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ESTIMATING THE OCCUPANCY, ABUNDANCE, AND DENSITY OF DUSKY GROUSE: DEVELOPING METHODS OF UNBIASED POPULATION MONITIORING IN MONTANA

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EXECUTIVE SUMMARY

This report summarizes the results of the third year (January–December, 2021) of a four-year (2019–2022) research project to develop methods for unbiased population monitoring for dusky grouse (*Dendragapus obscurus*; previously “blue grouse”) in Montana. The primary objectives of this study are to 1) generate a predictive model of habitat suitability for dusky grouse throughout their range in Montana, 2) develop and evaluate survey methods that provide unbiased statewide and regional estimates of dusky grouse densities and annual trend monitoring in Montana, and 3) develop methods that facilitate rigorous and cost-effective evaluations of grouse-habitat relationships and the effects of management.

We built and evaluated an updated statewide habitat model for dusky grouse in Montana. We obtained dusky grouse observations collected during the spring (April–June) from 2009–2020 from the Integrated Monitoring in Bird Conservation (IMBCR) program and extracted habitat information for detected/not-detected locations using remotely-sense geospatial datasets. We evaluated relative habitat use with resource selection functions calibrated using generalized linear mixed models. Candidate models representing hypothesized relationships between grouse detections/non-detections and habitat conditions (e.g., forest type and coverage, average elevation, slope) were compared using multi-model inference based on information theory. We found the following spatially-explicit habitat attributes to have a significant effect on whether or not a dusky grouse was detected at a site: proportion of area with a southeast facing or west facing aspect, average distance to nearest stream, proportion of foothill conifer wooded steppe, proportion of montane-foothill deciduous shrubland, proportion of montane sagebrush steppe, proportion of trees with a height of 1–5 m, and the proportion of trees with a height of 16–20 m. Our results indicate that relative use increased with higher proportions of area with a southeast facing aspect (β = 1.65 ± 0.70SE) and higher proportions of area with a west facing aspect (β = 1.24 ± 0.67). Both average distance to nearest stream (β = 7.28 ± 2.11, β = -7.49 ± 2.72) and proportion of foothill conifer wood steppe (β = 150.90 ± 32.53, β = -4167.49 ± 261.03) were predicted to have a quadratic relationship with relative use. Relative use was maximized at 0.5 km from a stream. Relative use increased rapidly until 2% of the survey area was classified as foothill conifer wooded steppe, where it then decreased rapidly to almost 0%. Proportion of montane-foothill deciduous shrubland (β = 0.11 ± 0.06), proportion of montane sagebrush steppe (β = 0.16 ± 0.06), and the proportion of trees with a height of 16–20 m (β = 0.46 ± 0.08) had positive nonlinear relationships with relative use by dusky grouse, where use initially increased exponentially and then either leveled off or increased at a linear rate. Relative use remained relatively constant after the proportion of the study area that was montane-foothill deciduous shrubland or proportion of montane sagebrush steppe approached 5–10%. After the proportion of the study area with trees 16–20m tall approached 5%, relative probability of use began to increase linearly instead of exponentially. The proportion of trees with a height of 1–5m (β = -0.63 ± 0.24) had a negative nonlinear relationship with relative use by dusky grouse, where relative use initially decreased rapidly and then became relatively constant. Our model had high predictive accuracy with an ROC value of 0.89 (95% CI: 0.84–0.93), and correctly classified 104/132 of the independently detected grouse locations collected by FWP. Our habit model classified 96,665 km^2 into the two highest relative probability of use categories, with the highest amounts of dusky grouse habitat predicted to occur in FWP administrative regions 1, 2, and 3.

We conducted spring surveys for dusky grouse in the western half of Montana in FWP Regions 1–5. Survey methods consisted of point-counts with electronic playback to increase detections,

and walking transect routes. Potential survey transects were randomly generated in areas identified to have high relative likelihood of dusky grouse occurrence as predicted by the model of relative habitat suitability we developed in 2019. The pool of potential transects was revised from the pool of potential transects in 2020, with 90% of the transects remaining the same. Montana State University staff, volunteers, and MFWP field biologists selected a total of 60 survey transects to survey in each region. Survey transects consisted of 6 independent survey points spaced 400 meters apart along a road or trail. Surveys were only conducted during the spring breeding season during April 10 – May 31 when vocalizations of male grouse are greatest. During the survey period, a total of 263 transects were surveyed, with 53 transects surveyed in Region 1, 55 in Region 2, 57 in Region 3, 53 in Region 4, and 42 in Region 5. The average number of dusky grouse detected per point count survey was 0.08 ± 0.30 SE for Region 1, 0.23 ± 0.54 for Region 2, 0.20 ± 0.53 for Region 3, and 0.07 ± for Region 4. Relative abundance estimates for Region 5 are unavailable at the time of this report.

We conducted a preliminary analysis to explore the effects of survey conditions on dusky grouse counts. Temperature, average wind speed, precipitation, cloud cover, day since the start of the survey period (April 10^{th} = day 0), and minutes from sunrise were associated with the max number of dusky grouse detected. The number of grouse observed was positively associated with increases in temperature ($\beta = 0.02 \pm 0.01$SE) and decreases in average wind speed ($\beta = -0.06 \pm 0.04$) . The number of grouse observed had a nonlinear quadratic relationship with both minutes since sunrise ($\beta = 0.01 \pm$ SE 0.003, $\beta = -0.00003 \pm$ SE 0.00001) and number of days since the survey period started ($\beta = 0.24 \pm$ SE 0.05, $\beta = -0.004 \pm$ SE 0.0007)). The number of dusky grouse observed peaked during May 5^{th}–May 20^{th}, and between 100–150 minutes post sunrise. Dusky grouse counts were greatest on clear days (0–15% cloud cover) and lower when it was snowing than if there was rain, fog, or no precipitation.

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OBJECTIVES

Objective 1: Generate a predictive model of habitat suitability for dusky grouse throughout their range in Montana

Accomplishments

We developed and evaluated a predictive model of habitat suitability that can be used to identify appropriate survey sites and to explore relationships between habitat characteristics and probability of use by dusky grouse. We obtained dusky grouse observation data from the Integrated Monitoring in Bird Conservation Regions monitoring program (IMBCR) administrated by the Bird Conservancy of the Rockies. The IMBCR program conducts avian point count surveys between May and July each year at randomly selected locations that vary between years across Montana and other western states (Pavlacky et al. 2017, Hanni et la 2018). We obtained observation data spring surveys from 2009–2020 for a total of 25,654 surveys conducted across 6,092 sites in Montana. We reduced observations from the IMBCR point counts to dusky grouse detected/ not detected data that we then used to represent sites that were used (detected) and available (not detected). If a dusky grouse was detected at least once during the 11-year period, a site was classified as used and if a dusky grouse was not detected the site was classified as available. Sites were classified as available instead of unused because it is possible that a dusky grouse was present but not detected. After reducing the data to used and available sites, we classified 132 used sites and 5,960 sites as available. Given that a dusky grouse call may be difficult to detect depending on call type at distances greater than 50–100m (Farnsworth 2020) and potential uncertainty with GPS locations, we assumed that all dusky grouse observed were located within 250 m of the point count location.

We used remotely-sensed geospatial datasets to extract habitat information within a circular 250-m buffer drawn around each point count location. We used digital elevation models (DEMs) from U.S. Geological Survey, ArcGIS Pro (Environmental Systems Research Institute, Redlands, CA) and geospatial modeling environment (GME) to measure average elevation and slope of the 250-m radii area (Beyer 2015, U.S Geological Survey 2017). We also used the DEMs, spatial analyst tools of ArcGIS Pro and GME to extract the proportion of N, NE, E, SE, S, SW, and W facing aspects and flat ground of the 250-m radii area (Beyer 2015, U.S Geological Survey 2017). We calculated the average distance of the 250-m radii area to the nearest stream and to the nearest road using the spatial analyst tools of ArcGIS Pro applied to the Montana Spatial Data Infrastructure (MSDI) Transportation Framework and Hydrography datasets downloaded from the Montana state library and GME (Beyer 2015, Montana Spatial Data Infrastructure 2017, 2018). We updated our previous vegetation geospatial datasets in order to define habitat conditions based off of a 2016 base map created using updated data and processing techniques instead of a 2001 base map (LANDFIRE 2020). We downloaded LANDFIRE geospatial data with a 30 × 30 m spatial resolution for existing vegetation type (EVT), existing vegetation cover (EVC), and existing vegetation height (EVH; Landfire 2016a, b, c) . EVT is the type of plant community present, of which in Montana there are 121 types; EVC is the vertically projected percent cover by a live canopy layer given in 1% increments; EVH is the average height of the dominant vegetation given in 1m increments (Landfire 2016a, b, c, 2019, 2020) . We created a forest layer based on the vegetation physiognomy (EVT_PHYS) description for the different LANDFIRE vegetation types and vegetation community name (Table 1; LANDFIRE 2016a). We used the spatial analyst tools of ArcGIS Pro and GME to calculate the average distance to the edge of the forest type from within and outside of the forest (Beyer 2015). We used GME to calculate the proportion of vegetation type, canopy cover, and height within 250 meters of the survey location (Beyer 2015). After the vegetation canopy and height information were extracted, we condensed the information from their 1% or 1m increments to larger categories. We condensed the 1% increments for the canopy vegetation to 10% increments and the 1-m increments for vegetation height to 5-m increments. For both types of habitat information there were also several categories of developed habitat or barren habitat that was grouped into two categories: developed and sparse vegetation. We removed variables from consideration if they occurred at less than 1% of the survey sites. Overall, we extracted geospatial habitat information for a total of 118 potential variables that were then used to build resource selection functions (RSF).

We evaluated relative habitat use with resource selection functions (RSFs) fitted using general linear mixed models (GLMMs) with a logit link function, binomial error distribution, and the "bobyqa" optimizer with a maximum of 100,000 iterations for approximating beta coefficients using the 'lme4' package in program R (Bates et al. 2015, R Core Team 2015). Our response variable was either a dusky grouse was detected (1) or not detected (0), with our habitat factors as independent variables, and a random intercept term for unique IMBCR transects to account for potential spatial autocorrelation in the observation data due to the survey points being grouped along survey routes (Zurr 2009, Hanni et la 2018).

Before fitting models with RSFs, we explored the possibility that the behavioral response of dusky grouse to some habitat variables may be nonlinear. Habitat variables such as proportion of conifer forest may exhibit a threshold response or variables like elevation may exhibit a quadratic response (Figure 1). Initially we explored potential nonlinear responses by plotting the relationship between the response variable (detected or not detected) and a "smoothed" function for each habitat variable using univariate generalized additive models (GAMs; Guisan and Zimmerman 2000, Guisan et al 2002, McNew et al 2013). If the variable showed no relationship with the response variable (e.g, Figure 2), we removed it from the dataset. With the remaining variables, we further explored potential linear and nonlinear relationships using linear equations to represent the hypothesized linear and nonlinear forms (Guisan and Zimmerman 2000). We used $[x + x^2]$ for the quadratic form and the natural log of the explanatory variable ($\ln[x + 0.001]$ to represent a pseudolinear threshold (Franklin 2000, Dugger et al 2005, McNew et al 2015). We performed the preliminary screenings of the three functional responses using univariate models built using GLMMs with a logit link function and binomial error distribution. We evaluated support for non-linear relationships for each variable by comparing Akaike's Information Criterion for small sample size (AIC_c) for GLMMs with linear and non-linear terms (Burnham and Anderson 2002). While evaluating the potential non-linear and linear relationships with AIC_c, if the change in AIC_c from the 'best' model to was < 2 then the models were considered to have similar support (Burnham and Anderson 2002), and we chose the simplest model (the model with fewest parameters). If the number of parameters was the same, we looked at figure of the plotted GAM function for that variable to determine which potential relationship best fit the variable. In the majority of the cases, the plotted GAM function best resembled the potential relationship with the lowest AIC_c. If problems with modeling a relationship occurred while attempting to evaluate one of the relationship forms, that relationship was not considered.

After preliminary screenings of the functional responses, we tested for multicollinearity in the remaining 89 habitat predictor variables using Spearman-rank correlations to prevent overfitting the model. If correlations were ($|r| > 0.5$), we considered the variables to be correlated. If variables were correlated, we first used general knowledge of dusky grouse habitat to evaluate which variable was more biologically relevant to dusky grouse. If we had no previous knowledge on whether one variable was more biologically relevant, we evaluated univariate models using AIC_c, and whichever variable had the lower AIC_c value was selected and the other variable was removed from our analysis (Aldridge et al 2012). If the delta AIC_c was < 2, then we selected the most parsimonious (simplest) model (Burnham and Anderson 2002, Arnold 2010). As a variable may be correlated with more than one variable, we evaluated correlations based upon the highest correlation to the lowest, removing the variable we considered to be less relevant from the variable pool as we went. After assessing correlation, we evaluated relative habitat use of the different habitat predictor variables using backwards stepwise selection of the resource selection function model (Hosmer et al 2013). We ordered variable removal based on p-values (Hosmer et al 2013). After removing a variable, we assessed support for each model using AIC_c (Burnham and Anderson 2002). If the models had similar support (Burnham and Anderson 2002, Arnold 2010), instead of removing a model from the model set, we retained all the models and we continued backwards selection until the newest model either had the lowest AIC_c or a $\Delta AIC_c \geq 2$.

We evaluated the remaining 42 predictors in groups. Within each group, we used backwards stepwise selection to determine the top performing variables for inclusion in the final candidate model set. The different groups included non-vegetation variables (aspect, distance to variables), conifer vegetation type, hardwood vegetation type, grassland vegetation type, shrubland vegetation type, riparian vegetation type, other vegetation type, vegetation canopy cover, and vegetation height. The top performing variables from each of categories were then added to the final model set and evaluated using backwards stepwise selection.

In a used versus available study design, we cannot estimate the true probability of use from a logistic regression model, we can only estimate the relative probability of use (Manly et al 2002). Because of this we used the coefficients from the estimated logistic regression for the corresponding slope coefficients (β_i) to estimate the relative probability of use for a site by dusky grouse.

$$w(\mathrm{x}) = \exp(\beta_1 X_1 + \beta_2 X_2, \ldots \beta_i X_i)$$

(Manly et al 2002, Boyce and McDonald 1999).

We evaluated the performance of our model and its predictive capability using the training (IMBCR) dataset using cross-validation, and an independent dataset of incidental grouse locations collected April–June from 2017–2019 by Montana Fish, Wildlife, and Parks (MFWP) personnel. We first used threshold-independent receiver operating characteristic plots (ROC) and area under the curve (AUC) to evaluate model performance (Zweig and Campbell 1993, Fielding and Bell 1997). For an ROC plot, we plotted the probability of detecting a true signal (sensitivity values) on the y-axis with their corresponding probability of detecting a false positive (1 – specificity) on the x-axis (Fielding and Bell 1997, Hosmer et al 2013). An AUC greater than 0.7 indicates a that the model has predictive power and that the performance is better than that of pure chance (Fielding and Bell 1997, Boyce et al 2002, Hosmer et al 2013, Bohnett et al 2020). We plotted and calculated ROC/AUC using cross validation of the original dataset, where we conducted a simulation with 500 iterations, where for each iteration 80% of the IMBCR data was used to train our model and the other 20% of the IMBCR data was used to test the model. We calculated the average AUC value with a 95% confidence interval.

We then used the independent dataset of incidental grouse observations collected by MFWP to further validate our model. We used our resource selection function to calculate the RSF value for each independent observation for the IMBCR dataset and the MFWP dataset. We used the IMBCR dataset to categorize the RSF values into 5 quantile bins that represented the relative probability of a point being classified as a site used by dusky grouse (Boyce et al 2002, Johnson et al 2006, McNew et al 2013). The bins represented low, medium-low, medium, medium-high, and high probability of relative use. We then regressed the observed proportion of grouse locations from the MFWP or test dataset in each quantile bin with the observed proportions of grouse locations in each quantile bin from the IMBCR or training dataset. We used linear regression to compare the training and testing datasets, and we considered a good model fit to have a high R^2 value, a slope of 1, and an intercept of 0 (Johnson et al. 2006, McNew et al 2013). We also conducted a simulation with 500 iterations, where we calculated the average percent of correctly predicted locations with a 95% confidence interval for a subset (80%) of the MFWP dataset. Instead of using an arbitrary threshold, we considered those observations whose RSF values fell into our quantile bins representing medium-high and high relative probability of use as correctly predicted and those that did not as incorrectly predicted.

To evaluate dusky grouse occurrence across Montana, we calculated the average or proportion within a 250-m circular moving window for each habitat variable and then used the coefficients from our final model and their corresponding variables to construct a predictive map of relative occurrence. We calculated the total area (km^2) predicted to fall within each quantile bin by summing the number of predicted for each category and multiplying by pixel size (0.0009).

Results. – After backwards stepwise selection, 8 variables were considered to have a significant effect on whether dusky grouse were detected or not detected at a survey site (Table 2). The variables included proportion of area with a southeast facing aspect or west facing aspect, average distance to nearest stream, proportion of foothill conifer wooded steppe, proportion of montane-foothill deciduous shrubland, proportion of montane sagebrush steppe, proportion of trees with a height of 1–5m, and the proportion of trees with a height of 16–20m. Relative use increased with higher proportions of area with a southeast facing aspect ($\beta = 1.65 \pm 0.70$SE) and higher proportions of area with a west facing aspect ($\beta = 1.24 \pm 0.67$; Table 3). The other 6 habitat characteristics exhibited non-linear relationships with relative use. Both average distance to nearest stream ($\beta = 7.28 \pm 2.11$, $\beta = -7.49 \pm 2.72$; Table 3) and proportion of northern rocky mountain foothill conifer wood steppe ($\beta = 150.90 \pm 32.53$, $\beta = -4167.49 \pm 261.03$; Table 3) had a quadratic relationship with relative use. Relative use increased until distance to stream was greater than 0.5 km, after which relative use decreased. Once the distance to stream was greater than 1.5km, relative probability of use was predicted to be almost 0%. Relative use increased rapidly until 2% of the survey area was classified as northern rocky mountain montane-foothill deciduous shrubland habitat, where it then decreased rapidly to almost 0%. Proportion of northern rocky mountain montane-foothill deciduous shrubland ($\beta = 0.11 \pm$ SE 0.06), proportion of inter-mountain basins montane sagebrush steppe ($\beta = 0.16 \pm$ SE 0.06), and the proportion of trees with a height of 16–20m ($\beta = 0.46 \pm$ SE 0.08) had positive nonlinear relationships with relative use by dusky grouse (Table 3). Relative use increased exponentially until the proportion of the study area for northern rocky mountain montane-foothill deciduous shrubland and proportion of inter-mountain basins montane sagebrush steppe each reached 5–10% and then leveled off and increased slowly as proportion of the two habitat characteristics increased. As proportion of trees with a height of 16–20m increased, the relative probability of use increased rapidly from 0 to 5%, and then increased at a more linear rate. The proportion of trees with a height of 1–5m (β = -0.63 ± SE 0.24) had a negative nonlinear relationship with relative use by dusky grouse (Table 3). Relative use decreased rapidly as the proportion of trees with a height of 1–5m increased from 0–5%, after which the relative use was near zero and continued to decrease at a slow rate as the proportion of trees with a height of 1–5m increased. Conditional and marginal R^2 for our model were 0.60 and 0.55, respectively, indicating that most of the variation in the response data from our model is described by the fixed effects, with only an additional 5% associated with our points being clustered along survey routes.

Several habitat characteristics hypothesized to be important for dusky grouse such as elevation, distance to conifer forest, or different conifer community vegetation types did not end up in the final model due to correlation with multiple other variables and thus were removed from the potential list of covariates. Proportion of trees with a height of 16–20m is highly correlated with many other forest type and non-vegetation type variables. Trees with a height of 16–20m is strongly and positively correlated with the proportion of canopy cover by trees where the percentage of canopy cover by trees is 30–39%, 40–49%, and 60–69%, and weakly correlated where the percentage of canopy cover by trees is 20–29%. Trees with a height of 16–20m are also positively correlated with slope and elevation, two other factors thought to be important for determining dusky grouse habitat. Also positively correlated are several different vegetation community types: rocky mountain lodgepole pine forest, northern rocky mountain dry-mesic montane mixed conifer forest, rocky mountain subalpine dry-mesic spruce-fir forest and woodland, and middle rocky mountain montane Douglas fir and woodland. Proportion of several percentages of herb canopy cover and herb height, as well as several shrub community vegetation types are also negatively correlated with the proportion of trees with a height of 16–20m. The other variables included in the final model set were not strongly correlated with most other variables.

Our habitat model had high predictive accuracy with a mean ROC value of 0.89 (95% CI: 0.84–0.93; Figure 3). In addition, our habitat model correctly classified 104 out of 132 (78.8%) of the independently detected grouse locations into the two categories with the highest relative probability of use (Figure 4). Linear regression produced an intercept close to zero (95% CI: -0.22, 0.02), a slope of 1.52 (SE = 0.14), and an R^2 value of 0.976; indicating high predictive accuracy for our resource selection model. Our simulation showed that our model correctly predicted the locations from the independent dataset as used 78.7% (95% CI: 0.75, 0.82) of the time.

Our habitat model classified 96,665 km^2 of Montana into the two highest relative probability of use categories (Figure 5). The highest total amounts of suitable dusky grouse habitat were predicted to occur in Montana FWP administrative regions 1, 2, and 3 (Table 4).

Goals for Next Quarter

Next quarter, we will expand the habitat modeling to include machine learning approaches like Random Forest. We will use an ensemble approach to estimate model-averaged predictions of habitat suitability and calculate amount of dusky grouse habitat by region in Montana. We will draft and submit a manuscript for publication in an open-source peer-reviewed journal.

Objective 2: Develop and evaluate unbiased survey methods that provide statewide and regional estimates of dusky grouse densities and annual trend monitoring in Montana

Accomplishments

<u>Methods</u>

Spring Surveys. —We used protocols identified previously to select and survey transects for grouse in 2021. In 2020, we used simulated datasets and N-mixture models to determine the survey effort required to get useful annual population estimates with the desired level of estimator precision of <15% using point-counts with electronic playback. Our results indicated that 360 independent points, with 4 replicate surveys, should on average, provide useful annual estimates of dusky grouse abundance (McNew et al. 2020).

We revised our potential pool of survey transects for spring 2021 to remove transects that were believed to be almost always inaccessible in the spring, were close to rivers/streams that inhibited our ability to detect dusky grouse, or were placed upon roads or trails that no longer existed. For each transect removed, we added an additional transect by randomly generating potential survey points using ArcGIS and a model of relative habitat suitability (McNew et al. 2018; Figure 1). Survey transects consisted of 6 points along a road or trail, spaced 400 m apart to ensure independence (though the traveled distance along the trail/road may be greater than 400 m). The first point for transects along trails was randomly placed between 100–200 m from the trailhead. The first point for transects along roads was 100 m from the parking location. Field biologists and volunteers specifically trained to conduct dusky grouse surveys selected among a randomly-generated set of potential transects and conducted surveys during 10 April – 30 May.

Surveys consisted of a total of four four-minute independent point counts at each point location along the transect. Two of the four independent point counts occurred as the observer traveled from the start to end of the transect, then a 10-minute break occurred, and two additional point counts occurred as observers traveled from the end to the beginning of the transect. Each pair of point counts was conducted consecutively with ≤ 1 minute between them, yielding in a total of 4 point-counts per point in one morning. In this way, a transect only needed to be visited once, while still achieving 4 replicate surveys at each point. To increase detections of male dusky grouse, each four-minute point count occurred with female calls played electronically through a portable music player or cell phone and speaker (SanDisk 8 GB Clip Jam Mp3 Player, JBL Charge 3 speaker; Stirling and Bendell 1966). The female calls consisted of a four-minute recording that consisted of a female cackle and cantus. Playback recordings consisted of alternating playback of 30 seconds of calling and 30 seconds of silence until the entire four minutes of survey had elapsed. Each 4-minute survey was treated as an independent sample and all grouse observed were recorded during each period. The distance to each observed grouse was measured with a laser rangefinder and recorded. All dusky, ruffed, and spruce grouse observed (visually or auditorily) during transit to and between survey points were also recorded and perpendicular distances to the transect recorded. We created an access database to store and organize all dusky grouse survey data.

Effects of survey conditions on counts of dusky grouse. — We conducted preliminary analyses using generalized linear models (GLMs) to examine the relationship between the maximum number of dusky grouse counted during each pair of point count surveys and cloud cover, precipitation, temperature (C°), average wind speed (km/hr), minutes since sunrise, and day since the survey period started. The number of dusky grouse observed, or relative abundance, is the result of true abundance in the area × the probability of detecting a grouse if it's available to be detected. Here we hypothesize that survey conditions actually affected the probability of detection and not local abundance. We recorded cloud cover, precipitation, and temperature at the beginning of each pair of point count surveys. We classified cloud cover into 4 categories: 0–15%, 16–50%, 51–80%, and 81–100% of the sky covered. We classified precipitation as fog (F), snow (S), rain (R), or none (N). We measured temperature and wind speed using a kestrel 2000 hand-held weather meter. To calculate minutes from sunrise for each region, we chose a representative city for each region and identified the time of sunrise for that city using TimeAndDate.com. We used the time of sunrise in Kalispell for Region 1, Missoula for Region 2, Bozeman for Region 3, White Sulphur Springs for Region 4, and Billings for Region 5. After we determined the time of sunrise for each survey day, we subtracted the time of sunrise from the start time for a pair of point count surveys to determine the minutes since sunrise for each pair of point count surveys. For day since the survey period started, we used April 10th as day 0, and then numbered the days consecutively until the end of the survey period; so April 11th was day 1, April 12th was day 2, and so on.

Before fitting models to explore the relationship between survey conditions and relative abundance, we examined the possibility of nonlinear relationships between relative abundance and a survey condition. We hypothesized that minutes from sunrise and day since the survey season started could exhibit nonlinear responses due to known temporal display behaviors of grouse (Bendell and Elliot 1967, Zwickel and Bendell 2004, Farnsworth 2020). We explored potential linear and nonlinear responses by using linear equations to represent our hypothesized relationships. We used $[x + x^2]$ for the quadratic form and the natural log of the explanatory variable ($\ln[x + 0.001]$ to represent a pseudolinear threshold (Franklin 2000, Dugger et al 2005, McNew et al 2015). We evaluated support for a non-linear relationship by using AIC_c to evaluate univariate models of the three different functional responses built using GLMs with a poisson error distribution (Burnham and Anderson 2002). After preliminary screenings of the different potential functional responses, we tested our quantitative variables for collinearity using Spearman-rank correlations. If correlations were ($|r| > 0.7$), we considered the variables to be correlated, and the variable with the lowest AIC_c was retained and the correlated variable removed. After assessing correlation, we evaluated the relationship between survey conditions and relative abundance using backwards stepwise selection, with variable removal based on p-values (Hosmer et al 2013). We evaluated support for each model using AIC_c, considering the model with the lowest AIC_c to be the best model (Burnham and Anderson 2002).

Preliminary Results

Spring Surveys.—During the spring survey period, field crews surveyed a total of 263 transects; 53 transects were surveyed in Region 1, 55 in Region 2, 57 in Region 3, 53 in Region 4, and 42 in Region 5. 41 transects were only partially surveyed (either all points were not reached or not all points were surveyed four times) due to equipment failure, presence of wildlife (bears and mountain lions), weather, or snow pack that made accessing the rest of a transect impossible. In Region 1, we surveyed 309 points with 99% of the points surveyed four times, 1 point surveyed 3 times, and 2 points surveyed twice. In Region2, we conducted surveys at surveys at 320 sites, with 94% of the points surveyed 4 times, 5 points surveyed 3 times, and 14 points only surveyed twice. In region 3, we conducted surveys at 353 points, with 98% of the points surveyed 4 times, 1 point surveyed 3 times, and 6 points surveyed twice. In Region 4, we surveyed 309 points with 96% of the points surveyed 4 times, 9 points surveyed 3 times, and 3 points surveyed twice. In Region 5, we surveyed 252 points and all points were surveyed 4 times. In total, we conducted 1,231 surveys in Region 1, 1,247 surveys in Region 2, 1,399 in Region 3, 1,221 surveys in Region 4, and 1,008 surveys in Region 5. Overall, 43 people assisted in conducting the surveys, with the majority (67%) of the transects completed by a MSU field crew. Surveys occurred during 10 April–31 May, with the majority of the transects (88%) surveyed in May.

In Region 1, we detected dusky grouse at 23 (7.4%) of 309 survey points (Table 5). In Region 2, dusky grouse were detected at 73 (17.8%) of 320 points (Table 5). In Region 3, we detected dusky grouse at 53 (15.0%) of 252 surveys. In Region 4, dusky grouse were detected at 20 (6.5%) of 309 points (Table 2). The maximum number of dusky grouse detected during a single point-count was 4, and the minimum was 0 (Table 3). The average number of dusky grouse observed at each point was 0.08 ± 0.30SD in Region 1, 0.23 ± 0.54 in Region 2, 0.20 ± 0.53 in Region 3, and 0.07 ± 0.26 in Region 4 (Table 4).

Effects of survey conditions on counts of dusky grouse.—No variables were removed using backwards stepwise selection. We found support for the effects of cloud cover, temperature, wind speed, minutes since sunrise, and day since the survey period started on the number of dusky grouse observed. Counts were highest on clear days and lowest when it was snowing (Table 9). Higher counts of dusky grouse were positively associated with temperature ($\beta = 0.02 \pm$ SE 0.01) and negatively associated with average wind speed ($\beta = -0.06 \pm$ SE 0.04; Table 8). The number of dusky grouse detected had a nonlinear quadratic relationship with both minutes since sunrise ($\beta = 0.01 \pm$ SE 0.00, $\beta = -0.00003 \pm$ SE 0.00) and number of days since the survey period started ($\beta = 0.24 \pm$ SE 0.05, $\beta = -0.004 \pm$ SE 0.0, Table 8). The number of dusky grouse counted peaked between May 5th–May 20th (25–40 days since the survey period started), and between 100–150 minutes post sunrise (Figures 5,6).

Goals for Next Quarter

We will build and evaluate N-mixture models and distance sampling models for the point count data and estimate regional densities of dusky grouse. We will evaluate support for the effects of environmental covariates on probability of detection and abundance that can be used to refine survey protocols for future grouse surveys in Montana. Future work in 2021 will evaluate the utility of open population N-mixture models for estimating regional changes in population sizes annually.

Objective 3: Develop methods that facilitate rigorous and cost-effective evaluations of grouse-habitat relationships and the effects of management (e.g. timber harvest)

Accomplishments

For effort/accomplishments, reference objective 2.

Goals for Next Quarter

For goals for next quarter, reference objective 2.

Table 1. Description of variables used to create a forest layer for Montana. Information taken from EVT_descriptions table LANDFIRE 2021). The vegetation lifeform for all variables is Tree.

EVT code (ecological systems)	Existing Vegetation Type (ecological systems name)	Vegetation Physiognomy	Collapsed Vegetation Type Name
7010	Northern Rocky Mountain Western Larch Savanna	Conifer	Western Larch Forest and Woodland
7045	Northern Rocky Mountain Dry-Mesic Montane Mixed Conifer Forest	Conifer	Douglas-fir-Ponderosa Pine-Lodgepole Pine Forest and Woodland
7046	Northern Rocky Mountain Subalpine Woodland and Parkland	Conifer	Subalpine Woodland and Parkland
7047	Northern Rocky Mountain Mesic Montane Mixed Conifer Forest	Conifer	Douglas-fir-Grand Fir-White Fir Forest and Woodland
7049	Rocky Mountain Foothill Limber Pine-Juniper Woodland	Conifer	Limber Pine Woodland
7050	Rocky Mountain Lodgepole Pine Forest	Conifer	Lodgepole Pine Forest and Woodland
7053	Northern Rocky Mountain Ponderosa Pine Woodland and Savanna	Conifer	Ponderosa Pine Forest, Woodland and Savanna
7055	Rocky Mountain Subalpine Dry-Mesic Spruce-Fir Forest and Woodland	Conifer	Spruce-Fir Forest and Woodland
7056	Rocky Mountain Subalpine Mesic-Wet Spruce-Fir Forest and Woodland	Conifer	Spruce-Fir Forest and Woodland
7057	Rocky Mountain Subalpine-Montane Limber-Bristlecone Pine Woodland	Conifer	Limber Pine Woodland
7062	Inter-Mountain Basins Curl-leaf Mountain Mahogany Woodland	Conifer	Mountain Mahogany Woodland and Shrubland
7165	Northern Rocky Mountain Foothill Conifer Wooded Steppe	Conifer	Douglas-fir Forest and Woodland
7166	Middle Rocky Mountain Montane Douglas-fir Forest and Woodland	Conifer	Douglas-fir Forest and Woodland
7167	Rocky Mountain Poor-Site Lodgepole Pine Forest	Conifer	Lodgepole Pine Forest and Woodland
7179	Northwestern Great Plains-Black Hills Ponderosa Pine Woodland and Savanna	Conifer	Ponderosa Pine Forest, Woodland and Savanna
7193	Recently Logged-Tree Cover	Conifer	Transitional Forest Vegetation
7197	Recently Burned-Tree Cover	Conifer	Transitional Forest Vegetation
7200	Recently Disturbed Other-Tree Cover	Conifer	Transitional Forest Vegetation
7061	Inter-Mountain Basins Aspen-Mixed Conifer Forest and Woodland	Conifer-Hardwood	Aspen-Mixed Conifer Forest and Woodland
7009	Northwestern Great Plains Aspen Forest and Parkland	Hardwood	Aspen Forest, Woodland, and Parkland
7011	Rocky Mountain Aspen Forest and Woodland	Hardwood	Aspen Forest, Woodland, and Parkland
7161	Northern Rocky Mountain Conifer Swamp	Riparian	Spruce-Fir Forest and Woodland
9019	Rocky Mountain Lower Montane-Foothill Riparian Woodland	Riparian	Western Riparian Woodland and Shrubland
9022	Rocky Mountain Subalpine-Montane Riparian Woodland	Riparian	Western Riparian Woodland and Shrubland

Table 2. Definitions for variables in final model for predicting dusky grouse occurrence.

Variable	EVT code	Definition	Vegetation Physiognomy	Relationship Form	Direction
SE facing aspect	N/A	Proportion of southeast facing aspect within a circle with a 250m radii	N/A	linear	positive
W facing aspect	N/A	Proportion of west facing aspect within a circle with a 250m radii	N/A	linear	positive
Distance to stream	N/A	Average distance to nearest stream (km^2) within a circle with a 250m radii	N/A	nonlinear: quadratic	positive, then negative
Foothill Conifer Wooded Steppe	EVT 7165	Proportion of northern rocky mountain foothill conifer wooded steppe within a circle with a 250m radii	Conifer	nonlinear: quadratic	positive, then negative
Montane Foothill Deciduous Shrubland	EVT 7106	Proportion of northern rocky mountain montane-foothill deciduous shrubland within a circle with a 250m radii	Shrubland	nonlinear: pseudo-linear threshold	positive
Montane Sagebrush Steppe	EVT 7126	Proportion of inter-mountain basins montane sagebrush steppe within a circle with a 250m radii	Shrubland	nonlinear: pseudo-linear threshold	positive
Tree Height 1–5m	N/A	Proportion of trees with a height of 1–5m within a circle with a 250m radii	N/A	nonlinear: pseudo-linear threshold	negative
Tree Height 16–20m	N/A	Proportion of trees with a height of 16–20m within a circle with a 250m radii	N/A	nonlinear: pseudo-linear threshold	positive

Table 3. Slope estimates for all terms in the final habitat model.

Variable	Estimated slope (β_i)	Lower 95% Confidence Interval	Upper 95% Confidence Interval
SE Facing Aspect	1.65	0.27	3.03
W Facing Aspect	1.24	-0.08	2.55
Distance to Stream	7.28	3.15	11.42
Distance to Stream^2	-7.49	-12.81	-2.16
Foothill Conifer Wooded Steppe	150.90	87.13	214.66
Foothill Conifer Wooded Steppe^2	-4167.49	-4679.10	-3655.89
ln(Montane Foothill Deciduous Shrubland + 0.001)	0.11	-0.01	0.23
ln(Montane Sagebrush Steppe + 0.001)	0.16	0.05	0.28
ln(Tree Height 1–5m + 0.001)	-0.63	-1.10	-0.16
ln(Tree Height 16–20m + 0.001)	0.46	0.31	0.61

Table 4. Estimated area (km^2) of potential dusky grouse habitat for Montana FWP administrative regions.

FWP Region	Low	Medium-Low	Medium	Medium-High	High
1	1,153.55	902.17	3,932.67	15,808.03	12,741.47
2	706.39	1,182.19	3,926.91	10,155.55	11,339.43
3	1,503.85	5,506.59	17,252.15	14,713.92	11,132.53
4	13,622.27	17,555.62	26,156.98	8,409.75	5,618.86
5	10,608.90	12,917.97	16,297.33	3,683.91	2,144.29
6	17,084.72	26,783.38	28,031.36	475.94	102.07
7	22,402.91	29,859.39	26,485.17	323.19	15.90

Table 5. Summary of spring 2021 survey site data for each FWP regions 1–4. The observed total population is the total number of dusky grouse observed or detected during the surveys. The maximum number of observed dusky grouse from the 4 repetitions from each survey site was used to calculate total observed population. The number of sites and percent of sites where dusky grouse were observed is presented, but dusky grouse could have been present at other survey sites and not been detected.

Region	**# of Survey Points**	**Observed total population**	**# of sites where observed**	**% of sites where observed**
Region 1	309	25	23	7.4
Region 2	320	73	57	17.8
Region 3	353	70	53	15.0
Region 4	309	21	20	6.5

Table 6. The maximum number of dusky grouse observed at each survey site over the four repetitions for FWP regions 1–4. Tallies for Region 5 were unavailable at the time of this report.

Region	**The maximum number of dusky grouse observed at each survey site**				
	0	**1**	**2**	**3**	**4**
Region 1	286	21	1	0	0
Region 2	263	43	13	0	1
Region 3	300	39	12	1	1
Region 4	289	19	1	0	0

Table 7. Average number of dusky grouse detected per point count survey during the 2020 spring survey period for each FWP region survey (Regions 1–4). Tallies for Region 5 were unavailable at the time of this report.

Region	**Average**	**Standard Deviation**
Region 1	0.08	0.30
Region 2	0.23	0.54
Region 3	0.20	0.53
Region 4	0.07	0.26

Table 8. Slope coefficients for the continuous survey condition variables: Temperature (C°), average wind speed (km/hr), minutes since sunrise, and day since survey period started (April 10^{th} = day 0).

Variable	Estimated slope (β_i)	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Temperature	0.021	-0.008	0.049
Average Wind Speed	-0.055	-0.128	0.012
Minutes Since Sunrise	0.008	0.003	0.015
Minutes Since Sunrise^2	-0.00003	-0.00005	-0.00001
Day Since Survey Period Started	0.242	0.157	0.334
Day Since Survey Period Started^2	-0.004	-0.005	-0.002

Table 9. Means parameterization for the categorical survey condition variables.

Variable	Estimate	Standard Error
Cloud Cover: 0-15%	-5.93	0.85
Cloud Cover:16-50%	-6.82	0.88
Cloud Cover: 51-80%	-7.03	0.89
Cloud Cover: 81-100%	-6.56	0.86
Precipitation: Fog	-5.93	0.85
Precipitation: None	-5.96	0.77
Precipitation: Rain	-5.92	0.84
Precipitation: Snow	-6.31	0.89

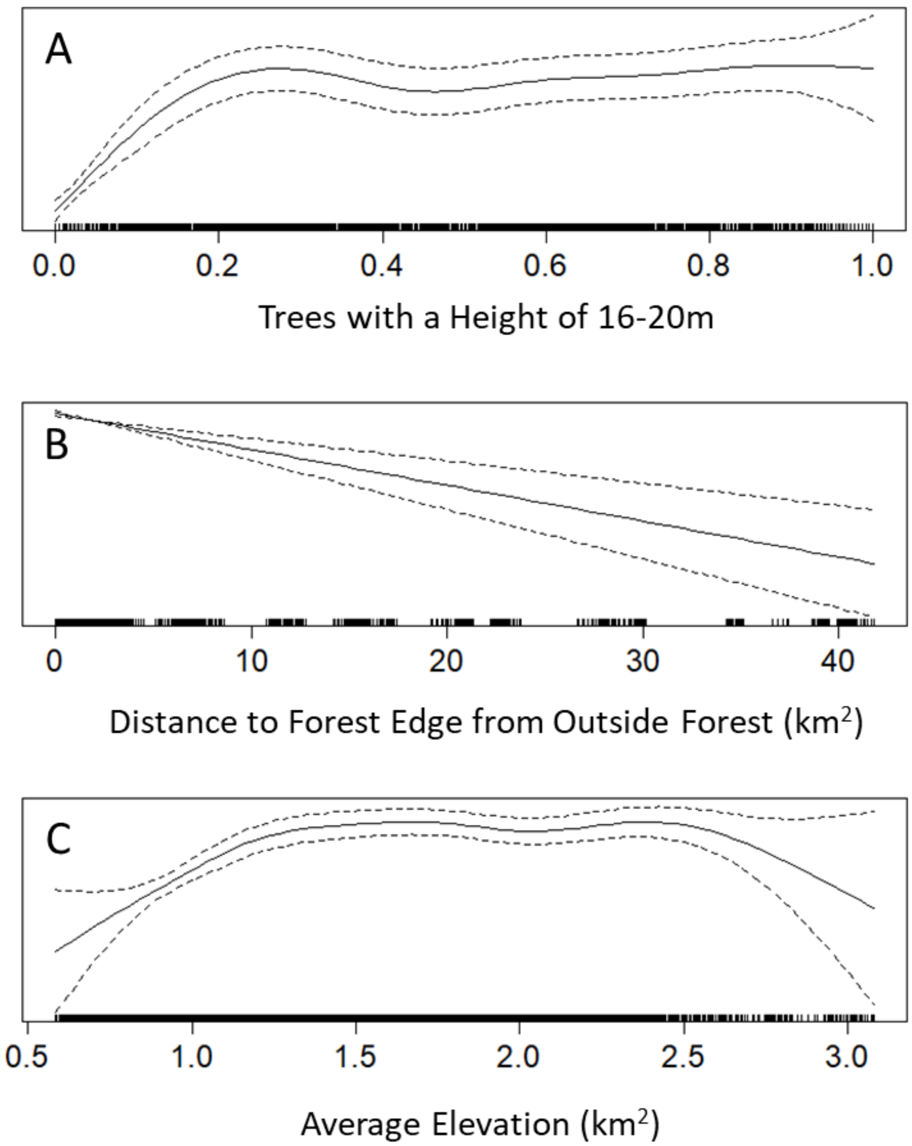

Figure 1. Examples of a pseudo-threshold (A) nonlinear relationship, a linear (B) relationship, and a quadratic (C) nonlinear relationship.

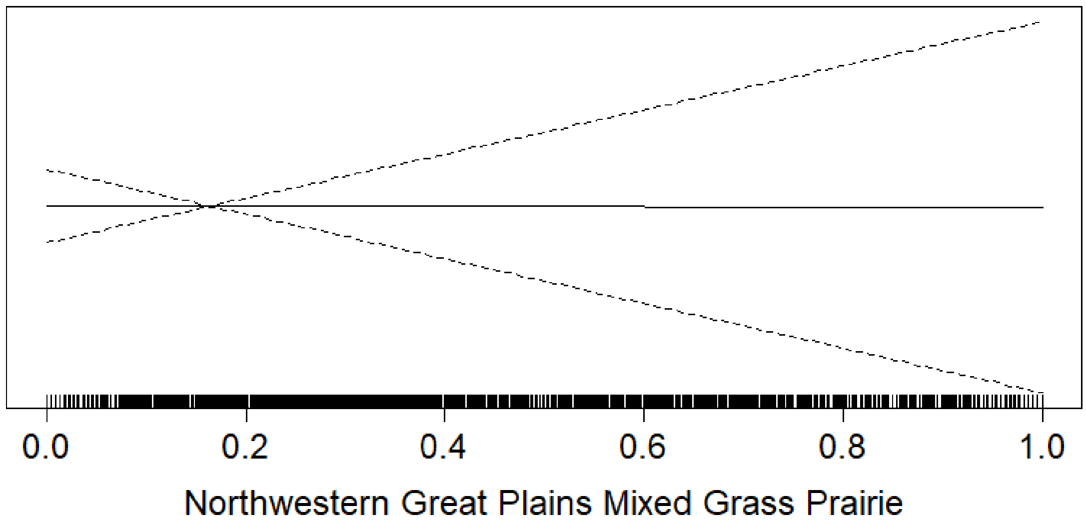

Figure 2: Example of a GAM plot where a variable showed no relationship with dusky grouse detection.

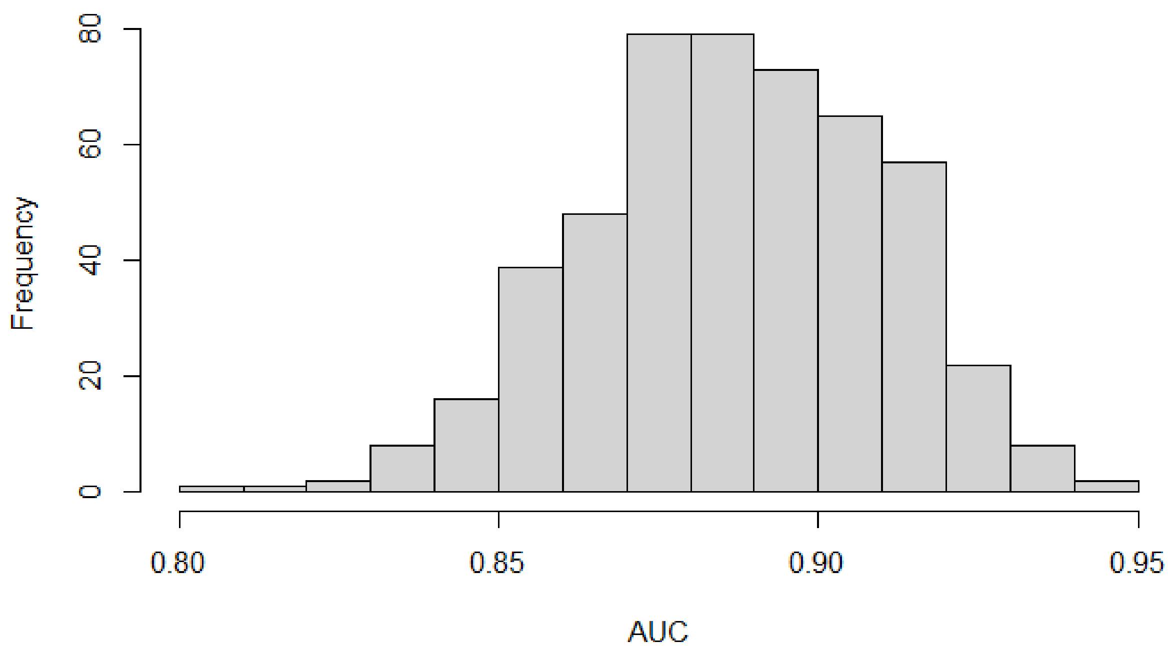

Figure 3. A histogram of the area under the curve (AUC) values for when we used receiver operating characteristics (ROC) and cross validation of the IMBCR dataset to evaluate model performance.

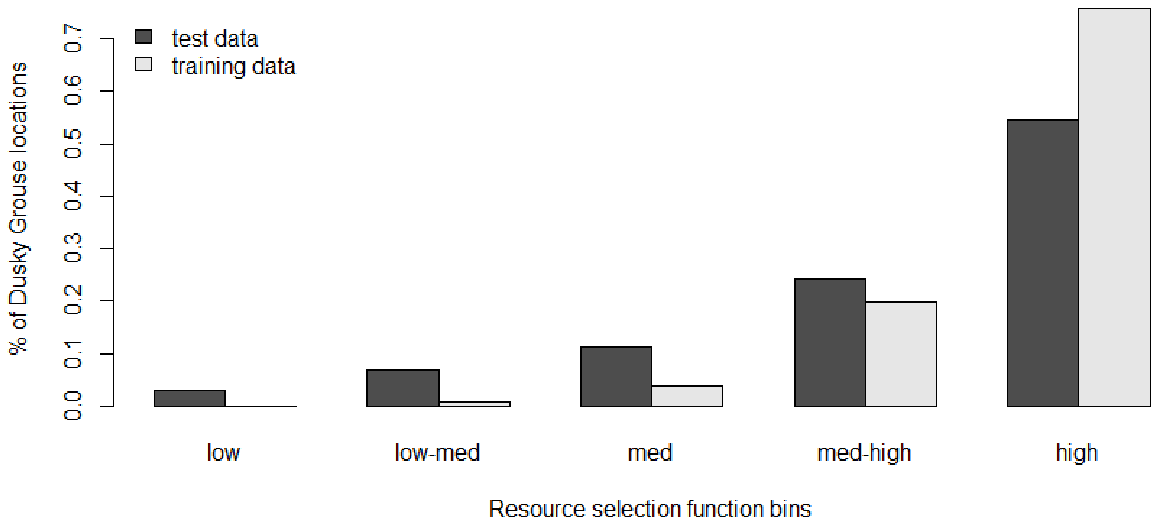

Figure 4. Proportion of dusky grouse locations in five bins of increasing resource selection function values that we used to train (n = 132) and test (n = 132) our model of relative habitat suitability. A good predictive model will assign most of the training and test dusky grouse locations to med-high or high categories of predicted use.

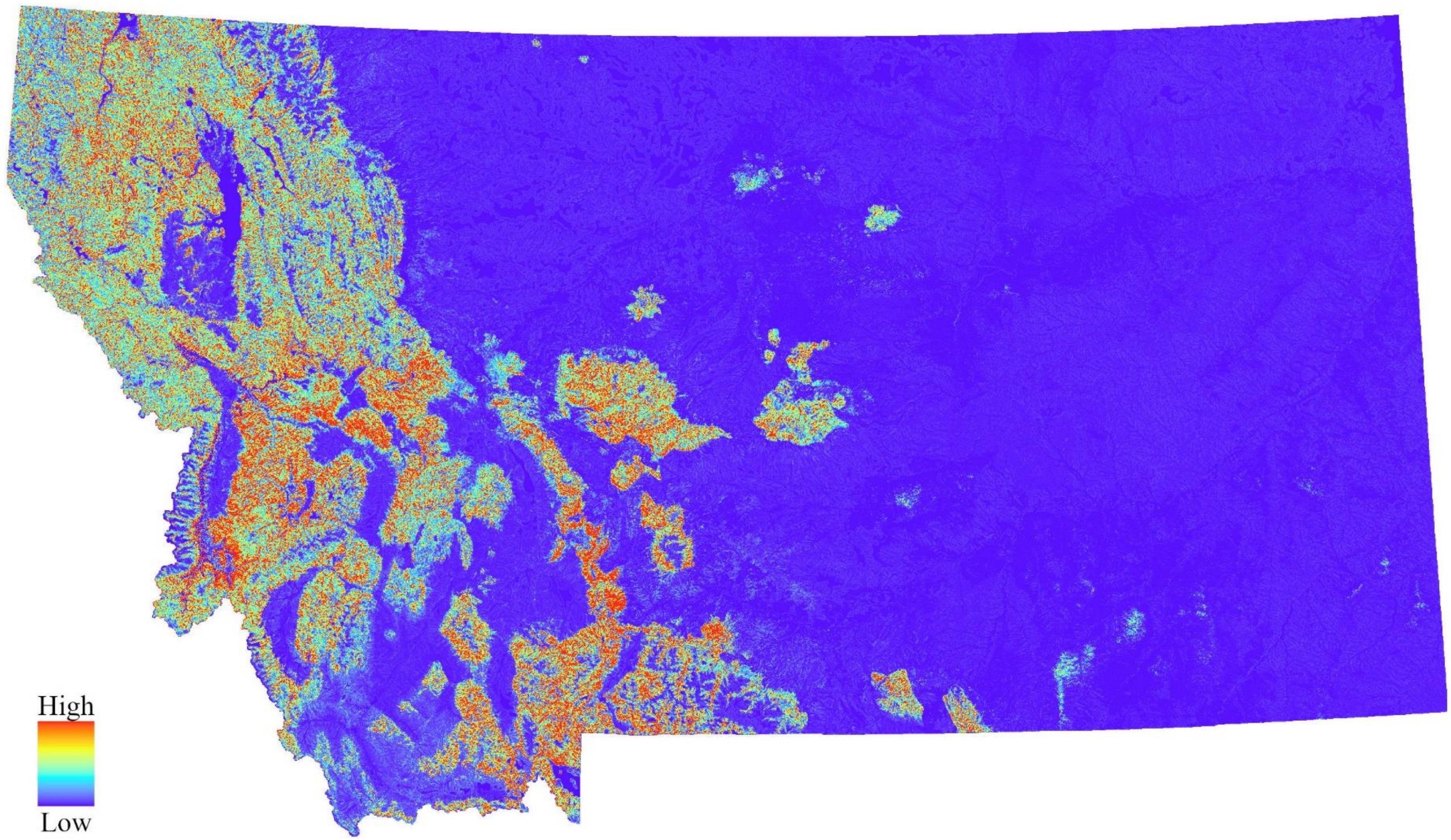

Figure 4. Predictive map of habitat suitability for dusky grouse for central and western Montana. This model has high predictive accuracy with a mean ROC of 0.89 (95% CI: 0.84–0.93). The geospatial datasets used to create this map included digital elevation layers, Montana spatial data hydrography datasets, and LANDFIRE vegetation datasets. Warmer colors (green-red) represent areas of higher relative use.

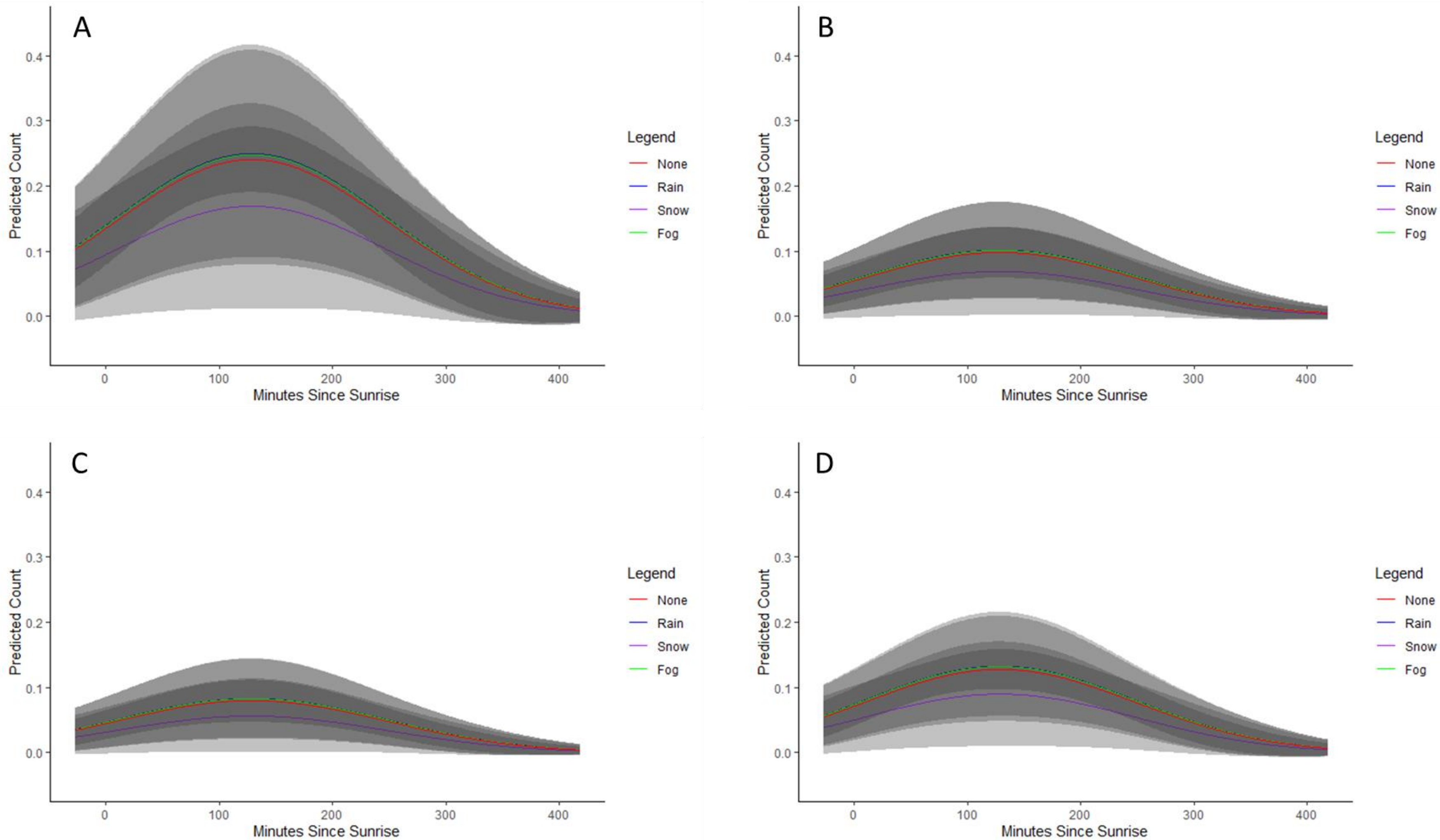

Figure 5. Predicted number of dusky grouse detected with 95% confidence interval during a point count as a minutes since sunrise under different precipitation and cloud cover conditions. A = 0–15% cloud cover, B = 16–50% cloud cover, C = 51–80% cloud cover, and D = 81–100% cloud cover

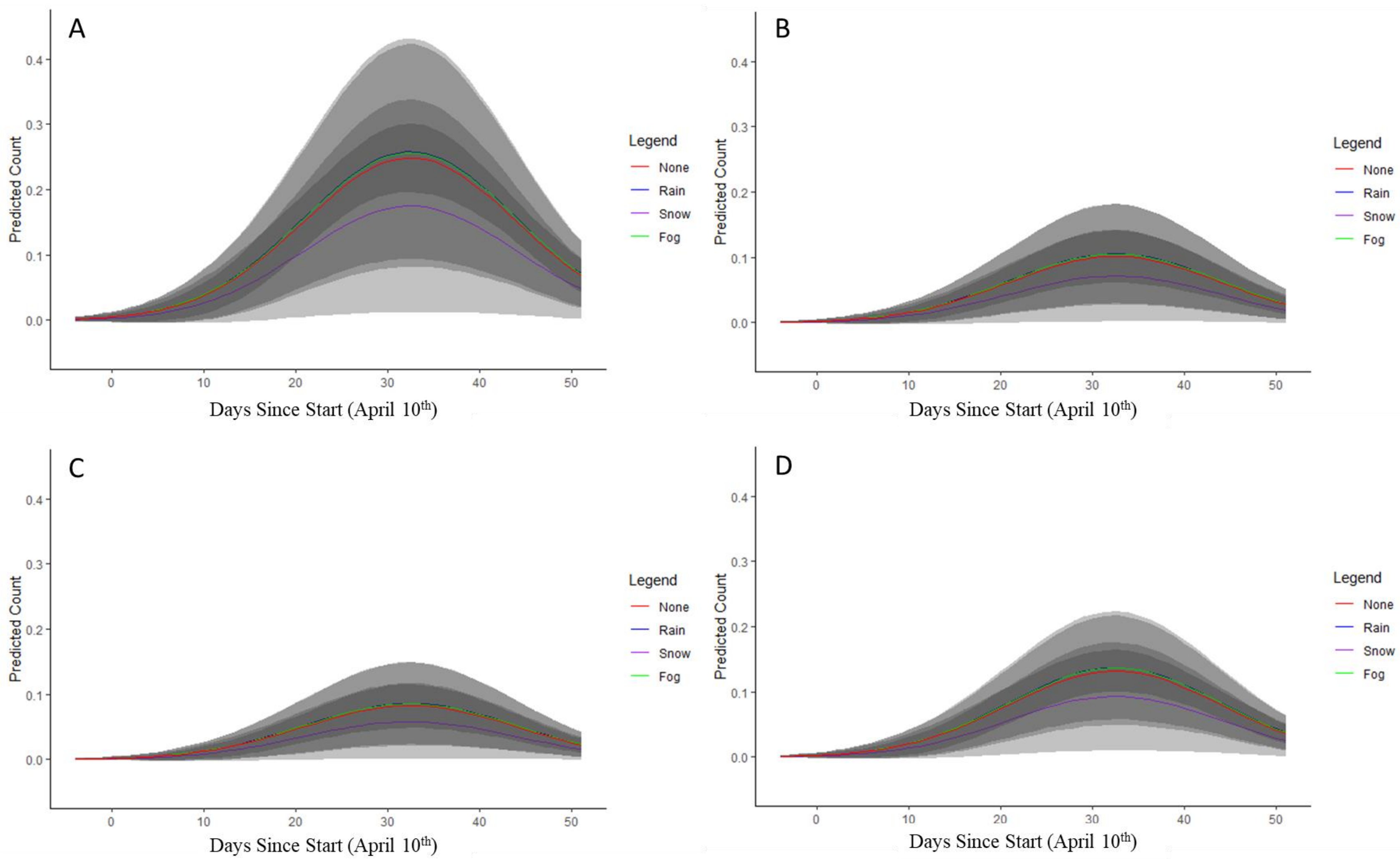

Figure 6. Predicted number of dusky grouse detected with 95% confidence intervals during a point count as a function of days since the start of the survey period (Day 0 = April 10th) under different precipitation and cloud cover conditions. A = 0–15% cloud cover, B = 16–50% cloud cover, C = 51–80% cloud cover, and D = 81–100% cloud cover

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