International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(Research Article)

Check for updates

A GIS based multi criteria analysis for determining COVID-19 vulnerability in Lagos state Nigeria

Akinpelu, Akinwumi Abodunrin [1], Igbokwe Joel Izuchukwu [2,*] Oliha Andrew Osagie [2] and Ojanikele Wille Augustine [3]

[1] College of Environmental Design and Technology, Lagos State University of Science and Technology, Lagos State, Nigeria.
[2] Department of Surveying and Geoinformatics, Nnamdi Azikiwe University Awka, Nigeria.
[3] Department of Surveying and Geoinformatics, Delta State University of Science and Technology, Ozoro, Delta State, Nigeria.

International Journal of Science and Research Archive, 2023, 10(02), 223–239

Publication history: Received on 28 September 2023; revised on 11 November 2023; accepted on 14 November 2023

Article DOI: https://doi.org/10.30574/ijsra.2023.10.2.0913

Abstract

The COVID-19 pandemic possesses intricate spatial dimensions that, when comprehensively examined, offer profound insights into various aspects of the crisis. Spatial analysis can unravel the multifaceted characteristics of the pandemic, shedding light on its distribution, dynamics, and impact. This research is driven by the imperative need to merge diverse variables, thereby gaining a nuanced understanding of the COVID-19 phenomenon, conducting spatial and spatiotemporal analyses, deciphering its geographical implications for decision-making and daily life, and crafting predictive models to anticipate its evolution. Consequently, this study has a primary objective: determining the COVID-19 vulnerability in Lagos State, Nigeria. The research aims to elucidate the pandemic's spread and distribution patterns, identify its hotspots within Lagos State, and assess COVID-19 vulnerability using the analytical hierarchy process (AHP). The methodology employed in this research encompasses several key steps. Initially, a comprehensive analysis of the spatial distribution of COVID-19 cases between 2020 and 2022 was conducted, allowing for an examination of how the pandemic evolved over this period. Subsequently, a COVID-19 prevalence analysis was performed to delineate the areas most affected by the virus, offering a detailed view of the pandemic's reach. Lastly, a vulnerability index analysis was executed to identify zones with varying levels of vulnerability to COVID-19 within Lagos State. The vulnerability index analysis unveiled diverse vulnerability levels across local government areas (LGAs) within Lagos State. Notably, LGAs such as Ikorodu, Badagary, Eti-Osa, Alimosho, and Epe exhibited relatively larger areas characterized by high vulnerability, signifying the elevated risk of COVID-19 transmission and impact in these regions. In contrast, LGAs like Agege, Ajeromi, Ifako, Ikeja, Mainland, Mushin, Oshodi, Shomolu, and Surulere displayed smaller areas characterized by low vulnerability, indicating a lower risk within these locales. These findings bear significant implications for public health management and decision-making. LGAs with the highest number of confirmed cases, particularly Alimosho and Eti-Osa, demand targeted interventions to curtail the spread of COVID-19 and ensure that resources are channeled where they are most urgently needed. This research underlines the utility of geospatial analysis in pandemic response, offering a valuable tool for governments, healthcare authorities, and policymakers to address the dynamic challenges posed by COVID-19 and protect public health effectively.

Keywords: COVID-19; GIS; Modelling; Pandemic; Prevalence

1. Introduction

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, has posed unprecedented challenges to global public health systems, economies, and societies. Nigeria, as Africa's most populous nation, has faced the complex task

* Corresponding author: Igbokwe J. I

of mitigating the spread of the virus. Within Nigeria, Lagos State, its economic and social epicenter, has emerged as a focal point for COVID-19 response and management. This research paper seeks to address the critical issue of COVID-19 vulnerability in Lagos State, employing a Geographic Information System (GIS)-based multi-criteria analysis. This approach integrates various spatial and non-spatial factors to evaluate the susceptibility and preparedness of communities within Lagos State to COVID-19.

Lagos State is a highly urbanized and densely populated region, characterized by a complex interplay of demographic, environmental, healthcare, and socioeconomic factors. Understanding and assessing the vulnerability of its diverse communities to COVID-19 is of paramount importance for efficient resource allocation, public health strategies, and effective policymaking.

This research is rooted in a multidisciplinary field that draws upon spatial science, epidemiology, and public health. It leverages the power of GIS, a technology that has been increasingly embraced for its utility in disease surveillance, mapping, and spatial analysis (Li, et al., 2020). Moreover, the use of multi-criteria analysis (MCA) integrates various indicators and criteria to provide a holistic assessment of vulnerability, making it suitable for addressing complex public health challenges (Malczewski, 2006).

The significance of assessing COVID-19 vulnerability within a GIS framework is well-established in the literature. A substantial body of research underscores the importance of spatial analysis for understanding disease transmission and identifying high-risk areas (Pullan, et al., 2020; Owusu, et al., 2020). Furthermore, previous studies have successfully employed MCA for vulnerability assessment in the context of disease outbreaks (Tay, et al., 2018; Flanagan, et al., 2011).

This research aims to contribute significantly to the knowledge base on GIS-based vulnerability assessment in the context of COVID-19. It seeks to provide actionable insights to guide public health strategies and resource allocation, ultimately enhancing the preparedness and response efforts within Lagos State.

1.1. Study Area

The study area, Lagos State is located between Longitudes 2° 40 E and 4° 15 E and Latitudes 6° 15 N and 6° 45 N, The State took off as an administrative entity on April 11, 1968. However, with the creation of the Federal Capital Territory of Abuja in 1976, Lagos ceased to be the capital of the State. Nevertheless, Lagos remains the nation's economic and the dominant vegetation of the State is the swamp forest of the fresh water and mangrove swamp forests, both of which are influenced by the double rainfall pattern of the state, which makes the environment a wetland region. Generally, the State has two climatic seasons: Dry [November-March] and Wet [April-October]. The drainage system of the State is characterized by a maze of lagoons and waterways, which constitutes about 22% or 787 sq. km. [75.755 hectares] of the State's territory. The major water bodies are the Lagos and Lekki Lagoons, Yewa, Ogun, Oshun, and Kweme Rivers. Others are Ologe Lagoon, Kuramo Waters, and Badagry, Five Cowries and Omu Creeks respectively.

2. Material and methods

The research embarked on a comprehensive data acquisition process, encompassing primary and secondary datasets, to delve into the intersection of healthcare facilities and COVID-19 within the confines of Lagos State. This multifaceted data acquisition phase was instrumental in obtaining a holistic understanding of the healthcare infrastructure's readiness and the vulnerability of communities to the COVID-19 pandemic.

- **Primary Data Acquisition:** The core of primary datasets was derived from rigorous field visits, facilitated by the utilization of GPS equipment. During these field visits, location data of healthcare facilities was precisely pinpointed, capturing the geographical coordinates and other essential descriptive information about these healthcare institutions. These field-acquired primary datasets were invaluable in constructing a thorough picture of the existing healthcare infrastructure's geospatial distribution within Lagos State.
- **Secondary Data Compilation:** Complementing the primary datasets, an array of secondary datasets was sourced from reputable and established sources. These encompassed datasets related to COVID-19, obtained from highly credible sources such as the World Health Organization's (WHO) COVID-19 dashboard, as well as a plethora of research papers. The amalgamation of secondary datasets offered a comprehensive snapshot of the pandemic's dynamics within Lagos State.
- **Data Processing and Modeling:** The amassed datasets underwent a meticulous data processing phase, aimed at refining, structuring, and preparing them for the in-depth analysis. This process comprised three modeling steps: conceptual modeling, logical modeling, and physical modeling. The conceptual modeling phase was centered on defining the data entities and the relationships between them. Logical modeling involved a

transformation of the conceptual model into a more structured representation. The final stage, physical modeling, ensured that the datasets were organized and optimized for the subsequent analytical procedures.

- **Spatial Distribution Analysis:** The research conducted an extensive spatial distribution analysis of COVID-19 cases and related fatalities within Lagos State. This involved the application of spatial interpolation techniques, which provided insights into the geographical dispersion and concentration of cases and deaths. By exploring the spatial patterns and clusters, the analysis contributed to the identification of areas that bore the most significant burden of the virus, thereby directing resource allocation and response strategies more effectively.
- **Prevalence Mapping:** Prevalence mapping emerged as another crucial component of the research. It facilitated the quantification of COVID-19 prevalence across different geographic regions within Lagos State. Through the calculation of a prevalence index, the study unveiled areas most profoundly affected by the virus, offering insights into the pandemic's reach, intensity, and impact. This prevalence mapping exercise was pivotal for making informed decisions regarding interventions, resource allocation, and healthcare preparedness.
- **COVID-19 Vulnerability Analysis:** To culminate the analysis, the study conducted a comprehensive COVID-19 vulnerability assessment utilizing a set of six criteria. These criteria encompassed confirmed deaths, confirmed cases, distance to healthcare facilities, proximity to public amenities, population density, and access to transportation networks. The analysis aimed to identify areas at a heightened risk of transmission and impact, thus guiding targeted responses and interventions to areas most in need.

3. Results and discussion

3.1. COVID-19 vulnerability evaluation in Lagos State

3.1.1. Identification and Selection of Evaluation Criteria

Selection of the criteria and factors for COVID-19 vulnerability evaluation using AHP was achieved based on their theoretical relevance as documented in (Gao *et al*, 2022), and as well as the available data.

The following criteria (factors/constraints) (table 1) were used in this research.

Table 1 Criteria (Factors/Constraints)

S/N	Criterion	Factor/ Constraint	Requirement	Reason for Selection	Original Data Structure	Resolution
1	Confirmed Deaths	Factor	High Death Index	Areas with higher death rates are considered more vulnerable, as they may indicate higher transmission rates and potential strain on healthcare systems.	Raster	30m
2	Confirmed Cases	Factor	High Case Index	Areas with higher cases are considered more vulnerable, as they may indicate higher transmission rates and potential strain on healthcare systems.	Euclidean Raster	30m
3	Distance to Health Care	Factor	< 1000m road networks	Areas with limited access to medical facilities may face challenges in providing timely and adequate care to COVID-19 patients, potentially leading to worse outcomes.	Euclidean Raster	30m

4	Distance from Public Amenities	Factor	(< 500m) Distance from Public Spaces	Overcrowded public spaces may contribute to higher transmission rates.	Raster	30m
5	Population Density	Factor		Areas with high population density may be more susceptible to outbreaks and rapid transmission.	Raster	30m
6	Distance to Transportation Network	Factor	Areas with highest population density	Well-connected regions might experience higher transmission rates.	Raster	30m

These factors (table 1), play critical roles in determining COVID-19 vulnerability in Lagos State.

The number of confirmed COVID-19 cases and deaths in different areas provides crucial data on the prevalence and severity of the virus. Areas with higher case and death rates are considered more vulnerable, as they may indicate higher transmission rates and potential strain on healthcare systems.

The proximity to healthcare facilities is important in determining vulnerability. Areas with limited access to medical facilities may face challenges in providing timely and adequate care to COVID-19 patients, potentially leading to worse outcomes.

Access to public amenities, such as parks, markets, and recreational areas, can impact population density and the likelihood of people coming into close contact with each other. Overcrowded public spaces may contribute to higher transmission rates.

Higher population density can lead to increased person-to-person contact, making it easier for the virus to spread. Areas with high population density may be more susceptible to outbreaks and rapid transmission.

The connectivity and accessibility of different areas through transportation networks can influence the movement of people and the spread of the virus. Well-connected regions might experience higher transmission rates.

By integrating these factors into a vulnerability assessment model, public health authorities and policymakers can gain insights into which areas are at higher risk for COVID-19 outbreaks and severe outcomes. This information can guide targeted interventions and resource allocation, such as deploying healthcare resources to areas with limited access, implementing testing and contact tracing efforts in high-risk regions, and promoting public awareness campaigns in densely populated areas.

These data are shown in figures 1 – 6.

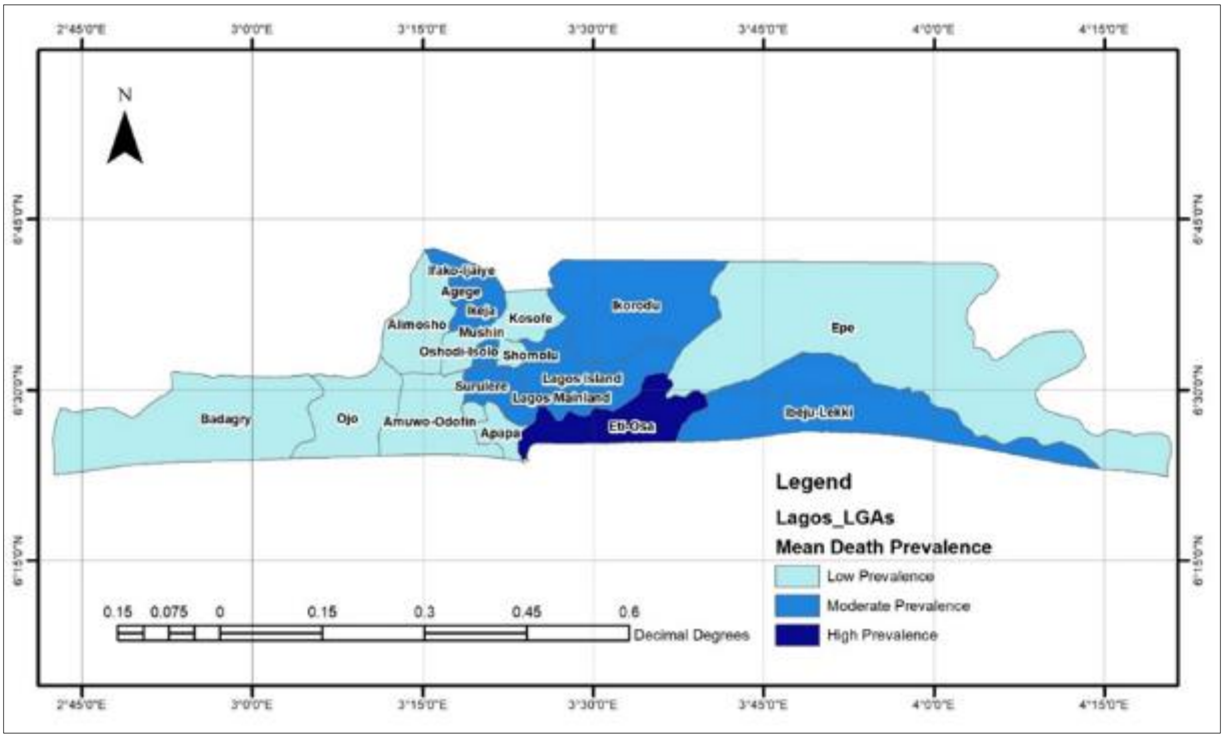

Figure 1 COVID-19 Confirmed Deaths in Lagos State

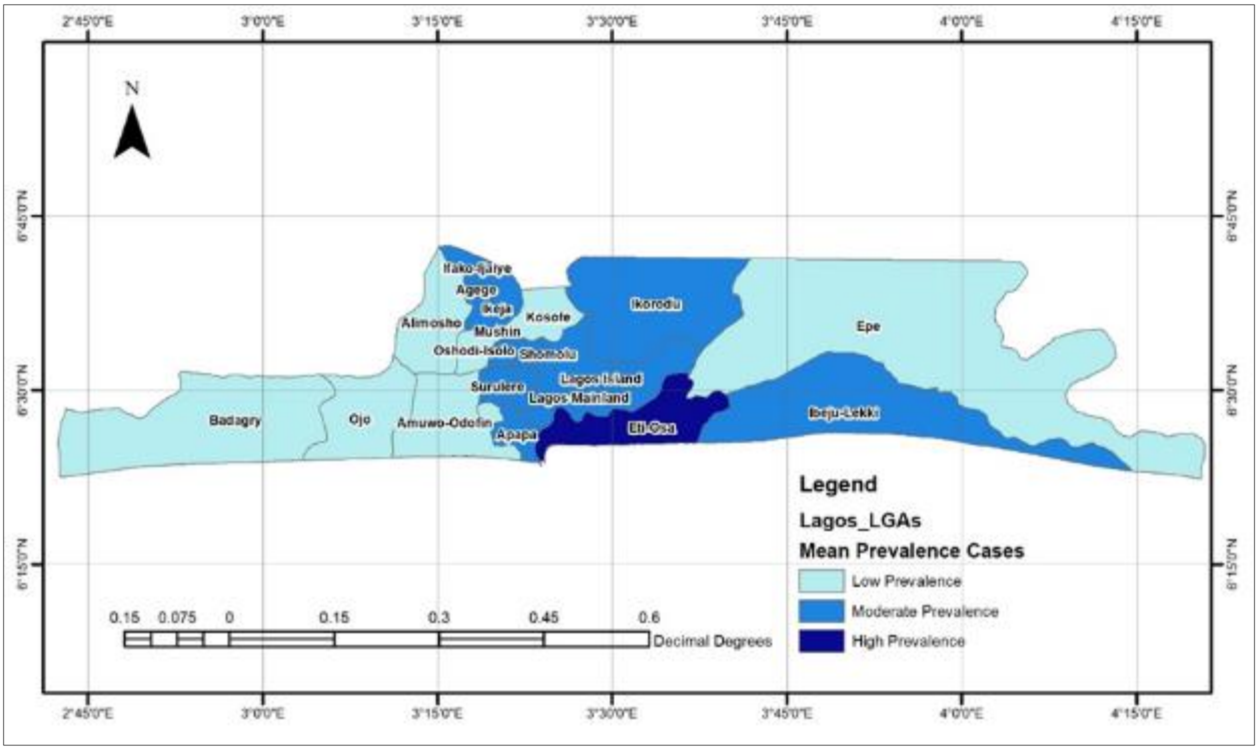

Figure 2 COVID-19 Confirmed Cases in Lagos State

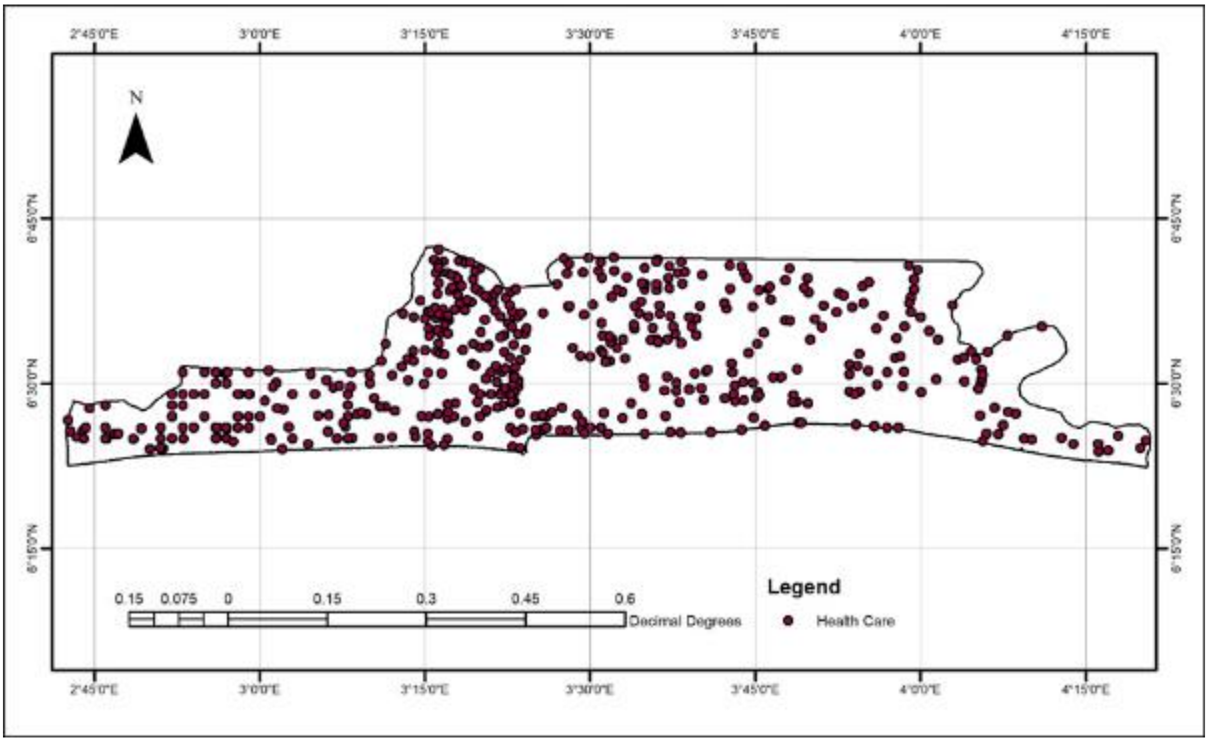

Figure 3 Health Care Data

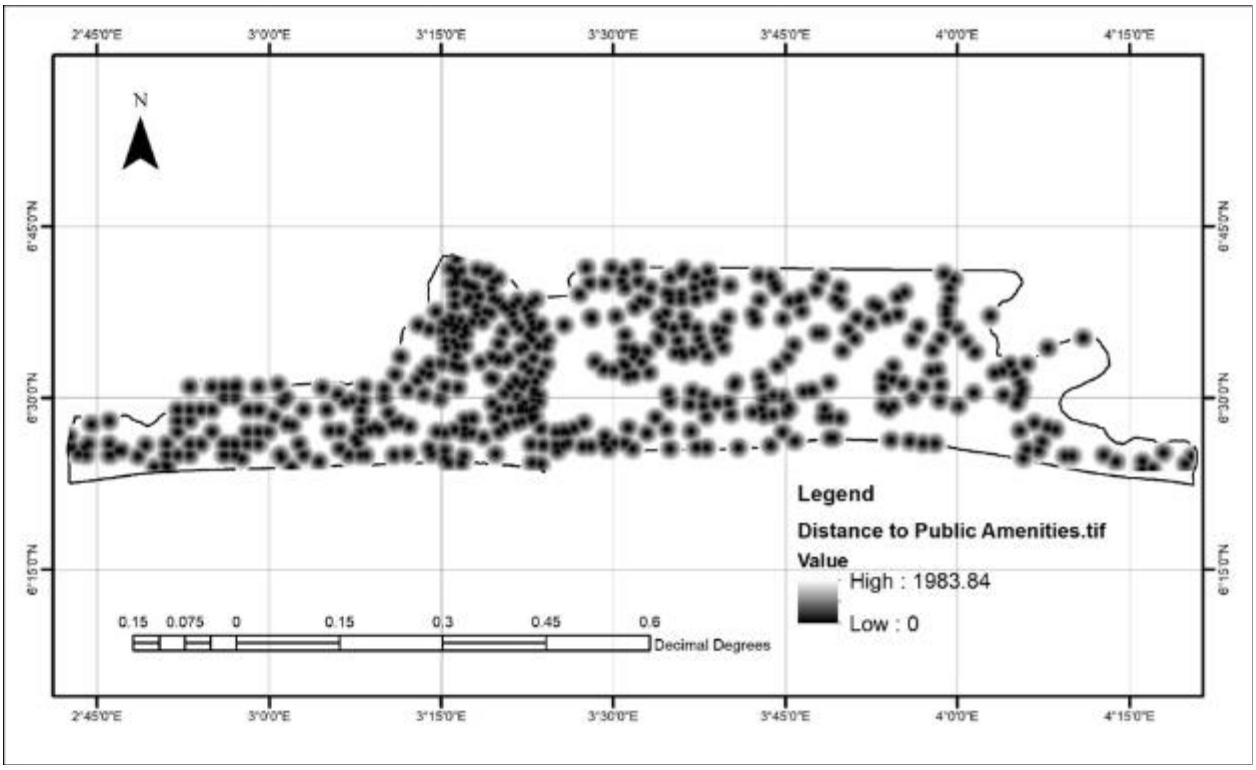

Figure 4 Distance to Public Amenities

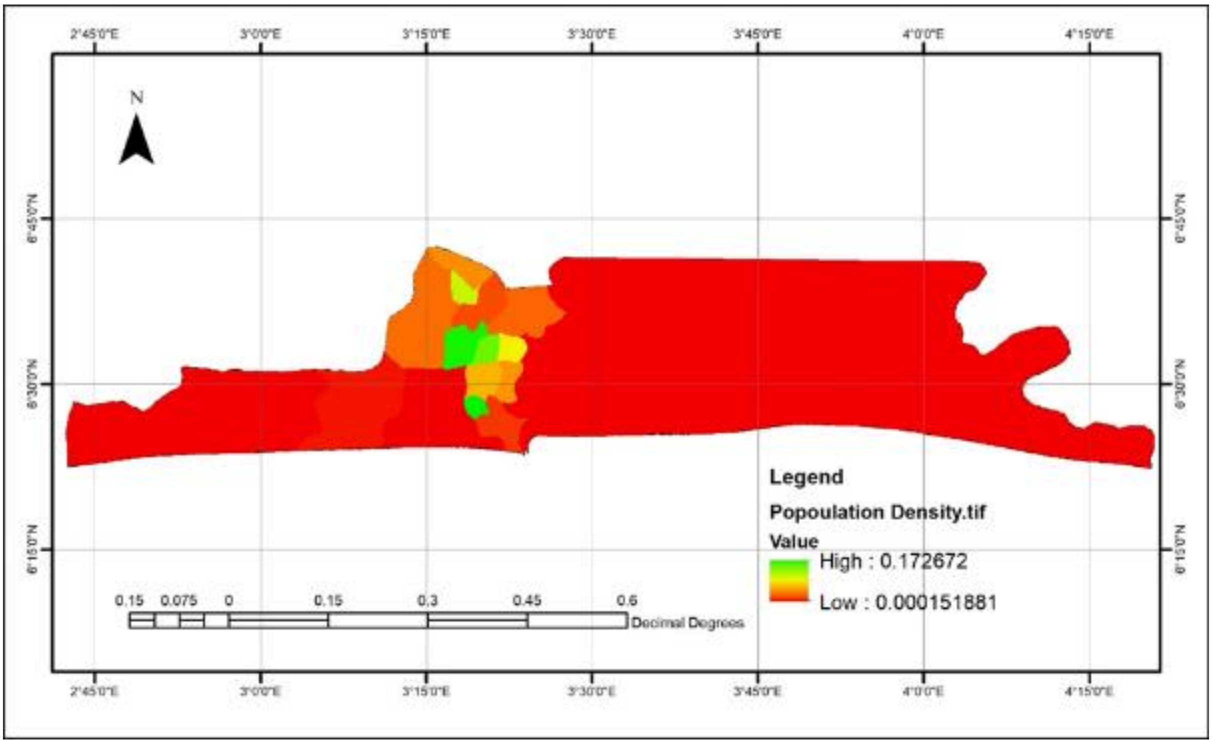

Figure 5 Population Density

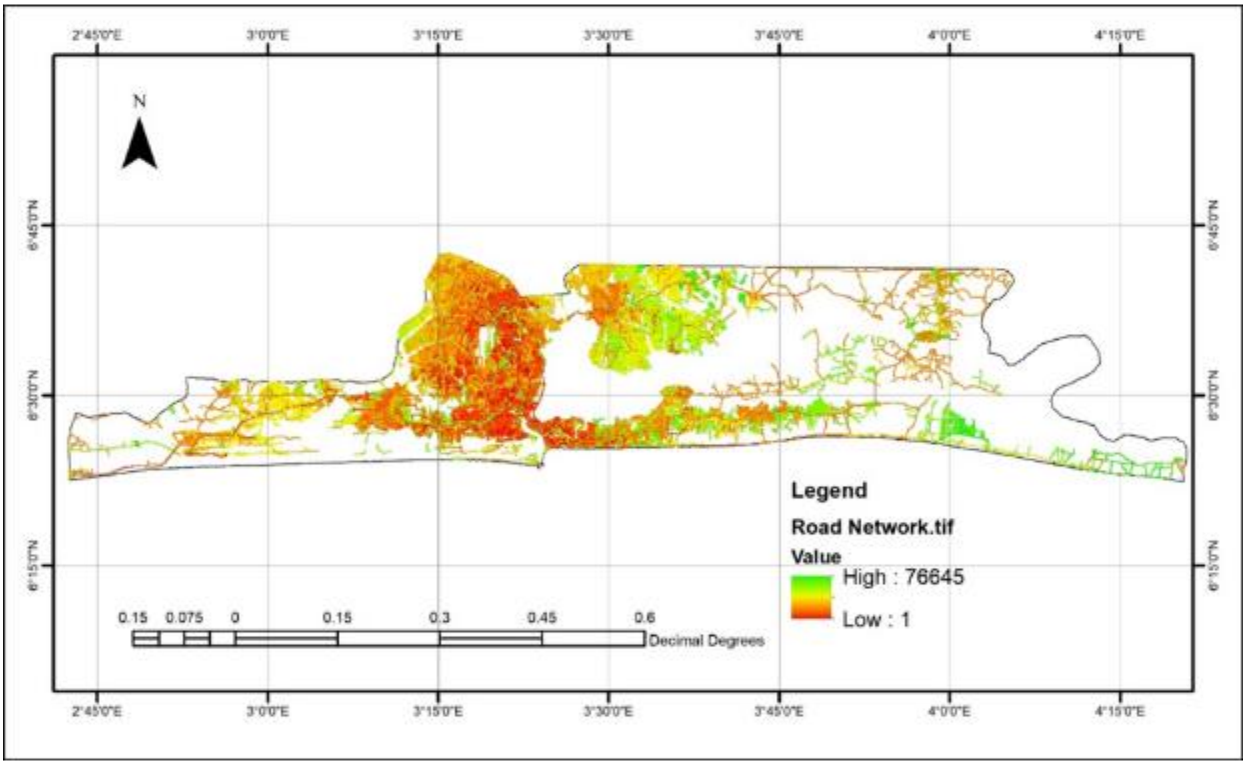

Figure 6 Proximity to Transportation Networks

3.1.2. Reclassification and Standardization of Criteria

For this research, all the datasets were reclassified into three classes: (1) for high vulnerability areas (2) moderate vulnerability areas and (3) low vulnerability areas. The initially derived datasets values categorized into ranges were floating and continuous in nature and there was a need for them to be reclassified so that each range of value can be assigned one discrete integer value such as 1, 2, 3 according to the measurement scale. This is because the inputs of the weighted overlay must contain discrete integer values. The reclassified and standardized criteria are shown in figure 7 - 12.

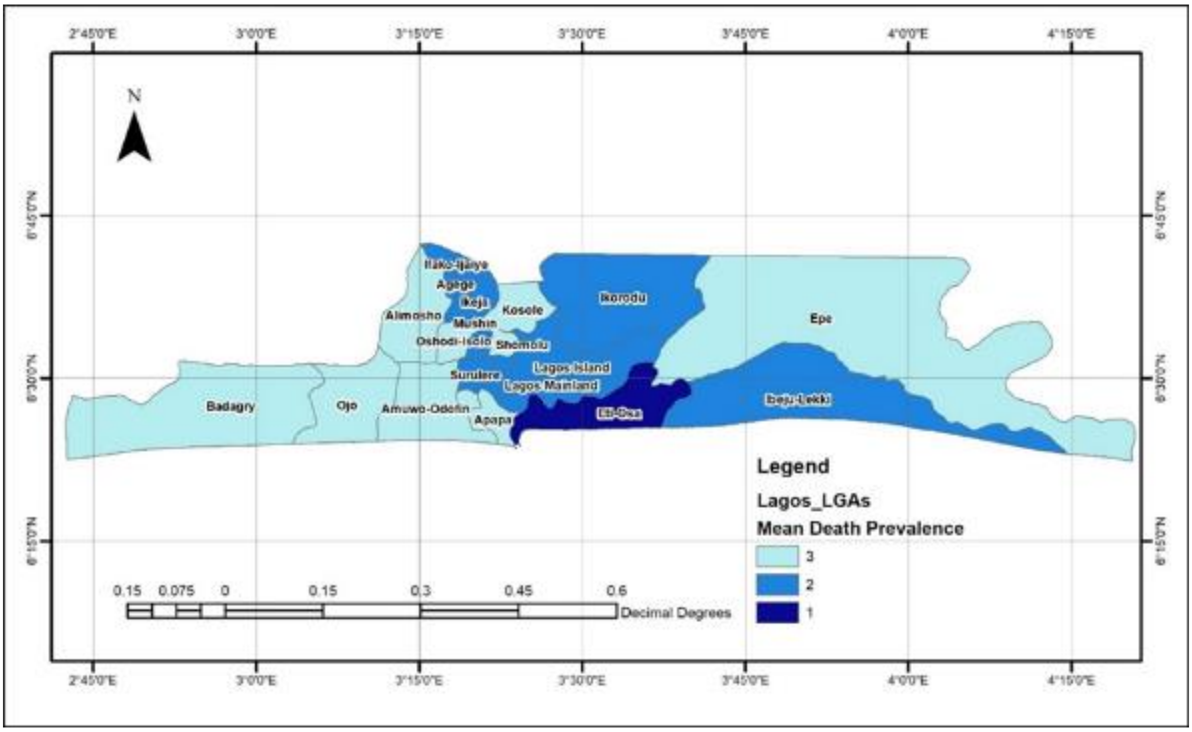

Figure 7 COVID-19 Confirmed Deaths reclassification and standardization

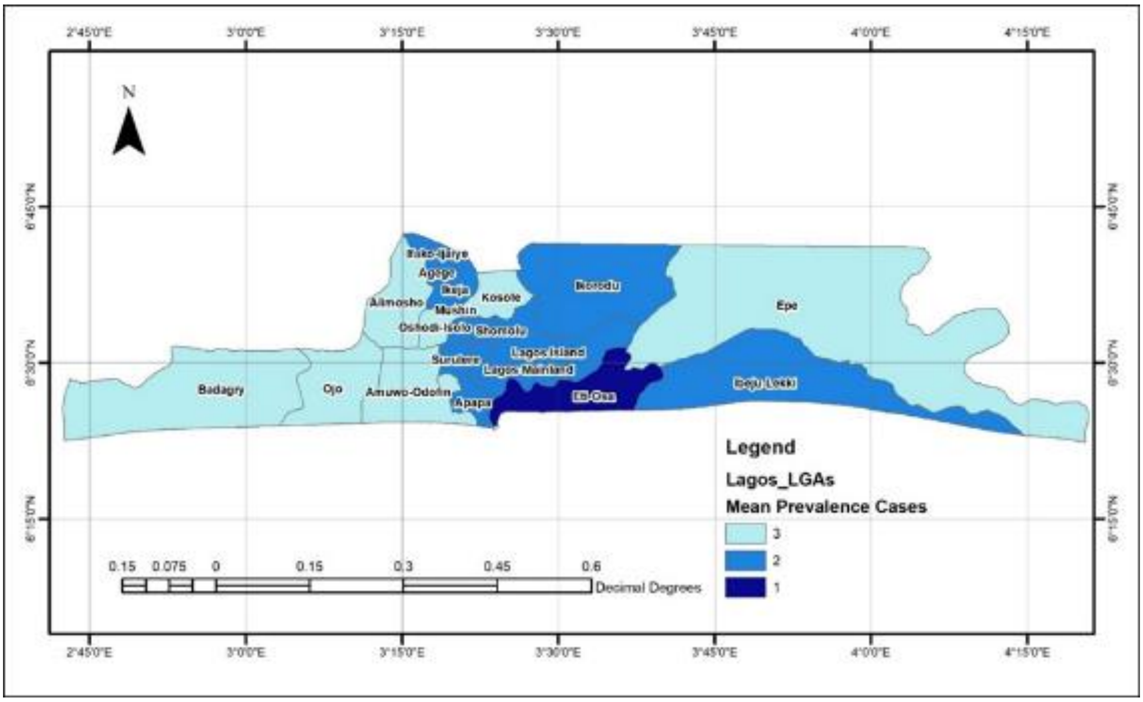

Figure 8 COVID-19 Confirmed Cases reclassification and standardization

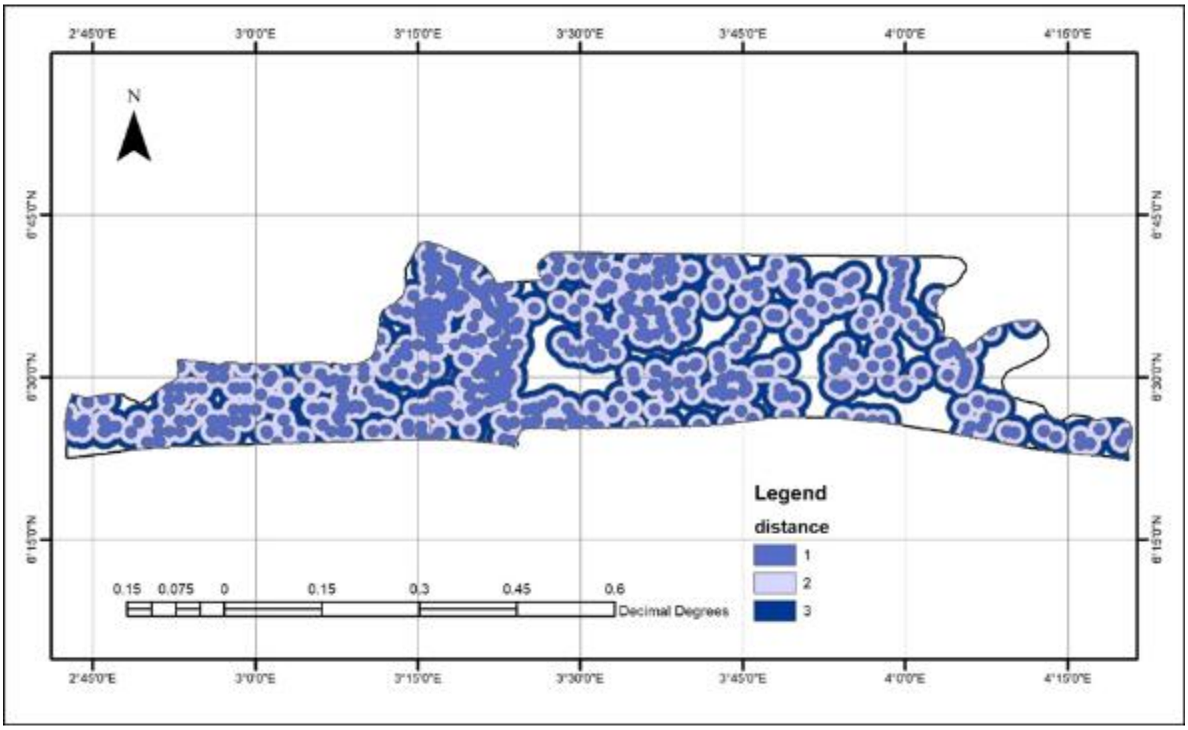

Figure 9 Distance to Health Care reclassification and standardization

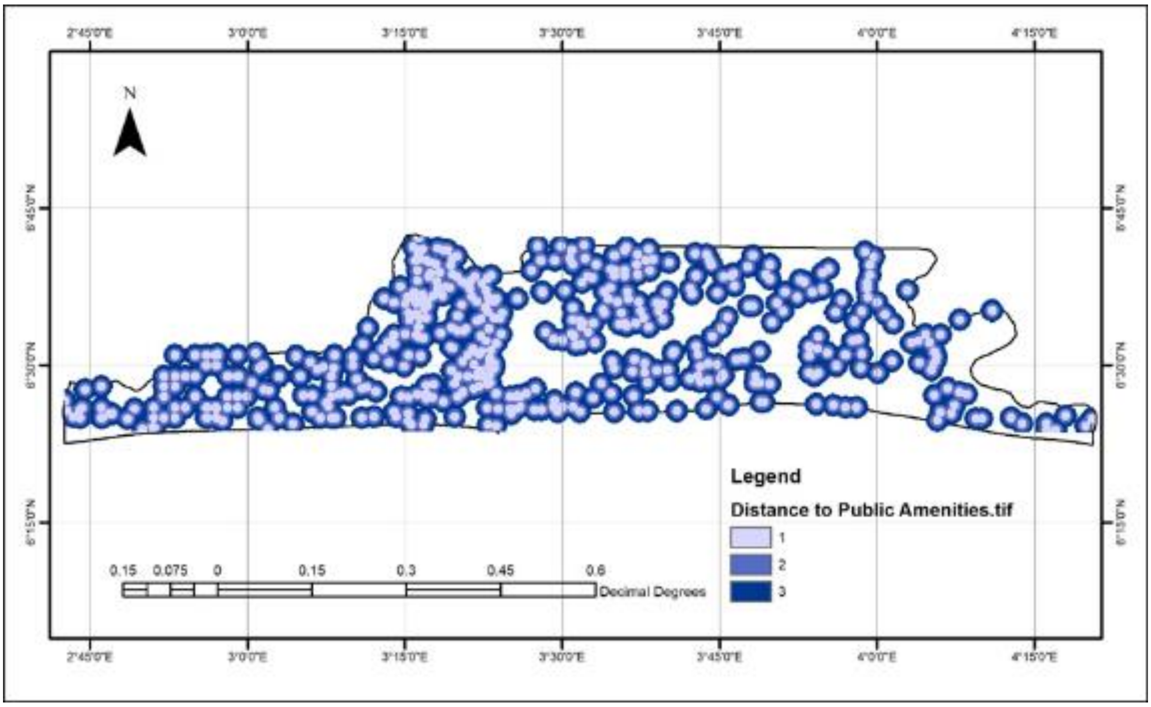

Figure 10 Distance to Public Amenities reclassification and standardization

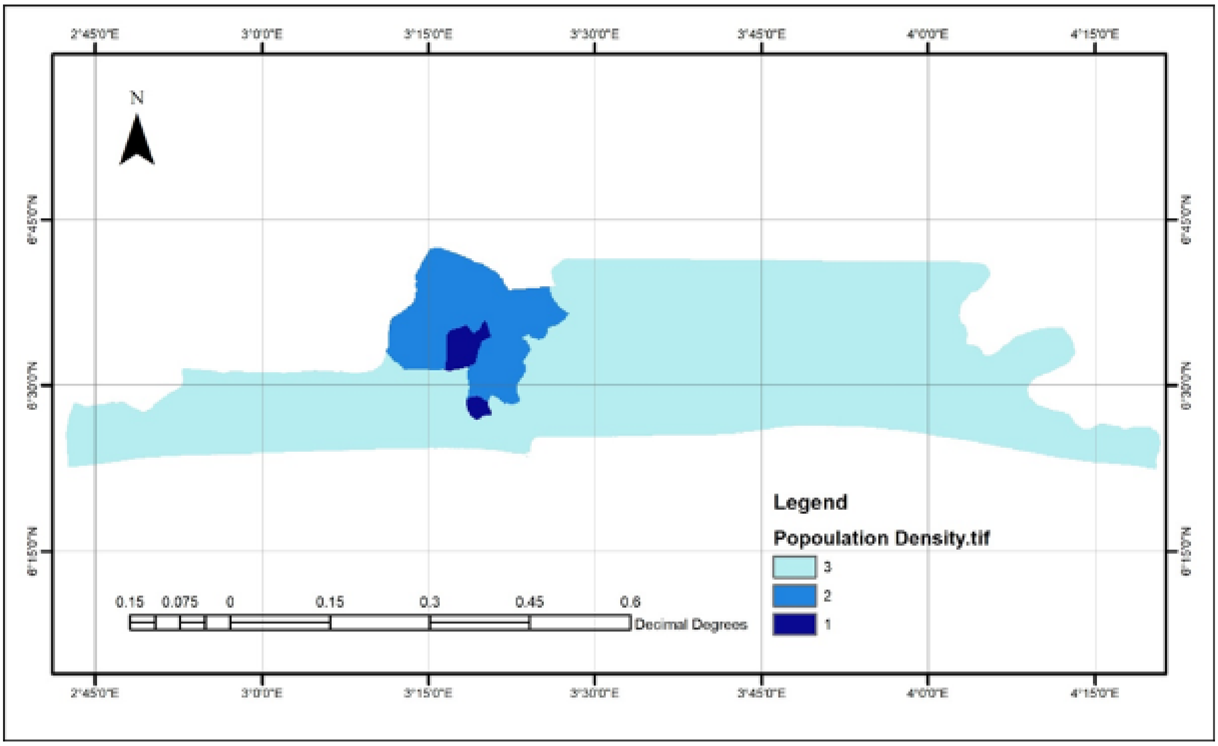

Figure 11 Population Density reclassification and standardization

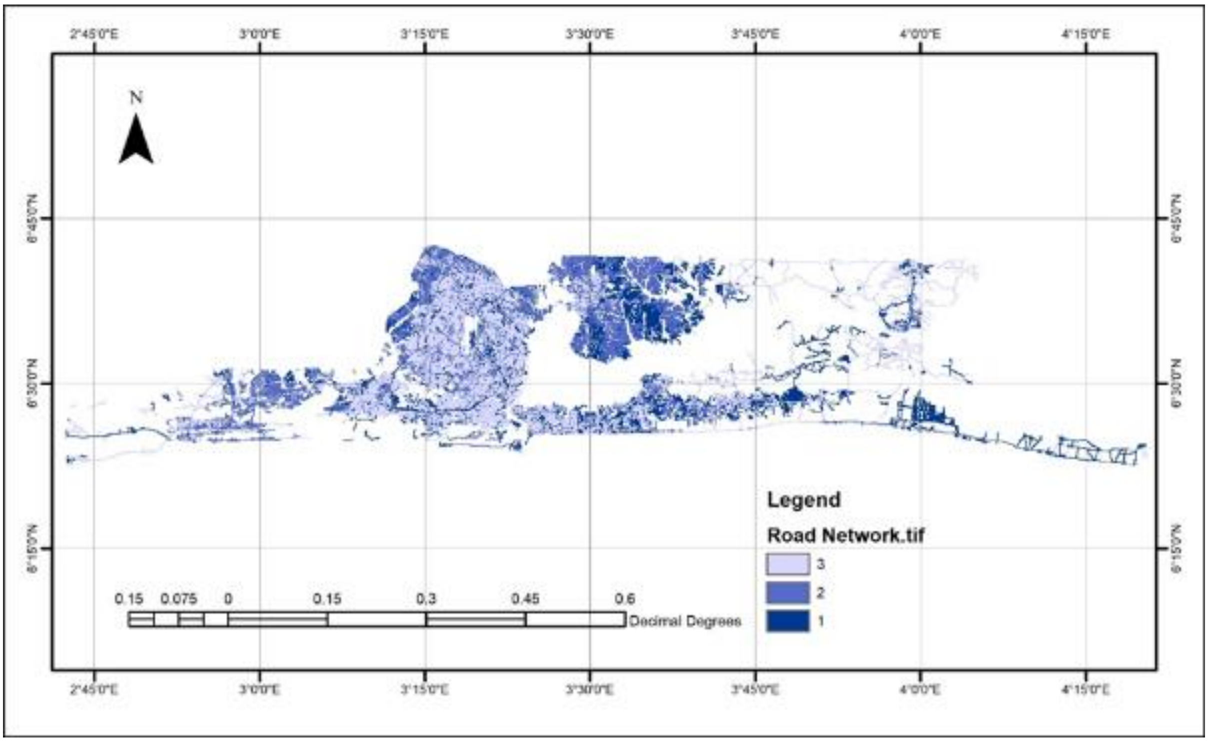

Figure 12 Distance to Transportation reclassification and standardization

3.1.3. Analytical Hierarchy Process and Determination of Criteria Weight

Analytical hierarchy process is an effective tool for dealing with complex decision-making, and may aid the decision maker to set priorities and make best decisions by reducing complex decisions to a series of pairwise comparisons, and then synthesizing the results. AHP helps to capture both subjective and objective aspects of a decision. Again, both benefits and risks can be weighed, assigning a number value to each criterion (benefit or risk factor under consideration), with more important benefits receiving a higher number on the scale to determine which projects have the highest overall value, or the most valued benefits and least risks.

AHP approach uses a ratio matrix known as the Eigenvector method to compare one criterion with another. Additionally, it uses a numerical scale with values ranging from 1 to 9, where 1 means that the two factors are equally important and 9 means that the one factor is absolutely more important than the other as shown in Table 2. If a factor is less important than another then this is indicated by reciprocals of the 1 to 9 values (1/1 to 1/9)

Table 2 Relative Importance in Pairwise Comparison

Judgment value	Description
1	Equal importance
3	Moderately importance
5	Strongly Importance
7	Very strongly important
9	Extremely important

3.1.4. Pairwise Comparison Matrix Formation

Pairwise comparison matrix was formed by inputting the judgment value between factors as the matrix elements by following the basic rules as established by Saaty. Using the table 2, table 3 was formulated using pairwise comparism matrix.

Table 3 Pair-wise comparison matrix of the study

	Confirmed Deaths	Confirmed Cases	Distance to Health Care	Distance from Public Amenities	Population Density	Distance to Transportation Network
Confirmed Deaths	1	2	2	2	3	3
Confirmed Cases	0.5	1	2	2	2	3
Distance to Health Care	0.5	0.5	1	2	2	3
Distance from Public Amenities	0.5	0.5	0.5	1	2	2
Population Density	0.33	0.33	0.5	0.5	1	2
Distance to Transportation Network	0.33	0.33	0.33	0.5	0.5	1
Total	3.16	4.66	6.33	8	10.5	14

3.1.5. Computation of the Criterion Weights

After the formation of pair-wise comparison matrix, computation of the criteria weights was done. The computation involved the following operations:

- Finding the sum of the values in each column of the pair-wise comparison matrix.
- Division of each element in the matrix by its column total (the resulting matrix is referred to as normalized pair-wise comparison matrix).

- Computation of average of elements in each row of the normalized matrix, i.e., dividing the sum of normalized scores of each row by the number of criteria. These averages provide an estimate of the relative weights of the criteria being compared. It should be noted that for preventing bias through criteria weighting, the consistency ratio (CR) was used.

3.1.6. Normalized Pairwise Comparison Matrix

Table 4.3 shows the normalized pairwise comparison matrix, it shows the relative importance or preference given to each factor compared to others for determining COVID-19 vulnerability in Lagos State. The values in the matrix range from 0 to 1, where 0 represents equal importance, and 1 indicates one factor is much more important than the other, as shown in the table 4.

Table 4 Normalized Pairwise Comparison Matrix

	Confirmed Deaths	Confirmed Cases	Distance to Health Care	Distance from Public Amenities	Population Density	Distance to Transportation Network	Mean
Confirmed Deaths	0.32	0.43	0.32	0.25	0.29	0.21	0.30
Confirmed Cases	0.16	0.21	0.32	0.25	0.19	0.21	0.22
Distance to Health Care	0.16	0.11	0.16	0.25	0.19	0.21	0.18
Distance from Public Amenities	0.16	0.11	0.08	0.13	0.19	0.14	0.13
Population Density	0.10	0.07	0.08	0.06	0.10	0.14	0.09
Distance to Transportation Network	0.10	0.07	0.05	0.06	0.05	0.07	0.07

3.1.7. Prioritization weight matrix

Table 5 shows the prioritized weight matrix. In computing the element of this matrix, the normalized sum of each row is divided by the total number of its criteria. The obtained averages provide an estimate of the relative weights of the criteria being compared. For instance, the criteria weight of flow accumulation as a factor can be obtained thus;

Landcover/Landuse = 0.32 + 0.43 + 0.32 + 0.25 + 0.29 + 0.21 (sum of the elements in row 1)

Total number of criteria in row 1 = 6

Therefore, A {weight of factor 1 (F1)} = 1.81/6 = 0.3016 = 0.30

A% (criteria in percentage) = A x 100 = 0.30 * 100 = 30%, see table 4.4 for more details.

Table 5 Prioritization weight matrix

	Confirmed Deaths	Confirmed Cases	Distance to Health Care	Distance from Public Amenities	Population Density	Distance to Transportation Network	Mean	W%	row total of normalized matrix
Confirmed Deaths	0.32	0.43	0.32	0.25	0.29	0.21	0.30	30.19	1.81
Confirmed Cases	0.16	0.21	0.32	0.25	0.19	0.21	0.22	22.39	1.34

Distance to Health Care	0.16	0.11	0.16	0.25	0.19	0.21	0.18	17.97	1.08
Distance from Public Amenities	0.16	0.11	0.08	0.13	0.19	0.14	0.13	13.38	0.80
Population Density	0.10	0.07	0.08	0.06	0.10	0.14	0.09	9.25	0.55
Distance to Transportation Network	0.10	0.07	0.05	0.06	0.05	0.07	0.07	6.82	0.41
Total	1	1	1	1	1	1	1	100	6

3.1.8. Estimation of the Consistency Ratio

This stage involved calculating a consistency ratio (CR) to check reliability of the judgments values which are relative to large samples of purely random judgments. The AHP deals with consistency explicitly because in making paired comparisons, just as in thinking, people do not have the intrinsic logical ability to always be consistent.

To determine consistency ratio, the analytical hierarchy process compares it by random index (R.I.). Mathematically, Consistency Ratio (C.R.), can be defined as:

$$CR = CI/RI$$

In calculating the constituency value, the mathematical formula CR = CI/RI was be used.

Random index (RI) is the consistency index of a randomly generated pair-wise comparison matrix of order 1 to 10 obtained by approximating random indices, see table 6.

Table 6 Random Index by Saaty

Size of matrix (n)	1	2	3	4	5	6	7	8	9	10
Random index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

Source: (Saaty, 2001).

Note: If the value of the obtained Consistency Ratio is less than 0.1, it means that there is a reasonable level of consistency in the pairwise comparisons, and that the computed weights are within the acceptable limit. If the reverse is the case (CR > 0.1) it means that the weights obtained are inconsistent and needs to be checked.

The value of Consistency index, CI was calculated from the preference matrix according to equation below

$$CI = \frac{\lambda\text{max} - \text{n}}{\text{n}-1} \text{……………….}(4.1)$$

λmax is the Principal Eigen Value; *n* is the number of factors

λmax = Σ of the products between each element of the priority vector and relative weights

$$\lambda\text{max} = (3.16*0.30) + (4.66*0.22) + (6.33*0.18) + (8*0.13) + (10.5*0.09) + (14*0.07)$$

$$= 0.94 + 1.02+ 1.13+ 1.04+ 0.94 + 0.98$$

$$\lambda\text{max} = 6.05$$

$$CI = (6.05 – 6)/ (6-1) = 0.01$$

$$CR = 0.01/1.24 = 0.008$$

$$CR = 0.008 < 0.10 \text{ (Acceptable)}$$

The consistency ratio (CR) is design in such a way that if CR<0.10, the ratio indicates a reasonable level of consistency in the pairwise comparisons; if, however, CR ≥ 0.10, the values of the ratio are indicative of inconsistent judgments. From the judgment a Consistency Ratio (CR) of 0.010 was achieved which was less than the maximum allowable ratio of 0.10.

3.1.9. Vulnerability Index

The vulnerability was determined by obtaining the summation of the product of the weight of each criterion with its standard suitability score according to Equation 4.2.

$$VI = \Sigma\, w_i x_i \text{ ....(4.2)}$$

Where;
VI = Vulnerability Index,
w_i= the relative importance (weight) of each criterion
and x_i = the standardized score of each criterion i.

Hence the vulnerability with the constraints was derived from equation

$$F = (\sum_{i=1}^{n} wi \ \times xi)\times\prod cj \text{ ....(4.3)}$$

With c_j=Boolean value of limited criterion

In order to make the map easily understandable, a reclassification was performed to reclassify the result to index levels/categories—low, moderate and high, then from which high potential areas were extracted. The natural breaks reclassification method in ESRI's ArcGIS Pro was used for this purpose. The natural breaks (jenks) classification algorithm finds data break points between classes depending on the natural patterns in which the data are clustered. Class break points are set where there are relatively huge jumps in the data values. Hence a model was developed using the formula and weighted linear combination to determine the development potential. The formular used is: FI is = **(**F1*0.30) + (F2*0.22) + (F3*0.18) + (F4*0.13) + (F5*0.09) + (F6*0.07)

Note: F1, F2, F3, F4, F5, and F6 are thematic layers representing the constraints, see table 7 and figure 13 for the results.

Table 7 Coding of Factors

F1	Confirmed Deaths
F2	Confirmed Cases
F3	Distance to Health Care
F4	Distance from Public Amenities
F5	Population Density
F6	Distance to Transportation Network

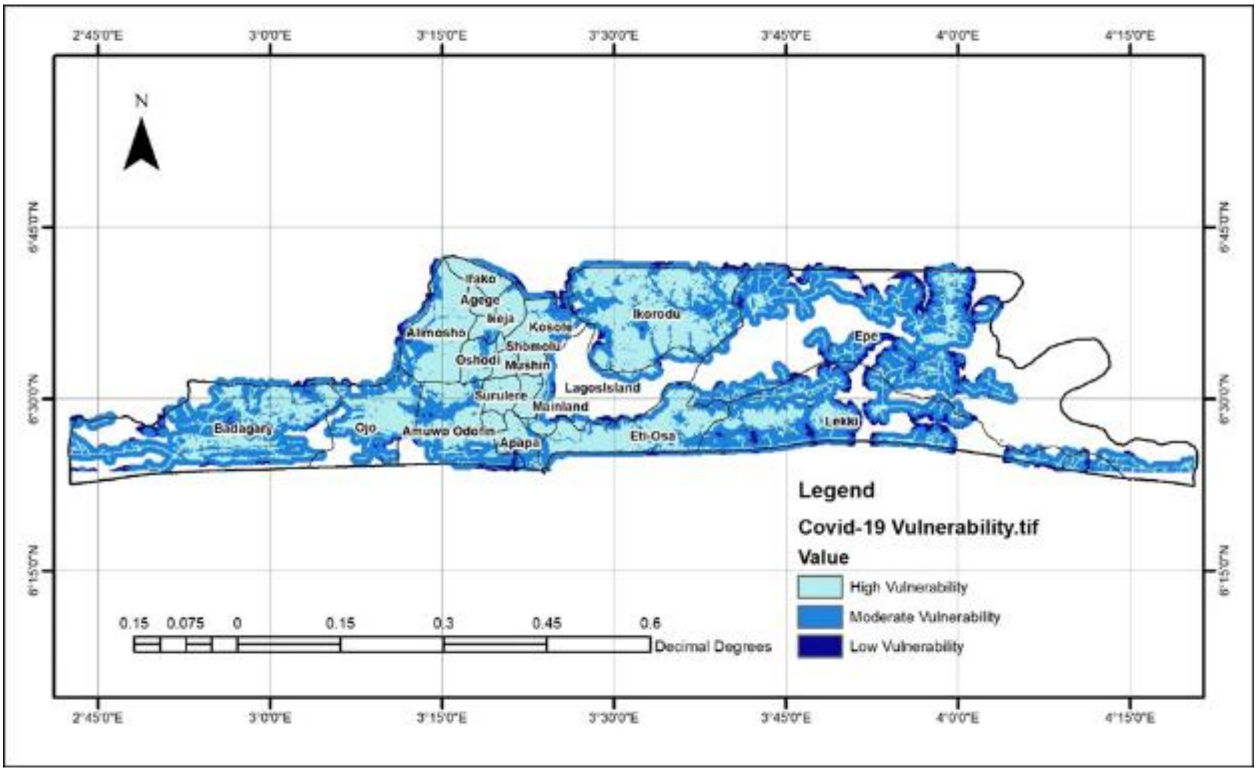

Figure 13 Lagos State COVID-19 Vulnerability Map

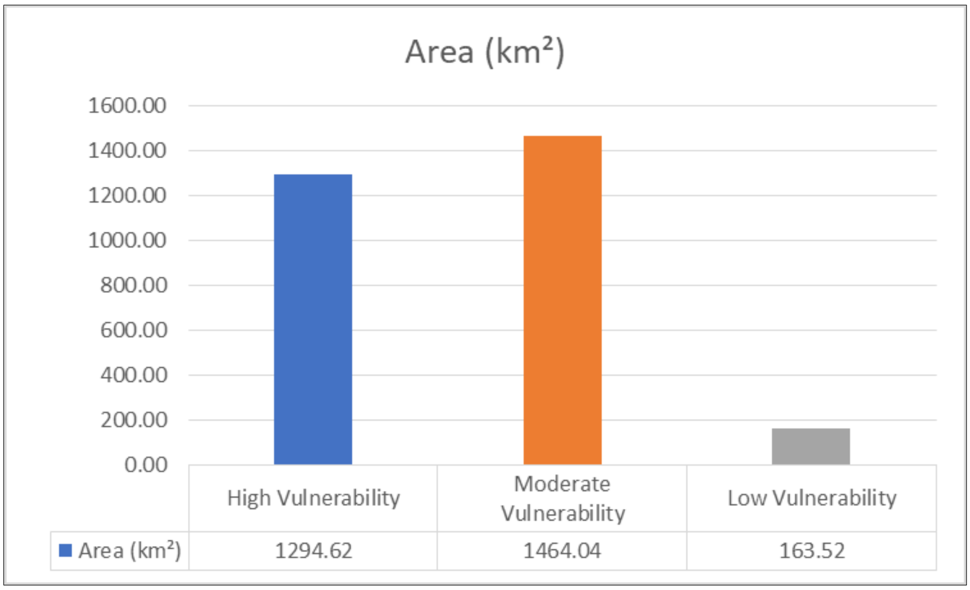

Figure 14 COVID-19 Vulnerability Distribution in Lagos State

According to the findings in figure 13 and 14, the vulnerability index analysis indicates that Lagos State had a significant high vulnerability zone, encompassing 44.30% of the total area, which corresponds to 1296.62 km^2. The moderate vulnerability zones covered a larger proportion, accounting for 50.10% of the total area, equivalent to 1464.04 km^2. In contrast, the low vulnerability zone represented a smaller portion, comprising 5.59% of the total area, with an area coverage of 163.52 km^2.

Moreover, the LGAs exhibit varying degrees of vulnerability to COVID-19. Notably, the LGAs with relatively larger areas of high vulnerability encompass Ikorodu (245.69 km^2), Badagary (135.14 km^2), Eti-Osa (124.17 km^2), Alimosho (117.15 km^2), and Epe (109.19 km^2).

In contrast, LGAs showing moderate vulnerability include Epe (417.82 km^2), Lekki (236.19 km^2), Badagary (225.63 km^2), and Ikorodu (111.88 km^2). These areas may face unique challenges in managing the spread of the virus.

Conversely, the LGAs with smaller areas of low vulnerability comprise Agege (16.47 km^2), Ajeromi (11.43 km^2), Ifako (32.55 km^2), Ikeja (39.76 km^2), Mainland (22.14 km^2), Mushin (17.14 km^2), Oshodi (30.08 km^2), Shomolu (18.12 km^2), and Surulere (29.96 km^2). this is illustrated in figure 15.

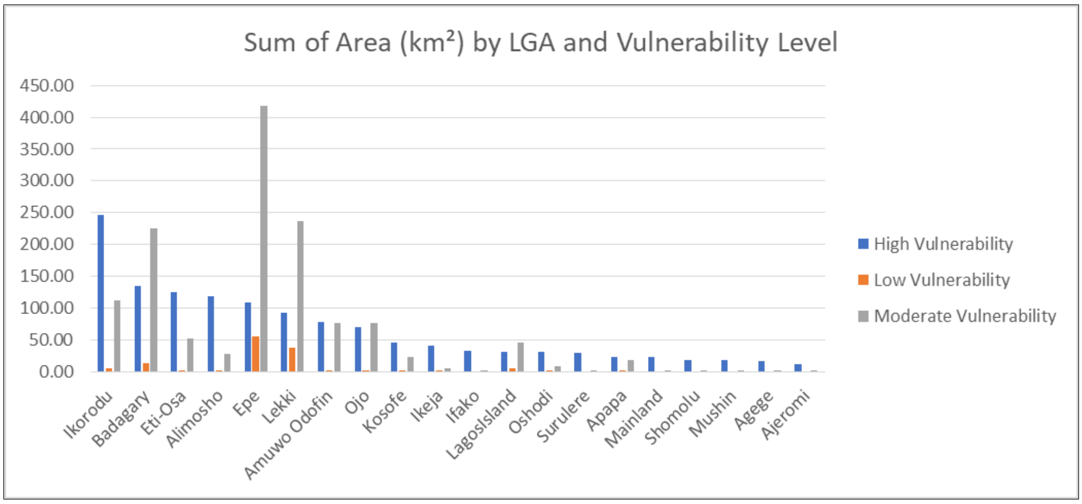

Figure 15 COVID-19 Vulnerability Distribution across Lagos State LGAs

4. Conclusion

The findings of this research reveal significant insights into the vulnerability of Lagos State to the COVID-19 pandemic, using a comprehensive GIS-based multi-criteria analysis. The vulnerability index analysis has delineated distinct zones within the state, allowing for a nuanced understanding of the spatial dynamics of COVID-19 risk. These findings offer valuable information for policymakers, public health authorities, and local communities in devising tailored strategies to combat the pandemic effectively.

The most prominent observation from the vulnerability index analysis is the presence of a substantial high vulnerability zone, covering 44.30% of Lagos State's total area, which corresponds to 1296.62 km^2. This zone represents an area where the risk of COVID-19 transmission and impact is notably elevated, warranting immediate attention. This high vulnerability zone may require intensified resource allocation, stringent public health measures, and targeted interventions to mitigate the spread of the virus.

Conversely, the moderate vulnerability zones cover a larger proportion of Lagos State, accounting for 50.10% of the total area, equivalent to 1464.04 km^2. These zones indicate areas where the COVID-19 risk is relatively lower compared to the high vulnerability zone. While the risk may be lower, it is crucial not to underestimate the importance of continued vigilance and preventative measures within these regions.

The low vulnerability zone, comprising 5.59% of the total area, with an area coverage of 163.52 km^2, represents areas with the least COVID-19 vulnerability. These areas may serve as exemplars of effective pandemic management and can provide valuable lessons for other regions.

Moreover, the vulnerability analysis at the local government level (LGAs) reveals varying degrees of vulnerability. The LGAs with relatively larger areas of high vulnerability encompass Ikorodu (245.69 km^2), Badagry (135.14 km^2), Eti-Osa (124.17 km^2), Alimosho (117.15 km^2), and Epe (109.19 km^2). These areas may face significant challenges in controlling the spread of the virus, necessitating focused efforts in terms of healthcare infrastructure, testing, contact tracing, and public awareness campaigns.

Conversely, LGAs showing moderate vulnerability include Epe (417.82 km^2), Lekki (236.19 km^2), Badagary (225.63 km^2), and Ikorodu (111.88 km^2). These areas, although displaying a moderate level of vulnerability, should not lower their guard and must remain vigilant to prevent a surge in COVID-19 cases.

The LGAs with smaller areas of low vulnerability, including Agege (16.47 km^2), Ajeromi (11.43 km^2), Ifako (32.55 km^2), Ikeja (39.76 km^2), Mainland (22.14 km^2), Mushin (17.14 km^2), Oshodi (30.08 km^2), Shomolu (18.12 km^2), and Surulere (29.96 km^2), have demonstrated a commendable level of preparedness and resilience. Their experiences can serve as examples of effective pandemic management practices that other areas can emulate.

The findings of this study have several critical implications for COVID-19 management and public health strategies within Lagos State:

- Resource Allocation: The identification of high and moderate vulnerability zones allows for targeted resource allocation. High-risk areas should receive priority in terms of medical supplies, testing facilities, and healthcare infrastructure enhancement.
- Preventative Measures: The LGAs exhibiting high vulnerability should implement stringent preventative measures, including lockdowns, strict quarantine protocols, and public health campaigns to raise awareness and promote compliance with safety guidelines.
- Sharing Best Practices: LGAs with low vulnerability areas can serve as models for effective pandemic management. Best practices employed in these regions should be shared and replicated in areas facing higher risk.
- Localized Response: The vulnerability analysis enables a more localized response, where interventions can be tailored to the unique needs of each area. For example, high-density areas may require different strategies than sparsely populated regions.
- Monitoring and Surveillance: Continuous monitoring and surveillance in high and moderate vulnerability zones are critical to detect and manage potential outbreaks promptly.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., Lewis, B., & Tidwell, B. (2011). Social Vulnerability and the Natural and Built Environment: A Model of Flood Human Health. Environmental Health Perspectives, 119(4), 511-517.

[2] Gao Z, Jiang Y, He J, Wu J, Xu J, and Christakos G. (2022). An AHP-based regional COVID-19 vulnerability model and its application in China. Model Earth Syst Environ, 8(2), 2525-2538. doi: 10.1007/s40808-021-01244-y.

[3] Li, X., Huang, H., Wang, H., Liao, S., Li, H., & Wang, Z. (2020). Mapping the Spatial Distribution of COVID-19 in Africa: An Exploratory Analysis. SSRN Electronic Journal.

[4] Malczewski, J. (2006). GIS-Based Multicriteria Decision Analysis: A Survey of the Literature. International Journal of Geographical Information Science, 20(7), 703-726.

[5] Owusu, F. A., Yawson, A. E., Twumasi, J., & Abdul-Rasheed, A. (2020). Analyzing the Spatial Distribution of COVID-19 Cases in Ghana. Journal of Geography and Geology, 12(2), 28-38.

[6] Pullan, S., Lindsay, S. W., Yap, Y. L., & Brooker, S. (2020). Mapping the Geographical Inequality of Access to Hospitals in Nigeria. PLoS ONE, 15(11), e0240685.

[7] Tay, G. K., Turner, N. C., Jones, S., & Zhang, Y. (2018). Measuring the Impact of Socioeconomic Indicators on Urban Vulnerability to Flooding in Portmore, Jamaica. Natural Hazards, 93(1), 219-239.