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Master Thesis

Modelling spatial health accessibility in Sub-Saharan African cities:

A Case Study in Yaounde, Cameroon

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Abstract

Delivering equitable healthcare to all by 2035 is the aim of the Cameroonian Ministry of Public Health (2015). Up to now, the main focus of the authorities has been to assess spatial inequalities between the rural and the urban areas, as health accessibility has been considered secondary in the urban Sub-Saharan setting. Although travel distances to the nearest facility in urban areas are unsubstantial compared to rural areas, disparities between neighbourhoods in service allocation and in value can be significant.

Modelling and assessing healthcare accessibility is important to identify and prioritise under-deserved areas with the purpose of improving healthcare utilisation. Modelling accessibility in the Sub-Saharan urban context possesses its own characteristics. First, the mobility patterns and city structures are specific to this part of the world. Neighbourhoods have poor connectivity between each other as most roads are unsealed. Secondly, poor data reliability and incompleteness can seriously impact the analysis. It is precisely with these particularities in mind that we have chosen Yaounde in Cameroon to develop our project.

The principal aim of this work was to develop a healthcare accessibility model based on a Two-Step-Floating-Catchment-Area (2SFCA) variant method adapted to the urban Sub-Saharan context. We performed several experiments in order to observe the impact of the different means of transportation, several sources of population data and different health facility databases.

The model results showed that the new urban areas towards the outskirts of the city and the compartments situated further away from major transport axis have the poorest accessibility and therefore are under-serviced. Improving healthcare accessibility in these areas can be done by optimising healthcare allocation and by improving transportation networks through and within the neighbourhoods. With the realisation of a sensitivity analysis, we assessed that the partial completeness and little reliability of the healthcare facility datasets were not decisive in modelling the outcomes of users of motorised transportation. However, concerning population data, the use of bottom-up approach estimates was needed to obtain prominent results. Finally, the model we have developed can be further used in similar contexts.

Résumé

Offrir des services de santé équitables à tous d'ici 2035, tel est l'objectif du Ministère de la Santé Publique du Cameroun (2015). Jusqu'à présent, les autorités se sont principalement concentrées à évaluer les inégalités spatiales entre les zones rurales et urbaines, l'accessibilité à la santé étant considérée comme secondaire dans le contexte urbain sub-saharien. Bien que les distances de déplacement jusqu'à l'établissement le plus proche dans les zones urbaines ne soient pas importantes par rapport aux zones rurales, les disparités entre les quartiers en termes de répartition et de valeur des services peuvent être significatives.

La modélisation et l'évaluation de l'accessibilité aux structures de santé sont importantes pour identifier et donner la priorité aux zones mal desservies dans le but d'améliorer l'utilisation des services de santé. La modélisation de l'accessibilité dans le contexte urbain sub-saharien possède ses propres caractéristiques. Tout d'abord, les schémas de mobilité et les structures urbaines sont spécifiques à cette partie du monde. Les quartiers sont peu reliés entre eux car la plupart des routes ne sont pas goudronnées. Deuxièmement, la mauvaise fiabilité des données et leur caractère incomplet peuvent avoir un impact sérieux sur l'analyse. C'est précisément en tenant compte de ces particularités que nous avons choisi Yaoundé au Cameroun pour développer notre projet.

L'objectif principal de ce travail était de développer un modèle d'accessibilité aux structures de santé basé sur une variante de la méthode 2SFCA (méthode des aires flottantes à deux étapes) adaptée au contexte urbain sub-saharien. Nous avons réalisé plusieurs expériences afin d'observer l'impact des différents moyens de transport, de plusieurs sources de données de population et de différentes bases de données contenant les positions des structures de santé.

Les résultats du modèle ont montré que les nouvelles zones urbaines situées à la périphérie de la ville et les zones en retrait des principaux axes de transport sont les moins accessibles et sont donc mal desservis. L'amélioration de l'accessibilité aux structures de santé dans ces zones peut se faire en optimisant la répartition des services et en améliorant les réseaux de transport entre et au sein des quartiers. Avec la réalisation d'une analyse de sensibilité, nous avons évalué que l'exhaustivité partielle et la faible fiabilité des données sur les établissements de santé n'étaient pas décisives pour modéliser les résultats des utilisateurs de transports motorisés. Cependant, en ce qui concerne les données de population, l'utilisation d'estimations provenant d'une approche ascendante était nécessaire pour obtenir des résultats probants. Enfin, le modèle que nous avons développé peut être utilisé dans des contextes similaires.

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1 Introduction

Improving access to healthcare is a top priority of public health authorities around the globe. The third United Nations (UN) Sustainable Development Goal (SDG) which aims to *Ensure healthy lives and promote well-being*, specifically targets universal health coverage (WHO, 2016). This concept defined by the UN ensures access to adequate healthcare to all, when and where they require it and without financial hardship. In the context of a global pandemic, the lack of access to healthcare has been frequently pointed out as a factor that has had a direct impact on population's mortality (Nature, 2021).

Healthcare access in Sub-Saharan Africa
Developed by the Global Burden of Disease Study (GBD), the Healthcare Access and Quality Index (HAQ) presented in Figure 1 scales a list of 195 countries from 0 (high mortality) to 100 (low mortality) (Fullman et al., 2018). It is used to monitor and evaluate the strength and expansion of a national or regional health system through amenable mortality. It designates deaths that could be avoided in the presence of effective medical care (Gianino et al., 2017). It identifies 32 causes of preventable deaths such as vaccine-preventable diseases, infectious diseases, non-communicable diseases such as cardiovascular disease, obstetrical and child health issues. Whereas Iceland and Norway, who provide universal health care to their citizens lead the ranking, healthcare access issues are emphasised in Africa and especially Sub-Saharan countries whose grades are among the lowest on Earth. Out of the last 50 listed countries, 40 are from the African continent. Health services delivery in Sub-Saharan Africa urban settings is enduring growing challenges associated with the extensive development of cities, the demographic growth and the urbanisation of poverty (Mokgalaka, 2014).

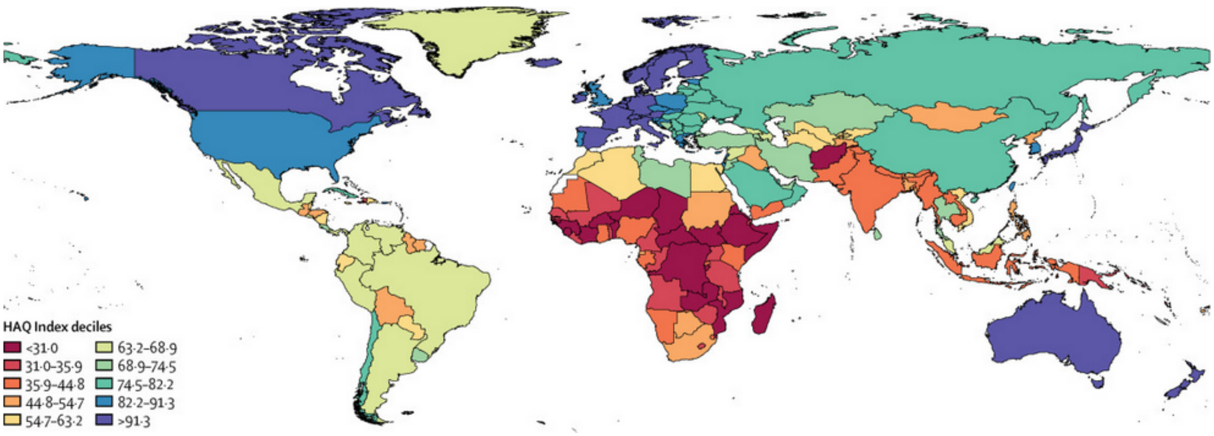


Figure 1 – The Healthcare Access and Quality Index around the globe (Fullman et al., 2018)

Barriers to health access
Developing healthcare access is undertaken by lowering barriers that prevent adequate care. Ensuring access necessitates the reduction of a combination of obstacles. They include the financial costs, the lack of knowledge, the cultural belief such as scepticism in vaccinations, or the geographical barrier (Shakya-Vaidya et al., 2014). Reducing the latter impediment implies situating the most vulnerable areas, but also optimising healthcare distribution in space to provide medical care anywhere. The different health barriers are related to each other, especially concerning spatial and socio-economical factors. To evaluate the degree of adequate health access,

the World Health Organisation (WHO) references a list of 100 core indicators (WHO, 2015). In this document, the WHO fixes as reference the presence of at least one health facility per 10'000 inhabitants and no further than 5 kilometres away from the place of residence.

Living location as a health factor
The location of where people live has been shown to be linked to health outcomes (Feldscher, 2011). Factors of influences related to location are classed by the US Office of Disease Prevention and Health Promotion (ODPHP, 2020) in three main categories: environmental circumstances, economic statute and social context. While the last two categories are directly related to each individual, the first typically refers to the quality of the neighbourhood. Environmental factors can be natural such as terrain topography and altitude, or constructed such as transportation options and buildings.

Socio-economical conditions have a strong dependency with their surroundings. Proximity to facilities, notably healthcare, has been deeply studied as a potential environmental factor of influence on healthcare utilisation and on health outcomes. Looking at low and middle or high income countries, most study findings relate an association between the location of health facilities and their usage, although there is no absolute consensus (Kelly et al., 2016; Okwaraji & Edmond, 2012). Various researchers have shown a decay with distance on healthcare utilisation and on health outcomes. Okwaraji and Edmond (2012) observed in their systematic review that proximity to health facilities is likely to be associated to higher child survival in low and middle income countries. In other words, negative health outcomes can be linked to the remoteness of healthcare.

Working on the ability to physically access a health facility is expected to improve their utilisation and to improve generals population health. The accessibility concept which we define and discuss in Section 2.1, is used to measure the spatial interaction potential between a set of locations. If the proximity refers exclusively on the distance and travel time, the accessibility can consider a wider spectrum of spatial variables including the number of health facilities per capita.

1.1 Accessibility modelling

Different accessibility needs for different contexts
Mobility patterns surrounding the healthcare system vary significantly according to the medical needs. Space and time have fluctuating levels of importance on the direct health outcomes: If access time plays a crucial role in case of medical emergencies, it has a more measured role for a physician consultation. But nonetheless, studies have shown that attendance declines for patients living at more distant locations and health outcomes decrease consequently (McLean et al., 2014). Primary health care (PHC) describes the first basic level of interaction between the health system and the patients. By delivering preventive, curative and rehabilitative service, it addresses the principal health issues of the population. As PHC is the most integrated into communities, its access and accessibility adequacy is fundamental for an effective health strategy.

The spatial settings are also of great importance on the accessibility to health facilities and besides rural and urban context are hardly comparable because of their proper specificity. Rural populations generally rely on the single closest health facility since there can be significant time lag with the subsequent ones. In an urban context, where population densities are much greater, a trip of few kilometres can already have a substantial cost in term of financial, temporal and physical efforts. Hundreds thousands of people might be living in the surroundings of the same health infrastructure and have disparate ease of access. Generally in cities, patients are provided with several health services alternatives within an acceptable displacement time which motivates the consideration of a number of structures and not only the closest one.

1.2 Accessibility modelling in urban Sub-Saharan Africa

Sub-Saharan cities specificities

With their urbanisation rates among the highest on the planet (Muggah & Kilcullen, 2016), cities in the sub-Saharan region face phenomenal challenges due to current and future spatial and demographic expansion. According to the UN, in 2018, 238 million people lived in slums or informal settlements which was about half of the region urban population (UN-Habitat, 2020). Most economic activities take place out of the legal system, in what some called the extra-legal system or the informal system (Kemajou Mbianda, 2020). In Yaounde for instance, only 27% of economic activities are registered in the formal system (Mbaye et al., 2015). In terms of affordability, health inequalities are important between the different socio-economic classes of society.

Cities in the region share a number of urban characteristics which are important to characterise accessibility and transportation issues. Lall et al. (2017) have identified in their report that Sub-Saharan cities are and will be more and more overpopulated, meaning that the resources within the cities are increasingly insufficient to serve their population. Population densities are not significantly rising but there are strong local variations of densities across the city. The urban extent has mostly been spreading horizontally together with the new inhabitants. Main services and infrastructures are grouped in centralised attractive areas. Peripheral neighbourhoods are poorly connected with each other, as most of the transportation networks are concentrated in the city centres. Outsides of these areas, networks quality worsen consequently such as illustrated in Figure 2 with the unsealed streets in one of Kinshasa's residential neighbourhood.

Figure 2 – Aerial image of Kinshasa residential area (Aeromapper, 2017)

Literature gap
Numerous studies have addressed the geographical (in-)accessibility issues in Low and Middle Income Countries (LMICs) at regional or national scales with recurrently the aim to emphasise the healthcare scarcity for rural populations (Ahmed et al., 2019). In African cities, such research studies are more limited. Ahmed et al. (2019) provide two main explanations for their sparsity. First, as distances are less substantial compared to rural areas, the focus is primarily set on the provincial areas, and accessibility in an urban context is only secondary. Secondly, they point out the deficiency of reliable data on health services and their characteristics Ndonky et al. (2015).

In terms of spatial accessibility to healthcare, the urban setting in Africa is considered as a secondary priority. Indeed, policy goals focus on reducing distances which are relatively unsubstantial in urban areas compared to rural areas. They also aim to dispose of enough facilities per population within administrative units which can lead to important local disparities in their distribution. The lower interest is also noticeable on the method implementation through their little consideration for contextual specificities. Indeed, in the literature, there are few applications of Floating Catchment Areas and its derivatives (FCA) that have a particular focus on African cities. FCA are widely accepted methods used to measure spatial accessibility (Tang et al., 2017), but even though their methodologies are repeatable, they are not adapted to the local context. Transportation networks and urban structures, particularly the neighbourhood poor penetrability and connectivity enables the addition of these characteristics in the model. Indeed, as the network condition is a major impediment to efficient travel, an adapted model needs to consider its heterogeneity. Adapting models to the Sub-Saharan urban context is important because refining the spatial hypotheses produces results that are more representative of the utilisation of healthcare facilities.

Another aspect of the little amount of literature that appears particularly relevant to us is the data inconsistency and poor reliability in health accessibility studies. The point of our analysis is to understand the impact of data on the results and their relevance. Although data quality improves constantly in Africa, trustful data remains a challenge.

1.3 Project objectives

The aim of this project is to develop a health accessibility model adapted to the urban Sub-Saharan context and to assess the usages and the limitations of such a tool. Cameroon capital Yaounde is used as a case study.

The objectives consist of three main forms: the development of the model, the critical analysis of the results and the re-usability of the model. First, the modelling objective aims to acquire appropriate data, and to adapt existing methods to the characteristics of the context. The second stage is to evaluate whether the hectometric indicator of spatial health accessibility can improve the decision process of future health structures allocation. Lastly, the geospatial tool constructed over a script is aimed to be conveniently reusable in other Sub-Saharan cities.

In this study, we first expose the definitions and nuances of accessibility before introducing the different methods used to model health accessibility with their respective benefits and limits including a particular focus on the urban sub-saharan setting and its related challenges. Then, we present our study area with its background specificities before exposing the data and the methodical proceedings of the project. Next, we discuss the results with a global and local viewpoint. Finally, we discuss their implications and limitations.

2 Theoretical framework of health accessibility in Sub-Saharan Africa

2.1 Spatial accessibility concept

Definitions and nuances
Although the concept of spatial accessibility is widely used throughout authors and policymakers, terms and definitions can be nuanced. Generally, it refers to the degree to which users can geographically connect to service providers. The cost-benefit principle is central to determine the level of potential connection. For it to be favourable the benefit derived from the spatial interaction must outweigh the cost of travel between the supply and demand (Chen & Jia, 2019). The central point of divergence among interpretations provides from the characterisation of the supplier, the quantification of opportunities and the considerated mobilities (Kwan, 1998).

Penchansky and Thomas (1981) designate accessibility as one of five distinct dimensions of the access concept. The four other dimensions are availability, accommodation, affordability and acceptability. They define the general concept as a fit adequacy measurement between providers and customers characteristics and expectations. The accessibility is specially viewed as the relationship between the supply location, the client location with the consideration of transportation resources, travel time, distance and cost. Even though the authors admit the close relationship between the dimensions, they suggest each of them can be distinctly measured.

The WHO (2013) also refers to distinct dimensions to characterise access, but diverge on their classification. For them, health access is dimensioned by physical accessibility, financial affordability and acceptability. If the last two are again related to users ability to pay and willingness to seek service, the physical accessibility designates this time the reachability and the availability of good health service when they are needed, which is a combination of Penchansky and Thomas (1981) first two dimensions.

In a more modelistic approach, Hansen (1959) defined in his paper accessibility as a measure of the intensity of potential of interaction. This proposition presents accessibility as being directly linked to the size of the provider and the separating distance with its user. The idea behind is that the intensity is increased not only with proximity, but also with the number of providers and their strengths.

Potential accessibility and revealed accessibility
Spatial accessibility research studies are partitioned into diagnostic and predictive approaches in order to model the revealed accessibility (RA) and the potential accessibility (PA). The first one aims to reveal spatial relations between the providers and the users. Authentic utilisation of the health services (providers) are studied through individual mobility patterns with patients personal informations. Such diagnostic studies are less common because of the significant individual level of personal data needed and its respective high cost, but they are essential for the effectiveness of second approaches (Casas et al., 2016). The latter uses models which are constrained by parameters provided from the RA. It aims to predict the possibility of utilisation of a health structure across a territory.

As an example with a local physicist, the analysis of all the registered clients addresses, transportations and consultations determines the RA. The resulting specificities such as the maximum acceptable distance or the average travelled distance are then used to determine the PA of a similar physicist, or to evaluate the potential of attraction of a future implantation.

Objective and subjective accessibility

Accessibility measurements conventionally tend to be determined by objective travel and environment attributes like the transport modes, the travel time and the geographical barriers. If theses aspects are objectively measurable, they aren't considered as sufficient to globally characterise accessibility for everyone since all individuals perceive accessibility differently (Lättman et al., 2018). Lättman et al. (2016) emphasise on users well-being in their accessibility definition where the indicator is related to the easiness to live a satisfactory life using the transport system. This notion reminds the acceptability dimension of Penchansky and Thomas (1981) who also was described as the user perception, however not of the transportation option but of the destination. Variables used to measure the travel perceptions are for instance the security, the comfort or the transport reliability. The inclusion of the subjective accessibility can enable a more complete understanding of the situation.

2.2 Methods and tools used to model health accessibility

Efficient planning of health structures in order to reach an equitable geographic distribution is one the major goals of health accessibility modelling. Approaches trying to achieve this objective vary on the spatial context and the spatial interactions hypothesis between providers and users. Through out the following subsection, we present the different methods, the frame for which they are designed and the limits they encounter.

2.2.1 Catchment area

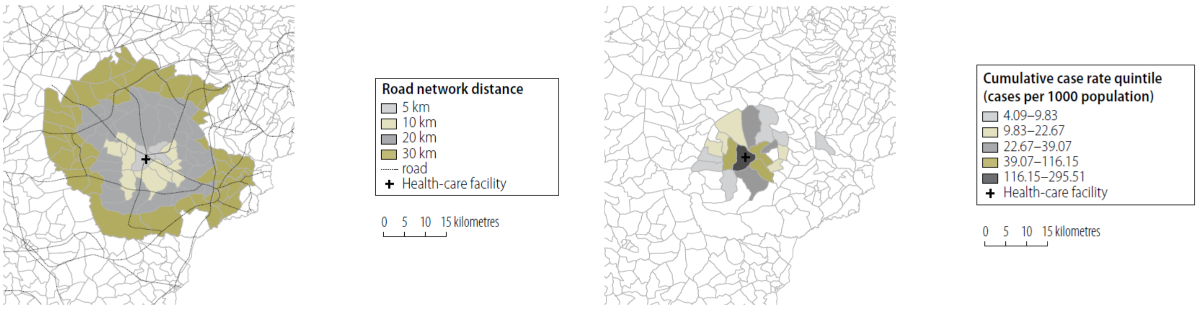
The area from which users of a health facility come or potentially come from is referred as the catchment area. The latter is of high interest for quantifying and evaluating the health care utilisation (Zinszer et al., 2014). Such assessments and understandings are important to ensure appropriate and effective managements for instance in identifying medical deserts. In addition, catchment areas are also of significant importance to determine population-based rates of diseases as for example COVID-19 case number comparison by administrative areas (Milucky et al., 2020).

Catchment area can either be formally calculated when working with revealed accessibility as explained in Section 2.1 or be estimated when working with potential accessibility over travel and spatial hypothesis. Two main methods are advanced to calculate catchment area. They can directly rely on questionnaires and patients registers informations or indirectly depend on mobility patterns such as the track of taxi movements in and out of hospitals (Pan et al., 2018) through large GPS datasets (Xia et al., 2019).

The first and most common method is the reported *trip distance* method which supposes that catchments are most importantly determined by an impedance cost. Their spans can be computed as euclidean distances (straight line), as travel distance, and as travel time according to the different transport modes. In order to refine the accuracy of trips, researchers have undertaken sophisticated analyses in considering traffic congestion (Ahmed et al., 2019).

The second method is the *patient flow* method and its derivatives. The principle is that a spatial unit is considered within a catchment if at least a proportion of users originate from this area. Although, this second approach gives limited reproducible material for models, it exceeds the previous distance-centred limitations by ignoring the trip, but considering the origin and destination.

Figure 3 below illustrates an Ugandan example of both methods. We observe that the catchment area related to the patient flow is much smaller than the one with the *trip distance* method.



(a) Trip related catchment area (b) Patient Flow related catchment area

Figure 3 – Catchment areas surrounding in the Nagongera health-care facilities in Uganda (Zinszer et al., 2014)

2.2.2 Ratio-based models

The *ratio-based* approach also known as the container approach is used to compare the supply and the demand within a service planning area (Yang et al., 2006). The indicator is typically used for evaluating limited resources over a country, a region or a county (Rekha et al., 2017). The supply provides logistical informations on the capacity of a certain structure or equipment whereas the demand can be a specified fraction or a whole population of a geographic container. The attractiveness of this method comes from the fact that it is easily understandable and requires data which is readily available (Zafri et al., 2020). Ratio-based models are of particular interest when availability is the focus. The aim of working with such a model is to answer to the question: is there enough supply in this area to fill the demand? The main limitations are, on the one hand, that accessibility isn't differentiated within the container and on the other hand, that there is no consideration of the spatial externalities interactions with the *inside* supplies, meaning that facilities and population out the container are ignored (Zafri et al., 2020). In the field of health, the number of hospital beds, intensive care beds or respirators per 100'000 inhabitants are example of common usage of this indicator. In Europe, during the COVID-19 pandemic, ratio-based indicators were crucial for health authorities in order to coordinate care within regions.

2.2.3 Space-time based models

Space-time method focuses on the proximity between a specific location to a facility or a group of facilities. The method can also refereed as the *travel impedance* or *travel cost* method. The result is a spatial accessibility index that is measured as a matter of distance or time, where the smaller the cost, the more favourable is the location (Zafri et al., 2020). This method is based on the assumption that people minimise travel distance. This factor has been shown to have fluctuating importance (Mokgalaka, 2014) depending on the facility and the frame. If euclidean distance is commonly used because of its simplicity, the travel distance following a transportation network such as a road or walking system to travel from a point to another is a more appropriate indicator (Rekha et al., 2017) because it does consider physical barriers. In urban settings, the time indicator complexity itself as it continuously evolve during the day with the traffic congestion. Space-time based models are composed of two main branches. First, the *nearest facility* approach whose name is explicit is assumed to be a good measure for rural areas or for emergency services. Its big biggest limitations are that capacity and alternatives facilities are not taken into consideration (Kim et al., 2018). Secondly, is the *average travel cost* approach. It is calculated as the average time or distance to reach a set of facilities. Main limitations consist that the influence of facilities which are sited on the urban periphery is over-weighted (Yang et al., 2006).

2.2.4 Gravity based models

Gravity based approaches propose a trade-off between the capacity of a healthcare facility and the travel cost needed to join a location (Neutens, 2015). As opposed to the previously presented models, this process considers both proximity and availability (Zafri et al., 2020).

The reference to gravity comes from Newton's well-known theory, where bodies are replaced in our subject by sanitary facility sized according to their capacities and distance by time or cost of travel. Gravity models have been evolving in a list of spatial analysis fields such as transportation route distribution, international trade or accessibility. Voorhees (1955) introduced the principle that the attraction strength of a destination was associated with its opportunity potential (Philbrick, 1973). Hansen (1959) was the first author to link the model to a measurement of accessibility where he related available building plots, their accessibility and their corresponding market value.

Accessibility measure of a gravity model, which is also considered as a cumulative opportunity measure, is calculated as the sum of opportunities (capacity) over travel impedance of all infrastructures. The mathematical expression of the model varies according to the subject, the general form of the accessibility index A_i can be formulated as:

$$A_i = \sum_{j}^{k} \frac{S_j}{f(c_{ij})} = \sum_{j}^{k} \frac{S_j}{d_{ij}^{\beta}} \tag{1}$$

For i associated to the users and j to the facility, S_j is the capacity of the health care facility j, also called its maximum potential of attractivity. The cost function $f(c)$ for the continuous travel distance depends on the travel cost c_{ij} between the user i and the facility j. This function can be substituted by a travel decay factor d^{β}, with β being the friction-of-distance exponent in health accessibility studies (Luo & Qi, 2009).

Many variations have since been developed from the original version. In the health sector, as the demand is a proportion of population, the consideration of the latter would improve the model (Guagliardo, 2004). Indeed, the capacity limit is relative to the size of the potentials users. Joseph and Bantock (1982) developed the Population Weighted Hansen model also called as the Modified Gravity Model with the following formula:

$$A_i = \sum_{j} \frac{S_j}{f(c_{ij})} \frac{1}{\sum_k (\frac{P_k}{f(c_{jk})})_j} = \sum_{j} \frac{S_j}{d_{ij}^{\beta}} \frac{1}{\sum_k (\frac{P_k}{d_{jk}^{\beta}})_j} \tag{2}$$

For k associated with the centroid of a population unit , P_k is the population at location k. According to Wang (2011), the development of such a model was not sufficient to assess accessibility. The two main limitations were the little manageability caused by the continuous functions and the non-consideration of spatial boundaries.

2.2.5 Two Steps Floating Catchment Area method

The Two Step Floating Catchment Area method (2SFCA) is a particular case of the previously presented Modified Gravity Model. Radke and Mu (2000) and Luo and Wang (2003) replaced in their study the continuous travel distance cost function with a dichotomous travel distance boundary which is called the travel threshold d_0 (Wang, 2011). The primary purpose of the 2SFCA method is to assess the spatial accessibility inequity to healthcare services. Applications have thereafter been broaden to the planning of other facilities such as parks, food stores or emergency shelters (Chen & Jia, 2019).

This index is constructed in two steps as its name suggests:

- ***Step 1*** For all j structures of interest, the population is summed over all centroids located at a distance d_{kj} that is within a catchment defined by travel distance d_0. Centroids are counted several times when facilities catchment overlap. This step results in a ratio for each infrastructure of its capacity per spatially covered population.

  The infrastructure to population ratio R_j can be expressed as:

$$R_j = \frac{S_j}{\sum_{k \in d_{kj} \leq d_0} P_k} \tag{3}$$

- ***Step 2*** The second step is to sum the calculated ratio for all centroid of all structures that fall within the catchment defined by d_0.

$$A_i = \sum_{j \in d_{ij} \leq d_0} R_j = \sum_{j \in d_{ij} \leq d_0} \frac{S_j}{\sum_{k \in d_{kj} \leq d_0} P_k} \tag{4}$$

Although the dichotomous limits are conveniently implementable and assignable in Geographic information system (GIS), their artificial sharpness are a limitation (Guagliardo, 2004). Indeed, facilities located right next to the border are counted in the same way as immediate neighbours, whereas those just beyong are simply not counted. A gradual decay of weight would ensure a more proportional travel distance consideration. Another limitation of the 2SFCA can be accessibility overestimation when multiple catchment areas confront for the same population (Wan et al., 2012), as with the presence of numerous reachable alternatives, when a supplementary facility does not add much tot the potential of spatial interaction. In the last decade, series of improvement have been added to the basic 2SFCA. The most relevant are presented in the next subsection.

2.2.6 Variants of the 2SFCA method

Three features of the 2SFCA method have been of particular interest for further developments of the model: the distance decay function, the catchment size and the local competition (Chen & Jia, 2019).

Distance decay

The distance decay function intends to differentiate the effects of a supplier in a specific location over distance. Integrating the decay function conceptualise the idea that users are progressively less inclined to use a remote service. The replacement of the basic dichotomous function in the 2SFCA model leads to the development of a series of variants which diverge on the decreasing process. The distance decay function major extensions include the Enhanced 2SFCA, the G2SCCA, the Gaussian 2SFCA and the Kernel Density 2SFCA.

The distance decay function $f(d_{ij})$ is introduced in both summation steps as follow:

$$A_i = \sum_{j \in d_{ij} \leq d_b} f(d_{ij}) R_j = \sum_{j \in d_{ij} \leq d_b} f(d_{ij}) \frac{S_j}{\sum_{k \in d_{kj} \leq d_a} f(d_{ij}) P_k} \tag{5}$$

The functions representing these models are expressed in Table 1.

The **Enhanced Two Steps Floating Catchment method (E2SFCA)** intends to overcome the catchment non-differentiation accessibility issue, by implementing multiple distance decay weights (Luo & Qi, 2009). Catchment areas are sub-divided into z travel zones to demarcate the gradual decaying attraction without using a continuous function. The weights are generally attributed by a Gaussian function such as $g(d_{ij}) = e^{-(z-1)^2/\beta}$ as it is done over numerous E2SFCA studies (Luo & Whippo, 2012; Pan et al., 2018; Zahnd et al., 2021).

The **Gaussian Two Steps Floating Catchment Area** method (Gaussian-based 2SFCA) addresses the distance decay dilemma by adjusting a continuous Gaussian function to the model. The strong added value of this alternative is that only one parameter is adjustable (d_0) which makes the model less subjective to modifiable parameters. (Tao et al., 2020).

The **Kernel Density Two Steps Floating Catchment Area** method (KD2SFCA) is another curve fitting alternative widely used in spatial domains where estimations are based on probability density. Several curves are used in accessibility modelling issues. The most commonly operated one is the *Epanechnikov* function because of its similarities with the normal distribution (Chen & Jia, 2019). The quartic KD function, which accentuates more the travel-distance, is said to better reflect health care user behaviours (Polzin et al., 2014).

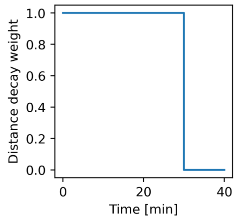
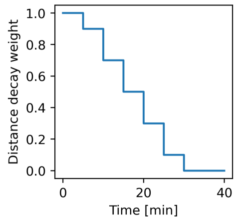
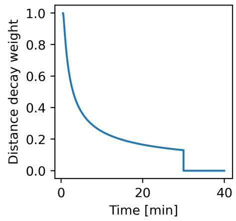
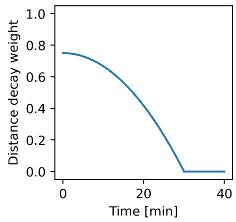
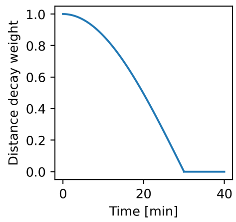
Model name	Distance decay function	Figure
Generalised 2SFCA	$$f(d_{ij}) = \begin{cases} \theta, & d_{ij} \leq d_0 \\ 0, & \text{otherwise} \end{cases} \quad (6)$$	
Enhanced 2SFCA	$$f(d_{ij}) = \begin{cases} \theta_1, & d_{ij} \in d_1 \\ \theta_2, & d_{ij} \in d_2 \\ \theta_{...}, & d_{ij} \in d_{...} \\ \theta_M, & d_{ij} \in d_M \end{cases} \quad (7)$$	
G 2SFCA	$$f(d_{ij}) = \begin{cases} d_{ij}^{-\beta}, & d_{ij} \leq d_0 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$	
Kernel 2SFCA	$$f(d_{ij}) = \begin{cases} \frac{3}{4} * [1 - (\frac{d_{ij}}{d_0})^2], & d_{ij} \leq d_0 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$	
Gaussian 2SFCA	$$f(d_{ij}) = \begin{cases} \frac{e^{(-1/2)*(d_{ij}/d_0)^2} - e^{-1/2}}{1 - e^{-1/2}}, & d_{ij} \leq d_0 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$	

Table 1 – Review of 2SFCA distance decay functions

Catchment size

Arbitrary defined as the service space in the basic 2SFCA model, the catchment size depends on the provider type (Wang, 2011). Some authors also relate its size to the consumer space and utilisation patterns. It means for them the catchment radius can be seen as function of the population density or the demand coverage ratio (Chen & Jia, 2019).

The **Dynamic Two Steps Floating Catchment Area** (D2SFCA) integrates the population density as a catchment size factor (McGrail & Humphreys, 2014). By differentiating the catchment radius by urban density level, catchment sizes are increased with higher population dispersion. The main applications of this variant model occur in studies that overcome large areas (country or region) and contrasting population densities between urban and rural areas.

The **Variable Two Steps Floating Catchment Area** (V2SFCA) is related to the D2SFCA in its intention, but differs in the adjustment of catchment size. Luo and Whippo (2012) employ a time incremental methodology to determine the service area and population catchment size in two steps. First for the service area, the search radius is gradually increased until a base population threshold is reached within a travel distance. Secondly, for the population catchment area, the search radius B is incremented until the sum of provider-to-population achieves an acceptable ratio. In other words, areas with higher population densities have locally smaller catchment size.

The **Nearest-Neighbour Modified Two Steps Floating Catchment Area** (NN2SFCA) associates population clusters with its neighbouring providers (Jamtsho et al., 2015). An identical number of providers are determined over every population centred catchment so that the size varies for most of the locations.

Local competition
To overcome the demand overestimation problem, competition between providers needs to be considered as a distribution of each sites attractiveness on overlapping catchment zones.

The **Three Steps Floating Catchment Area** (3SFCA) introduces a Gaussian competitive weight G_{ij} to each facility in the demand ratio calculation. A unique provider configuration induces a value of 1 (no change). A disposition with multiple sites generates a lower weight depending on the number of alternatives (Wan et al., 2012). The weight calculation is the supplementary step of the 3SFCA compared to the 2SFCA. The mathematical expression is as follows:

$$G_{ij} = \frac{T_{ij}}{\sum_{k \in d_{ik} \leq d_0} T_{ik}} \tag{11}$$

T_{ij} and T_{ik} are the associated Gaussian weights for the facility sites j and population centroids k.

2.2.7 Multi-modal 2SFCA

Although most health accessibility studies have focused on one specific travel mode, generally the car, the recent consideration of multi-modal transportation modes such as walking, bicycling and using the public transports has shown improvement in accuracy of the results (Zhou et al., 2020). Indeed, when considering reduced speeds for similar travel times, catchment areas are reduced in size and modified. Moreover, diverse transportation networks reveal shortcuts and detours which can significantly impact a neighbourhood crossing.

The travel mode choice is reported by Zhou et al. (2020) to be conditioned by time, spatial distance, economic cost, degree of urgency and residents preferences. It's worth to be emphasised that some users have the potential to adapt their transportation means.

Mao and Nekorchuk (2013) and latterly Langford et al. (2016) have developed and respectively updated a multi-modal 2SFCA, in which the population is divided in sub-groups associated to diverse transportation options. The method acknowledges a competition dependency between users of the different transportation modes. Indeed, the relative accessibility of a mode is subordinate to the proportion of all modes users within their catchment areas. To say it simply, the less travels options available in one place, the more accessible it will be for the beneficiary users because of the competition devaluation.

Tao et al. (2018) suggests the construction of the multi-modal index as follow:

$$A_{i,m_1} = \sum_{j \in d_{ij} \leq d_0} \frac{f(d_{ij,m_1})S_j}{\sum_{k \in d_{kj,m} \leq d_{a,m_1}} f(d_{ij})P_{k,m_1} + \sum_{k \in d_{kj,m} \leq d_{0,m_2}} f(d_{ij})P_{k,m_2} + \dots} \tag{12}$$

$$A_i = Modalsplit(m_1)A_{i,m_1} + Modalsplit(m_2)A_{i,m_2} \tag{13}$$

The overall accessibility index A_i for a population location i is the weighted sum of the accessibility $A_{i,m}$ for each transportation mode m. Different transportation modes can for instance be walking, driving, using the public transport. As previously, k refers to the population unit centroid. The population is subdivided in subgroups$P_{k,m}$.

2.3 Specific adjustments for Africa and LMICs

The 2SFCA method and its variants underlie a series of adjustable parameters including the catchment size, the distance decay function, the local competition and the transportation mode. To understand what are typical parameters adjustments, Table 2 summarises eight studies which focused in the urban context of LMICs. In completion we have extracted the explanations for some of their parameter choices.

City	Focus	References	Distances decay function	Catchment size threshold	Transport
Dakar, Senegal	Healthcare	Ndonky et al. (2015)	Enhanced	600 m for local care 1500 m for secondary health centre, 1800 m for PHC	-
Dhaka, Bangladesh	Emergency care for slums population	Ahmed et al. (2019)	Generalised	60 min 1 unit per 50'000 population	rickshaws
Kolkata, India	Health care facility allocation model	Basu et al. (2018)	Generalised	2 km	walk
Port-au-Prince, Haiti Nairobi, Kenya	Maternal health service	Gao and Kelley (2019)	Inverse distance weighting	5 km	ambulances
Tshwane, South Africa	Public ambulance	Baloyi et al. (2017)	Enhanced	15 min in suburban core area 40 min in low density outlying areas	ambulances
Shenzhen, China	General hospitals community level	Zhu et al. (2019)	Enhanced	15 min as target 30 min as universal threshold 60 min as severe outcome threshold	car
Mashhad, Iran	Emergency medical services	Hashtarkhani et al. (2020)	Enhanced	5, 10 and 15 min	ambulances
Ondo State, Nigeria	Cancer screening service	Stewart et al. (2020)	Enhanced	40 min for urban population	80% taxis 20% minubus

Table 2 – Review of urban settings parameters from 2SFCA studies in LMICs

Choice of parameters

The catchment size is determined by the travel time acceptability. No general consensual time exist, but according to Dos Anjos Luis and Cabral (2016) 30 to 60 minutes is a critical travel duration in cities that shouldn't be exceeded. Countries such as Rwanda have fixed objectives to provide entry-level care within 30 minutes walk (van Niekerk et al., 2017). In the Dakar agglomeration accessibility study, Ndonky et al. (2015) considered a maximum radius of 600 m for dispensary, maternity and physician cabinets, of 1500 m for secondary health centres and medical clinic, and of 1800 m for reference healthcare centres or primary health care. They based their choice on local studies which resulted in an average radius of 535 m for local dispensary and on a local survey which estimated at 500 m the average distance to reach health services . In order to differentiate the facility attraction within the catchment , the majority of the authors selected the enhanced method. They consider it as being an acceptable approximation of the continuous model. Finally, the transportation mean was dependent on the study focus. Ambulances were mostly considered when emergency treatment was assessed. For other healthcare services, authors choose different transportation means such as car, taxis or walking.

2.4 Data Challenges

This section presents the data used in the project with a spotlight on the providers, the challenges and the limitations that are faced when working with spatial data in Africa.

Challenges of population data in Africa
Reliable population data is essential for determining the needs in a wide range of decision support domains such as infrastructure planning, natural hazards prevention, emergency response or vaccination campaigns. Official censuses, which are collected by every country, are the main sources of data. In many developing countries, the task is proving to be considerably challenging through out its technical, financial and political aspects. The cost of organising such data collection is massive.

The UN recommends in its last *Principles and Recommendations for Population and Housing Censuses, Revision 3* (UN, 2017) to countries to undertake a census at least every ten years. In Africa, numerous countries haven't keep up with this objective, as for instance Cameroon which had its last census in 2005 (IHSN, 2019). In addition to the long-dated data, the reliability and the accuracy are also questionable. Indeed, since the data plays an important role in national funds distribution, a lot of pressure can be applied before the outcomes.

High spatial resolution population data in Africa is of high relevance, especially in health and planning issues. If having suitable data at the administrative unit scale is challenging, having it at household level is even more. With the progress of remote sensing technologies and settlement machine-learning identifying techniques, methods have been developed to produce high spatial-resolution grids (Wardrop et al., 2018). The two major means that are used are top-down and bottom-up approaches.

The principle of the **Top-Down** approach is to disaggregate unit-based population data estimates with the use of geospatial covariates which need to be strongly related to population such as landcover, topography, built settlement grids or climate data (Lloyd et al., 2019; Wardrop et al., 2018). Unit-based population data estimates are statistically constructed from existing census data. The result reliability and accuracy is dependant on the quality of the input data.

The **Bottom-up** is based on highly reliable micro-census population counts and ancillary data sets that are geospatial covariate, to scale up gridded population data sets (Wardrop et al., 2018). This approach allows to produce fine scale resolution data where census are unreliable or nonexistent. Although the predictive accuracy still has its limitations, it is measurable, as opposed to the population census data and top-down approach. Because of its incapacity to precisely estimate more detailed census data such as age, religion or income, bottom-up data should be seen as complementary data (Wardrop et al., 2018). But since many developing countries do not have yet reliable population data and will most likely not have it in the close future, the usage of bottom up constructed data offers a suitable population data source that is constantly updated.

3 Methodology

3.1 Setting

Yaounde, Cameroon's political capital, was chosen as a case study. With its recent impressive demographic and spatial expansion, the agglomeration illustrates in many ways of Sub-Saharan cities attributes given by Lall et al. (2017) and presented in Section 1.2. Among other spatial attributes, transportation networks are very heterogeneous between neighbourhoods and the penetrability inside residential areas is challenging.

Healthcare situation

Improving healthcare accessibility is one of the major issues in the 2016-2027 strategy report of the Cameroonian health sector, which aims to achieve universal and equitable access for all social classes by 2035 (Cameroon Ministry of Public Health, 2015). Through this document, the Ministry of Public Health recognises the existence of spatial disparities and the need to plan consistently in under-deserved areas. To achieve this task, the improvement of the national sanitary map is central in the assessment strategy (Cameroon Ministry of Public Health, 2015). In line with Cameroon's Ministry of Public Health, our project aims precisely to assess the equitable distribution of health structures with the development of an adapted model.

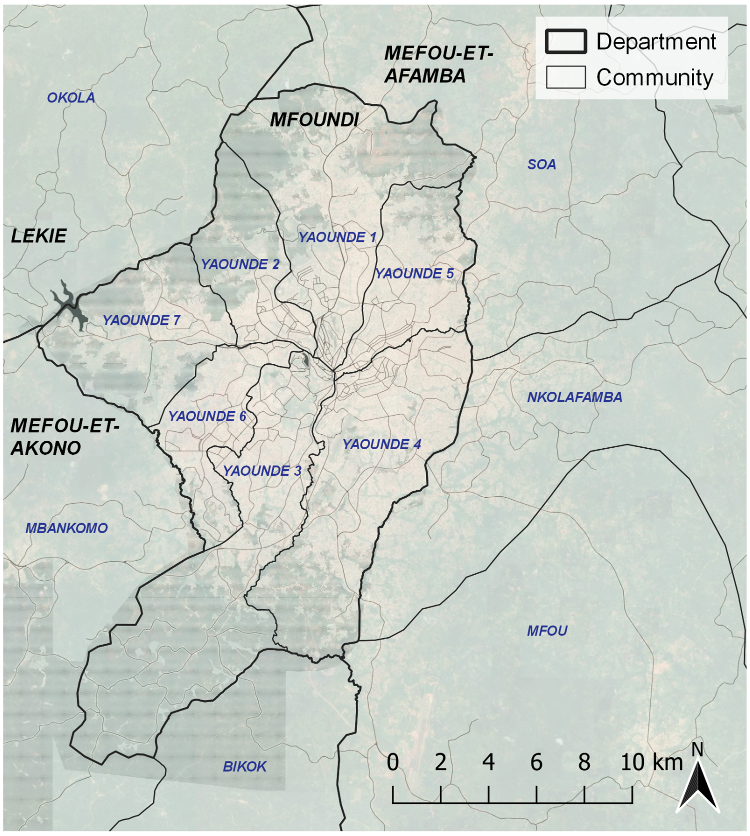


Figure 4 – Yaounde administrative area (OCHA, Google satellite and © OpenStreetMap Contributors)

Demographic and urban population expansion

Yaounde population was estimated in 2018 over 4 million according to the UN. It is facing a colossal population and urbanisation increase with a demographic growth rate that will likely stay above 3% for the next 15 years. Cameroon's population growth is the most visible through urban expansion. The share of Cameroon urban population was of 44% in 2000 and it is expected to reach 70% in 2050 if current predictions are correct (World Bank Group, 2018).

Constrained by the hills that shape Yaounde, the city has spread out with a tentacular shape following the valleys that contain the transportation axis. The hilly topography implies a discontinuous road network and produces routes with constrained directions. The newcomers tend to settle at the periphery and expand the urban areas.

Figure 5 – Photos of Yaounde (Armel Kemajou)

Transportation network and usage

Yaounde transport system suffers from a lack of adequate infrastructures (Bachmann et al., 2021). Out of the 2700 km of roads, only 300 are asphalted. They mostly correspond to the primary axis, and are situated mostly in the central area. Secondary and local roads are poorly maintained and can become hardly practicable after rainy periods. Although traffic congestion is already considered as very important in the denser neighbourhoods, it is expected to become much more important in the next 15 years as motorisation rates and income will increase. The vehicles, which are very old on average are very polluting.

In line with the transportation network contrasting quality, modal shares are very disparate between areas. According to the 2019 *Action plan of the Sustainable Urban Mobility Community of Yaoundé* (Bachmann et al., 2020), shared taxis, locally referred to as *Opep* and walking trips are globally the most common modes with each 38% and respectively 32% of shares. The latter vary significantly from 10% to almost 60% across the agglomeration. Come after, moto-taxis with 12%, private vehicles with 9% and public transport with 2.5% of shares. Walking trips proportion tends to be significantly higher in some peripheral neighbourhoods, whereas taxis and private vehicle trips are much more important in the city centre. Moreover, authorities have restricted moto-taxis usage in some parts of the city and between some neighbourhoods, although the rule is not fully respected.

As mass transportation is almost negligible and services transportation is poorly efficient, the cost of transport is very important. It is the third expenditure of Yaoundeans after housing and food, and it is significant for many households (Bachmann et al., 2020).

Inequalities

In Yaounde, most of the population works outside of the official system in what is said to be the informal system (Kemajou Mbianda, 2020). It is composed of all sorts of economic activities such as repair shops, restaurants or moto-taxis where participants manage themselves.

According to the UN, 60% of Yaoundeans live in informal settlements and 80% of the total are considered as poor. Informal settlements are not necessarily situated far from planned areas (UN-Habitat, 2020). They are often located where land is less valuable which is often on hill slopes or in marshes valley (Kemajou Mbianda, 2020). Voundi et al. (2018) explain that Yaounde urban landscape is dichotomously marked by strong habitat inequalities within close neighbourhoods. The map in the Appendix A2 exposes the standing categories of a number of Yaounde districts.

3.2 Healthcare organisation

Cameroon formal healthcare is provided by public, private confessional and private non-confessional sectors which is in the last case branched in lucrative and non-lucrative as illustrated in Figure 6. According to the Ministry of health, in Yaounde, 85% of health facilities is owned by private non-confessional lucrative structure, 9% by private confessional structure and 6% by public supervision Cameroon Ministry of Public Health and WHO (2019).

In addition to all of these registered structures, the informal sector plays a very important role in the primary health needs of the poors which, as already mentioned, represent about 80% of Yaounde's population according to the UN (UN-Habitat, 2020). According to Mendo et al. (2015), 70.9% of Cameroon's population relies on the auto-regulated health system which is, on one part, driven by traditional medicines and on the other, by informal micro-health units (IMHU). IMHU are mostly present in uncontrolled urban areas and propose modest treatments such as for small injuries, malaria or pre-natal care. The difficulty in characterising the informal health system is that the limits with the regulated system can be narrow as sometimes health units decide to formalise their activities.

In 2019, the ratio of sanitary facilities per capita in Yaounde is set at 1:3711 (Cameroon Ministry of Public Health & WHO, 2019) which is under the Cameroon average of 1:4227 and clearly under WHO standards of 1:10'000 (WHO, 2015). The statistics provided by the Ministry of Public Health is said to count facilities independently of their legal conformity.

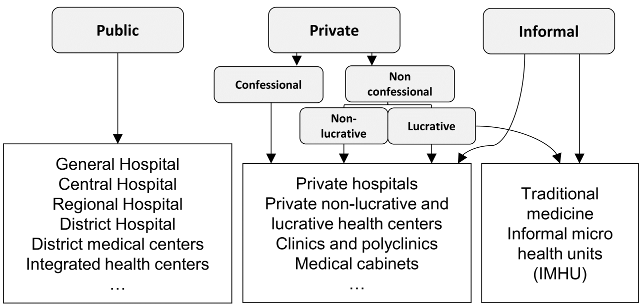


Figure 6 – Sanitary care (*formation sanitaire*) distribution in Cameroon (Foe Ndi, 2019)

3.3 Geographical delimitation

In our study, we are interested in the urban environment. To delimit the study area, we used the *urban footprinter* tool developed by Bosch (2020). We considered it as being part of the urban setting if, in a 420 m radius surrounding, there were at least 20% inhabited pixels. The spatial extent considered has an area of 589 km^2 with 46'438 inhabited hectares.

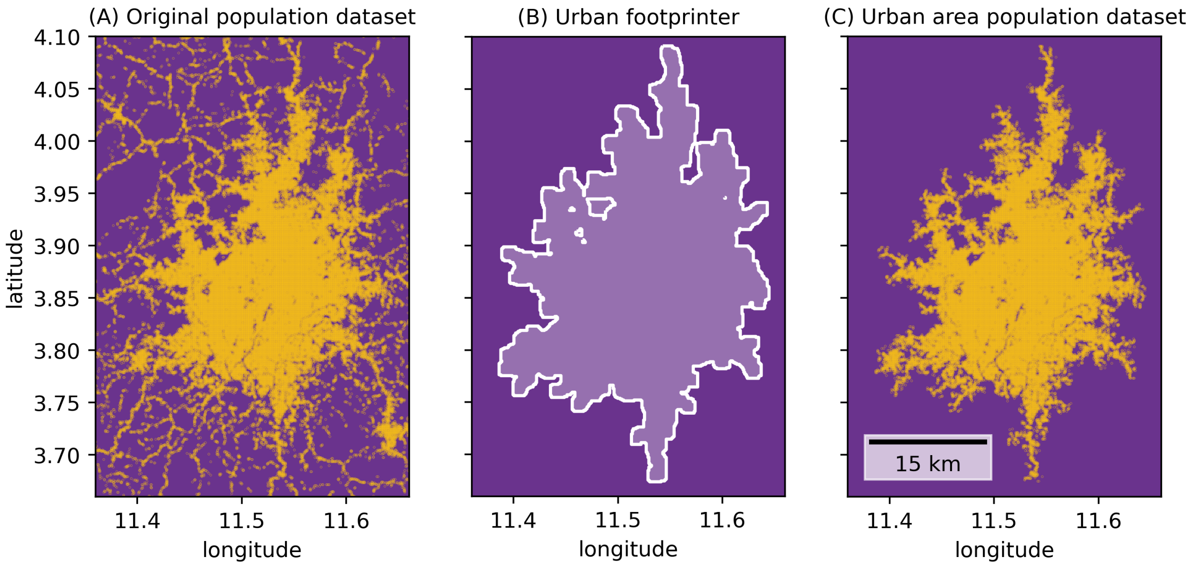


Figure 7 – Urban footprint construction. The left plot (A) shows the original population dataset with the estimate of at least one inhabitant per hectare. The central plot (B) shows the computed spatial frame of the study, according to the urban footprinter tool (Bosch, 2020). The right plot (C) shows the urban population dataset.

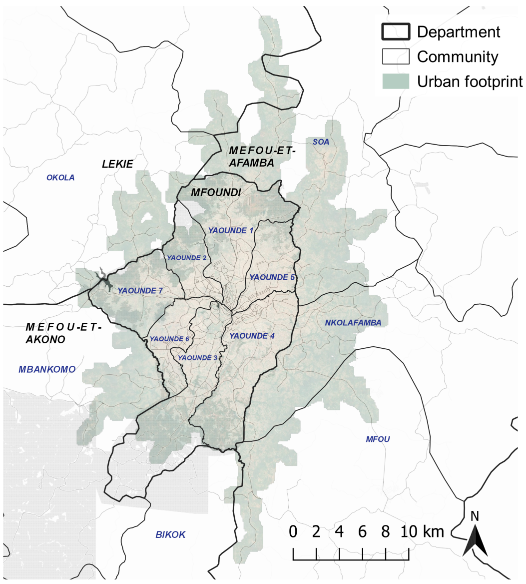


Figure 8 – Urban area delimitation

3.4 Data

Health facility databases

The health facility database is composed of the two spatial datasets illustrated in Figure 9. As the different collections of facilities we have inspected were non-reliable and had low overlap between each other, we decided to work with a set composed of aggregation and a full set.

The *mix dataset* is extracted from 3 sources. These are the *WHO Global Malaria Programme* database [1] (Maina, 2019; WHO, 2019), *GeOSM Cameroon*[2] (OpenStreetMap, 2021a) which is a geoportal platform based on OpenStreetMap and the UNESCO platform named *Hello Ado* (*Hello Teen* in english, UNESCO and RAES, 2020), which lists an important number of healthcare facilities for teenagers. The last set was provided to us by the company *SOGEFI* which was involved in the development of the project. The detailed location of each facility is visible in Appendix A3. In order to avoid duplicates of facilities, we manually removed repetitive points in a buffer of 50 m. Moreover, we also dropped data whose locations were suspiciously false, as some were placed in the forest.

The so-called full set originates from GeoPoDe [3] which is an open-Source data repository. We refer to this set as *gpd dataset*. Although the data is open-access in some countries, an access was freely granted to us for academic purpose.

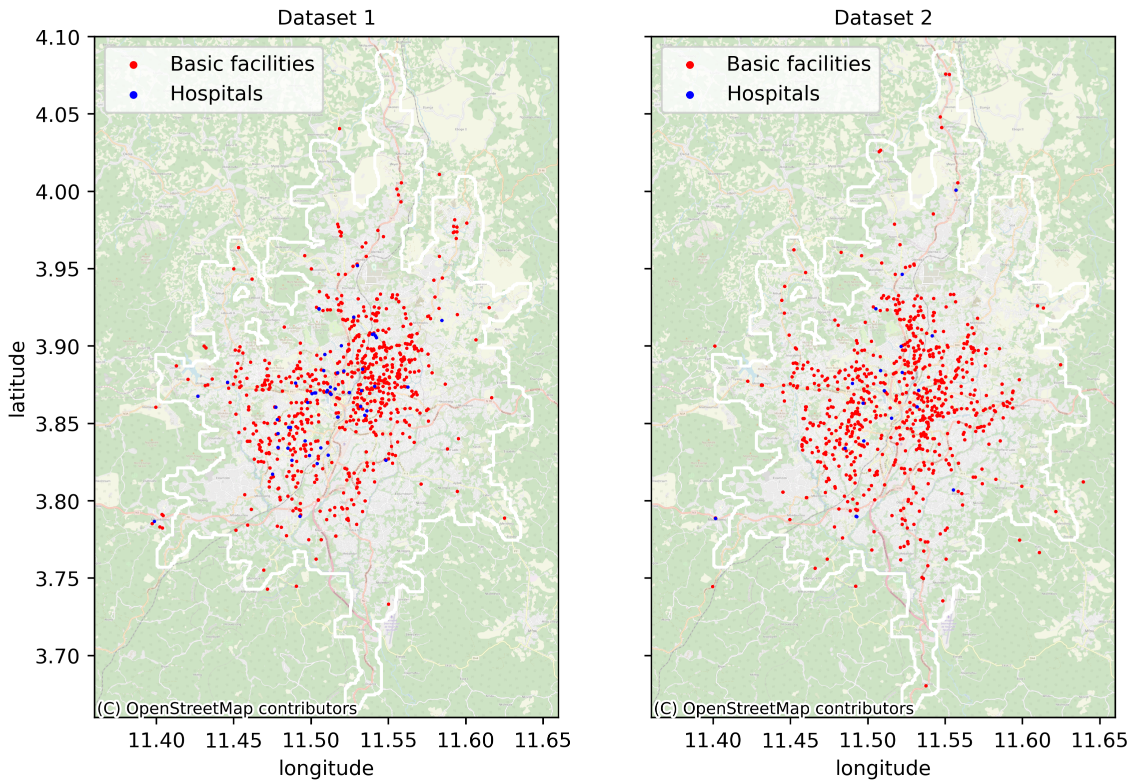


Figure 9 – Display of healthcare facility locations

[1] Accessible at : https://www.who.int/publications/m/item/who-cds-gmp-2019-01
[2] Accessible at : http://geocameroun.cm/
[3] Accessible at : https://geopode.world/

Health data are either in ESRI shapefile format or in *csv*. As a final preparation step, the health structures data were assembled and manually dispatched in 2 categories: (1) Hospitals, (2) Basic healthcare facilities. After these primary verifications, our datasets were composed for the first one of 724 basic facilities and 54 hospitals, for the second one of 718 basic facilities and of 68 hospitals. These number approach the number of facilities known by the Cameroon Ministry of Health, which are of 868 according to Cameroon Ministry of Public Health and WHO (2019). The information contained in the sets after cleaning where the facilities location, their name and their categories.

Population density estimates

The main set of finely gridded population estimates emanates from *GeoPoDe* [4] which stand for Geographic, Population and Demographic. This set is particular because of its bottom-up construction approach (see Section 2.4). Two other data estimates have been extracted out of the *peanutButter* [5] modeling tool (bottom-up approach) and of the WorldPop database[6] repository (top-down approach). Population estimates are illustrated in Figure 10. All of the datasets are GeoTIFF files with pixels resolution of 3 arc minutes which at the equator correspond approximately to 100m. Population datasets indicate a significantly different sum of population within the urban footprint as shown in Table 3. Over the whole urban agglomeration, GeoPoDe and peanutButter sets are well under the population estimates adjusted by the UN (2018). In Appendix A4, two histograms illustrate the different densities estimated according to our different population data providers.

Source	Population estimate
GeoPoDe	1'123'217
peanutButter	1'820'545
Worldpop non adjusted by UN estimates	4'524'882
Worldpop adjusted by UN estimates	4'257'174

Table 3 – Yaounde population estimates comparison

[4] Accessible at : https://geopode.world/
[5] Accessible at : https://apps.worldpop.org/peanutButter/
[6] Accessible at : https://www.worldpop.org/project/categories?id=3

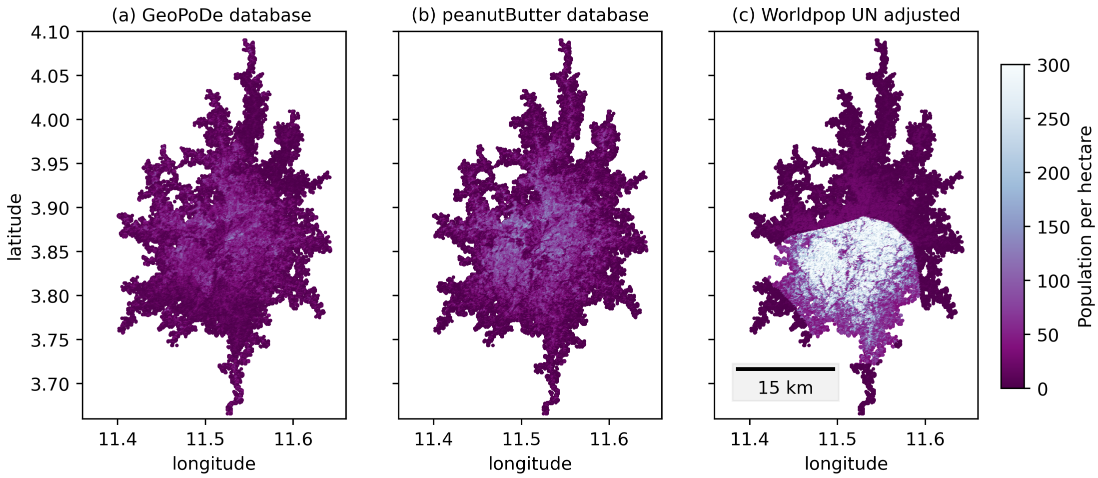


Figure 10 – Gridded population datasets over Yaounde urban area

Transportation network

The transportation network used in our project originates from the open and participatory geospatial data provider OpenStreetMap (OSM). It is illustrated on the following page in Figure 11. The Python package **OSMnx** (Boeing, 2016) provides abilities to extract, analyse and display transportation networks that comes from OSM. Holding on a *Networkx* graph (Hagberg et al., 2008), the toolkit allows us to operate route calculation over the system nodes.

Elevation model

The digital elevation model (DEM) serves as a support for the transportation network material by considering the effect of topography on travel speeds. We choose to extract the data from *ALOS World 3D - 30m* (AW3D30) [7] according to the guidance of Yap et al. (2019) who assessed the good quality of the data provider in Cameroon. The spatial resolution is 30 meters.

Pre-Processing steps

In addition to the data acquisition, a number of preparation steps are performed in order to execute the methodology smoothly. They include spatial framing, shapefile format standardising and health data structuring. All pre-processing steps are realised through Python scripts.

The previously calculated urban footprint of Yaounde's urban area in Section 3.3 is used to delimit the population's datasets via the *GeoPandas* (Jordahl, 2014) intersect function. For the healthcare datasets, the delimitation has been extended with a buffer of 5 km to take into account facilities that might still be at a conceivable distance from a population. Concerning the transportation network, a buffer of 10 km was applied.

[7]Accessible at : https://www.eorc.jaxa.jp/ALOS/en/aw3d30/data/index.htm

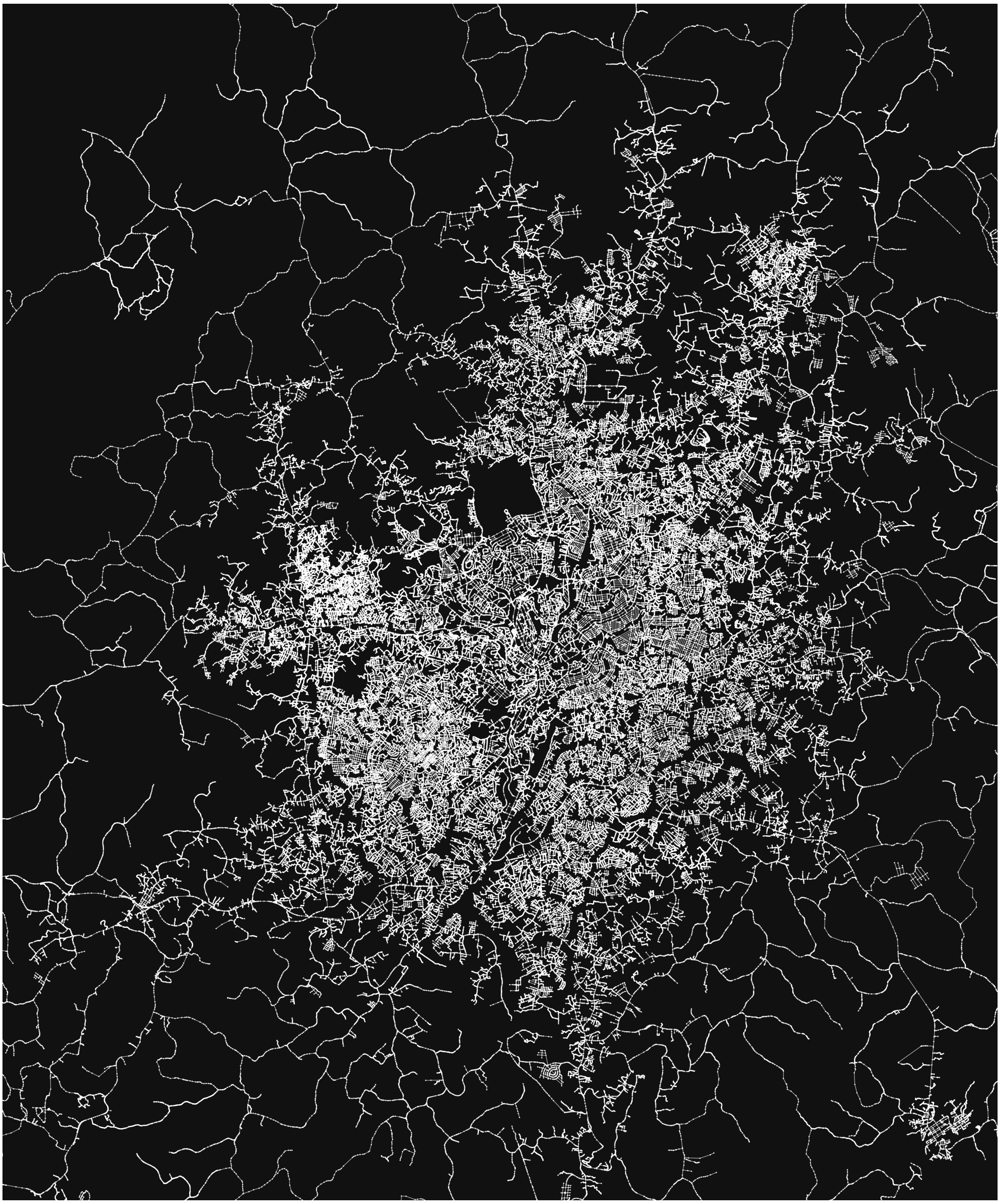


Figure 11 – Transportation network over Yaounde extracted with the use of OSMNx (Boeing, 2017; OpenStreetMap, 2021b)

3.5 Application

To obtain our accessibility scores, a number of computational steps are required. We outline them in the flowchart of Figure 12 and describe them in the following sections.

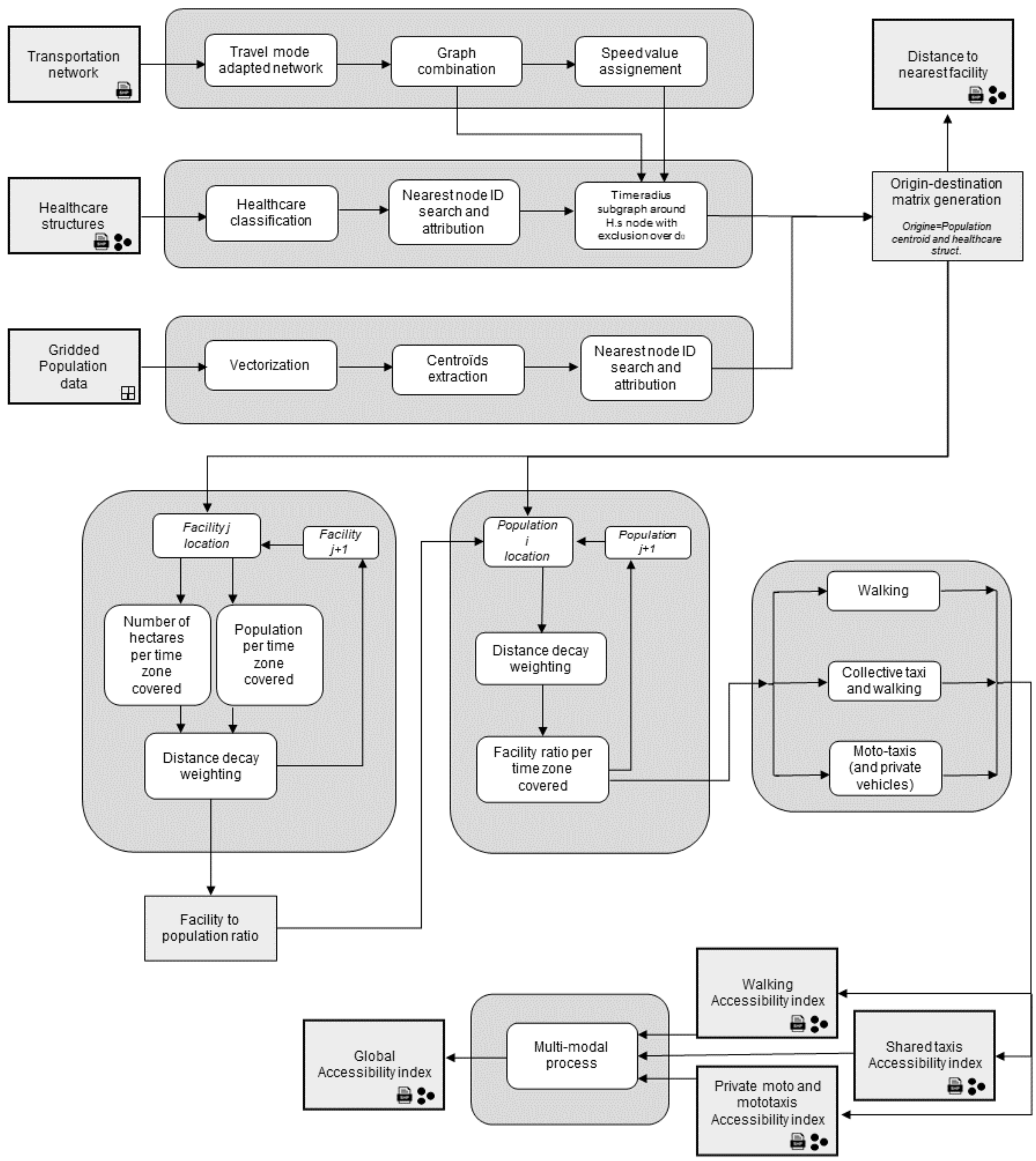


Figure 12 – Data processing flowchart

Construction of the matrix Origin-Destination
The Origin-Destination (O-D) matrix intends to present the travel time between all users and providers. The task is realised through a projected graph composed of nodes and edges, which we implement notably with functions provided by *OSMnx* (Boeing, 2017) and *Networkx* (Hagberg et al., 2008) Python packages.

The first essential task is to associate to all of our locations of interest their nearest nodes. We use the *distance.nearest.nodes* function with a *kdtree nearest-neighbour* search. At this point, 94% of population centroids and 99% are within 100 meters of their nearest nodes in the OpenStreetMap transportation network. None of them are situated at more than 540 meters.

The second step is to calculate the travel time from a facility towards all its surrounding nodes. To perform such a computationally demanding task, we work with *Networkx* (Hagberg et al., 2008) Python toolkit which allows the creation of time-delimited subgraphs. We fix the maximum time radius at 30 minutes. The idea is to attribute to all catchment nodes a trip cost (time) according to the last subgraph in which they appear. The incrementation works reversely which means the model first start tagging nodes with the largest radius. The method used to realise this task is an adaptation of the proposed isochrone calculation method from Boeing (2017). For the radius considered as a matter of time (and not distance), we converted the edges distances to time using the grades and the estimated transportation speeds.

We decided to scrutinise the three most common transportation alternatives in Yaounde in accordance with Bachmann et al. (2020) (see Section 3.1). It is the walk, the shared taxis and the moto-taxis. We acknowledged that the latter is forbidden in the central area. We did not considered private vehicles as we assumed it would only address a small minority of the population and overestimate accessibility in neighbourhoods where cars are rare.

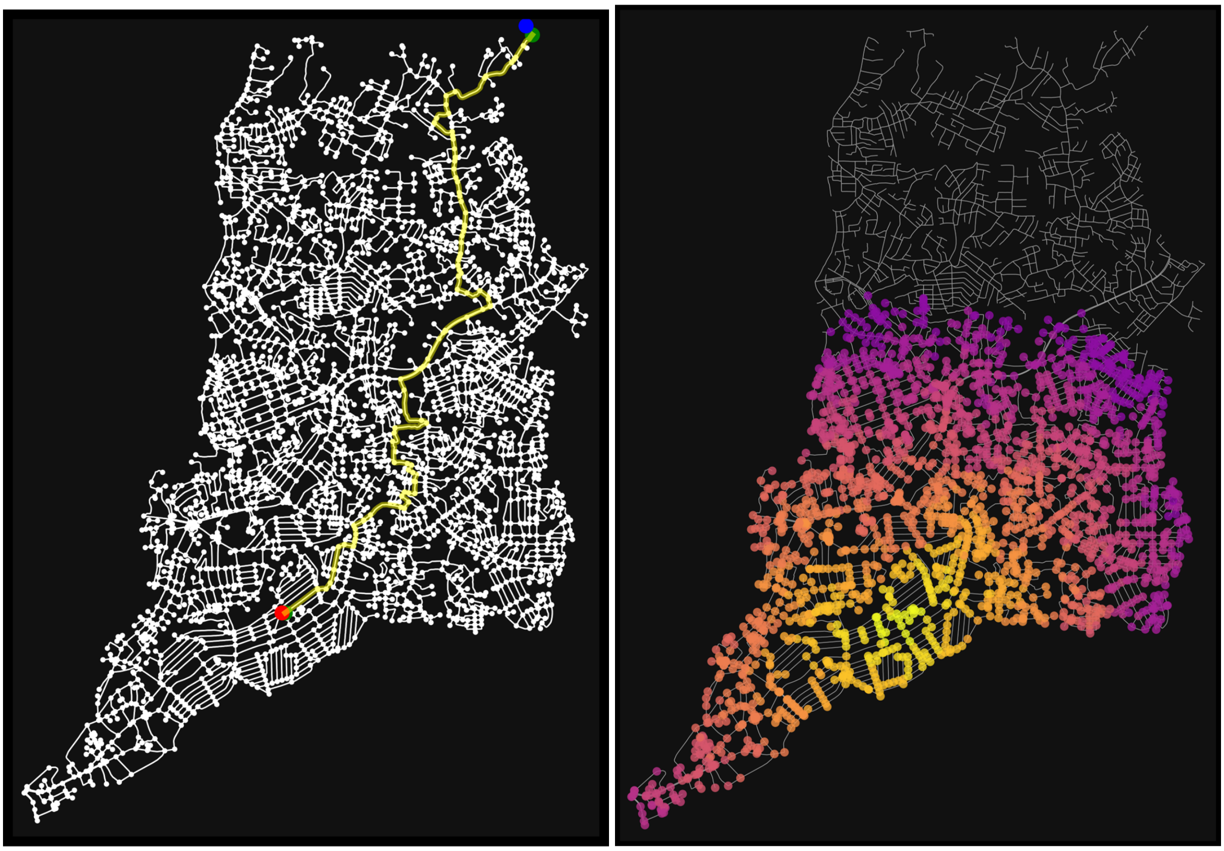
For walking, following Tobler (1993) empirical speed model revisited by Brundson (2018), we implemented a 3.57 km/h basic velocity and the following grade decay function to take into account the slope of the path:

$$Speed = 3.57e^{(-2.03|slope+0.133|)}$$

Concerning shared taxis, speeds were implemented as follows: 30 km/h on motorways, 18 km/h on primary, secondary and tertiary roads, and walking speed on residential roads. And for moto-taxis, 23 km/h were considered for primary and secondary roads and 14 km/h for all the rest. We have chosen these values based on gps-tracking analysis work produced in Yaounde by Kemajou et al. (2019).

The third task consisted of attributing the previously computed time cost to all populations centroids surrounding a healthcare structure. The fourth and final operation of the matrix generation was to loop over all health facilities of interest to apply processing.

With O/D matrix, we have withdrawn the time to the nearest facility for all locations as it was the minimal time given for all considered hectares. Moreover, we associated population estimates to the nearest facility distance results so that we could determine the population share as a function of healthcare distance.



(a) Shortest path

(b) Isochrome representation

Figure 13 – Construction of the origin destination matrix with OSMnx Python toolbox. (a) illustrates the shortest path between a facility node location (red) and a chosen node (blue). (b) illustrates a time-distance isochrone around this same departing location. Both figures represent applications over the district commune of Yaounde 5

Computation of the ratio of health care facilities over population

The first step of the 2SFCA implementation relied essentially on the computation of the distance decay function which is was to determine the reachable population associated with a healthcare facility or in other words the number of medical infrastructures per inhabitant. A Gaussian decay function was implemented over a maximum radius of a 30 minutes travel time (see Table 1). The resulting weights were then multiplied by the population size. If the time was above 30 minutes, there were no population contribution to the medical facility. The process was repeated for each facility. In Table 4, we have illustrated the process.

-	Population 1	Population 2	Population 3	...	Population n	Sum
N° of inhabitants	158	275	65	...	189	1’123’217
Walking time in min	27	- (>30)	5	...	- (>30)	
Gaussian Weight	0.06	0	0.93	...	0	
Reachable population	9.48	0	60.45	...	0	21’573
Facility to population ratio						$\frac{1}{21'573}$

Table 4 – Illustration of performed steps to obtain the facility to population ratio

Construction of the Accessibility index
Computationally, the second step is very similar to the first one, although this time it is the ratios that are multiplied to their related distance decay weights and summed according to all hectares to which they contribute. Accessibility scores were then in the first place presented according to their respective transportation alternatives and then in the second place as a total index. To compute it we used Tao et al. (2018) equations propositions and we approximated modal shares as 40% for walk, 40% for shared taxis and 20% for the moto-taxis group. We have computed for all three population estimates, four accessibility scores of both health facilities sets, which make a total of 24 scores.

Accessibility association
For the purpose of accessibility assessment, we undertook some complimentary analysis to understand its relation with environmental parameters and particularly the elevation. Boxplots are used to visualise this relation, urban hectares have been separated into three classes of at least 2500 samples, with a middle class surrounding the average height of 730m with ± 50m. In both datasets, after we have adjusted our samples to a normal distribution (Pedregosa et al., 2011), we have carried out a Student test to determine the p-value regarding the null hypothesis that elevation and accessibility are independent (Virtanen et al., 2020).

Sensitivity analysis
As a final methodological step, a sensitivity analysis was performed to understand the effect of the different inputs on the results. The idea was to evaluate the correlation level all of the computed accessibility scores with each other and with the population estimates. To realise this task, we created a correlation matrix.

Interview
In order to understand mobility patterns associated to healthcare utilisation in Cameroon, we interviewed eight persons currently living in Yaounde and Douala. The aim of the questioning was to withdraw qualitative informations over their experience and knowledge on the functioning of the health system and on its accessibility in Cameroon cities. We note that the interviewees were all living in favourable socio-economic conditions. The interviews followed a guide containing eight questions which are presented in Appendix A6.

4 Results and analysis

4.1 Distance to facility results

Using the developed models, accessibility to healthcare structures is initially assessed only in terms of distance to the nearest structure and secondly in terms of facilities per 1000 inhabitants by using the 2SFCA variant method with multiple means of transport.

Nearest structure inaccessibility
In Figure 14, we evaluate for the two healthcare datasets the distance separating each facility to all urban areas of Yaounde. We first present urban areas coloured according to distance to the closest health care facility with colormap plots. In the last column, we present the share of the population not able to reach a healthcare facility as a function of the distance to these facilities.

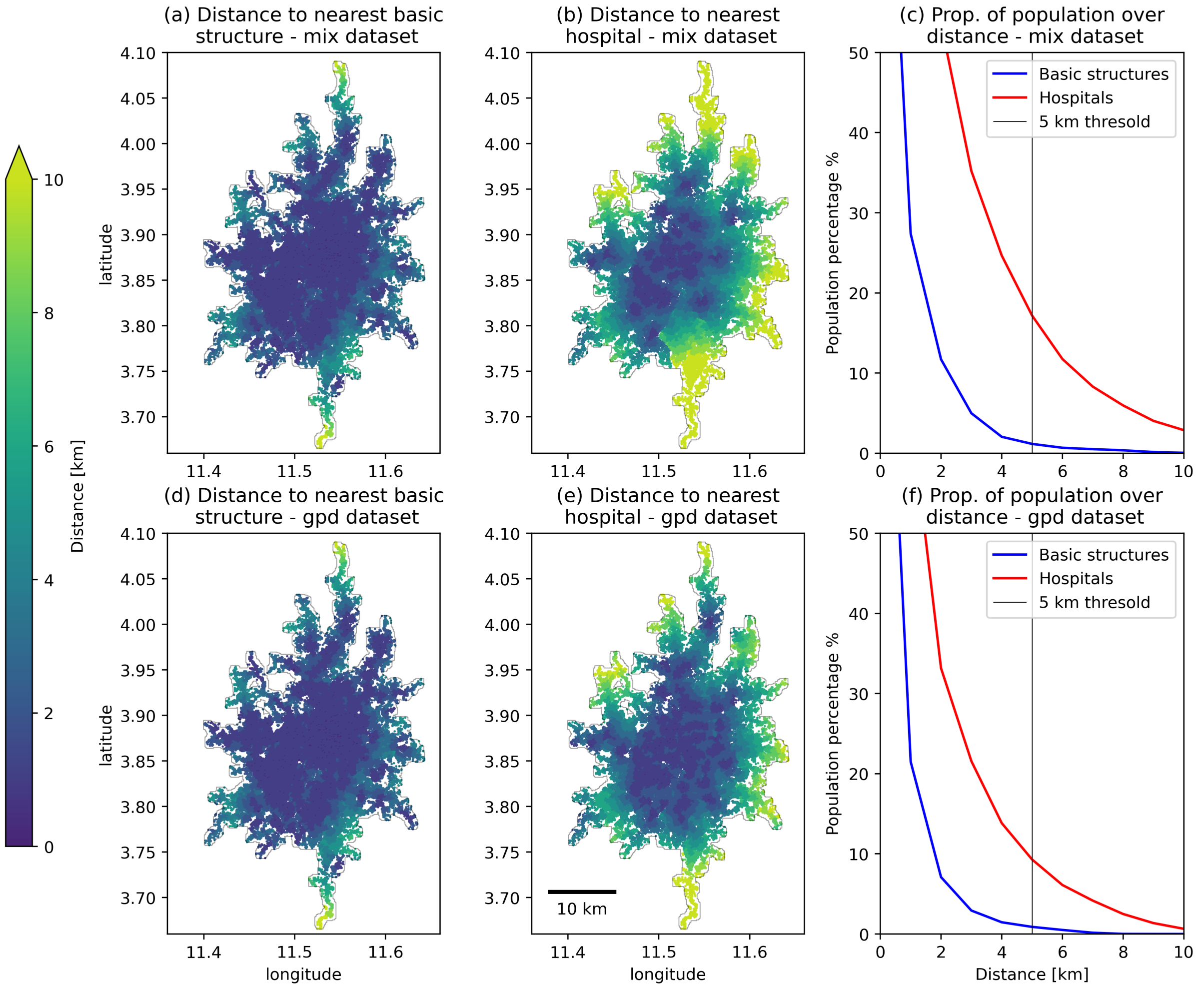


Figure 14 – Distance to the nearest facility analysis

As we can observe in Figure 14a,b,d,and e, the neighbourhoods located at the largest distance from the health facilities are situated towards the outskirts of Yaounde. The proportion of the population located less than 5 km away from a health facility strongly depends on the healthcare category.

The results show that 17.17% of the inhabitants for the mix dataset and 9.23% for the gpd dataset have to travel more than 5 km to reach a hospital. These areas highlighted in yellow in Figure 14b and e are in fact deeply associated with zones that urbanised in the last 20 years (see Kemajou Mbianda (2020)). Even though these areas are not densely populated areas, their spatial footprint is significant as they cover respectively 31% and 18% of the total current urban footprint.

As a matter of fact, basic facilities are more than 10 times more common than hospitals. As a result, in both basic facility sets, less than 1.5% of the inhabitants are situated at a distance superior to 5 kilometres. Our basic facility results are in line with the results of the third Cameroonian Household Survey (National Institute of Statistics, 2007) even though the city has widely expanded since then. In their study, they estimated that 0.7% of Cameron's urban population lives at a distance greater than 5km from a health facility. With a threshold of 2.5 kilometres, less than 10% of the people can not reach healthcare. Purely based on the distance, these results globally indicate a satisfactory distance coverage according to the WHO 5 km criterion.

4.2 Accessibility index results

This part presents the accessibility scores for basic healthcare structures according to different means of transportation. We first differentiate the behaviour of specific users before creating a unique multi-modal accessibility representation.

4.2.1 Walking accessibility

As we can observe in our walking results presented in Figure 15 on the following page, scores are closely related to the healthcare facilities' distribution. This strong association is explained by the small size of the catchment areas, which excludes completely all populations situated at more than 1.75 km from a basic facility. This corresponds to a 30 minutes walk at a speed of 3.57 km/h.

Globally, there is a high contrast between the outskirts and the large central areas where low walking accessible zones are rare. Outside the extended central area, well-deserved hectares appear more punctually. In some south-eastern neighbourhoods notably, proper catchment areas can distinctively be observed around basic healthcare facilitates. They are most likely to carry a rounded shape in urban areas because of the high density of paths and the regular walking speed. One illustration of the circular isochrone is presented in Appendix A6.

Inside the accessible areas, we can observe strong local variations in the scores within a few hectares. They are mostly due to the gaussian distance decay weights (see Subsection 3.5), which become consequential after 10 minutes and to variations in the population densities. Sparsely populated areas clearly stand out with high accessibility as they are associated with a higher ratio of facility per capita.

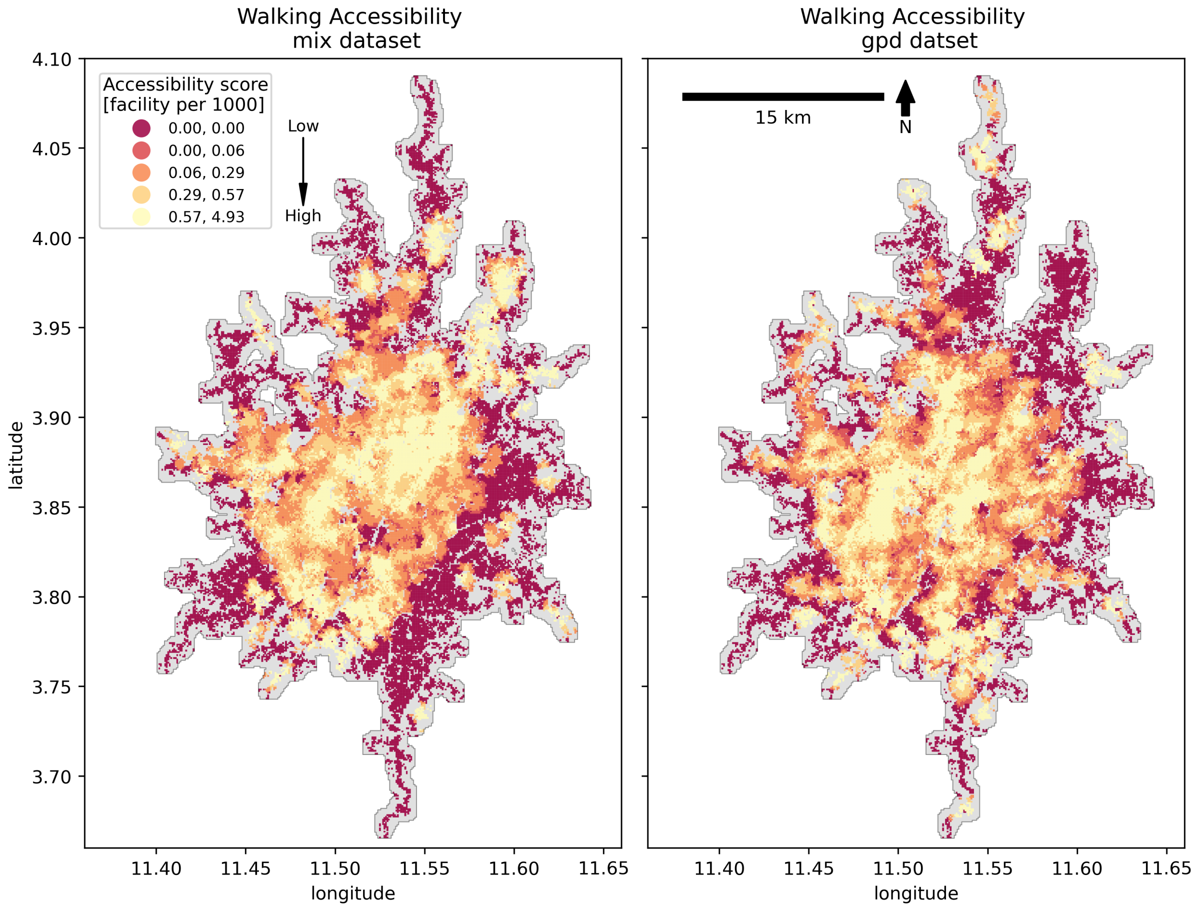


Figure 15 – Walking accessibility

Slope

As opposed to other transportation modes, walking speed is in the model considered as dependent on the street steepness.

The impact of slope on walking is determined by the magnitude of supplementary time caused by the slow down. In our project, the slope caused a walking travel time increase as high as 75% compared to a model ignoring the steepness of the roads in some areas. On average, for all considered trips (under 30 min), the mean time increase is 20.8%. In other words, on average for a 6 minutes trip, 5 minutes are caused by distance and 1 minute by the slope. Moreover, as it is related to the local environment, time increase varies a lot locally.

4.2.2 Shared-taxis accessibility

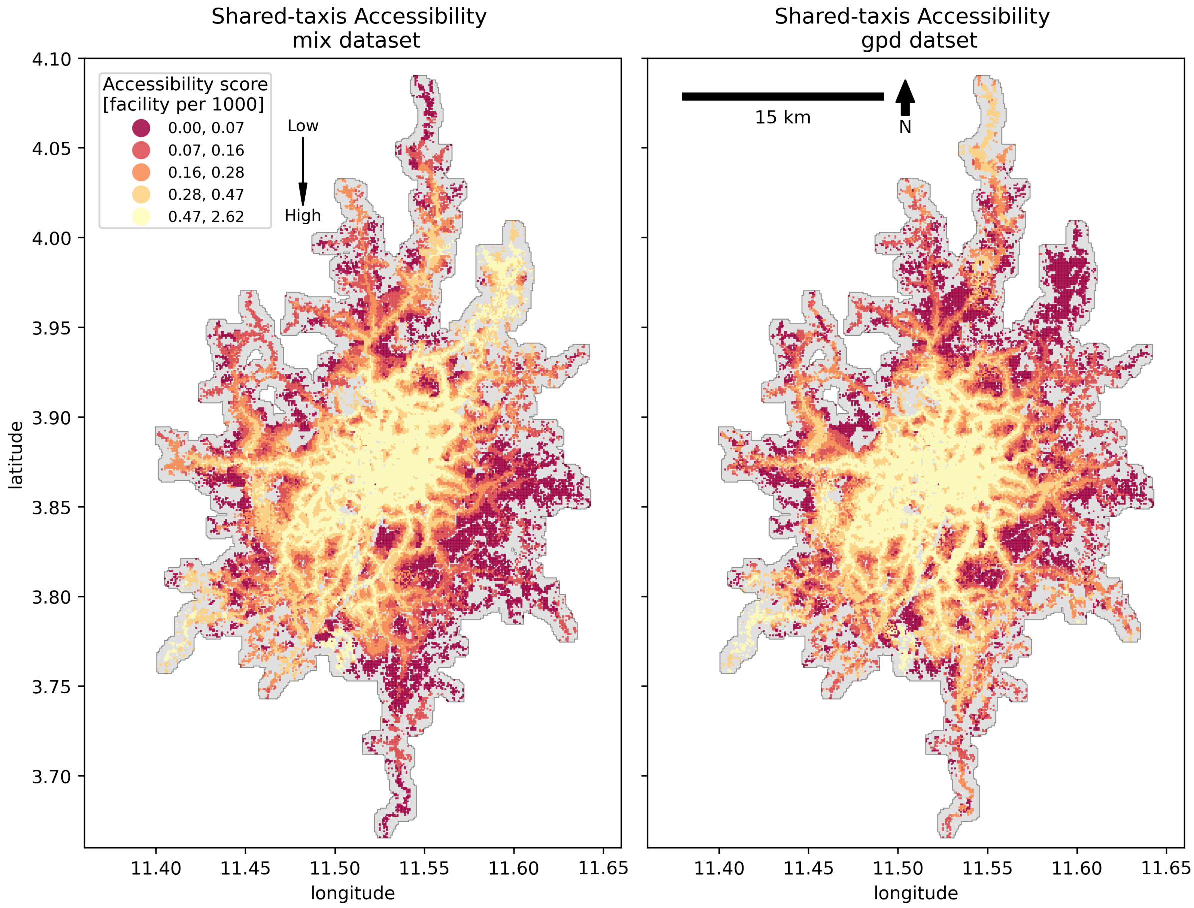


Figure 16 – Shared-taxis accessibility

Shared taxis analysis is in fact a combination of walking in residential streets and shared vehicles along with the primary and secondary street network. The binary structuring of the network is clearly visible in Figure 16. Catchment forms are now stretched out in the direction of the taxi roads. Indeed, proximity to the main structural roads is a significant advantage in terms of accessibility. On the contrary, settlements situated in the depth of neighbourhoods suffer from the demanding walking time needed to join the exchange pole.

In this model, practically all of Yaounde's population retains minimal accessibility to health coverage (acc. score > 0). Depending on the healthcare dataset only 0.7% (mix dataset) and 1.1% (gpd dataset) are still out of reach. 60.9% and 63.4% of the population respectively are above the median accessibility score of the area. Differently said, on average, the most accessible hectares tend to be the most populous.

4.2.3 Moto-taxis accessibility

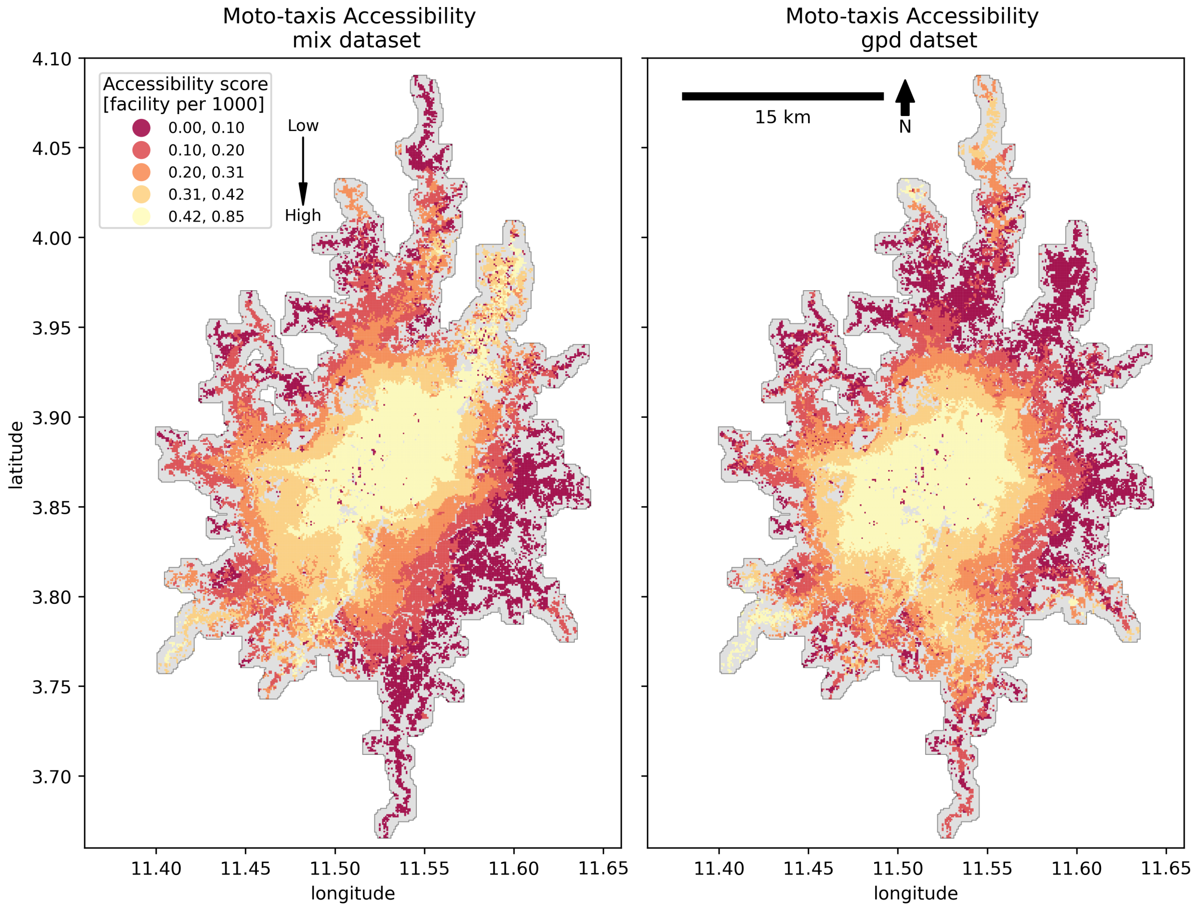


Figure 17 – Moto-taxis accessibility

Moto-taxis dispose of the fastest ability to travel in all settings, on the main axis but also in residential areas. As we can observe in Figure 17, local variations have been smoothed, and the enlarged central zone practically appears as one catchment area. With travel speeds approximately 4 to 7 times higher than by foot, catchment areas are larger and they tend to overlap more. Catchment areas surrounding single facilities do not appear on the map as opposed to the Walking accessibility map we can observe in Figure 15.

The local fluctuations caused by the distance decay which we could observe in Figure 15 in the central area are now completely compensated by the high number of reachable alternatives.

Isolated spots with low accessibility are present in the middle of some high score areas. With a diameter between 100 and 300 m, these neighbourhoods are not situated near a drivable road, but along a walking path which we have considered as not suitable for motorised vehicles.

4.2.4 Multi-modal accessibility combination

The multi-modal model combines the accessibility measures of walk, shared taxi and motos-taxis with respective splits of of 40%, 40% and 20%.

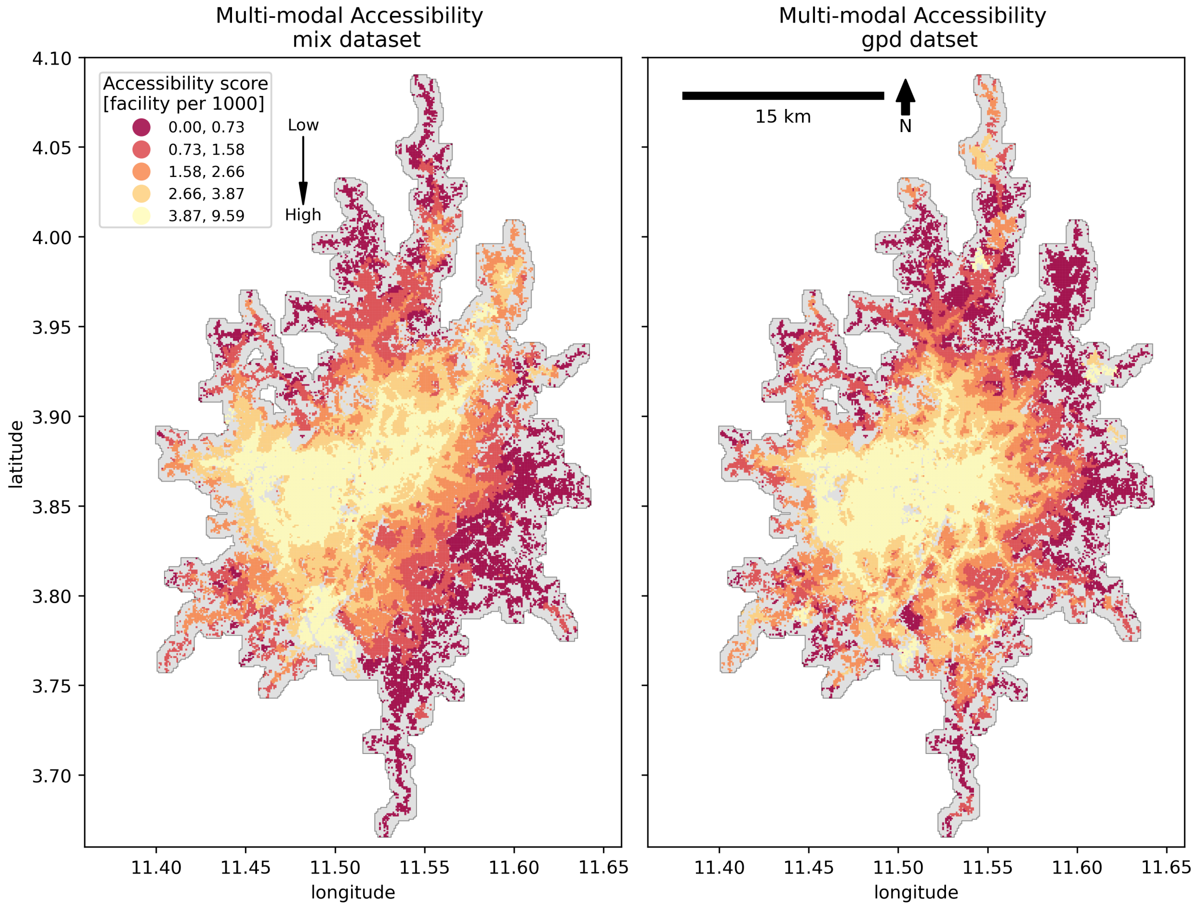


Figure 18 – Multi-modal accessibility score with GeoPoDe population estimates

As they are intended to, accessibility combination scores highlight neighbourhood's disparities over all considered available means of transportation. Nuance is brought to the previous results constructed over strict parameters. Except for some local exceptions of small catchment poorly populated in the eastern areas of gpd set, 5 km separate local highs from local lows. Motos-taxis attenuates the high local variations presented in the walking section 4.2.1, whereas taxi vehicles enable the distinction within neighbourhoods according to their proximity to structural roads.

In both plots, we can observe the best accessibility towards the Central (3.87 N, 11.52 E) and Melen (3.87 N, 11.50 E) neighbourhoods, where scores are high within all corners. Particularly with the mix dataset, we can observe a local high in the south of Yaounde 3.

Globally, we can determine that the worst accessibility takes place towards the outskirts of the urban footprint and backwards of the non-central neighbourhoods.

4.2.5 Multi-modal accessibility combination with WorldPop

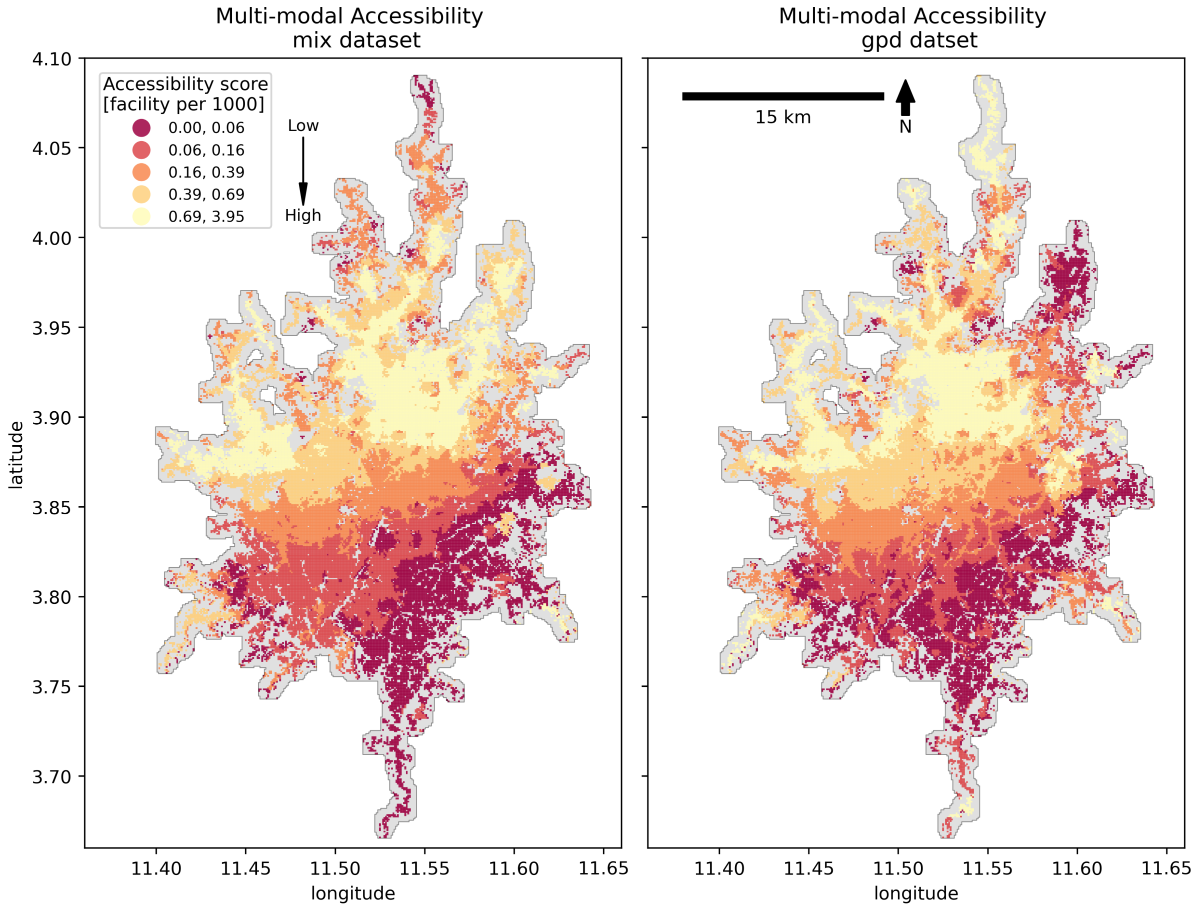


Figure 19 – Multi-modal accessibility score with WorldPop population estimates

In the accessibility results of the WorldPop dataset presented in Figure 19, we can distinctly observe the repercussions of the population distortion due to the census administrative area. This distortion could already be detected in Figure 10. In comparison to Figure 18, accessibility is mostly higher in the north and lower in the South. With such a bias between areas in the entry data, neighbourhoods discrimination becomes partial and inapplicable.

4.2.6 Association of accessibility and environmental parameters

A number of statistical associations between our scores and environmental parameters can be examined in order to determine prevalence factors of low accessibility.

Elevation effect
In Yaounde, as mentioned in Section 3.1, the spatial expansion has been constrained by the numerous hills and valleys that occupy the territory. This strong bond between the topography and the urban development can be observed through the accessibility as a function of the elevation.

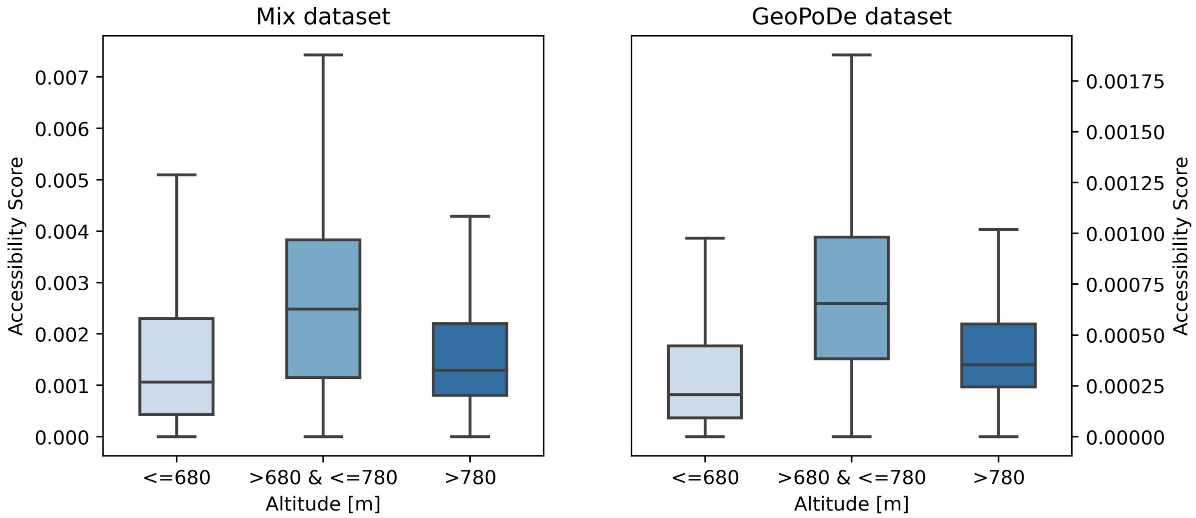


Figure 20 – Boxplots of accessibility scores grouped by elevation categories

As presented in Figure 20, our results show that spatial accessibility to healthcare is associated with the neighbourhood elevation across Yaounde urban areas. Student-test resulted in a significant ($p<0.0005$) negative effect of the lower and higher altitude classes on the accessibility scores. In other words, sites located at less than 680 m or at more than 780 m are significantly less accessible.

Figure 21 – Settlements constructed on one of Yaounde seven hills (Pfister, 2015)

4.2.7 Sensitivity analysis

This part present the results related to the sensitivity of the data and the parameters on the modelled accessibility.

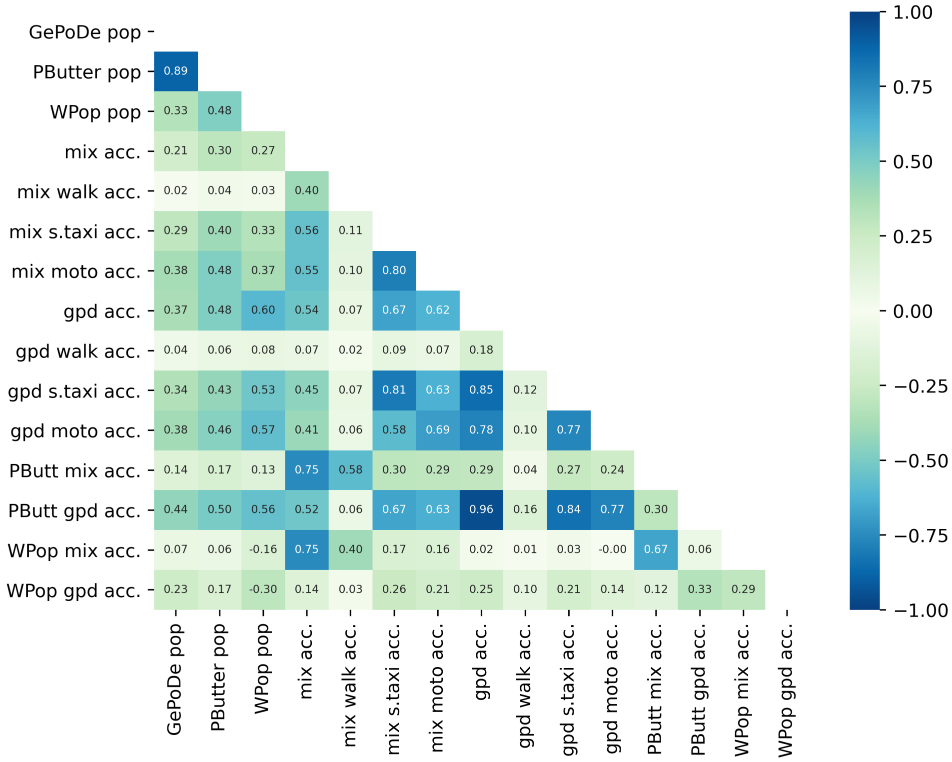


Figure 22 – Correlation coefficient matrix between computed accessibility scores and other parameters

In Figure 22, we have realised a correlation matrix between the three population datasets and all of the accessibility scores modelled. Such a grid allows an analysis of the sensitivity of the results to the different inputs.

As we could expect, both bottom-up population estimates are strongly (0.89) positively correlated, but not with the top-down estimates. Interestingly, the correlation between their related accessibility scores (*gpd acc.* - *PButt gpd acc.* and *mix acc.* - *PButt mix acc.* remains strong (0.96 and 0.75). It means the scores do not variate much for similar population sets, as opposed to scores with different populations estimates artificial bias.

A second relevant element of analysis is the effect of health facilities datasets on the various transportation scores. On the overall scores, the correlation of 0.54 between *gpd acc.* and *mix acc.* signifies a relevant dependency from the datasets on the results. A correlation of 1 would have meant no impact of different datasets as results would have been strongly related. The accuracy of the facilities data is even crucial for the Walking accessibility score as the two associated results are uncorrelated (correl=0.02), where catchment areas are small relative to the ones of other transportation means.

However, for motorised vehicles users (shared taxis and moto-taxis), accessibility dependency on the healthcare datasets is strongly decreased because of the greater catchment size and the greater number of reachable alternatives. With a strong correlation of 0.81 between the two shared taxi scores, this accessibility is more determined by the territory than by the health datasets. The sensitivity to the health facilities dataset depends on the means of transportation that a user chooses.

To summarise, the needed level of precision and reliability of the entry data really depends on the catchment areas choice and the level of detailed information wanted to be extracted.

4.3 Qualitative results

The interviews brought out complementary results to the accessibility modelling project. According to our subjects' answers, healthcare accessibility is not seen as a problem in Yaounde and Douala. This perceptive echoes the assessment of Ndonky et al. (2015), who claims that healthcare accessibility is undervalued in urban settings. The impression emerged that every neighbourhood possesses at least one basic health facility.

Interviewees were all from an affluent socio-economic background. For most of them, before the distance, the care quality and the reputation of the facility were the most important factors in the choice of a health structure. The price was not cited as being an actual key consideration, but it had been mentioned to be more important when subjects were younger.

No longer than 20 walking minutes was usually needed to reach the closest small facility. However, travel time to reach a hospital could be significantly more important and exceed 1 hour of driving depending on the traffic congestion. For the interviewees, four means of transport could be utilised: walk, shared-taxi, moto/moto-taxi and private vehicle. Walking more than 30 minutes was not seen as a realistic option, since it was considered too demanding and other options were proposed. That being said, they indicated that in poorer areas, walking was more prominent than in their neighbourhoods.

The means of transportation to a healthcare facility depends on the means of each person, but also on the importance of the medical need. In the case of not possessing a vehicle, someone such as a cousin or a neighbour could always be asked.

The transportation network was said to have strong traffic congestion in the centre where the roads have the best quality. The contrast between roads quality was particularly brought to light with strong rain conditions, which was the case at the time of the interviews. Certain axes can become unusable and influence travel choices. Less urgent trips could for instance be delayed and destinations could be modified.

5 Discussion

The following discussion starts by interpreting our results and examining their meanings over the discussion of the methodology. Next, we develop their limitations and propose a number of steps that could improve the results. Finally, we expose the re-usability potential of our project.

5.1 Discussion of the results

Spatial disparities in the healthcare accessibility
As explained in Section 4.1, the 5 km threshold to the nearest basic healthcare facility is exceeded for only about 1% of the Yaounde population. However important spatial disparities in terms of healthcare accessibility exist.

The differentiated transportation accessibility allows identifying zones in which users are most disadvantaged. For walkers, results vary sharply between neighbourhoods, very similar to the nearest facility plots. Although inaccessible zones are mostly situated in the city outskirts, a number of accessibility gaps are visible within the central region. For shared taxi users, accessibility is much more constrained by the proximity to major transport axes. In almost all neighbourhoods except for the central area, we can see this accessibility decay as a function of the progress into the deep neighbourhoods. During the interviews, we were told that the main axes and even more their crossroads play a key role in urban structure and service providing such as markets. For moto-taxis, penetrability in the neighbourhoods is greatly eased. For these users, globally all of the central area is smoothly accessible, whereas the outskirt is all considered as poorly accessible.

Comparison to previous work
Healthcare accessibility in Yaounde had already been assessed in the past by Manjia et al. (2018) with the use of GIS tools. Similarly to our project, they assess the accessibility to health infrastructures by means of an accessibility indicator. Similarly to our results, large disparities between neighbourhoods appear, the central neighbourhoods being better deserved, whereas the outskirts receives varying accessibility indices. A major difference with our model is that they only take into account public services which represents about 6% of the total facilities, while our model analyses several kinds of health infrastructures. Moreover, our study uses a model that compute distances based transportation networks, whereas their indicator is based on euclidean distances. For these reasons, it is difficult to compare more in details the outcomes of both studies.

Impact of natural environment on healthcare accessibility
As explained by Kemajou Mbianda (2020), bottom lands and hillsides are associated with less valuable land, notably because of their important vulnerability to natural disasters such as floods or landslides. Based on our results, the same exposed areas are also the less accessible ones. We explain this result on the one hand by the presence of strong natural obstacles (rivers, cliffs) which create a number of dead-ends and on the other hand by the danger related to the zones which might be an important allocation factor for a healthcare facility. Moreover, slopes were also considered as a slowing factor for walkers. This relationship is confirmed by both the mix and the gpd dataset which disposes of facilities at different location.

In theory, if the more than seven hundred basic facilities presented in each dataset were ideally distributed, all area neighbourhoods could be situated at an euclidean distance of 1 km or less, and largely be accessible. In reality, topography, population heterogeneity, physical barriers and historical development constrained and prioritised some areas.

5.2 Discussion of the methodology

While producing results is important, assessing their reliability is even more so, especially in urban Africa where acquiring the right data is a major challenge (Kemajou et al., 2019). The focal points of the section is to evaluate if the uncertainties and the scale of our data are determining in the results.

Incompleteness of health facility data sets
To analyse critically these results, we need to understand that our facility databases can not be considered as complete. The inclusion of health facilities in our database originates either from participatory mapping processes for the majority of them or from official sources. Going through our databases, we do find the presence of some common interest grouping, which we referred to as IMHU in Part 3.2 and other probable informal medical cabinets. An important proportion of them is supposedly missing, but our current knowledge does not permit to estimate it. A geosm collaborator explained for instance that some mapping campaigns have been specifically undertaken in Yaounde 5, which explains the high proportion of recorded facilities in this area. In distant neighbourhoods which are just emerging, we believe that mapping campaigns have been much rarer.

The informality of the new suburbs
Two other reasons explain the lack of health facilities in the newly urbanised territories. First, since until recently these areas were not constructed and had low population density estimates, they weren't attractive enough for numerous health facilities to get installed. Secondly, the owners of informal facilities might be afraid to be catalogued and are for some of them not visible, since they risk being ejected from the neighbourhood. This is even more the case during the first years of activity when their activities are more vulnerable.

Kemajou Mbianda (2020) highlights the transition phase between the first settlements in peripheral neighbourhoods and the development of basic services such as water, electricity or shops, which contributes to the attractiveness of the location. Included in these services, health facilities have we understand reasons to be as informal as the neighbourhood in which they are.

We could assess that for motorised users, accessibility was largely determined by territory heterogeneity, and that precise health facilities data sets were not decisive on the results. However, for slower modes, as catchment areas superposition are rare, their importance is more determinant.

Uncertainties on the demographic data sets
Population data influences results in absolute and relative terms. As we have seen in Subsection 2.2.5, accessibility scores are constructed over the summation of ratio facility over population. Underestimation of the catchment population implies overestimation of the ratios, and respectively overestimated scores. The extent of the bias is greatly dependent on the type of population data. Bottom-up estimates as in Figure 18 are useful to identify high and low-density neighbourhoods relative to each other. Because of the method interpolation systematic bias, population total can end up being in absolute over- or under-evaluated. Nevertheless, local areas accessibility is distinguishable and comparable to another neighbourhood without arbitrary limits.

Concerning top-down estimates, local variations are also considered. These estimates are strongly reliant on census data, which can be importantly biased in some countries as it was explained in Subsection 2.4.

Choosing population data depends on the type and on the scale of the study. Although using top-down estimates can produce consistent ratios within an administrative area, it does not allow a relevant distinction of local scores and should be avoided in case of unreliable census data and projections as it is the case in Yaounde.

5.3 Limitations

Knowing that accessibility models aim to approximate at best mobility patterns of users and their potential of spatial interaction with the facilities, a number of limitations exist.

First, we point out that the development of a model such as ours assumes that accessibility is one factor out of various others that influence healthcare utilisation. Although, a number of studies have assessed its link (Okwaraji & Edmond, 2012) in LMICs, we did not have "*ground-truth*" data to which we could have to compare our results and adjust our models. Indeed, the assessment of healthcare utilisation according to the different neighbourhoods would have been very valuable.

Then, information at our disposal did not allow us to delimit facilities by type of service or providers (public, private, informal). The databases we have manipulated was likely to include informal health units, but we could not identify them clearly as informality is not an attribute openly displayed and recognised. People with different socio-economic backgrounds, which are very disparate within the urban footprint, do not attend the same health facilities as it is in some countries with universal healthcare such as Norway. With these spatial disparities abilities to use more costly transportation modes are uneven in the population.

The assumptions we made reduced the complexity of the systems into two healthcare facility types (basic healthcare and hospitals). However in reality these facilities are only partially in a competitive relationship, as they address different types of care, with different quality and are attended by different users. For instance, facilities focused on obstetric care only attract pregnant women.

Concerning the route modelling, the time estimate is based on the average speed that depends on the street hierarchy. However, travel time can vary importantly with the conditions such as traffic, uncoated or degraded road, floods or rain.

Next, another transportation limitation is the lack of available knowledge regarding the travel options to attend basic healthcare in the urban Sub-Saharan settings. We assumed transportation splits to attend basic care were the same as the one to travel in general in Yaounde. We suspect healthcare users have a tendency to accept a higher travel cost, without being able to evaluate it.

Finally, we would like to conclude the with the temporal limitations. To assess accessibility, we assumed transportation conditions of 2018-2019 with data originating between 2019 and 2021. With the swift territorial and demographic expansion taking place and the new mobility trends that could emerge suddenly, prospect healthcare accessibility is a great challenge. This element is particularly important in a domain where health authorities want be in front and not behind development.

5.4 Potential improvements

The scores we have produced are measures of potential accessibility. Their precision can theoretically be improved as travel assumptions are ameliorated and refined. We propose here a number of developments that could overcome the key limitations.

Traffic congestion is an aspect more and more considered in accessibility studies to improve the O/D matrix accuracy (Tao et al., 2018). APIs of Google [8], Bing or Baidu web service provides path duration data according to traffic conditions. Adding an API to our model is realistically implementable but it is not free. With a small research, we find that most of Yaounde major axis are modelled in live by Google. Another way to consider traffic congestion can be by designating different transit speeds as a function of the hour as Ahmed et al. (2019) have done in their research.

The understanding of transportation options to reach healthcare facilities is a significant element of improvement. The choice of means of transportation and their relative weight is based on a mobility analysis of the Yaounde community (Bachmann et al., 2020). We could not find any quantitative documentation on the specific modes used to reach basic health facilities in the Sub-Saharan urban context. Choices could be improved by obtaining a quantitative survey on travelling information regarding healthcare facility clients' trips. We would expect these shares to be disparate across the neighbourhoods and depend on health service types. In line with the previous element, clients quantitative data can also be used to delimit catchment areas more accurately as it was done in the study of Dakar by Ndonky et al. (2015). Obtaining such surveys is costly and would need to take into account facilities with different typologies in different socio-economic neighbourhoods.

Distinguishing the healthcare clients according to their conditions and their medical needs allows to addresses accessibility according to specific health issues. Indeed, abilities to use certain transportation means can be seriously obstructed and some age or gender groups can be unconcerned about certain health services. COVID-19 or obstetric-care are examples of specific diseases where users and respectively their potential accessibility have been assessed (Gao & Kelley, 2019; Geldsetzer et al., 2021; Ouko et al., 2019). To carry out such studies, information about the providers' capabilities are needed which were rarely available in our project datasets.

Improvements we have mentioned until now considered an enhancement of the travel modelling assumptions and delimitation of the stakeholders. However, as we have seen in part 4.2.7, results are also sensitive to the input data reliability. In order to draw reliable and accurate local analyses, both are needed.

[8] Accessible at : https://developers.google.com/maps/documentation/javascript/directions

5.5 Model development and re-usability

Constructed over Python, the model scripts are openly accessible over the following link: https://github.com/christopherwillcocks/Health-facility-accessibility-Cameroon. In addition to the code, one population and health facility dataset is also provided to serve as an example for other uses.

Below, we have applied our healthcare accessibility model to the city of Douala in Cameroon to illustrate a re-usage application. We have used datasets provided by GeoPoDe database.

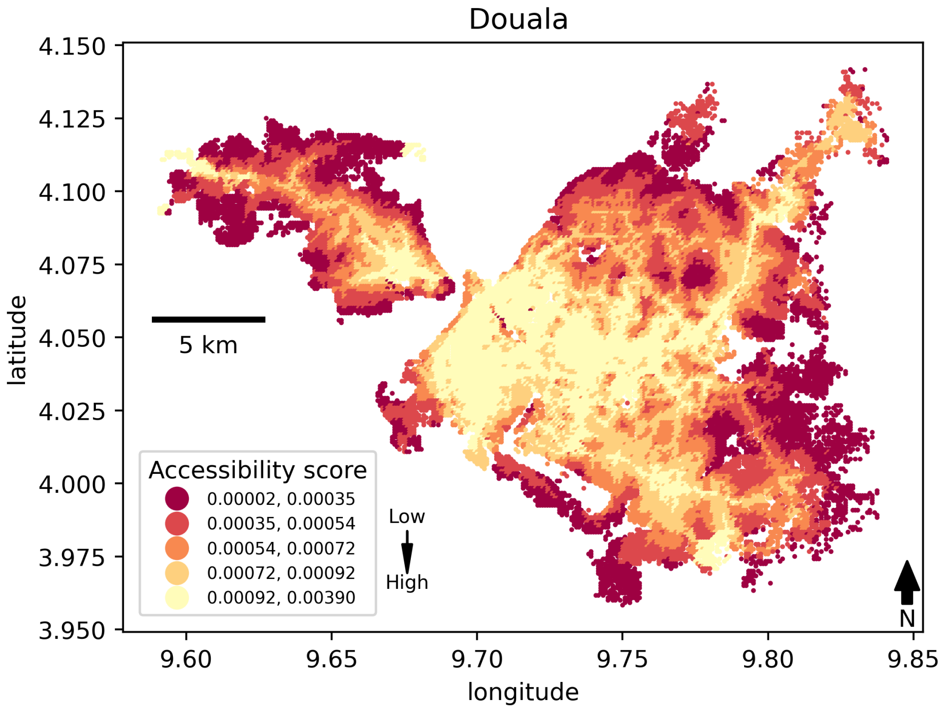


Figure 23 – Acessibility to basic healthcare facilities in Douala (GeoPoDe)

6 Conclusion

In this report, we discussed the development of a health accessibility model specifically implemented for the urban Sub-Saharan context that is in line with local authorities' ambition to improve health access for all. In order to apply the model and develop our analysis, we used Yaounde as a case study.

The theoretical background recalls that healthcare accessibility is not uniquely defined nor measured, but all researchers share the intention to expose spatial inequalities. In Sub-Saharan Africa, whether it concerns population data or the healthcare database, bias and incompleteness can strongly impact the studies study outcomes. This is the reason why three sources of population data are employed and four sources of healthcare information are joined in two databases. The study area is delimited as a function of the population gridded area, considering the significant year-to-year urban expansion taking place in the region.

Although the Two-Step-Floating-Catchment (2SFCA) method and its variants are widely employed to analyse the disparity of health distribution through the World, few examples of applications exist. The main challenges consisted in the data reliability and the modelling of the specific urban mobility patterns. These elements had a central place in the model development and in the assessment of the results. We addressed this gap by explicitly focusing on the significance of the results more than the results themselves. Keeping this in mind, we complemented our project with qualitative interviews.

Our first result indicated that only a slight (<1.5%) proportion of the urban population lived at more than the WHO 5 km threshold of the nearest healthcare structures. This results focused only on distance reinforced the apparent low accessibility issue by the authorities and interviewees. However, our adapted 2SFCA that considered walkers, shared taxi users and motorised private vehicle users, showed that healthcare accessibility is strongly disparate among neighbourhoods, but also between transportation modes. As pedestrians only dispose of a small catchment area, their accessibility is strongly dependent on the facility location and faces important local variations. Regarding the shared taxi, accessibility scores are shaped by the main road axis. For private motorised vehicles, the accessibility map appeared more smoother. Nevertheless, important contrasts are still evident between the central area and the surroundings where facilities are not apparent.

In order to assess the importance of data reliability, we carried out a sensitivity analysis. We concluded that for the motorised transportation modes, the exact location of facilities and the partial incompleteness were not decisive in the modelling. Concerning population density, we determined that demographic data need to be consistent to obtain coherent results. A relative estimate of the population as proposed by the bottom-up approach produced more meaningful results than with the use censuses data.

Globally, we have assessed in our models that the population living deep in neighbourhoods or in the new urban areas of the city have insufficient access to healthcare. We determined that in the first case, it was due to its poor connectivity and that in the second case it was due to the insufficient number of alternatives. A phase of transition is taking place between the urbanisation and implantation of basic infrastructures. The critical population and territorial growth rates will be very demanding for the authorities to be ahead of the game.

In our study we have focused on modelling healthcare accessibility. Complementary projects could improve the understanding of the spatial dynamics surrounding different types of care and particularly informal providers. As the informal healthcare system provides considerable medical care for a majority of the population, a better understanding of its scope would help to assess the imbalance between both healthcare systems and to improve the general utilisation of all facilities. To conduct such a study, facilities data sets would need to be completed with field data.

To conclude, the key recommendation we would like to draw from our assessment is that healthcare allocation decision-makers need to focus on the on new urban areas and on population that are deep in the neighbourhoods, not near a structural transportation's axis. Reducing inequalities in accessibility to healthcare services relies not only on the implantation of additional facilities in under-served areas, but also on the improvement of transportation networks.

A Appendix

A1: Healthcare accessibility in Dakar

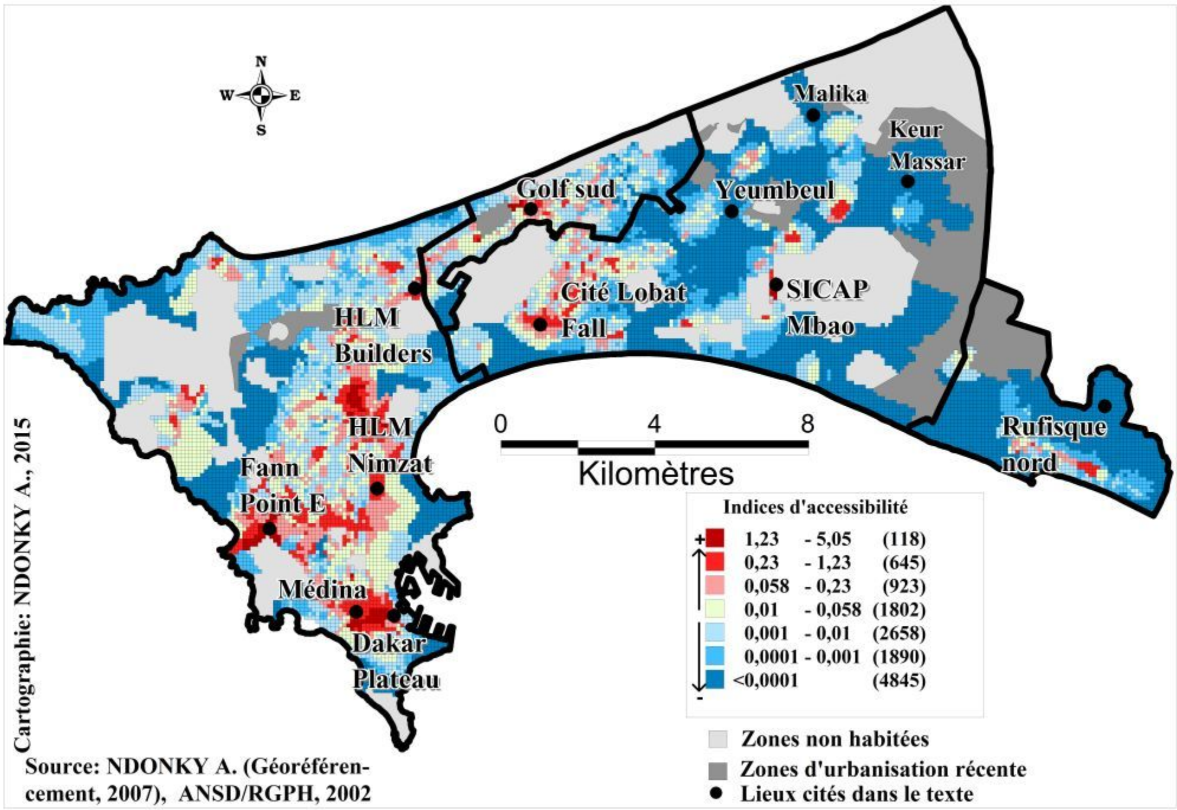


Figure 24 – Accessibility assessment regarding public health facilities in Dakar, Senegal (Ndonky et al., 2015)

A2: Yaounde neighbourhoods

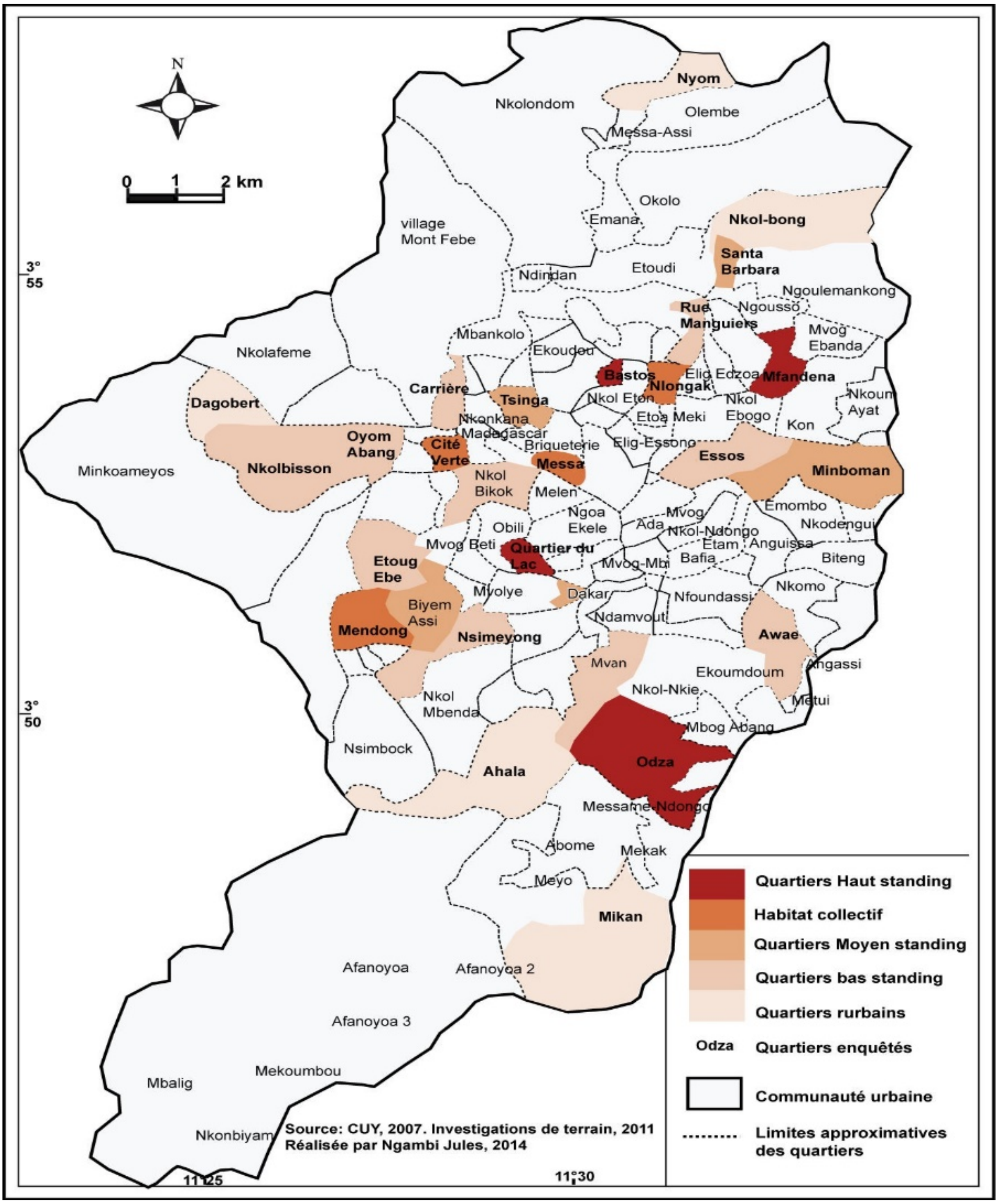


Figure 25 – Typological categorisation of Yaounde neighbourhoods (Voundi et al., 2018)

A3: Mix dataset combination

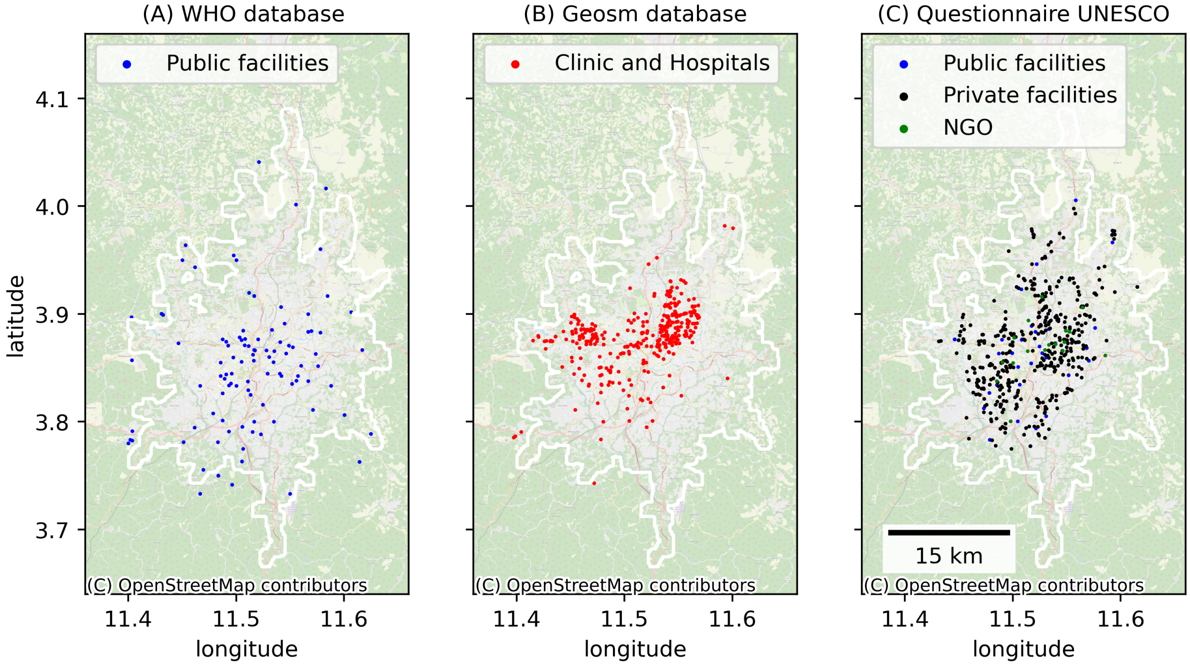


Figure 26 – Display of healthcare facilities locations of the mix dataset originating from three datasets

A4: Bottom-up population densities estimates in Yaounde region

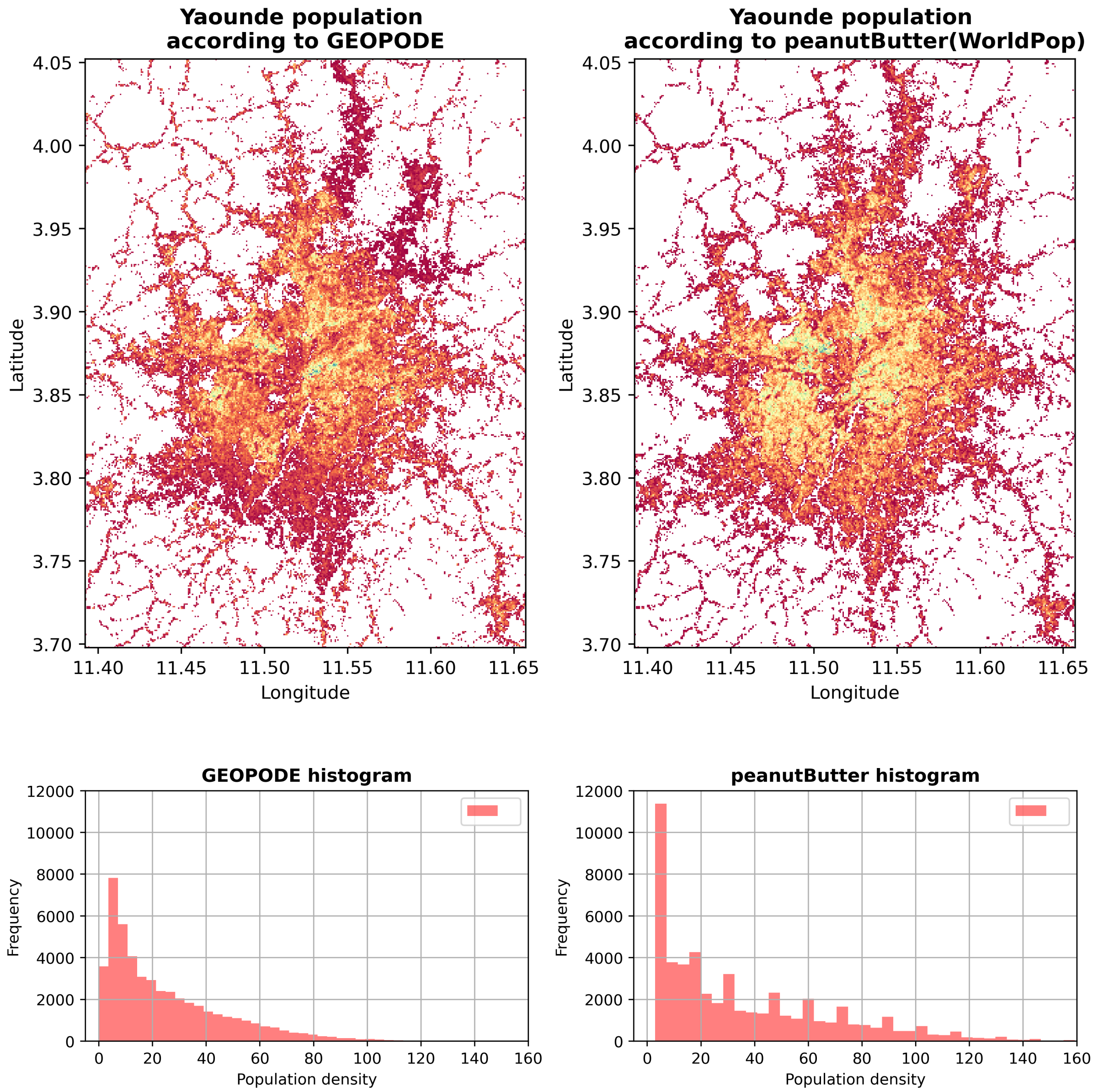


Figure 27 – Population density estimate (Maina, 2019)

A5: Walking isochrone map

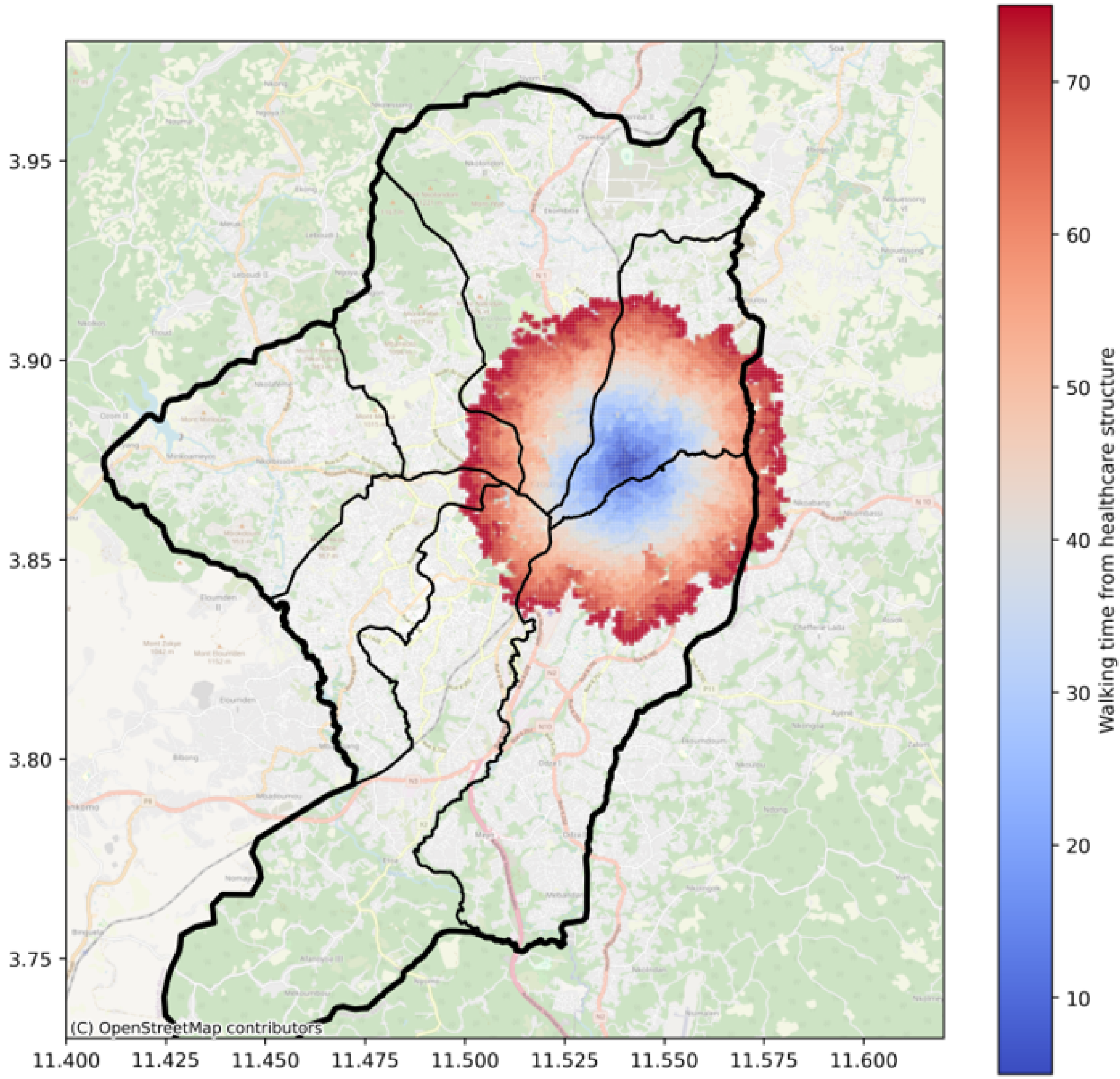


Figure 28 – Walking isochrone centred at a healthcare facility situated in Essos neighbourhood in Yaounde 5

A6: Interview questions

1. What transportation modes do you use to get to a health facility?

    - Can you give examples?

2. What other transportation modes can be used to reach a health facility?
3. Do you think that walking is a mode that many people use to get to a health facility?
4. Do you think there are many differences in the transportation modes used to get to a health facility between different neighbourhoods?
5. When you go to a health facility, how long does it take you to get there?

    - Can you give several examples of travel duration based on your experiences?

6. Are you willing to travel across town to get a better or cheaper healthcare facility?
7. What is a distance or travel time that you feel is unacceptable?
8. How does the weather affect your travel to health facilities?

    - Will you choose other facilities if the roads are unusable?

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