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Human and Black Bear Interactions in Buncombe County, North Carolina, from 1993–2013

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To the Graduate Council:

I am submitting herewith a thesis written by Adam Guy Alsamadisi entitled "Human and Black Bear Interactions in Buncombe County, North Carolina, from 1993–2013." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Geography.

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Dedication

This thesis is dedicated to the memory of Dr. Rosanna Cappellato, who generously shared her fascination with the environment and inspired me to pursue this degree.

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The North Carolina Wildlife Resources Commission, especially Dr. Colleen Olfenbuttel, organized and provided the data without which this project would not be possible. I would also like to express thanks to the open-source communities of the R Statistical Package, including the R Core Team, and of Quantum GIS, including their QGIS Development Team. Developers including Martin Jung, Kevin McGarigal, Eduard Ene, Sam Cushman, Maile Neel, and Barbara Marks, constructed the tools essential for this research.

Abstract

Over the past 20 years the frequency of interactions between humans and black bears in Buncombe County, North Carolina has been increasing, posing threats to human safety, black bear populations, ecological stability, and conservation support. During this time, both the human population and the American black bear population increased in southern Appalachia, which, combined with both urban expansion and landscape fragmentation, led to an increase in human and black bear interactions. Reducing future interactions with black bears is important as these interactions put support for conservation at risk. I performed a landscape analysis to better understand where human and black bear interactions occurred in this county from 1993–2013. After performing statistical analyses, I concluded that landscape fragmentation and urban characteristics likely played a role in where human and black bear interactions took place. Results of this statistical analysis were that human population density, proportion of forested landscape per block group, urban edge density, and the effective forest mesh size per census tract had statistically significant relationships with the geographic distribution of human and black bear interactions. This research can assist planning and conservation initiatives that aim to reduce human and wildlife interactions. This research will also contribute to the growing literature on human and wildlife interactions and the spatial analysis techniques employed to understand them.

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Introduction

The relationship between humans and predator species has always been adversarial and has resulted in enormous population losses for predator species. Interactions with predator species engender hostility, which puts support for conservation efforts at risk (Michalski, Boulhosa, Faria, and Peres, 2006). For this reason, Michalski et al. (2006) argued that developing effective conservation strategies for large predators relies on reducing interactions between them and people. This requires research on where these interactions occur.

Human and black bear interactions in Buncombe County, North Carolina increased in frequency from 1993–2013. In this 20-year period, Asheville attracted many new residents and industries. In 1995, Buncombe County, which includes Asheville and its associated metropolitan area (Figure 0.1), had a population of 192,997 people (U.S. Census Bureau, 2010). In 2012, the population was 244,490, an increase of 27% (U.S. Census Bureau, 2010). Asheville has become a thriving tourist destination; luring tourists by complementing natural experiences in the area with fine restaurants, live music, locally owned shops, street vendors, and regional art. The changes in land use and increased presence of infrastructure required to support this recent growth and activity might suggest dwindling wildlife populations, but the relationship is more complex.

The black bear population in southern Appalachia has been steadily increasing, attributed to conservation efforts beginning with the establishment of Great Smoky Mountains National Park and continuing with various other protected areas and wildlife sanctuaries in the region (Olfenbuttel, 2013). In 1980, the black bear population in western North Carolina consisted of an estimated 1000 individuals. In 1995, the population was estimated at around 2000, but the latest projections (2013) place the population between 6500 and 8000 individuals (Olfenbuttel, 2013).

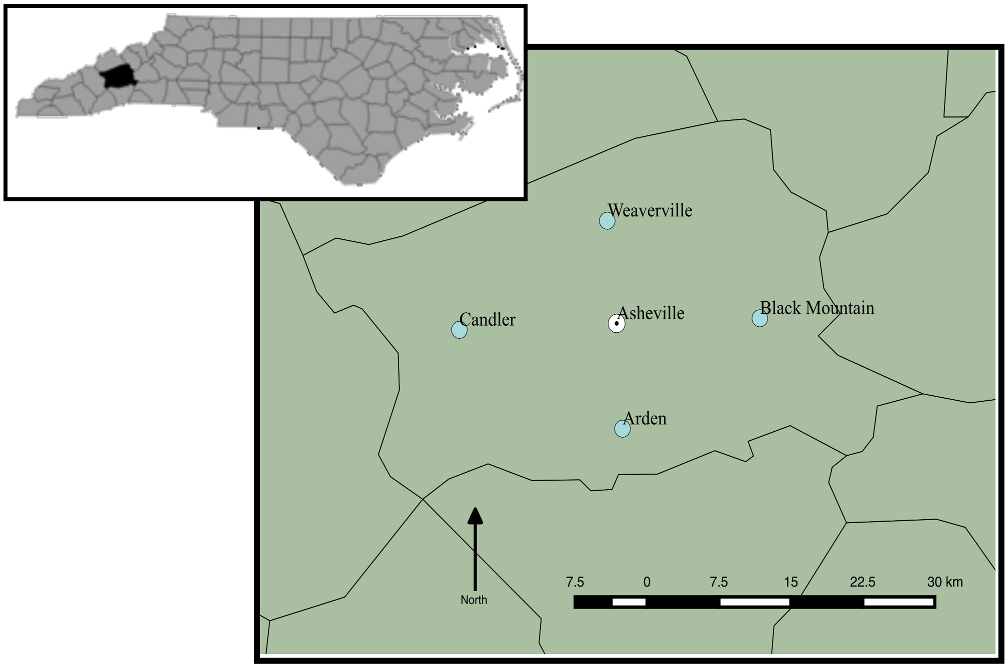

Figure 0.1 Buncombe County, which encompasses the city of Asheville, is located in western North Carolina

As both human and bear populations have increased, there has been an increase in human and black bear interactions (Figure 0.2). In 2005 the North Carolina Wildlife Resources Commission (NCWRC) found that 72% of residents in Buncombe County reported having at least one interaction with a black bear, a higher percentage than in all other counties in North Carolina (Palmer, 2005).

Likely for that reason, residents of Buncombe County are ranked as more knowledgeable on how to deal with black bears than residents in the rest of the state (Palmer, 2005). 25% of residents in Buncombe County were moderately to highly concerned that the bear population was a threat to public safety (Palmer, 2005). Still, 69% of surveyed Buncombe County residents reported having concerns for the health of future bear populations in the region and 18% of surveyed residents wanted their local black bear population to increase in the following five years (Palmer, 2005).

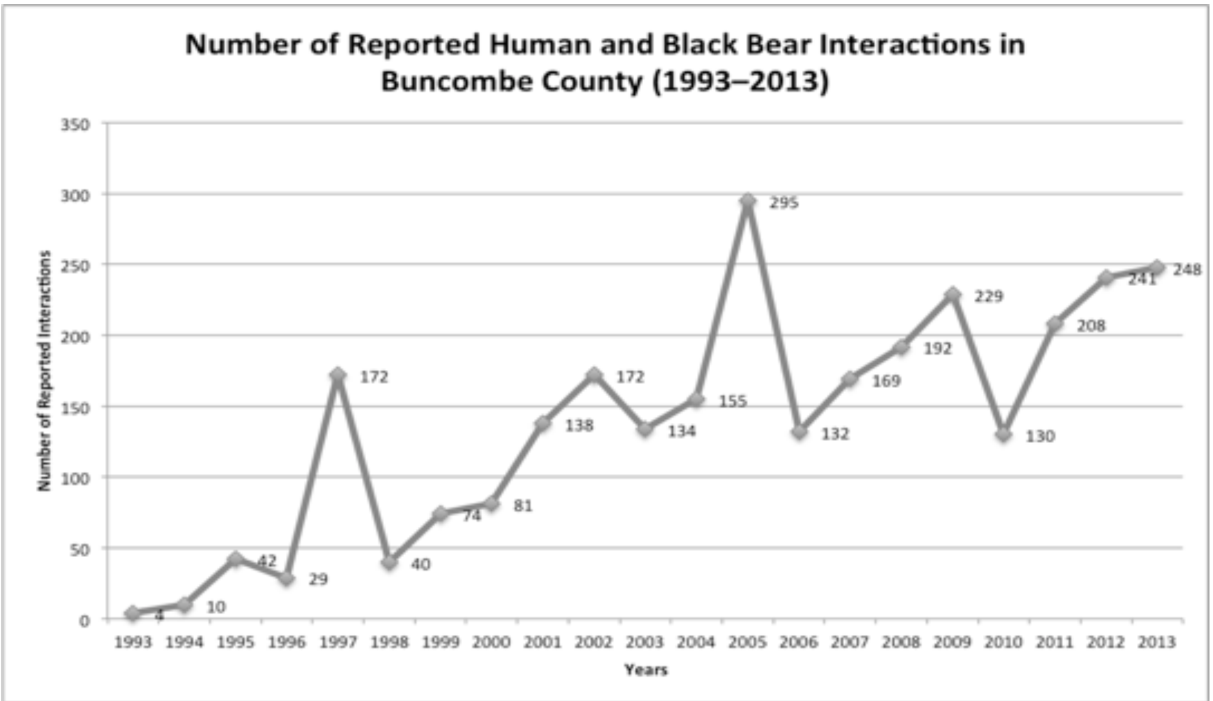

Figure 0.2 Number of human and black bear interactions in Buncombe County per year

Previous studies on human and wildlife interactions, including Beasley and Rhodes (2008), Honda, Yoshida, and Nagaike (2009), and Gorham and Porter (2011), have concluded that landscape patterns and urban characteristics influence locations of human and wildlife interactions. Using Buncombe County as a case study, I will investigate how these factors influence the locations of human and black bear interactions. This research will explore how landscape fragmentation, population density, and road density influence where human and black bear interactions occur.

Chapter 1: Literature Review

1.1 What is Landscape Fragmentation?

Landscape fragmentation is the process by which landscapes are divided by human infrastructure and development (Wilcove, McLellan, and Dobson, 1986). Urban sprawl, through the development of transportation infrastructure and low-density housing, results in fragmented natural landscapes and thus fragmented habitats. The extent of landscape fragmentation affects wildlife populations with respect to livelihood, genetic dispersal, resource acquisition, and migration. The presence of forest patches in a developed landscape, length of forest and urban edge, and proportion of different landscape types are some of the metrics used to describe and quantify landscape fragmentation. Beasley and Rhodes (2008), Gorham and Porter (2011), Honda, Yoshida, and Nagaike (2009), and Kindall and van Manen (2007) all found relationships between landscape fragmentation and human and wildlife interactions.

1.2 Landscape Ecology and Wildlife Interactions

Several researchers have observed the ways landscape patterns influence human and wildlife interactions. Beasley and Rhodes (2008) found that on farms where there were longer edges of forest, there was more evidence of crop damage from raccoons. In their study in central Japan, Honda, Yoshida, and Nagaike (2009) found that distance from forests was a significant indicator of interactions between humans and Asiatic black bears. Kindall and van Manen (2007) studied the effects of fragmentation on black bear populations in coastal North Carolina, and concluded that patterns in forest edge affected foraging strategies and influenced the locations of dens. Forest patches in developed landscapes provide habitats and resources (such as berries, acorns, and natural areas for dens) for many species, including black bears. Gorham and Porter

(2011) concluded that forest patches in the developed landscapes of upstate New York influenced the locations of vehicle collisions with white-tailed deer.

The relationship between what I have referred to as urban characteristics and human and wildlife interactions has also been researched extensively. Previous research has concluded that human population densities and road densities influence occurrences of human and wildlife interactions. Human population densities have implications for the availability of anthropogenic resources and the extent of disturbances in the landscape. Kretser, Sullivan, and Knuth (2008) found that interactions between humans and several species, including black bears, were geographically clustered. They concluded that human and wildlife interactions were most frequent in areas with low housing densities. They attributed this finding to the availability of anthropogenic food sources and the proximity of these areas to forests. Black bears in urban areas rely on dependable anthropogenic resources, through the availability of food in garbage, and become habituated to the developed landscape (Conover, 2002). Many reports used in this analysis are of bears seen digging through dumpsters, as suspects in cases of missing pets, reportedly unfazed walking through neighborhoods, or destroying bird feeders. Habituated bears that are unbothered by cars pose a serious safety threat on roads to people and themselves. Beckmann and Lackey (2008) found collisions with automobiles was the most frequent limit of black bear life in an observed bear population in Nevada.

The habituation of black bears has other impacts on the species' health and that of respective ecosystems. Beckmann and Berger (2003) reported on changes to a black bear community in Nevada through 20 years after habituation via the introduction of anthropogenic food sources. They concluded the bears changed significantly during this period. These changes included a reduction in individual black bear movement and home range sizes, a shift from diurnal activity to nocturnal activity, and an average 30% increase in body mass (Beckmann and Berger, 2003). Black bears play important ecological roles and so behavioral and biological changes have implications for entire ecosystems. The loss of the apex predator triggers major changes to the species composition of ecosystems, which leads to further ecological instabilities (Prugh et al., 2009).

1.3 The Premise of this Research

The premise of this research is that there has been a geographic pattern of human and black bear interactions in Buncombe County and that GIS and spatial statistics can help identify the causes of that pattern. In an issue of *Human and Wildlife Interactions* dedicated to human and bear interactions, du Toit (2008) posited that human and wildlife interactions are not random occurrences. Instead, he wrote, human and wildlife interactions are the product of "patterns of causal factors." For this thesis research, I determined the relationship between the locations of reported black bear interactions and geographic characteristics to answer my research question: **How have landscape fragmentation, human population densities, and road densities influenced locations of human and black bear interactions in Buncombe County, North Carolina from 1993–2013?**

Chapter 2: Methodology

2.1 Available Data on Human and Black Bear Interactions

The North Carolina Wildlife Resources Commission (NCWRC) has recorded statewide reports of human and black bear interactions since 1993. I obtained this data in February 2014 in an excel file. The database of statewide reports included 7686 reports of human and black bear interactions. Attributes of the reports included the date, location, and a description of the interaction, as well as an explanation of how the agency handled the interaction. About 3000, 38% of all reported human and black bear interactions for the state were recorded in Buncombe County. 449 of these reports had address information. I geocoded the addresses and created a point file, which became the data on human and black bear interactions that I used as the response variable in my analysis.

2.2 Other Data in This Analysis

To determine road density, I used the Buncombe County roads polyline file provided by the U.S. Census 2010. I used block group and census tract shapefiles and data provided by the U.S. Census 2010 as areal units and for calculations of human population density (U.S. Census Bureau, 2010). For landscape data, I used the 2011 land cover data provided by the National Land Cover Database (NLCD), which has a spatial resolution of 30 meters and is divided into 16 land-cover classifications (Jin, Yang, Danielson, Homer, Fry, and Xian, 2013). I reclassified the raster so that pixels that represented differing intensities of developed areas were classified as “Developed” and pixels that represented different types of forests were classified as “Forested”. I projected this data using North American Datum 1983 State Plane North Carolina (Figure 2.1)

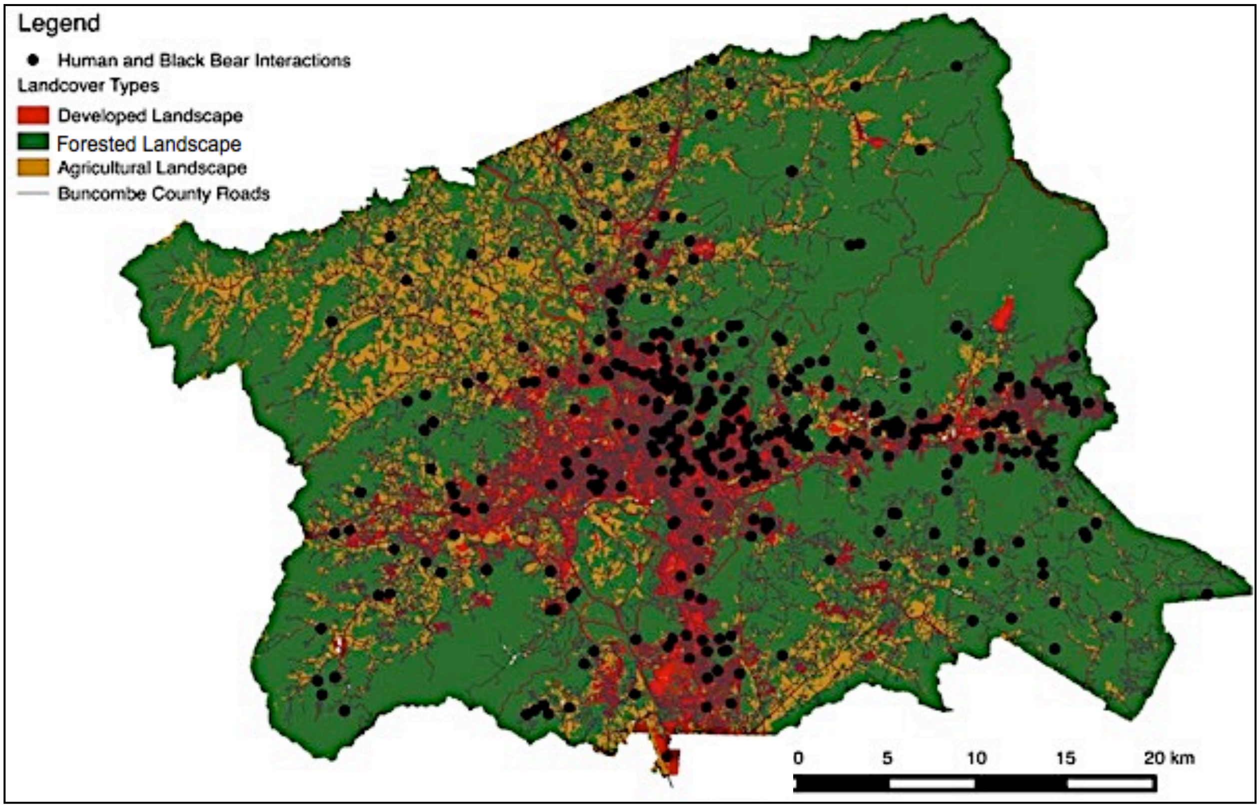

Figure 2.1 Map of human and black bear interactions in Buncombe County.

2.3 Limitations of the Data

The data included a large number of reported interactions (>2500 entries, about 75% of the data) without specific geographic locations. As a consequence they were excluded from the analysis. This opens the possibility that spatial patterns may have been omitted and values may have been incorrectly estimated. Also, Clevenger, Wierzchowski, Chruszcz, and Gunson (2002) suggested that models generated by publicly reported wildlife data are less robust when compared to models that are based on literature or information provided by experts in the field. This suggests that by relying on the data provided by the NCWRC, my analysis might not be as reliable as would be desired.

Additional biases may have arisen from the collection methods for this research. Poessel et al. (2013) analyzed locations of human and coyote conflicts in the Denver Metropolitan Area and found that the action of reporting was spatially inconsistent; residents in certain areas were less likely to report coyote interactions because they had become commonplace. The same sort of bias may be present in this data. Poessel et al. (2013) also found that this type of data can be temporally biased, which, in regards to my analysis, means that reports of human and black bear interactions may exhibit bias in that they temporally reflect when human activity is at its peak, during the day, and at certain but likely inconsistent intervals of the day.

A final source of bias in this analysis is the use of the National Land Cover Dataset. The most recently available land cover data for the coterminous United States was produced in 2011 (Jin et al., 2013). However, I used reports of human and black bear interactions that ranged in time from 1993–2013. A similar mismatch was present in the roads file, which was made accessible in 2010, and the census data, which reflected human population densities in 2010. Thus, this analysis did not take into consideration the changes and dynamics in the landscape and urban characteristics of Buncombe County through this 20-year period.

2.4 Methods and Preliminary Analysis

Based on my observation of the data, I chose several methods and tests to statistically analyze the pattern of interactions. I began with a preliminary analysis to determine if there was a pattern of interactions by calculating the average nearest neighbor index. I then looked for statistical correlations between the explanatory variables and the number of interactions per study unit. After determining the explanatory variables that did have significant correlations, I modeled the data using a generalized linear model.

2.5 Average Nearest Neighbor Index

In a preliminary analysis I used the Average Nearest Neighbor tool in the Geospatial Data Abstraction Library in QGIS 2.8 to determine if the locations of reported interactions were spatially clustered. The tool calculates the average nearest neighbor index, which determines if a number of points are clustered or dispersed based on the distances between points (human and black bear interactions). The average nearest neighbor index (*ANN*) is calculated by dividing the average observed distances between location points by a hypothetical distance between location points that would be expected given the size of the area, the number of points, and a hypothetical random distribution of points. The average nearest neighbor index is defined as:

$$ANN = \frac{\overline{D}_o}{\overline{D}_E}$$

Equation 1 Average Nearest Neighbor Index (ArcGIS Resources, 2013)

In this equation, $\overline{D}_o$ is defined as the observed average distances between nearest neighbors, and $\overline{D}_E$ is defined as the expected average distances, given points in a hypothetical random distribution. $\overline{D}_o$ and $\overline{D}_E$ are calculated using the following equations:

$$\overline{D}_o = \frac{\sum_{i=1}^{n} d_i}{n} \qquad \overline{D}_E = \frac{0.5}{\sqrt{\frac{n}{A}}}$$

Equation 2 Observed and expected distances in average nearest neighbor (ArcGIS Resources, 2013)

In this equation, d_i is defined as the distance between point *i* and the nearest neighboring point, *n* represents the total number of points, and *A* represents the area of the study area. If the index is less than 1, then the pattern exhibits clustering, but if the index is greater than one, the pattern is dispersed (ArcGIS Resources, 2013).

The average nearest neighbor index for this data was calculated as 0.54 and had a critical score (z-score) of -18.8 (less than -1.96 is significant at α=0.05), which demonstrates quantitatively that the points are clustered by rejecting the null hypothesis that the points are randomly distributed. After demonstrating that the data points were clustered with statistical significance, I developed my methodology looking for the underlying geographic forces that influence this cluster.

2.6 Reasoning for Hypotheses-Urban Characteristics

My initial observations prompted me to hypothesize that human and black bear interactions were clustered in areas with low human population density. This reasoning is in line with previous studies that have found wildlife interactions are concentrated in areas with a low human population density. As such, I hypothesized that there was an inverse relationship between human population density and the number of human and black bear interactions, as clusters of interactions seemed to appear in relatively low-density areas, on the outskirts of Asheville and town centers in Buncombe County (Figure 2.2).

My initial observations of the distribution of human and black bear interactions and the roads in Buncombe County prompted me to hypothesize a positive relationship. The locations of human and black bear interactions appeared to cluster in areas with many roads and dense road networks yet were seemingly dispersed in areas with fewer roads and sparse road networks (Figure 2.3). While few of the reported interactions in the data were classified as automobile-related accidents, as briefly discussed, roads have important implications for black bears and

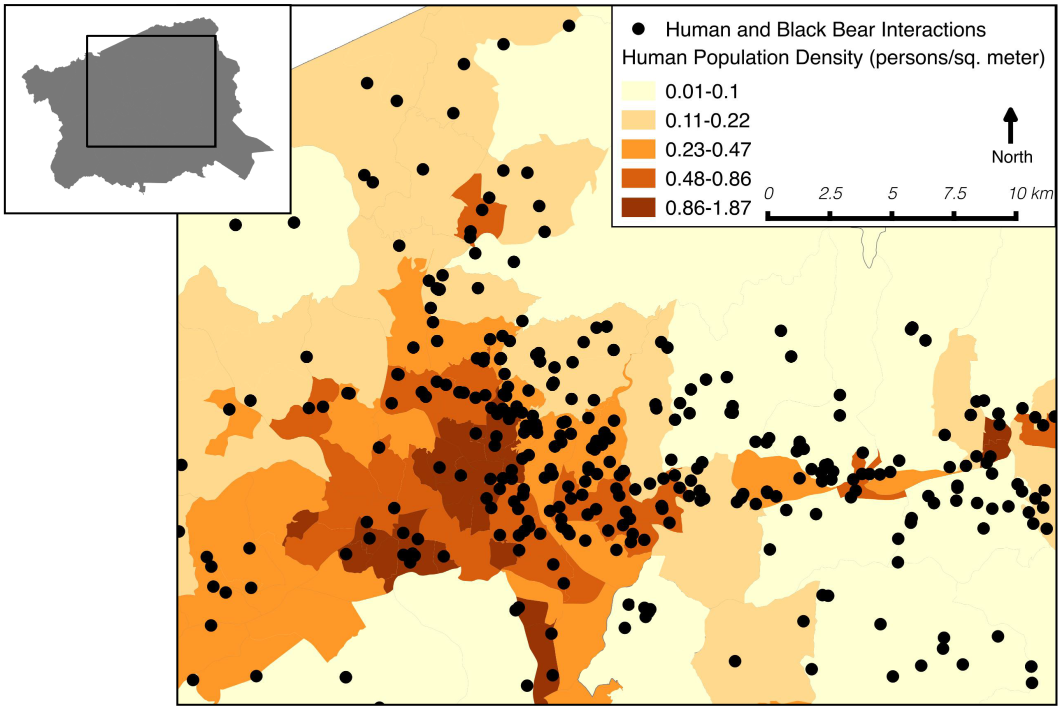

Figure 2.2 Human population density (by block group) and human and black bear interactions

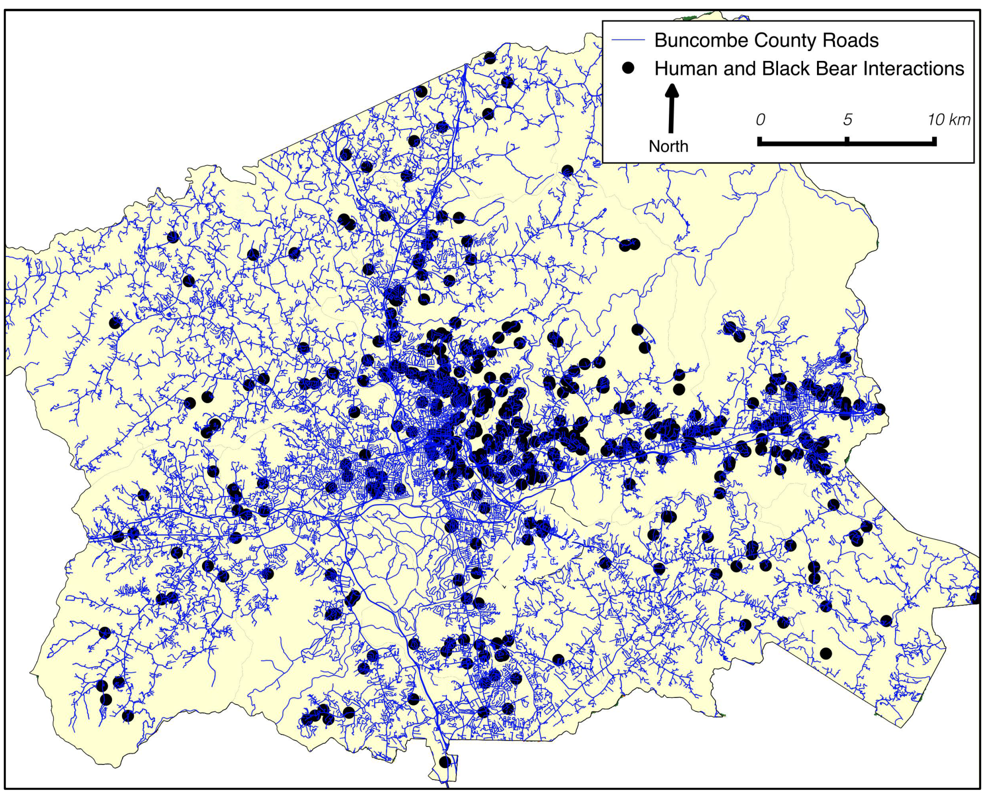

Figure 2.3 Roads and human and black bear interaction

ecosystems. Further investigating the relationship will indicate the extent that the presence of roads and dense road networks influence locations of human and black bear interactions.

2.7 Reasoning for Hypotheses- Landscape Fragmentation

There are examples in the data where landscape fragmentation appears to influence areas where human and black bear interactions occur. The types of common metrics used to measure landscape fragmentation include (1) area (2) edge (3) patch (4) nearest neighbor (5) geometric (Table 1). The values of these metrics were calculated using LecoS, a QGIS plugin that measures landscape fragmentation using land cover rasters (Jung, 2012).

Table 1 Landscape Metrics in this Analysis

Landscape Metric	Metric Type	Description	Source
Land Cover	Area	Provides the area of a particular landscape class	Jung 2013
Landscape Proportion	Area	Provides the percent of total area a particular class constitutes within the areal unit	Jung 2013
Edge Length	Edge	Provides absolute length of the edge of a particular class, used for areal units of the same size	McGarigal 2014
Edge Density	Edge	Standardizes the edge length of a particular class to a per unit area, used for areal units of differing sizes	McGarigal 2014
Number of Patches	Patch	Provides an absolute count of the number of patches of a class, used for areal units of the same size	McGarigal 2014
Patch Density	Patch	Standardizes the number of patches of a particular class to a per unit area, used for areal units of differing sizes	McGarigal 2014
Greatest Patch Area	Patch	Provides the area of the total landscape comprised of the largest patch of a particular landscape type	Jung 2013
Smallest Patch Area	Patch	Provides the area of the total landscape comprised of the smallest patch of a particular landscape type	Jung 2013
Mean Patch Area	Patch	Provides the arithmetic mean of the patches of a particular class within an areal unit	Jung 2013
Median Patch Area	Area	Provides the arithmetic median of patch area of a particular class within the areal unit	Jung 2013
Mean Patch Distance	Nearest Neighbor	A measure of patch isolation, finds the arithmetic mean of the straight-line distances between patches of a particular class	Jung 2013
Effective Mesh Size	Geometric	A measurement based on the probability that two randomly chosen points in the landscape are in the same type of patch, standardized for areal units of different sizes	Jaeger 2000

Area metrics are used to measure the total area or percent of the toal area of a landscape class within a study region. In this study, an area metric represents the percent or total area of forested or developed landscape within a study unit (McGarigal, 2014). Area metrics are not used to measure fragmentation per se; these metrics only represent the area that a chosen landscape class comprises. Previous studies have linked the accessibility of forest resources to increased human and wildlife interactions, and in this study, area metrics like the proportion of forested landscape per study unit indicated the extent that forest cover and accessibility to forest resources influence human and black bear interactions.

Edge metrics are often discussed in relation to wildlife damage management (McGarigal, 2014). There are many examples in the data of reported human and black bear interactions found along the edge of the forest (Figure 2.4), which is why I anticipated there would be a significant relationship found between length of forest edge and the number of interactions. Many interactions in the data were located near forest patches surrounded by developed landscape (Figure 2.5). As discussed, patches often serve as sources of food and areas to den for urban-dwelling species, so I hypothesized that forest patch density has a positive relationship with the number of interactions. Based on my observations of the data, I also expected the different characteristics measured by different forest patch metrics (greatest, smallest, mean, and median patch areas) have positive relationships with the number of human and black bear interactions. Patch metrics and the nearest neighbor metric, which is used to measure distances between patches, are widely used indices in wildlife studies in landscape ecology. Following the literature, I hypothesized that if forest patches were farther apart in a study unit, there would be more human and black bear interactions.

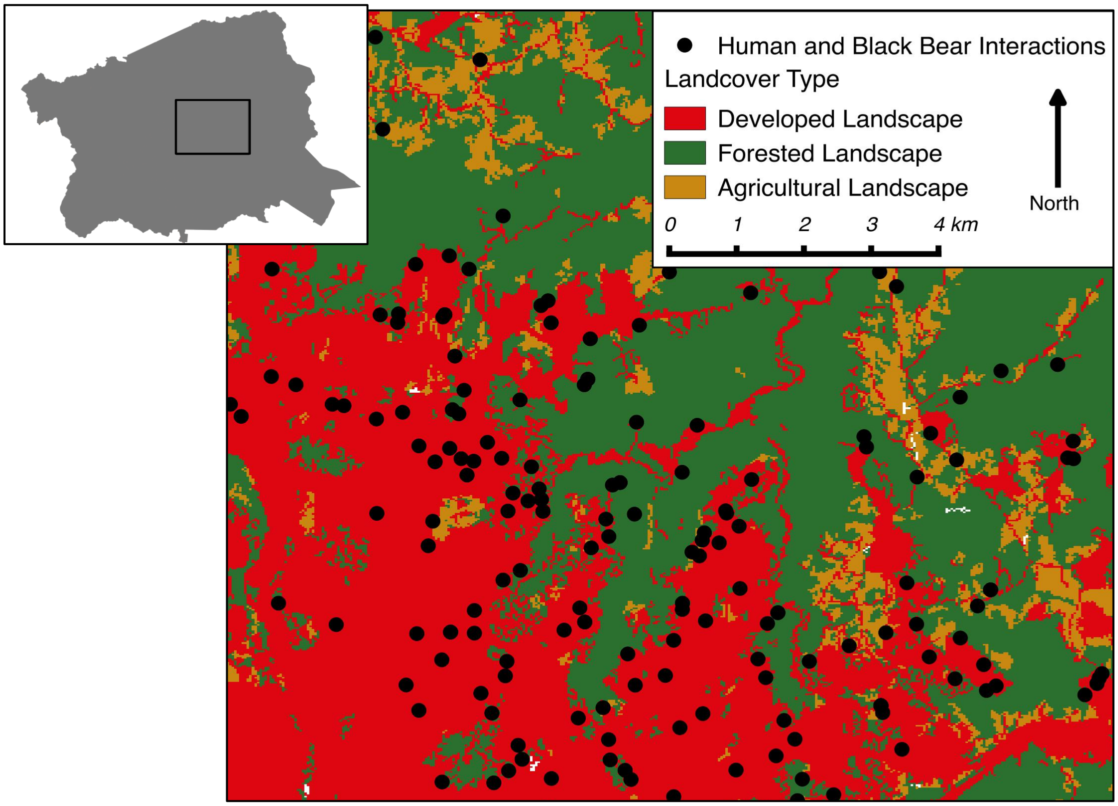

Figure 2.4 Human and black bear interactions along landscape edge

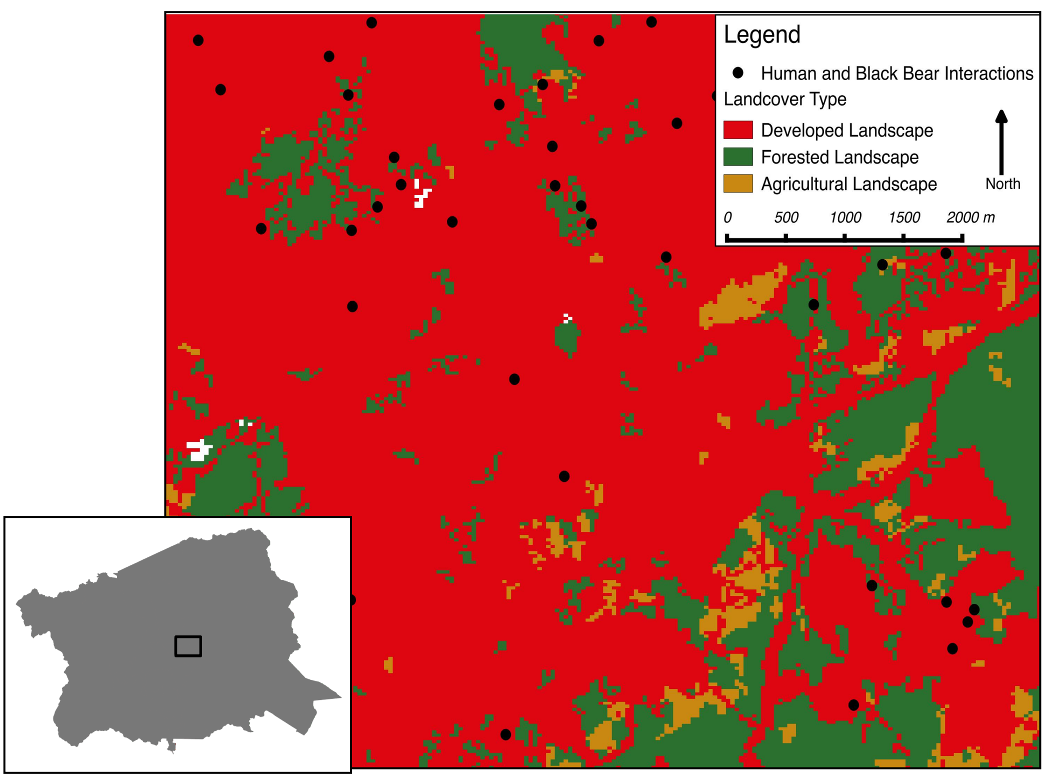

Figure 2.5 Human and black bear interactions near forest patches

The last metric type was introduced by Jaeger (2000). The geometric type encompasses three metrics: the landscape division index, the splitting index, and the effective mesh size (Jaeger, 2000). These metrics are based on the likelihood that two animals randomly placed in a study unit will be located in the same patch, without being separated by natural or anthropogenic barriers, such as rivers and roads, for reproduction purposes. These metrics are indicators of landscape, and in effect, habitat, continuity. Of these metrics, Jaeger (2000) posited that the effective mesh size is unique in that it is specifically well-suited for comparing the extent of fragmentation in study units of different sizes. As will be clarified in the next section, this makes this metric particularly useful in this study, and as such the effective mesh size will be the only metric investigated of the geometric type.

The effective mesh size is calculated in the following way: the probability of a random point being located in patch 1 of a landscape is $\left(\frac{Area(Patch\ 1)}{Area(Total\ Study\ Unit)}\right)$, and so the probability that two points being randomly located in the same patch is $\left(\frac{Area(Patch\ 1)}{Area(Total\ Study\ Unit)}\right)^2$. Thus, the probability that two points are randomly located in the same patch given all patches (1-n) in a study unit is defined by:

$$\left(\frac{Area(Patch\ 1)}{Area(Total\ Study\ Unit)}\right)^2 + \left(\frac{Area(Patch\ 2)}{Area(Total\ Study\ Unit)}\right)^2 + \left(\frac{Area(Patch\ 3)}{Area(Total\ Study\ Unit)}\right)^2 + \cdots + \left(\frac{Area(Patch\ n)}{Area(Total\ Study\ Unit)}\right)^2$$
$$= \sum_{i=1}^{n}\left(\frac{Area(Patch\ i)}{Area(Total\ Study\ Unit)}\right)^2$$

Equation 3 The first half of the effective mesh size equation, which is, in essence, the probability that two points will be randomly placed in the same patch within a landscape (Jaeger, 2000)

To make the result comparable to units of different total areas this value is multiplied by the total area of the study unit resulting in:

$$(Area\ of\ Total\ Study\ Unit) * \sum_{i=1}^{n} \left(\frac{Area(Patch\ i)}{Area(Total\ Study\ Unit)}\right)^2$$

$$= \frac{1}{Total\ Area\ of\ Study\ Unit} \sum_{i=1}^{n} Area(Patch_1)^2 + Area(Patch_2)^2 + \cdots + Area(Patch_n)^2$$

Equation 4 The second half of the effective mesh size equation, which multiples the result of the first half of the equation by the area of the study unit to make the measurement comparable for units of different sizes (Jaeger, 2000)

Larger effective mesh sizes indicate landscapes that are relatively uninterrupted by barriers, while those with values close to 0 indicate a landscape that is entirely divided by barriers (Jaeger, 2000). I hypothesized that the effective mesh size of an area had a positive relationship with the number of human and black bear interactions because of my initial observations of the data. In less fragmented landscapes with more habitat continuity, I hypothesized there were more human and black bear interactions. The next section will clarify the boundaries that I used to calculate these metrics and to observe relationships between these measurements and the response variable.

2.8 Areal Units Used in Analysis

I aggregated data and performed statistical analysis using two different areal units to determine if the explanatory variables were sensitive to the size and shape of study units, which prompts a discussion on the Modifiable Areal Unit Problem (henceforth MAUP) as it relates to my research question. I analyzed the relationship between the response variable (human and black bear interactions) and the explanatory variables (fragmentation and urban characteristics) using census tracts and census block groups as areal units (Figure 2.6). Census tracts and census block groups are standard divisions of populated areas used to understand human population and demographics. Census tracts are drawn to encompass entire neighborhoods, representing 1500–8000 people. Block groups are drawn to encompass smaller groups than neighborhoods,

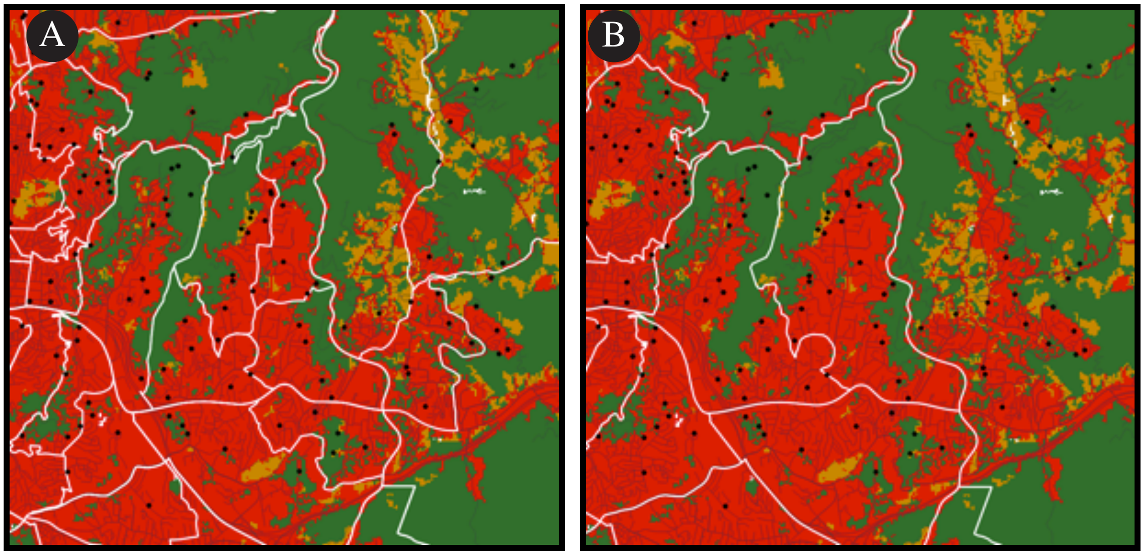

Figure 2.6 Areal units used in analysis (A) block group (B) census tract

representing populations ranging from 600–3000 people (U.S. Census Bureau, 2010). I measured the explanatory variables in each areal unit and tested the relationships between the explanatory variables and the numbers of interactions found in each areal unit.

The MAUP arises in geographic studies because the areal units that are used to observe relationships are arbitrary and modifiable (Openshaw, 1983). The MAUP manifests itself in two forms, the aggregation effect and the zoning effect (Figure 2.7). The aggregation effect arises when there are differences in statistical results that occur because of the scale of areal units (i.e. census tracts are a larger scale than block groups), and the zoning effect arises when there are differences in statistical results that occur because of the shape of the areal unit (i.e. the same analysis done using census areal units might yield different results had I used a grid in the analysis) (King, Tanner, and Rosen, 2004).

In regards to this study, the MAUP would arise if fragmentation metrics or urban characteristics had different relationships with the number of human and black bear interactions at different areal units. Jelinski and Wu (1996) provided ways to address the MAUP in landscape ecology research. One of these approaches, the *sensitivity analysis approach*, suggests

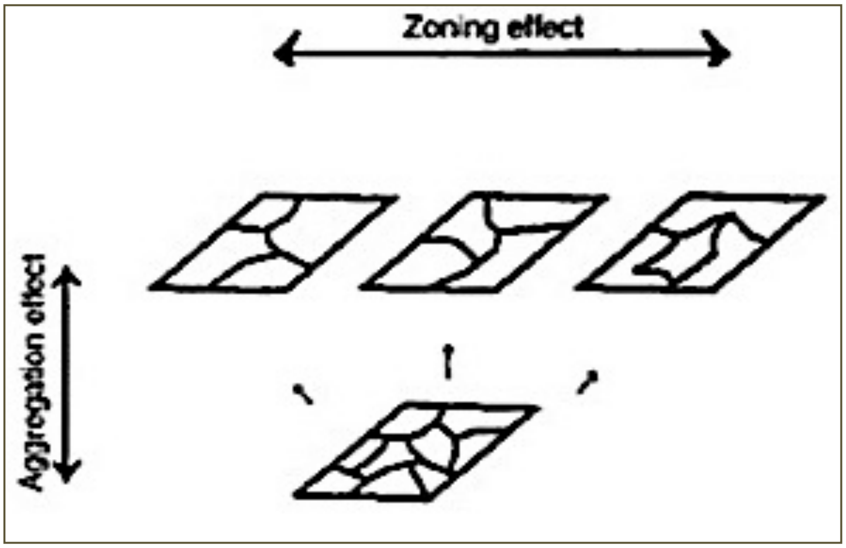

Figure 2.7 Effects of the modifiable areal unit problem (figure from King, Tanner, and Rosen (2004))

investigating the relationships between response and explanatory variables at different spatial scales and with different areal units to get a scope of the effects of the MAUP in the study. By performing this analysis using different areal units, I investigated if any of the explanatory variables had relationships with the number of human and black bear interactions, and at which areal units. As such, in my analysis, although I hypothesized that I would find relationships using both areal units, I also expected there to be differences in these relationships.

2.9 Hypotheses

My research hypotheses consider these metrics at these areal units to answer the following research question**: How have landscape fragmentation, human population densities, and road densities influenced locations of human and black bear interactions in Buncombe County, North Carolina from 1993–2013?** (Table 2). I investigated these research hypotheses using statistical tests, and so my statistical hypotheses are less specific versions of the research hypotheses (Table 3).

Table 2 Research Hypotheses

Explanatory Variables	Research Hypotheses
Road Densities	Reported interactions will be more associated with areas that have a high density road network at both the census tract and block group levels
Human Population Density	Reported interactions will be more prevalent in areas in areas with low population densities at both the census tract block group levels
Area Metrics	Densities of reported interactions will be higher near forests, and so landscape composition around reported interactions will have a relationship with the number of interactions at both the census tract and block group levels
Edge Metrics	In areas with longer forest edge and higher forest edge density, there will be more human and black bear interactions at both the census tract and block group levels
Patch Metrics	In areas with more forest patches and more forest patches per area, and those of greater average patch sizes, there will be more interactions at both the census tract and block group levels
Nearest Neighbor Metric	In areas where patches are farther apart, there will be more interactions at both the census tract and block group levels
Effective Mesh Size	In areas with a smaller effective forest mesh size, there will be fewer interactions at both the census tract and the block group levels.

Table 3 Statistical Hypotheses

Null Hypothesis	The explanatory variables do not have any relationship between the number of human and black bear interactions in Buncombe County at either the census tract or the block group level
Alternative Hypothesis	The explanatory variables do have a relationship between the number of human and black bear interactions in Buncombe County at both the census tract and block group level

2.10 Spearman's Rho Correlation

I determined the variables were not normally distributed using the Shapiro-Wilk test, which indicated I needed to use nonparametric statistical tests. I used Spearman's rho correlation (ρ) to determine the correlations between the explanatory variables and the numbers of reported interactions within each areal unit. Spearman's rho measures the statistical dependence of two variables by converting the values of X and Y's in the observations *n* to ranks where d_i=$x_i - y_i$ is the difference between ranks in the equation:

$$Spearman's\ rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

Equation 5 Spearman's rho (Yue, Pilon, and Cavadias, 2002)

Because the values of the variables are converted to ranks, Spearman's rho is less sensitive to outliers, which makes it a good method for data that are not normally distributed (Gauthier, 2001). ρ will range from -1.0 to 1.0. Positive coefficients indicate a positive relationship, and negative coefficients indicate an inverse relationship. The closer that ρ is to 0, the weaker the correlation between the two variables (Yue, Pilon, and Cavadias, 2002). If my alternative statistical hypotheses are correct there will be statistically significant correlations between the explanatory variables and the number of reported human and black bear interactions.

I produced a correlation matrix using Spearman's rho with the Correlate Tool in SPSS Statistics. This matrix reported which explanatory variables had statistically significant relationships with the number of interactions counted in each areal unit. By determining the explanatory variables that had significant relationships with the response variable, I had a choice of variables to use in a regression. By performing a regression, I could better understand the relationship between the explanatory variables and the number of human and black bear interactions at both sets of areal units. I performed all of the regression analysis using R Statistical Program (R Core Team, 2013).

2.11 An Overview of Negative Binomial Generalized Linear Models

I used a generalized linear model (GLM) to model the relationship between the explanatory variables and the number of human and black bear interactions. The GLM was chosen because the response variables, the number of human and black bear interactions per areal unit, were count data (numbers of occurrences per areal unit, thus only positive integers), which indicated classical linear regression was an inappropriate regression model for the data (Dunteman and Ho, 2006). I produced histograms and confirmed using the Shapiro-Wilk test that the response variables were not normally distributed, which further indicated that the GLM was an appropriate regression method for the data (Figures 2.8 and 2.9).

The three components of a GLM are the response variable distribution, the linear predictor, and the link function (Zuur et al., 2009). Because the response variables were count data, the first distribution I considered was the Poisson distribution (Zuur et al., 2009). However, the variance of the number of interactions per block group and per census tract was 102.6 and 18, respectively, while the mean values of this response variable were 8.1 and 3, respectively. An assumption of the Poisson distribution is that the variance and the mean are equal. GLMs based on the negative binomial distribution are used to fit data when the response variable is overdispersed count data, and variance exceeds the mean. This is defined by $var(\mu) = \mu + \frac{\mu^2}{k}$, where μ is the mean of the response variable and k is the dispersion parameter in the negative binomial GLM (Zuur et al., 2009). In negative binomial regression, the expected values of the

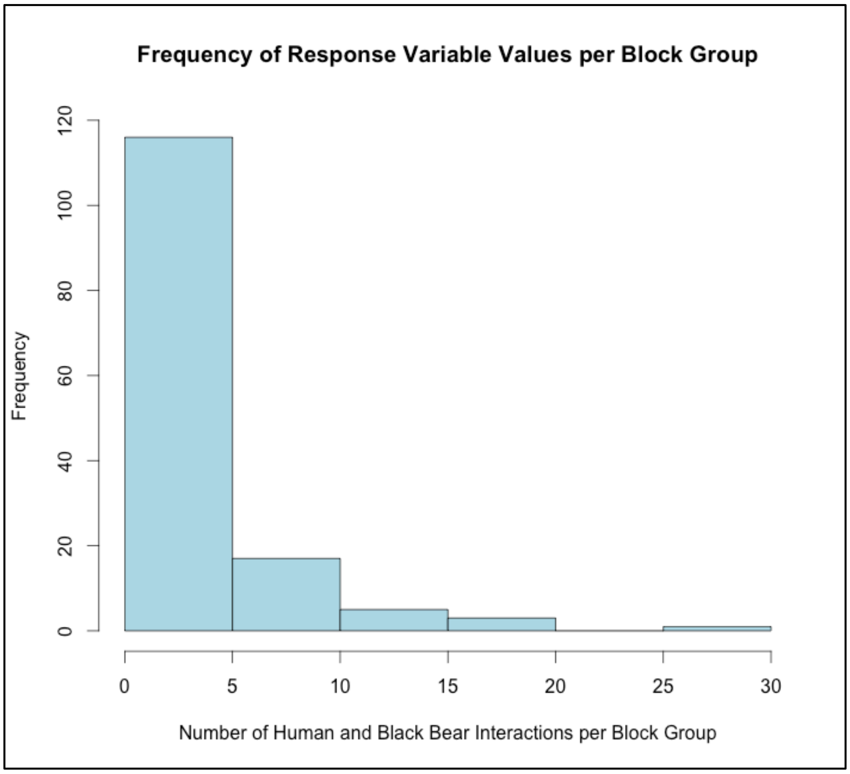

Figure 2.8 Histogram of the response variable per block group

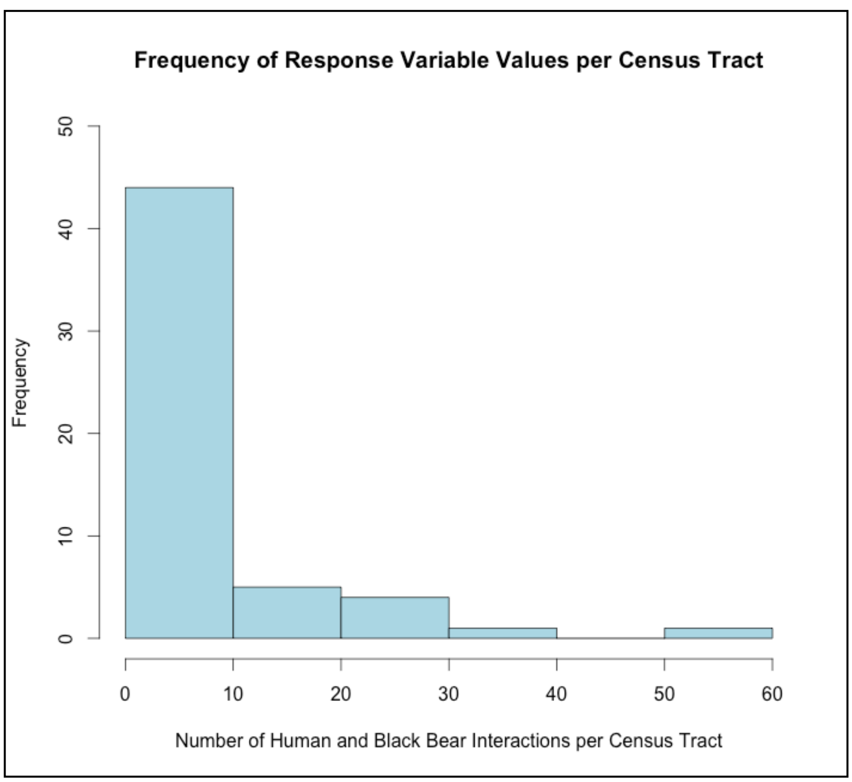

Figure 2.9 Histogram of the response variable per census tract

response variable (Y) follows a negative binomial distribution with μ as the mean and dispersion parmeter k. The second component of a GLM is the linear predictor (η), which is the linear combination of explanatory variables (X_i) and the coefficients (β_i), so that $\eta(X_{i1}, \dots, X_{iq}) = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_q X_{iq}$ (Zuur et al., 2009). The third component defines the expected values of the response variable as a function of the linear predictor. For these negative binomial GLMs I used the log link. This inclusion of the log link sets the equation for the negative binomial GLM as $\log(\mu_i) = \beta_0 + \beta_1 X_1 + \cdots \beta_i X_i$ (Table 4) and also ensures that the values determined by the negative binomial GLM are calculated as non-negative, as $\mu = e^{\beta_0 + \beta_1 X_1 + \cdots \beta_i X_i}$ and thus $\mu > 0$ (Zuur et al., 2009).

Table 4 Components of Negative Binomial GLMs

Response Variable in Negative Binomial Distribution	$Y \sim NB(\mu, k)$ $\quad var(\mu) = \mu + \frac{\mu^2}{k}$
Linear Predictor	$\eta(X_{i1}, \dots, X_{iq}) = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_q X_{iq}$
Link Function- Log Link	$\log(\mu_i) = \eta(X_{i1}, \dots, X_{iq})$
Negative Binomial GLM	$\log(\mu_i) = \beta_0 + \beta_1 X_1 + \cdots \beta_i X_i$

I reported the incident rate ratio (IRR) of the explanatory variables to interpret the coefficients determined by the model. The IRR, calculated by e^{β_i}, represents the change in the response variable from Y_0 to Y_1. Thus, this determines the rate of change in the response variable after a one-unit change in an explanatory variable while other explanatory variables are held constant (Hardin and Hilbe, 2007). This is calculated by a ratio that determines the rate of change in the outcome, the incidence of human and black bear interactions, given changes in an explanatory variable, which is calculated by:

$$IRR = e^{\beta_i} = \frac{Y_1}{Y_0} \text{ when } Y_0 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \text{ and } Y_1 = \beta_0 + \beta_1 (X_1 + 1) + \beta_2 X_2$$

Equation 6 Calculation of the incident rate ratio (IRR) (Hardin and Hilbe, 2007)

This indicates for a one-unit increase of an explanatory variable X_i with an estimated coefficient of β_i, the response variable is expected to change by a factor of e^{β_i}, the IRR (Hardin and Hilbe, 2007). The incident rate ratio provides an efficient structure for the interpretation of the coefficients of negative binomial GLMs.

2.12 Additional Steps in Fitting the Data to the GLM

Applying all of the explanatory variables with significant Spearman's rho correlations at each level of analysis would have falsely determined the regression model because of multicollinearity, defined as collinear relationships among several variables (Fox and Weisberg, 2011). I systematically removed variables that exhibited multicollinearity with other variables from the GLM using the following procedure. After creating the models, I ran the VIF function in R, which outputs the Variance Inflation Factor (VIF) of each variable in the model (Fox and Weisberg, 2011). VIF is a measure of the amount of variance that is increased because of multicollinearity. There is no consensus, but literature suggests that if the VIF value of an explanatory variable in a model is above 2.5 then the variable exhibits enough multicollinearity with other variables that the results of the model would be invalidated because the regression line would be drawn based on collinear relationships (Rogerson, 2001). Using the VIF function, I was able to ensure that my models did not have any combination of collinear variables that would invalidate GLM.

I determined the best models based on lowest AIC. This was done using the *step()* function in R and the models were verified by forward and backwards direction (R Core Team, 2013). AIC accesses the quality of statistical models by measuring both the goodness of fit of the model and the complexity of the model and is a useful criterion when comparing models derived from the same dataset (Aho, Derryberry, and Peterson, 2014). The GLMs that I reported had the lowest AIC of all combinations of explanatory variables at each set of areal units. I then had a model for each set of areal units that incorporated statistically significant coefficients of explanatory variables.

2.13 Assessing Fit of GLMs with Likelihood-Ratio Test

The likelihood-ratio test is a common approach to model and explanatory variable selection in regression. This test determines if data fit a so-called "complex" regression model better compared to another regression model that is referred to as "reduced," meaning the model is comprised of fewer explanatory variables (Zuur et al., 2009). To perform the likelihood-ratio test and test the GLMs produced with the data, which were considered the complex models, I compared them with two negative binomial GLMs that did not account for any explanatory variables, which were considered the reduced models (i.e. models with an intercept only). The test statistic follows a chi-squared distribution with the degrees of freedom equal to the number of parameters, the explanatory variables, in the model. If the test statistic is large enough, a significant p-value indicates that the complex model fits the data significantly better than the reduced model (Zuur et al., 2009).

2.14 Assessing Proportion of Variance Explained with D^2 and adjusted-D^2

R^2 and adjusted-R^2 values are typically reported with linear regression models to represent the proportion of deviance in the response variable for which a statistical model accounts. D^2 and adjusted-D^2 values are the equivalent for GLMs that can be calculated through the ‘modEvA’ package in R (Barbosa, Brown, and Real, 2014). This indicator of the proportion of the variance explained is assessed by the residual and null deviances. Smaller residual deviances of the model (relative to the null deviance) will result in larger D^2 values, because a smaller residual deviance indicates the model fits the data well. Similar to adjusted-R^2, adjusted-D^2 is calculated by taking into account the number of observations and the number of parameters (Guisan, Weiss, and Weiss, 1999). These values indicate the percentage of the variability in the response data that is accounted for by the model, which is helpful in understanding how the model helps answer the research question.

Chapter 3: Results

3.1 Correlations Between Explanatory Variables and Black Bear Interactions

I found several statistically significant correlations between the number of human and black bear interactions per areal unit and the explanatory variables (Table 5). The results of this analysis suggest that there were fewer human and black bear interactions in areas with higher

Table 5 Spearman's rho correlations between explanatory variables and number of human and black bear interactions at block group and census tract levels of analysis

Significant at Block Group	ρ	Sig.	Significant at Census Tract	ρ	Sig.
Population Density	-0.255	**	Population Density	-0.280	*
Road Density	-0.205	**	Road Density	-0.328	*
Forested Landscape Proportion	0.347	**	Forested Landscape Proportion	0.355	**
Forest Edge Density	-0.182	*	Forest Edge Density	-0.299	*
Greatest Forest Patch Area	0.417	**	Forest Patch Density	-0.347	**
Mean Forest Patch Area	0.389	**	Greatest Forest Patch Area	0.443	**
Mean Forest Patch Distance	0.406	**	Mean Forest Patch Area	0.412	**
Effective Forest Mesh Size	0.403	**	Mean Forest Patch Distance	0.424	**
Developed Landscape Proportion	-0.223	**	Effective Forest Mesh Size	0.467	**
Developed Edge Density	-0.281	**	Developed Landscape Proportion	-0.253	*
Developed Patch Density	0.217	**	Developed Edge Density	-0.349	**
Forest Patch Density	-0.242	**	Developed Patch Density	-0.395	*
Forest Edge Length	0.268	*	Forested Landscape Cover	0.37	**
Forested Land Cover	0.430	**	Forest Edge Length	0.182	
Number of Forest Patches	0.036		Smallest Forest Patch Area	0.119	
Median Forest Patch Area	0.291		Number of Forest Patches	0.113	
Smallest Forest Patch Area	-0.057		Median Forest Patch Area	-0.109	
Developed Land Cover	0.068		Developed Land Cover	0.111	
Developed Edge Length	0.083		Developed Edge Length	0.006	
Number of Developed Patches	0.095		Number of Developed Patches	0.03	
Greatest Developed Patch Area	0.054		Greatest Developed Patch Area	0.153	
Smallest Developed Patch Area	-0.035		Smallest Developed Patch Area	-0.102	
Mean Developed Patch Area	-0.006		Mean Developed Patch Area	0.179	
Median Developed Patch Area	-0.070		Median Developed Patch Area	0.182	
Mean Developed Patch Distance	0.017		Mean Developed Patch Distance	0.026	
Effective Developed Mesh Size	-0.121		Effective Developed Mesh Size	0.031	

** is significant at 0.01, * is significant at 0.05

human population densities and denser road networks. This finding is in line with conventional wisdom and the findings of Kretser et al. (2008) that suggested areas with low human population density are most susceptible to human and wildlife interactions. However some of the correlations that I found, at both the block group and the census tract levels, did not reflect conventional wisdom and thus warrant future research. These include some statistically significant inverse relationships found between several of the landscape fragmentation metrics at both levels of analysis. The results of the Spearman's rho correlation found that lower forest and developed edge densities and more forest patches in a landscape were significantly correlated with fewer interactions at both sets of areal units. Other patch metrics, however, had positive correlations, including measurements of forest patch distance and forest patch area, so in areas with larger patch sizes and in areas where patches were farther apart, there were a more reported interactions. It is worthy of future investigation that the relationship between human and black bear interactions and developed patch density, which was determined as significant at both units of analysis, had a correlation that was positive at the block group level but negative at the census tract level.

Area metrics were determined to have statistically significant relationships with the response variable, and with relatively large Spearman's rho values. In block groups and census tracts where there were larger proportions of forests, there were more human and black bear interactions, while in areas with larger portions of developed landscape, there were fewer human and black bear interactions. Because black bears rely on forest resources, this finding is important because it links the accessibility of forest resources to the frequency of human and black bear interactions.

3.2 Results of Negative Binomial Regression Models

The negative binomial GLMs with the lowest AICs each had two explanatory variables as statistically significant (Table 6). In the block group GLM, human population density and the proportion of forested landscape were the two explanatory variables determined as significant, the former having an inverse relationship and the latter a positive relationship. The census tract GLM also had two statistically significant variables: urban edge density and effective forest mesh size, the former having an inverse relationship with the number of interactions, and the latter having a positive relationship.

Table 6 Results of GLMs

Block Group Variable (n=142)	β	IRR	95% Confidence Interval of IRR	p-value
Intercept	0.367			
Proportion of Forested Landscape	0.018	1.02	1.01-1.03	3.1e-06
Population Density	-0.775	0.46	0.27-0.76	0.00243
Census Tract Variable (n=55)	β	IRR	95% Confidence Interval of IRR	p-value
Intercept	2.18			
Urban Edge Density	-1.06e-04	0.99989	0.99984-0.9999	0.0355
Effective Forest Mesh Size	2.47e-02	1.03	1.01-1.05	0.0111

3.3 Interpretation of Coefficients

The IRR for proportion of forested landscape was 1.02, so for a 1% increase in proportion of forested landscape the model indicates that the expected number of interactions increases by a factor of 1.02, increasing at a rate of 2% for a percentage increase of proportion of forested landscape. At a given proportion of forested landscape per block group, for a 10% increase in forested landscape proportion the expected number of interactions increases by a factor of 1.2, increasing at a rate of 20% for a 10% increase in proportion of forested landscape per block group. The IRR for human population density in the model was 0.46, so for a 1-person/m^2 increase in human population density at the block group level the model indicates that the expected number of interactions decreases by a factor of 0.46, decreasing at a rate of 54% for a 1-person/m^2 increase in human population density. At a given population density, for a 0.25-person/m^2 increase in human population density the expected number of interactions decreases by a factor of 0.82, decreasing at a rate of 18% for a 0.25-person/m^2 increase in human population density. Worth mentioning is that as human population density approaches zero, there is inherently less of a chance of human and black bear interactions because the phenomenon requires a human population. Future research might look at the thresholds of human population density and human and wildlife interactions.

The IRR for urban edge density was 0.99989, so for a 1-meter/km^2 increase in urban edge density the model indicates that the expected number of interactions decreases by a factor of 0.99989, decreasing at a rate of 0.0001% for a 1-meter/km^2 increase in urban edge density. At a given value of urban edge density, for a 1-kilometer/km^2 increase in urban edge density the expected number of interactions decreases by a factor of 0.90, or decrease at a rate of 10% for a 1-kilometer/km^2 increase in urban edge density. The IRR for effective forest mesh size is 1.03, so for an increase of 1-km^2 of the effective forest mesh size of the census tract the model indicates that the expected number of interactions increases by a factor of 1.03, or at a rate of 3% increase for a 1-km^2 increase in effective forest mesh size. At a given value of effective forest mesh size, for a 10-km^2 increase in effective forest mesh size the expected number of interactions increases by a factor of 1.30, or at a rate of 30% increase for a 10-km^2 increase in effective forest mesh size of the census tract.

3.4 Results of Likelihood-Ratio Test

The likelihood-ratio test showed that the models that included the explanatory variables were better than the reduced models (i.e., the models with an intercept only). The block group GLM (Likelihood-ratio statistic=33.4, degrees of freedom=2, X^2 test p-value< 0.001) and the census tract GLM (Likelihood-ratio statistic=18.3, degrees of freedom=2, X^2 test p-value< 0.01) both had significant p-values and therefore likelihood-ratio statistics large enough to indicate that the GLMs I produced that included the explanatory variables fit the data significantly better than a GLM that did not account for any explanatory variables. This confirmed that accounting for the explanatory variables significantly improved the fit of the model. This indicates accounting for these variables helped explain the geographic distribution of human and black bear interactions.

3.5 Results of D^2 and adjusted-D^2

The GLM created with block group data had a D^2 value of 0.20 and an adjusted-D^2 of 0.21 and the GLM created with census tract data had a D^2 value of 0.26 and an adjusted-D^2 value of 0.25. These values were relatively low probably because of missing important variables. Human and wildlife interactions, and ecological interactions in general, are difficult to predict or explain. Many published regression models in ecological literature report relatively low values compared to measures of variance explained in regression models found in other disciplines (Møller and Jennions, 2002). As such, this measurement indicates that the explanatory variables that comprised the models were able to, in part, explain the phenomenon, which indicates these results help answer the research question.

Chapter 4: Discussion

4.1 Review of Important Findings

The following sections will review and discuss how particular landscape attributes may have affected occurrences of human and black bear interactions. Before these sections, I would like to first make a larger point about landscape and evaluate its influence on human and black bear interactions in this study area. With respect to the research question of this study, the statistical analysis indicates that landscape fragmentation did have a statistically significant relationship with the location these interactions. Based on this statistical analysis, population density and road density also likely influenced where human and black bear interactions occurred.

Finding viable and effective solutions to what both residents and ecologists consider a serious problem demands looking at the patterns and considering their causes. Beyond the statistical analysis are a series of non statistical questions, such as "How did bears get into the area in the first place?," "Why do black bears reside in certain areas?," and "How are black bears adjusting to changes in the landscape of Buncombe County?" However this statistical analysis can act as a basis of answers to some of these questions.

There are particularities that make this study somewhat limited in its application to wildlife management, including when considering the specific ecological and biological characteristics of black bears. That is to say, black bears might respond to certain landscape aspects or urban characteristics differently than other urban-dwelling species. Still, the finding that fragmentation and urban characteristics had statistically significant relationships with human and black bear interactions is an important conclusion for research in this general field. Future studies can examine the dynamics of these types of relationships, and build from the finding that landscape fragmentation and urban characteristics had statistically significant relationships with locations of humans and black bear interactions.

The MAUP arose as different measures of fragmentation had different relationships when observed at different scales. By modeling the data collected at the block group level with a negative binomial GLM, I determined that human population density and the proportion of forested landscape were significantly related to the number of human and black bear interactions. These relationships were not the same at the census tract level of analysis, demonstrating that this relationship might change based on the geographic scale of analysis. By modeling the data collected at the census tract level with a negative binomial GLM, I determined that effective forest mesh size and urban edge density were significantly related to the number of human and black bear interactions. These relationships were not the same at the block group level of analysis, demonstrating that these relationships also might change based on the geographic scale of analysis.

4.2 Block Group GLM

By modeling the data collected at the block group level with a negative binomial GLM, I determined that the number of human and black bear interactions had an inverse relationship with population density at the block group level and a positive relationship with the proportion of forested landscape per block group. These relationships were determined while using the smaller geographic scale of analysis, as census tracts are usually constructed by merging a number of block groups.

4.3 Human Population Density and Human and Black Bear Interactions

The relationship between wildlife interactions and human population density is the most widely researched and easily understood. However, the relationship often has complexities and changes according to animal species, intensity of development, and local policies. My analysis found that higher population densities were associated with fewer human and black bear interactions (Figure 4.1). Other species might be more averse to human development, and so the relationship between population density and interactions with these species is likely not the same. While black bears are sensitive to increased human activity, they are able adapt in areas with low population densities and reduced human activity (Conover, 2002).

Population density is an important characteristic because this measurement provides an estimation of the degree of human activity in an area. Population density helps estimate

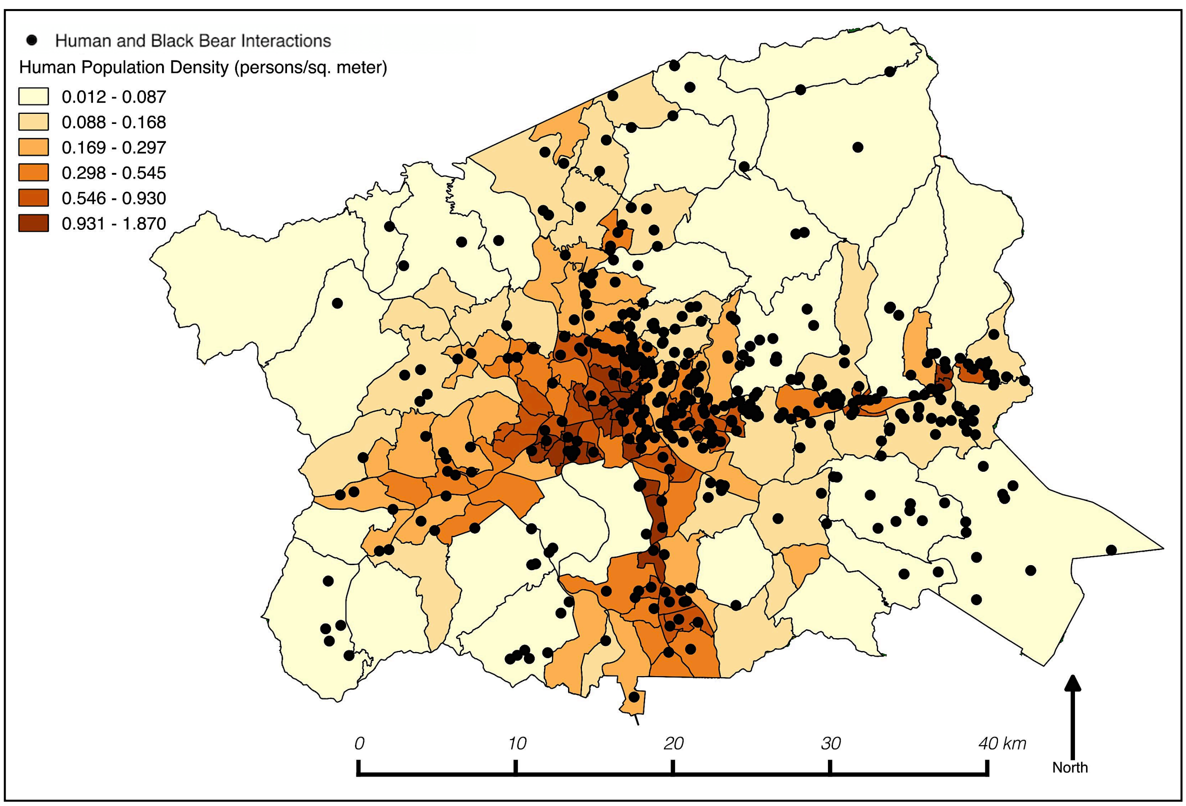

Figure 4.1 Human population density at the block group level and human and black bear interactions

important characteristics of developed areas, such as how many joggers that are there in a neighborhood, how many businesses or residential units there are, how much trash is available, and how many cars are on the road. The results of my analysis suggest that human and black bear interactions are more likely in areas with low human population density, and further research can be produced from this finding. This includes the thresholds at which human population density and human and black bear interactions occur and the types of neighborhoods and residencies that are more prone to human and black bear interactions

An important geographic concept relevant particularly in the recent history of landscape in the United States is sprawl. Sprawl is a phenomenon present in both rural and urban areas, and is defined by new residence dwellings along the fringe of either urban centers or historic towns in rural areas (Zhang and He, 2008). Sprawl increases the area of the Wildland-Urban Interface (WUI), an ecotone or a transition zone between two ecological types and in this case forested and developed landscapes. Zhang and He (2008) via the U.S. Department of Agriculture and the Interior (2001) define the WUI as an area with a low human population density where housing is situated near areas of heavy natural vegetation. Zhang and He (2008) found that in the southeastern U.S., including in western North Carolina, the area of the WUI is growing. As the WUI expands through sprawl and concurrent landscape fragmentation, residents in areas these low-density populations will likely continue to experience relatively more human and black bear interactions.

Previous studies have identified suburban areas as a primary land characteristic of the WUI. In this study, I am not able to make classifications without more data and analysis, and so I am only able to make conclusions about low-population density areas, refraining from speculations about residency types. Kretser et al. (2008) found that low-population density suburban, rural, and exurban landscapes were the areas where human and wildlife interactions were geographically concentrated (Figure 4.2). They and others have posited that low-density human development fundamentally alters wildlife behaviors by providing a landscape with dependable anthropogenic and natural resources, while also lacking the deterrents of high-density developed landscapes (Conover, 2002; Kretser et al., 2008).

Human-adapted animals like urban black bears thrive on resources provided by human populations, whereas human-averse species become locally extinct because they cannot adapt to human development and disturbance (Kretser et al., 2008). Krester et al. (2008) concluded that the residents in areas with low human population density are more likely to have interactions with human-adapted species than are residents in areas with high human population density because these areas lack sufficient natural resources. Landscapes with high human population density also host considerable deterrents for species that generally prefers avoiding human

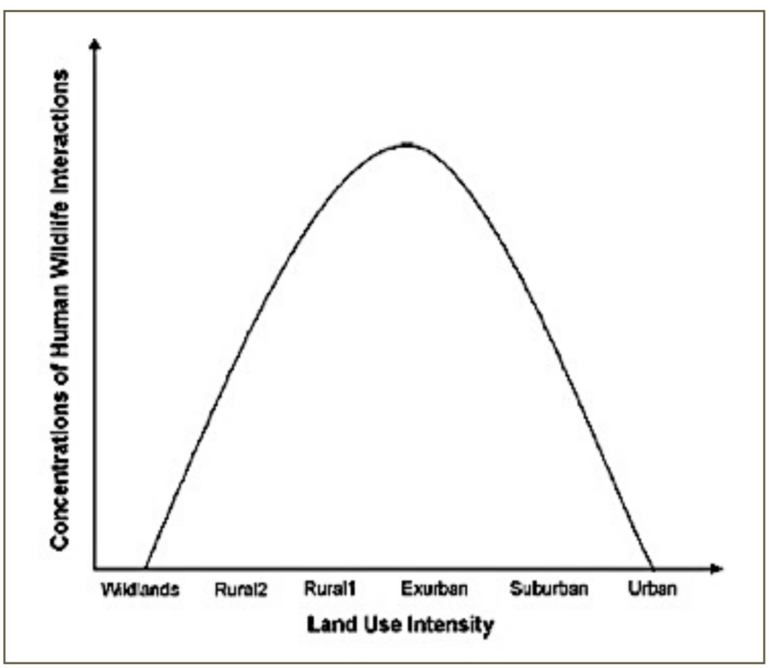

Figure 4.2 Theoretical model proposed by Kretser et al. (2008) indicating the concentration (numbers/area) of human and wildlife interactions based on land use intensities

interactions (Conover, 2002). My findings support the conclusions of previous studies that high-density development deters black bear interactions, whereas residents in areas with low-density human populations are more likely to have interacted with black bears.

In summary, this analysis corroborates what many studies about black bears in the urban landscape have concluded. Areas with low human population density, often considered the "Wildland Urban Interface," host anthropogenic resources that help human-adapted species to thrive, while also being situated near forested areas with natural resources. Further research needs in this subject include the types of human activity that deters wildlife from suburbs and other low-density areas, and the ways by which the availability of anthropogenic resources and other attractants can be minimized.

4.4 Proportion of Forested Landscape and Human and Black Bear Interactions

The proportion of forested landscape per areal unit had strong Spearman's rho correlations with the number of human and black bear interactions and was determined as significant in the regression analysis. This finding makes practical sense and resonates with conventional wisdom: block groups with a greater proportion of forest were likely to have more interactions, which is likely attributed to the greater accessibility of forest resources. In areas with limited access to natural landscapes and forest resources, there were fewer human and black bear interactions (Figure 4.3).

Black bears thrive in a hybrid habitat. Black bears residing in urban areas are referred to in literature as "urban black bears," as if a different species. Urban black bears are biologically and behaviorally different from wild black bears through the incorporation of anthropogenic resources in their habitat. In 2005, Amy Lyons of the California Department of Fish and Game observed urban black bears and reported on some of these differences. Lyons tagged black bears

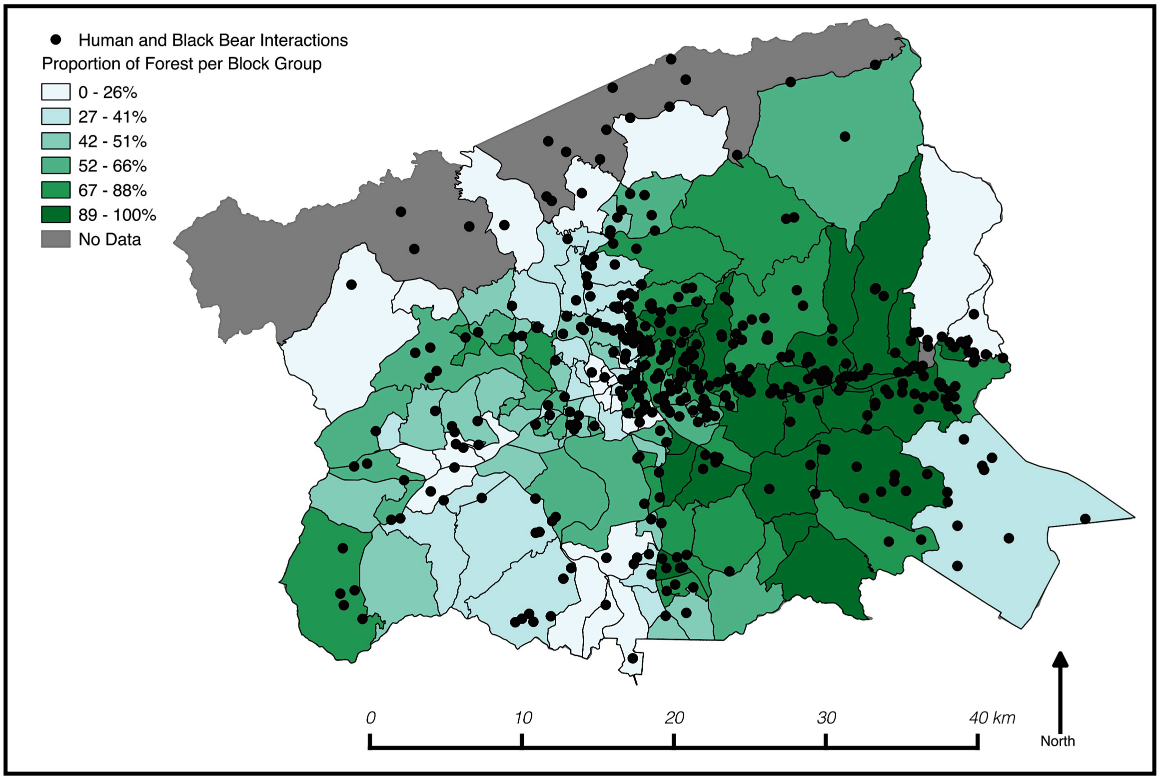

Figure 4.3 Proportion of forested landscape per block group and human and black bear interactions

around the San Gabriel Mountains of southern California in Los Angeles. Lyons found that while urban black bears became habituated to anthropogenic resources, they also traveled to forests for natural food resources particularly during times of high mast or robust forest productivity (Lyons, 2005). This indicates that while urban black bears are habituated to anthropogenic resources, they also rely and thrive on the accessibility on natural forest resources.

Lyons also found that during night hours, when human activity is relatively limited, urban black bears traveled around developed areas more than in than they did during the daytime (Lyons, 2005). While wild bears tend to expend most energy diurnally, urban bears have maintained diurnal activity patterns in natural areas, but then developed nocturnal activity patterns when in urban areas. This is attributed to black bears preferring to avoid human contact (Lyons, 2005). This point demonstrates how the urban black bear populations are reliant on natural food and other forest resources, discouraged by increased human activity (consider again the finding on human population density) and biologically changed by the dual accessibility of natural and anthropogenic resources.

A fundamental reason for the increased proportion of forested landscapes found within each areal unit is the sprawl of human development. As development sprawls, human dwellings invade forests, pushing into natural vegetation and increasing the exposure of developed areas to natural landscapes. This is why areal units along the fringe of urban centers have a higher proportion of forested landscape within their borders than the areal units that contain urban centers. While downtown Asheville is comprised mostly of developed landscape, forests surround developed areas along the edge of the city. These areal units that surround urban centers and that border the forested landscapes are the areal units with higher proportions of forested landscape.

There are other sources of forest resources in found in urban areas. These include patches of natural vegetation that are left over by development or protected for conservation or urban beautification purposes (Figure 4.4). Often, patches of forested areas are left over after a larger

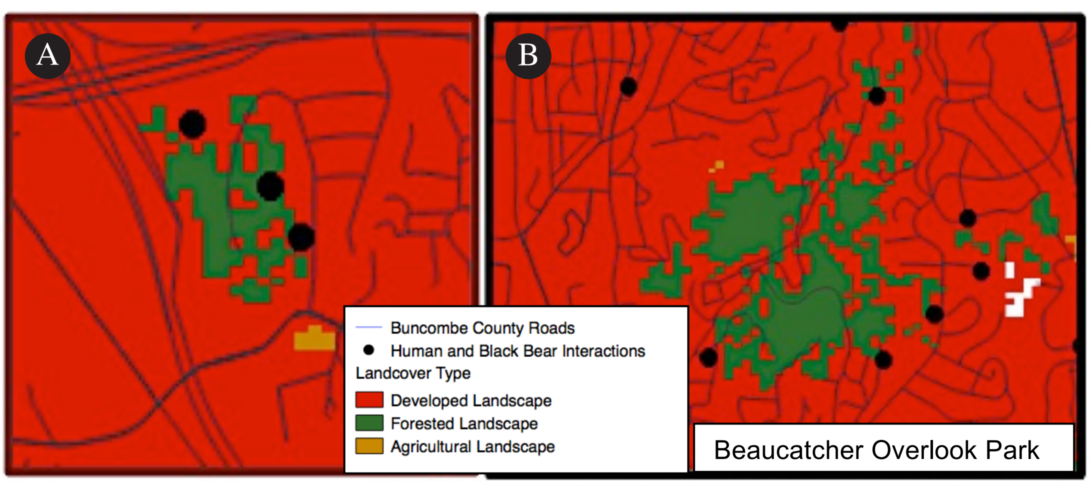

Figure 4.4 Examples of natural areas (A) left over from transportation routes and (B) for parks with a large forested area

natural area is reduced and split by transportation infrastructure. Urban green spaces and parks are other sources of natural resources that are situated in developed areas that have been found to promote human and wildlife interactions. In their study in Calgary, Lukasik and Alexander (2011) found that human and coyote interactions clustered near riparian areas surrounding creeks and in residential dwellings nearby parks, a pattern attributed to the natural resources provided by these features. In reviewing the data used in this study, I also found areas that fit these descriptions. Beaucatcher Overlook Park is a 30-acre park just outside the city of Asheville that has likely influenced where reported human and black bear interactions occurred.

4.5 Census Tract GLM

By modeling the data collected at the census tract level with a negative binomial GLM, I determined that the number of human and black bear interactions had an inverse relationship with urban edge density per census tract and a positive relationship with the effective mesh size per census tracts. These relationships were determined while using the larger geographic scale of analysis.

4.6 Urban Edge Density and Human and Black Bear Interactions

According to my results, lower densities of urban edge, less urban edge per census tract, were associated with more human and black bear interactions per census tract (Figure 4.5). Urban edge density is the sum of all of the lengths of the urban landscape edges per areal unit and then divided by the total size of the areal unit to standardize the measurement for comparison.

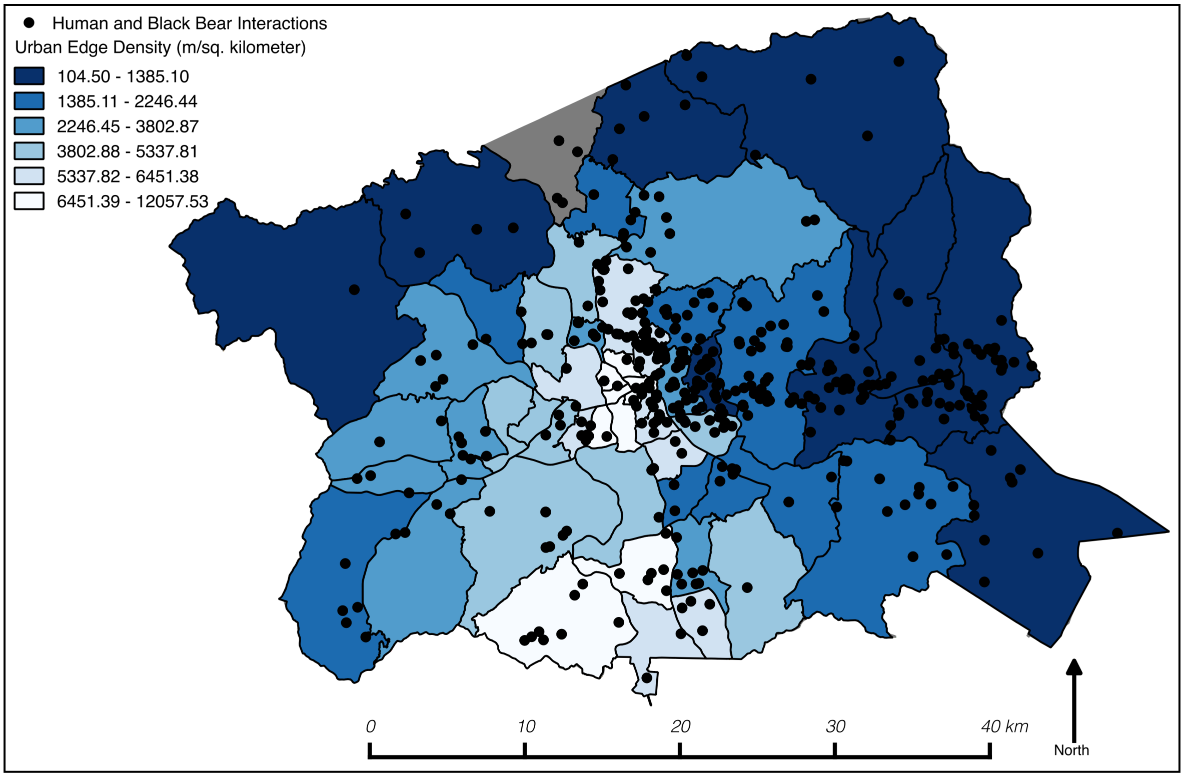

Figure 4.5 Urban edge densities per census tract and human and black bear interactions

The edge of the developed landscape is essentially the boundary of human-altered landscape (Figure 4.6). Based on these results I speculate that the more urban edge per area, the greater the length of the possible interaction zone between black bears and humans, and thus the lower probability of interaction per area. Urban edge density can also indicate the geometric positioning of developed landscape on natural vegetation. Increased urban edge is the result of several factors but as in other metrics, the expansion of developed areas is a primary driver. Sometimes edges are simply roads that divide areas of natural vegetation, while others are formed by the construction of new neighborhoods, parts of subdivisions that continue to push into natural forests with backyards comprised of large natural habitats.

Further work might try to understand the effect of edge density as a measure of the contrast between the two landscape types in this study area. Previous studies have weighted the

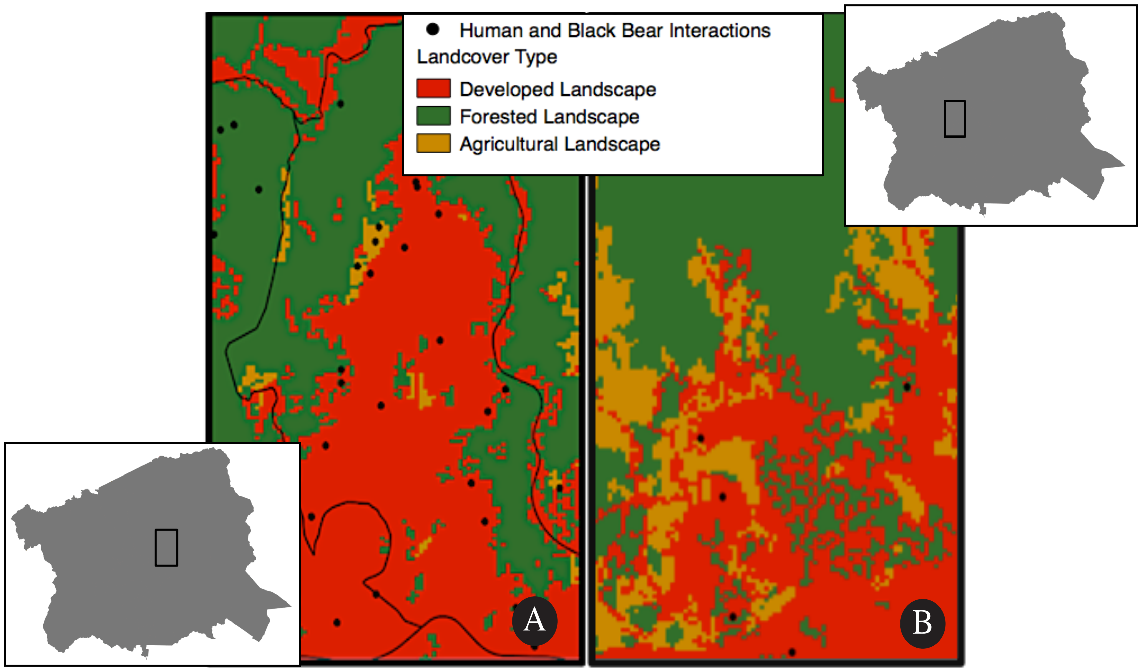

Figure 4.6 Landscape composition of a census tract (A) with a relatively low edge density (B) and area within a census tract with a relatively high edge density

values of edge densities, using this metric as the premise for a calculation of the contrast between landscape types (Echeverria, Gatica, and Fuentes, 2013). In areas with higher edge density and consequently a more mixed landscape in transition between landscapes, I speculate that the level of development deters black bears from moving forward into the urban landscape. In areas with lower edge density and a more abrupt division between forested and developed landscape, there were a more human and black bear interactions.

4.7 Effective Mesh Size and Human and Black Bear Interactions

Jochen Jaeger developed the effective mesh size metric in 2000. This metric is intended to capture the effect that human development and infrastructure has on the connectivity of a landscape by estimating the probability that two points placed randomly in a region will be located within the same patch. Originally developed for wildlife population statistics, the metric is based on the probability that two animals of the same species will be able to find one another in a landscape when placed randomly in an area (Jaeger 2000). Effective mesh size represents the effect of barriers on a landscape, whether they are roads, railways, or utility infrastructure, and thus is a representation of habitat continuity (Girvetz, Thorne, Berry, and Jaeger, 2008). If there are more barriers in an area there is a lower the probability that two animals will be able to reproduce, and thus there is a smaller effective mesh size of the area. The census tract GLM determined a positive relationship with this metric: as the effective mesh size increases so does the expected number of human and black bear interactions (Figure 4.7).

Although the effective mesh size has been tested and used in previous studies to indicate the degree of fragmentation in a landscape, it is at best an indicator of fragmentation and the connectivity of a landscape. The metric does not account for the structure of the patches within the landscape, which undoubtedly has an impact on the connectivity of the landscape. Additionally, although this metric has been employed in previous research to observe both ecological processes and processes within human-environment interactions, the fact that I am using the metric for a purpose other than its original intent, which is for the reproduction of individuals of the same species, demands future work to verify if the measure is an adequate explanatory variable for human and wildlife interactions. In regards to this phenomenon, the effective mesh size can at best be interpreted considering the following: the effective mesh size is not appropriate as a measure of the likelihood of humans and black bears to be found in the same patch, but is appropriate as a measure of the fragmentation of the area and that degree of fragmentation is related to the number of human and black bear interactions.

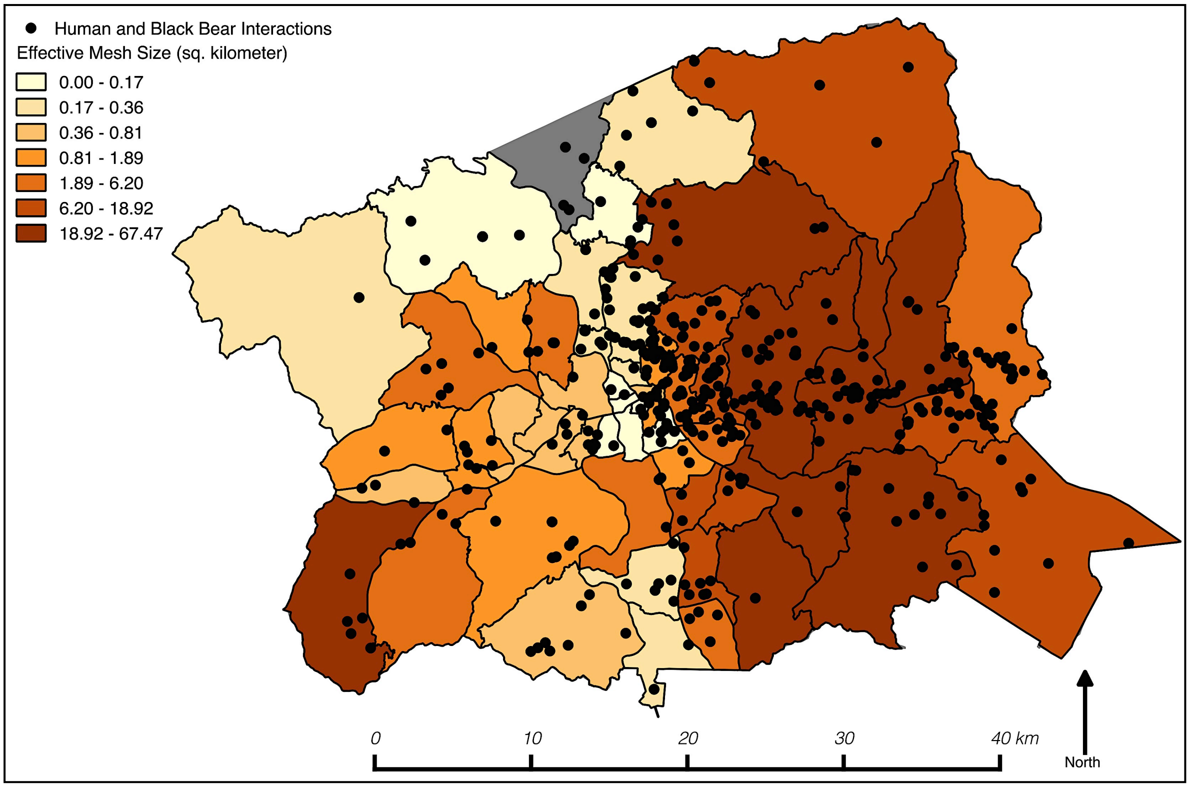

Figure 4.7 Effective forest mesh size per census tract and human and black bear interactions

Black bears prefer habitats with landscapes that are uninterrupted by anthropogenic barriers and increased human activity. With fewer anthropogenic barriers in a landscape, urban black bears might den in a relatively uninterrupted forest and be able to avoid most human contact when foraging for anthropogenic resources in nearby urban landscapes. In landscapes with a greater number of roads and other landscape barriers black bears may have been locally eradicated in the first place, since the degree of development makes the area unsuitable to establish a habitat. Though there are fewer barriers in landscapes in census tracts with high effective mesh sizes, those barriers are in a relatively continuous forest, and so where the interactions are prone to occur. This reasoning contextualizes the finding that census tracts with larger effective forest mesh sizes, and thus more continuous landscape and forest habitats, are associated with more human and black bear interactions.

Effective forest mesh size is a measurement based on disruptions and the size of forest patches. In Figure 4.8, I have taken an excerpt of my GIS to demonstrate the relationship between effective forest mesh sizes and the number of human and black bear interactions. The top portion of the figure is a fragmented area in western Buncombe County with a relatively small effective forest mesh size, and the bottom portion is a relatively less fragmented area in eastern Buncombe County with a relatively large effective forest mesh size. Agricultural lands and less-dense road networks fragment the landscape and form a mosaic of patches in the western part of the county, whereas the spatial division between continuous forested landscape and the developed landscape in the eastern part of the county is more abrupt and sharp. Instead of forest, developed, and agricultural landscapes dividing the area, the eastern part of the county has rigid divisions between continuous forest and developed land. I speculate that a black bear might

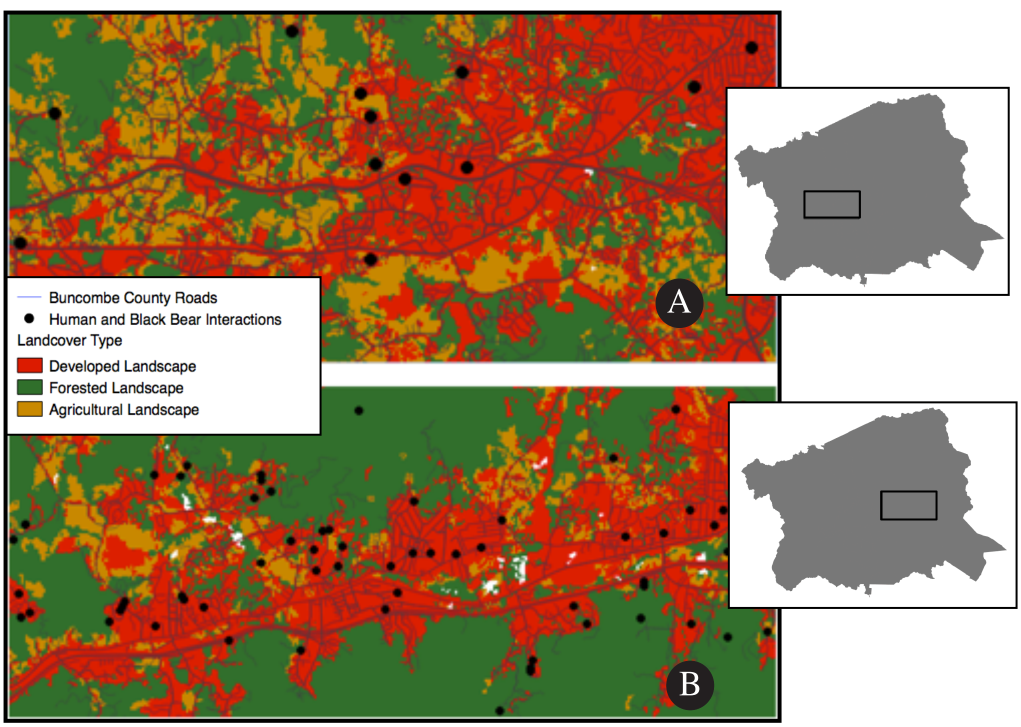

Figure 4.8 (A) The western side of the county shows a relatively fragmented landscape, with a low effective forest mesh size (B) The eastern side of the county, is a relatively uninterrupted landscape with rigid transitions from a continuous forest to developed landscape, with a high effective forest mesh size

be more likely to have an interaction with a human in the abrupt divisions in continuous forests in the eastern side of the county than in the heavily fragmented landscapes in the western side of the county.

4.8 Areal Units and the MAUP

In this study, I chose to use census block groups and census tracts as study units. Census units are heterogeneous and irregular shapes of social rather than ecological significance. Many environmental researchers divide study areas into grids with equal areas but in this study I used census units, which are drawn based on human population (Figure 4.9). Typically, areal units from the census are used in social science because their geographic organization is useful for understanding the socioeconomic demographics of residents in an area.

Using census units I found statistically significant relationships between the explanatory variables and the number of human and black bear interactions. In preliminary data analysis, I performed the same analysis using grids of several different sizes, however, most relationships between the response variables and the explanatory variables were not determined as statistically significant. This suggests with regard to the zoning effect of the MAUP, perhaps the shape of the

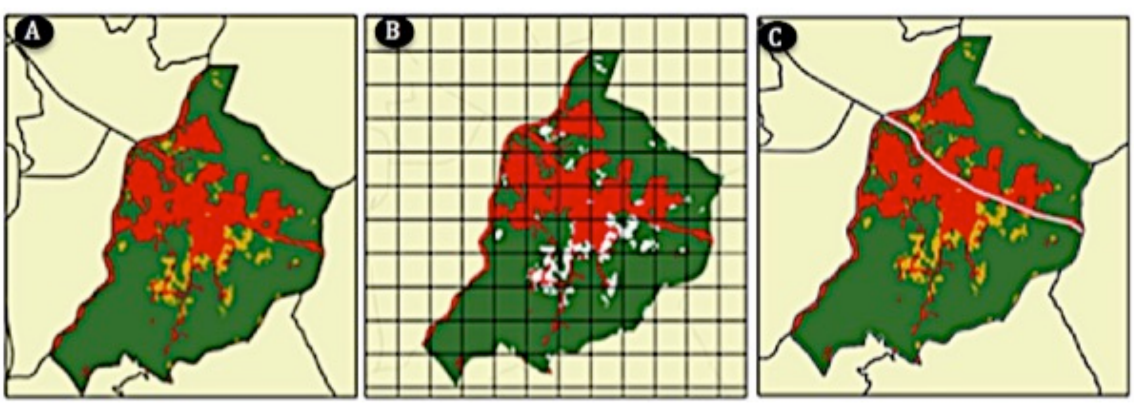

Figure 4.9 (A) An census tract south of Asheville in Buncombe County (B) The same area divided by an equal area grid (C) The census tract divided in two census block groups (divided by white line).

study unit mattered in determining the relationships between the number of human and black bear interactions and the explanatory variables investigated in this study.

Another important finding of this study is the difference in the explanatory variables that the two models determined as significant, which may be influenced by scale. The models were comprised of different metrics. The GLM that was fit with data collected using block groups had human population density and proportion of forested landscape as the statistically significant variables. The GLM fit with data collected using census tracts had effective forest mesh size and urban edge density as the statistically significant variables. This suggests that, with respect to the aggregation effect of the MAUP, perhaps the scale of the study unit mattered in determining the relationships between human and black bear interactions and the explanatory variables investigated in this study.

4.9 Conceptual Model of Human and Black Bear Interactions

One of the goals of performing this spatial and statistical analysis was to produce a conceptual model that clearly outlines what variables, particularly geographic ones, help explain the distribution of human and black bear interactions. In constructing a conceptual model, I determined the explanatory variables that most influence the occurrences of human and black bear interactions in this study. This conceptual model is not exhaustive: there are many spatial and non-spatial aspects of these occurrences not incorporated in the conceptual model, but these variables had the greatest influence on the distribution of human and black bear interactions according to this data analysis (Figure 4.10).

Due to the fact that urban edge density and effective forest mesh size were determined significant in the GLM and that several fragmentation metrics had significant Spearman's rho correlations with the number of human and black bear interactions, I accounted for landscape fragmentation in the conceptual model. In my analysis, I found that some landscape fragmentation metrics and characteristics had inverse relationships with the number of human and black bear interactions, while some had positive relationships. This indicates that several metrics of fragmentation have relationships with the number of human and black bear interactions. I represented this in the conceptual model by including the “extent and type of landscape fragmentation” as variables to help explain where interactions occur.

My analysis suggested that population density had an inverse relationship with human and black bear interactions. Residents in densely populated places were least likely to have interactions with black bears, while residents in areas with low human population density were more likely to have interactions with black bears. This finding corroborates previous findings regarding human population density and wildlife interactions in the United States. Low-density populations are prone to human and wildlife interactions because they are a source of anthropogenic and natural resources, while not providing many deterrents.

The proportion of forested landscapes per block group was significantly related to the number of human and black bear interactions. This finding supports conclusions of previous research and has noteworthy implications. Residents who live nearby forested landscapes will experience a more human and black bear interactions because of the natural resources that these landscapes are able to provide for black bears. By considering this explanatory variable, management efforts can focus in areas with greater proportions of forested landscape.

The final explanatory variables in my conceptual model are the local characteristics that either promote or discourage human and black bear interactions and other unknown variables. Though these were not studied or factored into this analysis, they were mentioned through the discussion and are certainly noteworthy. Many studies have found garbage disposal policies to be

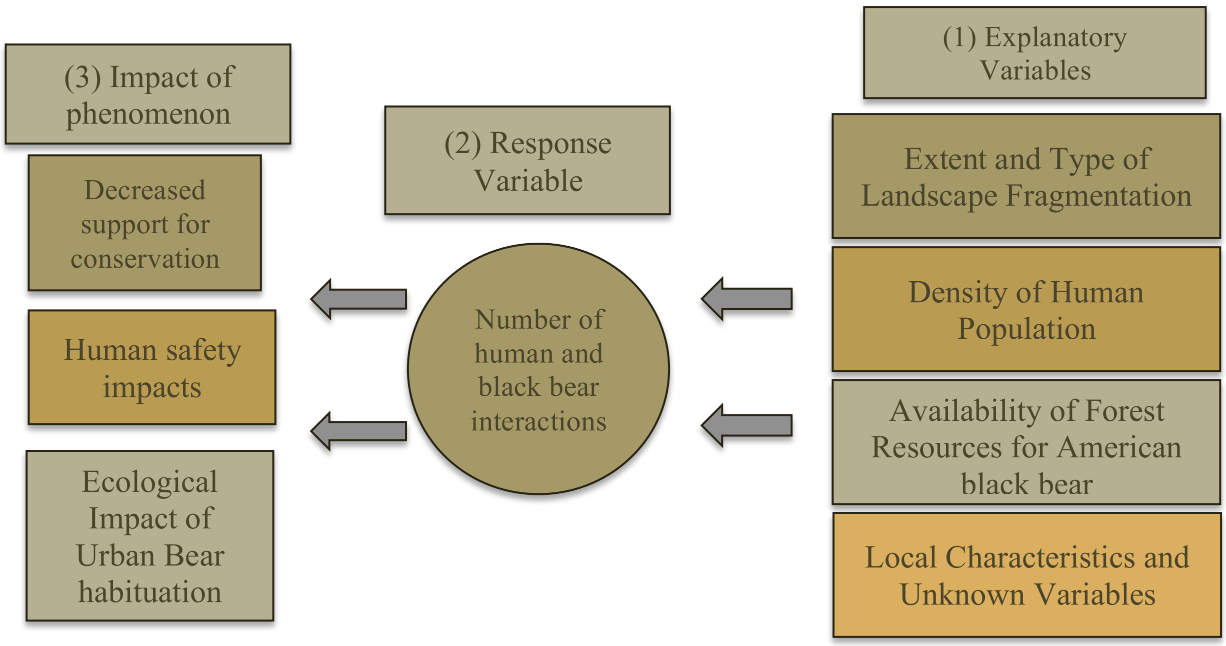

Figure 4.10 Conceptual model to understand locations of human and black bear interactions

a strong influence in black bear habituation in a particular neighborhood, while other studies have linked decreased forest mast to an increased number of human and black bear interactions (Peine, 2001). There may be wildlife corridors in parts of Buncombe County that promote interactions that were not considered. I did not account for the locations of natural or anthropogenic food sources in the county. The proximities to protected green spaces and parks were not considered. Further work investigating these and other contributing factors to human and black bear interactions are promising avenues of future research.

4.10 Suggestions to Reduce Human and Black Bear Interactions

There are a number of strategies to reduce interactions that either have been reported in literature or derive from my understanding of the phenomenon after conducting this research. This study divided Buncombe County into census units, and the analysis considered characteristics of these areal units. I found statistically significant relationships between the number of human and black bear interactions and the urban characteristics and extent of fragmentation using these areal units, and this finding is a basis for some important suggestions.

Because local geography was found to influence the locations of human and black bear interactions, they should be mitigated at a local scale. Incorporating educational materials into neighborhood watch or other neighborhood meetings might be an appropriate step. Identifying and disseminating information about the vulnerability of certain areas to black bear interactions, based on this statistical analysis and other work, would also be helpful in mitigating these wildlife problems. One suggestion might be to contact residents who live in areas with low population densities and with close proximity to uninterrupted forests, and suggest residents incorporate education or notification techniques at a neighborhood level to share information about black bear interactions. Notifying residents regarding which areas are the most vulnerable will help these citizens prepare for interactions with black bears.

This analysis showed that human and black bear interactions were more likely in census tracts with smaller effective forest mesh sizes, and thus fewer barriers in a landscape (such as roads, railways, or utility infrastructure) and an abrupt transition between continuous forest and developed landscapes. Presenting a greater number of deterrents and wildlife conscious landscape planning might be ways to address causal factors of human and black bear interactions. Smith, Linnell, Odden, and Swenson (2000) reviewed methods of deterring livestock predation and found that acoustic deterrents, electric fences, and chemical repellants were all somewhat effective at deterring bears from becoming habituated to an area. In areas with abrupt transitions between continuous forest and developed landscapes, I suggest that implementation of these sorts of management techniques in key locations would be helpful in reducing human and black bear interactions.

Particular attention and further research should be paid to reducing anthropogenic resources available to wildlife, the source of most interactions in this study and according to literature. Bear-proof trash cans, stronger enforcement of laws governing wildlife feeding and litter disposal for tourists and residents, and focused educational initiatives are important steps to help residents remove attractants and reduce human and black bear interactions (Peine, 2001). Removing natural food sources, like berry patches, near vulnerable residential dwellings might reduce the attractiveness of an area to black bears. Further research on trash disposal policies and on the effectiveness of educational campaigns is needed to strengthen these efforts.

Conclusions

I performed a landscape analysis and investigated how landscape fragmentation and urban characteristics are related to human and black bear interactions. I found that population density and proportion of forested landscapes influenced the number of human and black bear interactions at the block group level of analysis and effective forest mesh size and developed edge density influenced the number of human and black bear interactions at the census tract level of analysis. I also created a conceptual model to illustrate how the explanatory variables investigated in this study influence the occurrences of reported human and black bear interactions. However, I relied on data with several limitations for my analysis. Further work with more reliable data would strengthen the results of this analysis and our understanding of the phenomenon, which in turn would promote the conservation of black bears and other predator species.

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Vita

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