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Underreporting of wildlife-vehicle collisions does not hinder predictive models for large ungulates

Nathan P. Snow
Michigan State University, nathan.p.snow@aphis.usda.gov

William F. Porter
Michigan State University

David M. Williams
Michigan State University

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Underreporting of wildlife-vehicle collisions does not hinder predictive models for large ungulates

Nathan P. Snow [*,1], William F. Porter, David M. Williams

480 Wilson Rd., Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI 48823, USA

ABSTRACT

Conflicts from wildlife–vehicle collisions (WVCs) pose serious challenges for managing and conserving large ungulates throughout the world. However, underreporting of large proportions of WVCs (i.e., two-thirds of WVCs in some cases) creates concern for relying on governmental databases to inform management strategies of WVCs. Our objective was to test the sensitivity of WVC studies to underreporting using 2 species of large ungulates that experience substantial incidences of collisions but exist in different environmental settings: white-tailed deer (*Odocoileus virginianus*) in agricultural-dominated central Illinois and moose (*Alces alces*) in forest-dominated western Maine, USA. We estimated baseline relationships between the landscape, traffic, and abundance of wildlife on the probabilities of WVCs using the total number of reported WVCs. Then, we simulated underreporting by randomly excluding reports of WVCs and evaluated for relative changes in precision, parameter estimates, and prediction. Point estimates of the relationships between environmental influences and WVCs for both species were reliable until high rates of underreporting occurred ($\geqslant 70\%$). When underreporting occurred with spatial bias, shifts in point estimates were detected only for variables that spatially-corresponded with the rate of reporting. Prediction estimates for both species were also reliable until high rates of underreporting occurred ($\geqslant 75\%$). These findings suggest that predictive models generate reliable estimates about WVCs with large ungulates unless underreporting is severe; possibly because they occur in non-random patterns (i.e., hotspots) and variability in their environment influences is low. We recommend that concern about underreporting not impede research with existing databases, such as those in this study, for analyzing predictive models and developing management strategies for reducing WVCs.

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1. Introduction

Vehicular collisions with wildlife are one of the most widespread and persistent human–wildlife conflicts that exist throughout the United States and the world (Conover, 2010; Huijser et al., 2009). Predictive studies are used to identify high risk locations of WVCs for many species (Gunson et al., 2011), but these studies are afflicted by various sources of measurement error. These errors include: (1) the incidences of WVCs are underreported (e.g., Donaldson and Lafon, 2010), thus many WVCs are excluded from study or misclassified as non-collision locations, (2) the spatial locations of WVCs are inaccurately reported (e.g., Gunson et al., 2009), and (3) the attributes of the environment near WVCs (e.g., land cover) are misclassified (e.g., Foody, 2002). In this manuscript we focus on the primary source of error, underreporting. To our

knowledge, no studies have examined the extent at which underreporting effects predictive models of WVCs.

The degree of underreporting for WVCs is particularly concerning for natural resource and transportation managers that attempt to reduce collisions with large ungulates. These collisions represent the most dangerous WVCs for humans (Huijser et al., 2008), and fatalities have increased 104% since 1990 (Sullivan, 2011). Reducing collisions relies on accurate information about the ecological drivers of WVCs to determine cost-effective mitigation strategies (Forman et al., 2003). However, obtaining reliable information is difficult because two-thirds or more of WVCs go unreported in national crash databases each year in the United States (Huijser et al., 2008). This large amount of underreporting may reduce the ability to distinguish ecological drivers of WVCs, or shift the estimates of statistical relationships if underreporting is unevenly distributed throughout an area of study (i.e., spatially biased; Groves, 2004; Lavrakas, 2008).

Reporting of WVCs generally consists of 2 data collection methods: (1) collision reported data, or (2) carcass removal data (Donaldson and Lafon, 2010; Huijser et al., 2007; Lao et al.,

* Corresponding author. Tel.: +1 970 266 6041; fax: +1 970 266 6010.
  E-mail address: nsnow@msu.edu (N.P. Snow).
[1] USDA/APHIS, Wildlife Services, National Wildlife Research Center, 4101 Laporte Ave., Fort Collins, CO 80521, USA.

2011). Collision reported data are afflicted with underreporting because some WVCs include insufficient property damage to warrant reporting; motorist decide not to report; or police, natural resource, and transportation agency conclude that the accident does not merit reporting (Huijser et al., 2008). Carcass removal data are afflicted with underreporting because of long time intervals between carcass collection activities, injured animals move away from roads following collisions (e.g., Snow et al., 2012), carcasses are scavenged or decomposed, carcasses are out of sight and not detected, or the carcass is not a species of concern (e.g., Knapp et al., 2005; Olson et al., 2014). Reports of WVCs are usually greater in number for carcass removal data (e.g., Donaldson and Lafon, 2010), but the spatial coverage of carcass removal datasets often vary based on program funding and prioritized roads for carcass removal (e.g., Knapp et al., 2005). Also, not every state or county collects carcass removal data. Therefore, we chose to examine records of WVCs from governmental databases of collision reported data.

We examined collisions reports for 2 species of large ungulates that experience frequent WVCs and cause concern for human safety and property damage. Collisions with white-tailed deer (*Odocoileus virginianus*; Zimmermann, 1780) are the most frequently reported WVCs, estimated at >1 million each year in the United States (Conover et al., 1995). Deer–vehicle collisions generate the highest amount of monetary damage from WVCs, averaging $6717 per collision (Huijser et al., 2008). Collisions with moose (*Alces alces*; Linnaeus, 1758) generate the highest rate of human injuries and death. Up to 10% of collisions with moose result in human injury or fatality (Huijser et al., 2008). Databases of these WVCs provided the opportunity to independently assess sensitivity of predictive models to underreporting for 2 large ungulates that exist in differing environments with differing traffic regimes and population abundances.

The departments of transportation in Illinois and Maine prioritize collecting reports of deer– and moose–vehicle collisions, respectively. In Illinois, the reports are used to inform deer management strategies (University of Illinois Extension, 2013) and the reports in Maine provide information for managing moose–vehicle collisions (Maine Interagency Work Group of Wildlife/Motor Vehicle Collisions, 2001). Not all WVCs were accounted for because of underreporting, therefore we used 100% of the reported deer– and moose–vehicle collisions in these databases as baselines to approximate the true relationships between environmental variables and the probabilities of collisions. Thus, the baselines were limited in scope to the number of reported collisions.

The central question prompted by underreporting is whether statistical modeling of environmental conditions associated with WVCs is affected by lack of precision (i.e., estimates of regression coefficients with high degrees of uncertainty) or bias (i.e., inaccurate estimate of regression coefficients). Generally, statistical models are used to compare sites of collisions and non-collisions using logistic regression models and information theoretic procedures to evaluate how the landscape, traffic, and abundance of wildlife influence the probability of WVCs (Gunson et al., 2011). Regression coefficients and 95% confidence limits (CLs) are used to determine which variables influence the probability of WVCs (e.g., Danks and Porter, 2010; Finder et al., 1999; Snow et al., 2011) and infer management implications for reducing WVCs.

Our objective was to evaluate the sensitivity of statistical models that use collision data for detecting influences on the probability of WVCs from the surrounding landscape, traffic, and abundance of wildlife under varying degrees of underreporting. We used all of the reported collisions with deer and moose, respectively, to estimate baseline relationships between the environmental variables and the probabilities of deer– and moose–vehicle collisions. Then, we simulated underreporting of collision data by

removing records of WVCs, and examining the potential impacts for (1) reduction in precision of regression coefficients, (2) shifts in the regressions coefficients, and (3) reduction in the predictive power of models as underreporting increased. We sought to identify thresholds in reporting rates where precision, shifts in coefficients, and prediction became unstable and generated unreliable inferences. Our intent was to evaluate whether effects of underreporting were generalizable across different environmental conditions associated with different ecoregions, traffic, and population abundances by comparing WVCs with deer in Illinois and moose in Maine.

2. Materials and methods

2.1. Study area

Our study area (Fig. 1) included 50 counties in central Illinois (77,655 km^2) and portions of 3 counties in the western Maine (10,721 km^2). The vegetation in central Illinois was characteristic of the temperate, Prairie Parkland ecosystem province (Bailey, 1980, 1995). The landscape contained agriculture (74%), development (9%), intermixed deciduous trees (1.5%), and prairies and groves (<1%). Row crops are comprised primarily of a corn and soybean matrix (Rosenblatt et al., 1999). Central Illinois contains 71,498 km of public roads, for an overall road density of 0.9 km/km^2. During 2007–2008, density estimates for deer within central Illinois were estimated at 6.1–25.2 deer/km^2 (Anderson et al., 2013).

Vegetation in western Maine was characteristic of the Adirondack–New England Mixed Forest–Coniferous Forest–Alpine Meadow ecosystem province (Bailey, 1980, 1995; Maine Office of GIS, 2010). Vegetation in western Maine was composed of deciduous, conifer, or mixed forests (85%), interspersed shrub wetlands (6%), and development (3.5%). Western Maine contains 2474 km of public roads, for an overall road density of 0.2 km/km^2. The densities of moose in and near this region were estimated to be approximately 0.4–4.0 moose/km^2 during 2010–2011 (Kantar and Cumberland, 2013).

2.2. Study design

For each species, we attempted to reduce nuisance uncertainty in our predictive models from environmental variation by selecting study areas with evenly distributed human populations (i.e., no large cities) and uniform landscapes. For each species, we also attempted to reduce nuisance uncertainty from small sample sizes. Substantially more deer–vehicle collisions were reported annually in Illinois than moose–vehicle collisions in Maine, therefore we examined 1 year of collisions in Illinois and combined 10 years of collisions in Maine. Reports of moose–vehicle collisions in western Maine did not fluctuated widely (i.e., 100–160 collisions/yr.) during the last 2 decades (Danks and Porter, 2010), therefore combining years was reasonable.

Underreporting confounds identification of non-collision sites because (1) either no WVC occurred, or (2) a WVC occurred but was not reported. We included this uncertainty into the study by generating a set of independent, systematic sites for each species that were ⩾1.5 times the number of reported collisions for each species. We generated 1.5 times more systematic sites to create a large enough pool to draw new samples of independent sites for the simulations described below. The systematic sites were generated along the study roads at intervals of 5000 m ($n = 14,306$ random points) for deer, and 500 m for moose ($n = 4877$ random points) to create the desired sample size using ArcGIS (v10.1; Environmental Systems Research Institute, Inc., Redlands, CA).
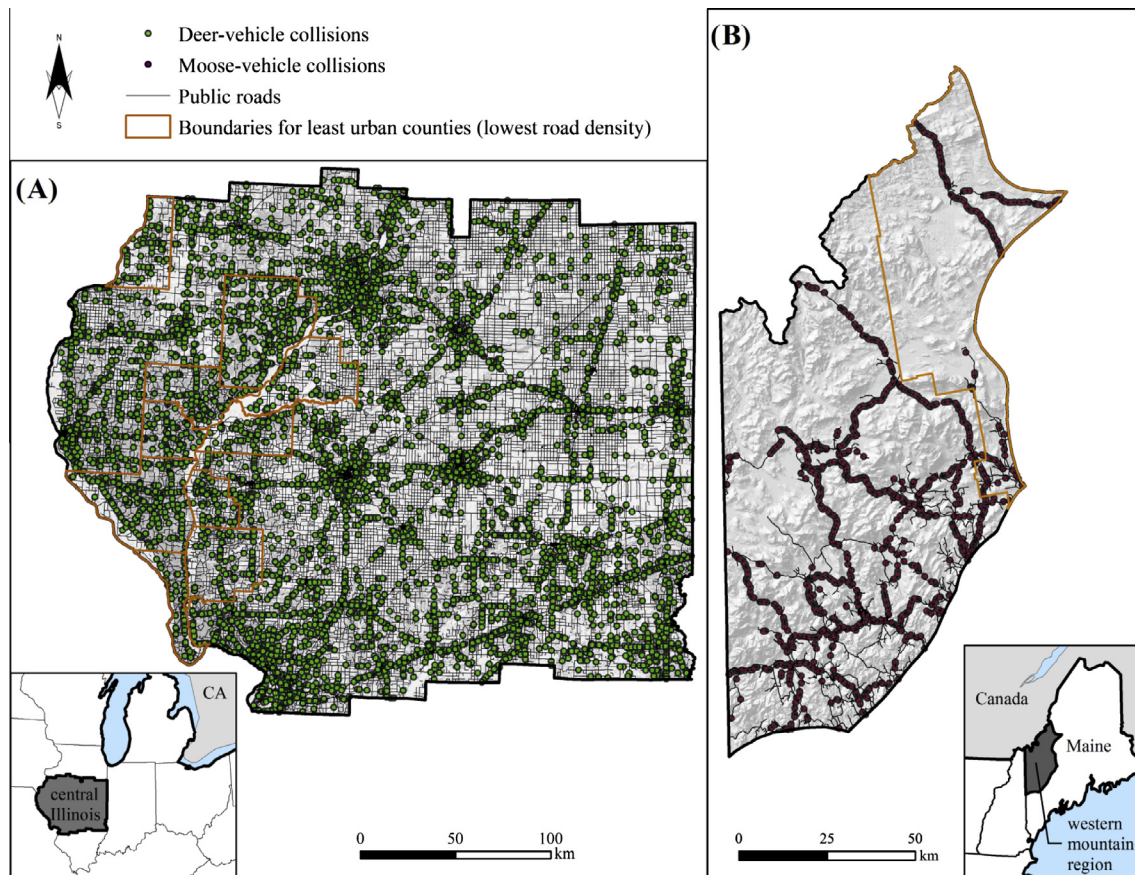
Fig. 1. Study area locations of reported (A) deer–vehicle collisions in central Illinois, USA during 2011, and (B) moose–vehicle collisions in western Maine, USA during 2000–2011.

2.3. Data collection

We used a governmental database of 8060 deer–vehicle collisions in central Illinois that occurred during 2011, provided by the Illinois Department of Transportation. These data were compiled from law enforcement officials where ⩾$1500 in property damage or human injury occurred, with an estimated location accuracy of ±400 m (C. Adams, Illinois Department of Transportation, personal communication). For moose–vehicle collisions, we used a governmental database of 1067 recorded collisions in western Maine during 2000–2010, provided by the Maine Department of Transportation. These data were compiled from law enforcement officials at accident sites where ⩾$1000 in property damage or a human injury occurred, with an estimated location accuracy of ±160 m (D. Brunell, Maine Department of Transportation, personal communication). The locations of both deer– and moose–vehicle collisions were recorded using distance measurements from reference points along public roads (e.g., intersections or bridges).

We used the 2006 National Land Cover Database with 84% classification accuracy (Wickham et al., 2013) to represent land cover and land use throughout central Illinois (Fry et al., 2011). For western Maine, we used the National Gap Analysis Program (GAP) Land Cover Data-Version 2 (U.S. Department of the Interior|U.S. Geological Survey, 2012). The classification accuracy for GAP data is currently being evaluated. Both land-cover and land-use databases were based on data collected with Landsat 7 Thematic Mapper with 30 m resolution. We reclassified the land-cover and land-use databases (see reclassification scheme in Appendix 1) to 7 classes for deer (Anderson et al., 1976; Williams et al., 2012) and 11 classes for moose (Allen et al., 1987; Danks and Porter,

2010; Koitzsch, 2002) to be consistent with the reported habitat requirements for each species (Table 1).

Previous studies, based on collision reports that were collected to the nearest mile marker, identified that 800 m buffers around observations were useful for explaining influences on deer–vehicle collisions (Finder et al., 1999; Ng et al., 2008). To maintain consistency with these studies, we used 800 m buffers to calculate composition and configuration metrics of the landscapes using FRAGSTATS (v4.1, University of Massachusetts, Amherst) for deer in Illinois. We calculated 3 composition metrics using the proportions of land-cover types, including the proportion of agriculture (AGRICULTURE), proportion of forest (FOREST), and proportion of water (WATER). We calculated 2 configuration metrics, contrast-weighted edge density (EDGE) and a contagion index (CONTAGION). These

Table 1
Reclassified land-cover and land-use types for 2 study species: (A) white-tailed deer in central Illinois, USA (2010), and (B) moose in western Maine, USA (2000–2010).

(A) Central Illinois		(B) Western Maine	
Class	%	Class	%
Agriculture	74.5	Deciduous-mixed forest	57.4
Forest	15.0	Coniferous forest	27.6
Developed	8.6	Shrub wetland	5.2
Water	1.3	Open water	3.9
Wetlands	0.3	Cutover Forest	2.2
Rangeland	0.2	Developed	1.4
Barren	0.03	Nonwoody wetland	1.0
		Agriculture	0.9
		Forested wetland	0.3
		Other	0.2

metrics represented measures of edge and fragmentation in the agro-forested landscape, because deer have higher densities in landscapes with these characteristics (Campa et al., 2011; Lovely et al., 2013). Contrast-weighted edge density was a measure of the length of edges between agriculture and forest land-cover classes, and between rangeland and forest classes within each county (km/km^2). Contagion served as an index of the aggregation and interspersion among all land-cover and land-use patches. A contagion value of 0 represented a highly fragmented and intermixed landscape, whereas a value of 100 represented a landscape comprised of a single patch.

A previous study, based on the same database of moose–vehicle collisions used here, identified that 2500 and 5000 m buffers around observations were most useful for explaining influences on moose–vehicle collisions (Danks and Porter, 2010). To be consistent with these findings, we used the same buffer sizes to calculate metrics of the landscape in Maine. We calculated 3 composition metrics that influenced landscape-level habitat suitability for moose (Allen et al., 1987; Dussault et al., 2006; Koitzsch, 2002). These included proportion of conifer forest (CONIFER), proportion of cutover forest (CUTOVER FOREST), and the Simpson's diversity index (SIDI) of land cover and land use within the 2500 m buffer. The SIDI was a measure of land-cover and land-use richness on a 0–1 scale, where 1 represents the richest landscape. We calculated 1 configuration metric to represent a measure of interspersion of land-cover and land-use patches, which is also important for habitat suitability for moose (Dussault et al., 2006). We used an interspersion–juxtaposition index (IJI) to examine the complexity of the landscape within the 5000 m buffer on a 0–100 scale, where a value of 100 represents high interspersion of patches.

For moose, we used some other measures of the landscape that were associated with moose–vehicle collisions (Danks and Porter, 2010). We used ArcGIS to calculate the nearest distances to 3 landscape features: distance to the nearest shrub-wetland land-cover patch (SHB_WETLAND), distance to the nearest stream (STREAM), and distance to the nearest developed area (DEVELOPED). We used shapefiles depicting streams and human development based on 1:24,000 quadrangles (Maine Office of GIS, 2010). We also calculated the degree slope (SLOPE) at each site using a 10-m digital elevation map from the United States Geological Survey, National Elevation Dataset (Gesch et al., 2002; Gesch, 2007).

We examined characteristics of the volume of traffic to examine for influences on WVCs. We used estimates of annual average daily traffic (AADT) provided by Illinois and Maine Departments of Transportation for deer and moose, respectively, at each observation. The estimates of AADT were used to represent the volume of traffic (TRAFFIC) in our models at each WVC location. For deer, we used an additional measure of the intensity of traffic: estimates of the numbers of registered vehicles per county (REGISTERED_VEH) provided by the Illinois Secretary of State. We used speed limits (SPEED) at each observation point for moose. We estimated the relative abundance of deer using estimates of antlered deer harvested by county provided by the Illinois Department of Natural Resources (ABUNDANCE). The numbers of harvested moose were not identified as good predictors of where moose–vehicle collisions occurred in western Maine (Danks and Porter, 2010), thus we did not include this variable in our analyses.

2.4. Data analysis

Current studies of WVCs often use model selection procedures to identify the best models for predicting where WVCs are most likely to occur (e.g., Danks and Porter, 2010; Ng et al., 2008; Snow et al., 2011). To imitate these studies, and to evaluate how underreporting affected models with differing predictive capabilities, we examined 2 predictive models for the probabilities of WVCs for each

species based on surrounding environmental conditions. One model was considered to have good predictive capabilities and the other had poor capabilities. Our criteria for the predictive capability was based on area under the receiver operating characteristic function (AUC) where good models had a value of $\geqslant 0.7$ and poor models had a value of <0.7 (Hosmer et al., 2013). We assessed these criteria for models conducted using 100% of the reported WVCs for each species. The models we evaluated were:

$$\text{Deer model (good)} : p = \text{TRAFFIC} + \text{ABUNDANCE} + \text{EDGE} \\ + \text{CONTAGION} + \text{AGRICULTURE} + \text{FOREST},$$

$$\text{Deer model (poor)} : p = \text{REGISTERED\_VEH} + \text{ABUNDANCE} \\ + \text{WATER},$$

$$\text{Moose model (good)} : p = \text{TRAFFIC} + \text{DEVELOPED} \\ + \text{SHB\_WETLAND} + \text{IJI} + \text{CUTOVER FOREST} \\ + \text{CONIFER} + \text{SPEED},$$

$$\text{Moose model (poor)} : p = \text{STREAM} + \text{SIDI} + \text{SLOPE},$$

where p was probability of a site being a WVC.

We conducted an intercorrelation analysis of the data and excluded the less biologically interpretable explanatory variable(s) from any correlated pair (i.e., $|r| \geqslant 0.70$; Program R v2.15.1; R Development Core Team). We scaled and centered the remaining variables (i.e., subtracted the mean and divided by the standard deviation) to allow standardized comparisons among regression coefficients. We examined for influences on locations of deer- and moose–vehicle collisions by comparing attributes of reported collisions to the systematic sites where WVCs were not reported using a maximum-likelihood approach with generalized linear models following binomial error terms and logit-link functions in Program R. We examined the logistic regression coefficients ($\hat{\beta}$) and 95% confidence limits (CLs) to ascertain the strength and directionality of the potential influences from each environmental variable on the probability of a location reportedly being a deer- or moose–vehicle collision.

2.5. Evaluating sensitivity in precision

First, we analyzed the above models using 100% of the reported WVCs for each species to identify the relative baselines of estimated relationships between the predictor variables and the probabilities of deer- and moose–vehicle collisions. Then, we evaluated the effects of underreporting by randomly excluding reports of deer- and moose–vehicle collisions, and examining for deviation from those relationships. We randomly excluded points by sampling collision locations, without replacement, for deer- and moose–vehicle collisions using the sample function in Program R. We sampled collisions in increments of 5% to represent levels of 0–95% underreporting ($n = 20$ levels of underreporting). At each level, we resampled and evaluated 10,000 Monte Carlo simulations for each of the 2 models for deer- and moose–vehicle collisions.

We randomly sampled from the systematic sites to represent locations where WVCs were not reported (i.e., non-collision sites) using a 2-step process for each simulation. First, we excluded any of the systematic sites that were within 500 m from the subsampled locations of WVCs being examined in the simulation to avoid confounding sites of reported WVCs with sites where WVCs were not reported. We used distances of $\geqslant 500$ m to ensure these sites were outside of the estimated accuracy distances of the reported sites of WVCs. Then we sampled the remaining systematic sites in numbers that were equivalent to the subsampled WVCs being examined in the simulation. This way we consistently

compared equivalent numbers of subsampled WVCs to subsampled systematic sites where WVCs were not reported, and ensured that these sites never overlapped each other.

We plotted the mean regression coefficients and 95% CLs from the 10,000 simulations to evaluate their sensitivity to different levels of underreporting. We evaluated the precision of the regression coefficients by examining the spread of the 95% CLs and examining for any changes in statistical significance (i.e., lost or gained significance) as underreporting increased. We considered reductions in precision by factors of 2 (i.e., doubling of the spread of 95% CLs) from the baseline estimates as undesirable for making statistical inferences.

2.6. Evaluating sensitivity to biased reporting

Reporting of WVCs may not be consistent among geographic jurisdictions (Knapp et al., 2005). Therefore, we conducted similar analyses as described above, but we included a spatial bias in reporting for deer– and moose–vehicle collisions based on jurisdictions of county boundaries. We simulated reporting rates to be biased low throughout 10 of the 50 counties in central Illinois, and 1 of the 3 counties in western Maine (Fig. 1), representing approximately 20% of each study area. We selected these counties because they had the lowest densities of roads and thereby represented the least urban counties in each study area. Urbanization has been identified as an important, county-level, predictor for the incidence of WVCs with ungulates (Farrell and Tappe, 2007; Finder et al., 1999; Iverson and Iverson, 1999). For these counties, we sampled deer– and moose–vehicle collisions to represent levels of 0–100% underreporting in 5% increments. The remaining counties were held constant at 100% reporting in order to isolate any effects from spatial bias. We randomly sampled the systematic sites where WVCs were not reported using the same methodology as described above. We conducted 10,000 Monte Carlo simulations of the logistic regression models for each level of underreporting. We plotted the mean parameter estimates and 95% CLs to evaluate their sensitivity to underreporting and determine whether reporting bias shifted the statistical interpretation for each explanatory variable.

2.7. Evaluating sensitivity in model prediction

For each simulation used to evaluate precision, we randomly withheld 10% of the subsampled deer– and moose–vehicle collisions and 10% of the subsampled systematic sites to predict and validate the models. We input these data into the logistic regression models and examined how well the models correctly classified the withheld data (i.e., collisions or non-collisions). We used the pROC package in Program R (Robin et al., 2011) to calculate the AUC values and their 95% CLs using for determining the predictive capabilities of the models. We plotted the mean AUC values and 95% CLs from the 10,000 Monte Carlo simulations for each analysis.

For each simulation used to evaluate bias, we randomly withheld 2 sets of data to compare how well the biased models predicted: (1) new-biased data, and (2) new-unbiased data. The first set of withheld data included 10% of the subsampled deer– and moose–vehicle collisions that were spatially biased, and an equivalent number of subsampled systematic sites. The second set included randomly sampled deer– and moose–vehicle collisions from the full datasets of reported WVCs (i.e., not spatially biased), and an equivalent number of subsampled systematic sites. Both the biased and unbiased sets of data had equal sample sizes so we could directly compare at each level of underreporting. We plotted the mean AUC values and 95% CLs from the 10,000 Monte Carlo simulations for both sets of data.

3. Results

Overall, we conducted 1,640,000 Monte Carlo simulations of logistic regression models to evaluate the sensitivity of precision, shifts in regression coefficients, and prediction of statistical models to underreporting of deer– and moose–vehicle collisions. When underreporting occurred without spatial bias (i.e., random underreporting) for deer–vehicle collisions, we found that the precision of regression coefficients remained relatively stable until $\geqslant 70\%$ of collisions were unreported (Fig. 2). Above this level of underreporting, the amount of uncertainty doubled. For 2 of 9 variables (EDGE and REGISTERTED_VEH), the 95% CLs began overlapping zero indicating a loss of statistical significance when $\geqslant 90\%$ of deer–vehicle collisions were unreported. The point estimates of the coefficients remained stable up to 95% of deer–vehicle collisions being unreported.

We found similar results for moose–vehicle collisions when underreporting occurred without spatial bias. The precision of regression coefficients were stable until $\geqslant 70\%$ of collisions were unreported (Appendix 2). For 1 of 10 variables (SHB_WETLAND), the 95% CLs began overlapping zero when $\geqslant 60\%$ of moose–vehicle collisions were unreported. Five other variables (CONIFER, IJI, DEVELOPED, STREAM, and SIDI) lost statistical significance after $\geqslant 85\%$ of moose–vehicle collisions were unreported. The point estimates of the coefficients remained stable with up to 95% of moose–vehicle collisions being unreported.

The 10 least urban counties in central Illinois contained 1458 reports of deer–vehicle collisions, representing 18% of the total records. When underreporting was spatially biased, we found the point estimates of regression coefficients for 1 variable in both models (ABUNDANCE) shifted starting at 5% of deer–vehicle collisions being unreported (Fig. 3). This shift became stronger as fewer collisions were reported. The average values of ABUNDANCE were substantially higher in the least urban counties compared to the other counties (Table 2), suggesting that the abundance of deer was spatially correlated with the biased rates of reporting. Point estimates for 5 other variables also shifted slightly as fewer collisions were reported (AGRICULTURE, FOREST, EDGE, CONTAGION, REGISTERTED_VEH), although these shifts did not change statistical inferences. The average values for these 5 variables were also unevenly distributed between the least urban and other counties (Table 2).

We found similar results for moose–vehicle collisions when underreporting was spatially biased. The least urban county in western Maine contained 229 reports of moose–vehicle collisions, representing 21% of the total records. Point estimates for 1 of 10 variables (SLOPE) shifted as fewer collisions were reported (Appendix 3) and changed statistical significance. The average degree of slope throughout the least urban county was lower than the other counties (Table 2), indicating a spatial correlation with the biased reporting. Statistical inferences for the other variables remained stable.

The predictive capabilities of both good and poor models for deer– and moose–vehicle collisions were similarly affected by underreporting of collisions. When underreporting occurred randomly, the estimated AUC values were not affected by underreporting (Appendix 4). The AUC values remained constant for predicting deer–vehicle collisions (i.e., $\sim$0.80 for the good model and $\sim$0.60 for the poor model), and for predicting moose–vehicle collisions (i.e., $\sim$0.87 for the good model and $\sim$0.67 for the poor model). However, imprecision around the AUC values doubled after approximately $\geqslant 75\%$ of collisions were unreported for deer and moose. When underreporting occurred with spatial bias, the predictive capabilities of the biased models were similar between the new-biased and new-unbiased data for deer– and moose–vehicle collisions (Fig. 4). The only situation in which we observed prediction was
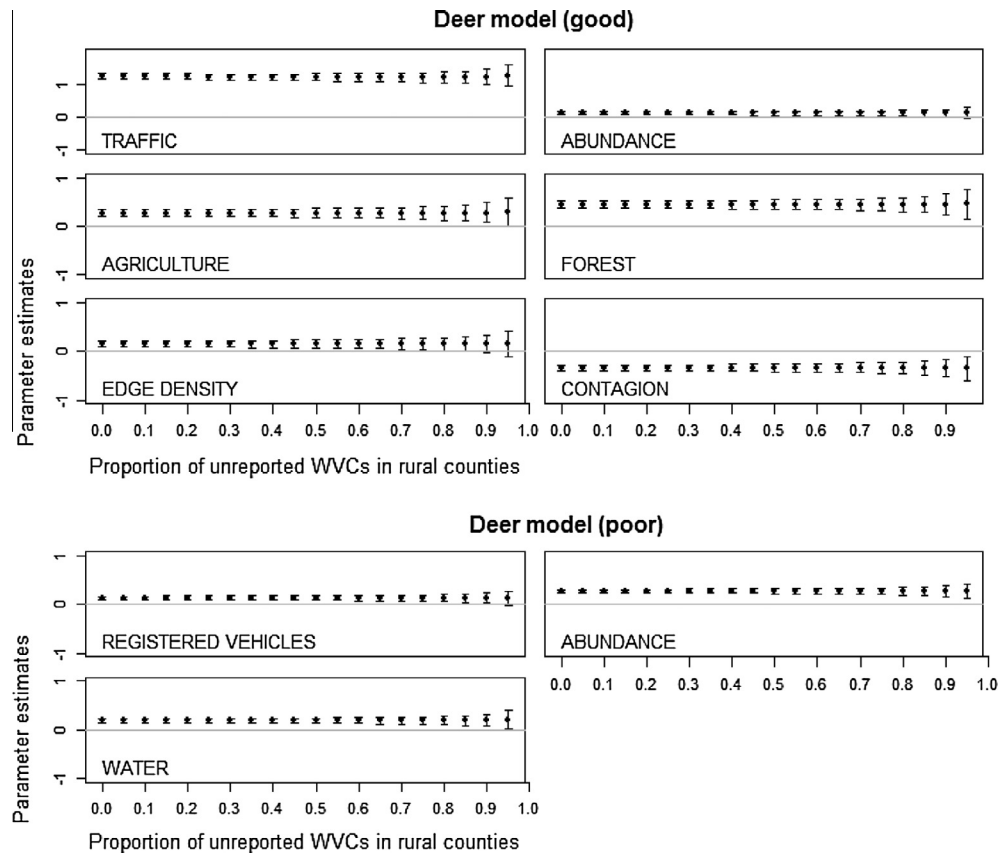
Fig. 2. Average parameter estimates (black circles) and 95% confidence intervals (black lines) from 10,000 Monte Carlo simulations of logistic regression analyses at different levels of underreporting for deer–vehicle collisions in central Illinois, USA, during 2011. We examined for changes in precision and shifts in estimates as fewer collisions were reported for models with good and poor predictive capabilities.

substantially affected by spatial bias in underreporting occurred at 100% underreporting for the poor model of deer–vehicle collisions in the least urban counties. Here, the ability to predict the new-unbiased data was reduced, indicating that the biased model was statistically significantly affected by underreporting.

4. Discussion

We sought to determine the extent that underreporting of WVCs with large ungulates affects statistical analyses for investigating the relationships between environmental variables and the probabilities of WVCs. The true relationships between environmental variables and the probabilities of WVCs are unknown in this study because not all WVCs were reported. Therefore, our findings are based on changes in statistical inferences from baseline relationships generated using the total number of WVCs that were reported. We expect these baseline relationships represented good approximations of the true relationships, given the stability of parameter estimates throughout most levels of underreporting.

We identified similar effects from underreporting for deer–vehicle collisions in central Illinois and moose–vehicle collisions in western Maine. These similarities suggest that the effects of underreporting are consistent across studies of WVCs. This consistency across species and landscapes can likely be explained by the tendency of WVCs with ungulates to occur in non-random patterns, or hotspots (e.g., Danks and Porter, 2010; Huijser et al., 2008; Ng et al., 2008). The existence of hotspots indicates there is little variation in how environmental conditions influence where WVCs occur. For any species with less aggregated patterns of WVCs, these results may not apply.

Where underreporting occurs without spatial bias (i.e., random underreporting), our findings indicate that the predictive models for locations of WVCs were mostly robust to underreporting. Estimates of precision for the regression coefficients were stable with a wide range (0–70%) of underreporting. With more underreporting, the decrease in sample size caused reduced statistical power (Krebs, 1999) and difficulty in detecting some relationships between the environmental variables and the probability of WVCs. Reporting rates for deer–vehicle collisions have been estimated at 42–50% (Decker et al., 1990; Marcoux and Riley, 2010; Romin and Bissonette, 1996), below the 70% underreporting threshold we identified. Reporting rates for moose are unknown, but we expect underreporting to also be below 70% because collisions with large animals often result in high property damage or human injury.

Where underreporting occurs with spatial bias, our findings indicate that models of WVCs are less robust to underreporting. We detected shifts in 2 of 9 estimates of regression coefficients for deer and 1 of 10 estimates for moose, but only for variables that spatially-corresponded with the biased rate of reporting. For example, the average ABUNDANCE was substantially higher (1043) in the 10 counties we selected to have lower reporting than in the other 40 counties (633). This discrepancy changed the statistical influence of ABUNDANCE because fewer collisions were reported in regions that had higher abundances of deer. In this case, the uneven rates of reporting combined with uneven distribution of environmental variables results in shifted statistical inferences, but the shifts were less noticeable at higher rates of reporting. Therefore, higher rates of reporting lessened shifts in regression coefficients, but did not eliminate it. These types of unreliable inferences are produced in survey studies because some groups
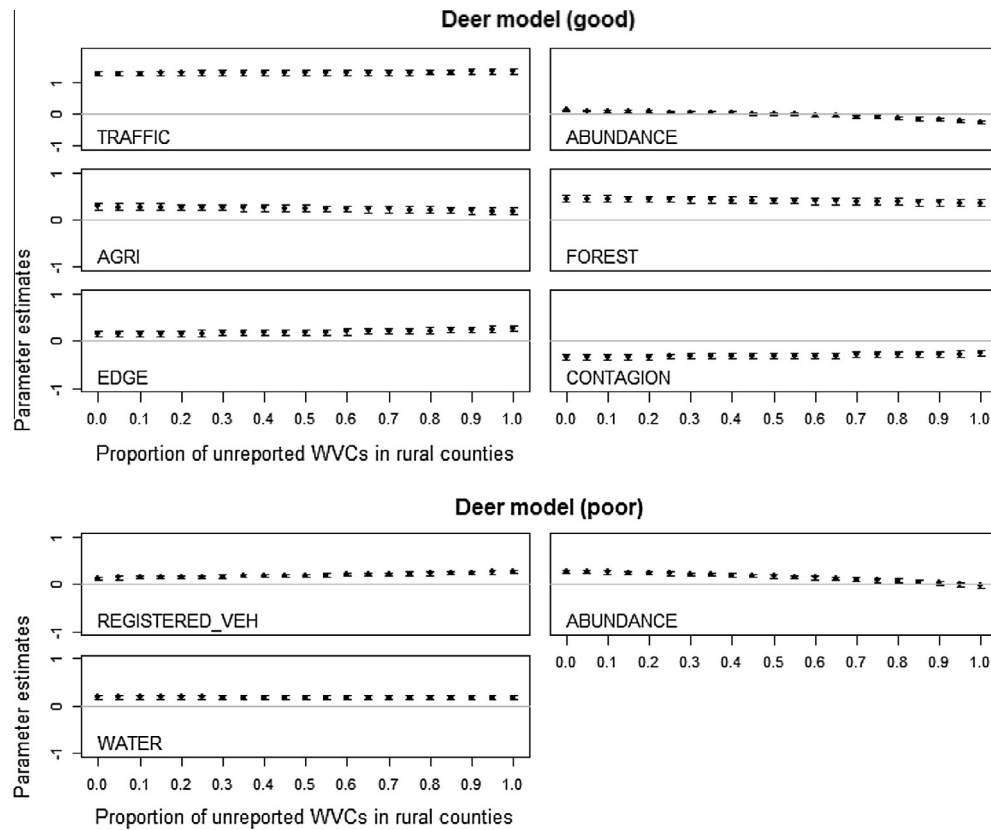
Fig. 3. Average parameter estimates (black circles) and 95% confidence intervals (black lines) from 10,000 Monte Carlo simulations of logistic regression analyses including spatial biases in reporting for different levels of underreporting for deer–vehicle collisions in the most rural counties in central Illinois, USA, during 2011. We examined for changes in precision and shifts in estimates as fewer collisions were reported for models with good and poor predictive capabilities.

Table 2
Averaged values for environmental variables in counties used to examine influences on the probabilities of deer–vehicle collisions in central Illinois (2010) and moose–vehicle collisions in western Maine (2000–2010). Biased counties represented counties in which the rates of reporting for collisions were simulated to be lower than unbiased counties.

| Central Illinois			Western Maine		
Environmental variable (deer)	Biased counties	Unbiased counties	Environmental variable (moose)	Biased counties	Unbiased counties
TRAFFIC	956	3301	TRAFFIC	1357	1684
CONTAGION	65.5	74.0	DEVELOPED (m)	3170	2493
EDGE (km/km²)	34.2	18.1	SHB_WETLAND (m)	289	408
ABUNDANCE*	1043	633	STREAM (m)	444	412
AGRICULTURE	0.60	0.77	IJI	50.0	54.3
FOREST	0.29	0.13	CONIFER	0.27	0.28
WATER	0.03	0.01	CUTOVER FOREST	0.02	0.02
REGISTERED_VEH	16,810	59,291	SIDI	0.59	0.58
			SLOPE (°)*	5.9	8.2
			SPEED (km/h)	75.8	72.9

TRAFFIC = annual average daily traffic, CONTAGION = contagion index of land-cover and land-use types, EDGE = contrast-weighted edge density among land-cover and land-use types, ABUNDANCE = index for abundance of deer from estimated harvest of antlered deer, AGRICULTURE = proportion of agriculture, FOREST = proportion of forest, WATER = Proportion of water, REGISTERED_VEH = number of registered vehicles, DEVELOPED = distance to nearest developed area, SHB_WETLAND = distance to nearest shrub wetland, STREAM = distance to nearest stream, IJI = interspersion/juxtaposition index of land-cover and land-use types, CONIFER = proportion of conifer forest, CUT-OVER FOREST = proportion of cutover (harvested) forest, SIDI = Simpson's index of diversity for land-cover and land-use types, SLOPE = degree of slope, SPEED = posted speed limit.
   * Represents variables with shifting regression coefficients from logistic regression models as fewer collisions were reported.

or locations may be sampled less and incomplete information is used in data analyses (Groves, 2004; Lavrakas, 2008). Our analysis indicated that where the distribution of explanatory variables correspond with biased reporting rates, the most risk of shifting regression coefficients and inaccurately characterizing the environmental influences of collisions exists.

The performances of the good and poor predictive models were similarly affected by underreporting. When underreporting was not spatially biased, the precision of AUC values remained stable until ⩾75% of WVCs were unreported. When underreporting was

spatially biased, the predictive capabilities of the models remained mostly stable, indicating a high degree of robustness to spatially biased underreporting. The one exception in predictive performance suggests that the robustness of models is related to the relative importance of each variable. Relative to other variables in the models, the importance was low for ABUNDANCE in the good model for deer–vehicle collisions but high in the poor model. In both cases, the strength and directionality of effects for ABUNDANCE were increasingly shifted as fewer deer–vehicle collisions were reported. However when underreporting was high, the good
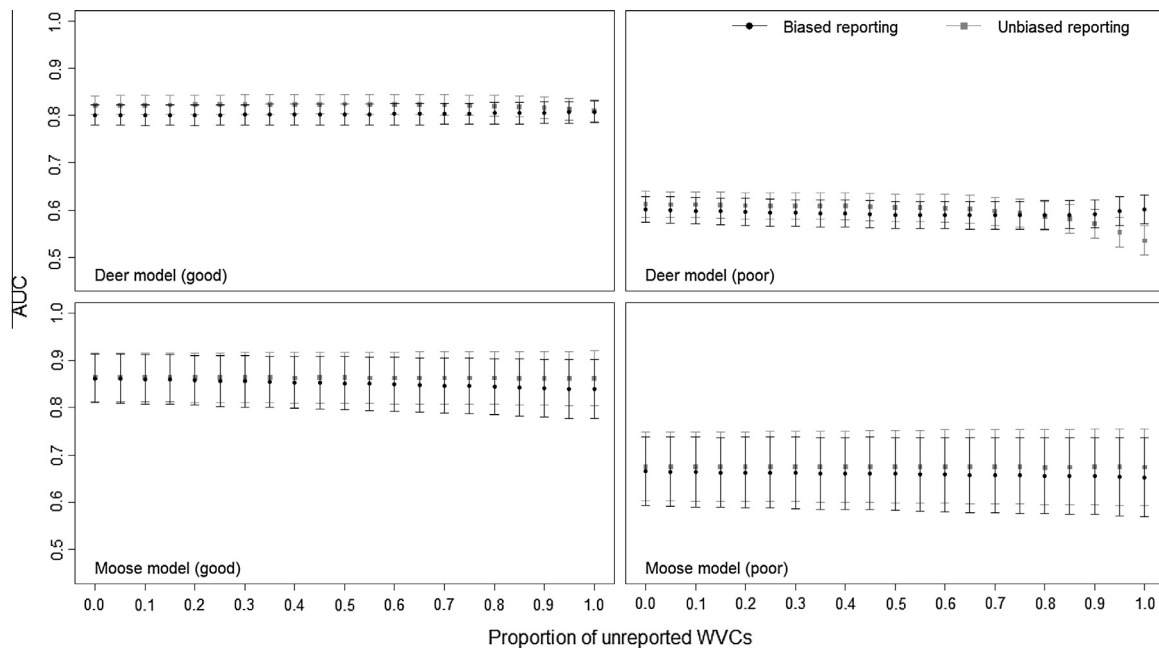
Fig. 4. Average receiver operating characteristic function (AUC) and 95% confidence intervals for logistic regression analyses including spatial biases in reporting for the least urban counties for deer–vehicle collisions in central Illinois, USA, during 2011 and moose–vehicle collisions in western Maine, USA during 2000–2011. The AUC values were calculated from 10,000 Monte Carlo simulations at different levels of underreporting.

model was capable of predicting new-unbiased data because the model indicated that ABUNDANCE has little for no impact for predicting the probability of WVCs. The poor model was less capable because the contribution of ABUNDANCE was more important in this model.

Findings from this study can be applied globally for large ungulates, particularly for deer and moose. For instance, Central European roe deer (*Capreolus capreolus*) experience frequent WVCs (e.g., Hothorn et al., 2012). With low to moderate levels of underreporting, planned road protection and hunting quotas can be relied on for reducing collisions. Similarly, models to predict risk of moose–vehicle collisions in Sweden (e.g., Seiler, 2005) should reliably inform mitigation strategies. In addition to large ungulates, our findings may provide new insights for WVCs with smaller animals, or for WVCs that are rare. Snow et al. (2012) found that only 50% of mortalities from vehicles for island foxes (*Urocyon littoralis*) would have been detected without radio-telemetry, even though active searches for road-killed foxes were being conducted. Collisions with the foxes were not strongly associated with environmental variables (Snow et al., 2011), perhaps because of increased statistical uncertainty from having less frequent collisions and high underreporting. In such cases, high underreporting decreases statistical power and lessens the ability to distinguish relationships between the environment and WVCs.

Our findings extend to other applications of WVC data. For instance, Baker et al. (2004) suggested that road-kills of red foxes (*Vulpes vulpes*) in the United Kingdom could be used to monitor population changes for foxes. Similarly, Gehrt (2002) examined for population changes of raccoons (*Procyon lotor*) using road-kill surveys in Illinois, USA. Our findings indicate that underreporting is an important consideration for such studies, because population indices may be unreliable if rates of reporting are spatially biased. Ensuring consistent reporting across space and time will generate the most reliable estimates.

We recognize that the biological inferences from the baseline relationships used in this study are afflicted by underreporting. These relationships were produced using 2 of the most comprehensive datasets of reported collisions available, to our knowledge.

We also recognize that the datasets of reported collisions used in this study are based on WVCs that occurred frequently, and therefore provide the benefit of examining large sample sizes. Underreporting for studies of rare events will likely generate more uncertain inferences because of reduced sample sizes (Krebs, 1999), and may need to be analyzed with more caution.

5. Conclusions

In conclusion, we address the concerns about underreporting of WVCs in governmental databases, and recommend that some caution is warranted. However, our findings suggest that such caution should not impede the use of these databases for developing statistically-based management strategies for reducing WVCs. Predictive models with reliable statistical estimates and accuracy can be generated by these databases, even with high degrees of underreporting. We offer assurance to researchers, and natural resource and transportation managers for fitting statistical models to datasets similar to those examined in this study.

Our simulations with databases of WVCs for deer in Illinois and moose in Maine illustrate that the 3 primary concerns about underreporting are overemphasized. First, we find that consistent statistical inferences about the relationships between WVCs and landscape, traffic, and abundance of wildlife can be drawn under wide ranges of underreporting (i.e., 0–70%). The baseline relationships for those environmental variables appear to represent good approximations of the true relationships, given the stability in parameter estimates with various levels of underreporting. Second, when underreporting is spatially biased (i.e., not random), shifts in parameter estimates only occur for explanatory variables that spatially-correspond with the rates of reporting. For instance, for counties have the lowest rate of reporting but the highest abundance of deer, the statistical influence of abundance on the probability of deer–vehicle collisions shift. The parameter estimates for all other explanatory variables are not affected by the spatial bias, suggesting a high degree of robustness. Third, we find that predictive capabilities of explanatory models are stable across most

levels of underreporting, until very high levels of underreporting ($\geqslant$75%) occur.

Underreporting is likely to occur randomly if reports are generated based on non-space-related criteria. For instance, the criteria for collision reports of deer– and moose–vehicle collisions often are based on the amounts of property damage or injury, not by location. Underreporting may also be random if data are collected using well-planned collection procedures (e.g., specifically-designed carcass collection). In these cases, predictive models can be reliably developed, even if the rates of underreporting are high. However, we do not recommend that fewer reports be collected as a consequence of this assurance, because predictive models will have higher accuracy with higher rates of reporting.

In situations where the consistency of reporting is unknown, we recommend that researchers examine the spatial patterns of explanatory variables for correspondence with the spatial pattern of WVCs. If the patterns are similar, spatial bias may exist in the data and cause shifts in regression coefficients. Increasing the rate of reporting will reduce shifts in parameter estimates, but will not overcome it. Where spatial bias is shown to occur, it will be important to determine the causes.

For WVCs that occur less frequently or that are less spatially aggregated than deer– or moose–vehicle collisions, higher rates of reporting may be necessary to produce reliable statistical inferences from predictive models. Consistency in the type of reports (e.g., collision or carcass), spatial resolution, and sample sizes remain important considerations for studies of WVCs. We hypothesize that our findings can be applied to other studies that use incidence reports to assess risk (e.g., survey studies).

Acknowledgments

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.biocon.2014.10.030.

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