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Research Method

Geographically Weighted Regression Analysis: A Statistical Method to Account for Spatial Heterogeneity

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Abstract
Ordinary linear regression (OLR) is one of the most common statistical techniques used in determining the association between the outcome variable and its related factors. This method determines the association that is assumed to be true for the whole study area – a global association. In the field of public health and social sciences, this assumption is not always true, especially when it is known that the relationship between variables varies across the study area. Therefore, in such a scenario, an OLR should be calibrated in a way to account for this spatial variability. In this paper, we demonstrate use of the geographically weighted regression (GWR) method to account for spatial heterogeneity. In GWR, local models are reported in which association varies according to the location accounting for the local variation in variables. This technique utilizes geographical weights in determining association between the outcome variable and its related factors. These geographical weights are relatively large (i.e. close to 1) for observations located near regression point than for the observations located farther from the regression point. In this paper, we demonstrated the application of GWR and its comparison with OLR using demographic and health survey (DHS) data from Tanzania. Here we have focused on determining the association between percentages of acute respiratory infection (ARI) in children with its related factors. From OLR, we found that the percentage of female with higher education had the largest significant association with ARI (P = 0.027). On the other hand, result from the GWR returned coefficients varying from -0.15 to -0.01 (P < 0.001) over the study area in contrast to the global coefficient from OLR model. We advocate that identifying significant spatially-varying association will help policymaker to recognize the local areas of interest and design targeted interventions.
Keywords: Acute Respiratory Infection (ARI), Geographically weighted regression, Ordinary linear regression, Tanzania
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Introduction

In the field of public health, geographic information system (GIS) is increasingly being acknowledged and utilized as one of the vital tools in investigation of spatial patterns.[1] GIS can be defined as a framework for automatic capture, storage, retrieval, analysis and visualization of spatial data.[2] Identifying that health related events are clustered within certain geographical location is necessary for the cost-effective and efficient distribution of health resources. In the classic epidemiological triangle of host, agent and environment, *place* is an axiomatic variable of environment. Tobler's first law of geography, "Everything is related to everything else, but near things are more related to than distant things"[3] provides the central framework of many geospatial statistics (i.e. spatial autocorrelation, spatial heterogeneity, etc). For example, attributes like temperature, climate, household income measured at a location are neither fixed nor changes drastically from place to neighboring place, but rather it progressively changes over space.

In determining the association between exposure and the continuous type of outcome variable, ordinary linear regression (OLR) is the most common statistical method used. This method relies on certain assumptions (i.e. normality, homogeneity, and independence of residuals) that should be held by the data to determine the unbiased estimate. Theoretically, such global models (see equation 1 of online Supplementary file 1, Section A) can provide reliable information in a situation if there is no variation across the study area. However, in the field of public health, such assumptions are not always true, especially when it is known that the variable varies across the study area (i.e. spatially non-stationary). Furthermore, in statistics, it is not uncommon that all observations are given equal importance. But in some scenarios, it might not be appropriate to treat all observations equally and therefore weight of each observation should vary. These weights can depend on the probability of sample selection, probability of receiving treatment (propensity score)[4] and geographical distances. Here, the objective is to present an expository research to demonstrate the use of geographically weighted regression (GWR) analysis.

Brief Note on Geographically Weighted Regression

The GWR, developed by Fotheringham and Brunsdon,[5] is a locally linear, non-parametric estimation technique for

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capturing spatial variations of the regression coefficients. Suppose we have a set of observations from certain number of cases on a set of explanatory variables. This is a standard data set that can be used for OLR modeling. Now, suppose that in addition to this, we also have a set of geographical location for each case. In this case, we can extend the OLR framework (equation 1 of Supplementary file 1, Section A) by incorporating geographical information that allows local rather than global estimation. In this sense, GWR is an extension of weighted regression, where the weights are defined by the geographical distance between observations and a new regression is run at each data point by scooping a sub-set of data. This allows parameter estimates to vary over the study area. The equation 2 of Supplementary file 1 (Section A) produces a continuous surface of parameter values with an inherent assumption that coefficients are deterministic functions of geographical (i.e. spatial) information within the model. These estimated coefficients at a given location can be mapped to reveal non-stationarity of the regression process.

One of the most important elements in implementing GWR is calibrating the model by a kernel regression method. Various weighting systems (kernel functions) have been proposed in the literature.[5-7] GWR uses a spatially-varying kernel function that is more intuitive in its application since it is based on the following assumptions:

a) observations near the index location have more influence on the estimation of parameter than do observations situated farther away from that index location, and
b) data points may not be distributed systematically with an equal distance across the study area.

Considering these two points, each local regression is based on a subset of data points located within specified distance. Fotheringham and Brunsdon[5] proposed using distance-weighted windows with each window consisting of certain number of nearest data points in which weight of each data point decreases continuously as the distance (i.e. bandwidth) between two points increases. Choosing the optimal size of the bandwidth is more important than selecting weighting function (discussed below). For specifying the spatially-varying kernel function, an adaptive (varying) distance was applied where the numbers of local data points are fixed within the search window (i.e. bandwidth). Adaptive kernel scheme was used as it is more suitable when the units of analysis are irregularly spread across the study area (Figure 1). To summarize the weighting mechanism, W_{ij} in equation 3 of Supplementary file 1 (Section A) is a weighting scheme that is conditioned in such a way that data points proximal to an index location receives larger weights which monotonically decreases towards the distal part of the window and ultimately reaching zero for observation just outside the window.

Application of Geographically Weighted Regression

In this section, we will demonstrate application of GWR using various packages in R. For simplicity, only important outputs are tabulated and significant spatial variation in the estimated local βs and their associated p values are shown by mapping. Also, see Supplementary file 1 (Section B) for R code that is written in Consolas font type to differentiate it from the general text.

Materials and Methods

To demonstrate the application and comparison of GWR with OLR, we analyzed the data from Tanzania Demographic and Health Survey (DHS) – 2015-2016.[8] In this survey, a two-staged sampling method was implemented in a way that final sample were representative at national level, sub-national level, rural and urban areas. All urban and rural areas were divided into smaller areas, known as Enumeration Area (EA). Within each EA, list of household served as the sampling frame for the selection of household for the second stage. In second stage of sampling, fixed number of households was selected through systematic sampling technique. A detailed note on DHS sampling technique can be found in the Supplementary file 1 (Section A) of Tanzania DHS report.[8] A nationally representative sample of about 13 400 households was selected, and with more than 90% of response rate, 13 000 women were interviewed. The survey collected detailed information relating to demographic, child health

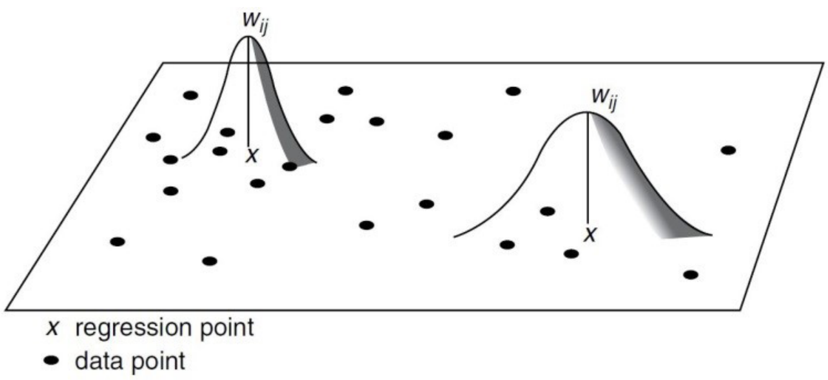

Figure 1. GWR with Adaptive Spatial Kernels (adapted from Fotheringham and Brunsdon[5]).

care and GPS coordinates from each EA. We extracted the information regarding episode of acute respiratory infection (ARI) from every mother with a child aged 0–59 months. The data was then exported to Esri ArcGIS 10.1 software, where data table was first merged with the DHS clusters and then aggregated at district level (n = 168). Beside the outcome variable, following seven explanatory variables were included in the model:

1. Percentage of mothers who belong to poor socioeconomic status in a district
2. Percentage of mothers residing in a rural area
3. Percentage of mothers who have completed secondary or higher education
4. Percentage of fathers who have completed secondary or higher education
5. Percentage of mothers who are not working
6. Percentage of mothers who has a girl child
7. Percentage of mothers who has a child aged between 48–59 months

Once the data is loaded in R, we can now run GWR to determine the association between percentage of mother whose child had an episode of ARI and seven explanatory variables.

Geographically Weighted Regression

As mentioned earlier, GWR is based on a framework in which kernel must be identified with an optimal size of the bandwidth. Bandwidth of a kernel can be user-defined or calibrated by an automatic process such as, cross-validation (CV) score or corrected Akaike Information Criteria (AICc). The AICc takes into account the different number of degrees of freedom in different models so that their relative performances can be compared more accurately. A model with a smaller AICc than another is considered to be a 'better' model. For this analysis, we used AICc-based methods using bw.gwr function from the GW model package. This function returns the number of nearest neighbours that will be used for local regression models. We found that model will be optimized with the smallest AICc by using 155 neighboring districts with highest weight assigned to the district which is located in the proximity to the index district. After obtaining bandwidth, we can feed this to the function gwr.basic to run the final model along with other specifications (Supplementary file 1, Section B).

Results

The descriptive statistics of all the explanatory variables of ARI in Tanzania are presented in Table 1, including the dependent variable. On average, there were almost 5% of the DHS cluster have a child having ARI in a district. The percentage of DHS cluster with an ill child ranges from 0% to 33% with relatively large standard deviation, indicating large variation within the study area. From Table 1, it can be seen that the range of percentage of poor household is wide with large standard deviation; consequently the spatial distribution of percentage of DHS cluster with poor household in Tanzania is widely varying without an observable pattern. The output of GWR analysis creates and stores both OLR and GWR. Table 2 shows the output of fitted OLR model. The F statistics (F = 3.05, *P* value = 0.005) indicate that the overall regression was significant. The variable % of female with higher education' had largest significant association with ARI (*P* value = 0.027) with one percent increase in the percentage of mothers who have completed secondary or higher education reduces the percentage of ARI in a given district by nearly seven percent. Similarly, percentage of ARI in a given district has a significant negative association with the percentage of mothers living in a rural area (*P* value = 0.014), and other variables are statistically insignificant. This OLR model identifies the 'global' relationship between exposure and explanatory variable, and it fails to report the local variation in the magnitude and direction of such relationship. To address the issue of multicollinearity, last column of table 2 reports the variance inflation factors (VIFs) for all explanatory variables are less than 5, indicating that the variables included in OLR are reasonable free from the effect of multicollinearity.

Table 1. Summary of Demographic Variables of Acute Respiratory Infection

Variables	Min	Max	Mean	SD
% of ARI	0	33	5	6
% of poor	0	100	60	32
% of rural	0	100	74	34
% of female with higher education	0	100	21	19
% of male with higher education	0	82	20	18
% of mother not working	0	78	18	15
% of girl child	5	80	49	8
% of child aged between 48-59 months	5	50	19	7

Abbreviation: ARI, acute respiratory infection.

On the other hand, GWR produces estimates for each location and therefore, number of local estimates is equal to the number of location. Table 3 presents the summary including minimum, maximum, 1st and 3rd quartile and median values of local estimates for all seven explanatory variables and intercept. It is evident from Table 3 that coefficients from GWR can vary from negative to positive association, explicitly showing that the relationship between outcome and explanatory variable is more complex than what appeared in OLR. Using the Monte Carlo technique, the result of randomization test on each of the coefficients is report in the last column of Table 3. It can be seen that the coefficients for intercept, % of poor, % of rural, % of female with higher education, and % of female children are significantly varying over the study area. For simplicity, we are only reporting coefficient and associated *P* value for one variable. Figure 2a gives a reflection of non-stationarity in the association between percentages of ARI and percentage of mothers who have completed

Table 2. Statistical Result of the OLR Model for Percentage of ARI

Coefficients	Estimate	SE	95% CI		*P* Value	VIF
			LL	UL		
Intercept	0.07	0.03	0.01	0.13	0.013	
% of poor	-0.02	0.03	-0.07	0.03	0.506	4.24
% of rural	-0.05	0.02	-0.08	-0.01	0.014	2.38
% of female with higher education	-0.07	0.03	-0.12	-0.01	0.027	1.93
% of male with higher education	-0.01	0.04	-0.06	0.08	0.753	2.42
% of mother not working	-0.03	0.03	-0.07	0.02	0.302	1.09
% of girl child	0.06	0.04	-0.02	0.13	0.122	1.08
% of child aged between 48–59 months	0.03	0.06	-0.09	0.15	0.595	1.07

Abbreviations: OLR, ordinary linear regression; ARI, acute respiratory infection; SE, standard error; LL, lower limit; UL, upper limit; VIF, variance inflation factor.

Table 3. Summary Statistics of GWR Model for Percentage of ARI

Coefficients	GWR Estimates					
	Min.	1st Quartile	Median	3rd Quartile	Max.	*P* Value*
Intercept	0.03	0.06	0.09	0.12	0.11	0.047
% of poor	-0.05	-0.04	-0.02	0.01	0.05	< 0.001
% of rural	-0.10	-0.07	-0.05	-0.03	-0.03	< 0.001
% of female with higher education	-0.15	-0.09	-0.09	-0.04	-0.01	< 0.001
% of male with higher education	-0.04	-0.01	0.02	0.03	0.05	0.969
% of mother not working	-0.07	-0.05	-0.04	-0.04	-0.03	1.000
% of girl child	-0.01	0.02	0.07	0.10	0.13	< 0.001
% of child aged between 48-59 months	-0.09	-0.04	-0.01	0.04	0.11	0.194

Abbreviations: GWR, Geographically Weighted Regression; ARI , Acute Respiratory Infection.
* *P* value significant at 95% confidence level.

secondary or higher education. Thus, GWR model does not yield a single interpretation on the association between dependent variable and explanatory variables. Looking at Figure 2b, we can identify that the observed association is not statistically significant in the Northwest region. Furthermore, to justify application of GWR, we calculated Moran's I for the residuals from GWR analysis and the pattern does not appear to be significantly different than random pattern (*P* value = 0.422).

Discussion

In this research, we demonstrated the application and comparison between OLR and GWR to determine the association between percentages of ARI at a district level with its related factors. The core element of GWR methodology is the use of distance weighted sub-sample of the data to produce locally linear regression estimates for each data point.[9] We illustrated that the associations between the dependent variable with its explanatory factors vary over the study area. This diversification in relationship can be attributed to the following two possibilities: *Firstly*, the spatial non-stationarity in the relationship between outcome and input variables is due to the fact that some relationships are naturally varying across space. Ha H, and Tu W. demonstrated spatially varying relationship between altitude and suicide rate in the United States of America.[10] Reich et al obtained individual-level explanatory variables with spatially varying associations with activity level in

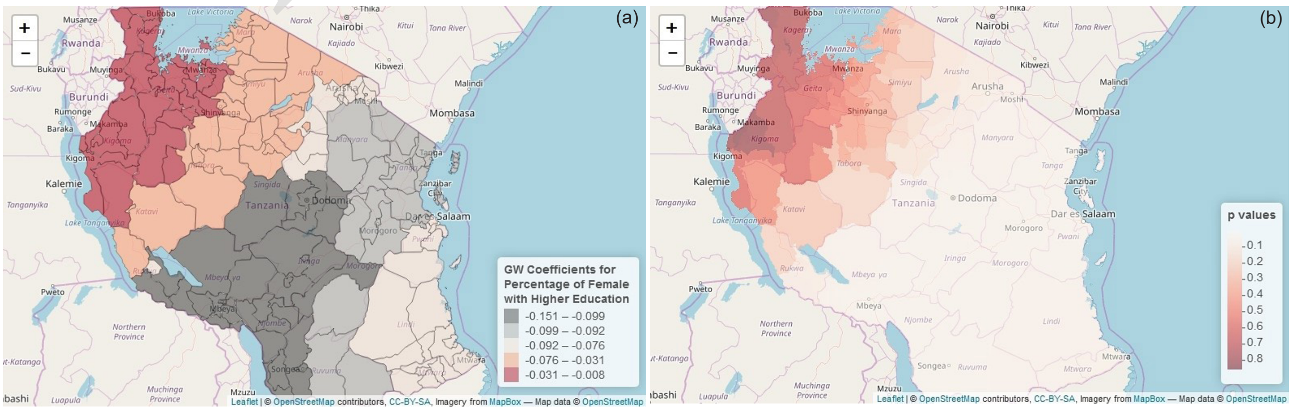

Figure 2. (**a**) Spatial Distribution of Adjusted Coefficients for the Percentage of Mothers Who Completed Secondary or Higher Education (**b**) and Their Associated *P* Value.

pregnant women.[11] Such findings that people's behavior have potential to vary over space is in concordance with the idea of importance of locality.[12] This is one of the most important advantages of the application of GWR models where regions with 'anomalous' relationships are being highlighted and become focus for future studies.[5] *Secondly*, it has been demonstrated by past research that GWR analyses are prone to estimate extreme coefficients including sign reversals. The massively fluctuating coefficients can be a sign of over-fitting in the local models or presence of local multicollinearity. This issue has been narrated by Fotheringham and Brunsdon in the context of variance-bias trade off, in which smaller bandwidth produces the tighter fitting estimators and may also result in extreme coefficients.[5]

Application of GIS in public health and epidemiology has profoundly improved the ability to analyze spatial data and generate spatially-varying etiological hypotheses. In most of the cases, epidemiological studies applying spatial analysis make use of an aggregated data incorporated within specific geographical boundary. In spite of the fact that such aggregation of an individual level data invariably results in loss of information, it also attains the propensity to investigate health related outcomes together with other additional data. In essence, GIS provides the ability to conduct repetitive tasks, rapid comparison of spatial data, handling large data set and voluminous outputs.[1]

Implementing and analyzing spatial methods on public health data within certain administrative units requires consideration of the fact that observations may be autocorrelated (i.e. the occurrence of an event within a given administrative unit makes more probable the occurrence of an event in neighboring administrative units). This concept is well-known as spatial autocorrelation. In accordance with Tobler's first law of geography,[3] disease patterns and its related demographic and environmental variables demonstrate spatial clustering. Therefore, influence of neighboring administrative units has to be taken into account.[13] In contrast to GWR, it is assumed in OLR that the observations have been selected randomly and cases are not spatially clustered. Nevertheless, when spatial autocorrelation is present, then the coefficients obtained from OLR would be biased because the area with higher concentration of events will have larger impact on the model estimate and will return overly precise estimates.

Inference for Policymakers

The outputs of this analysis gave richer understanding of the spatial epidemiology of the characteristics affecting ARI in Tanzania. Our expectation from these results is that such map will guide policymakers to direct interventions that are spatially and epidemiologically relevant to the region. This theoretical assumption is nevertheless limited by the fact that people migrating from one vulnerable region to another may change the regional profile of the relationship observed in GWR analysis.[14-16] Furthermore, the epidemiological implication of such a map is that the patterns observed can be related to possible (local) association with ARI in the study region. This offers significant leads for further investigation at the local level. Another inference that can guide policymakers, which emerges from this result is that the association between ARI and significant explanatory variables in a district is varying across the study area. Consequently, health policy directed towards reducing the burden of ARI should focus on local association and local influential demographic variables. In this view, regional health policy should build context-specific and integrated disease lowering policy should be designed for reducing the prevalence of ARI.

Recommendation for Researchers

There are various reasons to adopt local regression framework (such as GWR): Some association between dependent and independent variables are naturally varying across space. In such a case, coefficient from a global model may actually be a model misspecification.[17] The GWR model is a disaggregation of global models and the results are location-specific. GWR can be used as a model diagnostic to identify spatially varying associations. With this context, GWR can help to answer the question, "Does the association vary across space?" If the association does not vary across space, the global model should be appropriate specification for the data. Furthermore, it should be noted that GWR-facilitated local regression works reasonably well with binary,[18,19] count,[5,20] and discrete-response[21] data sets.

Limitation of the GWR Method

Like any other research that employs spatial analyses, this study can potentially suffer from modifiable areal unit problem (MAUP). MAUP arises when data gathered and subsequently analyzed may vary from the analysis conducted at an alternative modifiable unit.[22,23] Another important concern that needs to be addressed is multicollinearity within explanatory variables. In application of GWR methods, collinearity potentially becomes a more serious concern even if it is absent in the global model.[24] Therefore, it is necessary to conduct collinearity diagnosis (such as local VIFs for each independent variable and local condition number) in GWR analysis. In conclusion, in this paper, we have shown the application of GWR and compared the output from it with OLR. We illustrated that the associations between the dependent variable with its explanatory factors vary over the study area. The potential use of GWR is to identify such association at local level which will in turn assist policymakers to focus on a specific area to design health programs. Furthermore, when a health policymaker aims to reduce the burden of health outcome, GWR can show a researcher the most influential and deterministic factor working at local level that cannot be observed by OLR modeling.

Authors' Contribution

OR, MAM, ARF, and KHN conceptualized the paper, OR and MAM contributed in literature review. OR performed analysis, OR, MAM and ARF interpreted the results. OR wrote the initial draft, on which MAM, ARF and KHN gave their critical review for finalizing the manuscript. All authors read and approved the final manuscript.

Conflict of Interest Disclosures

The authors have no conflicts of interest.

Ethical Statement

This study used secondary data from DHS after removing respondent's identification information, and thus ethical approval for this work was not required. Ethics Committee of the Opinion Research Cooperation Macro International, Inc. (ORC Macro Inc., Calverton, MD, USA) approved this study.

Supplementary Data

Supplementary file 1 contains Sections A and B.

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