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**Running Head**: Human-Black Bear Interactions in Virginia
**Title:** The Spatial Distribution of Human-Black Bear Interactions in Virginia, USA
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***Abstract*:** Black bear (*Ursus americanus)* populations in Virginia have been recovering from near extirpation for the last century. The expansion of both human and bear populations has coincided with an increase in human-black bear interactions. Mitigating human-black bear problems is a management priority of the Virginia Department of Game and Inland Fisheries. While the number of reported interactions has increased, no formal analysis of the spatial distribution of these interactions has been completed for Virginia. To address this gap, we assessed the role of ecological and anthropogenic variables in explaining the spatial distribution of human-black bear interactions in Virginia, at both county- and individual interaction point-scales, from 2008 to 2015. The results of these analyses indicate that landscape features representing the interface of potentially suitable black bear habitat and human development combine to increase risk of human-black bear interactions. Point locations with the highest probability of a black bear interaction had intermediate housing densities (300-600 houses per km$^2$) and forest covered a high percentage of the surrounding landscape. At the county scale, interactions were predicted to be above average when the county exceeded roughly 67.7% forest,

27.2% agricultural cover, and 10.3% developed land. These results, combined with our generated high-resolution map of predicted relative risk, can be used to help target the strategic implementation of management actions aimed at reducing negative human-black bear interactions in Virginia, as well as throughout the Mid-Atlantic region.
***Key words*:** black bear, carnivore, human-black bear conflict, human-black bear interactions, human-wildlife conflict, *Ursus americanus*, Virginia

Human-carnivore conflicts challenge wildlife managers worldwide and are on the rise in many areas, with negative interactions between humans and carnivores increasing (Treves and Karanth 2003). Increased contact can be attributed to a range of factors, including the expansion of settlements and agriculture into previously wild areas as human populations grow (Treves and Karanth 2003, Ripple et al. 2014). Large carnivores in particular have high food requirements and extensive home ranges, increasing the likelihood that they will come into contact with people (Ripple et al. 2014) and at times pose a direct threat to livestock and human safety (Packer et al. 2005).

Of the large carnivore species in North America, American black bears (*Ursus americanus*) are implicated in a notable and increasing number of conflicts (Spencer et al. 2007). Black bears are opportunistic omnivores, which has enabled them to adapt to landscapes altered by human development and for their populations to persist or grow despite expanding human populations (Beckmann and Berger 2003, Spencer et al. 2007). Use of developed and fragmented landscapes by black bears is influenced by natural food availability, with use increasing during poor natural food years and decreasing during good food years (Baruch-Mordo et al. 2014, Johnson et al. 2015). In addition, fragmented landscapes contain patches of forest which can be used for cover and natural forage, while also frequently providing access to agricultural resources such as crops and anthropogenic food attractants such as garbage (Baldwin and Bender 2012, Evans et al. 2014).

Though once reduced to 39 percent of their original range (Laliberte and Ripple 2004), black bear populations have rebounded in North America since the mid-20th century due to a shift in values towards wildlife preservation, stricter harvest regulations, the natural succession of abandoned farmland, large public land purchases, and the availability of anthropogenic food resources (Howe et al. 2007, Hristienko and McDonald 2007). Today, black bears are present in 40 U.S. states (with occasional sightings in six additional states), throughout Canada, and parts of Mexico (Scheick and McCown 2004) and the management of human-black bear conflicts has become one of the most challenging priorities facing wildlife management agencies in North America (Spencer et al. 2007). In 2006, 48 wildlife management agencies in North America reported 43,000 black bear complaints annually, and 82% of agencies indicated that black bear problems were common, increasingly common, or a serious problem. The majority of conflicts involved bears raiding anthropogenic food sources (Spencer et al. 2007).

In Virginia, black bear populations were widespread prior to European colonization, but by the mid-18$^{th}$ century populations had declined steeply due to habitat loss, unregulated hunting, and bounties. By 1900, black bears were found in only a few western counties and in the Great Dismal Swamp in southeastern Virginia. By 1974, stricter harvest regulations, reforestation, public land purchases, and bear restoration efforts enabled populations to recover. As of 2012, there were an estimated 16,000-18,000 bears in the state, and bears can be found in almost every county (Virginia Department of Game and Inland Fisheries [VDGIF] 2012).

An increase in bear-related calls and complaints has coincided with the increase in bear populations in the state (VDGIF 2012). These complaints, hereafter referred to as "interactions" or "events", range from property damage to bear sightings (which may be perceived by the public as a threat to human safety). Common problems include damage to bird feeders, bears scavenging on garbage cans and foraging at dumps, and vehicle collisions. In rural areas, bears also damage agricultural commodities, such as apiaries, corn crops, orchards, and livestock (VDGIF 2012). To date, no bear-inflicted human fatality has been documented in the state. Historically, there have been infrequent minor injuries to humans from bears, with most events associated with bear hunting, walking dogs off leash, or inappropriate human behaviors, such as trying to hand feed a bear (VDGIF 2012).

As the agency responsible for managing Virginia's wildlife, VDGIF seeks to minimize negative human-bear interactions through proactive management that uses the best available science to inform the public about bear biology and how to prevent conflicts, as well as maintaining records of reported human-bear interactions (VDGIF 2012). However, no formal analysis of the spatial distribution of human-bear interactions has been completed for the state. In this study, we identify factors related to the probability or frequency of human-bear interactions to aid current and future management of these interactions in Virginia. Using an eight-year dataset of reported human-black bear interactions, we assessed the role of ecological and anthropogenic variables in explaining the spatial distribution of human-black bear interactions in Virginia, at both point and county scales. Analysis at the point scale allowed us to identify local conditions likely to increase the probability of human-black bear interactions within regions of the state known as suitable bear habitat, and allowed generation of a detailed map of relative risk of these interactions. Analysis at the county-scale provided a state-wide investigation of landscape-scale factors that influence the frequency of interactions (as opposed to probability of occurrence), and enabled the incorporation of datasets only collected at the county-scale, such as socioeconomic data.

Considering the results of other similar studies (e.g. Evans et al. 2014, Merkle et al. 2011), we hypothesized that locations at the forest-agriculture interface with intermediate human development would show a greater propensity for human-black bear interactions. We expected a similar pattern at the county level, with counties displaying a mix of agriculture, forest, and developed land being most susceptible to interactions. This study expands on previous findings by analyzing patterns of human-black bear interactions at multiple spatial scales. Improving our understanding of why these events occur where they do in Virginia will facilitate the development of appropriate conflict mitigation strategies and help guide management efforts that seek to target areas most at risk of negative human-bear interactions.

**Study area**

Much of Virginia provides potentially suitable bear habitat, and the population found in the state's western mountains belongs to the largest contiguous bear population in the southeastern U.S. (VDGIF 2012). Our point-scale analysis focused on the Blue Ridge and Allegheny mountains in the western half of Virginia, where the density of reported human-black interactions was highest (Fig. 1) and where the largest percentage of Virginia's bear population resides. Our focal area was defined by 10 of VDGIF's 22 Bear Management Zones (Fig. 1). These zones aggregate the state's counties and independent cities based on physiographic characteristics, bear population dynamics and biology, land use, and resources available to manage bears (VDGIF 2012). These 10 zones comprised a study area of 54,354 $km^2$ and included 47 counties and 20 independent cities. The study area contained five distinct ecoregions: Southern Appalachian Piedmont, Blue Ridge Mountains, Northern Ridge and Valley, and the Northern and Southern Cumberland Mountains. The mountainous regions are characterized by oak (*Quercus* spp.), hickory (*Carya* spp.), and pine (*Pinus* spp.) forests, while the Piedmont is characterized by oak and hickory forests (VDGIF 2012). The dominant land cover type in the study area was deciduous forest (55%), followed by pasture-hay (21%) (Homer et al. 2015). Elevation across the study area ranged from 5 m to 1,746 m (U.S. Geological Survey 1999). The population of the study area was 4.2 million people, and included the state's most populous county, Fairfax (approximately 1.1 million people), and its least populous county, Highland (approximately 2,300 people) (Census Bureau 2010).

We completed our county-scale analysis on 92 Virginia counties, and excluded the counties of Accomack, Northampton, and Arlington. Accomack and Northampton are part of Virginia's Eastern Shore and had no records of conflict during the study period. We removed Arlington County because it is an extreme outlier in terms of size (1/6 the size of the next smallest county), percentage of developed land (91%), and population density (three times higher than the next most densely populated county). There were no reported interactions in Arlington County during our study period. We also excluded Virginia's 38 independent cities from the county-scale analysis. These are small inholdings within counties that have disproportionately high population densities and little undeveloped habitat.

## Methods

### *Human-bear interaction dataset*

We completed the point-scale and county-scale analyses using VDGIF's Black Bear Event Complaint and Capture dataset. Since the 1970s, VDGIF has been recording public calls including complaints, sightings, and other observations made regarding black bears in Virginia. For each call, information is collected on the location of the interaction (street address, town, and/or county), whether the interaction was a sighting only or whether damage occurred, and the specific type of interaction (bird feeders, trash, bees or apiaries, corn or grain, orchards, property damage, livestock or poultry, livestock feed, public safety, or other). We decided to include interactions in which no damage occurred (i.e. bear sightings; 23% of the interactions), because these events represent the perception of or potential for conflict. All types of interactions were considered in our analyses and are referred to throughout as "interactions" or "events" (Hopkins et al. 2010). The full VDGIF database contained more than 15,000 events. However, reported interactions were not consistently recorded prior to 2007, and events were not consistently attributed with location information until 2008. Therefore, we only used interactions that occurred from 2008 to 2015. A total of 6,849 interactions were recorded during that time period, of which 71.5% ($n$ = 4,899) had address information and could be included in the point-scale analysis.

We used the ArcGIS World Geocode Service to geocode events based on street address, with a minimum match score of ≥ 85%. The match score reflects how closely the addresses in the database match their most likely candidate in the reference dataset. A match score of 85 or higher is generally considered to be a good match (Ratcliff 2004). As an additional step, we used Google Earth® to manually verify the location of events with a match score of <90% ($n$ = 108). A total of 4,355 interactions were located in the 10 bear management zones that made up the study area for the point-scale analysis.

To identify the landscape characteristics associated with a higher probability of human-black bear interaction, we compared a set of explanatory variables at the location of reported interactions with those at an equal number of randomly-selected locations, employing a "use-availability" design commonly used for generation of resource selection functions, and shown to be appropriate for identifying influential covariates in a regression framework (Johnson et al. 2006). Random points were generated within the study area without any restrictions. The final dataset used for analysis consisted of 8,710 observations. We buffered each point using a 3.5-km radius to enable calculations of the percentage of select land cover classes in the area surrounding each point. Similar to the method used by McFadden-Hiller et al. (2016), we selected this buffer size based on mean daily movements of black bears in the Mid-Atlantic region (Garshelis 1978, Fecske et al. 2002).

At the county-scale, we summed all reported interactions, by county, that occurred between 2008 and 2015 and had adequate location information to assign to a county. The 92 counties experienced a total of 6,238 reported interactions during this time period.

***Explanatory variables***

The location of suitable habitat, agricultural land, and human development are important variables to consider when analyzing the distribution of human-black bear interactions (e.g. Baruch-Mordo et al. 2008, Merkle et al. 2011). The proximity of human development to suitable bear habitat increases the rate of encounters between bears and humans and provides additional forage opportunities for black bears in the form of garbage, bird feeders, fruit trees, and other human-associated food sources. Preparation of explanatory covariates was performed both in ArcGIS (Environmental Systems Research Institute, Inc., Redlands, CA, USA) and in the R environment (R Core Team 2019).

***Point-scale.*** For point-scale analyses, we assessed characteristics related to forest and riparian habitats, as well as slope and elevation, to represent components of potentially suitable bear habitat. We used human population density, housing density, roads, and agricultural variables to represent human development (Table 1).

Forest characteristics at each point were represented by the percent of forest cover within our sampling radius, as well as the distance to forest patches of different size classes (Table 1). Here we aggregated deciduous, evergreen, and mixed forest land cover classes into a single forest cover class (deciduous forest covered 87% of the point-scale study area). The pooled forest dataset was then classified by fragment size into small (≤2 km$^2$), medium (>2–50 km$^2$), and large (>50 km$^2$) contiguous forest patches. As home range sizes of bears in Virginia range from 2.5–130 km$^2$ for females and 26–760 km$^2$ for males (VDGIF 2012), the medium and large forest patches represent those large enough to sustain the home range of a bear. Our small forest patches could not fully support a black bear home range, but may support occasional to frequent use by bears.

We calculated distance to riparian zones using a hydrologic dataset (Table 1), excluding only artificial connectors such as pipelines, which would not be representative of riparian habitat. For road features, we aggregated the roads dataset (Table 1) into major roads (roads attributed as primary or secondary) and minor roads (local neighborhood, rural, and city street roads). Minor roads were not included in the analysis because they are by necessity associated with housing address. The location of interactions was based on the address of the individual making the complaint, therefore the vast majority of interactions would inherently be associated with a minor road.

We represented human presence on the landscape by both housing and population density. For both variables, we found that point values drawn from source census blocks were not always representative of the general location. For example, very high housing density values could result from extremely small census blocks comprised of high-density housing units (average census block size = 0.39 $km^2$; range = 0.0000007 to 98.13 $km^2$). We therefore used the average housing and population density within a 500 m buffer surrounding each point. We first converted the polygon-based census map to a 30 by 30 m raster, with grid cells assuming the value of the census block at the cell center. For each point location, we then extracted the average census block value for housing and population density of all cells within 500 m of each point.

***County-scale.*** As with the point-scale analysis, our county-level investigation included both ecological and anthropogenic factors. Anthropogenic factors were described by road density, housing density, and population density, all summarized at the county level (Table 2). We used the percentage of each county comprised of a range of land cover classes to represent bear habitat suitability. Although 12 broad habitat categories were available, we focused on forest/woodland, agriculture, and developed lands, based on the variables we anticipated would be most important to bear habitat and the probability of potential interactions (Table 2). The county-level analysis also allowed us to incorporate socio-economic information, which may be related either to the probability of conflict, due to varying abundance of anthropogenic attractants, or the likelihood of bear-related interactions being reported (Evans et al. 2014). We used median household income to represent the economic situation across the county at a broad level.

***Point-scale modeling***

We used logistic regression (generalized linear model with a binomial error distribution) to compare the characteristics of interaction locations with those of random locations. We withheld all interactions reported in 2010 ($n$ = 272) for later use in assessing the predictive utility of the model. We completed all regression analyses (point- and county-scale) using the generalized linear model (glm) function in R and the glm.nb function from the MASS package (Venables and Ripley 2002).

We identified six variables to model with quadratic terms in the point-scale analysis: percent forest cover, slope, elevation, population density, housing density, and road density. These variables were selected based on our predictions that the likelihood of an interaction would increase as the values of these variables increased, until a threshold at which point the values would be so high that either human or bear presence would be limited and the likelihood of interactions would decrease.

To improve model convergence and facilitate comparisons among model coefficients, we centered the variables by subtracting the sample mean and scaled them by dividing by the sample standard deviation (Schielzeth 2010). We tested all covariates for multicollinearity using Pearson's correlation coefficient ($r$). Variables were assumed not to be collinear if $|r| < 0.7$ (McFadden-Hiller et al. 2016, Teichman et al. 2013). For variable pairs in which $|r| \geq 0.7$, we excluded the least ecologically important variable, based on previous bear ecology and conflict literature.

We constructed 28 *a priori* candidate models to test our hypotheses regarding the effects of ecological and anthropogenic variables on the occurrence of human-black bear interactions. Each variable was represented in 14 to 15 candidate models (S1). We divided the ecological variables into two sub-categories: natural habitat (distance to small, medium, and large forest patches, percent forest cover, and distance to riparian zone) and topographic (slope, elevation). We also divided the anthropogenic variables into two sub-categories: human population (housing density, major road density) and agricultural (distance to crops, distance to pasture-hay, and percent pasture-hay). The candidate models represent all possible combinations of these sub-categories.

We compared and ranked the models using Akaike's Information Criterion (AIC). We calculated Akaike weights (ω) to compare the probability that a given model was the best approximating model, given the data and the candidate set of models. For all variables that were significant in the best model, we back-transformed values to the original scale and assessed predicted values across the full range in our dataset of the variable of interest, while holding all other variables at their median value.

Coefficients from the best resulting model were used to predict relative probability of human-bear interaction values for each cell in a 1x1 km resolution grid overlaid atop the western Virginia study area, using values associated with the center point of each cell. We assessed the utility of our model using this prediction map, by assigning a predicted probability value to each of the 272 interaction events recorded for 2010. Following methods in Boyce et al. (2002), we calculated the Spearman rank correlation coefficient (ρ) between categories of predicted value ranges ($n$ = 8 equal-sized intervals), and the area-adjusted frequency of test locations assigned to each category. A value of 1.0 would, in this case, indicate the frequency was as expected due to chance. A strongly positive correlation coefficient would show evidence of a useful predictive model, where more interaction points, relative to expected, would continually be falling in higher classification intervals (Boyce et al. 2002).

***County-scale modeling***

We used a generalized linear model with a negative binomial error distribution to investigate the influence of our covariates on the frequency of human-bear interactions at the county-scale. An initial model was run with all non-correlated explanatory covariates, using a Poisson error distribution, and this model was confirmed to have high overdispersion. Although both a negative binomial and quasipoisson error distribution deal well with overdispersion, we preferred the use of the negative binomial because error variance, based on the full model, did not scale linearly with predicted values (Ver Hoef and Boveng 2007). This was confirmed by plotting mean predicted values of our fully generalized model in four quantiles, against their variance. Our response variable was the total count of interactions for each county across our study period, and we used an offset parameter representing the size of each county to account for its likely influence on interaction frequency. Relative model performance was compared using the AIC value corrected for small sample sizes ($AIC_c$), which is preferable to the AIC when sample sizes are small, and converges to the value of AIC as sample sizes increase (Burnham and Anderson 2002).

We considered explanatory variables highly correlated when $|r| \geq 0.70$. Here we proceeded by retaining the covariate from each correlated pair(s) most closely associated with the response variable. We compared $AIC_c$ values for single-variable models with the correlated variables in question, and retained the variable in the model with the highest support in this set.

Before modelling, we investigated histograms of all covariates, and utilized a log transformation for those with extreme values and large gaps in the data range. We also plotted raw data values for each covariate to search for potential non-linear relationships with interaction frequency. When these scatterplots indicated a potential quadratic relationship, and when this relationship made ecological sense, we added a quadratic term for that covariate to our model set.

After excluding correlated parameters and adding quadratic terms, we compared all possible model subsets, given that our full set of covariates was not large, based on $AIC_c$ values.

Because our goal was to investigate the relative importance of each variable on the frequency of human-bear interactions (and not to create a predictive model), we compared the summed model weights for all non-correlated variables across the full balanced model set (Burnham and Anderson 2002).

**Results**

VDGIF received 6,849 black bear calls from 2008 to 2015. Interactions were recorded in all Virginia counties with the exception of five (Accomack, Northampton, King and Queen, Northumberland, and Arlington). On average, VDGIF received 856 (SD = 313) reports annually during this period, with the minimum number of interactions reported in 2010 ($n$ = 390) and the maximum in 2013 ($n$ = 1,407). There was no consistent temporal trend in the number of interactions reported each year during this period (Fig. 2). Overall, 45% of interactions were reported during summer months (June-Aug), 36% in spring (March-May), 16.5% in fall (Sept-Nov), and 2.5% in winter (Dec-Feb). The greatest percentage of interactions during this period occurred in May (24.5%) and June (19.7%).

Of the 6,849 reported interactions, 77.2% were classified as “property damage”, such as a bear knocking over a trash can, damaging a bird feeder, or consuming crops. The remaining interactions were categorized as “sighting only”, meaning the bear involved in the event did not cause any property damage.

***Point-scale***

Percent pasture-hay cover, housing density, and road density showed collinearity with other variables (percent forest cover, population density, and housing density, respectively) and were removed from further analysis. Point-scale modeling proceeded with a final set of 11 predictor variables.

The global model containing all ecological and anthropogenic variables had the lowest AIC score (Table 3). The ΔAIC of the second-best model was 46.20, indicating that there were no competing models. In the final global model, there was substantial evidence that all parameters were important predictors of the probability of interaction occurrence (Fig. 3; Table S2). This full model explained 17.7% of the deviance in our binary response variable. Using the generated 1 km-resolution prediction map (Fig. 4), the model showed strong predictive ability with higher prediction category groups consistently including higher numbers of interaction points from our test data ($r_s$ = 0.976, Fig. S1).

Proximity to natural habitat features, including forest patches of all sizes and riparian areas, increased the probability of human-bear interactions. Areas of lower slope and intermediate elevation had the highest probability of an interaction occurring, with slope exerting a stronger influence than elevation (Fig. 3).

For agricultural features, distance to crops and distance to pasture-hay demonstrated opposing relationships to the occurrence of an interaction. The probability of an interaction increased as distance to pasture-hay decreased, but increased as distance to crops increased. As predicted, housing density had a more complex relationship with interaction occurrence. The probability of an interaction increased as housing density increased until a density of approximately 300 houses/km$^2$. The probability of an interaction then plateaued until a density of approximately 600 houses/km$^2$, at which point the probability decreased as housing density increased (Fig. 5).

***County-scale***

The number of human-bear interactions by county for our study period ranged from 0 (King and Queen County; Northumberland County) to 458 (Augusta County), with an average of

67.8 reported interactions per county from 2008-2015 (approximately 8.4/year). Density of interactions ranged from 0 to 0.467 (Roanoke County) events per $km^2$. Of the 6,238 reported interactions in the county dataset, 76.8% were categorized as resulting in property damage.

Housing density, population density, road density, and the % of developed land were all highly correlated covariates ($r > 0.93$). When modelled individually against human-bear interaction frequency, the % of developed land was the most effective predictor, based on $AIC_c$, so this covariate was retained and modelling proceeded with the four remaining covariates (% developed land, median household income, % forest cover, % agriculture). The full 4-variable model had the most weight of evidence, yet the slightly simpler model, which excluded median household income, was also supported (Table 4). Standard model diagnostics, including plotting residuals against predicted values, revealed no concerns or assumption violations. This 4-variable model explained 53.3% of the deviance in our response variable. Summed model weights indicated that all habitat-related variables were important predictors (all values = 1.0) for human-bear interaction frequency, whereas median household income was less so (summed model weight = 0.65). Further, response curves showed a relatively weak relationship between income and human-bear interaction frequency (Fig. 6). Increases in all three of the habitat covariates resulted in predicted increases in interaction frequency (Fig. 6).

Based on predictions from the top model, the habitat composition that predicts a level of human-bear interaction frequency in the top quartile of our observed frequencies (> 94.75 interactions over the 8-year period) includes 70% forest cover, 11.8% developed, and 29.6% agricultural cover. The habitat composition resulting in a predicted interaction frequency above average levels (67.8 interactions) occurs with 67.7% forest, 10.3% developed land, and 27.2% agricultural cover.

**Discussion**

The results of our point- and county-scale analyses demonstrate that landscapes comprised of suitable bear habitat and human development are at the greatest risk of experiencing human-bear interactions, roughly 75% of which resulted in some property damage in our sample. At the point-scale, high-risk areas were those with intermediate housing density that were close to major roads, forested areas, riparian zones, and pasture-hay fields and were far from crops. At the county-scale, counties that contained a mix of developed, agricultural, and forested habitats had the highest risk of interactions.

Black bears are a forest obligate species and their use of forests in both wildland and developed areas has been well-documented in the Northeast U.S. (Evans et al. 2014, Tri et al. 2016). Medium and large forest patches, as defined in this study, are large enough to sustain the home range of a black bear and provide forage and cover. These areas are better able to support larger bear populations than highly fragmented landscapes, which could be one explanation for the higher probability of interactions close to large forests, revealed by our point-scale analysis. Small forest patches, in contrast, are commonly part of fragmented landscapes with higher levels of human disturbance. Bears in these areas, although likely fewer in number, may have a higher probability of encountering humans. In fragmented landscapes, percent forest cover can be particularly valuable for understanding the occurrence of human-bear interactions (Evans et al. 2014). The significance of this variable in our study suggests that in fragmented landscapes, interactions are more likely to occur when some portion of the landscape is forested.

Proximity to riparian areas, a key habitat feature for black bears (Tri et al. 2016), was related to human-bear interaction risk, as was the case in Connecticut (Evans et al. 2014) and Montana (Merkle et al. 2011). We also found that both elevation and slope were predictors of human-bear interaction probability, with the highest predicted probabilities occurring at minimum slopes and intermediate elevations. Although bears in the region use moderately sloping terrain more frequently than steeper and flatter locations (Jones et al. 2015), and may use slopes and higher elevations to access hard or soft mast on ridge tops (Tri et al. 2016), these areas are typically less frequented by humans, thereby limiting the potential for human-bear interactions.

Pasture-hay is a common landcover type in the western Virginia study area (21%) and was included as a proxy for the potential location of livestock. We found that areas close to pasture-hay had a higher risk of interactions, yet only 8% of interactions in this study were classified as livestock or poultry-related events (VDGIF classifies these events as a single category). Considering the low number of livestock-related interactions, it is possible that the significance of pasture-hay is less a function of the potential presence of livestock and more a function of the broader landscape within which this feature occurs. In our study area, pasture-hay is frequently part of a matrix of forest and lower intensity human development, and this combination of forest, agriculture, and anthropogenic activities can facilitate human-bear interactions (McFadden-Hiller et al., 2016).

We included distance to crops in our analysis because bears occasionally damage corn and fruit orchards. However, the point-scale analysis revealed that areas farther from crops had a higher risk of interaction. The cultivated crop land cover type, which includes both corn and orchards, makes up only 1.5% of the western Virginia study area. In addition, only 2.5% of the events included in the point-scale analysis were classified by VDGIF as being related to corn or grain, while 1.8% were related to orchards. Given the relative rarity of crop-based interactions, it’s possible that landscape features favoring bear interactions were more common further from crops, for example where housing density was higher. An analysis focusing only on crop-related interactions could better identify factors increasing susceptibility of crops to bear damage, but the total sample of these interactions was not sufficient for such an analysis.

Similar to the point-scale analysis, results at the county-scale demonstrated that a mix of developed, agricultural, and forested habitats creates a landscape mosaic that provides both potentially suitable black bear habitat, as well as sufficient opportunities for bears to encounter and interact with humans. It is counterintuitive to assume that all three of the proportional habitat variables have positive effects on the frequency of interactions, since these proportions are linked, and increases in one must result in decreases in another at some threshold. However, the relative lack of counties showing high values for these proportions made it impossible to predict in this value range, and we saw exponentially increasing response curves for all three variables (Fig. 6). Nonetheless, the patterns observed allowed us to identify the mix of these three habitat classes (forest, developed land, and agriculture) that are likely to create environments most at risk for human-bear interactions. Indeed, the proportional habitat composition identified to predict above average frequencies of bear interactions (forest: 67.7%; developed: 10.3%; agriculture: 27.2%) aligns well with the habitat composition of the five counties with the highest reported numbers of interactions (forest: 57.6- 68.2%; developed land: 8.8-20.8%; and agriculture: 7.3-32.4%). It is also important to note that our % developed land predictor includes information about housing density, population density, and road density, which were highly correlated with % developed land and therefore excluded from the analysis.

Not only did we identify a particular percentage of developed land at the landscape level associated with increased interactions, but human features on the landscape, such as housing density and roads, clearly influenced the likelihood of interactions at a small-scale. The point-scale analysis revealed that interaction risk was highest close to major roads, and at intermediate housing densities (approximately 300 - 600 houses/km$^2$ (3-6 houses/ha). As expected, at a certain point, housing density becomes so high that there is not sufficient bear habitat in the area, and the chance that these areas will be frequented by bears becomes low. In Missoula, Montana, the probability of human-black bear interactions peaked in areas of intermediate housing density (6.59 houses/ha) (Merkle et al. 2011), and bears in Colorado and Nevada selected areas with a housing density of approximately 200-400 structures/km$^2$ (Johnson et al. 2015), revealing notable consistency in this metric across a wide geographic region. In Connecticut, for every additional 3,874 houses/km$^2$, conflict intensity increased by 1 conflict/km$^2$ (Evans et al. 2014). These results suggest that areas of intermediate development represent a balance between the reward of accessing high-calorie anthropogenic food sources and the risk of encountering humans.

Analysis at the county-scale allowed us to investigate whether frequency of human-bear interactions could be related to socio-economic factors, such as median household income. At least one previous study (Evans et al. 2014) demonstrated that bear conflict reporting was higher within higher income census tracts, resulting potentially from a reduced tolerance of bears among higher income residents. Our data do not support this suggestion, and even show a trend toward the opposite pattern, with interaction frequency tending to decline as median income level increased. Though this was not a strong pattern, this result may reflect an increased likelihood of reporting damage, when damage may represent a larger portion of an individual's income. In addition, many of the highest income counties in Virginia are located in parts of the state that have relatively small bear populations, and these counties likely have fewer opportunities for human-bear interactions. In general, however, high income disparities within many of the counties in our study area may have limited the relevance of median income levels to human-bear interactions, relative to broader habitat and development characteristics.

Based on our map of relative risk of human-bear interaction and a withheld set of interaction locations, we demonstrated that our model has strong predictive power. Because our modelling was based on "presence-only" data, in that we had no confirmed non-interaction locations, predicted values from our model, as depicted in the risk map (Fig. 4), should be interpreted carefully. A lack of confirmed absence points prevents interpretation as true probabilities (Keating and Cherry 2004), yet logistic regression with this design is shown to accurately assess the influence of predictor covariates (Johnson et al. 2006) and resulting predicted values should appropriately indicate relationships with those covariates mapped on the landscape in relative terms. In addition, although some random locations likely fell in areas with reported or unreported interactions, our use-availability design, paired with logistic regression modeling, has been shown to be robust to even relatively high levels of "contamination" of this type (Johnson et al. 2006).

It is also important to highlight that approximately one quarter of the interactions included in our analysis represented a reported bear sighting during which no damage occurred. We chose to include these events because they represent to some extent the perception of or potential for conflict. Sightings are also included as one of several types of events that constitute a human-bear interaction, as defined by Hopkins et al. (2010). In addition, from the standpoint of a wildlife management agency such as VDGIF, it is reasonable to adopt a conservative definition of conflict in this context as "any situation where wild bears use (undesirably) or damage human property; where wild bears harm people; or where people perceive bears to be a direct threat to their property or safety" (World Society for the Protection of Animals [WSPA] 2009:1). Although we do not strictly consider all reported interactions as conflict events, any call to

VDGIF or its partners, regardless of the level of property damage involved, results in the use of state or federal resources to address and process that call, and there is interest to manage these resources in the most efficient way possible.

**Management implications**

The results of this study can inform strategic implementation of human-bear interaction management at multiple scales in Virginia and other states in this region. Given current patterns of land use change in Virginia, we expect conditions favorable to human-black bear interactions (i.e. intermediate human development mixed in a forested mosaic) will only increase, such that proactive management of potential risks will be increasingly critical. Results of our analyses, in combination with models of land use patterns under alternative future scenarios, could be particularly effective in highlighting the most likely future hotspots of human-bear interactions.

Our resulting map of relative risk of human-bear interaction allows managers to visualize which specific areas of western Virginia are at highest risk of potential conflict with bears. The ability to narrow down which areas of the state managers should target with conflict prevention measures helps to ensure that these efforts represent an effective and efficient use of resources. Our analyses and resulting map could be used to implement a multi-scale management approach in which high-risk counties are targeted with low-cost, low-effort strategies (e.g. providing educational materials to residents), while areas within these counties that meet the conditions specified in the point-scale analysis could be targeted with more resource-intensive efforts. Such initiatives could include installing bear-resistant garbage containers or initiating Bear Smart Community programs. Implementation of a Bear Smart Community program in the Wintergreen community of Nelson County, Virginia, resulted in an 80% drop in conflict numbers in three years (Sajecki 2010).

The future of black bear conservation hinges on the ability of humans and bears to coexist. To achieve this goal, wildlife managers will need an effective means of identifying areas with the greatest risk of human-bear interactions. Our results can be used to inform the spatial allocation of management resources and the prioritization of management activities to reduce negative interactions and promote the long-term coexistence of humans and black bears in Virginia.

**Acknowledgements**

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**Supplemental information**

Table S1. The *a priori* candidate model set used to assess the relative importance of ecological and anthropogenic variables in influencing the occurrence of reported human-black bear interactions in western Virginia, USA, 2008 to 2015. Models with quadratic terms include the base term of the quadratic.

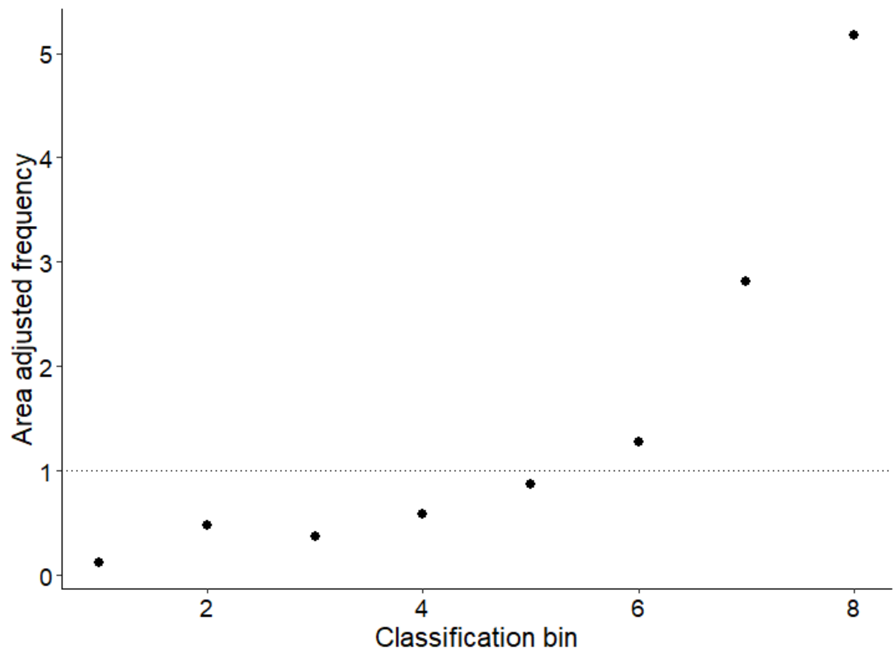
| Model name | Model covariates |
|---|---|
| Natural Habitat | |
| 1. NatHab | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian |
| 2. NatHab | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ |
| Topographic | |
| 3. Topo | Slope$^2$ + elevation$^2$ |
| Natural Habitat + Topographic | |
| 4. NatHabTopo | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian + slope$^2$ + elevation$^2$ |
| 5. NatHabTopo | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + slope$^2$ + elevation$^2$ |
| 6. NatHabTopo | D-Riparian + slope$^2$ + elevation$^2$ |
| Human Population | |
| 7. Pop | Housing density$^2$ + D-MajorRoad |
| Natural Habitat + Human Population | |
| 8. NatHabPop | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian + housing density$^2$ + D-MajorRoad |
| 9. NatHabPop | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + housing density$^2$ + D-MajorRoad |
| 10. NatHabPop | D-Riparian + housing density$^2$ + D-MajorRoad |
| Natural Habitat + Topographic + Human Population | |
| 11. NatHabTopoPop | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian + slope$^2$ + elevation$^2$ + housing density$^2$ + D-MajorRoad |
| 12. NatHabTopoPop | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + slope$^2$ + elevation$^2$ + housing density$^2$ + D-MajorRoad |
| 13. NatHabTopoPop | D-Riparian + slope$^2$ + elevation$^2$ + housing density$^2$ + D-MajorRoad |
| Topographic + Human Population | |
| 14. TopoPop | Slope$^2$ + elevation$^2$ + housing density$^2$ + D-MajorRoad |
| Agricultural | |
| 15. Ag | D-Crops + D-Pasture-hay |
| Agricultural + Human Population | |

| | |
|---|---|
| 16. AgPop | D-Crops + D-Pasture-hay + housing density$^2$ + D-MajorRoad |
| Agricultural + Natural Habitat | |
| 17. AgNatHab | D-Crops + D-pasture-hay + D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian |
| 18. AgNatHab | D-Crops + D-Pasture-hay + D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ |
| 19. AgNatHab | D-Crops + D-Pasture-hay + D-Riparian |
| Agricultural + Topographic | |
| 20. AgTopo | D-Crops + D-Pasture-hay + slope$^2$ + elevation$^2$ |
| Agricultural + Natural Habitat + Topographic | |
| 21.AgNatHabTopo | D-Crops + D-Pasture-hay D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian + slope$^2$ + elevation$^2$ |
| 22. AgNatHabTopo | D-Crops + D-Pasture-hay + D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + slope$^2$ + elevation$^2$ |
| 23. AgNatHabTopo | D-Crops + D-Pasture-hay + D-Riparian + slope$^2$ + elevation$^2$ |
| Agricultural + Natural Habitat + Human Population | |
| 24. AgNatHabPop | D-Crop + D-Pasture-hay + D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian + housing density$^2$ + D-MajorRoad |
| 25. AgNatHabPop | D-Crop + D-Pasture-hay + D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + housing density$^2$ + D-MajorRoad |
| 26. AgNatHabPop | D-Crop + D-Pasture-hay + D-riparian + housing density$^2$ + D-MajorRoad |
| Agricultural + Topographic + Human Population | |
| 27. AgTopoPop | D-Crop + D-Pasture-hay + slope$^2$ + elevation$^2$ + housing density$^2$ + D-MajorRoad |
| Natural Habitat + Topographic + Human Population + Agricultural | |
| 28. Global | D-ForestSmall + D-ForestMed + D-ForestLarge + %Forest$^2$ + D-Riparian + slope$^2$ + elevation$^2$ + housing density$^2$ + D-MajorRoad + D-Crop + D-Pasture-hay |

Table S2. Standardized parameter estimates (β), standard errors (SE), and significance levels (p) for predictor variables in the top-ranked point-scale analysis model.

| **Variable** | **Standardized coefficient (β)** | **SE** | ***p*** |
|---|---|---|---|
| *(Intercept)* | *-0.767* | *0.057* | *0.000* |
| D-ForestSmall | -0.302 | 0.044 | 0.000 |
| D-ForestMed | -0.170 | 0.031 | 0.000 |
| D-ForestLarge | -0.148 | 0.033 | 0.000 |
| %Forest | +0.411 | 0.048 | 0.000 |
| $\%Forest^2$ | +0.062 | 0.031 | 0.046 |
| D-Riparian | -0.076 | 0.026 | 0.004 |
| Slope | -0.500 | 0.041 | 0.000 |
| $Slope^2$ | -0.149 | 0.028 | 0.000 |
| Elevation | +0.054 | 0.032 | 0.097 |
| $Elevation^2$ | -0.438 | 0.031 | 0.000 |
| Housing density | +1.379 | 0.082 | 0.000 |
| Housing $density^2$ | -0.202 | 0.017 | 0.000 |
| D-MajorRoad | -0.166 | 0.028 | 0.000 |
| D-Crops | 0.167 | 0.032 | 0.000 |
| D-Pasture-hay | -0.183 | 0.034 | 0.000 |

Figure S1. Area-adjusted frequency of withheld human-bear interaction locations (*n* = 272) within each of 8 equal-interval classification bins of predicted probability of human-bear interaction in the western VA, USA study region. Frequency values at 1.0 would indicate a frequency of interactions predicted due to chance, based on the area availability in our study area, in each prediction category.



**Tables and figures**

**Table 1. Ecological and anthropogenic covariates, including the data sources, used in the point-scale analysis of human-black bear interactions in western Virginia, USA, 2008 to 2015.**

| Variables | Description | Source |
|---|---|---|
| Ecological – Natural Habitat | | |
| D-ForestSmall (km) | Distance to the nearest small (≤ 2 km$^2$) forest patch | Homer et al. 2015 |
| D-ForestMed (km) | Distance to the nearest medium (>2 – 50 km$^2$) forest patch | Homer et al. 2015 |
| D-ForestLarge (km) | Distance to the nearest large (>50 km2) forest patch | Homer et al. 2015 |
| %Forest (%) | Percent forest cover within a 3.5-km radius buffer | Homer et al. 2015 |
| D-Riparian (km) | Distance to nearest riparian zone | U.S. Geological Survey, accessed 14/3/2016 |
| Ecological - Topographic | | |
| Elevation (m) | Elevation above sea level | U.S. Geological Survey, 1999 |
| Slope (°) | Slope gradient | U.S. Geological Survey, 1999 |
| Anthropogenic – Human Population | | |
| Population density (people/km$^2$) | Number of people per km$^2$, within a 1 km buffer | U.S. Census Bureau, 2010 |
| Housing density (houses/km$^2$) | Number of houses per km$^2$, within a 500 m buffer | U.S. Census Bureau, 2010 |
| D-MajorRoad (km) | Distance to nearest major road | Virginia Geographic Information Network, 2016 |
| Road density (roads/km$^2$) | Number of roads per km$^2$ | Virginia Geographic Information Network, 2016 |
| Anthropogenic - Agricultural | | |
| %Pasture-hay (%) | Percent pasture-hay cover within a 3.5-km radius buffer | Homer et al. 2015 |
| D-Pasture-hay (km) | Distance to nearest pasture-hay patch | Homer et al. 2015 |
| D-Crops (km) | Distance to nearest cropland | Homer et al. 2015 |

**Table 2. Ecological and anthropogenic covariates used in the county-scale analysis of reported human-black bear interactions in Virginia, USA, 2008 to 2015.**

| Variables | Description | Source |
|---|---|---|
| Ecological - Natural Habitat | | |
| %Forest-C | Percent of county described by "Forest/Woodland" class | U.S. Geological Survey, 2011 |
| %Ag-C | Percent of county described by "Agricultural and Developed Vegetation" class | U.S. Geological Survey, 2011 |
| %Developed-C | Percent of county described by "Developed and other Human Use" class | U.S. Geological Survey, 2011 |
| Anthropogenic - Human population | | |
| Housing density | Number of housing units, per $mi^2$ | U.S. Census Bureau, 2010 |
| Population density | Number of people per $km^2$ | U.S. Census Bureau, 2010 |
| Road density | Kilometers of road (of any size) per $km^2$ | Virginia Geographic Information Network, 2017 |
| Income | Median household income per county | U.S. Census Bureau, 2012 |

**Table 3. Summary of the model results for the point-scale analysis of reported human-black bear interactions in western Virginia, USA, 2008 to 2015. Because the top model had all the weight, we show only this and the second competing model. Akaike's Information Criterion (AIC), relative difference in AIC value compared to the top-ranked model (ΔAIC), AIC model weight (ω), the number of model parameters (K), and log-likelihood (LL) values are reported.**

| Model | *K* | AIC | ΔAIC | ω | LL |
|---|---|---|---|---|---|
| 28.Global | 16 | 9,353.27 | 0.00 | 1.00 | -4,660.60 |
| 11.NatHabTopoPop | 14 | 9,399.48 | 46.20 | 0.00 | -4,685.71 |

**Table 4. Summary of model results for the county-scale analysis of reported human-black bear interactions in Virginia, USA, 2008 to 2015. Of the 16 models run, only those with non-zero weight values are shown. Akaike's Information Criterion corrected for sample size ($AIC_c$), relative difference in AIC value compared to the top-ranked model ($\Delta AIC_c$), AIC model weight (ω), the number of model parameters (*K*), and log-likelihood (*LL*) values are reported.**

| Model_Name | *K* | $AIC_c$ | $\Delta AIC_c$ | ω | *LL* |
|---|---|---|---|---|---|
| %Forest-C_%Ag-C_%Developed-C_Income | 9 | 878.095 | 0 | 0.647 | -427.69 |
| %Forest-C_%Developed-C_%Ag-C | 7 | 879.303 | 1.208 | 0.353 | -430.784 |

**Figure 1. Locations of reported human-black bear interactions in Virginia, USA from 2008 to 2015 study period. The density of reported interactions (interactions/km$^2$) of the Virginia Department of Game and Inland Fisheries (VDGIF) Black Bear Management Zones that make up the point-scale analysis study area is shown.**

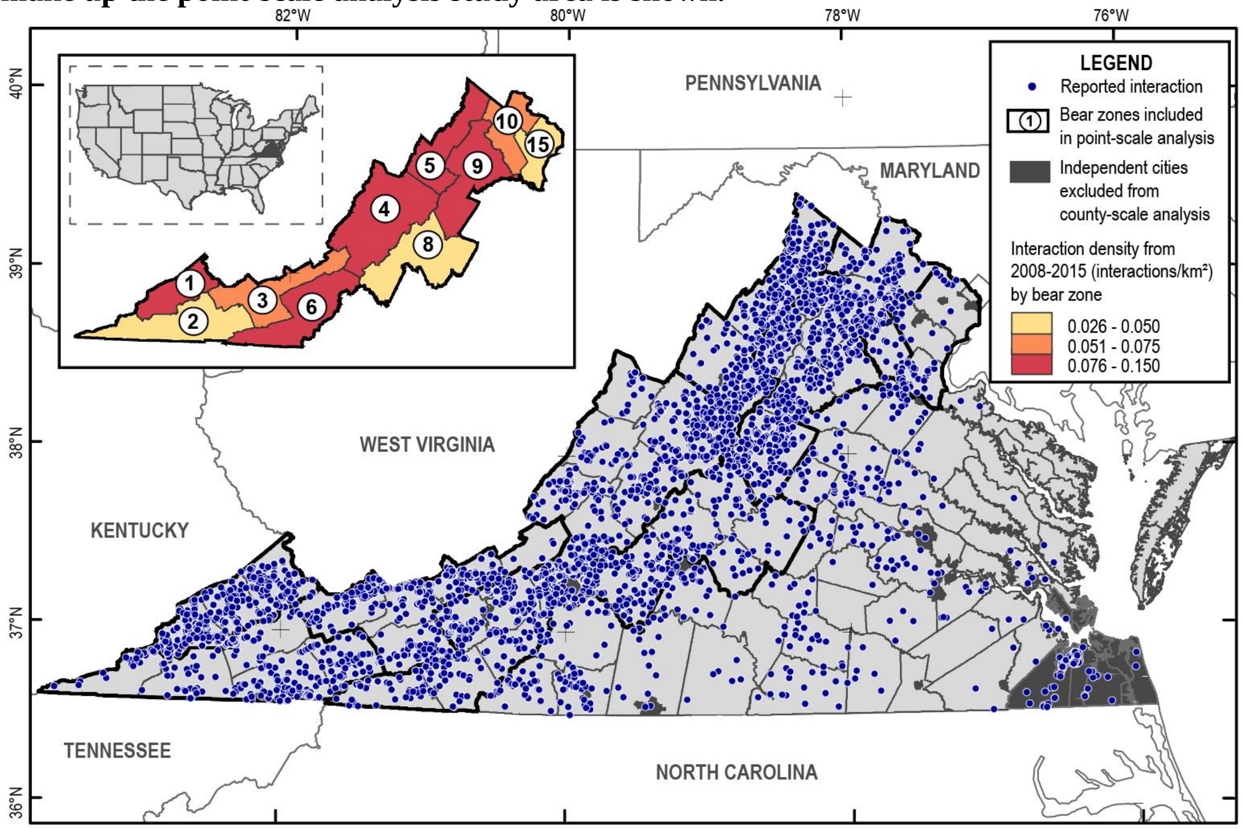


**Figure 2. Temporal pattern of reported human-black bear interactions in Virginia, USA during the 2008 to 2015 study period. All reported interactions from across Virginia during this time period are shown, regardless of the availability of spatial location information or interaction type or severity.**

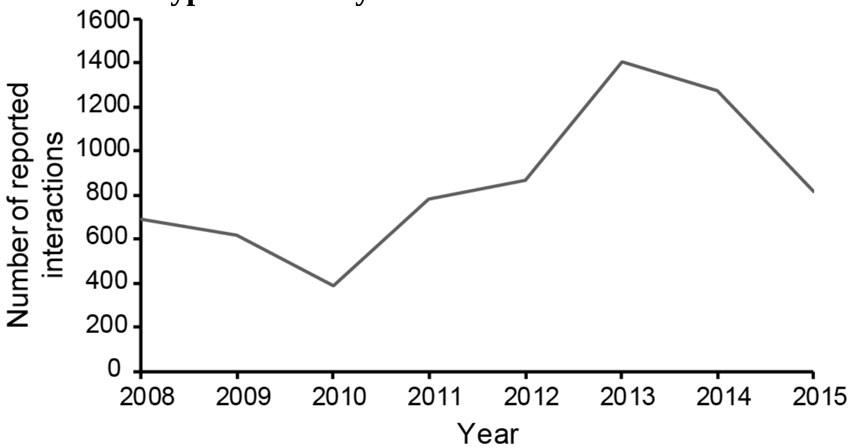


**Figure 3. Coefficient plot showing model coefficient values for parameters in the final point-based binomial/logistic regression model predicting probability of human-black bear interactions in Virginia, USA (2008-2015 data). All covariate values were standardized prior to modelling. Quadratic terms are denoted by "Q".**

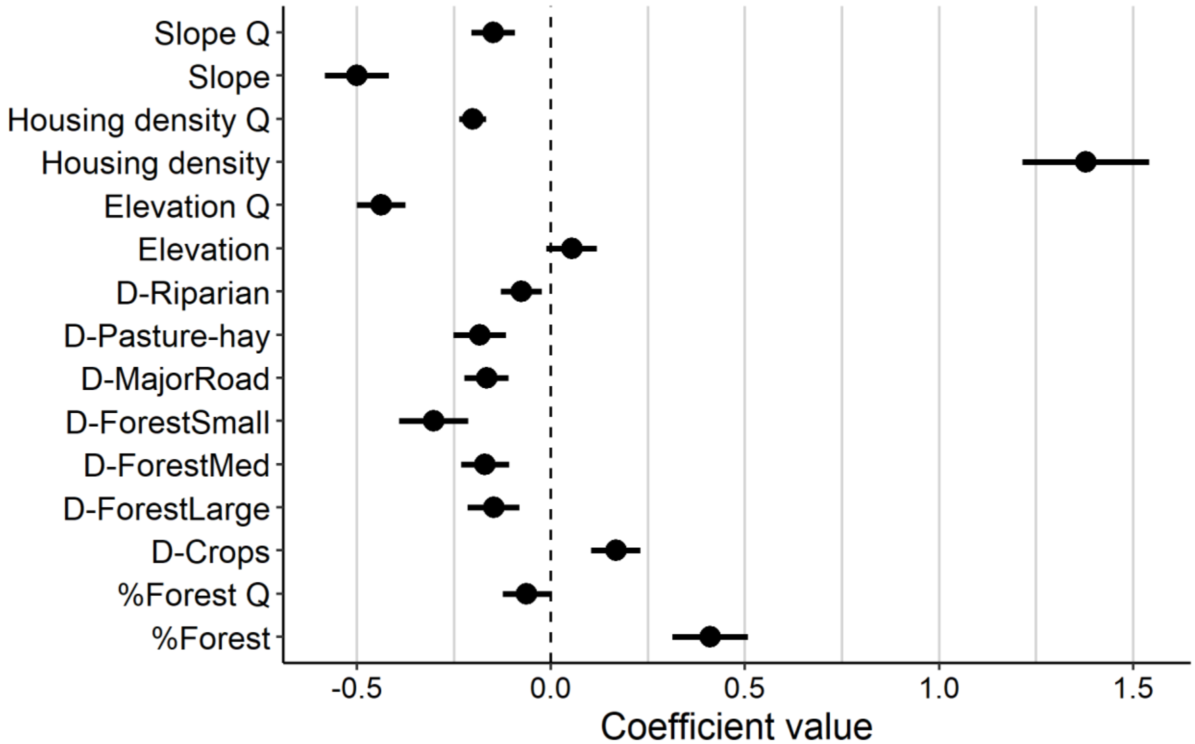



**Figure 4. Map of predicted human-black bear interaction risk in the western Virginia, USA study area at 1 km grid resolution. Predicted values at each grid cell center were generated using coefficient values from the top-ranked model in a point-scale analysis of 4,355 human-bear interaction locations, and an equal number of random locations. Select cities within each zone are displayed for reference. Inset shows detail for Bear Management Zone 9, which contains two of the top five counties in terms of number of interactions (Warren and Albemarle). County names and select cities within Zone 9 are included for reference.**

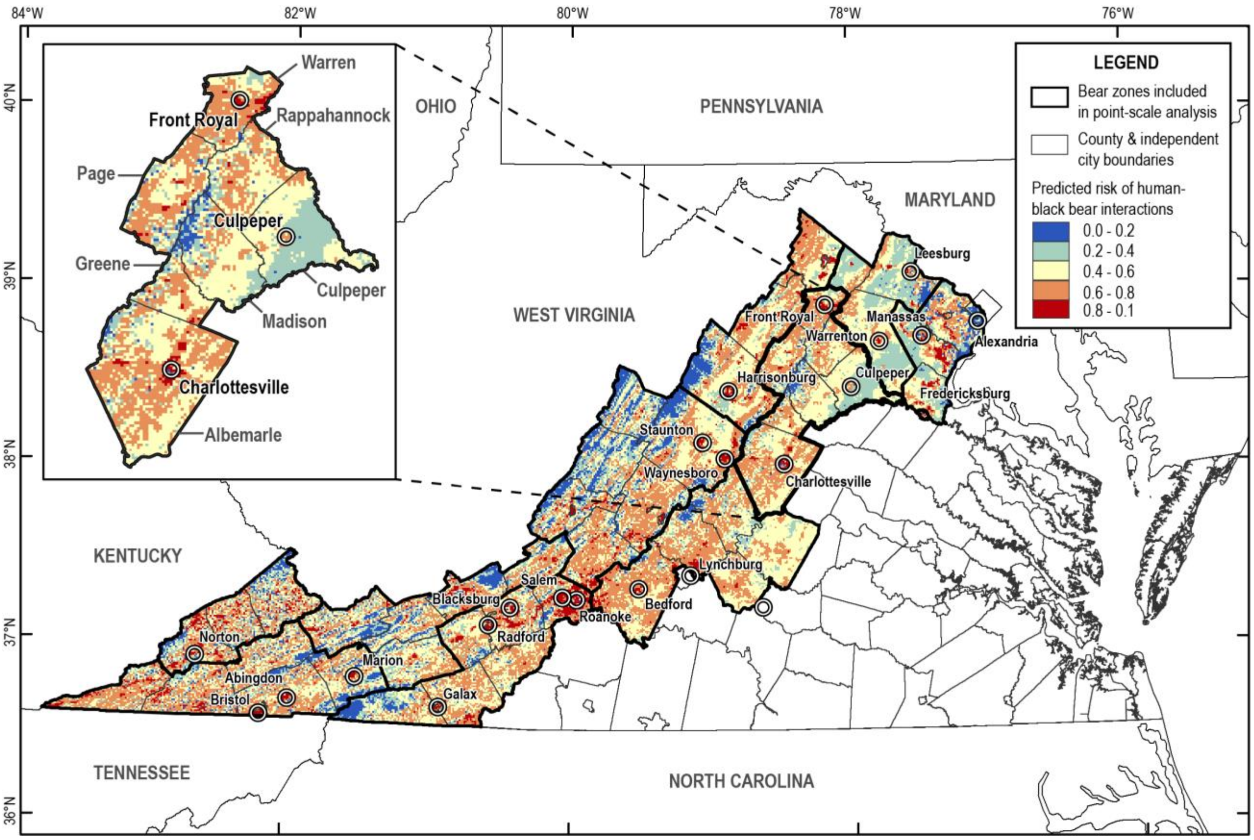

84°W
82°W
80°W
78°W
76°W
40°N
39°N
38°N
37°N
36°N
OHIO
PENNSYLVANIA
MARYLAND
WEST VIRGINIA
KENTUCKY
TENNESSEE
NORTH CAROLINA
LEGEND
Bear zones included in point-scale analysis
County & independent city boundaries
Predicted risk of human-black bear interactions
0.0 - 0.2
0.2 - 0.4
0.4 - 0.6
0.6 - 0.8
0.8 - 0.1
Warren
Front Royal
Rappahannock
Page
Culpeper
Greene
Culpeper
Madison
Charlottesville
Albemarle
Leesburg
Front Royal
Manassas
Alexandria
Warrenton
Harrisonburg
Culpeper
Fredericksburg
Staunton
Waynesboro
Charlottesville
Lynchburg
Blacksburg
Salem
Roanoke
Bedford
Radford
Norton
Abingdon
Marion
Bristol
Galax

**Figure 5. Response curves for covariates included in the final selected model (binomial/logistic regression) predicting point-scale probabilities of human-black bear interactions in Virginia, USA from 2008 to 2015. Covariates are shown across their full range from the dataset, and curves were generated holding other model covariates at their median value. Dashed lines represent 95% confidence intervals.**

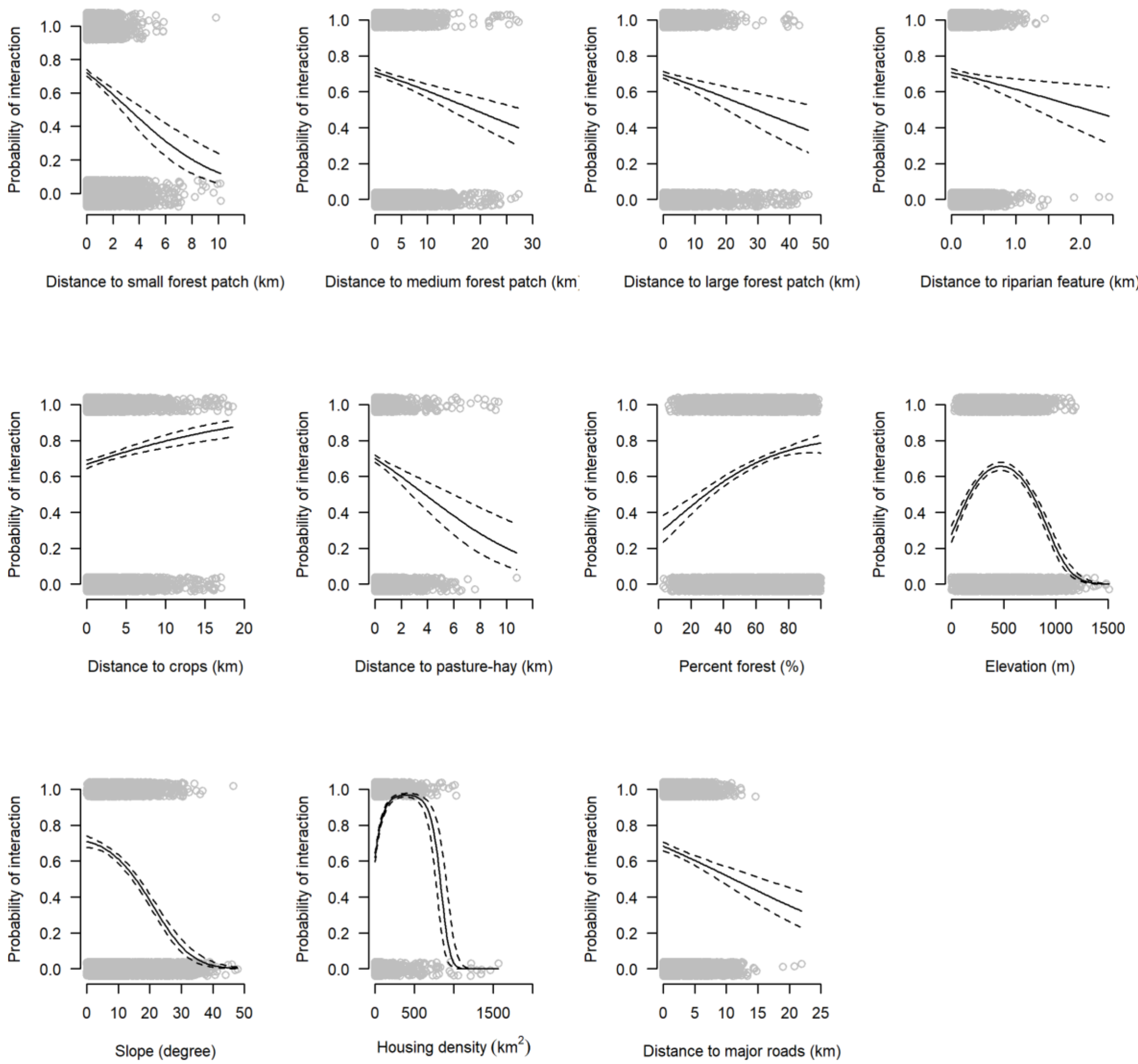


**Figure 6. Response curves for all 4 covariates in a final model (negative binomial) predicting the frequency of human-black bear interactions at the county-scale during the 2008 to 2015 study period. Covariates are shown across their full range from the dataset, and curves were generated holding other model covariates at their median value. Vertical dashed lines represent values of the covariate above which higher than average human-bear interaction frequencies are predicted. Additional dashed lines represent 95% confidence intervals.**