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Exploring Spatial Inequality in Educational Outcomes in Sokoto, Nigeria

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Exploring Spatial Inequality in Educational Outcomes in Sokoto, Nigeria

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Declaration

I, Zaineb Aftab Hussain Makati, declare that the Master Thesis titled "Exploring Spatial Inequality in Educational Outcomes in Sokoto, Nigeria", submitted to the GLODEP Consortium in 2021, is my original work completed under the supervision of Professor Jaromír Harmáček at the Palacky University and of Sophie Ochmann and Professor Sebastian Vollmer at the University of Goettingen. I confirm the work and ideas presented are my own and the theoretical and empirical literature, datasets and analysis adopted from other studies have been duly cited and referenced. I have adhered to academic honesty and integrity in creating this study and have not misrepresented any idea, fact or result.

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Zásady pro vypracování

According to the Demographic and Health Survey (DHS) Data, the locational divide among educational outcomes remain significantly large in many countries. For example, in Nigeria, the primary completion rate in rural areas is 67% while in urban areas is 92%. There are multiple spatial factors that change with the location of communities and schools which impact children education attainment as well as outcomes. These factors include access to resources, environmental and neighbourhood variables, among others. The spatial variations in socio-economic characteristics of the community where schools are based, are also expected to play a significant role in influencing the inequality in educational performance. This thesis aims to perform a local analysis of inequalities in educational outcomes which can go unnoticed in a global assessment. The local analysis can also prove to be highly beneficial for policy makers to implement relevant policies at the local level.

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ABSTRACT

Inequality in access to quality education remains a significant challenge for socioeconomic development across the world, specifically in low and middle-income countries. This study explores the spatial component of inequality in the educational outcomes of schools in the state of Sokoto, Nigeria using Moran's I Spatial Autocorrelation Index and Spatial Gini Index. Subsequently, the study analyses how space influences the production of education by employing GWR. The data has been taken from the evaluation study of the NIPEP project in Sokoto. Significant spatial dependency and spatial inequality is observed in the educational outcomes of schools in Sokoto. The inputs of school facilities, SBMC involvement and Headmaster's education level are found to have a significantly varying relationship with educational outcomes across space. The spatial analysis of education production can help policy makers explain geographically varying outcomes of projects, identify factors which result in its success and prioritize most deprived areas based on their need and effectiveness of intervention. Therefore, current policy outcomes should be evaluated spatially before being expanded and replicated to other areas.

Keywords: Education Inequality, Spatial Inequality, GWR, Moran's I, Spatial Gini, Nigeria.

Jel Codes: I21, I24, R15

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List of Abbreviations

AIC	Akaike Information Criterion
CO	Carbon Monoxide
CV	Cross Validation
GDP	Gross Domestic Product
GIS	Geographic Information Systems
GNI	Gross National Income
GWR	Geographically Weighted Regression
HFMD	Hand, Foot and Mouth Diseases
IPV	Intimate Partner Violence
NBS	National Bureau of Statistics, Nigeria
NIPEP	Nigerian Partnership for Education Project
MDG	Millennium Development Goals
OOSC	Out Of School Children
PPP	Purchasing Power Parity
RSS	Residual Sum of Squares
SBMC	School Based Management Committee
SDG	Sustainable Development Goals
UBEC	Universal Basic Education Commission, Nigeria
UGS	Urban Green Space
UIS	UNESCO Institute of Statistics
UNDP	United Nations Development Programme
UNESCO	United Nations Education, Scientific and Cultural Organization
UNICEF	United Nations Children's Fund
WB	World Bank

INTRODUCTION

About 58 million children and youth in the world remain out of school, which proves that education continues to be one of the biggest development challenges (UIS, 2018). The focus on access to education with Millennium Development Goal number 2 to achieve universal primary education has now been extended to access to quality education with Sustainable Development Goal number 4 (UNDP, 2015a). Despite the international campaign for free and compulsory education by 2030, developing countries continue to struggle to provide access to quality education (UNDP, 2015b). Furthermore, the access to schooling does not automatically translate into learning and 53% of all children in low and middle-income countries suffer from learning poverty i.e., inability to read and write by the age of 10 (Filmer *et al.*, 2020; World Bank, 2019b).

In addition to the challenges of access and quality, there are significant regional, urban-rural and gender disparities in educational outcomes across and within countries. For instance, the urban-rural divide in primary completion rate in lower middle income countries is 11% whereas in low income countries the gap increases to 29% and in Sub Saharan Africa to 28% (WIDE, 2020). Education leads to economic development by fostering economic growth and social development by reducing poverty, improving health, increasing gender equity and civic participation (OECD *et al.*, 2015). Therefore, disparities in educational outcomes not only form a hurdle for achieving SDG target 4.4 of equity in education but also SDG 10 of reducing social and economic inequalities. Education inequality further complicate the international and national journey of achieving economic equality and improving social mobility (Sahn and Younger, 2007; Brown, 2013; Corak, 2012).

Among many other low and middle-income countries[1], Nigeria is on the forefront of the global education emergency. The Ministry of Education of Nigeria reported 10.1 million out of school children (OOSC) in the country in March 2021, which is the highest number of OOSC in all Sub-Saharan countries (Bashir, 2021). Moreover, within Nigeria there are vast regional and locational disparities in education access and attainment. In 2013, for instance, the primary completion rate in the North East of the country was 44% while in the South East it was 96%. Similarly, there is a 31% percentage point urban-rural divide in primary completion rate in Nigeria: 88% of children of primary graduation age in urban areas have completed primary school while in rural areas 57% complete primary school on time (WIDE, 2013).

These regional and locational inequalities in education are a result of multiple social, economic and cultural factors which change with geography and space (McLafferty, 2008). On the one hand, communities and neighbourhoods can impact cognitive outcomes of children through various social factors such as exposure to violence and unemployment (Harding, 2009). On the other hand, the location of schools is also reported to have an impact on the educational achievement of children

[1] World Bank Income Classification

(Conduit *et al.*, 1996).

The objective of this research study is to examine the spatial variation in educational outcomes of schools in the North Western State of Nigeria called Sokoto. The study tries to answer four research questions:

RQ1: Is there spatial dependency in education outcomes of schools in Sokoto?

RQ2: Is there spatial inequality in educational outcomes of schools in Sokoto?

RQ3: Does the remoteness of schools have an impact on the school's academic performance?

RQ4: Are there spatial patterns in the effect of school inputs in the education production function?

The study uses data from an evaluation experiment conducted for the grant and training component of the Nigerian Partnership for Education Project (NIPEP). Spatial dependency in educational outcomes is captured with the help of Moran's I coefficient, a measure calculating autocorrelation of a feature in space. Spatial Inequality is measured with the help of the Spatial Gini Index. The spatial variation in educational outcomes is explained by an OLS model with remoteness of the school as an explanatory variable and by using Geographically Weighted Regression (GWR) Model to estimate local education production functions.

The remainder of this thesis is organised as follows: the first chapter reviews the literature which establishes the intellectual context of spatial inequalities in educational outcomes. The second chapter provides an overview of the state of education in Nigeria and particularly in Sokoto. The third chapter is of Data focusing on description and summary statistics of variables used in the analysis. The chapter of Methodology explains in detail the empirical methods adopted in this study. The fifth chapter is based on the discussion of the results from the analysis. Policy Implications followed by the Conclusion are the final two chapters of this research thesis which is an attempt to highlight the importance of spatial analysis in education policy based on the results.

CHAPTER 1
Literature Review

This chapter is subdivided into six parts with the first part defining terms frequently used in this study. The second section reviews literature on the spatial variations in educational outcomes of students and schools. The third section is based on spatial variations in education outcomes in Nigeria. The fourth section reviews the intellectual work available on the education production function output and inputs. The fifth section provides an overview of the studies which have used GWR to study spatial inequalities. Finally, the last section briefly identifies the gaps in the reviewed literature.

1.1 Definition of Terms

This sub-section of Introduction quickly reviews the definitions of different terms used frequently in this study which are taken from different sources of literature.

1.1.1 Inequality

Inequality refers to the existing differences in individuals' personal outcomes such as income, education, consumption, health etc., (Kanbur and Venables, 2005). The World Bank defines inequality as the dispersion in the distribution of an indicator related to the welfare of people, such as income or consumption, across the whole population (World Bank, 2009). All classic Inequality measures have the four properties of: anonymity (the identity of the poor does not matter), replication invariance (the size of the population should not change the total inequality), scale invariance (proportional changes in income should not change the level of inequality) and transfer (transfer from a rich person to poor person reduces inequality and vice versa) (Allison, 1978).

1.1.2 Spatial Inequality

Spatial inequality can be defined as the unequal distribution of income, education or other welfare indicators across spatial units under consideration which are exhaustive and mutually exclusive (Kanbur and Venables, 2005). Unlike the classic Inequality measures, the anonymity condition cannot be fulfilled by a spatial inequality measure. The spatial inequality measure would alter if we change the spatial locations of the individuals (Arbia, 2001).

1.1.3 Global vs. Local Model

A global model accounts for all individual observation in the dataset while estimating the coefficients for the explanatory variables. On the other hand, local models are calibrated using only those observations which are defined as neighbours geographically (Fotheringham *et al.*, 2002).

1.1.4 Spatial Autocorrelation

There are two types of spatial autocorrelations i.e., positive and negative. When data are distributed across a geographical space such that high values of a feature are close to high values and low values are close to low values then it is called positive spatial autocorrelation. Conversely, when high values are located near low values and vice-versa then the data exhibits negative spatial autocorrelation (Fotheringham *et al.*, 2002). When the values are distributed randomly or like the checkerboard then there is no spatial autocorrelation in the data (Rey and R. Smith, 2012).

1.1.5 Spatial dependency

Spatial dependency is defined as the degree to which a feature at one location in space is dependent on the values of the same feature located close to it (Fotheringham *et al.*, 2002).

1.1.6 Spatial Non-stationarity

Spatial Non-stationarity, in terms of association, can be defined as the condition when relationship between two or more variables vary geographically. More concretely when direction, magnitude and significance of the relationship between two or more variables is not spatially homogenous (England, 2014).

1.2 Spatial Variation in education

The space not on its own but the factors associated with it such as natural resources, climatic conditions, culture and traditions, infrastructure and institutions are the source of generating inequality among different spatial units (Shorrocks and Wan, 2005). The spatial inequality accounts for the one-third of total interpersonal inequality i.e., inequality between countries, in a sample of 25 countries from all regions of the world. Additionally, space contributes to two-third of inequality within these 25 countries. Understanding the spatial dimension of inequality is important for a variety of global challenges such as conflicts or migration. It is also crucial for informing policy decisions regarding, for example, market failures and infrastructure development (Kanbur and Venables, 2005). Spatial inequality in income and other social indicators is increasing in large economies but also in most of transitioning and developing countries.

The spatial inequality in education is mostly studied through the effects of neighborhood and urbanization in the literature. Different mechanisms are identified on how different neighborhood characteristics and urbanization may lead to varying educational outcomes. The role of neighborhood effects on education and schools are sometimes discussed separately in the current literature. Therefore, the first subsection of this section, covers neighborhood effects on student and the second on schools. The third subsection reviews studies on the effect of urbanization on educational outcomes.

1.2.1 Neighborhood Effects on Educational Outcomes of Students

The significance of this phenomena can be captured by the phrase “accident of birth” coined by Spiegelberg (1961) inspired from John Stuart Mill’s autobiography. The term “accident of birth” captures how based on where and to whom one is born can shape their natural, social, cultural, and economic circumstances. These circumstances to a large extent define a person's life trajectory including where he may go to school (England, 2014).

Sastry (2012) reviews ten years of research on neighborhood effects on student outcomes in the US and find negative effects of being born in a poor neighborhood on academic achievements of children. Another study by Crowder and South (2011) using panel data analyze the spatial and temporal effects of living in a disadvantaged neighborhood on educational outcomes of children. The study finds that the duration of living in a disadvantaged neighborhood negatively influences the likelihood of graduating from high school, with a higher effect for white than black children in the US. These studies however fail to identify different pathways leading to this outcome.

There are numerous studies analyzing the impact of neighborhoods on students' academic performance through various mechanisms other than income. Multiple studies captured the environmental neighborhood effects of air, water and noise pollution on children's cognitive outcomes. Ferguson *et al.* (2013) in their review find negative impact of pollutants and environmental toxins on cognitive and socioemotional development of children. Similarly, Currie *et al.* (2007) find an adverse effect of high levels of Carbon Monoxide (CO) on education outcomes due to increased absences. While a study by Reyes (2012) reveals that children with high lead levels in blood perform significantly worse in standardized tests. Noise pollution also impacts students' reading abilities which was discovered by a study done in a New York school. The students with homes and schools near noisy areas of elevated train lines or airline flight paths had poorer reading skills compared to other children (Bronzaft and McCarthy, 1975; S. Cohen *et al.*, 1980). These environmental based effects are however a result of the socioeconomic and political dynamics of the environmental inequality in neighborhoods (Suman, 1992).

Another mechanism covered in the literature is the effect of neighborhood violence on the academic achievements. The study by Sharkey (2010) in Chicago reveals that a homicide in a child's block within 7 days of the standardized test reduces their performance by 1.52 points. Another study by Sharkey *et al.* (2014) finds negative impact of experiencing a violent crime of murder, manslaughter, aggravated assault and robbery in the neighborhood on passing a standardized test exam. An empirical study by Harding (2009) found that violence accounts for 44% of the association between neighborhood disadvantage and whether a student graduates from high school.

Culture is also found to have a negative impact on educational attainment based on social isolation theory and oppositional culture theory. The first theory suggests that social isolation of certain neighborhoods deprives them of the social network required for higher educational outcomes. The second theory suggests that the negative impact is due to discrimination i.e., if educational achievement is associated with the privileged race or group then in order to maintain cultural association it will be discouraged among the underprivileged (Fordham and Ogbu, 1993; Massey, 1993). Educational outcomes and availability of jobs in the locality also impact children's educational attainment (Anderson, 2000; Manski, 2000). However, the selection problem exists in these effects i.e., whether the differences in educational outcomes are due to neighborhoods or due to the differences in characteristics of children living in a certain neighborhood (Harding *et al.*, 2010).

Apart from the US, there are some studies which examine neighborhood effects on educational outcomes in European countries. A study based in Scotland found a negative impact of neighborhood deprivations on educational attainment after controlling for student ability, family background as well as schooling (Garner and Raudenbush, 1991). An empirical study by Brattbakk (2014) in Norway identified significant block, neighborhood and district effects on adolescents future educational outcomes. Low levels of education in the locality is found to be the most significant geographical factor explaining future educational levels. This is attributed to the fact that the local environment of education influences future educational outcomes of youth in the area. Kauppinen (2007) found an effect of neighborhood not on the quality of educational attainment but on the type of education acquired in Finland. The concentration of affluence in the neighborhood was associated with pursuing upper-secondary schooling rather than vocational training.

There are only a handful of studies evaluating neighborhood effects on educational outcomes in developing countries. One of these was an empirical study conducted in the capital city of Uruguay (Kaztman and Reimoso, 2007). The authors found 17.6% of variation in educational outcomes between neighborhoods of Montevideo, attributed to differences in neighborhood's socio-cultural and economic composition. Varughese and Bairagya (2020) capture the variation in educational outcomes by rural and urban areas in India: finding a negative effect of residing in a rural area on years of schooling. A few more studies from developing countries, capture neighborhood effects at school level and are discussed in the next subsection.

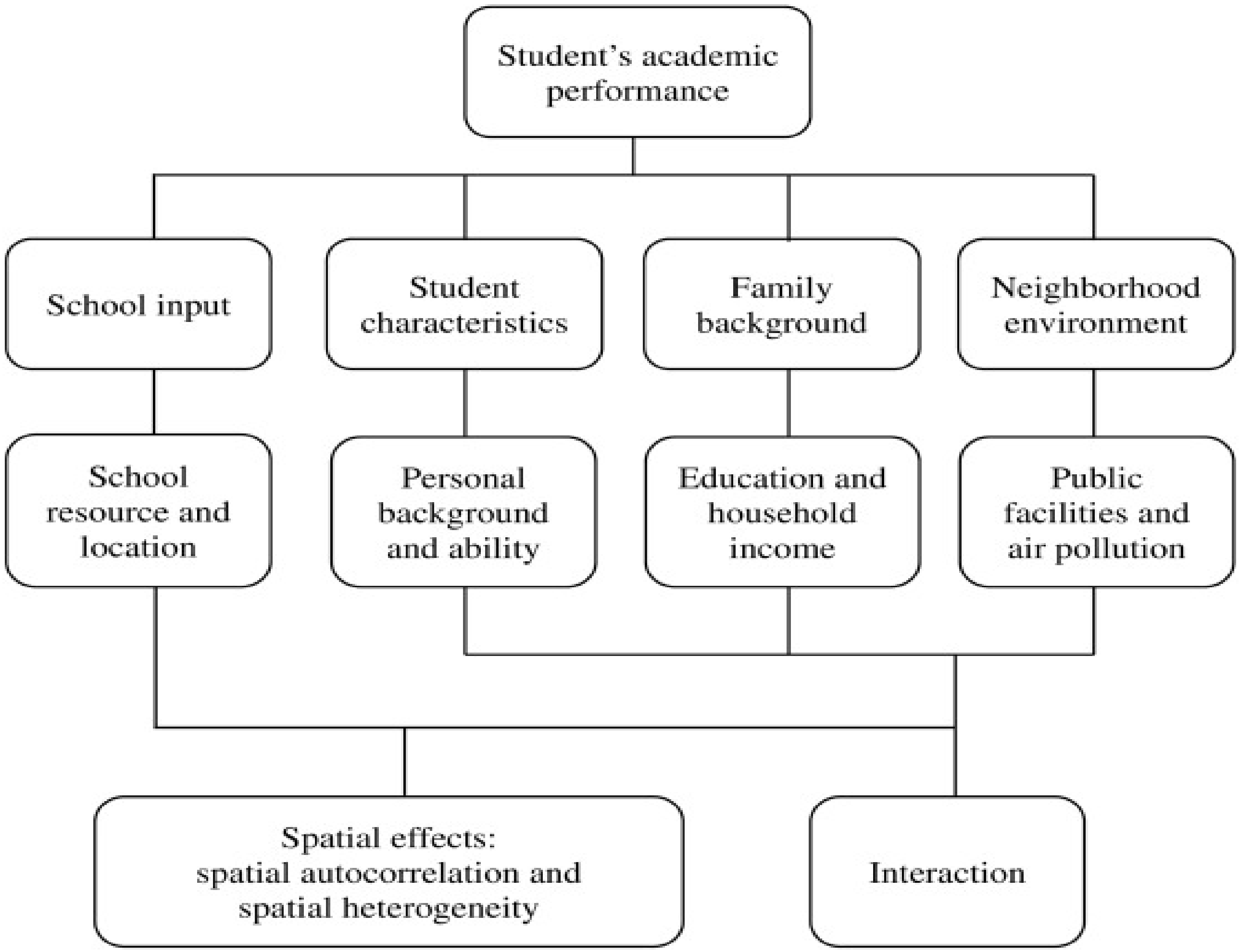
1.2.2 Neighborhood Effects on Educational Outcomes of Schools

The quality of local institutions and services vary across neighborhoods which have an effect on individual's well-being living in the area (Ellen and Turner, 1997). Schools being the main source of education in the neighborhood, play a key role in the educational outcomes of children in the locality. In the literature, the impact of school on educational outcome is sometimes discussed separately and other times along with the effect of neighborhood it is based in, called the school catchment areas (Conduit *et al.*, 1996; Schwartz, 2012; Wei *et al.*, 2018).

The significance of school and neighborhood effect over one another is highly contextual and the experiments have found mixed results (Burdick-Will *et al.*, 2011; Schwartz, 2012). Schwartz (2012) found that living in an advantaged neighborhood, in the Montgomery County in the US, did not produce the same effect as studying in an advantaged school which highlights the importance of school quality. While on the other end of spectrum, Burdick-Will *et al.* (2011) found significant improvement in test scores of children who moved out of a disadvantaged neighborhood with almost the same school quality as before. This suggests that local context influences which mechanism will play a more significant role on the academic outcomes of children (Sharkey and Faber, 2014).

However, as mentioned, a more integrated approach has also been adopted by various scholars. Figure 1.1 from the study by Wei *et al.* (2018) shows how neighborhood and school effects

Figure 1.1: Pathways through which Location Impacts Educational Outcomes



Source: (Wei et al.*, 2018)*

interact with each other and determine children's cognitive outcomes. The location of the school influences its resources and student body which directly impacts its academic performance. Public schools in poor neighbourhoods, like other public institutions, lack resources and infrastructure which adversely affect the school's academic results (Glaster *et al.*, 2007). Similarly, the composition of student body at school is influenced by the catchment area of the school which have a direct influence on overall school outcomes as a result of peer effects (Nieuwenhuis and Hooimeijer, 2016). The children from affluent families go to affluent schools with better teachers and a better curriculum and more affluent children become role models for other students in the school (Jencks and Mayer, 1990).

The socioeconomic status of households in the school's catchment area is also found to be positively correlated with its educational performance. Factors such as high unemployment, percentage of households living on rent and percentage of lone parent households in the school's neighbourhood can negatively impact a school's overall academic results (Conduit *et al.*, 1996; Fotheringham *et al.*, 2001). The pathways identified for this effect include limited educational support from home, lack of parental involvement and lower aspirations for their children and also a poor school's inability to retain teachers. These effects along with the emergence of "Choice" in schooling as education is marketized, make the neighborhood and space where the school is located an important issue (Gulson and Symes, 2007).

To conclude, neighbourhood plays an important role in influencing educational outcomes of children directly and via schools. Despite a high volume of published and unpublished work, current literature however provides little evidence on causal mechanisms of neighbourhood effects on educational outcomes of schools and children. How much each neighbourhood characteristic affect individual academic performance still remain a "black box" in this study area (Ellen and Turner, 1997).

1.2.3 Urbanization

The study by Ansong *et al.* (2015) identifies urbanization as one of the leading causes of spatial inequalities in education. According to the literature reviewed, the urban centres produce better educational outcomes due to three main factors: concentration of knowledge, higher income, and better public services (Dave, 2013; Glewwe *et al.*, 2007; Glaeser, 1999; Ludwig, 1999). The cities have a concentration of highly educated and highly skilled people which lead to spill-over effects resulting in better educational outcomes (Glaeser, 1999). The urban household, specially affluent urban households, also have better access to information and awareness about future labour market opportunities which is known to have an impact on the educational outcomes (Ludwig, 1999). Urban households' children are also exposed to the English language more than their rural counterparts, which is crucial for the educational outcomes in countries, like Kenya, where medium of education is English (Kimosop *et al.*, 2015).

Secondly, access and concentration of services such as electricity, water and sanitation, roads etc. as well as quality and school infrastructure are better in urban areas, specifically in the developing countries, which influence academic outcomes. For example, electricity improves test results by increasing the hours available for studying in the nighttime and by reducing the time spent on household chores. This was studied by Dave (2013) in rural India, where children from households having electricity have a higher probability of passing reading and mathematics tests. The urban-rural divide in the availability of public services including educational institutions is due to the urban-bias in many developing countries. For instance, the rural areas in China received far less for social expenditure as compared to cities in the planned era and since the decentralization in the late 70s, the rural areas have been facing difficulties to improve health and education due to budget constraints (Zhang and Kanbur, 2005).

Finally, the wages are also high in the urban areas and households can invest more in their children's educations (Glaeser, 1999; Wheeler, 2004). Rural and poor household children in developing countries face additional cultural and livelihood challenges such as contributing to the family income that have a negative impact on educational outcomes (Glewwe *et al.*, 2007). All of these factors cumulatively widen the gap between urban and rural educational outcomes which is a pressing issue for many low and middle-income countries.

1.3 Spatial Inequality in Education in Nigeria

Although educational attainment increased in Nigeria from 3.5 million children enrolled in primary schools in 1970 to 20 million in 2010, the low quality and inequality in access to education remain significant national challenges (Onwuameze, 2013). Socioeconomic status is one of the key determinants of education disparity in Nigeria and the gap widens when region, gender and urban-rural factors are also considered (Pittin, 1990). These spatial imbalances in the socioeconomic status of the different regions as well as the ethnic and religious divide translates into spatial inequality in education in the country. The author argues that inequality in education in the country follows a visible pattern from the pre-colonial times with Southern regions benefiting from the expansion of missionary education since the 1840s.

The regional divide between accessibility to education in Nigeria can be attributed to the advantage of coastal areas which had a long history of missionary settlements. Therefore, the Western and Southern regions of the countries had more educated elites than the Northern more remote regions. The regions in the South have also reaped the socioeconomic benefits of the 853 km long coastline of the country. These communities along the coast, due to their higher socioeconomic status, were able to finance their own education as compared to the communities far up in the North. Additionally, population density is considered to be one of the factors leading the socioeconomic development. The areas which are sparsely populated, especially in the north of Nigeria, are not considered viable for investments in social development projects (Pittin, 1990; Madu, 2006).

Another source of regional disparity in the educational outcomes in Nigeria is the ethnic and religious divide between the Northern and Southern regions. On one hand, the predominantly Christian South readily accepted the Western education while the Muslim majority in the North abstained from accepting Western education in light of the country's history of Western and Colonial rule. The Western education could not be forced into the Northern region because of the local power enforced by the British "indirect rule" during the colonial period. The indirect rule was the instrument of British Imperialism which gave semi-autonomous leadership roles to indigenous elites to minimize the dealings of colonial administrators with the local people. This allowed local Muslim authorities in the Northern region to control all political and social avenues including education and they heavily restricted the spread of Western education. As a result of this, regional and ethnic disparities in education in Nigeria persist until today (Onwuameze, 2013; Aguolu, 1979).

Finally, urbanization was also found to be a significant source of socioeconomic spatial inequality with North East and North West having the least percentage of urban population and the lowest values for socioeconomic indicators. The urban dwellers also enjoy higher incomes in Nigeria and therefore can spend more on education further widening the gap between educational outcomes. The rural neglect and poverty are also accounted as the sources of urban-rural divide in education in the country (Madu, 2006).

1.4 Education Production Function

The education production function has been used to model the educational outcomes of schools in this study. The function has widely been used to explore the relationship between school inputs and school outputs (Wei *et al.*, 2018). School outputs include short-term educational outcomes such as test scores but also long-term outcomes such as wages and employment (Betts, 1996; Hansen *et al.*, 2004). School inputs are monetary as well as non-monetary such as school resources and budget but also pupil's family backgrounds and neighbourhood effects (Wei *et al.*, 2018). The school inputs included in the analysis of this thesis are based on the literature reviewed in the following paragraphs.

The school facilities are defined as the school building and available amenities which are deemed essential for creating a quiet, secure, and comfortable environment. The school environment determined by the air quality, lighting, acoustics, building's quality, and age etc. are found to have an impact on teacher's and children's performance (Schneider, 2002). The school facilities form a positive or negative learning climate which is found to have an impact on educational outcomes of children (Earthman, 1998; Yielding, 1993). However, there have been other studies which have found no significant impact on educational outcomes of the school facilities, but the effect depends on how and what facilities have been evaluated. The facilities which can be directly linked to education performance of students prove to be significant determinants of educational outcomes such as daylight and lighting in the classroom rather than structural or technical components such as a broken door latch or worn carpeting (Earthman, 2017).

Similarly, grants have shown mixed results on improving school's academic performance. In rural Bolivia and Indonesia, grants led to little improvement in educational outcomes by improving dropout rates and enrolment, respectively (Newman *et al.*, 2002; Olken *et al.*, 2014). Likewise, the impact of improving school management on educational outcomes remains unclear. In case of Madagascar, training school management produced positive results in increasing attendance and decreasing grade repetition. Similarly in Gambia the school management training reduced teacher and student absenteeism specially in villages where average literacy levels were high (Blimpo *et al.*, 2015). Conversely, in other settings such as in the state of Uttar Pradesh in India, SBMC did not produce the expected outcomes (Banerjee *et al.*, 2008).

Finally, policy makers in the education sector consider teacher related inputs as one of the key elements of student learning and there are studies which have found significant results (S. W. Lee and E. A. Lee, 2020; OECD, 2005). For instance, a study based in Kenya found a positive and significant relationship between teacher effort and math and reading test scores of children. The author measured teacher's effort as the hours spent for lesson planning and grading of assignments (Atuhurra, 2016). Although teacher effort has been positively associated with educational outcomes but it is considered difficult to define and measure (Sindhi and Shah, 2013). On the other hand, there are some studies which claim that teacher inputs have limited impact. For instance, teaching experience which is used as one of the most common measure of teacher quality is found to have a positive impact only in the first 6 to 9 years of teaching (Shuls and Trivitt, 2015).

Based on the above evidence from literature, the school education production function for this study has been constructed. This function provides the basis of the spatial analysis of educational outcomes conducted with the help of Geographically Weighted Regression (GWR).

1.5 GWR as a Tool to Capture Spatial Patterns

When studying a phenomenon or dealing with a dataset which is expected to vary geographically, with a non-random pattern, then global average statistics produce inadequate representation of local conditions (Fotheringham *et al.*, 2002). Only if there is little or no spatial variation in the observations can a global model i.e., a model using all observations to predict parameter estimates, provide any reliable information about local relationships. Based on this rationale, GWR based local models have been used to detect spatial patterns in numerous areas which include measuring economic growth, CO2 emissions, social resilience, mortgage lending and education (Eckey *et al.*, 2005; Chun *et al.*, 2017; Fotheringham *et al.*, 2001; Wang *et al.*, 2019; Yu, 2006). All these studies reported GWR to increase the explanatory power of the model as well as help find local variations in the relationship between dependent and independent variables.

One of the studies detecting spatial variations in regional development was conducted in the Greater Beijing Area in China (Yu, 2006). The author finds strong local characteristics in the regional development of China and reveals the persistent urban-rural divide, a legacy of the biased urban industrialization policies of the country. Similarly, a study in Germany applied a Solow Model with the human development component to estimate the regional economic convergence of the country (Eckey *et al.*, 2005). The authors find disparity in the convergence speed of different regions, with the South estimated to progress the fastest. Interestingly, the study finds divergence tendencies in some peripheral regions of the country which get unnoticed using a global convergence model. Another study in Spain, explores spatial non-stationarity in the determinants of household disposable income in the country's provinces (Chasco Yrigoyen *et al.*, 2007). The study finds that education-qualification and employment activity does not have the same power to explain household disposable income in all provinces specially the ones which are agricultural, depending on subsidies, and the ones where remittances make a large share of disposable income.

In the field of environmental economics, GWR has been used to detect spatial patterns in CO2 as well as Urban Green Space (UGS) levels. The study by Wang *et al.* (2019) explores atmospheric CO2 concentration at the city level and finds that most of the cities in China were producing emissions lower than the average. The analysis identifies that private car ownership and economic growth had stronger impact in the western and central cities while energy consumption had a stronger effect in the Southern coastal cities. Although the direction of relationship between dependent and independent variables remains the same as in the global model, these patterns could not be observed in the global model. The study on urban compactness and UGS in Taiwan finds varying direction of their relationship in the southern and central area of the city which were not visible in the global model results (Chang and T. Chen, 2015).

GWR has also been increasingly used in social sciences such as a study in Uganda which explores the relationship between higher education and Intimate Partner Violence (IPV) geographically (Amegbor and Rosenberg, 2019). The study highlights location-based differences in the vulnerability of women which are hidden in the global model, after controlling for women characteristics, partner's characteristics and household income. Another study in the city of St. Louis in the US examines spatial variation between robbery rates and race and robbery rates and home ownership (T. A. Smith and Sandoval, 2019). The GWR model is better able to explain the local variation in these relationships than the global model.

Additionally, GWR has also found its use in the fields of Demography and Health where geography plays an important role (Matthews and Parker, 2013). Numerous studies have found significant local variations in fertility and migration trends with the use of GWR. A study by Hu *et al.* (2012) explores spatial variation in Hand, Foot and Mouth Diseases (HFMD) at the county level among children of age 9 years and below in China using GWR. The authors find a spatially heterogenous relationship between climate related factors, child population density and HFMD, both in terms of the strength of association and the direction.

Just like in the health sector spatial analysis can also be used to identify education disparities across a geographic region in terms of access, supply and outcomes as well as to understand the local relationship between education and space (Chaney and Rojas-Guyler, 2016). Therefore, GWR has also been used in the field of Education to capture spatial variation, but mostly in the global North. One of the first studies to use GWR for educational outcomes was conducted by (Fotheringham *et al.*, 2001), in northern England, who introduced the GWR method of modeling. The spatial results in their study help to identify various local relationships between the school's neighborhood and its performance in the standardized tests, which are hidden in the global model results. For instance, the percentage of people employed in managerial position in the school's neighborhood area showed a very small positive relationship with school performance in the global model. With the help of GWR they are able to identify the area where this relationship is strongest and the most significant.

Another study in the global North conducted in the Salt Lake County in the US, employs GWR to explore spatial patterns of neighborhood effects, student characteristics, family background and school inputs on the language, arts and math proficiency rate at school level (Wei *et al.*, 2018). The GWR model helps to identify a clear divide among academic achievements of schools in the northwest and southeast of the county and varying levels of the estimated coefficients of explanatory variables in different regions. Similarly, a study based in Missouri finds the influential factors of math proficiency varying locally (Qiu and Wu, 2019).

From the Global South countries, there is a dearth of published work employing GIS and GWR modelling in the field of education. Nevertheless, I was able to find a couple of studies in Kenya and Ghana using Point Pattern Analysis and GWR modelling to capture spatial variations in educational outcomes, respectively. The study in Ghana used GWR at the district level to examine spatial relationships between education and explanatory variables of household size, male and female employment, urbanization, electrification, male and female literacy, classroom congestion and teaching resources (Ansong *et al.*, 2015). The author finds spatial relationships of different significance, magnitude, and direction in different districts of the country. The study concludes that when there is spatial inequality in educational outcomes then where students live and attend school i.e., location, becomes an important explanatory factor.

The study in Kenya is based on school level data and uses Hot Spot and Cold Spot analysis i.e., features in the neighborhood with unexpectedly high and low values of a variable under study. The authors find that the school's performance in Kenya Certificate of Primary Education exams is significantly influenced by the location of the school in urban or rural area as well as by its distance from the major road networks. Due to the medium of instruction being English, the urban-rural influence on educational outcomes in Kenya is significant as students in the urban areas communicate more frequently in the English language. Therefore, as the school's distance increases from the city center the KCPE exam score decreases for both genders (Kimosop *et al.*, 2015).

1.6 Gap in the Literature

Based on the literature reviewed for this study, I have discovered gaps in the literature of spatial inequality in educational outcomes at three levels. First, there is a dearth of literature on neighborhood and spatial effects on education beyond the global North, specifically outside the US. As a result of this, the literature is also concentrated in urban areas and there are hardly any studies exploring educational inequality among rural communities in the global South. Second, the spatial inequality research and the application of GWR is still aggregated at state or region level which is unable to account for inequalities present within states or regions. The spatial aggregation may lead to Simpson's paradox i.e., the reversal of results when a group of data is evaluated separately and when combined (Fotheringham *et al.*, 2002). However, with the rapid increase in availability of spatial data this gap can be filled to realize the full explanatory potential of local spatial analysis.

Finally, countries in Africa are rapidly urbanizing and while on the one hand there are increasing social and economic urban inequalities in these urban centers, on the other hand, urban-rural gaps are also widening (B. Cohen, 2006; OECD, 2016). Spatial inequalities in Nigeria, specifically in education and within state, remain understudied despite being a large country in terms of land and population, with 470 ethnic groups having different beliefs, languages and customs and a history of uneven regional development (Mayowa, 2014).

CHAPTER 2
Education Landscape of Nigeria and Sokoto

Nigeria, with more than 200 million people, is the seventh largest country in the world in terms of population (Worldometer, 2021). Nigeria is a low-middle income country according to World Bank (2019a) income classification with the GNI per capita of $5190 (PPP adjusted in current international dollars). Nigeria's economy is highly dependent on oil as it generates half of the government's revenues and 80% of the country's exports. Although being one of the largest economies of Africa, 40% of the country's population live below the national poverty line with high inter-regional inequality. For instance, 81% of people live below the poverty line in Sokoto whereas in the Niger state the poverty rate is only 34% (Oxfam, 2017).

The economic inequality also translates to social inequality in the country by limiting people's access to social, political and physical resources. Poor people are unable to improve their standard of living due to their inability to meet their consumption, education and health needs (Ochmann *et al.*, 2020). The average literacy rate in Nigeria is 62% but the inter-regional and locational divide in the literacy rates, similar to income, is high and persistent. In a report by UNESCO (2012), Lagos had a literacy rate of 92% whereas the states in the North of the country, such as Katsina and Yobe, had a literacy rate of 26.6% and 21.7% respectively. The reported urban-rural divide in literacy was more than 25% with urban literacy rate at 74.6% and rural literacy at 48.7%. This divide is crucial as majority of people in Nigeria still live in the rural areas and specially the children of school going age (Nigeria Population Commission, 2015).

The education system in Nigeria, since 1982, follows the 9-3-4 structure with 9 years of compulsory primary schooling which include 6 years of primary and 3 years of lower-secondary school. During the oil boom in the 1970s, the government dedicated large funds for the education sector and introduced free universal primary education in the country. Despite these initiatives, the inequality in quality and learning outcomes in education remain a challenge for Nigeria (Onwuameze, 2013). There are both supply and demand side factors that have led to the increasing disparity in the quality and access to education in the country (Ochmann *et al.*, 2020).

The supply side factors most importantly include the supply and quality of teachers which is a big issue in the Northern states of the country. These states have the highest number of unqualified teachers which are not adequately trained to teach the assigned curriculum or manage large class sizes. According to Nigeria's Universal Basic Education Commission UBEC (2018), the public schools in the North West states of the country have the highest pupil to teacher ratio and pupil to qualified teacher ratio at all levels of primary education i.e., pre-primary, primary and junior secondary. Similarly, the amenities at schools and teaching and learning equipment, including libraries, playgrounds and textbooks, are disproportionately lower in the schools in the

North Western and Eastern states. The pre-primary schooling opportunities in these states are also severely limited, which is evident from the fact that only 7% children of age 4-5 years receive any schooling in the North West of Nigeria (Ochmann *et al.*, 2020). As a result, children in these areas are not prepared to excel in primary schools as compared to their counterparts in other regions of the country.

On the demand side, there are numerous issues revolving around the poverty and social norms of the communities which have a negative impact on educational outcomes. Although the primary education is free in Nigeria, the overall cost of schooling including uniforms, transport etc., adds up to one-fifth of per capita income of the poorest quintile households (Ochmann *et al.*, 2020). The poorest families also depend on the income from the labor of their children to meet their basic consumption needs which is the second biggest reason behind school drop-out after poverty (Nigeria Population Commission, 2015). Subsequently, as already discussed in Section 1.3, poverty in North of the country is higher than in the central and southern regions which further widens the gap in education.

Social norms influenced by the interpretations of religious teachings directly influence the education of children specially girls. According to National Bureau of Statistics NBS (2017), 23 to 33% girls in the North East and North West states are married off before the age of 15. The children, especially girls, in poor and conservative families are also involved in household chores and taking care of younger siblings. This is evident from the fact that these regions have the lowest primary to junior secondary transition rates in the country (UBEC, 2018). Additionally, in the predominantly Muslim states of the North West, where religion play an important role in the lives of the people, parents show lack of interest towards secular education for their children. This is also the reason that North West has the highest number of Islamic schools in the country. Moreover, the insecurity and violence, specifically in the North Eastern states of Nigeria have also had an impact on the educational outcomes. There have recently been multiple large-scale kidnapping of pupils from schools in Northern Nigeria which have added to the security concerns of parents in sending their children to school and of teachers to be willing to work in these areas (Busari *et al.*, 2021). All these factors have collectively pulled down the northern states in their progress in education, relative to other states of the country.

2.1 Sokoto

Sokoto is one of the 36 states of Nigeria, situated in the extreme North West of the country bordering with country Niger in the Savannah region. The state came into being in its current form in 1996 and has a total of 23 Local Government Areas (LGA). As of 2016, it has an estimated population of 4.9 million people who predominantly belong to the Hausa and Fulani ethnic groups and are Muslims (Education Sokoto, 2010; NBS, 2017). According to the State Government (2021), around 80% of the people are involved in agriculture including livestock and fishing. Based on the Nigeria Living Standards Survey, Sokoto has the highest poverty rate[2] of 87.73% amongst

[2]Poverty is measured using the consumption/expenditure-based approach in this report on Nigeria.

all states with the second highest poverty gap of 38.82% (percent of poverty line) (NBS, 2019). Sokoto has a Gini index of 28.02 which is lower than the national Gini index of 35.13.

2.1.1 Primary Education in Sokoto

The primary education in Sokoto is divided into public and private sectors. As of 2018, the private sector enrolled 69 thousand students whereas the public sector enrolled more than 816 thousand students in the first 9 years of Basic Primary Education schools. It is evident that public schools are the most common access point of education for the children in Sokoto. The primary school network in Sokoto contains more than 23 hundred schools with most of them located in the rural areas and a teaching staff exceeding 24 thousand (UBEC, 2018).

Table 2.1: Learners to Teacher Ratio

	Pre-Primary		**Primary**		**Junior Secondary**	
	Learners to Teacher	Learners to Qualified Teacher	Learners to Teacher	Learners to Qualified Teacher	Learners to Teacher	Learners to Qualified Teacher
Sokoto	112	219	34	82	23	29
National Average	70	79	34	47	20	25

Source: Universal Basic Education Commission, Nigeria 2018

Table 2.2: Amenities in Sokoto Public Schools

Amenities	**Number of Schools**	**Percentage of Total Schools**	**National Average (Percent of schools)**
Toilets	786	33.9	54.1
Portable water	754	32.6	34.6
Power	228	9.8	19.37
Computers	183	7.9	10.5
Playground	1315	56.8	59.9
Library	215	9.3	13.2

Source: Universal Basic Education Commission, Nigeria 2018

This large network of schools in Sokoto shows signs of inefficient management and limited availability of resources. This is apparent from the figures that teacher to learner's ratio in Sokoto is way worse than the national average at all levels of primary school as shown in Table 2.1. Based on the data published the amenities in public primary schools in Sokoto are very limited and below the national average as shown in Table 2.2.

The state performance on Gender Parity Index of enrollment in primary schools is also below the national average at all three levels of primary school i.e., pre-primary (0.81 vs 1.01), primary (0.69 vs 0.93) and junior-secondary (0.61 vs 0.91). The transition rate from primary to junior-secondary is 87.21% which is better than the national average of 83.3%. However, the Multiple Indicator Cluster Survey found only 18.7% of the children of primary school completion age attending the last grade of primary school in the households surveyed in Sokoto (NBS and UNICEF, 2017).

Although being supported by the government, primary education in Sokoto suffers from severe limitations as evident from these indicators of public education institutions. Consequently, these constrained school inputs then translate into poor quality of education production. According to the World Bank Human Capital Index, on average, Nigerians are expected to go to school for 10.2 years but the average years of learning is 5.0 years which is a proof of the weaknesses in the education system of the country[3] (World Bank, 2020).

[3]This is the status of Nigeria pre-COVID-19.

CHAPTER 3
Data

The data for this study were collected during an evaluation experiment conducted in Sokoto for the Nigerian Partnership for Education Project (NIPEP). NIPEP was designed and implemented by Global Partnership for Education in collaboration with World Bank and the Federal Government of Nigeria in 5 different states. The aim of the project was to support the Nigerian education system, especially in the Northern states, to achieve MDG-2 of universal primary education. The experiment took place in Sokoto, one of the five project states and evaluated two components of the project called the School Improvement Grants (SIGs) and the training of School Based Management Committee (SBMC). 128 primary schools from the rural areas of nine LGAs of Sokoto were selected for the experiment where (a) NIPEP had not yet been implemented and (b) the security situation was safe enough to conduct baseline surveys in 2018. The location of treated and control schools with the name of the LGAs are shown in Figure 3.1.

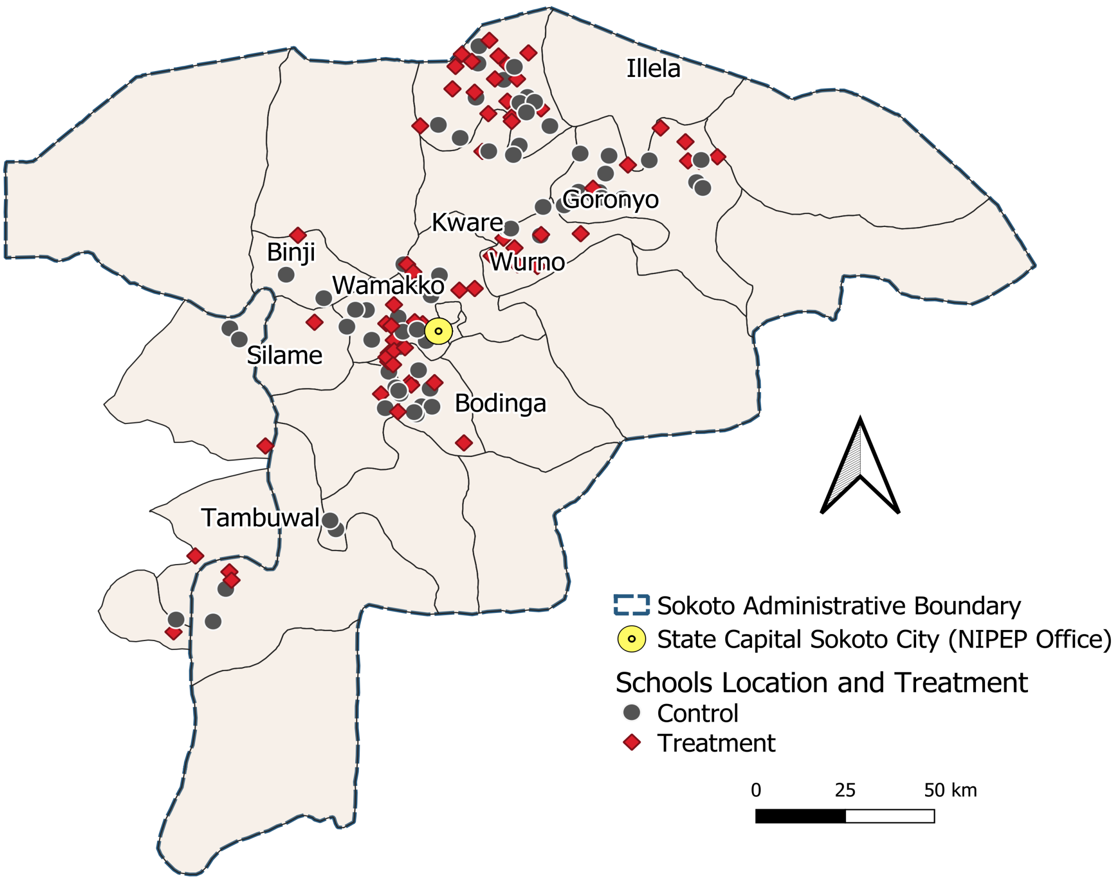
3.1 Geospatial Data

The locations of the schools in the sample were geocoded by Sophie Ochmann during her primary research for the Endline of the NIPEP evaluation experiment in Sokoto. The shape layers for the Sokoto state and LGAs were taken from the Database of Global Administrated Areas (GADM, 2018). Some of the schools in the sample lie outside the administrative boundary of Sokoto as shown in Figure 3.1.

3.2 NIPEP Evaluation Study Design

The evaluation was designed as a randomised control trial with half of the schools randomly selected to receive a grant and training for its SBMC while the other half receiving no intervention. One half of the 64 treatment schools were assigned to receive 250 thousand Naira (equivalent to PPP adjusted international $2272) while the other half were to receive 500 thousand Naira, to capture the impact of grant amount. The SBMC trainings included components of leadership, school management and community involvement. The impact of the project was evaluated by conducting two rounds of surveys: before the start of the project in August 2018 called Baseline and one year after the intervention in November-December 2019 called Endline. Th surveys were administered to students, teachers, headmasters, available SBMC members as well as an observational survey was conducted on the school infrastructure and environment. The survey questionnaires were in the local dialect of Hausa and the responses were recorded on a tablet. The enumerators were recruited from the Sokoto state and were trained to create an encouraging and

Figure 3.1: Sample Schools Location and Treatment



Source: Author's elaboration

trusting environment for the survey. In the Endline, a total of 6031 students, 175 teachers, 99 headmasters and 348 SBMC members were surveyed in all 128 schools.

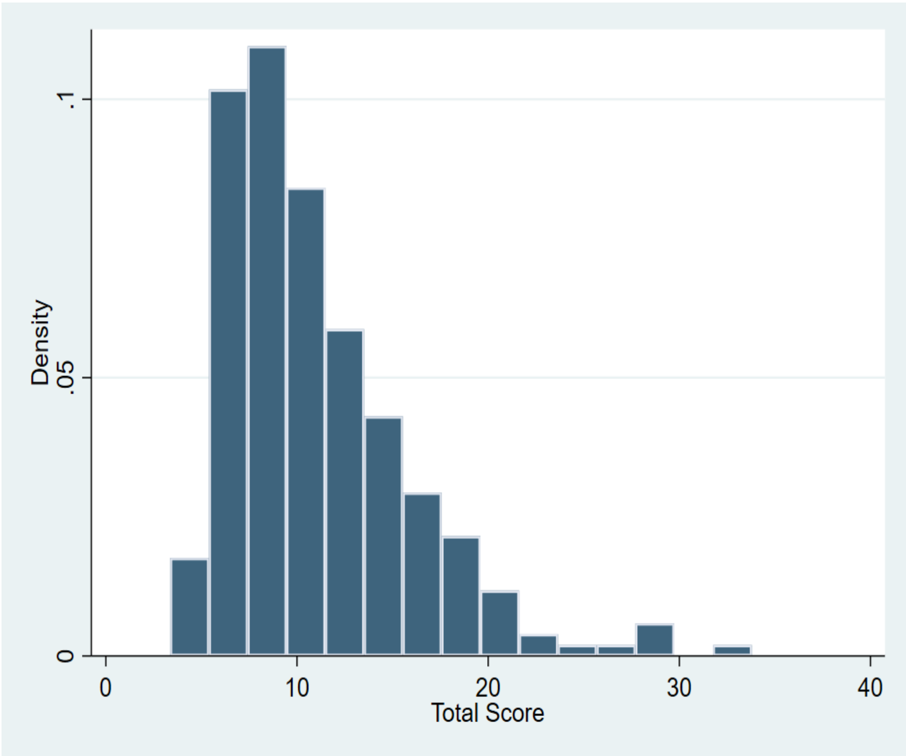
The study by Ochmann *et al.* (2021) did not find any impact of the grant (single and double) or training on educational outcomes of the schools. The data for this study is therefore taken from the Endline survey of the evaluation experiment because the treatment did not have any impact on educational outcomes of schools and therefore the Endline survey provides the most recent information on schools' inputs and academic output.

3.3 Dependent Variable

The study tries to measure and explain the spatial inequality in educational outcomes of schools in Sokoto which is captured with the help of the academic score of schools in reading and numeracy. Therefore, the dependent variable or the variable of interest is the Total Score i.e., the mean of numeracy and reading scores of students aggregated at school level. The students were asked mathematics questions on counting and simple mathematical computations such as addition and subtraction up to 2 digits. For reading, students were tested on their ability to read and understand basic alphabets, words and sentences of the Hausa language. Both numeracy and reading scores were marked out of twenty for each student and the mean of the combined score out of 40 was calculated at school level.

The Total Score variable have a skewed distribution, as shown in Figure 3.2, therefore the variable is log transformed to avoid heteroskedastic results (Marcellino, 2016). The distribution of the Log transformation of Total Score is presented in Figure 3.3. Out of 128 schools surveyed in the Endline, two schools don't have data on students and therefore I have Total Score for 126 schools.

Figure 3.2: Distribution of Total Score Variable



Source: Author's elaboration

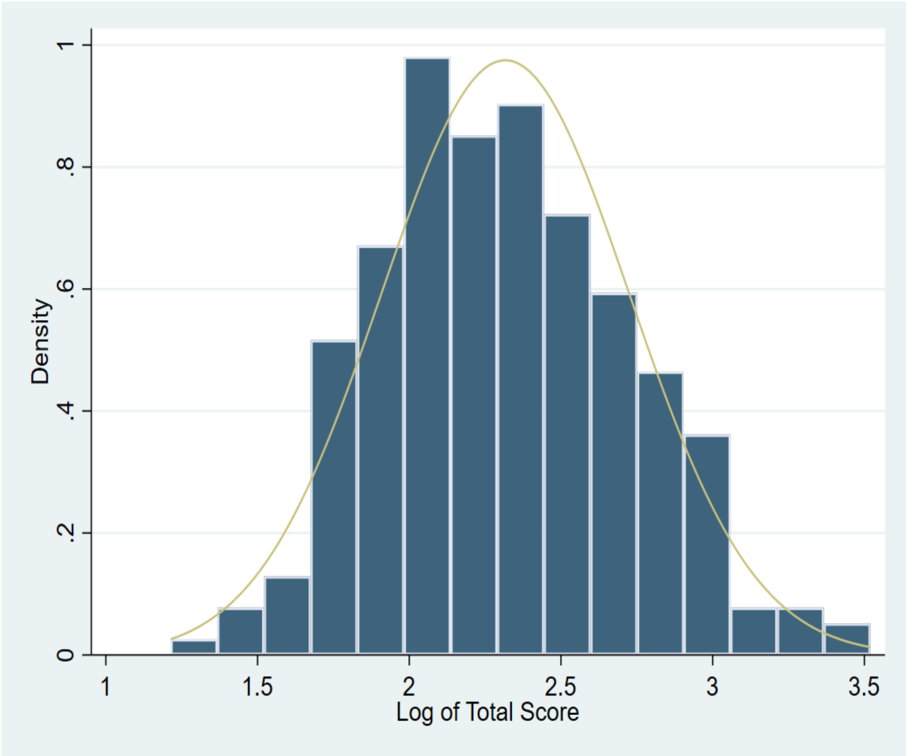
3.4 Independent Variables

There are two sets of independent variables used in models which are calibrated to answer research questions RQ3 and RQ4.

3.4.1 Independent Variable RQ3

The independent variable "Remoteness" is used to capture the relationship between the educational outcomes of school and its distance from the urban centre i.e., the state capital Sokoto city. The "Remoteness" is calculated as the travelling distance from the NIPEP office based in Sokoto City to the location of the schools. The STATA command "georoute" which uses an external Geo platform called HERE API is employed to calculate actual travelling distances by car between state capital and the schools (Weber and Péclat, 2016). The distances in kilometres calculated with georoute command are very close to the distances shown on Google Maps, unlike the Euclidean distances which fail to capture the remoteness of schools based on its accessibility by a mode of transportation.

Figure 3.3: Distribution of Log of Total Score Variable



Source: Author's elaboration

The closest school in the sample is 6.3 kms away by car from the NIPEP office in the Sokoto city and it is in the LGA called Wamakko. The farthest school in the sample is in the LGA Tambuwal and is approximately 132 kms away from the NIPEP office by car. The Euclidean distance for the school with the second largest travelling distance of 128.38 kms is 87.25 kms. This 41 km difference between the two proves the significance of using travelling distance instead of Euclidean distance as the latter is unable to capture the remoteness of the school.

3.4.2 Independent Variables RQ4

There are eight independent variables used as school inputs in the education production function. These variables are selected based on theory, on the availability of information from the survey questionnaires and their statistical significance in explaining educational outcomes of schools.

School Facilities

The variable School Facilities was calculated by Ochmann *et al.* (2021) from the observational survey of the school. The variable incorporates seven elements of school facilities: headmaster's office, staff room/break room, sport's field, library, storage room for learning materials, power supply and computer. One point was added to the score on the availability of each facility and then an unweighted average of facilities was calculated for each school. The average was then scaled down to an index from 0 to 1. The schools in the sample perform worse than the state average on the availability of these facilities: library (2.4% vs 9.3%), sports field (39.2% vs 56.8%), computer (0.8% vs 7.9%) and power supply (5.6% vs 9.8%). The state averages are taken from the report by UBEC (2018) as discussed in detail in Chapter 2.

Treatment Dummy

The variable Treatment Dummy is a dummy variable which takes the value 1 if the school was assigned into the treatment group and 0 if the school was not. The treatment involved receiving a School Improvement Grant (SIG) and a training for its SMBC members. Exactly 50% of the schools in the sample randomly received treatment and 50% i.e., 64 schools did not.

SBMC Involvement

The SBMC Involvement variable captures the involvement of SBMC members in different school related activities which were recorded in the survey responses. Each SBMC is given one point for each action: if they held a meeting in the previous term, if the committee has laid down a set of rules, if they are involved in the hiring process in the school, if they are involved in the school development plan and if they take part in different school related activities. These activities included but were not limited to mobilizing parents to send their children to school, raising funds for the school, repairing and buying school furniture, and building toilets. The score is then aggregated for each school and standardized to an index from 0 to 1. If more than one SBMC member for a school responded to the survey, then an unweighted average of the SBMC involvement index is taken which was calculated based on their responses. The actions for which the responses were not recorded were not included in the average. As shown in Table 3.2, most of the SBMC members reported that a meeting was held and that they contribute in the school development plan but, on average, only 16.5% of the members reported to be directly involved in school related activities.

SBMC Literacy

SBMC Literacy variable is based on the responding member's ability to read a letter and was calculated by Ochmann *et al.* (2021) for their analysis. Value 1 was assigned to the member who reported they could read and 0 otherwise. If more than one SBMC member for a school responded to the survey, then an unweighted average of their literacy index was taken and was scaled down between 0 and 1 to form an index. The SBMC members, who responded, had very low levels of literacy with 32% reporting that they could read and 60% of the members surveyed had received any formal education.

Headmaster Education

Headmaster education is an ordinal categorical variable which is generated based on the level of formal education acquired. It has the values, as shown in Table 3.1, in accordance with the education system of Nigeria (Onwuameze, 2013).

Table 3.1: Degrees with Number of Years of Study

Education Level	**Value**
No formal education or incomplete primary education	0
Complete primary education	9
Complete Secondary Education	12
Teacher Grade 2 Certificate	13
Nigeria Certificate in Education (NCE)	15
Ordinary Higher Diploma (OND)	14
Higher National Diploma (HND)	16
Bachelors	16
Post-Graduate Diploma (PGD)	17
Masters	18

Source: Adapted from Karugu et al. *(2013)*

The median education of the headmasters in the sample is 15 years. 3 headmasters reported to have not completed primary school while most of them reported to be trained as a teacher holding NCE or a Teacher Grade 2 certificate.

Teacher Involvement

All the teacher's surveyed were asked the percentage of students in their classes that they know by name. Teacher Involvement is simply the reported percentage of students a teacher remembers by name. This assumes that if a teacher spends more time with the children at school, she will remember a greater number of students by their names. Teachers from 73 schools responded to this question and on average reported to know 55% of their students' names.

Teacher Effort

This variable is based on a number of survey questions which tries to capture the effort exerted by a teacher in delivering and planning her lessons. Each teacher was given a score out of 1 based on the self-reported frequency of different teaching methods she/he used: using a blackboard, using learning materials, checking homework, reading out stories and developing a lesson plan. An average score was calculated for each teacher which was scaled down to an index from 0 to 1. If more than one teacher answered the survey from a school, then an unweighted average of the index was taken. Most of the teachers reported to use blackboard and check homework everyday but only 25% teachers reported to use learning material and 15% reported to read out stories every day. 88 teachers reported to have a written working scheme for the semester but only 35 of them were able to show a physical document to the enumerator.

Average Teacher Experience

Average Teacher Experience is the last teacher related independent variables which tries to capture teacher quality. It is an unweighted average of experience, in years, of all teachers in a school. In 80 schools where teachers responded to the experience question, on average, the age of teachers was 36.7 years and teaching experience was 11 years.

Table 3.2: Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Total Score	126	12.33	5.28	4.535	33.791
Log of Total Score	126	2.43	.402	1.512	3.52
Remoteness	128	60.845	34.265	6.299	132.113
School Facilities	125	.172	.195	0	.857
Headmaster Office	123	.374	.486	0	1
Staff room/break room	124	.185	.39	0	1
Sports Field	125	.392	.49	0	1
Library	123	.024	.155	0	1
Storage Room for Learning Material	124	.169	.377	0	1
Computer	124	.008	.232	0	1
Power Supply	124	.056	.09	0	1
Treatment Dummy	128	.5	.502	0	1
SBMC Involvement	116	.407	.2	0	.883
Meeting Conducted in the Last Term	93	.892	.331	0	1
Set Rules and Regulation	105	.638	.483	0	1
Involved in Hiring	109	.587	.495	0	1
Contributed to School Development Plan	46	.957	.206	0	1
Involved in School Activities	116	.155	.182	0	.833
SBMC Literacy	116	.452	.393	0	1
Headmaster Education	97	13.918	2.812	0	16
Teacher Involvement	73	.555	.263	0.04	100
Teacher Effort	80	.544	.193	0	1
Use of Blackboard	75	.823	.281	0	1
Use of Learning Materials	73	.455	.383	0	1
Checking Homework	77	.708	.310	0	1
Reading out Stories	80	.569	.292	0	1
Developing a Lesson Plan	78	.154	.363	0	1
Average Teacher Experience	80	12.381	7.065	1	33

Source: Author's calculations

CHAPTER 4
Methodology

The study adopts different spatial analysis tools to explain the inequality and spatial non-stationarity in the educational outcomes of schools in Nigeria. The chapter is divided into three main sections directly linked with the research questions of the study. The first section explains the statistical measures adopted for explaining spatial non-stationarity and inequality in educational outcomes of schools in Sokoto. The second section explains the model adopted to explore the relationship between educational outcomes and remoteness of schools. The third section elaborates the GWR model adopted to explain spatial variations in the relationship of input variables of the education production function with output variable i.e., school academic score.

Three different software have been used to support the analysis of this study. All computations have been performed on STATA 16, model calibrations have been conducted on RStudio whereas the maps have been created on QGIS 3.4. RStudio and QGIS 3.4 are open source with extensive help available online which has been cited in the study wherever used. EndNote has been used to cite all the sources in this study.

4.1 Spatial Variation in Educational Outcomes

Global measures of spatial variation or more specifically spatial dependency are being developed since the 1950s (Fotheringham *et al.*, 2001). This study employs the classic Global Moran's I spatial autocorrelation coefficient to detect spatial dependency in educational outcomes of schools in Sokoto. In order to capture Spatial Inequality, Spatial Gini Index has been calculated for the educational outcomes. RStudio's package "lctools" has been used to calculate both the Moran's I and Spatial Gini for this study (Kalogirou, 2020). The methods and associated test statistics are discussed in detail below:

4.1.1 Moran's I Spatial Autocorrelation Coefficient

The Moran's I coefficient measures the spatial autocorrelation for an attribute by using its values and the values' locations in space. The formula of the Moran's I coefficient is given by:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{4.1}$$

where,

I = Moran's I statistic

n = total number of observations

z_i = deviation of the observation i from the mean $(x_i - X)$

$w_{i,j}$ = spatial weight matrix for observation i and j

S_0 = aggregate of all spatial weights and can be written as:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$$

Based on (4.1), if there is a positive correlation among the nearby values, then the sum of the cross products of deviation z_i and z_j will be positive and the resulting statistic value will be positive. Conversely, if there is a negative correlation between the neighboring values then the sum of the cross products of z_i and z_j i.e., the covariance will be a negative value and the resulting statistic will be negative. If there is no correlation between neighbors, then the cross products will cancel out each other and the resulting statistic will be 0.

The Moran's I coefficient usually ranges from -1 to 1 as the numerator of the index is normalized by the variance of deviations z_i. The spatial matrix for the index can be computed using different weighting functions such as Binary, Bi-square or RSBi-square. The Binary weighting function gives weight 1 to all the neighbors and 0 otherwise while the Bi-square weighting function follows the following formula:

$$w_{i,j} = \begin{cases} \left[1 - \left(\frac{d_{i,j}}{b}\right)^2\right]^2 & \text{if } d_{i,j} < b \\ 0 & \text{otherwise} \end{cases}$$

where, $d_{i,j}$ is the distance in space between observations i and j and b is the bandwidth which can either be in terms of numbers called "fixed bandwidth" or in terms of distance called "adaptive bandwidth". The RSBi-square weighting functions uses the Bi-square weighting scheme with a slight change in the weighting formula i.e., the bi-square weights are divided by the sum of weights in each row of the matrix. However, Bi-square weighting scheme is used for calculating the Global Moran's I coefficient for Total Score of schools.

Moran's I Test Statistic

The Global Moran's I being an inferential statistic is evaluated in terms of its null hypothesis (ArcGISPro, 2021). The null hypothesis for the Global Moran's I is given below:

H0: the attribute being studied is randomly distributed across space in the study area/the spatial pattern observed in the study area is a random chance.

The test statistics for the Moran's I coefficient is calculated by using Monte Carlo simulations i.e., the observations are distributed randomly in space and the Moran's I index is calculated for that random distribution. The randomized index is then compared with the actual Moran's I statistic to see how different it is from the randomized version. This simulation is repeated multiple times and the test statistic is considered to be significant if the resulting randomized index is found different from the actual Moran's statistic. This confirms that the spatial autocorrelation is a result of some spatial processes and not due to some random allocation (O'Sullivan and Unwin, 2003).

4.1.2 Spatial Gini

Moran's I coefficient of spatial autocorrelation answers our research question of spatial dependency in education but not of inequality. The Global Moran's I index can account for the spatial clustering of attributes but does not measure the unevenness between the clusters. Spatial Gini helps to combines the measure of inequality with space (Rey and R. Smith, 2012).

Spatial Gini is calculated by the decomposition of the classic measure of inequality called the Gini coefficient. The Gini provides an aggregate value of disparity in the distribution of an outcome and informs us that there is inequality, but it is unable to identify where in space the inequality exists (Arbia, 2001). Similarly, an extension to the Gini index, the a-spatial or locational Gini coefficient by Krugman (1991) can account for concentration i.e., if certain regions have disproportionally high outcomes but does not account for polarization i.e., if there is any geographical pattern in the concentration of outcome within the region. The Spatial Gini, which can be calculated at any level of spatial unit, can help to account for inequality between but also within the spatial units (Rey and R. Smith, 2012).

The Gini coefficient is calculated using the equation 4.2:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n^2 \bar{x}} \tag{4.2}$$

where, x_i is the value of attribute x at location i and $\bar{x}$ is the mean of all observations. Rey and R. Smith (2012) spatially decomposed the above coefficient in the following way:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} |x_i - x_j|}{2n^2 \bar{x}} + \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (1 - w_{i,j}) |x_i - x_j|}{2n^2 \bar{x}}$$

where $w_{i,j}$ is the spatial matrix just as in Moran's I which determines the neighborhood relationship of observations at location i and j. Similar to Moran's I, a Bi-Square weighting scheme is used for calculating the Spatial Gini Index for Total Score of schools. If similar values are spatially nearby then the second term of the equation will grow i.e., in case of positive spatial autocorrelation. On the contrary, in case of negative spatial autocorrelation the first term will grow, and the second term will shrink.

This index helps to identify if the inequality is between or within spatial units. The spatial autocorrelation coefficient measures covariance between neighboring observations while the spatial Gini index also allows to capture covariance between different neighboring groups which is the inequality component:

$$SG = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (1 - w_{i,j}) |x_i - x_j|}{2n^2 \bar{x} G} \tag{4.3}$$

where G is the global Gini index.

Spatial Gini Test Statistic

Just like Moran's I, the significance of a Spatial Gini index is calculated using Monte Carlo simulations. The null hypothesis for the Spatial Gin significance test can be defined as:

H0: the component of non-neighbor inequality is a result of a random distribution of attributes across space in the study area.

The pseudo p-value for Spatial Gini is defined as:

$$p(SG) = \frac{1+C}{1+M}$$

where C is the number of those M=999 permutations sample which produced the value of Spatial Gini similar to the original data sample. The permutation samples are formed using Monte Carlo simulations which give random samples across space. The Spatial Gini coefficients for these samples are then calculated and compared with the original index to compute C, as explained above. If a large number of permuted sample Gini coefficients are similar to the one computed for the original data then the null hypothesis cannot be rejected (Rey and R. Smith, 2012).

4.2 OLS Regression Model

In order to understand the spatial variation in educational outcomes in Sokoto, remoteness of schools is analyzed as one of the influencing factors. This section explains the empirical method adopted to test the third research question i.e., does a relationship between the remoteness of schools and its educational outcomes exist?

As established in the Literature Review subsection 1.2.3, the urban areas in developing countries have better access to services which are required for quality education. For instance, in Pakistan, according to the Demographic and Health Survey conducted in 2017, the urban-rural divide in Household's access to the internet is 18% (Aslam, 2021). Access to services such as internet, electrification etc. and schools itself are higher in urban areas and decreases as the distance from the urban center increases (Brinkerhoff *et al.*, 2018). A study by Alesina *et al.* (2021) estimated that the probability of primary school completion significantly increases for children of uneducated parents if they spent an extra year in a high mobility region. Based on this evidence, the following regression model is employed to capture the relationship between remoteness i.e., distance of the school from the capital city of Sokoto and its aggregate academic score:

$$\text{Log of Total Score } = \beta_0 + \beta_1 \text{ remoteness } + \varepsilon_i \tag{4.4}$$

where β_0, β_1 are population parameters which are estimated using Ordinary Least Squares (OLS):

$$\text{Log of } \widehat{\text{Total}} \text{ Score } = \widehat{\beta}_0 + \widehat{\beta}_1 \text{ remoteness} \tag{4.5}$$

where $\widehat{\beta}_0$, $\widehat{\beta_1}$ are unbiased linear estimates of β_0 and β_1 respectively and $Log\ of\ \widehat{Total}\ Score$ are the predicted values by the model for the corresponding remoteness value. The difference between the actual value of Log of Total Score and the one predicted by the model is stored in $\widehat{\varepsilon_i}$ called the residuals of the model.

As a robustness check for the model and to justify our further exploration of spatial variation in educational outcomes in Sokoto, I calculate Moran's I correlation coefficient for the model residuals. This will help check two things: first if remoteness can consistently explain educational performance of schools across the study area and second, if there are spatial patterns in the overestimation and underestimation of school's academic performance by the model (Fotheringham *et al.*, 2001; Hu *et al.*, 2012; Javi *et al.*, 2014).

4.3 Geographically Weighted Regression (GWR)

As discussed in the Literature Review section 1.2, educational outcomes are expected to be affected by the location of schools and where children live due to the urban-rural divide in educational outcomes and neighbourhood effects. Therefore, GWR is being used in this study to explore spatial variation in the production of education dependent on spatially dependent input variables with the help of an education production function. As described by Shuls and Trivitt (2015), a standard additive education production is used for this study:

$$E_i = f\left(S_i, G_i, C_i, T_i\right)$$

The school output for our analysis is the mean of numeracy score and reading score calculated at school level E_i. The school inputs include the school resources S_i, treatment variable i.e., receiving grant and SBMC training G_i, SBMC inputs C_i and Headmaster and Teacher Inputs T_i. According to the literature, all of these have been considered as potential inputs for an education production function of schools but their impact on educational outcomes has been mixed. Data on student characteristics was not captured in the survey and thus not included in the model.

Before calibrating the GWR based models, OLS regressions are estimated to capture the global effect and for comparison with GWR estimates. Following OLS models are estimated in order:

$$E_i = \beta_0 + \beta_1 \text{ School Facilities }_i + \beta_2 \text{ Treatment }_i + \varepsilon_i \tag{4.6}$$

$$\begin{gathered} E_i = \beta_0 + \beta_1 \text{ School Facilities }_i + \beta_2 \text{ Treatment }_i + \beta_3 \text{ SBMC Involvement }_i \\ +\beta_4 \text{ SBMC Literacy }_i + \varepsilon_i \end{gathered} \tag{4.7}$$

$$\begin{gathered} E_i = \beta_0 + \beta_1 \text{ School Facilities }_i + \beta_2 \text{ Treatment }_i + \beta_3 \text{ SBMC Involvement }_i \\ +\beta_4 \text{ SBMC Literacy }_i + \beta_5 \text{ Headmaster Education }_i + \varepsilon_i \end{gathered} \tag{4.8}$$

$$\begin{gathered} E_i = \beta_0 + \beta_1 \text{ School Facilities }_i + \beta_2 \text{ Treatment }_i + \beta_3 \text{ SBMC Involvement }_i \\ +\beta_4 \text{ SBMC Literacy }_i + \beta_6 \text{ Teacher Involvement }_i + \beta_7 \text{ Teacher Effort }_i \\ +\beta_8 \text{ Average Teacher Experience }_i + \varepsilon_i \end{gathered} \tag{4.9}$$

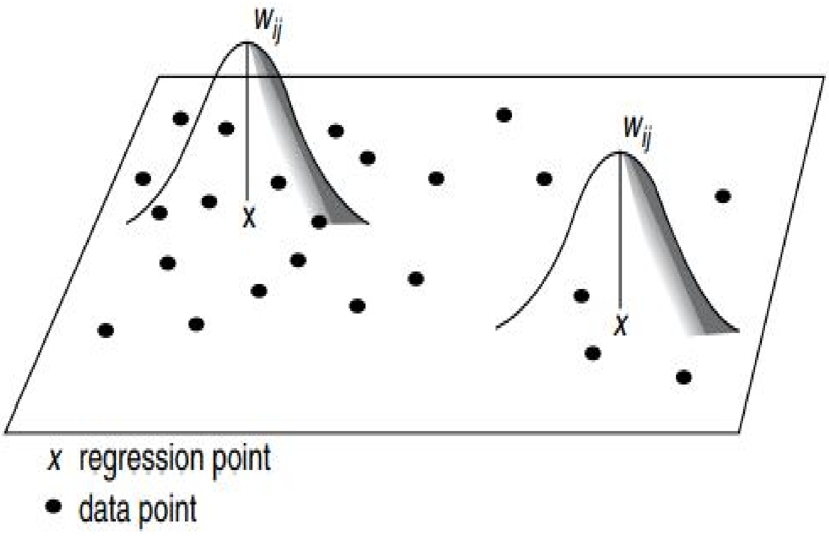
The same models are extended with the help of GWR to capture the geographical variation in the estimated coefficients Nakaya (2008). A multivariate GWR based regression model in general form is written as follows:

$$y_i = \beta_0\left(u_i, v_i\right) + \sum_k \beta_k\left(u_i, v_i\right) + \varepsilon_i \tag{4.10}$$

The (u_i, v_i) are the x and y coordinates or the longitude and latitude of the geographical location of observation i in the study area. The GWR model estimates a coefficient for each observation location which for example in our case is schools i.e., a local model is calibrated for each school. In this local model, only observations nearby are used to produce a parameter estimate for that school. There are two extra components required to estimate a GWR model as compared to the OLS: first is the bandwidth and the second is the weighting kernel.

The bandwidth determines how many nearby values, which are expected to have a greater influence than the entire dataset, are to be used to calibrate the local model. There are two types of bandwidth namely fixed and adaptive. Fixed bandwidth is in terms of distance i.e., all datapoints within a fixed distance will be used to calibrate the local model. On the other hand, adaptive bandwidth is in terms of number of neighbours i.e., a fixed number of datapoints will be used to calibrate the local model at each location. The graphical representation of fixed and adaptive bandwidth can be seen in Figure 4.1 and 4.2. Adaptive bandwidth is preferred over fixed bandwidth if the distribution of datapoints across the study area is not constant (Fotheringham *et al.*, 2002).

Figure 4.1: Fixed Spatial Kernel



Source: Fotheringham et al. *(2002)*

Variance-bias trade off in GWR is the trade-off between goodness of fit vs. degrees of freedom. The smaller number of local observations produce unbiased estimates based on the assumption that they have a higher influence on the local model estimates but result in high variances. In this study adaptive bandwidth is used because some school locations are isolated which can result in high variances due to the small number of observations used to calibrate the local model. The optimal bandwidth b^* is calibrated using the cross-validation (CV) technique which minimizes the residuals for the local model without including the observation for which the model is being calibrated:

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(b)]^2$$

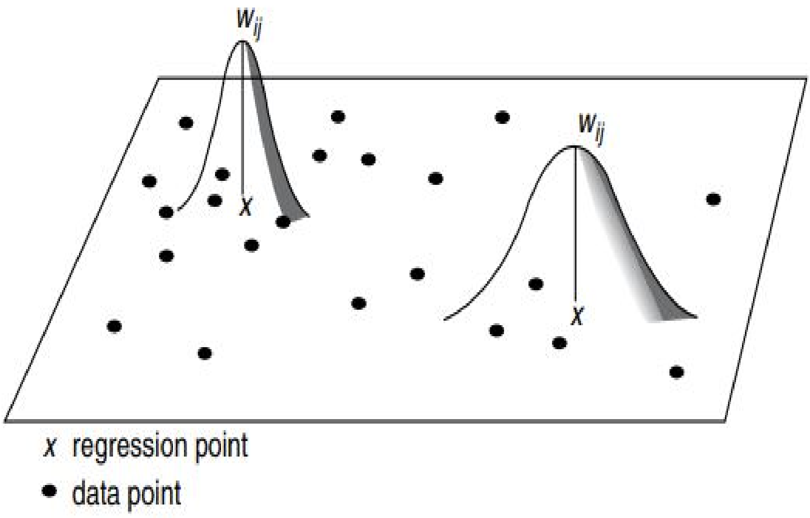
where, $\hat{y}$ are the fitted values and b is the bandwidth.

Just like for Moran's I and Spatial Gini, different weighting functions can be used including Binary, Bi-square and Gaussian etc. This study uses a Gaussian weighting function which has been used by most of the studies in the literature. It is given by:

$$w_{i,j} = \exp\left[-1/2\left(\frac{d_{i,j}}{b}\right)^2\right]$$

If datapoint j geographically coincides with datapoint i then observation j will have the weight 1 in estimating the coefficient for observation i. Similarly, as the distance between point i and j increases the weight for observation j will decrease (Fotheringham *et al.*, 2002). Finally, a GWR model is estimated with a Gaussian spatial weighting kernel using an adaptive bandwidth calibrated with the Cross-Validation technique. RStudio package "spgwr" is used to calibrate these models and the results are exported to QGIS 3.4 to graphically represent them (Bivand *et al.*, 2020).

Figure 4.2: Adaptive Spatial Kernel



Source: Fotheringham et al. *(2002)*

CHAPTER 5
Results

This chapter will follow the same order as the research questions of the study to present the results from the empirical methods adopted. Robustness tests, available in the literature, were also employed to validate the results obtained and are discussed in detail in each section.

5.1 RQ1: Spatial Dependency in Educational Outcomes in Sokoto

The Moran's I spatial autocorrelation coefficients calculated for the educational outcome of schools i.e., Total Score for different neighborhood sizes are presented in Table 5.1 and Figure 5.1. The coefficients are all significant at 99% significance level and are decreasing as the number of neighbors increases which proves that low performing schools are spatially clustered in Sokoto. For neighbors k=3 and k=5, the global Moran's I coefficient is greater than 0.3 which is an indication of a relatively strong positive spatial autocorrelation (O'Sullivan and Unwin, 2003). This allows us to respond in affirmative to the research question 1 that there is significant evidence to confirm that there exists spatial dependency in the school's educational outcomes in Sokoto.

Table 5.1: Log of Total Score Moran's I

No of neighbours	**Moran's I**	**P-value resampling**	**P-value randomization**
3	0.37	0.00	0.00
5	0.35	0.00	0.00
8	0.28	0.00	0.00
12	0.22	0.00	0.00
20	0.18	0.00	0.00

Source: Author's calculations

5.2 RQ2: Spatial Inequality in Educational Outcomes in Sokoto

The Spatial Gini is calculated for the Total Score of numeracy and literacy for different neighborhood sizes and the results are presented in Table 5.2. For all neighborhood sizes the between group Spatial Gini Indices constitute more than 96% of the total inequality in educational outcomes of schools i.e., within Sokoto there is disparity in educational outcomes of schools located in different locations. The within group spatial inequality for the total academic score increases with neighborhood size which is further evidence of spatial dependency in educational outcomes in Sokoto i.e., schools with lower scores are situated near other schools with lower scores and higher scoring schools are neighbors to other high scoring schools.

The component of inequality, in educational outcomes of schools in Sokoto, associated with

Figure 5.1: Log of Total Score Moran's I

Source: Author's elaboration

non-neighboring schools is significant at 95% confidence level for neighborhood size 5 and at 99% significance level for neighborhood sizes 10 and 15. On the basis of these results, it can be confirmed that there is evidence of spatial inequality in educational outcomes of schools in Sokoto.

Table 5.2: Total Score Spatial Gini Index

Global	**P-value (999 Simulation)**	**Number of Neighbours**	**Within (%)**	**Between (%)**
0.23	0.01	5	0.7	99.3
0.23	0.00	10	2.0	98.0
0.23	0.00	15	3.5	96.5

Source: Author's calculations

5.3 RQ3: Relationship between Remoteness of School and Academic Performance

An OLS based regression model is estimated to capture the effect of remoteness of schools on its total score of numeracy and reading. This is motivated by the urban-rural divide in educational attainment in the developing countries (García Palomer and Paredes, 2010; Khan *et al.*, 2019). The results of this regression are shown in Table 5.3 which answers research question 3 of the study that there exists a negative significant relationship between remoteness and educational outcomes of the school. For the schools in the sample, the mean travelling distance from the capital is 61 kilometers. This indicates that, ceteris paribus, on average the schools have 24.4% (9.76 points out of 40) lower score in numeracy and reading combined than schools in the capital city of Sokoto.

The R-squared of the model is however small which implies that there are other factors at play in explaining educational outcomes of schools in Sokoto. The Moran's I coefficient of the residuals of Model_1 are positive and significant and are presented in Table 5.4. Additionally, the residual map of Model_1 in Figure 5.2, where each point represents the location of a school,

Table 5.3: OLS Regression Model_1

	Model_1
dist	-.004***
	(-4.371)
_cons	2.691***
	(39.33)
Observations	126
R-squared	.133
Adj R2	.126
Akaike's Crit	112.966

t-values are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's Estimation

reveal spatial clustering in overestimation and underestimation by the model. This suggests that the distance have a varying explanatory power in different spatial clusters and schools which are at a similar distance from the capital have varying educational outcomes.

Table 5.4: Global Moran's I for Model_1 Residuals

No of neighbours	**Moran's I**	**P-value resampling**	**P-value randomization**
3	0.26	0.00	0.00
5	0.22	0.00	0.00
8	0.14	0.01	0.01
12	0.09	0.04	0.04
20	0.07	0.07	0.06

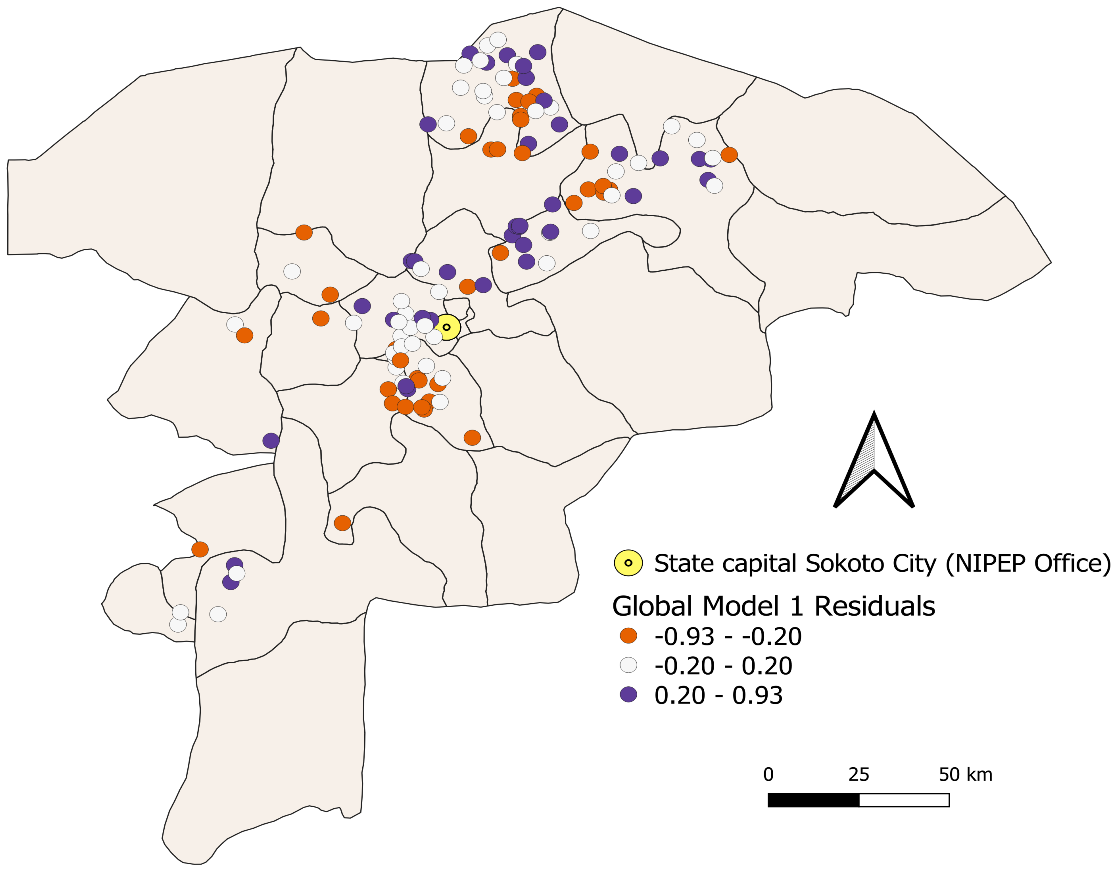
Source: Author's calculations

5.4 RQ4: Spatial Patterns in the Effect of School Inputs in the Education Production Function

In order to further explain spatial variation in the educational outcomes of school, education production function is modeled with GWR. In the first step, OLS regressions are estimated, and the results are available in Table 5.5. The input of school facilities remains significant and maintain a positive relationship with educational outcomes of schools. There are 52 schools in the sample with 0 facilities available. Therefore, if the facilities in these schools is increased to the sample average of 0.17 then according to Model_2 estimates, the educational outcomes of that school is expected to increase by approximately 14%. Receiving treatment does not have a significant effect on educational outcomes of school except in Model_5 where it is found to have a negative effect on schools which received treatment as compared to schools which didn't, but only at the 90% significance level.

SBMC variables are introduced in Model_3 and the impact of SBMC involvement in school related activities is found to have a positive and significant impact on educational outcomes

Figure 5.2: Spatial Pattern in Model_1 Residuals



Source: Author's elaboration

of schools. On the other hand, the SBMC's literacy level does not contribute significantly to explaining the academic performance of the schools. Furthermore, the headmaster's education variable is included as an input in the school production function in Model_4 and is unexpectedly found to have a negative impact on the total academic score of the schools.

Teacher related inputs are introduced in Model_5 with teacher's effort being positive and significant in explaining educational outcomes as compared to teacher involvement which is estimated to be insignificant. The average experience of teachers in a school has a negative significant effect on education performance of the school at 95% confidence. The improvement in the fit of the model was also tested using F-test and it was found to be statistically significant except for in Model_4 with addition of headmaster education. All of the models have been tested for heteroskedasticity using White's test and Breusch-Pagan tests for constant variance including Model_1 from section 5.3. The multicollinearity has been tested using Variance Inflation Factor (VIF) and the VIF value remain below 10 (X. Chen *et al.*, 2003). The results of these tests for all models are presented in table A1, A2 and A3 in the Appendix.

Model_5 is not estimated using GWR as teacher input variables are not found to be spatially dependent i.e., their distribution across space is random. In this case, the GWR program suggests estimating a global model using the whole dataset. As a substitute, Headmaster's education was used as an input variable as 97% of the headmaster also reported to teach and it was also found to be spatially dependent. Moreover, remoteness is not included in the school education production function as it leads to high multicollinearity in the local models in GWR. This is due to the fact that the neighboring schools have a similar travelling distance to the capital city of Sokoto.

Table 5.5: OLS Regression Model_2 to Model_5

	Model_2	**Model_3**	**Model_4**	**Model_5**
School Facilities	.843***	.668***	.739***	.433*
	(4.683)	(3.292)	(3.36)	(1.88)
Treatment Dummy	-.089	-.105	-.098	-.155*
	(-1.333)	(-1.503)	(-1.26)	(-1.827)
SBMC Involvement		.339*	.248	.542**
		(1.725)	(1.13)	(2.07)
SBMC Literacy		.107	.113	-.018
		(1.137)	(1.10)	(-.157)
Headmaster Education			-.017	
			(-1.19)	
				.265
				(1.655)
				.465*
				(1.687)
Average Teacher Experience				-.013**
				(-2.066)
_cons	2.341***	2.186***	2.428***	1.986***
	(41.601)	(24.524)	(12.16)	(9.218)
Observations	123	113	92	66
R-squared	.164	.221	.237	.396
Adj R2	.15	.192	.192	.324
AIC	108.215	98.516	81.859	46.982

t-values are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's estimations

5.4.1 GWR Models

In the second step, GWR models are estimated for Model_2, Model_3 and Model_4 and the results are represented in Table 5.6. The quartile range of all coefficient estimates is the first sign towards the geographically varying relationship of school inputs and educational outcomes. One of the strengths of GWR is the possibility of visualizing the results on maps and therefore school inputs, their t-statistics and local R-squared are mapped and represented geographically (Brunsdon *et al.*, 1999).

The GWR estimation provides Pseudo-t values which are calculated by dividing the local coefficients by their estimated standard errors. Similarly, the Quasi R-squared or Pseudo coefficient of determination is calculated using the following formula (Agiakloglou *et al.*, 2019):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}$$

Table 5.6: GWR Results

GWR_Model_2

N	b*	AIC	AICc	Quasi R-squared
123	0.23	94.56	108.33	0.273

	Min	P25	Median	P75	Max
School Facilities	.414	.608	.705	.81	1.05
Treatment Dummy	-.151	-.114	-.097	-.079	-.021
_const	2.263	2.313	2.371	2.428	2.547

GWR_Model_3

N	b*	AIC	AICc	Quasi R-squared
113	0.24	78.93	101.63	0.373

	Min	P25	Median	P75	Max
School Facilities	.116	.28	.499	.666	.916
Treatment Dummy	-.187	-.16	-.132	-.086	-.028
SBMC Literacy	.037	.078	.1	.17	.27
SBMC Involvement	.283	.381	.448	.512	.693
_const	2.053	2.128	2.201	2.241	2.418

GWR_Model_4

N	b*	AIC	AICc	Quasi R-squared
92	0.24	58.34	84.65	0.434

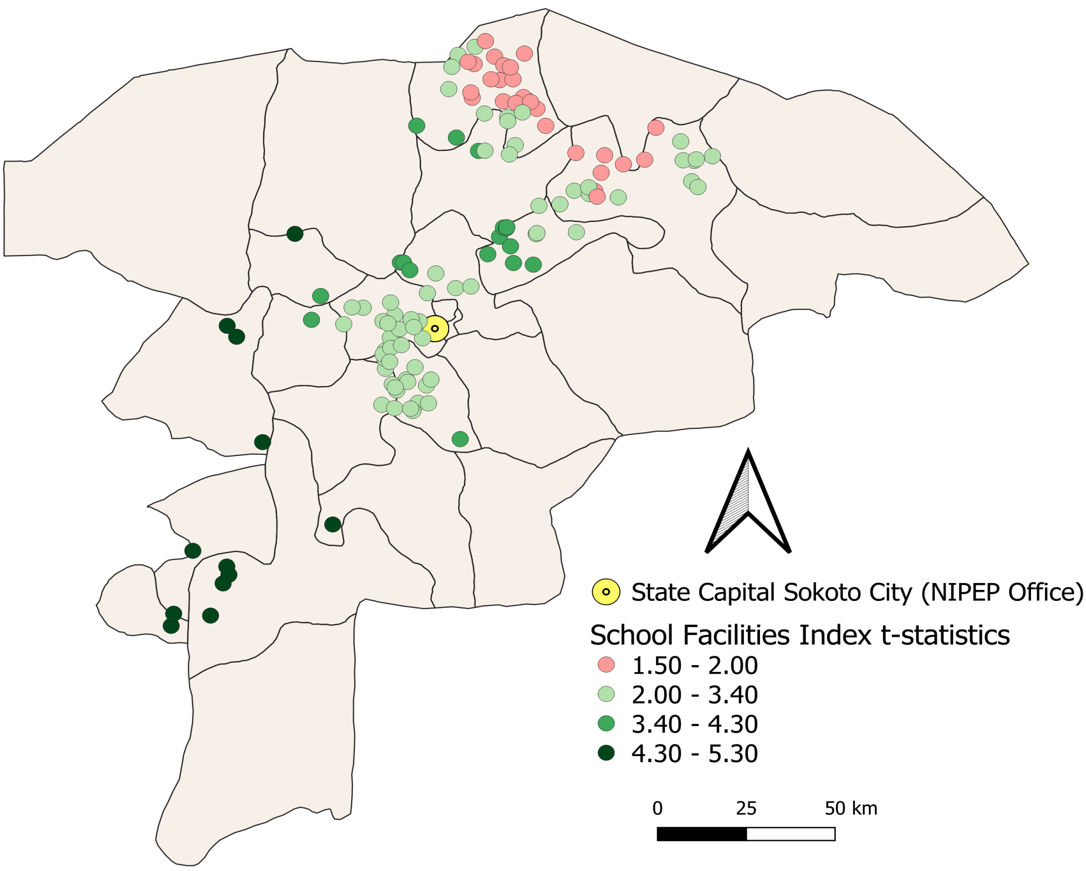
	Min	P25	Median	P75	Max
School Facilities	.281	.476	.582	.752	.998
Treatment Dummy	-.248	-.201	-.116	-.069	-.009
SBMC Literacy	.024	.108	.135	.174	.252
SBMC Involvement	.223	.306	.328	.412	.557
Headmaster Education	-.036	-.027	-.009	.016	.018
_const	1.793	2.068	2.381	2.593	2.641

Source: Author's estimations

The Quasi R-squared as well as the optimal bandwidth b^* estimated with the help of CV method are represented in the Table 5.6 for each model. The optimal bandwidth number indicates the proportion of observation or the nearest neighbors used to estimate the local model. For example, in GWR_Model_3 the optimal bandwidth is 0.24 which means approximately 26 nearest neighbors of the regression point. On average for this model, each LGA has 13 schools which means most of the local coefficients for GWR_Model_3 are estimated using datapoints of schools within its own LGA and the schools from the nearest LGA. Since the local coefficients are estimated with number of observations less than 30, therefore, only coefficients with Pseudo-t values greater than 2 are considered significant.

Additionally, Akaike Information Criterion (AIC) and corrected AIC (AICc), adjusted for degrees of freedom, are also available for all the three models. AIC and AICc estimate the distance of the distribution of dependent variable obtained with the help of the model, from the actual distribution. This provides a measure for deciding which model is a better approximation of reality. As a rule of thumb, if the difference between the AIC/AICc of any two models using the same dataset is more than 3, then the model with lower AIC/AICc value is a better fit for the data being analyzed (Fotheringham *et al.*, 2002). The difference between the AIC of OLS and GWR models, for all three models, is greater than 3 with GWR models having a lower value.

Figure 5.3: School Facilities t-statistics Map

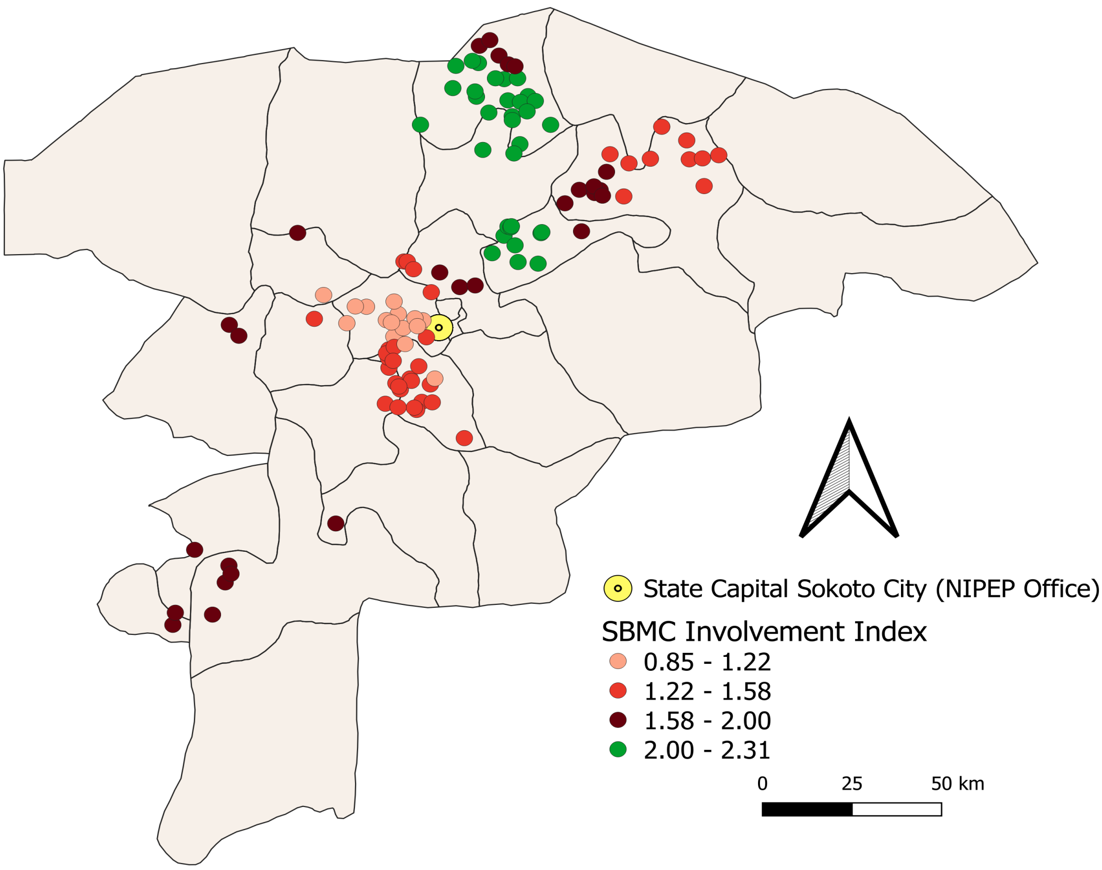


Source: Author's elaboration

In GWR_Model_2, the school facilities maintain the same direction of the relationship as in OLS Model_2 with the educational outcomes. However, when viewed graphically in Figure 5.3, there is a clear spatial pattern in the significance of school facilities as an explanatory variable for educational outcomes. The schools in the Southern LGA of Tambuwal have the highest significance although these schools have the lowest facilities with only one schStudent absenteeism is also reported to be second highest in these schools at 40% which maybe motivated by the lack of learning environment provided by the school. On the other hand, in the northern LGAs of Ilela and Goronyo most of the schools show a positive but insignificant relationship between total score and school facilities. This suggests that there are other factors at play affecting the performance of these schools. On further exploration, it is revealed that schools in Ilela have on average the lowest number of teachers per school i.e. 1.7 while the average for Sokoto is 5.7 and the student to teacher ratio of approximately 35 which is the second highest among all LGAs, while the average for all schools in Sokoto is 26.

The treatment effect, just like in the OLS based model, remains insignificant with the direction of relationship negative A3. Ochmann *et al.* (2021) identifies four reasons for the zero result of treatment in Sokoto: first, the intervention was implemented poorly by the authorities and only half of the headmasters and SBMC members reported to receive any grant money. It was also observed during the school surveys that grant money was misused and spent on matters not related to the school. Second, the grant amount was not sufficient to improve the facilities in most schools which were in very dire conditions and thus failed to have any impact on educational outcomes. Third, the teacher absenteeism was significant with 45% schools having no teacher at the time the survey team arrived at the school. Additionally, at 74% schools no learning was taking place which implied that grant money and SBMC training couldn't solve the issues which had a direct impact on educational outcomes. Finally, the SBMC couldn't contribute effectively to the improvement of schools with help of grants and training as their initial capacity was limited with a mean literacy of 44%.

Figure 5.4: SBMC Involvement t-statistics Map

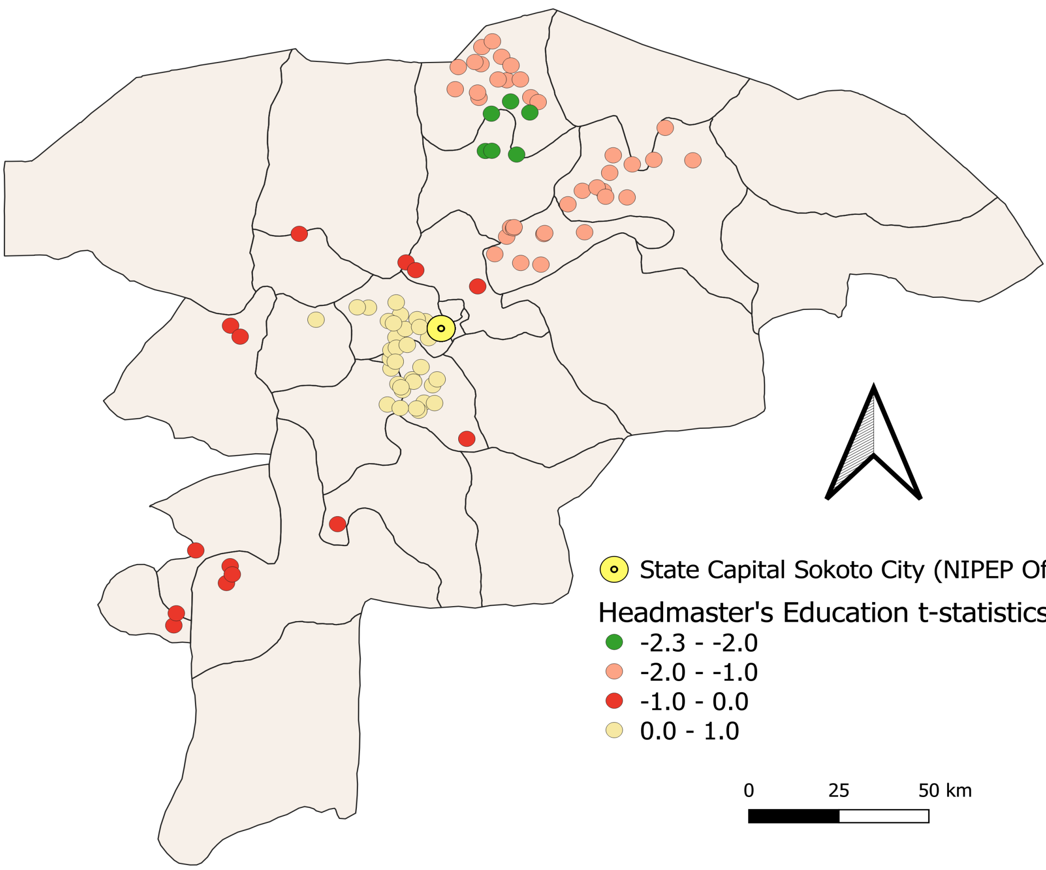


Source: Author's elaboration

However, in GWR_Model_3, the SBMV involvement variable is found to have a significant effect on educational outcomes of most of the schools in Ilela and Wurno LGAs as shown in Figure 5.4. The mean literacy of SBMC members, although being above the average in Wurno, is one of the lowest in Ilela. The SBMCs in LGA Wurno have the highest involvement in school related activities and in developing the school plan, after only LGA Binji which has two schools in the sample. On the other hand, LGA Ilela has some of the recently formed SBMCs relative to other LGAs. The average age of SBMCs in Ilela is 6 years with 22 out of 25 SBMCs formed in the past 10 years. Effective SBMC involvement may have decreased over the years since their inception without adequate training and support by the government as only 33% of SBMC members reported to receive some support out of the 336 who answered the question.

In GWR_Model_4, School's headmaster's education level is introduced as one of the inputs in the school production function. The magnitude, direction and significance, all three, of the headmaster's education estimated coefficients vary systematically across space. As shown in Figure 5.5, the schools near the state capital have a positive relationship between headmaster's education and its academic performance. Some schools in the LGA of Ilela have a significant but negative relationship between headmaster education and the numeracy and reading test scores. In order to explain this negative relationship, the information available from the headmaster survey was further investigated.

Figure 5.5: Headmaster Education t-statistics Map



Source: Author's elaboration

It is discovered that headmaster's education level is positively correlated with how far he/she lives from the school (0.13). Headmasters living in the community have on average 12.9 years of education while headmasters coming from outside the community on average have 14.3 years of education. This difference is significant (A4) as it differentiates between headmasters who did not pursue tertiary education and those who did. Subsequently, the headmasters coming from outside the community have a 22% higher absenteeism rate than headmasters who live inside the community. This suggests that more educated headmasters live far from the communities and have a higher absenteeism rate which can explain the negative relationship of educational outcomes with headmaster's education.

Furthermore, it is also discovered that on average only 25% of schools which have a negative relationship of headmaster education and academic score have a headmaster's office as compared to 49% of schools which have a positive relationship. The availability of a headmaster's office is even lower in schools with a significant negative relationship i.e., 16.7%. The availability of a headmaster's office and headmaster absenteeism rate is also negatively correlated (-0.15*) and the same is true for staff room and teacher absenteeism rate (-0.15*). This implies that headmaster education interacts with other spatially varying variables which define the direction of its relationship with the school's educational outcomes. These results are presented in tables A5 and A6 in the Appendix section.

Finally, there is a big difference in the R-squared of the OLS models and the Quasi R-squared obtained from the GWR models with latter being higher. For instance, the GWR_Model_4 have a R-squared of 43.4% where as the OLS Model_4 have R-squared of approximately 23.7%. The local R-squared are influenced by the significance of all explanatory variables i.e., it is higher for schools with significant local relationships between school inputs and educational outcomes. The local R-squared maps are presented in Figures A4, A8 and A10, available in the Appendix section.

Robustness Checks

Other than the rule of thumb of AIC difference greater than 3, other statistical tests have been formalized for comparing OLS and GWR models. The two tests conducted in this study were proposed by Leung *et al.* (2000) which evaluate the goodness of fit of GWR models as compared to OLS. The test statistics of these two tests are given by:

$$F_1 = \frac{RSS_g/\delta_1}{RSS_o/(n-p-1)}$$

$$F_2 = \frac{DSS/v_1}{RSS_o/(n-p-1)} = \frac{\left(RSS_o - RSS_g\right)/v_1}{RSS_o/(n-p-1)}$$

The RSS_g and RSS_o are the Residual Sum of Squares from GWR model and OLS based model respectively whereas DSS is their difference. n is the number of observations; p is the number of parameters and $(n-p-1)$ are the degrees of freedom in a conventional OLS based regression model. In a GWR model, since degrees of freedom change with every local model, δ_1 called the effective degrees of freedom is obtained by calculating the trace of the hat matrix i.e., the matrix which converts actual values of the dependent variable into the fitted values (Fotheringham *et al.*, 2002). The null hypothesis for the first test is that there is no significant difference between the goodness of fit of OLS and GWR model for the given data and the ratio RSS_g/RSS_o is close to 1. For the second test, the null hypothesis is that the GWR model does not significantly improve the explanatory power of the model for the given data.

The test statistics follow χ^2-distribution and a small value of F will result in the rejection of null hypothesis in favor of the alternate. The results of both the tests for all three models are given in Table 5.7. All the three models fail the first test and thus I fail to reject the null hypothesis that the goodness-of-fit of GWR is as good as OLS based model for the given data. However, GWR models pass the second test, and the null hypothesis can be rejected in favor of alternate hypothesis i.e., GWR significantly improve the explanatory power of the model for the given data at 90% significance level. Therefore, GWR can be complemented with OLS model, in case of availability of spatial data, to explore if and how outcomes vary across space which can be crucial for policy implications.

Table 5.7: Goodness-of-fit Tests

	RSS-OLS	RSS-GWR	Improvement	F1 (P-value)	F2 (P - Value)
Model_2	16.53	14.37	2.16	0.38	0.06*
Model_3	14.48	11.65	2.83	0.36	0.09*
Model_4	11.51	8.53	2.98	0.30	0.07*

**** p<.01, ** p<.05, * p<.1*

Source: Author's calculations

Based on the results from the GWR models and the spatial variation observed in the effectiveness of school inputs it can be confirmed that there are spatial patterns in the production of education in schools across Sokoto. However, the models can be improved by including characteristics of students studying at each schools which are an important input in education production function (Wei *et al.*, 2018). Also, some LGAs have a limited number of schools and therefore adding more schools from the same LGA can help define the local relationships better.

CHAPTER 6
Discussion and Policy Implications

The results from the GWR models show how relationships between school inputs and outcomes can vary locally which remain hidden in global models. This allows us to avoid the Ecological Fallacy which is the failure in reasoning when inferences about individuals are made from data at the group level (Martínez, 2009). This is essential in cases of spatial non-stationarity such as educational outcomes of schools like in the example of Sokoto, Nigeria, presented here.

The local analysis of school inputs and outcomes can be used to identify, design, and implement relevant policies based on the need of the schools in a particular area. GWR_Model_2 helped us identify schools where the relationship between educational outcomes and school facilities is positive and significant. Based on this result, an immediate policy recommendation would be to invest and improve the school facilities in the LGAs where the relationship is significant. Additionally, the schools in Tambuwal and Silame can be prioritized for investment in school facilities as they have the strongest relationship and the lowest level of amenities in the schools.

Similarly, based on the results from GWR_Model_3, the schools where SBMC involvement played a significant positive role in improving educational outcomes of schools can be distinguished. These schools are based in LGAs of Ilela and Wurno and although their SBMCs don't have the highest score for involvement or the highest literacy levels but are formed relatively recently than in other LGAs. The policy implication from this result would be to change SMBC members after every few years to involve new individuals who are interested in improving the state of education in their community. The local analysis can therefore assist policy makers in explaining the varying results from an intervention in different locations and replicate the successful elements in other areas keeping the local context in mind.

Finally, the results from GWR_Model_4, suggest that hiring teachers and headmasters from the community can help deal with absenteeism. Other studies confirm that teachers from the community tend to be less absent as compared to teachers coming from outside the community, specially female teachers due to their often limited mobility in developing countries (Ghuman and Lloyd, 2010). Teachers from the in-state are more effective as compared to their out-state counterparts for two reasons (Bastian and Henry, 2015). First, teachers prefer to work close to their hometown and those who end up working at large distances were less competent and were unable to secure a job near their homes. Second, the attrition rate for teachers from out-state is also higher as they actively seek work opportunities back in their hometowns. Additionally, headmaster and teacher absenteeism were also found to be correlated with the availability of a headmaster office and staff/break rooms. Therefore, investment in headmaster office and staffrooms can be prioritized in schools where it's not available and the negative relationship between headmaster education and educational outcomes is significant.

To summarize, spatial analysis of educational outcomes can help policy makers in three different ways. First, to explain the successes and failures of policy interventions in different areas. Second, to prioritize the implementation of interventions in areas based on their need and the expected effectiveness of the intervention. Finally, to identify and strengthen the local factors which improve educational outcomes and then replicate in other areas.

CHAPTER 7
Conclusion

With approximately 10 million of out of school children, the education system of Nigeria continues to struggle in providing quality education for all in the country (Bashir, 2021). Additionally, there are large gender, locational and regional disparities in educational outcomes of children specially in the North Western Region and in the state of Sokoto (Onwuameze, 2013). In order to tackle these imbalances, it is essential for policy makers to identify and understand the sources of inequality in education. Based on the results of this study, space, which determines the availability of public services, socioeconomic status of households, school facilities and quality and efficiency of teachers, headmasters and SBMCs, has been identified as one of the sources of education inequality in Sokoto.

The study confirms spatial non-stationarity as well as spatial inequality in the educational outcomes of schools in Sokoto. Remoteness of the school which determine student's access to public services which are significant for educational outcomes, socioeconomic status of the household and access to information regarding choices and future outcomes of education, is found to be a significant determinant of reading and numeracy scores in Sokoto. Spatial variation in education production by schools with school facilities, SBMC involvement and literacy and Headmaster education as inputs, has been confirmed with the use of GWR. The GWR models significantly improved the explanatory power of the school's education production function with the help of local analysis.

The thesis contributes to the literature of spatial inequalities in the academic performance of schools in a developing country context. Furthermore, it explores spatial inequality in education at a more disaggregated school level, within a state, with the help of GWR. This has rarely been attempted for a developing country and never for Nigeria or Sokoto. There are also certain limitations of the study that arise from the lack of data on student abilities and their household characteristics which have proved to be significant determinants of educational outcomes of schools (Wei *et al.*, 2018). Additionally, the schools in the sample are not distributed evenly across the Sokoto state or across its LGAs. This means that for some schools the local models include observations from a very distant school which is not ideal for local analysis.

Finally, the policy makers in the education sector should spatially evaluate the implemented policies before extending and replicating it to other areas and prior to designing new policies. The local analysis helps in understanding the local context by highlighting the factors which lead to varying educational output using the same inputs. This is important for countries, regions and states which are highly diverse in terms of culture, religion and socioeconomic characteristics. Sokoto being homogenous in terms of religion and ethnicity provide less variation but in more diverse states of Nigeria local analysis should be adopted. The spatial models and techniques are developed enough to complement if not replace aspatial modelling in social sciences.

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Appendix

Table A1: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

	Chi2(1)	Prob>chi2
Model_1	0.16	0.6900
Model_2	0.01	0.9342
Model_3	0.03	0.8584
Model_4	0.09	0.7690
Model_5	2.37	0.1236

Source: Author's calculations

Table A2: Cameron & Trivedi's decomposition of IM-test

		Heteroskedasticity	Skewness	Kurtosis	Total
	Chi-2	3.020	0.830	0.1370	5.220
Model_1	df	2	1	1	4
	p	0.221	0.363	0.241	0.266
	Chi-2	2.29	0.59	4.82	7.70
Model_2	df	4	2	1	7
	p	0.682	0.745	0.028	0.359
	Chi-2	6.68	3.24	5.49	15.41
Model_3	df	13	4	1	18
	p	0.918	0.519	0.019	0.634
	Chi-2	6.67	5.46	3.93	16.06
Model_4	df	19	5	1	25
	p	0.996	0.363	0.047	0.913
	Chi-2	30.85	14.42	1.42	46.69
Model_5	df	34	7	1	42
	p	0.623	0.044	0.234	0.286

Source: Author's calculations

Table A3: Variance Inflation Factor (VIF)

	Model_2		Model_3		Model_4		Model_5	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
School Facilities	1	1	1.248	.802	1.308	.765	1.22	.819
Treatment Dummy	1	1	1.03	.97	1.038	.963	1.109	.901
SBMC Involvement			1.262	.792	1.383	.723	1.35	.741
SBMC Literacy			1.125	.889	1.103	.906	1.094	.914
Headmaster Education					1.082	.924		
Teacher Involvement							1.12	.893
Teacher Effort							1.184	.845
Average Teacher Experience							1.165	.858
Mean VIF	1	.	1.166	.	1.183	.	1.178	.

Source: Author's calculations

Table A4: Headmaster Education Level Vs. Dwelling

	Model_A1
Headmaster from the community	-1.38**
	(-2.13)
_cons	14.26***
	(44.11)
Observations	97
R-squared	.046
Adj R2	.036

t-values are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's Estimation

Table A5: Headmaster Absenteeism Rate

	Model_A2
Availability of Headmaster's office	-.154*
	(-1.67)
_cons	0.61***
	(10.81)
Observations	123
R-squared	.022
Adj R2	.014

t-values are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's Estimation

Table A6: Teacher Absenteeism Rate

	Model_A3
Availability of	-.154*
Teacher Satff room	(-1.92)
_cons	0.41***
	(9.49)
Observations	66
R-squared	.055
Adj R2	.039

t-values are in parentheses
**** p<.01, ** p<.05, * p<.1*
Source: Author's Estimation

Figure A1: Total Score Geographical Distribution

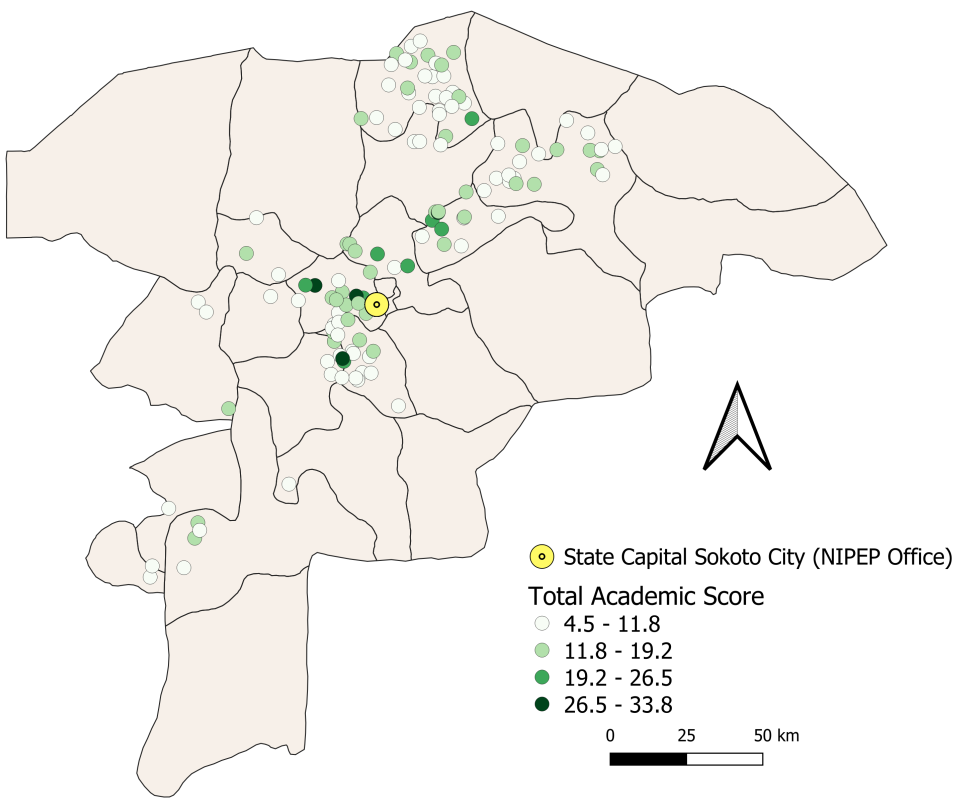
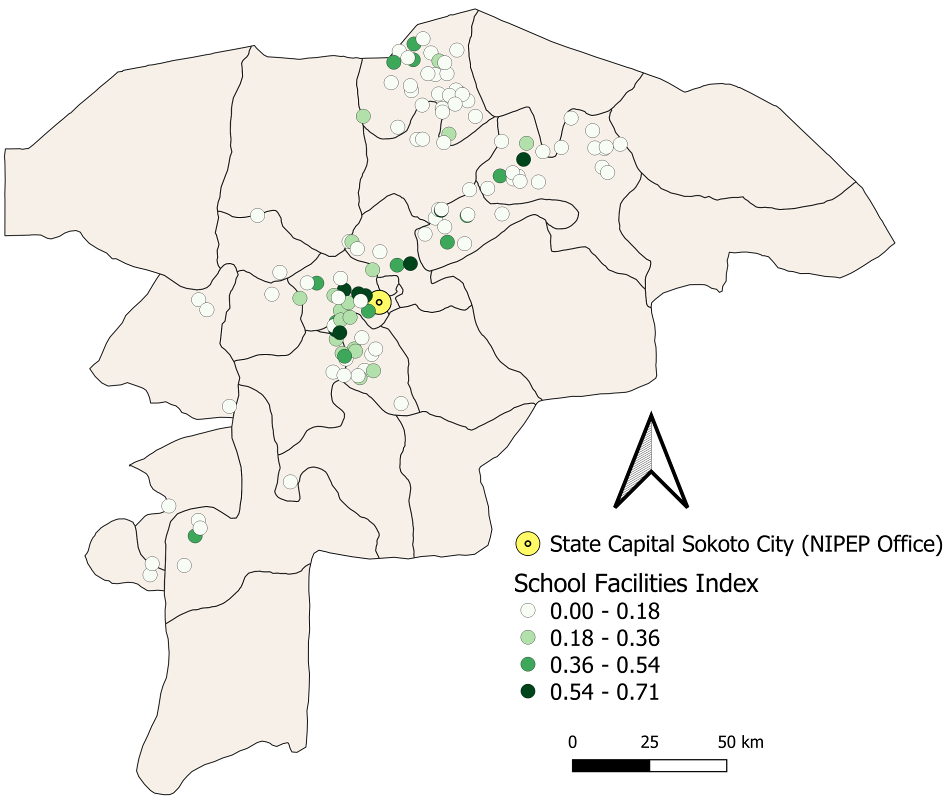
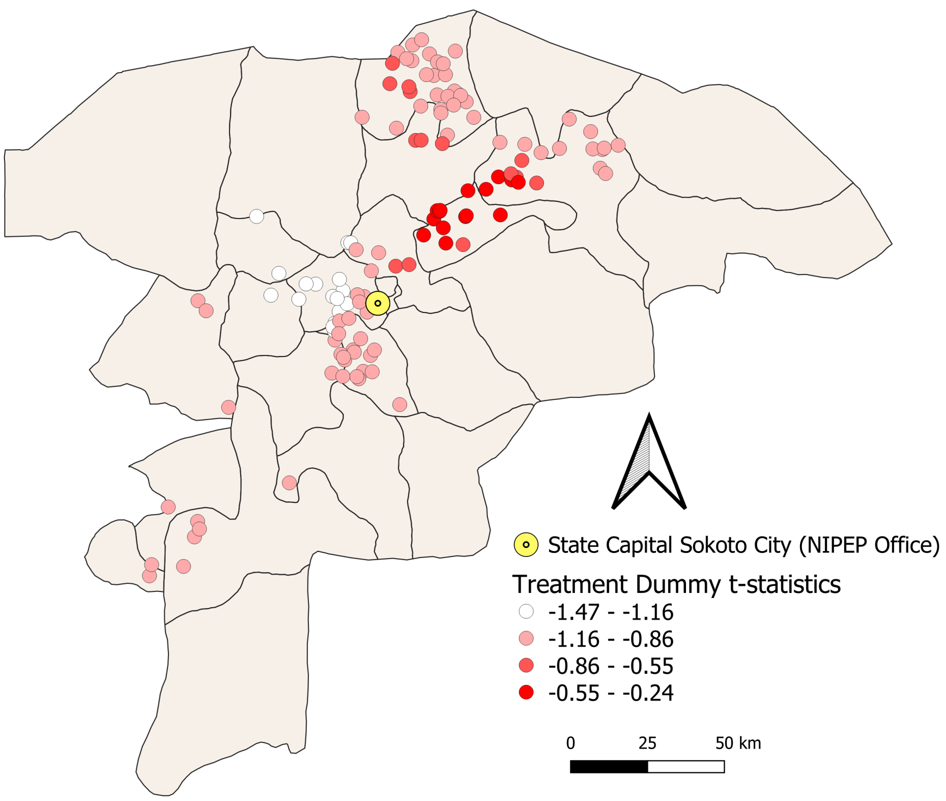


Figure A2: Index Facilities Geographical Distribution



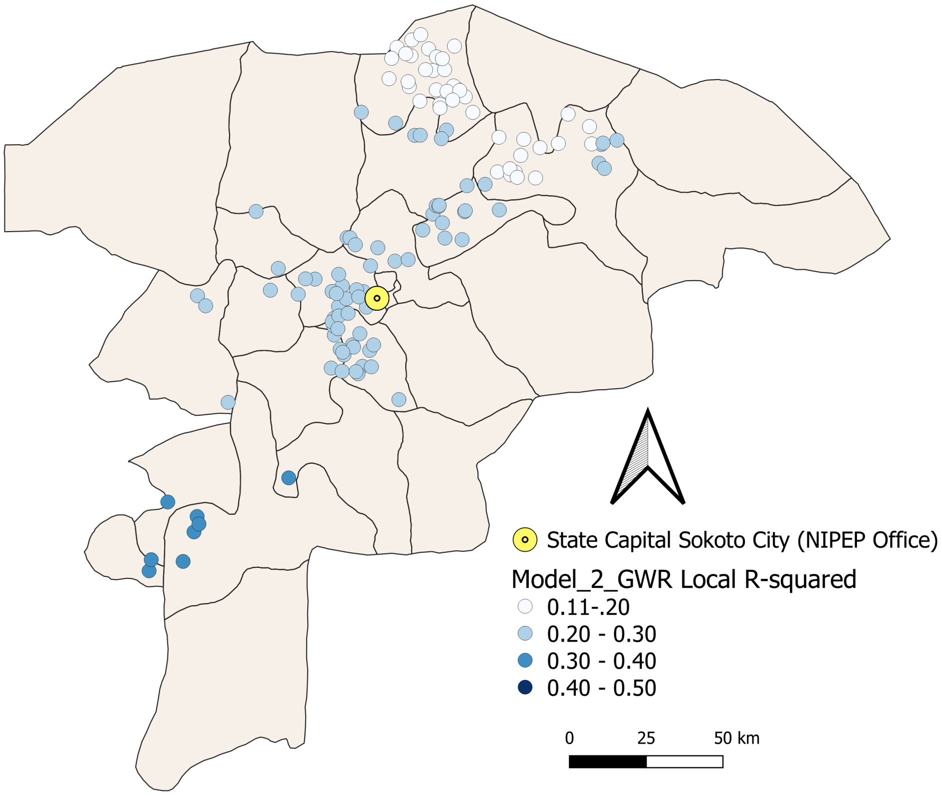
Source: Author's elaboration

Figure A3: Treatment Dummy t-statistics



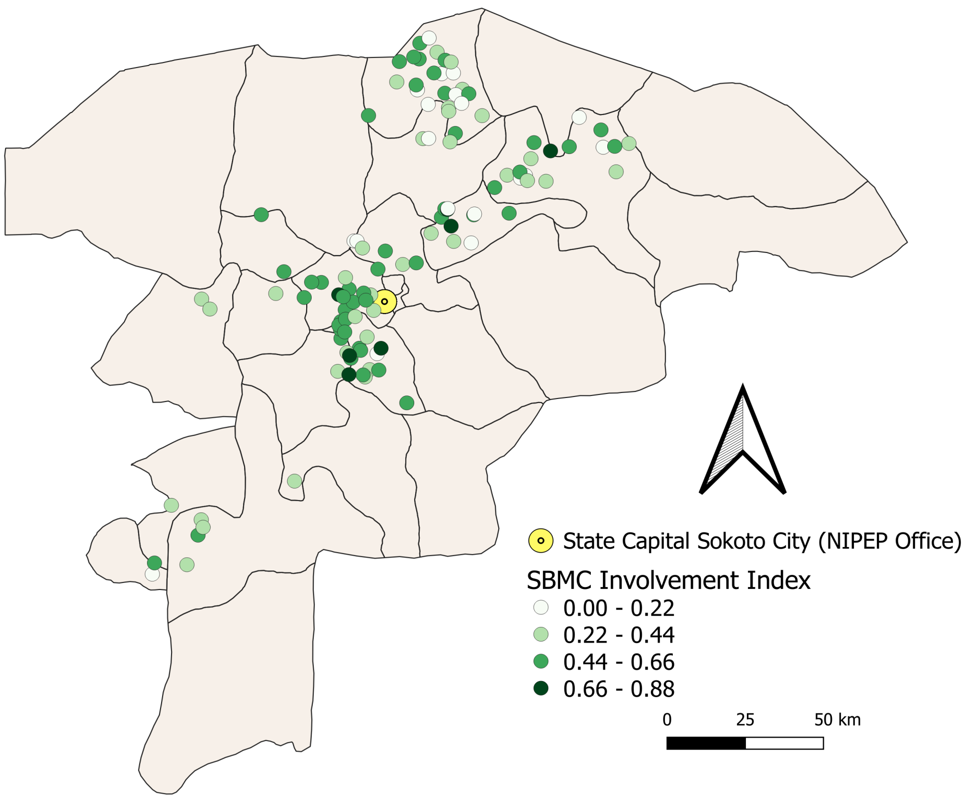
Source: Author's elaboration

Figure A4: GWR_Model_2 Local R-squared



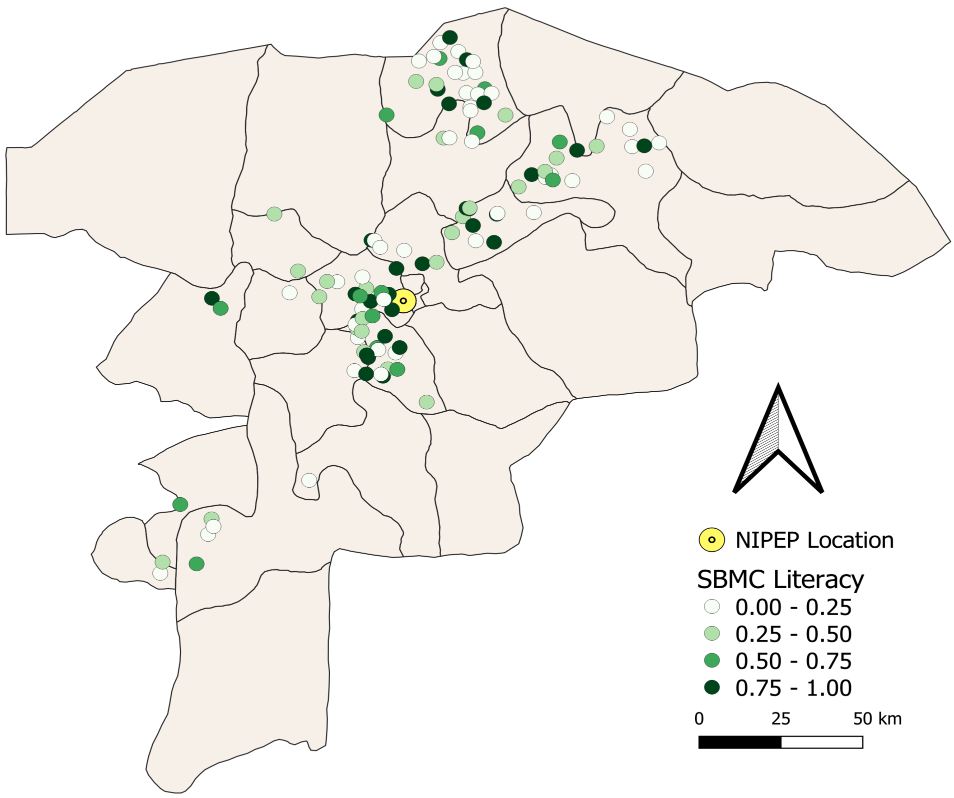
Source: Author's elaboration

Figure A5: SBMC Involvement Geographical Distribution



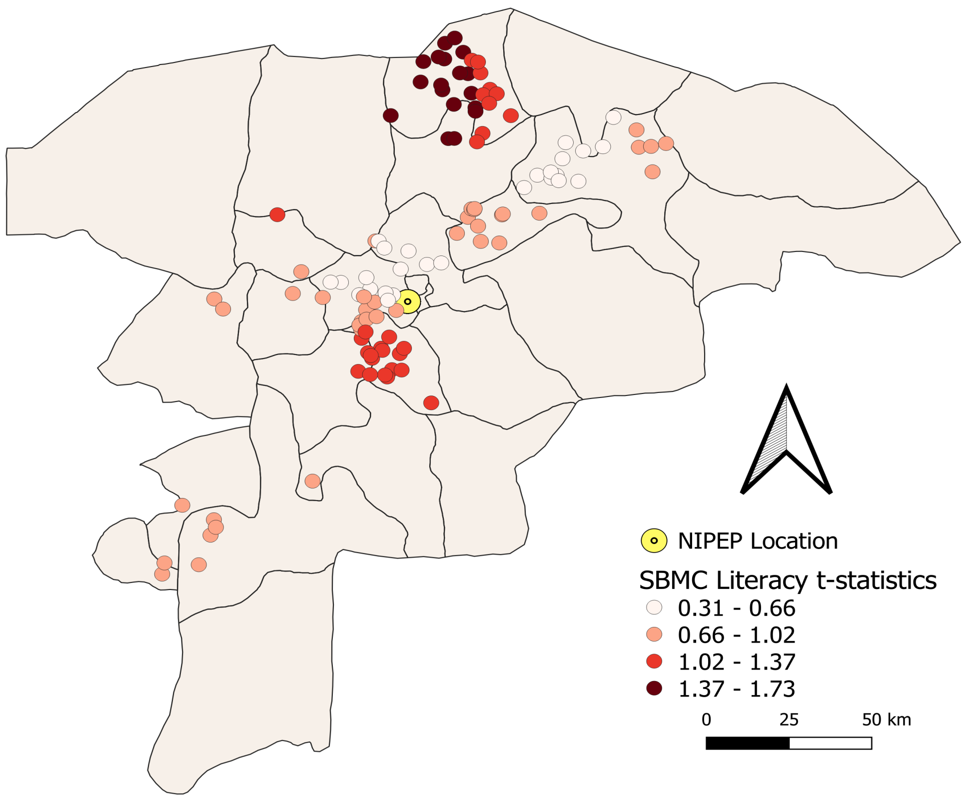
Source: Author's elaboration

Figure A6: SBMC Literacy Geographical Distribution



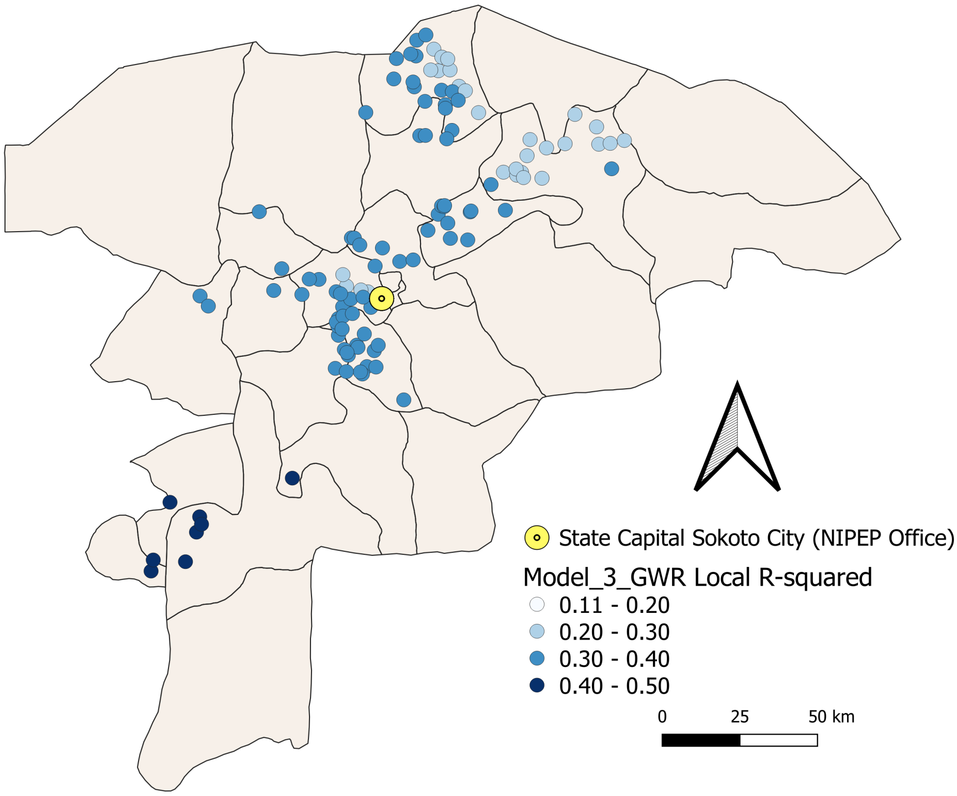
Source: Author's elaboration

Figure A7: SBMC Literacy t-statistics



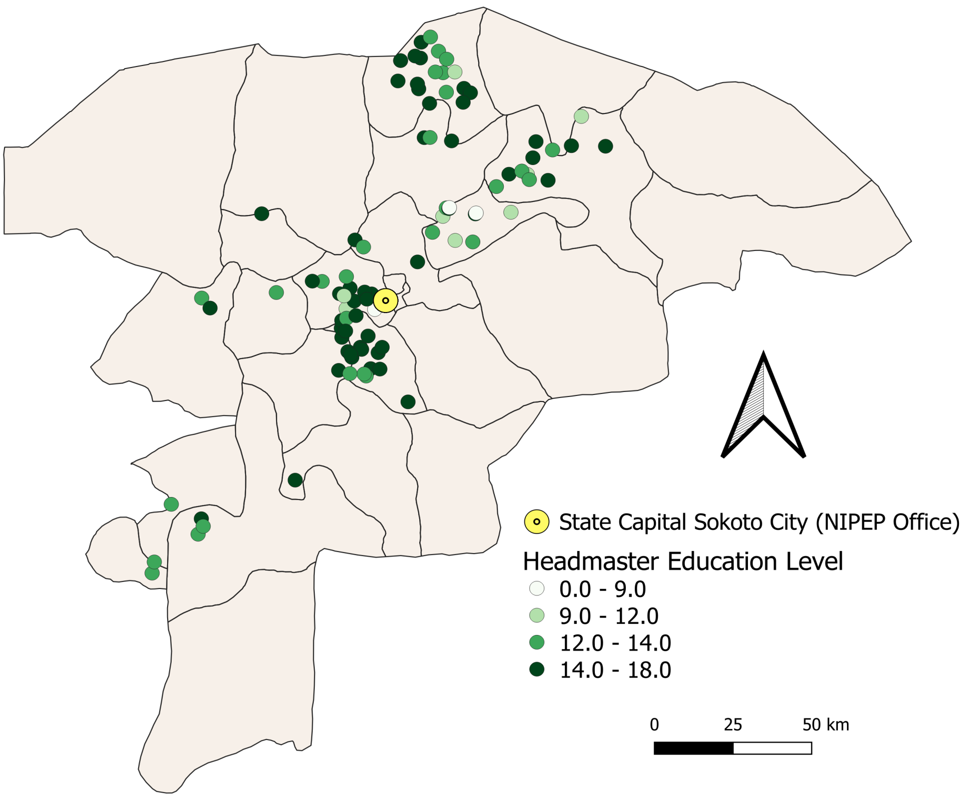
Source: Author's elaboration

Figure A8: GWR_Model_3 Local R-squared



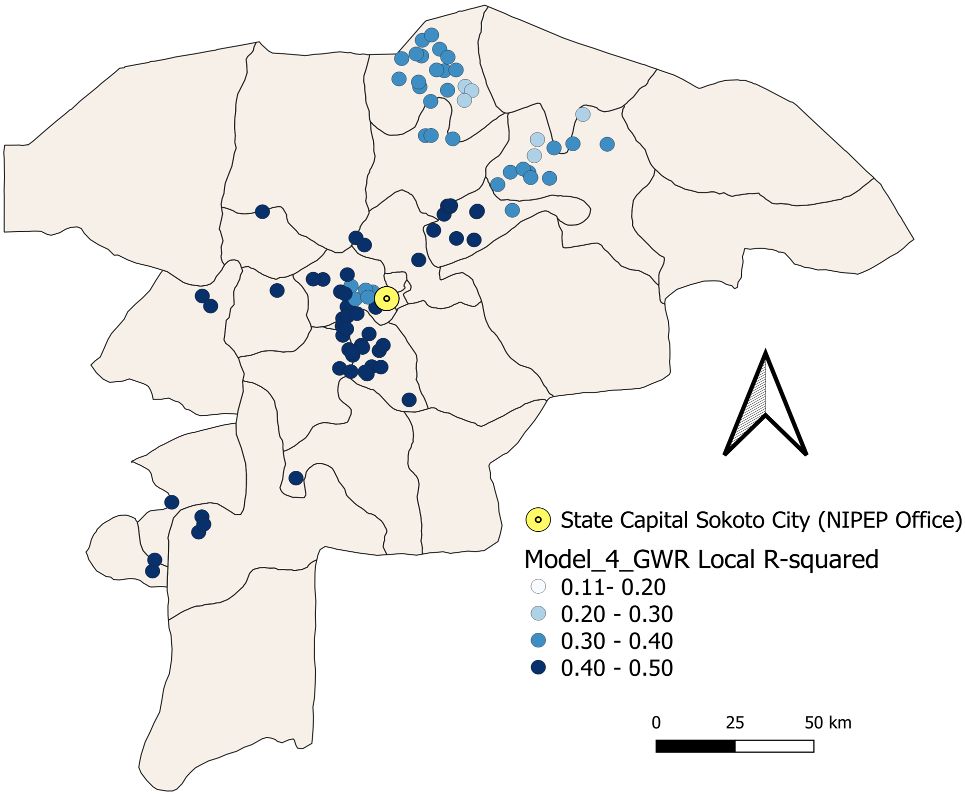
Source: Author's elaboration

Figure A9: Headmaster Education Geographical Distribution



Source: Author's elaboration

Figure A10: GWR_Model_4 Local R-squared



Source: Author's elaboration