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SPATIO-TEMPORAL ANALYSIS OF TUBERCULOSIS IN ANAMBRA STATE, NIGERIA USING GIS: EMERGING URBAN CLUSTERS AND THE ROLE OF BUILT-UP ENVIRONMENT (2013–2023)

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Abstract

Tuberculosis (TB) remains a significant public health challenge in Nigeria, with transmission dynamics increasingly influenced by rapid urbanization and high human mobility. This study investigated the spatio-temporal trends of TB transmission across the 21 Local Government Areas (LGAs) of Anambra State from 2013 to 2023, focusing on the emergence of TB clusters and their association with urban development. Retrospective data were analyzed using Geographic Information Systems (GIS), incorporating TB case notifications, population projections, and Land Use/Land Cover (LULC) changes. Spatial cluster analysis was performed using Global Moran's I, Local Indicators of Spatial Association (LISA), and Getis-Ord statistics, while multivariate regression assessed the impact of urbanization indicators. The study found that the Case Notification Rate (CNR) rose dramatically from 38.1 per 100,000 in 2013 to 183.7 per 100,000 in 2023, representing a 382.2% increase. The spatial distribution of TB shifted from a random pattern between 2013 and 2020 ($p > 0.05$) to a significantly clustered pattern from 2021 onward (Moran's I = 0.208, $p = 0.028$), with hotspots concentrated in the heavily built-up and commercial LGAs of Onitsha North, Onitsha South, Awka South, and Nnewi North, as well as the rapidly expanding Onitsha–Idemili axis (including Obosi and Nkpor). Correlation analysis revealed that built-up area is moderately positively correlated with TB rate ($r = 0.333$), while population density shows a weaker positive relationship ($r = 0.143$). The multivariate regression model explained approximately 12.1% of the variation in TB incidence ($R^2 = 0.121$), identifying built-up area (beta = +0.320) as a stronger predictor than population density (beta = +0.100). These findings suggest that TB transmission is primarily driven by the structural and functional intensity of the urban environment; specifically high-mobility commercial hubs and transit axis, rather than raw population size alone. This highlights the need for public health interventions to target high-activity urban centers and commercial hotspots to effectively curb the TB burden in Anambra State.

Keywords: tuberculosis; case notification rate; spatio-temporal analysis; GIS; urbanization; Anambra State; Nigeria

1. Introduction

Tuberculosis (TB) remains one of the most significant public health challenges of the 21st century, continuing to affect millions of people worldwide despite decades of global control efforts. As a communicable disease that has plagued humanity for centuries, TB represents a complex intersection of biological, social, environmental, and economic factors that influence its transmission patterns and burden distribution across different populations and geographic regions [1]. Tuberculosis (TB) remains the leading infectious killer worldwide and is concentrated in developing and middle-income countries. Eighty-seven percent of the estimated global TB cases were concentrated in 30 countries, and most are found in Sub-Saharan Africa and Asia [1]. Globally in 2023 one of every ten new TB cases was DR to at least one TB drug, with the fraction resistant to multiple drugs (MDR-TB) and extensively drug-resistant TB (XDR-TB) rising [2]. Mortality from TB in Africa are high among patients with MDR-TB (21%) and XDR-TB (43%) [3]. DR-TB, is a greater challenge that has remained largely unreported and underestimated in Nigeria where number of TB cases increased over the last 8 years, contributing to being one of the top contributing countries for MDR-TB globally, from 5.6% in 2015 to 38.7% in 2023. Meanwhile, initiating treatment among the populace has increased over the same period [4]. Recurrent TB, through re-infection or reactivation depends on DR, host factor, strain genotypes and presence of comorbid infection such as HIV/AIDS or diabetes mellitus [5]. TB is closely linked to social determinants of health including poverty, over-crowding, alcoholism, stress, substance abuse and malnourishment [6]. Malnourishment in relation to hunger increased risk of developing TB by 6–10 fold and is significant factor in latent-to-active TB development which now causes more cases of global TB than HIV, and represents the most important risk factor globally, where 2.3 Million new cases were estimated due to malnourishment alone in 2019 [6]. In many African countries, food insecurity may be exacerbated by HIV/AIDS epidemics, and TB thus posing a triple-disease burden on the community with rapid and intense interactive relationship [7]. Additionally, the COVID-19 pandemic further exacerbated TB control. In Nigeria following the index case in Feb 2020, restriction of movement led to decline in TB services where case notifications and GeneXpert testing declines to 17 and 30 percent respectively [8]. Anambra State (Anambra) is a highly populous State in Nigeria. A commercial alluvial State in south east Nigeria with major transport routes and business hubs such as the Onitsha business hub. High population growth rate and migration patterns may contribute to increased TB transmission within the state. Though, official data reported moderate TB prevalence, the true infection rates may have been hidden in the absence of sufficient data on diagnosis and treatment services. High burden of childhood and drug resistant TB are notable in the South East [9]. In light of these challenges spatial epidemiology becomes essential to providing the knowledge base for planning effective intervention strategies for TB. Spatial epidemiology is an emerging field of epidemiology that investigates the spatial and temporal components of disease diffusion and spread. Health practitioners have widely recognized the fact that patterns of diseases do not appear randomly, but rather depend on spatial factors and spatial autocorrelation [10]. Spatial statistics in public health are methods used to plot, analyze, and predict the spatial occurrence of health issues. Commonly utilized categories of spatial statistics include disease rate/count mapping, disease cluster identification, spatial correlation analysis, and modeling of health outcomes (explain/predict disease occurrence) [11]. GIS has proved instrumental to the study of infectious diseases, allowing researchers to pinpoint high-risk regions, track disease spatial-temporal evolution over time, and ensure adequate distribution of resources to vulnerable populations. Spatio-temporal analysis is particularly significant as it extends beyond static maps to demonstrate whether specific disease incidence pattern is random, grouped into statistically

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significant clusters, and how those clusters are evolving spatially over time. This allows for tailored and geographically focused interventions against the emergent spread pattern. This study attempts to map the spatio-temporal trends of TB within the Anambra State during the last decade (2013–2023), demonstrate spatial variation in the TB cases and the trend in CNR over time, in relation to population dynamics and analyze the impact of urbanization on TB spatial clusters.

Tuberculosis has significant spatial and temporal characteristics and clear evidence of clustered spatial patterns. Advances in the use of Geographical Information Systems (GIS) and spatial statistics have made the spatial features easier to detect and quantify. Spatially and temporally, patterns vary between localities. Spatial patterns at sub-national level can be assessed by density estimation, which uses GIS-based mapping techniques to estimate the incidence of disease at different geographic scales. Spatial and temporal distribution of TB cases within a particular administrative boundary varies significantly as demonstrated in studies carried out in Nigeria and Malaysia [12, 13], where TB cases were concentrated differently in various Local Government Areas (LGAs). More sophisticated spatial autocorrelation methods such as global and local Moran's I both detect high clustering of cases with higher spatial heterogeneity observed with increases in economic indicators [14, 15]. Spatio-temporal cluster patterns have also been identified showing persistence and seasonality, and were influenced by changing local patterns in demographic and environmental conditions as found in China and Ethiopia [16, 17]. A method such as space-time scan statistics (SaTScan) which identifies cluster patterns over time also detected emerging clusters over the periods evaluated in areas like Indonesia, specifically in high population cities [18, 19]. More complex techniques such as geostatistical interpolation and Bayesian spatial modeling can quantify risk surfaces and model spatial dependence and heterogeneity, identifying relationships between factors such as healthcare access and TB disease occurrence [20, 21]. Integrated approaches incorporating spatial analysis and machine learning are also increasingly common [22].

Both urbanization and the built environment play crucial roles in facilitating or impeding the transmission of tuberculosis. Growing populations in urban centers especially unplanned ones contribute to increasing spatial and temporal clustering of cases through increased proximity and distribution inequalities in health resources. Population density continues to be consistently identified as a major risk factor associated with TB transmission. In studies done in Ethiopia and Indonesia, higher TB incidence and prevalence were strongly associated with higher density areas where proximity to others leads to easier transmission of an infectious disease [18, 17]. For Malaysia and China, economic growth leads to denser urban population and intensified TB transmission through both domestic and migration forces [13, 15]. Studies carried out in Cali, Indonesia and Surabaya, Indonesia, demonstrated that the clustering effect and persistent incidence of TB could be related to poor housing quality and sanitation with limited ventilation [23,24], highlighting that general or evenly distributed programs might miss specific localized high risk areas due to inherent spatial variation in quality of housing and accessibility to services in these urban environments. These studies suggest planning and programmatic interventions at specific localities and consider the built environment as a potential modifiable risk factor for TB [25]. Socioeconomic and environmental factors were consistently linked with observed variations and the spatial distribution of the disease, for example, four of the studies discussed identified clustering of cases in areas that were poor and had high density with limited healthcare services thus making transmission harder to control and cases more difficult to detect [14, 21]. Conversely low reported cases could suggest detection problems due to restricted access to healthcare [21]. In addition, HIV and immunisation levels were identified as possible contributing factors along with trade and transport links for the urban clustering of TB [14, 19]. Therefore spatial patterns observed can generally be ascribed to interplay between the physical built environment, the social factors influencing it and general disease patterns.

2. Methodology

2.1 Study Area

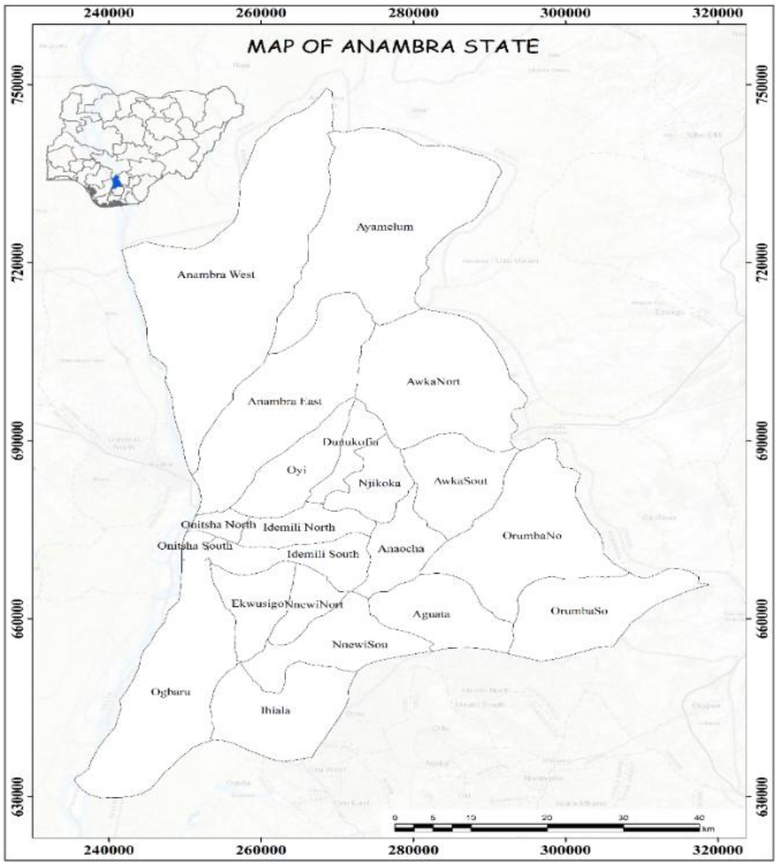

Figure 2.1: Map of Anambra State

The study area was Anambra State in southeastern Nigeria which is located between longitudes 7.24°E and 7.16°E and latitudes 5.25°N and 5.32°N. Its capital is Awka. Anambra shares its borders with Delta State to the West, Kogi to the North, Enugu to the East and Imo and Rivers States to the South. The state covers an area of approximately 4,844 km². The climate is characterized by wet and dry seasons. Anambra consists of 21 LGAs and is one of Nigeria's most urbanized states, with 62% population in urban centers. Anambra state has an approximate population of 7.1 million. The state is administratively divided into twenty-one (21) Local Government Areas (LGAs), which include: Aguata, Anambra East, Anambra West, Anaocha, Awka North, Awka South, Ayamelum, Dunukofia, Ekwusigo, Idemili North, Idemili South, Ihiala, Njikoka, Nnewi North, Nnewi South, Ogbaru, Onitsha North, Onitsha South, Orumba North, Orumba South, and Oyi. It is a busy commercial area.

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2.2 Study design and data sources

This research employed a quantitative, retrospective, ecological approach to assess patterns of TB cases at the local level. Yearly TB incidence data for each of the 21 LGAs and state was obtained from the Anambra State Tuberculosis and Leprosy Control Programme between 2013 and 2023. Annual population data per LGA was derived from census projections based on the 2006 National Population Census [26]. Land Use/Land Cover (LULC) data covering 2013, 2015, 2017, 2020 and 2023 was acquired from ESRI's Living Atlas, with built-up area identified within each LGA. Shape files delineating LGAs were acquired from the Office of the Surveyor General of Anambra State.

2.3 Spatial and statistical methods

ArcGIS 10.7 and Microsoft Excel were utilized in this spatial statistical analysis. Global Moran's I was used to calculate the overall pattern of TB case notification rates across all LGAs each year and observe trends of randomization over clustering of TB rates in the study area. LISA was used to assess local spatial association of TB case notification rates by identifying LGAs which contributed to clustering. LISA distinguishes between high notification rate neighborhoods surrounded by other high notification rate neighborhoods (high-high clusters/hotspots) and low notification rate neighborhoods surrounded by other low notification rate neighborhoods (low-low clusters/coldspots). Getis-Ord Gi* was applied to detect true clusters of high notification rates (hotspots) with z-scores and p-values to indicate statistically significant clustering unlikely due to random chance. Case notification rate (CNR) was calculated for the state total and for each LGA, as shown below: CNR = (total number of TB cases in year / estimated population) × 100,000. The result obtained represents the number of cases per 100,000 people annually and was presented up to one decimal place. Multivariate regression analysis was used to examine the independent relationship between TB incidence and urbanisation indicators. These indicators were the extent of the built-up area within each LGA and population density per km^2.

3. Results and Discussion

The table presents a comprehensive summary of tuberculosis (TB) case notifications and case notification rates (CNR) across all 21 LGAs in Anambra State from 2013 to 2023. There is a clear upward trend in both TB case counts and CNR over the study period, with rapid increases observed from 2020 to 2023. High-burden LGAs such as Onitsha North, Onitsha South, Idemili North, and Nnewi North consistently recorded the highest case counts and CNR values across different years, reflecting persistent spatial concentration of TB. The data also reveal distinct temporal variability, which can be grouped into three phases:

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Table 3.1: Anambra State Tb Case Notification Rate (CNR) Table — 2013 To 2023

S/N	LGA	2013			2014			2015			2016			2017		
		TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR
1	Aguata	55	165553	33.2	72	172379	41.8	55	179205	30.7	38	186030	20.4	68	192856	35.3
2	Anambra East	17	30513	55.7	32	34632	92.4	25	65752	38.0	20	96872	20.6	47	127991	36.7
3	Anambra West	3	267074	1.1	1	275264	0.4	5	283453	1.8	8	291643	2.7	20	299832	6.7
4	Anaocha	69	281610	24.5	56	293220	19.1	57	304830	18.7	51	316440	16.1	40	328050	12.2
5	Awka North	5	202977	2.5	10	211345	4.7	16	219713	7.3	30	228081	13.2	27	236449	11.4
6	Awka South	194	190851	101.6	155	198719	78.0	189	206587	91.5	144	214455	67.1	154	222323	69.3
7	Ayamelum	43	208494	20.6	46	217090	21.2	44	225685	19.5	42	234281	17.9	54	242876	22.2
8	Dunukofia	40	520116	7.7	28	541559	5.2	25	563002	4.4	16	584444	2.7	26	605887	4.3
9	Ekwusigo	24	342978	7.0	23	357118	6.4	8	371258	2.2	11	385397	2.9	12	399537	3.0
10	Idemili North	275	187585	146.6	201	195317	102.9	203	203050	100.0	278	210783	131.9	699	218516	319.9
11	Idemili South	41	179076	22.9	35	186459	18.8	29	193841	15.0	39	201224	19.4	36	208606	17.3
12	Ihiala	128	116563	109.8	81	121356	66.7	88	126149	69.8	73	130941	55.8	126	135734	92.8
13	Njikoka	32	446464	7.2	28	464871	6.0	30	483277	6.2	37	501684	7.4	50	520090	9.6
14	Nnewi North	271	151951	178.3	287	158216	181.4	243	164480	147.7	232	170745	135.9	164	177009	92.7
15	Nnewi South	43	134848	31.9	41	140484	29.2	31	146119	21.2	29	151755	19.1	37	157390	23.5
16	Ogbaru	66	364773	18.1	76	379811	20.0	54	394850	13.7	123	409888	30.0	96	424927	22.6
17	Onitsha North	400	191184	209.2	425	199066	213.5	360	206948	174.0	412	214830	191.8	432	222712	194.0
18	Onitsha South	67	183608	36.5	54	191178	28.2	55	198747	27.7	53	206316	25.7	125	213885	58.4
19	Orumba North	7	269488	2.6	23	280598	8.2	11	291709	3.8	11	302819	3.6	12	313929	3.8
20	Orumba South	32	228864	14.0	22	238300	9.2	22	247735	8.9	29	257171	11.3	22	266606	8.3
21	Oyi	52	222703	23.3	74	231885	31.9	79	241066	32.8	55	250248	22.0	53	259429	20.4
	Total	**1864**	**4887273**	**38.1**	**1770**	**5088867**	**34.8**	**1629**	**5317456**	**30.6**	**1731**	**5546047**	**31.2**	**2300**	**5774634**	**39.8**

S/N	LGA	2018			2019			2020			2021			2022			2023		
		TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR	TB Cases	Population	CNR
1	Aguata	73	199681	36.6	87	206615	42.1	67	213226	31.4	96	220050	43.6	118	227092	52.0	95	233810	40.6
2	Anambra East	55	159111	34.6	76	167303	45.4	88	251965	34.9	137	260027	52.7	216	268348	80.5	286	314710	90.9
3	Anambra West	50	308021	16.2	62	318473	19.5	96	321440	29.9	52	331726	15.7	131	342342	38.3	254	348969	72.8
4	Anaocha	50	339659	14.7	73	351452	20.8	80	362698	22.1	69	374305	18.4	61	386282	15.8	64	397709	16.1
5	Awka North	32	244817	13.1	38	253317	15.0	43	261423	16.4	311	269789	115.3	506	278422	181.7	727	286658	253.6
6	Awka South	170	230191	73.9	214	238183	89.8	174	245805	70.8	227	253671	89.5	447	261788	170.7	499	269532	185.1
7	Ayamelum	68	251472	27.0	87	260203	33.4	120	268529	44.7	101	277122	36.4	259	285990	90.6	468	294450	158.9
8	Dunukofia	25	627330	4.0	30	649110	4.6	70	669881	10.4	116	691317	16.8	156	713440	21.9	540	734544	73.5
9	Ekwusigo	20	413677	4.8	27	428039	6.3	45	441736	10.2	74	455872	16.2	92	470459	19.6	157	484376	32.4
10	Idemili North	650	226249	287.3	424	234104	181.1	460	241594	190.4	605	249326	242.7	1000	257303	388.6	1794	264914	677.2
11	Idemili South	50	215989	23.1	68	223488	30.4	50	230639	21.7	58	238019	24.4	71	245636	28.9	76	252902	30.1
12	Ihiala	124	140526	88.2	125	145359	86.0	125	150100	83.3	200	154810	129.2	522	159764	326.7	1597	164490	970.9
13	Njikoka	48	538496	8.9	46	557192	8.3	75	575023	13.0	172	593423	29.0	347	612413	56.7	1005	630529	159.4
14	Nnewi North	172	183274	93.8	183	189637	96.5	193	195706	98.6	181	201968	89.6	183	208431	87.8	266	214597	124.0
15	Nnewi South	37	163026	22.7	37	168965	21.9	32	173833	18.4	58	179952	32.2	82	185710	44.2	138	191204	72.2
16	Ogbaru	110	439966	25.0	159	455241	34.9	288	469808	61.3	423	484843	87.2	491	500358	98.1	583	515159	113.2
17	Onitsha North	428	230594	185.6	414	238600	173.5	593	246235	240.8	1080	254115	425.0	2229	262246	850.0	1997	270004	739.6
18	Onitsha South	132	221454	59.6	171	229143	74.6	209	236475	88.4	711	244042	291.3	747	251851	296.6	794	259301	306.2
19	Orumba North	14	325039	4.3	19	336324	5.6	45	347086	13.0	90	358193	25.1	238	369655	64.4	371	380590	97.5
20	Orumba South	23	276042	8.3	21	285626	7.4	51	294766	17.3	44	304199	14.5	47	313933	15.0	127	323220	39.3
21	Oyi	60	268610	22.3	86	277936	30.9	104	286831	36.3	141	296009	47.6	607	305481	198.7	1287	314518	409.2
	Total	**2391**	**6003224**	**39.8**	**2447**	**6214310**	**39.4**	**3008**	**6484799**	**46.4**	**4946**	**6692778**	**73.9**	**8550**	**6906944**	**123.8**	**13125**	**7146186**	**183.7**

Table 3.2: Anambra State TB Case Notification Rate (CNR), 2013–2023. YoY = year-on-year percentage change in CNR

Year	TB Cases Notified	Population Estimate	CNR (per 100,000)	YoY CNR Change
2013	1,864	4,887,286	38.1	—
2014	1,770	5,088,876	34.8	-8.7%
2015	1,629	5,317,465	30.6	-12.1%
2016	1,731	5,546,055	31.2	2.0%
2017	2,300	5,774,645	39.8	27.6%
2018	2,391	6,003,234	39.8	0.0%
2019	2,447	6,214,310	39.4	-1.0%
2020	3,008	6,484,799	46.4	17.8%
2021	4,946	6,692,778	73.9	59.3%
2022	8,550	6,906,944	123.8	67.5%
2023	13,125	7,146,186	183.7	48.4%
Total / Mean	43,761	—	62.0	—

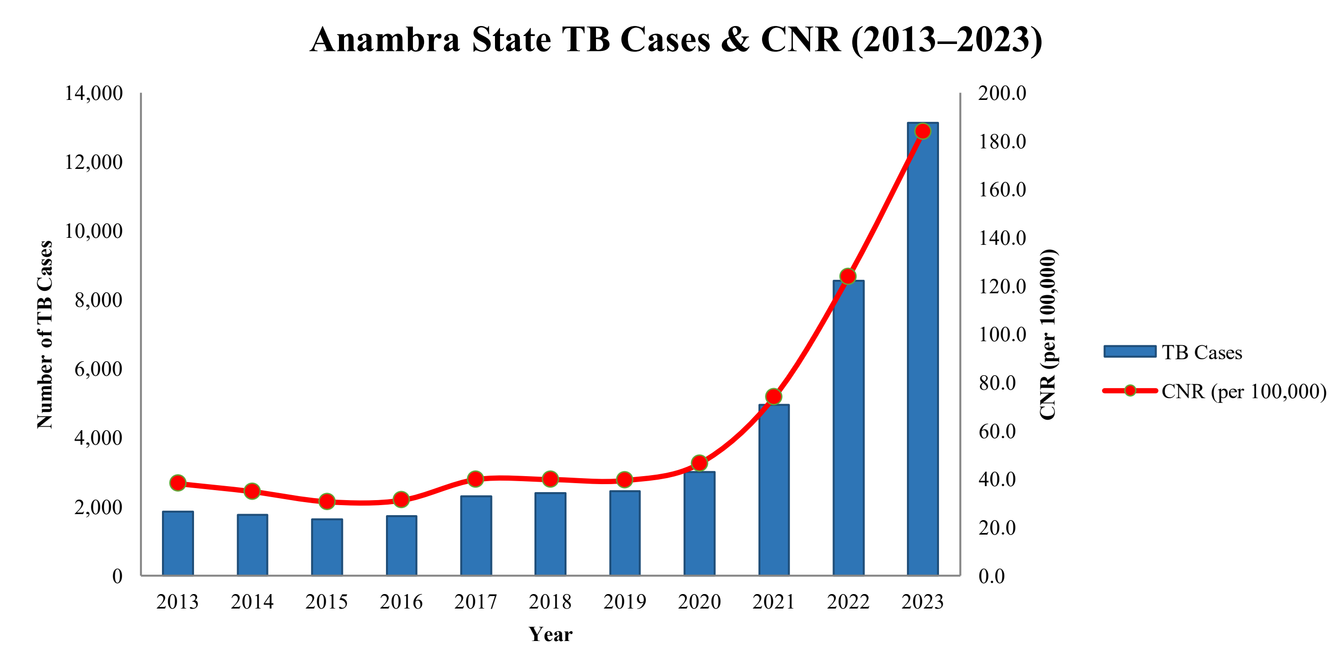

Figure 3.1: TB Cases Notified and Case Notification Rate for Anambra State, 2013–2023.

Phase 1 Decline (2013-2015): The CNR decreased steadily over this period, from 38.1 per 100,000 people in 2013 to 30.6 per 100,000 people in 2015, totaling a reduction of 7.5 per 100,000 people and a decline in the number of cases from 1,864 to 1,629. This decline was partly influenced by the challenges of rollout of GeneXpert testing machines across the LGA diagnostic centers.

Phase 2 Stabilisation (2016-2019): The CNR fluctuated around the 2015 low point, falling within a narrow range of 31.2 to 39.8 cases per 100,000 people. Cases reported rose from 1,731 to 2,447. The increase in coverage of GeneXpert testing centers and improved case-finding in the country likely account for the stabilization during this phase.

Phase 3 Accelerated rise (2020-2023): This phase witnessed a significant and sustained increase in CNR. Starting at 46.4 cases per 100,000 people in 2020, CNR jumped to 73.9 cases per 100,000 in 2021, 123.8 cases per 100,000 in 2022, and a staggering 183.7 cases per 100,000 in 2023, a 382.2% increase compared to the 2013 baseline. Cases reported increased from 2,447 in 2019 to 13,125 in 2023. The growth rate also accelerated each year, almost doubling from 2021 to 2022 and increasing by about 50% from 2022 to 2023. The surge from 2020 onwards reflects multiple factors; it is likely that lockdown restrictions during the COVID-19 pandemic delayed TB reporting, leading to accumulation of cases that were then identified once operational restrictions were lifted. It also coincides with intensified active case-finding strategies including the deployment of mobile GeneXpert machines in areas with high TB disease burden. While these programmatic improvements explain some of the increase in reported cases, they cannot entirely account for the magnitude of this surge, which strongly indicates a genuine increase in TB transmission within the dense urban localities.

3.2 Temporal changes in spatial distribution

A substantial transformation in the spatial distribution of TB in Anambra State was noted during the study period. From 2013 to 2020, Moran's I values ranged between -0.054 and 0.07, indicating that the location of TB cases was randomly scattered throughout the state (Table 3). However, spatial clustering became significant in 2021 (Moran's I = 0.208; Z = 2.19; p = 0.028), continued and intensified into 2022 (Moran's I = 0.174; Z = 2.30; p = 0.022) and 2023 (Moran's I = 0.207; Z = 1.97; p = 0.049). The change in pattern from random scattering to significant clustering has profound epidemiological implications: it signals a shift from non-localized disease patterns to localized and potentially increasing intensity of transmission within specific areas [23].

Table 3.3 Moran's I Spatial Autocorrelation Summary (2013-2023)

Year	Moran's Index	Expected Index	Variance	Z-Score	P-Value	Significance Level	Pattern Interpretation
2013	-0.031177	-0.050000	0.015170	0.152826	0.878536	Not Significant	Random
2014	-0.048006	-0.050000	0.013009	0.017479	0.986054	Not Significant	Random
2015	-0.054498	-0.050000	0.014635	-0.037179	0.970342	Not Significant	Random
2016	0.003793	-0.050000	0.011804	0.495131	0.620508	Not Significant	Random
2017	0.036768	-0.050000	0.010282	0.855716	0.392155	Not Significant	Random
2018	0.033038	-0.050000	0.010206	0.821957	0.411101	Not Significant	Random
2019	0.066978	-0.050000	0.014773	0.962439	0.335829	Not Significant	Random
2020	0.079268	-0.050000	0.013701	1.104365	0.269435	Not Significant	Random
2021	0.208048	-0.050000	0.013833	2.194026	0.028234	**p < 0.05**	**Clustered**
2022	0.174105	-0.050000	0.009518	2.297091	0.021614	**p < 0.05**	**Clustered**
2023	0.206804	-0.050000	0.017079	1.965013	0.049413	**p < 0.05**	**Clustered**

3.3 Spatial Distribution and Hotspot Evolution of Tuberculosis Cases in Anambra State, 2013–2023

Yearly maps depicting the spatial spread of TB incidences show that their concentration is limited to just a few Local Government Areas (LGAs) (Figure 3a-3d; Figure 4a-4d; Figure 5a- 5d). The largest cluster remains centered in Onitsha LGA and comprises a chain of high-incidence municipalities that extend through the south-western regions of the state, with Figure 3a illustrating the early concentration around Onitsha, Figures 3b and 3c demonstrating its persistence, and Figure 3d reflecting the consolidation of this core cluster. Through the study period, this core cluster has not only grown stronger in terms of infection rate, but also enlarged into neighboring built-up regions, as shown by Figure 4a which captures the initial outward expansion, Figures 4b and 4c which indicate further spread into adjacent LGAs, Figure 4d which presents a more continuous hotspot band, and

Figures 5a–5d which collectively demonstrate intensified spread, wider spatial coverage, and peak expansion.

Persistently High-Burden LGAs

Onitsha North and Onitsha South were among the regions that remained classified within the highest burden category during the entire study period, as consistently evidenced from Figure 3a through Figure 3d, continuing across Figure 4a to Figure 4d, and persisting in Figure 5a to Figure 5d where both LGAs remain within the highest hotspot class. In particular, the yearly number of TB patients in Onitsha North showed a strong increase from about 195–400 cases in 2013 to 2,229 patients in 2022, which amounts to a five-fold growth within the same territory, with Figure 3a reflecting the lower initial intensity, Figure 4c indicating a clear increase, and Figure 5d capturing the highest recorded intensity. Another LGA that recorded persistently high incidences of TB was Idemili North, which shares boundaries with Onitsha within the Nkpor–Ogidi axis, as seen in Figures 3b and 3c where it first appears within the hotspot, Figures 4a and 4b where clustering becomes more pronounced, and Figures 5a and 5b where high intensity is sustained. Other regions that belonged to this group included Ogbaru, and Nnewi North, with Figures 4b and 4c showing their emergence within the hotspot belt and Figures 5a to 5c confirming their continued classification within high-burden zones. As evidenced by structural analysis, these areas feature dense residential population, intense commercial activities, and active population movement. Ihiala, in the south-western zone, similarly appeared in the elevated categories from 2013 through at least 2020, confirming its status as a second persistent cluster that operates geographically independently of the Onitsha core yet follows the same upward trajectory.

Medium-Burden LGAs Transitioning Toward High Risk

Some of the LGAs initially categorized as having an upper-medium level of TB burdens began to show a consistent increase in infection rate, thus creating a trend towards the expansion of areas at risk to new territories adjacent to the core Onitsha region, as Figures 3.2c and 3.2d present these LGAs within moderate classes, Figures 3.3a and 3.3b demonstrate their upward shift, Figures 3.3c and 3.3d show continued progression, and Figures 3.4a and 3.4b confirm their transition into higher burden categories. For instance, Awka South progressed from the upper-medium to the high category of TB prevalence over the course of a few years (in 2017) and then maintained this burden level until 2023, with Figure 3.3a marking its transition into the high category, Figures 3.3b to 3.3d showing sustained classification, and Figures 3.4a to 3.4d confirming its persistence as a hotspot. Awka North followed the same trajectory, attaining high-level TB burden after the year 2020, as illustrated by Figure 3.4a where it first appears within the high category and Figures 3.4b to 3.4d where this status is maintained. In addition, LGA located along major urban routes (e.g., Orumba North and Oyi) have also witnessed a progressive increase in their infection rates, shifting from the medium to the upper-medium and even to the high category of TB burden, as shown by Figures 3.3b and 3.3c which capture initial increases, Figure 3.3d which indicates further elevation, and Figures 3.4b to 3.4d which confirm their inclusion within higher burden categories.

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Persistently Low-Burden LGAs

By contrast, some peripherally located LGAs, such as Anaocha, Idemili South, Orumba South, Ayamelum, and Anambra West, have been showing a consistently low TB incidence level during the study period, as demonstrated across Figures 3.2a-3.2d, Figures 3.3a-3.3d, and Figures 3.4a-3.4d where these LGAs remain within the lowest hotspot classes. In particular, Anaocha managed to remain a low-burden region despite being geographically positioned in the center of Anambra State, as evidenced in Figures 3b and 3c and continuing through Figures 3.3a and 3.3b and Figures 3.4a and 3.4b, while Idemili South was also low in TB burden despite its proximity to the high burdened Idemili North, as illustrated in Figures 3.3b and 3.3c and further reinforced in Figures 3.4a and 3.4b.

These differences between the persistently low-burden areas on the outskirts and the high-burden urban centers show a clear structural differentiation in how TB cases are spread across the state. This becomes more evident when examining how hotspot intensity changes over time.

The first is a deepening of intensity within the core Onitsha cluster. The highest burden category in 2013 encompassed 195 to 400 cases. By 2022, the equivalent upper bracket had risen to 1,002 to 2,229 cases, representing a more than fivefold increase in the threshold defining the highest-risk zone, within the same geographic area and anchored by the same LGAs. This intensification is not simply a reflection of overall population growth; it represents a genuine concentration of disease burden in a geographically bounded core. As seen in Section 4.2., starting in 2021, there is significant spatial clustering (Moran's I greater than 0.17, with p less than 0.05). In other words, higher case numbers are clustering in specific spots instead of showing up randomly.

The second trend is a spatial expansion of the high-burden zone. Whereas the elevated case counts in 2013 were largely confined to Onitsha North, Onitsha South, and Ihiala, the high-burden footprint by 2020 and 2023 visibly encompassed Idemili North, Nnewi North, and the Awka South and Awka North cluster. The maps document a clear south-to-north and partially west-to-east propagation of high-burden classification over the eleven-year period, consistent with the spatial diffusion of urbanisation from established centres into adjacent growth axis. This outward spread supports the positive Moran's I values showing that neighboring LGAs are getting more similar over time.

The third trend is the relative stability of low-burden peripheral LGAs. Despite the considerable intensification in core areas, the peripheral low-burden LGAs; Anaocha, Idemili South, Orumba South, Ayamelum and Anambra West, maintained their relatively low classification across all years. This clear spatial division between a growing high-burden core and a relatively stable low-burden outer areas suggests that TB transmission is mainly driven by urban structural conditions, rather than spreading evenly outward from existing hotspots. This stability in low-burden areas further reinforces the interpretation that clustering is not uniform across the state but is instead focused in certain high-risk zones.

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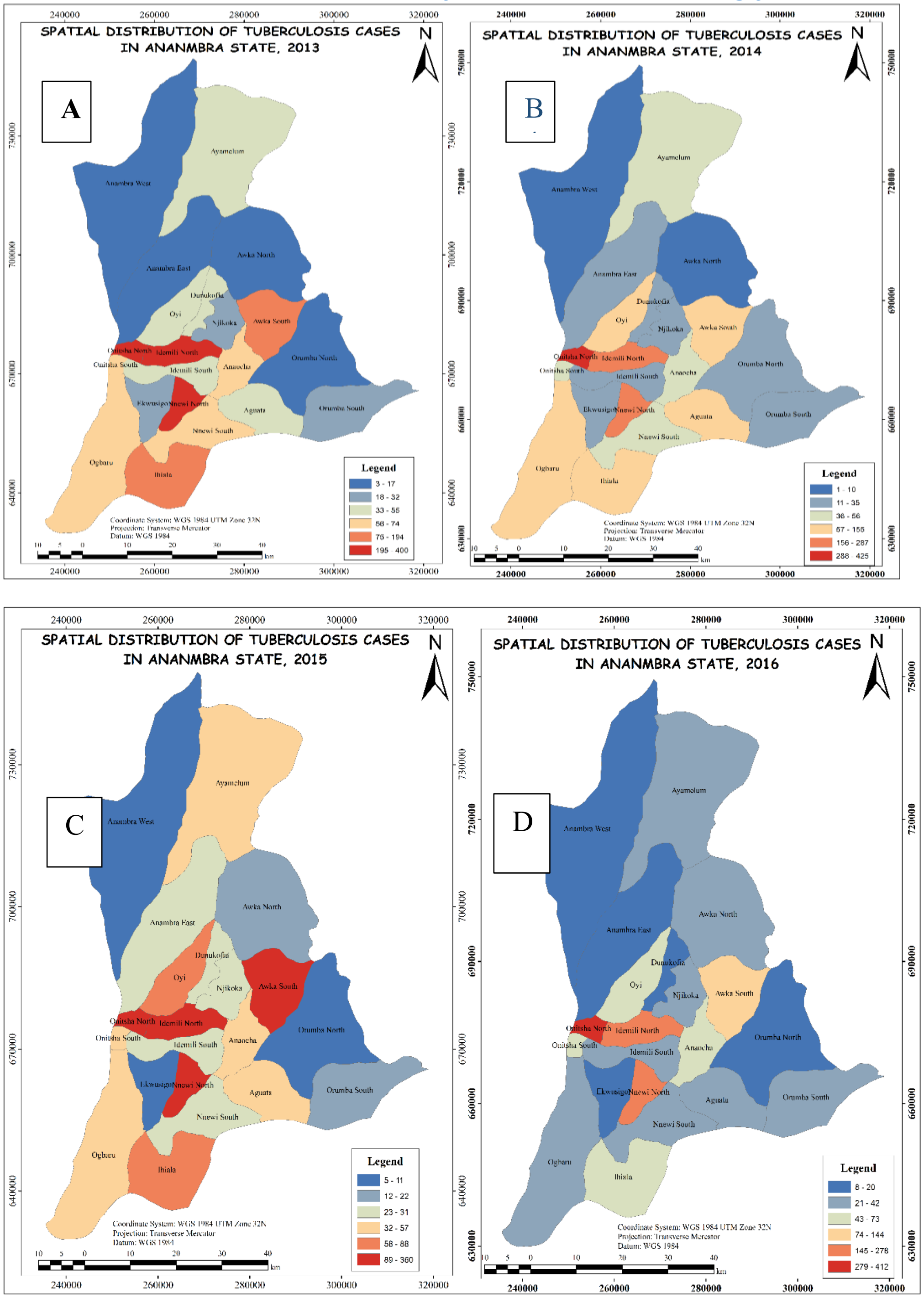

Figure 3.2 Hot Spot Analysis of TB cases from 2013 to 2016

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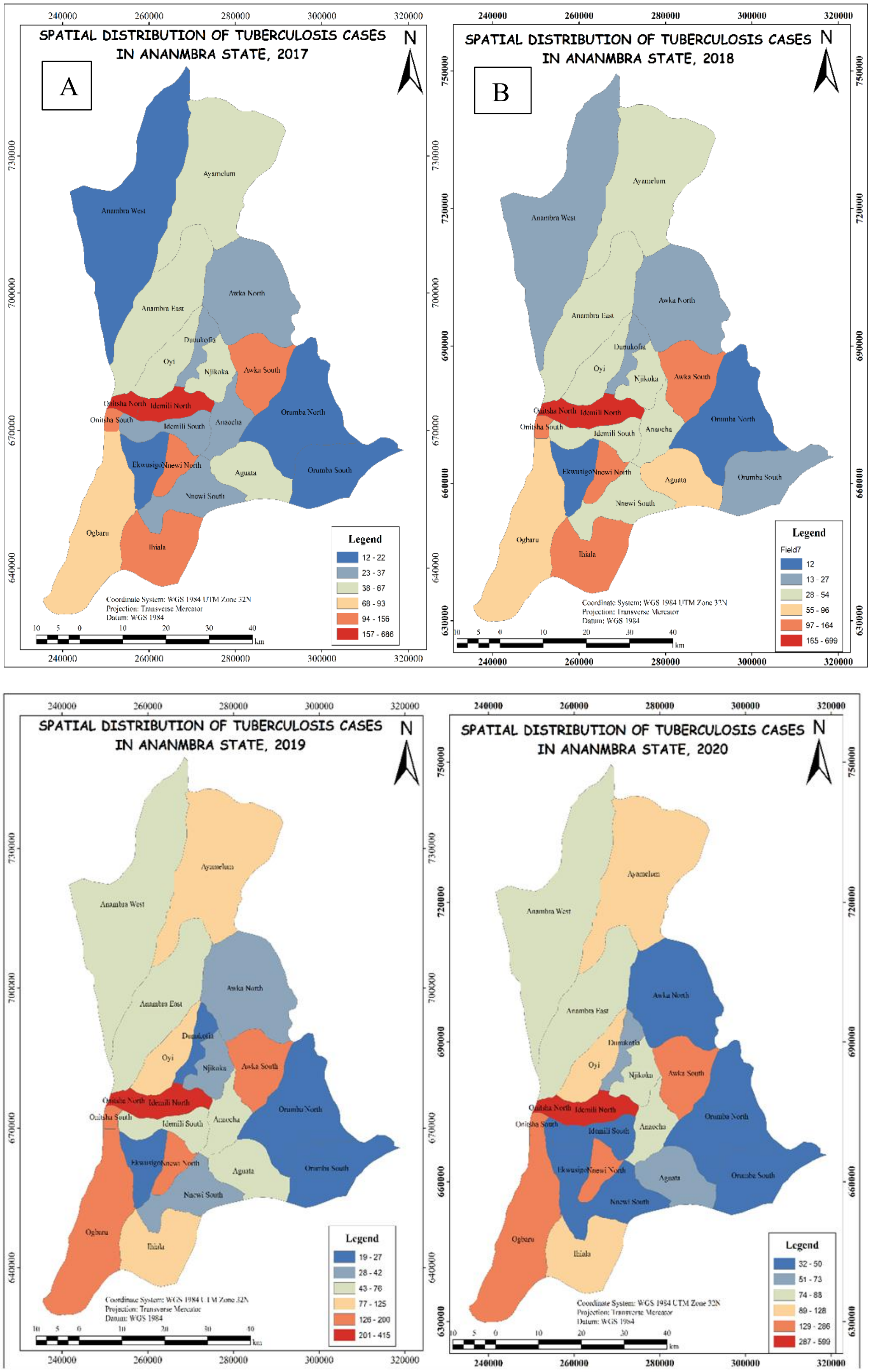

Figure 3.3 Hot Spot Analysis of TB cases from 2017 to 2020

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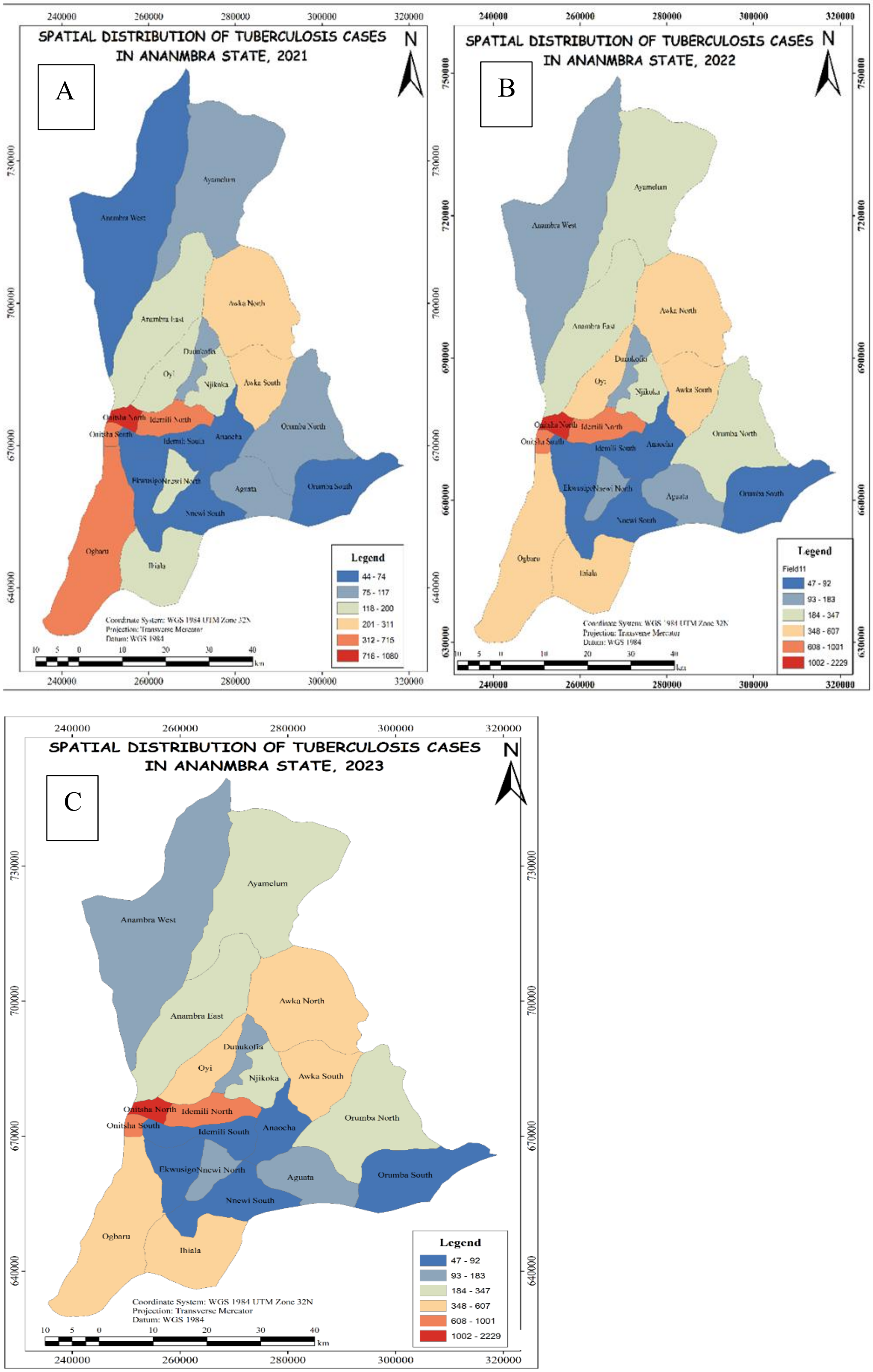

Figure 3.4 Hot Spot Analysis of TB cases from 2021 to 2023

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3.4 Land use/land cover change and urban expansion

Land use/land cover (LULC) analysis revealed a steady growth in built-up areas across Anambra State. The period between 2013 and 2015 saw an approximate 4.2% increase in built-up areas, followed by a 4.9% increase between 2015 and 2017. Growth accelerated to approximately 9.2% from 2017 to 2020, the highest recorded growth rate of urbanization during the study period, and continued at roughly 8.3% from 2020 to 2023. The spatial progression of this expansion is visualized in Figure 3.5 - 3.6, which illustrates the LULC changes from the baseline in 2013 through the peak expansion period of 2020.Overall, there has been significant expansion of the built-up landscape over the past decade, with rapid increases noted in Onitsha North, Onitsha South, Awka South and Nnewi North. Notably, these same LGAs also exhibited the most pronounced increases in TB case notification rates during the period. This spatial association suggests a link between urban development and rising TB burden. The rapid increase in CNR from 46.4 to 183.7 per 100,000 between 2020 and 2023 (a 382.2% jump compared to 2013) coincided with the peak of urban expansion. There was rapid population increase and densification particularly around the most populous LGAs. In the map (Figure 3.6), the most pronounced increases in TB cases were concentrated in the heavily built-up LGAs of Onitsha North, Onitsha South, Awka South, and Nnewi North.

Table 3.4 Spatio-Temporal Changes in Built-Up Area (m²) and Percentage Growth across LGAs in Anambra State (2013–2023)

LGA	2013 (m²)	2015 (m²)	%Δ	2017 (m²)	%Δ	2020 (m²)	%Δ	2023 (m²)	%Δ	Total %Δ
Aguata	12.4M	12.8M	+3.1%	13.2M	+3.0%	13.7M	+4.0%	14.3M	+4.5%	+15.4%
Anambra East	6.3M	6.7M	+6.2%	7.1M	+6.1%	8.0M	+11.8%	9.2M	+15.5%	+45.5%
Anambra West	8.2M	8.7M	+6.2%	9.8M	+12.7%	13.1M	+33.3%	13.5M	+3.6%	+65.2%
Anaocha	8.3M	8.4M	+2.0%	8.6M	+2.0%	8.7M	+0.9%	8.9M	+2.9%	+8.1%
Awka North	40.8M	43.0M	+5.5%	45.3M	+5.2%	54.2M	+19.6%	58.5M	+8.1%	+43.5%
Awka South	74.7M	77.4M	+3.6%	80.3M	+3.7%	88.7M	+10.5%	96.6M	+8.9%	+29.4%
Ayamelum	17.3M	18.4M	+6.7%	19.6M	+6.3%	23.0M	+17.4%	24.7M	+7.4%	+42.9%
Dunukofia	24.6M	25.8M	+5.0%	27.4M	+6.2%	28.4M	+3.7%	31.6M	+11.2%	+28.5%
Ekwusigo	41.6M	43.0M	+3.2%	43.0M	+0.1%	45.3M	+5.4%	48.6M	+7.2%	+16.7%
Idemili North	50.3M	52.3M	+4.0%	54.1M	+3.5%	59.9M	+10.8%	64.9M	+8.4%	+29.2%
Idemili South	61.8M	62.9M	+1.8%	62.9M	0.0%	64.8M	+3.1%	66.7M	+2.8%	+7.8%
Ihiala	9.9M	10.4M	+4.8%	10.8M	+4.6%	11.4M	+5.0%	12.3M	+8.1%	+24.3%
Njikoka	44.8M	46.6M	+3.9%	48.8M	+4.9%	50.5M	+3.5%	55.3M	+9.4%	+23.4%

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LGA	2013 (m²)	2015 (m²)	%Δ	2017 (m²)	%Δ	2020 (m²)	%Δ	2023 (m²)	%Δ	Total %Δ
Nnewi North	44.6M	46.9M	+5.3%	49.1M	+4.6%	50.8M	+3.5%	53.5M	+5.3%	+20.1%
Nnewi South	76.7M	81.1M	+5.7%	86.9M	+7.2%	93.1M	+7.1%	101.6M	+9.1%	+32.4%
Ogbaru	12.2M	12.5M	+3.1%	12.9M	+3.1%	14.0M	+8.4%	14.5M	+3.7%	+19.5%
Onitsha North	16.8M	17.0M	+1.1%	17.2M	+1.2%	17.3M	+0.4%	17.5M	+1.4%	+4.2%
Onitsha South	25.0M	25.3M	+1.3%	26.6M	+4.8%	27.3M	+2.8%	28.5M	+4.5%	+14.0%
Orumba North	75.7M	78.5M	+3.7%	81.4M	+3.7%	93.0M	+14.3%	101.9M	+9.6%	+34.7%
Orumba South	41.9M	44.0M	+5.0%	46.1M	+4.8%	53.6M	+16.2%	59.0M	+10.2%	+40.9%
Oyi	56.6M	60.5M	+6.9%	69.4M	+14.7%	77.6M	+11.8%	88.6M	+14.1%	+56.4%
State Total	**750.5M**	**782.4M**	**+4.2%**	**820.6M**	**+4.9%**	**896.5M**	**+9.2%**	**970.5M**	**+8.3%**	**+29.3%**

Table 3.4 shows the growth in built-up areas across all 21 LGAs in Anambra State, revealing an uneven pattern of urban expansion that broadly follows the distribution of TB case notification rates. At the state level, total built-up area grew from approximately 750.5 million sq m in 2013 to 970.5 million sq m in 2023, an overall increase of 29.3% over the decade. Growth was fastest between 2017 and 2020, when built-up area expanded by 9.2% state-wide, which coincided with the acceleration in TB notification rates observed during the same period. Among individual LGAs, Anambra West recorded the largest increase over the study period (65.2%), followed by Oyi (56.4%), Anambra East (45.5%), and Awka North (43.5%). Although Onitsha North showed a smaller proportional increase (4.2%), it was already one of the most densely built-up LGAs at the start of the study period, and continued additions to its already crowded built environment likely worsened housing conditions and reduced ventilation. Awka South and Nnewi North, both of which also recorded notable rises in TB case notifications, showed built-up area growth of 29.4% and 20.1% respectively.

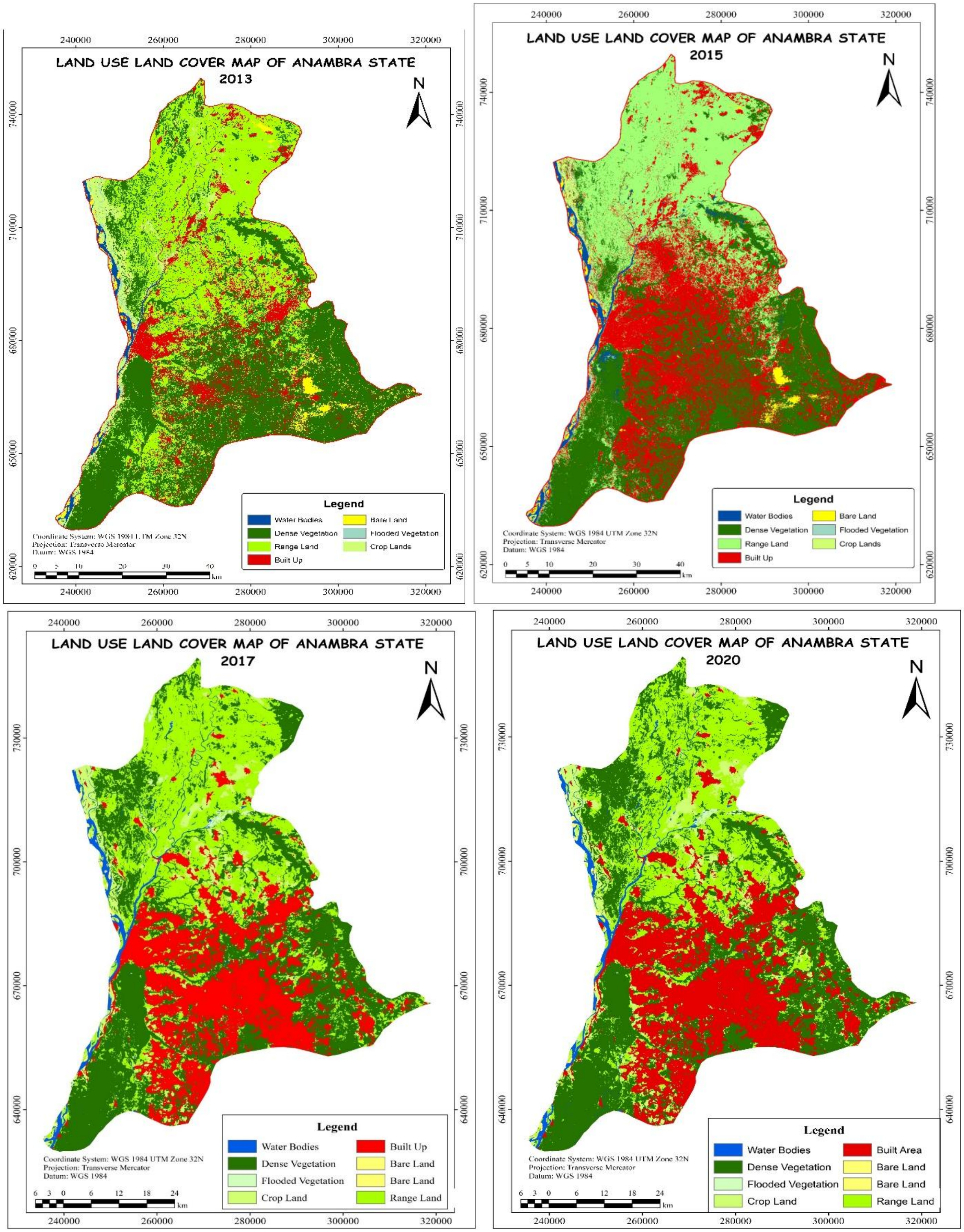

Figure 3.5: Land Use and Land Cover of Anambra State 2013, 2015, 2017, 2020.

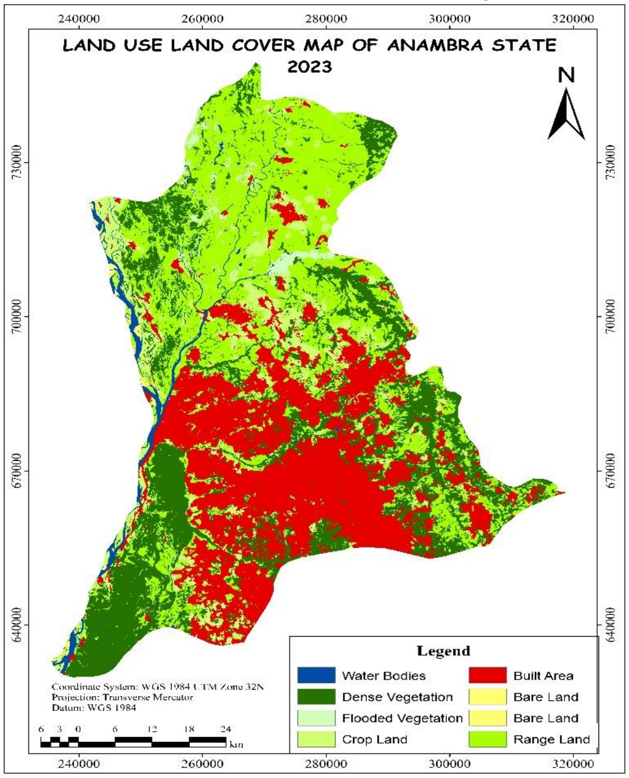

Figure 3.6 Land Use and Land Cover of Anambra State 2023

3.5 Association between the indicators of urbanisation and TB cases

Pearson correlation analysis was used to examine associations between TB notification rates and urbanisation indicators across the 21 LGAs:

Table 3.5: Pearson Correlation Coefficients between TB Rate, Built-Up Area, and Population Density

Variable Pair	Correlation (r)	Relationship Strength	Direction
Population Density ↔ Built-Up	0.1366	Very weak	Positive
TB Rate ↔ Built-Up	0.3333	Moderate	Positive
TB Rate ↔ Population Density	0.1433	Very weak	Positive

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The correlation analysis examined the relationships between population density, built-up area, and TB rate across LGAs in Anambra State. The results indicate that population density and built-up area are very weakly positively correlated (r = 0.137), suggesting that areas with higher population density tend to have slightly larger built-up areas, although the relationship is minimal. The TB rate and built-up area show a moderate positive correlation (r = 0.333), indicating that areas with more built-up structures tend to have higher TB notification rates. Finally, the TB rate and population density are very weakly positively correlated (r = 0.143), reflecting a minimal tendency for higher population density to be associated with increased TB incidence.

These findings suggest that while urban expansion contributes to TB risk, population density alone does not strongly predict TB incidence. Instead, structural characteristics of the urban environment, particularly built-up area, may play a more influential role in shaping spatial patterns of TB transmission.

Multivariate Regression Analysis

A multivariate regression model including both built-up area and population density as predictors was fitted to explain variation in TB notification rates across LGAs. The Model fit was computed using the formula:

$$R^2 = (r^2y1 + r^2y2 - 2 \cdot ry1 \cdot ry2 \cdot r12) / (1 - r^212) \text{ ……………………….Equation 1}$$

Where:

- ry1 = correlation between **TB incidence (Y)** and **built-up area (X_1)**
- ry2 = correlation between **TB incidence (Y)** and **population density (X_2)**
- r12 = correlation between **built-up area (X_1)** and **population density (X_2)**

The model explained approximately 12.1% of the variation in TB rates across LGAs ($R^2 = 0.121$). The R^2 value is modest, which is expected for a simple model with only two predictors of a complex disease like TB. Many other factors such as poverty, HIV, nutrition, healthcare access, and social networks also affect TB but are not included here. The fact that the built-up area still shows a significant effect suggests its true influence on TB risk may be even greater than what the model shows built-up area was the stronger predictor ($\beta = 0.320$) compared to population density ($\beta = 0.100$), indicating that TB rates slightly increase with increasing built-up area and population density, though the effects are moderate and weak respectively (Table 3.6). These findings suggest that physical characteristics of the urban built environment (e.g. building density, poor ventilation, overcrowding) are stronger determinants of TB risk than population density alone, consistent with studies in Brazil and Indonesia [25, 24]. These results indicate that urban structural characteristics explain only a moderate portion of TB variation, and other socio-economic and epidemiological factors play a much larger role in determining TB risk.

Table 3.6: Multivariate Regression Analysis – Association Between TB Incidence, Population Density, and Built-Up Areas in Anambra State

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Predictor Variable	**Coefficient (β)**	**Interpretation**
Built-Up Area	+0.320	Stronger predictor
Population Density	+0.100	Weaker predictor
Constant (Intercept)	+0.050	—
Model R²	**0.121**	**~12% variance explained**

3.6. Discussion

The present study recorded a dramatic increase in the CNR from 38.1 per 100,000 people in 2013 to 183.7 per 100,000 people in 2023. The state-level CNR has surpassed the Nigerian national average, the East African mean, and is far above WHO thresholds for targeting the reduction of the global TB burden by 2030. Diagnostic improvements contributed to the rise in CNR after 2020, but the substantial increase strongly indicates a genuine intensification of new infections. This trend reflects a transition toward sustained community-level transmission, particularly within the rapidly urbanizing LGAs of Onitsha North, Onitsha South, Awka South, and Nnewi North. Therefore, while the state has improved its capacity for identifying existing cases, the evidence suggests that the number of new infections is intensifying. The COVID-19 pandemic likely contributed to this pattern, as the large rise in notifications observed from 2020–2021 reflects an accumulation of undetected cases that were subsequently identified once diagnostic services resumed. However, the continued and increasing rise observed during 2022 and 2023 indicates that the pandemic alone does not explain the trend. This suggests that the observed increase reflects a transition toward sustained community-level transmission, particularly within rapidly urbanizing LGAs.

The transition from a random to a clustered spatial distribution of TB after 2021 signals a significant alteration in the epidemiological landscape of Anambra State. It represents a move from scattered detection of cases to evidence of concentrated, locally enhanced disease transmission. The updated correlation results provide insight into this shift. Built-up area is moderately positively correlated with TB rate ($r = 0.333$), whereas population density shows only a very weak positive relationship with TB rate ($r = 0.143$). Population density and built-up area themselves are very weakly positively correlated ($r = 0.137$). These results suggest that the arrangement and expansion of the urban environment, rather than population size or density alone, influences the observed clustering patterns. This aligns with observations from other rapidly urbanizing settings, such as Nairobi and Surabaya, where unplanned urban growth has been associated with increased TB transmission due to overcrowding, poor ventilation, and limited access to healthcare services [27, 24].

In Anambra State, constant mobility of vehicles and people occurs around and within these LGAs. Clustering and built-up expansion are particularly evident along the Onitsha–Idemili axis, where commercial and residential expansion is most aggressive. Based on the LULC maps and TB case notification rates, the most critical hotspots are concentrated in Onitsha (North and South), Awka, and Nnewi, with rapid "spillover" growth into the surrounding towns of Obosi, Nkpor, and Ogidi. The findings suggest that localized urban characteristics, such as the intensity of human interaction in commercial areas like the Onitsha Main Market and the residential-commercial axis of Idemili

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North, may contribute more directly to TB transmission than broad measures of urban size or population density. In these centres, the intensity of human interaction in commercial centers outpaces infrastructural development. Residents and traders increasingly occupy densely packed environments like markets, with inadequate ventilation, conditions perfectly suited for airborne transmission. This explains why Moran's I analysis identified statistically significant clusters in these zones from 2021 onward. These findings reinforce the notion that structural characteristics of the built environment, rather than population size alone, are key determinants of localized TB risk.

The weak correlations between TB incidence and population density, and the moderate correlation with built-up area, do not imply that TB is lower in denser or smaller cities. Instead, they reflect the overall pattern of urban growth: as cities expand, built-up areas increase while population density may not rise proportionally due to urban sprawl. In practice, TB transmission is concentrated in specific high-activity areas, such as the markets in Onitsha, the administrative and transit points in Awka, and the industrial zones in Nnewi, forming local hotspots even when city-wide averages suggest only a very weak relationship. This interpretation is supported by evidence showing that TB patients' activity spaces, including workplaces and transport routes, tend to cluster spatially, with a strong reliance on public transportation, highlighting the role of mobility-driven exposure [28, 29].

The disparity between urban and rural TB incidence rates remains significant, though emerging patterns indicate a reduction in the urban–rural divide. There are clear signs of increased clustering in sub-urban LGAs, such as Awka North and Orumba North. Rapid urbanization is extending beyond the Onitsha–Nnewi axis and the administrative center of Awka, with areas previously exhibiting low notification rates now beginning to show indications of elevated TB risk. This trend is consistent with patterns observed in Brazil and other developing countries, where urban expansion is associated with the spread of TB into newly urbanized, previously low-burden areas [25]. The spatial expansion of TB in Anambra State suggests that the drivers of transmission, particularly features of the built environment, are extending into newly urbanizing zones.

Furthermore, consistently low notification rates in rural LGAs may not reflect the true absence of disease but likely indicate under-detection. Evidence from northern Nigeria, where active population-level case finding led to a 72% increase in TB notifications [30], supports this interpretation. This suggests that gaps in rural disease surveillance exist, and that the observed urban–rural differences in TB burden may partly reflect unequal access to diagnostic services rather than a genuine absence of disease.

4.0 Conclusion

This study has demonstrated a significant increase in TB case notification rates in Anambra State between 2013 and 2023, alongside a clear shift from a random to a clustered spatial pattern of disease distribution. The findings highlight the growing importance of localized transmission dynamics, particularly within rapidly urbanizing LGAs and high-activity commercial axis.

The analysis revealed that urbanization indicators have only a weak relationship with TB incidence. Built-up area showed a moderate positive association with TB rates, population density showed weak positive associations with TB rates, while the multivariate regression model explained only a small proportion of the variation in TB incidence ($R^2 = 0.121$). Built-up area remained the relatively stronger predictor (β = 0.320), compared to population density (β = 0.100). This indicates that expansion of the built-up area is a more consistent factor associated with tuberculosis clustering than population density alone and so has a role in the disease transmission dynamics. These results suggest that TB transmission is not primarily driven by the overall size or density of urban areas, but rather by localized conditions within specific urban environments.

The emergence of statistically significant clusters, particularly along major urban and commercial axes, indicates that TB transmission is increasingly concentrated in areas characterized by intense human interaction, mobility, and potentially poor environmental conditions such as inadequate ventilation and housing quality. Furthermore, the gradual spread of clustering into sub-urban LGAs suggests that the drivers of TB transmission are extending into newly urbanizing areas.

Overall, the study emphasizes that TB control strategies should move beyond general urbanization metrics and instead focus on identifying and targeting high-risk local environments. Strengthening surveillance in underreported rural areas, improving housing and environmental conditions in urban hotspots, and enhancing access to diagnostic services will be critical for effectively reducing the TB burden in Anambra State.

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