QUANTIFYING EXPOSURE OF WYOMING'S WILDLIFE TO ENERGY DEVELOPMENT IN THE FACE OF EXPANDING PRODUCTION

Prepared by

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SUMMARY

Maintaining biodiversity in the face of rapid and extensive anthropogenic habitat change is exacerbated when national policies, such as the current push for increased and diversified energy production, accelerate development beyond the capacity of wildlife managers to respond, thus forcing them to initiate conservation with inadequate information. A priori species prioritization schemes help alleviate this problem, and while many such schemes have been proposed, all depend on gauging exposure of species to disturbance. Here, we apply a refined, quantitative method to estimate exposure for a wide range of species by calculating the weighted proximity of species' distributions to current and projected energy development. We also incorporate an objective assessment of uncertainty often lacking in multi-species assessments. This analysis can be used to assess whether site-specific impacts documented through local studies have the potential to translate into broader population impacts that could, in turn, affect wildlife management priorities. We identify a suite of species (e.g., pygmy rabbit, Wyoming pocket gopher, black-footed ferret, Great Plains toad) that are of concern in our focal landscape when considering conservation activities related to energy development. The methods we employ are widely applicable, using data often available to local and regional management agencies and conservation groups.

INTRODUCTION

Habitat change from anthropogenic activates is rapid and extensive, and recognized as the foremost cause of wildlife decline and extinction worldwide (Koh et al. 2004, Vié et al. 2009). Maintaining biodiversity in the face of such change is exacerbated when national policies, such as the current push for increased and diversified energy production, accelerate development beyond the capacity of wildlife managers to respond, thus forcing them to rapidly prioritize which species receive attention. This situation is exacerbated when there is a mismatch between the scales of development pressure and conservation management. This is exemplified by energy development, where national and international demand is driving rapidly expanding energy production, particularly of 'clean' energy sources like natural gas and wind-power, resulting in rapid impacts to local wildlife populations, management of which falls within the purview of state agencies that are ill-equipped to deal with the magnitude of such rapidly increasing disturbance (Naugle 2011). This situation often results in management focusing on species once they exhibit evident impacts and/or on politically important species, often on a case-by-case basis (Wainwright and Kope 1999, Vucetich et al. 2006, D'Elia and McCarthy 2010), when what is needed is an effective prioritization that identifies where populations are likely to decline but have not declined to a point where drastic intervention is necessary (Wilcove and Chen 1998, Drechsler et al. 2011).

Species prioritization schemes abound (e.g., Metrick and Weitzman 1998, Miller et al. 2006, Joseph et al. 2009, AFWA 2011), but their effectiveness hinges upon accurate evaluation of threat, which in turn hinges upon accurate assessment of species-specific levels of habitat alteration that is the driving factor behind impact. Unfortunately, the rapidity of change often results in a lack of quantitative and taxonomically complete assessments, even for fairly well-studied systems. For instance, Wyoming's State Wildlife Action Plan (SWAP) identified 279 species of greatest conservation need (SGCN), 235 (84%) of which were included due to lack of information necessary for management, the largest component of which is lack of data on distributions (WGFD 2005). Considering the United States as a whole, over 12,000 SGCN have been designated under SWAP programs, with individual states listing 100 to 1,200 species, most of which lack the quantitative information necessary to inform more detailed assessments of habitat disturbance (AFWA 2011). Thus, a critical first step in the prioritization process is quantifying the relative exposure of species' habitats to development.

Though spatial impact analysis is fairly well-developed in the realm of strategic environmental assessment (e.g., Geneletti 2013), it is less-often applied rigorously to species prioritization, particularly at state levels where much conservation is implemented. Analyses that seek to quantify exposure to development typically occur for particular sites and/or few species (e.g., Johnson et al. 2005, Nielsen et al. 2008, Bennett et al. 2009, Sawyer et al. 2009, Wilson et al. 2011). Quantitative, multi-species, landscape scale assessments of exposure are still rare except at large scales, and often rely on indicator species or overlays of coarse species range data with broad blocks of proposed development (e.g., Landres et al. 1988, McDonald et al. 2009, De Cáceres et al. 2010). The increasingly sophisticated science of niche modeling can be used to refine exposure analyses, resulting in an effective tool for conservation planning (Sattler et al. 2007, Carroll 2010, Crawford and Hoagland 2010, Hu et al. 2010). None-the-less few studies make full use of output from such models, generally simplifying analyses by binning results into binary output using standardized, but biologically arbitrary, thresholds (e.g., Carroll 2010, Yackulic et al. 2013). Further, recent syntheses of human impact studies have resulted a better understanding of effect distance functions that can be used in combined with the continuous output from such models to generate quantitative estimates of exposure to development (Copeland et al. 2009b, Benitez-Lopez et al. 2010).

Our objective in this study is to apply a refined, quantitative method to estimating exposure for a wide range of species that also includes an objective assessment of uncertainty that is often lacking in multi-species assessments. We use geospatial estimates of habitat suitability in concert with impact distance functions and development footprints to achieve a refined estimate of exposure to disturbance for a large number of species across a landscape that is increasingly influenced by energy development activities. Results of this analysis are used to assess whether site-specific impacts documented through local studies have the potential to translate into statewide population trends that could, in turn, impact wildlife management priorities. The methods we employ are widely applicable using data often available to local and regional management agencies and conservation groups.

METHODS

The following sections explain the main points of our analytical methods. A complete, detailed accounting of methods can be found in Appendix A.

FOCAL LANDSCAPE

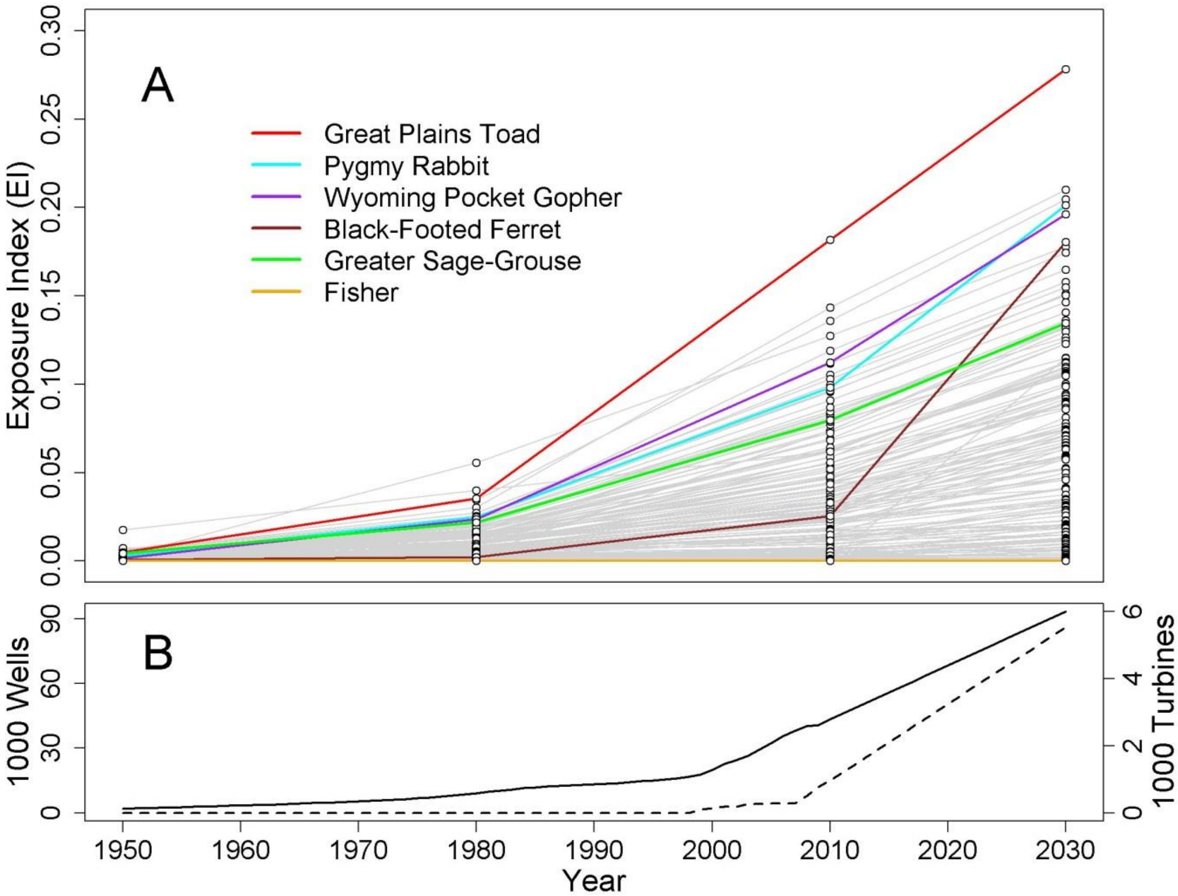
Our focal landscape is the state of Wyoming, where there are over 150, mostly poorly-understood SGCN (WGFD 2010b). State and local resource management agencies in Wyoming are increasingly overburdened due to a rapidly expanding energy footprint representing 14% of U.S. domestic production (EIA 2011c). We focus on petroleum (i.e., oil and natural gas) and wind-power production, both of which alter large tracts of habitat in Wyoming and are rapidly expanding due to strong national support for increased U.S. production of 'clean' energy. The number of oil and gas wells and wind turbines in Wyoming has increased drastically in recent years and continued increases of at least 130% and 615%, respectively, are predicted over the next 20 years (Fig. 1B).

MAPPING DISTRIBUTIONS OF SPECIES AND DEVELOPMENT

We constructed maps of current and projected petroleum (i.e., oil and natural gas) and wind power development in Wyoming by first estimating resource potential across the state. For oil and gas potential, we improved a previously published forecast for the Intermountain West (Copeland et al. 2009a) by using higher-resolution data on bedrock geology and geologic faults as input variables and more detailed maps of producing and non-producing oil and gas wells as the binary response variable in a Random Forests model (Breiman 2001). A similar model was generated for wind-power potential using maximum entropy methods (Phillips and Dudik 2008) with currently producing wind-turbines as the response variable and wind-resource potential in combination with topographic position variables as predictors. The energy potential models were highly discriminative based on multiple metrics, all of which indicated stable and acceptable predictions. The energy potential surfaces from these models were further adjusted to reflect spatially-explicit constraints to near-term development that could not be effectively captured in the modeling process (e.g., idiosyncratic legal constraints to development and facilitation of development from existing infrastructure). Development maps were generated by seeding the landscape with wells and turbines according to the energy potential model at rates predicted by energy production forecasts for Wyoming (e.g., Stilwell and Chase 2007).

For each SGCN (n = 156 species), we constructed a distribution model using documented occurrences as the response variable and statewide environmental layers representing climate, hydrology, land cover, substrate and terrain as predictor variables. We used maximum entropy methods because they have been demonstrated to be accurate and robust under the given data structure, particularly when sample sizes are small (Hernandez et al. 2006, Graham et al. 2008, Wisz et al. 2008a, Franklin 2009, Elith et al. 2011, Renner and Warton 2013). To avoid biases associated with opportunistically gathered data (e.g., Johnson and Gillingham 2008, Royle et al. 2012), we used background data selected from the sample set rather than randomly-generated pseudo-absences (Phillips et al. 2009) and employed a randomized, multi-pass filter to select model sets that minimized spatial bias and maximized the quality of occurrences in the final model. Most analyses employing distribution modeling to assess impact use a binary expression of the models, because it is computationally simpler to overlay with development maps. This requires selecting a presence threshold for all species, for which there is no good universal rule (Yackulic et al. 2013), and which unnecessarily eliminates valuable information regarding spatial context of potential habitat contained in the continuous models. Therefore, we used the continuous output of our distribution models, rescaled to sum to one over the entire state, so each location represented the relative likelihood of species presence relative to all other locations.

Figure 1. Changes through time in exposure to energy development for 156 Species of Greatest Conservation Need (SGCN) in Wyoming (A) relative to the cumulative number of oil and gas wells (B; solid line) and wind-power turbines (B; dashed line). Several species mentioned in the text are highlighted in colors that match those in Fig. 2. Data on energy infrastructure were compiled from sources listed in Appendix A.



For species distribution models the paucity of data and challenges of model specification make uncertainty a particularly important issue. Moreover, quantifying uncertainty can itself be used to inform conservation planning (Beale and Lennon 2012), although such quantification is difficult and therefore seldom done. We addressed this by validating our distribution models using several well-supported validation statistics that we used to develop an omnibus uncertainty index (UI) for each species, thus explicitly considering how uncertainty in our models might impact estimated exposure. Components of UI included area under the receiver operating characteristic curve based on withheld test data, predictive success based on 10-fold cross-validation, and the Boyce index (e.g., Hirzel et al. 2006), as well as quantitative assessments of input data quality and expert review of the final models. UI ranges from an upper limit of one when the resulting exposure estimate is relatively uncertain, to a lower limit near zero when we are relatively confident in the exposure estimate.

CALCULATING EXPOSURE TO DEVELOPMENT

We used our development projections to generate disturbance footprint maps, for which maximum disturbance (Exposure Value; $EV = 1.0$) occurred at developed sites (i.e., wells and turbines) and decayed to zero according to published distance thresholds (Benitez-Lopez et al. 2010). Specifically, the un-weighted exposure value of cell *i* relative to disturbance *d* (EV_{di}) is a logarithmically decaying function of the distance of cell *i* to the nearest well pad or wind turbine (D_i) according to the following equation:

$$EV_{di} = \frac{1+e^{a}}{1+e^{(a+bD_i)}} \tag{1}$$

where and *a* and *b* are constants defining a logarithmic curve that decays from 1.0 to 0.01 at a defined distance (1 km in our primary analysis). Species likely exhibit differential sensitivities to development, so decay curves of different radii may be appropriate for different taxa, but it is precisely this type of detailed response information that is lacking for most species, thus motivating this analysis. Since any taxa-specific adjustments would be speculative, it makes more sense to evaluate all species equally and initiate targeted studies of species thereby identified as highly exposed in order to quantify sensitivity to specific disturbance, thus providing information necessary to modify the impact function. Further, we investigated exposure shifts resulting the uniform application of different impact distance functions and found they introduced only slight variation in the final results (see Appendix A).

Energy development footprints were multiplied by the continuous species distribution models, and the result was summed across Wyoming according to the following equation:

$$EI_s = EI_{ogs} + EI_{ws} = \sum_i EV_{ogi} * DM_{si} + \sum_i EV_{wi} * DM_{si} \tag{2}$$

where, DM_{si} is the value of the distribution model for species *s* in cell *i*, and subscripts *og* and *w* represent values for oil/gas and wind development, respectively. Thus, EI_s is the exposure index for species *s*, representing the proportion of the species' potential distribution exposed to development weighted by the relative probability of species occurrence and by disturbance intensity. *EI* is thus a direct measure of relative exposure to development that incorporates the best available data on where species occur, which is more informative than simple overlays of range maps or binary distribution maps with anticipated development areas.

RESULTS

Our results demonstrate a clear ranking of species exposure to potential energy development (Figs. 1 and B2, Table C1). This ranking holds even in the face of large variation in the species-specific uncertainty, because species with the highest exposures tended to have highly discriminative models (Fig. 2). The majority of species in our study showed sufficiently low exposure to current and future energy development that range-wide impacts are not likely even with substantial distributional uncertainty. Generally speaking, montane obligates showed very low exposure (e.g., Fig. 2B: fisher, $Es < 0.001$), while species restricted to low and mid-elevation basin shrublands and grasslands showed higher exposure (e.g., Fig. 2C: Great Plains toad, $Es = 0.278$). Trajectories of exposure through time vary greatly among species, and we predict that several species will exhibit accelerated exposure in the future (e.g., Fig. 1A: black-footed ferret = 613% increase over current levels; pygmy rabbit = 105%; Wyoming pocket gopher = 75%).

Exposure to petroleum infrastructure will be much larger than to wind turbines (Fig. B2, Table C1), but petroleum and wind-energy footprints are largely non-overlapping (Figs. 3 and B3), resulting in spatially extensive disturbance from the combination of the two types of energy development. Despite its comparatively small footprint, wind power represents more than half the calculated exposure to energy development for 14 species. Of particular note, exposure of federally-listed back-footed ferret is driven largely by wind power (Fig. 3E: $Es_{wind} = 0.177$, $Es_{petroleum} = 0.004$), which leads to its ranking as the 6th most exposed species in our study.

Figure 2. Joint distribution of exposure index (*EI*) and uncertainty index (*UI*) for 156 SGCN in Wyoming. Higher *EI* values indicate greater exposure to development, while higher *UI* values indicate more uncertainty in the exposure estimate. Each species is symbolized by its exposure rank (see Table C1), with several species mentioned in the text highlighted in colors matching those in Fig. 1. Dashed lines delineate heuristic zones of concern discussed in the text (boundaries subjective).

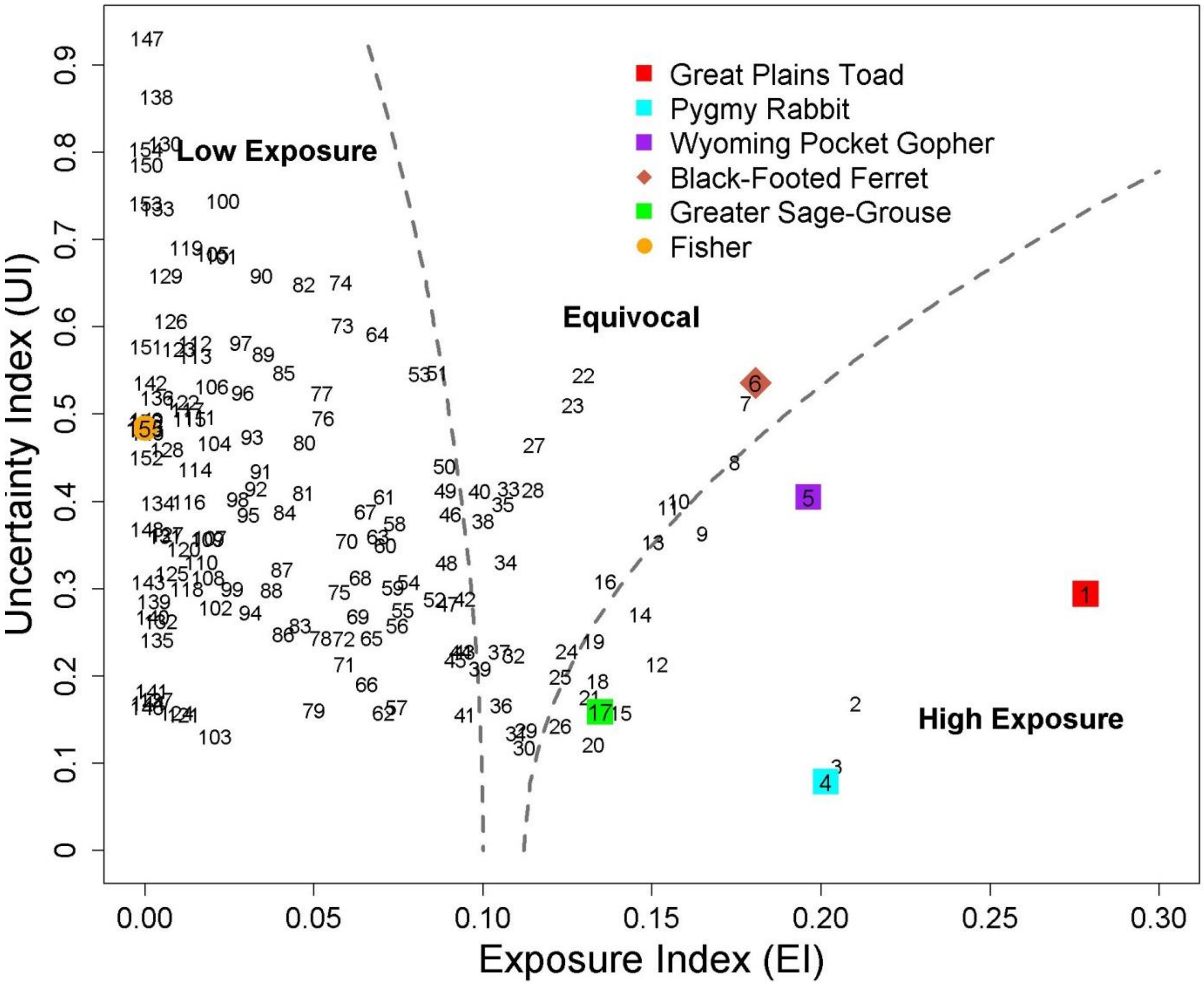
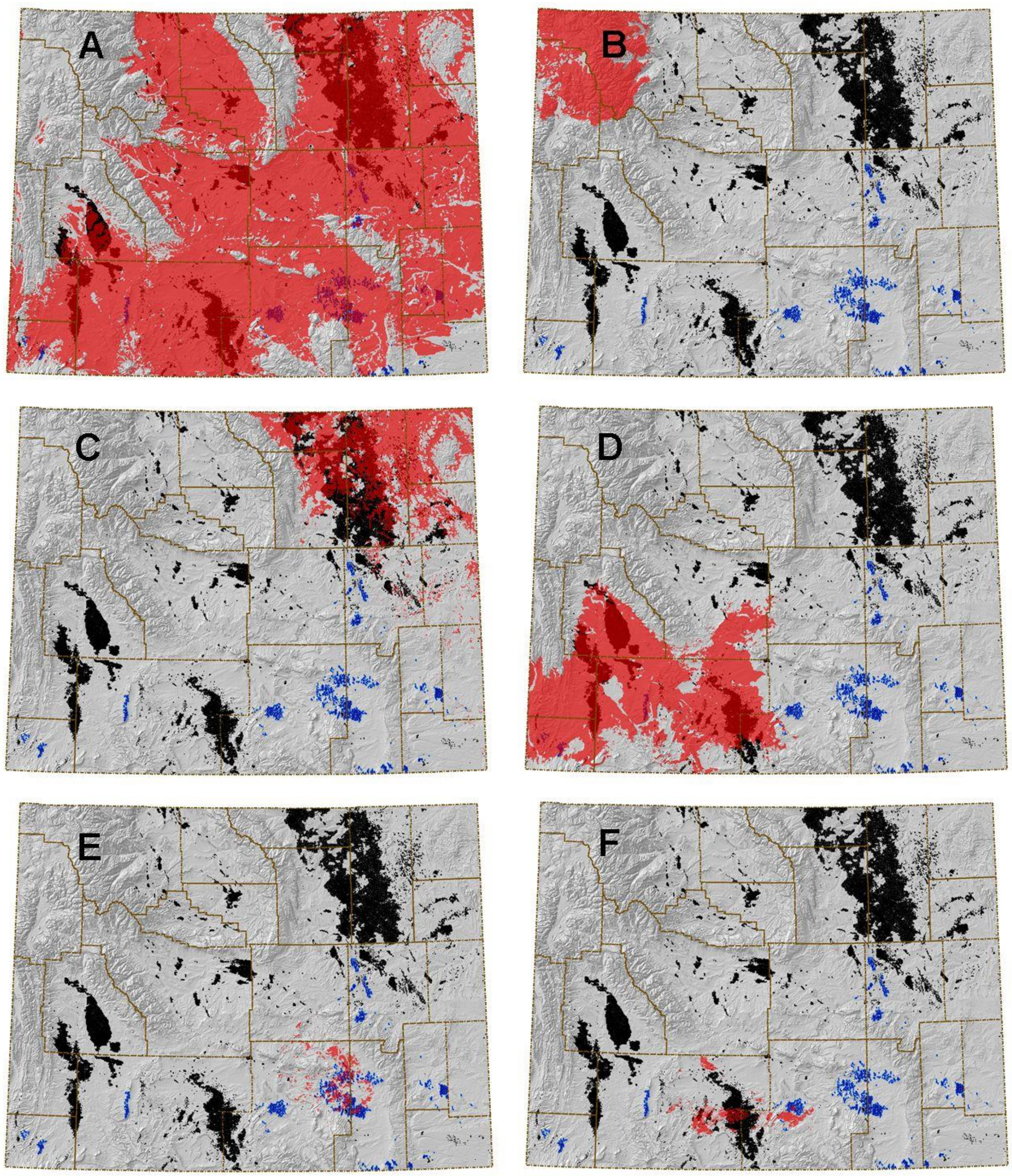


Figure 3. Wyoming distribution maps for the six Species of Greatest Conservation Need (SGCN) highlighted in Figs. 1 and 2 superimposed on energy development projections for 2030. Black shading represents the footprint from oil and gas development and blue represents the footprint from wind-power development. Red shading represents the area of predicted occurrence for greater sage-grouse (A; EI=0.135), fisher (B; EI<0.001), Great Plains toad (C; EI=0.278), pygmy rabbit (D; EI=0.201), black-footed ferret (E; EI=0.181), and Wyoming pocket gopher (F; EI=0.196). The latter species is endemic to Wyoming, so the model represents its entire global distribution. Background is a topographic relief map of Wyoming with county boundaries for reference.



DISCUSSION

At the most basic level, species with higher exposure to development should receive increased scrutiny when assessing conservation priorities, since a greater proportion of suitable habitat coincident to development indicates a correspondingly greater potential for population-level impacts (Naugle 2011). Sixteen of Wyoming's SGCN have EI values higher than greater sage-grouse, which has extensively researched impacts from this development. To our knowledge very few of these species are currently the focus of research or conservation relative to this exposure. We recognize that eventual decisions regarding conservation priorities will necessarily involve additional factors (e.g., cost, logistics, social concerns, political climate; Miller et al. 2006), but we believe that any species herein classified as High Exposure, and perhaps also Equivocal Exposure (Fig. 2), are worthy of increased scrutiny. This is particularly true when species demonstrate biological sensitivities that suggest exposure is likely to translate into impacts (e.g., Cardillo et al. 2005). For example, pygmy rabbit is highly exposed and exhibits known biological sensitivity stemming from restrictive habitat specificity that has already resulted in placing one sub-species on the U. S. endangered species list due to habitat disturbance (USFWS 2010b). Similar arguments can be made for other highly-exposed species in our analysis, notably Wyoming pocket gopher, black-footed ferret, and Great Plains toad (see Appendix A).

Three additional factors that we are able to evaluate with quantitative exposure analysis suggest that a small set of Wyoming's mammal species may be of particular concern. First, species with restricted distributions, and thus little capacity to spatially avoid development, are generally at higher risk from habitat alteration than others (e.g., Owens and Bennett 2000). This raises concern for species like black-footed ferret and Wyoming pocket-gopher (Figs. 3E, F) relative to more widely distributed basin species (e.g., Fig. 3A). In fact, the global distributions of these species are so restricted that conservation for the species as a whole hinges upon conservation in Wyoming. Second, large projected increases in exposure over current levels suggests that proactive conservation could have a greater potential to effect change, because efforts enacted now could avert impacts rather than mitigating damage to already impacted populations (Wilcove and Chen 1998, Drechsler et al. 2011). Pygmy rabbit and black-footed ferret are notable in this regard, because they are predicted to experience large increases in exposure (Fig. 1). Also, together with black-tailed prairie dog, these two species exemplify a third factor of concern, namely that projected exposure is concentrated in areas predicted as most suitable (i.e., areas that are more likely to be occupied), which suggests a greater potential for impact (e.g., Fig. B4).

The use of umbrella species has long been a dominant approach to multi-species conservation despite ambiguous scientific support (e.g., Ozaki et al. 2006, Branton and Richardson 2011). This is true of our focal landscape, where the role of greater sage-grouse as a purported umbrella species (Rowland et al. 2006) has contributed to intense conservation attention, culminating in an executive order in Wyoming to restrict new energy development in areas identified as 'core' sage-grouse habitat (Fig. B5). Our exposure analysis shows that complete cessation of future development in core areas would reduce predicted exposure of the 25 most-exposed species by an average of only 7% (Fig. B6). None-the-less, our analysis suggests the sage-grouse core area strategy can substantially mitigate impacts for a few species. Notably, 30% of exposure for the federally-endangered black-footed ferret, which is not generally viewed as falling under the sage-grouse umbrella, can be averted by precluding wind turbines in a relatively small area identified as core sage-grouse habitat. Similarly, anticipated exposure of pygmy rabbit to oil and gas development can be reduced by up to 20% with strict conservation of large-stature sagebrush in sage-grouse core areas. For other species sage-grouse core areas will not mitigate exposure to energy development, but could offset exposure by providing a refuge if a large proportion of those species' undeveloped habitats are coincident with sage-grouse core areas. In this context, limiting development in core areas may be effective for species like pygmy rabbit and black footed-ferret, which have close to half their distribution within core areas (Fig. B6), though further analysis is required to assess whether or not these areas are effected by other development pressures. In contrast, species like Wyoming pocket gopher and Great Plains toad have sufficiently small portions of their distribution within sage-grouse core areas that they are unlikely to benefit from core area policies.

A benefit of our comprehensive, quantitative approach to examining exposure is that it does not focus solely on species with plentiful data and political support, but assesses all species on the same scale and explicitly identifies deficiencies, thus allowing a more transparent assessment of risk. Relative uncertainty in exposure estimates is useful in this context and should be considered when assessing potential conservation targets and identifying next steps. Based on relative levels of exposure and uncertainty, we view species as falling into one of three heuristic categories; low exposure, high exposure, or equivocal exposure (Fig. 2). Most species in our study clearly have low exposure to energy development, even in the face of large distribution uncertainty, and thus are not urgent candidates for energy-related research or conservation. Species with large exposure values in combination with relatively low uncertainty in the exposure estimate (e.g., Great Plains toad, pygmy rabbit, Wyoming pocket gopher, greater sage-grouse) fall into the high exposure category and are logical targets of immediate conservation attention and/or intensive research to quantify and mechanistically understand local impacts that could translate into population-level effects (e.g., Walker et al. 2007, Arnett et al. 2008, Gilbert and Chalfoun 2011). Finally, species with sufficiently large uncertainties relative to exposure could be considered equivocal, because there is a distinct concern that the exposure estimate hinges upon our inability to accurately map their distribution (e.g., black-footed ferret). Next steps for these equivocal exposure species would logically involve resolving distributional uncertainties through additional field survey efforts before conducting more rigorous studies of local impacts. However, in these cases it must be recognized that, if the present level of exposure is already of a magnitude that declines have occurred, future distribution mapping efforts could be confounded by those declines.

Rapid expansion of anthropogenic development is a global concern, but impacts to wildlife are initially felt at local and regional levels, and it is at these geographic scales where management is typically implemented. Precautionary wildlife management suggests that we use available, though sometimes imperfect, information to prioritize conservation efforts so we can minimize the potential for costly, reactionary responses once impacts have reached obviously critical levels. Formal, quantitative exposure analysis, which we demonstrate here, can facilitate proactive conservation planning for the many understudied species for which wildlife managers are responsible. It is important to stress, however, that we do not suggest basing long-term policies solely on this analysis. Rather results from quantitative exposure analysis serve to better inform conservation prioritization schemes and impact assessments. Once exposure analysis has helped reduced the list of species of greatest concern to a manageable level, the logical next step is to identify areas for immediate protection while conducting targeted research to understand the biological vulnerability of individual taxa, reduce uncertainties, and inform the design of appropriate long-term conservation strategies. While our work has focused on energy development in Wyoming habitats, the approach we outlined could be easily employed to gauge threat exposure in other settings. In particular, while we have focused on energy development, spatial development models for agriculture, forest loss, or urban expansion could similarly be used to predict exposure to other threats, and thus to better inform how scarce conservation resources should be best used.

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APPENDIX A. DETAILED PRESENTATION OF MATERIALS, METHODS AND SPECIES SENSITIVITY

ENERGY DEVELOPMENT MODELS

We mapped current and potential energy development in Wyoming. Current development was obtained from the Wyoming Oil and Gas Conservation Commission (WOGCC 2010) and the U. S. Geological Survey (O'Donnell and Fancher 2010) Potential development was based on available, detailed industry projections, which we mapped through a two-step process wherein we first created models of resource potential based on current information and adjusted the output of these models based on near-term, site-specific development indicators. These near-term indicators of development where not related to resource potential, but rather influenced the probability and/or rate at which areas identified as having resources would be developed. The final maps of energy development potential were expressed as continuous raster datasets covering all of Wyoming at a cell size of 1-km^2. Cell values in these maps ranged from 0 (no potential for energy development in the next 20 years) to 1 (nearly certain development in the next 20 years). These maps were used to generate energy buildout scenarios wherein infrastructure was placed on the landscape according to published trend assessments, as discussed below.

ANALYTICAL APPROACH AND DATA SOURCES: OIL AND GAS.

To estimate spatially-explicit oil and gas resource potential across Wyoming, we refined a previously published forecast for the Intermountain West (Copeland et al. 2009b) by using more detailed maps of producing and non-producing oil and gas wells as our binary response variable (WOGCC 2010) and higher resolution data on bedrock geology and distance from geologic faults for predictor variables (Love et al. 2010). In total, nine topographic, geological and geophysical variables were used to predict development. These variables and sources were: aeromagnetic, gravimetric, isostatic gravity and Bouguer gravity anomalies (Phillips et al. 1993), detailed bedrock geology and Euclidean distance from geologic faults from the Wyoming State Geological Survey (Reed and Bush 2007, Love et al. 2010), 30 meter elevation data downloaded from the USGS National Atlas (http://nationalatlas.gov), generalized geologic data for the Coterminous United States downloaded from the National Atlas (http://nationalatlas.gov) and bedrock depth (Copeland et al. 2009a). Model-fitting was based on the nonparametric Random Forests method, which uses an iterative bootstrap with replacement (64% of data per bootstrap replicate) to construct an ensemble of ‘‘weak learners’’ (Classfication and Regression Trees (CARTs) based on random subsamples of the data). Thus, we made predictions through a majority vote across the ensemble, rather than the rule-set of a traditional CART model, resulting in both binary and continuous, probabilistic outputs. The derivation of a probabilistic output from a classification-based model was introduced by Evans and Cushman (Evans and Cushman 2009) as an extension of the original Breiman (Breiman 2001) algorithm. We used a further modified version of the Random Forests model allowing for bootstrapping subsets within the model, thus improving model fit (Evans and Cushman 2009). The final oil and gas potential model assigned each 1-km^2 grid cell in Wyoming a potential score ranging from 0 (no development) to 1 (certain development).

Output from the predictive model was adjusted to reflect factors preventing near-term development, primarily legal constraints, by setting the probability of cells where such restrictions occur to zero. Areas with a score of zero included BLM lands designated as "no surface occupancy", withdrawals (formal lands actions that set aside, withhold, or reserve federal land by statute or administrative order for public purposes), Wilderness Study Areas, Nature Conservancy Preserves, US Fish and Wildlife Service Refuges, and Wyoming Game & Fish Habitat Management Areas. Seasonal and timing stipulations (e.g., limiting surface activity in ungulate wintering grounds during the winter months) were not included, because these data are not consistently available across Wyoming and it is unclear how much development is actually restricted by them.

We created a buildout scenario of the Wyoming landscape by placing oil and gas wells according to the energy potential model described above. Wells were placed sequentially, beginning in areas with high potential values and minimum restrictions and continuing until projected levels of development were reached. The number of wells placed on the landscape was drawn from 20-year reasonable and Foreseeable Development Scenarios (RFDS) developed for the resource management plans of each Wyoming BLM field office (Stilwell and Crockett 2004, Braun 2006, Stilwell and Crockett 2006, Stilwell and Chase 2007). RFDS reports are based on best-available data on petroleum deposits, extraction technologies and energy markets, and have historically been conservative estimates of future development. There are currently over 40,000 active oil and gas wells in Wyoming, and RFDS reports suggest an increase of roughly 130% by 2030. RFDS reports do not explicitly project annual development rates, which will vary due to short-term market fluctuations, so we assumed a linearly increasing function over the length of our study. In specific locations, wells were placed up to densities allowed by current stipulations with existing wells included in all density calculations.

ANALYTICAL APPROACH AND DATA SOURCES: WIND POWER.

To estimate wind-power potential across Wyoming, we used wind turbine locations as a response variable (O'Donnell and Fancher 2010) to fit a predictive model using maximum entropy methods (Phillips et al. 2006, Phillips and Dudik 2008), implemented with Maxent® software version 3.3.3e (http://www.cs.princeton.edu /schapire/maxent/). We used Maxent® because our response variable consisted solely of presence data (i.e., locations of active wind turbines), and Maxent® has consistently been shown to be accurate and robust when using presence-only records, particularly with small sample sizes (Hernandez et al. 2006, Phillips and Dudik 2008, Wisz et al. 2008b, Franklin 2009). Predictor variables included the average wind resource potential at 50-m height (National Renewable Energy Laboratory 2008), percent slope derived from the National Elevation Dataset (Gesch et al. 2009), and topographic position using a 150-cell neighborhood (Majka et al. 2007). We assigned a value of zero to cells with output values occurring below the logistic threshold of 0.314, chosen to maximize training sensitivity plus specificity, and rescaled remaining values to range from 0 to 1.

The wind-power potential estimated with Maxent® represented the quality of wind resources across the state, but did not indicate where these widespread resources would have the highest likelihood of development. Therefore, we created an adjusted model using development indicators that reflect where development is most likely to occur. These short-term development indicators included density of existing meteorological towers (WGFD 2010a), distance to proposed electrical transmission lines with a capacity of at least 230 kV (Ventyx Energy 2010), proposed wind farm boundaries (Wyoming Department of Environmental Quality 2011), current land tenure (Bureau of Land Management 2005), and legal and operational constraints. Adjustments to the base wind potential model for each of these factors were handled sequentially as follows:

1. Wind farms that have already been proposed are highly likely to be developed in the near term, so locations within proposed boundaries were adjusted to increase the modeled value. Specifically, areas within proposed farms in Sweetwater and Unita Counties, which have already entered planning stages, were assigned a value of 2, and areas within all other proposed farms were assigned a value of 1. The resulting surface was then rescaled to range from 0-1.

2. Meteorological towers represent locations where developers are currently evaluating wind resources on the ground and indicate site-specific interest in development. Further, near-term development is more likely to be located near new transmission lines since existing lines are currently at capacity. We calculated the kernel density of meteorological towers using a 15-k search radius and the natural logarithm of distance to proposed electrical transmission lines and then scaled both surfaces from 0 to 1. These surfaces were added to the previously adjusted wind resource raster and the resulting raster was rescaled from 0 to 1.

3. Most current development has occurred on privately-owned and state trust lands, largely because they have fewer permitting restrictions than other, predominantly federally-owned, lands. We assigned each ownership category an adjustment factor from 0 (no development allowed) to 1 (no development restrictions) and applied the values as a multiplier to the previously-adjusted wind resource raster. Privately-owned lands were assigned an adjustment factor of 1, state lands a factor of 0.8 and federal lands a factor of 0.5. Following this adjustment, the resulting raster was rescaled to range from 0 to 1.

4. The final adjustment was to assign a value of zero to all areas where development was precluded by legal or operational constraints. Legal constraints that preclude development included wilderness areas, wildlife refuges, conservation easements, lands managed by the Bureau of Land Management that have "No Surface Occupancy" stipulations (Pocewicz et al. 2009), land within airport runway air space, (Federal Aviation Administration 2010), and urban areas (Wyoming Department of Revenue 2011). Operational constraints precluding development included mountainous areas above 2743-m, open water, and potential raster cells falling within clusters of less than 5 cells, since commercial wind-power development in Wyoming generally occurs as extensive farms rather than small, isolated patches.

After all adjustments were made, we took the square root of the resulting raster to normalize the data distribution and spatially smoothed it to match the resolution of oil and gas potential model, which was developed using 1-km^2 cells. The smoothing function was a simple average that calculated the arithmetic mean value of all 100-m cells within each 1-km^2 block. Thus, the final wind potential surface assigned each 1-km^2 grid cell in Wyoming a potential score ranging from 0 (no potential for wind-power development) to 1 (certain wind-power development).

We created a buildout scenario for wind-power development by placing turbines across the Wyoming landscape according to the wind development potential model described above. The magnitude of the buildout was based on existing projections that Wyoming can expect an additional 11.42 GW of installed capacity in the next 20 years (USDOE 2008), resulting in 4569 new turbines, assuming 2.5 MW per turbine, which is the current industry standard for Wyoming. Turbines were placed on the landscape by randomly selecting a raster cell from the set of cells with the highest wind development potential and randomly placing an initial turbine in the northern half of that cell. Additional turbines were successively placed 300 m south of the initial turbine until the cell boundary or limit of 3 turbines per 1-km cell was reached. This placement reflects the current, typical distance between 2.5-MW turbines and simulates the tendency for wind-farms in Wyoming to be oriented along north-south ridges to optimally capture prevailing westerly winds. To further reflect the fact that wind turbines generally cluster into farms extending over several sections (to take advantage of common infrastructure such as high-capacity transmission lines), we marginally increased the wind potential of the cells immediately north and south of a development by adding an adjustment factor (0.05) that best approximated typical wind farm size. Typical size was based on 17 wind facilities completed in Wyoming since 2008 that have turbines of similar size to those being projected; 75% of these facilities had between 15 and 66 turbines, with a median of 38 turbines. As for the oil and gas projections, we assumed the number of new wind turbines to increase linearly over the length of our study.

ENERGY MODEL VALIDATION

We validated the Random Forests model of oil and natural gas development using out-of-bag (OOB) testing techniques to produce standard error statistics including ROC AUC (Hanley and McNeil 1982b), Cohen's kappa (Cohen 1960), OOB error and overall classification success. AUC was 0.83, Cohen's kappa was 0.62, OOB error was 22.4%, and overall classification success was 82.5%. Additionally, we used the Boyce Index (Boyce et al. 2002, Hirzel et al. 2006, Petitpierre et al. 2012) to test the model against producing wells constructed in Wyoming since we generated the model (N = 6,240), which indicated a highly discriminative model (Boyce Index = 0.99; $P < 0.001$). Finally, we ran additional statistics on the error distribution, and found that the median absolute deviation (MAD) from the median error variance, where errors converge in the model, was small (0.004). Thus, all validation statistics indicated a stable and acceptable model of oil and gas development.

We validated the primary maximum entropy model of wind-power development using ROC AUC (Hanley and McNeil 1982b) and the Boyce Index (Boyce et al. 2002, Hirzel et al. 2006, Petitpierre et al. 2012), using 67% of the data to train the model (643 turbines in 32 wind farms) and 33% to test the model (319 turbines in 8 wind farms). To account for the fact that turbines within wind farms are not independent, we include all turbines within individual wind farms as either training or test data (Veloz 2009). Given the narrow temporal span of wind-power development, we used data from all available years to build the primary model, rather than using the most recent years for validation. However, to further assess the modeling approach, we fit a hind-casting model where turbines from wind farms constructed prior to and including 2008 were used as training data (502 turbines, 17 farms) and turbines from wind farms constructed post-2008 were used as test data (460 turbines, 11 farms). The hind-casting model had test AUC of 0.86 and a Boyce Index of 0.85 ($P = 0.002$), while the primary model had test AUC of 0.91 and a Boyce Index of 0.89 ($P <$

0.001). Thus, as with oil and gas development, all validation statistics indicated a stable and acceptable model.

SPECIES DISTRIBUTION MODELS

DATA SOURCES

We compiled occurrence records for all of Wyoming's terrestrial vertebrate SGCN (WGFD 2005, 2010b), resulting in a dataset of roughly 270,000 records of 156 species. Records were compiled between 2007 and 2010 from a variety of sources. Major sources included the Biotics database of the Wyoming Natural Diversity Database (http://uwadmnweb.uwyo.edu/wyndd/), the Wildlife Observation System (WOS) of the Wyoming Game and Fish Department (see WGFD 2005), the North American Breeding Bird Survey (http://www.pwrc.usgs.gov/bbs/), the Integrated Monitoring in Bird Conservation Regions program (http://www.rmbo.org/v3/OurWork/Science/-BirdPopulationMonitoring/IntegratedMonitoringinBCRsIMBCR.aspx), specimen records from museums across the country (notably the National Museum of Natural History, University of Kansas Natural History Museum, and the University of Michigan Museum of Zoology), and unpublished data sets from local biologists.

Individual occurrences varied greatly in their quality, and were not of equal value for constructing distribution models. To minimize model uncertainty due to occurrence data quality, we scored each record for three key criteria (date of occurrence, accuracy of location, and veracity of identification) and added these to compute an occurrence quality score for each record (Table A1). High-quality occurrences (i.e., those that were recent, accurately located and positively identified) could achieve a maximum score of 12, while poor-quality occurrences (i.e., those that were old, poorly located, and with little documentation) received a minimum score of 0. These scores were used to filter data prior to distribution modeling and to assess the overall quality of the available data for each model.

Environmental data used in modeling was drawn from a set of 73 variables falling within five major categories: climate, hydrology, land cover, substrate and terrain. In addition, some species-specific variables (e.g., distance to permanent snowfields, distance to cliffs) were used as appropriate. Detailed information regarding all variables is available online (Keinath et al. 2010), while the major variables are briefly discussed below.

Climate variables were generated by applying the BIOCLIM algorithms (Nix 1986) to DAYMET climate data (Thornton et al. 1997, Thornton and Running 1999, Thornton et al. 2000). This was done by running ARC/INFO AMLs, written by Robert Hijmans (available at http://worldclim.org) on 18-year DAYMET averages (available at http://www.daymet.org/ climateSummary.jsp). Hydrology layers were derived from the National Hydrography Dataset (Simley and Carswell 2009), and comprised metrics representing proximity to water features (e.g., lakes, reservoirs, streams) and degrees of permanence (i.e., ephemeral, intermittent, or perennial).

General land cover variables used in modeling included forest, shrub, herbaceous, and bare ground cover data from the LANDFIRE dataset (Rollins and Frame 2006). Many of the specific vegetation indices that influence individual species' distributions (e.g., percent conifer forest cover, percent deciduous forest cover) were not available in any one dataset, requiring the production of synthetic variables that typically incorporated values from LANDFIRE data (Rollins and Frame 2006), GAP Land Cover (Comer et al. 2003, National Gap Analysis Program 2010), and/or the USGS Sagebrush dataset (Homer et al. 2012). We created these synthetic indices by first assigning each GAP ecological system a score relative to the desired feature (e.g., dominance of conifer trees in each ecological system) and combining that score with the LANDFIRE estimate of canopy cover to come up with an index for each category that ranged from 0 (e.g., low canopy cover in a system that has a very small conifer component) to 1 (complete canopy cover in an ecological system dominated by conifers). Landscape pattern of land cover was assessed by computing contagion using Fragstats (O'Neill et al. 1988, Turner 1989, Li and Reynolds 1993, McGarigal and Marks 1994) based on a 4-category landscape classification (barren/developed, herbaceous, shrub-dominated, tree-dominated).

Common substrate variables (e.g., soil texture, depth to shallowest restrictive layer) were derived from STATSGO data as expressed in the Natural Resource Conservation Service's Soil Data Viewer 5.1 (Natural Resource Conservation Service 2006). Terrain variables (e.g., elevation, slope, ruggedness) were derived from the National Elevation Dataset (Gesch et al. 2009) using previously published algorithms (Beers et al. 1966, Gessler et al. 1995, Jenness 2006, Sappington et al. 2007).

ANALYTICAL APPROACH

We created species distribution models using documented occurrences of Wyoming's Species of Greatest Conservation Need (SGCN) as the response variable and statewide environmental layers as predictor variables. Models were generated using a maximum entropy approach, as it has consistently shown to be among the most accurate and robust algorithms for constructing distribution models from opportunistically collected data, particularly when sample sizes are small and processes driving distribution are complex (Graham and Elith 2005, Elith et al. 2006, Hernandez et al. 2006, Hijmans and Graham 2006, Phillips and Dudik 2008, Wisz et al. 2008a). We used Maxent® (Phillips 2009) to implement the maximum entropy algorithm and ArcGIS® (ESRI 2011) to spatially project distribution maps onto the Wyoming landscape. For each species, a set of 5-7 predictor variables was selected to construct the distribution model based on knowledge of the species biology and evaluation of variable importance measures from exploratory models using all relevant variables.

To avoid biases associated with opportunistically gathered data (Jimenez-Valverde and Lobo 2006, Graham et al. 2008, Johnson and Gillingham 2008, Veloz 2009), we used target-group background data (i.e., background data selected from the entire sample set rather than randomly-generated pseudo-absences) for model building (Phillips et al. 2009) and employed a randomized, multi-pass filter to construct model sets that minimized spatial bias while maximizing the quality of occurrences in the final model set. To implement this filtering procedure, we first thinned dense clusters of occurrences resulting from oversampling by removing those occurrences with lower point quality scores that were within 1,600 meters of other, higher-quality occurrences. Where equal quality occurrences occurred within 1,600 meters, we randomly selected which occurrence to remove. We constructed a final model set by drawing from the remaining occurrences with geographic stratification based on 12-digit hydrologic units. This was accomplished by selecting the highest quality point from each occupied hydrologic unit, then adding the next-highest quality occurrence from each hydrologic unit to our selection and repeating this until additional occurrences were selected from less than 20% of the previously selected hydrologic units. This guarded against model bias by preventing occurrences from clustering in a small subset of the species' range. In other words, it helped assure an even distribution of occurrences across the modeled area, even when sampling was not evenly distributed. We created distribution models for all species with final model sets of 5 or more documented occurrence locations, since MaxEnt® has been shown to generate reasonable distribution models with occurrence sets of this size (Hernandez et al. 2006), though these models were penalized heavily when assessing model uncertainty (see Uncertainty Assessment below), to acknowledge the possibility that sampling biases are likely with such low sample sizes.

It should be noted that there has been a recent criticism pointing out that modelers have over-reached in their interpretation when using algorithms like Maxent® and that other estimators are preferable when assumptions of detection probability are constant, sampling of space is truly random and ecological inference is a primary goal (Royle et al. 2012). This concern does not apply to this study, as our cross-taxonomic data are opportunistic in nature, we are primarily interested in spatial accuracy of prediction rather than ecological interpretation, and our application does not interpret results as truly probabilistic in nature. Further, our use of the Boyce index (Boyce et al. 2002) to evaluate model quality implicitly tests model output relative to the key characteristic underlying this criticism; namely it insures that higher model values are indeed indicative of greater likelihood of species presence. Under the real-world situations of this study, Maxent® has repeatedly been shown to produce robust predictions that are useful when applied with appropriate attention to caveats, as we have done here.

SPECIES MODEL VALIDATION

Model performance was evaluated using several metrics, including the area under the receiver operating characteristic curve based on withheld test data (ROC AUC; Hanley and McNeil 1982a, Liu et al. 2005), predictive success based on 10-fold cross-validation, expert review, and the Boyce index (Boyce et al. 2002, Hirzel et al. 2006, Petitpierre et al. 2012). The latter measures how model predictions differ from random across the prediction gradient and is thus particularly useful for presence-only data. For each species, we calculated the quantitative evaluation metrics for each of the cross validation models.

Distribution models varied widely in quality (Table C2), with poor models typically resulting from lack of suitable species occurrence data (i.e., small sample sizes) and/or lack of appropriate statewide predictor variables. Improvement of these models requires precisely the large-scale biological field effort that prohibits effective management and makes this study necessary, as discussed in the main article and the above section discussing the scope of this research. It is valuable for management to see the best available estimate of exposure for all species, clearly presented with model qualities that can be used to assess confidence in species-specific results and identify where those results could most benefit from improving understanding of species distribution. We have thus incorporated validation statistics into an overall assessment of uncertainty (see below).

CALCULATING EXPOSURE

EXPOSURE INDEX

We used the development build-out scenarios (described above) to generate energy footprints for Wyoming, wherein maximal disturbance occurs at well and turbine sites and decays to a negligible amount with increasing distance. Changes in the population abundance and density of wildlife have regularly been found at and beyond 1 kilometer from human infrastructure, with some extending out to 5 kilometers (Benitez-Lopez et al. 2010), although individual studies have shown shorter and longer distances (e.g., Nellemann and Cameron 1996, Ingelfinger and Anderson 2004, Bayne et al. 2008). Additionally, impact distance functions for terrestrial vertebrates seem to approximately follow logarithmic decay (Madsen 1985, Benitez-Lopez et al. 2010). Therefore, we chose 1 kilometer as a conservative impact distance and created an exposure function that logarithmically decayed to 1% of maximal exposure at that distance (Equation A1), where EV_{di} is the un-weighted exposure value of cell *i* relative to disturbance *d*, D_i is the distance of cell *i* to the nearest well pad or wind turbine, and *a* and *b* are constants defining a logarithmic decay curve that decays from 1.0 to 0.01 at a defined distance (in our case 1 kilometer; a = -4.564348 and b = 0.009169935). Alternative decay functions where considered, as discussed below.

We applied this impact decay function to well and turbine locations in our build-out maps, resulting in two continuous, statewide surfaces (one for oil and gas and one for wind power) that had values ranging from 0 (negligible exposure far from the nearest well or turbine) to 1 (complete exposure under a well pad or turbine).

$$EV_{di} = \frac{1+e^{a}}{1+e^{(a+bD_i)}} \qquad \text{(Equation A1)}$$

To evaluate cumulative exposure for each of the 156 species in our study, we first re-scaled each species distribution model to sum to one over the entire state, then multiplied it by each exposure surface and summed the resulting raster across the study area (Equation A2), where DM_{si} is the value of the distribution model for species *s* in cell *i,* and subscripts *og* and *w* represent values for oil/gas and wind development, respectively. This yielded the weighted average proportion of each species' habitat exposed to development, which we have termed the Exposure Index (*EI*). *EI* ranges from a lower limit of zero, representing complete separation of a species habitat from energy development, to a theoretical upper limit of one for complete development of all available habitat. In practice, over large landscapes the upper limit will never be reached, since it would mean that every available pixel of habitat, however marginal, falls near a well pad or wind turbine. Exposure levels can be conceptualized by considering the density of wells or turbines needed to reach specific *EI* values in an idealized, uniform landscape where all habitat is equal (Figure B1).

$$EI_s = EI_{ogs} + EI_{ws} = \sum_i EV_{ogi} * DM_{si} + \sum_i EV_{wi} * DM_{si} \qquad \text{(Equation A2)}$$

It is worth noting that species will likely exhibit differential sensitivities to development, so decay curves of different radii may be appropriate for different taxa. However, it is precisely this type of detailed response information that is lacking and thus makes the present analysis useful. Since any taxa-specific adjustments would largely be speculative, it makes more sense to evaluate all species equally (as shown above) and initiate targeted studies of species thereby identified as highly exposed in order to quantify sensitivity to specific disturbance, thus providing information necessary to modify the impact function. None-the-less, to evaluate the effect of changing the width of the exposure function we also conducted analyses using narrow (200 meter) and wide (5 kilometer) effect distances, chosen to represent a reasonable range derived from the literature (Benitez-Lopez et al. 2010). Analyses using all three exposure functions resulted in similar rankings (Spearman rank correlation: $r_s \geq 0.963$ and $P < 0.001$ for all tests), and although there were some relative rank shifts among species (Fig. S7), they did not alter any of the main conclusions presented in this study. Moreover, rank shifts did not generally move species between categories of concern; species that ranked high using the 1 kilometer effect distance also ranked high using the others. For example, the 10 most highly exposed species remained largely the same with all effect distances. The robustness of our analyses to these different effect distances is partially due to the large-scale clumping of energy resources (Figure B3), while the spacing of individual disturbance events (e.g., well pads and wind turbines) are typically highly regular within these clumps at scales on the order of roughly 0.5-2 kilometers (Figure B1), resulting in relatively little effect on ranks from altering impact distances.

Relative shifts within the highly-exposed group did, however, present additional reasons to be concerned for some species. For example, Pygmy Rabbit (the 4th most exposed species in the main analysis) was the most exposed species when we used the narrow exposure curve, while Black Footed Ferret (the 6th most exposed species in the main analysis) was the second most-exposed species when we used the wider exposure curve. Wyoming Pocket Gopher (the 5th most exposed species in the main analysis) ranked more highly when either the narrow or wide curve was used.

UNCERTAINTY ASSESSMENT

Map-based analyses are often misleading, in part because they appear to be (and are sometimes presented as) definitive, error-free projections of reality, despite the fact that uncertainty exists in the underlying data. This does a disservice to decision makers. However, presenting uncertainty in a form that allows incorporation into decision-making is difficult and therefore seldom done (Beale and Lennon 2012). This is especially the case when projections are derived from highly complex models based on multi-faceted data, in which simple estimation of error structures are not possible. We explicitly addressed uncertainty from the two main components of our exposure analysis; species distributions and energy development maps.

SPECIES DISTRIBUTIONS

There are a plethora of validation techniques for species distribution models, each with particular strengths and weaknesses, leading experts to suggest that multiple methods be used to assess any given model. Nonetheless, there is little guidance on how to synthesize information across such metrics (Franklin 2009, Carvalho et al. 2011). On the whole, models that validate well using multiple metrics are more robust, and therefore have less uncertainty. To assess uncertainty in our distribution models, we therefore derived an uncertainty index (UI) that placed several well-supported validation statistics on a 0 to 1 scale and combined them using a simple weighted average (Equation A 3),

$$UI = \frac{\left(\frac{NS + OQS}{2}\right) * 0.75 + \left(\frac{AUCS + OR + ERS + BIS}{4}\right) + EC}{2.75} \qquad \text{Equation A 3}$$

where the individual statistics are as follows:

NS (Number of occurrences Score): More occurrences, or a larger sample size, lead to more robust models and thus reduce uncertainty. NS values of 0 reflect species with more than 100 occurrences; NS values of 0.25 reflect species with between 50 and 100 occurrences; NS values of 0.5 reflect species with between 20 and 50 occurrences; and NS values of 1.0 reflect species with less than 20 occurrences.

OQS (Occurrence Quality Score): All occurrences were scored based on their quality, as noted in the text and Table A1. These data were used to calculate average occurrence quality for the each model set. The resulting values were rescaled to range from 1 (very poor quality dataset) to 0 (very high quality dataset).

AUCS (Area Under the Curve Score): We calculated the ROC AUC for each cross validation model based on a holdout dataset (Bradley 1997, Fielding and Bell 1997). A value of 0.5 indicates model performance no better than chance, values below 0.5 indicate counter prediction, and values above 0.5 indicate increasingly strong classification to an upper limit of 1. AUCS is simply one minus AUC, so values closer to 1 indicate a poorer model fit and thus a more uncertain model.

OR (Omission Rate): OR is simply the average omission error based on holdout datasets (i.e., the proportion of test data miss-classified using the optimal binary threshold) for each cross validation model. Omission rates closer to 1 indicate higher uncertainty in a model.

ERS (Expert Review Score): We scored the final model for each species using a simple categorical system reflecting how well local biologists felt it represented the species' true distribution in Wyoming. "High Quality" models were deemed to represent the species distribution well (ERS = 0). "Medium Quality" models represented the species distribution fairly well, but with minor errors of omission or commission (ERS = 0.5). "Low Quality" models were deemed to be either questionable or beyond our ability to accurately assess (ERS = 1).

BIS (Boyce Index Score): The Boyce index is essentially a spearman rank correlation coefficient (r_s) that varies between -1 (counter prediction) and 1 (positive prediction), with values statistically close to zero indicating that the model does not differ from a random model (Boyce et al. 2002). No model in this study had a negative Boyce Index. The Boyce Index Score is simply 1 minus the Boyce index, so values closer to 1 indicate a poorer model fit and thus a more uncertain model.

EC (Exposure Change): We calculated an Exposure Index for each cross validation model of each species, calculated the range of resulting values and divided the range by the minimum value. The resulting fraction ranges from near zero (very little variation in Exposure Index) to numbers greater than 1 (range of the Exposure Index was more than 100% of the minimum value). Values greater than 1 were given a value of 1.

The first two components (number of occurrences and occurrence quality) were given slightly less weight than the others, because they are indirect measures of model quality. A model constructed using a small or low-quality sample is likely to be more uncertain, but is not definitively poor. It is nonetheless useful to incorporate them in addition to true validation statistics, because a model built on a small sample is more likely to be uncertain even if it validates well. For instance, a small sample size could indicate under-sampling of the environment for the species in question, and additional survey effort could place the species in substantially different environments.

ENERGY DEVELOPMENT

For several reasons, we did not generate uncertainty indices for our energy development projections that would parallel those for our species distribution models. Foremost among these is that model fit for both oil and gas and wind-power were very good based on all metrics, giving us high confidence that they are reasonable approximations of potential energy resources in Wyoming relative to the scale of analyses in this study, namely statewide calculations of species impacts. Uncertainty is further reduced by our use of a two-step process (discussed above) where outputs from these models were adjusted to reflect known, near-term indicators of development (e.g., proximity to existing transmission infrastructure and surface exclusions such as wilderness area restrictions). These adjustments increase our confidence in the near-term spatial accuracy of the final buildout scenarios and further insures that our projections of the spatial pattern of energy development will be robust in the near future (i.e., 10-20 years), with higher uncertainty over time horizons beyond the scope of this study.

The most prominent sources of mid and long-term uncertainty are the advent of new technologies that allow development of resources not captured in currently developed sites and fluctuations in national and international energy markets. There is no practical way to objectively assess the former, as it is extremely difficult to predict advancements in technology that will ultimately become economically viable for industrial-scale operations. Regarding markets, the pace and magnitude of development was carefully assessed in the reports that we used to create both buildout maps. Moreover, given the consistently increasing demand for energy both globally and domestically, it is highly likely that most currently-identified petroleum resources will eventually be developed, and that wind-power will continue to be one of the most developed sources of renewable energy in the coming decades (Copeland et al. 2009a, EIA 2011a, b, 2012). Since we have good models of where currently extractable resources exist and what near-term factors influence their development, the biggest uncertainty over the time frame of this study is not where development will occur, but how quickly it will cover areas of predicted potential.

To evaluate how uncertainty in the rate and extent of currently feasible development on our estimates, we created unrestrained buildout scenarios for both energy models. For oil and gas, the unrestrained scenario used the Random Forests binary classification (noted above) to place wells at the allowable density in every cell with anticipated petroleum potential, resulting in nearly triple the number of wells from the anticipated scenario (Figure B3). For the wind-power unrestrained scenario, fewer development projections exist and it is not clear that all, or even most, potential areas will be eventually be developed. Therefore, rather than completely develop the resource we doubled the number of new turbines relative to the anticipated scenario (i.e., 9,138 turbines). Using these unrestrained scenarios to calculate exposure did not substantially alter results, as demonstrated by comparing the resulting species ranks to those from the anticipated scenario. As one would expect, the magnitude of exposures increased substantially (Figure B8) and resulted in some relative rank shifts among species (Figure B9), but these differences did not significantly alter the rankings (Spearman rank correlation: $r_s = 0.977$, $P < 0.001$) and thus did not alter any of the main conclusions presented in this study. In general, those species deemed at risk when analyzing the anticipated scenario were also deemed at risk in the unrestrained scenario, though the level of concern for some species increases with more development (e.g., Great Basin Spadefoot is the 16th most exposed species in the anticipated scenario, but becomes the 5th most exposed species in the unrestrained scenario).

Since large-scale, commercial development of the nation's wind-power is relatively new, we view the spatial pattern of its near-term expansion as somewhat more uncertain than that for petroleum resources. Fortunately, in the short-term wind power will undoubtedly have a much smaller footprint than that of oil and natural gas and as such will contribute much less to overall exposure for the vast majority of species (Figure B2). The only species for which wind-power development has the potential to substantially impact species viability over the course of this study is Black-Footed Ferret, which is the sixth most exposed species in this study due largely to wind-power development concentrated in the Shirley Basin of central Wyoming. We therefore assessed the variation in the exposure of Black-Footed Ferret caused by spatial uncertainty in wind-power buildout. This was accomplished by creating 10 wind-power potential models from subsets of the full dataset and assessing exposures resulting from each. This yielded a range of *EI* values from 0.169 to 0.177 (mean 0.172, standard deviation 0.002). Comparing these values to the anticipated *EI* values of other species (Table C1), this level of variation could shift the rank of Black-footed Ferret between the 6th and 9th most exposed species, which does not alter conclusions for Black-footed Ferret and is thus not expected to substantially change conclusions for other species in this study.

SPECIES SENSITIVITY

Much academic effort has been spent investigating the role of species-specific biological sensitivity to disturbance as a contributing factor to species decline, endangerment and extinction. Many studies have conducted global-scale assessments of particular taxonomic groups using surrogates of species endangerment (e.g., IUCN Red List scores) as a measure of sensitivity (e.g., Cardillo et al. 2005, Purvis et al. 2005, Davidson et al. 2009). Many others evaluated sensitivities for small components of local biota under specific habitat degradation scenarios (e.g., Pimm et al. 1988, Laurance 1991, Rottenborn 1999). The results of such studies are mixed and, moreover, must be interpreted within the scope of the individual analyses, making broad generalizations or application to other environments, such as assessing conservation priorities for a unique local fauna, difficult.

Despite these problems, a few broad themes emerge from this collection of literature that can provide hints regarding whether a given species might be more or less sensitive to disturbance than those co-occurring in a given landscape. In particular, species having one or more of the following traits may be particularly susceptible to disturbance. There are many other, often highly specific, traits that have been investigated, but this represents a concise accounting of those that are most broadly applicable across taxa. Each trait is presented with a selected set of pertinent references:

1. high degree specialization in one or more aspects of ecology, such as habitat use or diet (Wang et al. , Laurance 1991, Newmark 1991, Foufopoulos and Ives 1999, Manne et al. 1999, Rottenborn 1999, Owens and Bennett 2000, Purvis et al. 2000, Sekercioglu et al. 2002, Fisher et al. 2003, Blumstein 2006, Prugh et al. 2008),
2. low reproductive capacity (Newmark 1995, Owens and Bennett 2000, Purvis et al. 2000, Polishchuk 2002),
3. highly restricted geographic range or distribution (Gaston and Blackburn 1995, Manne et al. 1999, Mace and Balmford 2000, Brashares 2003, Fisher et al. 2003, Jones et al. 2003, Cardillo et al. 2005, Davidson et al. 2009),
4. large area requirements, or low intrinsic population densities (Wang et al. , Pimm et al. 1988, Newmark 1991, Tracy and George 1992, Harcourt 1998, Purvis et al. 2000, OGrady et al. 2004),
5. larger body size within an otherwise similar taxonomic group, usually as a surrogate for other traits such as reproductive capacity, population density or dispersal ability (Pimm et al. 1988, Robinson et al. 1992, Gaston and Blackburn 1995, Purvis et al. 2000, Cardillo and Bromham 2001, Johnson et al. 2002, Fisher et al. 2003, Cardillo et al. 2005, Okie and Brown 2009).

It stands to reason that taxa that are highly exposed to development will be more likely to be adversely impacted if they exhibit one or more of these traits. This is true of several species we identified as being highly exposed in our analysis. It is therefore likely that the level of exposure identified could result in population declines for any of these species. As such, managers should be concerned regarding the population viability of these species within energy developments in our study area. Brief notes regarding the sensitivities for species mentioned in the main article follow.

Great Plains Toad (*Anaxyrus cognatus*): Almost no research has investigated the biological sensitivity of *A. cognatus*, so no literature is available that directly assesses the issue. However, amphibians are widely recognized as sensitive to environmental perturbations, particularly water quality, due to a restrictive life history that ties them to both aquatic and terrestrial habitats at different life stages and limits their dispersal capabilities. This has led to their being considered indicators of ecosystem health (e.g., Welsh and Ollivier 1998), though their effectiveness as sentinel species is debated (Kerby et al. 2010). Considering the case presented in this study, exposure is largely due to coal bed natural gas development, a primary concern of which is the degradation of surface water quality (Ganjegunte et al. 2005, Jackson and Reddy 2007, Orem et al. 2007). Regarding *A. cognatus* in general, some have suggested populations have become more scattered and isolated compared to historical conditions, suggesting range-wide sensitivity, but this not conclusive due to lack of consistent surveys (Lannoo 2005).

Pygmy Rabbit (*Brachylagus idahoensis*): Pygmy rabbit has very specific habitat requirements, being restricted to one structural stage of one vegetation type; tall stands of sagebrush (*Artemesia tridentata*) (Heady and Laundré 2005, Burak 2006, Larrucea 2007). Modification of habitat has resulted in the extirpation of the species from other parts of its range, leading to listing of one subspecies as Endangered under the U. S. Endangered Species Act (USFWS 2003, Siegel Thines et al. 2004) and a failed petition to list the rest of the species (USFWS 2010c). Preliminary data from surveys in Wyoming's Green River Basin suggest pygmy rabbit density may be negatively correlated with the density of natural gas wells on the landscape (Germaine and Ignizio 2012). In addition, future habitat shifts from climate change could exacerbate the impact of local disturbances (Larrucea and Brussard 2008). Moreover, disturbance of sagebrush ecosystems has been extensive over the past several decades leading to concern over the conservation status of sagebrush obligate species in the face of additional habitat changes (Knick and Rotenberry 2000, Knick et al. 2003, Dobkin and Sauder 2004, Welch 2005).

Wyoming Pocket Gopher (*Thomomys clusius*): Wyoming Pocket Gopher has an extremely narrow geographic range, with its entire global distribution restricted to portions of two counties in central Wyoming (Keinath and Beauvais 2006). Within this area, it is further restricted to a narrow range of habitats, primarily saline basins characterized by Gardner's saltbush, to which it may be limited through competition with the much more common northern pocket gopher (*Thomomys talpoides*) (Keinath et al. *In Review*). Though demographics and population densities are largely unknown, it appears to occur in disjunct patches and very low densities across its range, and it is absent from many locations where it was previously known to occur (Griscom et al. 2010). In combination with extensive oil and natural gas development across its limited range, these concerns led to a petition to list Wyoming pocket gopher under the U.S. Endangered Species Act, though it was denied listing due primarily a general lack of information on the species (USFWS 2010a).

Black-Footed Ferret (*Mustela nigripes*): As one of the first federally recognized endangered species in the United States (USFWS 1967), extensive research has been conducted regarding the black-footed ferret that clearly distinguishes it as a species sensitive to disturbance. None of this research pertains directly to energy development, primarily because the ferret was functionally extinct before the advent of extensive energy development. Black-Footed Ferret has highly restricted habitat use and diet specialization, only occurring in large colonies of prairie dogs that also represent its primary prey (Biggins et al. 2005). The species has gone through near extirpation, where populations declined to such an extent that it caused a genetic bottleneck potentially limiting future fitness of the species (Wisely et al. 2002). The original decline and difficulty with subsequent recovery is further due in part to the loss of prairie dog colonies resulting from extensive grassland conversion, poisoning, and disease. Additionally, both ferrets and prairie dogs are susceptible to sylvatic plague, which can result in large-scale population crashes that could push already stressed populations to near extinction (Barnes 1993). Currently, the wild distribution of the Black-Footed Ferret is very limited, consisting of less than 20 reintroductions sites in the central Rocky Mountains, most of which are not considered viable and self-sustaining such that the global population is so limited that functional loss of any site would be detrimental to the species as a whole (Jachowski and Lockhart 2009).

Greater Sage Grouse (*Centrocercus urophasianus*): Sage Grouse is one of a few species that has undergone extensive research assessing impacts from energy development, and this has resulted in substantial evidence linking it to population declines (Naugle et al. 2011). Additionally, Sage Grouse is restricted to one habitat type; sagebrush. It can be found in a fairly broad structural range of sagebrush stands, but a specific combination of factors are necessary for successful breeding and recruitment, including the use of leks for mating, which are limited in the environment.

Table A1. Occurrence quality scoring system used to evaluate records based on spatial precision (A), age of record (B), and taxonomic certainty of identification (C). Unusable records were removed from the dataset.

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., Rock Creek 5 miles south of Laramie Peak).
U	Record is unusable; uncertainty > ~3,000 m	Old museum specimen located only by reference to a county.

B. Age of Occurrence Record

Score	Calendar Year of Observation	Definition
4	≥ 2000	Observation made within roughly 10 years of model creation
3	1990 - 1999	Observation made within roughly 20 years of model creation
2	1980 - 1989	Observation made within roughly 30 years of model creation
1	1960 - 1979	Observation made within roughly 50 years of model creation
0	≤ 1959	Observation made within roughly 100 years of model creation
U	Historic	Record is unusable, because the record is over 100 years old, the species is known to be extirpated from the area in question, or the habitat has changed drastically since its collection.

C. Taxonomic Certainty of Occurrence Record

Score	Category	Definition
4	Confirmed Identification	Adequate information exists within the occurrence record to consider it a valid observation of the species in question
2	Questionable Identification	Information within the occurrence record is insufficient to *confirm* correct identification of the species (e.g., no supporting documentation or observer credentials), but neither is there any reason to assume that the record is in error.
0	Possible Miss-identification	There is reason to believe that the observation could be erroneous (e.g., extra-limital observation by amateur biologists of species that are easily misidentified)
U	Misidentification	Record is unusable. Information in the occurrence record suggests it is misidentified

APPENDIX B: ADDITIONAL FIGURES PRESENTING EXPOSURE VALUES FOR ALL SPECIES, THE RESULTS OF SENSITIVITY ANALYSES, AND FOOTPRINT MAPS

Figure B1. Examples of Exposure Index (*EI*) values presented with equivalent densities of structures (wells or turbines), average inter-structure distances, and remotely sensed images of approximately equivalent areas of Wyoming's landscape (B-F). Approximate well locations shown as red dots. Equivalent well distances and densities were calculated assuming a 1-kilometer footprint and uniform well spacing across a landscape where all habitat is identical. Locations of images are shown on a county map of Wyoming (A).

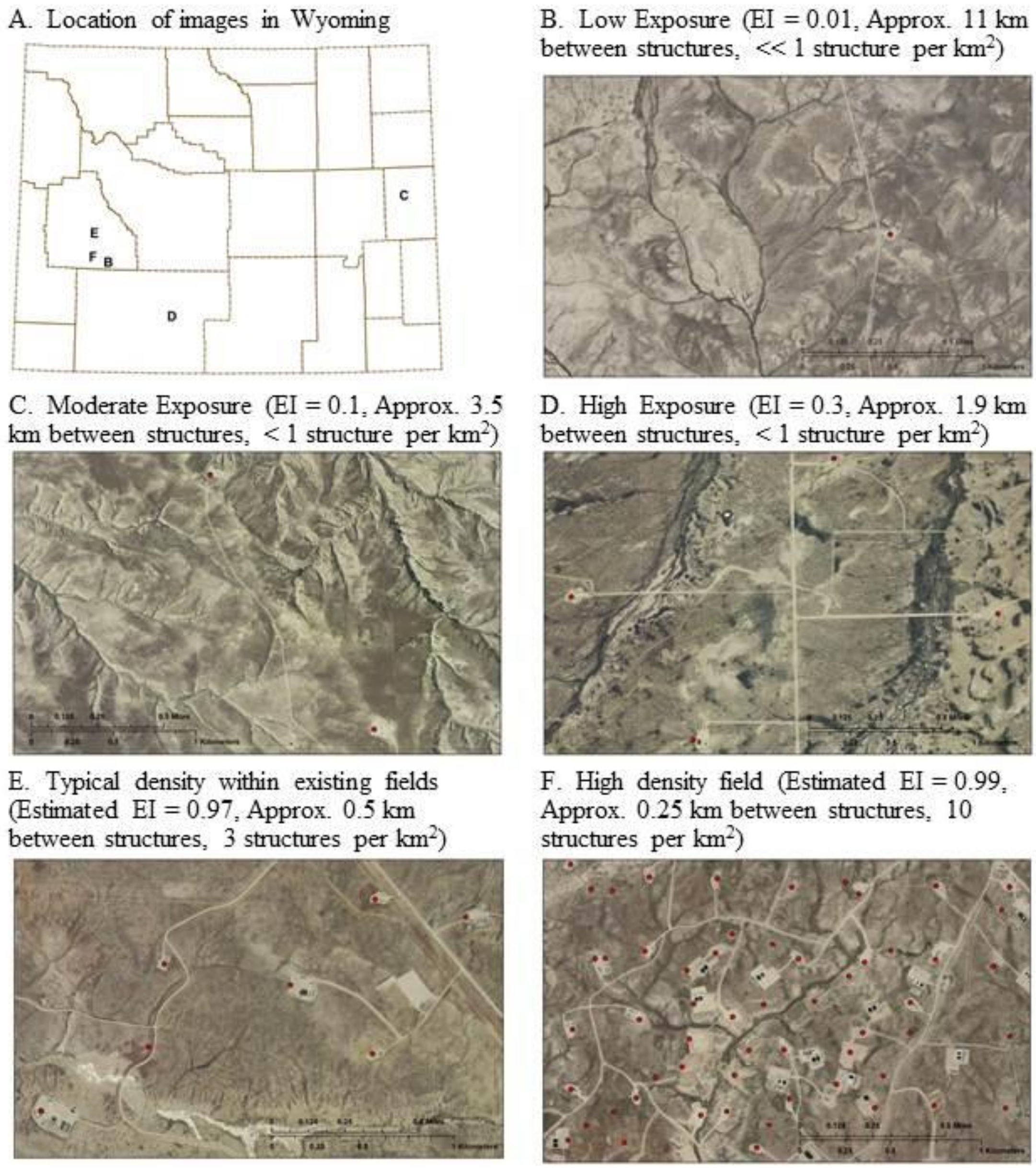


Figure B2. Projected 2030 total Exposure Index (*EI*) for 156 Wyoming Species of Greatest Conservation Need (SGCN) examined in this study. Ordinate shows individual species (codes provided in Table C1) ordered by their exposure rank using the 1-kilometer exposure curve. Grey portions of bars represent the proportion of *EI* due to wind-power development; white portions represent *EI* due to oil and gas development, error bars represent range in total estimated *EI* obtained by using all cross-validation models. Panels A-D show different subsets of the 156 species analyzed.

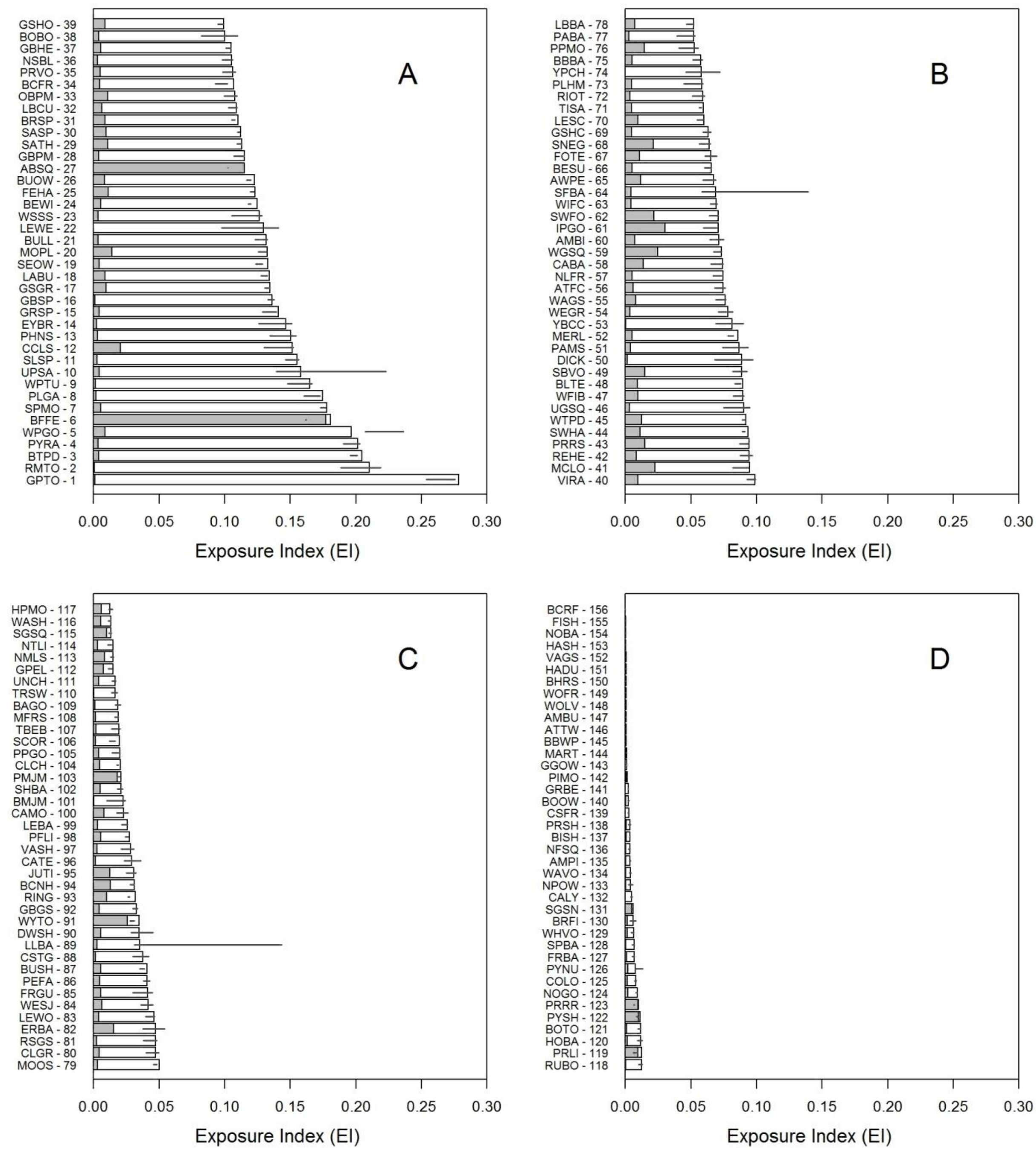


Figure B3. Energy footprint maps of Wyoming showing the 2030 predicted exposure surface for oil and gas wells and wind-power turbines under anticipated (A) and unrestrained (B) scenarios. Data are displayed over a shaded topographic relief map with county boundaries for reference.

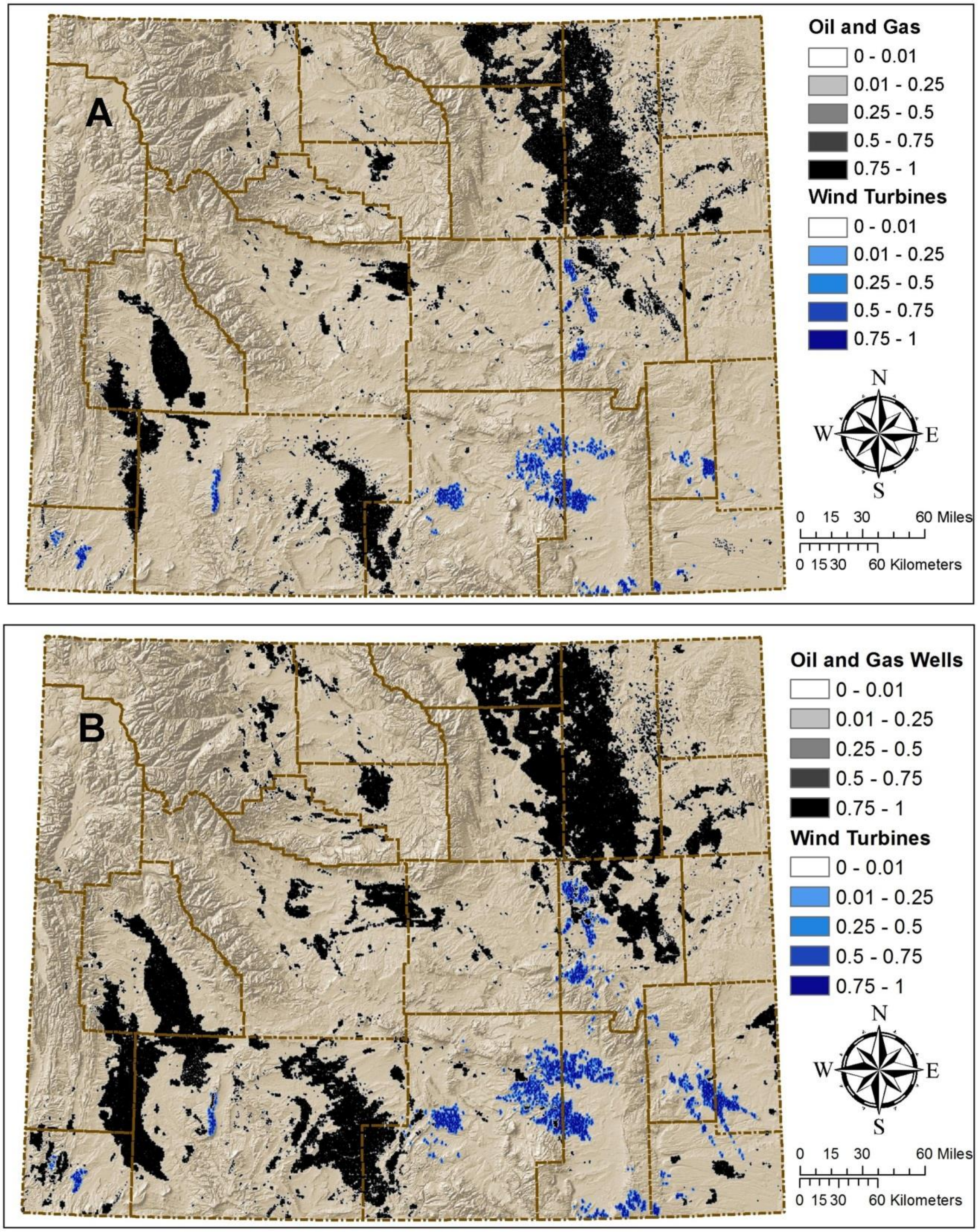


Figure B4. Distribution of exposure relative to modeled habitat for several Wyoming Species of Greatest Conservation Need (SGCN) with high Exposure Indices from energy development (Figure 1 and Table A1). Horizontal axis shows quantiles of habitat above a binary threshold maximizing test success, where the 100% quantile represents habitat most similar to sites of known occupation. Vertical axis shows the proportion of habitat falling within 1 kilometer of an oil or natural gas well or wind-power turbine based on 2030 projections. Colors reflect those in Figures 1 and 2 of the main article. Conservation action for species having exposure caused by intensive development in areas highly-similar to occupied habitat (e.g., Pygmy Rabbit or Black-footed Ferret) will likely be different than for species where exposure is due to larger portions of their distribution overlapping less-intense development (e.g., Wyoming Pocket Gopher or Great Plains Toad). In particular, the former might benefit greatly from site-specific conservation action (e.g., conservation easements or retirement of mineral rights) targeted toward core areas of distribution, similar to the approach taken for Sage Grouse. In contrast, the latter might require more broad-scale mitigation in the form of development stipulations (e.g., avoiding key habitat features wherever development occurs).

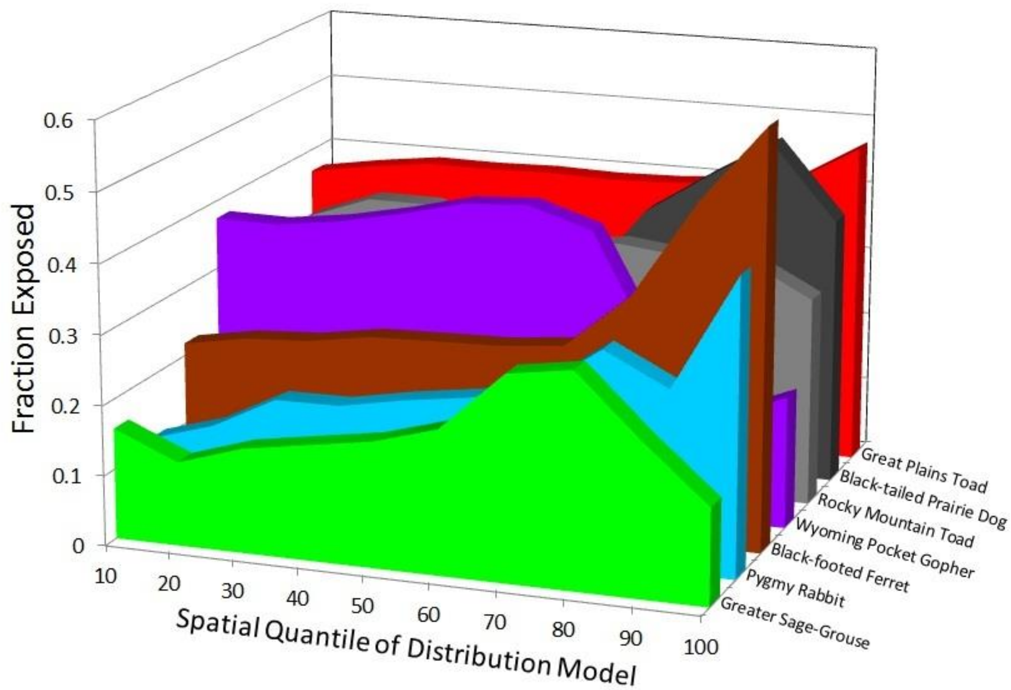


Figure B5. Map of Greater Sage Grouse ‘core areas’ (green shading) as defined by Wyoming Executive Order 2011-5. Also displayed are the 2030 predicted exposure surface for oil and gas wells and wind-power turbines, a shaded topographic relief map, and county boundaries.

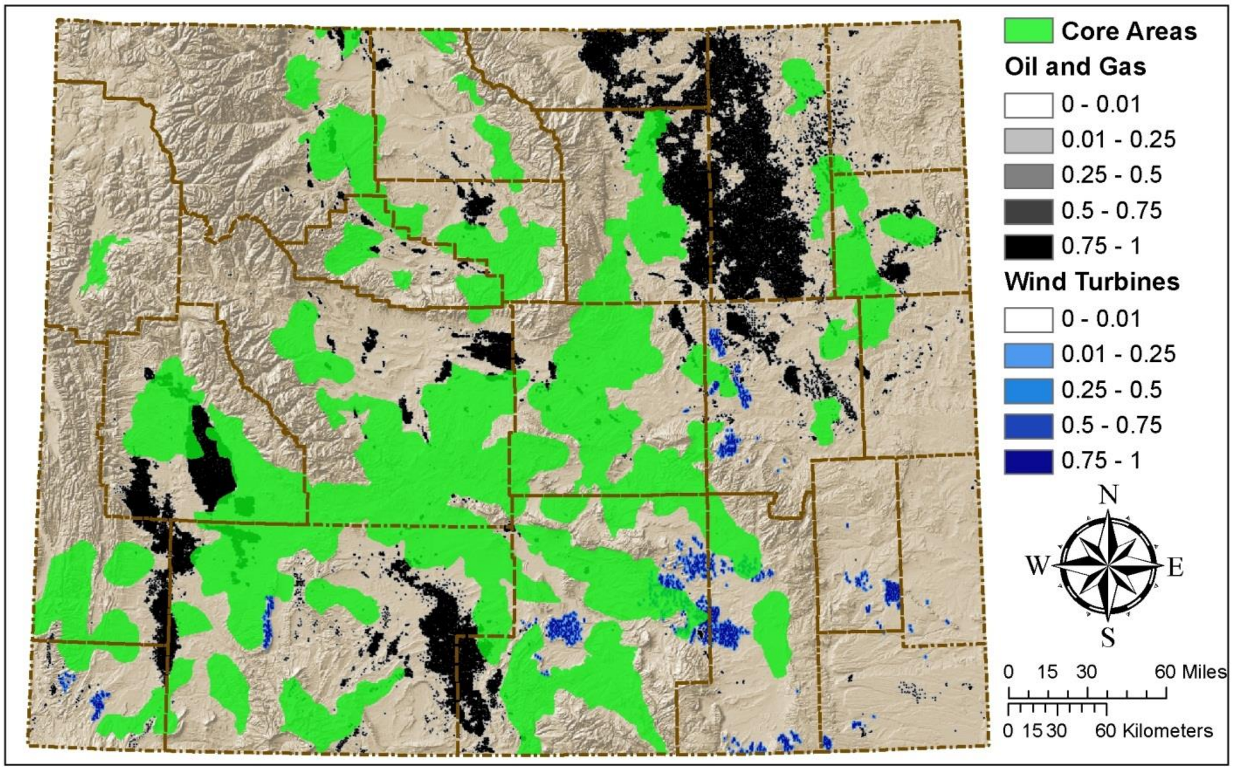

Core Areas
Oil and Gas
0 - 0.01
0.01 - 0.25
0.25 - 0.5
0.5 - 0.75
0.75 - 1
Wind Turbines
0 - 0.01
0.01 - 0.25
0.25 - 0.5
0.5 - 0.75
0.75 - 1
N
W
E
S
0 15 30 60 Miles
0 15 30 60 Kilometers

Figure B6. Fraction of the total 2030 Exposure Index (*EI; green*) and distribution model values (gray) falling within core areas of Greater Sage-Grouse. Bars represent the 25 most-exposed species in our study. Box plots represent a synthesis of all 156 species. Note that these values are best-case figures that assume a complete cessation of all development in core areas. The actual core area policy limits certain types of development but does not prohibit them

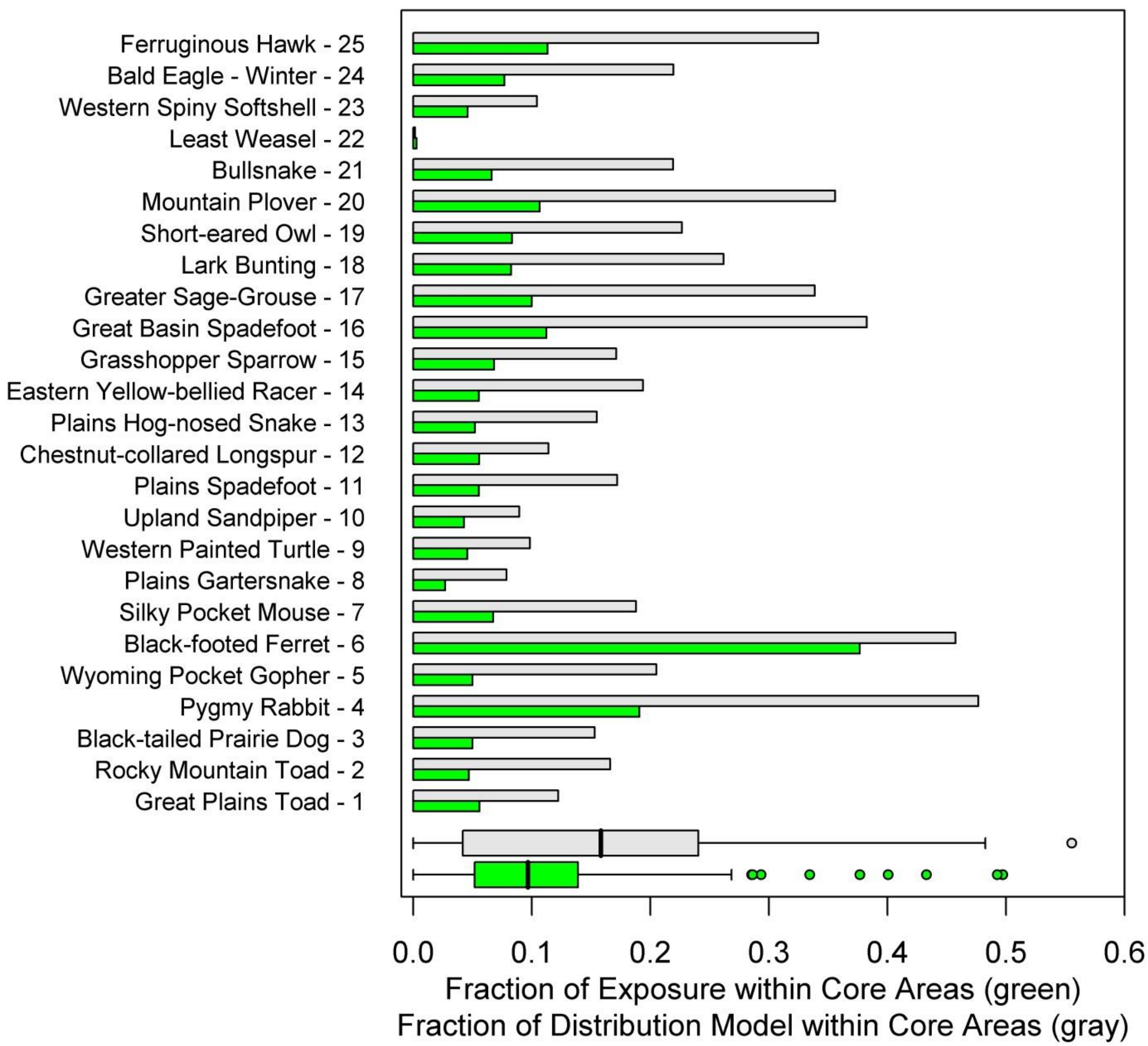


Figure B7. Range in exposure ranks resulting from using different exposure functions to quantify exposure to disturbance. Abscissa shows the exposure rank, with 1 being the most exposed to development. Ordinate shows individual species (see Table C1 for codes) ordered by their exposure rank using the 1-kilometer exposure curve (solid circles). Grey bars span the range of possible ranks when further considering the narrow curve (200 meters; open circles) and the wide curve (5 kilometers; open squares). Panels A-D show different subsets of the 156 species analyzed.

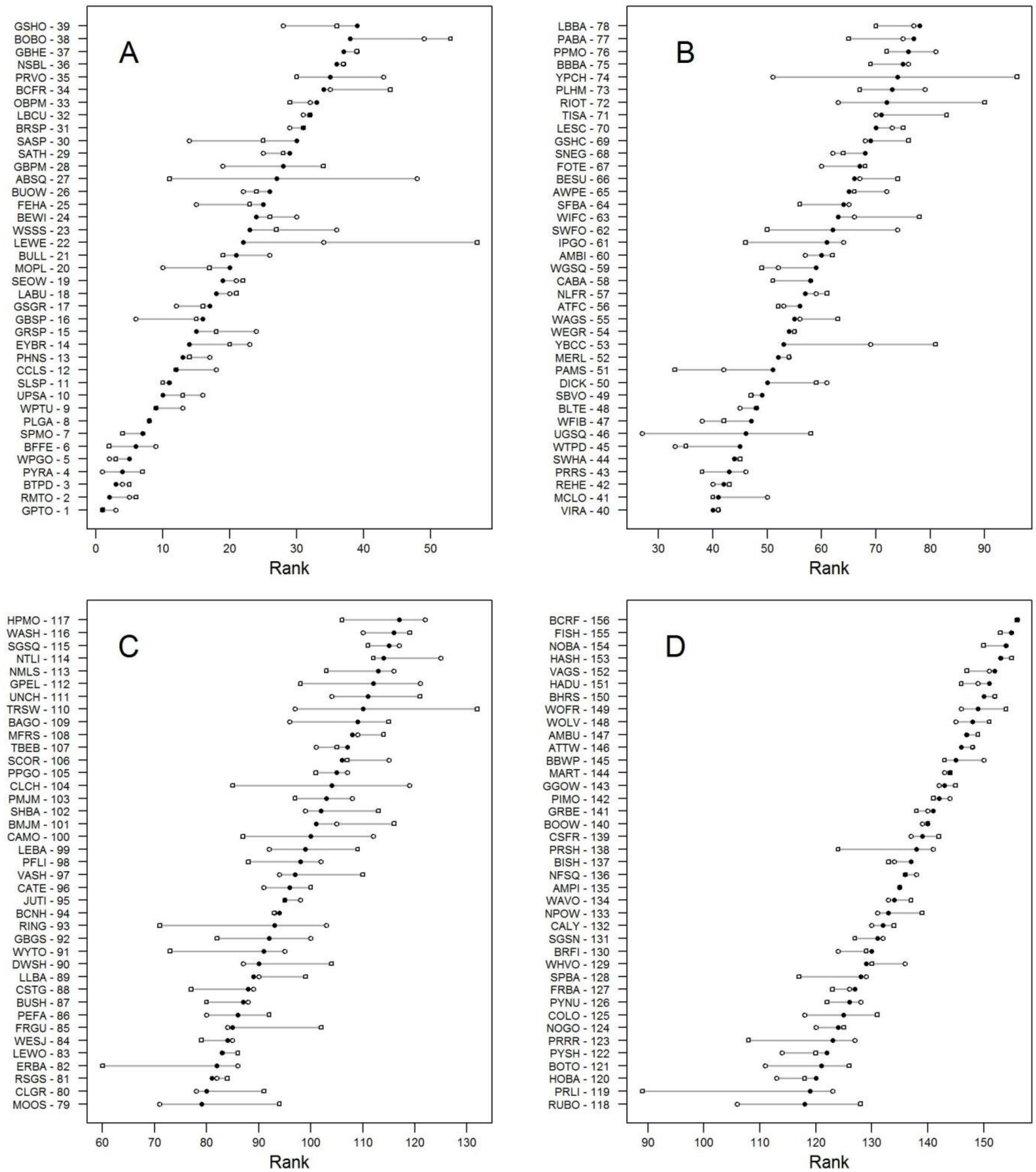


Figure B8. Projected 2030 total Exposure Index (*EI*) for 156 Wyoming Species of Greatest Conservation Need (SGCN) examined in this study under the anticipated (hollow bars) and unrestrained (gray squares) buildout scenarios. Ordinate shows individual species (codes provided in Table C1) ordered by their exposure rank under the anticipated scenario. Dotted lines represent the difference in *EI* between the scenarios. Panels A-D show subsets of the 156 species analyzed.

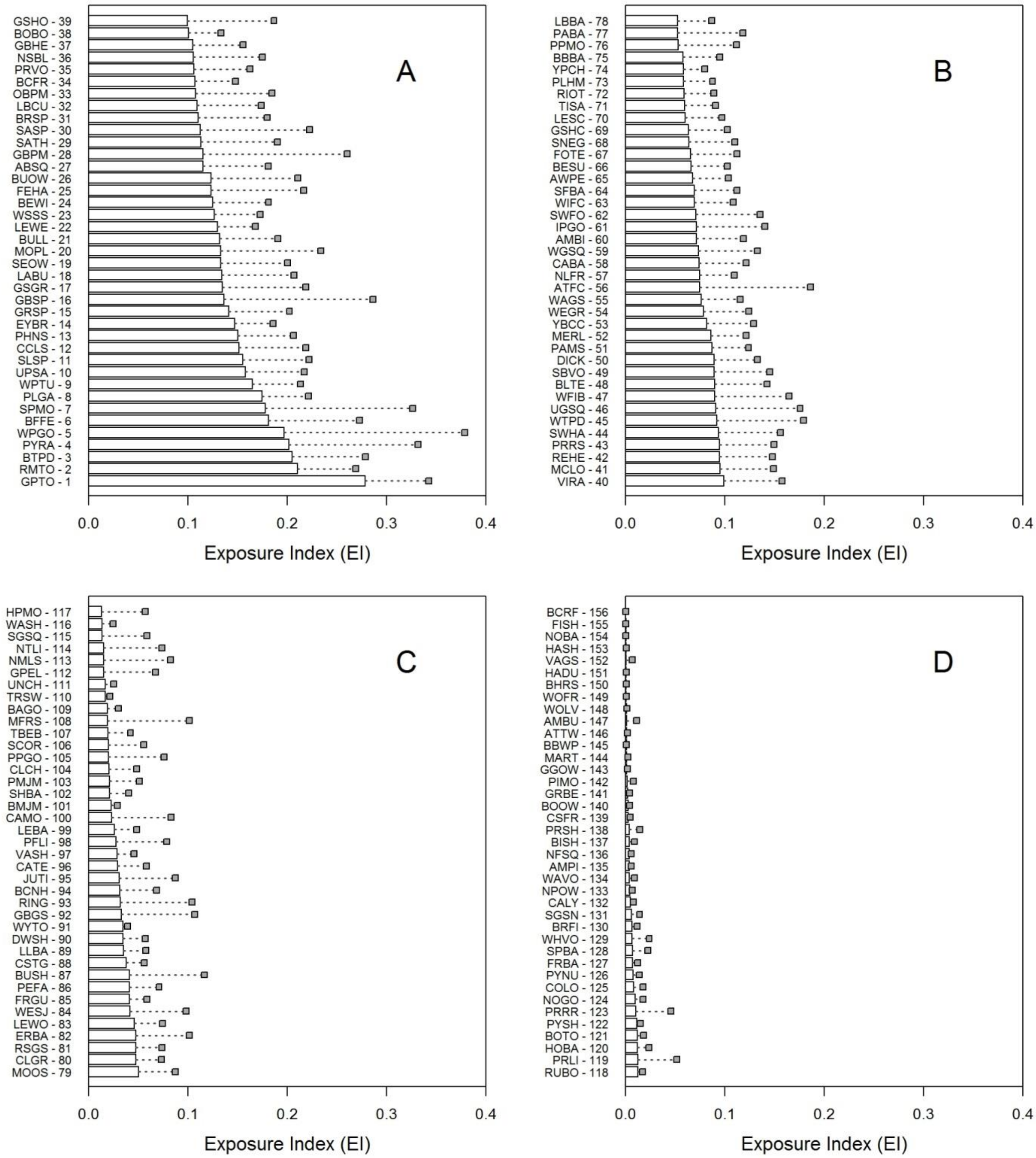
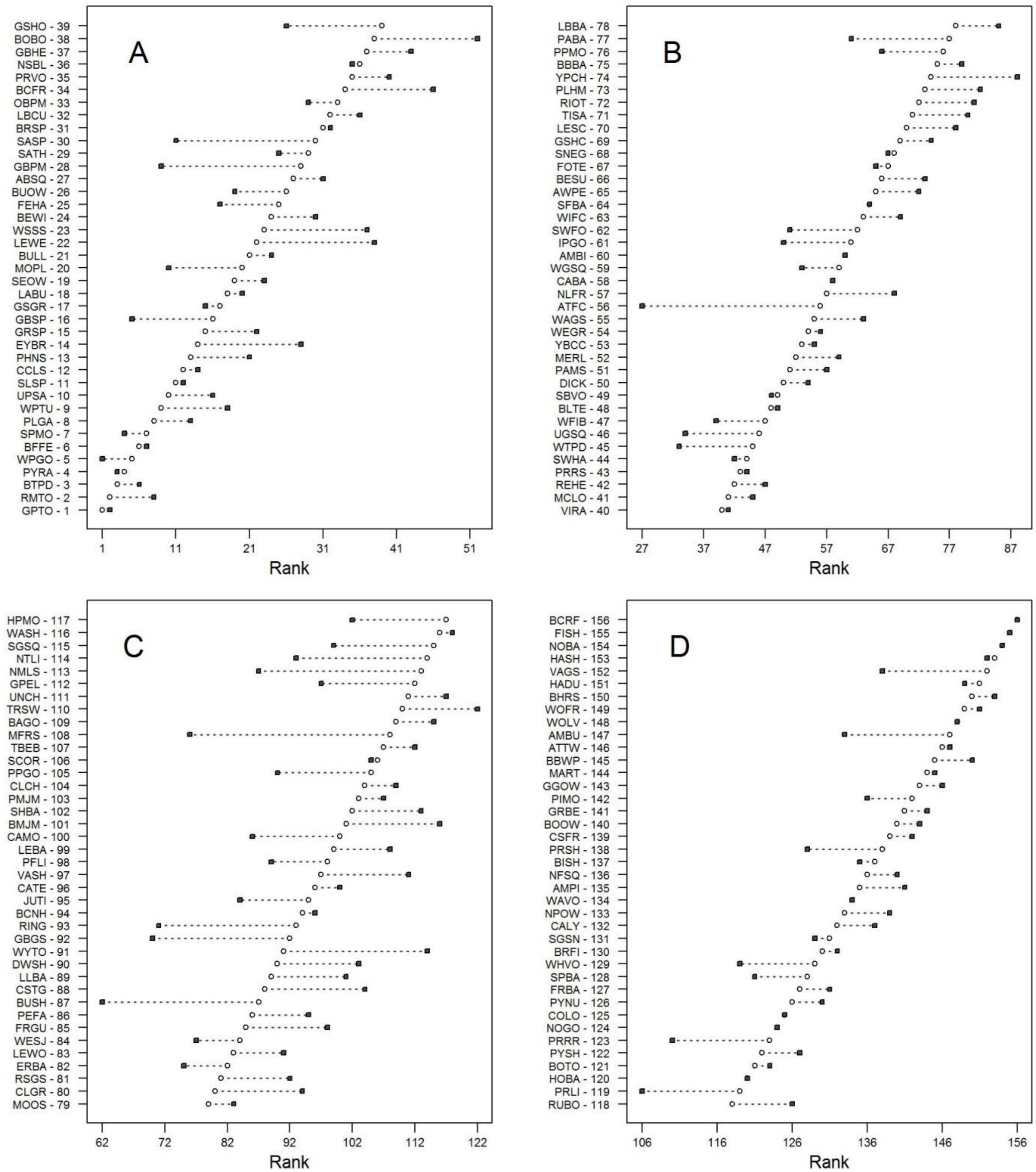


Figure B9. Range in exposure rank resulting from magnitude of buildout. Abscissa shows the exposure rank under the anticipated scenario (hollow circles) and unrestrained scenario (solid squares), where a rank of 1 is the most exposed to development. Ordinate shows individual species (see Table C1 for codes) ordered by their exposure under the anticipated scenario (see Figure B2). Dotted lines represent the difference in rank between the scenarios. Panels A-D show different subsets of the 156 species analyzed.



APPENDIX C: TABLES PROVIDING EXPOSURE AND UNCERTAINTY VALUES FOR ALL SPECIES.

Table C1. Exposure Index (*EI*) values for all 156 Wyoming Species of Greatest Conservation Need (SGCN) listed in order of decreasing 2030 total *EI*.

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
1	Great Plains Toad (Anaxyrus cognatus)	GPTO	0.005	0.036	0.182	0.278	0.277	<0.001	53%
2	Rocky Mountain Toad (Anaxyrus woodhousii woodhousii)	RMTO	0.006	0.030	0.143	0.210	0.209	<0.001	47%
3	Black-tailed Prairie Dog (Cynomys ludovicianus)	BTPD	0.005	0.034	0.136	0.205	0.201	0.004	51%
4	Pygmy Rabbit (Brachylagus idahoensis)	PYRA	0.003	0.025	0.098	0.201	0.198	0.004	105%
5	Wyoming Pocket Gopher (Thomomys clusius)	WPGO	0.002	0.024	0.112	0.196	0.188	0.009	75%
6	Black-footed Ferret (Mustela nigripes)	BFFE	<0.001	0.002	0.025	0.181	0.004	0.177	613%
7	Silky Pocket Mouse (Perognathus flavus)	SPMO	0.003	0.055	0.127	0.178	0.172	0.006	40%
8	Plains Gartersnake (Thamnophis radix)	PLGA	0.004	0.023	0.119	0.174	0.173	0.002	47%
9	Western Painted Turtle (Chrysemys picta bellii)	WPTU	0.006	0.024	0.112	0.165	0.163	0.001	48%
10	Upland Sandpiper (Bartramia longicauda)	UPSA	0.003	0.025	0.105	0.158	0.154	0.004	50%
11	Plains Spadefoot (Spea bombifrons)	SLSP	0.006	0.027	0.103	0.155	0.152	0.003	51%
12	Chestnut-collared Longspur (Calcarius ornatus)	CCLS	0.003	0.024	0.096	0.151	0.131	0.021	58%
13	Plains Hog-nosed Snake (Heterodon nasicus)	PHNS	0.006	0.025	0.100	0.150	0.147	0.003	51%
14	Eastern Yellow-bellied Racer (Coluber constrictor flaviventris)	EYBR	0.006	0.025	0.096	0.146	0.144	0.002	52%
15	Grasshopper Sparrow (Ammodramus savannarum)	GRSP	0.004	0.023	0.091	0.141	0.136	0.004	55%
16	Great Basin Spadefoot (Spea intermontana)	GBSP	0.002	0.020	0.083	0.136	0.135	<0.001	64%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
17	Greater Sage-Grouse (Centrocercus urophasianus)	GSGR	0.004	0.022	0.080	0.135	0.125	0.010	69%
18	Lark Bunting (Calamospiza melanocorys)	LABU	0.004	0.021	0.081	0.134	0.125	0.009	64%
19	Short-eared Owl (Asio flammeus)	SEOW	0.005	0.022	0.083	0.133	0.128	0.004	59%
20	Mountain Plover (Charadrius montanus)	MOPL	0.003	0.018	0.074	0.133	0.119	0.014	80%
21	Bullsnake (Pituophis catenifer sayi)	BULL	0.006	0.024	0.084	0.132	0.128	0.004	56%
22	Least Weasel (Mustela nivalis)	LEWE	0.002	0.003	0.074	0.130	0.130	<0.001	75%
23	Western Spiny Softshell (Apalone spinifera hartwegi)	WSSS	0.005	0.020	0.087	0.126	0.123	0.003	46%
24	Bald Eagle; winter (Haliaeetus leucocephalus)	BEWI	0.004	0.020	0.077	0.125	0.119	0.005	62%
25	Ferruginous Hawk (Buteo regalis)	FEHA	0.003	0.018	0.069	0.123	0.112	0.011	78%
26	Burrowing Owl (Athene cunicularia)	BUOW	0.003	0.019	0.072	0.123	0.115	0.008	70%
27	Abert's Squirrel (Sciurus aberti)	ABSQ	<0.001	<0.001	<0.001	0.115	<0.001	0.115	>1000%
28	Great Basin Pocket Mouse (Perognathus parvus)	GBPM	0.002	0.016	0.079	0.115	0.111	0.004	46%
29	Sage Thrasher (Oreoscoptes montanus)	SATH	0.004	0.017	0.062	0.113	0.102	0.011	83%
30	Sage Sparrow (Amphispiza belli)	SASP	0.003	0.016	0.059	0.112	0.103	0.009	92%
31	Brewer's Sparrow (Spizella breweri)	BRSP	0.003	0.017	0.062	0.110	0.101	0.009	77%
32	Long-billed Curlew (Numenius americanus)	LBCU	0.004	0.020	0.062	0.109	0.103	0.006	75%
33	Olive-backed Pocket Mouse (Perognathus fasciatus)	OBPM	0.004	0.017	0.063	0.108	0.097	0.011	71%
34	Boreal Chorus Frog (Pseudacris maculata)	BCFR	0.004	0.018	0.063	0.107	0.102	0.005	70%
35	Prairie Vole (Microtus ochrogaster)	PRVO	0.004	0.020	0.068	0.106	0.101	0.005	55%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
36	Northern Sagebrush Lizard (Sceloporus graciosus graciosus)	NSBL	0.004	0.015	0.064	0.105	0.102	0.003	64%
37	Great Blue Heron (Ardea herodias)	GBHE	0.004	0.017	0.064	0.105	0.099	0.005	63%
38	Bobolink (Dolichonyx oryzivorus)	BOBO	0.002	0.011	0.059	0.100	0.096	0.004	70%
39	Greater Short-horned Lizard (Phrynosoma hernandesi)	GSHO	0.003	0.015	0.048	0.099	0.090	0.009	105%
40	Virginia Rail (Rallus limicola)	VIRA	0.003	0.015	0.056	0.099	0.089	0.009	78%
41	McCown's Longspur (Calcarius mccownii)	MCLO	0.003	0.015	0.055	0.095	0.072	0.022	71%
42	Redhead (Aythya americana)	REHE	0.005	0.019	0.055	0.094	0.086	0.008	71%
43	Prairie Rattlesnake (Crotalus viridis)	PRRS	0.004	0.015	0.053	0.094	0.079	0.015	78%
44	Swainson's Hawk (Buteo swainsoni)	SWHA	0.003	0.014	0.051	0.093	0.082	0.011	84%
45	White-tailed Prairie Dog (Cynomys leucurus)	WTPD	0.004	0.014	0.044	0.092	0.079	0.012	106%
46	Uinta Ground Squirrel (Spermophilus armatus)	UGSQ	0.001	0.010	0.033	0.090	0.087	0.003	176%
47	White-faced Ibis (Plegadis chihi)	WFIB	0.004	0.016	0.047	0.090	0.080	0.009	90%
48	Black Tern (Chlidonias niger)	BLTE	0.004	0.015	0.047	0.089	0.080	0.009	91%
49	Sagebrush Vole (Lemmiscus curtatus)	SBVO	0.003	0.013	0.047	0.089	0.074	0.015	87%
50	Dickcissel (Spiza americana)	DICK	0.002	0.010	0.056	0.089	0.087	0.001	59%
51	Pale Milksnake (Lampropeltis triangulum multistriata)	PAMS	0.018	0.040	0.062	0.087	0.083	0.004	40%
52	Merlin (Falco columbarius)	MERL	0.003	0.013	0.052	0.086	0.081	0.005	64%
53	Yellow-billed Cuckoo (Coccyzus americanus)	YBCC	0.002	0.002	0.029	0.081	0.081	<0.001	180%
54	Western Grebe (Aechmophorus occidentalis)	WEGR	0.004	0.014	0.044	0.078	0.075	0.004	79%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
55	Wandering Gartersnake (Thamnophis elegans vagrans)	WAGS	0.003	0.010	0.041	0.076	0.068	0.008	85%
56	Ash-throated Flycatcher (Myiarchus cinerascens)	ATFC	0.002	0.011	0.048	0.075	0.069	0.006	56%
57	Northern Leopard Frog (Lithobates pipiens)	NLFR	0.004	0.014	0.045	0.074	0.069	0.005	67%
58	Canvasback (Aythya valisineria)	CABA	0.004	0.013	0.041	0.074	0.060	0.014	82%
59	Wyoming Ground Squirrel (Spermophilus elegans)	WGSQ	0.002	0.008	0.028	0.073	0.049	0.025	163%
60	American Bittern (Botaurus lentiginosus)	AMBI	0.003	0.012	0.037	0.071	0.064	0.007	93%
61	Idaho Pocket Gopher (Thomomys idahoensis)	IPGO	<0.001	0.004	0.026	0.071	0.041	0.030	173%
62	Swift Fox (Vulpes velox)	SWFO	0.002	0.011	0.040	0.071	0.049	0.022	78%
63	Willow Flycatcher (Empidonax traillii)	WIFC	0.002	0.010	0.039	0.069	0.065	0.004	79%
64	Western Small-footed Myotis (Myotis ciliolabrum)	SFBA	0.005	0.016	0.041	0.069	0.065	0.004	67%
65	American White Pelican (Pelecanus erythrorhynchos)	AWPE	0.003	0.010	0.036	0.067	0.055	0.012	86%
66	Bald Eagle; summer (Haliaeetus leucocephalus)	BESU	0.002	0.010	0.035	0.066	0.061	0.005	87%
67	Forster's Tern (Sterna forsteri)	FOTE	0.003	0.011	0.027	0.065	0.055	0.011	142%
68	Snowy Egret (Egretta thula)	SNEG	0.002	0.007	0.019	0.064	0.043	0.021	241%
69	Greater Sandhill Crane (Grus canadensis)	GSHC	0.002	0.011	0.033	0.063	0.059	0.005	89%
70	Lesser Scaup (Aythya affinis)	LESC	0.002	0.009	0.032	0.060	0.050	0.010	89%
71	Tiger Salamander (Ambystoma mavortium)	TISA	0.002	0.010	0.031	0.059	0.055	0.005	91%
72	River Otter (Lontra canadensis)	RIOT	0.001	0.008	0.025	0.059	0.055	0.003	138%
73	Plains Harvest Mouse (Reithrodontomys montanus)	PLHM	0.002	0.013	0.044	0.058	0.054	0.005	34%
74	Yellow-pine Chipmunk (Neotamias amoenus)	YPCH	<0.001	0.006	0.014	0.058	0.058	<0.001	301%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
75	Big Brown Bat (Eptesicus fuscus)	BBBA	0.003	0.013	0.033	0.058	0.052	0.005	75%
76	Plains Pocket Mouse (Perognathus flavescens)	PPMO	<0.001	0.008	0.031	0.053	0.038	0.014	71%
77	Pallid Bat (Antrozous pallidus)	PABA	0.005	0.017	0.034	0.052	0.050	0.003	56%
78	Little Brown Myotis (Myotis lucifugus)	LBBA	0.004	0.013	0.029	0.052	0.045	0.007	82%
79	Moose (Alces alces)	MOOS	0.001	0.007	0.021	0.050	0.047	0.003	140%
80	Clark's Grebe (Aechmophorus clarkii)	CLGR	0.003	0.007	0.023	0.047	0.043	0.004	107%
81	Red-sided Gartersnake (Thamnophis sirtalis parietalis)	RSGS	0.004	0.011	0.030	0.047	0.045	0.002	55%
82	Eastern Red Bat (Lasiurus borealis)	ERBA	0.002	0.013	0.028	0.047	0.032	0.015	67%
83	Lewis' Woodpecker (Melanerpes lewis)	LEWO	0.002	0.009	0.027	0.046	0.042	0.004	73%
84	Western Scrub-Jay (Aphelocoma californica)	WESJ	0.001	0.006	0.022	0.041	0.035	0.006	86%
85	Franklin's Gull (Larus pipixcan)	FRGU	0.002	0.006	0.022	0.041	0.036	0.005	85%
86	Peregrine Falcon (Falco peregrinus)	PEFA	0.002	0.007	0.021	0.041	0.036	0.004	96%
87	Bushtit (Psaltriparus minimus)	BUSH	0.002	0.010	0.033	0.041	0.035	0.005	23%
88	Columbian Sharp-tailed Grouse (Tympanuchus phasianellus columbianus)	CSTG	0.002	0.004	0.024	0.037	0.036	0.002	56%
89	Long-legged Myotis (Myotis volans)	LLBA	0.002	0.008	0.021	0.035	0.032	0.003	68%
90	Dwarf Shrew (Sorex nanus)	DWSH	0.001	0.005	0.018	0.035	0.029	0.005	89%
91	Wyoming Toad (Anaxyrus baxteri)	WYTO	0.007	0.008	0.011	0.034	0.009	0.026	216%
92	Great Basin Gophersnake (Pituophis catenifer deserticola)	GBGS	0.001	0.008	0.024	0.033	0.029	0.004	36%
93	Ringtail (Bassariscus astutus)	RING	0.003	0.009	0.024	0.032	0.022	0.010	34%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
94	Black-crowned Night-Heron (Nycticorax nycticorax)	BCNH	0.002	0.005	0.014	0.031	0.018	0.013	130%
95	Juniper Titmouse (Baeolophus ridgwayi)	JUTI	<0.001	0.004	0.011	0.031	0.018	0.012	179%
96	Caspian Tern (Sterna caspia)	CATE	<0.001	0.003	0.007	0.029	0.028	0.001	313%
97	Vagrant Shrew (Sorex vagrans)	VASH	0.001	0.004	0.015	0.028	0.026	0.003	86%
98	Plateau Fence Lizard (Sceloporus tristichus)	PFLI	<0.001	0.005	0.018	0.027	0.022	0.006	57%
99	Long-eared Myotis (Myotis evotis)	LEBA	0.001	0.006	0.013	0.026	0.023	0.003	101%
100	Canyon Mouse (Peromyscus crinitus)	CAMO	<0.001	0.005	0.013	0.023	0.015	0.008	74%
101	Bear Lodge Meadow Jumping Mouse (Zapus hudsonius campestris)	BMJM	<0.001	0.002	0.014	0.023	0.023	<0.001	61%
102	Silver-haired Bat (Lasionycteris noctivagans)	SHBA	0.002	0.005	0.010	0.021	0.016	0.005	115%
103	Preble's Meadow Jumping Mouse (Zapus hudsonius preblei)	PMJM	<0.001	0.002	0.003	0.021	0.003	0.018	534%
104	Cliff Chipmunk (Neotamias dorsalis)	CLCH	0.001	0.006	0.017	0.020	0.016	0.005	18%
105	Plains Pocket Gopher (Geomys bursarius)	PPGO	0.001	0.007	0.013	0.020	0.016	0.004	49%
106	Scott's Oriole (Icterus parisorum)	SCOR	0.001	0.006	0.017	0.020	0.018	0.001	16%
107	Townsend's Big-eared Bat (Corynorhinus townsendii)	TBEB	0.003	0.008	0.012	0.019	0.017	0.002	59%
108	Midget Faded Rattlesnake (Crotalus oreganus concolor)	MFRS	<0.001	0.004	0.015	0.019	0.017	0.001	27%
109	Barrow's Goldeneye (Bucephala islandica)	BAGO	0.001	0.005	0.009	0.019	0.018	<0.001	97%
110	Trumpeter Swan (Cygnus buccinator)	TRSW	<0.001	<0.001	0.005	0.017	0.017	<0.001	246%
111	Unita Chipmunk (Neotamias umbrinus)	UNCH	<0.001	0.003	0.006	0.016	0.012	0.004	173%
112	Great Plains Earless Lizard (Holbrookia maculata)	GPEL	<0.001	0.002	0.008	0.015	0.007	0.008	82%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
113	Northern Many-lined Skink (Eumeces multivirgatus)	NMLS	<0.001	0.001	0.006	0.015	0.006	0.008	128%
114	Northern Tree Lizard (Urosaurus ornatus wrighti)	NTLI	0.001	0.005	0.012	0.015	0.012	0.003	26%
115	Spotted Ground Squirrel (Spermophilus spilosoma)	SGSQ	<0.001	0.001	0.003	0.013	0.003	0.010	358%
116	Water Shrew (Sorex palustris)	WASH	<0.001	0.002	0.005	0.013	0.008	0.005	158%
117	Hispid Pocket Mouse (Chaetodipus hispidus)	HPMO	<0.001	0.003	0.006	0.013	0.007	0.006	98%
118	Rubber Boa (Charina bottae)	RUBO	<0.001	0.003	0.005	0.012	0.012	<0.001	154%
119	Prairie Lizard (Sceloporus consobrinus)	PRLI	<0.001	<0.001	0.003	0.012	0.003	0.010	328%
120	Hoary Bat (Lasiurus cinereus)	HOBA	0.002	0.005	0.007	0.011	0.010	0.001	56%
121	Boreal Toad (Anaxyrus boreas boreas)	BOTO	<0.001	0.002	0.004	0.011	0.011	<0.001	198%
122	Pygmy Shrew (Sorex hoyi)	PYSH	<0.001	0.001	0.003	0.011	0.001	0.010	290%
123	Prairie Racerunner (Aspidoscelis sexlineatus viridis)	PRRR	<0.001	<0.001	<0.001	0.010	<0.001	0.009	>1000%
124	Northern Goshawk (Accipiter gentilis)	NOGO	<0.001	0.002	0.004	0.009	0.007	0.002	106%
125	Common Loon (Gavia immer)	COLO	<0.001	0.001	0.003	0.008	0.007	0.001	151%
126	Pygmy Nuthatch (Sitta pygmaea)	PYNU	<0.001	0.001	0.004	0.008	0.006	0.002	80%
127	Fringed Myotis (Myotis thysanodes)	FRBA	0.001	0.003	0.004	0.007	0.006	<0.001	47%
128	Spotted Bat (Euderma maculatum)	SPBA	<0.001	0.004	0.006	0.007	0.007	<0.001	18%
129	Western Heather Vole (Phenacomys intermedius)	WHVO	<0.001	<0.001	0.005	0.006	0.005	0.001	16%
130	Black Rosy-Finch (Leucosticte atrata)	BRFI	<0.001	0.002	0.003	0.006	0.005	0.001	91%
131	Smooth Green Snake (Opheodrys vernalis)	SGSN	<0.001	<0.001	0.001	0.006	0.001	0.005	446%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
132	Canada Lynx (Lynx canadensis)	CALY	<0.001	0.001	0.002	0.005	0.005	<0.001	122%
133	Northern Pygmy-Owl (Glaucidium gnoma)	NPOW	<0.001	<0.001	0.001	0.004	0.004	<0.001	215%
134	Water Vole (Microtus richardsoni)	WAVO	<0.001	<0.001	0.002	0.004	0.004	<0.001	93%
135	American Pika (Ochotona princeps)	AMPI	<0.001	0.001	0.002	0.004	0.004	<0.001	60%
136	Northern Flying Squirrel (Glaucomys sabrinus)	NFSQ	<0.001	<0.001	0.002	0.003	0.003	<0.001	103%
137	Bighorn Sheep (Ovis canadensis)	BISH	<0.001	0.002	0.002	0.003	0.003	<0.001	42%
138	Preble's Shrew (Sorex preblei)	PRSH	<0.001	0.001	0.003	0.003	0.003	<0.001	11%
139	Columbia Spotted Frog (Rana luteiventris)	CSFR	<0.001	<0.001	<0.001	0.003	0.003	<0.001	592%
140	Boreal Owl (Aegolius funereus)	BOOW	<0.001	<0.001	0.001	0.002	0.002	<0.001	87%
141	Grizzly Bear (Ursus arctos)	GRBE	<0.001	<0.001	0.001	0.002	0.002	<0.001	63%
142	Pinyon Mouse (Peromyscus truei)	PIMO	<0.001	<0.001	0.001	0.001	<0.001	<0.001	27%
143	Great Gray Owl (Strix nebulosa)	GGOW	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	212%
144	Marten (Martes americana)	MART	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	53%
145	Black-backed Woodpecker (Picoides arcticus)	BBWP	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	22%
146	American Three-toed Woodpecker (Picoides dorsalis)	ATTW	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	80%
147	American Bullfrog (Lithobates catesbieanus)	AMBU	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	>1000%
148	Wolverine (Gulo gulo)	WOLV	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	215%
149	Wood Frog (Lithobates sylvaticus)	WOFR	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	157%
150	Black Hills Redbelly Snake (Storeria occipitomaculata pahasapae)	BHRS	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	10%

Exp. Rank	Species	Species Code	Total EI 1950	Total EI 1980	Total EI 2010	2030 Projected EI			Percent Change 2010 to 2030
						Total	Oil & Gas	Wind	
151	Harlequin Duck (Histrionicus histrionicus)	HADU	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	31%
152	Valley Gartersnake (Thamnophis sirtalis fitchi)	VAGS	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	113%
153	Hayden's Shrew (Sorex haydeni)	HASH	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	184%
154	Northern Myotis (Myotis septentrionalis)	NOBA	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	1%
155	Fisher (Martes pennanti)	FISH	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0%
156	Brown-capped Rosy Finch (Leucosticte australis)	BCRF	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	>1000%

Table C2. Factors used to assess distribution model quality and hence uncertainty for all 156 species in this study. Species codes are given in Table C1. Values following '±' are standard deviations. Numbers in parenthesis indicate the transformation of each value into an uncertainty score on a scale of 0 (low uncertainty) to 1 (high uncertainty), where such transformation was necessary. Factor definitions and explanation of how they were used to generate the uncertainty index (UI) are discussed in Appendix A.

Species Code	Input Data Quality		Model Validation				Exposure Change; EC	UI
	Number Occur. (NS)	Ave. Occur. Quality (OQS)	Ave. Test AUC (AUCS)	Ave. Test Omission Rate; OR	Expert Review (ERS)	Boyce Index (BIS)		
TISA	228 (0)	9.55 ± 2.94 (0.31)	0.71 ± 0.04 (0.29)	0.35 ± 0.12	Low (1)	0.85 ± 0.11 (0.15)	0.03	0.21
BOTO	256 (0)	8.97 ± 3 (0.38)	0.91 ± 0.02 (0.09)	0.03 ± 0.03	High (0)	0.76 ± 0.13 (0.24)	0.2	0.16
GPTO	20 (0.5)	9.65 ± 2.83 (0.29)	0.95 ± 0.05 (0.05)	0.15 ± 0.24	Medium (0.5)	na (1)	0.09	0.29
RMTO	106 (0)	10.36 ± 2.87 (0.21)	0.91 ± 0.03 (0.09)	0.14 ± 0.1	Medium (0.5)	0.82 ± 0.27 (0.18)	0.16	0.17
WYTO	10 (1)	6.1 ± 2.56 (0.74)	0.99 ± 0.02 (0.01)	0.2 ± 0.42	Medium (0.5)	na (1)	0.12	0.43
BCFR	97 (0.25)	7.88 ± 2.78 (0.52)	0.7 ± 0.06 (0.3)	0.42 ± 0.19	Low (1)	0.62 ± 0.32 (0.38)	0.1	0.33
SLSP	37 (0.5)	7.84 ± 2.73 (0.52)	0.77 ± 0.09 (0.23)	0.29 ± 0.15	Low (1)	na (1)	0.07	0.39
GBSP	27 (0.5)	7.96 ± 2.36 (0.5)	0.88 ± 0.07 (0.12)	0.12 ± 0.19	Medium (0.5)	na (1)	0.04	0.31

Species Code	Input Data Quality: Number Occur. (NS)	Input Data Quality: Ave. Occur. Quality (OQS)	Model Validation: Ave. Test AUC (AUCS)	Model Validation: Ave. Test Omission Rate; OR	Model Validation: Expert Review (ERS)	Model Validation: Boyce Index (BIS)	Exposure Change; EC	UI
AMBU	3 (1)	4.67 ± 0.58 (0.92)	0.3 ± 0.48 (0.7)	0.67 ± 0.58	Low (1)	na (1)	1	0.93
NLFR	225 (0)	9.8 ± 2.84 (0.28)	0.81 ± 0.06 (0.19)	0.29 ± 0.13	Medium (0.5)	0.96 ± 0.07 (0.04)	0.1	0.17
WOFR	62 (0.25)	10.32 ± 2.02 (0.21)	0.98 ± 0.02 (0.02)	0.05 ± 0.08	Medium (0.5)	0.78 ± 0.23 (0.22)	0.99	0.49
CSFR	291 (0)	10.33 ± 2.26 (0.21)	0.94 ± 0.01 (0.06)	0.02 ± 0.01	Medium (0.5)	0.67 ± 0.3 (0.33)	0.48	0.29
COLO	98 (0.25)	6.42 ± 2.21 (0.7)	0.95 ± 0.02 (0.05)	0.13 ± 0.14	Medium (0.5)	0.66 ± 0.37 (0.34)	0.26	0.32
WEGR	144 (0)	5.29 ± 1.38 (0.84)	0.87 ± 0.03 (0.13)	0.2 ± 0.1	Low (1)	0.82 ± 0.13 (0.18)	0.16	0.31
CLGR	29 (0.5)	6.45 ± 2.13 (0.69)	0.88 ± 0.12 (0.12)	0.28 ± 0.31	Low (1)	na (1)	0.24	0.47
AWPE	430 (0)	6.41 ± 1.89 (0.7)	0.82 ± 0.04 (0.18)	0.22 ± 0.06	Medium (0.5)	0.93 ± 0.13 (0.07)	0.17	0.24
AMBI	60 (0.25)	5.45 ± 1.68 (0.82)	0.65 ± 0.12 (0.35)	0.47 ± 0.23	Medium (0.5)	0.75 ± 0.27 (0.25)	0.17	0.35
GBHE	847 (0)	5.65 ± 1.32 (0.79)	0.69 ± 0.02 (0.31)	0.33 ± 0.04	Medium (0.5)	0.97 ± 0.05 (0.03)	0.04	0.23
SNEG	43 (0.5)	5.3 ± 1.47 (0.84)	0.91 ± 0.04 (0.09)	0.17 ± 0.17	Medium (0.5)	0.95 ± 0.07 (0.05)	0.16	0.31
BCNH	76 (0.25)	5.93 ± 1.8 (0.76)	0.88 ± 0.06 (0.12)	0.12 ± 0.1	Medium (0.5)	0.67 ± 0.38 (0.33)	0.11	0.27
WFIB	89 (0.25)	5.97 ± 2.03 (0.75)	0.74 ± 0.06 (0.26)	0.36 ± 0.19	Medium (0.5)	0.9 ± 0.12 (0.1)	0.1	0.28
TRSW	165 (0)	6.67 ± 2.06 (0.67)	0.95 ± 0.01 (0.05)	0.09 ± 0.09	Medium (0.5)	0.34 ± 0.13 (0.66)	0.34	0.33
CABA	62 (0.25)	5.66 ± 1.33 (0.79)	0.73 ± 0.09 (0.27)	0.36 ± 0.25	Low (1)	0.63 ± 0.32 (0.37)	0.14	0.37
REHE	99 (0.25)	5.69 ± 1.72 (0.79)	0.76 ± 0.06 (0.24)	0.18 ± 0.1	Medium (0.5)	0.73 ± 0.28 (0.27)	0.11	0.29
LESC	102 (0)	5.43 ± 1.35 (0.82)	0.64 ± 0.1 (0.36)	0.36 ± 0.15	Low (1)	0.43 ± 0.37 (0.57)	0.1	0.35
HADU	47 (0.5)	6.45 ± 2.06 (0.69)	0.94 ± 0.06 (0.06)	0.14 ± 0.19	Medium (0.5)	0.56 ± 0.45 (0.44)	0.86	0.58
BAGO	61 (0.25)	5.46 ± 1.4 (0.82)	0.87 ± 0.04 (0.13)	0.23 ± 0.21	Medium (0.5)	0.5 ± 0.34 (0.5)	0.24	0.36
BESU	353 (0)	6.36 ± 1.93 (0.71)	0.72 ± 0.04 (0.28)	0.34 ± 0.13	High (0)	0.92 ± 0.09 (0.08)	0.08	0.19
BEWI	2794 (0)	5.49 ± 1.53 (0.81)	0.69 ± 0.01 (0.31)	0.32 ± 0.04	Medium (0.5)	0.9 ± 0.08 (0.1)	0.02	0.23
NOGO	421 (0)	6.58 ± 2.41 (0.68)	0.89 ± 0.02 (0.11)	0.17 ± 0.06	High (0)	0.92 ± 0.1 (0.08)	0.09	0.16

Species Code	Input Data Quality		Model Validation				Exposure Change; EC	UI
	Number Occur. (NS)	Ave. Occur. Quality (OQS)	Ave. Test AUC (AUCS)	Ave. Test Omission Rate; OR	Expert Review (ERS)	Boyce Index (BIS)		
SWHA	861 (0)	5.64 ± 1.6 (0.8)	0.69 ± 0.02 (0.31)	0.35 ± 0.09	Medium (0.5)	0.94 ± 0.05 (0.06)	0.02	0.23
FEHA	1443 (0)	6.12 ± 1.92 (0.74)	0.74 ± 0.02 (0.26)	0.24 ± 0.1	Medium (0.5)	1 ± 0 (0)	0.02	0.2
MERL	182 (0)	6.35 ± 2.28 (0.71)	0.63 ± 0.07 (0.37)	0.64 ± 0.15	Medium (0.5)	0.6 ± 0.29 (0.4)	0.05	0.29
PEFA	181 (0)	7.39 ± 2.58 (0.58)	0.68 ± 0.05 (0.32)	0.37 ± 0.1	Medium (0.5)	0.81 ± 0.17 (0.19)	0.12	0.25
GSGR	1610 (0)	7.87 ± 1.48 (0.52)	0.86 ± 0.01 (0.14)	0.09 ± 0.03	Medium (0.5)	0.88 ± 0.14 (0.12)	0.03	0.16
CSTG	40 (0.5)	8.38 ± 2.82 (0.45)	0.98 ± 0.03 (0.02)	0.13 ± 0.18	High (0)	0.98 ± 0.06 (0.02)	0.42	0.3
VIRA	16 (1)	6.31 ± 1.54 (0.71)	0.76 ± 0.16 (0.24)	0.45 ± 0.37	Low (1)	1 ± 0 (0)	0.07	0.41
GSHC	1181 (0)	6.54 ± 1.88 (0.68)	0.75 ± 0.02 (0.25)	0.25 ± 0.03	Low (1)	0.97 ± 0.05 (0.03)	0.1	0.27
MOPL	302 (0)	8.63 ± 2.91 (0.42)	0.81 ± 0.04 (0.19)	0.23 ± 0.12	High (0)	0.9 ± 0.12 (0.1)	0.05	0.12
UPSA	120 (0)	6.08 ± 1.66 (0.74)	0.92 ± 0.02 (0.08)	0.11 ± 0.14	Medium (0.5)	0.78 ± 0.24 (0.22)	0.6	0.4
LBCU	341 (0)	6.17 ± 1.77 (0.73)	0.74 ± 0.05 (0.26)	0.35 ± 0.09	Medium (0.5)	1 ± 0 (0)	0.06	0.22
FRGU	33 (0.5)	4.97 ± 1.33 (0.88)	0.86 ± 0.08 (0.14)	0.29 ± 0.3	Medium (0.5)	na (1)	0.51	0.55
CATE	33 (0.5)	5.91 ± 2.1 (0.76)	0.92 ± 0.07 (0.08)	0.17 ± 0.22	Medium (0.5)	na (1)	0.54	0.53
FOTE	35 (0.5)	6.51 ± 2.13 (0.69)	0.85 ± 0.13 (0.15)	0.28 ± 0.27	Medium (0.5)	na (1)	0.15	0.39
BLTE	42 (0.5)	5.33 ± 1.48 (0.83)	0.83 ± 0.1 (0.17)	0.17 ± 0.19	Low (1)	0.93 ± 0.09 (0.07)	0.06	0.33
YBCC	19 (1)	6.79 ± 2.18 (0.65)	0.94 ± 0.04 (0.06)	0.25 ± 0.35	Low (1)	na (1)	0.3	0.55
NPOW	11 (1)	7 ± 1.41 (0.63)	0.95 ± 0.05 (0.05)	0.1 ± 0.32	Medium (0.5)	na (1)	1	0.74
BUOW	655 (0)	6.9 ± 2.41 (0.64)	0.78 ± 0.02 (0.22)	0.22 ± 0.05	High (0)	0.93 ± 0.07 (0.07)	0.03	0.14
GGOW	55 (0.25)	6.07 ± 1.74 (0.74)	0.92 ± 0.05 (0.08)	0.11 ± 0.16	High (0)	0.54 ± 0.3 (0.46)	0.31	0.31
SEOW	142 (0)	6.26 ± 1.81 (0.72)	0.73 ± 0.05 (0.27)	0.35 ± 0.1	Medium (0.5)	0.74 ± 0.25 (0.26)	0.04	0.24
BOOW	58 (0.25)	9.36 ± 1.98 (0.33)	0.94 ± 0.03 (0.06)	0.05 ± 0.11	High (0)	0.43 ± 0.37 (0.57)	0.35	0.27
LEWO	118 (0)	5.84 ± 1.55 (0.77)	0.88 ± 0.06 (0.12)	0.24 ± 0.12	Medium (0.5)	0.85 ± 0.16 (0.15)	0.17	0.26

Species Code	Input Data Quality		Model Validation				Exposure Change; EC	UI
	Number Occur. (NS)	Ave. Occur. Quality (OQS)	Ave. Test AUC (AUCS)	Ave. Test Omission Rate; OR	Expert Review (ERS)	Boyce Index (BIS)		
BBWP	11 (1)	7.73 ± 2.69 (0.53)	0.95 ± 0.07 (0.05)	0.1 ± 0.32	Medium (0.5)	na (1)	0.33	0.48
ATTW	110 (0)	9.94 ± 2.72 (0.26)	0.95 ± 0.02 (0.05)	0.09 ± 0.14	High (0)	0.75 ± 0.31 (0.25)	0.26	0.16
WIFC	95 (0.25)	6.24 ± 1.91 (0.72)	0.68 ± 0.08 (0.32)	0.45 ± 0.18	Low (1)	0.59 ± 0.24 (0.41)	0.08	0.36
ATFC	60 (0.25)	6.55 ± 2.73 (0.68)	0.9 ± 0.04 (0.1)	0.18 ± 0.17	Medium (0.5)	0.82 ± 0.16 (0.18)	0.12	0.26
WESJ	26 (0.5)	7.42 ± 2.8 (0.57)	0.97 ± 0.04 (0.03)	0.12 ± 0.19	Medium (0.5)	na (1)	0.25	0.39
JUTI	31 (0.5)	8.48 ± 3.03 (0.44)	0.97 ± 0.03 (0.03)	0.15 ± 0.25	Medium (0.5)	na (1)	0.29	0.39
BUSH	24 (0.5)	8.33 ± 3.67 (0.46)	0.91 ± 0.07 (0.09)	0.1 ± 0.21	Medium (0.5)	na (1)	0.1	0.32
PYNU	35 (0.5)	6.63 ± 2.66 (0.67)	0.94 ± 0.07 (0.06)	0.13 ± 0.19	Medium (0.5)	na (1)	0.81	0.61
SATH	635 (0)	8.95 ± 2.5 (0.38)	0.69 ± 0.03 (0.31)	0.19 ± 0.07	High (0)	0.69 ± 0.24 (0.31)	0.03	0.14
DICK	24 (0.5)	7.67 ± 2.32 (0.54)	0.95 ± 0.05 (0.05)	0 ± 0	Medium (0.5)	na (1)	0.43	0.44
BRSP	1372 (0)	8.8 ± 2.54 (0.4)	0.65 ± 0.02 (0.35)	0.26 ± 0.05	High (0)	0.82 ± 0.2 (0.18)	0.02	0.13
SASP	631 (0)	8.21 ± 2.83 (0.47)	0.78 ± 0.02 (0.22)	0.19 ± 0.06	High (0)	0.88 ± 0.13 (0.12)	0.02	0.12
LABU	407 (0)	6.02 ± 1.5 (0.75)	0.71 ± 0.02 (0.29)	0.28 ± 0.14	High (0)	0.71 ± 0.28 (0.29)	0.04	0.19
GRSP	261 (0)	7.79 ± 1.75 (0.53)	0.82 ± 0.03 (0.18)	0.26 ± 0.06	High (0)	0.82 ± 0.28 (0.18)	0.08	0.16
MCLO	152 (0)	8.24 ± 2.63 (0.47)	0.9 ± 0.03 (0.1)	0.17 ± 0.11	High (0)	0.84 ± 0.15 (0.16)	0.15	0.16
CCLS	90 (0.25)	7.38 ± 2.31 (0.58)	0.89 ± 0.05 (0.11)	0.22 ± 0.19	High (0)	0.9 ± 0.09 (0.1)	0.17	0.21
BOBO	46 (0.5)	6.72 ± 1.8 (0.66)	0.83 ± 0.11 (0.17)	0.27 ± 0.23	Medium (0.5)	0.84 ± 0.22 (0.16)	0.33	0.38
SCOR	9 (1)	6.56 ± 3.21 (0.68)	0.88 ± 0.31 (0.12)	0.22 ± 0.44	Medium (0.5)	na (1)	0.37	0.53
BRFI	7 (1)	7.86 ± 2.19 (0.52)	0.65 ± 0.46 (0.35)	0.29 ± 0.49	Low (1)	na (1)	1	0.81
BCRF	2 (1)	9 ± 2.83 (0.38)	0.15 ± 0.34 (0.85)	0.5 ± 0.71	Low (1)	na (1)	0	0.49
PRSH	3 (1)	4.33 ± 3.51 (0.96)	0.3 ± 0.48 (0.7)	1 ± 0	Low (1)	na (1)	0.72	0.86
VASH	22 (0.5)	4.86 ± 1.04 (0.89)	0.82 ± 0.18 (0.18)	0.33 ± 0.33	Low (1)	na (1)	0.45	0.58

Species Code	Input Data Quality		Model Validation				Exposure Change; EC	UI
	Number Occur. (NS)	Ave. Occur. Quality (OQS)	Ave. Test AUC (AUCS)	Ave. Test Omission Rate; OR	Expert Review (ERS)	Boyce Index (BIS)		
DWSH	15 (1)	5.8 ± 1.7 (0.78)	0.75 ± 0.27 (0.25)	0.5 ± 0.47	Medium (0.5)	na (1)	0.59	0.66
WASH	23 (0.5)	5.22 ± 1.31 (0.85)	0.85 ± 0.07 (0.15)	0.18 ± 0.24	Medium (0.5)	na (1)	0.14	0.4
PYSH	5 (1)	5.8 ± 1.64 (0.78)	0.5 ± 0.52 (0.5)	0.2 ± 0.45	Low (1)	na (1)	0.07	0.51
HASH	14 (1)	6.21 ± 2.26 (0.72)	0.97 ± 0.04 (0.03)	0.05 ± 0.16	Medium (0.5)	na (1)	1	0.74
LBBA	119 (0)	7.18 ± 3.54 (0.6)	0.75 ± 0.05 (0.25)	0.29 ± 0.14	Medium (0.5)	0.78 ± 0.16 (0.22)	0.13	0.24
LEBA	60 (0.25)	7.55 ± 3.15 (0.56)	0.8 ± 0.1 (0.2)	0.28 ± 0.24	Medium (0.5)	0.69 ± 0.33 (0.31)	0.2	0.3
FRBA	24 (0.5)	10.25 ± 2.36 (0.22)	0.94 ± 0.03 (0.06)	0.12 ± 0.19	Medium (0.5)	na (1)	0.31	0.36
LLBA	80 (0.25)	8.51 ± 3.26 (0.44)	0.8 ± 0.11 (0.2)	0.35 ± 0.23	Medium (0.5)	0.82 ± 0.23 (0.18)	1	0.57
SFBA	66 (0.25)	7.39 ± 2.58 (0.58)	0.8 ± 0.08 (0.2)	0.32 ± 0.18	Medium (0.5)	0.75 ± 0.31 (0.25)	1	0.59
NOBA	3 (1)	8.67 ± 2.89 (0.42)	0.28 ± 0.45 (0.72)	0 ± 0	Low (1)	na (1)	1	0.8
SHBA	63 (0.25)	7.92 ± 3.57 (0.51)	0.8 ± 0.08 (0.2)	0.27 ± 0.17	Medium (0.5)	0.88 ± 0.18 (0.12)	0.21	0.28
BBBA	83 (0.25)	6.94 ± 3.37 (0.63)	0.74 ± 0.07 (0.26)	0.26 ± 0.15	Medium (0.5)	0.67 ± 0.32 (0.33)	0.15	0.3
ERBA	5 (1)	5.4 ± 1.67 (0.83)	0.37 ± 0.41 (0.63)	0 ± 0	Low (1)	na (1)	0.44	0.65
HOBA	63 (0.25)	8.81 ± 3.23 (0.4)	0.83 ± 0.06 (0.17)	0.24 ± 0.08	Medium (0.5)	0.82 ± 0.26 (0.18)	0.44	0.35
SPBA	14 (1)	9.57 ± 2.14 (0.3)	0.98 ± 0.03 (0.02)	0.2 ± 0.42	Medium (0.5)	na (1)	0.35	0.46
TBEB	50 (0.25)	7.92 ± 1.95 (0.51)	0.9 ± 0.1 (0.1)	0.16 ± 0.16	Medium (0.5)	0.84 ± 0.22 (0.16)	0.47	0.36
PABA	16 (1)	7.38 ± 2.5 (0.58)	0.79 ± 0.24 (0.21)	0.3 ± 0.48	Medium (0.5)	na (1)	0.35	0.52
AMPI	170 (0)	6.08 ± 1.97 (0.74)	0.96 ± 0.02 (0.04)	0.11 ± 0.08	High (0)	0.65 ± 0.25 (0.35)	0.26	0.24
PYRA	278 (0)	10.39 ± 2.4 (0.2)	0.93 ± 0.01 (0.07)	0.09 ± 0.07	High (0)	0.86 ± 0.14 (0.14)	0.07	0.08
YPCH	12 (1)	4.25 ± 2.22 (0.97)	0.89 ± 0.09 (0.11)	0.35 ± 0.47	Medium (0.5)	na (1)	0.56	0.65
CLCH	8 (1)	6.25 ± 1.39 (0.72)	0.79 ± 0.42 (0.21)	0.13 ± 0.35	Low (1)	na (1)	0.06	0.47
UNCH	16 (1)	4.25 ± 2.27 (0.97)	0.84 ± 0.16 (0.16)	0.06 ± 0.02	Medium (0.5)	na (1)	0.2	0.5

Species Code	Input Data Quality: Number Occur. (NS)	Input Data Quality: Ave. Occur. Quality (OQS)	Model Validation: Ave. Test AUC (AUCS)	Model Validation: Ave. Test Omission Rate; OR	Model Validation: Expert Review (ERS)	Model Validation: Boyce Index (BIS)	Exposure Change; EC	UI
UGSQ	67 (0.25)	6.88 ± 3.14 (0.64)	0.88 ± 0.03 (0.12)	0.2 ± 0.1	Low (1)	0.47 ± 0.3 (0.53)	0.26	0.39
SGSQ	13 (1)	5.46 ± 2.07 (0.82)	0.91 ± 0.18 (0.09)	0.45 ± 0.38	Medium (0.5)	na (1)	0.17	0.49
WGSQ	268 (0)	6.13 ± 2.16 (0.73)	0.82 ± 0.04 (0.18)	0.17 ± 0.1	Low (1)	0.48 ± 0.34 (0.52)	0.09	0.3
BTPD	1132 (0)	12 ± 0 (0)	0.88 ± 0.01 (0.12)	0.03 ± 0.01	High (0)	0.18 ± 0.18 (0.82)	0.03	0.1
WTPD	1175 (0)	6.1 ± 2.05 (0.74)	0.8 ± 0.01 (0.2)	0.06 ± 0.03	High (0)	0.07 ± 0.09 (0.93)	0.03	0.22
ABSQ	4 (1)	5.25 ± 1.5 (0.84)	0.4 ± 0.52 (0.6)	0.25 ± 0.5	Medium (0.5)	na (1)	0	0.47
NFSQ	21 (0.5)	5.57 ± 1.5 (0.8)	0.92 ± 0.06 (0.08)	0.27 ± 0.44	Medium (0.5)	na (1)	0.48	0.52
WPGO	15 (1)	8.47 ± 3.52 (0.44)	0.97 ± 0.04 (0.03)	0.2 ± 0.42	Medium (0.5)	na (1)	0.14	0.41
IPGO	27 (0.5)	4.52 ± 1.16 (0.94)	0.97 ± 0.04 (0.03)	0.1 ± 0.22	Medium (0.5)	na (1)	0.17	0.41
PPGO	3 (1)	5 ± 1 (0.88)	0.28 ± 0.46 (0.72)	0.33 ± 0.58	Low (1)	na (1)	0.41	0.68
OBPM	28 (0.5)	5.89 ± 2.13 (0.76)	0.67 ± 0.13 (0.33)	0.47 ± 0.36	Medium (0.5)	na (1)	0.09	0.41
PPMO	11 (1)	7.91 ± 2.21 (0.51)	0.91 ± 0.1 (0.09)	0.15 ± 0.34	Medium (0.5)	na (1)	0.36	0.5
SPMO	3 (1)	4.67 ± 0.58 (0.92)	0.99 ± 0.01 (0.01)	0.67 ± 0.58	Low (1)	na (1)	0.02	0.51
GBPM	17 (1)	6.18 ± 2.48 (0.73)	0.93 ± 0.05 (0.07)	0.1 ± 0.21	Medium (0.5)	na (1)	0.07	0.41
HPMO	10 (1)	5.4 ± 2.22 (0.83)	0.98 ± 0.02 (0.02)	0.3 ± 0.48	Medium (0.5)	na (1)	0.25	0.51
PLHM	7 (1)	6.43 ± 3.1 (0.7)	0.65 ± 0.45 (0.35)	0.43 ± 0.53	Low (1)	na (1)	0.33	0.6
CAMO	3 (1)	4.67 ± 1.15 (0.92)	0.3 ± 0.48 (0.7)	0.67 ± 0.58	Low (1)	na (1)	0.49	0.74
PIMO	2 (1)	4 ± 0 (1)	0.1 ± 0.21 (0.9)	0 ± 0	Low (1)	na (1)	0	0.54
WHVO	7 (1)	5.29 ± 0.76 (0.84)	0.69 ± 0.47 (0.31)	0.14 ± 0.38	Low (1)	na (1)	0.51	0.66
PRVO	24 (0.5)	5.75 ± 1.39 (0.78)	0.78 ± 0.12 (0.22)	0.32 ± 0.34	Medium (0.5)	na (1)	0.1	0.4
WAVO	77 (0.25)	6.06 ± 2.36 (0.74)	0.94 ± 0.02 (0.06)	0.14 ± 0.14	Medium (0.5)	0.75 ± 0.21 (0.25)	0.49	0.4
SBVO	31 (0.5)	5.71 ± 2.42 (0.79)	0.76 ± 0.1 (0.24)	0.33 ± 0.27	Medium (0.5)	na (1)	0.14	0.41

Species Code	Input Data Quality		Model Validation				Exposure Change; EC	UI
	Number Occur. (NS)	Ave. Occur. Quality (OQS)	Ave. Test AUC (AUCS)	Ave. Test Omission Rate; OR	Expert Review (ERS)	Boyce Index (BIS)		
PMJM	48 (0.5)	10.44 ± 2.4 (0.2)	0.98 ± 0.01 (0.02)	0.04 ± 0.08	High (0)	0.83 ± 0.28 (0.17)	0.04	0.13
BMJM	20 (0.5)	6.05 ± 3.53 (0.74)	0.98 ± 0.03 (0.02)	0.1 ± 0.21	Medium (0.5)	na (1)	1	0.68
SWFO	223 (0)	6.64 ± 1.68 (0.67)	0.94 ± 0.02 (0.06)	0.13 ± 0.06	High (0)	0.88 ± 0.13 (0.12)	0.1	0.16
GRBE	639 (0)	7.07 ± 1.22 (0.62)	0.94 ± 0 (0.06)	0.04 ± 0.03	High (0)	0.64 ± 0.31 (0.36)	0.16	0.18
RING	7 (1)	7.14 ± 2.04 (0.61)	0.63 ± 0.44 (0.37)	0.29 ± 0.49	Low (1)	na (1)	0.04	0.47
MART	202 (0)	6.4 ± 1.8 (0.7)	0.94 ± 0.01 (0.06)	0.07 ± 0.05	High (0)	0.76 ± 0.19 (0.24)	0.11	0.17
FISH	14 (1)	4.93 ± 2.56 (0.88)	0.91 ± 0.09 (0.09)	0.2 ± 0.42	Medium (0.5)	na (1)	0.18	0.48
LEWE	9 (1)	6.22 ± 2.33 (0.72)	0.99 ± 0.01 (0.01)	0.11 ± 0.33	Medium (0.5)	na (1)	0.45	0.54
BFFE	4 (1)	5.25 ± 2.5 (0.84)	0.38 ± 0.49 (0.62)	0.5 ± 0.58	Low (1)	na (1)	0	0.54
WOLV	192 (0)	6.16 ± 2.5 (0.73)	0.92 ± 0.03 (0.08)	0.12 ± 0.08	High (0)	0.06 ± 0.66 (0.94)	0.46	0.37
RIOT	202 (0)	6.46 ± 2.5 (0.69)	0.86 ± 0.04 (0.14)	0.24 ± 0.09	Medium (0.5)	0.99 ± 0.03 (0.01)	0.19	0.24
CALY	232 (0)	5.84 ± 1.54 (0.77)	0.93 ± 0.03 (0.07)	0.1 ± 0.09	High (0)	0.69 ± 0.33 (0.31)	0.31	0.26
MOOS	4930 (0)	6.73 ± 1.44 (0.66)	0.64 ± 0.01 (0.36)	0.18 ± 0.02	High (0)	0.97 ± 0.05 (0.03)	0.05	0.16
BISH	1716 (0)	6.76 ± 1.47 (0.66)	0.8 ± 0.02 (0.2)	0.24 ± 0.03	High (0)	0.98 ± 0.04 (0.02)	0.12	0.17
WPTU	21 (0.5)	9.43 ± 2.48 (0.32)	0.93 ± 0.06 (0.07)	0.2 ± 0.35	Low (1)	na (1)	0.12	0.36
WSSS	19 (1)	7.42 ± 2.67 (0.57)	0.85 ± 0.16 (0.15)	0.25 ± 0.35	Low (1)	na (1)	0.22	0.51
GPEL	7 (1)	5.43 ± 1.4 (0.82)	0.69 ± 0.47 (0.31)	0.43 ± 0.53	Low (1)	na (1)	0.23	0.58
GSHO	148 (0)	8.11 ± 2.47 (0.49)	0.81 ± 0.05 (0.19)	0.19 ± 0.13	High (0)	na (1)	0.05	0.21
NSBL	112 (0)	9.54 ± 3 (0.31)	0.86 ± 0.05 (0.14)	0.19 ± 0.13	Medium (0.5)	0.79 ± 0.17 (0.21)	0.09	0.17
PFLI	34 (0.5)	7.26 ± 3.6 (0.59)	0.92 ± 0.04 (0.08)	0.29 ± 0.23	Low (1)	na (1)	0.11	0.4
PRLI	3 (1)	7 ± 1.73 (0.63)	0.3 ± 0.48 (0.7)	0.33 ± 0.58	Low (1)	na (1)	0.53	0.69
NTLI	13 (1)	7.62 ± 3.25 (0.55)	0.99 ± 0.01 (0.01)	0.05 ± 0.16	Medium (0.5)	na (1)	0.23	0.44

Species Code	Input Data Quality		Model Validation				Exposure Change; EC	UI
	Number Occur. (NS)	Ave. Occur. Quality (OQS)	Ave. Test AUC (AUCS)	Ave. Test Omission Rate; OR	Expert Review (ERS)	Boyce Index (BIS)		
NMLS	6 (1)	4.17 ± 0.41 (0.98)	0.97 ± 0.5 (0.03)	0.5 ± 0.55	Low (1)	na (1)	0.19	0.57
PRRR	4 (1)	4.5 ± 1 (0.94)	0.4 ± 0.51 (0.6)	0.5 ± 0.58	Low (1)	na (1)	0.08	0.57
RUBO	51 (0.25)	6.9 ± 2.09 (0.64)	0.9 ± 0.04 (0.1)	0.25 ± 0.2	Medium (0.5)	0.86 ± 0.15 (0.14)	0.25	0.3
EYBR	60 (0.25)	7.63 ± 3.2 (0.55)	0.86 ± 0.06 (0.14)	0.13 ± 0.15	Medium (0.5)	0.79 ± 0.2 (0.21)	0.2	0.27
PHNS	22 (0.5)	7.32 ± 3.05 (0.59)	0.83 ± 0.13 (0.17)	0 ± 0	Medium (0.5)	na (1)	0.15	0.35
PAMS	19 (1)	6.26 ± 1.79 (0.72)	0.9 ± 0.1 (0.1)	0.3 ± 0.26	Low (1)	na (1)	0.26	0.55
GBGS	15 (1)	6.93 ± 2.79 (0.63)	0.94 ± 0.05 (0.06)	0.1 ± 0.21	Medium (0.5)	na (1)	0.11	0.42
BULL	145 (0)	8.67 ± 2.82 (0.42)	0.82 ± 0.03 (0.18)	0.21 ± 0.1	Medium (0.5)	0.88 ± 0.09 (0.12)	0.08	0.18
BHRS	8 (1)	7.75 ± 3.06 (0.53)	0.78 ± 0.41 (0.22)	0.13 ± 0.35	Low (1)	na (1)	1	0.79
WAGS	129 (0)	8.19 ± 3.08 (0.48)	0.7 ± 0.08 (0.3)	0.36 ± 0.14	Low (1)	0.77 ± 0.28 (0.23)	0.11	0.28
PLGA	18 (1)	6.5 ± 2.92 (0.69)	0.8 ± 0.2 (0.2)	0.35 ± 0.41	Medium (0.5)	na (1)	0.08	0.44
RSGS	32 (0.5)	7.78 ± 1.91 (0.53)	0.85 ± 0.07 (0.15)	0.27 ± 0.22	Medium (0.5)	na (1)	0.26	0.41
VAGS	2 (1)	9 ± 1.41 (0.38)	0.1 ± 0.21 (0.9)	0 ± 0	Low (1)	na (1)	0	0.45
SGSN	24 (0.5)	7.5 ± 2.99 (0.56)	0.92 ± 0.16 (0.08)	0.13 ± 0.32	Medium (0.5)	na (1)	0.17	0.36
PRRS	281 (0)	6.88 ± 2.07 (0.64)	0.78 ± 0.03 (0.22)	0.36 ± 0.1	Medium (0.5)	0.82 ± 0.11 (0.18)	0.07	0.23
MFRS	35 (0.5)	9.6 ± 3.28 (0.3)	0.97 ± 0.03 (0.03)	0.03 ± 0.11	Medium (0.5)	na (1)	0.17	0.31