GEOGRAPHIC VARIATIONS OF CLANDESTINE METHAMPHETAMINE LABORATORIES IN NORTH CAROLINA

A Thesis
by
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Abstract

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This study investigates methamphetamine production in North Carolina from 2004 to 2006. Using address data from the National Clandestine Laboratory Registry, provided by the United States Drug Enforcement Agency, this study incorporates methods of spatial analysis, including nearest neighbor analysis and point density mapping to visualize where clandestine laboratories have been most problematic. Additionally, a Geographic Weighted Poisson Regression model was used to regress social and economic variables collected from the United States Census Bureau's American Community Survey to understand local conditions that may contribute to increased discoveries of clandestine laboratories. Spatial analysis conducted for this study found that areas of western North Carolina experienced higher levels of clandestine methamphetamine laboratory discoveries. Geographic Weighted Poisson modeling for this study also shows that traditional social and economic variables do not provide a strong basis for determining why methamphetamine production occurs within regions of North Carolina.

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Foreword

This thesis will be submitted to *Southeastern Geographer*, a quarterly publication of the Southeastern Division of the Association of American Geographers and published by University of North Carolina Press; it has been formatted accordingly to adhere to publication guidelines.

INTRODUCTION

Methamphetamine is a highly addictive drug with destructive consequences to both human health and the environment. While methamphetamine is desired for its effects, ranging from increased alertness and energy, it also carries the weight of severe side effects that can include stroke, cardiac arrhythmia, increased blood pressure, and death. Although these effects are limited to users of methamphetamine, the environmental consequences resulting from the production of methamphetamine have the potential to affect a greater number of individuals than users alone. For every one pound of finished methamphetamine product, nearly five pounds of hazardous waste is produced. This waste is often dumped into the surrounding environment, and can potentially sicken or kill wildlife. Alternatively, methamphetamine waste is often buried within pits in the ground. These burial pits, often the preferred method of disposal, have the potential to contaminate local water sources and leave the surrounding soil unusable (Barefoot and Hayes 2004).

Since 2004, North Carolina has experienced persistently high levels of methamphetamine laboratory discoveries, and has consistently ranked within the top fifteen states known for high levels of methamphetamine production. According the most recent data provided by the United States Drug Enforcement Administration (2016), North Carolina ranked fifth in discoveries of methamphetamine laboratory incidents. For the purposes of this study, North Carolina was chosen because of its high rate of laboratory discoveries, but also because of its rapidly changing nature. Although once known as a rural state with a focus on agriculture and manufacturing, North Carolina has experienced an increase in population and urban development, as well as a shift away from manufacturing and agriculture. Although these changes to the character of the state are significant, it is worthwhile to note that these changes have not occurred throughout the entire state. While major cities in the Piedmont region, such as Raleigh, Durham, and Charlotte have experienced rapid change, other regions of the state, including the Appalachian west and Coastal Plain have experienced slower growth.

LITERATURE REVIEW

Issues Related to Methamphetamine Production

When compared to other illicit drugs, such as marijuana, cocaine, or heroin, the production and consumption of methamphetamine does not follow typical assumptions. Previous studies have attempted to model methamphetamine production using established theories on drug crime, however, drug predictor variables, such as income, education, and mobility have yet to establish a strong relationship. The extent of methamphetamine production can vary greatly across regions, with some regions experiencing little to no activity, while others may experience heavy activity (Caulkins 2003). Production of methamphetamine has been described as complex, but only to a certain degree. Producers need only to perform a basic web search to find written instructions, as well as step-by-step videos related to producing methamphetamine. Using the phrase "how to make meth" in YouTube produces roughly 187,000 video entries that display a wide range of methamphetamine production methods, including full scale lab operations, to the one bottle "shake and bake" method. Despite the abundance of online articles and videos, the complexities associated with producing methamphetamine are often overcome, according to previous research, by the passing of intimate knowledge from experienced producer to new producer (Sexton et al. 2006).

The passing of knowledge from an experienced producer to a new producer is also needed due to the inherent dangers related to methamphetamine production. The chemicals involved with the production of methamphetamine, which include, but are not limited to: alcohol, lantern fuel, lye, drain cleaner, gasoline additives, paint thinner, starter fluid, battery acid, lithium, and antifreeze, combine to a form a dangerous mixture (North Carolina Department of Justice 2016). This mixture has the ability to explode if not handled properly, and can create ensuing fires resulting from explosions (Danks et al. 2004). These explosions, and hazardous materials in general, are also dangerous to individuals inhabiting areas of methamphetamine production, particularly in regards to children (Burge et al. 2009). Prior studies have also determined that children removed from methamphetamine laboratories were also more likely to test positive for methamphetamine, and are more likely be subjugated to further abuse once removed (Pennar et al. 2012).

Modeling Methods

Previous attempts have been made to model methamphetamine production, but generally at large scales, such as the county and state level. Weisheit and Fuller (2004) conducted a bivariate analysis of methamphetamine seizures within Illinois and found that while child abuse and neglect, teen births, truancy, and children living in poverty played a significant role in laboratory discoveries, other factors, such as rate of property crime, violent crime, delinquency petitions, or drug crimes were not significant. This study was expanded by Armstrong and Armstrong (2009), and found that a county's level of poverty and racial composition were also strong factors in predicting the location of methamphetamine laboratories. This expanded study also found social and demographic characteristics associated with methamphetamine production produced a different relationship with controlled substance arrests.

In a different study produced by Weisheit and Wells (2010), a multivariate study of 14,000 seized methamphetamine laboratories across the United States from 2004 to 2009 was conducted and found that counties with methamphetamine laboratory seizures were predominantly white in racial makeup, spoke English as a primary language, and contained a large number of evangelical churches. Weisheit and Wells also found that affected counties have high numbers of employment based on manufacturing, a large farm population, single female-headed households, a higher than average rate of property crime, high housing mobility, and high rates of housing occupancy. Despite these inclusions, Weisheit and Wells found that out of twenty variables, a strong relationship could not be determined in regards to predicting areas of methamphetamine production at the county level.

Wells and Weisheit (2012) conducted a similar study to expand upon their 2010 results, and increased the amount of methamphetamine laboratory discoveries to 17,720 based on new data provided by the United States Drug Enforcement Administration. The authors also created indices that focused on the loss of community structure and economic opportunities. These indices included data related to economic strain and deprivation, social disorganization, and civic engagement. Wells and Weisheit analysis included a regression model conducted with spatial lag to assess the spatial variation of methamphetamine production. Based on the results of their study, the authors found that social and economic variables attributed to methamphetamine production again failed to produce a strong model for predicting areas of methamphetamine production. However, the authors did determine a strong clustering pattern among methamphetamine laboratories, lending credence to the idea that the passing of knowledge from experienced producers to new producers may play a significant role in regards to better understanding why methamphetamine occurs in some regions, yet is absent in others.

Spatial Analysis

A study conducted by Brownstein et al. (2010) attempted to understand the spatial distribution of opioid abuse at the local level within the state of New Mexico. Using patient-level data from addiction treatment facilities in New Mexico, the authors applied the use of geographic information systems (GIS) in combination with a spatial scan statistic to create maps of clustered regions of opioid abuse. The spatial scan statistic for this study was created using the Kulldorf method that can detect space-time disease clusters. In this study, the authors found that the availability of opioids was partly responsible for clustering.

In a more recent study, Chaney and Rojas-Guyler (2015) studied patterns of drug use within five counties in Ohio using global and local methods of examining spatial auto-correlation within a GIS environment. The authors coupled this spatial analysis with traditional methods of statistical examination, and determined that the use of spatial analysis can in many ways help bolster the strengths and weaknesses encountered with traditional statistical modeling. Within the five county study area, Chaney and Rojas-Guyler found significant and varied clusters of regions with perceived notions of marijuana safety, peer approval for alcohol and other drugs, and were able to visually show how geography plays a pivotal role in attitudes towards drugs and alcohol.

Specifically related to methamphetamine production, Congdon-Hohman (2013) examined the relationship between the discovery of methamphetamine labs and the lowering of housing costs within neighborhoods. The analysis designates houses closest to methamphetamine labs as targets, while houses that are farther away acted as a comparison group. Congdon-Hohman's results show that the discovery of a methamphetamine laboratory has a significant effect on the property values of those homes closest to the location that peaks from 6 to 12 months after the lab's discovery. The estimates found in this study range from a decrease in sale prices of 10 percent to 19 percent in the year following a laboratory's discovery compared to the prices for homes that are farther away but still in the same neighborhood.

Also related to the spatial examination of methamphetamine, Sudakin and Power (2009) produce a method of using spatial statistics and geographic information systems to examine the production of methamphetamine within the state of Oregon. Sudakin and Power test the hypothesis that methamphetamine production within Oregon is more localized to specific regions, and is not simply a function of population size. Sudakin and Power extend their efforts through the use space-time scan statistics to explore geographic and temporal clusters in association with regulatory interventions. Through the use of SaTScan, the authors were able to determine major areas of illegal methamphetamine production through clustering analysis. The authors also found that following the introduction of control methods on pseudoephedrine, a decrease of illegal methamphetamine production was noticed in areas of significant clustering.

Using North Carolina as an example, this study proposes a method of understanding methamphetamine production that combines two established approaches: spatial analysis and regressive modeling. Previous research conducted on methamphetamine production has typically included some form of spatial analysis or regressive modeling, but rarely are the two conducted within the same study. In previous studies, it is often found that spatial analysis is used to understand where phenomena may occur, while regressive modeling often seeks to better understand why a certain phenomenon happens. While each approach is undoubtedly appropriate and useful, this study seeks to create a more comprehensive understanding of where and why methamphetamine production occurs within North Carolina.

DATA SOURCES

Addresses for discovered methamphetamine laboratories for North Carolina were collected from the U.S. Drug Enforcement Administration from 2004 to 2016. This data includes full addresses of discovered methamphetamine laboratories, as well as the date the laboratory was discovered.

Social and economic variables were collected from the U.S. Census Bureau's American Community Survey 2005 to 2009, five year estimate at the census tract level. This data set was chosen based on its more recent temporal scale when compared to the decennial census. This data is also representative of the general time frame that methamphetamine lab discoveries within North Carolina were at their highest (Table 1), and provide the lowest available sampling error. Social and economic variables chosen for this study were based on their inclusion in previous studies.

Additional data for spatial analysis, including shapefiles representing urban areas within North Carolina and land cover were collected from NC OneMap (2016). The urban area shapefile used for this study contains data collected from the 2010 decennial census, and creates an urban footprint for areas with populations greater than 50, 000 people. Land cover classifications for North Carolina represent fourteen unique categories ranging from high density land use, to woody wetlands, are listed in further detail in Table 2. Using the final shapefile containing both laboratory address points and U.S. Census variables, a point extraction was performed to assign a land cover value for each collected address point. A vector shapefile of major interstates was also used to examine the proximity of methamphetamine lab locations to major roadways. All spatial joins and extractions were conducted in ArcMap 10.3 (Environmental Systems Research Institute, Redlands, CA, U.S.).

METHODS OF ANALYSIS

Available PDFs of methamphetamine lab discoveries were converted to a basic text format and were imported into Microsoft Excel to create an address database. The resulting address table was geocoded using SmartyStreets (2016) geocoding services. Geocoding of addresses was conducted with a three tier system in an attempt to create the most accurate representation of discovered methamphetamine laboratories. Tier one allowed the SmartyStreets geocoding service to geocode all addresses as originally formatted on the first pass. Tier two required checking all addresses that were rejected by Smarty Streets for minor errors in address structure before resubmission to the Smarty Streets service. Tier three involved taking all addresses that were rejected on the second pass and attempting to manually geocode addresses using Google Maps. If an address entry did not provide sufficient data to successfully geocode, the address was noted and discarded from the final table. A total of thirty nine addresses were discarded, leaving 1,021 addresses out of 1,060 for analysis. After finalizing the geocoded address table, a point shapefile was created to represent methamphetamine laboratory discoveries in North Carolina.

Variables included from the American Community Survey included bachelor's degree attainment, unemployment, geographic mobility, median income, median house value, income below poverty, and the number of home owners versus renters. All U.S. Census Bureau variables were compiled into one spreadsheet and were joined with another polygon shapefile representing census tracts in North Carolina. This shapefile was then spatially joined with the address location point shapefile representing methamphetamine laboratory discoveries, and included a new column representing the raw number of lab discoveries within a particular census tract.

Multiple methods of spatial analysis were performed to explore the spatial characteristics of collected methamphetamine laboratory address data (i.e., mean center, nearest neighbor, and point density). A nearest neighbor analysis was conducted to examine clustering of address points within North Carolina census tracts. The average nearest neighbor statistic works by asserting that the null hypothesis should state that the features examined are randomly distributed. The nearest neighbor ratio is determined on a scale from zero (random distribution), to greater than zero (clustered) (ESRI 2016). Values that are less than zero are considered dispersed. A point density heat map was also generated to determine the highest densities of methamphetamine laboratories, while the mean center statistic of laboratory discoveries from 2004 to 2006 was used to determine shifts in lab production.

As rural areas have been previously shown to be more susceptible to methamphetamine production, a spatial query was used to determine the amount of discovered labs within urban regions of North Carolina. Additionally, a land cover analysis was conducted in an attempt to tease out information beyond a simple rural and urban dichotomy. This method was accomplished by extracting land cover classification values to discovered methamphetamine lab addresses within ArcMap. Interstate buffers were also created at distances of one, three, and five miles. This analysis was used to understand how many labs fell within reach of a major connecting artery within the state, as methamphetamine laboratories must transport their product.

A geographic weighted poisson model was performed using variables collected from the American Community Survey to attempt to understand what social or economic conditions play a significant role in explaining why methamphetamine production occurs within North Carolina census tracts when regressed against the number of discovered laboratories. However, due to high levels of covariance, only bachelor degree attainment, unemployment, income below poverty, and number of renters were included for the final analysis.

Since the dispersion of discovered laboratories creates a strong right skew and suffers from autocorrelation, a traditional ordinary least squares approach to regressive modeling would not produce a valid result. Attempts to convert the number of laboratories to a rate based on the population size of each tract with a constant of 10,000 also proved unsuccessful in normalizing lab discoveries. Normalizing the rate of lab discoveries included square root and log + 1 transformations; however, the number of lab discoveries remained skewed. To compensate for issues related to skew and autocorrelation, lab discovery rates were left as raw counts, and were regressed as a geographic weighted poisson model using GWR4 (GWR4.09, Nakaya, Tomoki, Kyoto, Japan).

Geographic weighted regression models are used to explore relationships between a dependent variable and independent variables that may differ geographically. As opposed to using a single global equation for the model, geographic weighted regression uses a moving window that fits a separate equation to examine each data point separately. As the moving window focuses on one data point in the study area, it also focuses on data points that surround the point of focus, and assigns a geographic weight based on how close or far apart other data points are in relation to the point under examination. For the purposes of creating points that the geographic weighted regression model could focus upon, centroids were calculated for each individual census tract. The window type used for conducting the geographic weighted regression was an adaptive Gaussian kernel. Of all available kernel options in GWR4, adaptive Gaussian proved to be the most appropriate, as census tracts vary in aspects of size and population. The golden-section search feature within GWR4 was used to determine the best bandwidth size for the model's moving window. GWR4 allows for golden-section and interval searches to be performed to determine appropriate bandwidth sizes, with the expectation that the golden-section search will identify an optimal bandwidth. The golden-section search also automatically selects a default lower limit that will maintain at least forty degrees of freedom for local regression fitting (GWR4). Based on the output suggestions of the golden search feature, a window size of thirty nine census tracts was selected.

RESULTS

Spatial Analysis

Results produced from the average nearest neighbor statistic show that methamphetamine laboratories discovered between 2004 to 2016 are spatially clustered. Methamphetamine labs were highly clustered with a nearest neighbor ratio of 0.48, a z-score of -31.32 and a p-value less than .001. Point density heat mapping also shows that there are four areas within North Carolina where major clusters of lab discoveries have occurred (Figure 1). Three of the four major clusters occur within the western part of the state, covering areas from the Appalachian Mountains to the Piedmont. In particular, census tracts within Watauga, McDowell, Burke, and Rutherford counties contain the heaviest areas of clustering. In Watauga County, the heaviest clustering appears north of the town of Boone, and east of the towns of Sugar Grove and Valle Crucis. The heaviest cluster within the state stretches east from the town of Marion in McDowell County, to the town of Morganton in Burke County. The third major cluster in western North Carolina includes the towns of Rutherfordton, Forest City, and Caroleen in Rutherford County. Although the heaviest cluster are scattered primarily in the mountain west, there is also a significant cluster located near the city of Dunn, located in Harnett County.

Of the 1,021 addresses available for analysis, 62 percent were discovered to be within rural counties, with 38 percent occurring in areas that are predominantly urban or suburban counties. Forty two lab discoveries fell within the urbanized area surrounding the City of Asheville in Buncombe County. Thirty eight lab discoveries were found within the Capital Area Metropolitan region of the city of Raleigh in Wake County. Forty seven lab discoveries were also found in the area surrounding the town of Hickory in Caldwell County. Although the majority of lab discoveries are outside of urbanized boundaries, a large majority of lab discoveries are still located close to what are considered urbanized areas. By adding a five mile buffer to the urbanized area shapefile, it is apparent that an additional 393 lab discoveries are at least within five miles of an urbanized area, which are in addition to the lab discoveries already within urban boundaries.

Overwhelmingly, the majority of lab discoveries have occurred in regions of North Carolina that are best described as developed open space (337 labs), as well as areas that are developed at a low intensity (177 labs) according to North Carolina land cover classifications. Progressing beyond areas or low development, areas that are considered farm lands, along with areas of deciduous forest also had relatively high numbers of lab discoveries. As expected, areas of medium developed intensity, as well as areas of developed high intensity contained very few lab discoveries. Within areas of developed high intensity, only eight labs were discovered between 2004 to 2016, while forty seven were discovered in areas of developed medium intensity (Table 2).

Although a majority of the discovered methamphetamine labs discovered within North Carolina from 2004 to 2016 are found in rural areas with low development, many of these discovered labs are still within a short distance of a major interstate. At a distance of one mile, 12 percent of all total labs discovered can be found. At three miles, this number increases to 30 percent, with a small increase to 39 percent at a distance of five miles

Modeling of Social and Economic Variables Related to Methamphetamine

Based on the output of the geographic weighted poisson model, it appears that traditional social and economic variables are not good predictors of methamphetamine production at the census tract level. Mean coefficient estimates for each variable are relatively near zero, with the exception of bachelor degree attainment, which was -0.62 (Table 3). Closer examination of the local percent deviance assigned to each tract also shows that the model tends to perform worse in the regions of North Carolina that experienced the highest densities of methamphetamine production. Of the four major clusters of methamphetamine labs produced, the model seems to fit best in census tracts located near Dunn in Harnett County, as well as the region around the southernmost cluster of census tracts located in Rutherford County. Surprisingly, the model seemed less suited in explaining why methamphetamine production occurs within the largest and most dense cluster, which extends across the towns of Marion, Morganton, and Hickory.

DISCUSSION

Understanding the spatial variations of where methamphetamine laboratories occur in North Carolina, as well as why they may occur within particular areas, is a complex process. Despite this, this study aims to determine the spatial characteristic of methamphetamine production, with particular attention given to understanding if methamphetamine laboratories within the state are clustered, as well as where any potential clusters may exist. In addition, this study also seeks to better understand what social and economic factors, if any, play a significant role in the clustering of discovered methamphetamine labs.

With a nearest neighbor ratio of 0.48 (p-value < 0.01, z-score = -31.32) methamphetamine lab discoveries are clustered. Additionally, the average observed distance between each laboratory was two miles. Even though the average nearest neighbor statistic does lend support to the idea that methamphetamine production may rely on the passing of knowledge between producers, as put forward by Sexton et al. (2006), it is difficult to determine how much of a role this process plays without some form of qualitative confirmation. What is more, the overall pattern presented in the density point heat map appears quite interesting, particularly in regards to directionality. Focusing on the major cluster in Watauga County, it is apparent that a line of sporadic clustering follows along the Appalachian Mountain region in a southwest pattern of movement. By focusing on Watauga County again, the three largest clusters within North Carolina appear seemingly one below the other, ending with the major cluster in Rutherford County.

It is difficult to pinpoint what relationship may exist with this pattern based on spatial patterns alone, but it does provide a starting place to better understand methamphetamine in North Carolina. For many of the state's rural counties, particularly those in the mountain west, the rate of poverty has been higher than state and national levels. Since 2003, the poverty gap in western North Carolina has expanded from 1.5 points above the national average, to 4.4 points above average in 2012 (Carolina Public Press 2014). The topography of western North Carolina also has the potential to play a significant role in regards to poverty, but also to methamphetamine production. Living in the rural isolation of the mountain west does pose problems with transportation and access to services. In many cases, transportation plays a significant part in the ability to acquire and maintain employment (Carolina Public Press 2014).

Considering that the majority of major discovered lab clusters are within the mountain west, it is possible that rural isolation and poverty create a chain reaction that leads many individuals to turn to methamphetamine production for sources of income.

Exploring this pattern further may also provide a means to explain why methamphetamine production has spread from the western region of the state into the eastern region. Based upon the first year that methamphetamine lab discovery data was made available, it does appear that the majority of discovered labs were focused in the western region of North Carolina, with a few sporadic lab discoveries in the eastern regions. By using the mean center statistic, it is apparent that between the years of 2004 to 2006, there was a small, southeastern shift in the number of labs. Beyond 2006, the mean center ceases to move any further, and remains within the western and Piedmont regions of the state. Again, it is difficult to pinpoint why these patterns and shifts in labs discoveries occur without some form of ground truth knowledge. However, by visualizing where the highest densities have occurred, and how lab discoveries have moved over time, it does provide a framework for further research.

North Carolina is a predominantly rural state, with eighty counties out of one hundred classified as rural (North Carolina Department of Commerce 2016). Due to its inherent nature as a rural state, it is difficult to determine exactly how methamphetamine labs rely on North Carolina's rural character to avoid detection. Considering that the majority of lab discoveries were found outside of major urban boundaries, as well as in mostly open, low developed areas, it does appear to play some role in the production process. As shown in the point density analysis, however, many of the heaviest clusters within the state do occur near or within towns and cities, but generally not within the bounds of major cities, such as Raleigh or Charlotte. This may not be surprising, however, as many methamphetamine labs have been reported to appear in single and multifamily residences throughout the United States since 1995 (United States Department of Justice 2016). Moreover, this same pattern was also discovered to have occurred in Oklahoma by Shukla and Bartgis (2008). For further research, this study recommends a more in-depth analysis of why methamphetamine laboratories choose to locate outside of major urban areas. One possible explanation that could reasonably arise from further exploration is the availability of ingredients and tools necessary for methamphetamine production within urban boundaries.

When examining the spatial patterns of discovered labs near interstates, interesting patterns begin to emerge. Of all interstates within North Carolina, Interstate 40, which runs from the western edge of the state to the eastern edge near the City of Wilmington appears to have the most labs that run with its general direction. In particular, many of the labs located close to Interstate 40 are also located within two of the major density clusters found in the point density analysis. In the western area of the state, clusters of labs start west of the city of Asheville, and move in an easterly direction towards Marion, Morganton, and Hickory. There is a noticeable gap east of Hickory along Interstate 40 that stretches from Statesville to the city of Raleigh, however, once near Raleigh, the amount of labs clustered around Interstate 40 increases once again. What is also noticeable is that a large amount of the discovered labs is also within the cluster found near the city of Dunn, which is close to where Interstate 40 intersects with Interstate 95.

Another major interstate that includes significant clusters is Interstate 85. Two major clusters that can be found along Interstate 85 are centered around the City of Gastonia, as well as the City of Lexington. Undoubtedly, it could be assumed that major interstates play an important role in the transportation of methamphetamine across the state, and perhaps into other states, but this patterns also creates further questions. As noted in research conducted by the United States Department of Justice, methamphetamine producers often rely on sizeable production networks. In many instances, networks function as a means of procuring or exchanging chemicals, recipes, glassware, and finished products. In the neighboring state of Tennessee, ten counties in eastern Tennessee account for a third of 9,000 discovered methamphetamine labs. Of the clusters that do form within these counties, roughly nine out of ten clusters are located on or near Interstate 75 (Lakin 2010).

The overall variation in pattern of discovered labs throughout the state, however, leads to some difficulties in producing a proper regression model. Out of the 1,1554 census tracts in North Carolina, 1,080 census tracts recorded zero laboratories discovered between 2005 to 2016. During this time period, the majority of census tracts that did report lab discoveries experienced mainly small quantities of production. 391 out of 1,554 census tracts experienced only one to three lab discoveries, while seventy five census tracts reported only four to seven lab discoveries. Beyond this, only eight census tracts reported discovery counts above seven, with a maximum of sixteen lab discoveries. As noted by Caulkins (2003), this pattern is not unique to North Carolina, as many states throughout the United States experience the same clustering phenomena.

Creating a useful geographic weighted regression model requires the creation of a non-geographic weighted regression, which may be in the form of a traditional ordinary least squares regression, or, in the case of this study, a regular poisson model. Fortunately, GWR4 addresses this issue by simultaneously running a regular global equation along with its geographic weighted counterpart for direct comparison. For the global regression result, coefficient estimates are small for unemployment, income below poverty, and amount of renters. Moreover, the estimated coefficient signs also run contrary to what would be expected with the production of methamphetamine. In regards to methamphetamine production, it would be more likely to observe positive coefficients related to unemployment and the amount of renters within a given census tract. While the global model does not provide a traditional R^2 value, GWR4 does provide a number for percent deviance explained, which is a type of pseudo R^2 value. For the global regression model, percent deviance explained is 0.15, which also highlights that the selected social and economic variables provide weak explanatory power (Table 4). Percent deviance explained increases significantly in the geographically weighted result to .50; however, the estimated coefficients still remain close to zero. The estimated coefficient signs also remain different than expected, as in the global regression model, with the exception of income below poverty. Despite this, comparing the AIC value of the global regression model (2482.80) to that of the geographic weighted model (1667.81) does show that the geographic weighted poisson is the better model. It should be noted, however, that even though the geographically weighted poisson model does provide a better fit, it cannot be relied upon to rescue poor model design.

Despite this, a closer examination of individual coefficient estimates and provided t-values for each census tract does provide some useful insight (Figure 2). For bachelor degree attainment, the coefficient estimate appears to be weaker in regions that experienced the highest counts of methamphetamine lab discoveries, particularly in areas near Boone and Marion. However, the coefficient estimates are stronger near Asheville and Smithfield, which did contain moderately high amounts of methamphetamine production. Despite this, t-values produced for each census tract show that the strengths for each coefficient estimate are not significant at the 95 percent confidence interval (+/- 1.96).

Throughout the entire state, it appears that unemployment does not play a significant role in the production of methamphetamine, as the many of the areas that experienced the highest levels of methamphetamine production have coefficient estimates that run contrary to what would be expected with the production of methamphetamine (Figure 3). Conversely, the areas with stronger positive coefficient strength are located in major urban regions of North Carolina, such as Charlotte and Greensboro, and experienced little methamphetamine production. This pattern is also evident when exploring weighted outputs for levels of income below poverty (Figure 4). In areas of major clusters, such as Boone and Morganton, the income below poverty coefficient estimate runs contrary to what would be expected, with the exception of the larger cluster that occurred near the cities of Dunn and Smithfield. For large clusters of methamphetamine production in the western region of North Carolina, the amount of renters within a census tract provides a weaker explanation for production, that is generally weakly negative or positive, with the exception of a small regions to the east of the town of Morganton that has a strong positive correlation. This area also exhibits a t-value of positive significance that falls within the positive 95 percent confidence interval (Figure 5).

As noted by Wells and Weisheit (2012), there is no current theoretical model that best describes the reasons for methamphetamine production. Both Wells and Weisheit have contributed a significant amount of research to better understanding the causes of methamphetamine production, and this study relied on areas of their previous research for guidance in creating a model. Many of the variables used in studies by Wells and Weisheit, as well as by Armstrong and Armstrong (2009) were incorporated into the model for this study. These variables included demographic factors, such as race, as well as income variables that included median income, income below poverty, and poverty assistance. Geographic mobility was also taken into consideration, which included variables related to home ownership, home renters, and the amount of time home owners had remained in their current residence.

Unfortunately, many of these variables were excluded from the final model due to high levels of covariance. The level of covariance for many of these variables should come as no surprise. Previous research has shown that regions with a predominantly white racial composition are highly susceptible to methamphetamine production. While this variable was originally selected for modeling attempts, it was discarded to due to high covariance, as North Carolina is a state with a predominantly white population. Other variables, such as median income and home ownership, where also excluded to high covariance. This is unsurprising, however, as variables related to level of education, income, home ownership, and length of home ownership would undoubtedly have some level of covariance and would need to be rejected. As was the case with the Wells and Weisheit study, the social and economic variables chosen for regressive modeling did not provide strong insight into why methamphetamine production occurs, even at the census tract level. This study does, however, find agreement with Wells and Weisheit that the spatial proximity of discovered methamphetamine labs plays a rather significant role.

LIMITATIONS

While this study attempts to map addresses of discovered methamphetamine laboratory discoveries in the most accurate manner, there exists the possibility that not all discoveries are reported. In this instance, it is possible that census tracts that reported no methamphetamine lab discoveries between 2004 to 2016 did in fact experience areas of methamphetamine production. Likewise, it is also possible that census tracts reporting methamphetamine lab discoveries may have had more labs than reported.

It should also be noted that while the American Community Survey provides data in a more timely manner than the decennial census, it also suffers from higher margins of error due to the nature of its design. Even though the social and economic variables for this study were shown to have marginal effects in regressive modeling, it is possible that higher margins of error may have impacted model outputs.

CONCLUSION

This study shows that while understanding the social and economic factors that lead to methamphetamine production are difficult to determine, it is possible to create a more comprehensive picture of methamphetamine production by combining spatial analysis with regressive modeling. Although methods of regressive modeling for the purposes of this study fell short in explanation, the inclusion of spatial analysis does add a greater context than regressive modeling alone. In the case of this study, a significant number of discovered methamphetamine laboratories were found primarily in western North Carolina, with a smaller cluster located in the eastern region of the state. The addition of this type of spatial analysis has the potential to aid in future research by allowing for a more in-depth, mixed methods approach. By understanding where discovered methamphetamine labs have previously clustered, future researchers may have the opportunity to apply a more community centered approach to understanding why methamphetamine production proliferates in some regions of North Carolina, but is mostly absent within others.

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Table 1. Discovered Methamphetamine Lab Seizures, 2004 to 2016.

Year	Lab Discoveries
2004	161
2005	119
2006	59
2007	45
2008	51
2009	43
2010	103
2011	81
2012	49
2013	32
2014	102
2015	120
2016	51

Table 2. Land Cover Classification of Methamphetamine Labs.

Land Cover Classification	Lab Count
Barren Land	1
Cultivated Crops	75
Deciduous Forest	111
Developed, High Intensity	8
Developed, Low Intensity	177
Developed, Medium Intensity	47
Developed, Open Space	337
Evergreen Forest	32
Hay/Pasture	133
Herbaceous	49
Mixed Forest	10
Open Water	5
Shrub/Scrub	26
Woody Wetlands	9

Table 3. Geographic Weighted Poisson Regression Output.

Variable	Mean	Std. Deviation	Minimum	Maximum
Bachelor Degree	-0.62	0.37	-1.5	0.55
Unemployment	-0.18	0.41	-1.61	0.81
Income Below Poverty	0.03	0.33	-1.42	0.66
Renter	-0.18	-0.18	-1.19	0.57

Percent Deviance	0.5
AIC	1652.91
Deviance/Freedom	1

Table 4. Global Regression Output.

Variable	Estimate	Std. Error	Z-Score	Expected(Estimate)
Bachelor Degree	-0.82	0.05	-15.21	0.43
Unemployment	-0.24	0.04	-5.25	0.78
Income Below Poverty	-0.02	0.04	-0.61	0.97
Renter	-0.19	0.04	-4.01	0.82

Percent Deviance	0.15
AIC	2484.81
Deviance/Freedom	1.59

Figure 1. Point Density Heat Map of Methamphetamine Labs, 2004 to 2016.

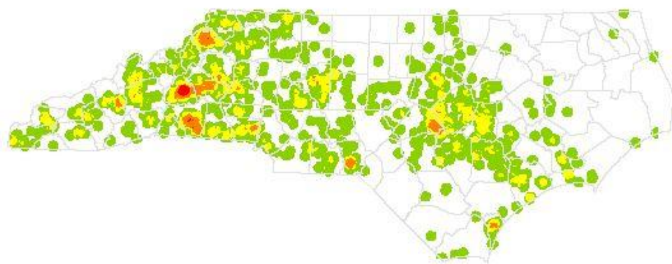


Figure 1. Point Density Heat Map of Methamphetamine Labs, 2004 to 2016.

Figure 2. Coefficient Estimates and T-Values for Bachelor Degree Attainment.

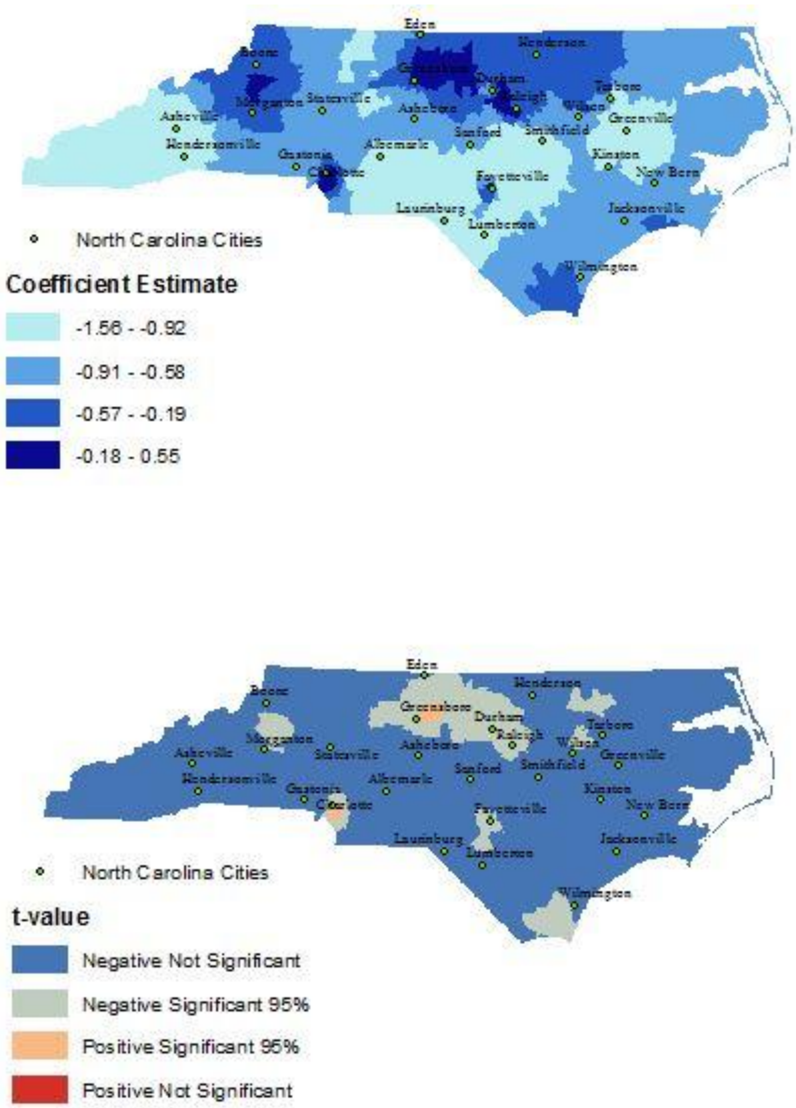


Figure 2. Coefficient Estimates and T-Values for Bachelor Degree Attainment.

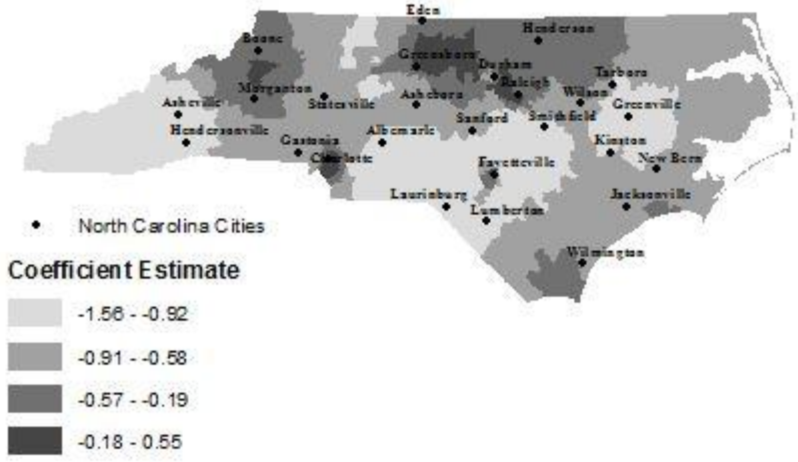
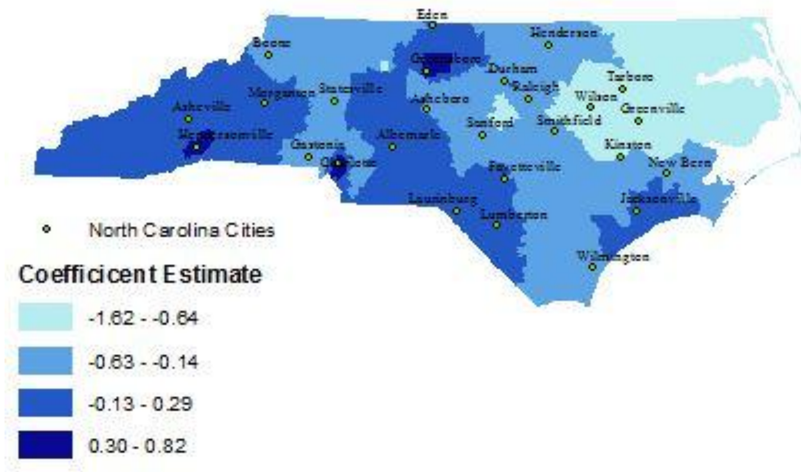


Figure 3. Coefficient Estimates and T-Values for Unemployment.



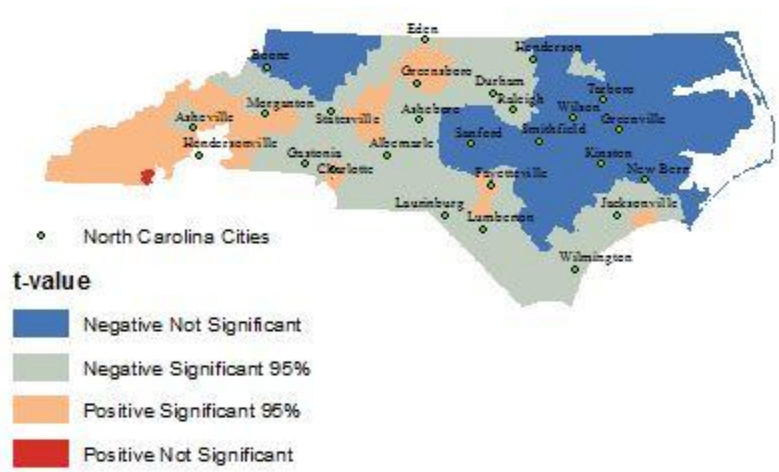
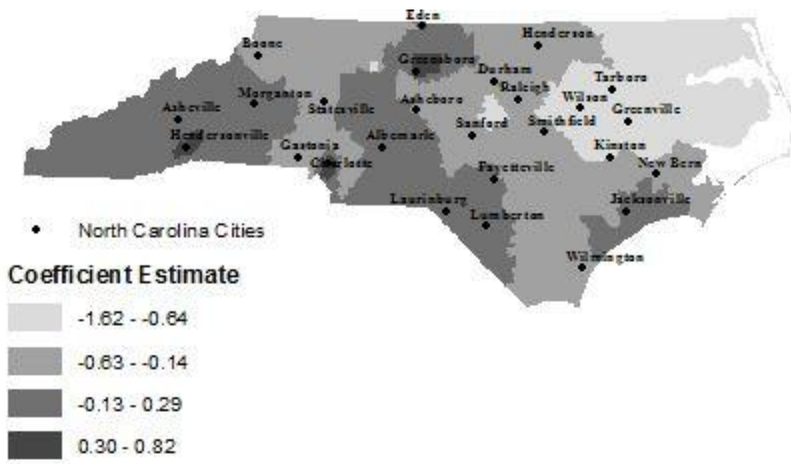


Figure 3. Coefficient Estimates and T-Values for Unemployment.



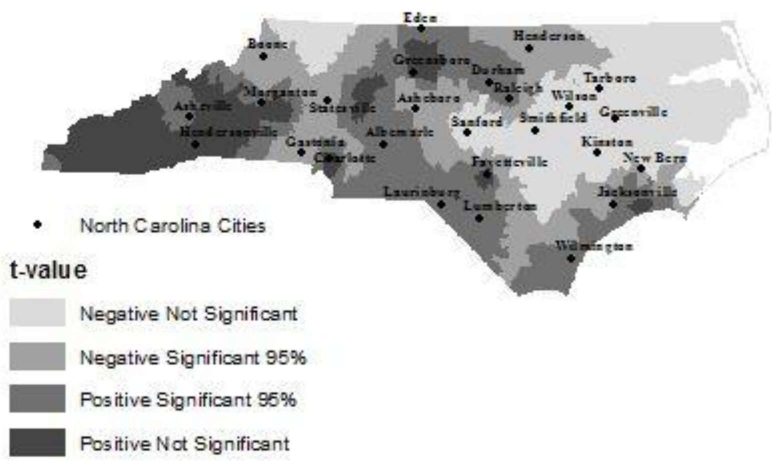
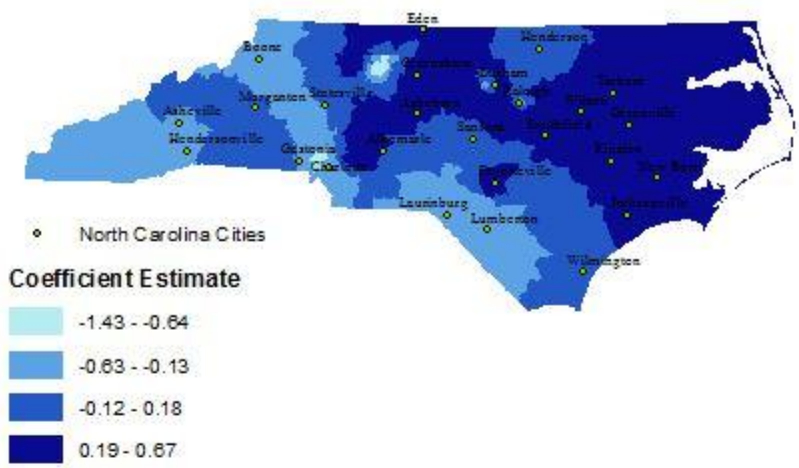


Figure 4. Coefficient Estimates and T-Values for Income Below Poverty.



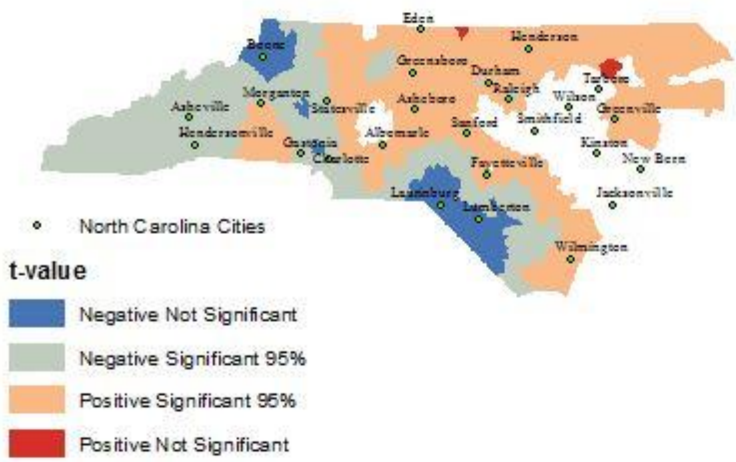
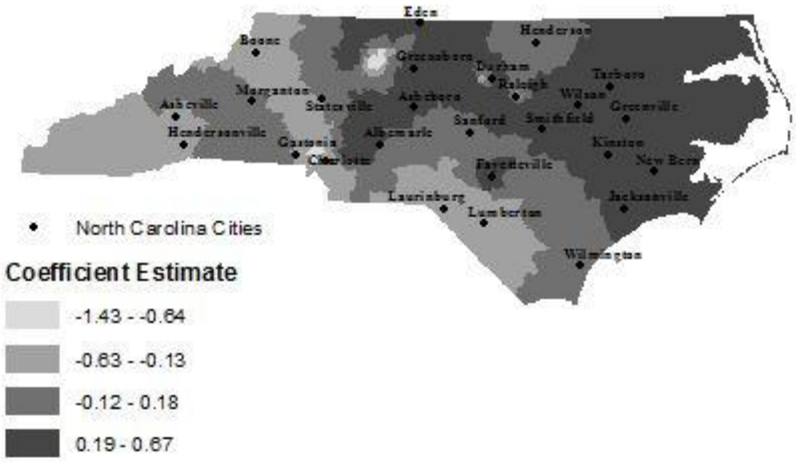


Figure 4. Coefficient Estimates and T-Values for Income Below Poverty.



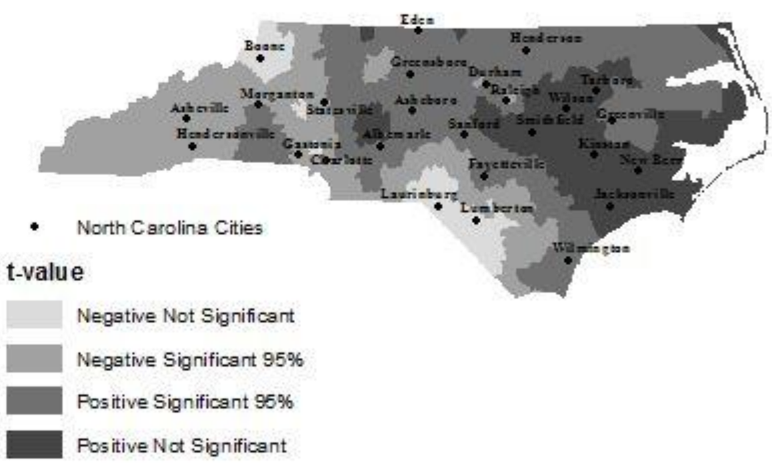
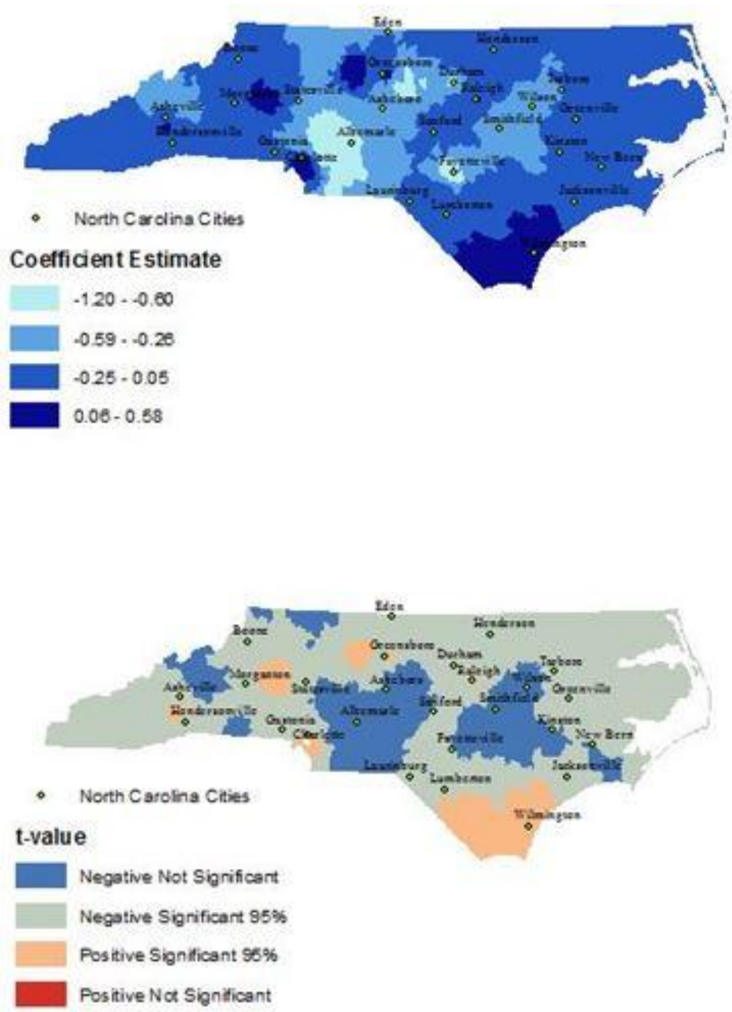


Figure 5. Coefficient Estimates and T-Values for Number of Renters.



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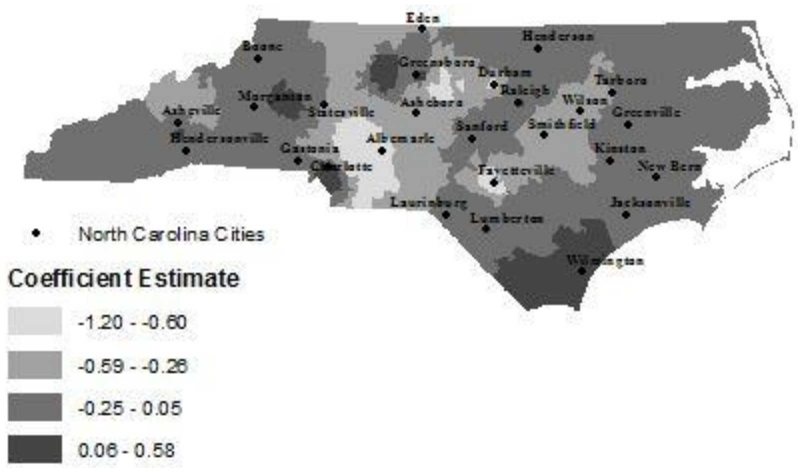

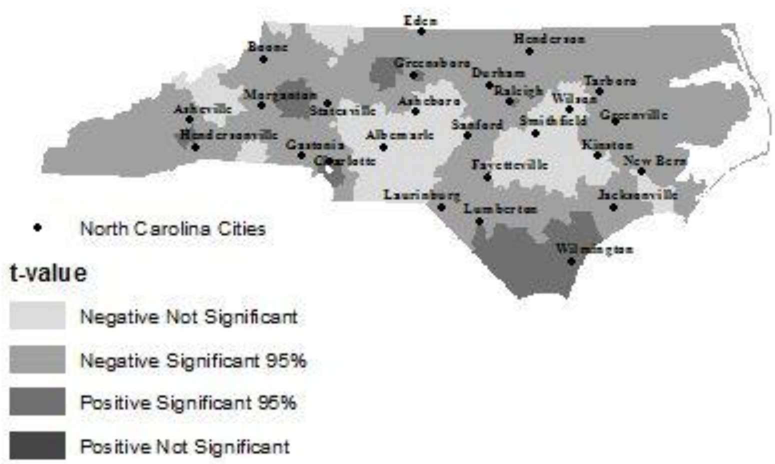

Vita

Garry Raynor was born in Fayetteville, North Carolina. He graduated from South View High School in Hope Mills, North Carolina in June 2002. Shortly after graduation, he served in the United States Navy from June 2005 until June 2011. In August 2011, he enrolled at Appalachian State University and graduated in December 2014 with a Bachelor of Science in Geography. He began work toward a Master of Arts degree in Geography, as well as a Certificate in Planning in August of 2015, and was awarded the M.A. and certificate in August 2017.