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Methods to measure spatial access to healthcare facilities in cities: A case study of the urban poor in Chennai

Rajeswari Parasa, Harsh Vardhan Pachisia and Isalyne Gennaro

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Abstract

Measuring and assessing the spatial access that the urban poor has to public healthcare facilities is critical in planning and improving service delivery in cities. Over the past two decades, studies have introduced a range of spatial methods to do this. However, most of these studies are agnostic to the provider type (private/public) and the target beneficiaries. This study fills that gap by focusing on measuring the access that urban poor have to urban primary health care facilities. It does this by deploying four models – Euclidean distance-based buffer analysis, road network distance-based buffer analysis, Euclidean distance-based nearest facility analysis, and finally, road network distance-based nearest facility analysis. The models are demonstrated for a non-representative sample of slums identified under Rajiv Awas Yojana (RAY) and the urban primary healthcare centres (UPHCs) in the city of Chennai. The study uses replicable open-source GIS-based tools and scripts that can be deployed by other studies. The limitations and computational challenges of each of the models are also briefly discussed. Such studies can generate evidence that feeds into facility planners' decision making on managing existing facilities and establishing new ones.

1. Introduction

Measuring access and identifying gaps in access to healthcare delivery are crucial aspects of urban planning and governance. This is especially true when it comes to servicing the poorest residents of cities who live in slums. It used to be difficult to measure spatial access within Indian cities due to either the lack of technology or a systemic lack of data. This is no longer the case.

It is now possible for a municipal corporation to implement a Geographic Information System (GIS), a computer system that can capture, store, and analyse geospatial or spatially-referenced data. In particular, it allows spatial data to be connected with non-spatial data points. This can be achieved through a variety of keys- for example, using latitudes and longitudes (i.e. location) to connect administrative and utilisation information about a hospital facility with its physical location. GIS can also be used to conduct temporal analysis of spatial and non-spatial datasets. Around the world, researchers and authorities employ GIS technologies in a wide range of sectors including urban planning, transport planning, waste management, crime prevention, ecological conservation and agriculture.

GIS is also widely used in gauging the availability of and access to healthcare facilities (Higgs, 2004). This is done by charting out the location data of every healthcare provider as well as its distance to the population of a particular geographic area. Robin et al., (2019), who worked in the rural Habiganj district of Bangladesh, mapped the locations of primary health centres, road networks and other physical elements to understand accessibility, i.e. distance to the facilities, and availability of services, i.e. the number of healthcare providers. They collected data on the demand for healthcare services in different parts of the district, such as the number of households, their economic status, the types of diseases, the locations of the households where neonatal deaths occurred, awareness of facilities, etc. To proceed with the analysis, the researchers anonymised and aggregated the personal data. Finally, they overlaid their datasets in a GIS to identify underserved areas. This methodology helped identify and address geographic inequalities in healthcare access.

To their credit, Indian governments are recognising the usefulness of GIS in public health, if not specifically in the value-add of measuring access to healthcare facilities for the urban poor. Various state health departments installed the Esri-enabled GIS technologies (Esri India, n.d.) for mapping risks of malaria (Bhattacharya, 2020). During the first wave of COVID-19, many policy officials demanded GIS tools for monitoring the spread of the virus. In Gujarat, for example, municipalities used a GIS app to track infected people who were home quarantined. Similarly in Maharashtra, the urban local bodies used GIS tools to publish data online informing citizens about the locations of cases (Bhattacharya, 2020). Researchers were also able to develop a GIS-based COVID-19 risk assessment and mapping (CRAM) framework for the city of Jaipur (Kanga et al., 2020). They collected hazard, vulnerability parameters and basic administrative data as a baseline. They attributed different weights to each COVID-19 risk indicator such as population density and land use and overlaid them to generate GIS-based COVID-19 hazard and vulnerability maps.

There have been city level studies that assess the spatial accessibility of health centres, irrespective of the provider type or level of service provided, from gridded population units or administrative units. However, very few studies look at spatial access to health centres that are essentially funded by the government, or public health centres, from slums or slum-like neighbourhoods, the target beneficiaries for these public health centres. Such studies are particularly limited in the Indian context. This can be partially attributed to a lack of city-level open data on locations of slums and public health centres and also to the computational complexity involved in performing the comprehensive spatial analysis (Zhu et al., 2020).

Our study addresses these underexplored areas by exploring two research questions:

1. How can replicable open-source GIS-based tools and models be used to study spatial access to urban primary healthcare facilities from the urban poor?
2. What data points should be collected by the facility planners and city administrators to improve the measurement of access to healthcare facilities for the urban poor?

We study the above questions in the city of Chennai mainly due to the availability of address data on facilities and slums in the public domain. The publicly available address datasets allowed for geocoding to obtain the location data used in the analysis.

The rest of this paper is organised as literature review, background and definitions, data, methods and tools, findings, discussions and policy recommendations, and finally, conclusions and limitations. The following section reviews the literature focusing on studies that introduce analysis models and frameworks to measure and assess spatial accessibility and discuss different distance metrics that can be considered. The third section provides background on existing public health facilities and slums in Chennai and the relevant policies for planning new facilities. The fourth and fifth sections describe the data used in the analysis and the methods and tools used, respectively. The section on methods describes the four analysis models used to study spatial access. The sixth and seventh sections discuss findings and recommendations. Finally, the last section makes concluding remarks and highlights the limitations of the study.

2. Literature Review

Accessibility is a spatial attribute; vehicular travel time and distance are accepted as good variables for measuring it. Depending on the area studied, traditional attributes such as distance and time are considered the most important factors for measuring geographic accessibility. However, there are non-spatial factors that also need to be considered when measuring accessibility. Researchers have employed multiple methodologies to do this as outlined below.

Geurs and Van Wee (2004) highlighted seven different models to measure spatial accessibility, investigating various factors. The major ones are outlined as followed:

- The spatial separation based model (distance-based): This measures accessibility by taking the exact distance between the physical locations of facilities as infrastructure points. This analysis does not require data on transport networks to measure access.
- The cumulative opportunity approach (time-based): It is a model which incorporates travel time to define the maximum amount of time people are willing to commute.
- The competition measure approach builds upon the spatial separation methodology. It considers the location of competing facilities and how that affects accessibility. For instance, this model is extremely useful when measuring accessibility in city centres where multiple facilities are equidistant and competing on other factors (such as quality) for the same customers.

- The time-space approach adds space-time/non-spatial constraints to these models. These constraints can be authority constraints (laws, rules, norms, time of operation, etc.), coupling constraints (social interaction), and capability constraints (physical/biological limit). This approach aims to understand the importance of other constraints to determine accessibility over time and distance. Comber and Radburn (2011) built upon this to develop a model which integrates indicators on long term illness, non-car ownership and bad health. By doing so, they showcased that accessibility should be treated as a multidimensional construct and not simply be based upon physical distance.

A traditional, spatial model used for health care planning in the United States is the origin-constrained model (Martin & Williams, 1992). It is a spatial interaction model which assumes and keeps the number of trips to a fixed area of origin using a zip code, census tract, and so on. In this model, the interaction of residents with healthcare facilities depends on the residents' choices, considering the distance, time, quality and other non-geographical characteristics. Based on that, the origin-constrained approach models the allocation of such trips to health care facilities. Conversely, in the UK, the decisions to plan and finance healthcare are centralised, requiring decision-makers to dictate and account for the capacity of healthcare facilities (Mayhew et al., 1986). They use a destination-constrained approach that models the flow of patients to specific facilities. It assumes a fixed total capacity for each facility (destination). Each facility serves a predefined number of patients.

In more recent years, various location-allocation models have been applied to solving problems of health services delivery. The allocation models assume that locations of facilities are fixed in the short term, so they identify the assignment of patients to facilities that minimise or maximise the objective function. To optimise the utilisation of the facilities, decision-makers can model the number of patients they cater to and minimise the total distance they travel. On the other hand, the location models find the optimal location of the facility, assuming that it will not change in the long term.

Yenisetty and Bahadure (2020) highlighted the access gaps that exist in India by measuring and ranking access to amenities via public transport in six cities. Beyond urban areas, there is also an evident lack of infrastructure in Indian villages (Barik, 2015) and there are many instances of exclusion. As urban areas continue to expand towards the periphery, the distance between new development and primary healthcare centres located in the existing parts grows, making access to facilities challenging.

While beyond the scope of this paper, measuring affordability i.e. comparing the needs and capacity to pay for healthcare services of a specific population, is also crucial. This was seen by Bhojani et al., (2016) who highlighted how out-of-pocket payments for outpatient care can affect populations with chronic conditions that endure the recurring costs of regular medical care services. Performance of the facilities themselves, i.e. their quality and utilisation also matter. Sethi et al., (2020) showcased this relationship by measuring proximity (physical closeness to the facility) to actual utilisation of health facilities in New Delhi. That is, the authors highlighted the negative correlation that larger physical distance (lower proximity) to a facility has on its actual utilisation by patients. Moreover, in India, three times more people use private facilities than public ones, despite the former being more expensive (Rout et al., 2021).

3. Background and definitions

To select the data, we needed to understand how public health facilities are planned in cities. Urban poor communities were more vulnerable to the COVID-19 pandemic. Without adequate sanitation services or access to healthcare (Patranabis et al., 2020), the spread of the virus exacerbated the precariousness of their livelihoods. In Chennai, substandard services and weak disaster management in situations such as COVID-19 and the 2015 floods, challenge the resilience of the poor communities (Resilient Chennai, n.d.).

In India, health is a state subject. State governments plan public health facilities based on population thresholds for rural and for urban areas. In cities, National Building Code that defines safety and engineering standards, and Urban and Regional Development Plans Formulation and Implementation Guidelines (URDPFI) guidelines, indicate the generic number and type of health facilities that the government is responsible for providing based on population thresholds. Urban planners re-assess them as and when they revise cities' Development Plans. Both are devised by the Ministry of Urban Development. Additionally, centrally sponsored schemes and state projects drive interventions to improve specific aspects of governance such as access to sanitation services or primary care through the building of new healthcare facilities or upgrading existing ones.

In Chennai, a slum area is any area that falls under sub-section (1) of Section 3 of the Tamil Nadu Slum Areas (Improvement and Clearance) Act, 1971, having squalid and unsafe living conditions. However, Resilient Chennai, n.d. highlights the issues with this definition. It points out that while "no new slums have been notified in the past three decades, the slum population has doubled." The report also notes that the lack of affordable housing in the city centre has pushed low and medium-income households to move to the periphery or closer to coastal areas. Moreover, slum communities in Chennai are heterogeneous and face different types of vulnerabilities; the communities in coastal areas have housing issues whereas urban homeless and migrant workers, in general, have other kinds of issues.

The National Urban Health Mission (NUHM) aims to address such systemic issues and improve the health of the urban poor by providing access to primary healthcare resources. The NUHM guidelines are the premise to the analysis of this paper as the standards prescribed by them for the location of a UPHC, in relation to the location of slums, have been used as a reference to interpret the findings of the study. The mission defines the Urban Primary Health Centres (UPHCs) as the nodal point for delivery of health care services, especially to address the unique health and livelihood challenges faced by urban poor communities (Ministry of Health and Family Welfare, Govt. of India, 2015). Such facilities provide multiple in- and out-patient services such as treating minor ailments and neonatal care.[1] Depending on the spatial distribution of the slum population, the population covered by a UPHC may vary from 50,000 to 75,000 for highly concentrated slums. The UPHC may cater to a slum population between 25,000-30,000 for cities with sparse slum populations and preferably be located within a slum or within ½ km-1 km distance from a slum.

4. Data

[1] A full list of services provided at these facilities is provided here: https://chennaicorporation.gov.in/about-chennai-corporation/Medical_Services.pdf

4.1. Locations of UPHCs - Mapping the supply

This study uses Chennai's UPHC data from the SmartCities data portal. UPHCs are considered as the supply points for accessing public health. The dataset on the SmartCities portal contained information on the addresses along with the corresponding zones and wards. The addresses are geocoded to obtain the spatial coordinates of the facilities. Of the 140 UPHCs listed, 138 were successfully geocoded. The two facilities that are excluded from the study were located in the areas of Sholinganallur and Royapuram. The locations of all the 138 facilities thus obtained are shown in Figure 1 below. Google's Geocoding API was used to obtain the spatial coordinates[2] for the facilities. This tool was able to provide the level of spatial accuracy needed for the analysis conducted in this paper. A sample of the final dataset is showcased in Table 1 below.

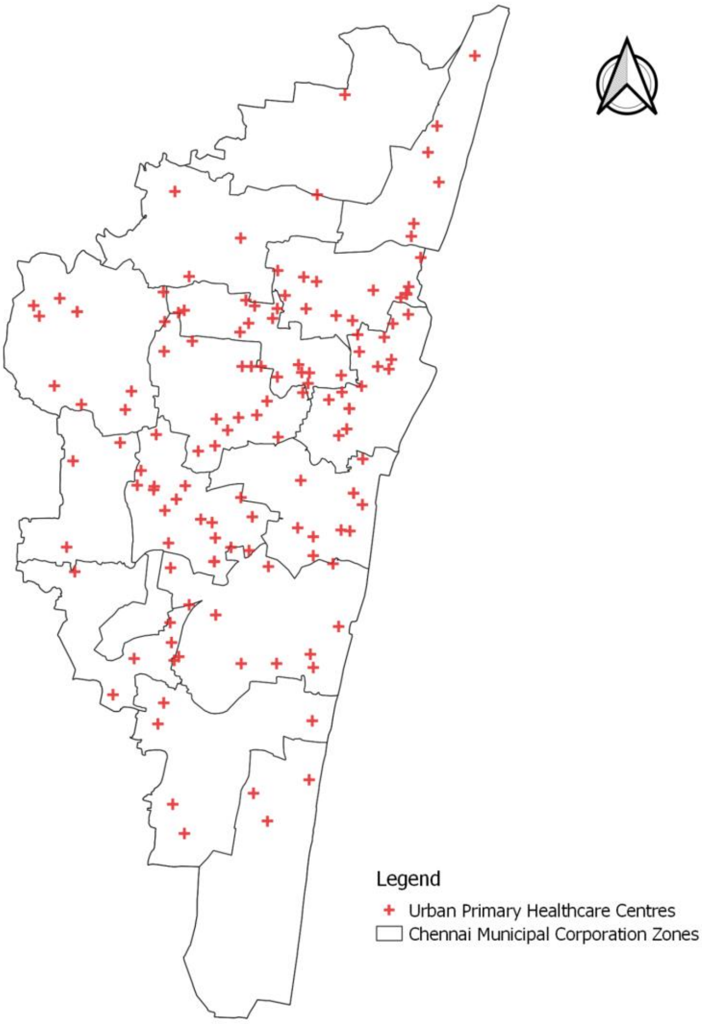

Figure 1: Map of 138 geocoded Urban Primary Healthcare Centres in Chennai

[2] An open source alternative for geocoding is Nomanatim https://nominatim.org/

UPHC ID	Zone No.	Ward No.	UPHC Name	Address	Latitude	Longitude
UPHC1	1	2	Kathivakkam	Urban Primary Health Centre, Kathivakkam, No 3 392; Kathivakkam High Road; Ennore; Chennai 57	13.216	80.318
UPHC2	1	3	Ernavoor	Urban Primary Health Centre, Ernavoor, No 63 Block Tsunami Quarters; All India Nagar; Ernavoor; Chennai 57	13.189	80.303
UPHC5	1	12	Sathangadu	Urban Primary Health Centre, Sathangadu, No 9A; Balakrishna Naidu Colony 2 Street; Kaladipet; Thiruvottiyur; Chennai 19	13.148	80.294
UPHC6	1	14	Thangal	Urban Primary Health Centre, Thangal, No 3 2; Poongavanapuram; Kaladipet; Thiruvottiyur; Chennai 19	13.153	80.295

Table 1: A 4-row snapshot of the geocoded data of UPHCs

4.2. Locations of Urban Poor in Chennai (Slums) - Mapping the demand

As per the Primary Census Abstract for Slum, Census of India-2011, 29% of Chennai's population live in slums. It is fourth among the major million-plus cities with the highest slum population proportion, following Mumbai (42%), Hyderabad (33%) and Kolkata (32%) (Ministry of Housing and Urban Poverty Alleviation, 2015).

All the cities under the Rajiv Awas Yojana Scheme were directed to prepare a Slum Free Plan of Action (SFPoA). The scheme envisages providing slum dwellers and the urban poor access to decent shelter and basic civic and social services. Under this directive, the Tamil Nadu Slum Clearance Board (TNSCB) identified 2,173 slums in Chennai as of February 2014 and surveyed 1,131 of them, comprising a population of 1.15 million. The details of these slums are listed in Annexure-II of the plan document. At the time of writing, the survey conducted under the SFPoA was perhaps the only source of authoritative data on the slums in the city.

From the full dataset, we created a sample of 393 slum locations (i.e. 34.7% of the total slum locations) housing about a population of 438,542 residents (i.e. about 38.3% of the total slum population). These were the only locations within the dataset that could be accurately geocoded up to the respective ward. The locations of all the 393 slums thus obtained are shown in Figure 2 below. A sample of the final dataset of the geocoded slums is showcased in Table 2 below. It should be noted that since the time of survey completion, there could be unaccounted changes in locations and population count in the slum areas within the present study. Such changes were out of the scope and control of this study.

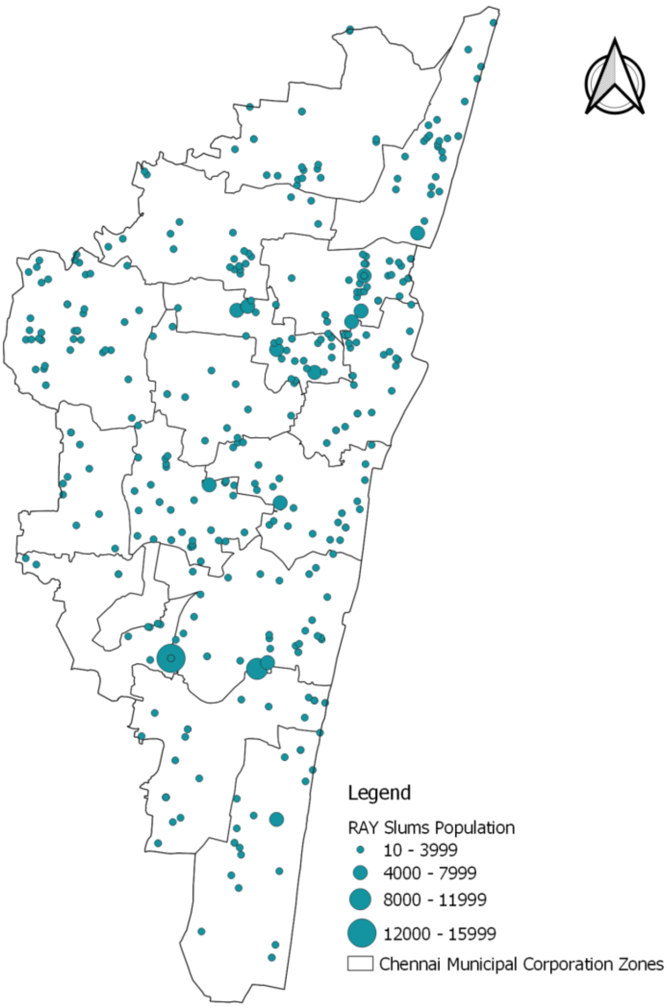

Figure 2: Map of 393 geocoded RAY slums in Chennai

Slum ID	Zone No.	Ward No.	Slum Name	No. of House holds	Populat ion	Address	Latitude	Longitude
S1-3-34	1	3	Periya Kasi Koil Kuppam	430	1493	Periya Kasi Koil Kuppam, Ward 3, THIRUVOTRIYUR, Chennai, Tamil Nadu, India	13.199	80.318
S1-2-11	1	2	ChinnaKuppam	239	786	ChinnaKuppam, Ward 2, THIRUVOTRIYUR, Chennai, Tamil Nadu, India	13.207	80.323
S1-2-24	1	2	PeriyaKuppam	280	918	PeriyaKuppam, Ward 2, THIRUVOTRIYUR, Chennai, Tamil Nadu, India	13.212	80.324
S1-1-4	1	1	Nettukuppam	403	1457	Nettukuppam, Ward 1, THIRUVOTRIYUR, Chennai, Tamil Nadu, India	13.229	80.329

Table 2: Sample of geocoded slum locations in Zone 1

4.3. Limitations of data:

One of the main limitations of the datasets used is the accuracy of the geocoded locations for both the slum settlements and the UPHCs. The location data used in the study was derived from a third party geocoding service and not collected from the ground through primary surveys. Hence, the findings of the study might suffer from the errors resulting from the geocoding process. Another limitation is the completeness of the spatial data on slum settlements. Since we consider only a subset of RAY slums (34.8%), the findings in this paper are limited to this set of slums and cannot be used to generalise access to UPHCs for all RAY slums in the city without further exploration with location data of the rest of the slums. However, the limitations of the data do not affect the efficacy of the methods and tools presented in the study. These methods can and should be used to perform a similar analysis with datasets for other cities.

5. Methods and tools

5.1. Analysis Models

The level of spatial access that slum dwellers have to UPHC in Chennai can be quantified using a class of spatial methods called proximity analysis methods.

In this paper, we use two well-known proximity analysis methods to measure spatial access to health facilities. First, buffer analysis, and second, nearest facility analysis. We implement the two methods using two different types of distance metrics: Euclidean distance (direct distance between two points) and road-network distance (distance by road or travel distance). The resulting four analysis models are represented in a matrix format in Table 3. These are, 1) Euclidean distance-based buffer analysis, 2) road network distance-based buffer analysis, 3) Euclidean distance-based nearest facility analysis, and finally, 4) road network distance-based nearest facility analysis. Table 3 also highlights the kinds of data inputs each of the four models can offer to inform policy.

	Euclidean Distance Based	**Road Network Distance Based**
Buffer Analysis	Count and location of settlements that have no UPHC in a 1km vicinity.	Count and location of settlements that have no UPHC within a **travel distance of** 1km.
Nearest Facility Analysis	• The average distance from the slums at which the nearest UPHC is located. • The number of individuals dependent on a given UPHC. (Assuming UPHCs at a shorter Euclidean distance are preferred to access primary care)	• The average distance or/and time a person is travelling to reach the nearest UPHC. • Of all the slums, the slums that are located the farthest from their nearest facility. • The number of individuals that are dependent on a given UPHC. This analysis also generates a profile for each UPHC showing the travel distances at which its

		dependent slums are located from it. (Assuming UPHCs at a shorter travel distance are preferred to access primary care)

Table 3: Data points generated by each of the different analysis models

The selection from the four models depends largely on two real-world constraints: one, use cases that can be mapped to the data points listed in Table 3. And two, the level of computational complexity that is feasible, assuming the location datasets for both facilities and slum neighbourhoods are available. Out of the four models, computationally, the Euclidean distance based buffer analysis is the simplest and the road network based nearest facility analysis is the most complex and takes longer computation time.

5.2. Buffer Analysis and Nearest Facility Analysis

Buffer Analysis: A buffer is a geographic region with a specified radius around a geographic feature, often deployed when trying to determine proximity to a point of interest (Mansour, 2016). For performing this analysis, a circular region (using Euclidean distance or travel distance/time) of a specified radius is considered around a geographic feature, and it is examined whether other points of interest lie within or outside this region.

Nearest Facility Analysis: This technique allows for mapping every demand area (or a residential settlement) in the study region to the nearest facility or service. Steps include first, calculating distances (using Euclidean distance or via road network) from each demand area to every facility in the region. Next, the demand area for each facility (the one closest to the slum) is assigned. Nearest facility analysis is often used for facility planning (Xu et al., 2020) and studying relationships between accessibility to healthcare and health outcomes (Wang, 2020).

5.3. Euclidean Distance and Road Network Distance

Yenisetty and Bahadure (2020) demonstrate in their accessibility study in six Indian cities that the percentage of amenities, facilities and services (ASFs) accessible within 400m range of public transit when considering network distance is nearly half of when the Euclidean distance is considered for the same range. This indicates that the choice of the distance metrics can strongly impact the accessibility study, underscoring the importance of using them carefully.

Measuring spatial access using Euclidean distance is extremely limiting, especially in unplanned cities with disparate road networks. While it does provide a rough estimate of distance and is easy to compute, it often does not reflect the actual travel distances as showcased in the findings section. For instance, two closely located points using Euclidean distance could in reality be far apart due to the absence of a road network or other impediments such as a canal. Given such scenarios, road network-based distances provide a realistic estimate of distance or travel distance.

5.4. Steps Undertaken

As an initial step, we measured the correlation between a slum's distance to the city centre and the closeness of its nearest facility, via road, to get an indication of whether geographical access to healthcare is better closer to the city centre. For this study, we took the municipal corporation's headquarters as the city centre.

Next, we implemented the first analysis model, i.e. buffer analysis using Euclidean distances. We made use of QGIS software, free and open-source software for spatial analysis, for this. In particular, through this technique, we were able to quantify the number of slums that have no single health facility within a reasonable distance. To define 'reasonable distance', we make use of the National Urban Health Mission guidelines for the location of a UPHC which prescribes that a UPHC should be located close to a slum or slum-like settlement at a distance of 1/2km to 1km. After creating the buffers, all the slums with no UPHC in their buffer regions are identified using a simple count tool offered by QGIS vector analysis.

The Euclidean distance-based buffer analysis gives a high-level estimate of the availability of a UPHC within a particular radius. However, it does not provide information on whether the facility within the buffer is reachable since it does not factor in the road network. As mentioned earlier, a resident might have to travel a longer distance than the direct distance to reach the facility. The next model in the study, road network-based buffer analysis, addresses this aspect.

To implement the second analysis model, i.e. road network-based buffer analysis, we start by creating the road-based buffers or iso-areas. For this purpose, we use OpenRouteService tools (ORS) (HeiGIT, 2008)—an open-source routing client. ORS only requires the point locations of the slums to be inputted and does not require spatial roads network data to be provided. Alternatively, if one has access to clean and reliable road network data, the QGIS Network Analysis Toolbox 3 (QNEAT3) (Raffler, 2018) plugin can be utilised over the QGIS platform for creating road network-based buffers. After creating the iso-areas, all the slums with no UPHC in their iso-areas are identified using a simple count tool offered by QGIS vector analysis. Results are compared with the Euclidean distance-based buffer analysis.

Next, for implementing the third model, i.e. nearest facility analysis based on Euclidean distances, the 'nearest facility analysis' function in QGIS was used. A hub and spoke map was generated connecting each slum to its nearest UPHC, or hub, via a spoke line. The average distance from the slums to their nearest facilities was calculated. For each facility, the farthest slum was identified.

Then, for calculating the road distance that would have to be traversed by the slum dwellers to reach the nearest UPHC, we implemented the fourth model, i.e. nearest facility analysis based on road network distances. Corresponding travel times were also calculated. For implementing this model, a combination of tools was used including, the OSMnx python package (Boeing, 2017), QNEAT3, Open-Source Routing Machine (OSRM) (Project-OSRM, n.d.) and open-source scripts (Appendix). Firstly, OSMnx was used to export cleaned roads data for the city of Chennai from OpenStreetMaps (OSM). The obtained road network was used as an input to QNEAT3 to calculate an origin-destination matrix[3] from every slum and to each UPHC, with slums as the origin points and UPHCs as the destination points. The resultant matrix was then queried to select the nearest UPHC for each slum (Gandhi, n.d.). Finally, to obtain the fastest travel routes,

[3] An origin destination matrix or OD matrix is a set of origin and destination pairs along with corresponding travel distance or travel times.

corresponding travel distances and travel times to the nearest UPHC (Appendix), we made use of OSRM's 'car' driving profile (Project-OSRM, 2020), one of the three travel-speed profiles currently offered by the platform. Alternatively, one could also use the combination of OSMnx and Networkx (Hagberg et al., 2008) to find the shortest route and corresponding travel distances to the nearest facility. However, since we were keen to calculate travel times as well, we preferred OSRM.

It's crucial to remember that the analysis considers the car driving profile for computing travel times. In reality, most people might need to walk or rely on public transport. Further, this computation method does not factor in street traffic that also impacts travel times. Hence, while the travel distances computed and presented in the study would be representative of the real world, the travel times in the study will be much less compared to the travel times in the real world.

Finally, to draw from insights of experiences of the researchers in the city, we interviewed Vanessa Peters, a policy researcher at the Information and Resource Centre for Deprived Urban Communities (IRCDUC), Chennai. Her experiences dealing with both demand and supply-side constraints provided insights into some of the challenges faced by decision-makers managing PHCs. She also provided insights on the importance of spatial data on slums, homeless shelters, health facilities and other medical resources while providing relief to the most vulnerable during emergencies such as COVID19. She emphasised the importance of carrying out vulnerability mapping across the city to identify types of vulnerabilities and the varying needs of different vulnerable groups.

6. Findings

In this section, we highlight the findings and insights that can be derived from each of the four analysis models described in the earlier section. First, we discuss the findings from the buffer analysis using Euclidean distance and then using network distance. Then, we discuss the findings from the nearest facility analysis using Euclidean distance followed by road network distance. We also demonstrate, with the help of an example from the study, the importance of selecting road network distance over Euclidean distance while conducting the nearest facility analysis.

As part of our exploratory analysis when gathering the data, we observed a positive correlation (Figure 3) between the proximity of the slum to the city centre and its travel distance to the nearest facility. Such a correlation indicates that slum settlements closer to the city centre have better geographical access to UPHCs as compared to the more peri-urban areas at the outskirts of Chennai.

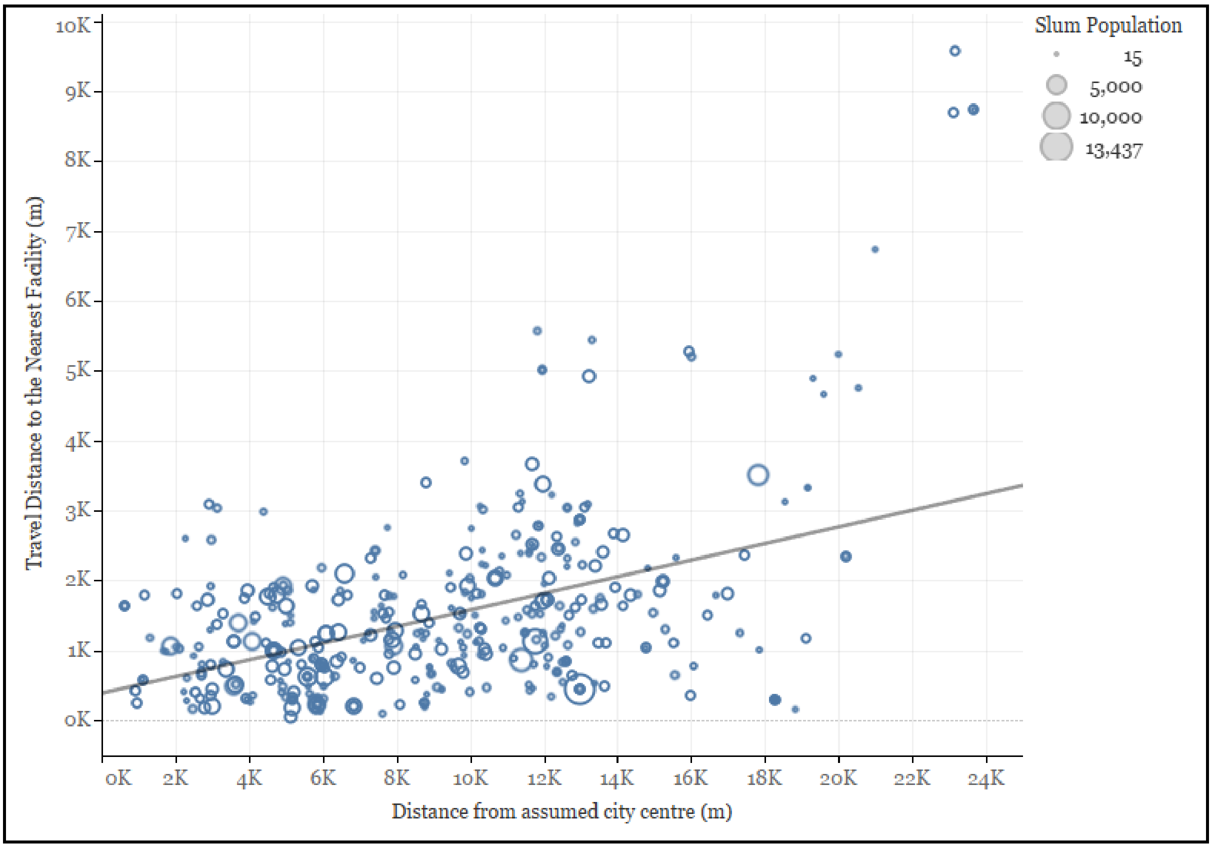

Figure 3: Travel distance to nearest facility vs distance of the slum from the city centre ($R^2 = 0.193$, $p < 0.0001$)

6.1. Summary of Findings

	Euclidean Distance Based	Road Network Distance Based
Buffer Analysis	About **117 slums** (29% of the sample) comprising a population of about **103,905** (24% of the sample) do not even have a single UPHC in a **1km vicinity.**	About **195 slums** (50%), home to a population of about 202,398 (46%), do not have a single UPHC in a reachable distance or **travel distance of 1km.**

Nearest Facility Analysis	1. Slums are located at an average distance of **0.7km** from their nearest UPHC. 2. Settlements in Uthandi are situated at a distance of **6.3km**. Compared to the rest of the settlements, this is the farthest distance from the nearest UPHC. Uthandi is followed by the settlements of Nainar Kuppam and Panayur Kuppam with a distance of **5.8km** and **4.7km** from the nearest UPHC, respectively.	1. A person living in the sample settlements has to travel an average distance of **1.5km** (or 2.6 min* at an average trip speed of 34.6kmph) to reach their nearest UPHC. 2. Of all settlements, Panayur Kuppam is situated farthest from the nearest UPHC at a travel distance of **9.5km** (or Travel Time= 13.3 min*, Avg. Trip Speed = 43 kmph), followed by settlements in Uthandi and Nainar Kuppam with travel distances of **8.7km** (or Travel Time = 8.7* min, Avg Trip Speed = 60kmph) and **8.6km** (or Travel Time = 9.3 min, Avg. Trip Speed= 56kmph) respectively. **Travel times computed here do not account for traffic conditions or public mode of transport as discussed in the previous section. Travel times for the respective routes in the real world would be much longer than those shown here.*

Table 4: Summary of findings

6.2. Buffer Analysis - Based on Euclidean distance

The buffer analysis, as shown in Figure 4 below, showcased a large disparity in access to PHCs. In the figures, all the slums that have zero UPHCs in their vicinity (of 500m or 1km) have red buffers. The rest of the slums have blue buffers. About 67% of the sample (263 slums) do not have a UPHC in a radius of 500m. That's a population of about 290,080 residents (66%). Even if a larger radius of 1km is considered, 29% of the sample does not have a UPC within the buffer region. That's a population of about 103,905 (23.6%).

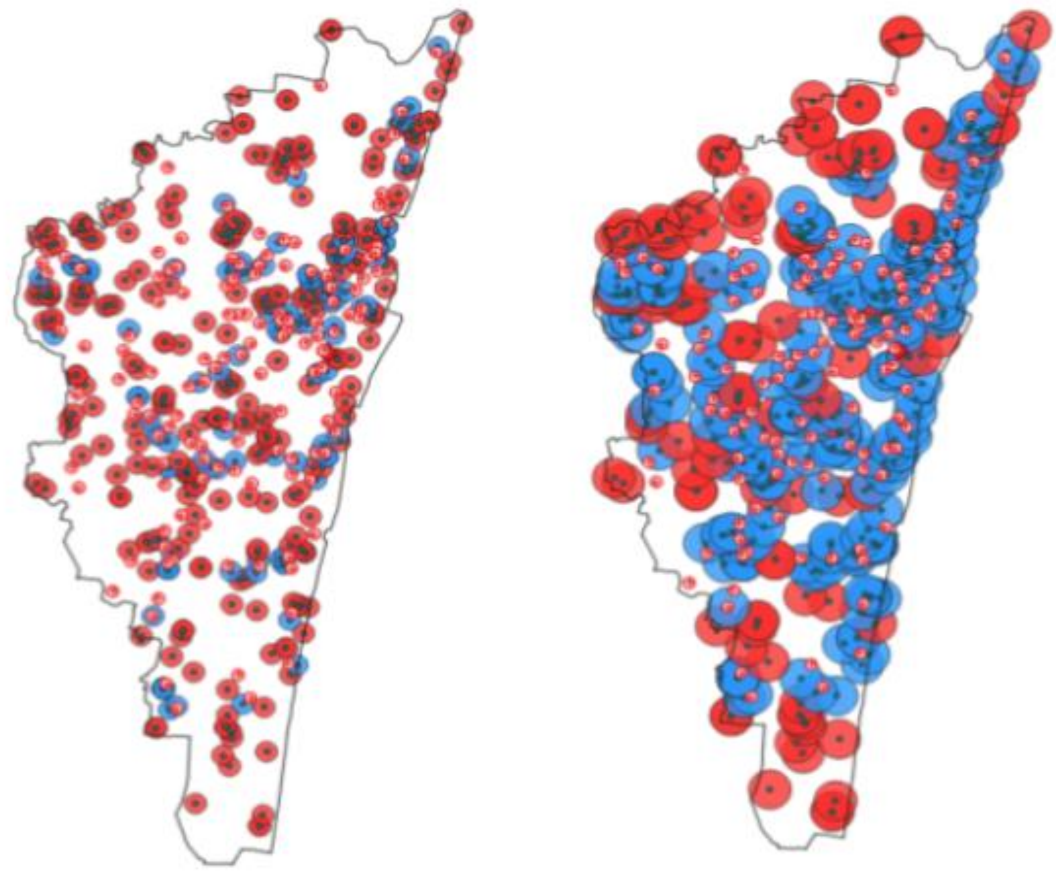

Figure 4: Slum settlements with Euclidean buffers – ½ km (left) and 1 km (right)

6.3. <u>Buffer Analysis - Based on road network distance</u>

The iso-area analysis (Figure 5) found that 76% of the sample do not have a single UPHC within a travel distance of 500m. These areas are home to a total of 337,227 people (~77% of the total sample population). When the radius is extended to 1 km, ~50% of the sample (195 slums) still do not have access to a UPHC within the region. That is a population of about 202,398 (~46% of the total sample population).

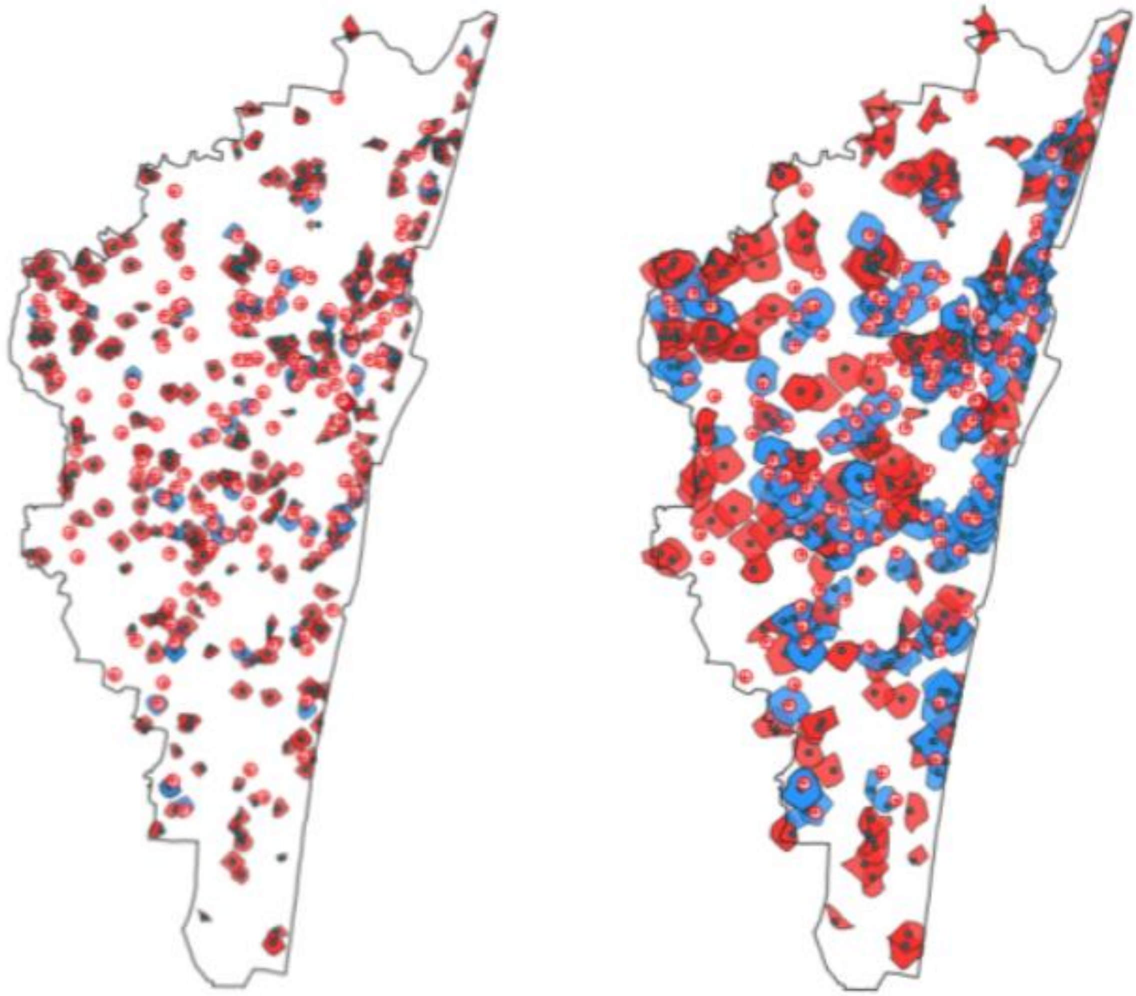

Figure 5: Slum settlements with road network-based buffers (or iso-areas) – ½ km (left) and 1 km (right)

6.4. Nearest Facility Analysis - Based on Euclidean

The Euclidean distance-based nearest facility analysis (Figure 6) reports that the settlements have their nearest UPHCs situated at an average distance of 0.7km. There are about 10 settlements, home to a population of about 6,000 that have their nearest UPHC at a distance farther than 3km. Of all the settlements, the ones in Uthandi (an area in Chennai) have their nearest UPHC at the highest distance of 6.3km. In Figures 6, 7, 9 and 10, the darker gradients of the spokes and routes indicate relatively longer distances.

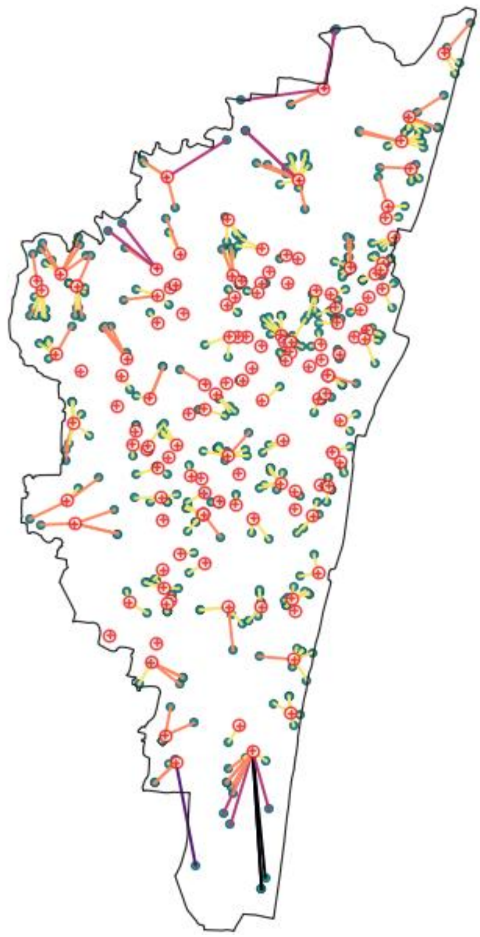

Figure 6: Nearest facility mapping based on Euclidean distance

The analysis yields the number of settlements and the slum dwellers residing therein, that are dependent on a particular UPHC. The assumption here is that the people would prefer to utilize the services at the facility closest to them. For example, if we consider UPHC Manali (a facility close to the city centre), we find that there are 15 slums (with a population of 5,796 residents) to which UPHC Manali is the closest facility as shown in Figure 7.

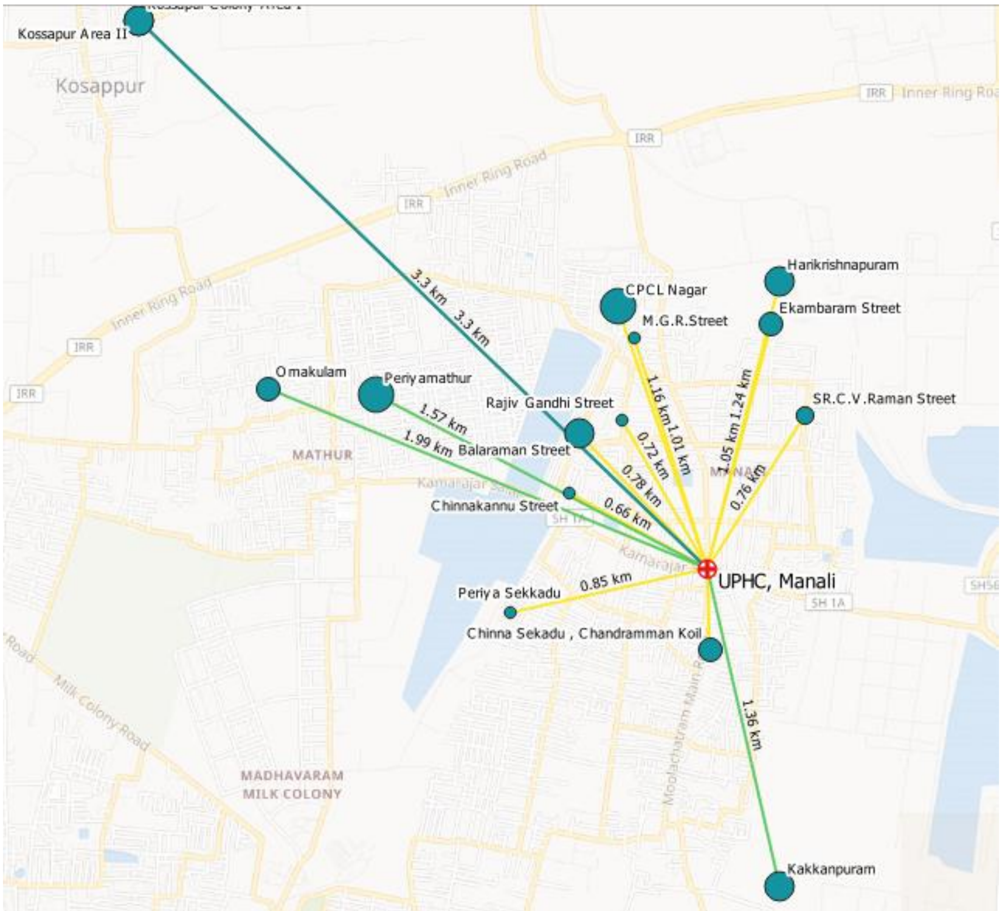

Figure 7: Slum settlements with UPHC Manali as their nearest UPHC

While conducting the nearest facility analysis, the limitations of using Euclidean distance were again highlighted as it assigned incorrect UPHCs to slum settlements. For example, the slum settlement in Bethel Nagar was assigned a UPHC in Kannagi Nagar which is situated at a distance of 0.75km (Figure 8). However, the canal separating the two and making them inaccessible to each other was not taken into consideration when using direct distance. When we add the road network, the assigned facility changes to UPHC Neelangarai which, while being 3.5 km from Bethel Nagar, is still more accessible to the slum than UPHC Kannagi Nagar. We next discuss the findings from a networked distance-based approach in more detail.

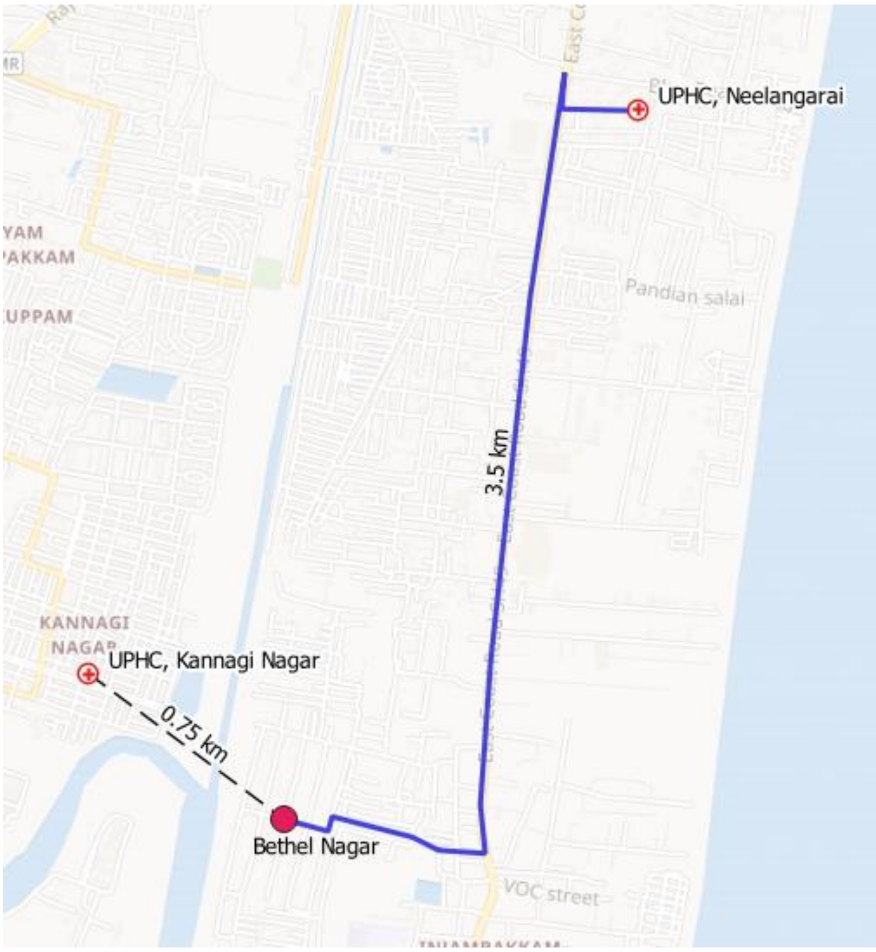

Figure 8: Showing mapping of Bethel Nagar to nearest facility based on both Euclidean distance and Networked distance

6.5. Nearest Facility Analysis - Based on road network distance

Using road networks in the nearest facility analysis where we mapped each slum to its nearest UPHC when measured along the road network (Figure 9), we found that a slum dweller has to travel an average distance of 1.5 km to reach their nearest UPHC. While this distance is close to the standard required by the government guidelines, the deviation from the average is considerable with many outliers. For instance, there are about 35 slum settlements with a population of over 30,000 residents travelling more than 3 km, i.e. about three times the prescribed distance, to access their nearest UPHC. In particular, residents of the slum in Panayur Kuppam have to travel the largest distance of 9.5 km followed by residents of Uthandi (8.7 km) and Nainar Kuppam (8.6 km).

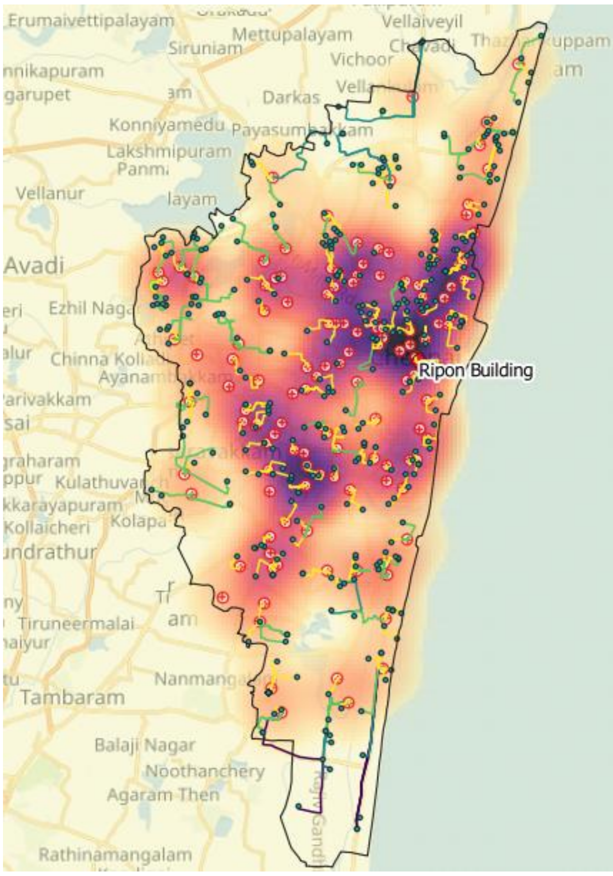

Figure 9: Fastest routes to the nearest UPHCs

On the other hand, when taking the facility as the origin, we find that the UPHC Manali has to cater to the residents of slums in Kossapur that are located 5 km away followed by Omakulam which is at a distance of 2.4 km from the facility (Figure 10).

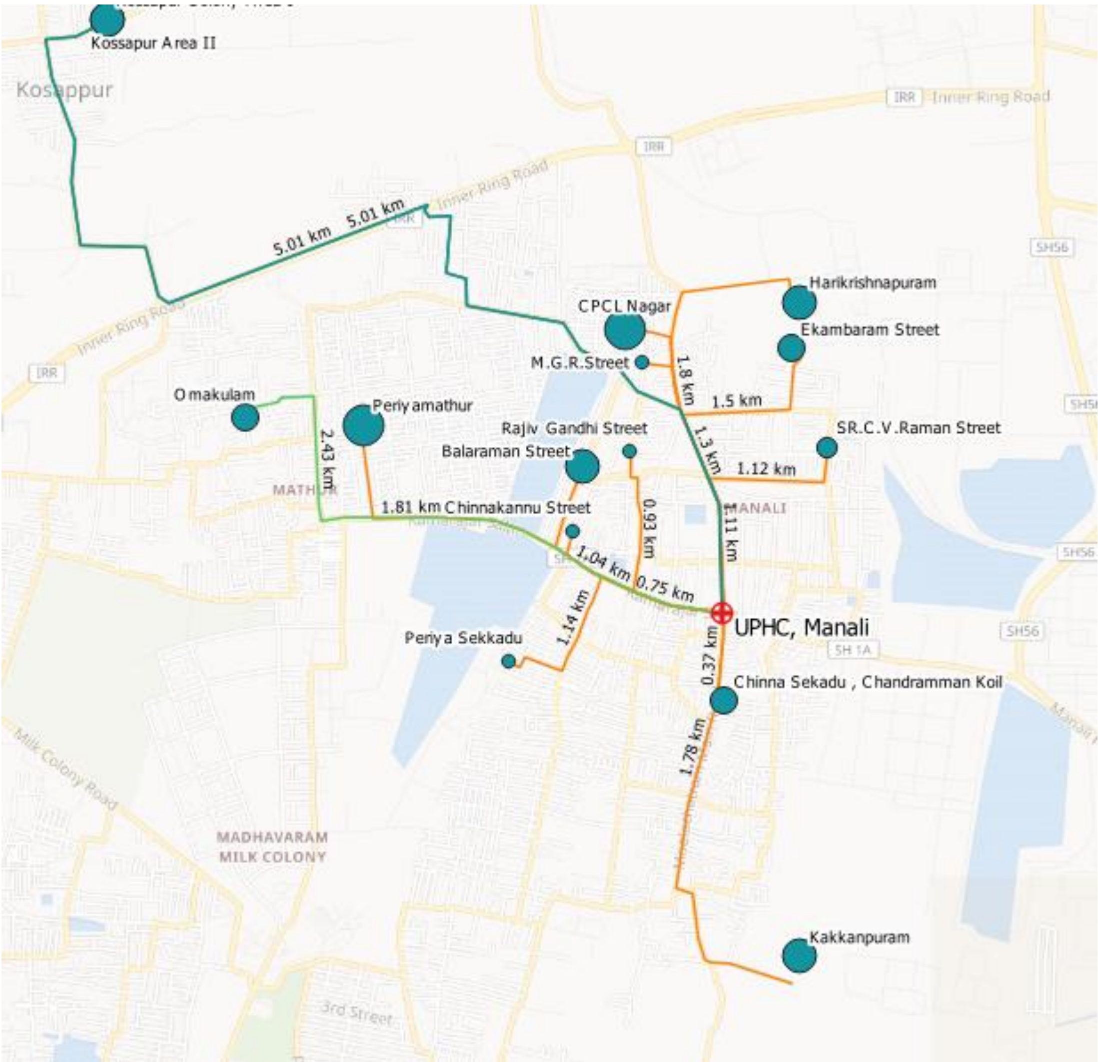

Figure 10: All settlements (in blue) that are dependent on UPHC Manali

7. Discussion and Policy Recommendations

The analysis conducted in this paper investigated the geographical factors of access (time and physical distance) to UPHCs that the urban poor have in Chennai. Local governments can use such models in a variety of ways to improve public health. In this section, we present some of the possible applications of these models. We also recommend the creation and maintenance of datasets that can make the models more insightful.

7.1. Rethinking coverage areas and planning outreach

In addition to quantifying the demand at each UPHC, as demonstrated in the nearest facility analysis sections, the facility planners and managers can use the techniques presented in this paper to rethink the geographical coverage areas or the catchment areas of the UPHCs in a city to factor in spatial accessibility from slums. This can ensure that none of the slums is missed out in the overall planning of primary healthcare services. Moreover, this can help plan travel and inform policy on providing mobility support to the settlements and to the health facilities for outreach workers such as Auxiliary Nurse Midwife (ANMs) and Accredited Social Health Activist (ASHAs). Outreach workers often travel to slums directly to cater to the needs of the residents. There have been instances in Chennai of outreach workers not being able to travel to such long distances due to uncovered travel costs or a lack of viable transport options (Times of India, 2019). Such challenges are true for outreach workers in other cities as well.

7.2. Catering to the nature of demand

The techniques presented in this paper can be developed further to optimise decision making by adding other relevant indicators at the ward/settlement level to understand the nature of demand and map vulnerabilities. As highlighted in the previous section, measuring access based on travel distance and time is useful in quantifying the situation faced by slum dwellers needing healthcare services. However, as mentioned earlier, decisions on healthcare are not only measured by travel time and distance but also by non-spatial factors such as quality of services. This can be seen in Figure 11 below where four UPHCs are within 1 km travel distance of a slum settlement. Such a situation negates the impact of distance with demand being driven by the kind and quality of services provided by each facility. Geurs and Van Wee (2004) outlined this as a 'competition measure' approach wherein decision-makers need to consider the presence of a competing facility when measuring access and making decisions on supply. Hence, data on health conditions, socio-economic profile, choice preferences for healthcare, mode of transport can be combined with this study and assessed at the facility level to control the quality of services including capacity and performance. To do this, the local government can overlay tabular data collected on each on a GIS portal using a slum household/slum area/ward, etc. as a geographical link between all the datasets collected.

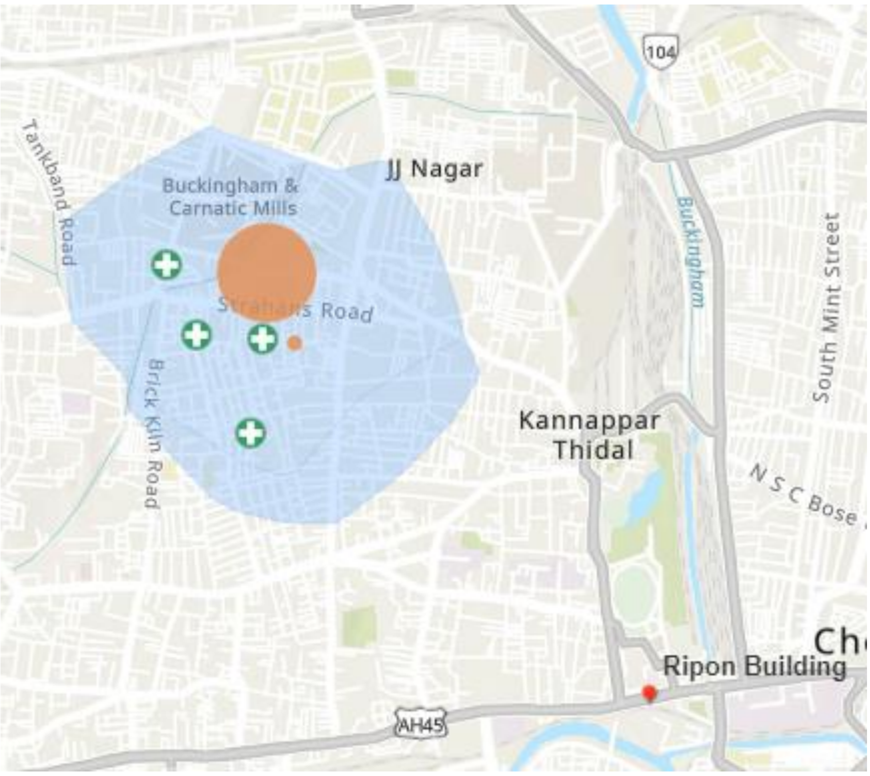

Figure 11: Iso Areas (blue polygons) of 1 km around slums (orange dots)

On the other hand, collecting and analyzing information on the health condition of the population living in slums, such as the percentage of the population with non-communicable diseases like diabetes, hypertension, anaemia, etc, maternal and infant health indicators and so on, will help understand the demand for health services. Behavioural indicators can help analyse the utilisation of UPHCs for the population living in their catchment area. Such statistics can be collected through carrying out periodic ward level household sample surveys.

7.3. Collecting and maintaining updated datasets

Decision-makers can use similar techniques to the one applied in this paper to map other healthcare facilities such as Urban Community Healthcare Centres (UCHCs) to get a holistic view of the network. Further, they can make such maps alongside related information on services provided publicly available to encourage innovation by citizens. For instance, an NGO could use the geocoded information to develop an application for slum dwellers to locate health facilities and provide real-time information on openings and availability of services. Finally, utilisation metrics of healthcare facilities can be tracked and aggregated up to the ward level to highlight patterns and trends. Some of the data can be based on the quality standards for the urban primary health centre framework devised under the NUHM guidelines of 2015. Information on the capacity of each facility (e.g. the number of beds, doctors, nurses, outreach health workers) along with the kinds of services delivered at each facility would help determine if the facilities are well equipped to deliver primary care as per the local health needs and overall coverage of health services in the region. The local authorities can work towards setting up a facility level reporting and monitoring system so that facilities can report updated information across metrics onto the platform.

New technologies and digital modes of data collection can facilitate the integration of data on access to health and the status quo of health among the population. However, this comes with obvious risks of infringing privacy. Care should be taken to ensure that privacy harms are minimised via relevant privacy protection techniques such as anonymisation. This is even more crucial in times of public health crises. Amidst the COVID-19 pandemic, studies discussed India's weakness in its health data collection system and approach when it came to following the virus' evolution in real-time (EPW Engage, 2020). For example, they pointed out the flaws (Daniyal, 2020) of the methodology used to monitor the aftermath of super-spreader events such as the Tablighi Jamaat event organised in Delhi in early March. Such instances also pose the question of privacy and personal data protection. The authors of this paper recently discussed geo-masking techniques that local governments can employ towards this end (Pachisia et al., 2021).

Well connected public transport is key to improving the utilisation of healthcare services by low-income vulnerable populations, especially those located > 5km from the nearest facility. Hence, the model should be applied to public transport stations vis-a-vis slum settlements. To achieve this, local governments would need to collect granular data on public transport, such as locations of bus stops and suburban train stations, transit routes, trip costs, and schedules. Doing so would help better understand the time and financial costs incurred by the populations in accessing various health services.

Finally, adding location and related information of quality and performance of private facilities can make the models more realistic. Research shows that citizens use private healthcare facilities around three times more than public ones (Rout et al., 2021). The government has slowly started publishing such datasets at the national level. However, we argue to develop such datasets at the city level (Parasa, 2020). This is particularly important for urban poor communities who choose to pay for private services rather than benefit from free public care.

With more data on the demand side and supply-side constraints, spatial methods can be further developed further to solve multiple objectives (Wang, 2018) of the health facilities network and to improve the overall planning of healthcare infrastructure in the cities. Moreover, beyond public health, such GIS-based models should be used to measure the spatial accessibility of other public service facilities such as fair price shops, public schools, and so on by target beneficiaries.

8. Limitations and Conclusion

8.1. Limitations

The study considers only urban primary healthcare centres, while there are other facilities such as urban community healthcare centres (UCHCs) that also provide some degree of primary healthcare services. These have not been included in the study. However, future studies using the models demonstrated in the study can include them with necessary modifications.

It's important to note that spatial access does not always translate to actual utilisation. For example, while the traversable route to the nearest facility could be only 3 km away, it might not have a public bus deployed, rendering the facility a less preferred option. Other factors such as financial affordability and quality of services also come into the picture. These factors are also not explored in the present study. Given these limitations, in addition to the data limitations, it's important to interpret the study and its findings as a methods paper useful for facility planning rather than a comprehensive spatial access assessment of healthcare for the city of Chennai.

Other limitations of the study include lack of primary research and lack of validation of the results of the models through ground-truthing. Also, the study hasn't been tested with facility planners or policy practitioners.

8.2. Conclusion

Studies in developing countries have widely explored spatial access to healthcare in specific and public amenities in general, in both urban and rural contexts. These studies do not differentiate the kind of provider (public/private) and the socioeconomic background of the target beneficiary or user. The present study looks at access to publicly funded health facilities with a focus on slum settlements. It is crucial to study this access for better facility planning and resource allocation by the government authorities to achieve healthcare access for all. The study demonstrates the use of four reproducible spatial analysis models using open source tools and scripts that can be deployed to study geographic access from slum settlements to UPHCs in the city of Chennai.

The study notes a considerable difference in findings between Euclidean distance and road network distance approaches and concludes that road network distance should be adopted for planning at the local level factoring in for the physical barriers on the ground. Some of the computational challenges involved in computing the road network distance can be overcome by utilising the open-source tools discussed in this paper in addition to the scripts accompanying the paper.

The buffer analysis reports that about half the sample slums have no reachable UPHC. The nearest facility analysis notes that while the average distance to the nearest UPHC is close to the prescribed distance of 1 km, there are a considerable number of slums where residents have to travel over three times the distance prescribed in the guidelines. The study also notes a positive correlation between the proximity of a slum to the city centre and its travel distance to the nearest health facility. The reasons for this correlation need to be further explored as they can have implications on the planning of facilities towards the periphery of the city. This is particularly relevant when the city's administrative limits are revised over time.

These methods can be utilised by facility planners and other decision-makers to identify slum settlements that are left out of the current network of primary healthcare services, including outreach services, offered in the city. They lend themselves as tools to better plan facilities and improve resource allocation accordingly. Finally, the methods should be utilised by researchers for replicating the study in other cities.

Appendix

The appendix of this paper is online. It can be accessed at:
https://github.com/rajesvariparasa/Measuring-Urban-Spatial-Access

References

Ananya Bhattacharya, qz.com. (2020, August 6). A mapping technology is helping India's healthcare sector in the fight against coronavirus. *Scroll.In*. https://scroll.in/article/968998/a-mapping-technology-is-helping-indias-healthcare-sector-in-the-fight-against-coronavirus

Barik, D., & Thorat, A. (2015). Issues of unequal access to public health in India. *Frontiers in public health*, 3, 245.

Bhojani, U., Thriveni, B. S., Devadasan, R., Munegowda, C. M., Devadasan, N., Kolsteren, P., & Criel, B. (2012). Out-of-pocket healthcare payments on chronic conditions impoverish urban poor in Bangalore, India. *BMC public health*, 12(1), 1-14.

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, 65, 126-139.

Comber, A. J., Brunsdon, C., & Radburn, R. (2011). A spatial analysis of variations in health access: linking geography, socio-economic status and access perceptions. *International journal of health geographics*, 10(1), 1-11.

COVID-19: Robust Collection of Health Data Will Ensure Better Health. (2021, January 12). *Economic and Political Weekly*. https://www.epw.in/engage/article/covid-19-robust-collection-health-data-will-ensure

Daniyal, S. (2020, April 7). Explained: Sampling bias drove sensationalist reporting around Tablighi coronavirus cases. *Scroll.In*. https://scroll.in/article/958392/explained-sampling-bias-drove-sensationalist-reporting-around-tablighi-coronavirus-cases

Delhi's Mohalla Clinics Hold the Potential to Significantly Improve. (2020, December 9). *Economic and Political Weekly*. https://www.epw.in/engage/article/delhi-mohalla-clinics-access-healthcare-poor-marginalised-residents

Esri India Technologies Private Limited. (n.d.). Esri India: GIS Mapping Software, Spatial Data Analytics & Location Platform. https://www.esri.in/en-in/home

Gandhi. (n.d.). Locating Nearest Facility with Origin-Destination Matrix (QGIS3) — QGIS Tutorials and Tips. *QGIS Tutorials and Tips*. Retrieved December 1, 2020, from https://www.qgistutorials.com/en/docs/3/origin_destination_matrix.html

Geurs, K. T., & Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 12(2), 127-140.

Hagberg, A., Swart, P., & S Chult, D. (2008). Exploring network structure, dynamics, and function using NetworkX (No. LA-UR-08-05495; LA-UR-08-5495). Los Alamos National Lab.(LANL), Los Alamos, NM (United States).

Heidelberg Institute for Geoinformation Technology. (2008). OpenRouteService [Software]. https://openrouteservice.org/

Higgs, G. (2004). A literature review of the use of GIS-based measures of access to health care services. *Health Services and Outcomes Research Methodology*, 5(2), 119-139.

Kanga, S., Meraj, G., Farooq, M., Nathawat, M. S., & Singh, S. K. (2020). Risk assessment to curb COVID-19 contagion: A preliminary study using remote sensing and GIS.

Mansour, S. (2016). Spatial analysis of public health facilities in Riyadh Governorate, Saudi Arabia: a GIS-based study to assess geographic variations of service provision and accessibility. *Geo-spatial Information Science*, 19(1), 26-38.

Martin, D., & Williams, H. C. (1992). Market-area analysis and accessibility to primary healthcare centres. *Environment and Planning A*, 24(7), 1009-1019.

Mayhew, L.D., Gibbard, R. W., & Hall, H. (1986). Predicting patient flows and hospital case-mix. *Environment and Planning A*, 18(5), 619-638.

Ministry of Health and Family Welfare, Government of India. (2015, December). Quality Standards for Urban Primary Health Centre. Retrieved 17th December 2021 https://www.nhm.gov.in/images/pdf/NUHM/Quality_Standards_for_Urban_Primary_Health_Centre.pdf

Ministry of Housing and Urban Poverty Alleviation, Government of India. (2015). Slums in India, A Statistical Compendium. http://www.nbo.nic.in/pdf/SLUMS_IN_INDIA_Slum_Compendium_2015_English.pdf

Open Source Routing Machine (OSRM). (n.d.). [Software]. http://project-osrm.org/

Pachisia, H., Gennaro, I., & Shah, K. (2021). Assessing geomasking techniques to protect the spatial privacy of individuals during COVID-19 and beyond. *Data Governance Network*. https://datagovernance.org/report/dgn-policy-brief-09-assessing-geomasking-techniques-to-protect-the-spatial-privacy-of-individuals-during-covid-19-and-beyond

Parasa, R. (2021). Status Quo of Spatial Datasets of Health Facilities in India. *IDFC Institute*. https://www.idfcinstitute.org/blog/2021/april/status-quo-of-spatial-datasets-of-health-facilities-in-india/

Patranabis, S., Gandhi, S., & Tandel, V. (2020). Are Slums More Vulnerable to the COVID- 19 Pandemic: Evidence from Mumbai. *Brookings* https://www.brookings. edu/blog/up-front/2020/04/16/are- slums- more- vulnerable- to- the- covid- 19- pandemic-evidence- from- mumbai/. Accessed April 28, 2020.

Raffler, C. (2018). QGIS Network Analysis Toolbox 3 [Software]. https://root676.github.io/

Resilient Chennai. Preliminary Resilience Assessment (n.d.)

Robin, T. A., Khan, M. A., Kabir, N., Rahaman, S. T., Karim, A., Mannan, I. I., ... & Rashid, I. (2019). Using spatial analysis and GIS to improve planning and resource allocation in a rural district of Bangladesh. *BMJ global health*, 4(Suppl 5), e000832.

Rout, S. K., Sahu, K. S., & Mahapatra, S. (2021). Utilization of health care services in public and private healthcare in India: causes and determinants. *International Journal of Healthcare Management*, 14(2), 509-516.

T. (2019, August 4). Chennai: Pregnant women made to visit primary health care centre for registration. *The Times of India*. https://timesofindia.indiatimes.com/city/chennai/pregnant-women-made-to-visit-primary-health-care-centre-for-registration/articleshow/70516953.cms

Wang, F. (2020). Why public health needs GIS: A methodological overview. Annals of GIS, 26(1), 1-12.

Wang, L., Shi, H., & Gan, L. (2018). Healthcare facility location-allocation optimization for China's developing cities utilizing a multi-objective decision support approach. Sustainability, 10(12), 4580.

Xu, Y., Olmos, L. E., Abbar, S., & González, M. C. (2020). Deconstructing laws of accessibility and facility distribution in cities. *Science advances,* 6(37), eabb4112.

Yenisetty, P. T., & Bahadure, P. (2020). Measuring Accessibility to Various ASFs from Public Transit using Spatial Distance Measures in Indian Cities. *ISPRS International Journal of Geo-Information*, 9(7), 446.

Zhu, A. X., Zhao, F. H., Liang, P., & Qin, C. Z. (2021). Next generation of GIS: must be easy. *Annals of GIS*, 27(1), 71-86.

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About the Authors

Rajeswari Parasa is a Senior Analyst at IDFC Institute who works on Data Science. Her interest lies in building open source tools for enhancing data-driven governance in Indian cities. Prior to joining IDFC Institute, Rajeswari worked as a Product Manager at a tech startup - Lakeer Foundation, where she worked on building open-source tools for visualising and interacting with city-data. She was an Urban Fellow at IIHS, Bangalore.

Harsh Vardhan Pachisia is a Senior Associate and leads the data science unit at IDFC Institute. His research focuses on topics of urban development, data science and governance. Prior to joining IDFC Institute, he worked as an Economics Teaching Fellow at the NYU Stern School of Business. Harsh has also been a Research Assistant to several NYU professors analysing topics such as ‘Shadow Banking around the World’ and ‘Social Media Entrepreneurship’.

Isalyne Gennaro is a Contributor at Helios.do. She was an Associate at IDFC Institute. Her research focused on urban development and public policy in India. Before joining IDFC Institute, she studied Indian land utilisation at HCP Design Planning and Management in Ahmedabad and worked on urban development regulations.