University of Nairobi

Faculty of Engineering

DEPARTMENT OF GEOSPATIAL AND SPACE TECHNOLOGY

MAPPING CHILD ABUSE VULNERABILITY,

CASE STUDY-NAIROBI COUNTY.

Project Report submitted for partial fulfillment of Degree in Master of Science in Geospatial Information Systems, in the Department of Geospatial and Space Technology of the University of Nairobi.

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F56/37297/2020

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Declaration

I, Chepkorir Tuei, hereby declare that this project report is my original work. To the best of myknowledge, the work presented here has not been presented for a project in any other university.

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Dedication

In dedication to my husband Bernard and my children Shylline and Gerald.

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Abstract

Child abuse is a major public problem in Kenya and most cases are informed by the social setting and surroundings of the children. Nairobi County being the capital city of Kenya leads in the number of child abuse cases reported. Increased stress levels among parents and caregivers are a predictor of child abuse. The neighbourhood of child abuse is largely informed by social organizations. Identifying neighbourhoods which are vulnerable to child abuse is the first step in abuse identification and prevention measures. This study aimed at identifying sub-counties that are most vulnerable to child abuse in Nairobi County using socio-economic risk factors.

Spatial data on child abuse with eight risk factors were identified. Ordinary Least Squares was used to determine redundancy of the risk factors their significance of the risk factors for modelling child abuse. Geographically Weighted Regression (GWR) was used to model child abuse vulnerability. Results were validated using spearman rank correlation coefficient

The study results were presented in tables, charts and maps. Unemployment, poverty density, population density, education, household size, age of the child, gender of the child and parental conflicts were the risk factors of child abuse. Unemployment, education, household size, poverty density and population density were used. Variance Inflation Factors of all the five risk factors were below 7.5 and therefore there were no redundant risk factors. Education, poverty density and population density were found to be significant factors for modelling child abuse. Model performance according to GWR R squared was 0.66. This is the percentage of vulnerability that the three risk factors accounted for. Spearman rank correlation coefficient was 0.375 which means there was fairly strong correlation between the predicted values and reported cases in 2022. Kibra, Embakasi North, Starehe and Kasarani sub-counties reported high cases to child abuse vulnerability. Population density was positively related with child abuse vulnerability while population density and education were negatively related with child abuse.

It was recommended that in management of child abuse, children departments are encouraged to take a broad view of the environment in which the children are growing up in and provide child protection mechanisms in the risk areas that will create a safer environment for the children to live in.

The study proposes further research to identify other risk factors that contributes to child abuse by increasing the scope of respondents.

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List of Abbreviations

GWR	Geographically Weighted Regression
OLS	Ordinary Least Squares
KNBS	Kenya National Bureau of Statistics
DCSs	Department of Children's Services
VIF	Variance Inflection Factors
AHC	Agglomerative hierarchical clustering
HLPF	High Level Political Forum
RTM	Risk Terrain Modeling
ANPPCAN	African Network for Prevention and Protection against Child Abuse and Neglect.
SDG	Sustainable Development Goals

1 Introduction

1.1 Background of the study

Any recent act or failure by the parent or caretaker which results in death, serious physical or emotional harm, sexual abuse, or exploitation on the child is known as Child Abuse. child abuse is categorized into three: sexual, physical, and verbal abuse(*Definitions of Child Abuse and Neglect*, n.d.).

The children Act of Kenya 2001 states that a child is any person who is under the age of 18 years and states that they are entitled to all forms of protection from any form of abuse. It defines child abuse as anything that causes physical, sexual, psychological, and mental injury(*No. 8 of 2001*, n.d.). In Kenya, the protection of this right is vested in the department of children's services under the Ministry of Labour and Social Protection.

Child Abuse has severe long-lasting effects on the child and it is a public health, social, and human rights problem that all countries deal with(Gracia et al., 2017). It has far-reaching physical, mental, educational attainment, and behavioral effects on the victim. It is a global problem that demands every country to try and minimize the number of cases. From a public health approach, it is a problem that can be prevented by identifying risk factors that can be targeted in preventive interventions.

Neighbourhood conditions which can be either social or economic influence people living within and are therefore important. Within the context of child abuse, neighbourhoods can inform prevention strategies. The first step in the avoidance of child abuse is the identification of children and families at risk. The neighbourhood approach is aimed at identifying individuals and families living within the associated characteristics which are said to be at high risk for potential child abuse.

The neighbourhood of child abuse is largely informed by social organizations (Barboza-Salerno, 2020a). Social organization child abuse is categorized by a social vulnerability which refers to effects of lack of socioeconomic resources such as population density, employment status, education level of households, poverty levels, and household's size. This social - vulnerability exposes children to the risk of being abused and also makes it difficult for child support systems to be responsive. Most of the analyses that have been done on child abuse mainly focus on sexual abuse because it is easily identified and mostly reported.

A social vulnerability framework shows that the socio-economic factors place children at high risk of being abused and also render government systems and even individual response systems difficult.

A good comprehension of where and how vulnerability influences probable child abuse is important during different phases of child welfare response, which in turn will result in efficient and effective resource allocation(Barboza-Salerno, 2020a).

In Kenya, the management of child welfare services rests with County children's services departments, whereas the country Children Act places responsibility for child welfare services on the Department of Children Services (DCS),

Nairobi County leads with the number of reported child abuse cases every year, according to the child protection report 2016-2019 by the Ministry of Labor and Social Protection. Nairobi County leads with a percentage of 8.8% of total cases in the country according to this report. In 2019, there were 13,122 cases of child abuse in Nairobi County(Republic, 2020).

Nairobi County houses the leading slums in the country whose social vulnerability index is high(Kimani-Murage et al., n.d.).The slums are overcrowded and are characterized by a lack of social amenities. According to the Nairobi County children's services coordinator, each sub-County in Nairobi records about 30 cases of child abuse cases daily.

Child Abuse research has long concentrated on individual and family risk factors but the place also matters (Gracia et al., 2017). Despite the large body of research exhibiting a substantial relationship between child abuse and neighbourhood characteristics influence, they fail to take into account the spatial dynamics of the neighbourhood(Gracia et al., 2017). Recent studies are taking into account spatial components in mapping child abuse. (Gracia et al., 2017) used the Bayesian Spatio-temporal modeling method to map child maltreatment risk in the European city. This study took into account the spatial and temporal components of risk factors. The results of this study revealed that neighbourhoods with low levels of education and economic status, high levels of policy activity, and high immigrant concentration had a higher risk of child abuse. In another study in California, San Diego County examined the spatial clusters of child maltreatment allegations in a social vulnerability framework(Barboza-Salerno, 2020a). This study used socio-economic, racial, household and transport vulnerability, poverty density, population density, and the population living close to an alcohol outlet as independent risk factors. The study used Ordinary

Least squares and Geographically Weighted Regression to map spatial clusters of child maltreatment. Agglomerative hierarchical clustering (AHC) was then used to produce clusters using coefficients of GWR. Six clusters with varying combinations of the risk factors were on a map. The study compared the performance of OLS and GWR in mapping child maltreatment. Neighbourhood risk factors are normally distributed in space and therefore a spatial method for mapping child abuse vulnerability is appropriate.

1.2 Problem statement

Child abuse is a public social problem in Kenya whose effects remain drastic and are not only limited to disease infection and schooling interruption but have also resulted in fatalities of the affected victims(Ireri, n.d.).

Child Abuse has severe long-lasting effects on the child and it is a public health, social, and human rights problem that all countries deal with(Gracia et al., 2017). It has physical, mental, educational attainment, and behavioural effects on the victim. From a public health approach, it is a problem that can be prevented by identifying risk factors that can be targeted in preventive interventions.

Nairobi County leads with the number of reported cases of child abuse in the country. This is according to the child protection report 2016-2019 by the Ministry of Labor and Social Protection. Reported child abuse cases to the Nairobi County Department of Children's Services provide a unique insight into the most vulnerable areas that may be impacted by child abuse.

Nairobi County being the capital city of Kenya hosts the leading slums in the country (Kibera slums, Mathare slums, Kware slums, Dandora, Huruma, Korogocho, Majengo, Mukuru Kwa Njenga, Matopeni, and Kawangware) and is also characterized by the presence of many areas where upper-class people in the country reside. The slums are characterized by overcrowding, rapid movements, high levels of violence, and exposure to the internet and video dens which pose a threat to the children and therefore children at higher risk of being abused in such environmental settings. This raises a need to assess and map child abuse vulnerability in Nairobi County.

A study was done by (Muhingi et al., 2021) in Langata sub-County in Nairobi on digital literacy and online child abuse among school-going children. The study found out that children in the sub-County were highly internet illiterate and therefore exposed to online child abuse. Another study on the prevalence and implications of child sexual abuse was done on healthcare givers in Nairobi women's hospitals (Adhiambo Juma et al., 2019). The study found out that the prevalence of sexual abuse among the children attended to in the hospital was high.

Child abuse assessment and mapping strategies are key in general planning and decision-making. These would help in directing the regulatory, monitoring, educational, and policy development efforts to those areas where they are most needed for the protection of children against child abuse and distribution of resources to the vulnerable communities. This study maps child abuse vulnerability in Nairobi County. It identifies sub-counties that are more vulnerable to child abuse. This will aid the Department of Children's services in the provision of child protection mechanisms in the risk areas that will create a safer environment for the children to live in.

1.3 Objectives

1.3.1 Main objective

The main objective of this study was to map child abuse vulnerability in Nairobi County.

1.3.2 Specific objectives

The specific objectives of this study were to:

1) Review risk factors associated with child abuse.
2) Identify spatial data on child abuse cases in Nairobi County.
3) Map child abuse vulnerability in Nairobi County.
4) Analyze the impacts of risk factors on child abuse in Nairobi County.

1.4 Research Questions

The following questions were formulated from the objectives:

1) What are the risk factors associated with Child abuse?
2) What is the spatial data on child abuse?
3) What is the child abuse vulnerability in Nairobi County?
4) What are the impacts of risk factors on child abuse?

1.5 Significance of the study

Kenya and especially Nairobi County has a challenge of rising cases of child abuse. The impacts of child abuse are physical, and mental which affects the educational attainment potential of the victim. Once the victim is affected, efforts to bring back that child to normalcy take time and the victim may not recover fully(Leeb et al., 2011)**.** Social and economic neighbourhoods play a critical role in child abuse. Identifying neighbourhoods at risk of child abuse is the first step in prevention intervention measures. One of the intervention measures to reduce child abuse cases is to come up with prevention measures that help to reduce the number of cases in the future. Prevention measures that focus on neighbourhood risk factors have a higher chance of creating and sustaining a safer environment for children. It also helps in identifying neighbourhoods that are at risk of child maltreatment to prioritize those areas in child abuse intervention measures by the authorities.

This research is intended to provide useful information that will be useful in making decisions to reduce the number of child abuse cases in the County. This will be achieved by painting a clear picture of the sub-counties that are most vulnerable to child abuse and the risk factors of child abuse. This information will help those charged with the mandate to protect children in Kenya like the Department of Children Services to be more focused on the most vulnerable areas. This study also adds to the pool of knowledge in academic research on child abuse which can be a reference guide for future studies.

1.6 Scope of the study

The study was conducted in Nairobi County, Kenya. The main focus of the study was to map child abuse vulnerability using neighbourhood social and economic factors. Social and economic factors were identified using questionnaires.

The study used secondary data for risk factors affecting child abuse from the Kenya national bureau of statistics. Child abuse cases data were secondary from the Nairobi County Department of Children's Services.

The study used population density, poverty density, household size, unemployment rate, and level of education as independent variables and child abuse cases for 2020 and 2021 in Nairobi County as dependent to model child abuse vulnerability.

Regression models were used to predict and map vulnerability using the risk factors identified. The significance of the risk factors was first identified using a global model (Ordinary Least Squares). Significant factors identified by OLS were then used to map vulnerability.

Results were presented using charts on risk factors of child abuse and impacts of child abuse on children, a table of significant variables, a map of child abuse vulnerability, a map of coefficients of risk factors, and a project report.

1.7 Limitations of the study

Child abuse vulnerability is a broad subject in which several factors can be used to model vulnerability. This study only used social and economic factors and parental conditions that can be quantified and whose data were easy to find. There are however other factors that influence child abuse vulnerability that cannot be quantified. Factors not considered in this study include the characteristics of the child (age, gender, disability, birth weight, lack of self-protection awareness,) and family environment (violence at home, single parents, divorce, and separation of the parents).

1.8 Organisation of the report

This project report is organized into 5 chapters.

Chapter 1 gives an introduction to the project, it explains the background, problem statement, objectives, justification of the study, limitations of the study, and the scope of the study. Chapter 2 discusses the literature of this study. It describes the concept of child abuse, the concept of child abuse vulnerability, theories associated with child abuse, and child abuse vulnerability methods.

Chapter 3 discusses the material and methods used in this study. It describes the study are, an overview of the methodology, data sources, and tools, data collection, mapping of child abuse vulnerability and results from validation.

Chapter 4 discusses the results of the study including the child abuse vulnerability map and the impacts of each independent variable on child abuse.

Chapter 5 is the last chapter that gives conclusions, recommendations, and areas of further research.

2 Literature Review

2.1 General Overview

In this chapter the previous studies which are relevant to child abuse, social vulnerability to child abuse, and risk factors for child abuse are discussed. The various methods used for assessment and mapping child abuse vulnerability and related work are also presented.

2.2 Child Abuse

2.2.1 Overview of child abuse

A child according to the children's act of Kenya is a person below 18years. Child abuse includes physical, mental, psychological, child neglect, and sexual injury to the child. Child abuse is grouped into three: physical abuse, sexual abuse, and, verbal/emotional abuse(Prevention et al., 2019).

Child abuse is a global problem that causes suffering among children and has long-term consequences for the child. It causes depression in early brain development. The consequences of child abuse are depression, suicide, obesity, being a victim of violence, unintended pregnancies, and alcohol and drug abuse(*Child Maltreatment*, n.d.2020). it also contributes to school dropout. Studies have shown that children who experience any form of violence have a 13% likelihood of not graduating from school(*Child Maltreatment*, n.d.2020.). Beyond health and educational consequences, child abuse has an economic impact on society as it increases hospitalization costs.

The normal development curve of the child is interfered with by the consequences of child abuse. It is crucial to prevent physical neglect, emotional neglect, and, child abuse in general but also to strive to build a strong bond between the children and parents or caregivers and create a sense of love and belonging (Tuikong, 2020).

In Kenya, the department of children's services under the ministry of labor and social protection is given the mandate to collect, document, respond to and manage any case dealing with child abuse.

A report on violence against children was carried out in 2019 by the ministry of labor and social protection on children and young adults aged between 13 and 24(*Violence against Children .:. Sustainable Development Knowledge Platform*, n.d.2019). The survey found that nearly half of girls and boys experienced violence during their childhood age. The type of violence they experienced includes sexual, physical, emotional violence, and child neglect. The results of these are stress among children, unwanted pregnancies, and sometimes sickness.

A situational analysis report on child abuse and neglect in Uganda by ANPPCAN in 2019 showed that 53.9% of the victims were girls and 46.1% were boys(*Uganda*, n.d.2019). Child Neglect was ranked as the highest type of child abuse. Boys were victims of physical punishment and beatings while girls faced sexual abuse and educational neglect. The abusers were parents, teachers, relatives, friends, and religious leaders. In Tanzania report on violence against children shows that early marriages, sexual abuse, physical attachment, and emotional abuse are the main types of child abuse. Physical violence is deeply rooted in the cultures and norms of people in Tanzania(*Child Protection*, n.d.208).

2.2.2 Concept of child abuse vulnerability

A review of the factors associated with child abuse exposes the complexity of child abuse because these factors range from individual to societal levels and vary in the level of influence. Beyond family and individual, child abuse is also influenced by community and the societal context in which it occurs(Coulton et al., 2007).

As described by health researchers, social vulnerability can be defined as an effect of a lack of socioeconomic resources such as population density, low level of educational level, age structure, housing deficiency, and poverty index(Barboza-Salerno, 2020a). These factors are important explanatory variables for child abuse vulnerability mapping.

Studying neighbourhoods is important because they affect the social condition of the individuals living in them and they have a unique potential to inform prevention measures against child abuse (Freisthler et al., 2006). Many social risk factors tend to come bundled together at a neighbourhood level and therefore it is important to use social and economic risk factors of the neighbourhood in child abuse vulnerability mapping.

Socioeconomic factors place children at high risk of abuse and also make government systems and even individual response systems difficult. During multiple phases of child welfare response, it is important to have a good knowledge of where and how vulnerability influences potential child abuse which in turn will result in efficient and effective resource allocation(Barboza-Salerno, 2020a).

Sustainable development goals(SDGs) target 16.2, targets, to end abuse, exploitation, trafficking, and all forms of violence and torture against children(*Violence against Children .:. Sustainable Development Knowledge Platform*, n.d.2019). It targets to eliminate any harmful practices against children and any form of child abuse. This, therefore, prompts any government to develop measures of protecting children against abuse. The first step in doing this is identifying vulnerable neighbourhoods.

Figure 2.1: SDG target 16.1 on the protection of children against any form of abuse.

(source: SDG-Postcard-infographic 2015)

A report by the UN on keeping the promise and ending violence against children by 2030 was presented to the High-level Political Forum (HLPF) on developments that have been made towards the achievements of SDG goal 16.2(Hub, n.d.2018). The report indicates that almost 100 countries worldwide have comprehensive policies in place to prevent and respond to violence against children. Countries like the UK, Mexico, Malta, and Lithuania have put in place legal and policy frameworks to protect children against violence and the detention of refugees and migrant children is prohibited by law in these countries. In Macedonia, this goal has undergone important milestones which include the improvement of policy and legal framework including protocols to protect children against violence(Jordanova Peshevska et al., 2016). Macedonia state promotes and encourages non-violent forms of punishment as alternatives to physical punishments through social marketing campaigns, by changing the traditional norm of violent disciplining.

World health organization describes parents who are likely to expose their children to abuse as those experiencing financial difficulties, those having mental disorders, those who were abused when young, and those who misuse drugs and take alcohol. Children who are likely to be abused are those below 18 years of age, those having special needs, those who feel they are unwanted, and those who are considered bisexual or transgender(*Child Maltreatment*, n.d.2020). Communities where the children live also determine whether the children are at risk of being abused or not. Characteristics of communities where children are at risk of being abused are inadequate housing or facilities to support families and institutions, high unemployment rates and poverty index, low levels of education, inadequate policies and programs to safeguard children against child abuse, poor living standards and easy availability of drugs and alcohol(Freisthler, 2004).

A study carried out by Sacha in Los Angeles, shows that there is a Spatio-temporal clustering of child abuse cases in socially and physically disorganized densely populated urban areas(Klein & Merritt, 2014).

A study in the City of Fort Worth, Texas used Risk Terrain Modeling (RTM) to analyze the collective effects of the environmental factors believed to be conducive to child abuse and develop a prediction model to identify areas that might be at high risk of child abuse in future(Daley et al., 2016). This study shows that GIS can be used in child abuse prediction modeling.

The most common type of child abuse that is reported to Childline Kenya is sexual abuse. Girls are at risk of being sexually abused more than boys("Supporting Children and Adolescents Who Have Experienced Sexual Abuse to Access Services," 2021). Access to services by the children who have been abused heavily relies on the status of the children's caregivers. Societies where child abuse is common normally lack child protection services.

Kenya's population growth rate is 2.3% according to the 2019 population census. This population is dominated by young people with those below 15 years at 39% of the total population(Kenya National Bureau of Statistics, 2019). There are several vulnerabilities and challenges that children face and which require a multi-sectorial approach to support these children until they finish their childhood phase of life. These vulnerabilities of child abuse are social issues that predispose children to abuse which include poverty, age of the children, the population density of the residence, educational level, and mental state of their caregivers, and parents(Leeb et al., 2011).

Poverty adversely affects children in Kenya. Children account for two-thirds of the total population in Kenya. 45% of children in Kenya experience child poverty(Kenya National Bureau of Statistics et al., 2017). Demographic and health data show that children are overrepresented in the households in the lowest wealth quintiles. Children's vulnerability to abuse is determined by the poverty level of the household, the highest level of education of any person in the household, the population density of the surroundings, and the age of the child.

A study in the city of Valencia, Spain used Spatio-temporal analysis to map child maltreatment risk caused by neighbourhood influences(Gracia et al., 2017). This study used neighbourhood economic status, neighbourhood education level, immigrant concentration, and residential instability as neighbourhood risk factors. Bayesian Spatio-temporal modeling was used to provide neighbourhood risk estimations. This study found that neighbourhoods with low levels of education, low economic status with a high level of concentration of immigrants, and policy activity have a higher level of child maltreatment rate.

To fully identify and respond effectively to child abuse, a good assessment of the risk factors of child abuse need to be done(Barboza, 2019). A study in Los Angeles quantified the risk of child abuse and neglect at a census tract level over four years using integrated nested Laplace approximations with Bayesian hierarchical spatial models(Barboza, 2019). Structural heterogeneity, social vulnerability, and racial segregation were found to be risk factors for child abuse and neglect in Los Angeles.

Developing knowledge of how and where vulnerability in the County influence potential child abuse will create a system where the resources will be efficiently allocated during a crisis to respond to child welfare.

2.3 Theories and models Associated with child abuse

2.3.1 Theories of child abuse

The relationship between risk factors and child abuse is influenced by two research traditions in which one focuses on social disorganization and the other one being ecological transactional development theory(Coulton et al., 2007).

Social disorganization theory was developed by social workers and sociologists. It describes the social process and structures within the neighbourhood that influences child abuse. However, social disorganization theory provides little specificity about how these neighbourhood characteristics might influence the behaviors and development of children and families

Ecological transactional development theory was led by developmental psychologists. It shows how child development and parenting are affected by the surrounding environment(Coulton et al., 2007). The strength of this approach is that it describes some of the specific ways the environment may influence the transactions between a parent and child and between a family and the neighbourhood. However, the ecological-transactional model provides a limited explanation of how neighbourhood conditions and social processes influence these transactions and how and why these neighbourhood conditions and processes occur.

Both social disorganization theory and ecological transaction theory explain that child abuse is determined by a variety of factors that are different and exist in different ecological contexts(Barboza-Salerno, 2020a).

This project builds on past research based on social disorganization and ecological transactional frameworks to map child abuse vulnerability in Nairobi County.

2.3.2 Models of Child Abuse

Social-ecological model is a model that addresses the condition of a child being abused. It addresses the risk factors from individuals to society.

Family and children reside in the neighbourhood which is one of the ecological units that is very important. This ecological view suggests that neighbourhoods influence the risk of children and may raise or lower the risk of child abuse(Coulton et al., 1999).

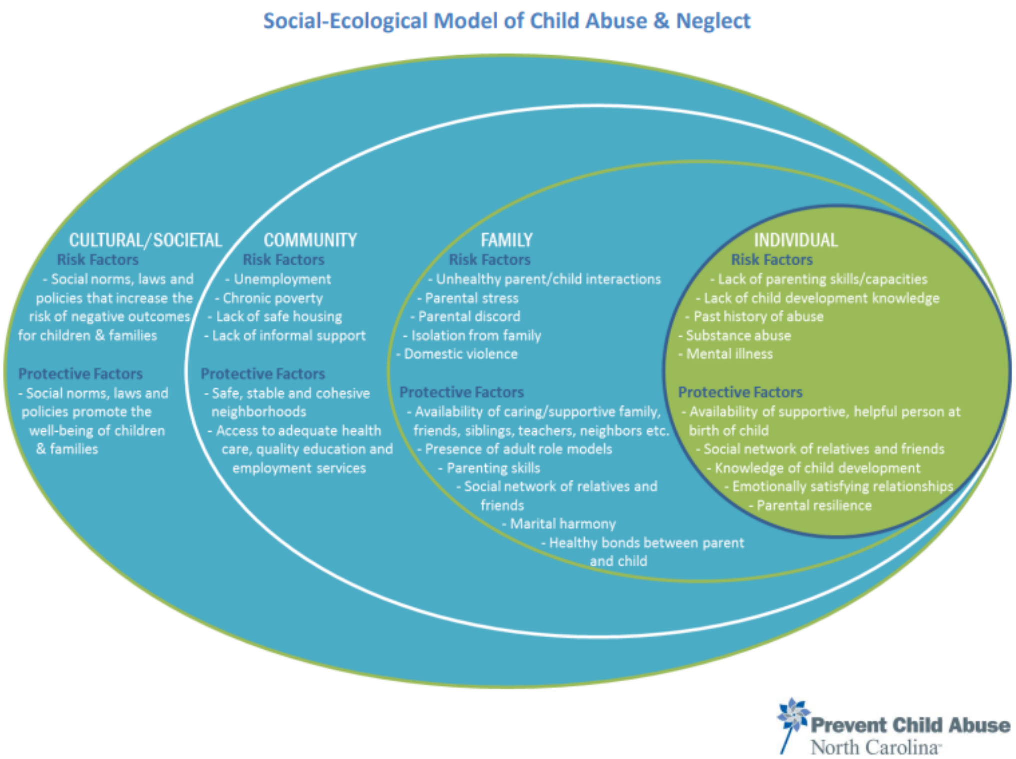


Figure 2.2: Social-ecological model of child abuse

Source:(The Social-Ecological Model, 2022)

2.4 Child abuse vulnerability mapping methods

2.4.1 Spatial analysis techniques

2.4.1.1 *Moran's 1*

Moran's 1 is one of the statistical tools used in a dataset to measure spatial autocorrelation. It is one of the leading measures used in a dataset to measure spatial autocorrelation. It uses the entire dataset and produces a single output value that ranges from -1 to +1(Tesema et al., 2021). Moran's value close to -1 will indicate that the dataset under study is dispersed while Moran's value close to +1 will indicate that the dataset is clustered. Moran's 1 value close to zero will indicate that the dataset is randomly distributed over the study area. Moran's 1 was used to study the spatial autocorrelation of child maltreatment cases in San Diego County, in the south-western corner of California which showed the data were spatially autocorrelated(Barboza-Salerno, 2020a). Moran's 1 formula is given by equation 2.1.

$$I = (N/W)*\Sigma\Sigma w_{ij}(x_i - x)(x_j - x)/\Sigma(x_i - x)^2 \_\_\_\_\_\_\_\_\_\_\_ (2.1)$$

Where: **N** is the number of spatial units indexed by *i* and *j*, **W** is the sum of all w_{ij}, **x** is the variable of interest **x** is the mean of x, and $\mathbf{w_{ij}}$ is the matrix of spatial weights.

This method is advantageous in showing the spatial autocorrelation between datasets but the method does not show hot spot areas.

2.4.1.2 Hot spot analysis Tool (Getis-Ord Gi*)

The hot spot analysis tool is one of the spatial analysis tools used to determine spatial clusters of high and low values. It is used to identify statistically significant hot spots and cold spots areas in spatial data The resultant z –scores and p-values where features with either high or low values cluster spatially. It determines the Getis-Ord Gi* for each feature in a dataset. The tool works by looking at each feature in the neighbourhoods. The formula for this tool is given by equation 2.2:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \qquad (2.2)$$

Where x_j is the attribute value for the feature, $w_{i,j}$ is the spatial weight between feature *i* and *j*, and *n* is equal to the number of features, and finally:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2} \qquad (2.3)$$

2.4.2 Modelling Techniques

2.4.2.1 *Ordinary Least Squares(OLS)*

OLS is a global model that uses one equation to represent the entire dataset identically normally distributed around a mean of zero. It relies on establishing the dependent variable through the production of the unbiased minimum sum of error square concerning the explanatory variables. This model produces a mean of zero residuals that are normally distributed and are independent. The relationship between the explanatory variables and the dependent is explained using a single equation in this model. There are certain assumptions that this model relies on which include: normality, homogeneity, and independence of residuals. The OLS model explores the global relationship between the independent variable and child abuse and neglect cases. This model has been used by Barbazo to examine child maltreatment cases in Diego County with social vulnerability(Barboza-Salerno, 2020a). The formula for OLS is given by equation 2.4.

$$Y = \beta_1 x_1 + \cdots += \beta_{1p} x_p + £ \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_} \quad (2.4)$$

Where Y is the dependent variable. β_1, *i = 1, 2, ..., p* is the coefficients of independent variables and, $x_1 \ldots . x_p$ are independent variables and £ is the random effect. OLS does not automatically check for redundancy in variables and this is the major set-back to OLS. The major advantage of OLS is that it can show global relationship among variables. The disadvantage of this method is that it assumes the homogeneity of data.

2.4.2.2 Geographically Weighted Regression(GWR)

Geographically Weighted Regression (GWR) is a tool that explores the spatial non-stationarity of the regression relationship in spatial data analysis(Ma et al., 2020). GWR fits the regression of each feature in a dataset and it is a local model. The basic idea used in this model is to use information from nearby points. It uses Tobler's first law which states that "near things are more related than distant things". From the location being estimated, subjects in the data are weighted according to the distance from that location when determining parameters for a specific location. In estimating the parameter for one specific location, subjects in the data are weighted according to their distance from this location and greater weights are assigned to closer subjects, whereby closer subjects have greater weights. (Ma et al., 2020).

The equation for GWR child abuse be written as:

$$Y(s) = \beta_1(s) x_1(s) + \cdots += \beta_{1p}(s) x_p(s) + £(s) \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_} \quad (2.5)$$

Where Y(s) refers to the response variable at location *s*. $\beta_1(s)$, *i = 1, 2, ..., p* is the coefficients of independent variables at location *s* and $£(s)$ is the random effect at location *s*.

The weights of each observation of child abuse are determined by the distance between that observation and s if a weighting function is given. Similar to the weighted least squares estimation of coefficients at locations s is formulated.

GWR has been used to model youth pregnancies in continental Portugal. The study used four risk factors to model youth pregnancy risk. The study found out that the unemployment rate of youths and females, number of households without amenities, the rate of those prematurely leaving school, and proportion of the percentage of social security beneficiaries explained youth pregnancy rates(David & Cabral, 2019). This study was successful in the use of GWR in modeling youth pregnancy rates. The model has been successfully used in California to determine the spatial clusters of child maltreatment rates in a social vulnerability framework(Barboza-Salerno, 2020a). The model grouped the study area into six spatial clusters with different combinations of risk factors of child maltreatment.

GWR automatically checks for redundancy, unlike OLS. In GWR binary variables are excluded as they will cause the problem with local multicolinearity, therefore having an advantage over OLS. However, GWR can only be used to show relation among variables in a local area and cannot be used for global purposes. GWR is not also appropriate for determining binary outcomes. GWR is however chosen in this study as it is important in showing the local spatial relationships among the dependent and independent variables.

2.4.2.3 Relationship between OLS and GWR

GWR is used with spatial data as it builds a regression equation for each dataset in every location GWR is unlike OLS which uses a single equation to represent all the features in a dataset. GWR is a great prediction model as it is more dunned by local circumstances. Unlike OLS where homogeneity of data is assumed, GWR data is heterogeneous. It determines the relationship between spatial variables independently for every point through local disaggregating global statistics. Global models do not hold anymore because data nowadays are dependent on geographic locations(Wu & Zhang, 2021).

In GWR, the distance between every data point to the regression point determines the weight of that data point. Therefore, a data point near the regression point has more weight than a point that is far from the regression point, and a point that is at the same location as the regression point has maximum weight.

2.5 Conceptual Framework of Child Abuse Vulnerability

A conceptual framework of child abuse vulnerability is presented in this section. It includes both the independent and dependent variables.

Neighbourhood characteristics and poverty at an individual level have a relation to child abuse as most published research has shown(Sidebotham & Heron, 2006). Poverty density when low can have an impact on child abuse as poor families then work extra time away from the children and therefore leaving children to care for themselves who may be abused in the process. Children from poor backgrounds tend to be at risk of being abused as they have no power to prevent any form of abuse. Population density is also a factor in neighbourhood characteristics(Drake & Pandey, 1996).

The dynamics and structure of the family have an impact on child abuse from research(Sidebotham & Heron, 2006). Domestic violence is a risk factor that increases the risk of children to abuse. Family size is an important factor where a high family size increases the risk of children to abuse.

The Parental background is an important aspect of the safety of a child. Young parents, adverse maltreatment of the parent when they were young, alcohol and drug abuse by the parents, and high rates of unemployment of the parents have been linked to child abuse(Sidebotham & Heron, 2006). Unemployment both at an individual and a social level has been linked to child abuse. The education level of the parent is significant in determining the safety of the child. Children of young parents and those with poor academic achievements have a high risk of maltreatment(Sidebotham & Heron, 2006).

Independents variables for this study are therefore population density, poverty density, education, household size, and unemployment. The dependent variable is child abuse cases as in figure 2.3.

Independent Variables **Dependent Variable**

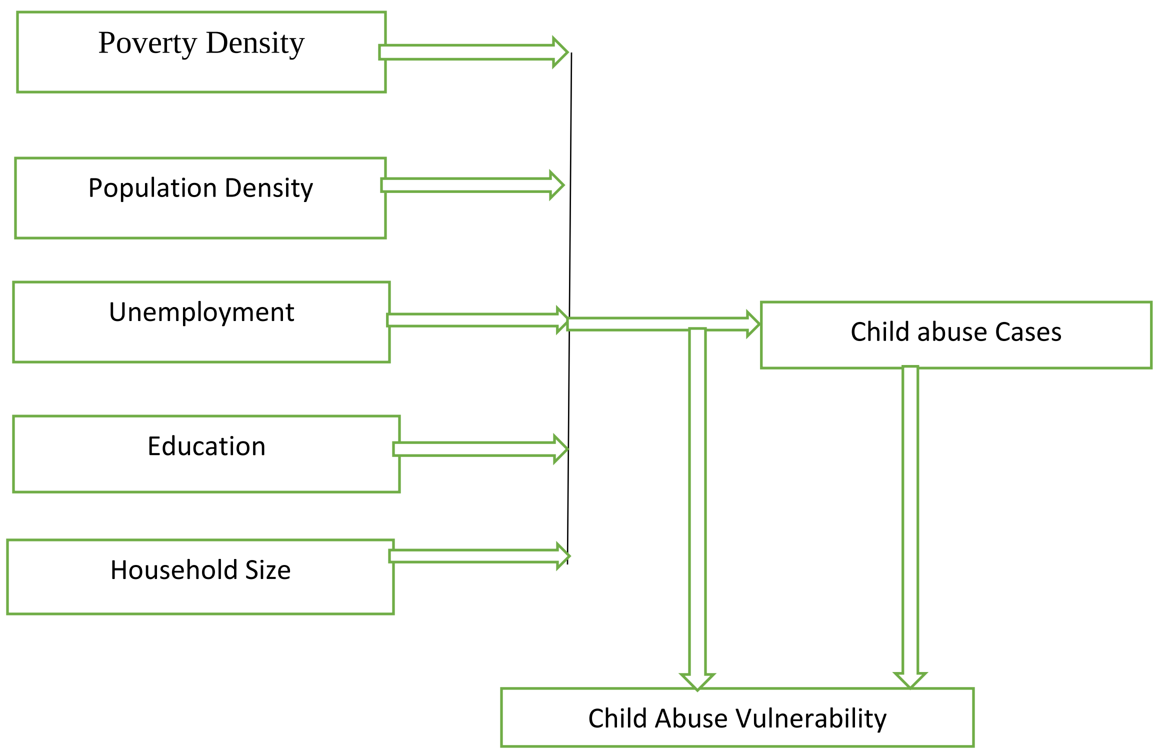


Figure 2.3: Child Abuse Vulnerability Conceptual Framework.

Independent variables differ in the rate of their importance in modeling child abuse vulnerability. The importance of each independent variable will be shown by its coefficient. Coefficient shows areas where the variable is important and the spatial spread of that variable.

2.6 Conclusion

This project builds on past research based on social disorganization and ecological transactional frameworks to map child abuse vulnerability in Nairobi County using geospatial methods. Geographically Weighted Regression and Ordinary Least Squares are used to assess the relationship between child abuse and risk factors of child abuse. This research is useful in adding to existing body of knowledge of mapping child abuse vulnerability using geospatial techniques.

3 Materials and Methods

3.1 Description of the Study area

The study area is Nairobi County. It is County number 047 in Kenya. It is found within the greater Nairobi metropolitan area and is the capital city as well as the largest city in Kenya. The County has 17 parliamentary constituencies and 85 wards. The map of Nairobi County is as shown by figure 3.1.

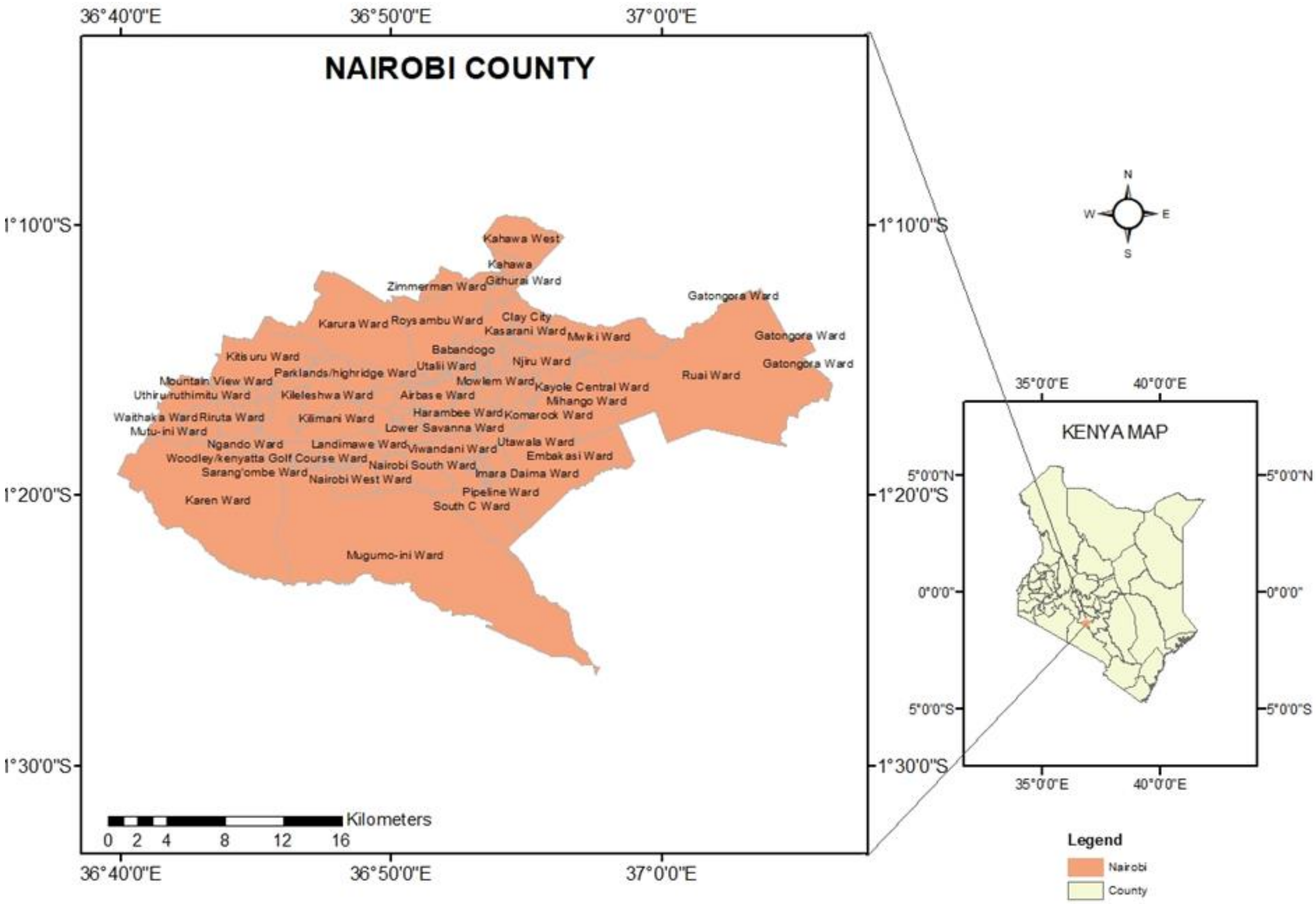


Figure 3.1: Nairobi County

It is the most populous and yet it is the third smallest in area size. According to the 2019 census report, Nairobi County has a total number of 4,397,073 people and 6,247 persons per kilometer square with an average household size of 2.9(Kenya National Bureau of Statistics, 2019).

It is situated in the south-central part of the country and is situated between the city of Kampala and Mombasa and is adjacent to the eastern edge of Rift Valley. It is situated in the highlands at an elevation of about 1,680 meters above the mean sea level. Temperature can range from an average of 9 °C during the cold seasons of June/July to 24 °C during the warmest months of the year. It receives an average rainfall of about 610mm per year. Figure 3.1 shows the location and boundary of Nairobi County in Kenya.

3.2 Overview of the Methodology

Figure 3.2 shows a flow chart of the methodology adopted in the study.

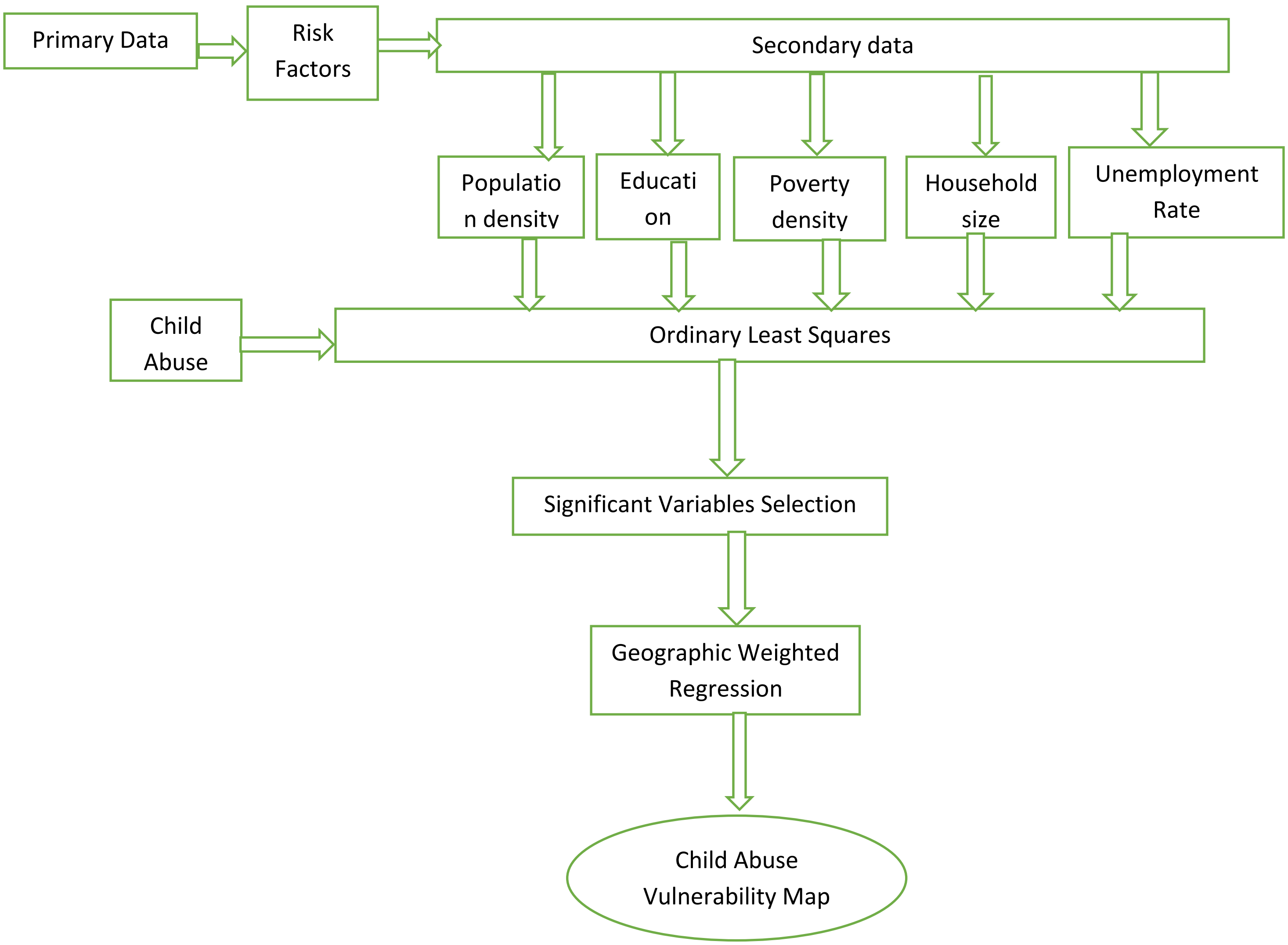


Figure 3.2: Methodology Flow Chart

Population density, poverty density, unemployment, education level, and household size were used as independent variables and child abuse cases were used as dependent variables. Ordinary Least Squares Regression was carried out to identify significant variables to use to model child abuse vulnerability and to check for the redundancy of the variables. Geographically weighted regression was used to model child abuse vulnerability.

3.3 Data Sources and Tools

3.3.1 Data Sources

The data used in this study were collected from both primary and secondary sources as shown in table 3.1.

Table 3.1: Data Sources

Data	Data type	Source	Date Specification
Risk factors associated with child abuse	Primary data	Questionnaires to key informants in children's departments in 11 sub-counties.	2022
Child abuse cases	Secondary	Nairobi County department of children's services	Incident cases of 2020-2021and 2022
Social risk Factors	Secondary	Kenya National Bureau of Statistics	2015-2019
Boundaries data	Secondary	Ocha services website	2020

3.3.2 Tools

Both hardware and software tools were used in this study.

Hardware used were;

- Laptop Computer
- Printer

Software used in this study were:

- ArcGIS desktop 10.3 for spatial analysis regression and map generation
- Microsoft word for writing and report compilation
- Excel for analysis of questionnaires
- XLSTAT for results validation using Spearman's rank correlation coefficient metric.
- Snipping tool for snipping figures and table added to the report.

3.4 Data Collection

3.4.1 Primary data

Questionnaires were used to collect data about the risk factors that contribute to child abuse in the County. The respondents were selected from 11 sub-County children's departments in the County. A total of 31 out of the targeted 40 respondents who included children protection officers and supervisors of children officers responded to the questionnaires. The respondents were sampled in each sub-County office based on the role they play in the sub-County office and their interaction with child abuse cases.

The questionnaires were semi-structured to allow the respondents flexibility in providing responses that are useful in answering the research questions. Close-ended questions collected quantitative data while qualitative data were obtained from the open-ended questions in the questionnaire.

The questionnaire was divided into two sections. The first section included questions on demographic data such as the name of the respondent, department, sub-County of service, specialization, and position. The next section included questions on Child abuse cases and risk factors associated with child abuse.

The questionnaires were delivered as google forms to be filled by the respondents. The questionnaire used is attached in the appendix 1 section of this report.

3.4.2 Secondary data

Secondary data on child abuse cases reported were obtained from the Nairobi County department of children's services. It contained the place of abuse, gender, age of the victim, and type of abuse. The cases were collected for two years from January 2020 to December 2021.

Population density data, Household size data, Unemployment data, and education level data were obtained from the Kenya National Bureau of Statistics(KNBS) for the year 2019. Poverty density data were obtained from the KNBS economic and health survey report of 2015.

The data on child abuse cases were unstructured and therefore they were geocoded in ArcGIS using the shapefile for sub-counties. This was to give a spatial component to the child abuse cases.

3.5 Mapping Child Abuse Vulnerability

3.5.1 Analyzing factors of child abuse

Before analysis, the data was organized and checked for completeness in readiness for analysis. An analysis of the questionnaires was done to identify social risk factors that contribute to child abuse in the County. The analysis was done using Microsoft excel. Sample excel sheet used is shown by figure 3.3.

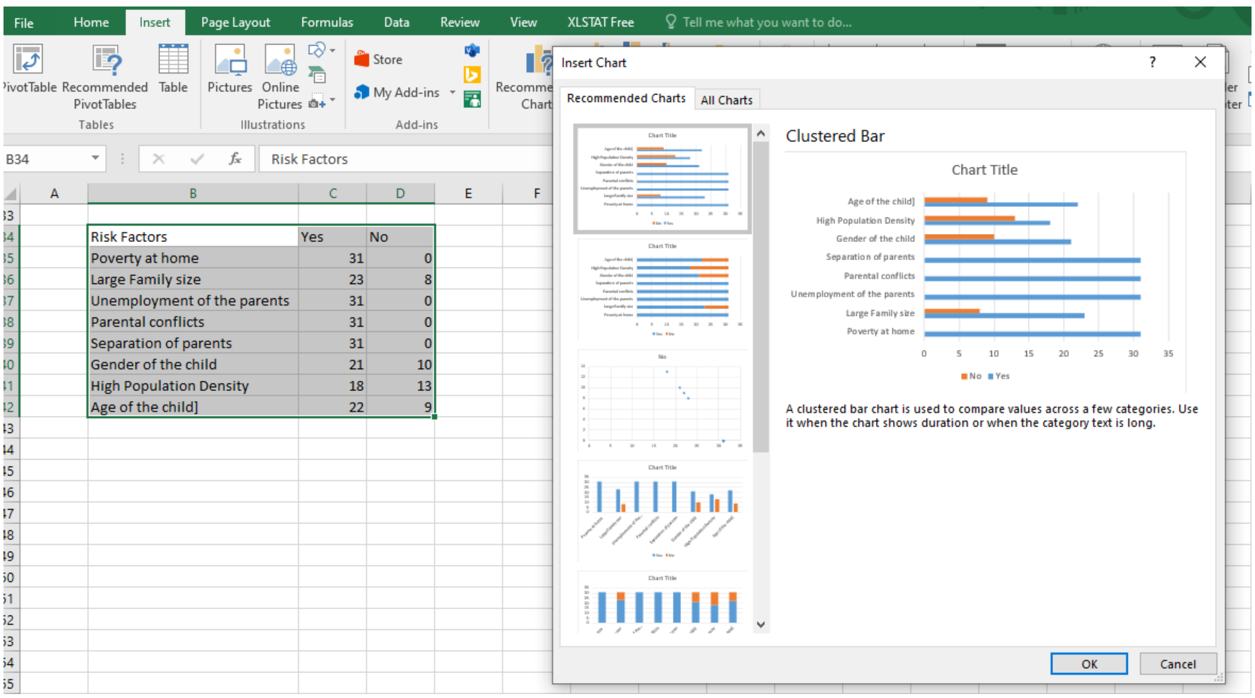


Figure 3.3: Risk Factors of child abuse Excel Input

The result of this excel input was a chart showing the risk factors of child abuse in Nairobi County.

3.5.2 Spatial distribution of child abuse

Data on child abuse for two and half years from January 2020 to December 2021 was obtained from the Nairobi County department of children's services. Child abuse cases were grouped according to the type of abuse. Spatial distribution of child abuse cases per sub-County was done in ArcGIS 10.3 to visualize the data. The child abuse cases CSV file was joined with a spatial shapefile for Nairobi sub-counties to visualize the spatial distribution of the cases. The input of the join tool is shown in figure 3.4.

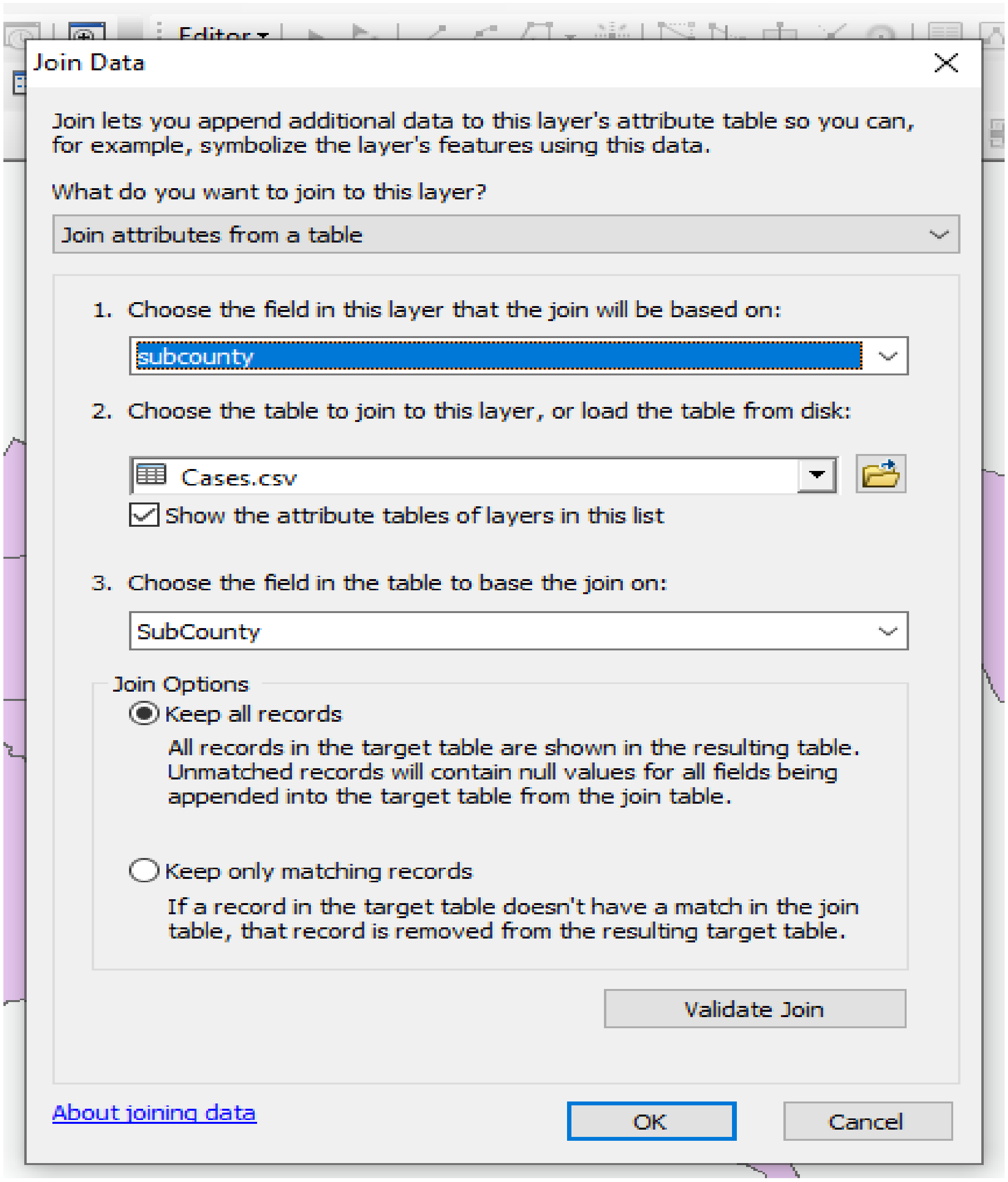


Figure 3.4: Join Tool

The output of this tool was a shapefile of child abuse cases per sub-County.

3.5.3 Child abuse vulnerability mapping

To map Child Abuse vulnerability, two models were used. The ordinary least squares regression model was first used to identify significant variables to be used in modeling child abuse. Child abuse cases were used as the dependent variable while population density, poverty density, household size, unemployment, and education level were used as independent variables. Using variance inflection factors(VIF) redundancy of the variables were checked. Using probability values, the significance of each independent variable was checked. The inputs for the Ordinary Least Squares tool are as shown in figure 3.5.

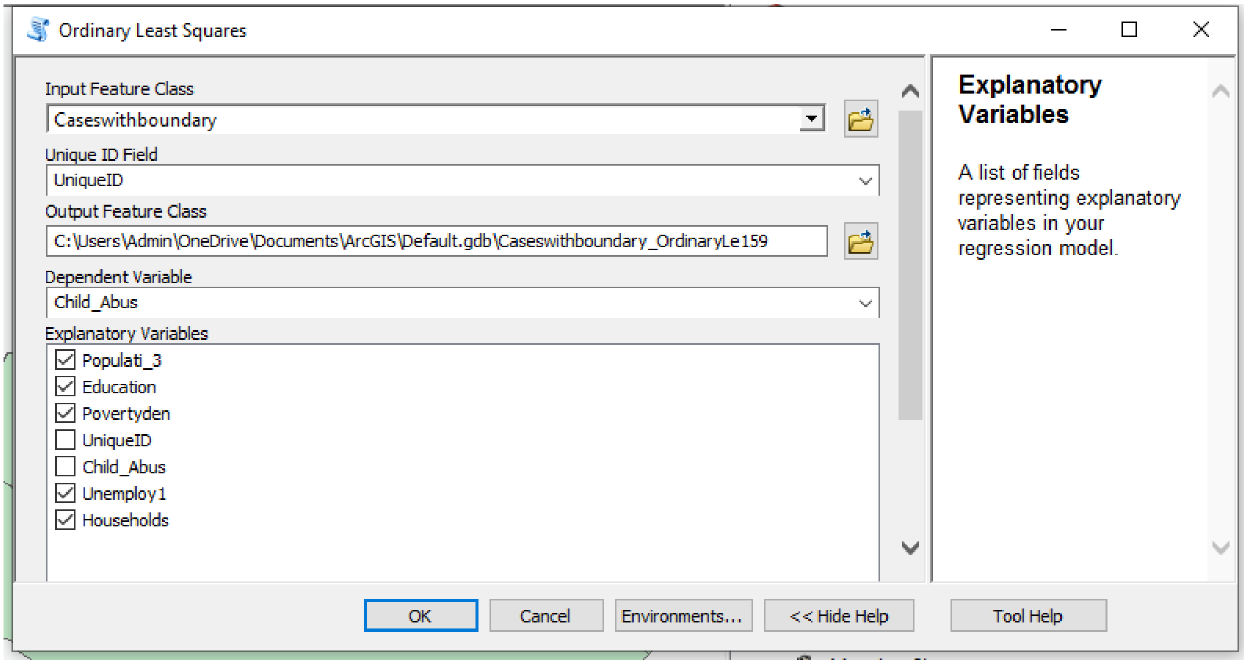


Figure 3.5: OLS Regression tool

The output of this was a table showing the significance of the risk factors and VIF values of each of the factors.

To examine the relationship between child abuse cases and social vulnerability factors, Geographically Weighted Regression(GWR) was then implemented. Predicted values from GWR were used to map child abuse vulnerability. The inputs for geographically weighted regression are as shown in figure 3.6.

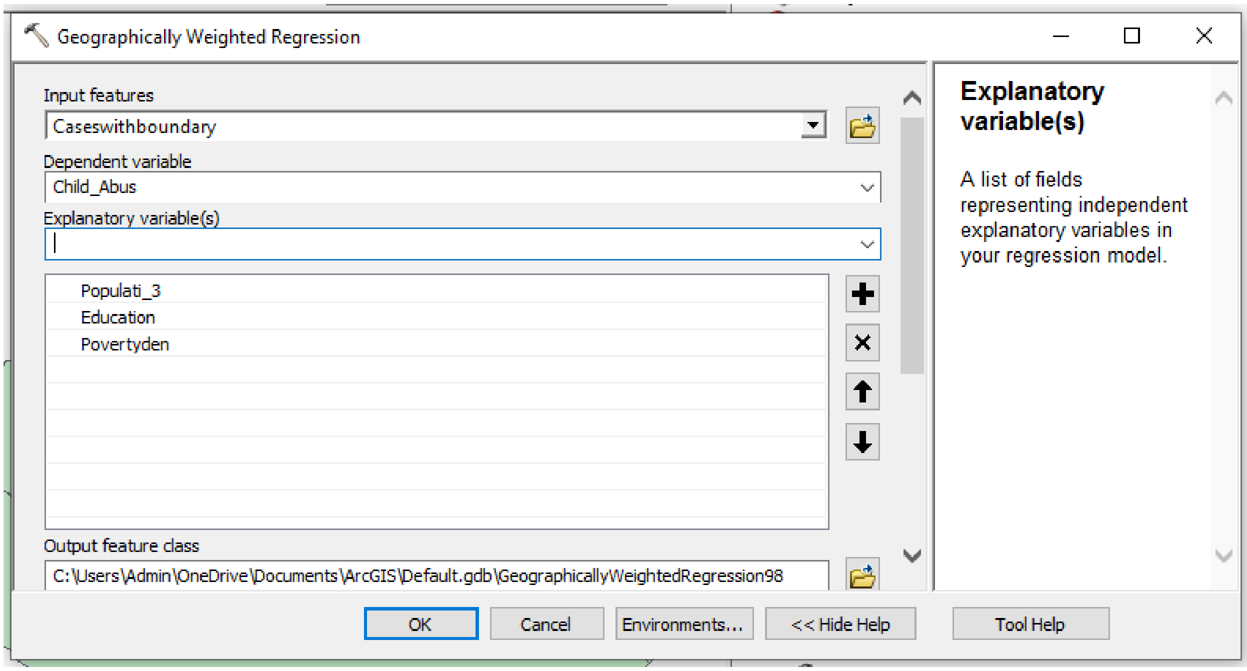


Figure 3.6: GWR Regression Tool

The results of this tool were predicted child abuse vulnerability values, coefficients of each of the risk factors, and standard residuals.

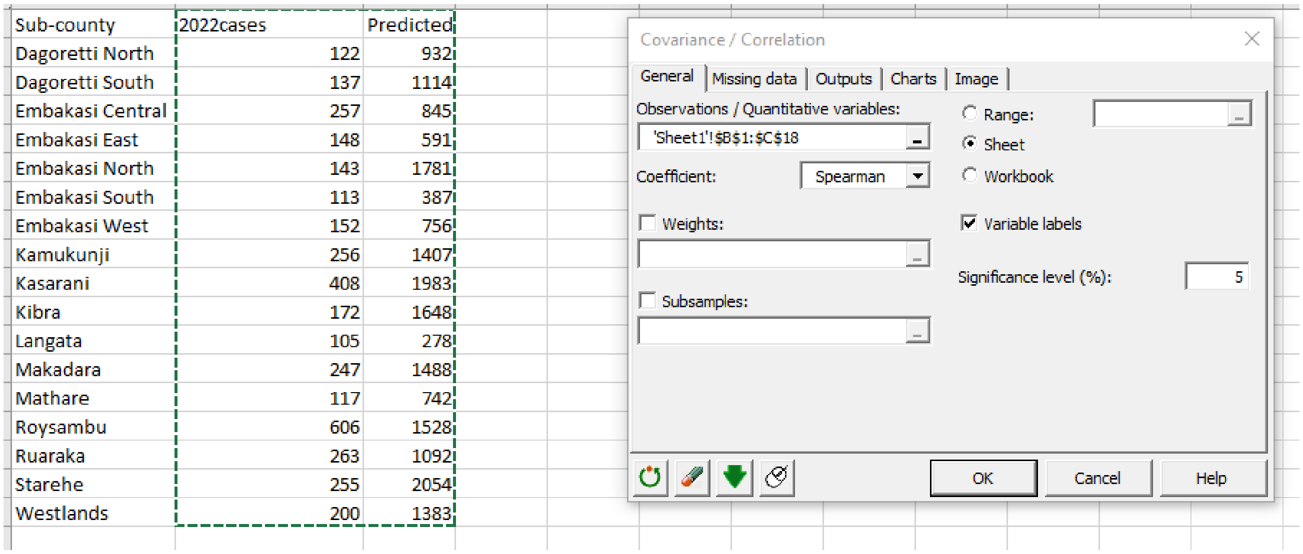
3.5.4 Impacts of child abuse vulnerability

To assess the impacts of each of the independent risk factors on child abuse, coefficients of independent variables were mapped. Coefficient values show the relationship between the dependent variable and independent variables. Areas with high values show that there is a strong relationship between the dependent variables and independent variables.

Maps of coefficients of independent variables also show the geographic changes of the various relationships and visualize how changing the independent variable influences child abuse. It shows where each of the risk factors is important in predicting child abuse.

3.6 Results Validation

The results were validated by comparing the cases predicted by the geographic model with the reported cases to the Nairobi County children's department in 2022. Spearman's rank correlation coefficient metric was used in the comparison. Using XLSTAT, spearman's rank correlation was run to check the relationship between reported cases of child abuse from 2022 January to April in Nairobi County and the predicted cases. This correlation compares the strength of the linear relationship between the two variables. The input of this metric is as shown by figure 3.7.



Sub-county	2022cases	Predicted
Dagoretti North	122	932
Dagoretti South	137	1114
Embakasi Central	257	845
Embakasi East	148	591
Embakasi North	143	1781
Embakasi South	113	387
Embakasi West	152	756
Kamukunji	256	1407
Kasarani	408	1983
Kibra	172	1648
Langata	105	278
Makadara	247	1488
Mathare	117	742
Roysambu	606	1528
Ruaraka	263	1092
Starehe	255	2054
Westlands	200	1383

Figure 3.7: Spearman Rank Correlation Input

The output of this input was a table showing the correlation coefficient of the reported cases and the predicted cases in the County.

4 RESULTS AND DISCUSSIONS

4.1 Introduction

The results of the study will be presented in this chapter. Child abuse risk factors were identified and listed. Charts are used to present these factors. Maps are used to show the distribution of child abuse cases and risk factors in the County. The vulnerability index map shows areas that are vulnerable to child abuse. Discussion of these results is the last section of this chapter.

4.2 Child abuse risk factors

From the data collected from 31 children officers and child protection officers in 11 sub-County offices of the Nairobi County department of children services, some risk factors contribute to child abuse.

First, to know the number of child abuse cases reported to the children's department in a day, the respondents were asked to give an approximate number of cases reported to their offices daily. It was found out that there are at least one or more cases reported to the department daily.

Figure 4.1 illustrates the responses to daily cases reported

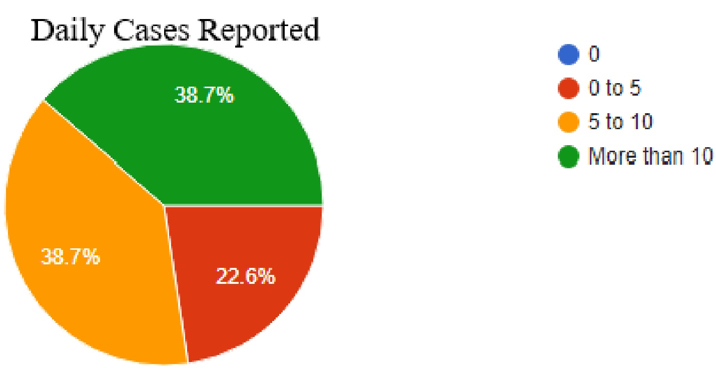


Figure 4.1 Daily child abuse cases reported

From the results, 0 to 5 constituted 22.6%, 5 to 10 constituted 38.7% and more than 10 constituted 38.7%. This show that daily, there is at least one case of child abuse reported to the department of children’s services in Nairobi County.

It was found that some social-economic factors contribute to child abuse in the County. These factors included: poverty at home, unemployment of the parents, parental conflicts, separation of the parents, high population density, gender of the child, age of the child, large family size, and education level of the caregiver.

Figure 4.2 illustrates these factors.

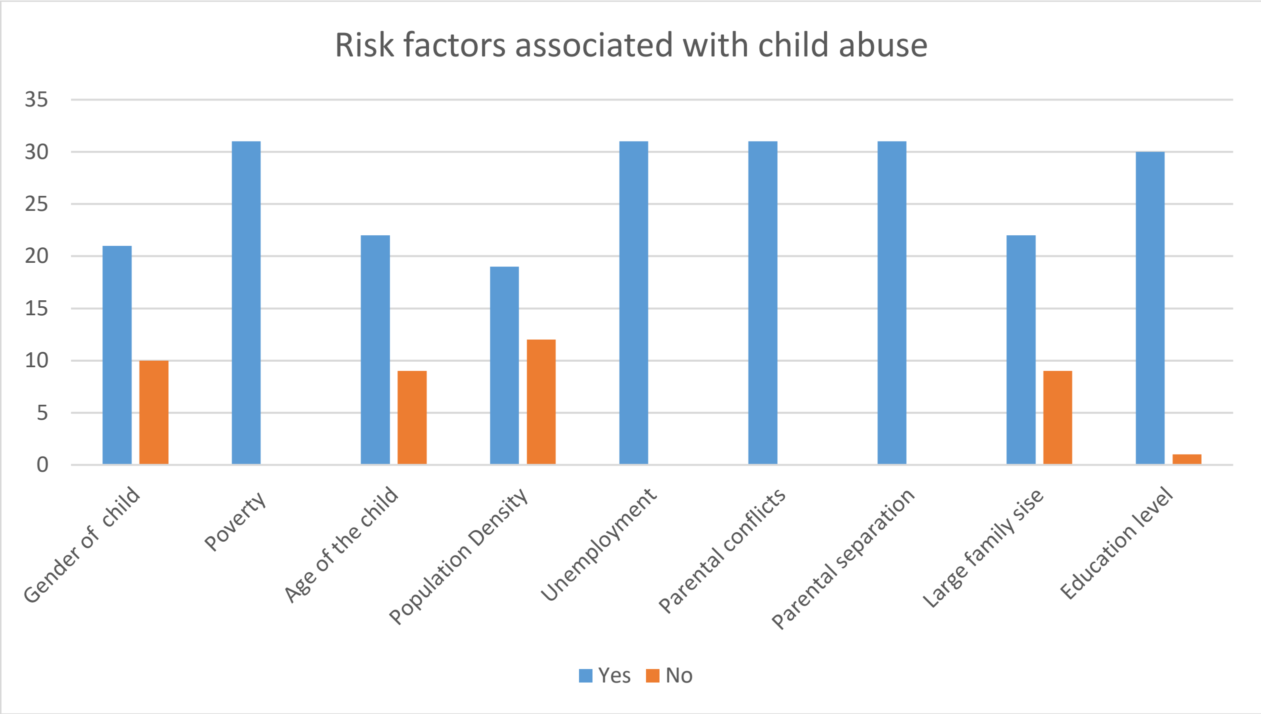


Figure 4.2: Risk factors associated with child abuse.

Figure 4.2 show that poverty density, parental conflicts, parental separation, and education level are the main risk factors for child abuse in Nairobi County. All the respondents said yes to these factors. Large family size, gender and age of the child, and population density were also other risk factors of child abuse as the majority of the respondents said yes.

The respondents were also asked to give other factors that contribute to child abuse in the County. Other factors that contribute to child abuse according to the respondents included: High cost of living, lack of parental responsibility, government neglect, unavailable parents, cultural practices, lack of parental skills, insufficient food in the family, lack of supervision from the parents, social media influence, and substance and alcohol use.

To understand the effects that child abuse has on the victims, the respondents were asked to give their views on the impacts that child abuse has on children. Figure 4.3 illustrate their responses. It was found that depression, stress, withdrawal symptoms, death, anger, post-abuse trauma, physical damage, and emotional damage are the main effects of child abuse.

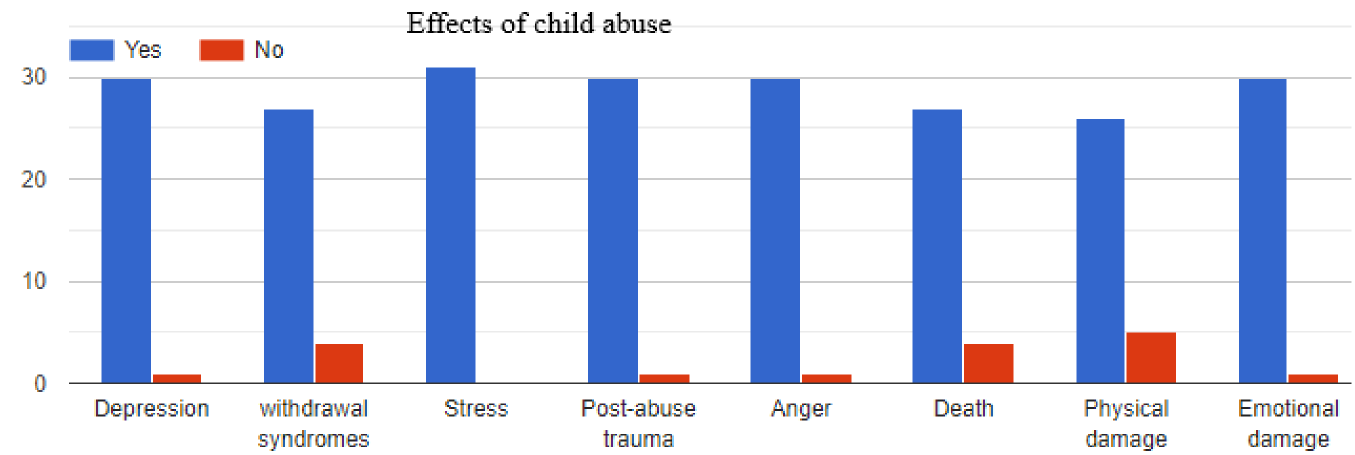


Figure 4.3: Effects of child abuse

Figure 4.3 show that stress is the main effect of child abuse. Emotional damage, depression, post-abuse trauma, and anger follow with majority of the respondents saying they are the effects of child abuse. Death, withdrawal syndromes, and physical damage are minor effects of child abuse compared to the others.

4.3 Child abuse vulnerability maps

A number of social-economic factors were identified from the risk factors of child abuse that were reviewed to be used in mapping child abuse vulnerability. These factors included: Age of child (ratio of children below 18 years to the total population), Poverty density, Population density, number of people with post-secondary education (university and college), Gender of children below 18 years, and unemployment rate. The other factors that were identified include parental conflicts, parental separation, and other society characteristics which cannot be quantified.

The relationship between independent variables and the dependent variable is suggested when independent variables are mapped(Charlton & Fotheringham, n.d.). Five independent variables were mapped namely population density, household size, poverty density, education, and unemployment.

Population density

A population density map was produced using the data from KNBS on population density as per the 2019 population census as shown by figure 4.4.

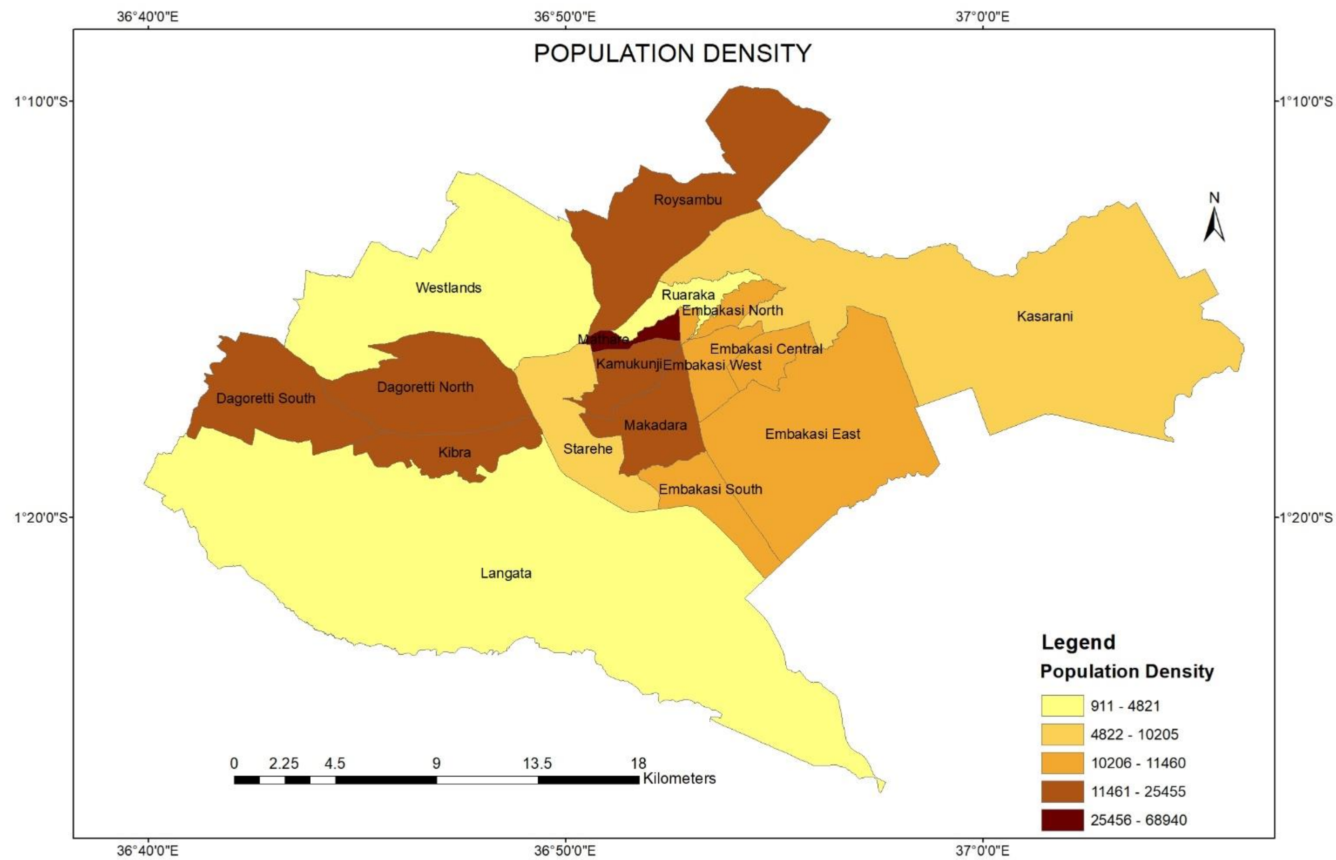


Figure 4.4: Population Density

From figure 4.4, Mathare, Kamukunji, Makadara sub-counties have high population densities with 68940,25455 and 16150 population densities respectively.

Education

The map showing the distribution of people with post-secondary education is as shown in figure 4.5.

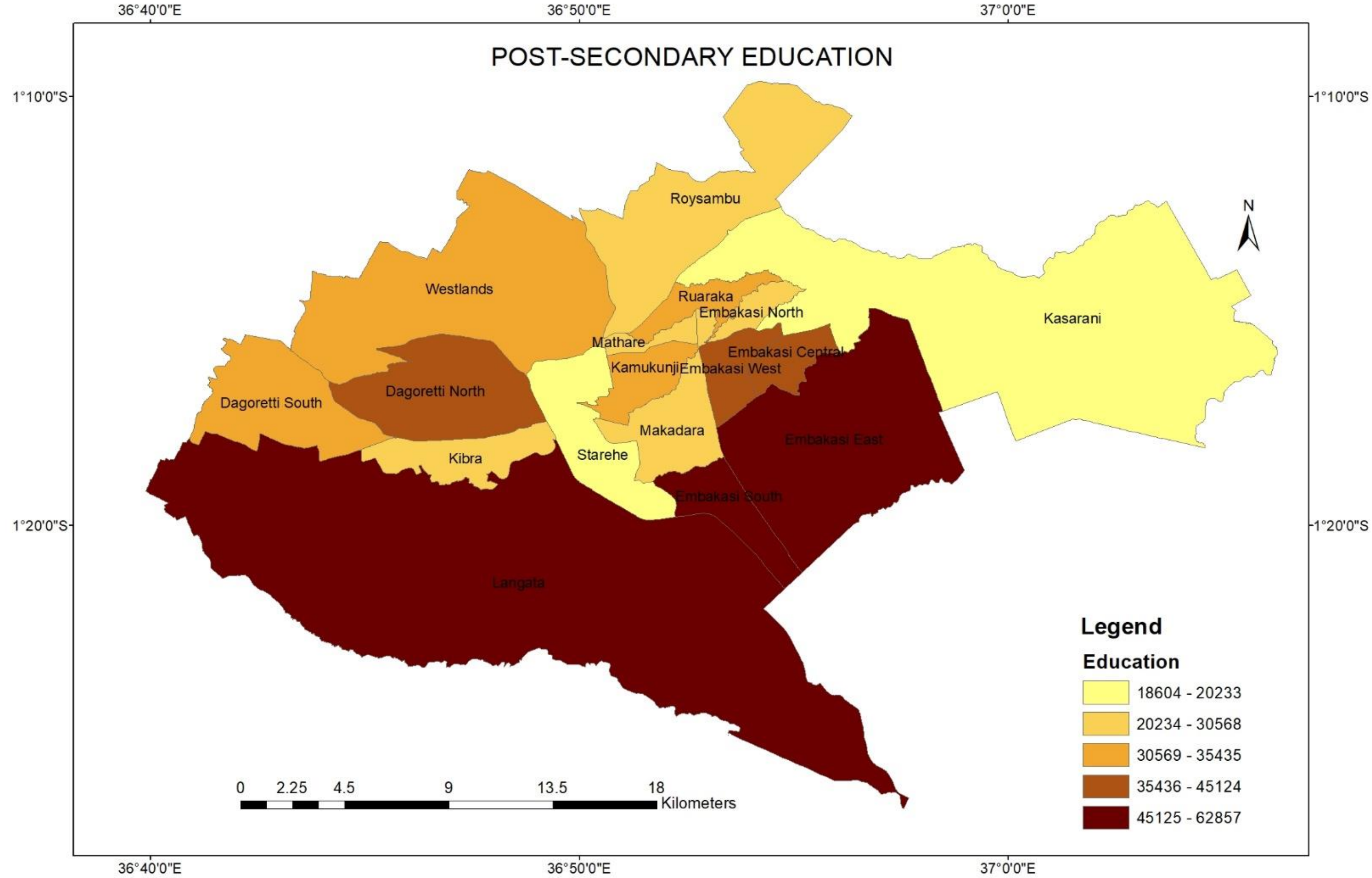


Figure 4.5: People with post-secondary training

From figure 4.5, Langata sub-County has the highest number of educated people and Starehe sub-County with the least number of educated people with 62857 and 18604 numbers of educated people respectively.

Poverty Density

Poverty density was distributed in the sub-counties as shown by figure 4.6.

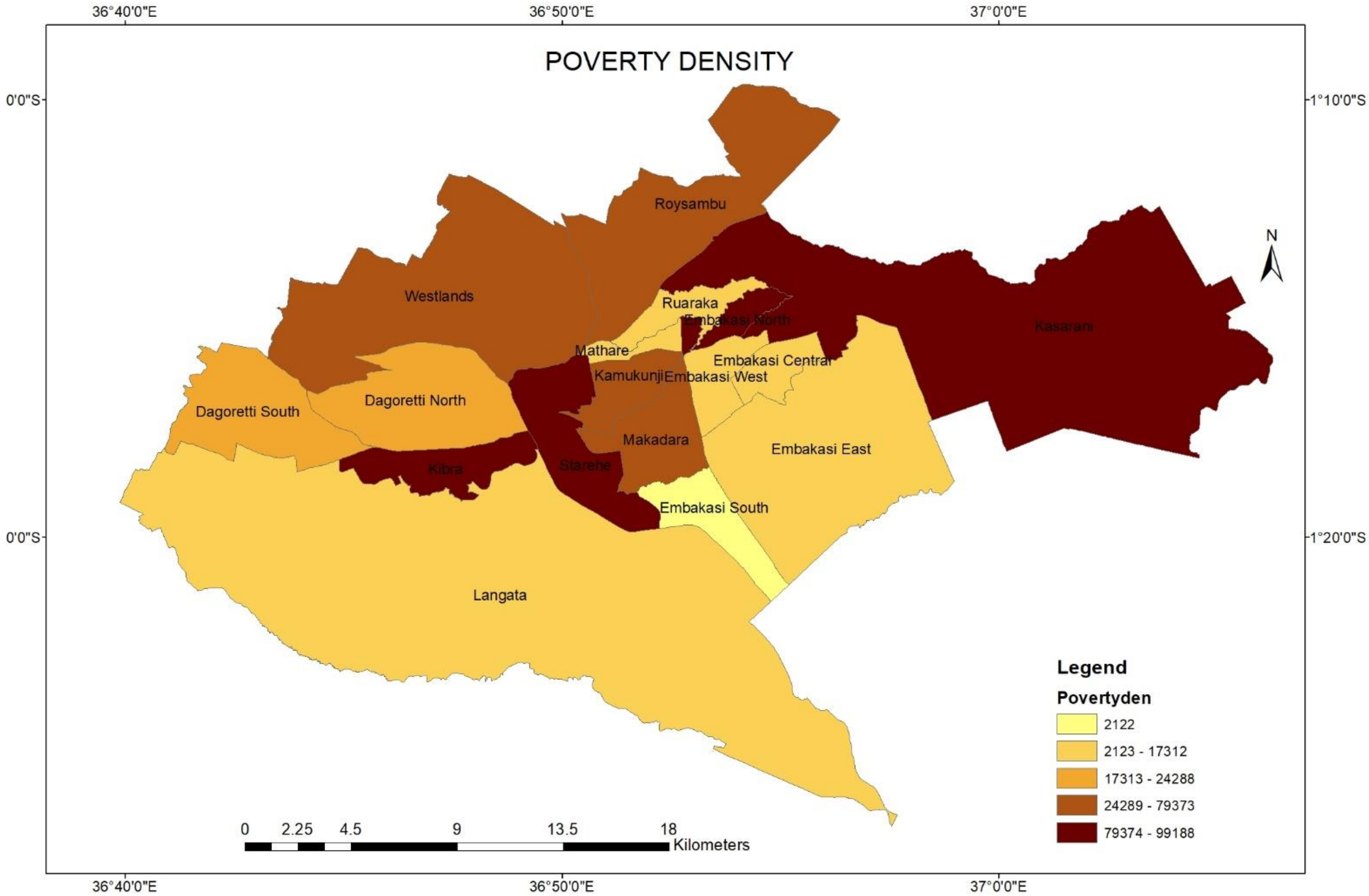


Figure 4.6:Poverty Density.

Starehe,Kasarani, and Kibra sub-counties have the highest level of poverty with 99188,93827 and 91849 poverty densities respectively.

Unemployment

The unemployment map was produced using the data from KNBS on unemployment as per the 2019 population census. The map is shown by figure 4.7.

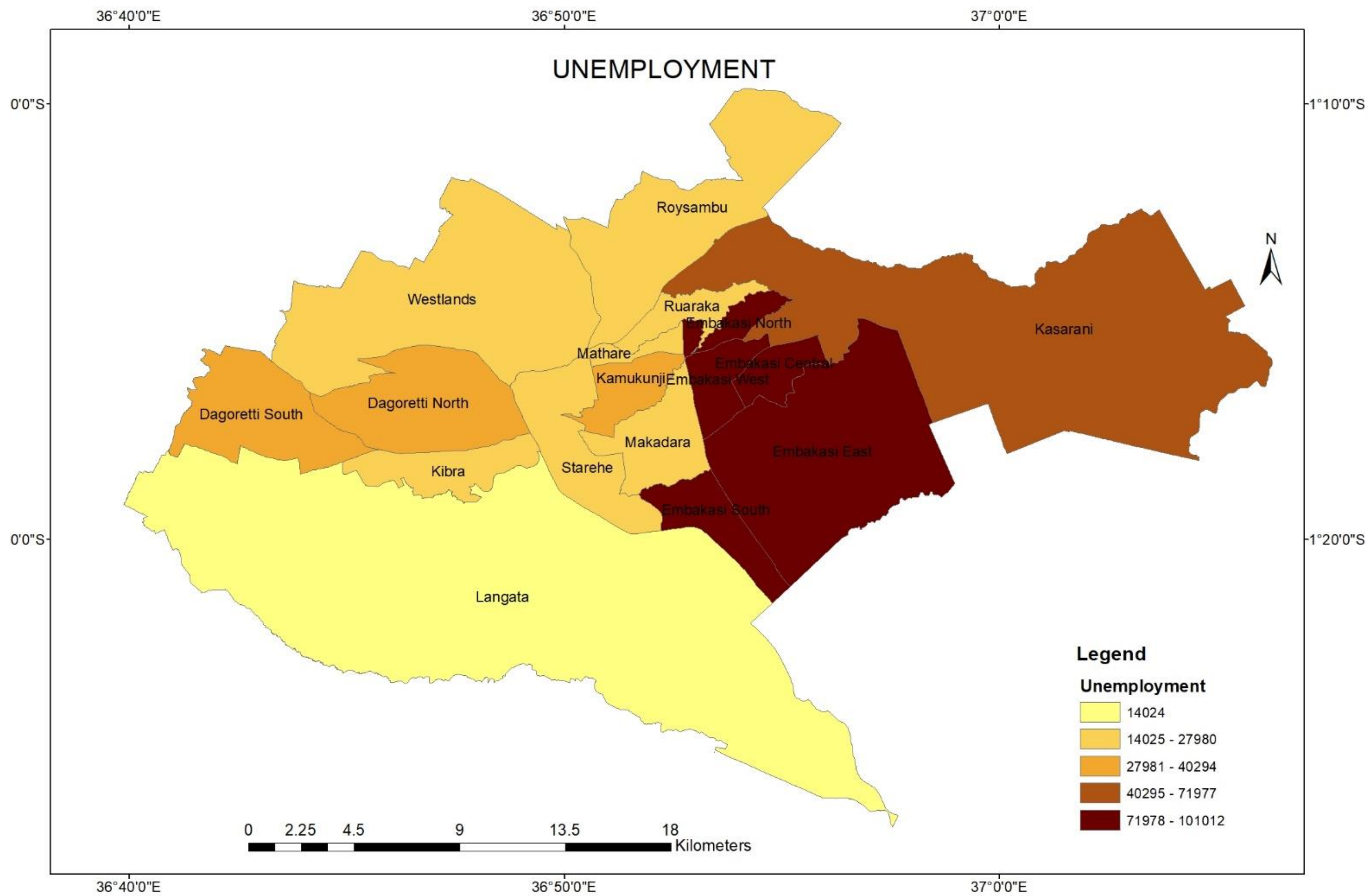


Figure 4.7: Unemployment

From figure 4.7, Embakasi east, Embakasi south, Embakasi west, Kasarani, and Embakasi central sub-counties have the highest number of people looking for employment.

Household Size

Household size was distributed in the sub-counties as shown by figure 4.8.

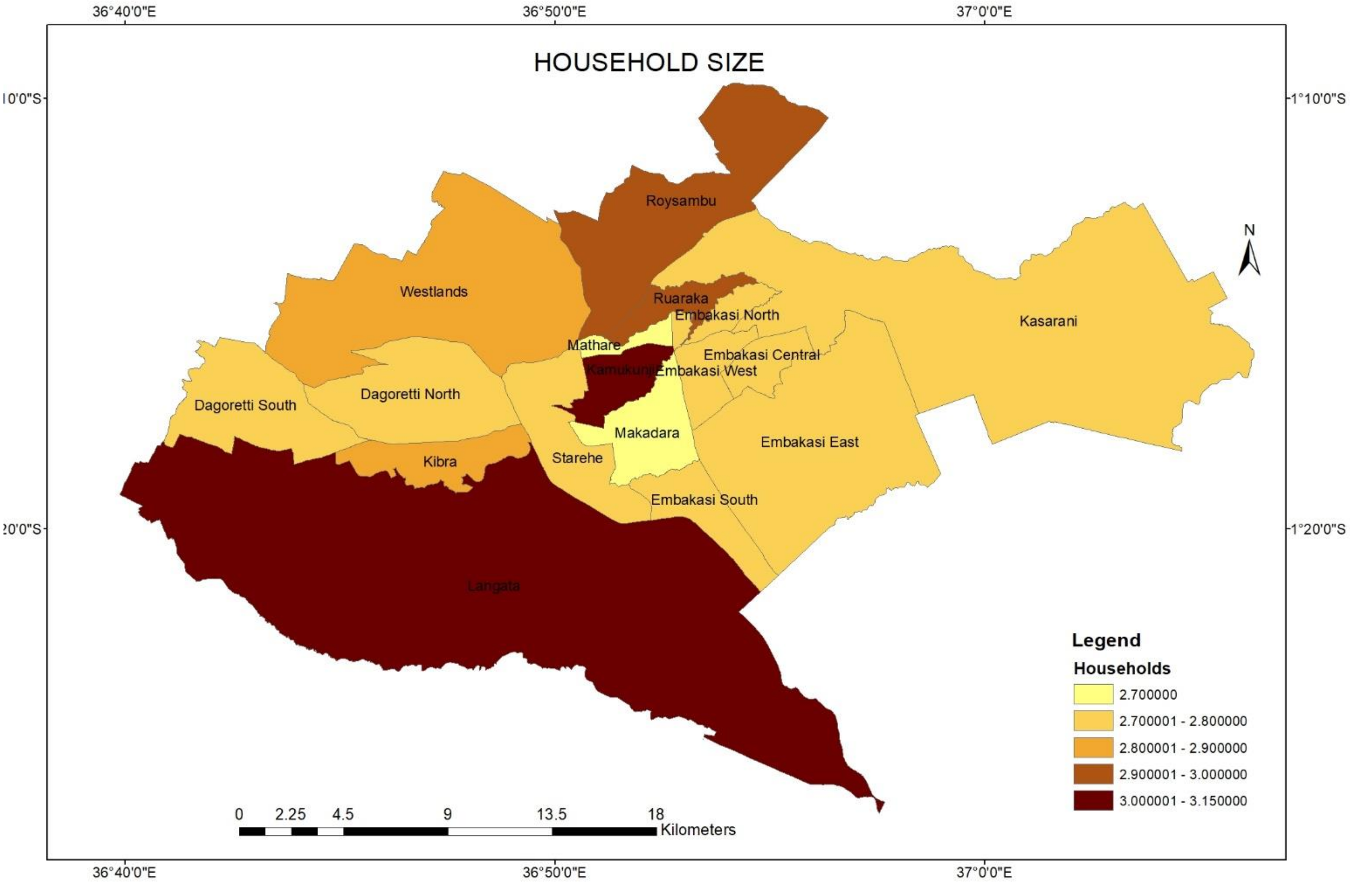


Figure 4.8: Household size

From figure 4.8, Langata, Kamukunji, and Roysambu sub-counties have large household sizes with 3.15,3.0 and 2.9 households size respectively.

4.4 Child abuse vulnerability map Index

4.4.1 ORDINARY LEAST SQUARES REGRESSION

A global regression model was carried out first on the variables to access the significance of the variables, check the redundancy of the variables, and access model performance multicollinearity and model bias.

OLS was carried out on the variables whereby the child abuse cases was the dependent variable and poverty density, population density, unemployment, education, and household size were the independent/ exploratory variable. This regression was done to determine the variables that are significant for mapping child abuse vulnerability.

The results of OLS were as shown in table 4.1

Table 4.1: Summary of OLS Results

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	1840.126792	884.100714	2.081354	0.061549	708.568875	2.596962	0.024825*	--------
POPULATI_3	-0.008009	0.002398	-3.340209	0.006601*	0.000842	-9.511091	0.000000*	1.459085
EDUCATION	-0.031037	0.005297	-5.858935	0.000103*	0.003101	-10.008880	0.000000*	4.512429
POVERTYDEN	0.005599	0.001596	3.508440	0.004908*	0.000987	5.671031	0.000138*	3.794506
UNEMPLOY1	0.000289	0.001071	0.270193	0.792022	0.001025	0.282222	0.783021	1.652148
HOUSEHOLDS	108.047763	319.542629	0.338133	0.741636	256.803172	0.420742	0.682051	1.935418

Table 4.2: OLS Diagnostics Results

OLS Diagnostics

Input Features:	Caseswithboundary	Dependent Variable:	CHILD_ABUS
Number of Observations:	17	Akaike's Information Criterion (AICc) [d]:	229.729272
Multiple R-Squared [d]:	0.667657	Adjusted R-Squared [d]:	0.652956
Joint F-Statistic [e]:	65.820912	Prob(>F), (5,11) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	1357.797548	Prob(>chi-squared), (5) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	5.417591	Prob(>chi-squared), (5) degrees of freedom:	0.367067
Jarque-Bera Statistic [g]:	0.359786	Prob(>chi-squared), (2) degrees of freedom:	0.835359

Explanatory variables with VIF values more than 7.5 should be removed from the model. VIF value of less than 7.5 shows that the variables are not redundant and therefore from my results, there was no redundant variable.

Probability and robust probability are used to show the statistical significance of the variable. Using probability, household size and unemployment were eliminated from the model because they are statistically insignificant since their probability is more than 0.05.

Independent variables that are to be used are Education level, poverty density, and population density. These variables are used because their probability values are below 0.05 meaning they are statistically significant for modeling child abuse vulnerability.

4.4.2 GEOGRAPHICALLY WEIGHTED REGRESSION(GWR)

After confirming nonstationary relationship among variables and the Significance of the variables, GWR was then performed using the explanatory variables identified. GWR deals with the issue precisely.

GWR is performed which yields coefficients that are used to map child abuse vulnerability. Table 4.3 shows statistical outcomes from the GWR modelling process.

Table 4.3: GWR Table

VARNAME	VARIABLE
Bandwidth	2.931258
ResidualSquares	157066.067406
EffectiveNumber	4.007325
Sigma	109.949156
AICc	218.945483
R2	0.667294
R2Adjusted	0.659724

GWR model performance is checked using R-SQUARED which is a measure of goodness of fit. Higher values close to 1 are preferred. Adjusted R-squared also performs the task of measuring the goodness of fit of the model. From the results of this study, the variables that were considered accounted for 0.66 of child abuse vulnerability as shown in table 4.3. This is the proportion that the explanatory variables that were considered in this project accounted for

AIC measures model performance and is often used when two models are involved. Low AIC values provide a better representation of the mapped data as compared to high values.

4.4.3 Results validation

Results predicted by GWR regression were validated using 2020 cases reported between January to April. The results of Spearman rank correlation coefficient were as shown by table 4.4.

Table 4.4: Spearman rank correlation coefficient

Variables	Jan-April 2022 Reported cases	Predicted child abuse cases
2022cases	**1**	0.375
Predicted	0.375	**1**

Spearman's rank correlation coefficient was 0.375 as in table 4.4. This shows that there is a positive correlation between the predicted cases and the reported cases. A positive one indicates a perfect positive correlation and therefore the results show a fairly strong positive correlation.

A diagram representation of the reported and predicted cases is as in figure 4.9.

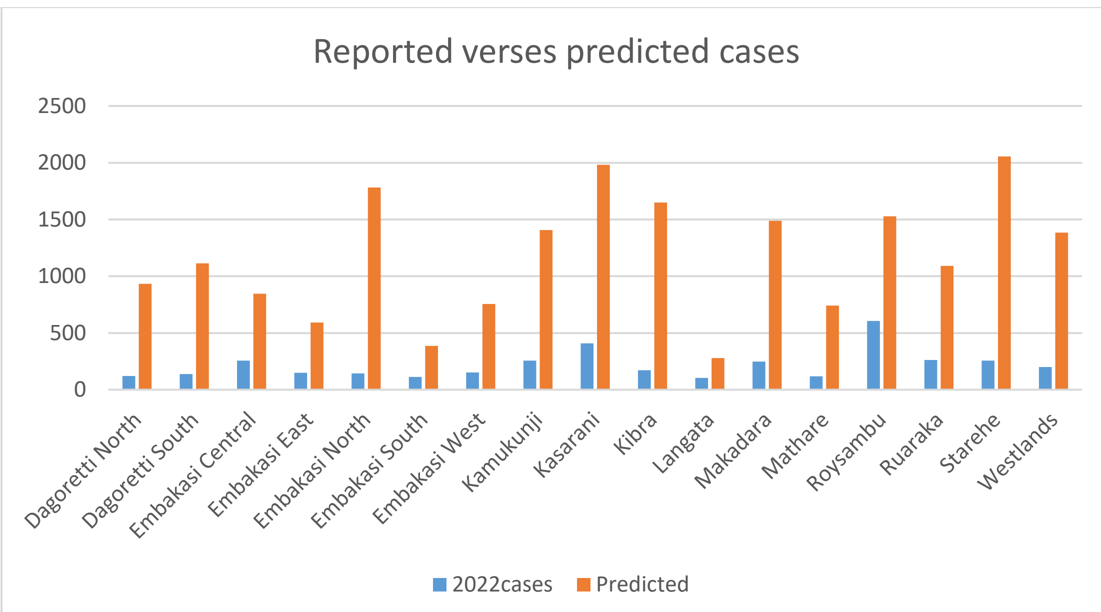


Figure 4.9: Reported cases versus predicted cases

From figure 4.9, Predicted cases are higher than actual cases because the number of month used for predicted cases are twelve months and the months used for actual cases reported in 2022 are four months.

Table 4.5: Ranking of predicted cases versus actual reported cases

Sub-county	2022cases(JAN-APRIL)	Predicted(JAN-DEC)
Dagoretti North	122	932
Dagoretti South	137	1114
Embakasi Central	257	845
Embakasi East	148	591
Embakasi North	143	1781
Embakasi South	113	387
Embakasi West	152	756
Kamukunji	256	1407
Kasarani	408	1983
Kibra	172	1648
Langata	105	278
Makadara	247	1488
Mathare	117	742
Roysambu	606	1528
Ruaraka	263	1092
Starehe	255	2054
Westlands	200	1383

From table 4.5, the predicted cases are higher than reported cases because the number of months taken for predicted cases are four months compared to the twelve months used for predicted cases.

4.4.4 Child Abuse Vulnerability

Using the predicted values from GWR regression, a map of child abuse vulnerability was produced and it is as shown by figure 4.10.

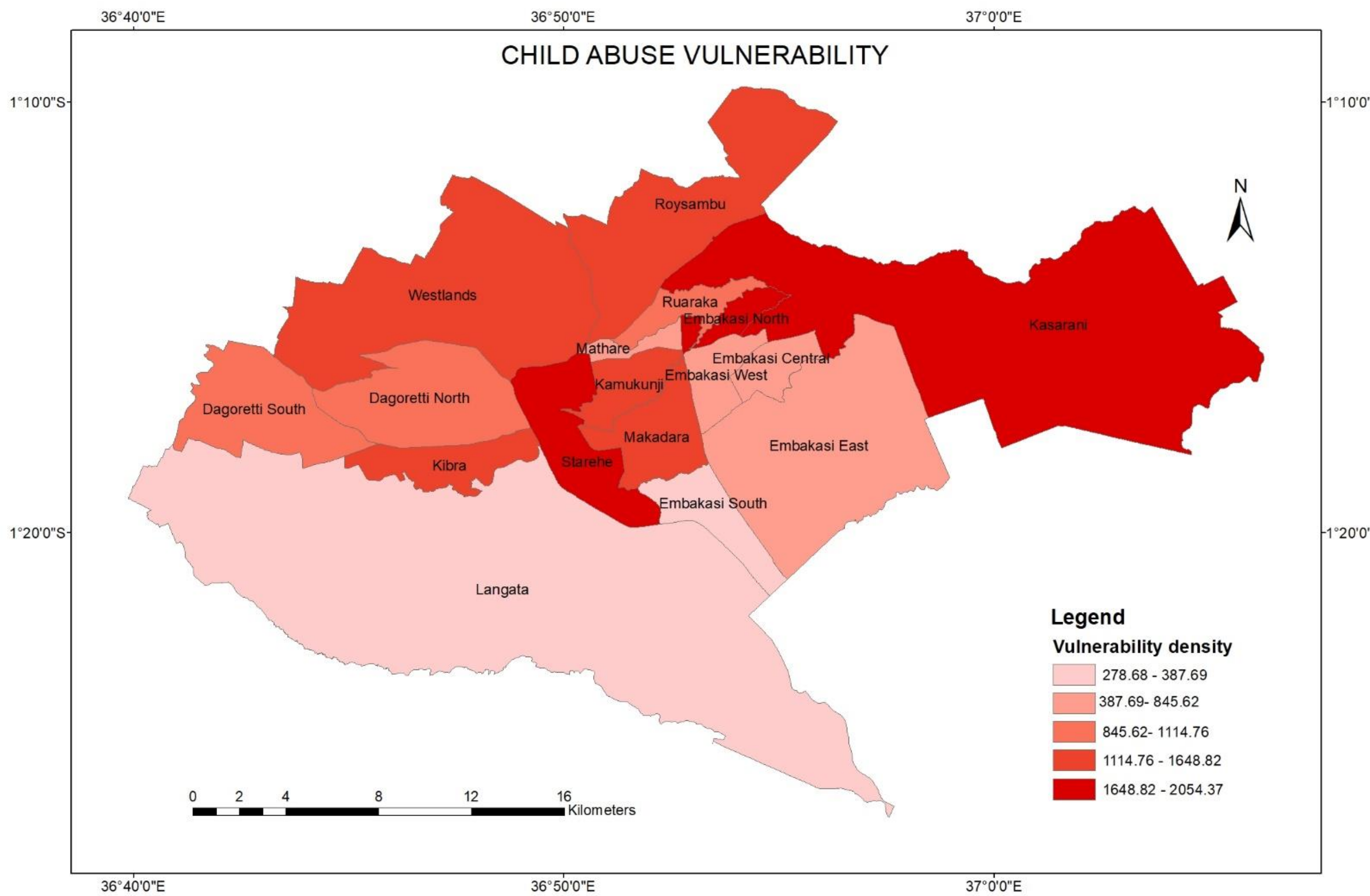


Figure 4.10: Child Abuse Vulnerability

Figure 4.10 shows Starehe, Kasarani, and Kibra are most vulnerable to child abuse when compared to other sub-counties. Langata sub-county is least vulnerable to child abuse in the County.

4.5 Impacts of risk factors on child abuse vulnerability

4.5.1 Local r squared

Local R2 is used to show data fit for regions. The local R2 was stronger for the south and North-Eastern parts of the County, indicating that the data fit better in those regions, and weaker in the Northwest, where the data did not fit as well. The amplitude of values, ranging from 0.67269to 0.667305, is noteworthy.

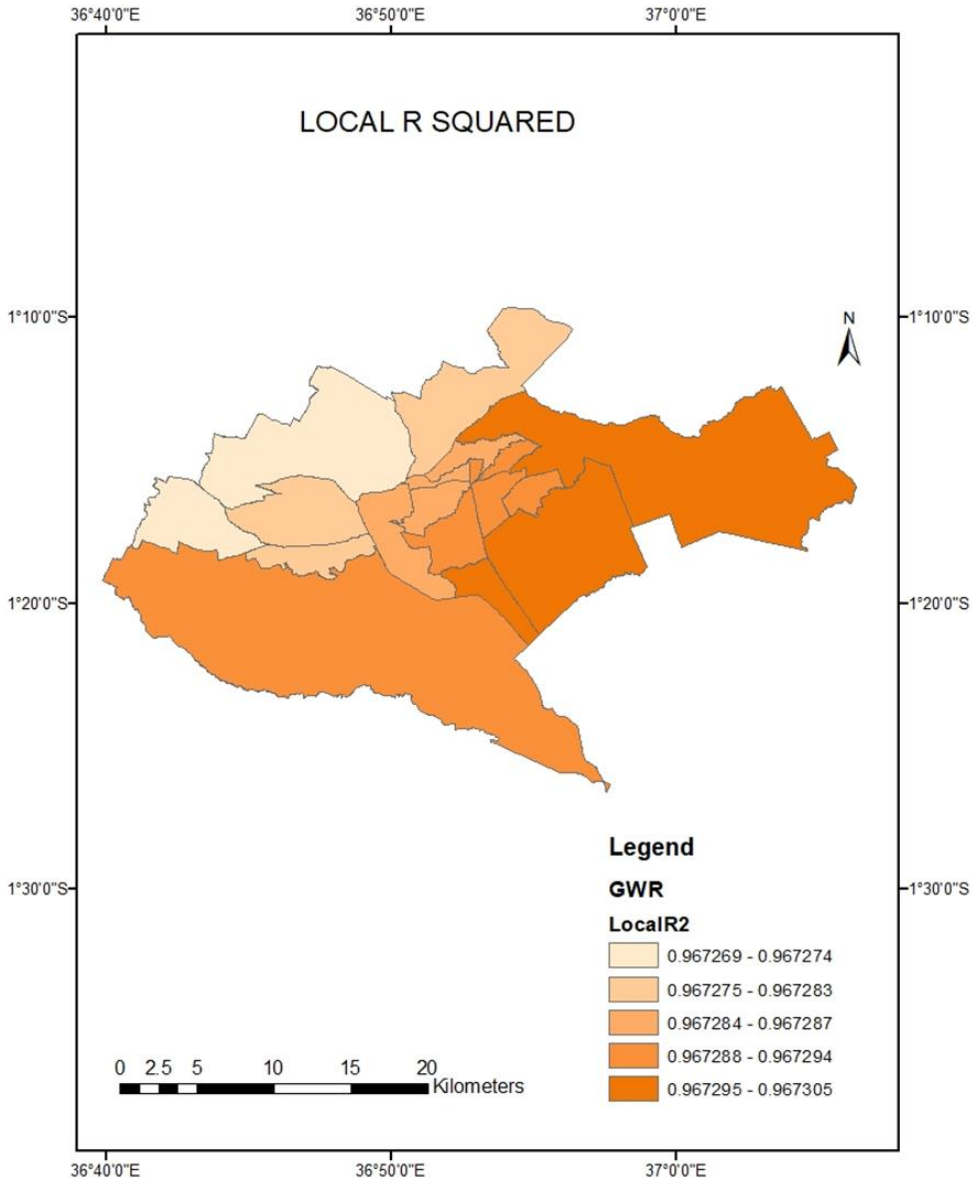


Figure 4.11: Local R Squared

4.5.2 Coefficients

To better understand the regional variation, independent variable coefficients were mapped. The results are shown in figure 4.12.

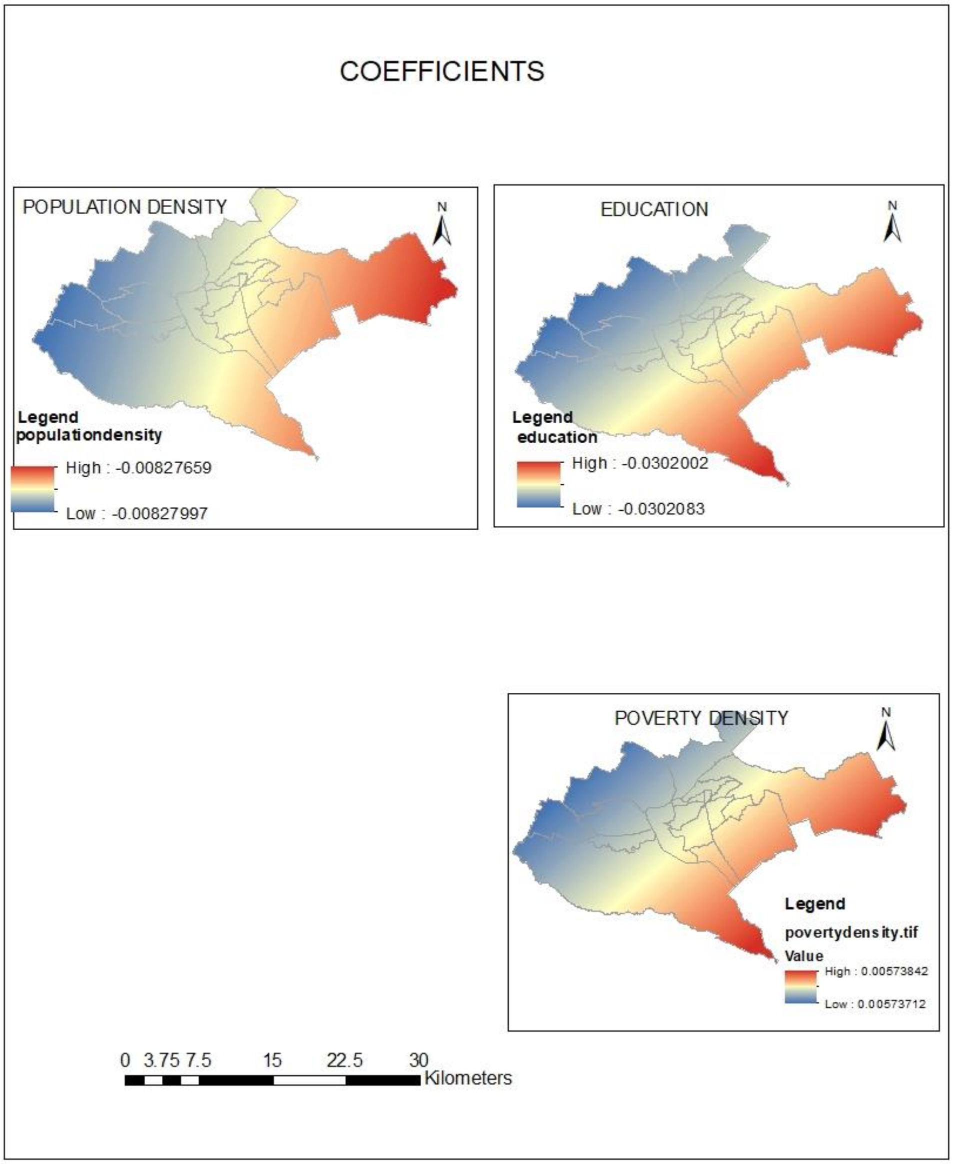


Figure 4.12: Coefficients

The areas with a strong relationship between the independent variable and child abuse cases are shown in red. The darker the shade, the stronger the association. Education has a stronger relationship with

child abuse in parts of Langata and Kasarani sub-counties. Poverty density and education are somehow similar in showing the strong association in Langata and Kasarani sub-counties

The variation of the coefficient variables also shows the strength of the spatial patterns(Charlton & Fotheringham, n.d.).

4.6 Discussion of results

This study depicts an important public social problem that can be minimized by understanding the vulnerable neighbourhoods and prevention measures put in place.

The map of child abuse vulnerability shows that Kibra, Kasarani, Starehe, and Embakasi North sub-counties are most vulnerable to child abuse. Special attention should be taken as child abuse vulnerability was higher in these areas due to the risk factors as demonstrated by the regression results and by inspecting coefficients of the risk factors.

Poverty density is high in Starehe, Kasarani, Kibra, and Embakasi North sub-counties and child abuse vulnerability is high in these sub-counties. Poverty density is low in the Langata sub-County and is less vulnerable to child abuse. This then shows that there is a direct positive relationship between poverty density and child abuse. This positive relationship can be shown by the coefficient of poverty density. The coefficient is positive in all the sub-counties. There is however a strong positive relationship in Langata, Kasarani, Embakasi east, and Embakasi North.

The level of education has a negative relationship with child abuse vulnerability as shown by the coefficient map of education. The higher the number of people who are educated, the lesser the number of child abuse cases. Areas with strong negative relationships are Kasarani, Embakasi East, and the Southeastern parts of the Langata sub-County. To reduce and prevent child abuse cases in the sub-counties, investing in education and supporting students should be done.

Population density had a strong impact in the Langata sub-County as shown by the population density coefficient. It had minimal impacts in Dagoretti North, Westlands, and Larger parts of Langata sub-County. Contrary to the expectation that population density is positively related to child abuse vulnerability, this study found that population density is negatively related to child abuse vulnerability as shown by the map of the population density coefficient.

The variations of coefficients show the strength of the spatial pattern. Education and poverty density had almost similar spatial pattern distribution in the sub-counties and population density had minimal impact compared to poverty density and education.

Government and children protection departments should define interventions and target efforts to tackle the problem in the sub-counties which are most vulnerable, for instance, by implementing strategic and directional programs where they would have the greatest impact.

5 Conclusions, Recommendations, and Areas of Further Research

5.1 Conclusions

This study mapped child abuse vulnerability in Nairobi County which is the leading County in the number of reported child abuse cases in the country. Spatial modeling techniques were used which at the end predicted a child abuse vulnerability that shows the sub-counties that are most vulnerable to child abuse.

Eight factors were identified as risk factors for child abuse. Five were used in the study in which three were statistically significant to child abuse and were used to model child abuse vulnerability. Household size and unemployment are not significant in determining child abuse vulnerability in Nairobi County. Population density, poverty density, and education are significant in determining child abuse vulnerability in the County.

Mapping of child abuse vulnerability has shown that child abuse vulnerability is high in sub-counties with high poverty density and a low number of people with post-secondary education qualifications.

Coefficients of the risk factors show that poverty density and education have a similar impact on child abuse vulnerability in terms of spatial spread. Poverty density is positively related to child abuse vulnerability and education is negatively related to child abuse vulnerability. Poverty density is negatively related to child abuse vulnerability.

Validation of results using the spearman correlation coefficient shows that the predicted cases have a fairly strong positive relationship with the reported cases in the County.

5.2 Recommendations

This study has demonstrated that GIS has a strong impact in mapping areas that are vulnerable to child abuse and can help in policy and decision making that is targeted at having a safer and healthy environment for children's stay and growth.

In the assessment and management of child abuse, children's departments are encouraged to take a broad view of the environment in which the children are growing up in. They should provide child protection mechanisms in the risk areas that will create a safer environment for the children to live in.

The interplay between socio-economic factors and social interactions at a family and community level and the importance of material disadvantage should be recognized during community-wide preventive strategies at a policy level.

5.3 Areas of Further research

Further research could be conducted to identify other risk factors that contribute to child abuse that were not identified in this study by expanding the scope of respondents.

The performance of the model can be improved by including other risk factors such as alcohol outlets in the model. This will improve the performance of the model.

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Appendices

Appendix 1: Questionnaire on social risk factors associated with child abuse

Introductions.

This is a study on child abuse vulnerability in Nairobi County.

The information provided will be treated with confidentiality and will not be used for any other purposes except for this research.

SECTION A: BACKGROUND INFORMATION

1. Name ____
2. Department ____
3. Sub-County of Service ____
4. Position ____
5. Area of specialization ____

SECTION B: CHILD ABUSE CASES SURVEY.

6. Approximately how many cases per day are reported to the department?

   [ ] 0

   [ ] 0 to 5

   [ ] 5 to 10

   [ ] more than 10

   [ ] other

7. Please indicate the main channel in which child abuse cases are reported through.

   [ ] Witness reporting

   [ ] Good Samaritan reporting

   [ ] Government official reporting

   [ ] Victim reporting

[ ] Parent/ Guardian

[ ] Other_________________

8. Do you think the following are the effects of child abuse?

Effect	Yes	No
Depression		
withdrawal syndromes		
Stress		
Post-abuse trauma		
Anger		
Death		
Physical damage		
Emotional damage		

9. How often have you Witness the following being reported?

Child abuse Type	Never	Monthly	Weekly	Daily	Always
Child Sexual abuse					
Child Physical abuse					
Child Neglect					
Child Abandonment					
Child Emotional abuse					
Child Labour					
FGM and early marriages					
Child trafficking					
Child kidnapping					

10. Do you think all child abuse cases are reported?

[ ] Yes

[ ] No

[ ] Not Sure

11. Do you think society settings contributes to child abuse?

[ ] Yes

[ ] No

[ ] Not Yet

12. In your own words please describe the characteristics of the society that you think contributes to child abuse.

____

____

____

SECTION C: RISK FACTORS THAT CONTRIBUTES TO CHILD ABUSE AND IMPACTS OF COVID-19 ON CHILD ABUSE

13. Can you say there was an increase in child abuse cases due to COVID-19 in Nairobi County?
[ ] Yes
[ ] No
[ ] May be

14. What are the places where children are mostly abused?
[ ] Homes
[ ] Schools
[ ] Churches
[ ] Communities
[ ] Other

15. Who were the main perpetrators of child abuse?
[ ] Neighbours
[ ] Strangers
[ ] Parents
[ ] Relatives
[ ] Classmates
[ ] Teachers
[ ] Other

16. Please indicate whether there is a correlation between the following measures introduced by the government to curb the spread of COVID-19 and child abuse.

	Not Related	Moderately Related		Highly related

School Closures				
Social distancing				
Closure of economy				
Restriction of Movement				

17. Do you think the following risk factors contribute to child abuse?

Factors	Tick
Large Family Size	
Unemployment of the parents	
Parental conflicts	
Separation of parents	
Gender of the child	
Age of the child	
Population density	

18. List other risk factors that you think contributes to child abuse in Nairobi County

____

____

____

19. During which time do you think there were more cases of child abuse?

[ ] Pre-COVID 19

[ ] During COVID-19

[ ] OTHER

20 Can you offer any other comments or observations concerning the impacts of COVID-19 on child abuse in Nairobi County: ___________________________?

____

____