



Research Article

Multi-Scale Assessment of Greater Sage-Grouse Fence Collision as a Function of Site and Broad Scale Factors

BRYAN S. STEVENS,¹ *Department of Fish and Wildlife Resources and Department of Statistics, P.O. Box 441136, University of Idaho, Moscow, ID 83844, USA*

JOHN W. CONNELLY, *Idaho Department of Fish and Game, 1345 Barton Road, Pocatello, ID 83204, USA*

KERRY P. REESE, *Department of Fish and Wildlife Resources, P.O. Box 441136, University of Idaho, Moscow, ID 83844, USA*

ABSTRACT Previous research in Europe and North America suggested grouse are susceptible to collision with infrastructure, and anecdotal observation suggested greater sage-grouse (*Centrocercus urophasianus*) fence collision in breeding habitats may be prevalent. However, no previous research systematically studied greater sage-grouse fence collision in any portion of their range. We used data from probability-based sampling of fences in greater sage-grouse breeding habitats of southern Idaho, USA, to model factors associated with collision at microsite and broad spatial scales. Site-scale modeling suggested collision may be influenced by technical attributes of fences, with collisions common at fence segments absent wooden fence posts and with segment widths >4 m. Broad-scale modeling suggested relative probability of collision was influenced by region, a terrain ruggedness index (TRI), and fence density per square km. Conditional on those factors, collision counts were also influenced by distance to nearest active sage-grouse lek. Our models provide a conceptual framework for prioritizing sage-grouse breeding habitats for collision mitigation such as fence marking or moving, and suggest mitigation in breeding habitats should start in areas with moderate-high fence densities (>1 km/km²) within 2 km of active leks. However, TRI attenuated other covariate effects, and mean TRI/km² >10 m nearly eliminated sage-grouse collision. Thus, our data suggested mitigation should focus on sites with flat to gently rolling terrain. Moreover, site-scale modeling suggested constructing fences with larger and more conspicuous wooden fence posts and segment widths <4 m may reduce collision. © 2012 The Wildlife Society.

KEY WORDS avian collision, *Centrocercus urophasianus*, fence management, greater sage-grouse, Idaho, infrastructure collision, modeling collision risk.

Collision with infrastructure is widespread and common for European grouse (Catt et al. 1994, Bevanger 1995, Baines and Summers 1997). Collision with fences and power lines caused mortality for a variety of grouse species, including capercaillie (*Tetrao urogallus*), black grouse (*Tetrao tetrix*), red grouse (*Lagopus lagopus scoticus*), and ptarmigan (*Lagopus* spp.; Bevanger 1990, Baines and Summers 1997, Bevanger and Brøseth 2000, Baines and Andrew 2003). Despite widespread collision, population level consequences of collision are not understood in most areas. However, capercaillie fence collision likely contributed to population declines in Scotland (Moss et al. 2000, Moss 2001), and tetraonid collision mortality may approach harvest in some areas (Bevanger 1995).

Limited research also documented collision mortality for North American tetraonids. Wolfe et al. (2007) studied

mortality of lesser prairie-chickens (*Tympanuchus pallidicinctus*) and reported 39.8% of mortality in Oklahoma was caused by fence collision. Patten et al. (2005) concluded fragmentation caused by fences, power lines, and roads in Oklahoma resulted in greater mortality rates for female lesser prairie-chickens in Oklahoma than in New Mexico. Additionally, 33% of mortality for juvenile radio-marked greater sage-grouse (*Centrocercus urophasianus*; hereafter sage-grouse) at an Idaho site was because of power-line collisions (Beck et al. 2006).

In a review of bird–infrastructure interactions, Bevanger (1994) provided a conceptual framework for understanding avian–infrastructure collision by grouping factors influencing collision into 4 categories: biological, topographic, meteorological, and technical. Examples of biological factors include morphology (Bevanger 1998, Janss 2000), vision and visual perception (Martin and Shaw 2010, Martin 2011), activity and movement patterns (Avery et al. 1978, Malcom 1982), space use (Baines and Summers 1997, Rollan et al. 2010), bird densities (Anderson 1978, Baines and Andrew 2003, Bevanger and Brøseth 2004), and structure and height

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¹E-mail: stev8930@vandals.uidaho.edu

of local vegetation (Bevanger 1990, Catt et al. 1994). Topographic features related to collision include geomorphic forms that influence flight corridors (Cooper and Day 1998), and sloping terrain and ridges hypothesized to affect flight altitude (Bevanger 1990, Rollan et al. 2010). Meteorological conditions can also affect collision, including fog, precipitation, and wind and weather conditions (Bevanger 1994, Brown and Drewien 1995, Savereno et al. 1996). Technical features related to infrastructure design and construction influenced power-line collision (Bevanger 1994, Bevanger and Brøseth 2004), and infrastructure density has been hypothesized to affect collision (Wolfe et al. 2007).

Concerns over sage-grouse have highlighted the lack of empirical data on collision frequency and grouse in North America. The spatial extent of fences and other structures increased dramatically in sagebrush habitats over the last 50 years, and impacts on sage-grouse have been hypothesized (Braun 1998, Connelly et al. 2000, Johnson et al. 2011, Knick et al. 2011). Previous studies reported sage-grouse collision with fences near lekking grounds (Scott 1942, Flake et al. 2010), but no work systematically studied fence collision and its contributing factors. Moreover, previous avian-collision research often focused on high risk areas, and many studies provided temporally intensive surveys over spatially restricted sites with limited application to other sites. Thus, we have little information on what broad-scale factors make an area high risk for most species. Moreover, few studies systematically studied collision over large geographic areas or addressed collision at multiple spatial scales, limiting our understanding of collision risk across the landscape. Therefore, we studied sage-grouse fence collision in breeding areas across southern Idaho, USA, and modeled relationships between sage-grouse fence collision and biological, topographic, and technical features at multiple scales. We did not consider meteorological effects on collision because we did not have resources to measure fine scale changes in weather conditions at each site. Moreover, 1 research priority was to identify site and landscape features related to collision to aide managers in prioritizing areas for fence-collision mitigation, thus site- and time-specific weather effects provide little information toward this objective.

STUDY AREA

We conducted fence collision surveys in sage-grouse breeding areas (2009: $n = 16$; 2010: $n = 14$) across 4 regions of southern Idaho (Stevens 2011). Sage-grouse exhibit a lek mating strategy, and each breeding area represented 1 lek route, defined as a group of leks in close spatial proximity believed to represent part or all of a single breeding population and adjacent sagebrush-grass habitats (Connelly et al. 2003). In 2009, we sampled fences at 2 sites in the East Jarbidge region, 4 sites in the northern Magic Valley region, 4 sites in the Big Desert region, and 6 sites in the Upper Snake region of southern Idaho (Stevens 2011). In 2010, we eliminated 1 site each in the northern Magic Valley and Big Desert regions to sample more intensively at remaining sites. Elevations on study sites ranged from approximately 1,450 to 2,000 m, and habitat types were variable and included stands

of big (*Artemisia tridentata*), little (*A. arbuscula*), black (*A. nova*), three-tip (*A. tripartita*), and mixed sagebrush types, as well as grasslands, pasture, and previously burned areas with sparse vegetation.

METHODS

Fence Collision Surveys

We used a stratified cluster sampling design to survey fences in sage-grouse breeding areas (Stevens 2011). We treated lek routes as strata in sampling, and selected areas for inclusion based on accessibility and breeding bird use. We used a Geographic Information System (GIS; ArcMap 9.3, Environmental Systems Research Institute, Inc., Redlands, CA) to buffer each known and active lek by 1.5 km, overlay the United States Bureau of Land Management's pasture boundary layer (our surrogate for fence), and overlay a 1×1 -km spatial grid at each site. We used 1×1 -km grid cells as sampling units (i.e., clusters), and randomly selected a stratified cluster sample from cells intersecting the lek buffer and pasture boundary layers. We searched fences for collision evidence in the form of carcasses, feather piles, and feather tufts on the barbed wire using 1–2 observers (1 on each side of the fence, or 1 searcher sampling each side in turn). Individual observers walked approximately 1–3 m from each side of the fence during surveys, and we sampled each side of the fence independently. We also located fence collisions opportunistically while traversing study sites (Stevens 2011). We counted collisions during fence sampling with no knowledge of fate of the individual collision victims. Therefore, our counts are number of collisions present at the time of sampling, and not of collision mortalities, as we had no way to assess crippling bias caused by individual birds flying into fences and dying at a later time or in a different area (Bevanger 1999). Moreover, no data currently exist on the proportion of sage-grouse collisions that ultimately result in mortality. We sampled all fences within randomly selected clusters during the sage-grouse breeding season in 2009 and 2010 (Mar–May; 2009: $n = 60$; 2010: $n = 80$), and recorded the number of collisions detected per square kilometer.

Characterizing Site-Scale Fence Collision Attributes

We measured biological, topographic, and technical characteristics at sage-grouse fence-collision locations. We measured height of closest shrubs not intersecting the fence plane (i.e., lateral shrub height) and distances to the closest non-intersecting shrubs lateral to the fence. We measured shrub canopy cover along 10-m transects oriented in the cardinal directions (Canfield 1941), and measured height of closest shrubs growing directly along the fence (i.e., longitudinal shrub height intersecting the fence plane) within 5 m of the collision site in both directions. We recorded maximum lek count (number of birds per lek) and distance to the nearest known lek for each site in the GIS using annual lek count data provided by Idaho Department of Fish and Game (IDFG; Jenni and Hartzler 1978, Connelly et al. 2003). We used only counts from leks where ≥ 1 male was counted displaying in 2009–2010, and deleted all leks with zero

counts in both years and all historical leks with unknown status.

We recorded technical attributes of fences at each collision site, including fence height, fence type, and distance between fence posts for each segment. We recorded types of posts bounding fence collision segments (i.e., wooden or steel t-post) later from pictures recorded at each site. We calculated differences between fence and vegetation height both laterally and longitudinally, and recorded topographic data including slope across and along the fence (measured over 20 m centered on the collision site), and recorded aspect using a digital elevation model (DEM) in the GIS.

We selected random fence points on study areas to assess significance of site-scale features recorded at collision locations. We randomly generated 1 spatial location for each collision found on each study area using ArcMap. We did not pair random fence points with collision points. We generated random fence points over the entire sampling frame at each site, not just in randomly selected 1×1 km sampling units. We did not specifically address spatial autocorrelation in site-scale data; however, statistical classification methods described below can show increased predictive accuracy with spatially correlated data (Marmion et al. 2009). Data collected at random points were identical to fence collision locations.

Characterizing Broad-Scale Fence Collision Attributes

We evaluated the influence of broad-scale characteristics on observed collision frequency. We used each sampled cluster as the unit of analyses, where each square km had an observed collision count. We measured biological, topographic, and technical variables over each sampled square km. We collected vegetation and topography attributes in the GIS using 30-m raster grid data. We measured topographic heterogeneity using the terrain ruggedness index (TRI; Riley et al. 1999), calculated from United States Geological Survey 30-m DEMs for each region (www.seamless.usgs.gov, accessed 24 Sep 2010). The TRI for each 30-m pixel is calculated as the square root of the sum of squared differences in elevation from the given pixel and the 8 surrounding pixels (Riley et al. 1999). We calculated mean TRI for each sampled square km using ArcMap. Lastly, we measured fence length per square km using digitized sampled fences in the GIS.

We measured vegetation characteristics of each sampled square km in the GIS using 30-m raster data obtained from the national Landfire database (www.landfire.gov, accessed 24 Sep 2010). We measured proportional coverage of sagebrush cover types, vegetation height categories, and shrub canopy cover categories over each sampled site using the Landfire Veg Type, Veg Height, and Existing Veg Cover datasets, respectively. Numerous studies at multiple spatial scales found sage-grouse habitat use during the nesting season was influenced by sagebrush presence, canopy cover, and shrub height (Connelly et al. 2000, Aldridge and Brigham 2002, Holloran and Anderson 2005, Doherty et al. 2010). Moreover, grouse–infrastructure collision studies suggested collision may be related to vegetation height

characteristics (Bevanger 1990, Catt et al. 1994). Therefore, we reclassified Landfire cover type values into big sagebrush, and low sagebrush cover types, vegetation height values into 0–0.5 m, 0.5–1.0 m, and >1 m height classes, and shrub canopy cover values into 10–20%, 20–30%, 30–40%, and 40–50% cover values. We did not use any other Landfire cover type, vegetation height, or canopy cover categories in our analyses. Landfire vegetation data used in this analysis were produced at the 30-m pixel resolution; however, the dataset was intended for landscape-scale analyses. We did not ground truth vegetation classifications produced by the Landfire dataset, thus the thematic accuracy of broad-scale vegetation data was unknown and could have varied by site.

We collected lek distribution and count data using annual lek survey and location data provided by IDFG (Jenni and Hartzler 1978, Connelly et al. 2003). We calculated distance to nearest lek, and number of known and active leks within 2 km of the centroid of each sampled cluster using ArcMap. We also recorded maximum count at the closest lek, and summed the maximum counts of all leks within 2 km of the centroid for each sampled cluster.

Statistical Methods

Site-scale analyses.—We used non-parametric multivariate classification methods to classify random and collision points based on site-scale attributes. No previous research addressed site-scale attributes of fence collision locations in sagebrush steppe. Therefore, this analysis was somewhat exploratory, and we used multivariate methods known to explore patterns in the data for site-scale analyses. We also suspected interactions among variables were possible when discriminating random and collision fence points. For example, the influence of technical attributes on classification may depend on a fence's proximity to nearest active lek. Lastly, missing covariate observations (e.g., fence post type; $n = 15$ missing values) required us to use analytical methods capable of using data with missing observations. Therefore, we used classification and regression trees (CART; Breiman et al. 1984, De'ath and Fabricius 2000) to discriminate random and collision points. We built CART models using the rpart package in the R statistical computing language (R Core Development Team 2006), and we maximized between group differences at each split by minimizing the Gini index. We estimated predictive accuracy of CART models using 10-fold cross-validation, and selected optimal tree size using the 1 standard error rule (De'ath and Fabricius 2000). We replicated this process 1,000 times and selected the modal tree size as the final model (De'ath and Fabricius 2000).

Because CART can have lower predictive success than other classification methods, we also used random forest algorithms to classify random and collision fence points using site-scale data (Breiman 2001, Cutler et al. 2007, Kampichler et al. 2010). Random forest classification fits multiple classification trees using bootstrapped samples of the original data, where observations not randomly selected in bootstrapped samples are referred to as out-of-bag (OOB) observations. Prediction success is estimated by running OOB observations through each generated classification tree,

where classification is determined by the majority vote over all generated trees (Cutler et al. 2007). Moreover, OOB observations are used to assess relative importance of individual variables by randomly permuting covariate values and evaluating the effects on model predictive success (Cutler et al. 2007). We used 10,000 iterations of the randomForest package (Liaw and Wiener 2002) in the R statistical computing language (R Core Development Team 2006), and we constructed CART and random forest models using 16 site-scale covariates (Appendix A, available online at www.onlinelibrary.wiley.com). Lastly, we only used opportunistically located collision data for site-scale analyses, and did not use collision data found outside randomly selected sampling units for broad-scale analyses.

Broad-scale analyses.—We modeled probability of sage-grouse collision presence per square km with logistic regression using the known fate model and logit link function in Program MARK (White and Burnham 1999). We used an information-theoretic framework to rank and compare models using Akaike's Information Criterion corrected for small samples sizes (AIC_c) and normalized Akaike model weights (w_i ; Burnham and Anderson 2002). Because the known fate model assumes perfect detection of individuals, known fate survival estimation using only 1 time interval is identical to estimating success probability from a binomial-likelihood model (i.e., probability given event occurred). Thus when used with 1 time interval and the logit-link function, the known fate model can be used for logistic regression, with results identical to those obtained using standard statistical software. Because we only sampled many sites once per year, and located very few collisions during subsequent sampling occasions on sites sampled >1 time per year, we only used data from the first sampling occasion for broad-scale analyses.

We constructed logistic regression models using 17 covariates hypothesized to influence collision a priori, all of which were hypothesized based on avian collision or sage-grouse research (Appendix A). We grouped sample units by region, with sites from East Jarbidge and northern Magic Valley in the Magic Valley region, and Upper Snake and Big Desert as stand-alone regions. We arcsine-square-root transformed all proportional vegetation coverage covariate data and tested for correlation between covariates using correlation *t*-tests. We did not include significantly correlated ($P < 0.05$) covariates together in the same model (Appendix B, available online at www.onlinelibrary.wiley.com). We used a 2-stage modeling process to select a final group of candidate models because of the large number of covariate combinations. We first constructed models using individual covariates divided into 3 groups: vegetation, lek distribution and count, and all other remaining covariates (i.e., region, year, TRI, and fence length; Appendix C, available online at www.onlinelibrary.wiley.com). We then used combinations of covariates from the top models from each group (i.e., $\Delta AIC_c < 2$) to construct a final suite of 23 models (Appendix C).

We evaluated goodness-of-fit, discrimination ability, and classification success for the top logistic model. We used the

Hosmer and Lemeshow test to assess the null hypothesis that the top model fit the data (Hosmer and Lemeshow 2000). We used area under the Receiver Operating Characteristic (ROC) curve to evaluate discrimination ability of the top model (Hosmer and Lemeshow 2000). We conducted goodness-of-fit testing and estimated ROC curves using SAS Version 9.2 (SAS Corporation, Cary, NC). We calculated an optimum prediction threshold for the top model as the intersection point for sensitivity and specificity curves, jointly minimizing both types of prediction error (Hosmer and Lemeshow 2000). We used the optimum prediction threshold to construct classification tables and estimate classification success in the R statistical computing language (R Core Development Team 2006).

We summed collision data over each sampled square km to evaluate influence of broad-scale covariates on expected collision counts. We conducted count-based modeling in addition to logistic regression analyses because relative abundance of collisions provides more information for managers than presence-absence alone. We corrected collision counts for undetected collisions using the intercept-only logistic regression model from detectability trial experiments, where each observed collision represented 1/0.54 corrected collisions, and 0.54 was the detection probability (Stevens et al. 2011). Assuming constant detection is an oversimplification of the detection process, but is currently standard procedure for avian-collision studies (e.g., Smallwood 2007). Since count based modeling requires integer-valued random variables, we summed corrected counts at each sample unit and rounded counts to the nearest whole number. Because of abundant zero counts in the dataset we used zero-inflated Poisson regression (ZIP) to model corrected collision counts (Lambert 1992, Welsh et al. 1996, Martin et al. 2005). The ZIP models are a type of generalized linear model that facilitate modeling expected counts and sources of zero inflation simultaneously as a function of covariates. We compared ZIP models using information-theoretic methods (Burnham and Anderson 2002), and fit models using the *pscl* package and *zeroinfl* function in R (R Core Development Team 2006, Zeileis et al. 2008). Covariates used in ZIP modeling were identical to those used in logistic regression (Appendix A), and we used the top logistic model to explicitly model the ZIP binomial mixture probabilities (i.e., probability of observed count coming from point mass at zero or Poisson distribution). We used the same 2-stage modeling process previously described for logistic regression analysis for ZIP modeling, which resulted in comparison of 21 models in the final model suite (Appendix D, available online at www.onlinelibrary.wiley.com).

We evaluated goodness-of-fit and prediction success for the top ZIP model with parametric bootstrap and cross-validation procedures (Efron and Tibshirani 1994). We used 1,000 parametric bootstrap samples of the Pearson χ^2 statistic to test the null hypothesis that the model fit the data. We used leave-1-out cross-validation to estimate prediction success, and calculated root-mean-squared error for each model to describe average error between observed and cross-validation predicted collision counts. We conducted

all bootstrap and cross-validation analyses in R (R Core Development Team 2006).

RESULTS

Site-Scale Analyses

We sampled 129.5 km of fence in 140 1 × 1-km clusters across southern Idaho during spring of 2009 and 2010. We detected 86 (2009: $n = 48$; 2010: $n = 38$) sage-grouse fence collisions, including 28 collisions recorded on 60 sites in 2009 and 30 collisions at 80 sites in 2010, and 28 opportunistically located collisions (2009: $n = 20$; 2010: $n = 8$). We collected site-scale data at 172 locations (collision: $n = 86$; random: $n = 86$). Our CART analyses resulted in an optimal model size of 1 split ($n = 574$), suggesting fence point type was influenced by presence of wooden fence posts. This model classified 67 points as random (28.4% error rate) with ≥ 1 wooden post present, and 105 points as collisions (36.2% error rate) with no wooden posts. Distance between fence posts was the best surrogate split for wooden post presence (78.5% agreement in predictions). Distance between posts predicted collisions with values >3.94 m, and random sites for distances <3.94 m, and observed distance between post measurements averaged 3.77 m (SD = 1.41 m; range = 1.24–9.78 m). Mean prediction success for 1-split models with 10-fold cross-validation was 63.6%. Random forest modeling increased prediction success slightly, with an OOB prediction success of 67.4% (collision: 72.1% success; random: 62.8% success). Variable importance plots suggested wooden post presence, distance between posts, and distance to lek ($\bar{x} = 1,248$ m; SD = 675 m; range = 86–3,841 m) were most important for discriminating collision and random points, and permuting these covariates in OOB data resulted in mean accuracy decreases of 7.2%, 4.5%, and 3.6%, respectively (Fig. 1).

Broad-Scale Analyses

We sampled 140 1 × 1-km clusters during spring of 2009 and 2010, however, 17 clusters had no fences. Therefore, all broad-scale analyses used 123 observations. Logistic regression suggested collision presence was influenced by region, TRI, and fence length per square km ($\Delta AIC_c = 0$; $w_i = 0.349$; Table 1). We also found weak evidence for the influence of proportional coverage of vegetation >1.0 m tall ($\Delta AIC_c = 1.509$; $w_i = 0.164$; Table 1). The top model suggested relative collision probability was less in the Magic Valley region ($\beta = -2.88$; 95% CI = -4.96 to -0.79 ; Fig. 2), as compared to the Big Desert ($\beta = 1.73$; 95% CI = 0.18 to 3.28; Fig. 2) and Upper Snake regions ($\beta = 2.15$; 95% CI = 0.78 to 3.53; Fig. 2). Moreover, the top model suggested collision decreased with increasing TRI ($\beta = -0.33$; 95% CI = -0.65 to -0.01 ; Fig. 2), and increased with fence length per square km ($\beta = 1.10$; 95% CI = 0.09 to 2.12; Fig. 2). Observed TRI and fence length per square km averaged 4.3 m ($n = 123$; SD = 3.8 m; range = 1.2–23.6 m) and 1.05 km ($n = 123$; SD = 0.56 km; range = 0.02–2.84 km), respectively. The second best model suggested increasing cover of vegetation >1.0 m tall increased collision ($\beta = 0.67$; 95% CI = -0.92 to 2.26);

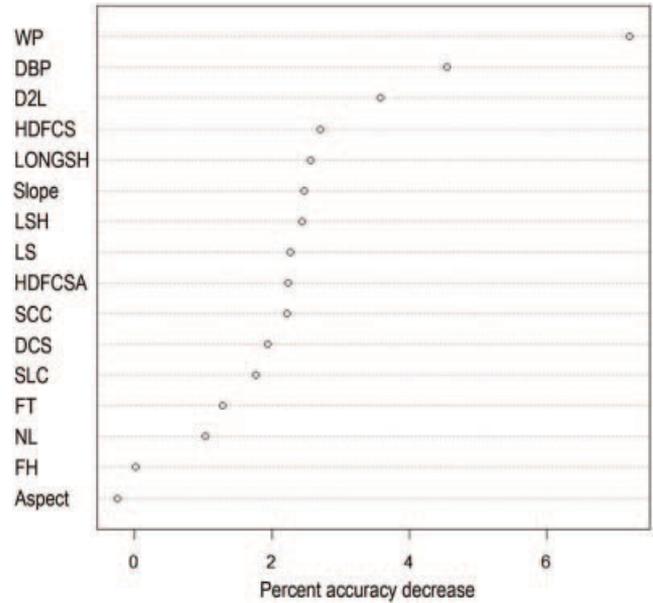


Figure 1. Site-scale random forest variable importance plot for factors discriminating sage-grouse collision fence points and random fence points as a function of covariates measured on southern Idaho rangelands during spring of 2009 and 2010. We used 10,000 replications of the random forest algorithm to rank variable importance based on the normalized difference in classification accuracy for out-of-bag predictions when the variable was included as measured, and the accuracy for out-of-bag predictions when the variable was randomly permuted (Cutler et al. 2007). Covariates used were: presence of wooden fence posts (WP), distance between fence posts (DBP), distance to nearest sage-grouse lek (D2L), height difference between the fence and the closest lateral shrub (HDFCS), longitudinal shrub height (LONGSH), slope, lateral shrub height (LSH), maximum count at closest lek (LS), height difference between the fence and the closest longitudinal shrub (HDFCSA), sagebrush canopy cover (SCC), distance to closest shrub (DCS), sum of lek counts within 2 km (SLC), fence type (FT), number of leks within 2 km (NL), fence height (FH), and aspect.

however, this parameter was estimated imprecisely and its confidence interval overlapped zero. Goodness-of-fit testing failed to reject the null hypothesis that the top model fit the data ($P = 0.83$; $\chi^2_8 = 4.26$), and area under the ROC curve was 0.82, suggesting excellent ability to discriminate between areas with and without sage-grouse collisions (Hosmer and Lemeshow 2000). Jointly maximizing sensitivity (0.75) and specificity (0.77) resulted in an optimum prediction threshold of 0.32 for the top model (i.e., $P \geq 0.32$ predicts event occurrence), and overall classification success of 0.76 suggested reasonable predictive accuracy.

We constructed ZIP models with the binomial mixture probability modeled as a function of region, TRI, and fence length per square km. The influence of distance to lek on collision count was most supported by the data ($\Delta AIC_c = 0$; $w_i = 0.181$; Table 2). The top model suggested a decrease in collision count with increasing distance to lek ($\beta = -0.0006$; 95% CI = -0.0008 to -0.0003 ; Fig. 3). Observed values of distance to nearest lek from the centroid of each sampled cluster averaged 1,367 m ($n = 123$; SD = 546 m; range = 158–2,704 m). We found weak evidence for sagebrush canopy cover and fence length in addition to distance to lek ($\Delta AIC_c < 2$; Table 2). However, additional cover and fence length terms were all estimated

Table 1. Top logistic regression models of sage-grouse collision presence during fence surveys within 1×1 -km clusters on sage-grouse breeding areas of southern Idaho, USA, during spring of 2009 and 2010. We ranked models using Akaike's Information Criteria corrected for small sample sizes (AIC_c) and normalized Akaike model weights (w_i ; Burnham and Anderson, 2002). Covariates were region (region = Magic Valley, Big Desert, Upper Snake), mean topographic ruggedness (TRI), length of fence (FL), proportion of area covered by vegetation > 1 m tall ($VH > 1.0$), and distance to nearest sage-grouse lek (D2L).

Model	K^a	AIC_c	ΔAIC_c	w_i	$-2LL^b$
Region + TRI + FL	5	109.524	0.000	0.349	99.011
Region + TRI + FL + $VH > 1.0$	6	111.033	1.509	0.164	98.308
Region + TRI + FL + D2L	6	111.550	2.026	0.127	98.826
Region + TRI	4	111.915	2.391	0.106	103.576
Region + TRI + $VH > 1.0$	5	113.018	3.494	0.061	102.506

^a K = no. of model parameters.

^b $-2LL = -2 \times$ maximized log-likelihood for model of interest.

imprecisely with 95% confidence intervals that overlapped zero. Moreover, cross-validated prediction error was similar among top models, suggesting weak evidence for parameters in addition to distance to lek (range = 1.51–1.61; Table 2). Parametric bootstrap goodness-of-fit testing failed to reject the null hypothesis that the top model fit the data ($P = 0.83$).

DISCUSSION

We found evidence for the influence of several site and landscape features on sage-grouse fence collision in breeding areas of southern Idaho. Site-scale analyses suggested technical factors influenced collision, including fence-post type and width of fence segments. We hypothesize these

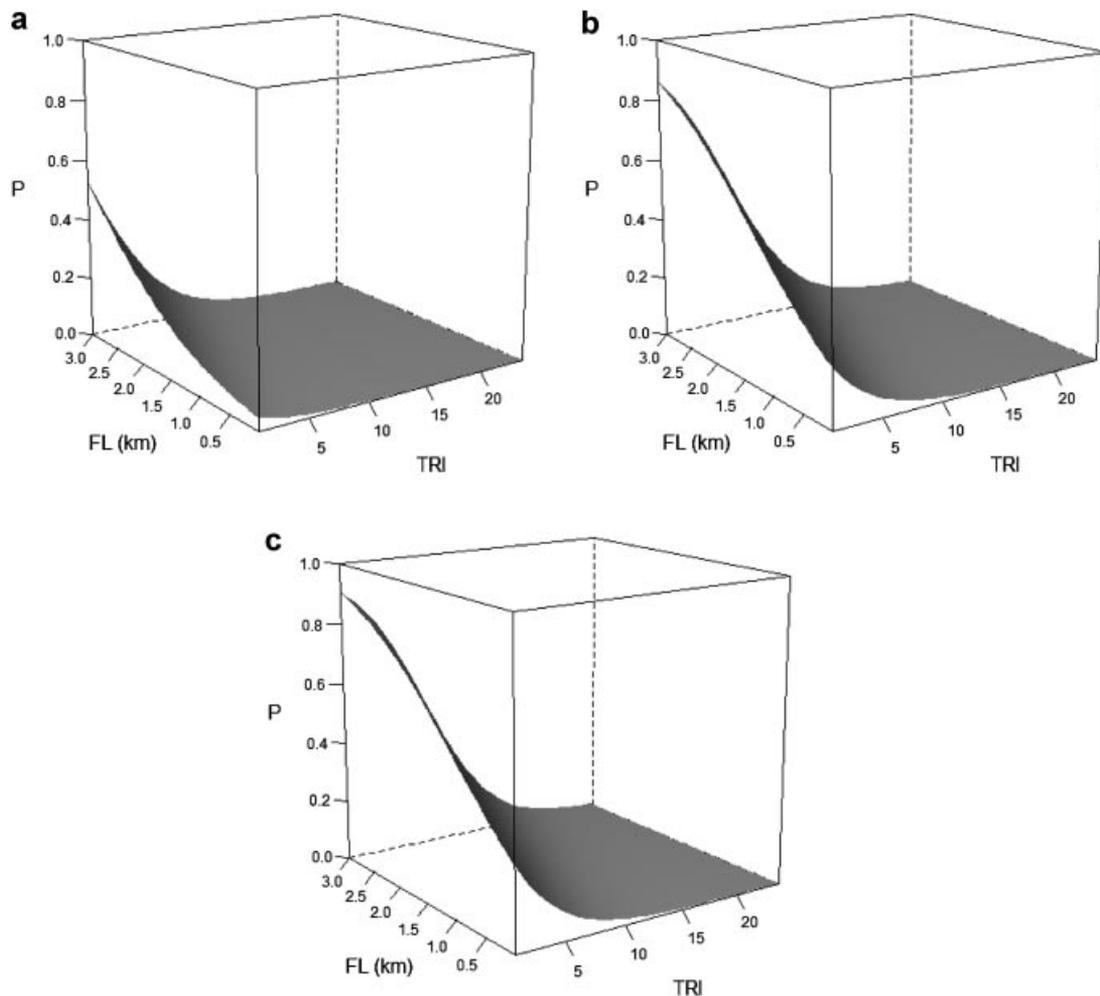


Figure 2. Plots of relative sage-grouse collision probability as a function of covariates in the top broad-scale logistic regression model, from sampling fences on southern Idaho, USA, rangelands during spring of 2009 and 2010. Probability of collision (P) as a function of terrain ruggedness (TRI) and fence length (FL) in the (a) Magic Valley, (b) Big Desert, and (c) Upper Snake regions.

Table 2. Top zero-inflated Poisson regression models of sage-grouse collision count during fence surveys on sage-grouse breeding areas of southern Idaho, USA, during spring of 2009 and 2010. We ranked models using Akaike's Information Criteria corrected for small sample sizes (AIC_c) and normalized Akaike model weights (w_i ; Burnham and Anderson, 2002). Covariates were distance to nearest sage-grouse lek (D2L), proportional cover of sagebrush canopy cover 10–20% (SCC1020), length of fence (FL), proportional cover of sagebrush canopy cover 20–30% (SCC1020), proportional cover of sagebrush canopy cover 30–40% (SCC3040), and proportional cover of sagebrush canopy cover 40–50% (SCC4050).

Model ^a	K^b	AIC_c	ΔAIC_c	w_i	$-2LL^c$	Prediction error ^d
D2L	7	214.393	0.000	0.181	199.419	1.543
D2L + SCC1020	8	214.711	0.318	0.154	197.448	1.511
D2L + FL	8	215.860	1.467	0.087	198.597	1.542
D2L + SCC4050	8	216.292	1.899	0.070	199.029	1.604
D2L + SCC3040	8	216.374	1.981	0.067	199.110	1.615
D2L + SCC2030	8	216.528	2.136	0.062	199.265	1.540

^a Model form is $\log(\lambda) = \beta_0 + \beta_1 \times X_1 + \dots + \beta_k \times X_k | \text{logit}(P) = \beta_0 + \beta_1 \times (\text{Region} = \text{Upper Snake}) + \beta_2 \times (\text{Region} = \text{Big Desert}) + \beta_3 \times \text{TRI} + \beta_4 \times \text{FL}$, where λ = expected collision count, P = binomial mixture probability, and TRI = topographic ruggedness index.

^b K = no. of model parameters.

^c $-2LL = -2 \times$ maximized log-likelihood for the model of interest.

^d Prediction error = root-mean-squared error calculated via leave-1-out cross-validation. This represents the square root of the average squared difference between predicted and observed collision counts for each model.

relationships are a function of infrastructure visibility to grouse. That is, fences constructed with larger and more conspicuous wooden fence posts and with more posts (i.e., shorter segment widths) are probably easier for grouse to see. Many previous collision studies focused on site-scale parameters, and several studies found significant factors

discriminating random and collision infrastructure points (Catt et al. 1994, Baines and Summers 1997, Bevanger and Brøseth 2004). Site-scale vegetation composition and height appeared to influence fence and power-line collision for European tetraonids (Catt et al. 1994, Baines and Summers 1997, Bevanger and Brøseth 2004), as did

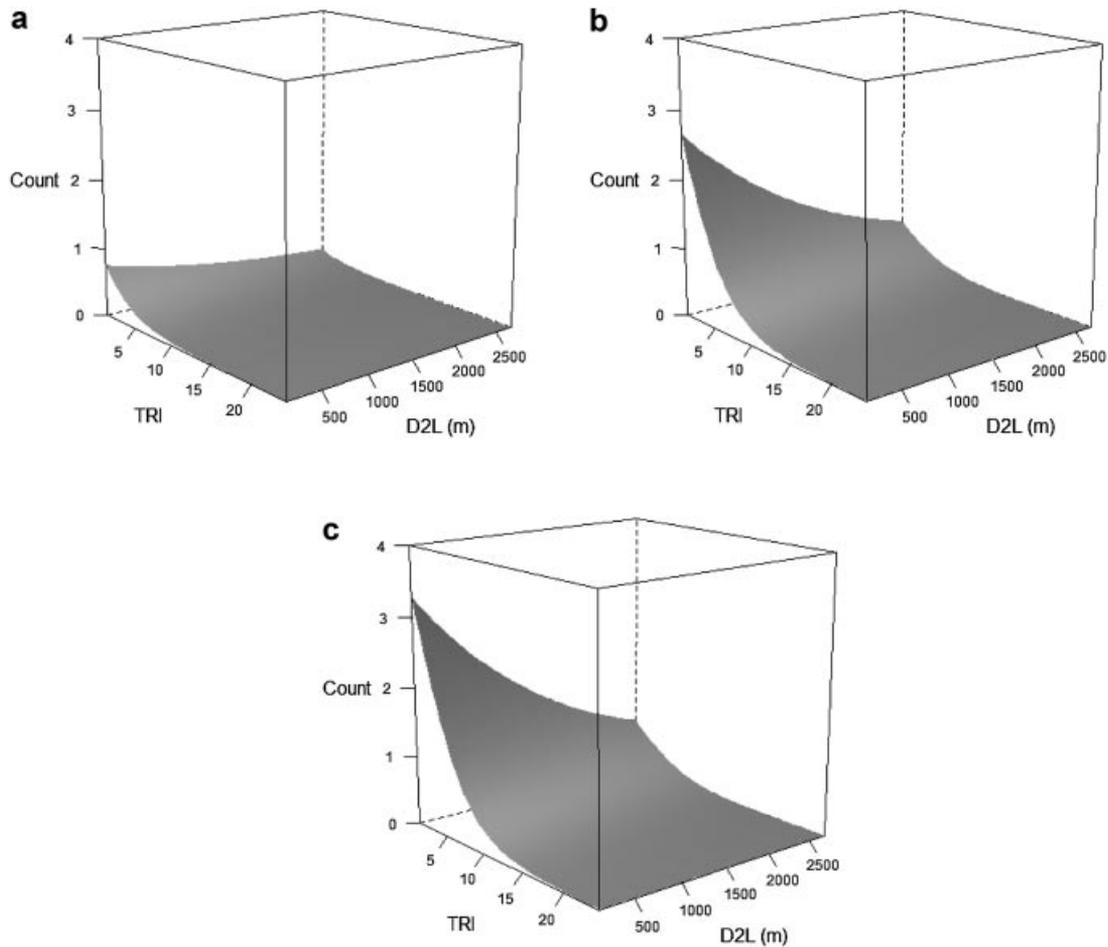


Figure 3. Plots of expected sage-grouse collision count as a function of covariates from the top zero-inflated Poisson regression model, from sampling of fences on southern Idaho, USA, rangelands during spring of 2009 and 2010. Expected collision count per square km was a function of terrain ruggedness (TRI) and distance to lek (D2L), with fence length (FL) held at its mean value in the (a) Magic Valley, (b) Big Desert, and (c) Upper Snake regions.

site-scale topography (Bevanger 1990). In contrast, few studies identified relationships between technical attributes of fences and tetraonid collision. However, wind-turbine design has been reported to influence burrowing owl (*Athene cunicularia*) collision risk at wind-power facilities in California (Smallwood et al. 2007).

At broad scales, we found evidence for the influence of biological, technical, and topographic features on sage-grouse fence collision. Relative probability of sage-grouse collision was related to region, topographic ruggedness, and fence length, and conditional on these factors collision counts were influenced by distance to nearest lek. Several previous studies also sampled fences over broad scales; however, measurement and analysis of predictor variables usually focused on site-scale covariates (Baines and Summers 1997, Bevanger and Brøseth 2000), limiting our understanding of what influences collision across the landscape.

Although most studies measured covariates at the site-scale, many studies reported spatial variability in collision risk at regional scales (Bevanger and Brøseth 2000, Barrios and Rodríguez 2004, Patten et al. 2005, Shaw et al. 2010). Differences in relative sage-grouse population densities and regional evidence-removal rates are plausible explanations for observed differences in collision. Broad-scale lek counts suggested sage-grouse densities may influence regional collision risk on southern Idaho rangelands. Lek counts within 8.5 km of sampling areas in the Big Desert and Upper Snake regions were more than double those observed in the Magic Valley during our study (Stevens 2011). Both relative collision probability and expected collision counts were greater in the Big Desert and Upper Snake regions than the Magic Valley region. Regional variation of avian-infrastructure collision as a function of population indices has been reported for a variety of avian species, infrastructure types, and regions (Baines and Andrew 2003, Barrios and Rodríguez 2004, Shaw et al. 2010). Although increased risk with regional abundance is an intuitive result, large differences in collision-evidence-removal rates were also observed between study regions (Stevens et al. 2011). Thus, observed regional effects may have been a function of reduced evidence-removal rates in the Big Desert and Upper Snake regions relative to the Magic Valley (Stevens et al. 2011). Moreover, regional variation may have been related to unmeasured covariates.

In addition to regional variation in risk, we found sage-grouse collision was a function of topographic ruggedness at our sites. Moderate increases in ruggedness resulted in strong reductions in fence collision risk. We hypothesize increasing topographic variation may result in higher flight altitudes, reducing risk of colliding with fences. Direct comparisons to topographic influences on collision reported in other studies are difficult because of differences in measurement and scale. Most previous studies treated topography as a categorical variable. Bevanger (1990) categorized topography of power-line sites, and reported tetraonid collision frequency was greatest at sites categorized as sloping, top formations, or depressions. Others reported geomorphic forms (e.g., coastlines and ridges) that affected local movement influenced

infrastructure collision (Bevanger 1994, Cooper and Day 1998); however, we are not aware of studies measuring the influence of broad-scale topographic variation on collision.

Similarly, we are not aware of studies measuring the influence of infrastructure density on broad-scale collision risk. Our results support the hypothesis that increasing fence density on the landscape increases collision on sage-grouse breeding areas. Both Patten et al. (2005) and Wolfe et al. (2007) suggested landscape-scale habitat fragmentation by infrastructure likely increased lesser prairie-chicken mortality in Oklahoma relative to New Mexico; however, they did not measure fence or power-line densities. Moreover, most studies used fences or power-line segments themselves as sampling units in analyses, obfuscating effects of infrastructure density on collision (Baines and Summers 1997, Bevanger and Brøseth 2000, Shaw et al. 2010).

Although relative collision presence was influenced by region, topography, and fence density, collision counts appeared to also be influenced by a sites' proximity to nearest sage-grouse lek. Leks are traditional congregation points and activity centers for sage-grouse during the breeding season, thus distance to lek effects are likely a function of spring space use (Scott 1942, Patterson 1952, Gibson 1996). Lekking behavior has been hypothesized to influence infrastructure-collision risk for both birds and bats (Bevanger 1994, Baines and Summers 1997, Cryan 2008), and observations of sage-grouse colliding with fences near lekking areas were first reported in the 1940s (Scott 1942). Moreover, multiple studies hypothesized infrastructure in close proximity to leks may pose a threat to lekking species (Bevanger 1994, Baines and Andrew 2003). However, previous studies did not provide a measurable link between infrastructure-lek proximity and tetraonid collision risk.

Observed relationships between sage-grouse collision and broad-scale factors suggest these models may be useful predictive tools to identify high-risk areas across the landscape. Bevanger (1994) suggested information on behavior, geography and other factors be synthesized to develop infrastructure-collision predictive models for species of concern. Many previous studies were limited in scope to worst-case-scenarios, making landscape-scale prediction difficult (Bevanger 1998). Inherent stochasticity in collision frequency and lack of fine scale space-use data has lead some authors to suggest collision is not predictable at broad scales (Brown and Drewien 1995, Shaw et al. 2010). Shaw et al. (2010) tested model-predicted collision risk for blue cranes (*Anthropoides paradiseus*) in South Africa, and reported the model was not successful at predicting high-risk sites. However, this model was constructed using expert opinion, not field-collected data (Shaw et al. 2010). Spatial aggregation of collision reported in this and other studies suggest predictability at some spatial scale, and our broad-scale models showed reasonable internally- and cross-validated prediction success despite lack of fine-scale space-use data. Moreover, limited predictability from previous avian-collision studies may be a function of extrapolation across

scales (Miller et al. 2004), because most research only measured factors at the site-scale, and did not attempt to identify the appropriate scale for collision prediction.

Despite the relative prediction success of our broad-scale models, several inferential limitations exist with our data, and the consequences of collision for sage-grouse populations remain unknown. No research has addressed the effects of collision on demography for sage-grouse populations, and it is unclear if collision mortality is additive or compensatory to natural mortality. Population-level impacts of collision likely depend on a number of factors, including the proportion of collisions that result in mortality, cumulative numbers of male and female fatalities, and the ability of local populations to compensate for collision mortality. Our sampling provided a survey of relative collision presence and abundance during the early-mid lekking season for sage-grouse across southern Idaho, and no data currently exist on the proportion of collisions resulting in mortality. By sampling over broad areas, we documented sage-grouse fence collision was relatively common and widespread; however, in doing so, we sacrificed fine-scale data on temporal dynamics of collision over the lekking season at each site. The lek mating strategy of sage-grouse suggests moderate levels of male mortality during the breeding season may have little effect on population productivity. Moreover, many sage-grouse populations exhibit density dependent fluctuations (Garton et al. 2011), suggesting the ability to compensate for collision mortality may exist. However, large numbers of female sage-grouse killed via fence collisions during the lekking season would likely be problematic for local populations. More research is necessary to address demographic consequences of avian-infrastructure collision.

Additional inferential limitations are warranted with interpretation of results from current statistical modeling techniques applied to avian-collision data. We used logistic regression modeling, which, assuming no false zeros, modeled probability of collision presence at the time of sampling. However, biological interpretation of these results is complicated. Point-in-time sampling tells us little about collisions that occurred more than a few weeks prior to sampling (Santos et al. 2011, Stevens et al. 2011) or collisions that occur later in time. Thus, true zero observations may not remain zero observations over the entire period of biological relevance (e.g., lekking season). Therefore, timing of sampling relative to the temporal dynamics of collision is important for meaningful interpretation of results using current modeling techniques. Stevens et al. (2012) documented a seasonal peak of sage-grouse fence collision early-midway through the lekking season in southern Idaho; thus, our results are likely representative of peak collision occurrence for sage-grouse in our region. False-zero observations (i.e., failed detection) and the potential for variable detection over space and time further complicate interpretation of results, and interpretation should proceed with caution. Detection of collision evidence in sagebrush steppe varies with local habitat conditions (i.e., shrub height, big sagebrush vs. little sagebrush; Stevens et al. 2011), which could have influenced our modeling results. However, habitats were variable within

study regions, and we did not observe systematic differences in habitat as a function of topographic ruggedness or fence density; thus, systematic bias due to detection error was unlikely. These interpretation issues are prevalent for both presence-absence (i.e., logistic) and count-based (i.e., Poisson) modeling methods, and applying these methods to collision counts corrected for detection or removal bias (e.g., Bevinger 1999, Smallwood 2007, this study) does not account for estimation error in bias corrections. Specialized statistical techniques for modeling temporal dynamics of avian-collision data under imperfect detection and evidence-removal bias should be a research priority.

Differences in statistical methodology also make comparing our modeling results across scales difficult. We used generalized linear models for modeling collision at broad scales, but exploratory machine learning methods for classifying random and collision fence points at the site-scale. We conducted an exploratory analysis with site-scale data because no previous research studied sage-grouse fence collision. Moreover, specific hypotheses underlying microsite measurements used in site-scale analyses from previous tetraonid collision studies were often unclear, and we had little data on how sage-grouse visualize their environment to deduce specific hypotheses regarding site-scale attributes of fence collisions. Differences in methodology make cross-scale comparisons of our results difficult; however, covariate differences and measurement techniques also make these comparisons difficult, regardless of analytical methodology used. For example, topographic characteristics at the site scale (i.e., slope and aspect) are not directly comparable with those calculated over a square km (e.g., TRI), nor are technical attributes of fences. However, site-scale modeling had poor prediction success relative to broad-scale models, suggesting broad-scale factors may influence sage-grouse collision more than site-scale factors.

Despite inferential limitations of this research, ours is currently the only dataset to base management decisions regarding sage-grouse collision. Anthropogenic infrastructure such as wind-power turbines and oil and gas developments are currently expanding in many parts of the sage-grouse range (Kuvlesky et al. 2007, Knick et al. 2011, Naugle et al. 2011). These developments bring associated infrastructure such as roads and power lines. Sage-grouse may avoid large point-based infrastructure such as oil and gas wells (Doherty et al. 2008, Holloran et al. 2010); thus, our models do not likely apply directly to other infrastructure. However, increased infrastructure associated with development may have cumulative effects (Kuvlesky et al. 2007, Knick et al. 2011). Moreover, sage-grouse occasionally collide with power lines (Beck et al. 2006); thus, cumulative effects of infrastructure on sage-grouse populations should be addressed in future research.

MANAGEMENT IMPLICATIONS

Since no previous work systematically examined sage-grouse fence collision across the landscape, our models could serve as a conceptual framework for prioritizing areas for future mitigation such as fence marking or moving. Wolfe et al.

(2007) suggested fences within 1 km of prairie-grouse leks be targeted for marking efforts, however, our data suggest this may not be adequate in some areas. Our data suggest management should start with areas of high fence densities (e.g., >1 km of fence per square km), and fences within approximately 2 km of leks. However, topographic ruggedness appeared to attenuate the influence of other variables on fence-collision risk, with reduced collision at mean TRI values >5 m per square km, and nearly eliminated collision risk at mean TRI values >10 m per square km. Therefore, the above recommendations primarily apply to areas with relatively flat topography. Site-scale data suggested constructing fences using larger and more conspicuous wooden posts and with posts spaced at intervals <4 m may also reduce collision. However, population-level impacts of fence collision on sage-grouse demography are unknown, and future research should address this topic to ensure management efforts are allocated appropriately. Moreover, future research should attempt to replicate this work in space and time, and independently validate our model predictions by treating them as testable hypotheses of factors influencing collision in other areas (Miller et al. 2004).

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