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Spatiotemporal Characterization of Variations in Road Traffic Accident Severity in Missouri Using Multiple GIS Techniques

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ABSTRACT

Whereas the recognition of the pattern of hotspot clusters is critical, this study fills the gap of understanding the spatiotemporal evolution of Road Traffic Accidents (RTAs) severity by selecting Cole County, which consists state's capital, Jefferson City, between 2020 and 2023. Leveraging an effective GIS-based framework, the research assesses "endurance efficiency" in a three-phased methodology that involved systematic data integration, calculation of an Accident Severity Index (ASI) and sophisticated spatial statistics. In order to ensure statistical significance in the detection of clusters, the research uses Global Moran's I for the spatial autocorrelation, Getis-Ord Gi* for the localized hot/cold spot detection and Kernel Density Estimation (KDE) for the high-resolution density mapping. The results show a steep fall in the number of accidents in April 2020, which is a direct byproduct of the containment measures against the coronavirus. Temporal analysis shows that Saturdays are the peak for RTAs in 2022 with adults (ages 25-64) making up 53% of all occurrences. Critically, high-severity incidents continued to cluster in the downtown of Jefferson City using multiple methods in the GIS analysis. These results deliver a granular, evidence-based foundation for urban planners and law enforcement to implement targeted safety interventions and optimize emergency response allocation.

Keywords: Spatial Autocorrelation; Hotspot Analysis; Accident Risk Assessment; Spatial Clustering; Geospatial Analysis.

1. Introduction

One realism of transportation systems when RTAs can be arisen any place during any time. Multiple reasons may trigger the occurrence of RTAs and can be related to human, vehicle, road infrastructure, environment, and traffic operational factors. The contributed factors in RTAs occurrence are related to the behavior of drivers, weather conditions, design of roads, drug and alcohol abuse, sex, age, and gender of drivers [1-5]. In addition to the property damages and economic losses, serious injuries and fatalities are also caused by accidents. For instance, World Health Organization (WHO) stated that around 1.9 million persons die each year due to the RTAs [6]. The yearly records reflect the tragic impact of accidents, when there were around 40,990 people has died in the US [7]. Also, Missouri has recorded a bad situation with around 995 fatalities during 2024 [8]. By 2030, the commercial vehicles are expected to reach around 40.29 million, when the growth rate has annually recorded as 2.17% [9]. Moreover, the population growth increases the need for multiple transportation modes, which has become urgent matter when it influences the causing of RTAs. For instance, the statistics illustrated that each 1 km/hr increasing of speed leads to 3% to 5% escalating of RTAs. Consequently, there is a high correlation between both speed and accidents [10-11].
Two major specifications are belonged to the RTAs, both geographical randomness and spatial dependance. Thus, researchers for safety enhancement should take into their consideration the spatiotemporal distribution of

RTAs, when the trend of accidents are performed dynamically rather than statistically. The RTAs severity is considerably fluctuated among different spatial places and temporal scales. Thus, it is crucial to assess these patterns for management of traffic safety and measures of planning by the techniques of GIS. Besides the consideration of spatial analysis, temporal aspect consideration is vital for analysis of RTAs [12-14].

Kernel Density Estimation (KDE) is regarded as one of these techniques for geospatial intensity assessment of RTAs [15-17]. This technique is helpful to produce smooth surfaces that illustrate the RTAs density over different spatial locations. This method is crucial also for identifying the hotspots where the efforts of intervention can be at the highest influence. Moreover, the spatial autocorrelation is critical for the significance evaluation of the severity of RTAs. For example, Moran's I is regarded as an indicator for geospatial dependency by estimating weather the spatial area of accidents has high or low severity [18-21]. On the other hand, the identification by Getis-Ord Gi* statistics of some spatial spots reflect the high severity (hotspots) or low severity (coldspots), and this can be calculated by regional metrics [16, 22-23]. In addition, locations with high accident severity are highlighted by positive Gi* values, while areas with low severity of accidents are highlighted by negative values of Gi*.

From the point of view of decision-makers and planners, spatiotemporal recognition is considered as an intricate challenge, when there are different impacted attributes which vary over location and time [24, 25]. These attributes impact due to the variance in characteristics of roads, volumes of traffic, behavior of drivers, conditions of weather, and variations of temporal scales [26-28]. It is crucial to mention that not all these contributing factors have the same impact on RTAs severity. The impact would be depended on their importance level which fluctuates based on spatial and temporal fluctuations and the related agencies goals [29]. Moreover, uncertainty and inconsistency in accidents reporting, severity classifications, and temporal aggregations of incidents may designate the details of RTAs. This would complicate the procedures of spatiotemporal analysis [30]. For the purpose of identifying hotspot patterns, both the consistency and availability of the dataset of RTAs are crucial, especially when high-quality spatiotemporal set of data is needed. Therefore, there is a vital necessity for an extensive spatiotemporal computational platform to handle the ambiguity of dataset and combine multiple factors that impacting traffic safety. Hence, the main issue of application is in obtaining an accurate statistical prediction, identifying reliable spatiotemporal clusters, and interpretation of clear outcomes.

While multiple researchers have approached the RTAs microscopic scale of analysis [31-35], their ability for supporting broader plans of safety are limited. Moreover, while using such models, both spatiotemporal correlation and geospatial uncertainty are tended to be disregarded. A considerable body of researches have approached RTA hotspot severity identification over multiple regions. However, limited studies have addressed these issues at a county wide scale. The diversity of traffic heterogeneous contexts is illustrated by RTAs distribution, such as metropolitan areas, suburban corridors, and rural highways. Thus, in order to capture these spatial variations, spatiotemporal GIS-based analytical framework at the county spatial level is crucial to adopt.

Unlike multiple researches that approached analyzing the RTAs datasets, this study presents a unique approach by utilizing four successive years of the collected set of accidents (i.e., from 2020 to 2023) for a macroscopic area, Cole County in the state of Missouri, USA. The study examines the macroscopic severity of accidents over an extensive spatial area. Also, the study estimates the emerging and persistence areas of hotspots of RTAs severity within yearly temporal scale. From the pattern’s viewpoint of emerging, enduring, or diminishing, this analysis examines the temporal evolution of the severity of RTAs over the selected temporal scale. Therefore, Global Moran’s I, Gi*, and KDE techniques are applied to detect, visualize, and understand the statistical significance of RTA severity hotspots.

While this research is focused on mitigation of RTAs severity, it is crucial to align with the goals of the United Nations Sustainable Development Goals (UNSDGs). Thus, the main goals are (1) minimizing road fatalities and catastrophic injuries by recognizing the hotspots of RTAs severity by utilizing spatiotemporal analysis of GIS (i.e., supporting SDG3: Good Health and Well-Being). (2) identifying the high-risk hotspot areas to enhance both accessibility and safety of roads (i.e., supporting SDG11: Sustainable Cities and Communities). (3) assisting the planners and lawmakers to use this study for safety protocols improvements and financial allocation optimization. This line up with SDG9, innovation, infrastructure, and industry.

Based on spatial and temporal prospects of GIS analysis, this study can be utilized to enhance the transportation safety besides decision-making of planners as its main significance. Therefore, by utilizing this methodology, decision-makers and planners can acquire a better grasp in detecting the emergence or preservation of high-risk spots, which is going beyond the standard statistical analysis of accidents. It is crucial to mention that using spatiotemporal analysis for hotspot detection creates both reliability and objectivity of safety estimation. Hence, this research adds to the literature in the field of illustrating how GIS-based statistical models can enhance eliminating the gap between transportation safety requirements of real-world and geospatial analysis safety on county level. In addition, the results of this methodology can help related authorities for developing robust safety plans, concentrating on safety measures, and allocating on safety measures effectively to identify both persistent and emerging hotspot areas. The proposed methodology of this study can be simply adaptable and useful over multiple geospatial areas, temporal scales, and transportation modes.

2. Dataset and Methodology

This study consists selecting the county of Cole that is located in Missouri State in the USA. Figure 1 illustrates the location of Cole County with the road networks. This county locates in the middle of Missouri state with an area of 1,040 km² and the population has reached to 77,625 people by 2024 [36]. This county has a strategic central location, which grant it as a vital role in administration and transportation. Also, it consists of Jefferson City, the capital of the state, which generates significant activities of daily governmental commutes. Figure 2 shows the location of Jefferson City within Cole County.

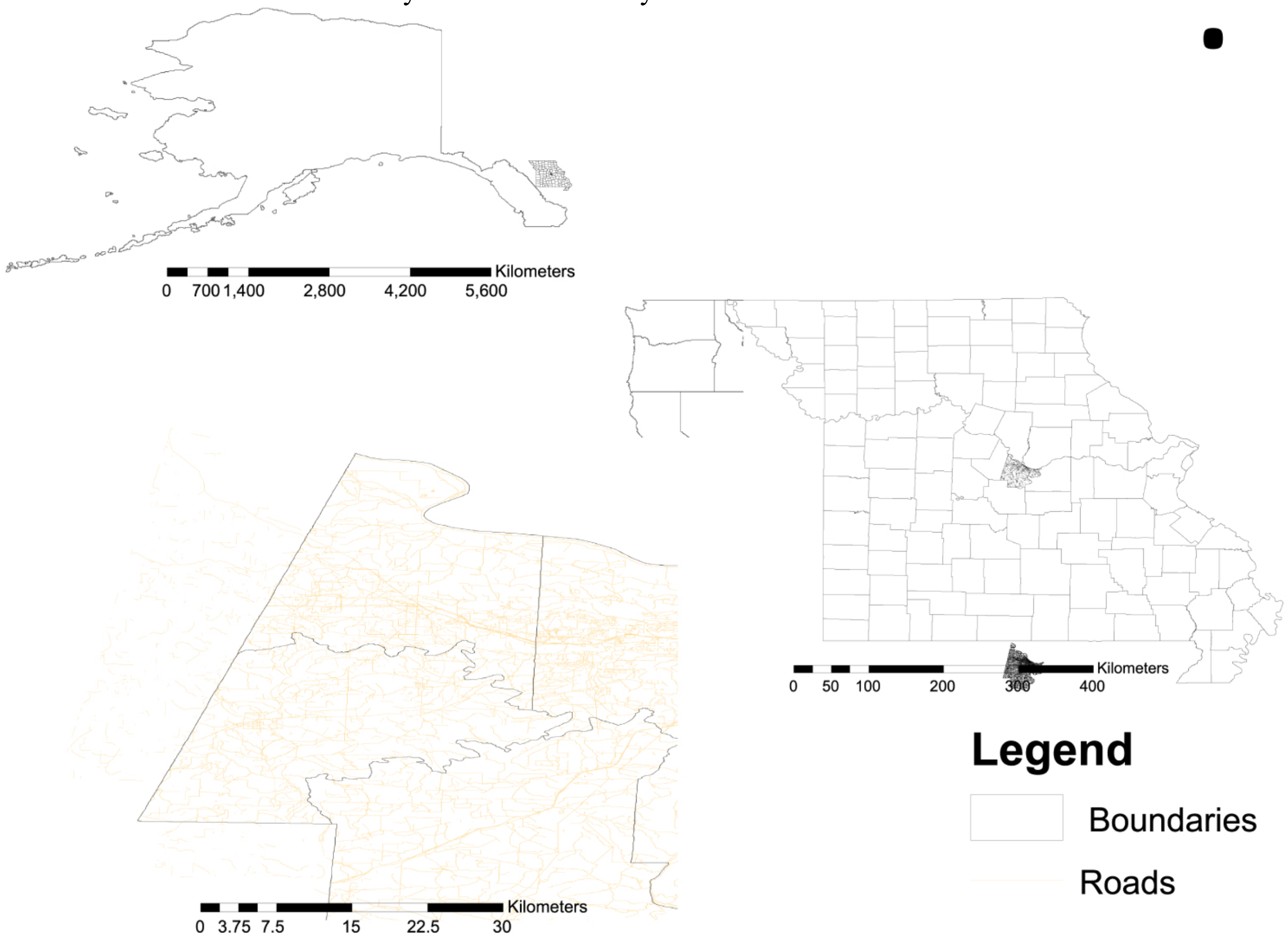

Figure 1. Study area, Cole County, Missouri, USA

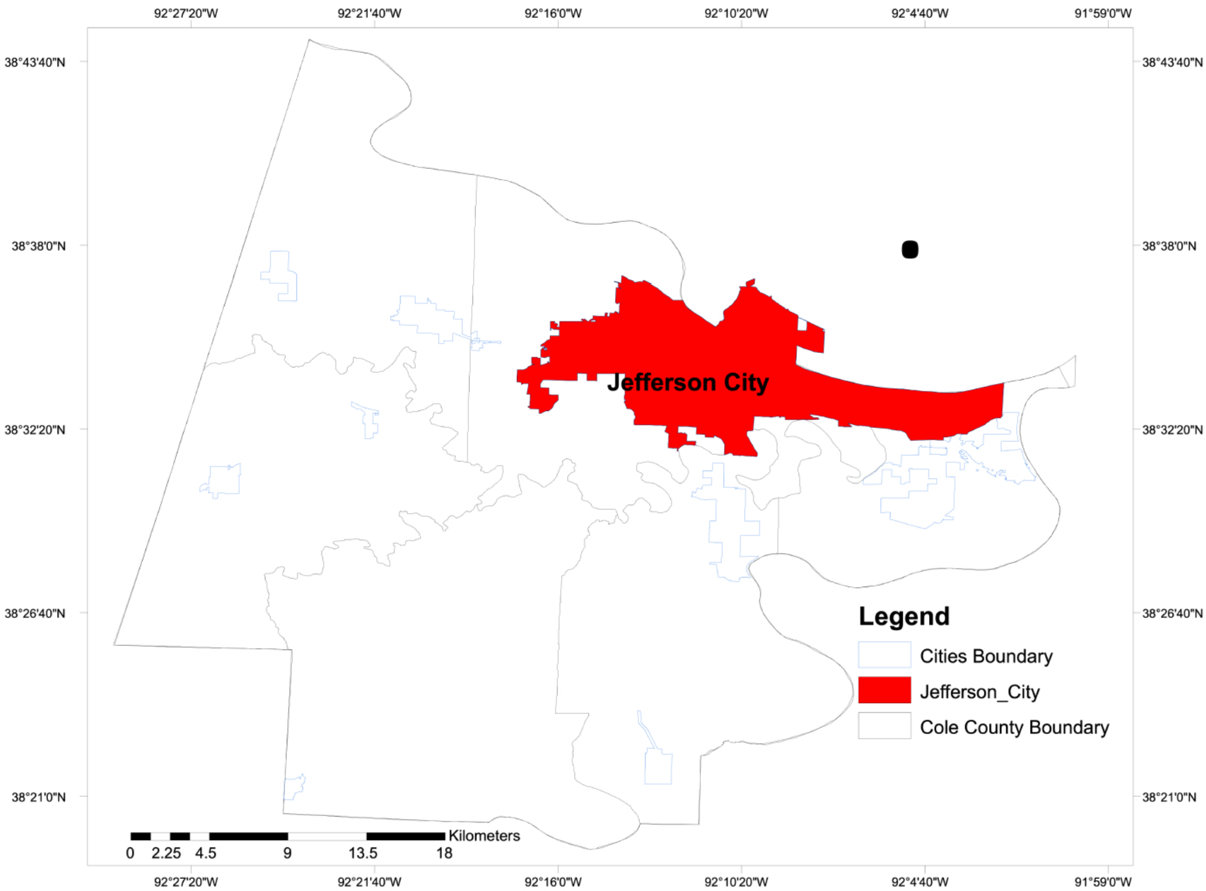

Figure 2. Jefferson City location

The methodology consists of three steps adopted for RTAs hotspots categorization, analytical robustness enhancement, and severity of RTA patterns examination. The first step involved dataset description and resources. The second part illustrates the density and severity determination methodology. By utilizing different methods of analysis, the last part presents the spatiotemporal analysis of RTAs severity for detection of the hotspot density and statistical significance of the selected study area. Figure 3 depicts the steps of methodology.

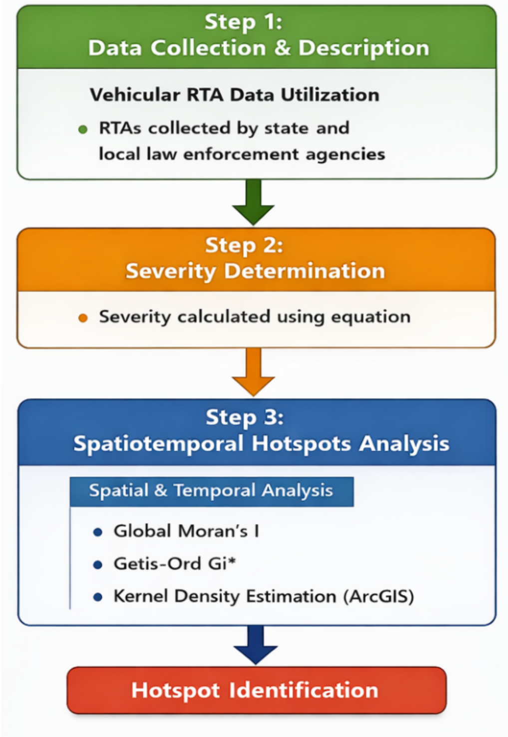

Figure 3. Methodology steps

2.1. Data Collection

For the purposes of data collection, the present study utilizes the collected set of RTAs data by local agencies and/or state law enforcement within county of Cole for four consecutive years (i.e., from 2020 to 2023) [37]. Different numbers of RTAs were reported over different temporal periods. However, the highest number of accidents was 1440 during 2021 as in Figure 4.

Besides the spatial coordination's, diverse attributes are correlated to each accident that can be utilized, such as date, time, type, and reason of accident occurrence. Moreover, fatalities and injuries recorded numbers are also incorporated within the set of data. Table 1 illustrates the numbers of injuries and fatalities (severity) for the selected years of analysis.

Multiple temporal scales can be selected for severity of RTAs analysis. For example, one-month scale can be selected for weather patterns or seasonal impacts capturing [38]. Also, smaller temporal scale can be used like hourly, daily, or even weekly according to the dynamic of accidents. Thus, the scale of one-year with spatial analysis is examined in this study to reduce the random fluctuations of the short-term scales in addition to increase the statistical reliability of the model estimation [39].

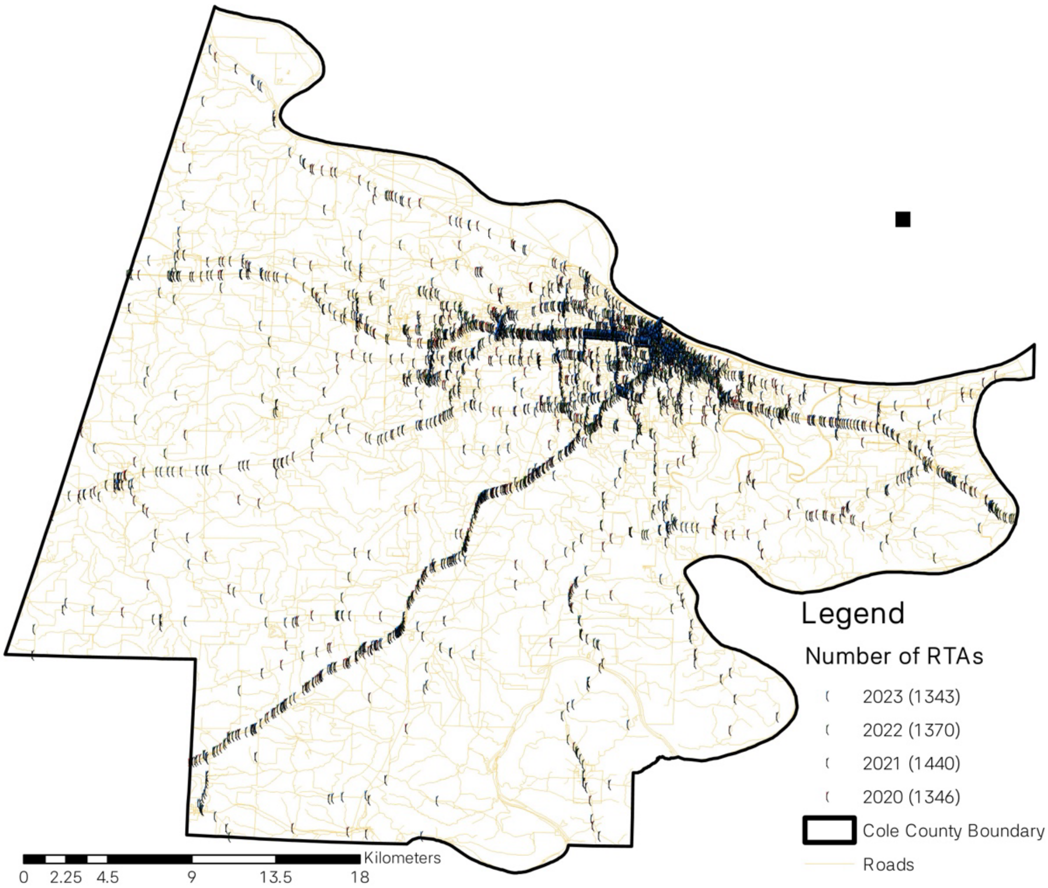

Figure 4. Number of accidents in Cole County from 2020 to 2023

Table 1. Severity statistics

	Severity Type		
Year	Minor Injuries	Severe Injuries	Fatalities
2020	437	34	11
2021	426	36	7
2022	452	25	7
2023	486	30	5

2.2. Accident density and severity calculations

To classify the hotspots of accidents spatially, the density of these accidents can be calculated by dividing the RTAs number of each selected spatial area by its area itself. This sort of calculation reveals the level of accident occurrence per each zone. The ASI can be also calculated at this study and used for further hotspot analysis instead of using the number of RTAs. The reason behind using ASI is to reflect the accident consequences, support the resources allocation priorities, and enable advanced statistical and spatiotemporal analysis [40-41]. This study utilized using severity index of the government of Belgian with the factors of 1, 3, and 5 for injuries, disabilities, and fatalities successively [42], as depicted in equation 1 below.

$$\mathrm{ASI} = \mathrm{M} + 3\mathrm{S} + 5\mathrm{F} \tag{1}$$

When M is the RTAs with minor injuries, S is severe injuries, and F is fatalities.

2.3. Spatiotemporal Hot Spot Severity Analysis

2.3.1 Global Moran's I

At the beginning, there is a need to examine whether the severity of RTAs is spatially clustered, dispersed, or randomly scattered over the selected study area. Thus, Global Moran’s I within a GIS environment can be utilized for this sort of analysis. This technique examines the spatial autocorrelation of incidents by evaluating the correlation among RTA spatial locations and their adjacent neighbors. At the case of a positive Morans’ I index associated with low p-value and high-z-score, implies the presence of significant clustering of incidents. While this method presents statistical proof of clustering of spatial trends, further hotspot applications of hotspot methods are justified to ensure spatial analyses. Equations 2 to 5 depict Global Moran's I index beside other related indices.

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{i=1}^{n} w_{i,j}} * \frac{\sum_{i=1}^{n} \sum_{i=1}^{n} w_{i,j}(x_i - \bar{X})(x_j - \bar{X})}{\sum_{i=1}^{n} (x_i - \bar{X})^2} \quad (2)$$

$$E[I] = \frac{-1}{(n-1)} \quad (3)$$

$$V[I] = E[I^2] - E[I]^2 \quad (4)$$

$$Z_{Score} = \frac{I - E[I]}{\sqrt{V[I]}} \quad (5)$$

Here, x_i is the amount of the feature at location i, while x_j is the feature at location j. $w_{i,j}$ represents the geospatial weight among features between i and j.

2.3.2 Getis-Ord Gi*

The determination of the autocorrelation of geospatial dataset for hotspot identifications of RTAs can be performed by Gi*. By taking into consideration the local spatial autocorrelation, this method is commonly utilized to detect the severity of high and low spatial clustering of RTAs. Instead of merely using the frequency of accidents as an input for Gi* hotspots identification, severity-weighted indicators (e.g., disabilities and fatalities) are more robust to inspect the high-risk areas with significant concentration of severe RTAs. Besides, Gi* detects any adjacent segments with similar attributes like geometric design or traffic conditions, then estimates the presence of accidents with high severity values surrounded by similar high severity accidents within a specific assigned threshold distance. The outcomes of both p-values and z-scores reflect the statistical robustness between both real severity of hotspots and spatially random fluctuations. Equation 6 depicts the spatial dependency of features.

$$G_i^* = \frac{\sum_{j=n}^{n} w_{ij} x_i}{\sum_{j=1}^{n} x_j} \quad (6)$$

Gi* here is the spatial correlated amount of i.

The analytical accuracy of accidents can be developed by utilizing severity attributes to identify the spatial locations with severe accidents instead of using only the number of accidents. The spatial weight determination between features (i.e., i and j) can be determined by central distance of the spatial correlation. Therefore, as per this distance, the Gi* statistics might provide different results according to the value of distance. Besides, w_{ij} can be binary or non-binary values, the weights sum (w_i) is shown in equation 7 below.

$$w_i = \sum_{j=1}^{n} w_{ij} \tag{7}$$

For depicting the variance and sample mean, equation 8 are employed for Gi* standardization.

$$Z(G_i^*) = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{x}\sum_{j=1}^{n} w_{ij}^2}{s\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \tag{8}$$

It is worth mentioning that the application of Gi* from the GIS-based framework allows a clear simulation of spatial trend severity of accidents. The local spatial autocorrelation reflects a set of distributed target attributes at the case of optimizing the optimum spatial autocorrelation among these specifications. In addition, this method provides a robust foundation for high-risk locations prioritizing and planning optimizations of road safety enhancement.

Either Manhattan or Euclidean distance can be used during the spatial planar analysis. The correlation among features can be estimated through the examination of spatial autocorrelation. This assessment provides information to comprehend the correlation of the RTAs severity occurrences. This connection among events can be spatially estimated through multiple perspectives, such as neighbors of K-nearest, fixed distance, or window model of space-time. The threshold distance that was selected for this research taking into consideration the variability of spatial autocorrelation of inherent [12].

2.3.3 Kernel Density Estimation (KDE)

Kernel density method is another spatial analysis technique by GIS, which regards as a non-parametric technique to transform any discrete incidents into a smooth density surface for hotspot identifications. This method determines the intensity of events within a specified search bandwidth radius [43]. Based on Kernel function, the closer incidents have the highest influence than the distant, provided a smoothed raster map. The kernel function assigns the weight of each incident based on its ID number for indication of its importance during calculations. This procedure let determining the entire number of accidents and assess their severity ratings. Equation 9 depicts the kernel density estimation.

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - xi}{h}\right) \tag{9}$$

The value of h here refers to the bandwidth, radius, or factor of smoothing. K here is the kernel, and f is the evaluator of the function of dense probability. The bandwidth impacts the accuracy of the kernel estimator. Therefore, selecting the optimum bandwidth is important according to the major goals of the study.

3. Results and Discussion

3.1. RTAs Trend

Figure 5 shows the monthly variation of accidents from 2020 to 2023 in Cole County. Generally, the fluctuation of monthly number of RTAs across the four years was clear when values ranged between 75 and 160. For instance, in 2020, the highest value of accidents was at January, equal to 135, then declined during April to 75 due to impact of pandemic closure. Later, the accidents were increased steadily to reach to the peak of 133, before declining again by the end of the year. In 2021, the trend was similar to the year of 2020 when the RTAs dropped from 127 in January to 93 in March, then increased to 158 during October, and later decreased again towards December. For the year of 2022, the situation was unique when the accident occurrences were stable (i.e., between 90 and 135), then increased during September and October before dropping by the end of the year. During 2023, the lowest recorded number of RTAs was during February, while the peak was during October. The records were ranged between 78 and 130. Generally, for all four years, the RTAs tended to increase during September and October and decrease from February to April.

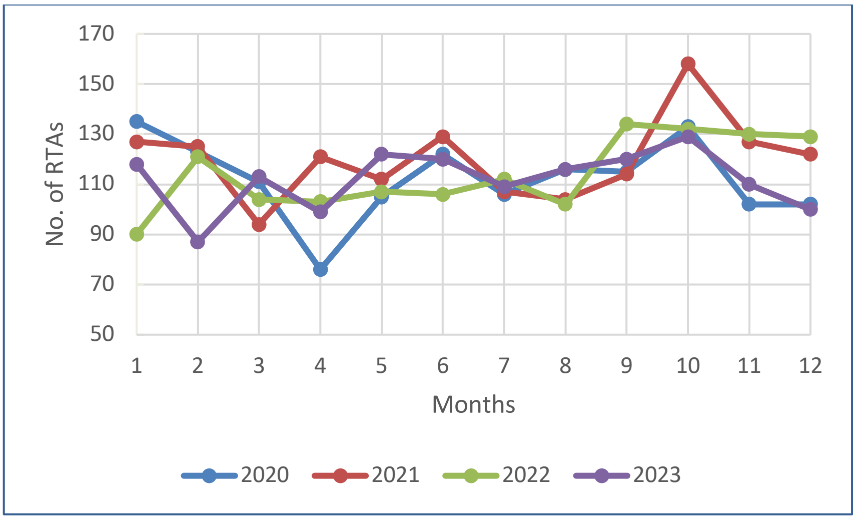

Figure 5. Monthly variation of RTAs per each year

Due to fluctuation of traffic demand or some external conditions like restrictions of mobility, the above temporal trends can be aligned with some prior studies which have approached the frequency dynamic of accidents [44-46]. Hence, RTAs occurrence is linked strongly to the exposure levels, not to random variations.

Figure 6 depicts the RTAs distribution by the days of the week in the state of Missouri for the collected dataset in 2022. The frequency of RTAs emerged by the weekend. However, the lowest recorded number of accidents was on Sunday (112 only), followed by both Monday and Wednesday. A gradual increasing was occurred on both Thursday and Friday. Saturday was the peak of accidents with around 168 accidents. Generally, accidents were more prevalent during weekends, especially on Saturday. The non-commuting periods of travelling have been approached by previous studies for exhibiting less predictable and much diverse conditions of driving. The outcomes also revealed that that RTAs occurrence are significantly related to the purposes of trips and patterns of driving [47-48].

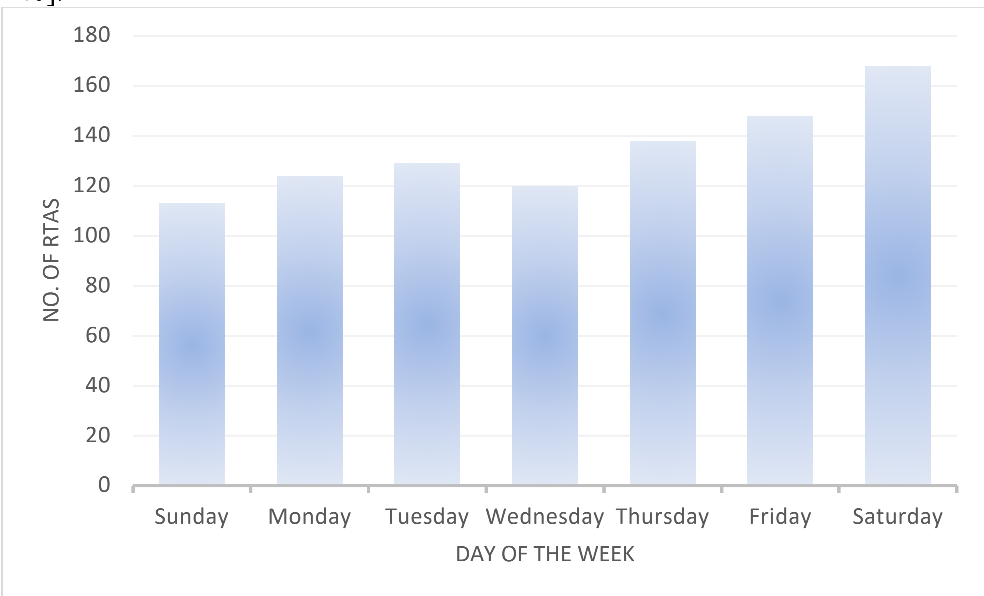

Figure 6. Daily variation of RTAs in Missouri, 2022

Figure 7 depicts the age impact on the occurrence of RTAs for the collected dataset during 2022. The major percentage of adults contributed with 53% of RTAs. This high percentage reveals that this group of people is highly contributed on the occurrence of RTAs. Besides, Seniors group of people shared also a high percentage with 24% of RTAs occurrence. However, teens and youths' groups reflected the lowest percentage of RTAs occurrence with only 11% and 12% successively.

The percentage distribution among different age groups reflects the driving activity roles of each group. For instance, previous studies inferred that the behavior variations due to different ages of drivers have a robust impact towards the accident's occurrence [49-50].

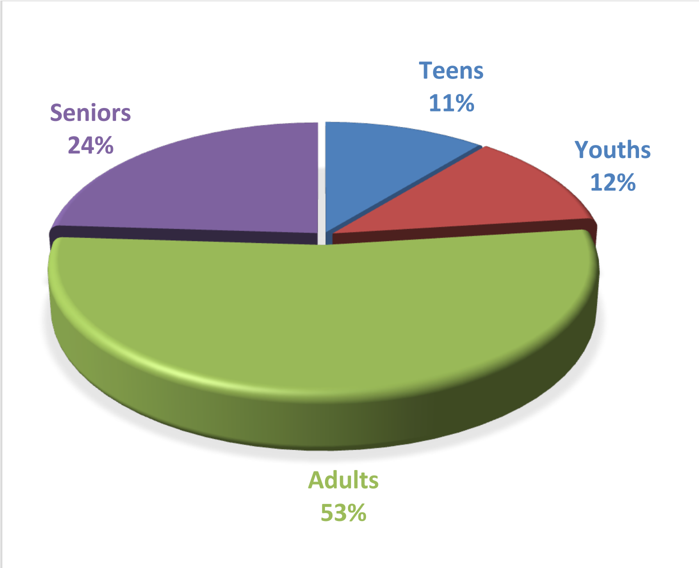

Figure 7. Statistics of RTAs by age group in Missouri, 2022

Cole County consists multiple townships and the density distribution of RTAs is spatially heterogeneous as in Figure 8. For instance, Jefferson township shows the highest density of RTAs compared to other townships, when it encompasses the state capital, Jefferson City that has concentration of the state and federal institutions. These administrative centers generate significant daily traffic volumes and increase the likelihood of collision occurrences. However, other townships depicted lower density of RTAs when they have less traffic movements with local roads and rural areas.
The concentration of spatial hotspot of accidents revealed the impact of land-use besides the traffic-generation of trips. A bunch of research has compared the spatial patterns of different sorts of incidents, when the areas with high complexity of function tend to reveal different safety levels of risks [51-52].

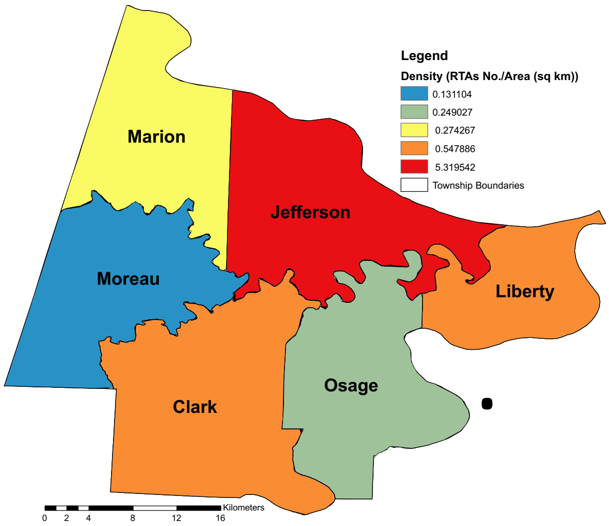

Figure 2: RTAs density distribution per each township (from 2020 to 2023)

3.2. Spatiotemporal Hot Spot Severity Analysis

Another utilized technique was used for inspecting weather the severity of RTAs is statistically significant clustered or not, Global Moran's I. Figure 9 highlighted the RTAs severity from 2020 to 2023. It can be noticed that there is a level of variations of spatial clustering, when the Moran's I values ranged from 0.023585 in 2022 (figure 9(c)) to 0.237627 during 2023 as in Figure 9(d). However, all results indicated a significant clustering of accidents severity when all p-values are equal to 0. Moreover, the z-values ranged between 17.17 and 171.23 for all four years, which revealed another validation of the presence of significant clustering rather than random distribution of clustering for RTAs severity. Therefore, due to some spatial factors like traffic volumes or geometric conditions, the results depicted that the study area has a dense persistent concentration of severe accidents along the selected four consecutive years. The results of this section revealed that the RTAs severity distribution is structurally underlined rather than randomness. Multiple literatures reported the same outcomes, especially when clustering is related to environmental characteristics and persistent roads [53].

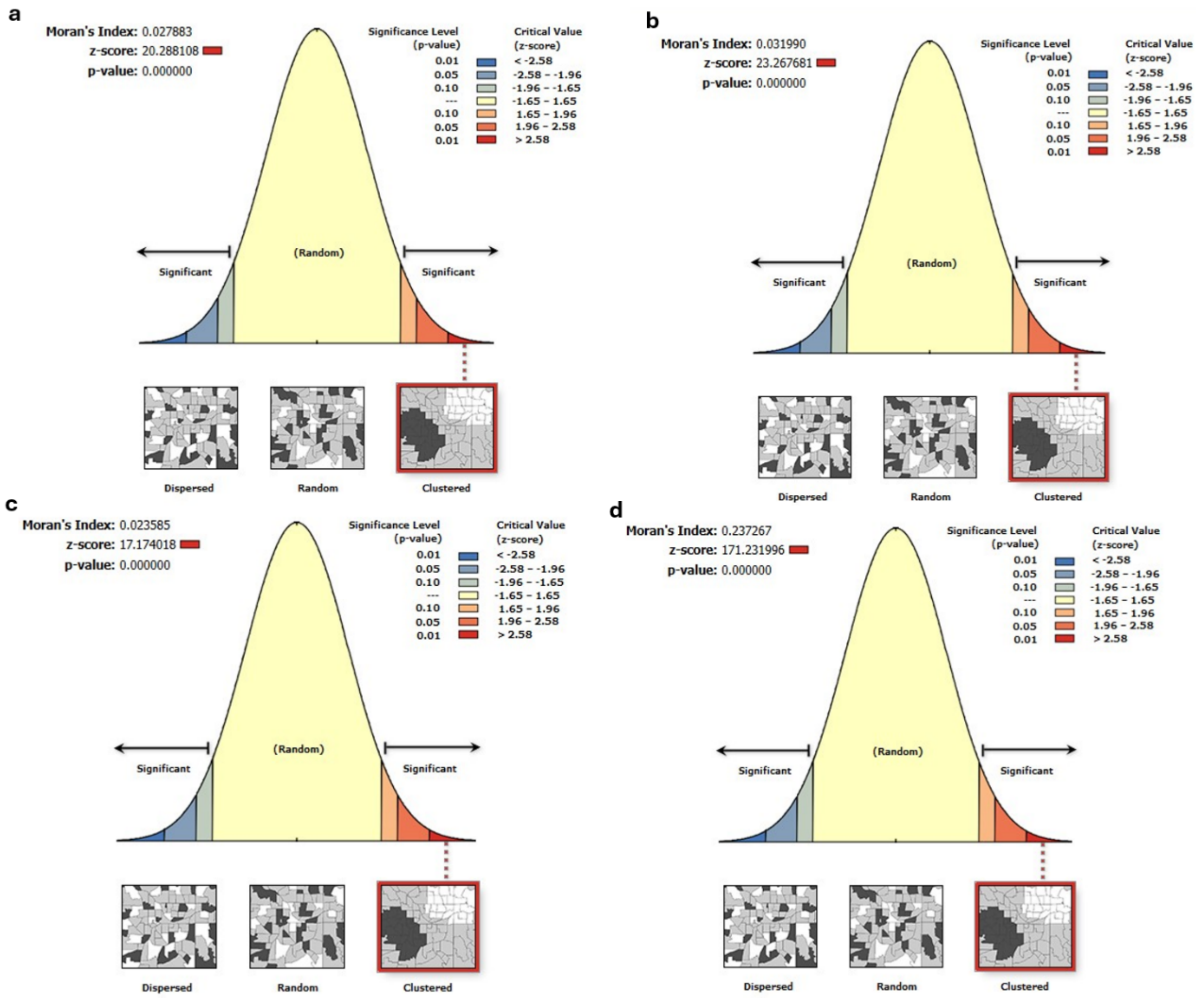

Figure 9: Global Morn's I results (a)2020, b)2021, c)2022, d)2023)

The spatial distribution of hotspots and coldspots of RTAs severity from 2020 to 2023 by Gi* are illustrated in Figure 10. The results revealed that the hotspot clusters are spatiotemporally persistent in the state capital, Jefferson City. These outcomes reflected the severe impact of the institutions of the state government in addition to the federal facilities towards the RTAs severity. Overall, the hotspots during both 2021 and 2022 (Figure 10(b) and (c) successively) illustrated a noticeable expansion on both intensity and size, especially during 2022 when the clusters increased in the central and eastern areas. However, during 2023 (Figure 10(d)), there was noticeable continuous spreading of hotspot intensity, indicating a spatial hotspot concentration. However, coldspots triggered sparsely over scattered in their distribution. The results illustrated an emergence and expansion of RTAs severity clusters and become more prominent over the four successive years. The clustering persistence over temporal scale reveals the presence of high-risk factors that should be mitigated. For instance, previous researches have inferred that such patterns are typically required a crucial intervention to stop any further emerging [54-55].

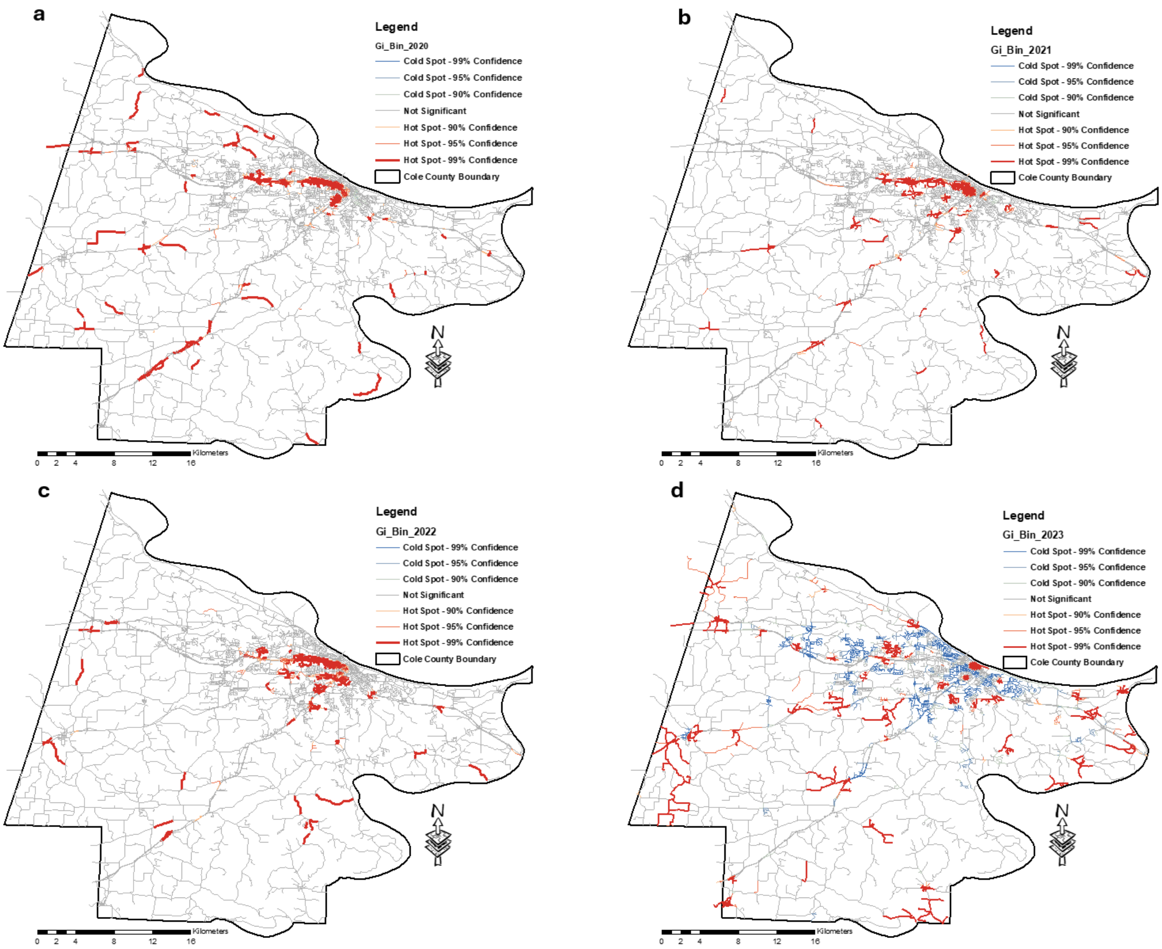

Figure 10: Getis Gi* results (a)2020, b)2021, c)2022, d)2023)

KDE analysis results for the four years (from 2020 to 2023) are illustrated in Figure 11. The results revealed a continuous surface of RTAs density over the selected study area. For instance, during 2020, the highest density areas are located in the central region and northeastern. Later, from 2021 to 2023 (Figure 11(b) to (d)), there is a noticeable shift, with an intensity increasing in the central and northeastern regions. Also, during 2023, Figure 11(d) shows a broader distribution of high-density clusters. Similar to Gi* analysis, the KDE analysis revealed a clear concentration and emerging of RTAs severity hotspots. It emphasizes the dynamic nature of spatiotemporal clustering with a clear trend of escalation and spreading of RTAs severity hotspots.

Emerging and enduring trend of hotspot intensity have been inferred from the overall selected methods of analysis along the four years of dataset. The robust correlation among the above techniques enhances the findings legitimacy and emphasizes the characteristics of spatial clusters over the selected study region. The results revealed a clear consistency in hotspot clustering as detailed in previous researches, which indicate a robustness of methodology over the accident spatial analysis [56].

The outcomes of this study integrate the analytical perspective by combining different spatial systematic techniques for capturing both patterns of density and behaviors of clustering through an assigned temporal scale. Utilizing multiple methods of analysis offers more comprehensive understanding of severity trend of emerging, compared to singly use of analysis method. Besides, this technique supports the applicability of traffic safety assessment.

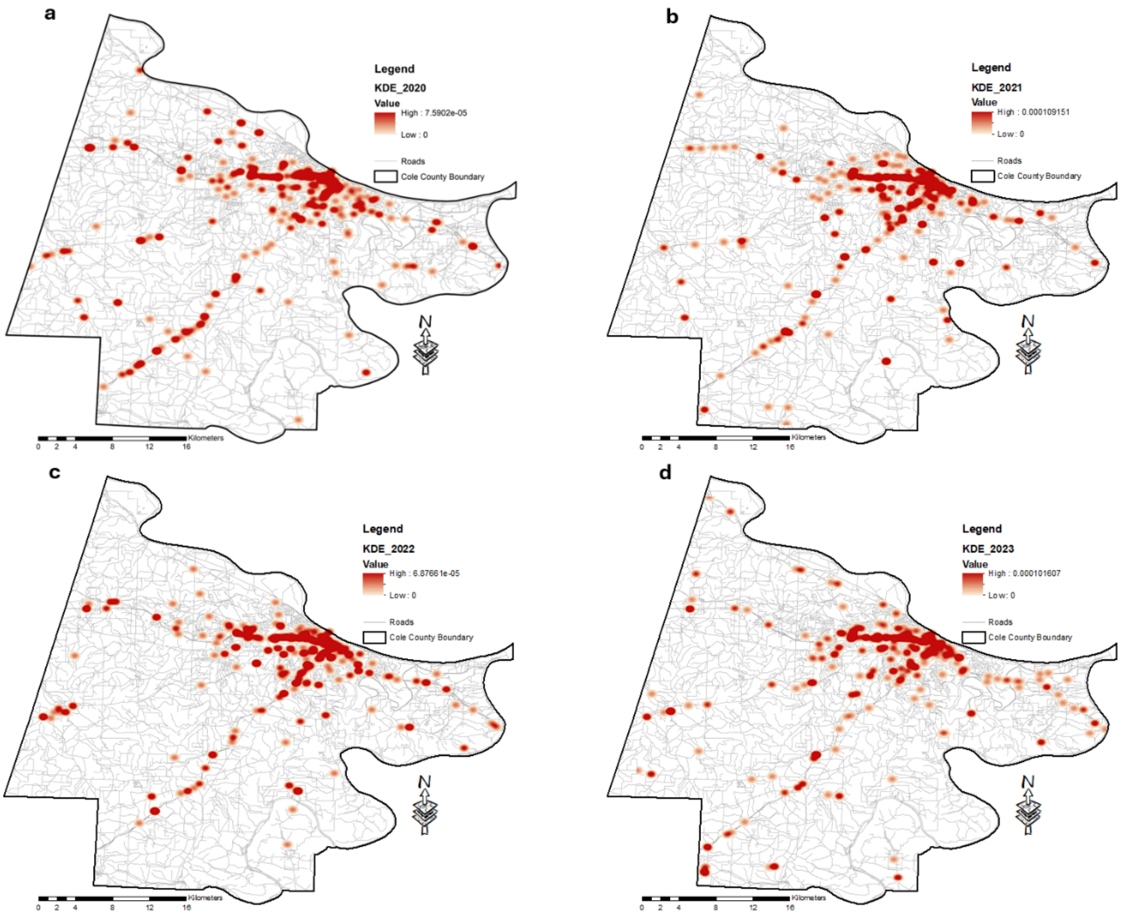

Figure 11: KDE results (a)2020, b)2021, c)2022, d)2023)

4. Conclusions

RTAs severity mitigation by inspecting, estimating, and optimizing is important for road safety enhancement. Accordingly, tracking the spatiotemporal fluctuations of RTAs severity, assessing the socioeconomic factors related to accidents' occurrence, and identifying high-risk areas over time is the main objective of this study. The methodology of the study utilized four consecutive years of RTAs (2020–2023) of Cole County in Missouri State, USA. To calculate the ASI, the selected dataset comprises attributes like number of minor injuries, disabilities, and fatalities. A clear seasonal variation of RTAs occurrence in Cole County from 2020 to 2023. For instance, RTAs decreased during the first months of the year and increased during fall. There was a decline during April 2020 due to the pandemic closure. A clear weekly pattern was observed, with the highest frequency on Saturdays and the lowest on Sundays. These outcomes revealed weekends like Saturdays are the most critical days for RTAs in Cole County. Statistics revealed that the main contributors to RTAs in 2022 in Missouri State were adults (~53%), followed by seniors (24%), while youths and teens reported the lowest percentages (12% and 11%). Jefferson City, the state capital, resulted in a high spatial density of RTAs, while rural areas revealed lower density. The distribution of RTAs severity in Cole County is spatiotemporally clustered rather than random, with high-risk areas showing persistent hotspot severity clusters over Jefferson City due to state administrative centers and federal institutes. The outcomes of GIS-based analysis methods (Global Moran's I, Gi*, and KDE) illustrated substantial and persistent spatiotemporal clustering of RTAs severity hotspots along four years (2020–2023). The intensity of severity hotspots emerged over the full temporal period, especially in the center and northeastern zones of the county, while coldspots remained scattered. These outcomes demonstrated the emerging and dynamic persistence and validated the spatiotemporal patterns of severity hotspot clusters. The results of this study bring into line with some performed researches indicating the usefulness of their methodologies for prioritizing of areas with high-risk for safety strategies interventions [21]. Also, these outcomes highlight the influence of the infrastructure of urban areas besides the design of city towards the severity of RTAs [20]. However, limitations include difficulty estimating hotspot rankings, and due to lack of attributes, the correlation between spatial coordination of RTAs and road geometry cannot be observed.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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