MEASURING AND COMPARING THE SPATIOTEMPORAL EVOLUTION OF ACCIDENT HOT SPOTS

A Dissertation

presented to

the Faculty of the Graduate School

at the University of Missouri-Columbia

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

---

by

MUQDAD AL HAMAMI

Dr. Timothy C. Matisziw, Dissertation Supervisor

MAY 2022

The undersigned, appointed by the dean of the Graduate School, have examined the Dissertation entitled

MEASURING AND COMPARING THE SPATIOTEMPORAL EVOLUTION OF ACCIDENT HOT SPOTS

Presented by Muqdad Al Hamami,

A candidate for the degree of Doctor of Philosophy,

And hereby certify that, in their opinion, it is worthy of acceptance.

Professor Timothy C. Matisziw

Professor Praveen Edara

Assistant Professor Yaw Adu Gyamfi

Assistant Teaching Professor Clayton Blodgett

DEDICATION

To My Father,

To My Mother,

To the Memory of My big Brother Muthana, (may ALLAH bless his soul),

To the Memory of My friend since childhood Mohammed, (may ALLAH bless his soul),

To My Brothers,

To My Wonderful Beloved Wife,

To My Beautiful Daughters and Loving Sons,

I dedicate this work.

Muqdad Al Hamami (MAY 2022)

ACKNOWLEDGEMENTS

First, and most of all, thanks to Almighty ALLAH for giving me the strength and ability to complete this work despite multiple difficulties I faced which would make the accomplishment of this work impossible.

All words of thanks will not be enough to my first teacher in the world whom I will never forget, my father.

My mother, thanks is never being fair enough for her encouragement, unconditional love, and prayers.

I would like to express my sincere love for my big brother who was assassinated by evil crows (may ALLAH bless his soul).

I would like to express my sincere love for my best friend since childhood who passed away from COVID-19 (may ALLAH bless his soul).

My beloved wife, my best choice and gift in life, I would like to express my gratitude and love for her support during the hard times of this long journey. My gratitude to my beautiful kids, Aya, Hiba, Hasan, Mohammed, and Ahmed.

I would like to express my deepest appreciation to my advisor Dr. Timothy C. Matisziw for his excellent guidance, patience, caring, and encouragement throughout this work.

I would like also to extend my thanks to my committee members Prof. Edara, Assistant Professor Yaw, and Assistant Teaching Professor Clayton Blodgett for their support and guidance.

I would like to thank my fellow doctoral students Khalid, Lan, and Ashkan for their feedback, support, cooperation, and of course friendship.

TABLE OF CONTENTS

ACKNOWLEDGMENTS ii

LIST OF FIGURES vi

LIST OF TABLES xi

CHAPTER 1 1

INTRODUCTION 1

1.1 Introduction 1

1.2 Research Motivation 3

CHAPTER 2 5

BACKGROUND 5

2.1 Assessing the Spatial Relationship Among Accidents 5

2.2 Assessing the Spatial and Temporal Relationship Among Accidents 12

2.3 Statistical Comparison Approaches of Accident Modeling 19

2.3.1 Parametric Methods 19

2.3.2 Non-Parametric Methods 22

2.4 Review of Some Statistical Approaches of Accident Modeling 24

CHAPTER 3 26

METHODS 26

3.1 General 26

3.1.1 Modeling Evolution of Cluster Size 26

3.1.2 Comparing Cluster Characteristics Methods 36

CHAPTER 4 40

APPLICATION TO CLUSTER MORPHOLOGY 40

4.1 Introduction 40

4.2 Study Area 40

4.3 Accident Data 41

CHAPTER 5 51

CLUSTER MORPHOLOGY AND CITY SCALE 51

5.1 Introduction 51

5.2 Study Area and Data Sources 51

5.3 Analysis and Comparison 54

CHAPTER 6 57

RESULTS AND DISCUSSION 57

6.1 General Clusters Sizes 57

6.2 Cluster Analysis Statistics 58

6.3 Cluster Frequency of Occurrence 72

6.4 Clusters Development 77

6.5 Clustering with Significant $Gi*$ values 80

6.6 Cluster Size Evolution 89

6.7 Cluster Analysis Distribution 102

6.8 Best Fit Statistical Model 105

6.9 Cluster Average Log Counts Comparison 109

CHAPTER 7 114

DISCUSSION AND GENERAL IMPLICATIONS 114

7.1 STAG and SCGC 114

7.1.1 Total Number of Clusters 114

7.1.2 Sum of Unique Temporal and Morphological Patterns 116

7.1.3 Clusters Size Evolution 118

7.2 Cluster Statistical Comparisons 121

CHAPTER 8 123

CONCLUSIONS AND FUTURE WORK 123

8.1 Conclusions 123

8.2 Future Work 127

REFERENCES 129

APPENDIX-A..151

APPENDIX-B..168

APPENDIX-C..225

VITA 273

LIST OF FIGURES

Figure 1. Example of Planar KDE for vehicular accidents 8

Figure 2. An example of NKDE for vehicular accidents 10

Figure 3. Spatial and temporal aggregation of point events into analysis areas ait 15

Figure 4. Spatial and temporal neighborhoods for analysis area ait (a) time t-1, b) time t), and c) the computation of $Git*$ 16

Figure 5. Pseudocode for Spatial-Temporal Aggregation of Groups (STAG) 31

Figure 6. Spatial-temporal aggregation of groups: a) group associated with each analysis area, b) cluster polygons created from merging spatially connected analysis areas of the same group, c) initial analysis areas attributed with the size of the cluster with which they are associated 33

Figure 7. Examples of cluster size evolution: a) sustained, b) fluctuating, c) increasing, and d) decreasing 35

Figure 8. Pseudocode for Statistical Comparing of Group Clusters (SCGC) 38

Figure 9. Example of assigned cluster sizes of analysis areas for three different cities 39

Figure 10. Columbia Missouri, USA 41

Figure 11. Accident locations in the years 2013 and 2014 42

Figure 12. Sample of attributes associated with accidents 43

Figure 13. Frequency of accidents in analysis periods: a) two-month, b) one-month, and b) two-week periods 44

Figure 14. Aggregation of accident points to analysis areas over a set of periods 47

Figure 15. Examples of analysis areas having significant G_i^* values $(p \leq 0.1)$ for: a) May 2013 and b) Weeks 9-10 in 2013 49

Figure 16. Roads in areas classified as urban in Missouri 52

Figure 17. Number of unique clusters (p≤0.1, over 12, two-month periods) 59

Figure 18. Number of unique clusters (p≤0.05, Over 12, two-month periods) 61

Figure 19. Number of unique clusters (p≤0.01, over 12, two-month periods) 62

Figure 20. Number of unique clusters (p≤0.1, over 24, one-month periods) 62

Figure 21. Number of unique clusters (p≤0.05, over 24, one-month periods) 64

Figure 22. Number of unique clusters (p≤0.01, over 24, one-month periods) 66

Figure 23. Number of unique clusters (p≤0.1, Over 53, two-week periods) 68

Figure 24. Number of unique clusters (p≤0.05, over 53, two-week periods) 70

Figure 25. Number of unique clusters (p≤0.01, over 53, two-week periods) 72

Figure 26. Cluster frequency of occurrence (p≤0.1, over 12, two-month periods) 73

Figure 27. Cluster frequency of occurrence (p≤0.05, over 12, two-month periods) 73

Figure 28. Cluster frequency of occurrence (p≤0.01, over 12, two-month periods) 74

Figure 29. Cluster frequency of occurrence (p≤0.1, over 24, one-month periods) 75

Figure 30. Cluster frequency of occurrence (p≤0.05, over 24, one-month periods) 75

Figure 31. Cluster frequency of occurrence (p≤0.01, over 24, one-month periods) 75

Figure 32. Cluster frequency of occurrence (p≤0.1, over 53, two-week periods) 76

Figure 33. Cluster frequency of occurrence (p≤0.05, over 53, two-week periods) 76

Figure 34. Cluster frequency of occurrence (p≤0.01, over 53, two-week periods) 77

Figure 35. Analysis areas having significant G_i^* values ($p \leq 0.1$) over 12, two-month periods 81

Figure 36. Analysis areas having significant G_i^* values ($p \leq 0.05$) over 12, two-month periods......82

Figure 37. Analysis areas having significant G_i^* values ($p \leq 0.01$) over 12, two-month periods......83

Figure 38. Analysis areas having significant G_i^* values ($p \leq 0.1$) over 24, one-month periods......84

Figure 39. Analysis areas having significant G_i^* values ($p \leq 0.05$) over 24, one-month periods......85

Figure 40. Analysis areas having significant G_i^* values ($p \leq 0.01$) over 24, one-month periods......86

Figure 41. Analysis areas having significant G_i^* values ($p \leq 0.1$) over 53, two-week periods......87

Figure 42. Analysis areas having significant G_i^* values ($p \leq 0.05$) over 53, two-week periods......88

Figure 43. Analysis areas having significant G_i^* values ($p \leq 0.01$) over 53, two-week periods......89

Figure 44. Analysis areas classified by type of evolution ($p \leq 0.1$) over two-month Periods......91

Figure 45. Analysis areas classified by type of evolution ($p \leq 0.05$) over two-month Periods......92

Figure 46. Analysis areas classified by type of evolution ($p \leq 0.01$) over two-month Periods.....93
Figure 47. Analysis areas classified by type of evolution ($p \leq 0.1$) over one-month periods.....95
Figure 48. Analysis areas classified by type of evolution ($p \leq 0.05$) over one-month periods.....96
Figure 49. Analysis areas classified by type of evolution ($p \leq 0.01$) over one-month periods.....97
Figure 50. Analysis areas classified by type of evolution ($p \leq 0.1$) over two-week periods.....99
Figure 51. Analysis areas classified by type of evolution ($p \leq 0.05$) over two-week periods.....100
Figure 52. Analysis areas classified by type of evolution ($p \leq 0.01$) over two-week periods.....101
Figure 53. Cluster frequency distribution histogram for small cities.....103
Figure 54. Cluster frequency distribution histogram for micropolitan cities.....104
Figure 55. Cluster frequency distribution histogram for metropolitan cities.....105
Figure 56. Rootgrams comparison for the best fit model for small urban cities group.....106
Figure 57. Rootgrams comparison for the best fit model for micropolitan cities group.....107
Figure 58. Rootgrams comparison for the best fit model for metropolitan cities group.....108
Figure 59. Total number of clusters over 12, two-month periods.....115
Figure 60. Total number of clusters identified over 24, one-month periods.....116
Figure 61. Total number of clusters identified over 53, two-week periods.....116

Figure 62. Sum of (Γ) and (M) patterns (over 12, two-month periods)...........................117

Figure 63. Sum of (Γ) and (M) patterns (over 24, one-month periods)...........................117

Figure 64. Sum of (Γ) and (M) patterns (over 53, two-week periods) 118

Figure 65. Number of cluster size evolution (over 12, two-month periods)....................120

Figure 66. Number of cluster size evolution (over 24, one-month periods)....................120

Figure 67. Number of cluster size evolution (over 53, two-week periods) 120

Figure 68. Percentage of similarity/dissimilarity frequency between different urban city scales for quarter-year periods 121

Figure 69. Percentage of similarity/dissimilarity frequency between different urban city scales for one-year periods..122

LIST OF TABLES

Table 1. Model notation 31

Table 2. Clusters' size development index samples 34

Table 3. Example of assigned cluster sizes of analysis areas for three different cities 39

Table 4. Summary of accidents over two-month periods 44

Table 5. Summary of accidents over one-month periods 45

Table 6. Summary of accidents over two-week periods 45

Table 7. Analysis Parameters for Hot Spot Analysis 48

Table 8. List of cities selected for comparative analysis 53

Table 9. Cluster size summary over 12 two-month periods 57

Table 10. Cluster size summary over 24, one-month periods 58

Table 11. Cluster size summary over 53, two-week periods 58

Table 12. Summary of cluster characteristics for the 12, two-month analysis periods (p≤0.1) (P* = period; C^ = number of clusters) 59

Table 13. Summary of cluster characteristics for the 12, two-month analysis periods (p≤0.05) (P* = period; C^ = number of clusters) 60

Table 14. Summary of cluster characteristics for the 12, two-month analysis periods (p≤0.01) (P* = period; C^ = number of clusters) 61

Table 15. Summary of cluster characteristics for the 24, one-month analysis periods (p≤0.1) (P* = period; C^ = number of clusters) 63

Table 16. Summary of cluster characteristics for the 24, one-month analysis periods (p≤0.05) (P* = period; C^ = number of clusters) 64

Table 17. Summary of cluster characteristics for the 24, one-month analysis periods ($p \leq 0.01$) (P^* = period; $C^\wedge$ = number of clusters) 65

Table 18. Summary of cluster characteristics for the 53, two-week analysis periods ($p \leq 0.1$) (P^* = period; $C^\wedge$ = number of clusters) 67

Table 19. Summary of cluster characteristics for the 53, two-week analysis periods ($p \leq 0.05$) (P^* = period; $C^\wedge$ = number of clusters) 69

Table 20. Summary of cluster characteristics for the 53, two-week analysis periods ($p \leq 0.01$) (P^* = period; $C^\wedge$ = number of clusters) 71

Table 21. Summary of the Akaike Information Criterion (AIC) 108

Table 22. Statistical comparison of small urban cities for one-year periods 110

Table 23. Statistical comparison of micropolitan urban cities for one-year periods 112

Table 24. Statistical comparison of metropolitan urban cities for one-year periods 113

Table 25. Summary of the number of clusters for each temporal scale analysis 115

Table 26. Sum of the number of (Γ) and (M) for each temporal scale 117

Table 27. Number of cluster size evolution trends occurrence 119

ABSTRACT

One reality of transportation systems is that vehicular accidents can happen practically anywhere and at any time. An increasing body of research suggests though that spatial and/or temporal dependencies (i.e., clusters or hot spots) among accidents likely exist. Along with understanding where and when such spatiotemporal dependencies may occur, another important facet to consider is the geographic extent or area associated with the hot spots. For example, an accident hot spot may involve a small, isolated portion of the transportation system or a much more expansive geographic area. Better delineation and quantification of the morphological characteristics of accident hot spots can provide valuable decision support for planning for accident hot spot mitigation and prevention. As the size and shape of accident hot spots may evolve over time, the capability to track such dynamics is vital, especially with respect to the identification of effecting processes of hot spot occurrence as well as assessments of the efficacy of efforts to mitigate factors underlying hot spot development. For example, a hot spot that is increasing in size over time may indicate areas that are started with a small cluster size then become a part of a larger cluster size during the next periods. Likewise, a cluster that is decreasing in size may signify that some areas may participate with a big cluster size then decrease to a smaller cluster size later.

Besides understanding the trend of cluster size evolution during multiple time periods, another important aspect to consider is the percentage or amount of similarity/dissimilarity of cluster morphological characteristics between different urban

areas. Better understanding and quantification of morphological characteristics of accident hot spots' similarity characteristics over different urban area levels can also provide valuable decision support for accident safety planning and improve accident alleviation and prevention.

To this end, a Geographical Information Systems (GIS) based framework is outlined to facilitate the analysis and comparison of the morphological characteristics of hot spots over time. The analysis framework is applied to a case study of vehicular accidents reported over a two-year period for Morphological analysis and a three-year period for statistical comparison computing to demonstrate its practical utility. The application results of the morphological analysis indicate that patterns of change in hot spot morphology can be effectively quantified, and a variety of informative spatial and temporal patterns can be detected. In addition, the results of cluster statistical comparison computing revealed that the level or percentage of cluster characteristics similarity between urban areas decreases with the increment of the urban city size and road levels complexity.

CHAPTER 1

INTRODUCTION

1.1 Introduction

The number of vehicles utilizing roadways worldwide continues to steadily increase with nearly 92 million vehicles produced by 2019 (Statista, 2020a) and is expected to grow to nearly two billion in 2040 (Forum, 2016; Statista, 2020b). As such, it is no surprise that the number of vehicular accidents has also increased, with between 20 to 50 million non-fatal and ~1.35 million fatal accidents occurring globally each year (ASRIT, 2020). An array of factors such as driver behavior, weather conditions, road geometrical design, driver drug/alcohol abuse, fatigue, gender, age, and sex are commonly thought to contribute to increased risk of accidents (Blazquez et al., 2018; Chen et al., 2017, 2018; Elvik, 2013; Kang et al., 2018). These factors would impact the accident occurrence from one case to another. For example, the factors of the behavioral accident are related to the mistakes of drivers while the non-behavioral accident factors are related to other sorts of factors like general environmental conditions, traffic flow conditions, and road geometric design (Caliendo et al., 2007a). Additionally, much research has indicated that patterns, trends, and dependencies in the spatial and temporal dimensions likely exist, often referred to as clusters or hot spots (Bíl et al., 2019; Chen et al., 2018; W. Cheng et al., 2018; Deepika and Saradha, 2014; Erdogan et al., 2015; Harirforoush and Bellalite, 2016; Huang et al., 2017; Matisziw et al., 2020; Sánchez-Martín et al., 2019).

Moreover, the cost of traffic accidents in most countries has reached 3% of the gross domestic product for these countries (WHO, 2020). Therefore, traffic accident modeling is important to improve and develop road network safety management. Much research has indicated that patterns, trends, and dependencies in the spatial and temporal dimensions of accidents likely exist (Huang et al., 2017). Thus, the main object for spatial and temporal analysis of vehicular accidents is to determine the clustering correlation of accident events by utilizing both positional information and the time/date of these events along with the road network segments. As a result, by selecting different time period scales, spatiotemporal analyses have been widely used to evaluate the space/time clustering of accident events (Cheng et al., 2017; Mountrakis and Gunson, 2009).

While there has been an increasing amount of research on the spatial and temporal dynamics of accident hot spots, their geographic extent (size) and the evolution thereof over time have been considered to a lesser extent. The ability to consistently measure hot spot size over time could provide valuable insight as to the factors underlying their appearance/disappearance, growth, and decline over time. To this end, a Geographical Information Systems (GIS) based framework for quantifying and tracking hot spot size is proposed. The hot spot morphologies resulting from this methodology can be further analyzed by classifying them based on their spatiotemporal characteristics. An example taxonomy is outlined to demonstrate how this could be applied in practice. To address these issues, this research first discusses methods that have been proposed to describe the spatial and temporal dependency among vehicular accidents. Next, a methodology for quantifying hot spot morphology over space and time is detailed. Later, another methodology for comparing cluster morphological specifications over multiple selected urban city scales is detailed also. Finally, an application is provided to illustrate how the developed methodologies work.

1.2 Research Motivation

A range of studies has investigated the spatiotemporal dynamics of accidents in transportation systems. For example, some have estimated the frequency of vehicular accidents occurring in a spatial unit of analysis (e.g., a road segment) within a specific time period. These studies have modeled the occurrence of accidents and inspected the independent spatial attributes though to impact accident frequency like roads' physical characteristics, traffic flow, human behavior, etc. (Anastasopoulos, 2016; Caliendo et al., 2007b). Other studies have sought to reason about the spatial concentration of accidents through the identification and analysis of geographic hot spots and cold spots (Bíl et al., 2019; Chen et al., 2018; Cheng et al., 2018; Deepika and Saradha, 2014; Erdogan et al., 2015; Harirforoush and Bellalite, 2016; Sánchez-Martín et al., 2019). In this sense, 'hot spots' and 'cold spots' refer to spatiotemporal intensity in accident occurrence. Once hot and cold spots are identified, their dynamics over space and time can be tracked and the factors and processes responsible for their occurrence can be better assessed (Cheng et al., 2018; Soltani and Askari, 2017).

Aside from the spatial distribution and periodicity of hot spot occurrence, their size development characteristics (e.g., their size and shape) are also important features to consider. Typically, hot spot identification methods are only used to assist in the classification of areal units of analysis as hot spots. However, measuring the size evolution qualities associated with portions of a study region classified as hot spots can also be beneficial in that evolution of size and can be evaluated over time. For instance, tracking changes in the size evolution characteristics of accident hot spots over different time periods (i.e., two-month, one-month, …etc.) with different confidence levels (i.e., 90%, 95%, and 99%) could potentially facilitate understanding of hot spots appearing, disappearing, increasing, and decreasing over time. Also, comparing cluster morphological characteristics can be useful in understanding hot spot characteristics of each urban area level.

To this end, this study pursues to contribute to this body of knowledge in several ways. Chapter 2 presents an overview of spatial and spatiotemporal clustering approaches, how they work, and major sources of error and uncertainty in accident data. The different types of methodologies that have depicted the accident clustering tracking, comparing evolution, and statistical comparing of multiple scales of urban cities are also reviewed in detail. A methodology for quantifying the geographic extent of accident clusters is presented in Chapter 3. Chapter 4 describes the experimental setup and associated data used to validate the proposed methodology for measuring cluster morphology. In this chapter, the developed method is applied to analyze the morphology of crash clusters over time for a single city to provide a detailed examination of modeling considerations. A comparative application of the methodology to multiple cities of various urban scales is then illustrated in Chapter 5. Chapter 6 details the analysis results of all applied methodologies. Discussion of the results and the broader implications of the research are presented in Chapter 7. Conclusions and recommendations for future work are detailed in Chapter 8.

CHAPTER 2

BACKGROUND

This chapter provides a general overview of research in accident modeling and spatial modeling techniques that have been used for spatiotemporal analysis of vehicular accidents.

2.1 Assessing the Spatial Relationship Among Accidents

A variety of geospatial analysis methods have been utilized in attempts to characterize accident hot spots. Given a set of accident locations (and their attributes), three general types of hot spot analyses are typically applied, clustering algorithms, spatial density estimation, and statistical models of spatial dependency.

An array of clustering algorithms has been used to partition a set of point-based events into clusters. K-means clustering is a common method used to identify a specified number of clusters (*k*) based upon the attributes of the events under consideration. After selecting the accidents of interest, K-means clustering can be applied to classify the accidents into groups based on the similarity of their attributes (Anderson, 2009; Kim and Yamashita, 2007). Given that K-means clustering algorithms are well established and have been implemented in many open source and commercial software packages, they have been widely applied in the analysis of accident events (Kim and Yamashita, 2007; Mohamed et al., 2013).

Ripley's K function has also been used to evaluate the spatial distribution of accident events concerning different spatial scales (Chen et al., 2018). Some researchers have evaluated the spatial clustering of discrete accident events by using Ripley's K function (Okabe and Yamada, 2001). For example, Ripley's K-function has been adapted to account for the spatial relationships among features within a set of time intervals (i.e., spatial clustering can be considered if the distinguished K is larger than the predicted K value for a particular distance) (Mountrakis and Gunson, 2009; Yamada and Thill, 2004). For instance, Warden et al. (2011) use a planar Ripley's K function to examine the degree of cluster intensity for accidents involving or not involving hazardous materials. The planar Ripley's K function is used to evaluate the spatial relationship (based on Euclidean distance) between different accident events x_i and x_j for the set of accident points P that are Completely Spatially Random (CSR) (Yamada and Thill, 2004).

DBSCAN is another commonly applied method for partitioning a set of events into clusters (Shi and Pun-Cheng, 2019). DBSCAN works to group accident events with similar attributes into clusters. This method is also premised on two main attributes, the longitude and latitude of the accident events. DBSCAN requires two analysis parameters: a) epsilon which specifies the distance threshold of clustering among points for clustering consideration, and b) minPts which stipulates the minimum number of neighboring accident events that should be considered (Agrawal et al., 2018).

Spatial density estimation has also been used to reason about accident hot spots. Shiode and Shiode (2009) utilize Planar Variable-Distance Clumping Method (PL-VCM) to develop a new methodology to analyze the distribution pattern of hot spot points observed over road networks. The point-pattern analytic methodology is characterized as the Network-Based Variable-Distance Clumping Method (NT-VCM). This method defines the group of accident events that are located within a certain Euclidean distance of one another as a clump. The Network-Based Variable Distance Clumping Method (NT-VCM) is used to analyze the spatial clustering of accident events on a road network. NT-VCM is regarded as an extension of the traditional Planar Variable Distance Clumping Method (PL-VCM) which utilizes Euclidean distance. For network spatial analysis, Okabe (2000) uses the planar hot spot spatial method to develop an extended network spatial hot spot analysis methodology by utilizing a network Voronoi diagram to determine the nearest neighborhoods to specified point events. This method generators are indicated in the road networks by a set of points, lines, and polygons whose distances between points are defined as the shortest network paths or shortest time periods.

Kernel Density Estimation (KDE) has also been used to reason about hot spots in the context of phenomena such as accident events (Bíl et al., 2013; Jia et al., 2018; Steenberghen et al., 2010). KDE can be used to estimate the spatial density of point-based events (Mountrakis and Gunson, 2009). It works by applying a planar kernel function to analyze areas a and their neighborhoods (i.e., defined as events b falling within a specified distance of a) to compute a measure of density for area a (Erdogan et al., 2015). Methods like KDE work by generating a tessellation (polygons or raster cells) over the study region and then aggregating points into polygons or raster cells comprising the tessellation. Once spatial density has been estimated, the analysis areas can be categorized into hot spots based upon the level of density (Jia et al., 2018; Le et al., 2019). Figure 1 depicts the results of a planar KDE for a set of selected accident events.

In cases in which interaction among events is thought to be confined to a network, Network Kernel Density Estimation (NKDE) can be used to estimate accident hot spots (Fan et al., 2018; Harirforoush and Bellalite, 2016; Mohaymany et al., 2013; Nie et al., 2015; Okabe et al., 2009, 2006; Xie and Yan, 2013). NKDE is a direct extension of the planar two-dimensional KDE but uses network distance to measure the distance between two points instead of using Euclidean distance (Nie et al., 2015; Okabe et al., 2009).

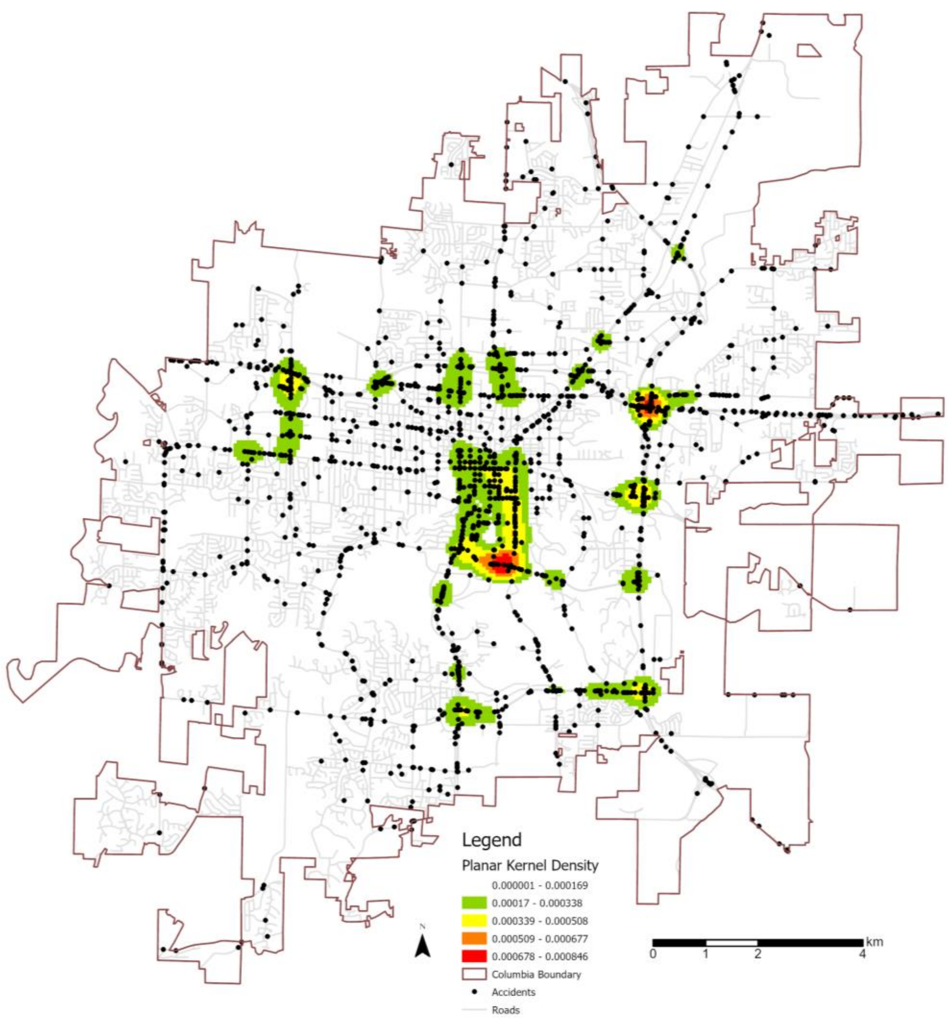


Figure 1. Example of Planar KDE for vehicular accidents

Whereas dividing a planar study area into equal-sized analysis areas is rather straightforward, partitioning a road network into equally sized analysis areas can be a bit more challenging. Therefore, Okabe et al. (2006) propose applying the shortest path distance method to obtain the straight path from arbitrary points for the provided object points that are called root. Okabe et al. (2006) also suggest applying the extended Voronoi diagram constructed method as another spatial network computational analysis technique to simplify the analysis of the network. Both create analysis areas and boundaries are sharply defined and deterministic. By using the accident events as an input for the NKDE analysis, the density of accidents along the portions of the roadway can be visually interpreted (Mohaymany et al., 2013). Figure 2 illustrates an example of NKDE for selected accident events.

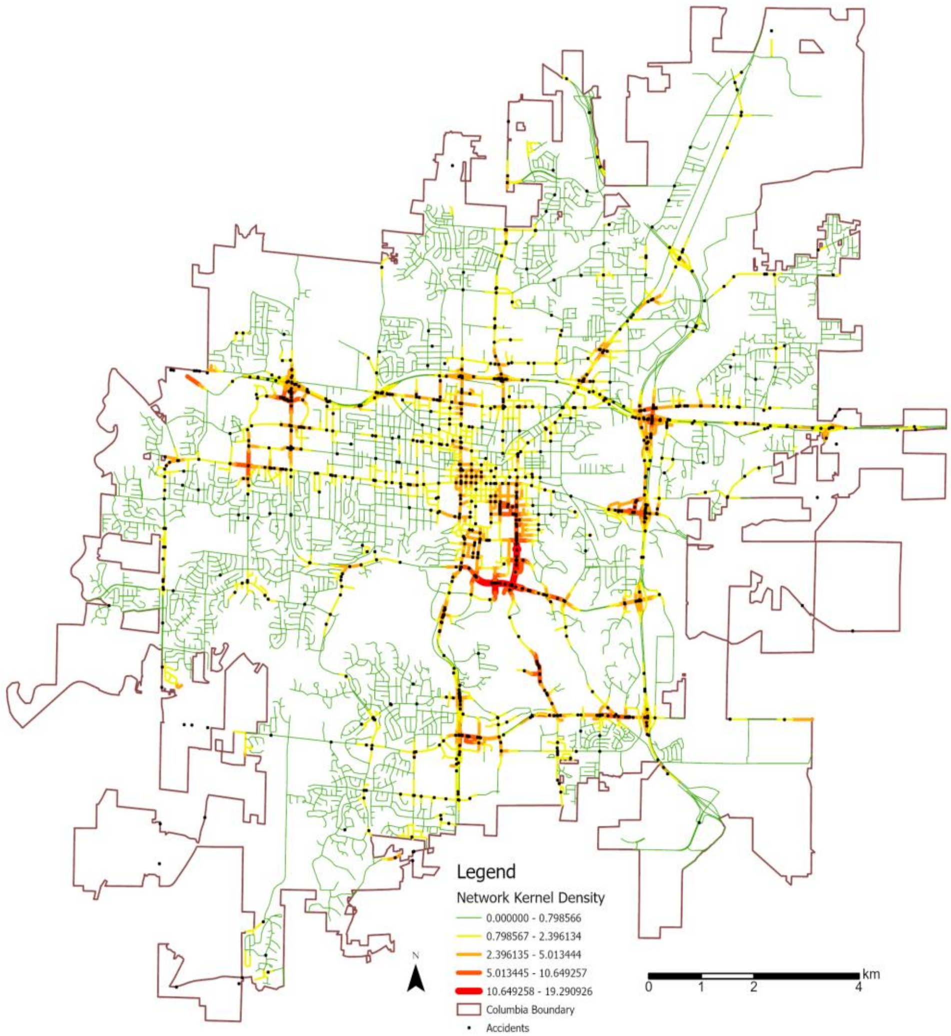


Figure 2. An example of NKDE for vehicular accidents

Though both KDE and NKDE have been widely used for vehicular accidents, the resulting hot spots are not associated with any measure of statistical significance (Le et al., 2019). To categorize the distribution frequency of accident events, there is a need to evaluate some parameters which may underly spatial autocorrelation (Jia et al., 2018). Spatial statistics such as Getis and Ord G_i^* and Moran's *I*, have been utilized to identify accident hot spots (Anselin, 1995; Ord and Getis, 1995). Moran's *I*, can be used to verify the existence of the spatial autocorrelation among the attributes of accidents (Blazquez and Celis, 2013; Matkan et al., 2013; Mohaymany et al., 2013). Global Moran's *I*, measures the spatial correlation of each object (x_i) to all other surrounding objects (x_j) located within a specified distance d. A spatial weights matrix is used to represent neighborhood relationships among analysis units (Anselin, 1995). The statistical significance of Moran's *I*, is provided by way of a z-score, assuming normal distribution with zero values of mean and one variance. A positive z-score indicates that the accident points (x_i) have similar surrounded values while a negative z-score indicates that accident points (x_i) have dissimilar surrounded features. In order to measure spatial dependence by using the z-score statistical significance for clustering, the statistical index of Moran's *I*, shall be used to evaluate the existence of spatial autocorrelation within the descriptive variables (Bao et al., 2017; Sánchez-Martín et al., 2019; Wuschke et al., 2013). The spatial correlation of global Moran's *I*, describes the pattern of a set of accident clusters by indexing them into different expressions like random or dispersed clusters (Al-Ruzouq et al., 2019).

G_i^* is another global spatial autocorrelation method for inspecting the accident events' hot spots (Nie et al., 2015). Given a specified radius distance d, G_i^* defines the correlation for all pairs of event points (x_i, x_j) (Ord and Getis, 1995). A negative value of G_i^* accompanied by an acceptable p-value can be viewed as a significant spatial clustering of low values or negative autocorrelation (e.g., low value surrounded by low values). A positive value of G_i^* accompanied by an acceptable p-value can be interpreted as signification clustering of high values or positive spatial autocorrelation (e.g., high value surrounded by high values) (Getis and Ord, 1992).

Though both global G_i^* and Moran's I are most commonly used in spatial autocorrelation analysis (Ouni and Belloumi, 2019), both do not provide a way to quantify spatial autocorrelation for specific locations (Grubesic et al., 2014). However, both statistics have been extended to provide the analysis of local spatial autocorrelation. The main difference between the local and global Moran's I is in the defined statistical mean of the local Moran's I (Anselin, 1995). The local versions of these statistics provide a z-score and p-value for each event location, rather than simply a single z-score and p-value for the entire set of sites as in the global Moran's I.

The local G_i^* has also been used in some studies to evaluate the spatial autocorrelation of accident events (Blazquez et al., 2018). A low value (LL) of G_i^* indicates low values which are surrounded by low values, while high value of G_i^* (HH) indicates that high values are surrounded by high values (Erdogan et al., 2015).

2.2 Assessing the Spatial and Temporal Relationship Among Accidents

Given a set of accident locations (and their attributes), a variety of geospatial analysis methods have been applied in efforts to characterize accident hot spots. Algorithms, such as *K*-means and DBSCAN, have been used to partition a set of point-based events into groups based on their proximity in attribute and/or geographic space (Agrawal et al., 2018; Anderson, 2009; Kim and Yamashita, 2007; Shi and Pun-Cheng, 2019; Xia and Yang, 2019). For example, a spatial neighborhood can be specified such that accident events within the neighborhood of one another can be considered candidates for the same group (Agrawal et al., 2018). The output of these types of algorithms is an assigned group for each of the input features. *K*-means and DBSCAN have been used to examine both spatial and temporal dimensions of accident clustering (Soheily-Khah et al., 2016). For example, DBSCAN method has been extended to incorporate a temporal neighborhood in addition to a spatial neighborhood (e.g., ST-DBSCAN (Birant and Kut, 2007)).

Spatial density estimation has also been used to reason about accident hot spots (Bíl et al., 2013; Jia et al., 2018; Steenberghen et al., 2010). Kernel Density Estimation (KDE) (Erdogan et al., 2015; Xie and Yan, 2008) and its network-based counterpart Network Kernel Density Estimation (NKDE) (Fan et al., 2018; Harirforoush and Bellalite, 2016; Mohaymany et al., 2013; Nie et al., 2015; Okabe et al., 2009, 2006; Xie and Yan, 2013), can be used to estimate the spatial density of point-based events within a set of analysis areas. Typically, these methods first aggregate the points to a tessellation (e.g., polygons or raster cells) of the study region. A kernel function that accounts for observed events within a geographic neighborhood of each analysis area is then applied to estimate the density of events (Erdogan et al., 2015). Once spatial density has been estimated, analysis areas can be categorized into hot spot types based upon the level of density (Jia et al., 2018; Le et al., 2019). KDE and NKDE have both been utilized to reason about the spatial and temporal dimensions of vehicular accidents (Harirforoush and Bellalite, 2016; Le et al., 2019; Xie and Yan, 2013).

Spatial statistics such as the Getis and Ord G_i^*, Moran's *I*, and Ripley's K-function have also been utilized to identify accident hot spots in both the spatial and temporal dimensions. These methods work by evaluating a set of input locations and their attributes for spatial dependency (Anselin, 1995; Ord and Getis, 1995). For example, the

Getis and Ord G_i^* is a local measure of spatial autocorrelation that accounts for the relationship between a feature at a location i with all other features i within a spatial neighborhood of i (N_i) (i.e., spatial weights) (Getis and Ord, 1992). Also, a negative value of G_i^* accompanied by an acceptable p-value can be viewed as a significant spatial clustering of low values or negative autocorrelation (e.g., low value surrounded by low values). A positive value of G_i^* accompanied by an acceptable p-value can be interpreted as signification clustering of high values or positive spatial autocorrelation (e.g., high value surrounded by high values). For example, Ripley's K-function has been adapted to account for the spatial relationships among features within a set of time intervals (Mountrakis and Gunson, 2009; Yamada and Thill, 2004). Moran's *I* and the Getis and Ord G_i^* have also been utilized to evaluate the spatial associations among accidents over different temporal scales (Blazquez and Celis, 2013; Matkan et al., 2013; Soltani and Askari, 2017).

Beyond analyzing spatial autocorrelation for different periods of time, there have been efforts to extend statistical methods to simultaneously account for both spatial and temporal dependency. For example, Hardisty and Klippel (2010) describe the LISTA-Viz tool as a spatiotemporal counterpart to the local Moran's *I* statistic. Similarly, Wang and Lam (2020) extend the G_i^* to include a temporal neighborhood. Likewise, ESRI has implemented a version of the G_i^* statistic to facilitate the analysis of spatiotemporal autocorrelation in its Emerging Hot Spot Analysis (EHSA) tool (ESRI, 2019) which has been applied to explore the relationships among vehicular accidents (Cheng et al., 2018; Kang et al., 2018).

ESRI EHSA (ESRI, 2019) tool works by partitioning a study region into a set of regularly sized areal units $i \in I$. The dimensions of the analysis areas a_i can be configured based upon the desired level of spatial resolution (Figure 3). Incident point events P_t are aggregated to the areal units of analysis within which they are located. The temporal frame is also partitioned into regularly sized periods $t \in T$. For each time period t, analysis areas a_{it} are then created. The time period size t unit is selected based on the desired level of temporal resolution. Therefore, the point-based events should be attributed with a temporal indicator (e.g., date/time stamp).

The EHSA tool determines the statistical significance of hot and cold spots for each analysis area a_{it} based on neighboring analysis areas a_{it}. A time step interval is defined to determine how the point events P_t should be temporally partitioned. For example, the point-based events could be portioned by day, week, month, or year. Whereas each analysis area a_{it} is assessed relative to its spatial neighborhood, the temporal neighborhood n_t can be defined to include the present as well as any number of previous time periods t, Figure 4.

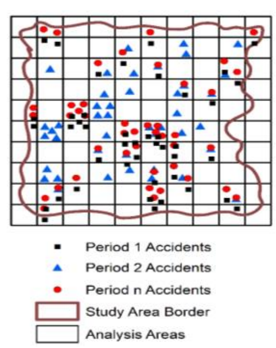


Figure 3. Spatial and temporal aggregation of point events into analysis areas a_{it}

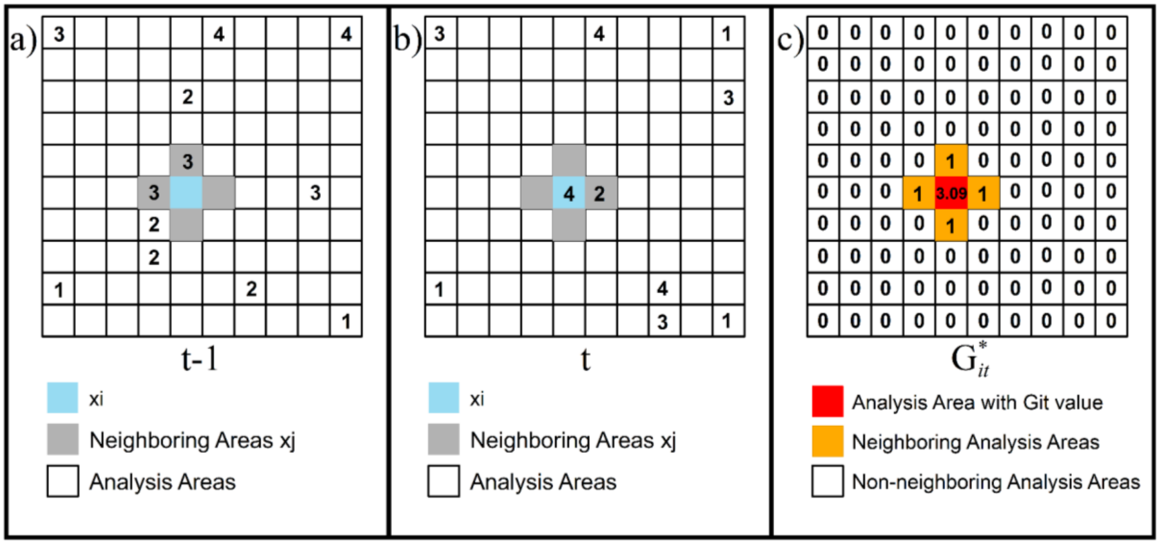


Figure 4. Spatial and temporal neighborhoods for analysis area a_{it} (a) time t-1, b) time t), and c) the computation of G^*_{it}

For example, one might elect to use analysis areas a_{it} having a spatial resolution of 250m x 250m, within which accidents occurring over one-week time periods t are analyzed the spatial and temporal neighborhood being the current week as well as the previous week. Given a spatial neighborhood defined as all areas whose centroids fall within 250m of each analysis area each neighborhood will consist of the four adjacent (horizontally and vertically) analysis areas a_{it} within the temporal neighborhood n_t. The output of the EHSA for each analysis area a_{it} is then a z-score and p-value that can then be evaluated. Figure. 4 depicts the G^*_{it} value (z-score) of an analysis area a_{it} with the spatial correlation values of the neighboring analysis areas. The analysis consists of the neighboring objects to the analysis area a_{it} which are located within a specified distance band or threshold distance and have an observed value greater than 0.0 (Figure. 4a&b). In this case, the spatial weight amount for each neighbor is binary, either 0.0 or 1.0. Hence, neighboring analysis areas are given a weight of 1.0 if they are located within the specified neighborhood distance and 0.0 if they are not (Figure. 4c). Figure. 4c depicts the resulting value of statistical G_{it}^* (z-score), considering the observed value of the one neighboring object x_j (i.e., observed value = 2) during the present time period t and object x_i (observed value = 4) (Figure. 4b) in addition to the dual neighboring objects x_j (i.e., observed value = 3) from the previous time period $t-1$ (Figure. 4a).

The EHSA tool characterizes the results by grouping them into different categories of spatial and temporal trends over the entire analysis period. For example, analysis areas may be labeled as exhibiting hot spot trends such as Consecutive, Intensifying, Persistent, Diminishing, Sporadic, etc. (ESRI, 2019). EHSA has been used to assess spatiotemporal dependency among accident events (Gudes et al., 2017). Given a set of observed point-based events over time, the EHSA aggregates the events into analysis areas at the specified temporal interval (e.g., one-month, two-week). The EHSA incorporates both spatial and temporal relationships among the analysis areas to compute the local G_i^* statistic. EHSA has been applied to investigate the spatiotemporal clustering trend of some sorts of disasters like forests loss, pandemics, and accidents. (Cheng et al., 2018; Gudes et al., 2017; Harris et al., 2017; Kang et al., 2018).

In addition to modeling the spatial and temporal dependencies among vehicular accidents, there is a need to understand the morphological characteristics of these dependencies, such as their geographic size or extent, and how that may evolve over time (Matisziw et al., 2020). From a traffic safety and accident prevention standpoint, it is essential to have firm measures of the spatial dynamics associated with accident occurrence to facilitate decision support as to where the need for accident mitigation resources exists as well as to document the level of success (or lack thereof) of past and/or current mitigation efforts (Levine and McEwen, 1985; Nazif-Munoz et al., 2020; Wang et al., 2020). Understanding the geographic extent (i.e., size/shape) of the portions of the transportation system to be treated is something that is particularly vital in this respect given that activity patterns in networks are rarely uniform over space and time. Provided a better characterization of hot spot morphology, assessments of system change can be improved as can attempt to identify higher quality resource allocation scenarios (Matisziw and Murray, 2009a, 2009b).

At the most basic level, 2-D and/or 3-D visualization has been used to describe the geographic extent of accident clustering over time (Cheng et al., 2018; Gudes et al., 2017; Harris et al., 2017). There have also been attempts to quantify the size of clusters. For example, given that algorithms such as DBSCAN assign features to groups, the number of features in each group can be used as a measure of cluster size (Agrawal et al., 2018; Shi and Pun-Cheng, 2019). However, in the case of accident analysis, not all accidents may be associated with a cluster in a period of time. That is, instances can occur in which an accident may not have a strong spatial or temporal relationship with other accidents. In this sense, statistical measures of spatial dependency do provide a way to quantify the significance of the spatiotemporal relationships among the areal units of analysis which can be used to refine the assignment of analysis areas to clusters. However, the measures of spatial dependency are typically summarized for the individual analysis units and are not directly equated to the broader characteristics of the cluster(s) associated with the analysis areas over time. Whereas prior researches on the spatial aspects of vehicular accidents have addressed temporal and spatial clustering (Blazquez et al., 2018; Blazquez and Celis, 2013; Cheng et al., 2017; Erdogan et al., 2015; Matkan et al., 2013; Ouni and Belloumi, 2019; Soltani and Askari, 2017; Stipancic et al., 2018; Wen et al., 2019), another important aspect is the size of the clusters and how they may change over time/space (Gudes et al., 2017; Harris et al., 2017). To this end, a methodology for computing and tracking changes in cluster morphology is now detailed. This methodology allows increases and declines in clusters of accident activity to be better assessed. Better definition and quantification of accident hot spot morphological characteristics can provide valuable decision support for accident mitigation and prevention planning strategies.

2.3 Statistical Comparison Approaches of Accident Modeling

A variety of statistical comparison tests have been applied to indicate the similarity/non-similarity of algorithm assumptions. There are two types of tests for statistical comparison of datasets, parametric and non-parametric. According to the assumption of the normality distribution and adequate sample size, parametric statistical methods depend on the shape of the normal distribution in the main population in addition to the means and standard deviations. Therefore, the failure to meet the normality distribution conditions could be a good motivation to use and utilize non-parametric statistical models (Awang et al., 2015).

2.3.1 Parametric Methods

A range of parametric comparison analysis methods has been utilized in attempts to compare groups of accidents within the same dataset or groups of accidents among different datasets. T-tests such as one-sample, unpaired (independent), and paired (dependent), have been applied in an effort to compare one group with a theoretical value

(Athwani et al., 2020; Harré and Sibley, 2007; Islam et al., 2021; Soltanzadeh et al., 2016). Some other researchers compare two unmated groups of data (Hsieh et al., 2016; Kogani et al., 2020a; Kuo et al., 2017; Maeda et al., 2009; Reazaul et al., 2016) while others compare two combined groups sequentially (Freitas et al., 2019; Hu and Zheng, 2009; Xu et al., 2017). By comparing how the means, frequencies, and standard deviation of a variable differs, the output of these types of t-tests are the size of the difference of the variation or mean between the two different datasets. For example, in such cases of paired t-test, if the p-value is greater than the statistically significant value, there is a significant difference between the two compared treatments (Tae Kyun Kim, 2015). Measuring the variation size by t-value implies the greater value of t-value and increases the evidence of the rejection of the null hypothesis.

In addition, in the case of comparing the mean of three group accident datasets or more (e.g., compare means of the same or different datasets), one-way and two-way analyses of variance (ANOVA) have also been utilized to examine the group means difference (Farah, 2011; Hunde and Aged, 2015; Kogani et al., 2020b; Lee et al., 2016; Mahdian et al., 2015; Sikdar et al., 2017; Syahira et al., 2014). ANOVA can be applied to verify whether there are any statistical differences between the means of more than two independent dataset groups by testing the null hypothesis. One-way ANOVA is accompanied by one factor or independent variable (Joni et al., 2020) while two-way ANOVA is complemented by two independent variables (Saifizul et al., 2011). To verify whether there is a variation between the means of the compared groups, the null hypothesis asserts that the population means of all dataset groups are all equal.

Therefore, if the p-value is less than or equal to the significance level, the null hypothesis is rejected and not all the population means are equal (Athwani et al., 2020).

The Pearson correlation is another parametric test that has been utilized to compute the correlation between two group means in an accident dataset (Dorn and af Wåhlberg, 2019; Ivan et al., 2015; Jones et al., 2007; Pei et al., 2019). Once the coefficient value of correlation has been estimated, it can be categorized into strong, medium, or small. For example, if the coefficient value is between ±0.5 and ±1, indicates a strong correlation (Cernovsky et al., 2021a). Moreover, medium correlation is for the coefficient value that is ranged between ±0.3 and ±0.49 while small correlation is for the value that is less than ±0.29. However, the nearest coefficient value to ±1 reflects the perfect correlation between variables.

Regression analysis can be utilized when there is a need to forecast a continuous dependent variable from multiple independent variables. Simple regression can be applied to model the correlation between two examined variables (e.g., x and y) (Cohen et al., 2003). Given a set of accident locations, simple regression has also been utilized by much researchers to identify the impact of some factors on the occurrence and frequency of accidents (Ahmed, 2017; Cohen et al., 2003; Hasanspahić et al., 2021; Ismail et al., 2010; Kim et al., 2014; Ratnayaka et al., 2017). Multiple regression is an extension of single regression when more than two or more explanatory variables are used to calculate the output of a response variable (X) (Science et al., 2021). For example, multiple regression has been utilized to inspect some common factors that influence the occurrence of accidents (Beppu et al., 2021; Endo et al., 2021; Hasanspahić et al., 2021; Ismail et al., 2010).

2.3.2 Non-Parametric Methods

Beyond performing statistical comparisons for different accident datasets that met the requirements of the normal distribution and equal variances between groups, there have been some efforts to extend statistical comparison methods for accident datasets that do not meet the requirements of the normality distribution (Torsen and Atule, 2018). Non-parametric tests have been considered as an extension of parametric tests, which sometimes terms as distribution-free tests. These tests assume the non-normality distribution of datasets and characterize the median as the center of the distribution dataset instead of the mean for the comparison procedures (Kitchen, 2009). Tests, such as the Wilcoxon test, have been utilized as an alternative to the one-sample t-test and paired t-test based on the non-normality distribution of datasets. For example, Macedo et al., (2021) employ the Wilcoxon test instead of a t-test on accident datasets due to the rejection of the theory of normality distribution. The main goal of the Wilcoxon test is to verify statistically significant similarity of medians between two sets of the dataset (e.g., crimes, accidents, pandemics). Therefore, the null hypothesis is rejected when the p-value is less than or equal to the significant level (e.g., $p \leq 0.05$) (Iqbal et al., 2021; Macedo et al., 2021; Prosen et al., 2021; Torsen and Atule, 2018; Upaphong et al., 2021). The Mann-Whitney test has also been used as a nonparametric alternative to the t-test (Hsieh et al., 2016; Shimizu et al., 2021). Typically, this method is used instead of the parametric unpaired t-test to compare two unpaired data groups. The rejection of the null hypothesis in the case of the Mann-Whitney test is proposed when there is no actual difference between the two groups of accident datasets and the p-value is equal to or less than the significance level (e.g., $p \leq 0.05$) (Goulart et al., 2020; Kuo et al., 2017).

Non-parametric contrasting methods such as the chi-square test have also been utilized to determine if the difference between both observed and expected different characteristics of accident datasets within the same or multiple groups of datasets is due to either relationship or chance. For example, Hunde and Aged (2015) test the association between the road accident type and damage severity. The chi-square analysis results illustrate the amount of the significant difference between the observed and the expected counts then verify whether the correlation between both observed and expected counts is due to relationship or chance. Therefore, a low chi-square means value can imply a high correlation between the groups of the compared datasets (Hunde and Aged, 2015; Kogani et al., 2020a; Mahdian et al., 2015; Upaphong et al., 2021). The Kruskal-Wallis test is a non-parametric version of the ANOVA test which assumes the non-normality dataset distribution. This test has been considered as a direct equivalent to the Chi-Square test and also as an extension to the Wilcoxon test (Torsen and Atule, 2018). This method has also been used for two or more independent group samples that have been utilized to compare three or more unpaired accident dataset groups (Wang et al., 2018). The rejection of the null hypothesis when the p-value is less or equal to the significance level (e.g., 0.05) indicates that the compared group medians are non-equal (Torsen and Atule, 2018).

The Spearman correlation coefficient has been applied to compute the correlation between two groups within a single accident dataset as a non-parametric alternative instead of the Pearson correlation test (Cernovsky et al., 2021b, 2021a). This method works by indicating the association between ranks (i.e., from +1 to -1). For example, the Spearman correlation coefficient, r_s of +1 and -1 signifies a perfect positive and negative correlation between ranks respectively (Sun et al., 2021a). Moreover, r_s values that are closer to zero indicate a weak correlation between the compared ranks. An alternative regression model in the case of non-normally distributed datasets is nonparametric regression which provides outputs in non-predetermined forms (Wang et al., 2018). This test has been used widely for correlation prediction between the dependent variables (Y) and independent variables (X) (Ma and Yan, 2014; Smith and Demetsky, 1994).

2.4 Review of Some Statistical Approaches of Accident Modeling

A set of different statistical analysis methods has been applied in efforts to determine the correlation between categorical variables over accident datasets. For example, Negative Binomial regression (Msengwa and Ngari, 2021; Mustefa and Belayhun, 2019; Wang et al., 2021; Zou et al., 2021) and Poisson regression (Genowska et al., 2021; Khan and Hussain, 2021; Msengwa and Ngari, 2021; Sagamiko and Mbare, 2021; Twenefour et al., 2021; Wang et al., 2021; Yang et al., 2021), have been widely used to model of count accident dataset to verify the impact of independent variables X on the given dependent variables Y. The main difference between Poisson and Negative Binomial when the later releases the restricted hypothesis and the mean value is equal to the variance that made by the Poisson model (Maxwell et al., 2018).

Beyond performing generalized linear models analysis for accident datasets, there have been some recent efforts to apply some statistical analysis methods to datasets that demonstrate excess zeros and overdispersion (Tang et al., 2015). For example, Katrakazas et al., (2021) utilize Zero Inflated Poisson (ZIP) model to account for such zeros excess. Similarly, Dong et al., (2014) exploit the Zero Inflated Negative Binomial (ZINB) over the accident dataset when the goodness of fit of the later model is higher than other compared models. The estimated maximum likelihood can be used to assess the parameters of both ZIP (Aga et al., 2021; Katrakazas et al., 2021; Sun et al., 2021b; Vazirizade et al., 2021) and ZINB (Briz-Redón et al., 2021; Gu et al., 2020; Khattak et al., 2021; Liu et al., 2018; Prasetijo and Musa, 2016; Sharma and Landge, 2013; Weng et al., 2016) regression models and confidence intervals that are constructed by likelihood ratio tests. Zero-inflated models have exhibited fantastic flexibility in both a logit (logistic) and probit (normal), although their prediction applicability to the accident dataset has been condemned because of the zero value of long-term mean in the safe state, and hence, biased estimates might cause (Lord and Mannering, 2010). Specific differences between three or more group mean methods such as the post hoc test has also been utilized after the rejection of the null hypothesis by the ANOVA test (Kerry et al., 2021; Kim et al., 2021; Lee et al., 2016, 2021; Maeda et al., 2009; Torsen and Atule, 2018). For example, Steiner et al., (2021) utilize Tukey post hoc to test the variance of accident frequency over a period of a week. Similarly, Syahira et al., (2014) perform Tukey's HSD to compare the mean of the three accident groups of unequal sample datasets after performing a two-way ANOVA.

CHAPTER 3

METHODS

3.1 General

There is a necessity to track the transportation system incidents in both spatial and temporal dimensions. Numerous studies provide diverse views towards defining the clustering of events from different perspectives. However, there is a need to characterize how morphologies of clusters (i.e., size and shape) may evolve over time. In this chapter, prospects for using methods such as the EHSA and other statistical approaches to shed light on the evolution of cluster morphology over time are discussed.

3.1.1 Modeling Evolution of Cluster Size

To reason about the morphological characteristics of accident hot spots, information on the time and location of accidents is essential. In many instances, accident records include information such as the date/time of an accident as well as a locational reference (e.g., longitude/latitude or linear reference), allowing them to be represented as a point feature. The accidents can then be analyzed for spatiotemporal clustering either as points or areas. This type of analysis is commonly supported by a variety of public and commercial software, especially geographic information systems (GIS). However, to facilitate the tracking of accident clustering over time, a consistent spatial areal unit of analysis (e.g., polygons or raster cells) is needed. The point-based information about accidents occurring in any period can then be related to the analysis areas, a task that can be easily accomplished using a GIS.

After the analysis areas $i \in I$ have been attributed with the characteristics of crashes occurring in a period, measure(s) of spatiotemporal clustering can be computed. For example, given N_i, the set of areas j assumed to constitute the spatial neighbors of the area i, the EHSA toolkit could be used to compute the G_i^* statistic for each analysis area over a set of time periods. In other words, the statistic is computed for each analysis area/time period as in Equations (1)-(5). Wang and Lam (2020) demonstrate a similar notion, but do not explicitly define a G_{it}^* statistic.

$$G_i^*(V_{ST}) = \frac{\sum_j w_{ij}\, x_j - \bar{x}^*\, V_i^*}{S_N^* \sqrt{\frac{N\, S^*{}_{Ni} - {V_i^*}^2}{N-1}}} \tag{1}$$

$$V_i^* = \sum_{j \neq i} w_{ij} + w_{ii} \tag{2}$$

$$S_{Ni}^* = \sum_j w_{ij}^2 \tag{3}$$

$$\bar{x}^* = \frac{\sum_j x_j}{n} \tag{4}$$

$$S_N^* = \sqrt{\frac{\sum_j x_j^2}{N} - (\bar{x}^*)^2} \tag{5}$$

$G_i^*(V_{ST})$ describes the spatial autocorrelation of i occurrence over all n events with the space-time connectivity matrix, while x_j describes the magnitude of x value (i.e., observed value) at neighbor location j over n values during both present t and previous $t - N$ time periods. Moreover, w_{ij} represents the binary spatial weight value (i.e., either 0 or 1) between i and j events, which reflects their spatial correlation during both present time t and previous time periods $t - N$. Also, w_{ii} represents the spatial weight of the object x_i itself when $w_{ii} \neq 0$ and n signifies the whole number of features. Also, equations 4 and 5 depict the mean and standard deviation respectively, where x_j, represents the attribute value at location j over n events.

Along with the computation of the G_{it}^* statistic, a z-score, and p-value are provided for each analysis area a_{it}. Hence, any analysis areas a_{it} feature with high z-score values (i.e., $z_{it} \geq 1.65$) and are surrounded by other features with high z-score values also can be defined as statistically significant hot spots (HH). Also, areas with low z-scores (i.e., $z_{it} \leq -1.65$) that are surrounded by areas also having low z-scores can be defined as statistically significant cold spots (LL). For each period, the analysis areas could then be classified into groups exhibiting similar statistical characteristics. Analysis area polygons of the same group could then be geometrically merged in cases where they are geographically connected to render the broader spatial extent and morphology of the cluster. Next, a methodology for accomplishing this general process is outlined in greater detail.

Once a measure of clustering has been obtained for a set of analysis areas $i \in I$ for each period $t \in T$, the *Spatial-Temporal Aggregation of Groups* (*STAG*) procedure described in Figure 5 can be applied. For each period and group (Steps 1-2), the subset of analysis areas Λ qualifying for membership in a group is selected (Step 3). The group membership of the area i can be indicated by the clustering technique (e.g., *K*-means) and/or derived with respect to a set of criteria, such as clustering indices (u_{it}), z-scores (z_{it}), *p*-values (p_{it}), etc., or some combination therein. For example, Figure 6a shows a set of areas that have been classified into two groups based on the G_i^* statistic, those exhibiting high levels of significant positive spatial autocorrelation (e.g., $z_{it} \geq 1.65$ and $p_{it} \leq 0.1$) and those exhibiting low levels of significant negative spatial autocorrelation (e.g., $z_{it} \leq -1.65$ and $p_{it} \leq 0.1$). A new empty polygon topology Q_{tk} is initialized to store the cluster polygons of a group k in time t that will be created. Steps 4-9 represent a breadth-first search procedure for identifying the spatial clusters, the sets of analysis areas that are geographically connected given a specified spatial neighborhood structure. The neighborhood structures that are used to define clusters can be the same as that used in the computation of the spatiotemporal clustering metric (e.g., the N_i used in the EHSA) or any other neighborhood structure $\hat{N}_i$ given the analysis context. First, a qualifying analysis area a_{it} (Step 4) is selected as the basis for a new cluster and is used to initialize a set of areas participating in the cluster (C). Ω is initialized to store the indices of areas for which the presence of other qualifying spatial neighbors has yet to be determined and L is initialized to store the indices of areas that are confirmed members of the current cluster (Step 5). As long as there are members of the cluster for which other qualifying spatial neighbors have not been determined (Step 6), one of those is selected (Step 7) and its qualifying spatial neighbors (if any exist) are added to the cluster, and it is removed from the sets of areas to be further evaluated (Steps 8-9). Once the membership for a cluster has been evaluated, the polygon representing the cluster is added to the cluster topology Q_{tk}. In the event the cluster only involves a single analysis area (Step 10), the original polygon representing that area a_{it} is added to the cluster topology (Step 11). Should the cluster be comprised of multiple analysis areas (Step 12), the union of those areas is computed and geometrically merged (Step 13) to create a representative polygon (or potentially multi-polygons) which is then inserted into the cluster topology (Step 14). Figure 6b illustrates the cluster polygon topology that is created based on the group membership and spatial neighborhoods of the qualifying analysis areas depicted in Figure 6a. For example, if each of the original analysis areas were 2,500 m^2, the merged hot spot cluster in the upper right corner of Figure 6b would have an area of 7,500 m^2. Finally, the original analysis areas participating in the cluster are labeled with the id of the cluster as well as the area of the cluster (Step 15-16). For example, Figure 6c depicts the areas of the clusters in Figure 6b related back to the original areal units of analysis. Steps 4-17 are repeated until all analysis areas have been assigned to a cluster. Table 1 also shows the model notation description of STAG Pseudocode.

Spatial-Temporal Aggregation of Groups (STAG) $\left(I, T, K, \hat{N}_i, u_{it}, p_{it}, u^k_{\min}, u^k_{\max}, p^k_{\min}, p^k_{\max}\right)$

for $t \in T$:
    for $k \in K$:
        $Q_{tk} = \{\varnothing\}$; $\Lambda = i \in I \mid u^k_{\min} \le u_{it} \le u^k_{\max}$ and $p^k_{\min} \le p_{it} \le p^k_{\max}$; $q = 1$
            for $i \in \Lambda$:
                $C = \{a_{it}\}$; $\Omega = \{i\}$; $L = \{i\}$
                    While $\Omega \ne \{\varnothing\}$:
                        Select a $v \in \Omega$
                            For $\forall j \in \hat{N}_v \in \Lambda$
                                $C.\text{append}(a_{jt})$; $\Omega.\text{append}(j)$; $\Omega.\text{remove}(v)$; $\Lambda.\text{remove}(v)$
                    if $|C| = 1$:
                        $Q_{tk}.\text{insert}(a_{it})$
                    else:
                        $G = \text{merge}(\bigcup_{c \in C} a_{ct})$
                        $Q_{tk}.\text{insert}(G)$
                    For $l \in L$:
                        $a_{lt}.\text{append}(q, \text{area}(G_q \in Q_{tk}))$
                    $q = q + 1$

Figure 5. Pseudocode for Spatial-Temporal Aggregation of Groups (STAG)

Table 1. Model notation

Notation	Description
T	total number of time intervals
I	total number of locations
K	total number of categories
a_{it}	analysis area at location i at time t
u_{it}	clustering indices at location i at time t
p_{it}	p-value at location i at time t

Again, the end result of the STAG process is the set of initial analysis areas for each time period a_{it} attributed with the *id* and area of their corresponding clusters in Q_{tk}. The areas that participate in a cluster in period t may or may not correspond with those in another period. For example, an area that was part of a large cluster in time t, may become part of a larger or smaller cluster or may no longer be associated with a cluster at all in time $t+1$. Thus, by comparing the size of the cluster to which an area belongs in one period with that in other periods, some basic trends in the evolution of cluster size can be conceptualized. Next, a very general and extendable taxonomy for describing the evolution of clusters is detailed.

Table 2 and Figure 7 provide some examples of how changes in cluster morphology over time can be categorized. The evolution of cluster size for an analysis area (e.g., a hot spot area) can be considered to fall within five broad categories: a) single occurrence, b) sustained, c) fluctuating, d) increasing, and e) decreasing. Some analysis areas may be associated with a cluster (of any size) only once throughout the entire set of time periods examined. Given there is only one observation of cluster size for these analysis areas, they can be classified as ‘single occurrence’. An example of a single occurrence cluster polygon, one that only occurs in Period 2, is shown in Table 2.

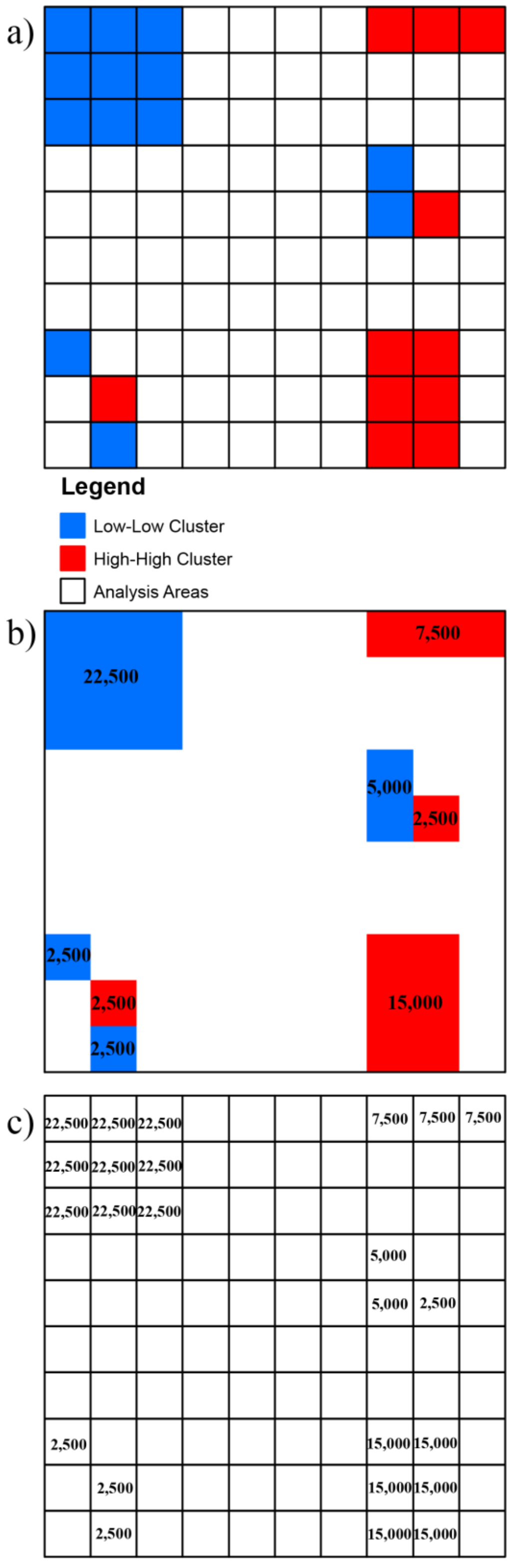


Figure 6. Spatial-temporal aggregation of groups: a) group associated with each analysis area, b) cluster polygons created from merging spatially connected analysis areas of the same group, c) initial analysis areas attributed with the size of the cluster with which they are associated

Sometimes, an analysis area may be associated with a cluster in multiple time periods. In such cases, the evolution of size can be characterized as sustained, fluctuating, increasing, or decreasing. The ‘sustained’ category refers to areas that are part of a cluster polygon whose size does not change each time it is observed. An example of sustained cluster size is shown in Table 2 and Figure 7a in which an analysis area is involved in a cluster polygon with a size of 5,000 m^2 in Periods 3 and 5. The ‘increasing’ category refers to areas that are associated with a cluster of increasing size over time. For instance, Table 2 and Figure 7c show an example of an area participating in a cluster polygon of 2,500 m^2 in Period 2 and then in one of 5,000m^2 in Period 4. Likewise, the ‘decreasing’ category pertains to areas that are part of cluster polygons of smaller size over time. The example in Table 2 and Figure 7d shows a case where the cluster associated with an area was 5,000 m^2 in Period 4 and then decreases to 2,500 m^2 in Periods 5 and 6. The size of the cluster associated with an analysis area may also fluctuate from increasing to decreasing (or vice versa) over time. The example shown in Table 2 and Figure 7b is an instance in which an area is associated with a 7,500 m^2 cluster in Period 2, a 10,000 m^2 cluster in Period 4, and then a 7,500 m^2 cluster in Period 5.

Table 2. Clusters’ size development index samples

Evolution Type	**Cluster Size (m^2) by Analysis Period**					
	1	2	3	4	5	6
Single occurrence	-	2,500	-	-	-	-
Sustained	-	-	5,000	-	5,000	-
Fluctuating	-	7,500	-	10,000	7,500	-
Increasing	-	2,500	-	5,000	-	-
Decreasing	-	-	-	5,000	2,500	2,500

Figure 7. Examples of cluster size evolution: a) sustained, b) fluctuating, c) increasing, and d) decreasing

Along with the five broad categories of cluster size evolution, there are many other ways in which areas could be classified to account for differences in the periodicity and morphology of the clusters with which they are associated. For instance, areas could also be classified based on temporal patterns Γ in the periodicity of clustering events. As an example, areas part of clusters occurring only in May, August, and October might be one unique temporal pattern that is observed, while areas part of clusters in only May, September, and October might be another pattern that manifests. Also, areas could be further classified based on patterns in the morphology of the clusters M with which they are associated. For example, the sizes of clusters of which areas are part of in May, September, and October may differ. The size of the clusters for one area might be 2,500 m^2, 5,000 m^2, and 5,000 m^2 in those three periods while the size of the clusters for another area might be 7,500 m^2, 10,000 m^2, and 10,000 m^2 for the same three periods. Given the enormous number of unique periodic and morphologic patterns that could occur there are many alternative taxonomies that could be devised in practice. In the following application, some potential ways of classifying size evolution in this respect are described.

3.1.2 Comparing Cluster Characteristics Methods

To reason about the morphological characteristics of accident hot spot evolution similarities and differences among and between different geographic locations, statistical methods (e.g., ANOVA, Zero Inflated Negative Binomial, chi-square, or post hoc) of comparing analysis are essential. On many occasions, the morphological trends identified within a study area consist of measures a such as the area of clusters of certain types which can then be compared according to morphological changes over time. This type of analysis is generally applied by an array of commercial and public software, such as Excel, SAS, SPSS, or RStudio. However, to facilitate using the cluster results as input data for comparing analysis, converting outputs from polygons or raster cells into tables or charts (ArcGIS shapefile to Microsoft excel form) is considered necessary.

Once the output of the STAG model dataset has been prepared for a set of analysis areas $i \in I$ during each period $t \in T$, the Statistical Comparing of Group Clusters (SCGC) analysis outlined in Figure 8 can be applied. For each set of analysis areas in groups (Step 1), Step 2 represents the application of statistical methods to a model probability distribution (e.g., Poisson, Negative Binomial, etc.). Identifying the best fit statistical model can be accomplished via some mode of model assessment. For example, the best fit model can be determined by some statistical comparative methods such as Akaike Information Criterion (AIC) and Rootgrams (Steps 3-4) (i.e., the best fit model is the one that stays closest to the zero-reference line or has the lowest AIC value). The best fit model can be selected according to the lowest AIC value (Steps 5-10). Once the best fit model has been selected, both observed and expected values are compared (e.g., chi-square model) and the significant correlation between categorical variables is assessed (Steps 11-12). After confirming the statistically significant correlation between variables in Step 12, a Comparing test (e.g., Post Hoc test) is used to reveal the difference between the mean values of group variables (Step 13).

Statistical Comparing of Group Clusters (SCGC) (WD, csv)

For (i) in groups:
    Run $GLM(x_i)$
    Run $AIC(x_i)$
    Run $RTGRM(x_i)$
    if $(AIC(x_a) < AIC(x_b))$
        min = $AIC(x_a)$
    else:
        min = $AIC(x_b)$
While: $AIC(x_i)$ is min:
    Select $AIC(x_i)$
        $AIC(x_i) = chisq$
        If $chisq \leq 0.05$:
            $AIC(x_i)$ = PostHoc

Figure 8. Pseudocode for Statistical Comparing of Group Clusters (SCGC)

The end result of the SCGC is a set of contrast of each two compared spatial locations (e.g., two cities) during a specific time period associated with a *p*-value. The null hypothesis states that the population mean values are all equal for both compared locations. For example, if the proposed significance level is equal to 0.05 and the resulting *p*-value is less or equal to the significance level, then the null hypothesis is rejected, and it accomplishes that not all area group mean values are equal.

Figure 9 illustrates some examples of different assigned cluster sizes to analysis areas for three different cities. Likewise, for the statistical comparison methodology, the STAG outputs for these three city areas could be set as in Table 3 after merging all these three sets of the STAG outputs in one table. The merged table consists of some sort of attributes such as city name, analysis area, temporal period, and cluster size.

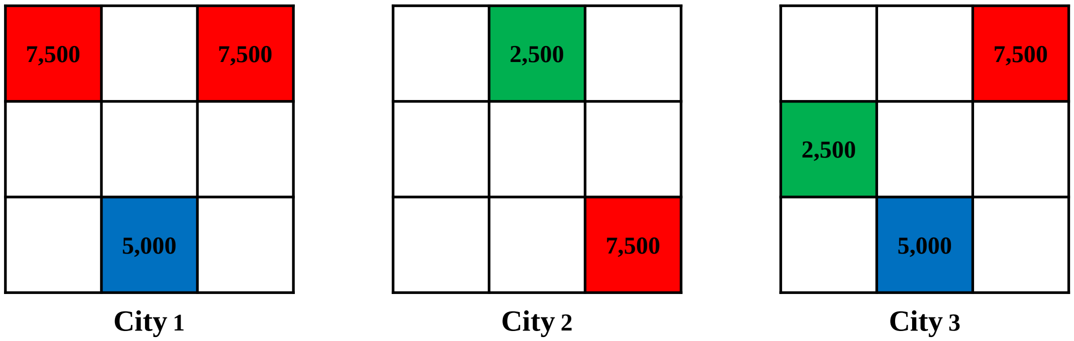


Figure 9. Example of assigned cluster sizes of analysis areas for three different cities

Table 3. Example of assigned cluster sizes of analysis areas for three different cities

City name	Analysis area	Temporal period	Cluster Size
City1	Area_1	Period_1	7,500
City1	Area_2	Period_3	7,500
City1	Area_3	Period_8	5,000
City2	Area_1	Period_2	2,500
City2	Area_2	Period_9	7,500
City3	Area_1	Period_3	7,500
City3	Area_2	Period_4	2,500
City3	Area_3	Period_8	5,000

CHAPTER 4

APPLICATION TO CLUSTER MORPHOLOGY

4.1 Introduction

This chapter describes a case study of cluster identification and hot spot assessment over time to illustrate the proposed methodology. First, the application data is documented. Next, the study site and the analysis parameters that were used in the analysis are described. Subsequently, the proposed clustering size tracking through different temporal scales with three different p-values is then implemented.

4.2 Study Area

Columbia, Missouri is a medium-sized college town (population of 126,254 in 2020), centrally located in the USA. The road system in the city of Columbia is composed of a diversity of road types (e.g., highways, interstate, arterials, collectors, etc.). A large interstate highway (I-70) traverses the city West/East for approximately 11.36 miles. Another major highway (Highway 63) crosses the Eastern portion of the city in the North/South direction for approximately 11.78 miles. Both principal and minor arterial roads are distributed over different locations around the city of Columbia as are a mix of both major and minor collector roads. Figure 10 depicts Columbia's roads and the city’s location in the USA.

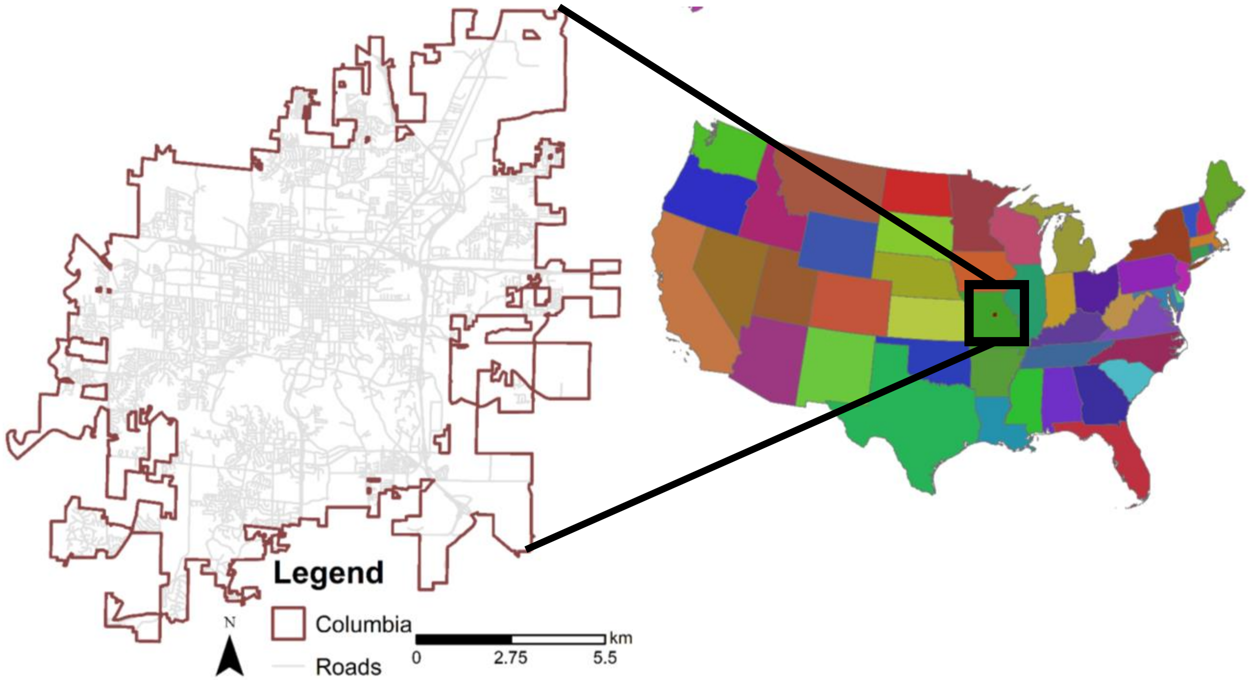


Figure 10. Columbia Missouri, USA

4.3 Accident Data

In this application, vehicular accidents recorded by local and/or state law enforcement agencies within the city of Columbia in the years 2013 and 2014 are examined (MSHP, 2020). In the year 2013, there were 1,500 reported accidents in the study area with another 1,469 in 2014 (Figure 11).

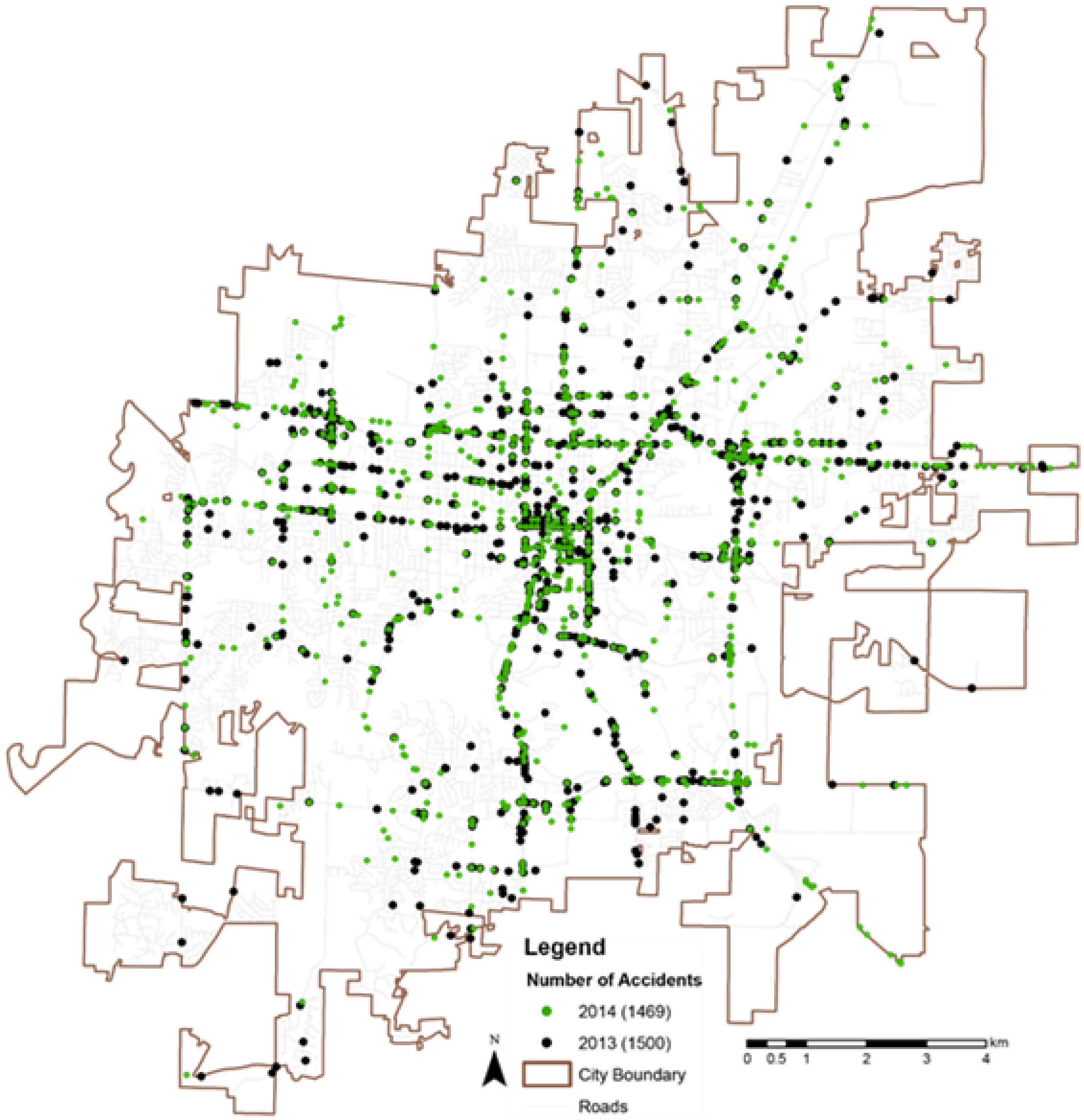


Figure 11. Accident locations in the years 2013 and 2014

Each accident record is attributed with the date and time of the event, geographic location (i.e., longitude and latitude), the number of vehicles that were involved in each accident, as well as a range of other details regarding the incident. Figure 12 depicts a sample of the attributes in the accident dataset.

Accidents - ArcGIS Pro

Crashes | *Fields: Crashes

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete Copy

OBJECT ID	ACCIDENT DATE	NO OF VEHICLES	GPS LATITUD	GPS LONGITUDE	ACCIDENT TIME
744881	7/23/2014	1	38.82533	-94.52082	16:56:00
758036	5/4/2015	1	38.8297	-94.52525	01:05:00
752874	1/1/2015	1	38.83516	-94.54558	21:28:00
743355	6/17/2014	2	38.83657	-94.52818	17:34:00
745721	8/11/2014	2	38.83975	-94.43682	16:30:00
758078	5/4/2015	2	38.84074	-94.46441	16:10:00
760686	6/23/2015	2	38.84074	-94.46441	08:00:00
758412	5/10/2015	1	38.84108	-94.43643	00:05:00
756122	3/24/2015	2	38.84148	-94.52977	15:59:00
754806	2/20/2015	1	38.84179	-94.49211	23:00:00
755538	3/11/2015	3	38.84228	-94.52953	16:30:00
730489	9/20/2013	3	38.84364	-94.52961	17:34:00
726508	7/1/2013	3	38.84366	-94.5296	16:45:00
727957	7/31/2013	2	38.84366	-94.5296	18:45:00
731101	10/2/2013	2	38.84366	-94.5296	16:45:00
731258	10/5/2013	2	38.84366	-94.5296	14:05:00
733857	11/26/2013	2	38.84366	-94.5296	16:30:00
735006	12/17/2013	1	38.84366	-94.52939	07:45:00
722360	4/3/2013	1	38.84366	-94.52939	07:20:00
726373	6/28/2013	4	38.84366	-94.5296	16:50:00
726458	6/30/2013	2	38.84366	-94.5296	11:10:00
746669	8/29/2014	2	38.84366	-94.5296	21:30:00
746707	8/30/2014	1	38.84366	-94.5296	19:00:00
747680	9/22/2014	2	38.84366	-94.5296	16:30:00
748871	10/16/2014	3	38.84366	-94.5296	15:15:00
750263	11/11/2014	2	38.84366	-94.5296	17:00:00
750426	11/14/2014	2	38.84366	-94.5296	18:30:00
752075	12/15/2014	2	38.84366	-94.5296	18:45:00
752456	12/22/2014	2	38.84366	-94.5296	17:00:00
736782	1/25/2014	2	38.84366	-94.5296	15:00:00
738572	2/28/2014	2	38.84366	-94.5296	15:50:00
738790	3/3/2014	2	38.84366	-94.5296	17:00:00
741309	5/2/2014	2	38.84366	-94.5296	16:55:00
741310	5/2/2014	3	38.84366	-94.5296	17:00:00
741892	5/16/2014	2	38.84366	-94.5296	15:00:00
741907	5/16/2014	2	38.84366	-94.5296	17:45:00
763867	8/28/2015	3	38.84366	-94.5296	17:54:00
753447	1/14/2015	2	38.84366	-94.52939	07:15:00

Figure 12. Sample of attributes associated with accidents

A variety of temporal scales of analysis can be considered for accident analysis such as single or multiple weeks or months. One-month periods are commonly selected, given that they are thought to capture seasonal effects (Kang et al., 2018) and broader variations in traffic activity and weather patterns (Wen et al., 2019). Smaller analysis periods (e.g., hours, days, weeks, etc.) could be used as well depending on accident dynamics in the study area. In the current application, the focus is on capturing broader trends in the manifestation of accident clusters given that the rate at which accidents were observed over the two years was not very high. Therefore, three different temporal scales of analysis are examined in this application: a) 12, two-month periods, b) 24, one-month periods, and c) 53, two-week periods. The frequency of accidents within the study area in each of the two-month, one-month, and two-week temporal periods is summarized in Figure 13a, 13b, and 13c, respectively. Tables 4, 5, and 6 summarize accidents recorded within Columbia in two-month, one-month, and two-week periods.

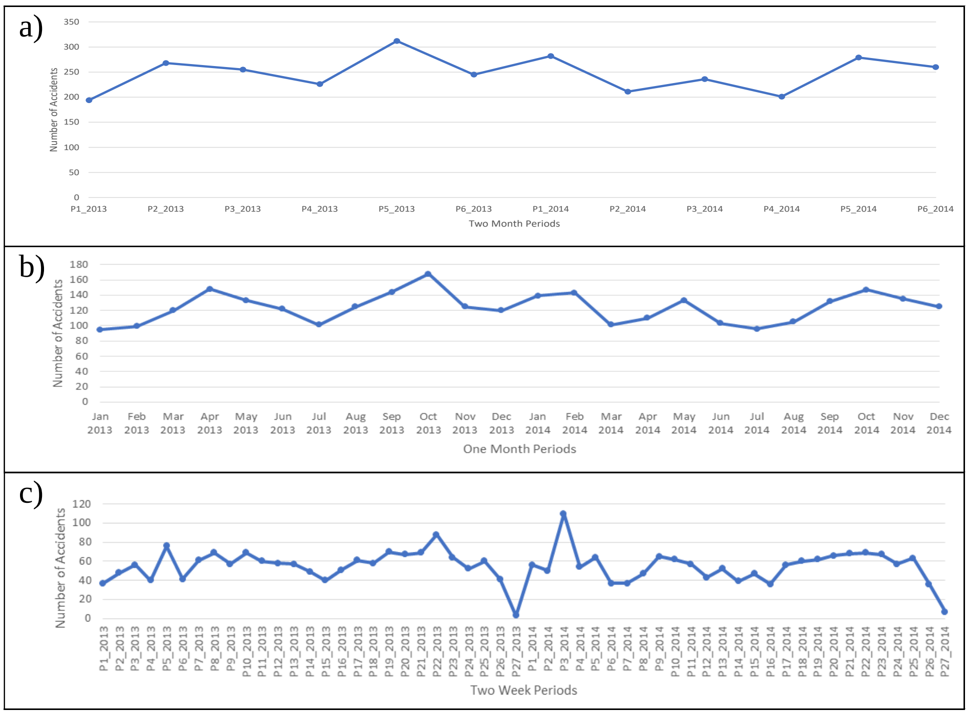


Figure 13. Frequency of accidents in analysis periods: a) two-month, b) one-month, and b) two-week periods

Table 4. Summary of accidents over two-month periods

Months of 2013	Number of vehicles per accident			No. of accidents	Months of 2014	No. of vehicles per accident			No. of accidents
	Min	Avg	Max			Min	Avg	Max	
Jan- Feb	1	1.83	5	194	Jan- Feb	1	1.93	6	282
Mar- Apr	1	1.87	5	268	Mar- Apr	1	2.03	8	211
May-June	1	1.97	5	255	May-June	1	1.97	5	236
Jul-Aug	1	2	4	226	Jul-Aug	1	2.02	5	201
Sep-Oct	1	2	5	312	Sep-Oct	1	1.99	6	279
Nov-Dec	1	1.83	5	245	Nov-Dec	1	1.94	5	260

Table 5. Summary of accidents over one-month periods

Months of 2013	Number of vehicles per each accident			No. of accidents	Months of 2014	No. of vehicles per each accident			No. of accidents
	Min	Avg	Max			Min	Avg	Max	
January	1	1.842	5	95	January	1	1.892	4	139
February	1	1.818	4	99	February	1	1.958	6	143
March	1	1.791	3	120	March	1	2.128	8	101
April	1	1.932	5	148	April	1	1.927	6	110
May	1	1.932	5	133	May	1	2.015	5	133
June	1	2.016	4	122	June	1	1.902	4	103
July	1	1.98	4	101	July	1	1.958	5	96
August	1	2.016	4	125	August	1	2.066	5	105
September	1	2.006	5	144	September	1	1.992	4	132
October	1	2.011	5	168	October	1	2	6	147
November	1	1.92	3	125	November	1	1.896	4	135
December	1	1.733	5	120	December	1	1.992	5	125

Table 6. Summary of accidents over two-week periods

Weeks of 2013	Number of vehicles per each accident			No. of accidents	Weeks of 2014	No. of vehicles per each accident			No. of accidents
	Min	Avg	Max			Min	Avg	Max	
1_2	1	1.81	3	37	1_2	1	1.8	4	56
3_4	1	1.875	5	48	3_4	1	1.94	4	50
5_6	1	1.84	3	56	5_6	1	2.02	6	110
7_8	1	1.725	3	40	7_8	1	1.87	3	54
9_10	1	1.85	4	76	9_10	1	2.14	8	64
11_12	1	1.83	3	41	11_12	1	2.05	4	37
13_14	1	1.74	4	61	13_14	1	1.92	5	37
15_16	1	1.91	5	69	15_16	1	1.94	4	47
17_18	1	2.14	5	57	17_18	1	1.97	6	65
19_20	1	1.89	4	69	19_20	1	1.98	4	62
21_22	1	1.95	4	60	21_22	1	1.95	4	57
23_24	1	1.96	3	58	23_24	1	1.76	3	43
25_26	1	2.08	4	57	25_26	1	2.11	4	52
27_28	1	1.84	3	49	27_28	1	1.92	4	39
29_30	1	2.075	3	40	29_30	1	1.96	5	47
31_32	1	1.96	4	51	31_32	1	2.19	5	36
33_34	1	2.03	4	61	33_34	1	2.01	4	56
35_36	1	2.1	5	58	35_36	1	1.93	4	60
37_38	1	1.94	4	70	37_38	1	2.09	4	62
39_40	1	2	4	67	39_40	1	1.92	4	66
41_42	1	2.04	5	69	41_42	1	2	4	68
43_44	1	1.98	5	88	43_44	1	1.94	6	69
45_46	1	1.93	3	64	45_46	1	1.925	4	67
47_48	1	1.86	4	52	47_48	1	2.01	4	57
49_50	1	1.75	5	60	49_50	1	1.92	4	63
51_52	1	1.63	3	41	51_52	1	1.91	4	36
53_54	2	2	2	3	53_54	1	2.28	5	7

Figure 14 illustrates the given set of accident point events that occur in the study region during multiple time periods (P_t); a set of analysis areas are duplicated and populated with the characteristics of the point events in the intersection with the analysis areas $S_{it} = P_t \cap a_{it}$. Now, each analysis area a_{it} has both location ID (x and y) and time step ID (t) which shows the assigned time period t scale.

Some analysis areas a_{it} have no located points of incidents P_t, so the analysis encompasses only analysis area a_{it} locations that have point events P_t of at least one space-time event for one time period t. So, for each analysis area a_{it}, the count value replicates the number of point events P_t that arose during the specified time period t at that analysis area unit a_{it}. The accident point events P_t are counted and their characteristics are evaluated to measure the trend for each analysis area a_{it}. Besides that, both the distance and the time period t of the neighborhood indicate the hot point results achieved by G_i^* statistics.

ESRI's EHSA tool (ArcMap 10.7) was used to assess spatiotemporal dependency among the accidents. Given a set of observed point-based events over time, the EHSA aggregates the events into analysis areas at the specified time interval (e.g., one-month, two-week) as illustrated in Figure 14a-c. The size of the analysis areas is an important consideration given that the spatial relationship among the areas influences the measure of spatiotemporal dependency as well as the creation of cluster polygons. As such, analysis areas should be sized to reflect the spatial structure of the network. Numerous experiments were conducted to evaluate the potential impact of analysis area size on the analytical results. In this application, the determination of analysis area size was based on the characteristics of the underlying road network. In particular, it was determined that the analysis areas best represented the system when their dimensions were approximately the length of the shortest road segment (i.e., arc) in the road network. In Columbia, the shortest road segment is around 50m, so, the study region was partitioned into 1,343, 50 m x 50 m (2,500 m^2) analysis areas.

The observed accidents occurring in the analysis areas in each period can then be analyzed. The EHSA incorporates both spatial and temporal relationships among the analysis areas to compute the local G_i^* statistic. The spatiotemporal weights for the EHSA were established using a spatial neighborhood distance of 500 m for the analysis areas and a temporal window that includes observations in period t as well as period $t-1$ for all the areas in the spatial neighborhood of each analysis area. The output of the EHSA is the G_i^* statistic (i.e., p-value and z-score) for each analysis area in each period. The spatial autocorrelation parameters that were selected to reflect the spatial correlation among the accident point events are illustrated in Table 7.

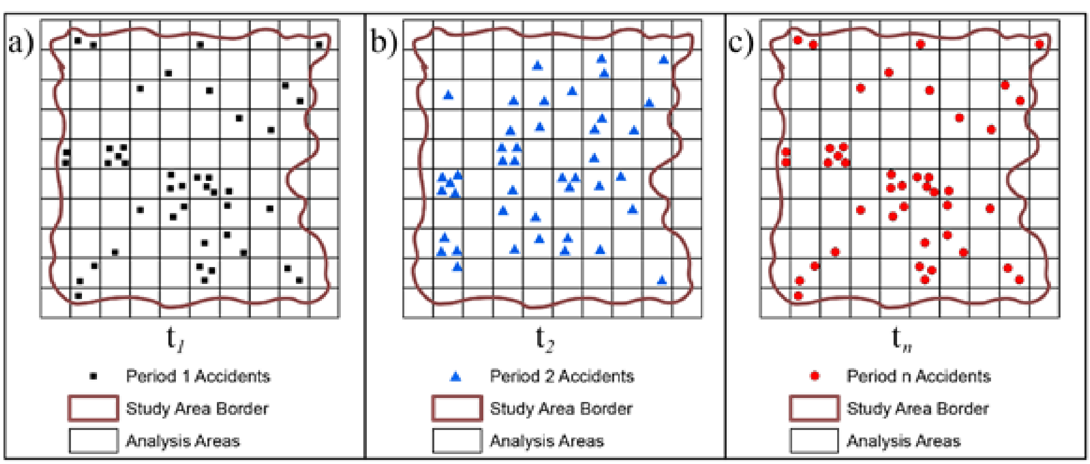


Figure 14. Aggregation of accident points to analysis areas over a set of periods

Table 7. Analysis Parameters for Hot Spot Analysis

Parameter name	Value of parameter
Neighbor distance (impedance cut off)	500 m
Maximum number of neighbor points	250
Spatial parameter for analysis (observed	No. of vehicles per each accident
Area of cluster	2500 m²
Selected p -value	0.1, 0.05, and 0.01
Dissolve field	Bin_ Hot Spot Value
Type of clustering	Hot spot (HH)
Temporal scale of analysis	Bimonthly, monthly, and biweekly

In this application, areas a_{it} having positive and significant z-scores $\left(p_{it} \leq 0.1\right)$, indicating the presence of positive spatiotemporal autocorrelation, are considered to be part of an accident hot spot. Additionally, areas a_{it} having negative and significant z-scores $\left(p_{it} \leq 0.1\right)$, indicating the existence of negative spatiotemporal autocorrelation, are considered to be part of an accident cold spot. As an example, the significant G_i^* hot spots for May 2013 in the one-month analyses are depicted in Figure. 15a while those for Weeks 9-10 in the two-week analyses are shown in Figure 15b.

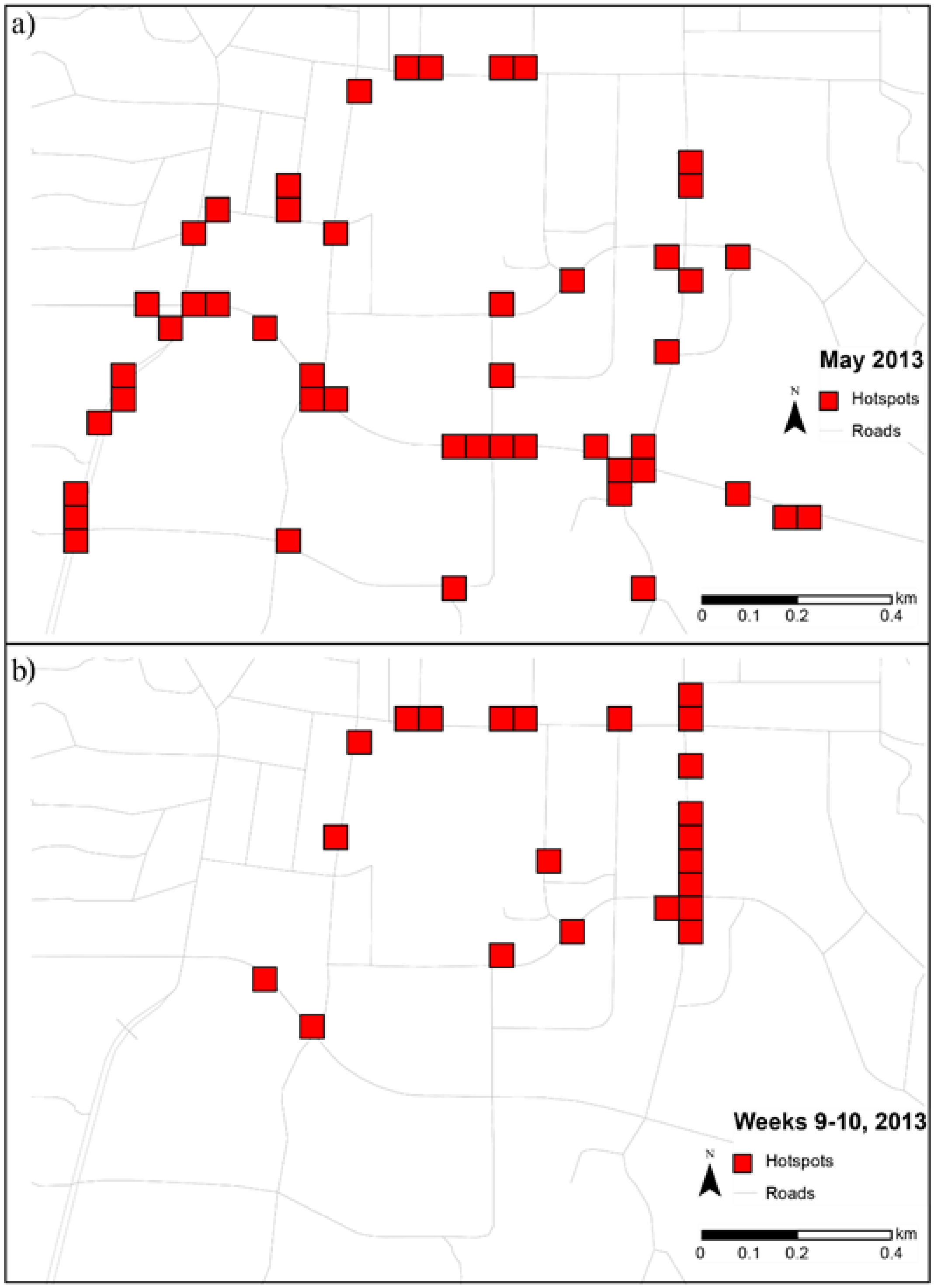


Figure 15. Examples of analysis areas having significant G_i^* values $\left(p \leq 0.1\right)$ for: a) May 2013 and b) Weeks 9-10 in 2013

Next, the STAG procedure (Figure. 5) was implemented in Python 3.7 utilizing the functionalities of ESRI's ArcGIS. The results of the EHSA (e.g., the p-value and z-score for each analysis area for each period) described earlier were used as the cluster metric to be evaluated by STAG. The spatial neighborhood for each analysis area $\hat{N}_i$ considered for cluster membership was specified to include all other analysis areas that shared a boundary arc with i. The procedure was iteratively applied 12 times for the two-month period analysis, 24 times for the one-month period analysis, and 53 times for the two-week period analysis to investigate the effect that temporal scale may have on the evolution of cluster morphology over time. Once each hot spot area was attributed with the size of the cluster it was found to be associated within each time period, the unique types of cluster evolution occurring in the study area were identified. First, hot spot areas that were found to be associated with a cluster in the exact same set of time periods were classified as having the same temporal pattern Γ. For example, a set of hot spot areas participating in clusters in only Periods 6 and 14 would be considered to have the same temporal pattern. Second, analysis areas exhibiting the same temporal pattern Γ were further classified according to the morphological characteristics M of their clusters. For example, given a set of hot spot areas classified as participating in clusters in only Periods 6 and 14, those areas also associated with the same sized clusters in the two periods (5,000 m^2 in Period 6 and 10,000 m^2 in Period 14) would be classified as having the same morphological pattern.

CHAPTER 5

CLUSTER MORPHOLOGY AND CITY SCALE

5.1 Introduction

The Statistical Comparing of Group Clusters (SCGC) methodology is now applied for comparing the cluster areas rendered using the STAG model. The STAG model result is the set of initial analysis areas for each time period attributed with the *id* and area of their corresponding clusters. Therefore, by comparing the size of the cluster to which an area belongs in one period with that in other periods, some basic trends in the evolution of cluster size can be conceptualized and a very general and extendable taxonomy for describing the evolution of clusters is detailed. First, the multi-city experimental design is explained. Following this, the comparison algorithm is then employed to evaluate similarities/differences in cluster morphology changes for groups of cities of similar size.

5.2 Study Area and Data Sources

The characteristics of cities may have some impact on the types of accident clusters and the observed cluster morphology. To analyze the extent to which this may be the case, a set of cities of different urban sizes are selected for analysis. The selected tagged portions of Missouri that are classified as urban areas are shown in Figure 16. The remaining areas are classified as rural. Here, urban cities are divided into three groups based on their total number of population: small (i.e., Census urban areas: 2,500 - 9,999), micropolitan (i.e., Census urban areas: 10,000 - 49,999), and metropolitan statistical areas (i.e., Census urban areas: ≥ 50,000) (Bureau, 2010; USDA, 2000). Three cities representative of each of the three city size groups were then selected for comparison of accident cluster morphologies. Table 8 lists the selected cities areas corresponding to each Census size group.

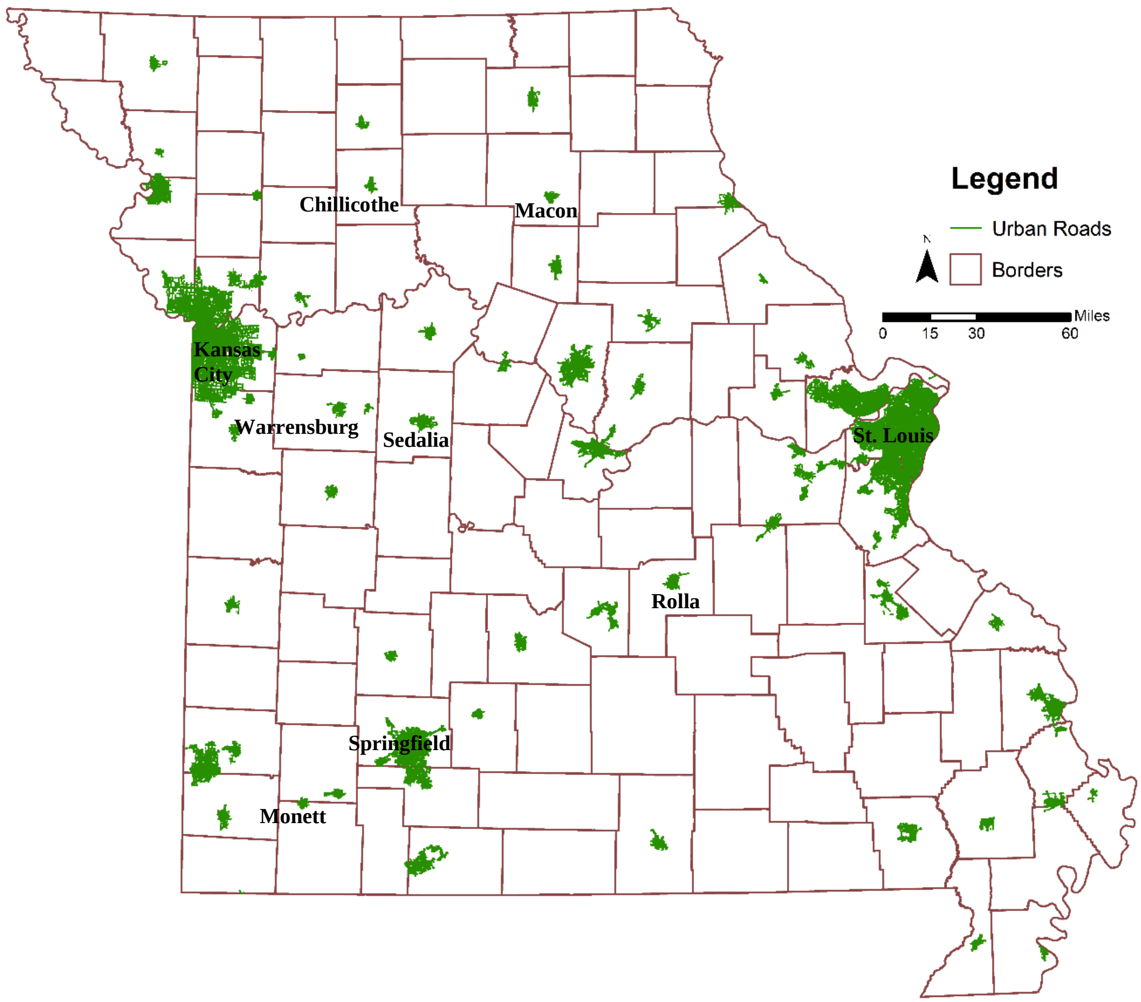


Figure 16. Roads in areas classified as urban in Missouri

Table 8. List of cities selected for comparative analysis

Small City	Micropolitan	Metropolitan
Macon	Rolla	St. Louis
Chillicothe	Sedalia	Springfield
Monett	Warrensburg	Kansas City

The small cities group in Table 8 comprises small-sized towns distributed over different locations in Missouri. Both Macon and Chillicothe are located in the Northern portion of the state while Monett is located on the Southwestern side of Missouri. Most of the selected Micropolitan group of urban cities are centrally located in Missouri (i.e., the three Metropolitan selected cities are Kansas City (West side of the state), St. Louis (East side of the state), and Springfield(Southwestern Missouri).

In this application, vehicular accidents recorded by local and/or state law enforcement agencies within the selected city areas in the years from 2013 to 2015 are selected to examine. Missouri accident data as reported by the Missouri State Highway Patrol (MSHP) and documented in the Missouri Statewide Traffic Accident Records System (STARS) are examined. STARS regards as the major resource of accident data in the State of Missouri since 1978. The STARS accident dataset, can be acquired from an online query portal on the MSHP website (MSHP, 2020). Each accident record is attributed with the date and time of the event, geographic location (i.e., longitude and latitude), the number of vehicles that were involved in each accident, as well as a range of other detailed attributes regarding each incident.

A variety of temporal scales of analysis can be considered for accident analysis. One-month periods are commonly selected given that they are thought to capture seasonal effects (Kang et al., 2018) and broader variations in traffic activity and weather patterns (Wen et al., 2019). Smaller analysis periods (e.g., hours, days, weeks, etc.) could be used as well depending on accident dynamics in each study area scale. Hence, the current application will focus on three different temporal scales of analysis: a) one-month periods for small city areas, b) two-week periods for micropolitan areas, and c) one-week periods for metropolitan areas.

5.3 Analysis and Comparison

ESRI's EHSA tool (ArcMap 10.7) was used to assess spatiotemporal dependency among the accidents in each of the 9 cities. Given a set of observed point-based events over time, the EHSA aggregates the events into analysis areas using a spatial neighborhood distance of 250 m at the specified time interval (e.g., one-month, two-week, and one-week). The size of the analysis areas is an important consideration given that the spatial relationship among the areas influences the measure of spatiotemporal dependency as well as the creation of cluster polygons. As such, analysis areas should be sized to reflect the spatial structure of the network. In this application, the study region was partitioned into 250 m x 250 m (62,500 m^2) analysis areas, to avoid road segments that are not adjacent from being considered part of the same analysis area with neighbor distance (i.e., impedance cut off equal to 250 m). The observed accidents occurring in the analysis areas in each period can then be analyzed. The EHSA incorporates both spatial and temporal relationships among the analysis areas to compute the local G_i^* statistic. The output of the EHSA is the G_i^* statistic (i.e., p-value and z-score) for each analysis area in each period. In this application, areas a_{it} having positive and significant z-scores

$(p_{it} \leq 0.1)$, indicating the presence of positive spatiotemporal autocorrelation, are considered to be part of an accident hot spot. Additionally, areas a_{it} having negative and significant z-scores $(p_{it} \leq 0.1)$, signifying the existence of negative spatiotemporal autocorrelation, are considered to be part of an accident cold spot.

The results of the EHSA (e.g., the p-value and z-score for each analysis area for each period) described earlier were used as the cluster metric to be evaluated by STAG. The spatial neighborhood for each analysis area $\hat{N}_i$ that was considered for cluster membership, was specified to include all other analysis areas that shared a boundary arc or vertex with i. The procedure was iteratively applied multiple times according to the temporal scale of analysis (e.g., 36 times for the one-month period analysis, 78 times for the two-week period analysis, and 157 times for the one-week period analysis) to investigate the effect that temporal scale may have on the evolution of cluster morphology over time. Once each hot spot area was associated with each period and attributed with the size of the cluster, the unique types of cluster evolution occurring in the study area were identified.

After calculating the clusters related to each city, both MS Excel and ESRI's ArcGIS were utilized to convert the Geodatabase Feature Class output results of STAG into listed input editable tables (e.g., csv, xlsx, etc.). For each city, the analysis areas were attributed with the size of the cluster with which they are associated and the analysis time period (one-year and three-month periods). The cluster size values were converted into rank values (e.g., 62,500 =1, 125,000 = 2, 187,500 = 3, etc.). The information for the three cities in each city size group were set together in one separate file for further statistical comparison.

The SCGC model was implemented later in RStudio version 1.4.1717. The results of the STAG (i.e., each hot spot area was attributed with the size of the cluster it was found to be associated within each period) described earlier were used as the statistical input to be evaluated by SCGC. According to the city size group, the estimation of the statistical similarity/dissimilarity between pairs of cities that were categorized within each size group of cities was calculated (e.g., metropolitan, micropolitan, etc.). Once pairs of compared cities within a specified time period were attributed with a *p*-value, the similarity or dissimilarity between both compared cities or each city itself during different time periods was identified. The null hypothesis is that the average log counts of clusters for all cities are equal. Therefore, the small *p*-value for the pair of cities (i.e., the p-value is equal to or less than the statistically significant level) indicates the rejection of the null hypothesis, which means there is a difference between the calculated amount value of the average log counts of clusters for the two compared cities.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 General Clusters Sizes

Changes in cluster size were examined, provided G_{it}^{*} clusters identified at three different levels of statistical significance (i.e., *p*-values ≤ 0.1, 0.05, and 0.01). Table 9 depicts the cluster sizes over the 12, two-month time periods. The maximum cluster size tends to have a large variation in size, ranging between 10,000 m^2 and 15,000 m^2 (i.e., from four to six dissolved spatial clusters) with an average cluster size of 5,337 m^2.

Table 9. Cluster size summary over 12 two-month periods

P-value	**Cluster Size (m^2)**		
	Min Clustering	Avg Clustering	Max Clustering
0.01	2,500	4,688	10,000
0.05	2,500	4,405	10,000
0.1	2,500	5,337	15,000

Analysis of the 24, one-month periods by far tend to be the larger size on average (e.g., 5,625 m^2). In general, cluster areas are ranged between 2,500 m^2 and 25,000 m^2 depending on the level of significance considered (Table 10). The cluster size of 25,000 m^2 means there are 10 adjacent analysis areas were participated in a cluster area. Table 11 depicts the minimum, average, and maximum size of clusters over the 53, two-week analysis periods. This analysis level reflects the constant maximum size of clusters that is equal to 20,000 m^2 (i.e., 20,000 m^2 cluster size means there are 8 adjacent analysis areas were participated in a cluster area). Also, the average size of clusters is ranged between 5,778 m^2 for $p \leq 0.1$ and 6,157 m^2 for $p \leq 0.01$.

Table 10. Cluster size summary over 24, one-month periods

P-value	**Cluster Size (m^2)**		
	Min Clustering	Avg Clustering	Max Clustering
0.01	2,500	5,625	17,500
0.05	2,500	5,610	25,000
0.1	2,500	5,530	25,000

Table 11. Cluster size summary over 53, two-week periods

***P*-value**	**Cluster Size (m^2)**		
	Min Clustering	Avg Clustering	Max Clustering
0.01	2,500	6,157	20,000
0.05	2,500	5,888	20,000
0.1	2,500	5,778	20,000

6.2 Cluster Analysis Statistics

This section depicts the details of the size of accident clusters over each of the three temporal scales considered. First, the cluster characteristics for over 12, two-month periods are described at the $p \leq 0.1$ (Table 12), $p \leq 0.05$ (Table 13), and $p \leq 0.01$ (Table 14) levels of statistical significance in addition to the number of unique temporal clustering patterns (Γ), unique morphological patterns (M), and the number of clusters for each time period. For clusters significant at $p \leq 0.1$ (Table 12), the highest average cluster size (3,796 m^2) was observed in period 7 (January/February 2014) which also was recorded as the maximum sized cluster (15,000 m^2) over the periods. The maximum number of clusters (61) occurs in the 6th period (November/December 2013) as in Figure 17. In addition, the average size of the clusters ranges between 2,500 m^2 and 3,796 m^2, while the maximum size of clusters ranges between 2,500 m^2 and 15,000 m^2. Up to 9 unique temporal clustering patterns (Γ) and 22 unique morphological patterns (M) were noticeable in the analysis periods.

Table 12. Summary of cluster characteristics for the 12, two-month analysis periods ($p \le 0.1$) (P* = period; C^ = number of clusters)

P*	**C^**	**Min. Area (m^2)**	**Avg. Area (m^2)**	**Max. Area (m^2)**	**# Γ**	**# M**
1	0	0	0	0	0	0
2	8	2,500	3,750	10,000	3	6
3	16	2,500	3,438	7,500	6	13
4	1	2,500	2,500	2,500	1	1
5	44	2,500	3,295	10,000	9	22
6	61	2,500	2,992	10,000	5	14
7	27	2,500	3,796	15,000	4	9
8	17	2,500	2,941	10,000	3	4
9	1	2,500	2,500	2,500	1	1
10	19	2,500	3,553	7,500	2	5
11	2	2,500	2,500	2,500	2	3
12	53	2,500	3,208	10,000	6	14

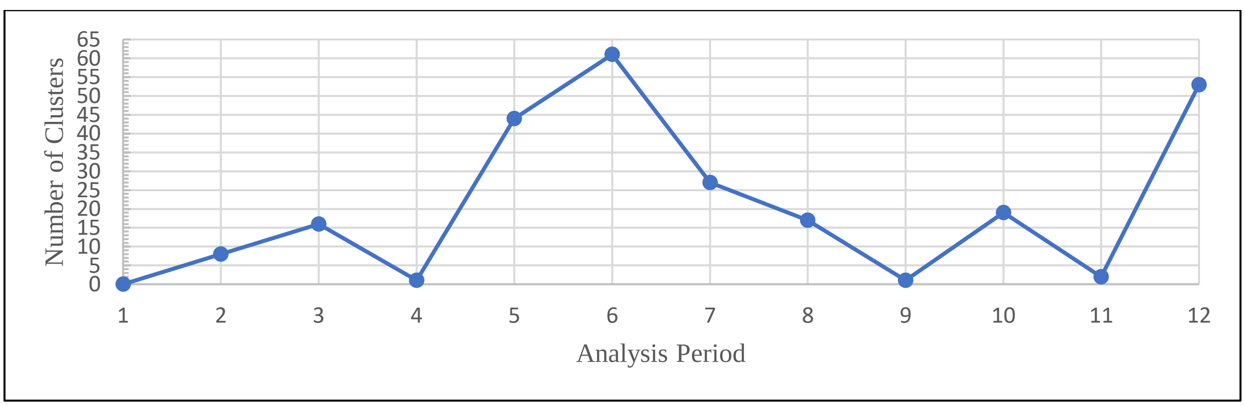


Figure 17. Number of unique clusters ($p \le 0.1$, over 12, two-month periods)

Table 13 summarizes characteristics of different sizes of clusters over the same 12, two-month periods at $p \leq 0.05$ significance level. The average size of clusters ranges between 2,500 m^2 and 3,889 m^2 while the maximum cluster size reaches (10,000 m^2) during the 6th (November/December 2013) and the 7th (January/February 2014) periods. Also, Figure 18 illustrates the highest number of clusters (37) that occurs during the 6th period (November/December 2013). Up to 3 unique temporal clustering patterns (Γ) and 7 unique morphological patterns (M) were discernable in the analysis periods.

Table 13. Summary of cluster characteristics for the 12, two-month analysis periods ($p \leq 0.05$) (P^* = period; $C^\wedge$ = number of clusters)

P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M
1	0	0	0	0	0	0
2	1	2,500	2,500	2,500	1	1
3	2	2,500	3,750	5,000	2	2
4	0	0	0	0	0	0
5	14	2,500	3,214	7,500	3	7
6	37	2,500	3,108	10,000	2	7
7	9	2,500	3,889	10,000	2	4
8	5	2,500	2,500	2,500	1	1
9	0	0	0	0	0	0
10	5	2,500	3,000	5,000	1	2
11	0	0	0	0	0	0
12	18	2,500	3,056	7,500	3	4

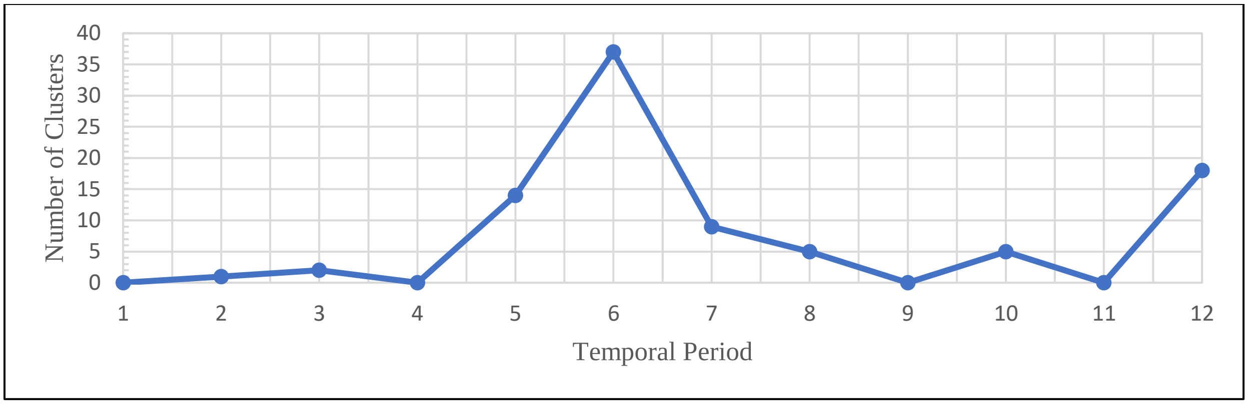


Figure 18. Number of unique clusters ($p \leq 0.05$, Over 12, two-month periods)

For clusters significant at the $p \leq 0.01$ level, the highest number of clusters (13) was observed in the 6th period (November/December 2013) as in Figure 19. Moreover, the maximum average size of clusters (3,750 m^2) occurs during period 12 (November/December 2014), while the 6th period (November/December 2013) exhibits the largest size clusters (10,000 m^2) as in Table 14. Up to two unique temporal clustering patterns (Γ) and four unique morphological patterns (M) were discernible over the 12 analysis periods.

Table 14. Summary of cluster characteristics for the 12, two-month analysis periods ($p \leq 0.01$) (P* = period; C^ = number of clusters)

P*	**C^**	**Min. Area (m^2)**	**Avg. Area (m^2)**	**Max. Area (m^2)**	**# Γ**	**# M**
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	2	2,500	2,500	2,500	1	1
6	13	2,500	3,654	10,000	2	4
7	2	2,500	2,500	2,500	1	1
8	0	0	0	0	0	0
9	0	0	0	0	0	0
10	1	2,500	2,500	2,500	1	1
11	0	0	0	0	0	0
12	4	2,500	3,750	7,500	1	2

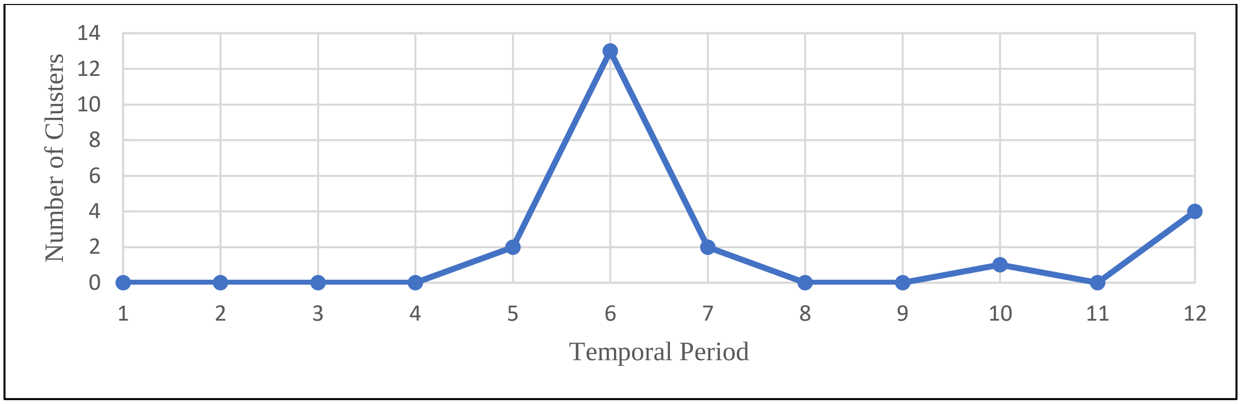


Figure 19. Number of unique clusters ($p \leq 0.01$, over 12, two-month periods)

One-month periods of analysis generally introduce a wider range of clusters size variety than two-month periods. For clusters significant at the $p \leq 0.1$, the average size of clusters ranges between 2,500 m^2 and 4,615 m^2, while the maximum cluster size ranges between 2,500 m^2 and 25,000 m^2. The maximum number of clusters (72) was recorded during period 10th (October 2013) while the maximum cluster size reaches 25,000 m^2 during period 18th (June 2014) as exhibited in Figure 20 and Table 15. Up to 32 unique temporal clustering patterns (Γ) and 54 unique morphological patterns (M) were discernible in the analysis periods.

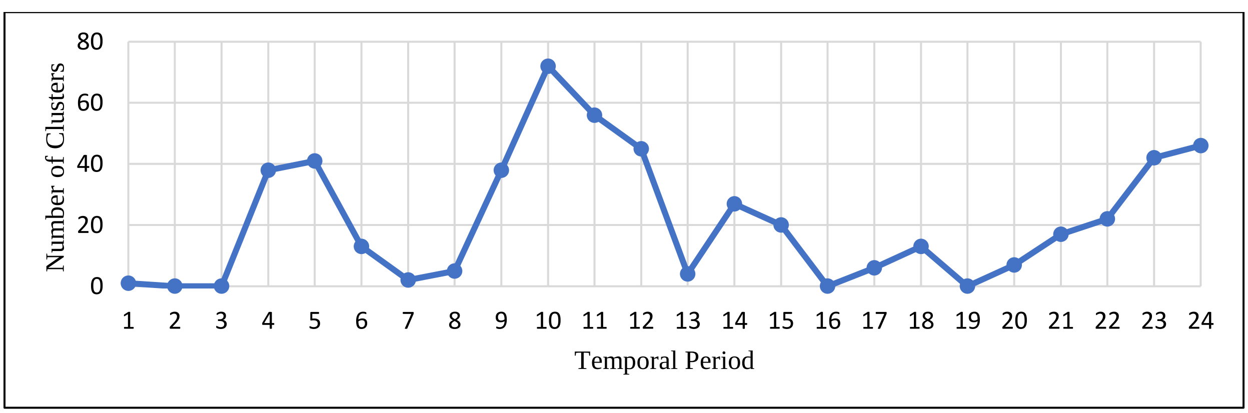


Figure 20. Number of unique clusters ($p \leq 0.1$, over 24, one-month periods)

Table 15. Summary of cluster characteristics for the 24, one-month analysis periods ($p \leq 0.1$) (P^* = period; $C^\wedge$ = number of clusters)

P^*	**$C^\wedge$**	**Min. Area (m^2)**	**Avg. Area (m^2)**	**Max. Area (m^2)**	**# Γ**	**# M**
1	1	2,500	2,500	2,500	1	1
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	38	2,500	3,553	10,000	22	37
5	41	2,500	3,293	10,000	25	40
6	13	2,500	3,269	10,000	2	5
7	2	2,500	3,750	5,000	2	2
8	5	2,500	2,500	2,500	2	2
9	38	2,500	3,882	12,500	25	43
10	72	2,500	3,403	17,500	32	54
11	56	2,500	3,437	10,000	17	33
12	45	2,500	3,167	7,500	11	20
13	4	2,500	2,500	2,500	3	3
14	27	2,500	3,241	12,500	7	12
15	20	2,500	3,125	7,500	6	10
16	0	0	0	0	0	0
17	6	2,500	2,917	5,000	1	2
18	13	2,500	4,615	25,000	2	4
19	0	0	0	0	0	0
20	7	2,500	2,500	2,500	2	2
21	17	2,500	2,941	5,000	12	19
22	22	2,500	2,727	5,000	17	23
23	42	2,500	3,214	10,000	18	30
24	46	2,500	2,935	10,000	22	35

Table 16 depicts that period 18 (June 2014) was associated with the biggest average and maximum size of clusters through the 24, one-month periods at the $p \leq 0.05$ significance level. A maximum Γ (27) and M (39) diversity were observed during the 10^{th} period. Moreover, Figure 21 summarizes the maximum number of clusters (53) that was recorded during the 10^{th} period (October 2013).

Table 16. Summary of cluster characteristics for the 24, one-month analysis periods ($p \leq 0.05$) (P^* = period; $C^\wedge$ = number of clusters)

P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	27	2,500	3,796	10,000	19	27
5	27	2,500	3,518	10,000	22	29
6	6	2,500	3,750	10,000	2	4
7	1	5,000	5,000	5,000	1	1
8	0	0	0	0	0	0
9	28	2,500	4,286	12,500	19	27
10	53	2,500	3,632	17,500	27	39
11	46	2,500	3,478	10,000	10	21
12	32	2,500	3,203	7,500	6	12
13	1	2,500	2,500	2,500	1	1
14	13	2,500	2,500	2,500	4	4
15	12	2,500	2,708	5,000	5	6
16	0	0	0	0	0	0
17	3	2,500	3,333	5,000	1	2
18	6	2,500	6,667	25,000	2	4
19	0	0	0	0	0	0
20	4	2,500	2,500	2,500	1	1
21	6	2,500	2,500	2,500	4	5
22	9	2,500	2,778	5,000	9	10
23	24	2,500	3,229	10,000	15	18
24	28	2,500	3,036	10,000	19	22

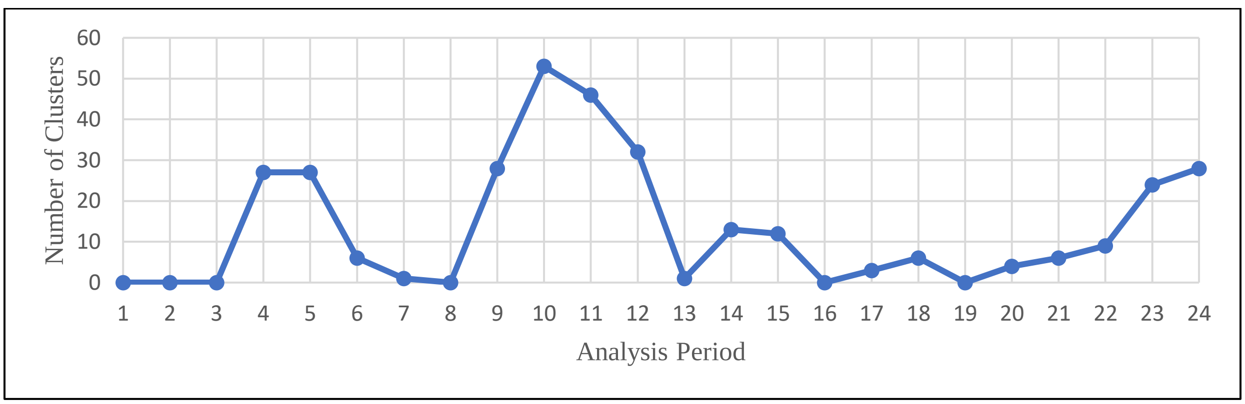


Figure 21. Number of unique clusters ($p \leq 0.05$, over 24, one-month periods)

For clusters significant at $p \leq 0.01$ level for one-month periods analysis, Period 10 (October 2013) was recorded as the highest cluster size (17,500 m^2), while Period 11 (November 2013) was recorded as the highest number of clusters (37) over the 24 periods of analysis as in Table 17 and Figure 22. Also, up to 16 unique temporal clustering patterns (Γ) and 23 unique morphological patterns (M) were identified in the analysis periods.

Table 17. Summary of cluster characteristics for the 24, one-month analysis periods ($p \leq 0.01$) (P^* = period; $C^\wedge$ = number of clusters)

P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	8	2,500	4,062	10,000	8	9
5	12	2,500	3,958	10,000	11	13
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	10	2,500	3,000	5,000	9	10
10	30	2,500	4,083	17,500	16	23
11	37	2,500	3,716	10,000	6	13
12	9	2,500	3,611	7,500	3	5
13	0	0	0	0	0	0
14	6	2,500	2,500	2,500	3	3
15	7	2,500	2,500	2,500	3	3
16	0	0	0	0	0	0
17	0	0	0	0	0	0
18	0	0	0	0	0	0
19	0	0	0	0	0	0
20	0	0	0	0	0	0
21	1	2,500	2,500	2,500	1	1
22	1	2,500	2,500	2,500	1	1
23	5	2,500	5,000	10,000	4	5
24	13	2,500	3,269	10,000	8	10

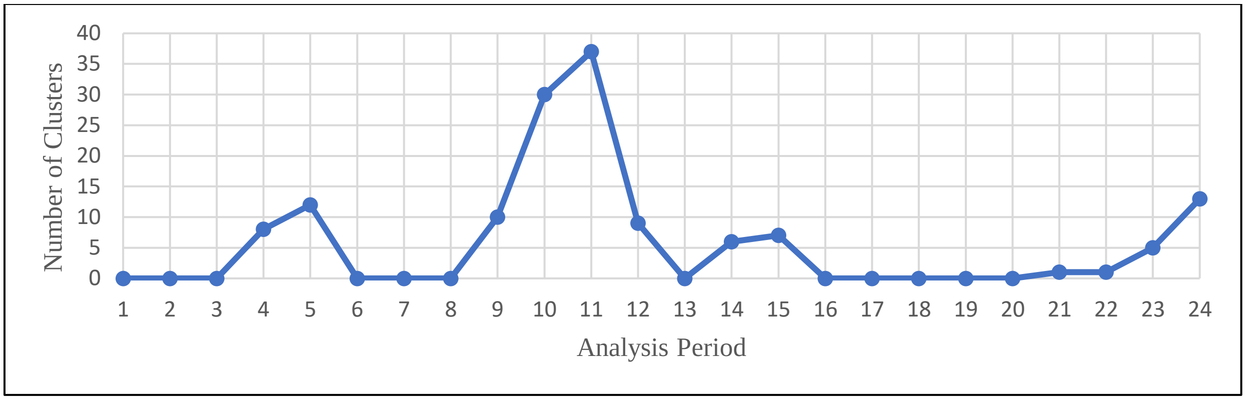


Figure 22. Number of unique clusters ($p \leq 0.01$, over 24, one-month periods)

A two-week period of analyses results in a more diverse number and size of clusters than both one-month and two-month analyses. For clusters significant at $p \leq 0.1$ (Table 18), the average cluster size ranges between 2,500 m^2 and 4,007 m^2 while the maximum cluster size was observed between 2,500 m^2 and 20,000 m^2 during periods 29th (last two-week periods of January 2014), 37th (mid-two-week periods of May 2014), and 45th (first two-week periods of September 2014) as in Table 18. Also, Figure 23 illustrates the highest number of clusters (102) that was observed during period 29th (last two-week periods of January 2014). Likewise, up to 59 unique temporal clustering patterns (Γ) and 75 unique morphological patterns (M) were discernible in the analysis periods.

Table 18. Summary of cluster characteristics for the 53, two-week analysis periods ($p \leq 0.1$) (P* = period; C^ = number of clusters)

P*	C^	Min. Area (m²)	Avg. Area (m²)	Max. Area (m²)	# Γ	# M	P*	C^	Min. Area (m²)	Avg. Area (m²)	Max. Area (m²)	# Γ	# M
1	0	0	0	0	0	0	**28**	18	2,500	3,194	7,500	16	20
2	1	2,500	2,500	2,500	1	1	**29**	102	2,500	3,627	20,000	55	74
3	2	2,500	2,500	2,500	2	2	**30**	54	2,500	3,657	15,000	23	33
4	2	2,500	2,500	2,500	2	2	**31**	7	2,500	2,500	2,500	3	3
5	19	2,500	3,158	7,500	20	22	**32**	16	2,500	2,656	5,000	16	17
6	17	2,500	3,088	5,000	18	20	**33**	17	2,500	2,794	7,500	6	7
7	0	0	0	0	0	0	**34**	2	2,500	2,500	2,500	1	1
8	33	2,500	3,485	10,000	35	39	**35**	7	2,500	2,500	2,500	4	4
9	49	2,500	3,775	17,500	51	59	**36**	45	2,500	3,500	15,000	35	43
10	35	2,500	3,143	10,000	32	37	**37**	40	2,500	3,625	20,000	12	24
11	9	2,500	2,500	2,500	5	6	**38**	6	2,500	2,917	5,000	1	2
12	2	2,500	2,500	2,500	2	2	**39**	0	0	0	0	0	0
13	7	2,500	2,857	5,000	2	3	**40**	15	2,500	2,667	5,000	7	7
14	6	2,500	2,917	5,000	1	2	**41**	3	2,500	2,500	2,500	4	4
15	1	2,500	2,500	2,500	1	1	**42**	43	2,500	3,256	15,000	6	12
16	14	2,500	3,929	15,000	3	6	**43**	6	2,500	2,917	5,000	3	6
17	13	2,500	2,885	5,000	4	10	**44**	9	2,500	2,500	2,500	7	7
18	35	2,500	3,786	15,000	38	46	**45**	73	2,500	4,007	20,000	55	74
19	59	2,500	3,644	15,000	46	60	**46**	74	2,500	3,446	15,000	57	75
20	92	2,500	3,206	10,000	63	70	**47**	28	2,500	3,214	10,000	33	37
21	67	2,500	3,246	10,000	55	62	**48**	36	2,500	3,889	15,000	32	39
22	84	2,500	3,542	17,500	59	71	**49**	53	2,500	3,821	17,500	51	61
23	73	2,500	3,664	17,500	56	69	**50**	40	2,500	3,500	10,000	36	47
24	53	2,500	3,679	17,500	27	38	**51**	13	2,500	3,846	10,000	11	14
25	13	2,500	3,654	10,000	6	9	**52**	3	2,500	3,333	5,000	5	6
26	7	2,500	2,857	5,000	2	3	**53**	0	0	0	0	0	0
27	11	2,500	2,954	5,000	3	4							

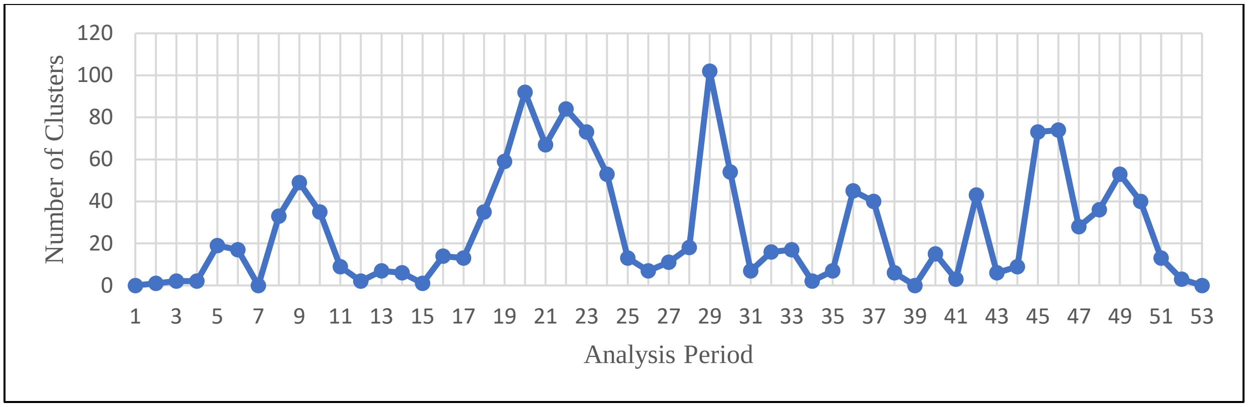


Figure 23. Number of unique clusters ($p \leq 0.1$, Over 53, two-week periods)

Table 19 illustrates the different sizes of clusters over the same 53, two-week periods at the $p \leq 0.05$ significance level. The average size of clusters ranges between 2,500 m^2 and 5,000 m^2. Likewise, the highest number of clusters (84) was observed during the 29th period (last two-week periods of January 2014) as in Figure 24. Up to 51 unique temporal clustering patterns (Γ) and 63 unique morphological patterns (M) were discernible in the analysis periods.

Table 19. Summary of cluster characteristics for the 53, two-week analysis periods ($p \leq 0.05$) (P^* = period; $C^\wedge$ = number of clusters)

P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M	P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M
1	0	0	0	0	0	0	**28**	11	2,500	3,182	7,500	11	15
2	1	2,500	2,500	2,500	1	1	**29**	84	2,500	3,750	20,000	42	62
3	1	2,500	2,500	2,500	1	1	**30**	44	2,500	3,807	15,000	11	20
4	0	0	0	0	0	0	**31**	5	2,500	2,500	2,500	3	3
5	12	2,500	3,333	7,500	14	14	**32**	9	2,500	2,778	5,000	11	12
6	9	2,500	2,778	5,000	11	11	**33**	12	2,500	2,917	7,500	5	6
7	0	0	0	0	0	0	**34**	2	2,500	2,500	2,500	1	1
8	25	2,500	3,800	10,000	27	29	**35**	3	2,500	2,500	2,500	2	2
9	37	2,500	4,122	17,500	43	49	**36**	36	2,500	3,403	15,000	32	37
10	26	2,500	3,365	10,000	26	32	**37**	24	2,500	3,854	20,000	10	16
11	3	2,500	2,500	2,500	2	2	**38**	6	2,500	2,917	5,000	1	2
12	1	2,500	2,500	2,500	1	1	**39**	0	0	0	0	0	0
13	1	2,500	2,500	2,500	1	1	**40**	12	2,500	2,708	5,000	4	6
14	4	2,500	2,500	2,500	1	1	**41**	1	2,500	2,500	2,500	1	1
15	0	0	0	0	0	0	**42**	30	2,500	3,500	15,000	2	5
16	5	2,500	2,500	2,500	3	3	**43**	1	5,000	5,000	5,000	1	1
17	10	2,500	2,750	5,000	3	7	**44**	3	2,500	2,500	2,500	4	4
18	26	2,500	4,135	15,000	32	36	**45**	52	2,500	4,471	20,000	45	57
19	45	2,500	3,944	15,000	37	45	**46**	59	2,500	3,602	15,000	43	57
20	61	2,500	3,361	10,000	46	52	**47**	15	2,500	3,000	10,000	16	19
21	42	2,500	3,452	10,000	36	41	**48**	28	2,500	4,196	15,000	25	36
22	65	2,500	3,654	17,500	51	63	**49**	43	2,500	3,953	17,500	45	54
23	63	2,500	3,770	17,500	47	59	**50**	23	2,500	3,804	10,000	25	31
24	42	2,500	3,810	17,500	15	29	**51**	8	2,500	4,375	10,000	8	9
25	11	2,500	3,636	10,000	3	7	**52**	2	2,500	3,750	5,000	4	4
26	2	2,500	2,500	2,500	1	1	**53**	0	0	0	0	0	0
27	4	2,500	3,125	5,000	2	3							

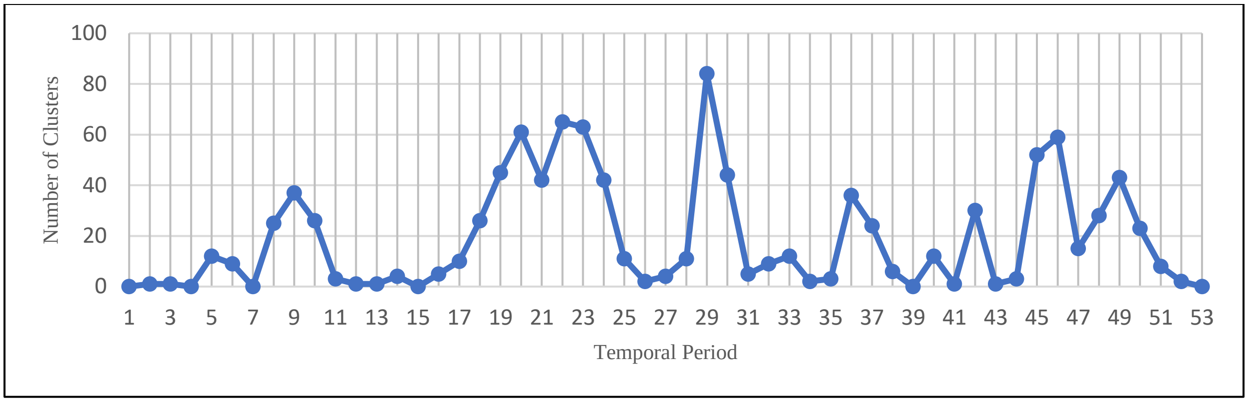


Figure 24. Number of unique clusters ($p \leq 0.05$, over 53, two-week periods)

For clusters significant at the $p \leq 0.01$ level, Table 20 illustrates the average size of clusters that ranges between 2,500 m^2 and 5,625 m^2 while the 29th period (last two-week periods of January 2014) was observed as the highest maximum size of clusters (20,000 m^2) and the highest number of clusters (53) during the 29th period (last two-week periods of January 2014) as exhibited in Figure 25. Up to 31 unique temporal clustering patterns (Γ) and 39 unique morphological patterns (M) were discernible in the analysis periods.

Table 20. Summary of cluster characteristics for the 53, two-week analysis periods ($p \leq 0.01$) (P^* = period; $C^\wedge$ = number of clusters)

P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M	P^*	$C^\wedge$	Min. Area (m^2)	Avg. Area (m^2)	Max. Area (m^2)	# Γ	# M
1	0	0	0	0	0	0	**28**	4	2,500	2,500	2,500	3	3
2	0	0	0	0	0	0	**29**	53	2,500	3,962	20,000	24	34
3	0	0	0	0	0	0	**30**	18	2,500	4,583	15,000	4	9
4	0	0	0	0	0	0	**31**	0	0	0	0	0	0
5	3	2,500	4,167	7,500	5	5	**32**	2	2,500	2,500	2,500	2	2
6	1	2,500	2,500	2,500	1	1	**33**	3	2,500	2,500	2,500	1	1
7	0	0	0	0	0	0	**34**	0	0	0	0	0	0
8	13	2,500	3,654	7,500	10	13	**35**	0	0	0	0	0	0
9	22	2,500	4,659	17,500	22	27	**36**	12	2,500	3,750	15,000	13	15
10	5	2,500	3,000	5,000	5	7	**37**	6	2,500	3,333	7,500	1	2
11	1	2,500	2,500	2,500	1	1	**38**	0	0	0	0	0	0
12	0	0	0	0	0	0	**39**	0	0	0	0	0	0
13	0	0	0	0	0	0	**40**	2	2,500	2,500	2,500	1	1
14	2	2,500	2,500	2,500	1	1	**41**	0	0	0	0	0	0
15	0	0	0	0	0	0	**42**	8	2,500	3,125	5,000	1	2
16	0	0	0	0	0	0	**43**	0	0	0	0	0	0
17	3	2,500	2,500	2,500	1	2	**44**	0	0	0	0	0	0
18	17	2,500	4,412	15,000	20	24	**45**	19	2,500	3,026	5,000	18	21
19	20	2,500	4,500	10,000	16	21	**46**	31	2,500	3,952	10,000	23	30
20	27	2,500	3,704	10,000	23	27	**47**	2	2,500	2,500	2,500	2	2
21	22	2,500	3,977	10,000	23	26	**48**	12	2,500	5,625	15,000	9	15
22	42	2,500	3,869	17,500	28	34	**49**	21	2,500	4,643	17,500	22	27
23	46	2,500	4,022	17,500	31	39	**50**	5	2,500	4,000	5,000	4	5
24	27	2,500	4,167	17,500	9	15	**51**	5	2,500	5,500	10,000	3	5
25	6	2,500	4,167	10,000	2	4	**52**	0	0	0	0	0	0
26	0	0	0	0	0	0	**53**	0	0	0	0	0	0
27	1	2,500	2,500	2,500	1	1							

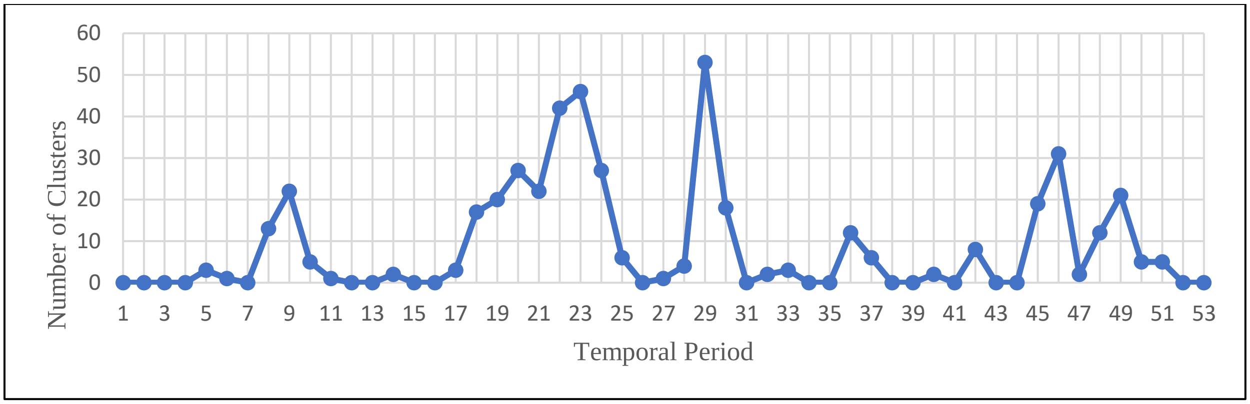


Figure 25. Number of unique clusters ($p \leq 0.01$, over 53, two-week periods)

6.3 Cluster Frequency of Occurrence

After reviewing the cluster size characteristics, the cluster frequencies of occurrences were examined by using three different statistical significance levels for each considered temporal scale. First, the frequency occurrence of clusters over the 12 two-month periods was described at the $p \leq 0.1$ (Table A. 1 Cluster size frequency and temporal trend (two-month Periods, $p \leq 0.1$) in Appendix A), $p \leq 0.05$ (Table A. 2 in Appendix A), and $p \leq 0.01$ (Table A. 2 in Appendix A) statistical significance levels. For clusters frequency at the $p \leq 0.1$ level (Table A. 1), there were 23 trends and 52 variations. The trend number defines the unique identifier for a particular trend while the variation number illustrates the unique identifier for a particular cluster size at the same trend. In addition, the highest number of cluster frequencies was occurred during Period 6 (November/December 2013) and Period 12 (November/December 2014) with 25 and 22 successively as in Table A. 1 and Figure 26.

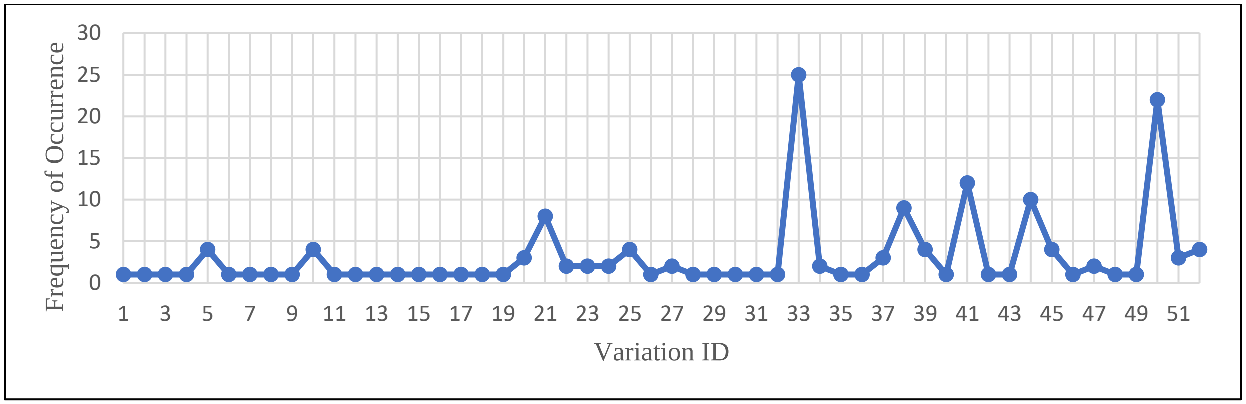


Figure 26. Cluster frequency of occurrence ($p \leq 0.1$, over 12, two-month periods)

For clusters frequency occurrence at the $p \leq 0.05$ level, there are 12 trends and 21 variations. The highest number of cluster frequency (20) was observed during periods 6 (November/December 2013) as in Table A. 2 in Appendix A and Figure 27. The clusters frequency occurrence of two-month periods at $p \leq 0.01$ level depicts the same highest number of clusters frequency during periods 6 (November/December 2013) as in Table A. 3 in Appendix A and Figure 28.

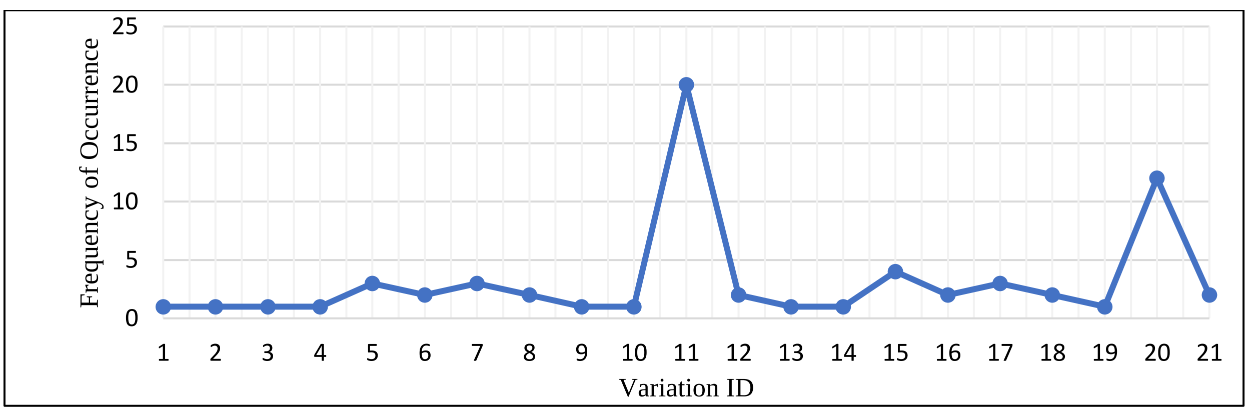


Figure 27. Cluster frequency of occurrence ($p \leq 0.05$, over 12, two-month periods)

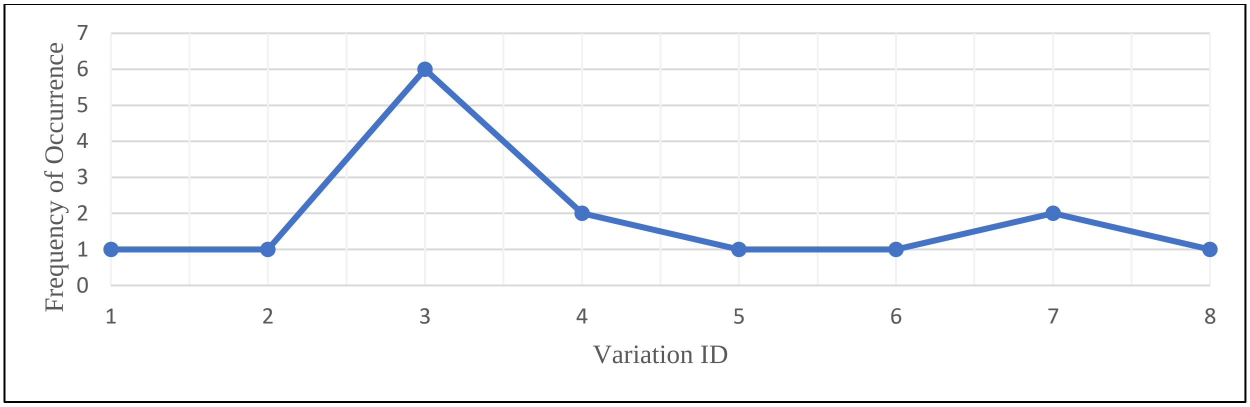


Figure 28. Cluster frequency of occurrence ($p \leq 0.01$, over 12, two-month periods)

One-month periods of analysis illustrates generally a higher number of trends and variations. For clusters frequency of 24, one-month periods at the $p \leq 0.1$ level (Table A.), the identified number of trends is 71 while the number of variations is 118. Period 14 (February 2014) records the highest number of clusters frequency, 12 as in Table A. and Figure 29. For clusters significant level at the $p \leq 0.05$, Period 12 (December 2013) depicts the highest number of cluster frequency (10) as in Table A. and Figure 30. Moreover, the total number of trends was 54 while the number of variations was 82. Table A. 6 in Appendix A shows that Period 11 (November 2013) recorded the highest number of clusters frequency (11) through the 24, one-month periods at the $p \leq 0.01$ significance level as in Figure 31. Moreover, this analysis illustrates 28 trends and 40 variations.

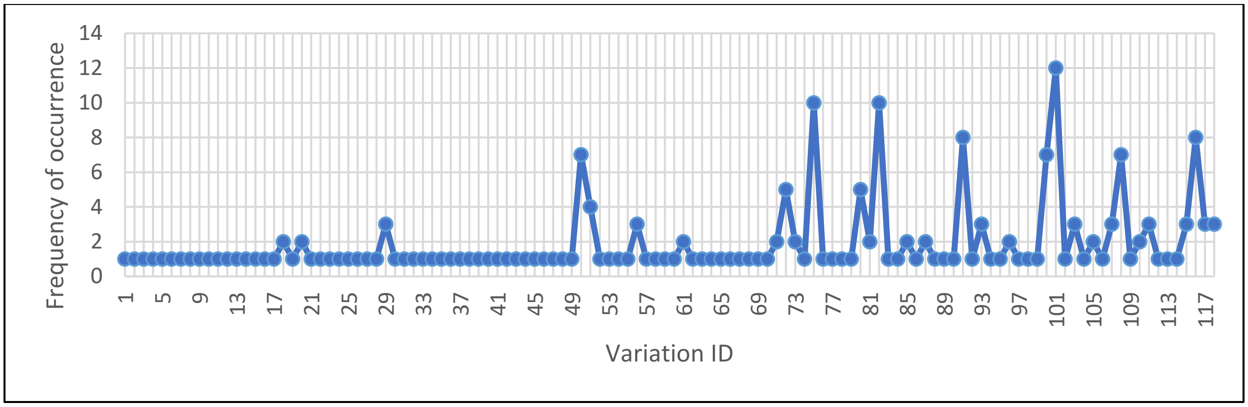


Figure 29. Cluster frequency of occurrence ($p \leq 0.1$, over 24, one-month periods)

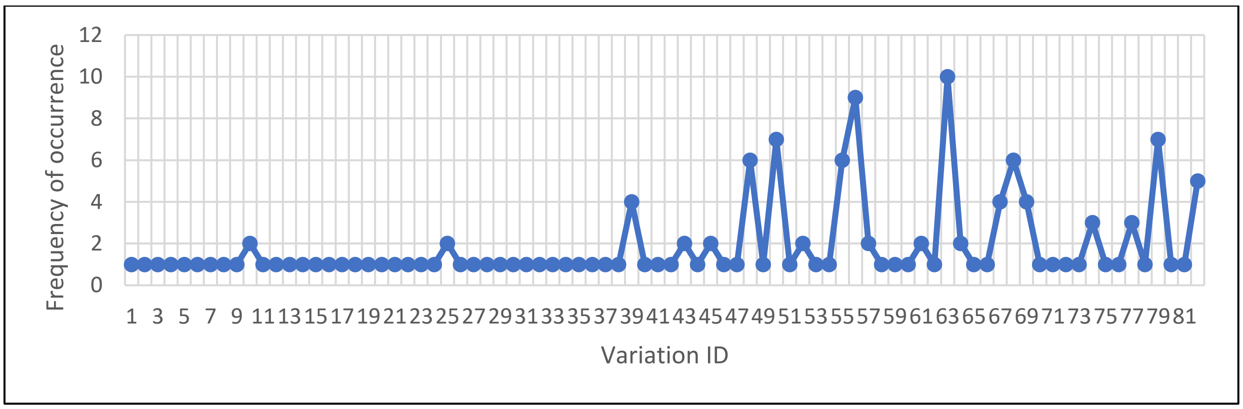


Figure 30. Cluster frequency of occurrence ($p \leq 0.05$, over 24, one-month periods)

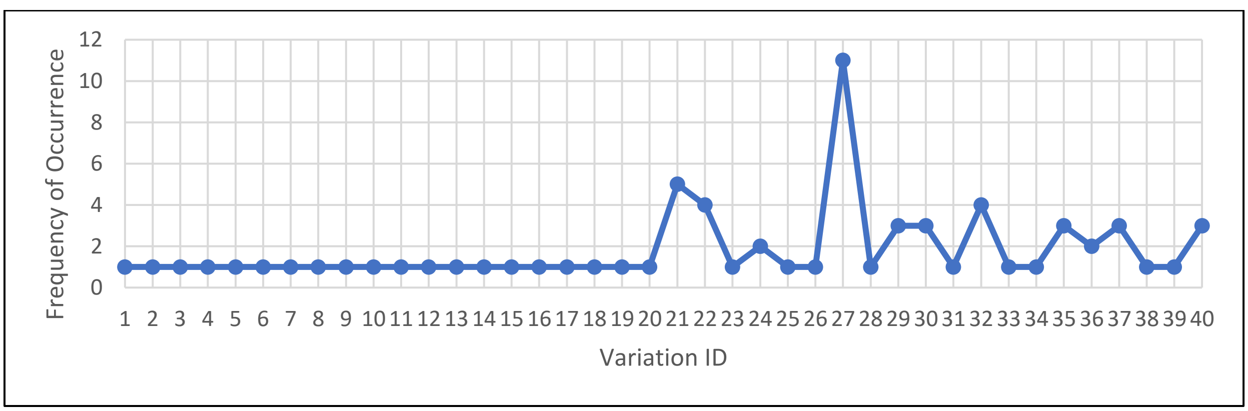


Figure 31. Cluster frequency of occurrence ($p \leq 0.01$, over 24, one-month periods)

Two-week periods with 53 time periods were much more varied in trend and variation numbers than both one-month and two-month periods (Table A. 7). For clusters significant at the $p \leq 0.1$ level, the number of variations is 257 and the highest number of clusters (19) was observed during period 42 (last week of July and the first week of August 2014) as in Figure 32. Table A. shows five examples of some cluster frequency occurrence for $p \leq 0.1$. A statistically significant level of 0.05 illustrates 203 variations as in Figure 33. For the $p \leq 0.01$ level, the total number of variations was 108 as illustrated in Figure 34.

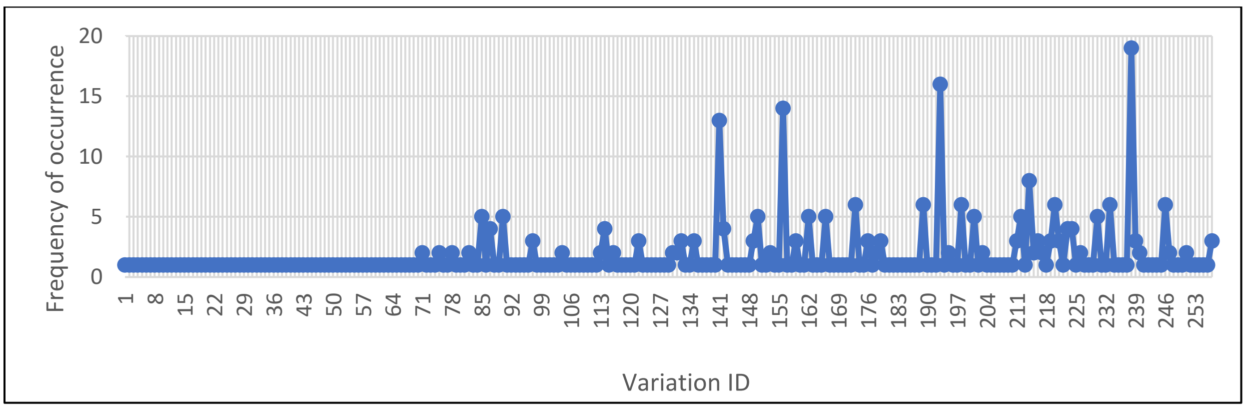


Figure 32. Cluster frequency of occurrence ($p \leq 0.1$, over 53, two-week periods)

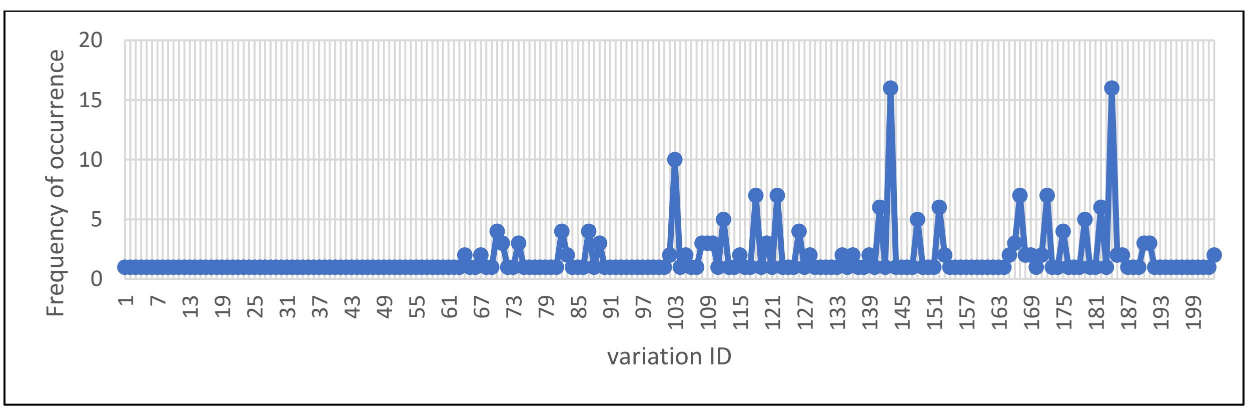


Figure 33. Cluster frequency of occurrence ($p \leq 0.05$, over 53, two-week periods)

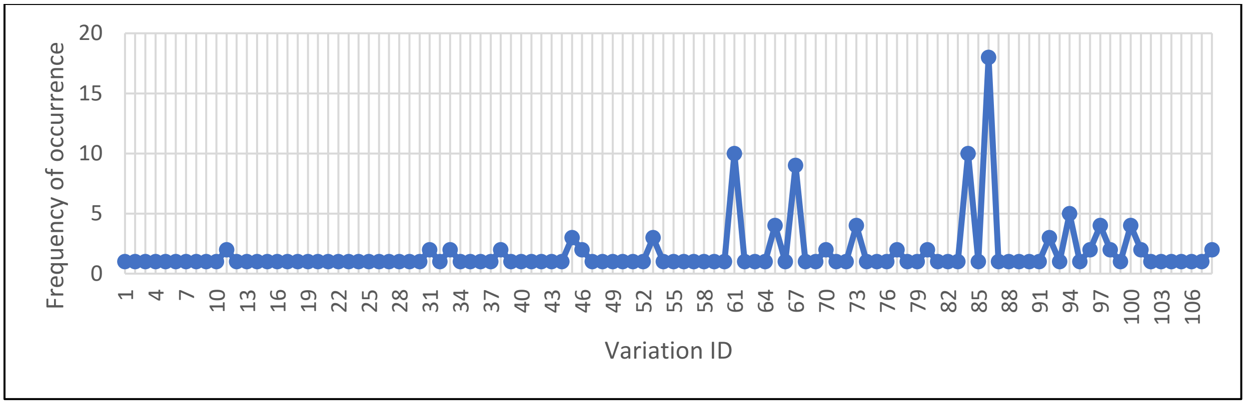


Figure 34. Cluster frequency of occurrence ($p \leq 0.01$, over 53, two-week periods)

6.4 Clusters Development

The tracking of the cluster size development is also calculated over each of the three temporal scales considered with the three levels of significance. The tracking of cluster size development is calculated for each time period by accounting for the number of clusters and sorting them according to the size of clusters and the kind of development that was observed, such as Vanishing, Decreasing, Sustained, Increasing, and New created. The cluster size evolution characteristics for over 12, two month periods were detailed at the $p \leq 0.1$ (Table B. 1), $p \leq 0.05$ (Table B. 2), $p \leq 0.01$ (Table B. 3) in Appendix B. Table B. 1 exhibits the development of the cluster for a 12, two-month periods scale of analysis for the selected $p \leq 0.1$ level. The first clusters appear during the second period and the size of clusters ranges between 2,500 m^2 and 10,000 m^2. This analysis demonstrates different values of cluster development. For example, the highest number of new created clusters was 52, which occurred during period 12 (November/December 2014), while the highest number of vanished clusters (59) was recorded during the 7^{th} period (January/February 2014). Moreover, the biggest size of clusters was 15,000 m^2, created during the 7^{th} period (January/February 2014) then vanished during the next 8th period (March/April 2014) as in Table B. 1. Table B. 2 exhibits the different cluster size evolutions over the same 12, two-month periods at the $p \leq 0.05$ significance level. Period 7 (January/February 2014) demonstrates the maximum number of clusters (37) that vanished during this period. Also, this analysis shows the 10,000 m^2 as the highest cluster size occurring during multiple periods classified as New, Increasing, or Vanishing as in Table B. 2 in Appendix B.

Table B. 3 in Appendix B depicts the $p \leq 0.01$ level of significance for the 12, two-month periods time scale of analysis and reflects more decline in the development of the cluster than both 0.1 and 0.05 *p*-values when the first new creation of clusters was observed during the 5th period and the development of the cluster was scattered through the 12 periods of analysis. Nevertheless, the highest number of new created clusters was created during the 6th period (November/December 2014) then later was vanished during the next 7th period (January/February 2014). In addition, the highest cluster size (10,000 m^2) was a new created during Period 6 (November/December 2014) then was vanished at the next 7th period (January/February 2014).

One-month period analyses result in different numbers of trends of clusters development. For clusters significant at $p \leq 0.1$, Table B. shows the highest number of new clusters that was recorded 43 clusters during the 10th period (October 2013) and ranges between 2,500 m^2 and 7,500 m^2. The highest number of vanishing clusters were observed during the 11th period (November 2013) which equals 47 clusters and ranges between 2,500 m^2 and 7,500 m^2.

Table B. illustrates the highest number of newly created clusters over the 24, one month periods at the $p \leq 0.05$ significance level which was observed during the 10th period

(October 2013), while the highest number of vanishing clusters (35) was observed in Period 12 (December 2013), which ranges between 2,500 m^2 and 10,000 m^2 as in Table B.

For clusters significant at the $p \leq 0.01$ level, Table B. 6 in Appendix B shows the development of clusters over the 24, one-month periods of analysis. The highest number of new created clusters was detected during both periods 10 (October 2013) and 11 (November 2013), while the highest number of vanished clusters was recorded during Period 12 (December 2013) with 35 clusters and ranges between 2,500 m^2 and 10,000 m^2. With the total of 53 periods, two-week periods of analysis introduce the highest number of clusters kinds of development among the three selected time scales.

For clusters significant at the two-week periods and $p \leq 0.1$ level, Table B. shows the highest number of new created clusters (95) that were detected during Period 29 (last two weeks of January 2014) with cluster sizes ranging between 2,500 m^2 to 20,000 m^2. In addition, the highest number of vanished clusters (54) occurred during Period 31 (the last two weeks of February). Table B. depicts the highest number of new created clusters (79), observed during the 29^{th} period (last two weeks of January 2014) at $p \leq 0.05$ level of significance. Also, the highest recorded number of vanished clusters (49) was recorded during Period 47 (last week of October and first week of November 2014), with ranges in cluster size between 2,500 m^2 and 15,000 m^2. For $p \leq 0.01$ cluster size development significance for two-week periods, Table B. 9 in Appendix B depicts that the highest recorded number of new created clusters (52), occurred during Period 29 (the last two weeks of January 2014).

6.5 Clustering with Significant G_i^* values

The variety of analysis areas having significant G_i^* values is depending on the temporal scale of analysis and the level of statistical significance (*p*-value). For example, Figure 35 illustrates the distribution of significant analysis areas for 12, two-month periods at the $p \leq 0.1$. These analysis areas were found at 290 locations, largely associated with downtown areas and main junctions over the city. Figure 36 depicts the significant analysis areas for 12, two-month periods at the scale of analysis at $p \leq 0.05$. The number of analysis areas (136) was less than the previous $p \leq 0.1$ significant analysis, distributed also over downtown and some main junctions. For significant analysis areas at $p \leq 0.01$, Figure 37 exhibits the lowest number of significant analysis areas (36), mainly associated with the Southern portion of the town with some scattered spots to the North.

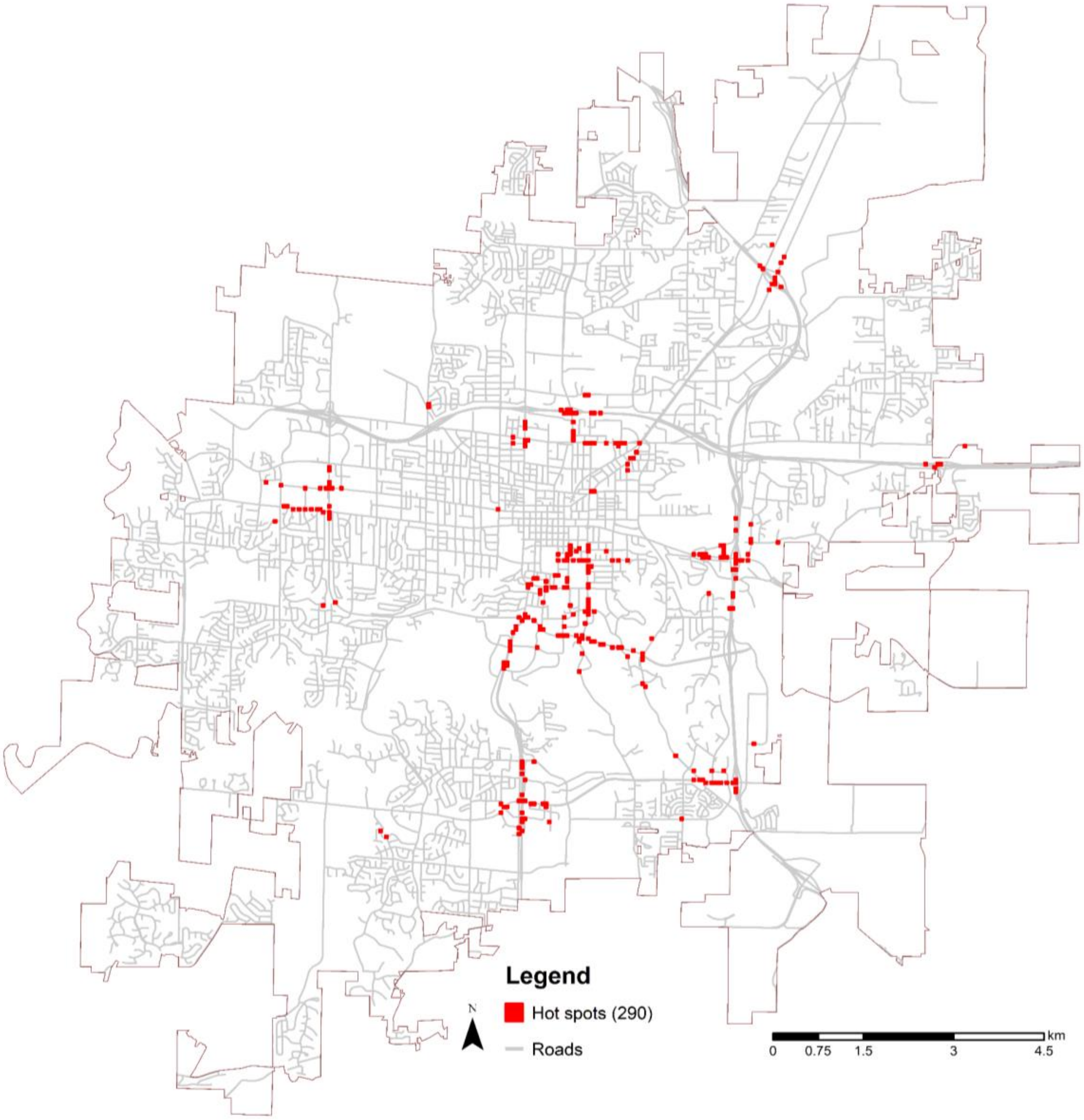


Figure 35. Analysis areas having significant G_i^* values ($p \leq 0.1$) over 12, two-month periods

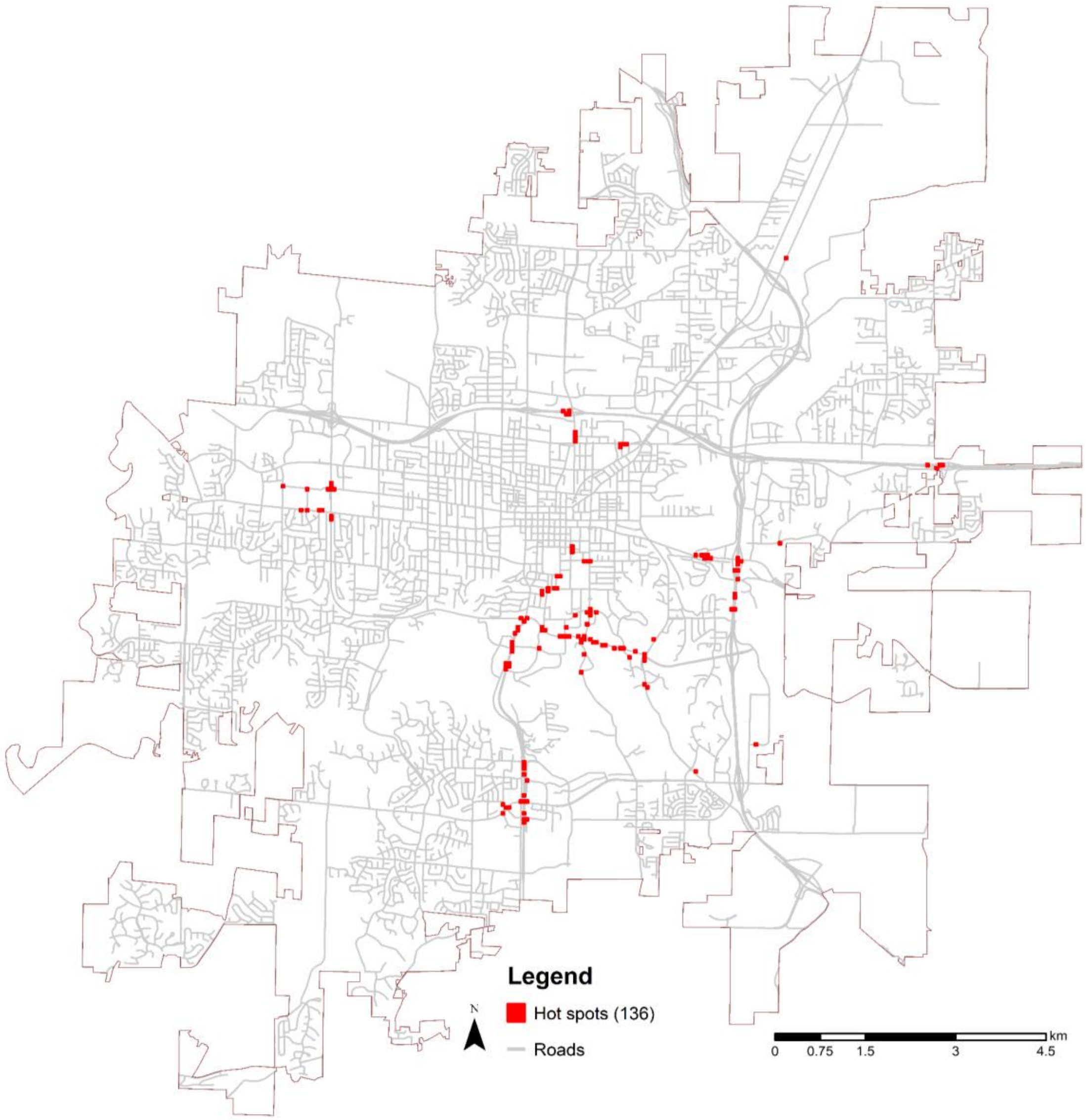


Figure 36. Analysis areas having significant G_i^* values ($p \leq 0.05$) over 12, two-month periods

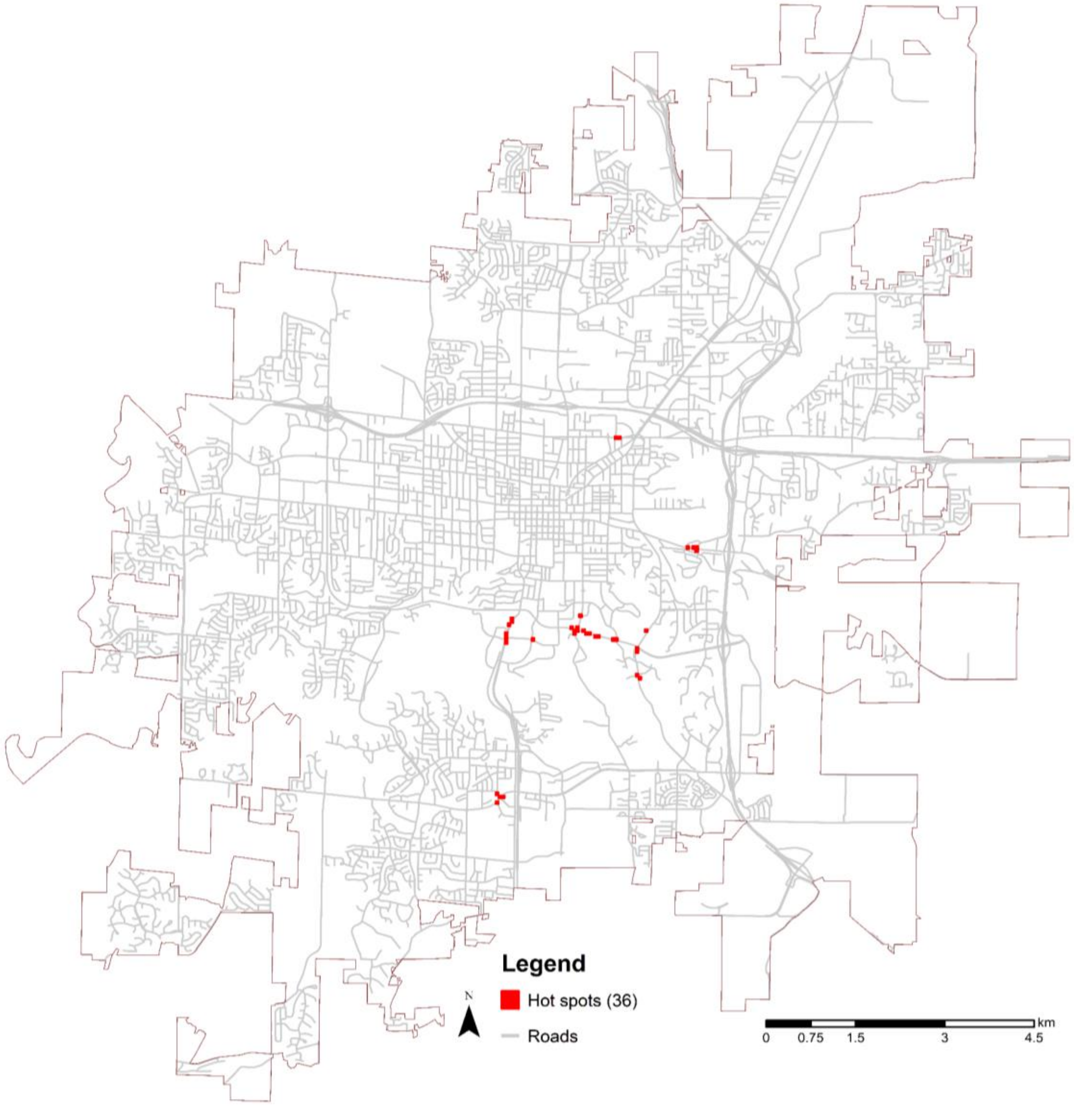


Figure 37. Analysis areas having significant G_i^* values ($p \leq 0.01$) over 12, two-month periods

Figure 38 illustrates the significant analysis areas of 24, one-month periods scale of analysis at $p \leq 0.1$ significance level. These analysis areas (364) were widely distributed around the middle, south, and both east and west of town. Both Figures 39 and 40 show significant analysis areas for the 24, one-month periods at $p \leq 0.05$ and $p \leq 0.01$ respectively and primarily less distributed than the first $p \leq 0.1$ significant.

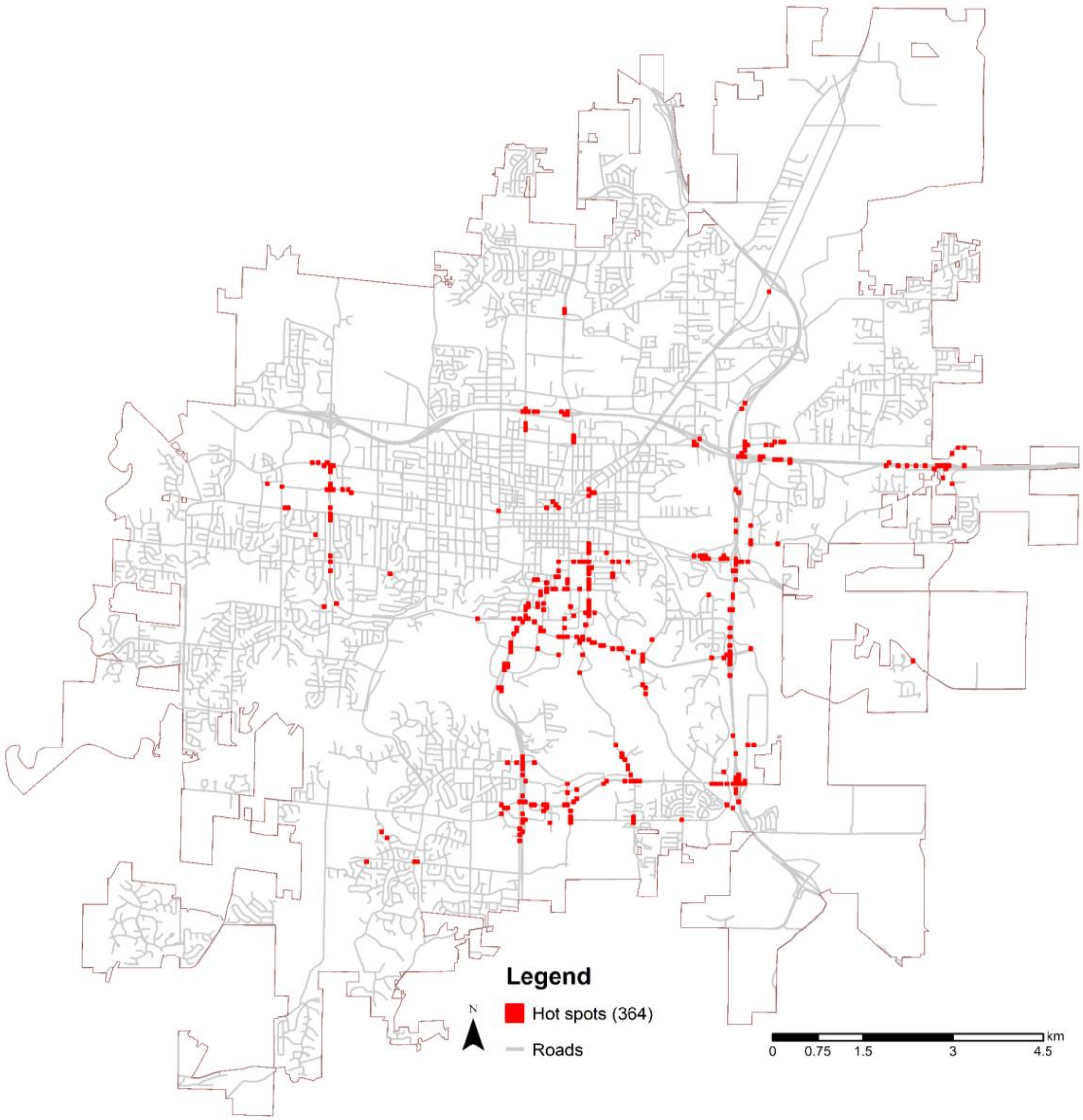


Figure 38. Analysis areas having significant G_i^* values ($p \leq 0.1$) over 24, one-month periods

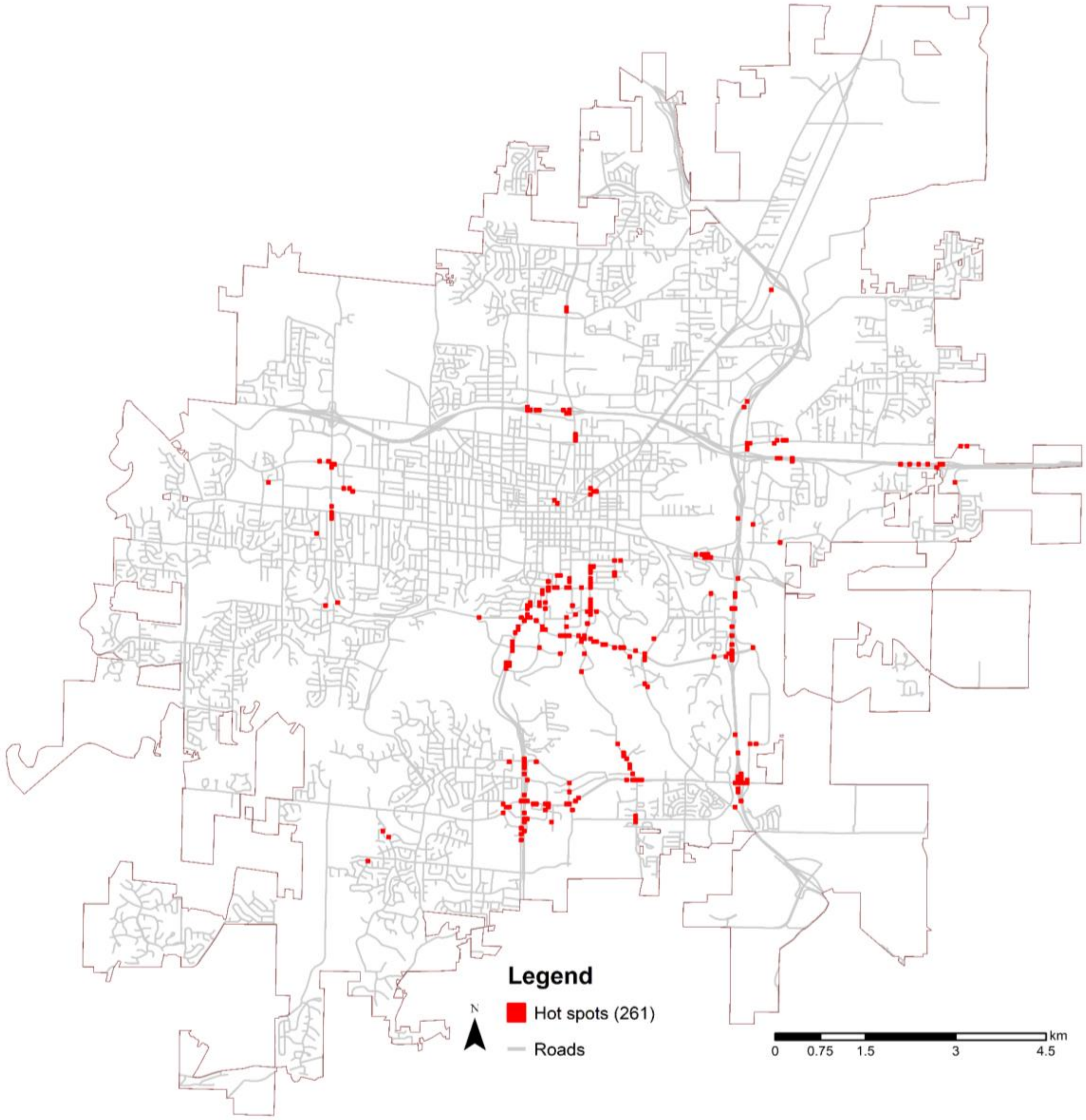


Figure 39. Analysis areas having significant G_i^* values ($p \leq 0.05$) over 24, one-month periods

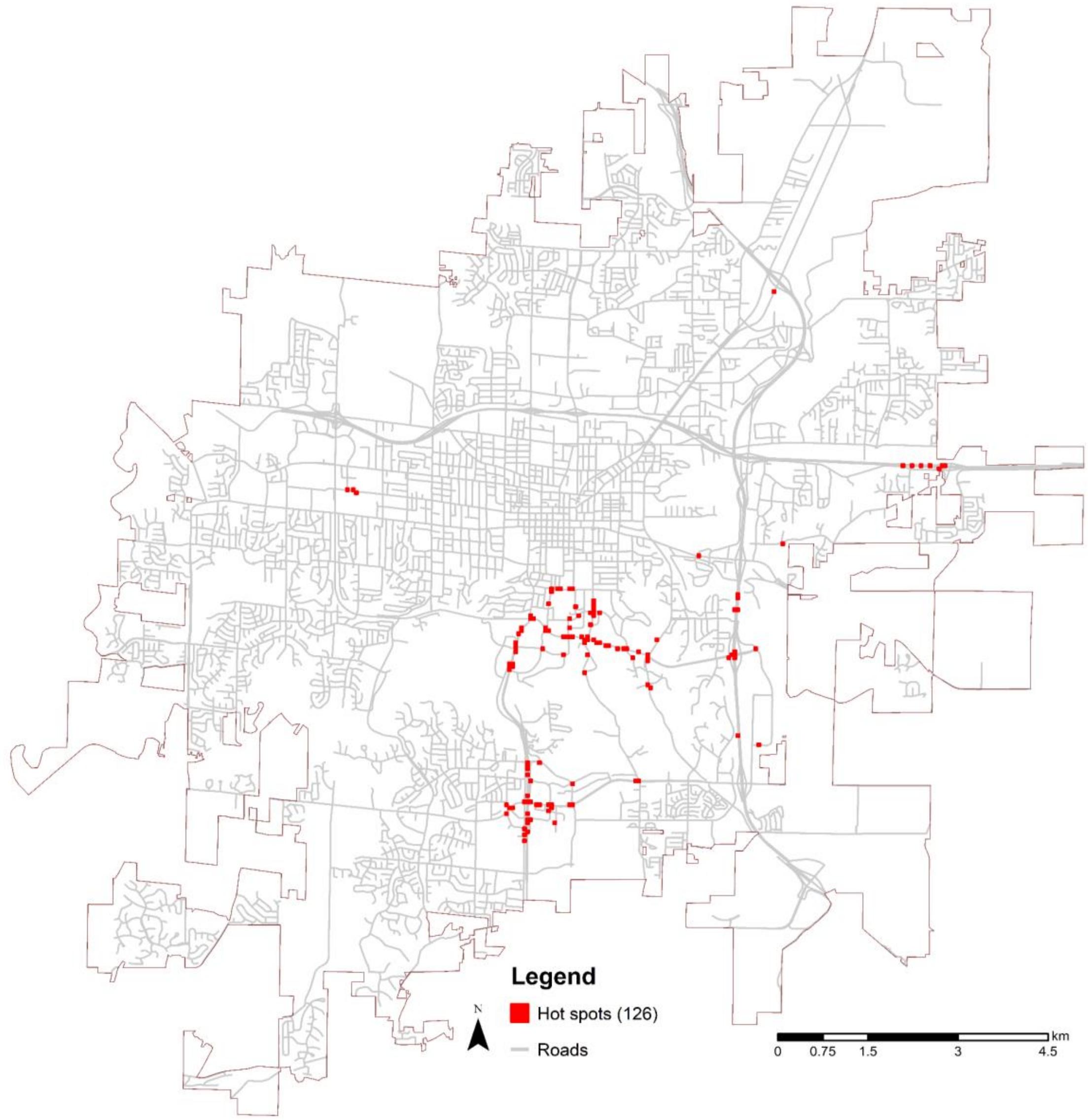


Figure 40. Analysis areas having significant G_i^* values ($p \leq 0.01$) over 24, one-month periods

Figure 41 depicts two-week periods, $p \leq 0.1$ significance level spatial locations for the analysis areas that have significant G_i^* Values which introduces the highest number of these areas (675) among all other temporal scales and p-values. For both 0.05 and 0.01 significant levels, Figures 42 and 43 depict the number of significant analysis areas (544) and (319) respectively and distributed over different spatial locations around Columbia.

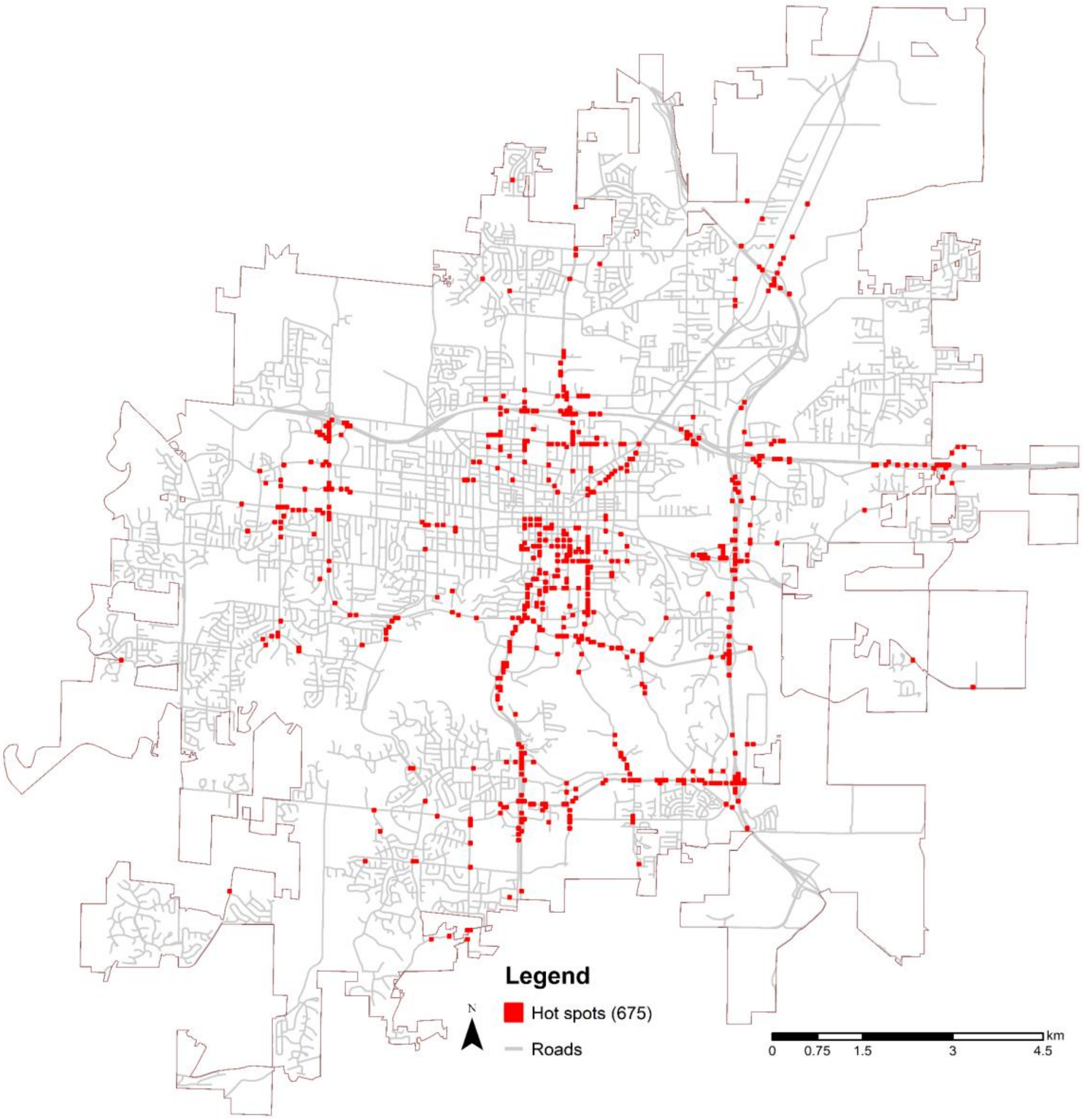


Figure 41. Analysis areas having significant G_i^* values ($p \leq 0.1$) over 53, two-week periods

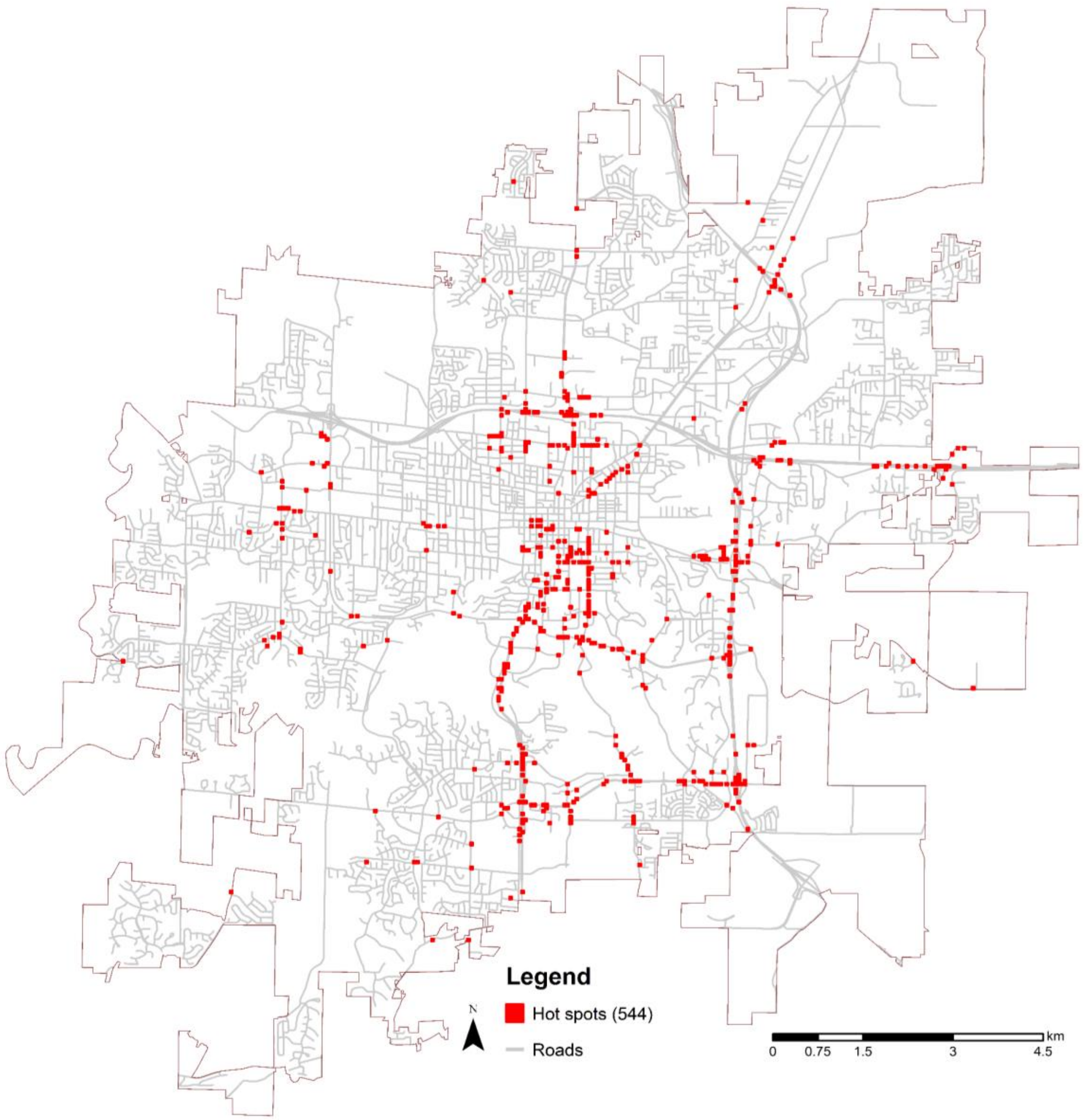


Figure 42. Analysis areas having significant G_i^* values ($p \leq 0.05$) over 53, two-week periods

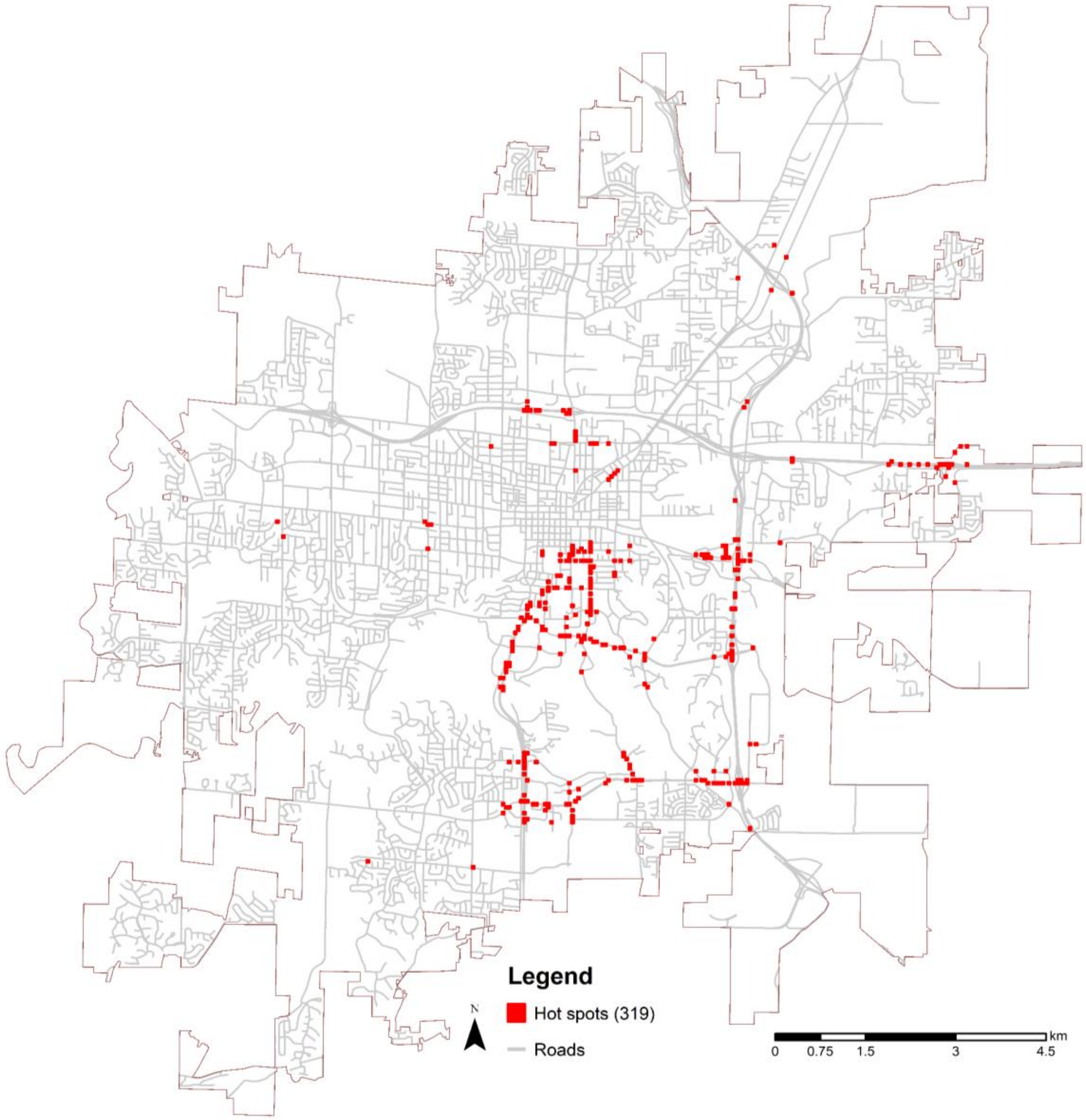


Figure 43. Analysis areas having significant G_i^* values ($p \leq 0.01$) over 53, two-week periods

6.6 Cluster Size Evolution

As detailed previously in Table 2, there are five categories of cluster evolution that illustrate the cluster associated with an area over a specified size. That could become later as larger, smaller, same size, or even not correspond with those in another time period. These trends were termed Single occurrence, Sustained, Fluctuating, Increasing, and Decreasing. This section illustrates the analysis areas associated with clusters and categories of evolution for all three temporal scales (i.e., two-month, one-month, and two-week periods with the three significant *p*-values (i.e., 0.1, 0.05, and 0.01). First, for over 12, two-month periods, the single occurrence was recorded as the highest number of occurrences at all $p \leq 0.1$ (Figure 44), $p \leq 0.05$ (Figure 45), and $p \leq 0.01$ (Figure 46) levels of statistical significance. For example, a single occurrence for clusters significant at the $p \leq 0.1$ level was recorded as the highest number of spatial locations (218) among other sorts of clustering and distributes over different locations around the city. However, other sorts of clustering were largely associated with main roads and intersections near a large hospital and university campus as in Figure 44.

Figure 45 illustrates the spatial distribution of clustering sorts of size development over the same 12, two-month periods at the $p \leq 0.05$ significance level. Analysis areas associated with clusters of single occurrence were found in 111 locations, largely associated with main roads and intersections near the south of town while the fluctuating trend of evolution was disappeared through this level of analysis. For clusters significant at $p \leq 0.01$ level, there were only 33 and 3 areas belonging to both single occurrence and increasing respectively, while the other types of clustering were disappeared as in Figure 46.

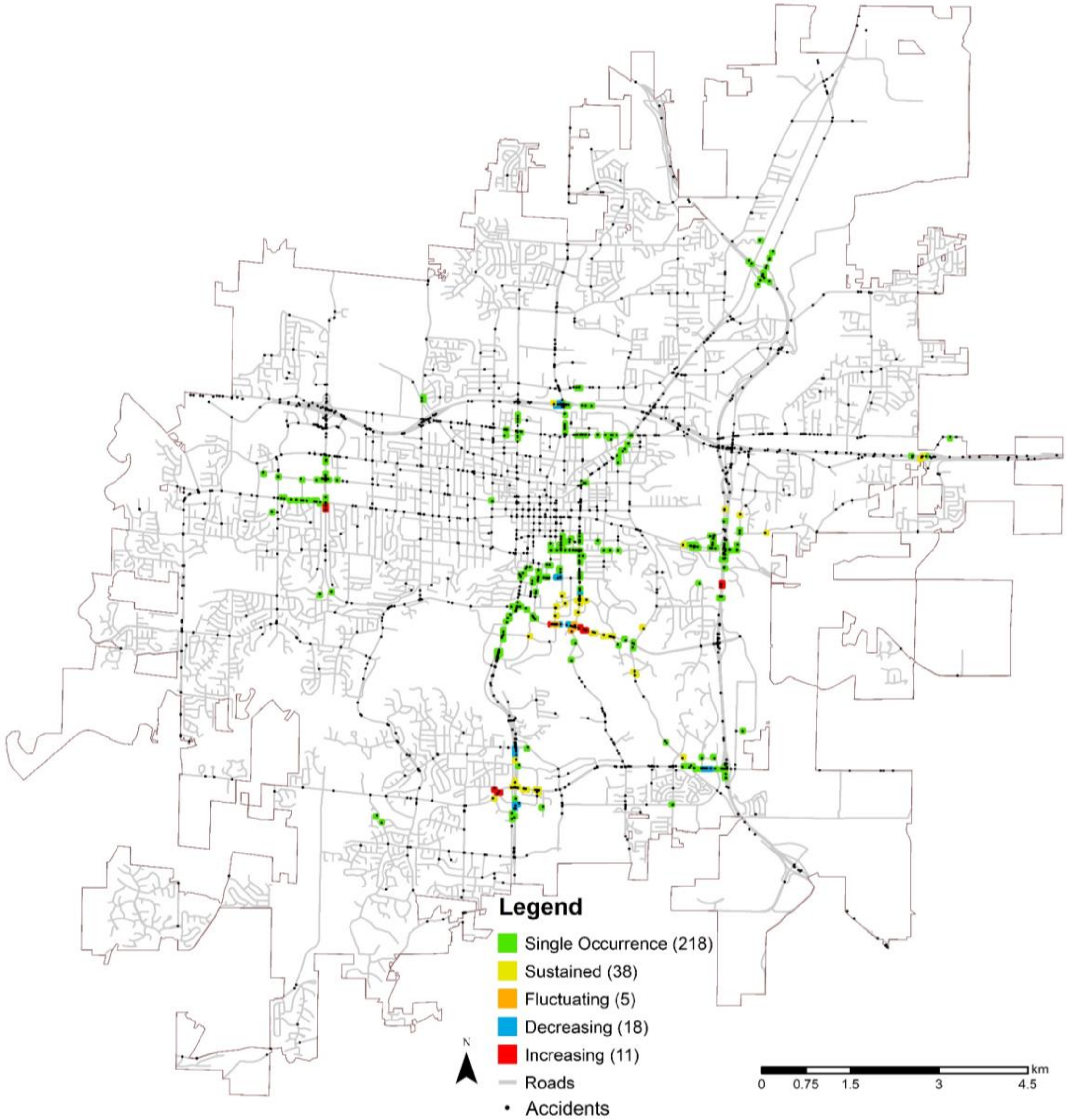


Figure 44. Analysis areas classified by type of evolution ($p \leq 0.1$) over two-month Periods

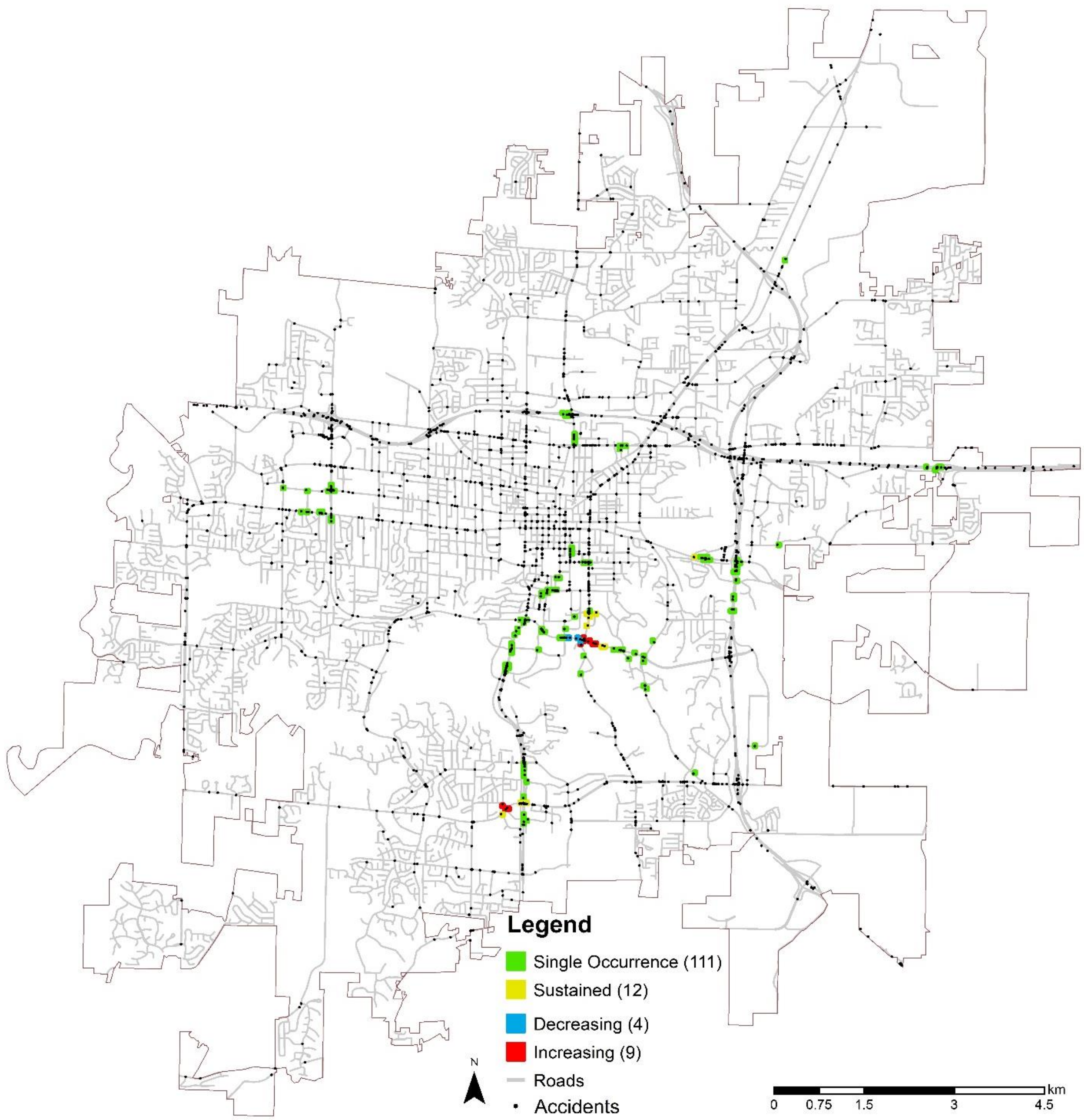


Figure 45. Analysis areas classified by type of evolution ($p \leq 0.05$) over two-month Periods

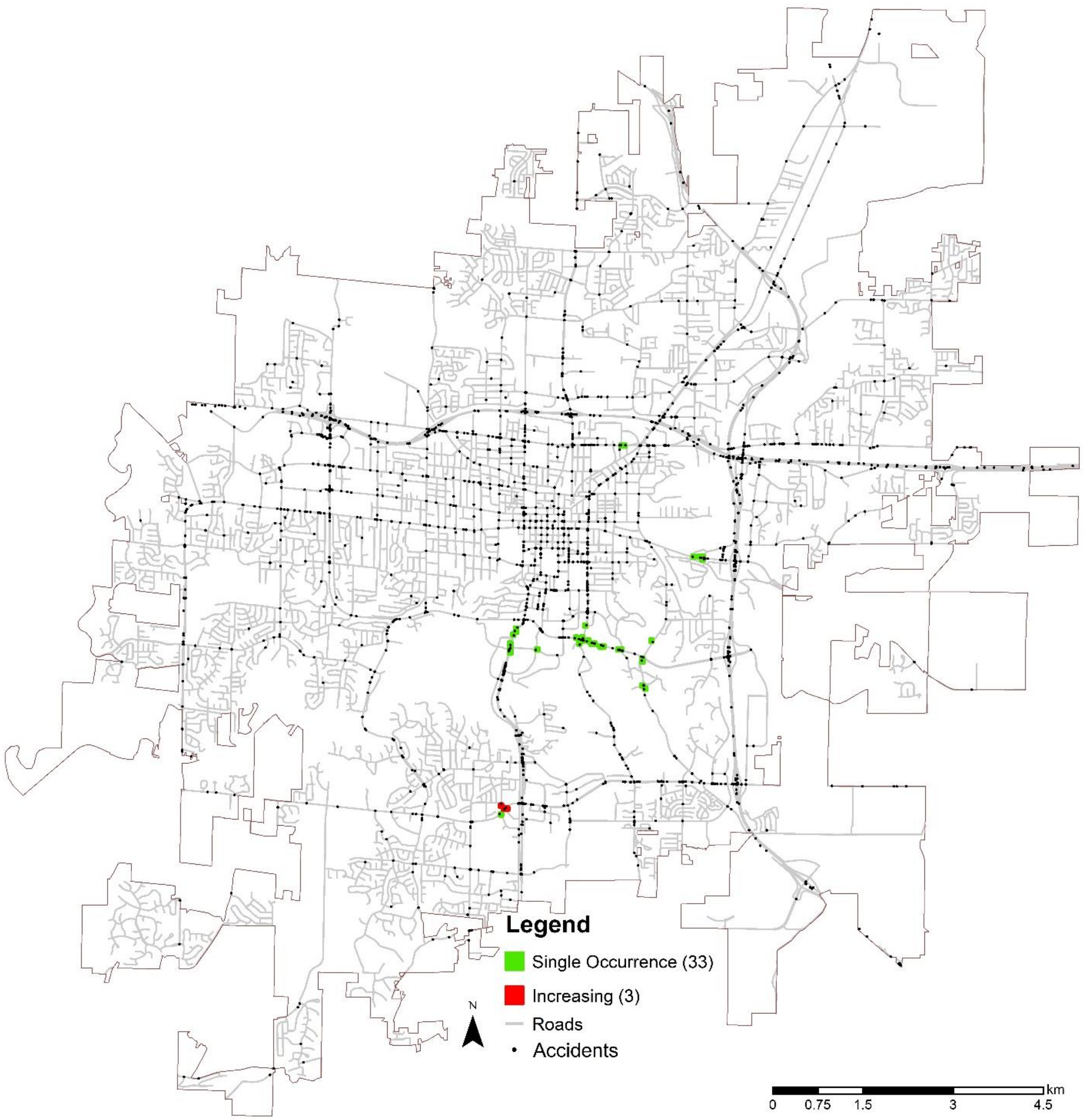


Figure 46. Analysis areas classified by type of evolution ($p \leq 0.01$) over two-month Periods

One-month periods of analysis generally introduce many more areas that were part of clusters than that observed in the two-month periods. For clusters significant at $p \leq 0.1$, Figure 47 shows the distribution of all five sorts of evolution over the city. Single occurrence clusters were associated with 184 analysis areas, primarily along minor arterials, and residential streets as well as near the approach to major roadways. 98 areas were part of sustained clusters and were located largely along major arterials and highways. Fluctuating clusters were associated with 37 analysis areas, mostly concentrated toward the central portion of the city (near a major university campus). 19 areas were part of clusters of increasing size and were primarily located near major intersections and were always adjacent to areas associated with other types of clusters (mostly sustained and fluctuating). The 26 areas associated with clusters of decreasing size were mostly located near minor intersections. Both Figures 48 and 49 for $p \leq 0.05$ and $p \leq 0.01$ successively illustrate partially the same distribution of clusters were associated with analysis areas as the one-month periods $p \leq 0.1$ but with less numbers. For example, Single occurrence clusters were associated with 138 and 60 analysis areas for $p \leq 0.05$ and $p \leq 0.01$ respectively which means less areas were part of clusters than that observed for the same one-month analyses $p \leq 0.1$ as in Figures 48 and 49.

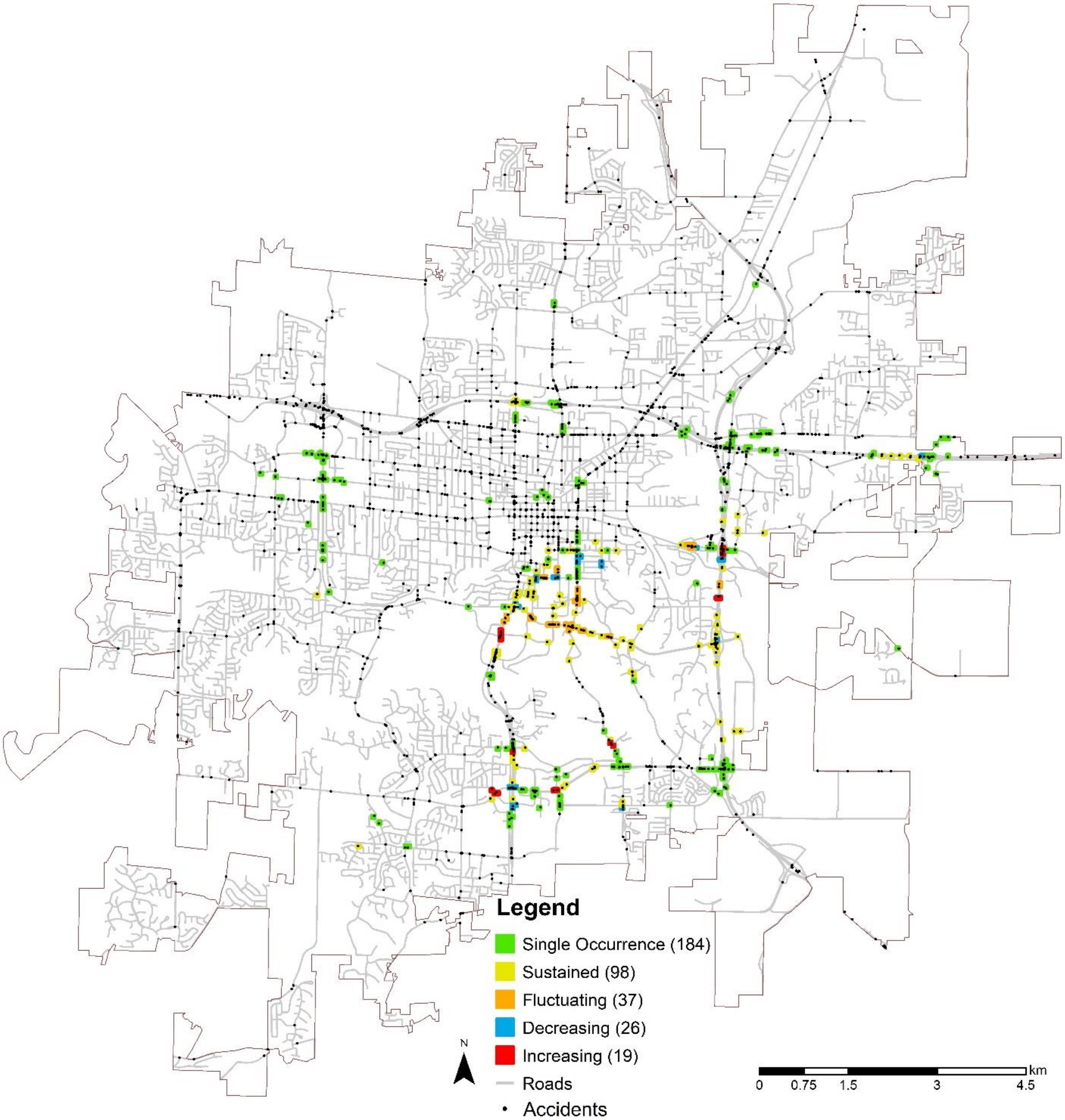


Figure 47. Analysis areas classified by type of evolution ($p \leq 0.1$) over one-month periods

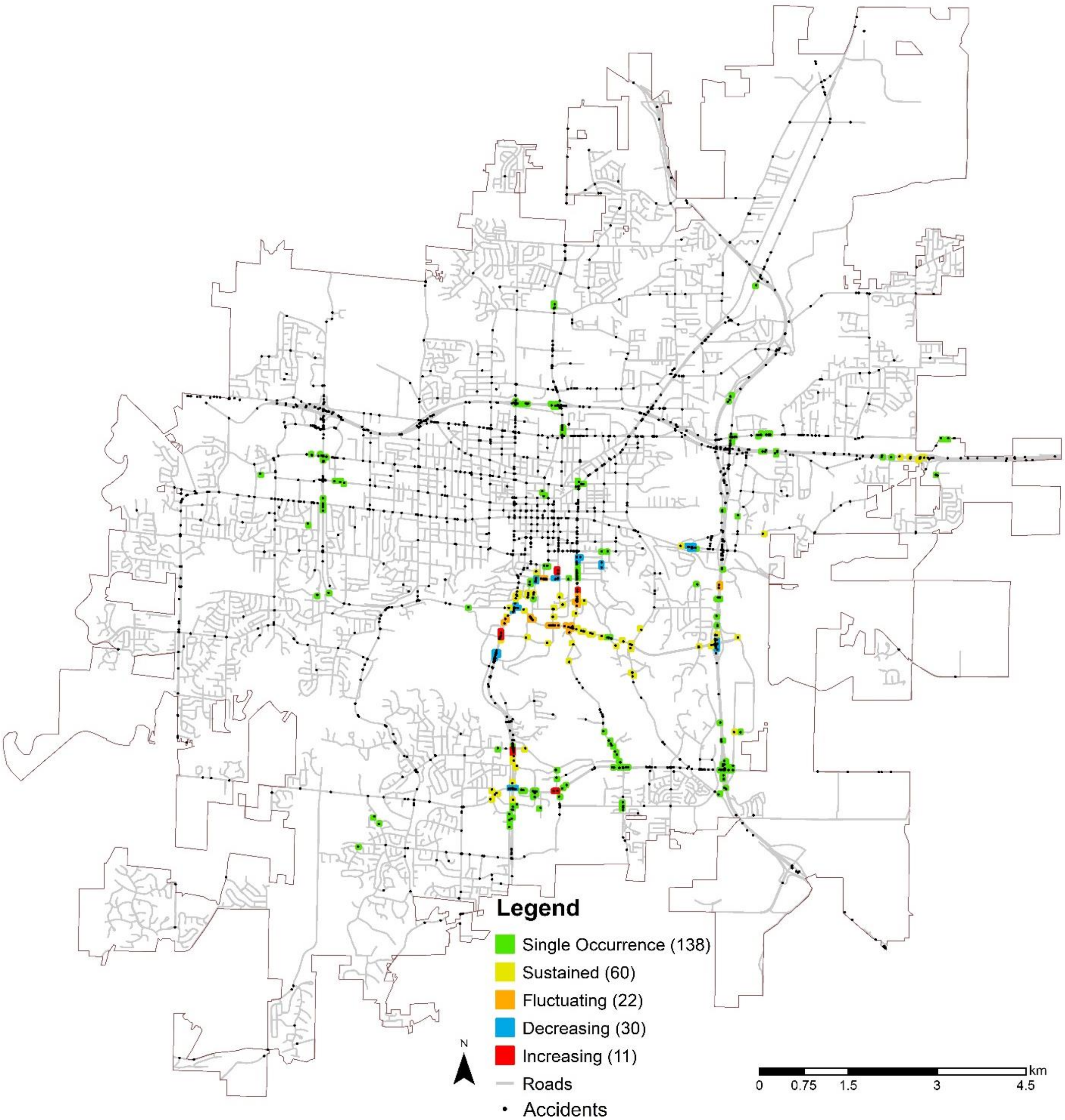


Figure 48. Analysis areas classified by type of evolution ($p \leq 0.05$) over one-month periods

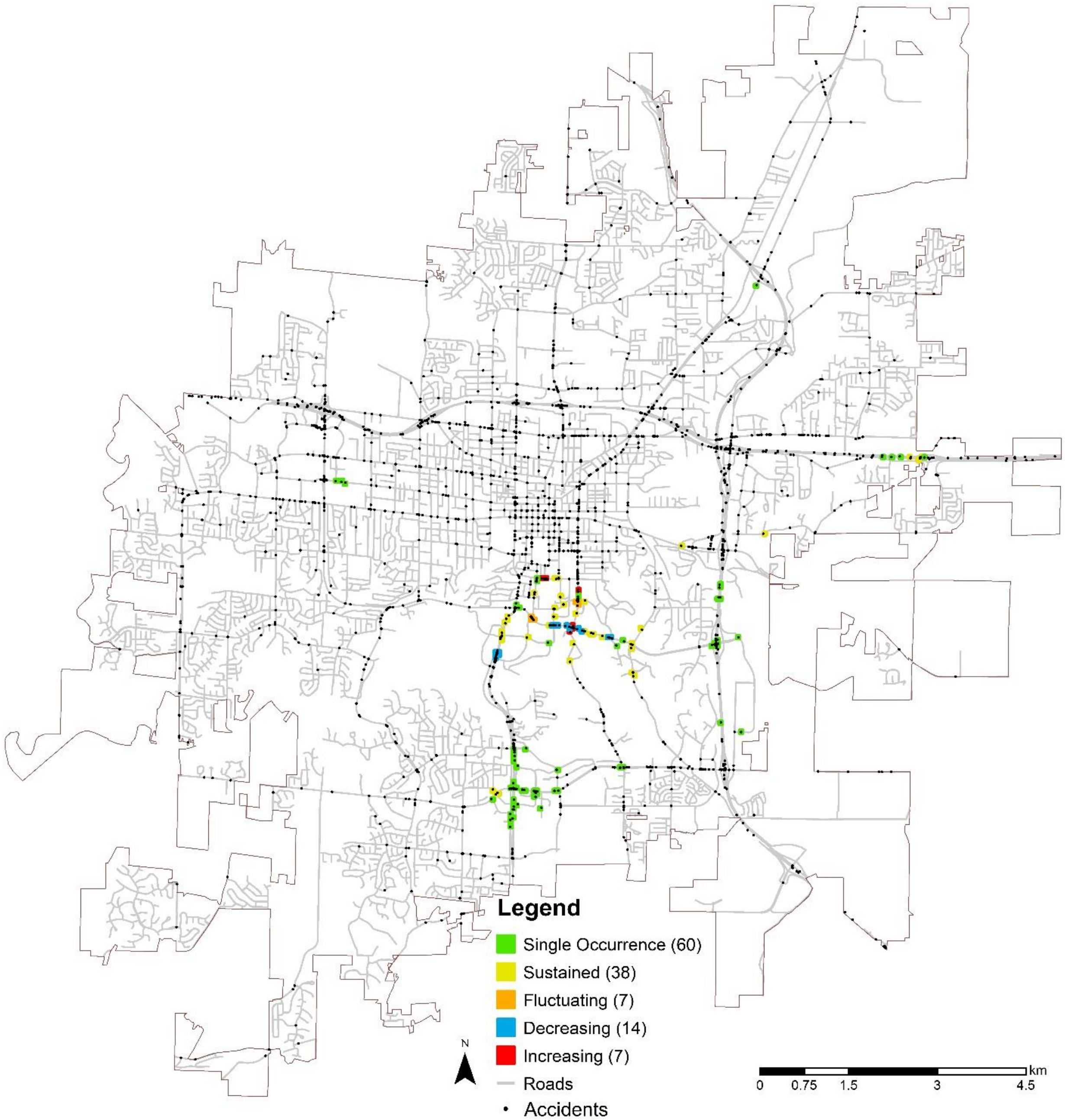


Figure 49. Analysis areas classified by type of evolution ($p \leq 0.01$) over one-month periods

Two-week periods of analysis introduce many more areas that were part of clusters than that observed in both two-month and one-month periods analyses. Figure 50 illustrates the analysis areas associated with clusters and categories of evolution for the two-week analysis periods ($p \leq 0.1$). Single occurrence clusters were associated with 273 analysis areas, primarily along minor arterials, and residential streets as well as near the approach to some major roadways. 218 areas were part of sustained clusters and were located largely along major arterials and highways. Fluctuating clusters were associated with 88 analysis areas, mostly concentrated toward the central portion of the city (near a major university campus). 51 areas were part of clusters of increasing size and were primarily located near major intersections and were always adjacent to areas associated with other types of clusters (mostly sustained and fluctuating). The 45 areas associated with clusters of decreasing size were mostly located near some minor and major intersections.

The other two statistically significant levels (i.e., $p \leq 0.05$ and $p \leq 0.01$) reveal fewer areas were part of clusters for the two-week analysis periods than $p \leq 0.1$. For example, Figures 51 and 52 illustrate that fluctuating clusters were associated with 69 and 29 analysis areas respectively which were less part of clusters than that observed in the $p \leq 0.1$ analyses as in Figure 50. In general, the types of locations associated with clustering were largely in line with what has been reported in other studies (e.g., Anderson, 2009; Eckley and Curtin, 2013; Erdogan et al., 2015; Fan et al., 2018; Nie et al., 2015; Steenberghen et al., 2011).

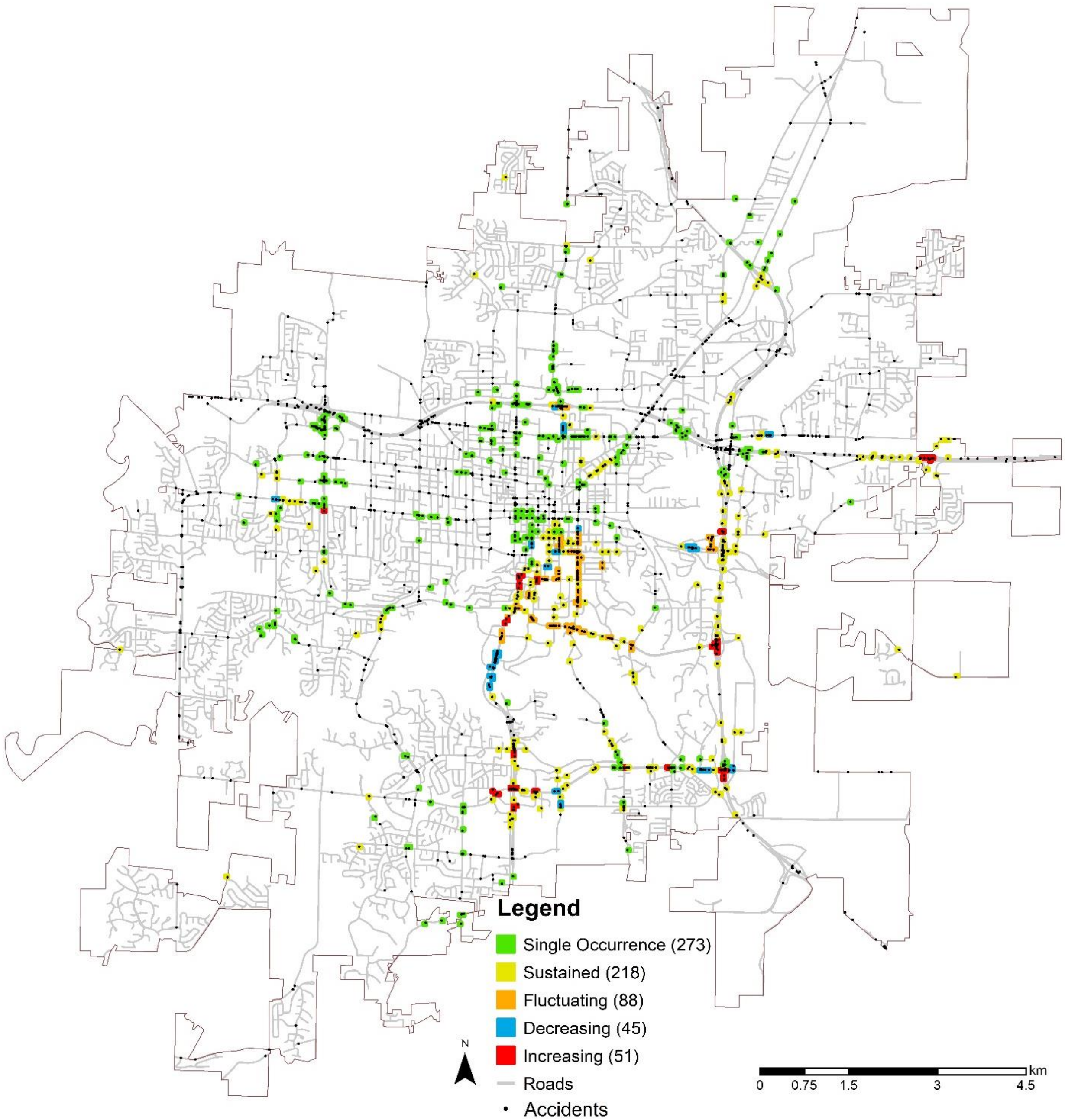


Figure 50. Analysis areas classified by type of evolution ($p \leq 0.1$) over two-week periods

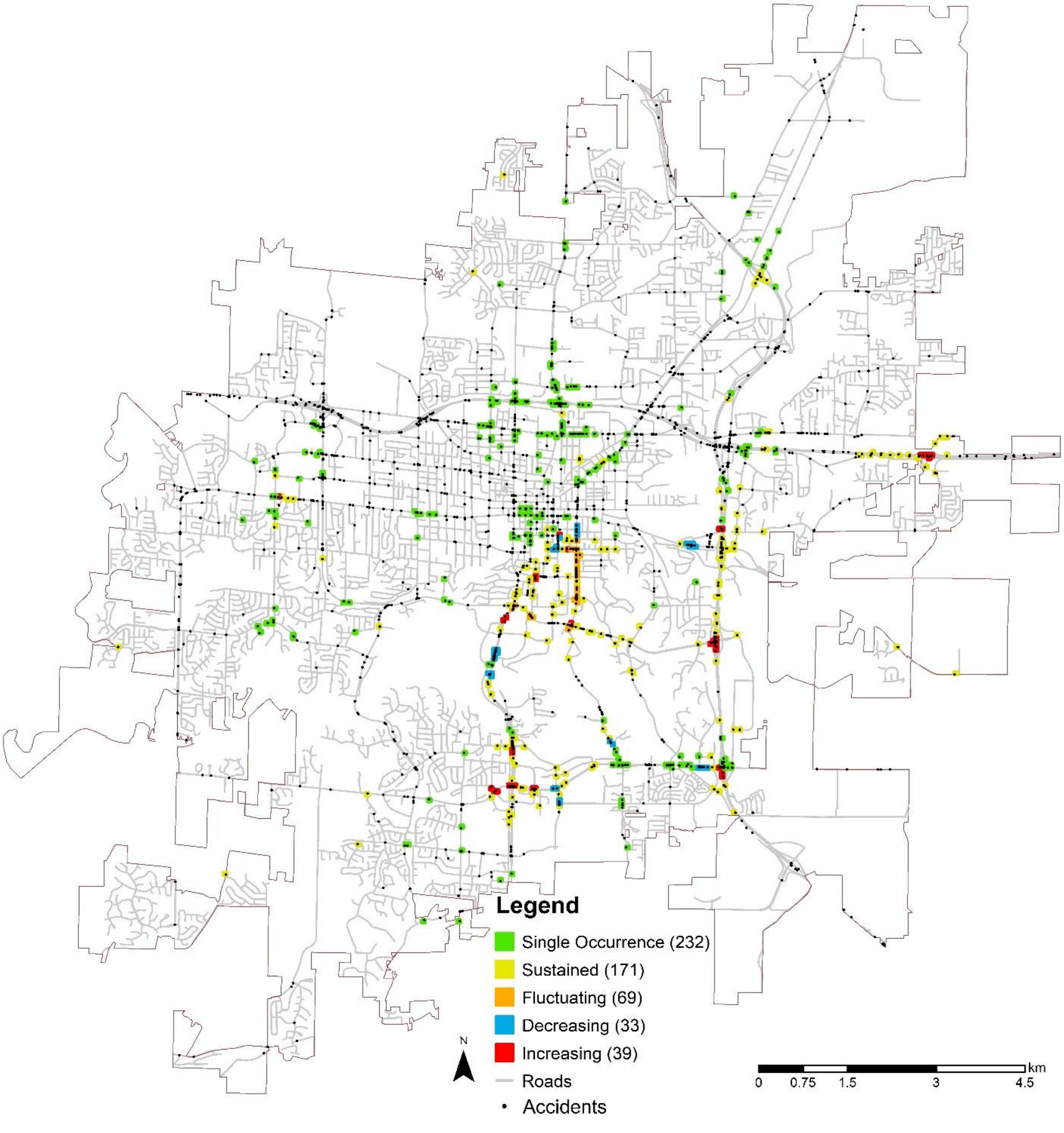


Figure 51. Analysis areas classified by type of evolution ($p \leq 0.05$) over two-week periods

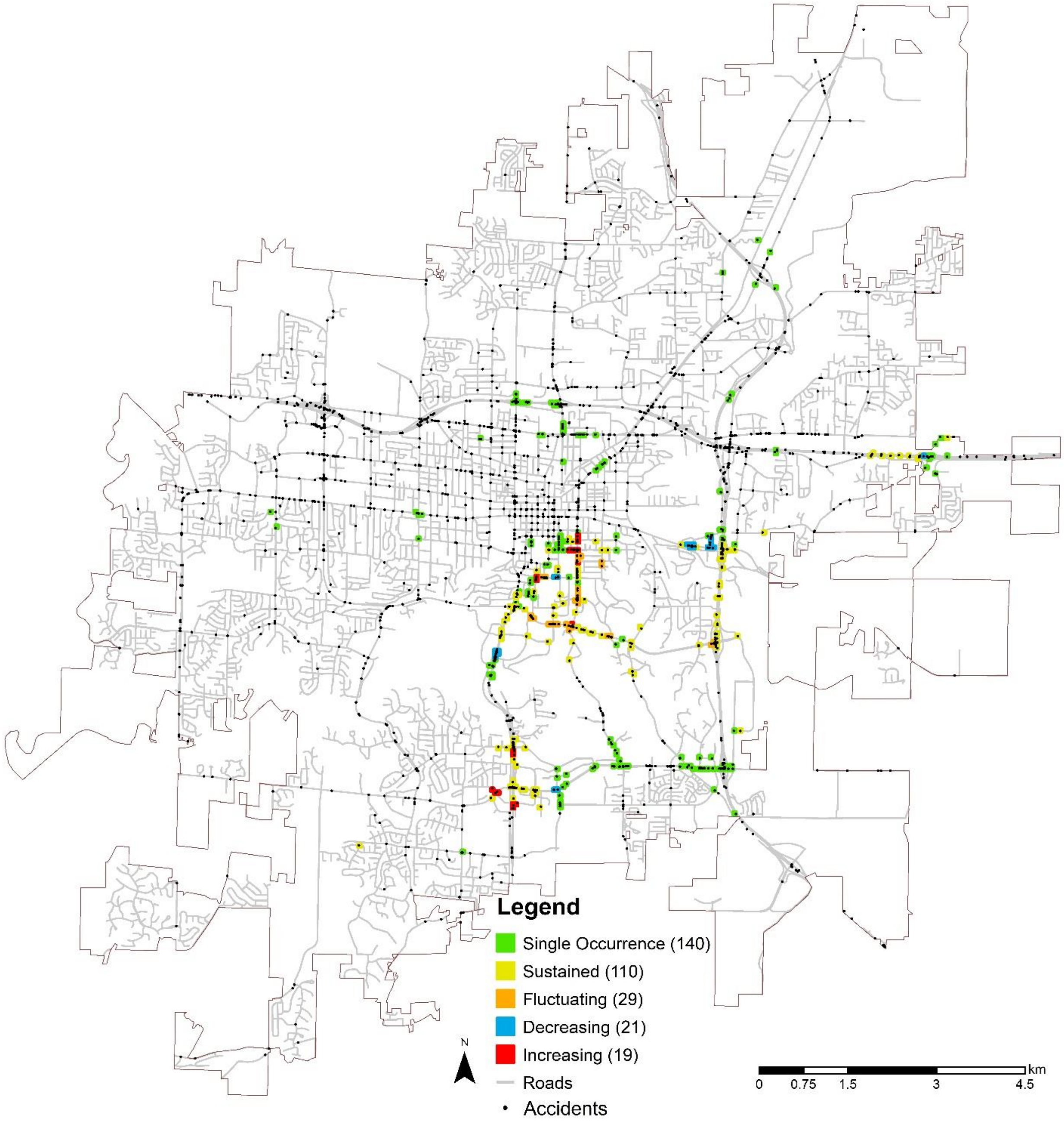


Figure 52. Analysis areas classified by type of evolution ($p \leq 0.01$) over two-week periods

Comparison of the trends shown in Figures 44 to 52 reveals some insight as to how the length of the analysis period can affect the results. Perhaps the largest implication of changing the lengths of the time periods is in the results of the clustering metric that is initially applied to the analysis units. That is, analyzing the accidents in one-month periods with a one-month temporal neighborhood can result in a different characterization of hot spots (spatial autocorrelation in this case) than analyzing the accidents in two-week periods using a two-week temporal neighborhood or two-month periods using a two-month temporal neighborhood. As such, there are cases in which an area is classified as part of a cluster in the one-month analysis but is not classified as part of one in the two-week or two-month analysis. Regardless, there are also many cases in which analysis areas are associated with clusters in all the two-month, one-month, and two-week analyses. In some instances, the cluster type associated with the areas can change among different temporal scales of analysis. For example, in the one-month analysis $p \leq 0.1$ (Fig. 47), areas spanning a major intersection (lower right side of the map) were found to be associated with single occurrence clusters. However, in the two-week analysis $p \leq 0.1$ (Fig. 50), many of those same areas are part of clusters of increasing, sustained, or decreasing size. In other instances, the cluster type associated with the areas is very similar among the three temporal scales of analysis. For example, in the one-month analysis $p \leq 0.1$ (Fig. 47), there are areas spanning another large intersection (middle right side of the map) that are categorized as part of sustained and a single decreasing cluster. In the two-week analysis $p \leq 0.1$ (Fig. 50), all but some of those areas are also part of a sustained cluster, with the remaining area categorized as part of a cluster of increasing size.

6.7 Cluster Analysis Distribution

Figures 53 summarizes the histogram distribution of cluster rank frequencies for the group of small cities (i.e., Macon, Monett, and Chillicothe). The cluster rank is defined as the value of cluster size divided by the minimum attributed amount of cluster size (i.e., 62,500 m^2) that were obtained from the STAG model. For example, the cluster rank of cluster size 187,500 m^2 is equal to 3 (i.e., 187,500 divided by 62,500 is equal to 3). Figure 53 illustrates a certain non-normality statistical distribution for the cluster ranks (i.e., calculated from cluster sizes) for the small urban group of cities when the distribution is clumped up to the left side (i.e., right or positive skewed) with a certain zero inflated probability distribution. In addition, the histogram distribution illustrates a zero-inflated probability distribution that would need further assessment to select the proper sort of statistical comparison analysis.

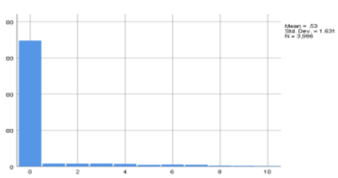


Figure 53. Cluster frequency distribution histogram for small cities

Figure 54 illustrates the histogram distribution of cluster rank frequencies for the micropolitan urban cities. Again, the histogram distribution of cluster ranks for a micropolitan group of urban cities introduces an apparent non-normality distribution (right-skewed) with a clear zero-inflated probability distribution when the number of zero cluster ranks were reached around 20,000.

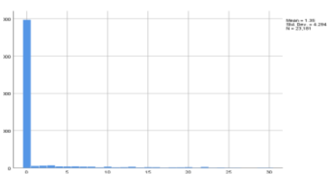


Figure 54. Cluster frequency distribution histogram for micropolitan cities

The histogram of the cluster frequency distribution of metropolitan urban areas introduces the highest number of zero cluster ranks (i.e., almost 800,000) among the two types of urban areas, small and micropolitan. Figure 55 illustrates that the three metropolitan areas were associated with a zero-inflated probability distribution and a clear non-normality distribution, especially when the cluster ranks were clumped up on the left side of the histogram (i.e., positive skewness).

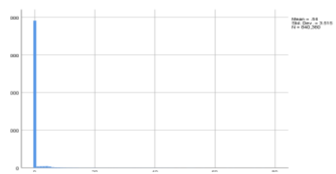


Figure 55. Cluster frequency distribution histogram for metropolitan cities

6.8 Best Fit Statistical Model

After showing the frequency of cluster rank by the distribution histogram for the three selected groups of urban areas, there is a need to select the best fit model for statistical comparison especially with the presence of both non-normality distribution and zero-inflated probability distribution. In this case, Poisson(p1), Negative Binomial(n1), Zero-Inflated Poisson (p2), and Zero-Inflated Negative Binomial(n2) were selected and compared for the best fit model by Rootgrams diagram. Figure 56 depicts a clear advantage for utilizing of Zero-Inflated Negative Binomial (n2) model when there is a significant least over-dispersion and/or under-dispersion among other selected models. The clustRank defines the set of ranks of cluster size values after dividing each cluster size by the minimum amount of cluster size calculated from the STAG model.

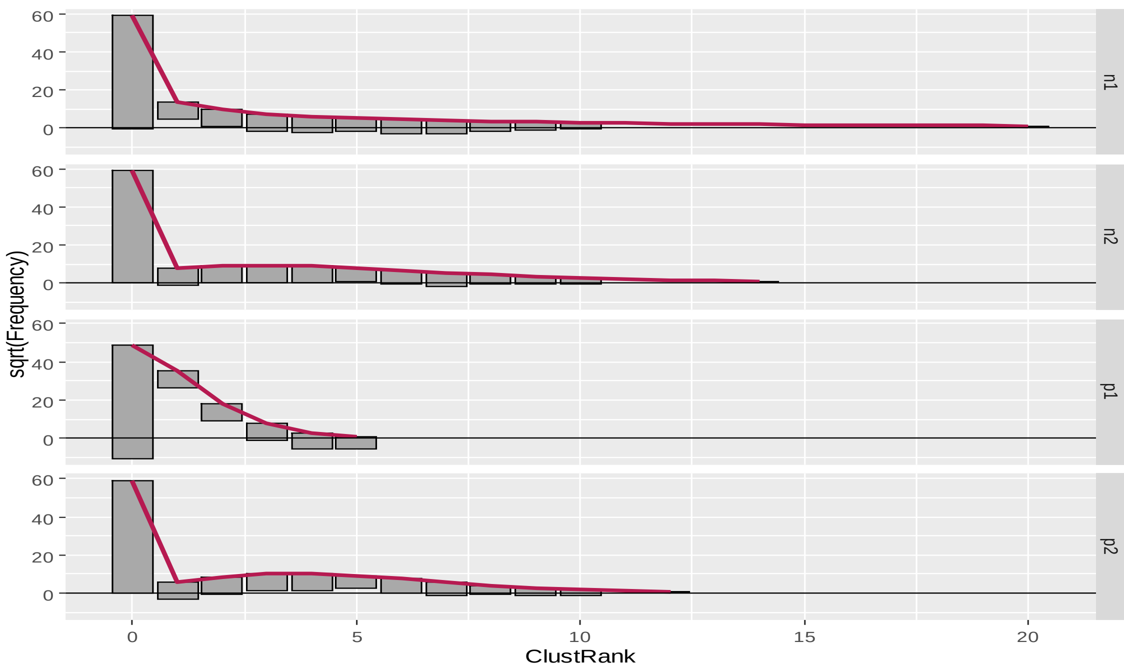


Figure 56. Rootgrams comparison for the best fit model for small urban cities group

Figure 57 depicts the comparison between the four selected models for the micropolitan urban areas for the best fit model. The Rootgrams diagram reflects that Zero-Inflated Negative Binomial (n2) model is the best fit statistical model for analysis of micropolitan urban areas when this model records the least over-dispersion and/or under-dispersion among the other three models.

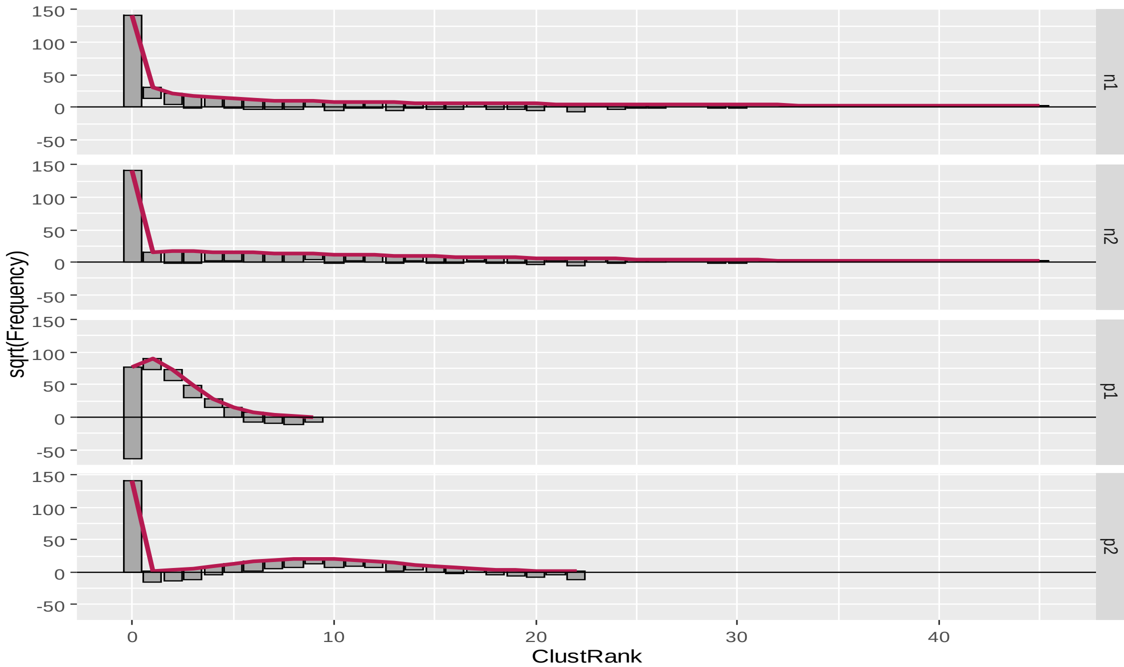


Figure 57. Rootgrams comparison for the best fit model for micropolitan cities group

Figure 58 summarizes the Rootgrams comparison between the four selected statistical models for the third biggest size of metropolitan urban areas. As mentioned, the best fit model could be concluded from the least over-dispersion and/or under-dispersion that were observed through Zero-Inflated Negative Binomial (n2) model.

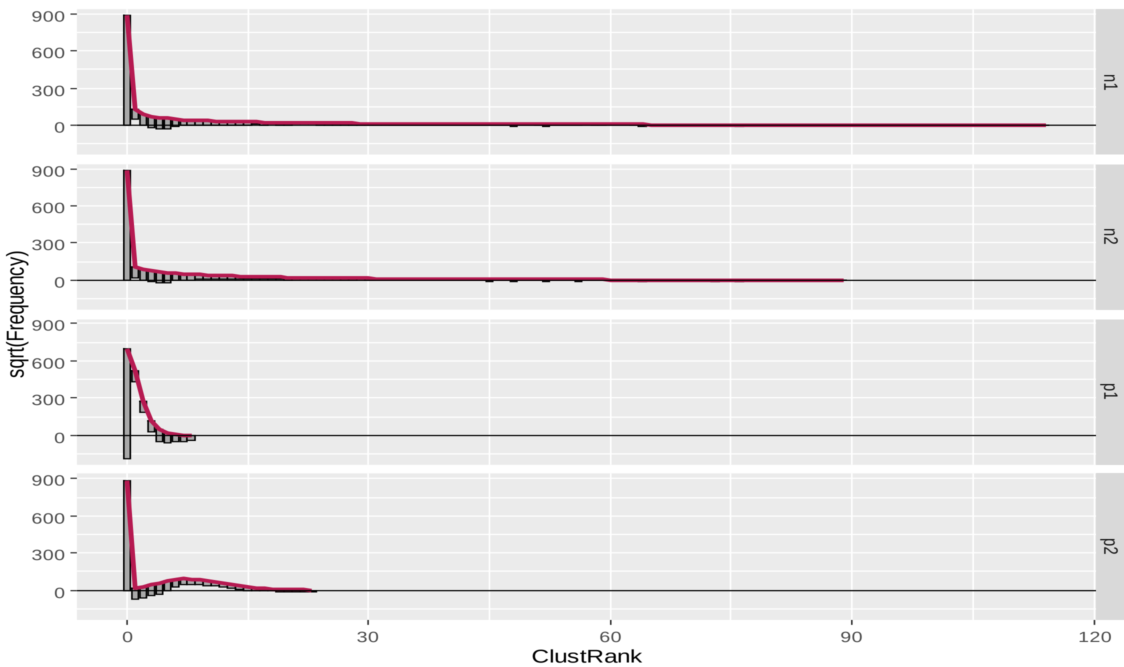


Figure 58. Rootgrams comparison for the best fit model for metropolitan cities group

Table 21 summarizes the comparison of the four selected statistical methods by Akaike Information Criterion (AIC) values that are associated with each type of the proposed method for each group of urban cities. The least values of AIC (5,593, 41,492, and 765,608) were observed during the Zero Inflated Negative Binomial (n2) method of analysis which categorizes as the best fit model for the statistical comparison datasets.

Table 21. Summary of the Akaike Information Criterion (AIC)

Urban Cities Group	Akaike Information Criterion (AIC)			
	Poisson (p1)	Zero Inflated Poisson (p2)	Negative Binomial (n1)	Zero Inflated Negative Binomial (n2)
Small	9,404	11,035	6,836	5,593
Micropolitan	140,888	152,123	68,902	41,492
Metropolitan	2,926,627	3,188,170	1,513,247	765,608

6.9 Cluster Average Log Counts Comparison

Tables 22 and Table C1 in Appendix C illustrate the statistical comparison between three small urban cities (i.e., Chillicothe, Macon, and Monett) over one-year and three-month periods, respectively. Both tables summarize the similarity or differences between these areas that are located within the same rank of urbanization over different time periods. For example, Macon and Monett during 2014 have been associated with *p*-value = 0.0634, indicating that both cities had similar average log counts of clusters during the same time period 2014 as in Table 22. In another case, Monett had a *p*-value = 0.0752 during 2013 and 2014, indicating that Monett had a similar value of average log counts of the cluster during both 2013 and 2014. The post hoc test calculates the amount of the average log counts of cluster sizes for each city within the group then compares these values between each pair of cities within a specific time period and assigns the similarity by labeled p-values. While the *p*-value is greater than 0.05 (i.e., fails to reject the null hypothesis), there is a notable similarity between the pair of the compared small urban group of cities during a specific time period. For example, Table C1 in Appendix C illustrates an obvious similarity between compared cities during quarter-year periods (three-month periods). The city of Chillicothe had a similar average log counts of clusters during both the second (April-June) and the third quarters of 2013 (July-September), both periods for the same city were associated with *p*-value =1.

Table 22. Statistical comparison of small urban cities for one-year periods

Contrast	Estimate	SE	df	Z.ratio	P-value
(Monett (2013)) - (Macon (2014))	-0.0384	0.0813	Inf	-0.472	0.9999
(Macon (2013)) - (Chillicothe (2014))	-0.0819	0.121	Inf	-0.677	0.9991
(Macon (2013)) - (Chillicothe (2015))	0.0893	0.1103	Inf	0.81	0.9966
(Monett (2014)) - (Macon (2015))	-0.0625	0.0663	Inf	-0.943	0.9905
(Monett (2013)) - (Macon (2015))	0.0722	0.0736	Inf	0.981	0.9876
(Macon (2014)) - (Chillicothe (2015))	-0.1138	0.0943	Inf	-1.206	0.9554
(Monett (2013)) - (Chillicothe (2015))	-0.1522	0.0855	Inf	-1.78	0.6954
(Monett (2014)) - (Monett (2015))	0.0732	0.0365	Inf	2.009	0.5371
(Macon (2014)) - (Macon (2015))	0.1106	0.0548	Inf	2.019	0.53
(Chillicothe (2014)) - (Chillicothe (2015))	0.1713	0.0846	Inf	2.025	0.5259
(Macon (2013)) - (Macon (2014))	0.2031	0.0699	Inf	2.907	0.0869
(Monett (2013)) - (Monett (2014))	0.1347	0.0455	Inf	2.96	0.0752
(Macon (2015)) - (Monett (2015))	0.1358	0.0458	Inf	2.961	0.0749
(Chillicothe (2013)) - (Chillicothe (2014))	0.3143	0.1054	Inf	2.981	0.0709
(Macon (2013)) - (Monett (2013))	0.2415	0.0808	Inf	2.989	0.0694
(Macon (2014)) - (Monett (2014))	0.1731	0.0573	Inf	3.02	0.0634
(Monett (2013)) - (Chillicothe (2014))	-0.3234	0.0956	Inf	-3.383	0.0206
(Macon (2014)) - (Monett (2015))	0.2463	0.0696	Inf	3.537	0.0121
(Monett (2014)) - (Chillicothe (2015))	-0.2869	0.0792	Inf	-3.623	0.0089
(Chillicothe (2015)) - (Macon (2015))	0.2244	0.0609	Inf	3.682	0.0072
(Chillicothe (2014)) - (Macon (2014))	0.285	0.0771	Inf	3.699	0.0067
(Chillicothe (2013)) - (Macon (2013))	0.3963	0.1066	Inf	3.719	0.0062
(Macon (2013)) - (Monett (2014))	0.3762	0.0955	Inf	3.938	0.0027
(Chillicothe (2014)) - (Macon (2015))	0.3956	0.0988	Inf	4.005	0.002
(Macon (2013)) - (Macon (2015))	0.3137	0.0688	Inf	4.56	0.0002
(Chillicothe (2013)) - (Chillicothe (2015))	0.4856	0.1026	Inf	4.732	0.0001
(Chillicothe (2013)) - (Macon (2014))	0.5993	0.1285	Inf	4.665	0.0001
(Monett (2013)) - (Monett (2015))	0.208	0.0442	Inf	4.708	0.0001
(Chillicothe (2013)) - (Macon (2015))	0.7099	0.1223	Inf	5.807	<.0001
(Chillicothe (2013)) - (Monett (2013))	0.6377	0.0956	Inf	6.672	<.0001
(Chillicothe (2013)) - (Monett (2014))	0.7724	0.1169	Inf	6.606	<.0001
(Chillicothe (2013)) - (Monett (2015))	0.8457	0.1131	Inf	7.476	<.0001
(Chillicothe (2014)) - (Monett (2014))	0.4581	0.0677	Inf	6.768	<.0001
(Chillicothe (2014)) - (Monett (2015))	0.5314	0.086	Inf	6.176	<.0001
(Chillicothe (2015)) - (Monett (2015))	0.3601	0.0554	Inf	6.5	<.0001
(Macon (2013)) - (Monett (2015))	0.4494	0.0908	Inf	4.95	<.0001

Table 23 depicts the contrast of average log counts of clusters that are part of the micropolitan urban cities group for one-year periods. The similarity and dissimilarity between the compared cities can be evaluated via the amounts of *p*-values. For example, For the city of Sedalia for both years 2014 and 2015, *p*-value= 0.9986, indicating that the average log counts of clusters values observed for both 2014 and 2015 were equal for the same city. Statistical comparison of quarter periods for micropolitan cities (Table C2 in Appendix C) by far tends to show a wide range of similarity between the compared average log counts of cluster values of three cities (Rolla, Sedalia, and Warrensburg) over different quarter-year periods. For example, for the comparison between different time periods such as the first and the second quarters of 2013 that associated with Rolla city, *p*-value = 0.0812, signifying that the amounts of the average log counts of clusters of Rolla city for both quarter periods were equal.

Tables 24 and C3 (Appendix C) also depict the contrast of one or two compared cities associated with p-values for the metropolitan size of urban cities group for one-year and quarter-year periods successively. In general, the level of similarity for the metropolitan group of three selected cities was largely in line with what has been reported in other studies (Casado-Sanz et al., 2020; Hosseinpour et al., 2014; Lobashov and Boikiv, 2020; Rolison et al., 2018; Saleem and Persaud, 2017; Sun et al., 2021a; Vandenbulcke et al., 2014; Wang et al., 2009). For example, two contrasts only were observed with similar average log counts of cluster values (*p*-value = 0.4683 and 1) for both St. Louis and Springfield for one-year periods as in Table 24. Contrasts associated with *p*-values equal or greater than 0.05 of metropolitan cities for quarter-year periods were also found to be less than both small and micropolitan urban cities groups as in Table C3 (Appendix C).

Table 23. Statistical comparison of micropolitan urban cities for one-year periods

Contrast	Estimate	SE	df	Z.ratio	P-value
(Sedalia (2014)) - (Sedalia (2015))	0.0206	0.0289	Inf	0.714	0.9986
(Rolla (2014)) - (Rolla (2015))	0.0566	0.0787	Inf	0.719	0.9985
(Warrensburg (2014)) - (Warrensburg (2015))	0.0738	0.0997	Inf	0.741	0.9982
(Warrensburg (2013)) - (Warrensburg (2015))	-0.0808	0.0969	Inf	-0.834	0.9958
(Rolla (2013)) - (Rolla (2015))	-0.0658	0.0765	Inf	-0.86	0.9949
(Sedalia (2013)) - (Sedalia (2015))	-0.0244	0.0281	Inf	-0.867	0.9946
(Warrensburg (2013)) - (Warrensburg (2014))	-0.1547	0.0999	Inf	-1.548	0.8328
(Rolla (2013)) - (Rolla (2014))	-0.1224	0.0787	Inf	-1.555	0.8292
(Sedalia (2013)) - (Sedalia (2014))	-0.045	0.0289	Inf	-1.559	0.8271
(Warrensburg (2013)) - (Rolla (2014))	0.3112	0.1229	Inf	2.533	0.2162
(Warrensburg (2013)) - (Rolla (2015))	0.3678	0.1223	Inf	3.008	0.0657
(Rolla (2014)) - (Warrensburg (2015))	-0.392	0.1231	Inf	-3.185	0.0388
(Warrensburg (2014)) - (Rolla (2015))	0.5224	0.1284	Inf	4.069	0.0016
(Rolla (2013)) - (Warrensburg (2015))	-0.5144	0.1209	Inf	-4.253	0.0007
(Rolla (2013)) - (Warrensburg (2014))	-0.5882	0.1269	Inf	-4.637	0.0001
(Rolla (2013)) - (Sedalia (2013))	0.9275	0.0587	Inf	15.808	<.0001
(Rolla (2013)) - (Sedalia (2014))	0.8825	0.0755	Inf	11.696	<.0001
(Rolla (2013)) - (Sedalia (2015))	0.9031	0.0752	Inf	12.01	<.0001
(Rolla (2013)) - (Warrensburg (2013))	-0.4335	0.0846	Inf	-5.124	<.0001
(Rolla (2014)) - (Sedalia (2014))	1.0048	0.0636	Inf	15.787	<.0001
(Rolla (2014)) - (Sedalia (2015))	1.0255	0.08	Inf	12.812	<.0001
(Rolla (2014)) - (Warrensburg (2014))	-0.4659	0.0913	Inf	-5.101	<.0001
(Rolla (2015)) - (Sedalia (2015))	0.9689	0.0601	Inf	16.116	<.0001
(Rolla (2015)) - (Warrensburg (2015))	-0.4486	0.0873	Inf	-5.141	<.0001
(Sedalia (2013)) - (Rolla (2014))	-1.0498	0.0796	Inf	-13.192	<.0001
(Sedalia (2013)) - (Rolla (2015))	-0.9933	0.0755	Inf	-13.154	<.0001
(Sedalia (2013)) - (Warrensburg (2013))	-1.361	0.0831	Inf	-16.382	<.0001
(Sedalia (2013)) - (Warrensburg (2014))	-1.5157	0.1059	Inf	-14.31	<.0001
(Sedalia (2013)) - (Warrensburg (2015))	-1.4419	0.098	Inf	-14.71	<.0001
(Sedalia (2014)) - (Rolla (2015))	-0.9482	0.0762	Inf	-12.447	<.0001
(Sedalia (2014)) - (Warrensburg (2014))	-1.4707	0.0907	Inf	-16.207	<.0001
(Sedalia (2014)) - (Warrensburg (2015))	-1.3968	0.0982	Inf	-14.224	<.0001
(Sedalia (2015)) - (Warrensburg (2015))	-1.4175	0.0838	Inf	-16.911	<.0001
(Warrensburg (2013)) - (Sedalia (2014))	1.316	0.0983	Inf	13.384	<.0001
(Warrensburg (2013)) - (Sedalia (2015))	1.3366	0.0988	Inf	13.526	<.0001
(Warrensburg (2014)) - (Sedalia (2015))	1.4913	0.1066	Inf	13.984	<.0001

Table 24. Statistical comparison of metropolitan urban cities for one-year periods

Contrast	Estimate	SE	Df	Z-ratio	P-value
(Springfield (2013)) - (StLouis (2015))	-5.67E-05	0.00727	Inf	-0.008	1
(Springfield (2013)) - (StLouis (2014))	1.54E-02	0.0073	Inf	2.107	0.4683
(StLouis (2014)) - (StLouis (2015))	-1.54E-02	0.00473	Inf	-3.262	0.0305
(Kansas (2014)) - (Kansas (2015))	-4.07E-02	0.01133	Inf	-3.591	0.01
(Springfield (2014)) - (Springfield (2015))	-2.10E-02	0.00566	Inf	-3.712	0.0064
(Kansas (2013)) - (Kansas (2014))	-8.87E-02	0.00999	Inf	-8.877	<.0001
(Kansas (2013)) - (Kansas (2015))	-1.29E-01	0.01106	Inf	-11.691	<.0001
(Kansas (2013)) - (Springfield (2013))	3.21E-01	0.00751	Inf	42.774	<.0001
(Kansas (2013)) - (Springfield (2014))	2.77E-01	0.01086	Inf	25.501	<.0001
(Kansas (2013)) - (Springfield (2015))	2.56E-01	0.0115	Inf	22.269	<.0001
(Kansas (2013)) - (StLouis (2013))	3.73E-01	0.007	Inf	53.373	<.0001
(Kansas (2013)) - (StLouis (2014))	3.37E-01	0.00975	Inf	34.522	<.0001
(Kansas (2013)) - (StLouis (2015))	3.21E-01	0.0099	Inf	32.427	<.0001
(Kansas (2014)) - (Springfield (2014))	3.66E-01	0.00799	Inf	45.78	<.0001
(Kansas (2014)) - (Springfield (2015))	3.45E-01	0.0114	Inf	30.221	<.0001
(Kansas (2014)) - (StLouis (2014))	4.25E-01	0.00772	Inf	55.052	<.0001
(Kansas (2014)) - (StLouis (2015))	4.10E-01	0.01036	Inf	39.569	<.0001
(Kansas (2015)) - (Springfield (2015))	3.85E-01	0.00847	Inf	45.51	<.0001
(Kansas (2015)) - (StLouis (2015))	4.50E-01	0.00879	Inf	51.275	<.0001
(Springfield (2013)) - (Kansas (2014))	-4.10E-01	0.01011	Inf	-40.531	<.0001
(Springfield (2013)) - (Kansas (2015))	-4.51E-01	0.01095	Inf	-41.143	<.0001
(Springfield (2013)) - (Springfield (2014))	-4.42E-02	0.00506	Inf	-8.745	<.0001
(Springfield (2013)) - (Springfield (2015))	-6.52E-02	0.0057	Inf	-11.438	<.0001
(Springfield (2013)) - (StLouis (2013))	5.22E-02	0.00569	Inf	9.178	<.0001
(Springfield (2014)) - (Kansas (2015))	-4.06E-01	0.01155	Inf	-35.193	<.0001
(Springfield (2014)) - (StLouis (2014))	5.96E-02	0.00656	Inf	9.086	<.0001
(Springfield (2014)) - (StLouis (2015))	4.42E-02	0.00803	Inf	5.503	<.0001
(Springfield (2015)) - (StLouis (2015))	6.52E-02	0.00707	Inf	9.224	<.0001
(StLouis (2013)) - (Kansas (2014))	-4.62E-01	0.00985	Inf	-46.894	<.0001
(StLouis (2013)) - (Kansas (2015))	-5.03E-01	0.01133	Inf	-44.389	<.0001
(StLouis (2013)) - (Springfield (2014))	-9.65E-02	0.00802	Inf	-12.032	<.0001
(StLouis (2013)) - (Springfield (2015))	-1.17E-01	0.00898	Inf	-13.078	<.0001
(StLouis (2013)) - (StLouis (2014))	-3.68E-02	0.00423	Inf	-8.72	<.0001
(StLouis (2013)) - (StLouis (2015))	-5.23E-02	0.00461	Inf	-11.33	<.0001
(StLouis (2014)) - (Kansas (2015))	-4.66E-01	0.01169	Inf	-39.871	<.0001
(StLouis (2014)) - (Springfield (2015))	-8.06E-02	0.00905	Inf	-8.908	<.0001

CHAPTER 7

DISCUSSION AND GENERAL IMPLICATIONS

7.1 STAG and SCGC

For the city of Columbia, three different temporal scales of analysis 12, two-month periods, 24, one-month periods, and 53, two-week periods with the application of $p \leq 0.1$, $p \leq 0.05$, and $p \leq 0.01$ for each temporal scale of analysis were applied. The total numbers of analysis areas obtained from EHSA for 12, two-month periods, 24, one-month periods, and 53, two-week periods are 16,116; 32,232; and 71,179, respectively. In addition, a statistical comparison of three different levels of urban city groups on the results of STAG methodology are generated multiple levels of similarity and dissimilarity between each group of urban areas. The following sections summarize the results of both analysis and comparison of the analysis areas, which resulted from the STAG and SCGC models.

7.1.1 Total Number of Clusters

Table 25 illustrates the total number of clusters that have a statistically significant value for all three temporal scales with three different p-values ($p \leq 0.1$, $p \leq 0.05$, and $p \leq 0.01$). As mentioned earlier, the two-week periods' analyses resulted in the highest number of clusters for different *p*-values if compared with both two-month and one-month analyses as illustrated in Table 25. The highest recorded number of clusters were observed during two-week periods *p*-value ≤ 0.1 while the least number of clusters were recorded during the two-month periods of analysis. Also, the number of clusters identified in the two-week analyses for both 0.05 and 0.01 *p*-values were higher than in other one-month and two-month analyses, as demonstrated in Figures 59, 60, and 61.

Table 25. Summary of the number of clusters for each temporal scale analysis

Temporal Period	*P*-value	C^t
	0.10	249
Two-Month	0.05	91
	0.01	22
	0.10	515
One-Month	0.05	326
	0.01	139
	0.10	1414
Two-Week	0.05	1009
	0.01	461

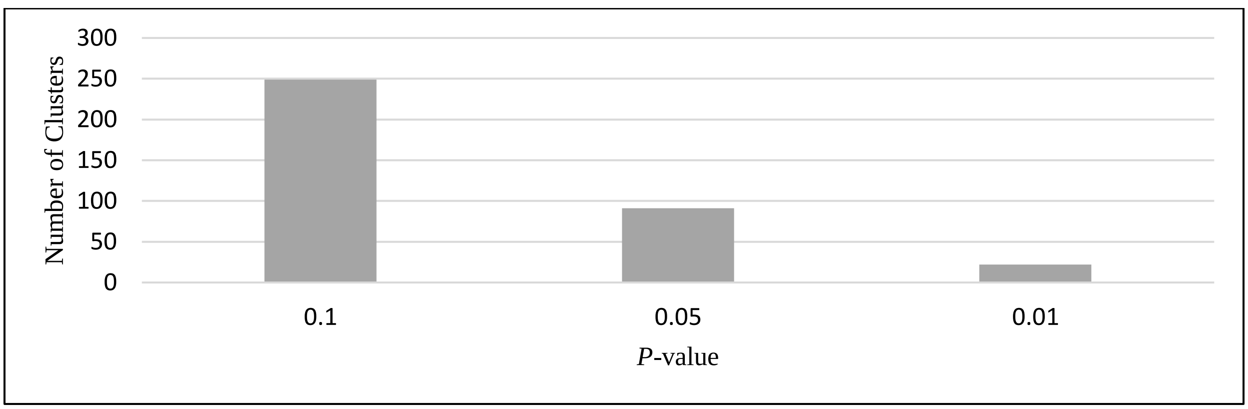


Figure 59. Total number of clusters over 12, two-month periods

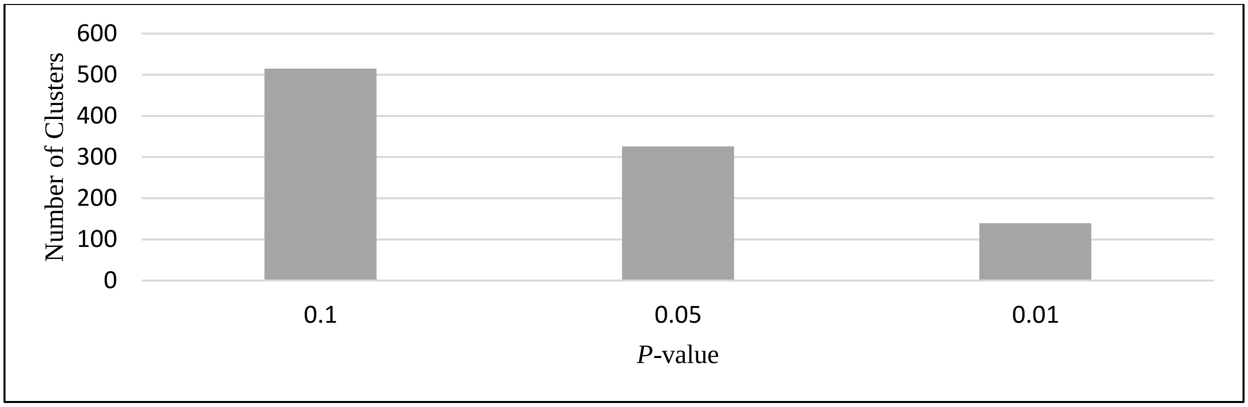


Figure 60. Total number of clusters identified over 24, one-month periods

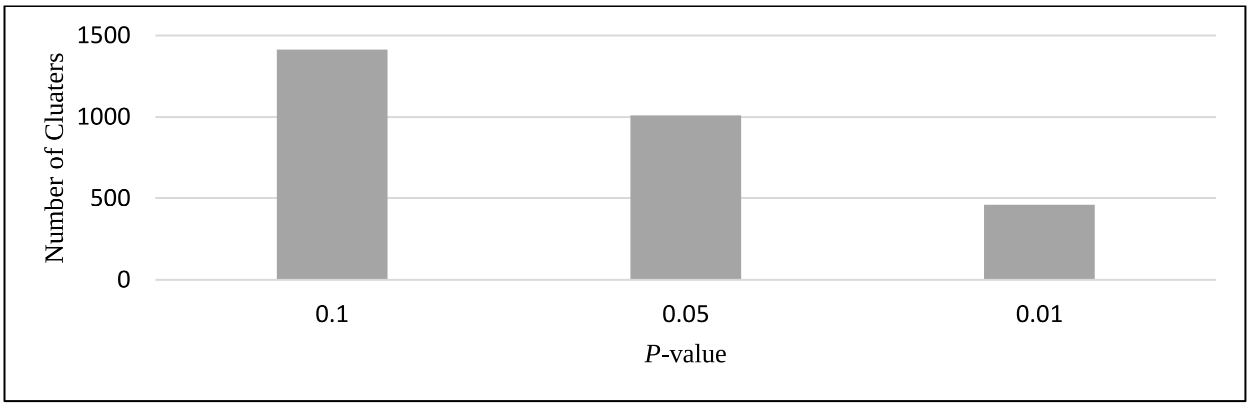


Figure 61. Total number of clusters identified over 53, two-week periods

7.1.2 Sum of Unique Temporal and Morphological Patterns

Each temporal scale consists of a specified sum number of unique temporal clustering patterns (Γ) and unique morphological patterns (M). As previously discussed, the 53, two-week periods scale of analysis has the highest number of both (Γ) and (M) as in Table 26. For example, the sum (Γ) of the two-week periods at $p \leq 0.1$ is 1,013, while for the same p-value of both 12, two-month and 24, one-month periods of analysis is 42 and 229 respectively. The number of (M) is within the same inclination of several trends when the two-week periods scale of analysis has also the highest number of unique morphological patterns among the three temporal scales at all p-values, as illustrated in Figures 62, 63, and 64.

Table 26. Sum of (Γ) and (M) for each temporal scale

Temporal Scale	P-value	$\sum \Gamma$	$\sum M$
	0.10	42	92
Two-Months	0.05	15	28
	0.01	6	9
	0.10	229	377
One-Month	0.05	167	233
	0.01	73	96
	0.10	1013	1261
Two-Weeks	0.05	756	948
	0.01	330	422

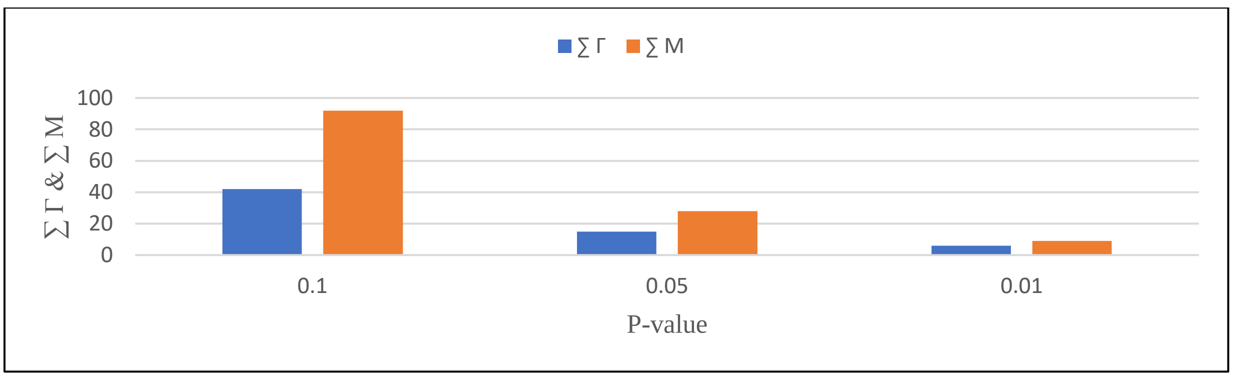


Figure 62. Sum of (Γ) and (M) patterns (over 12, two-month periods)

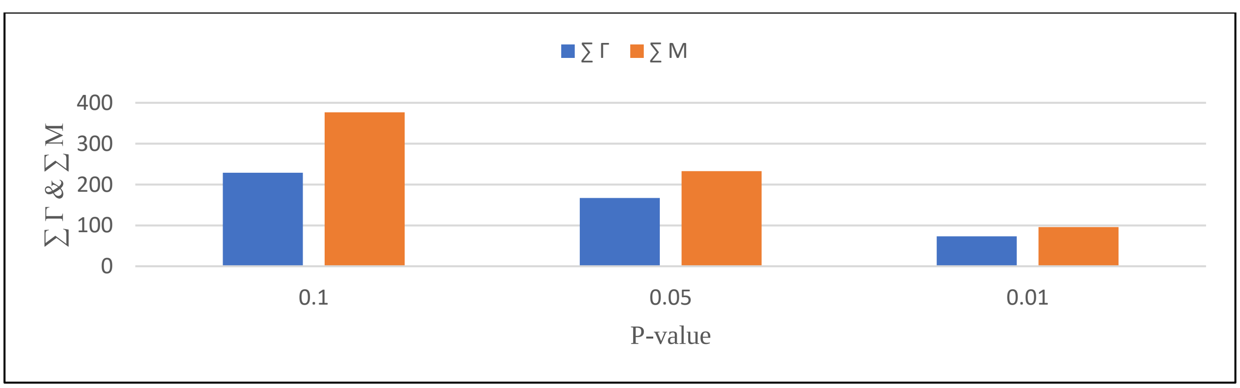


Figure 63. Sum of (Γ) and (M) patterns (over 24, one-month periods)

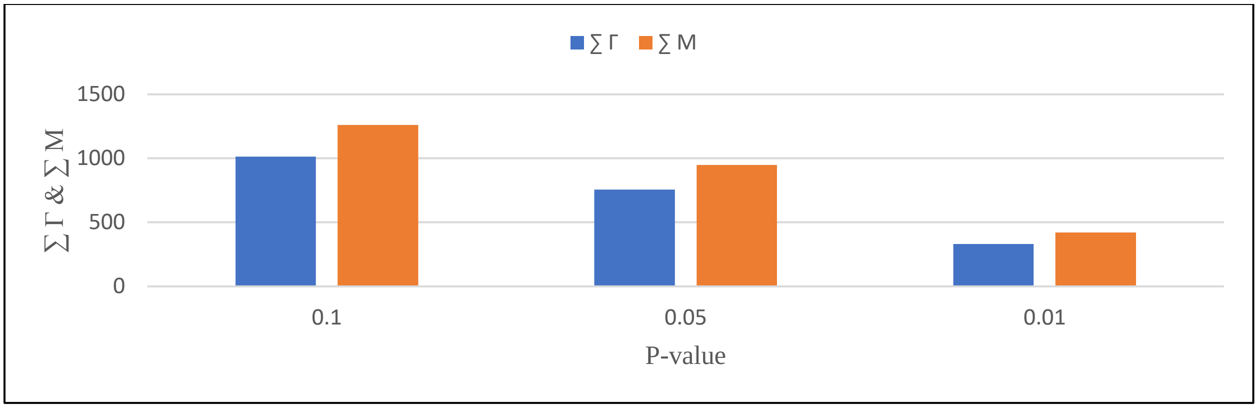


Figure 64. Sum of (Γ) and (M) patterns (over 53, two-week periods)

7.1.3 Clusters Size Evolution

The clusters' size evolution in Chapter 6 details the spatial locations of these clusters' development for each temporal scale and *p*-value. Table 27 summarizes the total number of occurrences for each temporal scale: two-month, one-month, and two-week periods with $p \leq 0.1$, $p \leq 0.05$, and $p \leq 0.01$ levels of statistical significance for each scale. The highest number of occurrences was recorded during two-week periods at $p \leq 0.1$ level of significance, while the lowest number of occurrences was observed during the two-month periods $p \leq 0.01$ for all sorts of cluster size evolution such as single occurrence, sustained, etc. Figures 65, 66, and 67 depict the bar charts for the number of occurrences of two-month, one-month, and two-week periods at $p \leq 0.1$, $p \leq 0.05$, and $p \leq 0.01$ level of significance successively.

The neighborhood structures that are used to define clusters can be the same as that used in the computation of the spatiotemporal clustering metric (e.g., the N_i used in the EHSA) or any other neighborhood structure $\hat{N}_i$ given the analysis context. Therefore, the created clusters will be a set of areas participating in borders, located within the specified distance, and have the same spatial value. Moreover, sets of analysis areas that are geographically connected by borders defined a specified spatial neighborhood structure. Data quality of accidents could impact the analysis results when it is the key for making precise and knowledgeable judgments. Data quality is established on some characteristics such as precision, comprehensiveness, stability, legality, individuality, and suitability. For example, assigning or recording a wrong accident location by police authorities could provide a different cluster morphological evolution which advances to different decision-making through these related safety agencies.

Table 27. Number of cluster size evolution trends occurrence

Temporal Period	P-value	Category of Evolution				
		Single Occur.	Sustained	Fluctuating	Decreasing	Increasing
Two-Month	0.10	218	38	5	18	11
	0.05	111	12	0	4	9
	0.01	33	0	0	0	3
One-Month	0.10	184	98	37	26	19
	0.05	138	60	22	30	11
	0.01	60	38	7	14	7
Two-Week	0.10	273	218	88	45	51
	0.05	232	171	69	33	39
	0.01	140	110	29	21	19

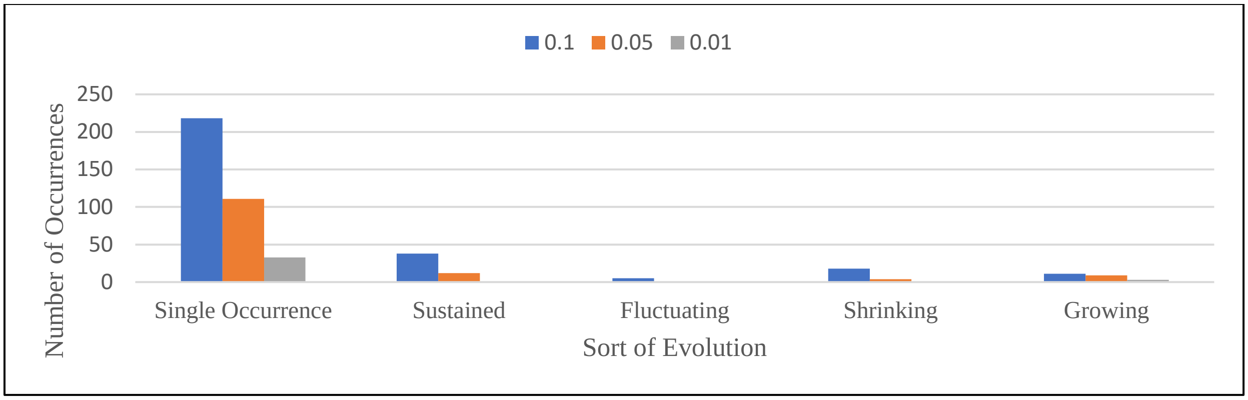


Figure 65. Number of cluster size evolution (over 12, two-month periods)

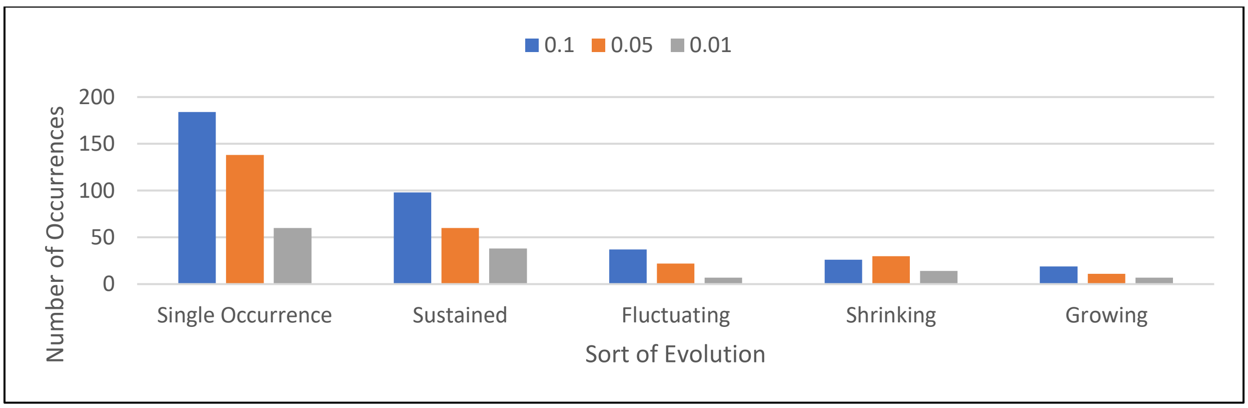


Figure 66. Number of clusters (over 24, one-month periods)

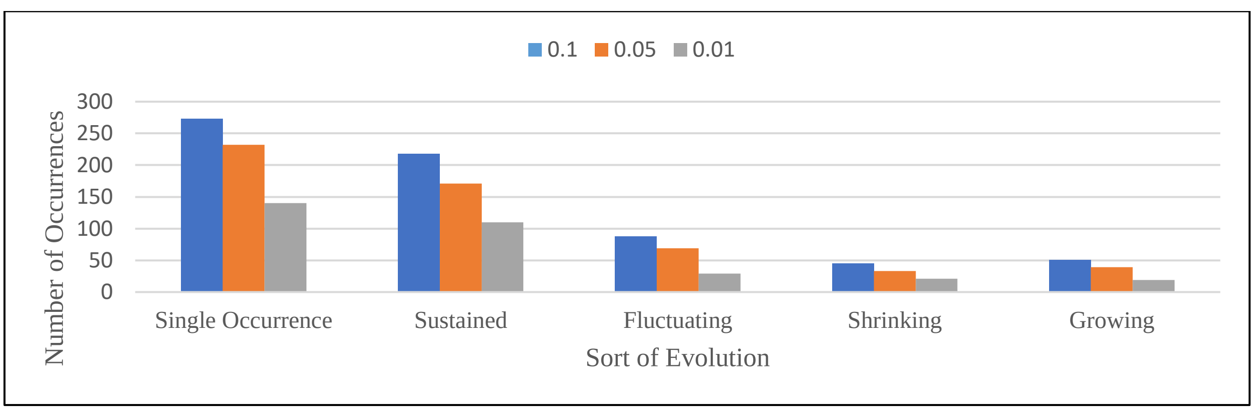


Figure 67. Number of clusters (over 53, two-week periods)

7.2 Cluster Statistical Comparisons

The comparison of average log counts of cluster values presented in Chapter 6 illustrates the presence of similarity/dissimilarity percentages between the three city groups (small, micropolitan, and metropolitan). For example, the percentage of similarity was always decreasing with an increase in the urban size of the compared cities. Comparing multiple cities according to the level of urban planning reveals some insight as to how the complexity of the road ranks and urban levels can affect the results of similarity/dissimilarity between the compared city areas over different periods (one-year and quarter-year periods). That is, comparing metropolitan cities such as Kansas with St. Louis and Springfield can result in fewer similarities of morphological cluster characteristics than smaller urban size cities. As such, comparing small cities like Monett, Macon, and Chillicothe can obtain more similar cases. Figures 68 and 69 illustrate the percentages of contrasts in similarity/dissimilarity of three city groups for both quarter-year and one-year periods.

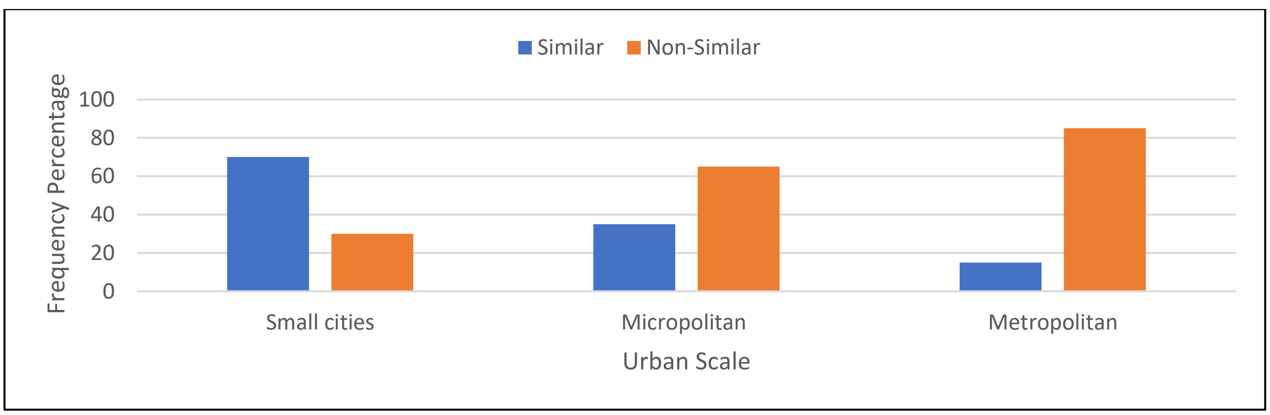


Figure 68. Percentage of similarity/dissimilarity frequency between different urban city scales for quarter-year periods

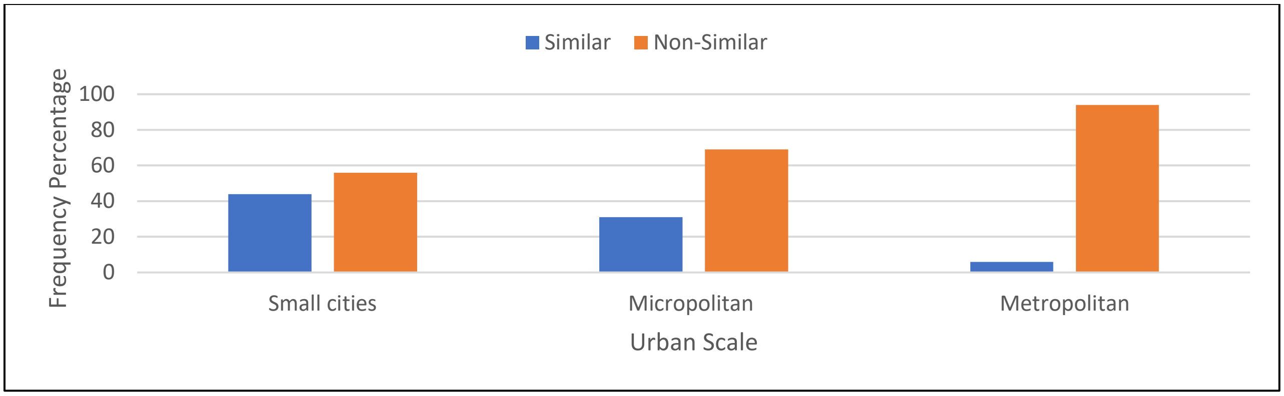


Figure 69. Percentage of similarity/dissimilarity frequency between different urban city scales for one-year periods

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

8.1 Conclusions

The ability to quantify, track, and compare morphological changes associated with accident hot spots can provide important insights to those charged with accident prevention and mitigation. This research describes a framework for accomplishing such a task. Given a set of analysis areas that have been associated with a measure of spatial clustering for a particular time period, a process for geometrically merging analysis areas associated with the same cluster type that are geographically connected based on a presumed spatial neighborhood structure then comparing these structures as per the urban city ranks is described. The resulting cluster polygons permit the morphology of the region impacted by accidents to be more clearly delineated and examined. The new cluster polygons can then be related to the original analysis areas such that changes in the size of clusters associated with the areas can be measured over time. An application to vehicular accidents spanning two years is examined to demonstrate the utility of the approach. Also, an application of comparison to clusters covering three years is evaluated to validate the efficiency of the approach. The application results indicate that both methodologies can be used to effectively evaluate, track, and compare the size evolution of clusters. In particular, it was found that the spatial extent of the clustered features can exhibit much change over time. In some instances, analysis areas were only associated with a cluster in a single period but varied with respect to cluster size and period of occurrence. In others, analysis areas were part of a cluster in multiple periods over which the size of the cluster stayed the same, increased, decreased, or fluctuated. The choice of analysis area parameters could impact or change the outcomes of models and lead to deviating conclusions. For example, selecting a large analysis area size (e.g., 62,500 m^2) over a small urban city could lead to wrong cluster morphological evolution conclusions. Therefore, in this study, analysis area sizes have been selected according to some practical criteria such as the shortest road segments or the land use.

Also, a statistical comparison application to hot spot cluster results associated with the three different urban level groups of cities is examined. Given a set of statistical results that have been associated with a measure of statistical similarity/dissimilarity between selected urban areas, a comparing process for selected urban areas associated with the same urban rank is described. In particular, it was found that the statistical similarity between the urban group of cities can be changed according to the size of the urban area. In some instances, the level of statistical similarity was highly associated between small urban areas groups (Macon, Monett, and Chillicothe). In others, the degree of statistical similarity between the metropolitan group of selected urban cities was low (St. Louis, Springfield, and Kansas City). In particular, it was found that the degree of similarity between different urban area ranks is related to the size of the urban area and the complexity of road networks. For example, comparing metropolitan areas that have a diverse design of road networks could provide a low statistical similarity between the compared cities.

While the output of traditional clustering methods provides insight as to where clustering is likely to exist and which accidents are associated with particular clusters, the methods demonstrated here provide for better quantification and comparison of cluster morphology. Accounting for the evolution of cluster size can provide valuable insight as to the factors underlying their appearance, disappearance, growth, and decline over time. For example, should cluster growth be detected, underlying processes could be investigated, and appropriate mitigation measures could be identified. Locations at which sustained clustering are presented might be indicative of a need for required persistent surveillance and monitoring. Those charged with managing traffic safety in a region could use these insights to better inform where and when resources should be best deployed to mitigate these problems. The 'fluctuating' category refers to areas that are part of a cluster polygon whose size does change from increasing to decreasing or decreasing to increasing which means there is a high fluctuation of car accidents in these areas and might need to monitor these areas constantly to improve safety. Detecting the declines in cluster size can be of managerial benefit as well. For example, a decline in cluster size could provide evidence that the allocation of safety resources (e.g., accident countermeasures) has been successful. The STAG methodology also could be practically utilized in safety-related applications. For example, improving the accident's safety of roads and intersections by DOTs or police departments could be realized by applying the STAG methodology towards any areas (e.g., urban or rural) and implying the sort of clusters morphological development over selected different time periods. Therefore, managing and deploying the required sources for accidents mitigation will be assigned accordingly to the outcomes of the STAG model which could manage and reduce the assigned budget to mitigate accidents and improve safety.

The high detected cluster similarity percentage between some urban cities (e.g., small urban cities) can provide valuable understanding as to the factors underlying this similarity. For example, the high similarity between small urban cities could improve the accidents monitoring and utilize the allocation of accident management resources. Therefore, SCGC could be useful for the related safety authorities who need to manage their budgets to cope with disasters, accidents, crimes, etc. Applying SCGC could imply the degree of similarity between a group of the compared areas. For example, the daily deploying scenario of highway patrols over main highways in Macon city could be utilized and applied over any city area that is ranked within the same urban level (e.g., Monett). Therefore, inferring or knowing the degree of similarity between the compared cities within each group could be practically important for applying the strategic plans (e.g., deploying of patrols) over the same sort level of areas. For example, applying the SCGC model concludes that there is a high degree of similarity between a group of cities (e.g., small urban cities) which provides a valuable guide for the related safety authorities to apply the same plans of roads safety for the same rank of these cities.

Certain components of road networks such as intersections are thought to be very important to accident management and prevention. The planning and design of the intersections define the safety, efficiency, traveling speed, and capacity of the roads network. While intersections have a high percentage of accidents than other road facilities, accounting for the evolution of cluster size at intersections could provide a valuable understanding of the strategies and plans for accident mitigation. Also, the period of analysis consideration may play an important role in accident management. For example, while the frequency of accidents in large cities (e.g., St. Louis) is high, with many occurring each day, smaller temporal periods (e.g., one-week or two-week periods) may be more appropriate. Therefore, selecting an optimal temporal frequency can be determined according to some criteria such as the size of the city and/or accident frequency. Additionally, large temporal periods with large metropolitan cities should be avoided when the frequency of accident over these areas are high and require small temporal periods.

8.2 Future Work

Numerous opportunities exist for extension and application of the proposed approach. In application detailed in this manuscript, two-month, one-month, two-week, and one-week analysis periods were considered given the number of daily crashes in the study region was not very large. While one-day periods could be explored, the clustering would likely be much more sporadic over time and the unique temporal and morphological patterns identified would likely be much more vast. Therefore, it could be fruitful to investigate the evolution of accident clusters in different regions (e.g., large county) to observe the effects of smaller temporal analysis periods. while the analysis framework was applied here to evaluate and compare clustering of vehicular accidents, it could be further applied to quantify clusters and evaluate changes in their morphology given other point-based events such as crimes, pandemics, natural hazards, etc. Also, the utilized methodology could be applied to investigate the frequency and compare the similarity/dissimilarity of cluster morphological specifications in different areas according to the traffic and geometric roads design specifications for both urban and rural areas. In this research, the number of vehicles per accident was considered as a spatial parameter for analysis, therefore, there is a good reason to use other spatial attributes like the presence of alcohol, drugs, mobile, drivers' age, etc. for inspecting the morphological evolution of accident clusters in different areas and apply the required safety tools to improve safety by the associated authorities.

Whereas traffic volumes could be exploited during similar periods of time to that of accident data, using traffic flow (the total number of vehicles passing a given point during a time period) could be utilized as an input dataset for both investigating (STAG) and comparing (SCGC) the morphological evolution over urban or rural areas. Also, accident rates for clusters morphological evolution could be utilized to calculate the accident rates at each spot or point.

This study utilized data of accidents for multiple cities in Missouri. However, there is a good reason to utilize other sorts of datasets from different areas for analysis (e.g., crimes, Pandemics, traffic volumes…etc.). For example, inspecting the sorts of clusters morphological evolution for crimes dataset over some metropolitan areas and comparing between these areas could provide crucial background for police authorities to deal with crimes around these areas.

In addition to taking the whole urban city as one area, it could be profitable to investigate and compare the morphological evolution of accident clusters by dividing each urban city (e.g., Kansas City) into different subregions (e.g., Commercial, Residential, Industrial, etc.) then comparing between these regions visually or statistically to extrapolate the degree of similarity/dissimilarity between these regions according to the land use of these subregions. Additionally, the definition of the neighborhoods by areas that participate in borders, located within the specified distance and have the same spatial value, it could be beneficial to define the neighborhoods that are used to define clusters by areas that share both borders and points of corners.

REFERENCES

Aga, M.A., Woldeamanuel, B.T., Tadesse, M., 2021. Statistical modeling of numbers of human deaths per road traffic accident in the Oromia region, Ethiopia. PLoS One 16 5 May , 1–17. doi:10.1371/journal.pone.0251492

Agrawal, K., Ruth, V.M., Nandini, Y., Sravani, K., 2018. Analysis of Road Accident Locations Using DBSCAN Algorithm 4 8 , 462–467.

Ahmed, L.A., 2017. Using logistic regression in determining the effective variables in traffic accidents. Appl. Math. Sci. 11 42 , 2047–2058. doi:10.12988/ams.2017.75179

Al-Ruzouq, R., Hamad, K., Abu Dabous, S., Zeiada, W., Khalil, M.A., Voigt, T., 2019. Weighted multi-attribute framework to identify freeway incident hot spots in a spatiotemporal context. Arab. J. Sci. Eng. 44 10 , 8205–8223. doi:10.1007/s13369-019-03881-z

Anastasopoulos, P.C., 2016. Random parameters multivariate tobit and zero-inflated count data models: Addressing unobserved and zero-state heterogeneity in accident injury-severity rate and frequency analysis. Anal. Methods Accid. Res. 11, 17–32. doi:10.1016/j.amar.2016.06.001

Anderson, T.K., 2009. Kernel density estimation and K-means clustering to profile road accident hot spots. Accid. Anal. Prev. 41 3 , 359–364. doi:10.1016/j.aap.2008.12.014

Anselin, L., 1995. Local indicators of spatial association—LISA. Geogr. Anal. 27 2 , 93–115. doi:10.1111/j.1538-4632.1995.tb00338.x

Arabpoura, M., Zareia, H., Borhaninejadb, V., Zahra Nekoeic, 2019. The Effect of Urban Safe Community Implementation on the Reduction of Traffic Accidents from 2004 to 2017 in the Municipality of Zarand. J. Inj. Violence Res. 11 2 , 2019. doi:10.5249/jivr.v11i2.1453

ASRIT, 2020. Road Safety Facts [WWW Document]. URL https://www.asirt.org/safe-travel/road-safety-facts/

Athwani, M., Pandey, R., Pradesh, U., 2020. ANALYSIS OF ROAD TRAFFIC ACCIDENTS IN INDIA WITH SPECIAL FOCUS ON UTTAR PRADESH 05 , 1062–1073.

Awang, Z., Wan Afthanorhan, W.M.A., Asri, M.A.M., 2015. Parametric and Non Parametric Approach in Structural Equation Modeling (SEM): The Application of Bootstrapping. Mod. Appl. Sci. 9 9 , 58–67. doi:10.5539/mas.v9n9p58

Bao, J., Liu, P., Yu, H., Xu, C., 2017. Incorporating twitter-based human activity information in spatial analysis of crashes in urban areas. Accid. Anal. Prev. 106, 358–369. doi:10.1016/j.aap.2017.06.012

Beppu, S., Hitosugi, M., Ueda, T., Koh, M., Nishiyama, K., 2021. Factors influencing the length of emergency room stay and hospital stay in non-fatal bicycle accidents: A retrospective analysis. Chinese J. Traumatol. - English Ed. 24 3 , 148–152. doi:10.1016/j.cjtee.2021.03.003

Bíl, M., Andrášik, R., Janoška, Z., 2013. Identification of hazardous road locations of traffic accidents by means of kernel density estimation and cluster significance evaluation. Accid. Anal. Prev. 55, 265–273. doi:10.1016/j.aap.2013.03.003

Bíl, M., Andrášik, R., Sedoník, J., 2019. A detailed spatiotemporal analysis of traffic crash hot spots. Appl. Geogr. 107, 82–90. doi:10.1016/j.apgeog.2019.04.008

Birant, D., Kut, A., 2007. ST-DBSCAN: An algorithm for clustering spatial-temporal data. Data Knowl. Eng. 60 1 , 208–221. doi:10.1016/j.datak.2006.01.013

Blazquez, C.A., Celis, M.S., 2013. A spatial and temporal analysis of child pedestrian crashes in Santiago, Chile. Accid. Anal. Prev. 50, 304–311. doi:10.1016/j.aap.2012.05.001

Blazquez, C.A., Picarte, B., Calderón, J.F., Losada, F., 2018. Spatial autocorrelation analysis of cargo trucks on highway crashes in Chile. Accid. Anal. Prev. 120, 195–210. doi:10.1016/j.aap.2018.08.022

Briz-Redón, Á., Mateu, J., Montes, F., 2021. Modeling accident risk at the road level through zero-inflated negative binomial models: A case study of multiple road networks. Spat. Stat. 43, 100503. doi:10.1016/j.spasta.2021.100503

Bureau, U.S.C., 2010. 2010 Urban Area FAQs [WWW Document]. URL https://www.census.gov/programs-surveys/geography/about/faq/2010-urban-area-faq.html

Caliendo, C., Guida, M., Parisi, A., 2007a. A crash-prediction model for multilane roads. Accid. Anal. Prev. 39 4 , 657–670. doi:10.1016/j.aap.2006.10.012

Caliendo, C., Guida, M., Parisi, A., 2007b. A crash-prediction model for multilane roads. Accid. Anal. Prev. 39 4 , 657–670. doi:10.1016/j.aap.2006.10.012

Casado-Sanz, N., Guirao, B., Attard, M., 2020. Analysis of the risk factors affecting the severity of traffic accidents on spanish crosstown roads: The driver's perspective. Sustain. 12 6 . doi:10.3390/su12062237

Cernovsky, Litman, L.C., Nosonova, V., 2021a. Validation of the Insomnia Severity Index on Patients Recovering from High Impact Car Accidents. Eur. J. Med. Heal. Sci. 3 3 , 29–33. doi:10.24018/ejmed.2021.3.3.858

Cernovsky, Velamoor, V.R., Mann, S.C., Litman, L.C., 2021b. Clinical Correlations of Posttraumatic Nightmares in Survivors of Motor Vehicle Accidents 2 3 , 19–21.

Chen, P., Yu, G., Wu, X., Ren, Y., Li, Y., 2017. Estimation of red-light running frequency using high-resolution traffic and signal data. Accid. Anal. Prev. 102, 235–247. doi:10.1016/j.aap.2017.03.010

Chen, X., Huang, L., Dai, D., Zhu, M., Jin, K., 2018. Hot spots of road traffic crashes in a redeveloping area of Shanghai. Int. J. Inj. Contr. Saf. Promot. 1–10. doi:10.1080/17457300.2018.1431938

Cheng, W., Gill, G.S., Dasu, R., Xie, M., Jia, X., Zhou, J., 2017. Comparison of multivariate poisson lognormal spatial and temporal crash models to identify hot spots of intersections based on crash types. Accid. Anal. Prev. 99, 330–341. doi:10.1016/j.aap.2016.11.022

Cheng, W., Gill, G.S., Ensch, J.L., Kwong, J., Jia, X., 2018. Multimodal crash frequency modeling: Multivariate space-time models with alternate spatiotemporal interactions. Accid. Anal. Prev. 113 November 2017 , 159–170. doi:10.1016/j.aap.2018.01.034

Cheng, Zu, Z., Lu, J., 2018. Traffic crash evolution characteristic analysis and spatiotemporal hot spot identification of urban road intersections. Sustain. 11 1 . doi:10.3390/su11010160

Cohen, W.B., Maiersperger, T.K., Gower, S.T., Turner, D.P., 2003. An improved strategy for regression of biophysical variables. Remote Sens. Environ. 4257 02 , 561–571.

Deepika, S., Saradha, R., 2014. Clustering crash hot spots to organize police dispatch routes using GIS. Int. J. Sci. Res. 3 2 , 44–50.

Dong, C., Clarke, D.B., Yan, X., Khattak, A., Huang, B., 2014. Multivariate random-parameters zero-inflated negative binomial regression model: An application to estimate crash frequencies at intersections. Accid. Anal. Prev. 70, 320–329. doi:10.1016/j.aap.2014.04.018

Dorn, L., af Wåhlberg, A.E., 2019. Behavioural culpability for traffic accidents. Transp. Res. Part F Traffic Psychol. Behav. 60, 505–514. doi:10.1016/j.trf.2018.11.004

Eckley, D.C., Curtin, K.M., 2013. Evaluating the spatiotemporal clustering of traffic incidents. Comput. Environ. Urban Syst. 37 1 , 70–81. doi:10.1016/j.compenvurbsys.2012.06.004

Elvik, R., 2013. Risk of road accident associated with the use of drugs: A systematic review and meta-analysis of evidence from epidemiological studies. Accid. Anal. Prev. 60, 254–267. doi:10.1016/j.aap.2012.06.017

Endo, S., Shimada, R., Ishikawa, T., Komine, T., 2021. Can the Visualization of Rip Currents Prevent Drowning Accidents ? Consideration of the Effect of Optimism Bias 1–14.

Erdogan, S., Ilçi, V., Soysal, O.M., Korkmaz, A., 2015. A model suggestion for the determination of the traffic accident hot spot on the Turkish highway road network: a pilot study. Bol. Ciencias Geod. 21 1 , 169–188. doi:10.1590/S1982-21702015000100011

ESRI, 2019. How emerging hot spot analysis works [WWW Document]. URL https://desktop.arcgis.com/en/arcmap/latest/tools/space-time-pattern-mining-toolbox/learnmoreemerging.htm

Fan, Y., Zhu, X., She, B., Guo, W., Guo, T., 2018. Network-constrained spatio-temporal clustering analysis of traffic collisions in jianghan district of Wuhan, China. PLoS One 13 4 . doi:10.1371/journal.pone.0195093

Farah, H., 2011. Age and gender differences in overtaking maneuvers on two-lane rural highways. Transp. Res. Rec. 2248 , 30–36. doi:10.3141/2248-04

Forum, W.E., 2016. The number of cars worldwide is set to double by 2040 [WWW Document]. URL https://www.weforum.org/agenda/2016/04/the-number-of-cars-worldwide-is-set-to-double-by-2040

Freitas, C.K.A.C., Rodrigues, M.A., Parreira, P.M.S.D., Dos Santos, A.C.F.S., Lima, S.V.M.A., Fontes, V.S., Freitas, J.P.A., De Jesus Santos, J.M., Mota, E.C.H., 2019. Educational program for the promotion of knowledge, attitudes and preventive practices for children in relation to traffic accidents: Experimental study. Rev. Paul. Pediatr. 37 4 , 458–464. doi:10.1590/1984-0462/;2019;37;4;00012

Genowska, A., Jamiołkowski, J., Szafraniec, K., Fryc, J., Pajak, A., 2021. Health care resources and 24,910 deaths due to traffic accidents: An ecological mortality study in Poland. Int. J. Environ. Res. Public Health 18 11 . doi:10.3390/ijerph18115561

Getis, A., Ord, J.K., 1992. The Analysis of Spatial Association by Use of Distance Statistics. Geogr. Anal. 24 3 , 189–206. doi:10.1111/j.1538-4632.1992.tb00261.x

Goulart, L.S., Rocha, L.P., de Carvalho, D.P., Barlem, E.L.D., Tomaschewski-Barlem, J.G., Brum, R.G., 2020. Risk perception among workers with previous occupational accidents in pre-hospital settings. Texto e Context. Enferm. 29, 1–11. doi:10.1590/1980-265x-tce-2018-0513

Grubesic, T.H., Wei, R., Murray, A.T., 2014. Spatial Clustering Overview and Comparison: Accuracy, Sensitivity, and Computational Expense. Ann. Assoc. Am.

Geogr. 104 6 , 1134–1156. doi:10.1080/00045608.2014.958389

Gu, X., Yan, X., Ma, L., Liu, X., 2020. Modeling the service-route-based crash frequency by a spatiotemporal-random-effect zero-inflated negative binomial model: An empirical analysis for bus-involved crashes. Accid. Anal. Prev. 144 May . doi:10.1016/j.aap.2020.105674

Gudes, O., Varhol, R., Sun, Q. (Chayn), Meuleners, L., 2017. Investigating articulated heavy-vehicle crashes in western Australia using a spatial approach. Accid. Anal. Prev. 106, 243–253. doi:10.1016/j.aap.2017.05.026

Hardisty, F., Klippel, A., 2010. Analysing spatio-temporal autocorrelation with LISTA-viz. Int. J. Geogr. Inf. Sci. 24 10 , 1515–1526. doi:10.1080/13658816.2010.511717

Harirforoush, H., Bellalite, L., 2016. A new integrated GIS-based analysis to detect hot spots: A case study of the city of Sherbrooke. Accid. Anal. Prev. 130, 62–74. doi:10.1016/j.aap.2016.08.015

Harré, N., Sibley, C.G., 2007. Explicit and implicit self-enhancement biases in drivers and their relationship to driving violations and crash-risk optimism. Accid. Anal. Prev. 39 6 , 1155–1161. doi:10.1016/j.aap.2007.03.001

Harris, N.L., Goldman, E., Gabris, C., Nordling, J., Minnemeyer, S., Ansari, S., Lippmann, M., Bennett, L., Raad, M., Hansen, M., Potapov, P., 2017. Using spatial statistics to identify emerging hot spots of forest loss. Environ. Res. Lett. 12 2 . doi:10.1088/1748-9326/aa5a2f

Hasanspahić, N., Vujičić, S., Frančić, V., Čampara, L., 2021. The role of the human factor in marine accidents. J. Mar. Sci. Eng. 9 3 , 1–16. doi:10.3390/jmse9030261

Hosseinpour, M., Yahaya, A.S., Sadullah, A.F., 2014. Exploring the effects of roadway characteristics on the frequency and severity of head-on crashes: Case studies from Malaysian Federal Roads. Accid. Anal. Prev. 62, 209–222. doi:10.1016/j.aap.2013.10.001

Hsieh, T.M., Tsai, T.C., Liu, Y.W., Hsieh, C.H., 2016. How does the severity of injury vary between motorcycle and automobile accident victims who sustain high-grade blunt hepatic and/or splenic injuries? Results of a retrospective analysis. Int. J. Environ. Res. Public Health 13 7 . doi:10.3390/ijerph13070739

Hu, S., Zheng, G., 2009. Driver drowsiness detection with eyelid related parameters by Support Vector Machine. Expert Syst. Appl. 36 4 , 7651–7658. doi:10.1016/j.eswa.2008.09.030

Huang, H., Zhou, H., Wang, J., Chang, F., Ma, M., 2017. A multivariate spatial model of crash frequency by transportation modes for urban intersections. Anal. Methods Accid. Res. 14, 10–21. doi:10.1016/j.amar.2017.01.001

Hunde, B., Aged, Z.D., 2015. Statistical Analysis of Road Traffic Car Accident in Dire Dawa Administrative City, Eastern Ethiopia. Sci. J. Appl. Math. Stat. 3 6 , 250. doi:10.11648/j.sjams.20150306.14

Iqbal, Z., Khan, M.I., Hussain, S., Habib, A., 2021. An Efficient Traffic Incident Detection and Classification Framework by Leveraging the Efficacy of Model Stacking. Complexity 2021. doi:10.1155/2021/5543698

Islam, Z., Abdel-Aty, M., Cai, Q., Yuan, J., 2021. Crash data augmentation using variational autoencoder. Accid. Anal. Prev. 151 July 2020 , 105950. doi:10.1016/j.aap.2020.105950

Ismail, A.M., Ahmed, H.Y., Owais, M.A., 2010. Analysis and Modeling of Traffic

Accidents Causes for Main Rural Roads in Egypt. JES. J. Eng. Sci. 38 4 , 895–909. doi:10.21608/jesaun.2010.125546

Ivan, K., Haidu, I., Benedek, J., Ciobanu, S.M., 2015. Identification of traffic accident risk-prone areas under low-light conditions. Nat. Hazards Earth Syst. Sci. 15 9 , 2059–2068. doi:10.5194/nhess-15-2059-2015

Jia, R., Khadka, A., Kim, I., 2018. Traffic crash analysis with point-of-interest spatial clustering. Accid. Anal. Prev. 121, 223–230. doi:10.1016/j.aap.2018.09.018

Jones, C., Harvey, A.G., Brewin, C.R., 2007. The organisation and content of trauma memories in survivors of road traffic accidents. Behav. Res. Ther. 45 1 , 151–162. doi:10.1016/j.brat.2006.02.004

Joni, H.H., Mohammed, A.A., Shakir, A.A., 2020. Classification of traffic accidents datasets between 2003–2017 in Iraq. Data Br. 28. doi:10.1016/j.dib.2019.104902

Kang, Y., Cho, N., Son, S., 2018. Spatiotemporal characteristics of elderly population's traffic accidents in Seoul using space-time cube and space-time kernel density estimation. PLoS One 13 5 . doi:10.1371/journal.pone.0196845

Katrakazas, C., Theofilatos, A., Islam, M.A., Papadimitriou, E., Dimitriou, L., Antoniou, C., 2021. Prediction of rear-end conflict frequency using multiple-location traffic parameters. Accid. Anal. Prev. 152 January , 106007. doi:10.1016/j.aap.2021.106007

Kerry, T.V., Abas, N.H., Affandi, H.M., Hussein, U.T., Malysia, O., National, T., Sri, T., Perdana, P., 2021. STAKEHOLDER ' S PERCEPTIONS ON THE SIGNIFICANT FACTORS AFFECTING SAFETY MANAGEMENT 13 2 , 68–80.

Khan, M.A.H., Hussain, I., 2021. Analysis of Road Traffic Accidents in the Punjab by

Using Panel Count Data Models. Stat. Comput. Interdiscip. Res. 3 1 , 1–13. doi:10.52700/scir.v3i1.23

Khattak, M.W., Pirdavani, A., De Winne, P., Brijs, T., De Backer, H., 2021. Estimation of safety performance functions for urban intersections using various functional forms of the negative binomial regression model and a generalized Poisson regression model. Accid. Anal. Prev. 151 October 2020 , 105964. doi:10.1016/j.aap.2020.105964

Kim, B., Yum, S., Kim, Y.-Y., Yun, N., Shin, S.-Y., You, S., 2014. An Analysis of Factors Relating to Agricultural Machinery Farm-Work Accidents Using Logistic Regression. J. Biosyst. Eng. 39 3 , 151–157. doi:10.5307/jbe.2014.39.3.151

Kim, K., Yamashita, E.Y., 2007. Using a K-means clustering algorithm to examine patterns of pedestrian involved crashes in Honolulu, Hawaii. J. Adv. Transp. 41 1 , 69–89. doi:10.1002/atr.5670410106

Kim, S.H., Sul, Y.H., Lee, J.Y., Kim, J.S., 2021. The Influence of Seasons and Weather on the Volume of Trauma Patients: 4 Years of Experience at a Single Regional Trauma Center. J. Trauma Inj. 34 1 , 21–30. doi:10.20408/jti.2020.0027

Kitchen, C.M.R., 2009. Nonparametric vs Parametric Tests of Location in Biomedical Research. Am. J. Ophthalmol. 147 4 , 571–572. doi:10.1016/j.ajo.2008.06.031

Kogani, M., Almasi, S.A., Ansari-Mogaddam, A., Dalvand, S., Okati-Aliabad, H., Tabatabaee, S.M., Almasi, S.Z., 2020a. Relationship between using cell phone and the risk of accident with motor vehicles: An analytical cross-sectional study. Chinese J. Traumatol. - English Ed. 23 6 , 319–323. doi:10.1016/j.cjtee.2020.08.002

Kogani, M., Almasi, S.Z.A.Z., Ansari-Mogaddam, A., Dalvand, S., Okati-Aliabad, H., Tabatabaee, S.M., Almasi, S.Z.A.Z., 2020b. Relationship between using cell phone and the risk of accident with motor vehicles: An analytical cross-sectional study. Chinese J. Traumatol. - English Ed. 23 6 , 319–323. doi:10.1016/j.cjtee.2020.08.002

Kuo, S.C.H., Kuo, P.J., Rau, C.S., Chen, Y.C., Hsieh, H.Y., Hsieh, C.H., 2017. The protective effect of helmet use in motorcycle and bicycle accidents: A propensity score-matched study based on a trauma registry system. BMC Public Health 17 1 , 1–10. doi:10.1186/s12889-017-4649-1

Le, K.G., Liu, P., Lin, L.T., 2019. Determining the road traffic accident hot spots using GIS-based temporal-spatial statistical analytic techniques in Hanoi, Vietnam. Geo-Spatial Inf. Sci. 23 2 , 153–164. doi:10.1080/10095020.2019.1683437

Lee, J.S., Kim, Y.H., Yun, J.S., Jung, S.E., Chae, C.S., Chung, M.J., 2016. Characteristics of patients injured in road traffic accidents according to the new injury severity score. Ann. Rehabil. Med. 40 2 , 288–293. doi:10.5535/arm.2016.40.2.288

Lee, S.Y., Sun, K.H., Park, C.Y., Kim, T.H., 2021. Characteristics of Traffic Accidents on Highways: An Analysis Based on Patients Treated at a Regional Trauma Center. J. Trauma Inj. doi:10.20408/jti.2020.0063

Levine, M.J., McEwen, J.T., 1985. Patrol Deployment.

Liu, C., Zhao, M., Li, W., Sharma, A., 2018. Multivariate random parameters zero-inflated negative binomial regression for analyzing urban midblock crashes. Anal. Methods Accid. Res. 17, 32–46. doi:10.1016/j.amar.2018.03.001

Lobashov, O., Boikiv, M., 2020. Increasing the complex intersections functioning efficiency by restriction of left-turn traffic flows. Transp. Technol. 2020 1 , 54–64.

doi:10.23939/tt2020.01.054

Lord, D., Mannering, F., 2010. The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. Transp. Res. Part A Policy Pract. 44 5 , 291–305. doi:10.1016/j.tra.2010.02.001

Ma, L., Yan, X., 2014. Examining the nonparametric effect of drivers' age in rear-end accidents through an additive logistic regression model. Accid. Anal. Prev. 67, 129–136. doi:10.1016/j.aap.2014.02.021

Macedo, M., Maia, M., Rabbani, E.K., Marinho, M., 2021. Spatial Analysis of the Variables Involved in the Frequency and Severity of Traffic Accidents on Rural Highways in Pernambuco. Technol. Sci. Am. Sci. Res. J. Eng. 78 1 , 226–246.

Maeda, M., Kato, H., Maruoka, T., 2009. Adolescent vulnerability to PTSD and effects of community-based intervention: Longitudinal study among adolescent survivors of the Ehime Maru sea accident. Psychiatry Clin. Neurosci. 63 6 , 747–753. doi:10.1111/j.1440-1819.2009.02031.x

Mahdian, M., Sehat, M., Fazel, M.R., Moraveji, A., Mohammadzadeh, M., 2015. Epidemiology of Urban Traffic Accident Victims Hospitalized More Than 24 Hours in a Level III Trauma Center, Kashan County, Iran, 2012. Arch. Trauma Res. 4 2 , 0–4. doi:10.5812/atr.4(2)2015.28465

Matisziw, T.C., Murray, A.T., 2009a. Area coverage maximization in service facility siting. J. Geogr. Syst. 11 2 , 175–189. doi:10.1007/s10109-009-0081-0

Matisziw, T.C., Murray, A.T., 2009b. Siting a facility in continuous space to maximize coverage of a region. Socioecon. Plann. Sci. 43 2 , 131–139. doi:10.1016/j.seps.2008.02.009

Matisziw, T.C., Ritchey, M., Mackenzie, R., 2020. Change of scene : The geographic dynamics of resilience to vehicular accidents. Networks Spat. Econ. 1–20. doi:10.1007/s11067-020-09513-6

Matkan, A.A., Mohaymany, A.S., Shahri, M., Mirbagheri, B., 2013. Detecting the spatial-temporal autocorrelation among crash frequencies in urban areas. Can. J. Civ. Eng. 40 3 , 195–203. doi:10.1139/cjce-2012-0374

Maxwell, O., Mayowa, B.A., Chinedu, I.U., Peace, A.E., 2018. Modelling Count Data; A Generalized Linear Model Framework. Am. J. Math. Stat. 8 6 , 179–183. doi:10.5923/j.ajms.20180806.03

Mohamed, M.G., Saunier, N., Miranda-Moreno, L.F., Ukkusuri, S. V., 2013. A clustering regression approach: A comprehensive injury severity analysis of pedestrian-vehicle crashes in New York, US and Montreal, Canada. Saf. Sci. 54, 27–37. doi:10.1016/j.ssci.2012.11.001

Mohaymany, A.S., Shahri, M., Mirbagheri, B., 2013. GIS-based method for detecting high-crash-risk road segments using network kernel density estimation. Geo-Spatial Inf. Sci. 16 2 , 113–119. doi:10.1080/10095020.2013.766396

Mountrakis, G., Gunson, K., 2009. Multi-scale spatiotemporal analyses of moose-vehicle collisions: A case study in northern Vermont. Int. J. Geogr. Inf. Sci. 23 11 , 1389–1412. doi:10.1080/13658810802406132

Msengwa, A.S., Ngari, F.D., 2021. Count Time Series Models for Road Traffic Accidents in Tanzania Mainland 47 2 , 495–506.

MSHP, 2020. Missouri State Highway Patrol [WWW Document]. URL https://mshp.dps.missouri.gov/HP68/search.jsp

Mustefa, Y.A., Belayhun, A., 2019. Expressway Traffic Accidents Involving Human Injuries and Fatalities in Ethiopia : Negative Binomial Regression Model.

Nazif-Munoz, J.I., Puello, A., Williams, A., Nandi, A., 2020. Can a new emergency response system reduce traffic fatalities? The case of the 911-emergency response system in the Dominican Republic. Accid. Anal. Prev. 143 October 2019 , 105513. doi:10.1016/j.aap.2020.105513

Nie, K., Wang, Z., Du, Q., Ren, F., Tian, Q., 2015. A network-constrained integrated method for detecting spatial cluster and risk location of traffic crash: A case study from Wuhan, China. Sustain. 7 3 , 2662–2677. doi:10.3390/su7032662

Okabe, A., Boots, B., Sugihara, K., Chiu, S.N., 2000. Spatial Tessellations: Concepts and Applications of Voronoi Diagrams, 2nd Edition.

Okabe, A., Okunuki, K.I., Shiode, S., 2006. The SANET toolbox: New methods for network spatial analysis. Trans. GIS 10 4 , 535–550. doi:10.1111/j.1467-9671.2006.01011.x

Okabe, A., Satoh, T., Sugihara, K., 2009. A kernel density estimation method for networks, its computational method and a GIS-based tool. Int. J. Geogr. Inf. Sci. 23 1 , 7–32. doi:10.1080/13658810802475491

Okabe, A., Yamada, I., 2001. The K-function method on a network and its computational implementation. Geogr. Anal. 33 3 .

Ord, J.K., Getis, A., 1995. Local spatial autocorrelation statistics: distributional issues and an application. Geogr. Anal. 27 4 , 286–306. doi:10.1111/j.1538-4632.1995.tb00912.x

Ouni, F., Belloumi, M., 2019. Pattern of road traffic crash hot zones versus probable hot zones in Tunisia: a geospatial analysis. Accid. Anal. Prev. 128, 185–196. doi:10.1016/j.aap.2019.04.008

Pei, L., Liang, F., Sun, S., Wang, H., Dou, H., 2019. Nursing students' knowledge, willingness, and attitudes toward the first aid behavior as bystanders in traffic accident trauma: A cross-sectional survey. Int. J. Nurs. Sci. 6 1 , 65–69. doi:10.1016/j.ijnss.2018.11.003

Prasetijo, J., Musa, W.Z., 2016. Modeling zero - Inflated regression of road accidents at Johor Federal Road F001. MATEC Web Conf. 47, 1–7. doi:10.1051/matecconf/20164703001

Prosen, S., Poljšak Škraban, O., Slana Ozimič, A., Repovš, G., Smrtnik Vitulić, H., 2021. The Emotion of Fear: Its Experience in Situations Involving Animals, Accidents, and Violence and Its Regulation by the Cognitive Reappraisal Strategy. Jpn. Psychol. Res. April , 1–13. doi:10.1111/jpr.12331

Ratnayaka, R.M., Chaturika, R.M.., Hewapathirana, A., 2017. Factors Affecting Industrial Accidents : Empirical Evidence from Manufacturing Setting . Factors Affecting Industrial Accidents : Empirical Evidence from. Proc. 6th Int. Conf. Manag. Econ. November 2017 , 299–318.

Reazaul, Habib, K., Md, Y., Samarjit, D., 2016. Knowledge of Tube Blockage and Its Management among Intensive Care Staff Nurses of Different Experiences. Indian J. Emerg. Med. 2 2 , 117–120. doi:10.21088/ijem.2395.311x.2216.5

Rolison, J.J., Regev, S., Moutari, S., Feeney, A., 2018. What are the factors that contribute to road accidents? An assessment of law enforcement views, ordinary drivers' opinions, and road accident records. Accid. Anal. Prev. 115 February , 11–

24. doi:10.1016/j.aap.2018.02.025

Sagamiko, T.D., Mbare, N.S., 2021. Modelling Road Traffic Accidents Counts in Tanzania : A Poisson Regression Approach 47 1 , 308–314.

Saifizul, A.A., Yamanaka, H., Karim, M.R., 2011. Empirical analysis of gross vehicle weight and free flow speed and consideration on its relation with differential speed limit. Accid. Anal. Prev. 43 3 , 1068–1073. doi:10.1016/j.aap.2010.12.013

Saleem, T., Persaud, B., 2017. Another look at the safety effects of horizontal curvature on rural two-lane highways. Accid. Anal. Prev. 106 April , 149–159. doi:10.1016/j.aap.2017.04.001

Sánchez-Martín, J.M., Rengifo-Gallego, J.I., Blas-Morato, R., 2019. Hot spot analysis versus cluster and outlier analysis: an enquiry into the grouping of rural accommodation in Extremadura (Spain). ISPRS Int. J. Geo-Information 8 4 . doi:10.3390/ijgi8040176

Science, C., Ni, T.V., Misiran, M., Supadi, S.S., Malaya, U., 2021. Assessing Youth Unemployment Rate in Malaysia using Multiple Linear Regression 7 1 , 23–34.

Sharma, A.., Landge, V.., 2013. Zero Inflated Negative Binomial for Modeling Heavy Vehicle Crash Rate on Indian Rural Highway. Int. J. Adv. Eng. Technol. 5 2 , 292–301.

Shi, Z., Pun-Cheng, L.S.C., 2019. Spatiotemporal data clustering: A survey of methods. ISPRS Int. J. Geo-Information 8 3 . doi:10.3390/ijgi8030112

Shimizu, H.E., Bezerra, J.C., Arantes, L.J., Merchán-Hamann, E., Ramalho, W., 2021. Analysis of work-related accidents and ill-health in Brazil since the introduction of the accident prevention factor. BMC Public Health 21 1 , 1–10. doi:10.1186/s12889-

021-10706-y

Shiode, S., Shiode, N., 2009. Detection of multi-scale clusters in network space. Int. J. Geogr. Inf. Sci. 23 1 , 75–92. doi:10.1080/13658810801949843

Sikdar, P., Rabbani, A., Dhapekar, N.K., Bhatt, G., 2017. Hypothesis Testing of Road Traffic. Int. J. Civ. Eng. Technol. 8 6 , 430–435.

Smith, B., Demetsky, M.J., 1994. Models - a Comparison of Neural. Sensors (Peterborough, NH) 1–4.

Soheily-Khah, S., Douzal-Chouakria, A., Gaussier, E., 2016. Generalized k-means-based clustering for temporal data under weighted and kernel time warp. Pattern Recognit. Lett. 75, 63–69. doi:10.1016/j.patrec.2016.03.007

Soltani, A., Askari, S., 2017. Exploring spatial autocorrelation of traffic crashes based on severity. Injury 48 3 , 637–647. doi:10.1016/j.injury.2017.01.032

Soltanzadeh, A., Mohammadfam, I., Moghimbeigi, A., Akbarzadeh, M., 2016. Analysis of occupational accidents induced human injuries: A case study in construction industries and sites. J. Civ. Eng. Constr. Technol. 7 1 , 1–7. doi:10.5897/jcect2015.0379

Statista, 2020a. Estimated worldwide automobile production from 2000 to 2019.

Statista, 2020b. Number of passenger cars and commercial vehicles in use worldwide from 2006 to 2015 in [WWW Document]. URL https://www.statista.com/statistics/281134/number-of-vehicles-in-use-worldwide/

Steenberghen, T., Aerts, K., Thomas, I., 2010. Spatial clustering of events on a network. J. Transp. Geogr. 18 3 , 411–418. doi:10.1016/j.jtrangeo.2009.08.005

Steenberghen, T., Dufays, T., Thomas, I., Flahaut, B., 2011. Intra-urban location and clustering of road accidents using gis: A belgian example. Int. J. Geogr. Inf. Sci. 18 2 , 169–181. doi:10.1080/13658810310001629619

Steiner, W., Scholl, E.M., Leisch, F., Hacklander, K., 2021. Temporal patterns of roe deer traffic accidents: Effects of season, daytime and lunar phase. PLoS One 16 3 March , 16–19. doi:10.1371/journal.pone.0249082

Stipancic, J., Miranda-Moreno, L., Saunier, N., Labbe, A., 2018. Surrogate safety and network screening: modelling crash frequency using GPS travel data and latent Gaussian spatial models. Accid. Anal. Prev. 120, 174–187. doi:10.1016/j.aap.2018.07.013

Sun, Liu, S.J., Xie, F.K., Huang, X.F., Tao, J.X., Lu, Y.L., Zhang, T.X., Yu, A.Y., 2021a. Influence of road types on road traffic accidents in northern Guizhou Province, China. Chinese J. Traumatol. - English Ed. 24 1 , 34–38. doi:10.1016/j.cjtee.2020.11.002

Sun, Sun, X., Rahman, M.A., Akter, M., Das, S., 2021b. Modeling two-way stop-controlled intersection crashes with zero-inflated models on Louisiana rural two-lane highways. IATSS Res. xxxx . doi:10.1016/j.iatssr.2020.12.007

Syahira, R., Abdul, R., Karim, M.R., Abdullahc, A.S., 2014. The effect of Gross Vehicle Weight on Platoon Speed and Size characteristics on Two-Lane Road 1, 708–723.

Tae Kyun Kim, 2015. T test as a parametric statistic. Recipes Sci. Table 2 , 167–206. doi:10.4324/9781315686875-6

Tang, W., Lu3, N., Chen1, T., Wang1, W., Gunzler4, D., Han1, Y., Tu, X.M., 2015. On Performance of Parametric and Distribution-free Models for Zero-inflated and Over-dispersed Count Responses. Physiol. Behav. 176 3 , 139–148.

doi:10.1002/sim.6560.On

Torsen, E., Atule, A.A., 2018. A Nonparametric Approach to Data Analysis on Road Traffic Accidents 6 3 , 1–8.

Twenefour, F.B.K., Ayitey, E., Kangah, J., Brew, L., 2021. Time Series Analysis of Road Traffic Accidents in Ghana. Asian J. Probab. Stat. 11 2 , 12–20. doi:10.9734/ajpas/2021/v11i230262

Upaphong, P., Supreeyathitikul, P., Choovuthayakorn, J., 2021. Open Globe Injuries Related to Traffic Accidents: A Retrospective Study. J. Ophthalmol. 2021. doi:10.1155/2021/6629589

USDA, 2000. Missouri - Rural Definitions: State-Level Maps [WWW Document]. URL https://www.ers.usda.gov/webdocs/DataFiles/53180/25580_MO.pdf?v=0

Vandenbulcke, G., Thomas, I., Int Panis, L., 2014. Predicting cycling accident risk in Brussels: A spatial case-control approach. Accid. Anal. Prev. 62, 341–357. doi:10.1016/j.aap.2013.07.001

Vazirizade, S.M., Mukhopadhyay, A., Pettet, G., Said, S. El, Baroud, H., Dubey, A., 2021. Learning Incident Prediction Models Over Large Geographical Areas for Emergency Response Systems.

Wang, C., Quddus, M.A., Ison, S.G., 2009. Impact of traffic congestion on road accidents: A spatial analysis of the M25 motorway in England. Accid. Anal. Prev. 41 4 , 798–808. doi:10.1016/j.aap.2009.04.002

Wang, C., Xu, C., Fan, P., 2020. Effects of traffic enforcement cameras on macro-level traffic safety: A spatial modeling analysis considering interactions with roadway and Land use characteristics. Accid. Anal. Prev. 144 June , 105659.

doi:10.1016/j.aap.2020.105659

Wang, K., Bhowmik, T., Zhao, S., Eluru, N., Jackson, E., 2021. Highway safety assessment and improvement through crash prediction by injury severity and vehicle damage using Multivariate Poisson-Lognormal model and Joint Negative Binomial-Generalized Ordered Probit Fractional Split model. J. Safety Res. 76, 44–55. doi:10.1016/j.jsr.2020.11.005

Wang, S., Li, R., Guo, M., 2018. Application of nonparametric regression in predicting traffic incident duration. Transport 33 1 , 22–31. doi:10.3846/16484142.2015.1004104

Wang, Z., Lam, N.S.N., 2020. Extending Getis–Ord statistics to account for local space–time autocorrelation in spatial panel data. Prof. Geogr. 72 3 , 411–420. doi:10.1080/00330124.2019.1709215

Warden, C.R., Duh, J. Der, Lafrenz, M., Chang, H., Monsere, C., 2011. Geographical analysis of commercial motor vehicle hazardous materials crashes on the Oregon state highway system. Environ. Hazards 10 2 , 171–184. doi:10.1080/17477891.2011.578207

Wen, H., Zhang, X., Zeng, Q., Sze, N.N., 2019. Bayesian spatial-temporal model for the main and interaction effects of roadway and weather characteristics on freeway crash incidence. Accid. Anal. Prev. 132 July , 105249. doi:10.1016/j.aap.2019.07.025

Weng, J., Ge, Y.E., Han, H., 2016. Evaluation of Shipping Accident Casualties using Zero-inflated Negative Binomial Regression Technique. J. Navig. 69 2 , 433–448. doi:10.1017/S0373463315000788

WHO, 2020. Road traffic injuries.

Wuschke, K., Clare, J., Garis, L., 2013. Temporal and geographic clustering of residential structure fires: a theoretical platform for targeted fire prevention. Fire Saf. J. 62 PART A , 3–12. doi:10.1016/j.firesaf.2013.07.003

Xia, F., Yang, Y., 2019. Analysis of black spot of traffic accident in Wuhan port. MATEC Web Conf. 296 2019 , 01001. doi:10.1051/matecconf/201929601001

Xie, Z., Yan, J., 2013. Detecting traffic accident clusters with network kernel density estimation and local spatial statistics: An integrated approach. J. Transp. Geogr. 31, 64–71. doi:10.1016/j.jtrangeo.2013.05.009

Xie, Z., Yan, J., 2008. Kernel density estimation of traffic accidents in a network space. Comput. Environ. Urban Syst. 32 5 , 396–406. doi:10.1016/j.compenvurbsys.2008.05.001

Xu, Q., Zheng, J., Sun, C., 2017. Digital modeling analysis of urban road traffic capacity under the condition of traffic accidents. Proc. 29th Chinese Control Decis. Conf. CCDC 2017 2015032 , 3496–3500. doi:10.1109/CCDC.2017.7979111

Yamada, I., Thill, J.C., 2004. Comparison of planar and network K-functions in traffic accident analysis. J. Transp. Geogr. 12 2 , 149–158. doi:10.1016/j.jtrangeo.2003.10.006

Yang, Y., Chung, H., Kim, J.S., 2021. Local or Neighborhood? Examining the Relationship between Traffic Accidents and Land Use Using a Gradient Boosting Machine Learning Method: The Case of Suzhou Industrial Park, China. J. Adv. Transp. 2021. doi:10.1155/2021/8246575

Zou, Y., Zhang, Y., Cheng, K., 2021. Exploring the impact of climate and extreme weather on fatal traffic accidents. Sustain. 13 1 , 1–14. doi:10.3390/su13010390

APPENDIX-A

Table A. 1 Cluster size frequency and temporal trend (two-month Periods, p ≤ 0.1)

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period											
				1	2	3	4	5	6	7	8	9	10	11	12
1	2	1	1		10,000	5,000									
2	3	2	1		10,000										
3	1	3	1		2,500	2,500		2,500							2,500
4	2	4	1		2,500	2,500									
5	3	5	4		2,500										
6	3	6	1		5,000										
7	5	7	1			2,500		2,500							2,500
8	5	8	1			2,500		5,000							2,500
9	6	9	1			2,500		5,000							
10	7	10	4			2,500									
11	5	11	1			5,000		2,500							2,500
12	4	12	1			5,000		5,000	5,000						
13	7	13	1			5,000									
14	4	14	1			7,500		2,500	10,000						
15	4	15	1			7,500		2,500	2,500						
16	4	16	1			7,500		7,500	10,000						
17	8	17	1				2,500			2,500	2,500				5,000
18	12	18	1					10,000							2,500
19	13	19	1					10,000							
20	9	20	3					2,500	2,500						2,500

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period											
				1	2	3	4	5	6	7	8	9	10	11	12
21	10	21	8					2,500	2,500						
22	10	22	2					2,500	5,000						
23	11	23	2					2,500		2,500					
24	12	24	2					2,500							2,500
25	13	25	4					2,500							
26	10	26	1					5,000	2,500						
27	10	27	2					5,000	5,000						
28	12	28	1					5,000							2,500
29	13	29	1					5,000							
30	10	30	1					7,500	5,000						
31	14	31	1						2,500	2,500					
32	14	32	1						2,500	5,000					
33	15	33	25						2,500						
34	15	34	2						5,000						
35	17	35	1							10,000					
36	17	36	1							15,000					
37	16	37	3							2,500	2,500				
38	17	38	9							2,500					
39	17	39	4							5,000					
40	18	40	1								10,000				
41	18	41	12								2,500				
42	19	42	1									2,500			
43	20	43	1										2,500	2,500	
44	21	44	10										2,500		
45	21	45	4										5,000		

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period											
				1	2	3	4	5	6	7	8	9	10	11	12
46	20	46	1										7,500	2,500	
47	21	47	2										7,500		
48	22	48	1											2,500	2,500
49	23	49	1												10,000
50	23	50	22												2,500
51	23	51	3												5,000
52	23	52	4												7,500

Trend ID*: a unique identifier for a particular trend.

Var. ID**: a unique identifier for a particular cluster size for the same trend.

Table A. 2 Cluster size frequency and temporal trend (two-month Periods, $p \leq 0.05$)

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period											
				1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1		2,500										
2	3	2	1			2,500									
3	2	3	1			5,000									2,500
4	4	4	1					2,500	2,500						2,500
5	5	5	3					2,500	2,500						
6	5	6	2					2,500	5,000						
7	6	7	3					2,500							
8	5	8	2					5,000	5,000						
9	5	9	1					7,500	10,000						
10	5	10	1					7,500	2,500						
11	7	11	20						2,500						
12	7	12	2						5,000						
13	9	13	1							10,000					
14	8	14	1							2,500	2,500				
15	9	15	4							2,500					
16	9	16	2							5,000					
17	10	17	3								2,500				
18	11	18	2										2,500		
19	11	19	1										5,000		
20	12	20	12												2,500
21	12	21	2												7,500

Trend ID*: a unique identifier for a particular trend.

Var. ID**: a unique identifier for a particular cluster size for the same trend.

Table A. 3 Cluster size frequency and temporal trend (two-month periods, $p \leq 0.01$)

No.	**Trend ID***	**Var. ID****	**Freq.**	**Cluster Size (m^2) by Analysis Period**											
				1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1					2,500	5,000						
2	2	2	1						10,000						
3	2	3	6						2,500						
4	2	4	2						5,000						
5	3	5	1							2,500					
6	4	6	1										2,500		
7	5	7	2												2,500
8	5	8	1												7,500

Trend ID*: a unique identifier for a particular trend.

Var. ID**: a unique identifier for a particular cluster size for the same trend.

Table A. 4 Cluster size frequency and temporal trend (one-month periods, p ≤ 0.1)

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1	1	1	1*																							
2	4	2	1				4*	4				1	4	1											1	1	1
3	4	3	1				4	4				1	4	1											1	1	2
4	12	4	1				4	4				1	4												1	1	2
5	14	5	1				4	4				2*	4														2
6	5	6	1				4	1				1	4	4												4	1
7	5	7	1				4	1				3*	4	4												4	2
8	5	8	1				4	3				1	4	4												4	1
9	11	9	1				1	1				5*	7*											2			1
10	11	10	1				1	1				5	7											2			2
11	2	11	1				1	1				1	1	1		1	1								1	1	1
12	3	12	1				1	1				1	1	1										1	1	1	1
13	5	13	1				1	1				1	1	1												4	1
14	8	14	1				1	1				1	1														
15	9	15	1				1	1				1	1											1	1		
16	10	16	1				1	1				1	1											1		1	1
17	12	17	1				1	1				1	1												1	1	1
18	15	18	2				1	1					1	1													
19	16	19	1				1	1					1													1	1
20	17	20	2				1	1					1														
21	18	21	1				1	1																			
22	10	22	1				1	2				2	1											1		1	2
23	6	23	1				1	3				1	1	1												4	
24	13	24	1				1	3				1	1													1	1
25	20	25	1				1					1	1													1	1

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
26	21	26	1				1					1	1														1
27	21	27	1				1					2	2														1
28	22	28	1				1						1	1													
29	23	29	3				1																				
30	13	30	1				2	1				1	1													1	1
31	7	31	1				2	1				2	2	2													
32	7	32	1				2	2				2	2	2													
33	10	33	1				2	2				2	2											1		1	1
34	17	34	1				2	2					2														
35	19	35	1				2					2	2	2													
36	3	36	1				3	1				5	7	1										2	1	1	2
37	4	37	1				3	1				5	7	1											1	1	1
38	17	38	1				3	2					1														
39	24	39	1					1					1	1										1	1	1	1
40	27	40	1					1					1														
41	28	41	1					1						1													
42	29	42	1					1																	1	4	4
43	30	43	1					1																		4	4
44	31	44	1					1																			
45	25	45	1					2					1											1	2	2	1
46	26	46	1					2					1												2	2	1
47	25	47	1					2					2											1	2	2	2
48	32	48	1						4						1												
49	32	49	1						4						3												
50	32	50	7						1						1												

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
51	33	51	4						1																		
52	32	52	1						2						2												
53	35	53	1							1																	
54	34	54	1							2					1			1							2		
55	36	55	1								1			2	2												
56	37	56	3								1				1												
57	43	57	1									4												2	1		
58	45	58	1									4													1		
59	46	59	1									4															
60	39	60	1									1	1											1			
61	41	61	2									1	1														
62	38	62	1									1	2	1													
63	42	63	1									1											1				
64	43	64	1									1												1	1		
65	44	65	1									1												1			
66	45	66	1									1													1		
67	46	67	1									1															
68	40	68	1									2	1														1
69	41	69	1									2	1														
70	46	70	1									2															
71	47	71	2										1	1	1												
72	48	72	5										1	1													
73	48	73	2										1	2													
74	49	74	1										1												1		
75	50	75	10										1														

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
76	48	76	1										2	2													
77	50	77	1										2														
78	48	78	1										3	3													
79	50	79	1										3														
80	51	80	5											1	1												
81	51	81	2											1	2												
82	52	82	10											1													
83	51	83	1											2	2												
84	52	84	1											2													
85	51	85	2											3	1												
86	51	86	1											3	2												
87	52	87	2											3													
88	53	88	1												1		1	1						1	1		
89	54	89	1												1		1	1									
90	55	90	1												1		2										
91	57	91	8												1												
92	56	92	1												2			1									
93	57	93	3												2												
94	54	94	1												3		4	3									
95	58	95	1													1	1										
96	59	96	2													1											
97	60	97	1														4	3									
98	60	98	1														5	1									
99	61	99	1														5										
100	60	100	7														1	1									

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
101	61	101	12														1										
102	61	102	1														2										
103	62	103	3															1									
104	62	104	1															3									
105	63	105	2																	1							
106	63	106	1																	2							
107	64	107	3																		1						1
108	65	108	7																		1						
109	65	109	1																		10*						
110	65	110	2																		2						
111	66	111	3																				1				
112	67	112	1																					1			
113	67	113	1																					2			
114	68	114	1																						1		
115	69	115	3																							1	1
116	70	116	8																							1	
117	70	117	3																							2	
118	71	118	3																								1

Trend ID*: a unique identifier for a particular trend.

Var. ID**: a unique identifier for a particular cluster size for the same trend.

1* : 2500 m2 2*: 5000 m2 3*: 7500 m2 4*: 10000 m2 5*: 12500 m2 7*: 17500 m2

10* : 25000 m2

Table A. 5 Cluster size frequency and temporal trend (one-month periods, $p \leq 0.05$)

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	6	1	1				4	4				1*	4												1	1	1
2	6	2	1				4	4				2*	4												1	1	2
3	8	3	1				4	4				2	4														2
4	3	4	1				4	1				3*	4	4*													
5	3	5	1				4	3				3	4	4													
6	2	6	1				1	1				5*	7*	1											1	1	
7	1	7	1				1	1				1	1	1			1									1	1
8	3	8	1				1	1				1	1	1													
9	4	9	1				1	1				1	1											1		1	1
10	5	10	2				1	1				1	1											1			
11	7	11	1				1	1				1	1													1	1
12	8	12	1				1	1				1	1														1
13	9	13	1				1	1					1	1													
14	12	14	1				1	1					1														
15	3	15	1				1	3				1	1	1													
16	10	16	1				1	3					1													1	1
17	17	17	1				1					1															
18	16	18	1				1					2	1														2
19	17	19	1				1					2															
20	18	20	1				1						1	1													
21	19	21	1				1																				
22	5	22	1				2	2				2	2											1			
23	13	23	1				2	2																			
24	15	24	1				2					1	1													1	1
25	14	25	2				2					2	2	2													

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
26	11	26	1				3	1					1														1
27	12	27	1				3	2					2														
28	20	28	1					1				5	7												1	1	
29	21	29	1					1				5	7														
30	22	30	1					1					1											1	1	1	1
31	25	31	1					1					1														1
32	26	32	1					1					1														
33	27	33	1					1																		4	4
34	28	34	1					1																			
35	23	35	1					2					1												1	2	1
36	24	36	1					2					2													2	2
37	29	37	1						4						1												
38	29	38	1						4						3												
39	29	39	4						1						1												
40	30	40	1						1																		
41	31	41	1							2					1			1							2		
42	34	42	1									4													1		
43	36	43	2									4															
44	32	44	1									1	1	1											1	1	1
45	36	45	2									1															
46	33	46	1									2	1														
47	35	47	1									2															1
48	37	48	6										1	1													
49	37	49	1										1	2													
50	38	50	7										1														

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
51	37	51	1										2	1													
52	38	52	2										2														
53	37	53	1										3	3													
54	38	54	1										3														
55	39	55	6											1	1												
56	39	56	9											1	2												
57	40	57	2											1													
58	39	58	1											2	2												
59	40	59	1											2													
60	39	60	1											3	2												
61	40	61	2											3													
62	41	62	1												1		1	1						1	1		
63	43	63	10												1												
64	43	64	2												2												
65	42	65	1												3			2									
66	44	66	1													1											
67	45	67	4														1	1									
68	46	68	6														1										
69	47	69	4															1									
70	47	70	1															2									
71	48	71	1																	1							
72	48	72	1																	2							
73	49	73	1																		1						1
74	50	74	3																		1						
75	50	75	1																		10*						

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
76	50	76	1																		2						
77	51	77	3																				1				
78	52	78	1																							4	4
79	53	79	7																							1	
80	53	80	1																							2	
81	52	81	1																							3	1
82	54	82	5																								1

Trend ID*: a unique identifier for a particular trend.

Variation ID**: a unique identifier for a particular cluster size for the same trend.

1* : 2500 m2 2*: 5000 m2 3*: 7500 m2 4*: 10000 m2 5*: 12500 m2 7*: 17500 m2
10* : 25000 m2

Table A. 6 Cluster size frequency and temporal trend (one-month periods, p ≤ 0.01)

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	4	1	1				4^{*}	4					4														1
2	5	2	1				4	4					4														
3	1	3	1				1^{*}	1				1	1											1			
4	2	4	1				1	1				1	1														1
5	3	5	1				1	1				1	1														
6	6	6	1				1	1																			
7	8	7	1				1					2															
8	4	8	1				2^{*}	3^{*}					1														1
9	7	9	1				2					2	2														
10	9	10	1					1				1	1														1
11	11	11	1					1					1												1	1	1
12	12	12	1					1					1													1	1
13	13	13	1					1																			
14	10	14	1					3					4	4													
15	10	15	1					3					1	1													
16	15	16	1									1	7^{*}	2													
17	16	17	1									1	7														
18	14	18	1									1	1	1												1	
19	15	19	1									1	1	1													
20	19	20	1										7														
21	17	21	5										1	1													
22	19	22	4										1														
23	17	23	1										2	1													
24	17	24	2										2	2													
25	18	25	1										2														2

No.	Trend ID*	Var. ID**	Freq.	Cluster Size (m^2) by Analysis Period																							
				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
26	17	26	1										3	3													
27	21	27	11											1													
28	20	28	1											2	2												
29	21	29	3											2													
30	21	30	3											3													
31	22	31	1												1		1	1									
32	23	32	4												1												
32	23	32	4												1												
33	23	33	1												2												
34	23	34	1												3												
35	24	35	3														1	1									
36	25	36	2														1										
37	26	37	3															1									
38	27	38	1																							4	4
39	27	39	1																							3	1
40	28	40	3																								1

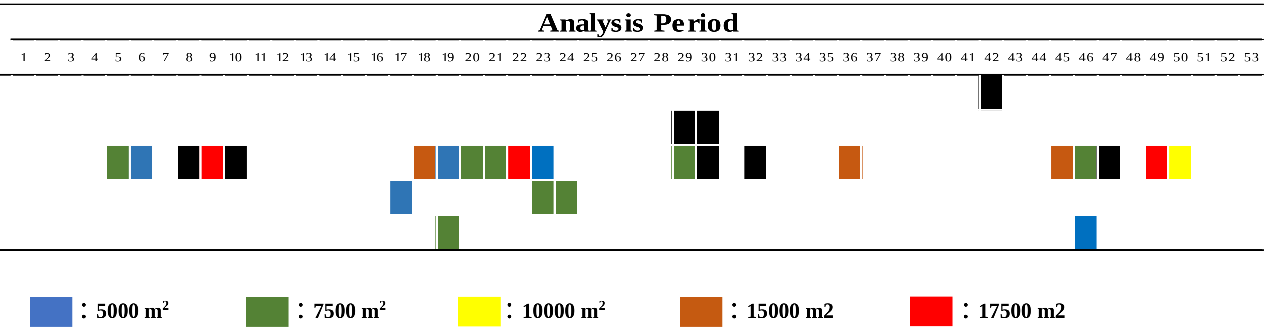
Trend ID*: a unique identifier for a particular trend.

Variation ID**: a unique identifier for a particular cluster size for the same trend.

1* : 2500 m2 2*: 5000 m2 3*: 7500 m2 4*: 10000 m2 7*: 17500 m2

Table A. 7 Five samples of cluster size frequency and temporal trend (two-week periods, $p \leq 0.1$)

Trend ID	Var. ID	Freq.
171	238	19
145	193	16
5	26	1
80	101	1
97	129	1



Trend ID*: a unique identifier for a particular trend.

Variation ID**: a unique identifier for a particular cluster size for the same trend.

APPENDIX-B

Table B. 1 Cluster size development (two-month periods, $p \leq 0.1$)

Period No.	**Sort of Develop.**	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	6	1		1						
3	Vanishing	4	1								
	Decreasing		1								
	Sustained	2									
	Increasing										
	New created	9	3	1							
4	Vanishing	11	4	1							
	Decreasing										
	Sustained										
	Increasing										
	New created	1									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
5	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	34	7	2	1						
6	Vanishing	14	3		1						
	Decreasing	3	1								
	Sustained	15	3								
	Increasing		2	1	1						
	New created	33	3								
7	Vanishing	49	9		1						
	Decreasing										
	Sustained	1									
	Increasing		1								
	New created	18	5		1		1				
8	Vanishing	15	6		1		1				
	Decreasing										
	Sustained	4									
	Increasing										
	New created	12			1						
9	Vanishing	16			1						
	Decreasing										
	Sustained										
	Increasing										
	New created	1									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	13	4	2							
11	Vanishing	13	4	2							
	Decreasing										
	Sustained	1									
	Increasing										
	New created	1									
12	Vanishing	1									
	Decreasing										
	Sustained	1									
	Increasing										
	New created	43	4	4	1						

Table B. 2 Cluster size development (two-month periods, p ≤ 0.05)

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
3	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	1	1								
4	Vanishing	1	1								
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
5	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	11	2	1							
6	Vanishing	3									
	Decreasing										
	Sustained	5	2								
	Increasing		2		1						
	New created	25	2								
7	Vanishing	30	6		1						
	Decreasing										
	Sustained										
	Increasing										
	New created	6	2		1						
8	Vanishing	5	2		1						
	Decreasing										
	Sustained	1									
	Increasing										
	New created	4									
9	Vanishing	5									
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	4	1								
11	Vanishing	4	1								
	Decreasing										
	Sustained										
	Increasing										
	New created										
12	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	16	2								

Table B. 3 Cluster size development (two-month periods, p ≤ 0.01)

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
1	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
2	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
3	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
4	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
5	Sustained										
	Increasing										
	New created	2									
	Vanishing										
	Decreasing										
6	Sustained	1									
	Increasing		1								
	New created	8	2		1						
	Vanishing	9	3		1						
	Decreasing										
7	Sustained										
	Increasing										
	New created	2									
	Vanishing	2									
	Decreasing										
8	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
9	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
11	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created										
12	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	3	1								

Table B. 4 Cluster size development (one-month periods, $p \leq 0.1$)

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
2	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created										
3	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
4	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	28	6	2	2						

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	8									
	Decreasing	5	1	1							
5	Sustained	15	4		1						
	Increasing		1	1							
	New created	10	1								
	Vanishing	32	6	2	1						
	Decreasing										
6	Sustained										
	Increasing										
	New created	11	1		1						
	Vanishing	11	1		1						
	Decreasing										
7	Sustained										
	Increasing										
	New created	1	1								
	Vanishing	1	1								
	Decreasing										
8	Sustained										
	Increasing										
	New created	5									
	Vanishing	5									
	Decreasing										
9	Sustained										
	Increasing										
	New created	25	9	1	2	1					

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing	3	1		2						
	Decreasing	4									
	Sustained	16	4								
	Increasing		1		1			1			
	New created	36	5	2							
11	Vanishing	40	6	1							
	Decreasing	5	1								
	Sustained	16	3	1	1						
	Increasing		1								
	New created	21	3	4							
12	Vanishing	33	6	3	1						
	Decreasing	2	1								
	Sustained	8	1								
	Increasing		1								
	New created	25	4	2							
13	Vanishing	35	8	2							
	Decreasing										
	Sustained										
	Increasing										
	New created	4									
14	Vanishing	2									
	Decreasing										
	Sustained	2									
	Increasing										
	New created	22	1		1	1					

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	14	1			1					
	Decreasing	1	1								
15	Sustained	10									
	Increasing			1							
	New created	6		1							
	Vanishing	6		1							
	Decreasing										
16	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
17	Sustained										
	Increasing										
	New created	5	1								
	Vanishing	5	1								
	Decreasing										
18	Sustained										
	Increasing										
	New created	10	2								1
	Vanishing	10	2								1
	Decreasing										
19	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
20	Sustained										
	Increasing										
	New created	7									
	Vanishing	7									
	Decreasing										
21	Sustained										
	Increasing										
	New created	14	3								
	Vanishing	7	2								
	Decreasing	2									
22	Sustained	6									
	Increasing		1								
	New created	12	1								
	Vanishing	7	1								
	Decreasing										
23	Sustained	12	1								
	Increasing				1						
	New created	22	3	1	1						
	Vanishing	11	3								
	Decreasing	4	1								
24	Sustained	20	1								
	Increasing		2								
	New created	16	1								

Table B. 5 Cluster size development (one-month periods, $p \leq 0.05$)

Period No.	**Sort of Develop.**	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
3	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
4	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	18	6	1	2						

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
5	Vanishing	7	3								
	Decreasing	2	1	1							
	Sustained	10	2		1						
	Increasing			1							
	New created	8	1								
6	Vanishing	20	4	2	1						
	Decreasing										
	Sustained										
	Increasing										
	New created	5			1						
7	Vanishing	5			1						
	Decreasing										
	Sustained										
	Increasing										
	New created		1								
8	Vanishing		1								
	Decreasing										
	Sustained										
	Increasing										
	New created										
9	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	16	8	1	2	1					

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing	3	2		2						
	Decreasing	2									
	Sustained	10	3								
	Increasing				2			1			
	New created	28	5	2							
11	Vanishing	26	5	1	1						
	Decreasing	3	1								
	Sustained	15	2	1	1						
	Increasing		1								
	New created	18	3	3							
12	Vanishing	26	5	3	1						
	Decreasing		1								
	Sustained	7	1								
	Increasing										
	New created	18	2	2							
13	Vanishing	25	5	2							
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
14	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	13									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	7									
	Decreasing										
15	Sustained	6									
	Increasing										
	New created	5	1								
	Vanishing	11	1								
	Decreasing										
16	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
17	Sustained										
	Increasing										
	New created	2	1								
	Vanishing	2	1								
	Decreasing										
18	Sustained										
	Increasing										
	New created	4	1								1
	Vanishing	4	1								1
	Decreasing										
19	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
20	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	4									
21	Vanishing	4									
	Decreasing										
	Sustained										
	Increasing										
	New created	6									
22	Vanishing	4									
	Decreasing										
	Sustained	2									
	Increasing										
	New created	6	1								
23	Vanishing	2	1								
	Decreasing										
	Sustained	6									
	Increasing										
	New created	14	2	1	1						
24	Vanishing	11	1								
	Decreasing	3									
	Sustained	8	1		1						
	Increasing										
	New created	12	2								

Table B. 6 Cluster size development (one-month periods, $p \leq 0.01$)

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
3	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
4	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	5	2		1						

Period No.	Sort of Develop.	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
5	Vanishing	1	1								
	Decreasing										
	Sustained	4			1						
	Increasing			1							
	New created	5		1							
6	Vanishing	9		2	1						
	Decreasing										
	Sustained										
	Increasing										
	New created										
7	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
8	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
9	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	8	2								

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing		1								
	Decreasing										
10	Sustained	6	1								
	Increasing							1			
	New created	15	4	1	1						
	Vanishing	11	2		1						
	Decreasing	1	1								
11	Sustained	10	2	1	1						
	Increasing										
	New created	14	4	3							
	Vanishing	24	6	4	1						
	Decreasing										
12	Sustained	1	1								
	Increasing										
	New created	5	1	1							
	Vanishing	6	2	1							
	Decreasing										
13	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
14	Sustained										
	Increasing										
	New created	6									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
15	Vanishing	2									
	Decreasing										
	Sustained	4									
	Increasing										
	New created	3									
16	Vanishing	7									
	Decreasing										
	Sustained										
	Increasing										
	New created										
17	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
18	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										1
19	Vanishing										1
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
20	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
21	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
22	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
23	Vanishing										
	Decreasing										
	Sustained	1									
	Increasing										
	New created	2		1	1						
24	Vanishing	1									
	Decreasing	2									
	Sustained	2			1						
	Increasing										
	New created	7	1								

Table B. 7 Cluster size development (two-week periods, $p \leq 0.1$)

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
3	Vanishing										
	Decreasing										
	Sustained	1									
	Increasing										
	New created	1									
4	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created	2									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
5	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created	15	3	1							
6	Vanishing	10	3								
	Decreasing	1	1								
	Sustained	3									
	Increasing		1								
	New created	9	2								
7	Vanishing	13	4								
	Decreasing										
	Sustained										
	Increasing										
	New created										
8	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	24	6	2	1						
9	Vanishing	6									
	Decreasing	4									
	Sustained	16	4	1	1						
	Increasing				1			1			
	New created	14	5	1							

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing	22	7	1	1						
	Decreasing	3	1		1						
	Sustained	12	2								
	Increasing										
	New created	13	1								
11	Vanishing	29	4	1	1						
	Decreasing										
	Sustained	5									
	Increasing										
	New created	4									
12	Vanishing	9									
	Decreasing										
	Sustained										
	Increasing										
	New created	2									
13	Vanishing	1									
	Decreasing										
	Sustained	1									
	Increasing										
	New created	5	1								
14	Vanishing	6	1								
	Decreasing										
	Sustained										
	Increasing										
	New created	5	1								

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
15	Vanishing	5	1								
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
16	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	11	1	1			1				
17	Vanishing	10	1	1			1				
	Decreasing										
	Sustained	1									
	Increasing										
	New created	10	2								
18	Vanishing	11	2								
	Decreasing										
	Sustained										
	Increasing										
	New created	24	8	1	1		1				
19	Vanishing	7	1	1							
	Decreasing		3								
	Sustained	16	4		1						
	Increasing		2	1							
	New created	26	4	1			1				

Period No.	Sort of Develop.	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	21	2	2	1						
	Decreasing	6	1								
20	Sustained	21	5								
	Increasing		1	1							
	New created	46	5	3	2						
	Vanishing	44	7	1							
	Decreasing	2	2								
21	Sustained	28	4	1	2						
	Increasing		1	1							
	New created	23	4								
	Vanishing	23	1								
	Decreasing	2									
22	Sustained	28	6	1	2						
	Increasing			1				1			
	New created	31	11	1							
	Vanishing	26	7	1							
	Decreasing	4	4		1						
23	Sustained	31	8	1	1						
	Increasing		1	3							
	New created	19	1	1				1			
	Vanishing	28	7	1	1						
	Decreasing	3		1							
24	Sustained	29	4	4				1			
	Increasing										
	New created	12	2		1						

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	31	4	5				1			
	Decreasing										
25	Sustained	7	2		1						
	Increasing		1								
	New created	2									
	Vanishing	9	3		1						
	Decreasing										
26	Sustained										
	Increasing										
	New created	6	1								
	Vanishing	6	1								
	Decreasing										
27	Sustained										
	Increasing										
	New created	9	2								
	Vanishing	8	2								
	Decreasing										
28	Sustained	1									
	Increasing										
	New created	13	1	2							
	Vanishing	8		1							
	Decreasing										
29	Sustained	4									
	Increasing			2	1						
	New created	79	8	4	2		1		1		

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
30	Vanishing	43	3	4	2						
	Decreasing	4		1		1					
	Sustained	36	5				2				
	Increasing					1					
	New created	5									
31	Vanishing	44	5	1		2	2				
	Decreasing										
	Sustained										
	Increasing										
	New created	7									
32	Vanishing	6									
	Decreasing										
	Sustained	1									
	Increasing										
	New created	15	1								
33	Vanishing	9	1								
	Decreasing										
	Sustained	6									
	Increasing										
	New created	10		1							
34	Vanishing	16		1							
	Decreasing										
	Sustained										
	Increasing										
	New created	2									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
35	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created	7									
36	Vanishing	6									
	Decreasing										
	Sustained	1									
	Increasing										
	New created	34	6	2	1		1				
37	Vanishing	25	6	1	1						
	Decreasing	1									
	Sustained	10		1							
	Increasing										
	New created	20	5	2					1		
38	Vanishing	31	5	3					1		
	Decreasing										
	Sustained										
	Increasing										
	New created	5	1								
39	Vanishing	5	1								
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
40	Sustained										
	Increasing										
	New created	14	1								
	Vanishing	13									
	Decreasing	1									
41	Sustained	1									
	Increasing										
	New created	1									
	Vanishing	2									
	Decreasing										
42	Sustained	1									
	Increasing										
	New created	35	4	2			1				
	Vanishing	32	4	2			1				
	Decreasing										
43	Sustained	4									
	Increasing										
	New created	1	1								
	Vanishing	5	1								
	Decreasing										
44	Sustained										
	Increasing										
	New created	9									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
45	Vanishing	4									
	Decreasing										
	Sustained	4									
	Increasing		1								
	New created	47	15	1	3		2		1		
46	Vanishing	22	10		1		1		1		
	Decreasing	2	2	1							
	Sustained	22	2		1						
	Increasing		2	2	2						
	New created	29		1			1				
47	Vanishing	44	3	1	2		1				
	Decreasing	2	1								
	Sustained	14	2								
	Increasing										
	New created	6	2								
48	Vanishing	14	2								
	Decreasing	3									
	Sustained	5	1		1						
	Increasing			1	1						
	New created	16	4	1			1				
49	Vanishing	7	1	1							
	Decreasing	2	1	2							
	Sustained	15	3		2						
	Increasing		1		1			1			
	New created	21	4								

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
50	Vanishing	23	6	2	1						
	Decreasing	4	3		1						
	Sustained	10	1								
	Increasing		2	1							
	New created	11	2								
51	Vanishing	27	6	2	1						
	Decreasing	1									
	Sustained	1									
	Increasing				1						
	New created	7	2	1							
52	Vanishing	9	2	1	1						
	Decreasing										
	Sustained										
	Increasing										
	New created	2	1								
53	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										

Table B. 8 Cluster size development (two-week periods, $p \leq 0.05$)

Period No.	**Sort of Develop.**	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
3	Vanishing										
	Decreasing										
	Sustained	1									
	Increasing										
	New created										
4	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
5	Sustained										
	Increasing										
	New created	9	2	1							
	Vanishing	8	2								
	Decreasing	1									
6	Sustained	1									
	Increasing										
	New created	6	1								
	Vanishing	8	1								
	Decreasing										
7	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
8	Sustained										
	Increasing										
	New created	16	6	2	1						
	Vanishing	6	1								
	Decreasing	4									
9	Sustained	9	3	1	1						
	Increasing				1						
	New created	11	5	1				1			

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing	13	6	1	1						
	Decreasing	3	2		1						
	Sustained	10	2								
	Increasing			1							
	New created	7	1								
11	Vanishing	19	4	1	1						
	Decreasing										
	Sustained	1									
	Increasing										
	New created	2									
12	Vanishing	3									
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
13	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
14	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	4									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
15	Vanishing	4									
	Decreasing										
	Sustained										
	Increasing										
	New created										
16	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	5									
17	Vanishing	4									
	Decreasing										
	Sustained	1									
	Increasing										
	New created	8	1								
18	Vanishing	9	1								
	Decreasing										
	Sustained										
	Increasing										
	New created	16	7	1	1		1				
19	Vanishing	6	1	1							
	Decreasing		3								
	Sustained	9	4		1						
	Increasing			1	1						
	New created	21	3	2			1				

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	16	3	2	1		1				
	Decreasing	3	1								
20	Sustained	14	4								
	Increasing			1							
	New created	30	4	2	2						
	Vanishing	30	5	1							
	Decreasing	2									
21	Sustained	14	3	1	2						
	Increasing		1	1							
	New created	15	2								
	Vanishing	9									
	Decreasing	1									
22	Sustained	20	4	1	2						
	Increasing							1			
	New created	26	8	2							
	Vanishing	19	6	1							
	Decreasing	4	4		1						
23	Sustained	24	3	1	1						
	Increasing		1	3							
	New created	16	2	1				1			
	Vanishing	26	7	1	1						
	Decreasing	3									
24	Sustained	19	3	4				1			
	Increasing										
	New created	9	2		1						

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
25	Vanishing										
	Decreasing										
	Sustained	7	2		1						
	Increasing										
	New created	1									
26	Vanishing	8	2		1						
	Decreasing										
	Sustained										
	Increasing										
	New created	2									
27	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created	3	1								
28	Vanishing	2	1								
	Decreasing										
	Sustained	1									
	Increasing										
	New created	8	1	1							
29	Vanishing	5		1							
	Decreasing										
	Sustained	2									
	Increasing			2	1						
	New created	65	6	3	2		2		1		

Period No.	Sort of Develop.	**Cluster Size (m²) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
30	Vanishing	33	3	4	3						
	Decreasing	1		1		1					
	Sustained	31	3				2				
	Increasing										
	New created	3									
31	Vanishing	35	3	1		2	2				
	Decreasing										
	Sustained	1									
	Increasing										
	New created	4									
32	Vanishing	4									
	Decreasing										
	Sustained	1									
	Increasing										
	New created	7	1								
33	Vanishing	5	1								
	Decreasing										
	Sustained	3									
	Increasing										
	New created	8		1							
34	Vanishing	11		1							
	Decreasing										
	Sustained										
	Increasing										
	New created	2									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
35	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created	3									
36	Vanishing	3									
	Decreasing										
	Sustained										
	Increasing										
	New created	30	3	1	1		1				
37	Vanishing	26	3	1	1						
	Decreasing	1									
	Sustained	4									
	Increasing										
	New created	14	2	2					1		
38	Vanishing	19	2	2					1		
	Decreasing										
	Sustained										
	Increasing										
	New created	5	1								
39	Vanishing	5	1								
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
40	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	11	1								
41	Vanishing	10	1								
	Decreasing										
	Sustained	1									
	Increasing										
	New created										
42	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created	24	3	2			1				
43	Vanishing	24	3	2			1				
	Decreasing										
	Sustained										
	Increasing										
	New created		1								
44	Vanishing		1								
	Decreasing										
	Sustained										
	Increasing										
	New created	3									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
45	Vanishing	1									
	Decreasing										
	Sustained	1									
	Increasing		1								
	New created	31	12	1	3		2		1		
46	Vanishing	17	8		1		1		1		
	Decreasing	3	2	1							
	Sustained	15	2		1						
	Increasing			1	2						
	New created	28	1	1			1				
47	Vanishing	36	6	3	3		1				
	Decreasing										
	Sustained	9									
	Increasing				1						
	New created	5									
48	Vanishing	9									
	Decreasing										
	Sustained	5			1						
	Increasing										
	New created	14	4	2	1		1				
49	Vanishing	4	2	1							
	Decreasing	1		1							
	Sustained	11	2		2						
	Increasing		1		1			1			
	New created	18	3								

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
50	Vanishing	21	4	2	2						
	Decreasing	3	1		1						
	Sustained	6	1								
	Increasing		2								
	New created	6	1	2							
51	Vanishing	14	4	2	1						
	Decreasing										
	Sustained	1									
	Increasing				1						
	New created	4	1	1							
52	Vanishing	4		1	1						
	Decreasing										
	Sustained	1	1								
	Increasing										
	New created										
53	Vanishing	1	1								
	Decreasing										
	Sustained										
	Increasing										
	New created										

Table B. 9 Cluster size development (two-week periods, $p \leq 0.01$)

Period No.	**Sort of Develop.**	**Cluster Size (m^2) by Analysis Period**									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
1	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
2	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
3	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
4	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
5	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	2	1								
6	Vanishing	2	1								
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
7	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created										
8	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	8	4	1							
9	Vanishing	5	1	1							
	Decreasing	1									
	Sustained	3	2								
	Increasing										
	New created	9	3	1	2			1			

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
10	Vanishing	11	5		1			1			
	Decreasing	2	1								
	Sustained	2									
	Increasing										
	New created										
11	Vanishing	4	1								
	Decreasing										
	Sustained										
	Increasing										
	New created	1									
12	Vanishing	1									
	Decreasing										
	Sustained										
	Increasing										
	New created										
13	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
14	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	2									

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
15	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created										
16	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										
17	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	3									
18	Vanishing	3									
	Decreasing										
	Sustained										
	Increasing										
	New created	10	5		1		1				
19	Vanishing	6	1								
	Decreasing		1	1							
	Sustained	4	3								
	Increasing				1						
	New created	6	2	1							

Period No.	Sort of Develop.	Cluster Size (m²) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
20	Vanishing	6	4	1	2						
	Decreasing	1									
	Sustained	4	2								
	Increasing										
	New created	14	3	1	2						
21	Vanishing	8	2	1							
	Decreasing										
	Sustained	10	3		2						
	Increasing			1							
	New created	5	1								
22	Vanishing	2									
	Decreasing	1									
	Sustained	12	2	1	2						
	Increasing							1			
	New created	16	7								
23	Vanishing	13	4								
	Decreasing	2	2		1						
	Sustained	15	3		1						
	Increasing		1	1							
	New created	14	2	3				1			
24	Vanishing	19	5	1	2						
	Decreasing	1									
	Sustained	12	2	3				1			
	Increasing										
	New created	6	1		1						

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing	15	2	3				1			
	Decreasing										
25	Sustained	4	1		1						
	Increasing										
	New created										
	Vanishing	4	1		1						
	Decreasing										
26	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
27	Sustained										
	Increasing										
	New created	1									
	Vanishing										
	Decreasing										
28	Sustained	1									
	Increasing										
	New created	3									
	Vanishing	3									
	Decreasing										
29	Sustained	1									
	Increasing										
	New created	42	2	3	2		2		1		

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
30	Vanishing	31	1	2	2						
	Decreasing	1				1					
	Sustained	12	1				1				
	Increasing										
	New created	1									
31	Vanishing	14	1			1	2				
	Decreasing										
	Sustained										
	Increasing										
	New created										
32	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created	2									
33	Vanishing	2									
	Decreasing										
	Sustained										
	Increasing										
	New created	3									
34	Vanishing	3									
	Decreasing										
	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
35	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
36	Sustained										
	Increasing										
	New created	10	1				1				
	Vanishing	10	1				1				
	Decreasing										
37	Sustained										
	Increasing										
	New created	5		1							
	Vanishing	5		1							
	Decreasing										
38	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
39	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
40	Sustained										
	Increasing										
	New created	2									
	Vanishing	2									
	Decreasing										
41	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
42	Sustained										
	Increasing										
	New created	6	2								
	Vanishing	6	2								
	Decreasing										
43	Sustained										
	Increasing										
	New created										
	Vanishing										
	Decreasing										
44	Sustained										
	Increasing										
	New created										

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
	Vanishing										
	Decreasing										
45	Sustained										
	Increasing										
	New created	15	4								
	Vanishing	7	1								
	Decreasing										
46	Sustained	8	2								
	Increasing				1						
	New created	14	1	2	1						
	Vanishing	21	3	3	3						
	Decreasing										
47	Sustained	1									
	Increasing										
	New created	1									
	Vanishing	2									
	Decreasing										
48	Sustained										
	Increasing										
	New created	6	2	1	2		1				
	Vanishing	2	1	1							
	Decreasing			1							
49	Sustained	4	1		2						
	Increasing										
	New created	11			1			1			

Period No.	Sort of Develop.	Cluster Size (m^2) by Analysis Period									
		2,500	5,000	7,500	10,000	12,500	15,000	17,500	20,000	22,500	25,000
50	Vanishing	15	1	1	3			1			
	Decreasing										
	Sustained										
	Increasing										
	New created	2	3								
51	Vanishing	2	3								
	Decreasing										
	Sustained										
	Increasing										
	New created	2	1	1	1						
52	Vanishing	2	1	1	1						
	Decreasing										
	Sustained										
	Increasing										
	New created										
53	Vanishing										
	Decreasing										
	Sustained										
	Increasing										
	New created										

APPENDIX-C

Table C. 1 Statistical comparison of small urban cities for quarter-year periods

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Apr_Jun-13) - (Macon Apr_Jun-15)	-0.115066	0.1373	Inf	-0.838	1
(Monett Apr_Jun-13) - (Monett Apr_Jun-15)	0.060898	0.1005	Inf	0.606	1
(Monett Apr_Jun-13) - (Macon Jan_Mar-13)	-0.159508	0.1392	Inf	-1.146	1
(Monett Apr_Jun-13) - (Monett Jan_Mar-13)	0.025133	0.1007	Inf	0.25	1
(Monett Apr_Jun-13) - (Chillicothe Jan_Mar-14)	-0.198522	0.1502	Inf	-1.321	1
(Monett Apr_Jun-13) - (Macon Jan_Mar-14)	0.053861	0.119	Inf	0.452	1
(Monett Apr_Jun-13) - (Monett Jul_Sep-13)	-0.141479	0.1148	Inf	-1.233	1
(Monett Apr_Jun-13) - (Chillicothe Jul_Sep-14)	-0.00984	0.1265	Inf	-0.078	1
(Monett Apr_Jun-13) - (Macon Jul_Sep-15)	-0.11543	0.1333	Inf	-0.866	1
(Monett Apr_Jun-13) - (Monett Jul_Sep-15)	0.056692	0.0977	Inf	0.58	1
(Monett Apr_Jun-13) - (Macon Oct_Dec-13)	-0.015441	0.1259	Inf	-0.123	1
(Monett Apr_Jun-13) - (Monett Oct_Dec-13)	0.132266	0.0948	Inf	1.395	1
(Chillicothe Apr_Jun-14) - (Monett Apr_Jun-15)	-0.088711	0.1008	Inf	-0.88	1
(Chillicothe Apr_Jun-14) - (Monett Jan_Mar-13)	-0.124476	0.1006	Inf	-1.238	1
(Chillicothe Apr_Jun-14) - (Macon Jan_Mar-14)	-0.095748	0.1089	Inf	-0.879	1
(Chillicothe Apr_Jun-14) - (Monett Jan_Mar-14)	0.032786	0.0898	Inf	0.365	1
(Chillicothe Apr_Jun-14) - (Chillicothe Jan_Mar-1	0.042905	0.0838	Inf	0.512	1
(Chillicothe Apr_Jun-14) - (Chillicothe Jul_Sep-14	-0.159449	0.1068	Inf	-1.492	1
(Chillicothe Apr_Jun-14) - (Macon Jul_Sep-14)	0.021454	0.0907	Inf	0.237	1
(Chillicothe Apr_Jun-14) - (Monett Jul_Sep-14)	0.113546	0.0784	Inf	1.448	1
(Chillicothe Apr_Jun-14) - (Monett Jul_Sep-15)	-0.092917	0.0992	Inf	-0.937	1
(Chillicothe Apr_Jun-14) - (Macon Oct_Dec-13)	-0.16505	0.1155	Inf	-1.43	1
(Chillicothe Apr_Jun-14) - (Monett Oct_Dec-13)	-0.017343	0.0938	Inf	-0.185	1
(Macon Apr_Jun-14) - (Monett Jan_Mar-14)	-0.088152	0.0751	Inf	-1.173	1
(Macon Apr_Jun-14) - (Chillicothe Jan_Mar-15)	-0.078032	0.0755	Inf	-1.034	1
(Macon Apr_Jun-14) - (Macon Jan_Mar-15)	0.027638	0.0536	Inf	0.516	1
(Macon Apr_Jun-14) - (Macon Jul_Sep-14)	-0.099484	0.0686	Inf	-1.45	1
(Macon Apr_Jun-14) - (Monett Jul_Sep-14)	-0.007392	0.0623	Inf	-0.119	1
(Macon Apr_Jun-14) - (Chillicothe Oct_Dec-15)	0.015706	0.0703	Inf	0.223	1
(Monett Apr_Jun-14) - (Macon Jan_Mar-15)	-0.033906	0.0513	Inf	-0.661	1
(Monett Apr_Jun-14) - (Monett Jan_Mar-15)	0.019914	0.0383	Inf	0.52	1
(Monett Apr_Jun-14) - (Monett Jul_Sep-14)	-0.068936	0.049	Inf	-1.406	1
(Monett Apr_Jun-14) - (Chillicothe Oct_Dec-15)	-0.045839	0.0626	Inf	-0.732	1
(Monett Apr_Jun-14) - (Macon Oct_Dec-15)	0.026808	0.0466	Inf	0.575	1

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Chillicothe Apr_Jun-15) - (Chillicothe Jan_Mar-13)	-0.062546	0.2009	Inf	-0.311	1
(Chillicothe Apr_Jun-15) - (Chillicothe Jan_Mar-14)	0.262721	0.187	Inf	1.405	1
(Chillicothe Apr_Jun-15) - (Macon Jul_Sep-13)	0.071987	0.2131	Inf	0.338	1
(Chillicothe Apr_Jun-15) - (Chillicothe Jul_Sep-15)	0.006315	0.195	Inf	0.032	1
(Chillicothe Apr_Jun-15) - (Chillicothe Oct_Dec-13)	0.155484	0.1919	Inf	0.81	1
(Chillicothe Apr_Jun-15) - (Macon Oct_Dec-14)	-0.050168	0.2234	Inf	-0.225	1
(Chillicothe Apr_Jun-15) - (Monett Oct_Dec-14)	0.227597	0.1957	Inf	1.163	1
(Macon Apr_Jun-15) - (Macon Jan_Mar-13)	-0.044442	0.1314	Inf	-0.338	1
(Macon Apr_Jun-15) - (Monett Jan_Mar-13)	0.140199	0.1337	Inf	1.048	1
(Macon Apr_Jun-15) - (Chillicothe Jan_Mar-14)	-0.083456	0.1675	Inf	-0.498	1
(Macon Apr_Jun-15) - (Macon Jan_Mar-14)	0.168927	0.1209	Inf	1.397	1
(Macon Apr_Jun-15) - (Monett Jul_Sep-13)	-0.026413	0.1478	Inf	-0.179	1
(Macon Apr_Jun-15) - (Chillicothe Jul_Sep-14)	0.105226	0.1447	Inf	0.727	1
(Macon Apr_Jun-15) - (Macon Jul_Sep-15)	-0.000364	0.1275	Inf	-0.003	1
(Macon Apr_Jun-15) - (Monett Jul_Sep-15)	0.171759	0.131	Inf	1.311	1
(Macon Apr_Jun-15) - (Chillicothe Oct_Dec-13)	-0.190693	0.1758	Inf	-1.085	1
(Macon Apr_Jun-15) - (Macon Oct_Dec-13)	0.099625	0.1244	Inf	0.801	1
(Macon Apr_Jun-15) - (Monett Oct_Dec-14)	-0.11858	0.1577	Inf	-0.752	1
(Monett Apr_Jun-15) - (Monett Jan_Mar-13)	-0.035765	0.0966	Inf	-0.37	1
(Monett Apr_Jun-15) - (Macon Jan_Mar-14)	-0.007037	0.1151	Inf	-0.061	1
(Monett Apr_Jun-15) - (Monett Jan_Mar-14)	0.121497	0.0872	Inf	1.393	1
(Monett Apr_Jun-15) - (Chillicothe Jan_Mar-15)	0.131617	0.0989	Inf	1.331	1
(Monett Apr_Jun-15) - (Chillicothe Jul_Sep-14)	-0.070738	0.122	Inf	-0.58	1
(Monett Apr_Jun-15) - (Macon Jul_Sep-14)	0.110165	0.0998	Inf	1.103	1
(Monett Apr_Jun-15) - (Macon Jul_Sep-15)	-0.176328	0.13	Inf	-1.356	1
(Monett Apr_Jun-15) - (Monett Jul_Sep-15)	-0.004205	0.0936	Inf	-0.045	1
(Monett Apr_Jun-15) - (Macon Oct_Dec-13)	-0.076339	0.1221	Inf	-0.625	1
(Monett Apr_Jun-15) - (Monett Oct_Dec-13)	0.071369	0.0904	Inf	0.79	1
(Chillicothe Jan_Mar-13) - (Macon Jul_Sep-13)	0.134532	0.2114	Inf	0.636	1
(Chillicothe Jan_Mar-13) - (Chillicothe Jul_Sep-15)	0.06886	0.1935	Inf	0.356	1
(Chillicothe Jan_Mar-13) - (Chillicothe Oct_Dec-13)	0.21803	0.1905	Inf	1.145	1
(Chillicothe Jan_Mar-13) - (Macon Oct_Dec-14)	0.012378	0.2232	Inf	0.055	1
(Chillicothe Jan_Mar-13) - (Monett Oct_Dec-14)	0.290143	0.1978	Inf	1.467	1
(Macon Jan_Mar-13) - (Chillicothe Jan_Mar-14)	-0.039014	0.1683	Inf	-0.232	1
(Chillicothe Apr_Jun-13) - (Chillicothe Apr_Jun-15)	0.126556	0.2097	Inf	0.603	1
(Chillicothe Apr_Jun-13) - (Chillicothe Jan_Mar-13)	0.06401	0.2072	Inf	0.309	1
(Chillicothe Apr_Jun-13) - (Chillicothe Jul_Sep-13)	-0.291382	0.2342	Inf	-1.244	1
(Chillicothe Apr_Jun-13) - (Macon Jul_Sep-13)	0.198542	0.2198	Inf	0.903	1
(Chillicothe Apr_Jun-13) - (Chillicothe Oct_Dec-13)	0.28204	0.1994	Inf	1.415	1
(Chillicothe Apr_Jun-13) - (Chillicothe Jul_Sep-15)	0.13287	0.2019	Inf	0.658	1

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Macon Jan_Mar-13) - (Macon Jul_Sep-13)	-0.229749	0.1499	Inf	-1.533	1
(Macon Jan_Mar-13) - (Monett Jul_Sep-13)	0.018028	0.1496	Inf	0.12	1
(Macon Jan_Mar-13) - (Chillicothe Jul_Sep-14)	0.149667	0.145	Inf	1.032	1
(Macon Jan_Mar-13) - (Macon Jul_Sep-15)	0.044077	0.127	Inf	0.347	1
(Macon Jan_Mar-13) - (Chillicothe Oct_Dec-13)	-0.146252	0.1764	Inf	-0.829	1
(Macon Jan_Mar-13) - (Macon Oct_Dec-13)	0.144067	0.1243	Inf	1.159	1
(Macon Jan_Mar-13) - (Monett Oct_Dec-14)	-0.074138	0.1604	Inf	-0.462	1
(Monett Jan_Mar-13) - (Chillicothe Jan_Mar-14)	-0.223655	0.1465	Inf	-1.527	1
(Monett Jan_Mar-13) - (Macon Jan_Mar-14)	0.028728	0.1153	Inf	0.249	1
(Monett Jan_Mar-13) - (Monett Jul_Sep-13)	-0.166612	0.1114	Inf	-1.495	1
(Monett Jan_Mar-13) - (Chillicothe Jul_Sep-14)	-0.034973	0.1218	Inf	-0.287	1
(Monett Jan_Mar-13) - (Macon Jul_Sep-14)	0.14593	0.0997	Inf	1.464	1
(Monett Jan_Mar-13) - (Macon Jul_Sep-15)	-0.140563	0.1301	Inf	-1.081	1
(Monett Jan_Mar-13) - (Monett Jul_Sep-15)	0.03156	0.0941	Inf	0.336	1
(Monett Jan_Mar-13) - (Macon Oct_Dec-13)	-0.040574	0.1222	Inf	-0.332	1
(Monett Jan_Mar-13) - (Monett Oct_Dec-13)	0.107133	0.0907	Inf	1.181	1
(Chillicothe Jan_Mar-14) - (Macon Jul_Sep-13)	-0.190735	0.1912	Inf	-0.998	1
(Chillicothe Jan_Mar-14) - (Monett Jul_Sep-13)	0.057043	0.1592	Inf	0.358	1
(Chillicothe Jan_Mar-14) - (Chillicothe Jul_Sep-14	0.188682	0.147	Inf	1.284	1
(Chillicothe Jan_Mar-14) - (Chillicothe Jul_Sep-15	-0.256407	0.1763	Inf	-1.454	1
(Chillicothe Jan_Mar-14) - (Macon Jul_Sep-15)	0.083092	0.1654	Inf	0.502	1
(Chillicothe Jan_Mar-14) - (Chillicothe Oct_Dec-1	-0.107237	0.1731	Inf	-0.62	1
(Chillicothe Jan_Mar-14) - (Macon Oct_Dec-13)	0.183081	0.1586	Inf	1.154	1
(Chillicothe Jan_Mar-14) - (Monett Oct_Dec-14)	-0.035124	0.1682	Inf	-0.209	1
(Macon Jan_Mar-14) - (Chillicothe Jan_Mar-15)	0.138654	0.1066	Inf	1.301	1
(Macon Jan_Mar-14) - (Monett Jul_Sep-13)	-0.19534	0.1308	Inf	-1.493	1
(Macon Jan_Mar-14) - (Chillicothe Jul_Sep-14)	-0.063701	0.1294	Inf	-0.492	1
(Macon Jan_Mar-14) - (Macon Jul_Sep-14)	0.117202	0.0949	Inf	1.235	1
(Macon Jan_Mar-14) - (Macon Jul_Sep-15)	-0.169291	0.1158	Inf	-1.462	1
(Macon Jan_Mar-14) - (Monett Jul_Sep-15)	0.002831	0.1118	Inf	0.025	1
(Macon Jan_Mar-14) - (Macon Oct_Dec-13)	-0.069302	0.1115	Inf	-0.622	1
(Macon Jan_Mar-14) - (Monett Oct_Dec-13)	0.078405	0.1084	Inf	0.724	1
(Chillicothe Apr_Jun-13) - (Macon Oct_Dec-14)	0.076388	0.2304	Inf	0.332	1
(Macon Apr_Jun-13) - (Chillicothe Apr_Jun-15)	-0.263354	0.1994	Inf	-1.321	1
(Macon Apr_Jun-13) - (Macon Apr_Jun-15)	0.082824	0.1372	Inf	0.604	1
(Macon Apr_Jun-13) - (Macon Jan_Mar-13)	0.038382	0.1362	Inf	0.282	1
(Macon Apr_Jun-13) - (Chillicothe Jan_Mar-14)	-0.000632	0.175	Inf	-0.004	1
(Macon Apr_Jun-13) - (Macon Jul_Sep-13)	-0.191367	0.1546	Inf	-1.238	1
(Macon Apr_Jun-13) - (Monett Jul_Sep-13)	0.056411	0.1564	Inf	0.361	1
(Macon Apr_Jun-13) - (Chillicothe Jul_Sep-14)	0.18805	0.1529	Inf	1.23	1
(Monett Jan_Mar-14) - (Chillicothe Jan_Mar-15)	0.01012	0.0878	Inf	0.115	1
(Monett Jan_Mar-14) - (Macon Jul_Sep-14)	-0.011332	0.0883	Inf	-0.128	1

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Jan_Mar-14) - (Monett Jul_Sep-14)	0.08076	0.0681	Inf	1.187	1
(Monett Jan_Mar-14) - (Monett Jul_Sep-15)	-0.125702	0.084	Inf	-1.497	1
(Monett Jan_Mar-14) - (Monett Oct_Dec-13)	-0.050129	0.0802	Inf	-0.625	1
(Monett Jan_Mar-14) - (Chillicothe Oct_Dec-15)	0.103857	0.0814	Inf	1.276	1
(Chillicothe Jan_Mar-15) - (Macon Jul_Sep-14)	-0.021452	0.0877	Inf	-0.245	1
(Chillicothe Jan_Mar-15) - (Monett Jul_Sep-14)	0.07064	0.0757	Inf	0.933	1
(Chillicothe Jan_Mar-15) - (Monett Jul_Sep-15)	-0.135822	0.0974	Inf	-1.395	1
(Chillicothe Jan_Mar-15) - (Monett Oct_Dec-13)	-0.060248	0.0918	Inf	-0.656	1
(Chillicothe Jan_Mar-15) - (Chillicothe Oct_Dec-1	0.093738	0.0793	Inf	1.182	1
(Macon Jan_Mar-15) - (Monett Jul_Sep-14)	-0.03503	0.0602	Inf	-0.582	1
(Macon Jan_Mar-15) - (Chillicothe Oct_Dec-15)	-0.011933	0.0683	Inf	-0.175	1
(Macon Jan_Mar-15) - (Macon Oct_Dec-15)	0.060714	0.0498	Inf	1.22	1
(Monett Jan_Mar-15) - (Chillicothe Oct_Dec-15)	-0.065753	0.0613	Inf	-1.072	1
(Monett Jan_Mar-15) - (Macon Oct_Dec-15)	0.006894	0.0449	Inf	0.153	1
(Monett Jan_Mar-15) - (Monett Oct_Dec-15)	0.043931	0.0346	Inf	1.269	1
(Chillicothe Jul_Sep-13) - (Chillicothe Oct_Dec-14	-0.183097	0.2578	Inf	-0.71	1
(Chillicothe Jul_Sep-13) - (Macon Oct_Dec-14)	0.36777	0.257	Inf	1.431	1
(Macon Jul_Sep-13) - (Chillicothe Jul_Sep-15)	-0.065672	0.2005	Inf	-0.328	1
(Macon Jul_Sep-13) - (Chillicothe Oct_Dec-13)	0.083498	0.1982	Inf	0.421	1
(Macon Jul_Sep-13) - (Macon Oct_Dec-14)	-0.122154	0.1725	Inf	-0.708	1
(Macon Jul_Sep-13) - (Monett Oct_Dec-14)	0.155611	0.1859	Inf	0.837	1
(Monett Jul_Sep-13) - (Chillicothe Jul_Sep-14)	0.131639	0.1365	Inf	0.964	1
(Monett Jul_Sep-13) - (Macon Jul_Sep-15)	0.026049	0.1446	Inf	0.18	1
(Monett Jul_Sep-13) - (Chillicothe Oct_Dec-13)	-0.16428	0.1684	Inf	-0.975	1
(Monett Jul_Sep-13) - (Macon Oct_Dec-13)	0.126038	0.1372	Inf	0.919	1
(Monett Jul_Sep-13) - (Monett Oct_Dec-14)	-0.092167	0.1309	Inf	-0.704	1
(Chillicothe Jul_Sep-14) - (Macon Jul_Sep-15)	-0.10559	0.1429	Inf	-0.739	1
(Chillicothe Jul_Sep-14) - (Monett Jul_Sep-15)	0.066533	0.1213	Inf	0.548	1
(Chillicothe Jul_Sep-14) - (Macon Oct_Dec-13)	-0.005601	0.135	Inf	-0.041	1
(Chillicothe Jul_Sep-14) - (Monett Oct_Dec-13)	0.142107	0.1164	Inf	1.221	1
(Chillicothe Jul_Sep-14) - (Monett Oct_Dec-14)	-0.223806	0.1485	Inf	-1.507	1
(Macon Jul_Sep-14) - (Monett Jul_Sep-15)	-0.11437	0.0969	Inf	-1.18	1
(Macon Jul_Sep-14) - (Monett Oct_Dec-13)	-0.038796	0.0924	Inf	-0.42	1
(Macon Apr_Jun-13) - (Chillicothe Jul_Sep-15)	-0.257039	0.1856	Inf	-1.385	1
(Macon Apr_Jun-13) - (Macon Jul_Sep-15)	0.08246	0.1324	Inf	0.623	1
(Macon Apr_Jun-13) - (Chillicothe Oct_Dec-13)	-0.107869	0.183	Inf	-0.589	1
(Macon Apr_Jun-13) - (Macon Oct_Dec-13)	0.182449	0.1304	Inf	1.399	1
(Macon Apr_Jun-13) - (Monett Oct_Dec-14)	-0.035756	0.1662	Inf	-0.215	1
(Monett Apr_Jun-13) - (Chillicothe Apr_Jun-14)	0.149609	0.1058	Inf	1.414	1
(Macon Jul_Sep-14) - (Chillicothe Oct_Dec-15)	0.11519	0.0834	Inf	1.381	1

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Jul_Sep-14) - (Chillicothe Oct_Dec-15)	0.023097	0.0699	Inf	0.33	1
(Chillicothe Jul_Sep-15) - (Chillicothe Oct_Dec-13	0.14917	0.1822	Inf	0.819	1
(Chillicothe Jul_Sep-15) - (Macon Oct_Dec-14)	-0.056482	0.2096	Inf	-0.269	1
(Chillicothe Jul_Sep-15) - (Monett Oct_Dec-14)	0.221283	0.1825	Inf	1.212	1
(Macon Jul_Sep-15) - (Chillicothe Oct_Dec-13)	-0.190329	0.1742	Inf	-1.092	1
(Macon Jul_Sep-15) - (Macon Oct_Dec-13)	0.099989	0.1194	Inf	0.837	1
(Macon Jul_Sep-15) - (Monett Oct_Dec-14)	-0.118216	0.1537	Inf	-0.769	1
(Monett Jul_Sep-15) - (Macon Oct_Dec-13)	-0.072134	0.119	Inf	-0.606	1
(Monett Jul_Sep-15) - (Monett Oct_Dec-13)	0.075574	0.0873	Inf	0.866	1
(Chillicothe Oct_Dec-13) - (Macon Oct_Dec-14)	-0.205652	0.2077	Inf	-0.99	1
(Chillicothe Oct_Dec-13) - (Monett Oct_Dec-14)	0.072113	0.178	Inf	0.405	1
(Macon Oct_Dec-13) - (Monett Oct_Dec-14)	-0.218205	0.1469	Inf	-1.485	1
(Macon Apr_Jun-13) - (Monett Jan_Mar-13)	0.223023	0.1429	Inf	1.561	0.9999
(Macon Apr_Jun-14) - (Monett Jan_Mar-15)	0.081458	0.052	Inf	1.568	0.9999
(Chillicothe Apr_Jun-15) - (Macon Jan_Mar-13)	0.301736	0.1928	Inf	1.565	0.9999
(Chillicothe Jan_Mar-13) - (Chillicothe Jul_Sep-13	-0.355392	0.2257	Inf	-1.575	0.9999
(Chillicothe Jan_Mar-14) - (Macon Oct_Dec-14)	-0.312889	0.1999	Inf	-1.565	0.9999
(Monett Jan_Mar-14) - (Macon Jan_Mar-15)	0.11579	0.0737	Inf	1.571	0.9999
(Macon Apr_Jun-13) - (Chillicothe Jan_Mar-13)	-0.325899	0.1984	Inf	-1.643	0.9998
(Monett Apr_Jun-13) - (Macon Jul_Sep-14)	0.171063	0.1045	Inf	1.637	0.9998
(Monett Apr_Jun-15) - (Macon Jan_Mar-13)	-0.220405	0.1358	Inf	-1.623	0.9998
(Macon Jan_Mar-13) - (Chillicothe Jul_Sep-15)	-0.295421	0.1792	Inf	-1.648	0.9998
(Macon Jan_Mar-13) - (Monett Jul_Sep-15)	0.2162	0.1331	Inf	1.624	0.9998
(Chillicothe Apr_Jun-14) - (Chillicothe Oct_Dec-1	0.136643	0.0818	Inf	1.671	0.9997
(Monett Jan_Mar-13) - (Chillicothe Jan_Mar-15)	0.167382	0.0985	Inf	1.699	0.9996
(Monett Jan_Mar-14) - (Chillicothe Jul_Sep-14)	-0.192235	0.1131	Inf	-1.699	0.9996
(Chillicothe Apr_Jun-13) - (Monett Oct_Dec-14)	0.354153	0.2059	Inf	1.72	0.9995
(Macon Apr_Jun-14) - (Macon Oct_Dec-15)	0.088353	0.0517	Inf	1.708	0.9995
(Chillicothe Apr_Jun-15) - (Monett Jul_Sep-13)	0.319764	0.1858	Inf	1.721	0.9995
(Monett Jul_Sep-14) - (Macon Oct_Dec-15)	0.095744	0.056	Inf	1.708	0.9995
(Macon Apr_Jun-14) - (Monett Oct_Dec-13)	-0.13828	0.0798	Inf	-1.733	0.9994
(Chillicothe Jan_Mar-13) - (Chillicothe Jan_Mar-1	0.325267	0.186	Inf	1.749	0.9993
(Monett Apr_Jun-14) - (Monett Oct_Dec-15)	0.063845	0.0363	Inf	1.759	0.9992
(Macon Jan_Mar-13) - (Macon Jan_Mar-14)	0.213369	0.1212	Inf	1.761	0.9992

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Chillicothe Jan_Mar-14) - (Monett Jul_Sep-15)	0.255215	0.1454	Inf	1.755	0.9992
(Monett Jan_Mar-14) - (Macon Oct_Dec-13)	-0.197836	0.1122	Inf	-1.763	0.9991
(Monett Apr_Jun-15) - (Chillicothe Jan_Mar-14)	-0.25942	0.1464	Inf	-1.772	0.999
(Monett Jan_Mar-13) - (Monett Jan_Mar-14)	0.157262	0.0876	Inf	1.795	0.9988
(Chillicothe Apr_Jun-15) - (Macon Jul_Sep-15)	0.345813	0.1918	Inf	1.803	0.9987
(Monett Oct_Dec-13) - (Chillicothe Oct_Dec-15)	0.153986	0.0857	Inf	1.797	0.9987
(Macon Apr_Jun-13) - (Monett Apr_Jun-15)	0.258788	0.143	Inf	1.809	0.9986
(Macon Apr_Jun-15) - (Macon Jul_Sep-13)	-0.274191	0.1517	Inf	-1.808	0.9986
(Monett Jul_Sep-13) - (Chillicothe Jul_Sep-15)	-0.31345	0.1732	Inf	-1.81	0.9986
(Monett Jul_Sep-14) - (Monett Oct_Dec-13)	-0.130889	0.0725	Inf	-1.806	0.9986
(Macon Apr_Jun-13) - (Monett Jul_Sep-15)	0.254582	0.1401	Inf	1.817	0.9985
(Monett Apr_Jun-15) - (Monett Jul_Sep-13)	-0.202377	0.1114	Inf	-1.817	0.9985
(Monett Jul_Sep-13) - (Monett Jul_Sep-15)	0.198172	0.1093	Inf	1.813	0.9985
(Chillicothe Apr_Jun-15) - (Chillicothe Jul_Sep-13	-0.417938	0.2294	Inf	-1.822	0.9984
(Chillicothe Jan_Mar-15) - (Macon Oct_Dec-13)	-0.207956	0.1131	Inf	-1.838	0.9981
(Monett Jan_Mar-15) - (Monett Jul_Sep-14)	-0.08885	0.0481	Inf	-1.848	0.9979
(Monett Apr_Jun-13) - (Chillicothe Jan_Mar-15)	0.192515	0.104	Inf	1.852	0.9978
(Macon Jul_Sep-13) - (Macon Jul_Sep-15)	0.273827	0.1477	Inf	1.854	0.9978
(Macon Jul_Sep-14) - (Macon Oct_Dec-13)	-0.186504	0.1006	Inf	-1.854	0.9978
(Macon Jan_Mar-15) - (Macon Jul_Sep-14)	-0.127122	0.0674	Inf	-1.887	0.9969
(Chillicothe Jul_Sep-13) - (Chillicothe Jul_Sep-15	0.424252	0.2244	Inf	1.891	0.9968
(Macon Apr_Jun-15) - (Chillicothe Jul_Sep-15)	-0.339863	0.1789	Inf	-1.9	0.9965
(Monett Apr_Jun-13) - (Chillicothe Oct_Dec-13)	-0.305759	0.16	Inf	-1.91	0.9962
(Monett Apr_Jun-13) - (Monett Oct_Dec-14)	-0.233646	0.1221	Inf	-1.913	0.9961
(Chillicothe Jul_Sep-14) - (Chillicothe Oct_Dec-13	-0.295919	0.1543	Inf	-1.918	0.9959
(Chillicothe Jan_Mar-15) - (Chillicothe Jul_Sep-14	-0.202355	0.1048	Inf	-1.931	0.9954
(Macon Apr_Jun-15) - (Monett Oct_Dec-13)	0.247332	0.1278	Inf	1.935	0.9953
(Macon Apr_Jun-13) - (Macon Oct_Dec-14)	-0.313521	0.1616	Inf	-1.94	0.995
(Chillicothe Apr_Jun-14) - (Macon Jan_Mar-15)	0.148576	0.0765	Inf	1.942	0.995
(Chillicothe Apr_Jun-13) - (Chillicothe Oct_Dec-1	-0.474479	0.2413	Inf	-1.966	0.9938
(Macon Apr_Jun-13) - (Macon Jan_Mar-14)	0.251751	0.1276	Inf	1.974	0.9934
(Monett Apr_Jun-13) - (Monett Jan_Mar-14)	0.182395	0.0919	Inf	1.985	0.9928
(Chillicothe Apr_Jun-13) - (Chillicothe Jan_Mar-1	0.389277	0.1949	Inf	1.997	0.992
(Macon Jul_Sep-15) - (Monett Oct_Dec-13)	0.247696	0.1237	Inf	2.003	0.9916
(Monett Jul_Sep-13) - (Macon Oct_Dec-14)	-0.369932	0.1827	Inf	-2.025	0.99
(Monett Apr_Jun-14) - (Chillicothe Jan_Mar-15)	-0.139576	0.0688	Inf	-2.028	0.9898
(Macon Jan_Mar-14) - (Monett Oct_Dec-14)	-0.287507	0.1404	Inf	-2.048	0.9881
(Chillicothe Jan_Mar-13) - (Monett Jul_Sep-13)	0.38231	0.1864	Inf	2.051	0.9879

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Macon Jan_Mar-15) - (Monett Oct_Dec-15)	0.097751	0.0473	Inf	2.065	0.9865
(Chillicothe Apr_Jun-14) - (Macon Apr_Jun-15)	-0.264675	0.1266	Inf	-2.09	0.9838
(Macon Jan_Mar-15) - (Monett Oct_Dec-13)	-0.165919	0.0784	Inf	-2.115	0.9807
(Monett Jan_Mar-13) - (Chillicothe Oct_Dec-13)	-0.330892	0.1563	Inf	-2.117	0.9804
(Macon Oct_Dec-15) - (Monett Oct_Dec-15)	0.037036	0.0175	Inf	2.12	0.9801
(Macon Apr_Jun-15) - (Chillicothe Jan_Mar-13)	-0.408723	0.1918	Inf	-2.131	0.9785
(Chillicothe Jan_Mar-13) - (Macon Jul_Sep-15)	0.408359	0.1914	Inf	2.133	0.9782
(Chillicothe Apr_Jun-13) - (Macon Jan_Mar-13)	0.428292	0.2005	Inf	2.136	0.9779
(Chillicothe Apr_Jun-14) - (Macon Jul_Sep-15)	-0.265039	0.1238	Inf	-2.141	0.9771
(Monett Jan_Mar-13) - (Monett Oct_Dec-14)	-0.258779	0.1199	Inf	-2.159	0.9742
(Macon Jan_Mar-14) - (Monett Jul_Sep-14)	0.209294	0.0963	Inf	2.174	0.9716
(Macon Jan_Mar-14) - (Chillicothe Oct_Dec-13)	-0.35962	0.1627	Inf	-2.21	0.9645
(Macon Jan_Mar-13) - (Macon Oct_Dec-14)	-0.351903	0.1581	Inf	-2.225	0.9612
(Macon Jul_Sep-13) - (Chillicothe Jul_Sep-14)	0.379416	0.1701	Inf	2.23	0.9599
(Macon Jan_Mar-13) - (Monett Oct_Dec-13)	0.291774	0.1299	Inf	2.247	0.9559
(Chillicothe Apr_Jun-13) - (Monett Jul_Sep-13)	0.44632	0.1956	Inf	2.281	0.9467
(Macon Jan_Mar-14) - (Chillicothe Oct_Dec-15)	0.232391	0.1017	Inf	2.285	0.9457
(Macon Jan_Mar-15) - (Monett Jan_Mar-15)	0.05382	0.0235	Inf	2.293	0.9432
(Monett Apr_Jun-14) - (Macon Jul_Sep-14)	-0.161028	0.07	Inf	-2.3	0.941
(Chillicothe Jan_Mar-13) - (Chillicothe Oct_Dec-1	-0.538489	0.2341	Inf	-2.301	0.9409
(Monett Jul_Sep-15) - (Chillicothe Oct_Dec-13)	-0.362452	0.1557	Inf	-2.327	0.9321
(Chillicothe Jan_Mar-14) - (Monett Oct_Dec-13)	0.330788	0.1415	Inf	2.337	0.9287
(Chillicothe Jan_Mar-15) - (Macon Oct_Dec-15)	0.166385	0.0711	Inf	2.339	0.928
(Monett Apr_Jun-13) - (Macon Jul_Sep-13)	-0.389257	0.1663	Inf	-2.341	0.9275
(Monett Apr_Jun-15) - (Chillicothe Oct_Dec-13)	-0.366657	0.1563	Inf	-2.345	0.9259
(Macon Apr_Jun-14) - (Monett Apr_Jun-14)	0.061544	0.0262	Inf	2.352	0.9234
(Chillicothe Apr_Jun-13) - (Macon Apr_Jun-15)	0.472733	0.2007	Inf	2.356	0.922
(Chillicothe Apr_Jun-13) - (Macon Jul_Sep-15)	0.472369	0.1999	Inf	2.363	0.9191
(Macon Apr_Jun-14) - (Monett Apr_Jun-15)	-0.209649	0.0882	Inf	-2.378	0.9131
(Macon Jul_Sep-14) - (Monett Jul_Sep-14)	0.092092	0.0387	Inf	2.381	0.9121
(Macon Apr_Jun-15) - (Monett Jan_Mar-14)	0.297461	0.1247	Inf	2.386	0.9098
(Monett Apr_Jun-14) - (Monett Jan_Mar-14)	-0.149696	0.0625	Inf	-2.396	0.9058
(Macon Apr_Jun-13) - (Monett Oct_Dec-13)	0.330156	0.1372	Inf	2.406	0.9016
(Chillicothe Apr_Jun-15) - (Macon Oct_Dec-13)	0.445802	0.1851	Inf	2.408	0.9005
(Monett Apr_Jun-15) - (Chillicothe Oct_Dec-15)	0.225355	0.0932	Inf	2.417	0.8963
(Macon Jan_Mar-14) - (Monett Jan_Mar-14)	0.128534	0.0531	Inf	2.419	0.8956
(Chillicothe Apr_Jun-14) - (Macon Jan_Mar-13)	-0.309117	0.1273	Inf	-2.429	0.8908
(Macon Jan_Mar-13) - (Monett Jan_Mar-13)	0.184641	0.076	Inf	2.429	0.8907
(Macon Oct_Dec-13) - (Monett Oct_Dec-13)	0.147707	0.0608	Inf	2.43	0.8902

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Macon Apr_Jun-13) - (Monett Apr_Jun-13)	0.19789	0.0814	Inf	2.431	0.8901
(Macon Jul_Sep-13) - (Monett Jul_Sep-13)	0.247778	0.1019	Inf	2.431	0.8901
(Macon Jul_Sep-15) - (Monett Jul_Sep-15)	0.172123	0.0708	Inf	2.431	0.8899
(Macon Apr_Jun-15) - (Monett Apr_Jun-15)	0.175964	0.0721	Inf	2.442	0.8845
(Monett Apr_Jun-15) - (Monett Oct_Dec-14)	-0.294544	0.1192	Inf	-2.472	0.8695
(Macon Apr_Jun-15) - (Chillicothe Jan_Mar-15)	0.307581	0.1243	Inf	2.474	0.8685
(Chillicothe Apr_Jun-14) - (Monett Jul_Sep-13)	-0.291088	0.1177	Inf	-2.474	0.8683
(Monett Jan_Mar-14) - (Macon Jul_Sep-15)	-0.297825	0.1203	Inf	-2.475	0.8678
(Macon Apr_Jun-14) - (Macon Jan_Mar-14)	-0.216686	0.0873	Inf	-2.482	0.8643
(Macon Oct_Dec-14) - (Monett Oct_Dec-14)	0.277765	0.1119	Inf	2.482	0.8641
(Macon Apr_Jun-15) - (Macon Oct_Dec-14)	-0.396345	0.1589	Inf	-2.495	0.8569
(Monett Jul_Sep-15) - (Monett Oct_Dec-14)	-0.290339	0.1163	Inf	-2.496	0.8562
(Macon Apr_Jun-14) - (Monett Oct_Dec-15)	0.125389	0.0498	Inf	2.516	0.845
(Monett Apr_Jun-15) - (Monett Jul_Sep-14)	0.202257	0.0803	Inf	2.518	0.8437
(Macon Apr_Jun-14) - (Monett Jul_Sep-15)	-0.213854	0.0849	Inf	-2.519	0.8431
(Monett Jul_Sep-15) - (Chillicothe Oct_Dec-15)	0.22956	0.0907	Inf	2.53	0.8367
(Chillicothe Jan_Mar-15) - (Macon Jul_Sep-15)	-0.307945	0.1216	Inf	-2.533	0.8349
(Monett Jan_Mar-13) - (Macon Jul_Sep-13)	-0.41439	0.1631	Inf	-2.541	0.83
(Monett Jan_Mar-14) - (Macon Oct_Dec-15)	0.176504	0.0694	Inf	2.544	0.8281
(Macon Jul_Sep-13) - (Macon Oct_Dec-13)	0.373816	0.1467	Inf	2.549	0.8252
(Chillicothe Apr_Jun-15) - (Chillicothe Oct_Dec-1	-0.601035	0.2357	Inf	-2.55	0.8242
(Macon Apr_Jun-13) - (Chillicothe Apr_Jun-14)	0.347499	0.1357	Inf	2.562	0.817
(Monett Jul_Sep-13) - (Monett Oct_Dec-13)	0.273745	0.1067	Inf	2.566	0.8142
(Macon Apr_Jun-15) - (Macon Jul_Sep-14)	0.286129	0.1113	Inf	2.571	0.8107
(Chillicothe Jul_Sep-15) - (Macon Oct_Dec-13)	0.439488	0.1707	Inf	2.574	0.8087
(Macon Jul_Sep-15) - (Macon Oct_Dec-14)	-0.395981	0.1536	Inf	-2.577	0.8067
(Chillicothe Jul_Sep-13) - (Chillicothe Oct_Dec-13	0.573422	0.2219	Inf	2.585	0.802
(Monett Apr_Jun-13) - (Chillicothe Apr_Jun-15)	-0.461243	0.1784	Inf	-2.586	0.8011
(Chillicothe Apr_Jun-14) - (Chillicothe Jan_Mar-1	-0.348131	0.1338	Inf	-2.601	0.7907
(Chillicothe Jan_Mar-14) - (Macon Jul_Sep-14)	0.369585	0.1405	Inf	2.63	0.7709
(Monett Jan_Mar-15) - (Macon Jul_Sep-14)	-0.180942	0.0686	Inf	-2.639	0.7638
(Chillicothe Jul_Sep-15) - (Chillicothe Oct_Dec-14	-0.607349	0.2293	Inf	-2.649	0.7568
(Chillicothe Apr_Jun-15) - (Chillicothe Jul_Sep-14	0.451403	0.1694	Inf	2.664	0.7455
(Macon Jul_Sep-13) - (Chillicothe Oct_Dec-14)	-0.673022	0.2526	Inf	-2.664	0.7455
(Monett Jul_Sep-14) - (Monett Jul_Sep-15)	-0.206462	0.0774	Inf	-2.667	0.7434
(Monett Jul_Sep-13) - (Macon Jul_Sep-14)	0.312542	0.1171	Inf	2.669	0.7422
(Chillicothe Oct_Dec-15) - (Macon Oct_Dec-15)	0.072647	0.0272	Inf	2.674	0.7381
(Monett Jul_Sep-14) - (Macon Oct_Dec-13)	-0.278596	0.104	Inf	-2.679	0.7344
(Macon Jul_Sep-14) - (Macon Jul_Sep-15)	-0.286493	0.1067	Inf	-2.685	0.7302

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Macon Jan_Mar-13) - (Monett Jan_Mar-14)	0.341903	0.1267	Inf	2.698	0.7195
(Macon Apr_Jun-14) - (Chillicothe Jul_Sep-14)	-0.280387	0.1037	Inf	-2.704	0.7148
(Monett Jan_Mar-14) - (Monett Jan_Mar-15)	0.16961	0.0622	Inf	2.726	0.6979
(Monett Apr_Jun-15) - (Macon Jan_Mar-15)	0.237288	0.0868	Inf	2.733	0.6923
(Chillicothe Jul_Sep-13) - (Monett Oct_Dec-14)	0.645535	0.2359	Inf	2.736	0.6894
(Chillicothe Jan_Mar-13) - (Macon Oct_Dec-13)	0.508348	0.1847	Inf	2.753	0.6763
(Monett Apr_Jun-15) - (Macon Jul_Sep-13)	-0.450155	0.1635	Inf	-2.754	0.6755
(Monett Apr_Jun-13) - (Chillicothe Jul_Sep-15)	-0.454929	0.1647	Inf	-2.762	0.6686
(Chillicothe Jul_Sep-14) - (Macon Oct_Dec-14)	-0.501571	0.1813	Inf	-2.767	0.6647
(Macon Jul_Sep-13) - (Monett Jul_Sep-15)	0.445949	0.1611	Inf	2.768	0.6635
(Macon Oct_Dec-13) - (Chillicothe Oct_Dec-15)	0.301693	0.1087	Inf	2.775	0.6582
(Chillicothe Apr_Jun-15) - (Monett Jan_Mar-13)	0.486376	0.1746	Inf	2.785	0.6495
(Macon Apr_Jun-14) - (Monett Jan_Mar-13)	-0.245414	0.0881	Inf	-2.787	0.6485
(Monett Jan_Mar-13) - (Chillicothe Oct_Dec-15)	0.261119	0.0933	Inf	2.8	0.6371
(Macon Jan_Mar-14) - (Macon Jan_Mar-15)	0.244324	0.0869	Inf	2.812	0.6275
(Chillicothe Jul_Sep-14) - (Chillicothe Jul_Sep-15	-0.445088	0.1583	Inf	-2.812	0.6268
(Macon Jul_Sep-14) - (Macon Oct_Dec-15)	0.187836	0.0667	Inf	2.817	0.6228
(Chillicothe Apr_Jun-14) - (Macon Oct_Dec-15)	0.20929	0.0742	Inf	2.819	0.6211
(Macon Jan_Mar-13) - (Chillicothe Jan_Mar-15)	0.352022	0.1247	Inf	2.822	0.6184
(Macon Apr_Jun-13) - (Monett Jan_Mar-14)	0.380285	0.1342	Inf	2.833	0.6093
(Chillicothe Jul_Sep-14) - (Chillicothe Oct_Dec-15	0.296092	0.1044	Inf	2.836	0.6071
(Monett Jul_Sep-14) - (Monett Oct_Dec-15)	0.132781	0.0467	Inf	2.841	0.6024
(Chillicothe Apr_Jun-15) - (Macon Jan_Mar-14)	0.515105	0.1808	Inf	2.849	0.5961
(Chillicothe Apr_Jun-14) - (Monett Jan_Mar-15)	0.202396	0.0703	Inf	2.878	0.5708
(Chillicothe Jan_Mar-15) - (Monett Jul_Sep-13)	-0.333994	0.1159	Inf	-2.882	0.5678
(Macon Jan_Mar-15) - (Monett Jul_Sep-15)	-0.241493	0.0838	Inf	-2.883	0.5667
(Monett Apr_Jun-13) - (Macon Apr_Jun-14)	0.270547	0.0933	Inf	2.899	0.5536
(Monett Apr_Jun-13) - (Chillicothe Oct_Dec-15)	0.286252	0.0984	Inf	2.91	0.5438
(Macon Apr_Jun-13) - (Chillicothe Jul_Sep-13)	-0.681291	0.234	Inf	-2.912	0.5424
(Monett Apr_Jun-13) - (Chillicothe Jan_Mar-13)	-0.523789	0.1791	Inf	-2.924	0.5321
(Macon Apr_Jun-13) - (Chillicothe Jan_Mar-15)	0.390405	0.1333	Inf	2.928	0.5287
(Chillicothe Apr_Jun-14) - (Monett Oct_Dec-14)	-0.383255	0.13	Inf	-2.947	0.5123
(Chillicothe Jan_Mar-14) - (Chillicothe Jan_Mar-1	0.391037	0.1326	Inf	2.948	0.5115
(Monett Apr_Jun-13) - (Macon Oct_Dec-14)	-0.511411	0.1732	Inf	-2.952	0.508
(Chillicothe Apr_Jun-13) - (Macon Oct_Dec-13)	0.572358	0.1937	Inf	2.955	0.5058
(Monett Jan_Mar-13) - (Monett Jul_Sep-14)	0.238022	0.0804	Inf	2.961	0.5005
(Chillicothe Apr_Jun-15) - (Monett Jul_Sep-15)	0.517936	0.1748	Inf	2.962	0.4995
(Monett Apr_Jun-14) - (Monett Oct_Dec-13)	-0.199824	0.0674	Inf	-2.964	0.4983
(Macon Jan_Mar-13) - (Macon Jul_Sep-14)	0.33057	0.1113	Inf	2.971	0.4923

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Jan_Mar-13) - (Chillicothe Jul_Sep-15)	-0.480062	0.1611	Inf	-2.979	0.4852
(Macon Jan_Mar-15) - (Chillicothe Jul_Sep-14)	-0.308025	0.1017	Inf	-3.027	0.4451
(Macon Apr_Jun-14) - (Macon Oct_Dec-13)	-0.285988	0.0941	Inf	-3.04	0.4347
(Monett Oct_Dec-13) - (Macon Oct_Dec-15)	0.226633	0.0743	Inf	3.049	0.4278
(Macon Jan_Mar-14) - (Macon Jul_Sep-13)	-0.443118	0.1449	Inf	-3.057	0.4208
(Macon Jan_Mar-14) - (Chillicothe Jul_Sep-15)	-0.50879	0.1661	Inf	-3.063	0.4158
(Chillicothe Jan_Mar-13) - (Chillicothe Jul_Sep-14	0.513949	0.1676	Inf	3.067	0.413
(Monett Apr_Jun-13) - (Monett Jul_Sep-14)	0.263155	0.0856	Inf	3.073	0.4086
(Monett Apr_Jun-14) - (Macon Jan_Mar-14)	-0.27823	0.0905	Inf	-3.075	0.4064
(Chillicothe Jan_Mar-15) - (Monett Oct_Dec-15)	0.203421	0.066	Inf	3.081	0.4017
(Chillicothe Jan_Mar-15) - (Macon Jan_Mar-15)	0.105671	0.0342	Inf	3.086	0.3978
(Macon Apr_Jun-13) - (Macon Jul_Sep-14)	0.368953	0.1191	Inf	3.098	0.3887
(Monett Jan_Mar-14) - (Monett Jul_Sep-13)	-0.323874	0.1043	Inf	-3.106	0.3827
(Chillicothe Jan_Mar-14) - (Chillicothe Jul_Sep-13	-0.680659	0.219	Inf	-3.108	0.3811
(Macon Jul_Sep-14) - (Monett Oct_Dec-14)	-0.404709	0.1291	Inf	-3.136	0.3596
(Monett Jan_Mar-13) - (Macon Oct_Dec-14)	-0.536544	0.1708	Inf	-3.141	0.3557
(Monett Jan_Mar-13) - (Macon Jan_Mar-15)	0.273052	0.0866	Inf	3.152	0.3475
(Macon Jan_Mar-13) - (Chillicothe Jul_Sep-13)	-0.719674	0.2276	Inf	-3.163	0.3397
(Macon Jul_Sep-14) - (Chillicothe Oct_Dec-13)	-0.476822	0.15	Inf	-3.179	0.3275
(Monett Oct_Dec-13) - (Monett Oct_Dec-14)	-0.365912	0.1149	Inf	-3.186	0.323
(Chillicothe Apr_Jun-14) - (Chillicothe Oct_Dec-1	-0.455368	0.1425	Inf	-3.196	0.3161
(Chillicothe Jan_Mar-13) - (Macon Jan_Mar-14)	0.57765	0.1806	Inf	3.199	0.3138
(Monett Apr_Jun-15) - (Chillicothe Jul_Sep-15)	-0.515826	0.1612	Inf	-3.199	0.3134
(Chillicothe Apr_Jun-14) - (Macon Apr_Jun-14)	0.120938	0.0376	Inf	3.215	0.3027
(Chillicothe Jul_Sep-14) - (Macon Jul_Sep-14)	0.180903	0.0561	Inf	3.224	0.2964
(Macon Oct_Dec-13) - (Macon Oct_Dec-14)	-0.49597	0.1536	Inf	-3.228	0.2937
(Monett Apr_Jun-13) - (Macon Jan_Mar-15)	0.298185	0.0921	Inf	3.237	0.2874
(Macon Apr_Jun-15) - (Monett Jul_Sep-14)	0.378221	0.1168	Inf	3.24	0.286
(Chillicothe Apr_Jun-13) - (Chillicothe Jul_Sep-14	0.577959	0.178	Inf	3.248	0.2807
(Chillicothe Oct_Dec-15) - (Monett Oct_Dec-15)	0.109684	0.0337	Inf	3.252	0.278
(Monett Jan_Mar-15) - (Monett Oct_Dec-13)	-0.219739	0.0672	Inf	-3.269	0.267
(Monett Jan_Mar-14) - (Chillicothe Oct_Dec-13)	-0.488154	0.1491	Inf	-3.273	0.2642
(Macon Jul_Sep-13) - (Monett Oct_Dec-13)	0.521523	0.1583	Inf	3.295	0.2506
(Chillicothe Jan_Mar-13) - (Monett Jul_Sep-15)	0.580482	0.1759	Inf	3.3	0.2477
(Chillicothe Jan_Mar-15) - (Monett Oct_Dec-14)	-0.426161	0.129	Inf	-3.303	0.2459
(Chillicothe Jan_Mar-14) - (Macon Jan_Mar-14)	0.252383	0.0762	Inf	3.311	0.241
(Chillicothe Apr_Jun-13) - (Monett Jan_Mar-13)	0.612932	0.1848	Inf	3.317	0.2375
(Macon Apr_Jun-15) - (Chillicothe Oct_Dec-15)	0.401318	0.1207	Inf	3.326	0.232
(Macon Jan_Mar-14) - (Monett Jan_Mar-15)	0.298144	0.0896	Inf	3.329	0.2302

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Apr_Jun-15) - (Chillicothe Jan_Mar-13)	-0.584687	0.1756	Inf	-3.33	0.2301
(Chillicothe Oct_Dec-13) - (Chillicothe Oct_Dec-1	-0.756519	0.2269	Inf	-3.334	0.2277
(Chillicothe Jul_Sep-13) - (Macon Jul_Sep-15)	0.763751	0.2288	Inf	3.339	0.2249
(Macon Jan_Mar-15) - (Macon Oct_Dec-13)	-0.313626	0.0937	Inf	-3.347	0.2204
(Macon Apr_Jun-15) - (Chillicothe Jul_Sep-13)	-0.764115	0.2283	Inf	-3.347	0.2201
(Monett Apr_Jun-15) - (Macon Oct_Dec-14)	-0.572309	0.1706	Inf	-3.354	0.2163
(Monett Jul_Sep-14) - (Macon Jul_Sep-15)	-0.378585	0.1128	Inf	-3.357	0.2144
(Macon Jul_Sep-14) - (Monett Oct_Dec-15)	0.224873	0.0669	Inf	3.361	0.2122
(Chillicothe Apr_Jun-13) - (Macon Jan_Mar-14)	0.64166	0.1897	Inf	3.382	0.2011
(Chillicothe Oct_Dec-13) - (Macon Oct_Dec-13)	0.290318	0.0857	Inf	3.387	0.1984
(Monett Jul_Sep-15) - (Macon Oct_Dec-14)	-0.568104	0.1674	Inf	-3.395	0.1946
(Chillicothe Apr_Jun-15) - (Macon Apr_Jun-15)	0.346177	0.1015	Inf	3.412	0.1856
(Macon Jul_Sep-15) - (Chillicothe Oct_Dec-15)	0.401682	0.1169	Inf	3.437	0.1733
(Chillicothe Apr_Jun-15) - (Monett Oct_Dec-13)	0.59351	0.1708	Inf	3.475	0.1561
(Chillicothe Apr_Jun-14) - (Macon Jul_Sep-13)	-0.538866	0.1549	Inf	-3.479	0.1545
(Monett Apr_Jun-14) - (Chillicothe Jul_Sep-14)	-0.341931	0.0983	Inf	-3.479	0.1543
(Chillicothe Apr_Jun-13) - (Monett Jul_Sep-15)	0.644492	0.1851	Inf	3.482	0.1532
(Chillicothe Jan_Mar-13) - (Macon Jan_Mar-13)	0.364282	0.1043	Inf	3.494	0.1482
(Monett Jan_Mar-14) - (Monett Oct_Dec-15)	0.213541	0.061	Inf	3.499	0.1459
(Chillicothe Apr_Jun-13) - (Monett Apr_Jun-15)	0.648697	0.1852	Inf	3.504	0.1441
(Chillicothe Jan_Mar-14) - (Monett Jul_Sep-14)	0.461677	0.1315	Inf	3.51	0.1415
(Chillicothe Apr_Jun-13) - (Macon Apr_Jun-13)	0.389909	0.111	Inf	3.512	0.1406
(Chillicothe Jan_Mar-15) - (Chillicothe Oct_Dec-1	-0.498274	0.1413	Inf	-3.527	0.1346
(Monett Apr_Jun-14) - (Macon Oct_Dec-13)	-0.347532	0.0985	Inf	-3.529	0.1337
(Macon Jan_Mar-14) - (Macon Oct_Dec-15)	0.305038	0.0863	Inf	3.535	0.1315
(Macon Apr_Jun-14) - (Chillicothe Jan_Mar-14)	-0.469069	0.1325	Inf	-3.541	0.1291
(Chillicothe Jul_Sep-13) - (Macon Jul_Sep-13)	0.489924	0.1378	Inf	3.556	0.1238
(Monett Apr_Jun-14) - (Monett Apr_Jun-15)	-0.271193	0.0761	Inf	-3.564	0.1206
(Chillicothe Apr_Jun-14) - (Monett Oct_Dec-15)	0.246327	0.0691	Inf	3.565	0.1205
(Macon Jan_Mar-13) - (Monett Jul_Sep-14)	0.422663	0.1183	Inf	3.573	0.1176
(Monett Apr_Jun-15) - (Macon Oct_Dec-15)	0.298001	0.0831	Inf	3.588	0.1123
(Macon Apr_Jun-13) - (Chillicothe Oct_Dec-14)	-0.864388	0.2402	Inf	-3.598	0.109
(Chillicothe Jul_Sep-15) - (Macon Jul_Sep-15)	0.339499	0.0938	Inf	3.619	0.1021
(Macon Apr_Jun-14) - (Macon Apr_Jun-15)	-0.385613	0.1061	Inf	-3.634	0.0975
(Macon Apr_Jun-13) - (Monett Jul_Sep-14)	0.461045	0.1266	Inf	3.641	0.0956
(Macon Jan_Mar-13) - (Chillicothe Oct_Dec-15)	0.44576	0.1216	Inf	3.665	0.0885
(Monett Jan_Mar-14) - (Macon Jul_Sep-13)	-0.571652	0.1556	Inf	-3.675	0.0859
(Chillicothe Jul_Sep-14) - (Macon Oct_Dec-15)	0.368739	0.1002	Inf	3.678	0.0849
(Chillicothe Jan_Mar-14) - (Chillicothe Oct_Dec-1	0.484774	0.1317	Inf	3.682	0.0839

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Jan_Mar-14) - (Monett Oct_Dec-14)	-0.416041	0.1127	Inf	-3.692	0.0812
(Chillicothe Oct_Dec-14) - (Macon Oct_Dec-14)	0.550867	0.1489	Inf	3.699	0.0793
(Macon Jan_Mar-14) - (Macon Oct_Dec-14)	-0.565272	0.1517	Inf	-3.725	0.0729
(Macon Apr_Jun-13) - (Chillicothe Oct_Dec-15)	0.484142	0.1299	Inf	3.728	0.0722
(Monett Jan_Mar-15) - (Chillicothe Jul_Sep-14)	-0.361845	0.097	Inf	-3.731	0.0715
(Chillicothe Jul_Sep-15) - (Monett Oct_Dec-13)	0.587195	0.1565	Inf	3.751	0.067
(Chillicothe Apr_Jun-15) - (Macon Jul_Sep-14)	0.632306	0.1684	Inf	3.754	0.0663
(Monett Jan_Mar-15) - (Macon Oct_Dec-13)	-0.367446	0.0975	Inf	-3.769	0.0632
(Monett Apr_Jun-14) - (Monett Jul_Sep-15)	-0.275398	0.0729	Inf	-3.78	0.0609
(Chillicothe Jan_Mar-14) - (Macon Jan_Mar-15)	0.496707	0.1311	Inf	3.788	0.0591
(Monett Jul_Sep-15) - (Macon Oct_Dec-15)	0.302207	0.0796	Inf	3.797	0.0574
(Macon Apr_Jun-14) - (Macon Jul_Sep-15)	-0.385977	0.1013	Inf	-3.812	0.0546
(Chillicothe Jan_Mar-15) - (Macon Jul_Sep-13)	-0.581771	0.1525	Inf	-3.815	0.0539
(Chillicothe Apr_Jun-15) - (Monett Jan_Mar-14)	0.643639	0.1684	Inf	3.822	0.0528
(Chillicothe Apr_Jun-14) - (Chillicothe Apr_Jun-1!	-0.610853	0.1598	Inf	-3.822	0.0527
(Chillicothe Jan_Mar-13) - (Monett Oct_Dec-13)	0.656056	0.1715	Inf	3.825	0.0522
(Monett Apr_Jun-15) - (Monett Jan_Mar-15)	0.291107	0.076	Inf	3.833	0.0508
(Monett Jul_Sep-13) - (Chillicothe Oct_Dec-15)	0.427731	0.1112	Inf	3.848	0.0482
(Macon Apr_Jun-14) - (Monett Jul_Sep-13)	-0.412026	0.1071	Inf	-3.849	0.0481
(Macon Jan_Mar-13) - (Chillicothe Oct_Dec-14)	-0.902771	0.2346	Inf	-3.848	0.0481
(Chillicothe Jan_Mar-14) - (Chillicothe Oct_Dec-1	-0.863756	0.2231	Inf	-3.872	0.0444
(Chillicothe Jul_Sep-13) - (Macon Oct_Dec-13)	0.86374	0.2225	Inf	3.882	0.0428
(Monett Oct_Dec-13) - (Macon Oct_Dec-14)	-0.643677	0.1654	Inf	-3.891	0.0414
(Macon Jan_Mar-14) - (Monett Oct_Dec-15)	0.342075	0.0879	Inf	3.892	0.0412
(Macon Apr_Jun-15) - (Macon Jan_Mar-15)	0.413251	0.1058	Inf	3.906	0.0393
(Chillicothe Apr_Jun-13) - (Monett Oct_Dec-13)	0.720066	0.1812	Inf	3.974	0.0306
(Monett Oct_Dec-13) - (Monett Oct_Dec-15)	0.263669	0.0662	Inf	3.981	0.0298
(Chillicothe Apr_Jun-14) - (Macon Oct_Dec-14)	-0.66102	0.1657	Inf	-3.989	0.029
(Macon Oct_Dec-13) - (Macon Oct_Dec-15)	0.37434	0.0936	Inf	3.998	0.028
(Monett Apr_Jun-14) - (Macon Apr_Jun-15)	-0.447157	0.1117	Inf	-4.004	0.0274
(Monett Jul_Sep-14) - (Chillicothe Oct_Dec-13)	-0.568914	0.1418	Inf	-4.011	0.0267
(Monett Jan_Mar-13) - (Macon Oct_Dec-15)	0.333766	0.0831	Inf	4.017	0.0261
(Monett Apr_Jun-13) - (Chillicothe Jul_Sep-13)	-0.879181	0.2185	Inf	-4.023	0.0256
(Monett Apr_Jun-14) - (Monett Jan_Mar-13)	-0.306958	0.0761	Inf	-4.031	0.0247
(Macon Apr_Jun-14) - (Macon Jan_Mar-13)	-0.430054	0.1065	Inf	-4.038	0.0241
(Macon Apr_Jun-14) - (Chillicothe Oct_Dec-13)	-0.576306	0.1424	Inf	-4.047	0.0234
(Macon Apr_Jun-15) - (Chillicothe Oct_Dec-14)	-0.947212	0.2341	Inf	-4.046	0.0234
(Monett Jul_Sep-13) - (Chillicothe Oct_Dec-14)	-0.920799	0.2276	Inf	-4.046	0.0234
(Monett Jan_Mar-15) - (Monett Jul_Sep-15)	-0.295312	0.0729	Inf	-4.053	0.0228

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Macon Jul_Sep-15) - (Chillicothe Oct_Dec-14)	-0.946848	0.2336	Inf	-4.053	0.0228
(Monett Apr_Jun-13) - (Macon Oct_Dec-15)	0.358899	0.0885	Inf	4.056	0.0226
(Chillicothe Jan_Mar-15) - (Monett Jan_Mar-15)	0.15949	0.0393	Inf	4.056	0.0225
(Monett Apr_Jun-13) - (Monett Apr_Jun-14)	0.332091	0.0818	Inf	4.061	0.0221
(Macon Jul_Sep-13) - (Macon Jul_Sep-14)	0.560319	0.1378	Inf	4.067	0.0216
(Macon Jul_Sep-14) - (Chillicothe Jul_Sep-15)	-0.625991	0.1539	Inf	-4.068	0.0216
(Macon Apr_Jun-13) - (Macon Apr_Jun-14)	0.468437	0.1149	Inf	4.078	0.0207
(Macon Jan_Mar-15) - (Macon Jul_Sep-15)	-0.413615	0.1012	Inf	-4.087	0.02
(Monett Jul_Sep-13) - (Monett Jul_Sep-14)	0.404634	0.0989	Inf	4.092	0.0196
(Chillicothe Apr_Jun-14) - (Chillicothe Jul_Sep-15	-0.604538	0.1467	Inf	-4.12	0.0176
(Chillicothe Apr_Jun-15) - (Chillicothe Jan_Mar-1	0.653758	0.1586	Inf	4.122	0.0175
(Monett Jan_Mar-14) - (Chillicothe Jul_Sep-15)	-0.637324	0.1539	Inf	-4.141	0.0162
(Chillicothe Jan_Mar-13) - (Macon Jul_Sep-14)	0.694852	0.1675	Inf	4.148	0.0158
(Macon Jan_Mar-15) - (Monett Jul_Sep-13)	-0.439664	0.1058	Inf	-4.154	0.0154
(Monett Apr_Jun-14) - (Chillicothe Jan_Mar-14)	-0.530613	0.1275	Inf	-4.162	0.0149
(Monett Apr_Jun-14) - (Macon Jul_Sep-15)	-0.447521	0.1074	Inf	-4.167	0.0146
(Chillicothe Jan_Mar-13) - (Monett Jan_Mar-14)	0.706184	0.1692	Inf	4.174	0.0142
(Chillicothe Oct_Dec-13) - (Chillicothe Oct_Dec-1	0.592011	0.1411	Inf	4.195	0.0131
(Monett Jan_Mar-13) - (Chillicothe Jul_Sep-13)	-0.904314	0.2147	Inf	-4.211	0.0122
(Chillicothe Jul_Sep-14) - (Monett Oct_Dec-15)	0.405776	0.0962	Inf	4.217	0.012
(Macon Apr_Jun-15) - (Monett Jan_Mar-15)	0.467071	0.1107	Inf	4.22	0.0118
(Macon Apr_Jun-14) - (Monett Oct_Dec-14)	-0.504193	0.1194	Inf	-4.223	0.0117
(Monett Oct_Dec-14) - (Chillicothe Oct_Dec-15)	0.519898	0.1227	Inf	4.236	0.0111
(Chillicothe Apr_Jun-14) - (Chillicothe Jan_Mar-1	-0.673398	0.1585	Inf	-4.25	0.0105
(Macon Jan_Mar-14) - (Chillicothe Jul_Sep-13)	-0.933042	0.2192	Inf	-4.256	0.0102
(Monett Jan_Mar-14) - (Macon Oct_Dec-14)	-0.693806	0.1627	Inf	-4.263	0.0099
(Chillicothe Apr_Jun-13) - (Macon Jul_Sep-14)	0.758862	0.1777	Inf	4.27	0.0096
(Chillicothe Jul_Sep-13) - (Chillicothe Jul_Sep-14	0.869341	0.2033	Inf	4.277	0.0094
(Macon Jan_Mar-15) - (Chillicothe Oct_Dec-13)	-0.603944	0.141	Inf	-4.284	0.0091
(Macon Oct_Dec-13) - (Monett Oct_Dec-15)	0.411377	0.096	Inf	4.287	0.009
(Chillicothe Jan_Mar-15) - (Macon Oct_Dec-14)	-0.703926	0.1639	Inf	-4.294	0.0087
(Chillicothe Apr_Jun-13) - (Monett Jan_Mar-14)	0.770194	0.1789	Inf	4.305	0.0083
(Monett Jan_Mar-13) - (Monett Jan_Mar-15)	0.326872	0.0759	Inf	4.307	0.0083
(Monett Apr_Jun-13) - (Monett Jan_Mar-15)	0.352005	0.0817	Inf	4.308	0.0082
(Chillicothe Jan_Mar-14) - (Macon Oct_Dec-15)	0.557421	0.1293	Inf	4.311	0.0081
(Macon Jan_Mar-13) - (Macon Jan_Mar-15)	0.457693	0.1061	Inf	4.314	0.008
(Macon Apr_Jun-13) - (Macon Jan_Mar-15)	0.496075	0.1147	Inf	4.325	0.0077
(Chillicothe Jul_Sep-13) - (Monett Jul_Sep-15)	0.935874	0.2162	Inf	4.328	0.0076
(Monett Apr_Jun-14) - (Macon Jan_Mar-13)	-0.491598	0.1131	Inf	-4.346	0.007
(Monett Oct_Dec-14) - (Macon Oct_Dec-15)	0.592545	0.1147	Inf	5.164	0.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Chillicothe Jan_Mar-14) - (Monett Jan_Mar-15)	0.550527	0.1267	Inf	4.346	0.007
(Macon Apr_Jun-13) - (Monett Apr_Jun-14)	0.529981	0.1217	Inf	4.354	0.0068
(Chillicothe Apr_Jun-13) - (Chillicothe Apr_Jun-14	0.737408	0.1692	Inf	4.359	0.0066
(Monett Apr_Jun-15) - (Chillicothe Jul_Sep-13)	-0.940079	0.2154	Inf	-4.365	0.0065
(Chillicothe Apr_Jun-14) - (Monett Apr_Jun-14)	0.182482	0.0417	Inf	4.379	0.0061
(Monett Jan_Mar-15) - (Macon Jul_Sep-15)	-0.467435	0.1065	Inf	-4.389	0.0058
(Macon Jul_Sep-13) - (Monett Jul_Sep-14)	0.652412	0.1481	Inf	4.405	0.0054
(Chillicothe Jan_Mar-15) - (Chillicothe Jul_Sep-15	-0.647443	0.1455	Inf	-4.449	0.0045
(Monett Apr_Jun-15) - (Monett Oct_Dec-15)	0.335038	0.0752	Inf	4.453	0.0044
(Macon Apr_Jun-15) - (Macon Oct_Dec-15)	0.473965	0.1063	Inf	4.459	0.0043
(Chillicothe Jul_Sep-14) - (Monett Jul_Sep-14)	0.272995	0.0612	Inf	4.458	0.0043
(Macon Jan_Mar-15) - (Monett Oct_Dec-14)	-0.531831	0.1187	Inf	-4.479	0.0039
(Chillicothe Apr_Jun-15) - (Monett Jul_Sep-14)	0.724398	0.1612	Inf	4.494	0.0037
(Macon Jul_Sep-13) - (Chillicothe Oct_Dec-15)	0.675509	0.1501	Inf	4.499	0.0036
(Macon Apr_Jun-14) - (Chillicothe Apr_Jun-15)	-0.73179	0.1617	Inf	-4.526	0.0032
(Monett Jul_Sep-14) - (Monett Oct_Dec-14)	-0.496801	0.1098	Inf	-4.523	0.0032
(Macon Apr_Jun-13) - (Monett Jan_Mar-15)	0.549895	0.1207	Inf	4.555	0.0028
(Chillicothe Jan_Mar-13) - (Chillicothe Jan_Mar-1	0.716304	0.1569	Inf	4.564	0.0027
(Macon Jan_Mar-13) - (Monett Jan_Mar-15)	0.511512	0.1119	Inf	4.57	0.0026
(Macon Oct_Dec-13) - (Chillicothe Oct_Dec-14)	-1.046837	0.2276	Inf	-4.6	0.0023
(Monett Apr_Jun-14) - (Chillicothe Oct_Dec-13)	-0.63785	0.138	Inf	-4.623	0.0021
(Macon Jul_Sep-14) - (Macon Oct_Dec-14)	-0.682474	0.1472	Inf	-4.637	0.0019
(Chillicothe Apr_Jun-13) - (Chillicothe Jan_Mar-1	0.780314	0.1679	Inf	4.647	0.0018
(Macon Apr_Jun-15) - (Monett Oct_Dec-15)	0.511002	0.1093	Inf	4.674	0.0016
(Macon Jul_Sep-15) - (Macon Oct_Dec-15)	0.474329	0.1014	Inf	4.678	0.0016
(Chillicothe Apr_Jun-15) - (Chillicothe Oct_Dec-1	0.747496	0.1595	Inf	4.685	0.0015
(Chillicothe Jan_Mar-14) - (Monett Jan_Mar-14)	0.380917	0.081	Inf	4.705	0.0014
(Chillicothe Jan_Mar-14) - (Monett Oct_Dec-15)	0.594458	0.1258	Inf	4.725	0.0013
(Monett Jul_Sep-15) - (Monett Oct_Dec-15)	0.339243	0.0718	Inf	4.722	0.0013
(Chillicothe Apr_Jun-15) - (Macon Jan_Mar-15)	0.759429	0.1602	Inf	4.741	0.0012
(Chillicothe Oct_Dec-13) - (Macon Oct_Dec-15)	0.664658	0.1395	Inf	4.763	0.0011
(Chillicothe Jul_Sep-13) - (Monett Oct_Dec-13)	1.011448	0.212	Inf	4.771	0.001
(Monett Apr_Jun-13) - (Chillicothe Oct_Dec-14)	-1.062278	0.2211	Inf	-4.804	0.0009
(Monett Jan_Mar-15) - (Chillicothe Oct_Dec-13)	-0.657764	0.1371	Inf	-4.799	0.0009
(Macon Apr_Jun-13) - (Macon Oct_Dec-15)	0.556789	0.1156	Inf	4.817	0.0008
(Macon Jan_Mar-13) - (Macon Oct_Dec-15)	0.518407	0.1071	Inf	4.84	0.0007
(Monett Apr_Jun-13) - (Monett Oct_Dec-15)	0.395936	0.0811	Inf	4.884	0.0006
(Macon Apr_Jun-14) - (Macon Jul_Sep-13)	-0.659803	0.1352	Inf	-4.881	0.0006
(Chillicothe Jan_Mar-13) - (Monett Jul_Sep-14)	0.786944	0.1612	Inf	4.882	0.0006
(Monett Jan_Mar-15) - (Macon Jul_Sep-13)	-0.741262	0.1425	Inf	-5.203	0.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Jul_Sep-13) - (Macon Oct_Dec-15)	0.500378	0.1027	Inf	4.872	0.0006
(Monett Jul_Sep-14) - (Chillicothe Jul_Sep-15)	-0.718084	0.1468	Inf	-4.892	0.0006
(Macon Jul_Sep-15) - (Monett Oct_Dec-15)	0.511366	0.1048	Inf	4.878	0.0006
(Chillicothe Oct_Dec-13) - (Monett Oct_Dec-13)	0.438026	0.0897	Inf	4.884	0.0006
(Macon Apr_Jun-14) - (Chillicothe Jan_Mar-13)	-0.794336	0.1609	Inf	-4.936	0.0005
(Monett Apr_Jun-14) - (Monett Jul_Sep-13)	-0.47357	0.0959	Inf	-4.939	0.0005
(Monett Jan_Mar-13) - (Monett Oct_Dec-15)	0.370803	0.0753	Inf	4.923	0.0005
(Monett Jul_Sep-14) - (Macon Oct_Dec-14)	-0.774566	0.1571	Inf	-4.931	0.0005
(Chillicothe Apr_Jun-13) - (Monett Jul_Sep-14)	0.850954	0.1717	Inf	4.957	0.0004
(Macon Apr_Jun-13) - (Monett Oct_Dec-15)	0.593826	0.1194	Inf	4.974	0.0004
(Macon Apr_Jun-14) - (Chillicothe Jul_Sep-15)	-0.725475	0.1466	Inf	-4.95	0.0004
(Chillicothe Apr_Jun-15) - (Monett Apr_Jun-15)	0.522141	0.1051	Inf	4.969	0.0004
(Monett Jan_Mar-13) - (Chillicothe Oct_Dec-14)	-1.087411	0.218	Inf	-4.987	0.0004
(Macon Jan_Mar-14) - (Chillicothe Oct_Dec-14)	-1.116139	0.2237	Inf	-4.99	0.0004
(Chillicothe Apr_Jun-13) - (Macon Apr_Jun-14)	0.858346	0.1714	Inf	5.008	0.0003
(Monett Apr_Jun-14) - (Chillicothe Apr_Jun-15)	-0.793334	0.1577	Inf	-5.03	0.0003
(Monett Apr_Jun-14) - (Macon Jul_Sep-13)	-0.721348	0.1436	Inf	-5.023	0.0003
(Macon Jan_Mar-13) - (Monett Oct_Dec-15)	0.555443	0.1107	Inf	5.018	0.0003
(Monett Jan_Mar-14) - (Chillicothe Jul_Sep-13)	-1.061576	0.21	Inf	-5.055	0.0003
(Chillicothe Jul_Sep-14) - (Chillicothe Oct_Dec-14	-1.052438	0.21	Inf	-5.013	0.0003
(Macon Oct_Dec-14) - (Chillicothe Oct_Dec-15)	0.797663	0.1598	Inf	4.992	0.0003
(Chillicothe Apr_Jun-13) - (Monett Apr_Jun-13)	0.587799	0.1142	Inf	5.145	0.0002
(Chillicothe Apr_Jun-15) - (Macon Oct_Dec-15)	0.820143	0.1592	Inf	5.153	0.0002
(Monett Apr_Jun-15) - (Chillicothe Oct_Dec-14)	-1.123176	0.218	Inf	-5.151	0.0002
(Chillicothe Jan_Mar-13) - (Monett Jan_Mar-13)	0.548922	0.1075	Inf	5.107	0.0002
(Chillicothe Jan_Mar-13) - (Chillicothe Oct_Dec-1	0.810041	0.1588	Inf	5.1	0.0002
(Macon Jan_Mar-15) - (Macon Jul_Sep-13)	-0.687442	0.135	Inf	-5.093	0.0002
(Monett Jan_Mar-15) - (Monett Jul_Sep-13)	-0.493484	0.0958	Inf	-5.149	0.0002
(Chillicothe Jul_Sep-13) - (Macon Jul_Sep-14)	1.050244	0.2073	Inf	5.067	0.0002
(Chillicothe Jul_Sep-15) - (Chillicothe Oct_Dec-15	0.741181	0.1453	Inf	5.102	0.0002
(Monett Jul_Sep-15) - (Chillicothe Oct_Dec-14)	-1.118971	0.2181	Inf	-5.131	0.0002
(Chillicothe Oct_Dec-13) - (Monett Oct_Dec-15)	0.701695	0.1363	Inf	5.147	0.0002
(Chillicothe Apr_Jun-13) - (Macon Jan_Mar-15)	0.885984	0.1699	Inf	5.215	0.0001
(Chillicothe Apr_Jun-13) - (Chillicothe Oct_Dec-1	0.874051	0.1692	Inf	5.165	0.0001
(Chillicothe Apr_Jun-14) - (Chillicothe Jul_Sep-13	-1.02879	0.1972	Inf	-5.216	0.0001
(Monett Apr_Jun-14) - (Monett Oct_Dec-14)	-0.565737	0.1075	Inf	-5.261	0.0001
(Chillicothe Apr_Jun-15) - (Monett Jan_Mar-15)	0.813248	0.1567	Inf	5.189	0.0001
(Chillicothe Jan_Mar-13) - (Macon Jan_Mar-15)	0.821974	0.1592	Inf	5.163	0.0001
(Macon Jan_Mar-15) - (Chillicothe Jul_Sep-15)	-0.753114	0.1452	Inf	-5.186	0.0001
(Chillicothe Jul_Sep-13) - (Monett Jul_Sep-13)	0.737702	0.1405	Inf	5.25	0.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Chillicothe Apr_Jun-13) - (Monett Apr_Jun-14)	0.91989	0.1682	Inf	5.469	<.0001
(Chillicothe Apr_Jun-13) - (Monett Jan_Mar-15)	0.939804	0.1672	Inf	5.622	<.0001
(Chillicothe Apr_Jun-13) - (Macon Oct_Dec-15)	0.946698	0.1692	Inf	5.596	<.0001
(Chillicothe Apr_Jun-13) - (Monett Oct_Dec-15)	0.983735	0.1667	Inf	5.902	<.0001
(Chillicothe Apr_Jun-14) - (Chillicothe Oct_Dec-1	-1.211887	0.2032	Inf	-5.964	<.0001
(Macon Apr_Jun-14) - (Chillicothe Jul_Sep-13)	-1.149728	0.2019	Inf	-5.694	<.0001
(Macon Apr_Jun-14) - (Chillicothe Oct_Dec-14)	-1.332825	0.2075	Inf	-6.422	<.0001
(Macon Apr_Jun-14) - (Macon Oct_Dec-14)	-0.781958	0.1448	Inf	-5.402	<.0001
(Monett Apr_Jun-14) - (Chillicothe Jan_Mar-13)	-0.85588	0.1576	Inf	-5.432	<.0001
(Monett Apr_Jun-14) - (Chillicothe Jul_Sep-13)	-1.211272	0.1994	Inf	-6.074	<.0001
(Monett Apr_Jun-14) - (Chillicothe Jul_Sep-15)	-0.787019	0.1428	Inf	-5.51	<.0001
(Monett Apr_Jun-14) - (Chillicothe Oct_Dec-14)	-1.394369	0.2038	Inf	-6.842	<.0001
(Monett Apr_Jun-14) - (Macon Oct_Dec-14)	-0.843502	0.1529	Inf	-5.518	<.0001
(Chillicothe Apr_Jun-15) - (Monett Oct_Dec-15)	0.857179	0.1562	Inf	5.487	<.0001
(Chillicothe Jan_Mar-13) - (Monett Jan_Mar-15)	0.875794	0.1564	Inf	5.601	<.0001
(Chillicothe Jan_Mar-13) - (Macon Oct_Dec-15)	0.882688	0.1587	Inf	5.563	<.0001
(Chillicothe Jan_Mar-13) - (Monett Oct_Dec-15)	0.919725	0.156	Inf	5.895	<.0001
(Monett Jan_Mar-14) - (Chillicothe Oct_Dec-14)	-1.244673	0.2125	Inf	-5.857	<.0001
(Chillicothe Jan_Mar-15) - (Chillicothe Jul_Sep-13	-1.071696	0.1959	Inf	-5.471	<.0001
(Chillicothe Jan_Mar-15) - (Chillicothe Oct_Dec-1	-1.254793	0.2026	Inf	-6.193	<.0001
(Macon Jan_Mar-15) - (Chillicothe Jul_Sep-13)	-1.177366	0.2002	Inf	-5.88	<.0001
(Macon Jan_Mar-15) - (Chillicothe Oct_Dec-14)	-1.360464	0.2063	Inf	-6.594	<.0001
(Macon Jan_Mar-15) - (Macon Oct_Dec-14)	-0.809596	0.1452	Inf	-5.577	<.0001
(Monett Jan_Mar-15) - (Chillicothe Jul_Sep-13)	-1.231186	0.1982	Inf	-6.212	<.0001
(Monett Jan_Mar-15) - (Chillicothe Jul_Sep-15)	-0.806933	0.1419	Inf	-5.686	<.0001
(Monett Jan_Mar-15) - (Chillicothe Oct_Dec-14)	-1.414283	0.203	Inf	-6.966	<.0001
(Monett Jan_Mar-15) - (Macon Oct_Dec-14)	-0.863416	0.1522	Inf	-5.673	<.0001
(Monett Jan_Mar-15) - (Monett Oct_Dec-14)	-0.585651	0.1081	Inf	-5.42	<.0001
(Chillicothe Jul_Sep-13) - (Monett Jul_Sep-14)	1.142336	0.2025	Inf	5.64	<.0001
(Chillicothe Jul_Sep-13) - (Chillicothe Oct_Dec-15	1.165433	0.1988	Inf	5.861	<.0001
(Chillicothe Jul_Sep-13) - (Macon Oct_Dec-15)	1.23808	0.2002	Inf	6.185	<.0001
(Chillicothe Jul_Sep-13) - (Monett Oct_Dec-15)	1.275117	0.198	Inf	6.439	<.0001
(Macon Jul_Sep-13) - (Macon Oct_Dec-15)	0.748156	0.1367	Inf	5.473	<.0001
(Macon Jul_Sep-13) - (Monett Oct_Dec-15)	0.785192	0.1414	Inf	5.553	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Monett Jul_Sep-13) - (Monett Oct_Dec-15)	0.537415	0.0956	Inf	5.623	<.0001
(Macon Jul_Sep-14) - (Chillicothe Oct_Dec-14)	-1.233341	0.2134	Inf	-5.781	<.0001
(Monett Jul_Sep-14) - (Chillicothe Oct_Dec-14)	-1.325433	0.2067	Inf	-6.412	<.0001
(Chillicothe Jul_Sep-15) - (Monett Jul_Sep-15)	0.511621	0.0951	Inf	5.379	<.0001
(Chillicothe Jul_Sep-15) - (Macon Oct_Dec-15)	0.813828	0.1438	Inf	5.659	<.0001
(Chillicothe Jul_Sep-15) - (Monett Oct_Dec-15)	0.850864	0.1411	Inf	6.031	<.0001
(Monett Oct_Dec-13) - (Chillicothe Oct_Dec-14)	-1.194545	0.2146	Inf	-5.567	<.0001
(Chillicothe Oct_Dec-14) - (Monett Oct_Dec-14)	0.828632	0.143	Inf	5.796	<.0001
(Chillicothe Oct_Dec-14) - (Chillicothe Oct_Dec-15)	1.348531	0.2036	Inf	6.622	<.0001
(Chillicothe Oct_Dec-14) - (Macon Oct_Dec-15)	1.421177	0.2051	Inf	6.928	<.0001
(Chillicothe Oct_Dec-14) - (Monett Oct_Dec-15)	1.458214	0.2025	Inf	7.203	<.0001
(Macon Oct_Dec-14) - (Macon Oct_Dec-15)	0.87031	0.146	Inf	5.962	<.0001
(Macon Oct_Dec-14) - (Monett Oct_Dec-15)	0.907347	0.1507	Inf	6.019	<.0001
(Monett Oct_Dec-14) - (Monett Oct_Dec-15)	0.629582	0.1075	Inf	5.857	<.0001

Table C. 2 Statistical comparison of micropolitan urban cities for quarter-year periods

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Rolla Apr_Jun-13) - (Sedalia Jul_Sep-13)	0.070653	0.0884	Inf	0.799	1
(Rolla Apr_Jun-13) - (Sedalia Oct_Dec-13)	0.105178	0.085	Inf	1.237	1
(Rolla Apr_Jun-14) - (Rolla Jan_Mar-13)	-0.017085	0.1256	Inf	-0.136	1
(Rolla Apr_Jun-14) - (Rolla Jan_Mar-14)	0.012563	0.1247	Inf	0.101	1
(Rolla Apr_Jun-14) - (Rolla Jul_Sep-14)	-0.12774	0.1234	Inf	-1.035	1
(Rolla Apr_Jun-14) - (Rolla Oct_Dec-15)	-0.132436	0.1257	Inf	-1.053	1
(Rolla Apr_Jun-15) - (Rolla Jan_Mar-15)	0.023919	0.1567	Inf	0.153	1
(Rolla Apr_Jun-15) - (Rolla Jul_Sep-15)	-0.003255	0.1539	Inf	-0.021	1
(Rolla Apr_Jun-15) - (Rolla Oct_Dec-13)	-0.200996	0.1609	Inf	-1.249	1
(Rolla Apr_Jun-15) - (Warrensburg Jan_Mar-13)	-0.01219	0.1848	Inf	-0.066	1
(Rolla Apr_Jun-15) - (Warrensburg Jan_Mar-14)	0.026999	0.1838	Inf	0.147	1
(Rolla Apr_Jun-15) - (Warrensburg Jul_Sep-14)	-0.155197	0.1836	Inf	-0.845	1
(Rolla Apr_Jun-15) - (Warrensburg Oct_Dec-15)	-0.173983	0.1897	Inf	-0.917	1
(Rolla Jan_Mar-13) - (Rolla Jan_Mar-14)	0.029647	0.1304	Inf	0.227	1
(Rolla Jan_Mar-13) - (Rolla Jul_Sep-14)	-0.110656	0.1292	Inf	-0.857	1
(Rolla Jan_Mar-13) - (Rolla Oct_Dec-15)	-0.115351	0.1313	Inf	-0.878	1
(Rolla Jan_Mar-14) - (Rolla Jul_Sep-14)	-0.140303	0.1283	Inf	-1.093	1
(Rolla Jan_Mar-14) - (Rolla Oct_Dec-15)	-0.144999	0.1304	Inf	-1.112	1
(Rolla Jan_Mar-15) - (Rolla Jul_Sep-15)	-0.027174	0.1532	Inf	-0.177	1
(Rolla Jan_Mar-15) - (Rolla Oct_Dec-13)	-0.224915	0.1601	Inf	-1.405	1
(Rolla Jan_Mar-15) - (Warrensburg Jul_Sep-14)	-0.179116	0.1795	Inf	-0.998	1
(Rolla Jan_Mar-15) - (Warrensburg Oct_Dec-15)	-0.197902	0.1856	Inf	-1.066	1
(Rolla Jul_Sep-13) - (Rolla Oct_Dec-13)	0.097031	0.1746	Inf	0.556	1
(Rolla Jul_Sep-13) - (Warrensburg Jul_Sep-14)	0.142829	0.1958	Inf	0.729	1
(Rolla Jul_Sep-13) - (Warrensburg Jul_Sep-15)	-0.268046	0.2136	Inf	-1.255	1
(Rolla Jul_Sep-13) - (Warrensburg Oct_Dec-15)	0.124044	0.2016	Inf	0.615	1
(Rolla Jul_Sep-14) - (Rolla Oct_Dec-15)	-0.004696	0.1297	Inf	-0.036	1
(Rolla Jul_Sep-15) - (Rolla Oct_Dec-13)	-0.197741	0.1576	Inf	-1.255	1
(Rolla Jul_Sep-15) - (Warrensburg Oct_Dec-15)	-0.170728	0.1859	Inf	-0.918	1
(Rolla Oct_Dec-13) - (Warrensburg Oct_Dec-15)	0.027013	0.1915	Inf	0.141	1
(Sedalia Apr_Jun-14) - (Sedalia Jan_Mar-13)	-0.005826	0.0462	Inf	-0.126	1
(Sedalia Apr_Jun-14) - (Sedalia Jan_Mar-14)	0.005099	0.0459	Inf	0.111	1
(Sedalia Apr_Jun-14) - (Sedalia Jul_Sep-14)	-0.046865	0.0453	Inf	-1.034	1
(Sedalia Apr_Jun-14) - (Sedalia Oct_Dec-15)	-0.047602	0.0463	Inf	-1.027	1
(Sedalia Apr_Jun-15) - (Sedalia Jan_Mar-15)	0.008811	0.0578	Inf	0.152	1
(Sedalia Apr_Jun-15) - (Sedalia Jul_Sep-15)	-0.000805	0.0567	Inf	-0.014	1
(Sedalia Apr_Jun-15) - (Sedalia Oct_Dec-13)	-0.073503	0.0594	Inf	-1.237	1
(Sedalia Jan_Mar-13) - (Sedalia Jan_Mar-14)	0.010925	0.0479	Inf	0.228	1
(Sedalia Jan_Mar-13) - (Sedalia Jul_Sep-14)	-0.041039	0.0474	Inf	-0.865	1
(Sedalia Jan_Mar-13) - (Sedalia Oct_Dec-15)	-0.041776	0.0484	Inf	-0.864	1
(Sedalia Jan_Mar-14) - (Sedalia Jul_Sep-14)	-0.051964	0.0471	Inf	-1.103	1

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Jan_Mar-14) - (Sedalia Oct_Dec-15)	-0.052701	0.048	Inf	-1.097	1
(Sedalia Jan_Mar-15) - (Sedalia Jul_Sep-15)	-0.009617	0.0565	Inf	-0.17	1
(Sedalia Jan_Mar-15) - (Sedalia Oct_Dec-13)	-0.082315	0.0591	Inf	-1.393	1
(Sedalia Jul_Sep-13) - (Sedalia Oct_Dec-13)	0.034525	0.0643	Inf	0.537	1
(Sedalia Jul_Sep-14) - (Sedalia Oct_Dec-15)	-0.000737	0.0477	Inf	-0.015	1
(Sedalia Jul_Sep-15) - (Sedalia Oct_Dec-13)	-0.072698	0.0582	Inf	-1.248	1
(Warrensburg Apr_Jun-13) - (Rolla Apr_Jun-14)	-0.122679	0.1302	Inf	-0.942	1
(Warrensburg Apr_Jun-13) - (Rolla Jan_Mar-13)	-0.139764	0.1364	Inf	-1.025	1
(Warrensburg Apr_Jun-13) - (Rolla Jan_Mar-14)	-0.110116	0.1351	Inf	-0.815	1
(Warrensburg Apr_Jun-13) - (Sedalia Oct_Dec-14)	0.088857	0.1154	Inf	0.77	1
(Warrensburg Apr_Jun-14) - (Rolla Apr_Jun-15)	-0.01633	0.1776	Inf	-0.092	1
(Warrensburg Apr_Jun-14) - (Rolla Jan_Mar-15)	0.007589	0.1738	Inf	0.044	1
(Warrensburg Apr_Jun-14) - (Rolla Jul_Sep-15)	-0.019585	0.1735	Inf	-0.113	1
(Warrensburg Apr_Jun-14) - (Rolla Oct_Dec-13)	-0.217326	0.1798	Inf	-1.209	1
(Warrensburg Apr_Jun-14) - (Warrensburg Jan_Mar-13)	-0.02852	0.1672	Inf	-0.171	1
(Warrensburg Apr_Jun-14) - (Warrensburg Jan_Mar-14)	0.010669	0.166	Inf	0.064	1
(Warrensburg Apr_Jun-14) - (Warrensburg Jul_Sep-14)	-0.171527	0.1637	Inf	-1.048	1
(Warrensburg Apr_Jun-14) - (Warrensburg Oct_Dec-15)	-0.190313	0.1679	Inf	-1.134	1
(Warrensburg Apr_Jun-15) - (Rolla Jul_Sep-13)	0.258831	0.2151	Inf	1.203	1
(Warrensburg Apr_Jun-15) - (Warrensburg Jan_Mar-15)	0.031672	0.2063	Inf	0.153	1
(Warrensburg Apr_Jun-15) - (Warrensburg Jul_Sep-15)	-0.009214	0.203	Inf	-0.045	1
(Warrensburg Apr_Jun-15) - (Warrensburg Oct_Dec-13)	-0.272867	0.2126	Inf	-1.284	1
(Warrensburg Jan_Mar-13) - (Rolla Jan_Mar-15)	0.036109	0.1812	Inf	0.199	1
(Warrensburg Jan_Mar-13) - (Rolla Jul_Sep-13)	-0.285837	0.1972	Inf	-1.45	1
(Warrensburg Jan_Mar-13) - (Rolla Jul_Sep-15)	0.008935	0.181	Inf	0.049	1
(Warrensburg Jan_Mar-13) - (Rolla Oct_Dec-13)	-0.188806	0.1869	Inf	-1.01	1
(Warrensburg Jan_Mar-13) - (Warrensburg Jan_Mar-14)	0.039189	0.174	Inf	0.225	1
(Warrensburg Jan_Mar-13) - (Warrensburg Jul_Sep-14)	-0.143007	0.1719	Inf	-0.832	1
(Warrensburg Jan_Mar-13) - (Warrensburg Oct_Dec-15)	-0.161793	0.1757	Inf	-0.921	1
(Warrensburg Jan_Mar-14) - (Rolla Jan_Mar-15)	-0.00308	0.1801	Inf	-0.017	1
(Warrensburg Jan_Mar-14) - (Rolla Jul_Sep-15)	-0.030254	0.1799	Inf	-0.168	1
(Warrensburg Jan_Mar-14) - (Rolla Oct_Dec-13)	-0.227995	0.1859	Inf	-1.227	1
(Warrensburg Jan_Mar-14) - (Warrensburg Jul_Sep-14)	-0.182197	0.1708	Inf	-1.067	1
(Warrensburg Jan_Mar-14) - (Warrensburg Oct_Dec-15)	-0.200982	0.1746	Inf	-1.151	1
(Warrensburg Jan_Mar-15) - (Rolla Jul_Sep-13)	0.22716	0.2178	Inf	1.043	1
(Warrensburg Jan_Mar-15) - (Warrensburg Jul_Sep-15)	-0.040886	0.2022	Inf	-0.202	1
(Warrensburg Jan_Mar-15) - (Warrensburg Oct_Dec-13)	-0.304538	0.211	Inf	-1.443	1
(Warrensburg Jul_Sep-13) - (Rolla Oct_Dec-14)	-0.025296	0.2663	Inf	-0.095	1
(Warrensburg Jul_Sep-13) - (Warrensburg Oct_Dec-13)	0.143728	0.231	Inf	0.622	1
(Warrensburg Jul_Sep-14) - (Rolla Jul_Sep-15)	0.151942	0.1792	Inf	0.848	1
(Warrensburg Jul_Sep-14) - (Rolla Oct_Dec-13)	-0.045799	0.1854	Inf	-0.247	1

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Warrensburg Jul_Sep-14) - (Warrensburg Oct_Dec-15)	-0.018785	0.1729	Inf	-0.109	1
(Warrensburg Jul_Sep-15) - (Warrensburg Oct_Dec-13)	-0.263652	0.2083	Inf	-1.266	1
(Warrensburg Oct_Dec-13) - (Rolla Oct_Dec-14)	-0.169024	0.2516	Inf	-0.672	1
(Warrensburg Jan_Mar-14) - (Rolla Oct_Dec-15)	0.27094	0.1679	Inf	1.614	0.9999
(Warrensburg Jan_Mar-15) - (Rolla Oct_Dec-13)	0.32419	0.2084	Inf	1.556	0.9999
(Rolla Jan_Mar-14) - (Sedalia Oct_Dec-14)	0.198973	0.1203	Inf	1.654	0.9998
(Warrensburg Apr_Jun-14) - (Rolla Jul_Sep-13)	-0.314357	0.1904	Inf	-1.651	0.9998
(Warrensburg Jan_Mar-14) - (Rolla Jul_Sep-13)	-0.325026	0.1962	Inf	-1.657	0.9998
(Warrensburg Jan_Mar-14) - (Rolla Jul_Sep-14)	0.275636	0.1669	Inf	1.652	0.9998
(Sedalia Apr_Jun-15) - (Sedalia Jul_Sep-13)	-0.108028	0.0633	Inf	-1.706	0.9995
(Sedalia Jul_Sep-13) - (Sedalia Jul_Sep-15)	0.107223	0.0622	Inf	1.723	0.9994
(Warrensburg Apr_Jun-15) - (Rolla Oct_Dec-13)	0.355862	0.2057	Inf	1.73	0.9994
(Rolla Apr_Jun-15) - (Rolla Jul_Sep-13)	-0.298026	0.1714	Inf	-1.739	0.9993
(Warrensburg Apr_Jun-14) - (Rolla Oct_Dec-15)	0.28161	0.1612	Inf	1.747	0.9993
(Rolla Jul_Sep-13) - (Rolla Jul_Sep-15)	0.294771	0.1684	Inf	1.751	0.9992
(Warrensburg Apr_Jun-14) - (Rolla Jul_Sep-14)	0.286305	0.1599	Inf	1.79	0.9988
(Warrensburg Jul_Sep-15) - (Rolla Oct_Dec-13)	0.365076	0.2039	Inf	1.79	0.9988
(Warrensburg Jul_Sep-15) - (Rolla Oct_Dec-14)	-0.432676	0.2389	Inf	-1.811	0.9986
(Warrensburg Jul_Sep-13) - (Warrensburg Jul_Sep-15)	0.40738	0.2236	Inf	1.822	0.9984
(Warrensburg Apr_Jun-15) - (Rolla Oct_Dec-14)	-0.441891	0.2409	Inf	-1.835	0.9982
(Warrensburg Apr_Jun-15) - (Warrensburg Jul_Sep-13)	-0.416595	0.2276	Inf	-1.83	0.9982
(Warrensburg Jan_Mar-13) - (Rolla Oct_Dec-15)	0.31013	0.1692	Inf	1.833	0.9982
(Warrensburg Jan_Mar-15) - (Warrensburg Oct_Dec-15)	0.351203	0.1916	Inf	1.833	0.9982
(Rolla Apr_Jun-14) - (Sedalia Oct_Dec-14)	0.211536	0.115	Inf	1.84	0.9981
(Sedalia Jan_Mar-15) - (Sedalia Jul_Sep-13)	-0.11684	0.063	Inf	-1.853	0.9978
(Warrensburg Apr_Jun-13) - (Rolla Jul_Sep-14)	-0.250419	0.1347	Inf	-1.86	0.9976
(Warrensburg Apr_Jun-13) - (Rolla Oct_Dec-15)	-0.255115	0.1364	Inf	-1.871	0.9974
(Warrensburg Jan_Mar-13) - (Rolla Jul_Sep-14)	0.314825	0.168	Inf	1.873	0.9973
(Rolla Jan_Mar-13) - (Sedalia Oct_Dec-14)	0.228621	0.1217	Inf	1.878	0.9972
(Rolla Jan_Mar-15) - (Rolla Jul_Sep-13)	-0.321945	0.1707	Inf	-1.886	0.997
(Rolla Jan_Mar-15) - (Rolla Oct_Dec-15)	0.274021	0.1445	Inf	1.897	0.9967
(Rolla Apr_Jun-13) - (Sedalia Oct_Dec-14)	-0.187573	0.0976	Inf	-1.921	0.9958
(Sedalia Jan_Mar-15) - (Sedalia Oct_Dec-15)	0.101861	0.053	Inf	1.922	0.9958
(Warrensburg Jan_Mar-15) - (Rolla Oct_Dec-14)	-0.473562	0.2432	Inf	-1.947	0.9947
(Sedalia Jan_Mar-15) - (Sedalia Jul_Sep-14)	0.102598	0.0525	Inf	1.954	0.9944
(Rolla Jan_Mar-15) - (Rolla Jul_Sep-14)	0.278716	0.1418	Inf	1.965	0.9939
(Warrensburg Jan_Mar-15) - (Warrensburg Jul_Sep-14)	0.369989	0.1877	Inf	1.971	0.9936
(Warrensburg Jan_Mar-15) - (Warrensburg Jul_Sep-13)	-0.448266	0.2261	Inf	-1.982	0.9929
(Warrensburg Apr_Jun-15) - (Warrensburg Oct_Dec-15)	0.382875	0.1925	Inf	1.989	0.9925
(Rolla Apr_Jun-15) - (Rolla Oct_Dec-15)	0.29794	0.1458	Inf	2.043	0.9886

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Apr_Jun-15) - (Sedalia Oct_Dec-15)	0.110672	0.0534	Inf	2.071	0.9859
(Warrensburg Jul_Sep-15) - (Warrensburg Oct_Dec-15)	0.392089	0.1888	Inf	2.076	0.9853
(Sedalia Apr_Jun-15) - (Sedalia Jul_Sep-14)	0.111409	0.0529	Inf	2.105	0.9821
(Rolla Jul_Sep-15) - (Rolla Oct_Dec-15)	0.301195	0.1424	Inf	2.115	0.9808
(Rolla Apr_Jun-15) - (Rolla Jul_Sep-14)	0.302635	0.1431	Inf	2.115	0.9808
(Warrensburg Apr_Jun-15) - (Warrensburg Jul_Sep-14)	0.40166	0.1884	Inf	2.132	0.9784
(Sedalia Jul_Sep-15) - (Sedalia Oct_Dec-15)	0.111478	0.052	Inf	2.142	0.9769
(Rolla Apr_Jun-13) - (Sedalia Apr_Jun-15)	0.178681	0.0827	Inf	2.16	0.9739
(Rolla Apr_Jun-13) - (Sedalia Jul_Sep-15)	0.177876	0.0817	Inf	2.178	0.9708
(Sedalia Jul_Sep-14) - (Sedalia Jul_Sep-15)	-0.112215	0.0514	Inf	-2.184	0.9698
(Rolla Jul_Sep-14) - (Rolla Jul_Sep-15)	-0.30589	0.1392	Inf	-2.198	0.967
(Warrensburg Jul_Sep-14) - (Warrensburg Jul_Sep-15)	-0.410875	0.184	Inf	-2.232	0.9595
(Rolla Apr_Jun-13) - (Sedalia Jan_Mar-15)	0.187492	0.0827	Inf	2.266	0.9509
(Rolla Jan_Mar-13) - (Warrensburg Jan_Mar-14)	-0.386292	0.1681	Inf	-2.298	0.9417
(Rolla Jul_Sep-13) - (Warrensburg Oct_Dec-13)	-0.531698	0.2269	Inf	-2.343	0.9267
(Warrensburg Apr_Jun-14) - (Rolla Jan_Mar-13)	0.396961	0.1613	Inf	2.461	0.8751
(Rolla Apr_Jun-14) - (Warrensburg Jan_Mar-14)	-0.403376	0.1629	Inf	-2.476	0.8675
(Rolla Apr_Jun-15) - (Warrensburg Jan_Mar-15)	-0.525186	0.207	Inf	-2.537	0.8324
(Warrensburg Jan_Mar-15) - (Rolla Jul_Sep-15)	0.521931	0.203	Inf	2.571	0.811
(Warrensburg Apr_Jun-14) - (Rolla Jan_Mar-14)	0.426608	0.1601	Inf	2.665	0.7449
(Warrensburg Jan_Mar-13) - (Warrensburg Jan_Mar-15)	-0.512996	0.1916	Inf	-2.677	0.7361
(Warrensburg Jul_Sep-14) - (Rolla Oct_Dec-15)	0.453137	0.1682	Inf	2.694	0.723
(Rolla Apr_Jun-14) - (Warrensburg Jan_Mar-13)	-0.442566	0.1642	Inf	-2.696	0.7217
(Rolla Jan_Mar-13) - (Rolla Jan_Mar-15)	-0.389372	0.1442	Inf	-2.7	0.7185
(Sedalia Jan_Mar-13) - (Sedalia Jan_Mar-15)	-0.143636	0.0532	Inf	-2.7	0.7184
(Warrensburg Jan_Mar-13) - (Rolla Jan_Mar-14)	0.455128	0.1681	Inf	2.707	0.7128
(Rolla Jul_Sep-14) - (Warrensburg Oct_Dec-15)	-0.476618	0.1729	Inf	-2.757	0.6726
(Warrensburg Apr_Jun-15) - (Rolla Jul_Sep-15)	0.553603	0.2	Inf	2.767	0.6642
(Rolla Jul_Sep-14) - (Sedalia Oct_Dec-14)	0.339276	0.1218	Inf	2.785	0.6495
(Rolla Apr_Jun-15) - (Warrensburg Jul_Sep-15)	-0.566072	0.2023	Inf	-2.798	0.6386
(Warrensburg Apr_Jun-15) - (Warrensburg Jan_Mar-13)	0.544668	0.1919	Inf	2.838	0.6049
(Rolla Apr_Jun-15) - (Rolla Jan_Mar-13)	0.413291	0.1454	Inf	2.843	0.6012
(Sedalia Apr_Jun-15) - (Sedalia Jan_Mar-13)	0.152448	0.0536	Inf	2.846	0.5984
(Sedalia Oct_Dec-14) - (Rolla Oct_Dec-15)	-0.343972	0.1204	Inf	-2.856	0.5899
(Warrensburg Jan_Mar-14) - (Warrensburg Jan_Mar-15)	-0.552186	0.1907	Inf	-2.896	0.5557
(Warrensburg Apr_Jun-15) - (Rolla Jan_Mar-15)	0.580777	0.2004	Inf	2.899	0.5535
(Sedalia Apr_Jun-14) - (Sedalia Jan_Mar-15)	-0.149463	0.0514	Inf	-2.91	0.5442
(Rolla Apr_Jun-14) - (Rolla Jan_Mar-15)	-0.406457	0.1392	Inf	-2.92	0.5351
(Rolla Jan_Mar-14) - (Rolla Jan_Mar-15)	-0.419019	0.1435	Inf	-2.921	0.5349
(Sedalia Jan_Mar-14) - (Sedalia Jan_Mar-15)	-0.154562	0.0529	Inf	-2.921	0.5341

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Rolla Jan_Mar-13) - (Rolla Jul_Sep-15)	-0.416546	0.1419	Inf	-2.936	0.5213
(Warrensburg Apr_Jun-14) - (Warrensburg Jan_Mar-15)	-0.541516	0.1844	Inf	-2.937	0.5211
(Sedalia Jan_Mar-13) - (Sedalia Jul_Sep-15)	-0.153253	0.0521	Inf	-2.94	0.5184
(Warrensburg Jan_Mar-13) - (Warrensburg Jul_Sep-15)	-0.553882	0.1883	Inf	-2.942	0.5165
(Rolla Jan_Mar-15) - (Warrensburg Jul_Sep-15)	-0.589991	0.1985	Inf	-2.973	0.4907
(Sedalia Apr_Jun-14) - (Sedalia Apr_Jun-15)	-0.158274	0.0518	Inf	-3.057	0.4207
(Warrensburg Apr_Jun-15) - (Warrensburg Jan_Mar-14)	0.583857	0.191	Inf	3.057	0.4206
(Rolla Apr_Jun-15) - (Rolla Jan_Mar-14)	0.442938	0.1447	Inf	3.06	0.4184
(Rolla Apr_Jun-14) - (Rolla Apr_Jun-15)	-0.430376	0.1405	Inf	-3.064	0.4154
(Sedalia Apr_Jun-15) - (Sedalia Jan_Mar-14)	0.163373	0.0533	Inf	3.065	0.4146
(Warrensburg Apr_Jun-14) - (Warrensburg Apr_Jun-15)	-0.573188	0.1847	Inf	-3.103	0.3843
(Rolla Jan_Mar-14) - (Rolla Jul_Sep-15)	-0.446193	0.1412	Inf	-3.161	0.3411
(Sedalia Apr_Jun-14) - (Sedalia Jul_Sep-15)	-0.159079	0.0503	Inf	-3.165	0.3378
(Warrensburg Jan_Mar-14) - (Warrensburg Jul_Sep-15)	-0.593072	0.1873	Inf	-3.166	0.3372
(Sedalia Jan_Mar-14) - (Sedalia Jul_Sep-15)	-0.164178	0.0518	Inf	-3.167	0.3367
(Rolla Apr_Jun-14) - (Rolla Jul_Sep-15)	-0.433631	0.1368	Inf	-3.171	0.3337
(Warrensburg Apr_Jun-13) - (Sedalia Jul_Sep-13)	0.347082	0.1081	Inf	3.21	0.3062
(Warrensburg Apr_Jun-14) - (Warrensburg Jul_Sep-15)	-0.582402	0.1809	Inf	-3.22	0.2991
(Warrensburg Jul_Sep-13) - (Rolla Oct_Dec-13)	0.772457	0.2343	Inf	3.297	0.2494
(Warrensburg Oct_Dec-13) - (Warrensburg Oct_Dec-15)	0.655742	0.1984	Inf	3.306	0.2442
(Warrensburg Jul_Sep-13) - (Warrensburg Oct_Dec-14)	-0.92666	0.2782	Inf	-3.331	0.2292
(Rolla Oct_Dec-13) - (Rolla Oct_Dec-15)	0.498936	0.1495	Inf	3.337	0.2259
(Rolla Jul_Sep-13) - (Rolla Oct_Dec-14)	-0.700722	0.2099	Inf	-3.338	0.225
(Sedalia Jul_Sep-13) - (Sedalia Oct_Dec-14)	-0.258225	0.0771	Inf	-3.348	0.2194
(Sedalia Oct_Dec-13) - (Sedalia Oct_Dec-15)	0.184175	0.0548	Inf	3.359	0.2136
(Sedalia Jul_Sep-14) - (Sedalia Oct_Dec-13)	-0.184912	0.0547	Inf	-3.383	0.2004
(Rolla Jan_Mar-13) - (Warrensburg Oct_Dec-15)	-0.587274	0.1735	Inf	-3.384	0.2
(Rolla Jan_Mar-13) - (Warrensburg Jul_Sep-14)	-0.568488	0.1679	Inf	-3.386	0.1989
(Sedalia Apr_Jun-13) - (Sedalia Jan_Mar-14)	-0.141257	0.0413	Inf	-3.419	0.1825
(Rolla Jul_Sep-14) - (Rolla Oct_Dec-13)	-0.503631	0.1469	Inf	-3.429	0.1773
(Warrensburg Jul_Sep-14) - (Warrensburg Oct_Dec-13)	-0.674527	0.1947	Inf	-3.464	0.1611
(Rolla Apr_Jun-13) - (Rolla Jan_Mar-14)	-0.386546	0.1116	Inf	-3.464	0.161
(Warrensburg Apr_Jun-13) - (Rolla Jan_Mar-15)	-0.529136	0.1506	Inf	-3.514	0.1396
(Warrensburg Apr_Jun-13) - (Warrensburg Jan_Mar-14)	-0.526055	0.1495	Inf	-3.518	0.1383
(Rolla Jan_Mar-14) - (Warrensburg Oct_Dec-15)	-0.616921	0.1723	Inf	-3.581	0.1148
(Rolla Oct_Dec-14) - (Warrensburg Oct_Dec-15)	0.824765	0.2302	Inf	3.583	0.1141
(Rolla Apr_Jun-14) - (Warrensburg Oct_Dec-15)	-0.604358	0.1685	Inf	-3.587	0.1129
(Warrensburg Apr_Jun-13) - (Rolla Apr_Jun-15)	-0.553055	0.1542	Inf	-3.587	0.1128
(Rolla Jan_Mar-14) - (Warrensburg Jul_Sep-14)	-0.598135	0.1667	Inf	-3.588	0.1125
(Rolla Apr_Jun-14) - (Warrensburg Jul_Sep-14)	-0.585573	0.1626	Inf	-3.601	0.108
(Warrensburg Apr_Jun-13) - (Sedalia Oct_Dec-13)	0.381607	0.1053	Inf	3.625	0.1003

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Rolla Apr_Jun-13) - (Sedalia Oct_Dec-15)	0.289353	0.0796	Inf	3.633	0.0979
(Sedalia Apr_Jun-13) - (Sedalia Jan_Mar-13)	-0.152183	0.0417	Inf	-3.645	0.0942
(Rolla Apr_Jun-13) - (Rolla Jan_Mar-13)	-0.416193	0.1127	Inf	-3.692	0.0812
(Rolla Jul_Sep-13) - (Rolla Oct_Dec-15)	0.595966	0.1609	Inf	3.703	0.0783
(Sedalia Jul_Sep-13) - (Sedalia Oct_Dec-15)	0.218701	0.0591	Inf	3.704	0.0782
(Warrensburg Apr_Jun-13) - (Rolla Jul_Sep-15)	-0.55631	0.1498	Inf	-3.714	0.0755
(Sedalia Jul_Sep-13) - (Sedalia Jul_Sep-14)	0.219438	0.059	Inf	3.717	0.0749
(Sedalia Apr_Jun-13) - (Sedalia Apr_Jun-14)	-0.146356	0.0393	Inf	-3.723	0.0734
(Warrensburg Jul_Sep-13) - (Warrensburg Oct_Dec-15)	0.79947	0.2144	Inf	3.728	0.0722
(Warrensburg Apr_Jun-13) - (Warrensburg Jan_Mar-13)	-0.565245	0.1508	Inf	-3.747	0.0678
(Rolla Apr_Jun-13) - (Sedalia Jul_Sep-14)	0.29009	0.0774	Inf	3.748	0.0676
(Rolla Apr_Jun-13) - (Rolla Apr_Jun-14)	-0.399109	0.1059	Inf	-3.769	0.0631
(Warrensburg Jul_Sep-14) - (Rolla Oct_Dec-14)	-0.843551	0.2228	Inf	-3.786	0.0597
(Rolla Jul_Sep-13) - (Rolla Jul_Sep-14)	0.600662	0.1585	Inf	3.789	0.059
(Warrensburg Apr_Jun-13) - (Warrensburg Apr_Jun-14)	-0.536725	0.1416	Inf	-3.791	0.0585
(Rolla Apr_Jun-15) - (Warrensburg Oct_Dec-13)	-0.829724	0.2166	Inf	-3.83	0.0512
(Warrensburg Jul_Sep-13) - (Warrensburg Jul_Sep-14)	0.818255	0.2113	Inf	3.873	0.0442
(Rolla Jul_Sep-15) - (Warrensburg Oct_Dec-13)	-0.826469	0.2127	Inf	-3.886	0.0422
(Sedalia Oct_Dec-13) - (Sedalia Oct_Dec-14)	-0.292751	0.0742	Inf	-3.947	0.0338
(Rolla Oct_Dec-13) - (Rolla Oct_Dec-14)	-0.797752	0.2015	Inf	-3.959	0.0324
(Warrensburg Oct_Dec-13) - (Warrensburg Oct_Dec-14)	-1.070388	0.2667	Inf	-4.014	0.0265
(Rolla Jan_Mar-15) - (Warrensburg Oct_Dec-13)	-0.853643	0.2125	Inf	-4.018	0.026
(Rolla Jan_Mar-14) - (Sedalia Jul_Sep-13)	0.457199	0.1126	Inf	4.059	0.0223
(Sedalia Jan_Mar-13) - (Sedalia Oct_Dec-13)	-0.225951	0.0553	Inf	-4.089	0.0199
(Warrensburg Jan_Mar-14) - (Sedalia Oct_Dec-14)	0.614912	0.1498	Inf	4.105	0.0186
(Warrensburg Jan_Mar-13) - (Warrensburg Oct_Dec-13)	-0.817535	0.1987	Inf	-4.114	0.018
(Rolla Jan_Mar-13) - (Rolla Oct_Dec-13)	-0.614287	0.1492	Inf	-4.116	0.0179
(Rolla Apr_Jun-15) - (Warrensburg Jul_Sep-13)	-0.973452	0.2332	Inf	-4.174	0.0142
(Warrensburg Jul_Sep-13) - (Rolla Jul_Sep-15)	0.970197	0.2296	Inf	4.226	0.0115
(Rolla Apr_Jun-13) - (Sedalia Jan_Mar-13)	0.331129	0.0781	Inf	4.239	0.011
(Rolla Jan_Mar-13) - (Sedalia Jul_Sep-13)	0.486846	0.1142	Inf	4.265	0.0098
(Warrensburg Jan_Mar-15) - (Rolla Oct_Dec-15)	0.823126	0.1923	Inf	4.28	0.0093
(Sedalia Jan_Mar-14) - (Sedalia Oct_Dec-13)	-0.236876	0.055	Inf	-4.308	0.0082
(Warrensburg Jan_Mar-13) - (Sedalia Oct_Dec-14)	0.654101	0.1513	Inf	4.322	0.0078
(Sedalia Apr_Jun-14) - (Sedalia Oct_Dec-13)	-0.231777	0.0535	Inf	-4.331	0.0075
(Warrensburg Jan_Mar-14) - (Warrensburg Oct_Dec-13)	-0.856724	0.1978	Inf	-4.331	0.0075
(Rolla Jan_Mar-14) - (Rolla Oct_Dec-13)	-0.643934	0.1486	Inf	-4.334	0.0074
(Warrensburg Jan_Mar-15) - (Rolla Jul_Sep-14)	0.827822	0.1909	Inf	4.336	0.0073
(Rolla Jan_Mar-15) - (Warrensburg Jul_Sep-13)	-0.997371	0.2293	Inf	-4.35	0.0069
(Warrensburg Apr_Jun-13) - (Sedalia Apr_Jun-15)	0.45511	0.1043	Inf	4.362	0.0065
(Rolla Apr_Jun-14) - (Rolla Oct_Dec-13)	-0.631372	0.1445	Inf	-4.371	0.0063

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Jan_Mar-13) - (Sedalia Jul_Sep-13)	-0.260476	0.0596	Inf	-4.373	0.0062
(Warrensburg Jan_Mar-13) - (Rolla Oct_Dec-14)	-0.986558	0.2252	Inf	-4.38	0.0061
(Rolla Apr_Jun-13) - (Sedalia Apr_Jun-14)	0.336955	0.0769	Inf	4.383	0.006
(Rolla Apr_Jun-13) - (Sedalia Jan_Mar-14)	0.342054	0.0779	Inf	4.392	0.0058
(Rolla Apr_Jun-14) - (Sedalia Jul_Sep-13)	0.469761	0.107	Inf	4.39	0.0058
(Warrensburg Apr_Jun-14) - (Sedalia Oct_Dec-14)	0.625581	0.142	Inf	4.406	0.0054
(Warrensburg Apr_Jun-13) - (Sedalia Jul_Sep-15)	0.454305	0.103	Inf	4.412	0.0053
(Warrensburg Apr_Jun-14) - (Warrensburg Oct_Dec-13)	-0.846055	0.1918	Inf	-4.412	0.0053
(Rolla Jan_Mar-13) - (Rolla Jul_Sep-13)	-0.711317	0.1607	Inf	-4.426	0.005
(Rolla Jan_Mar-15) - (Sedalia Oct_Dec-14)	0.617993	0.1384	Inf	4.464	0.0042
(Rolla Jan_Mar-14) - (Sedalia Oct_Dec-13)	0.491724	0.11	Inf	4.471	0.0041
(Warrensburg Jan_Mar-13) - (Warrensburg Jul_Sep-13)	-0.961263	0.215	Inf	-4.471	0.0041
(Warrensburg Apr_Jun-13) - (Sedalia Jan_Mar-15)	0.463922	0.1033	Inf	4.492	0.0037
(Warrensburg Apr_Jun-15) - (Rolla Oct_Dec-15)	0.854797	0.1898	Inf	4.504	0.0035
(Rolla Apr_Jun-15) - (Sedalia Oct_Dec-14)	0.641912	0.141	Inf	4.552	0.0029
(Warrensburg Apr_Jun-15) - (Rolla Jul_Sep-14)	0.859493	0.1883	Inf	4.565	0.0027
(Sedalia Apr_Jun-13) - (Sedalia Oct_Dec-15)	-0.193958	0.0425	Inf	-4.569	0.0026
(Sedalia Jan_Mar-14) - (Sedalia Jul_Sep-13)	-0.271402	0.0593	Inf	-4.575	0.0026
(Warrensburg Jan_Mar-14) - (Rolla Oct_Dec-14)	-1.025748	0.2244	Inf	-4.571	0.0026
(Warrensburg Jul_Sep-15) - (Rolla Oct_Dec-15)	0.864012	0.1881	Inf	4.593	0.0024
(Sedalia Apr_Jun-14) - (Sedalia Jul_Sep-13)	-0.266302	0.058	Inf	-4.595	0.0023
(Rolla Jan_Mar-14) - (Rolla Jul_Sep-13)	-0.740965	0.1601	Inf	-4.628	0.002
(Warrensburg Apr_Jun-14) - (Rolla Oct_Dec-14)	-1.015078	0.2193	Inf	-4.629	0.002
(Rolla Apr_Jun-14) - (Rolla Jul_Sep-13)	-0.728402	0.1563	Inf	-4.66	0.0017
(Rolla Jul_Sep-14) - (Warrensburg Jul_Sep-15)	-0.868708	0.1861	Inf	-4.669	0.0017
(Rolla Jan_Mar-13) - (Sedalia Oct_Dec-13)	0.521371	0.1115	Inf	4.675	0.0016
(Warrensburg Jan_Mar-14) - (Warrensburg Jul_Sep-13)	-1.000452	0.2141	Inf	-4.672	0.0016
(Rolla Jul_Sep-15) - (Sedalia Oct_Dec-14)	0.645167	0.1376	Inf	4.688	0.0015
(Rolla Apr_Jun-13) - (Rolla Oct_Dec-15)	-0.531545	0.1128	Inf	-4.713	0.0014
(Warrensburg Apr_Jun-14) - (Warrensburg Jul_Sep-13)	-0.989783	0.2086	Inf	-4.745	0.0012
(Sedalia Apr_Jun-13) - (Sedalia Jul_Sep-14)	-0.193221	0.0406	Inf	-4.757	0.0011
(Warrensburg Apr_Jun-13) - (Warrensburg Oct_Dec-15)	-0.727037	0.1526	Inf	-4.765	0.0011
(Rolla Apr_Jun-13) - (Rolla Jul_Sep-14)	-0.526849	0.1103	Inf	-4.776	0.001
(Warrensburg Apr_Jun-13) - (Rolla Oct_Dec-13)	-0.754051	0.157	Inf	-4.802	0.0009
(Warrensburg Apr_Jun-13) - (Warrensburg Jul_Sep-14)	-0.708252	0.1475	Inf	-4.803	0.0009
(Rolla Apr_Jun-14) - (Sedalia Oct_Dec-13)	0.504286	0.1042	Inf	4.84	0.0007
(Rolla Jan_Mar-13) - (Warrensburg Jan_Mar-15)	-0.938477	0.1923	Inf	-4.879	0.0006
(Sedalia Apr_Jun-15) - (Sedalia Oct_Dec-14)	-0.366254	0.0736	Inf	-4.979	0.0004
(Rolla Apr_Jun-15) - (Rolla Oct_Dec-14)	-0.998748	0.1991	Inf	-5.016	0.0003
(Sedalia Jul_Sep-15) - (Sedalia Oct_Dec-14)	-0.365448	0.0725	Inf	-5.037	0.0003
(Warrensburg Apr_Jun-13) - (Rolla Jul_Sep-13)	-0.851081	0.1689	Inf	-5.04	0.0003
(Warrensburg Apr_Jun-15) - (Warrensburg Oct_Dec-14)	-1.343255	0.2663	Inf	-5.044	0.0003

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Rolla Apr_Jun-14) - (Warrensburg Jan_Mar-15)	-0.955562	0.1877	Inf	-5.091	0.0002
(Rolla Jan_Mar-14) - (Warrensburg Jan_Mar-15)	-0.968124	0.1912	Inf	-5.063	0.0002
(Rolla Jan_Mar-15) - (Rolla Oct_Dec-14)	-1.022667	0.1985	Inf	-5.151	0.0002
(Rolla Jul_Sep-15) - (Rolla Oct_Dec-14)	-0.995493	0.196	Inf	-5.08	0.0002
(Sedalia Jan_Mar-15) - (Sedalia Oct_Dec-14)	-0.375065	0.0732	Inf	-5.123	0.0002
(Warrensburg Apr_Jun-15) - (Rolla Jan_Mar-13)	0.970149	0.1896	Inf	5.117	0.0002
(Warrensburg Jul_Sep-15) - (Warrensburg Oct_Dec-14)	-1.33404	0.2614	Inf	-5.104	0.0002
(Rolla Apr_Jun-13) - (Warrensburg Jan_Mar-14)	-0.802485	0.1502	Inf	-5.342	0.0001
(Rolla Apr_Jun-14) - (Warrensburg Apr_Jun-15)	-0.987233	0.185	Inf	-5.338	0.0001
(Rolla Jan_Mar-13) - (Warrensburg Jul_Sep-15)	-0.979363	0.1878	Inf	-5.215	0.0001
(Rolla Jan_Mar-14) - (Sedalia Jan_Mar-15)	0.574038	0.1081	Inf	5.308	0.0001
(Rolla Jan_Mar-14) - (Sedalia Jul_Sep-15)	0.564422	0.1073	Inf	5.262	0.0001
(Sedalia Apr_Jun-15) - (Rolla Jan_Mar-14)	-0.565227	0.108	Inf	-5.235	0.0001
(Sedalia Jul_Sep-13) - (Rolla Jul_Sep-14)	-0.597501	0.1142	Inf	-5.232	0.0001
(Sedalia Jul_Sep-13) - (Rolla Oct_Dec-15)	-0.602197	0.1128	Inf	-5.339	0.0001
(Sedalia Oct_Dec-14) - (Warrensburg Oct_Dec-15)	-0.815894	0.1532	Inf	-5.327	0.0001
(Warrensburg Apr_Jun-15) - (Rolla Jan_Mar-14)	0.999796	0.1886	Inf	5.302	0.0001
(Warrensburg Jan_Mar-15) - (Warrensburg Oct_Dec-14)	-1.374926	0.2635	Inf	-5.219	0.0001
(Warrensburg Jul_Sep-14) - (Sedalia Oct_Dec-14)	0.797109	0.1512	Inf	5.273	0.0001
(Rolla Apr_Jun-13) - (Rolla Apr_Jun-15)	-0.829484	0.1298	Inf	-6.39	<.0001
(Rolla Apr_Jun-13) - (Rolla Jan_Mar-15)	-0.805565	0.128	Inf	-6.294	<.0001
(Rolla Apr_Jun-13) - (Rolla Jul_Sep-13)	-1.127511	0.1469	Inf	-7.676	<.0001
(Rolla Apr_Jun-13) - (Rolla Jul_Sep-15)	-0.832739	0.1256	Inf	-6.63	<.0001
(Rolla Apr_Jun-13) - (Rolla Oct_Dec-13)	-1.03048	0.134	Inf	-7.69	<.0001
(Rolla Apr_Jun-13) - (Rolla Oct_Dec-14)	-1.828233	0.1801	Inf	-10.151	<.0001
(Rolla Apr_Jun-13) - (Sedalia Apr_Jun-13)	0.483311	0.0475	Inf	10.167	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Apr_Jun-13)	-0.27643	0.0494	Inf	-5.59	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Apr_Jun-14)	-0.813154	0.1425	Inf	-5.707	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Apr_Jun-15)	-1.386342	0.1737	Inf	-7.982	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Jan_Mar-13)	-0.841674	0.1516	Inf	-5.553	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Jan_Mar-15)	-1.35467	0.1762	Inf	-7.688	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Jul_Sep-13)	-1.802937	0.2053	Inf	-8.782	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Jul_Sep-14)	-0.984682	0.1497	Inf	-6.578	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Jul_Sep-15)	-1.395556	0.1714	Inf	-8.142	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Oct_Dec-13)	-1.659209	0.1867	Inf	-8.889	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Oct_Dec-14)	-2.729597	0.2561	Inf	-10.658	<.0001
(Rolla Apr_Jun-13) - (Warrensburg Oct_Dec-15)	-1.003467	0.1558	Inf	-6.44	<.0001
(Rolla Apr_Jun-14) - (Rolla Oct_Dec-14)	-1.429124	0.1875	Inf	-7.624	<.0001
(Rolla Apr_Jun-14) - (Sedalia Apr_Jun-14)	0.736064	0.065	Inf	11.333	<.0001
(Rolla Apr_Jun-14) - (Sedalia Apr_Jun-15)	0.577789	0.102	Inf	5.662	<.0001
(Rolla Apr_Jun-14) - (Sedalia Jan_Mar-13)	0.730237	0.0984	Inf	7.423	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Rolla Apr_Jun-14) - (Sedalia Jan_Mar-14)	0.741163	0.0982	Inf	7.548	<.0001
(Rolla Apr_Jun-14) - (Sedalia Jan_Mar-15)	0.586601	0.1022	Inf	5.737	<.0001
(Rolla Apr_Jun-14) - (Sedalia Jul_Sep-14)	0.689199	0.0978	Inf	7.044	<.0001
(Rolla Apr_Jun-14) - (Sedalia Jul_Sep-15)	0.576984	0.1013	Inf	5.696	<.0001
(Rolla Apr_Jun-14) - (Sedalia Oct_Dec-15)	0.688462	0.0997	Inf	6.903	<.0001
(Rolla Apr_Jun-14) - (Warrensburg Apr_Jun-14)	-0.414046	0.0728	Inf	-5.691	<.0001
(Rolla Apr_Jun-14) - (Warrensburg Jul_Sep-13)	-1.403828	0.2156	Inf	-6.512	<.0001
(Rolla Apr_Jun-14) - (Warrensburg Jul_Sep-15)	-0.996448	0.183	Inf	-5.444	<.0001
(Rolla Apr_Jun-14) - (Warrensburg Oct_Dec-13)	-1.2601	0.1978	Inf	-6.372	<.0001
(Rolla Apr_Jun-14) - (Warrensburg Oct_Dec-14)	-2.330488	0.2651	Inf	-8.792	<.0001
(Rolla Apr_Jun-15) - (Sedalia Apr_Jun-15)	1.008165	0.0879	Inf	11.469	<.0001
(Rolla Apr_Jun-15) - (Sedalia Jan_Mar-13)	1.160613	0.1268	Inf	9.152	<.0001
(Rolla Apr_Jun-15) - (Sedalia Jan_Mar-14)	1.171538	0.1267	Inf	9.246	<.0001
(Rolla Apr_Jun-15) - (Sedalia Jan_Mar-15)	1.016977	0.1302	Inf	7.812	<.0001
(Rolla Apr_Jun-15) - (Sedalia Jul_Sep-13)	0.900137	0.1341	Inf	6.71	<.0001
(Rolla Apr_Jun-15) - (Sedalia Jul_Sep-14)	1.119575	0.1264	Inf	8.855	<.0001
(Rolla Apr_Jun-15) - (Sedalia Jul_Sep-15)	1.00736	0.1292	Inf	7.797	<.0001
(Rolla Apr_Jun-15) - (Sedalia Oct_Dec-13)	0.934662	0.1318	Inf	7.089	<.0001
(Rolla Apr_Jun-15) - (Sedalia Oct_Dec-15)	1.118838	0.1282	Inf	8.725	<.0001
(Rolla Apr_Jun-15) - (Warrensburg Apr_Jun-15)	-0.556858	0.0953	Inf	-5.843	<.0001
(Rolla Apr_Jun-15) - (Warrensburg Oct_Dec-14)	-1.900113	0.2807	Inf	-6.769	<.0001
(Rolla Jan_Mar-13) - (Rolla Oct_Dec-14)	-1.412039	0.1911	Inf	-7.39	<.0001
(Rolla Jan_Mar-13) - (Sedalia Jan_Mar-13)	0.747322	0.0701	Inf	10.658	<.0001
(Rolla Jan_Mar-13) - (Sedalia Jan_Mar-14)	0.758247	0.1059	Inf	7.16	<.0001
(Rolla Jan_Mar-13) - (Sedalia Jan_Mar-15)	0.603686	0.1097	Inf	5.503	<.0001
(Rolla Jan_Mar-13) - (Sedalia Jul_Sep-14)	0.706283	0.1056	Inf	6.688	<.0001
(Rolla Jan_Mar-13) - (Sedalia Jul_Sep-15)	0.594069	0.1088	Inf	5.46	<.0001
(Rolla Jan_Mar-13) - (Sedalia Oct_Dec-15)	0.705546	0.1073	Inf	6.573	<.0001
(Rolla Jan_Mar-13) - (Warrensburg Jan_Mar-13)	-0.425481	0.0754	Inf	-5.646	<.0001
(Rolla Jan_Mar-13) - (Warrensburg Jul_Sep-13)	-1.386743	0.2197	Inf	-6.312	<.0001
(Rolla Jan_Mar-13) - (Warrensburg Oct_Dec-13)	-1.243016	0.2022	Inf	-6.146	<.0001
(Rolla Jan_Mar-13) - (Warrensburg Oct_Dec-14)	-2.313404	0.2687	Inf	-8.61	<.0001
(Rolla Jan_Mar-14) - (Rolla Oct_Dec-14)	-1.441686	0.1907	Inf	-7.56	<.0001
(Rolla Jan_Mar-14) - (Sedalia Jan_Mar-14)	0.7286	0.0687	Inf	10.598	<.0001
(Rolla Jan_Mar-14) - (Sedalia Jul_Sep-14)	0.676636	0.104	Inf	6.503	<.0001
(Rolla Jan_Mar-14) - (Sedalia Oct_Dec-15)	0.675899	0.1057	Inf	6.392	<.0001
(Rolla Jan_Mar-14) - (Warrensburg Jan_Mar-14)	-0.415939	0.074	Inf	-5.618	<.0001
(Rolla Jan_Mar-14) - (Warrensburg Jul_Sep-13)	-1.416391	0.2187	Inf	-6.478	<.0001
(Rolla Jan_Mar-14) - (Warrensburg Jul_Sep-15)	-1.00901	0.1867	Inf	-5.404	<.0001
(Rolla Jan_Mar-14) - (Warrensburg Oct_Dec-13)	-1.272663	0.2011	Inf	-6.328	<.0001
(Rolla Jan_Mar-14) - (Warrensburg Oct_Dec-14)	-2.343051	0.2678	Inf	-8.75	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Rolla Jan_Mar-15) - (Sedalia Jul_Sep-14)	1.095656	0.1237	Inf	8.855	<.0001
(Rolla Jan_Mar-15) - (Sedalia Jul_Sep-15)	0.983441	0.1267	Inf	7.762	<.0001
(Rolla Jan_Mar-15) - (Sedalia Oct_Dec-13)	0.910743	0.1293	Inf	7.046	<.0001
(Rolla Jan_Mar-15) - (Sedalia Oct_Dec-15)	1.094919	0.1255	Inf	8.724	<.0001
(Rolla Jan_Mar-15) - (Warrensburg Jan_Mar-15)	-0.549105	0.0963	Inf	-5.7	<.0001
(Rolla Jan_Mar-15) - (Warrensburg Oct_Dec-14)	-1.924031	0.2763	Inf	-6.965	<.0001
(Rolla Jul_Sep-13) - (Sedalia Jul_Sep-13)	1.198163	0.1022	Inf	11.723	<.0001
(Rolla Jul_Sep-13) - (Sedalia Jul_Sep-14)	1.417601	0.1445	Inf	9.81	<.0001
(Rolla Jul_Sep-13) - (Sedalia Jul_Sep-15)	1.305386	0.1471	Inf	8.875	<.0001
(Rolla Jul_Sep-13) - (Sedalia Oct_Dec-13)	1.232689	0.1494	Inf	8.252	<.0001
(Rolla Jul_Sep-13) - (Sedalia Oct_Dec-14)	0.939938	0.1576	Inf	5.963	<.0001
(Rolla Jul_Sep-13) - (Sedalia Oct_Dec-15)	1.416864	0.1461	Inf	9.699	<.0001
(Rolla Jul_Sep-13) - (Warrensburg Jul_Sep-13)	-0.675426	0.118	Inf	-5.724	<.0001
(Rolla Jul_Sep-13) - (Warrensburg Oct_Dec-14)	-1.602086	0.2884	Inf	-5.556	<.0001
(Rolla Jul_Sep-14) - (Rolla Oct_Dec-14)	-1.301384	0.188	Inf	-6.923	<.0001
(Rolla Jul_Sep-14) - (Sedalia Jul_Sep-14)	0.816939	0.0716	Inf	11.417	<.0001
(Rolla Jul_Sep-14) - (Sedalia Jul_Sep-15)	0.704724	0.1084	Inf	6.502	<.0001
(Rolla Jul_Sep-14) - (Sedalia Oct_Dec-13)	0.632027	0.1114	Inf	5.672	<.0001
(Rolla Jul_Sep-14) - (Sedalia Oct_Dec-15)	0.816202	0.1071	Inf	7.62	<.0001
(Rolla Jul_Sep-14) - (Warrensburg Jul_Sep-14)	-0.457833	0.0799	Inf	-5.732	<.0001
(Rolla Jul_Sep-14) - (Warrensburg Oct_Dec-13)	-1.13236	0.2009	Inf	-5.637	<.0001
(Rolla Jul_Sep-14) - (Warrensburg Oct_Dec-14)	-2.202748	0.2667	Inf	-8.258	<.0001
(Rolla Jul_Sep-15) - (Sedalia Jul_Sep-15)	1.010615	0.086	Inf	11.753	<.0001
(Rolla Jul_Sep-15) - (Sedalia Oct_Dec-13)	0.937917	0.1282	Inf	7.315	<.0001
(Rolla Jul_Sep-15) - (Sedalia Oct_Dec-15)	1.122093	0.1244	Inf	9.018	<.0001
(Rolla Jul_Sep-15) - (Warrensburg Jul_Sep-15)	-0.562817	0.097	Inf	-5.805	<.0001
(Rolla Jul_Sep-15) - (Warrensburg Oct_Dec-14)	-1.896858	0.2767	Inf	-6.855	<.0001
(Rolla Oct_Dec-13) - (Sedalia Oct_Dec-13)	1.135658	0.0929	Inf	12.228	<.0001
(Rolla Oct_Dec-13) - (Sedalia Oct_Dec-14)	0.842907	0.1452	Inf	5.805	<.0001
(Rolla Oct_Dec-13) - (Sedalia Oct_Dec-15)	1.319833	0.1327	Inf	9.947	<.0001
(Rolla Oct_Dec-13) - (Warrensburg Oct_Dec-13)	-0.628729	0.1091	Inf	-5.765	<.0001
(Rolla Oct_Dec-13) - (Warrensburg Oct_Dec-14)	-1.699117	0.2808	Inf	-6.05	<.0001
(Rolla Oct_Dec-14) - (Rolla Oct_Dec-15)	1.296688	0.1919	Inf	6.755	<.0001
(Rolla Oct_Dec-14) - (Sedalia Oct_Dec-14)	1.64066	0.1341	Inf	12.239	<.0001
(Rolla Oct_Dec-14) - (Sedalia Oct_Dec-15)	2.117586	0.1837	Inf	11.53	<.0001
(Rolla Oct_Dec-14) - (Warrensburg Oct_Dec-14)	-0.901364	0.1571	Inf	-5.738	<.0001
(Rolla Oct_Dec-15) - (Sedalia Oct_Dec-15)	0.820898	0.0703	Inf	11.673	<.0001
(Rolla Oct_Dec-15) - (Warrensburg Oct_Dec-15)	-0.471922	0.0834	Inf	-5.656	<.0001
(Sedalia Apr_Jun-13) - (Rolla Apr_Jun-14)	-0.88242	0.0935	Inf	-9.438	<.0001
(Sedalia Apr_Jun-13) - (Rolla Apr_Jun-15)	-1.312796	0.1228	Inf	-10.691	<.0001
(Sedalia Apr_Jun-13) - (Rolla Jan_Mar-13)	-0.899505	0.1016	Inf	-8.857	<.0001
(Sedalia Apr_Jun-13) - (Rolla Jan_Mar-14)	-0.869857	0.1	Inf	-8.702	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Apr_Jun-13) - (Rolla Jan_Mar-15)	-1.288877	0.12	Inf	-10.74	<.0001
(Sedalia Apr_Jun-13) - (Rolla Jul_Sep-13)	-1.610822	0.1412	Inf	-11.407	<.0001
(Sedalia Apr_Jun-13) - (Rolla Jul_Sep-14)	-1.01016	0.1004	Inf	-10.057	<.0001
(Sedalia Apr_Jun-13) - (Rolla Jul_Sep-15)	-1.316051	0.1185	Inf	-11.105	<.0001
(Sedalia Apr_Jun-13) - (Rolla Oct_Dec-13)	-1.513791	0.1273	Inf	-11.888	<.0001
(Sedalia Apr_Jun-13) - (Rolla Oct_Dec-14)	-2.311544	0.1785	Inf	-12.949	<.0001
(Sedalia Apr_Jun-13) - (Rolla Oct_Dec-15)	-1.014856	0.1008	Inf	-10.072	<.0001
(Sedalia Apr_Jun-13) - (Sedalia Apr_Jun-15)	-0.30463	0.0484	Inf	-6.292	<.0001
(Sedalia Apr_Jun-13) - (Sedalia Jan_Mar-15)	-0.295819	0.0479	Inf	-6.176	<.0001
(Sedalia Apr_Jun-13) - (Sedalia Jul_Sep-13)	-0.412659	0.0555	Inf	-7.441	<.0001
(Sedalia Apr_Jun-13) - (Sedalia Jul_Sep-15)	-0.305436	0.0466	Inf	-6.55	<.0001
(Sedalia Apr_Jun-13) - (Sedalia Oct_Dec-13)	-0.378134	0.0506	Inf	-7.477	<.0001
(Sedalia Apr_Jun-13) - (Sedalia Oct_Dec-14)	-0.670884	0.0675	Inf	-9.941	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Apr_Jun-13)	-0.759741	0.0714	Inf	-10.642	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Apr_Jun-14)	-1.296465	0.1257	Inf	-10.314	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Apr_Jun-15)	-1.869653	0.1604	Inf	-11.655	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Jan_Mar-13)	-1.324985	0.1361	Inf	-9.739	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Jan_Mar-14)	-1.285796	0.1344	Inf	-9.564	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Jan_Mar-15)	-1.837982	0.1624	Inf	-11.314	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Jul_Sep-13)	-2.286248	0.1929	Inf	-11.852	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Jul_Sep-14)	-1.467993	0.1348	Inf	-10.892	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Jul_Sep-15)	-1.878868	0.158	Inf	-11.889	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Oct_Dec-13)	-2.14252	0.1733	Inf	-12.366	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Oct_Dec-14)	-3.212908	0.2464	Inf	-13.04	<.0001
(Sedalia Apr_Jun-13) - (Warrensburg Oct_Dec-15)	-1.486778	0.1389	Inf	-10.701	<.0001
(Sedalia Apr_Jun-14) - (Rolla Apr_Jun-15)	-1.166439	0.1261	Inf	-9.249	<.0001
(Sedalia Apr_Jun-14) - (Rolla Jan_Mar-13)	-0.753148	0.1052	Inf	-7.159	<.0001
(Sedalia Apr_Jun-14) - (Rolla Jan_Mar-14)	-0.723501	0.1036	Inf	-6.982	<.0001
(Sedalia Apr_Jun-14) - (Rolla Jan_Mar-15)	-1.14252	0.1235	Inf	-9.255	<.0001
(Sedalia Apr_Jun-14) - (Rolla Jul_Sep-13)	-1.464466	0.1443	Inf	-10.152	<.0001
(Sedalia Apr_Jun-14) - (Rolla Jul_Sep-14)	-0.863804	0.1046	Inf	-8.259	<.0001
(Sedalia Apr_Jun-14) - (Rolla Jul_Sep-15)	-1.169694	0.1221	Inf	-9.576	<.0001
(Sedalia Apr_Jun-14) - (Rolla Oct_Dec-13)	-1.367435	0.1307	Inf	-10.464	<.0001
(Sedalia Apr_Jun-14) - (Rolla Oct_Dec-14)	-2.165188	0.1817	Inf	-11.919	<.0001
(Sedalia Apr_Jun-14) - (Rolla Oct_Dec-15)	-0.8685	0.1042	Inf	-8.338	<.0001
(Sedalia Apr_Jun-14) - (Sedalia Oct_Dec-14)	-0.524528	0.0692	Inf	-7.578	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Apr_Jun-14)	-1.150109	0.0977	Inf	-11.775	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Apr_Jun-15)	-1.723297	0.1629	Inf	-10.576	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Jan_Mar-13)	-1.178629	0.1388	Inf	-8.494	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Jan_Mar-14)	-1.13944	0.1371	Inf	-8.309	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Jan_Mar-15)	-1.691625	0.165	Inf	-10.253	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Jul_Sep-13)	-2.139892	0.1951	Inf	-10.968	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Apr_Jun-14) - (Warrensburg Jul_Sep-14)	-1.321637	0.1379	Inf	-9.581	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Jul_Sep-15)	-1.732511	0.1608	Inf	-10.774	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Oct_Dec-13)	-1.996164	0.1757	Inf	-11.361	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Oct_Dec-14)	-3.066552	0.2488	Inf	-12.328	<.0001
(Sedalia Apr_Jun-14) - (Warrensburg Oct_Dec-15)	-1.340422	0.1413	Inf	-9.486	<.0001
(Sedalia Apr_Jun-15) - (Rolla Jan_Mar-13)	-0.594874	0.1095	Inf	-5.434	<.0001
(Sedalia Apr_Jun-15) - (Rolla Jan_Mar-15)	-0.984246	0.1274	Inf	-7.729	<.0001
(Sedalia Apr_Jun-15) - (Rolla Jul_Sep-13)	-1.306192	0.1476	Inf	-8.852	<.0001
(Sedalia Apr_Jun-15) - (Rolla Jul_Sep-14)	-0.70553	0.1092	Inf	-6.459	<.0001
(Sedalia Apr_Jun-15) - (Rolla Jul_Sep-15)	-1.01142	0.1261	Inf	-8.024	<.0001
(Sedalia Apr_Jun-15) - (Rolla Oct_Dec-13)	-1.209161	0.1344	Inf	-8.999	<.0001
(Sedalia Apr_Jun-15) - (Rolla Oct_Dec-14)	-2.006913	0.1848	Inf	-10.86	<.0001
(Sedalia Apr_Jun-15) - (Rolla Oct_Dec-15)	-0.710225	0.1084	Inf	-6.554	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Apr_Jun-15)	-1.565023	0.1262	Inf	-12.405	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Jan_Mar-13)	-1.020355	0.1432	Inf	-7.128	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Jan_Mar-14)	-0.981166	0.1416	Inf	-6.931	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Jan_Mar-15)	-1.533351	0.1692	Inf	-9.061	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Jul_Sep-13)	-1.981618	0.1989	Inf	-9.963	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Jul_Sep-14)	-1.163362	0.1428	Inf	-8.145	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Jul_Sep-15)	-1.574237	0.1651	Inf	-9.533	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Oct_Dec-13)	-1.83789	0.1798	Inf	-10.219	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Oct_Dec-14)	-2.908278	0.2526	Inf	-11.514	<.0001
(Sedalia Apr_Jun-15) - (Warrensburg Oct_Dec-15)	-1.182148	0.1456	Inf	-8.118	<.0001
(Sedalia Jan_Mar-13) - (Rolla Jan_Mar-14)	-0.717675	0.1045	Inf	-6.867	<.0001
(Sedalia Jan_Mar-13) - (Rolla Jan_Mar-15)	-1.136694	0.1242	Inf	-9.152	<.0001
(Sedalia Jan_Mar-13) - (Rolla Jul_Sep-13)	-1.45864	0.1449	Inf	-10.069	<.0001
(Sedalia Jan_Mar-13) - (Rolla Jul_Sep-14)	-0.857978	0.1055	Inf	-8.133	<.0001
(Sedalia Jan_Mar-13) - (Rolla Jul_Sep-15)	-1.163868	0.1229	Inf	-9.47	<.0001
(Sedalia Jan_Mar-13) - (Rolla Oct_Dec-13)	-1.361609	0.1314	Inf	-10.365	<.0001
(Sedalia Jan_Mar-13) - (Rolla Oct_Dec-14)	-2.159361	0.1822	Inf	-11.854	<.0001
(Sedalia Jan_Mar-13) - (Rolla Oct_Dec-15)	-0.862673	0.105	Inf	-8.215	<.0001
(Sedalia Jan_Mar-13) - (Sedalia Oct_Dec-14)	-0.518702	0.0706	Inf	-7.35	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Jan_Mar-13)	-1.172803	0.1052	Inf	-11.152	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Jan_Mar-14)	-1.133614	0.1381	Inf	-8.211	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Jan_Mar-15)	-1.685799	0.1658	Inf	-10.166	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Jul_Sep-13)	-2.134065	0.1958	Inf	-10.896	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Jul_Sep-14)	-1.31581	0.1389	Inf	-9.471	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Jul_Sep-15)	-1.726685	0.1617	Inf	-10.681	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Oct_Dec-13)	-1.990338	0.1765	Inf	-11.276	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Oct_Dec-14)	-3.060726	0.2494	Inf	-12.27	<.0001
(Sedalia Jan_Mar-13) - (Warrensburg Oct_Dec-15)	-1.334596	0.1422	Inf	-9.386	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Jan_Mar-14) - (Rolla Jan_Mar-15)	-1.147619	0.124	Inf	-9.252	<.0001
(Sedalia Jan_Mar-14) - (Rolla Jul_Sep-13)	-1.469565	0.1447	Inf	-10.153	<.0001
(Sedalia Jan_Mar-14) - (Rolla Jul_Sep-14)	-0.868903	0.1053	Inf	-8.25	<.0001
(Sedalia Jan_Mar-14) - (Rolla Jul_Sep-15)	-1.174793	0.1228	Inf	-9.57	<.0001
(Sedalia Jan_Mar-14) - (Rolla Oct_Dec-13)	-1.372534	0.1312	Inf	-10.459	<.0001
(Sedalia Jan_Mar-14) - (Rolla Oct_Dec-14)	-2.170287	0.1821	Inf	-11.921	<.0001
(Sedalia Jan_Mar-14) - (Rolla Oct_Dec-15)	-0.873599	0.1048	Inf	-8.333	<.0001
(Sedalia Jan_Mar-14) - (Sedalia Oct_Dec-14)	-0.529627	0.0704	Inf	-7.526	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Jan_Mar-14)	-1.144539	0.1038	Inf	-11.03	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Jan_Mar-15)	-1.696725	0.1656	Inf	-10.248	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Jul_Sep-13)	-2.144991	0.1956	Inf	-10.966	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Jul_Sep-14)	-1.326736	0.1386	Inf	-9.569	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Jul_Sep-15)	-1.737611	0.1614	Inf	-10.765	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Oct_Dec-13)	-2.001263	0.1763	Inf	-11.354	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Oct_Dec-14)	-3.071651	0.2492	Inf	-12.326	<.0001
(Sedalia Jan_Mar-14) - (Warrensburg Oct_Dec-15)	-1.345521	0.1419	Inf	-9.48	<.0001
(Sedalia Jan_Mar-15) - (Rolla Jul_Sep-13)	-1.315003	0.1478	Inf	-8.894	<.0001
(Sedalia Jan_Mar-15) - (Rolla Jul_Sep-14)	-0.714341	0.1094	Inf	-6.531	<.0001
(Sedalia Jan_Mar-15) - (Rolla Jul_Sep-15)	-1.020232	0.1264	Inf	-8.071	<.0001
(Sedalia Jan_Mar-15) - (Rolla Oct_Dec-13)	-1.217972	0.1346	Inf	-9.048	<.0001
(Sedalia Jan_Mar-15) - (Rolla Oct_Dec-14)	-2.015725	0.185	Inf	-10.898	<.0001
(Sedalia Jan_Mar-15) - (Rolla Oct_Dec-15)	-0.719037	0.1085	Inf	-6.627	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Jan_Mar-15)	-1.542163	0.1283	Inf	-12.025	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Jul_Sep-13)	-1.990429	0.1977	Inf	-10.068	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Jul_Sep-14)	-1.172174	0.1416	Inf	-8.278	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Jul_Sep-15)	-1.583049	0.164	Inf	-9.652	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Oct_Dec-13)	-1.846701	0.1786	Inf	-10.342	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Oct_Dec-14)	-2.917089	0.2511	Inf	-11.616	<.0001
(Sedalia Jan_Mar-15) - (Warrensburg Oct_Dec-15)	-1.190959	0.1444	Inf	-8.248	<.0001
(Sedalia Jul_Sep-13) - (Rolla Jul_Sep-15)	-0.903392	0.1306	Inf	-6.915	<.0001
(Sedalia Jul_Sep-13) - (Rolla Oct_Dec-13)	-1.101133	0.1386	Inf	-7.946	<.0001
(Sedalia Jul_Sep-13) - (Rolla Oct_Dec-14)	-1.898885	0.1884	Inf	-10.077	<.0001
(Sedalia Jul_Sep-13) - (Warrensburg Jul_Sep-13)	-1.873589	0.1539	Inf	-12.171	<.0001
(Sedalia Jul_Sep-13) - (Warrensburg Jul_Sep-14)	-1.055334	0.1457	Inf	-7.244	<.0001
(Sedalia Jul_Sep-13) - (Warrensburg Jul_Sep-15)	-1.466209	0.1676	Inf	-8.747	<.0001
(Sedalia Jul_Sep-13) - (Warrensburg Oct_Dec-13)	-1.729861	0.1818	Inf	-9.513	<.0001
(Sedalia Jul_Sep-13) - (Warrensburg Oct_Dec-14)	-2.800249	0.2541	Inf	-11.021	<.0001
(Sedalia Jul_Sep-13) - (Warrensburg Oct_Dec-15)	-1.07412	0.1478	Inf	-7.266	<.0001
(Sedalia Jul_Sep-14) - (Rolla Jul_Sep-15)	-1.12283	0.1224	Inf	-9.175	<.0001
(Sedalia Jul_Sep-14) - (Rolla Oct_Dec-13)	-1.32057	0.1309	Inf	-10.085	<.0001
(Sedalia Jul_Sep-14) - (Rolla Oct_Dec-14)	-2.118323	0.1816	Inf	-11.662	<.0001
(Sedalia Jul_Sep-14) - (Rolla Oct_Dec-15)	-0.821635	0.1047	Inf	-7.849	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Sedalia Jul_Sep-14) - (Sedalia Oct_Dec-14)	-0.477663	0.07	Inf	-6.822	<.0001
(Sedalia Jul_Sep-14) - (Warrensburg Jul_Sep-14)	-1.274772	0.1064	Inf	-11.98	<.0001
(Sedalia Jul_Sep-14) - (Warrensburg Jul_Sep-15)	-1.685647	0.1611	Inf	-10.465	<.0001
(Sedalia Jul_Sep-14) - (Warrensburg Oct_Dec-13)	-1.949299	0.176	Inf	-11.075	<.0001
(Sedalia Jul_Sep-14) - (Warrensburg Oct_Dec-14)	-3.019687	0.2488	Inf	-12.137	<.0001
(Sedalia Jul_Sep-14) - (Warrensburg Oct_Dec-15)	-1.293557	0.1418	Inf	-9.12	<.0001
(Sedalia Jul_Sep-15) - (Rolla Oct_Dec-13)	-1.208356	0.1338	Inf	-9.032	<.0001
(Sedalia Jul_Sep-15) - (Rolla Oct_Dec-14)	-2.006108	0.1842	Inf	-10.89	<.0001
(Sedalia Jul_Sep-15) - (Rolla Oct_Dec-15)	-0.70942	0.1077	Inf	-6.585	<.0001
(Sedalia Jul_Sep-15) - (Warrensburg Jul_Sep-15)	-1.573432	0.126	Inf	-12.49	<.0001
(Sedalia Jul_Sep-15) - (Warrensburg Oct_Dec-13)	-1.837084	0.1787	Inf	-10.28	<.0001
(Sedalia Jul_Sep-15) - (Warrensburg Oct_Dec-14)	-2.907472	0.2514	Inf	-11.567	<.0001
(Sedalia Jul_Sep-15) - (Warrensburg Oct_Dec-15)	-1.181343	0.1445	Inf	-8.173	<.0001
(Sedalia Oct_Dec-13) - (Rolla Oct_Dec-14)	-1.93341	0.1866	Inf	-10.363	<.0001
(Sedalia Oct_Dec-13) - (Rolla Oct_Dec-15)	-0.636722	0.1102	Inf	-5.777	<.0001
(Sedalia Oct_Dec-13) - (Warrensburg Oct_Dec-13)	-1.764387	0.1389	Inf	-12.706	<.0001
(Sedalia Oct_Dec-13) - (Warrensburg Oct_Dec-14)	-2.834775	0.2525	Inf	-11.226	<.0001
(Sedalia Oct_Dec-13) - (Warrensburg Oct_Dec-15)	-1.108645	0.1458	Inf	-7.606	<.0001
(Sedalia Oct_Dec-14) - (Sedalia Oct_Dec-15)	0.476926	0.0699	Inf	6.819	<.0001
(Sedalia Oct_Dec-14) - (Warrensburg Oct_Dec-14)	-2.542024	0.2014	Inf	-12.623	<.0001
(Sedalia Oct_Dec-15) - (Warrensburg Oct_Dec-15)	-1.29282	0.1088	Inf	-11.883	<.0001
(Warrensburg Apr_Jun-13) - (Rolla Oct_Dec-14)	-1.551803	0.2002	Inf	-7.75	<.0001
(Warrensburg Apr_Jun-13) - (Sedalia Apr_Jun-14)	0.613385	0.0987	Inf	6.216	<.0001
(Warrensburg Apr_Jun-13) - (Sedalia Jan_Mar-13)	0.607558	0.0999	Inf	6.082	<.0001
(Warrensburg Apr_Jun-13) - (Sedalia Jan_Mar-14)	0.618484	0.0996	Inf	6.21	<.0001
(Warrensburg Apr_Jun-13) - (Sedalia Jul_Sep-14)	0.56652	0.0992	Inf	5.713	<.0001
(Warrensburg Apr_Jun-13) - (Sedalia Oct_Dec-15)	0.565783	0.1007	Inf	5.618	<.0001
(Warrensburg Apr_Jun-13) - (Warrensburg Apr_Jun-15)	-1.109912	0.1709	Inf	-6.496	<.0001
(Warrensburg Apr_Jun-13) - (Warrensburg Jan_Mar-15)	-1.078241	0.1713	Inf	-6.294	<.0001
(Warrensburg Apr_Jun-13) - (Warrensburg Jul_Sep-13)	-1.526507	0.1982	Inf	-7.7	<.0001
(Warrensburg Apr_Jun-13) - (Warrensburg Jul_Sep-15)	-1.119127	0.1672	Inf	-6.694	<.0001
(Warrensburg Apr_Jun-13) - (Warrensburg Oct_Dec-13)	-1.382779	0.18	Inf	-7.682	<.0001
(Warrensburg Apr_Jun-13) - (Warrensburg Oct_Dec-14)	-2.453167	0.245	Inf	-10.013	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Apr_Jun-15)	0.991835	0.1333	Inf	7.439	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Jan_Mar-13)	1.144283	0.1296	Inf	8.83	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Jan_Mar-14)	1.155208	0.1293	Inf	8.933	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Jan_Mar-15)	1.000646	0.1322	Inf	7.568	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Jul_Sep-13)	0.883807	0.1362	Inf	6.491	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Jul_Sep-14)	1.103244	0.129	Inf	8.55	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Jul_Sep-15)	0.99103	0.1321	Inf	7.499	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Oct_Dec-13)	0.918332	0.1338	Inf	6.861	<.0001
(Warrensburg Apr_Jun-14) - (Sedalia Oct_Dec-15)	1.102507	0.1301	Inf	8.472	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Warrensburg Apr_Jun-14) - (Warrensburg Oct_Dec-14)	-1.916443	0.2516	Inf	-7.618	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Jan_Mar-13)	1.717471	0.1638	Inf	10.487	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Jan_Mar-14)	1.728396	0.1635	Inf	10.568	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Jan_Mar-15)	1.573834	0.166	Inf	9.479	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Jul_Sep-13)	1.456994	0.1694	Inf	8.6	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Jul_Sep-14)	1.676432	0.1633	Inf	10.266	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Jul_Sep-15)	1.564218	0.166	Inf	9.425	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Oct_Dec-13)	1.49152	0.1675	Inf	8.905	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Oct_Dec-14)	1.198769	0.1744	Inf	6.875	<.0001
(Warrensburg Apr_Jun-15) - (Sedalia Oct_Dec-15)	1.675695	0.1644	Inf	10.195	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Jan_Mar-14)	1.183728	0.1394	Inf	8.491	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Jan_Mar-15)	1.029166	0.1421	Inf	7.241	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Jul_Sep-13)	0.912327	0.1458	Inf	6.256	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Jul_Sep-14)	1.131764	0.1392	Inf	8.132	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Jul_Sep-15)	1.01955	0.1421	Inf	7.176	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Oct_Dec-13)	0.946852	0.1437	Inf	6.591	<.0001
(Warrensburg Jan_Mar-13) - (Sedalia Oct_Dec-15)	1.131027	0.1402	Inf	8.069	<.0001
(Warrensburg Jan_Mar-13) - (Warrensburg Oct_Dec-14)	-1.887923	0.257	Inf	-7.345	<.0001
(Warrensburg Jan_Mar-14) - (Sedalia Jan_Mar-15)	0.989977	0.1405	Inf	7.045	<.0001
(Warrensburg Jan_Mar-14) - (Sedalia Jul_Sep-13)	0.873137	0.1442	Inf	6.054	<.0001
(Warrensburg Jan_Mar-14) - (Sedalia Jul_Sep-14)	1.092575	0.1376	Inf	7.942	<.0001
(Warrensburg Jan_Mar-14) - (Sedalia Jul_Sep-15)	0.980361	0.1405	Inf	6.979	<.0001
(Warrensburg Jan_Mar-14) - (Sedalia Oct_Dec-13)	0.907663	0.142	Inf	6.39	<.0001
(Warrensburg Jan_Mar-14) - (Sedalia Oct_Dec-15)	1.091838	0.1385	Inf	7.882	<.0001
(Warrensburg Jan_Mar-14) - (Warrensburg Oct_Dec-14)	-1.927112	0.2564	Inf	-7.516	<.0001
(Warrensburg Jan_Mar-15) - (Sedalia Jul_Sep-13)	1.425323	0.1714	Inf	8.316	<.0001
(Warrensburg Jan_Mar-15) - (Sedalia Jul_Sep-14)	1.644761	0.1653	Inf	9.95	<.0001
(Warrensburg Jan_Mar-15) - (Sedalia Jul_Sep-15)	1.532546	0.1681	Inf	9.118	<.0001
(Warrensburg Jan_Mar-15) - (Sedalia Oct_Dec-13)	1.459848	0.1694	Inf	8.615	<.0001
(Warrensburg Jan_Mar-15) - (Sedalia Oct_Dec-14)	1.167098	0.1761	Inf	6.628	<.0001
(Warrensburg Jan_Mar-15) - (Sedalia Oct_Dec-15)	1.644024	0.1663	Inf	9.886	<.0001
(Warrensburg Jul_Sep-13) - (Rolla Jul_Sep-14)	1.276088	0.2186	Inf	5.839	<.0001
(Warrensburg Jul_Sep-13) - (Rolla Oct_Dec-15)	1.271392	0.2196	Inf	5.788	<.0001
(Warrensburg Jul_Sep-13) - (Sedalia Jul_Sep-14)	2.093027	0.1954	Inf	10.71	<.0001
(Warrensburg Jul_Sep-13) - (Sedalia Jul_Sep-15)	1.980812	0.1979	Inf	10.011	<.0001
(Warrensburg Jul_Sep-13) - (Sedalia Oct_Dec-13)	1.908114	0.199	Inf	9.589	<.0001
(Warrensburg Jul_Sep-13) - (Sedalia Oct_Dec-14)	1.615364	0.2048	Inf	7.888	<.0001
(Warrensburg Jul_Sep-13) - (Sedalia Oct_Dec-15)	2.09229	0.1962	Inf	10.663	<.0001
(Warrensburg Jul_Sep-14) - (Sedalia Jul_Sep-15)	1.162557	0.1415	Inf	8.215	<.0001
(Warrensburg Jul_Sep-14) - (Sedalia Oct_Dec-13)	1.089859	0.1434	Inf	7.602	<.0001
(Warrensburg Jul_Sep-14) - (Sedalia Oct_Dec-15)	1.274035	0.1397	Inf	9.118	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Warrensburg Jul_Sep-14) - (Warrensburg Oct_Dec-14)	-1.744915	0.2518	Inf	-6.931	<.0001
(Warrensburg Jul_Sep-15) - (Sedalia Oct_Dec-13)	1.500734	0.1656	Inf	9.063	<.0001
(Warrensburg Jul_Sep-15) - (Sedalia Oct_Dec-14)	1.207984	0.1725	Inf	7.003	<.0001
(Warrensburg Jul_Sep-15) - (Sedalia Oct_Dec-15)	1.68491	0.1623	Inf	10.379	<.0001
(Warrensburg Oct_Dec-13) - (Rolla Oct_Dec-15)	1.127664	0.2022	Inf	5.577	<.0001
(Warrensburg Oct_Dec-13) - (Sedalia Oct_Dec-14)	1.471636	0.1863	Inf	7.899	<.0001
(Warrensburg Oct_Dec-13) - (Sedalia Oct_Dec-15)	1.948562	0.1769	Inf	11.012	<.0001
(Warrensburg Oct_Dec-14) - (Rolla Oct_Dec-15)	2.198052	0.2692	Inf	8.166	<.0001
(Warrensburg Oct_Dec-14) - (Sedalia Oct_Dec-15)	3.01895	0.25	Inf	12.074	<.0001
(Warrensburg Oct_Dec-14) - (Warrensburg Oct_Dec-15)	1.72613	0.2564	Inf	6.733	<.0001

Table C. 3 Statistical comparison of metropolitan urban cities for quarter-year periods

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Kansas Apr_Jun-13) - (StLouis Oct_Dec-14)	0.02464	0.02459	Inf	1.002	1
(Kansas Jan_Mar-14) - (Springfield Jul_Sep-15)	0.02349	0.01717	Inf	1.368	1
(Kansas Jan_Mar-15) - (Kansas Jul_Sep-14)	-0.00118	0.02317	Inf	-0.051	1
(Kansas Jan_Mar-15) - (Kansas Oct_Dec-13)	-0.03607	0.02507	Inf	-1.439	1
(Kansas Jul_Sep-13) - (Kansas Oct_Dec-13)	0.01886	0.02733	Inf	0.69	1
(Kansas Jul_Sep-14) - (Kansas Oct_Dec-13)	-0.03489	0.02547	Inf	-1.37	1
(Springfield Apr_Jun-13) - (Springfield Jan_Mar-13)	-0.0021	0.01323	Inf	-0.159	1
(Springfield Apr_Jun-13) - (Springfield Jul_Sep-14)	-0.01087	0.01296	Inf	-0.839	1
(Springfield Apr_Jun-13) - (StLouis Jan_Mar-15)	-0.00573	0.0136	Inf	-0.422	1
(Springfield Apr_Jun-13) - (StLouis Oct_Dec-13)	0.0141	0.01404	Inf	1.004	1
(Springfield Apr_Jun-14) - (Springfield Jul_Sep-15)	-0.00521	0.01508	Inf	-0.346	1
(Springfield Apr_Jun-14) - (Springfield Oct_Dec-13)	0.01028	0.01484	Inf	0.692	1
(Springfield Apr_Jun-14) - (StLouis Jul_Sep-15)	0.02329	0.01555	Inf	1.498	1
(Springfield Apr_Jun-15) - (Kansas Jan_Mar-13)	0.01653	0.02408	Inf	0.686	1
(Springfield Apr_Jun-15) - (StLouis Oct_Dec-14)	-0.02004	0.02429	Inf	-0.825	1
(Springfield Jan_Mar-13) - (Springfield Jul_Sep-14)	-0.00877	0.0131	Inf	-0.67	1
(Springfield Jan_Mar-13) - (StLouis Jan_Mar-15)	-0.00363	0.01396	Inf	-0.26	1
(Springfield Jan_Mar-13) - (StLouis Oct_Dec-13)	0.01621	0.01446	Inf	1.121	1
(Springfield Jan_Mar-15) - (StLouis Jul_Sep-13)	0.01445	0.01382	Inf	1.046	1
(Springfield Jan_Mar-15) - (StLouis Jul_Sep-14)	-0.00171	0.01317	Inf	-0.13	1
(Springfield Jan_Mar-15) - (StLouis Oct_Dec-13)	-0.00815	0.01416	Inf	-0.576	1
(Springfield Jul_Sep-13) - (Springfield Oct_Dec-14)	-0.02348	0.01694	Inf	-1.386	1
(Springfield Jul_Sep-14) - (StLouis Jul_Sep-15)	-0.01617	0.01462	Inf	-1.106	1
(Springfield Jul_Sep-15) - (Springfield Oct_Dec-13)	0.01549	0.01452	Inf	1.067	1
(StLouis Apr_Jun-13) - (Springfield Jan_Mar-14)	0.00843	0.01102	Inf	0.766	1
(StLouis Apr_Jun-13) - (StLouis Apr_Jun-14)	-0.00995	0.00993	Inf	-1.002	1
(StLouis Apr_Jun-15) - (Kansas Jul_Sep-13)	0.03008	0.02937	Inf	1.024	1
(StLouis Apr_Jun-15) - (Kansas Jul_Sep-15)	-0.02194	0.02975	Inf	-0.738	1
(StLouis Jan_Mar-15) - (Springfield Jul_Sep-14)	-0.00514	0.01403	Inf	-0.366	1
(StLouis Jul_Sep-13) - (StLouis Jul_Sep-14)	-0.01616	0.01139	Inf	-1.418	1
(StLouis Jul_Sep-14) - (StLouis Oct_Dec-13)	-0.00645	0.01161	Inf	-0.555	1
(StLouis Jul_Sep-15) - (Springfield Oct_Dec-13)	-0.01301	0.0148	Inf	-0.879	1
(Kansas Jan_Mar-13) - (StLouis Oct_Dec-14)	-0.03657	0.0233	Inf	-1.57	0.9999
(Springfield Apr_Jun-13) - (StLouis Jul_Sep-14)	0.02055	0.01326	Inf	1.55	0.9999
(StLouis Apr_Jun-14) - (Springfield Jan_Mar-14)	0.01838	0.01135	Inf	1.62	0.9998
(StLouis Jan_Mar-15) - (StLouis Oct_Dec-13)	0.01984	0.01219	Inf	1.627	0.9998
(Springfield Jan_Mar-13) - (StLouis Jul_Sep-14)	0.02265	0.01364	Inf	1.661	0.9997
(Springfield Jul_Sep-14) - (StLouis Oct_Dec-13)	0.02497	0.01481	Inf	1.686	0.9996
(StLouis Apr_Jun-15) - (Kansas Oct_Dec-13)	0.04894	0.02898	Inf	1.689	0.9996
(Springfield Jan_Mar-13) - (StLouis Jul_Sep-15)	-0.02493	0.01453	Inf	-1.716	0.9995

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Kansas Apr_Jun-13) - (Springfield Apr_Jun-15)	0.04468	0.02573	Inf	1.736	0.9994
(StLouis Jan_Mar-15) - (StLouis Jul_Sep-15)	-0.0213	0.01227	Inf	-1.736	0.9994
(Kansas Apr_Jun-14) - (Kansas Jan_Mar-15)	-0.04232	0.02416	Inf	-1.751	0.9992
(Kansas Apr_Jun-14) - (Kansas Jul_Sep-14)	-0.0435	0.02459	Inf	-1.769	0.9991
(Springfield Apr_Jun-14) - (Kansas Jan_Mar-14)	-0.0287	0.01625	Inf	-1.767	0.9991
(Springfield Apr_Jun-13) - (Springfield Jan_Mar-15)	0.02226	0.01217	Inf	1.829	0.9983
(Kansas Jul_Sep-13) - (Kansas Jul_Sep-15)	-0.05202	0.02797	Inf	-1.86	0.9976
(Springfield Apr_Jun-13) - (StLouis Jul_Sep-15)	-0.02704	0.01418	Inf	-1.907	0.9963
(StLouis Jul_Sep-13) - (StLouis Oct_Dec-13)	-0.02261	0.01164	Inf	-1.943	0.9949
(Springfield Jan_Mar-13) - (Springfield Jan_Mar-15)	0.02436	0.01233	Inf	1.975	0.9933
(StLouis Jan_Mar-13) - (Springfield Oct_Dec-15)	0.02303	0.01127	Inf	2.043	0.9885
(Kansas Jul_Sep-13) - (Kansas Jul_Sep-14)	0.05376	0.02626	Inf	2.047	0.9882
(Kansas Jan_Mar-14) - (Springfield Jul_Sep-13)	-0.03719	0.0179	Inf	-2.077	0.9852
(Kansas Jan_Mar-15) - (Kansas Jul_Sep-13)	-0.05494	0.02595	Inf	-2.117	0.9805
(Kansas Apr_Jun-13) - (Kansas Apr_Jun-14)	-0.05103	0.02371	Inf	-2.152	0.9753
(Springfield Jul_Sep-14) - (Springfield Oct_Dec-13)	-0.02918	0.01346	Inf	-2.168	0.9726
(StLouis Jan_Mar-15) - (StLouis Jul_Sep-14)	0.02628	0.01149	Inf	2.287	0.9451
(Springfield Jul_Sep-15) - (StLouis Jul_Sep-15)	0.0285	0.01233	Inf	2.311	0.9377
(StLouis Jan_Mar-15) - (Springfield Oct_Dec-13)	-0.03431	0.01422	Inf	-2.413	0.8982
(Kansas Jan_Mar-14) - (Springfield Oct_Dec-13)	0.03898	0.01592	Inf	2.449	0.8811
(Kansas Jul_Sep-15) - (Kansas Oct_Dec-13)	0.07089	0.0272	Inf	2.606	0.7874
(Springfield Jan_Mar-15) - (StLouis Jan_Mar-15)	-0.02799	0.01071	Inf	-2.613	0.7828
(Springfield Apr_Jun-13) - (StLouis Jul_Sep-13)	0.03671	0.01379	Inf	2.663	0.7465
(Springfield Jan_Mar-13) - (StLouis Jul_Sep-13)	0.03881	0.0142	Inf	2.733	0.6924
(Springfield Jan_Mar-13) - (Springfield Oct_Dec-13)	-0.03795	0.01385	Inf	-2.739	0.687
(Springfield Apr_Jun-14) - (Springfield Jul_Sep-14)	0.03946	0.01418	Inf	2.782	0.6522
(StLouis Jan_Mar-13) - (Springfield Jan_Mar-14)	-0.02857	0.01018	Inf	-2.805	0.6328
(Kansas Apr_Jun-13) - (Kansas Jan_Mar-13)	0.0612	0.02171	Inf	2.819	0.6216
(Springfield Jan_Mar-15) - (Springfield Jul_Sep-14)	-0.03313	0.01163	Inf	-2.849	0.5959
(Kansas Apr_Jun-14) - (StLouis Oct_Dec-14)	0.07567	0.02608	Inf	2.902	0.5509
(StLouis Jan_Mar-14) - (Springfield Oct_Dec-15)	-0.02985	0.01027	Inf	-2.906	0.547
(Springfield Apr_Jun-13) - (Springfield Oct_Dec-13)	-0.04005	0.01364	Inf	-2.937	0.521
(Springfield Apr_Jun-14) - (StLouis Jan_Mar-15)	0.04459	0.01505	Inf	2.962	0.4995
(StLouis Apr_Jun-14) - (StLouis Jul_Sep-13)	-0.03217	0.01075	Inf	-2.992	0.4745
(Springfield Jul_Sep-14) - (StLouis Jul_Sep-14)	0.03142	0.0104	Inf	3.021	0.4505
(StLouis Apr_Jun-15) - (Kansas Jan_Mar-15)	0.08502	0.02787	Inf	3.05	0.4263
(Kansas Apr_Jun-14) - (Kansas Oct_Dec-13)	-0.07839	0.02569	Inf	-3.051	0.4255
(StLouis Apr_Jun-15) - (Kansas Jul_Sep-14)	0.08384	0.02743	Inf	3.057	0.4213
(StLouis Jan_Mar-15) - (Springfield Jul_Sep-15)	-0.0498	0.01557	Inf	-3.199	0.3134
(Kansas Jan_Mar-14) - (Springfield Oct_Dec-14)	-0.06067	0.01858	Inf	-3.264	0.2698
(StLouis Jul_Sep-13) - (Springfield Jul_Sep-14)	-0.04758	0.01457	Inf	-3.266	0.2688
(StLouis Jul_Sep-15) - (StLouis Oct_Dec-13)	0.04114	0.0126	Inf	3.266	0.2687

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Springfield Apr_Jun-14) - (Springfield Jan_Mar-13)	0.04823	0.01443	Inf	3.341	0.2235
(Springfield Jul_Sep-14) - (Springfield Jul_Sep-15)	-0.04467	0.01331	Inf	-3.355	0.2156
(Kansas Jan_Mar-14) - (StLouis Jul_Sep-15)	0.05199	0.01542	Inf	3.371	0.207
(StLouis Jan_Mar-15) - (StLouis Jul_Sep-13)	0.04244	0.01216	Inf	3.489	0.1502
(Springfield Jan_Mar-15) - (StLouis Jul_Sep-15)	-0.04929	0.01412	Inf	-3.49	0.1496
(Kansas Apr_Jun-14) - (Springfield Apr_Jun-15)	0.09571	0.02719	Inf	3.52	0.1373
(Springfield Apr_Jun-13) - (Springfield Apr_Jun-14)	-0.05033	0.0142	Inf	-3.543	0.1283
(StLouis Apr_Jun-14) - (Springfield Jan_Mar-15)	-0.04662	0.01308	Inf	-3.565	0.1204
(Kansas Apr_Jun-14) - (Kansas Jul_Sep-13)	-0.09726	0.02652	Inf	-3.668	0.0878
(Springfield Jul_Sep-13) - (Springfield Jul_Sep-15)	0.06067	0.01613	Inf	3.761	0.0648
(Springfield Jan_Mar-13) - (Springfield Jul_Sep-15)	-0.05344	0.01412	Inf	-3.783	0.0601
(Springfield Apr_Jun-13) - (Springfield Jul_Sep-15)	-0.05554	0.01404	Inf	-3.956	0.0327
(Springfield Apr_Jun-14) - (Springfield Jul_Sep-13)	-0.06588	0.01661	Inf	-3.966	0.0316
(StLouis Jul_Sep-14) - (StLouis Jul_Sep-15)	-0.04759	0.01199	Inf	-3.968	0.0314
(StLouis Apr_Jun-13) - (StLouis Jul_Sep-13)	-0.04212	0.01057	Inf	-3.984	0.0296
(Kansas Jan_Mar-13) - (Springfield Oct_Dec-14)	0.08716	0.02187	Inf	3.985	0.0294
(Kansas Apr_Jun-13) - (Kansas Jul_Sep-14)	-0.09453	0.02335	Inf	-4.048	0.0232
(Kansas Apr_Jun-13) - (Kansas Jan_Mar-15)	-0.09335	0.02292	Inf	-4.074	0.0211
(StLouis Apr_Jun-13) - (StLouis Jan_Mar-13)	0.037	0.00903	Inf	4.1	0.0191
(Springfield Jan_Mar-14) - (StLouis Jul_Sep-13)	-0.05055	0.01219	Inf	-4.145	0.0159
(Kansas Jul_Sep-14) - (Kansas Jul_Sep-15)	-0.10578	0.02547	Inf	-4.154	0.0154
(Springfield Apr_Jun-14) - (StLouis Oct_Dec-13)	0.06443	0.01535	Inf	4.198	0.0129
(Kansas Jan_Mar-14) - (Springfield Jul_Sep-14)	0.06815	0.01596	Inf	4.271	0.0096
(Kansas Jan_Mar-15) - (Kansas Jul_Sep-15)	-0.10696	0.0249	Inf	-4.295	0.0087
(Springfield Jul_Sep-15) - (StLouis Oct_Dec-13)	0.06964	0.01617	Inf	4.307	0.0083
(StLouis Jul_Sep-14) - (Springfield Oct_Dec-13)	-0.0606	0.01398	Inf	-4.335	0.0073
(StLouis Apr_Jun-13) - (Springfield Jan_Mar-15)	-0.05657	0.01278	Inf	-4.427	0.005
(StLouis Apr_Jun-14) - (StLouis Jul_Sep-14)	-0.04833	0.01082	Inf	-4.464	0.0042
(Kansas Apr_Jun-14) - (StLouis Apr_Jun-15)	-0.12734	0.02845	Inf	-4.476	0.004
(Springfield Jan_Mar-14) - (Springfield Oct_Dec-15)	0.0516	0.01145	Inf	4.505	0.0035
(Kansas Jan_Mar-15) - (StLouis Oct_Dec-14)	0.11799	0.02508	Inf	4.704	0.0014
(Springfield Jul_Sep-13) - (Springfield Oct_Dec-13)	0.07616	0.01601	Inf	4.758	0.0011
(Kansas Jul_Sep-14) - (StLouis Oct_Dec-14)	0.11917	0.02482	Inf	4.802	0.0009
(Springfield Apr_Jun-14) - (StLouis Jul_Sep-14)	0.07088	0.01466	Inf	4.835	0.0008
(Kansas Apr_Jun-14) - (Kansas Jan_Mar-13)	0.11224	0.023	Inf	4.879	0.0006
(Springfield Jan_Mar-15) - (Springfield Oct_Dec-13)	-0.0623	0.01278	Inf	-4.874	0.0006
(StLouis Apr_Jun-14) - (StLouis Oct_Dec-13)	-0.05477	0.01113	Inf	-4.919	0.0005
(Kansas Jan_Mar-14) - (StLouis Jan_Mar-15)	0.07329	0.01481	Inf	4.948	0.0004
(Springfield Jan_Mar-13) - (Kansas Jan_Mar-14)	-0.07692	0.01553	Inf	-4.954	0.0004
(StLouis Apr_Jun-13) - (Springfield Oct_Dec-15)	0.06003	0.01196	Inf	5.02	0.0003
(StLouis Jul_Sep-14) - (Springfield Jul_Sep-15)	-0.07609	0.01521	Inf	-5.002	0.0003

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Springfield Oct_Dec-13) - (StLouis Oct_Dec-13)	0.05415	0.01061	Inf	5.104	0.0002
(StLouis Apr_Jun-14) - (StLouis Jan_Mar-13)	0.04695	0.00928	Inf	5.06	0.0002
(StLouis Jul_Sep-13) - (StLouis Jul_Sep-15)	-0.06375	0.01249	Inf	-5.105	0.0002
(Kansas Jan_Mar-13) - (Springfield Jul_Sep-13)	0.11064	0.0211	Inf	5.243	0.0001
(Springfield Apr_Jun-13) - (Kansas Jan_Mar-14)	-0.07903	0.01509	Inf	-5.238	0.0001
(Springfield Apr_Jun-13) - (StLouis Apr_Jun-14)	0.06888	0.01304	Inf	5.284	0.0001
(Springfield Jul_Sep-13) - (StLouis Jul_Sep-15)	0.08917	0.01673	Inf	5.33	0.0001
(StLouis Apr_Jun-14) - (Springfield Jan_Mar-13)	-0.07098	0.01348	Inf	-5.264	0.0001
(StLouis Jul_Sep-13) - (Springfield Oct_Dec-13)	-0.07676	0.01462	Inf	-5.251	0.0001
(Kansas Apr_Jun-13) - (Kansas Oct_Dec-13)	-0.12942	0.02461	Inf	-5.259	0.0001
(Kansas Apr_Jun-13) - (Kansas Apr_Jun-15)	-0.89907	0.03715	Inf	-24.201	<.0001
(Kansas Apr_Jun-13) - (Kansas Jan_Mar-14)	0.20903	0.01935	Inf	10.801	<.0001
(Kansas Apr_Jun-13) - (Kansas Jul_Sep-13)	-0.14829	0.02546	Inf	-5.824	<.0001
(Kansas Apr_Jun-13) - (Kansas Jul_Sep-15)	-0.20031	0.02522	Inf	-7.941	<.0001
(Kansas Apr_Jun-13) - (Kansas Oct_Dec-14)	-0.56537	0.02997	Inf	-18.862	<.0001
(Kansas Apr_Jun-13) - (Kansas Oct_Dec-15)	0.57139	0.01698	Inf	33.656	<.0001
(Kansas Apr_Jun-13) - (Springfield Apr_Jun-13)	0.28805	0.01268	Inf	22.72	<.0001
(Kansas Apr_Jun-13) - (Springfield Apr_Jun-14)	0.23772	0.02104	Inf	11.3	<.0001
(Kansas Apr_Jun-13) - (Springfield Jan_Mar-13)	0.28595	0.02058	Inf	13.896	<.0001
(Kansas Apr_Jun-13) - (Springfield Jan_Mar-14)	0.37531	0.01914	Inf	19.608	<.0001
(Kansas Apr_Jun-13) - (Springfield Jan_Mar-15)	0.31031	0.0205	Inf	15.134	<.0001
(Kansas Apr_Jun-13) - (Springfield Jul_Sep-13)	0.17184	0.02258	Inf	7.611	<.0001
(Kansas Apr_Jun-13) - (Springfield Jul_Sep-14)	0.27718	0.02117	Inf	13.092	<.0001
(Kansas Apr_Jun-13) - (Springfield Jul_Sep-15)	0.23251	0.02216	Inf	10.491	<.0001
(Kansas Apr_Jun-13) - (Springfield Oct_Dec-13)	0.248	0.02091	Inf	11.858	<.0001
(Kansas Apr_Jun-13) - (Springfield Oct_Dec-14)	0.14836	0.02355	Inf	6.3	<.0001
(Kansas Apr_Jun-13) - (Springfield Oct_Dec-15)	0.42691	0.01923	Inf	22.196	<.0001
(Kansas Apr_Jun-13) - (StLouis Apr_Jun-13)	0.36688	0.01221	Inf	30.055	<.0001
(Kansas Apr_Jun-13) - (StLouis Apr_Jun-14)	0.35693	0.01897	Inf	18.81	<.0001
(Kansas Apr_Jun-13) - (StLouis Apr_Jun-15)	-0.17837	0.02708	Inf	-6.588	<.0001
(Kansas Apr_Jun-13) - (StLouis Jan_Mar-13)	0.40388	0.01848	Inf	21.854	<.0001
(Kansas Apr_Jun-13) - (StLouis Jan_Mar-14)	0.45676	0.01787	Inf	25.562	<.0001
(Kansas Apr_Jun-13) - (StLouis Jan_Mar-15)	0.28232	0.01991	Inf	14.178	<.0001
(Kansas Apr_Jun-13) - (StLouis Jul_Sep-13)	0.32476	0.01967	Inf	16.51	<.0001
(Kansas Apr_Jun-13) - (StLouis Jul_Sep-14)	0.3086	0.0197	Inf	15.665	<.0001
(Kansas Apr_Jun-13) - (StLouis Jul_Sep-15)	0.26102	0.02039	Inf	12.802	<.0001
(Kansas Apr_Jun-13) - (StLouis Oct_Dec-13)	0.30216	0.01977	Inf	15.282	<.0001
(Kansas Apr_Jun-13) - (StLouis Oct_Dec-15)	0.59337	0.01697	Inf	34.964	<.0001
(Kansas Apr_Jun-14) - (Kansas Apr_Jun-15)	-0.84804	0.03783	Inf	-22.415	<.0001
(Kansas Apr_Jun-14) - (Kansas Jan_Mar-14)	0.26006	0.02085	Inf	12.47	<.0001
(Kansas Apr_Jun-14) - (Kansas Jul_Sep-15)	-0.14928	0.02635	Inf	-5.666	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Kansas Apr_Jun-14) - (Springfield Apr_Jun-14)	0.28876	0.01394	Inf	20.711	<.0001
(Kansas Apr_Jun-14) - (Springfield Jan_Mar-13)	0.33698	0.02222	Inf	15.164	<.0001
(Kansas Apr_Jun-14) - (Springfield Jan_Mar-14)	0.42634	0.02087	Inf	20.424	<.0001
(Kansas Apr_Jun-14) - (Springfield Jan_Mar-15)	0.36134	0.02219	Inf	16.282	<.0001
(Kansas Apr_Jun-14) - (Springfield Jul_Sep-13)	0.22287	0.02413	Inf	9.237	<.0001
(Kansas Apr_Jun-14) - (Springfield Jul_Sep-14)	0.32821	0.02283	Inf	14.375	<.0001
(Kansas Apr_Jun-14) - (Springfield Jul_Sep-15)	0.28355	0.02377	Inf	11.927	<.0001
(Kansas Apr_Jun-14) - (Springfield Oct_Dec-13)	0.29903	0.02254	Inf	13.265	<.0001
(Kansas Apr_Jun-14) - (Springfield Oct_Dec-14)	0.19939	0.02513	Inf	7.935	<.0001
(Kansas Apr_Jun-14) - (Springfield Oct_Dec-15)	0.47794	0.02088	Inf	22.885	<.0001
(Kansas Apr_Jun-14) - (StLouis Apr_Jun-14)	0.40796	0.01374	Inf	29.689	<.0001
(Kansas Apr_Jun-14) - (StLouis Jan_Mar-13)	0.45491	0.02025	Inf	22.461	<.0001
(Kansas Apr_Jun-14) - (StLouis Jan_Mar-14)	0.50779	0.01968	Inf	25.801	<.0001
(Kansas Apr_Jun-14) - (StLouis Jan_Mar-15)	0.33335	0.0216	Inf	15.43	<.0001
(Kansas Apr_Jun-14) - (StLouis Jul_Sep-13)	0.37579	0.02137	Inf	17.583	<.0001
(Kansas Apr_Jun-14) - (StLouis Jul_Sep-14)	0.35963	0.02142	Inf	16.789	<.0001
(Kansas Apr_Jun-14) - (StLouis Jul_Sep-15)	0.31205	0.02206	Inf	14.144	<.0001
(Kansas Apr_Jun-14) - (StLouis Oct_Dec-13)	0.35319	0.02146	Inf	16.461	<.0001
(Kansas Apr_Jun-14) - (StLouis Oct_Dec-15)	0.6444	0.01881	Inf	34.253	<.0001
(Kansas Apr_Jun-15) - (Kansas Jan_Mar-13)	0.96028	0.03671	Inf	26.156	<.0001
(Kansas Apr_Jun-15) - (Kansas Jan_Mar-14)	1.1081	0.03542	Inf	31.288	<.0001
(Kansas Apr_Jun-15) - (Kansas Jan_Mar-15)	0.80572	0.03643	Inf	22.118	<.0001
(Kansas Apr_Jun-15) - (Kansas Jul_Sep-13)	0.75078	0.03925	Inf	19.13	<.0001
(Kansas Apr_Jun-15) - (Kansas Jul_Sep-14)	0.80454	0.03729	Inf	21.577	<.0001
(Kansas Apr_Jun-15) - (Kansas Jul_Sep-15)	0.69876	0.03809	Inf	18.347	<.0001
(Kansas Apr_Jun-15) - (Kansas Oct_Dec-13)	0.76965	0.03848	Inf	20.002	<.0001
(Kansas Apr_Jun-15) - (Kansas Oct_Dec-14)	0.3337	0.0414	Inf	8.061	<.0001
(Kansas Apr_Jun-15) - (Kansas Oct_Dec-15)	1.47046	0.03415	Inf	43.055	<.0001
(Kansas Apr_Jun-15) - (Springfield Apr_Jun-15)	0.94375	0.02617	Inf	36.057	<.0001
(Kansas Apr_Jun-15) - (Springfield Jan_Mar-13)	1.18502	0.03574	Inf	33.153	<.0001
(Kansas Apr_Jun-15) - (Springfield Jan_Mar-14)	1.27438	0.03509	Inf	36.318	<.0001
(Kansas Apr_Jun-15) - (Springfield Jan_Mar-15)	1.20938	0.03528	Inf	34.278	<.0001
(Kansas Apr_Jun-15) - (Springfield Jul_Sep-13)	1.07091	0.03704	Inf	28.909	<.0001
(Kansas Apr_Jun-15) - (Springfield Jul_Sep-14)	1.17625	0.03596	Inf	32.706	<.0001
(Kansas Apr_Jun-15) - (Springfield Jul_Sep-15)	1.13159	0.0361	Inf	31.35	<.0001
(Kansas Apr_Jun-15) - (Springfield Oct_Dec-13)	1.14707	0.03611	Inf	31.769	<.0001
(Kansas Apr_Jun-15) - (Springfield Oct_Dec-14)	1.04743	0.03767	Inf	27.809	<.0001
(Kansas Apr_Jun-15) - (Springfield Oct_Dec-15)	1.32598	0.03525	Inf	37.612	<.0001
(Kansas Apr_Jun-15) - (StLouis Apr_Jun-15)	0.7207	0.02835	Inf	25.424	<.0001
(Kansas Apr_Jun-15) - (StLouis Jan_Mar-13)	1.30295	0.03539	Inf	36.82	<.0001
(Kansas Apr_Jun-15) - (StLouis Jan_Mar-14)	1.35583	0.03496	Inf	38.785	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Kansas Apr_Jun-15) - (StLouis Jul_Sep-13)	1.22383	0.03629	Inf	33.726	<.0001
(Kansas Apr_Jun-15) - (StLouis Jul_Sep-14)	1.20767	0.03652	Inf	33.068	<.0001
(Kansas Apr_Jun-15) - (StLouis Jul_Sep-15)	1.16009	0.0371	Inf	31.266	<.0001
(Kansas Apr_Jun-15) - (StLouis Oct_Dec-13)	1.20123	0.03659	Inf	32.83	<.0001
(Kansas Apr_Jun-15) - (StLouis Oct_Dec-14)	0.92371	0.04071	Inf	22.687	<.0001
(Kansas Apr_Jun-15) - (StLouis Oct_Dec-15)	1.49244	0.03412	Inf	43.739	<.0001
(Kansas Jan_Mar-13) - (Kansas Jan_Mar-14)	0.14782	0.01818	Inf	8.132	<.0001
(Kansas Jan_Mar-13) - (Kansas Jan_Mar-15)	-0.15456	0.02195	Inf	-7.041	<.0001
(Kansas Jan_Mar-13) - (Kansas Jul_Sep-13)	-0.20949	0.02476	Inf	-8.46	<.0001
(Kansas Jan_Mar-13) - (Kansas Jul_Sep-14)	-0.15574	0.02237	Inf	-6.961	<.0001
(Kansas Jan_Mar-13) - (Kansas Jul_Sep-15)	-0.26152	0.02434	Inf	-10.744	<.0001
(Kansas Jan_Mar-13) - (Kansas Oct_Dec-13)	-0.19063	0.02393	Inf	-7.968	<.0001
(Kansas Jan_Mar-13) - (Kansas Oct_Dec-14)	-0.62658	0.0293	Inf	-21.385	<.0001
(Kansas Jan_Mar-13) - (Kansas Oct_Dec-15)	0.51019	0.0154	Inf	33.124	<.0001
(Kansas Jan_Mar-13) - (Springfield Jan_Mar-13)	0.22475	0.01141	Inf	19.705	<.0001
(Kansas Jan_Mar-13) - (Springfield Jan_Mar-14)	0.31411	0.01754	Inf	17.908	<.0001
(Kansas Jan_Mar-13) - (Springfield Jan_Mar-15)	0.2491	0.01886	Inf	13.208	<.0001
(Kansas Jan_Mar-13) - (Springfield Jul_Sep-14)	0.21598	0.01952	Inf	11.063	<.0001
(Kansas Jan_Mar-13) - (Springfield Jul_Sep-15)	0.17131	0.02057	Inf	8.329	<.0001
(Kansas Jan_Mar-13) - (Springfield Oct_Dec-13)	0.1868	0.01938	Inf	9.639	<.0001
(Kansas Jan_Mar-13) - (Springfield Oct_Dec-15)	0.36571	0.01781	Inf	20.53	<.0001
(Kansas Jan_Mar-13) - (StLouis Jan_Mar-13)	0.34267	0.01127	Inf	30.402	<.0001
(Kansas Jan_Mar-13) - (StLouis Jan_Mar-14)	0.39555	0.01636	Inf	24.174	<.0001
(Kansas Jan_Mar-13) - (StLouis Jan_Mar-15)	0.22111	0.01842	Inf	12.006	<.0001
(Kansas Jan_Mar-13) - (StLouis Jul_Sep-13)	0.26356	0.01835	Inf	14.366	<.0001
(Kansas Jan_Mar-13) - (StLouis Jul_Sep-14)	0.2474	0.01824	Inf	13.565	<.0001
(Kansas Jan_Mar-13) - (StLouis Jul_Sep-15)	0.19981	0.01894	Inf	10.55	<.0001
(Kansas Jan_Mar-13) - (StLouis Oct_Dec-13)	0.24095	0.01844	Inf	13.07	<.0001
(Kansas Jan_Mar-13) - (StLouis Oct_Dec-15)	0.53216	0.01537	Inf	34.618	<.0001
(Kansas Jan_Mar-14) - (Kansas Jan_Mar-15)	-0.30238	0.01944	Inf	-15.551	<.0001
(Kansas Jan_Mar-14) - (Kansas Jul_Sep-13)	-0.35732	0.02274	Inf	-15.716	<.0001
(Kansas Jan_Mar-14) - (Kansas Jul_Sep-14)	-0.30356	0.0199	Inf	-15.255	<.0001
(Kansas Jan_Mar-14) - (Kansas Jul_Sep-15)	-0.40934	0.02213	Inf	-18.494	<.0001
(Kansas Jan_Mar-14) - (Kansas Oct_Dec-13)	-0.33845	0.02184	Inf	-15.495	<.0001
(Kansas Jan_Mar-14) - (Kansas Oct_Dec-14)	-0.7744	0.0275	Inf	-28.158	<.0001
(Kansas Jan_Mar-14) - (Kansas Oct_Dec-15)	0.36237	0.01116	Inf	32.48	<.0001
(Kansas Jan_Mar-14) - (Springfield Jan_Mar-14)	0.16628	0.00834	Inf	19.943	<.0001
(Kansas Jan_Mar-14) - (Springfield Jan_Mar-15)	0.10128	0.01519	Inf	6.667	<.0001
(Kansas Jan_Mar-14) - (Springfield Oct_Dec-15)	0.21788	0.01424	Inf	15.299	<.0001
(Kansas Jan_Mar-14) - (StLouis Jan_Mar-14)	0.24773	0.00805	Inf	30.776	<.0001
(Kansas Jan_Mar-14) - (StLouis Jul_Sep-13)	0.11574	0.01478	Inf	7.831	<.0001
(Kansas Jan_Mar-14) - (StLouis Jul_Sep-14)	0.09958	0.01457	Inf	6.832	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Kansas Jan_Mar-14) - (StLouis Oct_Dec-13)	0.09313	0.01491	Inf	6.247	<.0001
(Kansas Jan_Mar-14) - (StLouis Oct_Dec-14)	-0.18439	0.02041	Inf	-9.036	<.0001
(Kansas Jan_Mar-14) - (StLouis Oct_Dec-15)	0.38434	0.01106	Inf	34.739	<.0001
(Kansas Jan_Mar-15) - (Kansas Oct_Dec-14)	-0.47202	0.0298	Inf	-15.838	<.0001
(Kansas Jan_Mar-15) - (Kansas Oct_Dec-15)	0.66475	0.01666	Inf	39.91	<.0001
(Kansas Jan_Mar-15) - (Springfield Jan_Mar-15)	0.40366	0.01248	Inf	32.353	<.0001
(Kansas Jan_Mar-15) - (Springfield Jul_Sep-13)	0.26519	0.02161	Inf	12.271	<.0001
(Kansas Jan_Mar-15) - (Springfield Jul_Sep-14)	0.37053	0.01989	Inf	18.629	<.0001
(Kansas Jan_Mar-15) - (Springfield Jul_Sep-15)	0.32587	0.02062	Inf	15.805	<.0001
(Kansas Jan_Mar-15) - (Springfield Oct_Dec-13)	0.34136	0.02003	Inf	17.04	<.0001
(Kansas Jan_Mar-15) - (Springfield Oct_Dec-14)	0.24171	0.02217	Inf	10.905	<.0001
(Kansas Jan_Mar-15) - (Springfield Oct_Dec-15)	0.52026	0.01881	Inf	27.657	<.0001
(Kansas Jan_Mar-15) - (StLouis Jan_Mar-15)	0.37567	0.01297	Inf	28.961	<.0001
(Kansas Jan_Mar-15) - (StLouis Jul_Sep-13)	0.41811	0.01979	Inf	21.127	<.0001
(Kansas Jan_Mar-15) - (StLouis Jul_Sep-14)	0.40195	0.01974	Inf	20.365	<.0001
(Kansas Jan_Mar-15) - (StLouis Jul_Sep-15)	0.35437	0.02049	Inf	17.297	<.0001
(Kansas Jan_Mar-15) - (StLouis Oct_Dec-13)	0.39551	0.02002	Inf	19.756	<.0001
(Kansas Jan_Mar-15) - (StLouis Oct_Dec-15)	0.68672	0.01658	Inf	41.418	<.0001
(Kansas Jul_Sep-13) - (Kansas Oct_Dec-14)	-0.41708	0.03234	Inf	-12.895	<.0001
(Kansas Jul_Sep-13) - (Kansas Oct_Dec-15)	0.71968	0.0208	Inf	34.597	<.0001
(Kansas Jul_Sep-13) - (Springfield Jul_Sep-13)	0.32013	0.01547	Inf	20.688	<.0001
(Kansas Jul_Sep-13) - (Springfield Jul_Sep-14)	0.42547	0.02444	Inf	17.41	<.0001
(Kansas Jul_Sep-13) - (Springfield Jul_Sep-15)	0.3808	0.02537	Inf	15.01	<.0001
(Kansas Jul_Sep-13) - (Springfield Oct_Dec-13)	0.39629	0.02417	Inf	16.394	<.0001
(Kansas Jul_Sep-13) - (Springfield Oct_Dec-14)	0.29665	0.02649	Inf	11.198	<.0001
(Kansas Jul_Sep-13) - (Springfield Oct_Dec-15)	0.5752	0.0227	Inf	25.336	<.0001
(Kansas Jul_Sep-13) - (StLouis Jul_Sep-13)	0.47305	0.01517	Inf	31.178	<.0001
(Kansas Jul_Sep-13) - (StLouis Jul_Sep-14)	0.45689	0.02303	Inf	19.842	<.0001
(Kansas Jul_Sep-13) - (StLouis Jul_Sep-15)	0.4093	0.02358	Inf	17.357	<.0001
(Kansas Jul_Sep-13) - (StLouis Oct_Dec-13)	0.45045	0.02309	Inf	19.504	<.0001
(Kansas Jul_Sep-13) - (StLouis Oct_Dec-14)	0.17292	0.02718	Inf	6.361	<.0001
(Kansas Jul_Sep-13) - (StLouis Oct_Dec-15)	0.74166	0.02081	Inf	35.634	<.0001
(Kansas Jul_Sep-14) - (Kansas Oct_Dec-14)	-0.47084	0.03031	Inf	-15.533	<.0001
(Kansas Jul_Sep-14) - (Kansas Oct_Dec-15)	0.66592	0.01719	Inf	38.738	<.0001
(Kansas Jul_Sep-14) - (Springfield Jul_Sep-14)	0.37171	0.01285	Inf	28.916	<.0001
(Kansas Jul_Sep-14) - (Springfield Jul_Sep-15)	0.32705	0.02128	Inf	15.37	<.0001
(Kansas Jul_Sep-14) - (Springfield Oct_Dec-13)	0.34253	0.02049	Inf	16.718	<.0001
(Kansas Jul_Sep-14) - (Springfield Oct_Dec-14)	0.24289	0.02251	Inf	10.79	<.0001
(Kansas Jul_Sep-14) - (Springfield Oct_Dec-15)	0.52144	0.0193	Inf	27.015	<.0001
(Kansas Jul_Sep-14) - (StLouis Jul_Sep-14)	0.40313	0.01246	Inf	32.357	<.0001
(Kansas Jul_Sep-14) - (StLouis Jul_Sep-15)	0.35555	0.02057	Inf	17.284	<.0001
(Kansas Jul_Sep-14) - (StLouis Oct_Dec-13)	0.39669	0.02022	Inf	19.615	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Kansas Jul_Sep-14) - (StLouis Oct_Dec-15)	0.6879	0.01713	Inf	40.155	<.0001
(Kansas Jul_Sep-15) - (Kansas Oct_Dec-14)	-0.36506	0.0317	Inf	-11.518	<.0001
(Kansas Jul_Sep-15) - (Kansas Oct_Dec-15)	0.77171	0.01981	Inf	38.961	<.0001
(Kansas Jul_Sep-15) - (Springfield Jul_Sep-15)	0.43283	0.0148	Inf	29.24	<.0001
(Kansas Jul_Sep-15) - (Springfield Oct_Dec-13)	0.44832	0.02273	Inf	19.72	<.0001
(Kansas Jul_Sep-15) - (Springfield Oct_Dec-14)	0.34867	0.02458	Inf	14.187	<.0001
(Kansas Jul_Sep-15) - (Springfield Oct_Dec-15)	0.62722	0.02166	Inf	28.961	<.0001
(Kansas Jul_Sep-15) - (StLouis Jul_Sep-15)	0.46133	0.01471	Inf	31.362	<.0001
(Kansas Jul_Sep-15) - (StLouis Oct_Dec-13)	0.50247	0.0228	Inf	22.041	<.0001
(Kansas Jul_Sep-15) - (StLouis Oct_Dec-14)	0.22495	0.02722	Inf	8.265	<.0001
(Kansas Jul_Sep-15) - (StLouis Oct_Dec-15)	0.79368	0.01977	Inf	40.155	<.0001
(Kansas Oct_Dec-13) - (Kansas Oct_Dec-14)	-0.43595	0.03162	Inf	-13.787	<.0001
(Kansas Oct_Dec-13) - (Kansas Oct_Dec-15)	0.70082	0.01984	Inf	35.325	<.0001
(Kansas Oct_Dec-13) - (Springfield Oct_Dec-13)	0.37743	0.01488	Inf	25.362	<.0001
(Kansas Oct_Dec-13) - (Springfield Oct_Dec-14)	0.27779	0.02591	Inf	10.721	<.0001
(Kansas Oct_Dec-13) - (Springfield Oct_Dec-15)	0.55633	0.02182	Inf	25.501	<.0001
(Kansas Oct_Dec-13) - (StLouis Oct_Dec-13)	0.43158	0.01411	Inf	30.577	<.0001
(Kansas Oct_Dec-13) - (StLouis Oct_Dec-14)	0.15406	0.02669	Inf	5.771	<.0001
(Kansas Oct_Dec-13) - (StLouis Oct_Dec-15)	0.72279	0.01984	Inf	36.432	<.0001
(Kansas Oct_Dec-14) - (Kansas Oct_Dec-15)	1.13676	0.02566	Inf	44.293	<.0001
(Kansas Oct_Dec-14) - (Springfield Oct_Dec-14)	0.71373	0.01995	Inf	35.778	<.0001
(Kansas Oct_Dec-14) - (Springfield Oct_Dec-15)	0.99228	0.02714	Inf	36.56	<.0001
(Kansas Oct_Dec-14) - (StLouis Oct_Dec-14)	0.59001	0.01953	Inf	30.216	<.0001
(Kansas Oct_Dec-14) - (StLouis Oct_Dec-15)	1.15874	0.02562	Inf	45.229	<.0001
(Kansas Oct_Dec-15) - (Springfield Oct_Dec-15)	-0.14448	0.00823	Inf	-17.553	<.0001
(Kansas Oct_Dec-15) - (StLouis Oct_Dec-15)	0.02197	0.00169	Inf	12.991	<.0001
(Springfield Apr_Jun-13) - (Kansas Apr_Jun-14)	-0.33908	0.02182	Inf	-15.538	<.0001
(Springfield Apr_Jun-13) - (Kansas Apr_Jun-15)	-1.18712	0.03556	Inf	-33.386	<.0001
(Springfield Apr_Jun-13) - (Kansas Jan_Mar-13)	-0.22685	0.01865	Inf	-12.165	<.0001
(Springfield Apr_Jun-13) - (Kansas Jan_Mar-15)	-0.38141	0.01932	Inf	-19.744	<.0001
(Springfield Apr_Jun-13) - (Kansas Jul_Sep-13)	-0.43634	0.02354	Inf	-18.533	<.0001
(Springfield Apr_Jun-13) - (Kansas Jul_Sep-14)	-0.38258	0.01985	Inf	-19.276	<.0001
(Springfield Apr_Jun-13) - (Kansas Jul_Sep-15)	-0.48837	0.02213	Inf	-22.067	<.0001
(Springfield Apr_Jun-13) - (Kansas Oct_Dec-13)	-0.41748	0.02271	Inf	-18.386	<.0001
(Springfield Apr_Jun-13) - (Kansas Oct_Dec-14)	-0.85342	0.02758	Inf	-30.946	<.0001
(Springfield Apr_Jun-13) - (Kansas Oct_Dec-15)	0.28334	0.00996	Inf	28.448	<.0001
(Springfield Apr_Jun-13) - (Springfield Apr_Jun-1	-0.24338	0.01763	Inf	-13.804	<.0001
(Springfield Apr_Jun-13) - (Springfield Jan_Mar-1	0.08726	0.01146	Inf	7.616	<.0001
(Springfield Apr_Jun-13) - (Springfield Jul_Sep-1	-0.11621	0.01556	Inf	-7.469	<.0001
(Springfield Apr_Jun-13) - (Springfield Oct_Dec-1	-0.13969	0.01529	Inf	-9.138	<.0001
(Springfield Apr_Jun-13) - (Springfield Oct_Dec-1	0.13886	0.01303	Inf	10.656	<.0001
(Springfield Apr_Jun-13) - (StLouis Apr_Jun-13)	0.07882	0.00924	Inf	8.527	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Springfield Apr_Jun-13) - (StLouis Apr_Jun-15)	-0.46642	0.02245	Inf	-20.774	<.0001
(Springfield Apr_Jun-13) - (StLouis Jan_Mar-13)	0.11583	0.01201	Inf	9.645	<.0001
(Springfield Apr_Jun-13) - (StLouis Jan_Mar-14)	0.16871	0.011	Inf	15.331	<.0001
(Springfield Apr_Jun-13) - (StLouis Oct_Dec-14)	-0.26342	0.01937	Inf	-13.598	<.0001
(Springfield Apr_Jun-13) - (StLouis Oct_Dec-15)	0.30531	0.00964	Inf	31.664	<.0001
(Springfield Apr_Jun-14) - (Kansas Apr_Jun-15)	-1.1368	0.03583	Inf	-31.732	<.0001
(Springfield Apr_Jun-14) - (Kansas Jan_Mar-13)	-0.17652	0.0196	Inf	-9.007	<.0001
(Springfield Apr_Jun-14) - (Kansas Jan_Mar-15)	-0.33108	0.0201	Inf	-16.469	<.0001
(Springfield Apr_Jun-14) - (Kansas Jul_Sep-13)	-0.38601	0.02433	Inf	-15.866	<.0001
(Springfield Apr_Jun-14) - (Kansas Jul_Sep-14)	-0.33226	0.0207	Inf	-16.054	<.0001
(Springfield Apr_Jun-14) - (Kansas Jul_Sep-15)	-0.43804	0.02286	Inf	-19.161	<.0001
(Springfield Apr_Jun-14) - (Kansas Oct_Dec-13)	-0.36715	0.02348	Inf	-15.638	<.0001
(Springfield Apr_Jun-14) - (Kansas Oct_Dec-14)	-0.8031	0.02814	Inf	-28.544	<.0001
(Springfield Apr_Jun-14) - (Kansas Oct_Dec-15)	0.33367	0.01161	Inf	28.741	<.0001
(Springfield Apr_Jun-14) - (Springfield Apr_Jun-1	-0.19305	0.0185	Inf	-10.433	<.0001
(Springfield Apr_Jun-14) - (Springfield Jan_Mar-1	0.13759	0.01286	Inf	10.697	<.0001
(Springfield Apr_Jun-14) - (Springfield Jan_Mar-1	0.07258	0.0134	Inf	5.418	<.0001
(Springfield Apr_Jun-14) - (Springfield Oct_Dec-1	-0.08936	0.01641	Inf	-5.446	<.0001
(Springfield Apr_Jun-14) - (Springfield Oct_Dec-1	0.18918	0.0143	Inf	13.228	<.0001
(Springfield Apr_Jun-14) - (StLouis Apr_Jun-14)	0.1192	0.01044	Inf	11.42	<.0001
(Springfield Apr_Jun-14) - (StLouis Apr_Jun-15)	-0.41609	0.02355	Inf	-17.67	<.0001
(Springfield Apr_Jun-14) - (StLouis Jan_Mar-13)	0.16615	0.01342	Inf	12.382	<.0001
(Springfield Apr_Jun-14) - (StLouis Jan_Mar-14)	0.21903	0.01253	Inf	17.486	<.0001
(Springfield Apr_Jun-14) - (StLouis Jul_Sep-13)	0.08704	0.01505	Inf	5.784	<.0001
(Springfield Apr_Jun-14) - (StLouis Oct_Dec-14)	-0.21309	0.02055	Inf	-10.369	<.0001
(Springfield Apr_Jun-14) - (StLouis Oct_Dec-15)	0.35564	0.01132	Inf	31.426	<.0001
(Springfield Apr_Jun-15) - (Kansas Jan_Mar-14)	0.16435	0.02107	Inf	7.801	<.0001
(Springfield Apr_Jun-15) - (Kansas Jan_Mar-15)	-0.13803	0.02364	Inf	-5.839	<.0001
(Springfield Apr_Jun-15) - (Kansas Jul_Sep-13)	-0.19297	0.02855	Inf	-6.758	<.0001
(Springfield Apr_Jun-15) - (Kansas Jul_Sep-14)	-0.13921	0.02425	Inf	-5.74	<.0001
(Springfield Apr_Jun-15) - (Kansas Jul_Sep-15)	-0.24499	0.02592	Inf	-9.45	<.0001
(Springfield Apr_Jun-15) - (Kansas Oct_Dec-13)	-0.1741	0.028	Inf	-6.218	<.0001
(Springfield Apr_Jun-15) - (Kansas Oct_Dec-14)	-0.61005	0.03119	Inf	-19.557	<.0001
(Springfield Apr_Jun-15) - (Kansas Oct_Dec-15)	0.52672	0.01692	Inf	31.121	<.0001
(Springfield Apr_Jun-15) - (Springfield Jan_Mar-1	0.24127	0.01754	Inf	13.754	<.0001
(Springfield Apr_Jun-15) - (Springfield Jan_Mar-1	0.33063	0.01666	Inf	19.851	<.0001
(Springfield Apr_Jun-15) - (Springfield Jan_Mar-1	0.26563	0.01574	Inf	16.881	<.0001
(Springfield Apr_Jun-15) - (Springfield Jul_Sep-1	0.12716	0.01897	Inf	6.704	<.0001
(Springfield Apr_Jun-15) - (Springfield Jul_Sep-1	0.2325	0.01622	Inf	14.337	<.0001
(Springfield Apr_Jun-15) - (Springfield Jul_Sep-1	0.18784	0.0166	Inf	11.315	<.0001
(Springfield Apr_Jun-15) - (Springfield Oct_Dec-1	0.20333	0.0178	Inf	11.421	<.0001
(Springfield Apr_Jun-15) - (Springfield Oct_Dec-1	0.10368	0.01692	Inf	6.129	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Springfield Apr_Jun-15) - (Springfield Oct_Dec-15)	0.38223	0.01864	Inf	20.502	<.0001
(Springfield Apr_Jun-15) - (StLouis Apr_Jun-15)	-0.22305	0.01907	Inf	-11.694	<.0001
(Springfield Apr_Jun-15) - (StLouis Jan_Mar-13)	0.3592	0.01892	Inf	18.981	<.0001
(Springfield Apr_Jun-15) - (StLouis Jan_Mar-14)	0.41208	0.01804	Inf	22.849	<.0001
(Springfield Apr_Jun-15) - (StLouis Jan_Mar-15)	0.23764	0.01944	Inf	12.221	<.0001
(Springfield Apr_Jun-15) - (StLouis Jul_Sep-13)	0.28008	0.0205	Inf	13.66	<.0001
(Springfield Apr_Jun-15) - (StLouis Jul_Sep-14)	0.26392	0.01945	Inf	13.57	<.0001
(Springfield Apr_Jun-15) - (StLouis Jul_Sep-15)	0.21634	0.01997	Inf	10.834	<.0001
(Springfield Apr_Jun-15) - (StLouis Oct_Dec-13)	0.25748	0.02068	Inf	12.452	<.0001
(Springfield Apr_Jun-15) - (StLouis Oct_Dec-15)	0.54869	0.01666	Inf	32.927	<.0001
(Springfield Jan_Mar-13) - (Kansas Jan_Mar-15)	-0.3793	0.01963	Inf	-19.321	<.0001
(Springfield Jan_Mar-13) - (Kansas Jul_Sep-13)	-0.43424	0.02391	Inf	-18.164	<.0001
(Springfield Jan_Mar-13) - (Kansas Jul_Sep-14)	-0.38048	0.02016	Inf	-18.872	<.0001
(Springfield Jan_Mar-13) - (Kansas Jul_Sep-15)	-0.48626	0.02241	Inf	-21.698	<.0001
(Springfield Jan_Mar-13) - (Kansas Oct_Dec-13)	-0.41537	0.02309	Inf	-17.99	<.0001
(Springfield Jan_Mar-13) - (Kansas Oct_Dec-14)	-0.85132	0.02782	Inf	-30.597	<.0001
(Springfield Jan_Mar-13) - (Kansas Oct_Dec-15)	0.28544	0.01049	Inf	27.223	<.0001
(Springfield Jan_Mar-13) - (Springfield Jan_Mar-14)	0.08936	0.01177	Inf	7.595	<.0001
(Springfield Jan_Mar-13) - (Springfield Jul_Sep-13)	-0.11411	0.01571	Inf	-7.263	<.0001
(Springfield Jan_Mar-13) - (Springfield Oct_Dec-14)	-0.13759	0.0153	Inf	-8.991	<.0001
(Springfield Jan_Mar-13) - (Springfield Oct_Dec-15)	0.14096	0.01339	Inf	10.523	<.0001
(Springfield Jan_Mar-13) - (StLouis Jan_Mar-13)	0.11793	0.00923	Inf	12.773	<.0001
(Springfield Jan_Mar-13) - (StLouis Jan_Mar-14)	0.17081	0.01148	Inf	14.875	<.0001
(Springfield Jan_Mar-13) - (StLouis Oct_Dec-14)	-0.26131	0.01963	Inf	-13.315	<.0001
(Springfield Jan_Mar-13) - (StLouis Oct_Dec-15)	0.30742	0.01016	Inf	30.251	<.0001
(Springfield Jan_Mar-14) - (Kansas Jan_Mar-15)	-0.46866	0.01833	Inf	-25.573	<.0001
(Springfield Jan_Mar-14) - (Kansas Jul_Sep-13)	-0.5236	0.02265	Inf	-23.112	<.0001
(Springfield Jan_Mar-14) - (Kansas Jul_Sep-14)	-0.46984	0.01885	Inf	-24.928	<.0001
(Springfield Jan_Mar-14) - (Kansas Jul_Sep-15)	-0.57562	0.02126	Inf	-27.076	<.0001
(Springfield Jan_Mar-14) - (Kansas Oct_Dec-13)	-0.50474	0.0218	Inf	-23.157	<.0001
(Springfield Jan_Mar-14) - (Kansas Oct_Dec-14)	-0.94068	0.02688	Inf	-34.991	<.0001
(Springfield Jan_Mar-14) - (Kansas Oct_Dec-15)	0.19608	0.00775	Inf	25.3	<.0001
(Springfield Jan_Mar-14) - (Springfield Jan_Mar-15)	-0.065	0.01061	Inf	-6.127	<.0001
(Springfield Jan_Mar-14) - (Springfield Jul_Sep-13)	-0.20347	0.01434	Inf	-14.184	<.0001
(Springfield Jan_Mar-14) - (Springfield Jul_Sep-14)	-0.09813	0.01149	Inf	-8.539	<.0001
(Springfield Jan_Mar-14) - (Springfield Jul_Sep-15)	-0.1428	0.01275	Inf	-11.202	<.0001
(Springfield Jan_Mar-14) - (Springfield Oct_Dec-13)	-0.12731	0.01221	Inf	-10.427	<.0001
(Springfield Jan_Mar-14) - (Springfield Oct_Dec-14)	-0.22695	0.01408	Inf	-16.121	<.0001
(Springfield Jan_Mar-14) - (StLouis Jan_Mar-14)	0.08145	0.0068	Inf	11.971	<.0001
(Springfield Jan_Mar-14) - (StLouis Jan_Mar-15)	-0.09299	0.01195	Inf	-7.78	<.0001
(Springfield Jan_Mar-14) - (StLouis Jul_Sep-14)	-0.06671	0.01159	Inf	-5.756	<.0001
(Springfield Jan_Mar-14) - (StLouis Jul_Sep-15)	-0.1143	0.01261	Inf	-9.064	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Springfield Jan_Mar-14) - (StLouis Oct_Dec-13)	-0.07316	0.01246	Inf	-5.869	<.0001
(Springfield Jan_Mar-14) - (StLouis Oct_Dec-14)	-0.35068	0.01817	Inf	-19.299	<.0001
(Springfield Jan_Mar-14) - (StLouis Oct_Dec-15)	0.21806	0.00735	Inf	29.666	<.0001
(Springfield Jan_Mar-15) - (Kansas Jul_Sep-13)	-0.4586	0.0239	Inf	-19.189	<.0001
(Springfield Jan_Mar-15) - (Kansas Jul_Sep-14)	-0.40484	0.01978	Inf	-20.472	<.0001
(Springfield Jan_Mar-15) - (Kansas Jul_Sep-15)	-0.51062	0.02199	Inf	-23.217	<.0001
(Springfield Jan_Mar-15) - (Kansas Oct_Dec-13)	-0.43973	0.02307	Inf	-19.06	<.0001
(Springfield Jan_Mar-15) - (Kansas Oct_Dec-14)	-0.87568	0.02754	Inf	-31.791	<.0001
(Springfield Jan_Mar-15) - (Kansas Oct_Dec-15)	0.26109	0.0096	Inf	27.205	<.0001
(Springfield Jan_Mar-15) - (Springfield Jul_Sep-13)	-0.13847	0.01468	Inf	-9.431	<.0001
(Springfield Jan_Mar-15) - (Springfield Jul_Sep-15)	-0.07779	0.01254	Inf	-6.202	<.0001
(Springfield Jan_Mar-15) - (Springfield Oct_Dec-14)	-0.16195	0.01387	Inf	-11.68	<.0001
(Springfield Jan_Mar-15) - (Springfield Oct_Dec-15)	0.1166	0.0127	Inf	9.181	<.0001
(Springfield Jan_Mar-15) - (StLouis Oct_Dec-14)	-0.28567	0.01953	Inf	-14.624	<.0001
(Springfield Jan_Mar-15) - (StLouis Oct_Dec-15)	0.28306	0.00922	Inf	30.7	<.0001
(Springfield Jul_Sep-13) - (Kansas Jul_Sep-14)	-0.26637	0.02204	Inf	-12.083	<.0001
(Springfield Jul_Sep-13) - (Kansas Jul_Sep-15)	-0.37215	0.02415	Inf	-15.41	<.0001
(Springfield Jul_Sep-13) - (Kansas Oct_Dec-13)	-0.30127	0.02492	Inf	-12.09	<.0001
(Springfield Jul_Sep-13) - (Kansas Oct_Dec-14)	-0.73721	0.02929	Inf	-25.17	<.0001
(Springfield Jul_Sep-13) - (Kansas Oct_Dec-15)	0.39955	0.01357	Inf	29.444	<.0001
(Springfield Jul_Sep-13) - (Springfield Jul_Sep-14)	0.10534	0.01525	Inf	6.909	<.0001
(Springfield Jul_Sep-13) - (Springfield Oct_Dec-15)	0.25507	0.01587	Inf	16.075	<.0001
(Springfield Jul_Sep-13) - (StLouis Jul_Sep-13)	0.15292	0.0121	Inf	12.639	<.0001
(Springfield Jul_Sep-13) - (StLouis Jul_Sep-14)	0.13676	0.01601	Inf	8.543	<.0001
(Springfield Jul_Sep-13) - (StLouis Oct_Dec-13)	0.13031	0.01682	Inf	7.749	<.0001
(Springfield Jul_Sep-13) - (StLouis Oct_Dec-14)	-0.14721	0.02118	Inf	-6.949	<.0001
(Springfield Jul_Sep-13) - (StLouis Oct_Dec-15)	0.42153	0.0133	Inf	31.7	<.0001
(Springfield Jul_Sep-14) - (Kansas Jul_Sep-15)	-0.47749	0.02263	Inf	-21.102	<.0001
(Springfield Jul_Sep-14) - (Kansas Oct_Dec-13)	-0.40661	0.02368	Inf	-17.167	<.0001
(Springfield Jul_Sep-14) - (Kansas Oct_Dec-14)	-0.84255	0.0281	Inf	-29.981	<.0001
(Springfield Jul_Sep-14) - (Kansas Oct_Dec-15)	0.29421	0.01069	Inf	27.535	<.0001
(Springfield Jul_Sep-14) - (Springfield Oct_Dec-14)	-0.12882	0.01425	Inf	-9.039	<.0001
(Springfield Jul_Sep-14) - (Springfield Oct_Dec-15)	0.14973	0.01351	Inf	11.08	<.0001
(Springfield Jul_Sep-14) - (StLouis Oct_Dec-14)	-0.25255	0.01967	Inf	-12.838	<.0001
(Springfield Jul_Sep-14) - (StLouis Oct_Dec-15)	0.31619	0.01035	Inf	30.563	<.0001
(Springfield Jul_Sep-15) - (Kansas Oct_Dec-13)	-0.36194	0.02459	Inf	-14.719	<.0001
(Springfield Jul_Sep-15) - (Kansas Oct_Dec-14)	-0.79788	0.02866	Inf	-27.842	<.0001
(Springfield Jul_Sep-15) - (Kansas Oct_Dec-15)	0.33888	0.01224	Inf	27.691	<.0001
(Springfield Jul_Sep-15) - (Springfield Oct_Dec-14)	-0.08415	0.01512	Inf	-5.566	<.0001
(Springfield Jul_Sep-15) - (Springfield Oct_Dec-15)	0.1944	0.01474	Inf	13.191	<.0001
(Springfield Jul_Sep-15) - (StLouis Oct_Dec-14)	-0.20788	0.02102	Inf	-9.89	<.0001
(Springfield Jul_Sep-15) - (StLouis Oct_Dec-15)	0.36085	0.01191	Inf	30.306	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(Springfield Oct_Dec-13) - (Kansas Oct_Dec-14)	-0.81337	0.02811	Inf	-28.931	<.0001
(Springfield Oct_Dec-13) - (Kansas Oct_Dec-15)	0.32339	0.01102	Inf	29.352	<.0001
(Springfield Oct_Dec-13) - (Springfield Oct_Dec-14)	-0.09964	0.0155	Inf	-6.429	<.0001
(Springfield Oct_Dec-13) - (Springfield Oct_Dec-15)	0.17891	0.01383	Inf	12.934	<.0001
(Springfield Oct_Dec-13) - (StLouis Oct_Dec-14)	-0.22337	0.01971	Inf	-11.33	<.0001
(Springfield Oct_Dec-13) - (StLouis Oct_Dec-15)	0.34536	0.01072	Inf	32.203	<.0001
(Springfield Oct_Dec-14) - (Kansas Oct_Dec-15)	0.42303	0.01394	Inf	30.337	<.0001
(Springfield Oct_Dec-14) - (Springfield Oct_Dec-15)	0.27855	0.01614	Inf	17.256	<.0001
(Springfield Oct_Dec-14) - (StLouis Oct_Dec-14)	-0.12373	0.01605	Inf	-7.709	<.0001
(Springfield Oct_Dec-14) - (StLouis Oct_Dec-15)	0.44501	0.01367	Inf	32.551	<.0001
(Springfield Oct_Dec-15) - (StLouis Oct_Dec-15)	0.16646	0.00872	Inf	19.098	<.0001
(StLouis Apr_Jun-13) - (Kansas Apr_Jun-14)	-0.41791	0.02057	Inf	-20.32	<.0001
(StLouis Apr_Jun-13) - (Kansas Apr_Jun-15)	-1.26595	0.03579	Inf	-35.372	<.0001
(StLouis Apr_Jun-13) - (Kansas Jan_Mar-13)	-0.30567	0.01744	Inf	-17.532	<.0001
(StLouis Apr_Jun-13) - (Kansas Jan_Mar-14)	-0.15785	0.01369	Inf	-11.526	<.0001
(StLouis Apr_Jun-13) - (Kansas Jan_Mar-15)	-0.46023	0.01894	Inf	-24.302	<.0001
(StLouis Apr_Jun-13) - (Kansas Jul_Sep-13)	-0.51517	0.02232	Inf	-23.082	<.0001
(StLouis Apr_Jun-13) - (Kansas Jul_Sep-14)	-0.46141	0.01925	Inf	-23.974	<.0001
(StLouis Apr_Jun-13) - (Kansas Jul_Sep-15)	-0.56719	0.02185	Inf	-25.954	<.0001
(StLouis Apr_Jun-13) - (Kansas Oct_Dec-13)	-0.4963	0.02141	Inf	-23.178	<.0001
(StLouis Apr_Jun-13) - (Kansas Oct_Dec-14)	-0.93225	0.02707	Inf	-34.434	<.0001
(StLouis Apr_Jun-13) - (Kansas Oct_Dec-15)	0.20452	0.00814	Inf	25.127	<.0001
(StLouis Apr_Jun-13) - (Springfield Apr_Jun-14)	-0.12915	0.01413	Inf	-9.141	<.0001
(StLouis Apr_Jun-13) - (Springfield Apr_Jun-15)	-0.3222	0.01961	Inf	-16.43	<.0001
(StLouis Apr_Jun-13) - (Springfield Jan_Mar-13)	-0.08093	0.0132	Inf	-6.132	<.0001
(StLouis Apr_Jun-13) - (Springfield Jul_Sep-13)	-0.19504	0.01577	Inf	-12.37	<.0001
(StLouis Apr_Jun-13) - (Springfield Jul_Sep-14)	-0.0897	0.01355	Inf	-6.618	<.0001
(StLouis Apr_Jun-13) - (Springfield Jul_Sep-15)	-0.13436	0.01495	Inf	-8.99	<.0001
(StLouis Apr_Jun-13) - (Springfield Oct_Dec-13)	-0.11887	0.01362	Inf	-8.728	<.0001
(StLouis Apr_Jun-13) - (Springfield Oct_Dec-14)	-0.21852	0.01641	Inf	-13.317	<.0001
(StLouis Apr_Jun-13) - (StLouis Apr_Jun-15)	-0.54524	0.02016	Inf	-27.043	<.0001
(StLouis Apr_Jun-13) - (StLouis Jan_Mar-14)	0.08988	0.00821	Inf	10.949	<.0001
(StLouis Apr_Jun-13) - (StLouis Jan_Mar-15)	-0.08456	0.0112	Inf	-7.548	<.0001
(StLouis Apr_Jun-13) - (StLouis Jul_Sep-14)	-0.05827	0.01055	Inf	-5.524	<.0001
(StLouis Apr_Jun-13) - (StLouis Jul_Sep-15)	-0.10586	0.01167	Inf	-9.071	<.0001
(StLouis Apr_Jun-13) - (StLouis Oct_Dec-13)	-0.06472	0.01092	Inf	-5.927	<.0001
(StLouis Apr_Jun-13) - (StLouis Oct_Dec-14)	-0.34224	0.0168	Inf	-20.37	<.0001
(StLouis Apr_Jun-13) - (StLouis Oct_Dec-15)	0.22649	0.00778	Inf	29.113	<.0001
(StLouis Apr_Jun-14) - (Kansas Apr_Jun-15)	-1.256	0.03583	Inf	-35.059	<.0001
(StLouis Apr_Jun-14) - (Kansas Jan_Mar-13)	-0.29572	0.01761	Inf	-16.789	<.0001
(StLouis Apr_Jun-14) - (Kansas Jan_Mar-14)	-0.1479	0.01393	Inf	-10.619	<.0001
(StLouis Apr_Jun-14) - (Kansas Jan_Mar-15)	-0.45028	0.01909	Inf	-23.588	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(StLouis Apr_Jun-14) - (Kansas Jul_Sep-13)	-0.50522	0.02245	Inf	-22.5	<.0001
(StLouis Apr_Jun-14) - (Kansas Jul_Sep-14)	-0.45146	0.01942	Inf	-23.247	<.0001
(StLouis Apr_Jun-14) - (Kansas Jul_Sep-15)	-0.55724	0.02201	Inf	-25.321	<.0001
(StLouis Apr_Jun-14) - (Kansas Oct_Dec-13)	-0.48635	0.02153	Inf	-22.585	<.0001
(StLouis Apr_Jun-14) - (Kansas Oct_Dec-14)	-0.9223	0.02717	Inf	-33.95	<.0001
(StLouis Apr_Jun-14) - (Kansas Oct_Dec-15)	0.21447	0.00852	Inf	25.16	<.0001
(StLouis Apr_Jun-14) - (Springfield Apr_Jun-15)	-0.31225	0.0199	Inf	-15.695	<.0001
(StLouis Apr_Jun-14) - (Springfield Jul_Sep-13)	-0.18509	0.01603	Inf	-11.546	<.0001
(StLouis Apr_Jun-14) - (Springfield Jul_Sep-14)	-0.07975	0.01387	Inf	-5.751	<.0001
(StLouis Apr_Jun-14) - (Springfield Jul_Sep-15)	-0.12441	0.01521	Inf	-8.18	<.0001
(StLouis Apr_Jun-14) - (Springfield Oct_Dec-13)	-0.10892	0.01391	Inf	-7.828	<.0001
(StLouis Apr_Jun-14) - (Springfield Oct_Dec-14)	-0.20857	0.01674	Inf	-12.463	<.0001
(StLouis Apr_Jun-14) - (Springfield Oct_Dec-15)	0.06998	0.01224	Inf	5.719	<.0001
(StLouis Apr_Jun-14) - (StLouis Apr_Jun-15)	-0.5353	0.02038	Inf	-26.264	<.0001
(StLouis Apr_Jun-14) - (StLouis Jan_Mar-14)	0.09983	0.00852	Inf	11.715	<.0001
(StLouis Apr_Jun-14) - (StLouis Jan_Mar-15)	-0.07461	0.01153	Inf	-6.473	<.0001
(StLouis Apr_Jun-14) - (StLouis Jul_Sep-15)	-0.09591	0.01195	Inf	-8.027	<.0001
(StLouis Apr_Jun-14) - (StLouis Oct_Dec-14)	-0.33229	0.01702	Inf	-19.521	<.0001
(StLouis Apr_Jun-14) - (StLouis Oct_Dec-15)	0.23644	0.00818	Inf	28.921	<.0001
(StLouis Apr_Jun-15) - (Kansas Jan_Mar-13)	0.23957	0.0259	Inf	9.248	<.0001
(StLouis Apr_Jun-15) - (Kansas Jan_Mar-14)	0.38739	0.02333	Inf	16.604	<.0001
(StLouis Apr_Jun-15) - (Kansas Oct_Dec-14)	-0.387	0.03386	Inf	-11.429	<.0001
(StLouis Apr_Jun-15) - (Kansas Oct_Dec-15)	0.74976	0.02028	Inf	36.969	<.0001
(StLouis Apr_Jun-15) - (Springfield Jan_Mar-13)	0.46432	0.02269	Inf	20.467	<.0001
(StLouis Apr_Jun-15) - (Springfield Jan_Mar-14)	0.55368	0.02142	Inf	25.853	<.0001
(StLouis Apr_Jun-15) - (Springfield Jan_Mar-15)	0.48868	0.02279	Inf	21.438	<.0001
(StLouis Apr_Jun-15) - (Springfield Jul_Sep-13)	0.35021	0.02396	Inf	14.619	<.0001
(StLouis Apr_Jun-15) - (Springfield Jul_Sep-14)	0.45555	0.02278	Inf	20.002	<.0001
(StLouis Apr_Jun-15) - (Springfield Jul_Sep-15)	0.41088	0.02412	Inf	17.033	<.0001
(StLouis Apr_Jun-15) - (Springfield Oct_Dec-13)	0.42637	0.02267	Inf	18.808	<.0001
(StLouis Apr_Jun-15) - (Springfield Oct_Dec-14)	0.32673	0.02387	Inf	13.688	<.0001
(StLouis Apr_Jun-15) - (Springfield Oct_Dec-15)	0.60528	0.02209	Inf	27.403	<.0001
(StLouis Apr_Jun-15) - (StLouis Jan_Mar-13)	0.58225	0.02013	Inf	28.929	<.0001
(StLouis Apr_Jun-15) - (StLouis Jan_Mar-14)	0.63513	0.01987	Inf	31.961	<.0001
(StLouis Apr_Jun-15) - (StLouis Jan_Mar-15)	0.46069	0.01989	Inf	23.162	<.0001
(StLouis Apr_Jun-15) - (StLouis Jul_Sep-13)	0.50313	0.02057	Inf	24.454	<.0001
(StLouis Apr_Jun-15) - (StLouis Jul_Sep-14)	0.48697	0.02	Inf	24.351	<.0001
(StLouis Apr_Jun-15) - (StLouis Jul_Sep-15)	0.43938	0.02026	Inf	21.688	<.0001
(StLouis Apr_Jun-15) - (StLouis Oct_Dec-13)	0.48052	0.02037	Inf	23.586	<.0001
(StLouis Apr_Jun-15) - (StLouis Oct_Dec-14)	0.203	0.02187	Inf	9.282	<.0001
(StLouis Apr_Jun-15) - (StLouis Oct_Dec-15)	0.77173	0.02014	Inf	38.319	<.0001
(StLouis Jan_Mar-13) - (Kansas Jan_Mar-14)	-0.19485	0.01318	Inf	-14.786	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(StLouis Jan_Mar-13) - (Kansas Jul_Sep-15)	-0.60419	0.02144	Inf	-28.181	<.0001
(StLouis Jan_Mar-13) - (Kansas Oct_Dec-13)	-0.5333	0.02112	Inf	-25.255	<.0001
(StLouis Jan_Mar-13) - (Kansas Oct_Dec-14)	-0.96925	0.02674	Inf	-36.246	<.0001
(StLouis Jan_Mar-13) - (Kansas Oct_Dec-15)	0.16752	0.00713	Inf	23.483	<.0001
(StLouis Jan_Mar-13) - (Springfield Jan_Mar-15)	-0.09357	0.01191	Inf	-7.856	<.0001
(StLouis Jan_Mar-13) - (Springfield Jul_Sep-13)	-0.23204	0.01516	Inf	-15.311	<.0001
(StLouis Jan_Mar-13) - (Springfield Jul_Sep-14)	-0.1267	0.01278	Inf	-9.911	<.0001
(StLouis Jan_Mar-13) - (Springfield Jul_Sep-15)	-0.17136	0.01416	Inf	-12.105	<.0001
(StLouis Jan_Mar-13) - (Springfield Oct_Dec-13)	-0.15588	0.01294	Inf	-12.049	<.0001
(StLouis Jan_Mar-13) - (Springfield Oct_Dec-14)	-0.25552	0.01578	Inf	-16.192	<.0001
(StLouis Jan_Mar-13) - (StLouis Jan_Mar-14)	0.05288	0.0073	Inf	7.243	<.0001
(StLouis Jan_Mar-13) - (StLouis Jan_Mar-15)	-0.12156	0.01074	Inf	-11.321	<.0001
(StLouis Jan_Mar-13) - (StLouis Jul_Sep-13)	-0.07912	0.00997	Inf	-7.937	<.0001
(StLouis Jan_Mar-13) - (StLouis Jul_Sep-14)	-0.09528	0.00998	Inf	-9.543	<.0001
(StLouis Jan_Mar-13) - (StLouis Jul_Sep-15)	-0.14286	0.01121	Inf	-12.746	<.0001
(StLouis Jan_Mar-13) - (StLouis Oct_Dec-13)	-0.10172	0.0104	Inf	-9.779	<.0001
(StLouis Jan_Mar-13) - (StLouis Oct_Dec-14)	-0.37924	0.01665	Inf	-22.774	<.0001
(StLouis Jan_Mar-13) - (StLouis Oct_Dec-15)	0.18949	0.0067	Inf	28.289	<.0001
(StLouis Jan_Mar-14) - (Kansas Jan_Mar-15)	-0.55011	0.01772	Inf	-31.041	<.0001
(StLouis Jan_Mar-14) - (Kansas Jul_Sep-13)	-0.60505	0.02155	Inf	-28.081	<.0001
(StLouis Jan_Mar-14) - (Kansas Jul_Sep-14)	-0.55129	0.01815	Inf	-30.376	<.0001
(StLouis Jan_Mar-14) - (Kansas Jul_Sep-15)	-0.65707	0.0208	Inf	-31.589	<.0001
(StLouis Jan_Mar-14) - (Kansas Oct_Dec-13)	-0.58618	0.0206	Inf	-28.462	<.0001
(StLouis Jan_Mar-14) - (Kansas Oct_Dec-14)	-1.02213	0.0263	Inf	-38.87	<.0001
(StLouis Jan_Mar-14) - (Kansas Oct_Dec-15)	0.11464	0.00547	Inf	20.971	<.0001
(StLouis Jan_Mar-14) - (Springfield Jan_Mar-15)	-0.14645	0.01082	Inf	-13.538	<.0001
(StLouis Jan_Mar-14) - (Springfield Jul_Sep-13)	-0.28492	0.01434	Inf	-19.87	<.0001
(StLouis Jan_Mar-14) - (Springfield Jul_Sep-14)	-0.17958	0.01176	Inf	-15.268	<.0001
(StLouis Jan_Mar-14) - (Springfield Jul_Sep-15)	-0.22424	0.01323	Inf	-16.955	<.0001
(StLouis Jan_Mar-14) - (Springfield Oct_Dec-13)	-0.20876	0.01198	Inf	-17.418	<.0001
(StLouis Jan_Mar-14) - (Springfield Oct_Dec-14)	-0.3084	0.01488	Inf	-20.725	<.0001
(StLouis Jan_Mar-14) - (StLouis Jan_Mar-15)	-0.17444	0.00994	Inf	-17.548	<.0001
(StLouis Jan_Mar-14) - (StLouis Jul_Sep-13)	-0.132	0.00937	Inf	-14.087	<.0001
(StLouis Jan_Mar-14) - (StLouis Jul_Sep-14)	-0.14816	0.00923	Inf	-16.051	<.0001
(StLouis Jan_Mar-14) - (StLouis Jul_Sep-15)	-0.19574	0.01052	Inf	-18.602	<.0001
(StLouis Jan_Mar-14) - (StLouis Oct_Dec-13)	-0.1546	0.00978	Inf	-15.801	<.0001
(StLouis Jan_Mar-14) - (StLouis Oct_Dec-14)	-0.43212	0.01634	Inf	-26.451	<.0001
(StLouis Jan_Mar-14) - (StLouis Oct_Dec-15)	0.13661	0.00492	Inf	27.77	<.0001
(StLouis Jan_Mar-15) - (Kansas Jul_Sep-13)	-0.43061	0.02314	Inf	-18.605	<.0001
(StLouis Jan_Mar-15) - (Kansas Jul_Sep-14)	-0.37685	0.02009	Inf	-18.759	<.0001
(StLouis Jan_Mar-15) - (Kansas Jul_Sep-15)	-0.48263	0.02267	Inf	-21.294	<.0001
(StLouis Jan_Mar-15) - (Kansas Oct_Dec-13)	-0.41174	0.02244	Inf	-18.345	<.0001

Contrast	Estimate	SE	df	Z-Ratio	P-Value
(StLouis Jan_Mar-15) - (Kansas Oct_Dec-14)	-0.84769	0.02795	Inf	-30.332	<.0001
(StLouis Jan_Mar-15) - (Kansas Oct_Dec-15)	0.28908	0.00974	Inf	29.664	<.0001
(StLouis Jan_Mar-15) - (Springfield Jul_Sep-13)	-0.11048	0.01622	Inf	-6.81	<.0001
(StLouis Jan_Mar-15) - (Springfield Oct_Dec-14)	-0.13396	0.01626	Inf	-8.238	<.0001
(StLouis Jan_Mar-15) - (Springfield Oct_Dec-15)	0.14459	0.01301	Inf	11.117	<.0001
(StLouis Jan_Mar-15) - (StLouis Oct_Dec-14)	-0.25768	0.01673	Inf	-15.404	<.0001
(StLouis Jan_Mar-15) - (StLouis Oct_Dec-15)	0.31105	0.00946	Inf	32.895	<.0001
(StLouis Jul_Sep-13) - (Kansas Jul_Sep-14)	-0.41929	0.0201	Inf	-20.861	<.0001
(StLouis Jul_Sep-13) - (Kansas Jul_Sep-15)	-0.52507	0.02266	Inf	-23.169	<.0001
(StLouis Jul_Sep-13) - (Kansas Oct_Dec-13)	-0.45419	0.02215	Inf	-20.506	<.0001
(StLouis Jul_Sep-13) - (Kansas Oct_Dec-14)	-0.89013	0.02764	Inf	-32.206	<.0001
(StLouis Jul_Sep-13) - (Kansas Oct_Dec-15)	0.24663	0.00966	Inf	25.527	<.0001
(StLouis Jul_Sep-13) - (Springfield Jul_Sep-15)	-0.09225	0.01584	Inf	-5.825	<.0001
(StLouis Jul_Sep-13) - (Springfield Oct_Dec-14)	-0.1764	0.01734	Inf	-10.171	<.0001
(StLouis Jul_Sep-13) - (Springfield Oct_Dec-15)	0.10215	0.01305	Inf	7.824	<.0001
(StLouis Jul_Sep-13) - (StLouis Oct_Dec-14)	-0.30013	0.01726	Inf	-17.392	<.0001
(StLouis Jul_Sep-13) - (StLouis Oct_Dec-15)	0.2686	0.00932	Inf	28.832	<.0001
(StLouis Jul_Sep-14) - (Kansas Jul_Sep-15)	-0.50891	0.0225	Inf	-22.616	<.0001
(StLouis Jul_Sep-14) - (Kansas Oct_Dec-13)	-0.43803	0.02223	Inf	-19.701	<.0001
(StLouis Jul_Sep-14) - (Kansas Oct_Dec-14)	-0.87397	0.02769	Inf	-31.562	<.0001
(StLouis Jul_Sep-14) - (Kansas Oct_Dec-15)	0.26279	0.00926	Inf	28.389	<.0001
(StLouis Jul_Sep-14) - (Springfield Oct_Dec-14)	-0.16024	0.01627	Inf	-9.846	<.0001
(StLouis Jul_Sep-14) - (Springfield Oct_Dec-15)	0.11831	0.01266	Inf	9.343	<.0001
(StLouis Jul_Sep-14) - (StLouis Oct_Dec-14)	-0.28397	0.0167	Inf	-17.004	<.0001
(StLouis Jul_Sep-14) - (StLouis Oct_Dec-15)	0.28476	0.00891	Inf	31.973	<.0001
(StLouis Jul_Sep-15) - (Kansas Oct_Dec-13)	-0.39044	0.02286	Inf	-17.079	<.0001
(StLouis Jul_Sep-15) - (Kansas Oct_Dec-14)	-0.82639	0.02825	Inf	-29.256	<.0001
(StLouis Jul_Sep-15) - (Kansas Oct_Dec-15)	0.31038	0.01054	Inf	29.456	<.0001
(StLouis Jul_Sep-15) - (Springfield Oct_Dec-14)	-0.11265	0.01685	Inf	-6.684	<.0001
(StLouis Jul_Sep-15) - (Springfield Oct_Dec-15)	0.16589	0.01361	Inf	12.187	<.0001
(StLouis Jul_Sep-15) - (StLouis Oct_Dec-14)	-0.23638	0.01709	Inf	-13.829	<.0001
(StLouis Jul_Sep-15) - (StLouis Oct_Dec-15)	0.33235	0.01024	Inf	32.458	<.0001
(StLouis Oct_Dec-13) - (Kansas Oct_Dec-14)	-0.86753	0.02781	Inf	-31.192	<.0001
(StLouis Oct_Dec-13) - (Kansas Oct_Dec-15)	0.26924	0.00997	Inf	27.004	<.0001
(StLouis Oct_Dec-13) - (Springfield Oct_Dec-14)	-0.15379	0.01743	Inf	-8.822	<.0001
(StLouis Oct_Dec-13) - (Springfield Oct_Dec-15)	0.12475	0.01328	Inf	9.394	<.0001
(StLouis Oct_Dec-13) - (StLouis Oct_Dec-14)	-0.27752	0.01717	Inf	-16.161	<.0001
(StLouis Oct_Dec-13) - (StLouis Oct_Dec-15)	0.29121	0.00966	Inf	30.131	<.0001
(StLouis Oct_Dec-14) - (Kansas Oct_Dec-15)	0.54676	0.01681	Inf	32.528	<.0001
(StLouis Oct_Dec-14) - (Springfield Oct_Dec-15)	0.40227	0.01889	Inf	21.295	<.0001
(StLouis Oct_Dec-14) - (StLouis Oct_Dec-15)	0.56873	0.0166	Inf	34.256	<.0001

VITA

Muqdad Al Hamami gained his bachelor's degree in Building and Construction Engineering in addition to the Master of Science degree in Roads and Bridges Engineering at the University of Technology, Iraq. Besides his working experience in Urban Transportation Planning in CRHI consultants, Dubai, he started his career as an assistant lecturer at the University of Wasit. Later, Muqdad Al Hamami started his Doctoral degree in Transportation Engineering at the University of Missouri in 2015 and was granted his Ph.D. degree in 2022.

PUBLICATIONS:

Al Hamami, M., & Matisziw, T. C. (2021). Measuring the spatiotemporal evolution of accident hot spots. *Accident Analysis & Prevention*, *157*, 106133.