Socioeconomic and Environmental Correlates of Traffic Accident Hotspots: A Spatial Analysis of Denver County's Road Safety

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Traffic accidents remain one of the most preventable sources of injury and death in American cities, disproportionately affecting neighborhoods that receive the least amount of attention and resources. This study analyzes the spatial patterns of traffic crashes in Denver, Colorado from 2014 to 2024, examining how socioeconomic, demographic, and environmental characteristics relate to crash frequency, severity, and pedestrian involvement. Using spatial autocorrelation, cluster detection, and spatial regression modeling, this study evaluates whether lower-income and minoritized neighborhoods experience elevated crash risk and identifies the roadway and environmental conditions most strongly associated with severe outcomes. Results show that lower-income communities experience significantly higher traffic accidents, including pedestrian-involved crashes, reflecting a lack of safe road infrastructure in these vulnerable areas. Additionally, the share of minoritized residents exhibits a positive but marginally significant association with pedestrian crash risk. Environmental factors such as lighting conditions and roadway type strongly influence crash severity, with dark conditions and major roads associated with substantially higher odds of severe crash outcomes. These findings highlight persistent disparities in transportation safety and emphasize the need for targeted, equity-focused infrastructure investments. By identifying where risks are concentrated and which communities are most affected, this study provides evidence to support more equitable and effective transportation planning in Denver County.

I. Introduction

Traffic accidents remain one of the most preventable sources of fatalities around the world. In 2024 alone, the United States saw 39,345 traffic-related deaths [1]. The country sees more traffic fatalities per capita and traffic fatalities per vehicle mile traveled than any other developed country [2]. Given the U.S.'s continued reliance on personal vehicles, identifying the conditions under which crashes are most likely to occur is a critical step toward reducing this preventable toll as well as motivating public transit improvements.

A. *Crash frequency in lower-income areas*

Numerous studies across the world have demonstrated that traffic crash risk is not distributed equally across socioeconomic groups. Lower-income communities have been found to experience disproportionately higher amounts of traffic accidents, injuries, and deaths. Additionally, the disparities in pedestrian-related fatalities between different socioeconomic areas are even greater than that of vehicle-related fatalities, highlighting a need for improvement of pedestrian-focused infrastructure in these neighborhoods [3]. The cause of these increases in vehicle- and pedestrian-related accidents is likely due to these communities being located along major arterial roadways, as well as historical disinvestment in safe infrastructure [4].

B. *Crash risk and the environment*

In this study, environmental factors will fall under two categories: built and natural. The built environment encompasses all human-made infrastructure, such as roads, parks, sidewalks, and more. On the other hand, the natural environment refers to conditions such as lighting and weather. Additionally, road conditions can fall under a combination of both a natural and built environment, as this is dependent on the weather conditions, along with the road type.

Numerous studies have shown that accidents tend to concentrate at 4-way intersections [2]. Beyond intersections, street designs and laws such as speed limits, lane widths, and the presence of buffers, such as medians, have been shown to reduce crash severity [5]. Natural conditions like lighting and road conditions have also been shown to impact severity. Studies have shown that while crash count tends to be lower at night, the risk of a severe crash is higher [6]. On the other hand, the influence of road conditions and weather on severity tends to be more mixed, with some findings showing reduced crash severity, and others seeing an increase in winter months. This suggests that rather than a seasonal pattern, crash severity in colder climates may depend on local infrastructure, along with driver behavior in adverse weather conditions [6].

C. *Spatial dependency in crash data*

Road crashes vary spatially, and to better understand their patterns, their spatial dependency must be taken into account [7]. Spatial autocorrelation, the tendency of geographically neighboring areas to exhibit similar crash patterns, has been documented in many urban crash data [8]. These patterns arise due to neighboring areas sharing road infrastructure, traffic patterns, zoning laws, and demographic characteristics. Therefore, applying standard regression models, which assume independent observations, should be done with caution. Instead, spatial regression models, which model the relationships between neighboring data points, have become increasingly popular in crash analysis as a means of producing more reliable estimates of crash correlates.

Studies on neighborhood demographics and their potential influence on crash risk have been conducted in many cities worldwide. However, previous research regarding Denver's communities have yet to be sufficiently explored. This study hypothesizes that lower-income communities in Denver County face the same inequalities as similar communities worldwide in access to safe road systems. By identifying potential correlates of traffic hotspots, city planners will be better equipped to implement targeted interventions to improve road safety and equity in Denver and similarly structured cities.

II. Data

A. Data Overview

Crash data was obtained from the Denver Regional Council of Governments (DRCOG) online data catalog [9]. Annual data for the years 2014 through 2024 were aggregated into a single dataset, totaling 209,527 crashes within Denver county boundary lines. By the data cleaning process, the number of variables was reduced to 27, with descriptions of these located in the Data Dictionary. These variables contain a mixture of temporal, environmental, and contributing factors involved in the crash. Each of these variables was either preserved from DRCOG's original data structure, or recoded to ensure consistency across all years and fit the purposes of this report. While not all variables were utilized in this analysis, they were retained for further analysis, if necessary. Additionally, due to missing or incorrect coordinates, the number of observations was reduced to 196,712 due to a lack of spatial information.

Demographic data was sourced from The City and County of Denver's Open Data Catalog. This sample data contains 5-year average (2017-2021) data for 571 block groups in Denver County [10]. Demographic variables used in this analysis can be found in Table 1.

Table 1 Variable Table: Demographics Data

Variable	Description	Calculation
STFID	Block Group ID	from original dataset
prop_minority	Proportion of Minoritized Population	$\frac{\text{Sum of all non-White populations}}{\text{Total Population}}$
POP_DENS	Population Density	$\frac{\text{Total Population}}{\text{Area } (mi^2)}$
pop_zero	Zero Population Indicator	$\begin{cases} 0 & \text{if total population} \neq 0 \\ 1 & \text{if total population} = 0 \end{cases}$
geometry	Block Geometry	polygons from original shapefile

The population zero indicator variable allows for preservation of the ten block groups with zero population, but non-zero crash counts in the analysis, which will be discussed further in the methods.

Finally, street data from DRCOG's Complete Streets Street Typologies dataset was used to calculate total road length

(Variable: total_road_length) per block group [11]. This variable only accounts for major roadways such as arterials, collectors, mixed-use streets, and commercial corridors. Local residential streets, alleys, and minor connectors are not included. As a result, this variable represents exposure to major transportation infrastructure rather than total roadway mileage.

All data observations throughout this analysis fall in Denver County boundary lines, indicated by the blue region in Figure 1.

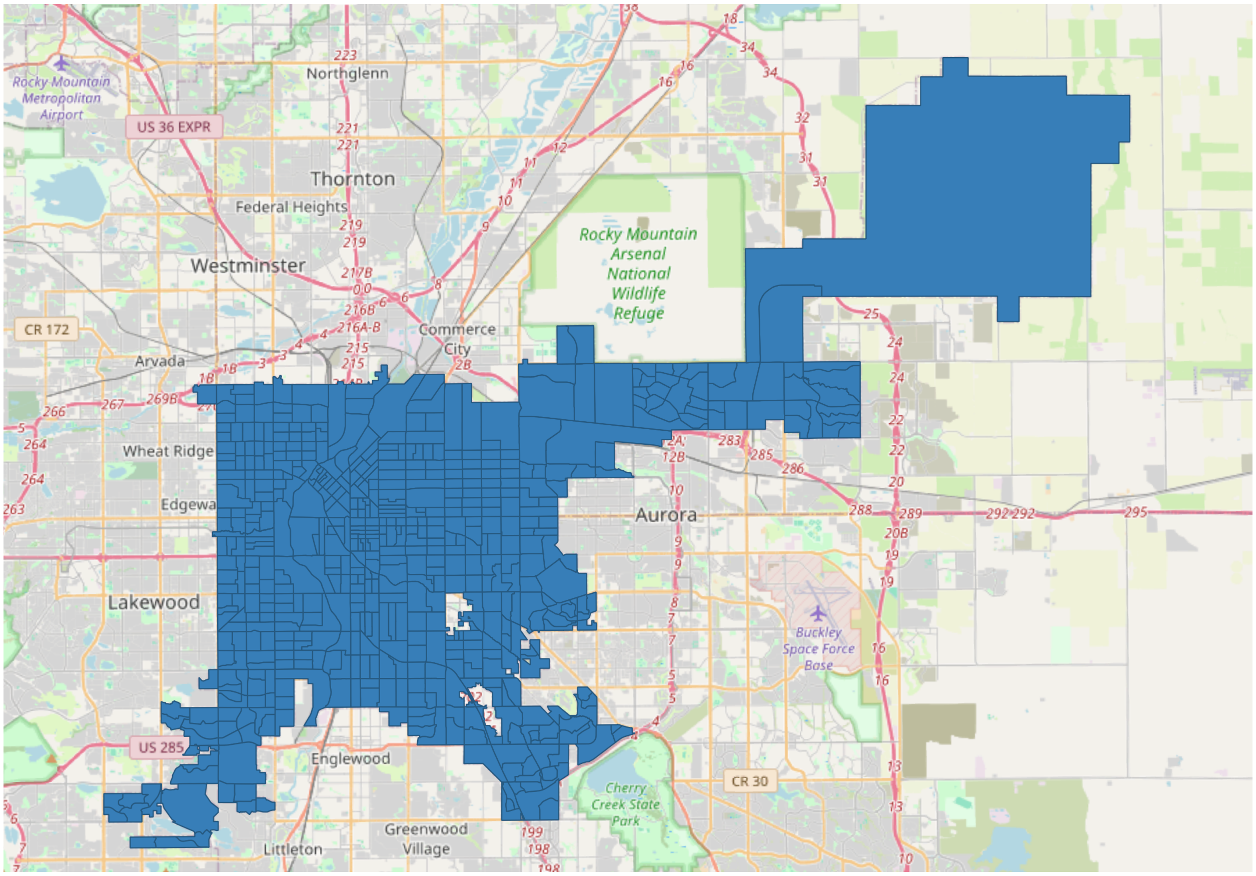

Fig. 1 Boundary Region of Denver County

B. Data Processing

To combine the crash and demographics data, point geometries (longitude/latitude coordinates) of the individual crashes were joined to their corresponding polygon block group. Prior to joining, crashes falling outside of Denver County boundary lines were removed based on their coordinates. Following the spatial join with the demographic data, an additional 3,329 crashes were omitted due to their coordinates falling outside of any block group boundary, bringing the final analytical dataset to 196,712. Additionally, 37 block groups were missing median household income information, and therefore, the mean value of their neighboring blocks was imputed as their median household income.

III. Methodology

A. Exploratory Analysis

1. Crash Data

In this analysis, two main outcomes regarding traffic crashes will be studied. The first is crash frequency, which will be calculated per block group. This value is found by placing each crash in its respective block based on its coordinates, and totaling the number of crashes in each block. Figure 2 shows the heat map of crash counts across the 571 block groups.

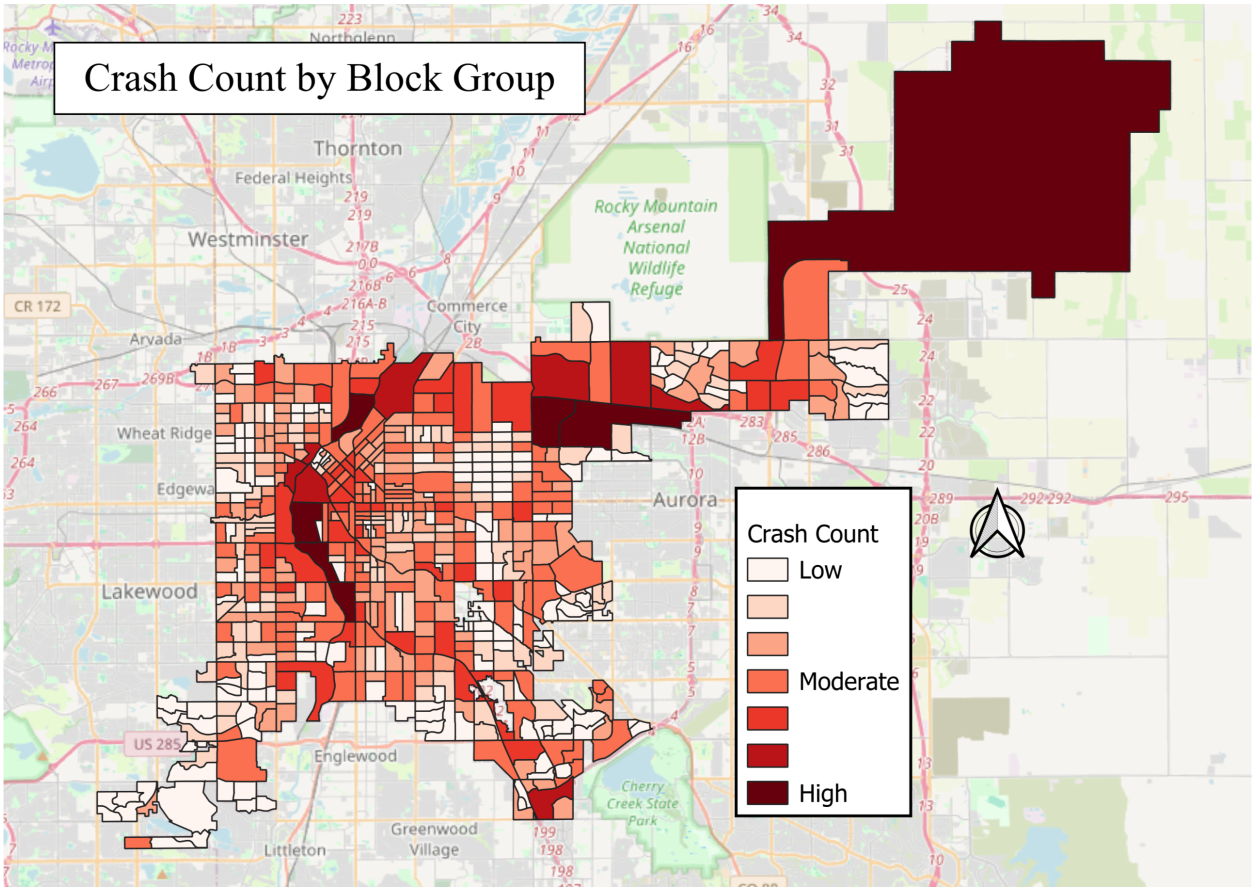

Fig. 2 Crash Count by Block Group

The second outcome involves crash severity per individual crash. Table 2 showcases the spread of crash severity levels among the data, with 2 observations omitted due to missing severity values.

Table 2 Crash Count by Severity

Severity	Description	Count	Proportion
0	No Injuries	153172	0.779
1	Possible Injuries	25047	0.127
2	Minor Injuries	12922	0.066
3	Severe Injuries	4962	0.025
4	Fatal Injuries	607	0.003

Later, one model will include a binary outcome of crash severity with 1 indicating a severe crash. An accident is considered severe if it falls under severity level 3 or 4, or in other words, if the crash involved severe injuries or fatalities. Figure 3 showcases the location and clustering of severe crashes in the region. The red stars symbolize more than one severe crash happening within 200 meters of another.

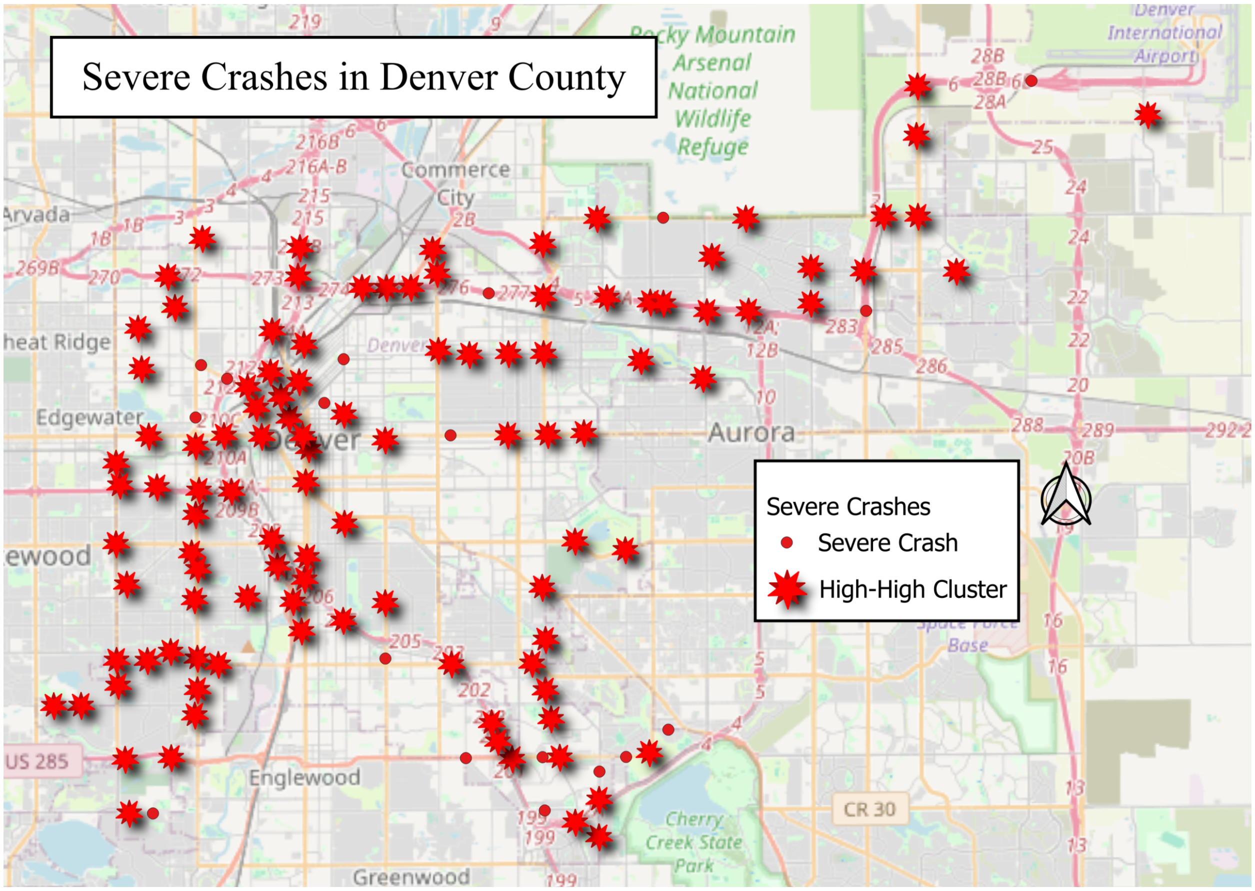

Fig. 3 Locations of Severe Crashes

2. Demographics Data

Block-group demographic factors will make up many of the predictors in this analysis. This report is most interested in median household income and its impact on crash counts in the local area. Figure 4 showcases the spread of income across Denver County. It should be noted that ten blocks have a population of zero and are indicated by the dark purple blocks on the map.

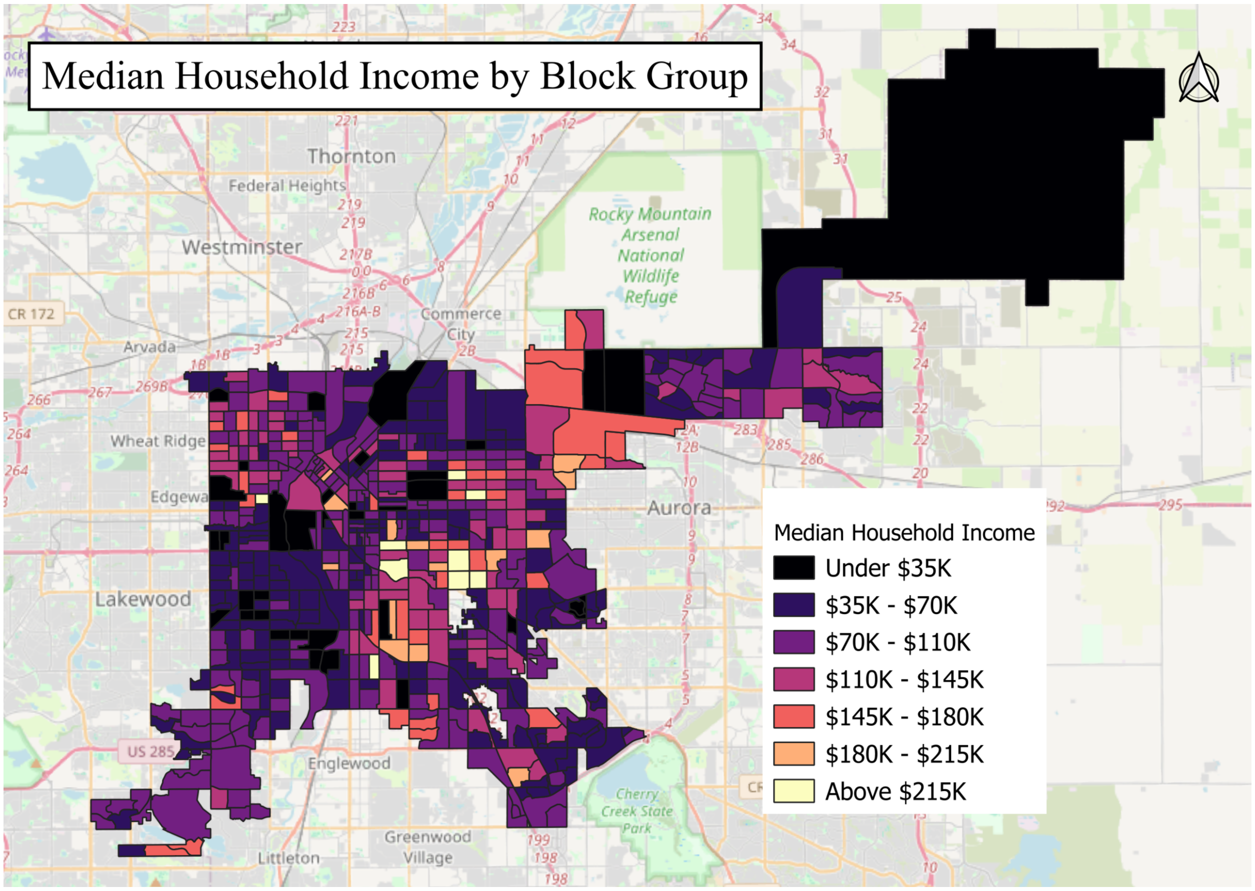

Fig. 4 Median Household Income per Block Group

B. Model 1: Spatial Negative Binomial Regression for Crash Counts

1. Rationale

Before fitting a spatial model, a Moran's I test was conducted to confirm spatial autocorrelation in crash counts among block groups. Global Moran's I is a tool used in spatial analysis to measure spatial dependency based on both feature locations and feature values simultaneously, and to indicate whether the pattern is clustered, dispersed, or random. Its value ranges from -1 to 1, with positive values suggesting clustered distribution, negative values indicating dispersed distribution, and 0 indicating randomness [7]. Results for Moran's I test for crash count yielded significant results, indicating spatial clustering among block groups' crash counts (Table 3).

Table 3   Results for Global Moran's I test on Crash Count

Moran I Statistic	Expectation	Variance	Pvalue
0.283	-0.0017	0.0006	<2.2e-16

After confirming spatial dependency, a negative binomial regression model was chosen due to overdispersion, or large variance, in the crash counts, which can be seen from Table 4.

Table 4   Summary Statistics of Crash Count by Block Group

Minimum	Maximum	Median	Mean	Std. Dev.
2	4752	196	344.5	503.42

The included predictors in this model were selected based on a combination of prior empirical research and the research interests of this analysis (Table 5). This first model focuses on the demographic predictors, but also includes a built environment factor to capture differences in crash exposure between blocks. Together, these predictors represent a blend of demographic, structural, and exposure-related factors known to influence crash frequency, consistent with prior road infrastructure literature.

Table 5   Model Specifications by Block Group

	Variable	Class	Attribute Values
Outcome	Crash Count	Integer	[2, 4752]
Predictor	Median Household Income	Float	[0, 250,001]
	Proportion of Minoritized Population	Float	[0, 1]
	Population Density	Float	[0, 60,957.05]
	Population Zero Indicator	Binary	0, 1
	Total Road Length	Float	[0, 3416612]

2. Model Specification

A spatial negative binomial regression model was fitted using the spaMM package in R to estimate block-group crash counts while accounting for overdispersion and spatial dependence. Let Y_i denote the crash count in block group i. The model assumes:

$$Y_i \sim NegBin(\mu_i, \theta)$$

where μ_i is expected crash count and θ is the overdispersion parameter. The mean structure is modeled using the log link function:

$$log(\mu_i) = \beta_0 + \beta_1 \cdot MedIncome_i + \beta_2 \cdot PropMinority_i$$
$$+\beta_3 \cdot PopDensity_i + \beta_4 \cdot PopZero_i + \beta_5 \cdot RoadLength_i + u_i$$

Here, the fixed-effects predictors include median household income, proportion of minoritized population, population density, population-zero indicator, and total road length. The population zero indicator ($PopZero_i$) identifies block groups with no residential population (10 total). These areas typically contain major roadways, industrial land, or recreational areas. Because demographic variables do not represent crash exposure in these areas, the indicator allows the model to capture structurally higher crash counts and prevents demographic effects being misestimated due to these areas.

Spatial dependence is incorporated through a conditional autoregressive (CAR) spatial error term:

$$u \sim CAR(W)$$

where W is the block-group adjacency matrix derived from queen contiguity. This method defines neighboring blocks as those sharing edges or vertices. The spatial error structure models unobserved spatial patterns shared among neighboring block groups, reducing the residual autocorrelation and improving model fit.

C. Model 2: Spatial Negative Binomial Regression for Pedestrian Crash Count

1. Rationale

Pedestrian crash count per block group was calculated the same way as total crash count. Each individual crash was mapped into its respective block group, and pedestrian crashes were totaled by the pedestrian-involved indicator on each pedestrian crash. The same predictors from Model 1 were used, which account for both demographic and built environment factors that may influence pedestrian crashes. Once again, a Moran's I test was conducted and indicated that pedestrian crashes were spatially dependent (Table 6). Therefore, the same CAR spatial error structure used in

Model 1 was applied to account for spatial clustering.

Table 6 Results for Global Moran's I test on Pedestrian Crash Count

Moran I Statistic	Expectation	Variance	Pvalue
0.361	-0.0017	0.0006	<2.2e-16

2. Model Specification

The same model framework from Model 1 was used for this analysis, replacing total crash count with pedestrian-involved crash count.

D. Model 3: Mixed-Effects Logistic Regression

1. Rationale

Crash severity was modeled at the individual crash level using a mixed-effects logistic regression. Severity was coded as a binary outcome indicating whether the crash resulted in a killed or seriously injured (KSI) outcome (1 = KSI, 0 = non-KSI). Because crashes are nested within blocks, observations within the same block groups are not independent. A mixed-effects model with a random intercept for block group accounts for this clustering and captures unobserved factors such as roadway design, street regulations, and neighborhood characteristics that influence severity but are not directly measured in the data. The categorical predictors used in this model are road system, lighting conditions, weather conditions, and road conditions. These variables were recoded into interpretable categorical groups based on standard crash reporting classifications. Weather was grouped into clear/cloudy, rain, snow, and other/unknown. Road surface conditions were categorized into dry, wet, snow/ice, and other/unknown. Lighting conditions were grouped into daylight, dawn/dusk, dark-lighted, dark-unlighted, and other/unknown. Road system type was categorized as interstate, state highway, private property, and other/unknown. These factors were chosen due to extensive research done on these built environment features and their impacts on crash frequency and severity.

2. Model Specification

Let crash i occur in block group i. The model assumes the outcome is:

$$Y_{ij} \sim Bernouilli(p_{ij})$$

with the log-odds of a severe crash modeled as:

$$logit(p_{ij}) = \beta_0 + \beta_1 \cdot RoadSystem_{ij} + \beta_2 \cdot Lighting_{ij} + \beta_3 \cdot Weather_{ij} + \beta_4 \cdot RoadCondition_{ij} + u_j$$

where

- $RoadSystem_{ij}$ = roadway classification (Interstate, State Highway, Private Property, Other/Unknown)
- $Lighting_{ij}$ = lighting conditions (Daylight, Dawn/dusk, Dark-lighted, Dark-unlighted, Other/Unknown)
- $Weather_{ij}$ = weather conditions (Clear/Cloudy, Rain, Snow, Other/Unknown)
- $RoadCondition_{ij}$ = road conditions (Dry, Snow/Ice, Wet, Other/Unknown)

The random intercept is assumed to follow:

$$u_j \sim N(0, \sigma_u^2)$$

This structure allows each block group to have its own baseline probability of a severe crash, reflecting unobserved spatial and contextual diversity.

IV. Results

A. Model Results 1: Spatial NB for total crash count

The results of the first analysis are summarized in Table 7, with significant predictors in bold.

Table 7 Spatial NB Results

Predictor	Coefficient	Cond. Stan. Error	IRR	P-value
Median Household Income	-1.92e-06	9.22e-07	0.999	**0.037**
Proportion Minoritized Population	3.06e-03	1.902e-03	1.003	0.108
Population Density	-1.96e-05	5.24e-06	0.999	**0.0001**
Population Zero Indicator	-4.32e-01	2.99e-01	0.649	0.148
Total Road Length	9.40e-06	7.03e-07	1.000009	**0.000**

Although several coefficients appear numerically small, this is a function of the units in which the predictors are measured. For example, median household income, population density, and total road length are measured in large units, so even small coefficient values can represent dramatic changes in crash counts. Interpreting the results through the Incident Rate Ratio (IRR) can provide a more intuitive understanding. This statistic represents the multiplicative change in crash counts for a one-unit increase in the predictor. Median household income was negatively associated with crash counts (IRR < 1), indicating that higher-income block groups see fewer crashes, holding other factors constant. With additional calculation using the estimated coefficient, the interpretation for this predictor is that for a $10,000 increase in median household income, the area sees a 2% decrease in crash counts. Population density also saw a significant negative association, suggesting that denser areas experience slightly lower crash counts after accounting for the other factors. On the other hand, total road length was positively associated with crash counts (IRR > 1), reflecting the increased exposure to traffic accidents as additional roadway miles are added within the block group.

B. Model Results 2: Spatial NB for Pedestrian-Involved Crashes

Table 8 Spatial NB Results

Predictor	Coefficient	Cond. Stan. Error	IRR	% Change	P-value
Median Household Income	-4.91e-06	1.295e-06	0.9999	4.8% per $10,000 increase	**0.0001**
Proportion Minoritized Population	4.80e-01	2.48e-03	1.004	0.48% per 1% increase	0.0529†
Population Density	-4.39e-06	7.03e-06	0.9999	0.01% per 1-unit increase	0.532
Population Zero Indicator	-8.54e-01	4.22e-01	0.425	57.5% relative difference	**0.043**
Total Road Length	9.40e-06	9.41e-07	1.000009	0.0009% per 1-foot increase	**0.000**

† p < 0.10 (marginally significant)

Median household income had a significant, negative association with pedestrian crashes (IRR < 1, p< 0.001), indicating that higher-income areas experience fewer pedestrian crashes. Additionally, the proportion of minoritized population shows a positive but marginally significant association with pedestrian crashes, indicating a possible pattern of inequitable exposure that warrants further investigation. Population-zero block indicator groups had substantially fewer pedestrian crashes (IRR = 0.43, p = 0.043), reflecting the absence of foot traffic in non-residential areas. Total road length was a strong positive predictor (IRR > 1, p < 0.001), consistent with increased exposure as additional roadway is considered.

C. Model Results 3: Mixed-Effects Logistic Regression

The mixed-effects logistics regression results are summarized in Table 9 and visualized in Figure 5.

Table 9 Mixed-Effects Logistic Regression Results for KSI Crashes

Predictor	Level	Estimate	Std. Error	OR	% Change in Odds	P-value
Road System	Interstate (Reference)					
	State Highway	0.398	0.054	1.49	+49.0%	<**0.001**
	Private Property	-0.335	0.231	0.716	-28.4%	0.15
	Other/Unknown	0.062	0.048	1.064	+6.4%	0.20
Lighting Conditions	Daylight (Reference)					
	Dark-lighted	0.953	0.029	2.59	+159%	<**0.001**
	Dark-unlighted	0.802	0.076	2.23	+123%	<**0.001**
	Dawn/Dusk	0.409	0.068	1.50	+50%	<**0.001**
	Other/Unknown	0.35	0.233	1.42	+42%	0.13
Weather Conditions	Clear/Cloudy (Reference)					
	Rain	-0.193	0.078	0.825	-17.5%	**0.014**
	Snow	-0.390	0.110	0.68	-32.0%	<**0.001**
	Other/Unknown	-0.536	0.09	0.585	-41.5%	<**0.001**
Road Conditions	Dry (Reference)					
	Snow/Ice Road	-0.807	0.104	0.45	-55.0%	<**0.001**
	Wet Road	0.149	0.099	1.16	+16%	0.16
	Other/Unknown	-0.379	0.215	0.68	-32.0%	0.078†

† $p < 0.10$ (marginally significant)

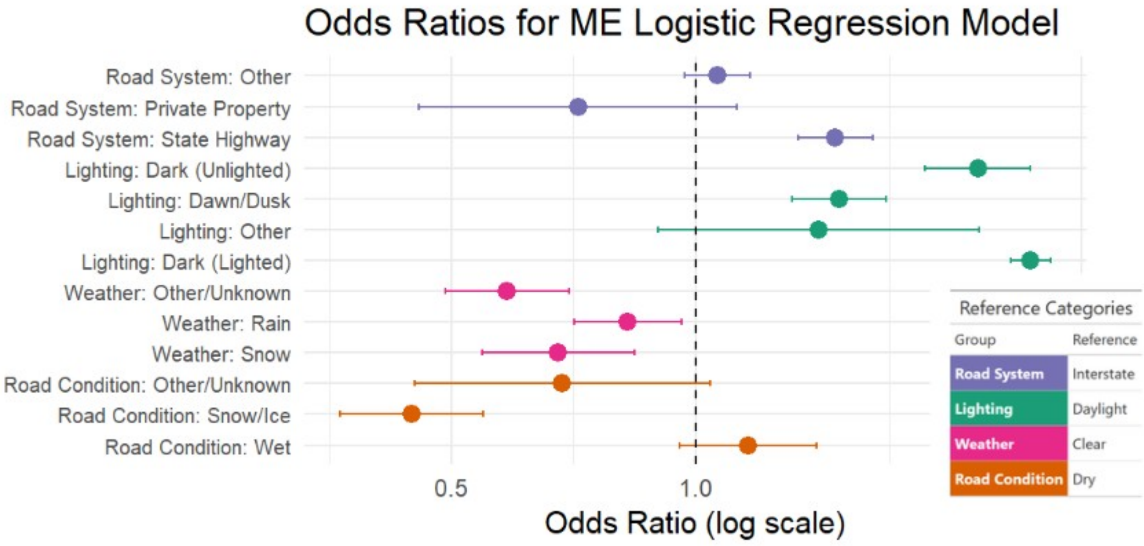

Fig. 5 Odds Ratio Plot for Mixed-Effects Logistic Regression Model

Several built and natural environmental factors were significantly associated with the odds of a crash resulting in a killed or seriously injured outcome. Crashes occurring on state highways saw a 49% increase in odds of being severe compared to crashes on the interstate (OR = 1.49, $p < 0.001$). Lighting conditions were among the strongest predictors, with crashes in dark-lighted conditions having 2.59 times higher odds of being severe (OR = 2.59, $p < 0.001$), and crashes in dark-unlighted conditions having 2.23 times higher odds (OR = 2.23, $p < 0.001$), relative to daylight conditions. Dawn and dusk conditions also increased the odds of severity by about 50% (OR = 1.49, $p < 0.001$).

Weather and road surface conditions showed an inverse relationship with crash severity. Crashes occurring in rain (OR = 0.82, $p = 0.017$) or snow (OR = 0.68, $p < 0.001$) were less likely to result in severe outcomes, which is consistent with evidence that drivers increase caution and reduce speed during adverse weather. Similarly, crashes on snow or ice-covered roads saw substantially lower odds of severity (OR = 0.46, $p < 0.001$).

V. Discussion

A. Demographic-related correlates

The results of this study align with a substantial body of research showing that areas with lower-income populations tend to experience disproportionately higher crash burdens. Median household income was negatively associated with both total crash counts and pedestrian-involved crashes, indicating that under-resourced communities remain a strong predictor of traffic risk. These disparities are even more pronounced for pedestrian-involved accidents, suggesting that residents of these areas face increased exposure to unsafe walking environments and limited access to pedestrian-friendly infrastructure.

Higher proportions of minoritized residents were also positively but marginally associated with increased pedestrian crash counts. While this relationship did not reach standard levels of statistical significance, this finding is consistent with prior literature documenting that minoritized communities, especially areas of concentration of Black residents, have increased exposure to traffic accidents, even after accounting for differences in income [4]. Together, these demographic patterns highlight persistent inequities in transportation safety outcomes.

Population density was found to have a negative relationship with crash counts, but was not significantly associated with pedestrian crashes. This may reflect the traffic-calming measures in dense urban areas, where slower speeds and shorter blocks reduce crash risk. Dense neighborhoods also tend to support alternative transportation modes, reducing vehicle exposure. Total road length was positively associated with both motor-vehicle and pedestrian crashes, reinforcing the notion that block groups containing more major roadway infrastructure experience more opportunities for traffic accidents.

B. Environmental-related correlates

The severity analysis revealed several infrastructural and environmental conditions that significantly influence the likelihood of a crash resulting in a fatality or serious injury. Crashes occurring on state highways, which fall under arterial roads, had substantially higher chances of severe crashes compared to interstates. This is consistent with prior research showing that roadways with fast speed limits, high volumes of traffic, and frequent access points create conditions favorable to severe crashes.

Lighting conditions were among the strongest predictors of severity. Crashes in dark environments (dark-lighted and dark-unlighted) had more than double the odds of resulting in a severe crash. Reduced visibility and challenges of nighttime driving likely contribute to this increased risk. Dawn and dusk conditions also increased severity odds, reflecting even minor impairment in visibility as a challenge.

Interestingly, adverse weather conditions such as rain and snow were associated with lower odds of severe crashes. This counterintuitive result likely reflects behavioral changes in inclement weather. Drivers tend to reduce speeds and increase caution in these conditions, lowering the severity of crashes even if frequency may increase.

C. Limitations

Several limitations should be considered when interpreting the results of this study. First, the analysis relies on reported crash data from the Denver Regional Council of Governments, which may under count minor crashes or misclassify factors such as environmental conditions, crash severity, etc. Inconsistent reporting practices may introduce measurement error into the models.

Secondly, the total road length variable, which was used in the two spatial negative binomial models, was included as a measure of roadway exposure. However, this variable only takes into account major roads such as state highways, arterials, and collectors, and does not include local residential streets. As a result, this may underestimate exposure in neighborhoods with extensive local street networks.

Third, the models do not include direct measures of vehicle and pedestrian volume, vehicle miles traveled, or traffic speeds, all of which are important determinants of crash risk. In the absence of these measures, variables such as road length and population density were used, but may not fully capture true exposure patterns.

Fourth, although spatial dependence was addressed using a CAR structure, unmeasured spatial processes, such as transit services, neighborhood design, and traffic regulations, may still influence crash outcomes. The random-effect variances for both crash counts and pedestrian counts indicated modest spatial clustering, but residual spatial autocorrelation may remain.

Finally, while this model identifies associations between demographic and environmental characteristics and crash outcomes, they cannot determine whether these factors directly cause higher crash risk or severity.

D. Recommended Countermeasures

The following countermeasures are proposed in direct response to the significant associations identified across the three models.

1. Pedestrian Safety Improvements

Based on the findings of Model 2, improving pedestrian-friendly infrastructure in lower-income neighborhoods is essential for reducing pedestrian crashes. These areas experience significantly higher pedestrian crash counts, likely due to outdated infrastructure. Effective interventions include curb extensions, chicanes, medians, and other traffic-calming measures that shorten crossing distance and reduce vehicle speeds. For busy, arterial intersections, more substantial infrastructure changes may be warranted. These can include separated crossing such as overpasses or underpasses.

2. High-volume roadway treatments

Model 3 indicated that state highways, or arterial roadways that experience high volumes of daily traffic, are significantly more likely to experience severe crashes. To counter this, the simplest intervention is reducing posted speed limits, which has well-focumented safety benefits. More extensive improvements include road diets, or the reduction or reconfiguration of roadways, to lower speeds, reduce conflicts points, and create space for alternative modes of transportation.

3. Lighting and visibility

Findings from Model 3 also highlight the strong influence of lighting conditions on crash severity. While nighttime driving inherently carries higher risk, improving visibility where possible remains critical. Interventions include LED streetlights and illuminated crosswalks which enhance driver awareness and reduce the likelihood of severe outcomes.

4. Equity-based investments

While improvements are needed across Denver County, Model 1 and Model 2 suggest that lower-income areas experience disproportionately high crash burdens. Local governments should prioritize equity-focused investments by allocating dedicated funding to these communities, ensuring equal access to safe transportation systems. These include both physical improvements and regular maintenance commitments

VI. Conclusion

This study examined the spatial distribution of traffic accidents in Denver County from 2014 to 2024 and evaluated how socioeconomic, demographic, and environmental factors shape both crash frequency and severity. A consistent pattern was found in both models that lower-income neighborhoods experience disproportionately higher crash burdens, especially for pedestrian-involved accidents. These findings underscore longstanding inequities in transportation safety, where communities with fewer resources face greater exposure to dangerous roadways and fewer investments in infrastructure improvements.

Built and natural environment factors also played a significant role in shaping crash outcomes. Major roadways and poor lighting conditions were strongly associated with severe crashes, while adverse weather conditions were linked to lower severity. Together, these results highlight the complex nature of traffic risk, shaped by both structural inequities and built-environment conditions.

The patterns observed in Denver likely reflect similar outcomes in cities across the country, where constant urban growth often outpaces investment in safe transportation systems. As urban regions expand, the burden of unsafe road design frequently falls on the neighborhoods least equipped to absorb it. By identifying where crashes concentrate and which communities face the greatest risks, this study provides spatial evidence that can guide more equitable transportation planning and targeted safety interventions. Ultimately, improving roadway safety in Denver and cities worldwide requires substantial investment in infrastructure that prioritizes vulnerable road users and addresses systemic disparities that shape safety outcomes.

VII. Supplementary Materials

The crash files, code, and data dictionary used throughout this report can be found at `https://github.com/mialin12/Socioeconomic-and-Environmental-Correlates-of-Traffic-Accident-Hotspots.git`

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References

[1] "NHTSA Releases 2023 Traffic Deaths, 2024 Estimates," , n.d. URL `https://www.nhtsa.gov/press-releases/nhtsa-estimates-39345-traffic-fatalities-2024`.

[2] Ewing, R., and Dumbaugh, E., "The Built Environment and Traffic Safety: A Review of Empirical Evidence," *Journal of Planning Literature*, Vol. 23, No. 4, 2009. https://doi.org/10.1177/0885412209335553, URL https://journals.sagepub.com/doi/epdf/10.1177/0885412209335553, dOI: 10.1177/0885412209335553.

[3] Noland, R. B., Klein, N. J., and Tulach, N. K., "Do lower income areas have more pedestrian casualties?" *Accident Analysis Prevention*, Vol. 59, 2013, p. 337–345. https://doi.org/10.1016/j.aap.2013.06.009.

[4] Dumbaugh, E., Li, Y., Saha, D., and Marshall, W., "Why do lower-income areas experience worse road safety outcomes? Examining the role of the built environment in Orange County, Florida," *Transportation Research Interdisciplinary Perspectives*, Vol. 16, 2022, p. 100696. https://doi.org/10.1016/j.trip.2022.100696.

[5] Goniewicz, K., Goniewicz, M., Pawłowski, W., and Fiedor, P., "Road accident rates: strategies and programmes for improving road traffic safety," *European Journal of Trauma and Emergency Surgery*, Vol. 42, No. 4, 2016, p. 433–438. https://doi.org/10.1007/s00068-015-0544-6.

[6] Haile, M. N., Dararo, K. F., Agumasie, Y. A., and Tiye, F. S., "Spatiotemporal modeling and mapping of traffic crashes using R programming and GIS: a case study of Bole sub city, Addis Ababa, Ethiopia," *Scientific Reports*, Vol. 15, No. 1, 2025, p. 36554. https://doi.org/10.1038/s41598-025-19651-x.

[7] Mohammed, S., Alkhereibi, A. H., Abulibdeh, A., Jawarneh, R. N., and Balakrishnan, P., "GIS-based spatiotemporal analysis for road traffic crashes; in support of sustainable transportation Planning," *Transportation Research Interdisciplinary Perspectives*, Vol. 20, 2023, p. 100836. https://doi.org/10.1016/j.trip.2023.100836.

[8] Wang, M., Yi, J., Chen, X., Zhang, W., and Qiang, T., "Spatial and Temporal Distribution Analysis of Traffic Accidents Using GIS-Based Data in Harbin," *Journal of Advanced Transportation*, Vol. 2021, No. 1, 2021, p. 9207500. https://doi.org/10.1155/2021/9207500.

[9] "Data | Regional Data Catalog," , n.d. URL https://data.drcog.org/data?category[0]=Transportation&page=1&q=&sort=title.

[10] "American Community Survey Blk Grp (2017-2021)," , n.d. URL https://opendata-geospatialdenver.hub.arcgis.com/datasets/09c6c280881240b9a64232a9a3f9e199_365/explore?location=39.754413,-104.926660,10.56.

[11] "Street Typologies from Complete Streets," , n.d. URL https://data.drcog.org/dataset/street-typologies-from-complete-streets.