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Deer-Vehicle Crash Patterns Across Ecoregions in Michigan

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DEER-VEHICLE CRASH PATTERNS ACROSS ECOREGIONS IN MICHIGAN

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Abstract: Deer-vehicle collisions (DVCs) impact the economic and social well being of humans. We examined large-scale patterns behind DVCs across 3 ecoregions: Southern Lower Peninsula (SLP), Northern Lower Peninsula (NLP), and Upper Peninsula (UP) in Michigan. A 3 component conceptual model of DVCs with drivers, deer, and a landscape was the framework of analysis. The conceptual model was parameterized into a parsimonious mathematical model. The dependent variable was DVCs by county by ecoregion and the independent variables were percent forest cover, percent crop cover, mean annual vehicle miles traveled (VMT), and mean deer density index (DDI) by county. A discriminant function analysis of the 4 independent variables by counties by ecoregion indicated low misclassification, and provided support to the groupings by ecoregions. The global model and all sub-models were run for the 3 ecoregions and evaluated using information-theoretic approaches. Adjusted R^2 values for the global model increased substantially from the SLP (0.21) to the NLP (0.54) to the UP (0.72). VMT and DDI were important variables across all 3 ecoregions. Percent crop cover played an important role in DVCs in the SLP and UP. The scale at which causal factors of DVCs operate appear to be finer in southern Michigan than in northern Michigan. Reduction of DVCs will likely occur only through a reduction in deer density, a reduction in traffic volume, or in modification of site-specific factors, such as driver behavior, sight distance, highway features, or speed limits.

Key words: deer-vehicle collisions, ecoregions, Michigan, *Odocoileus virginianus*, white-tailed deer.

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INTRODUCTION

Deer-vehicle collisions (DVCs) involving white-tailed deer (*Odocoileus virginianus)* create numerous impacts to society throughout the species range. An estimated minimum of 29,000 human injuries and 200 human fatalities are caused by DVCs annually in the US (Conover et al. 1995). DVCs result in property damage that costs society over $1 billion (Conover 1997). Hansen (1983) postulated total social costs are likely much greater due to missed work, physical and mental trauma, and added costs of highway safety officers. Michigan currently leads the nation in number of reported DVCs, with more than 65,000 annually and approximately $150 million in vehicle damage (Richard Miller, Public Safety Officer, AAA Michigan, pers. communication).

The goal of this study was to understand large-scale environmental patterns that provide insight into factors causing DVCs on the Michigan landscape. We started with a conceptual model of DVCs and built a parsimonious mathematical model. Our simple conceptual model of DVCs consists of 3 components: deer, drivers, and a landscape of deer habitat traversed by a network of roads, features perceived by wildlife and transportation managers as most affecting the distribution and abundance of DVCs (Sullivan and Messmer 2003). The interaction between these 3 components was expected to determine the distribution and frequency of DVCs. The full mathematical model and its sub-models were evaluated across 3 broad ecoregions in Michigan using the corrected Akaike's Information Criteria (AIC_c) to better understand patterns of DVCs. A Michigan county DVC model does not exist, though Finder (1997), and Iverson and Iverson (1999) have developed such models to predict the number of DVCs within counties in Illinois and Ohio respectively. The models for Illinois and Ohio are not parsimonious nor did the authors resolve the covariance between independent variables.

STUDY AREA

The 83 counties in Michigan were grouped into 3 broad ecoregions: the Southern Lower Peninsula (SLP) (38 counties), Northern Lower Peninsula (NLP)(30 counties), and Upper Peninsula (UP)(15 counties) (Figure 1). These ecoregions generally matched the landscape sections of Michigan characterized by Albert (1995) according to similar soils, vegetation, climate, geology, and physiography, except the UP ecoregion combined 2 sections. Human densities and proportion of the landscape in agricultural food crops decrease along a gradient from south to north (Sudharsan et al. 2005). We examined DVCs by county grouped into ecoregions because it provided a simple way to understand DVCs in relation to changes in the landscape. Furthermore, management decisions made by transportation and natural resource agencies often are made along the ecoregion administrative boundaries. For example, Wildlife Division administrative units may be grouped into areas that closely match these ecoregions (Figure 1).

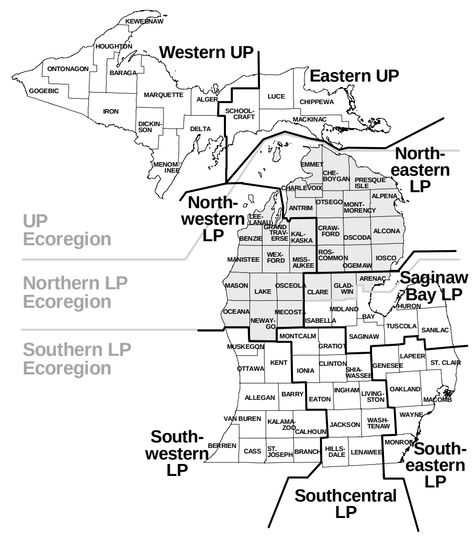

Figure 1. Counties (outlined by light black lines), Wildlife Division administrative units (outlined by heavy black lines), and ecoregions (outlined by heavy gray lines) of Michigan, USA.

METHODS

The conceptual model may be presented in the form Annual Number of DVCs = ∫ (deer, drivers, landscape). We used data on 4 independent variables available at the county level to parameterize this model: deer density index (DDI), annual vehicle miles traveled (VMT), percent forest cover, and percent crop cover. We believed these 4 variables parsimoniously captured the 3 components in our conceptual model well. Michigan crash data (Office of Highway Safety Planning, Michigan, unpublished data) was used to determine annual number of DVCs by county for years 1999-2003.

Absolute estimates of deer density by county in Michigan currently do not exist. We calculated an index of deer density for each county as a surrogate by dividing total firearm effort (days hunted) in the given county by the number of bucks killed within that county. The unit of DDI therefore was number of days taken to kill 1 buck. Our assumption was it took more days to kill a buck in counties with a lower deer density. Annual estimates of deer hunting participation and harvest in Michigan are generated using a mail survey of randomly selected deer license buyers following completion of the hunting season (Frawley 2000, 2001, 2002, 2003, 2004). The mean DDI, by county, was calculated for years 1999-2003.

Vehicle miles traveled by county were obtained for the years 1999 to 2003 (Office of Highway Safety Planning, Michigan, unpublished data) and the average over these 5 years was used in the analysis.

Percent forest and percent crop for each county was obtained (Michigan Agricultural Statistics Department 2005) and used to characterize landscape components important to deer. Forests provide food and cover for deer (Blouch 1984). Agricultural crops (e.g. soybeans, corn) may play an important supplemental role in meeting nutritional needs of deer (Nixon et al. 1970). We expected percent forest cover and percent crop cover to co-vary with each other, but they maybe differentially important to deer across Michigan depending on their composition and juxtaposition on the landscape. We also recognized that deer habitat quality is comprised of a complex assortment of variables (Felix et al. 2004) and the crop-forest measurements are only a coarse representation of deer habitat, but these data are readily available to most land use planners. All correlations between independent variables were calculated to examine inter-relatedness.

Prior to running the global model and the sub-models for the 3 ecoregions a discriminant function analysis was performed on the 4 independent variables based on ecoregion groupings. The purpose of the discriminant function analysis was to ascertain whether the ecoregions provide a suitable basis on which to group counties. If a large number of counties were misclassified then it would not make sense to run the models by ecoregions.

The next step in the analysis was to run the global model and all possible sub-models for the 3 ecoregions (15 total models). Our global model was Annual Number of DVCs = ∫ (%Forest + %Crop + DDI + VMT), where %forest = percent of landscape covered by forests, and so on…

We assumed that DVCs would be linearly related to the independent variables within the ecoregions. Within each ecoregion the models were evaluated using corrected Akaike Information Criterion scores (AIC_c) and weights (w_i;) (Burnham and Anderson 2002). Only competing models within 3 AIC_c points of the best approximating model were considered.

Finally DVCs by county by ecoregion were plotted against each of the 4 independent variables. The signs of the slope coefficients within ecoregions were compared. The relationship between DVCs and each of the independent variables was visually examined to cross check our *a priori* hypothesis of a linear relationship.

RESULTS

Discriminant function analysis differentiated Michigan counties into the 3 ecoregions (Figure 2). Along canonical variate 1 the separation among ecoregions was by percent forest cover, DDI, and percent crop cover (Table 1). Along canonical variate 1 SLP counties have negative values while the NLP and UP counties have positive values. Typically UP counties have higher values along variate 1 than NLP counties. The canonical variate 2 separated ecoregions by DDI, percent crop cover, and percent forest cover. Canonical variate 1 and variate 2 explained 98% and 1.6% of the variation between ecoregions respectively. A total of 7 counties were misclassified into the wrong ecoregion. Six of 7 misclassified counties occurred on the boundary between ecoregions (Figure 1). Midland and Muskegon are counties in the SLP that are along the boundary with the NLP. Chippewa, Luce, Mackinac, and Schoolcraft are counties in the UP adjacent to the NLP. Marquette in the UP was the only misclassified non-boundary county.

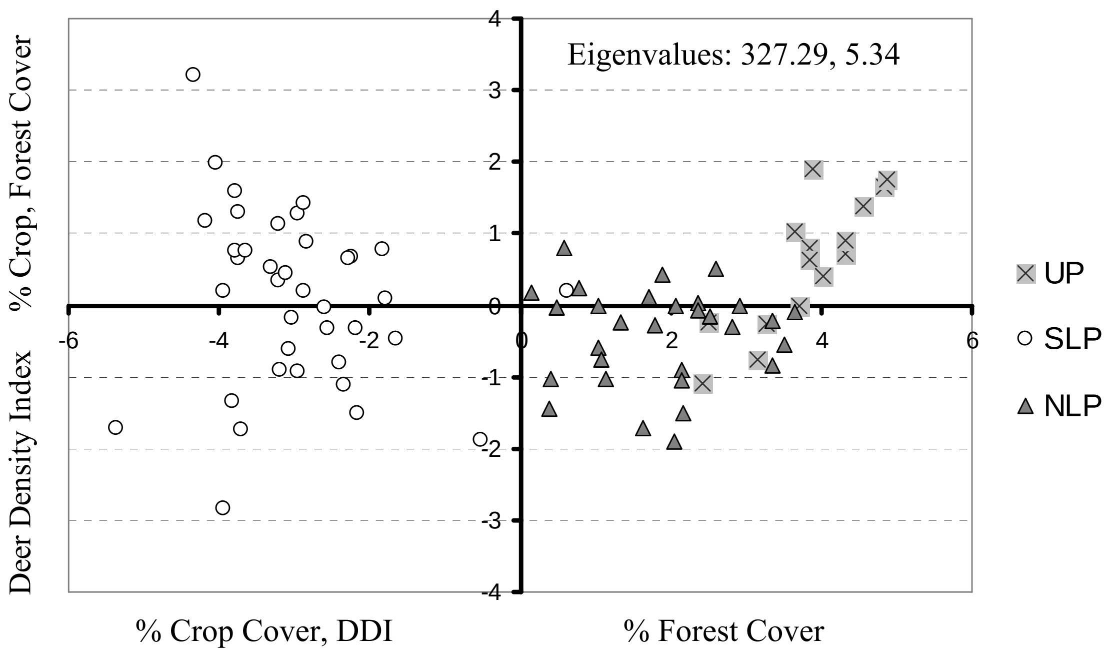

Figure 2. Discriminant function analysis of Michigan counties by ecoregions showing scores along linear discriminant axis 1 and linear discriminant axis 22.

Table 1. Discriminant analysis of the 4 independent variables showing standardized canonical coefficients and eigen values for the first two canonical variates.

Discriminant variable	Canonical variate 1	Canonical variate 2
Percent Forest Cover	0.09	0.08
Percent Crop Cover	–0.02	0.09
Deer Density Index	–0.06	–0.10
Vehicle Miles Traveled	0.00	0.00
Eigen Values	327.29	5.34

The equations for the global model for the 3 ecoregions were SLP DVCs = 3345.62 – 11.90 %Forest – 20.19 %Crop – 0.61 VMT – 31.97 DDI; NLP DVCs = 976.15 + 0.81 %Forest + 3.50 %Crop + 7.52 VMT – 23.75 DDI; UP DVCs = 599.32 – 1.60 %Forest + 84.42 %Crop + 11.02 VMT – 15.78 DDI. Four patterns are visible in the equations for the global models. First, the intercept value for the global models decrease in magnitude from the SLP to the UP (3345.62, 976.15, 599.32). Second, the sign and magnitude of the slope coefficient for % crop changed from negative and relatively high in the SLP (–20.19) to positive and small in the NLP (3.50) to positive and high in the UP (84.42). A 1% increase in percent crop cover by county leads to DVCs increasing by 84 in the UP. Thirdly, a similar change in sign but gradual increase in magnitude of the slope coefficient is seen from the SLP to UP for VMT (–0.61, 7.52, 11.02). Lastly, the magnitude of DDI decreases from the SLP to the UP (–31.97, –23.75, –15.78). In the UP percent crop cover was low and unequally distributed (mean crop area by county = 2.52 % and sd = 2.54 %) compared to percent forest cover (mean forest area by county = 81.22 % and sd = 5.86 %). In the NLP percent crop cover (mean forest area by county = 10.92 % and sd = 7.37 %) and percent forest cover (mean forest area by county = 65.19 % and sd = 11.36 %) were variable but the greatest landscape variability was in the SLP (mean crop area by county = 42.76 % and sd = 17.06 %; mean forest area by county = 21.72 % and sd = 8.94 %).

Slope coefficients for all 4 independent variables from the SLP were negative. For the NLP, percent forest cover, percent crop cover, and VMT had positive slope coefficients, while DDI had a negative slope coefficient. Yet, the slope value for percent forest cover was close to 0 (0.81). For the UP, percent crop cover and VMT had positive slope coefficients while DDI and percent forest cover had negative slope coefficients. It should be noted that the adjusted R^2 value for the global models increase from the SLP to the NLP to the UP (0.21, 0.51, and 0.73).

In the SLP there were 3 models within 3 AIC_c points of the best approximating model (Table 2). The SLP is the only ecoregion where the global model is present among the best models. The best approximating model in the SLP had percent crop cover and DDI as variables. In the SLP the Akaike weight for the best model was close to the weight for the next 2 models. The evidence ratios for the 2nd and 3rd best models were 1.24 (0.31/0.25) and 2.58 (0.31/0.12). The variables percent crop cover and DDI were present in all 3 top models for the SLP. In the SLP we excluded the 4th model as being competitive because its log likelihood was very close to the best model and it had 1 extra parameter.

The variables in the best approximating model for the NLP were VMT and DDI. There were 2 models within 3 AIC_c points of the best approximating model in the NLP. However, models 2 and 3 were not supported; the log likelihood of models 2 and 3 were identical to that of the best approximating model and they had 1 extra parameter. Neither percent forest cover nor percent crop cover were factors affecting DVCs in the NLP.

Table 2. Models within 3 AIC_c points of the best approximating model of factors influencing deer-vehicle collisions by ecoregions, Michigan, USA.

Region	Model	Log Likelihood	AIC_c[a]	ΔAIC_c	W_i[b]	K	Adjusted R^2
SLP	%Crop + DDI	-279.35	567.42	0.00	0.31	4	0.19
	%Crop + VMT + DDI	-278.32	567.85	0.44	0.25	5	0.21
	%Forest + %Crop + VMT + DDI	-277.75	569.39	1.97	0.12	6	0.21
	%Forest + %Crop + DDI	-279.30	569.80	2.39	0.09	5	0.17
NLP	VMT + DDI	-193.83	396.58	0.00	0.56	4	0.54
	%Crop + VMT + DDI	-193.70	399.01	2.43	0.17	5	0.52
	%Forest + VMT + DDI	-193.80	399.20	2.62	0.15	5	0.52
UP	%Crop + VMT	-98.87	207.92	0.00	0.40	4	0.72
	%Crop + VMT + DDI	-97.36	208.73	0.81	0.27	5	0.75
	%Crop	-101.36	209.73	1.81	0.16	3	0.64
	%Forest + %Crop + VMT	-98.23	210.85	2.93	0.09	5	0.72

[a] AIC corrected for small sample size
[b] Akaike weight

Three models were within 3 AIC_c points of the best approximating model for the UP. The evidence ratios for the 2nd and 3rd best models were 1.48 (0.40/0.27) and 2.50 (0.40/0.16). The UP was the only region where a 3-parameter model (% crop, intercept, residual variance) figured in the top models. The variable percent crop cover appeared in all 3 top models for the UP. Again, model 4 had little support since its log likelihood was very close to that of the best approximating model and it had 1 extra parameter.

The adjusted R^2 value for the best model in the 3 ecoregions increased in value from the SLP (0.19), to the NLP (0.54), and was highest in the UP (0.72). Percent of the landscape in forest and crop cover were most highly correlated across all ecoregions except in the SLP where percent crop cover and VMT had the highest correlation (Table 3). Counties with high percent forest cover had low percent crop cover (especially in the NLP). In the NLP percent forest cover and percent crop cover were more highly correlated to DDI than in the SLP and UP. Correlations between the independent variables were generally weak across all 3 ecoregions. Percent crop cover and VMT were negatively correlated to each other in the SLP but positively correlated in the NLP and UP. Percent forest cover and DDI were negatively correlated with each other in the UP but positively correlated in the SLP and NLP.

Table 3. Coefficient of determination (R^2) and correlation coefficient (R) values between the independent variables across 3 ecoregions, Michigan, USA.

Variables	SLP	NLP	UP
% Forest and DDI	0.00 (0.01)	0.37 (0.61)	0.11 (–0.33)
% Crop and DDI	0.12 (–0.34)	.39 (–0.63)	0.11 (–0.33)
% Forest and % Crop	0.20 (–0.45)	0.71 (–0.84)	0.20 (–0.45)
% Forest and VMT	0.04 (–0.20)	0.20 (–0.45)	0.03 (–0.17)
% Crop and VMT	0.42 (–0.65)	0.07 (0.27)	0.12 (0.34)
VMT and DDI	0.06 (0.25)	0.00 (0.01)	0.07 (0.26)

DISCUSSION

The discriminant function analysis indicated the ecoregions identified *a priori* provide a logical basis for grouping counties. Scale of analyses should be matched with the scale of decisions. Most decisions in wildlife or transportation planning do not occur at scales much smaller than counties. Trying to understand and manage all possible factors affecting the distribution and abundance of DVCs is overwhelming and probably not necessary. Managers may benefit from a simple classification system, such as the one used in the current analysis, which provides a framework to make decisions on larger scales.

At the county level, Finder (1997) found traffic volume and deer density to be important predictors of DVCs in Illinois. The presence of VMT and DDI in the set of best models across all 3 ecoregions indicates that regardless of the distribution of percent forest cover and percent crop cover 2 variables that consistently affect DVCs most are traffic volume (VMT) and deer density (DDI).

The first 3 models in the UP are all potentially useful. Percent crop cover is present in all 3 models and appears to be a primary landscape factor affecting DVCs in that ecoregion. Fall and winter foods may be especially important to deer in the UP because a continuous diet of woody browse can result in malnutrition (Mautz 1978). A significant portion of a deer's fall and winter food can be agricultural crops (Nixon et al. 1970). In a landscape, where percent crop cover is very low and unequally distributed compared to percent forest cover, we might expect areas with available agricultural crops to be especially attractive to deer. A higher percent crop cover in the UP appears to lead to greater deer density in a given area. At a county-level scale the combination of relatively higher percent crop cover combined with high traffic volume appears to lead to greater numbers of DVCs in the UP.

There also were 3 likely models of DVCs in the SLP. The presence of the global model among the best models suggests all 4 independent variables may be important as factors contributing to DVCs. In highly variable landscapes local factors such as visibility of deer to drivers, speed limit, or presence of riparian corridors, may have a greater effect on distribution and frequency of DVCs. The county-level scale may be too coarse to evaluate all factors affecting DVCs in the SLP.

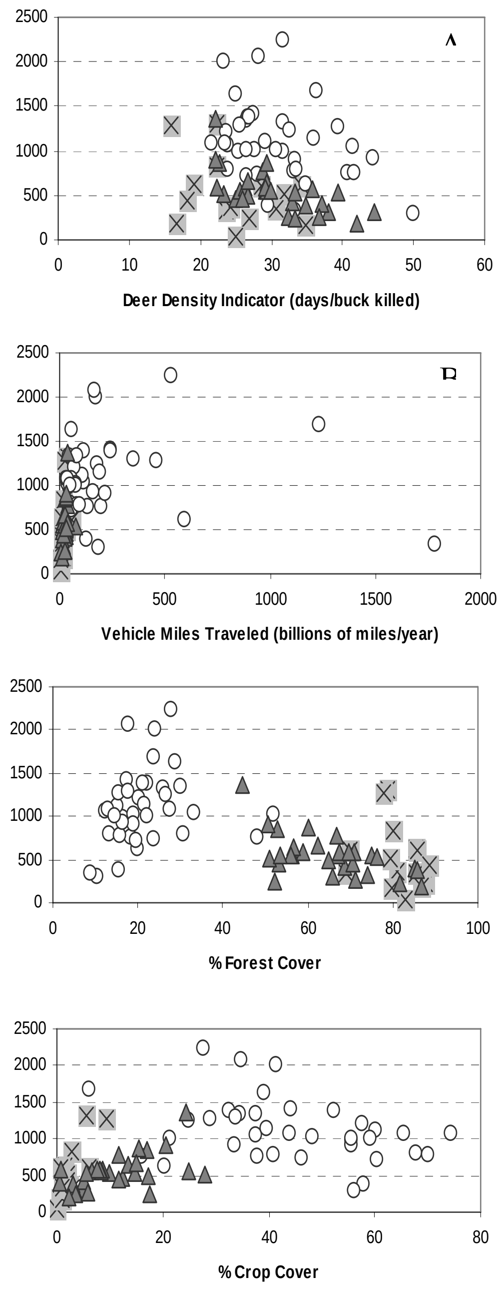

Figure 3. Deer vehicle collisions (1999–2003) by ecoregions as a function of (A) Deer Density Indicator, (B) Vehicle Miles Traveled, (C) Percent Forest Cover and, (D) Percent Crop Cover.

A non-linear relationship between percent forest cover and deer density exists throughout Michigan. Mean forest cover increases from the SLP to the NLP to the UP whereas the correlation between percent forest cover and DDI changes from the SLP (positive, weak, R = 0.01) to the NLP (positive, strong, R = 0.61) to the UP (negative, intermediate, R = – 0.33). As percent forest cover increases in the SLP and NLP deer density decreases. In the UP, however, there is an increase in deer density (i.e., higher DDI equates to lower deer density) as percent forest increases.

The inverse relationship between percent crop cover and VMT in the SLP may be because an increase in VMT is an indication of increasing urbanization and associated increases in traffic volume in a given landscape. As percent urban land cover increases we would expect a decrease in percent crop cover. Percent crop cover and VMT are positively correlated in the NLP and UP. Agricultural areas in the NLP and UP may have a more level terrain better and soil types suited for roads, hence the positive correlations.

The inverse relationship between DVCs and both VMT and percent forest cover in the SLP was mostly due to the presence of outliers. The 3 outlier counties represented in the graph of VMT and DVCs were Macomb, Oakland, and Wayne. The 2 outliers for the SLP in the graph of percent forest cover and DVCs were Midland and Muskegon. These outliers had the effect of turning a positive relationship between DVCs and the respective independent variables into a negative relationship for the SLP.

For simplicity we assumed a linear relationship between the independent variables and DVCs within the ecoregions. This assumption may be sufficient at the ecoregion level, but is inadequate at the state level. The variables VMT, percent forest cover, and percent crop cover seems to be non-linearly associated with DVCs at the statewide level. The abundance of DVCs increases with increases in these variables up to a certain threshold after which it begins to decrease. This issue of non-linearity raises 2 important aspects for modelers to consider. First, *a priori* consideration about the nature of relationships between independent variables and the dependent variable is needed. Second, in heterogeneous landscapes the size of the geographical units modeled should be explicitly considered since it may determine the nature of these relationships. Non-linear relationships with thresholds provide important information to transportation and wildlife planners. Notably efforts should be concentrated on areas where the return on mitigation is going to be maximized.

Our analyses point to several management implications. Different strategies to reduce DVCs are needed depending on landscape characteristics within the region of interest. Two variables considered, percent forest cover and percent crop cover, typically are outside the realm of control for most wildlife or transportation agencies. Reduction of DVCs will then occur only through a reduction in deer density, a reduction in traffic volume, or in modification of factors such as driver behavior sight distance, highway features, or speed limits (Marcoux et al. 2005). Yet, ability of managers to control white-tailed deer populations through public hunting is becoming limited, especially in areas with small tracts of private lands (Brown et al. 2000). Additional research is needed to evaluate mechanisms for adjusting driver behavior, and to achieve a better understanding of how finer scale characteristics of the landscape affect the distribution and abundance of DVCs.

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