

# Using GPS Telemetry to Determine Roadways Most Susceptible to Deer-vehicle Collisions

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**Abstract:** More than 1 million wildlife-vehicle collisions occur annually in the United States. The majority of these accidents involve white-tailed deer (*Odocoileus virginianus*) and result in >US \$4.6 billion in damage and >200 human fatalities. Prior research has used collision locations to assess site-specific as well as landscape features that contribute to risk of deer-vehicle collisions. As an alternative approach, we calculated road-crossing locations from 25 GPS-instrumented white-tailed deer near Madison, Georgia ( $n = 154,131$  hourly locations). We identified crossing locations by creating movement paths between subsequent GPS points and then intersecting the paths with road locations. Using AIC model selection, we determined whether 10 local and landscape variables were successful at identifying areas where higher frequencies of deer crossings were likely to occur. Our findings indicate that traffic volume, distance to riparian areas, and the amount of forested area influenced the frequency of road crossings. Roadways that were predominately located in wooded landscapes and 200–300 m from riparian areas were crossed frequently. Additionally, we found that areas of low traffic volume (e.g., county roads) had the highest frequencies of deer crossings. Analyses utilizing only records of deer-vehicle collision locations cannot separate the relative contribution of deer crossing rates and traffic volume. Increased frequency of road crossings by deer in low-traffic, forested areas may lead to a greater risk of deer-vehicle collision than suggested by evaluations of deer-vehicle collision frequency alone.

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**Key words:** deer-vehicle collision, GPS, human-wildlife conflict, *Odocoileus virginianus*, roadways, white-tailed deer

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The number of annual deer-vehicle collisions (DVCs) in the United States has been estimated to be over 1 million (Putman 1997, Hussain et al. 2007). These collisions result in >US \$4.6 billion in damage and >200 fatalities annually (Conover et al. 1995, Conover 1997, Conover 2002, National Traffic Safety Administration 2002, Huijser et al. 2009). Further, DVCs can impact deer populations with an estimated fatality rate of 90% (Conover et al. 1995, Huijser et al. 2009) resulting in the loss of 900,000 deer annually which approximates 15% of the annual deer harvest in the United States (Adams and Ross 2015). In many suburban areas, the number of deer killed via DVCs often outnumbers the number of deer harvested by hunters (Frye 2006).

Due to the crepuscular nature of deer, most accidents tend to occur in the hours surrounding dusk and dawn. These peaks are associated with patterns of traffic volume and deer activity (Al-

len and McCullough 1976, Kammermeyer and Marchinton 1977, Arnold 1978, Finder et al. 1999). Recent studies have found that there are relatively high frequencies of DVCs in areas of increased vehicle speed and increased traffic volume (Nielson et al. 2003, Ng et al. 2008, McShea et al. 2008). However, conflicting reports indicate that traffic volume and vehicle speeds are unrelated to the occurrence of DVCs (Bissonette and Kassar 2008).

Landscape structure can mediate deer behavior by influencing habitat selection, movement patterns, and home-range size (Kie et al. 2002). However, the role in which landscapes mediate road crossing is not clear, with regional studies often providing differing results (Bellis and Graves 1971, Puglisi et al. 1974, Rost and Bailey 1979, Hussain et al. 2007, Found and Boyce 2011a). Collisions most often occur on roadways that are adjacent to forested areas or that are in close proximity of riparian areas (Romin and Bissio-

nette 1996, Finder et al. 1999, Stewart et al. 2007, Farrell and Tappe 2007). The landscape configuration may also contribute to DVCs because edge density, patch density, and diversity have been shown to influence movement patterns in deer (Kie et al. 2002, Plante et al. 2004). For a more thorough analysis of past wildlife-vehicle collision research see Gunson et al. (2011).

Prior research has focused on post-hoc analysis, using white-tailed deer and mule deer (*O. hemionus*) mortality locations to determine likely causes (Bellis and Graves 1971, Puglisi et al. 1974, Rost and Bailey 1979, Romin and Bissonette 1996, Finder et al. 1999, Found and Boyce 2011a). Unfortunately, these analyses are confounded because many accidents are not reported, driver knowledge of DVC risk may bias realized risk, and the influence of traffic volume and deer road-crossing frequency cannot be separated when assessing DVC risk to motorists. We assessed whether an alternate approach using radio-instrumented deer would enhance assessment of DVC risk. Our objective was to determine landscape, anthropogenic, and hydrological characteristics that determine where deer are likely to cross roadways. We hypothesized that specific landscape features mediate deer crossings. Identifying such features can help focus DVC mitigation efforts in areas that pose the most risk to motorists.

## Study Area

The focal area was located immediately southeast of Madison, Georgia, in Morgan County (333517N 832821W). The city of Madison has approximately 4,000 residents and lies along U.S. Interstate 20 (I-20). The landscape within the study area transitions from the urban areas of Madison to large patches of deciduous and coniferous forests, and a variety of agricultural lands. Elevation of the region ranged from approximately 120 to 250 m, with the majority of the variation being a result of small hydrological features (streams and creeks). Our focal area consisted of approximately 101.73 km<sup>2</sup> and was split into two sections by I20. A 1.2-m woven wire fence, used to delineate the I-20 right-of-way, was in various stages of disrepair. There were additional roadways of varying activity, including U.S. Route 278, county roads (e.g., Bethany Road, Bethany Church Road), and smaller single-lane paved or dirt roads within the study area.

## Methods

### Capture

During winter and spring 2012 and 2013, we darted deer 32 white-tailed deer within 0.5km of I20 using 3-ml transmitter darts (Pneu-dart Inc., Williamsport, Pennsylvania) containing Telazol (500mg; tiletamine hydrochloride and zolazepam hydrochloride; Fort Dodge Animal Health, Fort Dodge, Iowa) and AnaSed

(450mg; xylazine hydrochloride; Congaree Veterinary Pharmacy, Cayce, South Carolina). We applied eye ointment (Dechra Veterinary Products, Overland Park, Kansas) and blindfolded immobilized deer. Captured deer were outfitted with ear tags for individual identification and FOLLOWiT Tellus Medium GPS collars with UHF download/remote drop-off capabilities (FOLLOWiT Wildlife, Lindesberg, Sweden). All animal capture and handling procedures were approved by the University of Georgia Institutional Animal Care and Use Committee (#A2011 08-023-R1). Collars were programmed to collect 24 locations per day at equal intervals for a two-year period. The collars were equipped with a VHF beacon allowing for regular mortality checks, a remote UHF drop mechanism, and a UHF download system allowing the user to download data remotely.

### Modeling Procedures

Of the 32 collared animals, we used the data of 25 individuals that crossed roads, including 8 adult females, 9 adult males, 1 juvenile female, and 7 juvenile males. Due to mortalities, collar failures, and premature releases, we did not obtain 24 continuous months of data from each individual animal; however, the cumulative data of all individuals represent a continuous 2-year period, March 2012 to February 2014.

We used ArcInfo v.10.1 (Environmental Systems Research Institute, Redlands, California) to perform data manipulation to estimate locations of deer crossings. We created line segments between chronologically ordered points for each individual and calculated where a line crossed a section of road (Georgia Department of Transportation 1993, Riginos et al. 2013). We excluded any road segments that were not within 200 m of a deer location point. Additionally, we removed I-20 from the analysis based on the assumption that the right-of-way fence may have acted as a semi-permeable barrier that would have influenced road crossings in that intact or broken sections of fence may have dictated where road crossings occurred rather than landscape features. To address the assumption that an individual crossed a roadway directly between the two GPS points, we used a 100-m circular moving window to calculate the total numbers of crossings within the window. We then created a sampling point every 100 m along all roadways within the focal region that represented the total number of deer crossings at each point between March 2012 and February 2014.

### Predictor Variables

We identified 10 variables as potential predictors of deer crossing locations, including road type, percent forest, percent agriculture, edge density, patch density, Shannon's diversity index, distance from stream, slope, terrain ruggedness, and slope position

**Table 1.** Definition and description of local and landscape variables included in the analysis of deer roadway crossing, Morgan County, Georgia, 2012–2014.

Variable	Definition
Local-level	
Road type	Three categories of assumed traffic activity level: low (dirt and single-lane roads), medium (county and local roads) and high (state routes)
Distance to stream	The distance of a sampling point from a stream or riparian area
Slope	The mean slope within a 200-m buffer of a sample location
Slope position	Equal to the elevation of the cell minus the mean elevation within 200 m.
Terrain ruggedness	The standard deviation of elevation within 200 m
Landscape-level	
Percent forest	Percentage of landscape classified as conifer, mixed or deciduous forest (NLCD 2011) within a 200-m or 500-m buffer surrounding the crossing location
Percent agriculture	Percentage of landscape classified as agriculture (NLCD 2011) within a 200-m or 500-m buffer surrounding the crossing location
Edge density	Sum of lengths (m) of all edge segments divided by the total landscape area (m <sup>2</sup> )
Patch density	The number of patches in the landscape divided by the total landscape area
Shannon's diversity	A measure of both patch type richness and relative abundance

(Table 1). We did not have access to traffic volume data; therefore, we binned the road segments into three categorical levels based on roadway size (i.e., low, medium and high use) with dirt and single-lane roads as low (e.g., private access roads), county and local roads as medium (e.g., Bethany Rd), and state routes as high (e.g., Route 278). We obtained habitat data from the 2011 National Land Cover Database (NLCD) which provided 20 land cover classes at a 30- x30-meter resolution (Jin et al. 2013). We reclassified the NLCD raster by combing all forest types (conifer, deciduous, and mixed) into one class and did the same for all types of agriculture (pasture/hay and cultivated crops). The reclassification was done because we assumed that all types of forest represent equal security cover as roads are perceived as threats, and we assumed that both types of agriculture presented foraging opportunities (Bellis and Graves 1971, Puglisi et al. 1974, Rost and Bailey 1979, Romin and Bissonette 1996).

The landscape metrics (patch density, edge density, and Shannon's diversity) were included as potential predictors because they have been previously identified as related to ungulate movements (Kie et al. 2002, Plante et al. 2004). Percent forest and agriculture, along with the three landscape metrics (edge, patch, Shannon's) were calculated via Fragstats V.4 (McGarigal et al. 2012) using a square moving window at two different spatial scales (200 m and 500 m). Two spatial scales were considered because landscape variability was hypothesized to differ between these selected habitat scales. We obtained riparian layers to calculate the distance of a sampling point from a stream or riparian area (Georgia Depart-

ment of Transportation 1996). We included the distance from riparian zones due to studies that have shown that drainages and riparian zones can influence deer movement, specifically when approaching roadways (Mansfield and Miller 1975, Dusek et al. 1988, Reeve 1988).

The three topographical metrics were derived from a digital elevation model (DEM) from the U.S. Geological Survey, National Map Server (2013). Slope, terrain ruggedness, and slope position were included because they can influence deer movements directly by aiding or hindering movement and indirectly by contributing to environmental constraints such as vegetation composition, sun exposure, and hydrology (Rost and Bailey 1979, Ganskopp and Vavra 1987). Terrain ruggedness was determined by calculating the standard deviation of elevation within 200 m and slope position is equal to the elevation of the cell minus the mean elevation within 200 m. Slope position values greater than 0 were elevated areas such as hilltops, values near zero were at median elevation or on side-slopes, and negative values were valleys or low-lying areas.

### Statistical Analyses

Statistical analysis was performed in R (R Core Team 2013). Given that the data for number of road crossings existed as discrete counts, we constructed generalized linear models with a negative binomial distribution, using a log<sub>e</sub>-link function in the MASS package (Poch and Mannering 1996, Venables and Ripley 2002). To address the zero inflation of the data of having over 6,000 values of zero deer crossings out of the 7,175 generated data points, we subset the data by randomly selecting 1,000 points from the original 6,000. The random sampling of zero-valued points created a total data set of 2,175 points. We calculated Pearson product-moment correlation coefficient among potential predictor variables twice, once including the 200-m landscape variables and then a second time using the 500-m landscape variables. We found that there were similar correlations regardless of landscape scale and excluded any variables that had a coefficient value greater than or equal to +/-0.70. After removing correlated predictor variables, we were left with seven potential predictor variables—road type, edge density, percent forest, distance to streams, slope, slope position, and terrain ruggedness.

We built 19 models using different combinations of land cover, hydrology, and terrain variables that may best explain the number of deer crossings. As we were interested in identifying the spatial scale (200 m or 500 m) at which land cover variables best explained deer crossings, we performed AICc model selection in two stages (Burnham and Anderson 2002). First, we conducted model selection for each spatial scale independently (200 m and 500 m), including a null model (i.e., the intercept-only model), calculated

AIC and reported models receiving at least 95% of the weight. Following the two scale-independent analyses, we then performed a final model selection using the top models from each buffer size, again including a null model.

**Results**

When performing model selection using the 200-m moving window for landscape characteristics, we found that the model containing only road type and edge density as predictor variables had the lowest AICc ( $AICc_{w_i}=0.64$ ) while the global model resulted in an AICc value that was greater than the top model by 1.17 ( $AICc_{w_i}=0.36$ ) (Table 2). Within the best model, road type and edge density were both significant ( $P \leq 0.05$ ) and had 95% confidence intervals that did not cross zero (Table 3); and in the global model, only road type and edge density were significant ( $P \leq 0.05$ ). All other considered models, including the null model, received less than 0.0001 model weight ( $w_i$ ). The parameter estimates for road type suggest that areas of high crossing frequency most often occur along less active or developed segments of road (dirt and single-lane roads) (Figure 1).

When model selection included landscape metrics from a 500-m moving window, there was a slight change in the outcome. The global model containing all seven predictors was the top model ( $AICc_{w_i}=0.498$ ), while the model containing only road type, distance to stream, and percent forest as predictors had an  $\Delta AICc$  value that was less than 2 ( $AICc_{w_i}=0.492$ ). In the top model, the predictors of road type, distance to stream, and percent forest were significant ( $P \leq 0.001$ ), as was slope position ( $P \leq 0.015$ ). The confidence intervals of all significant predictors did not cross zero. In

**Table 2.** Akaike’s Information Criterion including number of parameters (K), AICc,  $\Delta AICc$ , and Akaike weights ( $w_i$ ) for candidate models relating to variables influencing road crossing by white-tailed deer on a study area in Morgan County, Georgia, during 2012–2014. All other models evaluated received less than 0.01 weight.

Model	K	AICc	$\Delta AICc$	$w_i$
200m				
Road type + edge density	4	6603.88	0	0.64
Global	9	6605.05	1.17	0.36
500m				
Global	9	6584.63	0	0.50
Road type + distance to stream + percent forest	5	6584.65	0.02	0.50
Only top models				
Global (500m)	9	6584.63	0	0.50
Road type + distance to stream + percent forest (500m)	5	6584.66	0.03	0.50
Road type + edge density (200m)	4	6603.88	19.25	<0.01
Global (200m)	9	6605.05	20.42	<0.01
Null	1	7223.90	639.27	<0.01

**Table 3.** Model estimates and confidence intervals for the top models for each of the two spatially explicit analyses (200 m and 500 m) relating to variables influencing road crossing by white-tailed deer on a study area in Morgan County, Georgia, during 2012–2014.

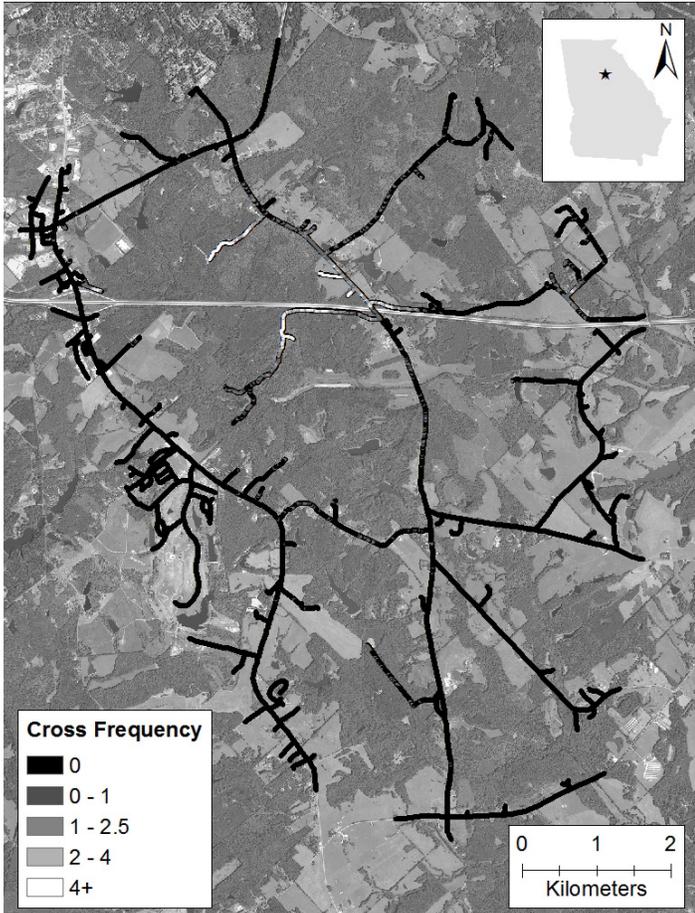
Model Name	Model predictors	Estimate	P-value	95% Confidence interval	
				2.5%	97.5%
200m					
Global	Intercept	1.39	< 0.0001	0.826	1.949
	Road type (medium)	-1.75	< 0.0001	-1.94	-1.559
	Road type (high)	-3.02	< 0.0001	-3.357	-2.6988
	Edge density	0.003	< 0.0001	0.002	3.319
	Percent forest	-0.002	0.133	-0.004	7.066
	Distance to stream	-0.0005	0.026	-0.001	-8.448
	Slope	-0.005	0.831	-0.049	4.015
	Terrain ruggedness	0.10	0.394	-0.147	3.475
	Slope position	0.017	0.310	-0.018	5.119
Road type + edge density	Intercept	1.267	< 0.0001	1.129	1.407
	Road type (medium)	-1.674	< 0.0001	-1.822	-1.529
	Road type (high)	-2.9	< 0.0001	-3.21	-2.606
	Edge density	0.003	< 0.0001	0.002	0.004
500m					
Road type + distance to stream + percent forest	Intercept	0.728	< 0.0001	0.409	1.047
	Road type (medium)	-0.948	< 0.0001	-1.161	-0.735
	Road type (high)	-2.177	< 0.0001	-2.523	-1.839
	Distance to stream	-0.001	< 0.0001	-0.001	-0.0002
	Percent forest	0.013	< 0.0001	0.009	0.017
Global	Intercept	1.481	< 0.0001	0.874	2.091
	Road type (medium)	-0.87	< 0.0001	-1.088	-0.654
	Road type (high)	-2.148	< 0.0001	-2.494	-1.81
	Edge density	-0.002	0.057	-0.003	0.0001
	Percent forest	0.0134	< 0.0001	0.009	0.017
	Distance to stream	-0.001	< 0.0001	-0.002	-0.0005
	Slope	0.015	0.592	-0.028	0.059
	Terrain ruggedness	-0.299	0.46	-0.554	-0.045
	Slope position	0.009	0.015	-0.025	0.043

the second best model, which only contained three predictors—road type, distance to stream and percent forest—each of the three parameters were significant ( $P \leq 0.05$ ) and their confidence intervals did not cross zero.

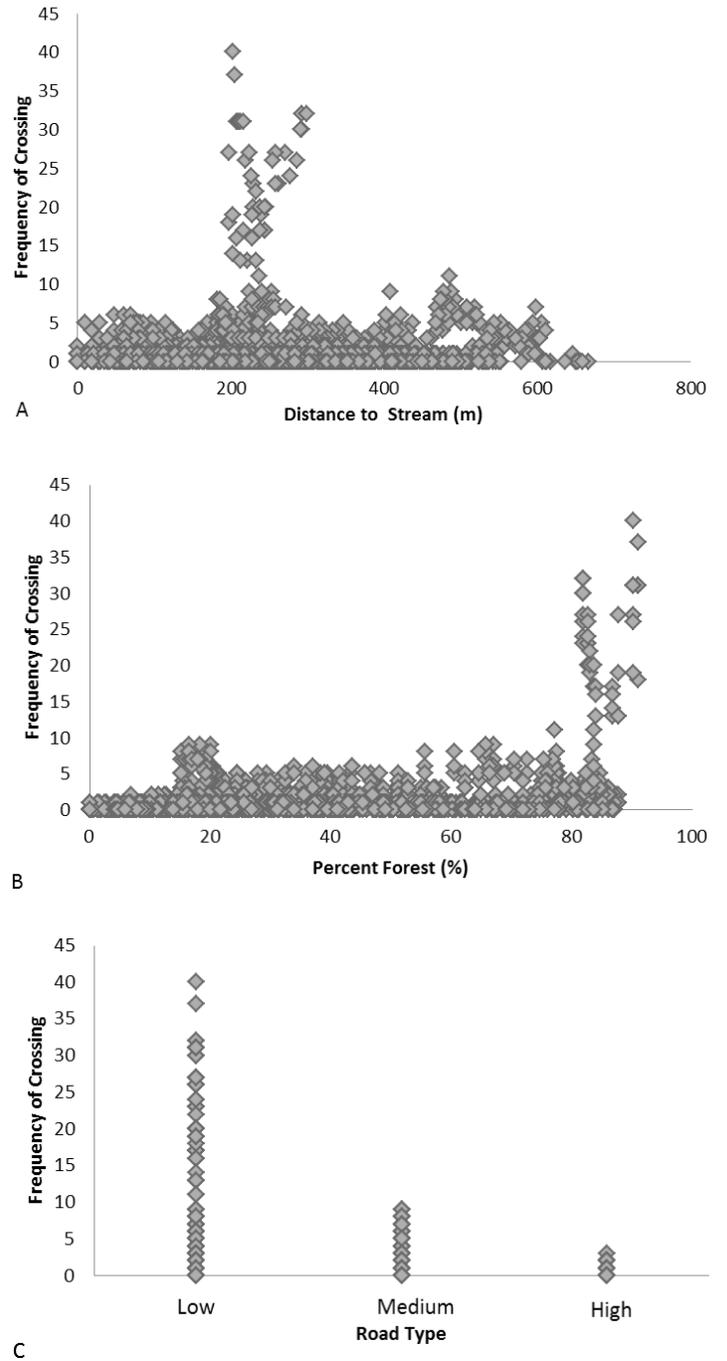
Following the combined model selection procedure, which included five models (the two top models from the 200-m landscape buffer, the two top models from the 500-m buffer, and a null model), we determined that the global model that included landscape predictors from a 500-m buffer best fit the data (Table 2, Figure 2). In this case, the top model carried a weight ( $AICc_{w_i}$ ) of 0.50, while the 500-m model of road type, distance to stream, and percent for-

est carried the remaining 0.496. We compared the observed values of the data against the predicted values created from our simplest of the two competing top model which contained the predictors of road type, distance to streams, and percentage of forest cover within a 500-m buffer (Figure 3). The largest discrepancy between the

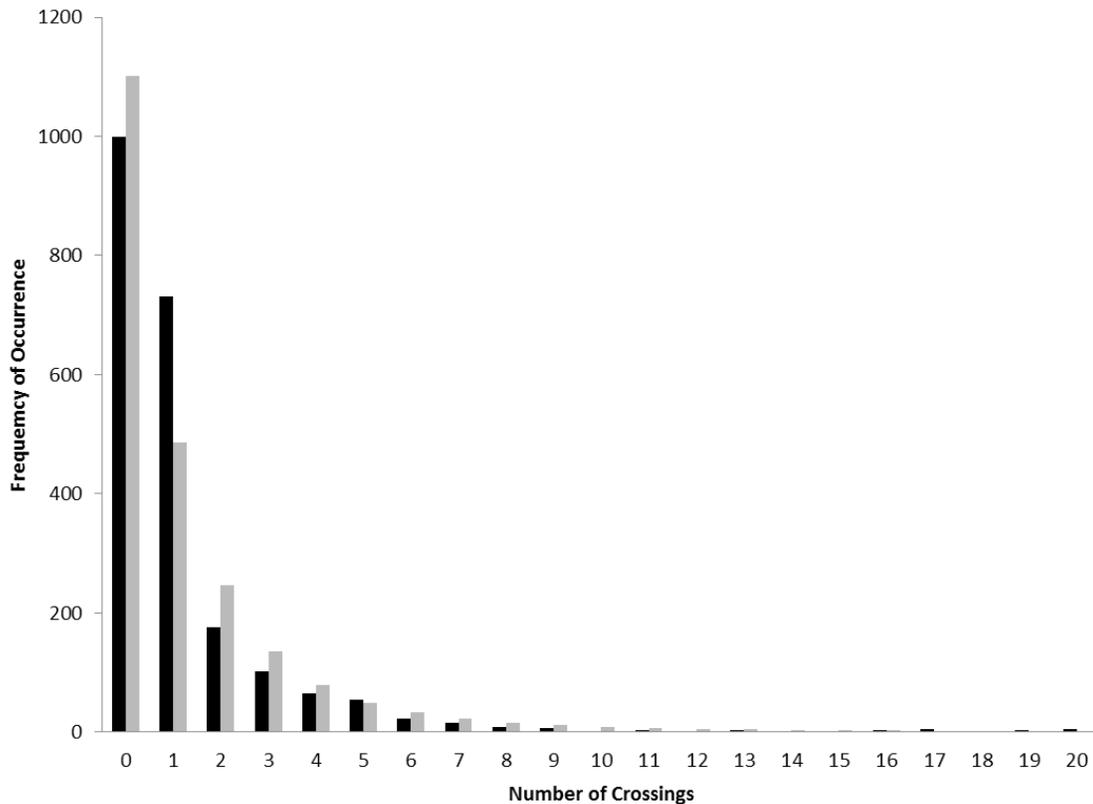
observed and predicted values occurred at crossing frequencies of 0 and 1, with observed values of 0 being under-represented, and values of 1 being over-represented. This pattern is likely due to our subset of the data, given the inflated frequency of 0 crossing values.



**Figure 1.** The frequency at which collared white-tailed deer crossed focal roadways during 2012–2014.



**Figure 2.** Landscape values associated with each observed crossing frequency, (A) the distance from stream (m), (B) the percentage of the forested landscape, and (C) the road type. Landscape values are associated to white-tailed deer crossing locations on a study area in Morgan County, Georgia, during 2012–2014.



**Figure 3.** The frequency of occurrence for the number of crossings that roadway sampling points experienced with observed crossing frequencies (black) and the modeled expected values per sampling location (gray). Crossings were conducted by white-tailed deer on a study area in Morgan County, Georgia, during 2012–2014.

## Discussion

The results of model selection suggest that the size of the road was a good predictor of whether there would be a higher frequency of crossings by deer. Smaller roadways (i.e., dirt and local roads), which we assumed had the lowest traffic value, were crossed much more frequently than larger roadways. It is likely that an increase in traffic volume would act as a deterrent, reducing the likelihood of crossing. When comparing landscape scales (200 m and 500 m), we found that a larger buffer size more accurately predicted crossing frequency and within those landscapes the percentage of woody cover and the distance to riparian areas were the most influential.

Our results coincide with previous research in that deer tend to avoid areas of high human activity (Bellis and Grave 1971, Romin and Bissonette 1996, Jepsen and Topping 2004, Sawyer et al. 2006, Sawyer et al. 2009), with crossings occurring in higher frequency in areas of low traffic volume. Additionally, vegetation cover has been documented to be an important factor in deer crossing, with deer in our study crossing more frequently (10 or more crossings) in areas that were composed of approximately 80%–90% forest

(Finder 1998, Iverson and Iverson 1999, Farrell and Tappe 2007).

While prior research suggests that deer tend to cross roadways along riparian areas (Romin and Bissonette 1996, Finder et al. 1999, Gunson et al. 2009), we found that areas 200–300 m from riparian areas experienced the highest frequency of crossings. The distance from riparian areas has implications for the construction of large underpass culverts along riparian areas to act as wildlife movement corridors (Reed et al. 1975, Braden et al. 2008).

Our method is unique in that we used GPS-instrumented deer to identify high frequency crossing areas to determine DVC risk, while previous works have focused on deer mortality locations to determine high-risk areas. Although using DVC locations can be useful for identifying landscape variables that contributed to deer mortality, DVCs may be influenced by road type. More specifically, roads with greater traffic volume, such as state highways, may negatively influence deer crossing behavior and success. Despite fewer crossings on high traffic roadways, lower crossing success may accumulate mortality data more quickly and in greater quantities than roadways with less traffic. Therefore DVC risk models using DVC data may be a better representation of increased risk for deer than for motorists. In our study, deer crossed low traffic

roads more frequently than high traffic roads. Because traffic volume was lower, individual motorist risk of encountering a deer was greater, thus justifying the need to identify landscape variables that facilitate road crossing.

Our technique can provide an additional tool for managers, allowing them to model segments of roadways that have an increased likelihood of deer crossings, and therefore better focus mitigation efforts. Possible solutions include the introduction of signage that warns motorists of an increased threat, which has been effective in mitigating DVCs (Sullivan et al. 2004, Found and Boyce 2011b). Alternatively the removal of dense vegetation along roadways removes security cover and may increase the ability of motorists to see deer (Rost and Bailey 1978, Jaren et al. 1991).

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## Literature Cited

- Adams, K. and M. Ross. 2015. QDMA's Whitetail Report 2015. Quality Deer Management Association, Bogart, Georgia.
- Allen, R. E. and D. R. McCullough. 1976. Deer-car accidents in southern Michigan. *Journal of Wildlife Management* 40:317–325.
- Arnold, D. A. 1978. Characteristics and costs of highway deer kills. Pages 92–101 in C. M. Kirkpatrick, editor. *Wildlife and People*, Proceedings of the John S. Wright Forestry Conference, Department of Forestry and Natural Resources and the Cooperative Extension Service, Purdue University, West Lafayette, Indiana.
- Bellis, E. D. and H. B. Graves. 1971. Deer mortality on a Pennsylvania interstate highway. *Journal of Wildlife Management* 35:232–237.
- Bissonette, J. A. and C. A. Kassar. 2008. Locations of deer-vehicle collisions are unrelated to traffic volume or posted speed limit. *Human-Wildlife Conflicts* 2:122–130.
- Braden, A. W., R. R. Lopez, C. W. Roberts, N. J. Silvy, C. B. Owen, and P. A. Frank. 2008. Florida Key Deer *Odocoileus virginianus clavium* underpass use and movements along a highway corridor. *Wildlife Biology* 14:155–163.
- Burnham, K. P. and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Springer, New York, New York.
- Conover, M. R. 1997. Monetary and intangible valuation of deer in the United States. *Wildlife Society Bulletin* 25:298–305.
- . 2002. Resolving human-wildlife conflicts: the science of wildlife damage management. Lewis Publishers, Boca Raton, Florida.
- , W. C. Pitt, K. K. Kessler, T. J. DuBow, and W. A. Sanborn. 1995. Review of human injuries, illnesses, and economic losses caused by wildlife in the United States. *Wildlife Society Bulletin* 23:407–414.
- Dusek, G. L., A. K. Wood, and R. J. Mackie. 1988. Habitat use by white-tailed deer in prairie-agricultural habitat in Montana. *Prairie Naturalist* 20:135–142.
- Farrell, M. C. and P. A. Tappe. 2007. County-level factors contributing to deer-vehicle collisions in Arkansas. *Journal of Wildlife Management* 71:2727–2731.
- Finder, R. A., J. L. Roseberry, and A. Woolf. 1999. Site and landscape conditions at white-tailed deer/vehicle collision locations in Illinois. *Landscape and Urban Planning* 44:77–85.
- Frye, B. 2006. *Deer Wars: Science, Tradition, and the Battle over Managing Whitetails in Pennsylvania*. Pennsylvania State University Press, University Park.
- Found, R. and M. S. Boyce. 2011a. Predicting deer-vehicle collisions in an urban area. *Journal of Environmental Management* 92:2486–2493.
- and ———. 2011b. Warning signs mitigate deer-vehicle collisions in an urban area. *Wildlife Society Bulletin* 35:291–295.
- Ganskopp, D. and M. Vavra. 1987. Slope use by cattle, feral horses, deer, and bighorn sheep. *Northwest Science* 61:74–81.
- Georgia Department of Transportation. 1993. Georgia Statewide Core Base Map. <<https://data.georgiaspatial.org>>. Accessed 1 May 2014.
- . 1996. Morgan County Rivers. <<https://data.georgiaspatial.org>> Accessed 1 May 2014.
- Gunson, K. E., A. P. Clevenger, A. T. Ford, J. A. Bissonette, and A. Hardy. 2009. A comparison of data sets varying in spatial accuracy used to predict the occurrence of wildlife-vehicle collisions. *Environmental Management* 44:268–277.
- Gunson, K. E., G. Mountrakis, and L. J. Quackenbush. 2011. Spatial wildlife-vehicle collision models: A review of current work and its application to transportation mitigation projects. *Journal of Environmental Management* 92:1074–1082.
- Huijser, M. P., J. W. Duffield, A. P. Clevenger, R. J. Ament, and P. T. McGowen. 2009. Cost-benefit analysis of mitigation measures aimed at reducing collisions with large ungulates in the United States and Canada: a decision support tool. *Ecology and Society* 12:15.
- Hussain, A., J.B. Armstrong, D.B. Brown, and J. Hogland. 2007. Land-use pattern, urbanization, and deer-vehicle collisions in Alabama. *Human-Wildlife Conflicts* 1:89–96.
- Iverson, A. L. and L. R. Iverson. 1999. Spatial and temporal trends of deer harvest and deer-vehicle accidents in Iowa. *Ohio Journal of Science* 99:84–94.
- Jaren, V., R. Andersen, M. Ulleberg, P. H. Pederson, and B. Wiseth. 1991. Moose-train collisions: the effects of vegetation removal with a cost-benefit analysis. *Alces* 27:93–99.
- Jepsen, J. U. and C. Topping. 2004. Modelling roe deer (*Capreolus capreolus*) in a gradient of forest fragmentation: behavioral plasticity and choice of cover. *Canadian Journal of Zoology* 82:1528–1541.
- Jin, S., L. Yang, P. Danielson, C. Homer, J. Fry G. and Xian. 2013. A comprehensive change detection method for updating the National Land Cover Database to circa 2011. *Remote Sensing of Environment* 132:159–175.
- Kammermeyer, K. E. and R. L. Marchinton. 1977. Seasonal change in circadian activity of radio-monitored deer. *Journal of Wildlife Management* 41:315–317.
- Kie, J. G., R. T. Bowyer, M. C. Nicholson, B. B. Boroski, and E. R. Loft. 2002. Landscape heterogeneity at differing scales: effects on spatial distribution of mule deer. *Ecology* 83:530–544.

- Mansfield, T. M. and B. D. Miller. 1975. Highway deer-kill District 02 regional study. Caltrans Internal Report. Sacramento, California.
- McGarigal, K., S. A. Cushman, and E. Ene. 2012. FRAGSTATS v4: Spatial pattern analysis program for categorical and continuous maps. University of Massachusetts, Amherst.
- McShea, W. J., C. M. Stewart, L. J. Kearns, S. Liccioli and D. Kocka. 2008. Factors affecting autumn deer-vehicle collisions in a rural Virginia county. *Human-Wildlife Conflicts* 2:110–121.
- National Highway Traffic Safety Administration. 2002. The economic impact of motor vehicle collisions 2000, U.S. Department of Transportation, Washington, D.C.
- Nielson, C. K., R. G. Anderson, and M. D. Grund. 2003. Landscape influences on deer-vehicle accident areas in an urban environment. *Journal of Wildlife Management* 67:46–51.
- Ng, J. W., C. Nielsen, and C. C. St.Clair. 2008. Landscape and traffic factors influencing deer-vehicle collisions in an urban environment. *Human-Wildlife Conflicts* 2:102–109.
- Plante, M., K. Lowel, F. Potvin, B. Boots, and M. Fortin. 2004. Studying deer habitat on Anticosti Island, Québec: relating animal occurrences and forest map information. *Ecological Modeling* 174:387–399.
- Poch, M. and F. Mannering. 1996. Negative binomial analysis of intersection-accident frequencies. *Journal of Transportation Engineering* 122:105–113.
- Puglisi, M. J., J. S. Lindzey, and E. D. Bellis. 1974. Factors associated with highway mortality of white-tailed deer. *Journal of Wildlife Management* 38:799–807.
- Putnam, R. J. 1997. Deer and road traffic accidents: Options for management. *Journal of Environmental Management* 51:43–57.
- R Core Team 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- Reed, D. E., T. N. Woodard, and T. M. Pojar. 1975. Behavioral response of mule deer to a highway underpass. *Journal of Wildlife Management* 39:361–367.
- Reeve, A. F. 1988. Vehicle-related mortality of mule deer in Nugget Canyon, Wyoming. Wyoming Cooperative Fisheries and Wildlife Research Unit, Laramie.
- Riginos, C., K. Krasnow, E. Hall, M. Graham, S. Sundaresan, D. Brimeyer, G. Fralick, and D. Wachob. 2013. Mule deer (*Odocoileus hemionus*) movement and habitat use patterns in relation to roadways in northwest Wyoming. Report of Conservation Research Center, Teton Science Schools to Wyoming Department of Transportation, Cheyenne.
- Romin, L. A. and J. A. Bissonette. 1996. Temporal and spatial distribution of highway mortality of mule deer on newly constructed roads in Jordanelle Reservoir, Utah. *Great Basin Naturalist* 56:1–11.
- Rost, G. R. and J. A. Bailey. 1979. Distribution of mule deer and elk in relation to roads. *Journal of Wildlife Management* 43:634–641.
- Sawyer, H., R. Nielson, F. Lindzey, and L. McDonald. 2006. Winter habitat selection of mule deer before and during development of a natural gas field. *Journal of Wildlife Management* 70:396–403.
- Sawyer, H., M. Kauffman, and R. Nielson. 2009. Influence of well pad activity on winter habitat selection patterns of mule deer. *Journal of Wildlife Management* 73:1052–1061.
- Stewart, C. M., W. J. McShea, and B. P. Piccolo. 2007. The impact of white-tailed deer on agricultural landscapes in 3 national historical parks in Maryland. *Journal of Wildlife Management* 71:1525–1535.
- Sullivan, T. L., A. F. Williams, T. A. Messmer, L. A. Hellinga, and S. Y. Kyrychenko. 2004. Effectiveness of temporary warning signs in reducing deer-vehicle collisions during mule deer migrations. *Wildlife Society Bulletin* 32:907–915.
- U. S. Geological Survey. 2013. National Map. <<http://nationalmap.gov/viewer.html>>. Accessed 10 May 2014.
- Venables, W. N. and B. D. Ripley, 2002. *Modern Applied Statistics with S*. Fourth Edition. Springer Publishing Company, New York, New York.