Introduction

This project created species habitat models for Golden Eagle bird locations, and Golden Eagle nest locations. These models were incorporated into the species accounts previously produced. All bird and nest localities and covariate Geographic Information System (GIS) layers used in modeling, as well as final modeling products are being submitted with this report.

Modeling Methods

Species data

This report summarizes habitat distribution modelling conducted for Golden Eagles, and Golden Eagle nests that occur within Clark County, NV and are covered under the Multi-Species Habitat Conservation Plan. To obtain point localities we searched available public databases (the Global Biodiversity Information Facility - http://www.gbif.org/; Biodiversity Information Serving Our Nation (BISON), http://bison.usgs.gov/; VertNet, http://vertnet.org/; iNaturalist, http://www.inaturalist.org/;and e-bird, http://ebird.org). When available these data were supplemented by species observation records provided by Clark County, the Nevada Department of Wildlife (NDOW), the Nevada Natural Heritage Program (NNHP), the National Park Service (NPS), the U.S. Forest Service (USFS), the Bureau of Land Management (BLM), the Nature Conservancy (TNC), and other independent contractors under the MSHCP. Observations were visually assessed for accuracy prior to model fitting, and duplicate records and / or those without sufficient locality information were removed. We separated the point sets based on whether they were indicated as a nesting location, or a general sighting location where eagles may have been observed foraging or in flight.

We consulted the species writeup from earlier modeling and species accounts (included below), and we then selected environmental covariates describing the range of environmental conditions necessary for establishment, growth, reproduction, and survival. Habitat distribution models were based upon biologically relevant variables for which we had *a priori* hypotheses relating to each Golden Eagles' life-history. This approach reduces the risk of spurious associations and potentially results in models with greater biological relevance (Austin 2002; Guisan and Thuiller 2005). Based on these criteria, we selected approximately 10-15 environmental covariates to include in habitat models for each Golden Eagles, and Golden Eagle nests, that were thought to influence their geographic distributions, and conduced model selection to reduce these to 10 input variables..

Environmental covariates

We evaluated a range of environmental covariates that might effectively discriminate habitat for multiple species within Clark County, including spatial layers available from the County, previously published datasets, climatic interpolations (Hamann et al. 2013; Wang et al. 2016), satellite-based vegetation indices from the USGS Eros Center (http://phenology.cr.usgs.gov/), and topographic features derived from a Digital Elevation Model (USGS National Elevation Dataset; http://ned.usgs.gov/). In total, we derived 25 covariate layers at a 250m resolution for potential inclusion in habitat distribution models (Table 1). These layers included climatic averages and extremes for precipitation and temperature, topographic features, and remotely-sensed vegetation indices (e.g., Normalized Difference Vegetation Index). Environmental covariates were assessed for collinearity prior to model fitting, and variables that showed strong correlations ($r > 0.75$) were not included within the same models for a given species.

Quantitative statistical modelling methods

The largest source of variability in habitat distribution model output stems from the type of algorithm used to generate predictions (e.g., Watling et al. 2015). For this reason, we used an ensemble modeling approach that incorporated three different algorithms: generalized additive models (GAM; using the "mgcv" method Wood 2006), random forests (RF; implemented in the R package "randomForest," Liaw and Wiener 2002), and MaxEnt (version 3..4.1, Phillips et al. 2006) ; all executed from the "biomod2" package in R, Thuiller et al. 2009). The use of multi-algorithm ensembles renders predictions less susceptible to the biases, assumptions, or limitations of any individual algorithm, while broadening the types of environmental response functions that can be identified (Araujo and New 2006). Moreover, empirical evaluations have found GAM, RF, and MaxEnt to be consistently strong performers among habitat distribution modeling algorithms (Franklin 2010). All modeling was conducted in R version 3.5.3 (R Core Team 2019).

True absence points were not available for Golden Eagles, or their nests, at this time. For this reason, all models were fit using randomly generated background points (pseudo-absences). Random selections of background points are already implemented in MaxEnt software, and are also considered a reliable method for regression techniques including GAM (Wisz and Guisan 2009; Barbet-Massin et al. 2012). Background points were randomly selected from within the modelling extent (Barbet-Massin et al. 2012) from all grid cells where the study species was not present. Following the recommendations in Barbet-Massin et al. (2012), GAM models and RF models were fit with an equal number of presences and background points (Barbet-Massin et al. 2012).

To keep models interpretable and to improve their generalization across the study area, we also did not include interaction terms. Because presence points tended to be spatially aggregated, which can lead to substantial bias in model predictions, we first rasterized the presence points to the modeling resolution (i.e., such that only one presence point could occur within each grid cell) and subsequently applied a geographically-weighted resampling procedure in which a maximum of three observations could be sampled from cells on a uniform grid at a spatial resolution 10 times larger than the modelling extent (e.g., 2.5 km^2 for a 250 m^2 model, and 10 km^2 for a 1 km^2 models). This systematic grid sampling approach for spatial thinning of presence points can be effective at reducing spatial bias under a variety of conditions (Fourcade et al. 2014). To further reduce bias in our predictions, we used cross-validations to fit and evaluate all habitat models. In this process, each algorithm was fit across 50 samples of randomly selected, spatially thinned presence points, with a 20% random sample (without replacement) withheld for model evaluation at each iteration (i.e., 80 % of presence points were used in model fitting, and 20% in model evaluation). Background points were also randomly drawn for each cross-validation.

Metrics of model prediction accuracy were calculated based on the evaluation data for each of the 50 cross-validation runs, and subsequently averaged across runs. Performance metrics included several threshold-independent measures: AUC (the area under the receiver operating characteristic; Fielding and Bell 1997), the Boyce Index (BI; Boyce et al. 2002; Hirzel et al. 2006), and the True Skill Statistic (TSS; Allouche et al. 2006). TSS takes into account both omission and commission errors and is insensitive to data prevalence (Allouche et al. 2006).

Habitat distribution models vary in their ability to effectively discriminate different classes of habitat along the full range of habitat suitability values (0 – 1; Hirzel et al. 2006). To evaluate this property, we calculated the continuous Predicted / Expected (P/E) ratio curves based on the BI (Hirzel et al. 2006) using the *ecospat* package (v 3.0) in R. These curves reflect how well each model deviates from random expectation, and inform the interpretation of biologically meaningful suitability categories by indicating the effective resolution of suitability scores for each model (i.e., the model's ability to distinguish different classes of suitability; Hirzel et al. 2006).

To generate predictive layers of habitat suitability for each Golden Eagles, and their nests, we selected the top candidate models from each algorithm, based upon model performance metrics across cross-validation runs (AUC and TSS). Models were selected that consistently performed highest across different metrics. Raster surfaces representing each of the selected candidate models were generated by averaging model predictions across the 50 cross-validation runs, such that each model's prediction surface corresponded directly to its average performance scores. This procedure also limits the influence of sampling bias on individual model predictions. Ensemble predictions for individual algorithms were generated by taking the weighted average among candidate models for each algorithm type (i.e., one ensemble prediction each for GAM, RF, and MaxEnt models), with the weights determined by TSS scores. Layers representing the standard error of the overall ensemble habitat suitability layer were calculated as the standard deviation in model predictions across all candidate models, divided by the square root of the number of candidate models considered. The same approach was used to derive standard error layers within each individual algorithm type. This ensemble approach was conducted using the modeling platform *biomod2* in R. (Thuiller 2003).

Quantitative model interpretation

To facilitate biological interpretations of the ensemble models, we calculated the relative importance of environmental predictors across candidate models for each algorithm in *biomod2*.

To illustrate the shape of the relationships between predicted habitat suitability and important environmental covariates, we derived partial response curves for the top 4 environmental parameters for each of the three algorithms. Partial response curves show the predicted habitat suitability across a single covariate's range of values, while holding all other covariates at their mean value (e.g., Elith et al. 2005). To indicate the overall distribution of covariate values across the study region, we overlaid the response curve plots with histograms representing the prominence of each environmental covariate throughout the study area. These histograms were calculated from the combined presence and pseudo absence locations.

Ecosystem and Impact Assessment Calculations.

Using the habitat models that were produced during this project, the ensemble model was reclassified into categorical indices of suitability as: 0-0.33 = Low, 0.33 – 0.66 = Medium, and 0.66 – 1 = High. Shapefiles provided by the Clark County Desert Conservation Program (DCP) representing Impacts, Conservation layers (ACECs etc.), and Disturbed layers (e.g. urban areas, power plants, landfills, etc.) were converted to rasters at a 30m cell size as these layers had inconsistencies in topography that hindered habitat intersects. The categorical Ecosystem raster provided by the Clark County Desert Conservation Program (DCP) developed by Heaton et al. (2011) was used for ecosystem intersections with the categorical habitat rasters. For each of the High, Medium and Low habitat categories for each species, the intersection of the habitat category with the Impact and Ecosystem assessment layers was calculated using standard raster algebra techniques. Tables and summaries of these intersections are included in the model writeups.

Table 1. *Environmental covariate names and their source.*

Name	Source
Ave Max Temp	Average of the maximum monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
Ave Min Temp	Average of the maximum monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
Clay	Downloaded from the Soil Grids 250m project. Hengl et al. 2017
Coarse frags	Downloaded from the Soil Grids 250m project. Hengl et al. 2017
CV Max Temp	Coefficient of Variation of the maximum monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
CV Min Temp	Coefficient of Variation of the maximum monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
Dist to cliffs	Distance of Cliffs - from Inman et al. 2014
Extreme Max Temp	Extreme Maximum of monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
Extreme Min Temp	Extreme Minimum of monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.

Flow Accum	Inman et al. 2014
NDVI Amplitude	USGS Phenology network - https://www.usgs.gov/land-resources/eros/phenology/science/deriving-phenological-metrics-ndvi?qt-science_center_objects=0#qt-science_center_objects
NDVI Length of Season	USGS Phenology network - https://www.usgs.gov/land-resources/eros/phenology/science/deriving-phenological-metrics-ndvi?qt-science_center_objects=0#qt-science_center_objects
NDVI Max	USGS Phenology network - https://www.usgs.gov/land-resources/eros/phenology/science/deriving-phenological-metrics-ndvi?qt-science_center_objects=0#qt-science_center_objects
Sand	Downloaded from the Soil Grids 250m project. Hengl et al. 2017
Silt	Downloaded from the Soil Grids 250m project. Hengl et al. 2017
Slope	Calculated from USGS National Map. https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map
Start of Season (day)	USGS Phenology network - https://www.usgs.gov/land-resources/eros/phenology/science/deriving-phenological-metrics-ndvi?qt-science_center_objects=0#qt-science_center_objects
Winter Precip	Average of the cumulative annual winter precipitation (October - March) for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
CV Winter Precip	Coefficient of Variation for the cumulative annual winter precipitation (October - March) for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
Surface roughness	Inman et al. 2014
Average Spring Max Temp	Average of the maximum monthly temperatures for March - May for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
CV Average Spring Max Temp	Coefficient of Variation for the maximum monthly temperatures for a 30-year normal period between 1988 and 2018 calculated from monthly PRISM data at 800m resolution and downscaled to a 250 m resolution with bicubic spline interpolation using gdal-warp in python.
Percent washes	Calculated from USGS National Map. https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map
Absolute depth to bedrock	Downloaded from the Soil Grids 250m project. Hengl et al. 2017

Species Account

Golden Eagle (Aquila chrysaetos)

As top avian predators, there is interest in Golden Eagles (*Aquila chrysaetos*) globally. Successful conservation and education efforts have formed around this iconic species since the time when they were shot for sport on their annual migrations in the eastern United States. While those types of losses have certainly been reduced, new threats have developed with the recent national thrust to create greater amounts of renewable energy. Since about 2010 there are re-doubled efforts to understand the status of Golden Eagle populations in North America and learn about their life histories and ecology on a continental basis. Golden eagles in the hot desert regions of the southwestern United States are among the least known populations in North America. The Desert Renewable Energy Conservation Plan (DRECP 2015) of southern California has invested some resources to improve our understanding of this species. Much more work will be required to better understand this far-ranging species.

Species Status

U.S. Fish and Wildlife Service Endangered Species Act: No Status

Migratory Bird Treaty Act: Protected

Bald and Golden Eagle Protection Act: Protected

U.S. Bureau of Land Management (Nevada): Sensitive

U.S. Forest Service (Region 4): No Status

State of Nevada: Protected (NAC 503.050.1)

NV Natural Heritage Program: Global Rank G5, State Rank S4

NV Wildlife Action Plan: Species of Conservation Priority

IUCN Red list (v 3.1): Least Concern

CITES: Appendix ii

Range

The distribution of Golden Eagles is circumpolar in the northern hemisphere (Bent 1961). They generally occupy relatively open areas that are not densely forested. Similarly, expansive grassland biomes are often suitable for establishing breeding territories where nesting substrate is present (e.g. cliffs or trees), and may be used by wintering eagles as well (Watson 2010). Currently, Golden Eagle populations are most robust west of the Great Plains with additional populations in northeastern Canada and isolated locations in the eastern U.S. (Kochert et al. 2002, DeLong 2004). There are six subspecies of Golden Eagle worldwide, however only *A. c. canadensis* occurs in North America. Golden eagles occupy mostly remote open country that is isolated from human activities. Foraging habitats for nesting eagles include many North American habitat types including: the fringes of Arctic habitats; mountains of the Pacific northwest; the taiga of North America; foothills and shortgrass steppe east of the Rocky Mountains; cold deserts of the Great Basin and Colorado Plateau; the Mojave and Sonoran hot desert ecoregions, mountains and coastal areas of California and Mexico; and mountains of eastern North America (Watson 2010, Longshore In Prep., Daniel Driscoll – AERIE, personal communication). Wintering Golden Eagles use these above habitat types when prey is available year-round and climatic conditions allow. They may also parts of the Great Plains, but in that region nesting is limited by lack of appropriate nesting substrate. In North America nesting substrates usually include cliffs and trees.

Habitat Models

Habitat Model – (All localities)

While the three model algorithms generally predicted similar habitat arrangements throughout the County, the Random Forest models generally predicted more habitat, organized in less cohesive patches, than the other models, while the MaxEnt models tended to retain moderate values where other models predicted lower values (Figure 1). Key areas of similarity among models in the County included the Sheep, Spring, Bird Spring, and Highland ranges, the McCullough and Lucy Gray mountains. Areas not well supported as habitat were large patches in the Mormon Mesa, Moapa Valley, Pahrump, lower elevation portions of Gold Butte, and the Lake Mead/Colorado river drainage (Figure 1). Important differences in predicted habitat for this species occur in the Las Vegas valley, where the MaxEnt model predicts a patch of high suitability, while the others do not (Figure 1).

The Ensemble model had high performance relative to other models, scoring the highest on all of the performance metrics AUC and BI, and with a similar TSS score (calculated on the blind testing dataset) as the RF model (Table 2). Relative to the other models, the MaxEnt model had poor performance on the AUC and TSS metrics. Overall AUC performance was moderate, with no models performing above 0.8, while BI scores were relatively high. The GAM and MaxEnt models shared the top four influential environmental variables, where the CV and Average of Maximum temperature, Extreme Maximum temperature, and the sand component of the soils were the largest contributors (Table 3). The RF model shared only the CV of Average of Maximum temperature in its top four contributing variables, and was more influenced by slope, minimum temperatures, and clay content. The standard error was relatively low throughout the County, where only the GAM model had values approaching (0.05 – which is not a value indicating large disagreement among models) which were located in small patches near Mt. Charleston (Figure 2). The Continuous Boyce Indices showed good model performance in all algorithms (Figure 3). The MaxEnt curve indicated some values of higher performance where point density was only moderate, indicating less discrimination between high and low habitat (Figure 4), this is likely due to the lack of lower suitability scores in areas with fewer points that retained moderate suitability scores (e.g. 0.5, Figure 1).

Table 2. Model performance values for *Aquila chrysaetos* models giving Area under the Receiver Operator Curve (AUC), Boyce Index (BI), and True Skill Statistic (TSS) for the ensemble model, and the individual algorithms for the testing data sets. PRBE is given as the "precision recall break-even point" - threshold value for the ensemble model

Model	AUC	BI	TSS	PRBE
Ensemble	0.77	0.98	0.43	0.52
GAM	0.75	0.98	0.39	
Random Forest	0.77	0.91	0.44	
MaxEnt	0.72	0.95	0.34	

Table 3. Percent contributions for input variables for *Aquila chrysaetos* for models using GAM, Maxent and Random Forest algorithms. The top 4 contributing variables are highlighted, and response curves for these variables within each algorithm are given in the corresponding sections below

Variable	GAM	RF	MaxEnt
Ave Max Temp	12.6	6.7	0
Ave Min Temp	6.7	5.3	2.5
Average Spring Max Temp	12.7	3.5	21.7
CV Average Spring Max Temp	21	14.7	39.2
Clay	3.2	10	0
Extreme Max Temp	17.4	9	18.7
Extreme Min Temp	7.9	12.2	1
Sand	14.1	9	11.7
Silt	3.1	9.7	1.7
Slope	1.3	20	3.4

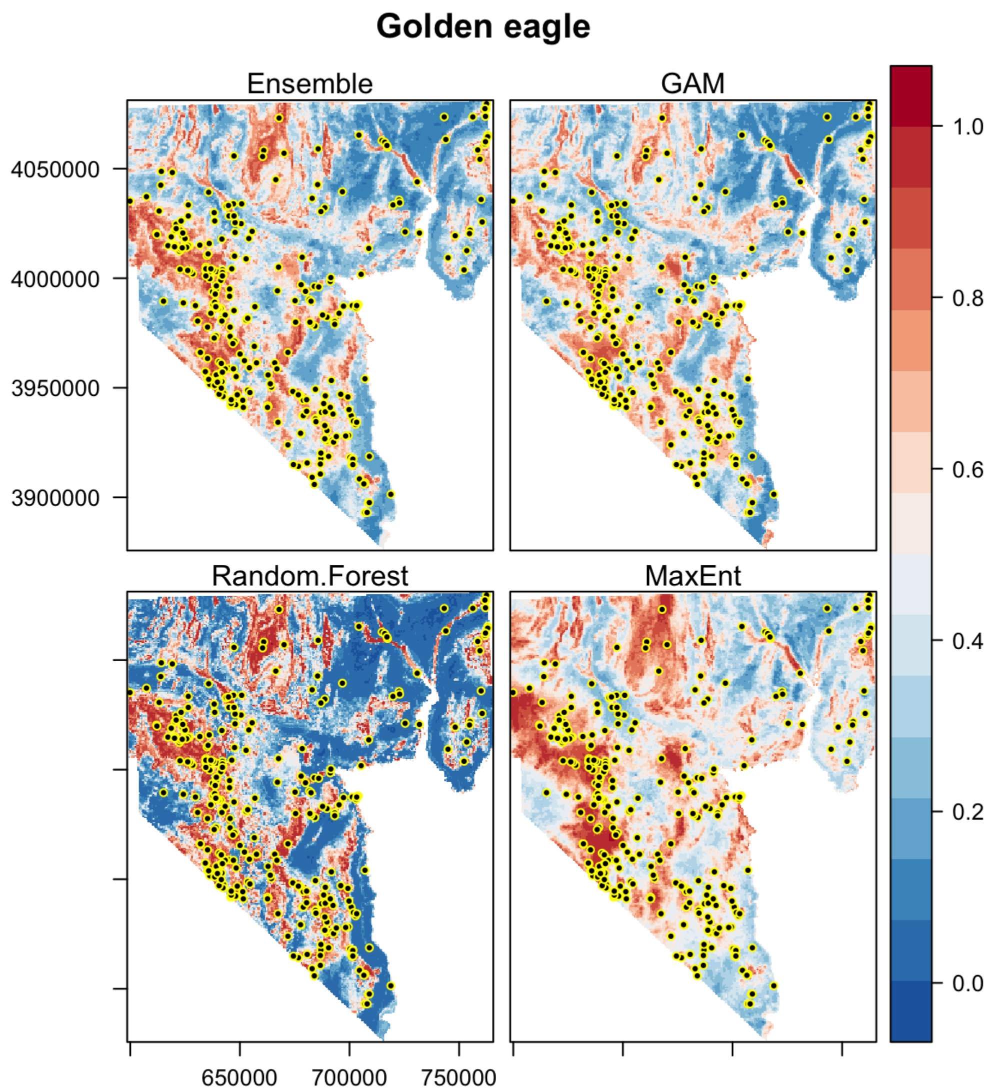

Figure 1. SDM maps for *Aquila chrysaetos* model Ensemble (upper left), and for averaged models of each of three modeling algorithms used (GAM - upper right, Random Forest – lower left, MaxEnt - lower right). Hotter colors indicate higher predicted habitat values, and black circles indicate the presence points used in training and testing the models.

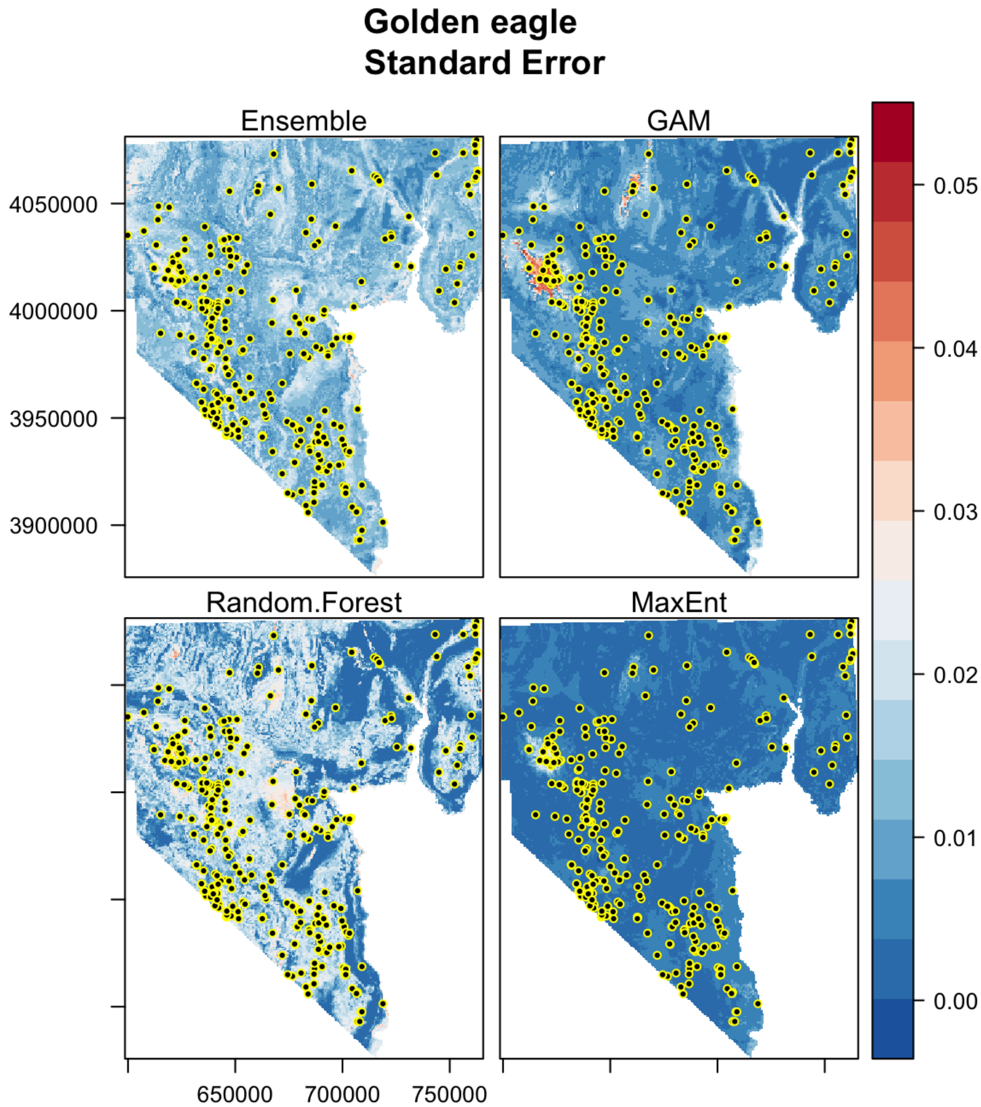

Figure 2. Standard error maps for *Aquila chrysaetos* models for each of three modeling algorithms used (GAM - upper right, Random Forest – lower left, MaxEnt - lower right), and an ensemble model averaging the three (upper left).

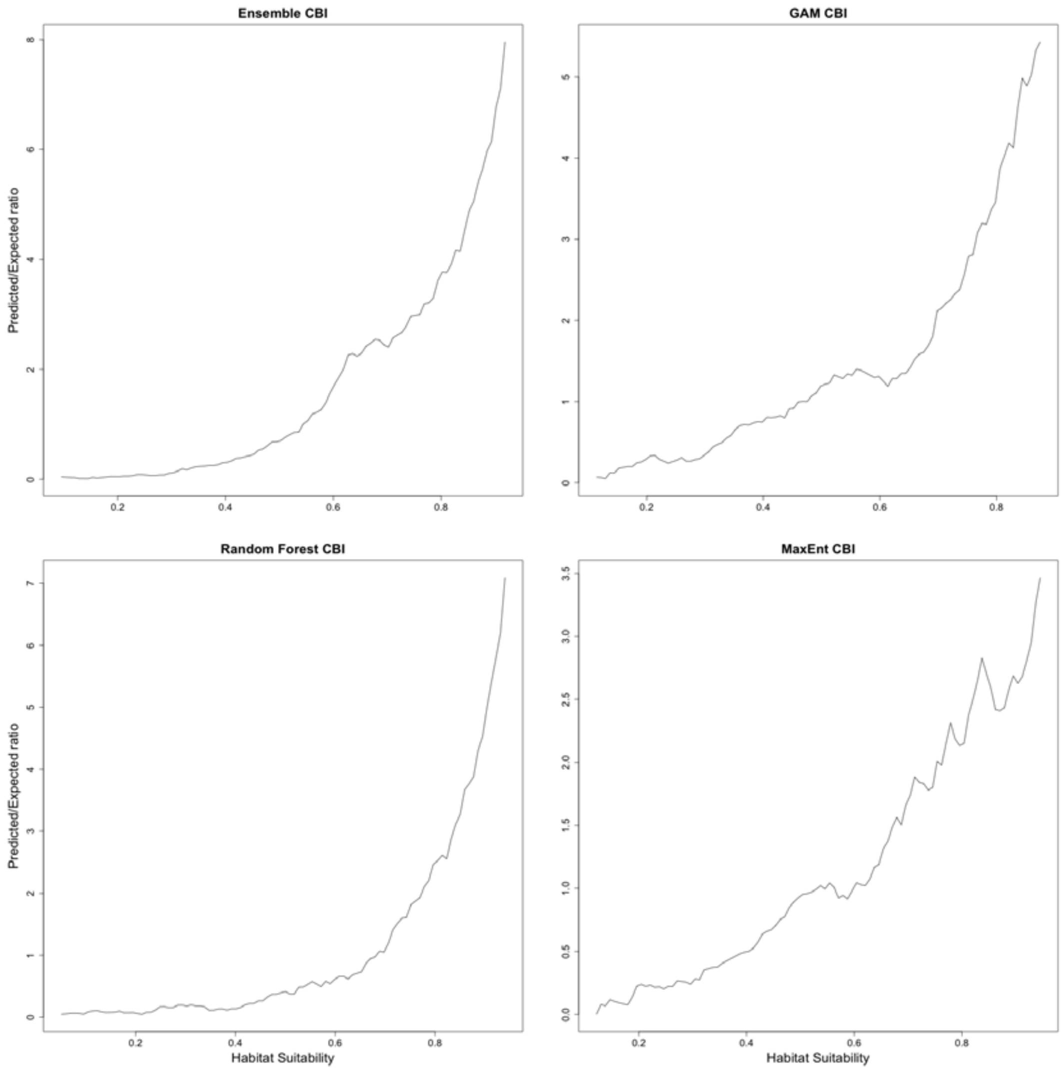

Figure 3. Graphs of Continuous Boyce Indices [CBI] for *Aquila chrysaetos* models for the ensemble model prediction (upper left) and for each of three modeling algorithms used (GAM - upper right, Random Forest – lower left, and MaxEnt - lower right).

General Additive Model

The top 4 contributing environmental layers were Average Maximum Temperature and its Coefficient of Variation, Extreme Maximum Temperature, and Sand component of the soil collectively accounting for 65% of total model contribution (Table 3). Model scores were higher in areas with cooler Extreme Max Temperatures (typically in the summer months, where the higher temperatures are well above 40 ºC) but with warmer Spring Maximum Temperatures (peaking above 30 ºC, Figure 4). Model predictions peaked at temperature CV's slightly higher than the mean environmental values and remained relatively higher thereafter. Habitat was also predicted to be higher in areas with a much lower Sand content than found in the County generally, with a strong negative response as sand content increased (Figure 4). This algorithm had very low standard error values, indicating similar predictions among the 50-model cross-validation runs (Figure 2). As stated above, there was only 1 patch of moderate error (0.05) located near Mount Charleston.

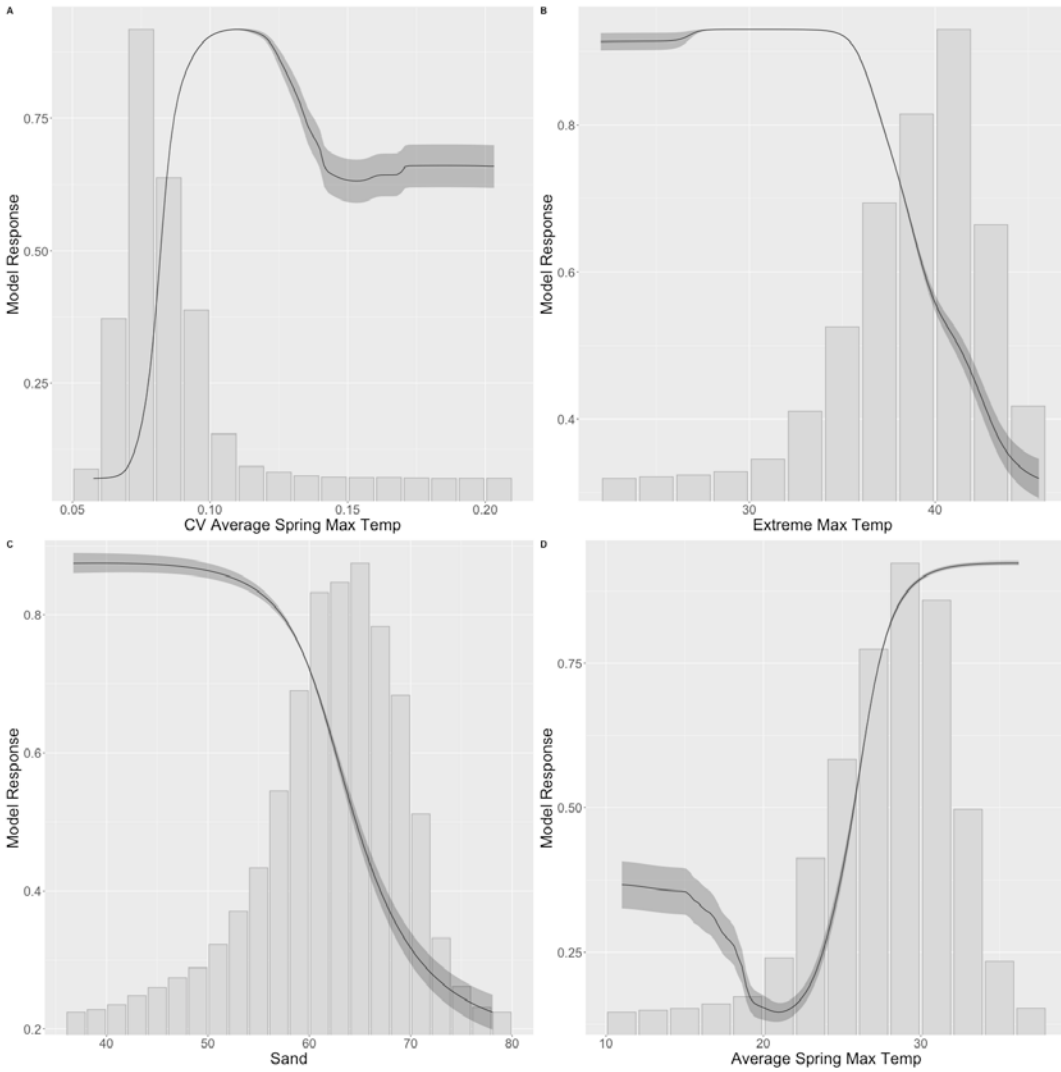

Figure 4. GAM partial response curves for the top 4 variables in the *Aquila chrysaetos* model overlaid over distribution of environmental variable inputs in the study area. Histograms represent the range of each environmental variable across the x-axis, and predicted dependence relative to habitat suitability values are on the y-axis.

MaxEnt Model

The MaxEnt models relied heavily on the same four top variables as those in the GAM models contributing 91% of total model contribution (Table 3). This model also had very similar response curves among algorithms to the GAM model indicating relatively robust model selection (Figure 4, Figure 5). The predicted response for the CV of Average Spring Temperature showed the only difference, where there was no decrease in predicted suitability at high values, but rather a threshold response (Figure 5).

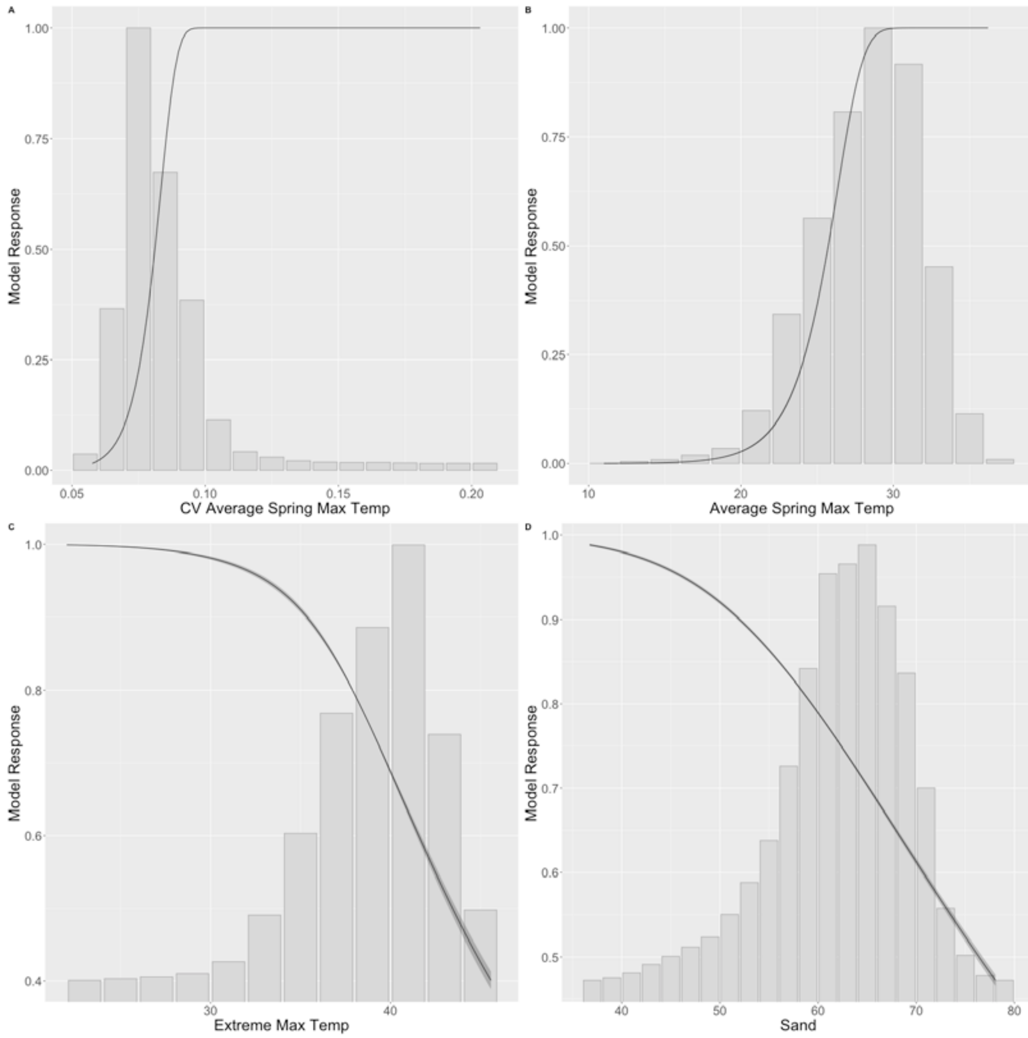

Figure 5. Partial response curves for the top environmental variables included in the MaxEnt ensemble model for *Aquila chrysaetos.* Histograms represent the range of each environmental variable across the x-axis, and predicted dependence relative to habitat suitability values are on the y-axis.

Random Forest Model

The Random Forest model was largely driven by Slope, CV of Average Maximum Spring Temperature, Extreme Minimum Temperature, and soil Clay content (Table 3). The collective model influence was 57%, where additional influence was proved by several other input variables (Table 3). Slope indicated higher habitat suitability at both high and low values, which could indicate habitat predictions for the animals use of different habitat resources those for either nesting sites or foraging sites, as both types of data are present in this model (Figure 6). The temperature variables indicated higher predicted habitat toward areas with warmer Spring Maximum Temperatures, and higher variability in Average Spring Maximum Temperatures. Habitat predictions relative to soil Clay content generally mapped the average available values in the County, remaining moderate at elevated values (Figure 6).

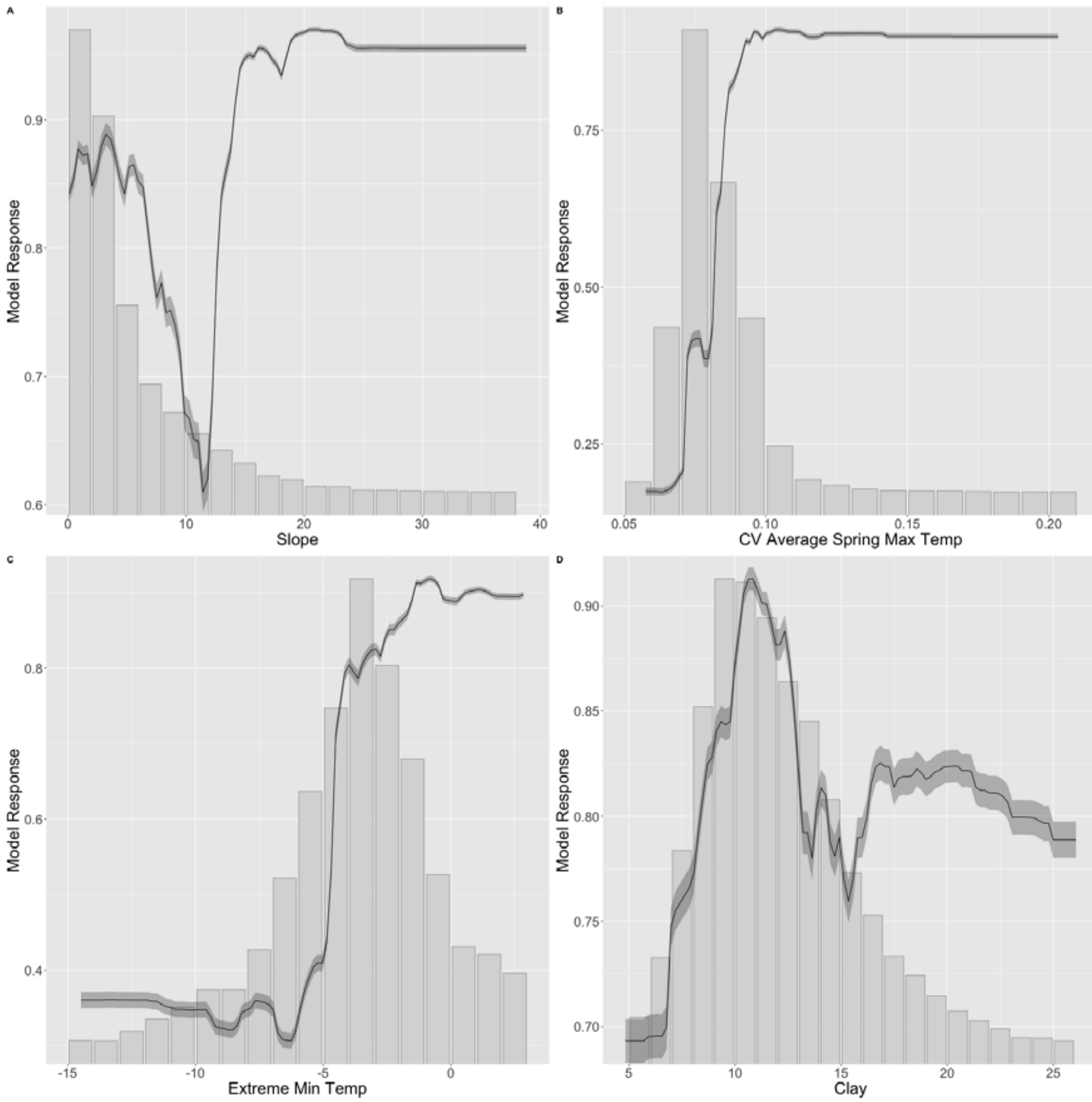

Figure 6. Partial response curves for the environmental variables included in the Random Forest ensemble model for *Aquila chrysaetos.* Histograms represent the range of each environmental variable across the x-axis, and predicted dependence relative to habitat suitability values are on the y-axis.

Model Discussion

This model depended on all available observations of this species, including nesting locations, as well as general sightings of individuals (e.g. foraging or flying). *Aquila chrysaetos* are spread relatively broadly across Clark County, NV (Figure 7). It should be noted that the species has a pan-hemispheric distribution, across North America and Eurasia, and that individuals can have extremely large home ranges. Home rang size exceeding 1000 km^2 is not uncommon (Braham et al. 2015). However, predicted habitat for the County was relatively restricted to higher elevation areas, and areas connecting the mountainous areas along the North South oriented ranges in the western half of the County.

The northeastern extent of the County, near Mormon Mesa was predicted to have lower habitat values, potentially due to the lower and flatter terrain associated with these areas, that may also experience higher maximum temperatures. Similar areas of lower habitat scores were predicted along the US 95 corridor, the immediate area surrounding Pahrump, CalNevAri, Laughlin, Eldorado Valley, and the area surrounding lake Mojave (Figure 7).

The locality data for this species consisted of 1304 records within the buffered modeling area, which had a very high degree of overlap. Spatial thinning of the data reduced the number of localities used for training and testing to 660 records.

Standard Error

The standard error map for the ensemble model indicated relatively low error (0.02) throughout much of the study area (Figure 7), with small pockets of moderate error (0.03) located in the Mt. Charleston area, at the Colorado River near Willow Creek, and other areas along the Lake Mead Shoreline. Overall errors were very low, indicating good agreement among the models used in the ensemble.

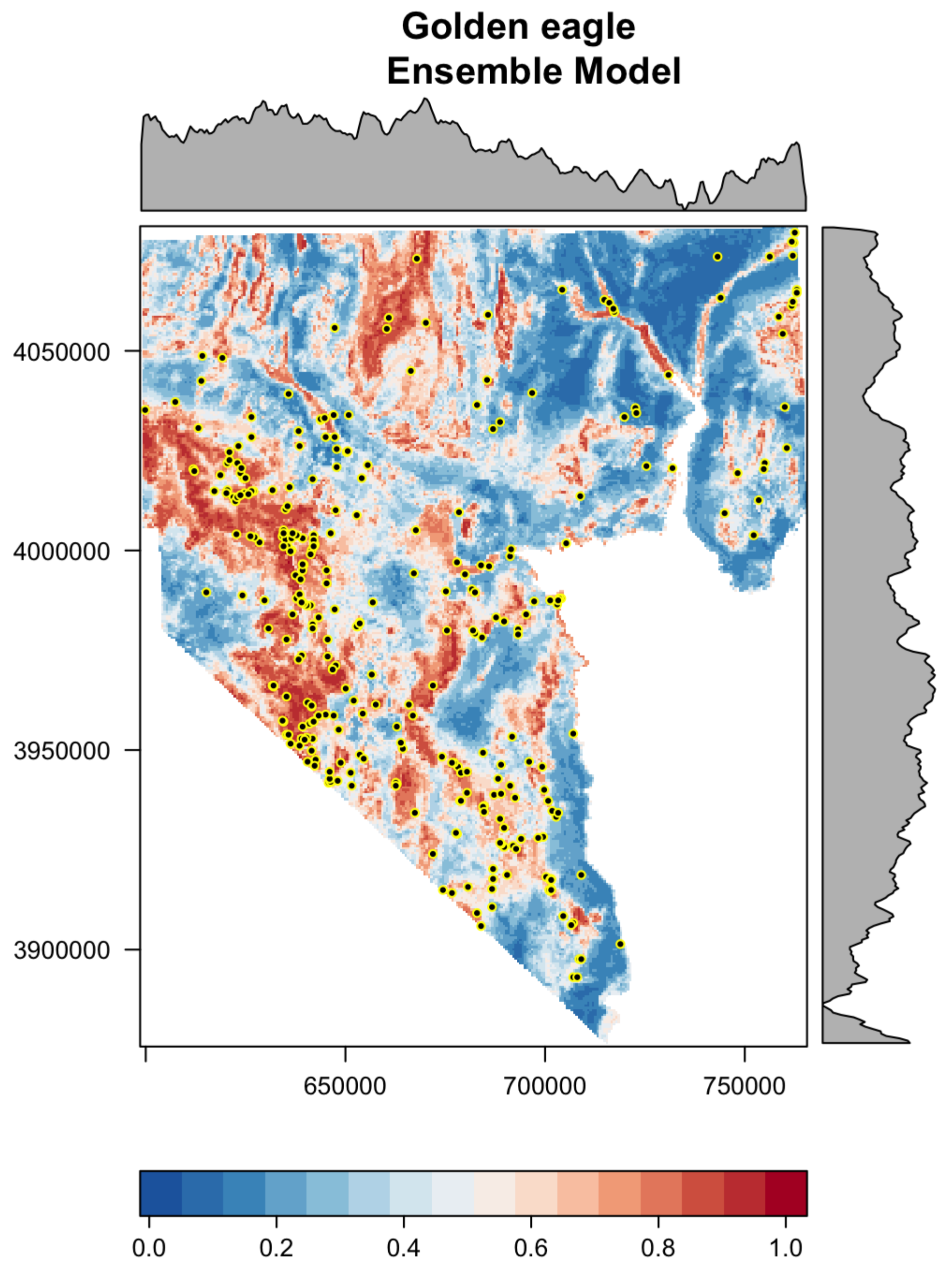

Figure 7. SDM map for *Aquila chrysaetos* Ensemble model for Clark County, NV.

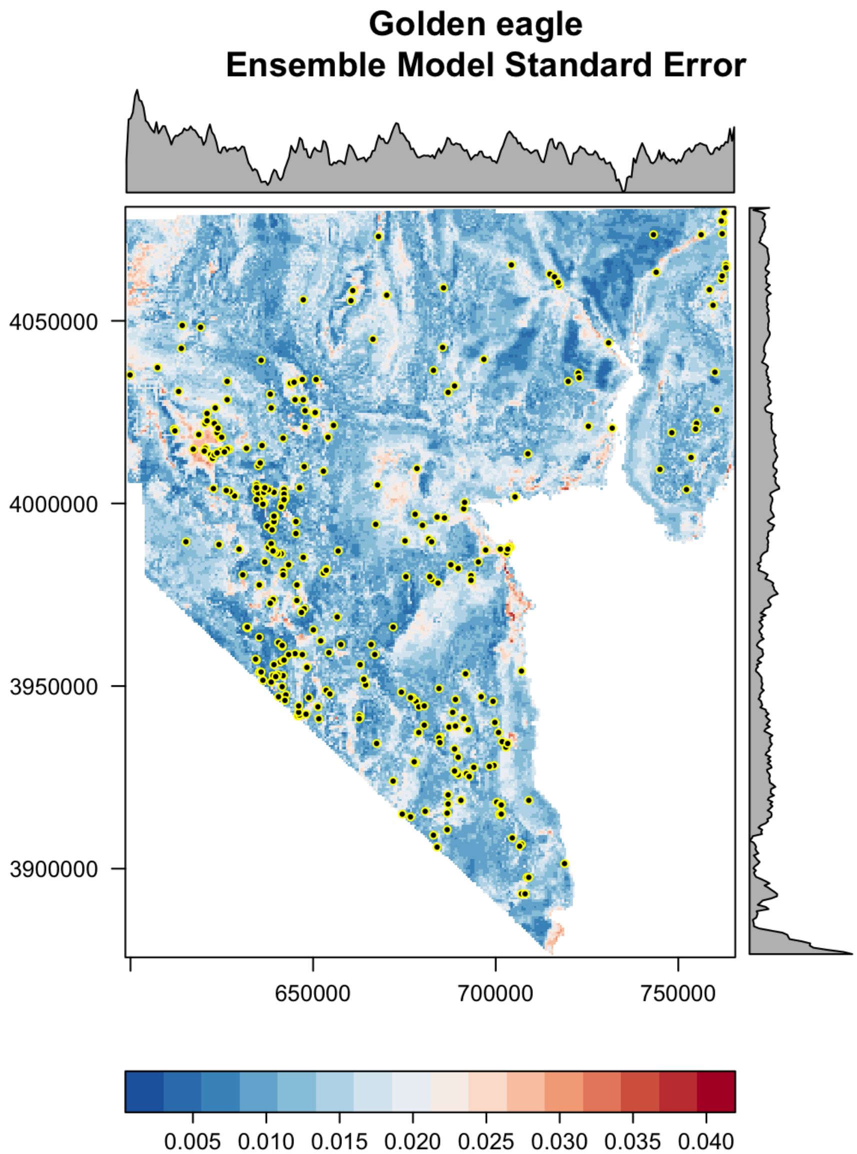

Figure 8. Standard Error map for the ensemble *Aquila chrysaetos* Ensemble model for Clark County, NV.

Habitat Model (Nesting Sites)

The three modeling algorithms had congruent predictions of suitable nesting habitat areas across the County (Figure 9). There were three larger areas of suitable habitat predicted surrounding each of the prominent mountain ranges (Spring, Sheep and Highland Range) in a circular like pattern around those features, with additional suitable habitat predicted areas in the Virgin Mountains, and the Bird Spring range near Goodsprings. Few differences among the models are noted. (Figure 9).

The Ensemble model had high performance relative to other models across all three metrics (Table 4). The AUC scores were highest for the RF and MaxEnt models, with GAM scoring slightly lower – but still with relatively high performance overall. The GAM model also had a 10-point lower TSS score than the other models, while the RF model had a much lower BI score relative to the others (Table 4). The GAM and MaxEnt shared 3 of the four most influencing environmental variables, while the RF model shared 3 with the MaxEnt Model, and only two with the GAM model. There was only one environmental variable in the top four (Extreme Minimum Temperature) shared by all models (Table 5). The most important variables included Slope, and measures of temperature extremes in the County. The Standard error maps indicated higher standard error among the GAM models than the others, with maximum SE's of approximately 0.06 (Figure 10). Areas of highest uncertainty were near Overton, Lake Mojave and the Spring Range. The other model algorithms had extremely low error among models (Figure 8). The MaxEnt model had an irregular Continuous Boyce Index curve, where there were several peaks in the mid-range (Figure 11), while the GAM and RF curves indicated good performance for this metric. The poor BI score for the RF model (Table 4) was likely due to the higher contrast between predicted habitat and adjacent non-predicted habitat (Figure 9), which resulted in the sharp increase in the CBI curve at the highest habitat values (Figure 11). Thus, the RF model was nearly binary in its predictions.

Table 4. Model performance values for *Aquila chrysaetos* nest habitat models giving Area under the Receiver Operator Curve (AUC), Boyce Index (BI), and True Skill Statistic (TSS) for the ensemble model, and the individual algorithms for the testing data sets. PRBE is given as the "precision recall break-even point" - threshold value for the ensemble model.

Model	AUC	BI	TSS	PRBE
Ensemble	0.89	0.84	0.69	0.44
GAM	0.84	0.78	0.53	
Random Forest	0.88	0.5	0.62	
MaxEnt	0.89	0.85	0.62	

Table 5. Percent contributions for input variables for *Aquila chrysaetos* nest habitat for models using GAM, MaxEnt and Random Forest algorithms. The top 4 contributing variables are highlighted, and response curves for these variables within each algorithm are given in the corresponding sections below.

Variable	GAM	RF	MaxEnt
Ave Max Temp	16.7	2.4	11.5

Ave Min Temp	12.5	2.8	9.7
Average Spring Max Temp	20.5	2.4	4.7
CV Average Spring Max Temp	8.5	6	26.6
CV Min Temp	0.2	2.3	9.7
Extreme Max Temp	14	6	0.7
Extreme Min Temp	16.1	11.5	17.7
Sand	1.2	3.6	0.5
Silt	0.7	2	0.9
Slope	9.7	61	18.2

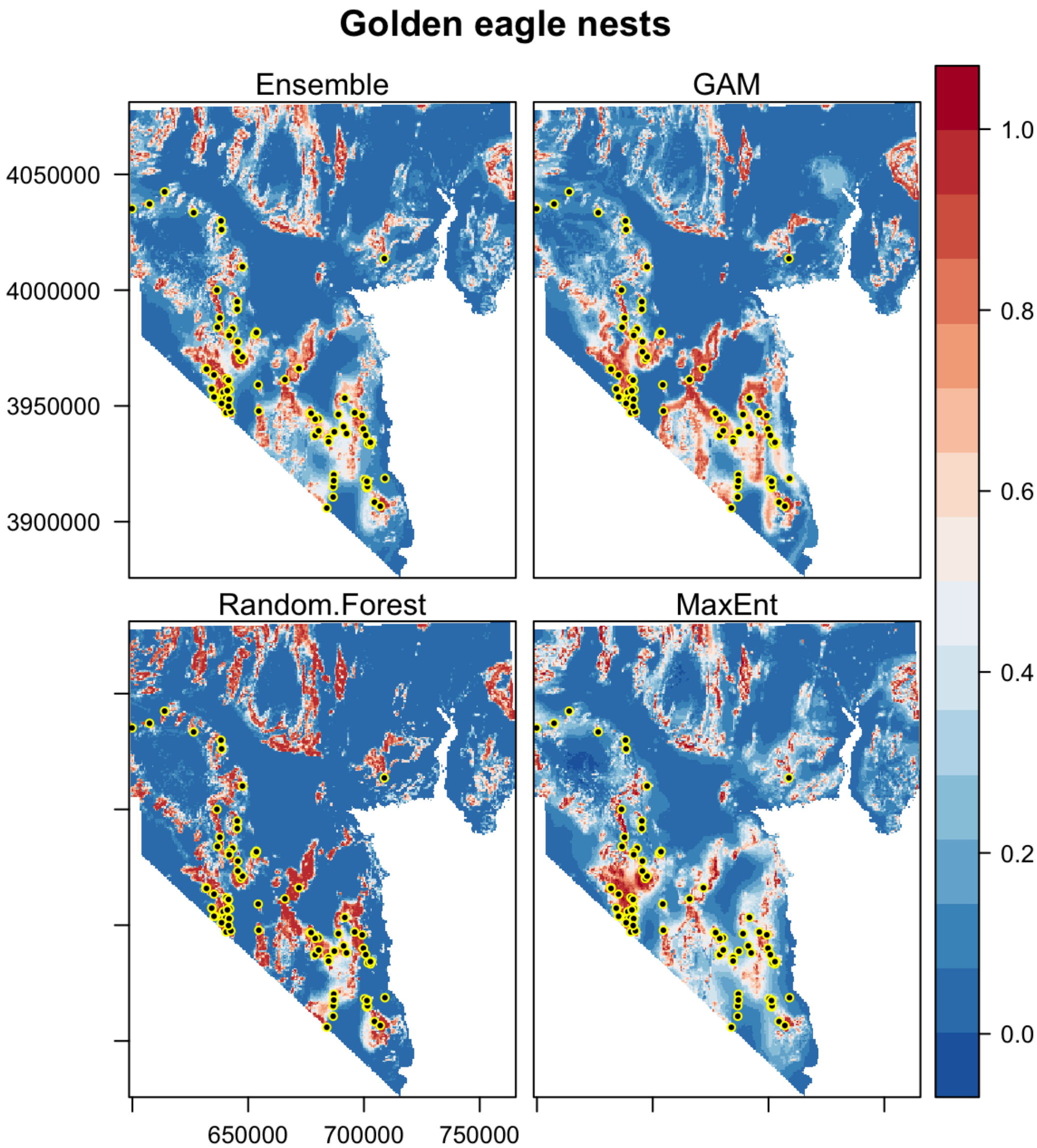

Figure 9. SDM maps for *Aquila chrysaetos* nest habitat models. Ensemble (upper left), and for averaged models of each of three modeling algorithms used (GAM - upper right, Random Forest – lower left, Maxent - lower right). Hotter colors indicate higher predicted habitat values, and black circles indicate the presence points used in training and testing the models.

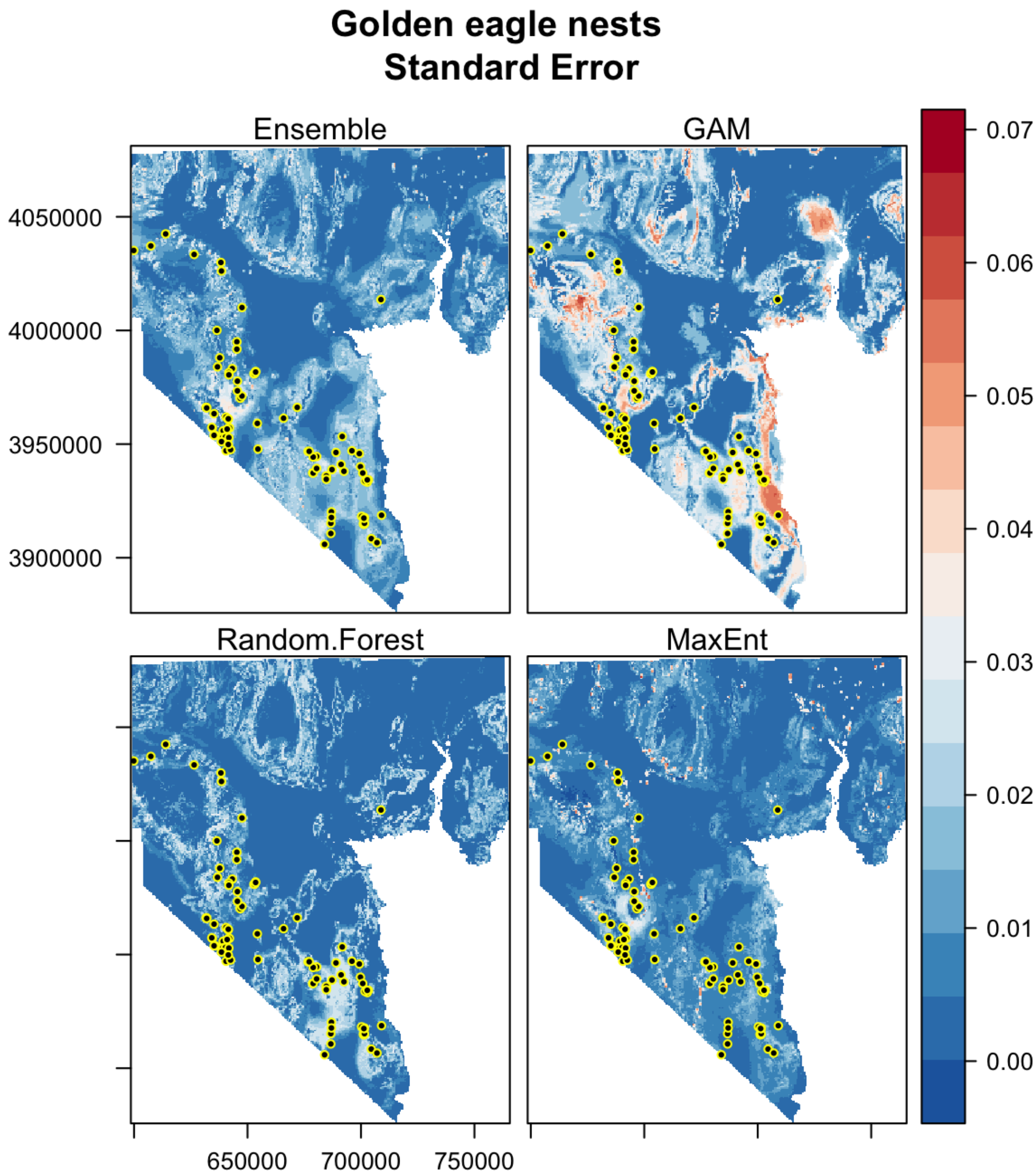

Figure 10. Standard error maps for *Aquila chrysaetos* nest habitat models for each of three modeling algorithms used (GAM - upper right, Random Forest – lower left, Maxent - lower right), and an ensemble model averaging the three (upper left).

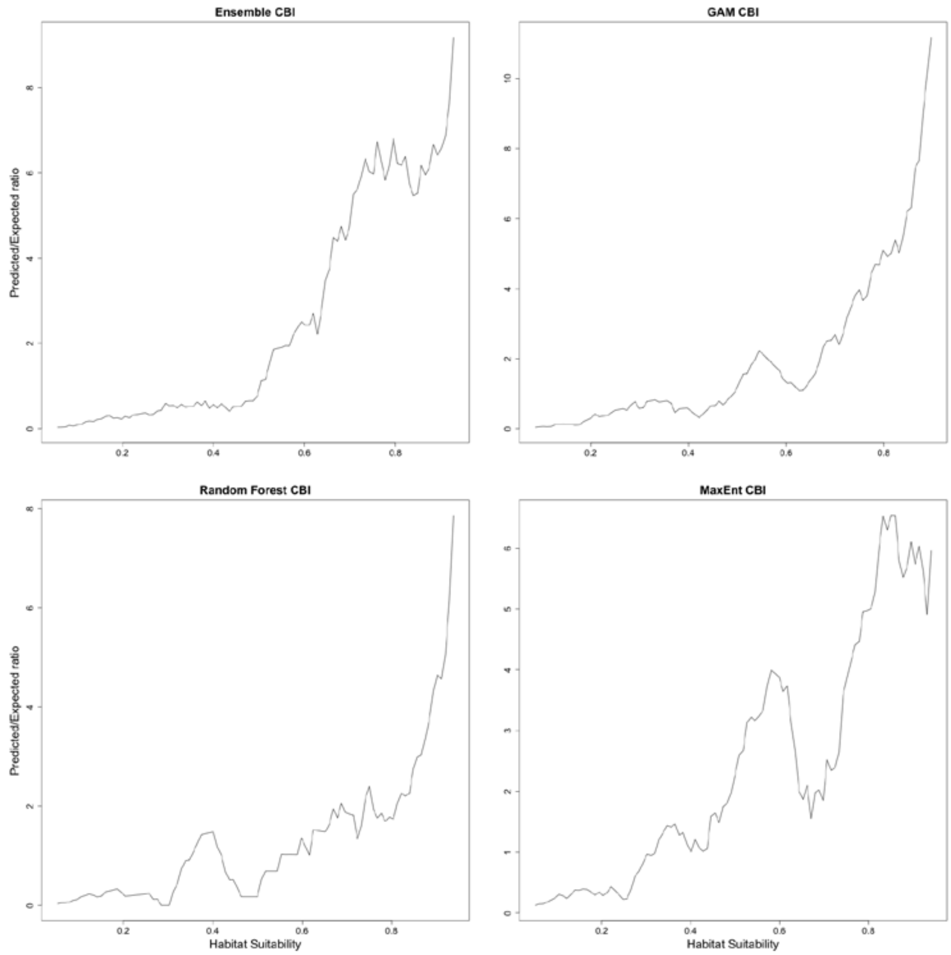

Figure 11. Continuous Boyce Indices [CBI] for *Aquila chrysaetos* nest habitat models for the ensemble model prediction (upper left) and for each of three modeling algorithms used (GAM - upper right, Random Forest – lower left, and MaxEnt - lower right).

General Additive Model

The top 4 contributing environmental layers were Average Spring Maximum Temperature, Average Maximum Temperature (i.e., summer), Extreme Minimum, and Maximum Temperatures (Table 5) contributing 66% of the total explained model parameters. Higher habitat scores for nesting areas were predicted in areas with higher Spring Maximum Temperatures, and Average Maximum Temperatures, but with higher Extreme Minimum (i.e., winter) temperatures, and lower Extreme Maximum (summer) Temperatures (Figure 12). Irregular dips in the response curves are likely due to the relatively lower sample sizes for nests localities. This algorithm had more disagreement among the model runs than did the others as discussed above (Figure 11).

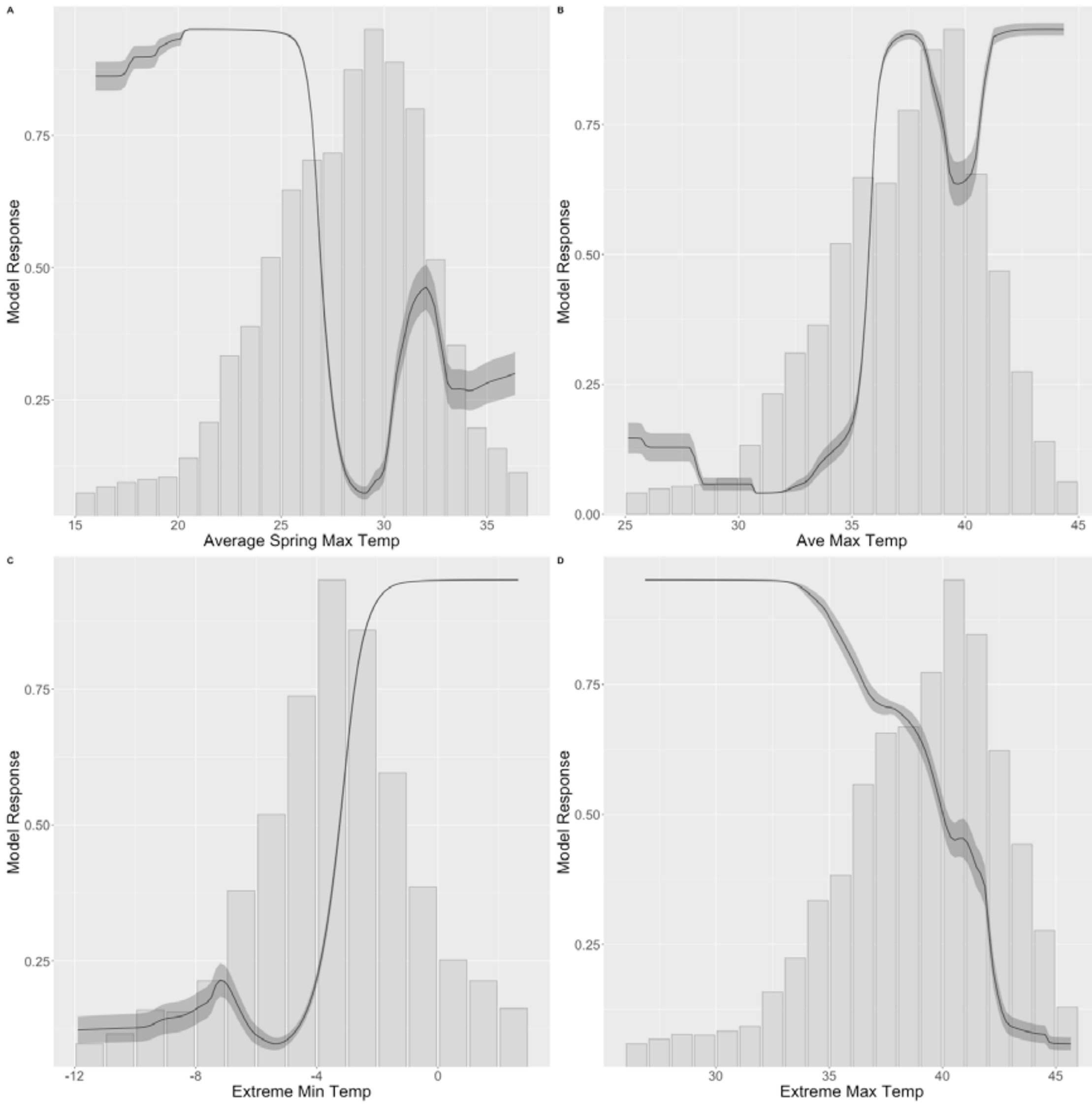

Figure 12. GAM partial response curves for the top 4 variables in the *Aquila chrysaetos* model overlaid over distribution of environmental variable inputs in the study area. Histograms represent the range of each environmental variable across the x-axis, and predicted dependence relative to habitat suitability values are on the y-axis.

MaxEnt Model

The MaxEnt models were most influenced by the CV in Average Spring Maximum Temperature, Slope, Extreme Min Temperature, and Average Maximum Temperature, accounting for 63% of the model importance (Table 5). Higher habitat was predicted where there was more variation in Spring Maximum Temperatures, higher slopes, and higher Extreme Minimum, and Average Maximum Temperatures (Figure 13). Note that the Average Maximum Temperatures, are not the Extreme Max Temperatures, but include both day and night temperatures for the summer months.

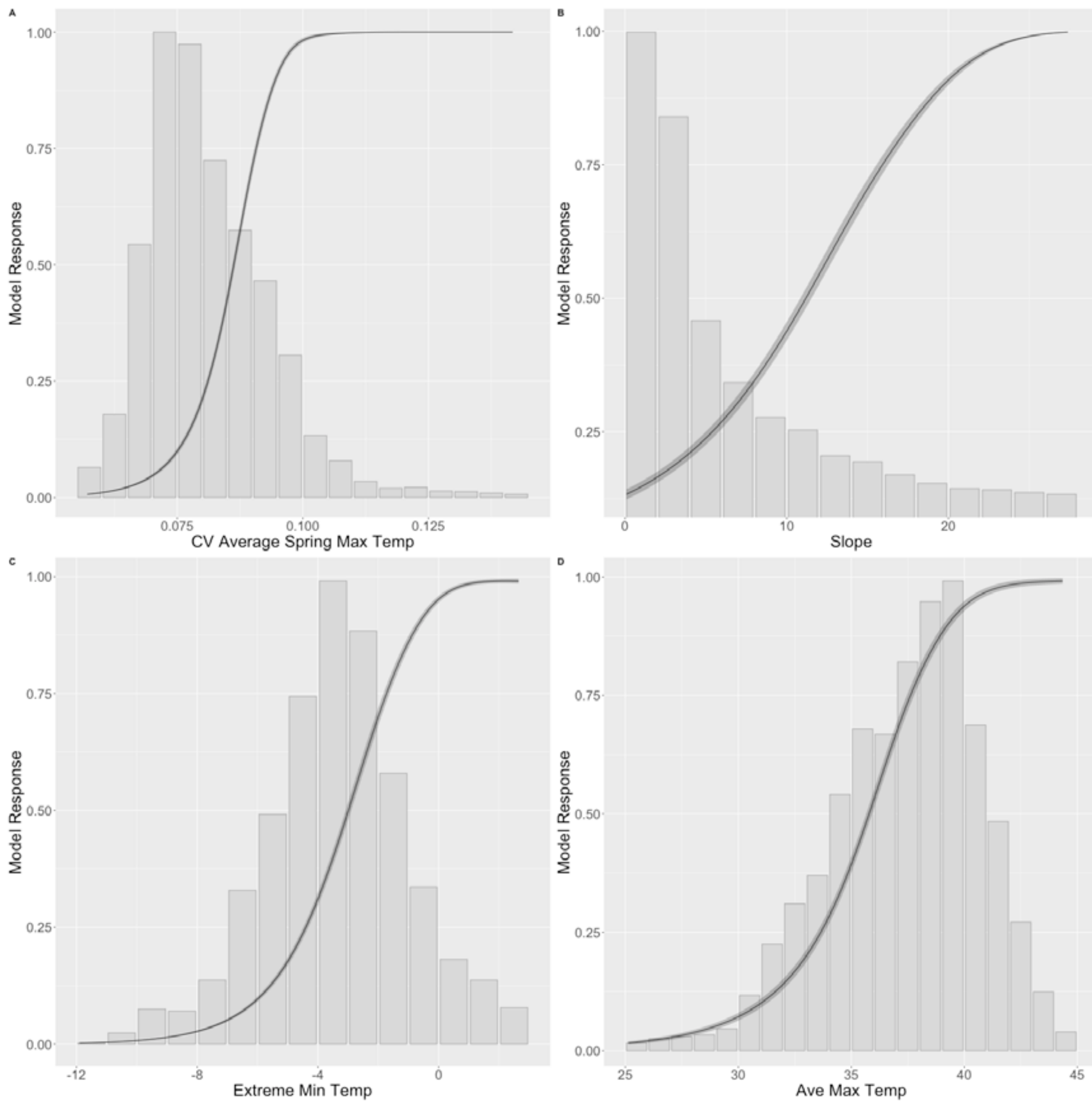

Figure 13. Partial response curves for the top environmental variables included in the MaxEnt ensemble model for *Aquila chrysaetos* nest habitat. Histograms represent the range of each environmental variable across the x-axis, and predicted dependence relative to habitat suitability values are on the y-axis.

Random Forest Model

The Random Forest model for this species was largely driven by Slope (61%) with additional influence of Extreme Maximum, and Minimum Temperature, the variation in the Average Spring Temperature adding an additional 24% (Table 5). Performance curves showed higher habitat predictions in areas with higher Slope, higher Extreme Minimum Temperatures (i.e. winter), higher variation in Spring Maximum Temperatures, and lower Extreme Maximum Temperatures (i.e., summer; Figure 14).

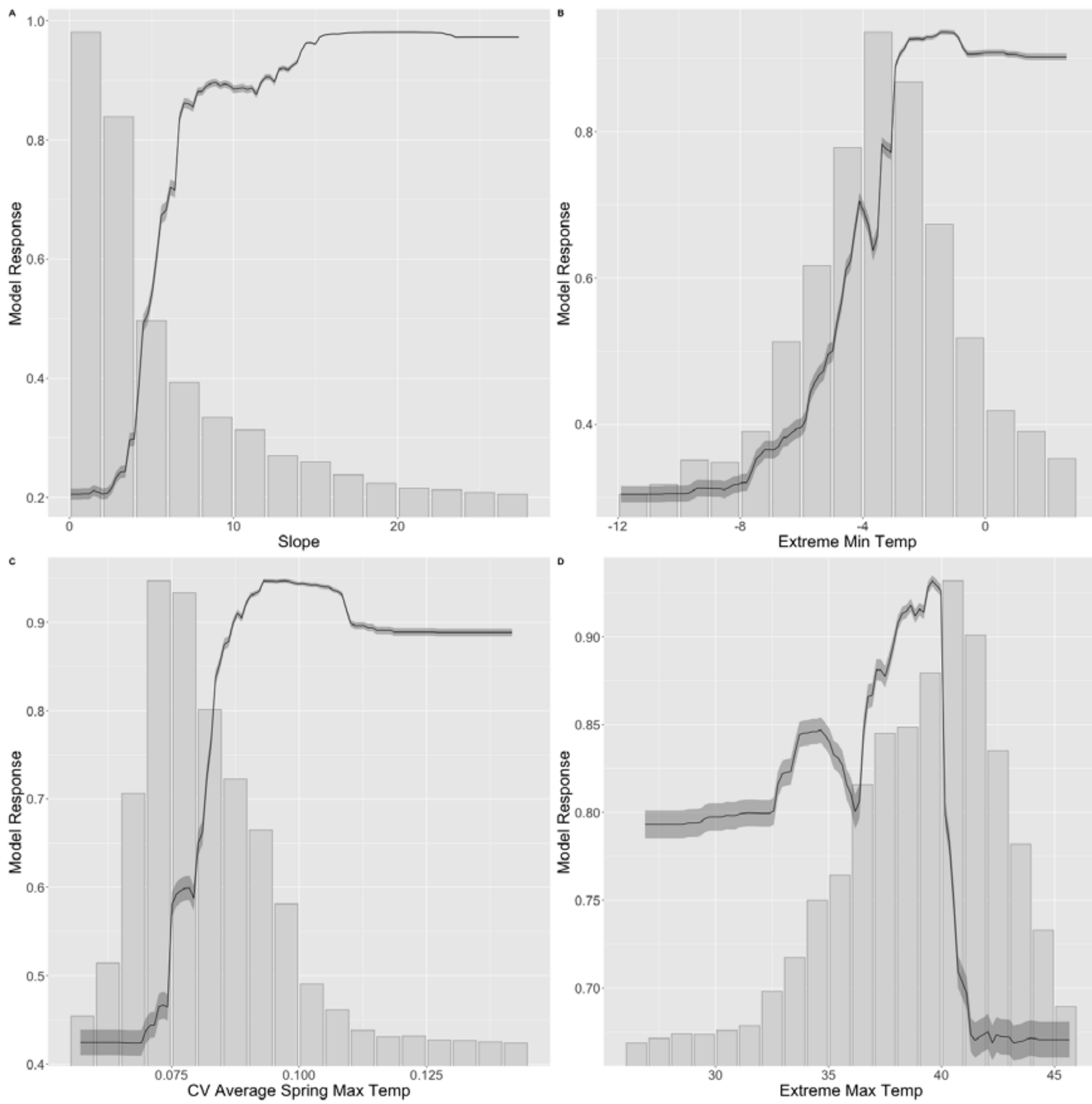

Figure 14. Partial response curves for the environmental variables included in the Random Forest ensemble model for *Aquila chrysaetos* nest habitat. Histograms represent the range of each environmental variable across the x-axis, and predicted dependence relative to habitat suitability values are on the y-axis.

Model Discussion

Predicted habitat for *Aquila chrysaetos* nests appear to be concentrated in areas surrounding the prominent mountain ranges in the County (Figure 15). As typical for these species they tend to be in areas of higher slope, and correspondingly more moderate temperatures, avoiding both winter and summer extremes. The areas of highest habitat concentration were located along the Spring and Bird Spring ranges, and throughout the Highland and McCullough ranges. All models predicted habitat in locations surrounding the Sheep Range, as well as the Virgin Mountains. While these areas lack some information because they are DOE and Military lands for the most part, it might be fruitful to acquire additional data in these areas (Figure 15). It should be noted that our dataset included many localities east of the Sheep range in the Mormon mountains in Lincoln County that likely contribute to these nesting habitat predictions

The locality data for this species consisted of 472 records within the buffered modeling area, which had a high degree of overlap. Spatial thinning of the data reduced the number of localities used for training and testing to 225 records.

Standard Error

Standard errors for the ensemble model were highest (but still only moderate values 0.03) in the area near Goodsprings, and along the mountains bordering I-15 corridor west of the freeway (Figure 16). The rest of the County has relatively low error rates.

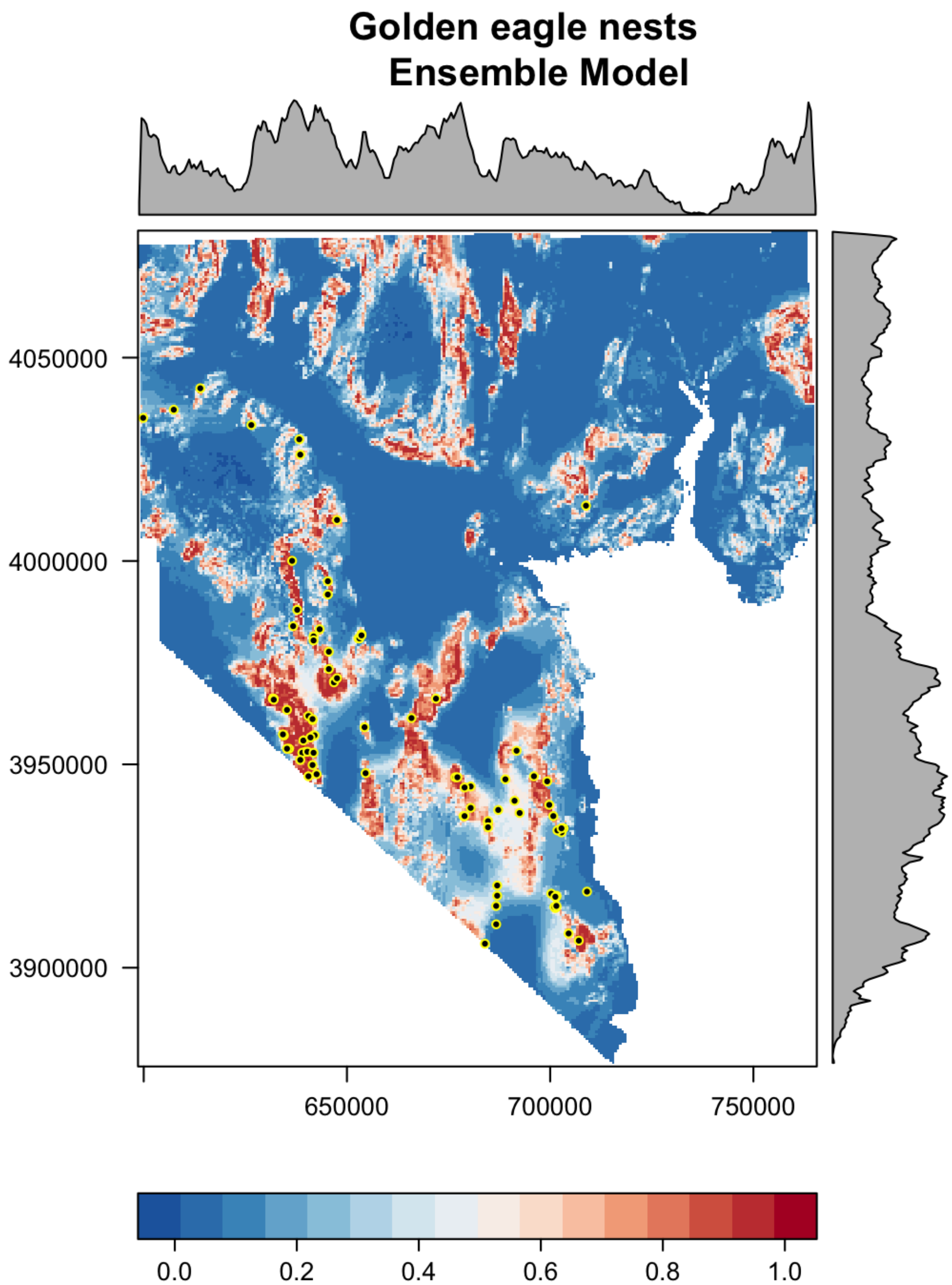

Figure 15. SDM map for *Aquila chrysaetos* nest habitat Ensemble model for Clark County, NV.

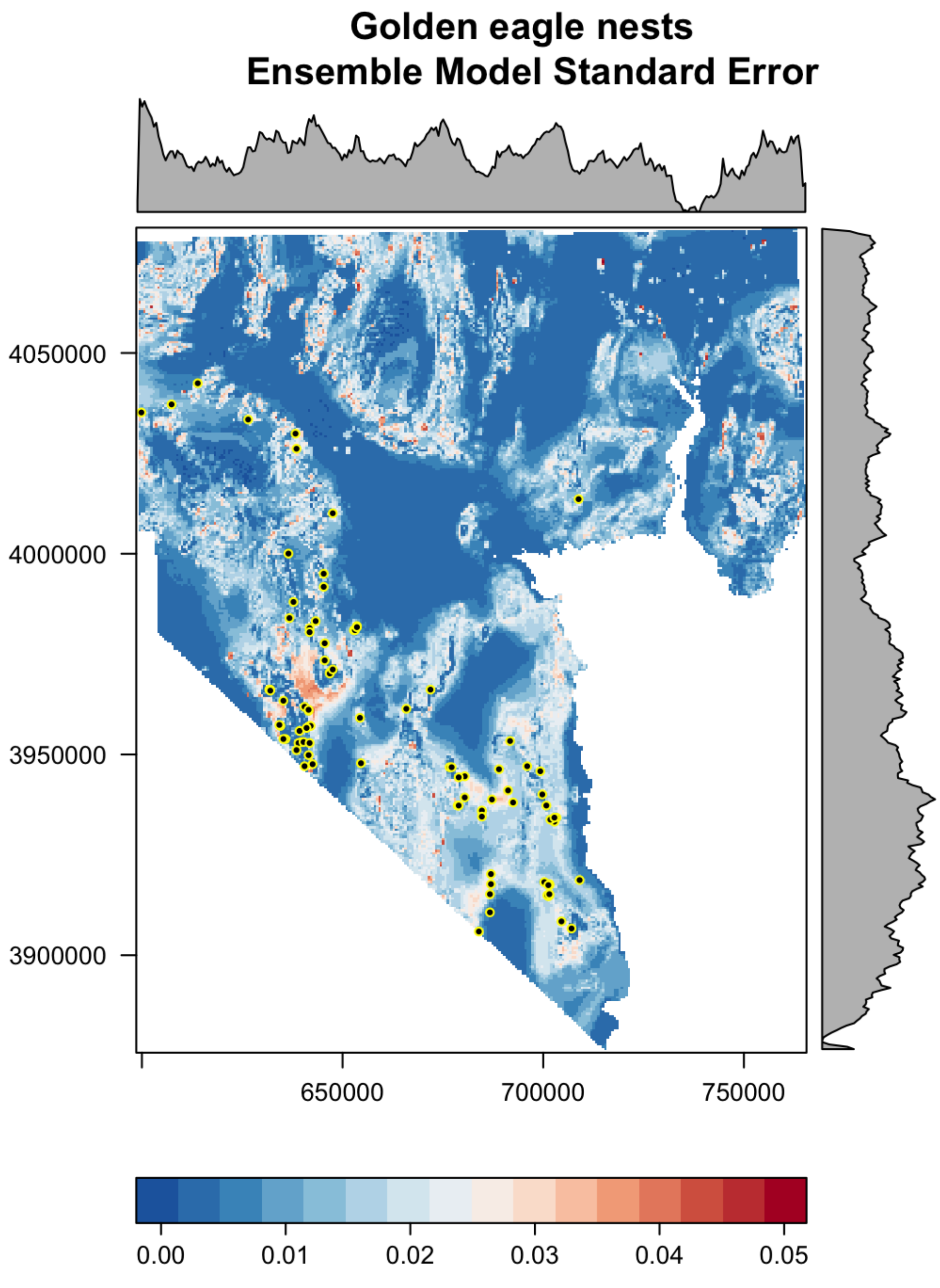

Figure 16. Standard Error map for the ensemble *Aquila chrysaetos* nest habitat Ensemble model for Clark County, NV.

Distribution and Habitat Use within Clark County

Golden Eagles nest in limited numbers throughout Clark County, Nevada. Every major mountain range and several smaller ones are occupied by resident Golden Eagles (unpublished NDOW raptor nest database). For example, there are multiple nests known from the Spring Mountains, Newberry Mountains, and McCullough Mountains. Modeled nesting habitat by the Great Basin Bird Observatory (Ammon 2015) was located largely within ecosystems classified as Mojave Desert Scrub and Blackbrush although it was restricted to mountains and cliffs within these ecosystems (Table 2).

Breeding pairs of Golden Eagles occupy and defend large home ranges with little overlap between the territories of pairs (Marzluff et al. 1997, Kochert 2002, DeLong 2004). Breeding season territories range in size from 20 to 54 km^2 (Kochert 2002). By contrast, in the Mojave Desert of southern California, Golden Eagle home ranges averaged 307.8 km^2 (SE± 66.4) (Braham et al. 2015). New technology that provides a high degree of spatial returns could partially account for the increased numbers on the newer analysis. In high density population with abundant nest substrate and high prey availability, occupied nests could be situated as closely as <1 km between neighboring pairs in some areas (Kochert et al. 2002). In Clark County, known adjacent nests are considerably further apart than reported in the literature (unpublished USGS Golden Eagle nesting database, NDOW raptor nest database).

Foraging has been documented in most the habitat types occurring in Clark County. Mojave desert scrub habitats in the expansive valley bottoms and outwash plains of Clark County comprise a great deal of the foraging areas, as do mountain slopes, and peaks (Longshore et al. *In Prep.*). Much of what we know about eagle habitat use comes from prey base studies. However, recent advances in tracking technology have provided opportunities to collect data on Golden Eagle movements relative to habitat use and foraging bouts. Golden eagles also forage near rural communities. Furthermore, eagles also fly over urban areas, and have been observed flying directly over the city of Las Vegas (Longshore et al. *Unpublished Data*). While Golden Eagles are capable of taking large prey such as bighorn sheep (*Ovis canadensis*) lambs or mule deer (*Odocoileus hemionus*) fawns, studies of prey delivered at nests in Clark County indicate black-tailed jackrabbits (*Lepus californicus*), rock squirrels (*Otospermophilus variagatus*), and cottontail rabbits (*Sylvilagus auduboni*) comprise a great deal of prey items delivered to young eagles (Dawson 1923, Bent 1961, Johnson et al. 2015). Other items include many medium-sized mammals, birds, reptiles and even fish. Golden eagles also will eat carrion that is scavenged from roadkill, escapees from sportsmen, or as refuse from agricultural activities (Olendorff 1976, Brown 1992, Kochert et al. 2002, Longshore et al. *In Prep.*).

Golden eagle nesting areas are frequently in remote mountainous areas, although a few are surprisingly close to human recreation sites (unpublished NDOW raptor nesting database). The known Golden Eagle nests in Clark County are all on cliff substrate. There are no known tree nests. In southwest Idaho, nesting density was found to depend on availability of good nesting substrate and territorial intolerance, but nesting substrate was more important than the latter factor (Beecham and Kochert 1975). Nests are large and made of sticks, often six feet across on the nesting platform with a central area lined with fine grasses, yucca leaves, pine boughs, and other materials. The accumulation of materials may be several feet thick, with extreme examples measuring upwards to 20 feet tall (Ellis et al. 2009). Most eagle nests have a commanding view of the surrounding area (Dawson 1923).

Resident Golden Eagle pairs generally remain in long-term pair bonds, but mates are sometimes lost due to a variety of reasons (e.g. mortality, intraspecies agonistic encounters), and in that case a mate may be replaced. Mates can be replaced rapidly, ranging from 1-8 days to replacement in Wyoming, if there are sufficient non-breeding adults in the local population (Philips et al. 1991). Courtship begins in December or January. Territories are often identified by the undulating flight of pairs, which is a behavior associated with courtship or territory defense in Golden Eagles (Harmata 1982). The behavior consists of a rise upward, tucking of the wings while continuing on a forward trajectory that dips, only to open the wings again and rise up and repeat that behavior (Dawson 1923). Fresh sprigs of vegetation such as pine boughs or *Ephedra* spp. In the Mojave Desert (Joe Barnes – NDOW, Pers. Comm.) may be brought to the nest as well, which is an indication of an occupied territory. Activity near the nest is generally very secretive; however, undulating flights often occur in front of the nest cliff face. Usually one or two eggs are laid, but there has been documentation of three eggs and rarely four (Beecham and Kochert 1975). Eggs may be laid in February or March and require 41-45 days to hatch (see Kochert et al. 2002 and Watson 2010 for associated citations). For the first three weeks, nestlings are not able to thermoregulate on their own, thus are particularly vulnerable to disturbance. For about 4 weeks, the eaglets are downy white. Another four weeks their plumage emerges as dark brown feathers, and for the next three weeks they continue to develop. Fledgling plumage is a little darker than adults with white windows in the wings and at the base of the tail persists for one year. Full adult plumage is acquired at about four years of age. Fledgling eagles in Clark County are known to have travelled as far as the Pinacate Region of northern Sonora, Mexico on their first summer (Joe Barnes – NDOW, *personal communication*). Eagles that are too young to breed or unpaired adult birds are also known as floaters and may range continentally as they mature and seek their own territories (DeLong 2004).

Ecosystems

Table 6. Ecosystems within Clark County, and the area (Ha) of Low Medium and High predicted suitability within each ecosystem for the models using all localities, and nesting localities only

	All Localities			Nesting Localities		
Ecosystem	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Alpine	0	113	10	124	0	0
Blackbrush	21339	188322	204437	158241	120348	135854
Bristlecone Pine	0	3091	4442	7565	0	0
Desert Riparian	207	4619	5335	10166	14	0
Mesquite Acacia	5510	9535	5135	16651	2667	901
Mixed Conifer	0	491	26839	27076	259	2
Mojave Desert Scrub	586508	555688	212613	1125187	144660	87801
Pinyon Juniper	2210	19448	94030	84043	18646	13041
Sagebrush	23	2234	2435	3954	300	450
Salt Desert Scrub	15322	43134	23881	63187	10439	8912

Ecosystem Level Threats

Widely known and direct ecosystem level threats include electrocution from landing on small poorly configured power poles, collision with transmission wires, gunshots, vehicular collisions while pursuing prey or scavenging roadkill, and toxicants such as lead shot from carcasses and misuse or non-targeted mortality by insecticides and rodenticides (DeLong 2004). With recent emphasis on renewable energy the proliferation of wind turbines to generate energy are the newest threat with considerable impacts to Golden Eagles in some areas of the western United States. Those direct threat factors can often permeate the entire landscape. Indirect ecosystem level threats include lack of prey availability and habitat degradation due to land use changes from renewable energy development (particularly solar arrays), transportation and utility corridors, and urban development.

Power poles are an attractant to raptors, especially at locations with few natural perches, because they provide an aid to habitat surveillance for prey (APLIC 2006). Areas of higher prey density may increase the attraction to these features. The broad wingspan of Golden Eagles increases their risk of electrocution by allowing them to span the distances between energized conductors and (APLIC 2006). The rates of Golden Eagle electrocutions may have declined during the past 30 years due to utility company efforts to reduce risk (APLIC 2006); however, electrocution risk is still great on many older or non-retrofitted utility lines in rural areas of Nevada (Joe Barnes and Cris Tomlinson – NDOW, Pers. Comm.).

While electrocution has long been known as a source of increased mortality on Golden Eagles, one study of 126 eagle carcasses along power lines indicated that 84% of the carcasses were killed by gunshot rather than electrocution (Olson 2001).

How wildfires affect prey populations for Golden Eagles is currently unknown, but the loss of cover over large areas of desert habitat could reduce jackrabbit abundance. Under similar circumstances of habitat conversion from shrubland to annual grassland in the Great Basin, eagles switched prey bases and average annual clutch sizes decreased (Steenhoff and Kochert 1988).

Population Trends

The population trends for Golden Eagles in the west are no doubt reduced from Pre-Columbian levels due to three primary factors. First, organized and sustained predator and prey controls have been instituted in some parts of the region for nearly a century. Second, active hunting by shooting, as well as poisoned baits (e.g. carcasses laced with poison), and non-target poisoning with eagles consuming rodents laced with rodenticide have reduced eagle populations. And third, the endeavor of egg-collecting for the science of oology is considered to have detrimentally influenced Golden Eagle populations early in the last century. However, the greatest influence of previous egg collection was usually closer to heavily populated municipalities like San Diego or San Francisco, California in the past.

While there are several large-scale efforts to determine population trends across the nation, the estimates tend to have wide margins of error. For example, a recent investigation of the Golden Eagle population in the western United Sates, based on the detection of 172 eagles in 148 aerial line transects across 12 western states, estimated a total population of 27,392, with a 90% confidence interval of 21,352 to 35,140, eagles (Good et al. 2007). However, this survey dealt primarily with the interior west; and large portions of the west, i.e. most of California, southern Nevada, southern Arizona, and southern New Mexico were not surveyed in this investigation, nor were coastal Oregon and Washington. Recent surveys by West Inc. reported low detections generally, and wide error on estimates of Golden Eagle density in the Mojave Desert of NV and California.

Threats to Species

All of the direct and indirect threats listed above are influential with this species.

Two of three eagles that were studied by USGS in Clark County in 2015 were killed prematurely. While one of them likely died in an encounter with a rival eagle, it also had measurable levels of rodenticide in its system. A second eagle, which also contained measurable levels of rodenticide, died from a collision with a car on Interstate 15 south of Mountain Pass, California. More data will be required to understand the role of poisoning in Golden Eagle populations.

Renewable energy development presents threats to Golden Eagles as well. First, wind energy is well documented for Golden Eagle mortalities due to wind turbine blade strikes. While wind energy is currently not a factor in Clark County, there are plans for increased use of this energy source in the future. Secondly, renewable energy (e.g. wind and solar) industries require extensive open spaces in open flat country that were once prime foraging areas for resident Golden Eagles. Thus, if enough habitat is converted to solar and wind farming there could be an influence on Golden Eagles, potentially through expanded territory sizes needed to support reproduction. Whether this would reduce fecundity, or the number if territories in the region is unknown. One important consideration of this scenario is that travelling greater areas may place the eagles in contact with more risk factors for mortality (Wiens et al. 2017).

Urban encroachment on Colorado's Front Range (i.e., at the eastern foot of the Rocky Mountains), was attributed to the abandonment of historically used Golden Eagle nests (Phillips 1986). Human disturbance or activity may cause nest abandonment, render a nest less productive, or prevent a suitable nest site from being used (GBBO 2010). Subsidized predators may also reduce the prey base in proximity to the ever-increasing boundaries of municipalities in Clark County (Esque et al. 2010).

Summary of Direct Impacts

Primary direct impacts most important to Golden Eagles include electrocution due to small gauge power lines (Benson 1982), vehicular collisions from eating roadkill, secondary poisoning due to lead shot and rodenticides in the environment, and loss of habitat due to renewable energy and urban development. High suitability habitat for all localities is 52% contained within conserved areas, while high suitability nesting habitat located within conserved areas comprises 31%. Twenty percent of predicted high suitability habitat for Golden Eagles is already located in disturbed areas , while very little nesting habitat falls in already disturbed areas. Potential impacts occur in 28% of highly suitable habitat considering all localities, and 70% of high habitat for nesting (Table 7).

Table 7. Categorized modeled habitat values (High, Medium, and Low) and the average area (Hectares) predicted in the potential impact areas, conservation areas, already disturbed areas, and overall area.

All Localities Model				
Habitat Level	**Impact**	**Conserved**	**Disturbed**	**Area (Hectares)**
High	46058	84821	31861	162740
Med	58241	231577	71045	360863
Low	22226	195901	17249	235376
Nesting Localities Model				
High	119215	52745	69	172029
Med	6166	89366	873	96405
Low	1526	371063	119590	492179

Existing Conservation Areas/Management Actions

The Golden Eagle is federally protected by the Migratory Bird Treaty Act, the Bald and Golden Eagle Protection Act, and the Lacey Act. The Nevada Wildlife Action Plan considers the Golden Eagle a Species of Conservation Priority, and recommends the following actions: protection of nesting and roosting sites, research to develop non-lethal wind turbine designs, and the continuation of helicopter surveys to monitor the population (Wildlife Action Plan Team 2012).

The Nevada Comprehensive Bird Conservation Plan considers the Golden Eagle a Conservation Priority Species, and recommends adequately managing habitat, including cliff nesting sites; managing habitats to encourage healthy prey populations; using Eagle Guards on transmission lines to minimize electrocution deaths; and the burial of mining drip lines to minimize risk of poisoning (GBBO 2010). Partners in Flight's population objective for the Golden Eagle is to increase the statewide population from 6,200 individuals to 6,800 individuals (Rosenberg 2004).

Both the Nevada Wildlife Action Plan and Bird Conservation Plan emphasize a need for improved monitoring to inform adequate and quantified population trends. Recent state-wide efforts by NDOW have been focused on compiling an inventory of existing cliff-nesting raptor nests, with emphasis on Golden Eagles, and were not designed to assess territory status or population size (Joe Barnes and Cris Tomlinson – NDOW, *personal communication*).

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