Predicting Animal-Vehicle Collisions for Mitigation in Texas

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ABSTRACT

Every year in the United States, over 1.5 million deer-vehicle collisions occur, resulting in one billion U.S. dollars in damages. Based on 2007-2009 data recorded in the Crash Records Information System (CRIS) database, the average annual number of collisions in Texas involving an animal is 12,123. The primary objective of this study is to identify the scenarios associated with severe animal-vehicle collisions in Texas. This information can assist engineers and planners to understand conditions that contribute to dangerous scenarios. Armed with this knowledge, mitigation techniques can be applied, reducing the frequency and severity of such events. With further development, safety-prediction models of these types could be implemented into transportation management systems. Using logistic regression, the probability of an animal-related accident resulting in 1) a severe injury or death, 2) a moderate or minor injury, and 3) property damage only was modeled using covariates such as vehicle type, month, hour, environmental characteristics, animal type, traffic, road width, light condition, median type, driver age, and highway lane type. Results showed that motorcycles have higher chance of severe injury or death upon collision with animals. Hour of the day, winter months, wildness of the animal (wild versus domestic) and the presence of unprotected medians on two way roads were determining factors for a crash to fall under "property damage only" category. If the collision occurs in a rural environment or on a two-way road with narrow shoulders, this increases the chance of death or severe injury. Wider ROW's and the presence of unprotected medians decrease the probability of moderate or minor injury.

1. INTRODUCTION

In 2001, approximately 1.5 million deer-vehicle collisions (DVCs) were estimated to occur each year in the U.S. (*1, 2*). The consequences from these collisions: 29,000 human injuries and more than 200 human fatalities, 1.3 million deer fatalities, and over 1 billion dollars of property damage each year (*1, 3*). In 2007-2009, State Farm estimated a total of 2.4 million deer-vehicle collisions in the U.S., an increase of 18% compared to 5 years earlier (*4*). State Farm annual claim statistics showed that the states with the highest number of deer-vehicle accidents between 2005 and 2006 were: 1. Pennsylvania, 2. Michigan, 3. Illinois, 4. Ohio, 5. Georgia, 6. Virginia, 7. Minnesota, 8. Texas, 9. Indiana, and 10. South Carolina (*5*).

Deaths due to animal-related collisions are increasing. Federal data show that in the U.S., 131 people died in 1994, and 210 in 2008 (*4*). The top five states with the most deaths from animal-related collisions in 2004-2008 were: Texas with 88 deaths, Wisconsin with 62, Ohio with 51, and Pennsylvania and Michigan, with 46 deaths each. The number of animal-vehicle collisions and the number of deaths due to animal-vehicle collisions are not highly correlated: Texas was ranked number 8 for highest number of deer-vehicle accidents in the U.S., but was ranked number 1 for the most deaths from these accidents.

Not only are collisions with animals a problem for existing roadways, but they pose a threat for future roadways to be built. The new Texas 130 toll highway, opened in October of 2012, allows drivers to travel at high speeds of 85 mph; however, hours after the road opening, collisions with animals were being reported on the newly opened highway (*6*). The first collision reported that a vehicle hit "a bunch of pigs." Later in the evening, a pickup hit a deer at 85 mph. At about 2:30am the following morning, a car driving at 65 mph was confronted by four hogs and struck two of them, leaving the vehicle in such a damaged condition to require a tow truck. Around the same time, another vehicle was also reported of hitting hogs, but the driver left the scene. After at least three collisions in the first few days after opening, two with wild hogs, the private company that runs the 41-mile portion of Texas Highway 130 decided to put animal warning signs up along the roadway (*7*). A local auto-body and paint shop estimator stated that he normally sees a "hog hit at least once a week." The owner of the shop expects that the problem will get worse, as vehicles were regularly coming to the shop for deer and hog damage repairs prior to the new toll-way opening (*6*). Figure 1 shows feral hogs running alongside the Texas Highway 130 at night (left photo), and an SUV after hitting 25-30 feral hogs on the same highway (right photo) (*8*). The family sustained serious injuries and one of their dogs in the vehicle died.

FIGURE 1 Animal collisions are a problem for Texas State Highway 130 (SH 130): a large group of feral hogs alongside SH 130 night (*left*), and an SUV after hitting 25-30 feral hogs on SH 130 (*right*) (photos from NBC 5 News)

In order to effectively manage animal-vehicle collisions, improved knowledge on the spatial distribution and severity of animal-vehicle collisions is essential. Prediction models can provide effective tools to identify high-risk accident roads for project-related impact assessment. Many prediction models have previously been developed for various regions world-wide.

A study in Edmonton, Alberta, created landscape models to predict deer-vehicle collisions within the city (*9*). Data for deer-vehicle collisions was based on deer carcasses collected within the city boundaries. Locations were converted to Global Positioning System (GPS) coordinates for analysis. Models based on roadside characteristics showed that roadsides with smaller groomed widths and denser, more diverse vegetation were more likely to experience deer-vehicle collisions. Models based on the landscape showed that landscapes with lower road densities, higher speed limits, and closer proximity to larger tracts of forest were more likely to experience deer-vehicle collisions. Logistic regression was used to build the models.

A diagonal inflated bivariate Poisson regression method was used to fit reported animal-vehicle collision data and carcass removal data sets collected in Washington State (*10*). The modeling showed that increasing the speed limit, annual average daily traffic, and shoulder width increased reported animal-vehicle collisions and carcass removals. It also showed that the presence of rolling and mountainous terrain decreased reported animal-vehicle collisions.

Lao et al (*11*) study presented a probability model to account for human factors and animal attributes in animal-vehicle collisions. Carcass removal data from the Washington State Department of Transportation (WSDOT), deer distribution data from the Washington Department of Fish Wildlife (WDFW) and road log data from the Highway Safety Information System (HSIS) were used to fit a microscopic probability (MP) model for vehicle collisions with drivers' responses and a vehicle-animal interaction-based probability (VAIP) model, which is an extension of the MP model to further investigate animal-related factors. The modeling showed that speed limit, rural versus urban environment and the presence of white-tailed deer habitat increases the risk of animal-vehicle collisions. It also showed that male animals, high truck percentage, and a large number of lanes decrease the risk of animal-vehicle collisions.

Logistic regression was applied to animal-vehicle collision records to find a relationship between animal-vehicle collisions and measured habitat features (*12*). A model on road sections with high collision rates was shown to be associated with high forest cover, low crop cover, low numbers of buildings, and high habitat diversity. It was more than 70% correct on predicting classification of cases. Another model on collision points predicted 85.1% of collision points, and it showed that the points typically had no guard-rails or lateral embankments, were not near underpasses, crossroads or buildings, and featured hedges or woodland near the road.

Modeling was used to identify "hot spots" where animals of five different species groups were most likely to be killed on the roadway in Australia (*13*). Counts of wildlife killed and their GPS locations were used to apply binomial logistic regression. It was found that models of species with fatalities distributed in clumps were effective at identifying hotspots; whereas, models of species with fatalities distributed evenly along the road were less effective.

Multivariate regression analysis was used to identify trends and spatial variations in vehicle collisions with moose and roe deer in Sweden in relation to traffic volume and animal density (*14*). The study found that the number of reported collisions with moose and roe deer was closely correlated with changes in annual harvest of both species and increase in traffic volume. Environmental factors such as preferred

habitat, road density, and the presence of wildlife underpasses were of higher significance than animal density and traffic volume.

A study in Sweden developed logistic regression models to predict moose-vehicle collision risks based on landscape data, road and traffic statistics, and moose density (*15*). The modeling showed that traffic volume, vehicle speed, and the presence of fencing contributed largely to risk of moose-vehicle collisions and identified 72.7% of accident sites. Road-traffic and landscape parameters combined produced agreement, with 83.6% of the predicted sites and correctly identified 76.1% of the test road sections.

Since Texas was found to have a large number of animal related crashes statewide and was ranked number one in the nation for most deaths from these crashes, it would be useful to develop prediction models for this region. The primary objective of this study is to identify the scenarios associated with severe animal-vehicle collisions in Texas. This information can assist engineers and planners to understand conditions that contribute to dangerous scenarios. With this knowledge, mitigation techniques can be applied, reducing the frequency and severity of such events. Using logistic regression, the probability of an animal-related accident resulting in 1) a severe injury or death, 2) a moderate or minor injury, and 3) property damage only was modeled using covariates such as vehicle type, month, hour, environmental characteristics, animal type, traffic, road width, light condition, median type, driver age, and highway lane type. Data used in this study was obtained from traffic crashes reported to law enforcement organizations.

2.   DATA

Texas collision data was collected for 2007-2009. The data was extracted from the Crash Records Information System (CRIS), which is the official state database for traffic crashes occurring in Texas. The average number of collisions involving an animal was 12,123 per year between 2007 and 2009. Figure 2 shows the latitude and longitude coordinates for all of the animal-related crashes in Texas for 2009. When compared with a map of Texas, the collisions are shown to have outlined the entire state; however, the collisions become denser in the central and eastern region where the major cities are located.
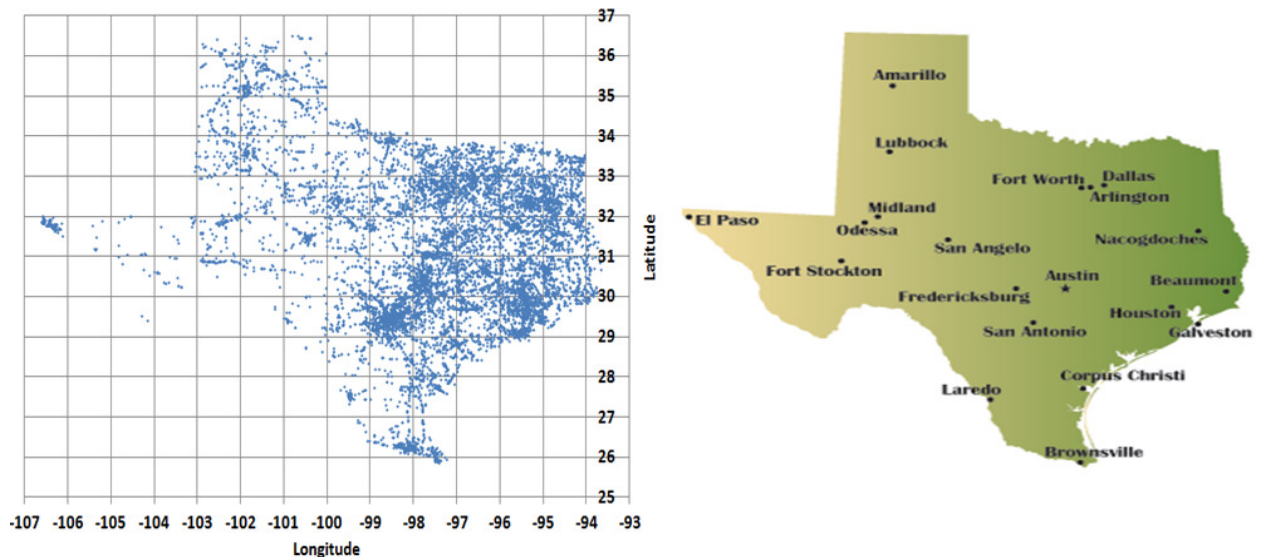
FIGURE 2 Latitude and longitude points plotted for each animal-related crash in Texas in 2009 (left) compared with a map of Texas (right).

2.1 INJURIES AND FATALITIES

Out of the crashes that involved animals in Texas, from 2007 to 2009, the average number of people killed per year was 32. The average number of people that endured injuries per year was 3,458. A summary of the 2007-2009 injury and death counts for crashes involved with animals in Texas is shown in Table 1.

TABLE 1: Injury and death counts from crashes involving an animal in Texas

	2007	**2008**	**2009**	**Average**
Incapacitating Injury Count	361	330	314	335.00
Non-incapacitating Injury Count	1298	1438	1410	1382.00
Possible Injury Count	1738	1710	1774	1740.67
Total Injury Count	**3397**	**3478**	**3498**	**3457.67**
Non-Injury Count	15302	16421	16767	16163.33
Unknown Injury Count	1418	1226	1157	1267.00
Death Count	**33**	**27**	**37**	**32.33**

2.2 VEHICLE TYPES

The top three vehicles involved in collisions with animals in Texas in 2007-2009 were 4-door sedans (4,252 crashes per year), pickups (3,462 crashes per year), and sport utility vehicles (2,138 crashes per year). Motorcycles were also involved in these collisions, with an average count of 343 per year. Figure 3 shows the average number of crashes for each vehicle type per crash severity level per year for 2007-2009. Motorcycles had the highest number of crashes that resulted in severe injury or death. In the category of moderate or minor injury or property damage only, 4-door sedans had the highest number of crashes.
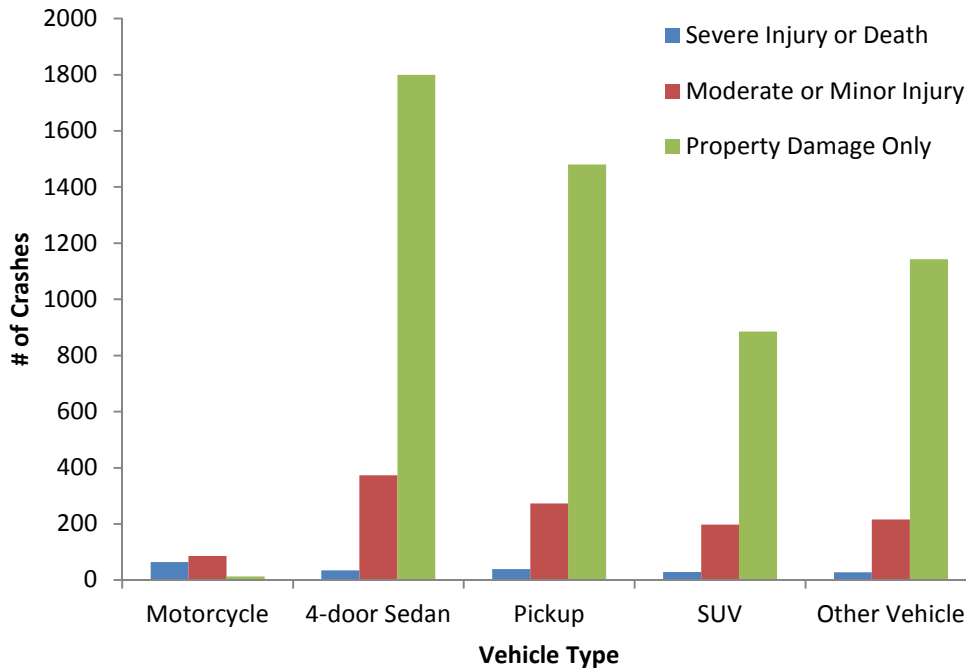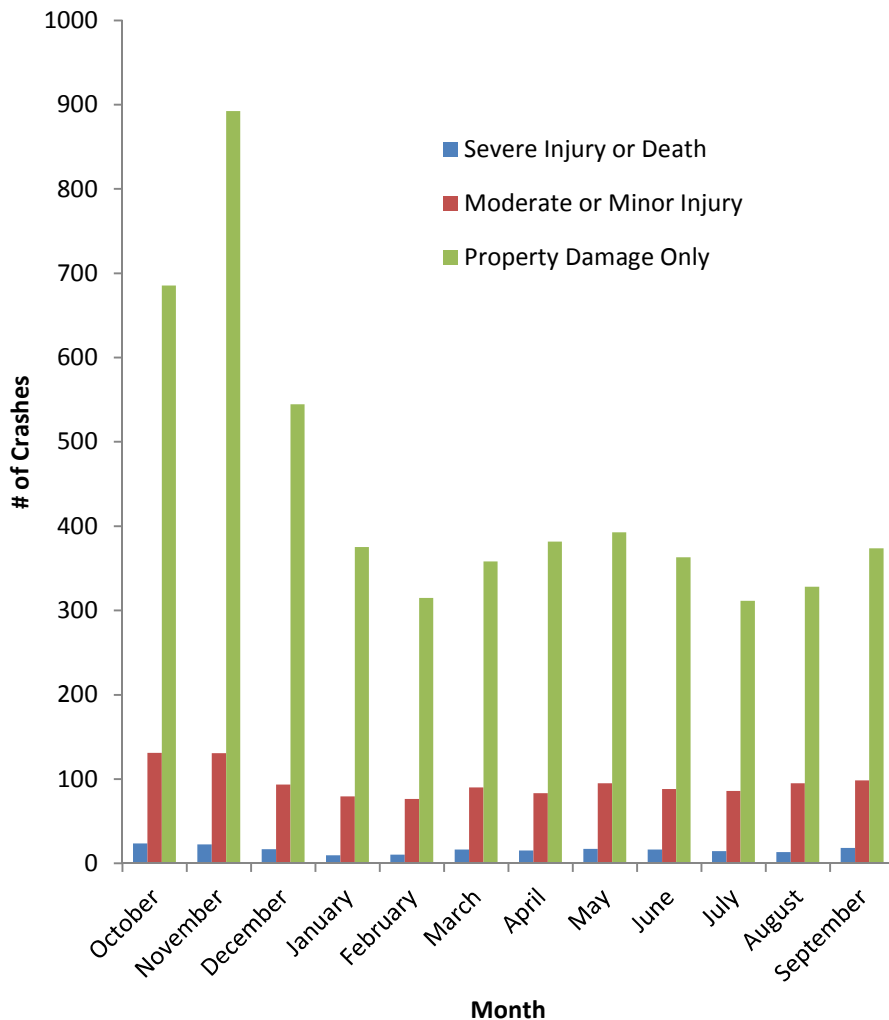

FIGURE 3 Average number of collisions per vehicle type per year resulting in severe injury or death, moderate or minor injury, or property damage only for 2007-2009

2.3   SEASON AND TIME OF DAY

Most of the animal-related crashes in Texas in 2007-2009 occurred in October (1,433 crashes per year), November (1,739 crashes per year), and December (1,196 crashes per year). Figure 4 shows the average number of crashes for each month per crash severity level for 2007-2009. In all severity levels, November and October had the highest number of crashes; however the rest of the distribution for number of crashes varied per severity level. For example, July had the lowest number of crashes resulting in property damage only, but January was the lowest for a result of severe injury or death.

Figure 5 shows the average number of crashes for each hour of the day per crash severity level for 2007-2009. The times that animal-related crashes occurred span throughout the day; however, there are some peak hours seen at which most of these collisions occur, depending on the crash severity level. Most collisions resulting in moderate or minor injury or property damage only occurred at 9 PM, while, most of the collisions involving severe injury or death occur at 8 PM, 12 AM, 4 AM, and 6 AM.

FIGURE 4 Average number of collisions per month resulting in severe injury or death, moderate or minor injury, or property damage only for 2007-2009
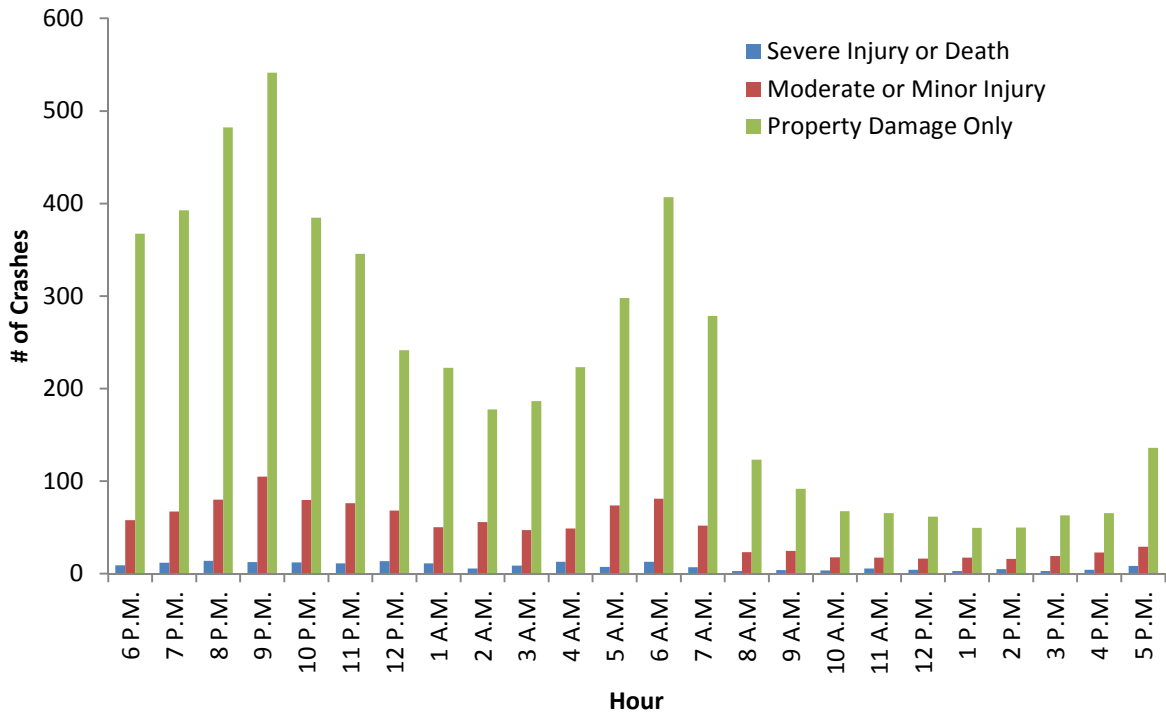
FIGURE 5 Average number of collisions per hour resulting in severe injury or death, moderate or minor injury, or property damage only for 2007-2009

2.4   LIGHTING CONDITION

In the context of outdoor light condition, the majority of animal-related crashes in Texas in 2007-2009 occurred in the dark where the road was not lighted by street lights (7,108 crashes per year). The second-most occurring outdoor light condition was daylight (3,115 crashes per year). These two outdoor light conditions as the most occurring conditions in terms of crashes belonging to three crash severity levels considered in the study.

2.5   ANIMAL TYPE

Most of the animal-related collisions in Texas in 2007-2009 were with wild animals (7,007 crashes per year). White-tailed deer are the most common animal-type involved in these collisions, and drivers are more likely to experience them during the "rut" time of year (November-December), which is the white-tailed deer breeding season (*16*). Feral hogs are also common animals involved in these collisions, and collisions with them occur more frequently during late summer or late winter when they feed along the roadways during this time.

A significant number of domestic animal-related collisions also occurred in Texas in 2007-2009 (4,136 crashes per year). Many livestock owners allow their animals to forage rather than be confined in a feedlot. Oftentimes these free-range animals walk onto a busy roadway and an unsuspecting driver crashes into one. Large animals, such as cattle or horses, can cause severe damage to vehicles in a collision. Other domestic animals, such as dogs, can cause accidents by running into the roadway.

Figure 6 shows photos of wild (left photo) and domestic (right photo) animals crossing the road in front of traffic in Texas. Figure 7 shows an example of how a collision can involve more than one animal, with two feral hogs found dead on the roadway in the left photo, and close-up of one of the feral hogs in the right photo.
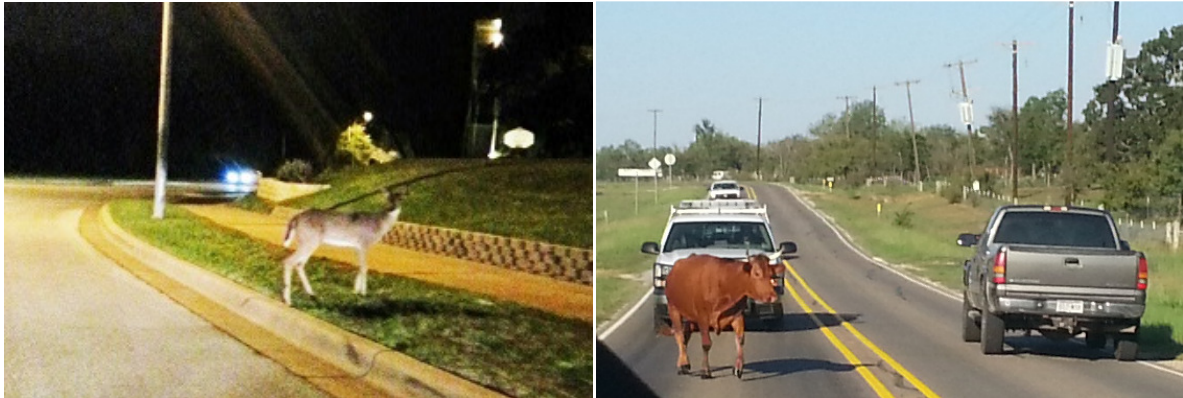
FIGURE 6 Wild and domestic animals will cross the road in front of traffic: a deer at night in a residential area in Austin, Texas (*left*), and a cow wandering off a ranch near Elgin, Texas (*right*)

FIGURE 7 Feral hogs from a collision near Elgin, Texas: two hogs indicated with red arrows (*left*), and a closer view of one of the hogs (*right*)

3. MODEL DEVELOPMENT

The reported crash injury severity, a categorical-type dependent variable is modeled using the available covariates in crash records. Logistic regression is a commonly used model structure for modeling categorical type variables. The logistic regression model form is shown in Equation 1.

$$P(y_i = 0 \mid x_i') = \frac{1}{1 + e^{-x_i'\beta}} \qquad [1]$$

Where,

$x_i'\beta = \beta_0 + \beta_1 x_{i1} + ... + \beta_k x_{ik}$

y_i: Crash category 1: $y_i = 0$; Crash category 2: $y_i = 1$

x: Covariates
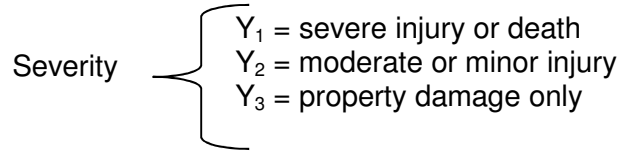
β: Regression coefficient

Separate logistic models were estimated for three severity types considered in this study: serious injury or death, moderate or minor injury, or property damage only. The probability of a crash falling under a particular severity type (P) is estimated forgiven set of variables, x_i, that describe the features of the crash scene. The variables used in this study are listed in Figure 8; y_i is the categorical dependent variable and x_i is the explanatory variables. The explanatory variables affect the probability P by the estimated value of their parameters β. The parameters are estimated using the maximum likelihood technique, and in this study the statistical computer package SAS was used to perform the model estimation.
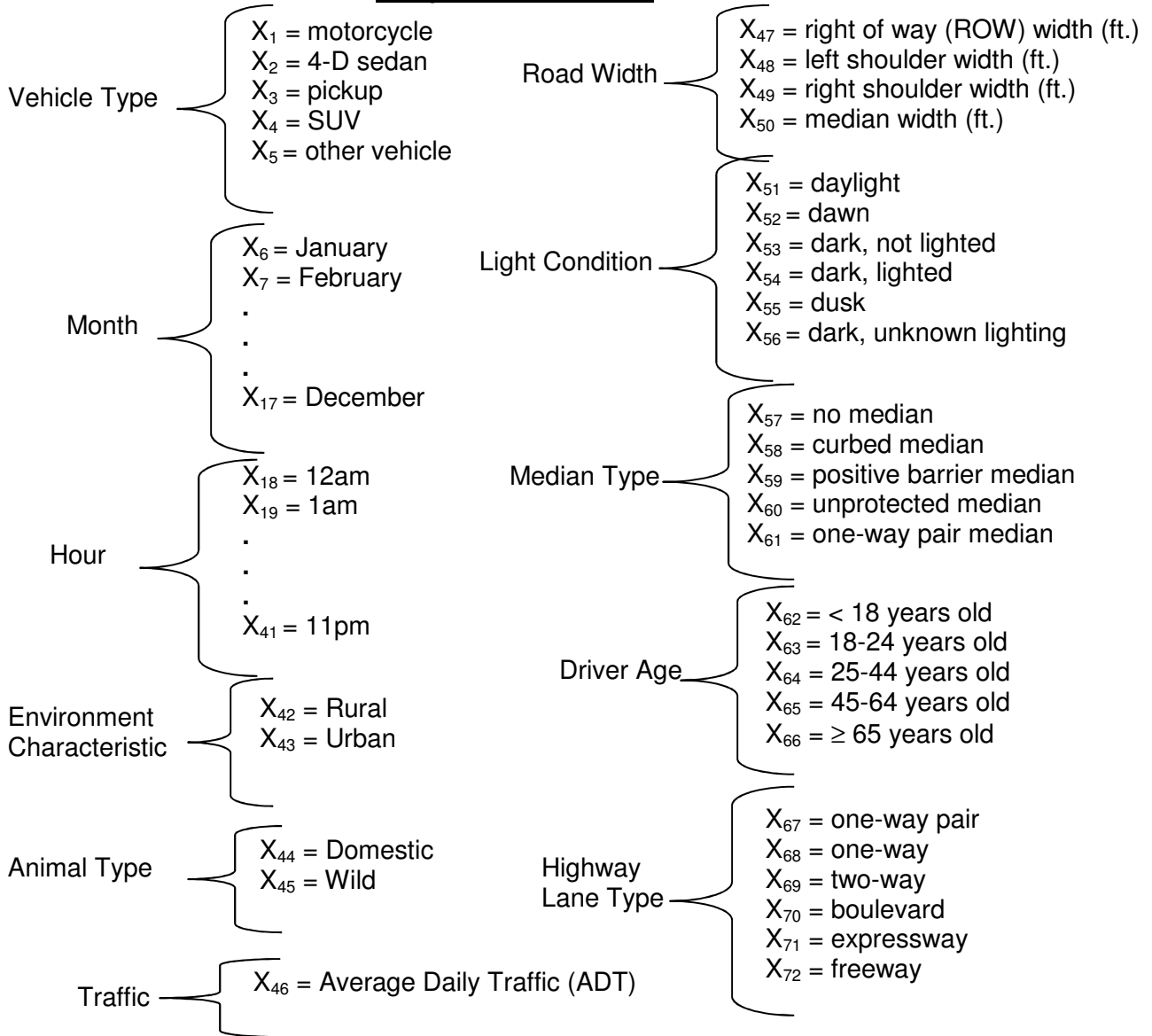
Independent variables include: vehicle type, month, hour, environment characteristic, animal type, traffic, road width, light condition, median type, driver age, and highway lane type. Except traffic, the covariates included in the model are categorical in nature as shown in Figure 8. Each categorical variable is introduced as a covariate using indicator variables. Separate indicator variables are generated for each category. For instance, the vehicle type indicator variables represent involvement of each vehicle type alone (no other vehicles present in the collision). This was the same with the driver age variables, indicating a particular age range alone (no other drivers in a different age range present in the collision), and the animal type variables, indicating involvement of each animal type alone (the other animal type not present at the same time). Variable types with multiple categories had one category removed so that it could be used as a reference category.

All the available covariates are utilized in the logistic models corresponding to three crash severity type. The PROC LOGISTIC function of SAS software was used to fit the logistic model to the data set. There were multiple possibilities for model options, depending on the iterative approach in removing variables with insignificant p-values. The behavior of the function will change relative to the variables that are included or excluded in the model. A final specification was chosen carefully based on a rigorous model development process including all the aforementioned variables. Model refinement was carried out using standard statistical tests and exclusion of statistically insignificant variables. Practical considerations played a role in the removal of insignificant variables, rather than solely adopting a statistically based mechanical approach.

Dependent Variable (3 different models)

Severity
- Y_1 = severe injury or death
- Y_2 = moderate or minor injury
- Y_3 = property damage only

Independent Variables

Vehicle Type
- X_1 = motorcycle
- X_2 = 4-D sedan
- X_3 = pickup
- X_4 = SUV
- X_5 = other vehicle

Month
- X_6 = January
- X_7 = February
- .
- .
- .
- X_{17} = December

Hour
- X_{18} = 12am
- X_{19} = 1am
- .
- .
- .
- X_{41} = 11pm

Environment Characteristic
- X_{42} = Rural
- X_{43} = Urban

Animal Type
- X_{44} = Domestic
- X_{45} = Wild

Traffic
- X_{46} = Average Daily Traffic (ADT)

Road Width
- X_{47} = right of way (ROW) width (ft.)
- X_{48} = left shoulder width (ft.)
- X_{49} = right shoulder width (ft.)
- X_{50} = median width (ft.)

Light Condition
- X_{51} = daylight
- X_{52} = dawn
- X_{53} = dark, not lighted
- X_{54} = dark, lighted
- X_{55} = dusk
- X_{56} = dark, unknown lighting

Median Type
- X_{57} = no median
- X_{58} = curbed median
- X_{59} = positive barrier median
- X_{60} = unprotected median
- X_{61} = one-way pair median

Driver Age
- X_{62} = < 18 years old
- X_{63} = 18-24 years old
- X_{64} = 25-44 years old
- X_{65} = 45-64 years old
- X_{66} = ≥ 65 years old

Highway Lane Type
- X_{67} = one-way pair
- X_{68} = one-way
- X_{69} = two-way
- X_{70} = boulevard
- X_{71} = expressway
- X_{72} = freeway

FIGURE 8 Variables used to apply logistic regression

4.   RESULTS

The model estimation results of three logistic regressions corresponding to property damage only, the moderate or minor injury, and severe injury or death are displayed in Tables 2, 3 and 4, respectively.

The probability of a crash falling under 'property damage only' category was found to be dependent upon vehicle type, month, hour, light condition, and either animal type or median type and highway lane type. Involvement of a motorcycle, 4-D sedan, or SUV all have negative effects on the probability of property damage only, with motorcycle involvement having a significantly higher negative effect (a lower chance of property damage only) compared to the other two vehicle types. This agrees with Figure 3, as it shows the motorcycle having the lowest number of collisions resulting in property damage only. The months of October, November, and December have positive effects on the probability, agreeing with Figure 4, which shows the three months having the highest number of collisions resulting in property damage only compared to the other months. The parameter for daylight has a negative effect on the probability of property damage only. These results agree with the fact that majority of animal collisions that resulted in property damage only from 2007 to 2009 occurred in dark not lighted conditions. If the collision occurs between 12 AM and 2 AM, or in the daylight, this will decrease the chances of a property-damage-only collision. If the collision occurs in the dark not lighted condition, this will increase the chances. The involvement of a wild animal or the existence of an unprotected median on a two-way road has a positive effect; one can be replaced with the other in the model, as both seem to be related (two-way roads with unprotected medians tend to have a high occurrence of wild animal crossings).

TABLE 2 Logistic Regression Model for the Probability of Property Damage Only

Variable	Parameter Estimate	St. Dev.	P-value
Constant	1.37	0.038	< 0.01
Indicator: Motorcycle	-4.04	0.17	< 0.01
Indicator: Sedan4D	-0.115	0.042	< 0.01
Indicator: SUV	-0.241	0.051	< 0.01
Indicator: October	0.205	0.059	< 0.01
Indicator: November	0.421	0.058	< 0.01
Indicator: December	0.199	0.065	< 0.01
Indicator: 12am	-0.390	0.080	< 0.01
Indicator: 1am	-0.213	0.089	< 0.01
Indicator: 2am	-0.431	0.091	< 0.01
Indicator: Wild	0.374	0.039	< 0.01
Indicator: Daylight	-0.249	0.046	< 0.01

The probability of moderate or minor injury was found dependent on vehicle type, month, hour, animal type, light condition, driver age, and median type or ROW width. Involvement of a motorcycle, 4-D sedan, or an SUV all have a positive effect on the probability of moderate or minor injury, which represents that these vehicles are more vulnerable to the crashes involving moderate or minor injury than the base vehicle

type. Though November is one of the months with the highest number of collisions that result in moderate or minor injury, as shown in Figure 4, it has a negative effect on the probability. Even with all of the months included in the model (before insignificant months were removed), November still showed a negative relationship. This may be because the frequency of collisions in November is not that much higher than other months for collisions resulting in moderate or minor injuries, so its effect is not captured in the model. In other words, a collision occurring in November causes a net decreasing effect on the probability of moderate or minor injury, relative to the other variables present in the model. According to this model, occurrence at 12 AM, 2 AM, 3 AM or 5 AM has a positive effect on the probability of moderate or minor injury, while occurrence at 8 PM has a negative effect. Involvement of a wild animal, occurrence in dark-not-lighted condition, or involvement of a driver 24 years of age or younger increases the chance of moderate or minor injury, while a driver between 45 and 64 years of age will decrease the chance. Increasing the ROW width or if there is an unprotected median has a negative effect, and one can be replaced by the other, as having a larger ROW width can be related to having an unprotected median.

TABLE 3 Logistic Regression Model for the Probability of Moderate or Minor Injury

Variable	Parameter Estimate	St.Dev.	P-value
Constant	-1.38	0.052	< 0.01
Indicator: Motorcycle	1.920	0.097	< 0.01
Indicator: Sedan4D	0.143	0.044	< 0.01
Indicator: SUV	0.266	0.054	< 0.01
Indicator: November	-0.330	0.059	< 0.01
Indicator: 8pm	-0.175	0.075	0.02
Indicator: 12am	0.279	0.084	< 0.01
Indicator: 2am	0.444	0.094	< 0.01
Indicator: 3am	0.235	0.099	0.02
Indicator: 5am	0.294	0.081	< 0.01
Indicator: Wild	-0.416	0.040	< 0.01
Indicator: Dark Not Lighted	-0.183	0.042	< 0.01
Indicator: Unprotected Median	-0.258	0.056	< 0.01
Indicator: Age <18	0.837	0.093	< 0.01
Indicator: Age 18-24	0.330	0.049	< 0.01
Indicator: Age 45-64	-0.124	0.047	< 0.01

The probability of severe injury or death was found dependent on vehicle type, month, hour, light condition, driver age, and either highway lane type or environment characteristic and shoulder width-left or right. Involvement of a motorcycle or SUV increases the probability of severe injury or death, with motorcycles increasing this chance at a higher rate compared to the SUV. Occurrence during the month of March, 12 AM, 1 AM, 3 AM, 4 AM, 11 AM, occurrence in a rural environment, during daylight condition, involvement of a driver less than 18 years of age, and occurrence on a two way road also increase the probability of severe injury or death. A driver less than 18 years of age actually shows a lower number of collisions per year when compared to other ages, so the fact that it has a positive effect in the model may be

because that this age was not that much higher in occurrence compared to the other ages for severe injury or death collisions, so that effect did not get captured. In other words, a driver less than 18 years of age causes a net increasing effect on the probability of severe injury or death, relative the other variables present in the model. Involvement of a 4-D sedan and increasing the left or right shoulder width has a negative effect on the probability of a vehicle falling under fatal category. The left and right shoulder width variables can be replaced by one-another, as they are both related (many shoulder widths are the same on both sides). In the model for severe injury or death, having a positive effect from a two way road can be interchanged with a positive effect from occurrence in a rural environment and a negative effect from increasing left shoulder width, as these variables are related (two way roads are often in rural areas with smaller shoulder widths).

TABLE 4 Logistic Regression Model for the Probability of Severe Injury or Death

Variable	Parameter Estimate	St. Dev.	P-value
Constant	-4.39	0.16	< 0.01
Indicator: Motorcycle	3.53	0.11	< 0.01
Indicator: SUV	0.407	0.12	< 0.01
Indicator: March	0.347	0.16	0.03
Indicator: 12am	0.637	0.18	< 0.01
Indicator: 1am	0.668	0.20	< 0.01
Indicator: 3am	0.626	0.22	< 0.01
Indicator: 4am	0.871	0.18	< 0.01
Indicator: 11am	0.597	0.30	0.05
Indicator: Rural	0.435	0.14	< 0.01
Indicator: Shoulder Width-Right	-0.0314	0.0079	< 0.01
Indicator: Daylight	0.259	0.11	0.02
Indicator: Age <18	0.500	0.23	0.03

5. CONCLUSIONS

The primary objective of this study is to identify the scenarios associated with severe animal-vehicle collisions in Texas. This information can assist engineers and planners to understand conditions that contribute to dangerous scenarios and apply mitigation techniques to reduce the frequency and severity of animal collisions. Separate logistic regression models were developed: the probability of an animal-related accident resulting in 1) a severe injury or death, 2) a moderate or minor injury, and 3) property damage only were modeled using covariates such as vehicle type, month, hour, environmental characteristics, animal type, traffic, road width, light condition, median type, driver age, and highway lane type. Data used in this study were obtained from CRIS database, which is the official state database for traffic crashes occurring in Texas.

Data suggested that the motorcycle has a higher chance of resulting in a collision with injuries or death, which agrees with the results of having a lower chance of property damage only. Depending on the crash severity level, different hours of the day have a positive or negative effect on the probability of the crash falling under the crash severity level. Occurrence of a collision at 4 AM is one of the most significant

times out of all three models, as it is the most dangerous time, having a high positive effect on the probability of a severe injury or death. The month was mainly significant for property damage model results, in which October, November, and December showed a positive effect on the probability of crash falling under property damage only category. Animal type was also mostly significant for property damage model results, where wild animals have more of a chance than domestic animals to create the risk of property damage only. Occurrence in a rural environment or on a two-way road with decreasing shoulder width increases the probability of severe injury or death, as narrow roads in rural environments are prone to sudden wildlife crossings. Wider ROW's (which relates to presence of unprotected medians) decrease the probability of moderate or minor injury, as a wider space may provide the driver higher visibility. In contrast, the presence of unprotected medians on two-way roads (which also involves many instances of wildlife crossings) increases the probability of crash falling under property damage only category.

The models were based on variables that were available from the CRIS database; however, there are other variables that should be included if they can be obtained that would have significant influence in predicting crash severity levels. The speed at which the driver was traveling before the collision would be expected to significantly affect the probability of a severe injury or death. The specific animal type would also have an impact; for example, a wild hog is more dense and low to the ground than a deer, so the results of colliding with one versus the other would be different. The distance from large amounts of tree cover could also have a significant effect.

Many of the animal-vehicle collisions result in more than just exterior damage of the vehicle; the accidents often threaten the safety of the driver and their passengers. Mitigation techniques are needed to prevent collisions in high-risk areas. The models developed as part of this study can help city and transportation managers understand scenarios that could be potentially dangerous, prioritize locations for implementation of crash mitigation measures, and determine which technologies are necessary for different settings. These safety-prediction models could be updated with newer data and further developed to be implemented into transportation management systems.

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Maria Burton is a graduate student at the University of Texas at Austin. She received her Bachelor's Degree in Civil Engineering at Washington State University, and then continued at Washington State University for her Master's Degree in Civil Engineering. During her Master's, she studied ways to remove air pollution while reducing storm water runoff with photocatalytic titanium dioxide on pervious concrete. Currently, at the University of Texas at Austin, Burton is part of the Transportation Engineering Department, where she has worked on several projects related to pavement management and infrastructure management. She has an additional passion for road safety, and this has motivated her to do research on a problem that still needs to be solved: animal-vehicle collisions.

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Prasad Buddhavarapu is currently a doctoral student at The University of Texas at Austin in the Department of Civil Engineering. He received his M.S. in Civil Engineering from the University of Texas at Austin in 2011. He is also currently working on another Master's degree in Statistics along with his doctoral degree. Prasad's primary research interests are in the areas of statistical modeling of transportation data and pavement management. He is currently working on developing a network level safety index which includes modeling of historical crash count data while accounting for spatial and temporal correlation using Hierarchical Bayesian modeling techniques. He has previously worked on a few research projects including pavement material engineering, quality management in pavement construction, pavement performance data collection and diamond grinding.