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Land-use pattern, urbanization, and deer–vehicle collisions in Alabama

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Abstract: With the rise in deer–vehicle collisions across the United States, the associated costs also have risen. Increasingly, however, researchers are learning that these collisions are not a random phenomena but follow a systematic pattern. Building on this insight, we explored the role of county characteristics in influencing the pattern and incidence of white-tailed deer- (*Odocoileus virginianus*) related auto collisions. Using county level data from 1994 to 2003 in Alabama, we tested several data models with the above mentioned factors as covariates. Our results showed that county characteristics, such as (1) having a deer population density ($\geq 31/\text{km}^2$), (2) being part of a metropolitan statistical area, (3) having a high proportion of pasture, urban and other land relative to woodland, and (4) having greater vehicle density per road km were more likely to increase the odds of deer–vehicle collisions. In contrast, high proportion of cropland relative to woodland, and wildlife management tools, such as increase in hunting license sales, and high deer bag limits, reduced the frequency of deer–vehicle collisions. These findings suggested that urban planners need to consider the impact of urban development and infrastructure activities on deer habitat and densities, and how wildlife management strategies (e.g., judicious manipulation of bag limits and ways to promote hunting license sales) can be used along with other mitigation techniques to reduce deer–vehicle collisions.

Key words: automobile–wildlife accidents, Critical Analysis Reporting Environment (CARE), deer–vehicle collision, human–wildlife conflicts, *Odocoileus virginianus*, white-tailed deer, wildlife damage

DEER–VEHICLE collisions (DVCs) have become a grave concern given the enormous costs they impose upon society. The phenomenon is widespread and commonly encountered in many parts of the United States with associated annual costs running in billions of dollars (Conover 2001, National Highway Traffic Safety Administration 2002, Schwabe and Schuhmann 2002). Previous studies suggest that DVCs are systematically related to a set of 4 factors: (1) road type and nearby topography; (2) season of the year and time of the day; (3) surrounding landscape and wildlife habitat; and (4) county-level characteristics, such as deer population density, deer harvest regulations, number of hunting licenses sold annually, number of farms and proportion of land under various uses, and population density. For instance, Bashore et al. (1985) characterized concentrations of collisions in 4 Pennsylvania counties along 2-lane highways as a function of highway and habitat features. They concluded that DVCs were concentrated around woodland–field interfaces in predominantly open habitat and that only a small percentage of locations accounted for a high percentage of DVCs. Their findings suggested that fencing would be the

cheapest and most effective measure to prevent such collisions.

Finder et al. (1999) compared 86 locations in Illinois that had experienced 15 or more DVCs from 1989 to 1993 to other segments of the same highway (control segments). They found that DVCs were closer to forest cover and public recreation property than control segments and were more likely to be adjacent to gullies and riparian areas that deer used as travel corridors. They recommended that DVCs could be reduced through the use of effective deer deterrents, sharpshooting, special archery hunts, reproductive sterilization, and trapping/relocating where harvest of deer was not feasible. They also proposed the removal of woody vegetation and leveling of topography immediately adjacent to the road to reduce concealment of deer.

Hubbard et al. (2000) analyzed DVCs in Iowa from 1990 to 1997 and concluded that as the number of bridges and lanes of traffic increased, so did the probability that an area would have a high number of DVCs. The finding that a greater number of lanes are associated with greater probabilities of collisions is understandable because, while more lanes



Scene of deer–vehicle collision.

facilitate a driver's maneuverability and should lessen the probability of a crash, they also put the deer in the danger zone for a longer period. Also, roads with 4 lanes generally have more vehicular traffic. They concluded that mitigation strategies for reducing DVCs should be focused on areas with a high number of bridges. This is understandable because more bridges mean more wetlands and more deer habitat. Furthermore, deer use these locations as corridors when they move across habitats fragmented by roads.

Nielson et al. (2003) analyzed DVCs in 2 suburbs of Minneapolis from 1993 to 2004. They concluded that the number of buildings increased the probability of a site being classified as low accident prone, while the number of public land patches increased the probability of a site being classified as high accident prone.

We noticed that the above mentioned studies took an engineering perspective of the issue, thus advancing our understanding as to how road design and adjacent wildlife habitat changes could mitigate DVCs. These insights can allow us to target high risk areas and focus on critical aspects of the problem. This line of research completely, however, ignored the influence of county level characteristics (e.g., relative proportion of crop, forest and other land uses, vehicle density/road-km, status of county as metropolitan statistical area as a proxy for population density, and deer density/km²) on the pattern and incidence of DVCs, and the role of wildlife management strategies (e.g., hunting license sales, deer bag limits and season length) in mitigating DVCs. Iverson and Iverson (1999) and Schwabe et al. (2002) are probably the only studies that underscored the importance of county characteristics in influencing DVCs and wildlife management strategies as complements to other mitigation measures.

Building on the insights by Iverson and

Iverson (1999) and Schwabe et al. (2002), the objective of the current research was to investigate the pattern and incidence of DVCs in Alabama from 1993 to 2004. Using count data models, we treated DVCs as a function of county attributes and wildlife management strategies. Our first set of hypotheses maintained that a county would be expected to have higher DVCs per year if (1) it belonged to a metropolitan statistical area (MSA), (2) had more vehicles per road-km, (3) had a relatively higher deer density/km², and (4) had much fragmented wildlife habitat. According to the second set of hypotheses, manipulation of wildlife management tools involving increases in hunting license sales, deer bag limits and season length would lead to reduced DVCs.

Methods

Data Sources

Data on the dependent variable "deer–vehicle collisions per year" from 1994 to 2003 at the county level were obtained using Critical Analysis Reporting Environment (CARE) software of the University of Alabama. The software is keyed to a centralized database maintained by the Alabama Department of Public Safety where each accident record, whether completed by a local police officer or a member of the Alabama Highway Patrol, is entered on a regular basis. CARE estimates of DVCs should be viewed as a lower bound on number of accidents because not all DVCs get reported for various reasons. Another limitation of the database is that animal-related accidents are not distinguished by type of animal. However, given that about 90% of the animal-vehicle accidents are attributed to deer, this should not pose a major problem. Descriptions of the data sets used for explanatory variables are provided below.

Deer density. Deer population density statistics for all the 67 counties in Alabama were obtained from Alabama Division of Wildlife and Freshwater Fisheries and the Quality Deer Management Association. The statistics are not the result of any formal surveys but are based on the opinions of wildlife biologists and statewide program coordinators who worked in these areas. As these data were available only for 1995, 1999 and 2000, we compacted the panel for missing data by assigning the 1995 figures to the year 1993 and 1994, the 1999 figures to the year 1996, 1997 and 1998, and the 2000 figures to the year 2001, 2002 and 2003.

The 1995, 1999, and 2000 deer density statistics were available in the following form: <16 deer/km², 16–30 deer/km² and ≥31deer/km².

As the number of counties characterized by deer density of $<16/\text{km}^2$ were disproportionately low, we collapsed the 2 deer density classes of " $<16/\text{km}^2$ " and "deer density ≤ 30 deer/ km^2 " into a single class to get "deer density ≤ 30 deer/ km^2 ".

Number of registered vehicles per road km. Data on the number of registered vehicles for each county over the study period were obtained from the Alabama Division of Motor Vehicles. Statistics on county road km were obtained from the Alabama Bureau of County Transportation. As the Bureau could provide road km statistics for all types of roads (federal, state, county, and municipal roads) only for 1995, 1996, 2000, and 2003, the panel was compacted by assigning these numbers to their adjacent years. Note that lack of data is not the issue here; rather year to year changes in road km occur only when there is additional investment in road infrastructure in a given year.

Land-use pattern. To construct the variables "proportion of cropland relative to woodland," and "proportion of other land (including pasture, urban, and other land) relative to woodland," data were obtained from the USDA website (<http://www.nass.usda.gov/census>) for 1992, 1997, and 2002. Again, to complete the panel by county and year, we assigned the available census figures to their adjacent years. For instance, the 1992 census figures were applied to the year 1993, 1994, 1995, and 1996; the 1997 census figures were applied to the year 1998, 1999, and 2000, while the 2002 census figures were assigned to the year 2001, and 2003.

Number of statewide hunting license sales, season and bag limits. Data for these variables were obtained from the Alabama Division of Wildlife and Freshwater Fisheries. From 1993 to 2003 Alabama sold a mean of 313,040 hunting licenses annually (Table 1). These included both resident and non-resident licenses. The number of hunting licenses sold declined significantly from 1993 to 1999 (Mehmood et al. 2003).

Metropolitan Statistical Area status. Data from U.S. Census Bureau website (<http://www.census.gov>) were used to ascertain if a county belonged to any of the 12 metropolitan statistical areas (MSAs) of Alabama. Alabama witnessed a slight increase in the number of MSA counties from 1994 to 2003, as the U.S. Census Bureau declared the Auburn-Opelika area as an additional MSA because of its increased population and urbanization. Huntsville and Birmingham were other areas of the state that also experienced increased human population.

TABLE 1. Variables used in the analysis of deer vehicle collisions in Alabama during 1994-2003.

Variable	Description	\bar{x}	SE
DVC	Number of DVCs per year from 1994 to 2003 in Alabama	41.5	31.3
VEHSMILE	Number of registered vehicles/mile road per year from 1994 to 2003 in Alabama	51.6	50.8
MSA	1 if Alabama county ($j = 1 \dots 67$) belonged MSA, else 0	0.3	0.5
SCARWA	Proportion of cropland relative to woodland in Alabama	1.5	0.9
SOARWA	Proportion of pasture, urban and other land relative to woodland in Alabama	1.6	0.7
D31OM	1 if Alabama county had deer density ≥ 31 deer/ km^2 , else 0	0.4	0.5
LICENSES	Number of hunting licenses (in 1000s) sold by Alabama per year from 1994 to 2003	313.0	3.5
BLALLAG	Bag limit for antlerless deer (in lagged form) from 1994 to 2003 in Alabama	48.6	56.3

Model development

Using county-level aggregate data on DVCs, we hypothesized that changes in DVCs were largely a function of changes in deer populations (dichotomized as " <31 deer/ km^2 " versus " ≥ 31 deer/ km^2 "); traffic density (number of registered vehicles/road km); wildlife management tools at the disposal of wildlife manager (changes in season length, deer bag limits, and hunting license sales); wildlife habitat factors (proxied by proportion of county land allocated to woods, crops, pasture, and urban uses); and whether a county belonged to a metropolitan statistical area (MSA) or not. Given the count character of the response variable (DVCs), we estimated regression parameters using count data models including Poisson, negative binomial, conditional fixed-effects negative binomial, and random effects negative binomial.

Poisson regression. In the Poisson regression model, the response variable y_i (number of DVCs) has a Poisson distribution with a conditional mean that depends on the set of covariates x_i (factors influencing DVCs) according to the model (Long 1997):

$$\mu_i = E(y_i | x_i) = \exp(x_i \beta) \quad [\text{Eq.1}]$$

Exponentiation of $(x_i\beta)$ forces the expected count of μ_i to be positive, which is required for Poisson distribution. The probability of a count conditional on values assumed by covariates is given as,

$$\Pr(y_i | x_i) = \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!} \text{ for } y_i = 0, 1, 2, 3, \dots, N. \tag{Eq. 2}$$

Because the model is nonlinear, changes in the conditional mean depend on the coefficient of the variable under consideration and the conditional mean itself, i.e.,

$$\frac{\partial E(y | x)}{\partial x_k} = \frac{\partial \exp(x\beta)}{\partial x\beta} \frac{\partial x\beta}{\partial x_k} = \exp(x\beta)\beta_k = E(y | x)\beta_k \tag{Eq. 3}$$

Negative binomial regression. The Poisson regression model has been criticized because of its assumption that the variance of the response variable equals its mean. Attention to this issue is important because when this assumption is violated (i.e., when there is over-dispersion in the data) the z-tests may overestimate the significance of the variables (Long 1997). The negative binomial regression makes up for this limitation of Poisson by allowing the variance of the response variable to differ from the mean. That is

$$\tilde{\mu}_i = \exp(x_i\beta + \varepsilon_i) \tag{Eq. 4}$$

$$\tilde{\mu}_i = \exp(x_i\beta) \exp(\varepsilon_i) = \mu_i \delta_i \tag{Eq. 5}$$

Assuming $E(\delta_i) = 1$, $E(\tilde{\mu}_i) = E(\mu_i \delta_i) = \mu_i$

According to negative binomial regression, the probability of a count conditional on covariates is

$$\Pr(y_i | x_i) = \frac{\Gamma(y_i + v_i)}{y_i! \Gamma(v_i)} \left(\frac{v_i}{v_i + \mu_i}\right)^{v_i} \left(\frac{\mu_i}{v_i + \mu_i}\right)^{y_i} \tag{Eq. 6}$$

with variance of the response variable as

$$\text{Var}(y_i | x_i) = \mu_i \left(1 + \frac{\mu_i}{\alpha^{-1}}\right) = \mu_i (1 + \alpha \mu_i) \tag{Eq. 7}$$

Rejection of the hypothesis $H_0: \alpha=0$ necessitates the use of negative binomial regression.

Panel data models. While more flexible than Poisson regression, the negative binomial regression has its own limitations. In particular, when data exhibit cross-sectional and temporal variation, negative binomial unnecessarily constrains data, and use of a panel model may be appropriate (Hausman et al. 1984). To account for temporal and spatial heterogeneity across counties, we used both fixed and random effects negative binomial models for panel data (i.e., groups of people or other subjects, such as counties or firms surveyed periodically over a given time span) to analyze the pattern and incidence of DVCs in Alabama.

Results

CARE descriptive results

From 1994 to 2003, Alabama experienced 27,780 DVCs (an average of 2,778/year). In terms of severity, 25,445 (92%) of these accidents entailed vehicle damage, 2,302 (8%) caused physical injuries, and 33 (0.1%) resulted in fatalities. In light of the Federal Highway Administration estimates that cost/road accident can range from \$10,000 to \$3 million, depending on the type of road accident severity, with a mean value of dollars (Gholston and Anderson 2005), the estimated cost of the DVCs in Alabama from 1994 to 2003 was thus \$376 million (or approximately \$38 million/year).

The CARE data also allowed us to highlight certain features of DVCs in Alabama. For instance, observations by individual year showed that collisions started rising from 2,187 during 1993 to peak at 3,153 in 1999 and then declined to 2,583 in 2003. Most (80%) DVCs were in rural areas adjacent to large urban centers; those in the Jefferson, Lee, Baldwin, Montgomery, and Madison counties (outside of the city of Montgomery) alone accounted for 20% of the DVCs. County roads accounted for 40% of all DVCs, state roads accounted for 30%, federal highways, 20%, interstate highways, 6%, and municipal roads, 4%.

Viewed on a daily basis, DVCs started rising on Friday evening and peaked Sunday morning and then began declining until Monday afternoon. On a particular day, DVCs were highest in the dawn (0500 to 0700 hours) and dusk (1700 to 2000 hours; Figure 1). Clearly, these timings closely overlapped with commuting rush hours. In a given year, collision frequency was highest from October to February (Figure 2). These are the months in which rut and hunting season occur.

Regression estimates

Maximum likelihood estimation results of the count data models are reported in Tables 2 and 3. First, while the overall fit for Poisson

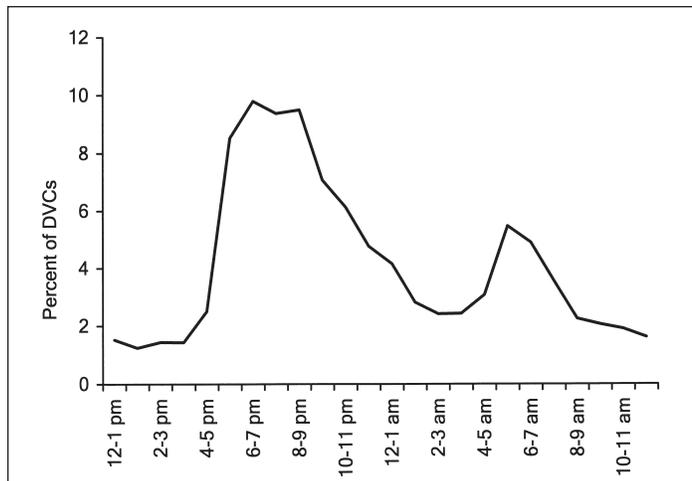


FIGURE 1. Hourly distribution of deer-vehicle collisions (DVCs) in Alabama.

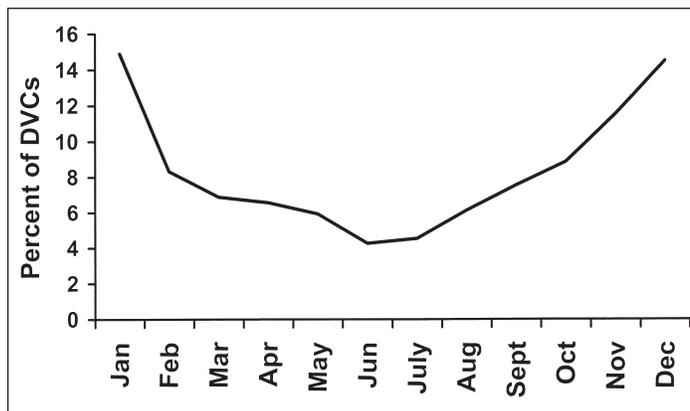


FIGURE 2. Monthly distribution of deer-vehicle collisions (DVCs) in Alabama.

regression is very significant ($P < 0.001$) and all the explanatory variables are statistically significant at 5% for each specification (Table 2), the likelihood ratio test favors the use of negative binomial regression over the restrictive Poisson counterpart ($H_0: \alpha = 0; \chi^2(1) = 6385, df = 1, P < 0.001$). This is understandable given that annual mean crash rate in each county significantly differed from its variance; use of Poisson unnecessarily constrained the data. Results of the negative binomial are, however, not appealing in comparison to the conditional fixed-effects negative binomial estimates and random-effects negative binomial estimates (Table 3). Furthermore, based on the Hausman test (Greene 2003), the null hypothesis of the independence of county-specific fixed effects and covariates could not be rejected. This implied that on statistical grounds we rejected

the conditional fixed-effects negative binomial results and retained estimates of the random-effects negative binomial model. Note that we also estimated models using percent shares as explanatory variables (i.e., % cropland, % woodland, and % other land), but due to multicollinearity and resulting low significance of coefficient estimates, those alternatives were abandoned.

In the remainder of this section, we confine the discussion to the maximum likelihood estimates of the random-effects negative binomial model. As indicated by the estimation re-sults reported in Table 3 (last 2 columns), all the 7 explanatory variables significantly influenced DVCs in Alabama. As expected, increases in the proportion of "other land" (defined to include pasture and urban land), being a metropolitan area (MSA) county, having ≥ 31 deer/km², and having a relatively greater vehicle density/road km had positive impact. In terms of incidence rate ratios (the equivalent of odds ratios in logistic regression) given in column 5 (Table 3) and other things being equal, a unit (= 406 ha) increase in the proportion of other land (defined to include pasture and urban land) relative to woodland increased the probability of a DVC by 8% (= $[\exp(.0755) - 1] * 100$); being an MSA county increased a county's chances of a DVC by 29%. Likewise, counties characterized by deer density ≥ 31 deer/km² were 9% more likely to have a DVC than counties that had < 31 deer/km².

In contrast, factors that reduced the probability of a DVC included an increase in the proportion of cropland relative to woodland, hunting license sales, and bag limits for antlerless deer. The variables that proxied wildlife management tools (i.e. license sales and bag limits) had statistically significant coefficients and directionally consistent with *a priori* expectations. Thus, other things being equal, a unit increase (=1,000 licenses) in license sales reduced the probability of a DVC by 0.7% (= $[\exp(-0.0066) - 1] * 100$), and a unit

TABLE 2. Maximum likelihood estimates of deer–vehicle collisions (DVCs) in Alabama from 1993 to 2004.

Variable*	Poisson		Negative binomial	
	Coefficient (SE)	Odds ratio	Coefficient (SE)	Odds ratio
Constant	13.627(0.797)**		12.159(3.003)**	
VEHSMILE	0.004(0.0001)**	1.004	0.005(0.001)**	1.005
MSA	0.431(0.018)**	1.539	0.393(0.066)**	1.482
SCARWA	-0.091(0.007)**	0.914	-0.064(0.032)**	0.938
SOARWA	0.187(0.010)**	1.205	0.202(0.043)**	1.224
D31OM	-0.052(0.014)**	0.950	-0.051(0.051)	0.951
LICENSES	-0.034(0.003)**	0.967	-0.029(0.010)**	0.971
BLALLAG	0.001(0.0002)**	1.001	0.001(0.001)	1.001
Alpha			0.319(0.019)**	
Likelihood ratio χ^2	5077.61		282.67	
P-Value	<0.001		<0.001	

* Variables defined in Table 1.

** $P \leq 0.10$.

TABLE 3. Maximum likelihood estimates of deer–vehicle collisions in Alabama from 1994 to 2003.

Variable*	Fixed effects negative binomial		Random effects negative binomial	
	Coefficient (SE)	Odds ratio	Coefficient (SE)	Odds ratio
Constant	5.181(1.292)**		5.222(1.274)**	
VEHSMILE	0.005(0.001)**	1.005	0.006(0.001)**	1.006
MSA	0.174(0.105)**	1.190	0.251(0.095)**	1.285
SCARWA	-0.188(0.059)**	0.828	-0.130(0.049)**	0.878
SOARWA	0.084(0.050)**	1.088	0.076(0.045)**	1.078
D31OM	0.099(0.051)**	1.105	0.085(0.046)**	1.089
LICENSES	-0.006(0.004)	0.994	-0.007(0.004)**	0.993
BLALLAG	-0.001(0.003)**	0.999	-0.001(0.0003)**	0.999
Wald $\chi^2(7)$	109.93		138.95	
P-Value	<0.001		<0.001	

* Variables defined in Table 1.

** $P \leq 0.10$.

increase (= 1 deer) in bag limits reduced the probability of a DVC by 0.11%. The significant coefficient on license sales indicated that hunting was an effective method to reduce DVCs. Note that the variable “changes in bag limits for antlerless deer” was significant with a 1-year lag. This is understandable because the impact of changes in bag limits is more likely to unfold in the following years.

Discussion

The finding that an increase in crop area is associated with reduced probability of a DVC is consistent with the findings of Iverson and Iverson (1999). Furthermore, the finding that an increase in other land (pasture and urban land use) relative to woodland is associated with a greater probability of a DVC can be explained because an increase in this land type causes deer habitat to be more fragmented and therefore forces deer to move greater distances to meet their survival needs. Collectively, these results and the finding that “being an MSA county” had the highest impact on the probability of a DVC have an obvious implication: changes in county land use pattern due to urbanization and increasing population density result in more DVCs. Likewise, the result that “an increase in deer hunting bag limit” and “an increase in hunting license sales” decreases the probability of DVCs demonstrates a clear role for wildlife managers in mitigating DVCs through wildlife management strategies.

We have attempted to look at these results and make suggestions for managing white-tailed deer and their associated habitat to reduce DVCs where possible. While the notion of changing the human density to change an MSA county into a non-MSA county might be appealing to many wildlife managers, it is only wishful thinking and impractical. However, reducing the deer density in MSA counties may be attainable. To do so, wildlife managers must undergo a paradigm shift from

management of deer as strictly a commodity to a more holistic and dynamic philosophy that takes into account the positive and negative attributes of a burgeoning white-tailed deer population. One suggestion is to make efforts to reduce deer density adjacent to roads by increasing deer harvest through nontraditional methods that are more compatible with

vehicular traffic (e.g., crossbows). This may be distasteful to those of us trained in the use of the North American model of wildlife management, but our success with that model has resulted because society has adapted the model as society's needs change.

Our results suggest that other possible management scenarios be used to reduce DVCs, including increasing the deer bag limits, recruiting more local hunters, and offering incentives to attract nonresident hunters to Alabama. Such strategies would be most effective if they were targeted at counties where deer population densities are above the local cultural carrying capacity. They should also be used in collaboration with strategies employed by the departments of transportation and highway safety to reduce DVCs.

As a final note, the DVC data analyzed here do not fully reflect the extent of the problem because only severe cases of collision are generally reported to state authorities. Future research efforts would need to document DVCs that currently go unreported. Only then will the true frequency of DVCs be known.

Conclusions

Results of this study demonstrate that county-level characteristics (e.g., land-use pattern, population density, vehicle density/road km, deer density/km²), and wildlife management strategies (e.g., hunting license sales, hunting bag limits) account for much of the spatial and temporal heterogeneity in the distribution of DVCs. Thus, to successfully mitigate the incidence of deer-vehicle collisions, accident location specific information (e.g., road design, adjacent topography, the significance of bridges as deer travel corridors, nature of road side vegetation) would need to be supplemented by information on specific county characteristics and judicious manipulation of wildlife management strategies.

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Literature Cited

Bashore, T. L., W. M. Tzilkowski, and E. D. Bellis. 1985. Analysis

of deer-vehicle collision sites in Pennsylvania. *Journal of Wildlife Management* 49:769-774.

Brown, S., H. Schreier, W. A. Thompson, and I. Vertinsky. 1994. Linking multiple accounts with GIS as decision support system to resolve forestry-wildlife conflicts. *Journal of Environmental Management* 42:349-364.

Conover, M. R. 2001. *Resolving human-wildlife conflicts: the science of wildlife damage management*. Lewis Publishers, Boca Raton, Florida, USA.

Critical Analysis Reporting Environment (CARE). 2003. <http://care.cs.ua.edu>. CARE Research and Development Laboratory, Department of Computer Science, University of Alabama, Tuscaloosa, Alabama, USA.

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.

Gholston, E. E., and M. D. Anderson. 2005. A GIS accident system to accompany CARE, UTCA Report 03304, University Transportation Center for Alabama, University of Alabama, Tuscaloosa, Alabama, USA.

Greene, H. W. 2003. *Econometric analysis*. Pearson Education, Inc., Delhi, India.

Hausman, J., B. H. Hall, and Z. Griliches. 1984. Econometric models for count data with an application to the Patents—R and D Relationship. *Econometrica* 52:909-938.

Hubbard, M. W., B. J. Danielson, and R. A. Schmitz. 2000. Factors influencing the location of deer-vehicle accidents in Iowa. *Journal of Wildlife Management* 64:707-713.

Iverson, L. A., and L. R. Iverson. 1999. Spatial and temporal trends of deer harvest and deer-vehicle accidents in Ohio. *Ohio Journal of Science* 99:86-94.

Long, S. J. 1997. *Regression models for categorical and limited dependent variables*. Sage, Thousand Oaks, California, USA.

Mehmood, S., D. Zhang, and J. B. Armstrong. 2003. Factors associated with declining hunting license sales in Alabama. *Human Dimensions of Wildlife* 8:243-262.

National Highway Traffic Safety Administration. 2002. *The economic impact of motor vehicle collisions 2000*, U.S. Department of Transportation, Washington, D.C., USA.

Nielsen, C. K., R. G. Anderson, and M. D. Grund. 2003. Landscape influences on deer-vehicle accidents areas in an urban environment. *Journal of Wildlife Management* 67:46-51.

Schwabe, A. K., P. W. Schuhmann, and M. Tonkovich. 2002. A dynamic exercise in reducing deer-vehicle collisions: management through vehicle mitigation techniques and hunting. *Journal of Agricultural and Resource Economics* 27:261-280.

Schwabe, A. K., and P. W. Schuhmann. 2002. Deer-vehicle collisions and deer value: an analysis of competing literature. *Wildlife Society Bulletin* 30:609-615.



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DAVID B. BROWN is a professor of computer science and the director of development of the Critical Analysis Reporting Environment (CARE) Research and Development Laboratory at the University of Alabama. He received a Ph.D. in industrial engineering from Texas Tech University in 1969. He designed and implemented CARE systems for crash records databases in Alabama, Delaware, North Carolina, Florida, Michigan, and Tennessee. Brown has directed projects to integrate roadway characteristics and crash data into CARE. The analytical model he developed for Alabama is being used to determine the effect of roadway attributes on safety.

JOHN HOGLAND (PHOTO RIGHT) received his undergraduate and M. S. degrees in forestry and Statistics from Auburn University. He works for the department of natural resources and conservation in Missoula, Montana, as a GIS specialist.

