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Identifying deer vehicle collision concentrations in Minnesota

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Deer-vehicle collisions (DVCs) represent a significant hazard on Minnesota roads, with roughly 1,200 DVCs reported annually to the Minnesota Department of Public Safety (MnDPS) and many more going unreported. While DVCs are common across Minnesota, local variations in deer density as well as roadway characteristics and use patterns make DVCs more likely to occur on some roadways than others. Moreover, the true extent of DVC concentrations is unclear due to the high proportion of DVCs that go unreported. This report presents findings from research that (1) uses data to identify areas of DVC concentration based on the specific roadway characteristics and (2) presents a methodology to estimate DVC reporting rate across the state. This methodology is applied in a pilot study in the Duluth area, as well as in an extended search area that includes highways spread across much of outstate Minnesota to estimate the DVC reporting rate.

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Identifying Deer Vehicle collision concentrations in Minnesota

Final Report

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

AADT – Annual average daily traffic

DNR – Department of Natural Resources

DOT – Department of Transportation

DVC – Deer-vehicle collision

MnDOT – Minnesota Department of Transportation

MnDPS – Minnesota Department of Public Safety

MNCRASH – Database of vehicle crashes in Minnesota maintained by MnDPS

MnDPS DVC data – Deer-vehicle collisions from 2006 to 2022 in MNCRASH database with associated data fields.

Executive Summary

Deer-vehicle collisions (DVCs) represent a significant hazard on Minnesota roads, with roughly 1,200 DVCs reported annually to the Minnesota Department of Public Safety (MnDPS) and many more going unreported. While DVCs are common across Minnesota, local variations in deer density, as well as roadway characteristics and use patterns make DVCs more likely on some roadways than on others. Moreover, the true extent of DVC concentrations is unclear due to the high proportion of DVCs that go unreported. This report presents findings from research that (1) uses data to identify areas of DVC concentration based on the specific roadway characteristics and (2) presents a methodology to estimate the DVC reporting rate across the state. This methodology is applied in a pilot study in the Duluth area, as well as in an extended search area that includes highways spread across much of outstate Minnesota to estimate the DVC reporting rate.

The statistical analysis uses both roadway characteristics such as annual average daily traffic (AADT) and roadway width, as well as geographic information such as adjacent ground cover and proximity to streams to develop several machine-learning-based models to predict DVC risk on individual road segments. The results show that the k-nearest neighbors (kNN) machine-learning algorithm, as well as logistic regression, both perform well in predicting DVC risk. Using the logistic regression model, a DVC risk index is computed for each road segment in Minnesota, and road segments that fall in the top 15% of segments overall by computed risk value are identified as high-risk. An interactive map with the input data as well as the resulting DVC risk computed for each road segment is available at https://z.umn.edu/DVChotspots.

In addition to a statistical analysis of spatial deer distributions, this report outlines a procedure for estimating the DVC reporting rate. This involves regularly driving pre-determined routes within a defined area and collecting roadkill information. The developed procedure is tested in a pilot study in the Duluth area, as well as on an additional corridor between Duluth and St. Cloud. The results show that, depending on facility type, DVC reporting rates vary substantially. Generally, the findings indicate that DVC reporting rate increases with the operating speed on the facility, with a notable exception being roads within city limits, which have the highest reporting rate. The reporting rate in the study area is found to vary from 0% to 38%, with an average of around 10% of DVCs reported.

The work presented in this report may provide insight into what leads to higher DVC rates, and how to better estimate the true DVC rate in areas with low reporting rates. This information is intended to help engineers and public officials design safer roads with lower DVC rates.

Chapter 1: Introduction

Deer-Vehicle collisions (DVCs[1]) lead to significant social, environmental, and economic costs. For example, in the United States in 2015, 58,000 DVCs resulted in human injury and there were 440 fatalities (Conover 2019). Costs of DVCs in Minnesota are significant, with about 1,200 DVCs reported per year on Minnesota roads from 2016 to 2020 (Table 1). The majority of deer in Minnesota are white-tailed deer (*Odocoileus virginianus*). Collisions with moose, elk, and mule deer do occur in Minnesota, but may not be distinguished from white-tailed deer during crash reporting. However, these other species represent a negligible number of DVCs given their small population size and geographic ranges within Minnesota. Using the average number of DVCs per year, the economic cost of reported DVCs is more than $20 million per year. If we assume that DVCs that are not reported are property damage only (PDO), the total economic cost of DVCs in Minnesota would be $40 million and $70 million at reporting rates of 20% and 10%, respectively (Table 1). Using the State Farm Insurance Company's estimate of 42,000 DVCs in Minnesota in 2016 (State Farm 2016), the estimated economic cost of DVCs in Minnesota would be almost $220 million per year. Reducing the number of DVCs by even 1% would provide significant benefits to citizens of Minnesota.

[1] Related acronyms include AVCs (Animal-Vehicle Collisions) and WVCs (Wildlife-Vehicle Collisions). AVCs typically include collisions with domesticated animals such as cattle and horses.

Table 1: Number of and annual cost of DVCs in Minnesota. DVC data from MnDOT (https://z.umn.edu/MnDOT_VeerForDeer) and economic cost of each event type is from US DOT (2022). Estimates of reporting rate for DVCs in the last 2 columns are 10% and 20%, and for DVCs that were not reported we assumed Property Damage Only (PDO).

Year	Crashes	Fatalities	Serious Injuries	Minor injuries	PDO (reported)	PDO 20% RR	PDO 10% RR
2016	1,295	1	29	221	1,295	5,180	11,655
2017	1,322	4	22	210	1,322	5,288	11,898
2018	1,226	6	26	182	1,226	4,904	11,034
2019	1,263	3	19	172	1,263	5,052	11,367
2020	1,112	4	28	146	1,112	4,448	10,008
Mean	1,244	3.6	24.8	186.2	1,244	4,974	11,192
Cost / event:		$11,600,000	$554,800	$151,100	$3,900	$3,900	$3,900
Average Cost / year:		$41,760,000	$13,759,040	$28,134,820	$4,851,600	$19,398,600	$43,648,800
Total Cost / Year (Reported):					$88,505,460		
Total Cost / Year (Reported + Unreported):						$103,052,460	$127,302,660

Reducing the number of DVCs in a cost-efficient manner requires an analysis of DVCs, using geographic, road type, land use, deer, traffic volume, and other data to identify locations where safety measures such as animal detection systems, dynamic warning systems, or other methods would be most beneficial. For this report, we have analyzed data from more than 36,000 DVCs that occurred in Minnesota since 2005 and identified factors that increase the risk of a DVC in Minnesota.

We use a pilot project in the Duluth area to estimate the reporting rate for DVCs. As we indicate below in the literature review (Chapter 2), across the U.S., fewer than 1 in 3 DVCs are reported to police agencies, and Minnesota follows that pattern. Many DVCs without significant vehicle damage or passenger injury are not reported to the Minnesota Department of Public Safety (MnDPS). We use a pilot project in the Duluth area to document the reporting rate for DVCs and to develop a methodology that could be used in a broader geographic area. This methodology is applied in an extended search area using a one-time survey on highways in outstate Minnesota. In the pilot project, we collect roadkill data by driving specific roads at regular intervals to estimate the number of unreported DVCs in 2021-2022 in the Duluth area. The pilot project data can also be used to compare characteristics of DVCs reported to MnDPS to characteristics of DVCs that are not reported to MnDPS.

DVC concentrations are identified via a logistic regression analysis, which provides insight into what roadway features correlate with high DVC rates. Using these features, a DVC risk index is calculated, which is then applied to all road segments in the network to visually identify DVC concentrations. The results indicate areas where DVCs are particularly likely, but in absolute terms, and in relative terms when taking vehicle traffic into account.

Chapter 2: Review of relevant literature

2.1 General:

Whether or not a DVC will occur is affected by three factors: (1) how often road segments are crossed by deer, (2) the number and the speed of vehicles on a road segment, and (3) characteristics of the road (Kammerle et al. 2017). Each of these factors can be further deconstructed to identify causative relationships. For example, in the most recent review on DVCs, a meta-analysis of 48 studies that included many deer species (mainly white-tailed deer (*Odocoileus virginianus*) and Roe deer (*Capreolus capreolus*)) indicated that traffic volume, traffic speed, forested cover, grassland cover, recreational cover types, and diversity of cover types were positively correlated with DVC rate (Pagany 2020). Other factors had either positive or negative effects on DVCs, including presence of wetland, agriculture, and urban cover types, topography, roadside vegetation, and road type (Pagany 2020).

In this literature review we identify various factors that have been found to be potentially important in affecting the probability of a DVC, and we identify statistical approaches that have been used to analyze DVCs. We do not cite every paper on DVC's that has been published over the past 40 years, although we do make an effort to include references to analyses of DVCs in the upper Midwest, which has habitats and deer populations that are similar to Minnesota.

There have been several literature reviews in peer-reviewed journals, some of which we refer to with collective results. Other reviews can be found in state-specific transportation related projects, e.g., Nichols et al. (2014) and Cramer et al. (2016). In other cases, we cite specific studies that are directly relevant to this project or to the upper Midwest. Seasonal and daily patterns in the distribution of DVCs have been consistent across North America and Europe, which is why some of the broader literature is relevant and appropriate to include.

Gunson et al. (2011) indicated that the obvious, broad-scale relationships between WVCs and predictors have been derived from many of the existing data sets, and localized studies with small-scale analysis could be a productive next step, in addition to further analysis of interactions between variables. It is intuitive that increasing traffic speeds and increasing traffic volume would lead to increased probability of DVCs. However, if deer respond to increased traffic or noise non-linearly, analysis of a DVC data set would benefit from understanding interactions among variables. For example, the frequency of road crossings by GPS-collared deer was negatively related to traffic volume (Stickles 2014, Osborn et al. 2015), which means that at some traffic volume the frequency of DVCs would decrease. Similarly, increasing deer densities should lead to an increased probability of DVCs, but this is confounded by the large spatial scale at which deer densities can be estimated compared to the small spatial scale of where and in what habitat a DVC occurs. In most cases, deer density explains no more than 50% of the variation in DVCs (e.g., Ramakrishnan 2005, Gritzka et al. 2010).

2.2 Low reporting rate of DVCs

One consistent feature of DVC research is that not all DVCs are reported. The reporting rate can be surprisingly low. For example, data on reporting of DVCs has been collected at multiple scales in Virginia. For every reported WVC crash in one county of Virginia there were 9.7 white-tailed deer carcasses collected (Donaldson and Lafon 2008). Similarly, on 30-miles of interstate highway, carcass removal data indicated that deer crashes were 5 times more frequent than DVCs in police crash reports (Donaldson et al. 2016). Finally for Virginia, a state-wide analysis showed that a little over 12% of DVCs were in police DVC reports compared to insurance company data (Donaldson et al. 2017). Collectively, the data from Virginia showed that fewer than 20% of DVCs are reported across spatial and temporal scales.

In a literature review, from 25% to 60% of DVCs were reported to insurance companies or police (Steiner et al. 2014). Nationally, fewer than 1/3 of WVCs are reported in national crash databases each year in the United States (Huijser et al., 2008). The reporting rate varies by state. About twice as many deer carcasses were removed compared to the number of police-reported DVCs in 2006 in Wisconsin (WI DOT 2006). In Utah, with several cervid species, over 5 carcasses were found on roads for every AVC reported to police (Olson 2013, Olson et al. 2014).

The location and type of road may also affect whether a DVC is reported. In areas with more people or more development with roads that have lower speed limits, DVCs may be more likely to be reported to police in order to clear the roadway. For example, in urban areas in Iowa, from 33% to 50% of crashes were reported (Gritzka et al. 2010). Reporting rate will likely be lower on roads with high speeds and high traffic volume. For example, reporting rate was lower on interstate highways in Iowa (Gritzka et al. 2010).

Surprisingly, data from Minnesota indicate an especially low reporting rate. Based on DVC data from MnDPS, about 1,200 DVCs occurred each year in Minnesota from 2016 to 2020 (Table 1). For one year in which insurance company data is available, 42,000 DVC crash claims were filed by drivers in Minnesota from July 1, 2015 to June 30, 2016 (Conover 2019) – if correct this would be a reporting rate of about 4%. It is possible that some of these claims were fraudulent, and it is also possible that the State Farm Insurance Company estimate, which used proprietary methods and included estimates from other insurance companies, was higher than it should have been, but the large discrepancy between reported DVCs and insurance claims is hard to reconcile.

One analysis used existing databases of DVCs and attempted to simulate reporting by randomly removing reported DVCs from analysis (Snow et al. 2015). The conclusion was that randomly removing DVCs from an existing DVC database did not affect conclusions about the causes of DVCs. A weakness in this approach is that all of the DVCs in this analysis were reported DVC's. To date there has not been an analysis to test if characteristics of actual unreported DVCs have similar characteristics to reported DVCs.

2.3 Non-random Spatial Distribution of DVCs

There are several examples which illustrate the non-random spatial distribution of reported DVCs. For the MnDPS database of about 37,000 reported DVCs in Minnesota from 2005 to 2022, about 50% of the reported DVCs occurred in just seven counties in the Twin Cities Metro area (Washington, Carver, Anoka, Stearns, Hennepin, Sherburne, Dakota). These counties cover about 5% of the land area in Minnesota, about 50% of the people in Minnesota live in these counties, and about 45% of the vehicle-miles travelled are in the 7-county Metro area (https://www.dot.state.mn.us/roadway/data/fun-facts.html). Similarly, DVCs in Georgia are clustered spatially, with 13% of Georgia's counties accounted for 55% of the reported DVCs (Bowers et al. 2005).

The importance of spatial scale can also be shown by analysis of DVCs without considering governmental units. For example, half of the 2-mile road segments on West Virginia interstate, federal, and state highways did not have a reported DVC over a 5-year period (Nichols et al. 2014). Road segments with the highest rates of WVC crashes contained 34 percent of the reported crashes and occurred on just nine percent of roads administered by the South Dakota DOT (Cramer et al. 2016). In an analysis of AVCs in the Czech Republic, the 100 most important clusters of AVCs were on only 19.7 km, or 0.05% of the entire road network (Bil et al. 2016). The Czech Republic is probably not representative of the road network in Minnesota, but it does illustrate the non-random spatial distribution of AVCs, and also the general nature of the problem of DVCs.

2.4 Road-related DVC Factors

The most common road-related factors identified as affecting the rate of DVCs are traffic volume (AADT) and traffic speed. Pagany (2020), for example, indicates that most studies show that increasing traffic volume leads to more WVC's. Similarly, Steiner et al. (2014) listed many references showing that there is an increase in WVCs with increasing traffic volume. Higher speeds lead to more WVC's, including DVCs (Pagany 2020). Ng et al. (2008) showed higher traffic speeds correlated with the number of DVCs. Similarly, in Iowa, over 80% of DVCs occurred on roads with posted speed limits > 50 mph (Gritzka 2010). However, traffic volume and traffic speed are probably not good predictors of the probability of a DVC location because there are so many miles of roads with high traffic volume and high traffic speeds.

Other factors that affect the number of DVCs are the type of roadway, roadway curvature, number of lanes and categorical travel speeds (Nichols et al. 2014). More DVCs were found on principal arterial roadways, particularly those with two lanes, lower traffic volumes, higher vehicle miles traveled, and travel speeds greater than 60 mph. Compared to other types of vehicle crashes, DVCs also occur more often on straight, dry roads. There are some discrepancies in the different analyses. For example, some of the analyses in Pagany (2020) indicated that more traffic lanes lead to more WVC's, in contrast to Nichols et al. (2014). Multiple lanes would also be associated with higher traffic speeds. Pagany (2020) also found that a common theme was that if vegetation was too close to the roadway the risk of a DVC increased. Similarly, narrower road shoulders and more curviness in a road can also increase the risk of

DVCs (Stapleton et al., 2019). This is consistent with the finding that as visibility on a roadway increases, the risk of DVCs decreases (Found and Boyce, 2011).

One complicating factor in a meta-analysis of DVC studies, and one of the reasons that state-specific research projects are needed, is that many road-related factors have been used in different analyses. Some of these are general and can be applied across geographic areas, others would be more specific (e.g., mountainous areas might consider the factor of cliffs or hairpin turns). In addition, inclusion of factors in final models when using some new statistical techniques is not consistent. For example, vehicle speed and AADT were not included as significant variables in several models of DVC risk (Table 2). Several other variables that might be expected to be included in models of DVC risk were also not included. In many cases it is likely that some variables may not be available in digital format for a certain area. Some variables become less clear when contrasting results of literature reviews with results in analyses. For example, it is intuitive that speed and AADT would be included in final models more often than either actually were included, based on the results in Table 2. A further complicating factor is that it is desirable to limit the number of variables that are in a statistical model. For no variable is there a clear set of "+" or "-" sign for most of the papers. Moreover, it is important to note that, even if specific factors are found to be statistically significant in a particular study, they may still have limited effect size and may have limited impact on actual DVC rates.

Table 2: Road-related variables used for analysis of DVCs (1 of 3). A "+" indicates an increasing effect on DVCs, a "0" indicates a statistically significant effect was not detected, and a "-" indicates that there was a decreasing effect on DVCs. Blank table cells indicate either that the variable was not included in the analysis, or that it was eliminated in the statistical analysis.

	Citation Number																	
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Speed					+	+	+					+/0	0	0				+
AADT	0					-	+	-	-	0		0	±				+	+
Road Density					-	-						0/-				+		
Lane Width	0	+																0/+
Lane Count							+						+					
Road Category	0					+									-			
Horizontal Curvature		0		0						+			0	0				0/-
Road Topography		±		±														
Slope		0								0					0			
Slope Position															0/+			
Guardrail		+											0					
Median	0/-							0/-										
Median Width								0/+										
Shoulder width	0/-					-		0/+										0
Shoulder Type						-	+											
Lighting						-			+									
Shoulder Type						-	+											
Lighting						-			+									
Corridor Width				+														
Building Density				+										-				
Driveway Density																		±

[1]Burton et al. 2014, [2]Clevenger et al. 2015, [3]Donaldson et al. 2016, [4]Finder et al. 1999, [5]Found et al. 2011, [6]Gkritza et al. 2010, [7]Gkritza et al. 2014, [8]Knapp et al. 2007, [9]Kreling et al. 2020, [10]Laliberté et al. 2020, [11]McCance et al. 2015, [12]Ng et al. 2008, [13]Nichols et al. 2014, [14]Nielsen et al. 2003, [15]Osborn et al. 2015, [16]Ramakrishnan et al. 2005, [17]Snow et al. 2018, [18]Stapleton et al. 2019

2.5 Deer-related factors

White-tailed deer have many collisions with vehicles because of their ubiquitous presence across Minnesota. While other deer species, such as mule deer, elk, and moose also exist in Minnesota, they would make up a small fraction of the total DVCs and thus are generally not included in analyses. Based on data in Norton and Guidice (2017) pre-fawning deer densities are about 13 deer / square mile in the farmland and transition zones, and about 4 deer / square mile in the forested region (Figure 1). Population size (and density) was estimated for most Deer Management Units, which average over 600 square miles. More recent deer population models done by the Minnesota DNR indicate a similar density of deer, but the spatial resolution of modelling has decreased, with DMUs being combined for modeling purposes (Michel and Giudice 2022). With this pre-fawning density of deer, a sex ratio that predominates towards females, and about 2 fawns per doe, it is likely that in the summer months deer density is about 30 deer / square mile in the Farmland and Transition regions, although many of these are fawns. Given a typical home range size of about 400 acres, along 1 mile of road there could be about 30 deer that could be in a DVC in the summer months. These crude calculations could be refined by an analysis of habitats available, but they do indicate one reason for the number of DVCs that occur in Minnesota.

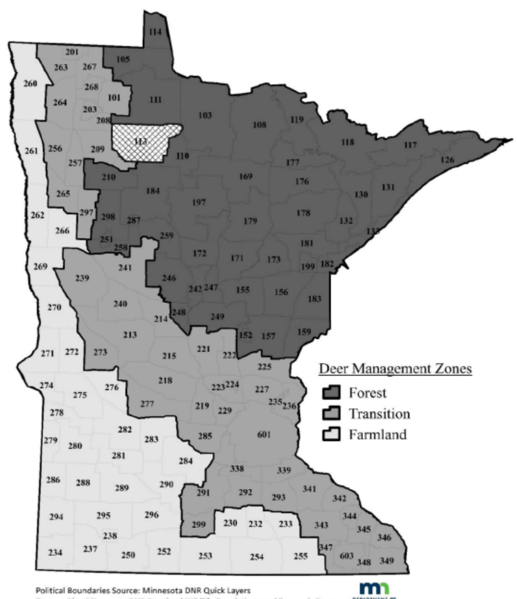

Figure 1: Deer management zones in Minnesota. Deer densities are about 13 deer / square mile in the farmland and transition zones, and about 4 deer / square mile in the forested region. Figure taken from Norton and Guidice (2017).

There are conflicting results for the effect of deer density on probability of a DVC in the literature reviews. Intuitively, if deer density is higher, then there should be more DVCs. Steiner et al. (2014)

indicated that the quantity of DVCs is clearly related to deer density, but the papers cited were on moose (*Alces alces*) and red deer (*Cervus elaphus*). Pagany (2020), in the most recent literature review on DVCs, did not include animal density as affecting probability of DVCs. Instead, traffic volume, traffic speed, land use (cover types), landscape diversity, and road characteristics were identified as important factors in predictive or explanatory models. Deer may be present at similar densities in too much of the landscape to be a significant predictor of DVCs.

Past attempts to correlate white-tailed deer density and the probability of a DVC may indicate why deer density is not often included as a significant variable in recent DVC modelling analyses. The best correlation was from an 8-year dataset from Wisconsin, which had correlation coefficients between DVCs and buck harvest of 0.72 to 0.97 (McCaffery 1973). For 3 counties in Michigan with a range of deer densities from 9 to 50 deer / square mile, the annual number of DVCs increased with deer density (Marcoux et al. 2005). The correlation between DVCs and deer density in Alabama was high, and deer density was included as a categorical variable (Hussain et al. 2007). Deer density was included in a predictive model for DVCs in South Dakota (Grovenberg et al. 2008). It may be that when data sets are selected to include low, medium, and high deer density areas that the intuitive correlation between DVCs and deer density becomes significant.

In other cases, deer density has explained relatively little variation in DVCs. Deer density was not correlated with DVCs in Virginia (McShea et al. 2007). The correlation between DVCs and deer population density in Pennsylvania was significant, but the correlation coefficient r was only 0.52 (Puglisi et al. 1974). Finally, in both Connecticut and Iowa, there was a weak correlation between deer density and DVC's, with r^2 values of 0.45 and < 0.50, respectively (Ramakrishnan 2005, Gritzka et al. 2010).

The low correlation between DVCs and deer density is in part due to uncertainty in estimating deer population size but may also be because of the relatively homogenous geographic landscape in each study, where relativity little diversity in landscape is actually present. Another contributing factor is spatial scale, because deer densities are estimated at large spatial scale relative to DVC locations. For example, deer density in Minnesota is estimated in DMUs of about 600 square miles.

2.6 Behavior – general

There are consistent patterns in the literature on seasonal and daily patterns in DVCs. On a seasonal basis, white-tailed deer DVCs were most frequent in the fall, sometimes with a smaller peak in the spring. Similarly, most DVCs occur near sunrise and sunset, with others occurring at night. Relatively few DVCs occur during the day. The seasonal and daily patterns are consistent across deer species, and across geographic range. In the summary below most studies are on white-tailed deer, although we also include some references to other cervid species to document the generality of the pattern.

Most DVCs occur in the fall during the white-tailed deer breeding season, with a smaller peak in the spring in May and June, based on meta-analysis of 23 different studies (Steiner et al. 2014). Most DVCs occurred in the fall in Georgia (Osborn et al. 2015). Almost half of DVCs in Connecticut occurred from

September to December (Ramakrishnan 2005). Over half of the DVCs in Winnipeg, Manitoba occurred from September to December (McCance et al. 2015). Most DVCs in West Virginia occurred in October and November (Nichols et al. 2014). Similar patterns occur for other deer species, e.g., roe deer (*Capreolus capreolus*) crossed roads most during rut (Kammerle et al. 2017). Most DVCs occur during the spring and fall (Stickles 2014, Donaldson et al. 2015). Peak DVCs occur in November in Pennsylvania (Puglisi et al., 1974)

Similar findings in regard to DVC occurrences during the fall months were documented in Iowa by Hubbard et al. (2000) and in Edmonton, Alberta, Canada, by Ng et al. (2008). Minnesota DPS data is consistent with seasonal timing of DVCs (Figure 2). About half of DVCs occur from September to December, and about 1/3 of DVCs occur in October and November.

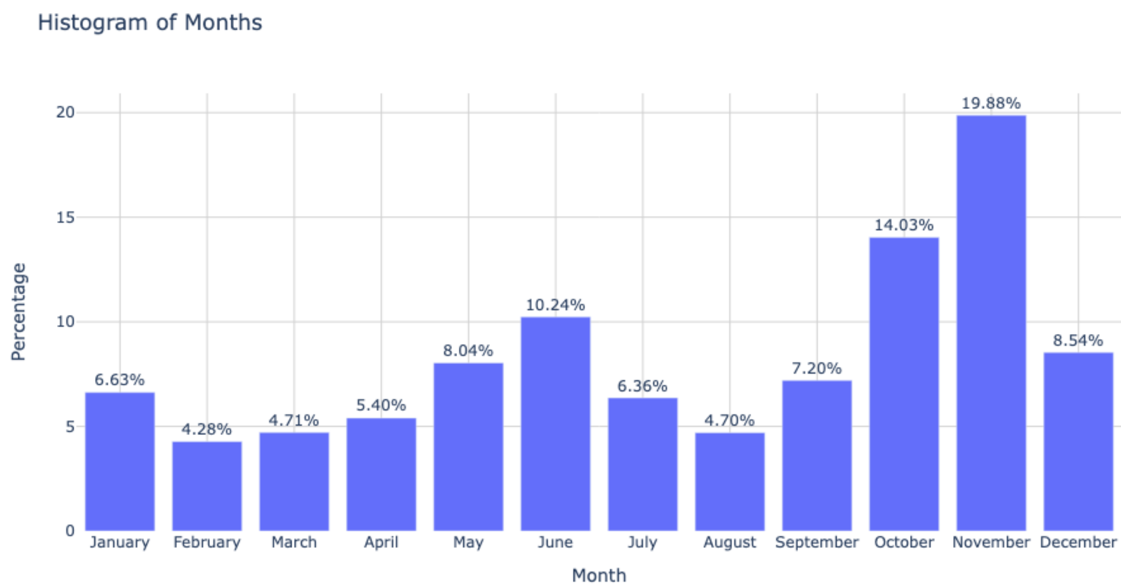

Figure 2: Percent of DVCs in each month in the Minnesota DPS DVC database from 2005 to 2022.

There is also a general pattern for when DVCs occur in relation to day and night. This pattern is affected by at least two factors: the biology of white-tailed deer and the pattern of traffic volume. The largest peak in DVCs occurs during the evening, and there is also a smaller peak in the morning around sunrise. There are also more DVCs at night than during the day, again related to both the biology of deer and interactions with traffic volume. Deer are more active at night than during the day, but traffic volume is lower at night. The daily cycle in DVCs was one of the first patterns to be identified in analysis of DVCs (Allen and McCullough, 1976; Arnold, 1978).

Independent of species and geographic location, sunset and sunrise had high DVC risk in a review that included 41 studies (Pagany et al. 2021), and another review that included 10 studies (Steiner et al. 2014). Biggs et al. (2004) and Neumann et al. (2012) are two examples for an increased risk for DVCs and MVCs (Moose-Vehicle Collisions) during the early evening hours, especially in autumn and winter. There was a distinct peak in DVCs in the morning (5:00 to 7:00 a.m.) and in the evening (6:00 to 10:00 p.m.) in Michigan (Marcoux et al. 2005). In some cases sunset or sunrise are specifically identified as peak times (e.g., Bíl et al. 2017, Hothorn et al. 2015).

GPS collar data support this daily pattern of DVCs. Deer movements and DVCs are primarily crepuscular based on GPS-collared deer on interstate highways in Georgia (Stickles 2014, Stickles et al. 2022). Road crossings occurred most frequently at night, with 44% of road crossings happening between midnight and 6:00 a.m. when traffic volume is lowest. This illustrates the interaction between traffic volume and deer behavior. About 75% of traffic on this interstate was from 7:00 a.m. to 7:00 p.m. A similar pattern exists for other deer species when GPS collars are deployed. For example, roe deer in Germany had most road crossings at night with peaks at sunset and sunrise (Kammerle et al. 2017).

Minnesota DPS data is consistent with daily timing of DVCs (Figure 3). About 70% of DVCs occur during sunrise and the hours after sunset, with 22% of DVCs occurring during around sunrise, and 48% occurring from 5:00 p.m. to 11:00 p.m. DVCs decrease at night because of reduced traffic volume. In Winnipeg, Manitoba 69% of DVCs occurred after sunset and before sunrise (McCance et al. 2015). Similarly, about 85% of DVCs in the Minnesota DPS database occurred from 5:00 p.m. to 7:00 a.m.

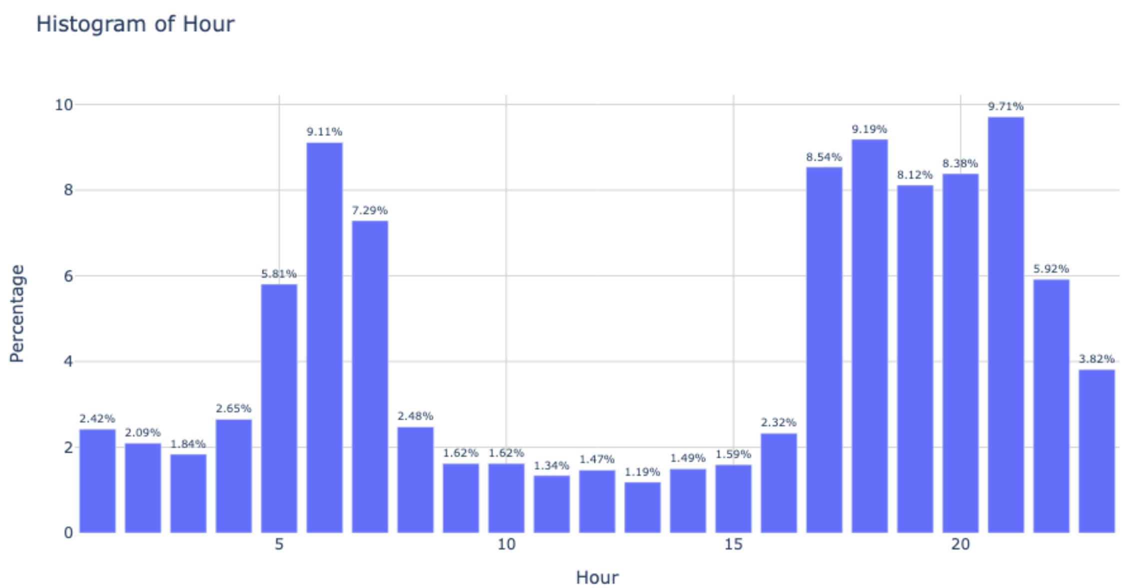

Figure 3: Percent of DVCs by hour of day in the Minnesota DPS DVC database from 2015 to 2019. Peak DVCs occur around sunrise and in the hours after sunset. Clock time has not been adjusted for variation in sunrise and sunset times throughout the year.

Steiner et al. (2014) concluded that deer behavior had the most impact on daily patterns in DVC frequency, which is intuitive because the hours of high deer activity are more likely to lead to a possible DVC. However, the deer activity effect is modulated by other factors, including traffic, habitat, and season. Separating out and understanding the interactions between deer behavior and traffic volumes is critical to a fuller understanding of when DVCs are likely to occur in space and time.

2.7 Behavior – specific

GPS collars and camera traps make it possible to increase our understanding of how deer respond to roads. In some cases data collected can provide a mechanistic or functional basis for observations based on DVC data. For example, deer with home ranges near interstate ROWs were more likely to cross the interstate (Stickles 2014, Stickles et al. 2022). The frequency of road crossings of GPS-collared deer increased near riparian areas and increased with the amount of forested area in Georgia (Osborn 2015).

Even though road crossings increased, there was not a concomitant increase in DVCs because of low traffic volume (Osborn 2015).

Camera traps can also be useful to identify deer behavior and responses to vehicles. Most deer detected in camera traps on an interstate ROW in Virginia were photographed in the dark, from 10:00 p.m. to 5:00 a.m. (Donaldson et al. 2016). This increase in deer activity was consistent with the increase in DVCs observed in DVC databases (Donaldson et al. 2016). In addition to an increase in activity in the dark, deer also appeared to be acclimated to vehicles, and did not show alert behaviors (Donaldson et al. 2016).

As additional GPS data is collected on deer the mechanistic or functional basis for DVCs will become better understood. Analysis of GPS collar data could provide a quantitative basis for estimating the number of times a deer crosses a road, one of the factors that affects the probability of a DVC. For example, in Georgia, 7 of 25 deer wearing GPS collars accounted for 90% of the observed road crossings (Stickles et al. 2022).

2.8 Habitat-related factors

There are two aspects of habitat that are typically analyzed with respect to DVCs. The first aspect is the cover type, usually based on analysis of satellite imagery. The National Land Cover Database (NLCD) is one of the cover type databases that is often used, in part because it has consistent coverage and analysis methods across the United States. The current version was published in 2019 (https://www.mrlc.gov/). Cover type is usually included in models as the percent of area in a buffer around a DVC location in a cover type (Table 3) or as the distance to a cover type.

The literature reviews indicate that across DVC studies, an increase in forested area typically leads to higher probability of a DVC occurring (Pagany 2020). The importance of forested cover types was found in some of the earlier literature. For example, increasing distance to forest cover was negatively related to DVC's (Finder et al. 1999). In a more recent analysis, forest land cover at the home range scale was the best landscape predictor for identifying DVC concentrations in upstate New York (Snow et al. 2014).

The presence of grassland and open areas, associated with foraging, also lead to higher probability of a DVC based on an analysis of many DVC studies (Pagany 2020). For example, developed land and grasslands were important cover types related to DVCs in Winnipeg, Manitoba (McCance et al. 2015). One complication of the developed land cover type is that deer feeding in residential areas can attract deer. Deer feeding could be locally important, but is unlikely to be important at a larger geographic scale.

The other habitat aspect is landscape diversity, or juxtaposition of different cover types that are used by deer. The measure of landscape diversity quantifies interactions between cover types. For example, the agriculture cover type would have a negative effect in intensive agriculture, but if the agricultural cover type is mixed with the forest cover type, deer density will increase and the probability of a DVC will increase (Pagany 2020). As indicated previously, forested cover types, for example, would be used for cover, while open areas and agricultural fields could be used for foraging. Roads with edge habitat boundaries and riparian habitats have more DVCs than roads in developed cover types with buildings. For example, the interface between land and river or streams are prone to DVCs, while urban areas have fewer collisions (Nichols et al. 2014). At a smaller scale, linear corridors of natural habitat, such as riparian areas and gullies can support increased deer movement, which lead to increased DVCs (Finder et al. 1999).

Table 3: Cover-type-related variables used for analysis of DVCs, with the variable being the percent of area in a buffer around the DVC or road segment. A "+" indicates an increasing effect on DVCs, a "0" indicates a statistically significant effect was not detected, and a "-" indicates that there was a decreasing effect on DVCs.

Source	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Variable															
Percent Natural Cover															
Forest		0		+	+						0		+	0/+	
Conifer									+						
Non-Forest					+						0				
Agriculture				-		+									0/+
Shrubland		0													
Grassland				+			+								
Open		0													
Water/Wetland				+					+				0		
Distance to:															
Cover		±													
Forest					-						0				
Non-Forest					-										
Water		+			-						0/-	0		-	
Agriculture										+					
Distance to Urban Structure															
Residential					+					+					
Non-Residential					+										
Structure		±													
Bridge			0/-												
Percent Urban Cover															
Developed	+/0					+							-		
Residential					-										
Non-Residential					-										
Vegetation Density					+										
Vegetation Diversity				+	+								+		
Vegetation Productivity											0				
Terrain			+	+								±		0	
Edge / patch variables															
Habitat Diversity					+							±			
Forest Patch Density				+											
Forest Edge				+	+						0				
APAR													0	0/+	0/+
APS													0		
Ecotone								+							

[1]Burton et al. 2014, [2]Clevenger et al. 2015, [3]Donaldson et al. 2015, [4]Finder et al. 1999, [5]Found et al. 2011, [6]Gkritza et al. 2010, [7]Gkritza et al. 2014, [8]Kreling et al. 2020, [9]Laliberté et al. 2020, [10]McCance et al. 2015, [11]Ng et al. 2008, [12]Nichols et al. 2014, [13]Nielsen et al. 2003, [14]Osborn et al. 2015, [15]Snow et al. 2018.

2.9 Special cases of habitat

One type of area with high deer densities is parks, because hunting is often prohibited. There are fewer studies on recreational areas (parks) because of the smaller size, and parks are probably not too important for this project because relatively few DVCs occur in parks. In part this is because parks generally have slower road speeds. There was an increase in DVCs in Illinois near recreational areas (Finder et al. 1999).

2.10 Methods for analysis

A common feature for analysis is to compare DVC locations to random locations that are near a DVC. For example, topographic features and highway variables (for examples see Table 2) were measured around high accident road segments and randomly selected control sites (Finder et al. 1999). Similarly, Ng et al. (2008) compared DVC locations to control segments.

2.10.1 Segment length

One issue to consider is how long segment lengths that identify DVC concentrations should be. This is partly dependent on spatial resolution of road databases, and partly dependent on the spatial resolution of DVC reporting. In past analyses, the spatial resolution of segment lengths has ranged from 0.1 miles to 5 miles (Table 4).

Table 4: Road segment lengths to determine hot spots.

Source	Segment length	Location	Comments
Finder et al. 1999	2.0 miles	IL	
Ng et al. 2008	0.5 miles	AB	Buffers
Nichols et al. 2014	2 miles	WV	Most ~2 miles, range 0 to 4
Nichols et al. 2014	0.5 to 5 miles	WV	Given without citations
Myers et al. 2008	1 mile	WA	
Found and Boyce 2011	1 mile	AB	
Hubbard et al. 2000	1 mile	IA	
Huijser and Begley 2014	0.1 mile / 0.31 miles	CA	Road database resolution / Search radius

2.10.2 High DVC concentration threshold

Many analyses use identification of DVC concentration as the method to determine risk. Over 60% of the analyses in Pagany (2020) used hot spots. The kernel density estimation method is used most frequently, for example as done by Bill et al. (2016). Another method has been to identify segments of roads that have a higher density of DVCs than other road segments (Table 5).

Table 5: Threshold for number of DVCs / mile of road used to identify areas of DVC concentration.

Source	Count	Location	Comments
Finder et al. 1999	1.5 / mile / year	IL	
Hubbard et al. 2000	1.75 / mile / year	IA	
Barthelmess 2014	1 to 8.3 / km / year	NY	Multiple species, not deer
Found and Boyce 2011	0.5 / 1.6 km / year	AB	800 m radius, 1 of 2 years
Found and Boyce 2011	> 1 DVC / 1.6 km / year	AB	800 m radius, at least 1 year
Nichols et al. 2014	1.3 / mile / year	WV	Most segment lengths ~ 2 miles
Myers et al. 2008	> 5.6 / mile / year	WA	
Huijser and Begley 2014	~ 4 / mile / year ~ 12 / mile / year	CA	Crash data approximation Carcass data approximation

2.10.3 Regression analysis methods

Several different regression models have been used in DVC analyses. Table 6 shows a summary of different types of regression analyses that have been used in predicting wildlife collisions. Logistic regression has been a commonly used tool to predict whether or not a DVC will occur, while more advanced forms of logistic regression such as conditional logistic regression have also been used. Similarly, linear regression along with other similar regression types have been used to model the number of DVCs and identify areas of DVC concentration. Finally, a variety of other regression types including binary logit, negative binomial, and Poisson regression have been used to predict various DVC-related response variables as summarized in Table 6.

Table 6: Type of model used for analysis of DVCs. All of these analyses are for white-tailed deer, mule deer (Odocoileus hemionus), or both species.

Source	Location	Model	Response Variable
Nichols et al. 2014	WV	0-Inflated Neg Bi (Abund, Presemce)	DVC
Gkritza et al. 2010	IA	Binary Logit	DVC Severity
Found et al. 2011	AB	Conditional Logistic Regression	Roadkill hotspot vs coldspot
Laliberté et al. 2020	QC	Conditional Logistic Regression	DVC
Ramakrishnan et al. 2005	CT	Direct comparison	DVC
Donaldson et al. 2015	VA	Direct comparison	Camera Trap
Clevenger et al. 2015	AB	Generalized Additive	Roadkill
Nichols et al. 2014	WV	Generalized Additive Negative Binomial	DVC
Osborn et al. 2015	GA	Generalized Linear Model w/ Negative Binomial Distribution	Crossing Road 200 m / 500 m
Nichols et al. 2014	WV	Hurdle Negative Binomial (Abund, Presence)	DVC
Ng et al. 2008	MB	Linear Regression	DVC hotspot, intersection
Snow et al. 2014	NY / ME	Linear Regression	DVC frequency
Kreling et al. 2020	CA	Linear Regression	Roadkill freq
Finder et al. 1999	IL	Logistic Regression	DVC
Nielsen et al. 2003	MN	Logistic Regression	DVC
Found et al. 2011	AB	Logistic Regression	DVC
Burton et al. 2014	TX	Logistic Regression	Property Damage Minor injuries Major injuries/death
Snow et al. 2015	IL & ME	Logistic Regression	DVC
Snow et al. 2018	IL, IA, MI, WI	Markov chain Monte Carlo	DVC, Cover type
Stapleton et al. 2019	MI	Mix Effects Negative Binomial	DVC, Road Type, Damage
McCance et al. 2015	MB	Multiple Models	DVC
Nichols et al. 2014	WV	Negative Binomial	DVC
Knapp et al. 2007	IA	Neg Binomial Regression	AVCs/mile-year, DVC removals/mile-year
Gkritza et al. 2010	IA	Negative Binomial Regression	DVC
Gkritza et al. 2014	IA	Negative Binomial Regression	DVC
Finder et al. 1999	IL	Paired-sample t-test	DVC
Smoot et al. 2010	WI, IA, MN	Multiple	DVC injury
Gkritza et al. 2010	IA	Poisson Regression	DVC Injury

2.11 Summary

The literature review shows how the relatively simple question of whether or not a DVC will occur is both simple and complex. Simplicity is shown by how DVC probability is affected by three factors: (1) how often road segments are crossed by deer, (2) the number and the speed of vehicles on a road segment, and (3) characteristics of the road (Kammerle et al. 2017). Complexity is shown by how there are many different potential predictor variables that can be applied to factors 1, 2, and 3. For example, how often road segments are crossed by deer is affected by deer population density, cover types, and deer behavior, as well as other factors. Similarly, the number and speed of vehicles on a road segment is affected by human population density, distance to cities, and human behavior, as well as other factors. Analyses of DVC databases should include both broad-scale components and local-scale components that are specific to a region, and also needs to be based on available databases that best represent road characteristics, human aspects, and deer behavior. Although databases in each of these areas are improving, selecting the best data to use to explain the probability of DVC occurring on a specific road section is still one of the most challenging aspects of any DVC project. This is supported by the many potential predictor variables that have been used in different DVC projects (Table 2). In addition, decisions need to be made on spatial resolution, definition of areas of DVC concentration, and types of statistical analyses to use. Table 4, Table 5, and Table 6 provide a summary of each of these factors such as road and habitat databases, and statistical techniques that have been found to be useful in predicting DVC rates.

Chapter 3: Estimation of DVC reporting rate

3.1 Overview

This is a pilot project to estimate the number of Deer-Vehicle Collisions (DVCs) that are not reported to MnDPS. About 1,000 miles per month were driven on selected routes in and around Duluth, MN. We also recorded DVCs opportunistically, and we obtained locations of DVCs from other individuals on ongoing research projects. We also completed a search for DVCs on selected highways in Minnesota in spring 2022. GPS coordinates and other data (e.g., sex and age class if possible, roadside vegetation) of each DVC observed were recorded. We compared the historical MnDPS DVC rate on selected road segments to the DVCs we recorded.

3.2 Methods

We identified routes to drive, developed the draft protocol for data collection at a DVC, and developed a method to compare DVC rates on road segments.

3.2.1 Roads Driven

The routes selected to drive at bi-weekly intervals were in 8 loops (Table 7). Each loop was driven at approximately a 2-week interval beginning in August 2021. The total distance driven on these loops is about 500 miles. We drove these routes from August 27, 2021 to December 31, 2022. DVCs were also recorded opportunistically when observed, but opportunistically recorded DVCs were not included in any analysis in this deliverable.

Table 7: Roads driven at regular intervals to record DVCs.

Loop	Roads	Start	End	Miles
Loop 1	US 53	Lavaque Road	Cotton, MN	66
Loop 2	US 2 / US 194	US 53	Floodwood	68
Loop 3	US 33	US 53	Cloquet	23
Loop 4	I 35	Hinckley	Cloquet	116
Loop 5	US 61	Duluth	Two Harbors	54
Loop 6	Martin Road, Jean Duluth Road, Pequayan Lake Road, Rice Lake Road, Pioneer Road, Beaver River Road, Taft Road, Munger Shaw Road	Martin Road	US 53	65
Loop 7	Midway Road, MN194, Midway Road, US 2, I 35, Grand Avenue, Becks Road, Midway Road	Martin Road	US 2	34
Loop 8	I 35, MN 210, MN 73	Midway Road	US 2	88

The loops of roads driven (Table 7) were separated into road segments for analysis (Table 8). Loops were divided into segments for grouping, for example, two-lane vs. four-lane roads. Similarly, speed limit varied among the roads within a loop. Segment lengths of some of the road sections in Table 7 were too short to provide meaningful data.

The period of data collection included September to December in 2021 and September to December in 2022. We standardized the collection period to one year by creating two 12-month data collection periods. The first period went from 8/27/2021 to 8/26/2022. The second period went from 1/1/2022 to 12/31/2022. Although not completely independent because of the overlapping days form 1/1/22 to 8/26/2022, this enabled us to include two collection periods in the fall, which has the highest number of DVCs seasonally. We averaged DVCs recorded in the two "years" to calculate the number of DVCs on each road segment standardized to a one-year sampling period.

For analysis, we standardized presentation to the number of DVCs / 10 miles of road per year. Standardization was required because the number of miles on each road segment varied (Table 8), and because the time frame of data collection for the MnDPS dataset was 15 years, compared to the 1-year time frame we used for the pilot project and for the extended search area.

Table 8: Road segments used to compare the number of DVCs in 2021 and 2022 to the number of DVCs recorded in the MnDPS database.

Road	Start	End	Miles
I-35	US 2	MN 23	70
MN 61	Duluth	Scenic 61	20
US 53	MN 194	Cotton	33
MN 194	US 53	MN 33	8
MN 33	Cloquet	US 53	17
US 2	MN 33	Proctor	14
MN 210	I-35	MN 73	19
Martin Road	Pike Lake	Jean Duluth Rd	11
Munger Shaw Rd	Taft	US53	8
Jean Duluth Rd	Martin Rd	Pequayan Lake Rd	8
MN 73	MN 210	US 2	17
Rice Lake Rd	Martin Rd	Camp 26 Truck Trail	26
Becks Rd	MN 23	I-35	4
MN 23	I-35	Beck Road	5
Midway Rd	Martin Rd	I-35	11
Taft Rd	Fredenburg	Taft	7

3.2.2 Extended Search Area

In Spring 2022 we also searched for DVCs in an extended search area outside of the pilot project area. The motivation for the extended search area was the observation of many DVCs on MN 23 between Hinckley and St. Cloud as the snow melted in April 2021. Road segments on highways in Minnesota were driven once in spring 2022 (Table 9).

Table 9: Road segments driven in the extended search area.

Road	Start	End	Miles
MN 95	MN 23	North Branch	53
MN 15 N	Dassel	St. Cloud	33
MN 23 N	St. Cloud	I-35	63
MN 371	MN 200	US 2	17
MN 23 S	Pipestone	Marshall	73
US 169	Elk River	Milaca	33
MN 34	Detroit Lakes	Walker	68
US 12	Morris	Cokato	92
MN 15 S	US 212	Dassel	25
US 59 S	Marshall	US 12	72
US 212	MN 15	Montevideo	72
MN 60	Mankato	Worthington	96
US 59 N	Detroit Lakes	US 2	58
US 75	Luverne	Pipestone	26
MN 7	Montevideo	Hutchinson	70
MN 200	MN 371	US 2	73

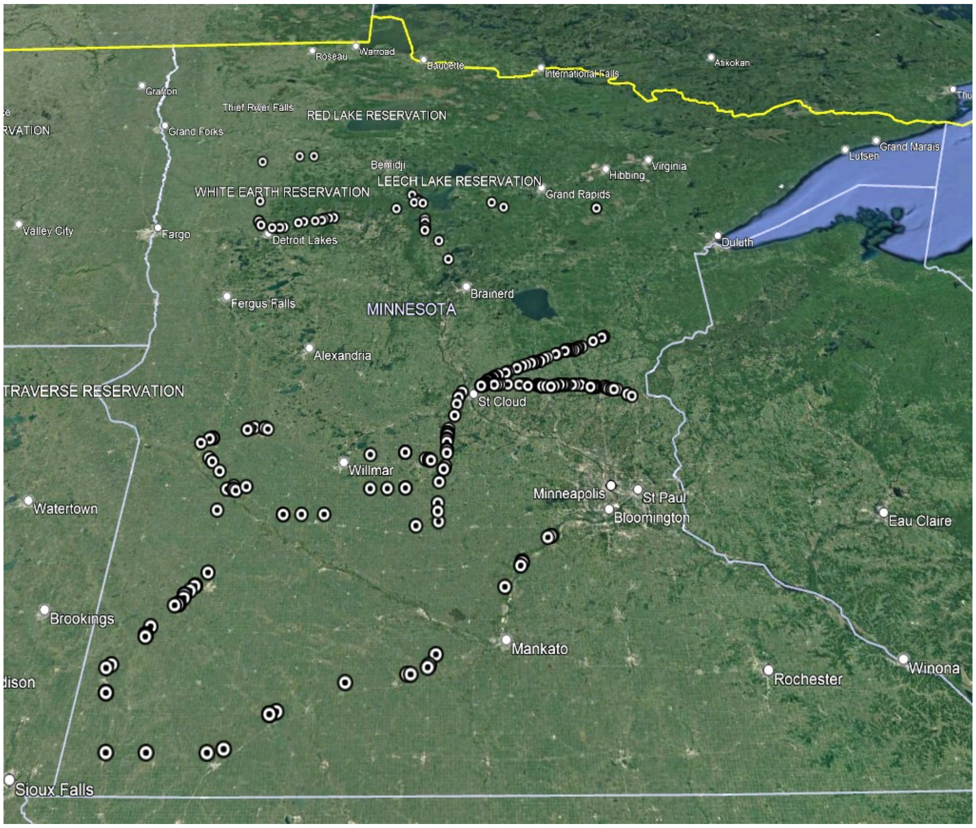

Figure 4: DVCs identified on extended area road searches between 3/15/2022 and 5/15/2022. These DVCs likely occurred after October 2021, although some DVCs could have occurred in summer 2021. Based on decomposition and disappearance rates, it is very unlikely they were more than 1 year old. Roads are not shown on this screenshot from GoogleEarth.

3.2.3 Deer-Vehicle Collisions Recording Protocol

The protocol for recording a DVC was refined to increase efficiency and maintain safety over the course of the project. In the narrative below we identify the steps taken to record data at a DVC. In some cases, alternative methods may be used to collect the same data.

<u>Stop at DVC</u>. On most DVCs, it is not possible to pull over when the DVC is first seen because of driving speed. It is necessary to drive to a safe location to reverse direction, loop back and reverse direction again, and then approach the DVC again with advance knowledge of the location. After stopping the vehicle at the DVC, turn on flashers, and turn on 360 degree warning light.

<u>Record data at DVC</u>. Pictures are taken and data is recorded at each DVC. We used both a Garmin handheld GPS unit and cell phones with location services turned on to record the location. Location data can be extracted from the metadata stored in the JPG file. We found that phone GPS locations were off by 100 to 500 m on a small number of DVCs when the vehicle was moving and the phone was moving inside the vehicle when the picture was taken. The vehicle roof may also have obstructed the GPS signal.

The handheld GPS unit is more accurate than the phone GPS, and waypoint data can be downloaded and imported into Excel to move location data into the DVC database. The program we used was DNRGPS (https://gisdata.mn.gov/dataset/dnrgps), other programs could also be used.

A series of example pictures illustrate how divider pictures and subject pictures document a DVC (Figure 5). The first picture taken should be of the deer at a distance of 1 to 3 m to document location of the carcass relative to the roadway. A second picture can be taken to identify sex of the deer if desired (head should show antler development, the genital region can also be photographed). Pictures should also be taken that serve as a divider between DVCs.

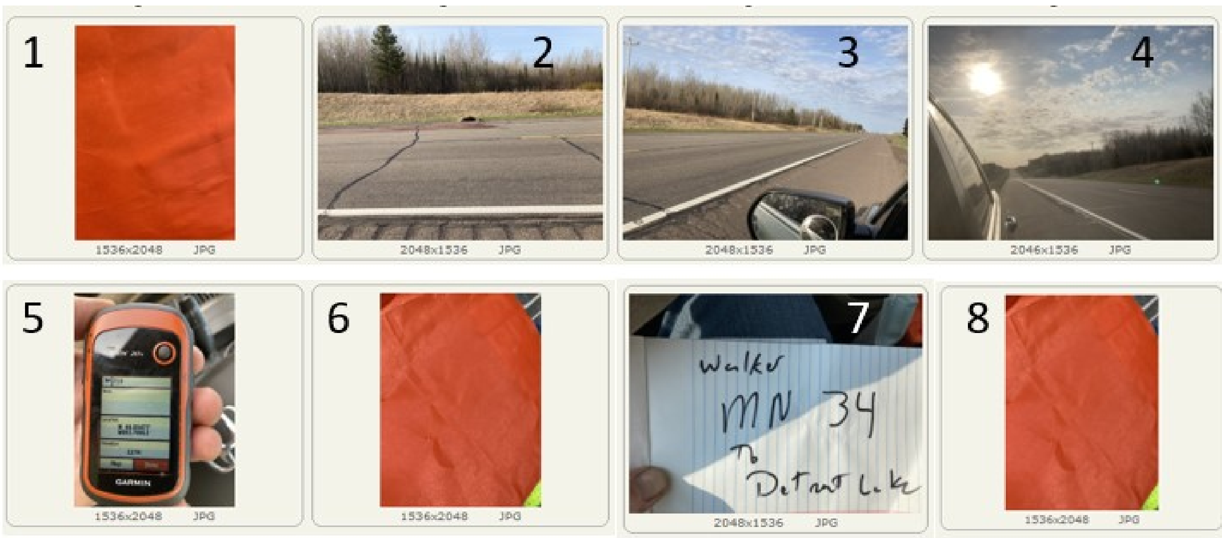

Figure 5: Example picture series taken at a DVC. Picture 2 shows the DVC, and pictures 3 and 4 show the roadway. A picture can be taken of the GPS waypoint as a backup (if GPS is used), and then picture 6 is another divider picture. Picture 7 is an example of switching roads, and then picture 8 is another divider picture.

The divider pictures (Figure 5) increase efficiency of entering data from each DVC. Divider pictures should be a solid bright color. Another useful divider picture is transitioning from one road to another (Figure 5), especially when longer routes are driven in a single day. Pictures of the roadside might be useful in the future for site-specific feature analysis. However, using GoogleEarth to virtually drive the road is probably a more efficient and more consistent way to view site-specific features.

Estimate the time since the DVC occurred, including a time-window that will vary based on appearance of the carcass. If on a regular route, the time-window could potentially go back to the last time the route was driven. Clues to time of DVC include the state of the carcass. In summer, the gut contents will cause the body to bloat relatively quickly. Flies will be present, and if maggots are present and hair is sloughing off the DVC has not occurred recently. Fresh blood on the pavement, or out of the deer's nostrils indicate a recent DVC, it is probably safe to estimate within the last 24 hours.

In winter, the time-window is extended because decomposition is less rapid. The time of the last snowfall is one indication of date. If the carcass is frozen solid this is also an indication the DVC is older, depending on recent air temperatures. Recent DVCs have not been scavenged by birds (crows, ravens, eagles, vultures). Pecking is usually evident on the eyes, the anus, and anywhere the skin has been broken or cut open.

Because DVCs occur infrequently at a specific location, even older decomposed DVCs should be recorded. The exact date of the DVC is unknown, but it can still be matched up against reported DVCs based on a space and time contrast. For example, if an old DVC is found, and there are no DVCs within 1 km of the DVCs in the MnDPS database, the DVC observation could be considered unreported. Old and decomposed DVCs cannot be used to evaluate seasonal patterns in DVCs, but it can be used to identify a DVC location.

After pictures are taken and data on the DVC is recorded, return to the vehicle, turn off the emergency flashers, turn off the 360 degree flashing light, and continue driving.

Data extraction and Geographic Location. After downloading pictures from the cell phone, use the BR EXIFextracter program (https://www.br-software.com/extracter.html) to extract time and date information for the DVC. An alternative method is to use the FastStone ImageViewer software (https://www.faststone.org/index.htm) and copy the image ExIF properties to an Excel template that extracts time, date, latitude, and longitude using text functions.

In some cases a DVC is observed but it is not safe to stop at the DVC location, or time constraints do not allow stopping at the DVC. Notes can be made of the location, using mileposts on the route, addresses, or landmarks such as a billboard, an exit sign, or other features. This method is possible on roads that have a higher density of houses with mailboxes. Newer mobile applications such as the ESRI Quick Capture app, which allows on-the-drive data collection could also be considered.

Street addresses can then be identified using GoogleEarth Pro to obtain geographic coordinates. The StreetView feature of GoogleEarth makes it possible to identify the precise location if the nearest street address is recorded even if a picture is not taken or if a GPS waypoint is not available (Figure 6). The most efficient way to extract the geographic coordinates is to copy the Untitled Placemark and switch to an Excel file where you have a template set up to extract the GPS coordinates using the Mid() text function.

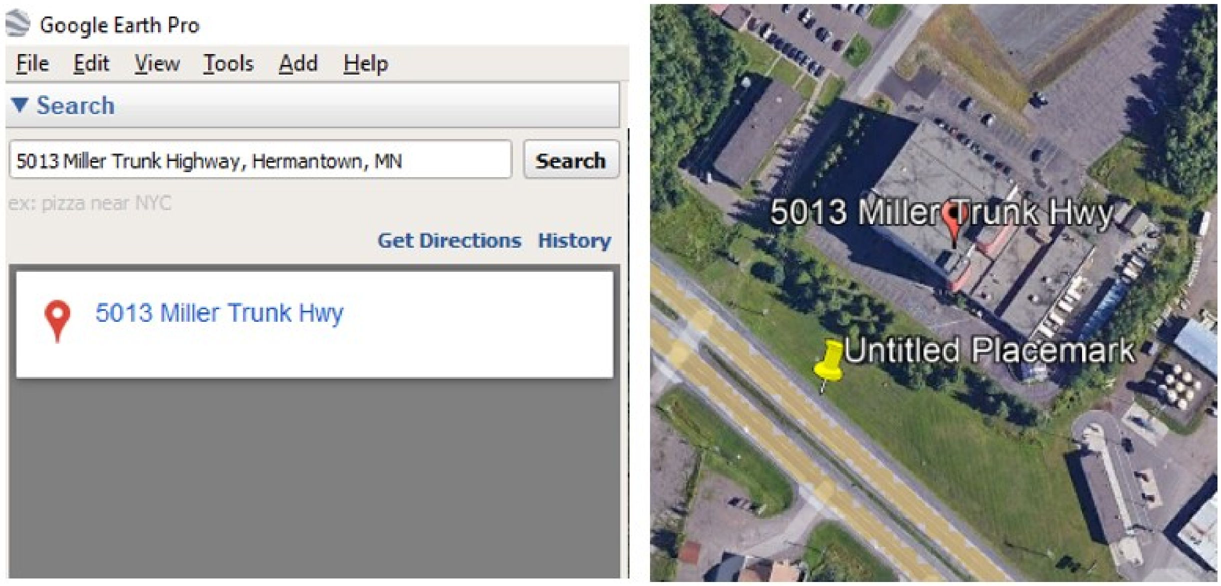

Figure 6: Using GoogleEarth Pro to obtain latitude and longitude of a DVC from a street address. If you type the street address into the search box, GoogleEarth zooms to the street addresses and puts the red balloon pin on the address. Next, create an Untitled Placemark where the DVC was located, carrying the pushpin to the correct location.

3.2.4 Historical Records of DVCs

We have obtained historical records of DVCs with the assistance of MnDOT from the Minnesota Dept. of Public Safety (MnDPS). This data set is similar to the MNCRASH data available to the public (https://mncrash.state.mn.us/Pages/Home.aspx) but provided more records and more data fields for analysis. We have records of DVCs from 2006 to 2020. A selected area shows the number and location of DVCs reported to MnDPS during this time period (Figure 7).

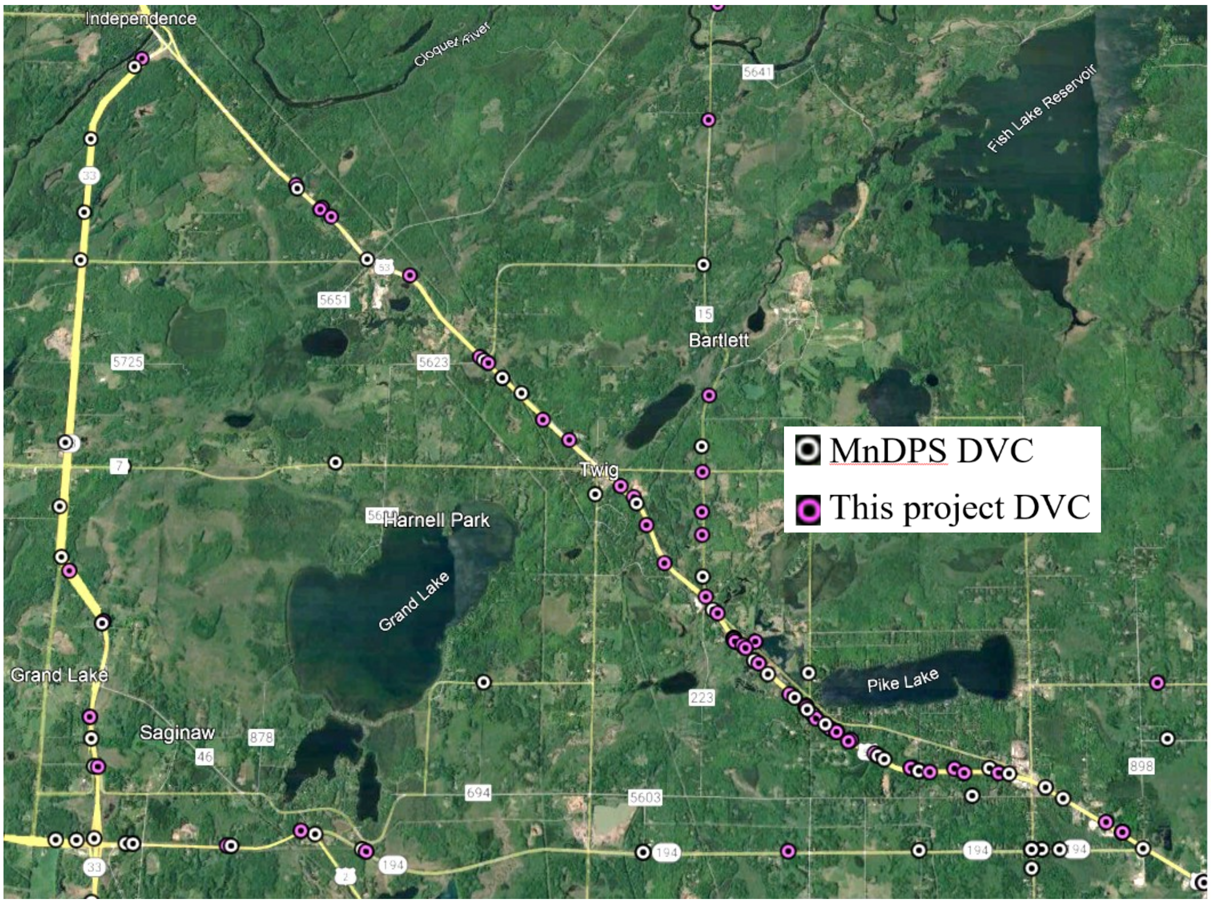

Figure 7: Example screenshot from GoogleEarth showing locations of DVCs reported to MnDPS from 2006 to 2020. Records in the MnDPS database are shown as white symbols with a black dot, and DVCs collected on this project are shown as magenta symbols with a black dot.

The DVC locations can be identified to specific road segments. For example, in Figure 8 we have zoomed in to a section of one of the routes being driven. The 15-year record of DVCs is a powerful tool to estimate reporting rate for DVCs. In the section of US 53 in Figure 8, the DVC rate was 0.33 DVCs / year, as compared to about 9 DVCs in 1.25 years during this project. The benefit of this method is that we can estimate DVC reporting rate based on the current year relative to DVCs reported in past years.

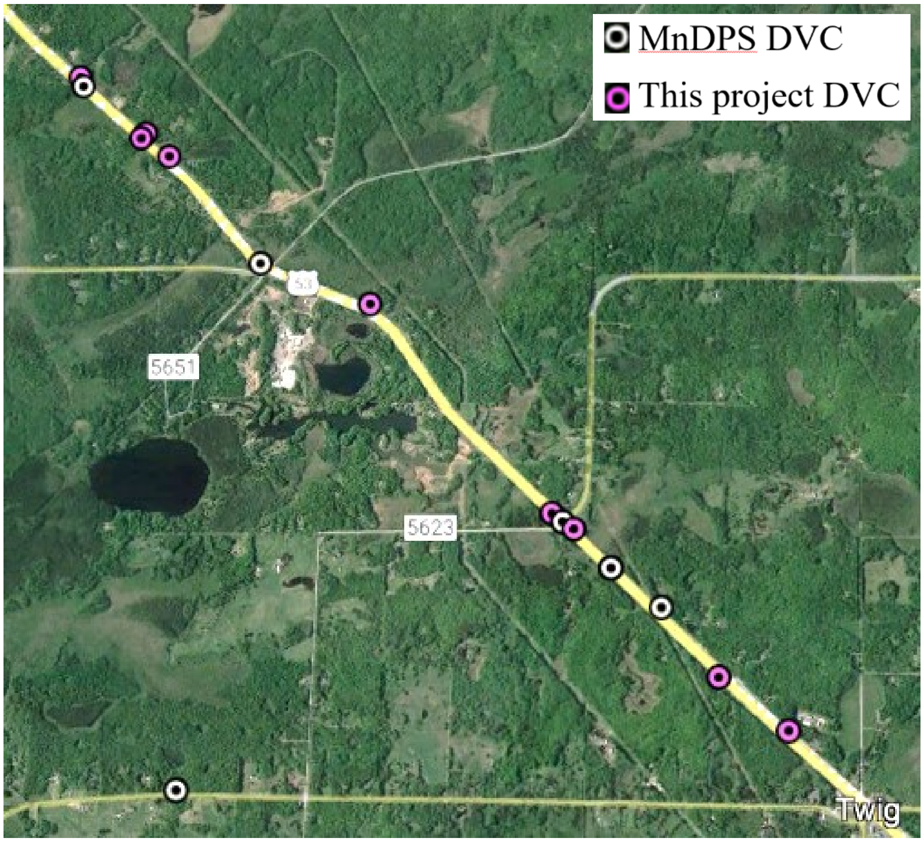

Figure 8: Section of US 53 from Twig to MN 33 showing DVC locations reported to MnDPS from 2006 to 2020. There were 5 DVCs reported over the 15 year period, or 0.33 DVCs / year, as identified by the black/white fisheyes, while in this project we found 9 DVCs over 1.25 years.

3.2.5 Changes in Reporting Rate in the MnDPS database

The number of DVCs reported per road segment seems to have declined from 2006 to 2020. The decline could be related to an actual decline in the number of DVCs. Alternatively, and probably more likely because of the magnitude of the decline, the reporting rate for DVCs has decreased. The decline is significant because it affects the baseline reporting rate for DVCs. A reporting rate for DVCs based on the entire DVC dataset from 2006 to 2020 will be larger than a reporting rate based on the DVCs reported in the DVC data set from 2016 to 2020.

The number of DVCs in each road segment was correlated with the number of DVCs in the complete MnDPS data set in each 5-year data collection period (Table 10). For example, the correlation coefficient (r) between the complete MnDPS data set and the number of DVCs on the same road segment between 2006 to 2010, 2011 to 2015, and 2016 to 2020 was 0.97, 0.97, and 0.86, respectively. For the highway road segments (Table 10), the number of DVCs / 10 miles of road / year declined by 67% between 2006 to 2010 and 2016 to 2020 (Table 10), with a 30% decline in the first 5-year period followed by a 50% decline in the second 5-year period.

Table 10: Summary statistics (mean ± SD) for changes in the number of DVCs / 10 miles of road / year in the MnDPS DVC database between 2006 and 2020. These changes are for the road segments in Table 8 and Table 9.

Pilot Project	All MnDPS	2006 to 2010	2011 to 2015	2015 to 2020
Pilot Project Not Highway	0.6 ± 0.4	0.7 ± 0.6	0.3 ± 0.3	0.7 ± 0.5
Highway	1.3 ± 0.8	1.8 ± 1.5	1.4 ± 0.8	0.6 ± 0.4
Extended Area	1.2 ± 1.4	1.8 ± 1.9	1.1 ± 1.3	0.6 ± 1.0

For the highway road segments analyzed for the Pilot Project, the decline in the number of DVCs / 10 miles of road / year in the first 5-year period was not significant (paired t-test, $t_7 = 1.22$, $p = 0.13$), but it was on the second 5-year period (paired t-test, $t_7 = 3.87$, $p < 0.003$). The number of DVCs in the smaller sample of non-highway roads did not decline (paired t-test, $t_5 = 1.53$, $p = 0.09$, and $t_5 = 1.94$, $p = 0.06$). For the road segments on the extended area search, the decline was highly significant in both time periods (paired t-test, $t_{15} > 3.72$, $p < 0.001$).

In addition to the road segments that were driven for the pilot project and for the extended search area, the number of DVCs / 10 miles / year also declined on the entire length of roads. The number of DVCs / 10 miles / year declined by about 40% from 2006 to 2010 compared to 2011 to 2015, and then declined by another 60% by 2016 to 2020 on Minnesota highways, US highways, and Interstate highways (Table 5). With the larger sample size, and the longer length of roads, the decline in the number of DVCs / 10 miles / year was highly significant for Minnesota highways from 2006 to 2010 to 2011 to 2016 (paired t-test, $t_{39} = 7.80$, $p < 0.001$) and from 2016 to 2020 (paired t-test, $t_{39} = 8.90$, $p < 0.001$). Similarly, for U.S. highways the number of DVCs / 10 miles / year declined in both periods (paired t-test, $t_{12} = 4.23$, $p < 0.001$, and $t_{12} = 5.37$, $p < 0.001$, respectively). The decline was similar for interstate highways (paired t-test, $t_5 = 4.11$, $p < 0.001$, and $t_5 = 2.90$, $p = 0.02$, respectively).

Table 11: Changes in the number of DVCs / 10 miles of road / year in the MnDPS DVC database between 2006 and 2020 for highways. These DVCs are for the entire length of a road (for example, MN 23 from Interstate 90 near the Iowa border to Duluth).

Road type	2006 to 2010	2011 to 2015	2015 to 2020
MN Highways	1.9 ± 1.4	1.2 ± 1.0	0.6 ± 0.7
US Highways	1.3 ± 0.7	0.9 ± 0.5	0.4 ± 0.2
Interstate	1.9 ± 0.7	1.2 ± 0.4	0.4 ± 0.3

3.3 Results

In this section we provide results for the roads followed on regular routes and also for the extended search area. The overall reporting rate was consistent with expectations based on reporting rates from other locations.

3.3.1 DVCs Identified

DVCs were recorded on 16 different roads in the pilot project. There were 199 DVCs recorded on the loops from 8/27/2021 to 12/31/2022. The highest number of DVCs on a road was on I-35, other highways also tended to have higher DVCs / year. However, by using an annualized time period and a road segment distance of 10 miles, comparisons are standardized (Table 11).

The reporting rate varied from 8% to 47% for specific highway segments (Table 12) when compared to the mean generated from the entire MnDPS data set (from 2006 to 2020). The average reporting rate weighted by segment length was 27% for highway segments, or about 1 in 4 DVCs reported in the full MnDPS dataset. If we use 2016 to 2020 as the baseline for the MnDPS dataset, the average reporting rate weighted by segment length was 16% for the same highway segments, or about 1 in 6 DVCs in the MnDPS database.

The number of DVCs per year on non-highway segments varied (Table 6), but was less than the number of DVCs per year on highway segments. One road segment, Taft Road, did not have any DVCs recorded in the pilot project. This is an example of the more random nature of locating DVCs on roads that have less traffic and fewer DVCs. Taft Road had DVCs that were within a couple months of the start and end of the pilot project, but no DVCs were seen during the pilot project time window.

The reporting rate varied from 5% to 44% for non-highway road segments (Table 12). The average reporting rate weighted by segment length was 28% for non-highway segments, or about 1 in 4 DVCs in the MnDPS database from 2006 to 2020. Using the MnDPS data from 2016 to 2020, the average reporting rate weighted by segment length was 25%, again about 1 in 4 DVCs in the MnDPS database. The reason the reporting rate did not change by time period was because the number of DVCs did not change over time for the non-highway loop segments (Table 10).

Table 12: Number of DVCs recorded on specific road segments in 2021 and 2022, compared to DVCs recorded in the MnDPS database. DVCs are standardized to an annual basis and calculated per 10 miles of road for both data sets. The reporting rate in the last column is the average number of DVCs / year in the MnDPS database between 2006 to 2020 divided by the number of DVCs in the pilot project.

Road	Historical MnDPS DVCs / 10 miles / Yr	Pilot MnDPS DVCs / 10 miles / Yr	Pilot DVCs seen / 10 miles / Yr	Reporting rate vs. Historical (%)	Reporting rate vs. Current[1] (%)
I-35	1.69	0.29	4.71	36	6
MN 61	2.67	0.00	9.50	28	0
US 53	0.71	0.45	8.48	8	5
MN 194	0.87	0.00	2.60	33	0
MN 33	1.29	0.88	8.53	18	10
US 2	1.90	0.73	9.12	21	8
MN 210	0.59	0.00	1.60	38	0
MN 73	0.27	0.00	0.57	47	0
Martin Road	0.61	0.00	5.00	12	0
Munger Shaw Rd	0.34	0.00	6.96	5	0
Jean Duluth Rd	0.48	0.57	2.41	20	24
Rice Lake Rd	0.35	0.57	1.52	23	38
Becks Rd	0.30	3.41	1.14	27	-[1]
Grand Ave. (MN 23)	1.23	0.00	2.78	44	0
Midway Rd	0.67	0.00	1.82	37	0
Taft Rd	0.10	0.00	0.00	-	-
	Summary statistics (mean ± SD)				
Highway	1.3 ± 0.8	0.4 ± 0.4	5.6 ± 3.7	29 ± 12	4 ± 4
Not Highway	0.6 ± 0.4	0.5 ± 1.2	3.3 ± 2.3	22 ± 14	10 ± 16

[1]These values are both lower and higher than were expected. For the highways, there are many 0 values because no DVCs were reported to MnDPS during the time of the pilot project. Becks Road was an outlier that was not included in summary statistic calculation because it had a 299% reporting rate, resulting from (a) 3 DVCs being reported when only one DVC was observed in the pilot project, and (b) Becks Road is only 4 miles long, which is the denominator when calculating DVCs / 10 miles / yr.

3.4 Extended Search Area

The Extended Search Area approach in Spring 2022 expanded the geographic coverage of DVC surveys. This was a one-time survey between snow-melt and green-up of vegetation. The goal was to obtain a minimum estimate of DVCs that would extend over a longer time period, covering from about mid-October to the date of the spring survey. It is a minimum estimate because roads are surveyed only once, some DVCs may have been picked up by humans or dragged off the roadway, and other DVCs could have been eaten by scavengers. Using this protocol we located 448 DVCs on several highways in Minnesota (Table 9, Figure 9).

The number of DVCs / 10 miles / year ranged from 0.68 to 12.26 in the extended search area (Table 7). Overall the average number of DVCs / 10 miles / year was 3.40 for the search area, compared to 1.16 in the MnDPS database using the 2006 to 2020 time frame (paired t-test, $t_{15} = 2.80$, $p = 0.006$). The reporting rate for DVCs was variable, ranging from 2% to 200% when using the MnDPS database from 2006 to 2020, and ranged from 2% to 50% when using the MnDPS database from 2016 to 2020. Overall, the average reporting rate was about 50%, or one half of the DVC rate reported in the MnDPS database from 2006 to 2020.

Table 13: DVCs per 10 miles per year from the Extended Search Area. DVCs/Yr/10 miles is calculated to standardize by distance, because road segment length varied. The reporting rate is calculated in the last column.

	MnDPS database			Extended Search	Reporting Rate		
	2006 to 2020	2015 to 2020	1:1 2022		2006 to 2020	2015 to 2020	1:1 2022
MN 95	1.28	0.38	0.19	12.26	10	3	2
MN 23 N	1.20	0.70	0.00	4.60	26	15	0
MN 371	5.96	4.24	0.32	3.84	45	42	8
MN 15 N	0.63	0.79	1.76	3.78	15	19	47
MN 23 S	1.16	0.08	0.00	3.01	38	3	0
US 169	2.00	0.97	0.91	2.73	73	36	33
MN 34	0.88	0.32	0.15	2.35	38	14	6
US 12	0.22	0.17	0.11	1.96	14	11	6
MN 15 S	1.44	0.24	0.00	1.60	90	15	0
US 59 S	0.03	0.03	0.00	1.53	2	2	0
US 212	0.54	0.19	0.14	1.39	39	14	10
MN 60	0.51	0.06	0.00	0.94	55	7	0
US 59 N	0.63	0.17	0.00	0.86	73	20	0
US 75	1.54	0.38	0.00	0.77	200	50	0
MN 7	0.15	0.09	0.43	0.71	21	12	61
MN 200	0.33	0.30	0.14	0.68	48	44	21
Mean	1.16 ± 1.40	0.57 ± 1.01	0.26 ± 0.47	3.40 ± 3.67	49 ± 47	19 ± 15	12 ± 19

The DVC rate was loosely related to the pre-fawn deer density in the deer modeling unit, and it also shows variability in DVCs / 10 miles / year (Figure 9). MN 95 was the largest outlier, with over 12 DVCs / 10 miles / year. Deer density was high in the Deer Modeling unit that MN 95 runs through, but there were also several other roads with a similar deer density that had fewer DVCs / 10 miles / year. MN 23 from Hinckley to St. Cloud, for example, had 37% as many DVCs as MN 95, using the same surveying method. MN 169 (Elk River to Milaca) and MN 15 N (St. Cloud to Dassel) had similar deer densities and also had fewer DVCs.

The roads in the southern half of the state were in areas with lower deer densities, and also had fewer DVCs / 10 miles / year (Fig. 5, t-test, $t_{13} = 1.92$, $p = 0.04$). However, reporting rate was not different between the southern and the northern roads (t-test, $t_{13} = 0.27$, $p = 0.39$).

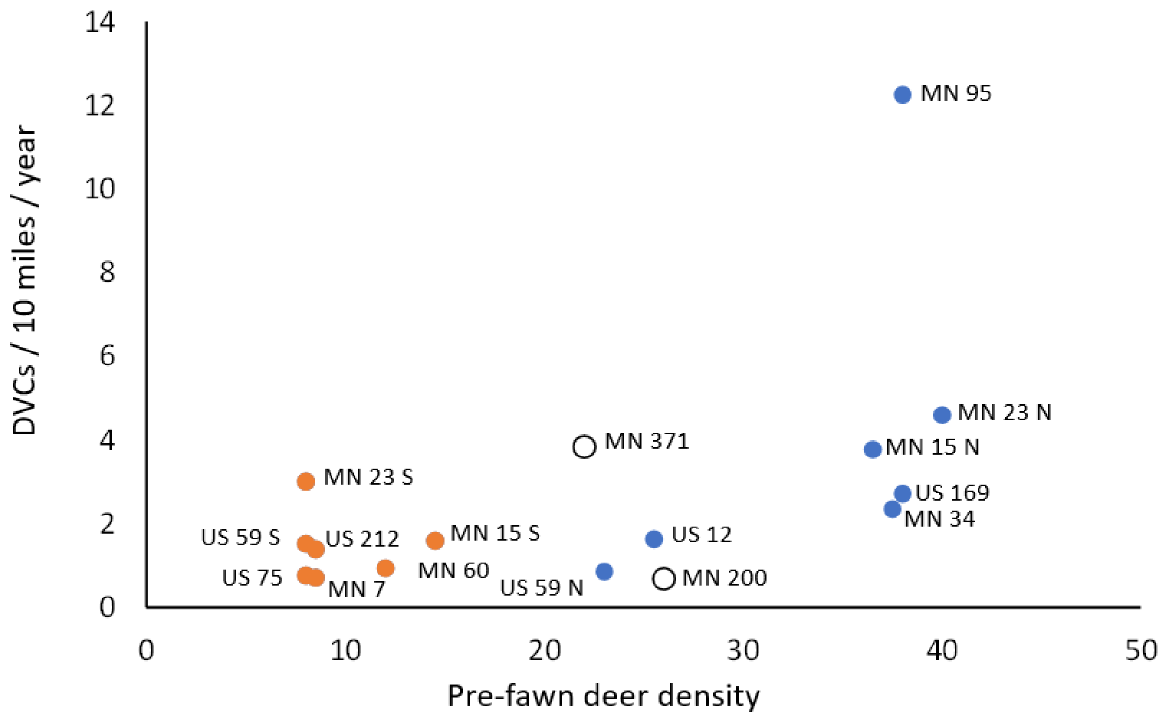

Figure 9: DVCs / 10 miles / year in extended search area compared to pre-fawn deer density in 2022 (Michel and Guidice 2022). Roads with orange symbols are in the southern half of Minnesota, while roads with blue symbols are in the northern half of Minnesota. The hollow symbols (MN 200 and MN 371) represent roads in the northern half of Minnesota that were driven prior to snowmelt.

3.5 Discussion

Both the pilot project and the extended search area methodologies documented that DVCs are under-reported in the MnDPS database. The average reporting rate was around 25%, but varied from about 15% to 50%. The reporting rate on a road segment varied much more, depending on the road segment length, location, road type, sampling method, and baseline method of calculating the reported DVCs. Specific roads were surprisingly variable, for example the 12 DVCs / 10 miles / year on MN 95 was an exceptional outlier. The range in reporting rate on single road segments ranged from 2% to 200%. The reporting rate of 38%.

If the road segment is short there can be no DVCs reported to MnDPS which means that a reporting rate cannot be calculated. Alternatively, if DVCs were removed before being observed in the pilot project, it was possible to have a reporting rate greater than 100%. This happened on one short road segment during the pilot project, and also happened on one segment in the extended search area part of the project. It might have been expected to happen more frequently in the extended search area part of the project than it actually did, because the roads were only driven once in spring after snowmelt.

Under-reporting was expected, because it is a consistent feature of DVC research. The lowest reporting rate is from a small-scale study in Virginia, with a reporting rate of about 10% (Donaldson and Lafon 2008). Insurance company data puts the reporting rate for Minnesota at less than 10% based on data in Conover (2019) and the MnDPS dataset. Other comparisons between insurance company data and DVC rates indicate from 25% to 60% of DVCs were reported to insurance companies or police (WI DOT 2006, Huijser et al. 2008, Olson 2013, Olson et al. 2014, Steiner et al. 2014, Donaldson et al. 2016), which is consistent with reporting rates from both the pilot project and the extended search area.

When the 2022 MnDPS data became available the reporting rate for highways was between 4% and 12%. This was lower than the reporting rate calculated from previous years of MnDPS data. It was also consistent with the declining trend in the number of DVCs / 10 miles / year in the MnDPS database from 2006 to 2020. This may be something for MnDOT to consider in the future if reporting of DVCs to MnDPS continues to decline. It should be possible to calculate, based on the historical DVC database and the pilot project data, how many miles of different road types would need to be driven, and in what geographic areas of Minnesota, to have a statistically valid estimate of the number of DVCs. A further consideration is the types of road that this estimate should be used on—all road types or limited to highways with speed limits of 50 mph or higher.

The baseline for comparison for determining the reporting rate is critical. Using the pilot project methodology of repeated sampling of a road throughout the year is the best methodology, but it is very time intensive and restricted to a relatively small scale. The study in Virginia, for example, was done on a single county (Donaldson and Lafon 2008). It would not be appropriate to extrapolate the results from the pilot project to all of Minnesota. The alternative we used was to compare the DVC rate to historical rates in the DVC data set. Because the number of DVCs has declined from 2006 to 2020, this baseline has shifted. If we use the MnDPS database DVCs from 2006 to 2010, the estimated reporting rate is about 3 times higher than if we use the MnDPS database DVCs from 2016 to 2020. However, using either of the time frames, the reporting rate is still consistent with reporting rates in the published literature.

Sampling the same road segment consistently throughout the year as we did on the pilot project resulted in identifying more DVCs than the single sampling event of the extended search area method. Using the same baseline of comparison of the MnDPS database from 2006 to 2020, the reporting rate was about 30% on the pilot project with repeated sampling events, compared to a reporting rate of about 50% when we sampled roads only once a year after snowmelt. Identifying additional DVCs came at a cost, however. In the pilot project we drove about 6,000 miles to record 199 DVCs, while in the extended search area we drove about 1,000 miles to record 448 DVCs. The additional driving documented the reporting rate going from about 50% to about 25%, if we use the entire MnDPS dataset from 2006 to 2020 as the baseline.

Chapter 4: Mapping of Geographic and DVC data

4.1 Data Sources

In this chapter, we fuse datasets from multiple sources to better understand DVC concentrations in Minnesota, and understand what factors lead to higher DVC rates. These data sources include data on roughly 37,000 historic DVCs reported in Minnesota between 2005 and 2022 as well as road features such as posted speed limit, width, AADT, and NLCD 2019 Land Cover. The data aggregated and source of each dataset are presented in Table 14 below.

Table 14: Data type, source, and units.

Data	Description	Unit	Source
Deer vehicle collisions (DVC)	Location of DVCs from 2005 to 2020 and their features	Count	Department of Public Safety (DPS)
Average annual daily traffic (AADT)	Average daily traffic of roadways in Minnesota	Count	Minnesota Department of Transportation (MnDoT)
Posted speed limit	Posted speed limit of roadways in Minnesota	Miles per Hour	Minnesota Department of Transportation (MnDoT)
Travel width and roadway factors	Total width of the roadway	feet	Minnesota Department of Transportation (MnDoT)
NLCD 2019 land cover	Raster data showing land cover in Minnesota	Categorical variables	Multi-resolution land characteristics (MRLC) https://www.mrlc.gov/

4.2 Data Collection Methodology

The methodological approach used to analyze DVCs is to study the Minnesota roadways at the level of the individual road segment. This is in contrast to a purely spatial analysis, where different types of road in the same area may be clustered together, despite having different traffic patterns and different DVC rates. To accomplish this, roadways are split into segments at intersections. Then, each segment is broken into four sub-segments of roughly equal length.

As an example, Figure 10 shows a portion of the Minnesota roadway network. Each individual road segment used for analysis is marked with red pins, while historic DVCs are marked with green circles. The AADT polyline data is used for the road segments. So, every segment is populated with the correct AADT value.

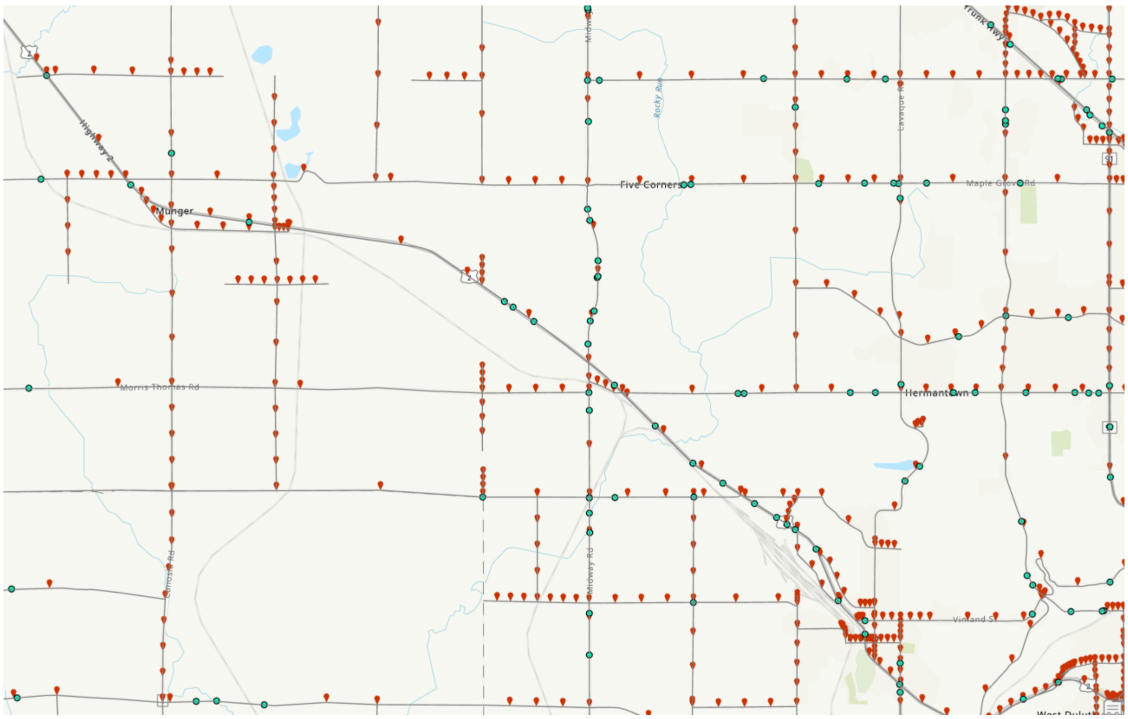

Figure 10: Sample of Minnesota roadway segments and DVC points. The start and the end of each roadway segment is denoted with red pins, while individual DVCs in the historic data are marked with green circles.

To associate DVCs with roadway segments, DVC points are attached to the nearest segment within 75 meters by using the “Near” tool in ArcGIS pro. Then, the number of DVCs associated with each segment was counted. Capturing DVCs within a 75 meters buffer of the segments resulted in counting 33,275 out of 34,783 of the reported DVCs from 2006 to 2020, which is about 96 percent of the data. The remaining DVC points are on the roads where AADT data is not available, or they were further than 75 meters from any segment – likely due to data recording inaccuracies. For instance, Figure 11 shows 5 reported DVCs on “Liberty Road Northeast” that were not counted since the AADT data is unavailable for that road.

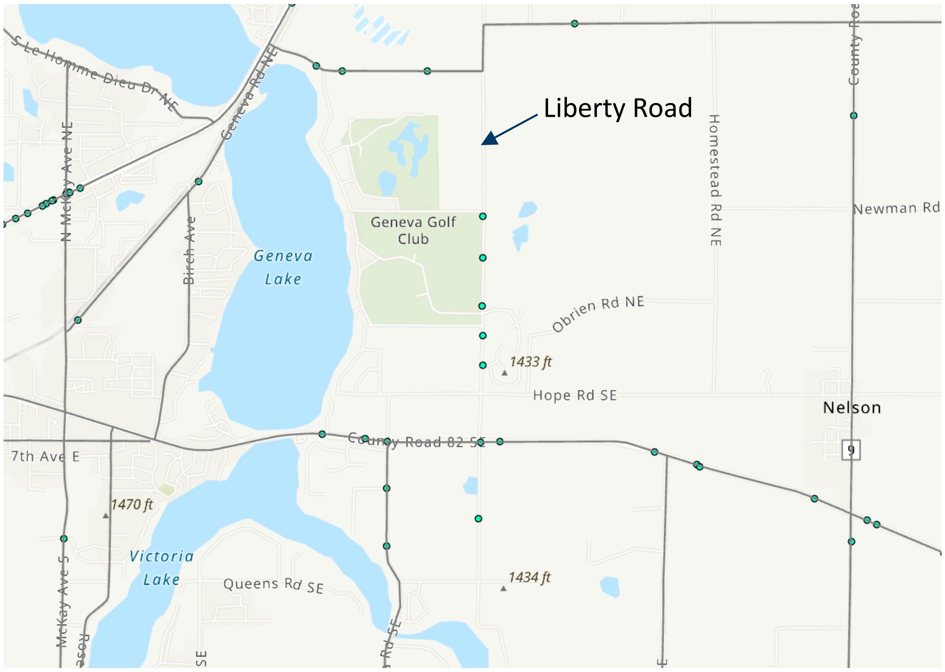

Figure 11: DVCs on Liberty Road Northeast that are not included since no data is available for Liberty Road Northeast.

In some instances, data is aggregated across travel directions for divided roads (e.g., Interstate highways or other larger, divided highways). This is because the provided shapefile for AADT is polyline data that passes from only one side of two-way highways. For example, Figure 12 shows a part of "I-35". This means that DVCs on the side of the road that is not included in the AADT shapefile need to be associated with the AADT shapefile for I-35 despite being further from the road segment in the shapefile. To solve this problem, 75 meters is selected as a reasonable distance to capture the DVC points from both directions of a road segment.

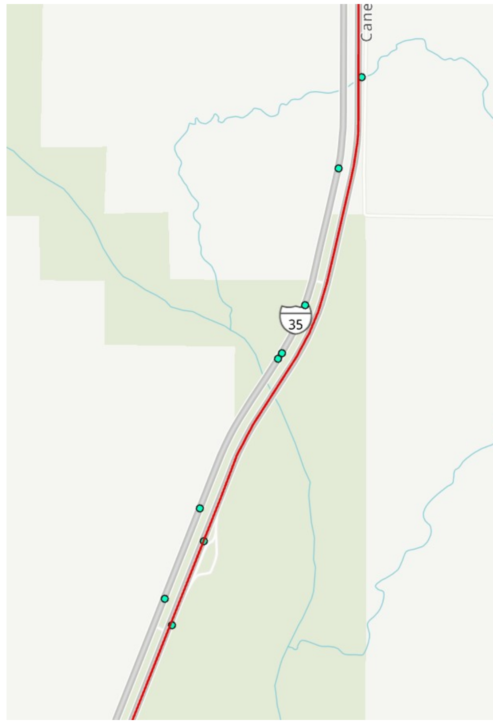

Figure 12: Example of AADT polyline data showing how only the north-bound lane of I-35 is digitized in the roads layer, shown as a red line. DVCs in green dots are shown in both lanes.

For analysis purposes, the roads are divided into two different categories: MnDOT managed roads and all roads for which there is data. Specifically, roads that are under the jurisdiction of the Minnesota Department of Transportation were named Minnesota Roads. These include Minnesota highways, US highways, and Interstate highways. The second group of roads includes all roads in Minnesota that have AADT data. These are referred to “All roads” in the analysis. Table 15 shows the attributes of Minnesota Roads and all roads.

Table 15: Comparison between Minnesota Roads and All roads in Minnesota. Minnesota Roads includes only roads managed by MnDOT.

	Minnesota Roads	All roads
Average length of segments	0.559 mi	0.354 mi
Total length	11,683.6 mi	61,031.4 mi
Total number of DVCs	15,349	33,275

Figure 13 and Figure 14 show the distribution of segment length (in kilometers) for the All roads and Minnesota Roads respectively. It can be seen that the majority of the segments are shorter than 0.5 kilometers on Minnesota roadways (All Roads) and 0.4 kilometers on Minnesota Roads, which is shorter than what is typically considered in similar analyses (Table 4).

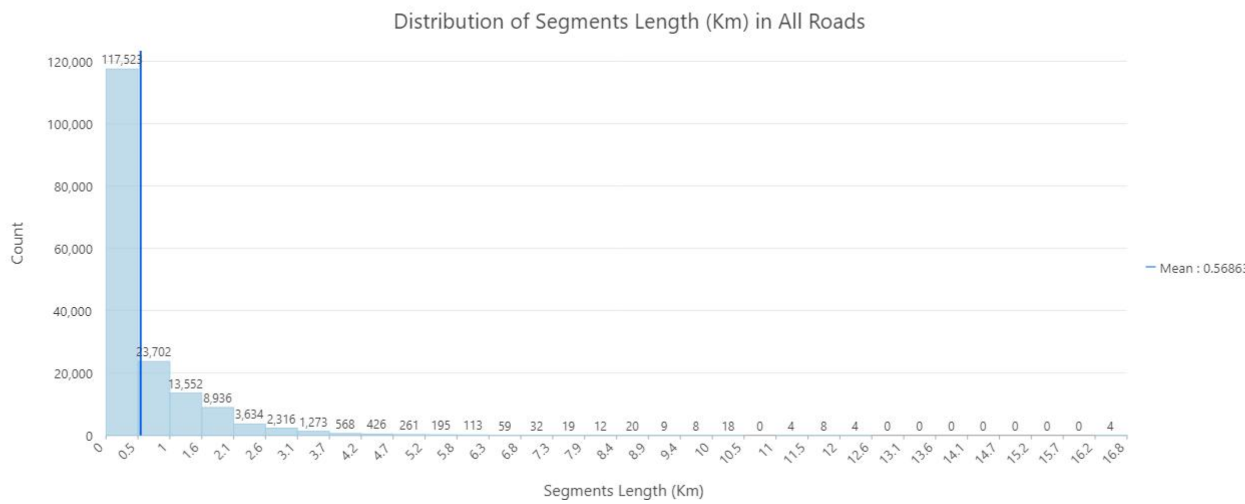

Figure 13: Distribution of segment length in All Roads (note that the average 0.56 km corresponds to 0.35 mi).

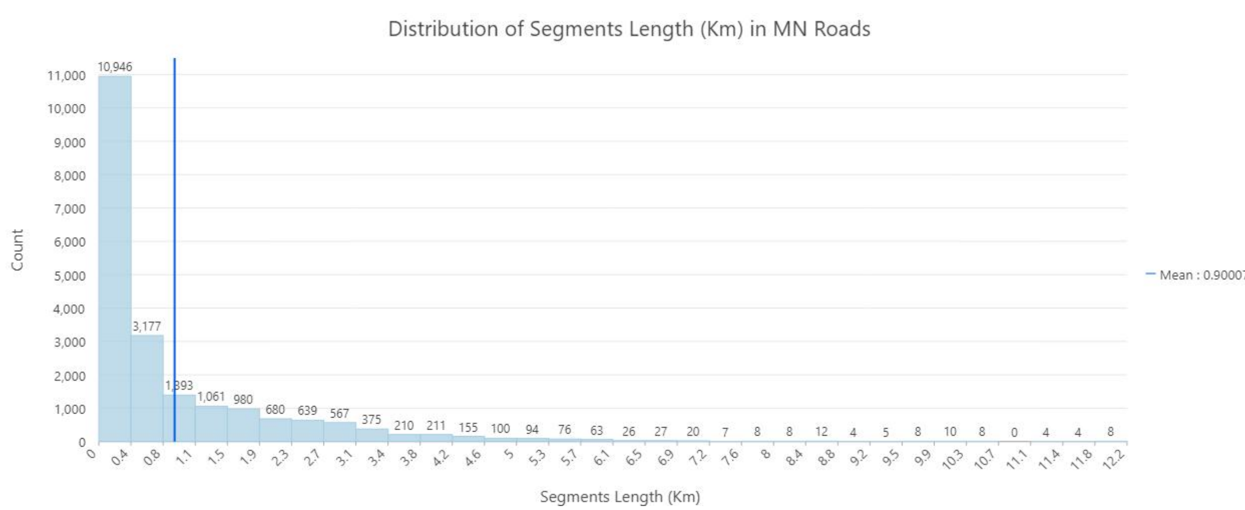

Figure 14: Distribution of segment length in Minnesota Roads (note that the average 0.9 km corresponds to 0.6 mi).

Additionally, the National Land Cover Dataset (NLCD) 2019 was used as one of the features to associate the most prevalent ground cover adjacent to each roadway with the individual road segments. To associate NLCD ground cover to the segment dataset, the most common NLCD class within a 500 meter buffer around each road segment was calculated and added to the dataset. Then the individual DVC points were associated with the road segment, and the corresponding land cover breakdown for the associated road segment were assigned to that DVC. For simplicity of analysis and to reduce the number of predictor variables, some similar NLCD ground cover categories were combined for this analysis. The original categories and their description can be found on the "National Land Cover Database Class Legend and Description" website. The NLCD categories are shown on the left in Table 16, and the modified categories are presented on the right.

Table 16: NLCD classifications.

NLCD subclasses	Combined NLCD class
Open Water areas	Open water
Developed, Open Space	Developed open space
Developed, Low-Intensity	Developed areas
Developed, Medium-Intensity	
Developed High-Intensity	
Barren Land (Rock/Sand/Clay)	Barren land
Deciduous Forest	Forested areas
Evergreen Forest	
Mixed Forest	
Shrub/Scrub	Shrub - scrub
Grassland/Herbaceous	Herbaceous
Emergent Herbaceous Wetlands	
Pasture/Hay	Planted - cultivated
Cultivated Crops	
Woody Wetlands	Woody wetlands
Unclassified	Unclassified

4.3 Computed Quantities

In addition to the data that can be directly added to the interactive map, additional quantities are computed. Specifically, the DVC rate (DVC per mile per AADT) is defined as:

$$\frac{Number\ of\ annual\ DVCs\ in\ each\ segment}{AADT\ of\ that\ segment \times Segment\ length}$$

The winding factor is a calculated value that tells the degree of curvature for each road and the computation is presented below. Literature suggests that curves may influence drivers' sight distance. Thus, the DVC rate can be increased on roads that are curvier and have poor sight distance. Therefore, the effect of the horizontal curviness of roads is taken into consideration.

$$\frac{Segment\ Length}{Distance\ between\ segment\ start\ point\ to\ its\ end\ point}$$

Chapter 5: Models for DVC risk

5.1 Grouping of road DVC risk

For any particular road segment, the presence of a DVC depends on many factors and, while observing DVCs may be an indication of a concentration of DVCs, the absence of DVCs in a particular year does not indicate that this is a low risk road, necessarily, since DVCs are still quite rare, and only about 10% of DVCs are reported to MnDPS. Therefore, we used the average number of DVCs happening over several years in the analysis. This allows us to average out annual fluctuations in the number of DVCs due to pure chance. Moreover, as the rate of DVCs in each segment is dependent on the length of that segment, we normalize the number of DVCs by length of segment for the purpose of comparison, so that we have a standardized DVC/mile rate calculated for each segment. The dependent variable of the analysis is thus the annual average number of DVCs per mile of roadway (i.e., linear mile of roadway centerline, not lane-mile).

However, with about 40,000 road segments used in the analysis, the average DVC rate normalized by segment length gives us a wide variety of values, and may not provide much insight into what leads to higher DVC rates. Therefore, we divide roads into distinct buckets based on the DVC rate, resulting in low and high-risk roadways. The low-risk segments are the segments in the first quartile of average DVC per mile, and the high-risk segments are segments that have a DVC rate higher than the third quartile.

5.2 Modeling methodology

In this section, we present the statistical analysis methods to model DVC rates on road segments. Using the developed models, we are able to identify significant factors in a deer collision and the likelihood of having a DVC on a road segment given the prevailing conditions.

As no DVC was reported for about 70 percent of the road segments in the dataset, these segments were excluded from the training data but included in the analysis data. The training set is part of the data from which the models learn how each feature works in having a DVC. However, after fitting the models on the training set, all the data was used as the test set. The test set is the part of data on which we test the learned models in training to find out how the models perform. Taking the training set from the road segments that has been reported to have at least one reported DVC resulted in better learning the features contributing to having a DVC and increasing the accuracy of models in tests.

5.2.1 Linear regression analysis

Linear regression is a linear approach for modeling the relationship between a scalar response and one or more explanatory variables. It is sometimes known as the most basic method of finding the relationship between the dependent variable and independent variables. We used linear regression in the first step to finding the effect of each variable on having a DVC and its significance. Then, we modified our models by just using the most significant variables.

5.2.2 k-nearest neighbors algorithm

The k-nearest neighbors algorithm (kNN) is a non-parametric supervised learning method that can be used both for classification and regression. As mentioned earlier, we classified the road segments into two classes, low-risk segments and high-risk segments. The kNN algorithm classifies each data point to the most common class in its "k" -a number- nearest neighbors. We chose the value of k with trial and error; we tried different values for k and chose the one that gave us the least error and highest accuracy in prediction. While kNN often performs quite well, the model has limited interpretability, since all that is learned is the training data, and very limited intuition can be gained on what factors lead to a particular model prediction.

5.2.3 Decision tree algorithm

Decision tree is a supervised machine learning algorithm that uses a set of rules to classify data points. This classifier was used to learn a model that predicted DVC risk based on what combination of features is present on each road segment.

5.2.4 Logistic Regression Model

Logistic regression has been shown to have robust performance in binary classification and provides a model with good interpretability (David G. Kleinbaum, 2002). Logistic regression can be used to model the probability of a certain event of a dependent variable *Y*. In this case, the logistic regression model analyses each class based on the features of each segment to classify it as one of the classes. We assume a linear relationship between the independent variable and the log-odds of the event.

5.2.5 Naive Bayes classifier

Abstractly, naive Bayes is a conditional probability model. In our case, the probability of each segment being in a class will be calculated based on the features of that segment, and the segment will be assigned to the class with the highest probability.

The probability for each "K" possible outcomes or classes C_K for $X = (x_1, x_2, \dots, x_n)$

Representing n features of each segment is:

$$p(C_k | x_1, x_2, \dots, x_n),$$

which is calculated based on Bayes' theorem:

$$p(C_K|X) = \frac{p(C_K)p(X|C_K)}{p(X)}.$$

5.3 Comparison of results

We apply each of the discussed methods below and compare their performance. The results are presented for two groups of datasets. The first one is the results of the models fitted on all road segments of Minnesota, or "All Roads". The second group is the "Minnesota Highways", the routes that are labeled by US, MN, and I. For evaluating the performance of models, we used three common metrics: accuracy, precision, and recall. Figure 15 explains these three methods of model evaluation.

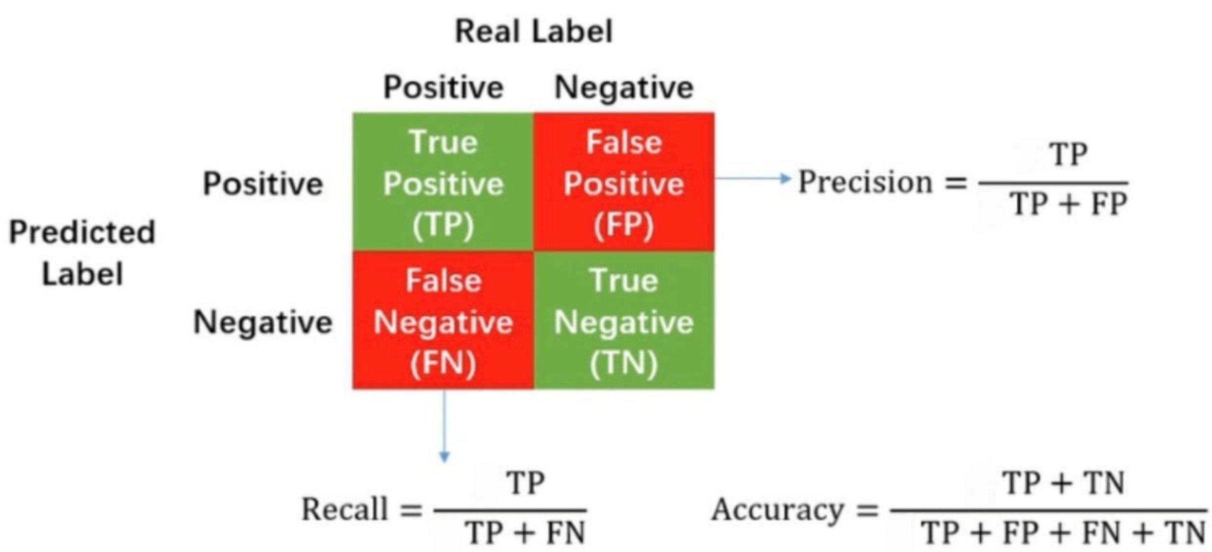

Figure 15: Model evaluation methods

5.3.1 Modeling All Roads

The first dataset used for modeling was "All Roads" data. This data contains the features of all the road segments of Minnesota. The accuracy, precision, and recall of each developed model is presented in the table below.

Table 17: All Roads including 0 DVC segments

	Models	kNN	Logistic regression	Decision tree	Naïve Bayes classifier
	Classes				
Precision	Low-risk	0.72	0.62	0.66	0.61
	High risk	0.74	0.75	0.65	0.73
Recall	Low-risk	0.74	0.81	0.64	0.8
	High risk	0.71	0.53	0.67	0.52
Accuracy		0.73	0.67	0.66	0.66

Table 17 describes the prediction performance for different models fitted on all road segments. The variables used in this classification are:

- $Y = \begin{cases} \text{High-risk segments (DVC/Year/mile } > \chi_{0.75}) \\ \text{Low-risk segments (DVC/Year/mile} < \chi_{0.75}\ \boldsymbol{including\ 0s}) \end{cases}$
- $X =$ AADT, Travel width, Winding factor, Posted speed limit, Bridge number, Culverts number, Stream cross times, Distance to stream, Presence of a roadway median, Deer density.

The following figures demonstrate the mapped results for kNN and Logistic regression models fitted on this data. The first map shows the road segments of Minnesota that are color-coded based on their labels (low-risk segments and high-risk segments) (Fig. 16). The next two maps (Fig. 17 and Fig. 18) show the road segments of Minnesota that are color-coded based on the labels predicted for them in kNN and logistic regression models respectively.

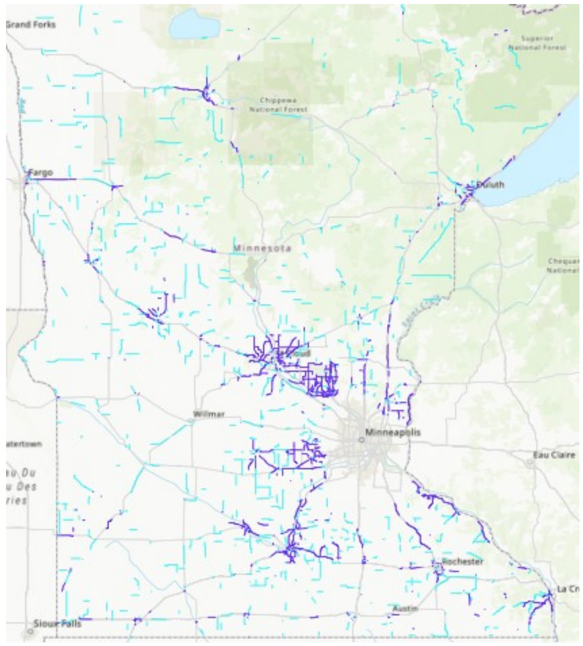

Figure 16: All Minnesota road segments color-coded based on the DVC rate labels. Purple links are high-risk segments, cyan colored links are low-risk, and grey links have incomplete data.

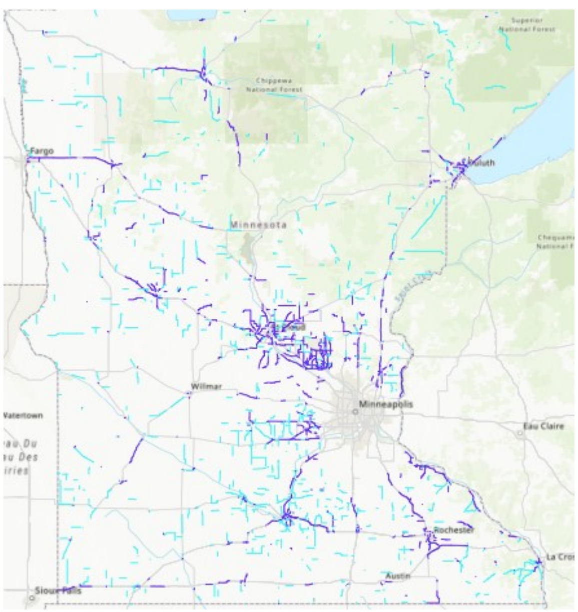

Figure 17: All Minnesota road segments color-coded based on the DVC rate predictions with kNN. The legend is the same as in Figure 16.

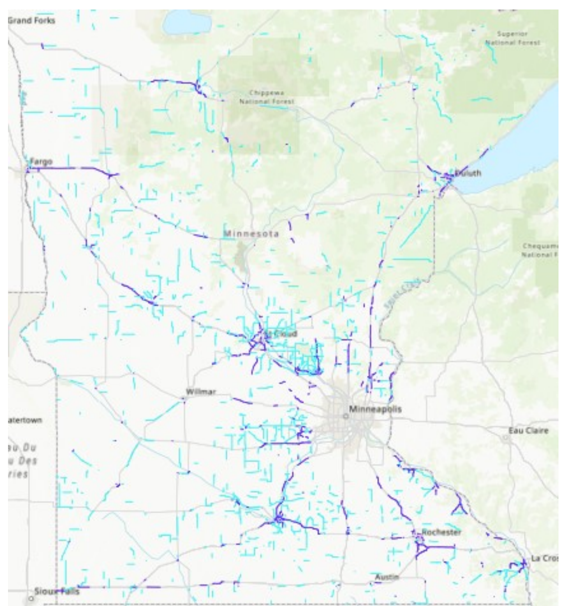

Figure 18: All Minnesota road segments color-coded based on the DVC rate predictions with Logistic regression. The legend is the same as in Figure 16.

Table 18 describes the prediction performance for different models fitted on all road segments when we remove the 0 DVC segments from the analysis. The variables used in this classification are:

- $Y = \begin{cases} \text{High-risk segments (DVC/Year/mile } > \chi_{0.75}) \\ \text{Low-risk segments (DVC/Year/mile} < \chi_{0.75}\ \boldsymbol{excluding\ 0s}) \end{cases}$
- $X =$ AADT, Travel width, Winding factor, Posted speed limit, Number of bridges, Number of culvers, Number of stream crossings, Distance to stream, Presence of roadway median, DMU.

Table 18: All road segments without 0 DVC segments.

	Models / Classes	kNN	Logistic regression	Decision tree	Naïve bayes classifier
Precision	Low-risk	0.74	0.65	0.66	0.64
	High risk	0.77	0.75	0.65	0.76
Recall	Low-risk	0.79	0.79	0.64	0.82
	High risk	0.72	0.59	0.68	0.56
Accuracy		0.75	0.69	0.66	0.68

The following figures demonstrate the mapped results for kNN and Logistic regression models fitted on this data. The first map shows the road segments of Minnesota except for the ones that had reported 0 DVC in the 15 years (Fig. 19). The road segments are color-coded based on their labels (low-risk segments and high-risk segments). The next two maps (Fig. 20 and Fig. 21) show the road segments of Minnesota that are color-coded based on the labels predicted for them in kNN and logistic regression models respectively.

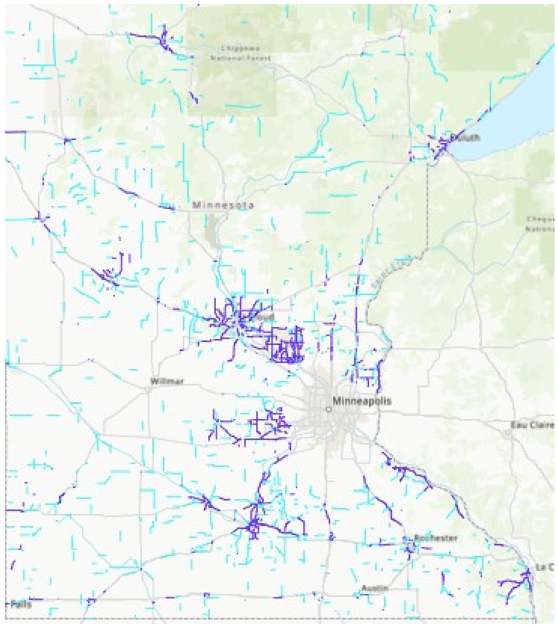

Figure 19: All Minnesota road segments color-coded based on the DVC rate labels. Segments labeled in purple are high-risk, segments labeled in cyan are low risk, and segments in grey have incomplete data.

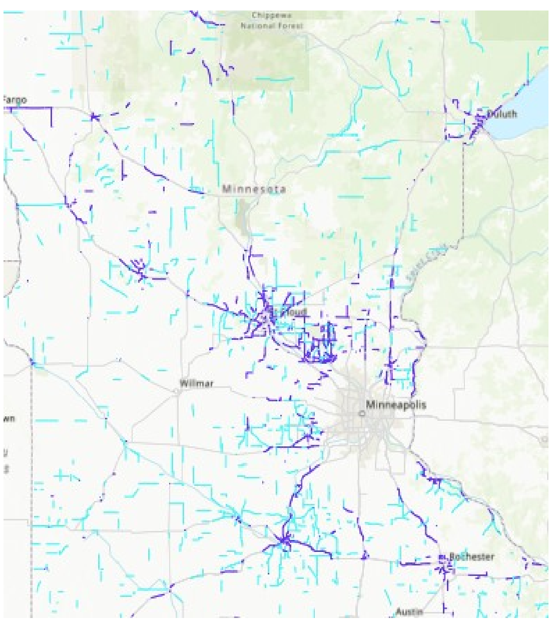

Figure 20: All Minnesota road segments color-coded based on the DVC rate predictions with kNN. Segments are labeled as in Figure 19.

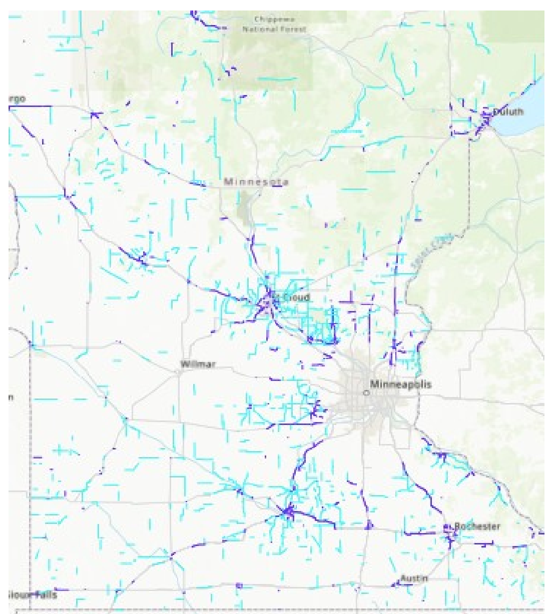

Figure 21: All Minnesota road segments color-coded based on the DVC rate predictions with Logistic regression. Segments are labeled as in Figure 19.

5.3.2 Modeling MN highways

The second dataset used for modeling was "MN highways" data. This data contains the features of the routes that are labeled by US, MN, and I. The accuracy, precision, and recall of each developed model is presented in the table below. The tables below describe the prediction performance for different models fitted on MN segments.

Table 19: MN segments including 0 DVC segments.

	Models / Classes	kNN	Logistic regression	Decision tree	Naïve bayes classifier
Precision	Low-risk	0.65	0.57	0.56	0.58
	High risk	0.7	0.73	0.56	0.71
Recall	Low-risk	0.74	0.79	0.59	0.74
	High risk	0.6	0.49	0.53	0.54
Accuracy		0.67	0.63	0.56	0.63

Table 19 describes the prediction performance for different models fitted on MN segments. The variables used in this classification are:

- $Y = \begin{cases} \text{High-risk segments (DVC/Year/mile } > \chi_{0.75}) \\ \text{Low-risk segments (DVC/Year/mile} < \chi_{0.75}\ \boldsymbol{including\ 0s}) \end{cases}$
- $X =$ AADT, Travel width, Winding factor, Posted speed limit, Bridge number, Culverts number, Stream cross times, Distance to stream, Median, Deer density.

The following figures demonstrate the mapped results for kNN and logistic regression models fitted on this data. The first map (Fig. 22) shows the Minnesota highways that are color-coded based on their labels (low-risk segments and high-risk segments). The next two maps (Fig. 23 and Fig. 24) show the Minnesota highways that are color-coded based on the labels predicted for them in kNN and logistic regression models respectively.

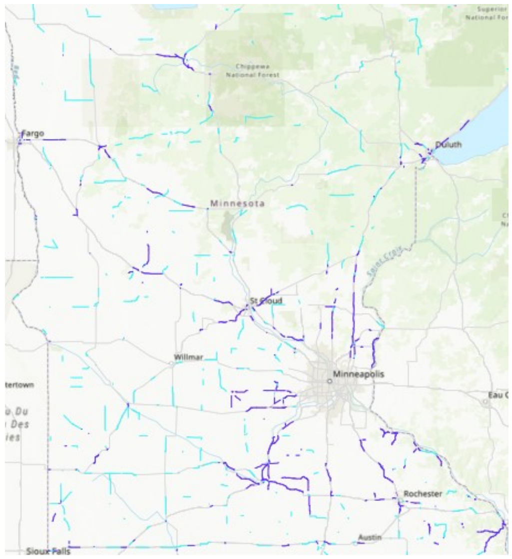

Figure 22: Minnesota highways color-coded based on the DVC rate labels. Purple segments represent high-risk segments, cyan segments represent low-risk segments, and grey segments indicate incomplete data.

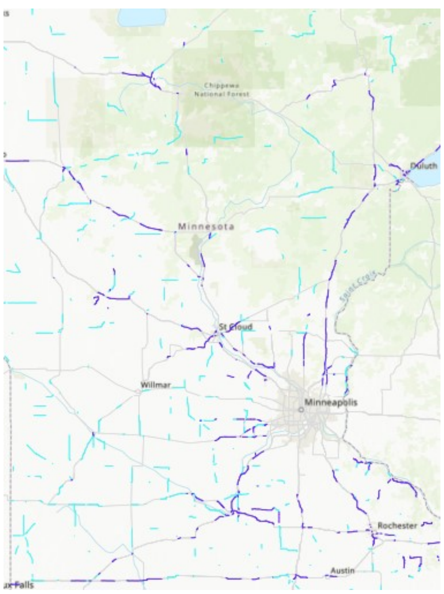

Figure 23: Minnesota highways color-coded based on the DVC rate predictions with kNN. Segments are labeled with the same legend as Figure 22.

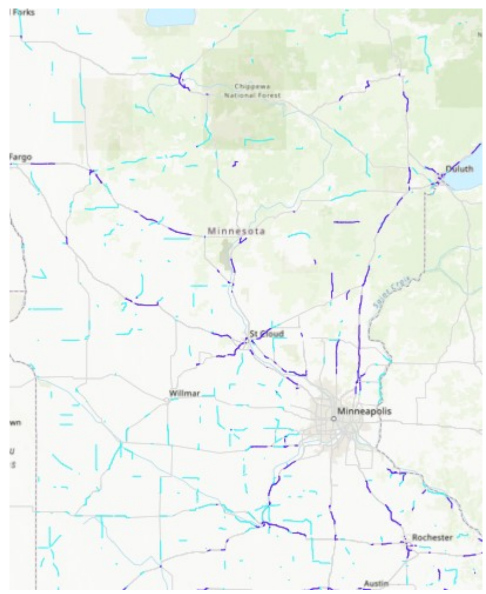

Figure 24: Minnesota highways color-coded based on the DVC rate predictions with Logistic regression. Segments are labeled with the same legend as Figure 22.

Table 20 describes the prediction performance for different models fitted on MN segments when we ignore the 0 DVC segments. The variables used in this classification are:

- $Y = \begin{cases} \text{High-risk segments (DVC/Year/mile } > \chi_{0.75}) \\ \text{Low-risk segments (DVC/Year/mile} < \chi_{0.75}\ \boldsymbol{excluding\ 0s}) \end{cases}$
- $X =$ AADT, Travel width, Winding factor, Posted speed limit, Bridge number, Culverts number, Stream cross times, Distance to stream, Median, Deer density.

Table 20: All road segments without 0 DVC segments.

	Models / Classes	kNN	Logistic regression	Decision tree	Naïve bayes classifier
Precision	Low-risk	0.75	0.71	0.68	0.7
	High risk	0.73	0.74	0.63	0.71
Recall	Low-risk	0.71	0.77	0.57	0.73
	High risk	0.76	0.67	0.72	0.68
Accuracy		0.74	0.72	0.65	0.7

The following figures demonstrate the mapped results for kNN and Logistic regression models fitted on this data. The first map (Fig. 25) shows the Minnesota highways except for the ones that had reported 0 DVC in the 15 years. The road segments are color-coded based on their labels (low-risk segments and high-risk segments). The next two maps (Fig. 26 and Fig. 27) show the road segments of Minnesota that are color-coded based on the labels predicted for them in kNN and logistic regression models respectively.

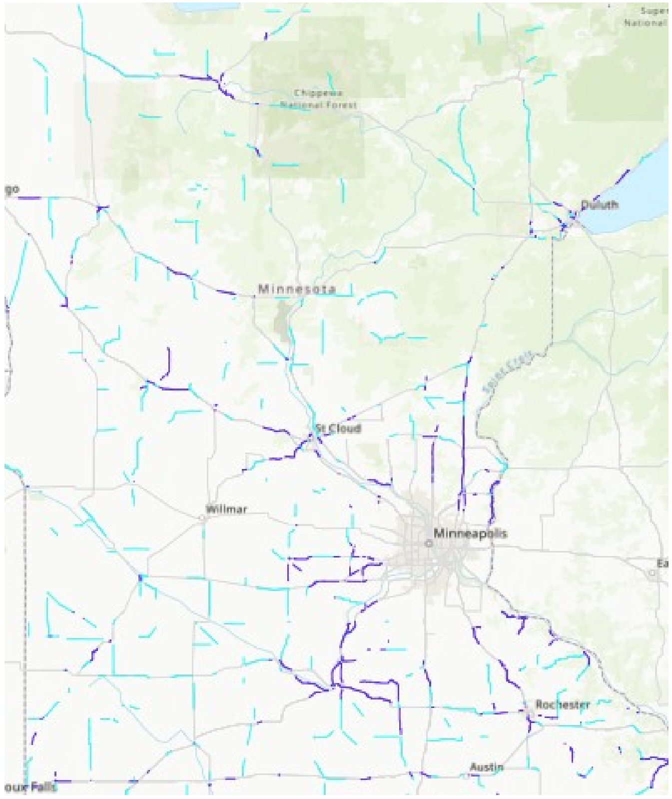

Figure 25: Minnesota highways color-coded based on the DVC rate labels. Purple segments represent high-risk segments, cyan segments represent low-risk segments, and grey segments indicate incomplete data. Note that there is incomplete input data for many road segments leading to a sparse map.

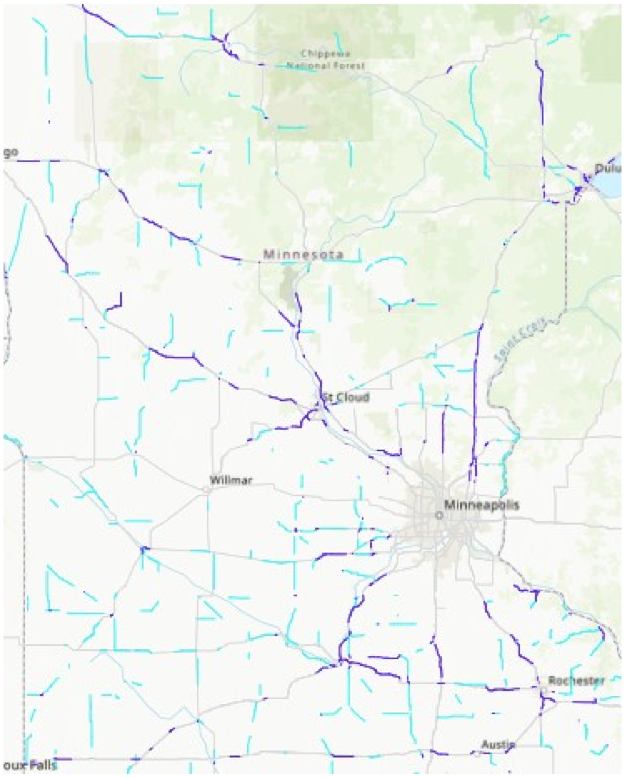

Figure 26: Minnesota highways color-coded based on the DVC rate predictions with kNN. Segments are labeled with the same color scheme as in Figure 25. Note that there is incomplete input data for many road segments leading to a sparse map.

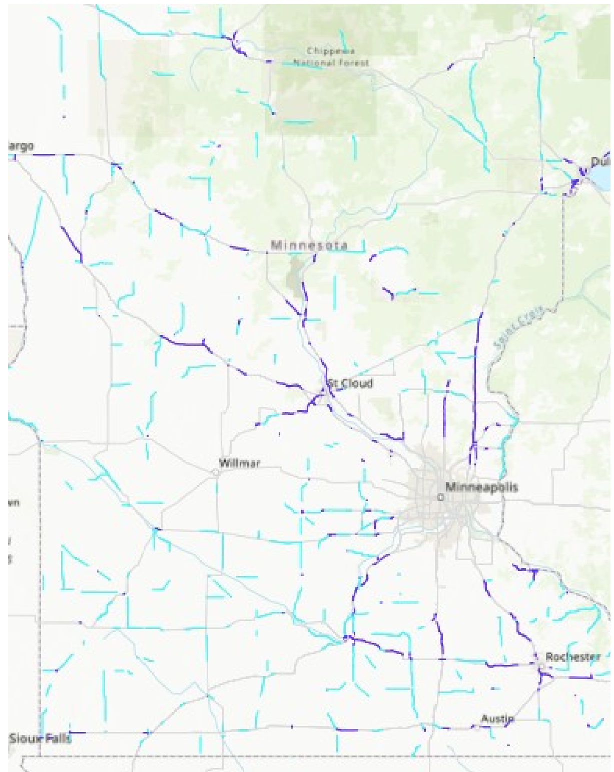

Figure 27: Minnesota highways color-coded based on the DVC rate predictions with Logistic regression. Segments are labeled with the same color scheme as in Figure 25. Note that there is incomplete input data for many road segments leading to a sparse map.

5.4 Features impact

We calculated the average performance of each variable for the logistic regression models to identify the most crucial variables in determining the occurrence of DVCs. Table 21 shows the impact of each variable on the likelihood of a DVC.

Table 21: The performance of each road feature based on the logistic regression model.

Variables	Coefficient	Std err	Effect	P-Value
AADT	4.403935	0.131	Positive	0.00
Travel width	2.505631	0.123	Positive	0.05
Winding factor	-1.293403	0.382	Negative	0.10
# of culverts	-2.205389	0.162	Negative	0.04
# stream crossings	-1.780782	0.098	Negative	0.00
Deer density	2.6402730	0.034	Positive	0.00

Our analysis, which involved fitting models on various datasets, finds that AADT is the most significant variable for predicting the probability of DVCs. Note, only factors that were statistically significant at the p = 0.10 level were included. As the AADT increases, we can anticipate a corresponding increase in the DVC rate. Alongside AADT, deer density emerged as another important variable in forecasting the likelihood of DVCs. Consequently, high-volume corridors with a high deer population density are the most crucial roadway segments for DVC management plans.

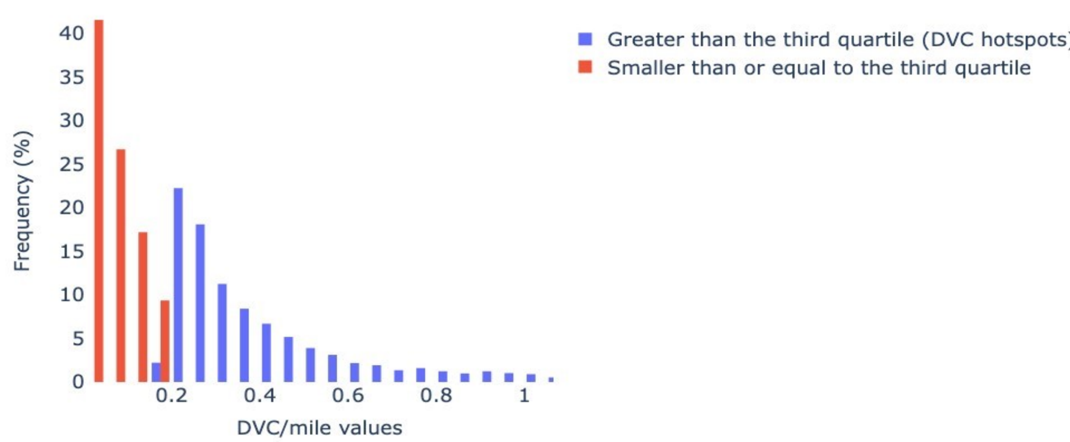

Figure 28: The frequency of DVC values.

The results suggest that road width generally has a positive correlation with DVC rates, meaning that wider roads tend to have more observed DVCs. This is likely due to several factors, including the fact that this is likely since wider roadway segments are the ones that have higher AADT.

The interactive online map with the DVC predictions is accessible at: https://z.umn.edu/ArcGIS_DVCmodel. To access the different layer groups, simply click on the layers option ( ) on the left side of the map viewer. Each layer group contains three distinct map layers. To view the map layers within a group, click on the triangle (▷) adjacent to the name of the group. The eye sign ( ) next to each layer can be toggled to make the layer visible or not. The map segments are color-coded according to their features, and the legend is provided on each interactive map. Darker segments indicate a higher rate of DVC (either labeled or predicted). Additional details on each segment can be viewed by clicking on it, which will bring up a table displaying its features.

5.5 Identifying DVC risk

Since the occurrence of a DVC is a probabilistic event, the lack of historic DVCs does not imply a lack of risk. Thus, we use the developed DVC risk models to identify road segments that have the characteristics of high-risk sites, even if few historic DVCs have been reported. The effect of each feature on the occurrence of DVCs on each road segment is estimated the odds ratio for the variables used in the logistic regression model. Then, by using this, we calculated the coefficient of each variable in the model. Therefore, a variable called the “DVC index”, representing the total risk of DVC, was calculated by Equation 2.

$$\text{DVC index} = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \qquad (2)$$

Where *Xs* represent the normalized value of each feature and *βs* are their coefficient taken from the logistic regression model. Table 2 shows the coefficient and odds ratio of each feature used to calculate *DVC index*.

Table 22: Features coefficients and odds ratio used for mapping the DVC concentrations in Minnesota.

Features	Coefficients	Odds Ratio
AADT	4.403935	81.772038
Travel width	2.505631	12.251282
Winding factor	-1.293403	0.274336
Number of culverts	-2.205389	0.110208
Stream crossing times	-1.780782	0.168506
Average prefawn deer density	2.6402730	14.01703

The value obtained for *DVC index* is in the range of [0,10]. We computed the DVC index for each road segment in the analysis and plot the identified risk in an interactive map (https://z.umn.edu/ArcGIS_DVCmodel). Note that the definition of bridges and culverts are the MnDOT definitions. The darker colors in the map represent a higher risk for DVC. Figure 26 shows the distribution of DVC concentrations in Minnesota. Some road segments of Minnesota are missing in the figure as well as the online interactive map. The reason is that the data was not available for all the segments of Minnesota. Moreover, as mentioned earlier, to estimate the prefawn deer density in areas lacking data, we calculated the average value based on the surrounding deer management units. However, we excluded the urban regions from our prediction results due to their distinct deer habitat and traffic patterns compared to other regions in Minnesota.

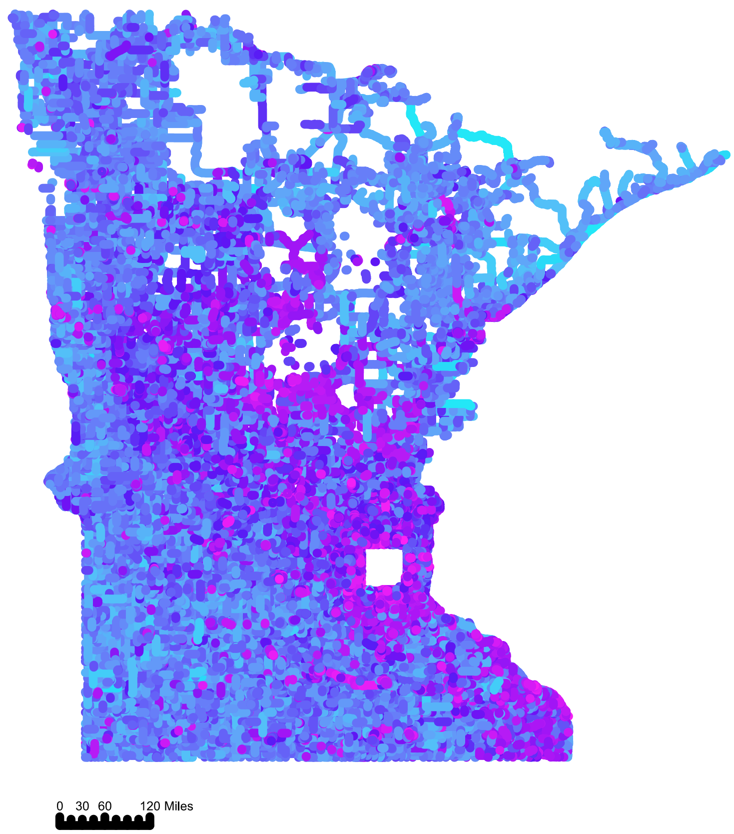

Figure 29: DVC index (total DVC risk) of road segments in Minnesota. Segment color varies from cyan (low risk for DVC) to magenta (high risk for DVC).

The normalized features and an interactive online map for the DVC index on road segments in Minnesota are available at: https://z.umn.edu/DVChotspots. To access different layer groups on the map viewer, click on the “layers” option ( ) on the left side. Each group contains three distinct map layers, which can be viewed by clicking on the triangle (▷) adjacent to the group’s name. The eye sign ( ) next to each layer can be toggled to make it visible or not. The map segments are color-coded based on their features, and the legend is provided on each interactive map. Darker segments indicate a higher rate of the feature displayed by the layer. Clicking on a segment will bring up a table displaying its features.

In the map layers, the layer *relative DVC risk* provides the estimated DVC risk measured on a scale of 1 to 10 with 10 being the highest DVC risk. This number is calculated for each road segments based on the features present on that road segment. Additionally, the average DVC risk for the MnDOT distract that that road segment is located in is provided in the map as seen in the screenshot in Figure 30. Here, the segment is also flagged as high risk if it is in the top 15% of DVC risk values. The average DVC risk in each MnDOT district is also shown in Figure 31. The layer "High Risk DVC Roads" (available in the layers tab on the online map) shows only those roads that are high risk (exceeding the 15% threshold) highlighted in red as seen in Figure 32.

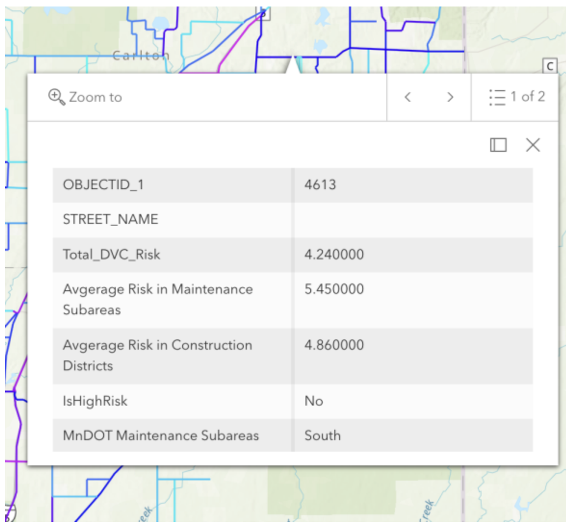

Figure 30: Road segment information obtained by clicking on a particular road segment. The total DVC risk for that segment is provided, as well as the average DVC risk for that MnDOT district, and whether or not this road segment is considered high risk (being in the top 15% of segment values).

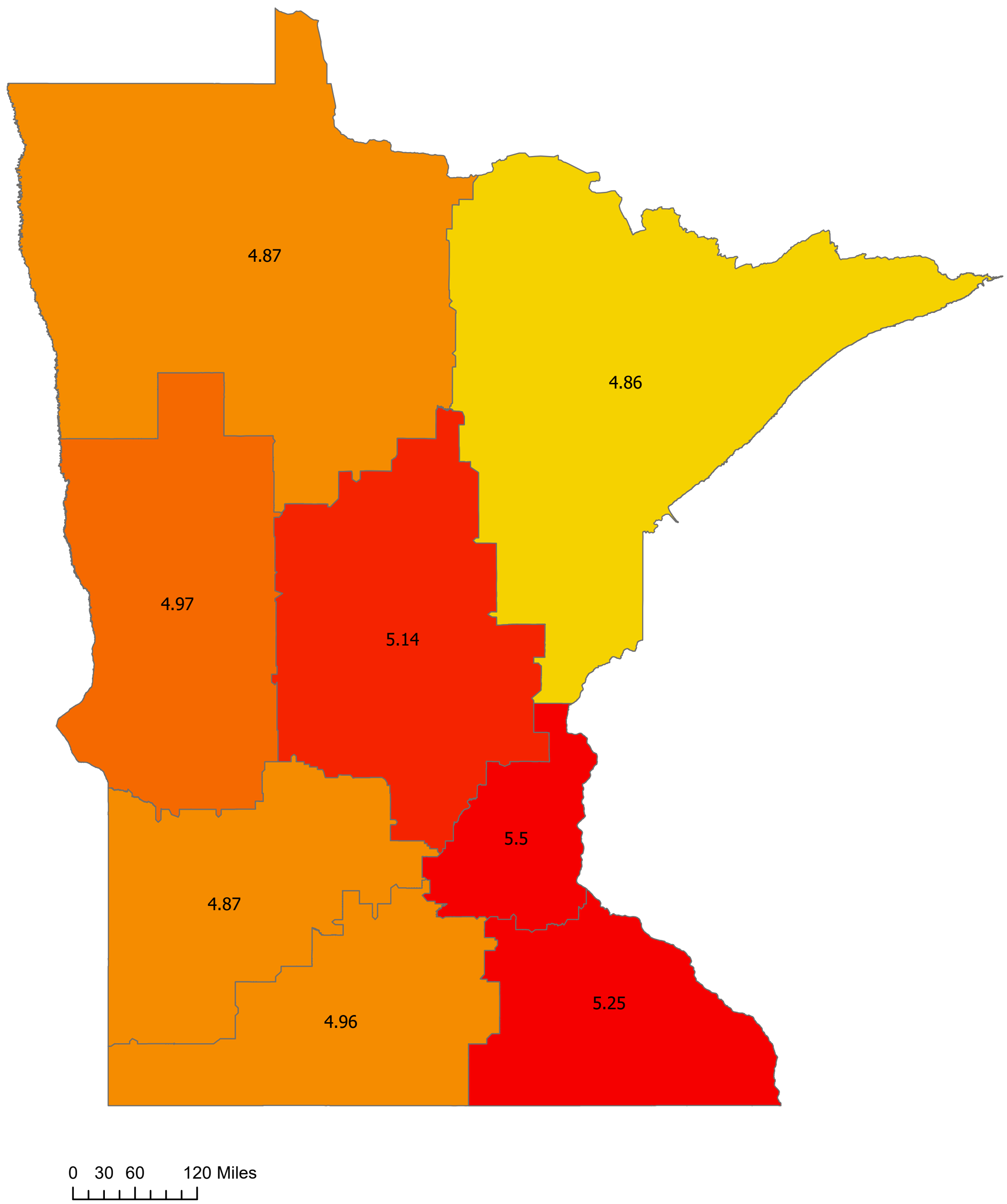

Figure 31: Average DVC risk in each MnDOT district.

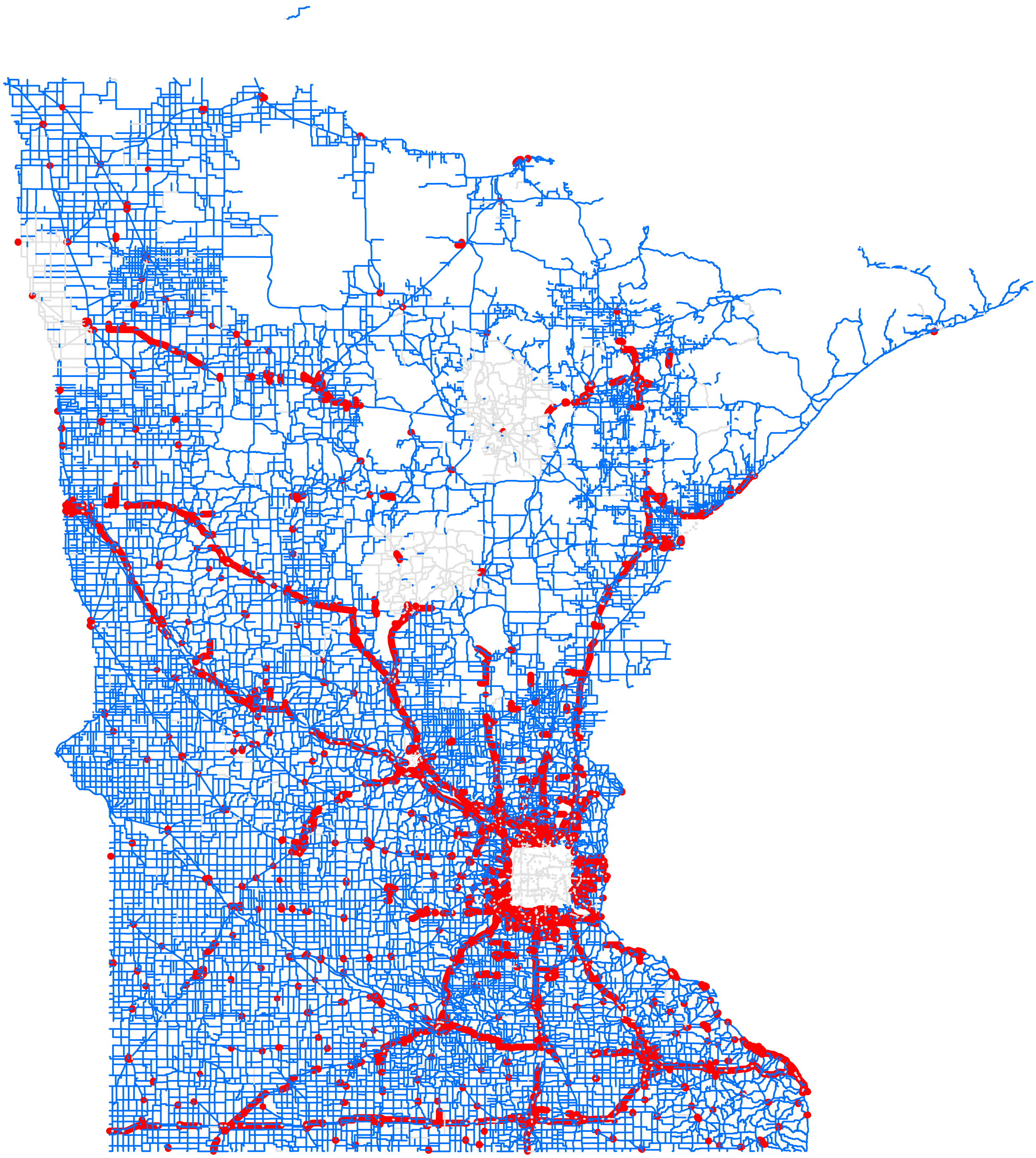

Figure 32: Map of roads in Minnesota with high DVC risk roads highlighted in red. DVC risk is estimated using the DVC Index developed in this study, and road segments with a DVC Index in the top 15% are considered high-risk). Note: areas with greyed out roads have incomplete data to estimate DVC risk.

Chapter 6: Conclusions, Project Benefits, and Implementation

In conclusion, deer-Vehicle Collisions (DVCs) are a significant risk to public safety on Minnesota roads, causing property damage and human injuries and deaths, and they also kill deer. In 2019, there were 1,573 DVCs reported to the Minnesota Department of Public Safety (MnDPS), or roughly 4.5 DVCs per day. Over the course of this project, that number fluctuated somewhat, but stayed relatively consistent, with 1,410 DVCs reported to MnDPS in 2022.

Reducing the number of DVCs in a cost-efficient manner requires an analysis of what factors lead to high DVC rates. Relevant data include geographic features, road type, land use, deer, traffic volume, and other data, which can be used to identify locations where safety measures or warnings are most beneficial. Over the course of this project, we analyzed data from roughly 37,000 DVCs reported to MnDPS that occurred in Minnesota between 2005 and 2022. We then used the insights gained from the data to identify concentrations in DVCs, which can be explored via an interactive online map.

Many DVCs without significant vehicle damage or passenger injury go unreported in Minnesota. Moreover, it has been unclear what percent of DVCs do not get reported, and whether there have been any trends in DVC reporting (e.g., types of roads or adjacent land use). Therefore, we collected roadkill data to estimate the number of unreported DVCs in 2021-2022 in the Duluth area and found that roughly 5% to 25% of DVCs observed were reported to MnDPS, depending on the roadway. The data collection procedure, which was developed, can be applied more broadly across Minnesota. This collected data demonstrates that DVCs that have caused significant property damage or injury to motorists, generally, are similar to those that did not and provides insight into the scale of DVCs in Minnesota.

We have used the results of the DVC analysis to construct a data-driven, machine-learning-based model to identify DVC concentrations in Minnesota. This model can identify road and habitat features that are associated with higher DVC rates. This will be useful in deciding what roads could be prioritized for effective DVC treatment options.

6.1 Project Benefits

Based on the MnDOT Research Steering Committee Criteria in Table 23, this project has two primary benefits: reduced risk and increased safety. By understanding deer-vehicle collision concentrations, MnDOT will be able to reduce risk to drivers and deer by designing target interventions that efficiently use limited resources. Meanwhile, a better understanding of high-risk areas for DVCs will allow for safer Minnesota roads.

Table 23: MnDOT Research Steering Committee Benefits Summary.

Benefit Category	Applicable	Can quantify	How benefits are quantified
Construction Savings	X	No	Difficult to quantify directly but may lead to reduction in costly countermeasures in low-risk areas.
Decreased engineering cost			
Environmental aspects	X	Yes	Number of underpasses installed.
Improved lifecycle costs			
Operation/maintenance saving			
Reduce risk	X	Yes	Measure reduction in DVCs if strategies are implemented after project
Reduce road user cost			
Safety	X	Yes	Measure reduction in DVCs if strategies are implemented after project
Technology			

6.2 Environmental aspects

DVC countermeasures often increase the permeability of the road by providing passage to wildlife under or over the highway corridor. Environmental aspects can be quantified by the number of underpasses that are added as a result of the research findings.

6.3 Reduced risk

This project has provided benefit by reducing risk to Minnesota motorists associated with DVCs. The analysis and resulting DVC concentrations map identify specific roadway segments (at the roughly ¼ mile length) that are particularly high risk for DVCs based on the factors present and correlations identified in the analysis. This information can be used during roadway construction or rebuilding to suggest relevant countermeasures.

6.4 Safety

By providing tools to help decisionmakers at the state and local levels understand where DVCs are most likely to occur, and under what circumstances they are most prevalent, this project has promoted motorist safety. Specifically, the conducted DVC concentration detection will enable MnDOT and local officials to identify which locations require immediate attention as well as locations where intervention would provide the greatest return on investment in terms of improved safety. The interactive map that has resulted from the analysis can be easily shared so that a wide range of stakeholders can use this tool for data-informed decisions relating to DVC risk.

Additionally, by providing a procedure for estimating the DVC reporting rate, this project has enabled continued monitoring of the actual DVC rate in Minnesota. If MnDOT or other state agencies opt to use this procedure for future data collection, it will be straightforward to monitor DVC reporting rates. This will provide additional data to help MnDOT and local agencies continue to improve safety by providing a complete picture of DVC rates in Minnesota.

6.5 Implementation of benefits

The deliverables that have been generated as part of this project can be used to guide MnDOT design and response to DVC concentrations when retrofitting identified high-risk corridors. By designing safer roads and understanding DVC concentrations, the priorities in Table 1 have been addressed.

The key deliverables presented in this project are listed below:

1. Literature review on DVCs.
2. An interactive map that identifies DVC concentrations.
3. Pilot project to estimate DVC reporting rate in and near Duluth and development of a protocol to apply across Minnesota.

Potential implementation steps for using each of the key deliverables is provided below.

Literature review on DVCs: This literature provided a detailed overview of other significant works that identify correlations between roadway characteristics and DVCs. This deliverable provided valuable information on what factors other researchers have found to be relevant (primarily in other states), and what countermeasures have been effective. MnDOT and local engineers can use this summary to guide design of roadways to reduce DVC risk.

Interactive map of DVC concentrations: This map provides an interactive tool to understand what roadway segments have a high DVC risk based on the factors identified in this research project. If shared with stakeholders in roadway design projects, this can be used as a tool to provide information for data-informed decisions on DVC risk. Moreover, the detailed information provided in this map allows users to understand what particular roadway feature is contributing most significantly to the estimated DVC risk.

Pilot project and procedure to estimate DVC reporting rate: This deliverable provides an analysis of the reporting rate in the Duluth area based on frequent monitoring for DVCs throughout the year, and for extended search area on highways in outstate Minnesota based on a one-time survey after snow melts in spring. In addition, we developed a protocol for data collection on DVCs that can be used to repeat estimates of the DVC reporting rate for future use either in the Duluth area or more broadly across the state. To implement this large-scale data collection, each MnDOT district would likely need to commit staff to collect roadkill data.

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