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Incorporating Road Crossing Data into Vehicle Collision Risk Models for Moose (*Alces americanus*) in Massachusetts, USA

Katherine A. Zeller [1] · David W. Wattles[1] · Stephen DeStefano[2]

Abstract

Wildlife–vehicle collisions are a human safety issue and may negatively impact wildlife populations. Most wildlife–vehicle collision studies predict high-risk road segments using only collision data. However, these data lack biologically relevant information such as wildlife population densities and successful road-crossing locations. We overcome this shortcoming with a new method that combines successful road crossings with vehicle collision data, to identify road segments that have both high biological relevance and high risk. We used moose (*Alces americanus*) road-crossing locations from 20 moose collared with Global Positioning Systems as well as moose–vehicle collision (MVC) data in the state of Massachusetts, USA, to create multi-scale resource selection functions. We predicted the probability of moose road crossings and MVCs across the road network and combined these surfaces to identify road segments that met the dual criteria of having high biological relevance and high risk for MVCs. These road segments occurred mostly on larger roadways in natural areas and were surrounded by forests, wetlands, and a heterogenous mix of land cover types. We found MVCs resulted in the mortality of 3% of the moose population in Massachusetts annually. Although there have been only three human fatalities related to MVCs in Massachusetts since 2003, the human fatality rate was one of the highest reported in the literature. The rate of MVCs relative to the size of the moose population and the risk to human safety suggest a need for road mitigation measures, such as fencing, animal detection systems, and large mammal-crossing structures on roadways in Massachusetts.

Keywords *Alces americanus* · Massachusetts · Moose · Road ecology · Road-kill · Wildlife–vehicle collisions

Introduction

Between 1998 and 2007, there were over 1000 moose (*Alces americanus*)–vehicle collisions (MVCs) in the northeastern United States, causing 2–8 human fatalities annually (Mountrakis and Gunson 2009; Danks and Porter 2010; Wattles and DeStefano 2011). Due to their large body size, long legs, and high center of gravity, MVCs often result in the vehicle hitting the legs of the moose, which causes the body of the moose to collide with the windshield and passenger compartment. These collisions often lead to the death of the moose, extreme damage to the vehicle, and driver and passenger injury or death. The risk and severity of MVCs increase as traffic volume and speed increase (Lavsund and Sandegren 1991; Joyce and Mahoney 2001; Seiler 2005; Danks and Porter 2010; Neumann et al. 2012). Huijser et al. (2009) estimated the cost per MVC collision in the United States ranged from $17,394 to $19,953.

The Commonwealth of Massachusetts is the third most densely populated state in the United States (U.S. Census Bureau 2010) and has a healthy population of moose (DeStefano et al. 2005). In areas of the state with established moose populations, mean road density is 1.64 km/km^2, with road densities increasing to 3.99 km/km^2 in adjacent areas. Therefore, as moose move about their home ranges (mean size of 62 and 89 km^2 for adult females and males, respectively; Wattles and DeStefano 2013), they encounter, interact with, and cross roads of various types,

✉ Katherine A. Zeller
  kathyzeller@gmail.com

1 Massachusetts Cooperative Fish and Wildlife Research Unit, University of Massachusetts, Amherst, MA 01003, USA

2 U.S. Geological Survey, Massachusetts Cooperative Fish and Wildlife Research Unit, University of Massachusetts, Amherst, MA 01003, USA

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traffic volumes, and speed limits (Wattles 2015). With each crossing, moose and drivers are at risk of injury and a potentially fatal collision, negatively impacting driver safety and the Massachusetts moose population.

There have been many studies that modelled MVCs with only collision data (Seiler 2005; Dussault et al. 2006; Joyce and Mahoney 2001; Danks and Porter 2010). These studies presume that mitigating sites with high MVC potential also will increase moose safety. However, McClure and Ament (2014) argue that this assumption is largely untested, and Clevenger and Ford (2010) contend that using only road-kill data omits biologically important information about where wildlife safely cross roads. McClure and Ament (2014) provide a conceptual framework for this issue and present four possible combinations of biological relevance and wildlife–vehicle collision risk as follows: (1) high biological relevance, low-risk areas; (2) low biological relevance, low-risk areas; (3) low biological relevance, high-risk areas; and (4) high biological relevance, high-risk areas. By focusing on the fourth quadrant, mitigation can be targeted toward areas that have both high biological relevance and pose a high risk for vehicle collisions. Neumann et al. (2012) were the first to compare MVC data with moose movement data and found that using movement data alone was insufficient to predict MVC sites, but using collision data alone over-predicted collision risk in certain areas. Although Neumann et al. (2012) acknowledged the shortcomings of using these data independently of one another,

they did not offer methodologies for combining the data into a single predictive framework.

We integrated MVC data from 1980 to 2015 and Global Positioning Systems (GPS) collar data from 20 moose in Massachusetts, USA, to identify road segments with both high biological relevance and high risk. We also examined the frequency of MVCs in Massachusetts and the impact of MVCs on the moose population and human safety. Lastly, we recommend mitigation strategies aimed at reducing MVCs in Massachusetts.

Methods

Study Area and Moose Data

The study area was located in Berkshire, Franklin, Hampden, Hampshire, and Worcester Counties of central and western Massachusetts (Fig. 1). Adult (> 1-year-old) moose were captured by stalking and darting them from the ground between March 2006 and November 2009. Moose were immobilized with xylazine hydrochloride (Congaree Veterinary Pharmacy, Cayce, SC, USA) administered from a Type C Pneudart dart (Pneudart, Inc., Williamport, PA, USA). We used Tolazolene (100 mg/ml) at a dosage of 1.0 mg/kg as an antagonist.

Twenty moose (5 females and 15 males) were fit with either ATS G2000 (Advanced Telemetry Systems, Inc.,
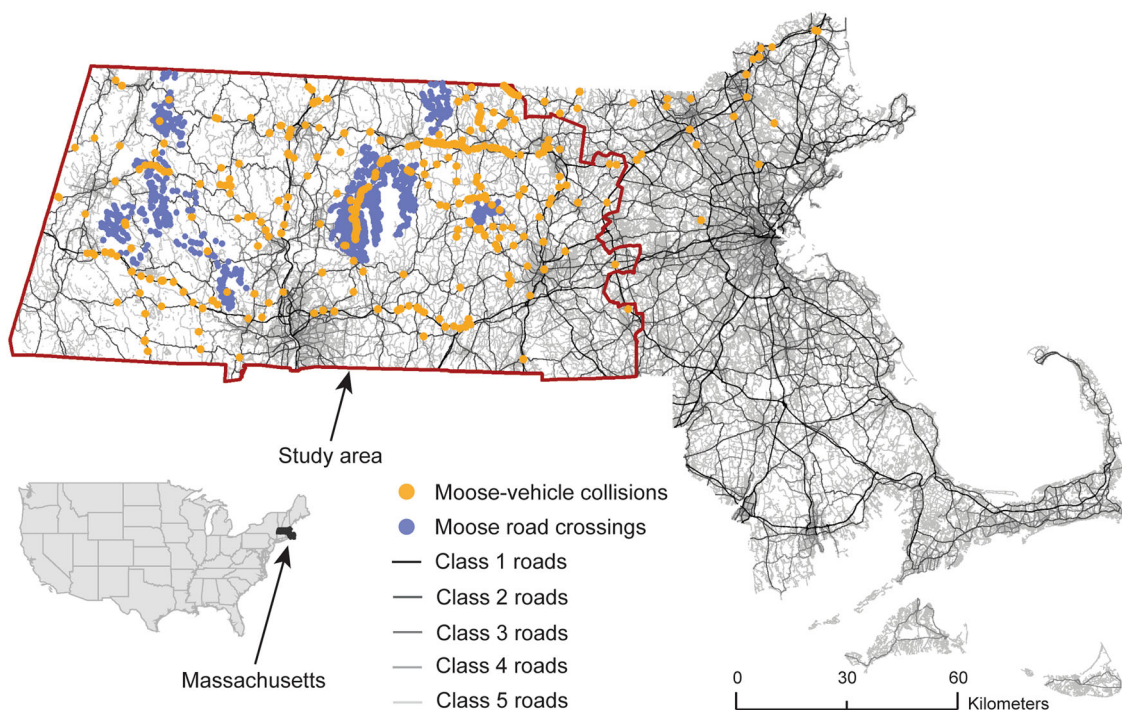

Fig. 1 Study area boundary in the state of Massachusetts, USA. Also shown are all moose–vehicle collisions from 1980 to 2015, moose road-crossing locations from 20 GPS-collared moose, and road class

Isanti, MN, USA) or Telonics TWG-3790 (Telonics, Inc., Mesa, AZ, USA) GPS collars. Capture and handling procedures were approved by the University of Massachusetts Institutional Animal Care and Use Committee (protocol numbers 25-02-15, 28-02-16, and 211-02-01). We programmed the collars to acquire a GPS fix as frequently as possible, while allowing the battery to last for at least 1 year. As such, a GPS location was attempted every 45, 75, or 135 min. We obtained 125,206 GPS fixes across our population of moose (median = 3130, range = 1037–15,182).

MVC and Road-crossing Locations

MVC data were obtained from records of reports to the Massachusetts Division of Fisheries and Wildlife, and the Massachusetts Environmental Police, from 1980 to 2015 (Fig. 1). The records contained information on the date, town, roadway, sex and age of the animal, and other data pertaining to the MVCs. Spatial accuracy of the MVCs were variable; therefore, we separated the reports into two classes. The first class included observations with the road mile, intersection, or other descriptor that allowed a relatively precise MVC location to be identified (n = 176). The other class consisted of

observations where the location was either unknown or only included vague information such as the road name (n = 335). We only used the former class in our models.

We identified 5537 moose road-crossing locations by finding points of intersection between the paths of the 20 moose and the road network. Because of the relatively long collar fix intervals, we used Brownian Bridge Movement Models (BBMMs) to identify the width of the area along the road where each road crossing may have occurred. We randomly selected 100 crossing locations from each moose collared at our longest collar fix interval and ran BBMM models using the BBMM package (Nielson et al. 2013) in R software (R Core Team 2017) with the three locations before and after the road crossing. The average width of the 95% BBMM contour was 423 m. We then rarefied the road-crossing locations with a 500 m buffer, which resulted in 1273 road-crossing locations for the analysis (Fig. 1).

Environmental variables

We identified several environmental variables known to influence moose habitat use and the location of MVCs (Table 1). For all variables except road class, speed limit, traffic

Table 1 Environmental variables used in the moose–vehicle collision and moose road-crossing models

Variable	Description	Source
Road class	Roadways represented as the following classes: 1. Interstate and major highways 2. State highways 3. Major local arteries 4. Light duty roads 5. Unpaved roads	McGarigal et al. 2015
Road speed limit	Posted speed limit	Massachusetts Department of Transportation 2013
Road traffic volume	Average daily traffic volume	McGarigal et al. 2015
Road salt	Intensity of road salt use	McGarigal et al. 2015
Road density	Road density calculated per km^2	Calculated from Massachusetts Department of Transportation 2013 road lines
Slope	Percent slope calculated from digital elevation model	Calculated from MassGIS Digital Elevation Model, MassGIS 2005
Topographic Position Index	Topographic Position Index calculated from digital elevation model	Calculated from MassGIS Digital Elevation Model, MassGIS 2005
Agriculture	Aggregated agricultural land cover types	McGarigal et al. 2015
Forest	Aggregated forest land cover types	McGarigal et al. 2015
Wetland	Aggregated wetland/marsh/swamp land cover types	McGarigal et al. 2015
Urban	Aggregated urbanized land cover types	McGarigal et al. 2015
Percent imperviousness	Percent impervious surface	McGarigal et al. 2015
Vegetative structure	Continuous representation of vegetative structure from no vegetation to shrubland to closed canopy forest	McGarigal et al. 2015
Soil wetness	Soil moisture as a gradient from xeric to hydric	McGarigal et al. 2015
Connectedness	Index of connectivity for each pixel	McGarigal et al. 2015
Similarity	Ecological similarity of each pixel to surrounding pixels	McGarigal et al. 2015

volume, and road density, we explored the following five scales to determine the characteristic scale of each environmental variable at MVC and road-crossing locations: 0.5 km, 1 km, 2.5 km, 5 km, and 10 km. We used the smoothie package (Gilleland 2013) in R to smooth each variable at each pixel at each scale with a Gaussian kernel. All variables were represented as rasters at a 30 m pixel resolution.

MVC and Road-crossing Models

We used logistic regression models in a use:availability framework (Manly et al. 2002) to model MVC and road-crossing locations. Gunson et al. (2009) determined that spatial error of ungulate vehicle collisions ranged from 401 m (SD, 219 m) for data referenced to the nearest mile marker to 516 m (SD, 808 m) for data referenced to the nearest landmark. Therefore, we summarized environmental variables at each MVC, road-crossing location, and available locations within a 500 m radius. For categorical variables, we calculated the proportion of that variable within the 500 m radius; for continuous variables, we calculated the mean (Supplementary Appendix Table S1). The available sample for the MVC models was generated by sampling 10,000 random points along the road network that were at least 500 m away from one another. The available sample for the road-crossing models was generated by sampling random points that were at least 500 m away from one another along the road network within minimum convex polygon moose home ranges. We attempted to sample 10,000 available points within the area of the moose home range polygons; however, limited road length only allowed us to sample a total of 32,800 points for the road-crossing models. Available points were weighted in the models to maintain a 1:1 ratio with the used points.

To create multi-scale models, we used a two-step modeling approach (McGarigal et al. 2016). First, we ran univariate logistic regression models for each variable at each scale and used Akaike information criteria corrected for small sample sizes (AICc; Burnham and Anderson 2004) to select the scale that resulted in the lowest AICc value. We then assessed correlations among variables at their selected scales and for any pair with a correlation > 0.6, omitted the variable with the higher AICc value. We created a global model with all uncorrelated variables and used the *drege* function in the MuMIn package (Bartón 2016) to identify the final candidate models. We then averaged the weighted parameter estimates across models that were within two ΔAICc units of the highest performing model to obtain our final MVC and road-crossing models (Burnham and Anderson 2004). We performed a 10-fold cross validation and assessed predictive ability for each model by comparing the predicted observations with the expected observations (Johnson et al. 2006) with Lin's (1989) concordance correlation coefficient (CCC).

To spatially predict the probability of an MVC or moose road crossing along the road network, we used the *predict* function in the Raster package (Hijmans 2016) for each model and rescaled the predictions to a 0–1 range. To identify road segments that represented both high biological relevance and high risk for moose, we used a Boolean argument to identify segments on both the MVC and moose crossing predicted surfaces that were above a relative probability threshold. To determine which threshold to use, we employed a metric (the contrast validation index (CVI)) that identified the largest proportion of MVCs captured by the road segments while minimizing the length of roadway that would need mitigation efforts (Fedy et al. 2014; Hirzel et al. 2006). For each of seven relative probability thresholds examined (0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9), we (1) used a Boolean argument to identify road segments on both the MVC and road-crossing surfaces that were at or above the threshold value, (2) calculated the proportion of MVC locations on primary and secondary roads captured by these road segments, (3) calculated the proportion of the primary and secondary road network these segments occupy in the study area, and (4) calculated the CVI by subtracting the road network proportion from the proportion of MVC locations captured on the road segments (Fedy et al. 2014). The threshold that resulted in the highest CVI value was used to create the final biologically based MVC risk surface. We focused this analysis on primary and secondary roads, as these are the roadways over which the state transportation department has authority and could implement mitigation measures. Primary and secondary roads in this study are defined as multi-lane highways or two-lane numbered state routes.

Results

From 1980 to 2015, 511 MVCs were reported to the Massachusetts Division of Fisheries and Wildlife. The frequency of MVCs increased steadily until 2002, after which MVC frequency remained relatively high compared with earlier years (Fig. 2a). MVCs occurred more frequently from late spring through late fall with a distinct peak in May (Fig. 2b). MVCs occurred on class 1 and class 2 roads at a rate that was highly disproportionate to the availability of those road classes across the study area (Fig. 2c). Three MVCs resulted in a human fatality, one each in 2003, 2007, and 2012, a rate of 1 human fatality for every 170 MVCs or 0.6% of reported MVCs. This is one of the highest documented rates of human fatalities from MVCs reported in the literature (Table 2). Of the three human fatalities, two occurred on class 1 roads and one occurred on a class 2 road. Seventy-nine percent of MVCs resulted in moose mortality, either from direct mortality or from being killed
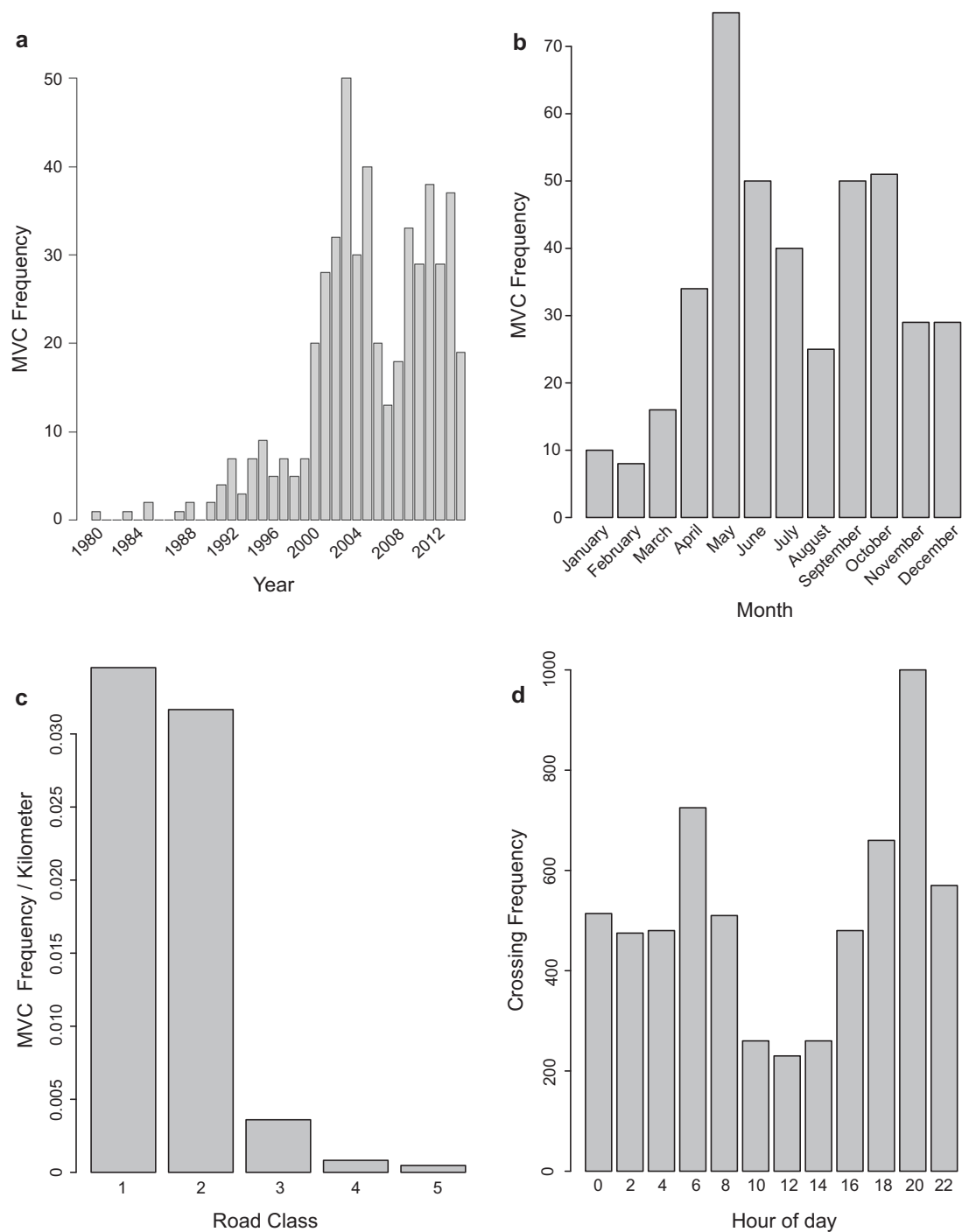
Fig. 2 Summary statistics of moose–vehicle collisions and moose road crossings. **a** Moose–vehicle collisions by year, **b** moose–vehicle collisions by month, **c** number of moose–vehicle collisions per kilometer of each road class, **d** moose road crossings by hour of day. Moose road-crossing times were calculated from GPS-collared moose as the average time of the locations immediately before and after the road-crossing event

due to injuries sustained from the collision. The moose population in Massachusetts is estimated to be ~ 1000 adults (Wattles 2015). Therefore, MVCs resulted in mortality of 3% of the population annually (Table 2). Moose crossed roads at all times of day, but we observed crepuscular peaks in road-crossing frequency (Fig. 2d).

The best performing scale and associated AICc value from the MVC univariate models indicated road class was the highest performing model, followed by road speed limit, and forest (Table 3). In contrast, the percent imperviousness model was the highest performing univariate road-crossing model, followed by road salt and vegetative structure

Table 2 Annual moose–vehicle collisions reported in the literature for states, provinces, and nations

Location	Annual number of MVCs	Moose population	% of moose population	Human fatality rate	Reporting period
Massachusetts, USA	28	1000	3	0.6	2002–2015
Vermont, USA[a]	150	4500	3	0.6	1995–2007
Maine, USA[a]	650	45,000	1	0.4	1995–2007
New Hampshire, USA[a]	250	5000	5	0.3	1995–2007
Sweden[b]	5000	225,000	2	0.3	1980–1990
Newfoundland, CAN[c]	757	150,000	1	0.3	1988–1994
Anchorage, Alaska, USA[d]	100	450	22	0	1991–1995

Annual moose–vehicle collisions reported in the literature for states, provinces, and nations including the number of moose–vehicle collisions, the estimated size of the moose population, the percent of the moose population affected by vehicle collisions, the human fatality rate, and the reporting period

[a]Wattles and DeStefano 2011

[b]Groot Bruinderink and Hazebroek 1996

[c]Joyce and Mahoney 2001

[d]Garrett and Conway 1999

Table 3 Best performing scales and associated standardized β-coefficients and AICc values from the moose–vehicle collision and moose road-crossing models

Moose–vehicle collision models					Moose road-crossing models				
Variable	β-Coefficient	SE	Scale (km)	ΔAICc	Variable	β-Coefficient	SE	Scale (km)	ΔAICc
Road class	−1.19	0.11	–	0	Percent imperviousness	−2.68	0.14	0.5	0
Road speed limit	1.20	0.12	–	22	Road salt	−2.19	0.11	0.5	20
Forest	0.85	0.14	10	61	Vegetative structure	1.62	0.08	0.5	39
Vegetative structure	0.87	0.1	2.5	62	Road density	−2.16	0.11	–	41
Urban	−0.88	0.15	10	64	Forest	1.43	0.07	0.5	60
Connectedness	0.72	0.12	10	65	Connectedness	1.23	0.06	0.5	67
Road traffic	0.72	0.15	–	66	Urban	−2.00	0.12	1	109
Percent imperviousness	−0.86	0.16	10	67	Agriculture	−1.61	0.09	2.5	135
Road salt	−0.80	0.16	10	69	Similarity	−1.08	0.05	1	146
Topographic position index	0.61	0.11	10	73	Road class	0.73	0.05	–	240
Similarity	−0.59	0.12	2.5	74	Topographic position index	0.87	0.05	2.5	243
Wetness	−0.52	0.13	2.5	77	Road speed limit	−1.25	0.12	–	317
Agriculture	−0.61	0.14	2.5	78	Road traffic	−1.66	0.23	–	354
Road density	−0.46	0.13	–	81	Wetness	−0.45	0.04	5	361
Wetland	0.35	0.11	0.5	82	Slope	−0.44	0.05	2.5	383
Slope	0.16	0.11	0.5	87	Wetland	0.09	0.04	0.5	433
Intercept-only model	0.0001	0.11	–	87	Intercept-only model	0.0003	0.04	–	435

All coefficients were significant (p-value 0.05)

(Table 3). Representative scales for the environmental variables were often different between the MVC and road-crossing models.

The top MVC models and associated AICc values and AICc weights are provided in Supplementary Appendix (Table S2). The final averaged MVC model indicated MVCs occur on larger, more heavily trafficked roads located in forested areas with wetlands, and some heterogeneity (low similarity; Table 4). MVCs were also associated with slightly higher topographic positions. The MVC model had a cross-validated CCC statistic of 0.94.

The top MVC models and associated AICc values and AICc weights are provided in Supplementary Appendix (Table S3). The final averaged moose road-crossing model indicated moose cross smaller, less trafficked roads, near wetlands, and further from areas with a high amount of

Table 4 Averaged standardized β-coefficients, SEs, and odds ratios for the final moose–vehicle collision model

Variable	β-Coefficient	SE	Odds ratio
Intercept	− 1.32	0.20	–
Forest*	0.73	0.18	155.26
Road class*	− 1.20	0.13	0.31
Similarity	− 0.30	0.27	0.01
Topographic position index	0.20	0.22	1.16
Wetland	0.06	0.13	2.75

Odds ratios were calculated on the unstandardized β-coefficients. Significant coefficients (p-value < 0.05) are indicated by an asterisk

Table 5 Averaged standardized β-coefficients, SEs, and odds ratios for the final moose road-crossing model

Variable	β-Coefficient	SE	Odds ratio
Intercept	− 1.78	0.12	–
Percent Imperviousness*	− 2.06	0.19	1.04e−15
Road class*	0.25	0.06	1.28
Slope*	− 0.71	0.08	0.84
Topographic position index*	0.53	0.07	1.05
Agriculture*	− 0.79	0.11	3.17e−09
Similarity	− 0.12	0.09	0.13
Wetland	0.04	0.06	2.12
Wetness	− 0.08	0.06	0.99

Odds ratios were calculated on the unstandardized β-coefficients. Significant coefficients (p-value < 0.05) are indicated by an asterisk

agriculture and impervious surface (Table 5). Moose road crossings were also associated with more heterogeneous areas (low similarity), areas with lower slopes, higher topographic position, and less soil wetness. The road-crossing model had a cross-validated CCC statistic of 0.83.

The MVC model (Fig. 3a) predicted high probabilities of collisions on most primary and secondary roads in the study area, despite the lack of moose habitat in some areas. The moose road-crossing model (Fig. 3b) predicted high probabilities of moose crossings far from urbanized areas and on smaller roadways.

Using a relative probability threshold of 0.75 resulted in the highest CVI value and captured 70% of MVCs (Table 6). The road segments that had > = 0.75 relative probability on both the MVC and road-crossing surfaces are shown in Fig. 3c. A subset of the study area, where detailed differences among the surfaces can be seen, is provided in Supplementary Appendix Figure S1.

Discussion

Since the year 2002, there have been an average of 28 MVCs in Massachusetts annually, affecting an estimated 3% of the moose population. The rate of human fatalities from these MVCs is one of the highest reported. We identified road segments in central and western Massachusetts, where mitigation may improve human safety and reduce moose mortality due to MVCs. Unlike other studies that only consider risk of vehicle collisions, we used an approach that combined areas of biological relevance with areas of risk to create a biologically based risk assessment for MVCs across the road network in central and western Massachusetts. This combined approach ensures the identification of areas that have high biological relevance for moose as well as high risk and is an improvement over approaches that use only MVC data (Clevenger and Ford 2010; McClure and Ament 2014), or only road-crossing data (Neumann et al. 2012). Using only MVC data may result in highlighting areas of high risk, but low biological relevance (McClure and Ament 2014; Teixeira et al. 2017). With our MVC-only predictive surface, risk was high on most segments of primary and secondary roads in the study area, except for road segments immediately in, or adjacent to, larger urban areas, which is likely an over-prediction of risk, especially in areas where moose are absent or exist at very low densities. Avoidance of developed areas was the main driver for our road-crossing surface, which predicted high probabilities of road crossings outside of highly developed areas and on smaller roadways, and may underestimate risk in more natural habitats bisected by thoroughfares. In this regard, our results are consistent with those of Neumann et al. (2012) who found differences between crossing sites and MVC locations where each data set alone overrated some variables while underrating others.

MVCs in Massachusetts were located on larger, more heavily trafficked roads in areas with forests, wetlands, lower slopes, and a heterogeneous mix of land cover types. These results are consistent with other studies on MVCs that found MVCs occurred more frequently on major roads that had higher speed limits (Neumann et al. 2012; Seiler 2005; Danks and Porter 2010; Litvaitis and Tash 2008; Joyce and Mahoney 2001), in more forested areas (Seiler 2005; Danks and Porter 2010), in the presence of water and wetlands (Danks and Porter 2010; Dussault et al. 2006), in areas where landscape composition was more heterogeneous (Gunson et al. 2011), and at lower slopes (Danks and Porter 2010; Dussault et al. 2006). Our road-crossing model was driven primarily by moose avoidance of human development and a preference for crossing smaller roadways and are consistent with the findings of Neumann et al. (2012).

Salting of roadways attracts moose to roadsides and increases exposure to vehicle traffic (Silverberg et al. 2002; Leblond et al. 2007). Although road salt is used for deicing in Massachusetts, it is used in lower amounts than in more northern areas and we did not find salt to contribute to MVC
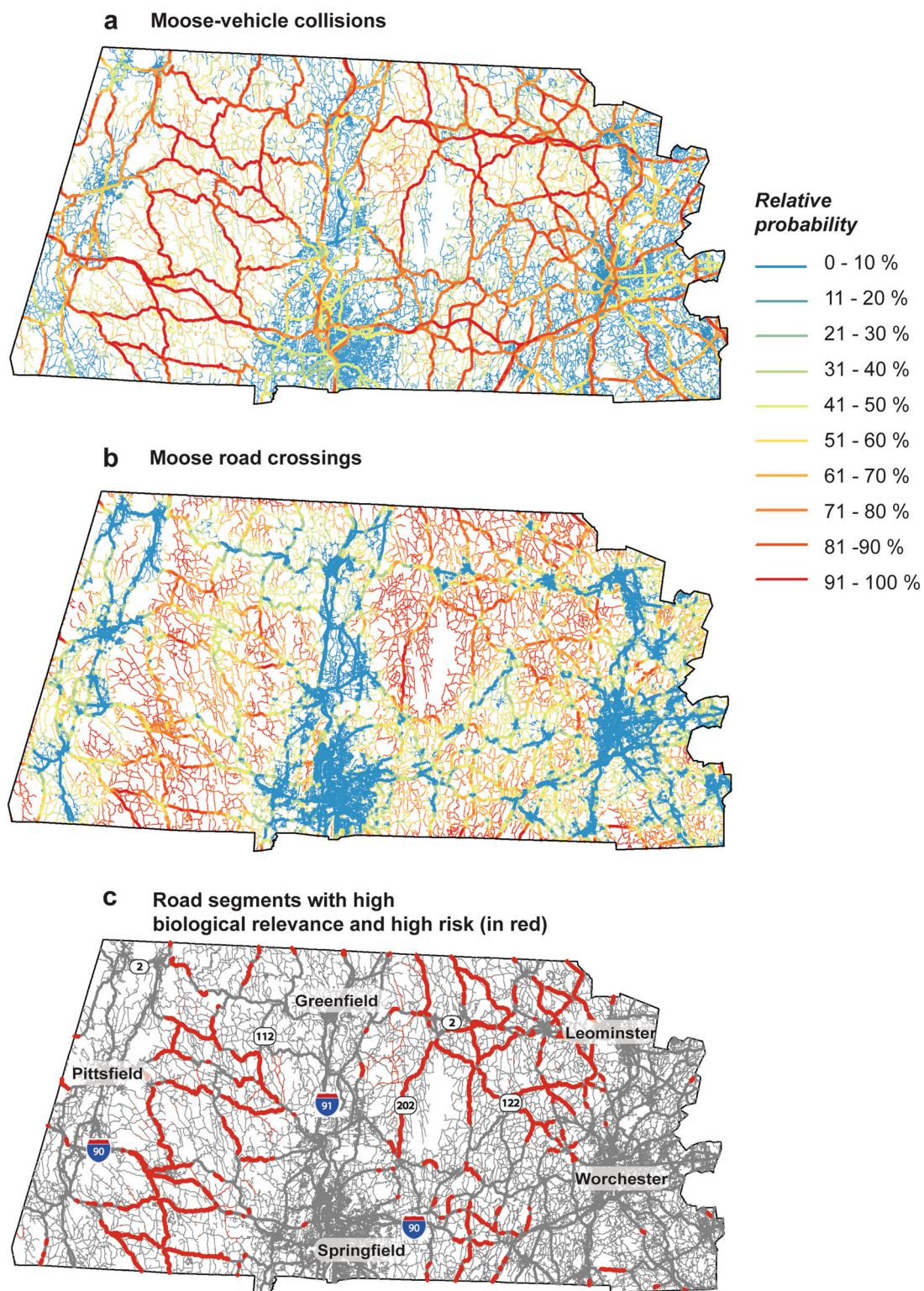
Fig. 3 Relative probabilities of **a** moose–vehicle collision and **b** moose road crossing. **c** Road segments with a relative probability of a moose–vehicle collision and a moose road crossing > 0.75. Primary and secondary roads are emphasized in all three figures

predictions. In the MVC univariate model, road salt had an AICc value 69 units greater than the highest performing univariate model. Salt did have better model performance in the moose-crossing univariate model. However, it was highly correlated with percent imperviousness, indicating a possibly confounding effect due to the association of roads

Table 6 Relative probability thresholds, proportion of moose–vehicle collisions (MVCs), proportion of primary and secondary road network, and contrast validation index (CVI) values

Relative probability threshold	Proportion MVCs captured	Proportion of road network	CVI
0.60	0.76	0.29	0.47
0.65	0.74	0.24	0.50
0.70	0.72	0.20	0.52
0.75	0.70	0.15	0.55
0.80	0.60	0.11	0.49
0.85	0.48	0.07	0.41
0.90	0.27	0.02	0.25

Thresholds were used to identify road segments at or above that value on both the moose crossing and MVC relative probability surfaces. The highest CVI value represents the threshold at which the highest number of MVCs were captured in the least amount of road length

with developed areas. In addition, because of the high correlation of road salt with the percent imperviousness and the better performance of the percent imperviousness model, road salt was not included in the variable set for our multiple regression models.

MVC frequency peaked in May and remained high into July, which corresponded to the peak of vegetation quantity and quality in Massachusetts, and the peak movement period outside of the reproductive season (Wattles and DeStefano 2013). Yearlings also disperse during this time, resulting in naive individuals moving about the landscape. Other studies have also documented peak MVC frequencies in late spring through summer (Neumann et al. 2012; Danks and Porter 2010; Dussault et al. 2006; Joyce and Mahoney 2001). We observed a smaller, secondary peak in MVC frequency during the fall rut, which was also observed by Danks and Porter (2010). The Massachusetts MVC data did not have information on time of day; therefore, we could not analyze daily risk temporally. Other studies have found MVCs tend to occur more often at night, which may also be a result of low visibility driving conditions (Joyce and Mahoney 2001; Danks and Porter 2010; Dussault et al. 2006). Data from our collared moose indicate moose cross roads more frequently during crepuscular and nighttime hours than during mid-day.

We found interstate, state, and other major highways in Massachusetts pose the greatest risk for moose and humans. Therefore, focusing mitigation efforts on these roadways may reduce MVCs. Mitigation options include permanent, seasonal, or enhanced signage, reducing speed limits, road-based animal detection systems, fencing, and wildlife crossing structures (Huijser and McGowen 2010). A recent collaboration between the Massachusetts Division of Fisheries and Wildlife, the Massachusetts Department of Transportation, and the USGS Massachusetts Cooperative

Fish and Wildlife Research Unit has resulted in the placement of permanent warning signs on certain road sections where MVCs have occurred. However, permanent, seasonal, and even enhanced warning signs (with flashing lights) have not been shown to prevent wildlife–vehicle collisions (Huijser and McGowen 2010; Rytwinski et al. 2016), and the signs along roadways in Massachusetts may not decrease the number MVCs in the state. Reducing speed limits on road sections is another relatively inexpensive option; however, effectiveness has been mixed. Gunther et al. (1998) showed a reduction in wildlife–vehicle collisions with reduced speed limits, although on other roadways only 20% of drivers obeyed the new speed limits, drivers continued to speed, and wildlife–vehicle collisions increased (Huijser and McGowen 2010).

Large animal detection systems have been shown to be 57% effective at reducing wildlife–vehicle collisions (Rytwinski et al. 2016), provided they work reliably and signage is appropriately placed. Large animal detection systems coupled with fencing to direct wildlife to cross a specific section of road is estimated to be ~80% effective (Huijser and McGowen 2010). Wildlife fencing combined with a wildlife crossing structure is the most effective mitigation strategy, resulting in an 83–87% reduction in wildlife–vehicle collisions (Huijser and McGowen 2010; Huijser et al. 2016; Rytwinski et al. 2016). Fencing alone can reduce MVCs by 70–95% (Lavsund and Sandgren 1991). Of these options, Massachusetts has fenced all interstate highways with 2 m high chain link fencing. However, the fencing was installed 20–30 years ago along the edge of the right-of-way (T. Dexter, Massachusetts Department of Transportation, personal communications) has not been maintained, is often in forested areas, and currently allows wildlife access to roadways. Furthermore, fencing the right-of-way is not consistent with wildlife mitigation best management practices, which recommend fencing as close to the roadway as possible (Huijser et al. 2008). The most effective options for reducing MVCs in Massachusetts could be (1) to erect wildlife-specific fencing with large animal detection systems at gaps in the fence, (2) retrofit existing underpasses to accommodate moose and use directional fencing, or (3) build new crossing structures with directional fencing. Underpasses for large mammals are recommended to be 7–8 m wide and 4–5 m high, and overpasses are recommended to be at least 50 m wide (Huijser et al. 2008). We would like to note that although fencing has been shown to be an effective mitigation option, there may be negative effects of fencing large lengths of roadway such as creating barriers for movement and gene flow of other species (Jaeger and Fahrig 2004).

The mitigation options presented above focus on installing structures to help route animals safely across the road. However, an often-overlooked mitigation option is altering

negative human behavior while driving. The majority of drivers believe it is safe to travel above the posted speed limit (Mannering 2009) and distracted driving statistics indicate that each day over 100,000 Massachusetts drivers are manipulating handheld electronic devices while driving (National Highway Traffic Safety Administration 2016). Controlling risky driving behaviors to increase human safety and reduce traffic deaths may also have a positive effect on wildlife safety along roadways. Such controls include automated speed enforcement and strict laws regarding the use of handheld electronic devices.

Our methodological approach integrated moose road-crossing location data with MVC data and resulted in biologically relevant predictions of MVC hotspots across central and western Massachusetts. We also employed a sensitivity analysis to determine the relative probability threshold at which the highest number of MVCs were captured in the least amount of road length (Fedy et al. 2014), making our approach transparent and useful to managers implementing mitigation measures. Although our study was focused on moose in Massachusetts, the methods present herein can be applied across a variety of species and road configurations.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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