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Mapping School Accessibility in Africa: High-Resolution Spatial Analysis Uncovers Inequalities in Education Access

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ABSTRACT

Education is a cornerstone of sustainable development, yet large disparities in access persist across and within countries—particularly in Africa, where millions remain underserved. Among several factors influencing educational participation, physical accessibility to schools (in terms of travel time) is not comprehensively understood, especially in data-scarce contexts. This study presents 90-m resolution maps of school accessibility in Africa, offering a detailed and systematic view of spatial variability. Leveraging advances in geospatial data and modeling, the analysis highlights substantial inequalities, especially in rural areas where many live more than a 3-h walk from the nearest school. Comparisons with national statistics reveal substantial gaps in existing school datasets, while model validations demonstrate the results' rigor. A case study in Malawi illustrates how accessibility intersects with wealth and educational attainment, and elucidates model sensitivities. The results provide tools to inform evidence-based planning, prioritize interventions, and advance progress toward equitable and inclusive education.

1 | Introduction

Education is a fundamental human right and is widely considered a pillar of development, a crucial driver of poverty reduction, and a key determinant of quality of life (United Nations Educational, Scientific and Cultural Organization 2014; Universal Declaration of Human Rights 1948). Increasing access to education has been recognized as a key development priority in global international agreements, like the Millenium Development Goals (MDGs) and the Sustainable Development Goals (SDGs). Despite significant progress, education sector goals have not been met and are unlikely to be met by 2030 (United Nations Department of Economic and Social Affairs 2023). MDG 2, which aimed at achieving universal access to primary education by 2015, was unmet and subsumed under the follow-up SDG 4, which expanded the scope to achieve equitable and universal access to quality education at all levels, with an emphasis on reducing inequalities by 2030 (Arkorful et al. 2020; Friedman et al. 2020), yet with only 5 years left for the SDG deadline, universal access to education has not been achieved and large disparities persist (Klees 2024).

Disparities are particularly acute in many parts of the African continent, with several countries falling short on achieving inclusive, equitable, quality education (Friedman et al. 2020; Zickafoose et al. 2024). Low enrolment rates and poor educational outcomes are attributable to a range of complex and multidimensional factors that vary between and within countries and individuals. Among these, travel time to school has been identified in the literature as a significant concern (Al-Sabbagh 2022; Rodriguez-Segura and Kim 2021), one especially critical in many parts of the African continent where children still face long travel distances and the majority of children walk to school (Macharia et al. 2023; Siiba 2020). Although it is most certainly not the only determinant of educational outcomes, having a school physically nearby, within a reasonable travel time, is often considered a first-order necessity for attending school and a critical first step in the pursuit of universal school enrolment (Rodriguez-Segura and Kim 2021). Decreasing the distance to children's nearest school has been found to increase enrolment (Glewwe et al. 2011) and improve academic achievement (Afoakwah and Koomson 2021; Falch et al. 2013; Tigre et al. 2017). This effect has been identified as particularly important for girls, low-income children and those on the edge of failing (Dube 2015; Lehman 2013; Stokenberga et al. 2024). As a result, improving geographic access to schools has become a key goal across the region (Macharia et al. 2023). Yet, efforts remain hampered by a lack of a systematic understanding of the variability in spatial distribution of access.

1.1 | Literature Review

Despite widespread recognition of the importance of improving geographic access to schools, relatively few studies have empirically defined travel time to school or applied spatial methods to analyse educational accessibility. This gap is particularly pronounced in the African continent, where access to education remains a pressing challenge.

Since the development of the present study, Moner-Girona et al. (2025) have provided the first continental model of school accessibility by generating 1 km resolution travel-time maps to electrified and nonelectrified schools as part of their electrification costing analysis (Moner-Girona et al. 2025). While this work has set an important precedent and provided valuable georeferenced data for education planning, a detailed understanding of the distribution of access and the patterns of inequalities remains lacking. In this study, we revisit this question, comparing our high-resolution (90 m) outputs to the 1 km surfaces produced by Moner-Girona et al. (2025) in order to extend their analysis with distributional, validated, and socioeconomic perspectives.

Beyond this continental-scale study, most other analyses of school accessibility in Africa have been conducted at national or subnational levels, and have often relied on simplified measures such as straight-line (Euclidean) distances or threshold-based assumptions. For example, Rodriguez-Segura and Kim (2021) introduced a generalizable methodology for identifying "education deserts" where families lack physical access to education by estimating Euclidean distances between population centres and their nearest schools. Although the case study was presented for Guatemala, six other countries were also analysed, including four African countries (Tanzania, Kenya, Rwanda, and South Africa). While their approach provides a useful first step, it does not account for real-world travel constraints, obstacles, and facilitators of movement. Similarly, Lehman (2013) assessed school accessibility in Mali using a 5 km Euclidean distance threshold, a method that may not accurately capture the barriers children face when traveling to school. Also using straight-line distances, De Kadt et al. (2014) explored multiple ways to measure school travel in Soweto-Johannesburg using the Haversine distance formula.

Other studies have adopted more refined techniques to estimate accessibility to schools; however, these have only been applied at limited geographical scales. Macharia et al. (2023) used raster-based methods to model pedestrian travel time to the nearest public primary school at 100-m resolution across eight counties in Kenya, introducing a 24-min travel time threshold and offering a more dynamic assessment of accessibility over time, comparing the years 2009 and 2020. Oloko-oba et al. (2015) performed a network analysis using an origin–destination (OD) matrix in the Ilorin West Local Government Area in Nigeria, highlighting variations in accessibility based on road infrastructure. Other GIS-based studies, such as Bulti et al. (2019) have used buffer polygons of varying distances to assess accessibility in Bishoftu Town, Ethiopia.

Several other studies have employed GIS techniques for education planning in Africa, providing insights into school location patterns but without directly quantifying accessibility. These include Al-Sabbagh (2022) in Mansura City, Egypt; Ajala and Asres (2008) in Ethiopia's Amhara region; Ngigi et al. (2012) in Busia County, Kenya; Oluwaseun et al. (2013) in Kano State, Nigeria; and Aschale (2017) in Debre Markos Town, Ethiopia.

Outside of Africa, spatial accessibility studies have been conducted in various subnational contexts, including in China (Gao et al. 2016; Jiang et al. 2022; Ye et al. 2018), India (Jayalakshmi et al. 2024; Meena et al. 2022; Rekha et al. 2020; Sharma and Patil 2022), Brazil (Moreno-Monroy et al. 2018; Pizzol et al. 2021), and Turkey (Deniz 2024; Köse et al. 2021). These studies demonstrate the value of using travel-time-based approaches in identifying disparities in school access and informing education policy. The methodologies used in these studies vary in complexity, ranging from simple Euclidean distance measurements to more advanced floating catchment methods and models incorporating transportation networks and environmental factors. Despite these methodological advancements, studies remain largely confined to subnational contexts, often limited to a single city or region.

By contrast, the health sector has made significant advances in accessibility mapping at large scales. Weiss et al. (2020) produced global maps of travel-time to hospitals and clinics using raster-based methods for both motorized and walking transportation modes at a 1 km resolution. Also using raster-based methods but at a regional level, Ouma et al. (2018) and Geldsetzer et al. (2020), calculated spatial accessibility to healthcare in Sub-Saharan Africa. Most recently, Watmough et al. (2022) demonstrated the importance of undertaking these analyses at higher resolutions, producing 20-m resolution health facility travel time maps for Uganda, Zimbabwe, Tanzania, and Mozambique. These studies demonstrate the feasibility and policy relevance of high-resolution, large-scale accessibility modeling, and the methodologies developed in these contexts provide useful frameworks for applications in the education sector.

1.2 | Study Aims and Structure

Building on these gaps, this study aims to:

1. Provide the first dedicated, continent-wide analysis of travel-time accessibility to schools in Africa at 90 m resolution, offering a more detailed picture than previous continental analysis (Moner-Girona et al. 2025).

2. Evaluate the accuracy of model outputs against independent household survey data and explore the implications of modeling choices and assumptions.
3. Examine the intersection of accessibility with socioeconomic conditions, using Malawi as a case study to show how travel times interact with wealth and educational attainment to produce patterns of inequality.

The remainder of the paper is structured as follows. Section 2 details the data collection, processing and methodological approach, including (Section 2.1) assessing the geolocated schools database, (Section 2.2) calculating spatial accessibility, (Section 2.3) validating model outputs, and (Section 2.4) exploring socioeconomic hotspots. Section 3 presents the results as well as the findings from the model validation and comparisons. Section 4 demonstrates the applications of the results through the socioeconomic exploration of disparities in Malawi. Section 5 interprets the results in the broader context of education accessibility and discusses limitations, policy implications, and highlights directions for future research. Lastly, Section 6 summarizes the key findings.

2 | Materials and Methods

2.1 | Step 1: Assess Geolocated Schools Database

Understanding the spatial distribution of educational facilities in relation to the communities they serve is a cornerstone of this research. Most countries have aggregate statistics on number of schools, and several countries have master lists of educational facilities. However, these efforts have not been universal, and most inventories lack a spatial dimension. Large-scale studies which require geolocated school data have often relied on Open Street Map (OSM), an open-source geographic database updated and maintained by a community of volunteers via open collaboration. For instance, OSM educational facilities have been used in harmonized infrastructure datasets produced at the European (Batista E Silva et al. 2019) and at the global scale (Nirandjan et al. 2022). Yet, significant gaps remain in OSM coverage of social infrastructure, particularly schools, and data quality varies widely both within and across countries, with certain regions remaining particularly underrepresented (Anderson et al. 2022; Barrington-Leigh and Millard-Ball 2017; Herfort et al. 2023).

For this study, we use the School Electricity Access Database (SEADB) for Africa recently published by the European Commission's Joint Research Centre (JRC) (Fahl et al. 2024). SEADB integrates and harmonizes multiple sources, including UNICEF's GigaMaps, GRID3, OSM, and national-level datasets, supplemented with artificial intelligence models trained on satellite imagery to address data gaps in school locations (Moner-Girona et al. 2025). While developed primarily to support electrification planning, SEADB provides the most comprehensive georeferenced school dataset currently available for Africa,[1] making it especially suitable for large-scale accessibility analysis.

A major limitation in assessing the accuracy and completeness of existing datasets is the lack of transparent "ground-truth" data for comparison and validation (Anderson et al. 2022). Without such reference data, it is difficult to quantify the extent of missing or inaccurate information. To evaluate the coverage of both SEADB and OSM,[2] government-reported statistics on the total number of schools were compiled for each country in Africa. This involved a detailed search through primary government sources such as annual statistical reports published by national ministries of education. Given the diversity of sources and languages across the continent, this required reviewing documents in English, French, Portuguese, and Arabic. Comparisons with government-reported statistics provide an indicative benchmark for assessing coverage, rather than a definite measure of accuracy. Government figures may include schools that are nonoperational, repurposed, or affected by conflict (e.g., occupied by rebel groups) or be several years out of date. Despite these limitations, this compilation offers a novel regionally comprehensive estimate of total school infrastructure against which geospatial datasets can be compared. A summary of these findings is presented in Figure 4a,b in the Results section, and a complete table, including sources, is provided in Table S2. The implications of using different school database sources are discussed further through a comparison of model outputs presented for Malawi in Figure 10 in the Discussion section.

2.2 | Step 2: Calculate Spatial Accessibility

The term spatial accessibility can be defined as the ease with which individuals can reach a specified destination (Nicoletti et al. 2022) and is often measured as the travel impedance in distance or in time (Guagliardo 2004). Estimated travel times were computed using AccessMod, a free and open-source tool created by the World Health Organization (WHO) which has been widely used in the health sector (Geldsetzer et al. 2020; Ouma et al. 2018). Recently, AccessMod has also been applied to schools to compute travel times to the nearest public primary school for eight counties in Western Kenya (Macharia et al. 2023).

AccessMod facilitates the use of raster-based cost-distance algorithms to model physical accessibility to facilities (Ray and Ebener 2008). Raster-based methods apply a regular grid across the Earth's surface and use a "friction surface" that represents the time required to traverse each grid cell (or pixel) (Weiss et al. 2018). The time needed to get to a destination is thus determined by cumulatively adding the time needed to cross each pixel in the least-time path from the origin to the destination.

The rates of movement for each grid cell are determined by a variety of spatial features, such as landscape characteristics like elevation, land cover, and transport infrastructure. Elevation data were obtained from MERIT DEM at a resolution of 3 arc sec, approximately 90 m at the equator (Yamazaki et al. 2017) and land cover data were acquired from Copernicus (Copernicus Climate Change Service 2019). The land cover raster, originally at a resolution of 300 m, was resampled at a resolution of 90 m, using nearest neighbor interpolation, chosen to preserve categorical integrity.

Road networks were extracted from OpenStreetMap.[3] For walking speeds on roads, the average of urban and rural median

TABLE 1 | Sample sizes for assessed household surveys.

Number of responses	Malawi	Nigeria	Ethiopia	Uganda	Tanzania
Total survey responses	50,476	116,320	22,688	14,494	23,592
Non-empty responses to travel time question	17,045	38,387	6978	5174	6074
Primary and secondary school children only (excluding tertiary education)	16,907	28,432	5168	4109	5392
Of which are walking-only	16,466	24,591	4755	3925	4876
Percentage walking-only	97%	86%	92%	96%	90%

pedestrian speeds for children of 4 km/h was assumed from Makalew et al. (2020). The nonroad raster cells were assigned walking speeds based on the land cover and slope of that pixel. The average walking speeds for each different landcover type was taken from a study conducted in Weiss et al. (2018). The complete list is available in Table S1. Walking speeds are adjusted to factor in elevation using Tobler's formula, $V = V_F \times e^{-3.5 \times abs(S+0.05)}$, where V is the corrected walking speed, V_F is the walking speed on a flat surface and S is the slope in hundredth of percent (Ray and Ebener 2008). The implications of using different walking speed assumptions are discussed further through a comparison of model outputs presented for Malawi in Figure 10 in the Discussion section.

The resulting friction surface and the location of schools were used to calculate the least-time path from any given grid cell to the closest school using Dijkstra's algorithm. The analysis was confined to within the national borders, assuming populations do not cross borders to access schools in neighboring countries.

The accessibility maps were then overlaid with population data to explore how school access varies with the spatial distribution of people. The Global Human Settlement Layer (GHSL) for 2020 was used (Pesaresi 2022). Although this population dataset does not specifically refer to school-age children, it was selected for its high spatial resolution (3 arc-sec, approximately 90 m), which matches the resolution of the travel time maps. While age-disaggregated population data were considered, available datasets were at a coarser resolution (typically 1 km) and were therefore not used in order to preserve spatial fidelity in the analysis. As a result, no explicit assumptions about the proportion of school-aged children were made.

The model assumes that all areas within a country's boundaries are passable and does not account for potential movement restrictions imposed by land ownership, protected areas (such as national parks and game reserves), or contested and occupied territories. Similarly, pedestrian movement across water bodies was modeled using a very low travel speed of 1 km/h (following Weiss et al. 2018), to reflect occasional crossings in contexts where ferries, boats, or informal routes may exist but are not explicitly mapped. These assumptions are driven by the lack of consistent, high-resolution data on access restrictions across the continent. While necessary for model implementation at this scale, they represent simplifications that may lead to overestimation of accessibility in certain locations.

To situate our results within the emerging literature, we compared our 90 m travel time surfaces to the 1 km continental maps produced by Moner-Girona et al. (2025). Their maps were generated by computing least-time paths to schools using the 1 km friction surfaces developed by Weiss et al. (2018, 2020), implemented through the R gdistance package and companion code (Weiss et al. 2018, 2020). The resulting travel time maps were obtained via the public WMS geoserver of JRC's Clean Energy Access Tool (JRC 2025). Full details of this comparison are provided in the Supplementary Note: Model Comparisons in Data S2.

2.3 | Step 3: Compare and Validate Model Outputs

In order to validate the accessibility model, results were compared with self-reported travel time to school from nationally representative household surveys. The relevant survey questions, data fields, and processing steps are detailed in Table S3. A review of nationally representative and publicly available surveys was conducted for all countries in Africa. At the time of publication, the following five nationally representative surveys were found to include a relevant question about travel time to the respondent's school measured quantitatively. These are: the fifth wave of the Ethiopia Socioeconomic Panel Survey 2021–2022 (Ethiopian Statistical Service 2024), Malawi's Fifth Integrated Household Survey 2019–2020 (National Statistical Office 2020), Nigeria's Living Standards Survey 2018–2019 (National Bureau of Statistics 2021), the fifth wave of the Tanzania National Panel Survey 2020–2021 (National Bureau of Statistics 2023), and the Uganda National Panel Survey 2019–2020 (Uganda Bureau of Statistics 2021). Note that Ghana's Socioeconomic Panel Survey from 2009–2010 (Institute of Statistical, Social and Economic Research and Economic Growth Center 2016) does include a question about travel time to school but was excluded since it is more than 10 years old, and the outdated data may not reflect current infrastructure.

The selected surveys were subsequently filtered to only include nonempty responses from children attending primary and secondary schools. Table 1 below summarizes the number of responses available for each country's surveys.

Due to confidentiality restrictions on the exact geographic locations of the households, direct spatial comparisons were not feasible. Instead, the cumulative distribution functions (CDFs) of reported travel times were compared with the CDF generated in our analysis. Where survey samples were stratified rather than being randomly selected from the population, the data were adjusted using sampling weights. The methodology for calculating household weights is detailed in the respective survey documentation. The subset of surveys where the respondents walk to school was compared with the pedestrian accessibility raster maps, and the results are summarized in the Model validation and comparisons results section.

While this approach offers a practical means of comparison, it makes several assumptions. Reported travel times in household surveys may be affected by perception bias, and the subset of respondents who answered the travel time question—shown to be a minority in Table 1—may not be fully nationally representative.

We conducted a comparison of our 90 m model with the publicly available 1 km travel time maps produced by Moner-Girona et al. (2025). We overlaid the 1 km raster outputs with our own high-resolution travel time maps and compared their spatial distributions, cumulative travel time functions, and resulting population access estimates. All comparison methods and results are reported in the Supplementary Note: Model Comparisons in Data S2.

2.4 | Step 4: Explore Socioeconomic Hotspots

The high-resolution outputs produced can be explored together with other socioeconomic data layers in order to identify patterns, relationships, and visualize hotspots of educational disadvantage. To explore relevant inter-relationships, the travel time accessibility maps were combined with relative wealth and educational attainment data. For wealth, gridded micro-estimates of the distribution of relative poverty and wealth were used (Chi et al. 2022). Data are available at a 2.4 km resolution for all low- and middle-income countries. Estimates on educational attainment were taken from Graetz et al. (2018), who estimated years of schooling by age and sex at a 5 km resolution for the continent of Africa. Data for 2015 were used, as it is the latest year available.

To analyse spatial patterns, a hexagonal aggregation approach was employed. This method enables the identification of areas where multiple disadvantageous factors coincide, such as high travel times, low educational attainment, and low relative wealth. Hexagonal binning preserves local spatial relationships without imposing artificial boundaries or providing a false sense of accuracy when downscaling coarser datasets. A hexagonal grid was then generated using the H3 hexagonal grid at a resolution of 6, corresponding to approximately 36 km^2 per hexagon (Uber 2025). Summary statistics were computed for three key indicators: accessibility, measured as travel time to closest school in minutes; wealth, measured by the relative wealth index; and attainment, measured as mean years of female educational attainment in years. Female educational attainment was used as the primary indicator variable to incorporate a gender-focused perspective, given the persistent disparities in educational access and completion rates between boys and girls in the region.

Each hexagon was classified as being "high" or "low" for each indicator if more than 50% of the values inside the hexagon were above or below a given threshold. For accessibility, a 30-min threshold was used, based on the UNESCO standard of a 2 km walking travel distance to school (Oloko-oba et al. 2015) at an assumed 4 km/h speed (Makalew et al. 2020). For wealth, given the relative nature of the metric, the country's median wealth value was used as the threshold. For educational attainment a threshold of 6 years of education was used, in line with universal primary schooling goals (Friedman et al. 2020). Hexagons were then classified into distinct cluster categories based on the prevalence of high or low values for each indicator. This classification helps identify spatial patterns, explore within country inequalities, and visualize critical hotspots of educational disadvantage.

3 | Results

Given that the vast majority of children walk to school, this analysis focuses exclusively on pedestrian accessibility. Both the existing literature (Macharia et al. 2023) and the household survey data support this decision. For instance, 97% of respondents in Malawi reported walking as their primary mode of travel to school, with the remaining sample too small to allow for meaningful CDF comparisons at a national scale. While an individual's selection of travel mode is complex and shaped by a range of geographical, social, and economic factors (Henne et al. 2014; Meena et al. 2022), walking represents the most inclusive and commonly used form of school travel, serving as a reasonable lower bound for estimating accessibility. In contrast, models of motorized travel assume access to a private vehicle and direct, door-to-door routes—assumptions that are often unrealistic in the education context, where journeys frequently involve multiple modes of transport, public transport, and indirect journeys. As such, the remainder of this analysis presents results based solely on walking accessibility.

Figure 1a below depicts the calculated travel time to the closest school for the entire continent of Africa at the 90 m grid resolution. Figure 1b aggregates the average travel time weighted by population at the subnational regional level. Administrative zones are taken from the Global Administrative Areas levels 1 and 2 (GADM 2022).

At the continental scale, our 90 m accessibility surfaces reveal substantial variation in travel times to the nearest school, with marked differences between urban and rural regions. Accessibility is highest in densely populated corridors of Western, Eastern, and Southern Africa, while remote areas of the Sahel, Central Africa, and the Horn of Africa face the longest travel times.

Across Africa as a whole,[4] 47.3%, 62.3%, and 73.1% of people are within a 15, 30, and 60-min walk respectively from their closest school. A staggering 16.5% of the population remains without access to a school within a 3-h walk. Subnational patterns show strong within-country disparities, with long travel times clustered in pockets of inaccessibility even in countries with high national averages. These disparities highlight how national statistics can obscure important local accessibility gaps.

By intersecting these results with the GHSL 1 km resolution degree of urbanization maps (Schiavina et al. 2023) the relationship between accessibility and population density can be explored. As expected, accessibility varied significantly across the degree of urbanization, with urban areas having significantly

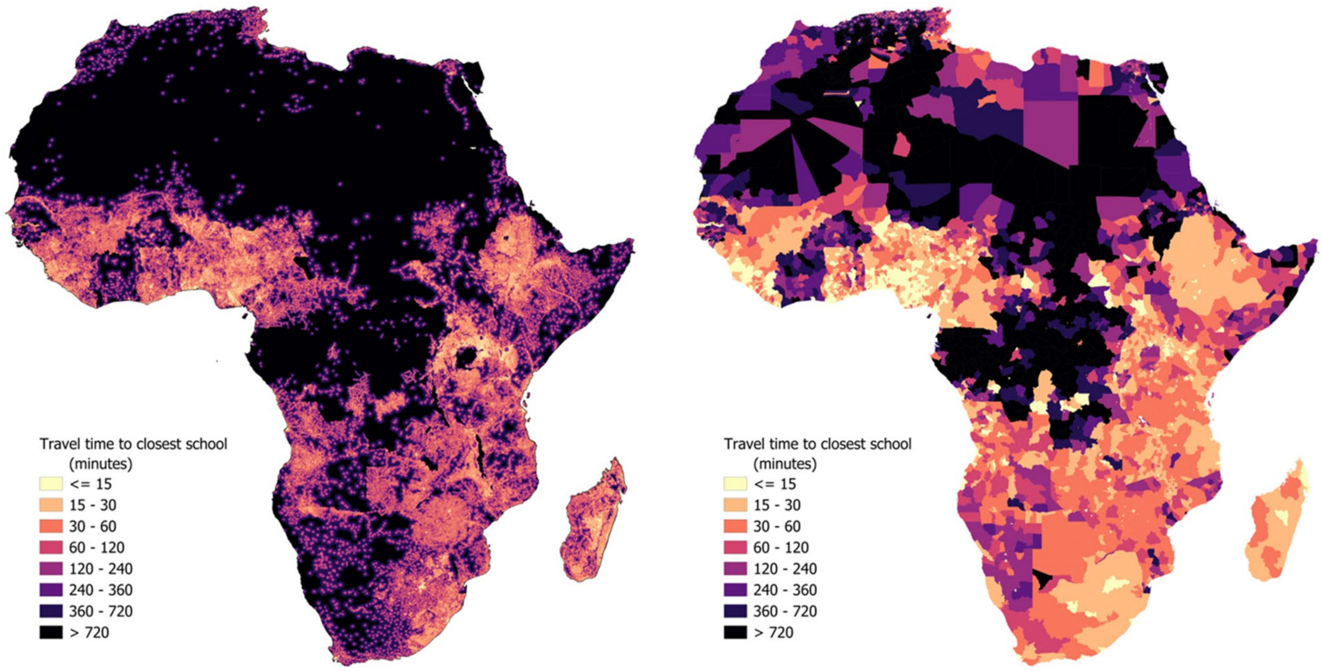

FIGURE 1 | Travel time (minutes) to closest school in Africa at (a) the 90 m grid level and (b) weighted by population at the subnational regional level.

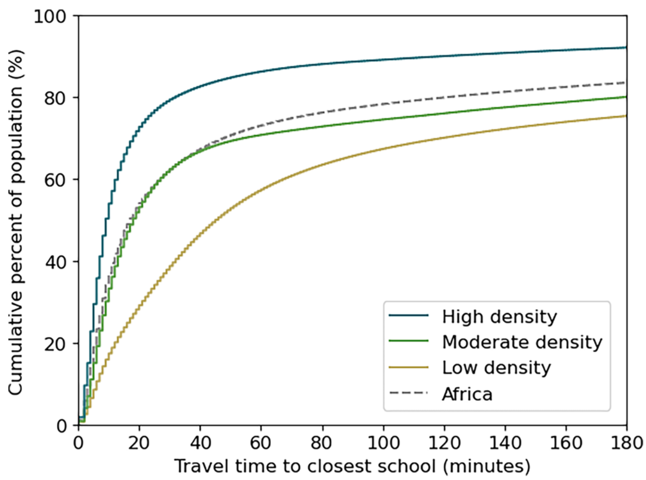

FIGURE 2 | Cumulative population distribution of travel time to closest school, by degree of urbanization.

lower travel times than rural areas. Figure 2 compares the cumulative population distribution of travel time for different degrees of urbanization across the continent.

When broken down by country, accessibility ranged from less than 25% of the population within a 30-min walk to the closest school in Burundi, Burkina Faso, Algeria, Chad, and Sudan to more than 90% in Sierra Leone, Gambia, and South Africa. The breakdown of population distribution for each country at different travel time thresholds is depicted in Figure 3. For the countries where the total number of geolocated schools is within a 30% margin of reported schools, the database is considered to be representative and marked in bold. Results for countries not highlighted in bold should be interpreted with caution, as the limited data completeness for these countries may affect the national representativeness of the findings. This is discussed further in the following section.

4 | Model Validation and Comparisons

4.1 | Comparing School Dataset With Government Statistics

In order to assess the completeness of school datasets, Figure 4a,b below show the aggregate numbers of schools per country as a percentage of reported national statistics for OSM and JRC respectively. While the JRC dataset appears to be more complete, there is still a large discrepancy between reported schools and those included in school datasets. There are only 19 countries where the number of schools is within 70% margin of those reported. This goes down to only three countries if using OSM. Table S2 includes the complete statistics and sources for each country.

To illustrate the implications that incomplete underlying data can have on model outputs, the following example provides a comparison of pedestrian accessibility to schools using JRC government data ($n = 7062$) and OpenStreetMap data ($n = 968$) in Malawi. In Figure 5, the cumulative population distribution is compared for both scenarios demonstrating the vital implications incomplete data can have on model outputs. When using the incomplete school locations provided by Open Street Map, the model significantly overestimates travel time and paints a very different picture of the national reality.

4.2 | Comparing Travel Time Distributions With Household Survey Data

To assess the model's accuracy, we compared modeled travel times against household-level survey data. The resulting population cumulative distribution functions are illustrated in Figure 6a–e for Malawi, Uganda, Tanzania, Nigeria, and Ethiopia. As highlighted in the Materials and Methods Section 2,

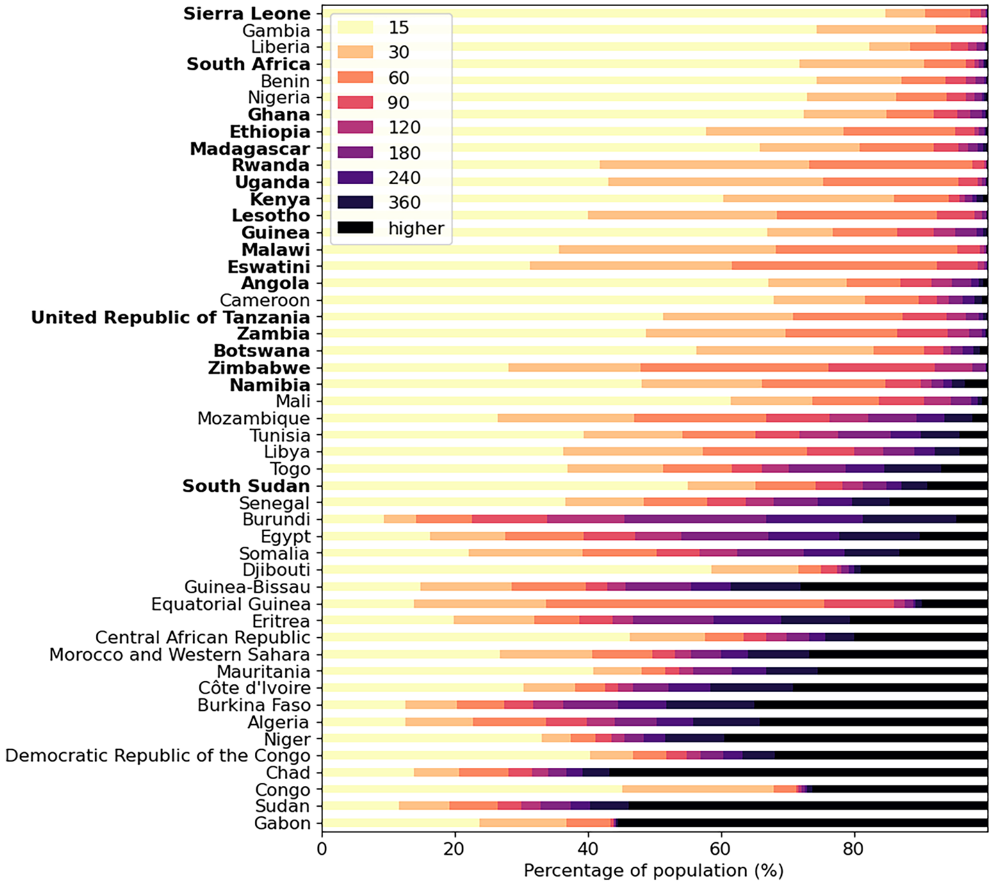

FIGURE 3 | Percentage of population within given travel time thresholds to closest school, ranked by population weighted average travel time. Countries marked as bold are considered nationally representative.

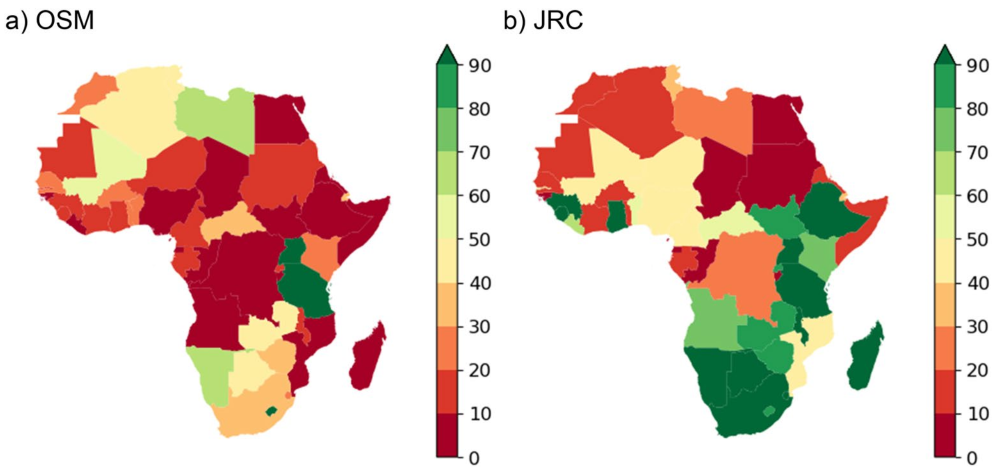

FIGURE 4 | Total numbers of schools in a country as a percentage of reported national statistics for (a) OpenStreetMap and (b) JRC datasets respectively.

these were the only countries where household data were available for comparisons. Note that in all five countries, the total number of geolocated schools in the JRC dataset is within a 30% margin of reported schools.

When validated against household survey data, the model demonstrates a reasonable level of accuracy in calculating travel time. Across all cases, the distributions align closely in both shape and range. In Nigeria and Ethiopia, the stepwise pattern observed in the survey data reflects that responses were recorded in only six discrete time intervals. Despite this, the overall shape of the distribution still mirrors the modeled results, indicating some consistency in the underlying travel time structure. In Uganda in particular, there is a slight tendency to underestimate travel times, a tendency that is explored further in the Discussion section.

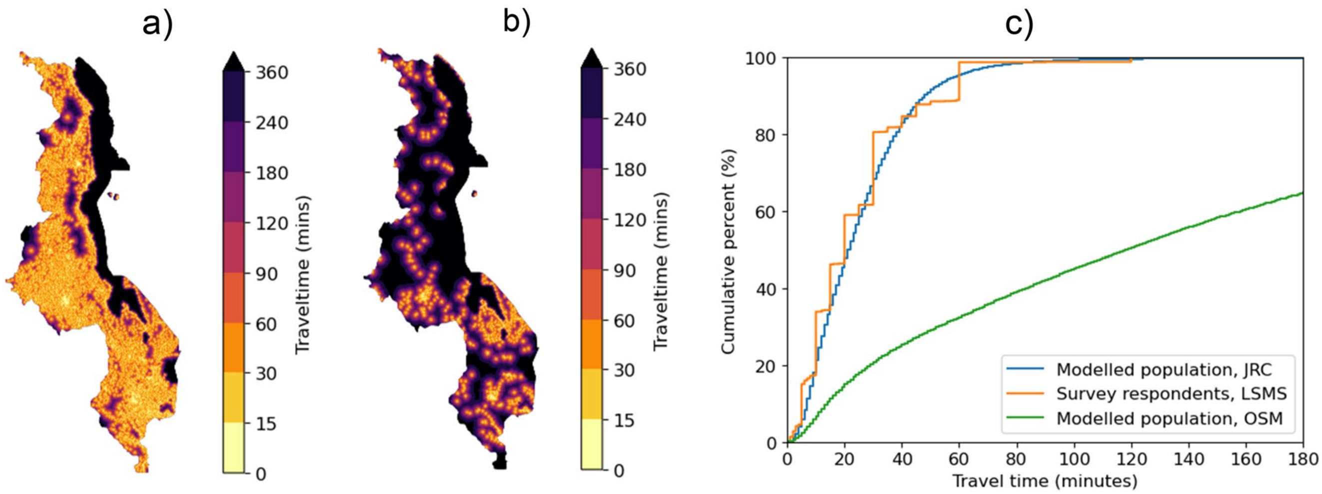

FIGURE 5 | Travel time (minutes) to closest school in Malawi using (a) JRC government schools dataset, (b) OpenStreetMap schools dataset, and (c) the cumulative population distribution of household survey respondents.

4.3 | Comparing Results With Published 1 km Travel Time Maps

We compared our results using the 90 m travel-time surfaces with the 1 km continental maps produced by Moner-Girona et al. (2025). Full details of this comparison methods and results are reported in the Supplementary Note: Model Comparisons in Data S2.

Figure 7 below maps the difference in travel time estimates between the two models (Δ = 90 m–1 km), masked to include only populated areas. Purple areas indicate where the 90 m model predicts longer travel times, while orange areas show where it predicts shorter times. The map reveals a general trend toward shorter travel times in the lower-resolution model. This is particularly pronounced in the Mediterranean woodland and forest region of Northern Africa, as well as in Burkina Faso, Côte d'Ivoire, and Togo in Western Africa. In contrast, there are a few areas where the 90 m model estimated shorter travel times, particularly around the Sahel region south of the Sahara Desert.

Comparing population distribution curves confirmed that the 1 km model consistently estimates shorter travel times than the higher-resolution 90 m model, particularly at short distances—suggesting that coarser-resolution approaches may substantially overestimate school accessibility. Reasons for this discrepancy are explored in the Discussion section below. These modeling differences are significant: an estimated 11.4 million fewer people fall within a 30-min threshold when using the finer-resolution model. Additional results are available in the Supplementary Note: Model Comparisons in Data S2.

5 | Applications

5.1 | Socioeconomic Hotspots in Malawi

The socioeconomic analysis examined the relationship between modeled travel time to schools, educational attainment, and wealth at a subnational level. To ensure analytical robustness, this exploration was limited to Malawi[5]—where school location data appeared complete, and where validation showed the closest alignment between modeled and observed travel time distributions, with the lowest absolute difference (A^{abs}) among all validated countries (see Supplementary Note Table N2 in Data S2).

Figure 8 below illustrates the relationship between female education attainment, travel time to the closest school, and the relative wealth index for every populated hexagon grid cell in Malawi. The results reveal a negative association between travel time and female educational attainment: as travel time increases, educational attainment declines. The fitted regression indicates that a tenfold increase in travel time is associated with an estimated 1.8-year reduction in average years of schooling for girls. The explanatory power of this relationship is modest ($R^2 = 0.11$), suggesting that while school accessibility plays a role in shaping educational outcomes, many other factors also contribute. Additionally, wealthier areas (shown in blue) tend to exhibit both higher levels of educational attainment and better school accessibility.

To further investigate spatial patterns, a hexagonal grid approach was used to classify areas based on the proportion of the population experiencing high or low values for each variable. High and low classifications are based on thresholds defined in the Methods section (6 years of schooling, country median wealth, and 30 min for travel time). This approach yielded four key cluster categories, summarized in Table 2 and mapped in Figure 9. Table 2 reports the population shares associated with each cluster, while Figure 9 presents the corresponding spatial distribution across Malawi.

"Well-served areas" (22.5% of the population) are predominantly located in major urban centres, including the capital of Malawi, Lilongwe, and Blantyre, Zomba, and Mzuzu, as well as in surrounding peri-urban zones. "Critical areas," where accessibility, wealth, and attainment are all low, account for 15.5% of the population, with scattered patterns across central and southern Malawi. These clusters highlight where overlapping disadvantages can reinforce educational exclusion and emerge as clear priority regions for intervention.

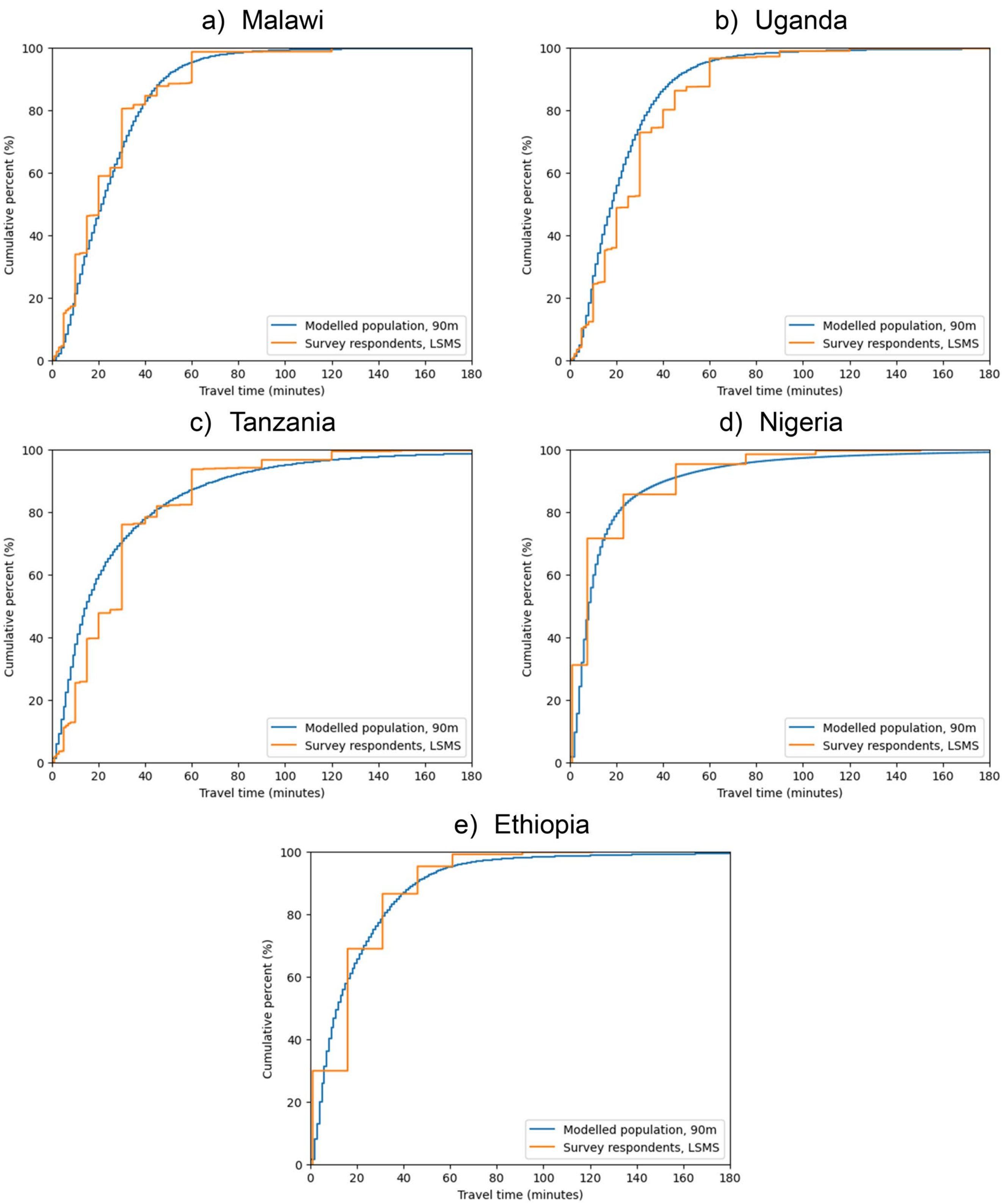

FIGURE 6 | Cumulative population distribution of travel time to closest school for modeled population (in blue) and household survey respondents (in orange) for (a) Malawi, (b) Uganda, (c) Tanzania, (d) Nigeria, and (e) Ethiopia.

In contrast, several regions in the northern part of Malawi stand out as "underserved yet educated". Despite long travel times and economic disadvantage, these areas demonstrate educational attainment levels that exceed what might be expected given the structural barriers present. This cluster makes up 4.2% of the population and is concentrated in isolated pockets, particularly in the northern part of the country. These patterns may reflect strong local education cultures, community resilience, or informal support systems that enable children to attend and succeed in school despite structural barriers. Highlighting these

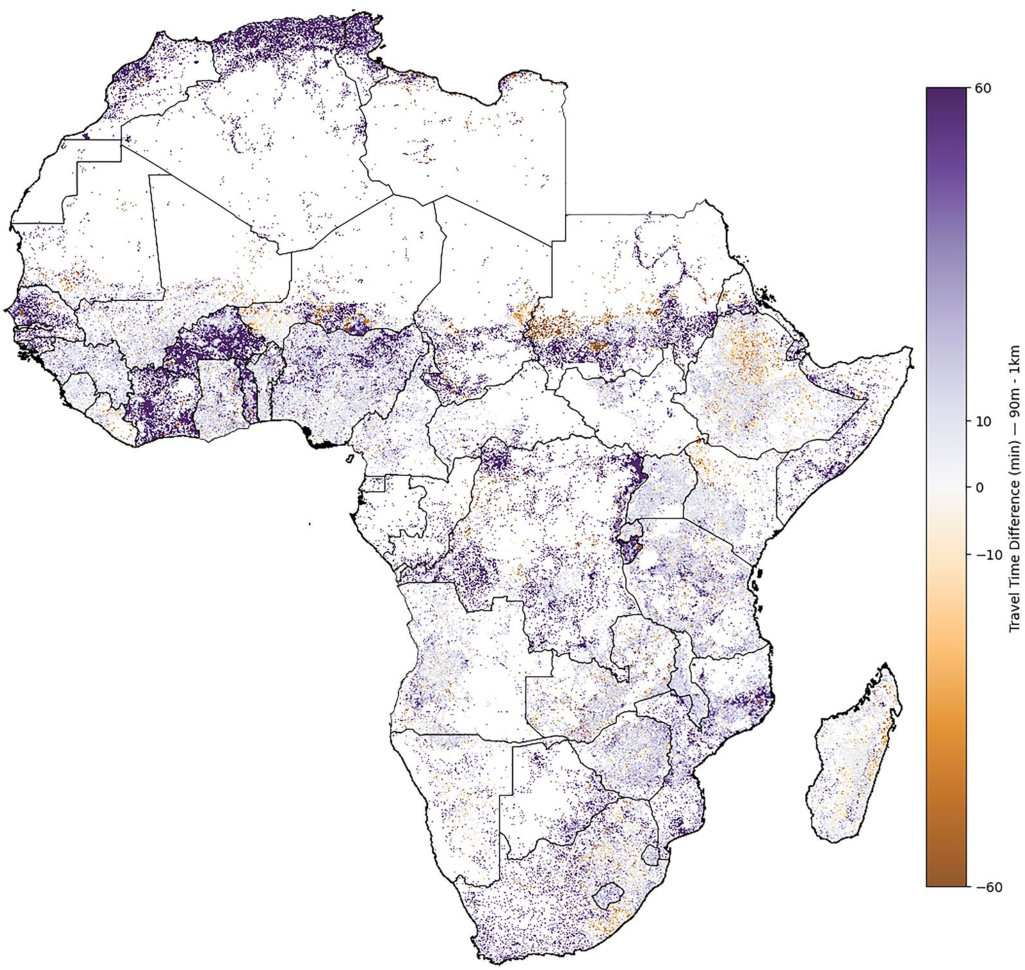

FIGURE 7 | Difference in estimated travel time to the nearest school between the 90 m and 1 km models (Δ = 90 m–1 km). The map is masked to include only populated areas (population > 0).

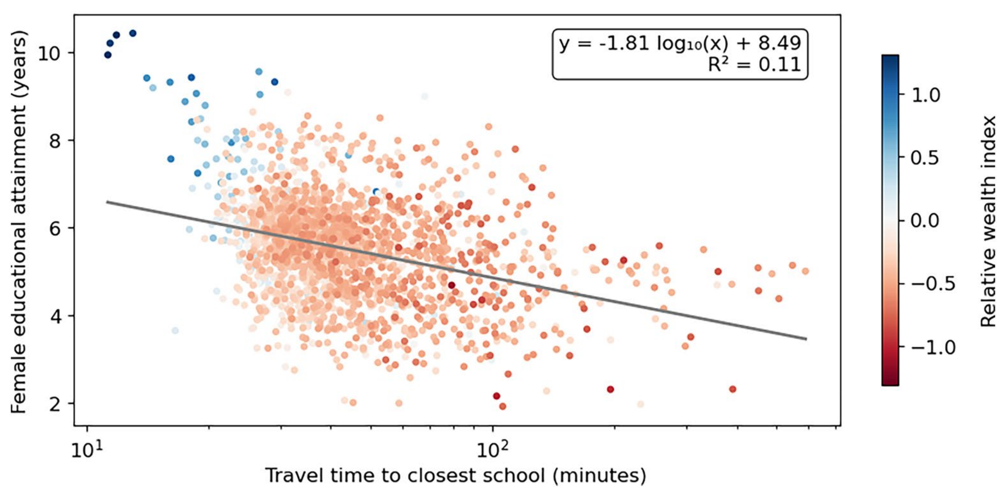

FIGURE 8 | Relationship between female educational attainment in years, travel time to closest school, and relative wealth in Malawi.

combinations provides direction for further study of explanatory factors.

These results highlight the complex interplay between socioeconomic factors and school accessibility and reveal geographic variation in how educational opportunity and disadvantage are distributed across the country. This classification approach reveals that the relationship between accessibility and education is not uniform across space and that interventions must be responsive to different local dynamics. While areas of compounded disadvantage demand urgent support, places of resilience offer valuable insights for what works under constraint and may inform effective, context-sensitive strategies elsewhere.

TABLE 2 | Cluster classifications and definitions for socioeconomic hotspot exploration, with percentage of total population in each cluster.

Cluster	Interpretation	Attainment	Wealth	Accessibility	% Pop[a]
Critical areas	Urgent need for intervention—remote, poor, and low education	Low	Low	Low	15.5%
Local educational gaps	Schools are nearby, but other issues are limiting learning	Low	Low	High	3.5%
Underserved yet educated	Despite long travel times and low wealth, attainment is still high	High	Low	Low	4.2%
Well-served areas	No major concerns; good access, wealth, and attainment	High	High	High	22.5%

[a]These four clusters account for 54.2% of the total population. The remainder, 45.8%, falls into unclassified areas.

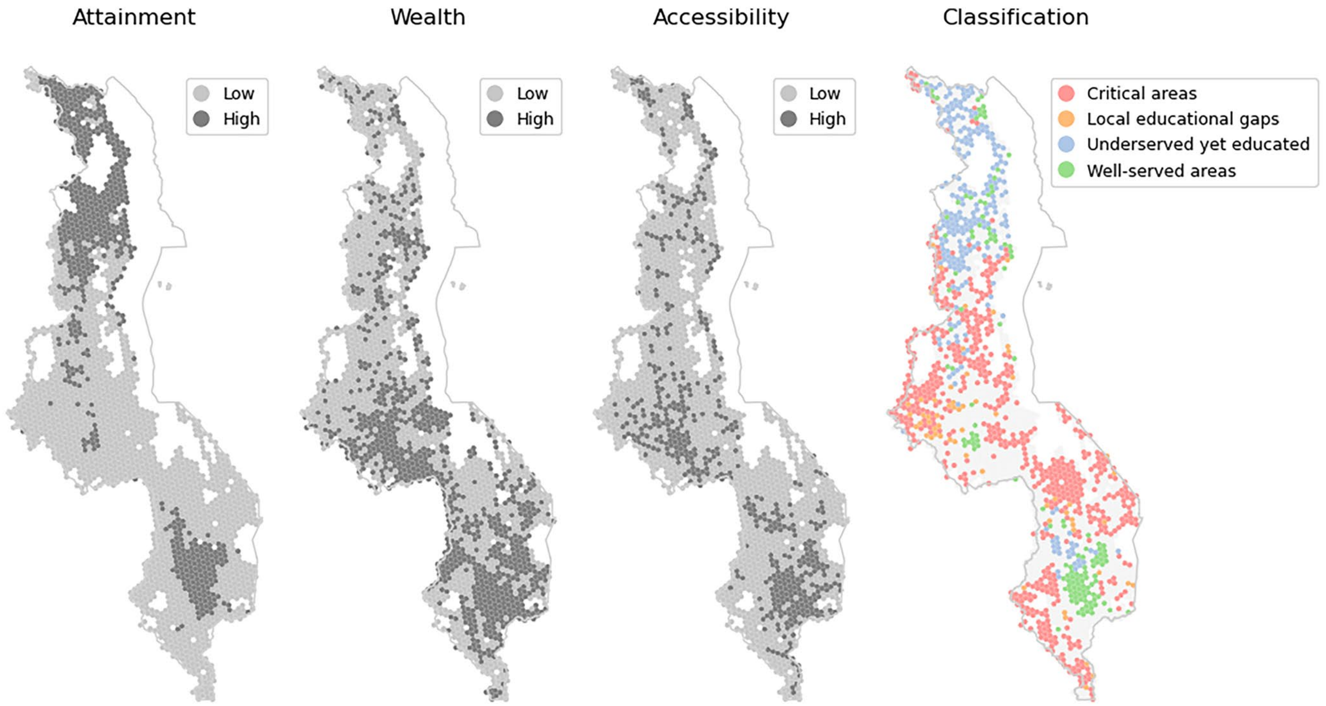

FIGURE 9 | Threshold-based classification maps for female educational attainment, wealth, and accessibility followed by cluster classification (left to right) in Malawi.

Overall, this application underscores the potential of spatial accessibility analyses to inform our understanding of educational disparities while aligning with the Sustainable Development Goals' mandate to leave no one behind.

6 | Discussion

This study set out to address three main objectives. First, it aimed to provide the first dedicated, continent-wide assessment of travel-time accessibility to schools in Africa at 90 m resolution, offering a more detailed picture than previous continental-scale analyses. Second, it sought to evaluate the accuracy of the resulting accessibility estimates using independent household survey data, and to examine how key modeling choices and assumptions influence model outcomes. Third, the study aimed to explore how accessibility interacts with socioeconomic conditions, using Malawi as a case study to examine how travel time, wealth, and educational attainment intersect to shape patterns of inequality. The results are discussed below in relation to these objectives.

The findings of this study reveal substantial spatial heterogeneity in travel time to school across and within African countries. While some areas demonstrate relatively high accessibility, large segments of the population still face long travel times, underscoring persistent geographic inequities that hinder progress toward SDG 4. These disparities align with broader patterns of urbanization, with low-density regions performing particularly poorly. The results reaffirm that physical distance continues to constitute a major barrier to educational opportunity across much of the continent.

6.1 | Advancing the Evidence Base

This study makes several contributions to the growing literature on spatial accessibility and education planning. First, it

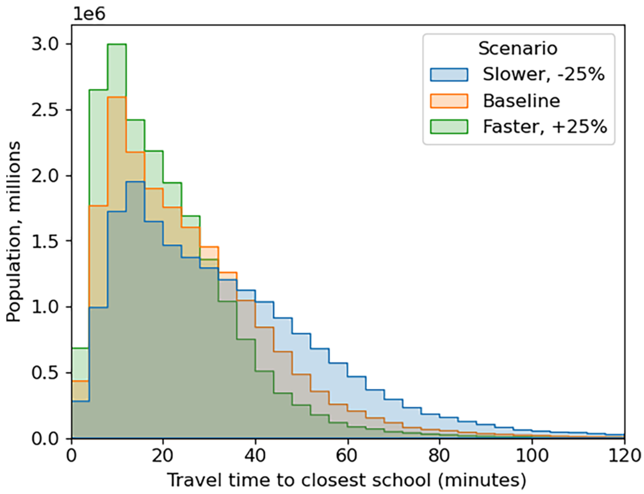

FIGURE 10 | Population frequency distribution of travel time to closest school in Malawi under baseline walking speeds (in orange), 25% slower speeds (in blue) and 25% faster speeds (in green).

introduces a high-resolution modeling framework to estimate travel time to school at a 90 m resolution, an order of magnitude finer than the 1 km products used in earlier continental analyses. Second, it provides a continent-wide comparison between spatial school databases and nationally reported government statistics, revealing substantial gaps in spatial data and demonstrating how incomplete school inventories can severely distort accessibility estimates. Third, validation against household surveys in five countries adds a novel level of empirical grounding, improving understanding of model performance and providing an important step forward in a context where the validation of GIS-based accessibility models remains limited (Rudolfson et al. 2020). Finally, by linking travel time to subnational educational attainment and wealth, the study further demonstrates how spatial models can be used not only to assess access but also to identify geographic patterns of educational inequality and compounded disadvantage. Collectively, these contributions extend both the methodological and the applied scope of accessibility modeling for the education sector.

6.2 | Contributions Relative to Existing Work

The travel time output maps generated in this study broadly align with those recently published as intermediate outputs in Moner-Girona et al.'s school electrification study (Moner-Girona et al. 2025). Both maps produce similar spatial patterns of travel time when compared at the continental level. However, a closer inspection reveals important differences and offers insights into how resolution and methodological decisions can shape accessibility outcomes.

The 90 m model consistently predicts longer travel times than the 1 km model across most of the continent. The population distributions of the 1 km model depict unrealistic jumps due to discretization. This is particularly pronounced at shorter time thresholds. The discrepancy at a 0-min journey is also very significative. The 1 km model assigned nearly a third of the continent's population (32.0%) a 0-min journey, much more than the 90 m model (1.1%). The distribution function comparisons show this clearly, and it aligns with known effects of spatial averaging in coarser models (Watmough et al. 2022).

Such differences in the models, especially at lower travel time thresholds, have significant implications when statistics are aggregated to national or regional levels and used to evaluate progress toward accessibility policy targets. Policymakers relying on coarse models may significantly misrepresent the number of people with poor school access, especially around the 15–30 min policy thresholds.

6.3 | Why Resolution Makes a Difference

In raster-based modeling, each grid cell represents an area of uniform terrain and speed conditions. Coarser models, such as those using 1 km cells, therefore treat everyone within each square kilometer as starting from the same point and moving at the same average speed. For example, if a school exists within a cell, the travel time assigned to the entire population in that cell is zero. In reality, unless someone lives at their school, the journey to school will take longer than 0 min. This example also demonstrates the significance of resolution in raster-based analyses. The coarser the cell resolution, the more erroneous this assumption becomes, as the probability a school falls in any given grid cell increases, and larger areas will be assigned 0-min travel times. The unaccounted time needed to cross a single cell will also be more substantial. For instance, traveling across a 90-m cell at 4 km/h would only add 81 s to your journey. Meanwhile for a coarser cell of 1 km, this could add 15 min.

Because travel times are accumulated cell by cell, the possible outcomes occur in fixed increments corresponding to the time required to traverse a single cell. This discretization produces the stepwise or "jumpy" shapes visible in cumulative distribution functions, reflecting the limited set of possible travel-time values.

In the finer-resolution model, the travel-time increment per step is around 1 or 2 min. This allows for smoother gradients of travel time and more continuous accessibility distributions. The finer grid also captures local variation in land cover, slope, and transport networks that would otherwise be averaged out in coarser models. As a result, higher-resolution models not only generate smoother statistical distributions but also reduce spatial aggregation errors, better represent heterogeneity within settlements, and more accurately align with high-resolution population datasets used to assess educational access. Studies exploring the implication of rasterization on travel time estimations to health care have also suggested that a reduction in cell size provides better travel time estimates and more accurate routing results (Delamater et al. 2012; Watmough et al. 2022).

It is important to also consider technological barriers and the computational burden of finer resolution modeling. Higher resolution raster maps are larger in size, which has implications on data storage requirements and could present computational challenges, ultimately limiting who can actually use this data. This is especially relevant for actors interested in travel time maps for the entire continent. For context, the continental 1 km friction surfaces are 320.9 MB in size compared to the 90 map which is 25.8 GB. The large file size puts into question the practical benefits of finer resolution. However, if users were only interested in a single country or in a small region, the computational burden of the increased resolution becomes even more feasible. The 90 m Malawi map, for instance, is only 71 MB. The map for the country with largest area in the continent, Algeria, is 1 GB. While not negligible, these file sizes are much more manageable for stakeholders interested in a national scale. These country maps are available to download as tiffs on Zenodo. Refer to the Data availability statement section for more details.

7 | Limitations and Future Directions

7.1 | Rasterization

Whether at 1 km or at 90 m resolution, the process of rasterization has an inherent loss of detail which inevitably introduces errors (Buzzelli 2020). While the efforts in producing high-resolution maps (90 m) aimed at reducing those, there are still many limitations inherent to the method. Rasterization inevitably simplifies a complex and continuous landscape into squares, which average the heterogeneity of terrain, infrastructure, and settlement patterns. As a result, some local detail and nuance are lost, and travel times can only ever be represented as approximate averages rather than exact journeys.

An alternative to raster travel time maps, object-based models represent transport networks as a network, comprised of a collection of nodes and connected edges (Thacker et al. 2017). Travel time is then calculated primarily based on the road network and its properties. While network-based methods have advantages, especially when representing dense complex networks, they are largely dependent on the completeness of the road network, with areas not reached by the road network simply being considered out of range (Petricola et al. 2022). This limitation has particularly vital implications in the African continent, where (1) road network data completeness varies significantly by country (Barrington-Leigh and Millard-Ball 2017); (2) most schools are not accessible via paved roads (GEM Report UNESCO 2023); and (3) although walking routes to school do often entail walking alongside major roads (Watmough et al. 2022), they often also require crossing cultivated farmlands, shrublands, and bush areas (Porter et al. 2010).

To overcome their respective limitations, future research could consider constructing combined network- and raster-based methods. Raster methods can be used to assess rural accessibility, where broader spatial patterns dominate, and the resolution of raster data is less restrictive, while network methods can be more suited for assessing urban accessibility, where network data quality tends to be better.

7.2 | Travel Speed Assumptions

Another limitation of this model is that it does not account for several important factors which can impact travel speeds. Pedestrian walking speed assumptions are uniform and simplified and do not account for factors that influence actual travel times. First of all, the model remains static, assuming a constant pace regardless of journey length without incorporating the effects of fatigue or exhaustion that may slow pedestrians over longer distances. External conditions such as weather and road quality which can further impact walking speeds (Mroz et al. 2023) are also not considered. Additionally, individual human characteristics and circumstances play a significant role, with children of different ages moving at varying speeds and children with disabilities or mobility challenges as well as mothers carrying young children traveling slower than estimated.

Raster-based least-time accessibility models have been found to be particularly sensitive to travel speed assumptions (Delamater et al. 2012; Petricola et al. 2022). Given the variability of real-world walking speeds, the model outputs were regenerated assuming different walking speeds. As an illustrative example of the sensitivity of the model to speed assumptions, Figure 10 below depicts the travel time distribution in Malawi with 25% faster (in green) and 25% slower (in blue) walking speeds.

With walking speeds 25% faster, a total of 86.0% of the population is within 30 min from the closest school, compared with 59.4% with walking speeds 25% slower. This is equivalent to 5.2 million people that are no longer within the 30-min threshold. Given the variability demonstrated in this example, it is important to consider travel speed assumptions carefully when modeling school accessibility.

The landcover walking speeds used in this analysis, and in many other accessibility analyses including Moner-Girona et al. (2025), reference the survey reported in Weiss et al. (2018):

> The [baseline speed of movement overland on foot] was created by summarizing results from an online survey designed to crowd-source estimates of how long it takes individuals to traverse each land cover type. The survey consisted of representative photos and global maps of each land cover type. Respondents were asked to estimate the amount of time it would take them to travel one kilometre (or one mile) on foot through each land cover type. The survey received 407 complete responses and, after standardizing the distance units, the median values for the fifteen land cover classes within the survey (in units of km h−1) [were reported]

The comparisons in Malawi conducted in this study, found that the accessibility model was highly sensitive to walking speed assumptions. Yet, these highly sensitive parameters are rooted on the opinions of 407 people. Of those, it is questionable how many have actually walked across a desert, or through a wetland. Given the importance of this underlying dataset, human travel speeds in different contexts merits further research that is grounded in observation rather than survey responses.

7.3 | Behavior

While the model assumes that children travel via the shortest-time path to the nearest school, real-world travel behavior often diverges from this assumption. Including behavioral realism to spatial accessibility models remains a challenge, due to insufficient data to adequately characterize and conceptualize actual travel behavior and choice (Kwan et al. 2003; Mroz et al. 2023). Localized studies of school travel have found that children's routes frequently deviate to avoid unsafe or busy roads, physical barriers, poorly lit areas, or to walk with peers (Dessing et al. 2016; Duncan and Mummery 2007; Ikeda et al. 2019). Furthermore, children do not always attend the geographically nearest school (Kwan et al. 2003). While physical convenience remains an important factor in school choice (Ngware and Mutisya 2021), selection is also influenced by a range of factors, including school quality, fees, religious affiliation, language of instruction, and parental preferences (De Kadt et al. 2014; Immelman and Roberts-Lombard 2015). As such, the modeled travel times represent potential accessibility, rather than *actual* journeys undertaken by all children.

Travel time estimates of potential accessibility can serve as a first-order assessment to identify regions with particularly poor access but should not be used in isolation to make definitive policy decisions. Instead, they should guide further local-level investigations and inform resource allocation, ensuring that interventions are responsive to the specific needs and lived experiences of communities. Combining spatial analyses with qualitative and community-based approaches will be essential to develop a more comprehensive understanding of barriers to education and to design context-sensitive, effective policy responses.

8 | Conclusion

This study has leveraged technological advancements and the increased availability of high-resolution geospatial data to generate school accessibility maps across the continent of Africa at a 90-m resolution. By systematically mapping pedestrian accessibility at this scale and resolution, the research found significant spatial heterogeneity in walking times to school. Only in Liberia and Sierra Leone are over 80% of the population within a 15-min walk to their closest school, whils 16.5% of the population across Africa remains more than a 3-h walk away from their closest school.

The study exposed data gaps in commonly used school inventories, and the implications that poor data quality has on accessibility estimates. A dataset of nationally reported aggregate statistics on school numbers for every country in Africa was compiled. By comparing this to the total number of schools included in the underlying spatial databases, we identified 31 countries where poor data quality is likely jeopardizing the accuracy of the results. These accessibility maps, while not necessarily representing the ground-truth in these contexts, still provide important signals that targeted improvements in geospatial school data quality are urgently needed. The findings also serve as a cautionary reminder to researchers and practitioners about the risks of relying uncritically on OSM educational facility data, which, despite its widespread use in global and large-scale studies (Mühlhofer et al. 2024; Nicoletti et al. 2023; Nirandjan et al. 2022), often suffers from incomplete and uneven coverage, undermining the validity of model outputs.

Comparisons with household survey data and with recently published 1 km travel time maps provided important context for interpreting the model results. The 1 km model was found to overestimate accessibility relative to the 90 m model, with pronounced discrepancies at short travel time thresholds and most notably, an unrealistic share of the population assigned 0-min journeys.

The analyses conducted in this study illustrate how small technical decisions in model design can scale up to produce substantial differences in population statistics. Such high-level headline indicators are frequently cited to assess progress toward goals like the SDGs, yet they are highly sensitive to underlying modeling assumptions. The study therefore highlights that while spatial resolution matters, uncertainties in input data and travel speed assumptions may exert an even stronger influence on accessibility estimates, underscoring the importance of transparency and validation in future modeling efforts.

Where the underlying data is considered representative and there is close alignment between modeled and observed travel time distributions, the high-resolution travel time estimates provided here can offer a powerful tool for education planners, practitioners, and policymakers. Especially when combined with other relevant datasets, such as wealth and educational attainment, these maps can help identify vulnerable areas that risk being left behind. As an illustrative example, this study combined travel time model outputs with additional socioeconomic data layers in Malawi, identifying critical hotspots where educational attainment, relative wealth, and accessibility remain low. As Nicoletti et al. highlight, "systematically understanding the variability in spatial distribution of access and the associated demographic distribution is instrumental in designing targeted and equitable policies for addressing inequalities" (2023). These outputs can support education sector planning by providing policymakers with data-driven insights for targeted interventions, such as optimizing new school locations, enhancing transport links in isolated areas, or supporting community-based education initiatives. For instance, in Sierra Leone GIS-based school accessibility analyses have been used to optimize new school locations (Momoh and Atherton 2022). By increasing the efficiency of resource allocation, these insights can help maximize the impact of limited resources aimed at reducing disparities in educational access. School accessibility maps can also have broader cross-sector applications: for example, informing the design of health service delivery strategies where school facilities serve as platforms for interventions such as vaccination campaigns or the distribution of bed nets and deworming treatments (Vijil-Morin et al. 2023).

Looking ahead, future research should continue prioritizing improving the completeness and quality of school location data, particularly in underrepresented regions of the Global South. Improved data collection efforts—encompassing details on school capacities, enrolment figures, teacher qualifications, and facility conditions—could also unlock more nuanced understandings of educational access.

As the deadline to achieve the SDGs draws near, progress remains uneven and, in many instances, far behind target. Judging by current trajectories, even the most basic goal of universal access to primary education may not be reached until the end of this century (Klees 2024). By systematically mapping disparities in school access, the results presented here play a crucial role in highlighting particularly marginalized areas, aligning with the SDG's core commitment to "leave no one behind and reach those furthest behind first" (Stuart and Woodroffe 2016). This highly granular, spatial approach provides an evidence base to support tailored and efficient policies that reach those most in need (Frola et al. 2024). Pairing these insights with grounded, context-specific action will be essential for accelerating progress toward the SDGs and upholding our fundamental right to education for all.

Acknowledgments

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The complete set of travel time raster maps generated in this study are available on Zenodo under an open license (https://doi.org /10.5281/zenodo.15261112). The accompanying GitHub repository (https://github.com/dianajjaramillo/schools-access) provides the full Snakemake workflow used to prepare the input datasets, process outputs, and reproduce all analyses and figures presented in the manuscript. This includes scripts for: data acquisition and preparation; postprocessing of the resulting travel-time surfaces; generation of population metrics and summary statistics; replication of all tables and figures presented here; validation against household survey data, comparison with the 1 km outputs; and generation of the hotspot hexagon maps. Because the scripts are organized within a Snakemake workflow, users can execute only the rules needed for their country or region of interest, making the analysis feasible even on a standard laptop. Running the workflow requires basic coding experience, including cloning a GitHub repository, creating and activating software environments, and executing Snakemake commands from the terminal.

Endnotes

[1] For Egypt, the GigaMaps school dataset was used directly, as SEADB does not include coverage for this country.

[2] An OpenStreetMap planet file was downloaded for April 1, 2024, using Amazon Web Service (AWS) Command Line Interface. Schools were extracted using the amenity tag. More information is available here: https://wiki.openstreetmap.org/wiki/Tag:amenity=school. Where schools are represented as lines, or polygons, the centroid point is returned.

[3] An OpenStreetMap planet file was downloaded for April 1, 2024, using Amazon Web Service (AWS) Command Line Interface. Road networks were extracted using the highway tag. More information is available here: https://wiki.openstreetmap.org/wiki/Key:highway. The following values were included: motorway, motorway link, trunk, trunk link, primary, primary link, secondary, secondary link, tertiary, tertiary link, unclassified, residential, service, track, footway, and path.

[4] Note that aggregate statistics at the continental level should be interpreted with caution, as they may not fully reflect ground realities due to the challenges of data completeness discussed in the subsequent sections.

[5] The reproducible framework developed in this study is fully generalizable and could be applied to any given country, by simply providing the Snakemake workflow with another ISO3 code wildcard. Refer to the GitHub repository (https://github.com/dianajjaramillo/schools-access) for instructions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Table of contents. **Data S2:** Supplementary Note: Model Comparisons.