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Developing a Road Risk Model for Large Animal Crashes in Virginia: A Safe System Approach to Cost-Effective Safety Improvements

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Abstract:

In 2020, the Virginia General Assembly enacted the Virginia Wildlife Corridor Action Plan (WCAP; *Code of Virginia* § 29.1-579), which directed the Virginia Department of Transportation (VDOT) and other state agencies to identify wildlife corridors and areas with a high risk of wildlife-vehicle collisions to prioritize wildlife crossing projects that improve driver safety and habitat connectivity. Elements of this directive align with VDOT's adoption of the Safe System Approach, which emphasizes proactive road design and management to reduce crash risk. Meeting both WCAP and roadway safety objectives requires reliable tools to identify roadway segments where wildlife crashes are most likely to occur. However, police-reported crash data substantially underrepresent large animal crashes and do not account for road and landscape factors that influence crash risk.

The study developed a predictive large animal road risk model to identify Virginia road segments with elevated risk of white-tailed deer and black bear crashes. The model integrates police-reported crash data with road characteristics, traffic volumes, land cover, and other variables to produce crash risk estimates across the road network. To address crash underreporting, correction factors were evaluated using additional crash data sources, and these factors were incorporated into model outputs and subsequent benefit-cost analyses. A benefit-cost calculator spreadsheet was developed to support the evaluation of the appropriate level of investment based on expected safety benefits.

Model performance evaluation demonstrated that a small proportion of roadway segments identified as highest risk account for a disproportionately large share of reported deer and bear crashes, including crashes that occurred after the study period on which the model was developed. This occurrence indicates that the model is effective at targeting high-risk roadway segments. The large animal road risk model and supporting benefit-cost approach will contribute to the WCAP prioritization process and will supplement VDOT safety efforts by improving evaluation of large animal crash risk, the cost-effectiveness of safety countermeasures, and decision-making that is consistent with VDOT safety evaluation practices. It is recommended that VDOT (1) provide the deer and bear road risk model and accompanying report to the team developing the next version of the WCAP for use in wildlife crossing project prioritization and (2) incorporate the study findings and deliverables into its safety evaluation and reporting practices to support roadway risk assessment and benefit-cost analyses.

Supplemental materials can be found at https://library.vdot.virginia.gov/vtrc/supplements.

FINAL REPORT

DEVELOPING A ROAD RISK MODEL FOR LARGE ANIMAL CRASHES IN VIRGINIA: A SAFE SYSTEM APPROACH TO COST-EFFECTIVE SAFETY IMPROVEMENTS

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Charlottesville, Virginia

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ABSTRACT

In 2020, the Virginia General Assembly enacted the Virginia Wildlife Corridor Action Plan (WCAP; *Code of Virginia* § 29.1-579), which directed the Virginia Department of Transportation (VDOT) and other state agencies to identify wildlife corridors and areas with a high risk of wildlife-vehicle collisions to prioritize wildlife crossing projects that improve driver safety and habitat connectivity. Elements of this directive align with VDOT's adoption of the Safe System Approach, which emphasizes proactive road design and management to reduce crash risk. Meeting both WCAP and roadway safety objectives requires reliable tools to identify roadway segments where wildlife crashes are most likely to occur. However, police-reported crash data substantially underrepresent large animal crashes and do not account for road and landscape factors that influence crash risk.

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INTRODUCTION

Wildlife Corridor Action Plan

In 2020, the Virginia General Assembly enacted the Virginia Wildlife Corridor Action Plan (WCAP; *Code of Virginia* § 29.1-579), which directed the Virginia Department of Wildlife Resources (VDWR), in collaboration with the Virginia Department of Transportation (VDOT), the Virginia Department of Conservation and Recreation, and the Virginia Department of Forestry, to "[i]dentify wildlife corridors, existing or planned barriers to movement along such corridors, and areas with a high risk of wildlife-vehicle collisions" and to "[p]rioritize and recommend wildlife crossing projects intended to promote driver safety and wildlife connectivity." The WCAP is required to be updated every 4 years.

The final WCAP was released in May 2023 and included three primary themes: (1) promote driver safety; (2) improve wildlife corridor connectivity; and (3) advance mutual benefits (VDWR et al., 2023). In addition to the WCAP document, mapped products included: (1) road segments experiencing high occurrences of white-tailed deer or black bear conflicts; (2) Wildlife Biodiversity Resilience Corridors; and (3) locations of 26 Nexus Areas (25 square miles in size) that represent opportunities to advance mutual benefits where wildlife crossings could provide both driver safety and wildlife corridor conservation benefits. Specific wildlife crossing projects, including precise locations and target species, were not identified in the WCAP as a result of data gaps that were encountered.

One of the WCAP's mapped products illustrated 1-mile road segments with the highest percentages of deer or bear conflicts. Police-reported crash data served as the source of this analysis. However, the WCAP points out that this method of identifying crash hotspots fails to account for the underreporting of deer-related crashes, which are underreported by a factor of 4 to 9, depending on the location (Donaldson, 2017), and it does not consider road and landscape factors that are essential for predicting crash risk (VDWR et al., 2023).

To address these and other limitations, the WCAP provides several "recommendations for future actions" for its next iteration. These recommendations include (1) the development of a predictive model to identify site-specific road segments at higher risk of deer- and bear-vehicle collisions and (2) the identification of "wildlife crossing concern areas" for known at-risk species and other species of interest (VDWR et al., 2023). These efforts are crucial for fulfilling the primary intent of the legislation, which is to identify wildlife crossing projects in Virginia.

To fund these efforts and thereby advance the work of the next WCAP, VDOT's Environmental Division applied for a federal grant through the Federal Highway Administration's (FHWA) Wildlife Crossings Pilot Program (WCPP). Established under the Bipartisan Infrastructure Law (H.R. 3684, 2021), the WCPP is a competitive grant program with the goal of reducing wildlife-vehicle collisions while improving habitat connectivity for terrestrial and aquatic species. Virginia was one of 17 states awarded fiscal year 2022–2023 WCPP funding. VDOT's WCPP grant application describes the deliverables to be provided, which includes the development of a large mammal road risk predictive model.

Alignment with National and State Roadway Safety Strategies

The U.S. Department of Transportation has adopted the Safe System Approach, a proactive policy that promotes a more resilient and multi-strategy approach to preventing deaths and serious injuries on the nation's roads (U.S. Department of Transportation, 2024). This approach replaces traditional road safety strategies that react to historic crashes rather than address the risk of a crash occurring. The *Virginia 2022–2026 Strategic Highway Safety Plan* describes Virginia's adoption of the Safe System Approach (VDOT, 2022), which includes reducing driving risks by focusing on design and management of road infrastructure in a proactive manner.

Transportation staff and decision-makers require reliable crash data to apply Safe System Approach principles and identify strategic opportunities for safety measures. Research has shown that the high volume of deer crashes in Virginia—57,000 to 60,000 deer-related insurance claims per year in recent years (Philips, 2026)—represents a considerable and costly safety hazard (Donaldson, 2017). Because many wildlife crashes are not reported to law enforcement, insurance claims data are widely considered one of the most reliable indicators of total collision frequency (Huijser et al., 2008). However, the locations of these crashes are not publicly available, and police records remain the primary data source used in VDOT safety evaluations. The underrepresentation of deer crash volumes creates missed opportunities for cost-effective countermeasures. A predictive model that uses a combination of police-reported crashes, roadway attributes, and contextual factors to flag high-risk road segments would provide a more realistic indication of risk and support more accurate benefit-cost evaluations. The resulting risk map would support VDOT's Safe System Approach and a primary objective of the WCAP.

The cost-effectiveness of safety improvements is also an important consideration in transportation decision-making. Benefit-cost analyses (BCAs) are frequently required for funding programs that support road safety projects. Because of the underrepresentation of large animal crashes in police-reported crash datasets, traditional safety evaluations can underestimate both crash risk and the potential benefits of countermeasures. Integrating predictive crash risk modeling with a consistent BCA framework therefore provides a more realistic basis for evaluating wildlife crossing and other countermeasure investments, supporting both WCAP implementation and VDOT's Safe System Approach evaluation practices.

PURPOSE AND SCOPE

The purpose of this study was to develop a predictive model to identify road segments in Virginia at high risk of white-tailed deer- or black bear-vehicle collisions. A related objective was to develop a benefit-cost methodology that complements the predictive model and supports consistent and defensible BCAs for large animal-vehicle collision safety improvements in Virginia.

METHODS

The research team conducted the following nine tasks to fulfill the study purpose:

1. Reviewed the literature to identify factors associated with deer and bear crash risk.
2. Reviewed sources of deer and bear crash data and established correction factors that account for underreporting.
3. Aggregated relevant data sources for model development.
4. Determined the appropriate road segmentation and developed the basemap.
5. Developed the dataset.
6. Developed the large animal road risk model and evaluated its performance.
7. Converted the model's crash probability values into expected deer and bear crash frequencies.
8. Developed a BCA methodology that can be used in conjunction with the model.
9. Illustrated the use of the model and the BCA approach with a case study of a Virginia road segment.

In transportation safety practice and road ecology, a distinction is often made between *animal-vehicle collisions (or crashes)*, which involve a direct collision with an animal and are documented in police reports or carcass removal data, and animal-vehicle *conflicts*, a broader term that can include crashes resulting from avoiding an animal and other road impacts, such as habitat fragmentation. Because this study is based on crash-derived data and produces predictions expressed as crash risk, the term *crash* is used throughout for consistency. Although crash risk may capture some non-reported crashes and avoidance-related crashes, the study does not address the broader ecological impacts of roads.

Literature Review

The research team conducted a literature review to evaluate road segment lengths commonly used for wildlife crash evaluation and to identify factors associated with deer- and bear-related crashes. The findings were used to assess the consistency of model performance with literature on variables associated with white-tailed deer and black bear crash risk. The review focused on landscape, roadway, and traffic characteristics associated with deer and bear crashes, including land cover (e.g., proximity to forested habitats and riparian corridors) and road characteristics (e.g., functional class and traffic volume).

Reviewing Large Animal Crash Data Sources and Establishing Correction Factors to Account for Underreporting

The research team reviewed deer and bear crash data sources to establish a clear understanding of data availability and the strengths and limitations of each data source. Characterizing these limitations helped to inform model development and the benefit-cost approach, particularly the use of correction factors to account for underreporting in police-reported crash data. The application of these correction factors ensures that predicted crash risk and associated costs are better representations of actual crash conditions.

For the review of police records, the research team submitted a request to the Virginia Department of Motor Vehicles (DMV) for 2024 police reports to identify potential deer avoidance, or "near-miss," deer-related crashes. In these cases, the recorded "collision type" is often "fixed object off road" (e.g., guardrail or tree) rather than "deer," in which the collision may have resulted from avoiding a deer rather than a direct strike. Identifying these events requires review of detailed crash narratives, which are not publicly available because of the inclusion of personally identifiable information. The Virginia DMV provided 2024 police report data on deer-related crashes that were not captured through the standard practice of identifying deer crashes using the "deer" classification in the collision type field (Phan, 2025a). These deer avoidance crashes were not included in the model development but provided additional context regarding the underreporting of deer-related crashes.

To obtain statewide information on deer carcasses removed from Virginia roadways, the research team submitted a request to VDOT staff responsible for the Highway Maintenance Management System (HMMS), which contains non-public work order records for dead animal removal. Animal groups are represented in 10 categories, including deer and bear (Myers, 2025). HMMS data for 2024 were reviewed for deer and bear work orders and compared with other sources of crash data.

Finally, the State Farm Insurance company's corporate communications office provided the insurance claims data. These data were provided with July 1st start dates. Information provided for the period from July 1, 2024, to June 30, 2025, was evaluated and compared with Virginia 2024 police records and VDOT work order data.

These data sources were collectively reviewed to evaluate the magnitude of underreporting in police-reported wildlife crash records and to inform the use of correction factors for both deer and bear crashes. For deer, the use of a previously established correction factor of 5 was evaluated and contextualized using 2024 crash data (Donaldson, 2022). For bears, a new correction factor was estimated. These factors were used to inform how crash risk is represented in the predictive model and BCA to more fully reflect the volume and cost of large animal crashes.

Aggregating Data Sources for Model Development

The research team compiled and aggregated datasets from various sources. These data helped facilitate the subsequent modeling steps and identification of risk factors for deer and bears in Virginia. Key data sources included:

- VDOT.
- VDWR.
- Virginia DMV.
- Virginia Department of Conservation and Recreation.
- U.S. Geological Survey.
- Multi-Resolution Land Characteristics Consortium.
- Federal Emergency Management Agency.
- U.S. Census Bureau.

Police-reported deer and bear crash data were obtained from the Virginia DMV for a 10-year period, from 2014 to 2023 (Phan, 2025b). Deer-related crashes in this dataset include only those events in which deer were identified as the primary collision event (i.e., deer was selected as the "collision type").

This approach could not be applied to bear-related crashes because bears are not listed as an option under the "collision type" field. To identify bear-related crashes, the research team requested that the Virginia DMV review crash records during the same timeframe using confidential crash narratives. This process involved searching for the term "bear" within the narratives and screening the text to exclude instances in which the term referred to unrelated meanings (e.g., "Bear Hill Road") rather than animal involvement.

For other data sources used in model development, Appendix A summarizes the datasets reviewed for this research by their respective source. This summary includes the date that the research team obtained or the relevant version of the data the research team used.

Road Segmentation and Basemap Development

The following sections describe the key technical steps to (1) assess an appropriate segment length and (2) integrate roadway, traffic, and environmental variables for crash analysis.

Segment Length Analysis

As part of the literature review, the research team noted that states used varying segment lengths for their wildlife crash safety analyses. No consensus "ideal" segment length has been determined for these types of analyses. As a result, an analysis of segment lengths in Virginia was conducted to determine the appropriate uniform segment length for this study. Based on the literature review, the research team investigated uniform segment lengths of 0.5, 1, and 2 miles by comparing the 10-year deer and bear crash distribution across each segmentation interval using the available tools in ESRI ArcGIS Pro.

The 0.5-mile segmentation interval was determined appropriate for this study. Specifically, the 0.5-mile segments maximized the sample size of segments with at least one crash, both by count and percentage compared with the crash distributions for the 1- and 2-mile segment intervals. This approach provided more segments with a police-reported crash for the risk modeling phase. See Appendix B for tables listing crash distribution by segment length.

In addition, shorter segments allow for a more refined analysis of where crashes occur. Longer segments may result in a "smoothing" effect (i.e., the same segment may capture two distinct crash locations), making specific location identification (i.e., where VDOT may locate crash countermeasures) less precise (Figures 1 to 3).

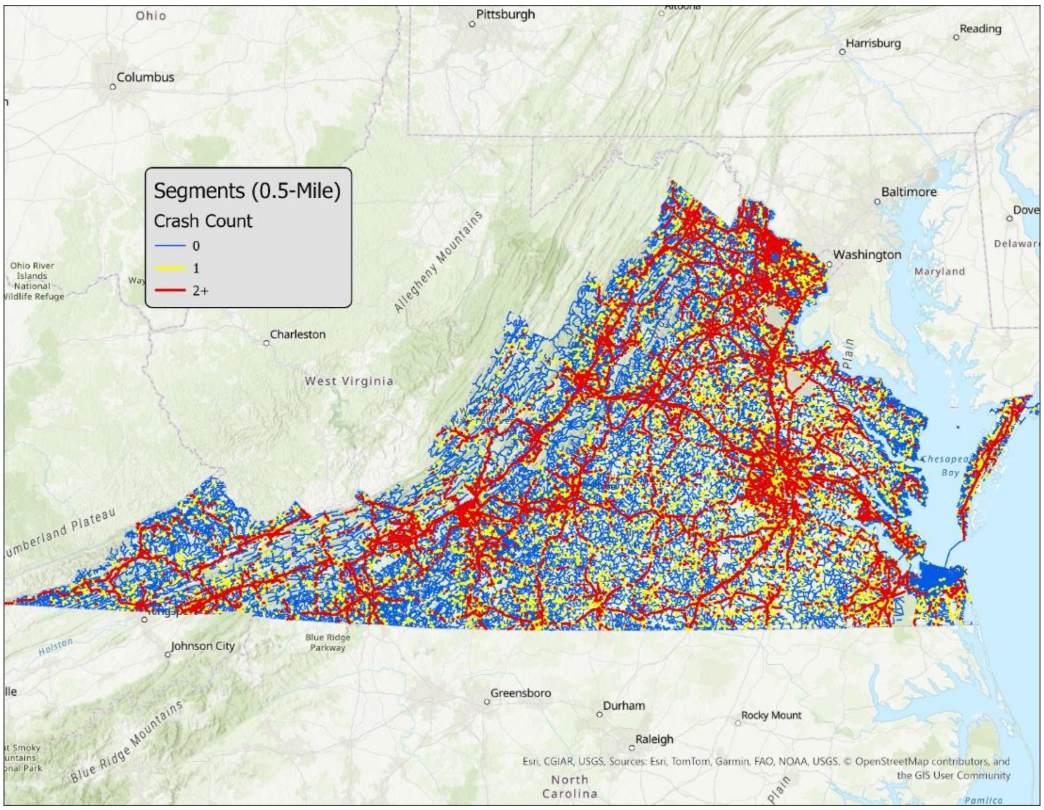

Figure 1. Statewide Deer and Bear 10-Year Crash Distribution for 0.5-Mile Segments

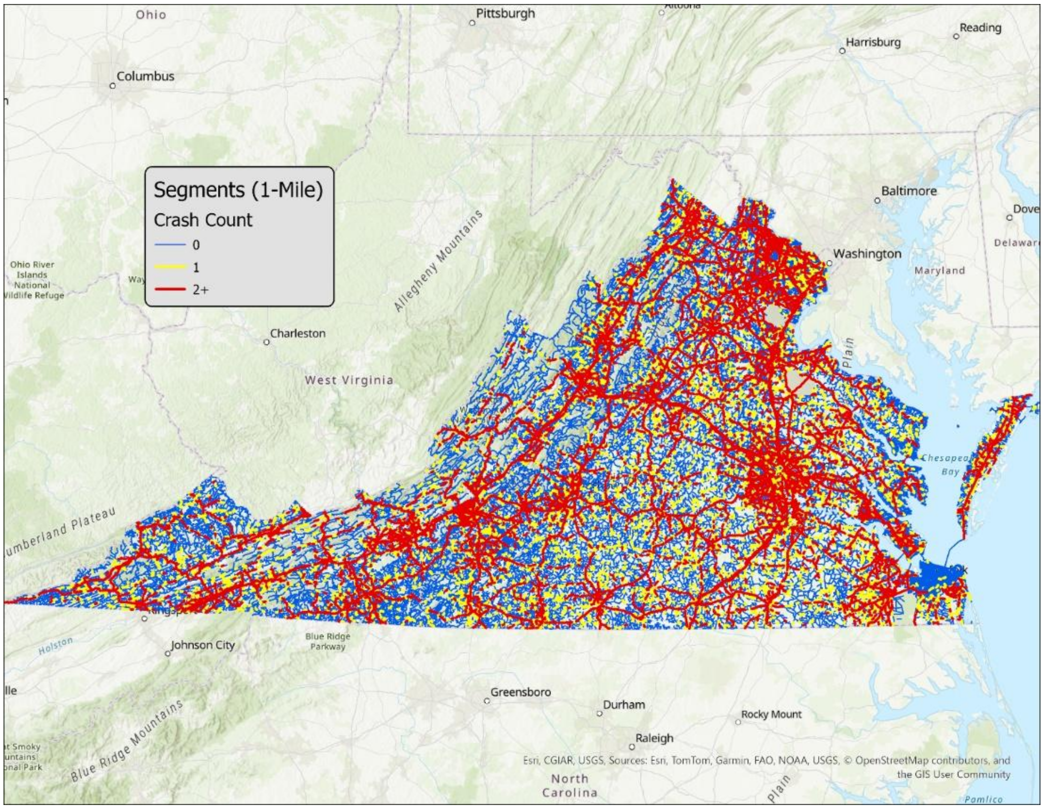

Figure 2. Statewide Deer and Bear 10-Year Crash Distribution for 1-Mile Segments

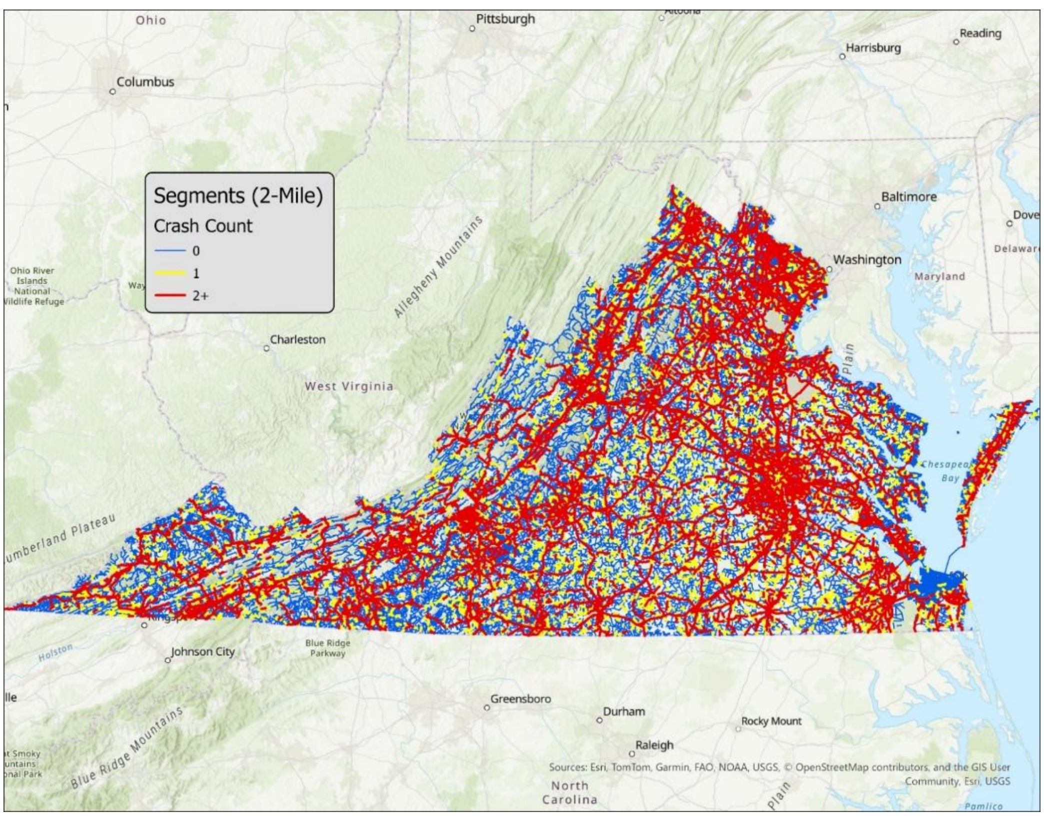

Figure 3. Statewide Deer and Bear 10-Year Crash Distribution for 2-Mile Segments

Dataset Development

The research team integrated analysis variables with the 0.5-mile segment basemap dataset. This dataset can be conceptualized in two categories by relationship to the roadway: (1) roadway characteristics variables and (2) surrounding environment variables. Roadway characteristic variables describe attributes of the roadway, including but not limited to traffic volume, lane count, posted speed limit, and deer and bear crashes. Surrounding environment variables describe attributes proximal to the roadway but not directly attributes of the roadway, including but not limited to stream and river mileage within a distance of each road segment, deer and bear population density of the jurisdiction in which each road segment is located, building footprint density, and total square footage within a distance of each road segment, etc. For this task, feedback was obtained from a technical advisory committee composed of VDWR staff with expertise in black bears and white-tailed deer. See Appendix C for the full list of analysis variables examined.

Roadway Characteristics Variable Integration

Using the available tools in ESRI ArcGIS Pro, the research team integrated roadway characteristic variables with individual segments through linear referencing (e.g., route ID and milepost values), spatial methods, or a combination of both techniques. See Appendix A for the source data for each variable. Due to the uniform 0.5-mile segmentation used for the analysis dataset, opposed to dynamic segmentation or segmentation that splits only a segment when any attributes change in value, the research team used the attribute value for each roadway characteristic variable that made up most of each segment. For example, if 80% of a 0.5-mile segment had two through lanes and 20% had four through lanes, the entire segment would be represented as having two through lanes.

Prior to integrating analysis variables with the segments dataset, the research team removed the "non-primary" direction of divided roadways to mitigate redundancy during the risk analysis for these locations. This elimination means the centerline for the primary direction of travel was used to represent both directions of travel for divided highways (e.g., a six-lane divided roadway with three travel lanes in each direction is represented by a single centerline with the lane count attribute having a value of six total lanes).

In addition, the research team integrated most of the roadway characteristics data directly from their source datasets as described previously. However, the total lane count variable required additional pre-processing steps before integration with the segments dataset. The research team processed the VDOT statewide lane count dataset to aggregate the bidirectional lane count for divided roads where applicable (i.e., summing primary and non-primary direction lane counts on the primary direction centerline). To overcome the lack of lane-count data for urban and municipal roads, the research team used the Urban Maintenance Inventory System roadway inventory dataset from VDOT's Road Inventory Management System to fill these gaps in the lane-count data.

Surrounding Environment Variable Integration

Surrounding environment variables describe attributes proximal to the roadway, but they are not attributes of the roadway. Surrounding environment variables can represent both the natural environment, such as land cover, and the human environment, such as building density. Using the available tools in ESRI ArcGIS Pro, the research team integrated surrounding environment variables with the segment dataset using various spatial methods.

If a surrounding environment variable is represented at a defined geographic boundary unit, such as human population tied to a census tract, or the black bear population density index tied to predefined "Bear Management Zones," the research team assigned values to segments according to the spatial location of the segment midpoint. Alternatively, if a surrounding environment variable is continuous and not confined to a geographic boundary unit, such as land cover or linear river and stream features, the segments were calculated based on characteristics within a defined distance of each segment.

To provide additional flexibility during the subsequent risk modeling phase, some surrounding environment proximity metrics were separated based on side of the road, and each of these variables was calculated for "Side 1" and "Side 2" of each road segment. Splitting up the representation of surrounding environment variables by side of the road provided flexibility during the risk modeling phase, allowing for comparison of the resulting forecasted risk between segments with certain attributes present on both sides of the road versus only one side of the road. The labeling of each side of the road as either "Side 1" or "Side 2" is arbitrary (i.e., consistently labeling Side 1 as the east, west, north, or south side of the road was not necessary), with the main goal of this attribution being to differentiate the attributes on one side of the road from the other. Figure 4 illustrates this revision for a single 0.5-mile segment, displaying the linear hydrography dataset for reference as an example of a surrounding environment dataset that was integrated separately for each side of the roadway.

Model Development

To support deer and bear crash risk analysis for Virginia roads, the research team organized data for the 0.5-mile segments according to a generic segment facility type. These facility types were based on (1) the type of countermeasures that would be relevant to individual road segments (e.g., the addition of wildlife fencing to existing underpasses is typically most feasible along access-controlled freeways) and (2) the data available for risk-based scoring. The following sections describe the facility type stratification process and the associated data available for risk modeling.

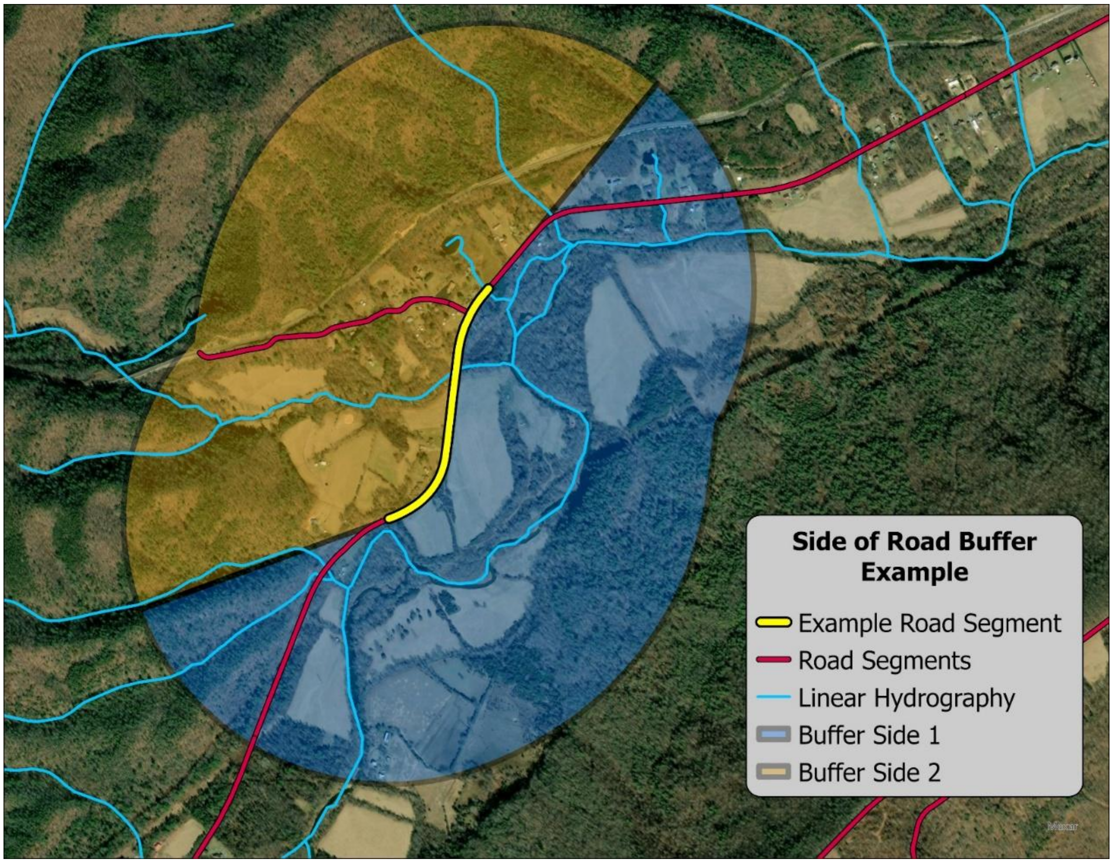

Figure 4. Example of Separation of Proximal Attribute Integration Between Either Side of a Road Segment

Facility Type Stratification

The research team developed three different facility types for risk analysis:

- **Access-Controlled Freeways:** Defined as all roadways with the functional class interstate or other freeways and expressways. These locations are where wildlife fencing is expected to be most effective because access (i.e., at-grade intersections and driveways) is limited.
- **Non-Freeway, Federal Aid Roads:** Defined as roadways with the functional class other principal arterial, minor arterial, major collector, and minor collectors that are not in rural areas. These locations are where roadway access is not limited, and annual average daily traffic (AADT) estimates are generally available.
- **Non-Freeway, Non-Federal Aid Roads:** Defined as roadways that are rural minor collectors and roadways with a functional classification of local. These locations are where roadway access is not limited, but AADT estimates are generally not available for risk assessment.

Ramps (i.e., connections between freeways and grade-separated crossings) were not included in the analysis dataset.

Six risk models were developed based on animal crash type and segment facility type:

- Deer/Access-Controlled Freeways.
- Deer/Non-Freeway, Federal Aid Roads.
- Deer/Non-Freeway, Non-Federal Aid Roads.
- Bear/Access-Controlled Freeways.
- Bear/Non-Freeway, Federal Aid Roads.
- Bear/Non-Freeway, Non-Federal Aid Roads.

Summary Statistics

Table 1 provides summary statistics for key variables in risk analysis. The research team considered additional variables, but they were not included in the final risk models (Appendix A).

Table 1. Summary Statistics for Key Variables in Risk Analysis

Variable	Observations [a]	Mean	Std. Dev.	Min.	Max.
Annual average daily traffic	160,319	2,689.71	10,617.24	0	241,000
Deer Density Rating	310,567	0.83	0.38	0	1
Bear Density Rating	310,567	0.51	0.5	0	1
Population Density	310,567	1352.26	2905.8	0	152,888.18
Urban Area Flag	310,567	0.39	0.49	0	1
Area of Forest Land Cover [b]	310,566	0.39	0.33	0	1.829
Area of Cultivated Land Cover [c]	310,566	0.19	0.24	0	1.250
Area of Open-Uncultivated Land Cover [d]	310,566	0.03	0.07	0	1.066
Grass Median Present	167,644	0.04	0.19	0	1
Median Barrier Present	167,644	0.004	0.07	0	1
Intersection Density	310,565	57.14	931.6	0	505,980.7
Building Density	310,566	782.38	926.3	0	82,706.3
Three or More Lanes Present	205,520	0.062	0.24	0	1
Natural Land Use Mix	263,966	0.52	0.27	0	1
Hydro Crossing Count	310,567	0.24	0.55	0	7
Median Presence	310,567	0.033	0.18	0	1
Median Width	167,650	1.8	9.86	0	220

[a] Excluding all observations with missing values. [b] Includes Mixed Forest, Deciduous Forest, and Evergreen Forest classifications from the Multi-Resolution Land Characteristics (MRLC) National Land Cover Database (NLCD). [c] Includes Pasture/Hay and Cultivated Crops classifications from MRLC NLCD. [d] Includes Shrub/Scrub, Barren Land, and Grassland/Herbaceous classification from MRLC NLCD.

Natural Land Use Mix is a combined variable that indicates how balanced the natural area (forest, cultivated, and open-uncultivated) land cover is around a particular segment. The formula is:

$$\sum_{i=1}^{n} p_i \frac{\ln p_i}{\ln n}$$

Where:

p_i represents the proportion of estimated area attributed to land use i.

n represents the number of land uses per segment.

Risk Analysis Methodology

The following sections describe the risk analysis methodology and the process by which variables were included in the final risk models.

Variable Review

The research team used a correlation matrix to test variables for correlation at every step of the iterative model-creation process. Some variables are naturally related (e.g., number of through lanes and AADT), so some correlations are to be expected. However, any unexpected variables that had a high correlation warranted further exploration and model testing.

Model Form

The research team elected to use logistic regression to assess correlation between risk factors and large animal crash risk. Rather than an estimated crash frequency, logistic regression determines a probability that an event (e.g., a crash) will occur. Due to the relative scarcity of documented crashes, the limited number of segments with more than one large animal crash, and noted issues with crash underreporting, logistic regression is a more flexible approach to safety analysis. In addition, logistic regression can take in both continuous (e.g., traffic volume counts) and categorical (e.g., bear population density rating) variables, making it ideal for this dataset. Equation 1 gives the model form of logistic regression:

$$p = \frac{1}{1+e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}} \qquad \text{Equation 1}$$

Where:
p is the probability that a specific event will occur, in this case a bear or deer crash.
β represent the coefficient for each x value.

Logistic regression output can be translated into a value between 0 and 1, where a value near 0 indicates a low likelihood of an event occurring (i.e., a deer or bear crash), and a value near 1 indicates a high likelihood of an event occurring. This value can be associated with segments so that high-risk segments (i.e., segments with a value closer to 1) can be mapped.

Model Process

Although the logistic regression analyses identify the degree to which roadway and land cover variables are associated with police-reported deer and bear crashes, the model applies these relationships across all evaluated road segments. This predictive component estimates where crashes are most likely to occur and produces a crash probability for each segment.

The research team developed models for bear and deer crash likelihood (all severities considered) for all three facility types, and the modeling process for all six models followed a similar procedure. Variables were added to the model one at a time, and the research team assessed the effect of the introduced variables on model fit and correlation with existing variables. Variables that were too highly correlated with existing parameters or had an insignificant effect on the model were excluded. The process began with exposure-related variables, such as AADT, population density, and the respective bear or deer densities.

After exposure-related variables, land cover variables were added to the models. This addition included forest cover variables, cultivated land cover, uncultivated land cover, wetland, open water, and binned variables of the percentage of development. After an initial assessment, the research team converted individual forest cover variables (e.g., deciduous forest, evergreen forest) into one comprehensive forest cover variable. A similar process was followed for cultivated and open-uncultivated land covers. After land cover, the research team incorporated road-specific variables, such as the number of lanes, median type, and number of curves, as well as the average centerline slope. Continuous and categorical variables were aggregated into “bins” (i.e., combinations of values) when appropriate based on model performance. Finally, built environment variables, such as intersection density, roadway density, and building density, were added to all models, as well as roadside slope and hydro-feature density and crossings.

The research team tested variables for each side of the roadway (e.g., dissimilarity indices comparing land cover on either side of a roadway). However, these variables were typically insignificant and did not add significant performance benefits to the risk models. The result of the modeling was a value between 0 and 1 for all road segments in Virginia, where a value closer to 1 indicated a higher likelihood of a crash during a 10-year period.

Evaluation of Model Performance

The research team evaluated model performance based on the consistency of the results with existing literature and conducted an assessment of the model’s ability to efficiently identify roadway segments with higher deer- and bear-vehicle crash risk. This task was quantified by determining the concentration of reported deer and bear crashes on segments the model identified as highest risk. The proportion of total crashes occurring on the highest risk segments was calculated and compared with the proportion of total roadway mileage represented by those segments.

The research team further compared the model against more recent crash data (i.e., 2024 bear and deer crashes). Because these data became available after model development was completed, they helped demonstrate the ability of the model to proactively target crash risk. Model performance was assessed by calculating the proportion of 2024 police-reported deer and bear crashes occurring on the highest risk roadway segments and comparing this figure with the proportion of total roadway mileage represented by those segments.

Finally, the performance of the risk model was compared with the performance of the original 2023 WCAP. The number of crashes that occurred in the model’s high-risk road segments was compared with the number that occurred on the 2023 high-conflict road segments.

Converting Crash Probability to Expected Crash Frequency

To support transportation safety evaluations and BCAs, the model-predicted crash probabilities were converted to expected deer and bear crash frequencies for each 0.5-mile road segment. Expected crash frequencies were derived by assuming crashes follow a Poisson process, consistent with crash count modeling practice in the Safety Performance Function Development Guide (Srinivasan and Bauer, 2013) and FHWA traffic safety research (Garber et al., 2005). The Poisson method translates probability estimates into expected crash counts, which are needed for conducting BCAs.

Under this assumption, the expected number of crashes (λ) corresponding to a predicted probability of at least one crash (P) during the same time period is calculated in Equation 2:

$$\lambda = -\ln(1 - P) \qquad \text{Equation 2}$$

Where:
λ = expected number of police-reported deer crashes during the specified time period (e.g., 10 years).
P = model-predicted probability of at least one deer crash occurring on the road segment during the same time period.
ln = natural logarithm.

Benefit-Cost Analysis

A BCA method was developed to illustrate how predicted crash reductions can be translated into monetized safety benefits and compared with the costs of the safety improvement. A BCA and the resulting benefit-cost ratio (BCR) are often important components of funding applications. A BCR compares the present value of total expected benefits (of a safety improvement, in this case) with the present value of total expected costs during the analysis period, or the service life of the safety improvement. The BCR indicates whether a project's benefits justify its costs from an economic standpoint. A value greater than 1 indicates that the benefits exceed the costs. The BCR can help to assess and justify the appropriate level of investment based on expected safety benefits. Many funding programs require a minimum BCR threshold for projects to be competitive. Example uses include:

- Highway Safety Improvement Program applications that require cost-effectiveness to be considered as part of the planning process (23 CFR 924.9(a)(6)).
- SMART SCALE or similar state programs that incorporate benefit-cost or safety-effectiveness scoring criteria.
- Federal WCPP and related grants that require demonstrating expected safety and habitat connectivity benefits relative to project costs.

To facilitate consistent application of the methodology, the BCA calculations were implemented in a spreadsheet that calculates the BCA equations described in this section. Although this report focuses on the BCA and BCR, the calculator spreadsheet and a description of the underlying methodology are available in a supplemental file. The spreadsheet can be used to conduct BCAs for large animal crash safety improvement projects and modified as needed to align with funding program requirements and other WCAP and VDOT needs.

Average Unit Crash Costs for Deer and Bear Crashes

Methods for Cost Calculations Using Police-Reported Crashes

To calculate the benefits of preventing large animal crashes, the average costs of those crashes were first determined. These costs were calculated by using crash severity values to quantify crash costs, an approach used by practitioners in Virginia when calculating the BCR for specific safety treatments (VDOT, 2025) and applied in previous BCAs for wildlife crash countermeasures (Donaldson et al., 2024).

Ten years of Virginia police report records (2014–2023) were used to determine the proportion of crash severities by crash type for deer and bear. The average crash costs were first calculated by attributing a cost to each crash severity type. These costs were obtained from VDOT Traffic Crash Costs (VDOT, 2025), which was developed to use in highway safety project evaluations. VDOT developed these costs by using FHWA's *Crash Costs for Highway Safety Analysis* and the accompanying spreadsheet tool to adjust the comprehensive crash costs to Virginia (Harmon et al., 2018).

VDOT Traffic Crash Costs uses KABCO crash unit costs to attribute a different cost to each of five levels of crash severity (VDOT, 2025)—where K is the unit cost of fatal crashes; A, B, and C are the unit costs of injury crashes that vary in severity; and O is the unit cost of property-damage-only (PDO) crashes. Table 2 provides Virginia crash unit costs, which include all crash types and severities, for 2025. The resulting Virginia-specific comprehensive crash costs are a combination of economic crash unit costs (tangible effects) and quality-adjusted life years crash unit costs (monetized pain and suffering) that sum to equal the comprehensive crash cost.

Table 2. Virginia KABCO Crash Unit Costs (2025)

Severity	Economic Crash Unit Costs	QALY Crash Unit Costs	Comprehensive Crash Costs
K	$2,404,686	$14,438,170	$16,842,856
A	$181,961	$803,246	$985,207
B	$80,469	$244,541	$325,011
C	$57,257	$131,343	$188,599
O	$17,130	$0	$17,130

QALY = quality-adjusted life years.

Equation 3 determines the average cost per deer and bear crash ($C_{Average}$):

$$C_{Average} = C_O \text{ x } P_O + C_C \text{ x } P_C + C_B \text{ x } P_B + C_A \text{ x } P_A + C_K \cdot P_K \qquad \text{Equation 3}$$

Where:
$C_{Average}$ = average comprehensive crash cost (computed separately for deer and bear).
C_O = crash cost for PDO crashes.
P_O = proportion of crashes resulting in PDO.
C_C = crash cost for C injury crashes.
P_C = proportion of crashes resulting in a C injury.
C_B = crash cost for B injury crashes.
P_B = proportion of crashes resulting in a B injury.

C_A = crash cost for A injury crashes.
P_A = proportion of crashes resulting in an A injury.
C_K = crash cost for fatal crashes.
P_K = proportion of crashes resulting in a fatality.

Methods for Cost Calculations for Factored Crashes

As described previously, prior research established that applying a correction factor of 5 to police-reported deer crashes (i.e., multiplying reported deer crashes within a roadway segment by 5) better reflects actual deer crash volumes and associated crash cost estimates. Equation 3 was adapted to integrate the correction factor. This correction factor was applied only to PDO crashes because it was assumed that unreported crashes likely resulted in property damage rather than an occupant injury.

Table 3 summarizes the distribution of deer crashes by severity between 2014 and 2023, as well as the total and proportion of crashes after the factors were applied to deer PDO crashes. As the PDO row of Table 3 shows, represented by "O," the police-reported PDO crashes were multiplied by 5 to determine the factored deer crash volume. This same analysis was applied to bear crashes using a newly estimated correction factor for bears, which a subsequent section details.

Table 3. KABCO Crash Distribution by Severity (2014–2023)—Reported and Factored

Severity	Deer Crash Total—Reported [a]	Deer Crash Total—Factored	Deer Crash Proportion—Factored
K	19	19	< 0.001
A	470	470	0.002
B	2,469	2,469	0.009
C	1,786	1,786	0.006
O	54,594	272,970	0.983

[a] Roughly 17% of reported deer crashes occur on freeways, with the remaining occurring on non-freeway roads.

Equation 4 determines the average cost per factored deer and bear crash ($CF_{Average}$):

$$CF_{Average} = C_O \times PF_O + C_C \times PF_C + C_B \times PF_B + C_A \times PF_A + C_K \times PF_K \qquad \text{Equation 4}$$

Where:
$CF_{Average}$ = average comprehensive crash cost for factored crashes (computed separately for deer and bear).
C_O = crash cost for PDO crashes.
PF_O = proportion of factored crashes resulting in PDO.
C_C = crash cost for C crashes.
PF_C = proportion of factored crashes resulting in a C injury.
C_B = crash cost for B crashes.
PF_B = proportion of factored crashes resulting in a B injury.
C_A = crash cost for A crashes.
PF_A = proportion of factored crashes resulting in an A injury.
C_K = crash cost for fatal crashes.
PF_K = proportion of factored crashes resulting in fatality.

These crash cost methodologies resulted in four crash cost values: an average deer crash cost (unfactored), an average bear crash cost (unfactored), an average factored deer crash cost, and an average factored bear crash cost. The Results section provides these costs.

Benefit-Cost Analysis and Benefit-Cost Ratio

Safety benefits are estimated by monetizing the reduction in wildlife crashes attributable to a proposed countermeasure and comparing those benefits to estimate costs during the countermeasure's service life. Annual predicted crashes for deer and bears, which can be obtained from the large animal road risk model and map, are multiplied by the deer or bear crash cost and adjusted using the expected crash reduction to estimate crash cost savings during the lifetime of the countermeasure. The use of annual crash costs, rather than 10-year crash totals, allows crash cost savings to be estimated on an annual basis and projected during the service life of the countermeasure.

The economic structure of the BCA follows standard BCA methods (e.g., calculating the net present value (NPV) and discounting the future benefits using a discount rate), and the inputs (e.g., predicted crash frequencies from the large animal road risk model and the assumed crash reduction from the countermeasure) reflect the application of these methods to large animal crash mitigation.

Crash reduction is often represented using a crash modification factor (CMF), which is the ratio of crashes expected after implementation of a countermeasure to the number of crashes expected without treatment. For example, a CMF of 0.20 corresponds to an 80% reduction in crashes, and a CMF of 0.50 corresponds to a 50% reduction. Large animal wildlife crossing studies from the United States and Canada were used to inform the selection of a wildlife crossing CMF for a BCA example presented in this report, as detailed in the following.

An example BCA was conducted for a Virginia road segment. The following section describes the general notation and calculation methods used in the analyses, and the Results section presents the resulting estimates for the Virginia road segments. The BCA approach requires four inputs: (1) crash frequency for the roadway segment, which can be obtained from the large animal road risk model; (2) an expected crash reduction, or CMF, for the countermeasure; (3) the service life of the countermeasure; and (4) the discount rate used in the economic calculations.

λ_d = factored annual predicted deer crashes on the evaluated segments (crashes/year).
λ_b = factored annual predicted bear crashes on the evaluated segments (crashes/year).
CF_d = benefit (average comprehensive factored cost per deer crash) (dollars/crash).
CF_b = benefit (average comprehensive factored cost per bear crash) (dollars/crash).
C_c = present-day cost of countermeasure construction and implementation.
C_m = annual cost of countermeasure maintenance per year.
CMF = crash modification factor for the countermeasure (unitless).
r = real discount rate (per year, expressed as a decimal).
n = service life of the countermeasure (years).

Crash Cost Reduction and Present Value of Benefits

The total crash costs expected in the absence of a countermeasure are calculated as the sum of deer and bear crash costs (Equation 5):

$$\text{Baseline Crash Cost} = \lambda_d \text{ x x } C_d + \lambda_b \text{ x x } C_b \qquad \text{Equation 5}$$

The countermeasure effectiveness is represented by (1 − CMF), which reflects the portion of crashes the countermeasure is expected to prevent.

The crash cost avoided each year is therefore given in Equation 6:

$$\text{Cost Reduction per Year} = (\lambda_d \text{ x } C_d + \lambda_b \text{ x } C_b) \text{ x } (1 - \text{CMF}) \qquad \text{Equation 6}$$

The present value of savings (or benefits) is then calculated during a uniform annual series to convert avoided crash costs during the service life of the countermeasure into a single Present Value of Benefits (Equation 7):

$$\text{PV Benefits} = (\lambda_d \text{ x } C_d + \lambda_b \text{ x } C_b) \text{ x } (1 - \text{CMF}) \text{ x } [\ (1 - (1 + r)^{-n}) / r\ ] \qquad \text{Equation 7}$$

Present Value of Countermeasure Costs

Similar to benefits, countermeasure costs are created by calculating the present value of countermeasure costs (Equation 8):

$$\text{PV Cost} = C_c + C_m \text{ x } [\ (1 - (1 + r)^{-n}) / r\ ] \qquad \text{Equation 8}$$

Net Present Value

The overall economic result of a proposed wildlife countermeasure can be summarized using NPV, shown in Equation 9, which represents the difference between the present value of safety benefits and the present value of countermeasure costs:

$$\text{NPV} = \text{PV Benefits} - \text{PV Costs} \qquad \text{Equation 9}$$

A positive NPV indicates that the monetized crash reduction benefits exceed the costs of the countermeasure during its service life, and a negative NPV indicates that costs exceed benefits.

BCR and Maximum Cost of a Countermeasure for BCR Greater than 1

The BCR for a proposed countermeasure is defined as the ratio of the present value of safety benefits to the present value project cost (Equation 10):

$$\text{BCR} = \text{PV Benefits} / \text{PV Cost} \qquad \text{Equation 10}$$

As mentioned previously, a BCR greater than or equal to 1.0 indicates that the monetized safety benefits are at least as large as the project cost during a countermeasure service life.

Because the costs of wildlife crash countermeasures can vary widely, this benefit-cost approach does not attempt to estimate countermeasure costs. Instead, it can be applied in two ways. If the countermeasure costs are known, the equations can be used to estimate the safety benefits and the resulting BCR. Alternatively, the equations can be rearranged to estimate the maximum construction cost at which benefits would equal or exceed costs (i.e., BCR $\geq$ 1). The calculator spreadsheet developed for this study was designed to support both applications by allowing users to either input known or estimated costs to calculate a BCR or determine the maximum project cost that would still yield benefits greater than costs.

RESULTS AND DISCUSSION

The research team reviewed available wildlife crash and mortality data sources in Virginia and evaluated their suitability for model development. Police-reported crash data were then compared with other sources to inform the use of correction factors for underreported crashes.

Review of Crash Data and Rationale for Deer and Bear Crash Correction Factors

Crash Data Overview

Table 4 summarizes the primary sources available for evaluating wildlife crash data and wildlife mortality data along Virginia roads. Table 4 highlights differences among data sources in terms of public availability, coverage, and location accuracy, which influence their suitability for planning-level screening, project-level evaluation, and safety analysis.

Table 4. Summary of Wildlife Crash and Mortality Data Sources in Virginia

Data Source	Description	Publicly Available	Statewide Coverage	Location Accuracy
Police Crash Records	Primary source for evaluating wildlife crashes, including official crash statistics used in VDOT safety analyses. Records are generated by law enforcement at the time of reported crashes.	Yes (deer) No (other animals)	Yes	High (recorded at crash site)
VDOT Work Orders	Maintenance records documenting activities, such as removal of animal carcasses from roadways. Entries are typically triggered by public reports or road maintenance staff observations and logged as maintenance tasks.	No	Yes	Variable or low
VDOT Wildlife Carcass Removal App	Mobile application used by maintenance contractors to record wildlife carcass removals. Currently used for a subset of Virginia interstates and primary roads.	Yes	No	High (recorded at site of removal)
Crowdsourced Wildlife Data	Wildlife observations submitted by the public or volunteer efforts (e.g., iNaturalist).	Varies	No	Variable

Data Source	Description	Publicly Available	Statewide Coverage	Location Accuracy
Insurance Claim Estimates	Statewide estimates of animal-vehicle collision claims published by insurance providers. Used to estimate overall crash frequency.	Yes	Yes	Locations not available

VDOT Work Orders represent a potentially useful data source. However, the data are not publicly available, and the mapped locations are typically based on information interpreted from phone calls or reports sent to the VDOT Customer Service Center. Previous research in Virginia has shown that logging wildlife carcass removals at the location of each removal provides the most accurate means of documenting wildlife mortality along roadways (Donaldson et al., 2021), which precipitated the development of the VDOT Wildlife Carcass Removal App (Virginia Roads, 2026). If application-based data are not available for the roadway segment of interest, carcass removal records can still be obtained at the project-specific level by requesting that maintenance personnel document removals at the site.

For statewide analyses, police-reported crash data remain the most commonly used source for roadway safety analyses because of their comprehensive coverage and high location accuracy and, therefore, served as the basis for model development. However, the subsequent section describes the extent to which this data source underrepresents actual wildlife crashes and reinforces the value of a predictive modeling approach.

Police-Reported Deer Avoidance Crashes

Although police-reported crash data are the basis for most road safety analyses, they do not fully capture large animal-related crashes. Many wildlife collisions are not reported to law enforcement, and animal avoidance events are typically excluded from standard evaluations of police report data.

Using 2024 as an example, 7,486 deer crashes and an additional 1,148 deer-involved deer-avoidance crashes occurred (Table 5). For these crashes, the police officers did not record "deer" as the collision type, and therefore, it was not flagged as an animal-related crash. These avoidance crashes could only be identified by reading restricted crash narratives.

Table 5. Descriptions of Deer Crash Data in Police Records

Deer Crash Description	Explanation	Total	Proportion that Results in Injury (%)
Collision type: Deer	Standard means of determining deer crashes in evaluations of police report data. Publicly available.	7,486	8.2
Deer Avoidance Crashes	Not used in standard evaluations of police report data. Requires access to restricted crash narrative sections.	1,148	26.0

Table 5 also lists the higher percentage of deer avoidance crashes that result in injury, determined by comparing the number of injuries from deer crashes, when "deer" was the collision type, to injuries from deer avoidance crashes from 2024. This difference in injury proportions is important because injury-related crashes are associated with substantially higher economic costs than crashes that result only in property damage. As an outcome, evaluations that rely on police-reported crash data alone result in conservative estimates of both deer-related crash volumes and associated crash costs. Although these cost implications were not applied in this study, they represent an important consideration for future safety and cost analyses.

Data Source Comparisons and Correction Factors to Account for Underreporting

According to State Farm's annual assessments of vehicle insurance claims, Virginia is consistently among the 10 states with the highest number of deer collision claims (Philips, 2026), and the most recent dataset (July 1, 2024, to June 30, 2025) indicates that Virginia drivers rank eighth in the nation for the number of animal collision claims. The review of deer-related crash data from insurance claims, police reports, and VDOT work orders for animal carcass removal provided important context for interpreting police-reported wildlife crash data. Figure 5 illustrates the differences among deer crash data sources that are available statewide.

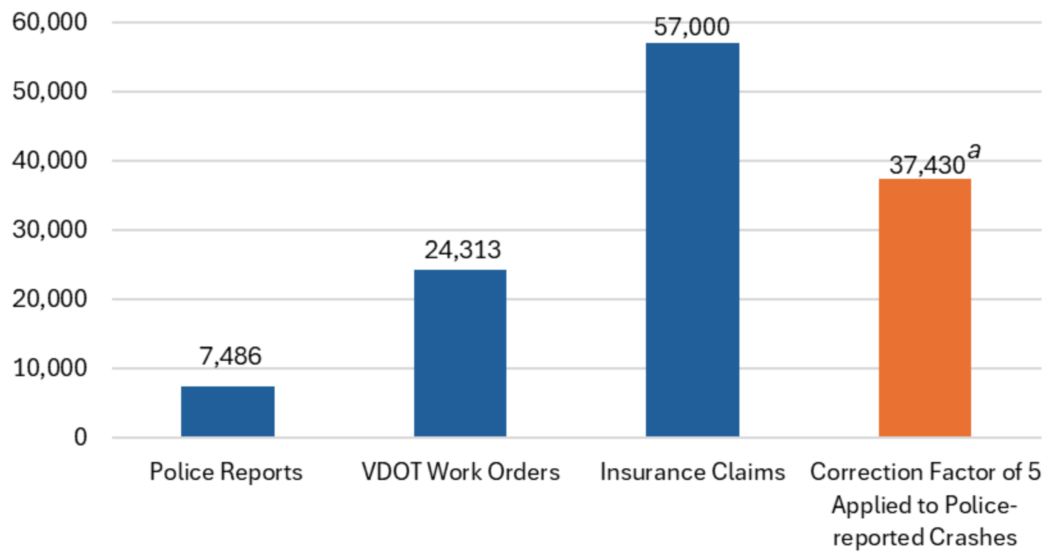

Figure 5. Comparison of 2024 Statewide Deer Crash Data, Including the Applied Correction Factor.
[a] Estimated deer crash volume after applying the previously established correction factor to account for unreported crashes.

Figure 5 also shows how applying a correction factor to police-reported deer crashes aligns with other data. Consistent with previous research findings, VDOT technical guidance for large animal crash countermeasures recommends applying a factor of 5 to police-reported deer crash counts to approximate the actual number of these crashes better (Donaldson, 2022). As Figure 6 shows, applying this factor to 2024 crash data yields an estimated crash total that falls between values derived from VDOT deer carcass removal work orders and insurance claim data. This comparison suggests that the factor of 5 adjustment represents a conservative estimate of deer-related crashes compared with insurance claims data.

Bear crash data from 2024 were also evaluated. Unlike deer crashes, which can be identified using publicly available, police-reported, collision-type data, bear crashes can only be identified by reviewing the restricted crash narrative section of police reports. As Figure 6 illustrates, the number of VDOT work orders for bear removal and insurance claims for bear-related vehicle crashes is approximately twice the number of bear crashes identified in police reports (Lafon, 2026). Therefore, applying a correction factor of 2 to police-reported bear crashes provides a reasonable estimate of actual crash frequency.

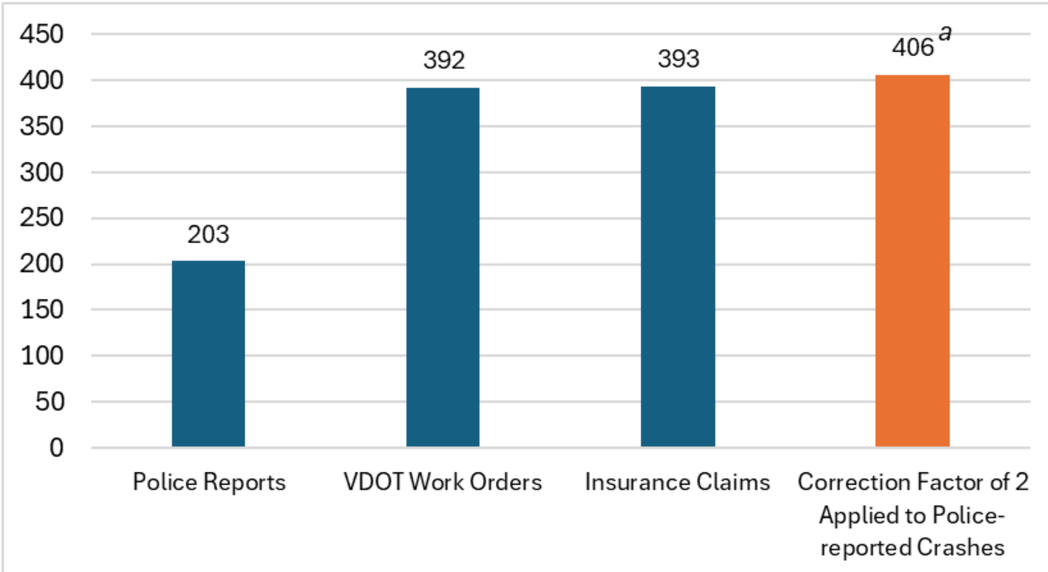

Figure 6. 2024 Bear-Related Crash Sources and Values in Virginia. [a] Estimated bear crashes after applying a correction factor of 2 to the number of bear-related crashes identified in the narratives of police reports.

Risk Analyses for Model Development

Several risk factors evaluated for model development were found to have a statistically significant effect on the likelihood of a bear or deer crash on a 0.5-mile segment. The results are presented separately for deer and bear.

White-Tailed Deer

Tables 6 to 8 provide the deer model results for the access-controlled freeway, non-freeway federal aid roads, and non-freeway non-federal aid roads.

Table 6. Deer/Access-Controlled Freeways [a]

Variable	Estimate	Std. Error	z-Value	p-Value
(Intercept)	– 4.257	1.024	– 4.159	< 0.001
Natural Log of Annual Average Daily Traffic	**0.260**	**0.083**	**3.116**	**0.002**
Deer Density Rating	**1.001**	**0.167**	**5.987**	**< 0.001**
Urban Area Flag	**0.8475**	**0.218**	**3.890**	**< 0.001**
Area of Forest Land Cover	0.2965	0.326	0.911	0.362
Area of Cultivated Land Cover	**1.322**	**0.394**	**3.355**	**< 0.001**
Area of Open-Uncultivated Land Cover	**– 2.926**	**1.164**	**– 2.514**	**0.012**
Grass Median Present	**0.9003**	**0.162**	**5.552**	**< 0.001**
Intersection Density	– 0.0023	0.002	– 1.500	0.134
Natural Land Use Mix	**1.730**	**0.334**	**5.184**	**< 0.001**
Hydro Crossing Count	0.1227	0.077	1.594	0.111
Median Presence*Median Width	**0.0089**	**0.002**	**4.420**	**< 0.001**

[a] Bold rows indicate statistically significant results ($p < 0.05$); number of observations = 2743; log likelihood = -1041.871; null deviance = 2580.8; residual deviance = 2083.7; McFadden's R-squared = 0.1926; Akaike information criterion = 2107.741.

Table 7. Deer/Non-Freeway, Federal Aid Roads [a]

Variable	Estimate	Std. Error	zValue	p-Value
(Intercept)	– 10.18	0.162	– 62.926	< 0.001
Natural Log of Annual Average Daily Traffic	**0.9836**	**0.015**	**65.517**	**< 0.001**
Deer Density Rating	**0.4522**	**0.050**	**9.040**	**< 0.001**
Human Population Density	**– 0.00008**	**< 0.001**	**– 7.026**	**< 0.001**
Urban Area Flag	**0.2381**	**0.052**	**4.558**	**< 0.001**
Area of Forest Land Cover	**1.380**	**0.075**	**18.445**	**< 0.001**
Area of Cultivated Land Cover	**1.634**	**0.078**	**20.959**	**< 0.001**
Area of Open-Uncultivated Land Cover	**– 0.8796**	**0.211**	**– 4.167**	**< 0.001**
Three or More Lanes Present	**0.1677**	**0.046**	**3.610**	**< 0.001**
Grass Median Present	**0.3714**	**0.059**	**6.328**	**< 0.001**
Median Barrier Present	**– 1.299**	**0.212**	**– 6.122**	**< 0.001**
Intersection Density	**– 0.0016**	**< 0.001**	**– 2.554**	**0.011**
Building Density	**– 0.0003**	**< 0.001**	**– 6.884**	**< 0.001**
Natural Land Use Mix	**1.256**	**0.069**	**18.220**	**< 0.001**
Hydro Crossing Count	**0.2165**	**0.018**	**11.936**	**< 0.001**

[a] Bold rows indicate statistically significant results ($p < 0.05$); number of observations = 38,778; log likelihood = -20801.95; null deviance = 52895; residual deviance = 41604; McFadden's R-squared = 0.2135; Akaike information criterion (AIC) = 41634.

Table 8. Deer/Non-Freeway, Non-Federal Aid Roads [a]

Variable	Estimate	Std. Error	z-Value	p-Value
(Intercept)	– 4.998	0.119	– 42.067	< 0.001
Deer Density Rating	**0.2267**	**0.072**	**3.131**	**0.002**
Human Population Density	– 0.000004	< 0.001	– 0.251	0.802
Urban Area Flag	0.0992	0.070	1.416	0.157
Area of Forest Land Cover	**0.9290**	**0.084**	**11.048**	**< 0.001**
Area of Cultivated Land Cover	**1.975**	**0.086**	**23.062**	**< 0.001**
Area of Open-Uncultivated Land Cover	**0.8460**	**0.205**	**4.125**	**< 0.001**
Intersection Density	0.0001	< 0.001	1.162	0.245
Building Density	**– 0.0003**	**< 0.001**	**– 5.528**	**< 0.001**
Natural Land Use Mix	**1.028**	**0.082**	**12.553**	**< 0.001**
Hydro Crossing Count	**0.1172**	**0.021**	**5.572**	**< 0.001**

[a] Bold rows indicate statistically significant results ($p < 0.05$); number of observations = 169,838; log likelihood = -21862.22; null deviance = 47870; residual deviance = 43724; McFadden's R-squared = 0.0866; Akaike information criterion (AIC) = 43746.

The research team observed the following results:

- Higher AADTs are associated with higher deer crash risk.
- Communities with a higher deer population density tend to be associated with higher deer crash risk.
- Urban areas have a higher deer crash risk. However, communities with a higher human population density, all other things being held constant, tend to have a lower deer crash risk. This trend is also present with the negative correlation associated with intersection density and building density (i.e., a greater density of buildings and intersections is

correlated with a lower crash risk), suggesting that more rural roads or roads in less developed urban areas might have the highest risk.

- Although forest land cover has a positive correlation with deer crash likelihood (i.e., a greater proportion of forest cover is associated with increased crash risk), it is a lower correlation than observed with bear crashes, as the subsequent section describes. Furthermore, the proportion of cultivated land cover (e.g., managed fields) has a stronger positive association with deer crash likelihood.
- Similarly, the natural land use mix, with a higher value associated with greater crash likelihood, corresponds with an increase in deer crash likelihood. This result indicates that a greater mix of natural land cover, a mix of forests and fields, is where deer crash risk is highest.
- A greater number of stream and river crossings is associated with an increase in deer crash likelihood.

The relationships found from this analysis are similar to findings reported in the deer crash literature. Studies indicate that higher traffic volumes increase crash risk, although the strength of this relationship can vary by road type and landscape (Gunson et al., 2011; Pagany, 2020). Research has also shown that areas with greater deer abundance often experience higher collision frequencies. However, measures for deer population density show inconsistent relationships with crashes depending on data sources (Found and Boyce, 2011; McShea et al., 2008). Literature also consistently reports that deer crashes are higher in suburban or semi-urban environments rather than dense urban areas, where higher building and intersection density and increased human activity can reduce deer movement and road crossings (Gunson et al., 2011; McShea et al., 2008). Landscape characteristics have similarly been shown to influence crash risk, with areas of mixed forest and field and other natural land use mixes associated with increased crash risk because of greater food availability and movement between habitat types (Finder et al., 1999; Found and Boyce, 2011; Snow et al., 2015). In addition, riparian corridors and stream crossings are widely recognized as important wildlife movement pathways, and road segments intersecting these features have been shown to have higher deer crash frequencies (Finder et al., 1999; Stern et al., 2023).

Black Bear

Tables 9 to 11 provide the bear model results for the access-controlled freeway, non-freeway federal aid roads, and non-freeway non-federal aid roads.

Table 9. Bear/Access-Controlled Freeways [a]

Variable	Estimate	Std. Error	z-Value	p-Value
(Intercept)	– 5.634	0.576	– 9.784	< 0.001
Bear Density Rating	**2.093**	**0.218**	**9.609**	**< 0.001**
Area of Forest Land Cover	**2.966**	**0.441**	**6.720**	**< 0.001**
Area of Cultivated Land Cover	0.5992	0.460	1.302	0.193
Area of Open-Uncultivated Land Cover	**– 3.376**	**1.338**	**– 2.523**	**0.012**
Intersection Density	**– 0.0089**	**0.004**	**– 1.996**	**0.046**
Natural Land Use Mix	**1.336**	**0.379**	**3.528**	**< 0.001**
Hydro Crossing Count	0.0564	0.086	0.658	0.511
Median Presence*Median Width	0.0047	0.003	1.789	0.074

[a] Bold rows indicate statistically significant results ($p < 0.05$); number of observations = 2767; log likelihood = -821.1563; null deviance = 2154.5; residual deviance = 1642.3; McFadden's R-squared = 0.2377; Akaike information criterion (AIC) = 1660.3.

Table 10. Bear/Non-Freeway, Federal Aid Roads [a]

Variable	Estimate	Std. Error	z-Value	p-Value
(Intercept)	– 10.444	0.535	– 27.008	< 0.001
Natural Log of Annual Average Daily Traffic	**0.9092**	**0.044**	**20.554**	**< 0.001**
Bear Density Rating	**1.560**	**0.102**	**15.259**	**< 0.001**
Human Population Density	– 0.00004	< 0.001	– 0.377	0.706
Area of Forest Land Cover	**2.70**	**0.317**	**8.532**	**< 0.001**
Area of Cultivated Land Cover	**1.227**	**0.316**	**3.885**	**< 0.001**
Area of Open-Uncultivated Land Cover	1.108	0.628	1.764	0.078
Three or More Lanes Present	**0.3712**	**0.094**	**3.968**	**< 0.001**
Intersection Density	– 0.0009	0.003	– 0.267	0.789
Building Density	**– 0.0014**	**< 0.001**	**– 4.855**	**< 0.001**
Natural Land Use Mix	**0.7855**	**0.195**	**4.028**	**< 0.001**
Hydro Crossing Count	**0.2156**	**0.043**	**4.994**	**< 0.001**

[a] Bold rows indicate statistically significant results ($p < 0.05$); number of observations = 38,833; log likelihood = -3577.129; null deviance = 8992.9; residual deviance = 7154.2; McFadden's R-squared = 0.2045; Akaike information criterion (AIC) = 7178.3.

Table 11. Bear/Non-Freeway, Non-Federal Aid Roads [a]

Variable	Estimate	Std. Error	z-Value	p-Value
(Intercept)	– 8.564	0.735	– 11.656	< 0.001
Bear Density Rating	**1.006**	**0.262**	**3.844**	**< 0.001**
Human Population Density	– 0.00002	< 0.001	– 0.096	0.924
Area of Forest Land Cover	**1.269**	**0.604**	**2.102**	**0.036**
Area of Cultivated Land Cover	1.011	0.605	1.670	0.095
Area of Open-Uncultivated Land Cover	0.1822	1.326	0.137	0.891
Intersection Density	– 0.0160	0.010	– 1.547	0.122
Building Density	– 0.0002	< 0.001	– 0.420	0.674
Natural Land Use Mix	0.3767	0.463	0.814	0.415
Hydro Crossing Count	0.1051	0.113	0.927	0.354

[a] Bold rows indicate statistically significant results ($p < 0.05$); number of observations = 169,838; log likelihood = -1013.753; null deviance = 2197.0; residual deviance = 2027.5; McFadden's R-squared = 0.0771; Akaike information criterion (AIC) = 2047.5.

The research team observed the following results:

- Higher AADTs are associated with higher bear crash risk on non-freeway roads, although this association is less relevant for freeways.
- Communities with a higher bear population density tend to be associated with higher bear crash risk.
- Like deer crashes, communities with a higher human population density, all other things being held constant, tend to have a lower bear crash risk. This trend is also present with the negative correlation associated with intersection density and building density (i.e., a greater density of buildings and intersections is correlated with a lower crash risk). However, urban areas did not have a strong correlation with increased bear crash risk, indicating that bear crashes tend to be more rural.

- Forest land cover has a stronger positive correlation with bear crash likelihood (i.e., a greater proportion of forest cover is associated with increased crash risk) than deer crash likelihood. In other words, forested land cover is a strong indicator of bear crash risk on a segment-level basis.

The relationships observed for bear crash risk in this analysis are generally consistent with patterns reported in the literature, particularly with respect to landscape context and development intensity. Prior research indicates that black bear movements and road crossings are strongly associated with forested habitats, and bear crashes are more likely on road segments adjacent to forest cover (Lewis et al., 2011; Zeller et al., 2020). Although stream crossings were associated only with increased bear crash risk on non-freeway federal aid roads in this analysis, prior studies indicate that black bears frequently travel along drainages and cross roads at streams and riparian corridors (Brandenburg, 1996; Gilbert and Wooding, 1996; McCowen et al., 2004). This finding suggests that bear crash risk is particularly elevated at stream crossings where roadway design and traffic conditions remain permeable to bear movement.

The literature also suggests that bear crashes tend to occur more frequently in rural or suburban areas than in urban areas, where higher building density, intersection density, and human activity can limit bear presence and movement (van Manen, 2023; Zeller et al., 2020). With respect to traffic volume, research shows that increasing traffic can act as a movement barrier for bears, particularly on high-volume freeways, whereas crashes are more likely to occur on less trafficked or non-freeway roads. Therefore, AADT can influence crash risk differently by road type (van Manen et al., 2012; Zeller et al., 2020). That finding is reflected in the findings from this study's bear crash risk analysis, in which the relationship between AADTs and bear crash risk was stronger on non-freeway roads. Finally, the literature indicates that indirect measures of bear population density, such as VDWR's harvest-based population reconstruction estimates per square mile of suitable habitat, show variable relationships with crash occurrence, underscoring the importance of using landscape and movement-based predictors rather than population metrics alone when screening for bear crash risk (Gantchoff and Belant, 2017).

Mapping Predicted Deer and Bear Crash Risk Values

Using the risk analysis results, risk score values were generated for both deer and bear crash risk for all road segments in Virginia. As Figure 7 illustrates, road segments were assigned a risk score between 0 and 1 based on the degree to which risk factors (e.g. road variables, landcover, etc.) were associated with deer and bear crashes. Higher values correspond to higher probability of a deer or bear crash. As Figure 7 illustrates, interactive map features allow users to select individual road segments to view associated crash metrics; the displayed information can be customized. For example, for the selected 0.5-mile segment, the model estimates a 94.4% probability of at least one deer crash occurring during a 10-year period, which corresponds to an expected police-reported crash frequency of 2.88 deer crashes. Applying the underreporting correction factor of 5 results in an estimated 14.4 factored deer crashes during 10 years, or 1.44 crashes per year on the 0.5-mile segment.

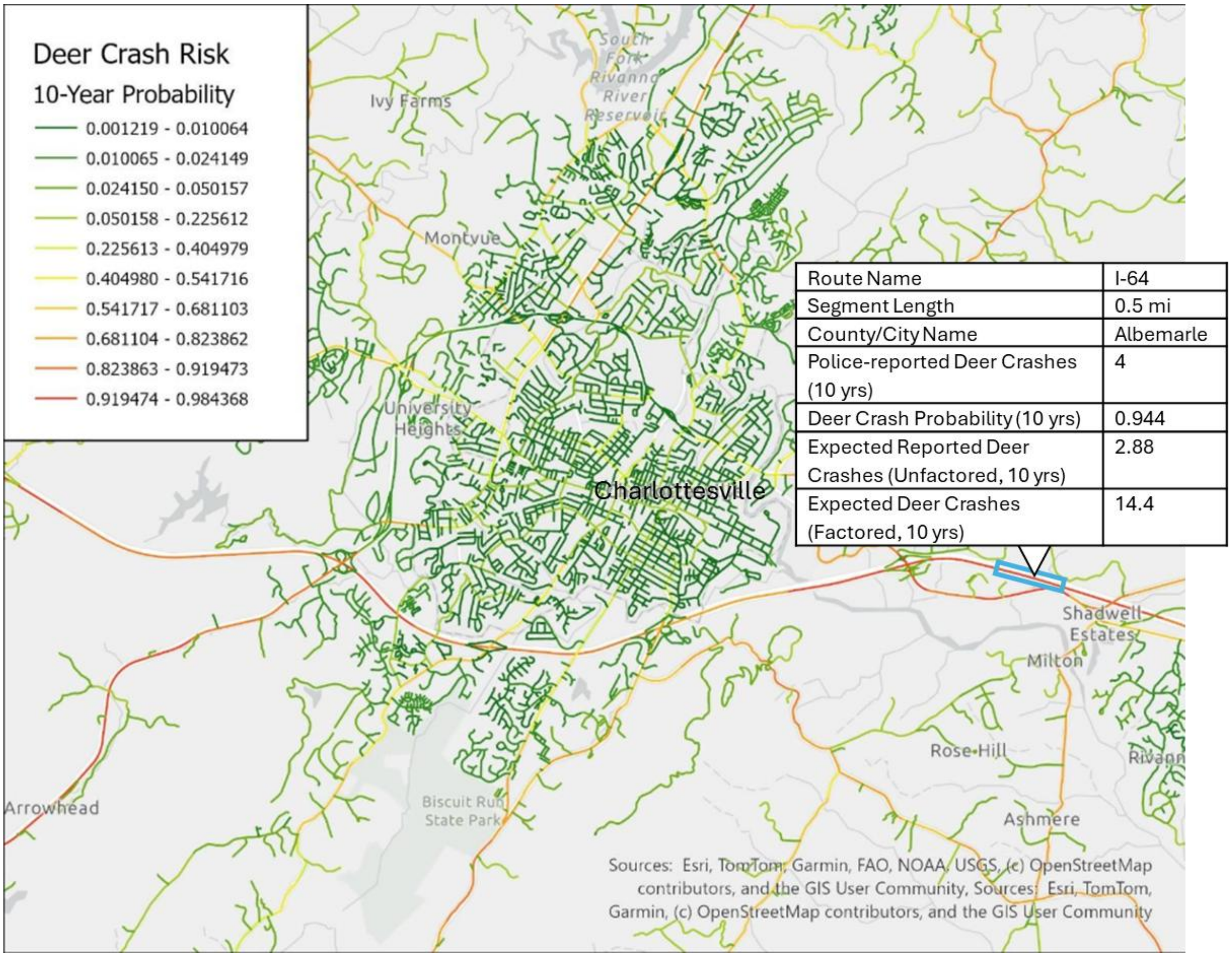

Figure 7. Example Output from the Deer Crash Risk Model and Metrics Displayed for a 0.5-Mile Segment

As the Methods section describes, the research team developed separate deer and bear analyses for the probability of a crash (see the Risk Analysis Methodology section), as well as a methodology for translating crash probabilities into predicted crashes (see the Converting Crash Probability to Expected Crash Frequency section) and an associated cost of those predicted crashes (see the Benefit-Cost Analyses section). In addition to the separate deer and bear analyses, the research team combined the deer and bear analyses to provide an additional display option. In coordination with the study's technical review panel, the research team determined that highlighting the highest risk roadway segments (e.g., a selected top percentage such as 0.5%) is an effective approach.

The risk analysis displays include:

- The top 0.5% highest risk road segments for deer crashes.
- The top 0.5% highest risk road segments for bear crashes.
- The top 0.5% highest risk road segments for combined deer and bear crashes.

Figure 8 illustrates the top 0.5% of segments for combined deer and bear crashes. Unlike the separate deer and bear analyses and their associated top 0.5% segments, the combined deer and bear analysis was created by incorporating the average deer and bear crash costs (see the Average Unit Crash Costs for Deer and Bear Crashes section). This approach accounts for differences in crash severity between species. Although deer crashes occur more frequently, bear crashes tend to have substantially higher average costs, as detailed in a subsequent section. Therefore, ranking road segments based on combined expected crash cost reflects both the likelihood and severity of crashes, providing a more representative indicator of combined deer and bear crash risk than crash frequency alone. For this analysis, the predicted number of crashes on each road segment for each species was multiplied by the corresponding average cost per crash for that species. The resulting deer and bear crash costs were then summed to estimate the combined expected crash cost for each segment. Road segments were ranked statewide based on this combined expected crash cost, and the highest ranking 0.5% of segments were identified for mapping.

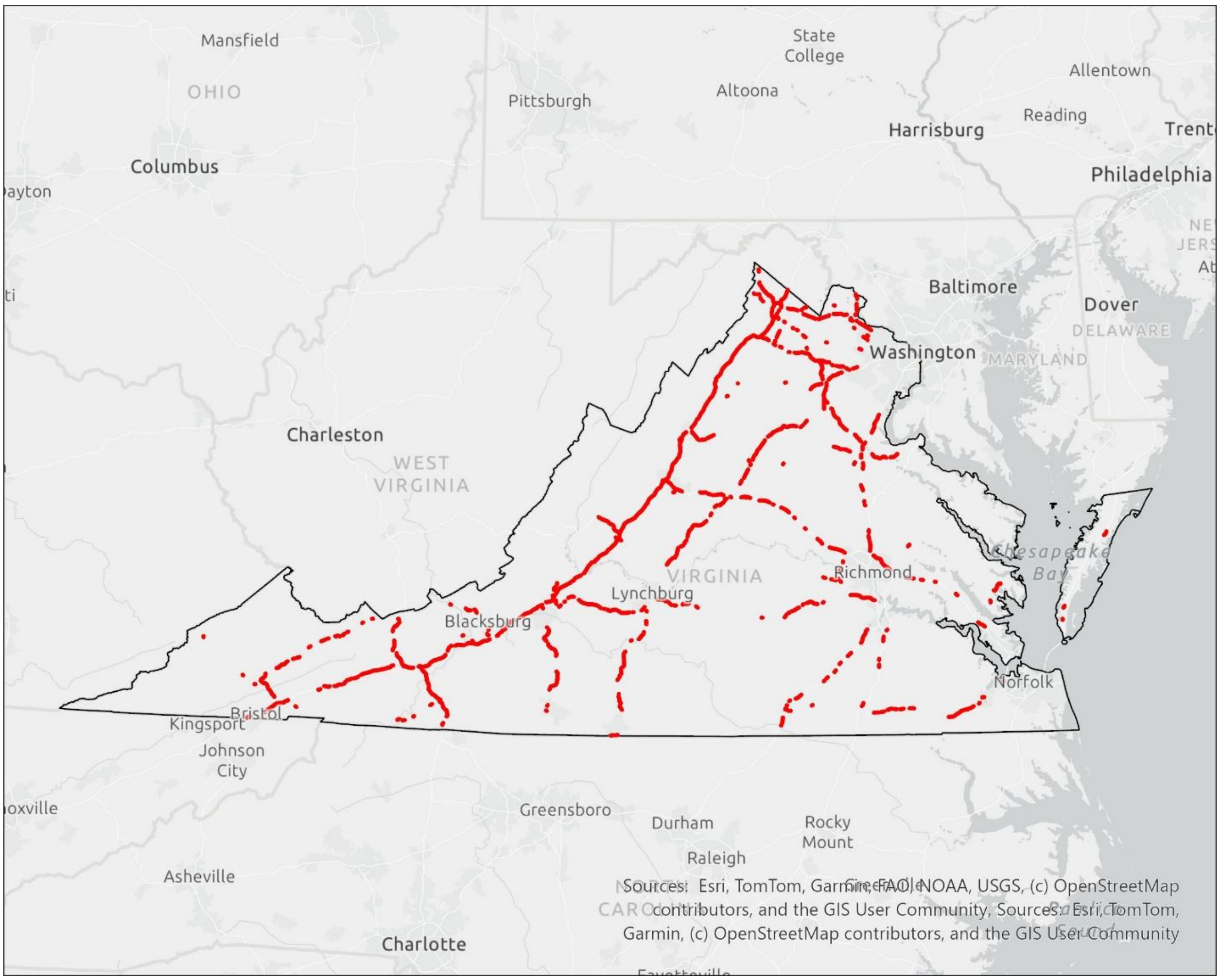

Figure 8. Example Top 0.5% of High-Risk Segments Based on Combined Deer and Bear Crash Risk

The data produced by the research team can be mapped to flexibly display results to support WCAP and VDOT applications. For instance, segments can be ranked by specific geography (e.g., VDOT district, county, or city) or by facility type (e.g., freeway or non-freeway), and these adjustments can be made as implementation efforts advance.

Model Performance

Concentration of Deer and Bear Crashes on High-Risk Segments

As part of the risk analysis evaluation, the research team assessed the proportion of total deer and bear crashes covered by the highest risk road segments (i.e., segments with probability values closer to 1). If risk were evenly distributed across the roadway network, the share of crashes occurring on high-risk segments would be similar to the share of total roadway mileage they represent. Instead, the results show that crashes are disproportionately concentrated within a small subset of roadway segments identified by the model, indicating that the model efficiently targets locations where crash risk is highest. As Table 12 shows, the top 1.4% of roadway mileage ranked as highest risk for deer crashes accounted for nearly 20% of all reported deer crashes in Virginia between 2014 and 2023.

Table 12. Crash Coverage for High Deer Crash Risk Segments [a]

	High Risk Segments	Statewide Segments	Percent
Mileage	**1,324**	**96,398**	**1.4%**
Freeway	623	1,572	39.6%
Non-Freeway	701	94,826	0.7%
Number of Segments	**2,653**	**332,695**	**0.8%**
Freeway	1,251	3,178	39.4%
Non-Freeway	1,402	329,517	0.4%
Total Crashes	**11,158**	**58,298**	**19.1%**
Freeway	5,582	9,990	55.9%
Non-Freeway	5,576	48,308	11.5%
Injury Crashes	**767**	**4,643**	**16.5%**
Freeway	370	719	51.5%
Non-Freeway	397	3,924	10.1%
Fatal Crashes	**2**	**18**	**11.1%**
Freeway	1	3	33.3%
Non-Freeway	1	15	6.7%

[a] All facility types included; segments with a crash likelihood of 0.9 and higher.

Similarly, Table 13 shows that the top 1.7% of high-risk mileage for bear crashes in Virginia accounted for nearly 50% of total bear crashes between 2014 and 2023.

Table 13. Crash Coverage for High Bear Crash Risk Segments [a]

	High Risk Segments	Statewide Segments	Percent
Mileage	1,642	96,398	1.7%
Freeway	603	1,572	38.4%
Non-Freeway	1,039	94,826	1.1%
Number of Segments	3,315	332,695	1.0%
Freeway	1,211	3,178	38.1%
Non-Freeway	2,104	329,517	0.6%
Total Crashes	914	1,851	49.4%
Freeway	448	543	82.5%
Non-Freeway	466	1,308	35.6%
Injury Crashes	94	235	40.0%
Freeway	48	60	80.0%
Non-Freeway	46	175	26.3%
Fatal Crashes	1	3	33.3%

	High Risk Segments	Statewide Segments	Percent
Freeway	1	1	100.0%
Non-Freeway	0	2	0.0%

[a] All facility types included; segments with a crash likelihood of 0.1 and higher.

Validation Using Post-Model Crash Data

The second evaluation of model performance included assessing the distribution of future crashes, using the 2024 crash dataset, on high-risk segments. This assessment indicated that the 2024 crashes occurring after model development were disproportionately concentrated within roadway segments identified as highest risk. As Figure 9 shows, the top 3% of roadway segments ranked by predicted risk accounted for approximately 30% of all police-reported deer crashes and 50% of all police-reported bear crashes in 2024. This concentration of post-model crashes within a small subset of high-risk segments suggests that the risk analysis effectively prioritizes locations with a high likelihood of future deer- and bear-vehicle crashes.

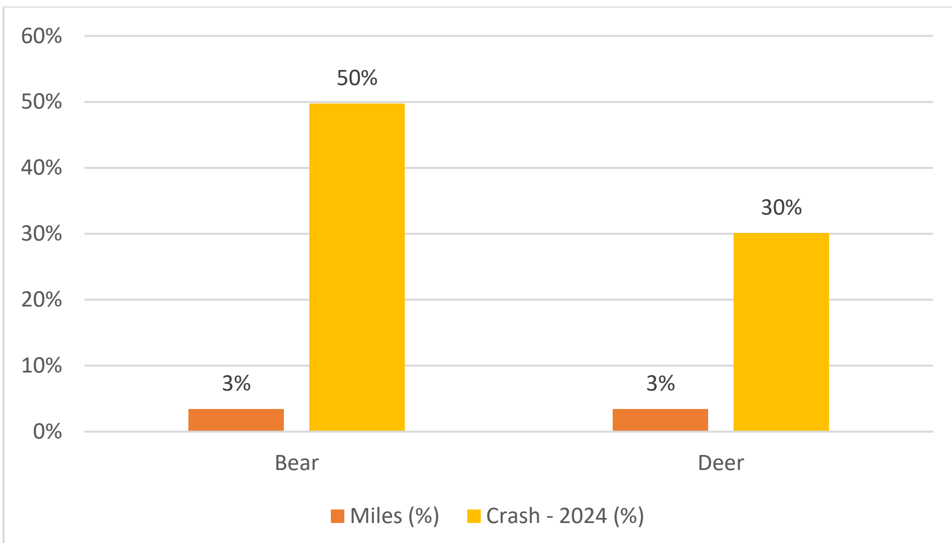

Figure 9. Comparison of 2024 Police-Reported Deer and Bear Crashes, Occurring After Model Development, on High-Risk Segments

Comparison of High-Risk Segments with Previous WCAP (2023) and Implications for Model Application

The research team assessed the performance of the risk models with the performance of the original 2023 WCAP, which was strictly based on police-reported crashes. For the analysis, the research team used the Areas of High Wildlife-Vehicle Conflict Occurrences layer illustrated in Figure 4-1 of the 2023 WCAP. Figure 10 shows the crash coverage of the highest risk deer segments from this study's model and risk analysis (i.e., how many crashes occurred on high-risk segments) compared with the crash coverage of the 2023 Areas of High Wildlife-Vehicle Conflict Occurrences layer (i.e., how many crashes occurred on high conflict road segments). With respect to deer crashes, the risk analysis performs similarly to the original Areas of High Wildlife-Vehicle Conflict Occurrences; roughly 1% of miles account for roughly 20% of 2014–2023 deer crashes.

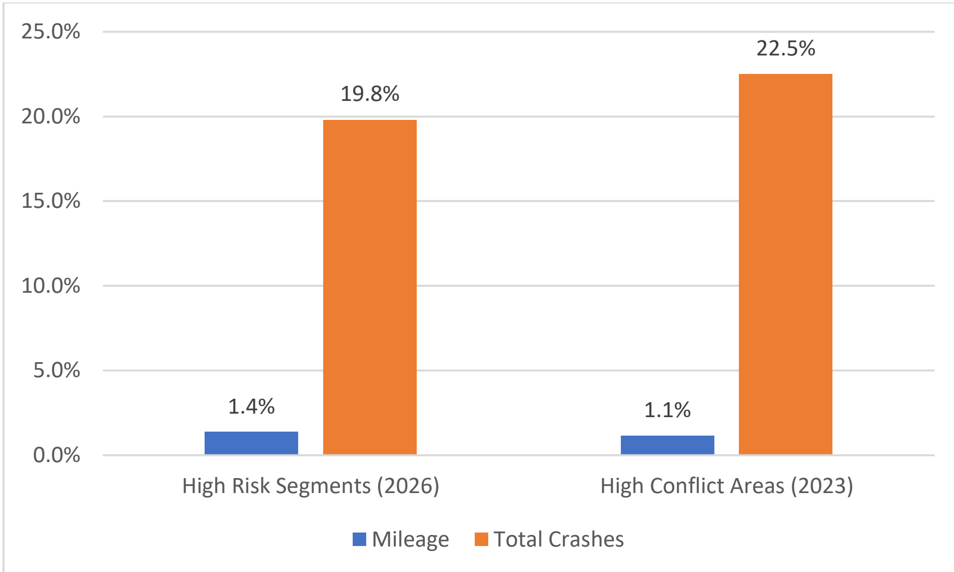

Figure 10. Comparison of Deer Crash Coverage (2014–2023) Between High-Risk Segments and High-Conflict Areas

With respect to bear crashes, the risk analysis performs much more efficiently compared with the original WCAP's Areas of High Wildlife-Vehicle Conflict Occurrences (Figure 11). In the risk analysis, the top 1.7% high-risk segments accounted for nearly one-half of all bear crashes between 2014 and 2023. A similar number of segments in 2023 WCAP conflict areas accounted for less than 25% of crashes during the same period. The high-risk segments in this analysis (2026) are a very targeted approach, prioritizing segments for reducing the risk of bear crashes.

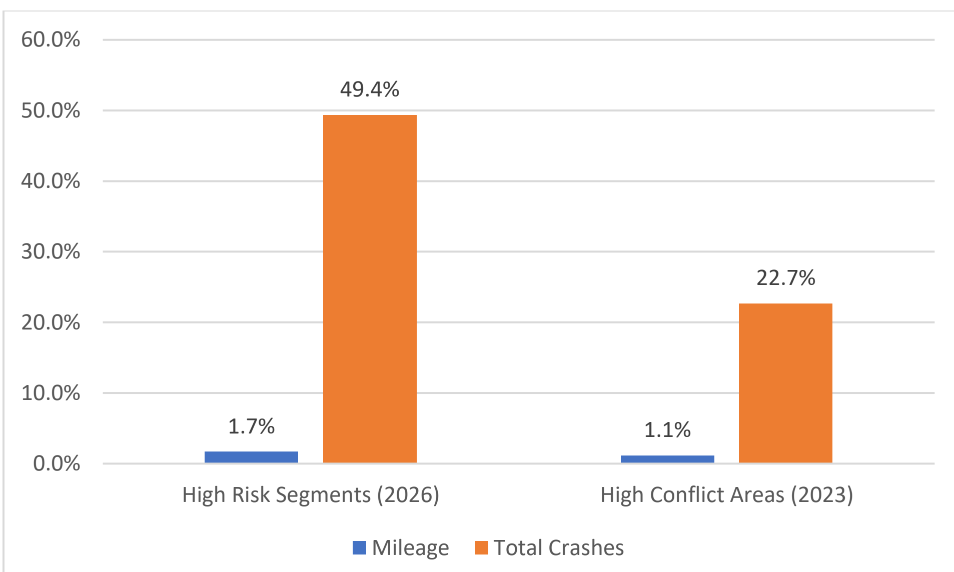

Figure 11. Comparison of Bear Crash Coverage (2014–2023) Between High-Risk Segments and High-Conflict Areas

Interestingly, the high-risk segments and the original Areas of High Wildlife-Vehicle Conflict Occurrences seem to be very complementary; one accounts for historic crash frequency, and the other considers characteristics associated with the risk of a crash occurring. The combination of high-risk segments and conflict area segments was also evaluated and was very effective at capturing potential risk for deer crashes. When segments having a high predicted crash likelihood are combined with the WCAP's (2023) segments identified as conflict areas (based on police-reported data), a larger share of reported deer-vehicle crashes is captured. Together, these segments make up about 2,400 miles of road (only about 2.5% of the network), but they accounted for approximately 42% of all reported deer crashes from 2014 to 2023. Where both methods agree (overlap) accounted for 300 miles of road (approximately 0.3% of the network) but nearly 10% of all deer crashes.

Given these findings, the following are two effective approaches for targeting roadway segments for deer-related safety improvements:

1. Segments classified as high risk based on this study's crash risk model.
2. Segments within this study's high-risk segments that *also* have at least one to two reported deer crashes per mile per year, consistent with the WCAP's (2023) thresholds for the top 5% and top 1% of deer crash segments, respectively.

Benefit-Cost Analyses

Crash Costs

Table 14 shows both police-reported crash costs and factored crash costs. Practitioners conducting a BCA using the "factored" deer or bear crashes from the large animal road risk model should apply the corresponding factored crash cost values from Table 14. When analyses are based on police-reported crash counts, the "Reported" crash cost values should be used.

Table 14. Virginia-specific Average Costs for Deer and Bear Crashes

	Deer—Reported	Deer—Factored [a]	Bear—Reported	Bear—Factored [a]
Total Cost	$48,157.11	$23,759.43	$90,212.25	$56,169.04

[a] Factored costs reflect the inclusion of underreported, likely less severe crashes, which increases crash counts and reduces the average cost per crash.

As Table 14 shows, factored crash costs are lower because the additional crashes introduced through the correction factors (a factor of 5 for deer and 2 for bears) are assumed to be PDO crash types, which carry substantially lower costs than injury crashes. However, although the average cost per crash is lower, the total number of crashes represented by the factored estimates is substantially higher on a statewide scale.

Case Study of a Benefit-Cost Application of the Large Animal Road Risk Model

Overview

This case study illustrates how the large animal road risk model can be applied as a planning-level screening and prioritization tool, and how its factored deer and bear crash outputs can serve as a starting point for BCA and BCR calculations. The example also demonstrates how site-specific data can refine and strengthen BCAs at the project level.

A 1-mile segment of Interstate 64 (I-64) in Virginia was evaluated using three different sources of crash data:

1. Police-reported deer and bear crashes, representing the most commonly available planning-level data.
2. Expected (predicted) crash frequencies from the large animal road risk model.
3. Observed carcass removal data collected as part of a site-specific evaluation following installation of wildlife fencing.

Comparing results across these three approaches illustrates how crash frequency estimates influence monetized safety benefits and BCRs.

Study Site and Safety Improvement

A study conducted in 2020 on I-64 west in Charlottesville, Virginia, evaluated the effectiveness of enhancing two underpasses with wildlife fencing. Approximately 1 mile of 8-foot-high wildlife fencing was installed at each site, a bridge spanning a river and a large box culvert (Donaldson et al., 2021; Figure 12). The sites were selected based on three primary characteristics associated with suitable locations for wildlife fencing: a high frequency of deer crashes; the presence of existing underpasses with documented deer and bear use; and an approximate 1-mile road segment with the underpass at its center that is uninterrupted by intersecting roads or driveways.

Figure 12. Study Sites on Interstate 64 Where Existing Underpasses Were Enhanced with 1 Mile of Wildlife Fencing (Donaldson et al., 2021)

Carcass removal records were obtained from the highway maintenance contractor, and the study compared 2 to 3 years of data before fencing installation with 2 to 3 years of data after installation to assess changes in crash frequency. Post-installation monitoring indicated 88% and 96.5% reductions in deer crashes at the bridge underpass and the box culvert sites, respectively, and up to a 410% increase in deer using the underpasses.

Average annual fencing maintenance costs were obtained from the VDOT maintenance manager. Because the fencing at this site is installed along a high-speed interstate, where vehicles departing the travel lane are less able to stop before striking the fence, and along a tree line where falling branches are more likely to cause damage, maintenance costs at this site may be relatively high compared with other locations.

Benefit-Cost Analysis Approach

BCAs were conducted for a 1-mile road segment at the bridge underpass site. The same assumptions were applied consistently across all analyses:

- Countermeasure: wildlife fencing added to an existing underpass.
- Construction cost: $450,000.
- Annual fencing maintenance cost: $16,509.
- Discount rate: 0.05.
- Service life: 25 years.

Deer and bear crash costs were monetized using values presented previously (Table 14). For the police-reported analysis, unfactored crash costs were applied, reflecting the lower reported crash counts. For the model-based and site-specific analyses, predicted factored crash costs were applied to reflect underreporting and observed conditions.

For the planning-level analyses (police-reported and model-based), an assumed 80% crash reduction was applied, corresponding to a CMF of 0.20. This value reflects conservative estimates supported by the literature (Appendix D). For the site-specific analysis, the observed 88% crash reduction from the post-installation study was applied (CMF = 0.12).

Calculations and Benefit-Cost Analysis Results

For each scenario, the following steps were applied to the BCA:

1. Estimate annual deer and bear crashes per mile from the selected data source.
2. Apply the crash reduction percentage to estimate the number of crashes avoided annually as a result of the fencing enhancement.
3. Monetize the crashes avoided using appropriate crash cost values.
4. Calculate the benefits during the project life and compare them with total project costs.
5. Calculate the maximum justified construction cost, the cost at which BCR = 1.
6. Calculate the BCR using the assumed project cost of $450,000.

Table 15 lists the input values and results.

Table 15. Input Values and Results for the Benefit-Cost Analyses Using Crash Data at a 1-Mile Segment on Interstate 64

Category	Planning Level [a]		Project Level [a]
	Police Reported Data	Large Animal Road Risk Model	Carcass Removal Data/ Site-specific Study
Crash Inputs			
Average deer crash (mi/yr)	1.0 (reported pre-fencing)	2.5 (expected)	8.5 (observed, pre-fencing)
Average bear crash (mi/yr)	0	0.1	0
Crash Reduction	80% (CMF = 0.20)	80% (CMF = 0.20)	88% (CMF = 0.12)
Annual Crashes Avoided (Calculated)	0.8	2.1	7.48
Economic Assumptions			
Wildlife Fencing Cost	$450,000	$450,000	$450,000
Annual Maintenance Cost	$16,509	$16,509	$16,509
Discount Rate	0.05	0.05	0.05
Benefit-Cost Analysis Results			
Present Value of Benefits (also the Maximum Justified Cost) [b]	$542,978	$733,060	$2,277,076
Present Value of Net Benefits (benefits – cost) [c]	– $139,699	$50,383	$1,594,399
Benefit-Cost Ratio	0.80 (BCR < 1)	1.1 (BCR > 1)	3.3 (BCR > 1)

BCR = benefit-cost ratio. CMF = crash modification factor. [a] Planning-level analyses are based on police-reported or model-predicted crash data, whereas project-level analyses use site-specific observed data. [b] The maximum justified cost is the highest cost at which the benefits equal the costs (BCR = 1). [c] Present value of net benefits represents the cost savings associated with adding a $450,000 wildlife fencing to an existing underpass.

Implications

As Table 15 shows, the BCA based on police-reported crash data substantially underestimates crash frequency and associated safety benefits, resulting in a BCR below 1.0 and net costs exceeding benefits by nearly $140,000. In contrast, the model-based analysis incorporates factored deer and bear crash predictions, better reflecting underlying risk conditions and producing a positive BCR of 1.1. Under this approach, wildlife fencing results in an estimated net benefit of approximately $50,383 and a maximum justified construction cost of approximately $733,000.

The site-specific analysis based on carcass removal records indicates substantially higher crash frequency and greater observed effectiveness of the countermeasure, resulting in an estimated net benefit of approximately $1.6 million and a BCR of 3.3.

The large animal road risk model correctly flagged this roadway segment as a high-risk location, reinforcing its value as a screening and prioritization tool and supporting earlier findings from the model performance evaluation. Although the model's use of a uniform statewide correction factor of 5 (for deer crashes) provides a consistent and defensible planning-level approach, it may result in conservative estimates in areas with highly localized crash hotspots. Once high-risk locations are identified, incorporating site-specific data, particularly carcass removal records, can substantially improve benefit estimates and strengthen project-level BCAs.

Programmatic Application of the Large Animal Road Risk Model

To illustrate the potential programmatic benefits of applying this approach more broadly, the net safety benefits of $1.6 million observed at the I-64 site can be scaled to a set of comparable high-risk locations. Using the large animal road risk model to identify sites for wildlife fencing enhancements at 10 high-risk roadway segments, the cumulative safety benefits from fencing implementation at those sites would be approximately $16 million.

This simplified example assumes each site experiences similar crash frequencies and that the same countermeasure (wildlife fencing integrated with an existing underpass) achieves a similar crash reduction after installation. Under these conditions, implementing one comparable project per year for 10 years would yield cumulative safety benefits of approximately $16 million in present-value dollars.

For WCAP project prioritization efforts, the large animal road risk model can similarly be used as one of the inputs for screening and prioritizing corridors where wildlife crossing and fencing projects are most likely to address both habitat connectivity needs and elevated crash risk. This process creates a consistent framework for identifying projects that provide driver safety benefits while supporting WCAP implementation.

Considerations for Integration

As described previously, the road risk model was developed to use both as an input to WCAP prioritization efforts and as a tool to support VDOT safety evaluations. For the latter application, the anticipated release of the next WCAP update may influence implementation timing. During the period leading up to completion of the WCAP update, opportunities could occur in the background to explore how the model will be incorporated into VDOT safety applications.

Effective application of new analytical tools typically involves a period of internal familiarization and workflow development. During the transition from research completion to operational use, divisions may need time to review model assumptions and outputs; explore how risk layers are displayed within existing geographic information system (GIS) platforms; evaluate how results could potentially be incorporated into safety screening, scoping, or BCAs; and consider where model outputs might fit within existing project development or programming processes. Activities during this period could include staff reviewing model outputs, testing GIS display formats, evaluating how the model could interface with safety screening, and conducting initial discussions with relevant divisions to better understand how the model might be incorporated into existing processes. Early coordination can help ensure that divisions are familiar with the model’s capabilities and potential applications within existing safety evaluation frameworks.

CONCLUSIONS

- *Limitations of publicly available deer and bear crash data reinforce the value of the predictive modeling approach over reliance on police records alone*. Police-reported crash data undercounted deer-related crashes by approximately 16% in 2024 by excluding crashes that result from avoiding an animal, most of which are attributed to fixed-object, off-road crashes and are associated with higher injury rates and higher costs. Comparing VDOT deer carcass removal work orders and insurance claim data with police-reported crashes shows that multiplying the number of police-reported crashes by 5 within a road segment of interest produces more appropriate, although conservative, estimates of actual deer-related crash volumes. A similar comparison with available bear crash data suggests that applying a lower correction factor of approximately 2 to police-reported bear crashes within a road segment of interest is appropriate for bear crashes.

- *The crash risk model developed in this study demonstrated that a predictive, risk-based approach can effectively identify roadway segments in Virginia with elevated deer- and bear-vehicle crash risk*. The map allows flexibility in how results are displayed to support WCAP and VDOT applications, and segments can be ranked across both large mammal species (i.e., deer and bear) or for individual species and across different jurisdictions (e.g., statewide, VDOT district, county, or other geography).

- *Many factors associated with a higher risk of large mammal crashes in Virginia are consistent with those identified elsewhere*: higher traffic volumes, mix of forest and open-field land uses, high number of stream crossings, suburban development or other urban and rural transition areas (for deer crashes only), and rural areas (for bear crashes only).

- *Evaluations of the predictive model performance indicated that (1) the model efficiently identifies a small proportion of Virginia's roadway network that accounts for a disproportionately large share of deer- and bear-related crashes and (2) the model is able to identify high-risk segments for future years*. The model was built using only 2014-to-2023 data. With the 2024 (future) dataset, the model showed that 2% of the highest risk roadway segments accounted for nearly one-third of all police-reported deer crashes and one-half of all police-reported bear crashes. This concentration of risk supports the model's usefulness for planning safety improvements, WCAP prioritization of roadway segments for countermeasures, and further site-specific evaluation.

- *Based on evaluation of the crash risk models, safety improvements for deer crashes may be prioritized on roadway segments that are either (1) identified as high risk based on this study's risk model or (2) located within a high-risk segment and have at least one reported deer crash per mile per year, consistent with WCAP's (2023) thresholds for the top 5% of high conflict segments, respectively*. For bears, safety improvements may be prioritized on roadway segments identified as high risk based on this study's bear crash risk model.

- *A BCA framework was developed to estimate the safety benefits of reducing deer and bear crashes and to compare those benefits with the costs of a potential countermeasure*. Average factored deer and bear crash costs were estimated at \$23,759.43 and \$56,169.04, respectively.

These values correspond to the application of correction factors of 5 for deer and 2 for bear to account for underreported crash frequency and, when used, produce a BCA that more closely aligns with actual crash frequencies. The BCA equations were implemented in a spreadsheet to facilitate consistent application of the methodology when evaluating potential wildlife crash safety improvements.

- *The large animal road risk model provides an effective screening and prioritization tool for planning-level decisions related to large-animal crash safety improvements and for screening in WCAP prioritization efforts.* In a case study, the model independently identified a high-risk deer crash location that coincided with a wildlife crossing and fencing site, allowing a comparison of model-based BCA results with project-level BCA results with benefits of approximately $1.6 million.

RECOMMENDATIONS

1. *VDOT should provide the deer and bear road risk model and accompanying report to the team developing the next version of the WCAP for use in wildlife crossing project prioritization.*

2. *VDOT should incorporate the study findings and deliverables into its safety evaluation and reporting practices to support roadway risk assessment and cost-benefit analyses.*

IMPLEMENTATION AND BENEFITS

The researcher and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and determine the benefits of doing so. This process is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

Regarding Recommendation 1, the road risk model has been shared with the team developing the next version of the WCAP, and the final report will be shared within 1 week of its publication.

Regarding Recommendation 2, within a year of study completion, the Traffic Operations Division will coordinate the integration of wildlife vehicle crash reduction strategies into the *2027–2031 Strategic Highway Safety Plan*. Because some wildlife crash countermeasures are not low-cost systemic initiatives—which is the focus of the Commonwealth Transportation Board—and instead are site- or corridor-specific, appropriate treatments will be promoted and considered for Highway Safety Improvement Program projects.

Following 6 months of VDWR's publication of the next WCAP update, which will include a wildlife crossing prioritization framework and crossing projects, the Traffic Operations Division and the Environmental Division will publish and promote large mammal crash-related analysis tools, risk prediction mapping, a dashboard for tracking outcomes, and information on related countermeasures. The Traffic Operations Division and the Environmental Division will collaborate with the affected divisions and process workflows to determine the appropriate application of large mammal crash-reduction treatments into VDOT's project planning and programming process.

Benefits

The benefits of implementing Recommendation 1 are to support VDOT's role in the collaborative development of the updated WCAP by addressing data gaps in police-reported crash records and enabling consistent screening and prioritization of road segments where wildlife crossings can improve both driver safety and habitat connectivity.

The benefits of implementing Recommendation 2 are to provide a means of implementing the Safe System Approach for large animal crash risk by identifying areas of elevated crash risk early in project development, which will help with selecting locations for safety investments where they will provide the greatest safety and cost benefits.

Using a simplified, example planning-level application of the large animal road risk model to identify a high-risk road segment, adding 1 mile of wildlife fencing to an existing large underpass along a suitable road segment (i.e., with no intersecting roads or driveways) can substantially reduce crashes, as the case study example in this report illustrates. Implementing one project per year at high-risk locations could yield cumulative safety benefits of approximately $16 million during 10 years.

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APPENDIX A

Table A1. Datasets Used in Road Risk Model Development

Source	Name	Description
VDOT	Master Routes	Statewide spatial inventory of roadway centerlines in Virginia used as the basis for analysis basemap generation and segmentation (Linear Referencing System [LRS] version 24.1).
VDOT	Lanes	Statewide spatial dataset of lane counts on roads in Virginia (LRS version 24.1).
VDOT	Traffic Volume	Statewide spatial dataset of traffic volume as average daily traffic on roads in Virginia (LRS version 24.1).
VDOT	Speed Limit	Statewide spatial dataset of posted speed limit on roads in Virginia (LRS version 24.1).
VDOT	Functional Classification	Statewide spatial dataset of functional classification of roads in Virginia (LRS version 24.1).
VDOT	Route Responsibility	Statewide spatial dataset of ownership and maintenance of roads in Virginia (LRS version 24.1).
VDOT	Travelway	General statewide spatial dataset of roadways and associated characteristics in Virginia, specifically used for access control designation and median information (e.g., presence, type, width) attributes for this effort (downloaded March 2025).
VDOT	Counties	Virginia counties spatial dataset.
VDOT	Districts	VDOT districts spatial dataset.
VDOT	RIMS/UMIS Events	Spatial dataset of urban inventory segments providing lane count data for municipal and urban roads lacking these data in VDOT's statewide lane count dataset (2023).
VDOT	Horizontal Curves	Statewide spatial dataset of horizontal curves in Virginia, created by Old Dominion University in collaboration with VDOT (2021).
Department of Motor Vehicles	Large animal crash data	Statewide police reported crash data for deer and bear crashes in Virginia from 2014 to 2023. Crashes (by type of animal) were curated by Department of Motor Vehicles staff (Phan, 2025b).
VDWR	Deer Population Density Index	Statewide map of VDWR's deer density index by county for Virginia (2025–2034 Deer Management Plan; Folks, 2025).
VDWR	Bear Population Density Index	Statewide map of VDWR's bear density index by county for Virginia (Lafon, 2025).
DCR	Protected Lands	Statewide spatial dataset of conservation lands and easements for Virginia (April 2025).
USGS	Digital Elevation Model (DEM)	Nationwide continuous DEM spatial dataset extracted for Virginia and neighboring states (various years by region; downloaded March 2025).
USGS	National Hydrography Dataset	Nationwide spatial dataset of hydrographic features extracted for Virginia and neighboring states (2023).
USGS	Protected Areas Database	Nationwide spatial dataset of conservation lands and easements extracted for neighboring states (DC, KY, MD, NC, TN, WV) needed for protected lands proximity attribution (in addition to the protected lands data acquired through Virginia Department of Conservation and Recreation's conservation lands database). Including these data minimizes the "border effect" of data being skewed for road segments near state borders.
MRLC	National Land Cover Database	Nationwide spatial land cover and use classification dataset extracted for Virginia and neighboring states (2023).
FEMA	Building Footprints	Nationwide spatial inventory of building footprints (more than 450 square feet) extracted for Virginia and neighboring states (downloaded March 2025).

Source	Name	Description
U.S. Census Bureau	Population	2019–2023 American Community Survey 5-year population data extracted for Virginia and neighboring states.
U.S. Census Bureau	Urban Areas	2020 Census urban areas data extracted for Virginia and neighboring states.
U.S. Census Bureau	TIGER/Line	Roadway centerline spatial datasets extracted for neighboring states (DC, KY, MD, NC, TN, WV), which is needed for intersection and road density calculations, in addition to the roadway centerline data acquired for Virginia through VDOT. Including these data minimizes the "border effect" of data being skewed for road segments near state borders (2024).

DCR = Virginia Department of Conservation and Recreation; FEMA = Federal Emergency Management Agency; MRLC = Multi-Resolution Land Characteristics Consortium; USGS = U.S. Geological Survey; VDWR = Virginia Department of Wildlife Resources.

APPENDIX B

Table B1. Statewide Deer and Bear 10-Year Crash Distribution by Segment Length (by Percentage of Segments)

Segment Length (Mi)	% Segments 0 Crashes	% Segments 1 Crashes	% Segments 2+ Crashes	Total Number of Segments
0.5	92.12%	4.20%	3.68%	335,324
1	92.68%	3.42%	3.90%	261,565
2	94.11%	2.56%	3.33%	232,433

Table B2. Statewide Deer and Bear 10-Year Crash Distribution by Segment Length (by Count of Segments)

Segment Length (Mi)	Segments with 0 Crashes	Segments with 1 Crash	Segments with 2+ Crashes	Total Number of Segments
0.5	308,905	14,069	12,350	335,324
1	242,415	8,952	10,198	261,565
2	218,733	5,951	7,749	232,433

Table B3. Deer and Bear 10-Year Crash Distribution by Segment Length by VDOT District (by Percentage of Segments)

District	Name	Segment Length (Mi)	% Segments 0 Crashes	% Segments 1 Crashes	% Segments 2+ Crashes	Total Number of Segments
1	Bristol	0.5	92.04%	4.09%	3.86%	34,492
		1	92.17%	3.70%	4.13%	25,464
		2	93.39%	2.93%	3.68%	21,594
2	Salem	0.5	90.70%	4.60%	4.71%	40,573
		1	91.11%	3.93%	4.96%	30,127
		2	92.69%	3.05%	4.26%	25,947
3	Lynchburg	0.5	91.24%	5.26%	3.50%	27,355
		1	90.46%	5.01%	4.53%	18,897
		2	91.51%	3.98%	4.51%	15,352
4	Richmond	0.5	91.15%	4.93%	3.92%	48,575
		1	91.84%	3.84%	4.32%	38,448
		2	93.54%	2.78%	3.69%	34,589
5	Hampton Roads	0.5	94.54%	3.15%	2.31%	51,285
		1	95.14%	2.44%	2.43%	42,704
		2	96.11%	1.82%	2.07%	39,452
6	Fredericksburg	0.5	91.08%	4.86%	4.06%	25,863
		1	91.59%	3.94%	4.48%	19,906
		2	93.44%	2.68%	3.89%	17,596
7	Culpeper	0.5	88.46%	5.55%	5.99%	24,138
		1	88.97%	4.69%	6.33%	17,850
		2	91.02%	3.56%	5.42%	15,346
8	Staunton	0.5	90.89%	4.68%	4.43%	34,018
		1	91.07%	4.00%	4.93%	24,669
		2	92.57%	3.12%	4.31%	20,850
9	Northern Virginia	0.5	95.49%	2.36%	2.16%	49,017
		1	96.28%	1.73%	1.98%	43,497
		2	97.08%	1.36%	1.56%	41,704

Table B4. Deer and Bear 10-Year Crash Distribution by Segment Length by VDOT District (by Count of Segments)

District	Name	Segment Length (Mi)	Segments with 0 Crashes	Segments with 1 Crash	Segments with 2+ Crashes	Total Number of Segments
1	Bristol	0.5	31,748	1,412	1,332	34,492
		1	23,470	942	1,052	25,464
		2	20,166	633	795	21,594
2	Salem	0.5	36,798	1,866	1,909	40,573
		1	27,449	1,184	1,494	30,127
		2	24,050	791	1,106	25,947
3	Lynchburg	0.5	24,960	1,438	957	27,355
		1	17,095	946	856	18,897
		2	14,049	611	692	15,352
4	Richmond	0.5	44,276	2,393	1,906	48,575
		1	35,311	1,477	1,660	38,448
		2	32,353	960	1,276	34,589
5	Hampton Roads	0.5	48,484	1,617	1,184	51,285
		1	40,628	1,040	1,036	42,704
		2	37,916	719	817	39,452
6	Fredericksburg	0.5	23,557	1,256	1,050	25,863
		1	18,231	784	891	19,906
		2	16,441	471	684	17,596
7	Culpeper	0.5	21,352	1,339	1,447	24,138
		1	15,882	838	1,130	17,850
		2	13,968	547	831	15,346
8	Staunton	0.5	30,918	1,592	1,508	34,018
		1	22,465	987	1,217	24,669
		2	19,300	651	899	20,850
9	Northern Virginia	0.5	46,804	1,156	1,057	49,017
		1	41,881	754	862	43,497
		2	40,487	568	649	41,704

APPENDIX C

Table C1. Variables Used in Road Risk Model

Variable	Unit	Search Radius	Description	Source
RTE_NM	-	-	VDOT route ID.	VDOT Master Routes
VHB_SEGMENT_ID	-	-	Arbitrary unique segment ID assigned to each segment.	-
LENGTH_MILES	Mi	-	Length of each segment in miles.	-
DISTRICT_NAME	-	-	VDOT district name.	VDOT Districts
DISTRICT_CODE	-	-	VDOT district code.	VDOT Districts
COUNTY_CITY_NAME	-	-	Virginia county and city name.	VDOT Counties
RTE_COMMON_NM	-	-	VDOT common route name.	VDOT Master Routes
VDOT_SPEED_LIMIT	MPH	-	VDOT posted speed limit.	VDOT Speed Limit Events
VDOT_ADT	Vehicles	-	VDOT average daily traffic.	VDOT Traffic Volume Events
TOTAL_LANES	Count	-	VDOT lane count. Divided roads have full cross-section count.	VDOT Lanes Events, RIMS/UMIS
DIVIDED	-	-	Divided roadway indicator.	VDOT Lanes Events, RIMS/UMIS
INJURY_CRASHES_DEER	Count	-	Number of deer crashes along segment with at least one injury.	DMV Police Reported Crashes
FATAL_CRASHES_DEER	Count	-	Number of deer crashes along segment with at least one fatality.	DMV Police Reported Crashes
TOTAL_CRASHES_DEER	Count	-	Number of deer crashes along segment.	DMV Police Reported Crashes
INJURY_CRASHES_BEAR	Count	-	Number of bear crashes along segment with at least one injury.	DMV Police Reported Crashes
FATAL_CRASHES_BEAR	Count	-	Number of bear crashes along segment with at least one fatality.	DMV Police Reported Crashes
TOTAL_CRASHES_BEAR	Count	-	Number of bear crashes along segment.	DMV Police Reported Crashes
INJURY_CRASHES	Count	-	Number of deer and bear crashes along segment with at least one injury.	DMV Police Reported Crashes
FATAL_CRASHES	Count	-	Number of deer and bear crashes along segment with at least one fatality.	DMV Police Reported Crashes

Variable	Unit	Search Radius	Description	Source
TOTAL_CRASHES	Count	-	Number of deer and bear crashes along segment.	DMV Police Reported Crashes
BEAR_DENSITY_RATING	Category	-	Bear population density rating 1–5.	VDWR Bear Population Density Index
DEER_DENSITY_RATING	Category	-	Deer population density rating 1–5.	VDWR Deer Population Density Index
Z_MIN_FULL	Meters	0.5 Mi	Minimum elevation within a half mile of each segment.	USGS DEM
Z_MAX_FULL	Meters	0.5 Mi	Maximum elevation within a half mile of each segment.	USGS DEM
Z_MEAN_FULL	Meters	0.5 Mi	Mean elevation within a half mile of each segment.	USGS DEM
SAREA_FULL	Sq Feet	0.5 Mi	Surface area of the ground within a half mile of each segment.	USGS DEM
MIN_SLOPE_FULL	Percent	0.5 Mi	Minimum slope within a half mile of each segment.	USGS DEM
MAX_SLOPE_FULL	Percent	0.5 Mi	Maximum slope within a half mile of each segment.	USGS DEM
AVG_SLOPE_FULL	Percent	0.5 Mi	Mean slope within a half mile of each segment.	USGS DEM
HUMAN_POPULATION_DENSITY	Sq Mile	0.5 Mi	Human population per square mile of the census tract within which the segment is located.	U.S. Census Population
Z_MIN_RIGHT	Meters	0.5 Mi	Minimum elevation within a half mile to the right of each segment.	USGS DEM
Z_MAX_RIGHT	Meters	0.5 Mi	Maximum elevation within a half mile to the right of each segment.	USGS DEM
Z_MEAN_RIGHT	Meters	0.5 Mi	Mean elevation within a half mile to the right of each segment.	USGS DEM
SAREA_RIGHT	Sq Feet	0.5 Mi	Surface area of the ground within a half mile to the right of each segment.	USGS DEM
MIN_SLOPE_RIGHT	Percent	0.5 Mi	Minimum slope within a half mile to the right of each segment.	USGS DEM
MAX_SLOPE_RIGHT	Percent	0.5 Mi	Maximum slope within a half mile to the right of each segment.	USGS DEM
AVG_SLOPE_RIGHT	Percent	0.5 Mi	Mean slope within a half mile to the right of each segment.	USGS DEM
Z_MIN_LEFT	Meters	0.5 Mi	Minimum elevation within a half mile to the left of each segment.	USGS DEM
Z_MAX_LEFT	Meters	0.5 Mi	Maximum elevation within a half mile to the left of each segment.	USGS DEM
Z_MEAN_LEFT	Meters	0.5 Mi	Mean elevation within a half mile to the left of each segment.	USGS DEM
SAREA_LEFT	Sq Feet	0.5 Mi	Surface area of the ground within a half mile to the left of each segment.	USGS DEM
MIN_SLOPE_LEFT	Percent	0.5 Mi	Minimum slope within a half mile to the left of each segment.	USGS DEM
MAX_SLOPE_LEFT	Percent	0.5 Mi	Maximum slope within a half mile to the left of each segment.	USGS DEM

Variable	Unit	Search Radius	Description	Source
AVG_SLOPE_LEFT	Percent	0.5 Mi	Mean slope within a half mile to the left of each segment.	USGS DEM
GEOID20	-	-	2020 Census 5-digit ID of urban area.	U.S. Census Urban Areas
GEOIDFQ20	-	-	2020 Census 14-digit ID of urban area.	U.S. Census Urban Areas
NAME20	-	-	2020 Census “common” name of urban area.	U.S. Census Urban Areas
URBAN_RURAL	-	-	Urban/rural indicator. Urban if segments falls within 2020 Census Urban Areas.	U.S. Census Urban Areas
Z_MIN_CENTERLINE	Meters	-	Minimum elevation along each segment centerline.	USGS DEM
Z_MAX_CENTERLINE	Meters	-	Maximum elevation along each segment centerline.	USGS DEM
Z_MEAN_CENTERLINE	Meters	-	Mean elevation along each segment centerline.	USGS DEM
SLENGTH_CENTERLINE	Feet	-	Length of each segment centerline surface along the ground.	USGS DEM
MIN_SLOPE_CENTERLINE	Percent	-	Minimum slope along each segment centerline.	USGS DEM
MAX_SLOPE_CENTERLINE	Percent	-	Maximum slope along each segment centerline.	USGS DEM
AVG_SLOPE_CENTERLINE	Percent	-	Mean slope along each segment centerline.	USGS DEM
FUNCTIONAL_CLASS_ID	-	-	VDOT State functional class ID.	VDOT Functional Classification Events
FUNCTIONAL_CLASS_DESC	-	-	VDOT State functional class description.	VDOT Functional Classification Events
FUNCTIONAL_CLASS	-	-	VDOT State functional class ID + description.	VDOT Functional Classification Events
ACCESS_CONTROL	-	-	Access control (full, partial, or none).	P4P Travelway
MEDIAN_TYPE	-	-	Type of median present.	P4P Travelway
MEDIAN_WIDTH	Feet	-	Width of median present.	P4P Travelway
MEDIAN_WIDTH_1	Feet	-	Width of other median present.	P4P Travelway
MEDIAN_PRESENCE	-	-	Indicator of median presence.	P4P Travelway
AREA_RIGHT_HALF_MILE	Sq Mile	0.5 Mi	Area to the right of each segment within a half mile.	-
AREA_LEFT_HALF_MILE	Sq Mile	0.5 Mi	Area to the left of each segment within a half mile.	-
AREA_RIGHT_2_MILE	Sq Mile	2 Mi	Area to the right of each segment within 2 miles.	-
AREA_LEFT_2_MILE	Sq Mile	2 Mi	Area to the left of each segment within 2 miles.	-
JURISDICTION_CODE	-	-	Jurisdiction numeric code or ID. Seems to include only county, city, and local, not state or federal.	VDOT Master Routes

Variable	Unit	Search Radius	Description	Source
JURISDICTION_NAME	-	-	Jurisdiction "common" name. Seems to include only county, city, and local, not state or federal.	VDOT Master Routes
INTERSECTIONS_COUNT_RIGHT	Count	2 Mi	Count of intersections within 2 miles to the right of each segment	VDOT Master Routes, U.S. Census TIGER/Line
INTERSECTIONS_COUNT_LEFT	Count	2 Mi	Count of intersections within 2 miles to the left of each segment	VDOT Master Routes, U.S. Census TIGER/Line
BUILDINGS_COUNT_RIGHT	Count	0.5 Mi	Count of buildings within a half mile to the right of each segment.	FEMA Building Footprints
BUILDINGS_COUNT_LEFT	Count	0.5 Mi	Count of buildings within a half mile to the left of each segment.	FEMA Building Footprints
ROAD_MILEAGE_RIGHT	Mile	2 Mi	Length of roads within 2 miles to the right of each segment.	VDOT Master Routes, U.S. Census TIGER/Line
ROAD_MILEAGE_LEFT	Mile	2 Mi	Length of roads within 2 miles to the left of each segment.	VDOT Master Routes, U.S. Census TIGER/Line
BUILDINGS_AREA_RIGHT	Sq Feet	0.5 Mi	Total building footprint square footage within a half mile to the right of each segment.	FEMA Building Footprints
BUILDINGS_AREA_LEFT	Sq Feet	0.5 Mi	Total building footprint square footage within a half mile to the left of each segment.	FEMA Building Footprints
HYDROGRAPHY_LENGTH_RIGHT	Mile	0.5 Mi	Length of linear hydrography (e.g., streams, rivers, etc.) within a half mile to the right of each segment.	USGS NHD
HYDROGRAPHY_LENGTH_LEFT	Mile	0.5 Mi	Length of linear hydrography (e.g., streams, rivers, etc.) within a half mile to the left of each segment.	USGS NHD
EMPLOYMENT_DENSITY	Sq Mile	-	Total employment per square mile of the census tract within which the segment is located.	U.S. Census Employment
CONSLANDS_AREA_RIGHT	Sq Mile	0.5 Mi	Area of protected lands within a half mile to the right of each segment. Can combine protected lands and easements for total protected lands.	DCR Protected Lands, USGS PAD
CONSLANDS_AREA_LEFT	Sq Mile	0.5 Mi	Area of protected lands within a half mile to the left of each segment. Can combine protected lands and easements for total protected lands.	DCR Protected Lands, USGS PAD
EASEMENTS_AREA_RIGHT	Sq Mile	0.5 Mi	Area of conservation easements within a half mile to the right of each segment. Can combine protected lands and easements for total protected lands.	DCR Protected Lands, USGS PAD

Variable	Unit	Search Radius	Description	Source
EASEMENTS_AREA_LEFT	Sq Mile	0.5 Mi	Area of conservation easements within a half mile to the left of each segment. Can combine protected lands and easements for total protected lands.	DCR Protected Lands, USGS PAD
H_CURVE_COUNT	Count	-	Count of horizontal curves along each segment.	VDOT/ODU Horizontal Curves
SLOPE_GREATER_1TO3_AREA_RIGHT	Sq Mile	0.5 Mi	Area of slope greater than 33.333% within a half mile to the right of each segment.	USGS DEM
SLOPE_GREATER_1TO3_AREA_LEFT	Sq Mile	0.5 Mi	Area of slope greater than 33.333% within a half mile to the left of each segment.	USGS DEM
SLOPE_GREATER_1TO2_AREA_RIGHT	Sq Mile	0.5 Mi	Area of slope greater than 50% within a half mile to the right of each segment.	USGS DEM
SLOPE_GREATER_1TO2_AREA_LEFT	Sq Mile	0.5 Mi	Area of slope greater than 50% within a half mile to the left of each segment.	USGS DEM
SLOPE_GREATER_1TO1_AREA_RIGHT	Sq Mile	0.5 Mi	Area of slope greater than 100% within a half mile to the right of each segment.	USGS DEM
SLOPE_GREATER_1TO1_AREA_LEFT	Sq Mile	0.5 Mi	Area of slope greater than 100% within a half mile to the left of each segment.	USGS DEM
GRIDCODE_43_AREA_RIGHT	Sq Mile	0.5 Mi	Area of MIXED FOREST within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_43_AREA_LEFT	Sq Mile	0.5 Mi	Area of MIXED FOREST within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_71_AREA_RIGHT	Sq Mile	0.5 Mi	Area of GRASSLAND/HERBACEOUS within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_71_AREA_LEFT	Sq Mile	0.5 Mi	Area of GRASSLAND/HERBACEOUS within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_11_AREA_RIGHT	Sq Mile	0.5 Mi	Area of OPEN WATER within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_11_AREA_LEFT	Sq Mile	0.5 Mi	Area of OPEN WATER within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_81_AREA_RIGHT	Sq Mile	0.5 Mi	Area of PASTURE/HAY within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_81_AREA_LEFT	Sq Mile	0.5 Mi	Area of PASTURE/HAY within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_42_AREA_RIGHT	Sq Mile	0.5 Mi	Area of EVERGREEN FOREST within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_42_AREA_LEFT	Sq Mile	0.5 Mi	Area of EVERGREEN FOREST within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_22_AREA_RIGHT	Sq Mile	0.5 Mi	Area of DEVELOPED, LOW INTENSITY within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_22_AREA_LEFT	Sq Mile	0.5 Mi	Area of DEVELOPED, LOW INTENSITY within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_21_AREA_RIGHT	Sq Mile	0.5 Mi	Area of DEVELOPED, OPEN SPACE within a half mile to the right of each segment.	MRLC NLCD

Variable	Unit	Search Radius	Description	Source
GRIDCODE_21_AREA_LEFT	Sq Mile	0.5 Mi	Area of DEVELOPED, OPEN SPACE within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_52_AREA_RIGHT	Sq Mile	0.5 Mi	Area of SHRUB/SCRUB within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_52_AREA_LEFT	Sq Mile	0.5 Mi	Area of SHRUB/SCRUB within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_41_AREA_RIGHT	Sq Mile	0.5 Mi	Area of DECIDUOUS FOREST within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_41_AREA_LEFT	Sq Mile	0.5 Mi	Area of DECIDUOUS FOREST within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_31_AREA_RIGHT	Sq Mile	0.5 Mi	Area of BARREN LAND (ROCK/SAND/CLAY) within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_31_AREA_LEFT	Sq Mile	0.5 Mi	Area of BARREN LAND (ROCK/SAND/CLAY) within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_23_AREA_RIGHT	Sq Mile	0.5 Mi	Area of DEVELOPED, MEDIUM INTENSITY within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_23_AREA_LEFT	Sq Mile	0.5 Mi	Area of DEVELOPED, MEDIUM INTENSITY within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_90_AREA_RIGHT	Sq Mile	0.5 Mi	Area of WOODY WETLANDS within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_90_AREA_LEFT	Sq Mile	0.5 Mi	Area of WOODY WETLANDS within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_24_AREA_RIGHT	Sq Mile	0.5 Mi	Area of DEVELOPED, HIGH INTENSITY within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_24_AREA_LEFT	Sq Mile	0.5 Mi	Area of DEVELOPED, HIGH INTENSITY within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_82_AREA_RIGHT	Sq Mile	0.5 Mi	Area of CULTIVATED CROPS within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_82_AREA_LEFT	Sq Mile	0.5 Mi	Area of CULTIVATED CROPS within a half mile to the left of each segment.	MRLC NLCD
GRIDCODE_95_AREA_RIGHT	Sq Mile	0.5 Mi	Area of EMERGENT HERBACEOUS WETLANDS within a half mile to the right of each segment.	MRLC NLCD
GRIDCODE_95_AREA_LEFT	Sq Mile	0.5 Mi	Area of EMERGENT HERBACEOUS WETLANDS within a half mile to the left of each segment.	MRLC NLCD
HYDRO_CROSSINGS_COUNT	Count	-	Count of linear hydrography features crossing each segment.	USGS NHD

DCR = Virginia Department of Conservation and Recreation; DEM = digital elevation model; DMV = Department of Motor Vehicles; FEMA = Federal Emergency Management Agency; MRLC NLCD = Multi-Resolution Land Characteristics National Land Cover Database; NHD = National Hydrography Dataset; ODU = Old Dominion University; P4P = Pathways for Planning; PAD = Protected Areas Database; USGS = U.S. Geological Survey; VDWR = Virginia Department of Wildlife Resources.

APPENDIX D

Table D1 summarizes findings from North American studies of large mammals that were used to inform the selection of a wildlife crossing crash modification factor for the benefit-cost analysis example presented in this report and for consideration within the cost tool when evaluating wildlife crossing countermeasures. The studies include before-after or before-after-control-impact evaluations of wildlife crossings with exclusion fencing and document reductions in crashes involving large mammals (e.g., elk, white-tailed and mule deer, pronghorn, and black bear).

Table D1. Reported Crash Reduction from Large Animal Wildlife Crossings (with Fencing) Studies

Location	Target Species	Project Description	Percent Crash Reduction	Citation
Arizona, I-17	Elk	Retrofitted wildlife fencing connecting existing bridges/underpass structures (5.9 miles).	97.5	Gagnon et al., 2016
Arizona, State Route 260	Elk	Wildlife fencing integrated with existing passage structures.	86.8	Dodd and Gagnon, 2007
Colorado, State Hwy 9	Large mammals	Seven large wildlife crossings (two overpasses, five underpasses) with 10.3 miles wildlife exclusion fencing.	92	Kintsch et al., 2021
Montana, US 93	Large mammals	Wildlife crossing structures (multiple under/overpasses) and wildlife exclusion fencing.	80	Huijser et al., 2008
Virginia, I-64	White-tailed deer and black bear	Wildlife fencing integrated with existing underpass structures.	88, 96.5 (average 92)	Donaldson and Elliott, 2021
Alberta (TransCanada Hwy)	Large mammals	Wildlife crossing structures and fencing.	80	Clevenger et al., 2001
Global Meta-analysis [a]	Large mammals	Wildlife crossing structures and fencing.	83	Rytwinski et al., 2016
FHWA Report to Congress [a]	Ungulates	Wildlife crossing structures and fencing.	80 to 95	FHWA, 2008

FHWA = Federal Highway Administration. [a] These sources synthesize results from multiple studies evaluating crash-reduction effectiveness from wildlife crossings.