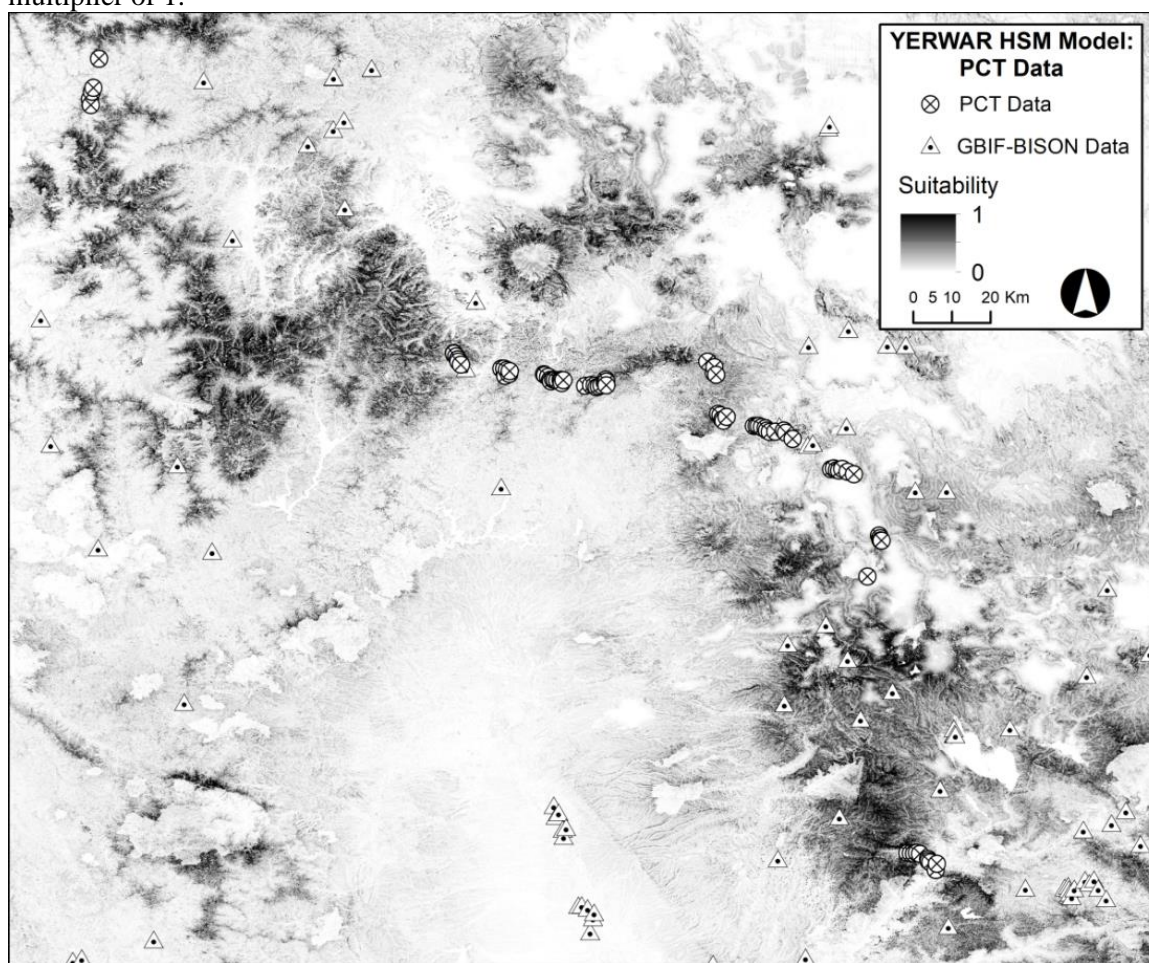
Appendix G: HAIWOO habitat suitability model built from the GBIF-BISON Dataset with a regularization multiplier of one.



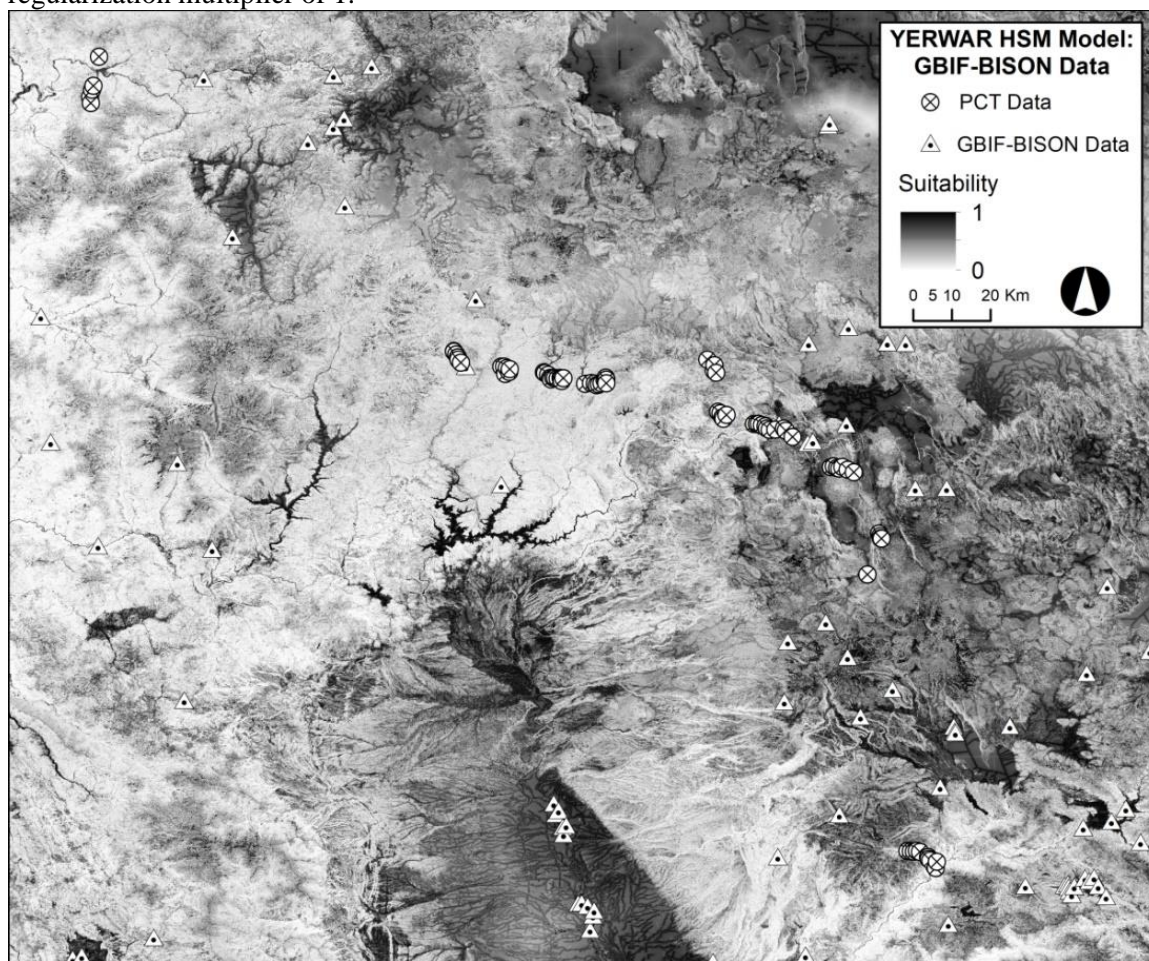
Appendix H: HAIWOO habitat suitability model built from the PCT Data with a regularization multiplier of one.



Appendix I: YERWAR habitat suitability model built from the PCT Data with a regularization multiplier of 1.



Appendix J: YERWAR habitat suitability model built from the GBIF-BISON Data with a regularization multiplier of 1.



Appendix K: R-Script code to find the correlation between environmental covariates and find the mean value of suitability for each species.

```
# Finding the correlation between environmental covariates
#adding data to R
dat<-(read.csv("", head=T))
attach(dat)
# Assessing correlations from the 12th column to the end
cor(dat[,12:ncol(dat)], use="pairwise.complete.obs",method="pearson")
#####
#####
# R script to compare the suitability values for all the occurrence records for BKHGRO
# Import the suitability comparison csv file
BKHGRO=read.csv("")
plot(BKHGRO$Point, BKHGRO$maxent_R_4, pch=21, bg="black", xlab="Occurrence
Record Number", ylab="Habitat Suitability")
# Finding the mean value of suitability
mean(BKHGRO$maxent_R_4)
#####
#####
# R script to compare the suitability values for all the occurrence records for HAIWOO
# Import the suitability comparison csv file
HAIWOO=read.csv("")
plot(HAIWOO$Point, HAIWOO$MaxEntR3, pch=21, bg="black", xlab="Occurrence
Record Number", ylab="Habitat Suitability")
# Finding the mean value of suitability
mean(HAIWOO$MaxEntR3)
#####
#####
# R script to compare the suitability values for all the occurrence records for YERWAR
# Import the suitability comparison csv file
YERWAR=read.csv("")
plot(YERWAR$Point, YERWAR$MaxEntR3, pch=21, bg="black", xlab="Occurrence
Record Number", ylab="Habitat Suitability")
# Finding the mean value of suitability
mean(YERWAR$MaxEntR3)
#####
#####
```

Appendix L: Python script for calculating the standard error in the aspect and slope rasters.

#Python Script for calculating the standard error in the aspect and slope rasters

```

import os
import sys
# Open source spatial libraries
import shapely
import numpy
import gdal
import math
import random
# SpaPy libraries
from SpaPy import SpaBase
from SpaPy import SpaPlot
from SpaPy import SpaVectors
from SpaPy import SpaView
from SpaPy import SpaReferencing
from SpaPy import SpaDensify
from SpaPy import SpaView
from SpaPy import SpaRasters
from SpaPy import SpaTopo
from SpaPy import SpaRasterVectors
# set the input to the path where the original files are
#InputPath="C:\\Projects\\ProjectsPython\\HollsPaper\\Elevation.tif"
#InputPath="C:\\Projects\\ProjectsPython\\HollsPaper\\Sampled.tif"
InputPath1="C:\\Projects\\ProjectsPython\\HollsPaper\\ProjectedDEM_NoMask.tif"
OutputPath1="C:\\Projects\\ProjectsPython\\HollsPaper\\Slope1.tif"
OutputPath2="C:\\Projects\\ProjectsPython\\HollsPaper\\Slope2.tif"
OutputPath3="C:\\Projects\\ProjectsPython\\HollsPaper\\Temp.tif"
# Load the initial DEM
TheDEM=SpaRasters.SpaDatasetRaster()
TheDEM.Load(InputPath1)
WidthInPixels=TheDEM.GetWidthInPixels()
HeightInPixels=TheDEM.GetHeightInPixels()
# Create the base slope raster with no error
TheSlope=SpaTopo.Slope(TheDEM,OutputPath1)
TheSlope=SpaRasters.SpaDatasetRaster()
TheSlope.Load(OutputPath1)
# Setup the StdDev variables
SumOfSquares=0
N=0
# Loop over and over to improve the StdDev
Index=0
while (Index<1):
    # Load the DEM
    TheDEM3=SpaRasters.SpaDatasetRaster()

```

```

TheDEM3.Load(InputPath1)
TheBand=TheDEM3.GetBand(0)
Row=0
while (Row<HeightInPixels):
    Column=0
    while (Column<WidthInPixels):
        Value=TheBand[Row][Column]
        Random=numpy.random.normal(0,2.42)
        Value+=Random
        TheBand[Row][Column]=Value
        Column+=1
    Row+=1
TheDEM3.SetBands([TheBand])
TheDEM3.Save("C:\\Projects\\ProjectsPython\\HollsPaper\\TempDEM.tif")
SpaTopo.Slope("C:\\Projects\\ProjectsPython\\HollsPaper\\TempDEM.tif",Output
tPath2)
TheSlope2=SpaRasters.SpaDatasetRaster()
TheSlope2.Load(OutputPath2)
#
TheBand1=TheSlope.GetBand(0)
TheBand2= TheSlope2.GetBand(0)
Row=0
while (Row<HeightInPixels):
    Column=0
    while (Column<WidthInPixels):
        Value1=TheBand1[Row][Column]
        Value2=TheBand2[Row][Column]

        if (Value1!=-9999) and (Value2!=-9999):
            SumOfSquares+=(Value1-Value2)**2
            N+=1
        Column+=1
    Row+=1
Index+=1
StdDev=math.sqrt(SumOfSquares/N)
print(StdDev)

```

CHAPTER 2: DISTRIBUTION SHIFTS FOR BLACK-HEADED GROSBEAK, HAIRY
WOODPECKER, AND YELLOW-RUMPED WARBLER IN THE PACIFIC
NORTHWEST DUE TO DROUGHT, FIRE, AND BARK BEETLE INFESTATIONS

Abstract

The California multi-year drought, beginning in 2011, severely impacted vegetation health along with increased fire intensity and bark beetle infestation. These impacts to the environment have shifted bird distributions, which rely on these vegetative communities to provide food and shelter. It is critical to see how birds have shifted and understand how they may be impacted in the future. My objectives were to (1) analyze how Black-headed Grosbeak, Hairy Woodpecker, and Yellow-rumped Warbler have shifted their distributions due to drought, fire, and bark beetle infestation through building habitat suitability models using data pre- and post-drought datasets and (2) compare these changes back to changes in vegetation productivity from remotely sensed data. I found that these three birds that occupy distinct habitat types have shifted largely due to drought, fire, and bark beetle infestation between my two years of habitat models. I was able to find a weak correlation between the productivity of vegetation and the habitat suitability models I created. Hairy Woodpeckers, which normally can use fire impacted habitat, have shifted out of burned areas, which may be due to increased fire intensity and longevity that mismatches with their food resource. Yellow-rumped Warblers and Black-headed Grosbeaks have shifted out of vegetative areas largely

impacted by the drought and have tightened in around areas with available surface water sources. As climate change continues to influence the intensity of droughts and fire, these avian species may continue to shift to where the available habitat can meet their biological requirements.

Introduction

For most montane birds, vegetation is a crucial habitat component. It provides a number of key resources, including food, cover, nest sites, and it provides for the vertical positioning of foraging and breeding behaviors. Many montane species are well-known to partition these resources to avoid competition (Whittaker et al., 1973). Bird distributions may be impacted by changes in vegetation through human land use (Arau et al., 2008) or environmental factors, including drought. Drought alters the plant species composition, vegetation structure, and productivity of forests (Allen et al., 2010). The combination of extreme temperatures and water deficit weakens the plant physiology of forests (Eamus et al., 2013), leaving them vulnerable to a cascade effect of bark beetle infestations and fire (AghaKouchak et al., 2014; Asner et al., 2015). Droughts are expected to grow in frequency and intensity due to climate change (AghaKouchak et al., 2014; Asner et al., 2015; Trenberth et al., 2013). Through drought and the accompanying impacts of fire and bark beetle infestations, tree-dominated habitats are expected to transition into the alternative stable states of grasslands and shrublands (Jiang et al., 2013).

Beginning in December, 2011, California experienced one of its worst multi-year droughts of the last millennium. In 2014 alone, high temperatures intensified drought conditions by 36% (Griffin & Anchukaitis, 2014) and scientists observed that the drought was the most severe that the region has experienced in the last 1,200 years (Robeson, 2015). By 2015, water stress was observed in high elevation forests (Asner et al., 2015) which usually see little impact due to the availability of snowpack runoff (Mote et al.,

2005). Many plant communities experienced significant declines, including high elevation pinyon-juniper, lodgepole pine, and red fir (Asner et al., 2015).

Dendrochronological studies show that no other drought in tree ring history comes close to the magnitude of this most recent drought (Robeson, 2015).

As drought increases tree mortality and continues to change ecosystems (Breshears et al., 2005), forest-dependent species may be sensitive to these changes and birds are excellent indicators of this change (Tingley et al., 2009). The Passeriformes (songbirds) are the largest order of forest birds, making over half of all avian species. Also, the Piciformes (woodpeckers) take advantage of habitats with dead trees and bark beetle infestations due to their preference for wood-boring larva as a food resource. I chose to focus on species from these two orders due to their vocalization habits and potential to determine how other elusive forest-dependent species may be impacted by drought. It is crucial to understand how avian distributions have shifted due to this recent multi-year drought in order to conserve bird habitat in the face of increasing drought intensity and frequency. One method to analyze shifts in species distributions is habitat suitability models.

Habitat suitability models predict the spatial occurrence and distribution of a focal species (Peterson et al., 2011). These models are typically represented as grid-based maps of the spatial distribution of the estimated suitability of the habitat (Kimble, 2016); suitability is derived from the correlation between environmental variables (specific characteristics of the habitat) and the locations of species occurrences. Some examples of the environmental covariates that are commonly used as predictors are elevation,

topography, precipitation, and temperature (Hedley & Buckland, 2004; Kadmon et al., 2016; McGrann & Thorne, 2014; Odion et al., 2010) and habitat models have been created for many of the species included in this study: Hairy Woodpecker (*Picoides villosus*) (Russell et al., 2007), Yellow-rumped Warbler (*Dendroica coronata*) (Price, 2000; Ralston & Kirchman, 2013), and Black-headed Grosbeak (*Pheucticus melanocephalus*) (St-Louis et al., 2014).

Remotely sensed data are also employed as covariates to estimate suitability. For example, Landsat satellites, at 30 m spatial resolution data and within 16-day temporal resolution (Chander & Markham, 2003; Roy et al., 2014), sense near-infra red and red reflectance to derive the Normalized Difference Vegetation Index (NDVI) as a measure of plant productivity (Tucker, 1979). To determine how the drought may be shifting avian distributions and to correlate these changes with plant productivity, I used habitat suitability modeling to create models for three avian species that represent a generalist, a species that may favor increases in bark beetle infestation and fire, and a species that relies on water sources for nest cooling. Yellow-rumped Warblers are considered habitat generalists that favor coniferous forests in all elevations with close association to water sources. Black-headed Grosbeaks are neotropical migrants that prefer a mixture of hardwood and conifer forests, but require access to water sources for nest cooling. Hairy Woodpeckers, although seen in green forests, are associated with burned forests which yield an abundance of snags that foster wood-boring insects, an important food source.

My objectives were: (1) to determine the impact of drought, fire, and bark beetle infestations on the distributions of Hairy Woodpecker, Black-headed Grosbeak, and

Yellow-rumped Warbler and (2) determine how much of the shift could be caused by the change in plant productivity.

Methods

Study Area

I studied a region in northern California from Bucks' Lake Wilderness (39.907°, -121.127°) to the Oregon Border (42.005°, -122.913°)(Figure 10). This region exhibits diverse ecosystems from low elevation mixed hardwood/conifer forests, to mid- to upper-elevation mixed conifer and subalpine forests, and to semiarid sagebrush (*Artemisia tridentata*) and montane chaparral (Schoenherr, 1992) in the south and to the east.

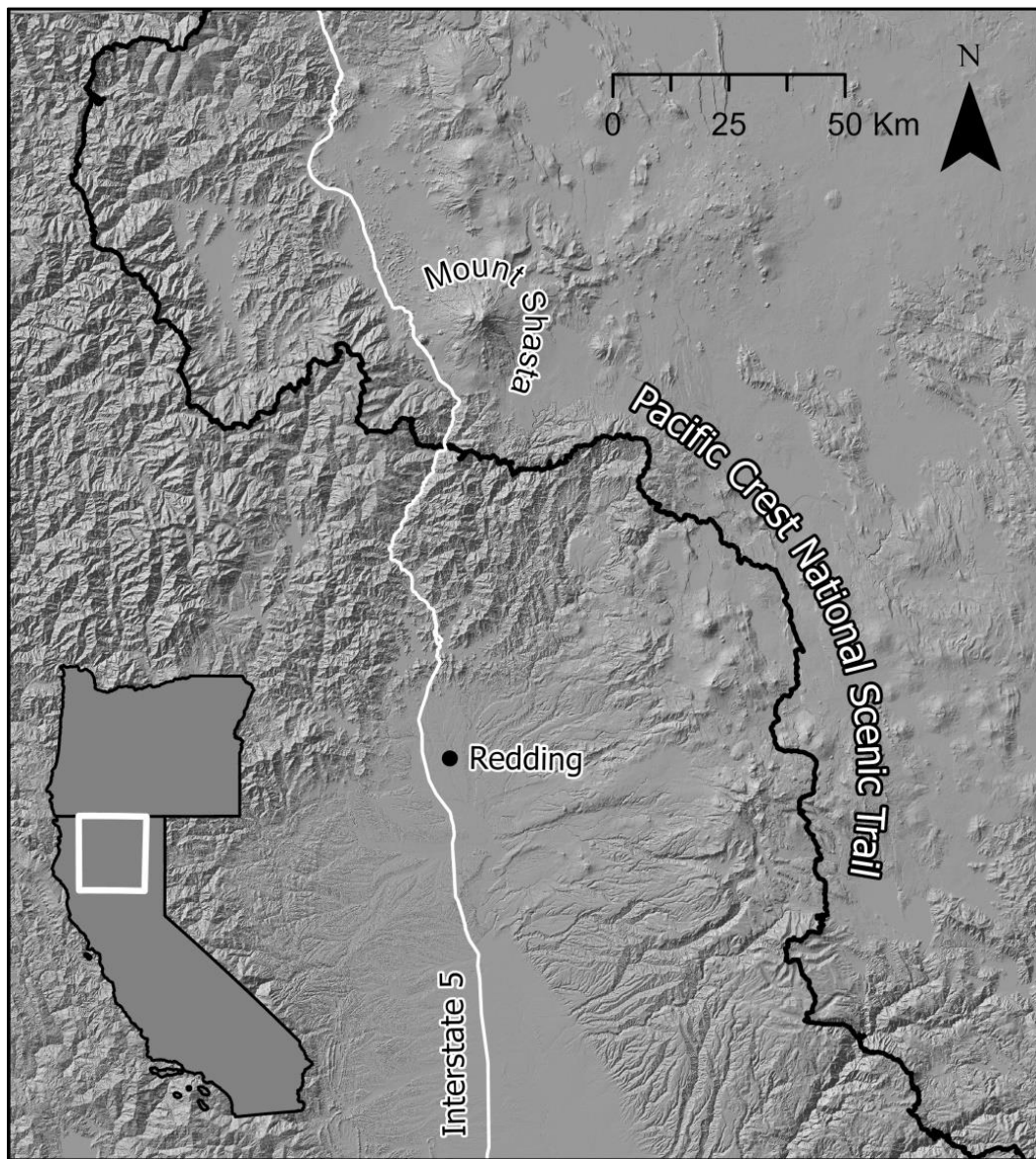


Figure 10. Study region in northern California that extends from Buck's Lake Wilderness to the Oregon border. Road data from the U.S. Census Bureau (2020) and the digital elevation map from the U.S. Geologic Survey (2013).

Occurrence Data

I collected avian occurrence data from the Global Biodiversity Information Facility (GBIF), the Biodiversity Information Serving Our Nation (BISON), and

published data from McGrann and Furnas (2016). I also acquired data from McGrann and Furnas for the year 2010 and 2016 which contains data along the Pacific Crest National Scenic Trail (PCT) via fixed-radius point-counts (50 m) and automated recorders in a standardized method as described in detail in McGrann and Furnas (2016) and Furnas and Callas (2015). The combined data from GBIF and BISON contain records from iNaturalist, Cornell lab of Ornithology, the eBird Observation Dataset, and the Great Backyard Bird Count (GBIF, 2021; BISON, 2021). Data was collected from GBIF and BISON and selected for the months May, June, and July in 2010 and 2016 to match the dates of the McGrann and Furnas data. I reference the chosen species using a six-letter alpha coding system (Pyle & DeSante, 2003). Black-headed Grosbeak (BKHGRO) had 167 occurrences for 2010 and 675 for 2016. Hairy Woodpecker (HAIWOO) had 130 occurrences in 2010 and 598 for 2016. Yellow-rumped Warbler (YERWAR) had 401 occurrences for 2010 and 844 for 2016.

Environmental Covariates

I assessed 14 environmental covariates that are formed around the habitat requirements and natural history as defined in DeGraaf & Rappole (1995) and Sousa (1987). I obtained eight variables from the Oregon State University's Landscape Ecology, Modelling, Mapping and Analysis (LEMMA) program (30 m resolution; Landscape Ecology Modeling, Mapping, 2020; Ohmann & Gregory, 2002), which consisted of hardwood and conifer canopy cover, total canopy cover, quadratic mean diameter of dominant and codominant trees (qmd_dom), forest type centered around the basal area of dominant tree species (Fortypba)(Appendix Table 5), vegetation class based

off of the canopy cover and basal area (vegetation class), and density of live trees and snags. I generated a distance to fire raster by using fire polygons from Monitoring Trends in Burn Severity (Eidenshink et al., 2009) and utilizing the Euclidian distance function in ArcGIS. I attained stream and river polylines from the National Hydrography Dataset (1:24,000; FGDC, 2008; US Geologic Survey, 2019; Terziotti & Archuleta, 2020). I downloaded bark beetle infestation polygons from the USDA Forest Service (2010). The same approach as for the fire polygons was used to transform streams and rivers polylines into a distance to water raster and to convert bark beetle infestation polygons into a distance to beetle infestation raster. I downloaded digital elevation maps (DEMs) from the U.S. Geologic Survey (30 m resolution; U.S. Geological Survey, 2013), representing a surrogate covariate for temperature (Rose, 2019). The DEMs were merged together and used to create aspect and slope rasters, which act as a surrogate covariate for precipitation (Geroy et al., 2011; Phillips & Schümm, 1987). Aspect was converted from a linear raster into categorical values for the Hairy Woodpecker, which found this covariate important in model building (Pruhsmeier et al., 2021). Using ArcGIS, all covariate rasters were scaled to 30 m, clipped to the study area, and converted into ASCII Grid files.

Model Selection and Evaluation

Models were created in MaxEnt and I followed established protocols from Pruhsmeier et al. (2021) to select the best model for each species. I used spatial coordinates from bird occurrences and environmental covariates, which were based upon the criterion of contributing at least 2% to the model, and increasing the regularization multiplier by increments of 0.5 until the lowest AIC was reached. Higher regularization

multipliers smooth out the response curves, reducing the complexity of the model, and creating the most parsimonious model to be based on what I expect from literature. Response curves should have an optimal point and then decrease in suitability on either side; therefore, anything more complex would be more complex than the natural history of the species (Hutchinson, 1957). These MaxEnt models were built for the 2010 dataset in the paper by Pruhsmeier et al. (2021). I used the same covariates to build the 2016 model and followed the same process as with building the 2010 models. The regularization multiplier chosen for the final models for both 2010 and 2016, along with each model's AUC, and the environmental covariates used to create the model are listed in Table 5: Six covariates for BKHGRO, six for HAIWOO, and five for YERWAR.

Table 5. Environmental covariates selected for each species along with the final model's regularization multiplier and AUC for the years 2010 and 2016.

Species	Year	Regularization Multiplier	AUC	Environmental Covariates
BKHGRO	2010	1.5	0.88	1) distance from bark beetle infestations 2) elevation 3) fire distance 4) stream distance 5) Fortypba 6) slope
BKHGRO	2016	3	0.77	(Same as above.)
HAIWOO	2010	1	0.83	1) Fortypba 2) distance from bark beetle infestations 3) slope 4) hardwood canopy cover 5) aspect 6) fire distance
HAIWOO	2016	1	0.77	(Same as above.)
YERWAR	2010	1	0.80	1) Fortypba 2) slope 3) hardwood canopy cover 4) fire distance 5) stream distance
YERWAR	2016	2.5	0.73	(Same as above.)

Spatial Methods

I used the generated habitat suitability models from MaxEnt for the 2010 and 2016 data and performed a raster calculation by subtracting the 2016 model from the 2010 model. This means that values near zero would indicate little to no change. Values near one indicate a substantial increase in suitability in 2016. A value near negative one indicates a substantial decrease in suitability in 2016. I then visually evaluated how the changes might impact the distribution of the three bird species.

NDVI

To see if the areas predicted to have a reduction in suitability were correlated with the drought and reduced vegetation productivity, I selected two years of Landsat data (Masek et al., 2006) with the criteria of being within June or July and contain less than 10% cloud cover. I selected Landsat 5 satellite imagery for the year 2010, which represents pre-drought vegetation conditions. Landsat 5 offers a resolution of 30 meters for reflective bands and contains 7 bands from the wavelengths of 0.45 to 2.23 micrometers. For post drought conditions, I selected Landsat 8 satellite imagery for the year 2016. Landsat 8 offers a resolution of 30 meters for reflective bands and contains 11 bands from 0.4 to 12 micrometers. To cover the range of the study area, I downloaded four rasters for each year that covers the study area from the U.S. Geologic Survey's (USGS) EarthExplorer website. The four Landsat 5 images were taken on the following dates: July 20th, 2010 and July 29th, 2010. The four Landsat 8 images were taken on the following dates: July 20th, 2016 and July 29th 2016. These dates were used due to the images having less cloud cover and July being the hottest month to show the greatest

amount of vegetation change. Using ArcGIS, the Landsat rasters were mosaicked together to create a seamless raster for both years. I clipped the combined rasters to the focal study area.

I used the Normalized Difference Vegetation Index (NDVI) to identify and assess vegetation productivity using the formula:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where NIR is the near infrared band and Red is the red band.

The following bands were used for Landsat 5: four (NIR) and three (red). The following bands were used for Landsat 8: five (NIR) and four (red). Using the raster calculator, I calculated the NDVI for both years and then found the difference between the values using the formula:

$$\Delta NDVI = Post\ NDVI - Pre\ NDVI$$

A California lake polygon layer was downloaded (California Department of Fish and Wildlife, 2012) and erased from the study area polygon. To ensure that lakes would have no data values, I extracted the $\Delta NDVI$ raster from the new study area polygon with lakes. Values near one indicate a substantial increase in vegetation productivity in 2016. A value near negative one indicates a substantial decrease in vegetation productivity in 2016. A value near zero would indicate minor change.

Comparison of Vegetation Productivity to Avian Habitat Suitability Models

To compare the correlation between the vegetation productivity impacted by the drought and the shifting bird distributions, I began by removing the lake polygons from

the habitat suitability models to ensure the two rasters both had the same number of cells. I then exported the rasters into BlueSpray and resampled the rasters to the same cell size. BlueSpray offers raster statistics, so I calculated the correlation with the Spearman's Correlation to determine the strength of correlation between vegetation productivity and habitat suitability of each bird species.

Results

Black-headed Grosbeak

Response curves for BKHGRO are shown in Figures Figure 11Figure 12. In the 2010 model, distance from bark beetle shows a clear distinction that proximity to these areas indicated higher suitability where as in 2016, this suitable areas was not as critical although closer distances to these areas were still highly suitable. Elevation in 2016 seems to suggest that higher elevations have become more suitable. Distances further from fire impacted appeared to be more suitable in 2016 than in 2010. Distance to streams appears to have tightened around close proximity to water sources in the 2016 model. I can see that important tree species have slightly shifted (Appendix P). In 2010, important tree communities included white fir (*Abies concolor*), ponderosa pine (*Pinus ponderosa*), California incense cedar (*Calocedrus decurrens*), sugar pine (*Pinus lambertiana*), Douglas fir (*Pseudotsuga menziesii*), tanoak (*Lithocarpus densiflorus*), California black oak (*Quercus kelloggii*), canyon live oak (*Quercus chrysolepis*), and Oregon white oak (*Quercus Garryana*). In 2016, the tree community occupied appeared to grow to include red fir (*Abies procera*), western juniper (*Juniperus occidentalis*), blue

oak (*Quercus douglasii*), and valley oak (*Quercus lobate*). Percent contribution of each environmental covariate between the years is shown in Table 6. The difference between the two models to show change in suitability from 2010 to 2016 are shown in Figure 13 and Figure 14, which shows increase and decrease between the two years.

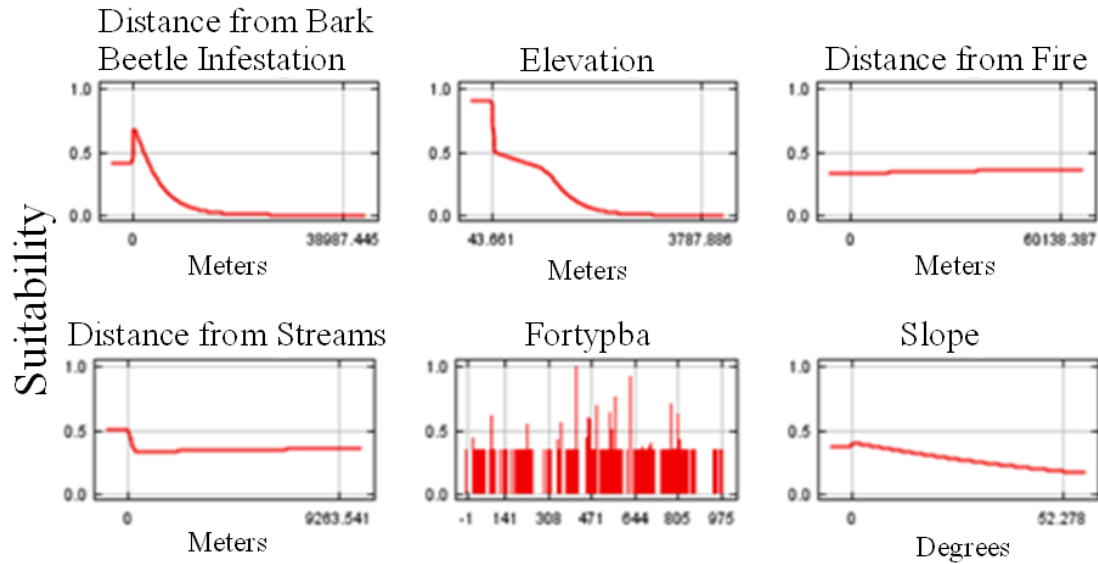


Figure 11. Response curves in 2010 for the BKHGRO using a regularization multiplier of 1.5.

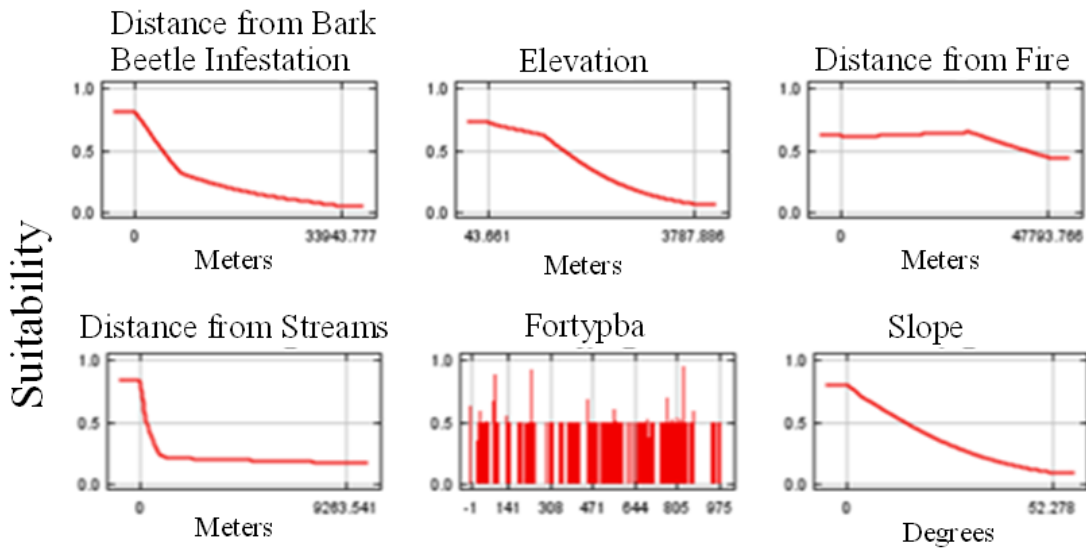


Figure 12. Response curves in 2016 for the BKHGRO using a regularization multiplier of three.

Table 6. Percent contribution of each environmental covariate in the 2010 and 2016 BKHGRO models.

Environmental Covariate	2010 % Contribution	2016 % Contribution
Distance from bark beetle infestation	19.5%	10%
Elevation	29.6%	2.3%
Distance from fire impacted habitat	13.7%	0.2%
Distance from streams	9.6%	45%
Fortypba	9%	16%
Slope	18.7%	26.1%

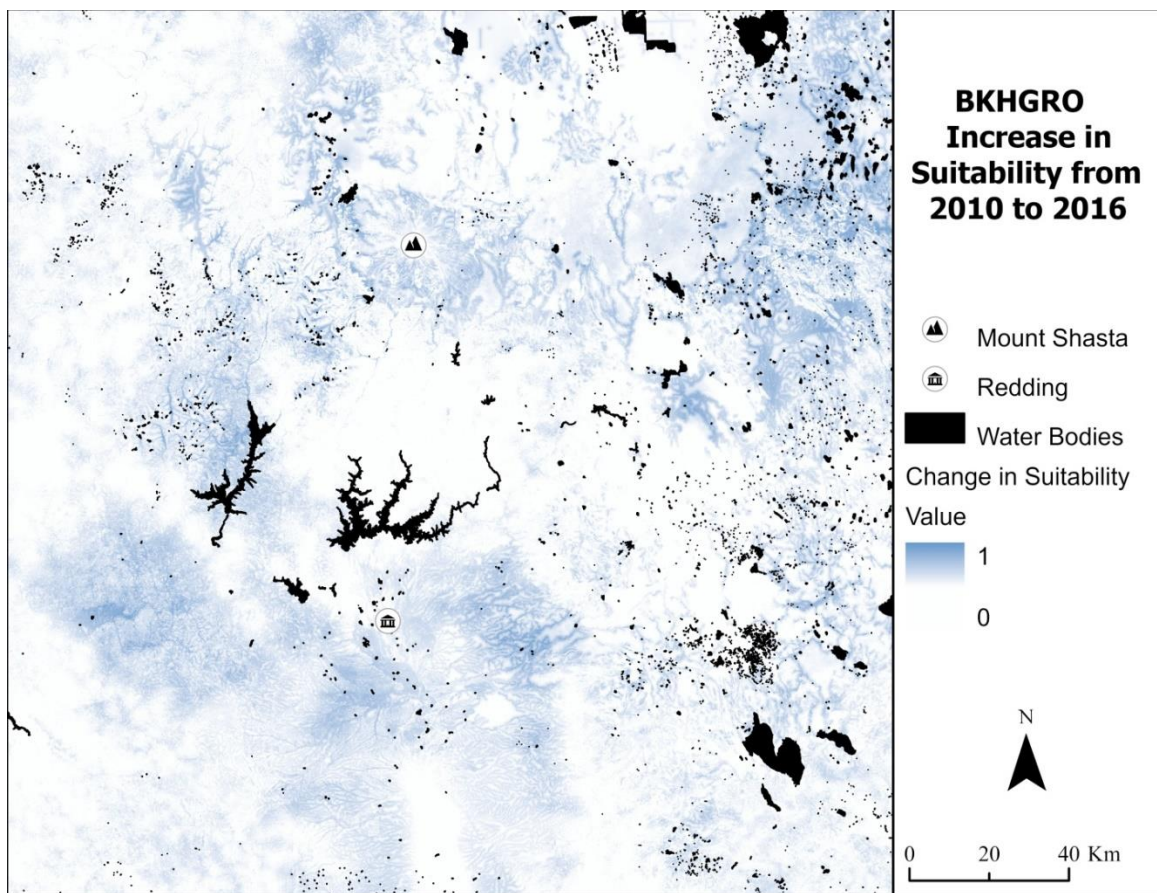


Figure 13. Increase in suitability for the Black-headed Grosbeak from the 2010 model to the 2016 model. Blue areas show an increase in suitability from 2010 to 2016.

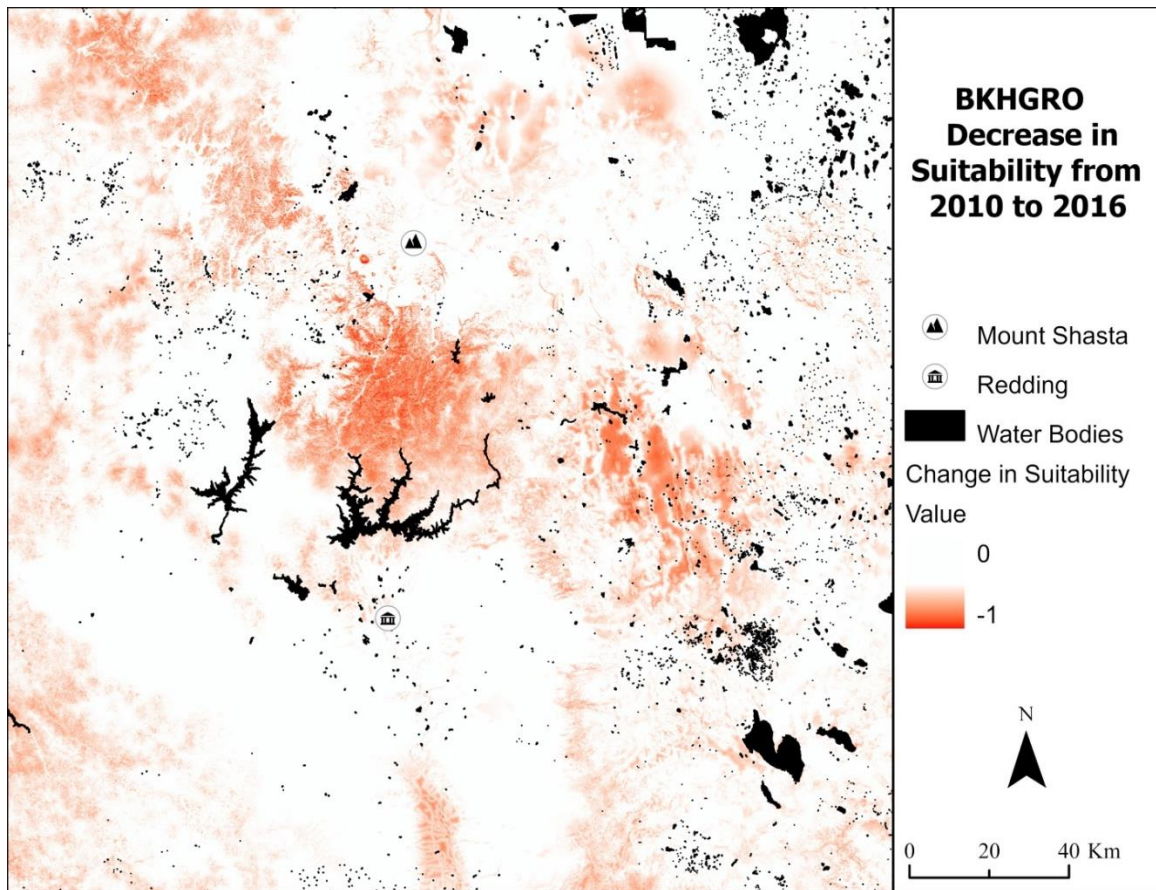


Figure 14. Decrease in suitability for the Black-headed Grosbeak from the 2010 model to the 2016 model. Red areas show a decrease in suitability from 2010 to 2016.

Hairy Woodpecker

Response curves for HAIWOO are shown in Figure 15 and Figure 16. The response curves in both years for distance to bark beetle infestations are the same in which the species find closer distances to beetle infested habitat as highly suitable. In 2010, the species appears to prefer south facing slopes and in 2016, the category shifted to preferring southeast slopes. Distance to fire in 2010 shows a clear relationship of closer distances being more suitable, but in 2016, this relationship shows a huge peak at close

distances, but then evens out. In 2010, the curve for hardwood canopy cover showed lower percentages to be more favorable, but in 2016, this shifted to preferring higher percentages. The response curve for slope has shifted to higher suitability at slopes under 30 degrees or higher at 50 degrees. In 2010, the tree communities that were suitable were red fir, white fir, Jeffrey pine (*Pinus jeffreyi*), ponderosa pine, white birch (*Betula papyrifera*), white oak (*Quercus garryana*), and California black oak. In 2016, these communities increased to include California incense cedar, Douglas fir, western white pine (*Pinus monticola*), Lodgepole pine (*Pinus contorta*), canyon live oak, California black oak, and blue oak. Percent contribution of each environmental covariate between the years is shown in Table 7. The difference between the two models to show change in suitability from 2010 to 2016 are shown in Figure 17 and Figure 18, which shows increase and decrease between the two years.

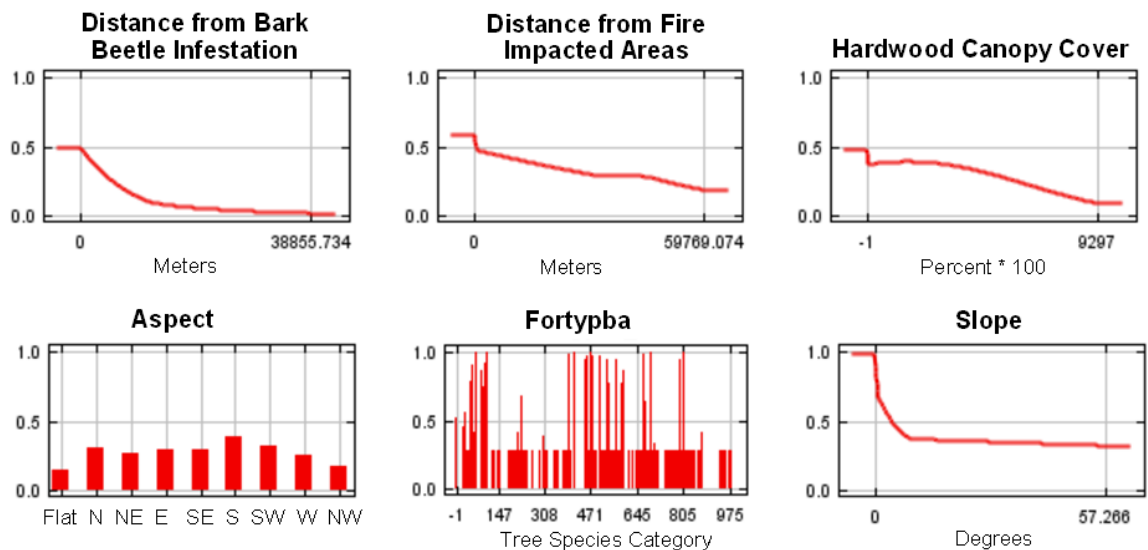


Figure 15. Response curves in 2010 for the HAIWOO using a regularization multiplier of one.

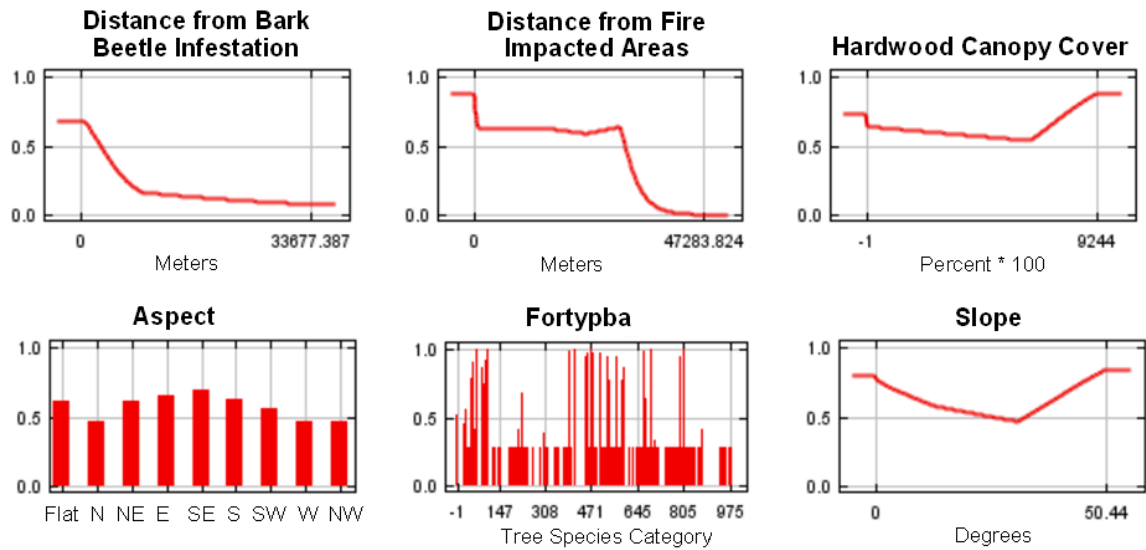


Figure 16. Response curves in 2016 for the HAIWOO using a regularization multiplier of one.

Table 7. Percent contribution of each environmental covariate in the 2010 and 2016 HAIWOO models.

Environmental Covariate	2010 % Contribution	2016 % Contribution
Fortytpba	37.4%	24.6%
Distance from bark beetle infestation	21.9%	27.3%
Slope	17.6%	5.4%
Hardwood canopy cover	10.6%	24.2%
Distance to fires	7.1%	10.5%
Aspect	5.4%	8%

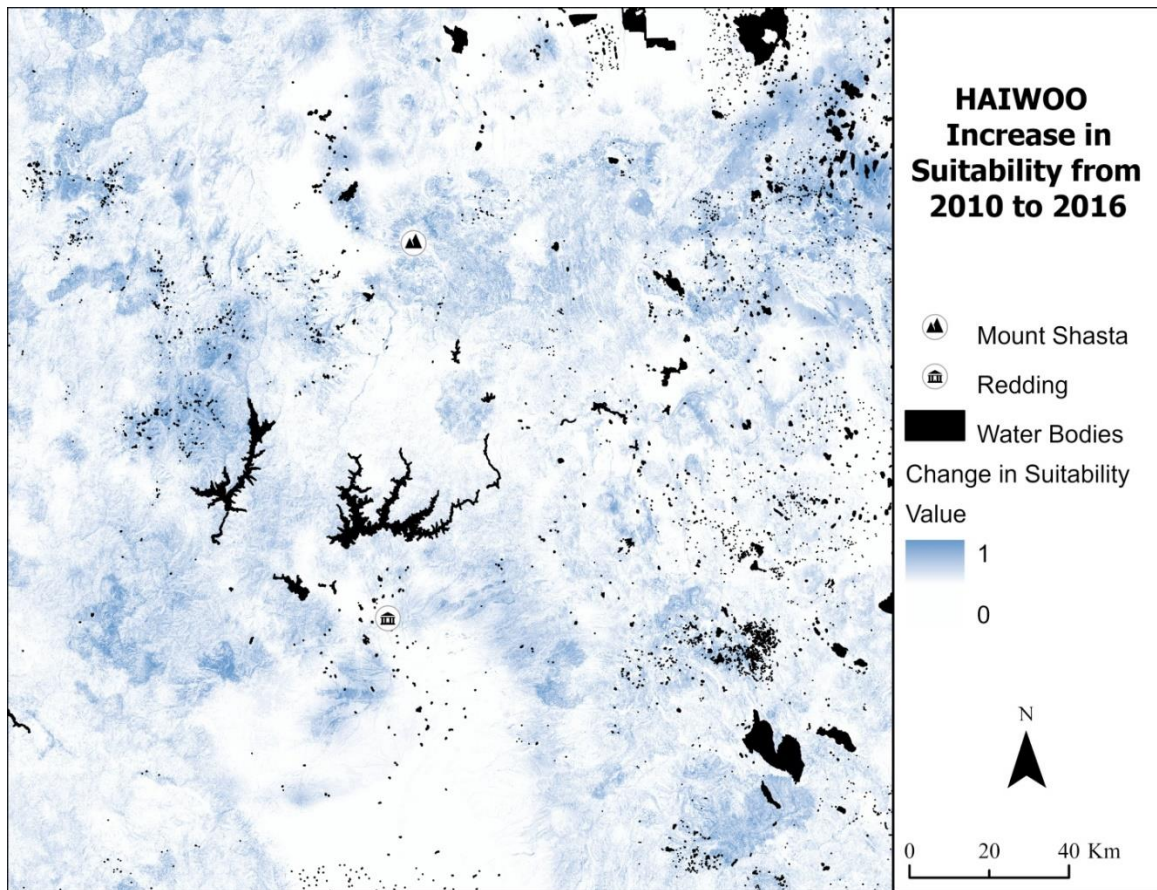


Figure 17. Increase in suitability for the Hairy Woodpecker from the 2010 model to the 2016 model. Blue areas show an increase in suitability from 2010 to 2016.

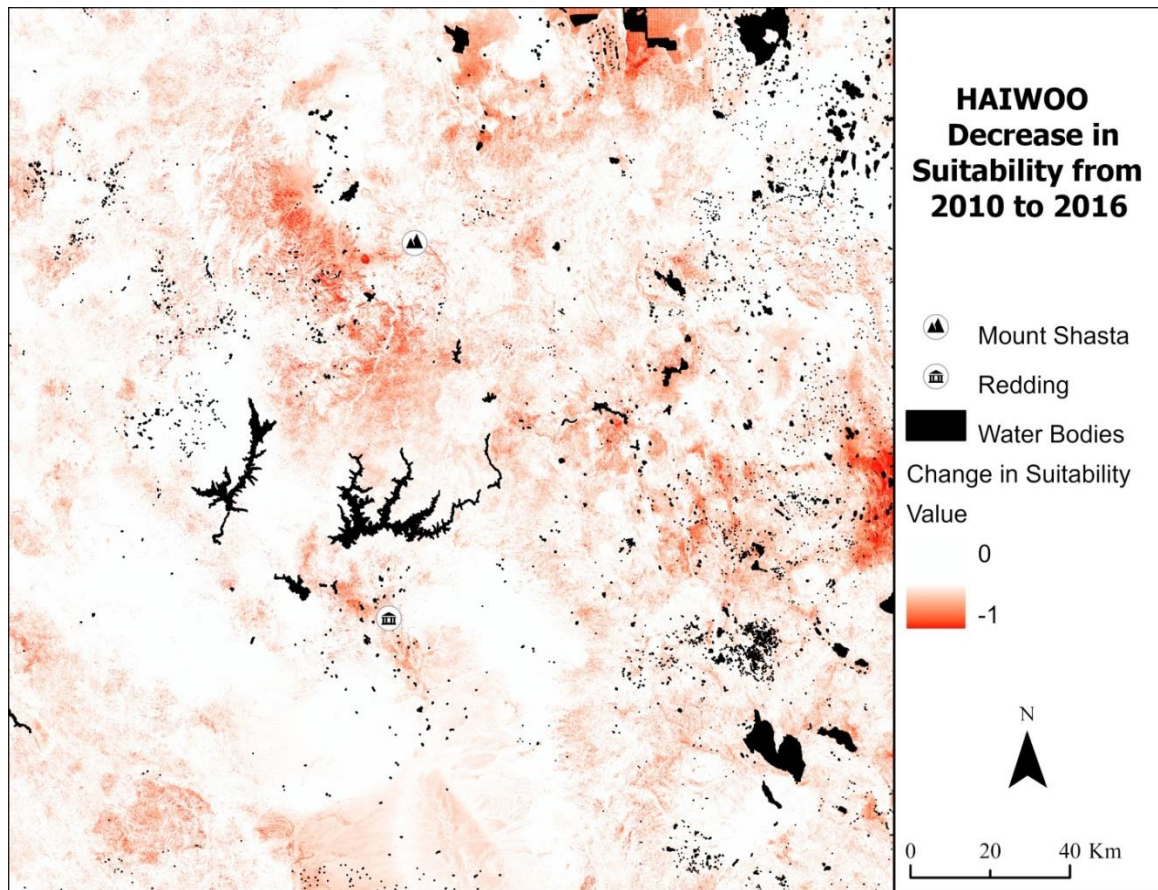


Figure 18. Decrease in suitability for the Hairy Woodpecker from the 2010 model to the 2016 model. Red areas show a decrease in suitability from 2010 to 2016.

Yellow-rumped Warbler

Response curves for YERWAR are shown in Figure 19 and Figure 20. In 2010, suitability was greatest in habitats dominated by coniferous trees, including white fir, red fir, California incense cedar, Jeffrey pine, sugar pine, Western white pine, ponderosa pine, Douglas fir, mountain hemlock (*Tsuga mertensiana*), knobcone pine (*Pinus attenuate*), Brewer spruce (*Picea breweriana*), Lodgepole pine, canyon live oak, subalpine fir (*Abies lasiocarpa*), white oak, bitter cherry (*Prunus emarginata*), blue oak, and Pacific silver fir

(*Abies amabilis*). In 2016, these communities did not include knobcone pine, Brewer spruce, canyon live oak, subalpine fir, bitter cherry, or Pacific silver fir. The 2016 communities did increase to include western juniper, and Oregon white oak. In 2010, YERWAR appeared to have slightly higher suitability close to fires. In 2016, this changed to less of a preference for habitat near fires with suitability dropping slightly near the fire. In 2010, there was a clear distinction that YERWAR prefers lower amounts of hardwood canopy cover. In 2016, this changed to YERWAR preferring lower amounts, but still finding higher amounts suitable. In 2010, closer proximity to streams was more suitable and this was the same in 2016, but at a more intense suitability rate. Slope appeared to reverse in importance between the two years, which is interesting as it shows 2016 needing lower slopes potentially due to water availability and less runoff. But in 2010, when the covariate is run by itself, shows little preference for any slope. When the covariate is combined with the other predictors, it takes on a shape that indicates a slight suitability peak at lower slopes, but increases at higher slopes, which could mean that the species normally does not prefer any slope, but may be interacting with distance to streams since there is a slight negative correlation with that covariate. Percent contribution of each environmental covariate between the years is shown in

Table 8. The difference between the two models to show change in suitability from 2010 to 2016 are shown in Figure 21 and Figure 22, which shows increase and decrease between the two years.

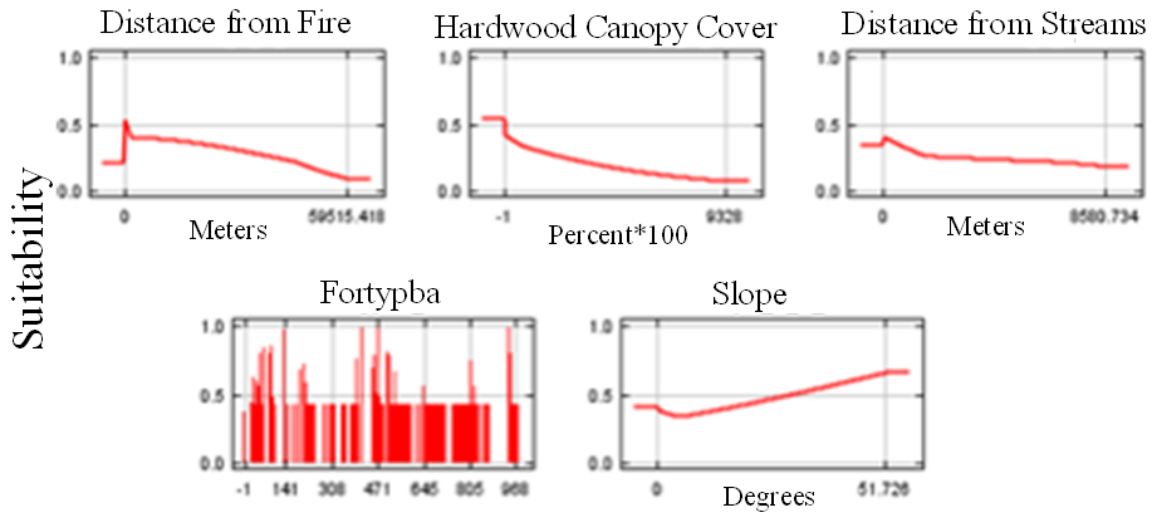


Figure 19. Response curves in 2010 for the YERWAR using a regularization multiplier of one.

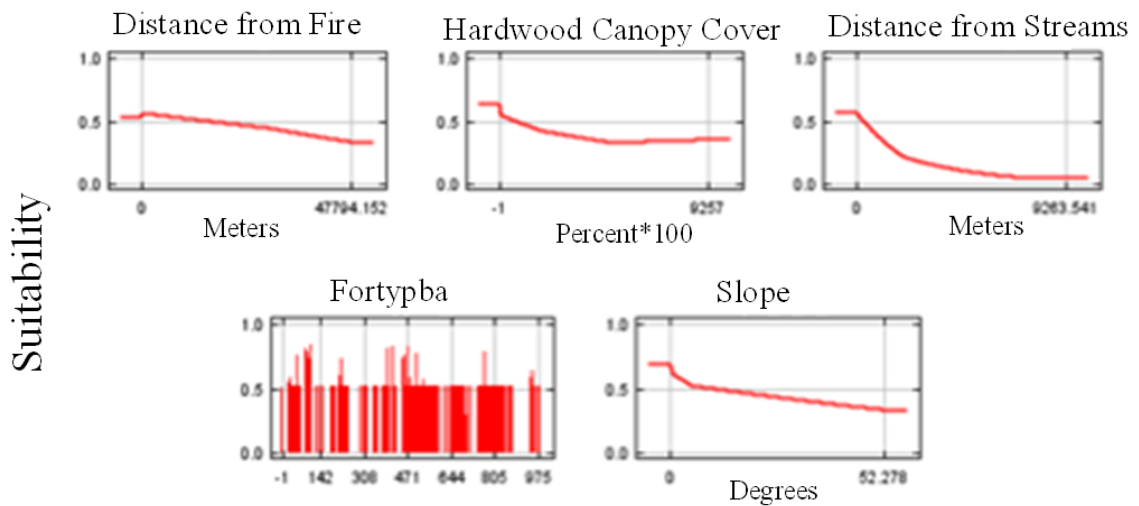


Figure 20. Response curves in 2016 for the YERWAR using a regularization multiplier of 2.5.

Table 8. Percent contribution of each environmental covariate in the 2010 and 2016 YERWAR models.

Environmental Covariate	2010 % Contribution	2016 % Contribution
Fortypba	35.4%	19.8%
Slope	7%	10.5%
Hardwood Canopy Cover	41.1%	54%
Distance from fires	12.8%	2.2%
Distance from streams	3.7%	13.6%

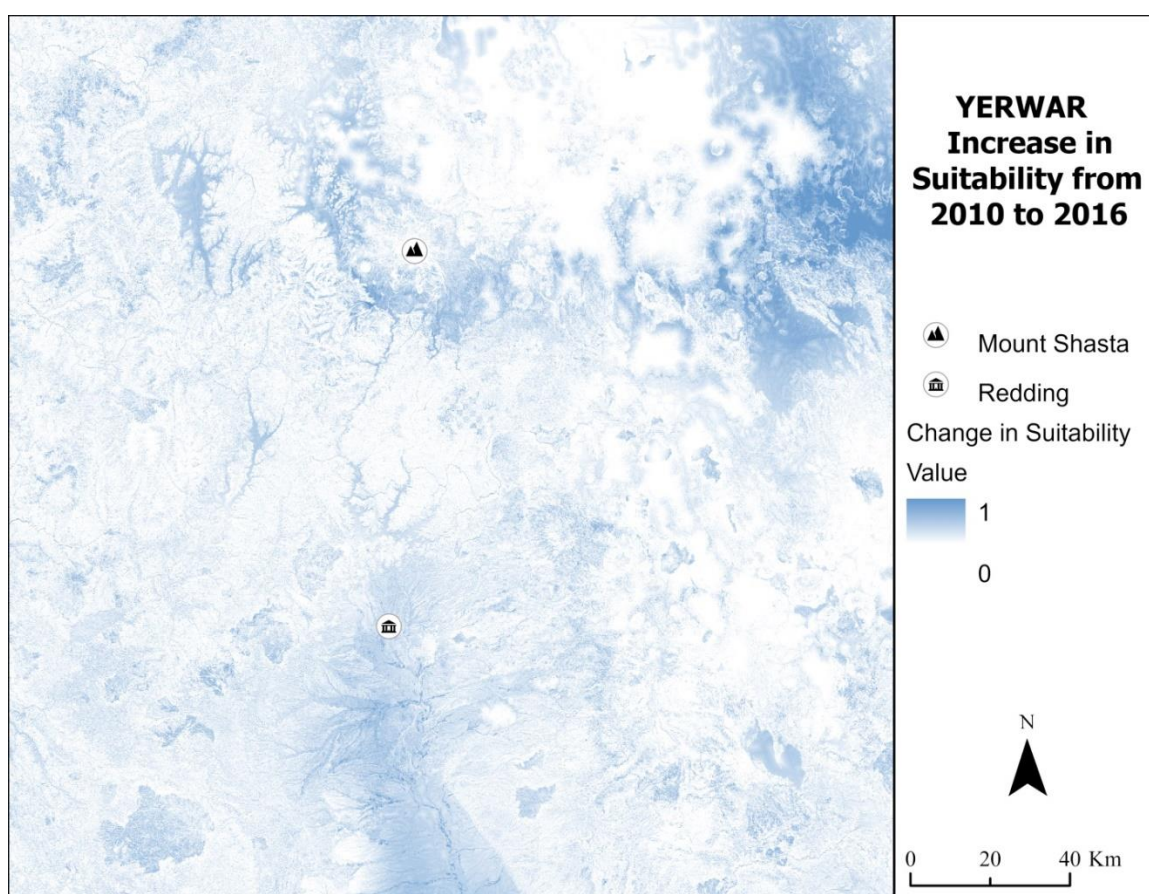


Figure 21. Increase in suitability for the Yellow-rumped Warbler from the 2010 model to the 2016 model. Blue areas show an increase in suitability from 2010 to 2016.

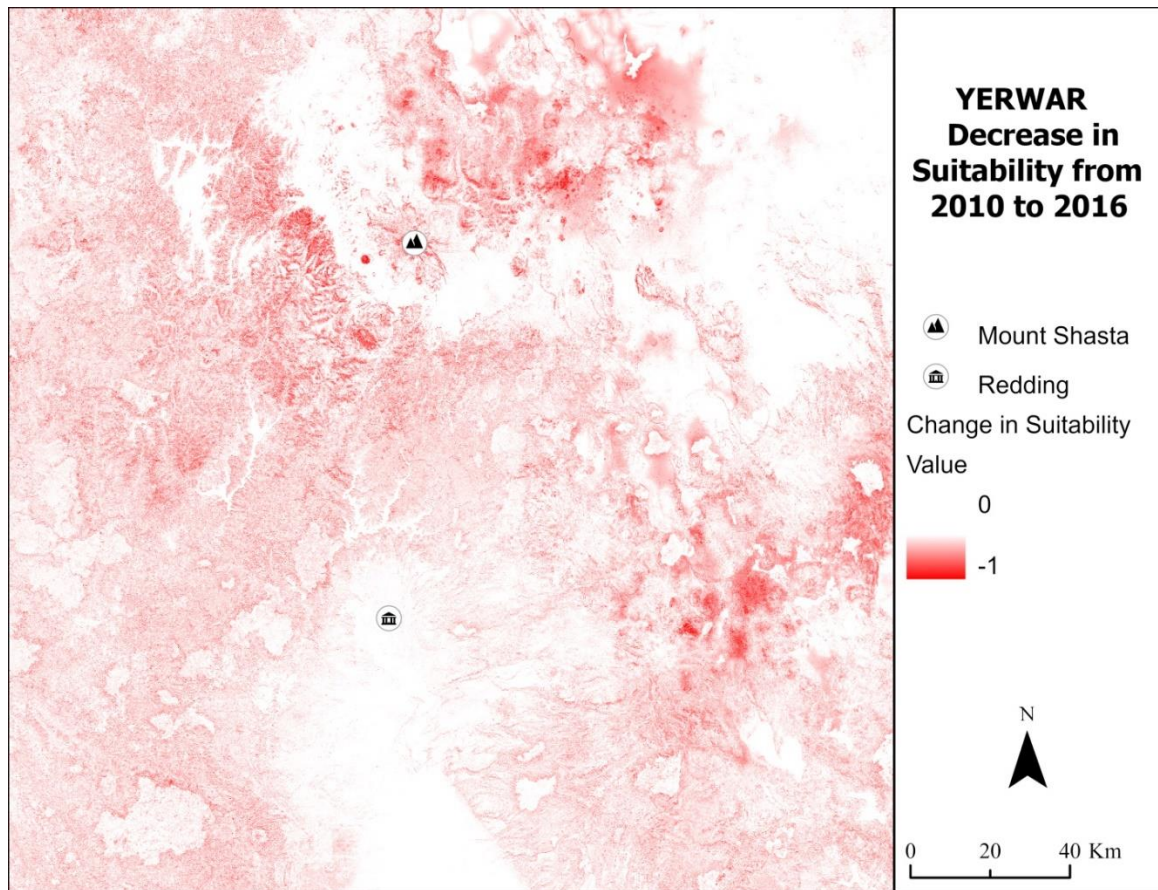


Figure 22. Decrease in suitability for the Yellow-rumped Warbler from the 2010 model to the 2016 model. Red areas show a decrease in suitability from 2010 to 2016.

NDVI Change in Vegetation Productivity

I assessed the change in NDVI between 2010 and 2016 and found a majority of the study area had a decrease in vegetation productivity due to the drought, fire, and bark beetle infestation (Figure 23 and Figure 24). I found that the correlation between BKHGRO and YERWAR showed a weak positive correlation while HAIWOO showed a weak negative correlation (Schober et al., 2018) (Table 9).

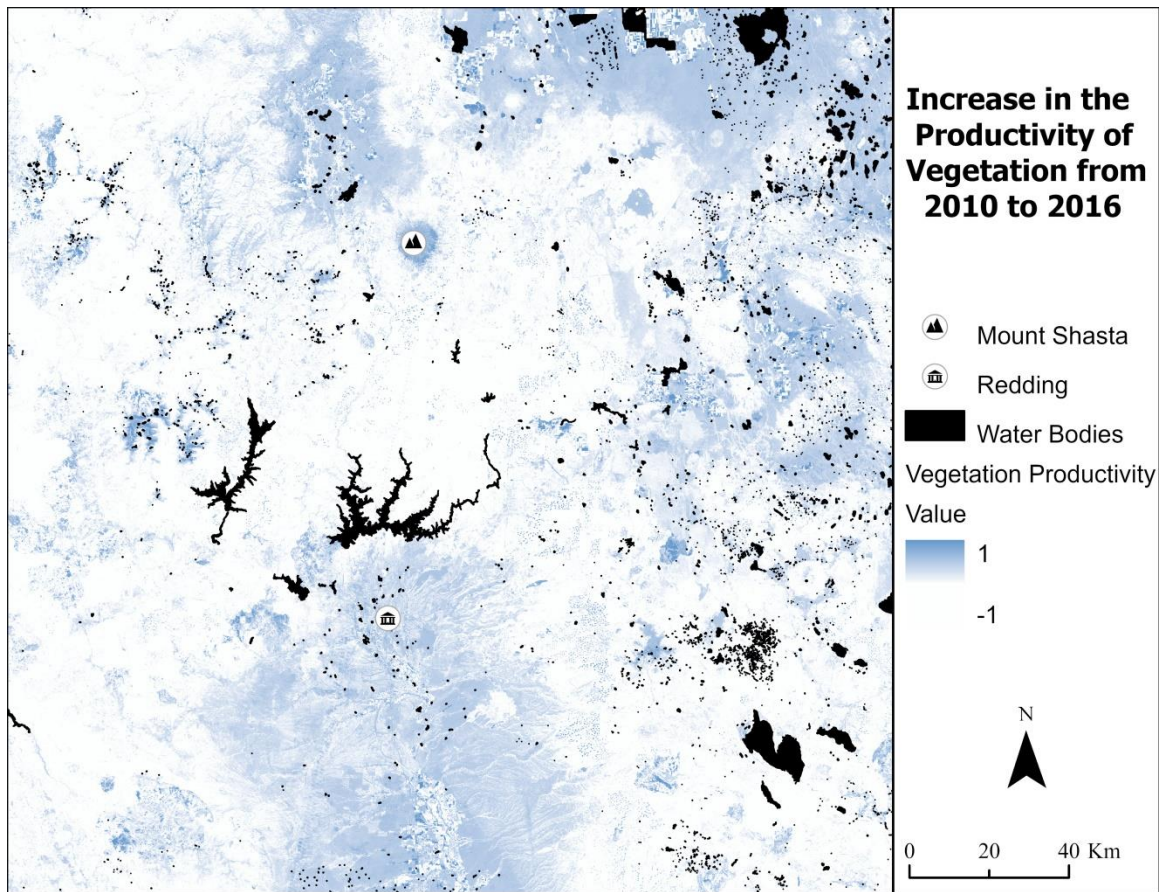


Figure 23. Δ NDVI from 2010 to 2016 where blue areas show an increase in vegetation productivity and white is the combination of no change and negative change. Landsat-5 and Landsat-8 image courtesy of the U.S. Geological Survey (USGS, 2010; USGS 2016). Lake polygon layers provided by California Department of Fish and Wildlife (2012).

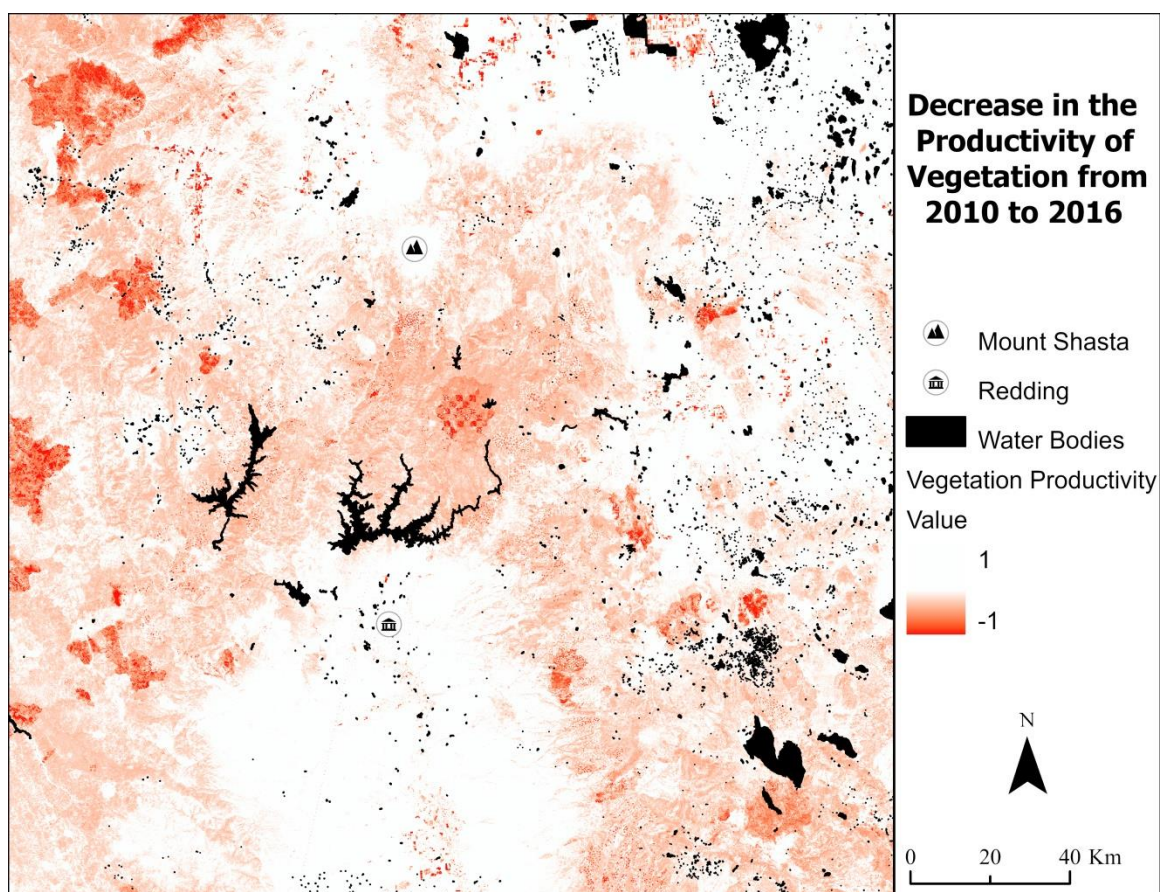


Figure 24. Δ NDVI from 2010 to 2016 where red areas show a decrease in vegetation productivity and white is the combination of no change and an increase in productivity. Landsat-5 and Landsat-8 image courtesy of the U.S. Geological Survey (USGS, 2010; USGS 2016). Lake polygon layers provided by California Department of Fish and Wildlife (2012).

Table 9. Spearman's Correlation between Δ NDVI and bird suitability models.

Bird Species Compared to Productivity of Vegetation	Spearman's Correlation Coefficient
BKHGRO	0.2496
HAIWOO	-0.1412
YERWAR	0.2177

Discussion

The three avian species have seen large shifts in their distributions in relation to their habitat due to changes in fire, bark beetle infestation fluctuations, and drought. The changes for Black-headed Grosbeak and Yellow-rumped Warbler have similar results in that they have both tightened around streams due to their reliance on water sources for survival. Hairy Woodpecker appears to shift in the opposite direction of the other two species as it uses habitat that may have increased insect populations.

Black-headed Grosbeak appears to have tightened around streams and have moved up in elevation to access cooler temperatures during the 2016 drought. This change between years could indicate that the species is sensitive to drought conditions. Part of the Grosbeak's life cycle is using close stream proximity for temperature regulation of their nests (Becker, 2013), so due to higher temperatures and less water runoff during the drought, habitat suitability near streams is critical and contributed 45% toward building the model. Vegetation near streams may be less impacted by drought conditions due to a water source or melting snowpack, which can explain why preference for certain tree species increased in its contribution to the model. New tree species were included in the model that area associated with higher elevations, such as western juniper and red fir. These tree species are known to feed off the melting snowpack to sustain them through the summer months (Royce & Barbour, 2001) and have been seen to have higher death rates with below average snowpack (Guarín & Taylor, 2005). Further distances from fire were more suitable, which could also be correlated with the dryness of

forests in which Black-headed Grosbeak would prefer more moist areas for nest cooling along with the underbrush where the grosbeak nests to generally be burned causing less available nesting options. The model built for the grosbeak shows areas decreased substantially in suitability in the Central Valley, in the Shasta Trinity National Forest, in the Klamath National Forest, and southeast of Mount Shasta in Lassen National Forest. These high elevation forests seem to have decreased substantially in suitability for Black-headed Grosbeak. Areas that increased substantially in suitability are near streams and lakes, east of Redding where there are high concentrations of streams, and south of the Shasta Trinity National Forest around Shasta Lake.

Hairy Woodpecker seems to have most of the response curves remain the same, except there appears to be a larger amount of suitability further from fire impacted areas. This could be because with increased amounts of bark beetle infestations, Hairy Woodpecker may not necessarily require fire impacted areas for these food sources. This could also be due to higher fire intensity during 2016. The wildfire season in California has been extending later into summer and fall (Jolly et al., 2015) due to drought and has begun to mismatch with the laying period between bark beetles and fire ignition date to cause these burned areas to become ecological sinks (Ray et al., 2019). Generally, Hairy Woodpeckers are found in burned forest habitat than unburned forest habitat, but use the edges of high severity burns where they can take advantage of live trees (Covert-Bratland et al., 2006). In 2016, the drought may have induced more high intensity fires which decreased pyrodiversity and mismatched with the laying period of bark beetles. This could potentially cause Hairy Woodpeckers to prefer areas away from these burns and

towards other locations where bark beetles have infested. Contribution of distance to bark beetle infestations remained the greatest contributor to the model as the species utilizes these areas as a food source (Saab et al., 2019). With more food sources from these beetle outbreaks, the population of Hairy Woodpecker has been seen to increase (Mosher, 2011). The preferred tree species was seen to increase to include several more species, which could be due to more trees being infested by bark beetles. Lower amounts of hardwood canopy cover increased in contribution to model creation, which could be due to lower amounts of canopy cover due to an increase in tree mortality due to the drought. Since the woodpecker forages on dead snags, higher densities of lower canopy cover can benefit the woodpecker population and increases suitability. The species appears to have a preference for southeast facing slopes. South facing slopes tend to have more solar radiation and experience greater evaporation, which may then experience greater effects of the drought on tree mortality. Hairy Woodpecker still appears to prefer a mix of live and dead trees, which could be the case for the increase in suitability for north and northeast facing slopes. Areas that appeared to decrease significantly are on the south east side of mountain ranges and further distances from bark beetle infestations. Areas that appear to increase in suitability are located in the Marble Mountain Wilderness area and Klamath National Forest. The Central Valley appears to have little change in suitability between the two years.

For Yellow-rumped Warbler, close proximity to streams increased in contribution to the model which can indicate that the species tightened in around water sources. The warbler has been seen to have positive associations with surface water

(Kirkpatrick et al., 2009) and this increase in suitability near streams can indicate that the warbler is impacted by less water availability from the drought in 2016. Being close to streams could also indicate that vegetation in these parts are better supported through drought conditions and is therefore more favorable to the species. The warbler has been known to consume bark beetle adults (Martin et al., 2006) when given the opportunity, which can explain why they may prefer habitat on the edges of fire impacted habitat. In 2016, the contribution of proximity to fire decreased significantly, which can potentially be due to more bark beetle infestations elsewhere or because the forest in 2016 burned at higher intensities due to drier conditions and mismatched with the lay period of bark beetles. Studies have shown that Yellow-rumped Warbler responds negatively to increasing fire severity (Fontaine & Kennedy, 2012; Zlonis et al., 2019), so I do consider this to be the case for what my response curves indicate as well. In my 2010 model, there was a clear distinction that the warbler prefers lower amounts of hardwood canopy cover, potentially due to them preferring conifer canopies. In 2016, this changed to the warbler preferring lower amounts, but still finding higher amounts suitable, potentially due to less available conifer habitat due to the drought and increased fires. This species could potentially be shifting into higher amounts of hardwood canopy cover to survive the impacts of the drought as they have been known to only nest and forage in live canopies (Fontaine & Kennedy, 2012). In general, Yellow-rumped Warbler has had slight increases or decreases in suitability in the study area, with decreases seen in the Klamath National Forest, Shasta-Trinity National Forest, Lassen National Forest, and the Six

Rivers National Forest. Areas that appear to have slightly increased in suitability are areas near water sources, in the Modoc National Forest, and in the Central Valley.

When I correlate these areas to the difference between water availability from Landsat imagery, I found that the habitat suitability models did not have a high enough correlation to directly say that reduced vegetation productivity is the driving factor for the shifting suitability models. I can say that many other factors that went into creating the habitat models are a larger driving influence upon the shifting habitats rather than vegetation directly. For Black-headed Grosbeak and Yellow-rumped Warbler, it does make sense that this correlation, albeit a weak correlation, would be a positive relationship. These two species are dependent on the availability of water, which in turn impacts the productivity of the vegetation. For Hairy Woodpecker, a possible reason there would be a low negative correlation is due to how bark beetles are more available in areas with weakened vegetation productivity. Potentially, since the fires have been burning more intense than in past conditions, this could reduce that correlation that I would hope to see. A reason these correlations could be so low could be due to the fact that I were not able to sample every bird occurrence and every tree, so the correlation may not be as pronounced as if I were to have all the data at my hands. These species are also operating under complex phenomena that influences and reduces the correlation between just the models and vegetation productivity. I would need more data over a longer period of time to potentially see an improvement in these correlations.

Model Limitations and Future Steps

The sample area may be limited to what I can conclude since the area is only in northern California. A next step would be to create these models for all of California to see on a massive scale how avian communities are being impacted by drought, fire, and bark beetle infestations. As always, I would need to acquire more occurrence and environmental covariate data to really produce the best models to describe these phenomena.

Another limitation is that I have only created habitat suitability models for two years and compared those. Potentially, the avian distributions could have seen greater shifts during years in between 2010 and 2016, such as when the drought considered being at its worst state in 2014. A future study could create models for 2014 and compare these shifts to the pre-drought model for a more direct comparison with the worst stage of the drought rather than a later stage, like in 2016. I created models for 2016 because I had detailed data along the PCT for this year from McGrann and Furnas (2018). Within two years of data, the McGrann and Furnas (2016) data does revisit the same locations in the northern portion of California along the PCT, although the 2016 data was restricted to just the Klamath portion. Data from GBIF and BISON, on the other hand, do not necessarily have locations revisited as it is a databank of occurrences conducted from various locations. Since GBIF and BISON data is opportunistic, this data may not revisit the same sites, so I was unable to remove the bias of site selection between years. Not having surveyors collect data in a range of environmental covariates would impact the model more in the sense that I could be missing whole areas that a species could prefer

because people simply did not collect occurrences there. I recognize that some of my data sources, such as GBIF and BISON, have limited occurrence points in areas more preferential to surveyors, such as fewer occurrence locations in fire impacted areas (Pruhsmeier et al., 2021), so I only have a snapshot of these locations. To account for this, in the future, I should collect more data across more site locations to build models that encompass a wider range of covariates.

I also note that models for additional species, such as rare or threatened birds, may be of great value in determining areas that could be conserved for their preservation in the face of future droughts, increased fire intensity and longevity, and bark beetle infestation impacts.

Conclusion

I met my first objective and created models that show the change in suitability from 2010 to 2016 due to three environmental factors that play a key role in altering the forests of Northern California. These models showed that the three avian species are greatly shifting their habitat into areas that meet their needs. I found that avian species histories are complex and to build habitat suitability models that well describe presence locations, a researcher needs adequate covariates. Changes in water availability appear to have the greatest influence on generalist species and water-dependent species, such as Yellow-rumped Warbler and Black-headed Grosbeak. I see these two species also shift into areas of higher canopy cover, potentially in areas that have seen less impacts in the drought, which leads back to availability of water as those vegetation communities might

experience less impacts from the drought. Hairy Woodpecker appears to be shifting into areas with food resource availability while shifting out of habitat impacted by high intensity fires. In the future as climate change increases the intensity and longevity of fires, I will expect more birds that normally use these habitats to be in search elsewhere for the resources they need to survive. This makes habitat reserves near water sources critical for species as drought and fire are expected to greatly impact the habitats that normally support wildlife.

I was able to meet my second objective and correlate the habitat suitability models back to how the overall productivity of vegetation has been impacted during this drought period. Although the correlations were weak, I suspect that the complex phenomena of bird habitat selection was also driven by food resource availability and many other factors used to build the suitability models. The weak correlations did correspond in the direction I suspected the species to relate with the environment. For example, Hairy Woodpecker would display a negative relationship with vegetation productivity possible due to increases in bark beetle infestation and fire, while Yellow-rumped Warbler and Black-headed Grosbeak would show a positive relationship as they may depend on the productivity of vegetation to provide resources. Overall, I conclude that avian species are having large shifts due to the drought and its other associated variables such as fire and increased bark beetle infestations.

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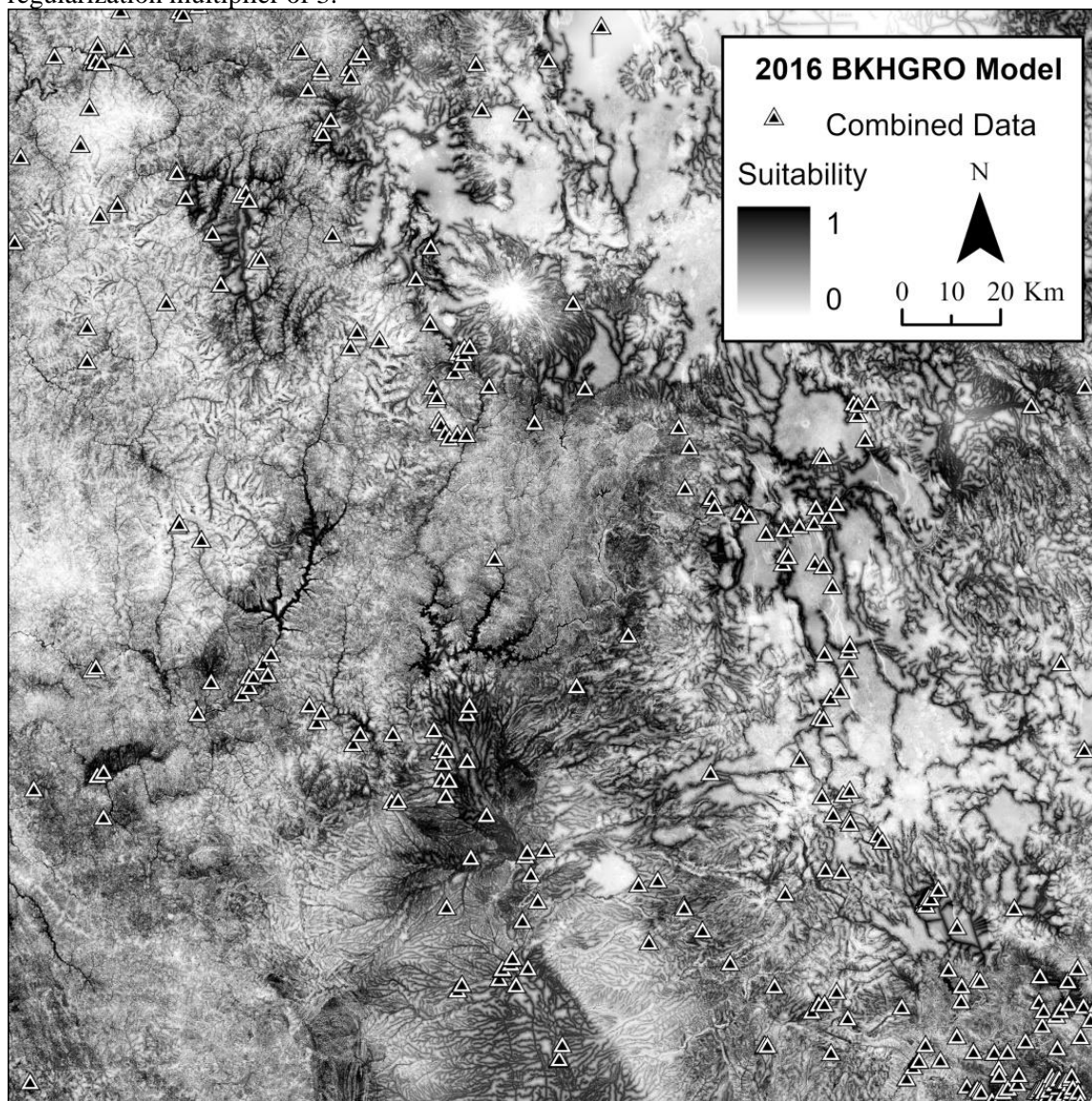
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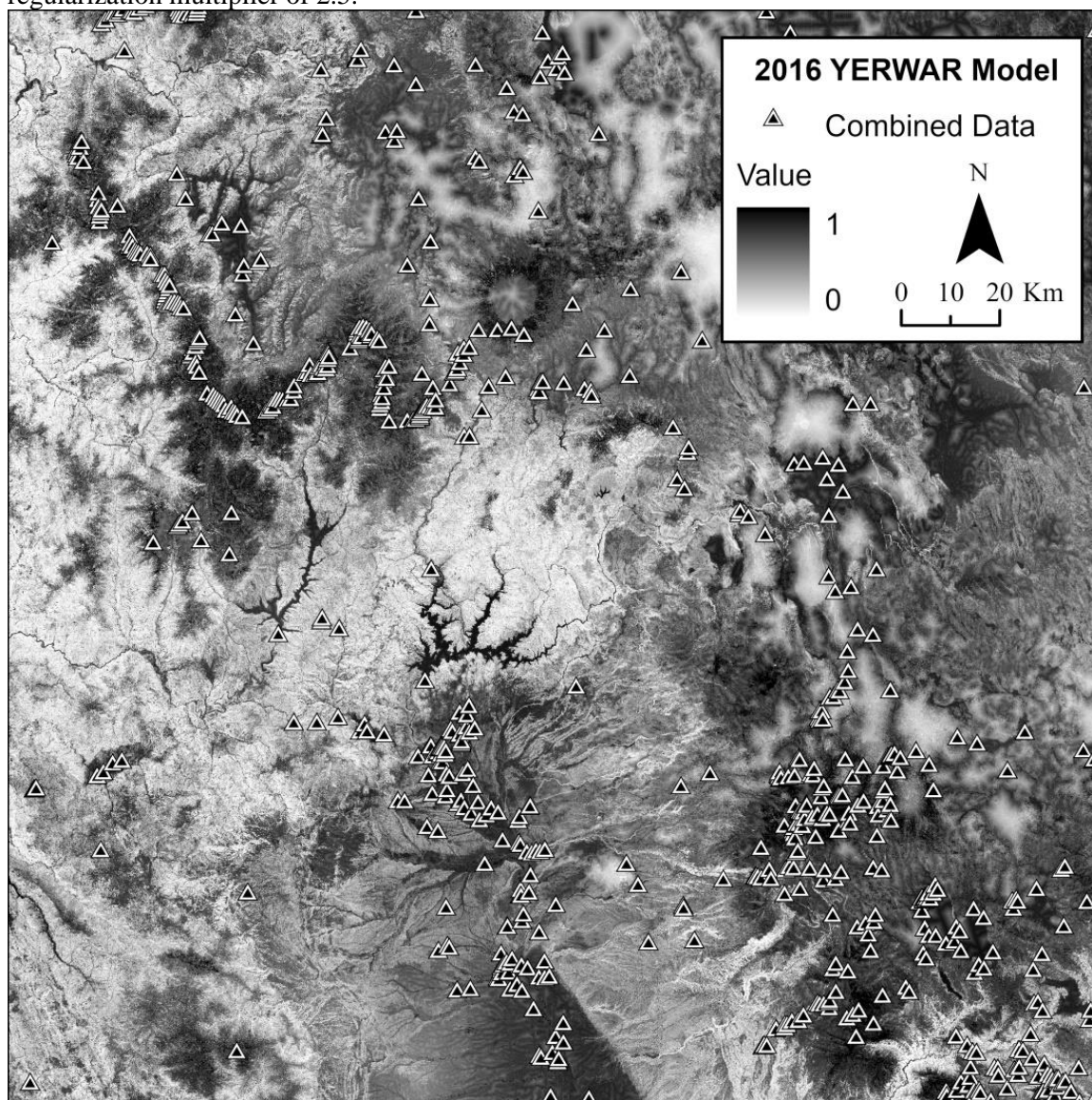
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Appendices

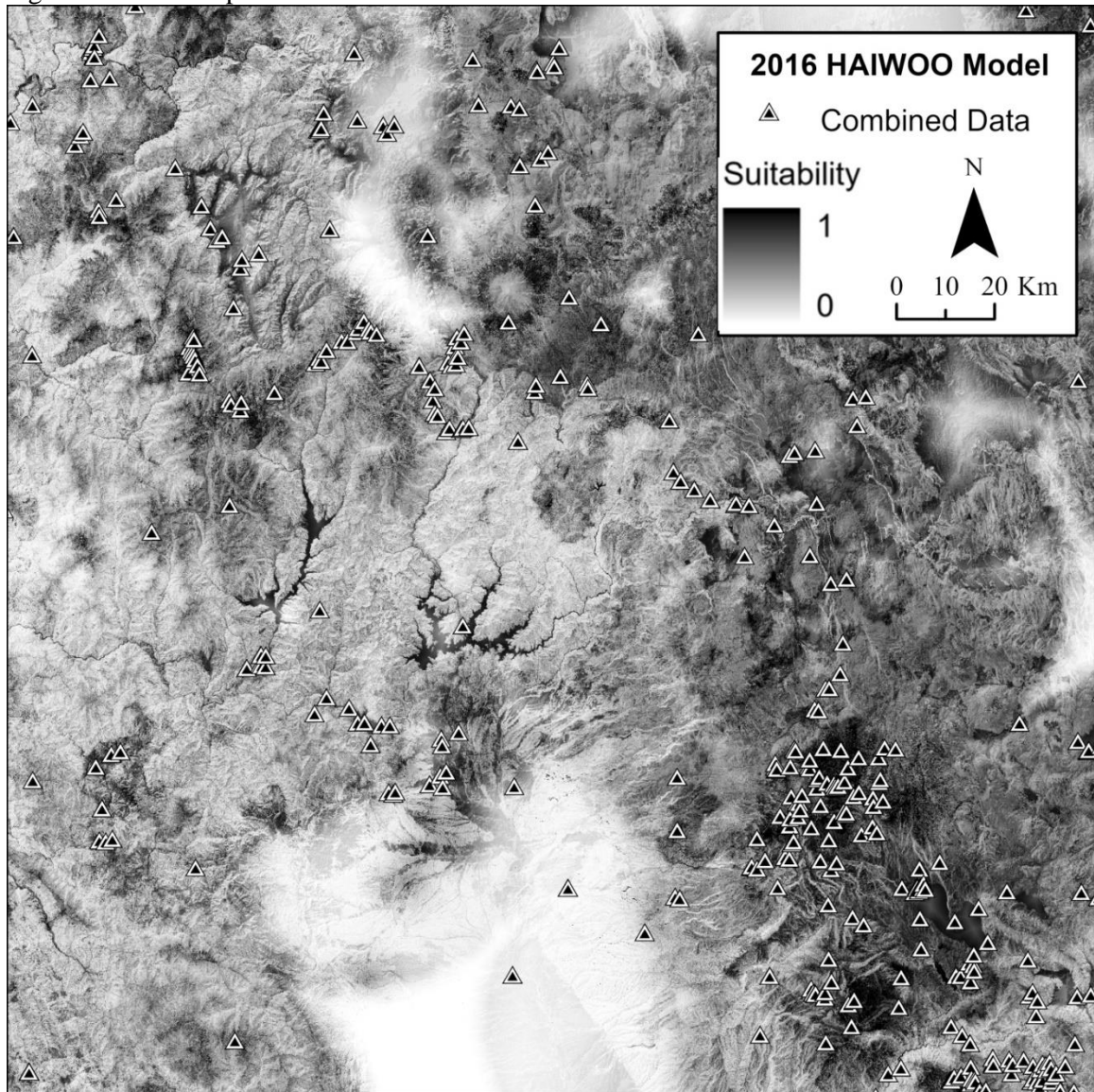
Appendix M: Habitat suitability model for the BKHGRO built from the Combined Dataset with a regularization multiplier of 3.



Appendix N: Habitat suitability model for the YERWAR built from the Combined Dataset with a regularization multiplier of 2.5.



Appendix O: Habitat suitability model for the HAIWOO built from the Combined Dataset with a regularization multiplier of one.



Appendix P: BKHGRO, YERWAR, and HAIWOO occurrences within tree communities for 2010 and 2016. The number associated with each tree community in the Fortypba layer is the community number selected by Oregon State University's LEMMA program. The sections of

codes are grouped by the dominant tree species followed by subdominant species within the community.

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
White Fir Dominated (27-71 total)	22	53	73	110	16	93
White Fir Only (27)	10	7	22	35	3	18
Red Fir (31)	1	6	12	16	2	15
Big Leaf Maple (33)	1		1			
California Incense Cedar (39)		11	9	17	1	23
Pacific Dogwood (43)			1			
White Fir and Jeffrey Pine (54)	1	2	7	6	2	7
White Fir and Sugar Pine (55)		2	2	7	1	8
White Fir and Silver Pine (56)			8	5	1	
White Fir and Ponderosa Pine (57)	9	12	3	10	3	12
White Fir and Douglas Fir (61)		11	6	13	2	10
Black Oak (64)		2		1		
Mountain Hemlock (70)			2		1	
Red Fir Dominated (88-107 total)	1	19	65	88	9	64
Red Fir Only (88)		5	23	34		20
White Fir (90)		9	15	18	4	20
Incense Cedar (92)				1		

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Knobcone Pine (95)			2			
Brewer Spruce (96)			2	1		
Lodgepole Pine (97)	1	4	9	10	1	12
Jeffrey Pine (99)			1	1		
Sugar Pine (100)		1		2		1
Western White Pine (101)			11	10	2	7
Ponderosa Pine (102)				1		
Mountain Hemlock (107)			2	10	2	4
Big Leaf Maple Dominated (112)	0	0	0	0	0	1
California Buckeye Dominated (142)	0	2	2	0	0	0
Madrone Dominated (188-207 total)	1	6		2	0	3
Madrone Only (188)		2	1	1		
Douglas Fir (198)	1					
Canyon Live Oak (200)		1				
Oregon White Oak (202)		3	1	1		2
Valley Oak (204)						1
Incense Cedar Dominated (216-240 total)	7	17	15	32	6	23
Incense Cedar Only (216)			1	2		
White Fir (217)		5	5	11	1	10

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Jeffrey Pine (227)			4	3		1
Sugar Pine(228)		2	1	7	2	
Ponderosa Pine (230)	7	5	3	4	2	7
Douglas Fir (233)		2	1	3	1	3
Black Oak (237)		3		2		2
Mountain Mahogany Dominated (241-251 total)	0	4	1	2	0	0
Mountain Mahogany Only (241)		4		2		
Western Juniper (244)			1			
Wester Juniper Dominated (308-325 total)	0	10	4	10	3	8
Western Juniper Only (308)		6	4	7	3	7
Mountain Mahogany (313)				1		
Jeffrey Pine (315)				1		1
Ponderosa Pine (318)		2		1		
Oregon White Oak (323)		2				
Tan Oak Dominated (351-370 total)	2	2	1	1	0	1
Tan Oak Only (351)	1	2				
Ponderosa Pine (361)	1					
Knobcone Pine Dominated (384-397 total)	0	2	1	1	0	1

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Knobcone Pine Only (384)						1
Canyon Live Oak (395)		2		1		
Black Oak (396)			1			
Lodgepole Pine Dominated (403-431 total)	1	3	10	15	4	15
Lodgepole Pine Only (403)		2	5	6	2	5
White Fir (405)		1	1	2	1	2
Red Fir (407)				2		1
Jeffrey Pine (420)	1		3	3	1	4
Western White Pine (423)				1		2
Ponderosa Pine (424)			1			
Mountain Hemlock (431)				1		1
Coulter Pine Dominated (432)	0	0	0	1	0	0
Jeffrey Pine Dominated (460-484 total)	10	26	22	46	12	35
Jeffrey Pine Only (460)	3	16	11	16	4	17
White Fir (462)	1		2	9	2	4
Madrone (464)		1		3		1
Incense Cedar (465)	3	3	5	7	3	9
Mountain Mahogany (466)		1		1		3
Western Juniper (468)	1	3	1	1	2	1

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Western White Pine (475)			1	1		
Ponderosa Pine (476)	2			1		2
Quaking Aspen (478)			1	1	1	
Douglas Fir (479)		1		6		1
Canyon Live Oak (480)			1			
Oregon White Oak (481)		1				
Sugar Pine Dominated (485-499 total)	8	0	1	5	2	4
Sugar Pine Only (486)			1	4	2	1
Ponderosa Pine (495)				1		3
Douglas Fir (497)	8					
Western White Pine Dominated (513-530 total)	0	2	4	7	1	2
Western White Pine Only (515)			2	3	1	
Rocky Mountain Fir (516)		1	2	3		1
Red Fir (517)						1
Jeffrey Pine (524)		1		1		
Ponderosa Pine Dominated (536-579 total)	27	62	35	63	32	61
Ponderosa Pine Only (536)	2	26	15	27	9	28
White Fir (539)	2	4	12	16	8	17
Incense Cedar (548)	2	9	2	10	5	10

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Mountain Mahogany (549)	1					
Tan Oak (556)	6					
Jeffrey Pine (561)		2		2		
Sugar Pine (562)		4		2		1
Douglas Fir (570)		3	2	4		3
Canyon Live Oak (571)		1			1	
Oregon White Oak (573)	4	4	4	1	4	
California Black Oak (574)	10	9		1		2
Foothill Pine Dominated (582-596 total)	0	5	0	5	2	4
Foothill Pine Only (582)		2		2		
Oregon White Oak (592)		1		2	1	3
Interior Live Oak (595)		2		1	1	1
Frémont's cottonwood Dominated (629-631 total)	2	4	1	4	0	0
Frémont's cottonwood Only (629)	1	2	1	3		
Boxelder Maple (630)	1					
Oregon Ash(631)		2		1		
Bitter Cherry Dominated (645)	0	0	2	1	0	0
Western Chokecherry	0	2		3	0	0

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occur- rence Number	BKHGRO 2016 Occur- rence Number	YERWAR 2010 Occur- rence Number	YERWAR 2016 Occur- rence Number	HAIWOO 2010 Occur- rence Number	HAIWOO 2016 Occur- rence Number
Dominated (652-653 total)						
Western Chokecherry Only (652)				1		
Douglas Fir (653)		2		2		
Douglas Fir Dominated (661-723 total)	107	47	21	37	9	30
Douglas Fir Only (661)	18	8	2	7		4
White Fir (664)	2	6	3	13		6
Big Leaf Maple (669)	4	3		2		2
White Alder (672)			1	1	1	
Cut-leaf Red Alder (673)	3	1				
Madrone (674)	1			1		
Incense Cedar (678)	24	7	3	2	2	4
Tan Oak (688)	1	2				
Jeffrey Pine (696)			1			
Sugar Pine (697)	5	8	1	7	2	4
Western White Pine (698)			1		1	
Ponderosa Pine (700)	16	4	3	3	1	7
Canyon Live Oak (708)	19		3			
California Black Oak (711)	14	8	3	1	2	3
Canyon Live Oak Dominated (745-773 total)	9	19	1	6	0	13
Canyon Live Oak Only (745)	7	3	1	1		7

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Madrone (752)	1					
Incense Cedar (753)		1				
Douglas Fir (767)		2				1
Blue Oak (768)		2				
California Black Oak(770)	1	11		5		5
Blue Oak Dominated (774-786 total)	3	29	9	32	1	6
Blue Oak Only (774)		25	7	26	1	6
Foothill Pine (779)				1		
Oregon White Oak (783)	3	2		1		
Interior Live Oak (786)		2	2	4		
Oregon White Oak Dominant (790-812 total)	8	18	3	11	1	7
Oregon White Oak Only (790)	4	12	3	8		4
Madrone (794)		2				
Mountain Mahogany (796)				1		1
Ponderosa Pine (800)	1	3		1		1
California Black Oak (809)	2	1		1		1
Valley Oak (810)	1				1	
California Black Oak Dominated (813-834 total)	19	37	5	6	2	14

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
California Black Oak Only (813)	13	14	2	5	1	4
White Fir (814)	1	2	2		1	2
California Buckeye (816)	1					
Incense Cedar (819)		1				
Ponderosa Pine(824)		7		1		5
Douglas Fir (826)	4	2	1			1
Canyon Live Oak (828)		1				1
Oregon White Oak (830)						1
Valley Oak Dominated (835-850 total)	7	7	0	3		2
Valley Oak Only (835)		7		1		
Western Juniper (839)				1		1
Ponderosa Pine (841)				1		
Canyon Live Oak (846)	7					1
Interior Live Oak Dominated (851-873 total)	1	3	1	1	0	3
Interior Live Oak Only (851)	1	1				1
Foothill Pine (861)		1		1		1
Frémont's Cottonwood (863)		1				1
Blue Oak (868)			1			
Remnant Vegetation (874)	16	42	24	52	8	40

Dominated Tree Community and Fortypba Reference Number Range	BKHGRO 2010 Occurrence Number	BKHGRO 2016 Occurrence Number	YERWAR 2010 Occurrence Number	YERWAR 2016 Occurrence Number	HAIWOO 2010 Occurrence Number	HAIWOO 2016 Occurrence Number
Mountain Hemlock Dominated (950-964 total)	0	4	10	12	0	4
Mountain Hemlock Only (950)		2	3	5		3
White Fir (952)		1	4	2		1
Red Fir (954)		1	3	4		
Western White Pine (960)				1		
California Laurel Dominated (965-983 total)	0	1	0	3	0	1
California Laurel Only (965)				1		
Interior Live Oak (981)		1		2		1