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Comparing paratransit in seven major African cities: An accessibility and network analysis

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ABSTRACT

Accessibility to transit, together with other important system characteristics such as network coverage and frequency, is a crucial driver of modal choice for urban commuting. In turn, commuting is a major driver of energy consumption and of socio-environmental externalities in cities. So far, few quantitative and comparative assessments of paratransit in cities of Africa have been carried out due to data scarcity and the prevalence of informal services. Here we leverage the recent release of General Transit Feed Specification (GTFS) data to produce comparative metrics of accessibility, network, and service quality of paratransit in seven major cities in sub-Saharan Africa (Abidjan, Accra, Addis Ababa, Freetown, Harare, Kampala, Nairobi). Our results allow for a first-order assessment and comparison of different crucial paratransit characteristics in these cities, shedding light on transport inequality and urban segregation dynamics. The analysis and metrics produced can support transport systems planners in major cities of low-income countries. Further research should focus on approaches for overcoming the residual data limitations and expand the quantitative understanding of paratransit.

1. Introduction

Over the past twenty years, in most regions of the developing world the urbanisation rate - the share of the population residing in urban areas - has grown at an incessant pace (Castells-Quintana and Wenban-Smith, 2019). According to the World Bank (2020), in sub-Saharan Africa this figure jumped from 31% to 41%, while the United Nations' Urbanisation Prospects project that it will reach 58% by 2050 (United Nations, 2018).

Such a rapid growth of urban populations has been accompanied by a strong territorial expansion of cities (Denis et al., 2008) while also increasing the inequalities within and across them and the dynamics of territorial segregation (Smit et al., 2017). In response, urbanisation is connected to a massive growth in the demand for mobility in the entire population: for work, study or to access services (Pirie, 2014).

These critical issues have become evident through different dimensions: physical accessibility and geographical proximity to mobility infrastructure (Preston and Rajé, 2007); affordability of mobility services (Venter, 2011; Carruthers et al., 2005) and their reliability and punctuality Pirie (2014); environmental pollution caused by the transport sector; coordination between the different modes of transport (Cervero, 2005).

Yet, the pervasive informality of transit services in developing cities has caused recurrent issues in quantitatively understanding and comparing paratransit in those urban areas (Behrens et al., 2015; Noussan and Falchetta, 2020; Venter and Zuidgeest, 2020; Sietchiping et al., 2012).

In this paper we leverage the recent release of standard General Transit Feed Specification (GTFS) data (Eros et al., 2014) collected by *DigitalTransport4Africa*, an open data commons for transport in African cities committed to sustainable mobility. The data for seven major cities of sub-Saharan Africa considered in this paper was collected over the period 2017–2020. Standard GTFS databases for each city have been compiled in different projects through collaboration with local transport companies, authorities, apps, and through crowd-sourcing. Processing these data using geospatial and network analysis algorithms, we produce comparative metrics of accessibility, network centrality, and service quality of paratransit that allow for a first-order quantitative comparative evaluation of the paratransit situation in the major cities analysed. In turn, our results can highlight critical issues and intervention areas.

The paper is structured as follows: Section 2 carries out a systematic

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review of previous studies on paratransit and access to transport in African cities and of methodologies based on GIS to quantitatively appraise these dimensions. Section 3 introduces the data and methodology adopted, also with focus on the issue of defining a comparable urban centre unit. Results are presented and commented in Section 4, while a broader discussion of the implications for infrastructure planners is found in Section 5.

2. Background and literature review

2.1. Paratransit in African cities

The rapid growth of urban populations in Africa is being accompanied by a strong territorial expansion of cities, which in turn is at the same time increasing inequalities and territorial segregation (Smit et al., 2017). In response, urbanisation is resulting in a massive growth in demand for mobility throughout the population for work, study or for other reasons (Pirie, 2014). In many cases, the expansion of the transport infrastructure and services did not evolve as quickly, thus making mobility one of the most critical challenges of African cities (Sietchiping et al., 2012; Venter and Zuidgeest, 2020).

Urban mobility in developing countries therefore presents a series of peculiarities not typical of the transport systems that for decades have dominated the urban landscape of the cities of the *global North* (Noussan and Falchetta, 2020). Features such as informality, sharing and the massive use of active mobility are the key characteristics distinguishing the transport systems of developing and Global North cities.

Interesting statistics on the modal share for a broad range of cities in developing countries is offered by Middleton (2018), who show that paratransit accounts for very large shares of total public transport supply. For instance in Accra it is above 90%; in Abidjan it meets half of the entire mobility demand; in Addis Ababa it stands at about 35%, in Dar Es Salaam, it is above 60%, and in Lagos it reaches almost 40%.

Characteristics such as informality are an integral part of the urban landscape in developing countries and respond to very concrete needs: informality is a response to the shortcomings of the systems of public transport (Rink, 2020); sharing is the result of low ownership rates of private means of transport, also due to the significant cost compared to average salaries (Olvera et al., 2008); active mobility generally responds to the need to cope with service constraints, including the need to travel with flexibility and without wasting time in crowded vehicles stuck in the traffic.

Yet, as discussed in Klopp and Cavoli (2019), despite the pervasive presence of paratransit in African cities, these systems have usually been poorly understood or scarcely considered by transportation planners. Most consideration was attributed to large-scale infrastructure projects (e.g. highways, commuter rail or bus rapid transit systems). They call for the collection and analysis of bottom-up transport data for paratransit to foster a more inclusive planning debate among urban decision makers.

Behrens et al. (2015) engage in an extensive discussion on the origins, operations and key regulatory challenges, and future of paratransit in developing countries. The authors argue that there are path dependencies and constraints that limit the possible extent of a broad public transport system reform. They suggest that public transport planners should engage with paratransit providers rather than trying to replace them with institutional or state-owned transport. They predict the future paradigm to become a hybrid one, where paratransit is recognised and integrated with public transport. A similar position is expressed by Salazar-Ferro et al. (2013), who explore different categories of hybrid public transport systems through case studies in South Africa. Yet, some of the main roadblocks in this integration process are highlighted by Boutueil et al. (2020), who found that both in Cape Town and Nairobi - their case studies - the focus in the documents is still mainly on developing infrastructure rather than improving mobility. They conclude that while the role of paratransit is increasingly recognised, the trend is still more apparent in regulation than in planning.

Finally, since - as argued by Woolf and Joubert (2013) - *"understanding paratransit at disaggregate level improves formalisation attempts"* - some studies have collected and analysed the GTFS data for a set of African cities, including some of those considered in our paper. These papers - mainly led by the research teams involved in the primary data collection - detail the data collection methodologies and calculate some relevant metrics to evaluate paratransit coverage and reliability. For instance, Saddier et al. (2016) describe the data collection process conducted by the Department of Transport of the Metropolitan Assembly of Accra, Ghana. The paper describes how through the use of GPS-enabled smartphones the project team collected and mapped 315 jitney routes (the entire operational network in the city) in less than 2 months. In a follow-up paper, Saddier et al. (2017) calculate indicators traditionally applied to formal transit systems to assess the level of reliability of Accra's paratransit. They argue that that the most appropriate unit of analysis for such research is the station because operations on any given route are influenced by forces at the station level. Yet, they empirically verify that most routes are stable over time.

Williams et al. (2015) illustrate in detail the data collection procedure of a similar experiment in Nairobi, and they focus on the large potential to upscale their methodology and develop reliable GTFS information for paratransit in cities of developing countries. A similar conclusion is suggested by Klopp and Cavoli (2019), who provide further evidence comparing transport data collection projects in Nairobi and Maputo. Building on previous work, also Tembe et al. (2019) engage with paratransit analysis in Nairobi and Maputo, albeit with a specific focus on understanding the transport demand drivers. They use logistic regression on household survey data and find significant effects on factors such as age and private vehicle ownership on paratransit use. Du Preez et al. (2019) collected geospatial and operational data for more than 500 paratransit routes in Cape Town and used a clustering algorithm to classify the routes by their typology and interconnection capabilities.

2.2. Accessibility analysis with GIS

Accessibility refers to *"people's ability to reach goods, services and activities, which is the ultimate goal of most transport activity"* (Litman, 2008). A broad stream of literature has engaged with accessibility analysis. The most common approach is the general Dijkstra's algorithm for finding the shortest paths between nodes (Dijkstra et al., 1959). The general formulation assumes that the travel cost is constant across the network of points under consideration, so that the selected path corresponds with the line connecting each point i with the point j with the shortest Euclidean distance. In any travel time accessibility analysis, moving towards each other point implies however a cost, generally defined by a friction matrix expressing the speed (i.e. the required time) to move in a given direction (Weiss et al., 2018).

A wide range of applications based on this methodology is found in the literature, both in the transport research and in other applied sciences. For instance, Weiss et al. (2018) evaluated the global picture of accessibility to cities, while Weiss et al. (2020) produced global maps of travel time to healthcare facilities, and a similar analysis has been carried out by Falchetta et al. (2020) for sub-Saharan Africa. The Dijkstra's algorithm is also used broadly in road planning (Parsakhoo and Jajouzadeh, 2016) or electrical grid network detection (Arderne et al., 2020) and planning (Ortiz-Matos et al., 2017).

In a seminal paper Morris et al. (1979) reviewed and classified measurable specifications of accessibility, highlighting their relevance to transport planning. They discuss how *"accessibility measures are based on the premise that space constrains the number of opportunities available"*. They refer to Ingram (1971)'s categorisation of accessibility metrics into those of relative and integral accessibility. The former describe the relation or degree of connection between any two points, whereas the latter describes the relation or-degree of interconnection between a given point and all others within a spatial set of points. In our analysis, we rely on an integral accessibility approach.

Recent relevant applications include the work of Rode et al. (2017), who reviewed the different accessibility pathways followed by a set of case study cities globally. Particular focus is devoted to the relationship between urban sprawl, modal choice, and environmental impact of urban commuting.

More recently, Saif et al. (2019) carried out a systematic review of public transport accessibility. Their main conclusion is that not just the performance of public transportation but its impact on other social aspects should be considered while planning the public transport facilities.

Saghapour et al. (2016) introduced and tested a new index for measuring public transport Accessibility. The index considers public transport service frequency and population density, and it is found to be a stronger predictor of public transport use compared to existing indexes.

Finally, in Falchetta and Noussan (2021) the authors carried out an accessibility analysis (considering motorised transport) to electric vehicle charging points in the European Union, a crucial enabler of a larger uptake of EVs.

2.3. Network analysis of transit

To conclude the literature review, it is worth summarising some recent studies that have engaged with the application of network analysis techniques on the assessment of transit in cities.

With regards to this growing field, Cabodi et al. (2020) discusses how each transportation network is a graph represented by an L-space topology, where stops and stations represent nodes and their connections edges, such as a bus travelling from stop A to stop B. Yet, the author shows that public transport networks are neither small-world nor scale-free, two crucial properties of complex networks analysis theory.

Jafino et al. (2020) carried out an analytical review of transport network criticality analysis, namely the technique based on *"ranking transport infrastructure elements based on their contribution to the performance of the overall infrastructure network"*. They classify metrics both in terms of their mathematical formulation and of their underlying ethical principles, as well as of their spatial disaggregation. They conclude proposing a guideline for transport planners for choosing among the metrics space based on their most pressing policy questions.

Another perspective is offered by Aydin et al. (2019), who introduced a modified (called origin-destination) measure of betweenness centrality (a metric first introduced by Freeman (1977)). The metric is used to identify critical locations in case of a random disruption (such as an accident or a traffic jam) when moving towards a single service. A similar approach is followed by Rupi et al. (2015), who designed a methodology able to prioritise the links of a transport network for maintaining a proper connectivity between all origin-destination pairs.

3. Materials and methods

Fig. 1 illustrates the framework of the inputs, methodology and outputs of the analysis carried out in this paper. The analysis is divided into three main parts: (i) the GIS-based analysis of paratransit stop accessibility; (ii) the calculation of comparative local (i.e. grid-cell level) and global (i.e. city level) metrics describing the quality of the paratransit available; (iii) the network analysis.

3.1. Data and software

General Transit Feed Specification (GTFS) data (Eros et al., 2014) - a data specification that allows transit agencies to publish their data such as stops, routes, and timetables in a standardised form - are drawn from the Git repository[1] of *DigitalTransport4Africa*, an open data commons for transport in African cities committed to sustainable mobility. We select the cities based on their size and their relevance in order to enhance comparability, as well as on the type of data available (only those with GTFS data for urban paratransit are considered). The data thus refers to seven major cities of sub-Saharan Africa collected over the period 2017–2020. As detailed in the documentation of each Git repository, the standard GTFS databases for each city have been compiled through different projects through collaboration with local transport companies, authorities, apps, and through crowd-sourcing. The paratransit network of each city is plotted in Figures Appendix A.6-Appendix A.12.

Accessibility is estimated following procedures, code, and data described in Weiss et al. (2018, 2020). The approach is based on a high-resolution (1 km) friction raster layer, where each pixel expresses a nominal walking speed, namely the land travel time required to traverse it (in minutes/m). The layer[2] is calculated based on local landscape characteristics (e.g. land cover, slope), infrastructure (e.g. roads) and additional constraints. In our analysis we adopt the 2019 walking transport friction layer from (Weiss et al., 2020), which is based on the OpenStreetMap and Google Roads datasets.

Very high-resolution (30 m) population maps - useful to weight the accessibility analysis - are drawn from the High Resolution Settlement Layer (Lab and for International Earth Science Information Network-CIESIN-Columbia University, 2016) by Facebook and CIESIN[3] - where population estimates are based on recent census data and high-resolution (0.5 m) satellite imagery from DigitalGlobe. The settlement extent data are extracted with computer vision techniques to classify blocks of optical satellite data containing buildings, over which proportional allocation is applied to distribute population data from sub-national census data.

Administrative boundaries are drawn from the GADM database,[4] a global, multi-level, frequently updated dataset of administrative units.

The accessibility analysis is carried out in the cloud through Google Earth Engine (Gorelick et al., 2017) interface (based on Javascript). All the following steps of the analysis are carried out in the R scientific computing programming environment. Accessibility statistics are then processed in R using the *raster* (Hijmans and van Etten, 2016), *sf* (Pebesma, 2018), *tidyverse* (Wickham et al., 2019), *gDistance* (Etten, 2017), *tidytransit* (Poletti et al., 2020) package suites. For the network analysis, we rely on *igraph* (Csardi et al., 2006) and *brainGraph* (Watson, 2020) packages.

Finally, given the crucial role of the definition of city boundaries on the outcomes of the analysis, a specific discussion on the geographical definition of urban areas and the relevant data is deemed necessary.

3.1.1. Urban centres definition

The discussion on where to "draw the line" between urban and rural areas is a very debated one. For decades researchers and practitioners have been discussing the key challenges of the task and the limitations of the variety of approaches adopted. For instance, Dorélien et al. (2013) compare the popular (but today outdated) *Global Rural-Urban Mapping Project* (GRUMP) project by SEDAC (Center for International Earth Science Information Network (CIESIN), 2004) (based on gridded population and nighttime lights data) with urban classification found in Demographic and Health Surveys (DHS), which relies on the urban definitions of individual countries' national statistical offices, highlighting good consistency but issues with distinguishing peri-urban from rural areas and in areas with low electricity access levels (a question relevant to our analysis, e.g. see Falchetta et al. (2019)).

Dahly and Adair (2007) discuss why the discrete urban-rural

[1] https://git.digitaltransport4africa.org/data/africa

[2] https://malariaatlas.org/research-project/accessibility-to-healthcare/

[3] https://data.humdata.org/dataset/highresolutionpopulationdensitymaps

[4] https://gadm.org/data.html

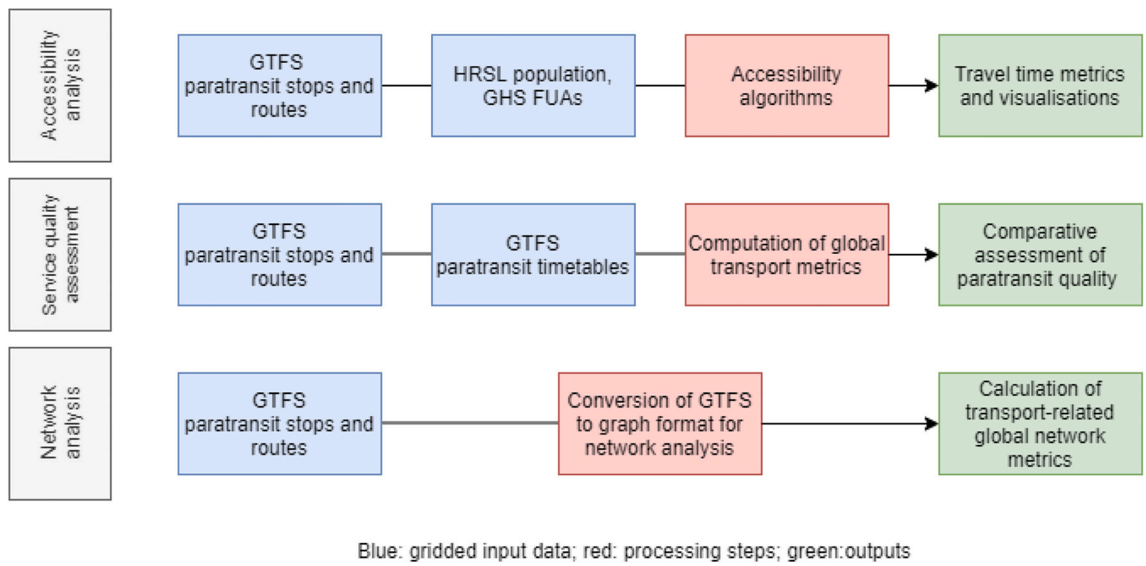

Fig. 1. Framework of the inputs, methodology and outputs of the spatial analysis carried out in this paper.

dichotomy is generally a false one, and suggested that continuous urbanisation indexes are more suitable for classifying human settlements. This concept found strong support with the introduction of the *degree of urbanisation* by Dijkstra and Poelman (2014).

Recently, OECD, European Commission et al. (2020) offer a new perspective on urbanisation by trying to systematise the previous knowledge on what a city is, highlighting that *"substantial differences in the way cities, metropolitan, urban, and rural areas are defined across countries hinder robust international comparisons and an accurate monitoring of SDGs"*. In the report, both the Degree of Urbanisation and the Functional Urban Area (Dijkstra et al., 2019) definitions of human settlements are applied globally.

These discussions are even more relevant in the application of spatial statistics and GIS algorithms, as the outcomes of the analysis can be very sensitive to the modifiable areal unit problem (MAUP) (Openshaw, 1983). The MAUP affects results when point-based measures of spatial phenomena (e.g., bus stops and population distribution) are aggregated into a bounding shape (such as administrative areas or n-km radius buffers). The resulting summary values are influenced by both the shape and scale of the aggregation unit.

In our analysis, we refer to the novel Functional Urban Areas (FUA) database developed by the European Commission Joint Research Center (EU-JRC) (Florczyk et al., 2019). In this dataset, urban areas are defined in a consistent way across geographical locations and over time, applying the "Global Definition of Cities and Settlements" developed by the European Union to the Global Human Settlement Layer Built-up (GHS-BUILT) areas and Population (GHS-POP) grids.[5]

3.2. Accessibility assessment

The paratransit routes and stops data is processed together with the friction layer using a cumulative cost GIS algorithm in Google Earth Engine (Gorelick et al., 2017). The process follows the analysis of Weiss et al. (2020) and is based on the Dijkstra's least-cost-path algorithm (Dijkstra et al., 1959). The process generates a raster layer of the travel time (in minutes) to the most accessible paratransit route at each location within each city's boundaries. Note that due to consideration of transportation infrastructure patterns encapsulated in the friction layer, the most accessible route needs not be the closest in terms of Euclidean distance. Moreover, it must be remarked that due to the specific context of sub-Saharan African cities under analysis, we calculate accessibility metrics based on routes rather than stops. The existence of fixed stopping points is questionable when dealing with paratransit. Paratransit vehicles typically stop anywhere to load passengers if they are not full. Similarly, drivers generally drop off passengers on request and as close as possible to their destination. Supplementary results based on accessibility to stops as recorded in the GTFS databases under analysis can be found in the Appendix and compared to the results presented below.

[5] The approach is based on the application of a slightly edited "Degree of Urbanisation" model (*"high-density clusters of contiguous grid cells of 1 km^2 with a density of at least 1500 inhabitants per km^2 and a minimum population of 50,000"*, (Dijkstra and Poelman, 2014). In the EC-JRC Urban Centres data, the approach differs from the original one of Dijkstra and Poelman (2014) as an alternative criterion to population density is applied: namely, urban centres are defined as *"the spatially-generalised high-density clusters of contiguous grid cells of 1 km^2 with a density of at least 1500 inhabitants per km^2 of land surface or at least 50% built -up surface share per km^2 of land surface, and a minimum population of 50,000."*. The Functional Urban Areas are then derived based on those Urban Centres (UC), namely including the less densely populated local units that are part of the city's labour market (at least 15% of their working population commuting to the city). Refer to the documentation `https://ghsl.jrc.ec.europa.eu/documents/GHSL_FUA_2019.pdf?t=1583246033` for a detailed account of the underlying methodology. Figures?? -?? compare the land area and populations in GHS UC and FUA, showing that FUAs are on average significantly larger than UCs, but population counts do not differ largely as a result of the lower population density outside of UCs.

We then calculate population-weighted travel time (TT^{popw}) in each Functional Urban Area shape (FUA_c) as the following:

$$TT^{popw}_{FUA_c} = \sum_{i}^{N} TT_i \cdot \frac{POP_i}{POP_{FUA_c}} \tag{1}$$

where N is the number of pixels falling within each NUTS unit; i identifies each pixel; TT is the travel time to the most accessible charging station; POP is the population. ECD (empirical cumulative distribution) curves are calculated with a similar approach at FUA_cl level.

To calculate the number of paratransit routes that can be reached with a n-minute walk from any location within each city considered, we count the unique route segments intersecting any of the grid cells that lie within the n-minute walk buffer of grid cell i. The procedure is iterated for all grid cells in each city to produce maps (Fig. 2).

3.3. Metrics on route design and operation

The metrics for paratransit that are considered for a comparison across cities can be divided into two groups. The first is based on the transport system planning, and it includes the number of routes, stops, the route lengths and some combinations of these indicators. The second group of metrics represents transport system operation, and it includes the average speed of the trips, the total number of trips offered per day and the total vehicle-km (vkm) that are offered daily to the citizens. Unfortunately it is not possible to estimate the number of passenger-km nor the number of seats-km that are offered, given the lack of information on the characteristics of the vehicles that are used in each route (as well as on average load factors).

The metrics that are calculated for the cities are the following:

- number of routes;
- number of stops;
- average number of stops per route;
- average route length;
- average distance between stops;
- median bus speed;
- total daily bus trips;
- total daily vehicle-km (vkm).

The last two metrics have also been divided by the total population, to improve comparability across cities. While some metrics are easily obtained from the GTFS data, such as the number of unique routes or bus stops, in other cases additional calculations and hypotheses are required.

The route length has been calculated by considering the information reported in the file "shapes.txt". The GTFS standard includes a column with the information on the total length of each route, but this column is missing for most cities, and in some cases we also fund wrong numbers.

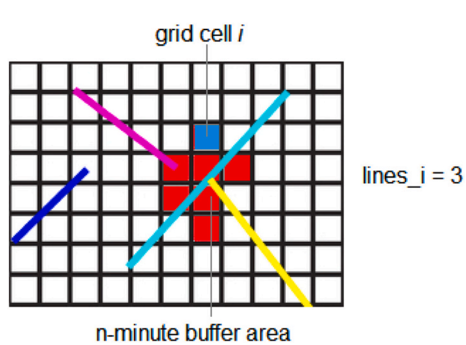

Fig. 2. Schematic example of the procedure to calculate the number of routes within a n-minute walk from each grid cell i. In this example, the route count at grid cell i sums to 3.

Thus, the length of each route has been computed by considering the distance across all the points reported in the dataset for each "shape" (which can be easily linked to the route).

The average bus speed for each trip has been calculated by considering the information reported in the file "stop_times.txt" to obtain the total duration of each trip. It is important to remark that the duration is available for each trip, which means that a route can have different trips based on the hour of the day (peak or off-peak) or the day of the week (weekdays or weekend). The median speed that is considered for this indicator is the median value across all the trips that are available for each city. As for other metrics, it is important to highlight that these data may not be a statistically-significant representation of the actual bus speed, due to traffic or other issues, since only one record per trip is available. However, this still seems to be a valuable metric to compare the service offered in different cities.

To compute the number of total daily bus trips it is necessary to join the "trips" and "frequencies" datasets, and calculate the total number of buses per each trip (which is defined as a combination between a route and a time slot). For all the cities considered in this paper the information related to bus frequencies are provided as trips' frequency (in the column "headway_secs") instead of the exact time of departure. The information on trips' frequency is missing for the city of Addis Ababa: thus, this metric and the vkm cannot be calculated.

The combination of the number of daily trips and the trip length allows calculating the daily vkm related to paratransit in each city (vkms are defined as the product between the number of vehicles and the distance they travel). It is important to note that this indicator is based on the planned frequency of the trips, and it is not possible to verify if this frequency is actually guaranteed in the real operation of the transport system. Such a verification would need a huge amount of data on the real-time operation of the system, which is not available at this stage.

3.4. Network analysis: Metrics considered

To shed additional light on the underlying structure and properties of the transport systems, we included in our analysis two sets of metrics derived from network theory. We represent the transport system as a set of nodes and links where a node corresponds to a stop and a link (or edge) represents the connection between two adjacent stops. The first group of metrics captures the networks' topological properties providing high-level information about the network. This includes the number of links, the number of nodes, the diameter the network, its density and travesty. The diameter of a network is the length of the longest geodesic in the network. The density of a graph is calculated as the ratio of the number of edges and the number of possible edges (Wasserman et al., 1994). The transitivity of a network is an alternative measure of connectivity of a network and is calculated as the average clustering coefficient based on the number of connected triples in the network (Wasserman et al., 1994; Barrat et al., 2004; Rodrigue, 2020).

The second group of metrics are helpful to understand the network dynamics and functionality. This includes the following metrics:

- Efficiency: the efficiency of a network is a measure of how efficiently it exchanges information. In our case, we used a global measure of efficiency to quantifies the extent to which the transport networks support exchanges in the flows of users (Latora and Marchiori, 2003).
- Betweenness Centrality: The betweenness centrality is an important measure of accessibility calculated on the node level as the number of time it is traversed by the shortest paths in the graph. As a global network measure, it is calculated as the average of each whole network with higher values indicating that the nodes are strategically placed connecting different regions of the transportation network more effectively (Freeman, 1978; Rodrigue, 2020).
- Closeness Centrality: The closeness centrality is defined as the inverse of the sum of the length of the shortest paths between a given

node and all others nodes in the graph. It measures how close is a node, on average, to all other nodes (Freeman, 1978).

- Average Path Length: Average path length is the average number of stops needed to reach two nodes (i.e. two other stops) in the network. A low average path length would characterise an Efficient network that facilitates circulation (Rodrigue, 2020).
- Clusters and Modularity: Densely related nodes are referred to as communities or clusters. They tend to have many edges inside the community and few edges that connected them to the rest of the network. We used a clustering algorithm based on the simulated annealing algorithm to find regions of the network where the transportation are tightly knit, and the connections between them are sparse. We then measured the resulting configuration's modularity to quantify the strength of division of a network into clusters. The higher the modularity the denser is the connections within the clusters and the sparser between the other groups(Clauset et al., 2004; Rodrigue, 2020).

3.5. *Key limitations*

The recent, standardised GTFS databases collected by different initiatives and published by *DigitalTransport4Africa* offer a great opportunity to provide a first-order quantitative comparative evaluation of the current state of paratransit networks in major cities of sub-Saharan Africa which was hitherto very limited. Yet, for the sake of transparency, it is also important to acknowledge some important data-related limitations that should walk the reader through the results presented in the following sections.

The database includes multiple features, but in some cases the unavailability of data (e.g. frequencies) in some cities can limit the significance of the results. The GTFS databases under analysis have been compiled through different projects with different quality standards: for instance, in Addis Ababa the data collection was coordinated by the World Resources Institute (WRI) Africa in close collaboration with the Ministry of Transport and Addis Ababa Transport Authority but carried out by a team of 40 students from Addis Ababa University; in other cities (e.g. Accra, Abidjan) the projects were coordinated by a join effort of the local authorities and the OpenStreetMap project; in other cities, the World Bank or other development agencies played a key role (e.g. Harare, Kampala); finally, in Nairobi the effort has been promoted by different academic institutions. Nonetheless, the general methodology has been similar across cities: groups of data collectors equipped with GPS-enabled smartphones and dedicated tracking applications travelled extensively across the cities' paratransit networks and mapped the real operations (routes, stops, speed, frequency) of local service providers.

Despite these important data collection efforts, the completeness of the data cannot be appraised or empirically validated by the authors with field visits. To overcome the latter limitation, we have engaged with expert elicitation (see Acknowledgements) from researchers and practitioners living their daily life in the cities under examination. This assessment suggested that only Accra seems to be lacking a number of routes linking the city centre to the Greater Accra metropolitan areas a high population density territory. We thus highlight a caveat in the interpretation of the accessibility analysis results for Accra.

Moreover, it remains uncertain whether the reported data are inclusive of all active paratransit operators, stops, and routes or if for some cities the data is only a subset of a larger array of transport services providers for dwellers. Concerning this latter point, it is worth remarking that the analysis carried out in this paper does not include services such as light rail and official public bus services, and consideration of alternative means of transport such as motorbike taxis or small scale paratransit (e.g. mini-cars with a capacity of few passenger) is mixed across the GTFS databases of the seven cities considered. In addition, heavy traffic at peak hours and the lack of paratransit fast lanes can seriously question the reliability of the routes' frequency and timetables information (Sietchiping et al., 2012).

Overall, the current analysis is a first step in the direction of assessing paratransit with quantitative metrics and a comparative approach, a scarcely investigated research area in the literature. Irrespective of the limitations discussed, we believe that our methodology provides an important advancement for understanding the current situation of paratransit networks in large cities of sub-Saharan Africa. Further research should focus on leveraging novel approaches for overcoming the residual data limitations and expand the quantitative understanding of paratransit in developing urban areas.

4. Results

4.1. *Accessibility: situation and inequality*

Fig. 3 presents paratransit accessibility maps for each of the seven cities under examination, according to the GTFS data from *DigitalTransport4Africa*. The colour palette expresses the average walking time to the nearest (i.e. most accessible) paratransit route at each point of each functional urban area shape. The figure allows to evaluate the coverage of the paratransit network in relation to the city's sprawl, including areas with weak paratransit coverage. These maps are particularly insightful when compared with the underlying population distribution (visualised in Figure Appendix A.5). Gridded population and accessibility information allows to calculate empirical cumulative distribution (ECD) curves (Fig. 4), which provide a more immediate comparative understanding of the share of each city's functional population living within a given walking threshold from the nearest paratransit route. A necessary remark is that paratransit is not necessarily the only or the main shared mobility option in the cities considered, and therefore a comparatively 'worse' paratransit accessibility outcome does not automatically imply an overall inferior transport system.

The figures show that in most functional urban areas about than three quarters of the population live within a 10-min walk from the nearest mapped paratransit route, with the exception of Accra, Kampala, and Nairobi where only about five to six in ten people are residing within this threshold. The three latter cities seem in fact to be those with the most accessibility inequality to paratransit, once again remarking that this result is conditional to the GTFS data quality and extent of mapped routes.

Relevant summary statistics are then produced in Fig. 5, showing the population-weighted average walking time for each city, and both the population share and the absolute number of people not within a 15-min walk from the nearest mapped paratransit route. The results highlight that, on average, citizens of the seven urban areas analysed live between 5 and 12 min from a paratransit route. Nonetheless, the analysis also shows that according to the GTFS data, in most of the seven urban areas hundred of thousands people live more than 15-min walk from the nearest mapped paratransit route. Together, these results show that while in relative terms accessibility to the paratransit network seems not to be a big barrier, in absolute terms there are still several populous areas within each city which appear to be segregated from the existing paratransit network.

A different insightful dimension of paratransit accessibility is visualised in Fig. 6, which shows maps of the seven urban areas analysed in terms of the number of routes that can be accessed within a 15-min walk from each grid cell. This metric goes beyond a binary concept of accessibility, allowing to evaluate the quality of each location in terms of paratransit network accessibility and interconnection potential. Note that the statistic is such that a route travelling in both directions is counted twice. The figure shows that all cities are characterised by a similar pattern, with a high density of routes towards the city core and a diminishing set of routes available as one moves towards the functional urban area boundaries. Yet, the result also allows observing some across-city heterogeneity, with the Addis Ababa, Accra an Abidjan high transit routes density areas looking significantly broader than those of cities like Harare, Kampala and Freetown. Nairobi stands somewhere in

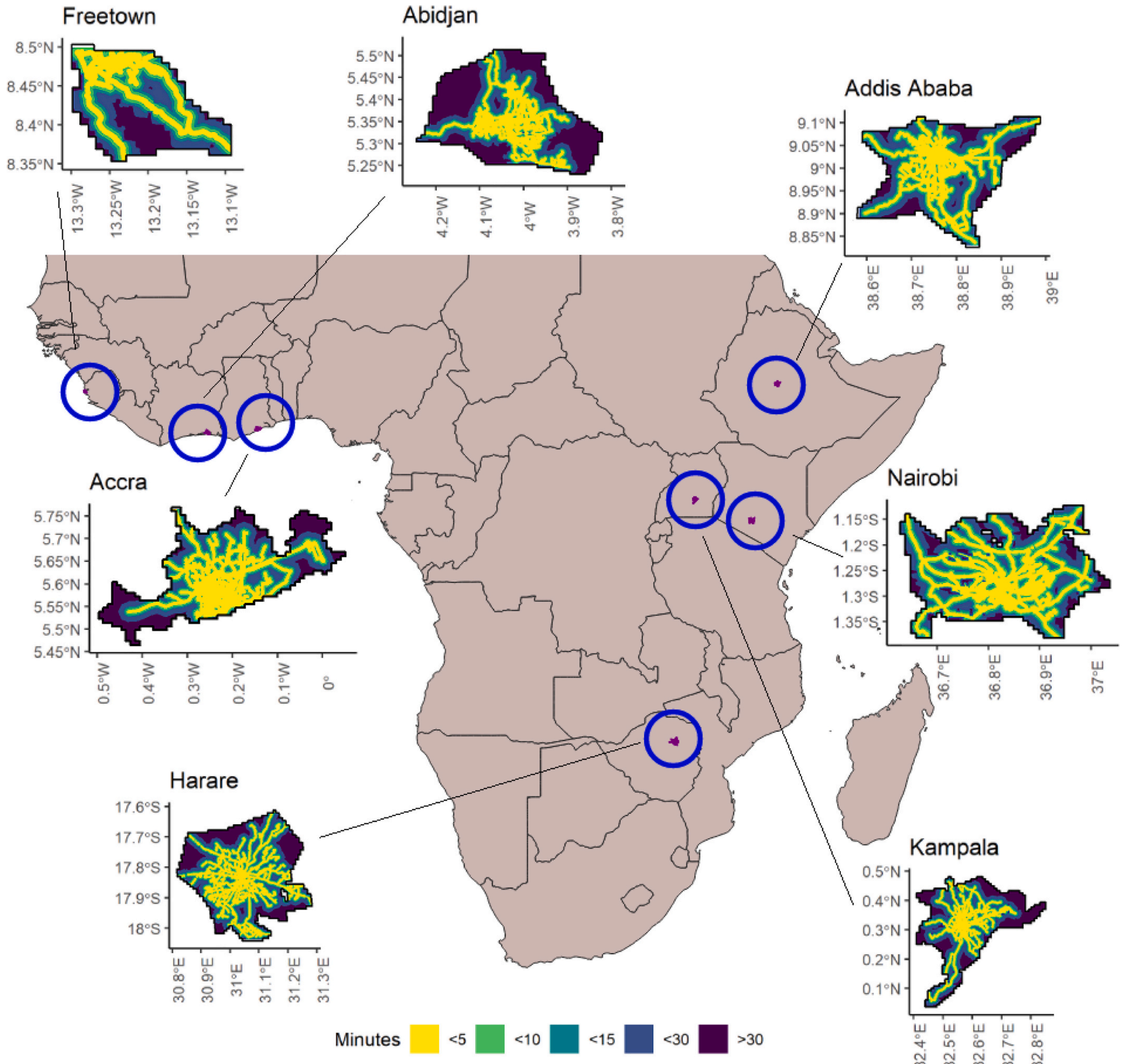

Fig. 3. Accessibility maps to the nearest paratransit route (walking minutes).

between the two groups of cities.

4.2. Beyond accessibility: comparative paratransit metrics

The main metrics comparing the performance of paratransit services across the different cities are reported in Tables 1 and 2. As described in Section 3.3, those indicators are calculated based on both design parameters (Table 1) and operational parameters (Table 2).

The metrics show a significant variability across cities, although some clusters of values are noticeable. It is important to remember that current paratransit systems are often the result of a complex evolution over the years from multiple stakeholders, rather than the implementation of a central design based on specific urban planning strategies.

In general, cities show a similar route length, mostly around 9–10 km, although Nairobi and Harare have longer routes. The average distance between stops shows two separate clusters, with cities having frequent stops up to 1 km between each other (with Nairobi showing the narrower stops each 400 m) and other cities with a stop each 3 km, suggesting that an important part of the network spans beyond the city centre.

Additional information is available on the operation of transit systems, as GTFS data report the scheduled frequencies and the duration of each trip. All the cities but Addis Ababa report complete information on both frequencies and trips duration, which allows evaluating a range of indicators. It is important to remember that such figures represent theoretical frequencies of trips, which may be affected in their real operation by congestion or other issues. Similarly, although trips duration are often measured during real operation, the single timeline of each trip is not statistically significant to represent its average duration.

Given those limitations, the median speed of collective transport systems in the cities ranges from less than 5 km/h in Addis Ababa to

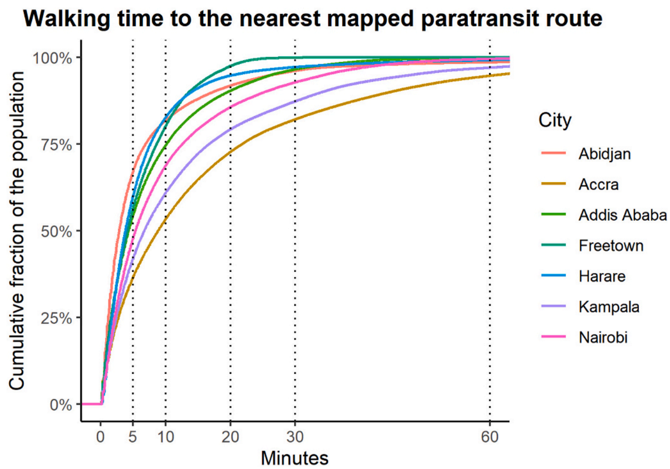

Fig. 4. Empirical cumulative distribution curves of the walking time to the nearest paratransit route.

more than 20 km/h in Harare and Nairobi. While the high median speed in Harare seems to be compatible with the high distance between stops, which suggests an important role of long-distance routes, the value for Nairobi is difficult to interpret when considering that stops are on average at a 400 m distance. This issue may be related to the different hypotheses when mapping stops (e.g. maybe including on-demand stops) or on other aspects related to the trip duration recording.

Other cities show more similar values, mostly around 12–15 km/h, which are in a range that is coherent with other results from research works. However, while some works have highlighted higher average speeds for paratransit in some cities, such as Cape Town (Du Preez et al., 2019), in other cases the authors highlight the very important role of bus stops duration when computing the commercial speed. Ndibatya and Booysen (2020) highlight that in Kampala's paratransit operation, the hold-back time of the minibuses at stops can significantly lower the actual average speed of the service. In our study, these speed values are obtained by calculating the average speed for each trip, and additional information on their distributions is available in Figure Appendix A.3, where boxplots are reported for each city.

In addition to average speed, the available information allows quantifying the total supply of paratransit services to the citizens. While a lack of information on the average capacity of the vehicles, in addition to the significant potential variability of occupancy, we calculated the offer of daily trips and total vehicle-km (vkm) scaled on the population of each city. Only Freetown and Harare report a different schedule for the weekends, with a lower number of trips resulting from a decreased frequency. The other cities report the very same frequency data for each day of the week.

Results show again a variability of these indicators, with Kampala and Harare having the highest values for both metrics (with a very similar offer of vkm per 1000 inhabitants). The other cities show around 10 daily trips per 1000 inhabitants, and almost 100 vkm per 1000 inhabitants (with Abidjan showing a value 40% lower). Again, these figures report daily service supply based on the frequencies reported by the GTFS data, which in some cases may not reflect the real operation of the paratransit services.

4.3. Insights from network analysis

The seven networks vary widely in their topological features (Table 3). For example, Kampala has the highest number of links and a diameter that is almost 35 times bigger than Addis. Nairobi and Abidjan are in the same range on the number of nodes (2968 and 2473) and links (7261 and 7761), but the diameter of Nairobi is twice of Abidjan (130 and 62 respectively). On the other hand, all the networks exhibit very low density, highlighting how they are internally loosely connected. Similarly, the network's probability of having adjacent stops interconnected as measured by the transitivity is very low.

Table 4 presents a set of measures that capture the transportation networks' dynamic aspects (e.g. fault tolerance, circulation, and exchanges in users' flows).

We first consider Global efficiency, a measure that has been widely used to study and optimise transportation (Ek et al., 2015). On a global scale, all the networks under analysis exhibit a low level of efficiency. That is, they are likely to be vulnerable to disruptions and delays affecting the level of service and connectivity.

Centrality network measures are used to measure the accessibility of a transportation network, but to facilitate the comparison among graphs of different size we normalised the average betweenness centrality and the average closeness centrality. While the former is calculated on each city network as a whole, the latter is computed only on the network's biggest component given how all the networks are not fully connected. In both cases we see that all the cities have low accessibility values but on average, the Betweenness centrality of Kampala is higher than the other cities, hence its bus stops are more strategically placed and links several other stops in the network more effectively than the other cities. Turning to Closeness centrality Addis Ababa has the higher average value, highlighting greater ease of movement along its public transport network.

The efficiency of a network in facilitating the user's circulation can be captured by the average number of stops needed to reach two other stops in the network (the average path length). In these terms, Addis Ababa has the most efficient transport network (5 stops on average) while Nairobi has the least efficient network (37 stops on average). It must be remarked that these results might (at least in part) depend on the differences in GTFS data collection protocols across cities.

Given the relative sparsity of the connection within the networks, we used a clustering algorithm to explore whether the transportation systems could be divided up into discrete regions where the bus stops are tightly connected (Table 5). To measure the strength of the division of each network in clusters, we used modularity. As per the closeness centrality, we run the clustering algorithm on the biggest component of each network.

Addis Ababa and Freetown, have a small number of clusters (11 and 16 respectively) as compared with the rest of the cities. The city that exhibits the most substantial community structure as measured by modularity is Harare (0.73), followed by Nairobi and Abidjan. The rest of the cities have modularity values close to 0, indicating that the community division is not better than random.

5. Conclusions

In this paper, we carried out an analysis of comparative metrics of accessibility, network centrality, and service quality of paratransit in seven major cities in sub-Saharan Africa (Abidjan, Accra, Addis Ababa, Freetown, Harare, Kampala, Nairobi). Our results highlight the importance of high-quality, granular transport data for understanding needs and barriers and enhancing urban planning in rapidly evolving developing cities.

We calculate that in most of the functional urban areas analysed, nearly three quarters of the population lives within a 10-min walk from the nearest mapped paratransit route. Yet, in absolute terms several hundreds of thousands are found to reside outside of these thresholds. In addition, we observe much broader inequality in terms of the number of routes available in different areas of the city, as well as in the service operations, such as median speed, number of trips or of vehicle kilometers. These results suggest that while crucial, accessibility is only one dimension of paratransit service quality in developing cities, and it is not necessarily correlated with operations quality. A more equally accessible network is thus only a necessary, but not a sufficient condition for ensuring efficient and equitable transit within functional urban areas of

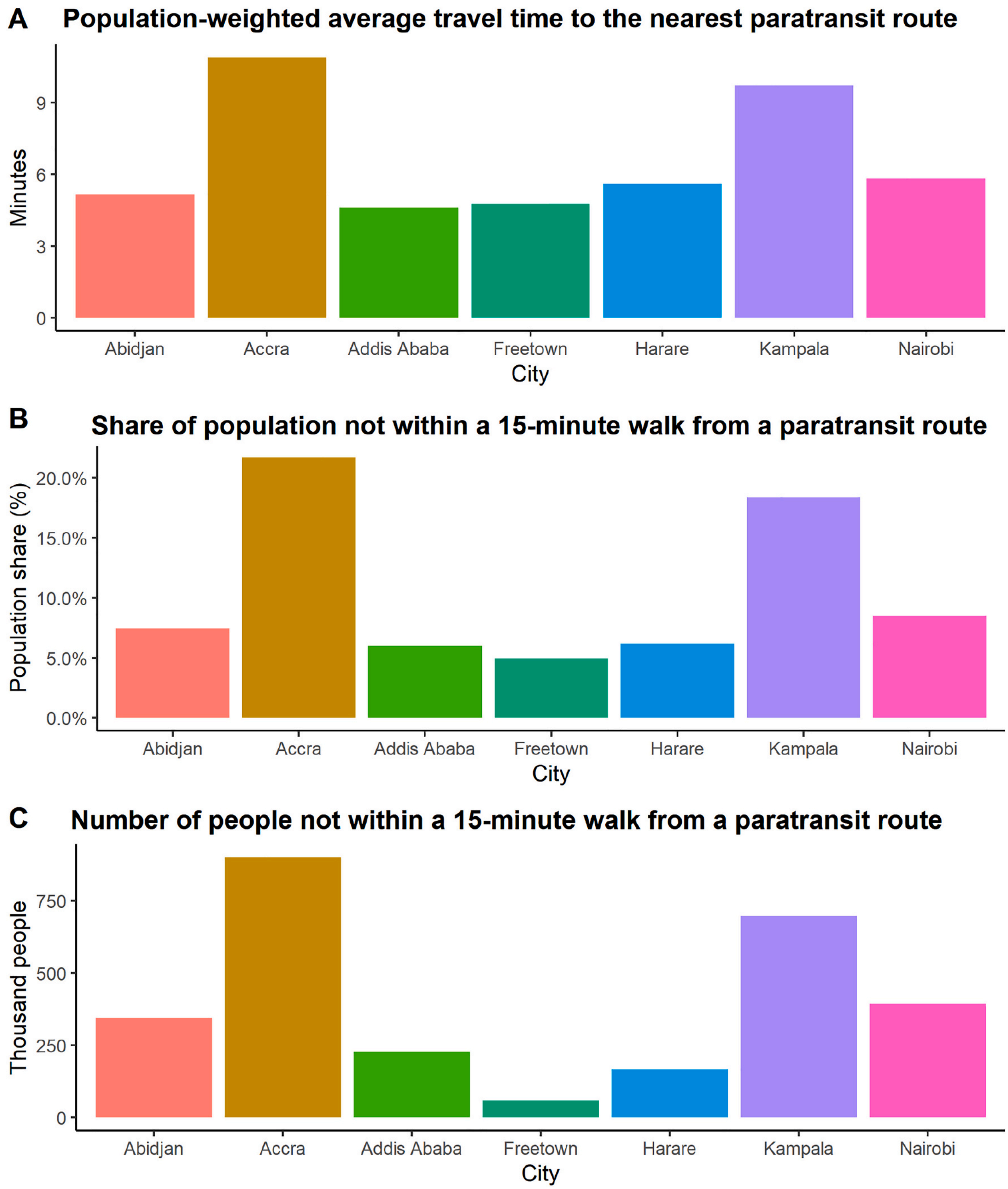

Fig. 5. (A) Population weighted average travel time to the nearest paratransit route in the seven cities considered; (B): Share of population not within a 15-min walk from a paratransit route; (C) Absolute number of people not within a 15-min walk from a paratransit route.

large sub-Saharan African cities.

Economic development has historically been associated with growing transport demand but considerably different outcomes in infrastructure development and passenger modal choice. In the 'global north' people are generally accustomed to strict classifications, such as public/private or legal/unauthorized transport. We believe that it is instead crucial to avoid these false dichotomies when studying mobility in cities with strong demographic and territorial growth. The focus should move on what really is important: to ensure accessible, efficient, sustainable and affordable transit.

This does not only relate to aspects of modal shift, i.e. the transition from a modal transport to another, but on the deep drivers of the demand for mobility, namely access to services and goods. A smart planning of services, such as efficient positioning of hospitals, schools, markets, and a growing use of digital technologies allowing citizens to access services without physically moving, together bear huge potential for reduction of the urban mobility demand. If digitalisation keeps shaping developing countries' society as observed over the last decade, achieving a transport system that is sufficient to meet citizens' needs will likely not require (at least in the near future) to match the levels of transport infrastructure and transit frequency of high-income cities. Multiple services and jobs will partially or entirely move online, without need for physically moving within different areas of a city.

We encourage future research to leverage similar methodologies to those applied in this paper with increasingly large and precise crowd-sources, georeferenced information on paratransit of developing cities

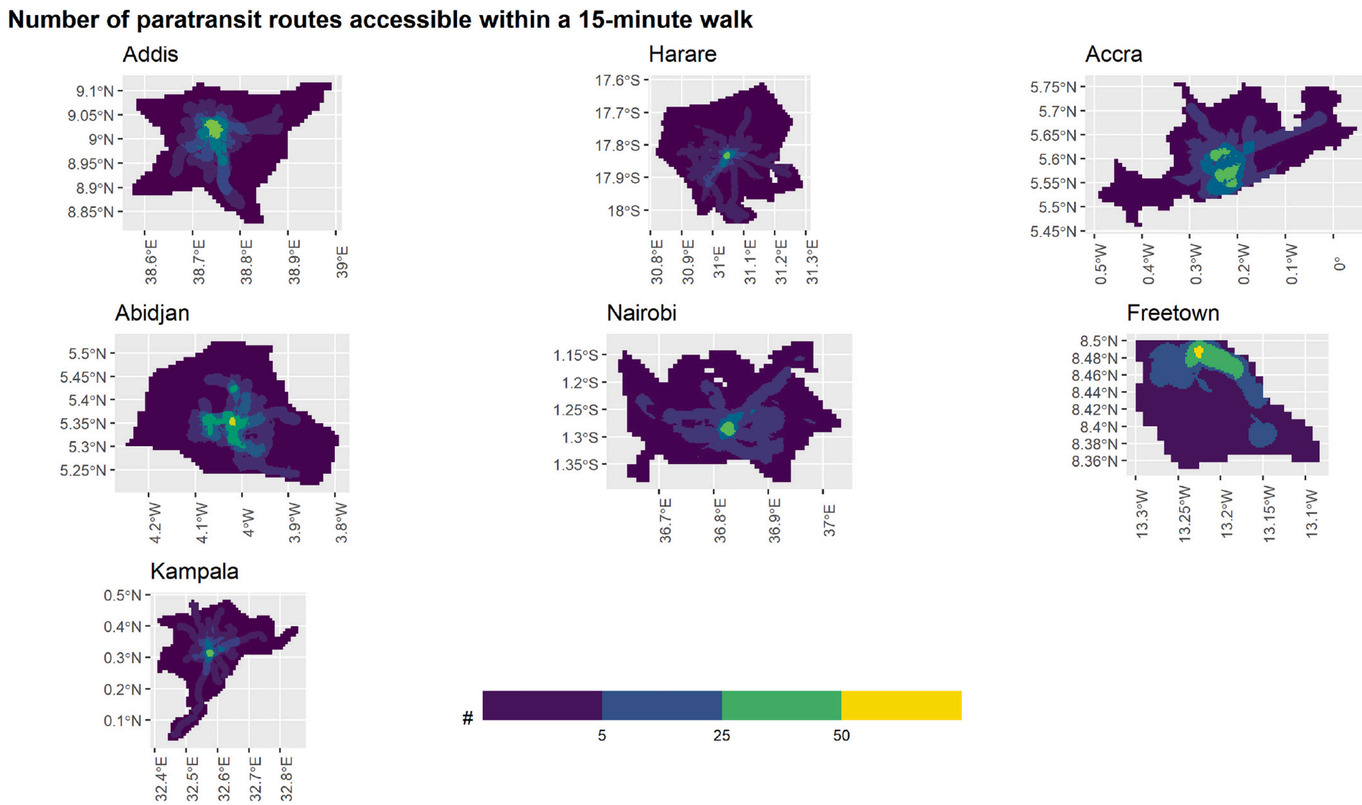

Fig. 6. Number of routes within a 15-min walk from each grid cell.

Table 1
Comparative paratransit design metrics.

	Million inhabitants	Routes	Stops	Avg. stops per route	Avg. route length (km)	Avg. distance between stops (km)
Abidjan	4.7	325	3339	10.3	9.2	0.9
Accra	4.8	277	4171	15.1	9.3	0.6
Addis Ababa	4.0	398	1221	3.1	8.7	2.9
Freetown	1.2	103	843	8.2	8.6	1.0
Harare	2.9	491	2271	4.6	15.2	3.3
Kampala	4.0	397	1242	3.1	10.7	3.4
Nairobi	4.7	136	4284	31.5	13.1	0.4

Table 2
Comparative paratransit operation metrics.

	Median speed (km/h)	Weekday (weekend) trips	Weekday (weekend) vehicle-km	Trips per inhab.	vkm per inhab.
Abidjan	13.8	43,845	288,691	9.3	61.4
Accra	13.1	53,278	436,609	11.1	91.0
Addis Ababa	4.5	–	–		
Freetown	15.5	13,938 (10,828)	116,931 (84,433)	11.6	97.4
Harare	23.7	45,424 (38,493)	643,123 (542,659)	15.7	221.8
Kampala	12.4	94,183	945,611	23.5	236.4
Nairobi	21.4	34,848	455,503	7.4	96.9

Table 3
Topological properties of the networks.

	Number of links	Number of nodes	Diameter	Density	Transitivity
Abidjan	7761	2473	62	0.0013	0.146
Accra	10,753	1576	61	0.0043	0.2295
Addis Ababa	5643	964	25	0.0061	0.2119
Freetown	1802	635	220	0.0045	0.216
Harare	2947	1686	46	0.001	0.0575
Kampala	16,756	1174	864	0.0122	0.197
Nairobi	7261	2968	130	8e-04	0.1667

Note: Number of links, Number of nodes and Diameter are absolute values. Density and Transitivity range from 0 to 1.

Table 4
Dynamic properties of the networks.

	Global efficiency	Avg betweenness centrality	Avg closeness centrality	Max component size	Avg path length
Abidjan	0.0939	0.0051	0.0914	2092	16.6052
Accra	0.1121	0.0097	0.0928	1560	16.4727
Addis Ababa	0.0851	0.001	0.2727	304	5.235
Freetown	0.0656	0.0197	0.0519	589	13.7983
Harare	0.1573	0.0048	0.1477	1439	10.4641
Kampala	0.0084	0.0208	0.0065	1101	27.2885
Nairobi	0.046	0.0118	0.0362	2862	37.8459

Note: Global Efficiency, Betweenness Centrality and Closeness Centrality range from 0 to 1. Max Component Size and Average Path Length are absolute values.

Table 5
Clusters and Modularity of the networks.

City	Number of clusters	Modularity
Abidjan	25	0.4348
Accra	25	0.2531
Addis Ababa	12	0.3615
Freetown	18	0.1847
Harare	24	0.7293
Kampala	25	0.0111
Nairobi	25	0.5491

Note: Modularity ranges from 0 to 1 with value close to 1 indicating strong community structure.

and provide transport developers with ever more detailed picture of the situation and key challenges.

Code and data availability

The R and Google Earth Engine Javascript code to replicate the analysis and the figures are publicly hosted at https://github.com/giacfalk/GFTS_african_cities.

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Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2021.103131.

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