BATS OF WYOMING:
MODELED DISTRIBUTION

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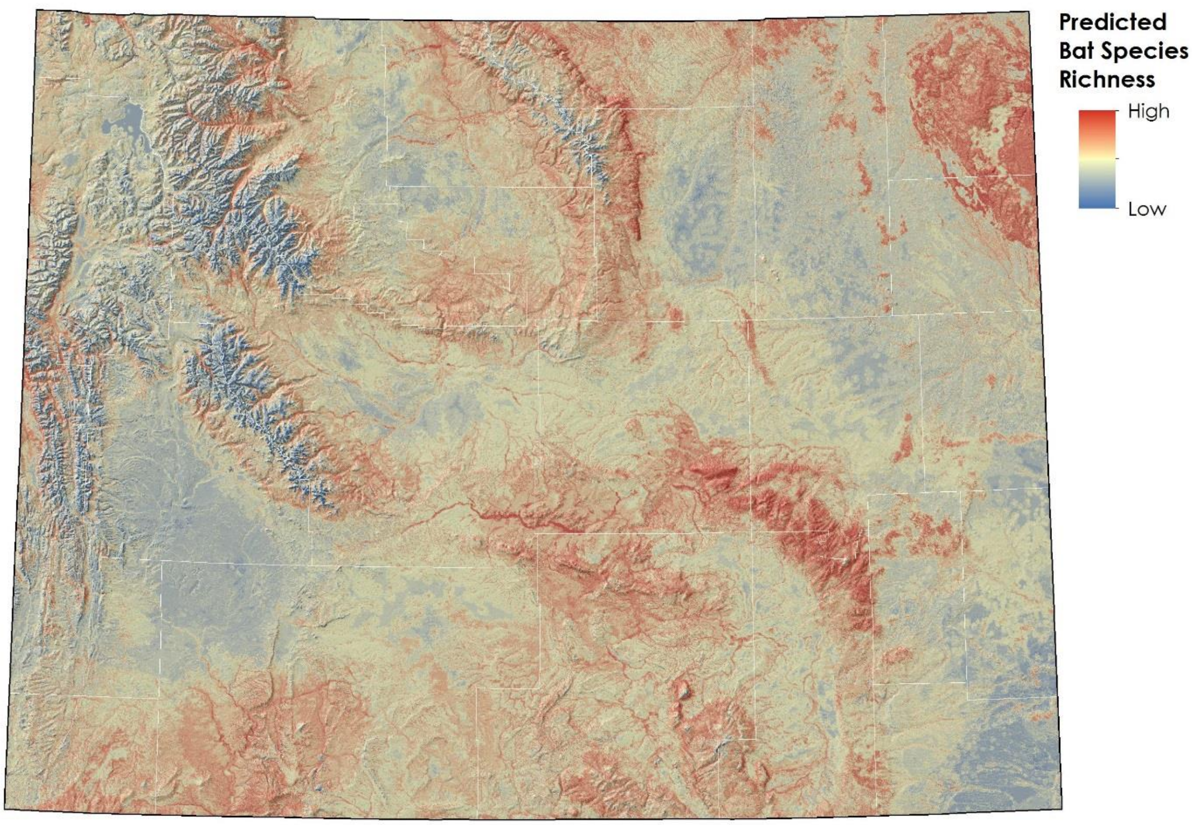

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Executive Summary

Distributions and habitat associations of bats in Wyoming were poorly understood until recent efforts put forth by the Wyoming Natural Diversity Database (WYNDD), the Wyoming Game and Fish Department (WGFD) and other federal agencies and research entities. Globally, bats face numerous threats including but not limited to wind energy development, disease (White-Nose Syndrome in particular), and habitat loss. In recognition of these threats, considerable attention has been devoted to bat specific research in recent years. In Wyoming in particular, numerous studies have been implemented to enhance our understanding of the distributions of bat species and important habitat features across the state.

The primary objective of this work is to better understand summer distribution and migration stopover habitat of bats in Wyoming. More specifically, we used occurrence data form the WYNDD database and Maximum Entropy (MaxEnt) modeling algorithms to predict important ecological, climatic, and habitat features that influence summer distributions to generate predictive distribution models encompassing all of Wyoming. The models presented in this report reflect one of the few attempts to incorporate bat observations made by numerous researchers through time across all of Wyoming. We also used a deductive modeling approach to predict areas used as stopover and foraging habitat by Wyoming's three migratory bat species while migrating through Wyoming in the late summer and fall. In turn, land managers can make better informed management decisions when evaluating potential impacts to local bat populations and migrating bats across the state.

We generated predictive distribution models for the summer season for 15 bat species that reside in Wyoming. These models represent areas used by these species during the summer when bats raise young and build fat stores they rely upon during migration or hibernation. Models generally predict that areas near water, especially river and large stream corridors, and foothills areas surrounding major mountain ranges are likely to support many bat species. There was considerable overlap in predictor variables included in summer distribution models among species which generally included combinations of forest cover, indices of topographic position, distance to water, and climatic variables. We also present migratory stopover habitat models created by Griscom et al. (2012) that have been extrapolated to encompass all of Wyoming. These models suggest that the foothills of major mountain ranges and riparian corridors are likely to be used by the three migratory bat species in Wyoming during their fall migrations.

Introduction

Bats are an important component of ecosystems worldwide comprising approximately 20% of all mammal species globally (Kunz and Parsons 2009). They are integral pollinators and seed-dispersers for many plant species. Bats also consume large quantities of insects, many of which cause significant agricultural losses and threaten human health (Kunz and Parsons 2009). It is estimated that in North America alone, bats prevent $3.7 billion in damage to agricultural resources each year (Boyles et al. 2011). Unfortunately, many bat species have undergone large population declines and are faced with increasing risk of extinction. For example, of the 47 bat species known to occur in the United States, six are currently listed as “Endangered” and one is listed as “Threatened” under the Endangered Species Act (ESA) and at least one other species is under an active petition for ESA protections (Harvey et al. 2011, United States Fish and Wildlife Service 2011, 2013).

A total of 18 bat species have been documented in Wyoming. Of these, 15 are resident though Wyoming is on the periphery of the accepted range of California Myotis, Yuma Myotis, and Eastern Red Bat (Hester and Grenier 2005). Bats represent approximately 15% of Wyoming’s mammal species making the group an important component of the state’s biodiversity. Historically, bats have been poorly studied, especially in Wyoming. However, in light of realized ecosystem services and large declines from persecution, habitat loss, and disease, considerable bat specific research has been conducted globally and in Wyoming.

Three bat species in Wyoming undergo long-distance migrations out of state in the fall to spend the winter in warmer areas. These include Eastern Red Bat, Hoary Bat, and Silver-haired Bat, which are all tree-roosting species. In general, migration is one of the least understood aspects of bat ecology (Cryan 2003, McGuire et al. 2012). It is thought that Eastern Red Bat winter in the southeastern United States, Hoary Bat winters in southern California and Mexico, and Silver-hair Bat is more widely distributed at more southern latitudes. At a broad scale, it is clear that these bats undergo long-distance movements towards their respective wintering grounds but specific migration routes remain unclear (Cryan 2003). Evidence suggests that migratory bats make multi-day stopovers to forage and regain fat supplies during migration (McGuire et al. 2012). Additionally, geographic and habitat features (e.g. lakes, mountain ranges, riparian corridors) may promote stop-over behavior, foraging, and influence migration paths (McGuire et al. 2012). While these features are poorly understood, evidence from existing literature may be useful in generating models to predict suitable stop-over and foraging habitat in Wyoming.

Uncertainty in distribution of bats during migration is particularly problematic form a conservation standpoint. While mortalities of many bat species have been documented at wind facilities in North America, migratory species are particularly prone to fatalities at wind facilities and comprise the vast majority of bat mortalities observed at wind farms (Arnett et al. 2008, Jain et al. 2011). More importantly, the majority of bat fatalities at wind energy facilities occur in the late summer and early fall when bats are migrating (Arnett et al. 2008). Although results vary across studies, some have shown that fatalities can be reduced by placing turbines in locations where fewer bats are likely to come into contact with them in the first place (Baerwald and Barclay 2009).

Predictive modeling of species distributions has become a common and important tool for biologists and land managers (Phillips et al. 2006, Elith et al. 2011). Species distribution models are created by evaluating the relationships between species occurrences and remotely sensed environmental and spatial characteristics of the occurrence locations (Elith et al. 2011). MaxEnt (Phillips et al. 2006) is a commonly used program for modeling species distributions and is well suited for modeling distributions of bats because most common bat survey techniques generally produce presence-only occurrence data.

Using occurrence data form the WYNDD database and MaxEnt modeling algorithms, we generated predictive distribution models encompassing all of Wyoming. We also used a deductive modeling approach to predict areas used as stopover and foraging habitat by Wyoming's three migratory bat species while migrating through Wyoming in the late summer and fall. The models presented below make useful predictions of summer distribution for 15 bat species and predictions of stopover and foraging habitat for three migratory bat species. Using these models, land managers can make better informed management decisions when evaluating potential impacts to local bat populations and migrating bats across the state.

Methods

Distribution and Migration Models

Summer Distribution Models

We present models predicting species distribution across the entire state of Wyoming. We used Maximum Entropy Species Distribution Modeling software (Maxent), a commonly used modeling software (Phillips et al. 2006), to model the spatial distribution of 15 bat species that occur in Wyoming during the summer season. For the purposes of this modeling effort, we defined the summer season as June 1 through August 31 for non-migratory species, and from June 1 through August 15 for migratory species. Maxent can generate useful models with relatively limited training data (Hernandez et al. 2006) and does not require absence data for model building, making it well suited for our data. Multiple iterations of modeling via Maxent were used to arrive at a set of final models for all species. Final summer models for each species were combined to generate a single map representing predicted bat richness in summer across Wyoming.

Summer Input Presence Data

Occurrence (i.e., species presence) data used for model building came from the WYNDD Biotics database (Wyoming Natural Diversity Database 2015). These data were collected by many researchers and resource management agencies across the state. Occurrence data include both capture data (e.g. mist-net and harp-trap captures) and acoustic monitoring data (e.g. AnaBat, Songmeter). We eliminated presence data that were imprecisely mapped (i.e., potential error greater than 3,000 m).

Occurrence data were first attributed with a Point Quality Index (PQI), based on the mapping precision, age, and certainty of taxonomic identification for each point (Table 1). The overall PQI score was an additive combination of the PQI score components for mapping precision, age, and taxonomic certainty, and ranged from 0 (lowest quality) to 12 (highest quality). Then, any points for a given species within 1,600 m of a higher quality (i.e., higher PQI) point for the species were eliminated. This reduces spatial biases in occurrence data at a fine scale. The presence locations selected using this routine comprised the final model training dataset.

Summer Input Background Data

Maxent uses background locations – a sample of available environmental conditions available to species – in place of true absence data to identify environments where a species is more likely to occur (Phillips et al. 2006). When presence data result from spatially biased sampling, as with this modeling effort, where sampling is biased towards water features where bats obtain water and forage, the resulting models would describe a mixture of true distribution and sampling effort (Jimenez-Valverde and Lobo 2006, Johnson and Gillingham 2008). To reduce the effects of sampling bias, Phillips et al. (2009) suggest using "target group" background points that represent presence points for other species for which sampling effort and methods are similar. For example, if modeling the distribution of a particular songbird species, presence locations for *all other songbird species* are used as the background data, so as to reflect the sampling effort and biases associated with songbirds as a whole. For this modeling work, there were not a sufficient number of bat presences across species to use as background data, as 10,000 background points is the rule-of-thumb suggested by the software authors (Phillips 2006). Instead, we used a multi-step process to generate a set of background points matching the spatial bias in our existing bat presence points.

To generate the points, we first generated a model of overall sampling effort for bats, by including observations for all bat species as the presence points, with a random set of 10,000 background points. This resulted in a spatial model of all prior sampling effort for bats, and included predictors such as distance to roads, human disturbance, and other standard environmental predictors. Next, we used the "Generate Random Points" tool in the Geospatial Modeling Environment (Beyer 2012) to place 10,000 random points, with the probability of point placement being determined by the probability value from the underlying cell in the sampling effort model. Generating background points in this manner provided us with an adequately sized set of background points that reflected the inherent spatial biases in bat sampling within Wyoming, allowing us to make a more meaningful contrast between presence locations and sampled environments.

Summer Predictor Data Layers

Predictor data layers used to generate summer season models were created by previous researchers (Keinath et al. 2010). These predictors spanned basic categories of environmental variation, and included representations of climate, topography, hydrology, soil and substrate, land cover and landscape metrics, as well as variables intended to identify unique habitat features important to bats (e.g., caves, cliffs, and rock outcrops). Additionally, we generated a "distance to forest cover" layer, by finding the distance to the nearest raster cells where at least some tree cover was present, according to the LANDFIRE dataset (Rollins 2009). This layer was intended to help map limitations in roosting sites for tree-roosting species. Presence training data and background points were attributed with each of the potential predictors.

Summer Model Building and Selection

We evaluated a set of 110 GIS layers for their potential utility in modeling bat species' distributions, culling those not likely to be biologically relevant for bats, resulting in an initial list of approximately 60 predictors. We further reduced this set of potential predictor layers to 46 by evaluating for multicollinearity among the layers, and eliminating those predictors that were highly correlated with other, more biologically-relevant predictors.

We then constructed initial models of 15 species in Maxent based on the selected predictor layers, using 5-fold cross-validation (Kohavi 1995). Cross-validation was used in these runs to reduce the possibility of over-fitting models to noise in the training data, by ensuring that variables included in the final models were those that were most important in predicting occurrence across each of the 5-folds of training data (Baumann 2003).

Although Maxent is relatively robust to over-fitting, even with large numbers of predictors and relatively small numbers of samples (Phillips and Dudík 2008), our experience with similar modeling projects has shown that reducing the number of variables included typically improves model performance, as it causes model to be more generalizable. Thus, we used an iterative approach to perform backward-stepwise reduction of the variable set, at each step removing the variable for which removal was associated with the smallest reduction in test gain, or model accuracy with respect to the cross-validation points. The final model for each species was the smallest model that achieved 99% of the maximum test AUC.

Logistic output rasters were generated from the final models constructed for each of the modeled species. Though not strictly interpretable as logistic probability, these rasters provide an indication of habitat similarity relative to all the cells in a study area (Phillips et al. 2006). To generate a predicted index of summer bat species richness, binary expressions of the models (i.e., predicted absent/predicted present) were then created for each species by applying a threshold (specifically, the "Minimum Training Presence" threshold identified by Maxent) to each logistic raster. A predicted index of summer bat species richness map was generated by combining the above binary versions of each species' model. This was done by performing a simple additive overlay, resulting in a model with values ranging from 0 (no bat species predicted present) to 15 (all modeled bat species predicted present).

Migration Stopover Habitat Models

We extrapolated the models specified by Griscom et al. (2012) to the entire state of Wyoming. It is important to note that migration stopover habitat models are deductive models, meaning that they were generated based on our interpretation of habitat needs informed from the literature, rather than modeled statistically as with the summer models. Also, these models predict habitat that may be used for foraging and roosting while bats are migrating as opposed to areas of migration flight (i.e. migration corridors).

Migration stopover habitat was modeled separately for Hoary Bat, Silver-haired Bat, and Eastern Red Bat. These models used Multi-Criteria Decision Analysis methods (Belton and Stewart 2002). Using these deductive methods, habitat features required for roosting and feeding were incorporated into multiplicative, weighted models and ranked raster cells based on the product of habitat criteria included in each species' model. Habitat features included in each model included the presence of trees and the proximity of perennial water sources to trees. Only areas below 2500 m in elevation were included in these models. For specifics regarding each model, data sources used, and literature reviewed for habitat variables included in each model, please refer to Griscom et al. (2012).

Results

Summer Distribution Models

The most important predictor in our model of sampling effort (Figure 1) was distance to roads, followed by topographic position indices, various vegetation indices, human disturbance index, and land ownership. As expected, sampling was far more likely to occur on public lands, near roads, and in low-lying areas with available water, where mist-netting is most practical. The model reflects the relatively dense sampling that has occurred in many foothills regions, in the Black Hills, and in the southern portion of the state as part of the ongoing collaboration between WYNDD and WGFD. Areas that have had little sampling to-date include the Red Desert, Thunder Basin and the Upper Powder River Basin, portions of the Bighorn Basin, and extreme southeastern Wyoming. Likewise, the upper elevations of the major mountain ranges, including the Absarokas, the Wind River Range, and the highest portions of the Bighorn Mountains, have scarcely been sampled. Background points generated from this model represent the same overall pattern, thereby helping to factor out the influence of sampling bias on our species models.

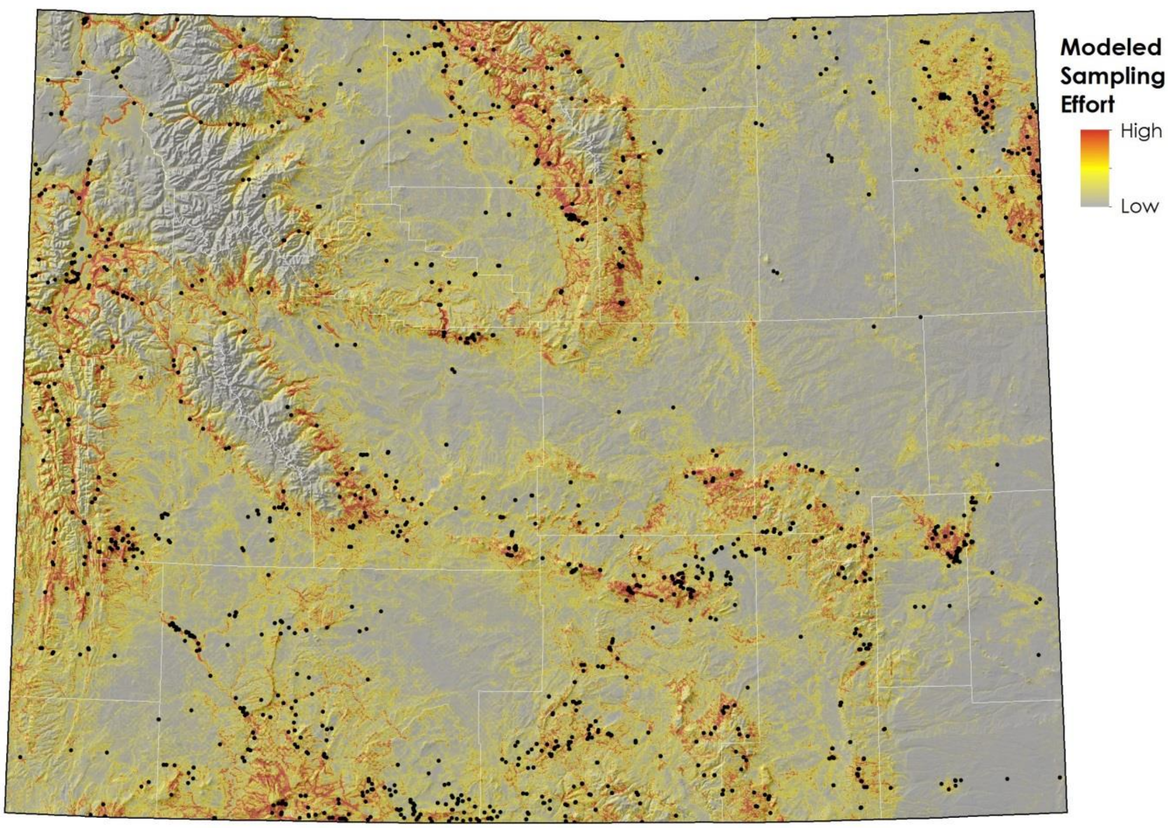

Figure 1. Sampling effort model. Red indicates areas most similar to those where bat sampling has occurred, in terms of natural (e.g., topography and climate) and anthropogenic (e.g., human disturbance and land ownership) patterns. Black dots show the locations of observations for all bat species contained in WYNDD's central database.

We were able to model summer distributions for 15 species that occur in Wyoming (Table 2). Between 3 and 16 predictor variables were used to create each species' summer distribution model. There was considerable similarity in which predictor variables were included in summer distribution models between species, with distance to forest cover being the most commonly included predictor (12 species models). Other important predictors (and the number of species' models in which they were included) were slope (10), mean diurnal temperature range (9), minimum temperature of the coldest month (9), permanent standing water in a 300 m neighborhood (8), and topographic position (8). Similarly, there was considerable overlap in predicted species distribution among species. Summer distribution models are displayed in Appendix 1. Output from Maxent including full details on each of the inductively-generated model is provided in Appendix 3. Figure A1-16 in Appendix 1 displays the combined species richness model for 15 species during the summer season.

All of our summer distribution models had high training Area Under Curve (AUC; range 0.839 – 0.991) and test AUC (range 0.802 – 0.987) values (Table 3). This indicates that our models are of excellent (AUC > 0.90) or good (AUC between 0.80 – 0.89) quality (Swets 1988, Eskildsen et al. 2013). Additionally, the lower 95% confidence interval of the test AUC for all models was greater than 0.5, indicating that all models were significantly better than random at correctly predicting species presence (Table 3). Differences between training and test AUC values were generally very small (range 0.004 - 0.111) suggesting that all models are generalizable and useful for predicting presence at new locations and are likely not over-fit to the training data (Table 3).

Migration Stop-over Habitat Models

We generated state-wide migration stopover habitat models for Eastern Red Bat, Hoary Bat, and Silver-haired Bat. Migration stopover habitat models are displayed in Appendix 2. Areas predicted to be used by the three migratory bat species in Wyoming include foothills of the major mountain ranges and riparian corridors.

Discussion

Summer Distribution Models

Not surprisingly, our sampling model shows that sampling effort for bats has been focused on public lands, and that comparatively little sampling has been done on private lands. This has led to large gaps in sampling in the eastern third of the state, where private lands dominate the landscape. The addition of this model in our summer distribution modeling process proved very beneficial to overall model predictions by reducing the effect of spatial sampling bias. This sampling model also highlights areas in Wyoming that have received little or no survey effort. These areas should be targeted for future survey efforts to better understand bat distribution and habitat associations in these areas.

In a broad sense, our summer distribution models are fairly similar to those created by Griscom et al. (2012) and Keinath et al. (2010). For example, models generally predict that areas near water, especially river and large stream corridors, and foothills areas surrounding major mountain ranges are likely to support many species. However, summer distribution models included in this report were generated using much larger sample sizes than previous modeling efforts lending themselves to stronger inferences (Table 2). The largest changes in predicted distribution occurred in under-sampled areas such as the Thunder Basin in northeastern Wyoming, where previous models suggested an apparent lack of suitable habitat for any bat species. Our updated models suggest that these areas may support several bat species. Additionally, considerable survey effort has occurred in upland areas of the Red Desert and Great Divide Basin and suggest that these areas contain suitable habitat for several bat species, especially those typically associated with arid environments such as the Pallid Bat. These changes in predicted distribution from earlier models highlight the importance of spatially balanced sampling across the state.

All of our inductive models included occurrence data from both captured bats and acoustic recordings of bat echolocation calls. Caution should be used when interpreting acoustic data and assigning species classifications, particularly for some bat species (e.g. Silver-haired Bat and Big Brown Bat) that have very similar echolocation calls and may be difficult to classify with certainty. Some researchers have demonstrated that species distribution models generated with acoustic data may differ from those generated with physical capture data (Barnhart and Gillam 2014). Evaluation of previous models efforts (Keinath et al. 2010, Griscom et al. 2012) suggests that mist-net occurrence data in Wyoming is spatially biased because it almost exclusively occurs on water bodies. Inclusion of acoustic data reduces this bias because we included survey data from studies where acoustic sites were randomly placed (Abernethy et al. 2012, 2014). As a result, we feel confident that our models make useful predictions.

Our summer distribution models make predictions for the entire state for all species even though the currently accepted range of some bat species does not encompass all of Wyoming (e.g. California Myotis). We chose to extrapolate models beyond currently accepted range limits because there is still uncertainty in actual distribution. Furthermore, test statistics (i.e. training and test AUC) are no longer valid if models are clipped after being generated at a larger scale. Areas beyond the accepted range with predicted probability of occurrence can be viewed as areas with similar habitat and climatic conditions to areas where the species has been documented. As such, our models suggest that areas outside of the species range may contain suitable habitat but may not necessarily support the species. Users should consult resources such as Wyoming's State Wildlife Action Plan to determine currently accepted ranges of these bat species. Species with limited ranges in Wyoming for which considerable predictions beyond the currently accepted range include Yuma Myotis, California Myotis, and Eastern Red Bat.

Migration Stop-over Habitat Models

Migration stopover habitat models were extrapolated to include all of Wyoming. In the context of wind energy development, these models would suggest that wind facilities should not be place in proximity to the foothills of major mountain ranges and riparian corridors with trees. For Eastern Red Bat, we predicted fall migration stopover and foraging habitat for all of Wyoming even thorough its currently accepted distribution is limited to eastern Wyoming. The species is known to occur in Montana east of the Rocky Mountains and it is possible that Eastern Red Bat may occur in all of Wyoming during migration (Adams 2003).

It is important to note that our migration stopover habitat models are deductive. Important habitat features were identified through literature review and represent attributes that are important for foraging and roosting while bats migrate. However, most aspects of bat migration remain unknown (Cryan 2003, McGuire et al. 2012). To better model potential migration routes, generating movement models that incorporate physiological constraints, species specific maximum flight distances, and other important biological and ecological factors may be useful.

Model Caveats

There are some caveats inherent to all species distribution models, including the models presented in this report, and caution should be used in their interpretation. First, when applying these models in a planning context, they should be used as conceptual tools rather than for fine-scale planning and decision-making. These models predict general areas of habitat use, but limitations in observation data, environmental predictor layers, predictive layers, and differences in map scales lead to errors that make interpretation at scales less than 2km inaccurate. Second, a relatively small number of bat occurrences were used to create summer distribution maps of some species including California Myotis, Northern Myotis, and Eastern Red Bat. Generally-speaking, the reliability of a model declines as the number of occurrences upon which it was based declines. While some recent monitoring efforts have implement random sampling (e.g. Abernethy et al. 2012; 2014), it is likely that oversampling in mesic areas has skewed the results to favor water features and probably does not represent the full spectrum of bat habitat use on the landscape. Third, bats are able to move easily between roosting and foraging sites. Although our maps may predict where bats spend most of their time, they may not account for movement between areas of heavy use. For example, although ridge tops are generally not predicted to be important habitat features for bats in our models, bats undoubtedly fly over ridge tops in order to access roosting and foraging habitat and may even forage above ridge tops when insect swarms are present (McCracken et al. 2008, Rydell et al. 2010). Further investigation and movement modeling may provide insight to areas that are used for travel between suitable foraging and stopover sites. Forth, the lack of predicted species richness in some portions of the study area (for example the plains of eastern Wyoming) could be an artifact of minimal sampling in those regions rather than a true reflection of limited bat habitat. Future surveys should focus on sampling within these areas.

Conclusions

We feel confident that models presented in this report make useful predictions of summer distribution and migration stopover habitat for bats in Wyoming. All of our summer distribution models had high training and test AUC values and are considered of excellent or good quality using standard interpretations of AUC values (Swets 1988, Eskildsen et al. 2013). Additionally, our results indicate that all models were significantly better than random at correctly predicting species presence, meaning they make useful and accurate predictions of species occurrence across the state. While some portions of Wyoming have not been extensively surveyed, our results suggest that all summer distribution models are generalizable and useful for predicting presence at unsampled locations. As a result of increased bat research over the past several years and collaborative data sharing, we now have a clearer picture of bat distribution across Wyoming and what habitats are most important for bats. In turn, land managers can make better informed management decisions when evaluating potential impacts to local bat populations and migrating bats across the state.

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Tables

Table 1. Scoring system used to evaluate the quality of occurrence records based on spatial precision (A), age of record (B), and taxonomic certainty of identification (C).

A. Spatial Precision of Occurrence Record

Score	Definition	Example
4	Location uncertainty ≤ 30 meters	Location via GPS
3	Location uncertainty > 30 meters and ≤ 100 m	Location via 7.5' quad map
2	Location uncertainty > 100 meters and ≤ 300 ms	Location via 100k quad map
1	Location uncertainty > 300 meters and ≤ 600 m	Location via large-scale map or detailed written directions
0	Location uncertainty > 600 meters and < ~3,000 m	Location via landscape description (e.g., 5 miles south of Laramie Peak)
U	Record is unusable; uncertainty > ~3,000 m	Museum specimen located by reference to a county

B. Age of Occurrence Record

Score	Calendar Year of Observation	Definition
4	≥ 2005	Observation made within roughly 10 years of model creation
3	1995 - 2005	Observation made within roughly 20 years of model creation
2	1985 - 1995	Observation made within roughly 30 years of model creation
1	1965 - 1985	Observation made within roughly 50 years of model creation
0	≤ 1965	Observation made within roughly 100 years of model creation

C. Taxonomic Certainty of Occurrence Record

Score	Category	Definition
4	High Confidence (ID_CONFID =H)	Identification confirmed by expert
3	Medium Confidence (ID_CONFID =M)	Identification not confirmed, but no reason to doubt
1	Low Confidence (ID_CONFID =L)	WYNDD has relatively low confidence in the species identification, due lack of documentation, location outside the species' mapped range, or other issues
U	Misidentification (ID_CONFID =FQ or FK)	Record is unusable. Information in the occurrence record suggests it is misidentified

Table 2. Bat species that occur in Wyoming for which predictive distribution models were generated, their relative abundance in the state, number of occurrences used in modeling, and seasonal residency.

Common name	Scientific name	Relative abundance	Occurrences used in modeling	Season of residency
Big Brown Bat	*Eptesicus fuscus*	Less common	243	Year round
California Myotis	*Myotis califonicus*	Very uncommon	20	Year round
Fringed Myotis	*Myotis thysanodes*	Uncommon	77	Year round
Hoary Bat	*Lasiurus cinereus*	Common	279	Spring, summer, fall
Northern Long-eared Myotis	*Myotis septentrionalis*	Uncommon	22	Year round*
Little Brown Myotis	*Myotis lucifugus*	Common	442	Year round
Western Long-eared Myotis	*Myotis evotis*	Common	351	Year round
Long-legged Myotis	*Myotis volans*	Common	270	Year round
Pallid Bat	*Antrozous pallidus*	Less common	115	Year round
Eastern Red Bat	*Lasiurus borealis*	Uncommon	20	Spring, summer, fall
Silver-haired Bat	*Lasionycteris noctivagans*	Less common	255	Spring, summer, fall
Spotted Bat	*Euderma maculatum*	Very Uncommon	31	Year round
Townsend's Big-eared Bat	*Corynorhinus townsendii*	Uncommon	98	Year round
Western Small-footed Myotis	*Myotis ciliolabrum*	Common	407	Year round
Yuma Myotis	*Myotis yumanensis*	Very uncommon	42	Year round

*There are no known hibernacula where Northern Long-eared Myotis are known hibernate in Wyoming

Table 3. Training AUC, test AUC, 95% confidence intervals of test AUC, and training/test AUC differences for summer distribution models for 15 species. AUC values of 0.5 suggest a model is no better than random in its discriminatory power. Models for which the lower 95% confidence interval boundary is above 0.5 are significantly better than a random model at correctly predicting presence/absence. Larger differences between training and test AUC indicate models that perform worse at predicting presence/absence at new locations, and typically result from overfitting of a model to the training data.

Species	Average Training AUC	Average Test AUC	Lower 95% Test AUC Confidence Interval	Upper 95% Test AUC Confidence Interval	Difference between Training and Test AUC
Little Brown Myotis	0.870	0.834	0.793	0.875	0.036
Long-eared Myotis	0.844	0.805	0.751	0.859	0.039
Long-legged Myotis	0.853	0.818	0.757	0.879	0.036
Western Small-footed Myotis	0.857	0.802	0.752	0.852	0.055
California Myotis	0.977	0.866	0.710	1.023	0.111
Silver-haired Bat	0.839	0.808	0.744	0.873	0.031
Big Brown Bat	0.912	0.858	0.808	0.908	0.054
Hoary Bat	0.871	0.814	0.753	0.875	0.057
Eastern Red Bat	0.971	0.932	0.844	1.019	0.039
Fringed Myotis	0.928	0.867	0.794	0.941	0.060
Townsend's Big-eared Bat	0.890	0.836	0.755	0.918	0.054
Spotted Bat	0.974	0.956	0.905	1.007	0.017
Pallid Bat	0.923	0.869	0.801	0.938	0.054
Northern Long-eared Myotis	0.991	0.987	0.972	1.002	0.004
Yuma Myotis	0.954	0.858	0.748	0.969	0.096

Appendices

Appendices are included as separate documents and can be found at http://www.uwyo.edu/wyndd/reports-and-publications.

Appendix 1: Summer Distribution Models

Appendix 2: Fall Migration Stopover Models

Appendix 3: Summer Model Detailed Output