Research Article

Power Pole Density Informs Spatial Prioritization for Mitigating Avian Electrocution

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ABSTRACT Raptor and corvid electrocutions cause continental conservation concerns for breeding, migrating, and wintering birds. Although concerns are widespread, mitigation is implemented primarily at local scales of individual electric utilities. By not considering landscape-scale patterns, conservation strategies may fail to focus mitigation where efforts are needed most. To enable resource managers to consider electrocution risk at larger scales, we developed a regional model of distribution power pole (pole) density in a grid of 1-km^2 cells throughout Colorado and Wyoming. To do so, we obtained data on pole locations from a sample of electric utilities covering 31% of Colorado and Wyoming, and developed a predictive model of poles throughout the remainder of the 2 states. Pole density was influenced by road lengths, number of oil and gas wells, slope, development, and land cover. Poles were densest in areas with high road lengths, high numbers of wells, and relatively flat terrain, and in areas developed for agriculture or human residences. When model predictions are viewed together with species-specific habitat maps, locations where high pole densities overlap habitat suggest areas where mitigating electrocution risk could be prioritized. Communication between resource managers and local utilities could then clarify the poles that caused the highest risk to raptors from electrocution. Thus, the model provides a framework for systematic spatial prioritization in support of regional conservation planning to minimize electrocution of raptors and corvids.

KEY WORDS *Aquila chrysaetos*, Colorado, electric utility, golden eagle, model, random forest, raptor electrocution, Wyoming.

In western North America, electrocutions of raptors and corvids have been reported from Canada to Arizona and northern Mexico (Cartron et al. 2005, Kemper et al. 2013), from California to Colorado and Wyoming, and throughout the Great Plains (Harness and Wilson 2001, Dwyer et al. 2013). Concerns persist despite concerted efforts to address avian electrocutions (Lehman et al. 2007, Loss et al. 2014) through retrofitting distribution power poles (poles) to minimize avian contact with energized equipment (Avian Power Line Interaction Committee [APLIC] 2006).

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Despite the continental scale of concern, mitigation occurs primarily at the scale of individual electric utilities (Harness and Wilson 2001, Dwyer and Mannan 2007, Lehman et al. 2010), which range from local municipalities to portions of multiple states. In the United States, application of corrective actions will likely continue primarily at local scales as a consequence of how the electric grid is structured, but development of a larger scale model of poles on the landscape may be useful in identifying which local utilities are most in need of support. Colorado is the only state to have assembled a set of coordinated statewide Avian Protection Plans (APPs; Harness and Nielsen 2006), though large, multi-state utilities also have programs with coordinated risk prioritization over large areas (S. Ligouri, APLIC, personal communication). Avian Protection Plans are documents describing a utility's program to minimize avian risk of mortality, including electrocution, associated with power lines (APLIC and U.S. Fish and Wildlife Service 2005, Harness and Nielsen 2006). Because electrocution mitigation rarely has been attempted at these scales, localized, uncoordinated approaches may not focus mitigation where conservation efforts are most needed, allowing persistence of areas where high-risk poles occur. In contrast, other conservation initiatives are moving toward regional scales guided by principles of systematic spatial prioritization (Margules and Pressey 2000, Doherty et al. 2011). For example, Sauer et al. (2014) and Glissen et al. (2015) analyzed continent-wide trends in avian breeding and occupancy data, respectively, to identify focal points for avian conservation in North America. Similarly, Copeland et al. (2009) mapped oil and gas development potential throughout the western United States to facilitate regional conservation planning, and the AdaptWest Project (2015) developed a continent-wide predictive model for climate change in North America. Similar to large-scale electrocution mitigation efforts in Spain (López-López et al. 2011), regional-scale strategies to address avian electrocutions in the United States could follow these examples, positioning resource managers to identify specific local-scale concerns within a broader ecological context.

Mitigation of avian electrocution has historically focused on assessing risk on individual poles (Janss and Ferrer 1999, 2001; Dwyer and Mannan 2007). These studies yielded consistent factors contributing to risk. Specifically, electrocutions tend to occur at distribution voltages (2.4 kilovolts [kV] to <69 kV; APLIC 2006) on poles supporting multiple energized phases, equipment, and pole-top grounding (Tintó et al. 2010, Dwyer et al. 2013, Harness et al. 2013). Electrocutions also tend to occur where high numbers of poles are present within the habitats of species of interest (Harness and Wilson 2001, Dwyer and Mannan 2007, Lehman et al. 2010), indicating a clear but unquantified link between pole numbers and the likelihood of electrocution (Pérez-García et al. 2011). For example, in a study where 75% of the study area consisted of wooded and rugged protected land with relatively few poles, 95% of electrocutions were found in human-impacted areas where pole density was high (Tintó et al. 2010).

Given the consistency of pole-specific factors influencing electrocution risk, we hypothesized that if regional maps of poles were available it would be possible to support regional systematic spatial prioritization of conservation goals by identifying broad areas where avian risk may be of concern. Our goal was to produce a predictive model of pole density throughout Colorado and Wyoming, and to demonstrate the utility of the model by comparing it to golden eagle (*Aquila chrysaetos*) habitat in north-central Wyoming.

STUDY AREA

Colorado elevations ranged from 1,000 m to 4,400 m above sea level (asl). Eastern Colorado was characterized by semi-arid grasslands and irrigated agriculture with scattered towns and homesteads. Central and western Colorado was characterized by shrub-covered foothills, plateaus, valleys, and forested mountains (Landfire 2014). Urban corridors occurred primarily along river valleys and the Front Range where the mountains meet the plains. Wyoming elevations ranged from 2,000 m to 4,200 m asl. Wyoming was characterized by sage-brush and sage-brush steppe ecosystems interspersed with arid plateaus and forested mountains. Human occupancy was primarily rural with urban areas scattered irregularly near centers of resource extraction (Landfire 2014).

METHODS

To develop a regional map of pole density, in this study, we secured pole location data from a voluntary sample of electric utilities throughout Colorado and Wyoming so we could model pole density statewide, thus, facilitating a regional conservation approach to systematic spatial prioritization for mitigating avian electrocution risk. Species-specific habitat models displaying variation in space use are commonly developed, but are less commonly linked explicitly with threat maps (Tulloch et al. 2015), like pole density. Electrocutions of golden eagles (*A. chrysaetos*) have been reported throughout the western United States (Harness and Wilson 2001, APLIC 2006, Dwyer et al. 2013). To exemplify how our model could operate as a threat map contributing to a framework for systematic spatial prioritization, we coordinated with the Draper Natural History Museum (DNHM; Cody, WY, USA) to identify breeding season foraging habitat of golden eagles in the Bighorn Basin of north-central Wyoming. We then viewed our pole density map with DNHM's golden eagle data to identify areas where high pole densities occurred within golden eagle breeding season foraging areas.

Model Development

Our model was designed to identify general areas of high pole density so resource managers can coordinate with individual utilities operating in those areas. To gather samples of pole locations current through 2014, we contacted 27 electric utility operators in Colorado and 16 in Wyoming, including investor-owned utilities, municipalities, oil and gas operators, and rural electric cooperatives. We selected these utilities based on existing relationships with EDM International (EDM; Fort Collins, CO, USA). This facilitated obtaining proprietary data on pole locations but simultaneously created a convenience-sampling approach, rather than a random sample. To protect potentially sensitive electric infrastructure within the service areas of electric utilities contributing data, the pole density model reported here does not distinguish pole density estimates between source locations where spatial data on poles originated and the remainder of each state where we used the model to predict pole densities.

We created a 1-km^2 grid covering all of Colorado and Wyoming. By using a 1-km^2 grid, we maximized consistency with existing regional conservation-oriented models (Copeland et al. 2009, AdaptWest Project 2015). Within each cell, we identified road lengths, numbers of oil and gas wells, the mean and standard deviation of slope, presence of pivot irrigation, land cover type, and the presence of development. Specifically, we used Topologically Integrated Geographic Encoding and Referencing (TIGER) products (Census Bureau 2010) to identify the length of primary, secondary, local, 4-wheel drive, and private roads in each cell because poles typically run along road rights-of-way; therefore, roads potentially correlated with pole locations. Primary roads were divided limited-access highways with access ramps and interchanges. Secondary roads were main arteries with ≥ 1 lane of traffic in each direction, usually with at-grade intersections. Local roads were generally paved non-arterial streets with a single lane of traffic in each direction. Four-wheel drive roads were unpaved dirt trails. Private roads were privately maintained for service, extractive industries, or other purposes (e.g., logging, oil fields, and ranches).

We used a map of all types of oil and gas wells (e.g., producing, plugged, injection) in the western United States as of 2014 (IHS Energy 2014) to identify well locations within Colorado and Wyoming. Because oil and gas wells are typically operated with electric power, the number of wells present influences the number of poles in an area. We used methods from Jarvis et al. (2008) to quantify slope and standard deviation of slope in each 1-km^2 cell because poles tend to be routed through less rugged terrain when possible (e.g., valleys rather than mountain tops). Pivot irrigation facilities also require electric power, so we quantified the presence of pivot irrigation by visually evaluating each 1-km^2 cell in Google Earth (Google; Mountain View, CA, USA) to identify the presence of large crop circles or partial circles characteristic of pivot irrigation. Other types of pump irrigation also require electric power but are indistinguishable through remote sensing from flood irrigation, which is not necessarily electrically powered. We accounted for these irrigated areas through incorporation of roads in our analyses because where pump irrigation was present, roads tended to occur in regular grids with spurs accessing terminal poles.

We used Landfire (2014) to identify the dominant land cover in each 1-km^2 cell. Landfire uses an Existing Vegetation Type —System Group Physiognomy (EVT_PHYS) attribute to assign land cover categories to 30-m^2 cells. To assign a land cover category to each 1-km^2 cell, we selected the most common 30-m^2 land cover attribute within each 1-km^2 cell and assigned that value to the entire cell. For example, if a 1-km^2 cell contained 70% forest, 20% open water, and 10% high density developed, we characterized the cell as forest. Because this approach could mask developments such as small neighborhoods, which require electric power, we also recorded the number of 30-m^2 cells within each 1-km^2 cell identified by Landfire (2014) as developed high intensity, developed medium intensity, and developed low intensity (Table 1). Landfire uses development intensity classes from the National Land Cover Database (Jin et al. 2013). High-intensity development was defined as areas where impervious surfaces accounted for 80–100% of total cover (e.g., apartment complexes, row houses, commercial or industrial sites). Medium-intensity development indicated areas where impervious surfaces account for 50–79% of total cover (e.g., single-family residences). Low-intensity development indicated areas where impervious surfaces accounted for 20–49% of total cover. Areas with <20% impervious surfaces were categorized as land cover categories other than developed (e.g., agriculture, forested, open water).

Table 1. Variable importance ranking of all variables from the random forest model for predicting power pole density in 2015 for 1-km^2 cells throughout Colorado and Wyoming, USA.

Predictor variable	Variable importance rank	Mean decrease in predictive accuracy
Road length (all roads)	1	102.92
No. oil and gas wells	2	99.41
$\bar{x}$ slope	3	93.06
Any development present (low, medium, and high)	4	85.01
Road length (private roads)	5	84.83
Pivot irrigation present	6	76.50
Land cover type	7	76.45
Standard deviation of $\bar{x}$ slope	8	65.21
Road length (local roads)	9	61.60
Road length (4-wheel drive roads)	10	55.67
Road length (secondary roads)	11	38.93
Road length (primary roads)	12	29.69
Low-density development present (rural)	13	22.58
Medium-density development present (suburban)	14	21.56
High-density development present (urban)	15	7.09

To demonstrate the utility of our model, we coordinated with the Draper Natural History Museum (DNHM) to compare foraging habitat during the breeding season for golden eagle in the Bighorn Basin with our model. The DNHM maintains a database of golden eagle nest locations throughout the Bighorn Basin of north-central Wyoming (Preston 2015). We defined any 1-km^2 cell entirely or partially within 3 km (area $= 28.3$ km^2) of a golden eagle nest as part of a breeding season foraging area for the species because golden eagles forage within an area of about 20–30 km^2 and defend this area from conspecifics (Kochert et al. 2002). We then evaluated which foraging areas overlapped areas of high predicted pole densities to indicate areas where electrocution risk may be highest, thus, offering an example of systematic spatial prioritization.

Model Fitting and Validation

We used a random forest machine learning classification procedure (random forest; Breiman 2001, Cutler et al. 2007) to model the density of distribution poles. Random forest uses machine learning (computationally intensive automated pattern recognition processes) to develop multiple classification trees for randomly sampled subsets of data from a dataset, and then combines the forest of classification trees into a single, averaged, best-possible classification tree, given the data. Classification trees are created by iteratively partitioning random samples of data into increasingly homogeneous subgroups until inclusion of additional subgroups no longer increases the classification accuracy of a given tree. Random forest is almost completely focused on prediction. Products of random forest include a predictive model, measures of the importance of each variable in the final classification, and out-of-sample validation, rather than the confidence intervals, beta estimates, and effect sizes associated with generalized linear modeling (Breiman 2001, Cutler et al. 2007). Key benefits of random forest is that the approach is non-parametric, so it can model complex non-linear interactions among predictors, accommodates collinearity among predictors, and is robust to overfitting data (Cutler et al. 2007, Hastie et al. 2009). Because the procedure accommodates collinearity, random forest is highly accurate when incorporating non-independent variables. This sets random forest apart from most generalized linear modeling approaches, which require elimination of collinear variables to meet the assumptions of parametric modeling (Hosmer et al. 2013, but see Gerber et al. 2015). Random forest is also robust to datasets with relatively high proportions of zero values like ours, where the number of poles in many cells was known to be zero. The final model from the random forest procedure is validated by comparing predicted values (in this case, no. poles/1 km^2) to known values from a sample of data not used in creating the model. The data used to create the model are referred to as training data, distinguishing them from test data used to validate the model.

To develop the model, we used data from Colorado and Wyoming together, and randomly assigned 93.5% of the data (152,774 1-km^2 cells) as training data, and 6.5% of the data (10,621 1-km^2 cells) as test data. We used the package randomForest (Liaw and Wiener 2002) implemented in the R programing language (R Core Team 2013) to fit 3,000 trees to the training data. To validate the model, we compared predicted pole density from the model to actual counts of poles in each cell in the test data. We used the mean decrease in predictive accuracy to evaluate the impact of variables on pole density. In random forest, the importance of variables is measured in terms of mean decrease in accuracy, which is the loss of predictive accuracy due to the exclusion (or permutation) of a variable. The more important a parameter is, the larger the decrease in accuracy for classifying the data. Variables with relatively large mean decreases in predictive accuracy have large effects on the model. Variables with relatively small mean decreases in predictive accuracy have less effect. We explored the relationship between pole counts and predictor variables by determining variable importance (ranking of the impact of each predictor based on predictive accuracy; Breiman 2001, Cutler et al. 2007), and by graphing estimates of poles per 1 km^2 for a variety of the most important predictor variables. We then used the random forest model to predict pole density for all 1-km^2 cells throughout Colorado and Wyoming.

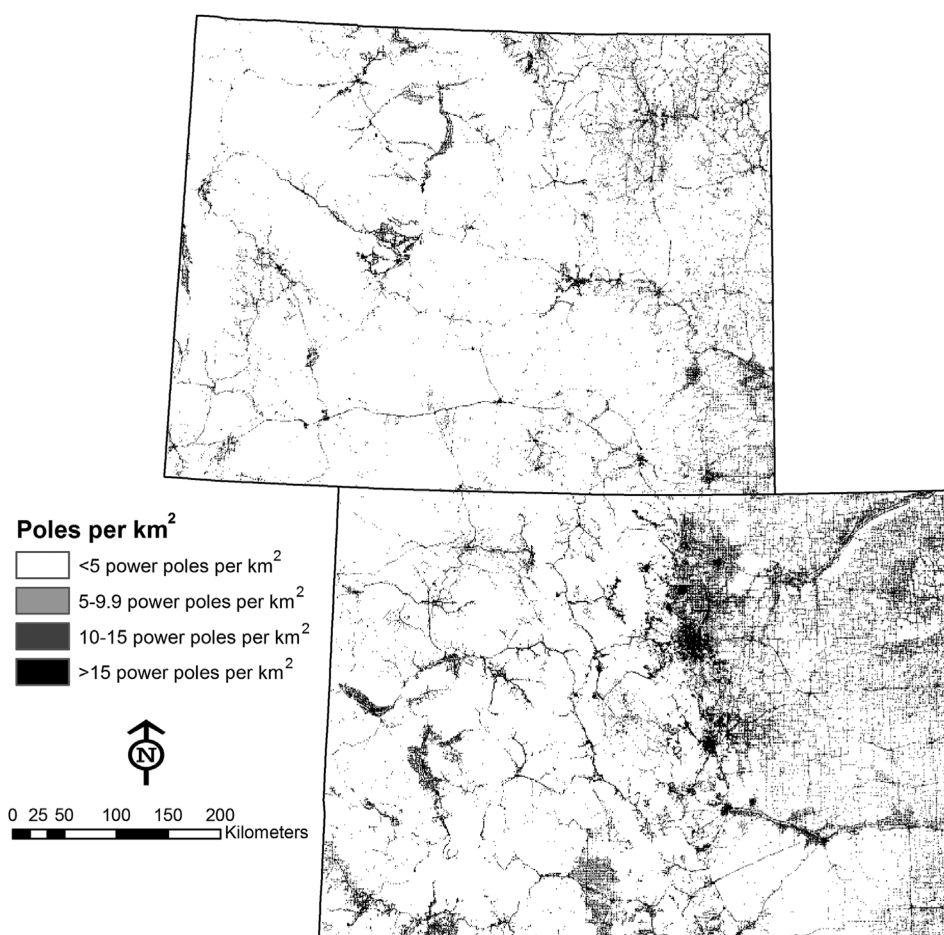

Figure 1. Predicted power pole densities in 2015 for 1-km^2 cells throughout Colorado and Wyoming, USA.

RESULTS

We received spatial data describing electric power distribution systems from 17 dispersed electric utility operators in Colorado and 2 in Wyoming, covering 163,395 km^2 (31%) of the land area of the 2 states combined. Pole density was influenced by the length of roads of all types, lengths of roads of specific types, number of oil and gas wells, mean slope, standard error of mean slope, presence of development, and the land cover type within each 1-km^2 cell (Table 1). As indicated by quantitative output from our model, pole density was influenced by land cover primarily in 3 ways. First, pole density in mountainous areas was focused in valleys. Second, pole density in the eastern plains was linear, focused along roadways serving agricultural areas. Third, pole density was greatest in urban areas. Specifically, poles were densest in the urban and agricultural areas of eastern Colorado and in the oil and gas fields of Wyoming, both relatively flat landscapes with high road densities (Figs. 1 and 2). Central and western Colorado and Wyoming were characterized by relatively low pole densities overall, except along the Front Range and in mountain valleys, where agriculture, roads, and oil and gas wells were concentrated. Specifically, pole density increased predictably with increasing road length, and increasing numbers of oil and gas wells up to an inflection point of about 16 km of roads (Fig. 3a), above which oil and gas wells declined as urban development increased. In comparing predicted pole density to foraging areas in the breeding season for golden eagles identified by DNHM, we located 6 areas where cells with predictions of high pole densities overlapped foraging areas during the breeding season (Fig. 4).

Model Validation

We tested the model on 10,621 out-of-sample cells with known pole locations. We found 62% of the predicted pole counts were within one pole of the true number of poles indicated by the test data (Fig. 3b), exceeding the accuracy of generalized linear regression models used to evaluate the same data (B. D. Gerber, Colorado State University, unpublished data). Overall, the within-sample mean squared error estimated from the random forest model was 1.96. Specifically, the model did a good job of distinguishing cells with poles from cells without poles (81% accuracy) but overestimated the number of cells with low pole densities (0–8 poles/km^2) and underestimated the number of cells with higher pole densities (>8 poles/km^2). However, because the errors were generally within 1–2 poles, cells with relatively low or high numbers of poles were still classified correctly overall.

The sampling protocol relied on electric utilities voluntarily contributing data, and, thus, created an unavoidable convenience sampling approach. Some of the utilities we contacted declined to contribute data, reinforcing the convenience sampling. Specifically, 17 of 27 (63%) utilities contacted in Colorado returned data, but only 2 of 16 (13%) utilities contacted in Wyoming returned data. However, one of the Wyoming companies returning data encompassed 17% of the state's total area, providing good inference to the state. Because utilities contributing data included service areas in all landscape types in Colorado and Wyoming including urban to undeveloped land covers, absent to abundant oil and gas wells, and flat to mountainous terrains, the data thoroughly reflected combinations of variables occurring statewide; model validation indicated good fits to out-of-sample test data. Thus, though our sampling scheme was unavoidably imperfect, model validation supported the accuracy of the resulting random forest model.

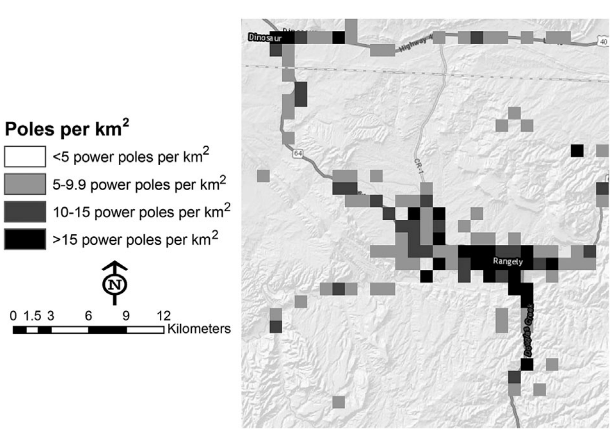

Figure 2. Predicted power pole densities in 2015 for 1-km^2 cells throughout the Rangely Oil Field, Colorado, USA, a focal point of raptor electrocution research (Harness and Wilson 2001, Lehman et al. 2010). Within the field, electrocutions historically occurred more frequently where poles were most dense.

DISCUSSION

The scale of conservation planning should be analogous to the scale of concern (Doherty et al. 2011). Our model is intended to serve as a guide, offering a spatially explicit stepping stone from threat mapping to systematic spatial prioritization for a regional-scale concern. To facilitate this, our model assumes pole density as a surrogate for avian electrocution risk. This assumption works specifically because within high-quality habitats electrocution risk per pole increases with increasing pole complexity (Dwyer et al. 2013, Harness et al. 2013), which increases with increasing pole density, though the specific relationship remains unquantified. Thus, though future research should quantify the relationship between numbers of poles and numbers of electrocutions, pole density can be used as a general surrogate for avian electrocution risk at a regional scale. To complete mitigation actions, evaluation of individual pole-specific risks would still be needed within areas identified as having high pole density (Tintó et al. 2010, Dwyer et al. 2013, Harness et al. 2013).

The effectiveness of systematic spatial prioritization hinges on consistently and transparently using limited resources to the greatest effect so conservation decisions can be critically reviewed (Margules and Pressey 2000). To achieve this, systematic spatial prioritization can involve 6 stages proposed by Margules and Pressey (2000): 1) compilation of data on species of concern; 2) identification of conservation goals; 3) review of existing conservation areas; 4) selection of

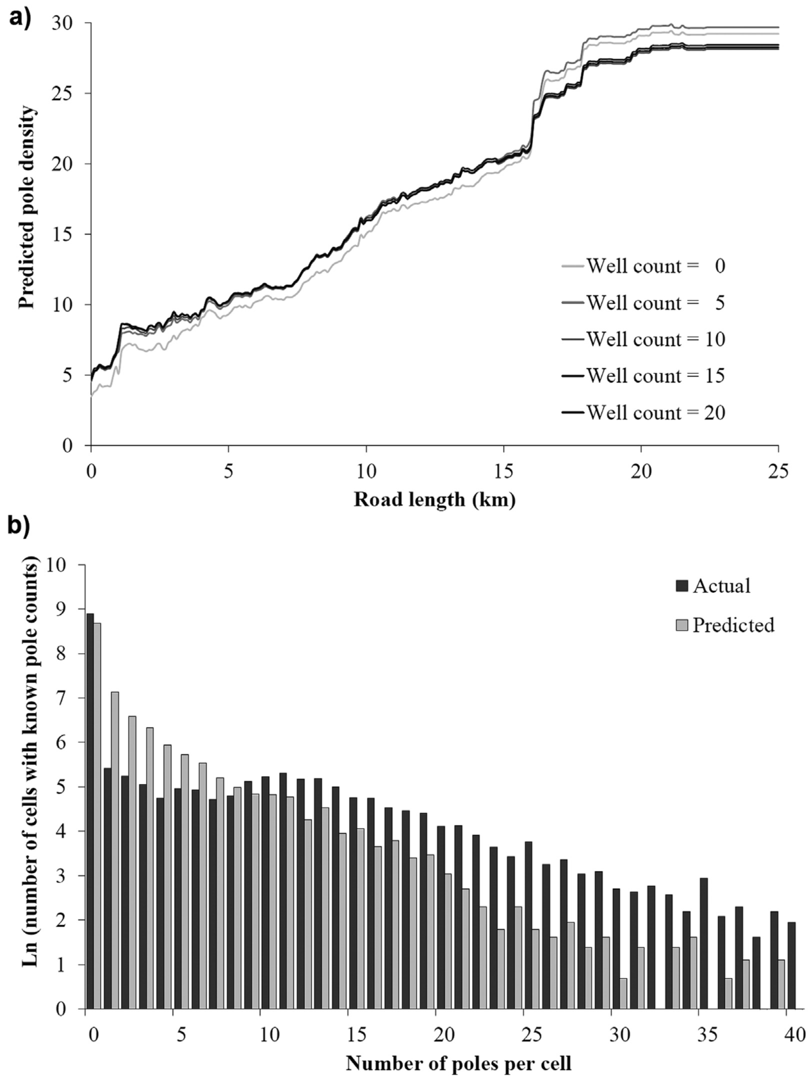

Figure 3. (a) Predicted power pole density in 2015 across a range of road lengths and well densities (the most important predictive variables) in Colorado and Wyoming, USA from a random forest model. (b) Comparison of predicted power pole density and out-of-sample data used to validate the model.

additional conservation areas; 5) implementation of conservation actions; and 6) maintenance. Our model specifically builds on stages 1 and 2, to facilitate assessment of stage 3, carry out stages 4 and 5, and set up stage 6. Thus, our model provides a tangible framework for systematic spatial prioritization in support of regional conservation planning.

Specifically, our model is designed to be viewed in a geographic information system (GIS) together with a habitat map for species of interest. This approach facilitates simultaneous consideration of species' distribution with electrocution risk (stage 1). By identifying where habitats and high densities of poles co-occur, resource managers can identify specific focal areas for conservation (stage 2). Systematic spatial prioritization requires feedback loops (Margules and Pressey 2000). Our model facilitates such loops because where areas of high-quality habitat overlap areas of high pole density, resource managers must coordinate with electric utilities to identify whether an APP and retrofitting already exist, and whether and how additional retrofitting is needed (stage 3). Avian Protection Plans should be applied to all electric utilities, but where key areas lack APPs, either entirely, or through incomplete retrofitting, the need for additional conservation actions becomes apparent (stage 4). An Avian Risk Assessment and supporting APP can be used to develop a local index of electrocution risk and mitigation (Dwyer et al. 2013, Harness et al. 2013), and prioritize poles for retrofitting (stage 5). Poles within areas can be ranked via a risk index, and all poles above a specific index value can be retrofitted. This facilitates adoption of specific conservation goals, an important component of systematic spatial prioritization when economic factors also must be considered (Margules and Pressey 2000). Because the state of the art in APPs evolves with new information, and because retrofitting materials must be maintained, maintenance of conservation actions will be ongoing (stage 6). Implementation (stage 5) and maintenance (stage 6) can provide information on the effectiveness and errors in mitigation approaches, and can be used to create additional feedback loops (stage 1) and guide selection of additional conservation actions (stage 4). In this way, our

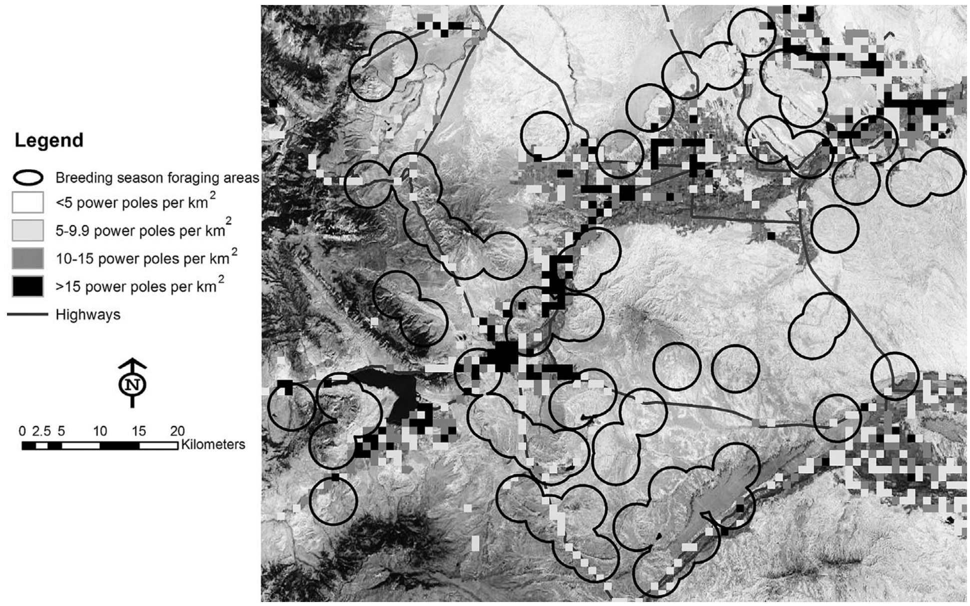

Figure 4. Some foraging areas during the breeding season of golden eagles in 2015 overlap with 1-km^2 cells with high power pole densities in north-central Wyoming, USA.

model provides a novel framework supporting systematic spatial prioritization at a regional scale.

Once areas of interest have been identified via the regional model and APPs have been evaluated, resource managers can coordinate with electric utilities to use a fine-scale model of electrocution risk to identify and prioritize high risk poles for retrofitting based on pole-specific hazard and exposure (Fig. 5; Dwyer et al. 2013, Harness et al. 2013). Hazard describes the likelihood that a bird will be electrocuted if it lands on a given pole, thus, reflecting electrocution risk as a function of the configuration of engineered electrical components (Dwyer et al. 2013, Harness et al. 2013). Hazardous poles can be retrofitted by installing devices to prevent contact with energized equipment, or by modifying construction practices to provide greater separation between energized equipment and other components (APLIC 2006). Exposure describes the likelihood a pole will be encountered by a species of interest, thus, reflecting habitat-driven species-specific levels of use. Using the model described here to direct where pole-specific retrofitting occurs at the spatial scale at which birds select poles and habitat will provide a powerful approach to allocating limited resources most efficiently.

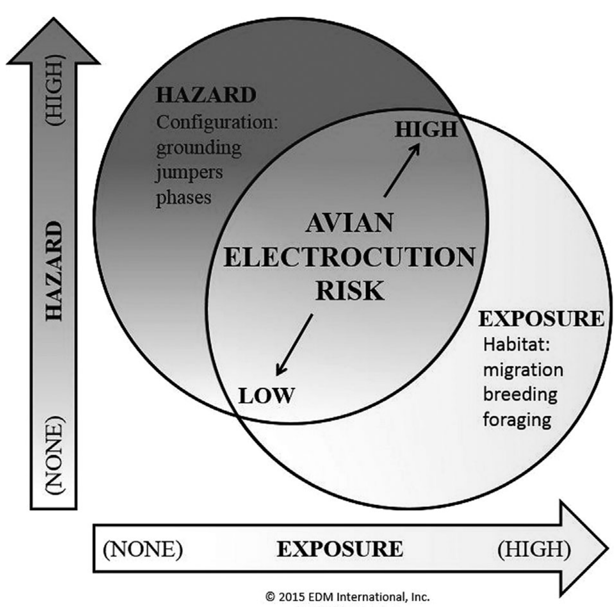

Figure 5. Conceptual model of the relationship between electrocution hazard, avian exposure, and avian electrocution risk.

One key strength of our model is that anthropogenic factors affecting pole density are clear. For example, oil and gas well density is a primary predictor of pole density in Colorado and Wyoming. The Rocky Mountain West contains 26% of the natural gas reserves in the United States (Doherty et al. 2011), and well density is likely to increase to access these reserves (Copeland et al. 2009). The information on the relationship between oil and gas wells and pole density provided here clarifies the importance of applying electrocution prevention techniques at new wells as facilities are developed. Another important characteristic of our model is that road length is a key predictive variable. Though generally useful, this will be misleading in those urban areas where electric systems are underground, a feature that would eliminate avian electrocution risk but was not predictable from our source data. This will also be misleading for particular species in some areas, such as golden eagles, which tend not to occupy urban areas regardless of electric systems. This serves to highlight the importance of coordinating conservation efforts with local utilities and species biologists, and of incorporating feedback loops between stakeholders. We coordinated with the DNHM to compare foraging habitat in the breeding season for golden eagles with predictions from our model, and identified 6 areas where cells with predictions of high pole densities overlapped foraging areas. Prioritizing retrofitting within these areas might be most beneficial if the affected poles have not already been addressed under an APP.

Application of our model must incorporate an understanding of potential biases, particularly with regard to pole construction. In the United States, poles are uniformly constructed to meet National Electric Safety Code (NESC) rules. Thus, poles are very similar throughout the United States with legally defined separations between components of different electric potentials. In areas where pole designs are more variable, as in Spain (Janss and Ferrer 1999, 2001; Ferrer 2012), the modeling approach used here may not be viable because implications of pole construction from sampled areas may not apply well across the landscape.

MANAGEMENT IMPLICATIONS

Though imperfect, our model offers the first approach to developing an evaluation of electrocution risk at a regional scale. Because we do not know how well the model might apply to other areas, future work should expand this approach across western North America, incorporating pole location data from samples of electric utilities in other regions. Comparison of models in different states will provide insight on whether additional state-by-state models are needed, or whether relatively few models could be extrapolated throughout the region. Because the model does not include species-specific parameters, a similar approach could be used for other species at risk of electrocution, such as bald eagles (*Haliaeetus leucocephalus*) or osprey (*Pandion haliaetus*) based on proximity to open water or other habitat features. The model may also be useful for managers concerned with the presence and abundance of anthropogenic perches in natural landscapes (Boarman 2003, Coates and Delehanty 2010).

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