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Spatial pattern of tuberculosis cases in Jos Metropolis, Nigeria in the period 2019-2022

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Abstract

Plateau State is one of Nigeria's 14 states with a high Tuberculosis (TB) burden. In this state and its capital city, Jos Metropolis, TB cases have been on the increase. There are no reported studies on the spatial mapping of TB cases from Jos Metropolis. Thus, it is not known how TB hotspots and clusters may contribute to the propagation of area-wide TB transmission in this area and the implications for prevention and control. The objective of this study was to determine the spatial pattern of TB cases in Jos Metropolis from 2019-2022 based on existing TB data in the treatment registers and their residential addresses. We geolocated the cases to the nearest Polling Unit (PU) in their Electoral Ward (EW) using the Global Positioning System (GPS) coordinates obtained from the Polling Unit Locator (PUL) on the website of the Independent National Electoral Commission (INEC). In ArcGIS Pro (version 3.5.3) environment, TB hotspots were determined. Using the SaTScan software (version 10.3.2), a retrospective purely spatial analysis was carried out to identify purely spatial TB clusters based on the discrete Poisson model. A total of 4,897 TB cases were mapped. Significant TB hotspots (Z-score >1.96 and p-value <0.05) and primary TB clusters were found for each of the study years. The hotspots and clusters were located in the northern part of the Jos Metropolis, particularly the more centrally located areas. We found both a potential for future increase in TB cases and a spread to other areas of the Jos Metropolis from these TB hotspots and clusters in the northern part of the metropolis. Hence, there is an urgent need for a targeted TB screening and treatment, resource allocation and health education campaigns in the identified EWs.

Key words: tuberculosis, hotspots, clusters, spatial pattern, spatial analysis, electoral wards, Nigeria.

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Introduction

The World Health Organisation (WHO) currently estimates that there are 10.8 million Tuberculosis (TB) cases globally (WHO, 2023). Of these cases, 87% are in the 30 high-burden TB countries, with eight accounting for two-thirds of the cases, namely India (26%), Indonesia (10%), China (6.8%), the Philippines (6.8%), Pakistan (6.3%), Nigeria (4.6%), Bangladesh (3.5%) and the Democratic Republic of the Congo (3.1%) (WHO, 2023). TB remains a major public health problem in Nigeria, a country ranking 1st in Africa and 6th in the world among the 30 high-burden countries (Federal Ministry of Health -FMOH, 2019; Knowledge Network for Disease Control and Vigilance - KNCV Nigeria, 2023; Ogbudebe *et al.*, 2023). In 2023, the National Tuberculosis and Leprosy Control Programme (NTBLCP) recorded over 371,000 TB cases (NTBLCP, 2023), and the number of TB cases have been increasing since 2018 in the Nigerian Plateau State (PLS), including its capital city Jos Metropolis (FMOH, 2019). With regard to TB, PLS is one of Nigeria's 14 high-burden states (Ogbudebe *et al.*, 2023). Despite a high treatment success rate of about 80% among notified TB cases in PLS, the Plateau State TB and Leprosy Control Programme (PLSTBLCP) reports that the case detection rate (CDR) remains low at 26% (PLSTBLCP, 2019). This CDR is comparable to the national CDR of 23% for Nigeria for the year 2018, which increased to 43% in 2021 (World Bank, 2023a).

In recent times, spatial mapping and analyses of TB hotspots and clusters are increasingly being used in TB control strategies (Tiwari *et al.*, 2006; Onozuka & Hagihara, 2007; Randremanana *et al.*, 2009; Touray *et al.*, 2010; Dowdy *et al.*, 2012; Liu *et al.*, 2012; Shaweno *et al.*, 2018; Cudahy *et al.*, 2019; Gwitira *et al.*, 2021). Geospatial approaches are also used for targeted TB prevention and control by focusing on high-incidence hotspots and clusters for active case finding (ACF) (Dowdy *et al.*, 2012; Cudahy *et al.*, 2019). Various TB transmission risk factors or drivers that may affect the spatial distribution of TB have been identified, e.g., overcrowding, poor housing, poverty and high population densities (Trauer, 2019). According to one report, overcrowding, which is a key indicator of slum housing, poverty and social deprivation, is an important risk factor for TB transmission (WHO, 2018).

In Nigeria, there are a few studies on the application of geospatial approaches in the study of TB cases (Ugwu *et al*., 2021; Balogun *et al.*, 2022; Ogbudebe *et al.*, 2023; Teibo *et al.*, 2025). There is only one such study from PLS, and it did not include Jos Metropolis (Kefas et al., 2022). It is an ecological descriptive study examining the spatial and temporal distribution of TB at the Local Government Area (LGA) level, which is a secondary administrative level (Kefas *et al*., 2022). In Nigeria, the Electoral Ward (EW), which is a tertiary administrative level, is where TB prevention, control and treatment are carried out (Ogbudebe *et al.*, 2023). There are no reported studies on the spatial mapping of TB cases from Jos Metropolis, especially not at the EW level. Thus, it is not known how TB hotspots may contribute to the propagation of area-wide TB transmission in the metropolis and the implications of this for TB prevention and control. The objective of this study was to determine the spatial pattern of TB cases in Jos Metropolis from 2019 to 2022. The findings could contribute to the reduction of the TB burden in Jos Metropolis and Nigeria at large.

Materials and Methods

Study design

This was an observational study in which geospatial techniques were applied to already existing TB data to carry out geospatial mapping and spatial analysis.

Study location

The study was carried out in Jos Metropolis, the PLS capital. It is the 11th largest city in Nigeria - a cosmopolitan city with various ethnic groups and a population of 478,609 based on the 2006 population census (National Population Commission - NPC, 2010) - with PLS the 12th largest state in Nigeria, with a population of 3,206,531. The state has 17 LGAs, with Jos Metropolis having two of them: Jos North (JN) and Jos South (JS).

Based on the current Independent National Electoral Commission (INEC, 2025) mapping, each LGA is divided into EWs (also called Registration Areas), with the JN LGA having 14 EWs and the JS LGA 12 (Table 1, Figure 1). The EW is the spatial geographic unit of analysis used in this study and the justification

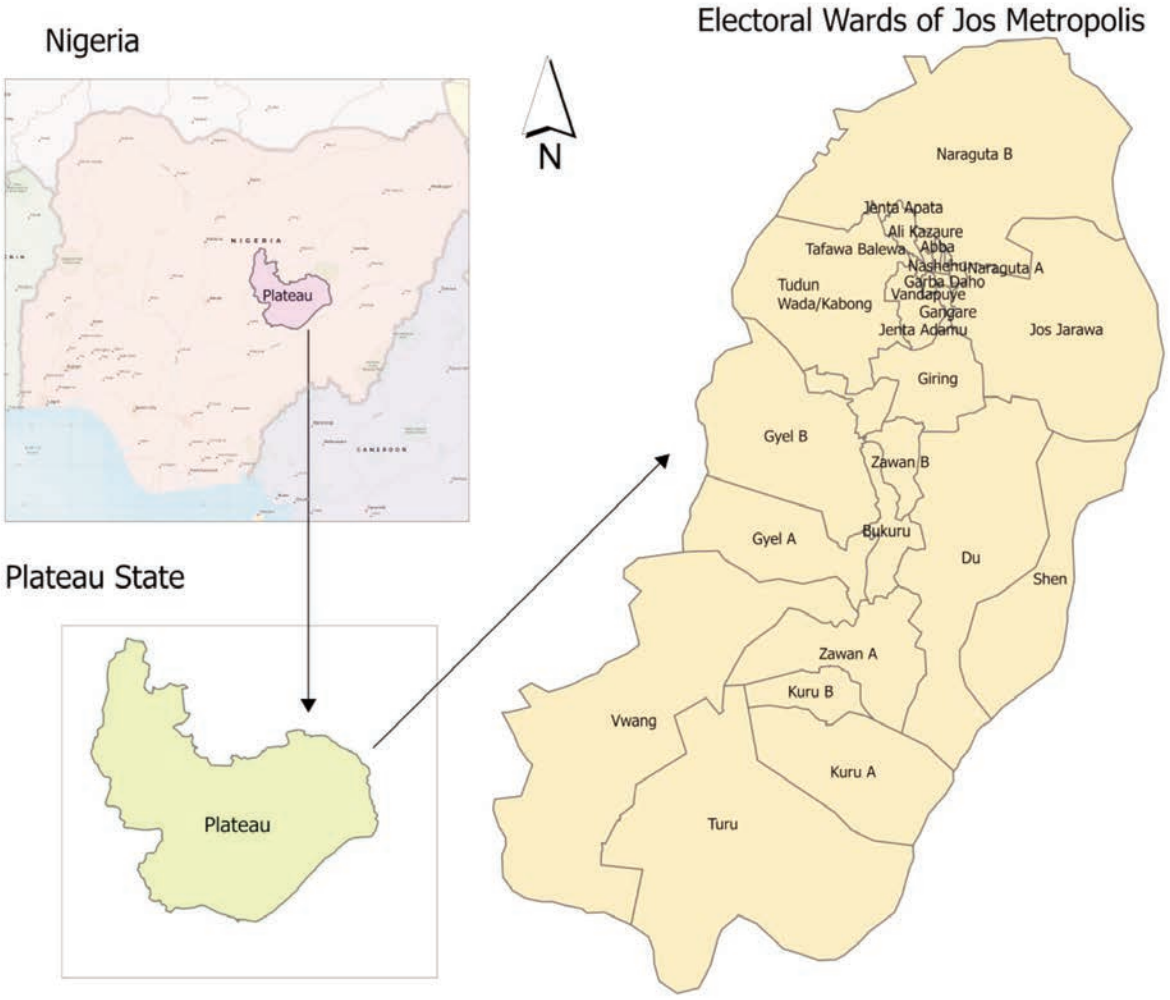

Figure 1. Overview map including the study area - Jos Metropolis with its electoral wards.

for this was that this unit represents one of the levels at which TB interventions are carried out in Nigeria (Ogbudebe *et al.*, 2023). For electoral voting, each EW was divided by INEC into Polling Units (PU), which is where voting takes place during elections. PUs are located in close proximity to homes/residences; thus, every TB patient has a PU close to their residence.

Study population

The study population consisted of both children and adult patients diagnosed and treated as recorded in the TB Treatment Registers (TBTRs). The TB treatment is based on the NTBLCP guidelines of 2015 (FMOH, 2015). The study's inclusion criteria were TB cases that had residential address information (complete or incomplete) captured in the TBTRs and residing in the JN or JS LGAs of Jos Metropolis. Patients with incomplete addresses are those without a detailed residential address but with a residence close to a well-known, popular landmark. The exclusion criteria were patients with unknown addresses and those not residing in the study area.

Data collection and sources

The TB data used were the routinely collected TB diagnosis and treatment data recorded in the TBTRs that are centrally archived by the PLSTBLCP, which is part of NTBLCP. The PLSTBLCP is an agency of the PLS Ministry of Health (PLSMOH). All TB data are routinely collected and entered into the TBTRs in every TB treatment unit in health facilities. This treatment unit is called the Directly Observed Therapy Short-course (DOTS) unit. TB data from DOTS units were collated at the LGA and state levels by trained TB personnel-DOTS Officers, TB LGA Supervisors and State TB Control Officers, respectively. The TB data collected included demographic variables (age, sex and home/residential address of the patient), clinical variables such as the form of the disease [Pulmonary TB (PTB) and extra-pulmonary TB (EPTB), HIV status (positive, negative or unknown] and type of TB [drug-sensitive TB (DS-TB) and drug-resistant TB (DR-TB)]. The residential addresses, which may be complete or incomplete, of the patients were extracted from the TB treatment records.

The geolocation data (geographical coordinates) were obtained from the Polling Unit Locator (PUL) at the INEC portal/website (INEC, 2025). Every PU has a Global Positioning System (GPS) giving the coordinates and every EW has several PUs. The GPS coordinates of a PU were determined from the PUL. Since every TB patient's residence is close to a PU, the PUL was used to geolocate each TB patient to the PU coordinates closest to their residence within their EWs. The EW centroids (geographical coordinates) were created from the EW polygon shapefile in an ArcGIS Pro (version 3.5.3) environment and exported into a Microsoft Excel sheet (version LTSC 2024).

The geodatabases were the raster data and ward boundaries/shapefiles. The population raster data was obtained from the WorldPop raster data (WorldPop, 2019), which gives the spatial distribution of population, including population counts for countries for each year. The ward shapefiles were the shapefiles of administrative level 3 (Ward boundaries) obtained from GRID3 (2021) and administrative level 2 (LGA) obtained from GADM (2025). The administrative level 3 shapefile contains the tertiary administrative level EW layers, while the administrative level 2 shapefile contains the LGA layers, including the JN and JS LGAs.

The EW populations

There are no available population data for the current EWs, either from INEC or NPC. The current INEC EWs consist of 14 in JN and 12 in JS, while the old EWs had 20 in JN and 20 in JS LGA (INEC, 2025). Therefore, in order to determine the population of the current EWs, a new shapefile that contained the current INEC EWs was created in an ArcGIS environment. It was created by merging some of the old EW boundaries using the shapefiles of administrative level 3 (Ward boundaries) obtained from GRID3 (2021) and administrative level 2 (LGAs) obtained from GADM (2025). Using the newly created shapefile and the 2019 WorldPop raster data (2019), the population count for the current EWs for the year 2019 was extracted using ArcGIS. Thus, using each preceding year's population count as the baseline population, the projected population for the EWs for the years 2020, 2021 and 2022 were determined. In determining each year's projected population, the Nigeria population annual growth rates for each of those years were obtained from the World Bank data (2023b) and the assumption was that population growth is geometric. The growth rates for each of these three years were the same at 2.1%.

Table 1. List of the electoral wards in Jos Metropolis and local governmental areas.

Electoral ward (EW)	Jos North Local Government Area (JN LGA)	Jos South Local Government Area (JS LGA)
1	Abba NaShehu	Bukuru
2	Ali Kazaure	Du
3	Garba Daho	Giring
4	Gangare	Gyel A
5	Ibrahim Katsina	Gyel B
6	Jenta Adamu	Kuru A
7	Jenta Apata	Kuru B
8	Jos Jarawa	Shen
9	Naraguta A	Turu
10	Naraguta B	Vwang
11	Sarki Arab	Zawan A
12	Tafawa Balewa	Zawan B
13	Tudun Wada/Kabong	
14	Vandapuye	

Geolocation

The coordinates of each TB patient were taken as those of the PU closest to the patient's residence, within their EW (Registration Area). We used patients' address information or a well-known or popular landmark close to their residence to geolocate them to the closest PU based on the PUL, as seen in Figure 2.

Data management

Patient data were anonymised, except the physical addresses of patients, which were required for the geolocation of TB cases. The TB data (attribute data) was entered into a Microsoft Excel spreadsheet (version LTSC 2024). The Electoral Ward was the spatial geographic unit of analysis.

Case notification rate

The TB case notification rate per 100,000 of the population (CNR) for each EW was calculated by dividing the total number of notified TB cases in that EW in a given year by the projected population for that year, then multiplying by 100,000.

Spatial autocorrelation

The EW was used as the spatial unit of analysis, which was first performed to ascertain the existence of TB clusters, but without specifying the location of these clusters. Global Moran's *I* statistic was used in the ArcGIS environment. Its value ranges from +1 to -1, where a value of 0 indicates no clustering (null hypothesis), a positive value indicates clustering and a negative value means dispersion across EWs. The test was considered significant if the Z-score was >1.96 and the *p*-value <0.05.

Hotspots analysis

After the determination of the existence of TB clusters, hotspots analysis was performed to ascertain the location of these clusters. The optimised hotspot analysis was used for the detection of hotspots and coldspots in ArcGIS Pro. The polygons for the feature class in this study were the 26 EWs under study. As the polygons were less than 30, we used the 'count incidents within fishnet grid' method (ESRI, 2025a) for detecting the clusters, particularly as it also best reflects the spatial pattern of the original point data (ESRI, 2025b). In this study, the geographical point coordinate of each TB case, *i.e.* rectangular polygons, were used to aggregate incident point data into standardised areas that are comparable and where the count of incidents within each cell becomes the field of analysis. The size of the grid in meters was automatically determined in ArcGIS Pro by calculating the optimal cell size, which was done for each of the study years. For the spatial extent of the analysis neighbourhood (i.e., spatial weighting matrix), the optimal fixed distance band was used with the exact number of k neighbours fixed at 8. Clusters with a Z-score of >1.96 and $p < 0.05$ were considered significant and classified as hotspots, while clusters with Z-scores <-1.96 were classified as coldspots, and those with Z-scores between -1.96 and +1.96 were considered as having non-significant clusters.

Purely spatial clusters

Following the hotspots analysis, SaTScan analysis was performed to further detect both the location and the extent of TB clustering across the EWs. SaTScan has the advantage of having a higher sensitivity and specificity, as well as better power in cluster detection compared to spatial autocorrelation and hotspots analy-

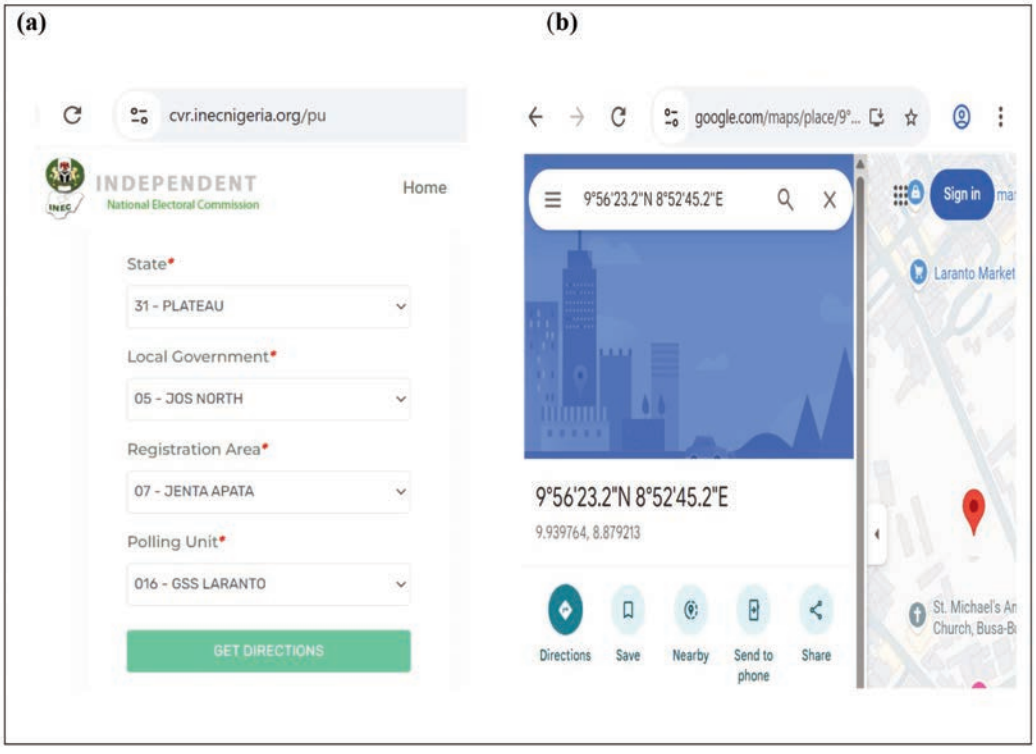

Figure 2. Polling unit locator (**a**) and Google map (**b**) for geolocation.

sis, in addition to combining both exploratory and confirmatory capabilities for cluster detection (Song & Kulldorff, 2003). To identify purely spatial clusters, a retrospective purely spatial analysis was carried out using SaTScan software (version 10.3.2) (https://www.satscan.org/), based on the discrete Poisson model (Kulldorf, 1997). The centroids of the EWs were used in the SaTScan analysis. Also, for the SaTScan analysis, the number of TB cases was used because they are compared in SaTScan: observed cases versus expected cases under the null hypothesis of no clustering. Additionally, using the number of cases allows SaTScan to detect statistically significant TB clusters without any *a priori* assumptions about cluster location, size and shape. The data input files used for this analysis were the case file (the total number of TB cases per EW for each of the study years), population file (the projected population for each EW for each of the years) and the coordinate file (the centroid points of each EW). The TB clusters were ranked based on their Relative Risk (RR), Likelihood Ratio (LLR) and *p*-value. The cluster with the maximum LLR, *i.e.* the Most Likely Cluster (MLC), was chosen as the primary cluster and the remaining ones as secondary clusters. In reporting secondary clusters, the criteria of the hierarchical most likely cluster and no geographical overlap were used (Kulldorf, 1997). For the presence of clusters, $p < 0.05$ was considered statistically significant. The scan window size was set at 50% of the total population at risk of TB, with the spatial window being circular. We used 999 Monte Carlo replications for the outcome.

Results

Characteristics of the study population

The study, which covered the period January 2019-December 2022, enrolled 4,897 patients who met the inclusion criteria. The median (IQR) age of the study population was 66 years (54-81), and the majority of them were adults, with only 24 (0.5%) children aged 0-15 years. The majority of the patients were males (64%), with PTB (91%) the commonest form of TB and 18% (848/4585) of those tested for HIV being positive. Of the notified TB cases, 90% (4401/4897) were new cases and 1% (61/4897) DR-TB cases.

Tuberculosis case notification rate

The TB CNRs increased over the years from 2019 -2022 for most of the EWs. The overall mean rate for the entire Jos Metropolis over the 4-year period was 117 per 100,000 of the population. Most of the EWs with the highest TB CNRs were in JN, namely, Abba NaShehu, Ali Kazaure, Garba Daho, Gangare, Ibrahim Katsina, Jenta Apata, Naraguta A,Sarkin Arab, and Tudun/Wada Kabong. They had a mean TB CNRs > 200 per 100,000 population over the study period. Most of these wards are in the central part of JN - Abba NaShehu, Ali Kazaure, Garba Daho, Gangare, Ibrahim Katsina, Jenta Apata and Sarkin Arab. The EWs with the lowest CNRs were spread across JS (Table 2 and Figure 3). The spatial distribution (pattern) of TB CNRs for the EWs in Jos Metropolis for the years 2019 to 2022 are shown in Figure 3. The CNRs were highest in the northern part of the metropolis, where the EWs - Abba NaShehu, Ali Kazaure, Garba Daho, Gangare, Jenta Apata and Sarkin Arab are located.

Table 2. Tuberculosis case notification rates by electoral wards in Jos Metropolis 2019-2022.

Electoral Ward (EW)	2019			2020			2021			2022		
	TB cases	EW Pop	TB CNR	TB cases	EW Pop	TB CNR	TB cases	EW Pop	TB CNR	TB cases	EWPop	TB CNR
Jos North												
Abba NaShehu	20	2885	693	30	2946	1018	32	3007	1064	29	3071	944
Ali Kazaure	18	4666	386	22	4764	462	43	4864	884	40	4966	805
Garba Daho	17	3196	532	6	3263	184	20	3332	600	23	3402	676
Gangare	27	5258	514	34	5368	633	16	5481	292	24	5596	429
Ibrahim Katsina	11	2734	402	9	2791	322	11	2850	386	15	2910	515
Jenta Adamu	45	26244	171	35	26795	131	27	27358	99	35	27932	125
Jenta Apata	40	14033	285	43	14328	300	75	14629	513	45	14936	301
Jos Jarawa	80	79972	100	79	81651	97	90	83366	108	124	85117	146
Naraguta A	22	5107	431	35	5214	671	43	5324	808	47	5436	865
Naraguta B	159	126297	126	210	128949	163	251	131657	191	264	134422	196
Sarkin Arab	10	2316	432	9	2365	381	12	2414	497	14	2465	568
Tafawa Balewa	8	2698	297	5	2755	182	2	2813	71	3	2872	104
TudunWada/ Kabong	143	83900	170	165	85662	193	215	87461	246	213	89297	239
Vanderpuye	0	3750	0	1	3829	26	2	3909	56	3	3991	75
Jos South												
Bukuru	50	59988	83	43	61248	70	69	62534	110	55	63847	86
Du	47	136429	34	38	139294	27	45	142219	32	47	145206	32
Giring	52	58336	89	39	59561	65	67	60812	110	56	62089	90
Gyel A	27	31015	87	35	31666	111	37	32331	114	42	33010	127
Gyel B	33	49893	66	37	50941	73	41	52011	79	32	53103	60
Kuru A	8	49440	16	6	50478	12	7	51538	14	15	52621	29
Kuru B	15	20945	72	12	21385	56	20	21834	92	24	22292	108
Shen	11	19995	55	4	20415	20	13	20844	62	8	21281	38
Turu	40	70854	56	26	72342	36	36	73861	49	49	75412	65
Vwang	64	65402	98	55	66775	82	60	68178	88	56	69609	80
Zawan A	51	69621	73	45	71083	63	55	72576	76	77	74100	104
Zawan B	57	22685	251	53	23161	229	64	23648	271	73	24144	302
Total	**1055**	**1017659**	**104**	**1076**	**1039030**	**104**	**1353**	**1060849**	**128**	**1413**	**1083127**	**130**

EW, Electoral ward, Pop, population, TB, Tuberculosis, CNR, Case notification rate per 100,000 of the population.

Global spatial autocorrelation analysis

There was a very strong positive spatial autocorrelation of the TB cases over the period 2019-2022, with of global Moran's *I* of 0.926 (p=0.0001). For the year 2019, the value was 0.875 (p=0.0001), and for the year 2020, 0.927 (p=0.0001). Also, for the years 2021 and 2022, there was a strong positive autocorrelation with Moran's *I*: 0.939 (p=0.0001) and 0.894 (p=0.0001). These results suggest clustering in the distribution of TB cases in the EWs of Jos metropolis.

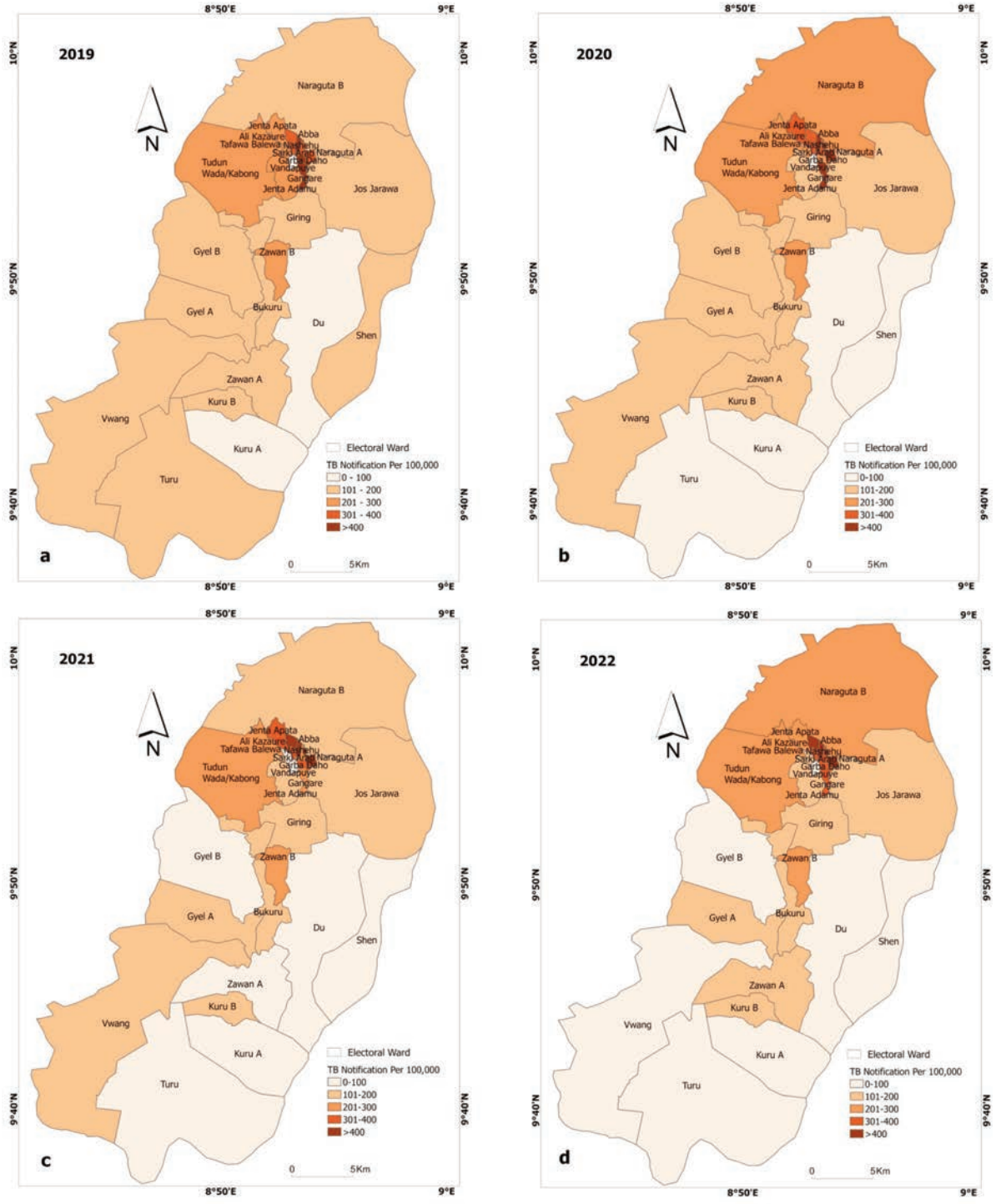

Figure 3. Spatial distribution of Tuberculosis case notification rate per 100,000 at Electoral Ward level, Jos Metropolis 2019 (**a**), 2020 (**b**), 2021 (**c**) and 2022 (**d**).

Hotspots analysis

Significant TB hotspots (Z-score >1.96 (p <0.05) were found across all the years (2019-2022). The hotspots were characteristic of JN, particularly the more centrally located area in the EWs that includes: Abba NaShehu, Naraguta A, Ali Kazaure, Garba Daho, Sarkin Arab, Gangare, Jenta Apata and Tudun/Wada Kabong (Figure 4). These EWs were also among those with the highest mean TB CNRs in the metropolis for the period 2019-2022 (Table 2 and Figure 3). There was only one significant coldspot (Z-scores <-2.23018 (p <0.0001) identified during the study period and this was in 2021, in JS, specifically in the EW of Du (Figure 4c).

Purely spatial analysis using SaTScan

Significant TB clusters were observed in each of the four years of study, 2019-2022, with each year having one primary and one secondary cluster (Figure 5 and Table 3). For the primary clusters, the number of observed TB cases was higher than expected. The year 2022 had the highest number of TB cases compared to the year 2019 (1008 versus 709). The primary clusters were all in JN, while the secondary ones were in JS. The EWs within which these primary clusters were located (Figure 5) consistently corresponded to those same EWs with the highest TB CNRs (Table 2 and Figure 3) and significant hotspots (Figure 4), namely - Abba NaShehu, Naraguta A, Ali Kazaure, Garba Daho, Sarkin Arab, Gangare, Ibrahim Katsina, Jenta Apata and Tudun/Wada Kabong. The hotspots and SaTScan analyses gave similar results, i.e. both the hotspots and the spatial clusters were found in the same EWs, which is an indication of consistency in the study's findings of clustering.

Discussion

This study's finding that the EWs with the highest TB CNRs were also those with significant TB hotspots and primary clusters is similar to the findings of previous studies (Shaweno *et al.*, 2018; Gwitira *et al.*, 2021), while the discovery of TB clusters occurring in the EWs with the highest TB CNRs is reminiscent of an older study showing that clustering of TB cases occur in areas of high TB incidence (Munch *et al.*, 2003). This suggests that the factors that drive TB also vary in the geographical space. These findings are important for optimal allocation of scarce resources by national TB control programmes, particularly in resource-limited countries such as Nigeria. The results could be used to guide targeted interventions focusing on areas characterised by hotspots and clusters instead of the application of a uniform approach to TB prevention and control (Dowdy *et al.*, 2012). This, in turn, may enhance the success of TB control programmes since resources will be allocated based on requirements. Additionally, it could also enhance the prioritisation of TB surveillance.

The persistence of significant TB clusters and hotspots in the same locations of the above EWs in each of the four years of the study period suggests a sustained TB infection/disease transmission over these years. One explanation for this may be that existing TB control strategies, such as active case finding, are not targeted or not properly implemented. Another explanation may be that the strategies are properly implemented, but are unable to control potential socio-economic risk factors for TB, such as overcrowding/high population density, inadequate housing with poor ventilation and poverty. A study on 'an analysis of inner-city decay in Jos city' by Lekwot *et al.* (2015) showed that some of the locations where TB hotspots and clusters were found are in fact part of the urban slums of the Jos Metropolis, which is plagued by overcrowding and poverty. Overcrowding has long been recognised as a marker of poverty and social deprivation, with the United Nations identifying it as one of the key indicators of a slum (WHO, 2018). In overcrowded conditions, there is increased close contact and poor ventilation, both of which enhance airborne transmission of *Mycobacterium tuberculosis*. Poverty is also associated with poor nutrition, which could result in a weakened immune system and hence susceptibility to TB (CDC, 2025). TB incidence or occurrence naturally exhibits spatial dependence due to the airborne transmission enhanced by overcrowding (Im *et al.*, 2021). This is one of the explanations why TB hotspots and clusters are observed in overcrowded and poor settings (Lee *et al.*, 2022).

The approach adopted in this study provides some unique perspectives, with its uniqueness lying in the methodology of geolocating the TB patients. Here, we leveraged an existing geolocator - the INEC EW PUL, available on the INEC website. The use of the PUL for geolocation is logistically simple by saving cost and time when used in the initial/preliminary assessment/exploration of the geospatial TB distribution based on existing records, before a real-time geolocation with a hand-held GPS and spatial analysis can be carried out. This approach can find application in Nigeria for exploratory geospatial mapping and analysis of TB and other disease conditions using already available PUL and existing records. Geolocating TB patients, for example, in the case of DR-TB, will be critical for the prompt isolation of such cases, as it would prevent the spread of DR-TB in the community.

The use of the EW as the geographic unit for the analysis was an advantage since this unit represents one of the levels at which TB interventions are carried out in Nigeria (Ogbudebe *et al.*, 2023) and thus would be valuable to the relevant TB policy makers in PLS and in Nigeria at large. We used geolocated individual TB cases, which we then aggregated to EW levels for the spatial anal-

Table 3. Significant tuberculosis clusters detected by purely spatial analysis in Jos Metropolis.

Year	Type	Radius (km)	Location (no.)	Observed cases (no.)	Expected cases (no.)	RR	LLR	P
2019	A	8.6	16	709	460	2.65	118.80	0.001
	B	9.7	6	182	369	0.39	82.19	0.001
2020	A	5.8	13	604	299	3.32	188.98	0.001
	B	9.7	6	148	377	0.30	124.45	0.001
2021	A	5.8	13	749	376	3.22	225.20	0.001
	B	11.4	9	346	639	0.38	134.40	0.001
2022	A	8.6	16	1008	616	3.21	221.58	0.001
	B	9.4	5	202	466	0.34	128.76	0.001

A, Primary Cluster, B, Secondary cluster, RR, Relative risk, LLR, Log likelihood ratio.

ysis, as this approach provides detailed information about the spatial pattern and clustering of TB, offering the advantage of a more focused intervention at the community level as reported in an Ethiopian study (Dangisso *et al.*, 2020). Additionally, spatial analysis at this scale helps to reduce ecological bias due to its proximity to the individual level (Elliot & Wartenberg, 2004). Two previous studies from Nigeria (Ugwu *et al*., 2021; Balogun *et al.*, 2022) on spatial analyses of TB used the LGAs as the geographic unit of analysis, thereby limiting their usefulness for TB prevention and control, since the EW, rather than the LGA, is one of the levels at which TB interventions take place in Nigeria.

A limitation of this study was that we did not explore the TB

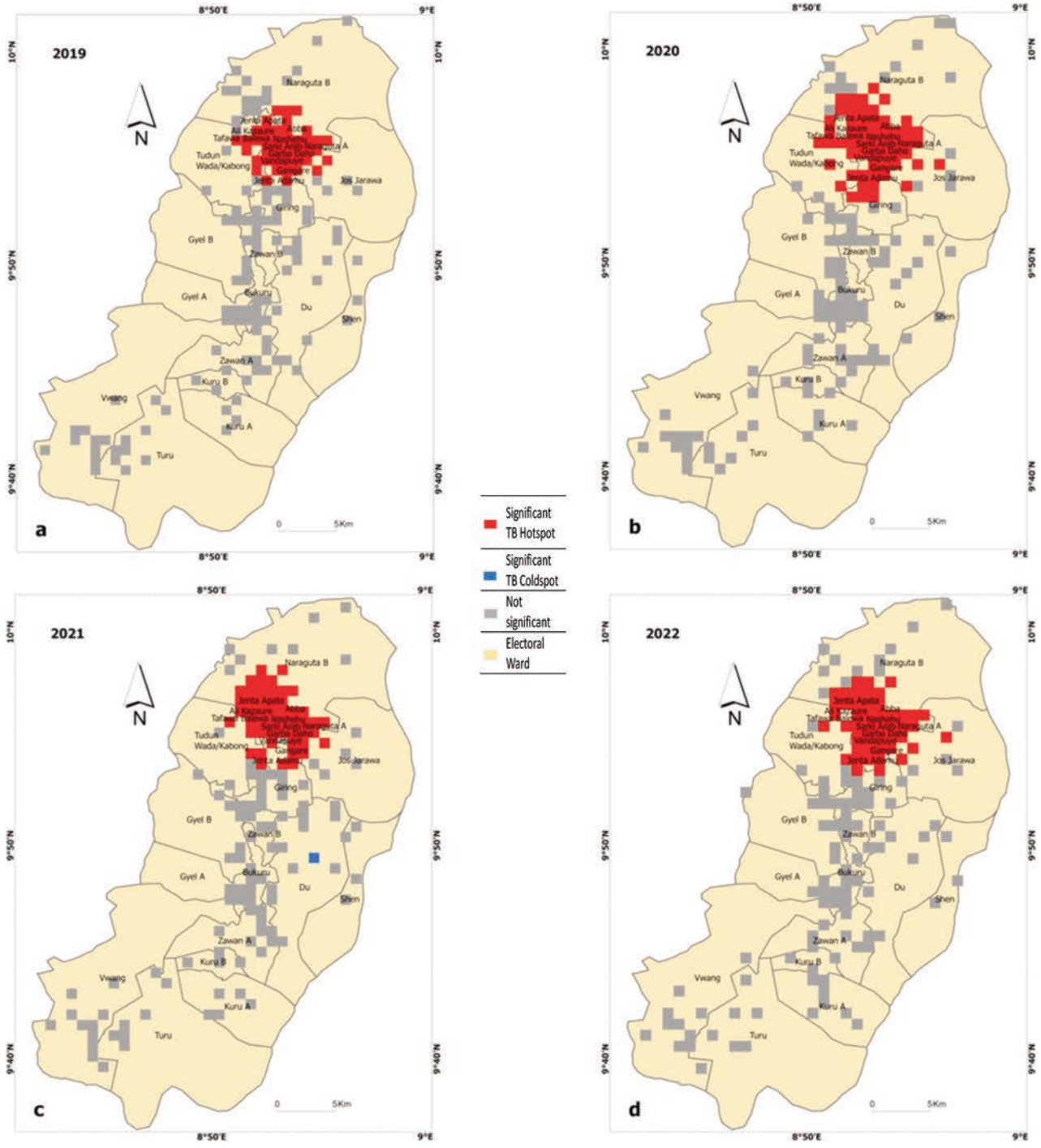

Figure 4. Spatial distribution of Tuberculosis Hotspots in Jos Metropolis 2019 (**a**), 2020 (**b**), 2021 (**c**) and 2022 (**d**).

risk factors, such as socio-economic and environmental factors, that might have helped to explain the clustering of TB cases in the particular EWs of Jos Metropolis studied. Another limitation was that this study did not include patients whose residential addresses were unknown or whose incomplete addresses lacked a well-known/popular landmark close to their residence that could be used for geolocation. This exclusion could have influenced the spatial pattern detected, as they may be those in the poverty-prone areas of Jos Metropolis and this could have biased the study results towards those who have easier access to health. However, the absence of a spatial reference would have been negative. On the positive side, it must be mentioned that the results of this study are useful for targeted TB control interventions in the EWs with the highest CNRs, TB hotspots and TB clusters. This is important for

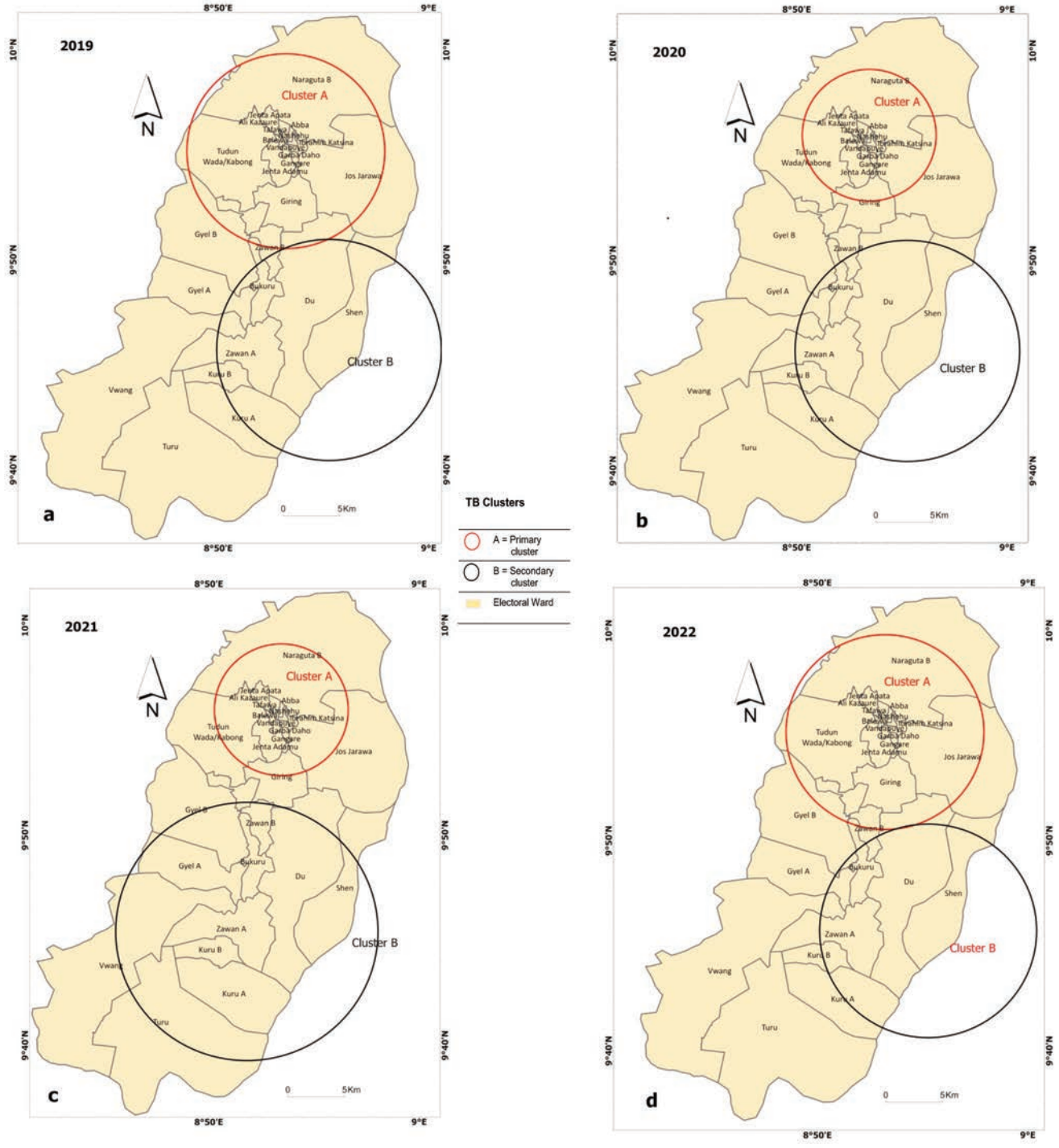

Figure 5. Spatial distribution of purely spatial clusters of Tuberculosis in Jos Metropolis 2019 (**a**), 2020 (**b**), 2021 (**c**) and 2022 (**d**).

optimal allocation of resources, such as TB diagnostics facilities and treatments in these EWs. This should be coupled with intensive health education campaigns on TB prevention measures, as well as early presentation to the hospital for evaluation and treatment for those with symptoms.

Finally, there is a need for improvement in other socio-economic parameters, such as better housing conditions. There is a need for real-time geolocation of patients diagnosed with TB in specific treatment centres, including DOT units, which would help determine TB spatial patterns with their hotspots and clusters as a means of rapid TB surveillance for prompt intervention/control.

Conclusions

The spatial distribution of TB cases showed that the highest TB case notification rates, as well as significant TB hotspots and primary clusters, were located in the northern part of Jos metropolis, particularly the central part of the area. There is thus both the potential for increased numbers of TB cases in the future and spread to other areas of the metropolis. Hence, there is an urgent need for a targeted TB screening and treatment, resource allocation and health education campaigns in the identified EWs by the responsible government agencies.

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Conflict of interest: this is correct and should be here.

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