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SPATIAL AND TEMPORAL DISTRIBUTION OF TUBERCULOSIS INFECTION IN PLATEAU STATE, NIGERIA: A DESCRIPTIVE ECOLOGICAL STUDY.

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Abstract
Background
This study aimed to describe the spatial and temporal patterns of notified TB patients in 2018, 2019, and 2020 in Plateau State.

Methods
The data were obtained from the State Tuberculosis and Leprosy Control Programme Unit, and the population information was obtained from the National Population Commission. The spatial analysis techniques and time series considered the 17 local government areas as the unit of analysis. The global Moran statistic was used to demonstrate a trend towards clustering over the years of study.

Results
7804 TB cases were reported during the three years of the study from 2018 to 2020. The LGAs with high incidences of tuberculosis were Jos North, Jos South, Mangu, and Langtang North. The global Moran statistic demonstrated an increasing trend towards clustering over the years of study. The Local Indicators of Spatial Association (LISA) statistics showed an insignificant relationship between LGAs and their neighbors (z score of -0.035124 and a p-value of 0.886253). Nevertheless, Jos North, Jos South, and Riyom were the LGAs found to have clustered.

Conclusion
A spatial-temporal pattern that revealed the dynamics of disease spread as the tendency of TB patients to cluster and hot spots of space-time disparities provides useful and detailed information to guide policy formulation to address the burden of TB in the state briefly.

Recommendations
Spatial analysis techniques should be integrated into routine epidemiological surveillance to monitor tuberculosis risk factors in Nigeria. Government policies should support mapping high-risk areas for infectious diseases among the general population to understand prevalence better and enable precise public health interventions.

Keywords: *Tuberculosis, Spatial TB, Temporal TB, Plateau State, TB in Nigeria.*
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Background

Tuberculosis (TB) is an infectious disease that is one of the leading causes of ill health and probably returned to being the world's leading cause of death from a single infectious agent following 3 years in which it was replaced by COVID-19 and caused almost twice as many deaths as HIV/AIDS [1,34]. Estimated over 10 million people continue to fall ill with TB every year and the number has been rising since 2021. [34] The global rise in the number of people falling ill with TB (incident cases) that started during the COVID-19 pandemic has slowed and begun to stabilize. The total was 10.8 million in 2023, a small increase from 10.7 million in 2022 although still much higher than 10.4 million in 2021 and 10.1 million in 2020.[34]

Globally, TB caused an estimated 1.25 million deaths in 2023, including 1.09 million among HIV-negative people and 161,000 among people with HIV. The total was down from best estimates of 1.32 million in 2022, 1.42 million in 2021, and 1.40 million in 2020, and below the pre-pandemic level of 1.34 million in 2019 [34].

Nigeria has the highest TB burden in Africa. The disease kills 268 people in the country every day. Yet TB cases are under-reported, increasing the high risk of transmission. It is estimated that one missed case can transmit TB to 15 people in a year [35,36]. Estimated over 361,000 TB cases were reported in Nigeria in 2023, 9% of these in children. Overall, this marked a 26% increase in cases compared with 2022[37]

Although gradual progress has been made in the fight against tuberculosis, progress toward the achievement of global targets for TB control remains slow [12]. Reducing this burden requires faster progress towards UHC and better levels of social protection [34]

Geographically, the majority of TB cases in 2023 were in the WHO regions of Southeast Asia (45%), Africa (24%) and the Western Pacific (17%) [36]. Eight countries contributed to two-thirds of the worldwide TB cases, with India leading at 27%, followed by China (9%), Indonesia (8%), the Philippines (6%), Pakistan (6%), Nigeria (4%), Bangladesh (4%), and South Africa (3%). These and 22 other countries in the WHO list of 30 countries with a high burden of tuberculosis accounted for 87% of the global cases [1].

The seasonality of the incidence of tuberculosis has been widely reported in different parts of the world, and understanding season-specific risk factors for active tuberculosis can help in developing national TB control policies; however, previous studies have reported conflicting incidence peaks of tuberculosis in spring, summer, and winter [14][15]. Although the exact mechanisms underlying the fluctuation of TB during particular times of the year remain unclear, several studies have suggested that environmental factors (including cold weather, sunlight, and air pollution) and social factors (such as crowding, person-to-person contact, and healthcare-seeking behavior) contribute to the seasonality of the incidence of TB [14][15][16][17].

To gain a deeper understanding of tuberculosis's distribution and evolution across different geographic areas, it would be beneficial to adopt a broader approach that considers both spatial heterogeneity and temporal trends. [18][19]. This study, therefore, aimed to describe the spatial and temporal patterns of notified TB patients from 2018 to 2020 in Plateau State, Nigeria.

Methods and tools

Study Area

The plateau is in the North-Central zone of the six geopolitical zones in Nigeria. It is geographically unique due to its boundaries of elevated hills surrounding the Jos Plateau, its capital, and the entire plateau itself. It covers an area of 30,913 km2[20]. The Plateau State is celebrated as "The Home of Peace and Tourism. Although it is located in a tropical zone, a higher altitude means that the plateau state has a nearly temperate climate with an average temperature between 13 and 22 °C. Harmattan winds cause the coldest weather between December and February. The warmest temperatures usually occur in the dry months of March and April. The mean annual rainfall varies between 131.75 cm (52 in) in the southern part and 146 cm (57 in) on the plateau [20][21]. It has a projected population of 4.8 million according to the 2006 population census. It has 17 local government areas (LGAs) divided into 3 Senatorial districts. The Ministry of Health coordinated all health activities in the state, working together with nongovernmental organizations [22][23]. The Epidemiology Unit coordinates the activities of the National Tuberculosis and Leprosy Control program unit in the state. The NTBLCP was established in 1989 by the government of Nigeria to coordinate TB and leprosy control efforts in Nigeria. Its mandate was further expanded to include Buruli ulcer control in 2006. The Plateau National Tuberculosis and Leprosy Programme State has four tertiary hospitals and over 800 private and public secondary and primary healthcare facilities. NTBLCP coordinates all TB activities in 391 public and private facilities providing TB activities in the state [24]. The data collected at these facilities are reported monthly to the NTBLCP unit in the state.

Study design and study population

This study was a descriptive ecological study with a temporal and spatial component, using notification of TB cases in the plateau state from 2018 to 2020.

All confirmed TB cases registered, as defined by the NTBLCP, created between 2018 and 2020 in all 17 local government areas in the plateau state were considered for the study. The spatial analysis techniques and time series from 2018 to 2020 considered the 17 local government areas as a unit of analysis.

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Inclusion criteria

All registered TB patients who were receiving treatment, including HIV-positive TB patients, registered between January 2018 and December 2020.

Exclusion criteria

Registered TB patients with incomplete treatment records or missing demographic data within the study period.

Data Source

This study used secondary data obtained with permission from the State Tuberculosis and Leprosy Control Programme (STBLCP) Unit in Plateau State, and information on the Plateau State population census was obtained from the National Population Commission. The TB infection was confirmed based on the results of chest X-ray, sputum smear microscopy, and gene experts in all registered facilities that provide TB treatment in the LGAs. The monthly case notification data for all the facilities in Plateau State were extracted from the database from January 2018 to December 2020.

Data Analysis

The data frame was constructed from the dependent variable and the explanatory variables in Microsoft Excel. The data were checked for errors and out-of-range values. Initial data exploration was performed with SPSS to check for normality by using the descriptive analysis function and by plotting histograms, QQ plots, and stem and leaf plots of all variables. Frequency distributions were generated for categorical variables with minimum and maximum values, while for continuous variables, the mean, median, standard deviation, interquartile range, and minimum and maximum values were determined. In addition, scatter plots were constructed for all variables to check for outliers.

The epidemiological and operational indicator that was analyzed in this study was TB incidence. Descriptive statistics were obtained for the extracted explanatory variables, such as the number of case facilities in each local government area, the number of health facilities, and the CNR.

The monthly reported Tb cases were aggregated at the local government area level and analyzed using the X-12 autoregressive integrated moving average (X-12-ARIMA) developed by the US Census Bureau to define seasonal adjustments for the time series. The identified TB cases were decomposed into three components: seasonal variation and random irregular noise. Seasonal factors from 2018 to 2020 were calculated to explore the seasonality of TB.

The global and local Moran indices were used to evaluate the spatial autocorrelation of the TB incidence rate in the geographical space analysed, which varied between 1 and + 1. Values close to 0 indicate spatial randomness, values between 0 and + 1 indicate positive spatial autocorrelation, and values between 1 and 0 indicate negative spatial autocorrelation [24]. The level of significance was set at 5%. The Moran index will be used to investigate whether the distribution occurs randomly or follows a spatial pattern of occurrence.

Ethical Consideration

This study used secondary data obtained with permission from the Tuberculosis and Leprosy Control Programme in Plateau State. The population data were obtained from the websites of the National Population Commission (NPC). The data from this study were aggregated in local government areas (LGAs) without individual personal identifiers. The data were stored as encrypted files on a secure computer that was password protected. Hard copies of the data obtained from various sources were kept in a safe and locked cabinet from unauthorized access. The ownership of the data used for this study is acknowledged in full. Ethical approval was obtained from the Ethics Committee of the Plateau State Ministry of Health. Permission was obtained from the State Epidemiology Unit and the NTBCP in the Plateau State.

Results

Demographics of patients

Seven thousand eight hundred and four TB cases were reported during the three years of the study (2625 for 2018, 2503 for 2019, and 2676 for 2020) (Figs. 1 & 2). The cases included forms of TB in both adults and children. This yielded an incidence of 64/100,000 people in the year 2018, 58/100,000 people in the year 2019, and 61/100,000 people in the year 2020. Although there was a decrease in the total number of cases in 2019 compared to that in 2018, the number of cases increased again in 2020 (Figs. 1, 2 & 3).

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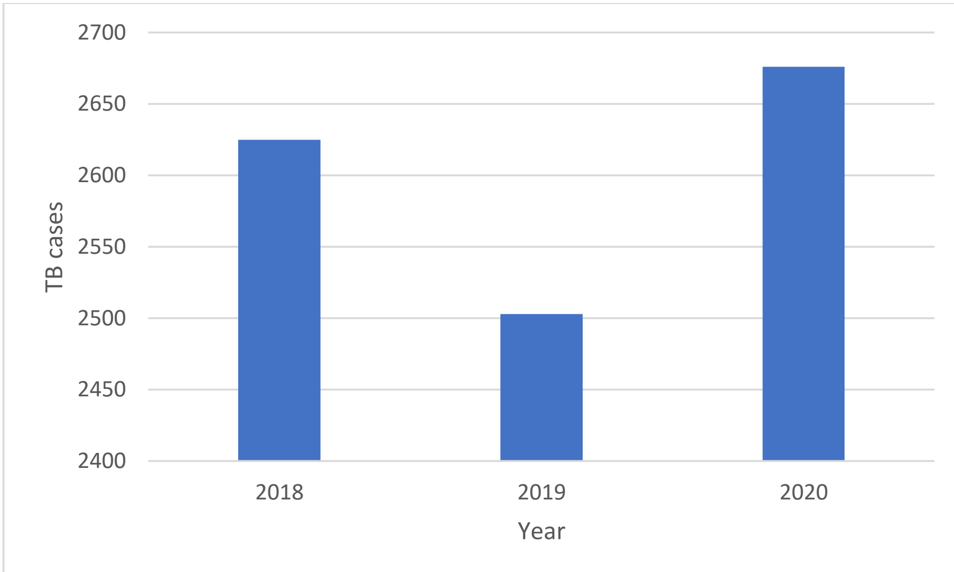

Figure 1: Graph showing the number of cases of tuberculosis in 2018, 2019, and 2020.

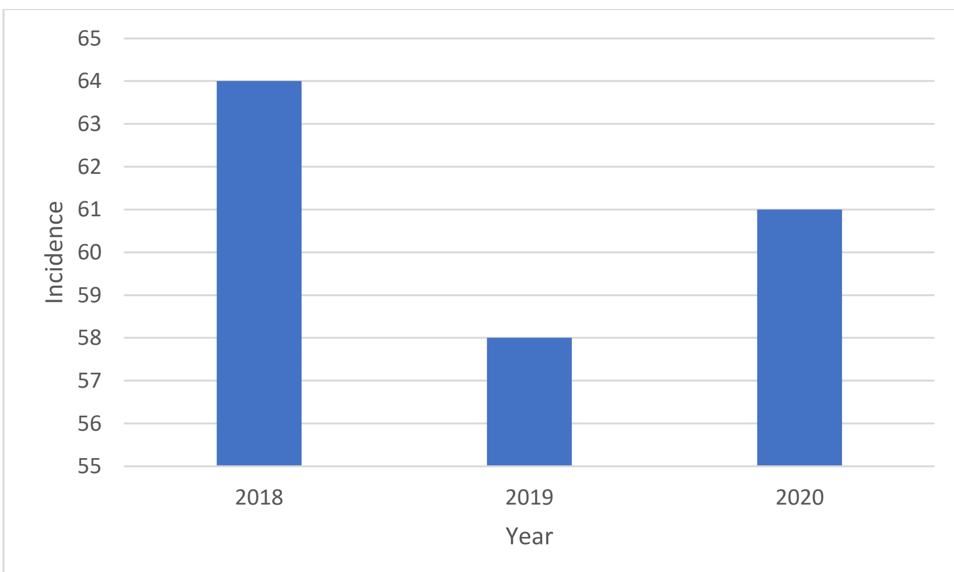

Figure 2: A graph showing the incidence rate of tuberculosis for three years per 100,000 people

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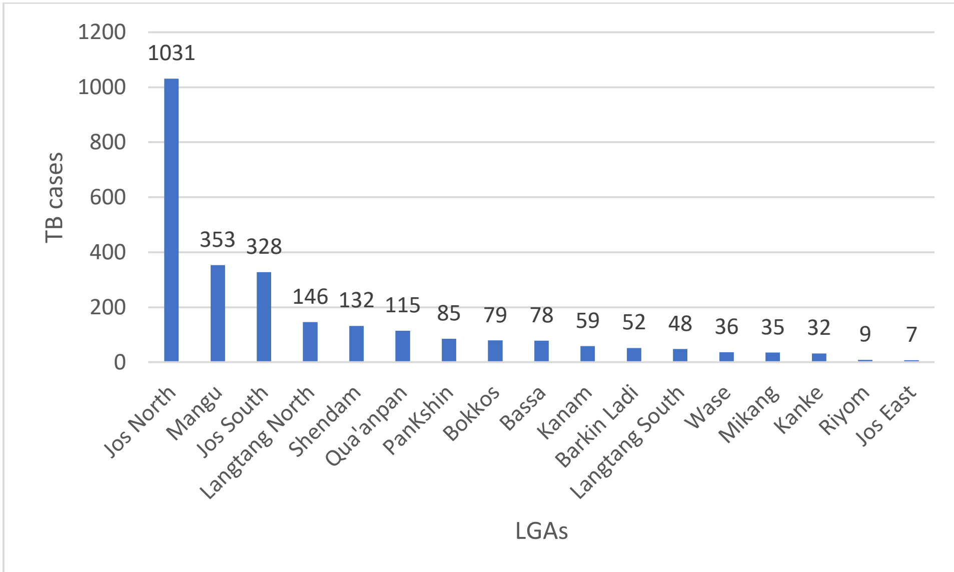

Figure 3: Graph showing the distribution of TB cases in various LGAs in the Plateau State for 2018

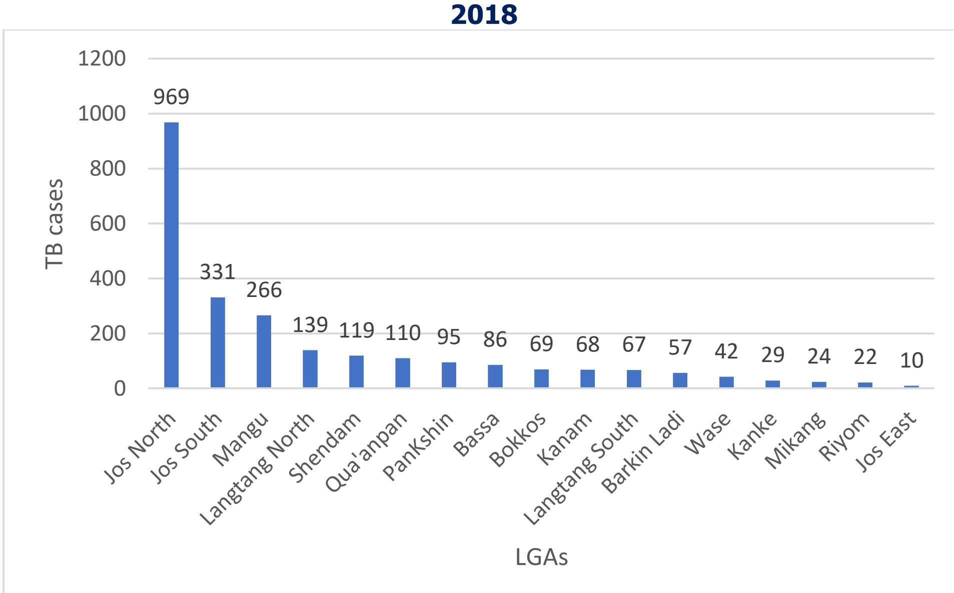

Figure 4: Graph showing the distribution of TB cases in the various LGAs in Plateau State for the year 2019

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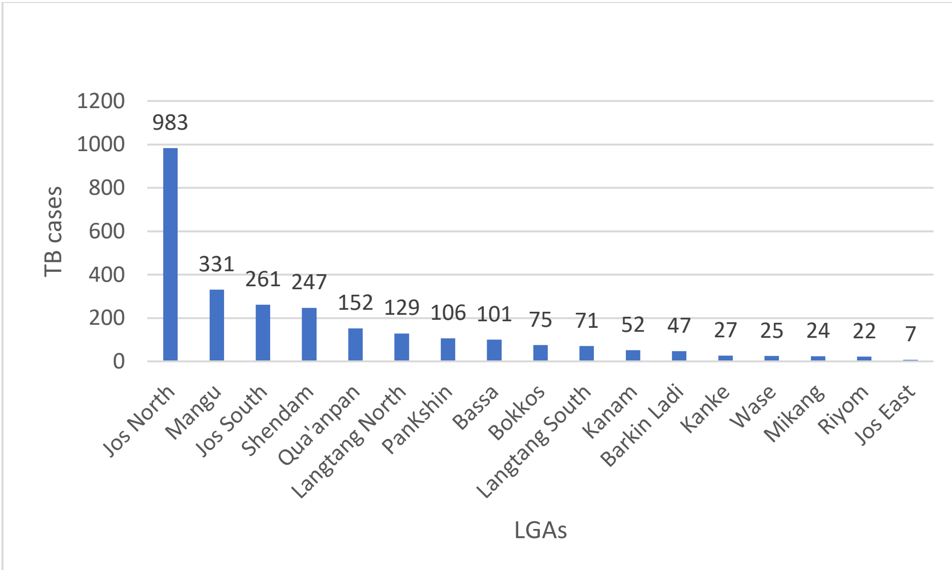

Figure 5: Graph showing the distribution of TB cases in the various LGAs in Plateau State for the year 2020

In Figures 3,4 and 5, Jos North has the highest distribution of TB cases and Jos East has the lowest distribution of TB cases from 2018 to 2019

Global Moran I index

The global I index is a composite index that measures the overall clustering of the data and is used to evaluate the overall spatial association of the total research area. It uses the 'z' statistic to evaluate the existence of clusters in the spatial arrangement of the given data and shows the level of significance with the rule that if the 'z' statistic value is greater than the value 1.96, then there is statistical significance. Additionally, while a positive sign represents positive spatial autocorrelation, the reverse is true for negative signs [24].

Table 1: Summary of global Moran's I results for 2018 and 2020

Global Moran' Index Summary	2018	2019	2020
Moran's Index	-0.033162	0.047626	0.0972873
Expected Index	-0.029674	-0.031533	-0.022937
Variance	0.002436	0.0005732	0.005167
Z score	0.035124	0.964131	1.666428
P value	0.886253	0.363728	0.128253

The results in Table 1 give the summary output for the global Moran index for 2018. The study observed the global index to be -0.033162, with an expected value of -0.029674, a z score of -0.035124, and a p-value of 0.886253. The Moran index evaluates whether the expression pattern is clustered, dispersed, or random. The index found to be -0.032628 indicated a weak negative spatial autocorrelation in our data. Although our calculated index was close to zero, it suggested a tendency toward a dispersion of TB cases for the year 2018. This indicated a map pattern in which the geographic units (which are LGAs in our research) of similar values are scattered throughout the map. A z score of -0.035124 and a p-value of 0.886253 indicated statistical insignificance. The feature values of 2018 were randomly distributed throughout the study area.

For the year 2019, the global's was 0.047626, with an expected value of -0.0315533, a z score of 0.964131, and a p-value of 0.363728. The Moran's index was found to be 0.047626, indicating weak positive spatial autocorrelation in the data. A positive Moran Indicated a tendency towards clustering in the TB cases for the year 2019, which indicated a map pattern in which the geographic units of similar values tended to cluster on the map. Additionally, the z-value was 0.964131, and the p-value of 0.363728 in 2019 indicated that the difference was not statistically significant. This indicated that feature values, again as in 2018, were also randomly distributed in the study area. Of importance to

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note was the magnitude of both Moran's index and the p-value, as they exhibited increasing and decreasing trends, respectively.

In 2020. The Moran statistic was 0.0972873, with an expected value of -0.022937, a z score of 1.666428, and a p-value of 0.128253. The Moran index was 0.0972873, indicating weak positive spatial autocorrelation in our data. Although our calculated index was close to zero, it suggested some form of clustering of TB cases for 2020. Similar to the 2019 results, there was an increase in the Moran index to 0.096283, and the positive spatial autocorrelation indicated a map pattern in which geographic units of similar values tended to cluster on the map. The z score of 1.666428 and a p-value of 0.128253 still indicated that there was a statistically nonsignificant difference in our data for 2020 [24]. Although our data were not statistically significant, there was a trend toward statistical significance, as indicated by the trend over the three years of the study.

LGAs with a high incidence of TB in the state included Jos North, Jos South, and Mangu LGA, with Jos North contributing the most cases as shown in Figure 6.

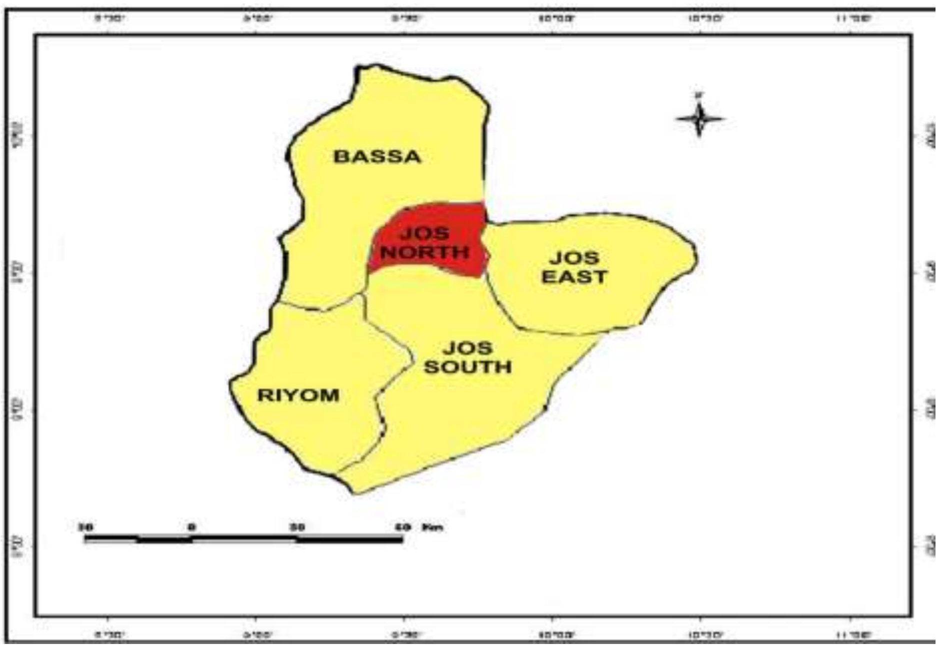

Figure 6: A snipping map showing the area with the highest incidence in 2018, 2019, 1na, and 2020

Local Indicators of Spatial Association

Local spatial statistics look for specific areas in an image that have clusters of similar or dissimilar values. The local index was used to identify the clustering of counties. Positive values for the local Moran index indicate that a feature has neighboring features with similarly high or low attribute values; this feature is part of a cluster, while negative values for the local Moran index indicate that a feature has neighboring features with dissimilar values; this feature is an outlier [24].

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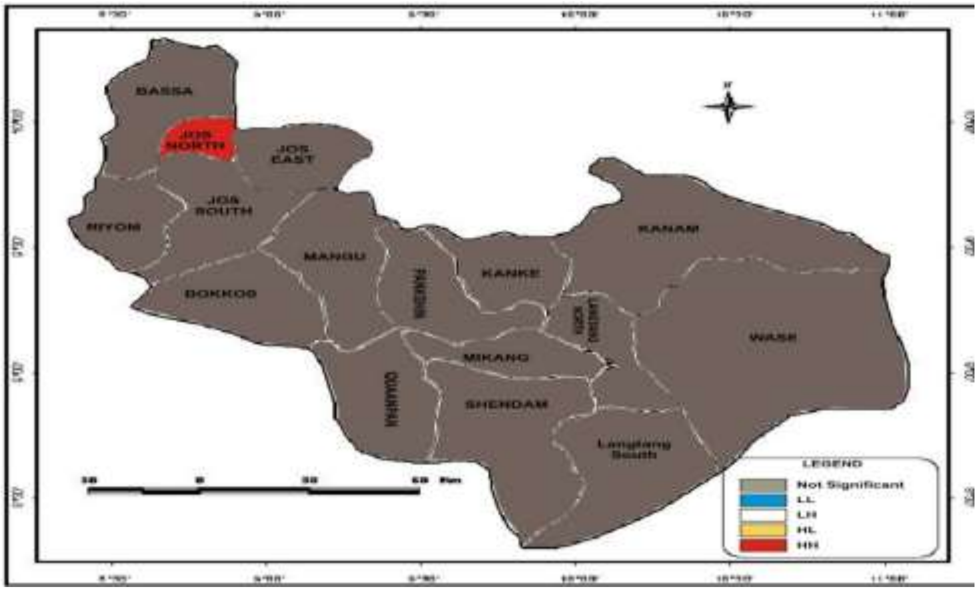

Figure 7: Choropleth map showing a statistically significant relationship between counties and their neighbours in 2018

Figure 7 shows that Jos North LGA in the year 2018 had a strong relationship with its neighbours. The other variables have no significant relationship. Although there was no statistically significant relationship for almost all LGAs, only Jos North had a high correlation, which indicated that there was a high incidence of TB in LGAs and that it was surrounded by LGAs with a low incidence. This is an indication of clustering in these LGA.

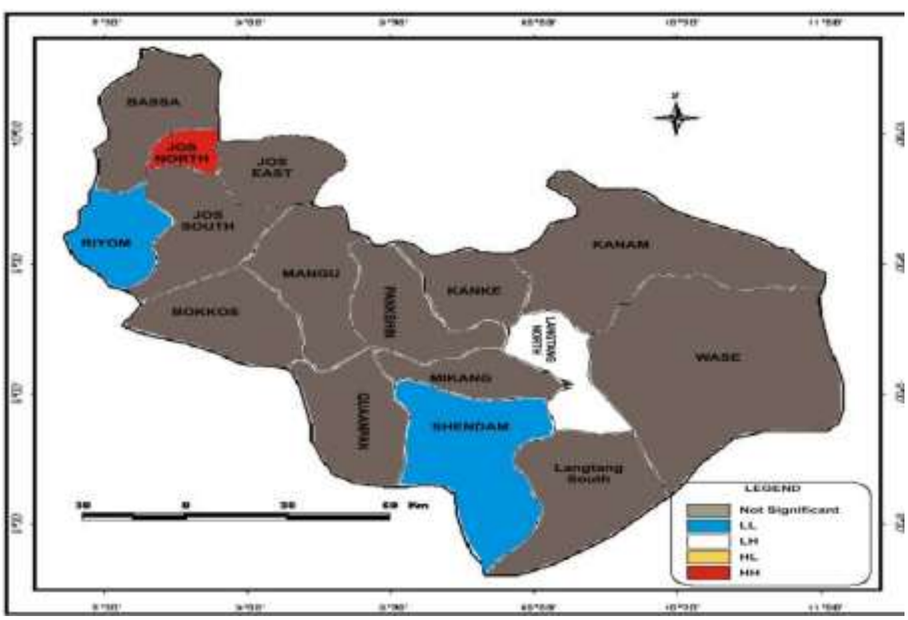

Figure 8: A choropleth map showing a statistically significant relationship between counties and their neighbours in 2019

Figure 8 shows that LGAs had a statistically significant relationship with their neighbors. These included Jos North, Riyom, and Langtang North, while others showed no significant relationships. Relationships of the four LGAs surrounding the LGAs with reported TB cases

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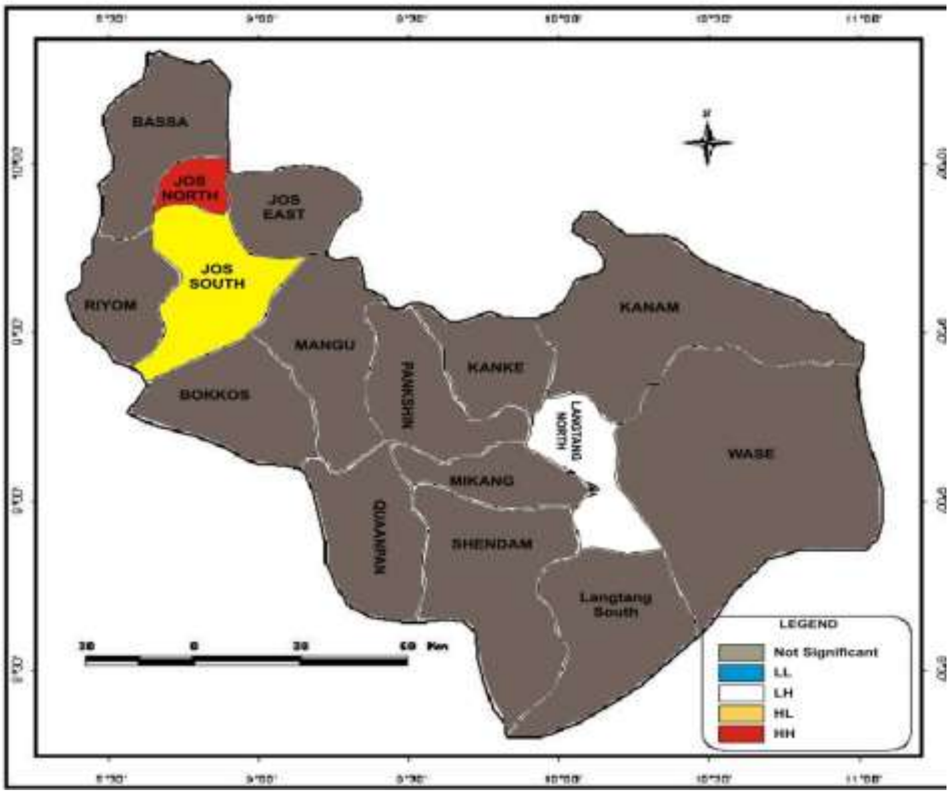

Figure 9: Choropleth map showing a statistically significant relationship between counties and their neighbours in 2020

Figure 9 shows that LGAs, including Jos North, Jos South, and Langtang North, had a statistically significant relationship with their neighbors.

Temporal Analysis

Table 2: Summary table of the computed global Moran'sI for 2018, 2019 and 2020

Year	Moran's I	Expected	Variance (1)	Z- value	P value
2018	-0.033162	-0.029674	0.002436	-0.035124>-1.96	0.886253
2019	0.047626	- 0.031533	0.005732	0.964131< 1.96	0.363728
2020	0.097287	0.022937	0.005167	1.666428<1.96	0.128253

In Table 2, it was observed that the global Moran I changed from -0.033162 for the year 2018 to 0.047626 for the year 2019 and then to 0.097287 for the year 2020, which represents an upward trend in the global statistics. The expected value (-0.031533) gave us the Morans I value when the pattern was random.

Discussion

This study was carried out on a state-wide scale in 17 LGAs and allowed for the first-time spatial visualization, exploration, and modelling of TB variation at the LGA level in Plateau State. The result of this research showed that TB was spatially clustered in the Jos North, Jos South, and Mangu LGAs. The study revealed a more widespread TB pattern in the state that was not localized to any particular LGA. This study also found that TB cases are reported more often in urban LGAs. Similarly, a study carried out in 17 LGAs in Enugu state concluded that the reporting of TB cases was associated with urban residence [25]. The LGAs classified as more urban were the Enugu North, Nsukka, and Igbo-eze LGAs, which had high TB incidence, while the Nkanu West and Nkanu East LGAs classified as rural LGAs had the lowest incidence of TB [24].

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A spatial and temporal analysis using GIS techniques to analyze routine TB surveillance data around a university community in Ibadan, Oyo State, Nigeria, identified significant TB groups in overcrowded areas via nearest-neighbour distance analysis [26]. Another study in Ibadan used nearest-neighbour distance analysis to detect clusters of TB cases in the inner city of five local government areas in Oyo state, namely, Ibadan North, Northwest, Northeast, Southeast, and Southwest [27]. Similarly, a study of the spatial distribution of TB in 21 LGAs in Kebbi state was conducted. Detected some clusters, especially in the 2010 data. Understanding the spatial distribution of TB in Plateau State has implications for public health intervention and TB control.

However, earlier studies on the spatial distribution of disease or health-related events in the country, such as studies on the spatial distribution of childhood mortality and [28,29] childhood stunting, have reported more localized patterns. The widespread pattern of tuberculosis observed in this study may be the result of the spatial unit (LGA) used in this study, in contrast to the state-level analysis used by other studies [30]. This study represents the first attempt at conducting a spatial analysis of TB at the LGA level in Plateau State. It highlights that LGAs within the state are not homogeneous units, but show marked differences in economic, cultural, environmental, and social characteristics that may determine the distribution of risk factors for the development of TB.

Spatial autocorrelation can be a valuable tool for studying how spatial patterns change over time. The result of this type of analysis leads to a better understanding of how spatial patterns change from the past to the present or estimations of how spatial patterns will change from the present to the future.

Although using the three global maps produced for the years 2018, 2019, and 2020, I was unable to exactly visually discern whether or not spatial patterns were becoming concentrated or more dispersed, the calculated Moran's I statistic for the three years depicted an increasing trend in the value of Moran's I. Therefore, it was evident that there was an overall clustering of TB cases over the three years of study.

There is still a significant population that can be classified as a vulnerable group in the sense that, if infected, they are likely to develop the disease. Additionally, if not treated, they are likely to be the agents of future epidemics. Although there has been improvement in the identification of cases, obtaining an exact picture of the incidence of TB is difficult due to the difficulties in identifying TB cases in the community. The incidence rates of 67/100,000 people in the year 2018, 58/100,000 people in the year 2019, and 62/100,000 people in the year 2020 are useful approximations of the incidence. It is important to note that the number of cases could be underestimated, as some patients would die undiagnosed.

It was also observed that despite statistical significance in major parts of the state, the entire state has been reporting an increasing incidence of TB, and this, if not prevented, may result in the disease being a future epidemic. Local Moran I statistical analysis revealed a region with a high incidence of TB. This study revealed that the distribution of the incidence cases was not stochastic in space or time and that there were clusters. This finding corroborated a study conducted in China on new smear-positive pulmonary TB [31].

Considering LISA, which is the localized version of the global Moran index, the findings revealed that the incidence of TB varied for different LGAs. This indicated that the distribution of the cases was not random; rather, there was a high concentration of cases in some parts, while others had a low concentration. This finding is supported by the findings of previous studies which indicated that the transmission of infectious diseases is closely linked to the concepts of spatial and temporal proximity; hence, transmission is more likely to occur if at-risk individuals are close in a spatial and temporal sense [32,33]. Lastly, it was evident that there was an overall clustering of TB cases over the three years of study. However, this study did not evaluate the interaction of TB with any explanatory variables such as socioeconomic determinants, as TB refers to a disease of poverty and overcrowding. Further studies can be conducted on the spatial distribution of paediatric TB due to the peculiarities of the challenges in the identification of paediatric TB.

Conclusions

Understanding disease detection in spatial and/or temporal clusters may play a great role in public health policy-making. The systemic use of cluster detection techniques for the regular surveillance of TB can aid TB programs in disease control activities. This study identified significant space-time clusters of TB in Plateau State to improve targeted cost-effective interventions.

Limitations

The study was unable to capture those with latent tuberculosis. Ecological characteristics will not include individual characteristics or risk factors.

Recommendation

Government and nongovernmental organizations should consider spatial analysis techniques integrated into routine epidemiological surveillance of risk factors for tuberculosis. Government policy should encourage hot spot area mapping for infectious diseases among the general population to determine the prevalence of the population so that proper public health measures can be instituted.

Abbreviations

AIDS Acquired immune deficiency syndrome
ARIMA Autoregressive Integrated Moving Average
HIV Human Immune Deficiency Virus
LISA Local Indicators of Spatial Association
LGA Local Government Area
MDR-TB Multidrug-Resistant Tuberculosis
NPC National Population Commission
NTBLCP National Tuberculosis and Leprosy Control Programme
PLHIV People living with HIV
PTB Pulmonary tuberculosis
STBLCP State Tuberculosis and Leprosy Control Programme Unit
TB Tuberculosis

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

Data availability

The data used for this research are available upon request from the corresponding author and can also be accessed through the website of the National Population Commission of Nigeria upon request (http://nationalpopulation.gov.ng/survey-data).

Funding

There was no funding for this study.

Authors' Contributions

IBK conceptualized the study, II, IBK, and LNO analysed the data, IBK, II, OLN, IJK, HI, JPIM, EOO, JMD, and JMA wrote the first draft of the manuscript, IBK, LNO, EOO, and II wrote the final draft of the manuscript. All authors reviewed and approved the final manuscript for submission.

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