Measuring geographic access to emergency obstetric care: a comparison of travel time estimates modelled using Google Maps Directions API and AccessMod in three Nigerian conurbations

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Abstract

Google Maps Directions Application Programming Interface (the API) and AccessMod tools are increasingly being used to estimate travel time to healthcare. However, no formal comparison of estimates from the tools has been conducted. We modelled and compared median travel time (MTT) to comprehensive emergency obstetric care (CEmOC) using both tools in three Nigerian conurbations (Kano, Port-Harcourt, and Lagos). We compiled spatial layers of CEmOC healthcare facilities, road network, elevation, and land cover and used a least-cost path algorithm within AccessMod to estimate MTT to the nearest CEmOC facility. Comparable MTT estimates were extracted using the API for peak and non-peak travel scenarios. We investigated the relationship between MTT estimates generated by both tools at raster cell-level (0.6 km resolution). We also aggregated the raster cell estimates to generate administratively relevant ward-level MTT. We compared ward-level estimates and identified wards within the same conurbation falling into different 15-minute incremental categories (<15/15-30/30-45/45-60/+60). Of the 189, 101 and 375 wards, 72.0%, 72.3% and 90.1% were categorised in the same 15-minute category in Kano, Port-Harcourt, and Lagos, respectively. Concordance decreased in wards with longer MTT. AccessMod MTT were longer than the API's in areas with ≥45min. At the raster cell-level, MTT had a strong positive correlation (≥0.8) in all conurbations. Adjusted R^2 from a linear model (0.624-0.723) was high, increasing marginally in a piecewise linear model (0.677-0.807). In conclusion, at <45-minutes, ward-level esti-

mates from the API and AccessMod are marginally different, however, at longer travel times substantial differences exist, which are amenable to conversion factors.

Introduction

Access to healthcare is essential to achieve Universal Health Coverage as enshrined in the Sustainable Development Goal target 3.8 (United Nations, 2015). Healthcare access is multi-dimensional and includes availability, acceptability, accommodation, affordability, and accessibility (Aday & Andersen, 1981; Guagliardo, 2004; Penchansky & Thomas, 1981). Availability evaluates the degree to which the provider has the necessary resources to meet the needs of the patient. Acceptability refers to the patient's interaction with the health care system in terms of choice and the perception of the provider towards acceptable personal characteristics of the patient. Accommodation refers to the extent in which health services are organised to meet client demands. Affordability is the population's ability and willingness to meet financial obligations while accessibility refers to how easily a patient can physically reach the healthcare location. Availability and accessibility (referred to as geographic or spatial accessibility) are critical due to the fixed nature of health facilities and dynamic populations, especially in low-and middle-income countries (LMICs). In such settings, unique solutions are needed to adapt the location and availability of health facilities including their capacity to provide services to meet the demands of the population that has complex mobility patterns, for example in urban areas (Diaz Olvera *et al.*, 2013). Consequently, travel from where a need arises to a healthcare facility is routinely researched in LMICs to improve population accessibility to life-saving interventions found at health facilities (Juran *et al.*, 2018; Ouma *et al.*, 2018). Estimates of spatial accessibility are essential and powerful in informing health service planning and decision-making (Banke-Thomas *et al.*, 2024; Wong *et al.*, 2024).

Geographic accessibility to healthcare is mainly characterised in terms of travel time or distance between two locations (Macharia, Banke-Thomas, *et al.*, 2023; Ouma *et al.*, 2021). It is often captured using indicators of self-reported travel time (Bouanchaud *et al.*, 2022), modelled travel time (Moturi *et al.*, 2022), distance (Bouanchaud *et al.*, 2022), or the percentage of population living within a specified threshold of travel time/distance to a healthcare service (Curtis *et al.*, 2021; Juran et al., 2018; Ouma *et al.*, 2018). Various methods have been used to estimate travel distance and time, for example, Euclidean distance, least-cost path algorithm, self-reported travel time and routing Application Programming Interface (APIs) (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021; Cuervo *et al.*, 2022; Mutono *et al.*, 2022; Ouma *et al.*, 2021). These approaches require four data elements: location of health services, their capacity, underlying population with need for healthcare, and the infrastructure which facilitates modality of travel (Banke-Thomas, Macharia, et al., 2022; Macharia, Ray, et al., 2021). Such datasets may include road network, land cover, topography, travel barriers, user preferences, spatial distribution of the target population, availability of facility, facility location, opening times, mode of transport, road speeds, traffic conditions, and seasonality (Banke-Thomas, Macharia, *et al.*, 2022; Macharia, Ray, *et al.*, 2021; Makanga *et al.*, 2017; Molenaar *et al.,* 2023). How accurately available data captures how the population travels to care is strongly reflected in the outputs and policy recommendations.

Various tools bring these datasets together to estimate the travel time to the nearest facility. Such tools include AccessMod (Ray & Ebener, 2008; University of Geneva/GeoHealth group *et al.*, 2023), Geographic Information System (GIS) software such as ArcGIS Pro (ESRI Inc., Redlands, CA, USA), and QGIS (QGIS Development Team, 2023), packages in R software environment (R Core Team, 2021) such as *gdistance* (van Etten, 2017), and Open-Source Routing Machine (OSRM) (OSRM, 2023). Among these tools, AccessMod is one of the most used to estimate travel time in LMICs, particularly in African countries (Juran *et al.*, 2018; Ouma *et al.*, 2018). It is a free, open-source, user-friendly tool supported by the World Health Organization (WHO) to analyse geographic accessibility via a least-cost path algorithm. AccessMod imports user-provided geospatial datasets (vector such as road network, raster such as land cover, and tabular such as travel speeds). This information is used to set the parameters required to calculate the travel time to the closest health facility (Ray & Ebener, 2008; University of Geneva/GeoHealth group *et al.*, 2023). However, data imported to AccessMod concerning localised transport such as road speeds, roadblocks, (near-) real-time traffic conditions and weather variability, are rarely available or accessible (Ahmed *et al.*, 2019; Macharia, Ray, *et al.*, 2021). Even when they are available, they might be outdated, inaccurate, incomplete, or at a low resolution (Ahmed *et al.*, 2019; Macharia, Ray, *et al.*, 2021). Therefore, pragmatic assumptions are generally made, for example, about modes of transport and associated average speed on each type of road and off-road (Juran *et al.*, 2018; Ouma *et al.*, 2018), and reduced speeds due to traffic in urban areas (Blanford *et al.*, 2012; Ouma *et al.*, 2021) or during a rainy season (Blanford *et al.*, 2012; Ouma *et al.*, 2021). Hence, this allows the least-cost path algorithm to execute and generate travel time estimates (Juran *et al.,* 2018; Ouma *et al.*, 2018). These assumptions should typically be captured through workshops involving local expertise (Molenaar *et al.*, 2023). However, this approach is not easily scalable (Molenaar *et al.*, 2023). Depending on the availability and accuracy of the data, this may result in non-location specific and generic estimates of travel times. The information that AccessMod requires to compute travel times is similar to that of GIS software such as QGIS (QGIS Development Team, 2023) and most of the packages in R (R Core Team, 2021).

On the other hand, routing tools such as Google Maps Directions API (Google, 2023) and Esri routing services (Esri, 2022) are increasingly being used in research to derive travel time (Banke-Thomas, Avoka, *et al.,* 2022; Banke-Thomas *et al.*, 2024; Cuervo *et al.*, 2022; Mutono *et al.*, 2022; Wong *et al.*, 2024). The APIs use a range of specifications (such as mode of transportation), current and historic road traffic patterns and road network data within a machine learning environment to predict travel time or distance (Lau, 2020; Shashidharan, 2023). Attributes of road network such as surface, size, speed limits, tolls, and incident reports from drivers due to weather conditions or construction are incorporated (Lau, 2020; Shashidharan, 2023). Google Maps Directions API traffic data is based on Global Positioning System (GPS) enabled devices in mobile phones collected through crowdsourcing from users who have switched their location 'on' in the Google Maps application. By relaying anonymous phone locations, the time it takes to move from one location to another can be computed (Barth, 2009). Both the Google Maps Directions API and AccessMod depend on road network data, account for mode of transport, travel barriers and speeds. However, how these two tools incorporate these datasets and account for parameters that affect travel is different, which in turn affects the estimated travel time. Google Maps Directions API depends on traffic data to govern travel speeds along a route (indirectly accounting for congestion due to different factors, time of the day, and day of the week when the journey was made). AccessMod depends on user-defined speeds that can vary according to road and landcover category, but rarely vary across a given road category due to data limitations. However, users of smart phones whose traffic data are collected, (hence traffic from Google Maps Directions API) make journeys for different purposes that are not specific to healthcare-seeking behavior. For example, in an obstetric emergency case, Google Maps Directions API might over-estimate travel time because most of its data points could be routine users of road sections who are not in an emergency (Macharia, Banke-Thomas, *et al.*, 2023). On the other hand, AccessMod inputs (geospatial data, travel modes and speeds) can be tailored to the specific use case, in this case, an obstetric emergency. Further, while AccessMod has a user-friendly interface which is simpler to use, the computational expertise and financial resources needed to extract travel time from the Google Maps Directions API are high. This may explain why the application of Google Maps Directions API to derive geographic accessibility estimates to healthcare services is limited. Only a few applications of the tool in deriving travel time to healthcare have been published (Gligorić Kristina *et al.,* 2023; Macharia, Banke-Thomas, *et al.*, 2023), mainly in urban areas of LMICs, including Nairobi, Kenya (Mutono *et al.*, 2022), Lagos, Nigeria (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021; Banke-Thomas, Wong, Collins, *et al.*, 2021), and Cali, Columbia (Cuervo *et al.*, 2022).

Emerging evidence suggests that travel time estimates from routing APIs reflect reconstructed travel times of women in obstetric emergencies more closely than outputs from the least cost-path algorithm or OSRM (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021). This is likely due to the use of generic input data that are not context-specific and travel speeds that are exaggerated in the modelling of travel times in least-cost path algorithms (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021). Closer to reality estimates of travel time are critical. For example, timely accessibility to facilities that can offer comprehensive emergency obstetric care (CEmOC), provided by skilled health personnel, can reduce maternal deaths by 15-50% and intrapartum stillbirths by 45–75% (Paxton *et al.*, 2005). Hence there is a need to interrogate estimates derived from these two independent modelling frameworks. However, to date, there are no systematic evaluations comparing travel time estimates to CEmOC derived from AccessMod (based on a least cost path algorithm) and Google Maps Directions API (that is more likely to yield realistic travel times because of the quality and novelty of the input data it relies on (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021)) in urban settings. Therefore, in this study, we model and compare estimates of travel time to the nearest CEmOC facility derived from Google Maps Directions API with those modelled using a least-cost path algorithm in AccessMod. Specifically, we assess the extent of differences between estimates from these two tools and summarise the possible reasons for such differences in three large Nigerian conurbations (city and adjacent suburbs) (Cambridge Dictionary, 2023): Kano, Port Harcourt, and Lagos.

Materials and Methods

Study setting

The study was conducted in Nigeria which is made up of 36 states and a Federal Capital Territory. At a smaller administrative level, the country is divided into 774 local government areas (LGAs) and 8,813 wards. In this study, our administrative level of analysis was conurbations (aggregation of wards including those within the central city and surrounding suburbs) and included Kano (in Kano state) comprising 16 LGAs and 189 wards, Port Harcourt (in Rivers state), nine LGAs and 101 wards and Lagos (in Lagos State) 20 LGAs and 375 wards. The three conurbations are a subset of 15 conurbations from a larger study on geographic accessibility to CEmOC facilities (Banke-Thomas et al., 2024). They were selected as they represent the most populous urban areas in the three major regions of Nigeria, North, South and West, respectively: Kano (4.2 million people), Port Harcourt (3.3 million people) and Lagos (15.4 million people; Figure 1). According to the 2018 Nigeria Demographic and Health Survey, only 19.2% of births in Kano state occurred in health facilities, 48.2% (7.4%) in Rivers state and 75.7% (12.5%) in Lagos state. Also, the percentage of women aged 15-49 years who reported distance to a health facility as the main problem in accessing health care was highest in Kano (17.7%) and relatively lower in Rivers (13.3%) and Lagos (12.7%) states (National Population Commission Nigeria & The DHS Program ICF, 2019).

Study approach

We applied a four-step approach (Figure 2). The first step entailed the assembly of spatial layers of CEmOC facilities and factors which affect travel to facilities for import in AccessMod. Second, we estimated median travel time (MTT) from every location to the nearest CEmOC facility within each conurbation using the least-cost path algorithm in AccessMod, at raster cell-level and aggregated at subnational units of decision making (wards). Third, using the Google Maps Directions API, equivalent MTT estimates to the nearest CEmOC facilities were extracted (for each raster cell and ward) within each of the three conurbations. Finally, we compared the estimated MTT derived from the two tools. The comparison was at raster cell-level (based on correlation coefficient, linear model and a smoothed curve approximated by a piecewise linear function) and wards (based on 15-minute bins of ≤15, >15-≤30, >30-≤45, >45-≤60, >60).

Step 1: assembly of spatial layers of CEmOC facilities and factors affecting travel for import in AccessMod

Defining spatial extent of conurbation boundaries

As there were no administratively defined spatial extents of conurbations in the selected urban areas we defined these boundaries by overlaying three geospatial layers: the population map showing the distribution of people (Bondarenko *et al.*, 2022), the Global Human Settlement Layer showing the degree of urbanisation (Schiavina *et al.*, 2022), and Google Maps to show road network and built-up areas. Any wards and LGAs which intersected with the overlay of these three spatial layers were deemed part of the conurbation. The wards and LGAs included in each conurbation are shown in Figure 1.

Assembly of a geocoded database of CEmOC health facilities

We utilised an existing database of geocoded CEmOC facilities, both public and private in 15 conurbations in Nigeria. We included all known 1,021 CEmOC facilities within the boundaries of the three conurbations: 145 (16 public and 129 private) in Kano, 84 (5 public and 79 private) in Port Harcourt and 792 (27 public and 765 private) in Lagos (Macharia, Wong, *et al.*, 2023; Olubodun *et al.*, 2023).

Population distribution of women of child-bearing age (WoCBA)

These 2020 estimates were available from the WorldPop Open spatial demographic data and research portal (Tatem, 2017). We downloaded and summed the constrained version of population distribution maps showing 5 year-age groups between 15 and 49 years for females to obtain estimates of WoCBA. Data on WoCBA and the list of the CEmOC facilities were the only common datasets (same source) that were used in both AccessMod and Google Maps Directions API.

Factors affecting travel to health facilities

We used publicly available spatial layers of factors which affect travel to CEmOC facilities. These included road networks from OpenStreetMap (OSM) from 2022 (Geofabrik GmbH, 2023), Sentinel-2 land cover at 10m resolution that included water bodies (travel barriers) from 2021 (Karra *et al.*, 2021), and Shuttle Radar Topography Mission digital elevation model (DEM) at 30m resolution (Van Zyl, 2001). The road network represented routes for motorised transport when accessing healthcare from residential areas. Roads were reclassified into four classes: primary, secondary, tertiary, and minor, based on the road attributes data from OSM (Geofabrik GmbH, 2023). The Land cover dataset was used to represent areas where no roads existed to represent the geographical space that people need to traverse. In these areas without road network, people often walk (patients might be carried) to get to the road. The DEM was used to calculate the slope of the land for adjusting the walking speeds uphill and downhill (Tobler, 1993). Travel barriers that impede travel include water bodies and flooded vegetation (except in the presence of a bridge). The maps are shown as an Supplementary materials.

Travel speeds to CEmOC facilities

In obstetric emergencies occurring to urban residents, women and their families are likely to opt for motorised transport (Ekpenyong *et al*., 2022), unless a particular section of the journey is inaccessible by motorised transport, in which case walking becomes the predominant means of travel. We assigned travel speeds to various types of road classes as outlined in Table 1, maintaining consistency with previous studies on emergency healthcare accessibility in Africa (Ouma *et al.*, 2018; Rudolfson *et al.*, 2020; Stewart *et al.*, 2016). In areas lacking roads (or areas where road data might be incomplete based on OSM), we assumed that women in an emergency either walked or were carried to the nearest road before commencing motorized travel (Ouma *et al.*, 2018). Consequently, all areas without road connectivity were assigned a speed of 4 or 5 km/h (approximate walking speed) (Ouma *et al.,* 2018).

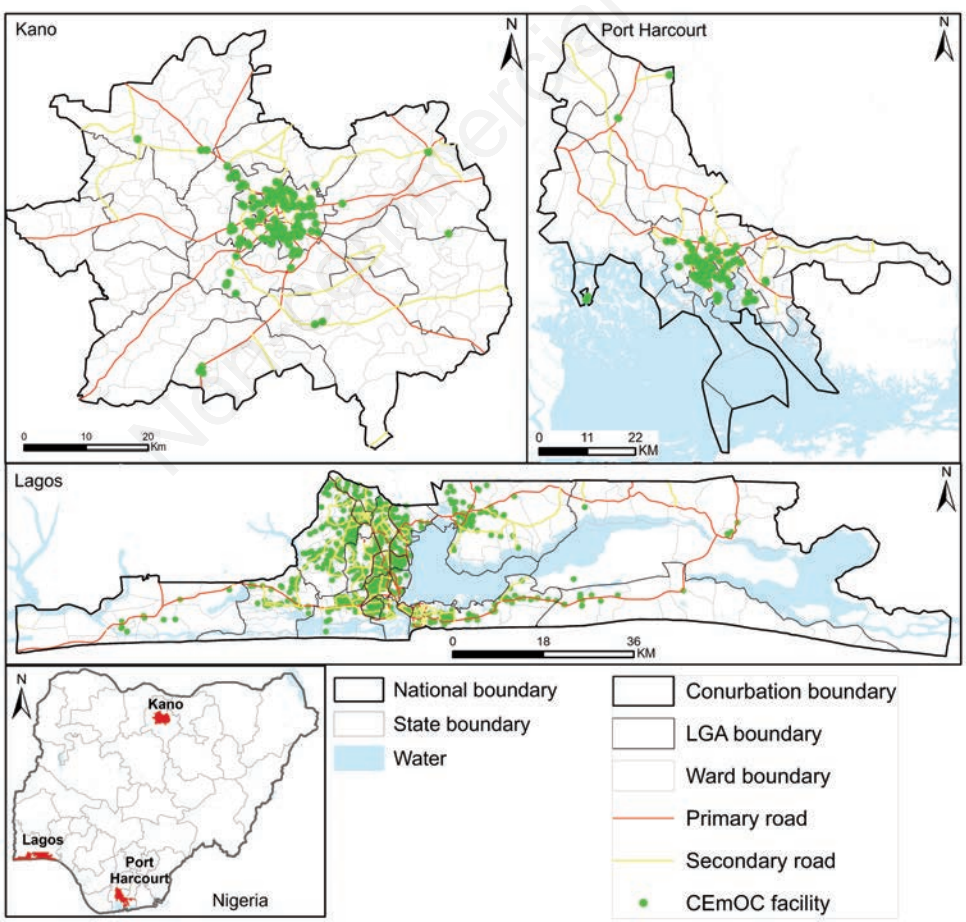

Figure 1. The study area location showing three conurbations (Kano, Port Harcourt, and Lagos) in Nigeria.

Step 2: estimating travel time in AccessMod

To estimate travel time to the nearest CEmOC facility in AccessMod, we combined data from the assembled layers of factors that affect travel and the defined travel speeds based on literature and used a least-cost path algorithm. For this, we modelled travel time to reach the nearest CEmOC facility for a multi-modal transport scenario (walking and motorised transport) using a least-cost path algorithm in AccessMod 5.7.17 (Ray & Ebener, 2008) at 0.09km spatial resolution. To harmonize all the input datasets to that spatial resolution, the landcover and the DEM were resampled to 0.09km using the majority and the bilinear interpolation techniques, respectively. The resampled land cover was then merged with the road network via the "merge land cover" module in AccessMod to create a merged gridded surface.

The resulting merged gridded surface, corresponding travel speeds (Table 1) and location of CEmOC facilities were used to compute cumulative travel time from each raster cell to the nearest CEmOC facility considering the least cost path (cost measured in terms of time). To factor in topography, walking speeds were adjusted for slope based on Tobler's formulation, which characterises changes in human walking velocity due to slope variation (Tobler, 1993). The model was executed for each conurbation at a time. The raster cell travel time estimates were aggregated at the ward level to obtain MTT to the nearest CEmOC facility per conurbation using the 'Zonal statistics' tool in ArcGIS Pro version 3.2.2 (ESRI Inc., Redlands, CA, USA). The extraction was done within populated areas based on the population distribution of WoCBA.

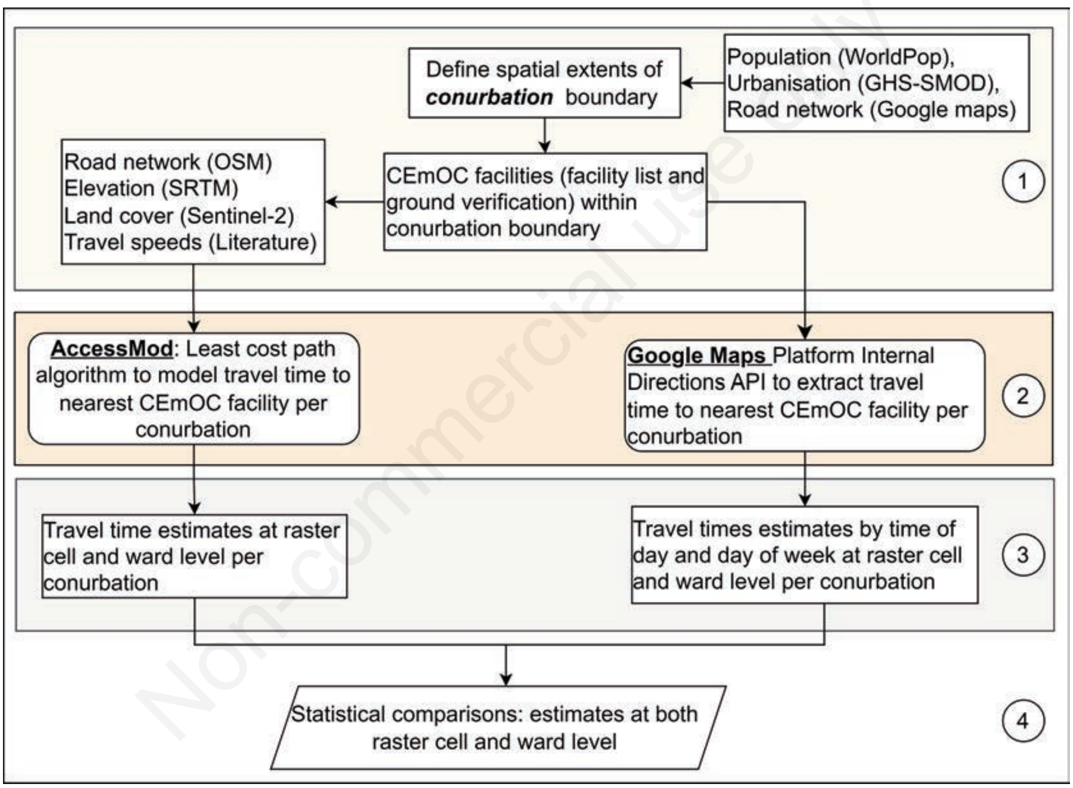

Figure 2. Analytical flow of estimating travel time to facilities using cost friction surface and routing services and their comparisons. OSM, OpenStreetMap; SRTM, The Shuttle Radar Topography Mission; GHS-SMOD, Global Human Settlement Layer Settlement Model Grid; CEmOC, Comprehensive Emergency Obstetric Care; API, Application Programming Interface

Table 1. Travel speeds assigned to different road categories and landcover types for AccessMod.

Category	Class/type	Speed (km/h)	Mode of transport
Road network	Primary road	100	Motorized
	Secondary road	50	
	Tertiary road	30	
	Minor road	20	
Non-road areas	Trees, crops, rangeland	4	Walking
	Bare ground, built-up	5	
Barriers to travel	Water, flooded vegetation	0	Non-traversable (routed around or through a bridge)

Step 3: estimating travel time to the nearest CEmOC facility in Google Maps Directions API

We extracted estimates of travel time for each conurbation from a database of MTT calculated using Google Maps Directions API for 15 Nigerian conurbations (Macharia, Wong, *et al.*, 2023). The detailed approach to creating this database is outlined elsewhere (Macharia, Wong, *et al.*, 2023). Briefly, travel time estimates were based on Google Maps Directions API extracted in January 2023 (Google, 2023). To predict travel time, Google Maps Directions API uses real-time and historical traffic patterns, road network data (and its attributes such as speed limits and incident reports from drivers), and specified modes of transport (Cuervo *et al.*, 2022; Google, 2023) within a machine learning environment (Lau, 2020; Shashidharan, 2023). Therefore, the travel speeds are based on Google traffic data while road network and travel barriers are based on Google Maps. The mode of transport, spatial resolution, and the origin-destination matrix were specified by the users. The destination was the location of each CEmOC facility from our assembled database, while the origin was raster cells of approximately 0.6 km x 0.6 km (The s2geometry.io, 2022). For this analysis, we used two extreme traffic scenario estimates: weekday/6-8pm (peak) and weekend/1-3am (non-peak), representing when travel time is likely to be longest and shortest because of traffic congestion, respectively. Like AccessMod, for every populated raster cell (based on population distribution WoCBA), there was an estimate of tavel time which was also aggregated to the ward level to MTT.

Step 4: comparing travel time estimates from AccessMod and Google Maps Directions API

We compared travel time estimates from AccessMod and Google Maps Directions API at two levels, separately for each conurbation. First, we compared the agreement/concordance in the classification of wards into travel bands for aggregated (ward) travel estimates. Second, for each conurbation, we compared the raster cell travel time estimates between AccessMod and Google Maps Directions API travel time using correlation coefficients and three statistical models. In the comparison, four wards (two in Kano and Lagos each) were excluded since a majority of the space was water bodies and we did not account for water transport.

Ward-level comparisons

We used the ward-level MTT (aggregated from raster cell values) from both AccessMod and Google Maps Directions API (peak and off-peak) to classify and create choropleth maps of 15-minute incremental bands (band 1: ≤15 minutes, band 2: >15-≤30 minutes, band 3: >30-≤45 minutes, band 4: >45-≤60 minutes, and band 5: >60 minutes). We compared the 15-minute bands from AccessMod estimates and identified the percentage of wards that fell into different categories against the two estimates of travel time from Google Maps Directions API (peak and non-peak). We used these 15-minute bands because they are widely used as benchmarks for policy and research on spatial access to services in general and healthcare in particular (Curtis *et al.*, 2021; Geldsetzer *et al.*, 2020; Moturi *et al.*, 2022). For example, Target 4 of the strategies for Ending Preventable Maternal Mortality uses a threshold of 120 minutes to assess physical access (EPMM Working Group, 2015) while the 15-minute city concept envisions services being accessible within 15 minutes by urban dwellers (Allam *et al*., 2022).

Raster cell level comparisons

Beyond the ward-level estimates produced for policy relevance, we sought to explore and better understand the relationship between these three estimates (AccessMod, Google Maps Directions API-peak and non-peak) at the level of raster cell. The raster cell estimates from AccessMod were resampled to 0.6km resolution to match the Google Maps Directions API's raster cell resolution. First, Pearson's product-moment correlation coefficient was estimated across the three datasets and classified as either very high (≥0.9), high (0.7 to 0.9), moderate (0.5 to 0.7), low (0.3 to 0.5), or very low (≤0.3) (Mukaka, 2012). Second, we fitted three statistical models between AccessMod (predictor-x) and Google Maps Directions API (outcome-y) raster cell estimates. We started with a simple linear model. However, as the relationship between estimates from these two tools might exhibit a non-linear relationship, we also fitted a smoothing curve to allow for better visualisation of the nature of non-linear relationships. However, as such curves are not easily interpretable, we used a piecewise linear function (broken-stick models) with one knot to obtain more interpretable parameters whilst accounting for any potential non-linear relationships (Giorgi *et al.*, 2021). Fitting was done using the 'mgcv' package (Wood, 2017) in the R software environment (version 4.1.2) (R Core Team, 2021). All the maps were created in ArcGIS Pro version 3.2.2 (ESRI Inc., Redlands, CA, USA), while statistical analyses were done in the R software environment (R Core Team, 2021).

Results

We present the comparison results separately for Kano, Port Harcourt, and Lagos due to the different characteristics of the cities. For each conurbation, we first describe the congruence in the classification of wards into 15-minute bands followed by the raster cell-level comparison of travel time estimates from both tools.

Kano

In Kano, the median of all 189 ward-level MTT estimates to the nearest CEmOC facility based on AccessMod tool was 7.0 minutes (interquartile range (IQR): 18.5). The ward-level estimates were heterogeneous; the majority (66.1%) were in band 1 (≤15 minutes) while only one ward was in band 5 (>60 minutes) (Table 2). There was minimal difference between peak and non-peak travel scenarios from the Google Maps Directions API for the percentage of wards falling in the same 15-minute bins (Table 2 and Figure 3). The ward-level MTT from Google Maps Directions API peak was 14.0 minutes (IQR: 19.4) while during non-peak it was 13.5 minutes (IQR: 19.0) or twice as long relative to AccessMod. By grouping wards into 15-minute incremental bands (Figure 3), 138 (73%) and 136 (72%) wards were classified into the same band based on MTT estimates from both AccessMod and Google Maps Directions API, peak and non-peak scenarios, respectively (Table 2). For wards in band 3 (>30-≤45 minutes), the concordance between AccessMod and Google Maps Directions API reduced to 50% (peak) and 44% (non-peak), compared to 80% concordance in wards band 1 (≤ 15 minutes) in both peak and non-peak travel scenarios. In 87.0% of wards, ward-level MTT estimates from Google Maps Directions API (peak) were longer than those from using AccessMod by a median of 3.7 minutes (IQR: 5.7) (Supplementary materials). In the rest of the wards (13%), ward-level MTT estimates from AccessMod were longer than Google Maps Directions API by a median of 2.7 minutes (IQR: 6.2). The results for the non-peak scenario followed a similar trend (Supplementary materials).

The MTT to the nearest CEmOC facility of all the 2,158 raster cells in Kano was 9.0 minutes (IQR: 17.0) based on AccessMod, while those from Google Maps Directions API were 14.2 minutes (IQR: 17.3) during peak and 13.7 minutes (IQR: 16.7) during non-peak. The median absolute difference between AccessMod and Google Maps Directions API travel time estimates was 4.8 minutes (IQR: 6.5) during peak and 4.5 minutes (IQR 5.8) during non-peak. During peak and non-peak scenarios, 80.3% and 83.7% of the raster cells each had a difference of <10 minutes, respectively. Only 3.2% (peak) and 2.9% (non-peak) of the raster cells had a difference of over 20 minutes. Travel time estimates from AccessMod were shorter than those from Google Maps directions API in 80% of the 2,158 raster cells during either peak or non-peak scenarios.

Table 2. Categorisation of wards based on travel time from AccessMod compared to Google Maps internal Directions API (peak and non-peak) in Kano, Port Harcourt, and Lagos conurbations. Green indicates 100% agreement between the time bands.

Time bands (minutes) AccessMod (wards)	Google Directions API	Agreement between Google Directions API and AccessMod Peak: No. of wards (%)	Non-peak: No. of wards (%)
Kano Conurbation (189 wards)			
Band 1: ≤15 (125)	≤ 15	99 (79.2)	101 (80.8)
	> 15 - ≤30	26 (20.8)	24 (19.2)
Band 2: >15 - ≤30 (47)	≤ 15	4 (8.5)	7 (14.9)
	> 15 - ≤ 30	30 (63.8)	27 (57.4)
	> 30 - ≤ 45	12(25.5)	12 (25.5)
	> 45 - ≤ 60	1 (2.1)	1 (2.1)
Band 3: >30 - ≤45 (16)	> 15 - ≤ 30	4 (25.0)	5 (31.3)
	> 30 - ≤ 45	8 (50.0)	7 (43.8)
	> 45 - ≤ 60	3 (18.8)	4 (25.0)
	> 60	1 (6.3)	0 (0.0)
Band 4: >45 - ≤60 (0)	-	-	-
Band 5: >60 (1)	>60	1(100.0)	1 (100.0)
Overall (189 wards)		138 (73.0)	136 (72.0)
Port Harcourt conurbation (101 wards)			
Band 1: ≤ 15 (70)	≤ 15	54 (77.1)	57 (81.4)
	> 15 - ≤30	15 (21.4)	13 (18.6)
	> 30 - ≤ 45	1 (1.4)	0 (0.0)
Band 2: > 15 - ≤ 30 (13)	> 15 - ≤ 30	9 (69.2)	11 (84.6)
	> 30 - ≤ 45	3 (23.1)	2 (15.4)
	> 45 - ≤ 60	1 (7.7)	0 (0.0)
Band 3: > 30 - ≤ 45 (16)	> 15 - ≤ 30	9 (56.3)	10 (62.5)
	> 30 - ≤ 45	6 (37.5)	5 (37.5)
	> 45 - ≤ 60	0 (0.0)	0 (0.0)
	> 60	1 (6.3)	1 (6.3)
Band 4: > 30 - ≤ 45	-	-	-
Band 5: > 60 min (2)	> 45 - ≤ 60	2 (100)	2 (100)
	> 60	0 (0)	0 (0)
Overall (101 wards)		69 (68.3)	73 (72.3)
Lagos conurbation (375 wards)			
Band 1: ≤ 15 (357)	≤ 15	331 (92.7)	334 (93.6)
	> 15 - ≤30	22 (6.2)	19 (5.3)
	> 30 - ≤ 45	4 (1.1)	4 (1.1)
Band 2: > 15 - ≤ 30 (7)	> 15 - ≤ 30	2 (28.6)	2 (28.6)
	> 30 - ≤ 45	1 (14.3)	1 (14.3)
	> 45 - ≤ 60	4 (57.1)	4 (57.1)
Band 3: > 30 - ≤ 45 (5)	> 15 - ≤ 30	0 (0.0)	0 (0.0)
	> 30 - ≤ 45	1 (20.0)	1 (20.0)
	> 45 - ≤ 60	1 (20.0)	2 (40.0)
	> 60	3 (60.0)	2 (40.0)
Band 4: > 30 - ≤ 45 (0)	-	-	-
Band 5: > 60 min (6)	≤ 15	2 (33.3)	2 (33.3)
	> 45 - ≤ 60	1 (16.7)	3 (50.0)
	> 60	3 (50.0)	1 (16.7)
Overall (375 wards)	337 (89.9)	338 (90.1)	

The raster cell-level travel time estimates between the two tools exhibited a high positive correlation in both peak (0.845 [CI:0.833 - 0.857]) and non-peak (0.850 [CI:0.838 - 0.862]) (Table 3). The scatter plot showed a strong linear relationship up to around 45 minutes (Figure 4). The adjusted R^2 based on the simple linear model indicated that AccessMod estimates accounted for a consistently high variance of the Google Maps Directions API estimates, 0.714 during peak and 0.723 during non-peak hours. After 45 minutes, the direction of the relationship changes and is represented by a spline with an adjusted R^2 of 0.749 and 0.757, respectively, slightly higher than the simple linear model (Table 3).

Port Harcourt

In Port Harcourt conurbation (101 wards), AccessMod MTT to the nearest CEmOC facility in all wards was 6.0 minutes (IQR:19.0). The ward-level MTTs were very heterogeneous; the majority (69.3%) were in the first band (≤15 minutes), 12.9% in band 2 (15 to 30 minutes), 15.8% in band 3 (30 to 45 minutes), while only 2 wards (2.0%) were in the fifth band (>60 minutes). On the other hand, based on the Google Maps Directions API, during peak hours, the median of all ward-level MTT estimates was 14.1 minutes (IQR:19.7), and 12.1 minutes (IQR:19.7) during non-peak hours, (Figure 5). In both traffic scenarios, most of the wards (at least 50%) had a ward level MTT of ≤ 15 minutes while at least 16% were either band 3, 4 and 5 combined in both traffic scenarios. In Port Harcourt conurbation, just like in Kano, there was a two-fold difference in the median ward-level MTT estimates between the AccessMod and the Google Maps Directions API (both traffic scenarios). When wards were grouped in 15-minute bands, 68.3% (peak) and 72.3% (non-peak) of wards were in the same band for estimates from both AccessMod and Google Maps Directions API. Similar to Kano, concordance decreased for wards in which MTT was longer. That is across the 15-minute bands, 77.1%, 69.1% and 35.1% of the wards were classified in the same band for the first three bands, respectively, considering AccessMod and Google Maps Directions API's peak estimates (Table 2). A similar trend was observed for the non-peak travel scenario (Table 2). Finally, in 85 out of the 101 wards (84.2%), Google Maps Directions API ward level MTT were longer than those of AccessMod by a median of 5.0 minutes (IQR: 6.8) (Supplementary materials). In the rest of the wards (15.8%), ward-level TT estimates from AccessMod were longer by a median of 10.9 minutes (IQR: 13.1) (Supplementary materials). The MTT to the nearest CEmOC facility of all the 1,395 raster cells in Port Harcourt conurbation was 7.0 minutes (IQR: 10.5) based on AccessMod, while those from Google Maps Directions API were 14.4 minutes (IQR: 15.9) during peak and 12.3 minutes (IQR: 13.9) during non-peak. The median absolute difference between AccessMod and Google

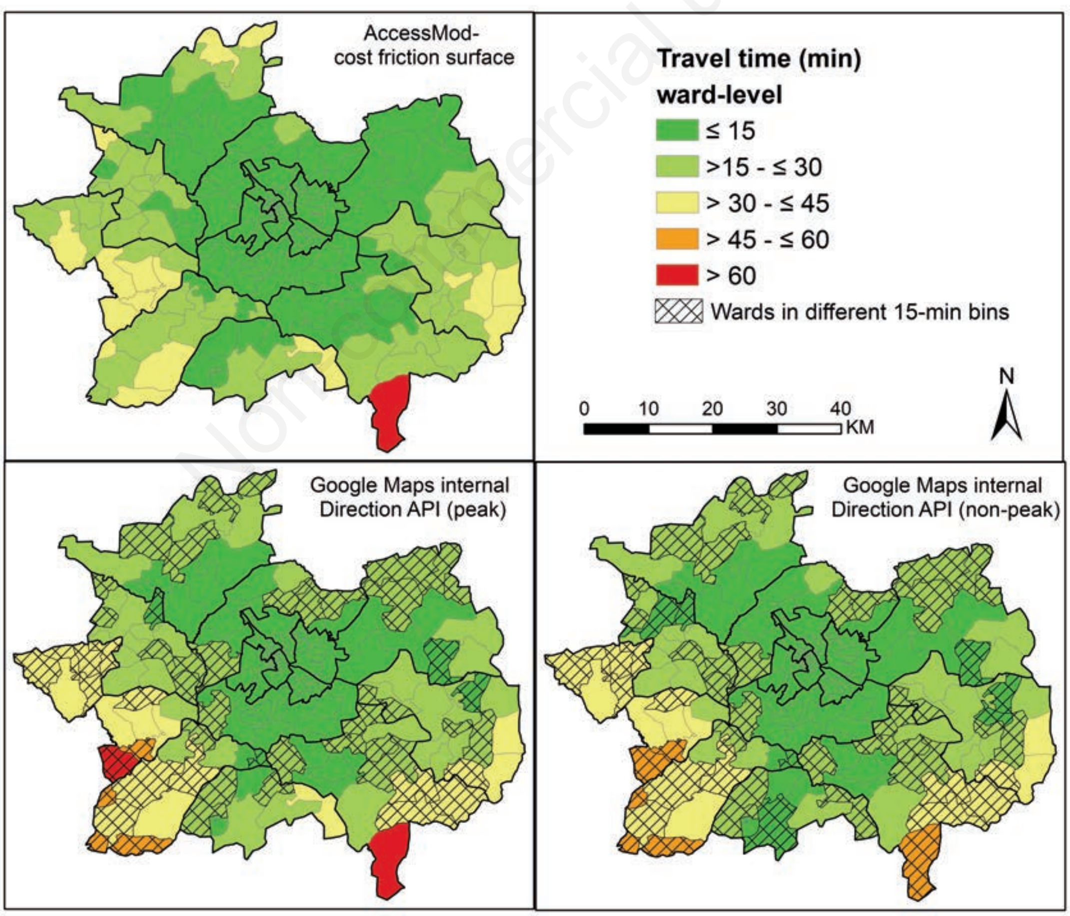

Figure 3. Travel time to CEmOC facilities using least-cost path in AccessMod and Google Maps internal Directions API during peak and non-peak times classified into 15-minute bands in Kano, Nigeria. Wards falling into different bands comparing AccessMod and Google Directions API are hatched.

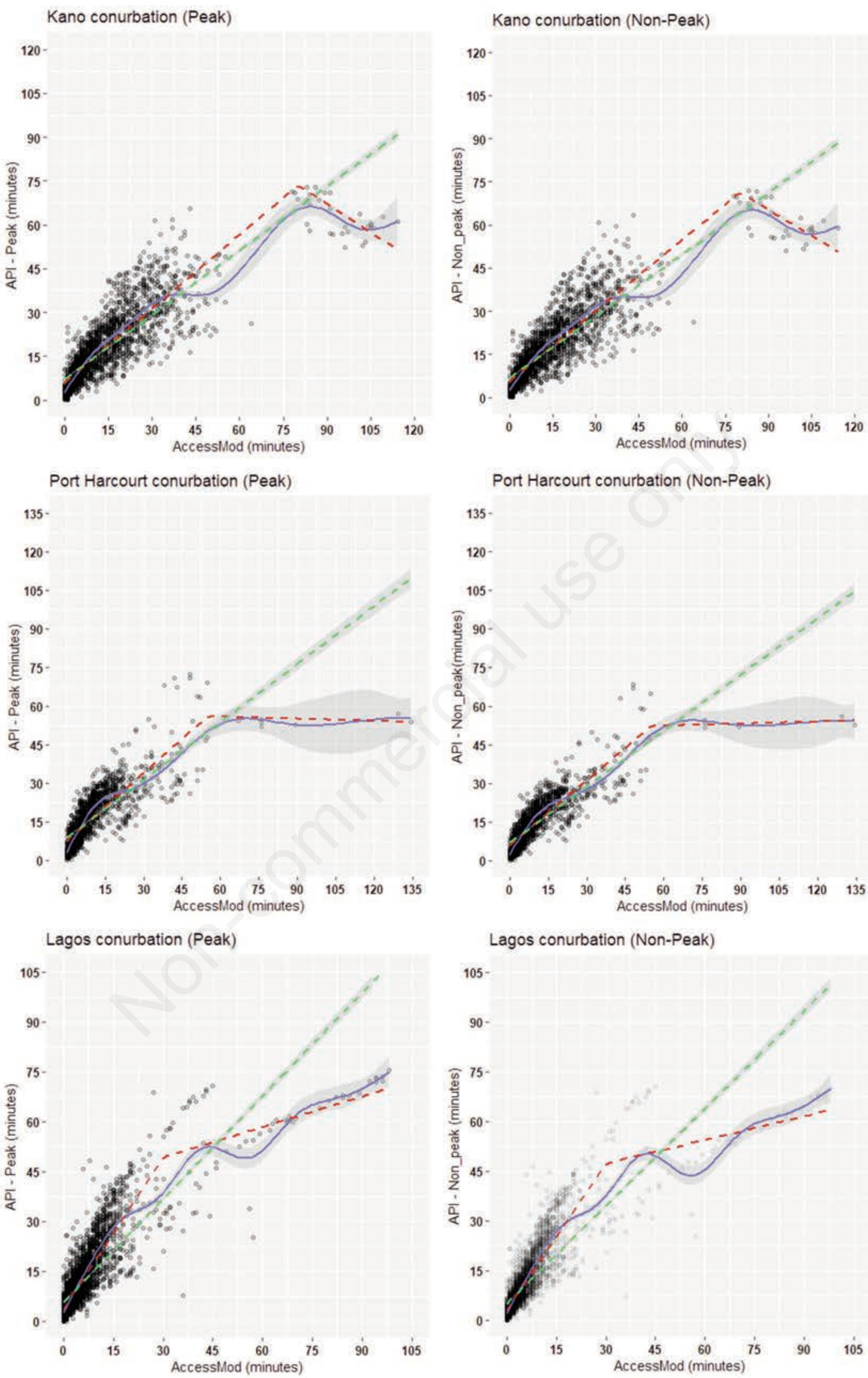

Figure 4. Scatter plots of travel time (in minutes at 0.6km grids) from Google Maps internal Directions API (peak and non-peak) against those from AccessMod in Kano, Port Harcourt, and Lagos. The blue and red lines are natural and linear (with 2 knots splines, respectively. The green line is a simple linear model.

Maps Directions API travel times was 6.8 minutes (IQR: 7.5) during peak and 4.9 minutes (IQR: 5.8) during non-peak. During peak and non-peak, 70.9% and 85.9% of the raster cells had a travel time difference of less than 10 minutes, respectively, when AccessMod was compared with Google Maps Directions API. Only in 30 raster cells (2.2%) was the difference >20 minutes in the peak scenario and in 0.8% raster cells in the non-peak scenario. Travel time estimates from AccessMod were always shorter than those from Google Directions API in 90.6% and 87.4% of the raster cells during peak or non-peak scenarios, respectively. The raster cell level estimates from AccessMod and Google Directions API had a strong positive correlation in both peak (0.790 [CI:0.770–0.809]) and non-peak (CI:0.834 [0.817- 0.849]) travel scenarios (Table 3). The scatter plot showed a linear relationship up to about 50 minutes; the fitted linear model had an adjusted R^2 of 0.624 for the peak and 0.695 for the non-peak travel scenario (Figure 4). After approximately 60 minutes, the direction of the relationship changed slightly; piecewise linear function adjusted R^2 increased to 0.677 for peak and 0.746 for non-peak travel scenario, respectively (Table 3 and Figure 4).

Lagos

The AccessMod modelled median of all ward-level TT estimates (to the nearest CEmOC facility), was 1.0 (IQR:2.0) in Lagos conurbation (375 wards). Almost all wards (95.2%) were in the first band (≤15 minutes), while all the remaining 15-minute bands had approximately 1.5% of the wards each (Table 2 and Figure 6). Based on Google Maps Directions API estimates, the median of all ward-level TT estimates for Lagos was 4.6 minutes (IQR: 4.7) and 3.8 minutes (IQR 3.9) during the peak and non-peak travel scenario. Similarly, the majority of the wards were within the first band (at least 15 minutes): 89.3% for peak and 90.1% for non-peak scenarios. Therefore, Google Maps Direction API was about four times longer relative to those of AccessMod level MTT. When considering the proportion of wards falling within the same 15-minute bands, 90% of the wards were classified in the same band by AccessMod and Google Maps Directions API estimates. These were driven mainly by similarities in the first band of 15 minutes (Table 2). In 364 out of the 375 wards (97.1%), Google Maps Directions API ward level MTT were longer than those of AccessMod by a median of 3.4 minutes (IQR: 2.6) (Supplementary materials). In the rest of the wards (2.9%), ward level TT estimates from AccessMod were longer by a median of 13.1 minutes (IQR: 14.4 minutes) (*Supplementary materials*).

The MTT to the nearest CEmOC facility of all the 3,460 raster cells in Lagos conurbation was 3.0 minutes (IQR: 5.0) based on AccessMod, while those from Google Maps Directions API were 7.5 minutes (IQR: 10.2) during peak and 6.6 minutes (IQR: 9.5) during non-peak. The median absolute difference between AccessMod and Google Maps Directions API travel times was 4.4 minutes (IQR: 5.8 minutes) during peak and 3.7 minutes (IQR 4.9 minutes) during non-peak. During peak and peak, 81.9% and 85.3% of the raster cells had a travel time difference of less than 10 minutes, respectively when AccessMod was compared with Google Maps Directions API. In 3.8% of the raster cells was the difference >20 minutes in the peak scenario and in 2.7% of raster cells in the non-peak scenario. Travel time estimates from AccessMod were always shorter than those from Google Maps Directions API in 96% of the raster cells during peak both and non-peak scenarios. Raster cell-level estimates between AccessMod and Google Maps Directions API exhibited high positive correlations in both peak (0.840 [0.829 - 0.849]) and non-peak hours (0.839 [0.829 - 0.849]) (Table 3). The scatter plot showed a strong linear relationship up to around 45 minutes. The adjusted R^2 from the simple linear model shows that AccessMod estimates accounted for 0.705 (during peak) and 0.704 (during non-peak hours) vari-

Table 3. The correlation coefficients, linear and spline models, adjusted R-squared values depicting the relationship between travel time estimates from AccessMod and Google Maps internal Directions API (peak and non-peak) in Kano, Port Harcourt, and Lagos.

Kano conurbation	**Peak**	**Non-peak**
r [95% CI]	0.845 [0.833 - 0.857]	0.850 [0.838 - 0.862]
Linear model	y = 7.159 + 0.735X	y = 6.785 + 0.716X
Adjusted R^2	0.714	0.723
Spline model	y = 5.951+ I((0.845X - 80) * (-1.492 X>80))	y = 5.633 + I((0.821X - 80) * (-1.425 X>80))
Adjusted R^2	0 .749	0.757
Port Harcourt conurbation		
r [95% CI]	0.790 [0.770 - 0.809]	0.834 [0.817- 0.849]
Linear model	y = 8.66+ 0.753X	y = 6.870 + 0.727X
Adjusted R^2	0.624	0.695
Spline model	y = 7.530+ I((0.882X - 55) * (-0.910X>55))	y = 5.85+ I((0.843X - 55) * (-817X>55))
Adjusted R^2	0.677	0.746
Lagos conurbation		
r [95% CI]	0.840 [0.829 - 0.849]	0.839 [0.829 - 0.849]
Linear model	y = 5.589+ 1.037X	y = 4.965 + 0.984X
Adjusted R^2	0.705	0.704
Spline model	y = 3.592+ I((1.520X - 30) * (-1.214 X>30))	y = 2.923 + I((1.477X - 30) * (-1.240 X>30))
Adjusted R^2	0.794	0.807

r, Pearson correlation coefficient, travel time estimates form Google Directions API (y) and AccessMod tool (X).

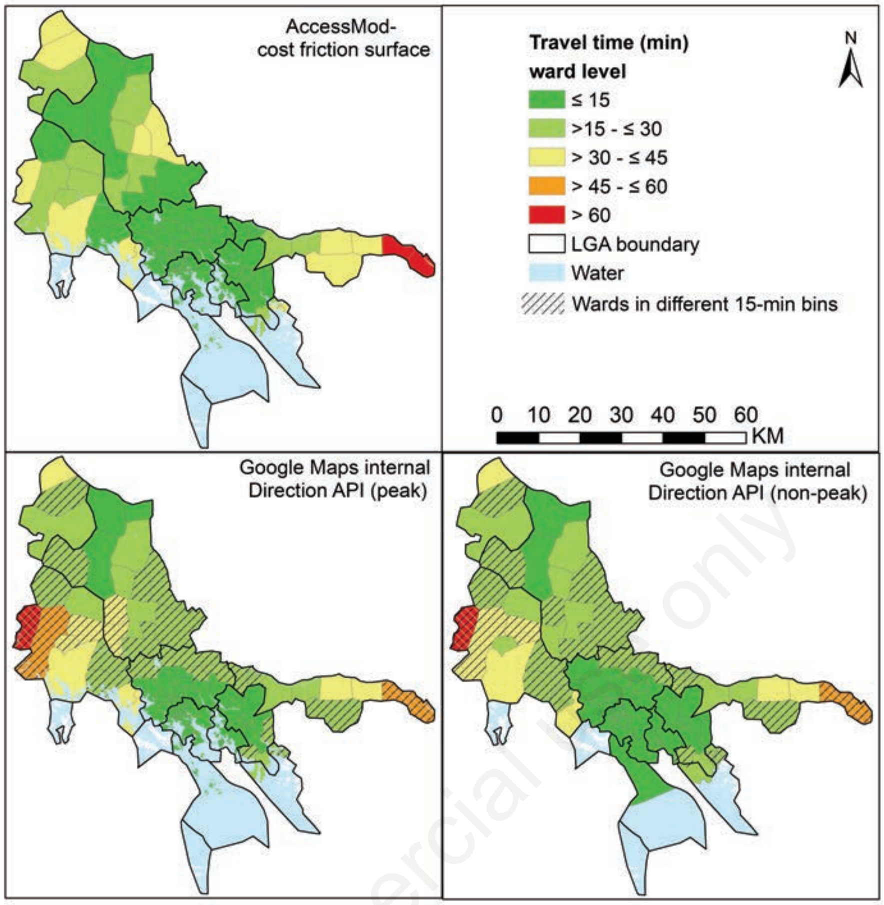

Figure 5. Travel time to CEmOC facilities from AccessMod and Google Maps internal Directions API during peak and non-peak times classified in 15-minute bands in Port Harcourt, Nigeria. Wards falling into different bands are hatched.

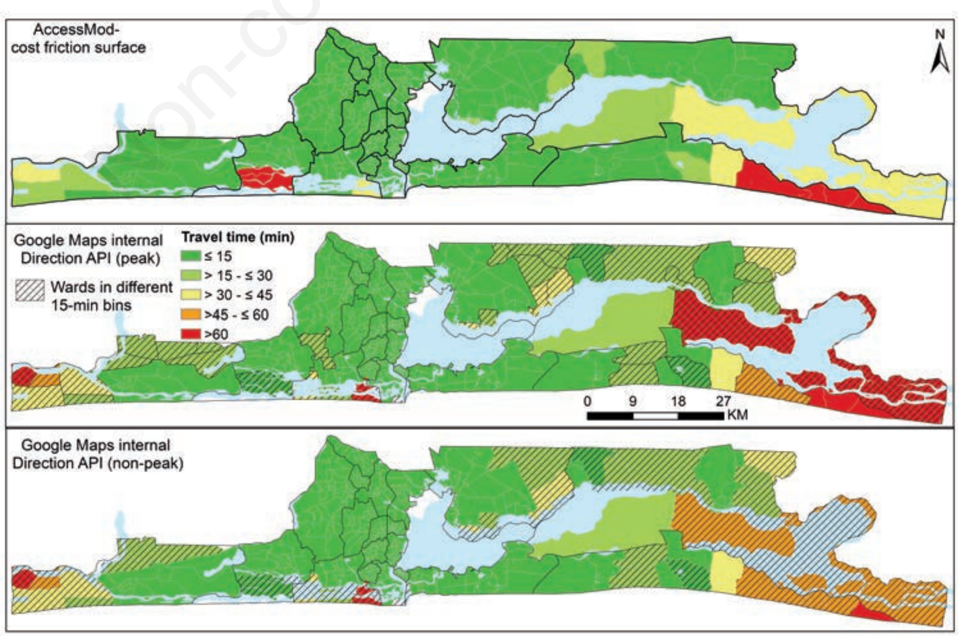

Figure 6. Travel time to CEmOC facilities compared using AccessMod and Google Maps internal Directions API during peak and non-peak times in Lagos conurbation Nigeria. Wards falling into different bands are hatched.

ance in the Google Maps Directions API estimates. At travel times longer than 45 minutes, the direction of the relationship changed and was approximated by splines, with adjusted R^2 of 0.794 and 0.807, respectively (Table 3 and Figure 4).

Discussion

We evaluated the relationship between travel time estimates derived from a least-cost path algorithm in AccessMod and those from Google Maps Direction API (during peak and non-peak travel scenarios) for three conurbations in Nigeria. Overall, about 70% of wards in all three conurbations were classified in the same 15-minute bands by both tools. There were negligible differences between peak and non-peak travel scenarios in terms of generated MTT for wards falling within the same 15-minute bins. At the raster cell level, the travel time estimates exhibited a strong correlation across the conurbations between the two tools, and moderate agreement was observed at lower travel times, while large differences were observed after 45 minutes.

MTT estimates to the nearest CEmOC facility were more similar across AccessMod and Google Maps Directions API at shorter travel times (AccessMod estimates being somewhat shorter), at both raster cell and ward levels. These areas with shorter travel times are associated with a high number of facilities, density of road network, and occupy a small densely populated area within and around the core urban area of the conurbation. Thus, the role played by the nearest facility approach is less evident. In such an area, the choice of the tool used to define spatial accessibility does not have a substantial effect on the outputs. Similar travel time estimates were also observed when Euclidean distance and modelled least cost distances were compared in four urban to semi-urban settings with good road networks and a high density of health facilities in Kenya (Bouanchaud *et al.*, 2022).

However, our results suggest substantially longer travel time estimates by AccessMod for a small number of wards and raster cells beyond the 45-minute threshold. These areas were mainly located at the edge of conurbations (typically suburbs), adjacent to a water body or with a low density of health facilities and road networks. The observed differences could be due to how both tools compute travel time. Specifically, as you move away from the city centre, there is much more walking allocated in AccessMod than the amount of walking in Google Maps Directions API i.e in areas with low densities of roads, the spaces (raster cells) in between the roads are travelled through walking in AccessMod. However, in these areas without a road network, Google Maps snaps to the road that is nearest to the starting point when a user initiates directions. Hence, more walking in AccessMod leads to longer travel time compared to the Google Maps Directions API.

In any case, road coverage and amount of walking are not the only factors that could have contributed to the observed differences; other factors, such as traffic lights and travel speeds, could have also played a part. The speeds used in AccessMod were based on previously published literature (Ouma *et al.*, 2018; Rudolfson *et al.*, 2020; Stewart *et al*., 2016) to allow comparability and contextualisation. These speeds do not vary across different sections of the roads as they should, given that they are influenced by personal driving traits, speed limits, weather variations, traffic on the road, and road conditions. Indeed, assigning an objective speed across various road types is challenging and often seen as the most significant barrier to achieving accurate estimates in cost friction modelling (Molenaar *et al.*, 2023). Molenaar et al. proposed strategies to optimise and harmonise knowledge elicitation practices for developing travel scenarios that approximate reality as much as possible for a given target population (Molenaar *et al.*, 2023). Such a strategy could improve the accuracy of cost friction estimates and reflect on-ground realities. However, eliciting speeds requires resources, which partly explains why most accessibility studies rarely incorporate localised speeds. Further research is needed on i) how well such workshops can capture the variability of traffic scenarios in urban areas, ii) who should attend these workshops (e.g., residents, traffic controllers, commuters, health workers, urban and regional planners) to better reflect the speeds, and iii) how well do these cadres recognise traffic fluctuations and changes throughout a day or a week.

On the other hand, the Google Maps Directions API will indirectly account for speed variation by considering on-ground realities such as weather variability, road accidents, tolls, speed limits, time of the day, and day of the week when the journey was made, among others by using historical and current traffic data. Consequently, these different strategies of accounting for speeds may have led to variable results. However, we ruled out the issue of heavy traffic since peak and off-peak were similar in these three conurbations when considering the percentage of wards within 15-minute bins. This observation is not generalisable to other conurbations where peak hours could have a much larger impact.

Implication for policy, practice and research

At longer travel times (above 45 minutes), there were larger differences between the tools for a small number of wards and raster cells. This translated to seven in 10 wards being classified in the same 15-minute bin for either AccessMod or Google Maps Direction API. Therefore, which tool (AccessMod or Google Maps Direction API) is used will matter for policy when identifying which of the remaining three wards have longer travel times. The coefficients from the piecewise linear model might be used as an adjustment factor in urban areas, allowing for the conversion of cost friction estimates from AccessMod to Google Maps Directions API-like estimates when routing services are unavailable. Here, we default to Google Maps Directions API as the reference because emerging evidence indicates that its outputs—compared to those from the least cost-path algorithm or OSRM more closely reflect travel time reconstructed for women in obstetric emergencies in urban areas (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021). That is when the travel time between a residence and a health facility for women is mimicked or replicated by a professional motor vehicle driver, it is closer to the Google Maps Directions API travel time estimate relative to AccessMod. However, as the inputs of AccessMod are facilitated by the end-user, there are two lenses with which we prospect as a way of generating and making available travel time estimates closer to reality. First, we recommend that providers of routing services (such as Google Maps Directions API) consider making their services open source and more widely accessible through user-friendly portals. This would enable decision-makers and researchers to generate more accurate estimates, particularly for emergencies where interventions are needed promptly to save lives compared to routine care where health-seeking can be timed to a larger extent. It is also known that the APIs are based on data from much fewer users as you move from urban to peri-urban (suburbs) to rural areas (Gligorić *et al.*, 2023; Macharia, Banke-Thomas, *et al.*, 2023). This calls for the added value of additional voluntary geographic information such as a front-end (web portal or mobile application) that would allow the user to indicate average travel time on roads (and off-road) in rural areas to improve the utility of travel time generated from the APIs in rural settings. Google also collects data from traffic sensors and cameras installed by government transportation agencies and select private companies. However, the network of sensors is limited and mostly on major roads. This could be expanded to facilitate a fuller picture of on-ground movement of vehicles.

The success and widespread application of AccessMod can be attributed to several reasons. Its open-source, user-friendly graphical user interface, and WHO-endorsed approach with facilitated capacity building activities in many countries. AccessMod has a wide array of proximity related analyses that are not implemented in other API's. For example, scaling up analysis, geographic coverage to obtain catchments, and referral times among different types of health services, among others. In addition, AccessMod was developed originally to better understand accessibility in rural areas (historically associated with healthcare accessibility challenges) for which APIs are particularly limited due to lower ownership of smartphones in LMICs (Milusheva *et al.*, 2021).

Second, several other aspects of least-cost path modelling can be improved to make its output closer to reality or more similar to that of the API. Some factors not routinely included in cost friction analyses but indirectly accounted for in APIs can be incorporated into the cost friction estimates. For instance, accounting for traffic variability (Ahmed et al., 2019), seasonal and weather variation (Makanga et al., 2017) and other localised aspects specific to an area, such as flooding (Hierink et al., 2020) could enhance the accuracy of the estimates. However, these factors are often not considered in cost friction modelling, partly due to data limitations and a lack of clear guidelines for incorporating them. Finally, beyond the use of open-source data on road networks, complementing these with country road networks whenever possible, would more accurately capture means of travel (access) to emergency care.

Separately, there is a need to generate uncertainty bounds of travel time by adjusting the mean speed used in AccessMod modelling by a percentage, for instance, ±20%. Instead of a point estimate, the generated range from AccessMod is more likely to capture the true value. Therefore, the estimates from cost friction modelling and those of API could be more comparable (and fall within the same class given the uncertainty bounds based on input speeds), as weather, traffic, automobile type, personal preferences, time of day, and other differences may be accounted for and reflected in the upper and lower boundaries (Hierink *et al.*, 2020; Macharia, Mumo, *et al.*, 2021). However, most spatial access studies seldom take this step, with only a few examples available in the literature (Curtis *et al.,* 2021; Hierink *et al.*, 2020; Macharia, Mumo, *et al.*, 2021; Ouma *et al.*, 2018). Related to travel speeds, it is only possible to target a particular subgroup of the population in AccessMod but not in Google Maps Directions API. Travel speeds in AccessMod can be flexibly defined to correspond to different travel scenarios specific to population sub-groups, for example, emergency care (Juran *et al.*, 2018; Ouma *et al.*, 2018), urban areas settings (Macharia, Mumo, *et al.*, 2021) and primary school education (Macharia, Moturi, *et al.*, 2022; Macharia, Ray*, et al.*, 2022).

In terms of implication for research especially in urban areas, it is clear that within conurbations there is good connectivity of road network with complex travel patterns, for example, public transportation with dedicated bus and trap stops, and one-way traffic with sections controlled by traffic lights. Travel to seek care almost always follows the road network and patterns, therefore, a vector-based tool that computes spatial accessibility to healthcare along a network will provide the most realistic estimates in urban areas when compared to raster-based approach (Delamater *et al.*, 2012). For example, the routing services in the market (such as the Google Maps Directions API) compute accessibility along these routes while accounting for traffic patterns or the vector-based Network Analyst (in ArcGIS Pro), which are thus more suited for urban areas. On the other hand, raster-based approaches (for example, in AccessMod) are more suited to areas with lower road connectivity and complexity of travel patterns, such as rural areas (Delamater *et al.*, 2012). The future thus would be to have a mix of methods that would use big data (or network-based approaches) in urban areas and least-cost approach in rural areas (Delamater *et al.,* 2012). A combination of these approaches would be more suitable in peri urban (suburbs), which were more affected both by longer travel times and by discrepancies in the travel time estimates. Suburbs are a key urbanisation frontier where growth happens, therefore, should not be left behind in improving their accessibility and health outcomes.

In addition, our analysis largely utilized MTT derived from motorized transport. However, other modes of transport such as walking and biking utilise private or unofficial paths between home and health facilities are also used in urban settings (Avoka *et al.*, 2022; Macharia, Mumo, *et al.*, 2021), although to a minimal degree. These paths are not mapped as part of the road network, for example in slum areas and are not affected by congestion in the same way as motorized transport. Therefore, in such scenarios AccessMod will be more relevant in computing spatial accessibility to care through walking and bicycling.

Strengths and limitations

First, our study contributes to the ongoing discussion of how best to assess spatial accessibility to healthcare in low-resource urban settings and focuses on two emerging tools relevant to such settings (Banke-Thomas *et al.*, 2024; Cuervo *et al.*, 2022; Mutono *et al.*, 2022; Wong et al., 2024). We are hopeful that our results will inform future decision-making processes in both research and implementation settings. Increasingly, there is literature aiming to provide a better understanding of how different methods and input data affect estimates of travel time. For example, the role of different gridded populations (Hierink *et al.*, 2022), road networks (Lin *et al.*, 2021), and vector versus raster-based methods (Delamater *et al.*, 2012). Second, previous comparator studies have considered public facilities only, especially those contained in the country's master health facility list. However, in this study, we included both public and private facilities, which were further validated using on-ground surveys to capture all facilities, whether recorded in master facility lists or not. It is clear from our findings that if we had considered public facilities only, MTT would have been longer and the agreement between AccessMod and Google Maps Directions API would have been reduced.

On the other hand, the findings of this study should be interpreted while considering some limitations. First, our study considered only travel time to the nearest health facility, ignoring bypassing that some pregnant women might do due to trust-related issues, cost, and quality of care, which could also influence healthcare-seeking behaviour in emergencies (Keyes *et al.*, 2019; Kruk *et al.*, 2009; Makacha *et al.*, 2020; Yao & Agadjanian, 2018). By generating travel time to the nearest facility which women may bypass, it means the actual MTT could have been longer, leading to potentially less agreement with Google Maps Directions API and AccessMod. Therefore, considering the bypassing mechanism is critical for realistic estimates, there is a need to adjust AccessMod outputs based on the piecewise linear coefficients we generated if bypassing is not considered.

Second, the use of generalisable speeds for comparability with previous studies poses a limitation. Expert-elicited speeds with uncertainty bounds would have been more appropriate for realistic estimates. However, we deliberately applied speeds derived from literature to better understand how the current state of implementing accessibility compares with the closer-to-reality estimates from Google Maps Directions API (Banke-Thomas, Wong, Ayomoh, *et al.*, 2021). Third, it is possible that women in emergency residing in the selected wards may seek care from adjacent wards outside the conurbation which we did not capture in our analysis. However, the focus of this comparison study is on the relationship in the estimates from both tools and not the precise location where women seek care.

Finally, our estimates from both tools are only as good as the underpinning data. For example, if the road network data we used from OSM was more comprehensive than those available on Google (used within the Google Maps Direction API), this likely contributed to the differences observed in larger travel times between the two tools. For example, OSM's reliance on community contributions can provide a more up-to-date and localised view in some cases. This includes voluntary mapping communities such as Humanitarian OpenStreetMap Team (HOT) Tasking Manager0F, Missing Maps1F and YouthMappers2F. Particularly for areas such as urban slum areas with limited road networks but local routes could be mapped through OSM's communities.

It has been shown that depending on the nature of street networks used, with different levels of completeness there will be considerable differences in travel times (Lin *et al.*, 2021). These differences will be more pronounced in less urbanised regions relative to the core metropolitan areas (Lin *et al.*, 2021). We made the same observation; the core urban area outputs were more similar, while differences became more pronounced outward to the suburbs when contrasting AccessMod and Google Maps Directions API (Lin *et al.*, 2021). Data on road network in the suburbs are likely to be incomplete, even when complete, suburbs might arguably have fewer roads because of the fewer services that need to be connected. Further, the completeness of the spatial data plays a key role. For example, where OSM has lower completeness than Google, it means more walking speeds will be assigned in some sections, while the API will use driving speeds if Google Maps has better completeness of road network data. These issues will likely be observed at the edges of the conurbations where volunteered geographic information may not be as widely available as in the developed core urban area.

Conclusions

Estimates obtained from the AccessMod correlated to those from the Google Maps Directions API and classified in the same 15-minute bands for areas with median travel times <45 minutes which formed the majority of the wards and raster cells. However, significant differences were observed for longer travel times (mainly in suburban settings), with AccessMod estimates being longer than Google Maps Directions API's estimates beyond 45 minutes for a small proportion of the raster cells and the wards. This relationship can be approximated using a piecewise linear function, which can be used as the basis to convert AccessMod to Google Maps Directions API-like estimates. Ultimately, in emergencies, timely access is critical, such as in cases where pregnant women face complications and need to reach a health facility quickly (Banke-Thomas, Avoka, *et al.*, 2021; Chavane *et al.*, 2018). In such scenarios, the estimates must accurately reflect the actual conditions on the ground, as every minute counts. Therefore, assessment of accessibility to emergency care using accessible, comparable datasets and innovative methods is key for making sure women can access life-saving interventions that they need with no physical access barriers.

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Online supplementary materials

Maps of factors that affect travel to healthcare and comparison of travel time estimates derived from AccessMod and Google Maps Directions API

Figure S1. Health facilities in Kano.

Figure S2. Land cover in Kano.

Figure S3. Digital elevation model in Kano.

Figure S4. Road network in Kano.

Figure S5. Population density in Kano.

Figure S6. Comparison of travel time estimates generated from AccessMod (least-cost Path algorithm) and Google Maps internal direction Application Programming Interface (API) in Kano.

Figure S7. Health facilities in Port Harcourt.

Figure S8. Land cover in Port Harcourt.

Figure S9. Digital elevation model in Port Harcourt.

Figure S10. Road network in Port Harcourt.

Figure S11. Population density in Port Harcourt.

Figure S12. Comparison of travel time estimates generated from AccessMod (least-cost Path algorithm) and Google Maps internal direction Application Programming Interface (API) in Port Harcourt.

Figure S13. Health facilities in Lagos.

Figure S14. Land cover in Lagos.

Figure S15. Digital elevation model in Lagos.

Figure S16. Road network in Lagos.

Figure S17. Population density in Lagos.

Figure S18. Comparison of travel time estimates generated from AccessMod (least-cost Path algorithm) and Google Maps internal direction Application Programming Interface (API) in Lagos.