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Modelling multidimensional access to inpatient paediatric emergency hospital care in Kenya: A geospatial-statistical approach

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Abstract

Background: Equitable access to paediatric emergency care (EC) is fundamental to reducing child mortality, yet its conventional measures rely largely on travel time, overlooking barriers in availability, affordability, accommodation and acceptability that shape care seeking. Existing composite indices also often aggregate access dimensions additively, allowing well-performing components to mask critical deficits, and rarely account for local variation in barrier importance. We address these gaps by developing a high-resolution, multidimensional composite index of access to inpatient paediatric EC in Kenya and testing its relevance for child survival and policy targeting.

Methodology: Drawing on the Penchansky & Thomas framework, we quantified five access dimensions - availability, geographic accessibility, affordability, accommodation, acceptability - as continuous 1 km × 1 km surfaces using national health facility censuses, demographic surveys, and spatial datasets. Availability was modelled using an Enhanced Two-Step

Floating Catchment Area method; geographic accessibility via least-cost path modelling; affordability, accommodation and acceptability via Bayesian geostatistical methods. Spatially adaptive weights were derived using geographically weighted principal component analysis, and the composite index constructed using ordered weighted averaging (OWA), a non-compensatory method penalising severe deficits. OWA was compared with arithmetic and geometric means and validated against under-five mortality using quantile regression as a plausibility check.

Results: Access to inpatient paediatric EC was unevenly distributed (median composite access index 0.45, IQR: 0.35,0.57). Although 70% of children resided within 1-hour of a facility offering inpatient paediatric EC services, this threshold misclassified access: 9/20 counties within 1-hour fell into the lowest composite quartiles due to deficits in other dimensions. OWA produced systematically lower scores than arithmetic/geometric means in unbalanced areas, avoiding overestimation from compensatory effects. In quantile regression, OWA-based access showed a protective association with under-five mortality, strongest at higher mortality quantiles, whereas compensatory methods produced slopes near zero or inconsistent across quantiles.

Conclusions: Access barriers cluster and combine differently across space, and these patterns matter for child survival. The index and underlying approach offer a practical advance beyond travel time alone, providing a transferable way to measure access and target investments in Kenya and other sub-Saharan African settings where EC resources are scarce and inequities are wide.

Key words: Paediatric emergency care, Access to healthcare, Multidimensional composite index, Spatial accessibility, geographically weighted principal component analysis, Ordered weighted averaging, non-compensatory aggregation, Spatial accessibility, Child mortality, child health, catchment area

Introduction

Promoting health and well-being for all is a central tenet of the United Nations' 2030 Sustainable Development Goals (SDG) [1]. A key strategy for achieving this, specifically under Target 3.8, is the realization of Universal Health Coverage (UHC), which is fundamentally dependent on equitable access to quality emergency care services [1,2]. This is particularly critical for time-sensitive conditions like obstetric complications during labour and childbirth, and acute paediatric emergencies, where delays contribute to the ongoing crisis of preventable maternal and under-five mortality; in 2021 alone, approximately five million children under five years of age died, predominantly from conditions that are treatable with timely, effective care [3].

Access to time-sensitive emergency care (EC) services is a critical determinant of survival and clinical outcomes especially for children. Childhood illnesses and injuries can progress rapidly, with delays in definitive inpatient interventions - such as resuscitation, intravenous medications, or surgical procedures - directly contributing to mortality and long-term morbidity [4]. Although access to primary care remains essential for prevention, equitable provision of specialized paediatric EC services functions as a vital safety net for acutely ill or injured children, rendering it an indispensable element of both UHC and child survival strategies [5]. Robust monitoring of population-level access to paediatric EC remains an important benchmark of health system performance.

Current research predominantly uses travel time as the measure of EC access, typically estimated with least-cost path algorithms [6]. At continental scales, studies have quantified travel times to trauma and emergency obstetric care across sub-Saharan Africa [7], whereas at national level, examples include travel time to comprehensive emergency obstetric care and vaccination in Kenya [8–10], to sickle cell disease centres in Uganda [11], to HIV centres in Malawi [12] and to emergency departments in Kenya [13]. Other studies have been conducted across sub-Saharan Africa to assess geographic access at subnational level [14–17]. While these models have been invaluable for highlighting spatial inequities and defining

travel time bound access thresholds (such as the “golden-hour” for trauma care and two-hours for emergency obstetric care [18,19]), they capture only one dimension of access - geographic proximity, overlooking critical non-spatial barriers to EC services.

Access to EC is inherently multidimensional, making its assessment challenging. Established frameworks conceptualize access through distinct yet interrelated dimensions - availability, accessibility, affordability, accommodation and acceptability [20,21]. While geographic accessibility has been widely modelled, other dimensions remain siloed: facility readiness surveys assess availability [22–24], expenditure analyses examine affordability [25–27] while patient satisfaction studies address accommodation/acceptability [28]. These fragmented approaches, though individually valid, fail to capture how barriers intersect and compound in real-world care-seeking pathways for acutely ill children [29].

A recent systematic review on methods for modelling composite indices of access to healthcare facilities identified only 19 studies globally that constructed a multidimensional composite index of healthcare access; none conducted in sub-Saharan Africa [30]. The review cited a lack of integrated data and methodological consensus as key barriers. Notably, no study has developed such a multidimensional composite index of access specifically for paediatric EC access encompassing all the five interrelated dimensions.

Methodologically, developing a robust composite index of EC access demands adherence to two key principles: the relative importance (weighting) of dimensions and their non-substitutability [20,21,30]. The relevance of dimensions varies by context; for instance, geographic distance predominates in rural pastoralist settings, whereas affordability might prevail in urban informal settlements. Moreover, access dimensions intersect and compound multiplicatively: a family in a remote area (poor geographic access) who also lacks financial capacity (poor affordability) experiences exclusion that is exponentially worse than that from any single barrier. Additionally, access dimensions exhibit non-substitutability: profound deficits in one (e.g., complete service unavailability) cannot be offset by strengths elsewhere, as they preclude access altogether. Consequently, a composite index that accounts for these

intersecting, compounding, and non-substitutable interactions surpasses the mere aggregation of metrics, yielding a single, interpretable measure of barrier confluence. This approach pinpoints populations at maximal exclusion risk from multidimensional access failures - a subtlety obscured by isolated dimension analyses.

To address these evidence and methodological gaps, this study presents the construction of a high spatial-resolution composite index of access to inpatient paediatric emergency hospital care across Kenya. We apply a spatially adaptive Ordered Weighted Averaging (OWA) method, informed by Principal Component Analysis (PCA). This technique enables geographic variation in dimension weights to capture locale-specific barriers while implementing non-compensatory aggregation to penalize severe deficits in any single dimension. In addition, this study explicitly assesses the utility of the conventional “golden hour” (60-minute travel time) access classification by examining residual non-geographic disparities among geographically proximate areas.

Methodology and Data

Study area and context

This study is based in Kenya, a sub-Saharan African country in East Africa (Supplementary Figure 1), characterised by diverse climates ranging from the central and western highlands to the vast arid and semi-arid lands (ASALs) of the north and northeast. For governance, the country is divided into 47 devolved counties responsible for healthcare delivery (Supplementary Figure 1 displays the boundaries and names of all counties) [31–33]. This decentralised governance operates within the Kenya Health Sector Strategic Plan (KHSSP) six-tier system, which includes both public and private healthcare facilities across all levels of care. Within this system, EC services concentrate at Levels IV-VI: Level IV primary care hospitals offer inpatient and emergency obstetric care; Level V County referral hospitals provide comprehensive surgical and medical services including blood transfusion; and Level VI national referral hospitals handle tertiary care [34]. Lower levels (I-III) lack the

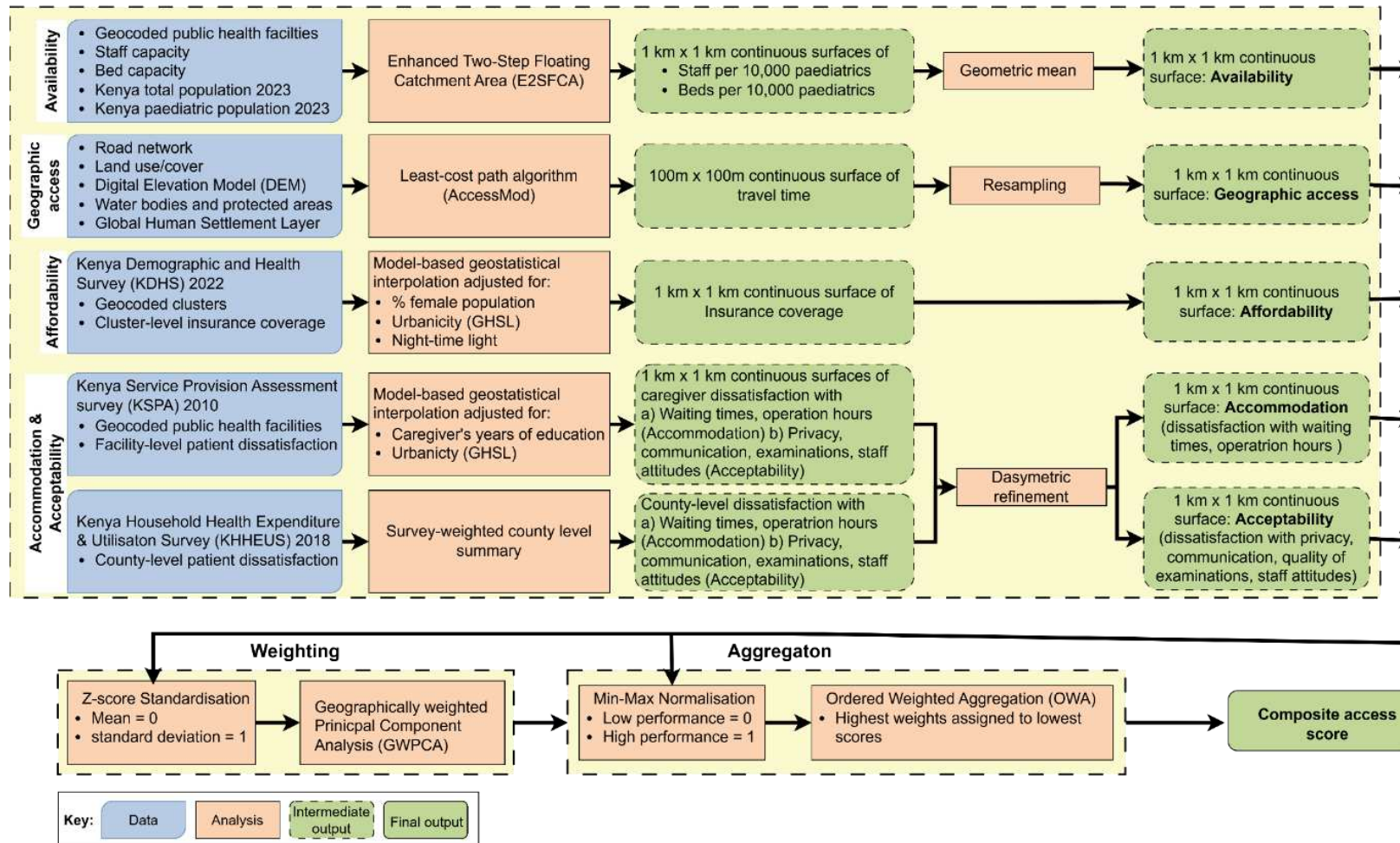
infrastructure for definitive paediatric emergency management; however, some level III facilities offer Inpatient services for emergency clients awaiting referral or under observation (Supplementary notes 2; Supplementary Table 1). Although EC in public facilities is often intended to be affordable, households may still face out-of-pocket costs for transport, medicines, diagnostics, supplies, and other care-related expenses [27], making financial protection an important determinant of access.

Under-five mortality in Kenya remains a major health concern, with stark regional disparities ranging from 15 per 1,000 live births in Marsabit County to 73 per 1,000 in Migori County, and a national median of 41 per 1,000 [35]. These pronounced inequities highlight the critical role of access to timely and effective care, underscoring the need for multidimensional approaches that capture the full spectrum of barriers influencing child survival.

Methods overview

Guided by the Penchansky & Thomas framework [20] on the multidimensionality of access to healthcare services, datasets for dimension indicators were assembled and processed using a combination of geospatial modelling and statistical interpolation to generate 1 km × 1 km continuous surfaces of each dimension across Kenya, as illustrated in the schematic overview in Figure 1. The continuous surfaces were then aggregated using a spatially adaptive non-compensatory approach to generate a 1 km x 1 km continuous surface of a composite score of access to inpatient paediatric EC services in Kenya.

Data Assembly and geospatial modelling



160

161 **Figure 1:** Schematic overview of the methodological framework for creating a composite access score.

Data

All data used in this study were sourced from secondary, multiple data repositories. Indicator selection was guided by common practices identified from existing literature reviews [29,30] and by data availability. Table 1 summarises the assembled datasets for each access dimension.

Table 1: Assembled datasets per access dimension

Dimensions	Datasets	Resolution	Source
Availability	• Geocoded public health facilities • Staffing and bed capacity per facility • Geocoordinates of the facilities	Point	Kenya health facility census 2023 [36]
	• Total population 2023 • Paediatric population (0-14 years) 2023	100m x 100m	WorldPop [37]
Geographic access	• 2023 Road network	Line	Kenya Roads Board [38]
	• 2023 Land use/cover	10m x 10m	European Space Agency (ESA) Sentinel-2 imagery
	• Digital Elevation Model (DEM)	30m x 30m	Shuttle Radar Topographic Mission (SRTM) [39]
	• Waterbodies and game reserves	Polygon	World Database on Protected Areas [40]
	• Urbanicity	1km x 1km	Global Human Settlement Layer (GHSL) [41]
Affordability	• Insurance coverage	Point (survey clusters)	Kenya Demographic and Health Survey (KDHS) [35].
Accommodation	Caregiver dissatisfaction with service organisation • Waiting times	Point	• Kenya Service Provision Assessment survey (KSPA) 2010 [42] - a nationally representative survey that assesses facility-level

	• Operation hours	(survey facilities)	readiness to provide healthcare services and includes patient satisfaction exit interviews by type of care sought
Acceptability	Caregiver dissatisfaction with service provision • Privacy • Communication • Quality of the examinations • Staff attitudes		• Kenya Household Health Expenditure and Utilisation Survey (KHHEUS) 2018 [43] - a nationally representative survey designed to explore health-seeking behaviour, health service utilisation, health spending and health insurance coverage.

168

169 **Dimension definitions and pre-processing**

170 Availability

171 The availability dimension examines service capacity relative to population needs [20]. To
 172 operationalise this dimension, we first identified public health facilities (government-owned)
 173 providing inpatient paediatric EC services (n = 183) using predefined inclusion and exclusion
 174 criteria detailed in Supplementary notes 2, Supplementary Figures 2 and 3. From these
 175 facilities, data on service capacity, including numbers of medical staff and inpatient beds
 176 were extracted (Table 1). In addition, the geographic coordinates of each facility were
 177 extracted.

178 Geographic access

179 To quantify geographic accessibility - defined by Penchansky and Thomas [20] as the
 180 relationship between the location of health services and the location of the population -
 181 geospatial auxiliary datasets that inform care seeker travel time from home to the nearest
 182 inpatient paediatric EC facility were assembled (Table 1; Supplementary Figure 4).

183 Affordability

Data on the population's financial ability to pay for the EC services, affordability dimension, were obtained from the 2022 Kenya Demographic and Health Survey (KDHS) [35] (Supplementary notes 2). Affordability was conceptualised as the population's financial capacity to meet healthcare costs associated with obtaining EC. Insurance coverage was used as a proxy for financial protection and the ability to pay for both care and associated expenses. Specifically, individual-level data on insurance coverage and cluster geocoordinates were obtained for the creation of 1 km by 1 km surface of affordability (Supplementary Figure 5).

Accommodation

The accommodation dimension evaluates how service organisation aligns with caregiver preferences and constraints, including appointment schedules, waiting times and operation hours [20]. Unlike availability, which can be measured from facility resources, accommodation reflects the interaction between service organisation and user expectations [20]. Consequently, caregiver-reported experiences were used to operationalise this dimension. Two datasets were available to operationalise this dimension: the 2010 Kenya Service Provision Assessment (KSPA) [42] and the 2018 Kenya Household Health Expenditure and Utilisation Survey (KHHEUS) [43] (Table 1).

The accommodation dimension was operationalised using KSPA exit interviews, with caregiver responses to questions about waiting times and facility operating hours/days. A binary indicator was defined, where a caregiver was considered dissatisfied (coded as 1) if they reported any of these items as a "major problem" or "minor problem"; otherwise, they were considered not dissatisfied (coded as 0). The KSPA dataset included facility-level geocoordinates for all surveyed facilities where the caregiver exit interviews were conducted. This allowed the dissatisfaction scores to be linked to specific facility locations for the creation of a continuous 1 km by 1 km surface of accommodation (Supplementary Figure 5). The second survey, KHHEUS, provides county-level representative estimates of health

service experiences, including satisfaction with service organisation, but lacks cluster coordinates; therefore, survey-weighted satisfaction summaries were obtained from the KHHEUS at the county level (Supplementary Figure 6). These county-level estimates allow the 2010 KSPA-derived surfaces to be scaled to more recent (2018) levels. Both KSPA and KHHEUS sampled users of public and private healthcare facilities. However, to align with the study focus on public-sector EC, only observations relating to government-owned facilities were extracted and included in the analysis.

Acceptability

Acceptability pertains to the alignment between the population expectations about personal and practice characteristics of providers, including patient privacy, communication, perceived quality of care and staff attitudes in the provision of care [20]. Data for the acceptability dimension were assembled in the same manner as described for accommodation. A binary indicator was defined, where a caregiver was considered dissatisfied (coded as 1) if they reported patient privacy, communication, quality of examinations or staff attitudes as a "major problem" or "minor problem"; otherwise, they were considered not dissatisfied (coded as 0). Dissatisfaction scores were linked to the specific facility locations for the creation of a continuous 1 km by 1 km surface of acceptability (Supplementary Figure 5), while the county-level summaries from the KHHEUS enable this surface to be updated to 2018 levels (Supplementary Figure 6).

Modelling of dimension indicators

Service Availability: Enhanced Two Step Floating Catchment Area (E2SFCA)

For each of the 183 selected public health facilities providing inpatient paediatric EC, the goal was to express staffing and bed capacity per paediatric population (facility-level supply-to-demand ratios) following the principles of the Service Availability and Readiness Assessment (SARA) [44], which necessitated the definition of facility catchments. Simple

catchment approaches such as Thiessen polygons or distance thresholds often assume that all populations within a fixed radius have equal access and those outside have none (a binary view), or they define non-overlapping service areas that ignore competition and distance decay [45,46]. However, patients may travel varying distances to different facilities, and the influence of a facility on a population decreases with distance. Moreover, multiple facilities may be accessible to the same population, particularly where facilities at different levels of care are in close proximity. In such settings, a population may potentially draw services from more than one facility. To capture these complexities, we used the Enhanced Two-Step Floating Catchment Area (E2SFCA) method, which incorporates continuous distance decay and allows overlapping catchments [47].

First, for each of the 183 selected public health facilities providing inpatient paediatric EC services, the population catchments specified in the KHSSP guidance were translated into spatial catchments. The KHSSP defines catchments in terms of level-specific service population targets rather than explicit geographic boundaries (Supplementary Table 1). Using WorldPop population estimates [37], the nearest 1 km populated cells (based on Euclidean distance) were identified and accumulated until the prescribed population threshold for each facility level was reached. For example, Level IV facilities are expected to serve approximately 100,000 people. This set of cells, C_j , constituted the catchment of facility j . The maximum distance to the farthest cell in the set ($d_{\max}$) was recorded and later used to scale the distance-decay function for each facility level.

Second, within each facility catchment, the contribution of a population cell to the facility's demand should not be equal; it should be reduced for cells farther from the facility to reflect that people are less likely to use a facility as travel distance increases [47]. To achieve this, a Gaussian distance-decay weight function, w_{ij} , was defined for each facility j and cell i at distances d_{ij} :

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{\beta^2}\right)$$

where $\beta = d_{\max}/2$. Scaling β to half the maximum distance makes the decay relative to the size of each catchment - larger catchments (higher-level facilities) have a more gradual decay, reflecting that patients are willing to travel farther for specialised care. The weighted paediatric population (demand) for facility j was then defined as:

$$P_j = \sum_{i \in C_j} \text{paed_pop}_i \cdot w_{ij}$$

Using the weighted paediatric (0-14 years) population, supply-to-demand ratios were computed for beds and staff, representing the number of beds (or staff) available per paediatric person from facility j . For cells within multiple facility catchments, they had multiple ratios corresponding to the number of facilities whose catchments covered them.

$$R_j^{\text{beds}} = \frac{\text{beds}_j}{P_j} \quad \text{and} \quad R_j^{\text{staff}} = \frac{\text{staff}_j}{P_j}$$

The third step was to account for catchment overlap - populated cells within catchments of multiple facilities. For every 1km cell, the bed and staffing ratios were summed up allowing for a cell to receive contributions from multiple facilities, thus reflecting realistic care-seeking behaviour where a population may be served by several neighbouring facilities.

$$A_k^{\text{beds}} = \sum_{j: k \in C_j} R_j^{\text{beds}} \cdot w_{kj} \quad \text{and} \quad A_k^{\text{staff}} = \sum_{j: k \in C_j} R_j^{\text{staff}} \cdot w_{kj}$$

The result was two continuous 1 km-resolution surfaces: one for total beds and one for total staff per 10,000 paediatric population available at that location (Supplementary Figure 7).

Lastly, the availability dimension score was obtained by combining the pixel-level staff and bed densities using the geometric mean as it penalises imbalances between the two resources. That is, in EC, having an adequate number of beds without sufficient staff (or vice versa) creates a critical bottleneck: beds cannot be effectively utilised without staff, and staff cannot deliver care without beds.

Modelling travel time for Geographic Accessibility

To quantify the geographic accessibility dimension, travel time was modelled from every location to the nearest of the 183 eligible facilities. This was implemented using the anisotropic least-cost path algorithm in WHO's AccessMod software version 5.9 [6], following the methodology outlined in Bouanchaud et al. [48] (Supplementary notes 3).

Briefly, a friction surface was generated by merging the road network, LULC, and barriers (waterbodies and protected areas). Travel speeds for walking, cycling, and motorised transport were assigned to each land cover and road class based on established literature ([49]; Supplementary Table 2). Speeds on roads classified as 'urban' using the GHSL index were reduced by 20% to account for congestion [50–53]. The DEM was integrated to adjust walking speeds for slope using Tobler's hiking function, while cycling speeds were adjusted using slope-based power correction that limits downhill speed increases to a maximum of twice the flat-surface speed [6,15]. The least-cost path algorithm in AccessMod calculated the minimum travel time (in minutes) from each 100m x 100m pixel to the nearest facility, allowing automatic switching between travel modes along the fastest route. The 100m x 100m travel time surface was then resampled to the 1km x 1km resolution for analysis.

Model-based geostatistical interpolation for Affordability, Accommodation and Acceptability

The point-referenced survey data (KHDS cluster-level data for affordability and KSPA facility-level data for accommodation and acceptability; Supplementary Figure 5) required interpolation to create continuous surfaces. Evidence of spatial autocorrelation was first investigated by fitting semi-variograms before utilising Bayesian Model-based geostatistical interpolation methods within the stochastic partial differential equations (SPDE) approach, using the Integrated Nested Laplace Approximation (INLA) in R (R-INLA) [54,55] (supplementary notes 3).

Let y_i be the observed number of individuals at cluster/facility i with the assembled survey characteristic, n_i be the total number of individuals in cluster/facility i , and p_i the probability of observing the survey characteristic in cluster/facility i . Then,

311
$$y_i \sim \text{Binomial}(n_i, p_i)$$

312
$$\text{logit}(p_i) = \beta_0 + \beta X + \omega_i$$

313 where β_0 is the intercept, X is a vector of covariates, β the corresponding covariate
314 coefficients, and ω_i are spatially structured random effects. The model was fitted to
315 interpolate a) cluster level insurance coverage from the KDHS as an indicator for affordability
316 (covariates included urbanisation, night-time lights and proportion of female population), b)
317 facility level dissatisfaction with service organization to indicate accommodation (covariates
318 included years of education and urbanicity) and c) facility level dissatisfaction with service
319 provision to indicate acceptability (covariates included years of education and urbanicity).
320 See supplementary notes 3 on covariate extraction and detailed explanation.

321 To adjust the 2010 KSPA accommodation and acceptability surfaces to 2018 levels, a
322 dasymetric adjustment was employed (Supplementary notes 3). This approach uses the
323 detailed spatial patterns from the 2010 1 km by 1 km surfaces as a template but shifts the
324 pixel values within each county so that the county-wide average of the surfaces matches the
325 more recent 2018 KHHEUS survey estimates. In effect, the fine-scale spatial patterns of the
326 original 1 km geostatistical surfaces are preserved, while county-level averages are updated,
327 thereby avoiding the crude approach of assigning uniform county values to all pixels.

328 **Access composite score construction**

329 Composite indices aggregate multiple indicators into a single interpretable metric to capture
330 complex multidimensional phenomena that individual measures cannot fully represent [56].
331 Key methodological considerations include assigning indicator weights to reflect relative
332 importance and choosing an aggregation rule, which determines whether deficits in one
333 indicator can be compensated by strong performance in others (compensatory versus
334 non-compensatory aggregation). In this study, the construction of the composite index for
335 access to inpatient paediatric EC in Kenya comprised three steps: dimension processing

(handling outliers, normalisation and standardisation), assigning weights to the access dimensions, and aggregation.

Dimension raster processing

Each of the five access dimensions was extracted to a 1 km × 1 km raster grid with its own measurement scale. Extreme values (outliers) can distort subsequent normalisation and aggregation steps [56]. Therefore, a distribution-based statistical method that identifies unusually high or low values and adjusts them towards the data bulk while preserving the relative order of observations was used [57]; details in Supplementary Note 3. After outlier handling, the dimension values were a) standardised to z-scores (mean = 0, variance = 1) for weight calculation and b) normalised using a min-max approach with polarity correction, so that for every dimension a score of 1 represents the best possible access and 0 the worst, for aggregation.

Spatially Adaptive Weight Calculation

Recognizing that the relative importance of access barriers varies, dimension weights were calculated within the Principal Component Analysis (PCA) framework. This approach identifies groups of correlated dimensions and derives weights based on how much each access dimension contributes to the total variance in the five-dimension scores across all locations. [58]. PCA used the standardised access dimension indicators because the five access dimensions have vastly different scales and variances (e.g., geographic access ranging from 0 to >700 minutes versus affordability from 0 to 100%). Without standardisation, dimensions with naturally larger ranges would dominate the analysis and receive inflated weights, regardless of their true relevance in explaining access patterns [58]. First, we performed a global PCA (using the entire dataset) to obtain a single set of weights that represents the average relative importance of each dimension across the whole country. The global PCA was implemented using the princomp function in base R, and components were selected based on the Kaiser-Guttman criterion (eigenvalue > 1).

To derive weights that reflect not only the relative importance of access barriers but also how this importance varies geographically, Geographically Weighted Principal Component Analysis (GWPCA) was employed [58]. Unlike global PCA, which assumes a constant importance structure across the entire country, GWPCA calculates a separate set of weights for each 1 km × 1 km pixel based on its local statistical neighbourhood; a set of nearby pixels used for model calibration. For each pixel u , an adaptive statistical neighbourhood was selected based on the number of nearest neighbouring pixels, determined by cross-validation [58,59] (Supplementary Figure 10). Within each neighbourhood, PCA was performed, and components with eigenvalue > 1 (Kaiser-Guttman criterion) were retained. Dimension weights derived from the squared factor loadings of the retained components and normalised to sum to 1 [56]. Let $\omega_j^{(u)}$; $j = 1, 2, \dots, 5$ denote the dimensions weights within pixel u (Supplementary notes 4).

Non-compensatory aggregation using Ordered Weighted Averaging (OWA)

To aggregate the dimension scores at each pixel into a single composite index, $\mathcal{C}(u)$, the OWA operator was used [60]. This method consistently penalises severe deficits in any one dimension, aligning with the theoretical principle of non-substitutability in healthcare access. At each pixel, the dimension scores, $\hat{x}_j(u)$, were sorted in ascending order,

$$\hat{x}_{(1)}(u) \leq \hat{x}_{(2)}(u) \leq \hat{x}_{(3)}(u) \leq \hat{x}_{(4)}(u) \leq \hat{x}_{(5)}(u)$$

where $\hat{x}_{(j)}(u)$ is the j -th smallest dimension score at pixel u . The corresponding dimension weights were sorted in descending order and assigned to the sorted scores. Thus, the lowest-performing dimension in a given pixel receives the highest weight. The composite index, $\mathcal{C}(u)$ was then computed as:

$$\mathcal{C}(u) = \sum_{i=1}^5 \omega_j^{((u))} \hat{x}_j(u)$$

385 The composite index data was extracted at subnational levels (county) and summary
386 statistics obtained.

387 **Sensitivity analysis**

388 Several methodological choices influence the construction of composite indices [56]. The
389 OECD Handbook on Constructing Composite Indicators recommends evaluating the
390 robustness of composite indicators through sensitivity analyses that examine the influence of
391 alternative methodological assumptions on index estimates and resulting interpretations [56].
392 In particular, weighting and aggregation choices are recognised as major determinants of
393 composite indicator behaviour and should therefore be systematically assessed.

394 Weighting techniques can be categorised as either subjective, expert-based methods or
395 objective, data-driven techniques. Subjective weighting methods, such as the Analytical
396 Hierarchy Process (AHP) and the Delphi method, rely on stakeholder elicitation. These have
397 the inherent advantage of incorporating external policy priorities or user-defined preferences,
398 which could be an important extension for stakeholder-driven decision-making. However,
399 given the national scope and high spatial resolution of this study, data-driven approaches
400 such as the PCA framework are more practical for high-resolution spatial analysis. Likewise,
401 the choice of aggregation rule - whether compensatory (e.g., arithmetic mean), partially
402 compensatory (e.g., geometric mean), or non-compensatory (e.g., the OWA method used
403 here) - can affect the resulting composite scores.

404 Consequently, to assess the sensitivity of the composite index to these methodological
405 choices, the OWA index was compared against traditional compensatory aggregations:
406 unweighted arithmetic and geometric means of the five normalised access dimensions.
407 Global PCA weights (spatially constant) and GWPCA weights (locally varying) were further
408 applied to both arithmetic and geometric means. These comparisons evaluated the effects of
409 compensation (fully compensatory arithmetic versus partially compensatory geometric) and
410 spatial heterogeneity in dimension importance (global versus local weights).

Uncertainty intervals were not estimated for the composite index. Although uncertainty can theoretically be propagated for some modelled dimensions (affordability, accommodation and acceptability), comparable uncertainty measures were not available for the other dimensions. Consequently, any resulting confidence intervals would capture only a subset of the total uncertainty and could give a misleading impression of precision. Consistent with OECD recommendations, emphasis was therefore placed on sensitivity analyses to evaluate the robustness of the index to key methodological assumptions [56].

Validation analysis

Validation was necessary to assess whether the constructed composite indices demonstrated expected associations with an external health outcome, thereby providing evidence of construct validity. Because the barriers to accessing EC may affect health outcomes differently depending on how severe those outcomes already are - for example, a given improvement in access might have a larger impact where child health is already very poor than where it is relatively good - quantile regression was chosen over mean-based methods such as ordinary least squares. Quantile regression allows the association to be examined at different points of the outcome distribution and is less sensitive to outliers and heteroscedasticity [61,62].

For validation, we used under-five mortality probability as an external plausibility metric of construct validity, recognising that under-five mortality reflects a broader set of child health determinants than paediatric EC access alone. The 1 km composite access index surface was linked to the corresponding 2017 Institute for Health Metrics and Evaluation (IHME) [63] under-five mortality probability surface and extracted pixel-level observations for analysis.

Quantile regression models were then fitted between mortality and access metrics, using the OWA composite index and, for comparison, the alternative arithmetic and geometric mean indices. The resulting quantile-specific coefficients were used to assess whether

higher access was associated with lower mortality across the distribution and to compare the performance of the different composite measures.

Relationship between travel time, access dimensions and composite access score

Existing literature predominantly defines access using travel time thresholds (e.g., "golden hour" ≤ 60 minutes), yet this unidimensional approach may miss critical relationships with non-geographic barriers. Two complementary analyses were implemented to test this: (1) modelling the nonlinear association between travel time and each non-geographic dimension (availability, affordability, accommodation, acceptability), and (2) examining residual inequities within the golden hour (≤ 60 minutes). If travel time were a sufficient proxy for access, little variation would be expected in the other dimensions among geographically proximate areas.

Results

Dimensions of access datasets

Spatial distribution

Staff and bed density per paediatric population had national medians of 3.96 and 2.31 per 10,000 paediatric population, with marked gradient between urban and rural areas (Supplementary figure 7). Their combined metric, availability, showed a similar pattern (Figure 2) with a national median availability score (normalised 0-1) of 0.31 (IQR: 0.15, 0.42).

Travel time to the nearest facility offering inpatient paediatric EC had a national median of 105 minutes (IQR: 58, 194). Travel times < 60 minutes clustered around major urban centres (Nairobi, Mombasa, Kisumu) and in much of western Kenya. In contrast, travel times exceeded 180 minutes across large expanses of eastern, southeastern and northern arid lands (Figure 2). Nationally, 71% of the paediatric population lived within 60 minutes of a facility; 7% faced travel times exceeding three hours.

461 Affordability (insurance coverage) exhibited strong regional gradients, with the highest
462 values concentrated in central Kenya and the lowest in north-eastern counties (Figure 2),
463 with a national median of 13.6% (IQR: 9.9%, 19.2%). Accommodation (caregiver
464 dissatisfaction with service organization; waiting times, operating hours, days of operation),
465 had a median of 12.9% (IQR: 8.7%, 21.6%) with diffuse geographic patterns across both
466 urban and rural areas (Figure 2). Acceptability (caregiver dissatisfaction with service
467 provision; privacy, communication, staff attitudes, examination quality), had a median of
468 1.1% (IQR: 0%, 3.4%) with elevated levels (>10%) in Nairobi, western, and northeastern
469 counties (Figure 2).

470 In summary, the five dimensions exhibited contrasting spatial patterns. Availability,
471 affordability and travel time followed clear urban-rural gradients, with central and urban
472 counties outperforming the arid north-east, and a minority of the population facing travel
473 times exceeding three hours. Accommodation and acceptability showed more diffuse
474 patterns, with dissatisfaction present across both urban and rural areas. These distinct
475 spatial signatures - infrastructure-driven gradients versus more ubiquitous service delivery
476 challenges - underscore the need for a multidimensional index that captures layered,
477 non-overlapping barriers rather than relying on any single-dimension proxy.

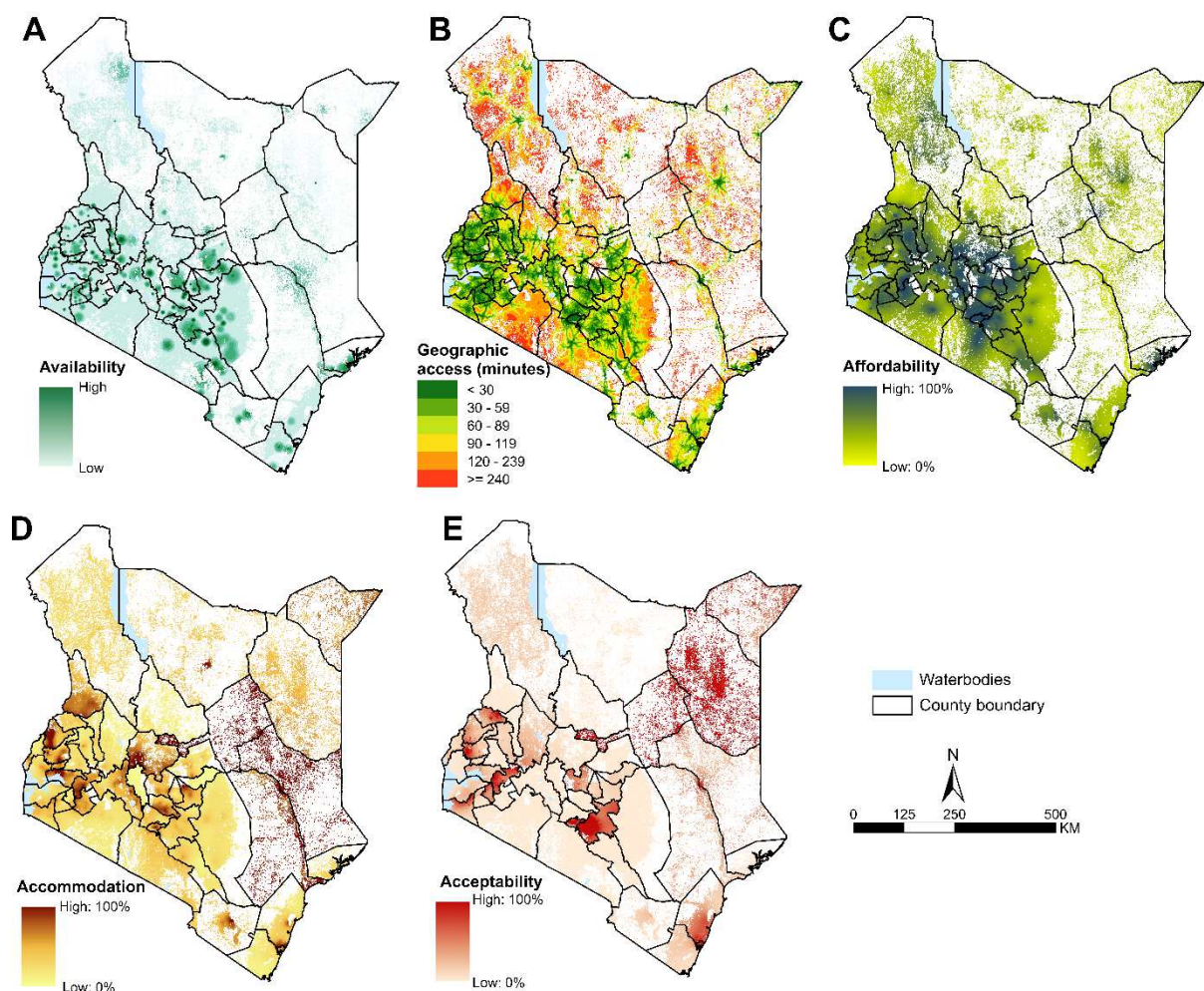


Figure 2: Maps showing the spatial distribution of access dimensions. **Panels a)** Availability (bed and staff capacity), **Panel b)** Geographic access (travel time), **Panel c)** Affordability (insurance coverage), **Panel d)** Accommodation (dissatisfaction with service organisation), **Panel e)** Acceptability (dissatisfaction with service provision).

Association with travel time

Generalized additive models (GAMs; cubic splines, $k=10$) revealed nonlinear dimension-travel time relationships (Figure 3).

Availability decreased progressively, with a sharp decline up to 120 minutes and plateaued at 420 – 480 minutes (Figure 3). Affordability mirrored this pattern, declining steadily with increasing travel time. The smooth terms were highly non-linear for both dimensions

(availability: effective degrees of freedom; EDF = 8.76, $p < 0.001$; affordability: EDF = 8.95, $p < 0.001$).

Accommodation exhibited a non-monotonic pattern with travel time (EDF = 8.80, $p < 0.001$), peaking at ≈ 70 minutes before declining (Figure 3). Acceptability showed a complex nonlinearity pattern (EDF = 8.89, $p < 0.001$). The fitted curve increased steeply from very short travel times to a maximum around 40 minutes, then decreased gradually, with a notable dip after 130 minutes and a subsequent rise at the extreme tail (Supplementary Figure 11).

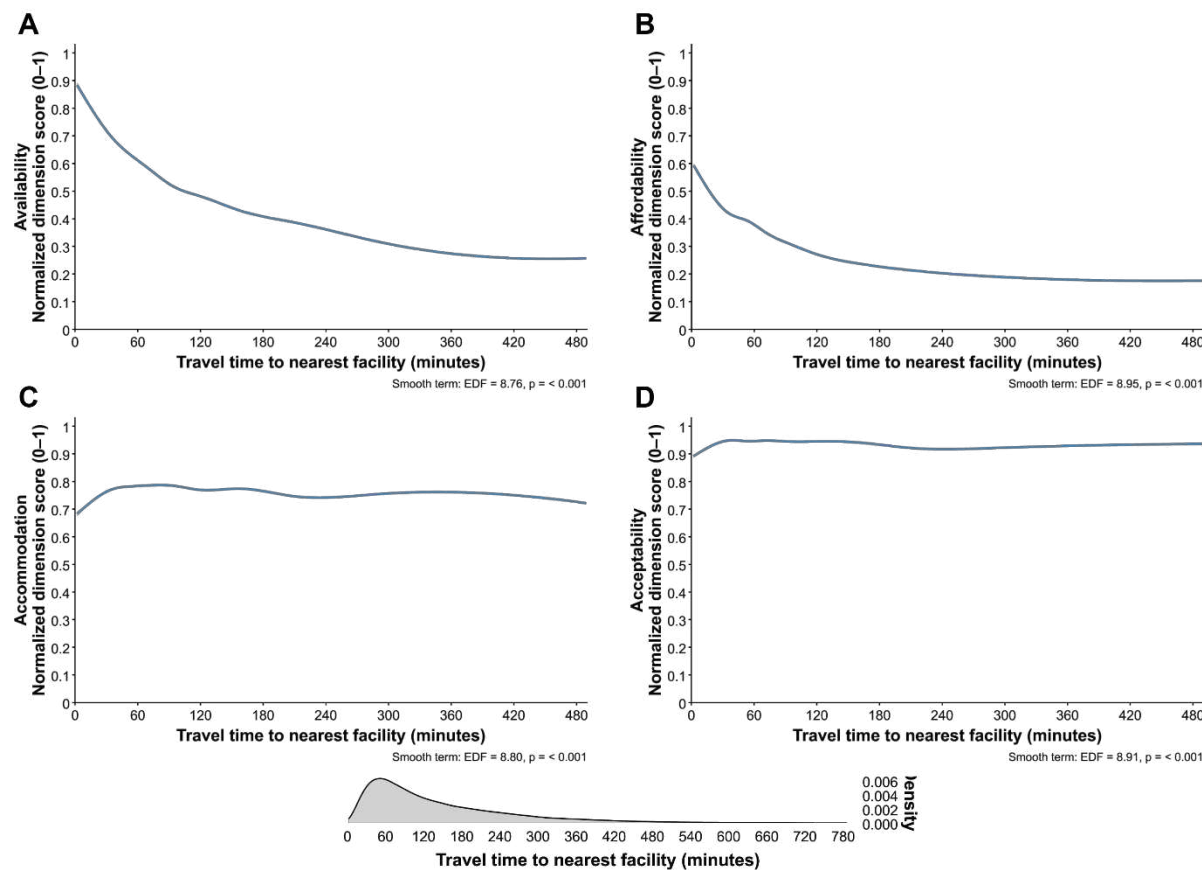


Figure 3: Association of the dimensions (normalised scale; 0 = poor, 1 = best) with travel time to the nearest facility from GAM model. The y-axis has been kept constant across the plots and may conceal small dips/troughs - see supplementary figure 11. The 95% confidence intervals (shaded ribbons) are extremely narrow due to the large sample size.

The density plot shows the sample sizes (number of pixels) across travel time. The plots have been trimmed to 480 minutes as this represent 98% of the pixels.

Composite index

Spatial distribution

The composite index, scaled from 0 (worst access) to 1 (best access), had a national median of 0.45 (IQR: 0.35,0.57). The distribution of the paediatric population across the four quartiles of the composite score was 9.8%, 19.9%, 26.7% and 43.5%. Significant variation was observed with parts of Nairobi, Central, and Coastal regions having areas with the highest access scores (Figure 4 Panel A). The lowest access scores were observed in the western, north-western and eastern parts of the country (Figure 4). At county level, the highest county access scores were Lamu (0.72), Kiambu (0.71), Nyeri (0.69), Kirinyaga and Nyandarua (0.68 each) while the lowest counties were Turkana (0.25), Mandera (0.29), Wajir (0.29), West Pokot (0.32) and Marsabit (0.37) (Figure 4 Panel B). Subcounty level analysis revealed further regional differences ranging from 0.15 in Turkana West subcounty, Turkana County to 0.80 in Kiambu subcounty, Kiambu county (Figure 4 Panel C).

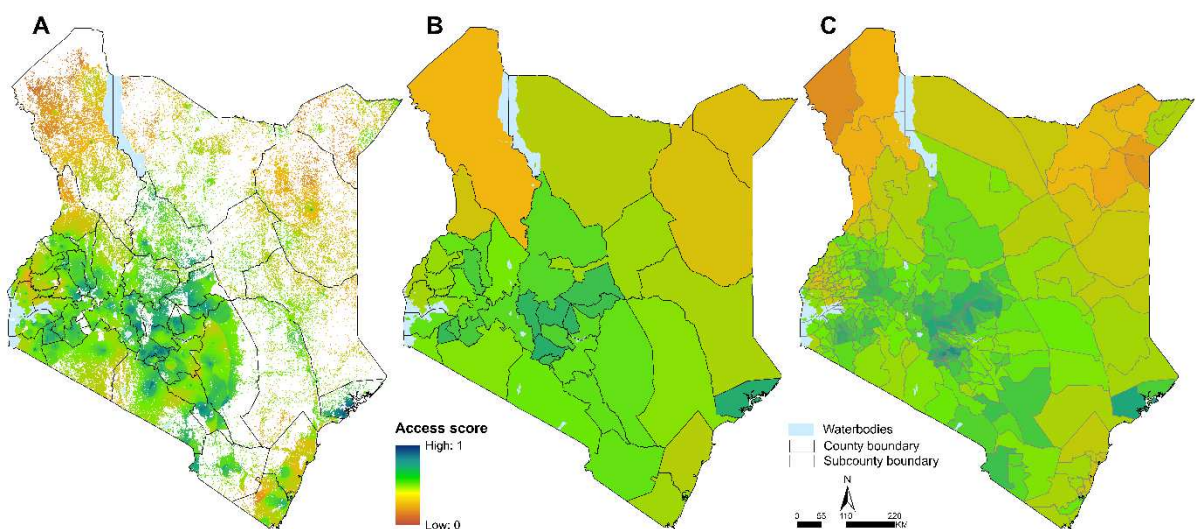


Figure 4: Spatial distribution of the access composite score. **Panel A)** 1km x 1km surface,
Panel B) County level summary, **Panel C)** Subcounty level summary.

The heatmap of dimension scores (Figure 5) reveals clear patterns driving the OWA composite index. Among the lowest-performing counties (e.g., Turkana, Mandera, Wajir, West Pokot), severe deficits in both availability and affordability were the dominant constraints, typically below 0.25. However, affordability varied more widely across all counties: while many high-performing counties (e.g., Kiambu, Nyeri, Nairobi) had affordability scores above 0.6, most counties in the middle and lower ranges had affordability below 0.5, indicating that financial barriers are nearly universal. In contrast, availability was only severely depressed in the 11 worst-performing counties; better-ranking counties generally had availability scores above 0.5. Accommodation was also low in some low-performing counties (e.g., Isiolo, Garissa, Tana River), but geographic access and acceptability were consistently high (normalised scores >0.75) across almost all counties. Thus, the spatial variation in the OWA composite index is primarily driven by uneven availability and accommodation, whereas affordability is a widespread barrier that distinguishes very low-ranking counties but is also poor in many mid-ranking counties.

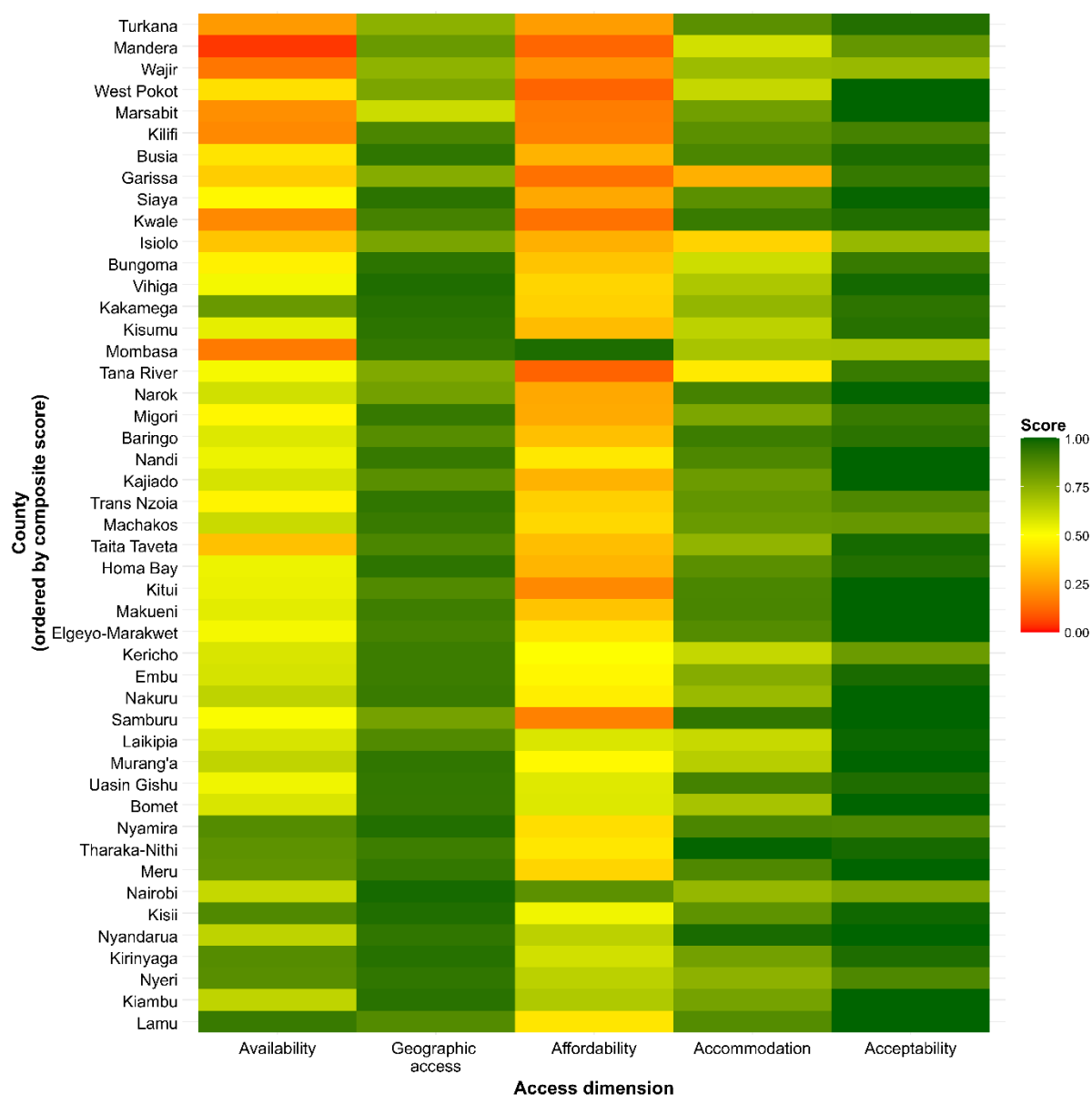


Figure 5: Heatmap plot showing the performance of the individual dimensions at county level summarised by the median. The counties (y-axis) have been sorted according to the OWA composite score; Lamu = highest access and Turkana = lowest access.

Sensitivity analysis

When plotted against the OWA composite score, the unweighted arithmetic mean lay predominantly above the line of equality ($x = y$), with none of the points crossing below the line of equality and some isolated points on the lines of equality (Supplementary Figure 12).

The composite score from unweighted arithmetic mean did not reach 1 and the minimum was above 0.2. The global PCA-weighted arithmetic mean showed a similar pattern with fewer points on the line of equality. In contrast, the GWPCA-weighted arithmetic mean exhibited greater dispersion: when OWA was <0.3 , some pixels had values <0.2 while others approached 1. Notably, no points were below the line of equality across all the arithmetic mean variations (Supplementary Figure 12).

The unweighted geometric mean had points on both sides of the line of equality, $x = y$, across OWA values (Supplementary Figure 12). Neither score reached 1. The global PCA-weighted geometric mean closely resembled the unweighted version, with the score deviating further from the line of equality (Supplementary Figure 12). The GWPCA-weighted geometric mean mirrored the GWPCA arithmetic pattern, showing extreme values near 0 and 1, particularly many points near 0 when OWA <0.6 .

At the county level, the OWA index leads to substantially different classifications than simpler arithmetic and geometric means (Supplementary Figure 13). Counties with balanced dimension profiles (e.g., Kiambu, Kirinyaga) maintain similar ranks across most methods, but counties with extreme imbalances are re-ranked drastically. For example, Turkana County - ranked last (47th) by OWA - is ranked as high as 21st (Geometric GWPCA) and 24th (Arithmetic GWPCA) under some compensatory methods, due to its relatively good acceptability and geographic access masking severe deficits in availability and affordability. Similarly, Siaya and Busia counties, ranked 39th and 41st by OWA, are placed as high as 3rd and 5th by Arithmetic GWPCA, respectively, because their good geographic access and accommodation scores are over-weighted in the fully compensatory approach. These discrepancies highlight that compensatory methods systematically overestimate access in counties with one or two strong dimensions while ignoring critical deficits, whereas the non-compensatory OWA index correctly penalises those deficits and provides a more realistic ranking for targeting interventions.

Validation

Quantile regression showed that the OWA index had the most coherent and substantively plausible association with under-five mortality across the outcome distribution (Figure 6). The OWA fitted lines indicated a generally stronger protective relationship at the middle and upper quantiles, with a clear and statistically significant downward slope from the 25th through the 90th percentile - meaning that higher access scores were associated with lower mortality precisely where child mortality risk was greatest (Figure 6). In contrast, the arithmetic mean indices showed weak, flat, or directionally inconsistent associations, with several models remaining positive or near zero for much of the distribution (Supplementary figure 14). The geometric means performed somewhat better than the arithmetic means but still exhibited unstable patterns, including positive slopes at lower quantiles and reversal or attenuation at higher quantiles (Supplementary figure 14). Taken together, the quantile regression lines demonstrate that OWA most effectively captures the access gradients that matter for mortality risk, providing stronger evidence of construct validity than any of the compensatory indices.

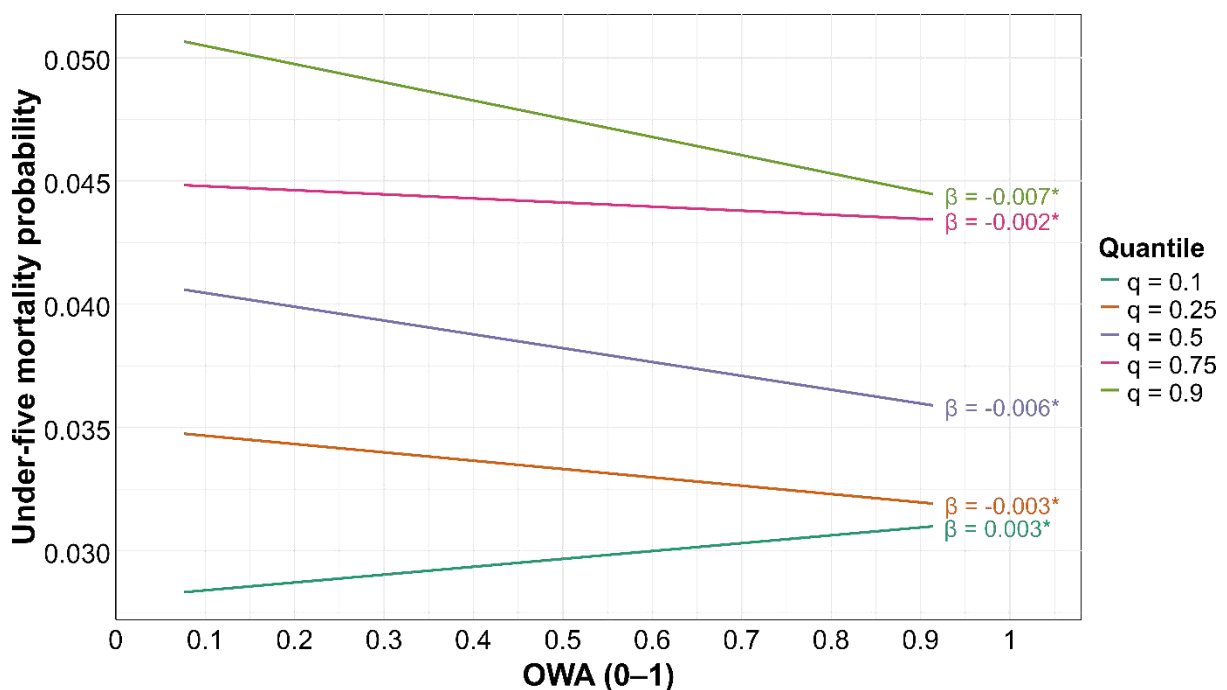


Figure 6: Validation analysis. Quantile regression lines and associated coefficient estimates for Ordered Weighted Averaging (OWA). At the 90th percentile, the OWA index had reduced

paediatric mortality probability by 0.007; 0.003 at 75th percentile, 0.006 and 0.003 at 50th and 25th percentiles respectively. At the lowest 10th percentile, the OWA index was associated with increased mortality probability (0.003).

Utility beyond travel time

To assess whether geographic proximity alone guarantees adequate access, we restricted the analysis to areas within the “golden hour” (≤60 minutes travel time) - places that are similarly close to emergency facilities. Even among these geographically proximate areas, large inequities remained. For the lowest composite quartile (worst overall access) compared to the highest quartile (best access), availability and affordability showed very large gaps (median scores: 0.47 vs. 0.86 for availability; 0.28 vs. 0.61 for affordability), indicating that these dimensions are the main drivers of inequity for populations residing within 60 minutes of travel time (Figure 7). In contrast, accommodation and acceptability displayed much smaller differences (medians: 0.75 vs. 0.83 for accommodation; 0.95 vs. nearly 1.00 for acceptability), with even the worst-off quartile maintaining high scores. Notably, for all four dimensions, the cumulative distribution for the lowest quartile lay entirely above that for the highest quartile across the entire range of travel time, with no crossing.

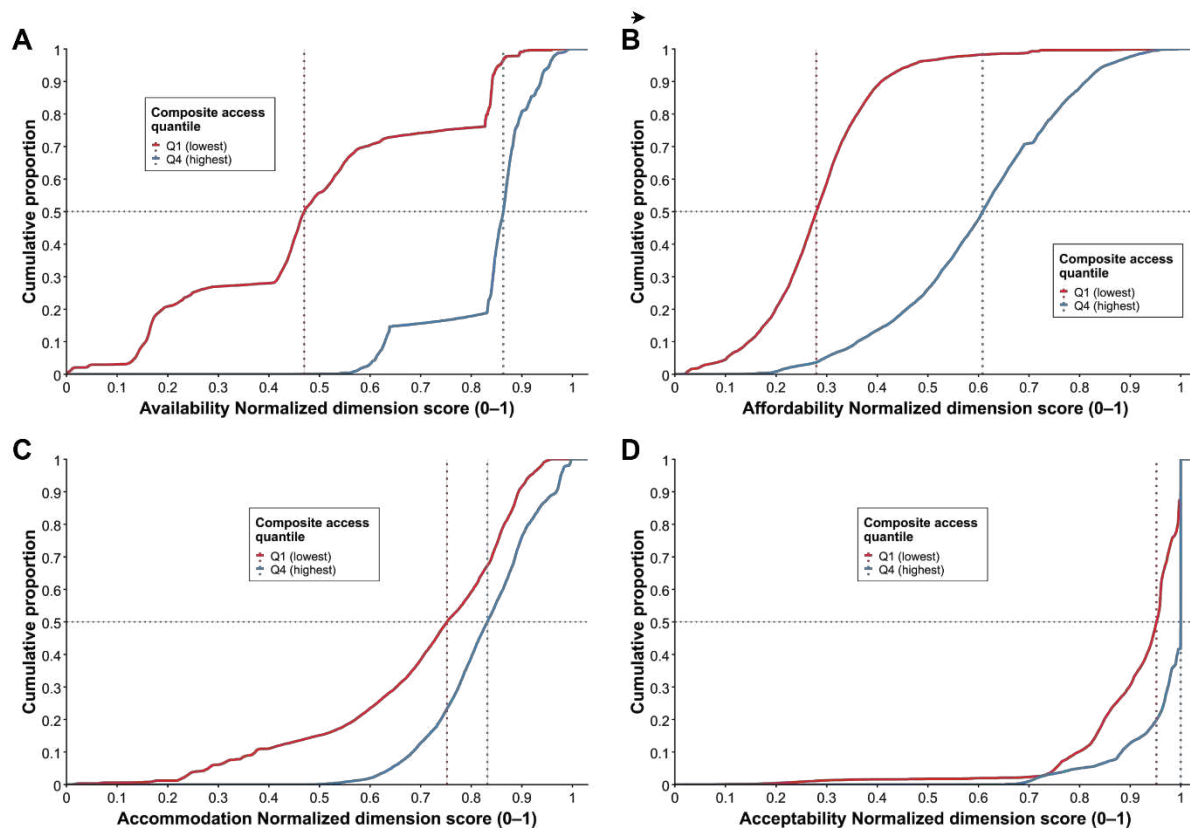


Figure 7: Empirical Cumulative Distribution functions of the non-geographical dimensions. **Panel A)** Availability, **Panel B)** Affordability, **Panel C)** Accommodation, **Panel D)** Acceptability.

Using the "Golden-hour" threshold to classify county-level access, 20 counties had travel time of less than an hour, 14 counties within two hours, five counties within three hours and eight counties with more than three hours of travel time to a public facility for inpatient paediatric EC services (Figure 8). Among those within one hour of travel time, three (Bungoma, Busia, Siaya) and six (Kakamega, Kisumu, Migori, Mombasa, Trans Nzoia, Vihiga) counties were classified within the lowest and second-lowest quartiles of the composite score, respectively (Figure 8). Notably, three counties, Lamu, Meru and Tharaka-Nithi, classified above the one-hour travel time threshold, were classified to be in the highest quartile of the composite score.

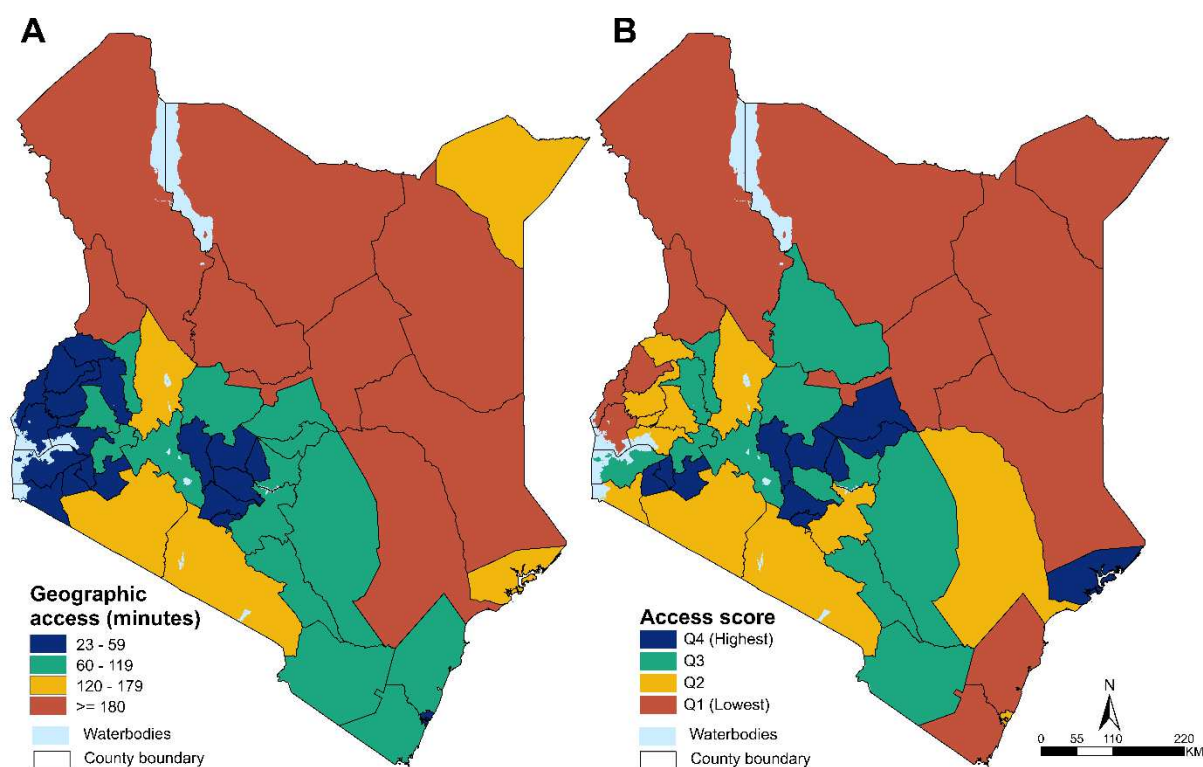


Figure 8: Classification of counties by **Panel A)** Travel time and **Panel B)** Ordered Weighted Averaging (OWA) composite access score.

Discussion

Equitable access to inpatient paediatric EC saves lives, yet conventional metrics such as travel time alone systematically underestimate the true extent of exclusion. This study developed a high-resolution, multidimensional composite index of access to inpatient paediatric EC in Kenya and demonstrated its added value over single-dimensional (especially travel-time) measures. Crucially, the index recognises that barriers to access do not cancel each other out - a nearby facility is of little help if a family cannot afford care. It also allows the importance of each access dimension to vary across space, recognizing that the most critical barriers differ from one community to another. Together, these features allowed us to identify communities that are truly poorly served, something that simpler, single-measure approaches routinely miss.

Multidimensional access to inpatient paediatric EC services was low across the country; less than half of the paediatric population fell into the highest quartile of the composite score, and only two counties had a composite score above 0.7. This indicates that most Kenyan children live in areas where at least one critical access barrier severely constrains their ability to receive timely EC services. Such widespread multidimensional deprivation directly undermines progress toward Universal Health Coverage and child survival targets, as even well-resourced counties fail to achieve good access across all dimensions. Notably, several counties in western Kenya - a region characterised by a high number of facilities [36] - had low composite access scores. This finding suggests a substantial misalignment between service capacity, large population sizes and low socioeconomic status in western Kenya, where short travel times coexist with severe deficits in other dimensions [64]. Similarly, Nairobi County, home to Kenya's capital city, exhibited a low composite score, likely reflecting its heterogeneous population structure, including densely populated informal settlements where healthcare infrastructure and service capacity may not have kept pace with population demand despite good geographic coverage. Conversely, Lamu County had the highest average access score, which can be attributed to its overall low population density and the concentration of population along the more urban coastline, striking a relative balance between service availability and demand. These patterns underscore that relying on any single dimension - even geographic access - would lead to an incomplete and often misleading picture of where children are most disadvantaged.

The heterogeneous performance of individual dimensions across the highest- and lowest-performing counties calls for targeted, context-sensitive interventions. For counties where availability is the principal constraint (e.g., Turkana, Mandera, Wajir), investments in facility expansion - specifically to increase staffing and bed capacity - would be most appropriate. For counties where availability is relatively good, but affordability or accommodation is the binding constraint (e.g., western Kenya counties), policy should instead focus on expanding insurance coverage, reducing waiting times and improving

patient-centred care. The composite index thus provides a granular, evidence-based tool for allocating scarce resources to the specific barriers that matter most in each location - a level of precision that no single-dimension measure can offer.

Our findings challenge the common assumption that travel time alone is an adequate measure of access to emergency paediatric care. Within the golden hour (travel time < 60 minutes), the composite index revealed large differences in availability, affordability, accommodation and acceptability between the lowest and highest composite quartiles (Figure 7). Furthermore, at the county level, relying on the "golden hour" threshold would misclassify access for millions of children: 20 counties had mean travel times under 60 minutes, yet nine of these counties fell into the two lowest quartiles of the composite access score, indicating severe deficits in non-geographic dimensions. Among these nine counties, the dominant constraints were availability (staff and bed capacity) and affordability (insurance coverage), indicating that physical proximity alone does not ensure effective access. These findings emphasise that even geographically well-served areas may require targeted investments in workforce capacity, facility resources, and financial protection to translate proximity into meaningful access.

These findings carry important implications for health policy and planning. Geographic measures such as the golden hour threshold, while operationally convenient, risk systematic misclassification of access when used in isolation. Counties that appear adequately served by travel-time criteria may harbour significant deficits in non-geographic dimensions of access, rendering them invisible to conventional targeting approaches. The composite index developed here offers a spatially sensitive and multidimensional basis for identifying truly underserved populations, one that more faithfully reflects the barriers families face in seeking emergency paediatric care. We argue that such approaches should replace or substantially complement single-metric measures in resource allocation decisions and health system strengthening efforts in Kenya and comparable settings.

687 Further, non-geographic dimensions revealed distinct spatial patterns that single metrics
688 miss. Availability declined consistently with increasing travel time, indicating that greater
689 distance is associated not only with transport barriers but also with reduced service capacity
690 - a pattern consistent with prior Kenyan studies [65-66]. Affordability exhibited a pro-rich
691 gradient: poorer households faced systematically greater travel burdens, compounding
692 geographic marginalisation with socioeconomic disadvantage - the poorest families endure
693 both the longest journeys and least financial protection [66-70]. This urban-rural gradient
694 reflects the concentration of formal employment (driving insurance enrolment) in central
695 Kenya, compared with pastoralist/rural-poor populations [35].

696 In contrast, accommodation and acceptability showed non-linear relationships with travel
697 time, indicating that proximity does not guarantee respectful, well-organised care. Urban
698 facilities suffer overcrowding, queues, and understaffing, driving "bypassing" - caregivers
699 travelling further for better-organised/respectful services [71-73]. In rural and remote areas,
700 poor accommodation and acceptability might stem from chronic staff shortages, lack of
701 supervision, and cultural or language mismatches. Qualitative studies have highlighted that
702 discrimination by healthcare workers and lack of privacy are major barriers to acceptability,
703 particularly for poor and marginalised populations [74].

704 Validation analyses reinforced the construct validity of the OWA index and clarified the role of
705 the aggregation rule in shaping access estimates. Compensatory arithmetic and geometric
706 means did not provide a strict one-to-one comparison with OWA because they differed not
707 only in weighting but also in how they allowed compensation across dimensions; however,
708 this is precisely why they should be interpreted as alternative aggregation strategies rather
709 than direct equivalents. In practice, compensatory methods tend to yield higher access
710 scores by allowing strong dimensions to offset weak ones, thereby masking important
711 deficits. By contrast, OWA consistently penalises low scores, thereby producing lower values
712 in areas with unbalanced access profiles, which aligns with the non-substitutability principle
713 and makes it more suitable for identifying truly underserved areas.

This pattern was mirrored in the quantile regression results. OWA showed the most coherent and substantively plausible association with under-five mortality, with a clearer protective gradient emerging in the upper parts of the mortality distribution - precisely where access constraints are likely to matter most. The weak and inconsistent associations observed for the compensatory indices suggest that their tendency to smooth over deficits also obscures the relationship between access and mortality. This reinforces the argument that non-compensatory aggregation is better suited to capturing the access gradients that matter for child survival. Together, findings from the sensitivity and validation analysis indicate that OWA is not merely another weighted score but a construct-valid measure that better captures how access barriers combine in practice, whereas compensatory approaches systematically smooth over important deficits.

Strengths and limitations

This study has several strengths and methodological novelties. First, to our knowledge, it is the first study in sub-Saharan Africa to integrate multiple dimensions of healthcare access into a high-resolution (1 km × 1 km) composite index of access to inpatient paediatric EC. By moving beyond conventional travel-time measures, the study operationalises the multidimensional nature of healthcare access and provides a more comprehensive assessment of the barriers that shape care-seeking and service utilisation. Second, the index combines diverse datasets spanning health facility readiness, population characteristics, care-seeking experiences, and physical accessibility within a unified geospatial framework, enabling identification of geographically specific patterns of access deprivation that would not be apparent from any single dimension alone.

Third, the use of non-compensatory OWA aggregation respects the non-substitutability of access dimensions, a feature lacking in arithmetic or geometric means, which remain the most common aggregation methods reported in the literature [30]. This allows severe deficits

in one dimension to remain visible rather than being masked by strengths in others, thereby aligning the index more closely with the practical realities of healthcare access. Fourth, the use of GWPCA with adaptive bandwidths allows dimension weights to vary spatially, capturing local contextual differences in the relative importance of access barriers rather than imposing a single national weighting structure.

Fifth, extensive sensitivity analyses demonstrated that the study conclusions were robust to alternative weighting and aggregation specifications. In line with OECD recommendations for composite indicator development [56], the index was evaluated against multiple arithmetic and geometric formulations using unweighted, PCA-derived, and GWPCA-derived weights. Across these alternative specifications, the OWA framework consistently identified more pronounced deficits in areas with unbalanced access profiles, highlighting the importance of accounting for non-compensability when measuring healthcare access. Finally, the index was validated against an independent under-five mortality surface using quantile regression, providing evidence of construct validity. Notably, OWA was the only aggregation approach to demonstrate a coherent protective association with mortality across the distribution, providing additional support for both the methodological framework and the resulting access estimates.

Several limitations should also be acknowledged. First, the accommodation and acceptability dimensions relied on 2018 KHHEUS data aggregated to county level, which may not fully capture recent changes in patient experience or service organisation. The dasymetric refinement applied to the 2010 KSPA surfaces assumes that within-county spatial patterns remained stable, a limitation that future surveys with georeferenced clusters could help overcome. Second, the travel-time surface specifically reflects access to inpatient paediatric EC, but the other facility-level dimensions were not limited to paediatric emergency services alone; they therefore capture broader facility readiness and service environment rather than paediatric EC only. This means the index is best interpreted as a measure of potential access to facilities that can deliver EC to children, while also reflecting elements of general

emergency service capacity that may apply to adults and young people as well. Third, the travel-time surface represents theoretical minimum times under optimal conditions; it does not account for transport costs, seasonal road disruption, or delays in seeking care, all of which likely increase real-world access barriers. Fourth, the 2017 IHME under-five mortality surface, although the latest high-resolution outcome available for validation, incorporates both neonatal and post-neonatal mortality and is influenced by determinants beyond paediatric EC access, including maternal, perinatal, and broader health-system factors. Consequently, it should be interpreted as a plausibility-based validation outcome rather than a direct measure of paediatric EC performance. An additional limitation is that while the GWPCA weights vary spatially, they are derived from the internal correlation structure of the five dimensions and do not incorporate external policy priorities or user preferences, which could be an important extension for future stakeholder-driven applications. Lastly, the analysis focused exclusively on government-owned facilities and did not consider private, faith-based, or other non-state providers. This may underestimate access in locations where such providers deliver a substantial share of emergency services. Nevertheless, the restriction was deliberate, as these facilities constitute the primary platform through which governments plan, finance, and implement equitable healthcare services. Consequently, the findings should be interpreted as representing access to public-sector paediatric EC rather than total EC provision.

Conclusions

Ensuring that every child can reach life-saving EC when needed is both a moral imperative and a measurable health system goal. Yet, as this study shows, relying on whether a family lives within the “golden hour” is a poor proxy for true access. Many children who live close to a facility still face major barriers: they may not be able to afford care, the facility may lack trained staff or essential medicines, or previous experiences of disrespect may discourage caregivers from returning. Monitoring access by travel time alone therefore hides where the real problems lie.

794 This study provides a practical, evidence-based approach for making those hidden deficits
795 visible. The composite index developed here, which combines geospatial data, household
796 surveys, and a non-compensatory statistical method, can be used to track progress, guide
797 investment, and support accountability. In Kenya, it shows that counties such as Turkana
798 and Mandera need urgent improvements in infrastructure and staffing, while several western
799 counties require better insurance coverage and shorter waiting times. More broadly, this
800 framework can be adapted across sub-Saharan Africa, where many health systems are
801 expanding but still struggle to turn physical proximity into real access. Single-metric
802 measures should therefore be replaced or, at minimum, complemented by multidimensional
803 indices that better reflect the barriers families face. Doing so will make Universal Health
804 Coverage more equitable and, ultimately, help save children's lives one community at a time.

805

806 **List of abbreviations**

807 AHP - Analytical Hierarchy Process

808 ARI - acute respiratory infection

809 DEM - digital elevation model

810 EC - emergency care

811 EDF - effective degrees of freedom

812 GAM - Generalized additive model

813 GHSL - Global Human Settlement Layer

814 GWPCA - Geographically Weighted Principal Component Analysis

815 HIV - Human Immuno-deficiency virus

816 IHME - Institute for Health Metrics and Evaluation

817 IQR - Interquartile range

818 KDHS - Kenya Demographic and Health Survey

819 KHHEUS - Kenya Household Health Expenditure and Utilisation Survey

820 KHSSP - Kenya Health Sector Strategic Plan

821 KSPA - Kenya Service Provision Assessment

822 LULC - land use/cover

823 OWA - ordered weighted averaging

824 PCA - Principal Component Analysis

825 R-INLA - Integrated Nested Laplace Approximations in R

826 SARA- Service Availability and Readiness Assessment

827 SDG - Sustainable Development Goals

828 SPDE - stochastic partial differential equations

829 UHC - Universal Health

830

831 **Declarations**

832 **Ethics approval and consent to participate**

833 Not applicable.

834 **Consent for publication:**

835 Not applicable.

836 **Availability of data and materials**

837 The dataset(s) supporting the conclusions of this article were obtained from open-source

838 repositories.

Competing interest

All authors declare no competing interests.

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Authors' contributions

MMM, PMM and RWS conceived the study. MMM undertook formal analysis under the supervision of PMM; SKM, EO, CM and SAO assisted in data assembly. MMM wrote the initial draft with inputs from PMM, EAO and RWS. RWS, EAO, LB and CL provided intellectual input on the methodology and subsequent manuscript versions. All authors had access to the data and have reviewed the paper and Supplementary Information.

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