2019

Developing a Predictive and Dynamic Moose-vehicle Collisions Model in Maine

Yue Yu
Colby College

Developing a Predictive and Dynamic Moose-vehicle Collisions Model in Maine

Yue Yu (Anna)
Environmental Studies Program
Colby College
Waterville, Maine

May 20th, 2019

A thesis submitted to the faculty of the Environmental Studies Program in partial fulfillment of the graduation requirements for the Degree of Bachelor of Arts with honors in Environmental Studies

Philip Nyhus, Advisor	Nicholas Record, Reader 1	Gail Carlson, Reader 2

ABSTRACT

Wildlife-vehicle collisions are a major form of human-wildlife conflict. Predictive animal-vehicle collision models have been developed to identify collision hotspots in Maine and guide mitigation strategies. However, most current models are static and unable to produce dynamic forecasts that incorporate changing climate and weather. The goal of my study was to develop a predictive and dynamic model of animal-vehicle collisions in Maine, USA. More than 6,700 moose-vehicle collisions (MVC) occurred from 2003 to 2017 in Maine, raising road safety, socio-economic, and wildlife conservation concerns. I sought to identify factors that contribute to a higher probability of MVCs by comparing two methodological approaches. I obtained 14 years of moose-vehicle collision data from Maine Department of Transportation. I developed a spatial MVC model using static spatial data. I then collaborated with the Bigelow Laboratory for Ocean Sciences to import temporal data in a Maximum Entropy (MaxEnt) model and create dynamic hourly MVC forecasts. My models show that MVCs in Maine are more likely to happen on roads with intermediate to high speed limits and volumes, in or near forest cover, and close to wetlands. Sunlight, snow depth, humidity, and soil moisture were also significantly associated with MVC probabilities. The result of this study suggests that predictive and dynamic MVC models can be developed to inform drivers of crash hotspots in Maine. Effectively applying these models allows for a more proactive, timely, and diagnostic response to MVCs and provides a novel approach to more comprehensively understand and predict human-wildlife conflicts.

ACKNOWLEDGEMENTS

I would like to express my gratitude to Associate Professor of Environmental Studies Philip Nyhus and Senior Research Scientist Dr. Nicholas Record from the Bigelow Laboratory for Ocean Sciences for their constant guidance and advice throughout my work. I gratefully acknowledge Research Associate Benjamin Tupper from the Bigelow Laboratory for Ocean Sciences, GIS & Quantitative Analysis Specialist and Research Scientist in Environmental Studies Manuel Gimond, and Associate Professor of Statistics James Scott for their technical supports. I would like to thank for Mr. Duane Brunell, Mr. Shawn MacDonald, and Ms. Lorry Plante from the Maine Department of Transportation and Mr. Lee Kantar and Ms. Amy Meehan from Maine Department of Inland Fisheries and Wildlife for their data support. My special thanks go to Alexandra Jospe ‘06 for her inspiration on this project and to my fellow research student Bertha Pushan Wu ‘19 for her help in collecting data and conducting preliminary analyses over the summer of 2017. This thesis would not have been possible without the financial support of the Environmental Studies Program F. Russel Cole Student Research Fellowship and the Colby College Kathryn Ellis Fredricks Student Research Fund. Finally, I appreciate Assistant Professor of Environmental Studies Gail Carlson for reading my thesis.

TABLE OF CONTENTS

CHAPTER I. LITERATURE REVIEW

Introduction

Human population growth and economic development has led to increasing infrastructure expansions and resource extraction, escalating conflicts between humans and wildlife (Distefano 2005). Wildlife-vehicle collisions (WVC) is a unique form of human-wildlife conflicts (HWC). Construction of road networks significantly decreases ecosystem connectivity and causes more wildlife and vehicles to encounter each other (Tanner and Leroux 2015). In the United States, around one to two million vehicles collide with wildlife every year (Niemi et al. 2017). In Sweden, these accidents constitute more than 60% of total accidents happened on the road (Seiler 2005).

WVCs with large-size animals, such as moose (*Alces alces*), are a particularly serious road safety problem because of the high fatality risks (Niemi et al. 2017). Moose are an ungulate species that inhabit northern Europe and North America (Renecker and Schwartz 2007). Moose-vehicle collisions (MVC) are common across this range (Tanner and Leroux 2015).

To prepare for my research, I reviewed 24 journal articles published between 1998–2018 to investigate the impacts, study methods, patterns, and mitigations of MVCs around the world. The main goal of this literature review was to learn about biological, physical, and cultural factors that may influence the probability of MVCs across the world.

MVC impacts

Attributed to successful conservation efforts and increasing urban developments, MVCs are considered a major road-safety concern in Finland, Norway, Sweden, Russia, the United States, and Canada (Niemi et al. 2013). Moose are characterized by their large body mass, long legs, and high center of gravity, which can contribute to the severity of accidents (Zeller et al. 2018, CDC 2006). When a collision happens, the vehicle typically hits the moose's legs from under the abdomen. Stress responses and momentum of the moose cause it to knock back and sweep up the vehicle's hood and windshield into passenger compartments (Garrett and Conway 1999).

Public safety threats, socio-economic loss, and animal welfare and conservation concerns are the three main impacts that MVCs cause (Tanner and Leroux 2015, Seiler 2005). Around 15% of MVCs resulted in human injuries or deaths, rating 34 times higher than other animal-traffic accidents (Garret and Conway 1999). In Sweden, over 80% of road accidents that involved fatal and non-fatal injuries were MVCs (Seiler 2005). The annual death rate from MVCs fluctuates between 0.5% and 0.8% in the United States (Zeller et al. 2018, Garrent and Conway 1999), while the same measurement is 0.4% in Canada (Tanner et al. 2017). Fortunately, with various mitigation strategies, this number has decreased in multiple countries in recent years (Niemi et al. 2017).

Direct costs associated with MVCs include patient hospitalization and accident clean-ups (Rea et al. 2014). Material damage was estimated to exceed $3,000 dollars per crash in Canada between 1995 and 2000 (Christie and Nason 2003) and around $18,000 in the United States (Niemi et al. 2017). MVCs also lead to an indirect loss in work time and incomes from meat and hunting licenses (Garrett and Conway 1999). On average, the annual total economic loss due to MVCs in Canada surpasses 25 million dollars (Rea et al. 2014).

MVCs also raise wildlife conservation concerns. Road-killed large-sized animals are difficult to track in time and require specialized persons for clean-up and removal (Snow et al. 2015). Moose killed from traffic crashes were estimated to be between 300 and 1200 per year in British Columbia, Canada (Rea et al. 2014), over 150 in Sweden (Seiler 2005), and 3% of total moose populations in Massachusetts, USA (Zeller et al. 2018).

Study methods of MVCs

McClure and Ament (2014) suggested that WVC interventions should consider areas with both high biological relevance and high vehicle collision risks. Biological data, such as moose population ranges, are often obtained using radio collars. To locate risk regions and understand the cause from a driver's perspective, conservation biologists also study what transpires preceding and during a crash. Traditionally, this information can only be obtained by interviewing crash participants, which is usually hard due to high physical and mental trauma rates (Rea et al. 2018, Langley and Mathison 2008). Modern technologies, such as dash cameras and traffic monitoring systems, record road conditions and driver behaviors.

These videotapes reflect motorists' physical and psychological reactions towards what is being encountered and can be used to analyze crash patterns (Rea et al. 2018).

Another commonly used methodology to investigate crash mechanisms and evaluate mitigation strategies is to develop predictive MVC models (Tanner et al. 2017). These models draw on ecological data to summarize MVC patterns and then apply these findings on broader temporal and spatial scales. Early MVC studies typically focused on using moose movement to characterize crash locations (Neumann et al. 2012, Gundersen and Andreassen 1998); more recent models incorporate additional baseline information to investigate what landscape, traffic, and wildlife factors are associated with the occurrence of MVCs (Tanner et al. 2017, Rea et al. 2014, Snow et al. 2014). Common statistical analyses applied to identify crash hotspots include building multivariate logistic regression models and generalized linear mixed models (Eldegard et al. 2011, Seiler 2014, Litvaitis and Tash 2008). Overall, these models explain why some road sections have significantly higher collision frequencies and help to pinpoint potential problematic roads that future management plans should focus on (Rea et al. 2014, Danks and Porter 2010, Dussault et al. 2007).

MVC models are generally built upon accident report data from police departments and carcass removal data (Snow et al. 2015, Niemi et al. 2013). Underreporting is a consistent issue in WVC studies across species and geographical locations (Snow et al. 2015). Insufficient reporting from motorists, insurance companies, and government agencies and time delays between the crash and carcass removal can lead to MVC miscounts (Hujiser et al. 2007). In Newfoundland, Canada, only crashes with over $1000 damages or involving in injuries will be filed in police documents (Tanner et al. 2017), which leads to an underreporting rate of over 50% (Gunson et al. 2009, Dussault et al. 2007). These data collection errors can limit model accuracy and precision (Snow et al. 2014).

MVC patterns

MVC distributions frequently display non-random patterns that vary across space and time (Neumann et al. 2012, CDC 2006, Dussault et al. 2007). Differences in spatial patterns may be attributed to variations with geographic locations of study (Rea et al. 2014). MVCs in Massachusetts and western Maine, USA, typically occur on larger, faster, and more heavily trafficked roads near coniferous forests and wetlands, with lower slopes (Zeller et al. 2018, Danks and Porter 2010). In contrast, in British Columbia, Canada, landscape features, such as non-browse vegetation, swamps, and sphagnum bogs, play a more determinative role in predicting MVCs compared to road features (Rea et al. 2014). Temporal MVC patterns are often related to roadside habitat usage and migration patterns of moose (Rea et al. 2018, Niemi et al. 2017). In Massachusetts, USA, MVCs peak from May to July when vegetation quantity and quality are the highest and revive again in November during the migration and reproductive seasons (Zeller et al. 2018, Snow et al. 2014). In European countries, including Finland and north Sweden, crashes are more likely to occur in autumn and winter when the light and road conditions are poorer (Niemi et al. 2017, Neumann et al. 2012).

Moose behaviors, driver behaviors, and environmental features have been linked to forecasting the probability of MVCs (Rea et al. 2018). Based on the 24 journal articles that I reviewed, I identified 17 common factors used in previous studies to build MVC models (Appendix 1). Land cover, moose density, traffic volume, and speed limit were found to be significant MVC predictors in more than 10 articles. The only temporal variable that has been evaluated in more than 3 papers is sunlight. MVCs happen most frequently before and after dusk and dawn because moose are more mobile (Hikonen and Summla 2001, Joyce and Mahoney 2001, Gundersen Andreassen) and visibility of drivers is lower during these periods (Niemi et al. 2013, Hikonen and Summala 2001). This emphasis on spatial variables leads to most existing MVC models being static, which means they produce a general prediction of MVC probabilitty and are unable to adapt to weather changes. Later in Chapter II, I used all 17 variables to develop both static and dynamic MVC models in Maine.

Landscape features

Landscape characteristics, including land cover and distances to the nearest forests, waterbody, and wetlands, are the most mentioned variables. Land cover type, specifically, were mentioned in 13 out of 24 studies. These environmental characteristics influence MVC distributions by indicating moose migration and foraging behaviors (Rea et al. 2014). Roadside forest types influence to which degree the moose use the habitats and thus affect their decision making in balancing between foraging benefits and collision risks (Snow et al. 2014, Eldegard et al. 2012, Neumann et al. 2012). In winter, moose prefer coniferous forests that can provide more favorable thermal and predator covers compared to deciduous forests

(Rea et al. 2014). Frequently cleaned roadside vegetations and harvested timberland are also more desirable for their newly grown nutritious sprouts (Danks and Porter 2010, Seiler 2004). Wetlands, swamps, ponds, and blackish pools provide aquatic macrophytes that are favored by moose especially in summer (Niemi et al. 2013). Lakes and rivers also grow riparian vegetation, such as the willow family (*Salicaceae*) and the alder genus (*Alnus*), along the shoreline, but their larger waterbody sizes also potentially create movement barriers for moose (Rea et al. 2014).

Moose population and behavioral features

Moose density is another variable that is closely related to moose behaviors. Moose population size has been found to be positively related to the occurrence of MVCs (Niemi et al. 2017, Seiler 2015, Joyce and Mahoney 2001). This explains why more collisions are likely to happen within the home range of a moose population (Neumann et al. 2012, Danks and Porter 2013). However, while a higher density increases the probability of encountering a moose on the road, more than one moose on or near traffic reduces the likelihood of collision (Rea et al. 2018). This is because drivers can more accurately identify a large group of objects wandering on the road rather than a single individual crossing alone (Rea et al. 2018). Population structure is also important because males and females with and without calves display different road-crossing behaviors (Beyer et al. 2013). Male moose tend to search closer to roads than females when looking for food (Eldegard et al. 2012) and are more often killed during the rutting season (Niemi et al. 2013). Female moose roadkill peaks from May to June and from November to January during the reproductive and breeding periods (Neumann et al. 2012, Joyce and Mahoney 2001).

Human behavior and road features

Road conditions are closely related to driver behaviors and reactions. Traffic volume, although mentioned in 12 out of the 24 articles, has a varied contribution in different predictive MVC models (Rea et al. 2018, Niemi et al. 2017, Niemi et al. 2013). Some studies find that a higher traffic volume leads to more vehicle collisions (Zeller et al. 2018), while others find that moose crosses smaller roads more often because lower traffic volume weakens movement barriers (Tanner et al. 2017, Eldegard et al. 2012). Impacts of speed limits remain constant across models. A lower speed allows for more reaction time so that the drivers are three times more likely to avoid a crash (Rea et al. 2018, Beyer et al. 2013, CDC 2006). Overall, vehicles traveling above the speed limit of a road have significantly higher injury and fatality rate, and this risk is even higher when traveling with passengers (Niemi et al. 2013, Joyce and Mahoney 2001). Similarly, driving along straight roads poses a higher chance of MVCs because drivers may reduce speed when riding around curves (Tanner et al. 2017), although swerving raises the probability of colliding with secondary objects (Rea et al. 2018).

MVC mitigation

MVCs are challenging to mitigate. Humans cannot remove moose from environments near roads, as ungulates are popular game species that contribute to local economies (Tanner et al. 2017). Following McClure and Ament's WVC management framework (2004), modern MVC mitigation strategies often fall into three categories: redirecting animal movements, influencing driver behaviors, and modifying road environments (Rea et al. 2018). However, these strategies described below can sometimes be hard to implement due to the economic, social, and political impacts on stakeholders (Danks and Porter et al. 2010). Recent intervention efforts have been advised that they should aim to reduce collisions to a socially acceptable level determined by local governments (Dussault et al. 2007, Seiler 2004). In some regions, the percentage of WVCs in total road accidents has successfully decreased in recent years as described below (Niemi et al. 2017). However, more follow-up studies are necessary to determine the long-term effects of mitigation plans (Christie and Nason, 2003).

Moose movement redirection

Fencing combined with wildlife corridors are widely considered the most effective WVC mitigation strategy. In both central and western Massachusetts, USA and Sweden, these two strategies have reduced over 80% of MVCs in study areas (Zeller et al. 2018, Seiler 2005). Wildlife corridors refer to bridges and tunnels that provide wildlife with alternative passways near and around roads. This strategy is typically expensive due to construction costs and requires customization based on sites.

Newly constructed fences that are in good conditions can effectively prevent MVCs. In Sweden, more than 5,000 kilometers of major roads were fenced to preclude moose from accessing the road (Tanner and Leroux 2015, Seiler 2005). However, some fences were installed 20 to 30 years ago and were not well maintained, allowing wildlife to enter freely (Zeller et al. 2018). Biological impacts of wildlife fences are trapping animals, reducing land connectivity, and preventing gene flows across the landscape (Tanner and Leroux 2015, Seiler 205). In addition, studies have found that accidents have increased significantly where the fences terminated (Seiler 2005). These constraints must be considered and resolved before fencing can be widely applied on the state and national levels (Seiler 2004)

Driver behavior guidance

Public education programs aim to inform drivers of potential MVC risks and raise awareness about creating a safer driving environment (Rea et al. 2018). Two most adopted and least expensive types of program are reducing night-time speed limits and establishing warning signs. Speed limits are found to be positively correlated with MVC frequencies (CDC 2006). In northern British Columbia, Canada, experiments showed that a 45 mph nighttime driving speed on highways allowed for enough reaction and braking time to avoid MVCs (Rea et al. 2014). However, only about 20% drivers strictly obeyed the new speed limit when it was implemented (Zeller et al. 2018). Therefore, more strict road laws, such as serious punishments for exceeding the speed limit, are suggested to supplement this strategy (Tanner et al. 2017). Warning signs are implemented to advise drivers to decelerate on certain road segments (Rea et al. 2018), although their effectiveness at preventing MVCs remains untested (Zeller et al. 2018, Rea et al. 2014). MVC patterns and hotspots change over time (Rea et al. 2014). Dynamic and seasonal signs have thus been proposed to improve mitigation efficiency (Niemi et al. 2013, Danks and Porter 2010). Other innovative public awareness programs suggest using driver simulators to replicate real-life scenario and training drivers in practical skills such as hazard perception and quick decision making, so that drivers can be more prepared when encountering collisions in real life (Rea et al. 2018).

Road environment modification

Roadside vegetation attracts moose to forage and obscures the view of drivers (Rea et al. 2018). Properly removing brush along the road helps motorists to see wildlife in advance and allows for more reaction time (Tanner and Leroux 2015). In Norway in the late 1990s, this method was found to reduce MVCs by 40 to 50% (Gundersen and Andreassen 1998). Studies also found that new vegetations after cleanup contained more nutrition and were more desirable for moose populations (Rea 2003). Continuing to cut the new vegetation growth may further prevent moose foraging at the road edge (Franzmann 1978). Some places incorporate MVC patterns in road planning. In Northern British Columbia, potential routes were advised in regions with more lake and rivers, fewer swamps, and fewer sphagnum bogs. The timber industry was also advised in some geographical ranges to alter landscape features (Rea et al. 2014). Roadway salting attracts ungulate species to the mineral-rich water and increases their exposures to vehicles (Niemi et al. 2017). In Quebec, Canada, salt pools increase the MVC probability by nearly 80% (Leblond et al. 2007). Therefore, the Quebec government drained and filled problematic pools with rocks to prevent moose access. Follow-up studies showed that this approach reduced the frequency and duration of moose visits at night. Long-time monitoring should be continued to better understand how this moose behavioral change influences collision risks (Leblond et al. 2007).

Conclusion

MVCs are a common form of HWCs in North America and Europe, posing serious road safety, socio-economic, and wildlife conservation threats. Previous studies suggested a range of spatial variables that can help to identify areas of high MVC risk and to predict potential crash hotspots. Current mitigation strategies developed upon these static models aim to reduce collision frequencies by redirecting animal movements, influencing driver behaviors, and modifying road environments. However, most interventions are expensive and not entirely effective. Future studies are advised to consider more dynamic temporal variables, such as weather conditions, to further refine predictive MVC models and advise MVC mitigations.

CHAPTER II. DEVELOPING A PREDICTIVE AND DYNAMIC MOOSE-VEHICLE COLLISIONS MODEL IN MAINE

Introduction

With the rapid growth of human populations, increasingly natural habitats have been exploited and transformed into human settlements. This global trend of resource extraction and land development brings more people into direct contact with wildlife, escalating human-wildlife conflicts worldwide (Distefano 2005). Road network expansion indicates urbanization. Constructions of infrastructures decrease land connectivity and cause more wildlife and vehicles to encounter each other (Tanner and Leroux 2015). Wildlife-vehicle collisions have thus become a common form of human-wildlife conflicts around the world.

Globally, most wildlife-vehicle collisions occur between vehicles and small to medium-sized ungulates, but accidents with large-size ungulates, such as moose (*Alces alces*), can have more serious road safety and conservation impacts (Niemi et al. 2017). When a vehicle collides with a moose, the large body mass, long legs, and high center of gravity cause the animal to knock the vehicle from above and sweep up the hood of the car into passenger compartments (Zeller et al. 2018, CDC 2006, Garrett and Conway 1999). The injury and mortality rates of moose-vehicle collisions (MVC) are estimated to be 34 times higher than any other urban wildlife-vehicle collision types (Joyce and Mahoney 2001).

Moose are the dominant herbivore species in Maine, USA. They forage in shallow water and woodland regions (Innes 2010), and so can potentially inhabit much of the state. Moose-vehicle collisions (MVC) is one of the most impactful types of human-wildlife conflicts in Maine. Since the late 1990s, attributed to successful ungulate management and road network expansions, MVCs have constituted 15% of total road accidents in the state (CDC 2006). In the past 3 years, more than 1,200 MVC occurred in Maine (MEDOT 2018), raising great road safety, socio-economic, and wildlife conservation concerns (Dussault et al. 2007).

Various mitigation strategies have been adopted by the state of Maine to reduce MVC frequencies: animal movements redirection, driver behavior guidance, and road environments modification (Rea et al. 2018). Common approaches include implementing wildlife fencing, establishing warning signs, and removing roadside vegetations (Rea et al. 2009), yet none of these methods have been entirely effective in Maine.

One way to reduce MVC risks is to increase driver awareness of possible collision hotspots. Predictive MVC models are developed to investigate what landscape, traffic, and wildlife factors characterize the occurrence of MVCs and pinpoint potential problematic road segments (Tanner et al. 2017, Rea et al. 2014, Snow et al. 2014). These models collect existing ecological data to generalize MVC patterns and then apply these findings on broader temporal and spatial scales (Kendall 2015, Evans 2012, Jospe 2006). However, a major disadvantage of current MVC models is that most are static and produce a general hotspot map for all conditions. A dynamic MVC model enables updating its forecast as weather changes and is thus more flexible and robust.

The goal of this study was to develop both static and dynamic models to forecast MVC locations in Maine using geographic information system (GIS) and maximum entropy (MaxEnt) methods. With the models that I constructed, I hope to answer the following questions: (1) Can MVC forecasts be developed to be adaptive to changing weather conditions? (2) What factors help characterize MVC hotspots in Maine? (3) Which of the GIS static and MaxEnt spatial models can more effectively and robustly forecast future collisions and provide a more comprehensive understanding of MVCs in Maine?

Methods

Study Area

The study was conducted in the state of Maine, USA, which covers a total area of approximately 84,000 km^2. Maine has a humid continental climate, which is characterized by warm and wet summers and cold and humid winters (Peel et al. 2007). Forest takes up about 89% of Maine land area, making Maine the most forested state in the US (Butler, 2017). These geographic features also make Maine a suitable habitat for moose. Since the early 1900s, the moose population in Maine has increased from 2,000 to the current estimated population of 76,000 (MDIFW, n.d.). I based all my analyses on the 37,805 kilometers of road networks in Maine, because the Maine Department of Transportation (MEDOT) only documented MVCs happened on the roads.

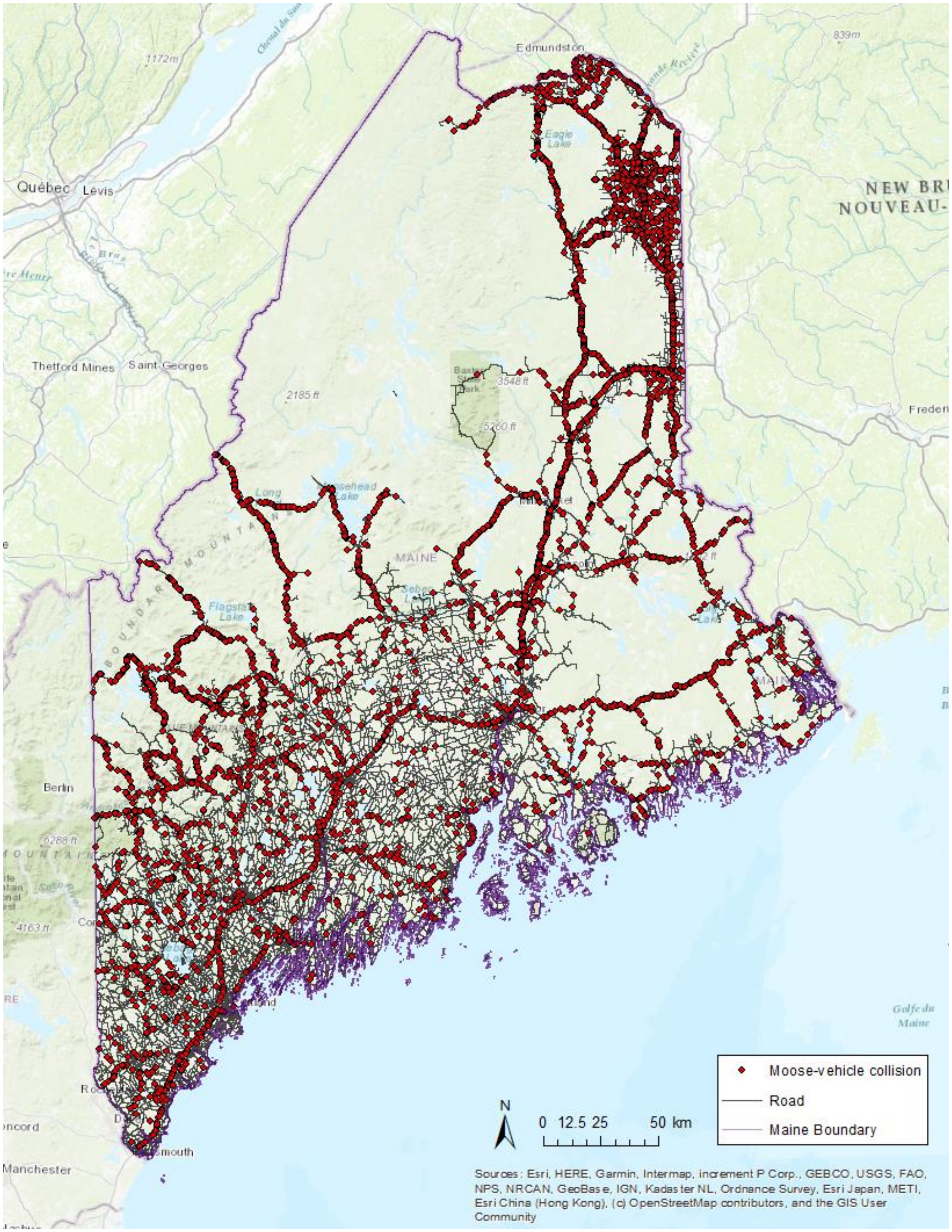

Figure 1. Locations of 6,765 MVCs in Maine, USA between 2003 and 2013.

Data Collection

I obtained MVC data from 2003 to 2016 from MEDOT. Each record included the crash ID, crash location by latitude and longitude, road offset, accident date and time, light condition, crash road type, crash road speed limit, and crash road traffic volume. I discarded 83 entries that had unknown date, time, or GPS location information, leaving 6,765 complete records for statistical analysis (Figure 1).

I reviewed 24 journal articles on MVC patterns published between 1998–2018 to identify variables hypothesized to influence the probability of MVCs (Appendix 1). I based my selection on variable frequencies in the literature and data availability. I defined spatial variables as any predictors that remained constant over time and temporal variables as any predictors that changed values over time. I acquired 2011 National Land Cover Database (NLCD) from USDA (National Agricultural Library, 2011), 1-meter Digital Elevation Models (DEM; 2017), and National Hydrology Dataset (NHD; 2018) from USGS. I collected Maine road data from MEDOT (2018), which included road location, functional type, speed limit, and annual average daily traffic volume. I obtained data on annual moose harvest by township from 2005 to 2017 from Maine Department of Inland Fisheries and Wildlife (WDIFW).

For temporal data, I obtained daily air temperature, precipitation, relative humidity, snow cover, snow depth, soil moisture, vegetation cover, solar elevation, and solar angle data beginning January 1, 2005 from the National Oceanic and Atmospheric Administration (NOAA; 2019). The first seven layers were accessed through the North American Mesoscale Forecast System (NAM; National Centers for Environmental Information, 2019), which self-updates online every three hours and is synchronized daily to a server at Bigelow Laboratory for Ocean Sciences. I decomposed the solar angle layer into U (East-West) and V (South-North) directions in radian units.

GIS Analysis

I used ArcGIS 10.6 (ESRI 2018) to display and analyze spatial data. All layers were projected in NAD 1983 UTM Zone 19N. I converted the road data into a 30 m^2 raster layer and resized and snapped all layers to the same resolution. I chose this resolution because 30 m^2 was the least common multiple resolution of all data layers.

For the GIS model, I split the 6,765 MVC accident records into 80% modeling data and 20% validation data. I generated the same number of non-crash control points along road pixels for both modeling and validation. The GIS model was constructed using only spatial variables. I identified 16 quantitative and 2 categorical variables related to four different aspects: land features, topography, animal features, and road features (Table 1). I extracted and matched specific variable values to accident and control points after processing all raster data layers.

Table 1. Names, definitions, and units of 16 quantitative and 2 categorical predictors evaluated to build the GIS model.

Variable	Definition	Units
Quantitative variables		
Water and wetland	% water and wetland cover within 500 m radius	%
Deciduous forest	% deciduous forest cover within 500 m radius	%
Evergreen forest	% evergreen forest cover within 500 m radius	%
Mixed forest	% mixed forest cover within 500 m radius	%
Shrub	% shrub cover within 500 m radius	%
Grassland	% grassland cover within 500 m radius	%
Developed	% developed area cover within 500 m radius	%
Other	% other land cover within 500 m radius	%
Distance to forest	Distance to the nearest forest	m
Distance to waterbody	Distance to the nearest waterbody	m
Distance to wetland	Distance to the nearest wetland	m
Elevation	Surface elevation above the Earth's sea level	m
Slope	Degree elevation rise from neighboring locations	Degree
Moose harvest density	Moose harvest density by township	#/km^2
Road density	Road density	Roads/km^2
Traffic volume	Annual average daily traffic	#/day
Categorical variables		
Road functional type	Federal functional classification	-
Speed limit	Speed limit classification	-

I reclassified the 2011 NLCD layers into eight classes: water and wetland, deciduous forest, evergreen forest, mixed forest, shrub, grassland, developed area, and other (Appendix 2). I created a 500-meter ring buffer around each road pixel and calculated the percentage area of each land cover type within the buffer (Figure 2; Zuberogoitia et al. 2014, Danks and Porter 2010, Gonser et al. 2009). I extracted all three types of forest raster pixels and

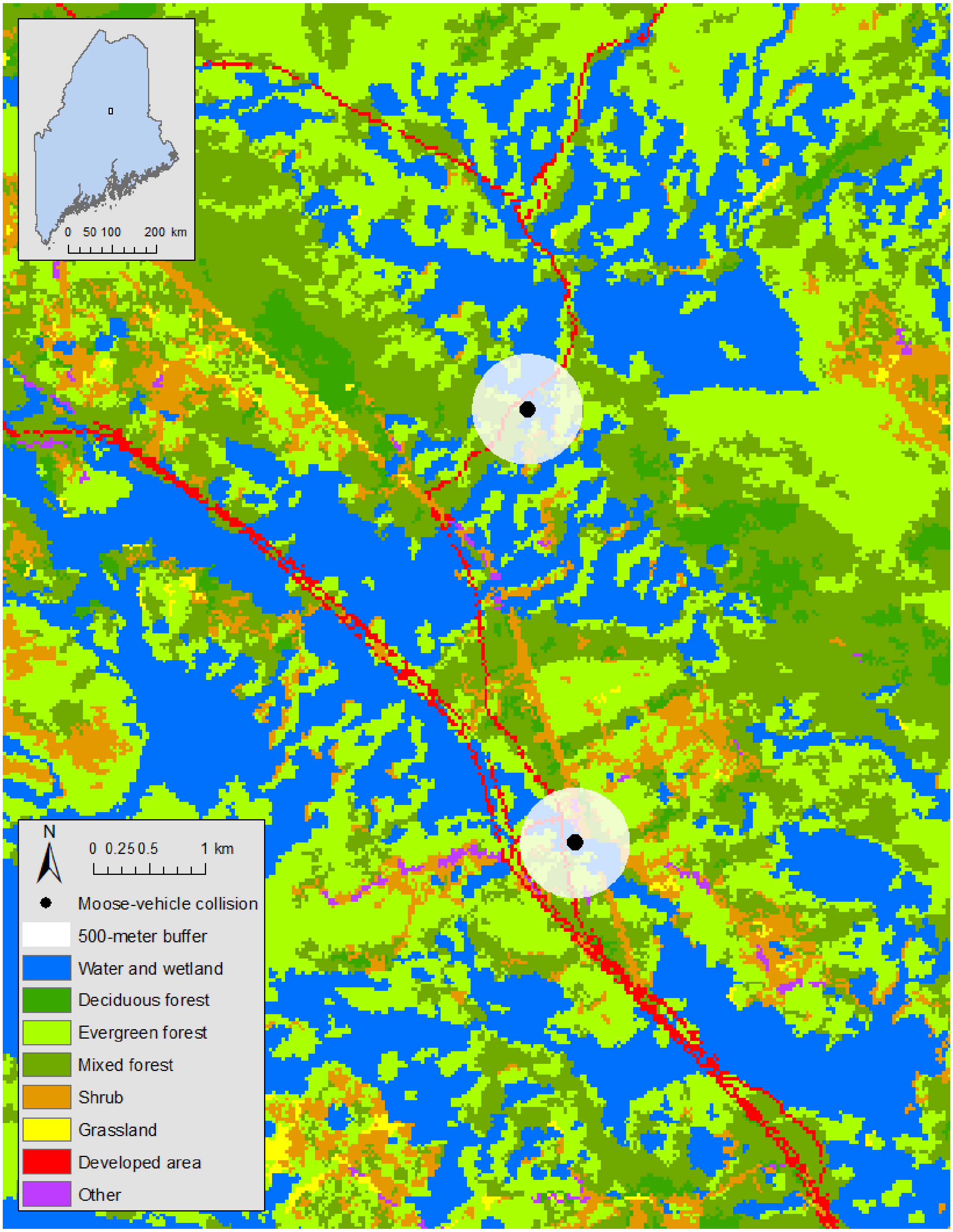

Figure 2. Sample MVC points with a 500-meter ring buffer overlaid on the reclassified 2011 NLCD layer. The percentage of each land cover type within the buffer was calculated for each road pixel.

Table 2. Names, definitions, units, and treatments of 11 temporal and 13 spatial variables evaluated to build the MaxEnt model.

Variable	Definition	Units
Spatial variables		
Land type	Dominant land type within 500 m radius	-
Dist. to forest	Distance to the nearest forest	m
Dist. to waterbody	Distance to the nearest waterbody	m
Dist. to wetland	Distance to the nearest wetland	m
Elevation	Elevation above Earth's sea level	m
Slope	Elevation rise from neighbor locations	Degree
Aspect u direct.	U direction of elevation rise in radian	-
Aspect v direct.	V direction of elevation rise in radian	-
Moose harvest den.	Moose harvest density by township	$\#/km^2$
Road density	Road density	$Roads/km^2$
Traffic volume	Annual average daily traffic	#
Road function	Federal functional classification	-
Speed limit	Speed limit	mph
Temporal variables		
Air temperature	Mean daily surface air temperature	K
Precipitation	Total daily precipitation	mm
Relative humidity	Daily relative humidity above the ground	%
Snow cover	Mean surface snow cover	%
Snow depth	Mean surface snow depth	m
Soil moisture	Mean surface soil moisture transpiration	kg/m^3
Vegetation cover	Daily surface vegetation cover	%
Solar elevation	Solar elevation angle above horizon	degree
Azimuth u direct.	U direction of azimuth angle	radian unit
Azimuth v direct.	V direction of azimuth angle	radian unit

converted them into a forest polygon shapefile. I split the NHD data into waterbodies and wetlands layers based on the types attribute. I then calculated the distances to the nearest forests, waterbodies, and wetlands from each road pixel.

I processed the 1-meter DEM data to obtain a slope layer. I summed the total moose harvested from 2005 to 2017 in each township and divided it by a town's area to calculate the moose harvest density. I then used kernel density to calculate the number of roads per square kilometer. All roads were categorized into one of the seven federal road function classifications (Appendix 3; MEDOT 2018). I reclassified the speed limit data into three speed classes: low (10–40 mph), medium (45–55 mph), and high (60–75 mph).

The MaxEnt model included 13 spatial variables (Table 2). I combined the eight land cover layers into a land type layer, which used an index number to demonstrate the dominant land cover type within 500-meter buffer (Appendix 2). I recoded the road functional type using an index number from 1 to 2 (Appendix 3). I used the original quantitative data for speed limit. Finally, I calculated an aspect layer from the 1-meter DEM data and decomposed it into U and V directions in radian units. These changes were made to avoid overfitting the models.

Statistical Analysis

All statistical analyses were conducted in RStudio (R 3.5.1 2018). I first ran descriptive analyses to plot MVC trends by year, month, hour, and road speed limit. I tested the normality of spatial data and took the log values with base 10 to normalize skewed variables. I incremented all variable values by 1 before normalization to avoid taking log on zeros, which are not defined. I ran Welch's two-sample *t*-tests on each quantitative variable and Pearson's Chi-squared tests on each categorical variable to identify those that differed significantly between control and accident sites ($p < 0.05$; Seiler 2005, Malo et al. 2004, Mladenoff et al. 1995). I applied a correlation matrix on quantitative variables ($r > 0.5$) and Pearson's chi-squared tests and Fisher's exact tests on categorical variables ($p < 0.05$) to determine and remove any significantly correlated variables based on the Welch's two-sample *t*-test results. All categorical variables were then converted into dummy variables which take the value 0 or 1 to indicate the absence or presence of some categorical effect I also ran a prune tree to apply cost-complexity pruning on all data and to identify interaction terms to be included in the final model.

I ran a binary logistic regression test on all independent variables that distinguished between control and accidents sites and interaction terms identified from the prune tree (Rea et al. 2018, Beyer et al. 2012, Dussault et al. 2007). I used a stepwise model selection to optimize my model and a likelihood ratio test to check if either model fit the MVC data significantly better ($p < 0.05$). I repeated this optimization process until the variable set became stable.

My final logistic regression model was plugged into ArcGIS to generate MVC probability predictions on each road pixel. I extracted predicted values of validation accident and control sites and converted values to a scale of 0 to 1. I then ran a one-tailed Welch's two-sample *t*-test to validate if accident sites displayed significantly higher predicted MVC probabilities than control sites ($p < 0.05$).

MaxEnt Analysis

All MaxEnt analyses were completed in an online version of RStudio that is installed on a server at Bigelow Laboratory for Ocean Sciences in East Boothbay, Maine. I used *dismo* (Hijmans et al. 2017) and *dismotools* (Record and Tupper 2018) R packages to run MaxEnt modeling and forecasting, but I also compiled all my algorithms to a new *moosecrash* package loaded on the Bigelow server. Maxent has a built-in measurement called area under the Receiver Operating Characteristic curve (AUC), which quantifies how accurately a model can identify a presence point from background ones (Yackulic et al. 2012). On a scale of 0 to 1, an AUC value of 0.5 means a random model while an AUC value of 1 presents perfect predictions. The AUC index can be measured in two ways: the training AUC, which reflects the training gain of a model, and the testing AUC, which shows the forecasting accuracy (Yost et al. 2008). For this study, I sought the most parsimonious model that maximized the testing AUC with the fewest variables.

The MaxEnt model evaluated both static spatial and dynamic temporal variables. I used MVC records from 2005 to 2017 to build the MaxEnt model because the temporal data I obtained began in 2005. I divided the 5,495 MVC entries into 80% training data and 20% testing data. All these locations were treated as presence sites in MaxEnt modeling. I then generated 10 different sets of random non-crash points as unknown background sites following the 1:1 presence-unknown ratio for both training and testing data. I assigned each background site with a random date and time between 2005 and 2017 to assign them with temporal data.

Using the date, time, and cell number information, I was able to extract and match variable values to each presence and unknown sites. I ran the MaxEnt model 10 times using each variable individually and ranked on their mean testing AUC values. I calculated a correlation matrix on all variables for 1,000 times to construct 95% confidence intervals on correlations. I identified any significantly correlated variable pairs ($r > 0.5$) and removed elements with a lower mean testing AUC.

I then grouped all independent variables into either a static set or a dyanmic set. For each variable set, I ran the MaxEnt model 10 times with different randomly selected background points, calculated the mean contribution of each variable, removed the least contributing one, and re-ran the model 10 times (Yost et al. 2008). I applied a one-tailed Wilcoxon signed rank test on their testing AUCs to determine if deleting a variable significantly dropped the model accuracy ($p < 0.05$; Yost et al. 2008). I repeated this process to find significant spatial and temporal variable sets with fewest variables and the highest testing AUC level. I combined the two significant variable sets and repeated the process above to finalize my MaxEnt base model.

With the MaxEnt base model that I developed, I was able to produce daily MVC forecasts. For any desired date after April 30, 2019, my algorithm used MVCs that happened within five days before and after the same date of every year between 2005 to 2017. The 10-day window was selected to obtain enough data for modeling as well as to better detect climate patterns for a given time of the year. The model then randomly sampled 1,000 unknown background points and assigned them with date and time within the same period. Using all variables in my model, MaxEnt adjusted itself to best fit these data and produced hourly MVC forecasts, which can be displayed on an interactive map (https://eco.bigelow.org/moosecrash_v0.001).

Results

Both of my models suggest that MVCs in Maine are more likely to happen on roads with intermediate to high speed limits and traffic volumes, in or near forest cover, and close to wetlands. The MaxEnt model also incorporates sunlight, snow depth, humidity, and soil moisture in forecasting MVCs in Maine. My final MaxEnt model yielded a forecast AUC over 0.9, indicating a high forecast accuracy. Hourly MVC prediction can be accessed at https://eco.bigelow.org/moosecrash_v0.001.

Descriptive analysis

The annual number of MVCs in Maine has decreased from a high of 671 in 2004 to a low of 293 in 2016 (Figure 3). MVCs happen most frequently in the summer and fall (Figure 4), between dusk and midnight (Figure 5), and on medium speed roads (Figure 6). June was the peak month for MVCs. Outside of medium-speed roads, interstate highways with a speed limit of 75 mph account for the most collisions.

Static spatial model

My spatial analyses identified 14 out of 16 quantitative variables that differed significantly between accident and control sites ($p < 0.05$), 12 of which even significant at the $p < 0.01$ level (Table 3). Four groups of variables were significantly correlated (Appendix 4): percentage developed area cover and distance to forest ($r = 0.559$), elevation and road density ($r = –0.513$), road density and moose harvest density ($r = –0.570$), and elevation and moose harvest density ($r = 0.622$). Percentage developed area cover, elevation, and road density were then removed to avoid multicollinearity. Although both road functional type ($\chi^2 = 4309.4$, df = 7, $p < 0.01$) and speed limit ($\chi^2 = 1532$, df = 3, $p < 0.01$) had significant associations with MVCs, these two categorical variables were also significantly correlated to each other ($\chi^2 = 11315$, df = 21, $p < 0.01$). Therefore, only speed limit was used in the logistic regression model. The prune tree identified two interaction terms to be considered: traffic volume and speed high, and speed high and moose harvest density.

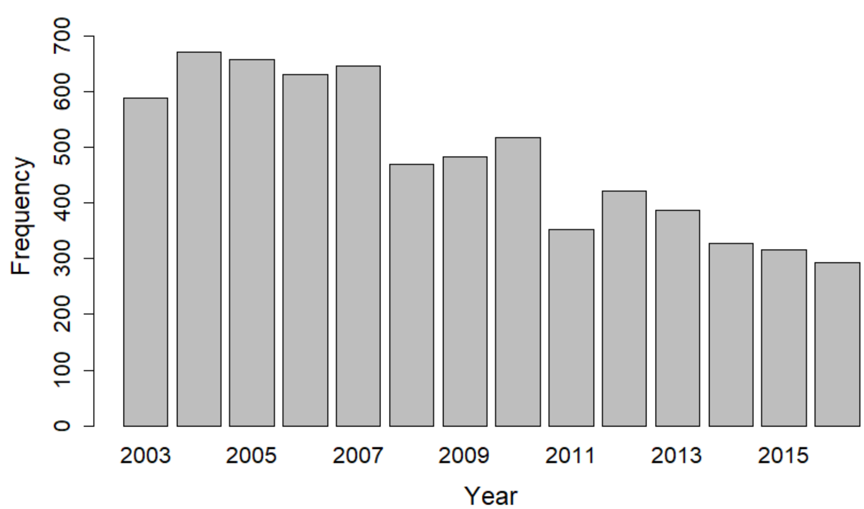

Figure 3. Frequency of MVCs in Maine from 2003 to 2016 by year.

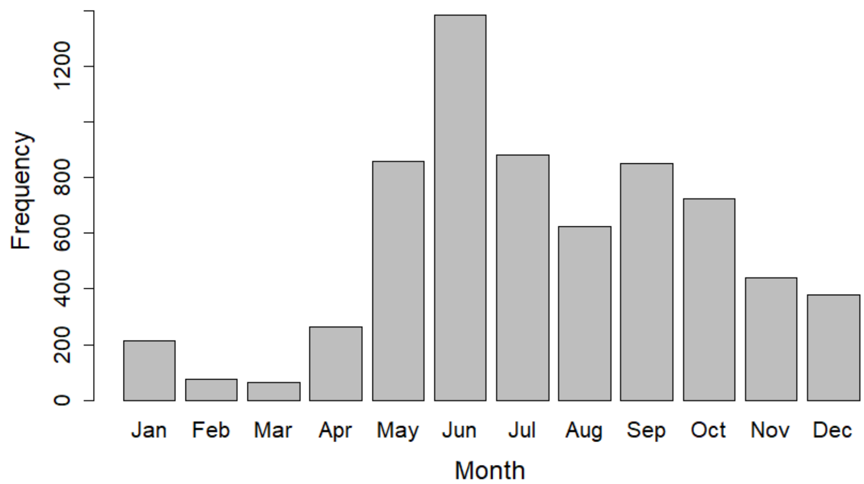

Figure 4. Frequency of MVCs in Maine from 2003 to 2016 by month.

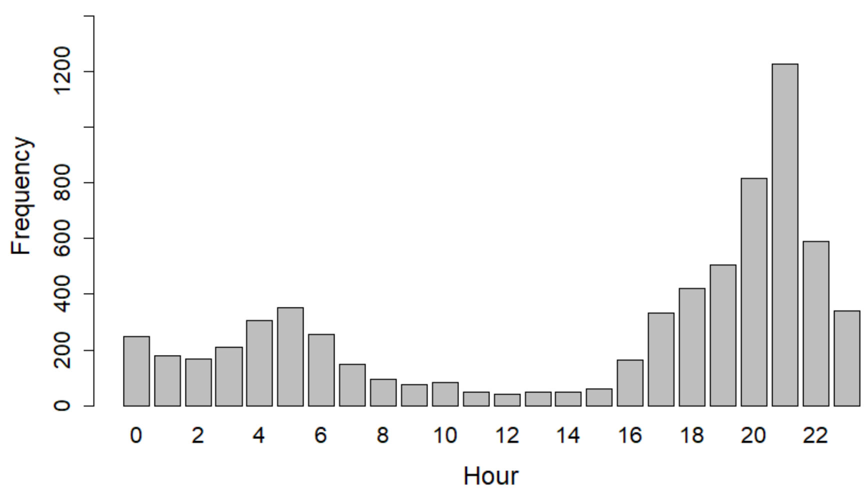

Figure 5. Frequency of MVCs in Maine from 2003 to 2016 by hour.

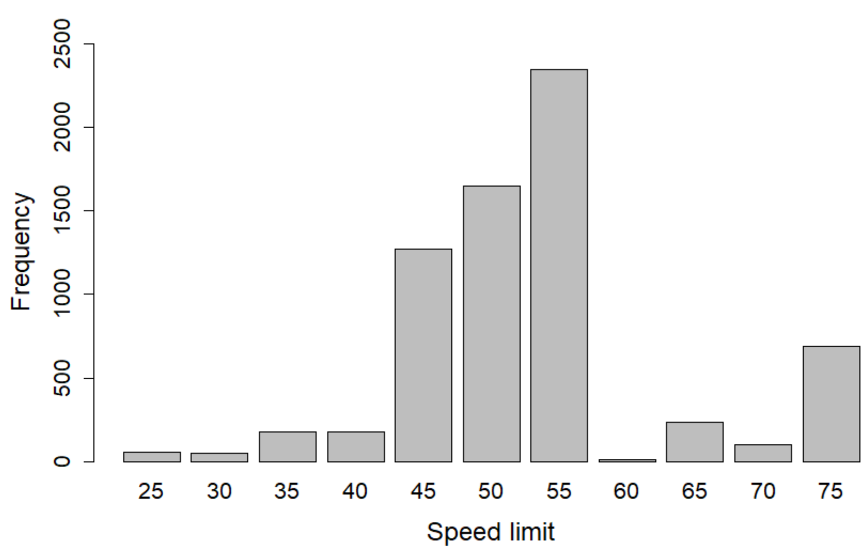

Figure 6. Frequency of MVCs in Maine from 2013 to 2016 by road speed limit.

Table 3. Results of Welch's two-sampled *t*-tests comparing means of quantitative variables at accident and control sites. Significance: * < 0.05, ** < 0.01, *** < 0.001.

Variable	Accident mean	Control mean	*t*-value	p-value	Significance
% Water and wetland	0.958	0.948	–1.102	0.270	
% Deciduous forest	0.787	0.843	5.676	<0.001	***
% Evergreen forest	1.292	1.269	–2.895	0.004	**
% Mixed forest	0.988	0.918	–7.487	<0.001	***
% Shrub	0.613	0.483	–17.583	<0.001	***
% Grassland	0.173	0.175	0.393	0.694	
% Developed	1.203	1.184	–3.270	0.001	**
% Other	0.609	0.697	7.361	<0.001	***
Distance to forest	1.581	1.357	–17.844	<0.001	***
Distance to waterbody	2.251	2.197	–5.867	<0.001	***
Distance to wetland	2.095	2.162	6.309	<0.001	***
Elevation	2.186	1.871	–44.591	<0.001	***
Slope	0.723	0.755	4.638	<0.001	***
Moose harvest density	3.240	2.663	–48.106	<0.001	***
Road density	1.621	1.914	44.774	<0.001	***
Traffic volume	1.294	0.482	–60.401	<0.001	***

Table 4. Regression coefficients and p-values of spatial variables included in the final logistic regression model (AIC = 8441). Significance: * < 0.05, ** < 0.01, *** < 0.001.

Variable	Coefficients	*z*-value	p-value	Significance
(Intercept)	–8.895	–26.935	<0.001	***
Deciduous forest cover	0.127	1.953	0.051	
Evergreen forest cover	0.513	7.077	<0.001	***
Mixed forest cover	0.307	3.658	<0.001	***
Shrub cover	0.343	4.642	<0.001	***
Other land cover	–0.517	–10.462	<0.001	***
Distance to forest	0.214	3.781	<0.001	***
Distance to wetland	–0.163	–3.212	0.001	**
Moose harvest density	1.060	22.613	<0.001	***
Traffic volume	1.795	5.301	<0.001	***
Speed high	3.438	3.773	<0.001	***
Speed medium	1.176	14.340	<0.001	***
Traffic volume: moose harvest den.	0.065	4.429	<0.001	***
Traffic volume: speed high	–0.476	–2.011	0.044	*

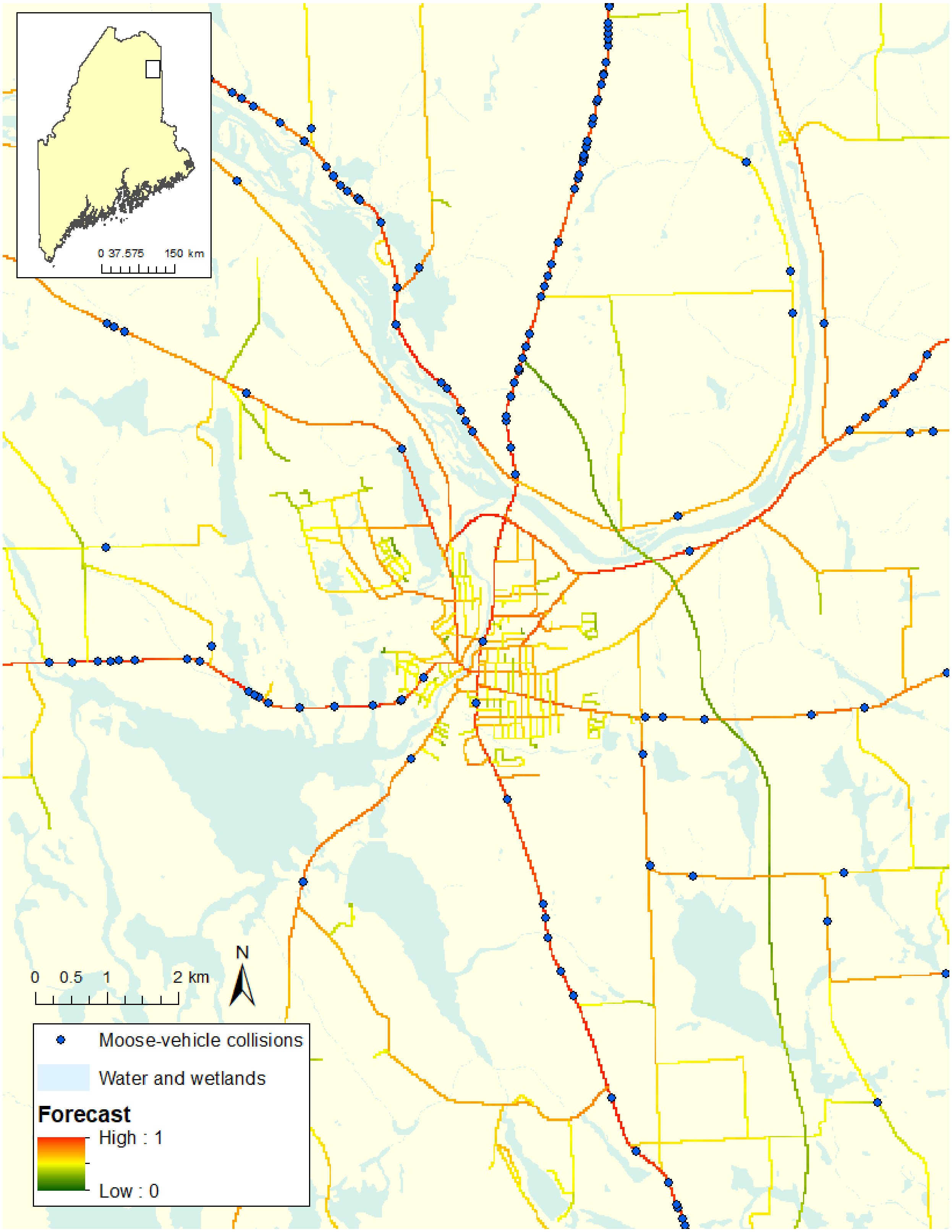

Figure 7. Sample likelihoods to encounter MVCs at given road segments calculated based on the GIS logistic regression model.

My final static spatial model consisted of nine quantitative variables, two categorical variables, and two interaction terms (AIC = 8441; Table 4). The MVC probability of a given road pixel can be calculated by the following formulas (Figure 7):

$$P(MVC) = 1 / (1 + e^{-(-8.895 + 0.127[deciduous] + 0.513[evergreen] + 0.307[mixed] + 0.343[shrub] - 0.517[other] + 0.214[forest\ dist] - 0.163[water\ dist] + 1.795[traffic\ volume] + 1.060[moose\ den.] + 3.428[speed\ high] + 1.176[speed\ medium] + 0.290[traffic\ volume * moose\ den.] - 0.476[traffic\ volume * speed\ high])})$$

Predictions based on this logistic regression model reported a significantly higher mean MVC probability for validation accident sites compared to control sites ($t = -53.424$, $df = 2699$, $p < 0.001$; Figure 8). This means that the model can effectively distinguish MVC hotspots in Maine.

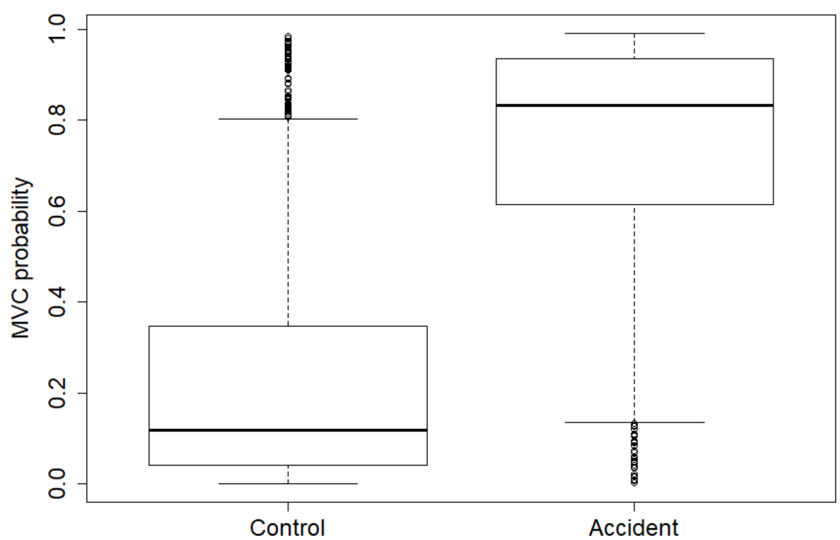

Figure 8. Comparison of predicted likelihoods to encounter MVCs at validation accident sites and control sites.

Dynamic model

MaxEnt models constructed using single variables alone had mean testing AUC values ranging from 0.502 to 0.676. I removed traffic volume and road density from the spatial variable list, and azimuth v direction, air temperature, and snow cover from the temporal variable list to avoid multicollinearity (Appendix 5; Appendix 6). I identified seven significant spatial variables and six significant temporal variables that maximized the mean testing AUC of the corresponding variable group (Table 5). The final MaxEnt based dynamic model, constructed by combining these two sets, achieved a mean testing AUC of 0.721

Table 5. Summary for MaxEnt models and Wilcoxon signed ranked tests to determine significant spatial, temporal, and combined MaxEnt variable sets. Variables with * represent sets with the highest testing AUC level and fewest variables.

# of variables	Removed variable	Mean testing AUC	p-value
Spatial variables			
11	-	0.7068	1.000
10	Aspect u direction	0.7068	0.423
9	Distance to water	0.7067	0.116
8	Aspect v direction	0.7068	0.053
7	*Slope	0.7067	0.097
6	Distance to wetland	0.7065	<0.001
Temporal variables			
7	-	0.6575	1.000
6	*Precipitation	0.6575	0.116
5	Relative humidity	0.6571	0.025
Spatial + temporal variables			
18	-	0.7207	1.000
13	*(Significant sets only)	0.7207	0.188
12	Distance to wetland	0.7206	0.019

Table 6. Variables selected in the MaxEnt model and their mean contributions after 10 simulations.

Variable	Mean contribution (%)
Spatial variables	
Road functional type	61.963
Moose harvest density	17.933
Speed limit	3.699
Elevation	0.879
Distance to forest	0.738
Land type	0.127
Distance to wetland	0.036
Temporal variables	
Solar elevation	6.836
Vegetation cover	4.253
Azimuth u direction	2.236
Snow depth	0.816
Soil moisture	0.337
Relative humidity	0.146

(Table 6), which is above the generally acceptable model AUC standard of 0.7 (Yost et al. 2008). All daily MVC forecasts simulated using these variables yielded a forecasting AUC over 0.9, indicating a high accuracy for these forecasts. The contributions of each variable vary among daily models, but remained the same ratio scales. Detailed hourly results are displayed on https://eco.bigelow.org/moosecrash_v0.001 (Figure 9).

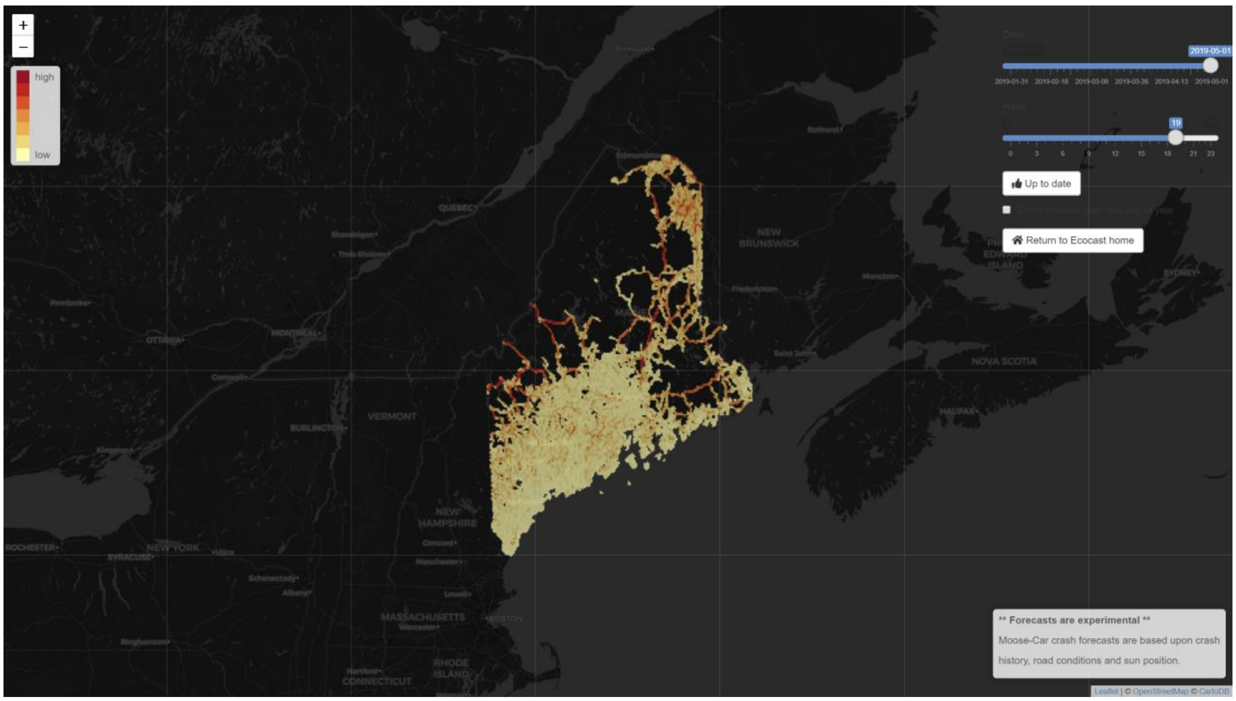

Figure 9. Sample MVC forecast at 7 pm, May 1, 2019, using variables identified in the MaxEnt model. The simulation is displayed on https://eco.bigelow.org/moosecrash_v0.001.

Discussion

The results of this study suggest that predictive and dynamic MVC models can be developed to inform drivers of crash hotspots in Maine. I showed that both static spatial and dynamic models can identify key spatial and temporal factors that influence the probability of MVCs. Effectively applying these models allows for a more proactive, timely, and diagnostic response to MVCs in Maine and proposes a novel method to more comprehensively and generally understand and predict human-wildlife conflicts.

MVC predictors

My spatial model suggests that MVCs in Maine are more likely to happen on roads with intermediate to high speed limits and volumes, in or near forest cover, and close to wetlands. The dynamic MaxEnt model confirm the significance of forests, wetlands, and road features in predicting MVCs and identifies sunlight, snow depth, humidity, and soil moisture as significant temporal indicators in generating daily and hourly forecasts. This spatial MVC pattern identified by my model is very similar to MVC patterns identified in central and western Massachusetts and western Maine, USA (Zeller et al. 2018, Snow et al. 2015, Snow et al. 2014). Six out of the 17 potential MVC predictors appeared in both the static GIS model and the dynamic MaxEnt model (Table 7). Variables that were only included in one model were removed due to multicollinearity in the other model. These common factors further support that MVCs are influenced by moose behaviors, driver behaviors, road features, and landscape features (Rea et al. 2018).

My model shows that high speed limits significantly increases the likelihood of MVCs in Maine. Road functional type had the highest contribution in the MaxEnt model but was removed due to multicollinearity in the spatial model. Vehicle speed is directly related to the reaction and decision-making time of a driver (Rea et al. 2018). In Maine, only 2.6% of the roads have a speed limit greater than 60 mph, yet 15.3% of crashes occurred on these roads. The majority (78.1%) of MVCs occurred along medium speed roads, which account for 65.9% of all roads in Maine.

Roadside vegetation influences moose foraging pattern and the ability of drivers to see animals (Rea et al. 2019). Moose are generalist browsers that consume 90% of their diet from browsing and less than 10% from grazing (Renecker and Schwartz 2007). Signature deciduous hardwood species in Maine, such as the willow family (*Salicaceae*), the cottonwood genus (*Populus*), and the birch genus (*Betula*) as well as softwood species such as the conifers division (*Pinophyta*) are found on nearly 90% of Maine's land, providing important leaf, stem, and bud resources for foraging (Peek 1974). This supports the significances of all three forest land cover types and the distance to forest variable in both models. The closer a road is to forest clear-cuts and the larger its surrounding woodland, the more likely moose will appear (Tanner and Leroux 2015, Danks and Porter 2010, Seiler 2004). To avoid foraging limitations, moose also seek low elevations and low snow depths in winter and return to more elevated and forested regions in summer (Kennedy-Slaney et al. 2018). This pattern explains the role of elevation and snow depth in predicting MVCs using the MaxEnt model.

Table 7. Comparison between variables used in the GIS logistic regression model and the MaxEnt model.

Variable	GIS model	MaxEnt model
Spatial variables		
Land cover / type	✓	✓
Distance to forest	✓	✓
Distance to wetland	✓	✓
Elevation		✓
Moose harvest density	✓	✓
Traffic volume	✓	
Road functional type		✓
Speed limit	✓	✓
Temporal variables		
Solar elevation		✓
Vegetation cover		✓
Azimuth u direction		✓
Snow depth		✓
Soil moisture		✓
Relative humidity		✓

Water plays a minimal role in both of my models, contrasting previous research that the presence of visible waterbodies significantly predicts MVCs (Rea et al. 2004). The only water-oriented variable that appears in both models is the distance to wetlands, which is widely supported by other studies (Snow et al. 2014, Danks and Porter 2010, Dussault et al. 2007). Moose use wetlands and bogs for seasonal foraging and cooling (Innes 2010). Moose also favor moist woodland during dry seasons (Kennedy-Slaney et al. 2018), supporting my finding that soil moisture and relative humidity are significant predictors in the dynamic model. Moose typically prefer to forage at shallow edges of waterbodies (Innes 2010) because large rivers and lakes create movement barriers (Rea et al. 2014). Therefore, watercourse density may provide a more accurate representation of water compared to what I used to build my model.

Solar elevation and azimuth u direction are two of the most influential temporal variables identified in my dynamic model. Solar position and sun intensity determine the light condition when a crash happens. Their significance is supported by finding that MVCs occur most frequently before and after dusk and dawn because moose are more mobile

(Hikonen and Summla 2001, Joyce and Mahoney 2001, Gundersen Andreassen) and visibility of drivers is lower during those time periods (Niemi et al. 2013, Hikonen and Summala 2001).

Model comparison

I used different statistical methods to build the static GIS and dynamic MaxEnt models, which create boundaries in quantitatively comparing the effectiveness of two models. However, qualitatively speaking, the spatial model explicitly describes the effect of each variable by showing whether it leads to a higher or lower probability of crashes, while the dynamic model ranks predictors by their importance and contributions. During model construction, MaxEnt assigned numeric indices to categorical variables for calculation. As a result, the final model only indicates if variables such as land cover and road function are significant indicators of MVC, but the model is not able to compare the impacts of specific land cover and road functional types.

The objective of this study was to develop a predictive and dynamic model of MVCs in Maine. The underlying mechanism of both models is collecting presence and unknown data to summarize ecological patterns and make predictions on a broader scale. The static model considers spatial factors only and meets the goal of being predictive by providing a generalized representation of potential crash hotspots. This is the most common type of predictive ecological model (Jackson et al. 2000) and resembles existing products in forecasting wildlife-vehicle collisions (Zeller et al. 2018, Snow et al. 2015, Gundersen and Andreassen 1998). The dynamic model, on the other hand, incorporates both spatial and temporal factors and subdivides the MVC patterns into numerous conditions based on the climate data. The MaxEnt tool applies a machine learning technique to look through all probabilities and find the model with the highest information entropy (Yost et al. 2008). This technique allows the model to react to as many sub-conditions as the user requests and generate new forecasts accordingly. Therefore, the dynamic model not only considers environmental features more comprehensively but can also adapt to changes in weather flexibly and provide a more accurate and realistic representation of MVC hotspots. This model can then be adopted to develop innovative mitigation approaches that are potentially effective over a longer period of time.

Future research

This study evaluated 32 potential MVC indicators identified from previous literature to build static and dynamic models of MVCs in Maine. These variables were selected based on their frequencies in the literature and data availability. Difficulties in collecting and obtaining adequate data and quantifying descriptive factors prevent more variables to be considered. Land connectivity, complexity, and similarity determine the extent to which a landscape can support density and biodiversity and facilitate species movements and interactions (Rudnick et al. 2012). Adding in measurements on forest connectivity, edge effects, and road curvature may enhance understandings of how moose use the landscape (Rea et al. 2014, Christie and Nason 2004).

The only directly moose-related variable used in my study was moose harvest density at the township scale. I used this is an indirect estimate of moose abundance because Maine does not have detailed moose distribution data. MVCs are not evenly distributed in space and time, which means that patterns observed at broader and finer scales may not necessarily correspond (Seiler 2004). Using a state-wide inventory of moose presence, distribution, and abundance would provide a more useful and accurate representation of where moose populations are high.

Moose behavioral characteristics such as breeding, herding, and migration also affect moose distribution (Innes 2010), but are harder to measure quantitatively. Climate change is leading to increased tick (order Ixodida) abundance, which leads to increased moose mortality and may cause moose populations to shift their range (Rempel 2010). This may partially explain the decrease in MVC frequency over time and impact the ability of the model to predict future collisions without better moose distribution and behavior data. My descriptive analyses also demonstrate that seasonal patterns exist in MVCs. Generating and comparing seasonal MVC models may provide a more comprehensive understanding of the relative impacts of variables by season, and thus contribute to a more accurate prediction of MVCs.

The MaxEnt model developed in my study is essentially “static-dynamic.” Usage of the same variable combination throughout the entire process hinders its ability to be fully auto-learning. A “dynamic-dynamic” MVC model will ideally enable updating and filtering which variables to use every time it needs to make a new prediction. This also demonstrates the potential and importance of incorporating citizen science data in present HWC studies. For example, it could be improved to receive real-time crash and moose sighting reports (Record et al. 2017). Constantly enlarging the learning library from data input can significantly improve the robustness of my model and enhance current understandings of MVC patterns. Modelers also need to be aware of the risk of multi-collinearity and avoid overfitting as more variables are included, which leads to an inaccurate representation of predictors' impacts on MVCs.

Overall, my static spatial model and dynamic model provide a proactive and diagnostic strategy to identify areas with high MVC risks. This information could be used to further advise existing MVC mitigation methods and developing new interventions in Maine. This study also constructs a framework that can be replicated in other geographical locations and with other species to identify and manage areas with high risks of animal-vehicle conflicts. My model suggests that it is possible to combine spatial static data and dynamic weather data to develop innovative approaches to model human-wildlife interactions and contribute to a more comprehensive understanding of complex coupled human-nature system.

Literature Cited

Beyer, H. L., Ung, R., Murray, D. L., & Fortin, M. J. (2013). Functional responses, Seasonal variation and thresholds in behavioural responses of moose to road density. *Journal of Applied Ecology*, *50*(2), 286–294. doi: 10.1111/1365-2664.12042

Butler, B. J. (2017). *Forests of Maine, 2016*. Retrieved from www.fia.fs.fed.us.

Center for Disease Control and Prevention. (2006). Injuries from motor-vehicle collisions with moose - Maine, 2000-2004. *Morbidity and Mortality Weekly Report*, *55*(47), 1272–1274.

Christie, J. S., & Nason, S. (2003). *Analysis of vehicle collisions with moose and deer on New Brunswick arterial highways*. Moncton: The 31st Annual Conference of the Canadian Society for Civil Engineering.

Danks, Z. D., & Porter, W. F. (2010). Temporal, spatial, and landscape habitat characteristics of moose–vehicle collisions in western Maine. *Journal of Wildlife Management*, *74*(6), 1229–1241. doi: 10.2193/2008-358

Distefano, E. (2005). *Human-Wildlife Conflict Worldwide: A collection of case studies, analysis of management strategies and good practices*. Rome.

Dussault, C., Ouellet, J.-P., Laurian, C., Courtois, R., Poulin, M., & Breton, L. (2007). Moose movement rates along highways and crossing probability models. *Journal of Wildlife Management*, *71*(7), 2338. doi: 10.2193/2006-499

Dussault, C., Poulin, M., Courtois, R., & Ouellet, J.-P. (2007). Temporal and spatial distribution of moose-vehicle accidents in the Laurentides Wildlife Reserve, Quebec, Canada. *Wildlife Biology*, *12*(4), 415–425. doi: 10.2981/0909-6396(2006)12[415:tasdom]2.0.co;2

Eldegard, K., Lyngved, J. T., & Hjeljord, O. (2012). Coping in a human-dominated landscape: Trade-off between foraging and keeping away from roads by moose (Alces alces). *European Journal of Wildlife Research*, *58*(6), 969–979. doi: 10.1007/s10344-012-0640-4

Franzmann, A. W. (1978). Moose. In D. L. Gilbert (Ed.), *Big game of North America—ecology and management* (StackpoleBooks). Harrisburg: Stackpole Books.

Garrett, L. C., & Conway, G. A. (1998). Urban encroachment on the wilderness: moose-vehicle collisions in Anchorage, Alaska, 1991-1995. *International Journal of Circumpolar Health*, *57 Suppl 1*, 527–531.

Garrett, L. C., & Conway, G. A. (1999). Characteristics of moose-vehicle collisions in Anchorage, Alaska, 1991-1995. *Journal of Safety Research*, *30*(4), 219–233.

Gibson, L. A., Wilson, B. A., Cahill, D. M., Hill, J., & Gibson, L. (2004). Spatial prediction of rufous bristlebird habitat in a coastal heathland: a GIS-based approach. In *Journal of Applied Ecology* (Vol. 41).

Gonser, R. A., Jensen, R. R., & Wolf, S. E. (2009). The spatial ecology of deer-vehicle collisions. *Applied Geography*, *29*(4), 527–532. doi: 10.1016/j.apgeog.2008.11.005

Gundersen, H., & Andreassen, H. P. (2018). The risk of moose (Alces alces) collision: A predictive logistic model for moose-train accidents. *Wildlife Biology*, *4*(1), 103–110. doi: 10.2981/wlb.1998.007

Gunson, K. E., Clevenger, A. P., Ford, A. T., Bissonette, J. A., & Hardy, A. (2009). A comparison of data sets varying in spatial accuracy used to predict the occurrence of wildlife-vehicle collisions. *Environmental Management*, *44*(2), 268–277. doi: 10.1007/s00267-009-9303-y

Haikonen, H., & Summala, H. (2001). Deer-vehicle crashes: Extensive peak at 1 hour after sunset. *American Journal of Preventive Medicine*, *21*(3), 209–213. doi: 10.1016/S0749-3797(01)00352-X

Hijmans, R. J., Phillips, S., Leathwick, J., & Elith, J. (2017). dismo: Species Distribution Modeling. R package version 1.1-4. https://CRAN.R-project.org/package=dismo

Huijser, M. P., Wagner, M. E., Hardy, A., Clevenger, A. P., & Fuller, J. A. (2007). *Animal-vehicle collision data collection throughout the United States and Canada*. 387–391. Raleigh.

Innes, R. J. (2010). Alces americanus. In: Fire Effects Information System.

Jospe, A. C. (2006). *Modeling spatially explicit human-wildlife conflict: GIS and moose-vehicle collisions in Maine* (Colby College). Retrieved from http://digitalcommons.colby.edu/honorstheses/390

Joyce, T. L., & Mahoney, S. P. (1973). Spatial and temporal distributions of moose-vehicle collisions in Newfoundland. In *Source* (Vol. 29). Wildlife Society Bulletin.

Kennedy-Slaney, L., Bowman, J., Walpole, A. A., & Pond, B. A. P. (2018). Northward bound: the distribution of white-tailed deer in Ontario under a changing climate. *Wildlife Research*, *45*(3), 220–228.

Langley, R. L., & Mathison, J. (2008). Worldwide characteristics and mitigation strategies for motor vehicle-animal collisions. In G. P. Bartley (Ed.), *Traffic Accidents: Causes and Outcomes* (pp. 75–96). Hauppauge: Nova Science Publishers.

Leblond, M., Dussault, C., Ouellet, J., Poulin, M., Courtois, R., & Fortin, J. (2007). Management of roadside salt pools to reduce moose–vehicle collisions. *Journal of Wildlife Management*, *71*(7), 2304. doi: 10.2193/2006-459

Litvaitis, J. A., & Tash, J. P. (2008). An approach toward understanding wildlife-vehicle collisions. *Environmental Management*, *42*(4), 688–697. doi: 10.1007/s00267-008-9108-4

Maine Department of Inland Fisheries & Wildlife. (n.d.). Moose.

Maine Department of Transportation. (2018). *Roads - DOT (MEDOTPUBRDS)*. Augusta: Maine Department of Transportation.

Malo, J. E., Suárez, F., & Díez, A. (2004). Can we mitigate animal-vehicle accidents using predictive models? In *Journal of Applied Ecology* (Vol. 41).

McClure, M., & Ament, R. (2014). *Where people and wildlife intersect: prioritizing mitigation of road impacts on wildlife connectivity.* Bozeman.

Mladenoff, D. J., Sickley, T. A., Haight, R. G., & Wydeven, A. P. (1995). A regional landscape analysis and prediction of favorable gray wolf habitat in the northern Great Lakes region. *Conservation Biology*, *9*(2), 279–294. doi: 10.1046/j.1523-1739.1995.9020279.x

National Agricultural Library. (2011). *National Land Cover Database*. Washington D.C.: United States Department of Agriculture.

National Centers for Environmental Information. (2019). *North American Mesoscale Forecast System (NAM)*. Silver Spring: National Oceanic and Atmospheric Administration.

National Oceanic and Atmospheric Administration. (2019). *Solar Position Calculator*. Silver Spring: National Oceanic and Atmospheric Administration.

Neumann, W., Ericsson, G., Dettki, H., Bunnefeld, N., Keuler, N. S., Helmers, D. P., & Radeloff, V. C. (2012). Difference in spatiotemporal patterns of wildlife road-crossings and wildlife-vehicle collisions. *Biological Conservation*, *145*(1), 70–78. doi: 10.1016/j.biocon.2011.10.011

Niemi, M., Rolandsen, C. M., Neumann, W., Kukko, T., Tiilikainen, R., Pusenius, J., … Ericsson, G. (2017). Temporal patterns of moose-vehicle collisions with and without personal injuries. *Accident Analysis and Prevention*, *98*, 167–173. doi: 10.1016/j.aap.2016.09.024

PEEK, J. M. (1974). A review of moose food habits studies in North America. *Le Naturaliste Canadien*, *101*, 195–215.

Peel, M. C., Finlayson, B. L., & McMahon, T. A. (2007). Updated world map of the Köppen-Geiger climate classification. *Hydrology and Earth System Sciences, 11*(5), 1633–1644. doi: 10.5194/hess-11-1633-2007

Rea, R. V. (2003). Modifying roadside vegetation management practices to reduce vehicular collisions with moose (Alces alces). *Wildlife Biology*, *9*(2), 81–91.

Rea, R. V., Johnson, C. J., Aitken, D. A., Child, K. N., & Hesse, G. (2018). Dash Cam videos on YouTube™ offer insights into factors related to moose-vehicle collisions. *Accident Analysis and Prevention*, *118*, 207–213. doi: 10.1016/j.aap.2018.02.020

Rea, R. V., Johnson, C. J., & Emmons, S. (2014). Characterizing moose–vehicle collision otspots in Northern British Columbia. *Journal of Fish and Wildlife Management*, *5*(1), 46–58. doi: 10.3996/062013-jfwm-042

Record, N. R., & Tupper, B. (2018). dismotools: Handy tools for the raster and dismo packages. R package version 0.1. https://github.com/BigelowLab/dismotools

Record, N. R., Tupper, B., & Pershing, A. J. (2018). The jelly report: Forecasting jellyfish using email and social media. *Anthropocene Coasts*, *1*(1), 34–43.

Rempel, R. S. (2011). Effects of climate change on moose populations: Exploring the response horizon through biometric and systems models. *Ecological Modelling*, *222*(18), 3355–3365. doi: 10.1016/j.ecolmodel.2011.07.012

Renecker, L. A., & Schwartz, C. C. (2007). Food habits and feeding behavior. In A. W. Franzmann, C. C. Schwartz, & R. E. McCabe (Eds.), *Ecology and management of the North American moose* (2nd ed., pp. 403–440). Boulder: University Press of Colorado.

Rudnick, D. A., Ryan, S. J., Beier, P., Cushman, S. A., Dieffenbach, F., Epps, C. W., … Trombulak, S. C. (2012). The Role of Landscape Connectivity in Planning and Implementing Conservation and Restoration Priorities. *Issues in Ecology*, *16*, 1–20.

Seiler, A. (2018). Trends and spatial patterns in ungulate-vehicle collisions in Sweden. *Wildlife Biology*, *10*(1), 301–313. doi: 10.2981/wlb.2004.036

Seiler, A. (2005). Predicting locations of moose-vehicle collisions in Sweden. *Journal of Applied Ecology*, *42*(2), 371–382. doi: 10.1111/j.1365-2664.2005.01013.x

Snow, N. P., Porter, W. F., & Williams, D. M. (2015). Underreporting of wildlife-vehicle collisions does not hinder predictive models for large ungulates. *Biological Conservation*, *181*, 44–53. doi: 10.1016/j.biocon.2014.10.030

Snow, N. P., Williams, D. M., & Porter, W. F. (2014). A landscape-based approach for delineating hotspots of wildlife-vehicle collisions. *Landscape Ecology*, *29*(5), 817–829. doi: 10.1007/s10980-014-0018-y

Sullivan, J. M. (2011). Trends and characteristics of animal-vehicle collisions in the United States. *Journal of Safety Research*, *42*(1), 9–16.

Tanner, A. L., & Leroux, S. J. (2015). Effect of roadside vegetation cutting on moose browsing. *PLoS ONE*, *10*(8). doi: 10.1371/journal.pone.0133155

Tanner, A. L., Leroux, S. J., & Saunders, P. W. (2017). Road characteristics best predict the probability of vehicle collisions with a non-native ungulate. *Ecoscience*, *24*(1–2), 1–11. doi: 10.1080/11956860.2017.1292100

United States Geological Survey. (2017). *1 meter Digital Elevation Models*. Washington D.C.: United States Geological Survey.

United States Geological Survey. (2018). *National Hydrology Dataset*. Washington D.C.: United States Geological Survey.

Yackulic, C. B., Chandler, R., Zipkin, E. F., Royle, J. A., Nichols, J. D., Campbell Grant, E. H., & Veran, S. (2013). Presence-only modelling using MAXENT: When can we trust the inferences? *Methods in Ecology and Evolution*, *4*(3), 236–243. doi: 10.1111/2041-210x.12004

Yost, A. C., Petersen, S. L., Gregg, M., & Miller, R. (2008). Predictive modeling and mapping sage grouse (Centrocercus urophasianus) nesting habitat using Maximum Entropy and a long-term dataset from Southern Oregon. *Ecological Informatics*, *3*(6), 375–386. doi: 10.1016/j.ecoinf.2008.08.004

Zeller, K. A., Wattles, D. W., & DeStefano, S. (2018). Incorporating road crossing data into vehicle collision risk models for Mmose (Alces americanus) in Massachusetts, USA. *Environmental Management*, *62*(3), 518–528. doi: 10.1007/s00267-018-1058-x

Zuberogoitia, I., Del Real, J., Torres, J. J., Rodríguez, L., Alonso, M., & Zabala, J. (2014). Ungulate vehicle collisions in a peri-urban environment: Consequences of transportation infrastructures planned assuming the absence of ungulates. *PLoS ONE*, *9*(9). doi: 10.1371/journal.pone.0107713

Appendix 1.

Variables hypothesized to influence probability of MVCs identified by reviewing 25 journal articles on MVC patterns, sorted from the most to least mentioned.

Author	Year	LC	TV	MD	SL	L	RD	RT	DF	EL	SP	WL	AP	SD	SM	TP	WB	PP
Rea et al.	2018	x	x	x	x	x			x									
Zeller et al.	2018	x			x		x	x		x	x				x			
Niemi et al.	2017		x	x														
Tanner et al.	2017							x									x	
Tanner and Leroux	2015	x	x	x					x	x								
Snow et al.	2015	x	x		x						x	x						
Snow et al.	2014	x										x						
Rea et al.	2014	x			x					x		x					x	
Niemi et al.	2013																	
Beyer et al.	2013						x											
Eldegard et al.	2012	x						x										
Neumann et al.	2012	x		x	x			x										
Danks and Porter	2010	x	x	x	x	x			x		x		x					
Litvaitis and Tash	2008		x					x	x									
Leblond et al.	2007					x												
Dussault et al.	2007	x	x	x			x			x	x		x			x		x
Seiler	2005	x	x	x	x		x											
Seiler	2004	x	x	x			x											
Christie and Nason	2003	x	x	x	x	x												
Haikonen and Summala	2001		x			x												
Joyce and Mahoney	2001		x	x	x	x												
Garret and Conway	1999					x								x				
Gundersen and Andreassen	1998				x									x		x		
Garret and Conway	1998					x									x			
Total counts	/	13	12	10	10	8	5	5	4	4	4	3	2	2	2	2	2	1

(LC = Land cover, TV = Traffic volume, MD = Moose density, L = Sunlight, RD = Road density, RT = Road type, DF = Distance to forest, EL = Elevation, SP = Slope, WL = Distance to wetlands, AP = Aspect, SD = Snow depth, SM = Soil moisture, TP = Temperature, WB = Distance to waterbody, PP = Precipitation)

Appendix 2.
Land cover categories before and after reclassifying the 2011 NLCD data and their correponding index used in the MaxEnt model (National Agricultural Library, 2011).

Reclassification	NLCD index	NLCD classification	MaxEnt index
Water and wetland	11	Open water	1
	12	Perennial ice/snow	
	90	Woody wetlands	
	95	Emergent herbaceous wetlands	
Deciduous forest	41	Deciduous forest	2
Evergreen forest	42	Evergreen forest	3
Mixed Forest	43	Mixed forest	4
Shrub	51	Dwarf scrub	5
	52	Shrub/scrub	
Grassland	71	Grassland/herbaceous	6
	72	Sedge/herbaceous	
	73	Lichens	
	74	Moss	
Developed area	21	Developed, open space	7
	22	Developed, low intensity	
	23	Developed, medium intensity	
	24	Developed, high intensity	
Other	31	Barren land (rock/sand/clay)	8
	81	Planted/hay	
	82	Cultivated crops	

Appendix 3.

Road function classifications according to Federal Highway Administration (FHWA) with detailed definitions and index numbers used in the MaxEnt model (MEDOT, 2018).

Class	Definition	Index
Interstate	Roads with the highest speeds over the longest uninterrupted distance	1
Other freeway or expressway	Freeways and multilane highways	2
Other principal arterial	Other important roadways that supplement the Interstate System	3
Minor arterial	Other minor roadways that supplement the Interstate System	4
Major/urban collector	Major roads that connect local roads and streets	5
Minor collector	Minor roads that connect local roads and streets	6
Local	Primary road to local areas	7

Appendix 4.

Correlation matrix of all variables evaluated to build the GIS model.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	1.000																									
B	-0.254	1.000																								
C	-0.100	0.309	1.000																							
D	0.144	-0.274	0.329	1.000																						
E	-0.037	0.015	0.181	0.182	1.000																					
F	0.025	-0.028	-0.025	-0.005	0.272	1.000																				
G	-0.050	-0.261	-0.434	-0.315	-0.133	0.014	1.000																			
H	-0.130	0.042	-0.171	-0.306	-0.130	0.033	-0.038	1.000																		
I	-0.002	-0.259	-0.455	-0.324	-0.094	0.024	0.555	0.182	1.000																	
J	-0.249	-0.044	0.014	-0.016	0.032	0.010	-0.012	-0.019	-0.001	1.000																
K	-0.497	0.170	0.022	-0.109	0.007	0.025	0.052	0.069	-0.058	0.271	1.000															
L	-0.249	0.186	0.222	0.074	0.180	-0.100	-0.325	0.045	-0.124	0.082	0.070	1.000														
M	-0.100	0.239	0.112	-0.016	-0.013	-0.007	-0.118	0.007	-0.145	-0.075	0.133	0.101	1.000													
N	0.038	0.016	0.063	0.020	-0.011	0.015	-0.116	0.039	-0.055	-0.013	-0.019	-0.028	0.016	1.000												
O	-0.003	0.008	-0.054	-0.004	0.007	0.037	0.092	0.000	0.099	-0.016	-0.001	0.103	0.037	-0.104	1.000											
P	0.007	-0.063	0.042	0.117	0.174	-0.002	-0.088	-0.068	0.023	0.023	-0.023	0.190	-0.059	-0.163	-0.214	1.000										
Q	0.070	-0.090	0.014	0.004	-0.071	0.001	0.266	-0.143	0.160	0.037	-0.070	-0.129	-0.048	-0.091	-0.120	-0.186	1.000									
R	-0.048	0.073	0.001	-0.049	-0.136	-0.035	-0.195	0.073	-0.287	-0.010	0.076	-0.237	0.044	-0.200	-0.263	-0.410	-0.229	1.000								
S	-0.031	0.042	-0.060	-0.096	0.034	0.003	0.150	0.084	0.180	-0.020	-0.001	0.133	0.011	-0.106	-0.140	-0.218	-0.122	-0.268	1.000							
T	0.007	-0.025	-0.034	-0.025	-0.019	-0.004	0.064	-0.028	0.025	-0.020	-0.013	-0.071	-0.018	-0.010	-0.013	-0.020	-0.011	-0.024	-0.013	1.000						
U	-0.026	-0.072	-0.173	-0.142	-0.096	-0.036	0.260	0.005	0.063	-0.045	0.065	-0.311	-0.029	0.005	-0.073	-0.091	-0.157	0.296	-0.099	0.004	1.000					
V	-0.025	0.117	0.133	0.116	0.125	0.031	-0.388	0.083	-0.152	0.016	-0.013	0.350	0.054	0.052	0.139	0.196	-0.484	-0.118	0.163	-0.025	-0.779	1.000				
W	0.075	-0.084	0.031	0.015	-0.064	0.001	0.250	-0.138	0.151	0.037	-0.070	-0.120	-0.045	-0.089	-0.118	-0.184	0.980	-0.226	-0.120	0.034	-0.159	-0.495	1.000			
X	0.062	-0.093	-0.096	-0.059	0.008	0.026	0.404	0.002	0.373	-0.034	-0.085	-0.069	-0.050	-0.046	0.278	0.068	0.362	-0.696	0.340	0.058	-0.077	-0.160	0.358	1.000		
Y	-0.014	0.041	-0.196	-0.306	-0.328	-0.064	0.311	0.268	0.125	-0.083	0.001	-0.513	0.009	0.033	-0.007	-0.320	0.096	0.298	-0.118	0.051	0.328	-0.342	0.083	0.102	1.000	
Z	-0.085	-0.014	-0.025	-0.053	0.194	0.044	-0.166	0.148	0.081	0.123	0.038	0.623	-0.006	-0.016	0.119	0.188	-0.065	-0.337	0.192	-0.038	-0.317	0.316	-0.058	0.012	-0.571	1.000

(A–Z: % water and wetland, % deciduous forest, % evergreen forest, % mixed forest, % shrub, % grassland, % developed, % other, distance to forests, distance to waterbody, distance to wetland, elevation, slope, minor collector, minor arterial, major collector, interstate, local, other freeway or expressway, other principal arterial, speed low, speed medium, speed high, traffic volume, road density, moose harvest density)

Appendix 5.

95% confidence intervals of the correlation matrix of spatial variables evaluated to build the MaxEnt model.

Lower	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**
A	1.000												
B	-0.174	1.000											
C	0.417	0.051	1.000										
D	-0.058	0.058	0.009	1.000									
E	0.204	-0.257	0.125	0.418	1.000								
F	-0.200	0.157	-0.104	0.568	0.231	1.000							
G	-0.386	0.527	-0.205	0.018	-0.404	0.287	1.000						
H	0.197	-0.154	0.018	-0.054	0.033	-0.082	-0.141	1.000					
I	-0.006	0.030	0.012	-0.017	-0.018	-0.006	0.013	-0.003	1.000				
J	0.031	-0.001	0.036	0.004	0.002	-0.009	-0.004	0.081	0.024	1.000			
K	0.100	0.106	0.098	-0.036	-0.002	-0.061	-0.007	-0.017	-0.007	0.035	1.000		
L	0.143	0.205	0.050	-0.069	-0.109	-0.041	0.103	0.174	0.007	0.036	0.274	1.000	
M	-0.066	0.364	0.175	0.034	-0.168	0.132	0.359	-0.134	0.018	-0.010	0.015	0.103	1.000

Upper	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**
A	1.000												
B	-0.173	1.000											
C	0.417	0.052	1.000										
D	-0.057	0.060	0.010	1.000									
E	0.205	-0.255	0.125	0.420	1.000								
F	-0.199	0.159	-0.104	0.569	0.233	1.000							
G	-0.385	0.528	-0.204	0.020	-0.403	0.289	1.000						
H	0.199	-0.153	0.019	-0.052	0.034	-0.081	-0.139	1.000					
I	-0.004	0.031	0.013	-0.016	-0.017	-0.005	0.014	-0.002	1.000				
J	0.032	0.001	0.037	0.006	0.003	-0.008	-0.003	0.082	0.025	1.000			
K	0.102	0.108	0.099	-0.035	0.000	-0.060	-0.005	-0.015	-0.006	0.036	1.000		
L	0.144	0.207	0.051	-0.067	-0.108	-0.039	0.105	0.175	0.008	0.037	0.276	1.000	
M	-0.065	0.365	0.177	0.035	-0.167	0.133	0.360	-0.133	0.019	-0.009	0.016	0.105	1.000

(A–M: Elevation, distance to forest, moose harvest density, road type, speed limit, traffic volume, road density, slope, aspect u direction, aspect v direction, distance to water, distance to wetlands, land type)

Appendix 6.
95% confidence intervals of the correlation matrix of spatial variables evaluated to build the MaxEnt model.

Lower	A	B	C	D	E	F	G	H	I	J
A	1.000									
B	0.067	1.000								
C	-0.738	-0.049	1.000							
D	0.241	0.012	0.310	1.000						
E	0.010	0.025	-0.026	0.009	1.000					
F	0.016	0.000	-0.024	0.119	0.376	1.000				
G	-0.196	-0.015	-0.234	-0.751	0.029	-0.048	1.000			
H	-0.144	-0.016	-0.127	-0.541	0.030	-0.003	0.614	1.000		
I	-0.022	-0.033	0.033	0.002	0.009	-0.004	0.125	0.080	1.000	
J	0.243	0.007	0.326	0.850	-0.016	0.072	-0.708	-0.477	0.268	1.000

Upper	A	B	C	D	E	F	G	H	I	J
A	1.000									
B	0.069	1.000								
C	-0.738	-0.047	1.000							
D	0.244	0.015	0.313	1.000						
E	0.013	0.028	-0.024	0.012	1.000					
F	0.018	0.003	-0.022	0.122	0.378	1.000				
G	-0.193	-0.012	-0.231	-0.750	0.032	-0.046	1.000			
H	-0.141	-0.013	-0.125	-0.539	0.032	-0.001	0.617	1.000		
I	-0.020	-0.030	0.035	0.004	0.011	0.000	0.126	0.082	1.000	
J	0.246	0.010	0.329	0.851	-0.013	0.075	-0.707	-0.475	0.271	1.000

(A–J: Solar elevation, azimuth u direction, azimuth v direction, air temperature, precipitation, relative humidity, snow cover, snow depth, soil moisture, vegetation cover)