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Using Gis to Understand the Spatial and Spatiotemporal Pattern of Covid-19 Cases and Deaths in Oklahoma

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Abstract
COVID-19, which hit the world in December 2019 has been a great cause of concern, requiring intense research to curb the virus and create focused polices and management. Therefore, the focus of this research is to provide invaluable insights and add to existing knowledge on the COVID-19 virus by using GIS based models to analyze the spatial and spatiotemporal patterns of COVID-19 in Oklahoma. Due to the nature of the virus, it is important to continually assess the geographic distribution of cases and deaths as well as factors that contribute to the patterns. The study therefore uses GIS based methods such as the Getis-Ord Gi statistic, space time cube and time series clustering to identify hotspots of COVID-19 cases and deaths in Oklahoma.

The result showed that hotspots of COVID-19 cases were found around Oklahoma City where hotspots of Blacks and Hispanics are located. Whereas for COVID-19 deaths, significant hotspots pattern was found in rural areas majorly where significant hotspots of American Indians are located. In addition, a significant uptrend of COVID-19 cases was found in few zip codes, and a significant decrease in COVID-19 deaths was found in most zip codes located in the state. Lastly areas experiencing similar increase and decrease trends in both COVID-19 cases and deaths were identified. Future work is needed to identify the binding factors that may be causing the similarities in trend in places that share similar upward and downward trend the virus.

Introduction
The Coronavirus disease (COVID-19) is a highly contagious and pathogenic viral infection caused by the respiratory syndrome coronavirus 2 (SARS-CoV-2). The virus first emerged in Wuhan, China in December 2019 and quickly spread worldwide, resulting in millions of deaths and poor health conditions [1]. The initial spread of the virus was facilitated by a lack of effective policies or abrupt actions to curtail the virus, leading to cluster outbreaks in sports, religious, and entertainment events [2]. Spatial assessments of COVID-19 cases have shown that areas with high population density, poor urban planning, and overcrowding issues tend to have a higher risk of virus transmission. Major cities have been found to be at a higher risk of contracting the virus than rural areas. In many countries, statistically significant hotspots for COVID-19 cases and deaths have been found in urban areas, especially in heavily populated cities with many social events and places of gathering.

For example, Sao Paulo, Brazil, Hubei Province of China, northern Italy, and several US states including California, Washington, Florida, New York, New Jersey, Massachusetts, Michigan, and Illinois have been identified as having significant COVID-19 hotspots [3]. This information underscores the importance of effective policies to prevent the spread of the virus, especially in highly populated urban areas. \In Europe, a spatial assessment of COVID-19 cases ratio between week 9 to 34 of 2020 suggested a cluster distribution of high incidence across England with higher risk areas concentrated in and around metropolitan areas such as Leicester, Birmingham, Liverpool, and Manchester.

Significant hotspots for COVID-19 related mortality was highly clustered and were identified in North London, West Midlands northwest, Sheffield, and Newcastle Manchester, indicating that major cities tended to have a higher risk of contracting the virus than rural areas. Due to the virus's infectious nature, areas that are heavily populated with poor urban planning and overcrowding issues tend to have a greater risk of virus transmission. In addition, small clusters of significant COVID-19 case rates were also found in suburban areas throughout England such as Ashford, Kings Lynn, and West Norfolk, and Burrow-in-Furness.

These clusters may be centers of events such as stadiums, theaters, religious houses where people are mostly crowded. In Brazil, as of May 2020, over 233,142 COVID-19 cases and 15,633 COVID-19 related deaths had been recorded. The city of São Paulo had the highest clustering of COVID-19 with a significant hotspot for both confirmed cases and deaths [4]. São Paulo is Brazil's largest city and the world's seventh-largest city, with over 12 million people. In early March 2020, China had the most confirmed cases of COVID-19, followed by Italy. In the middle of March 2020, European countries had more confirmed cases than other continents. However, since November 2020, the United States has been the leading country of the COVID-19 outbreak [5].

Given the virus's contagious nature, it is clear how population density, high numbers of social events, and places of gathering tended to play a key role in the transmission of the virus, given the higher prevalence of cases found in major cities. Spatial epidemiology is an essential field for identifying the spread and distribution of infectious diseases, such as COVID-19. Spatial clustering analysis is a fundamental tool for distinguishing between random and significant clusters of disease cases, and it is of great value in identifying potential underlying causes of such clusters.

It is possible to account for different risk factors, including socioeconomic and environmental conditions, by analyzing the spatial and temporal variability of the clusters. By utilizing the data and maps generated by spatial clustering analysis, we can develop targeted public health interventions and effectively implement public health programs that cater to the specific etiological characteristics of COVID-19. Such measures can significantly help prevent and control the spread of the disease, and by extension, reduce morbidity and mortality.

The recent emergence of the COVID-19 virus has resulted in a significant and ongoing public health crisis that has affected people around the globe. Although there have been many studies exploring the spatial and temporal patterns of the virus, given the recent emergence of the virus, there are still many gaps in our understanding of its spatiotemporal trends. The objective of this research is to conduct a spatial and spatiotemporal analysis of COVID-19 cases and deaths in the state of Oklahoma. Specifically, the study aims to identify statistical hotspots of COVID-19 cases and deaths in the state, as well as to identify areas where there have been significant increases or decreases in the number of cases and deaths over time.

By utilizing advanced statistical and spatial analysis techniques, this study will help to identify patterns and trends in the spread of COVID-19 in Oklahoma. The results of this analysis can inform public health officials and policymakers in the development of targeted interventions and policies to prevent and control the spread of the virus. Overall, this research has the potential to provide critical insights into the spatiotemporal dynamics of COVID-19 in Oklahoma, which can help to mitigate the impact of the pandemic and save lives.

Therefore, this study will provide valuable insights and add to the existing body of knowledge on the current global pandemic. By analyzing the recent spatiotemporal trends of the virus, we can gain a better understanding of how it spreads and identify potential hotspots where public health interventions can be implemented to control its spread. This knowledge can help inform public health policies and aid in the development of effective strategies for managing pandemic. Overall, this study will be a crucial contribution to the ongoing efforts to combat the COVID-19 pandemic, and it has the potential to provide significant benefits to global public health.

Literature Review

Overview of COVID-19 Cases and Deaths in the United States

The COVID-19 pandemic has had a devastating impact on the United States since it was first detected in January 2020 (CDC 2020). According to the Centers for Disease Control and Prevention (CDC), as of February 2023 there had been over 102 million confirmed cases of COVID-19 and over 1.1 million total deaths in the country . The pandemic has affected every state in the country, with significant disparities based on factors such as age, race, and socioeconomic status [6]. Early in the pandemic, New York City was hit particularly hard, with over 190,000 cases and 15,000 deaths attributed to COVID-19 by May 2020 [7].

However, as the pandemic has progressed, other states and regions were also heavily impacted. As of February 2023, California, Texas, and Florida had the highest number of confirmed cases in the country, with over 11 million, 8 million, and 7 million cases, respectively. Older adults and those with underlying health conditions have been particularly vulnerable to severe illness and death from COVID-19. Black and Hispanic individuals have also been disproportionately affected by COVID-19, with higher rates of hospitalization and death compared to White individuals [6,8].

The response to the COVID-19 pandemic in the United States has been complex and has varied widely depending on the state and local government policies. Many states implemented social distancing measures, such as school closures and stay-at-home orders, to slow the spread of the virus. However, the effectiveness of these measures has been debated, and there have been significant political and public health controversies surrounding the pandemic response in the United States [9].

In summary, the COVID-19 pandemic has had a significant impact on the United States, with over 102 million confirmed cases and over 1.1 million deaths. The impact of COVID-19 has been felt across the country, with significant disparities based on factors such as age, race, and socioeconomic status. The response to the pandemic has been complex and controversial, and it remains a significant public health challenge in the United States.

Spatial Pattern of COVID-19 Cases and Deaths in the United States

The COVID-19 pandemic has significantly affected the United States, with numerous cases and deaths recorded since its emergence. Understanding the spatial pattern of the virus is critical in controlling its spread, as it helps in identifying hotspots and determining areas that require targeted interventions. In the US, several studies have been conducted to better understand the spatial pattern of COVID-19. Analyzed the spatial pattern of COVID-19 cases in the US using the kernel density estimation method [10].

The study found that the highest concentration of cases was in urban areas, particularly in the Northeast and Midwest regions. Similarly, Andersen used cluster analysis to identify three clusters of high COVID-19 prevalence: New England, Southeast, and Southwest [11]. The authors noted that the clustering of COVID-19 cases was influenced by the level of urbanization, whereas COVID-19 deaths were influenced by high concentrations of Black population and people living with disability. Other related studies using diverse methods have consistently found similar high clusters of COVID-19 cases and deaths, particularly in urban areas [12-14].

The spatial distribution of COVID-19 cases and deaths has varied widely across the country, with some regions and communities being hit particularly hard by the pandemic. Studies have shown several statistically significant COVID-19 clusters for both incidence and mortality. Found hotspots of COVID-19 cases and deaths in the United States in major cities such as New York City, New Orleans, and Chicago, with several small rural clusters as well. At the national level, at the initial stage of the pandemic, results of COVID-19 prevalence rates were greater in urban areas compared to rural counties in the Northeast and Mid-Atlantic regions of the United States. However, later the intensity of the virus shifted to a rapid surge in rural areas [15,16].

High prevalence states located in rural areas in the Midwest of the country had more than 3,400 COVID-19 cases per 100,000 population compared to 1,284 cases per 100,000 population in urban counties nationwide between August 30 and November 12, 2020 [12].

Studies analyzing the spatial pattern of COVID-19 in the United States have consistently identified clustering of cases in urban areas especially during the initial stage, particularly in the Northeast and Midwest regions. Population density and mobility patterns are significant contributors to the clustering of cases. However, recent findings have found a great insurgence in rural areas. Targeted interventions in these hotspots are recommended to control the spread of the virus. Furthermore, due to the novelty of the virus, further investigation is required to obtain up-to-date information on the current locations where the virus is prevalent. The findings from these studies are useful in developing effective public health policies to prevent the spread of COVID-19 in the United States.

Spatiotemporal Pattern of COVID-19 Cases and Deaths in the United States

Just like the spatial patterns, understanding the spatiotemporal pattern of the virus is likewise critical in controlling the spread of COVID-19, as it helps in identifying hotspots and determining areas that require targeted interventions at different periods. Spatiotemporal analysis, which integrates spatial and spatiotemporal structures, is used to study the space-time variation by identifying disease patterns persisting over time and over spatial units. Several studies on COVID-19, in a bid to understand the nature of the virus, have employed spatial temporal analysis by analyzing the COVID-19 cases at specific period to determine varying clusters to help make useful predictions [16].

The COVID-19 pandemic in the United States showed a distinct geographic and temporal pattern. Initially, major metropolitan areas such as New York City experienced a surge in cases, but as the pandemic progressed, the Southeast and Southwest regions of the country became new hotspots during the summer months. In the fall, the upper Midwest became the next region to see a significant increase in cases. From the start of the pandemic, the number of cases steadily increased until October 2020, at which point there was an exponential surge that continued through the end of the year.

This surge in cases was attributed to a variety of factors, including colder weather driving people indoors, relaxed social distancing measures, and pandemic fatigue. In terms of deaths, there was an initial exponential increase in the spring months of March and April, followed by a decrease and relative stability through October. However, the number of deaths from COVID-19 experienced another exponential increase in November and December, which was linked to the surge in cases in the preceding months. Investigated the spatial and temporal patterns of the COVID-19 pandemic in the United States and found substantial regional clustering patterns that varied on both an annual and weekly scale. At the initial stage, the Great Plains, Southwestern, and Southern areas showed divergent COVID-19 experiences [17-19].

However, after examining the data by epi week (also known as epidemiological week, which is a standardized way of collecting, organizing and reporting health data on a weekly basis), the space-time analyses discovered three separate clusters of cases from November 2020 to January 2021 in the West/Southwest, Ohio-Mississippi Valley, and Northeast. The reason for this was an abrupt rise in cases at the close of 2020. When analyzing COVID-19 deaths, four unique space-time clusters were found. Early clusters were discovered in the New York Metropolitan area (August 3, 2020-January 31, 2021), the South (October 12, 2020-January 31, 2021), the Midwest and Great Plains (November 23, 2020-January 31, 2021), and the West, (December 21, 2020-January 31, 2021).

These findings suggest that the pandemic's spatial and temporal patterns have varied significantly across the United States, and that different regions have experienced the pandemic differently. The study's results may help inform public health policies and interventions aimed at mitigating the spread of COVID-19 in the United States. Hence, further exploration of these patterns in specific regions can provide valuable insights into the local spatiotemporal patterns of COVID-19 transmission and deaths, which can then be used to inform local policies and interventions.

For example, regions with high case and death rates may require more aggressive measures to mitigate the spread of the virus, such as stricter lockdowns and increased testing and contact tracing efforts. On the other hand, regions with lower case and death rates may be able to implement less stringent measures, such as targeted interventions and phased reopening plans. Understanding the local patterns of COVID-19 transmission can also help identify disparities and inequities in access to healthcare and other resources, which can then be addressed through targeted policies and interventions. Therefore, continued research into the spatial and temporal patterns of COVID-19 at the local level is essential for effective pandemic management and control.

GIS Methods Relevant to Spatio-Temporal Analysis

GIS has become a crucial tool in understanding and analyzing health related data. This is because it has the capability to integrate spatial and non-spatial data, enabling researchers to explore relationship between health outcomes as well as various social economic and socio demographic factors. The space time cube technique for example is a powerful tool in GIS that is used for spatio-temporal analysis. It integrates spatial and temporal dimensions into single visualization and analytical framework and allows researchers to explore how phenomenon changes over space and time. In their study, utilizes the Space-Time Cube analysis to explore the spatio-temporal patterns of tornado occurrences in Virginia. Temporal clusters of tornado events were identified, highlighting periods when tornado activity was particularly concentrated or when there were notable shifts in spatial patterns [20].

Likewise, the space-time cube was employed by , to analyze the spatiotemporal patterns of road traffic crashes [21]. This involves aggregating crash data from 2015 to 2019 into space-time bins. The Mann-Kendall statistic was used to evaluate trends within each bin, identifying areas with increasing or decreasing crash frequencies over time. The analysis revealed a higher clustering of crashes during weekdays in 2019 compared to 2015. This suggests systematic issues, related to increased traffic during workdays or specific behavioral patterns.

Another GIS method used for spatio-temporal analysis is the trajectory analysis method. This method is used in analyzing the movement patterns of objects or entities over space and time. This involves tracking flights, calculating speeds, accelerations, and identifying hotspots or clusters of movement . Groff, Weisburd, and Morris 2009 in their study employed the trajectory analysis method to map the movement patterns of juveniles involved in crimes. This approach helps in understanding the routes and behaviors of offenders, identifying frequent pathways and stop points [22].

Lastly, Agent-Based Modeling (ABM) is another powerful tool in GIS used for spatiotemporal analysis. It allows researchers to model the behavior and interactions of individual agents within a spatial and temporal framework. The ABM is used to visualize changes over time using animations, time sliders, or temporal plots to observe dynamics like the spread of disease, traffic congestion, or wildlife migration. Wise et al 2023, used the ABM technique to simulate the spread of infectious disease and explore how different spatial and temporal resolutions influence the study by incorporating different spatial scales and time unit. The result suggests that both time and spatial resolution have significant effect on a study given that finer resolution tends to capture localized outbreaks compare to coarse resolution, so also finer resolution in time unit provides more details into the progression of a disease outbreak [23].

In summary, the space-time cube, trajectory analysis, and agent-based modeling (ABM) are some of the common GIS methods used for spatiotemporal analysis. These methods are integral to spatiotemporal analysis, providing a comprehensive understanding of how spatial and temporal factors interact and influence various phenomena. However, for this study the space time cube will be utilized to identify patterns, trends and differences across both space and time.

GIS as an Important Tool in Analyzing Spatial and Spatiotemporal Pattern of COVID-19 Geographic Information Systems (GIS) have become an essential tool for spatial studies in a variety of fields, including public health, environmental science, urban planning, and more. GIS allows for the processing, analysis, and visualization of data, providing unique insights into complex ecological questions. Its use in health promotion, medicine, and epidemiology is gaining recognition, as it enables the integration of multiple data sources and the application of various spatial analytic techniques [24].

GIS approaches can help answer questions related to public health, such as identifying how disease rates vary across the country or exploring whether there are higher rates of disease in communities closer to certain environmental factors, such as industrial areas. By integrating and analyzing spatial data, GIS provides a vivid and meaningful way to understand complex patterns and relationships.

In a review article on the application of GIS on COVID-19, research showed that hotspot analysis using kernel density functions or other density techniques was the most frequently used spatial analysis, followed by spatial autocorrelation analysis using global or local Moran's Index in studies that involved spatial and spatiotemporal analysis. Utilized the space-time analysis technique in GIS to identify active high-risk transmission clusters of COVID-19 in Sergipe, Brazil [25,26].

The prospective space-time statistics detected "active" and emerging spatiotemporal clusters comprising six municipalities in the south-central region of the state. The spatial spread of epidemics is a critical property that depends on the epidemic mechanism, human mobility, and control strategies. Geospatial tools such as GIS and spatial statistics can be used to analyze and respond to the spatial spread of epidemics. By using GIS and spatial statistics, we can generate scientific information that can help to identify spatial correlations with other variables, such as demographic factors, environmental conditions, and human behavior, which can influence the spread of epidemics.

GIS and spatial statistics can also help to identify transmission dynamics by mapping the spread of the disease over time and space. This information can be used to identify areas of high transmission and to target interventions, such as social distancing measures, contact tracing, and vaccination campaigns, to reduce the spread of the disease. The use of GIS and spatial statistics can help to generate scientific information that can guide public health responses to epidemics and help to mitigate their impact. By understanding the spatial spread of the disease, we can identify areas of elevated risk and take proactive measures to reduce transmission and prevent further spread [27].

Overall, the spatiotemporal trend of the pandemic in the United States demonstrated the complex nature of the virus and its ability to impact different regions and communities at different times. Despite ongoing efforts to mitigate the spread of the virus, the pandemic has had a profound impact on the country, with millions of confirmed cases and hundreds of thousands of deaths. The spatial and temporal disparities in the COVID-19 pandemic in the United States highlight the need for ongoing monitoring and analysis to better understand how the virus spreads and impacts different regions and communities. These findings can inform public health policies and interventions to mitigate the spread of the virus and save lives.

GIS also offers a powerful spatial technique for generating scientific information that can help guide public health responses to epidemics. By leveraging the power of GIS, we can improve our understanding of the spatial dynamics of infectious diseases such as COVID-19 and develop evidence-based strategies that can mitigate their impact on public health.

Based on the review so far, the spatial and spatiotemporal pattern of COVID-19 cases and deaths in the United States had been evolving since the first case was reported in January 2020.

Based on the variations in geographic distribution of the virus, it is evident that COVID-19 cases and deaths in the United States were not evenly distributed across the country. Some of the biggest states in the country with major airports, such as New York and California, had a higher number of cases and deaths than other states. Some studies found urban areas to have higher numbers of cases and deaths than rural areas, while others found rural areas to have higher COVID-19 cases and deaths. The number of COVID-19 cases and deaths in the United States fluctuated over time [28].

There were peaks and valleys in the number of cases and deaths, which were influenced by factors such as public health interventions, changes in social distancing measures, and vaccination rates. Overall, the spatial and spatiotemporal pattern of COVID-19 cases and deaths in the United States is complex and evolving. As the pandemic continues to evolve, it is important to continually assess the geographic distribution of cases and deaths, as well as the factors that contribute to these patterns. This information can be used to identify areas that are at higher risk and to target resources and interventions to those areas.

Ongoing research on the spatiotemporal pattern of COVID-19 cases and deaths can help

- Identify areas that are experiencing outbreaks or that are at higher risk of outbreaks, so that resources can be directed to those areas.
- Monitor changes in the geographic distribution of cases and deaths over time, so that response efforts can be adjusted as needed.
- Assess the effectiveness of public health interventions in different areas, so that best practices can be identified and shared.

- Identify and address disparities in the distribution of cases and deaths across different demographic groups and geographic areas.

Research Questions

The study aims to answer three main research questions

- Where were the hotspots of COVID-19 cases and deaths in Oklahoma from January 2020 to October 2023?
- Which areas experienced an increase or decrease in COVID-19 cases and deaths over time?
- Where were the clusters of places experiencing an increase and decrease in COVID-19 cases and deaths at the same time?

Methodology

Study Area

The state of Oklahoma provides a unique area for this study. The Oklahoma State Department of Health (OSDH) was the primary agency responsible for coordinating the state's COVID-19 response. The OSDH provided regular updates on COVID-19 case numbers, hospitalizations, and deaths through its website and social media channels. The state also established a COVID-19 hotline for residents to call with questions or concerns. However, in terms of healthcare capacity, Oklahoma faced challenges during the pandemic due to a shortage of healthcare workers and hospital beds. One major limitation was the state's low vaccination rate, which put residents at greater risk for severe illness and hospitalization from COVID-19. As of February 8, 2023, only around 60% of the state's population was fully vaccinated, compared to the national average of around 69% [6,29].

Another limitation was the shortage of healthcare workers and hospital beds in the state. Hospitals in Oklahoma faced significant strain during surges in COVID-19 cases, with some hospitals reporting having to turn away patients due to lack of space and staff. At a later stage of the COVID-19 virus, the state implemented emergency measures to increase bed capacity and recruit healthcare workers and increase bed capacity, including the conversion of non-hospital facilities into COVID-19 treatment centers. Additionally, the state partnered with the Federal Emergency Management Agency (FEMA) to set up temporary medical facilities in response to surges in COVID-19 cases, implemented mobile vaccination clinics to reach underserved populations, and had partnered with pharmacies and healthcare providers to expand vaccine access. But these efforts were sometimes limited by shortages in staffing and resources.

Finally, Oklahoma faced challenges in addressing COVID-19 vaccine hesitancy and misinformation. Despite efforts to expand vaccine access and education, some residents remained skeptical of the vaccine and were unwilling to get vaccinated. This reluctance was sometimes fueled by misinformation and conspiracy theories circulating on social media and other channels. January 2022 was the month with the highest average cases, while April 2021 was the month with the highest average deaths in Oklahoma. As of February 16, 2023, there have been 1,281,551 total cases of COVID-19 in Oklahoma and a provisional death count of 17,827 and 5,251 active cases (OSDH 2023). With a population of about 3.987 million, it means at least 1 in 224 residents died from the coronavirus. As of March 23, 2023, an average of 291 daily cases were reported in Oklahoma in the previous week. Cases had decreased by 43% and deaths by 47% [30].

Despite the measures taken by the state of Oklahoma to curb the spread of COVID-19, the virus continues to surge in the state. This highlights the importance of this research to better understand the current situation that would develop into more targeted and effective measures to lower the number of cases and deaths. Using GIS and spatial analysis techniques, this research aims to identify hotspots and clusters of COVID-19 cases, and deaths, assess the effectiveness of existing interventions, and develop evidence-based strategies to mitigate the spread of the virus. By understanding the spatial and temporal patterns of the disease, the study aims to identify vulnerable populations and areas that require targeted interventions and monitor the effectiveness of interventions over time.

This research using GIS and spatial analysis can provide valuable insights into the contemporary spread of COVID-19 in Oklahoma and guide the development of more effective strategies to control the disease. This can help to protect public health and prevent the continued surge of COVID-19 in the state.

Data Collection

For this study, secondary data was obtained and used for analysis. Up-to-date COVID-19 data were obtained from the OSDH at the zip code level from January 2020 until October 2023. The zip code level data is the smallest available unit data for COVID-19. The zip code level measures have more within unit variations compared to county. Census tract data has been established to provide better variation for spatial analysis. However, health data are not usually provided at the census tract level. In addition, studies have shown that there are few differences in results when comparing the zip code analysis and census tract analysis, hence utilizing the zip code also yields a reliable result. Lastly, the zip code boundary data shape file for Oklahoma was downloaded from the US Census Bureau Tiger/Line shapefile [31].

Data Analysis Procedure: Getis-Ord Gi Statistic

The Getis-Ord Gi statistic, also known as hot spot analysis, is one of the most-used methods to determine hotspots and clusters in health analysis. In this study, the Getis-Ord Gi statistic is used to determine the spatial pattern of COVID-19 cases and deaths in Oklahoma. The Getis-Ord Gi* statistics are a measure of spatial autocorrelation that assesses whether a feature is clustered or randomly distributed in geographic space. It was developed by Getis and Ord 1992 and is widely used in geography, urban planning, and related fields. The Getis-Ord Gi* statistic is calculated with respect to a specified threshold distance (defined by the user) rather than to an inverse distance, as with Moran's I [32,33].

GIS uses the formula below in calculating the Gi* statistic for a feature i in a set of n

Equation 1: $$G_i^* = \frac{\sum_{j=1}^{n} \omega_{i,j} x_j - \bar{X} \sum_{j=1}^{n} \omega_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} \omega_{i,j}^2 - \left(\sum_{j=i}^{n} \omega_{i,j} \right)^2 \right]}{n-1}}}$$

Equation 2: $$\bar{X} = \frac{\sum_{j=1}^{n} xj}{n}$$

Equation 3: $$S = \sqrt{\frac{\sum_{j=1}^{n} x2_j}{n}} - (\bar{X})^2$$

Where:
x^j is the value of the feature j.
$\bar{X}$ is the mean value of all the features?
$w_{i,j}$ is a spatial weight that measures the proximity of feature i to feature j.
n is the total number of units in the study area.
S is the variance of the values of all the features.

This formula for the G_i* statistics is a z-score, so no further calculations are needed [34,35]. For statistically significant positive z-scores, the concentration of high values increases with increasing z-score (hot spot), whereas for statistically significant negative z-score, the concentration of low values results in lower z-score (cold spot). Positive values indicate clustering (i.e., high values tend to be near other high values), negative values indicate clustering (i.e., low values tend to be near other low values), and values close to zero indicate randomness (i.e., high values or low values are not related to the spatial distribution of other high values or low values) [36].

The statistical significance of the G_i* statistic can be assessed using a permutation test or a Monte Carlo simulation, in which the spatial locations of the features are randomly shuffled many times to create a null distribution of the statistic under the assumption of random spatial arrangement. The observed value of the Gi* statistics can then be compared to this null distribution to determine if it is statistically significant at a given level of confidence . Some major advantages of the G_i* statistics are that it is a simple and easy-to-use measure of spatial autocorrelation that does not require advanced statistical knowledge, especially as it can be easily calculated with ArcGIS software. It provides a quantitative and interpretable measure of the degree and direction of spatial clustering or dispersion, which can be used to identify spatial patterns and trends in geographic data [32].

The G_i* statistic can be applied to a wide range of data types, including both continuous and discrete variables, and it is robust to outliers and non-normal distributions. It can be used to compare the spatial autocorrelation of different variables or at different scales, which can help to identify factors that contribute to spatial patterns. Lastly, the G_i* statistic is widely used in recent studies compared to the local Moran's I due to its many advantages as outlined by Braithwaite and Li (2007; 285-287). Despite these advantages, the technique has been found to have several limitations. First, it assumes that spatial weights are known and accurately reflect the underlying spatial relationships between features, which can be subjective and arbitrary.

Given that the weights are usually subjective, this can lead to bias and variations in the result. Different weighting schemes can lead to different results and interpretations. Also, it does not account for the underlying processes or mechanisms that generate spatial patterns, which can limit the ability to draw causal inferences. Lastly, it can be affected by edge effects and boundary conditions, which can distort the results and lead to false conclusions [37,38].

In conclusion, while the Getis-Ord G_i* statistics are not without limitations, it remains a valuable and widely used tool for spatial analysis. It is a useful and efficient tool for analyzing local patterns of disease and can provide valuable insights for policymaking and management. For example, it can be used to identify "hotspots" of disease incidence or prevalence, which can help to target limited resources and interventions to areas of greatest need. It can also be used to evaluate the effectiveness of disease control measures and monitor changes in disease patterns over time. Moreover, the Getis-Ord G_i* statistics can be combined with other methods, such as spatial regression models and geographic information systems (GIS) to provide a more comprehensive and robust analysis of spatial patterns and their underlying determinants [39].

This can help to improve the accuracy and reliability of the results and enhance the usefulness of the analysis for decision-making.

Space-Time Cube Statistics

Many academic disciplines strive to identify and understand patterns in time series, but geographers face the biggest challenges because they look at the world through a spatial lens. The space-time cube can help address this data management problem. The space-time cube is a powerful tool for visualizing and analyzing geospatial data that varies over time. It is a three-dimensional representation of a set of spatiotemporal data points, where the x-axis and y-axis represent spatial coordinates/geography, and the z-axis represents time [40,41].

Each cube is referred to as a Bin. Geographers face unique challenges in analyzing time series data because they are interested in how spatial patterns change over time. This requires managing and analyzing large amounts of data that are both spatially and temporally referenced. The space-time cube is an effective solution to this problem because it allows geographers to explore and analyze spatiotemporal data in a single, intuitive framework. In the space-time cube, each data point is represented as a block with a specific spatial location, time, and attribute value. These blocks can be stacked to create a 3D visualization that allows users to explore patterns and trends over time . The cube can be rotated and sliced to provide different perspectives on the data and reveal spatial and temporal patterns that might be missed with other visualization techniques [42,43].

By using the space-time cube (Figure 2.1), geographers can identify and understand patterns in time series data more effectively. They can analyze how these patterns change over time and how they relate to specific spatial locations. This information can be used to inform a range of applications, from urban planning and environmental monitoring to disaster response and public health.

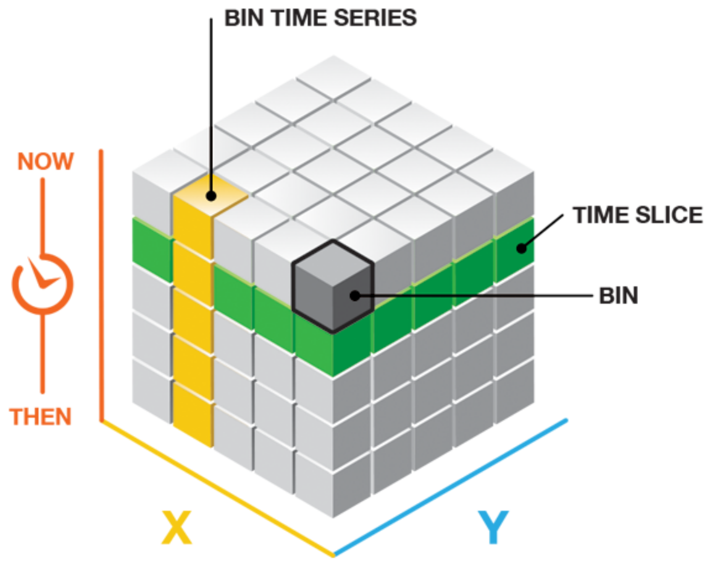

Figure 2.1: Space Time Cube (ArcMap 2023)

The space-time cube is not the only way to explore spatial patterns across time. Small multiples are another effective technique but becomes less useful as the scale of data analyzed becomes finer [44].

In GIS, the space time cube is conducted using the create space time cube tool. Once the spatial and temporal data is imported into the software, the tool allows one to define the parameters, such as the spatial extent, and time extent, which could be days, months or years depending on the data and analysis needs. For this study, the data used was reported weekly on a three-year basis from January 2020 to October 2023. The space time cube would be used to capture the three-year period as it allows for easy identification of longer trends and cycles that may not be visibly apparent in shorter time frames. In addition, this duration can reveal seasonal variation, annual patterns, and the overall direction of change. This means that studying shorter periods such as a single year or months may be affected by short term anomalies or seasonal effects which may result in misleading conclusions.

The result of this study using a three-year period would provide a comprehensive understanding of how COVID -19 evolved in the state as well as enable policy makers to make more informed and strategic decisions regarding the virus. In addition, Policy makers can prioritize resource allocation based on identified trends and direct resources to locations and areas with the greatest need. It could also help in providing more informed predictions and mange risks proactively, reducing the impact of potential problems in the future.

In answering the second and third research questions (Which areas are experiencing an increase or decrease in COVID-19 cases and deaths over time? Where are the clusters of places experiencing an increase and decrease in COVID-19 cases and deaths at the same time?) The ArcGIS Pro software is used to calculate the space time cube that would be used for further analysis.

Mann-Kendall Trend Statistics

The Mann-Kendall trend statistic is a non-parametric method used to detect trends in time series data. The Mann-Kendall test is based on the notion of rank correlation between data points in a time series. It involves calculating the difference between all pairs of data points and counting the number of pairs where the direction of the difference (i.e., increasing or decreasing) is the same. This count is known as the Kendall score. The Mann-Kendall test is used to determine whether there is a significant trend in the time series data [45,46].

The null hypothesis of the test is that there is no trend, while the alternative hypothesis is that there is a trend. The Mann-Kendall test is widely used in climate research, hydrology, and other fields where trends in time series data are of interest. It has the advantage of being robust to outliers and non-normality in the data. However, it can be less powerful than parametric methods when the assumptions of those methods are met. To answer the second research question, which is to identify the spatial trend of COVID-19 cases and deaths in Oklahoma, the Mann-Kendall trend test is performed in ArcGIS Pro using the space time cube created for the data. The software provides tools for spatial and temporal data analysis, including trend analysis. ArcGIS Pro provides a user-friendly interface for conducting trend analysis on space-time series data and allows for the visualization of the results.

Time Series Clustering

To answer the last research question, which is to identify areas that experienced increases or decreases in COVID-19 cases and deaths at the same time, time series clustering statistics is employed using ArcGIS Pro. Time series clustering is a method of grouping similar time series data into clusters or groups based on their similarity in pattern and behavior over time. This approach is useful for analyzing large volumes of time series data, identifying patterns, detecting anomalies and classification of time series data [47].

In ArcGIS, we can group time series together based on two approaches; if they have similar values at the same time, or if they have similar profiles. By similar values, the time series clustering groups time series data based on the similarity in their value, i.e. whether they are high or low, whereas by cluster profile, the time series cluster groups the time series data based on whether they are increasing or decreasing at the same time regardless of the value. For this research, the time series clustering by profile is utilized. Recognizing dynamic changes in time-series data involves identifying when the data undergoes sudden changes or transitions.

This is important in fields such as health geography to determine the effectiveness of policies. Evaluating the effectiveness of policies involves assessing whether they have achieved their intended outcomes and whether any unintended consequences have occurred. Clustering time-series data in this case based on whether they are increasing or decreasing at the same time can provide valuable insights and help solve complex problems in various fields. Additionally, clustering time-series data based on whether they are increasing or decreasing at the same time can lead to improved prediction of future trends.

By identifying patterns in the data, it may be possible to make more accurate predictions about future trends and adjust policies or strategies accordingly. Determining the number of clusters when conducting time series clustering involves a range of statistical methods and approaches. Some of which involve using appropriate clustering algorithms such as K- means, hierarchical clustering, and visualization. For this study visualization techniques were utilized. This involves visualizing the clusters on a map to see the spatial distribution and then checking for geographic coherence to ensure that the temporal patterns are meaningful and distinct.

Results

To answer the first research question, "where were the hotspots of COVID-19 cases and deaths in Oklahoma from January 2020 to October 2023?" a Gi* hotspot analysis was carried out using GIS based on the rate of COVID-19 cases and deaths per 1000 population. The result showed varied locations of hotspots for COVID-19 cases and deaths in Oklahoma. Also, the distribution of the rate of COVID-19 cases and deaths are mapped (Figure 2.2 & 2.3), to show how the virus is distributed across the state. Locations in red shows a higher cases/deaths compared to locations in yellow color. For the hotspot analysis of COVID-19 cases rate (Figure 2.4), significant hotspots of COVID-19 virus with a 99% significant level can be found in zip codes in Oklahoma, Cleveland, McClain, Pottawatomie, the eastern part of Grandy, and Canadian Counties. For COVID-19 deaths, significant hotspots from the Gi* analysis with a 95% and 90% statistical level are shown in Figure 2.5. From the map statistical hotspots of COVID-19 deaths are found in zip codes in Cherokee, Mayes, Muskogee, and Stephens Counties and some parts of other counties such as Jefferson, Blaine, and Roger Mills.

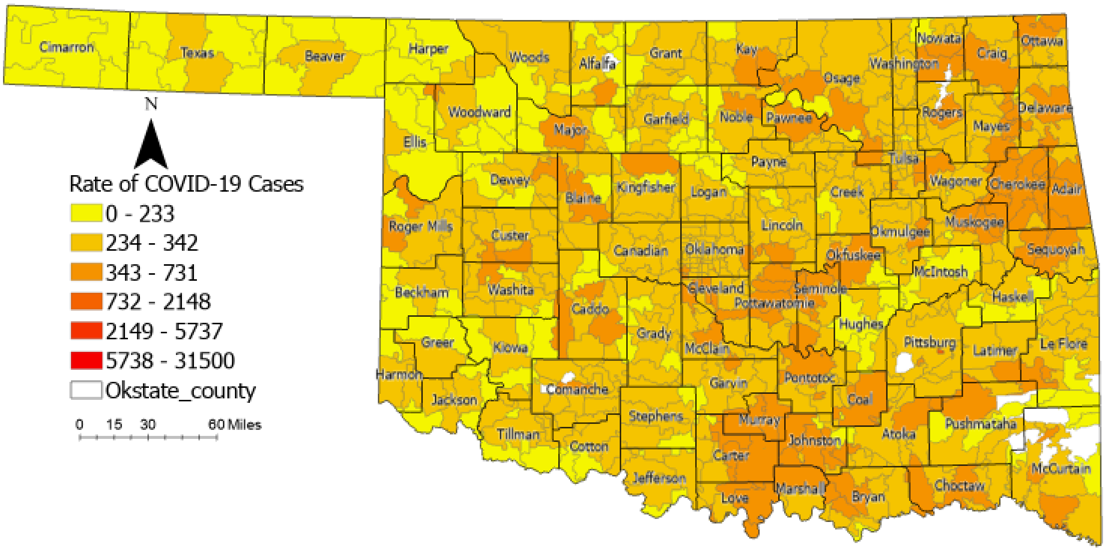

Figure 2.2: COVID-19 Case Rate Per 1000 Population

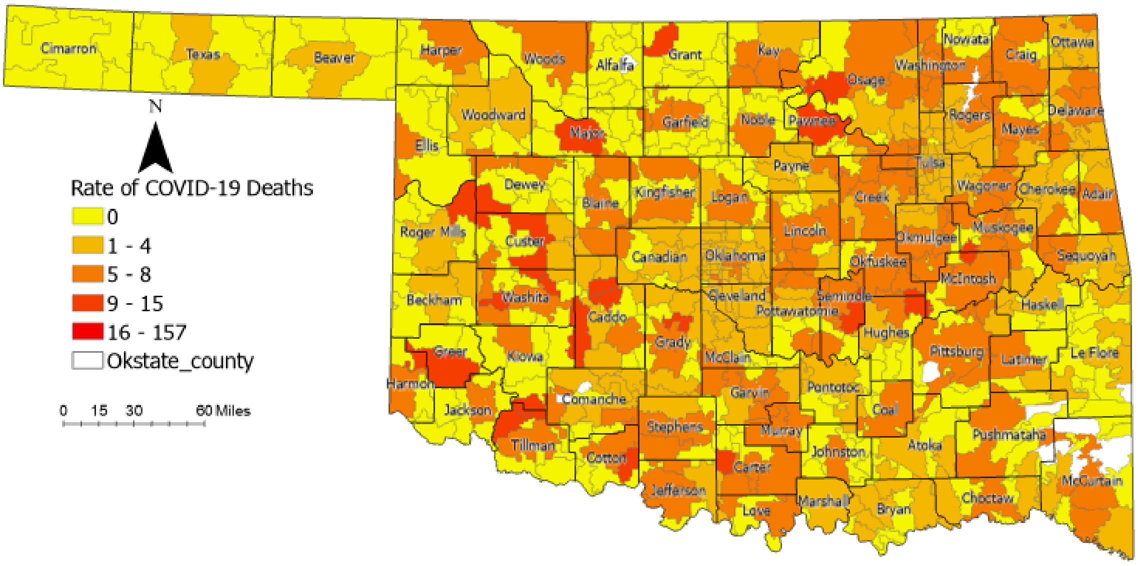

Figure 2.3: COVID-19 death rate per 1000 population

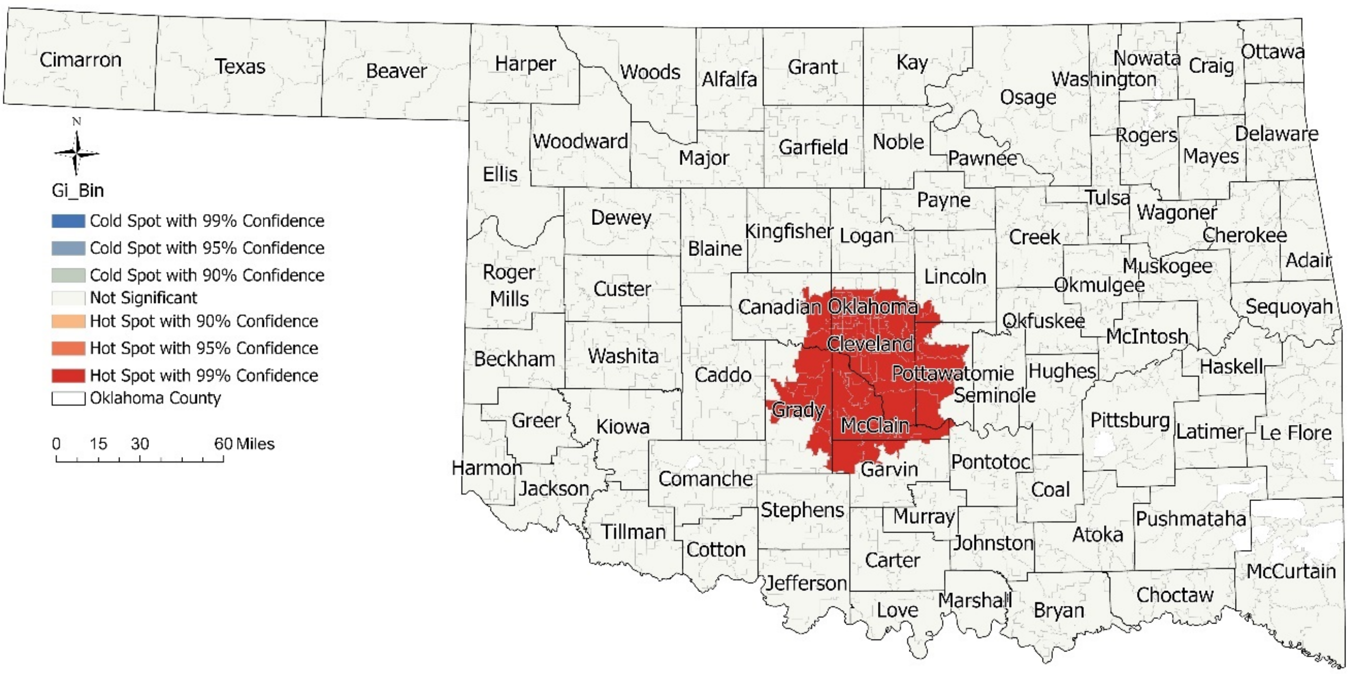

Figure 2.4: Significant Hotspots and Cold Spots of Covid-19 Case Rate Per 1000 Population

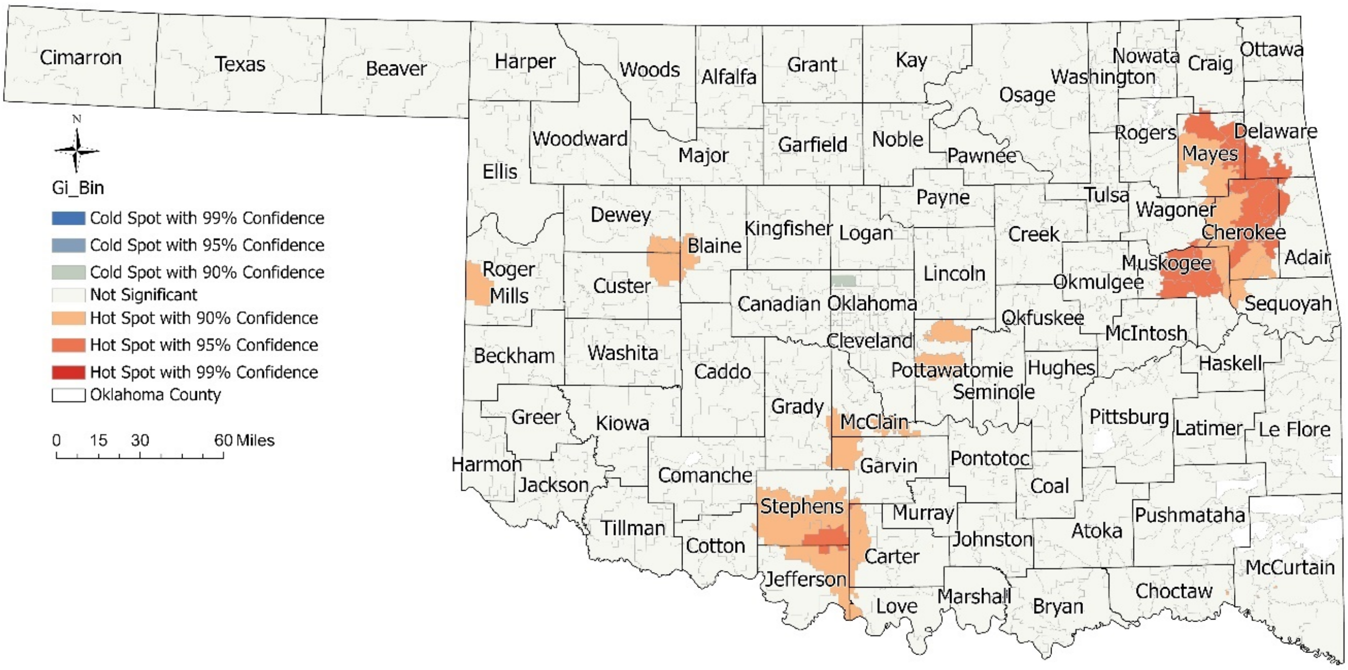

Figure 2.5: Significant Hotspots and Cold Spots of Covid-19 Death Rate Per 1000 Population

The second research question, which identifies areas experiencing an increase or decrease in COVID-19 cases and deaths over time, was answered using the space time cube analysis in GIS, which uses the Mann-Kendall test statistical method to determine statistical spatial trend in the data. First, the weekly reported COVID-19 case, and death data were explored using the data engineering tool in GIS to create a bar chart based on the sum of the weekly reported count data (Figures 2.6 and 2.7). The result of the COVID-19 cases on a global scale with a trend statistic value of -0.05999 and a trend p-value of 0.9522 indicates that there is no significant statistical trend direction in the data. However, on a local scale, a few zip codes showed significant spatiotemporal increases and decreases in COVID-19 cases (Figure 2.8).

For example, Texas County showed a 99% significant confidence of a down trend/decrease in COVID-19 cases whereas Pontotoc County had significant uptrend of the COVID-19 virus. For the COVID-19 deaths the space time cube test on a global scale revealed a significant decreasing trend direction of the virus with a -5.6002 significant trend statistic and 0.000 trend p-value. The local scale results also reveal clusters of zip codes showing significant downtrend direction of COVID-19 deaths with few zip codes having no significant trend and no location showing an upward trend (Figure 2.9).

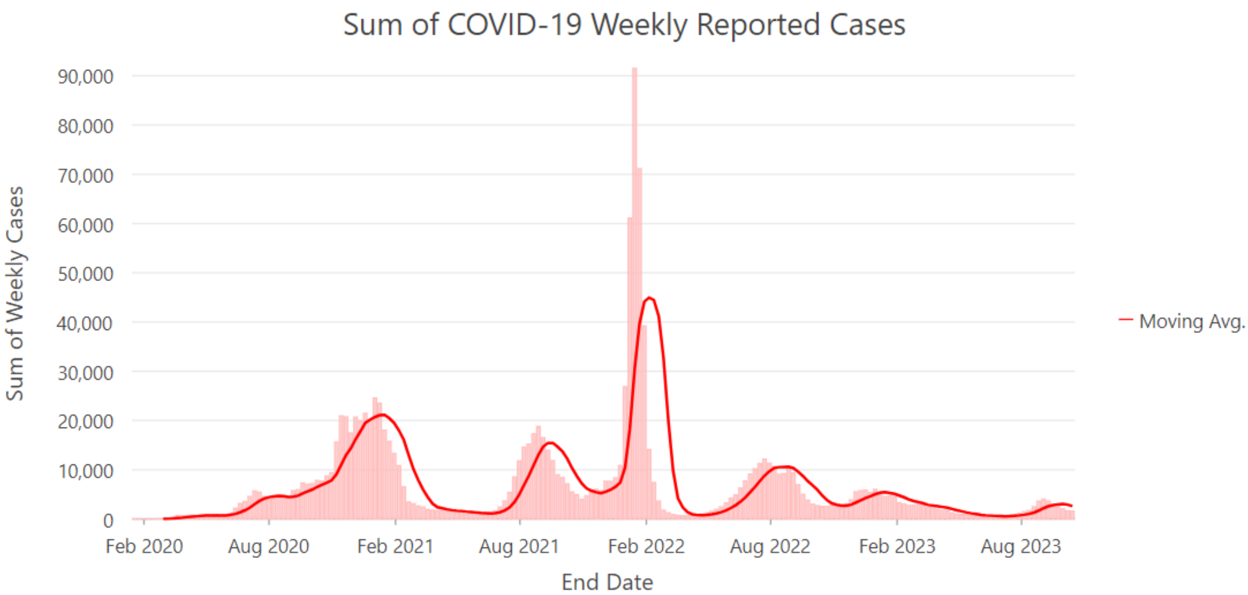

Figure 2.6: Sum of Weekly COVID-19 Cases

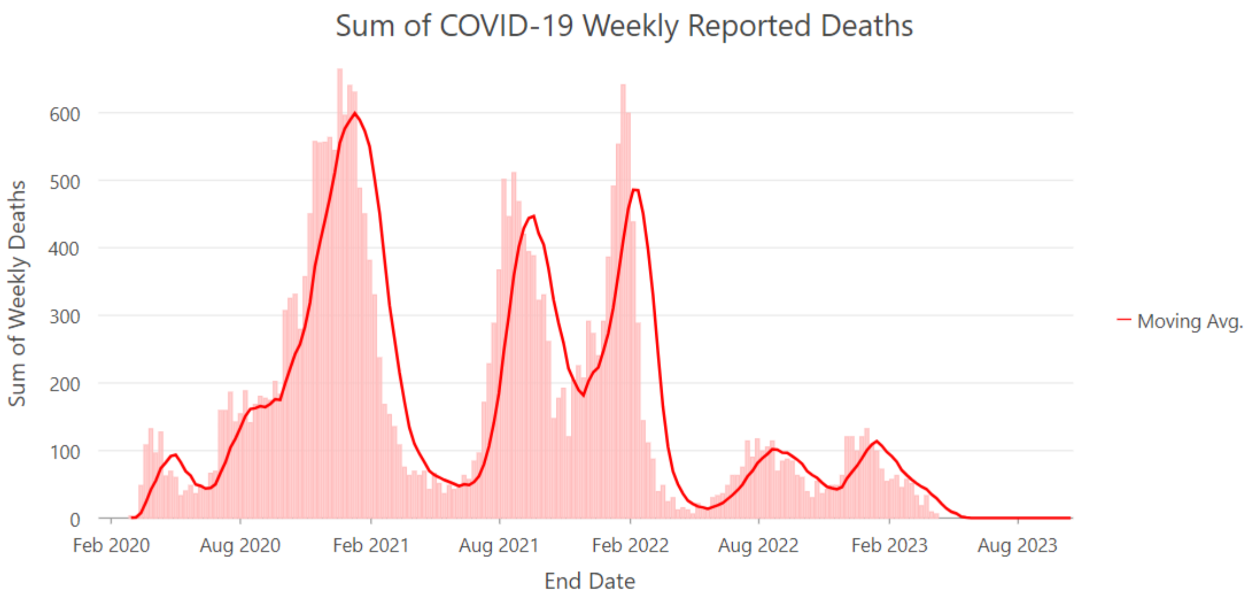

Figure 2.7: Sum of Weekly COVID-19 Deaths

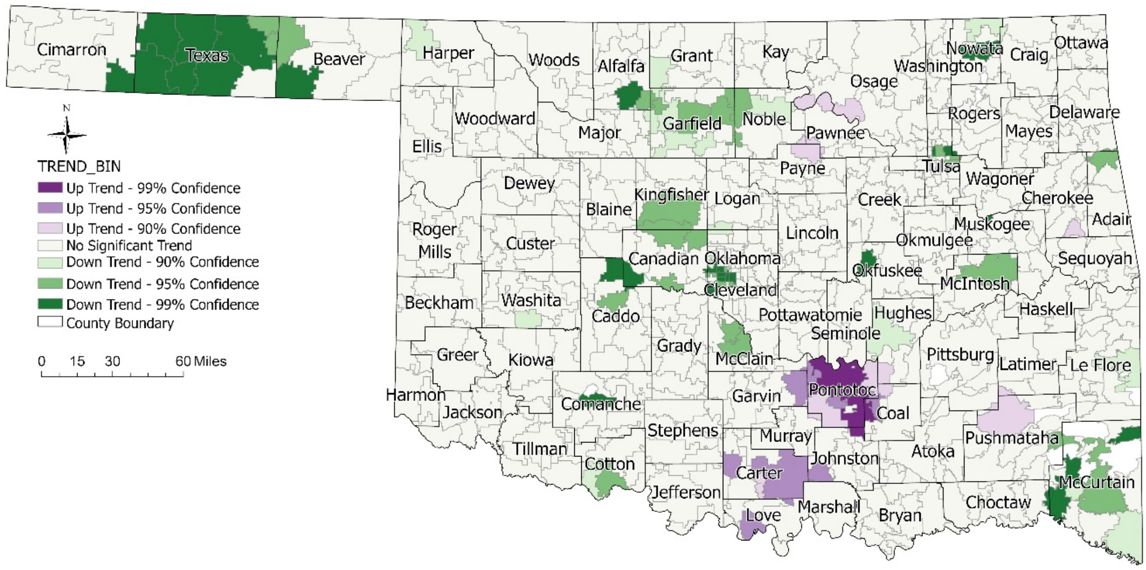

Figure 2.8: Space-Time Cube Trend Statistics of COVID-19 Cases

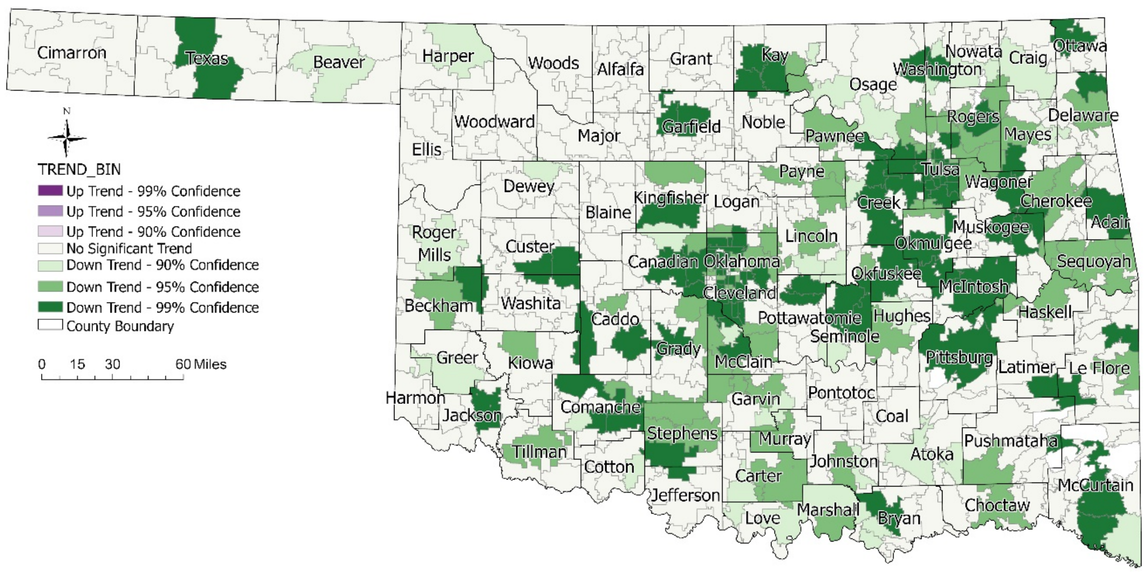

Figure 2.9: Space-Time Cube Trend Statistics of COVID-19 Deaths

To answer the third research question, a time series cluster analysis in GIS is carried out to determine where the clusters of location experiencing increase and decrease in COVID-19 cases and deaths at the same time are located. Pseudo-F-statistics were used to determine the number of clusters. Pseudo F statistics are used in cluster analysis to evaluate and determine the optimal number of clusters. It is calculated as a ratio of the variance between clusters and within clusters.

Larger pseudo-F statistics suggest that the clusters are well dispersed with large variance between them and small variance within each cluster whereas a lower cluster indicates that the variance are not well dispersed with small variance between the clusters and large variance within each cluster. For COVID-19 cases 2 clusters were determined based on the highest pseudo-F value, whereas for COVID-19 deaths 3 clusters were determined based on the highest Pseudo F value (Table 1 & Table 2).

The time series cluster map is accompanied with a line chart that describes the movement of the data in time. The result of the COVID-19 cases shows clusters of places that experience similar traits of the virus at the same time (Figure 2.10). The chart shows the movement of each cluster at a particular time (Figure 2.11). Locations in blue (Group 1) had the highest rate of COVID-19 during the period compared to locations in red (Group 2) (Figure 2.10). Group 1 experienced the highest COVID-19 cases between November 1, 2020, to December 6, 2020. Between December 19, 2021, and February 6, 2022, Both Group 1 and Group 2 tend to have a high spike in COVID-19 cases.

Number of Clusters	Pseudo F
2	54.281
3	42.454
4	32.125
5	26.996
6	25.069
7	23.138
8	22.096
9	20.455
10	20.078
Note: Optimal number of clusters is 2 based on the highest pseudo F statistic.	

Table 1: Pseudo F-Statistic Summary for COVID-19 Case Rate

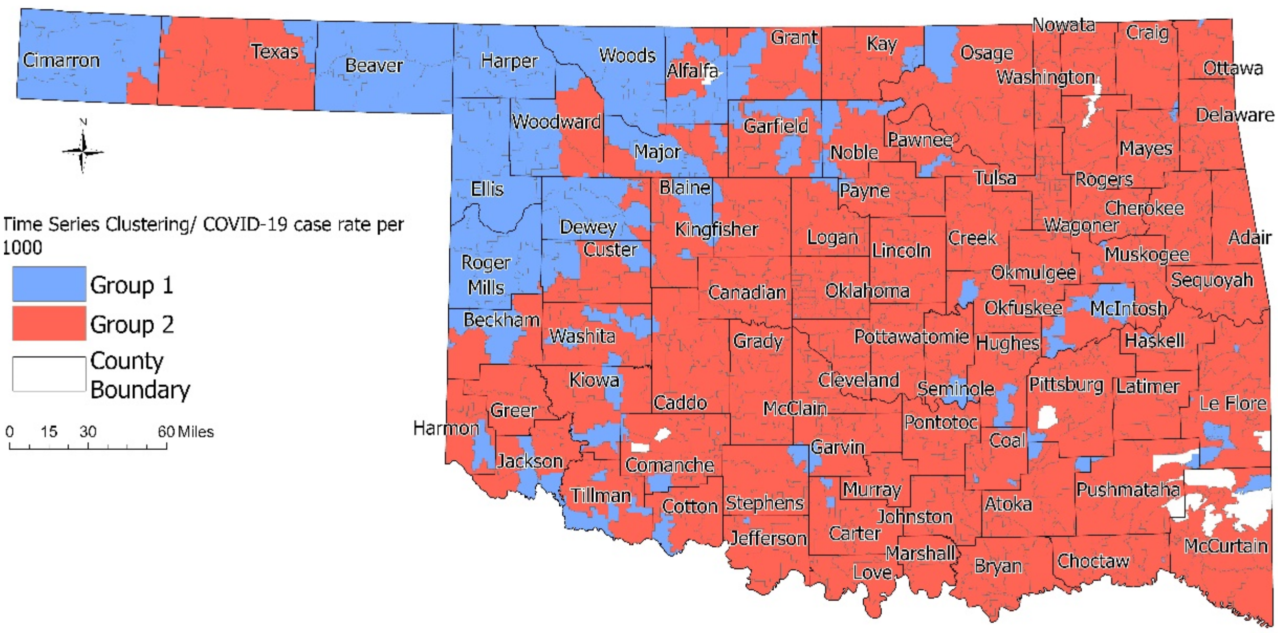

Figure 2.10: Time Series Clustering COVID-19 Case Map

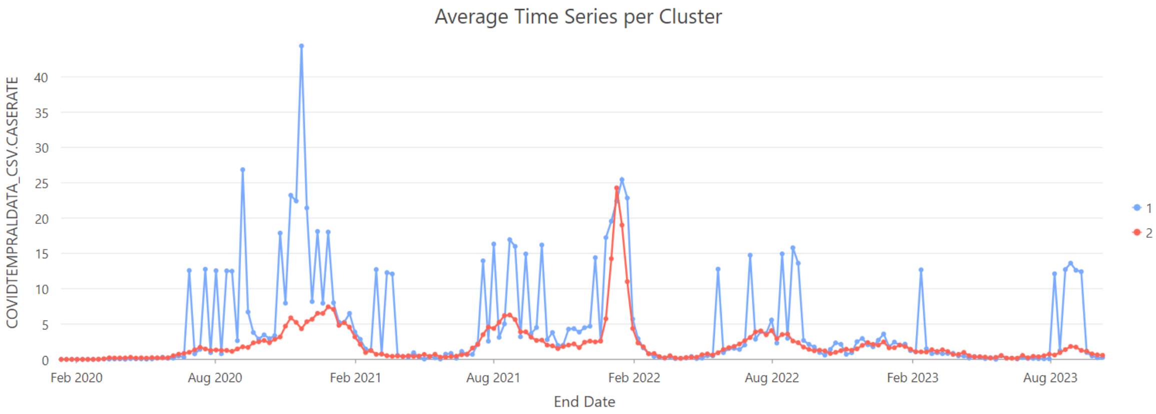

Figure 2.11: Time Series Clustering COVID-19 Case Map Chart

For COVID 19 deaths, the result of the time series clustering (Figures 2.12 and 2.13) reveals places experiencing similar spatiotemporal trend of COVID-19 deaths.

Number of Clusters	Pseudo F
2	0.000
3	55.388
4	52.278
5	48.334
6	46.473
7	45.053
8	43.537
9	41.576
10	40.243
Note: Optimal number of clusters is 3 based on the highest pseudo F statistic.	

Table 2: Pseudo F-Statistic Summary for COVID-19 Deaths Rate

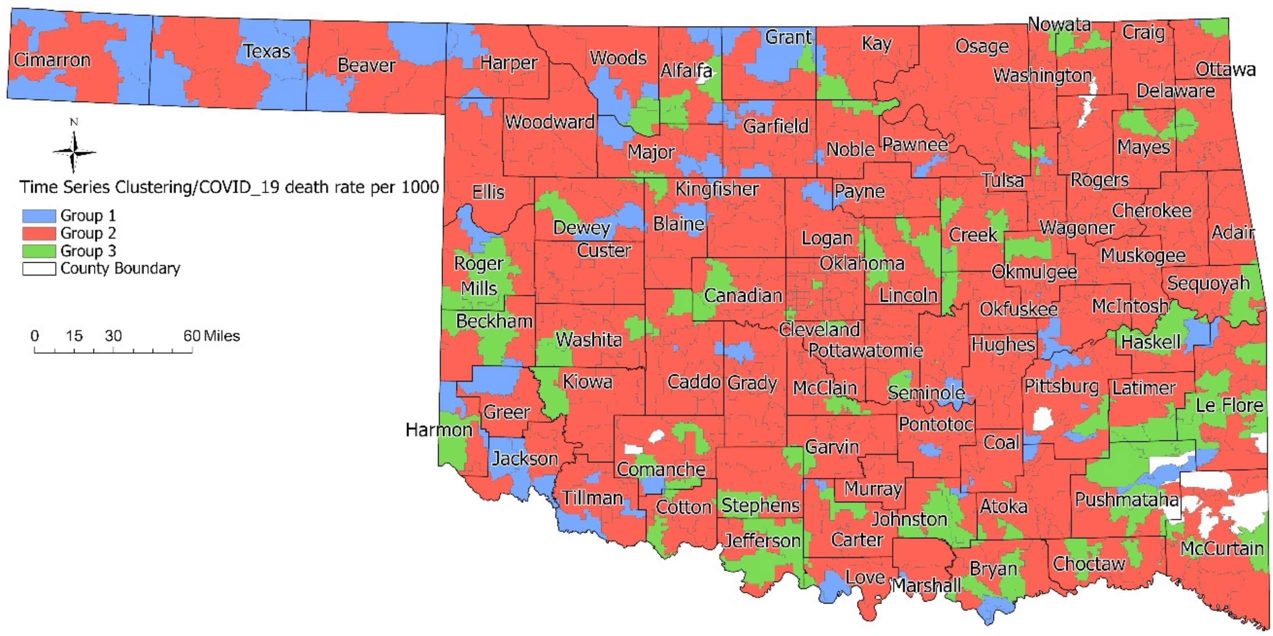

Figure 2.12: Time Series Clustering COVID-19 Deaths Rate Map

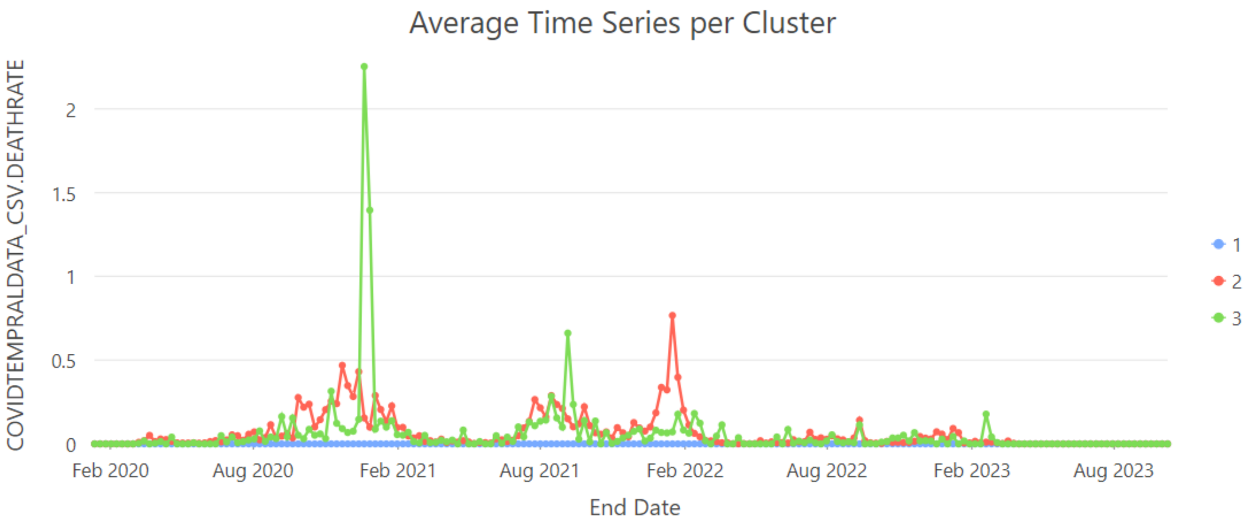

Figure 2.13: Time Series Clustering COVID-19 Deaths Map Chart

As shown in the map, zip codes in blue (Group 1) experienced zero spatiotemporal deaths trend, whereas zip codes in red (Group 2) and green (Group 3) had spikes of COVID-19 deaths at different times, with each group showing similar spatiotemporal trend, respectively. Between December 13, 2020, and January 3, 2021, Group 3 experienced the highest death rate whereas Group 2 experienced the highest death rate between December 19, 2021, and February 6, 2022. However, after March 5, 2023, the death rate seems to have dropped to zero for both groups.

To better understand and explain some of the factors that may lead to the similarities and dissimilarities in patterns shared by the time series clusters result, the population density as well as the median income of Oklahoma state were mapped using ACS 5-year estimate data (Figure 2.14 & 2.15)

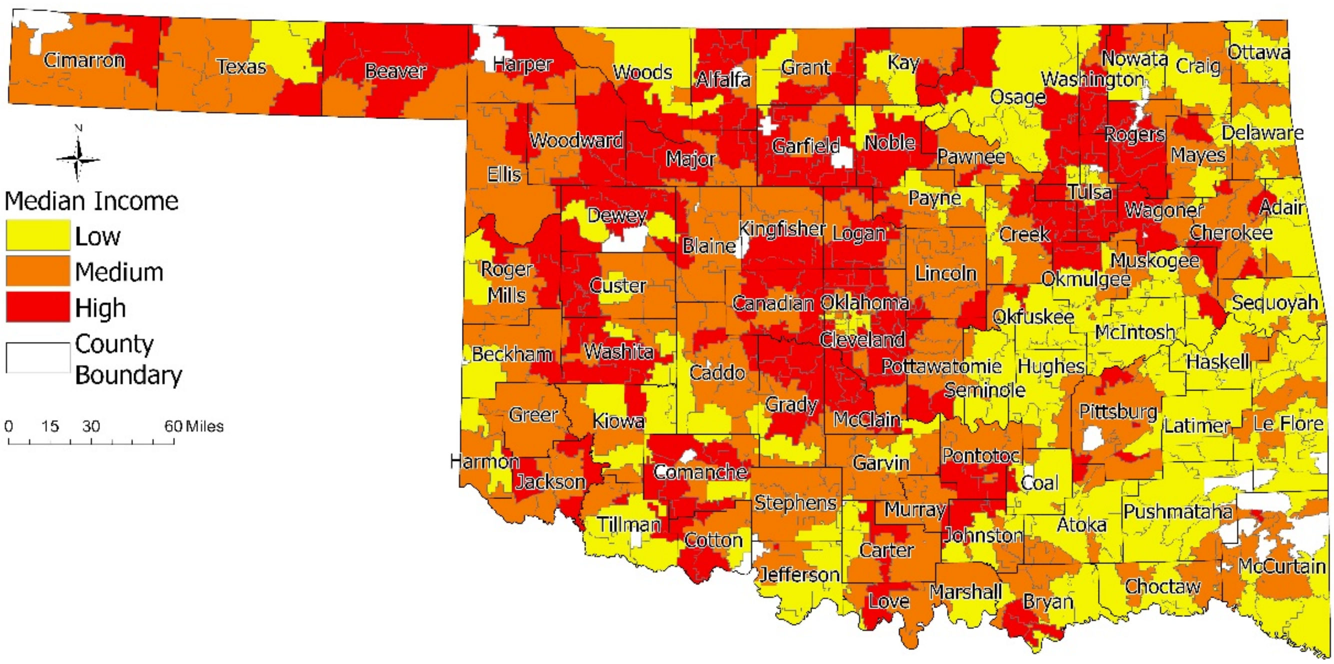

Figure 2.14: Median Income Map

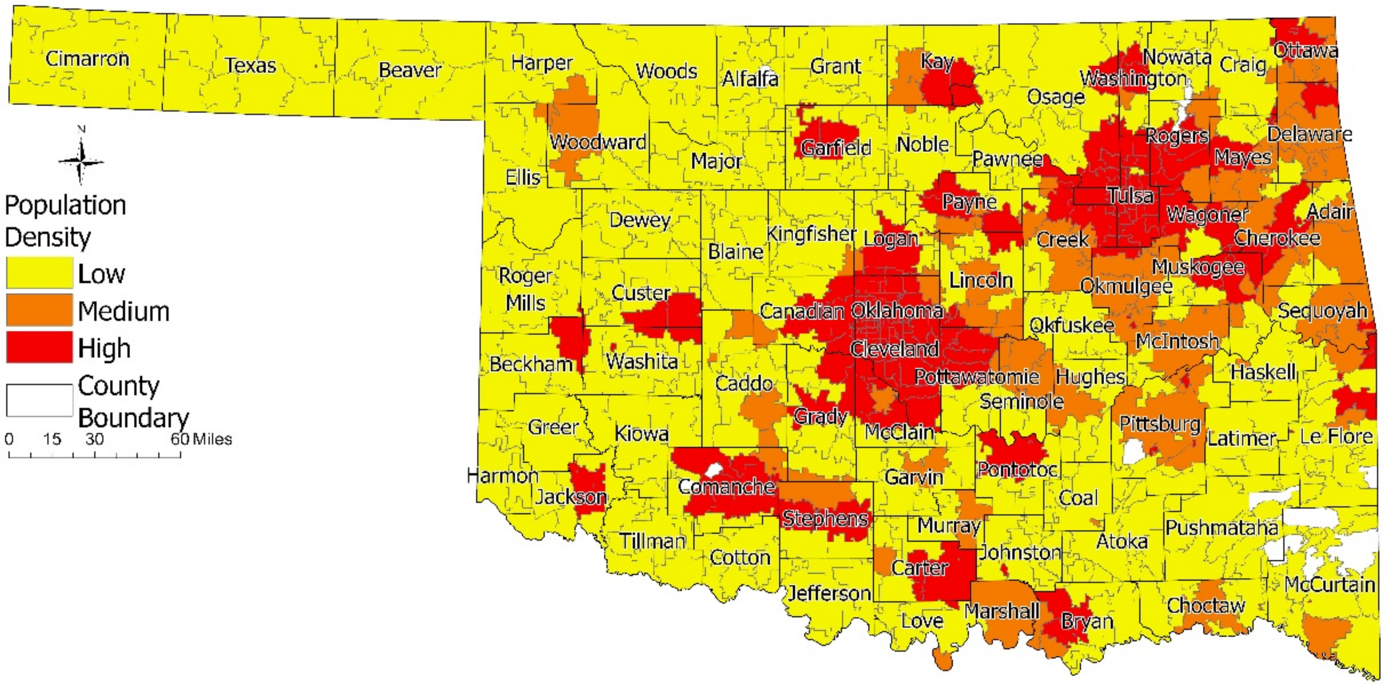

Figure 2.15: Population Density Map

The COVID-19 case time series clustering map reveals that most areas with higher spikes in COVID-19 cases, often share common traits of lower population density and higher median income. This suggests that the lower population density must have caused a reduced person to person contacts. However, the income level shows higher economic activity and mobility which may be contributing to the spread of the virus.

Residents in those areas might have engaged in more social and professional associations, increasing their exposure. For COVID-19 deaths, based on the time series clustering map and the population density map, group 1 with zero death rates recorded tend to have higher income and lower population density, group 2 tend to show places with both low population and high population density and major places with high income, and in group 3, majority of the places showed low population density with a mixed of high and low median income population.

For group 1, higher income areas have better access to health care services, including preventive care and testing hence more likelihood for a lower or zero death rate. For group 2 and group 3, these areas tend to have experience some spikes in COVID-19 deaths at a similar time of the year, which is around the Fall season suggesting related death to have to do with the cold weather. Colder weather leads to more indoor gatherings, where viruses spread easily. In addition, the fall season often brings an increase in other respiratory diseases such as influenza, which can further exacerbate the impact of COVID-19 leading to related deaths.

Discussion

The objective of this study has been to identify statistical hotspots of COVID-19 cases and deaths in Oklahoma, determine the statistical trend of the virus, and identify clusters of location experiencing similar trend of the virus based on profile. The results of the study found statistical hotspots of COVID-19 cases and deaths. For COVID-19 cases, the cluster of high significant cases were found around Oklahoma, Cleveland, and McClain Counties (Figure 2.4). Alternatively, clustered COVID-19 deaths were found in multiple locations such as Cherokee, Stephens, Mayes, and Muskogee Counties (Figure 2.5). Clusters of COVID-19 cases are found around where significant clusters of Hispanics and Blacks are located, and clusters of COVID-19 deaths are found where significant clusters of American Indians are located. According to the U.S. Census Bureau's 2020 data, 46% of the population in Oklahoma County identifies as minorities, with over 30% being Black and Hispanic [48].

This demographic composition corresponds with the observed concentration of COVID-19 cases in the county, particularly in urban areas such as Oklahoma City, where higher population densities and increased interactions may contribute to the spread of the virus. Whereas, among the 54% of minorities living in Cherokee were hotspots of COVID-19 deaths were found, over 31% were American Indian. The result also reveals that although significant hotspots of COVID-19 cases are found around major cities such as Oklahoma City, significant hotspots of deaths are found in the rural areas (Figure 2.4). The result of the study agrees with past research such as Amin , Hamidi, Sabouri, and Ewing, and Andersen, who all found high concentration of COVID-19 cases in urban areas. In addition, the study also revealed the effect of the pandemic on minority groups, which is in accordance with previous research [9,11,12,16].

These studies revealed that high concentrations of COVID-19 virus cases and deaths were in areas where there are high concentrations of minorities. For example, Amune found similar hotspots of COVID-19 cases where Blacks and Hispanics are highly concentrated and similar hotspots of COVID-19 deaths where American Indians are highly concentrated. The result of the study suggests the need to implement targeted public health measures in urban hotspots, such as increased testing, vaccination campaigns, and public awareness initiatives.

This is particularly important in areas with high Hispanic and Black populations, where socioeconomic factors might contribute to higher transmission rates and worse outcomes. In addition, the study has shown that minority communities have been disproportionately affected by COVID-19, with higher rates of infection and mortality [7,9].

Therefore, tailored interventions in these communities can help address these disparities. The study also reveals the need to improve healthcare access and resources in rural areas with significant American Indian populations to address higher death rates. Rural areas often face challenges such as fewer healthcare facilities, longer distances to travel for care, and lower health literacy. Therefore, there is need to focus on mobile health units, telemedicine, and community health workers to bridge the gap in healthcare access.

Furthermore, in a bid to understand the spatial trend of the virus, the study has found locations still experiencing significant uptrend in COVID-19 cases as of October 2023. This local result is useful to policy makers to help determine targeted areas for immediate response. In addition, researchers can concentrate on these areas to determine factors responsible for the uptrend which may include vaccination problems and other socioeconomic factors. For COVID-19 deaths, the study found only a significant downtrend in COVID-19 deaths, with majority of the zip codes experiencing a significant decrease in COVID-19 deaths. The result is in accordance with a recent paper by Horita and Fukumoto who found that the global COVID-19 case fatality had decreased by 96.8% with 95% confidence level [49].

However, there is need to investigate areas with continuous uptrends in COVID-19 cases to identify underlying factors such as vaccination challenges, public compliance with health measures, and socioeconomic conditions. Understanding these factors can help tailor more effective interventions. In addition, detailed epidemiological studies and community surveys can provide insights into barriers to vaccination and adherence to public health guidelines.

Lastly, this study was able to determine clusters of locations experiencing similar spatiotemporal trend in the COVID-19 cases and deaths based on profile (i.e., places experiencing decrease and increase at this same time). This particular result is useful in determining the several factors responsible for the observed trend. Hence, the population density map and the median income map as shown in Figures 2.14 & 2.15 further throw more light on the likely reasons for the similar trend observed in specific groups. For the COVID-19 case time series clustering results, the observation that areas with higher spikes in COVID-19 cases tend to have lower population densities and higher median incomes highlights the complex interplay of sociodemographic and economic factors in the spread of the virus.

By understanding these patterns, public health officials and policymakers can develop more effective, tailored strategies to mitigate the impact of COVID-19, ensuring that interventions are both context-sensitive and evidence-based. This approach will help in managing current and future public health challenges more efficiently. For COVID-19 deaths time series clustering result, the observed seasonal spikes in COVID-19 deaths in Group 2 and Group 3 areas, particularly during the Fall, highlight the need for targeted and seasonal public health interventions.

This includes promoting flu vaccinations, reinforcing public health guidelines, and ensuring healthcare systems are prepared for potential increases in caseloads. Seasonal patterns in respiratory illnesses, including COVID-19, have been noted globally, with colder months often seeing increased transmission due to more indoor gatherings and lower humidity levels that favor viral spread [50].

The result of the study also stresses the need to address healthcare disparities by ensuring equitable distribution of resources and services among minority groups and rural populations. This includes not only healthcare services but also economic and social support to mitigate the broader impacts of the pandemic. Policies should focus on social determinants of health, such as improving living conditions, access to nutritious food, and economic opportunities, which can significantly affect health outcomes. By understanding the factors contributing to these patterns, public health officials and policymakers can implement effective strategies to mitigate the impact of COVID-19 during high-risk periods, ensuring better health outcomes and preparedness for future outbreaks.

The spatial and spatiotemporal patterns of COVID-19 cases and deaths identified in this study align with existing literature, highlighting the significant impact of sociodemographic and economic factors on health outcomes. By addressing the identified hotspots and understanding the underlying causes, public health officials and policymakers can implement targeted and effective strategies to mitigate the impact of COVID-19 and prepare for future public health challenges.

The findings from this study provide a foundation for further research and informed decision-making, ensuring that interventions are context-sensitive and evidence-based. This approach will help in managing current and future public health challenges more efficiently. In addition, the result of this study can be modeled into future endemic and pandemic related issues to ensure timely interventions among health programs professionals and policy makers.

Strengths and Limitations

The study utilizes up-to-date COVID-19 data in Oklahoma obtained from the Oklahoma State Department of Health from January 12, 2020, to October 8, 2023, the time this study was conducted. The use of up-to-date data for the analysis of the study is an advantage as it provides an updated significant result of COVID cases and deaths in Oklahoma. In addition, the study utilizes GIS methods for its analysis, which serves as an advantage as it allows for a contemporary and greater efficiency and reliability in the results. However, one limitation of the study is that for some suppressed zip codes in the data that have values less than six cases of deaths due to privacy, an average value of three was used.

Although this method of accounting for suppressed data has been proven effective, it is also a disadvantage as it only provides an estimated value for those cells and not an actual value. In addition, the COVID-19 data used for this study were compiled by the OSDH based on probable and confirmed cases and deaths. Furthermore, there were few cells in the data that the OSDH were unable to associate with any zip code due to wrong addresses. Such data were removed from the analysis, and this may lead to distorted results due to unavoidable misrepresentation in the data. However, given that the results were in conformity with current literature, the study provides a useful contemporary understanding of COVID-19 cases and deaths in Oklahoma that could be useful for policy makers and health program management in making contemporary COVID-19 related decisions for the state.

Conclusions

This study examined the spatial and spatiotemporal pattern of COVID-19 cases and deaths in Oklahoma, providing a contemporary useful understanding of the virus in the state. GIS was used for the study to perform hotspot analysis using the Getis-Ord Gi* statistics, trend analysis using space-time cubes, and spatiotemporal cluster analysis using space-time cube and time series clustering. Hotspots of COVID-19 cases were found around Oklahoma City where hotspots of Blacks and Hispanics are located. In contrast for COVID-19 deaths, significant hotspots pattern was found in rural areas majorly where significant hotspots of American Indians are located. In addition, a significant uptrend of COVID-19 cases was found in few zip codes, whereas a significant decrease in COVID-19 deaths was found in most zip codes located in the state. Lastly, clusters of locations experiencing similar increase and decrease trends in the COVID-19 cases and deaths were identified.

The result of this study will be useful to health care management and policy makers in identifying current locations in need of immediate attention with regards to COVID-19 virus. In this case attention may be given to locations such as Pontotoc and Carter Counties, which were still experiencing a significant increase in COVID-19 cases in October 2023 when this study was conducted. In addition, future work needs to be done to determine the common factors among those locations experiencing similar uptrends and down trend in COVID-19 cases and deaths to enable better interventions in the case of future endemic and pandemic situations in the state [51-53].

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