

# ANIMAL-VEHICLE COLLISIONS IN TEXAS: HOW TO PROTECT TRAVELERS AND ANIMALS ON ROADWAYS

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Published in *Accident Analysis & Prevention* 131: 157-170 (2019).

## ABSTRACT

Animal-vehicle collisions (AVCs) are a growing problem in the United States, resulting in countless loss of animal life and considerable human injury and death every year, especially to motorcyclists. In addition to being a serious safety concern, these collisions can create trauma among all animal populations including declining species, household pets, and livestock investments. Due to underreporting, collision data is usually a gross underestimation of the actual impact of AVCs and often lacks key details such as the species of animals involved. This paper investigates both wild and domestic animal-vehicle collisions through statistical and spatial analysis of police-reported collision data in Texas.

51,522 animal-related crashes were reported in Texas from 2010 through 2016, at a total cost over \$1.3 billion annually to Texas motorists – not including the value of lost animal lives. Wildlife-vehicle collisions (WVC) are 64% of total reports, events involving domestic animals (like dogs and cattle) are 31%, and the remaining 5% of reports are unspecified. Most AVCs in the state occur at night in unlit locations, usually on rural roads with very low traffic volumes.

Using ordinary least-squares (OLS) regression analysis across Texas' n=254 counties, this work finds that less densely populated counties, marked as rural, and those with fewer vehicle-miles traveled (VMT) per capita but more lane-miles per capita, tend to experience the greatest number of AVCs per VMT after controlling for rainfall, share of VMT on on-system roadways, job densities, and vehicles per capita.

Intervention options for the mitigation of animal-vehicle collisions are numerous and diverse. Overpasses and culverts, along with wildlife fencing (which can steer animals to safe crossings), show promising results for both AVC reduction and habitat connectivity. Longer term, mobile reporting, by DOT employees, smartphone users, intelligent cameras and other devices, plus real-time information dissemination (tied to existing navigation apps) can enable safer driving along specific roadway sections as animals arrive.

For wildlife collisions specifically, this work finds that large crossing structures (underpasses and overpasses) at the highway link level return benefit-to-cost ratios near 3.0, while their lower cost counterparts (wildlife fencing and animal detection systems) delivered ratios of values up to 30.

## BACKGROUND

Animal-vehicle collisions (AVCs) makeup 5% of all U.S.-reported motor vehicle collisions every year and represent a growing problem (FHWA, 2008; Sullivan, 2011). In fact, between 2014 and 2017, insurance claims related to animal collisions increased a total of 6% in the United States (NICB, 2018). About 200 people – often motorcyclists – lose their lives on U.S. roadways each year from collisions involving wild or domestic animals, and thousands more are seriously injured (Donaldson and Lafon, 2008). In addition to being a serious safety concern for human travelers and their property, such collisions create trauma among animal populations and endanger dwindling species. A five-state study found that, in a single month, 15,000 reptiles and amphibians, 48,000 mammals, and 77,000 birds die due to collisions with vehicles (Havlick, 2014). For some animals, including the endangered Texas ocelot, the number one threat to survival is vehicle collisions (Haines et al., 2005; Miller, 2016). Many collisions also destroy household pets and livestock investments.

This research focuses on the centrally located state of Texas, the U.S.'s second largest state spatially (after Alaska) and with regards to population (after California). The Texas Department of Transportation is responsible for more centerline-miles of highway than any other U.S. state<sup>1</sup>, and the state's landscape offers a wonderful diversity of wildlife, topography, and climate.

Following the literature review and numerical and spatial analysis of collision data, this paper offers further details on the state of animal-vehicle collisions in the state of Texas and suggests similar realities at a national or global context. Specifically, the following information clarifies and highlights at-risk persons, travel times, and locations and assesses the benefits of possible mitigation strategies.

### Wildlife Impact

Millions of animals die every year in the U.S. as a result of animal-vehicle collisions (AVCs) (Donaldson and Lafon, 2008). Most animal-vehicle collisions go unreported - with the exception of those involving large ungulates, such as deer, elk, and moose. In insurance claims, when a species of animal is named, the most commonly reported animal is deer. In fact, deer show up over 25 times more than the next animal, raccoons (NICB, 2018). Smaller species, though they might not pose immediate threat of injury to a driver, also face great impacts from collisions. Turtle populations including red-eared sliders and Missouri River Cooters suffer from AVCs, especially

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<sup>1</sup> <https://www.fhwa.dot.gov/policyinformation/statistics/2008/hm60.cfm>

females as they travel to higher lands to lay their eggs (Steen and Gibbs 2004). These populations then become male dominated and cannot maintain reproductive sustainability. Endangered animals - like the Texas ocelot (*Leopardus pardalis*, which has fewer than 50 living individuals [U.S Fish and Wildlife Service, 2010]) - have populations that are especially vulnerable to vehicle collisions because even a few deaths notably impacts this species' potential for reproductive continuation. Further, carcass counts will normally be very low for endangered species, relative to more common species, resulting in "bias(ed) mitigation measures based on small samples" (Neumann et al., 2012) and generally inadequate protective measures for these species.

### **Crash Costs and Under-reporting**

There were 51,522 animal-related crashes reported to authorities in Texas from 2010 through 2016. However, most property-damage-only crashes go unreported, and wildlife experts tend to find 5 to 10 wildlife carcasses for every reported wildlife crash (Donaldson and Lafon, 2008; Olson et al., 2014). Even in documented cases, police reports often fail to specify the species of animal hit, which would be of obvious value in targeted mitigation strategies. Stewart (2015) found that more than 50% of US deer-vehicle collisions nationwide go unreported.

The FHWA's (2008) best estimate of US AVC collision costs was \$8.39 billion annually based on 2007 numbers. The economic costs of death and injuries arising from US AVCs exceed \$1 billion per year (Donaldson and Lafon, 2008). Approximately 26,000 AVCs each year (4-10% of total AVCs in the US) result in injuries to vehicle occupants each year (FHWA, 2008). Overall, these types of collisions represent roughly 0.6% of all injurious crashes nationwide (GES, 2015).

Though motorist injuries may be relatively rare, "more than 90 percent of collisions with deer result in damage to the driver's car or truck" (FHWA, 2008, p. 8). State Farm Insurance Company (2015) estimates that 1 out of 169 US drivers had a claim from hitting a deer, moose or elk in 2015. The company's analysis shows an average cost of \$4,135 per claim involving a collision with one of these 3 animals, an increase of 6% from 2014. However, these estimates cannot paint a complete picture of AVC-related property damages, since many motorists do not file a claim with their insurance company (to avoid increased coverage costs in future years, for example).

A 2008 US Federal Highway Administration (FHWA, 2008) investigation identified "21 federally listed threatened or endangered animal species in the United States for which road mortality is among the major threats to the survival of the species." While the survival of species is of clear significance to biodiversity on our planet and humanity as a whole, it is hard to ascribe an exact cost to losing an endangered animal. This 'intrinsic value of a species' is an under-researched topic. Economic value estimates for the Texas ocelot, for example, range from \$50,000 to \$5 million (Haines et al., 2007). Deaths of such animals can also become a liability risk as well as a public-perception hazard for transportation departments, since these animals are irretrievable assets in a diverse ecosystem.

Other less easily quantifiable but very common consequences of most animal-vehicle collisions include traffic delays, diversions of law enforcement or emergency personnel and road maintenance crews. For example, deer carcass removal costs are estimated to be \$30.50 per deer (FHWA, 2008).

### **Wildlife Crossing Mitigation**

U.S. infrastructure project planning and delivery normally requires an environmental review process to avoid or at least mitigate detrimental project impacts on human and natural communities, as well as historic and cultural sites. For complex transportation projects, this process often is the most time-consuming part of project delivery (Evink, 2002; US GAO, 2003). Brown's (2006) "Eco-Logical: An Ecosystem Approach to Developing Infrastructure Projects" report provides guidance and examples for streamlining environmental reviews while more effectively protecting natural resources and ecosystem processes (Brown, 2006). Planners and engineers applied these ideas to create the Integrated Transportation and Ecosystem Enhancements for Montana (ITEEM) process. Many measures can be taken to connect habitats and wildlife populations and increase motorist safety while lowering wildlife mortality. Iuell et al. (2005) summarized these measures into five categories:

- Wildlife overpasses
- Wildlife underpasses
- Specific measures: fencing, gates and escape ramps, signage, vehicle-animal detection systems, speed reduction, lighting and reflectors
- Habitat adaptation: manage habitat and right-of-way, intercept feeding
- Infrastructure adaptation: modify road infrastructure (curbs, drainage, gates, etc.) to better accommodate wildlife movement (e.g. increase width of road median).

Many U.S. states have been implementing some of these measures and other strategies. For example, work done on Florida's I-75 seeks to protect the endangered Florida Panther, North Carolina is building several wildlife underpasses on U.S. 64 to reduce vehicle conflict with white-tailed deer, American black bears, and red wolves, a federally-listed endangered species (Jones et al., 2010). TxDOT budgeted \$5 million for four wildlife crossings under Highway 100 (between Laguna Vista and Los Fresnos) to reduce ocelot deaths (Sommer, 2014). States like Washington and Montana have recently pursued major crash-mitigation projects, with Montana providing more than 40 new wildlife crossings in the reconstruction of a 56-mile segment of US-93 (Jones et al., 2013). As of 2007, Texas had 10 major terrestrial wildlife crossings (Bissonette and Cramer, 2008). The following data analyses help us understand where AVCs are high and investments may be most cost-effective.

## DATA ANALYSIS

The AVCs analyzed in this paper come from the TxDOT Crash Records Information System (CRIS), an online database containing crash data for the state of Texas submitted by law enforcement officers and available at <https://cris.dot.state.tx.us>. Almost all (with the exception of a few collisions of unspecified animal type) of these AVCs are coded as 'wild' or 'domestic' animals involved. The data referenced here contains incidents from the years 2010 through 2016. The spatial and temporal accuracy of the data may vary by region and setting (e.g., under-reporting may be higher in rural contexts, at night, and for larger vehicles).

Using these 2010-2016 AVC data, with TxDOT's (2018) comprehensive crash costs (, the loss from *reported* AVCs is about \$21 per Texan per year. 67% of this is attributable to wild-animal collisions, and 33% is attributable to domestic-animal collisions. Interestingly, though the domestic animals are often smaller (e.g., dogs rather than deer) and just one-third of all reported AVCs in Texas, the costs of these crashes is 44% of total costs, indicating higher crash severity for domestic animals. This may be due to their occurring in higher-population-density settings (see Figure 9 vs 10), with more cars and trucks alongside when the collision occurs. Alternatively, it

may be due to drivers swerving more dramatically to avoid harming someone's beloved pet. Table 1 provides costs estimates of the AVCs analyzed in this paper.

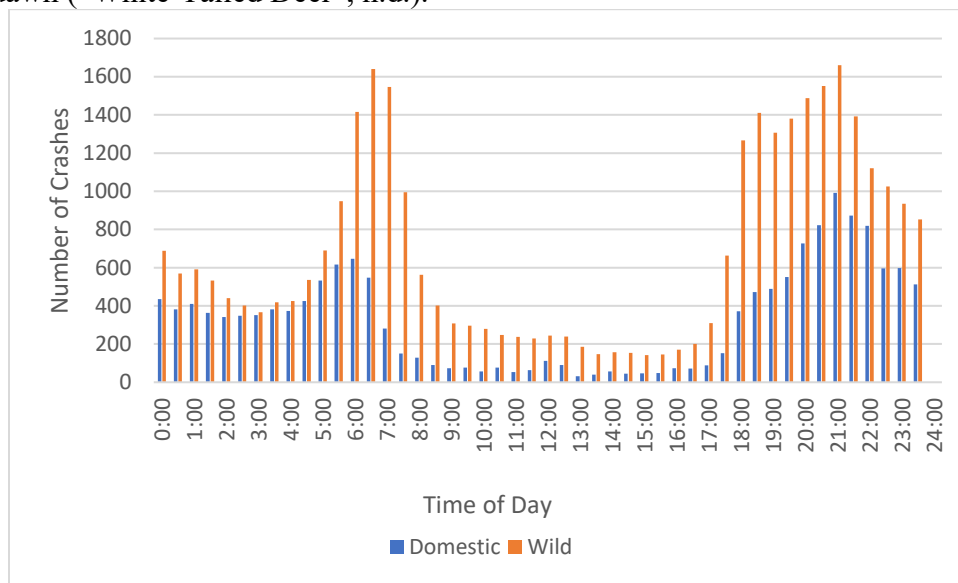
**TABLE 1 CRIS Crash Cost Estimates (Texas AVCs, 2010-2016)**

Crash Year	Contributing Factor	Killed	Incapacit. Injury	Non-Incapacit. Injury	Possible Injury	Not Injured	Not Known	Cost (\$M)
2010	Animal - Domestic	9	43	194	214	1997	12	\$279
	Animal - Wild	6	52	173	185	3722	12	\$290
	Total	15	95	367	399	5719	24	\$568
2011	Animal - Domestic	9	38	214	225	1936	14	\$272
	Animal - Wild	12	67	230	191	3981	14	\$392
	Other			1	1	1		\$0.48
	Total	21	105	445	417	5918	28	\$664
2012	Animal - Domestic	9	51	207	197	1943	18	\$ 314
	Animal - Wild	5	65	191	207	3828	20	\$340
	Other					1		\$ -
	Total	14	116	398	404	5772	38	\$654
2013	Animal - Domestic	13	37	163	191	1781	11	\$256
	Animal - Wild	4	49	201	215	4108	16	\$286
	Other			1	1	2		\$0.48
	Total	17	86	365	407	5891	27	\$543
2014	Animal - Domestic	7	42	135	158	1668	19	\$239
	Animal - Wild	13	61	172	234	4115	22	\$345
	Other			1		1		\$0.48
	Total	20	103	308	392	5784	41	\$584
2015	Animal - Domestic	10	40	172	183	1761	12	\$261
	Animal - Wild	12	61	206	250	4610	23	\$358
	Total	22	101	378	433	6371	35	\$620
2016	Animal - Domestic	5	46	181	181	1876	17	\$269
	Animal - Wild	10	74	246	287	5131	44	\$417
	Other					1		\$ -
	Total	15	120	427	468	7008	61	\$686

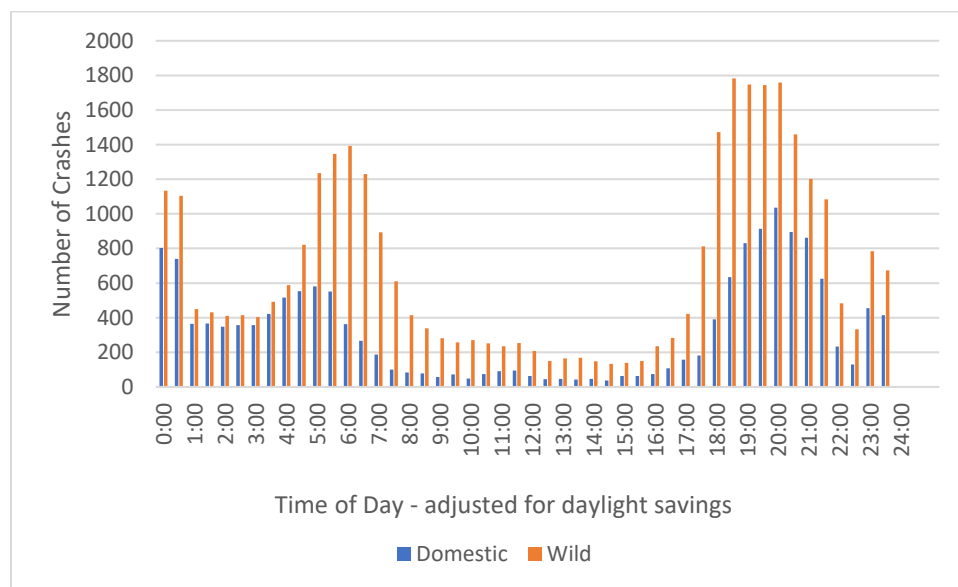
## Crash Time of Day

As shown in Figures 1 and 2, (reported) AVCs peak twice a day: between 5 and 8 AM (with 20% of AVCs happening) and from 6 PM to midnight (47%), with heavy peaking between 6 and 7 am (8.6%) and between 8 and 9 pm (9.3%). When the times of day are adjusted (Figure 2) for daylight savings time shifts, the evening peak consolidates further (vs. Figure 1's wide evening peak). Since travel or VMT demand does not peak at those same times of day or in quite the same way, AVC peaking implies that animal movement choices are key. Animal behavior is regularly based on the sun's placement, while human behavior is dictated more often by clock time (for work and school start and end times, for example), as well as day of week (with Friday and Saturday nights often

involving late-night socializing and the associated return travel). Interestingly, domestic animals tend to experience more crashes earlier in the day than wild animals do (e.g., a 5 or 6 am peak). Deer, unlike most domestic animals, are a crepuscular species, meaning they are most active during dusk and dawn (“White-Tailed Deer”, n.d.).



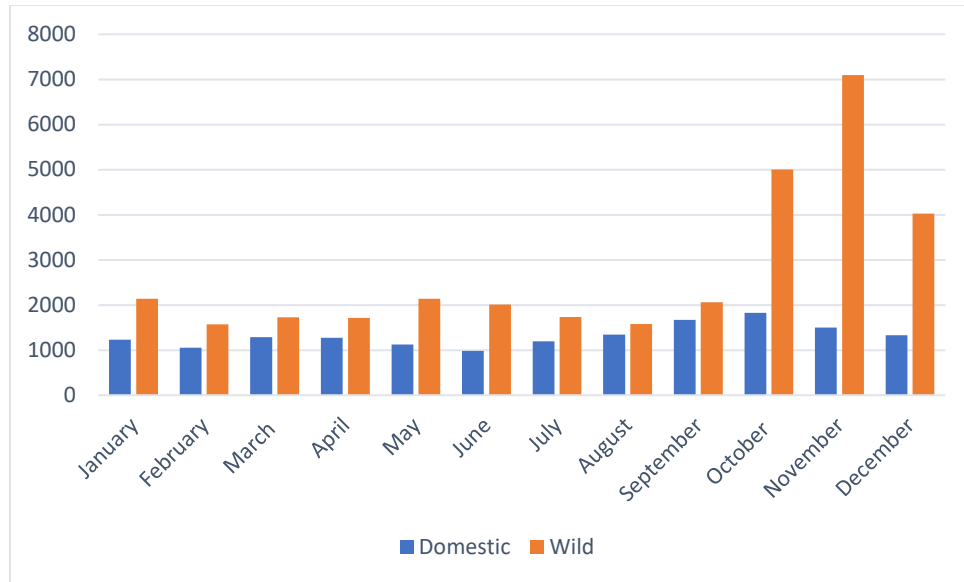
**FIGURE 1 Crash counts by time of day (30-min intervals, Texas AVCs, 2010-2016)**



**FIGURE 2 Crash counts by adjusted time of day (to eliminate daylight savings time effects, 30-min intervals, Texas AVCs, 2010-2016)**

### Time of Year

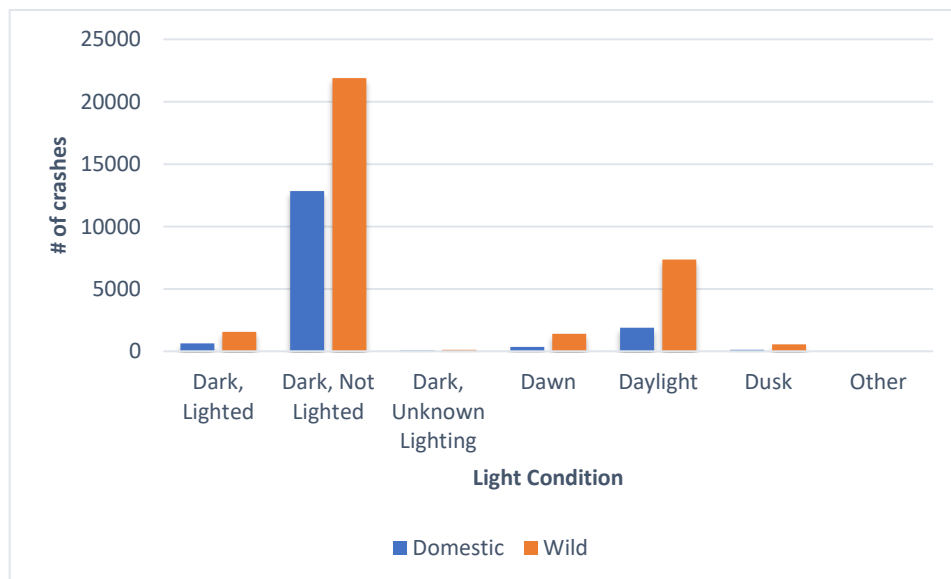
State Farm indicates that drivers are more than twice as likely to have a collision with a deer, elk, or moose during the months October, November and December (State Farm, 2015). Texas AVC data delivers similar results, as shown in Figure 3.



**FIGURE 3 Crash counts by month of year (Texas AVCs, 2010-2016)**

### Light Condition

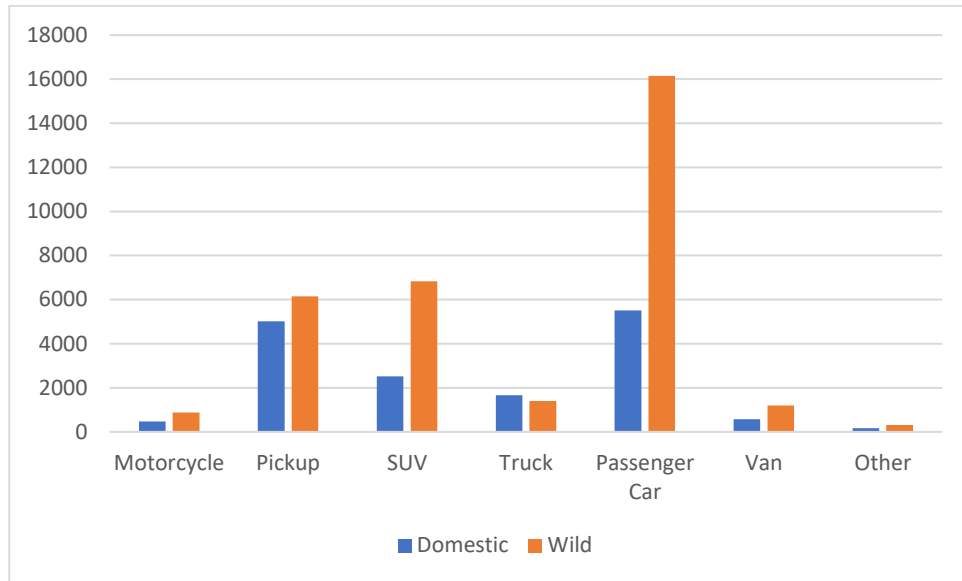
Most AVCs (71%) occur at night in unlit locations. Unlike cars and trucks - with their headlights on, animals running across the road are virtually invisible in the darkness until it is too late. Reported crash frequencies are also much higher in dark settings, as shown in Figure 4. Such settings can be especially problematic for smaller animals, such as turtles, armadillos, raccoons, possums, and the endangered Texas ocelot. It is difficult to know the rates of such incidents because crashes involving small animals are rarely detected by the involved motorists (excepting, for example, motorcyclists) and almost never reported. Swedish research (Neumann et al. 2012, p. 70) notes how higher collision risk for moose is “largely due to low light and poor road surface conditions rather than to more animal road-crossings”.



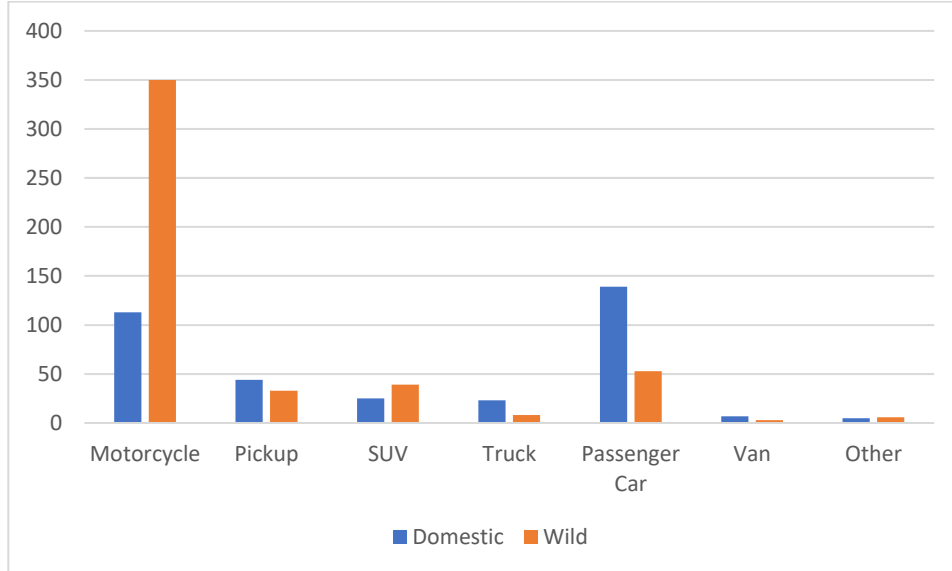
**FIGURE 4 Number of crashes by light condition (Texas AVCs, 2010-2016)**

## Vehicle Type

Based on observations from the CRIS data show in Figures 5 and 6, during the years 2010-2016 motorcycles comprised only 2.2-3.5% of total reported AVCs, yet accounted for at least half of all fatal or injurious crashes. These animal-motorcycle collisions are especially deadly, as the driver has no physical protection between himself and the animal.



**FIGURE 5 Number of crashes by vehicle type (Texas AVCs, 2010-2016)**



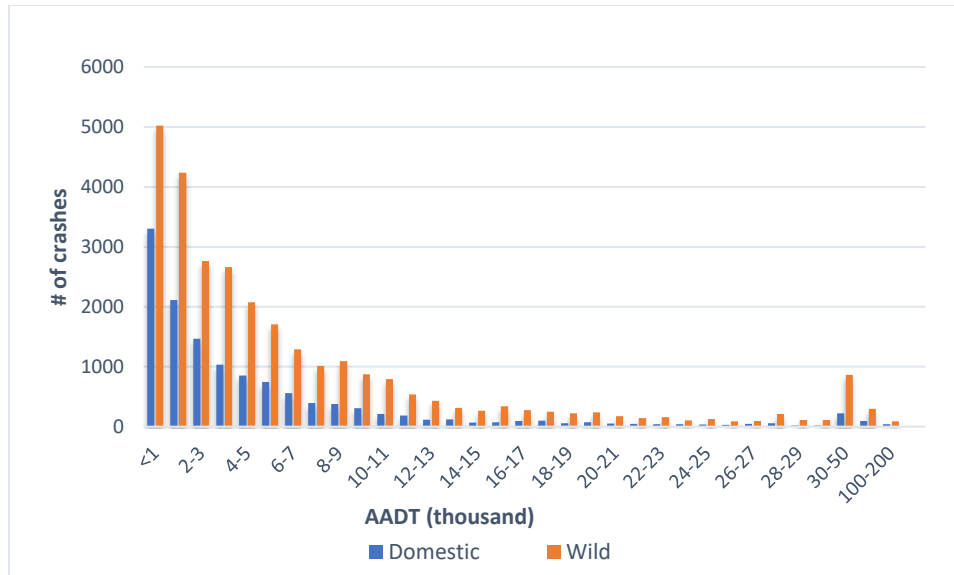
**FIGURE 6 Number of fatal or injurious crash reports by vehicle type (Texas AVCs, 2010-2016)**

Additionally, when compared to other vehicle types, motorcycles see a large spike in AVCs on Saturdays and Sundays (the average weekend day sees a 44% increase from the average weekday), likely due to those using motorcycles as recreational vehicles on the weekends.



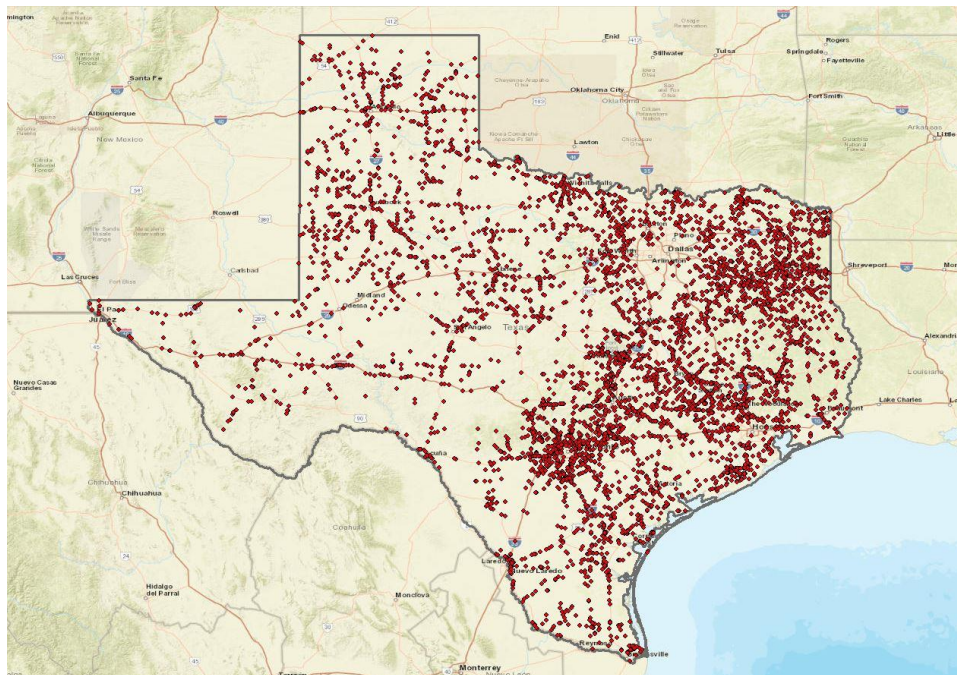
## Location and Density

51,522 collisions with wild animals were reported by Texas law enforcement between 2010-2016, including 254 human fatalities, 6,914 human injuries, and thousands more animal deaths. Most of these crashes happen on rural roads with very low traffic, as demonstrated in Figure 7.



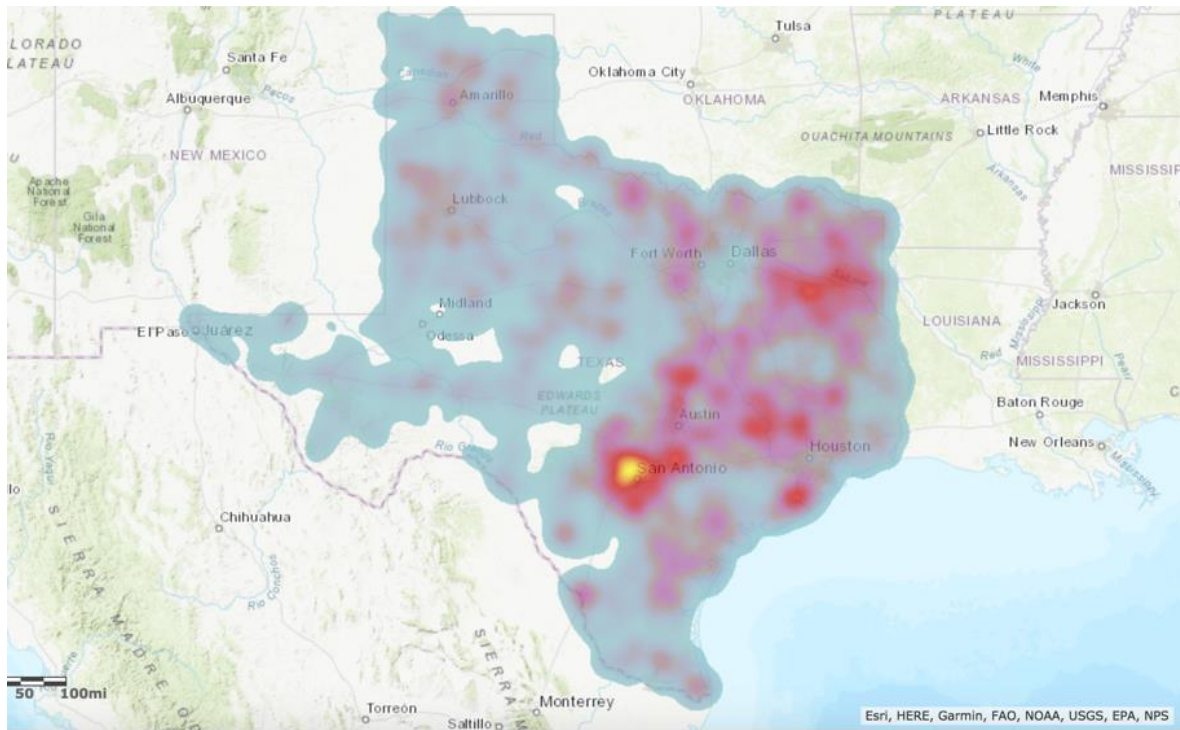
**FIGURE 7 Crash counts by average annual daily traffic (Texas AVCs, 2010-2016)**

Using location coordinate data provided in the CRIS reports, a detailed map of all studied collisions (excepting 4% of reports lacking coordinate data) was created in ESRI's ArcGIS software, shown in Figure 8.

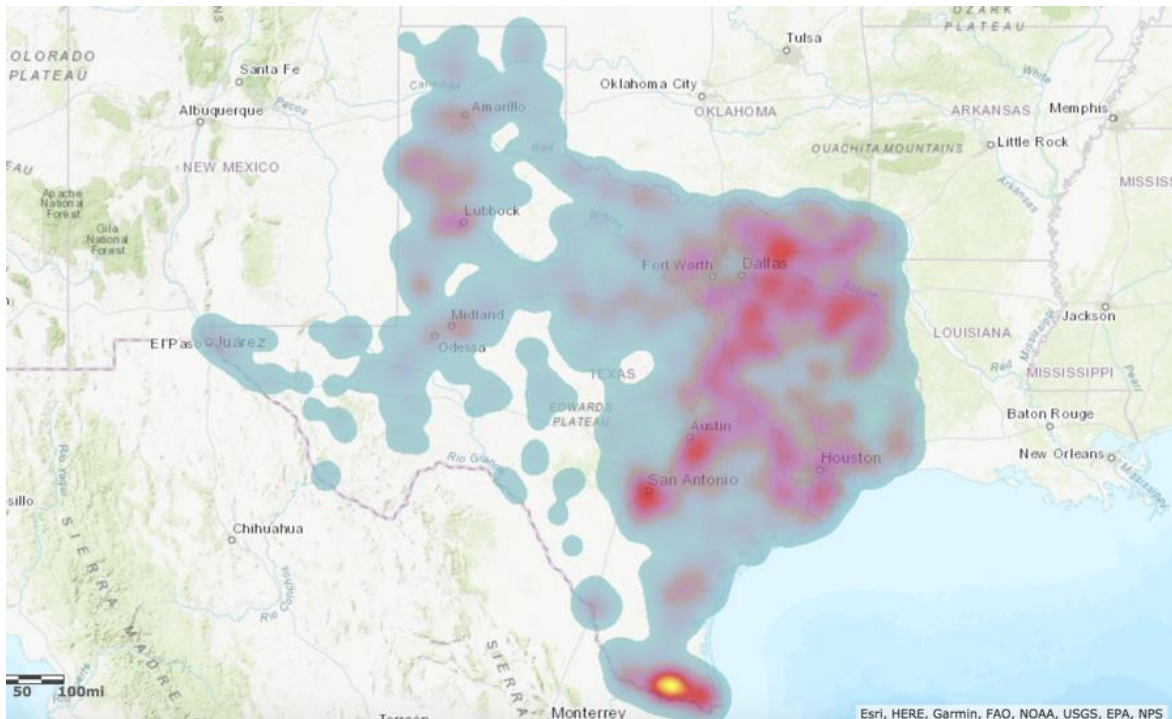


**FIGURE 8 All reported-AVC locations across Texas (2010-2016)**

From these coordinates, it is possible to develop a generic heat map (Figures 9 and 10) based on the respective concentrations of the data points shown in Figure 8. A bright yellow spot indicates a very dense collection of data points whereas a light blue area suggests that crashes are fewer and farther between. The heat maps for all animal vehicle collisions indicated that the San Antonio metropolitan area had the most concentrated AVCs. This is consistent with a 2018 report by the National Insurance Crime Bureau which stated that San Antonio and Austin, TX are the top 2 cities for animal loss claims across the whole U.S (NICB, 2018).



**FIGURE 9 Crash count hot spots for wild animals (Texas AVCs, 2010-2016)**



**FIGURE 10 Crash counts hot spots for domestic animals (Texas AVCs, 2010-2016)**

Though collisions with domestic animals make up a smaller proportion of total reported crashes than collisions with wild animals and are researched less often, they are not to be discounted. Out of the 51,522 AVCs reported in the state of Texas between 2010-2016, 15,890 (31%) of these can be attributed to collisions with domestic animals and 32,920 (64%) with wild animals, where the rest were unspecified in the data.

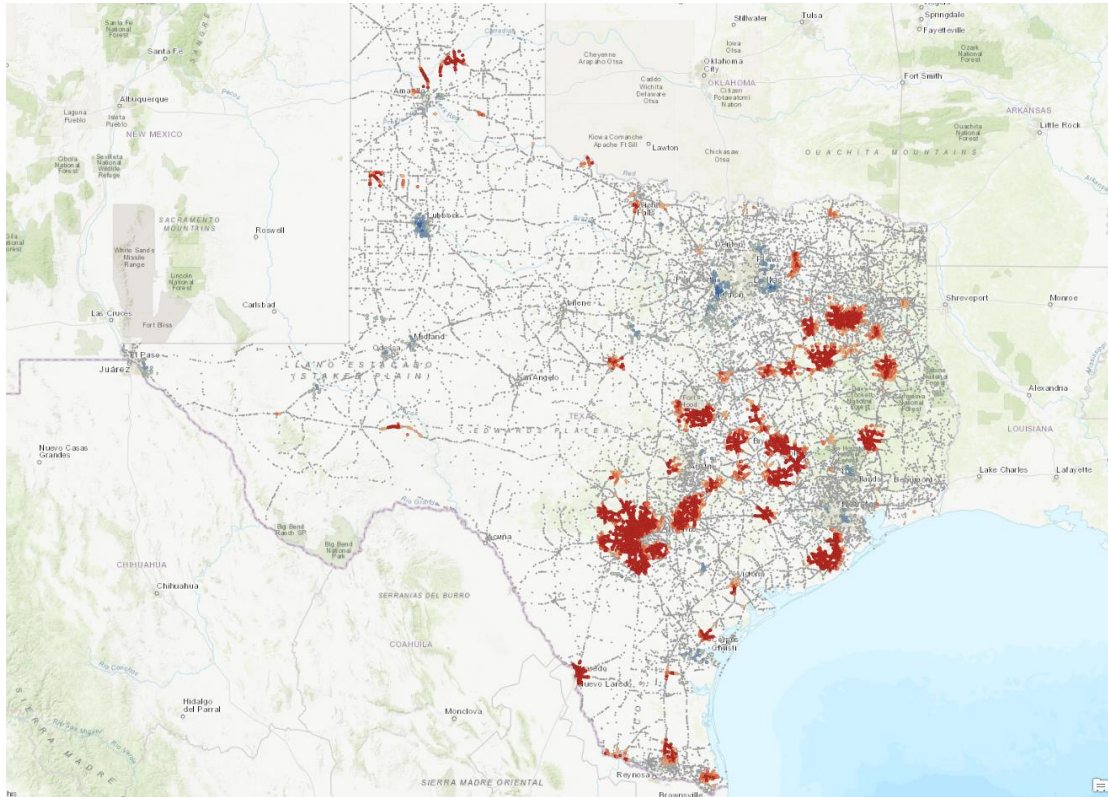
As shown in Figure 10, collisions with domestic animals seem to experience a high spike in the Rio Grande Valley region. This is possibly due to the unusually high number of stray animals in the region. According to Keely Lewis, board secretary for the Palm Valley Animal Center, the Valley has one of the highest populations of stray animals in the country. Owner of a no-kill shelter in the city of McAllen suggests that many, if not most, residents of the Valley do not opt for rabies shots or microchips or will decline spaying and neutering services in favor of trying to turn a profit on the animal's offspring (Gonzalez 2018). He believes that McAllen's main roads are more residential than those in neighboring cities like Brownsville, making it more likely for runaway dogs to access the streets and cause crashes in that area (Gonzalez 2018). However, it is worth noting that according to national data, dogs made up only 1.2% of animal-related insurance claims between 2014 and 2017 (NICB 2018).

The heat maps developed in Figures 9 and 10 are very helpful in visualizing the density of crash occurrence. However, the results of such a process are dependent upon user-defined "class and cell ranges to set up the gradient," and therefore are highly subjective (Dempsey, 2014). Developing a hotspot map, however, "uses statistical analysis in order to define areas of high occurrence versus areas of low occurrence," (Dempsey, 2014). Since the resulting areas are statistically significant, they are much less subjective.

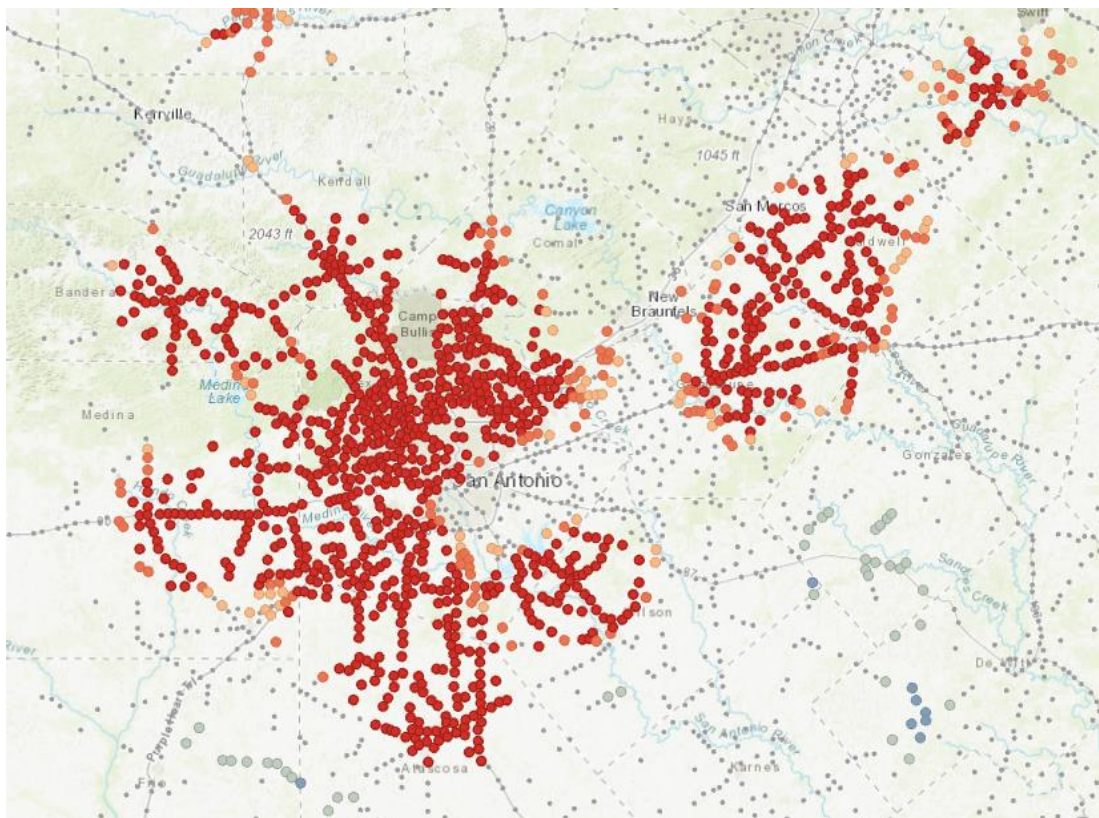


Figure 11 shows the results of ArcGIS' Optimized Hot Spot Analysis Tool for the entire state. Figure 12, on the other hand, displays a closer look at just the results for the San Antonio area, to demonstrate the model's enhanced capability for showing specific problem areas on a detailed scale. The software uses the Getis-Ord  $G_i^*$  statistic (Getis and Ord, 2002, Ord and Getis, 2005) to create a map of statistically significant hot and cold spots or crash clusters.

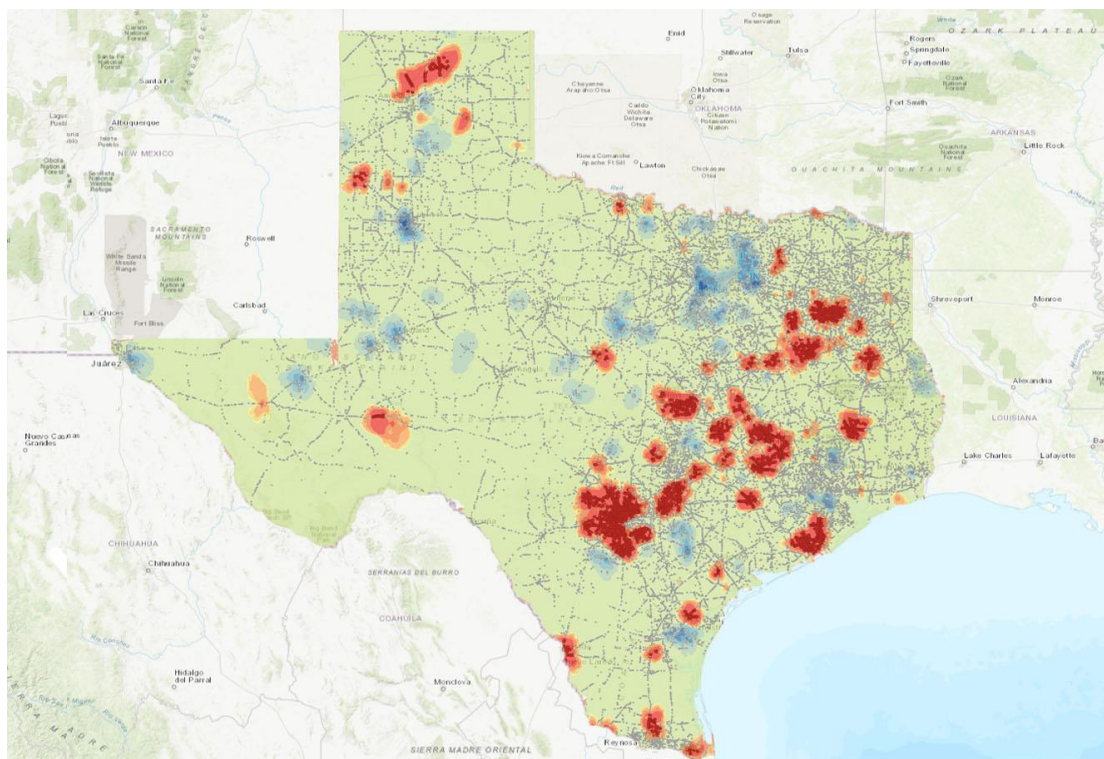
The  $G_i^*$  values were then interpolated using ArcGIS' Inverse Distance Weighting (IDW) tool to create a legible map of hotspots over the whole state, as shown in Figure 13. The darkest red areas indicate the most significant hotspots, and darkest blues indicate the most significant cold spots, where AVCs are much less of a concern for that area.



**FIGURE 11 Getis-Ord  $G_i^*$  Hotspot Map of AVCs 2010-2016**



**FIGURE 12 Getis-Ord Gi\* Hotspot Map of AVCs 2010-2016 in the San Antonio Area**



**FIGURE 13 Getis-Ord Gi\* Hotspot Analysis with IDW Interpolation**

## Regression Analysis

Using ordinary least-squares (OLS) regression across n=254 Texas counties, the following analysis highlights county attributes that are strong predictors of AVC crash rates (per VMT in each county). For further investigation, similar methods can be implemented at a link-based level, to identify problematic road segments.

Table 2 summarizes key statistics for the explanatory variables used in this analysis. Collision data were averaged over the 7-year data set (Texas AVCs 2010-2016 CRIS data).

**TABLE 2 Summary Statistics for Texas County Data**

Variable	Description	Min	Max	Mean	Median	SD
AVC/VMT	Animal-vehicle collisions per million annual VMT	1.17E-03	0.60	0.11	0.09	0.08
POP DENS	Population per square mile	2.6E-04	4.62	0.18	0.03	0.53
VMT/CAP	Annual VMT per capita	498.53	312,372	18,948	11081	33,402
VEH/CAP	Vehicles registered per capita	0.04	8.81	1.21	1.12	0.78
LANEMI/CAP	Lane-miles per capita	4.59E-03	2.10	0.19	0.10	0.27
RAINFALL	Average annual rainfall (inches)	9.10	60.57	31.39	28.57	11.93
ON SYSTEM	% VMT occurring on TxDOT managed-roadways	34.60	180.66	88.96	91.05	12.61
RURAL POP	Proportion of population that lives in rural areas	0	2.53	0.063	0.54	0.24
JOBS DENS	Employees per acre	0.0069	1.00	0.56	0.01	0.32

**TABLE 3 OLS Regression Results for Y = AVC per Million-VMT Prediction**

<i>Explanatory Variable</i>	<i>Coef. Estimates</i>	<i>Std. Error</i>	<i>t Stat</i>	<i>p-value</i>	<i>Std. Coef.</i>
Intercept	0.08	0.04	2.26	0.025	
POP DENS	-0.03	0.03	-0.91	0.36	<b>-0.18</b>
VMT/CAP	-1.1E-06	1.7E-07	-6.66	0.000	<b>-0.45</b>
VEHICLES/CAP	-0.01	0.01	-1.40	0.16	<b>-0.08</b>
LANEMI/CAP	0.15	0.03	6.01	0.000	<b>+0.48</b>
RAINFALL	4.0E-04	4.2E-04	0.95	0.34	<b>+0.06</b>
ON SYSTEM	-2.9E-04	3.9E-04	-0.75	0.45	<b>-0.04</b>
RURAL POP	0.09	0.02	4.60	0.00	<b>+0.33</b>
JOBS DENS	0.01	0.07	0.16	0.87	<b>+0.03</b>

## Model Results

Table 3 offers a column of standardized coefficient (*Std. Coef.*) values, which are a valuable way to compare the relative (predicted) impacts of competing explanatory variables. The *Std. Coef.* is simply the coefficient estimate itself times the standard deviation of the associated X variable divided by 1 std. deviation in the response variable (Y = AVC/VMT), and is the model's estimate



of how much of a change in AVCs per VMT will result from a one-standard-deviation increase in the associated X. In this way, one can sense that roadway provision per capita (LANEMI/CAP) and driving per capita (VMT/CAP) are the two most important or impactful predictive variables in this count-level AVC-focused data set, with standardized coefficients of almost one-half (+0.48 and -0.45), which means that a single standard deviation increase in those variables changes AVC rates by nearly 50 percent. This is a substantial effect, but these two variables' impacts are at odds with one another: everything else constant, higher VMT/CAP tends to reduce AVCs, because of slower speeds (due to greater congestion on the existing roadways) and because of animals avoiding relatively congested/high-demand roadways (thanks to motor-vehicle noise, greater risk perceptions when more vehicles are visible, and perhaps more visible dead animals on the roadside - making some species more aware of the dangers ahead). Of course, high VMT is often followed by more road building (LANEMI) and vice versa, so these two variables often rise together. Thus, in practice, it can be difficult to find counties with low VMT/CAP but high LANEMI/CAP, which would result in very high AVC rate predictions.

As also evident in Table 3's *Coef.* and *Std. Coef.* columns, when a county's rural-population share rises, its AVC rates are found to rise (per VMT), everything else constant. Jobs densities and rainfall also have slightly positive impacts on AVC rates here, but they are not practically significant (with *Std. Coef.* values of just +0.03 and +0.06, respectively). Conversely, higher population density and higher vehicle ownership rates tend to lower AVC rates, along with VMT/CAP, as discussed above, since those counties and their highways are presumably less welcoming to wild animals and may have lower shares of domesticated animal ownership (due to less land for raising and exercising cattle, dogs, and such).

#### **Benefit-Cost Analysis of Treatments to Reduce AVCs**

While heat mapping and an OLS regression can alert DOTs, states, nations, counties and cities to a potential issue or even show a fairly specific idea of where the problems are located, more localized methods are needed to identify specific problem areas on specific roadways. Moreover, choice of intervention needs to be done thoughtfully, to maximize return and cost-effectiveness. This work estimates benefit-cost ratios (BCRs) at the link or segment level for four kinds of treatments, to identify and quantify which locations are likely to benefit most from mitigation.

Using the 2010-2016 CRIS data set, 31,677 WVCs were mapped by latitude and longitude and overlaid on TxDOT's 2016 Roadway Inventory Routed Network. Each collision data point was matched to its closest link to deliver total AVC counts for each of the 640,123 links. CRIS sorts collisions into six categories: Killed (K), Incapacitating Injury (A), Non-Incapacitating Injury (B), Possible Injury (C), No Injury (O), and Unknown, as reflected in Table 4.

**TABLE 4 Crash shares by type in CRIS 2010-2016 AVC data**

Type of Crash	# of Crashes	% of Total WVC
K	60	0.19 %
A	407	1.28%
B	1276	4.03%
C	1491	4.71%

O	28317	89.39%
Unknown	126	0.40%
<b>TOTAL</b>	<b>31,677 AVCs reported</b>	

The following formula was used to calculate the BCR:

$$BCR = \frac{\sum_{i=0}^{i=n} \left( \frac{B_{ij}}{(1+d)^i} \right)}{\sum_{i=0}^{i=n} \left( \frac{C_{ij}}{(1+d)^i} \right)}$$

where  $B_{ij}$  represents the benefits of the project in year  $i$  for mitigation strategy  $j$  and is calculated for each network link as follows:

$$B_{ij} = \frac{[\sum_{k=KA}^{k=O} (N_{ik} * C_k)] * (E_j)}{7}$$

where  $N_{ik}$  is the number of collisions of type  $k$  in year  $i$ ,  $C_k$  is the average cost for collision type  $k$  (as detailed in Table 5), and  $E_j$  represents the effectiveness of mitigation strategy  $j$ . Additionally, the term  $C_{ij}$ , or the costs of the project in year  $i$  for mitigation strategy  $j$ , is equal to the initial cost of the structure for year  $i=0$ , and is equal to the annual maintenance cost for all consecutive years  $i=1$  through  $i=n$ . Finally,  $d$  represents the discount rate, to bring all future crash costs and treatment maintenance costs into present dollars.

Estimation of  $C_{ij}$  consists of imposing a baseline cost for shorter segments by assuming 1-mile and 2-mile fencing minima, on both sides of the highway, for animal-crossing underpasses and overpasses, respectively. The assumed treatment costs rises linearly with segment length for those segments above 1 mile in length. This approach may favor longer segments.

The following BCR results assume discount rate of 7%, which is the same rate used by the Army Corps of Engineers for BCRs, as established by the Office of Management and Budget (OMB) Circular A-94 (Economagic.com, 2015). They also assume comprehensive crash costs by severity, as shown in Table 5, based on the FHWA's 2018 Crash Costs for Highway Safety Analysis report. Due to the very rare nature of fatal (K-type) collisions, K and A counts were summed into one category, with one average cost.

**TABLE 5 FHWA-based Crash Costs**

Severity	Comprehensive Crash Unit Cost (2016 Dollars)
K+A (fatal & severe injury)	\$2,244,210*
B (injurious)	\$198,500
C (what's this?)	\$125,600
O (property-damage only)	\$11,900

\* K+A cost is a crash-weighted average of the K and A costs (\$11,295,400 & \$655,000) separately.



Four design treatments were identified as both effective and well-tested in the literature and in practice. These are fencing with double cattle guards, fencing in combination with overpass structures, fencing in combination with underpass structures, and animal detection systems or “ADS”. Their assumed costs and effectiveness are shown in Tables 6 and 7, respectively.

**TABLE 6 Costs (Initial and Annual Maintenance) of Mitigation Strategies**

Wildlife Items	Initial Cost (USD\$ 2015)	Annual Maintenance Cost (USD\$ 2015)	Source
Overpass	\$2,059,210 each	\$3363 each	CDOT (2016)
Underpass	\$1,569,271 each	\$3363 each	CDOT (2016)
Deer Fence	\$153,785 each	\$1657 per mile	CDOT (2016), Huijser & Duffield et al. (2009)
Double Cattle Guard <sup>2</sup>	\$45,000 per driveway entrance	negligible	Cramer & Flower (2017)
Animal Detection Systems	\$135,000 per mile	\$17,800	Huijser et al. (2006)

**TABLE 7 Assumed Effectiveness Rates of Intervention Options**

Mitigation Strategy	Crash Count Reduction (Estimate)	Notes	Source	Location	Species
Overpass + Fencing	90%		Stewart (2015)	Nevada	Deer
Underpass + Fencing	70%		Cramer (2014) Olsson et al.	Utah	Mule Deer
Animal Detection Systems (ADS)	80%	1 mile hypothetical segment used to estimate effectiveness	Huijser et al. (2006)	Arizona	Deer
Fencing with Double Cattleguards	94%	Warning: treatment greatly reduces habitat connectivity	Cramer and Flower (2017)	Utah	Mule Deer

This analysis also assumes that an AVC always results in the eventual death of the animal, so the value of each reported collision’s animal’s life was added to collision costs. Since the CRIS data do not generally specify the animal type involved in the motorist-reported crash, this work assumes an animal life value of \$4,990, which is the value assigned to deer by the Nevada Department of Transportation (Stewart, 2015). To account for the gap between reported and actual collisions, additional factors were added when calculating total collision costs per link. First, all costs attributed to O-type crashes were multiplied by a factor of 2, since property-damage-only crashes often go unreported, by about 50 percent (Munro, 2011). Second, the cost attributed to species value was multiplied by factor of 8.5, since 8.5 carcasses tend to be counted by maintenance crews

<sup>2</sup> Little information is available regarding the costs of installing such a design. The initial cost of \$45,000 was inferred as an average of the \$30000-\$60000 estimate provided in Cramer & Flower (2017). A maintenance cost of \$0 was inferred from the following reference to the same report: “double cattle guards and wildlife guards require minimal post-installation maintenance” (p. 32).

for each collision reported (Donaldson, 2018).

When assessing the possibility of implementing an overpass structure, this study assumed a frequency of one structure every two miles. When looking 100 segments that showed the greatest potential benefit from mitigation (highest BCRs), the BCRs ranged from 1.32 to 2.00. The average length of these top 100 segments was 1.43 miles.

When assessing the possibility of implementing an underpass structure, this study assumes the placement of one structure every mile. The benefit to cost ratios returned from the top 100 segments ranged from 1.46 to 2.97, with an average length of 1.15 miles.

Finally, in order to avoid very large BCRs for fencing and ADS along very short segments, a minimum of 1 mile of treatment was assumed for these two treatments, with costs scaled upward (i.e., rising in proportion to length) for segments over 1 mile. Due to their similar costs, cattle guards and roadside, camera-based ADS provided near-identical results in the benefit-cost analysis, with the exception of the scale of the BCRs. For the animal detection system, the benefit-to-cost ratios of these top 100 segments ranged from 7.16 to 14.55. Those same segments, for the strategy of animal fencing in combination with cattle guards, have BCR values ranging from 14.59 to 29.65, with an average length of just 0.54 miles. While this may seem to suggest an advantage for the fencing option, it is critical to be aware of the loss of species' habitat connectivity that comes with fencing.

Looking at the 100 highest-BCR segments for each of the 4 treatments, underpasses tend to favor longer segments, suggesting that some strategies might be better suited to more widely distributed concentrations of AVCs than others. Crash types for the ADS and fencing options tended to have higher shares of severe crashes (56.0% KA-type) than those for overpasses (33.6% KA-type) or underpasses (43.2% KA-type).

For actual BCR determination, reduction calculations should be based on actual animal collisions reduced over at least 2 years. Mitigation selection must also recognize the effects such strategies can have on the greater ecosystem and animal populations. Ungulates like deer and elk tend to prefer overpass structures, while feline species - such as the ocelot - prefer to use underpasses (FHWA, 2008). The translation of effectiveness rates to Texas roadways certainly requires further investigation as Texas' wildlife composition varies from that of the locations of in previous studies.

The options detailed here offer possible partial solutions and mitigation strategies that are most likely to reduce AVCs. Long-term monitoring is necessary to ensure the effectiveness of any mitigation technique for an area and to determine local species' preferences. It is important to remember that this analysis makes many assumptions and there are still many variables to explore.

## **External Factors and Driver Attitudes**

There is evidence to suggest that driver attitudes and many other non-animal related conditions may have a large impact on crash density, as in the case of light condition. Therefore, solutions such as improved lighting or driver awareness of road conditions conducive to AVCs should be considered.

Unfortunately, there is some evidence to suggest that AVC rates' correlation with lighting conditions may not have a cause-and-effect relationship. Though there have been a very limited number of studies conducted to analyze roadway lighting's effect on AVCs, one of these studies reported no observable reduction of AVCs in the presence of new lighting (Reed & Woodward, 1981). However, Sullivan et al. (2009) used a logistic regression model to find that night vision enhancement "may provide valuable assistance in helping drivers avoid animal-vehicle collisions."

Dynamic signage (warning signs that are initiated at the detection of an animal's presence) can impact the mindset of drivers and encourage them both to be alert and to reduce speed, possibly preventing and certainly lessening the impact of a collision were it to occur (Sullivan, 2009). In the case of domestic animal collisions, it is recommended that cities and states cultivate cultures where dogs are spayed and neutered rather than being raised as an investment. City animal control agents should have the appropriate resources delegated so that they can actively and effectively keep these animals off the road. Sharpshooting to reduce the abundance of deer populations has been considered (DeNicola et al., 2008) but has drawbacks including population impacts and public perception.

Looking to the future, some experts believe that the proliferation of sensing-enabled vehicles, which may be able to thoughtfully avoid or at least notify drivers of the presence of an obstacle, will greatly reduce the number of animal-vehicle collisions and may even result in a "rewilding" of the predators that have been methodically killed off by animal-vehicle collisions over the last 100 years (Wollan, 2018). Connected vehicles may also provide awareness of "hot spots for migrations of all animal types, even ones that will not harm cars or their occupants," which may encourage a driver to reroute around that critical path for the day.

### **Improving Animal-Vehicle Collision Reporting**

Mobile reporting, both from DOT employees and the average smartphone user, shows potential for increased frequency and specificity of WVC reporting. The Washington and Utah state Departments of Transportation for employees to report carcasses upon spotting them (Myers et al., 2008; Lee, 2018). In Malaysia and Israel, government and non-profit organizations, respectively, are working with popular navigation app Waze to show WVC hotspots on their maps so that drivers may be alerted and consider slowing down as they approach these areas (Udasin, 2017; Malaymail 2018). WIRES, a wildlife rescue app based in Australia, claims to have rescued over 68,000 animals in 2014 with the help of mobile reporting from citizens (Inverell Times, 2014). These promising applications demonstrate that ordinary citizens may be eager to download and utilize wildlife reporting apps.

Some researchers point to more detailed crash reports as simple strategy for fostering an environment of reliable data-gathering regarding AVC and its mitigation in the future. In the state of Nevada, officers reporting WVCs "have 14 species to select from a computer software pull down menu of species options, which includes wildlife and domestic animals" (Olson et al., 2014). Such detailed reporting provides transportation and wildlife departments with more accurate data to use in planning future mitigation strategies (Loftus-Otway et al., 2017).

## CONCLUSIONS

In this report, the authors look at the typical attributes and spatial frequency of animal vehicle collisions in Texas over a 7-year period. Each of the methods presented can hint at part of a complete idea of what future crashes will look like or where they will happen. Hotspot analysis of AVC collision data demonstrates clusters in the San Antonio region for wild animal collisions, and along the national border near the city of McKinney for domestic animal collisions. An ordinary least squares regression suggests that county-level attributes including population density, lane-miles per capita, vehicle-miles traveled per capita, and percent of population which live in rural areas are among the strongest predictors of AVC collision density. In a benefit-cost analysis, the lowest-cost methods of mitigating AVC returned the highest benefit-to-cost ratios. Crossing structures tended to favor longer segments (more spread out collisions) and segments with more property-damage-only (non-injurious) collisions than their counterparts. That being said, it may be helpful to consider a variety of strategies when making decisions about the placement of AVC mitigation. Ultimately, long-term monitoring is necessary to ensure effectiveness of any mitigation for the area and to determine local species' specific preferences for such devices.

Animal-vehicle collisions are a rising share of crash counts, but can be thoughtfully addressed by recognizing their specific locations, times of day, and months of year, as well as employing meaningful crossings, lighting, and/or real-time warnings. Best-practice projects, including infrastructure changes and behavioral strategies, are lowering such crash rates while raising driver awareness of AVCs. Communities and authorities throughout the world can address these issues by not only looking to infrastructure investments of the past but also to innovations of the future – including image processing on cameras, linked to smartphones and smarter cars and trucks – shifting crash reduction responsibilities to motorists. Intelligent investments, designs, and applications can save many lives and much property, while enabling longevity of endangered and near-endangered species in Texas.

## REFERENCES

- A-Z Animals. 2018. Ocelot. Retrieved November 10, 2018 from: <https://a-z-animals.com/animals/ocelot/>
- Beck, Alan. (2002). *The Ecology of Stray Dogs: A Study of Free-ranging Urban Animals*. Retrieved from: [https://books.google.com/books?id=9k11of3IHJUC&source=gbp\\_navlinks\\_s](https://books.google.com/books?id=9k11of3IHJUC&source=gbp_navlinks_s)
- Bissonette, J. A., P. C. Cramer. 2008. Evaluation of the use and effectiveness of wildlife crossings. Report 615 for National Academies', Transportation Research Board, National Cooperative Highway Research Program, Washington, D.C. URL: [http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp\\_rpt\\_615.pdf](http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_615.pdf)
- Clean Malaysia. 2018. Navigation App could help Save Wildlife. URL: <http://cleanmalaysia.com/2018/03/27/navigation-app-could-help-save-wildlife/>
- Cramer, Patricia. 2013. Culvert, Bridge, and Fencing Recommendations for Big Game Wildlife Crossings in Western United States Based on Utah Data. Accessed at <https://www.ail.ca/wp-content/uploads/2017/07/Utah-Wildlife-Paper.pdf>
- Cramer, Patricia. 2012. Determining Wildlife Use of Wildlife Crossing Structures Under Different Scenarios. Accessed at: <https://rosap.ntl.bts.gov/view/dot/24501>

Cramer, P. and J. Flower. 2017. Testing new technology to restrict wildlife access to highways: Phase 1. Final Report to Utah Department of Transportation. <http://www.udot.utah.gov/main/uconowner.gf?n=37026229956376505>

Dempsey, Caitlin (2014). What is the Difference Between a Heat Map and a Hot Spot Map? Gislounge.com Accessed at <https://www.gislounge.com/difference-heat-map-hot-spot-map/>

DeNicola, A. J. and S. C. Williams. 2008. Sharpshooting suburban white-tailed deer reduces deer-vehicle collisions. *Human-Wildlife Conflicts*, 1(1): 28-33.

Donaldson, B. and N. Lafon. 2008. Testing an Integrated PDA-GPS System to Collect Standardized Animal Carcass Removal Data. VTRC Report 08-CR10. Available at [http://www.virginiadot.org/vtrc/main/online\\_reports/pdf/08-cr10.pdf](http://www.virginiadot.org/vtrc/main/online_reports/pdf/08-cr10.pdf).

Federal Highway Traffic Safety Administration, 2008. Wildlife-Vehicle Collision Reduction Study: Report to Congress, FHWA-HRT-08-034.

Frair, J.L., Merrill, E.H., Beyer, H.L., Morales, J.M., 2008. Thresholds in landscape connectivity and mortality risks in response to growing road networks. *Journal of Applied Ecology* 45, 1504–1513.

Getis, A. and J.K. Ord. 1992. The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis* 24 (3).

Gonzalez, C. 2018. Phone interview with Dr Kara Kockelman on May 15, Texas Pet Rescue owner.

Haines, A. M., Tewes, M. E., Janecka, J. E., & Grassman, L. I. (2007, Evaluating the benefits and costs of ocelot recovery in southern texas. *Endangered Species Update*, 24, 35-41. Retrieved from <http://ezproxy.lib.utexas.edu/login?url=https://search-proquest-com.ezproxy.lib.utexas.edu/docview/215052745?accountid=7118>

Haines, A., Tewes, M., & Laack, L. (2005). Survival and Sources of Mortality in Ocelots. *The Journal of Wildlife Management*, 69 (1), 255-263. Retrieved from <http://www.jstor.org/stable/3803603>

Inverell Times. 2014. Wildlife rescue volunteers receive thanks for dedication. January 10. Accessed at: <https://www.inverelltimes.com.au/story/2015444/wildlife-rescue-volunteers-receive-thanks-for-dediation/>

Iuell, B., G.J. Becker, R. Cuperus, J. Dufek, G. Fry, C. Hicks, C. Hlavac, V.B. Keller, C. Rosell, T. Sangwine, N. Torslov, and B. le Maire Wanddall. 2003. Cost 341 – wildlife and traffic: A European handbook for identifying conflicts and designing solutions. Office for Official Publications of European Communities, Luxembourg.

Jones, G., Parker, C., & Scott, C. 2013. Designing America's Wildlife Highway: Montana's U.S. Highway 93. Accessed at: <http://articles.extension.org/pages/26900/designing-americas-wildlife-highway:-montanas-us-highway-93>

Jones, Mark & Manen, Frank & W. Wilson, Travis & R. Cox, David. (2010). Wildlife Underpasses on U.S. 64 in North Carolina: Integrating Management and Science Objectives. 223-238. Accessed at: [https://www.researchgate.net/publication/322661665\\_Wildlife\\_Underpasses\\_on\\_US\\_64\\_in\\_North\\_Carolina\\_Integrating\\_Management\\_and\\_Science\\_Objectives](https://www.researchgate.net/publication/322661665_Wildlife_Underpasses_on_US_64_in_North_Carolina_Integrating_Management_and_Science_Objectives)

Lee, Jasen. 2015. UDOT Launches New Mobile App to Help Drivers Report Road Concerns. Accessed at : <https://www.deseretnews.com/article/865619035/UDOT-launches-new-mobile-app-to-help-drivers-report-road-concerns.html>

Lewis, Keely. 2016. Reducing Stray Animals in the RGV. The Monitor April 15. Accessed at: [http://www.themonitor.com/opinion/columnists/article\\_0c249a06-715d-11e6-9e80-073e40f45585.html](http://www.themonitor.com/opinion/columnists/article_0c249a06-715d-11e6-9e80-073e40f45585.html)

Loftus-Otway, L., Oaks, N., Cramer, P., Kockelman, K., Jiang, N., Murphy, M., Sciara, G. 2018. Final Report for TxDOT Project 0-6971. Accessed at: <https://library.ctr.utexas.edu/ctr-publications/0-6971-1.pdf>

Malaymail (2018) Wildlife Department to work with Waze on roadkill hot spots. Available at <https://www.malaymail.com/s/1606581/wildlife-department-to-work-with-waze-on-roadkill-hot-spots>. Miller, Matthew. 2016. A Shocking Surge of Ocelot Deaths in Texas. *Cool Green Science*. <https://blog.nature.org/science/2016/05/25/shocking-surge-ocelot-deaths-texas-roadkill-wildlife/>

National Geographic. 2018. *White-Tailed Deer*. Retrieved November 10, 2018 from: <https://www.nationalgeographic.com/animals/mammals/w/white-tailed-deer/>

National Insurance Crime Bureau. 2018. *ForeCAST Report Regarding: 2014-2017 United States Animal Loss Claims*. Accessed at: <https://www.nicb.org/news/news-releases/animal-related-insurance-claims-top-17-million-four-years>

Neumann, W., G. Ericsson, H. Dettki, N. Bunnefeld, N. S. Keuler, D. P. Helmers, and V.C. Radeloff. 2012. Difference in spatiotemporal patterns of wildlife road-crossings and wildlife-vehicle collisions. *Biological Conservation*, 145:70-78. Accessed at: <https://pdfs.semanticscholar.org/56a7/da3f915f4c8390017b452a4ebc1a013d24aa.pdf>

Olson, D., J. Bissonette, P. Cramer, A. Green, S. Davis, P. Johnson and Daniel Coster, 2014. Monitoring Wildlife-Vehicle Collisions in the Information Age: How Smartphones Can Improve Data Collection

Ord, J.K. and A. Getis (1995) Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis* 27 (4).

Reed, D., & Woodward, T. 1981. Effectiveness of Highway Lighting in Reducing Deer-Vehicle Accidents. Accessed at: <https://www-jstor-org.ezproxy.lib.utexas.edu/stable/3808706>

Sommer, K. 2014. TxDOT to pay \$5M for Ocelot crossings on Highway 100. The Monitor October 17. Accessed At: [https://www.themonitor.com/premium/article\\_137a4732-55a4-11e4-bd8f-001a4bcf6878.html](https://www.themonitor.com/premium/article_137a4732-55a4-11e4-bd8f-001a4bcf6878.html)

State Farm Insurance. 2015. Drivers Beware: The Odds Aren't In Your Favor. Newsroom September 14. Accessed at: <https://www.statefarm.com/about-us/newsroom/2015/09/14/deer-collision-data>

Steen, D. A., and J. P. Gibbs. 2004. Effects of Roads on the Structure of Freshwater Turtle Populations. *Conservation Biology* 18:1143–1148

- 1 Stewart, Kelly. 2015. Effectiveness of Wildlife Crossing Structures to Minimize Traffic Collisions  
2 with Mule Deer and Other Wildlife in Nevada. Accessed at:  
3 <https://www.nevadadot.com/home/showdocument?id=6485>
- 4 Sullivan, John. 2009. Relationships between Lighting and Animal-Vehicle Collisions. Accessed  
5 at: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.581.5895&rep=rep1&type=pdf>
- 6 TxDOT. 2018. Texas Dept. of Traffic, Highway Safety Improvement Program Call,  
7 <http://ftp.dot.state.tx.us/pub/txdot-info/trf/hsip/2018/program-call.pdf>
- 8 Udasin. 2017. SPNI, Waze Identify Most Dangerous Roads for Animals. Accessed At:  
9 [https://www.jpost.com/Business-and-Innovation/Tech/SPNI-Waze-identify-most-dangerous-](https://www.jpost.com/Business-and-Innovation/Tech/SPNI-Waze-identify-most-dangerous-roads-for-animals-497206)  
10 [roads-for-animals-497206](https://www.jpost.com/Business-and-Innovation/Tech/SPNI-Waze-identify-most-dangerous-roads-for-animals-497206)
- 11 U.S. Fish and Wildlife Service. 2010. Draft Ocelot (*Leopardus pardalis*) Recovery Plan, First  
12 Revision. U.S. Fish and Wildlife Service, Southwest Region, Albuquerque, New Mexico.
- 13 Wollan, M. 2018. The End of Roadkill. *The New York Times Magazine* (Nov 8): 62.
- 14 Washington State Department of Transportation (WSDOT). 2018. Tracking Wildlife Carcasses  
15 Removed by WSDOT Maintenance Staff. Accessed at:  
16 <https://www.wsdot.wa.gov/environment/technical/disciplines/fish-wildlife/>

17