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Modelling Accessibility to Primary Healthcare Facilities in Argungu LGA: Using Multiscale Geographically Weighted Regression (MSGWR) Approach

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ABSTRACT: This study uses socioeconomic and demographic data to demonstrate the value of a novel multidimensional approach to healthcare accessibility. The optimum location for healthcare facilities in relation to demand areas was determined using location-allocation models and local multiscale geographically weighted regression (MGWR) to explore spatially non-stationary relationships. The result shows that the potential accessibility of a community to primary healthcare depends on the geographic and socioeconomic characteristics of various places. The results of this study may be used to inform policy planning and decision-making for increasing accessibility to healthcare services, particularly in rural areas for achieving the Sustainable Development Goals (SDGs).

KEYWORDS: Healthcare, accessibility, location-allocation, demand, GWR

1. INTRODUCTION

Access to health facilities is a vital aspect of providing adequate health care to individuals especially in rural areas of developing countries (Murawski & Church, 2009). Planning and allocating health resources must be done using an accurate assessment of current healthcare accessibility (Ma, Luo, Wan, Hu, & Peng, 2018). Accessibility to healthcare services refers to how easily medical care may be obtained from a specific location (Polo, Acosta, Ferreira, & Dias, 2015). Due to limited resources and increasing demand, there will always be an imbalance between the supply and demand for healthcare resources. As a result, spatial distributions of healthcare resources need to be carefully assessed and continually improved for the sake of social equality (Gong et al., 2021). Certainly, the cost of obtaining health care is determined by a variety of factors, including the distance traveled to obtain healthcare services (Kizito & William, 2020). However, prior research have not concentrated on aspects of accessibility such age group, educational level, religious conviction, gender preference, cost of travel, cost of services, and availability of staff (Fu, Liu, & Fang, 2021). Travel impedance (travel time, distance, and cost) has been amply established by academics to be one of the most significant variables affecting people's physical access to service facilities (Zhou, Yu, Yuan, Wang, & Wu, 2020). To avoid healthcare inequities, it is advised by international standards that healthcare facilities be situated 5 kilometers or less from the place of demand. As stated in the Sustainable Development Goals (SDGs), the World Health Organization (WHO) states that the goal of creating health standards is to serve as a tool in the administration of health services and to strive for the highest quality of care feasible within the resources available. One of the 17 provisions of SDGs is the provision of adequate healthcare and population wellbeing. According to the World Health Organization, primary health care (PHC) is "basic healthcare that is universally accessible to individuals and families in the community at an affordable cost, based on practical, scientifically sound and socially acceptable methods and technology". PHC is the cornerstone of Nigerian health policy and most Nigerians' first point of contact with the healthcare system (NPHCDA, 2015). The Ward Minimum Health Care Package (WMHCP) was created to address this current strategy for delivering PHC services, and it consists of a set of health interventions and services that address health and health-related problems, resulting in significant health gains at low cost to the government and its partners. Among the primary support areas are child survival, maternal and newborn care, nutrition, non-communicable disease prevention, and health education and community mobilisation (NPHCDA, 2015). PHCs have recently been included in the fight against the Covid-19 pandemic.

According to estimates, around 54% of Nigeria's population has access to modern healthcare. Because of a lack of personnel and infrastructure, rural communities and the urban poor are underserved (PRIMASYS, 2017). Kebbi states has some of Nigeria's worst public healthcare services, according to previous surveys (Omoleke, Usman, Kanmodi, & Ashiru, 2021; Oyekale, 2017). Yauri, Dankani, and Wali (2018) attempted to explain geospatial access to healthcare facilities in Birnin Kebbi albeit using spatial pattern mapping. However, the major limitation of these studies is that they did not fully assess the relationship between healthcare accessibility (facility) and population (demand) in order to arrive at their conclusions. In order to gain a better understanding of Kebbi State's healthcare system, it is necessary to investigate this relationship.

Despite government policy mandating the establishment of at least one PHC in each ward several areas remain unserved since some healthcare facilities are located far from the people in need. Again, it is necessary to assess the geographic accessibility of healthcare facilities and make recommendations for methods to improve geographic accessibility in accordance with global best practices (Kizito & William, 2020). PHC facilities are still insufficient to fulfill the demands of an ever-increasing population in the study area. The few facilities that are available are not uniformly located and are not often within a reasonable distance of most settlements. A lack of equal healthcare facility distribution would have a significant impact on the healthcare delivery system especially, the sustainable development goal (SDG) (Lawal & Anyiam, 2019). As a result of these trends, new measures to reduce disparities in access to PHC facilities in the state and meet SDG's by 2030 are needed. This study, which is the first of its kind in the study area to our knowledge, combines location allocation and assesses the variations in the health service facilities then examines the variables that affect these variations. A location-allocation model is a method for finding optimal sites for facility locations. The method involves simultaneously selecting a set of locations for facilities and assigning spatially distributed sets of demands to these facilities to optimize some specified measurable criterion (Rahman & Smith, 2000). The rest of the paper is structured as follows: Section 2 reviews the related literature, while Section 3 discussed the main data source and methods of analyses. In Section 4, the results of the analyses are presented and models are discussed in Section 5. Finally, in Section6 the main findings are summarized, and future research is prospected.

2. LITERATURE REVIEW

2.1 Location-Allocation Model in Public Healthcare Delivery

The World Health Organization (WHO) recognizes the value of incorporating GIS in public health activities, especially, in modelling geographic heterogeneity in health behavior and outcome (Shaltynov, Rocha, Jamedinova, & Myssayev, 2022; Wang, 2020). In order to achieve the SDGs, geospatial data and methodology can be utilised to track progress and provide a solid framework for policymaking in health-related activities (WHO, 2018). The relationships between health, place and space including analyses of geographical patterns of healthcare access, monitoring, and intervention planning is well understood (Foley, Charlton, & Fotheringham, 2009; Shen & Tao, 2022). A framework for examining the use of health services and producing alternatives, either to suggest an efficient service or to improve health services, is provided by the integration of location-allocation and accessibility models (Abdelkarim, 2019). The goal of facility location decisions, also known as location-allocation problems, was to optimize the location of facilities to reduce cost and distance from demand and supply regions (Cooper, 1963). These choices are crucial in the long-term design of health-care programs (Zhang, Cao, Liu, & Huang, 2016). To achieve this, it is necessary to ensure that healthcare centers and other important health facilities are evenly spread and well-located so that people can easily access them. Previous studies have demonstrated that disparity exist among different socioeconomic and demographic settings in society (Fitzpatrick, Powe, Cooper, Ives, & Robbins, 2004; Kohlenberger, Buber-Ennser, Rengs, Leitner, & Landesmann, 2019; McMaughan, Oloruntoba, & Smith, 2020). This study aim to combined geospatial models and related socioeconomic and demographic attributes to explore their influence on access to healthcare facilities in Argungu LGA.

3. DATA AND METHODS

3.1 Study Area

Argungu Local Government Area (LGA) of Kebbi state was created in 1976 with headquarters at Argungu comprising 11 Wards. Argungu is also the headquarters of Argungu Emirate council which existed since the year 1515 founded by Muhammadu Kanta. It is the oldest emirate in the state and also home of the famous and widely attended Argungu international fishing and cultural festival which is the oldest known festival of its kind in Nigeria. According to 2019 population estimates, Argungu LGA has a population of 199,889 (NPC, 2019). Argungu LGA has total land area of 428 Km2 about 9.6 percent of the total landmass of Kebbi state. Most of the inhabitants of the area leaves along the marshy Fadama land and are mostly farmers, fisher men and hunters. Major crops produce in area include rice, vegetables and fruits in the fadama area while sorghum, millet, beans are the upland or rain-fed crops. Argungu LGA is located between latitude $12^0$30'0"N to $12^0$50'0"N and longitude $4^0$10'0"E to $4^0$50'0"E covering an area of 491.128 Km2 and elevation of 241 meters above sea level.

The study area enjoys tropical continental type of climate, which is largely controlled by two air masses namely; tropical maritime and tropical continental blowing from Atlantic and Sahara desert respectively. The air masses determined the two dominant seasons, wet and dry. Humidity is 27% while wind blow at 15Km/h in ESE direction. Argungu receive a mean annual rainfall of 800mm between May to September with a peak period in August, the remaining period of the year is dry. The average temperature is 26^0C and can rise up to 40^0C in the peak of hot season (March-July). However, during harmattan, (December – February) temperature falls to 21^0C. Figure 1 shows the location map PHC in Argungu LGA ward boundaries.

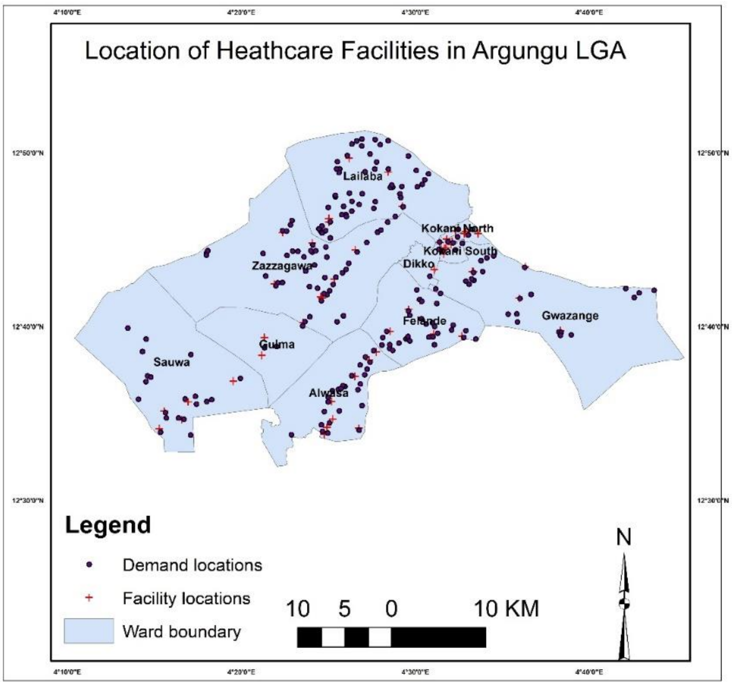

Figure 1 Location map of PHC in Argungu LGA ward boundaries

3.2 Data

In this study, data from both primary and secondary sources (Table 1) were used to complete the research successfully. The primary data, which include socioeconomic and demographic survey was designed and collected using the Open Data Kit (ODK) application tool during a field exercise. ODK is a free open source data gathering application that works with Android mobile devices and makes data available instantly via an online server. The Open Data Kit (ODK) is a commonly used data collection tool for research (Loola Bokonda, Ouazzani-Touhami, & Souissi, 2019). Based on the sample size determined in each ward, the questionnaire was then administered to households in all 11 wards of Argungu local government. The data collected are broadly grouped into 5 dimensions of access to healthcare: accessibility, availability, affordability, acceptability and adequacy based on literature (Levesque, Harris, & Russell, 2013). Recent literature have demonstrated the impact of contextual socioeconomic and demographic characteristics (e.g. age, gender and home ownership) on the community access to healthcare facilities (de Carvalho Dutra et al., 2021; Dotse-Gborgbortsi et al., 2022; Mansour, Al Kindi, Al-Said, Al-Said, & Atkinson, 2021).

Table 1. Secondary data sources

	Name	Description	Source
1	eHealth Africa data portal. Ward shapefiles, population estimates and healthcare facilities.	eHealth Africa has a wide variety of free geospatial datasets for research	https://hfr.health.gov.ng/facilities
2	OpenStreetMap (OSM). Road network datasets	OSM is a free open license collaborative geospatial database of the world	https://www.openstreetmap.org/export
3	Nigeria Health Facility Registry (HFR). Health facility locations and	HFR is a national database for all health facilities in Nigeria maintained by the Federal Ministry of Health.	https://hfr.health.gov.ng/facilities

3.3 Method of Data Analysis

In this study, the OSM data was first converted to network datasets in ArcGIS Pro software. These data were then clipped to the study area, and the Nigerian Health Facility Registry (HFR) website was used to verify the geolocation of the facilities acquired from eHealth Africa (see Table 1).

Accessibility Models

To measure spatial accessibility, the geometry centre (centroid) of each demand location is used to measure the travel distance between facility and demand areas (Polo et al., 2015). The location allocation tool is then used to choose the optimum candidate facility to serve a demand population according to specified parameters (e.g. between 1000 metres and 5000 metres). One of the most popular models for public facility location problems is the p-median problem (Basti & Sevkli, 2015; Gwalani, Tiwari, & Mikler, 2021; Mladenović, Brimberg, Hansen, & Moreno-Pérez, 2007; Shaltynov et al., 2022). In this model, the number of p facilities is determined for a given demand in order to minimize the overall weighted travel distance or time between facilities and demand centers Polo et al. (2015). This model assumes that the demand population users use the nearest facility. However, Jia et al. (2014) However, Jia et al. (2014) claim that one significant drawback of the traditional p-median model is that facilities might not always be assigned to demand locations. The p-median model can be formulated based on ReVelle and Swain (1970) Equation 1-5.

$$\min \sum_{i}^{n} \sum_{j}^{n} \alpha_i \, d_{ij} x_{ij}$$

(1)

Subject to

$$\sum_{j} ij = 1 \forall i$$

(2)

$x_{ij} \leq y_j, \forall i, j,$

(3)

$$\sum_{j} yj = p$$

(4)

$x_{ij} \leq y_j \in \{1,0\}$

(5)

where $x_{ij} = 1$ if demand i is assigned to facility j and $x_{ij} = 0$ otherwise, n is the number of demand sites, α_i is the population of demand i, d_{ij} is the shortest distance between i and j and p is the number of facilities to be located.

In this analysis there were 212 demand communities competing for only 50 healthcare facilities in the study area. Figure 2 shows some of the selected locations in the location-allocation model.

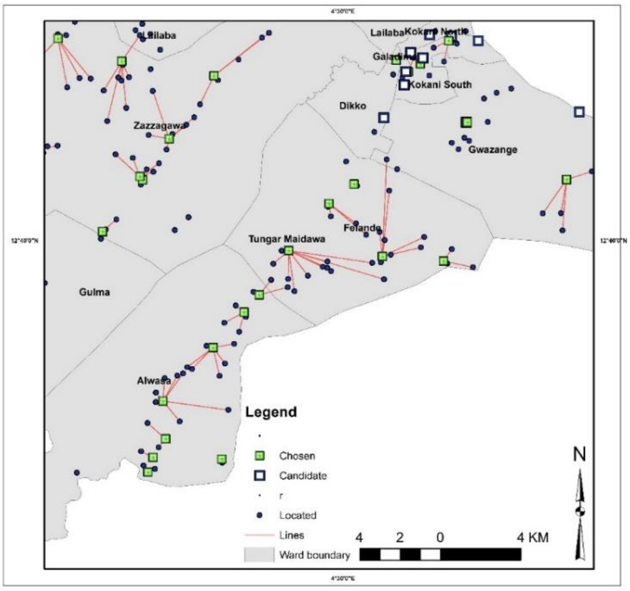

Figure 2. Some selected locations in the location-allocation models

Regression Models

In the second stage of the analysis, different regression analyses (global and local) were performed to explore the relationship between physical accessibility to healthcare and socioeconomic factors affecting it. To begin with, correlation analysis was conducted to assess the relationship between the variables (Figure 3).

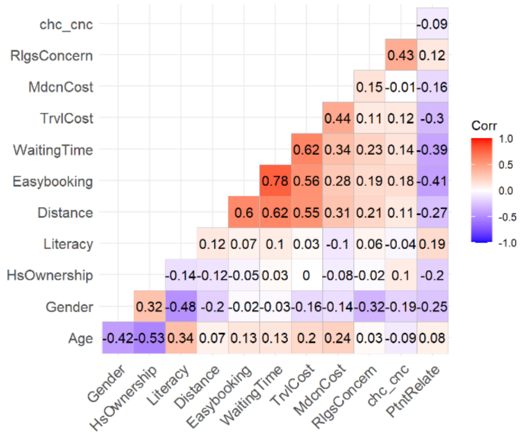

Figure 3. Correlation analysis between the variables

Ordinary Least Square OLS)

Initially, the ordinary least square (OLS) otherwise known as global regression (stepwise) was performed to reduce collinearity between the variables (Equation 6). However, the global model parameters derived from the OLS assumed that variables are constant over space (Charlton, Fotheringham, & Brunsdon, 2009) this assumption does not always hold as spatial variations in relationships is not stationary (Erdogan, Yalçin, & Dereli, 2013). The general specification of a multiple regression model takes the form of Equation 6:

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_n X_n + \varepsilon \qquad (6)$$

where Y is the value of the dependent variable, β_o is the constant intercept, β_1, β_2, β_3, β_n are the slope coefficients of the independent variables X_1, X_2, X_3, X_n,, while ε is a standard error of component.

If X_1 is significant it is retained, otherwise dropped

$$Y = \beta_o + \varepsilon \qquad (7)$$

In the next iteration variables with a higher correlation with Y are added

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \qquad (8)$$

Geographically Weighted Regression (GWR)

Spatial heterogeneity exist across space, hence the need for a localised model such as Geographically Weighted Regression (GWR) (Charlton et al., 2009). GWR is a (local) modelling technique to estimate regression models with spatially varying relationships (Fotheringham, Brunsdon, & Charlton, 2003). For model calibration in GWR, the choice of bandwidth is an important step (Equation 7). A bandwidth is a distance search window over which a localised model is controlled (Lu, Harris, Charlton, & Brunsdon, 2014). Bandwidths are locally chosen by a data-driven method based on minimization of a local cross-validation (CV) criterion (Arlot & Celisse, 2010; Vieu, 1991). A CV score is essentially the estimated squared production errors (Fotheringham, Charlton, & Brunsdon, 1998). However, different service facilities may have different characteristics resulting in spatial homogeneity heterogeneity to coexist (Liu et al., 2022). A typical GWR model is given in equation 9:

$$y_i(u) = \beta_{oi}(u) + \beta_{1i}(u) X_{1i} + \beta_{2i}(u) X_{2i} + \beta_{3i}(u) X_{3i} \ldots\ldots + \beta_{ni}(u) X_{ni} + \varepsilon \qquad (9)$$

$y_i(u)$ is independent variable at location *i,* (u) is a vector of two dimensional coordinates describing location *i,* $\beta_{oi}(u)$ is the intercept parameter at location *i* specific to that location, $\beta_{ni}(u) X_{ni}$ is the local regression coefficient for *nth* explanatory variable at location *i*.

Multiscale Geographically Weighted Regression (MSGWR)

In the standard form, a single bandwidth is used to calibrate GWR. This may be unrealistic because it implicitly assumes that each response-to-predictor relationship operates at the same spatial scale. Some relationships may operate at larger scales and others at smaller scales (Comber et al., 2022). GWR using single bandwidth is not capable to express such features, while MSGWR could alleviate such problems by assigning specific bandwidths for each variable based on iteration. MSGWR allows the relationship between the response variable and explanatory variables to vary spatially and at different scales (Fotheringham, Yang, & Kang, 2017; Mansour et al., 2021). GWR and its recently improved version-MSGWR have been widely used in the modelling of health-related issues to explore spatial variations in the parameter estimates in the study area (Foley et al., 2009; Fu, Liu, & Fang, 2021; Gao, Guhl, Boukebous, & Deguen, 2021; Liu et al., 2022). In this study, R statistical software and specifically, the GWmodel library was used for the calibration of the multiscale geographically weighted regression (MSGWR) using socioeconomic data obtained from the field survey. The optimum bandwidth for each independent variable was chosen using the AIC. The fact that AICc indicates model parsimony adjusted for small degrees of freedom and that its use helps to prevent over-fitting GWR models make its bandwidths more preferable to those discovered by CV and uncorrected AIC (AICc bandwidths tend to be larger than bandwidths found using CV and AIC) (Comber et al., 2022). In this study the AICc was used based literature.

RESULTS

In this study, the results of the location-allocation set at 5,000 metres (5KM) impedance cutoff, only 37 (about 74%) out of 50 facilities were allocated. Within this cutoff, 137 (about 65%) out of 212 demand communities were allocated to different healthcare facilities. The remaining 75 (about 35%) demand communities lies further away from the global benchmark based on Euclidean distance decay. The results indicate that 10 out of the 37 chosen facilities were allocated 1 demand community each. Tungar Maidawa facility in Felande ward has the highest allocation of 11 demand communities and population weight of 17,395. On the other hand, Ummara facility having 7 demand community allocation has the largest population weight of 18,285. Additionally, Gijiya facility has a population weight of 17,851 from 4 demand communities. The result also show that Ela Tungar Zazzagawa facility in Zazzagawa ward and Gwabare facility in Alwasa ward have the lowest population weight of 27 and 20 demand population respectively.

The results of the OLS model shows that only 5 statistically significant variables (age, gender, house ownership, travel cost and ease of booking) were retained. (Table 2).

Table 2. Stepwise OLS regression results

Variables	Estimate	Std. Error	t-value	p-value	VIF
(Intercept)	3.3739	0.4181	8.070	0.0000***	
Age	0.0185	0.0057	-3.219	0.0015**	1.605
Gender	0.3480	0.1089	-3.193	0.0016**	1.269
HsOwnership	0.1740	0.0682	-2.551	0.0110*	1.450
TrvlCost	0.4737	0.0922	5.135	0.0000***	1.659
Easybooking	0.8706	0.1198	7.262	0.0000***	1.469
Adjusted R^2	0.46				

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

To explore the spatial variation in the relationships with accessibility to healthcare facilities, GWR and MSGWR were applied to the same set of significant variables used in the global OLS models. Table 3 shows the comparison of the global and local models. The performance of the global OLS model was improved by the local models. MSGWR produced the largest adjusted R-squared (0.53) and lowest AICc (438.5963). In this analysis, the local models fit reduces the AIC by more than 3 units reflecting a more robust model of parsimony (Comber et al., 2020)

Table 3. Model comparison between OLS, GWR and MSGWR

Model	R^2	Adjusted R^2	AIC	AICc
OLS	0.47	0.46	439.2491	440.8252
GWR	0.49	0.47	431.2486	439.7979
MSGWR	0.53	0.49	419.0811	438.5963

The coefficients of the variable estimates of MSGWR model were also mapped to explore the spatial variation in the study area (Figure 4).

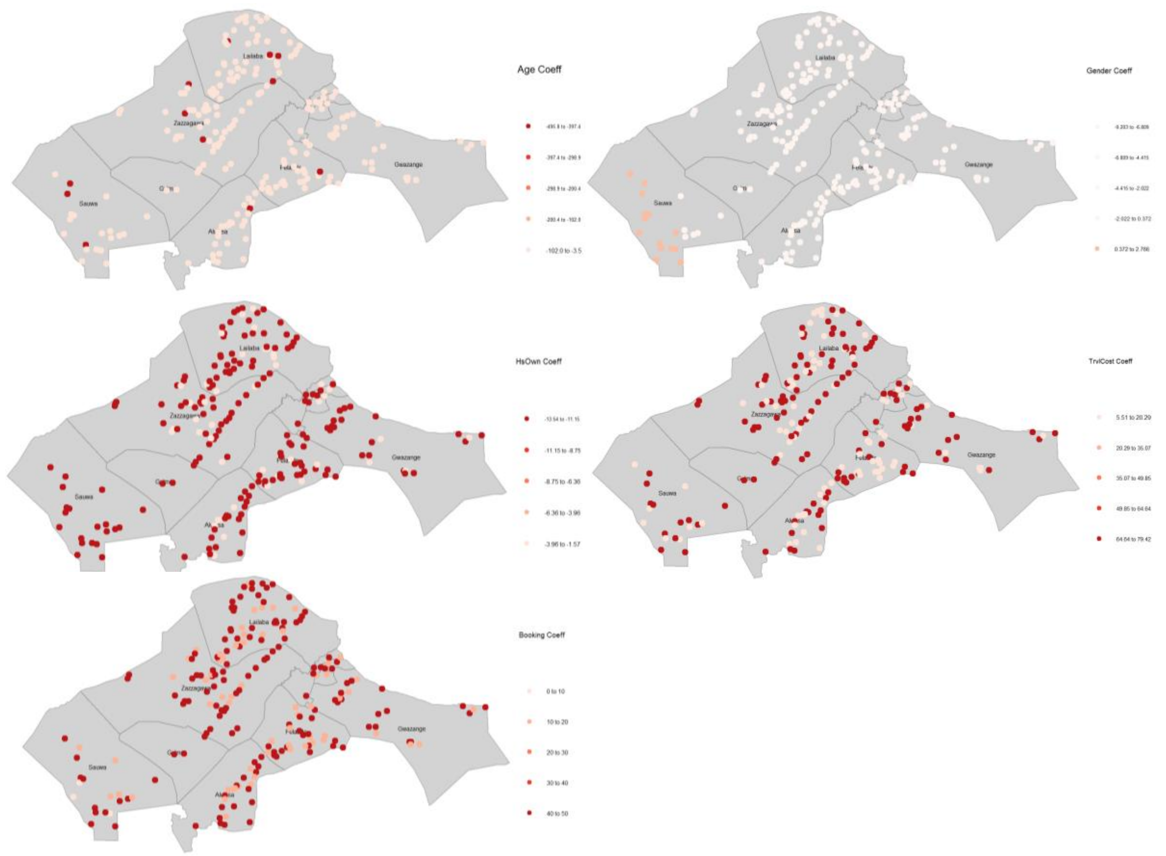

Figure 4. MSGWR coefficients of the estimates in the variation of accessibility to healthcare facilities.

The spatial distribution of the coefficient of age is negative across the study area. A possible reason for this relationship might be because the relatively older adults are more likely to access healthcare services than younger age group. Older adults might have different medical condition that requires them to seek for healthcare services.

The local spatial variation of the gender coefficient is negative in most of the communities except in communities in southern Alwasa ward where the coefficient is positive. This shows that women are most likely to seek for healthcare services than their male counterparts, however, the case is different in the communities in Alwasa ward. A possible explanation to this occurrence could be religious concern, though this has not been established in this study.

The negative coefficient of the home ownership used here as a proxy for socioeconomic status, revealed that access to healthcare services decreases with decrease in the socioeconomic status of individuals across the study area. Those who are economically more affluent are more likely to access healthcare services, considering that fact that healthcare delivery is dependent to some extent on affordability.

In terms of the distribution of coefficient of transportation cost, it can be seen that it has positive correlation with accessibility to healthcare services. This relationship indicate that as accessibility to healthcare services increases so also affordability of transportation cost increases. People who can afford transport fare are potentially more likely to access healthcare services.

The coefficient estimates of ease of booking for healthcare services is also positively correlated with accessibility across the study area. The relative ease with which individuals can book appointment for healthcare services is a factor of availability, which in turn affects their willingness to access healthcare services.

DISCUSSIONS

This study explored the multiscale impact of socioeconomic and demographic factors such as age, gender, home ownership on accessibility to healthcare facilities. The key findings from this research were that a set of sociodemographic variables were found to impact on accessibility to healthcare service and that these factors vary geographically, a factor also found in (Mansour et al., 2021). The study also found that socioeconomic and demographic characteristics of different areas, can complement location-allocation models for better understanding of accessibility to healthcare facilities (Heise et al., 2019; McMaughan et al., 2020). Surprisingly, healthcare facilities in Gulma, Dikko and Kokani wards were not allocated. Possible explanation for Dikko and Kokani wards might be because of their proximity to the general hospital in Argungu. Further research is needed investigate this occurrence.

CONCLUSION

This study explore the multiscale effect of socioeconomic and demographic factors on accessibility to healthcare facilities in Argungu LGA. The findings of this study might benefit policy planning for decision making for improving accessibility to healthcare facilities especially in the rural areas as stated in the Sustainable Development Goals (SDGs). This study used the threshold of 5KM to allocate demand communities to available facilities, therefore further analysis is needed to investigate how facilities can be relocated to increase accessibility.

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