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USING QUADRAT ANALYSIS AND CLUSTERING TECHNIQUES TO QUANTIFY PATTERNS OF BEAR SIGHTINGS IN NORTHWEST NEW JERSEY

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Abstract: *The relationship between Black Bear and humans in New Jersey is a tenuous one at best. Black Bear have been sighted in all 21 of New Jersey's counties because of their relationship to the human, physical, environmental, and topographic factors that exist throughout the state. A GIS is used to illustrate spatial relationships of nuisance and threatening bear sightings, as well as these factors in a five county region of Northwest New Jersey. Using GIS data provided by the New Jersey Department of Fish and Wildlife, a Poisson Distribution of bear sightings in Northwest New Jersey do in fact articulate distinct non-random spatial patterning of this phenomenon. Sighting density at the pixel level using a search radius based on the size of a typical bear habitat can be averaged within a square quadrat. This metric shows concentrations of bear sightings in areas of Passaic and Sussex Counties near the New York-New Jersey border and was confirmed using cluster analysis techniques.*

Keywords: *Black Bear, GIS, New Jersey*

INTRODUCTION

The relationship between Black Bear (*Ursus americanus*) and humans in New Jersey is a tenuous one at best. Although it is the nation's most densely populated state, black bear are able to thrive because of prime habitat such as forested land, undisturbed wetlands, undeveloped open space, access to waterways in conjunction with plentiful access to natural and anthropogenic sources of food (Carr and Burguess, 2011). However, expansion and movement of the bear population combined with increased human population growth into traditional bear habitats has forced wildlife officials to make reconciliations between enforcement, public education, euthanization of problem bears and bear harvesting in order to minimize bear-human conflicts.

While bear sighting data are collected for the entire state, this study is focused on the Northwest New Jersey counties of Hunterdon, Morris, Warren, Sussex and Passaic (Figure 1). These five counties generally align with Bear Management Zones (BMZ) 1 through 5 created by the New Jersey Department of Fish and Wildlife (NJDFW). Only sightings of Category I (threat to life and property) and Category II (nuisance) bears were mapped based on GIS data provided by the NJDFW. Current estimates place the New Jersey bear population at about 3,500 (Carr and Burguess, 2003; Diefenbach, 2006). It is estimated that this number is now slightly less due to limited yearly bear hunts designed to contain population growth (Huffman et al., 2010). Besides a court-ordered hiatus in 2004, these hunts have occurred every year since 2003 (Carr and Burguess, 2011). The location of black bear, like almost any phenomenon, can be visualized and mapped within a GIS (Geographic Information System) to determine how and where to dedicate resources to minimize these conflicts and educate the public.

Literature focusing on using GIS to explore spatio-temporal patterns of animal movement has covered an entire gamut of animals and environments, ranging from elephants in Africa (Sitati, Smith and Leader-Williams, 2003; Smith and Kasiki, 1999) to Leopards in India (Agarawl et al., 2011). Given the impossibility of individually counting lions across many countries in Africa, GIS was used to model lion habitat and estimate population counts throughout ten lion strongholds in Sub-Saharan Africa (Ferreras and Cousins, 1996; Riggio, 2011). In England, GIS was integrated into monitoring bird movements with the burgeoning construction of wind turbines as an alternative to conventional forms of energy (Allan et al., 2004).

Domestically, however, much of the literature explores spatial dimensions of deer-vehicle collisions. It is no surprise that deer-vehicle collisions are increasing in the United States (Gkritza et al., 2013; Bissonette et al., 2008) as well as New Jersey, which has reported one of the nation's largest increases (State Farm 2009). Whether

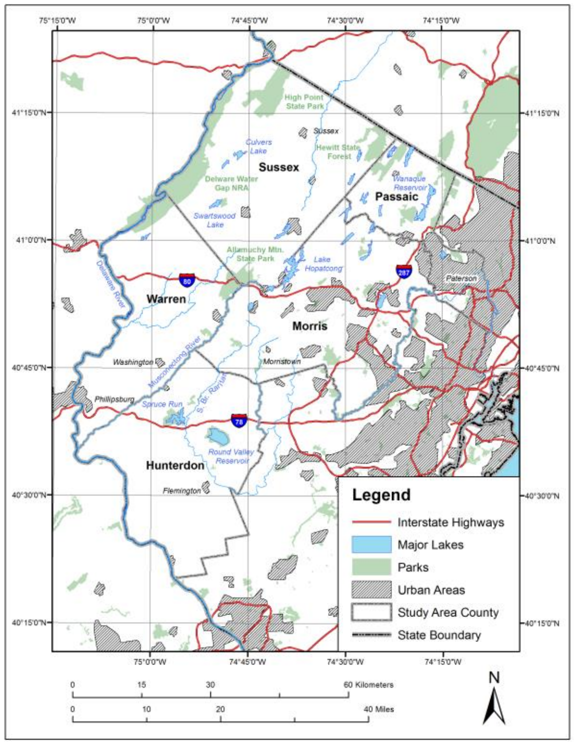

Figure 1. The five Northwestern New Jersey counties
that compose the study area.

at the national (Huijser et al., 2007), state (Shuey and Cadle, 2001) or local (McKee and Cochran, 2012; Seifert, 2010) scale, the general tenor behind research is that deer-vehicle collisions exhibit spatial patterning and are not statistically random. Studies to explore why this occurs have also been undertaken by researchers. Using GIS, researchers attributed patterns of deer-vehicle collisions to speed limits during peak dear seasons (Ng, Nielsen and St. Clair, 2008), road attributes and development (McShea et al., 2008), proximity to elevated roadways (Hubbard, Danielson and Schmitz, 2003) and landscape heterogeneity (Hussain et al., 2007). Given regional variations, accessibility to adequate data, reporting of data, reporting biases and problems working with scale (Shuey and Cadle, 2001), it is difficult if not impossible to model deer-vehicle collisions with any certainty that can be applied to other parts of the country.

GIS is also utilized as a tool in determining potential wildlife management strategies and its connection to urban growth and development. Studies (Davenport and Switalski, 2006) have shown that byproducts of urbanization such as road development have had a negative impact upon game and non-game species. In this research, prime bear habitat within the study region lies west of Interstate Route 287 and north of Interstate Route 78. While it was found that road closures have aided movement and reproduction of black bear, in addition to wolves, elk and small mammals, that option is not feasible in this study area.

GIS has been used to quantify the spatial distribution of bear throughout North America in hopes of understanding where bear-human conflicts do and can occur. In Colorado, a well-known study (Baruch-Mordo et al., 2008) used GIS and geostatistical methods to explore clusters of bear-human conflicts at a coarse scale of 4.76 kilometers (2.96 miles). Although methodologies varied, other GIS-based studies throughout North America included those in British Columbia using geostatistics (von der Porten, 2010), Montana using multivariate regression (Wilson et al. 2005), Alaska using buffer analysis and ANOVA testing (Smith, Herrero, DeBruyn, 2005) and Georgia using spatial models (Cook, 2007).

The NJDFW publishes an annual Black Bear Status Report (Carr and Burguess, 2011) which not only summarizes the types of bear calls (Category I – III), but maps both black bear sightings and habitat potential at the municipality and coarse pixel level. A comprehensive study expounding on NJDFW data was undertaken by Rohrbach (2008) by using descriptive spatial statistics to look at general point patterns of bear sightings in New

Jersey. Like von der Porten (2010) observed in British Columbia, Rohrbach found it is difficult to quantify reasons within the confines of a GIS why this phenomenon occurs. I believe that bear sightings do in fact exhibit spatial patterning and clustering in Northwest New Jersey, especially in Sussex County. Factors such as proximity to roads and parks combined with modest population density make this area conducive to potential conflict. This research will try to reinforce this pattern using GIS.

METHODS

Quadrat Analysis

Quadrat analysis uses a base polygonal unit called a *quadrat* which is represented using equal sized squares created along a lattice. The size of the quadrat is important as it needs to be large enough to capture a distinct spatial pattern, but not small enough to have many quadrats with zero frequency (Mitchell, 2005). The use of the quadrat in this study is unique because bear sighting frequency within non-overlapping sub-county enumeration units such as boroughs, cities, towns and townships have been mapped by the NJDFW (Carr and Burguess, 2011). However, the varying sizes and shapes of these units, which include annular shapes (as shown in Figure 2 for Chester Township and Chester Borough), may skew results and subsequent interpretation. Wieczorek et al. (2011) showed this with point pattern phenomena when grouped within zip codes versus computer generated (hexagon and lattice) polygonal units.

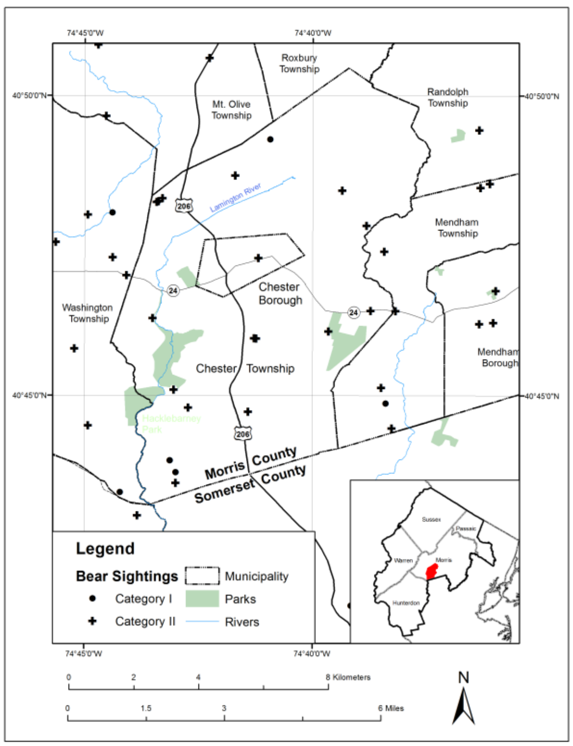

Figure 2. Example of annular unit (Chester Township) used as enumeration unit in prior analysis and maps.

All categories of bear sightings data were provided by the NJDFW for the entire state in digital format. They were provided as addresses and geocoded into a GIS as points using the New Jersey State Plane Coordinate System. With 4,704 recorded bear sightings (n) of this type in the study area of approximately 5,051 km^2 (1948.22 mi^2) (A), the length of the quadrat *(l)* can be computed using a simple formula. The l value was computed to be 1.46 kilometers (.91 miles), thereby making each quadrat to be approximately a square 2.15 km^2 (.83 miles^2) in area.

$$l = \sqrt{\frac{2 * A}{n}}$$

Quadrat analysis uses probability analysis to determine the actual frequency of bear sightings within each quadrat versus an expected value for each frequency. This can be visualized by fitting a Poisson Distribution to the data using a formula where P(x) represents the expected number of sightings for frequency x, λ represents the average number of sightings per quadrat for the entire dataset, x represents the number of sightings for a particular quadrat and e is the base of the natural logarithmic function (Mitchell, 2005).

$$P(x) = \frac{(\lambda^x)(e^{-\lambda})}{x!}$$

Range Density Analysis

The *Point Density* function calculates for every cell a density (number of bear sightings per unit area) that lie within a user-defined radius of the cell in question (Mitchell, 2005). Based on an approximate range of 3.2 km^2 (2 mi^2) for Black Bear females in New Jersey and more for males (Carr and Burgess, 2004), a density surface with 100 meter pixel resolution was created from all bear sightings in the study area using a 1.61 kilometer (1 mile) circular buffer neighborhood.

An interpolated density surface for the bear range was created using the aforementioned quadrats as input polygons. A *Zonal Statistic* function was run to compute the average density for all resulting *Point Density* pixel values within each quadrat. This generalized range density metric may be better than computing the number of sightings per unit area or counting the number of sightings per quadrat for a couple of reasons. It gives the dependent variable more granularity for better use in future analysis against explanatory variables grouped at the quadrat level. While the raster-based *Combine* function can assign values between bear sighting density and explanatory variables (land cover classification, for example) at the pixel level, sheer data volume (more than 500,000 pixels compose the study area) and its interpretation can make this problematic and exponentially difficult for multiple explanatory variables.

In addition, the circular search neighborhood allows proximate points in adjacent quadrats to be captured by counting all point features that lie within this buffer defined by wildlife biologists. As a result, there were many fewer zero values when computing range density based on a search radius (342 zero values) versus a point-in-polygon result (1,142 quadrats with no sightings) which may be due to data inaccuracy, geocoding error or the placement of the lattice. This difference can be articulated in Figure 3, which shows a small section of Passaic

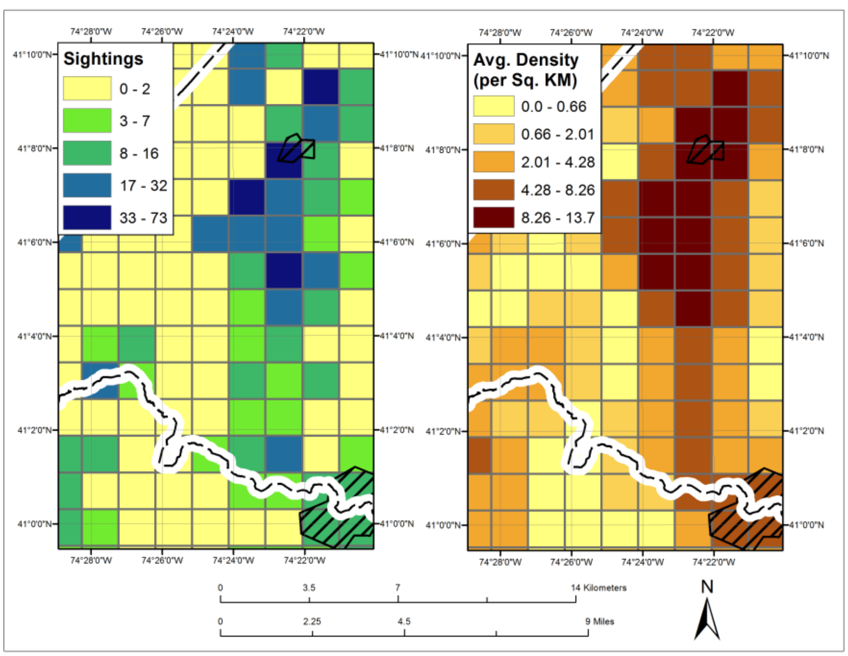

Figure 3. Difference between point-in-polygon analysis (left) versus averaged bear density metric computed in this research.

County using point-in-polygon analysis versus the range density surface grouped at the quadrat level. The difference between the point-in-polygon surface against the smoothed interpolated density surface is apparent between the two maps. However, further analysis would need to be done to determine the strength of this technique over others and ultimately falls outside of the scope of this research.

Cluster Analysis

Tobler's First Law of Geography states that phenomena located near each other are more related than phenomena that are farther apart (Tobler, 1970). Cluster analysis quantitatively measures this closeness, or spatial autocorrelation. Metrics such as Moran's I, Ripley's K and Nearest Neighbor measure the amount of spatial autocorrelation for an entire data set, returning a single value for the entire layer that can be compared to other metrics or other parts of the country. Each describes spatial autocorrelation on a continuum from clustered to random to dispersed in their own way.

Local Moran's I is a Local Indicator of Spatial Autocorrelation (LISA) that calculates local variation based on adjacency patterns. A LISA returns an individual value for each polygon, showing whether it is near other like values with a statistical significance. In the case of Local Moran's I, patterns that are similar and located near each other will return a high value for Local Moran's I. This is regardless of the fact that range densities may be high or low. If quadrats with low range densities are located near each other, Local Moran's I will return a value just like polygons that have high range densities located near each other.

Expounding on Local Moran's I is another LISA that delineates the high-high and low-low relationships of clusters that are more useful in research and application. The Getis-Ord Gi* uses a binary (1 or 0) neighborhood weight (defined by the user as adjacency or proximity *d* from the enumeration unit in question) to determine a weighted average of only those nearby values that satisfy the adjacency or proximity criteria. The end result is an inferential statistic that takes this Gi* calculation and returns a z-value, indicating a statistical significance of clustering in concert with a p-value assigned to an individual enumeration unit. The Getis-Ord Gi* is able to identify hot spots (high range density quadrats surrounded by other high range density quadrats) and cold spots, representing low range density quadrats surrounded by other low range density quadrats (Mitchell 2005).

$$G_i^*(d) = \frac{\sum_j w_{ij}(d) x_j}{\sum_j x_j}$$

RESULTS

Quadrat Analysis

A square lattice representing base units for quadrat analysis was generated using a GIS from a derived length of 1.46 kilometers (.91 miles). 2,679 quadrats compose the study area. Because of the study area's shape, 374 quadrats (13.96% of all quadrats) were not entirely contained within the study area. However, since an averaged Point Density calculation was used that is not dependent on quadrat size, all quadrats were included in forthcoming analyses. 1,106 quadrats (41.28% of all quadrats) contained at least one bear sighting and a quadrat located within West Milford Township in Passaic County experienced a high frequency of 73 bear sightings.

The frequency distribution for the quadrat analysis is shown in Figure 4. A large gap between the observed number of sightings and expected number of sightings at the quadrat level is apparent. This can be reinforced using a Kolmogorov-Smirov test, which measures the difference between the expected number of sightings versus the observed number or proportion of sightings against a critical value based on a K value (based on a confidence interval) and the number of quadrats. This difference was well above the critical value of .032 (for a 99% CI). This shows that in fact bear sightings do not follow the expected Poisson Distribution and their distribution can be attributed to factors besides pure randomness.

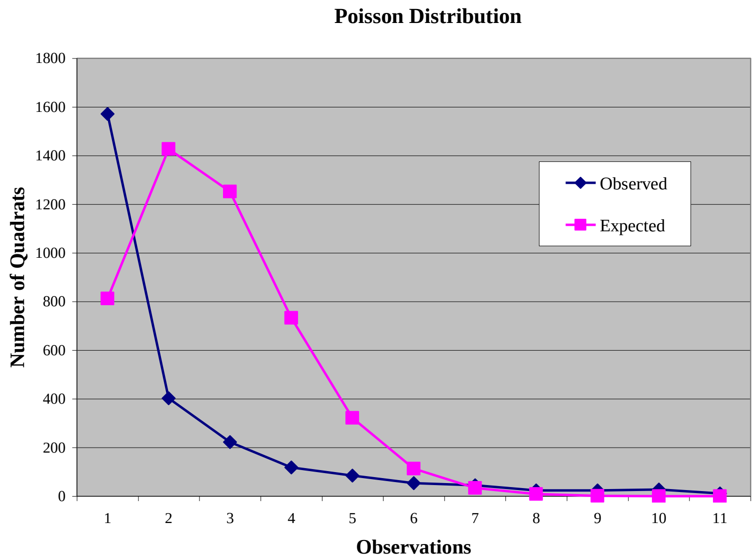

Figure 4. Observed vs. expected distribution of nuisance and threatening bear sightings by quadrat. The Kolmogorov-Smirnov test for these data show do not follow expected Poisson Distribution.

Range Density Analysis

Using the *Point Density* function, sighting densities at the pixel level ranged from 0 in some places to 20.01 sightings per km^2 (51.88 sightings per mi^2). When averaged within each quadrat, range densities at the quadrat level ranged from 0 to 13.80 sightings per km^2 (35.76 sightings per mi^2) as shown in Figure 5. The highest densities appear in the Northwestern Passaic County municipality of West Milford Township, as well as Hamburg and Vernon Township in Sussex County. Other concentrations of range densities occur in Jefferson Township and Rockaway Township (Morris County), Frankfort Township, Newton, Stillwater Township and Fredon Township (Sussex County). While containing lower densities, concentrations further south and west occur in Blairstown Township and Knowlton Township (Warren County), as well as Bethlehem Township and Glen Gardner (Hunterdon County).

Cluster Analysis

Clusters were computed based on the average bear sighting density by quadrat and are shown in Figure 6. The most significant clusters are found around Hewitt State Forest in Passaic and Sussex Counties. Other significant clusters appear closer to the Delaware Water Gap National Recreation Area in Sussex and Warren Counties, as well as Swartswood National Forest in Sussex County. Besides a cluster in Rockaway Township in Central Morris County, clusters appear around major lakes in the study area such as Greenwood and Echo Lake (Passaic County), Highland, Swartswood and Culvers Lake (Sussex County), Lake Hopatcong (Morris County) and Yards Creek Reservoir (Warren County).

DISCUSSION

Analyses of these types are only as good as the data themselves. It would be irresponsible to ignore the processes that go into creating the GIS data used in this research. As with any study in which personal reports are quantified within a digital environment, they can be subject to interpretation which ultimately affect the results. Bear sighting data are collected by the NJDFW from individual reports of bear sightings and consolidated into a single data file. Since Category III (bears exhibiting normal behavior) sightings were excluded from this study because it looked at the potential for conflict, a determination as to what constituted a Category I or Category II bear was done on a sighting by sighting basis by a number of different people and reported to the NJDFW. More than

3,500 bear sightings were labeled as Category III during the study period and therefore excluded from this study. As a result, there may be errors of omission and commission regarding data included in this database.

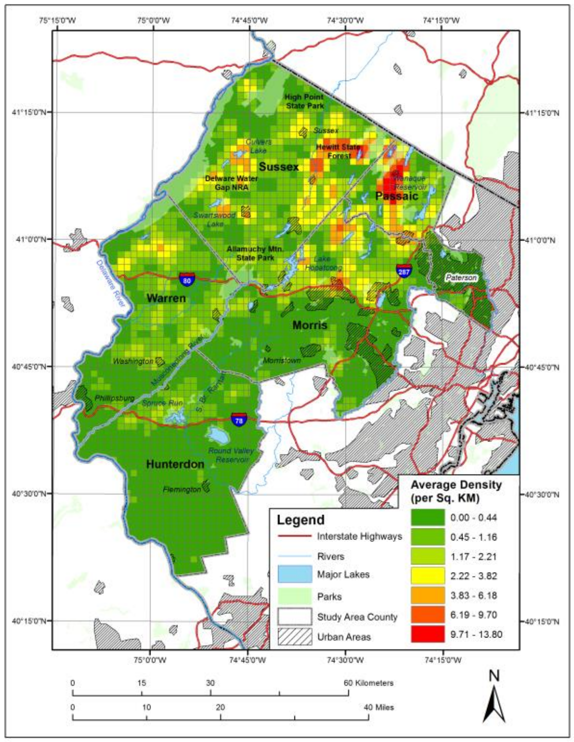

Figure 5. Average bear density sighting by quadrat based on 1.61 km (1 mile) search radius.

Care must be taken when determining an appropriate aggregation unit in which to display data. The aggregation unit used in this study was the quadrat, a square unit whose dimensions were derived from size of the study area and the number of sightings. It is within these quadrats that sightings were counted and aggregated. Given a goal of thematic choropleth maps such as these is to highlight regional differentiation, the use of different scale units which may show different patterns may tell completely contradictory stories. Openshaw (1984) coined this term as the 'Modifiable Areal Unit Problem' (MAUP). It is important that issues of MAUP be addressed by using a scale that adequately dictates and explains transparency between results rendered at various scales. While the quadrat size was derived from parameters used in popular literature and subject to the number of sightings, sighting density at different scales did in fact show the same trends as highlighted in the results.

CONCLUSIONS

New Jersey has dealt with issues of human encroachment onto traditional black bear habitat. While bear attacks are rare, they have happened, including a fatal bear attack nearby in New York State in 2002. Using bear sighting data provided by the New Jersey Department of Fish and Wildlife from 2010 through 2012, more than 4,700 Category I (bears that are threat to life and property) and Category II (nuisance) bear sightings were mapped and analyzed within the study area of Northwest New Jersey. While these point patterns have aesthetic value, they have little computational value beyond descriptive statistics to explain the entire dataset. GIS analysis and spatial univariate statistics were used to better discern these patterns at a finer level.

Using quadrat analysis techniques, these points were counted within one of 2,679 square enumeration units and counted. The distribution of these counts can be compared to a Poisson Distribution with the same input parameters. A Kolmogorov-Smirov test showed that bear sightings do not follow the expected Poisson Distribution and their distribution can be attributed to factors besides pure randomness.

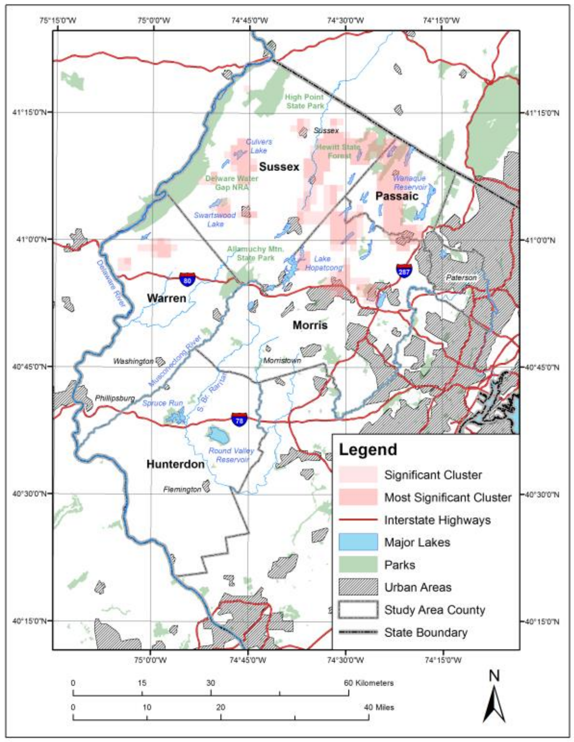

Figure 6. Result of Getis-Ord Gi* hotspot cluster analysis showing significant ($1.96 < z < 2.56$) and most significant ($z > 2.56$) clusters.

A density surface was created using a 1.61 km (1 mile) search radius based on the size of typical bear habitat in New Jersey. These pixel-level density measures were averaged within each of the aforementioned quadrats to show a bear sighting density on a quadrat by quadrat basis. This method used a uniformly-sized enumeration unit which cannot be taken out of context, as prior studies grouped sightings by sub-county administrative units (borough, city, town, township) that range in area from .36 km^2 (.14 mi^2) in the Borough of Victory Gardens (Morris County) to West Milford Township (Passaic County) at 210.1 km^2 (81.01mi^2).

When summarized at this quadrat level, the highest concentrations of bear sighting densities were apparent in Northern Passaic County (West Milford Township), Northeastern Sussex County (Hamburg Borough, Hardyston Township) and Northern Morris County (Rockaway and Jefferson Township). Other concentrations were found in Stillwater Township, Fredon Township and Franklin Township (Northeast Sussex County) as well as Knowlton and Blairstown Township (Warren County). These patterns were reinforced using a Getis-Ord Gi* metric, which highlights hot-spots of bear sightings clusters with statistical significance. Though not statistically significant, other concentrations were seen in Northern Hunterdon County (Bethlehem Township and Union Township) and Southeastern Morris County (Harding Township and Long Hill Township) near the Great Swamp National Wildlife Refuge. This partially aligns with the original hypothesis that bear sightings are not random in nature and would occur most frequently in Sussex County. However, equally high densities and accompanying clusters were unexpected in both Morris and Passaic Counties.

It is interesting to understand why these spatial patterns occur. The most significant clusters occurred in more mountainous areas with sparse population closer to those lakes highlighted in the results. Proximity to parks and roadways where sightings were thought to be more prone to occur seemed to play much less of a role than previously expected. Quantitative factors to explain bear density such as land cover classification, population, population density, elevation and proximity to landfills, roadways, and water as well as their derivations (e.g. pixel variety, slope, aspect) can be captured at the quadrat level to address why these patterns occur. However, this analysis falls outside of the scope of this work and may be subject for future work.

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