Research Article

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Do pre-existing medical conditions affect COVID-19 incidence and fatality in Nigeria? A Geographical Perspective

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Abstract: Clinical evidence shows the incidence of novel coronavirus is associated with pre-existing medical conditions. Thus, people with pre-existing medical conditions are more likely to be infected with COVID-19. In light of this, this paper examined the extent to which pre-existing medical conditions are related to COVID-19 incidence and mortality in Nigeria from a geographical perspective. We used the geographically weighted regression (GWR) to determine the effect and extent to which pre-existing medical conditions affect COVID-19 incidence in Nigeria. Our findings show that besides the remarkable spatial variation in COVID-19 incidence and mortality, obesity was a significant predictor of COVID-19 with its effect strongest in southwest Nigeria and other parts of the country. The conclusion of the paper is that areas with high prevalence of pre-existing medical conditions coincide with areas with high COVID-19 incidence and fatality. We recommended that there should be a spatially explicit intervention on the reduction of exposure to COVID-19 among states with high prevalence of pre-existing medical conditions through vaccination.

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1 Introduction

The COVID-19 pandemic continues to spread unchecked across the globe, bringing in its wake significant health and economic crises that have crippling effects on even the most developed nations. There is sufficient clinical evidence that suggests a strong association between COVID-19 and pre-existing medical conditions such as hypertension, cancer, diabetes, cardiovascular diseases, obesity, among others [1-4]. According to the International Diabetes Federation [5], viral infection among people living with diabetes is usually difficult to treat due to fluctuations in blood glucose levels. This is attributed to the fact that the immune system becomes compromised and finds it difficult to ward off the disease. Besides, the virus thrives with elevated blood glucose levels [6].

People with cardiovascular disease are at risk of contracting COVID-19. According to Vuorio et al. [7], viral infections are one of the leading causes of cardiovascular disease, which decreases pro-inflammatory cytokines, which may result in a weaker immune system [8]. Furthermore, Guo et al. [1] reported that viral diseases, including COVID-19, may be responsible for about 5 percent of the cases of acute heart failure globally. Similarly, patients with malignancies are at greater risk of infection than those without any form of tumour [9]. This has been adduced to the fact that anti-cancer treatments involving chemotherapy and surgery exposes this group of people to immunosuppressive states, and subsequently at risk of viral infections [10].

Furthermore, it has been reported that those with abnormally low level of lymphocytes in the blood are more susceptible to COVID-19 [11], since viral particles are capable of damaging cytoplasmic components of the lymphocyte [12], which compromises the immune system. It has also been established in the literature that patients with respiratory diseases are prone to infection. This was evident in the study of Zheng et al. [8], which showed that patients with respiratory diseases such as chronic obstructive pulmonary disease have damaged lungs as well as lower resistance to the virus. This is further reinforced in the studies of Richardson et al. [13], Garg et al. [14] and Goyal et al [15], demonstrating that asthmatic patients are more likely to die from COVID-19 because they are more exposed to common viral respiratory infections due to deficient antiviral immune response.

Also, some studies have linked hypertension to the susceptibility of COVID-19 due to the higher number of COVID-19 cases among hypertensive patients. In China for instance, 25 to 50 percent of people who were diagnosed with COVID-19 had high blood pressure. This has been largely attributed to weak immune systems in people with high blood pressure [8]. Similarly, in the United States, high blood pressure affected between 30% and 50% of hospitalized COVID-19 patients [16]. Elezkurtaj et al. [17], following full body autopsies on 26 patients at the Charite University Hospital, Germany, found that septic shock and multi-organ failure are the most common causes of death among COVID-19 patients, due to suppurative pulmonary infection.

Some studies have also shown that people with chronic kidney diseases may also be vulnerable to infection. Reports from China and the United States reveal that about 30 percent of patients hospitalized with COVID-19 had severe or moderate kidney failure [18]. A possible explanation for this is that kidney cells have a receptor (angiotensin converting enzyme) that enables the virus to attach to them and subsequently damage the tissues. Another reason is that kidney problems in patients with the virus arise from low levels of oxygen in the blood which is mostly seen in severe cases of the disease [18].

Lastly, obesity is a major risk factor of COVID-19 [19]. This has been affirmed in the study of Simmonnet et al. [4] in France, where they observed an "…unexpected high frequency among patients with obesity admitted to intensive care for SARS-CoV2". This was also the case in New York City where people with a body mass index between 30-34kg/m^2 and above 35kg/m^2 were respectively 1.8 times and 3.6 times more likely to be admitted to critical care units [20]. In a descriptive observational study in South Africa, Mash et al. [21] found obesity to be linked with COVID-19 mortality. Elsewhere in Mexico, similar findings on the relationship between obesity and COVID-19 were revealed by Aguirere et al. [22]. According to Tan, He and MacGregor [23], multiple mechanisms could explain the relationship between obesity and COVID-19. One is the presence of angiotensin converting enzyme-2 (ACE) and transmembrane enzyme which are present in large quantities in people with obesity. Given that these enzymes are used as entry points by SARS-COV-2 (ibid.), the adipose tissue of people living with obesity may be a potential target and reservoir for viruses such as COVID-19, before it spreads to other parts of the body. It is said that obesity and excess ectopic fat weaken insulin resistance and beta-cell function which reduces the potency of the immune system to fight the virus [24]. Obesity, according to Zhou et al. [25], induces reduced oxygen saturation of blood which comes from impaired ventilation of the lungs, due to greater resistance in the airways [23]. It also damages the immune system, and this reduces the ability to fight the infection leading to a poor recovery from the disease [6].

Based on the current and emerging literature, there is substantial evidence on the novel coronavirus and its links with pre-existing medical conditions. However, these studies are mainly limited to individual and multiscale levels of analysis which largely lack a geographic perspective. Though there are relatively few and upcoming geographic studies on COVID-19 and its association with pre-existing medical conditions, particularly in the United States of America [26-28], it is still not clear if a spatial co-occurrence between these two exists in African countries. Therefore, this research seeks to analyse the geographic distribution of COVID-19 in relation to pre-existing medical conditions using Nigeria as a case study. Apart from being Africa's most populous country, it has one of the largest numbers of diabetes cases [5] with a rising prevalence of obesity among Nigerians [29]. Nigeria's index case, whose origin was Italy, was detected in Lagos State on the 27th February, 2020. It has since spread to 35 States and the Federal Capital Territory (FCT). On August 25, 2021, the country recorded a total of 188,880 confirmed COVID-19 cases, and 2,288 deaths [30]. Sadly, Nigeria has the largest number of cases and deaths in West Africa [31]. Five epicenters—namely Lagos, Federal Capital Territory (FCT), Rivers, Kaduna and Plateau States—were collectively responsible for 63.6 percent of confirmed cases in the country as at August 25, 2021.

This study specifically has three objectives: first, determine the degree of spatial clustering of COVID-19 and pre-existing medical conditions in the country. Second, assess the extent to which states with COVID-19 coincides with states with pre-existing medical conditions. Lastly, examine if there is any evidence of spatial non-stationarity in these associations. These set objectives will be accomplished with spatial statistical tools. Spatial statistics, according to Osayomi [32], are “a collection of tools specifically designed, and commonly used for the analysis of spatial patterns; detection of spatial clusters and modelling of spatial relationships”. Geographic data are naturally characterised by two distinctive attributes, namely spatial autocorrelation and spatial non-stationarity. Spatial autocorrelation occurs when similar values of an object of interest cluster in geographic space, while spatial non-stationarity is a situation in which a relationship between a dependent and independent variable(s) is geographically variable and not spatially homogenous, as it is often depicted in global regression models. Their significance in geospatial health research studies cannot be underestimated [33-34]. The results should help in control and management of COVID-19, particularly directions on whom and where to intervene, especially now in recent vaccination campaigns.

2 Methods

2.1 Data sources

Data used in this research were assembled from different publicly available sources (Table 1), such as the Nigeria Centre for Disease Control Agency Situation Report for August 25, [30], the 2008/2009 Harmonised Living Standard Survey report published by the National Bureau of Statistics [35], the 2018 Nigeria Demographic Health Survey (NDHS) report published by the National Population Commission (NPC) in partnership with the National Malaria Elimination Programme (NMEP) of the Federal Ministry of Health, Nigeria [36], and the 2006 National Population Census report produced by the National Population Commission [37].

Numbers of confirmed COVID-19 cases in each state and the Federal Capital Territory (FCT)-Abuja as at August 25, 2021 were obtained from the daily and weekly NCDC COVID-19 epidemiological situation reports hosted by the Nigeria Centre for Disease Control (NCDC) (see www.covid.ncdc.gov.ng for details). These reports provide data on new and cumulative infection cases across Nigeria on a daily basis. Most recent state-level data on diabetes mellitus (DM) and hypertension were extracted from the 2008/2009 HNLSS report [35]. The report compiled data with a view to influencing national development [35]. The most recent edition of the NDHS [36] report, published in 2018, provided information on maternal overweight and obesity, which serve as proxies for large body mass for the general population. Like previous editions, NDHS provides up-to-date estimates on demographic, household, social and health indicators so as to assist policy makers to improve the health of the country’s population [36]. State population figures came from the 2006 National Population Census report [37].

2.2 Statistical analysis

A variety of statistical and spatial analytic techniques, such as the Pearson moment correlation technique, Global Moran’s I, the ordinary least square (OLS) regression and the geographically weighted regression (GWR), were used in analysing the study data. The Pearson correlation technique was useful in ascertaining the direction and strength of the relationship between COVID-19 and pre-existing medical conditions. The dependent variables were COVID-19 incidence rate (CIR) and fatality rates. They were computed by dividing the number of confirmed cases/deaths by the population of a given state multiplied by 100,000. GeoDA 1.8 was employed to conduct the global spatial autocorrelation, perform the bivariate correlation analysis and produce the scatter plot matrix showing the interrelationships among explanatory variables. Ordinary Least Square (OLS) and the Geographically Weighted Regression (GWR) were possible with the aid of ArcGIS 10.4.1.

The OLS regression analysis estimated the relationship between the dependent variable CIR and the independent variables—pre-existing medical conditions which include diabetes (DM), hypertension, overweight and obesity (see Table 3). A major assumption of the OLS regression is that the relationship between the Y variable and the X variables is uniform in space. The OLS regression diagnostic tests include the Koeneker statistic (for the detection of spatial non-stationarity), Studentised Breusch Pagan (BP) (for the presence of homoscedastic-

Table 1: Study variables and their sources

Study variable	Source
COVID-19 confirmed cases COVID-19 confirmed deaths	NCDC (www.covid.ncdc.gov.ng)
Overweight	NDHS (2018)
Obesity	NDHS (2018)
Hypertension	HNLSS 2010
Diabetes Mellitus	HNLSS 2010

ity), Jarque Bera (to check for the absence of normality) and Variance Inflation Factor (VIF) (indicates multicollinearity). Spatial non-stationarity is established when the Koeneker statistic is statistically significant, while Jarque Bera signifies the normal distribution of residuals when significant. An independent variable is redundant only if its VIF value is 7.5 or above. GWR, on the other hand, is a local spatial regression method used to analyse spatially varying relationships over space [38]. The Akaike Information Criterion (AIC) is a key indicator for the evaluation of model performance. In relative terms, models with lower AIC values are regarded to be better fits than those with higher AIC figures as far as spatially varying relationships are concerned.

2.3 Results

2.3.1 Spatial Pattern of COVID-19

A total of 188,880 confirmed cases and 2,288 deaths had been recorded from February 27 to August 25, 2021 (NCDC, 2021). The dependent variables, CIR and fatality were mapped so as to show their geographical distribution across the country (Fig 1). The highest incidence rates were found in FCT (93.85/100,000), Lagos (50.60/100,000), Plateau (18.35/100,000), Rivers (12.42/100,000) and Edo (10.44/100,000) states. With regard to fatality, FCT had the highest fatality rate (8.01/100,000) followed by Edo (3.84/100,000), Lagos (3.33/100,000), Oyo (1.84/100,000) and Kwara (1.53/100,000).

2.3.2 Bivariate correlations

Figure 3 shows the results of the bivariate correlation analysis. All pre-existing medical conditions, except overweight and obesity, had no association with COVID-19 incidence and fatality (Table 2). Obesity is positively associated with COVID-19 incidence ($r= 0.476$; $p<0.05$) and fatality ($r= 0.418$; $p<0.05$). Like obesity, overweight has a positive relationship with incidence ($r=0.438$; $p<0.05$) and fatality ($r= 0.468$; $p<0.05$). These result certainly suggest that states with high overweight and obesity prevalence coincide with states with similarly high COVID-19 incidence and fatality rates. This, to some extent, points to a spatial match between COVID-19 and pre-existing medical conditions.

2.4 Spatial clustering of COVID-19 and pre-existing medical conditions

The global Moran's I test demonstrated that there was evidence of geographic clustering except for COVID-19 incidence, fatality, and hypertension (see Table 2).

2.4.1 OLS regression

A summary of OLS regression results is set out in Table 3. Overweight was dropped on account of the multicollinearity problem ($r=0.795$ with obesity) in the two estimated models. The results of the regression model indicate that obesity is positively associated with COVID-19 incidence. In addition, the OLS regression reveals that obesity is responsible for twelve per cent of the variation in incidence, with an F-value of 10.523397 ($p<0.05$) and AIC of

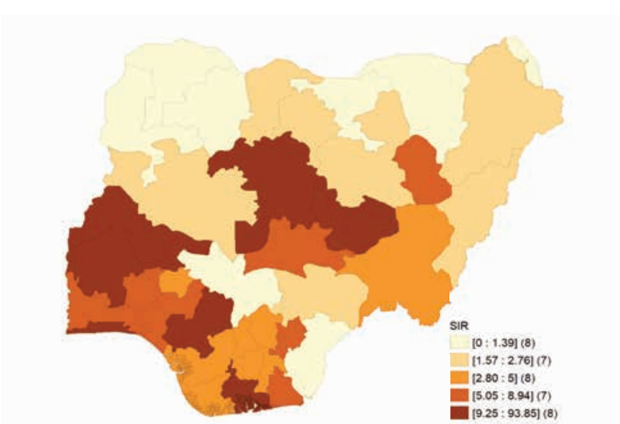

Figure 1: Geographical distribution of COVID-19 incidence in Nigeria as at August 25, 2021

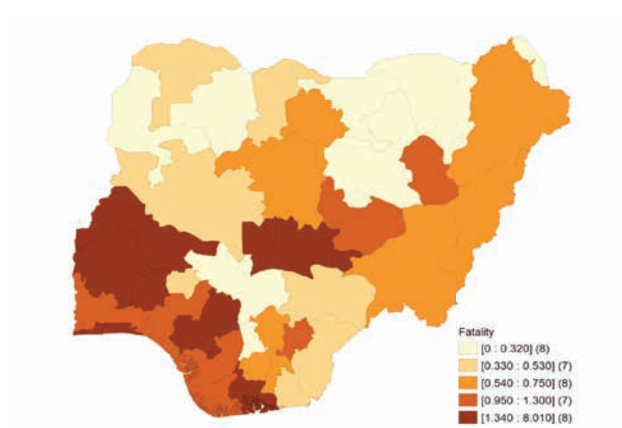

Figure 2: Geographical distribution of COVID-19 fatality in Nigeria as at August 25, 2021

Table 2: Results of Global Moran's I

Variable	I	z	p	Remark
Incidence	0.011	0.5688	0.195	Random
Fatality	0.006	0.0.3986	0.318	Random
Obesity	0.4622	4.4541	0.0002	Positive autocorrelation
Overweight	0.332	3.0729	0.0002	Positive autocorrelation
Diabetes mellitus	0.211	2.4443	0.016	Positive autocorrelation
Hypertension	0.0921	1.546	0.136	Random

317.128928920, but the Koeneker statistic of 5.984538 ($p < 0.05$) indicates the presence of spatial non-stationarity in the relationship. The Jarque Bera statistic was significant ($JB=381.474493$; $p<0.05$), which means the residuals are not normally distributed.

Like incidence, obesity is positively related to fatality and accounts for nineteen percent of the variance in fatality ($F=7.64393$; $p<0.05$). The diagnostics similarly indicate the presence of spatial non-stationarity (Koeneker: 5.2209956; $p<0.05$) and non-normal distribution ($JB=236.105210$; $p<0.00$) (Table 4).

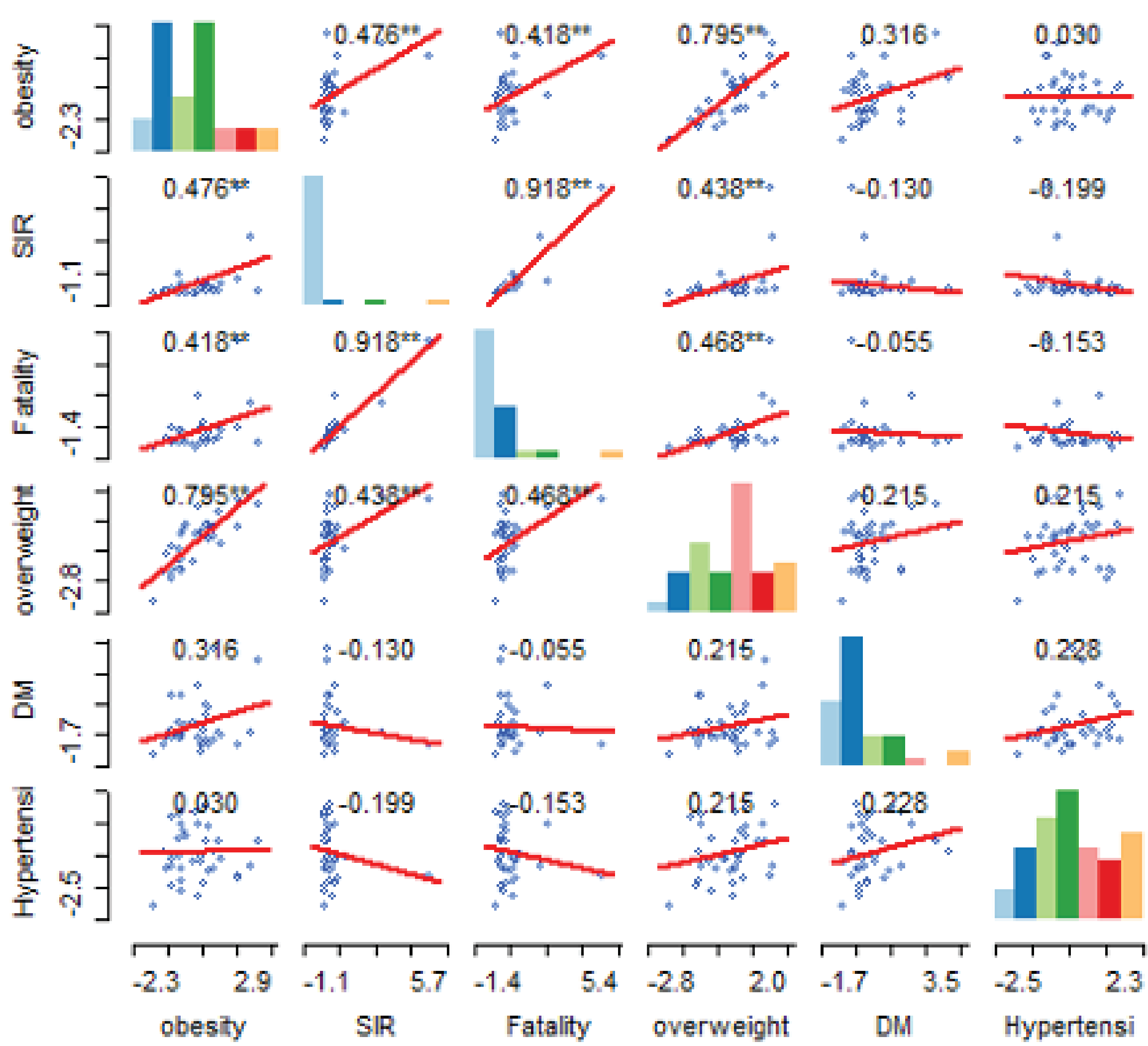

Figure 3: Scatter Plot Matrix

Table 3: OLS regression results (Incidence)

Variable	Coefficient	Std error	T stat	Probability	Robust SE	Robust T	Robust Prob
Intercept	-6.002706	5.0044815	-1.199386	0.238213	5.597447	-1.072401	0.290677
Obesity	2.582989	0.796241	3.243979	0.002546	1.376070	1.877076	0.068630
-	-	-	**Diagnostics**	-	-	-	-
Multiple R	0.226196	-	Adjusted R	0.204701	-	AICc: 317.128928920	
Joint F	10.523397	-	p	0.002546	-	-	-
Koeneker	5.984538	-	p	0.014432	-	-	-
Jarque Bera	381.474493	-	p	0.000000	-	-	-

Table 4: OLS regression results (Fatality)

Variable	Coefficient	Std error	T stat	Probability	Robust SE	Robust T	Robust Prob
Intercept	-0.001703	0.438497	-0.003883	0.996923	0.448598	0.003796	0.996993
Obesity	0.192872	0.069763	2.764687	0.008929	0.10914	1.766328	0.085820
-	-	-	**Diagnostics**	-	-	-	-
Multiple R	0.175135	-	Adjusted R	0.152222	-	AICc: 132.083997	
Joint F	7.643493	-	p	0.0008928	-	-	-
Koeneker	5.2209956	-	p	0.022316	-	-	-
Jarque Bera	236.105210	-	p	0.000000	-	-	-

The GWR model (Table 5) truly confirms the presence of spatial non-stationarity in the relationship between COVID-19 incidence and obesity. In addition, obesity significantly varies across Nigeria. On the basis of the AIC values, the GWR model (313.159696) was adjudged to be a better fit than the OLS model (317.12892).

Like the above, spatial non-stationarity was detected in the relationship between COVID-19 fatality and obesity. However, the GWR model is a weaker fit (AICc: 132.086517729) than the OLS model (AICc: 132.08399).

The model explains 0.00 to 0.90 percent of the variation in CIR (Fig 4). There is a unique pattern in the level of explanation. The highest local R^2 values are in the extreme southwest corner, especially Lagos, Ogun and Oyo States and in the central area of Nigeria, Federal Capital Territory, Niger, Kaduna and Plateau to be specific. In the extreme south lies states with relatively lower local R^2 values. Figure 5 depicts the differential effect of obesity on incidence in space. Obesity has the greatest effect on incidence in most parts of central region and the least effect in the southernmost part, particularly Rivers, Cross River, Bayelsa, Imo, Enugu, Anambra, and Ebonyi States.

Table 5: GWR Summary

Diagnostics	Incidence	Fatality
R^2	0.797105845	0.175227
Adj R^2	0.611295715	0.152185
AICc	313.159696435	132.086517729

Figure 6 illustrates the degree to which obesity has an effect on fatality. The values range from 0.17519 to 0.17534. A north-south divide in local R^2 values is very glaring along the northern fringe of the country. Specifically, Borno, Yobe, Jigawa, Kano, Sokoto, Zamfara, Katsina and Kebbi had the largest values. The values decline southwards. Like Figure 6, Figure 7 depicts the differential impact on obesity. Its greatest impacts are along the northern fringe. It means that obesity is a more significant factor of COVID-19 fatality in the north than in the south.

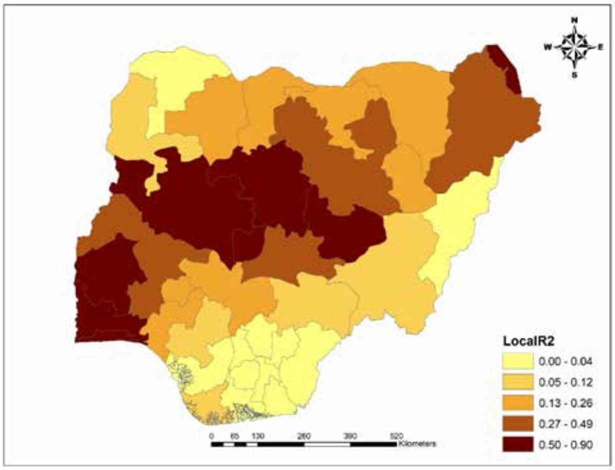

Figure 4: Local R^2 value (Incidence)

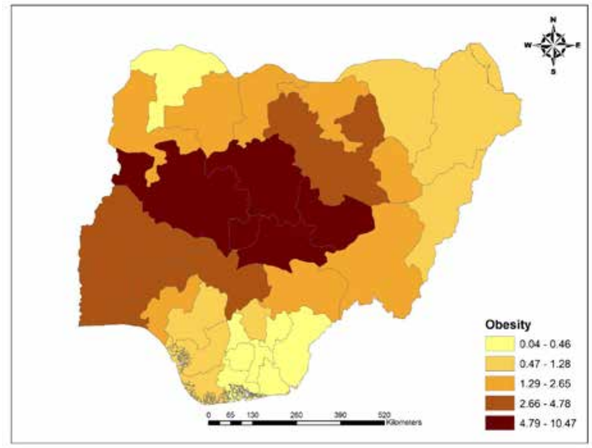

Figure 5: Obesity and COVID-19

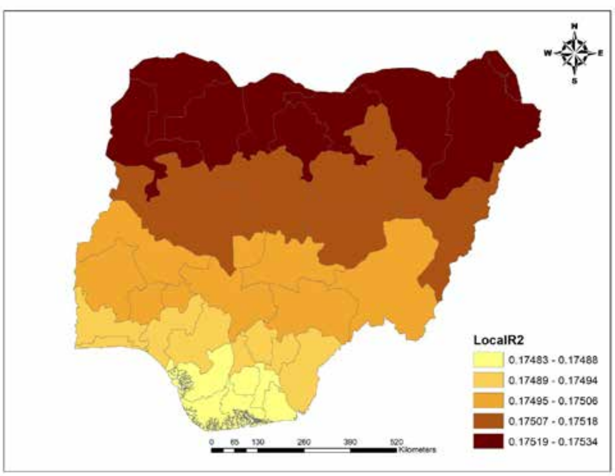

Figure 6: Local R^2 values (Fatality)

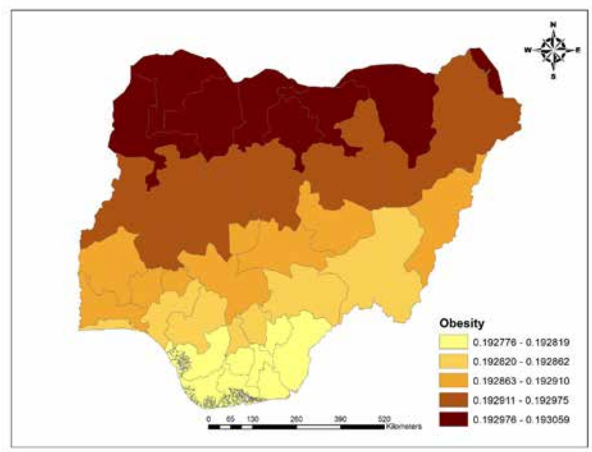

Figure 7: Differential effect of obesity on fatality

In summary, there is evidence of spatial non-stationarity in the relationship between COVID-19 and pre-existing medical conditions.

3 Discussion

Though there is remarkable spatial variation in the distribution of COVID-19 incidence and fatality, there was no evidence of spatial clustering. Statistical and spatial analysis have shown that there is an association between COVID-19 and obesity. As earlier mentioned, obesity has the strongest effect on COVID-19 incidence in southwest Nigeria and fatality in the extreme north. In 2018, the obesity prevalence rate in Nigeria stood at between 20.3% and 35.1% [39]; this stems from a multitude of risk factors such as rapid and unplanned urbanization, western lifestyle, unhealthy diets, sedentary occupations as well as economic development [40-42]. Another important factor is the “glorification of the large body size” [32], [42].Large body size in Nigeria has strong societal and cultural connotations. It is often construed as a strong indicator of affluence, marital welfare and good health [43], [32], [42]. In other words, people with smaller or thinner body frames are very often perceived to be deviants.

Besides the symbolic significance associated with obesity, it is envisaged that obesity will be a more serious public health challenge in the new normal given the lockdown circumstances. Apart from Lagos, FCT, and Ogun which were locked down by the executive order of President Muhammadu Buhari on March 30, 2020 [44] and later extended [45], many other states enforced stay-at-home orders on residents. As expected, these series of lockdowns drastically limited human movement within and outside these states. Many residents were ordered to stay home and refrain from non-essential activity. To further buttress this point, Google's Community Mobility Report [46] on Nigeria indicated that visits to all places, except for residential areas, fell. Visits to retail, recreation centres and workplaces decreased by nearly 35 percent, and these have reduced the levels of physical activity. Hence, increased body mass arising from these lockdowns or the "lockdown cost of weight gain", as Satter et al. [24] succinctly puts it, certainly has grave implications for co-morbidity in the new normal. This viewpoint is similar to those of Rundle et al. [47], who were of the opinion that school closures, restricted movements and sedentariness on account of the COVID-19 pandemic would certainly increase children's BMI and ultimately affect their health status. Osayomi et al. [31], as a matter of fact, had expressed fears of a looming NCD epidemic in Nigerian cities in the new normal. They envisaged that besides the lingering spillover effects of the lockdown periods, the remote and sedentary nature of work regimes in the new normal would exacerbate NCD burden.

Based on our finding, it is therefore likely that states with pre-existing medical conditions—particularly obesity—will have higher likelihood of COVID-19 infection and deaths in Nigeria. The situation may have even worsened in Nigeria. Our findings are in agreement with Mollalo et al. [27]. They found that counties in the United States with higher mortality of respiratory infections and cancers overlapped with COVID-19 clusters. Likewise, Ramirez and Lee [48] showed evidence of spatial autocorrelation with asthma, specifically in northern Colorado. Similarly, Saffary et al. [28] found spatial dependence in COVID-19 mortality and diabetes in US counties. Elsewhere in Mexico, COVID 19 mortality rate and cardiovascular disease were geographically clustered in Quintana Roo, Baja California, Chihuahua, and Tobasco [49]. This was further confirmed in the study of Javaheri [50], which showed that the municipalities with the highest cases of diabetes, cardiovascular disease, asthma and hypertension recorded the highest COVID-19 morbidity and mortality rates. In Tehran, Iran, COVID-19 cases and mortality were significantly clustered in its eastern region where there were underlying diseases such as heart disease, diabetes, cancer and respiratory disorders [51].

4 Conclusion

The strength of this study was to determine the effect of pre-existing medical conditions on the spatial pattern of COVID-19 in Nigeria. It found a spatially varying relationship between COVID-19 and obesity. Obesity as a pre-existing medical condition was a risk factor of COVID-19 in Nigeria. This further buttresses the fact that states with high prevalence of underlying health challenges have high COVID-19 prevalence. Although obesity as a risk factor of COVID-19 was strongest in some parts of the country, the prevalence of obesity across the country has been an issue of serious health concern even before the arrival of COVID-19 [29]. As a result, it is important that adequate measures are put in place to check the prevalence of obesity, given its risk effect on COVID-19 and human health in general. However, there is a major limitation of the study that needs to be stressed. The data on obesity is not representative of the Nigerian population, because it is based on women between the ages of 15 and 49. Another limitation is the study could not examine the effect of other pre-existing medical conditions such as cancer and cardiovascular diseases, due to the paucity of data. Though the lockdown was beneficial to some extent, it has the possibility of increasing the risk of being obese if any is enforced in the near future. In light of the results, we recommend that geographically targeted interventions such as non-pharmaceutical (face mask use, physical distancing, hand hygiene, public awareness campaigns) and pharmaceutical (increased COVID-19 vaccination allocation and uptake) measures should be directed at states with the greatest need.

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Conflict of interest

The authors state no conflict of interest.

Ethical approval

The conducted research is not related to either human or animal use.

Data availability statement

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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