Does higher intersection density correlate with increased crash frequency Mecklenburg County?

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The design and connectivity of the built environment play a critical role in shaping transportation safety outcomes. In urban areas like Mecklenburg County, North Carolina, intersection density is a key feature of street network design that may influence the frequency and severity of vehicle crashes. While dense intersections and grid layouts can provide better connectivity and lower speeds, they also increase the number of conflict points for drivers, cyclists, and pedestrians. This study investigates the relationship between intersection density and crash frequency across Mecklenburg County to better understand whether certain street network designs are associated with higher or lower crash rates.

To explore this relationship, spatial analysis techniques were employed using ArcGIS Pro. Crash data were joined to census tracts as spatial units, while intersection points were generated from the county's road network shape file using spatial tools. Intersection density was calculated as the number of intersections per square kilometer, and crash frequency was measured as the count of reported crashes within the same units. A spatial join was used to combine crash and intersection data at the tract level, and the relationship between the two variables was analyzed using descriptive statistics and linear regression models. This approach allows for the identification of spatial patterns and informs urban planning efforts aimed at reducing transportation-related injuries and fatalities.

Literature Review

This literature review synthesizes recent studies focusing on traffic crashes in urban settings, particularly how they relate to intersection density and safety. This serves to highlight various influencing factors and methodologies used in crash analysis.

One significant study by Chen et al. (2021) examined the impact of commercial vehicle proportions (CVP) and roadway attributes on crash rates. It utilized a Bayesian random-parameter Tobit model, which is effective in capturing the complexities of intersection safety by accounting for spatial and temporal correlations among crash data. This model demonstrates that the influence of CVP on crash tendency varies significantly across different severity levels. Moreover, the study identified that roadway attributes, including geometric characteristics, mediate this relationship, reinforcing the need to consider these factors in urban road safety management. The findings advocate for targeted urban planning strategies and safety interventions to improve the safety of commercial vehicle operations .

In line with this focus on spatial analysis, more studies emphasized the importance of accurately defining neighborhood radii in crash density assessments. By proposing parameters like minimum intersection spacing, Megat-Johari et al (2018) underscored that precise spatial definitions improve the ability to interpret traffic crash distributions. This approach is crucial for effective urban planning and crash prevention strategies. Moreover, the density of access points near signalized intersections was also investigated by Megat-Johari et al. (2018), revealing that a higher number of driveways correlates positively with crash frequency within a specified radius. This connection suggests the importance of access management in urban safety strategy development, indicating that effective management of access points can reduce crash risks significantly.

One of these studies also demonstrates that the Point Density Estimation method is more effective than Kernel Density Estimation for identifying high crash rate intersections (Jima & Sipos, 2023). This same study also did a separate investigation indicating that high-risk intersections could be prioritized based on traffic volume and crash density assessments derived from historical data. The study advocated for urban planning strategies to mitigate crash occurrences at identified high crash rate locations.

Lee et al. (2017) contributed to this discussion by integrating macro-level data into intersection crash prediction models. Their results indicated that models combining both micro and macro-level data yielded better prediction performance, suggesting a mixed approach to understanding the variables influencing crash rates. This methodology can significantly improve safety by capturing the complexities of crash occurrences in densely populated urban environments. This article also contributes to the idea that the relationship between intersection density and crash rates may not be suited for a linear model. Additionally, Raha et al. (2025) focused specifically on pedestrian safety at signalized intersections, finding that proximity to schools and transit stops significantly predicts turning vehicle–pedestrian crash frequency. The study emphasized the need for implementing Leading Pedestrian Intervals (LPI) in high-risk areas, enhancing pedestrian safety measures.

Several more studies have examined factors influencing traffic safety and crash occurrences. Hu and Cicchino (2017) found that red light camera enforcement in large cities reduced fatal crashes, with fatal red light running crashes decreasing by 21%, while the removal of these programs led to an increase in fatal crashes. Xie et al. (2013) focused on intersection safety in Shanghai, revealing that intersections under elevated roads had a 58% higher crash rate, while 3-legged intersections were 25% safer than 4-legged ones. The study also highlighted the impact of traffic volume and signal phases on crash frequency. Similarly, Xie et al. (2014) developed a hierarchical conditional autoregressive (HCAR) model to better capture spatial and hierarchical correlations in crash data at closely spaced intersections, stressing the importance of considering intersection proximity and spatial arrangements for urban planning.

Azimian et al. (2021) used a hierarchical Bayesian approach to examine crash severities, revealing that higher primary roadway density was associated with increased crash severities, while greater intersection density was linked to fewer injury and no-injury crashes. This study also identified the significance of factors like mean travel time to hospitals and urbanity in shaping crash severity. The importance of comparing models effectiveness in this context was explored by Wang et al (2019). This study analyzed traffic crashes in Tianjin, China using four spatial models—Ordinary Least Squares (OLS), Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). It found SDM with the Rook spatial weight feature to be most effective at analyzing the relationship between multiple variables and crash rate. This study found that population and road density increase crash risks, while areas with more companies and hotels tend to have fewer crashes.

In conclusion, the analyzed studies collectively reinforce the necessity of incorporating a variety of factors—including vehicle types, pedestrian activity, intersection characteristics, and data-driven methodologies—into urban safety planning. Such approaches promise advancements in traffic safety and a reduction in crash occurrences across various settings, highlighting the multifactorial nature of road safety challenges. The main conclusion of this review is that fixing correlation of crashes to one single variable can help better understand the common characteristics of dangerous road design, but is unlikely to prove causation or be explanatory.

Data and study area

This study focuses on Mecklenburg County, North Carolina, with a particular emphasis on the City of Charlotte. The primary dataset used was obtained from the City of Charlotte Open Data Portal, which includes detailed records in the form of a CSV file of approximately 500,000 reported traffic crashes of varying severity occurring between 2010 and 2025. Each crash has X/Y location data, which makes it possible to map and group them by area. In addition to crash data, the portal provided a comprehensive shapefile of all roads in Mecklenburg County, which was used to generate intersection points for spatial analysis. These datasets enabled a detailed examination of the relationship between road network design and crash frequency at the local level.

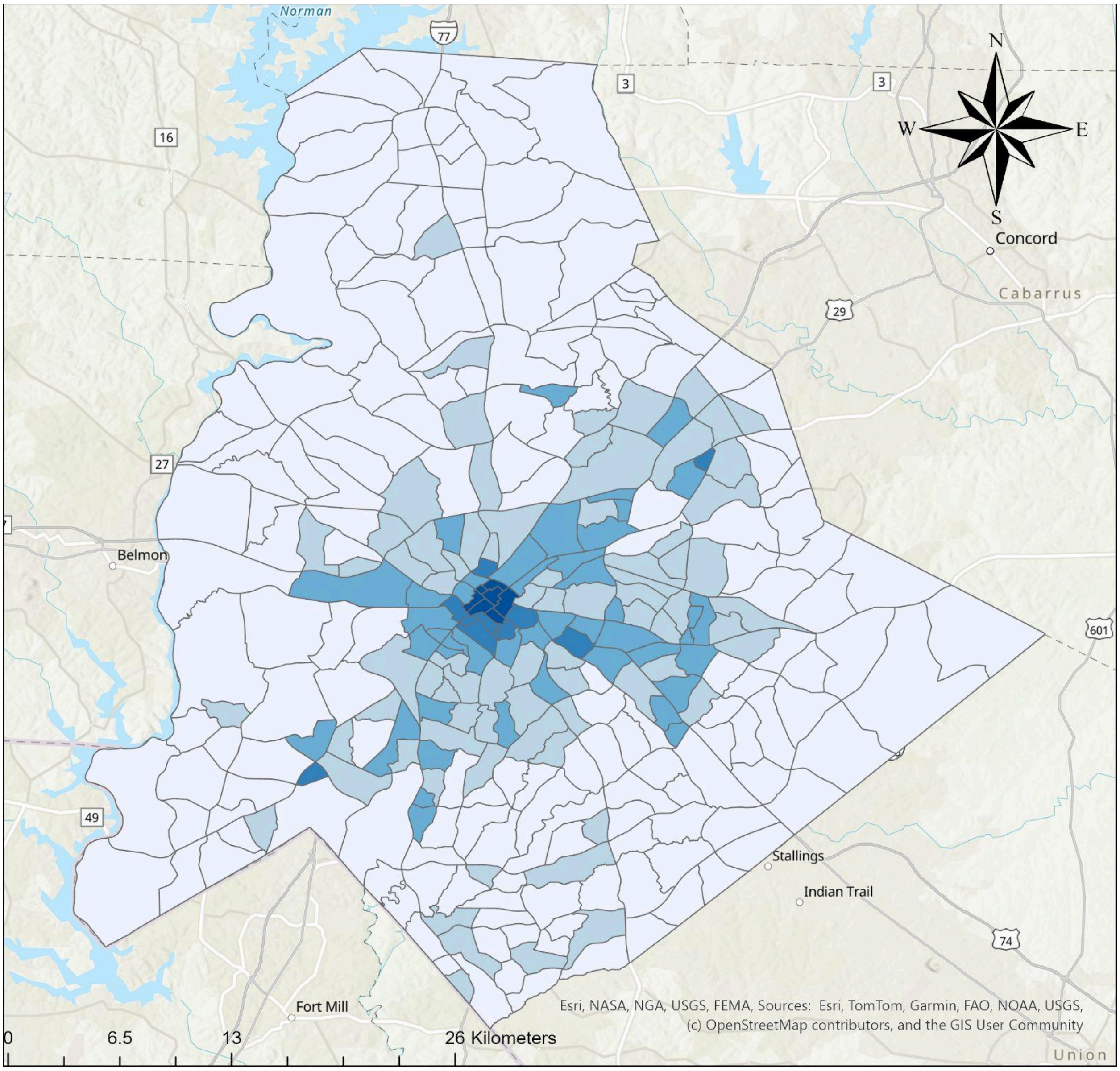
Methodology

To begin, crash data was collected for Mecklenburg County, with each record containing geographic coordinates for the location of the incident. These data were mapped to produce a point feature class representing individual crash events. Road network data for the county was also obtained in the form of polyline features representing streets and highways. Because the Intersect tool failed to identify proper intersection points from the original road network, the Planarize Lines tool in ArcGIS Pro was used to force the network to break at all visible crossings, enabling accurate generation of intersection points. Duplicate points were removed, and this allowed for the creation of meaningful intersection points. Intersection locations were derived using the Feature Vertices to Points tool, which extracted points at all line intersections. The resulting point dataset served as a proxy for measuring street network density within census tracts. Census tracts were selected as the spatial unit of analysis in order to join both crash and intersection data to a standardized geographic unit.

To quantify crash activity, a spatial join was performed to associate crash points with their corresponding census tracts. This join operation produced a count of total crashes per tract. A second spatial join was conducted to assign intersection points to tracts, resulting in a count of intersections within each tract. These counts were used to calculate several derived metrics for each tract. First, intersection density was computed as the number of intersections per square kilometer. This required confirming or converting the tract area field into square kilometers. Second, crash rate per square kilometer was calculated by dividing the crash count by the tract area. Third, crashes per intersection were computed to assess how crash burden relates to network connectivity within each tract.

To explore spatial patterns, several maps were created using ArcGIS Pro. Single-variable maps visualized crash rate, intersection density, and crashes per intersection using graduated color symbology. Bar charts were also generated to visualize and compare the number of tracts that have each level of the variables. In addition, a bivariate map was created that grouped tracts into nine categories based on low, medium, or high levels of both intersection density and crash rate. These categories were visualized using a bivariate color scheme, allowing for the identification of areas that exhibit both high connectivity and high crash risk, as well as those that are low on both or either metrics. A bar chart was produced to illustrate the distribution of census tracts across the nine bivariate categories, offering a visual summary of the risk typologies present within the county. These spatial analyses established a foundation for the statistical modeling of the relationship between intersection density and crash frequency. Lastly, to better understand how the relationship between intersection density and crash rate varies across space, a Geographically Weighted Regression (GWR) was performed using ArcGIS Pro. This method fits a separate linear regression at each tract while accounting for nearby data, producing local R-squared values that show how well the model explains crash rates in different areas. The resulting R-squared values were mapped to visualize where intersection density is a strong or weak predictor of crash frequency.

Results


Norman
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Indian Trail
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Fort Mill
Esri, NASA, NGA, USGS, FEMA, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS,
(c) OpenStreetMap contributors, and the GIS User Community
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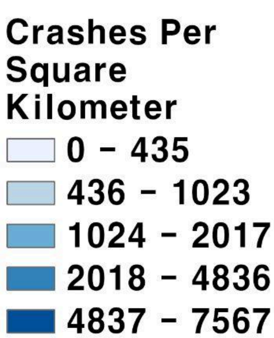
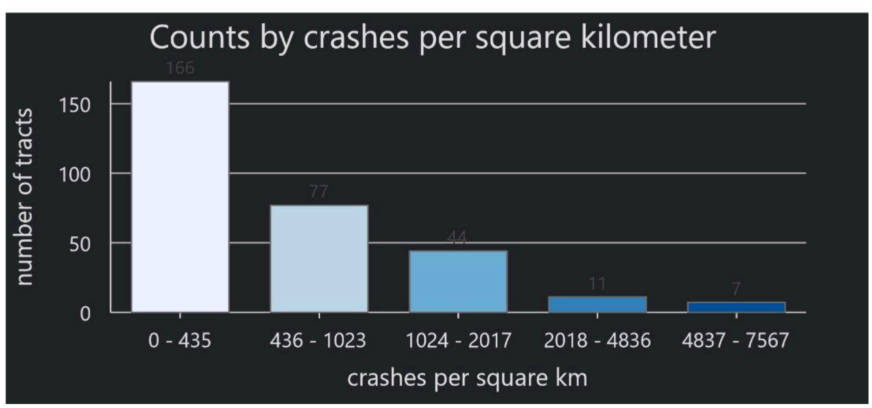
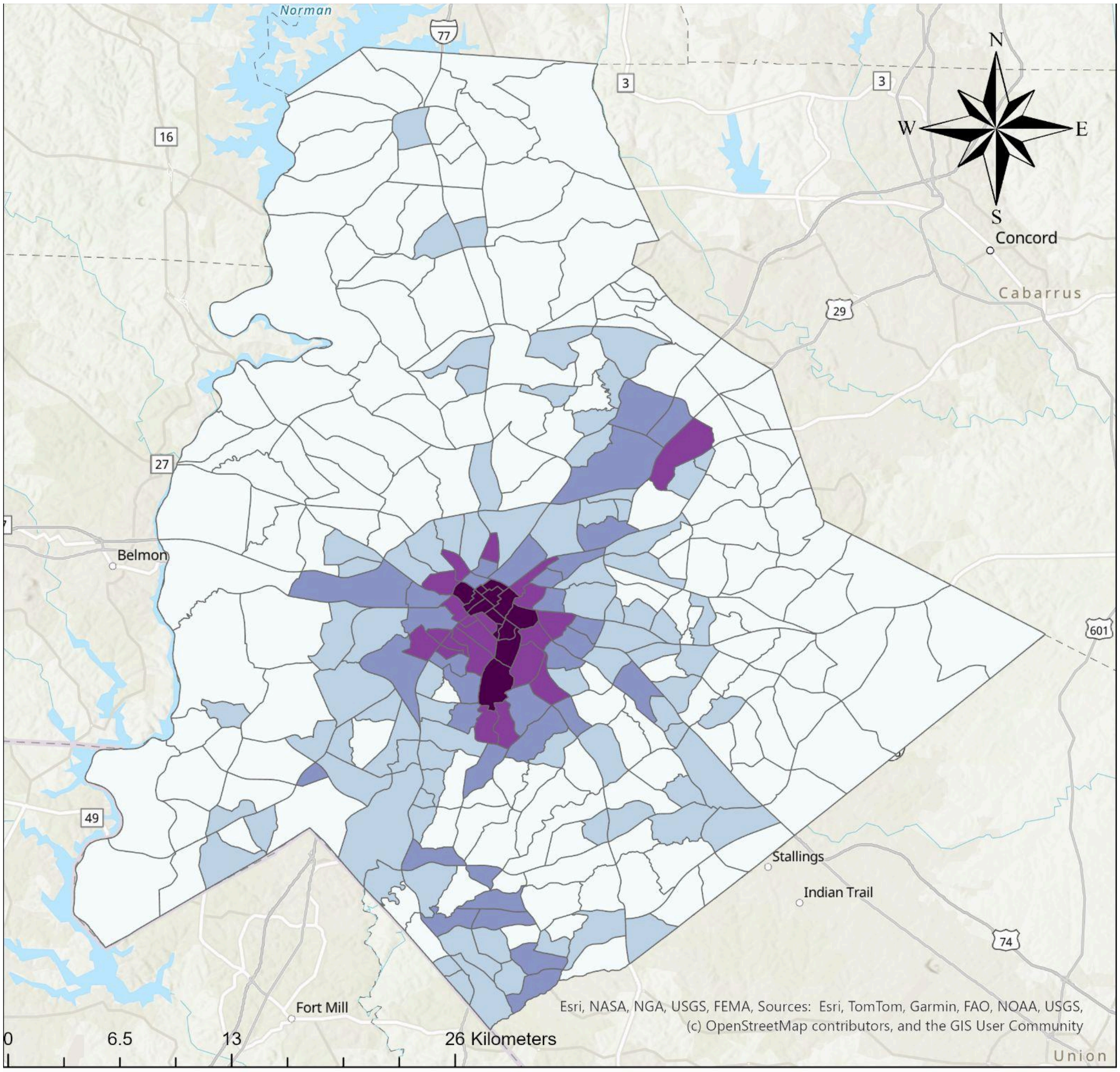
6.5
13
26 Kilometers
Union


Crashes Per Square Kilometer
0 - 435
436 - 1023
1024 - 2017
2018 - 4836
4837 - 7567


Counts by crashes per square kilometer
number of tracts
0
50
100
150
166
77
44
11
7
0 - 435
436 - 1023
1024 - 2017
2018 - 4836
4837 - 7567
crashes per square km

The map showing crashes per square kilometer visualizes the spatial intensity of traffic crashes across Mecklenburg County by normalizing crash counts by the land area of each census tract. Rather than simply showing where the highest number of crashes occurred, this map accounts for the size of each area, giving a more accurate comparison between the urban center, suburbs, and rural zones. High crash counts in large areas may appear less severe once normalized, while dense clusters of crashes in smaller areas become more apparent. This provides a more meaningful depiction of crash concentration and risk intensity.

This map helps identify hotspots of crash density, it is the compact urban center where limited space coincides with high traffic volumes and intersections. It can inform decisions about where to prioritize traffic safety interventions, such as signal improvements, speed management, pedestrian infrastructure, or intersection redesign. Highlighting areas where crashes occur more frequently per unit of land provides a clearer picture of where the built environment may be contributing to transportation-related injuries and fatalities.

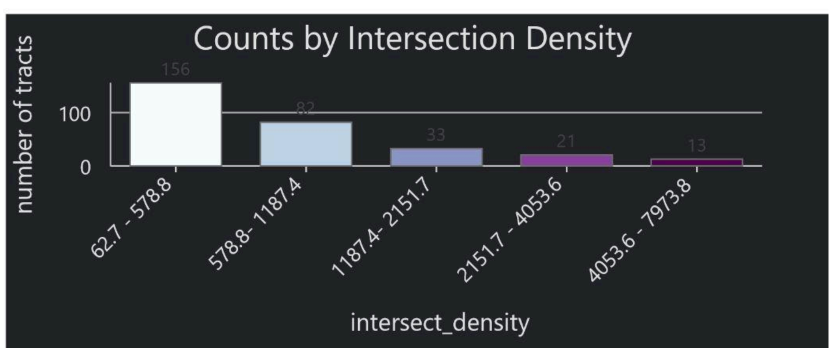


Mecklenburg Intersection Density by Census Tract

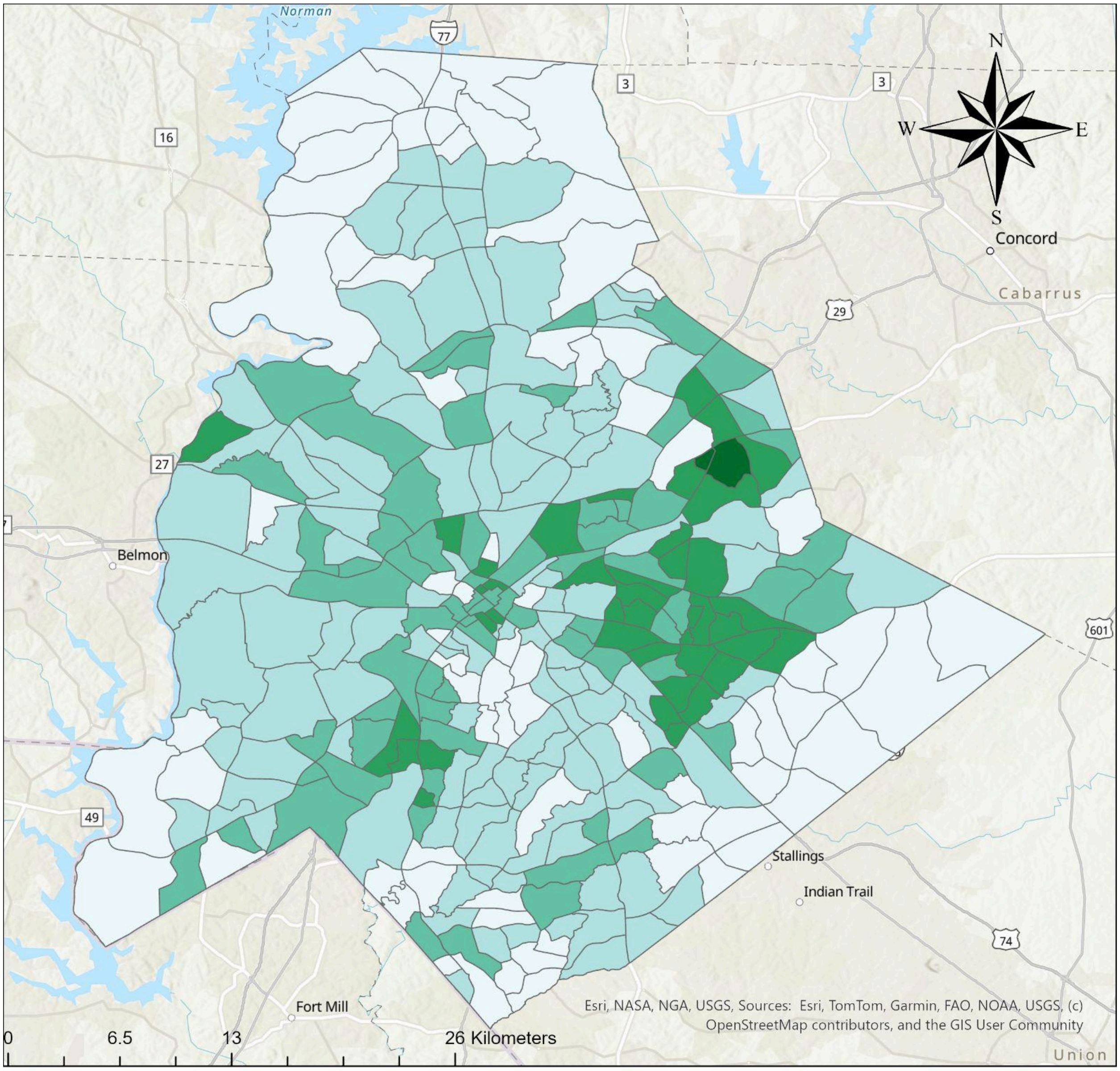
Intersection Density (Intersections per square kilometer)

intersect_density

- 62.7 - 578.8
- 578.8- 1187.4
- 1187.4- 2151.7
- 2151.7 - 4053.6
- 4053.6 - 7973.8



The intersection density map visualizes how connected and compact the street network is across Mecklenburg County by displaying the number of intersections per square kilometer within each census tract. This metric reflects the structural layout of the built environment, where higher intersection density often corresponds with traditional grid-like street patterns that support walkability, slower vehicle speeds, and shorter travel distances. In this analysis, the highest intersection densities are concentrated in the urban core of Charlotte, particularly in and around Uptown and adjacent neighborhoods like Elizabeth and Dilworth. These areas exhibit a classic grid layout with frequent intersections, reflecting historical development patterns that prioritize connectivity. In contrast, lower intersection densities dominate the suburban and rural parts of the county, where street networks are more hierarchical and fragmented, with longer blocks, cul-de-sacs, and fewer through-routes. These lower-density patterns are typical of car-centered development and can influence traffic behavior by increasing speed and limiting alternate routes. This map is instrumental for understanding how street network design varies spatially and sets the foundation for evaluating its relationship to crash outcomes. It helps identify which areas may benefit from urban design interventions aimed at increasing connectivity and improving traffic safety.


Norman
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Concord
Cabarrus
29
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Belmon
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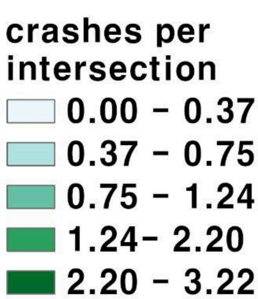
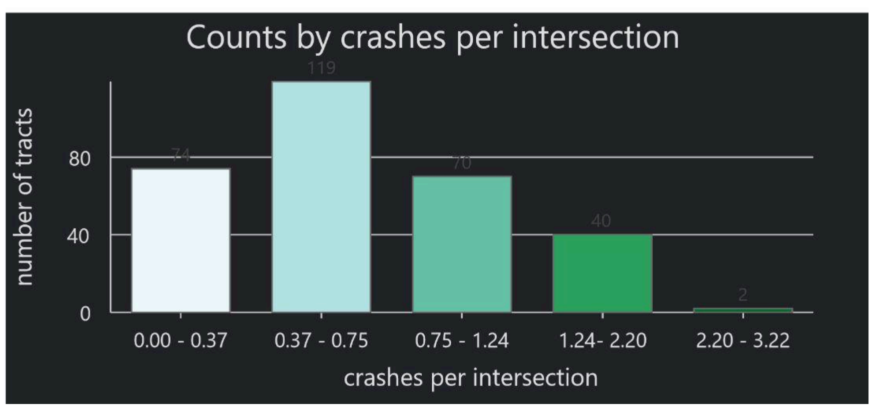
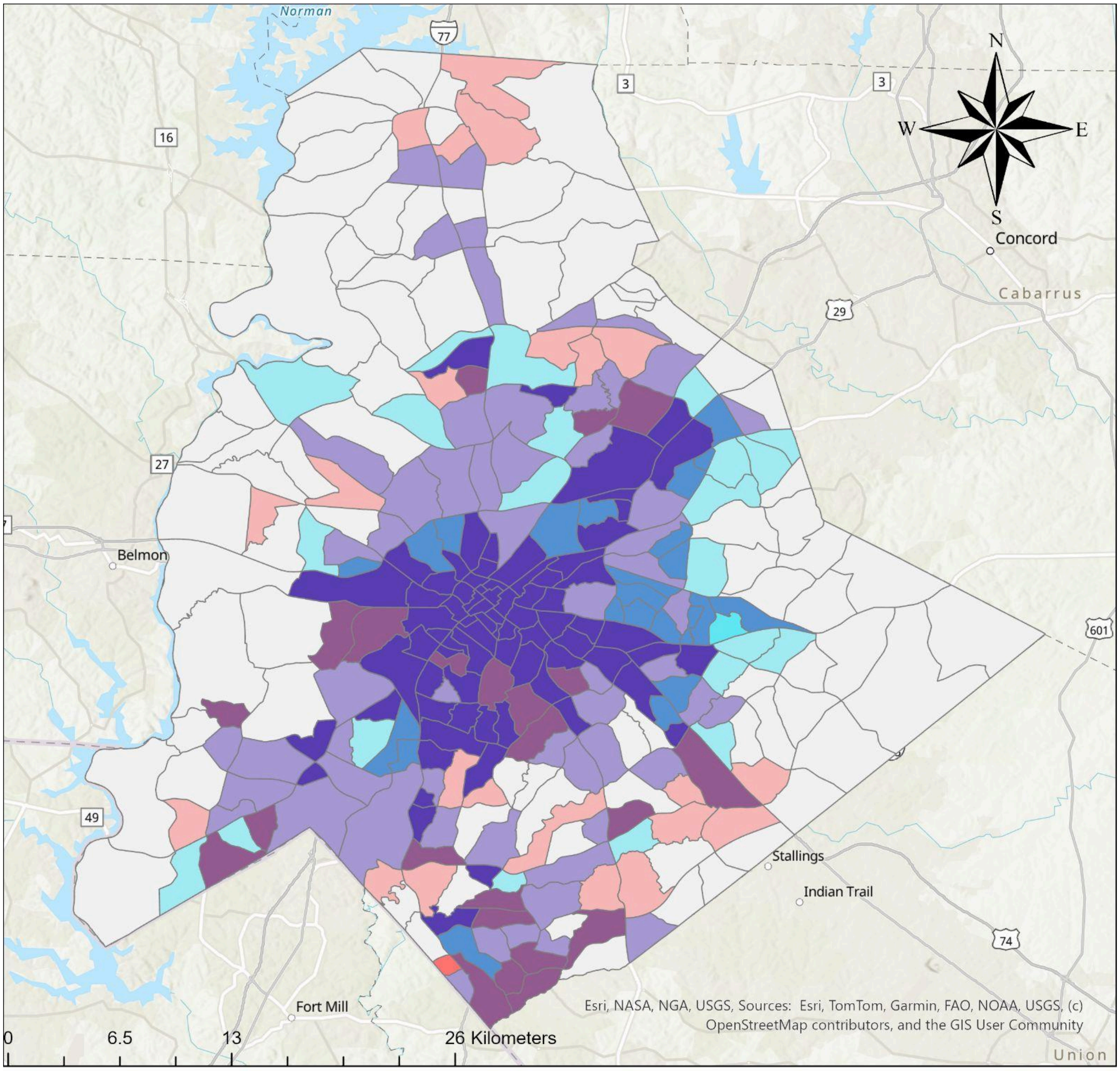
49
Stallings
Indian Trail
74
Fort Mill
0
6.5
13
26 Kilometers
Esri, NASA, NGA, USGS, Sources: Esri, TomTom, Garmin, FAO, NOAA, USGS, (c) OpenStreetMap contributors, and the GIS User Community
Union


crashes per intersection
0.00 - 0.37
0.37 - 0.75
0.75 - 1.24
1.24- 2.20
2.20 - 3.22

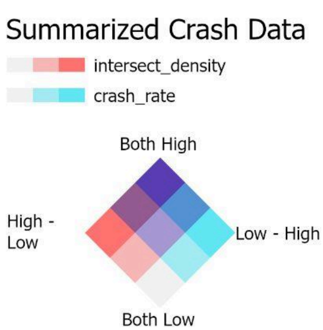

Counts by crashes per intersection
number of tracts
0
40
80
74
119
70
40
2
0.00 - 0.37
0.37 - 0.75
0.75 - 1.24
1.24- 2.20
2.20 - 3.22
crashes per intersection

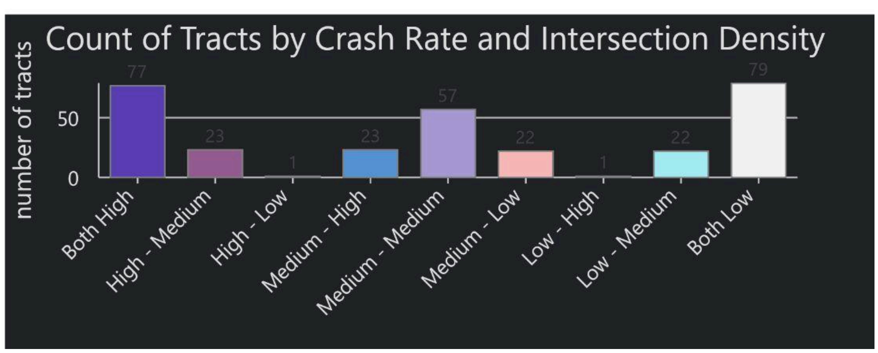
The map of crashes per intersection offers a more precise view on the relative safety of the street network by highlighting where crashes are most associated with intersections. In Mecklenburg County, this analysis reveals that the highest crash rates per intersection are clustered in the eastern suburban areas, particularly around College Downs and the tracts immediately south of it. These areas, while not the most intersection-dense in the county, show a disproportionate number of crashes occurring at a limited number of intersections. This suggests that the intersections themselves may be high-risk, potentially due to design factors such as wide roadways, insufficient traffic control, or poor visibility—common traits in suburban layouts. The pattern points to a need for more targeted intersection-level safety interventions in these communities, such as traffic calming measures or redesigns to improve pedestrian and vehicular safety.

In contrast, the Myers Park area—commonly referred to as part of "the wedge"—stands out for its significantly lower crash rate per intersection. Despite its high intersection density and active transportation environment, intersections in this part of the county appear to function more safely, possibly due to factors like slower traffic speeds, better infrastructure, and stronger multimodal planning. This contrast between the College Downs/eastern suburbs and Myers Park underscores how not all intersections carry equal risk. This spatial pattern offers important guidance for future planning efforts, highlighting specific geographic targets for infrastructure investment and policy change.

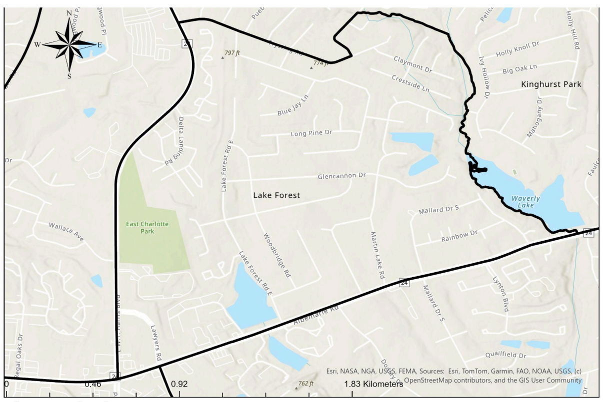


Crash Rate Normalized by Area vs Intersection Density

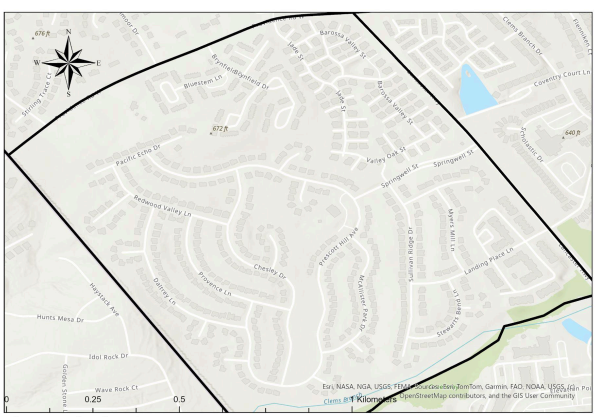




This bivariate map comparing crash rate normalized by area (crashes per square kilometer) with intersection density provides a nuanced view of how street network structure may influence the frequency and distribution of traffic crashes across Mecklenburg County. By displaying these two variables simultaneously, the map reveals patterns that go beyond simply identifying areas with high or low crash counts. Intersection density serves as a proxy for how connected and compact the road network is—often associated with urban form, walkability, and vehicle speeds—while crash rate per square kilometer captures the intensity of crash occurrences regardless of population or intersection count.

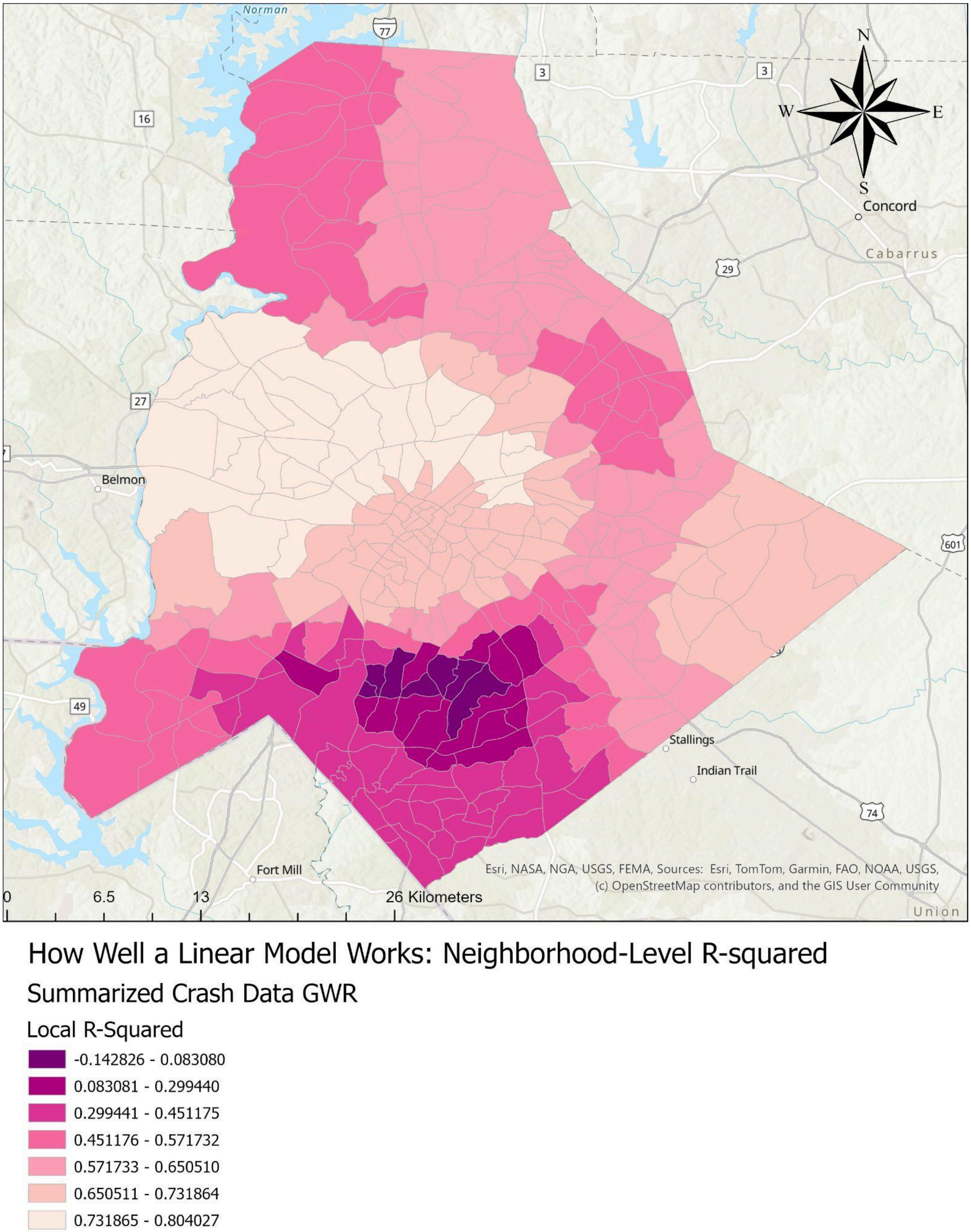


the only low intersection
density, high crash rate census tract



the only high intersection
density, low crash rate census tract

Visualizations identify areas where crash rates are high despite low intersection density, suggesting potentially hazardous environments with fewer but more dangerous intersections. In this case, certain suburban census tracts in Mecklenburg are characterized by low intersection density but high crash rates. Conversely, areas with high intersection density and low crash rates may reflect safer, more walkable environments where slower speeds and more crossings reduce the likelihood or severity of crashes. Areas that are high in both metrics may indicate congested urban nodes where the high volume of users and interactions between vehicles, pedestrians, and infrastructure contribute to increased crash risk. Overall, this map supports a deeper spatial understanding of the relationship between built environment patterns and transportation safety, and helps pinpoint locations where targeted interventions—such as intersection redesign or traffic calming—may be most impactful.



The local R-squared map derived from the Geographically Weighted Regression (GWR) model illustrates the spatial variation in how well intersection density explains crash rate across

Mecklenburg County. R-squared values range from 0 to 1 and indicate the strength of the relationship at a local level. Higher values suggest a stronger local fit of the linear model, while lower values indicate that the explanatory variable (intersection density) does not adequately account for crash rate patterns in that area. In this map, higher local R-squared values are found primarily in the western and central parts of Charlotte, including neighborhoods such as Oakdale, West Boulevard, and parts of the urban core. This suggests that in these areas, intersection density is a strong predictor of crash rate.

In contrast, lower R-squared values are concentrated in the southern and northern parts of the county, especially within the "wedge" area in South Charlotte (including Myers Park, SouthPark, and surrounding neighborhoods) and in the suburban tracts of North Charlotte. This indicates that in these areas, crash rates are less closely tied to intersection density, and other factors—such as traffic volume, driver behavior, road design, or land use—may be more influential.

Limitations

While this analysis provides useful spatial insights, several limitations should be acknowledged. First,The GWR model only incorporated intersection density. Crash occurrence is likely influenced by additional factors such as traffic volume, speed limits, road types, lighting conditions, enforcement presence, and pedestrian activity — none of which were included in this model. Second, the limitations of a linear model in this case cannot be overstated. Even local models like GWR assume that relationships are linear or at least consistently directional within local windows. Global Moran's I showed spatial clustering in crash rate, intersection density, and crashes per intersection. Examining nonlinear relationships and controlling for confounders were outside the scope of this project were not examined. Third, the shape file containing all intersections in Mecklenburg county included intersections of footpaths. This means that areas with more parks and sidewalks will be disproportionately shown as having more intersections. This means that areas with more pedestrian infrastructure may have an exaggerated view of having fewer accidents per intersection

Discussion & Conclusion

This project set out to examine whether higher intersection density is associated with increased crash frequency in Mecklenburg County. Spatial and statistical analysis revealed that the relationship between these two variables is complex and varies significantly across different parts of the county. While certain high-density areas did experience elevated crash rates, the association was not consistent countywide, suggesting that intersection density alone does not universally predict crash frequency.

One of the most notable findings emerged from the analysis of crashes per intersection, which showed that some of the highest crash rates occurred not in the dense urban core, but in suburban eastern neighborhoods such as College Downs and Hickory Grove. These areas, despite having moderate crash counts and relatively low intersection density, exhibited disproportionately high crash rates per intersection. This pattern suggests that intersections in these lower-density areas may present unique safety challenges, potentially due to factors such as higher driving speeds, poor visibility, limited pedestrian infrastructure, or outdated intersection design. This highlights the idea that intersection quality should be explored to determine whether or not it is a better predictor of crash rate than intersection quantity.

Conversely, areas like Myers Park — a dense, affluent neighborhood known for its irregular street network — had relatively low crash rates per intersection, despite high intersection density. This suggests that high density does not inherently lead to more crashes, especially in environments that may benefit from better street design, traffic calming, or lower vehicle speeds. These contrasting examples show that the relationship between intersection density and crashes may not be strictly linear, but there is a moderate association.

To further investigate this idea of a linear model, a Geographically Weighted Regression (GWR) model was applied. The results showed substantial spatial variation in how well intersection density explains crash rate. In some areas, such as the Oakdale neighborhood in western Mecklenburg County, the model performed well, indicating a relatively strong local relationship between density and crash frequency. In contrast, the model explained very little variation in areas like Myers Park and parts of northern Charlotte. These findings correspond to the well-documented “arc and wedge” spatial structure of Mecklenburg County, where demographic, infrastructural, and historical factors differ significantly between the central urban wedge and the surrounding suburban arc.

Ultimately, the findings from this study suggest that while intersection density is an important factor, it is not a universal predictor of crash frequency. This coincides with the results of the literature review, and ultimately non-linear, multifactorial models will likely be more effective at predicting and minimizing crash rates. The spatial variability in the strength and direction of the relationship underscores the need for localized, context-sensitive planning strategies. Urban planners and transportation engineers should focus on examining where crash exposure per intersection is elevated – especially in suburban tracts where unsafe intersections may otherwise go unnoticed. Interventions such as enhanced signage, pedestrian crossings, or signal timing improvements may be especially effective in these areas. Additionally, lessons can be drawn from high-density areas with low crash rates, which may reflect successful urban design practices worth replicating elsewhere.

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