Geospatial Modeling of Socio-Economic and Environmental Determinants of Typhoid Fever in Kano State, Nigeria

Ishaq A. Abdulkarim (✉ iaaliyu.geo@buk.edu.ng)

Bayero University Kano <https://orcid.org/0000-0001-9539-365X>

Hassana Sulaiman Salisu

Bayero University Kano

Mohammed Ahmed

Bayero University Kano

Murtala Uba Mohammed

Bayero University Kano

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Geospatial Modelling of Socio-Economic and Environmental Determinants of Typhoid Fever in Kano State

By

Ishaq Aliyu Abdulkarim¹, Hassana Sulaiman Salisu², Mohammed Ahmed³, and Murtala Uba Mohammed⁴

^{1,2,3,4}. Department of Geography, Bayero University, Kano, PMB. 3011, Nigeria

Corresponding Author: iaaliyu.geo@buk.edu.ng

Abstract

Typhoid is a significant health problem, particularly in developing countries like Nigeria where access to sanitation is still a challenge. This study modeled the socio-economic and environmental determinants of typhoid fever in Kano State, the most populated state located in the northwestern part of Nigeria. Data was collected from the State Hospital Management Board after submitting the requirement for ethical approval. Landsat 8 image was downloaded from an open-source website USGS earth explorer and Kano state administrative boundaries from GRID3 websites. Land use/land cover maps and Kano priority data were collected from the Department of Geography, Bayero University Kano. The study used 6 variables: literacy rate, population density, housing density, urbanization, NDVI, and LST to model typhoid fever. Based on the study's findings the Kano Municipal, Gaya, Gezawa and Bebeji recorded the highest prevalence per 10,000 persons of above 300. That there is a significant association between 5 of the 6 factors (with exception of land surface temperature (LST)). Out of the 5 factors, 4 showed positive significance (literacy rate, Population Density, Household density, and Percentage Urban) while the mean NDVI is the only one that showed a negative significance. The coefficient of determination (R square) is < 0.5 (0.374488) which showed the variable poorly described the prevalence rate. The model was also found to be biased because the Jarque-Bera Statistic is statistically significant which means the study is missing one or more key explanatory variables. It was recommended that the government should invest more in Data acquisition to help improve the quality of research in the study area.

Key Words: Typhoid fever, Prevalence, Prediction, GIS,

Introduction

The paucity of epidemiological data regarding invasive Salmonella disease often known as typhoid in sub-Saharan Africa led the WHO to call for a continent-wide approach in generating more accurate disease incidence and antimicrobial susceptibility data in 2008 (WHO, 2008).

Typhoid and paratyphoid fever have acute clinical manifestations with an incubation period ranging from 5 to 12 days. The symptoms associated with typhoid fever include general malaise abdominal manifestations, rosella, sweating, headache, anorexia, cough, weakness, sore throat, dizziness and muscle pain, neuropsychiatric manifestations (between 5 and 10% of cases), and when the case is severe patients suffer from bradycardia, splenomegaly, and hepatomegaly (Parry *et al.*, 2011). After 3-4 weeks of pro infection 10-15% of infected patients, in some untreated cases S. Typhi infection subsequently leads to gastrointestinal bleeding, intestinal perforation, and encephalopathy, finally patients will experience shock (Parry *et al.*, 2011; Azmatullahet *et al.*, 2015).

In Nigeria, typhoid fever remains a major disease because of factors such as increased urbanization, inadequate supplies of potable water, regional movement of large numbers of immigrant workers, inadequate facilities for processing human waste,

overburdened healthcare delivery systems, and overuse use of antibiotics that contribute to the development and spread of antibiotic-resistant *S. Typhi* (Abdulkarim and Mohammed, 2017; Akinyemi *et al.*, 2018).

Getting a true incidence of typhoid fever is difficult to evaluate in Nigeria because of the lack of a proper coordinated epidemiological surveillance system (Abdulkarim and Mohammed, 2017). Nevertheless, information on typhoid fever prevalence has been documented by several researchers in some states in Nigeria (Ifeanyi 2014; Isa *et al* 2013; Uttah *et al.*, 2013). Studies on typhoid in Nigeria, such as Ibegbulam-Njoku, Chijioke-Osuji, and Duru (2014) observed a high prevalence among people aged 26-35years. This is in line with an earlier study by Isa, *et al* (2013) who reported high cases for patients 13- 24 and 25-46years, some observed high prevalence among children aged 0-5years and 13-24years (Ifeanyi 2014; Isa *et al.*, 2013; Utah *et al.*, 2013).

Modeling has been applied in the disease prevalence studies like Cvjetanović, *et al* (1971) that estimates the possible effect of improvements in sanitation. The incidence decreases to a new level of stability when the transmission of the infection is reduced because of improved sanitation. Tilahun *et al.*, (2017) modeled the Optimal Control of Typhoid Fever Disease with Cost-Effective Strategies, which indicated that is the best cost-effective strategy. Spatial modeling uses some physical factors (Akullian *et al*, 2015), spatial autocorrelation, and moran *I* (Corner *et al.*, 2013; Dewan *et al.*, 2013). Several studies on Typhoid fever have been conducted in the study area; however, most of the researches are clinically based researches including Diagnostic Value of Widal Test in Febrile Children (Adeleke and Nwokedi, 2008), leukocyte count of Typhoid fever patients (Sarkinfada and Abubakar, 2001), Prevalence and Multiple Antibiotic Resistance (Mas'ud and Tijjani, 2015), Typhoid enteric perforation, (Edino, *et al.*, 2004) and incidence of Salmonella species, (Abdullahi, 2010). The few non-clinical studies used records of not more than 5 years from very few major health care facilities leaving out records from the general hospitals and records from the State Ministry of Health. Statewide studies done include spatial and temporal analysis of Typhoid Fever morbidity and mortality (Benjamin 2002, Abubakar 2015, Abdulkarim and Mohammed, 2017, Abdulkarim and Adamu 2019; Abdulkarim, Yakudima and Zakari, 2018).

In Nigeria typhoid risk mapping using GIS is still an area that needs attention, as there is little research on such. Typhoid cases have been a very huge problem for day-to-day activities in Nigeria. The use of Geospatial techniques will help. In taking necessary measures to mitigate the diseases. It is on this note that this study adopts the used the socioeconomic and environmental factors using geospatial techniques to model typhoid fever. GIS not only provides the maps and plots of the cases but also gives the spatial combination of various data including the socioeconomic, distribution of disease, geographical data such as the landscape, rivers, and weathers.

Material and Methods

Study area

Kano State lies between latitudes 10°30'N and 12°30'N, and longitudes 7°30'E and 9°25'E. It is bordered on the north and east by Jigawa State, on the west by Kaduna and Katsina States, and the south by Bauchi and Kaduna States (Figure 1). The state lies within the Sudan Savanna, with a very small portion lying within the Guinea Savannah to the south. The climate of the area is tropical wet and dry, categorized as Aw by Koppen's (Achugbu & Anugwo, 2016), with high temperatures all year (Mustapha *et al*

2014) and determined by the movement of the Inter-Tropical Discontinuity (ITD) zone (Abdulhamid, Badamasi & Mohammed, 2014).

Figure 1: Kano State

Three distinct seasons have been recognized by temperature regimes. Cold and dry, hot and dry, and warm and wet are the three seasons. The cool dry season, which lasts through February, begins in November. The average monthly temperature is between 21 and 23 degrees Celsius, with a high of 23 degrees and a diurnal range of 12 to 14 degrees Celsius. The Harmattan winds characterize this period. Between March and the middle of May, there is a hot and dry season that follows. It has a high mean monthly temperature of 30 degrees Celsius and a diurnal temperature range of up to 200 degrees Celsius. The wet season is the third phase; it is hot, with a mean monthly temperature of around 260 C and a diurnal range of 100 C, which can reach 130 C in September (Olofin, 2008). From the middle of May through the end of October the third season is the longest. This period is marked by the Harmattan winds. There is a hot and dry spell between March and the middle of May. The wet season is the third phase; it is hot, with a mean monthly temperature of 260 degrees Celsius and a diurnal temperature range of 10 degrees Celsius, which can reach 13 degrees in September.

The wet season is the third phase; it is hot, with a mean monthly temperature of 260 degrees Celsius and a diurnal temperature range of 10 degrees Celsius, which can reach 13 degrees in September. The third season is the longest, lasting from the middle of May until the end of October. Rainfall in the typical year ranges from 800mm in Kano metropolitan areas to 1000mm in the state's southern region (Olofin, 2008; Mustapha, *et al*, 2014). Qualities of the study area make it suitable for the bacterium that causes typhoid fever, as well as the disease itself thrive.

Data collection

The type of datasets used for this study includes:

1. Landsat 8 image with a spatial resolution of 30m acquired from USGS earth explorer

2. Kano State, local governments and ward Administrative boundary shapefiles acquired from Geography Department Bayero University Kano, Nigeria
3. Land use and Land cover maps from Department of Geography Bayero University Kano, Nigeria
4. Kano State priority Data from National Bureau of Statistics
5. Data record of 2006-2015 Typhoid cases local government and ward-level data from, Ministry of Health Kano State. This data was collected from the Kano Ministry of health after submitting the entire requirement and receiving ethical approval to have access to the data. The ward and local government level data was received from the records department in all general hospitals in excel file format. It was proofread to select those that are accurate for the research work. The Landsat 8 image was downloaded from an open-source website USGS earth explorer and Kano state administrative boundaries from GRID3 websites. Land use/land cover maps and Kano priority data were collected from the Department of Geography, Bayero University Kano.

Literacy rate

The percentage of people with a minimum of secondary calculated from the Kano Literacy data from National Bureau Statistics for each Local government.

Population density

Given that population density is among the factors that influence the incidence of typhoid (Corner et al, 2013), the population density of the study areas was then estimated based on Nigeria's 2006 Census data using the total population and total area for each local government. This was done using the following equation.

$$\text{Population density} = \frac{\text{Total population}}{\text{Total land area}} \quad (2)$$

Household density

This was derived from the Kano State priority data where the number of households in each local government was used to estimate the household density in the area using the following equation.

$$\text{Household density} = \frac{\text{Total household}}{\text{Total land area}} \quad (3)$$

Percent urbanisation

Salmonella Typhi (typhoid fever) occurs in urban areas with poor sanitation (Akullian *et al.*, 2015). So this is a very important variable. This was derived from the Land use/ Land cover shapefile map source from the Department of Geography, Bayero University Kano. The urban areas (Major and Minor Urbans) were selected using the selection by attribute tool in ArcGIS 10.5 and exported as new shapefile data. The area of the urban area for each local government was calculated to calculate geometry in the attribute table in ArcGIS 10.5 and the percentage urban was calculated using the following equation:

$$\text{Percentage urban} = \frac{\text{Urban Area}}{\text{Total land area}} \times 100 \quad (4)$$

The normalised differential vegetation index and land surface temperature

The Landsat images were downloaded as compressed files. Each of these files was extracted and some of the Landsat bands 2, 3, 4, 5, 6, 7, 10, and 11 were stacked using a multi-stack image tool in ENVI software. Image atmospheric correction was done using the dark pixel subtraction algorithm as well as image sub-setting in ENVI software.

The Normalised Differential Vegetation Index (NDVI) which is a vegetation indicator plays a role in the cycle of Salmonella Typhi, hence various researches used it in modeling typhoid (Corner *et al.* 2013; AbuTaleb *et al.*, 2018; Wang *et al.*, 2013). The NDVI, acquired by images, reflects the rate of vegetation intensity. This makes it an efficient indicator of vegetation and eco-environment in the locations where typhoid/paratyphoid Salmonellae occur. The study used the index values with spatial resolution 30 by 30 meters from the Landsat 8 image. As indicated by Rouse *et al.*, (1974) the NDVI is based on the difference between the maximum reflection of radiation in the near-infrared spectral bands (0.78–0.90 μm) and the maximum absorption of radiation in the red spectral band (0.63–0.69 μm). The difference of the reflectances is normalized by their sum, reducing the effect of shadows, resulting in equation (5)

$$\text{NDVI} = \frac{(B_{\text{INR}} - B_{\text{RED}})}{(B_{\text{INR}} + B_{\text{RED}})} \quad (5)$$

Where BINR is in the near-infrared band and Bred is the red band i.e. bands 4 and 5 in Landsat 8. This was computed using the raster calculator tool in ArcGIS 10.5 and the Mean NDVI for each local government using the Zonal Statistics Tool.

Another aspect of the remote sensing data (Landsat) is the generation of Land Surface Temperature (LST). This is an important climate variable, related to surface energy balance and the integrated thermal state of the atmosphere within the planetary boundary layer. Land surface temperature plays a basic role in the Salmonella Typhi life cycle. It has been reported that different activities are corresponding to the LST (Dewan *et al.*, 2013). Calculating LST uses the two thermal bands of the Landsat 8 image (band 10 & band 11) and converts them to Top of Atmosphere (TOA) temperature (Eq. (6)) then TOA to Brightness Temperature conversion (Eq. 7). Emissivity is required to calibrate the TOA temperature to LST. Emissivity can be estimated using the NDVI using the linear relationship provided in Eq. (8). According to El-Shirbeny *et al.* (2016), LST is calculated using Eq. (9).

$$\text{TOA (L)} = M_L * Q_{\text{cal}} + A_L \quad (6)$$

$$\text{BT} = \left(\frac{K_2}{\left(\ln\left(\frac{K_1}{L}\right) + 1 \right)} \right) - 273.15 \quad (7)$$

$$\varepsilon = 0.004 * P_v + 0.986 \quad (8)$$

$$\text{LST} = \left(\frac{BT}{\left(1 + \left(\frac{0.00115 * BT}{1.4388} \right) * \ln(\varepsilon) \right)} \right) \quad (9)$$

Where:

M_L = Band-specific multiplicative rescaling factor

Q_{cal} = Corresponds to band 10

A_L = Band-specific additive rescaling factor

K_1 = Band-specific thermal conversion constant

K_2 = Band-specific thermal conversion constant

L = TOA

P_v = proportion of vegetation P_v

$$P_v = \text{Square} ((NDVI - NDVI_{\min}) / (NDVI_{\max} - NDVI_{\min})) \quad (10)$$

BT = Brightness Temperature

ε = Emissivity

The TOA and BT were calculated using the Radiometric tool in ENVI 5.1. and imported into the ArcGIS 10.5 as TIF. The ε (emissivity) was calculated using a raster calculator and used to calibrate BT into LST using the raster calculator in ArcGIS 10.5. The mean temperature for each local government was calculated using a zonal statistic tool.

Modelling the prevalence rate

Regression tools in ArcGIS were used to examine, and explore spatial relationships, to better understand the factors behind observed spatial patterns, and to predict outcomes based on that understanding. To model this spatial relationship in this study Geographically Weighted Regression (GWR) was used as Dewan *et al.* (2013); and Corner *et al.* (2013). GWR attempts to capture this variation by calibrating a multiple regression model which allows different relationships to exist at different points in space. This technique is loosely based on kernel regression. The method itself is introduced and related issues such as the choice of a spatial weighting function are discussed. To use this model a range of statistical techniques were employed in this study.

Pearson's correlation

First of all, a matrix of pair-wise Pearson's correlation coefficients was computed using SPSS 25 to determine the interrelationship between the potential predictor variables and the relationship to incidence rate. After the correlation, any variable which has no significant relationship will not be used in the next model for more accurate results or swift implementation of the model.

Ordinary least squares regression (OLS)

Geographically Weighted Regression (GWR) is a local, spatial, regression method that allows the relationships you are modeling to vary across the study area. This is an upgrade on OLS and the last step in this study. It extends the conventional regression model by incorporating spatial information such as coordinates in the data (Corner *et al.* 2013). It is a measure of local rather than global parameter estimates and is effective in determining the underlying local factors for particular spatial patterns.

All the factors and incidences were inserted in excel corresponding with each local government. Each government was given a unique id and save for easy access from both SPSS 25 and ArcGIS for the analysis above.

Geographically weighted regression

The complete theory and background of the GWR model are presented in Fotheringham *et al.* (2002). The GWR is an extension of the global regression model, presented in Equation 11.

$$y = \beta_0 + \beta_1 x_i + \varepsilon_i \quad (11)$$

Where y represents the dependent variable, x is the independent variable, β_0 are the intercept and slope coefficients, and ε_i represents the error term.

Result and Discussions

Typhoid fever prevalence in Kano state

From the study's findings, there is a variation in the prevalence rate of typhoid in the state. Kano Municipal, Gaya, Gezawa, and Bebeji recorded the highest incidence per 10,000 persons of above 300 while Doguwa Kibiya and Tsanyawa have the lowest with less than 10 prevalence rates. (Figure 2A)

Data collected from the National Bureau of Statistics shows that Fagge, Tarauni, and Kumbotso are the only local government above 30% with their population with a minimum of secondary school education which is the highest. While the worst with less than 15% can be found in Rimin Gado, Kunchi, Dambatta, Makoda, Kabo, Karaye, Rogo, Minjibir, Warawa, Ajingi, Gaya, Takai, Bunkure, Rano, Kibiya, Garko, Takai, Tudun and Sumaila. In general, the literacy level in the state is poor (Figure 2B)

Population density and housing density

Kano State is the most populous state in Nigeria with one of the highest population densities in the country, especially in the Metropolitan Kano. The finding of the study indicates that Ungogo, Kumbotso, Tarauni, Gwale, Dala, Fagge, Nassarwa, and Kano Municipal are the local government with the highest population density of above 10,000 persons/km². All of these 8 local government areas are located within the metropolis (Figure 2C). Just like the population density the data analyzed also shows that the housing density varies across the state with the highest being among the eight local governments that constituted the Kano Metropolis. Kano municipal, Nassarwa, and Dala have the highest Household Density with above 2000 households/km² (Figure 2D)

Percentage urban

The land use land cover map shows Major and Minor Urban areas which were combined as one for this study. The urban areas are concentrated towards the metropolis area of the state (Figure 2E). Kano municipal has the highest percentage of urban area 98.3% of the total land area being urban which is closely followed by Dala 90% and Nassarawa 75%. There are also local government with 0% urban which include Garun Malam, Kunchi, Madobi, Makoda, Minjibir, Rano, Rimin Gado, Rogo, Shanono, Tsanyawa and Warawa (Table 1).

Figure 2: Spatial Distribution, Socioeconomic and Environmental Determinants of Typhoid Fever in Kano State

Table 1: Percentage urban of each local government area

Local Government	% Urban	Local Government	% Urban	Local Government	% Urban
Ajingi	0.18	Gwarzo	0.65	Nassarawa	75.00
Albasu	0.35	Kabo	0.29	Rano	0.00
Bagwai	0.22	Gaya	45.64	Rimin Gado	0.00
Bebeji	0.19	Gezawa	0.52	Rogo	0.00
Bichi	0.16	Gwale	0.19	Shanono	0.00
		Kano			
Bunkure	0.44	Municipal	98.63	Sumaila	0.09
Dala	90.00	Karaye	0.30	Takai	0.55
Dambatta	0.36	Kibiya	0.20	Tarauni	74.42
Dawakin Kudu	0.87	Kiru	0.93	Tofa	0.27
Dawakin Tofa	0.71	Kumbotso	4.31	Tsanyawa	0.00
Doguwa	0.14	Kunchi	0.00	Tudun Wada	0.10
Fagge	60.18	Kura	1.96	Ungogo	27.92
Gabasawa	0.06	Madobi	0.00	Warawa	0.00
Garko	0.40	Makoda	0.00	Wudil	0.59
Garun Malam	0.00	Minjibir	0.00		

NDVI and land surface temperature

The vegetation (NDVI) indicators (-1 to +1). Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0 to 0.1) generally correspond to barren areas of rock, sand, or snow. Low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (Gandhi, *et al.* 2015; Bid, 2016). The data analysis shows that the minimum value is -0.945 while the maximum value is +0.987 which is within the range. With lower values indicating water bodies in the state (-0.945 – +0.00147). While the values +0.00147 – 0.15 show barren lands and 0.4 – 0.987 showing vegetation (Figure 2F). The land surface temperature shows a minimum temperature value of 14.57°C and a maximum value of 35.72°C. The low temperature is distributed in locations closer to the water bodies (Figure 2G).

Relationship between the typhoid fever prevalence and socioeconomic and environmental factors

To model the factors, three models which involve Pearson's correlation, Ordinary Least Squares regression (OLS), Geographically Weighted Regression (GWR) were done using the SPSS 20.0 and ArcGIS software.

The Pearson's correlation result shows that there is a positive and very significant correlation between typhoid fever incidence and percentage literate ($r=0.394^{**}$). Population density ($r=0.537^{**}$), household density ($r=0.550^{**}$) and percentage Urban ($r=0.570^{**}$).

Table 2: Correlation between the factors and prevalence

	Incidence /	% Literate	pop density	household density	% Urban	Mean NDVI	Mean LST
Incidence	1						
% Literate	.394**	1					
pop density	.537**	.692**	1				
household density	.550**	.620**	.972**	1			
% Urban	.570**	.739**	.941**	.928**	1		
Mean NDVI	-.381*	-.566**	-.770**	-.737**	-.731**	1	
Mean LST	-.006	-.330*	-.324*	-.308*	-.332*	.570**	1

**Correlation is significant at the 0.01 level (2-tailed)

*Correlation is significant at the 0.05 level (1-tailed).

While there is a significant negative correlation with NDVI ($r=-0.381^*$) and a weak one with LST ($r=-0.006$). This is a clear pointer that surface temperature change is not much related to the incidence of Typhoid fever.

Modeling typhoid fever

From the result it shows that all of the factors used in the study have a statistical significance with the incidence rate as the Probability and Robust Probability, measure coefficient statistical significance (Table 3). . All but NDVI (2.475117) and Percentage Literacy (2.641076) showed a poor Variance Inflation Factor (VIF) values (> 7.5) which indicates redundancy among the variables as indicated by Breyer (2013) (see Table 4). The result in this study shows a low R squared of 0.3745 (Table 4) which indicated that the model can explain just 37% (which is weak a performance indicating the existence of other factors that is needed to incorporate in the model. These factors not considered by the study include the hygienic practice, behavioural factors, and access to water and sanitation.

Table 3: Summary of OLS results

Summary of OLS Results - Model Variables								
Variable	Coefficient [a]	StdError	t- Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
% Literate	7.205787	2.590382	2.7817	0.008064*	2.579602	2.793371	0.007824*	2.641076
Population Density	0.009100	0.002208	4.1217	0.000173*	0.001712	5.316947	0.000004*	27.342297
Household Density	0.068955	0.016155	4.2683	0.000110*	0.013037	5.289013	0.000004*	22.688898
% URBAN	2.632829	0.585881	4.4937	0.000054*	0.368157	7.151371	0.000000*	11.054453
NDVI	-2075.005	777.244135	-2.6696	0.010750*	745.974546	-2.78160	0.008067*	2.475117

* Statistically significant p-value ($p < 0.01$).

Table 4: OLS diagnostics

OLS Diagnostics			
Input Features:	KanoTyphoid	Dependent Variable:	Incidence
Number of Observations:	44	Akaike's Information Criterion (AICc) [d]:	678.523610
Multiple R-Squared [d]:	0.447222	Adjusted R-Squared [d]:	0.374488
Joint F-Statistic [e]:	6.148735	Prob(>F), (5,38) degrees of freedom:	0.000288*
Joint Wald Statistic [e]:	125.902556	Prob(>chi-squared), (5) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	4.900206	Prob(>chi-squared), (5) degrees of freedom:	0.428180
Jarque-Bera Statistic [g]:	16.659350	Prob(>chi-squared), (2) degrees of freedom:	0.000241*

* Statistically significant p-value ($p < 0.01$).

Figure 3: Scatter Plots of Variables

Geographically weighted regression (GWR)

GWR is designed to explore spatial non-stationarity in parameters i.e. a variable might be an important predictor of typhoid incidence in some locations of the study, but perhaps a weak predictor in other locations. This means the model results can likely be improved by moving to Geographically Weighted Regression (Breyer, 2013).

Table 5: Geographically weighted regression

Geographic Weighted Regression		
Bandwidth	44	
Residual Squares	427399.79805	
Effective Number	6.000883	
Sigma	106.054818	
AICc	545.955553	
R²	0.496843	
R²Adjusted	0.476843	
Dependent Field	0	INCIDENCE
Explanatory Field	1	% Literate
Explanatory Field	2	Population Density
Explanatory Field	3	Household Density
Explanatory Field	4	% Urban
Explanatory Field	5	NDVI

The GWR used to test the two variables showed also an adjusted R squared of 0.476843 which is low (Table 5) but better than that of the OLS. This shows that the GWR has a

better performance than the OLS (see Table 4). This coefficient of determination of 0.497 indicates that the variable used in the equation explained up to half of the variation in the prevalence of the disease and these points to the moderate performance of the model.

The study of Corner *et al.* (2013) contradicted the findings of this study which shows that the R square of the GWR was 0.731 which is above the desired outcome making the model performance very good. This difference might be as a result of other factors (Sanitation, Distance to water bodies, Sewage, and Access to good water) used in the previous studies (Corner *et al.*, 2013; Dewan *et al.*, 2013; Akullian *et al.*, 2015) which are very related to typhoid prevalence (Wang *et al.*, 2013; Abdulkarim and Mohammed, 2017; Akinyemi, 2018) and are missing in this study.

Conclusion and Recommendations

This study demonstrated the application of Geographic Information System (GIS) and remote sensing in an epidemiological study by predicting mapping, and modeling diseases using different environmental factors that can assist in the intervention and measures in eradicating the disease in this area. The result from this study provides a unique tool to understand the epidemiology of typhoid fever in Nigeria. The study provided a gap for feature research to improve the application. The study found that key variables are missing in the process of modeling which the study find hard to acquire due to time factor and poor availability of local government level and ward level data in Nigeria.

The study recommends the use of GIS by the health sector should be adopted by Government and NGOs to help in understanding and eradicating diseases. Government should invest more in Data acquisition to help improve the quality of research in the study area. Government should put more emphasis on Health so that the sector can be sufficiently funded to improve health service delivery.

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