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Modelling Spatial Accessibility for Precision Targeting of School-based Interventions: A Case Study of Kilifi County

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Abstract

School-based interventions are an effective way to improve health outcomes for school aged children (SAC). However, the effectiveness of these interventions depends on the children's spatial accessibility to schools. Through modelling of spatial access and accurate identification of the coverage of SAC within and without access to schools at certain travel time thresholds, precise targeting can be done to maximize on allocation of limited resources.

Travel time to public primary schools (PPS), as a measure of spatial accessibility, was computed using the AccessMod software alpha version 5.8. The locations of public primary schools were overlaid on top of a friction surface that takes into consideration roads, land cover, and physical barriers including rivers, parks and reserves using the least cost path algorithm. The cost given to each cell is the travelling time to cross the cell, which is determined through the travelling speed attributed to the landcover of the cell. Accessibility raster surfaces based on travel time were generated at both 100m and 1km spatial resolution to match the resolution of the available population raster dataset obtained from WorldPop. To quantify the proportion of SAC within the catchment of the nearest PPS at a recommended threshold of 24 mins, population were intersected with the resulting travel time estimates to extract spatial accessibility coverages of SAC.

Spatial access to schools varied across the county ranging from minimum to 804 and 775 minutes at 100m and 1km spatial resolution, respectively. When considering the 24-minute travel time threshold, the population of school-aged children covered at 1km was 302,256 (72.53%) in comparison to 293,031 (70.31%) at 100m spatial resolution. The school catchment areas (SCAs) generated at 1km spatial resolution overestimates the size of SCA by 1.17 km^2 by average and number of SAC by an average of 70. There were heterogeneities in coverage of SAC within 24 mins travel time threshold at subcounty level. While 4 subcounties (Rabai, Malindi, Kilifi North and Kilifi South) located in the eastern central and southern regions of the county had more than 70% of the SAC covered, 2 sub-counties (Magarini and Ganze) in the western region of the county had less than 55% coverage. The results of the study can help to inform precise targeting of school-based interventions to the SAC and maximize on limited resources.

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List of Acronyms

Abbreviation	Meaning
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ESRI	Environmental Systems Research Institute
MOE	Ministry of Education
PPS	Public Primary School
SAC	School Aged Children
SCA	School Catchment Areas
SSA	Sub-Saharan Africa
TT	Travel time
USGS	United States Geological Survey

1 CHAPTER 1: INTRODUCTION

1.1 Background

Spatial access to schools is critical for attaining educational equity, a pivotal objective outlined in the fourth United Nations Sustainable Development Goal (SDG). This goal emphasizes the need to guarantee inclusive and fair access to quality education while fostering lifelong learning opportunities for everyone (United Nations, 2016). While concerted efforts have seen improvement in enrolment rates globally (Filmer & Rogers, 2019), sub-Saharan Africa (SSA) experiences the lowest rates in enrolment (Lewin, 2009; Lewin & Akyeampong, 2009) and the highest drop-out rates (Alegana et al., 2021; Hunt, 2008; UNESCO, 2018). A major restraint is the time it takes children to travel from their homes to reach the primary schools which ultimately have an adverse effect on the students' learning, academic success, and enrolment (Afoakwah & Koomson, 2021; Evans & Mendez Acosta, 2021; Ngware & Mutisya, 2021; Rodriguez-Segura & Kim, 2021).

Schools not only provide educational services but also serve as cost-effective platforms for delivering fundamental and safe public health-based interventions to school-age children (SAC) (Bundy et al., 2017) including distribution of long-lasting insecticide treated nets (Atieli et al., 2011), administration of mass drugs for treatment of soil-transmitted helminths (STH) and schistosomiasis (Abudho et al., 2018; Aiken et al., 2015; Montresor et al., 2002; Mwandawiro et al., 2019; Okoyo et al., 2016) and malaria (Bundy et al., 2000; Leslie et al., 2011; Nankabirwa et al., 2014; Temperley et al., 2008). While measuring spatial accessibility, two types of measures have been commonly employed: distance and time. However, using travelling time instead of distance has been considered better because it provides a more comparable measure across different regions or countries, and it takes into account the mode of transportation used (Ray & Ebener, 2008). To accurately target school-based interventions, it is crucial to quantify the spatial access of SAC to schools in terms of travel time and to delineate school catchment areas (SCAs) to estimate the population who are eligible. Adequate knowledge on the location of public primary schools (PPS) and the travel times threshold, which is the maximum justifiable travel time taken for a child to access a school, are important in obtaining SCAs. The overarching objective is to ensure that schools are situated as near as possible to the residences of children (Theunynck, 2009).

The Ministry of Education in Kenya aspires to have a school within 2 kilometres of every household (GoK/MoE, 2018). The travel time thresholds provide information on number of children that can or cannot be serviced by school-based interventions. The knowledge on the catchment population is vital for effective planning and allocation of limited resources. Despite evidence on using travel times to school as a measure of quantifying geographical access, little is known about the influence of using travel time surfaces generated at different spatial resolutions on the coverage estimates of SAC.

A critical challenge faced by school-based control programs is the substantial number of SAC in many developing nations who are not enrolled in educational institutions (Bundy & Guyatt, 1996; Bundy et al., 2006; Montresor et al., 2001; Olsen, 2003). The rates of children who are out of school is exceptionally high (20.8%) across the globe, especially in SSA, and aggravated by gender disparity (Alegana et al., 2021). In low-income countries, 12 million girls (23.5%) are more likely drop out of school compared to 9 million boys (18.1%) as they encounter considerable barriers to education (UNESCO, 2018). Drop-out rates also vary by age and grade by grade (Lewin, 2009). These patterns reveal various action points for investment targeted towards expanding access to different levels of SAC. To derive spatial coverage statistics for SAC within this threshold requires a spatial overlay of the geographical extent of SCA and high-resolution population data.

Recent global advancements in population mapping efforts using a combination of satellite imagery and machine-learning algorithms have enabled availability of gridded population datasets at different spatial resolutions (Alegana et al., 2015; Sorichetta et al., 2015; Tatem et al., 2007). Such datasets have been used in combination with data on school locations, to model geographic accessibility to schools (Macharia et al., 2022; Rekha et al., 2020). WorldPop database provides gridded population datasets which uses a country's most recent census to uniformly redistribute population data summarized in administrative units by using ancillary variables to apply dasymetric modelling techniques to obtain estimates at fine spatial and temporal resolution (Stevens et al., 2015). These datasets are provided at fixed five-year age groups by male and female across the years from 2000-2020 and available at both 100m and 1km spatial resolution (Bondarenko et al., 2020; Bondarenko et al., 2022). For example, the population of SAC are summarized as 5-9 and 10-14. The two five-year age group datasets were used to quantify total number of SAC aged 5-14 years. The overall objective of this study was to quantify the differences in coverage of SAC within SCAs generated from two different spatial resolutions: 100m and 1km in Kilifi County. This was done by first assessing spatial accessibility of the SAC to their nearest PPS based on how much time it took them to travel from their homes. Travel time raster surfaces were generated at the two spatial resolutions and SCAs were delineated based on a travel time threshold of 24 minutes. The SCAs were then intersected with population datasets with matching spatial resolutions of 100m and 1km consisting of children aged 5-14 years to obtain the counts of SAC within each catchment. The differences in terms of absolute counts and percentages between coverage of SAC within the catchment areas generated at different spatial resolutions were quantified.

1.2 Problem Statement

Despite the critical importance of access to schools for education equity in sub-Saharan Africa, many children still face significant challenges in reaching primary schools due to long travel times. Achieving the highest rates of children covered is vital in intervention programs administered in schools, as it ensures that there are no out-of-school subpopulations who are left behind, a potential challenge for areas with low school enrolment. To address these issues, it is crucial to understand the spatial reach of the school aged child to their nearest school based on how much time it takes them to move from their households. Without accurate information on spatial accessibility, it is difficult to obtain accurate figures on eligible children and those at risk of exclusion during delivery of intervention programmes. Previous analyses have produced travel time surfaces at varying spatial resolutions on a national and global scale. However, the local-level impact of utilizing travel time surfaces at different spatial resolutions on the coverage of school-aged children remains poorly demonstrated. It is essential to investigate and quantify the extent of influence that arises from employing travel time surfaces at resolutions of 100m and 1km on the coverage of school-aged children. This research is crucial in informing the appropriate choice of spatial resolution to be adopted to ensure precise allocation of limited resources.

1.3 Objectives

1.3.1 General objective

To use age-structured population data to assess differences in coverage estimates of school aged children (5-14 years) within school catchment areas based on travel times to the nearest public primary schools at 100m and 1km spatial resolution in Kilifi County.

1.3.2 Specific objectives

1. To model travel time to the nearest public primary school at 100m and 1km spatial resolution.
2. To obtain school catchment areas at a threshold of 24mins based on travel times at 100m and 1km spatial resolution.
3. To compare the coverage of school aged children within the school catchment areas based on 100m and 1km spatial resolution.

1.4 Justification for the study

Kilifi county has been the focal point for some school-based intervention programs aimed at controlling of poly-parasitic infections. The use of spatial modelling to determine school accessibility can offer valuable metrics for guiding intervention strategies within schools and enhancing the effectiveness of health programs. Accurately identifying a school's catchment area is crucial for understanding the specific population of school-aged children being served. Even slight variations in the sizes and shapes of these catchment areas, resulting from differences in travel time resolutions, can lead to disparities in the number of school-aged children covered within specific thresholds. This, in turn, affects resource allocation decisions for the estimated number of school-aged children. To ensure precise targeting of the eligible population, it is important to gather evidence on the influence of using different spatial resolutions of travel time on estimates of school-aged children. This research holds significant value as it will provide information that contributes to informed decision-making, ensuring the appropriate allocation of resources to eligible children and ultimately achieving a substantial impact.

1.5 Scope of Work

The scope of work will involve conducting a spatial analysis within Kilifi county to model spatial access of school-aged children by means of the time they take to reach the nearest public primary school and delineation of school catchment areas based on a 24-minute threshold. Only public primary schools will be adopted in the analysis because a majority of children attend public schools. The project will analyze the impact of different spatial resolutions of travel time on estimating the coverage of school-aged children within and outside catchment areas. The project also aims to provide recommendations for optimizing catchment areas to improve access to education.

Table 1-1: Research matrix summarizing data and methods

Objective	Research Question	Methods	Data	Output
To model travel time to the nearest public primary school in Kilifi County	What is the average travel time taken by school aged children to their nearest public primary school?	Travel time was calculated by overlaying school locations on top of a cost friction raster at 100m resolution using the least-cost path distance algorithm	School locations, roads, land cover and travel barriers including major rivers, water bodies, games & reserves)	Travel time surfaces at 100m and 1km spatial resolution
To obtain school catchment areas for school aged children in Kilifi	What is the number of school aged children within 24minutes to their nearest public primary school?	Zonal statistics was used to extract the population within travel time thresholds of 24mins by overlaying population rasters with travel time	Travel time surfaces, population	Maps showing school catchment areas at 24mins travel time threshold Number of children within reach
To compare the coverage of school aged children within and without the school catchment areas.	What is the difference in population of children within a school catchment area based on travel times obtained at different spatial resolution?	Comparison statistics were computed between the population obtained from school catchment areas based on the different travel time surfaces	Extracted population of school aged children within 24mins travel time obtained from both raster surfaces	Comparison tables showing absolute numbers and percentages differences between population of school aged children

1.6 Organization of the report

This report comprises four chapters. Chapter one contains an introduction on the topic, the problem statement, objectives of the study, justification for the study and scope and limitations. Chapter two consists of the literature review. Chapter three describes the methodology including data collection, description of the area of study and data analysis. Chapter four is composed of the results and discussions. Chapter five contains conclusion and recommendations from the study.

2 CHAPTER 2: LITERATURE REVIEW

2.1 School-based interventions

The education system provides opportunities for promoting children's health especially in poor and rural communities who lack access to effective health systems and schools are often common than health facilities (Bundy et al., 2017). Although schools cannot serve as a substitute for formal health systems, they can enhance health delivery mechanisms by offering outreach opportunities. In low-income countries, it is estimated that school-based public health intervention programs can have a reach of 575 million SAC (UNESCO, 2008) and have potential in generating long-term benefits such as better health outcomes for both individuals and the wider community. However, achieving high coverage rates among children is crucial for school-based intervention programs. Additionally, it's important to address any persistently untreated sections of populations, which may pose a challenge for school-based programs in regions with low school enrolment (Burnim et al., 2017). However, many children still stay out of school, some due to drop-outs (Hunt, 2008). Studies have shown that deworming programs implemented in schools are effective in reaching children on a large scale and reducing disease transmission within the community (Drake et al., 2021; Bundy et al., 1990; Miguel & Kremeer, 2004).

2.2 Modelling spatial access to schools

Generally, there are five dimensions of access: availability, accessibility, affordability, acceptability, and accommodation (Levesque et al., 2013). The first two dimensions, availability and accessibility, are spatial in nature. Availability refers to the number of local service points (schools) that are available for children to choose from, while accessibility measures the travel impedance, such as distance or time, between a child's location and the service points (schools) (Guagliardo, 2004). Spatial accessibility refers to the ease with which a specific population can physically reach resources and services (Ray & Ebener, 2008).

Availability coverage signifies the availability and quantity of resources required to provide an intervention. It relates to the capacity of the service points relative to the size of the target population (Tanahashi, 1978). On the other hand, accessibility coverage assesses the physical accessibility of resources for the population. Even if resources are available, inconvenient locations can impede physical access. Combining availability and accessibility coverage in a comprehensive analysis introduces the concept of spatial coverage. Analyzing spatial coverage entails a multifaceted approach, encompassing factors such as the precise location and capacity of each provider, the geographic distribution of the population, the environment that children have to navigate to reach school, and the transportation mode they will utilize. Neglecting to account for the correct combination of these factors can significantly impact the delineation of catchment areas based on maximum transportation time (Ray & Ebener, 2008).

Travel time to the nearest school can vary significantly depending on the mode of transportation, landcover characteristics, and obstacles such as rivers or wetlands that require navigation or circumvention. Moreover, children's travel time can differ based on the direction: the duration it takes to travel from a residence to a school may not match the time for the journey back. This occurrence, referred to as 'anisotropy,' is influenced by geographical constraints that can either accelerate or decelerate movement, like descending slopes (Tobler, 1993). While AccessMod is a well-known open-source tool for modelling spatial accessibility, other tools are also widely available including: Google Maps API, OpenStreetMap (OSM) and GraphHopper, Isochrones.org, Network Analyst (ArcGIS extension) and TravelTime Platform API (Thuranira, 2022; Wang & Xu, 2011). For this study, AccessMod was adopted because it models travel time and consequently computes geographic coverage using terrain information, modes of transportation, factors influencing travel and population distribution.

Within the context of cost-distance analysis for walking individuals, the consideration of anisotropic movements can lead to significantly divergent outcomes compared to the isotropic approach (Wood & Wood, 2006). Anisotropic movements emphasize the importance of the direction of travel. In this analysis, slopes are typically calculated using a Digital Elevation Model (DEM). In the classical isotropic method, only the steepest positive slope between a focal grid cell and its eight neighbouring cells is considered, disregarding the impact of movement direction on constraints. However, in the alternative 'anisotropic' approach, slopes between all adjacent grid cell pairs are considered, and the direction of movement (uphill or downhill) becomes pivotal in determining movement constraints. In the process of deriving travel time for each class, the algorithm incorporated a slope correction derived from elevation data. This adjustment allowed the calculation of travel speeds for every degree of slope rise, leveraging Tobler's equation (Tobler, 1993):

$$\boldsymbol{V = 6^{e^{-3.5(|\frac{\tan(slope\ in\ degrees)}{57.296}+0.05|)}}}$$ --------------------- Equation 2-1

where V is the calculated speed. Therefore, on a terrain that is flat, the average walking pace is approximately 5.0 km/hour, whereas while on a 20° slope rise, the pace diminishes to 1.4 km/hour. In this study, it was presumed that children move towards the closest school, and they adjust their travel speed to take advantage of downhill slopes leading to the school. As a result of anisotropy, the catchment area undergoes alterations, expanding slightly more in the direction of elevated topography.

By integrating a base land use grid with a network of roads and movement barriers, it becomes possible to generate a merged landcover surface, which in turn facilitates the definition of a travel scenario (Ray & Ebener, 2008). This scenario determines the landcover classes utilized for transportation as well as the corresponding travel speed and mode of travel for each landcover class. The resulting travel time surface is directly influenced by the resolution of three grids employed, namely the Digital Elevation Model (DEM), population, and landcover grids. If a relatively coarse resolution is employed, subtle variations in slope may not be accurately represented, and linear features like roads and rivers could appear larger in the resulting landcover grid compared to their actual size in reality (Ray & Ebener, 2008).

2.3 Existing methods used to model spatial access.

Spatial models that simulate the accessibility of schools for children are valuable tools in identifying areas with lower or higher access to schools and consequent evaluation of disparities in spatial access. These models offer insightful information for decision-makers who aim to improve health outcomes through the implementation of public health interventions (Talen, 1998). It is crucial to model spatial access to identify gaps in coverage and support targeted optimization and planning efforts

In recent years, numerous studies have explored spatial accessibility to services using a variety of methods. These methods include Euclidean distance, network analysis, provider-to-population ratios, cost distance techniques, gravity models, and the kernel density method (Drake et al., 2021; Guagliardo, 2004; Higgs, 2004; Ouma et al., 2021). Over time, the approaches for assessing spatial access have expanded, with some methods undergoing changes. Despite efforts to enhance their accuracy and applicability, each method still has its limitations. Understanding the pros and cons of each approach is essential to choose the best method for a particular application, as the outcomes can vary significantly based on the selected measures.

2.3.1 Provider to population ratio

The most straightforward approach to determine accessibility is through the calculation of the ratio between service providers and the population within specified boundaries. This method does not necessarily require advanced technical skills, and accessibility indices are computed at defined administrative units (Ouma et al., 2021). This approach has proven to be valuable in revealing disparities within spatial areas of a study region, allowing for the identification of gaps in service availability (WHO 2010). Despite being a more basic method of measuring accessibility, it has been widely applied, serving as the basis for many policy decisions. Its popularity stems from its simplicity and ease of interpretation. However, a major limitation is that it assumes that all the providers are accessible to people within their geographic area. Furthermore, the method fails to consider the possibility of individuals accessing services outside of their geographical area (Drake et al., 2021).

2.3.2 Euclidean distance

The most fundamental distance-based approach for quantifying geographical accessibility to service providers is Euclidean distances. This method presupposes a direct route of transit between residential points and service provider locations (Ouma et al., 2021). It is effective in areas where specific distance thresholds have been recommended such as rural areas where schools are scarce and motorized transportation is limited. A drawback of employing this method is that it assumes travel occurs solely in straight lines, thereby disregarding the impact of transportation barriers and various factors that affect physical accessibility during travel (Guagliardo 2004).

2.3.3 Gravity models

The constraints of the provider to population ratio and Euclidean distance approaches led to the emergence of gravity methods (Luo, 2004). The gravity model, in general, is a synthesis of availability and accessibility within defined spatial units (Neutens, 2015). Gravity models aim to depict the possible interaction between a given population location and all service locations within a reasonable distance, disregarding the diminishing potential as distance or travel obstacles increase. Broadly speaking, this method aligns more closely with the assumption that populations primarily utilize services within their respective catchment areas. Its vantage arises from the capability to account for capacity of a service point, competition among service points and flexibility of obtaining gravity values. The models take the following general form:

$$\boldsymbol{A_i} = \sum_{\boldsymbol{j}} \frac{\boldsymbol{a_j}}{\boldsymbol{f(c_{ij})}} \quad \text{------------------ Equation 2-2}$$

Where A_i refers to the accessibility at location *i; i* and *j* represent the demand and supply location respectively; *a* signifies the size or quality of supply at *j; f* denotes distance or travel time decay function and c_{ij} refers to the travel time, distance, or generalized cost between *i* and *j* (Neutens 2015). Over time, the models have undergone significant advancements, transitioning from utilizing basic supply and demand data to incorporating distance decay effects, multiple transportation models, and the integration of variable catchment areas (McGrail and Humphreys 2009; Mao and Nekorchuk 2013). Nevertheless, this approach exhibits two inherent weaknesses. Firstly, the model remains static, lacking the ability to account for dynamic and time-dependent relationships. Secondly, demand is typically defined within specific spatial units. While this approach may seem intuitive for analysis, it introduces limitations due to the Modified Areal Unit Problem (MAUP). This issue arises from the aggregation of population locations and introduces spatial bias as a consequence.

2.3.4 Network analysis

Network-based analysis is a commonly used approach, which involves creating a network of roads or other transportation infrastructure and using algorithms to calculate the shortest travel times between points on the network. By using network analysis, one can determine catchment areas, delving into the realm of identifying population proportions within a particular area holds the potential for accessing services within a carefully defined network (Nykiforuk & Flaman, 2011).

2.3.5 Cost models

One common approach is the creation of cost surfaces, which assigns a cost to each cell or point in a grid based on factors such as road network density, speed limits, and terrain. These cost surfaces can then be used to calculate travel times between different points in the study area. For analysing patterns in which people move across a continuous surface, the least-cost path approach is the most frequently used tool. This technique determines the shortest distance between a focal point and all neighbouring cells (Adriaensen et al., 2003). Within the context of spatial accessibility, Euclidean distance, cost distance and travel time are types of measures that may be adopted. However, travel time is often considered as a better measure because it considers the various modes of transportation that people may use to reach their destination (Ouma et al., 2021). Travel time may be influenced by a range of factors such as the type of landcover and the barriers to movement that people will need to cross or circumvent. To model travel time, a cost distance surface is often used, which takes into account a range of transport factors, such as mode of transportation, speeds, travel barriers (such as game parks, reserves, water bodies, and forests), as well as other travel factors like road networks, land cover, and topography. By considering these factors, the cost distance surface can accurately model the travel time needed to reach a particular destination, providing a more comprehensive understanding of spatial accessibility.

2.3.6 Kernel density method

The other method is the kernel density model, which is a variation of the gravity model, which disseminates a discrete point value across a continuous surface adding a fresh perspective (Schuurman et al. 2010). Kernel density serves as a non-parametric approach to depict the distribution of a variable, specifically applied to depict the distribution of population and provision of service. In the realm of service provision, a captivating concept emerges; the kernel density encompasses a 'sphere of influence' around a service provider defined by the kernel density's bandwidth.

Despite its widespread use, this method is not without its profound methodological and conceptual drawbacks. Foremost among them is its reliance solely on straight line distances, disregarding the intricate road network's impact on accessibility to schools. This disconnection from reality fails to account for situations where road networks significantly influence one's ability to access educational institutions. Secondly, choosing the radius of the kernel density is normally arbitrary, in most cases leading to service densities that spill over from the study area (Guagliardo 2004). Moreover, an intriguing facet of this method lies in its presumption of a smooth population distribution emanating from a centroid, with density gradually decreasing as distance from the centroid increases. However, this assumption is impractical, as real-world population distributions often exhibit complex and non-uniform patterns (Schuurman et al. 2010).

In all the methods described, the key is to be able to accurately represent the distribution of both service providers and the demand population. Within each method's description, a fascinating revelation emerges—there is no definitive "gold standard" for measuring spatial accessibility. Consequently, an original approach to this challenge lies in conducting a meticulous analysis of the trade-offs between various methods and understanding their respective limitations. Only then can an informed decision be made regarding the most suitable method for the specific context at hand. However, for this study, travel time to schools was adopted as the measure for spatial accessibility because it takes into account both the mode of transport and accounts for the factors associated with movement.

2.4 School attendance behaviour

To accurately ascertain the time taken by children to commute from their homes to schools, a thorough understanding of their travel habits becomes imperative. Various studies have explored the underlying factors that shape children's behavior regarding school travel. These investigations have revealed that the process of children traveling to school involves a complex socio-economic activity, influenced by a multitude of factors that impact their choice of transportation mode. Among these factors are travel costs, household income, gender, travel duration, proximity between home and school, attributes of the neighborhood's physical environment, and the perceptions of parental or guardians' regarding neighborhood safety and trip characteristics (Chacha & Bwire, 2013).

Amidst the wealth of literature in high-income countries exploring how children make their way to schools, the landscapes of Sub-Saharan Africa (SSA) remain shrouded in a dearth of documentation on this very subject. Yet, a glimpse into the existing literature from SSA reveals a captivating pattern where the majority of children undertake their school journeys on foot. Take Nairobi (Kenya), for example, where in 2008, an impressive 68.9% of students relied on the sheer power of Non-Motorized Transport (NMT) to traverse the path to educational institutions. Similarly, in the bustling streets of Dar es Salaam (Tanzania) in 2018, a remarkable 60.3% of school trips were embarked upon using NMT (Bwire 2020).

To promote access and equality in education and address existing disparities based on location and gender, the Kenyan national education sector strategic plan for 2018-2022 (GoK/MoE, 2018) recommends constructing schools within a reasonable walking distance of 2km from children's homes. Based on the average walking speed of 5 km/hr for human beings, this corresponds to a travel time of approximately 24 minutes for a 2km distance which was adopted as a threshold for this study.

2.5 Defining school catchment areas

A school catchment area refers to a geographical area around a school that consists of the population that utilizes the available school infrastructure. Different approaches, simple and complex, have been developed to define catchment areas. One of the most commonly used approach has been use of subnational administrative boundaries, for example wards or subcounties (Macharia et al., 2021). The boundaries of a polygon within which the school is located forms the SCA. Here, the location of the school and the administrative boundaries combined with auxiliary datasets were the minimum datasets required. However, an intriguing drawback of this approach lies in its omission of cross-border movement and migration, both in and out of the catchment area, over time particularly evident in rural regions with limited alternatives.

Another rudimentary method used historically to define a catchment area is the use of buffers around the school (Phibbs & Robinson, 1993). The location of the school is the only required input for this approach. A threshold of distance, time or population to a school, assuming that children will go to the closest school to them. In this approach, distance is regarded as the major factor influencing attendance to a school. Due to its simplicity, this approach has been the most commonly used.

Thiessen polygons have been used to define a catchment area; the polygon contains all points in space that are closest to its centre than any other school. Two assumptions are made: all children choose to utilize the school nearest to them, regardless of its type and the per-capita utilization rate is constant throughout a catchment (Gething et al., 2004). The inclusion criterion for a particular administrative region is if its proportion exceeds a set minimum (Baker, 2010; Shortt et al., 2005). Other methods include K-means clustering (Gilmour, 2010), Generalized Additive Models (Wheeler & Wang, 2015) and Bayesian hierarchical regression modelling approach (Wang & Wheeler, 2015).

To overcome the limitations of using administrative areas, buffers, and Thiessen polygons, a new and improved method has been introduced. This approach cleverly uses a specific threshold to define catchment areas based on travel time or distance. By considering factors like transportation mode, speeds, obstacles (such as game parks, reserves, water bodies, and forests), and travel conditions (like road networks, land cover, and topography), this innovative model shapes how long it takes to travel to a place. The threshold chosen is inspired by previous studies, recommendations from the Ministry of Health, or global experts. All of these creative ideas come together to create a fresh way of analyzing spaces, breaking the norms of traditional methods. This exciting approach opens up new possibilities for spatial analysis, making it an essential part of research and planning. In this study, the use of a threshold travel time was used to define SCAs based on its advantages over the other methods of defining catchment areas.

2.6 Gaps in literature review

Several studies have examined spatial accessibility to healthcare (Moturi et al., 2022; Ouma et al., 2018; Ouma et al., 2021). Some studies have also explored spatial access to schools (Lewin, 2009; Macharia et al., 2022; Rekha et al., 2020). Additionally, there is a relative scarcity of research exploring spatial access to schools compared to the studies on healthcare accessibility. These spatial analyses were carried out at different global and national scales and at different spatial resolutions. However, there is a gap in the research regarding the comparison of datasets at different spatial resolutions. The gaps in the literature include the limited focus on comparing datasets at different spatial resolutions, which can significantly impact the accuracy of spatial accessibility models.

Hierink conducted a study that found significant impacts on geographic access measures to healthcare in SSA depending on the choice of population dataset (Hierink et al. 2022). The differences between six gridded population datasets at varying spatial resolutions had a strong influence on the uncertainty of healthcare accessibility models and the subsequent decisions based on them. Another recent study (Macharia et al., 2022) investigated the use of geospatial modelling to define geographic access and school catchment areas for public primary schools in Western Kenya. The study estimated the coverage of school-going children within a recommended travel threshold of 24 minutes and corresponding school catchment areas for the years 2009 and 2020.

The findings of this study were useful for identifying marginalized school-going children living outside of the catchment areas, potentially informing targeted interventions.

Building onto these significant studies, this study sought to investigate whether using different spatial resolutions of travel times as a measure of spatial access have an influence on the coverage by quantifying the differences in of SAC within school catchment areas generated from two different spatial resolutions.

3 CHAPTER 3: METHODS AND MATERIALS

3.1 The Kenyan education context

The Kenyan government has made significant efforts to enhance access to education for all. One notable initiative was the introduction of the Free Primary Education program in 2003. This endeavour led to a rise in net primary enrolment rates from 88.1% in 2013 to 92.4% in 2018 (GoK/MoE 2018; KNBS, 2021). However, there was a slight gender disparity, with male enrolment at 5.0 million (50.7%) and female enrolment at 4.8 million (49.2%) (MOE, 2014). Although progress has been made, there is still a 7.6% of children who are not enrolled in school. Moreover, primary school completion rates have shown improvement, reaching 84.2% which implies that more children are being retained within the primary schools. Over time, national dropout rates have declined, dropping from over 20% in 1994 to less than 10% in 2015/16, with a more rapid decline observed among girls. These trends suggest a positive development in attendance rates for female learners.

3.2 Kilifi County

While the methodology employed in this study can be broadly applicable at a national context, this study focusses on Kilifi County (figure 1). The county has historically benefited from school-based interventions for treatment of STH and malaria to school children. This has seen improvements in educational attainment. However, there is need to refine the targeting of these interventions at school level.

In 2012, Kilifi's primary school had an impressive enrolment of 303,990 students. Over the years, the primary school enrolment in Kilifi saw remarkable growth, soaring from 122,221 in 1993 to 303,990 in 2012, with an average annual increase of 6.53% (Knoema, 2023). Among children of primary school age, a significant 84% were enrolled, with 81.4% being boys and nearly 87% being girls. However, the picture changes when we look at secondary school enrolment. Only 26% of children in the secondary school-age group are enrolled, which is nearly half of the national secondary school enrolment rate of 47%. Interestingly, while girls have a higher enrolment rate than boys at the primary school level, the trend reverses at the secondary school level in Kilifi. In 2014, only 24% of girls were enrolled, which is 4% lower than the enrolment rate for boys (CSA, 2021). These findings reveal the educational landscape in Kilifi, highlighting the growth in primary school enrolment and the challenges in secondary school participation, as well as shedding light on gender differences in enrolment rates.

Kilifi county is one of the six counties located along the Kenyan coast. The county covers an area of 12,245.90 km^2 with a population of 1,453,787 people stretching across 7 sub-counties which are administrative units for health planning. The county is located between latitude 2° 20" and 4° 00" South and longitude 39° 05" and 40° 14" East. Three topographic zones with various possible land uses can be found in the county. These include the coastal plain's narrow belt at 30m above sea level, the foot plateau with nominally undulating terrain falling between 60m and 150m altitude, and the Nyika plateau rising from 100m to 340m above sea level and suitable for ranching (CIDP, 2018). In Kilifi, the pillars of its economy rest upon the thriving sectors of tourism and fishing. Additionally, agriculture plays a pivotal role, taking advantage of the region's abundant arable land, where maize and cassava stand proud as the principal subsistence crops nurtured by the local communities.

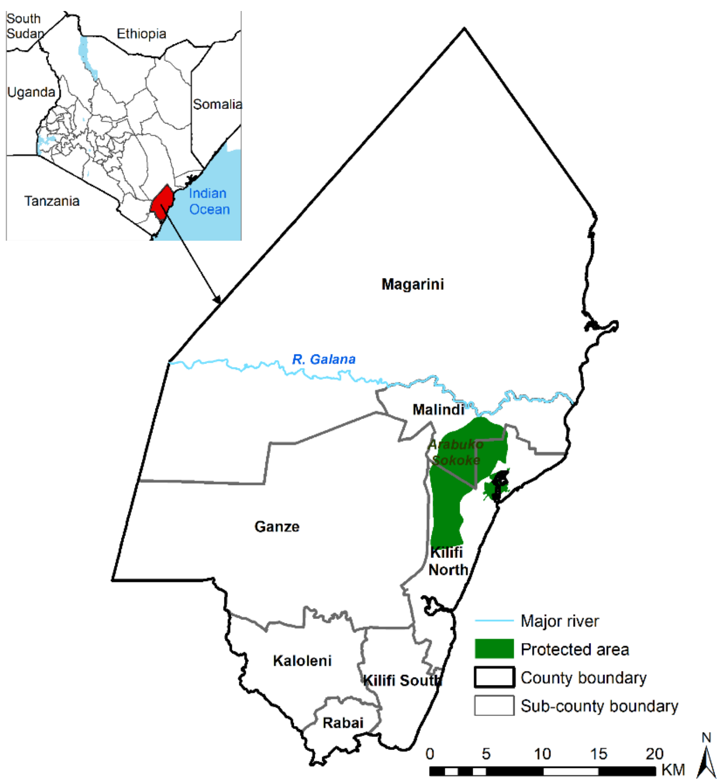

Figure 3-1: Map showing the study area: location of Kilifi county (red) in Kenya shown on upper left panel and map of Kilifi county at the center

3.3 Estimating spatial access

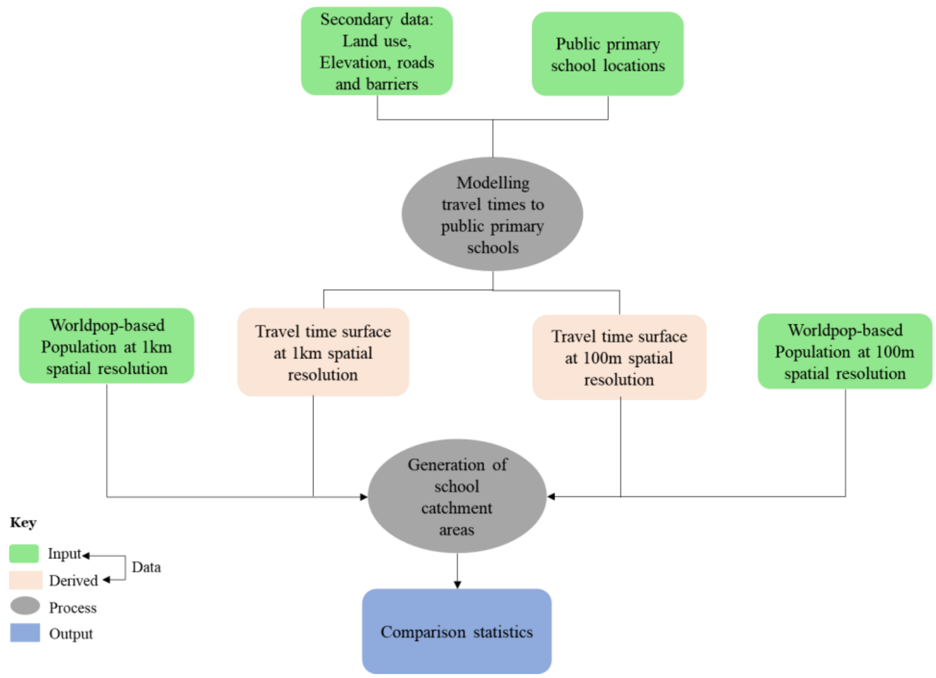

Figure 3-2: Schematic diagram showing the methodology used in the study

Figure 3-2 shows a summary of the methods used in modelling spatial accessibility to schools and consequently comparing the coverage of SAC at two spatial resolutions. The first step involved assembling a geo-coded inventory of PPS by combining six national school databases and cross-referencing with the World Bank Kenya schools database. Geospatial factors affecting travel time, including the road network, land cover, elevation, and population distribution, were also assembled. Travel time to the nearest PPS was computed based on walking scenarios using the least-cost algorithm in AccessMod. School catchment areas were defined with a maximum travel time of 24 minutes to the nearest PPS, and population counts for school-aged children within each catchment area were estimated. The analysis was conducted at both 100m and 1km spatial resolutions to understand the effect of spatial resolution on accessibility results.

3.3.1 Data Assembly

3.3.1.1 Developing a geo-coded inventory of public primary schools

Majority of the children in Kenya, (10.3 million) attended public primary schools (PPS) in 2021 (Statistica, 2023). These institutions offer a practical and affordable setting to interact with a large number of children, especially those from low-income families and marginalized groups who are more likely to benefit from interventions. Therefore, the location of PPS is key in planning for integrated school-based interventions. However, there is no existing up-to-date database of PPS in this region. To assemble a current geographical database of PPS within the Kilifi county, six current and national school databases (the MOE 2010, 2018, and 2020 master lists, a web-based listing, and a World Bank Kenya schools' database) were consulted. The MOE 20010 master list, which included all public and private primary schools in the county, along with their respective latitude and longitude coordinates was first assessed. Additional schools were added from a database obtained from surveys conducted by the Kenya Medical Research Institute--Wellcome Trust program and Eastern and Southern Africa Centre of International Parasite Control (KEMRI-ESACIPAC). To obtain more recent school listings, Step 3 involved reaching out to colleagues working in school health programs at the MOE and Evidence Action. A list from the MOE 2018 master list, which provided information on the institution's name, provider, level, county, and sub-county, was obtained. In addition, a web-based database of Kenyan primary schools, was accessed on January 3, 2023, which provided comprehensive information such as school status, sponsorship, enrolment, and location. Finally, the compiled list was cross-referenced with primary schools with the World Bank Kenya schools database. Primary schools were checked from the World Bank database and respective shapefiles whose last update was indicated as 21st August 2020 online. It is, however, not clear whether it is a most recent census of schools or merely latest update of older information. World Bank contact information is supplied as rjordan@worldbank.org. An additional excel listing of national school enrolment data from MOE 2020 was used.

These databases were combined, duplicates eliminated, and the schools' latitude and longitude positions confirmed using Google Earth. The inclusion criteria encapsulated all PPS run by local governments, the local community, the Ministry of Education, non-governmental organizations, and religious institutions. Exclusion criteria included special schools serving the deaf and blind children because travel times were computed based on walking scenarios only. Further, pure boarding schools were not included because children do not commute every day therefore spatial accessibility is not an issue.

3.3.1.2 Geospatial factors affecting travel time

3.3.1.2.1 Road network

Where there are roads, children use them to move from their homes to schools. Datasets containing detailed information on the road network were assembled from the Ministry of Transport website (http://www.krb.go.ke/road-network/road-maps) which had been mapped using the gold standard global positioning system (GPS) receiver in 2016. These road layers were overlaid with those obtained from the OpenStreetMap (OSM) (https://www.openstreetmap.org/) in ArcMap version 10.5 (ESRI Inc., Redlands, CA, USA). Data quality checks were performed on the roads to remove duplicates, corrected for road sections with undershoots and overshoots as a result of digitization from the resultant vector file. The roads were then reclassified as primary, secondary, county and rural roads based on two reasons: first according to the Kenya Roads Act 2007 & Bill 2017 and secondly, the speeds available for each road classes in Kenya from the literature follow these classes. Primary roads were those running across the county connecting cities in other counties. Secondary roads were those feeding into primary roads and connecting major towns within the county. County roads were those that linked secondary roads, weaving together smaller towns and market centres. Rural roads were those connecting count roads while joining villages and market centres.

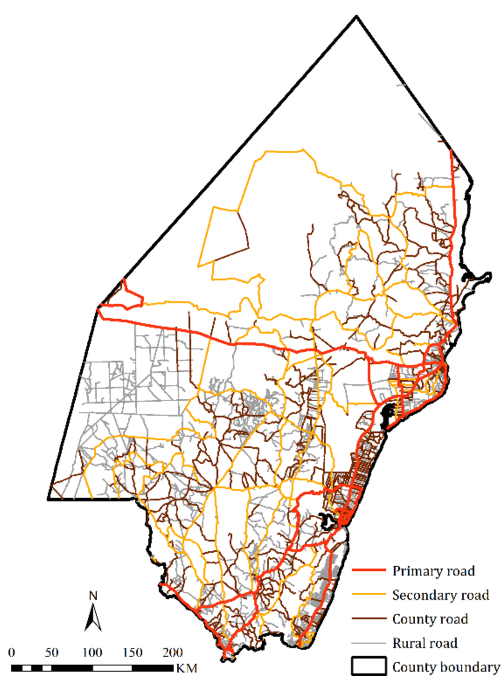

Figure 3-3: Distribution of road network within Kilifi county

3.3.1.2.2 Land cover

Landcover data for the year 2019 was obtained from the ESRI Landcover website (https://livingatlas.arcgis.com/landcover/). This landcover product was obtained based on existing artificial intelligence (AI) models of land classification fuelled by immense training dataset of billions of image pixels labelled by humans. Applying these models, the Seninel-2 scene collection utilizing six spectral bands annually spanning 6 years from 2017 to 2022 maps were generated at 10m spatial resolution (Karra et al., 2021). The output provides a 11-class map of the surface including: water, trees, grass, flooded vegetation, crops, shrubs, built-area, bare ground, snow/ice, clouds and rangeland. However, for Kilifi county, only 7 land cover classes were adopted as shown in figure 3. Overall, the accuracy of the product has been recorded to be as high as 85%. This landcover was resampled to 100m and 1km spatial resolution and matched to the population data for subsequent analysis. The mapped land cover and the varying classes are shown in Figure 3-4 below.

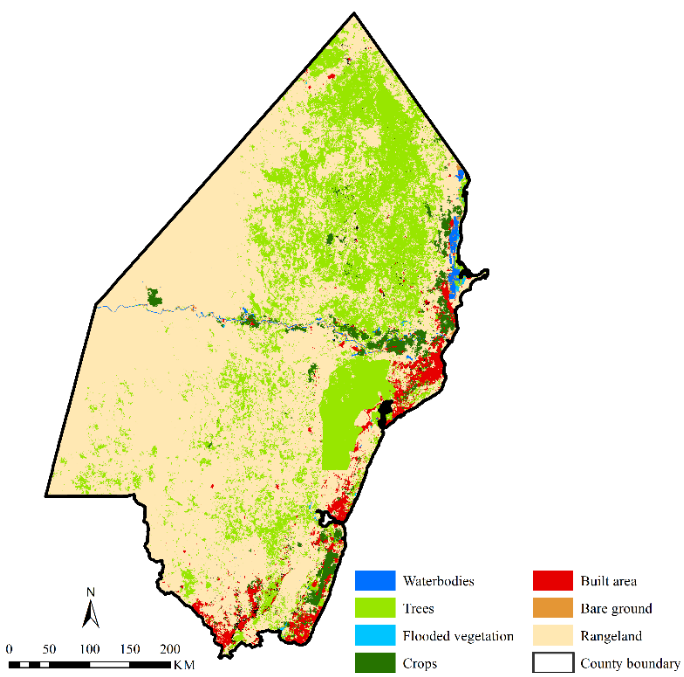

Figure 3-4: Landcover map of Kilifi county

3.3.1.2.3 Elevation

A digital elevation model (DEM) is a representation of the terrain. There are a number of sources of digital elevation models, and these include ASTER, the SRTM and METI. They are presented in different resolutions and their applications vary depending on such characteristics. Regional surfaces of Kenya's DEM was downloaded from NASA's Shuttle Radar Topography Mission (SRTM) at the USGS Land Processes Distributed Active Archive Center (LP DAAC) website (http://gdex.cr.usgs.gov/gdex/) at 30m spatial resolution and clipped to Kilifi county boundary. This Dem was downloaded based on ease of availability and the spatial resolution resampled to match both 100m and 1km spatial resolutions. The variation in elevation is shown in figure 3-5 below.

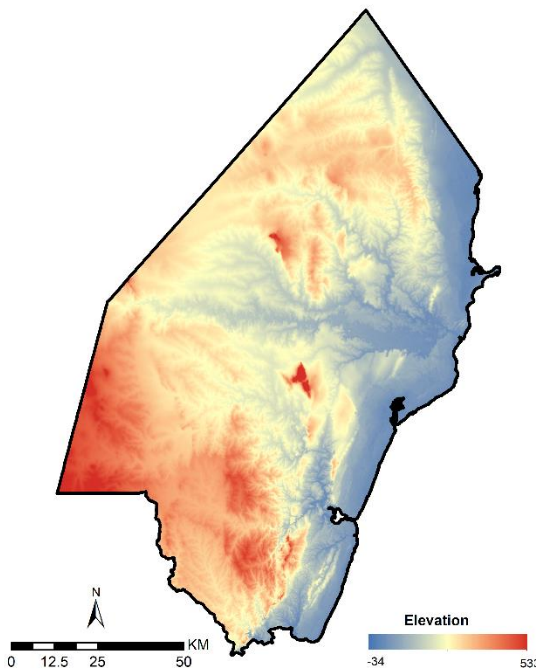

Figure 3-5: Topography map of Kilifi county

3.3.1.2.4 Population

The WorldPop project (WorldPop, 2023) provides gridded population data at spatial resolutions of 3 and 30 arc-seconds (approximately 100m and 1km at the equator respectively). These datasets provide human population distribution estimates for all years between 2000-2020 disaggregated by sex and five-year age groups. This level of detail is a result of a remarkable fusion of census and satellite imagery data, meticulously curated through the application of cutting-edge machine learning algorithms (Stevens et al., 2015). A collaboration between various institutions including the Center for International Earth Science Information Network (CIESIN) at Columbia University Department of Geography and Geosciences, at the University of Louisville, School of Geography and Environmental Science at University of Southampton and the Department of Geography, University of Namur yielded generation of these datasets. For this study context, it was possible to isolate the population of school aged children by combining two age groups: 5-9 and 10-14.

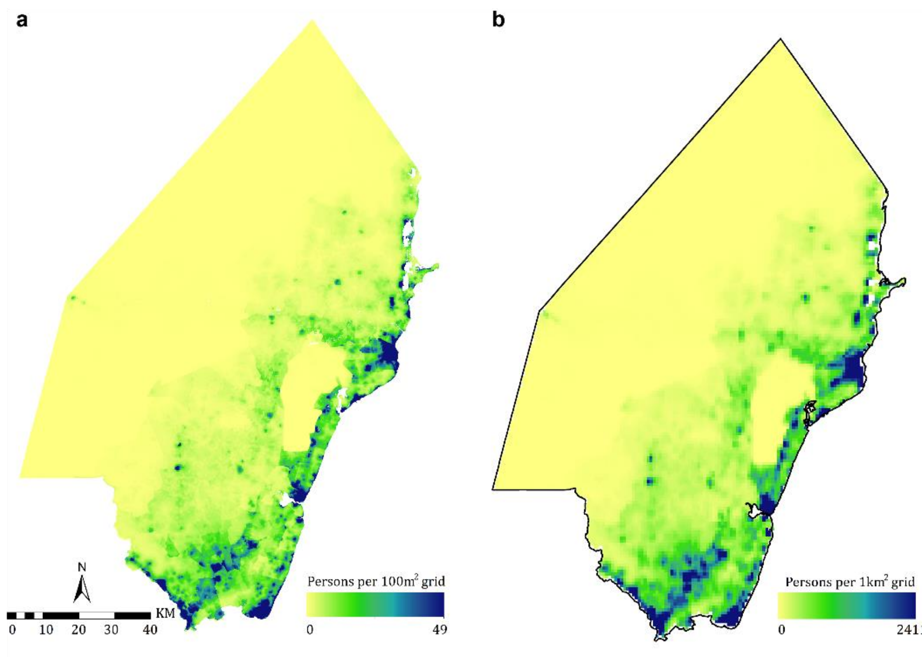

Figure 3-6: Population maps at a) 100m and b) 1km spatial resolution in Kilifi county

3.3.2 Computing travel time to public primary schools

AccessMod boasts an array of four distinctive analysis types, each designed to unlock various dimensions of insights. The first analysis lies in modelling catchment areas linked to an existing location with travel time offering a unique measure of spatial accessibility. The second analysis is geographic coverage analysis which unravels patterns of optimization of service utilization. The last two analysis are referral analysis and zonal statistics.

Accessibility of SAC to public primary schools (PPS) within the Kilifi County was modelled in terms of travel time to the nearest PPS based on the least cost algorithm as implemented in AccessMod software (alpha version 5.8). Both raster and vector data were used as inputs, but the latter are always transformed into raster data during the analysis. Travel time based on walking was calculated by overlaying school locations on top of a cost friction raster modelled and invoking the Dijkstra least-cost path algorithm (Adriaensen et al., 2003). It assumes that the travelling time from any location to the public primary school is always obtained by travelling along the optimum (fastest) route. This algorithm operates by accounting for topography and the movement barriers to obtain the least-cost path for children walking from their homes to school. The cost assigned to each individual cell is the amount of travelling time needed to traverse it, determined by the speed of travel attributed to the distinct cell's landcover (Ray & Ebener, 2008).

In AccessMod, the 'merge land cover' function was used to create a unified landcover grid by integrating landcover with the road network and barriers to movement (rivers, and protected areas). Roads were assigned priorities over the barriers. For this reason, certain road segments acted as bridges over rivers, even if they were not explicitly labelled as such in the road network layer. This further enabled river to be crossed on bridges therefore permitting the realistic extension of catchment areas. The resulting landcover raster held unique identifiers for each land use category. The friction raster represents an overview of the likely scenarios experienced by a child on their way to school. This dataset was then be subjected to walking speeds. After reviewing literature on walking to schools in low-income countries (Macharia et al., 2022), different speed limits were allocated to all road class and each land cover type in the one travel scenarios (walking only) as shown in table 3-1. The geolocation of schools were overlaid with the resulting friction surface and a cumulative cost function invoked the most proximate (shortest travel time) to the nearest PPS using the accessibility module. The shortest travel time was calculated factoring in diverse speeds at which a child would navigate through different land cover types and road networks. As a result, the travel time raster surfaces were generated for the most at a 100-m and 1km spatial resolution.

Table 3-1: Summary of travel speeds adopted in the study

Road/Land Cover	Walking speed km/h	References
All Roads	5	Cavagna et al 1983
Tree Cover Areas	3.5	
Shrubs cover and sparse vegetation	4.5	Ewing et al. 2004
Grassland	4	
Cropland	3.5	McDonald 2008
Bare areas and built-up areas	5	
Open Water	0	Toor et al. 2001

3.3.3 Defining school catchment areas

School catchment areas were delineated in AccessMod based on maximum travel time of 24 minutes to the nearest public primary school. These SCAs were derived at both 100m and 1km spatial resolution. Population counts for school aged children in each catchment area were estimated. Derived population from each SCA were then compared as raw counts and as percentage. Comparisons were made based on the absolute difference in number of SAC within SCAs generated based on travel times at two different spatial resolutions: 100m and 1km. To illustrate the effect of choice of spatial resolution of travel time, the spatial variation and sizes of SCAs together with the resulting absolute difference in the number of SAC will be obtained from the different spatial resolutions.

4 CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Summary of primary schools' data

From the MOE 2009 database, 291 public primary schools were initially identified resulting in a list of 284 schools after removing duplicates and special schools. The school surveys database added 167 public primary schools, including some that were surveyed multiple times, and 40 previously unrecorded schools. Any discrepancies in school names were resolved to match those in the MOE 2009 database. The MOE 2018 database contained 457 public primary schools, of which 398 remained after removing duplicates and special schools. Notably, 135 schools were not documented in the MOE 2009 database, and their coordinates were verified through Google Earth. The web-based database contributed 242 public primary schools, of which 221 matched schools in the MOE 2018 database. The World Bank which contained 37,930 primary and secondary schools with longitude and latitude coordinates. After removing secondary schools, private primary schools, duplicates, and special schools, a final database of 355 schools was obtained. The MOE 2020 database resulted in the identification of 874 schools in Kilifi County. After excluding secondary schools, private primary schools, duplicates, and special schools, 422 schools remained, including 11 schools not identified in the previous steps. Ultimately, the comprehensive examination of all these databases resulted in the identification of 435 public primary schools within Kilifi County for the study.

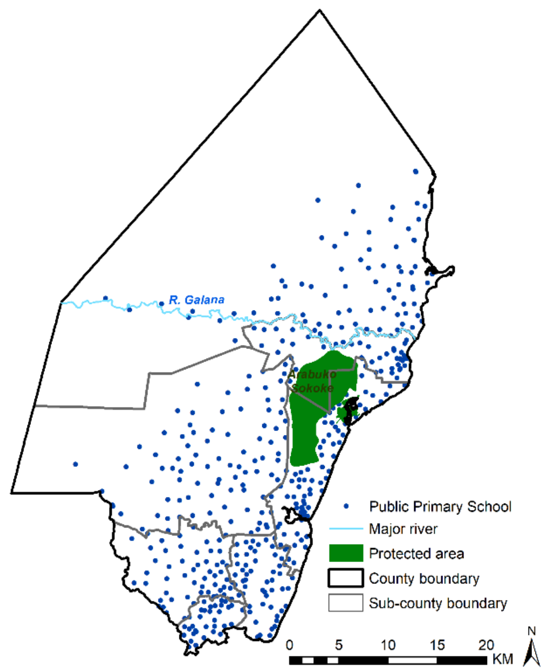

Figure 4-1: Map showing the spatial distribution of public primary schools within Kilifi County

4.2 Spatial access to schools

The results of modelling travel time to the nearest PPS within Kilifi county at both 100m (left panel) and 1km (right panel) spatial resolution are shown in Figure 4-2. Overall, the majority of the SAC were spatially accessible to their nearest primary schools irrespective of the resolution. The Northern and Western areas which are predominantly dry rangelands of Kilifi county had the highest travel times. The area is predominantly semi-arid with no population; bordering Tana River and Taita Taveta counties. On the contrary, areas with high population and good road network had the shortest travel time.

Spatial access to schools varied across the county ranging from minimum to 804 and 775 minutes at 100m and 1km spatial resolution, respectively. The average travel time also varied from 138 to 127 across the two travel time surfaces, respectively. The difference between the average travel times across the two spatial resolutions is 11 minutes, a difference which is relatively small. The travel time surface at 100m spatial resolution displays smooth transitions across different time classes, unlike the 1km resolution surface, which was coarse with indistinct classes (Figure 4-2).

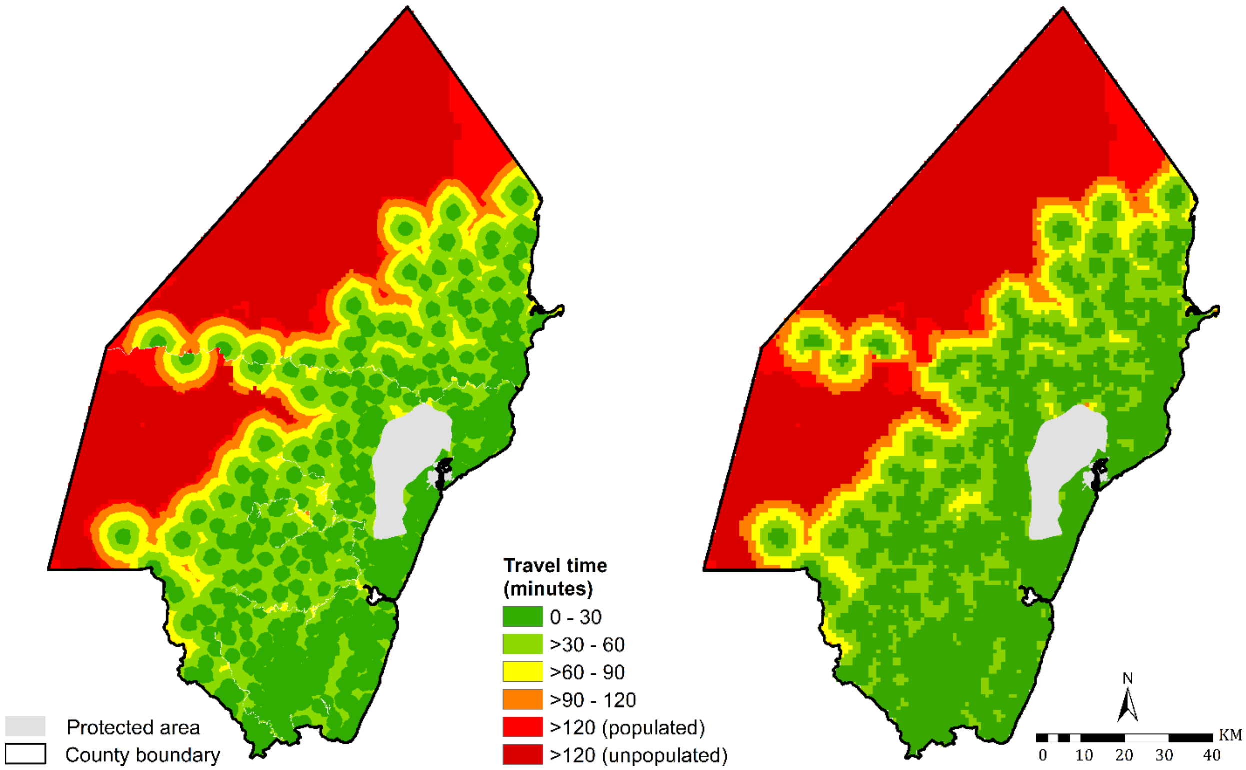

Figure 4-2: Modelled travel time raster surfaces at a) 100m and b) 1km spatial resolution in Kilifi county

In general, the majority of school-aged children within the study were found to be located within a 10-<20-minute travel time from their nearest PPS. Specifically, at a 1km spatial resolution, 179,210 children (43%) fell within this travel time range, while at a 100m resolution, 124,285 children (29.82%) were within the same range. Consequently, there was a larger absolute difference between the two resolutions in the 10-<20-minute class (36.85%) compared to the 0-<10-minute class (44.19%). The reason behind this could be explained by the granularity of the input data used. At 100m spatial resolution, local variations were noted revealing captured differences in travel times for children living near the school. However, this was different at 1km spatial resolution where the slight distinctions in travel time were blurred resulting in clustered travel times of about 10-20 minutes within the same regions. The 100m spatial resolution offers a significant advantage by providing detailed and precise data on the road network, facilitating the identification of shorter and more efficient routes to schools. On the other hand, the coarse 1km resolution may overlook smaller, more direct pathways, resulting in potential underestimation or suboptimal route selection during accessibility analysis. Moreover, the finer resolution allows for the detection of minor barriers or obstacles, such as rivers, that can impact travel time to schools. In contrast, the 1km resolution might miss some of these obstacles, leading to less accurate assessments of travel impediments and potentially overestimating accessibility.

As travel time increased beyond 20 minutes, the absolute difference decreased as shown in Figure 4-3.

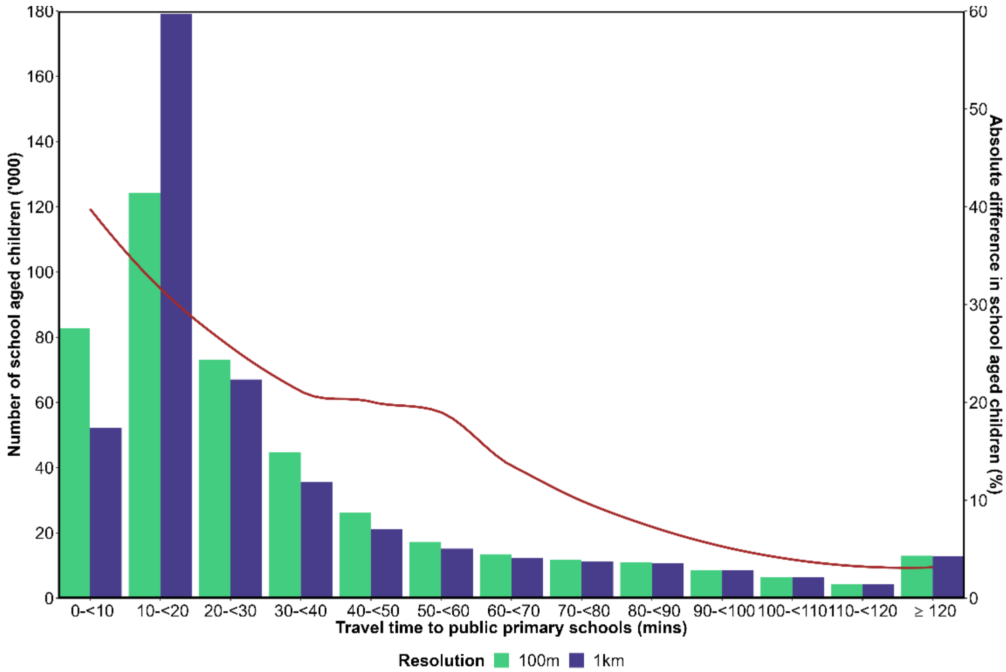

Figure 4-4: Comparison of actual numbers and absolute differences of school aged children at 100m and 1km spatial resolution

4.3 School catchment areas

At a 100m spatial resolution, all 435 public primary schools in Kilifi county were found to be reachable within a 24-minute travel time. However, when considering a 1km spatial resolution, five schools (Hawewanje, Kakokeni, Madunguni, Mitsedzini, and Shakahola) were found to be located outside the 24-minute threshold. These schools are situated near the river Galana. The relatively coarse resolution of 1km represents the river as larger than its actual size on the ground, resulting in exaggerated barriers to children's movement towards these schools.

The spatial resolution of travel time surfaces at 100m and 1km had an impact on the size and shape of the school catchment areas. There were noticeable differences in the size and shape of the catchment areas obtained at the two resolutions. At 1km spatial resolution, the catchment areas were slightly larger and displayed a coarser representation at the edges compared to those at a 100m spatial resolution. In areas where the catchments were closer together, the differences in catchment sizes between the two resolutions were almost negligible. However, in other areas, where the catchment areas were dispersed, the disparities were more pronounced. These differences in catchment areas can be attributed to the varying levels of spatial resolution in the input datasets (100m vs 1km), which affected the accuracy and granularity of the results.

An overestimate in the number of children within a particular SCA obtained at 1km spatial resolution is as a result of the "exaggerated" size of the catchment area relative to that obtained at 100m spatial resolution. This difference stems from the fact that the input datasets at 1km spatial resolution are already bigger than they would be in reality while the input raster datasets at 100m spatial resolution in the real world would be representing 100m by 100m. In areas with many schools close to each other, the discrepancies in SCA sizes were quite negligible however, it ultimately has an impact in the no. of SAC estimated. This was evident in areas which were highly populated meaning that a small difference in the shape and size of the catchment area would reflect on the difference in the population extracted.

When considering a 24-minute travel time, the population of school-aged children covered within this threshold was higher at a 1km spatial resolution with 302,256 (72.53%) children falling within the catchment areas. In comparison, at a 100m spatial resolution 293,031 (70.31%) of all school aged children within Kilifi county were covered within 24 minutes. This indicates a slightly higher coverage of school-aged children within the threshold at the 1km resolution.

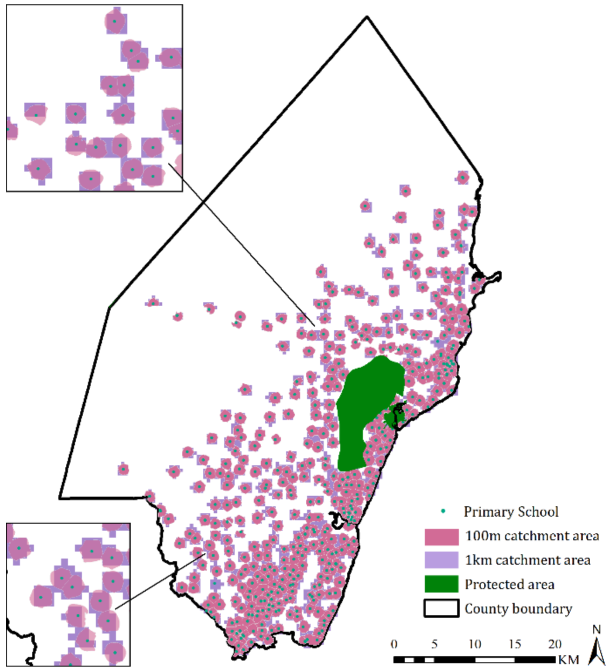

Figure 4-5: Visual comparison of school catchment areas generated at 100m and 1km spatial resolution in Kilifi county

4.4 Differences in catchment population

The area of school catchment areas varied from 0.75km^2 to 9.10 km^2 at 100m and 0.75km^2 to 12.84km^2 at 1km spatial resolution. The biggest difference in catchment size was 6.44km^2. The highest number of schools 165 (37.93%) had the smallest difference in school catchment area with size of less than 0.5 Km^2. This can be explained by the fact that most schools especially in Kilifi North, Kilifi South, Malindi and Rabai subcounties are closer to each other connected with good road network and limited barriers to movement. The number of schools gradually decrease with increase in school catchment area size differences. However, the actual difference in the number of school aged children varied across the catchment area sizes with the smallest difference (45) in the 4-<4.5 class while the highest difference was 1,633 in the 2.5-<3 class.

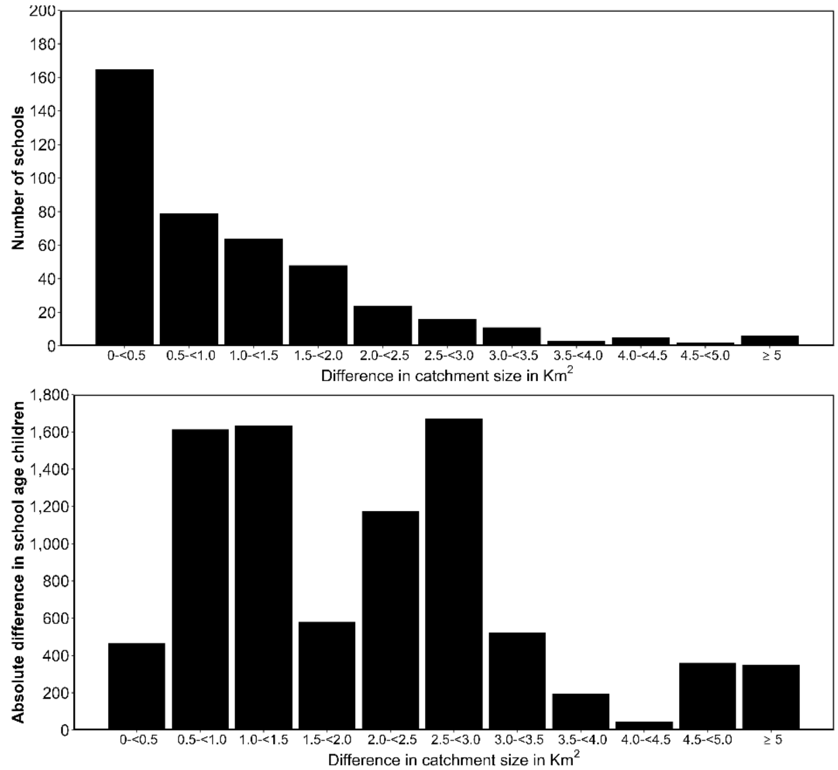

Figure 4-6: Absolute number and difference of school age children and difference in school catchment area sizes

Across the 7 sub-counties within Kilifi county, Rabai and Kilifi North sub-counties had more than 80% of SAC covered within 24mins of travel time to their nearest PPS at both spatial resolutions. However, Ganze sub-county had more than half of its SAC population not covered within the threshold of 24 mins. Absolute differences in no. of SAC at the two spatial resolutions at ward level are further mapped in figure 11. Strong absolute differences are observed in wards in the Southwestern regions while differences remain small in the northern regions. Table 2 highlights these differences at sub-county level.

Table 4-1: Absolute numbers and percentage differences in the coverage of school aged children at subcounty level

Subcounty	No. of schools	Total population	Population covered, n (%)		Absolute Difference	
			100m	1km	Number	Percentage
Kilifi North	77	80,922	65,508 (80.95)	65,522 (80.97)	14	0.02
Rabai	35	35,815	31,938 (89.17)	31,978 (89.29)	40	0.12

Magarini	81	67,692	35,478 (52.41)	35,881 (53.01)	403	0.60
Malindi	43	54,984	42,569 (77.42)	43,249 (78.66)	680	1.24
Kaloleni	53	59,350	40,089 (67.55)	42,421 (71.48)	2,332	3.93
Kilifi South	56	69,662	55,656 (79.89)	58,661 (84.21)	3,005	4.32
Ganze	90	48,335	21,793 (45.09)	24,544 (50.78)	2,751	5.69

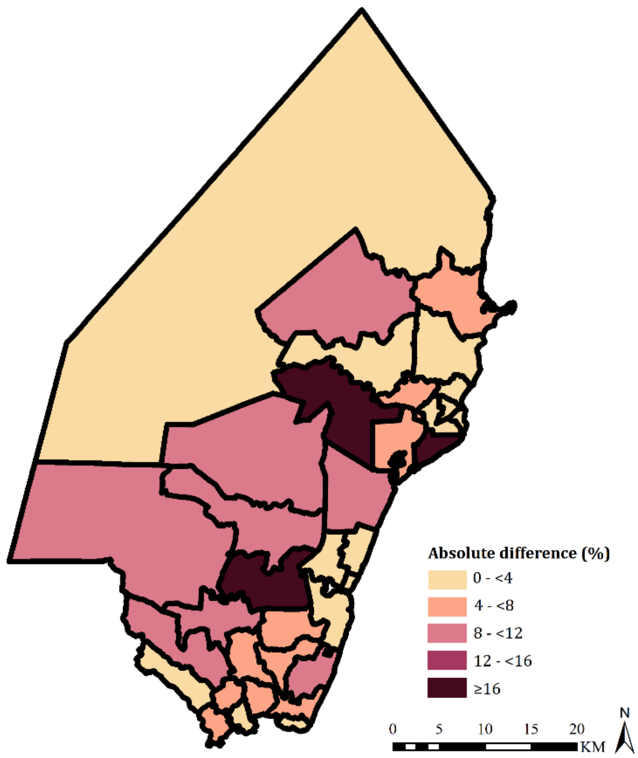

Figure 4-7: Map showing the absolute difference in the coverage of school aged children at Ward level.

4.5 Discussion of results

Spatial accessibility performed at national and global scales at low spatial resolution have asked what impact the results have at a local level. While the choice of resolution for spatial accessibility in previous studies has dependent on many factors including spatial resolution of the input data, the application of the analysis, computational capacity required during analysis and the scale of analysis i.e. regional, it is important to be cognizant on what impact this has at the local scale.

When evaluating the spatial accessibility of SAC to schools, the choice of the spatial resolution of travel time surface will generate different results in terms of coverage of SAC within a determined threshold leading to significant measures. For example, an overestimate of the number of SAC living within a catchment area could underestimate the coverage of interventions. It has been evident in this study that the resulting size of catchment areas played a major role in the absolute differences of SAC across the SCAs at both spatial resolutions. Moreover, the coarse catchment areas at 1km spatial resolution had an effect of underestimating population in areas that are sparsely populated and overestimating in areas that are highly populated. Even though before extracting the number of SAC in each of the catchment areas, unsettled areas including protected areas were masked out of the population datasets, population counts were likely to be underestimated because of the geographic size of the input datasets at 1km spatial resolution which appeared as larger grid cells compared to those at 100m spatial resolution.

The generated travel time metrics have important implications for policymakers. Fundamentally, they provide a better understanding of the time students spend walking each day and how that time varies at different spatial resolutions (100m and 1km). A key take-away from the gridded accessibility comparison at different spatial resolutions is that numbers vary substantially depending on the level of spatial resolution potentially leading to different conclusions and decisions about the targeting of interventions to the population in need. This study underscores the need to understand fine-scale accuracy across travel time surfaces to inform future choices of spatial resolution in future analysis.

5 CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This work presents the first assessment of the influence of using travel time raster surfaces at two different spatial resolutions on the coverage estimates of SAC at a local level. By modelling spatial accessibility to PPS with walking only as the travel scenario and using input datasets at two spatial resolutions (100m and 1km), the coverage differences were evaluated. The two spatial resolutions were selected to match the resolutions of Worldpop population datasets. The analysis was focussed on the setting of Kilifi County and so the results do not necessarily generalize to other counties or regions. Results from this study can provide helpful insights to decision-makers and healthcare providers on how best to precisely allocate limited resources.

Over the past years, studies have modelled spatial accessibility at spatial resolutions at global scales and recommending their work for use in planning purposes. Although these studies may be useful for implementation at larger scales, the impact at local scale have not been investigated. The results shown in this study illustrate the impotence on considering the spatial resolution on the decisions made at the local scale. The choice of spatial resolution is critical: accessibility computed at 100m spatial resolution, though may not be the most accurate, yield better coverage metrics compared to 1km spatial resolution. However, there is need to go higher in spatial resolution for future studies.

5.2 Recommendations

The following recommendations were drawn from the study:

1. Researchers should consider variations in coverage estimates based on different spatial resolutions in spatial accessibility to inform decision makers in optimization of intervention effectiveness.

2. Findings from this study could inform basis for future work in other regions of the country for researchers interested in knowing the effect of using different spatial resolutions based on different measures other than for planning of intervention strategies.

3. Future research could consider the influence of different child attendance behaviour on spatial accessibility metrics in addition to travel time measures at different spatial resolutions.

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