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COMPARING TWO PREDICTIVE MODELS TO DETERMINE SUITABLE HABITAT FOR THE COMMON BLACK-HAWK *(Buteogallus anthracinus)*

Final Report

BIRD'S EYE VIEW GIS

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Project Overview

The goal of this project was to produce two robust, defensible, and predictive models to inform the potential distribution and quality of potential Common Black-hawk (CBH) nesting habitat in New Mexico. Two modeling approaches were used, one a deductive expert opinion based model and the other an inductive nest site based model. The results were evaluated in terms of relative similarities and differences and quantitatively against a set of nest occurrence points.

The models utilized similar input datasets. Typically data gathering and formatting requires significantly more effort than the modeling itself. Therefore, it was very practical to use and compare two modeling techniques once the input data has been prepared. By comparing the rule-based deductive model of species habitat preference with the inductive approach, holding input data fairly constant, the degree of variability in model results attributable to the modeling method used is better understood.

Several common black hawk experts suspect that the CBH may be expanding its range northward due in part to climate change. This project has identified areas that have similar environmental niche conditions to currently occupied habitat. These areas are candidates for field surveys for nest locations that may represent this northward expansion. Therefore the results provide a much better understanding of both the current range and potential habitat for the Common Black-hawk than previously existed. These data and the other analysis results should prove useful in future recovery planning efforts. This has also provided insight into the best technique to use for modeling habitat for other riparian species with limited ranges such as Arizona gray squirrel.

Black-hawk Nesting Data

An initial search was done to obtain all CBH occurrences. The initial search returned over 300 occurrence records many of which were nest sites. It was determined that nesting locales would be most informative of potential habitat. Hawks can cover a variety of terrain during migration but will nest in more suitable habitat. The nest site data were used to drive the inductive model, and to evaluate model outputs from both models. An emphasis was placed on gathering nesting sites beyond the core population area in the Gila. This was done to ensure that areas of recent expansion are represented in the model. Occurrence points were gathered from numerous sources including: the New Mexico Ornithological Society database, New Mexico Natural Heritage occurrence data, the 2010 Pilot Riparian Raptor Surveys and Feasibility Assessment for Project Black Hawk (Neal 2010), Ron Troy and Dale Stahlecker, Giancarlo Sadoti (Sadoti 2008), Mark Watson (personal communication), and records maintained by Hira Walker of the New Mexico Department of Game and Fish (NMDGF). A summary of the data found is in Table 1.

Source	Nest Records	Training Nest Records	Non-nest Records	Total Records
NMOS db	179	30	48	227
NMNHP	52	52	0	52
Project Black Hawk	24	24	0	24
Troy/Stahlecker	12	12	0	12
Watson	0	0	2	2
NMDGF	1	1	9	10
TOTAL	**268**	**119**	**59**	**327**

Table 1. Common Black-hawk occurrence data summary

All of the occurrence data points were normalized in terms of geospatial projection and attribute columns. Redundant records were removed and an estimate of accuracy entered based on information from the source. To be considered for inductive model training the accuracy had to be greater than +/-100 meters and it had to be a nest location. The training data contained 119 points (Figure 1).

The NMOS data were mapped via Geographic Names Information System (GNIS) points which placed them at the center of towns, lakes mountain ranges etc. It was possible to increase the accuracy of some of those points based on accompanying descriptions. That was done where possible. This allowed some of these points to be included in the model training set.

Several sources were queried but produced no results, these included: the Breeding Bird Survey database, NatureServe, the Global Biodiversity Information Facility (GBIF), the University of Kansas Biodiversity Institute, and the International Union for Conservation of Nature (IUCN).

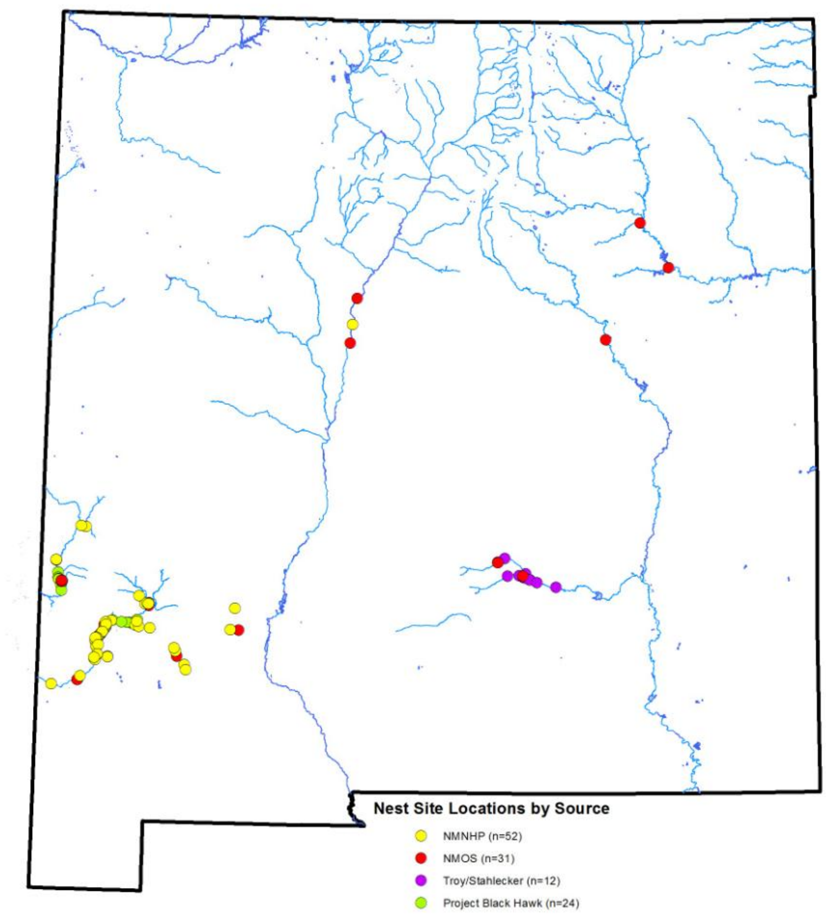

Figure 1. Nest site locations by source

Two Modeling Approaches

Two modeling approaches were developed and compared, one deductive and one inductive. In the deductive approach, the environmental requirements for the target species were identified via literature reviews and experts in CBH distribution within New Mexico. A weighting scheme for environmental factors was developed based on expert input. Potential habitat was generated by combining the distribution of environmental characteristics via the weighting scheme. The inductive approach involved taking measurements of environmental characteristics important to the species from CBH nest locations and using Maxent to generate potential nesting habitat.

Environmental Data

A literature review was performed to gain an understanding of the habitat requirements. Common black-hawk are riparian obligates associated with mature riparian woodlands (Sadoti, 2010). Nest sites found for the this study ranged between 1,150 and 2,000 meters above sea level. The woodland species they've been shown to nest in include: cottonwoods (*Populus spp*.), willows (*Salix spp*.), Arizona sycamore (*Platanus wrightii*), box elder maple (*Acre negundo*) and other deciduous trees (Sadoti, 2010). In more sparsely wooded or higher elevation areas they have been observed nesting in cliffs, ponderosa pine (*Pinus ponderosa*), Douglas fir (*Pseudotsuga menziesii*) Arizona alder (*Alnus oblongifolia*), and netleaf hackberry (*Celtis reticulata*; Mike Neal personal communication, August 8, 2011). The individual trees chosen as nest sites tend to be tall mature trees with broad crowns (Schnell 1998).

These findings suggested that vegetation type, canopy height, canopy cover, distance to perennial surface water, elevation and climatic data would be important environmental inputs to the models. Vegetation data were obtained from LandFire and the Southwest Regional GAP. Comparison of nest sites against each source, along with aerial photography, showed that the LandFire data more consistently identified riparian vegetation types. LandFire was also the source for Canopy Cover and Canopy Height. These data have a 30 meter resolution. Each raster dataset was clipped to New Mexico.

Climatic data was obtained from the PRISM Climate Group at Oregon State University. Data representing U.S. average annual precipitation from (1971-2000), U.S. average annual minimum temperature (1971-2000) and U.S. average annual maximum temperature (1971-2000) were obtained. These data were converted to American Standard Code for Information Interchange (ASCII) grids. The temperatures were then converted to Fahrenheit and the data clipped to New Mexico.

A statewide digital elevation model was obtained from the U.S. Geologic Survey. This data has 30 meter resolution. Perennial streams were obtained from the 2010 National Hydrographic Dataset (NHD) high resolution geodatabase. From perennial streams a Euclidian distance raster was generated and will be referred to from here on out as distance to streams. Since input data were at widely varying resolutions all data were resampled to an intermediate cell size of 200 meters.

Deductive Model

This model is a classic raster based site selection analysis. The weighted sum operation was used with the input variables to generate the model result. The model was weighted via expert opinion. The experts who gave feedback included: Mike Neal (HawkWatch International), Leland Pierce (NMDGF), Christopher Rustay (Playa Lakes Joint Venture), Giancarlo Sadoti (NMNHP), Ron Troy (The Nature Conservancy), and Hira Walker (NMDGF).

Pair-wise Comparison

A form of analytic hierarchy process (AHP) was used to rank the habitat variables from expert input. AHP is a decision making framework that provides a means of assigning numeric weights to subjective preferences. Each CBH expert was asked to rank the habitat variables in a pair-wise fashion. The AHP pair-wise approach lets each decision maker focus on one piece of the overall problem at a time. The final results can then be put into a matrix from which the overall habitat model weights can be derived. AHP was developed by Dr. Thomas Saaty at the Wharton School of Business (Saaty, 1980).

Each expert was presented with the suite of environmental variables as unique pairs. The site MakeItRational (http://makeitrational.com) was used. This web based approach allowed for each expert to receive the internet link via email, rank the variables at a time and place of their choosing, and save the results back to the site. The seven habitat variables resulted in 21 pairs of variables to rank relative to one another. Each pair could be ranked from equality to total dominance with the possibility of intermediate vales on a 9-point scale (Figure 2).

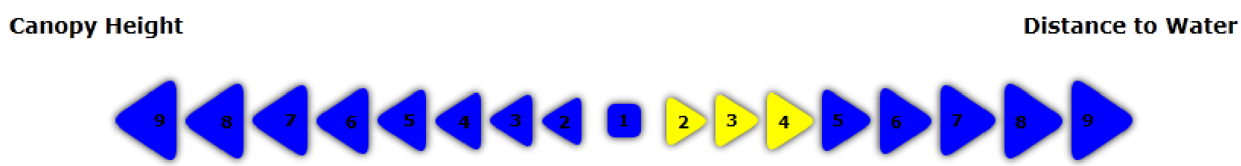

Figure 2. Example of one pair-wise comparison

When all the rankings were complete the site also provided the AHP tools to calculate the final rankings. The results showed that vegetation type, distance to water and canopy height as the three most important variables (Figure 3).

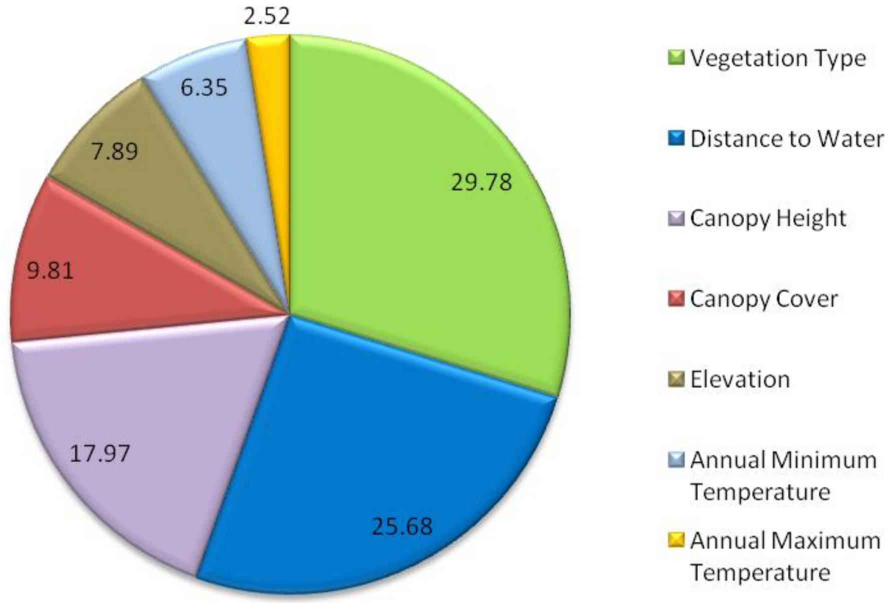

Figure 3. Pair-wise environmental variable ranking results

The deductive model was constructed in ArcGIS 10 using Spatial Analyst and the Weighted Sum tool. This is one of many geoprocessing tools available within ArcGIS 10. This tool works with a set of rasters which have been reclassified on a common numeric scale. The tool then multiplies the values of each raster input by the specified weight. It then sums all the rasters together to create the output.

Rasters were reclassified to values of 1 - 10, with ten representing optimum conditions and one poor conditions. Some inputs were continuous rasters (climate data, elevation, and distance to water) and others were categorical (vegetation type, canopy height and canopy cover). To determine the break points for reclassifying the rasters we used the Extract Multi Values to Points tool. This extracts the cell values of each environmental variable at each nest site point. The data for continuous rasters were then summarized to get the minimum, maximum and mean values for nest sites (Table 2). One standard deviation on either side of the mean was used to define the optimum value of 10 for an environmental variable. The values between the minimum and maximum values and the previously assigned optimum values were assigned values of 5. Other values beyond the minimum and maximum were assigned values of 1 representing poor conditions.

Variable	Min	Max	Mean	St Deviation
Annual Minimum Temperature (F)	32.96	43.79	39.23	1.71
Annual Maximum Temperature (F)	68.25	78.48	73.68	2.40
Elevation (meters)	1,151	1,899	1,494	165
Distance to Streams (meters)	0	7,697	317	1,054

Table 2. Values of continuous rasters at nest sites

A summary table was created against the nest site values for all categorical environmental variables. These summary tables counted the number of nests in each vegetation type, canopy cover class and canopy height class. These rasters were then reclassified into values of 10, 7, 3 and 1 based on the prevalence of the nest sites in each category. The final result of the deductive expert opinion based model is seen in Figure 4.

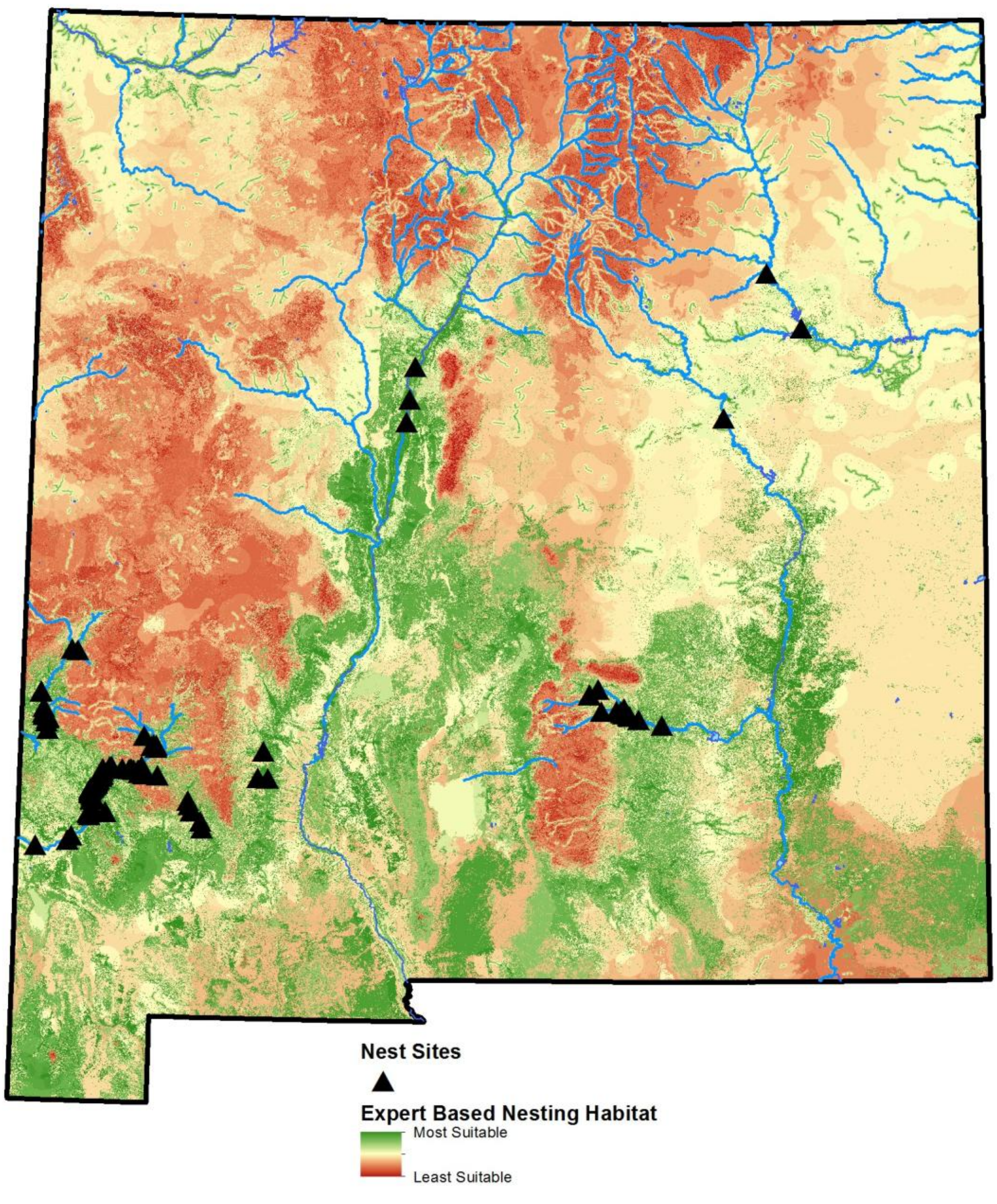

Figure 4. Deductive expert opinion based model

Deductive Model Evaluation

The values in the expert opinion weighted suitability model ranged from the 4.4 (least suitable) to 100 (most suitable). The model values for the 119 nest sites were obtained to get a measure of how well this model would predict their presence. The mean model value for nest sites was 87.6. The maximum value was 100 and the minimum value 52.6 with a standard deviation of 11.4. These figures show that the vast majority of nest sites would be predicted well via the deductive model.

Inductive Model

MaxEnt (v3.3.3j) was used to create the inductive model (Phillips 2004). This is a software product developed and maintained by Princeton University. It is based on the maximum entropy approach for species habitat modeling, whereby it takes as input a set of layers or environmental variables (such as elevation, precipitation, etc.), as well as a set of occurrence locations, and produces a model of the range of the given species (Phillips 2006). MaxEnt was chosen for several reasons. First it does not require species absence data. Second, it has been shown to perform well with species that have restricted ranges and when there are a limited number of occurrence points, as is the case for CBH. Third it allows for environmental data be both continuous and categorical.

MaxEnt Environmental Variables

MaxEnt requires model training occurrence data be in a specific format. All occurrence points were converted to the following format:

```
"SName","Long","Lat"
Buteogallus anthracinus,-104.68195,34.93861
Buteogallus anthracinus,-104.404761,35.694374
```

Maxent also requires that environmental data need to be in ascii grids of the same resolution, extent and pixel alignment. As stated earlier, the input environmental data had spatial resolutions ranging from 30 meter to 800 meter. Having the model developed at the resolution of the coarsest input was not practical for a species with such local scale habitat requirements. It also wasn't sound to resample the coarse data down to 30 meter resolution. Therefore an intermediate resolution of 200 meters was chosen. The Export to Circuitscape Tool for ArcGIS was used to process all raster inputs for use in MaxEnt (Jenness 2011).

Eighteen different runs were tried before the most robust model was developed. The runs employed differing spatial resolutions, different combinations of environmental layers and different MaxEnt settings. Elevation was left out of the final runs since it is tied to temperature, precipitation and vegetation types. Feedback from the experts on the deductive model weights included suggestions for additional variables that might be important to characterize CBH nesting habitat. It was suggested that prey availability would be important. CBH prey consists largely of aquatic and semi-aquatic vertebrates and macro invertebrates (Sadoti 2010). Unfortunately data representing the availability of those taxa does not exist statewide. Surrogates for prey were suggested including measures of geomorphic complexity of the local stream system**,** riparian vegetative zone width**,** bank vegetative protection, channel sinuosity, and quantity/quality of epiphaunal substrate (Mike Neal personal communication, August 8, 2011). Sadoti mentioned that arrival time and breeding is correlated with leaf-out of riparian trees, which is related to minimum spring (e.g., March-April) temperatures. Additionally, he felt that CBH may prefer nest sites that are closer to water, further from forest/woodland edges, and in larger forest/woodland patches when compared to random locations in riparian forests. Sadoti also felt it would be useful to incorporate some measure of human presence (Giancarlo Sadoti personal communication, August 30, 2011).

All of the additional expert suggested environmental variables were considered. Many were either impossible to generate due to a lack of source data, lack of time or were not possible to represent at the scale of the study. Those that fall into the latter category are local niche characteristics that would require a much finer grained analysis. All the remaining environmental variables that were possible to represent at the scale of the study were created and tried as inputs to the model. A measure of stream sinuosity was generated against a digital elevation model and perennial streams (Dilts 2009). Average minimum temperature for the months March and April (1971 - 2000) were acquired from the PRISM group. These two rasters were averaged to create an average minimum spring temperature raster. A forest fragmentation index was generated against the woodland/forest classes of the vegetation type raster (Parent 2009). The tool divides the landscape up into patch, edge, perforated, and core. The core category is further subdivided into large, medium, and small cores. Human presence on the landscape was represented using the USGS Human Footprint of the West (Leu et al. 2008). This dataset classifies human impact on the landscape into 10 classes. It incorporates a wide variety of human activities including: roads, energy development, agriculture, human population density, railroads, power lines, grazing and wildfires.

Several researchers felt that average annual maximum temperature was not as important as average annual minimum temperature. Given that it was also likely to be high correlated with average annual maximum temperature it was left out of the final analysis.

In early runs the distance to streams variable was heavily driving the model. By definition riparian habitat is associated with water-as would be a riparian habitat obligate nester. The data backed this up, the average Euclidean distance from a nest site to perennial water is only 317 meters. Asking the model to predict probable nesting habitat statewide, in an arid state, makes this variable overly important. Therefore a proximity to perennial waters mask layer was created to minimize the effect of this variable, and to force the model to work harder to predict the nuances of the habitat. The mask was a 7 kilometer buffer around perennial streams. This distance corresponds to the farthest distance from a nest site to perennial streams in the state. The mask constrained the model to operate within 7 kilometers of a nest site. The layer itself wasn't used by the model since all cells have the same value.

Stream sinuosity was shown in jackknife tests (see below) of variable importance to be insignificant in determining nesting site locations. This is due to its extremely high correlation to distance to streams rather than its the actual importance in predicting CBH nesting habitat. The variables used in the final run are shown in Table 3. Distance to streams and average annual minimum temperature were the two most important variables. Average annual precipitation, vegetation type and average annual spring minimum temperature were also very important in predicting nest site locations. Forest fragmentation, canopy cover, human footprint and canopy height also contributed slightly.

Variable	Percent contribution
Distance to Streams	56.5
Average Annual Minimum Temperature	16.1
Average Annual Precipitation	9.6
Vegetation Type	8.5
Average Annual Spring Minimum Temperature	5.2
Forest Fragmentation	1.9
Canopy Cover	1.3
Human Footprint	0.8
Canopy Height	0.1

Table 3. Variables used in the final run shown by their percent contribution to the model

A jackknife test is an alternative way to look at which variables are most important to the model. This test runs nine iterations as we had nine environmental variables. Each run excludes one of the environmental layers and the model is created with the remaining layers. Nine additional runs are then processed whereby each variable is used in isolation. Finally the model is run with all the variables. The result can be seen in Figure 5. The red bar shows the model gain when run with all variables. The dark blue bars show how well the model performs relative to that, when run it with just that one variable. We can see that the model does not gain much by being run against canopy cover, canopy height, forest fragmentation or human footprint alone. The teal bars show how well the model performs leaving that one variable out. Here we see that the model does not perform as well when the distance to streams is left out. This confirms the percent contribution shown in Table 3.

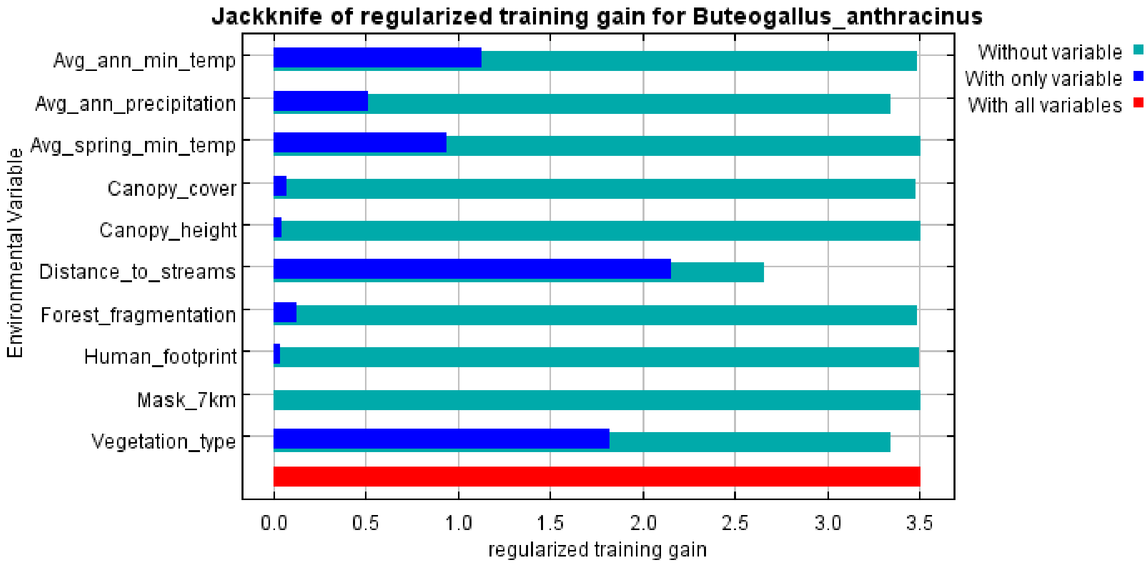

Figure 5. Jackknife test of individual variable importance

Figure 6 shows the results of the final run. Model output values range from 0 to 1 for probability of presence. Values of 1 represent the highest probability for nesting and 0 the least probability of nesting.

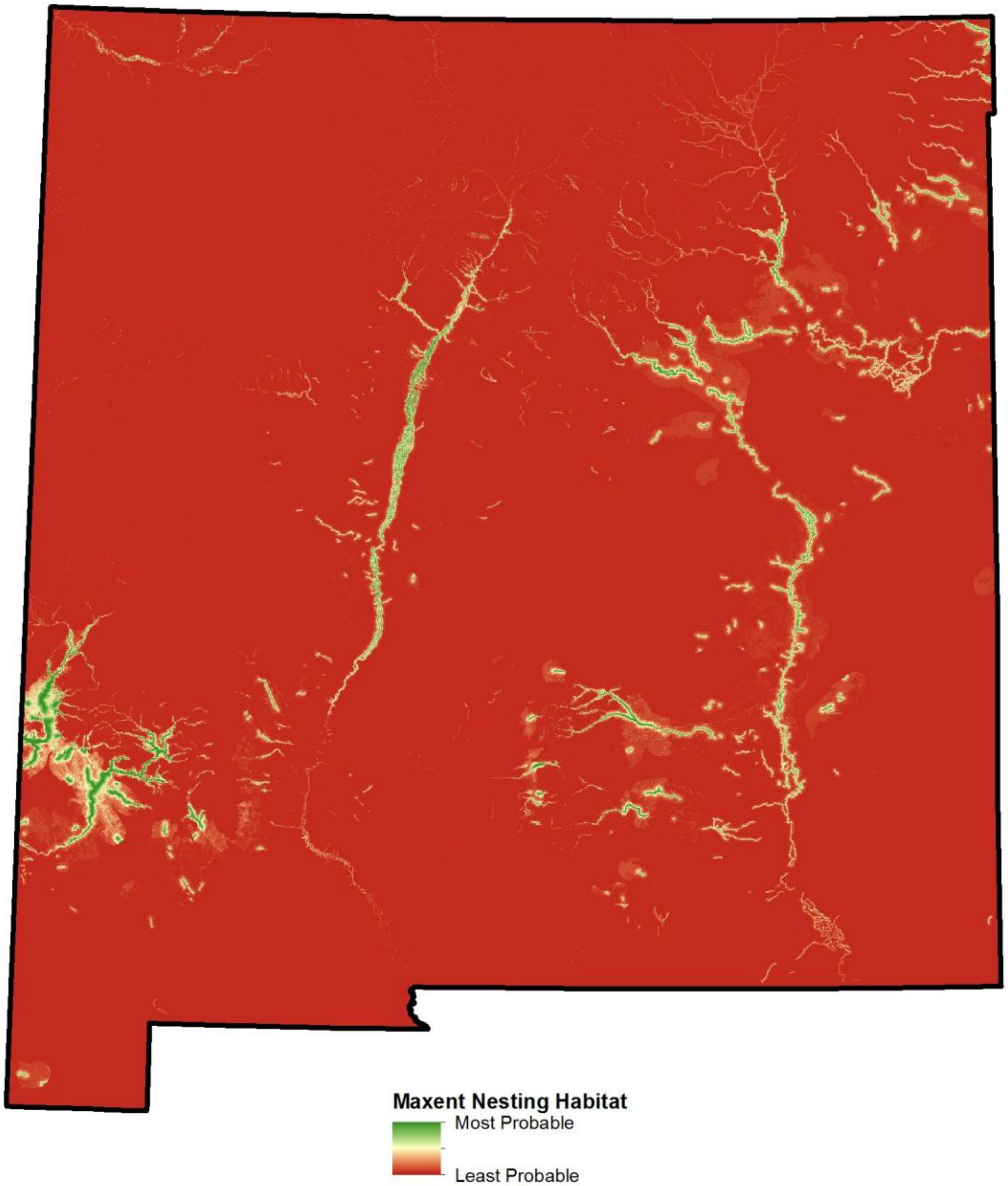

Figure 6. Result of the MaxEnt Final Run

Inductive Model Evaluation

MaxEnt is very strong at providing metrics one can use to measure the predictive power of a given model. One way to measure how well the model is performing is to have one set of occurrence points for model training and one for model evaluation. MaxEnt can measure how well the model predicts the presence of the evaluation points. Since we only had 119 nest sites it was difficult to choose a small set for evaluation. Instead the MaxEnt Random Test Percentage feature was used. This setting allows you to specify a percentage of the training points that can be set aside for evaluation. The percentage was set to 25% which resulted in 30 points being held out for model evaluation. In Figure 7 we see the predicted omission rate which is a straight black line. The omission on test samples is a very good match to the predicted omission rate which is a good indication of a model with good predictive power.

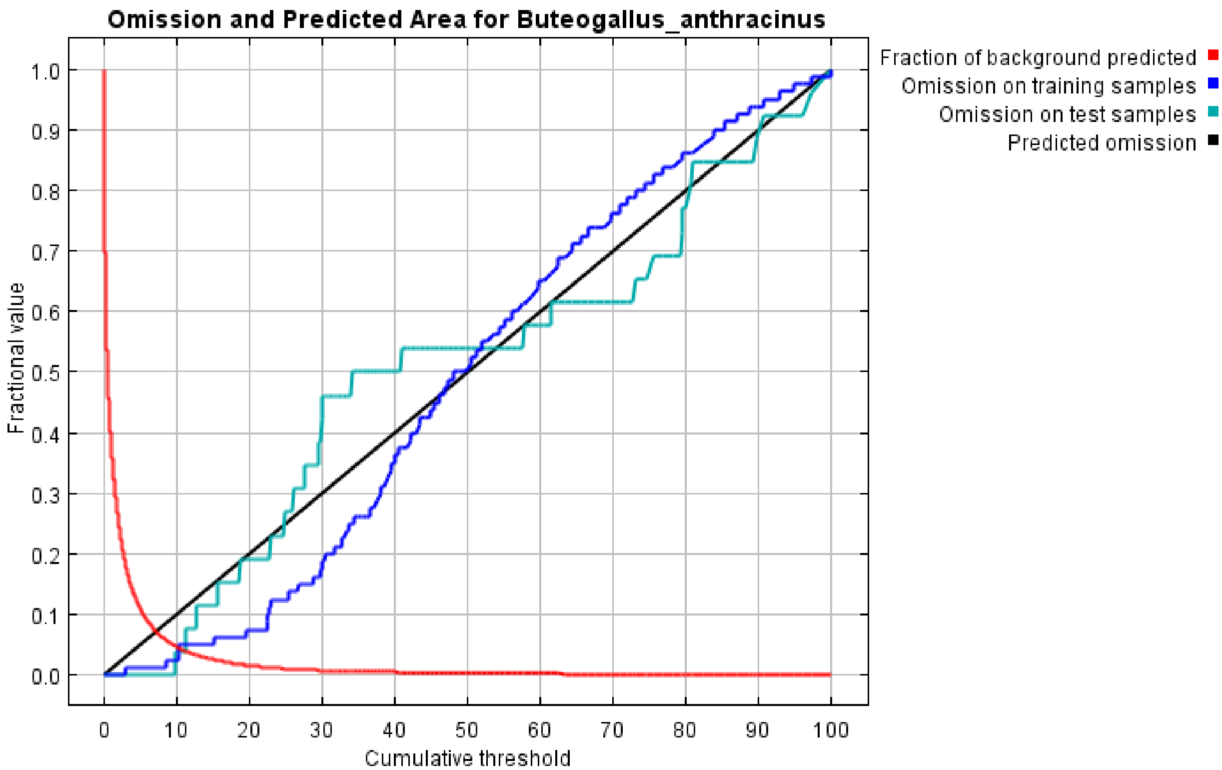

Figure 7. Omission vs. Predicted Area

Figure 8 shows the receiver operating curve for both training and evaluation points. A random prediction is shown by the straight black line. A model should obviously predict quite a bit better than a random prediction. The red line shows the fit of the model to the training data. The blue line shows the fit of the model to the evaluation data, and is the real test of the models predictive power. MaxEnt reports the area under each curve (AUC) as a value between zero and one. A random prediction has an AUC of 0.5. It is normal for the training (red) line to show a higher AUC than the evaluation (blue) line. For the final model the AUC was 0.991 for the training data and 0.990 for the evaluation data. This shows that the model has almost perfect predictive power against the training data and most importantly for the 25% of the nest site locations held out for evaluation. Once it was determined that the model was performing well the final run was trained on all 119 nest sites to get the most robust model possible.

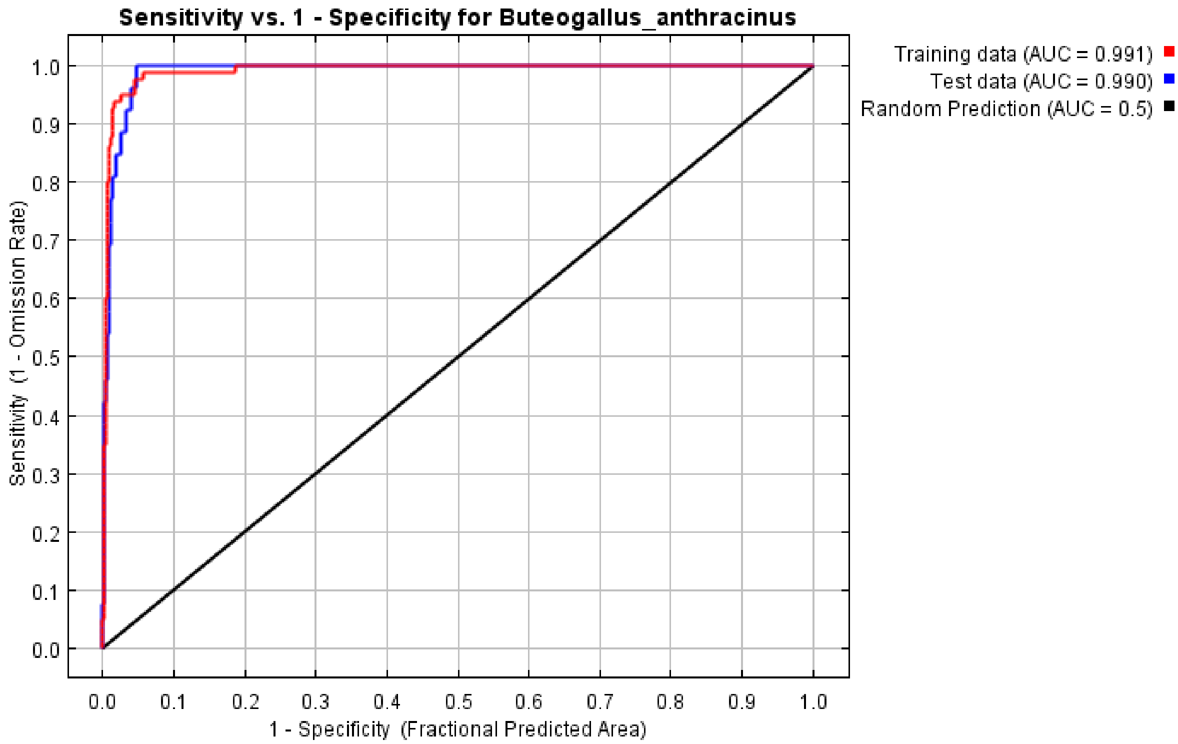

Figure 8. AUC curves for training and evaluation nest sites

Discussion

The goal of having an identical suite of environmental variables in both models was not realized. This is partially due to project planning. The pair-wise survey was sent out early in the process so that experts would have enough time to respond. By the time the inductive modeling was underway there was good feedback on the initial suite of environmental variables, and as a result several new variables were included in the inductive model. However, there was not sufficient time to go back to the experts and have them re-rank the new suite of variables. Five variables were used in both models (Table 4). In hindsight it would have been wise to get the expert input on relative variable weights earlier in the year. Then there would have been time to solicit their feedback on additional variables. However, the process for ranking expert opinion via MakeItRational and pair-wise variable comparisons worked very well and should be considered in future efforts.

Variables	Deductive Model	Inductive Model
Distance to Streams	✓	✓
Annual Maximum Temperature	✓	✓
Annual Minimum Temperature	✓	□
Average Annual Precipitation	□	✓
Average Annual Spring Minimum Temperature	□	✓
Existing Vegetation Type	✓	✓
Canopy Height	✓	✓
Canopy Cover	✓	✓
Elevation	✓	□
Forest Fragmentation	□	✓
Human Footprint	□	✓
Stream Sinuosity	□	□

Table 4. Variables used in the project

Many of the suggested environmental phenomena for predicting CBH nesting habitat are not modeled well in GIS yet. They represent local scale environmental niches which are difficult to assess using remotely sensed datasets. When looking at high resolution aerial photography of the sites where CBH nests were observed, many were in isolated riparian tree stands. These stands were not well identified via any existing vegetation datasets. All modern statewide vegetation datasets are derived from satellite imagery. Isolated or small patches of riparian woodlands are simply not represented well in these data. The related canopy cover and canopy height datasets also did not adequately represent these areas. If these datasets were stronger they would have likely been much more heavily used by the MaxEnt model. LiDAR data is a potential source for improving these datasets. Table 5 lists environmental datasets which would greatly enhance the model.

Both models displayed very good predictive power for identifying currently occupied nest site locations. The deductive model appears to have done this in spite of many false positives. That model identified many locations too far from streams to be likely nesting sites. On the other hand, the inductive model was purposely constrained to an area within 7 kilometers of perennial streams. If this same mask was applied to the deductive model the results would certainly be much more conservative. However, even with these stipulations it seems that the model developed in MaxEnt did a much better job of precisely identifying potential common black-hawk nesting habitat. The inductive model is a very strong predictor while not over predicting habitat. This author feels that the MaxEnt model is the more authoritative of the two.

The American Museum of Natural History is currently working a set of PRISM climate data representing future climate change scenarios. One feature of MaxEnt is the ability to project a model onto a different suite of environmental layers. These layers can cover a different spatial extent or may represent different future or past scenarios. When these data are available later in 2012 the MaxEnt model can be projected onto future climate scenarios which would show potential range shifts related to climate change.

Collectively the data synthesized from the common black hawk experts, the measures of conditions at current CBH nest sites and the model results constitute a robust new resource which can be used in developing a CBH recovery plan. These data should also serve useful for identifying new nest localities. As new localities are observed the model can be re-run to refine the potential nesting habitat layer.

Dataset
Prey availability
More accurate canopy height (LiDAR)
More accurate canopy cover (LiDAR)
Riparian vegetative zone width
Bank vegetative projection metric
Water temperature
Distance to stream source (spring etc.)
Watershed health metric
Quality/quantity of epiphaunal substrate
Future climate scenario's
Additional CBH Nest Locations
CBH Nest absence points - negative surveys

Table 5. Data which could strengthen the model

Glossary

ArcGIS 10 - a suite of desktop GIS software produced by the Environmental Systems Research Institute (ESRI). It is the industry standard and has robust capabilities for storing, analyzing, querying and displaying geospatial data. The latest product is version number 10.

Attribute columns - each GIS dataset has tabular or textual data describing the geographic features. These can be names, dimensions, or other values. The attribute data is contained in a table with different columns. Each column contains a specific type of data.

Cell size - the dimensions on the ground of a single cell in a raster dataset. The values are measured in map units. This is sometimes referred to as pixel size or raster resolution.

Clipping - an operation that extracts portions of a GIS layer within a spatial envelope. It acts like a cookie cutter producing a new GIS dataset at the smaller spatial extent.

Euclidean distance - The straight-line distance between two points on a plane.

Geoprocessing - a GIS operation used to manipulate GIS data. A typical geoprocessing operation takes an input dataset, performs an operation on that dataset, and returns the result of the operation as an output dataset.

Geospatial projection - a method by which the curved surface of the earth is portrayed on a flat surface. In GIS a full definition for a spatial reference includes the projection, coordinate system, and the geodetic datum. In a GIS analysis all data layers must be in the same projection.

LandFire - also known as the Landscape Fire and Resource Management Planning Tools Project, is a five-year, multi-partner project producing consistent and comprehensive maps and data describing vegetation, wildland fuel, and fire regimes across the United States. http://www.landfire.gov/

LiDAR - Light Detection And Ranging is an optical remote sensing technology that can measure the distance to, or other properties of a target by illuminating the target with light, often using pulses from a laser.

Maxent - a software for species habitat modeling that utilizes the maximum entropy approach. In this sense maximum entropy means it identifies the probability distribution that is the most spread out or closest to uniform. It takes as input a set of layers or environmental variables (such as elevation, precipitation, etc.), as well as a set of georeferenced occurrence locations, and produces a model of the range of the given species.

Model run - refers to one instance of a model such as Maxent with a specific set of inputs and parameters set.

Omission rate - The number of test locations that do not fall in an area predicted by the model as suitable habitat.

Raster dataset - a data model that defines space as an array of equally sized cells arranged in rows and columns. Each cell contains an attribute value such as the elevation above sea level. The other common GIS data model is vector.

Southwest Regional GAP Analysis Program - An update of the Gap Analysis Program's mapping and assessment of biodiversity for the five-state region encompassing Arizona, Colorado, Nevada, New Mexico, and Utah. It is a multi-institutional cooperative effort coordinated by the U.S. Geological Survey Gap Analysis Program. The primary objective of the update is to use a coordinated mapping approach to create detailed, seamless GIS maps of land cover, all native terrestrial vertebrate species, land stewardship, and management status, and to analyze this information to identify those biotic elements that are underrepresented on lands managed for their long term conservation or are "gaps." http://fws-nmcfwru.nmsu.edu/swregap/

Vector dataset - a representation of geographic features using points, lines and polygons. Vector datasets have discreet boundaries. The other common GIS data model is raster.

Weighting scheme - a method for ranking the relative importance of variables in a model. For example, the factor that is most important to identifying CBH habitat would receive the highest weight. Collectively the weights assigned to all the environmental variables are called a weighting scheme.

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