5-2020

Spatiotemporal analysis of traffic crashes involving pedestrians and cyclists in Jefferson County, Kentucky.

Joseph M. Garcia
University of Louisville

Spatiotemporal Analysis of Traffic Crashes Involving Pedestrians and Cyclists in Jefferson County, Kentucky

By

Joseph M. Garcia

Submitted in partial fulfilment of the requirements

for graduation summa cum laude

University of Louisville

May, 2020

Acknowledgements

I would like to thank my mentor, Dr. Wei Song, for his constant guidance and support throughout this endeavor. I would also like to thank all the faculty and staff of the Geography and Geosciences Department who have not only helped me with my thesis but have encouraged me throughout my academic career. Finally, I’d like to thank my friends and family who have been my biggest fans and have listened to me talk about this topic more times than they’d probably like to have.

Table of Contents

List of Equations

List of Figures

Abstract

Walking and cycling are health-conscious, environmentally friendly modes of transportation, yet very few American trips are accomplished using these methods. A major factor behind this is the fear of being involved in a crash with an automobile. From 2009-2019 there were over 5,200 automobile crashes involving either pedestrians or cyclists in Louisville/ Jefferson County, Kentucky. Researchers have found that these kinds of crashes exhibit spatiotemporal patterns in different cities across the globe. The objective of this study was to determine if there exist any spatial and/or temporal patterns regarding these kinds of crashes. Data for this study came from the Kentucky State Police and encompassed all pedestrian and cyclist crashes from 2009-2019. GISsystems were used to perform a network-based kernel density estimation for the spatial analysis. For the temporal analysis, the scales of time, day and month were observed and plotted. Hot-spots were found to exist within the study area, with some locations being hot-spots for both pedestrian and cyclist crashes. These shared hot-spot locations were analyzed in detail, using the original Kentucky State Police data, as well as Google Earth and Street View imagery.

INTRODUCTION

Walking and cycling are the methods of transport that comprise the transportation category of “active transport”. Engaging in active transport has been shown to improve one’s health (Hamer and Chida 2008; Oja et al. 2011) and produce little to no carbon emissions compared to automobiles (Blondel, Mispelon and Ferguson 2011; World Health Organization 2011). Despite these benefits, only 10.5% of American trips are accomplished by walking, and only 1% of trips are via bicycle (U.S. Department of Transportation 2017).

One of the most common reasons for transportation, in general, is to commute to and from work (U.S. Department of Transportation 2017). From 2008-2012, only 2.8% of American workers walked to work, and only 0.6% cycled. For Louisville (Jefferson County), the number of walking commuters went down from 4.1% to 2.2% from the 2000 census to the 2008-2012 American Community Survey; for cycling, the percentage stayed at a low 0.4% (McKenzie 2014).

One factor that has been shown to deter people from engaging in active transport is the perceived risk of being involved in an automobile crash (Dill and Voros 2007; Handy, Xing and Buehler 2010). Data from the Kentucky State Police indicates that from 2009-2019, there were over 5,200 crashes in Jefferson County (Louisville) that involved pedestrians or cyclists. Previous research has shown in other cities that traffic crashes involving pedestrians and cyclists have exhibited spatiotemporal patterns (Dai 2012; Chen 2015; Dai and Jaworski 2016; Kaygisiz and Hauger 2017), “spatiotemporal” meaning to have attributes relating to time and location. These studies have shown that active transport traffic crashes are influenced by many different factors such as the number of crosswalks present, the presence of stoplights, the speed limit of roads, season, lighting conditions, weather, income, and local population (among other factors). Studies in the past have specifically sought to test if specific groups of variables account for spatiotemporal patterns such as built environment (e.g., crosswalks, stoplights) or physical conditions (e.g., season, lighting conditions). For this study, the scope was limited to identifying if spatiotemporal patterns exist regarding pedestrian and cyclist crashes. Other conditions were factored into the discussion of results, but they were not the central focus of this project.

One point of note is the use of the word "crash" in reference to a vehicular collision, compared to "collision" or "accident". In 1997, the National Highway Traffic Safety Administration (NHTSA) began to encourage phasing out the use of the word "accident" in regards to automobile collisions, instead opting for alternatives such as "crash" and "collision" (Anikeeff 1997). Most of the studies used in the literature review for this project have used the term "crash" and this precedent dictates the usage of the word in this work.

The objectives of this study were to determine if any spatiotemporal patterns exist regarding traffic crashes involving pedestrians and cyclists in Jefferson County, Kentucky. If so, the secondary objective was to determine what, if any, characteristics were present at significant crash locations that may have influenced the presence of crashes. Based on the results of previously mentioned studies showing that spatiotemporal patterns exist regarding these kinds of crashes in different cities, I hypothesized that spatiotemporal patterns do exist regarding traffic crashes involving pedestrians and cyclists in the study area. A study of this kind had not yet been performed in Jefferson County.

LITERATURE REVIEW

Previous studies on traffic crashes involving pedestrians and cyclists have had a focus on identifying causal factors that influence spatial patterns of traffic incidents. Most studies are based upon the assumption that spatial patterns exist regarding traffic crashes and devote most of the projects to analyzing the causal factors that dictate these patterns. One of the more important factors for this project that has been researched is physical environment, which influences both the spatial and temporal aspects of this study. Kaygisiz and Hauger showed that crash hot-spot locations for cyclists and automobiles in Vienna, Austria varied based upon season, light condition and precipitation (2017). Seasonality and light condition are two important factors that can be easily determined using temporal data for crash records. By knowing the time of day on a particular date, the light conditions can be determined as well as the seasonality. Precipitation levels can also be tied to seasonality and thus contain an element of temporal influence.

When studying pedestrian injuries from traffic crashes in the Atlanta, Georgia region, Dai's study showed that more injuries occur in the summer months than in any other season. Injuries to pedestrians were also shown to be more likely to occur on the weekend (2012). According to Dai, these temporal factors should be considered when implementing preventative measures. Dai's study not only discussed environmental factors relating to time but also environmental factors that had a more spatial component. One significant factor was the pedestrian's maneuver, what this boiled down to for Dai's study was whether a pedestrian crossed at a crosswalk or not proved to be a significant risk factor in receiving an injury from a car crash. Although Dai attributed crossing at a crosswalk to be a human factor, another perspective could be to view the presence of a crosswalk as being a factor in the spatial distribution of crashes

In 2015, Chen found that other spatially influenced factors like speed limit of a traffic analysis zone, density of intersections and presence of on-arterial (road) or off-arterial bike paths. Unsurprisingly, he found that zones with lower average speed limits experienced fewer crashes and that riding on an off-arterial bike path was safer than an on-arterial bike path. Interestingly, for three-way intersections he observed a negative correlation to bike crash frequency, other studies had observed positive corrections for all types of intersections to bike crashes. Chen's explanation for this theorized that the greater number of intersections there are in an area, the slower the speed limit must be and thus it is the lower speed limit that is more so affecting the frequency of bike crashes.

While most studies focus primarily on the causal factors associated with spatiotemporal patterns of traffic crashes, for the purposes of this study the more significant takeaway was that all these studies observed a spatiotemporal correlation or pattern. Studies have used a variety of methodologies and all come to same conclusion that spatiotemporal patterns exist, this is discussed in further detail in the "methodology" section. One point that this study aims to make is to emphasize both spatial and temporal patterns as being equally significant.

In determining the presence of spatiotemporal patterns of traffic crashes, researchers have used a variety of statistical techniques and procedures. Fournier, Christofa and Knodler used available daily bicycle traffic counts combined with crash records to come up with a bicycle crash rate along road corridors in Cambridge, Massachusetts (2017). This method is simple and straight-forward but for this study would require official daily bicycle and pedestrian counts on roads which Louisville does not possess.

When analyzing the spatial patterns of pedestrian injuries in automobile crashes, The Dajun Dai study used a statistical software package called SatScan to run a Bernoulli model of cluster identification (2012). The Bernoulli model assumes that cases have the same geographical distribution of controls. This method works well for studies that aim to test the spatial distribution between two types of a single event, e.g. pedestrian crashes with no injury vs pedestrian crashes with injury. This project was not not aimed to test the spatial distribution between cyclists and pedestrians as in Dajun and Dai's study, but rather test them separately as individual analyses.

Scheider et al used nearest-neighbor cluster analysis to identify spatial clustering of traffic crashes involving pedestrians on the University of North Carolina's campus (2014). The nearest neighbor analysis works by analyzing the distance between points and calculating if the difference is statistically significant compared to the expected value which is if all points were placed at random. This method is suitable for determining spatial patterns in a 2 dimensional space but does not account for the limitations that roads provide in a study focused on traffic crashes.

STUDY AREA, DATA AND MEHTODS

STUDY AREA

The study area of Jefferson County, Kentucky, is home to over 750,000 residents (Kelly et al. 2015) and shares consolidated government and geographic boundary with the city of Louisville, Kentucky. It has an area of approximately 400 square miles and has approximately 3760 miles of roads (LOJIC). Figure 1 shows the location of Jefferson County and street centerlines the network-based KDE used for analysis (see METHODS).

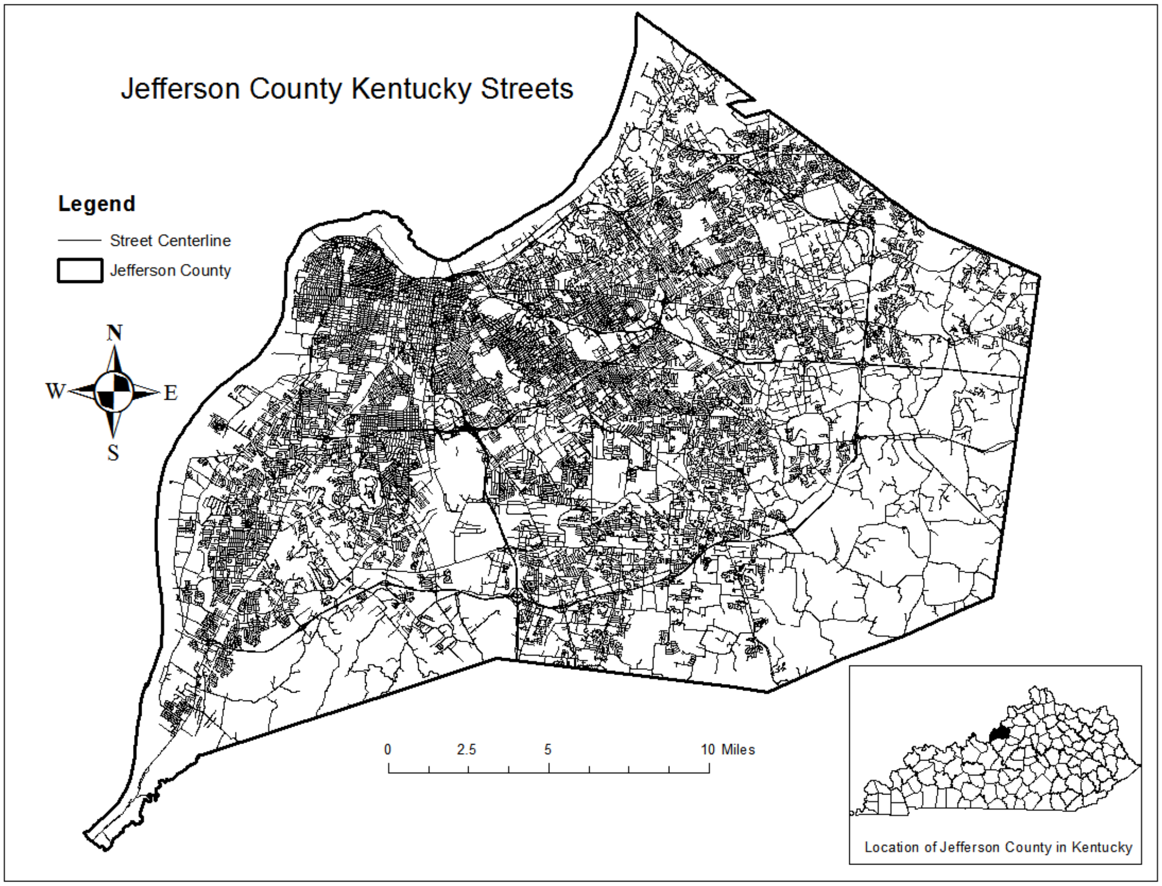

Figure 1. Jefferson County Kentucky with street centerlines

DATA

Data for traffic crashes came from the Kentucky State Police (KSP), which keeps detailed records for all traffic crashes in the state of Kentucky. This data is publicly available through a web service. For this project, only crashes that occurred between 2009 and 2019 were studied. No data from 2020 was used in order that all 12 months (and thus any environmental factors associated with them) were represented the same number of times. This dataset provided a decade’s worth of data and over 5,200 data points for crashes involving pedestrians and cyclists in Jefferson County. No data from before 2009 was considered for this project due to the ever-changing nature of city development. It is likely that many of the major roads in the county have undergone changes that have altered the characteristics of the road in the last decade, including data from beyond ten years ago could have introduced error to the analysis by identifying patterns of crash activity that are no longer present due to a physical change in the road.

This data did not come without errors however, 20 records from the pedestrian crash dataset and 42 records from the bicycle crash dataset were identified as occurring at the coordinates 38.201667, -85.536667 exactly. The specificity of this location, and the fact that it is located in the middle of a field, suggests that this was the default XY coordinates for a crash in Louisville and that the original recorder of the data did not change the record to accurately reflect the true location of the incident. Two records from the pedestrian dataset were given a latitude value of “3” rather than approximately “38”, this resulted in crash locations being identified in the Pacific Ocean. Two other records from the pedestrian dataset fell just outside the county line, it is possible that this is a result of a recording error of a police officer mistakenly believing that they were within the county boundary at the incident location. All 66 records identified as erroneous were excluded from the study.

Another dataset crucial to the implementation of the objectives was a comprehensive spatial collection of all the roads found within Jefferson County. This piece was critical in determining where crashes occur since locations of automobile crashes are inherently tied to the road network. This data came from the Louisville/Jefferson County Information Consortium (LOJIC). The data was available free of charge through the Louisville Open Data Portal website.

METHODS

The methodology for this project's analysis utilized a network-based kernel density estimation model to identify clusters of incidents. Kernel density estimation (KDE) is a statistical method that is well-suited for point pattern analysis. Normally KDE is used to detect hot-spots over a two-dimensional plane. KDE assumes that there is complete spatial randomness to the data. In essence, the KDE model assumes that a crash would be just as likely to occur at any location within the area of analysis. This can be problematic for studies analyzing phenomena that take place on roads. Studies on traffic crashes have pointed out that crashes only occur along road networks. A traditional KDE would not account for the significance of roads and would consider spaces like backyards, factories and other unpaved settings away from roads as being just as likely to have a traffic crash compared to a paved road.

To account for this, a network-based model can run along the one-dimensional space of a street center line (a line that represents the center of a physical street). This one-dimensional platform and is more effective at identifying clusters of traffic crashes (Xie and Yan 2008). In this way, spatial randomness can still be assumed, but results are made more accurate by only calculating along a refined portion of the study area. This methodology has been proven to be effective in identifying hot-spots of traffic collisions and has been used in previous studies in this field, as seen below.

In order to carry out this analysis, Geographic Information Systems (GISystems) were employed to plot traffic crashes involving pedestrians and cyclists. The GISystem "ArcGIS" (ESRI) was used as the primary tool for visualizing and manipulating data. The Kentucky State Police data came with X and Y coordinates that were plotted to a map using the ArcGIS function, "Display XY Coordinates". Once this was completed, a network-based kernel density estimation was employed. A GISystem tool called “Spatial Analysis on a Network” or SANET (Okabe, Okunuki and Shiode 2006) was used to perform the network-based KDE. The program uses the following function to find the density of crashes. For a single point, the kernel density function can be defined in equation (1).

$$K_q(p)\begin{cases} \geq 0\ for\ p \in L_q \\ = 0\ for\ p \in \tilde{L} \setminus L_q \end{cases} \qquad (1)$$

$$\int_{p \in L_q} K_q(p)\mathrm{d}p = 1 \qquad (2)$$

Where q is an arbitrary point on a non-directed (meaning not a one-way street) network $\tilde{L}$. From this we construct the subnetwork L_q within the larger $\tilde{L}$ (street) network. L_q is comprised of $\tilde{L}$ divided into segments whose length is determined by user input as the “cell width”. Point q is set as the center of the line segment L_q. This is constructed in such a way that the shortest-path distance between q and any point on L_q is less than or equal to h, which is the buffer threshold set by the user as “band width”. $\tilde{L} \setminus L_q$ is the complement of L_q with respect to $\tilde{L}$. Essentially this means that point q becomes the kernel center of the function $K_q(p)$. L_q is the linear support of $K_q(p)$ and h is the bandwidth that extends from either side of point q to the end of L_q. The integral function equation (2) represents the area within the $K_q(p)$ function.

The equation that represents the kernel density along the entire network is represented in equation (3).

$$K(p) = \frac{1}{n}\sum_{i=1}^{n} K_{p_i}(p) \qquad (3)$$

Where n is the number of points p. When applied to equation (1), we can see if the values are either added to an existing $K_q(p)$ function (thus exhibiting clustering) or stand alone (Okabe and Sugihara 2012).

Previous researchers have used SANET to map car crashes involving pedestrians and cyclists (Xie and Yan 2008; Dai and Jaworski 2016; Kaygisiz and Hauger 2017). This software is free to use if permission is granted by the development team for users who agree to use the tool for academic purposes only. Permission to use SANET for this project was granted via email. Because the network-based KDE only analyzes along one-dimensional subsets such as road line segments, traffic crashes that normally would be represented by points based on their coordinates have their data transferred to a road segment. Since the point level crash data was created independently of the road network, almost all points do not fall exactly along the road segment in a GISystem. SANET includes a tool that allows for point level data to be transferred to the nearest line segment and thus allow for a network-based KDE to work.

It was important to determine that points collected from the KSP were not artificially assigned to points on the network when they were not intended to be placed on a road. A preliminary analysis of the data showed that 95.5% of KSP points fell within 50ft. of a street centerline in the network. This 50 ft. buffer was determined from the Louisville Planning and Design Land Development Code which states that 50 ft. is the legal right of way width for a local urban road which accounts for 78% of all roads in the study area. All other road classifications in this data set have wider right of way standards. This validated the assumption that crash points are tied to the road network. Once the network-based KDE process was performed, the resulting network KDE function was exported as a shapefile which was then processed using ArcGIS.

An important point to note is that all density values were determined without accounting for the volume of traffic on individual streets. Comprehensive datasets of traffic volumes for automobiles, pedestrians or cyclists in Jefferson County do not exist. If this was available, results would perhaps be more reflective of the severity of hotspots. The density values here represent what data is currently available for Jefferson County.

In order to analyze the temporal patterns of traffic crashes, time and date data from the Kentucky State Police dataset were extracted and plotted. For this project, three distinct time scales were observed: time of day, day of the week, and month. For the sake of simplicity, time values were rounded to the nearest half-hour. Rounding to the nearest half-hour allowed for the potential determination of the amount of daylight present, general temperature characteristics and general volume of automobiles on the road while remaining simplistic. Day of the week was left as is, as daily patterns of traffic vary with the work week. Date values were taken from their month only, months were more significant for this analysis than individual days in the month because months correlate more strongly with changes in the physical environment due to seasonality. In total there were 47 possible “hour values”, 7 “day values” and 12 “month values”. Temporal data was observed from data points collectively as well as within individual clusters of crashes in hotspots when applicable. To test the statistical significance of the temporal data, t-tests and chi-squared tests were utilized. The significance threshold was set at 0.05.

Different factors that could not be extracted from the data include the physical characteristics of a location that cannot be tabulated. Both the 2012 Dai study and 2016 Dai and Jaworski study used in-person audits to obtain physical characteristics data from hot-spots in Georgia. Due to time constraints, an in-person audit could not be performed. Rather than perform an in-person evaluation, Google Street View and Google Earth were used to obtain image data on the conditions of certain hot-spots. An added benefit of using these tools was the wide availability of archived imagery from both remotely sensed satellite imagery and in-situ street-view imagery. This was helpful in seeing how physical characteristics changed over time for hotspot locations.

RESULTS

Temporal Patterns

The temporal attributes of the data showed that there are indeed patterns regarding the occurrence of crashes for both pedestrians and cyclists. First, focusing on the daily temporal patterns, figure 2 shows that bicycle crashes have a statistically significant "peak" that exists approximately between 3:30 PM and 6:30 PM ($P<0.000$). This time frame constitutes the afternoon rush-hour period during the work week when the amount of traffic in the city is much higher than at other times. The temporal distribution of pedestrian crashes, also seen in figure 2, also exhibits a peak period. This can be observed to be between approximately 6:30 to 8:30 AM ($P<0.000$). The pedestrian peak correlates to the morning rush-hour when the amount of traffic is highest in the morning.

Comparing the two datasets, seen in figure 2, yielded further observations. Bicycle and pedestrian crashes switch between being more pervasive and less pervasive throughout the day. From midnight to approximately 8:30 AM, pedestrian crashes are more prevalent than bicycle crashes. After this time there is a dramatic increase in the proportion of crashes that involve bicycles. These bicycle crashes are more pervasive than pedestrian crashes until approximately 6:30 PM, when the pervasiveness of pedestrian crashes surpasses bicycle crashes for the remaining hours of the evening—which then carries over from midnight to

8:30 AM.

The results show that there are relatively more pedestrian crashes before and after normal work hours compared to bicycle crashes. Conversely, there are relatively more bicycle crashes during normal work hours compared to pedestrian crashes. This suggests that there is more pedestrian traffic present before and after work. Pedestrian traffic may be greater than bicycle traffic before and after work hours due to the higher proportion of Louisville residents who walk to work compared to cycle, these pedestrian commuters would have peaks on their morning commute and their afternoon commute

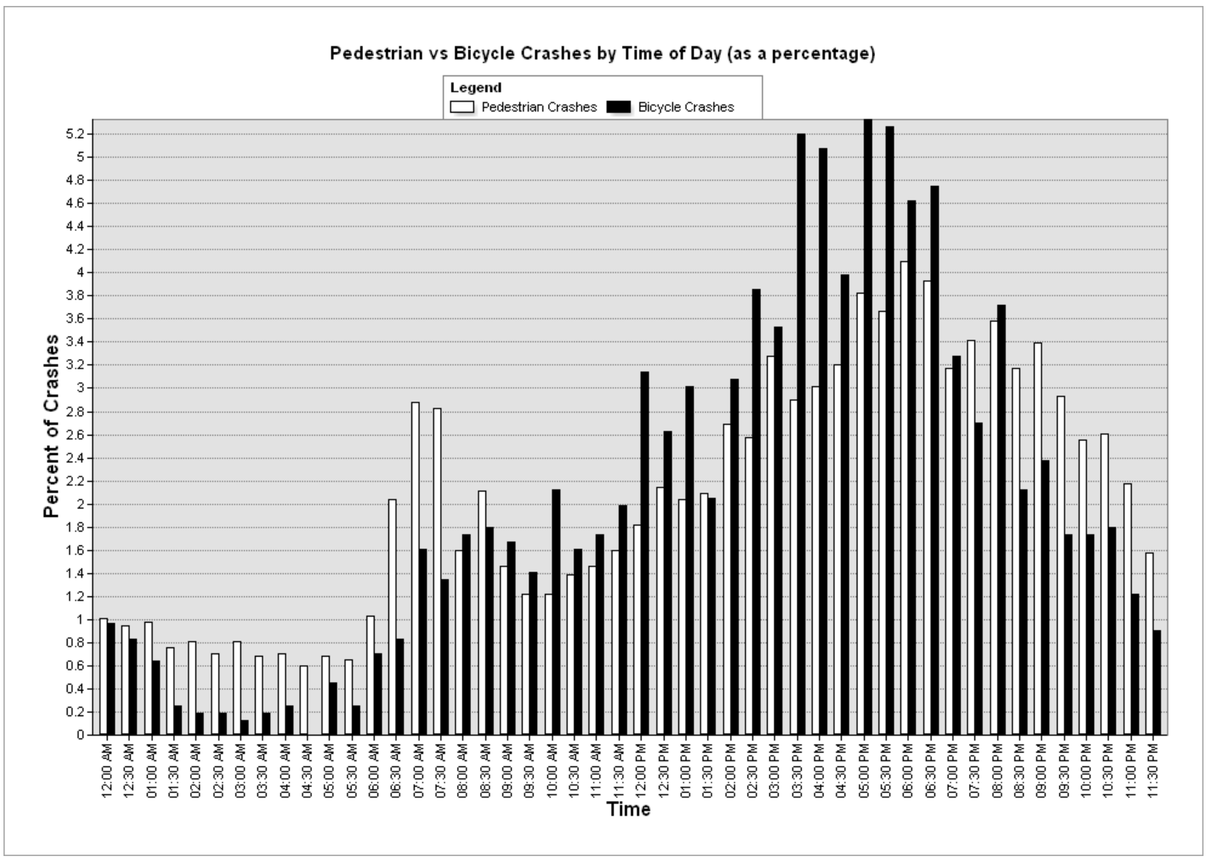

Figure 2. The daily temporal patterns of pedestrian and bicycle crashes

Increasing the temporal analysis scope from daily trends to weekly. Figure 3 shows that both pedestrian and cyclist crashes follow a similar pattern regarding the division of crashes throughout the week. A t-test confirmed there was no statistically significant difference between the weekly patterns of pedestrian and cyclist incidents ($P<0.000$). For both pedestrians and cyclists, there is a general increase in the number of crashes that occur from Monday to Friday, followed by a large drop-off for Saturday and Sunday. This weekend drop-off was found to be statistically significant through a t-test (Bicycle: $P=0.027$ Pedestrian: $P=0.014$). These results could be interpreted in two ways. One view would be that the decreased number of crashes on the weekends is a result of a decreased amount of automobile traffic compared to weekdays. An alternative interpretation of the data could say that the decreased amount of pedestrian and cyclist crashes on weekends comes as a result of there being a decreased amount of pedestrian and cyclist traffic

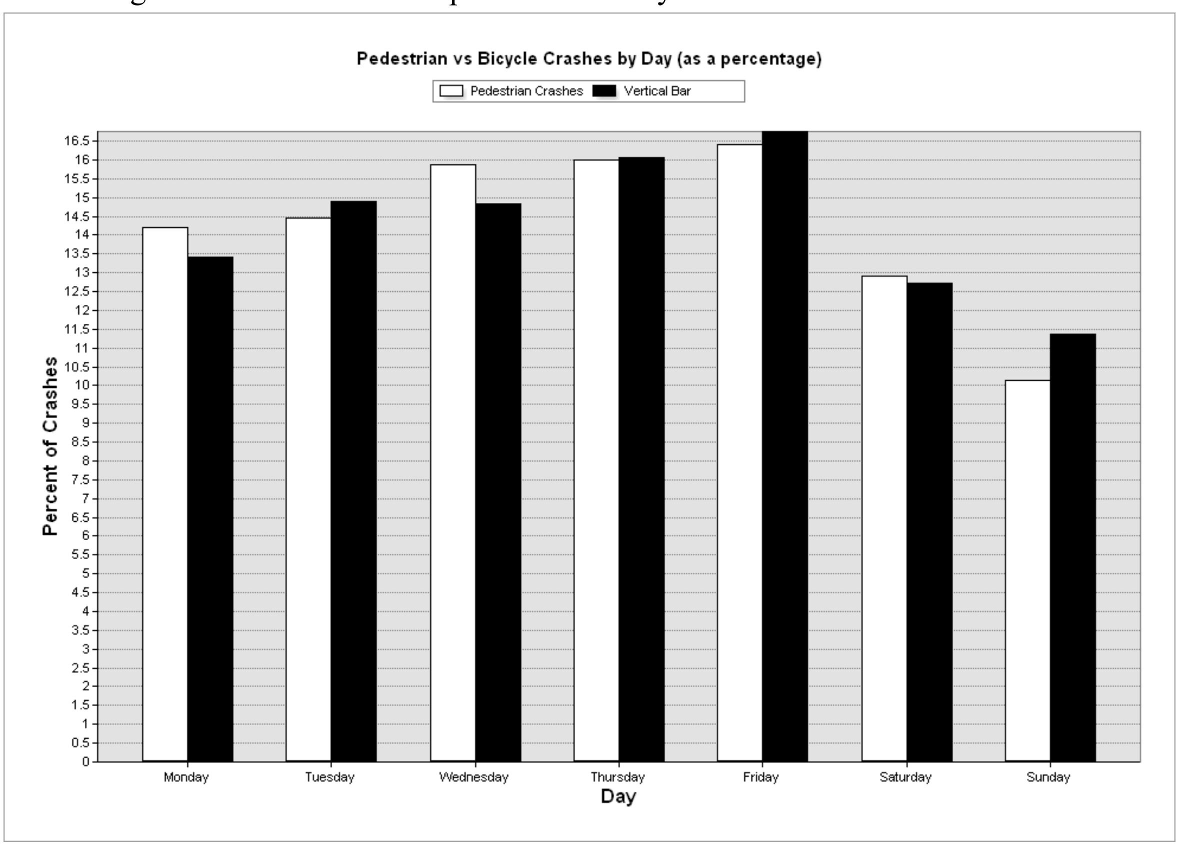

Figure 3. The weekly temporal patterns of pedestrian and bicycle crashes

Expanding to the broadest temporal unit of the month, figure 4 shows that there exist patterns at this scale as well. The distribution of crashes for both pedestrians and cyclists were determined not to be caused by random chance (both *P* values <0.000). For bicycle crashes, the number of crashes generally increases from January to the peak month of August, at which point the number of crashes steadily declines through December. Analyzing bicycle crashes by month in terms of the seasonality of the months shows that bicycle crashes occur the least amount in the winter months, increasing through spring until the highest frequency of crashes occur in the summer, after which the rate of crashes declines through fall until reaching its lowest frequency in the winter once again. Although the distribution of pedestrian crashes is generally more even compared to the bicycle crashes, when plotted against the bicycle crash data, it becomes apparent that there is a kind of inverse temporal relationship between the two types of crashes. The frequency of pedestrian crashes remains relatively stable in the winter and spring months and dips down in a statistically significant way during the summer months (defined as June, July and August with a *P* value of 0.003) and resumes a stable frequency in the fall and winter months.

The prevalence of bicycle crashes in the summer months compared to the other seasons may be related to an increased number of cyclists in the summer months. One possible explanation for this increased cyclist traffic is the summer break for schoolchildren. For grade-school children, the months of May through August provide ample time to play outside, one of the most popular outdoor activities for children is bike riding. Children also are generally not as cautious as adults due to a lack of experience. The increased volume of young, inexperienced cyclists could account for the high proportion of bicycle crashes during the summer months.

The reasons why there aren't as many pedestrian crashes could be due to multiple factors, one reason could be that walking exposes the participant to prolonged exposure of the elements, the summer months of Jefferson County are characterized by extremely hot and humid conditions that might discourage people from walking.

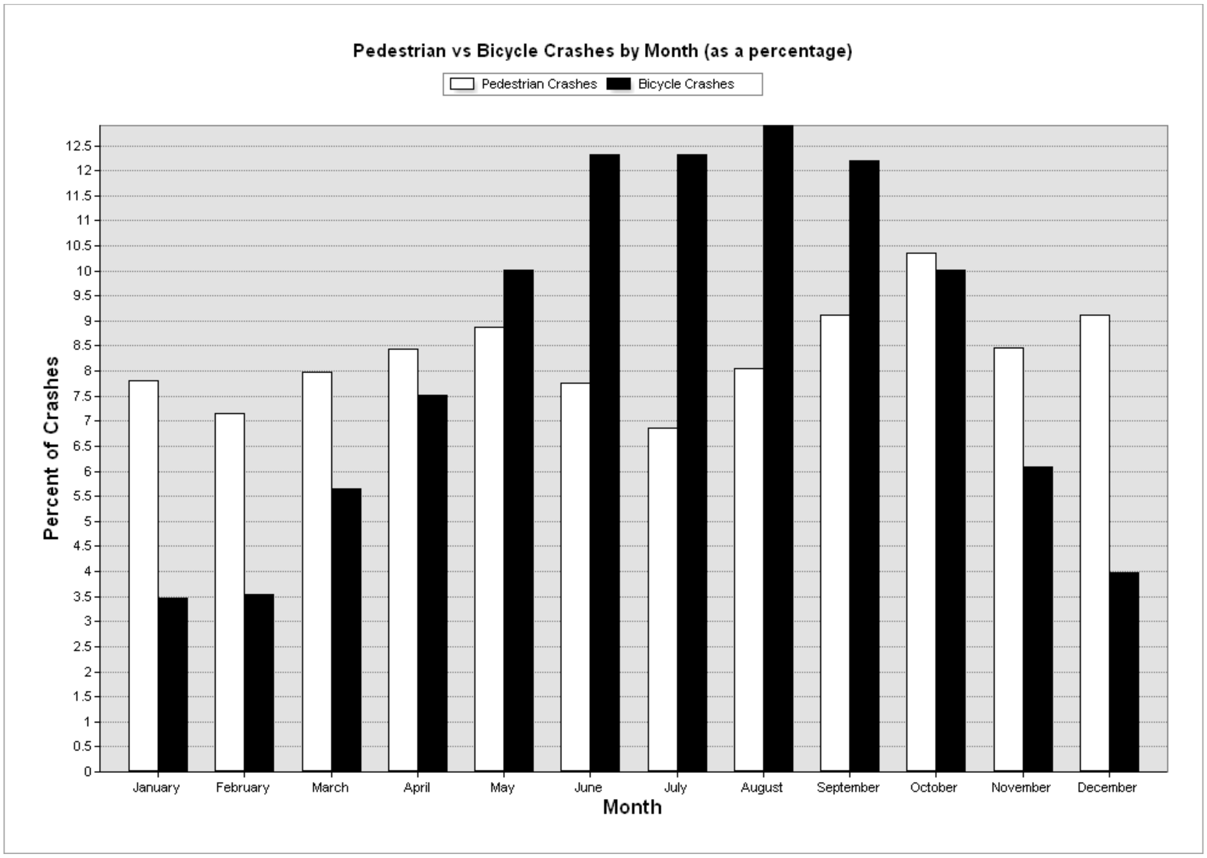

Figure 4. Monthly temporal patterns of pedestrian and bicycle crashes

Spatial Patterns

An analysis of the network-based kernel density estimation (NKDE) output revealed that there are hot-spots of high density crash sites throughout Jefferson County. Figure 5 shows that for pedestrians, clusters of hot-spots are spread mostly throughout the northwest of the county. There is a mass of hot-spots located in the central northern region of the study area, with two other prominent hot-spots being located along roads that sprout from this area. Other smaller hotspots are dispersed to the south and east of these most prominent hot-spots. Figure 6 displays a very similar pattern for bicycle crashes, there are multiple hot-spots located within the same central northern area, with two other prominent hot-spots being located in approximately the same location as the two prominent pedestrian hot-spots. Other smaller hot-spots are subsequently spread throughout the county while generally remaining in the northwest portion. For this study, pedestrian and bicycle NKDE's were overlaid. Figure 7 shows the hot-spots with the highest density values that were shared by both the pedestrian and bicycle NKDE's. These locations were then analyzed in detail.

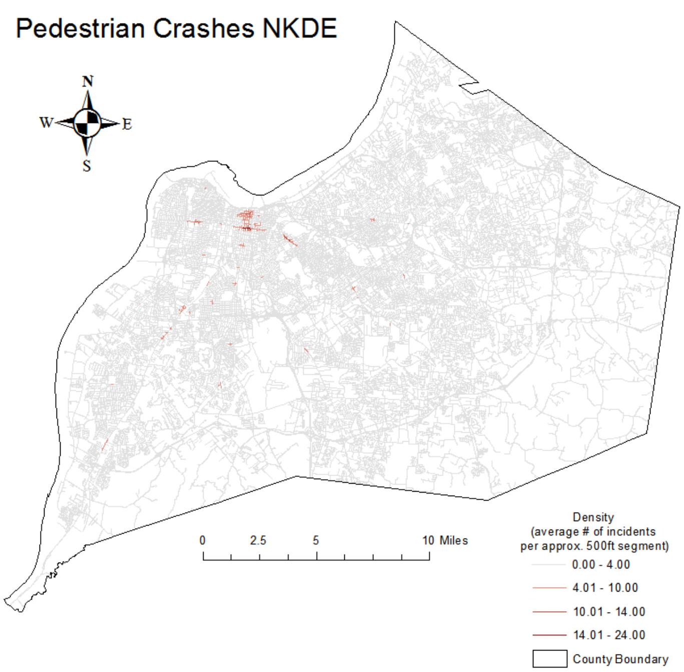

Figure 5. NKDE for pedestrian crashes

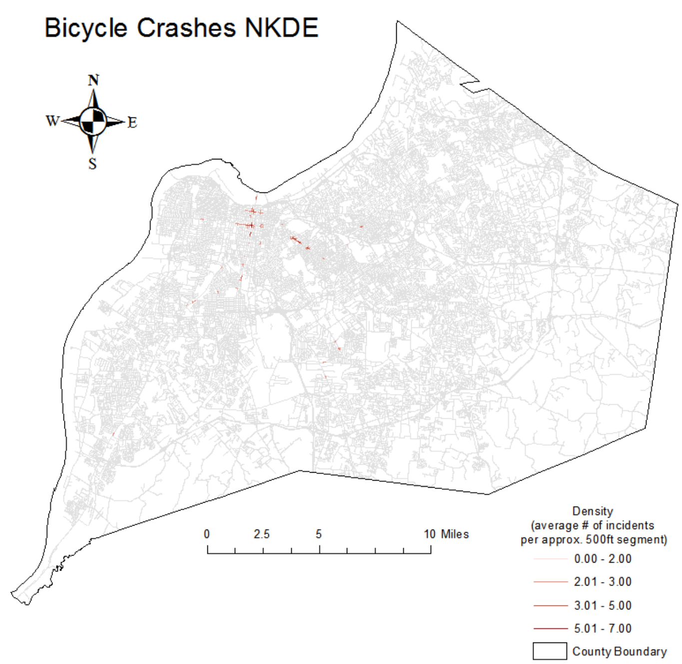

Figure 6. NKDE for bicycle crashes

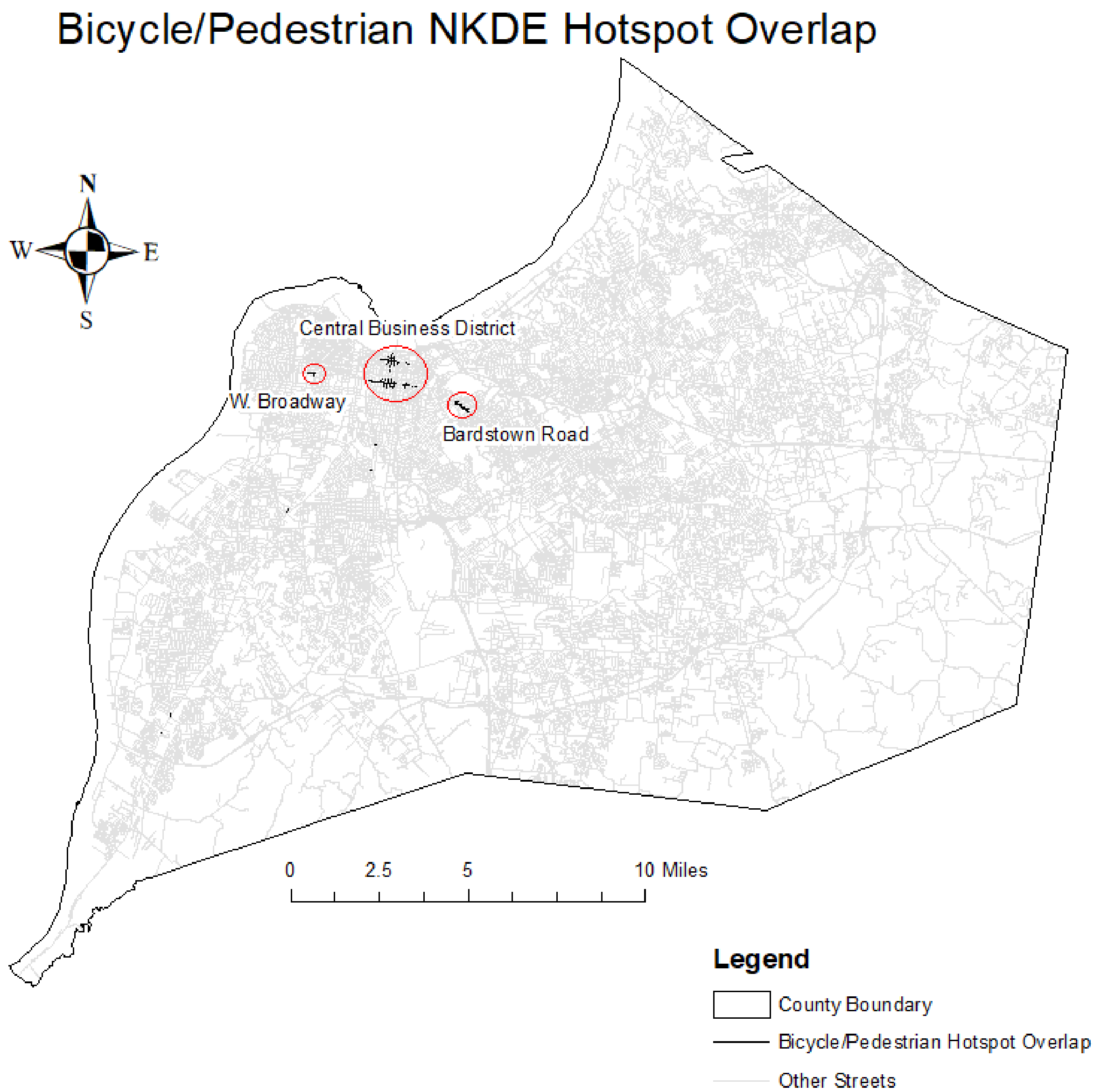

Figure 7. Hotspots shared by both pedestrian and bicycle crash NKDE's

Due to the small scale of the Figures 5 and 6, Figures 8 and 9 have been provided in order to better showcase the actual density values for the three hot-spots being analyzed for both pedestrians and cyclists.

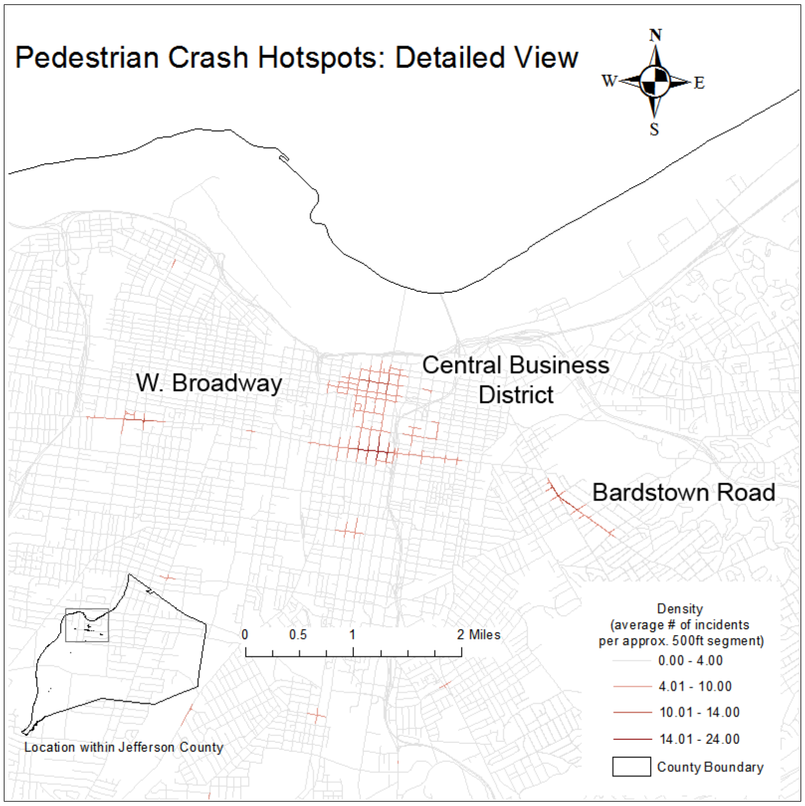

Figure 8: Detailed View of Pedestrian Crash Hotspots

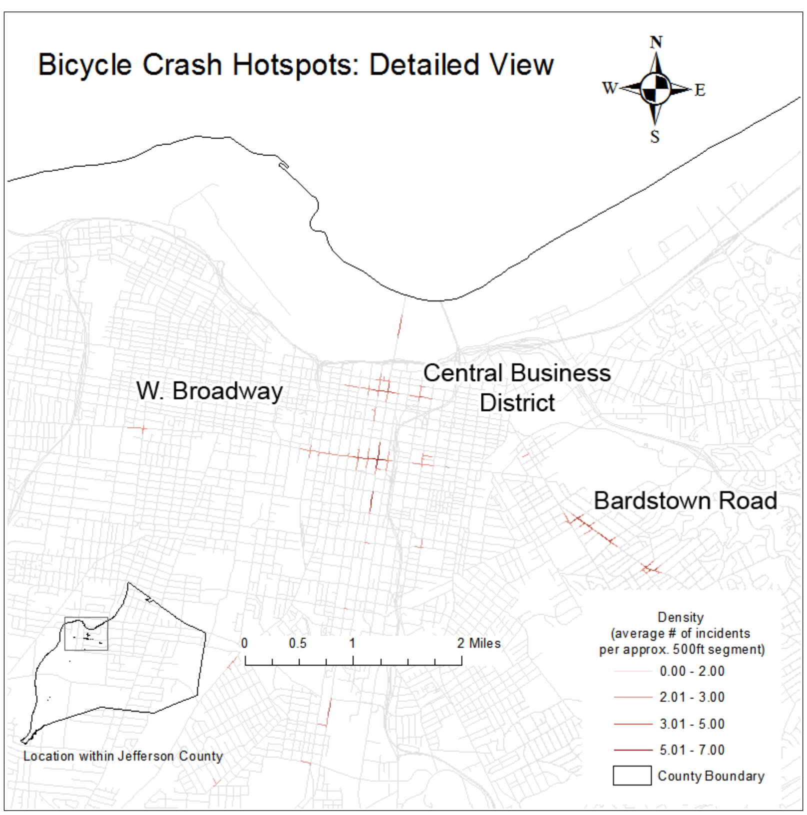

Figure 9: Detailed View of Bicycle Crash Hotspots

The largest clustering of hot spot activity for both pedestrians and cyclists was found to be in what is known as the "Central Business District" of Louisville, as seen in figure 10.

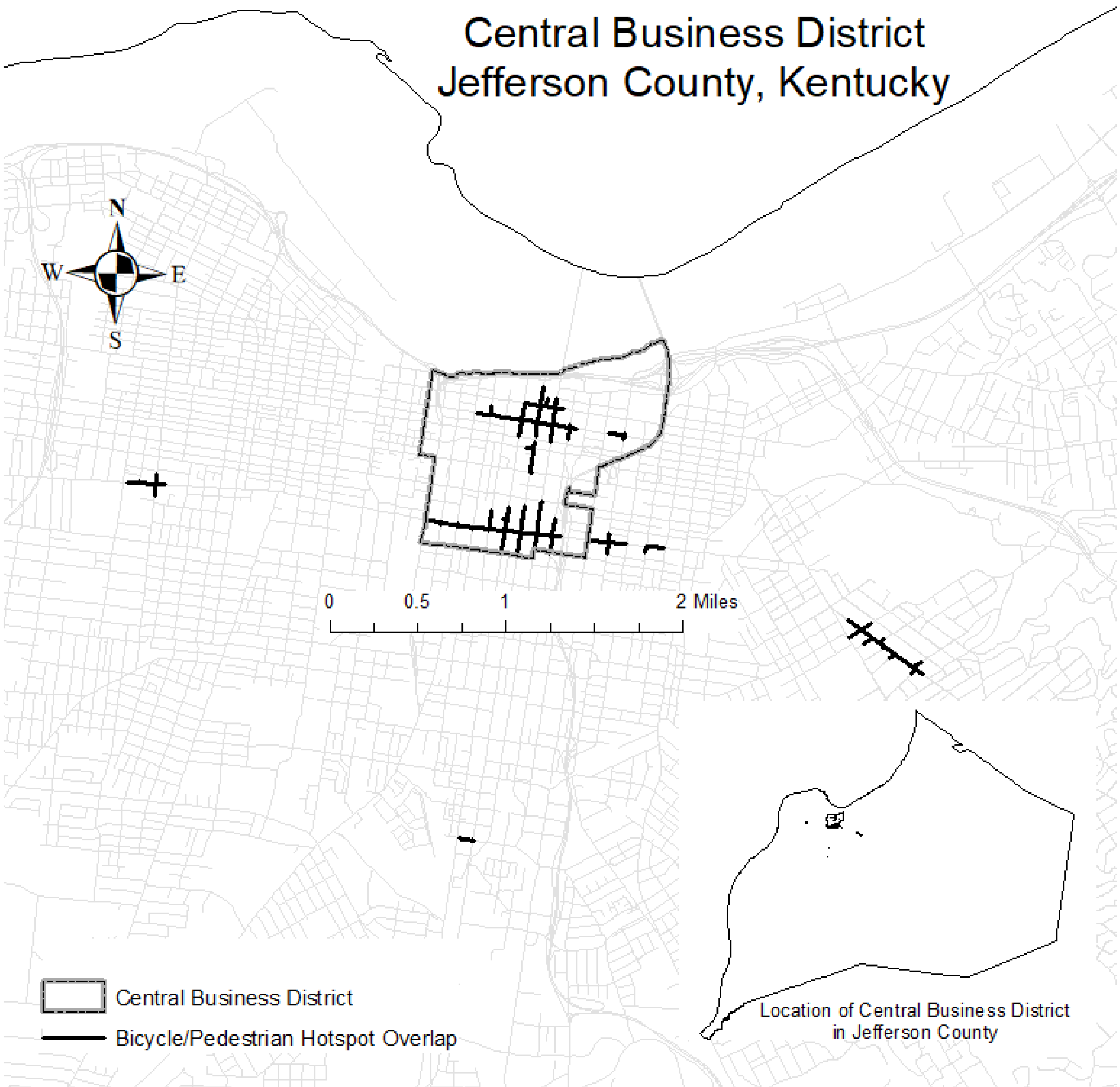

Figure 10. Shared hot-spots in the Central Business District

Although this area has multiple intersections and streets with high density values, for this study all road segments located within the city defined limits of the Central Business District were grouped together. This is because of the homogeneity of the conditions in the Central Business District.

This area contains a large number of automobiles, pedestrians and cyclists that are concentrated in a condensed area where many high rise buildings are located with thousands of workers who must commute each day. Not only does this result in a high volume of automobile traffic with people trying to get to work on time, but in an area with such limited open space for parking lots directly connected to places of work, it is not unlikely that many commuters, even if they drive or take public transit to work, must also walk a certain distance from their parked car or bus stop in order to complete their commute.

In addition to the large workforce that populates the area during the weekday work hours, the Central Business District also is home to a number of restaurants, shopping venues, sports stadiums, theaters, museums and other recreational facilities that also face the same issue of having limited connected parking lots, resulting in the possibility of there being hundreds of pedestrians and automobiles sharing the same small space during a large portion of any given day.

The explanation for the high volume of cyclist crashes is somewhat unclear. Figure 11 shows that bicycle crashes in this area follow the general trend of having significantly fewer crashes on the weekends compared to weekdays (P=0.002).

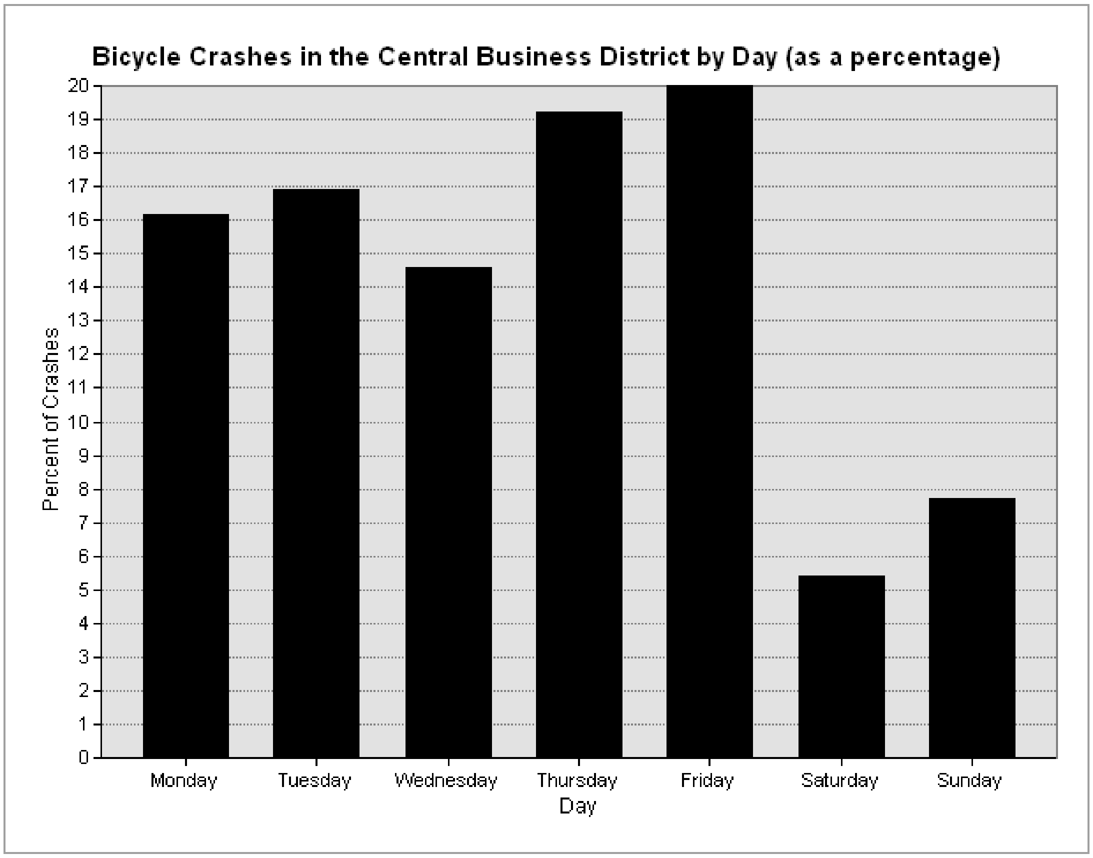

Figure 11. Weekly temporal patterns of bicycle crashes in the Central Business District

This could suggest that out of the relatively few people who do commute to work via bicycle, a significant proportion may do so in the Central Business District. The traffic delays caused by the morning and afternoon rush hours is an incentive for one who works in the central business to cycle to work in the interest of time. This high volume of cyclists sharing congested narrow lanes with automobiles may account for the large amount of bicycle crashes in this area.

The sheer volume of automobiles, pedestrians and cyclists is likely to blame for the high density values observed in the Central Business District. If daily traffic volume data was available for the central business district and was factored into analysis, it is possible that proportional to the volume of traffic, the Central Business District does not have as many crashes as other parts of town.

In both the pedestrian and bicycle NKDE's, two other large hot-spots are visible in figure 7. These hot-spots are located on West Broadway and Bardstown Road. These two hot-spot clusters have very different characteristics that may influence the number of crashes that occur at these locations. First examining the West Broadway hot-spot, its location is within the "West End" of Louisville. This area is characterized by its relatively high level of poverty compared to the rest of the city. For this reason it is likely that many people do not have access to an automobile and instead must walk or cycle as a means of transportation.

Both the pedestrian and bicycle crash NKDE's showed that both had hot-spots in the same general area of West Broadway, the one hot-spot intersection they share is located at West Broadway and 26th Street. Using Google Street View it is possible to view the conditions of the location. An up-to-date image seen in figure 12 shows that at the intersection of 26th and West Broadway, there is a gas station on one side of the road, with a now abandoned bank, gas station and bus stop on the other side of the road. There are four lanes of traffic, with a cross-walk and divider separating the two directions of traffic. Upon first glance this does not appear to be a recipe for a high number of pedestrian and bicycle crashes to occur. By examining the temporal data from crash points located at this intersection, possible explanations become apparent.

Google and the Google logo are registered trademarks of Google LLC, used with permission.

Figure 12. Google Street View image of W. Broadway and 26th, 2017

Until 2017 there was at least one crash per year at the intersection that involved either a pedestrian or cyclist. In 2015, there were seven crashes that either involved a pedestrian or cyclist. Using Google Earth historic imagery seen in figure 13, it is shown that at in the time between September, 2016 and April, 2017, a separate turn lane was added with a divider put in place between traffic lanes that remains of June of 2019. Figure 14 shows what the intersection looked like in 2015, before the roadwork and the year with the highest number of crashes. It is likely that this single action is responsible for the decrease in pedestrian and cyclist crashes at this location. The last bicycle crash at this location was recorded in 2015 and the last pedestrian crash was recorded in January, 2017, with this being the only pedestrian crash recorded in total from September, 2016 to April, 2017.

Google and the Google logo are registered trademarks of Google LLC, used with permission.

Figure 13. Google Earth historic imagery showing addition of turn lane and dividers

Google and the Google logo are registered trademarks of Google LLC, used with permission.

Figure 14. Google Street View image of W. Broadway and 26th, 2015

Moving to the Bardstown Road location, this area is much more affluent compared to the West End. This segment of Bardstown road is highly concentrated with a wide variety of businesses. The hot-spot area shared by both pedestrian and bicycle crash NKDE's stretches from the intersection of Bardstown Road with Grindstead Drive, to the intersection with Longest Avenue. In-between these intersections with main roads are a number of roads leading into and out of residential areas. An analysis of the temporal data for this location did not yield any significant findings. Turning back to Google Street View, physical conditions were observed that have potential influence over the rate of crashes in this location.

The length of Bardstown Road between Grinstead Drive and Longest Avenue has four lanes of traffic with no turn lanes or dividers between lanes. There are no bike lanes, however there is a wide sidewalk that covers the length of the area on both sides. While there are three intersections with stoplights and crosswalks, there are other crossings that do not have a stoplight or even a stop sign. Where businesses have parking lots or drive-thru's, there is usually no stoplight, stop sign or even yield sign when crossing from the business' property, over the sidewalk and onto the road.

Not only is this dangerous for the slow moving pedestrian, the potential for a crash with a cyclist becomes more dangerous when the cyclist fears they cannot safely ride on the road and must use the wide sidewalk to ride. Automobile drivers are not likely to be looking out for a fast moving cyclist crossing the sidewalk as they seize the limited opportunity they have to enter Bardstown Road where there is no stoplight. Figure 15 exemplifies the issues of cyclists being forced to ride on the sidewalk and pedestrians and cyclists alike having to cross four lanes of traffic with no street sign, marking or stoplight. Figure 13 was captured at the intersection of Bardstown Road and Patterson Avenue, within the hot-spot boundaries, in

2014. Although captured in 2014, the intersection remains unchanged as of May 2019.

Google and the Google logo are registered trademarks of Google LLC, used with permission.

Figure 15. A pedestrian and cyclist prepare to cross four lanes at Bardstown and Patterson

The lack of stoplights, dividers or turn lanes also may encourage more risky maneuvers from automobile drivers trying to cross lanes of traffic to make a turn. There may be only a small window of time for a driver to make a turn across the oncoming traffic lane, the driver may be so focused on timing their turn right in relation to oncoming traffic, they do not take appropriate to watch out for pedestrians and cyclists that may be crossing at the edge of the road. Figure 15 is representative of most of the intersections in the Bardstown Road hot-spot cluster. There is no turn lane present, if a driver wished to turn down Patterson coming from the right lane, they would have to cross two lanes of oncoming traffic. Where Patterson intersects with Bardstown there is no crosswalk signal, no signage, no road markings or anything that might draw attention to a pedestrian or cyclist attempting to cross Patterson parallel to Bardstown.

CONCLUSION

This study falls in line with studies performed in cities across the globe that show there are spatiotemporal patterns regarding crashes involving pedestrians and cyclists. Although the specifics of Jefferson County's patterns do not necessarily align with previous research, such as there being fewer pedestrian crashes in the summer and fewer crashes on weekends, the presence of spatiotemporal patterns at all allows for the possibility of further research into why these patterns exist. Future studies might perform in-person audits not only for the three locations analyzed in this study, but also perhaps at all the shared hot-spot locations. Another more in-depth study could also be performed exploring why pedestrians and bicycle crashes have hot-spots that do not overlap at all.

This study also shows that Jefferson County has a dynamic crash landscape, for instance the West Broadway hot-spot that represents crash sites from years ago and is no longer relevant thanks to action on the part of local leaders, however, it took until at least 2016 for that action to be taken. Methods such as the ones used in this study should be used by local leaders on a regular basis to take proactive steps in preventing pedestrian and bicycle crashes, which one day may encourage more active participation by the public in walking and cycling as a means of transport.

REFERENCES

Anikeeff, P. 1997. Crashes Aren't Accidents Campaign. *NHTSA Now 3* (11). http://web.archive.org/web/20040409081644/http://www.nhtsa.dot.gov/nhtsa/announce/NhtsaNow/Archive/1997/v3.11/ (accessed October 31st, 2019)

Blondel, B., C. Mispelon, and J. Ferguson. 2011. Cycle more Often 2 cool down the planet! - Quantifying CO2 savings of Cycling. European Cyclists Federation. https://ecf.com/sites/ecf.com/files/ECF_CO2_WEB.pdf (accessed October 31st 2019)

Chen, P. 2015. Built environment factors in explaining the automobile-involved bicycle crash frequencies: A spatial statistic approach. *Safety Science 79:* 336-343. https://doi.org/10.1016/j.ssci.2015.06.016.

Dai, D. 2012. Identifying clusters and risk factors of injuries in pedestrian–vehicle crashes in a GIS environment. *Journal of Transport Geography* 24 doi: 10.1016/j.jtrangeo.2012.02.005

Dai, D. and D. Jaworski. 2016. Influence of built environment on pedestrian crashes: A network-based GIS analysis. *Applied Geography* 73: 53-61. doi: https://doi.org/10.1016/j.apgeog.2016.06.005.

Dill, J. and K. Voros. 2007. Factors Affecting Bicycling Demand Initial Survey Findings from the Portland, Oregon, Region. *Transportation Research Record: Journal of the Transportation Research Board* 2031 (1): 9-17. doi:10.3141/2031-02.

ESRI 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute

Hamer, M. and Y. Chida. 2008. Walking and primary prevention: a meta-analysis of prospective cohort studies. *British Journal of Sports Medicine* 42 (4): 238-243. doi:10.1136/bjsm.2007.039974.

Handy, S. L., Y. Xing and T. J. Buehler. 2010. Factors associated with bicycle ownership and use: a study of six small U.S. cities. *Transportation* 37 (6): 967-985. doi:10.1007/s11116-010-9269-x.

Kaygisiz, O. and G. Hauger. 2017. Network-Based Point Pattern Analysis of Bicycle Accidents to Improve Cyclist Safety. *Transportation Research Record: Journal of the Transportation Research Board* 2659 (1): 106-116. doi:10.3141/2659-12.

Kelly, J. R., S. Ehresman, R. Marshall, Shaughnessy, J. Tackett, and J. Trawick. 2015. Louisville Metro Demographic and Economic Projections 2010-2040. ed. Lousiville Metro Government Planning and Design.

Kentucky State Police. 2019. Collision Data. Available at http://crashinformationky.org/AdvancedSearch (accessed October 31st, 2019)

LOJIC Louisville Jefferson County Information Consortium. 2019. Open Data Portal Street Centerlines. Available at https://services1.arcgis.com/79kfd2K6fskCAkyg/arcgis/rest/services/OpenDataAddresses/FeatureServer/1 (accessed October 31st, 2019)

McKenzie, B. 2014. Modes Less Traveled—Bicycling and Walking to Work in the United States: 2008-2012. American Community Survey Reports. U.S. Dept. of Commerce, Economics and Statistics Administration, U.S. Census Bureau. Available at http://web.archive.org/web/20170120092441/http://www.census.gov/hhes/commuting/files/2014/acs-25.pdf (accessed October 31st, 2019)

Oja, P., S. Titze, A. Bauman, B. de Geus, P. Krenn, B. Reger-Nash and T. Kohlberger. 2011. Health benefits of cycling: a systematic review. *Scandinavian Journal of Medicine & Science in Sports* 21 (4).

Okabe, A., Okunuki, K., Shiode, S., 2006. SANET: a toolbox for spatial analysis on a network. Geographic Analysis.

Okabe, A., and K. Sugihara. 2012. *Spatial Analysis along Networks*. West Sussex, United Kingdom: John Wiley and Sons Ltd.

Land Development Code. 2006. ed. Louisville Metro Department of Planning and Design Chapter 6 Mobility Standards

U.S. Department of Transportation. 2017. National Household Travel Survey https://nhts.ornl.gov/ (accessed October 31st, 2019).

World Health Organization 2011. Health in the green economy: health co-benefits of climate change mitigation – transport sector. Available at https://www.who.int/hia/examples/trspt_comms/hge_transport_lowresdurban_30_11_2011.pdf (accessed October 31st, 2019)

Xie, Z. and J. Yan. 2008. Kernel Density Estimation of traffic accidents in a network space. *Computers, Environment and Urban Systems* 32 (5): 396-406. doi:10.1016/j.compenvurbsys.2008