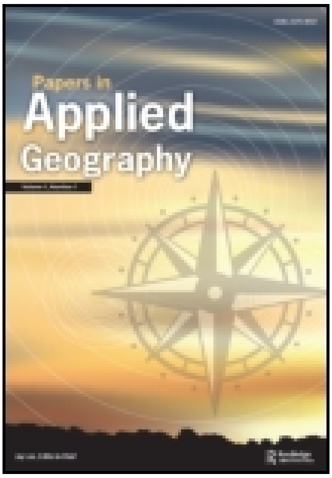

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Geography of Infrastructure Functionality at Schools in Nigeria: Evidence From Spatial Data Analysis Across Local Government Areas

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Geography of Infrastructure Functionality at Schools in Nigeria: Evidence From Spatial Data Analysis Across Local Government Areas

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Is functionality of electricity, sanitation and water infrastructure at schools unequally distributed geographically in Nigeria? Are there significant disparities in infrastructure functionality between Northern and Southern geopolitical zones in the country as has been posited in previous studies? In this study, we answer these questions with an examination of functionality at schools, with metrics for functionality aggregated at the smallest administrative unit available in the country, the local government area (LGA). We employ spatial statistical techniques to examine the spatial autocorrelation of power, sanitation and water (or 'infrastructure') non-functionality across 68,627 schools for 764 of 774 local government areas in Nigeria using a novel survey dataset courtesy of Nigeria's Office of the Senior Special Assistant to the President on the Millennium Development Goals. We find evidence for the existence of LGA clusters of infrastructure non-functionality, aligned along Nigeria's six geopolitical zones. The results also reveal a significant cluster of LGAs in the Northwest zone, the zone with the highest income-based poverty rate (70%) in the country, outperforming LGAs in both other Northern and some Southern zones on all functionality indicators. The results hold up to multiple testing correction, controlling the false discovery rate using the Benjamini-Hochberg method. These results highlight the need for a spatially targeted policy approach, at finer spatial scales, to poverty reduction efforts through infrastructure access expansion in the country. **Keywords: clusters, geopolitical zone, infrastructure access, local government area, Nigeria, spatial autocorrelation.**

Is functionality of electricity, sanitation, and water at schools unequally distributed geographically in Nigeria? Are there significant contiguous (or closely located) clusters of schools with disparities in metrics that define access to these infrastructure elements between the northern and southern geopolitical zones in the country, as has been posited in previous studies (Akinyosoye 2006; Kanbur and Venables 2007; Sowunmi et al. 2012)? We answer the aforementioned questions with an examination of electricity, sanitation, and water functionality at schools, with metrics for functionality aggregated at the smallest administrative unit available in the country, the local government area (LGA). We employ spatial statistical techniques along with geographic information systems (GIS) to examine the spatial autocorrelation of electricity, sanitation, and water (henceforth referred to as infrastructure) functionality across 68,627 schools for 764 of 774 LGAs in Nigeria. The underlying data were from a recent survey courtesy of the herculean efforts of the Nigeria's Office of the Senior Special Assistant to the President on the MDGs (OSSAP; MDGs stand for the Millennium Development Goals[1]).

We find evidence for the existence of LGA clusters of infrastructure nonfunctionality, aligned along Nigeria's six geopolitical zones. Our results also reveal a significant cluster of LGAs in the Northwest zone, the zone with the highest income-based poverty rate (70 percent) in the country, outperforming LGAs in both other northern and some southern zones on all functionality indicators. Our results hold up to multiple testing correction, controlling the false discovery rate using the Benjamini–Hochberg method (Benjamini and Hochberg 1995; Caldas de Castro and Singer 2006). These results highlight the benefits of detailed microspatial data for identifying infrastructure functionality distribution in the country. They also suggest evidence of structural, geopolitically based disparities in functionality of public infrastructure services at the school facility level in Nigeria with potentially useful insights for planners and policymakers in the country.

In the first known comprehensive analysis of infrastructure functionality at the LGA level, we use data from a 2011–2012 survey conducted by OSSAP in an effort spearheaded by the Nigerian government, which received responses from point persons at 68,627 schools (over 80 percent public or government owned) in 764 LGAs on available functionality of power, sanitation, and water. We then employed well-known spatial statistical methods, including global Moran's I and Getis–Ord Gi*(d) to analyze the spatial autocorrelation of infrastructure functionality for each LGA and discover conclusively the answers to the following questions:

1. How is infrastructure functionality spatially associated at the local level in Nigeria? Is there spatial autocorrelation of infrastructure functionality at the LGA and zonal levels in Nigeria? Are there LGA clusters of infrastructure nonfunctionality (high values of infrastructure nonfunctionality) in the country or clusters of infrastructure functionality (low values of infrastructure nonfunctionality)?
2. If so, where are these clusters located? Do we see a strict north–south zonal divide in the distribution of functionality?

Table 1 *Summary statistics at national and geopolitical zonal levels*

Zone	Number of LGAs in study	Population density	Poverty rate (%)[a]	Proportion I = 0	Proportion power = 0	Proportion sanitation = 0	Proportion water = 0
National	764	1,028	61	0.41	0.78	0.55	0.68
North-Central	121	273	60	0.52	0.82	0.67	0.72
Northwest	184	912	70	0.37	0.86	0.54	0.60
Northeast	104	203	69	0.51	0.91	0.64	0.73
South-South	123	551	56	0.37	0.73	0.48	0.67
Southwest	137	3,017	50	0.32	0.62	0.48	0.59
Southeast	95	1,214	59	0.37	0.75	0.47	0.74

Note: Data are author estimates. LGA = local government area.
[a]Poverty rate, measured as proportion of persons living on under US$1 per day (National Bureau of Statsitics 2010).

Nigeria's northern geopolitical zones with average poverty rates[2] of 66 percent, 11 percentage points above the Southern average, are often identified as the underperformers of their regional neighbors on development metrics, including access to public infrastructure services (Madu 2006; Foster and Briceño-Garmendia 2010; National Bureau of Statistics 2010; Sowunmi et al. 2012; Foster and Pushak 2011). When infrastructure functionality, a component of access, is examined at the small-scale LGA level, which lists among its duties the management of sanitation and water supply, we view unexpected, relative to the Northwest zone's status as the area with the worst reported poverty rate in the country (at 70 percent), LGAs that consistently outperform other northern and some southern LGAs on all infrastructure functionality indicators in ways not fully explained by population density alone (see Table 1). We also find certain Southeast LGAs that outperform southern neighbors on the sanitation functionality variable, an unexpected finding given the Southeast zone's status as the zone with both the highest poverty rate (59 percent) among its southern neighbors and the worst water functionality at schools of zones in our sample. These LGAs, outliers for their zones, could serve as blueprints for the creation of policies facilitating infrastructure functionality expansion and improvement in the country. Our results also point to evidence for geopolitically based inequality of infrastructure functionality in Nigeria. In the subsequent sections, we present our approach, testing our methods on the novel survey data set, with the accompanying results presented. A brief discussion of our results is then proffered.

Methods

To examine the spatial association of infrastructure functionality at the LGA level in Nigeria, we employ aspatial and spatial statistical techniques along with GIS to analyze spatial autocorrelation of infrastructure functionality across schools in the country. We do this in three steps. First, we create a simple, aggregated measure for each LGA of the proportion of schools in each LGA reporting zero functionality (nonfunctionality) to a particular infrastructure metric, namely electricity, water, and sanitation. Important to note here is the fact that although electricity might not be a primary infrastructure objective at primary schools, the simple aggregate LGA-wide measure appears to reasonably proxy LGA-wide functionality of power in correlations against the Defense Meteorological Satellite Program and Operational Linescan System (DMSP-OLS) nightlights data from the 2011–2012 period of study with a significant correlation of −0.67.

We then run simple Pearson correlation tests to examine the aspatial bivariate relationship between our infrastructure indicators. Initial visualization, descriptive statistics, and correlation test results are presented in the next section. We then assess overall patterns of spatial association in the LGA infrastructure functionality indicators with the global Moran's I statistic. Finally, we identify local patterns of spatial autocorrelation in the infrastructure functionality indicators with the Getis–Ord Gi*(d) statistic.

Data, Descriptive Statistics, and Initial Visualization

In an effort spearheaded by the Nigerian government, researchers from the OSSAP in collaboration with the Sustainable Engineering Lab at Columbia University conducted extensive, comprehensive surveys of schools at LGAs, obtaining responses to questions concerning power, water, and sanitation functionality, among other indicators. The surveys were collected from principals at 68,627 schools across 764 of 774 LGAs in Nigeria (with the last ten LGAs dropped due to unreliable data). Over 80 percent of the schools were public schools. For power functionality, respondents were asked true–false questions about both availability and functionality. An aggregate power score of 0 or 1 was assigned to a school depending on if the respondent answered false or true to the question of whether the respondent had available functional power from the national grid, functional power from a generator, or functional power from a solar system. Similarly, an aggregate sanitation score of 0 or 1 was assigned to a school depending on if the respondent answered false or true to the question of whether the respondent had functional improved sanitation in the form of a functional flush or improved pour flush toilet, or a functional improved ventilated latrine or pit latrine with a

Table 2 *Descriptive statistics: Pearson's product–moment correlation coefficient*

Variable	Proportion power = 0	Proportion sanitation = 0	Proportion water = 0
Proportion power = 0	1.00	0.62*	0.57*
Proportion sanitation = 0	0.62*	1.00	0.47*
Proportion water = 0	0.57*	0.47*	1.00

Note: Data are author's estimates.
**p* < .001.

slab. If respondents responded true to any one of these improved sanitation options, they were assigned a sanitation score of 1. If they responded false to all of the aforementioned options, then they were assigned a sanitation score of 0. Lastly, for water functionality, which was potable water functionality, we assigned an aggregate potable water functionality score of 0 or 1 to a school depending on if respondents answered false or true to the question of whether they had available functional potable water in the form of functional piped water or functional borehole or tube well water.

Next, an aggregated infrastructure score between 0 and 3 was created for each school, which was a simple sum of the three functionality scores for power, water, and sanitation. Finally, for each LGA, the proportions of schools (as a fraction of the total number of schools) with overall infrastructure and individual power, water, and sanitation scores of 0 were calculated and used as our metrics of overall infrastructure nonfunctionality and power, water, and sanitation nonfunctionality. Tables 1 and 2 show the summary statistics for the total number of schools sampled, population density, and infrastructure functionality aggregated at the national and geopolitical zonal levels. Table 2 provides correlation coefficients on the relationship between each of the infrastructure functionality measures.

Infrastructure functionality rates at schools are lowest for power nationally, with 78 percent of schools in LGAs reporting no available, functional power. Water and sanitation functionality rates are the second and third lowest of the three functionality indicators, respectively, with respondents reporting nonfunctionality rates of 68 percent and 55 percent nationally. Note that almost all northern LGAs report nonfunctionality figures higher than the national average, with the Northwest zone managing to remain below the national mean on the sanitation and water nonfunctionality indicators.

We also see a significant correlation between infrastructure functionality indicators, with the strongest positive linear association between the power and sanitation functionality indicators, the next strongest association between power and water, and the weakest, but still significantly positive, association between sanitation and water functionality indicators.

Initial visualization of these functionality indicators is presented in Figure 1 and was done in ArcGIS's ArcMap 10.2 (Environmental Sciences Research Institute [ESRI], Redlands, CA). Note the broad swaths of northern LGAs with high infrastructure nonfunctionality indicators compared to lower nonfunctionality patches in the southern zones of the country. The initial visualization gives us an idea of the trends to expect in terms of the distribution of infrastructure functionality across LGAs in the country. However, it tells nothing about which LGAs are in the extremes of the functionality distribution; that is, areas of intense infrastructure nonfunctionality, with functionality scores significantly below the global mean or areas of significant infrastructure functionality, with functionality scores above the global mean for each variable. It is also difficult to identify which LGAs outperform or underperform significantly on all indicators based solely on the initial visualization.

Results

Global Association of Infrastructure Functionality Rates Across LGAs

The results for the global Moran's I test for overall spatial autocorrelation in our 764 LGA sample are given using Equation 1:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad (1)$$

wherew_{ij} is a contiguity weight matrix that equals 1 if locations i and j are neighbors and 0 otherwise; x_i is the variable of interest, in our case each of the infrastructure functionality rates; n is the number of observations, equal to 764 LGAs in our study; and $\bar{x}$ is the global mean for infrastructure functionality variable x in the sample.

The results are presented in Table 3. We settle on the $k = 8$ nearest neighbors weight matrix for the rest of this study, based on our knowledge of the study area, as it allows for every entity to have an adjacent neighbor (not the case in the Queen's matrix) and does not overemphasize smaller LGAs due to the irregularity of polygon sizes in the Nigeria region (as is the case with the 80 km conceptualization, where the minimum distance for every entity to have a neighbor is about 72 km). To assess the significance of the observed I statistic, the I statistic is compared to the expected value of I in the absence of spatial autocorrelation, E(I)= $-1/(n-1)$, which tends to 0 as n gets larger; a larger I (i.e., I > E(I)) reflects positive spatial

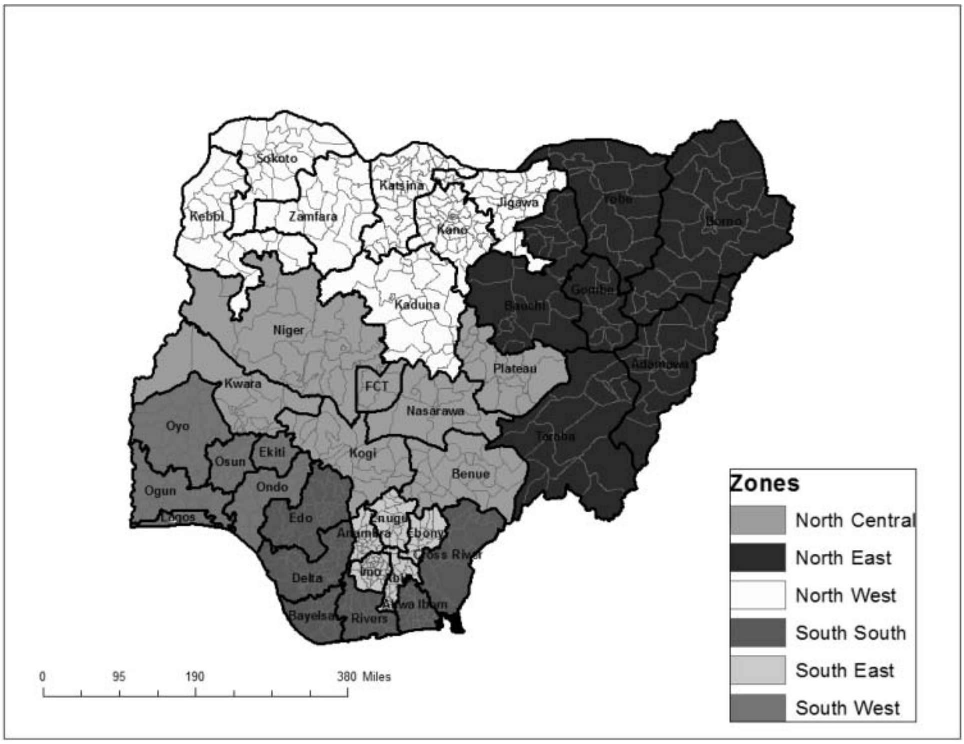

Figure 1 *Initial visualization of infrastructure nonfunctionality variables by local government area (LGA) with (A) overall infrastructure, (B) power, (C) sanitation, and (D) water.*

autocorrelation (spatial cluster) and a smaller I (I < E (I)) reflects negative spatial autocorrelation (spatial dissimilarity; Yu and Wei 2008). Significance of the global Moran's I statistic is assessed by a test of a null hypothesis of spatial randomness, rejection of which indicates a spatial pattern to the data. Significance is then tested by comparison to a reference distribution. The issue of the reference distribution against which to test significance is much discussed in the literature (Anselin 1995; Bivand, Pebesma, and Gómez-Rubio 2008; Yu and Wei 2008) as the exact distribution of the statistic is often computationally restrictive. Two reputable methods in the literature are the normal approximation (Anselin 1995) and the saddlepoint approximation method (Tiefelsdorf 2002). The results from both are equivalent and significant. This implies that there is positive spatial autocorrelation in the distribution of infrastructure functionality across LGAs in Nigeria.

Local Association: Clustering of Infrastructure Functionality Rates Along Geopolitical Zone

Local spatial association is examined using the Getis–Ord Gi*(d) statistic, which is a distance-based metric that measures the proportion of a variable located within a specific radius of a point, respective to the total sum of the variable in the study region (Páez and Scott 2005). In other words, it measures "the overall concentration of all pairs *xi*, *xj* such that *i* and *j* are within *d* of each other" (Getis and Ord 1992) as

Table 3 *Global Moran's I statistic for spatial autocorrelation in infrastructure nonfunctionality indicators using different spatial weights and different methods*

Global Moran's I: Spatial weight	I = 0	Pp0	Wp0	Sp0
Queen	0.457*	0.481*	0.377*	0.467*
Nearest neighbors (8)	0.430*	0.466*	0.366*	0.427*
80 km	0.345*	0.360*	0.261*	0.325*
Global Moran's I: Method (w = knn(8))				
Normal approximation	0.430*	0.466*	0.366*	0.427*

*All significant at $p < .001$.

depicted in Equation 2 (all variables defined as in Equation 1):

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{ij}(d)x_j}{\sum_{j=1}^{n} x_j} \quad (2)$$

Testing for the Gi*(d) is straightforward because the Gi*(d) values are expressed as standard normal variates Z[Gi*(d)]). Under the null hypothesis of spatial randomness, Z[Gi*(d)] are asymptotically normally distributed, $N(0, 1)$ as $n \to \infty$ (Getis and Ord 1992; Caldas de Castro and Singer 2006). Significance is determined by an examination of these *z* scores, with large positive *z* scores and a *p* value $< .05$ indicating clustering of high values and large negative *z* scores with a *p* value $< .05$ indicating clustering of low values within distance *d*. It has a straightforward interpretation with clustering of high (positive) values regarded as high clusters or hot spots and indicating clusters of extreme values above the global mean and clustering of low (negative) values regarded as low clusters or cold spots and indicating clusters of extreme values below the global mean.

As a final note on the local Gi*(d) statistic results, as local spatial statistics depend on tests of spatial association for each location in the sample, the problem of the effect of multiple comparisons on the significance levels of the tests has been raised by a number of authors (Anselin 1995; Williams, Jones, and Tukey 1999; Caldas de Castro and Singer 2006). When multiple tests are performed on a sample, the probability that some effects will be retained as significant solely by chance rises as the number of tests grows and must be controlled. The Type I error rate or the probability of rejecting one or more null hypotheses when they are, in actuality, true grows with the number of tests, leading to false discoveries in our results. To control for these false discoveries, we apply the Benjamini–Hochberg (BH) procedure, regarded as the most powerful in its class of multiple comparison procedures (MCPs) for controlling the proportion of Type I errors, to adjust the *p* values from our original Gi*(d) results (Benjamini and Hochberg 1995; Caldas de Castro and Singer 2006; Williams, Jones, and Tukey 1999). Given a significance level of $\alpha = .05$, the BH procedure controls the FDR $< \alpha$ where:

$$FDR = E\left(\frac{F}{R}|R > 0\right)P(R > 0)$$

FDR is the false discovery rate, *F* is the number of false positives (false discoveries) or Type I errors, and *R* is the set of rejected null hypotheses or the sum of false positives (*F*) and true positives (*T*). The BH adjusted Gi*(d) results are presented here.

An examination of local association in our 764 LGA sample provides some very interesting results depicted in Figure 2. In summary, although the Northwest zone is stated as the most income poor in the country, it actually registers the second highest infrastructure

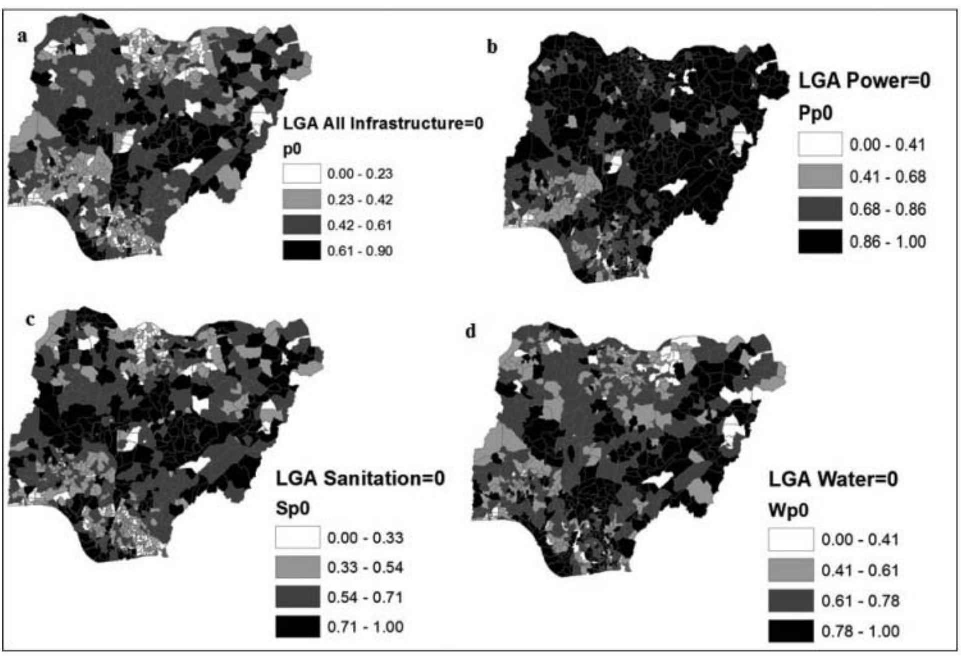

Figure 2 *GI*(d) Benjamini–Hochberg FDR results: Distribution of significant low and high clusters by infrastructure nonfunctionality variable for (A) overall I = 0, (B) power = 0, (C) sanitation = 0, and (D) water = 0.*
Note: LGA = local government area; FDR = false discovery rate.

Table 4 *GI*(d) Benjamini–Hochberg FDR corrected results: Intensity of clustering by zone, (percentage of total local government areas in each zone in high clusters for all (I = 0) and each infrastructure nonfunctionality variable) along with poverty rate and average infrastructure nonfunctionality rates for each zone*

Geopolitical zone	Poverty rate	High Gi*_all	High Gi*_power	High Gi*_sanitation	High Gi*_water
North-Central	0.60	0.45	0.01	0.33	0.24
Northeast	0.69	0.37	0.19	0.19	0.13
Northwest	0.70	0.04	0.01	0.07	0.00
South-South	0.56	0.04	0.00	0.05	0.05
Southeast	0.59	0.07	0.00	0.03	0.25
Southwest	0.50	0.01	0.00	0.01	0.00
Geopolitical zone	Poverty rate	Proportion I = 0	Proportion power = 0	Proportion sanitation = 0	Proportion water = 0
North-Central	0.60	0.52	0.82	0.67	0.72
Northeast	0.69	0.51	0.91	0.64	0.73
Northwest	0.70	0.37	0.86	0.54	0.60
South-South	0.56	0.37	0.73	0.48	0.67
Southeast	0.59	0.37	0.75	0.47	0.74
Southwest	0.50	0.32	0.62	0.48	0.59
Geopolitical zone	Poverty rate	Low Gi*_all	Low Gi*_power	Low Gi*_sanitation	Low Gi*_water
North-Central	0.60	0.01	0.02	0.00	0.03
Northeast	0.69	0.01	0.00	0.00	0.05
Northwest	0.70	0.22	0.04	0.16	0.17
South-South	0.56	0.27	0.13	0.31	0.07
Southeast	0.59	0.15	0.03	0.39	0.00
Southwest	0.50	0.27	0.29	0.23	0.21

functionality rates in the country (tied with the Southeast and South-South zones at .37 for I = 0) as shown in Table 4. In terms of intensity of clustering, this zone registers the second greatest proportion of LGAs in the low cluster for all infrastructure nonfunctionality (I = 0) and the second least proportion of LGAs in the high cluster for I = 0 as shown in Table 4, located primarily in Kano, Katsina, and Jigawa states. Again, this is an unexpected result, if we expect income poverty and infrastructure nonfunctionality to be strongly positively correlated as discussed earlier.

In contrast, the North-Central zone appears to be the worst off both in terms of overall infrastructure functionality and intensity of clustering of infrastructure nonfunctionality in the region. Again this contrasts with its position as the zone with only the third highest income-based poverty rate in the country, as shown in Table 4, and the zone

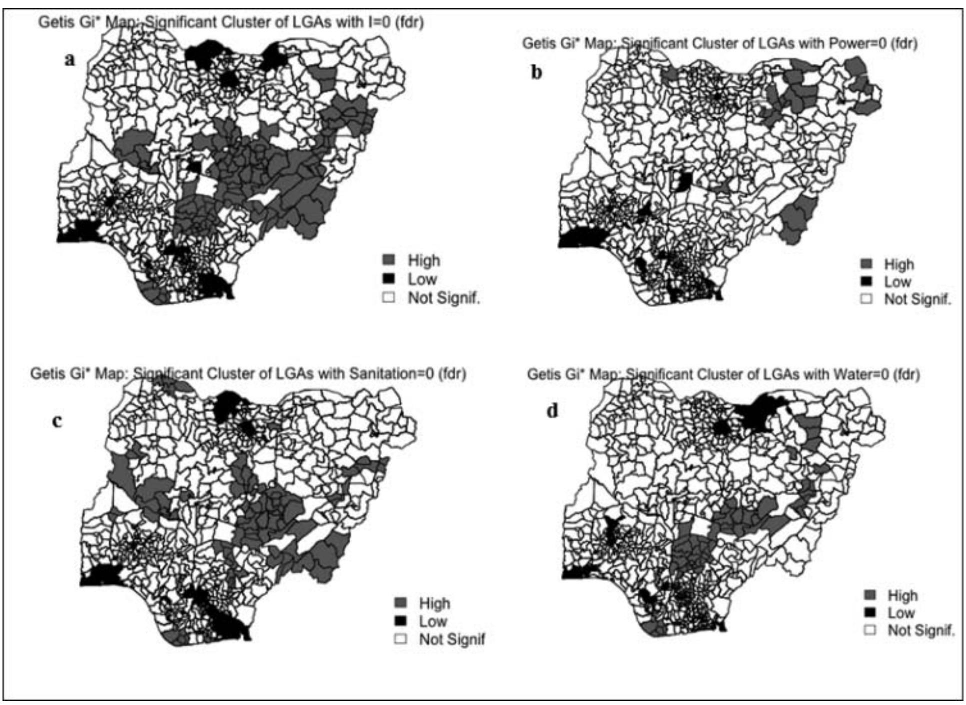

Figure 3 *Six geopolitical zones in Nigeria with thirty-six states labeled and 774 local government areas in faint outline.*

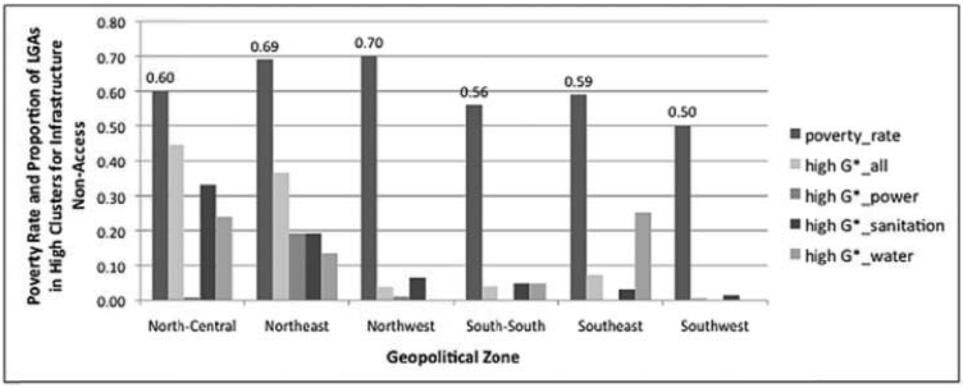

Figure 4 *GI*(d) Benjamini–Hochberg corrected results: Intensity of clustering by zone and each infrastructure nonfunctionality variable along with poverty rate for each zone.*
Note: LGA = local government area.

containing the country's federal capital, Abuja. For intensity of clustering, even when the effect of the presence of the federal capital Abuja is accounted for, we see significant high clusters of infrastructure nonfunctionality across the North-Central zone concentrated in Plateau, Nasarawa (a state that shares a border with the Federal Capital Territory (FCT) where Abuja is located, as shown in Figure 3) and Benue states. Northeast LGAs, with the highest proportion of power nonfunctionality (0.91 for power = 0), also score highly on the intensity of clustering of power nonfunctionality, with 19 percent of all Northeast LGAs located in the high cluster for power, and located primarily in Borno, Yobe, and Taraba states.

The Southeastern LGAs appear to underperform significantly relative to their zonal neighbors for water functionality in the country (0.74 for water = 0), also scoring highly on the intensity of clustering of water nonfunctionality concentrated in Enugu and Imo states. There also appears to be an outlier cluster (for its zone) of high sanitation and water nonfunctionality LGAs in Bayelsa state in the South-South zone of the country.

Overall, the Northeast and North-Central LGAs appear to dominate the high clusters across most infrastructure indicators, with the Northwest LGAs standing out as the outperformers of all LGAs in their zonal neighbors and Southeast LGAs outperforming on sanitation, but lagging significantly on water functionality. The results are summarized in Figures 2 and 4 and Table 4.

Discussion and Further Research

Recognition of spatial autocorrelation is important for adjustment of regression models for further research investigating why these patterns occur due to the violation of the independence assumption (Anselin 1995). The results presented here are an important first step toward investigating the drivers of these spatial patterns and speak to structural inequality of infrastructure functionality aligned along geopolitical zones in Nigeria. This is the first known study investigating the spatial distribution of infrastructure functionality at schools at the LGA level in Nigeria and the first, to our knowledge, to apply a BH procedure to correct the false discovery rate to investigate local spatial association of infrastructure functionality at the LGA level in Nigeria. The results presented here have important policy implications and the lauded efforts of OSSAP's microfacility and LGA-level survey efforts enable a shift away from broad, macro, purely income-based poverty assessments toward a more holistic approach to poverty reduction through infrastructure access and functionality expansion that considers the role of geography in shaping differential functionality of public infrastructure in the country. They also serve to partly debunk the narrative of pervasive northern underperformance in the country, by identifying clusters of LGAs in the Northwest zone that outperform southern and other regional neighbors on our overall, power, sanitation, and water infrastructure functionality indicators, which might serve as a blueprint for LGAs in lagging northern and some southern zones. The results also reveal a similar cluster of Southeast LGAs that outperform their regional neighbors on the sanitation functionality score, partly upsetting the trend of Southeastern underperformance among their southern neighbors. The detection of nonfunctionality hot spots or LGAs with critically high rates of infrastructure nonfunctionality and cold spots can be a useful starting point for planning and policy decision making in determining which areas have the most pressing infrastructure needs overall and disaggregated by variable: power, water, and sanitation in the country.

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Notes

[1] The MDGs from can be found at http://nmis.mdgs.gov.ng/.

[2] Poverty rates are measured as the percentage of persons living on under US$1 per day (National Bureau of Statistics 2010).

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