Estimating minimum travel time to emergency medical services in Nairobi, Kenya

Maya Fraser

A thesis
submitted in partial fulfilment of the requirements for the degree of
Master of Public Health

University of Washington
2017

Committee:
Herbie Duber, Chair
Abie Flaxman

Program Authorized to Offer Degree:
Global Health

© Copyright 2017
Maya Fraser

University of Washington

Abstract

Estimating travel time to emergency services in Nairobi, Kenya

Maya Fraser

Chair of the Supervisory Committee:

Associate Professor Herbert Duber

Global Health

Long travel times pose a barrier for those seeking emergency medical treatment in many developing countries. But little is known about travel times to facilities within cities and how this varies by type of facility and under different traffic conditions. The literature contains some estimates of travel times to emergency care, but most take place within a developed setting or are surveys that do not specify the origin of travel. Our study uses a network approach to calculate minimum travel times to different types of facilities in Nairobi, Kenya under both congested and uncongested traffic conditions. We find that higher-level facilities are much less accessible than low-level facilities and that those in poverty must travel slightly farther than the general population to reach care. We expect that this approach will provide policy-makers with granular geographic data to reduce travel times and improve access in Nairobi and other cities.

Contents

Introduction

Many people lack access to emergency healthcare in the developing world where burden of emergency conditions is the highest[1]. A recent study estimated median utilization rates of emergency care in high-income countries to be 33 times that of those in low income countries[1]. Access to healthcare is the product of many supply-side and demand-side factors, including financial accessibility, availability of care, acceptability of the services, and geographic accessibility[2]. To access care people need to know when and where they should seek it, be able to afford the care, and be able to reach a facility that is open, adequately-staffed, and offering needed services. Because the factors that lead to delays, e.g. knowledge, finances, transportation, are not evenly distributed across the population, certain vulnerable groups may be left without adequate access to care. This is especially true for those who are in poverty in low-and-middle income countries (LMICs). In LMICs, those in the highest economic quintile have significantly better coverage than those in the lowest quintile, with up to more than 100% better access depending on the service[2].

For emergency care, the speed at which care is obtained is very important in defining access. Because effective treatment for many emergency conditions, such as stroke, myocardial infraction, and trauma are time-sensitive, minimizing travel times is important in improving patient prognoses. The amount of time it takes to receive care can be examined through the "three delays" framework, which was originally developed in the context of maternal mortality[3]. In this framework, delay in service is broken down into the time it takes the patient or someone they know to decide to seek care, the time it takes to get to a facility that can provide appropriate care, and then the time it takes to actually receive needed services. The second delay is often discussed for rural patients who live far from facilities and may need to travel a long time over low-quality roads to reach care[4]. However, this delay can also be a problem in urban areas, where traffic congestion can make nearby facilities difficult to reach quickly. Poor street design, an increase in the number of cars on the roads, and a lack of active traffic management in many developing countries has left them particularly at risk for congestion[5].

In most low-income countries, delay due to congestion is compounded by lack of access to ambulances or other emergency transportation. When ambulances are available, they usually cannot provide any services besides transportation[6]. This is in contrast to many middle- and high-income settings where ambulances contain medical equipment and employ trained healthcare workers to help stabilize patients before they reach the hospital. These countries also usually do not have systems where traffic is halted to allow ambulances to move quickly. This results in many patients either traveling to emergency facilities in private or hired vehicles, or traveling in ambulances that are little better.

Little is known about how long patients spend waiting in traffic before they receive emergency care. In this paper we estimate travel times to care in Nairobi, Kenya under congested and uncongested traffic conditions. We break this down by different levels of care and public/private status, both important in the access to care model. If people are unable to access the level of care they need, or are not able to afford a private facility, access will be reduced. We also disaggregate by poverty status to see whether those in poverty have to travel longer to get to care.

Background

Nairobi is the capital city of Kenya. Its greater metropolitan area consists of Nairobi county and parts of the surrounding counties of Kiambu, Kajiado, and Machakos. Encompassing 700 square kilometers, Nairobi contains dense residential areas towards the center of the city, with a mix of industrial, agricultural, less dense residential, and scrubland areas towards the outer parts of the county[7]. The southern section of the city also contains Nairobi National Park, a large wildlife preserve.

Nairobi's population was estimated to have risen from 3.1 million in 2010 to 4 million in 2014, an increase of about one third. Infrastructure development has not kept up with the increased number of inhabitants and cars on the road, leading to congestion and long travel times. The cumulative number of registered vehicles increased from 1,297,520 in 2008 to 2,022,955 in 2012, a difference of 3/4 of a million vehicles, or 55.9%. In

2015, a traffic jam between Nairobi and Mombasa made headlines as cars sat unmoving on the highway for several days[8]. Within the city, the frequently occurring Mombasa road traffic jam has a Facebook page with over 6,000 check-ins[9].

Health facilities in Kenya are a mix of public and private. Public facilities are organized into Kenya Essential Packages for Health (KEPH) levels. Facilities potentially capable of handling emergencies would constitute levels 4 and above. Level 4 facilities are primary care hospitals, which should provide comprehensive services including surgery, but do not necessarily offer emergency care. Level 5, or secondary hospitals, should provide emergency services, including intensive care. Finally, level 6 facilities provide a full compliment of tertiary care services[10]. However, many facilities may fall short of the level of care that corresponds to their KEPH level. In a survey of facilities in Kenya, only 41% of the level 4 and level 5 public hospitals had an accident or emergency unit. Even those that do may not have necessary equipment - only 19% of level 4 and 5 public hospitals had access to an ultrasound, and none had access to a CT scan[11]. This lack of resources has led to a lack of access: of the 40 countries included in an emergency room utilization study by Chang et. al, Kenya had the lowest utilization rate[1].

As the capital of Kenya, Nairobi contains most of the high-capacity medical facilities in the country, with one public level 6 hospital, Kenyatta, and four level 5 facilities, one of which is public[12]. There is one non-profit ambulance service in Nairobi, St. John Ambulance and some private facilities also have ambulance services. However, most patients still arrive at facilities by private vehicle[13]. A recent qualitative study showed that only 14% of patients reached facilities by ambulance in urban Kenya, while 31% arrived by private vehicle, 20% by motorcycle, and 9% each by taxi or walking[14]. This lack of access to ambulances and the heavy burden of traffic make Nairobi the perfect setting to study the distribution of travel times to reach health facilities capable of providing various levels of emergency care.

Data Sources and Analysis Tools

We downloaded street network data from Open Street Map, an open-source database of street maps maintained by a global community[15]. Population data in 100m by 100m squares in 2015 and percent of the population below the poverty line at the 1km by 1 km square level in 2008 were obtained from the Afripop database[16][17]. Road network data were stored in a PostgresSQL database hosted on a Docker container created using the pamtrak06/postgis-pgrouting-osm Docker file[18]. Docker is a platform that allows users to create lightweight virtual machines[19]. PostgreSQL is an open-source relational database system that uses the SQL language[20]. The Open Street Maps network dataset was converted to a query-able geographic database using PostGIS and pgrouting, extensions to PostgresSQL that allow databases to store geographic data and use algorithms to do different types of routing[21][22]. Database queries, data analysis, and data visualizations were performed using R. We used the RPostgreSQL package to query PostgresSQL databases, the raster package to manipulate raster data, and MapSuite to select color palettes.

Facility data were downloaded from the Kenyan Ministry of Health Website[12]. We selected Level 4, 5, or 6 facilities that were in Nairobi, or the surrounding counties of Kiambu, Machakos, or Kajiado. We included facilities from surrounding counties in the event that those were the closest facilities for those living on the edge of Nairobi county. We excluded specialty facilities, e.g, maternal, eye, mental, or those that were only dispensaries or only saw outpatients. This left us with 70 facilities to consider as part of the analysis. See Figure 2 for facility locations and Appendix Table 2 for the complete list with additional information.

The shapefile for Nairobi was downloaded from the Kenyan Elections portal via the Humanitarian Data Exchange.[23]

Methods

Using the network data from Open Street Maps, we created a queryable geographic database, consisting of vertices and edges that correspond to intersections and streets. Because Nairobi lacked speed limit information

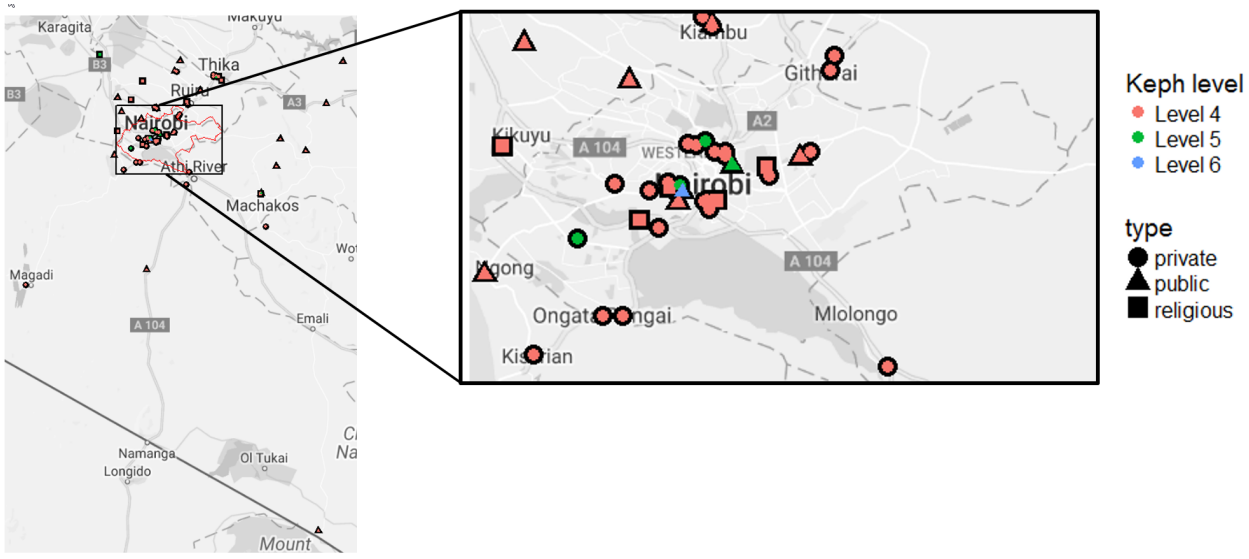

Figure 1: Facilities included in the analysis by level and type

for most streets, we assigned speeds for both uncongested and congested traffic using the speeds suggested by Avner and Lall(see Appendix Table 1)[24]. Speed limits that *were* available in the data set were used unless they exceeded the maximum of motorway speed of 110 km/hour. For congested speeds in roads not covered by Avner and Lall, we used 2/3 of the uncongested speed.

We created a grid of 0.5 x 0.5 km squares to use as samples, resulting in 2903 sample points throughout the city of Nairobi. This size was selected because it could both show variation over small areas and was computationally manageable. For each grid square centroid we found the nearest node in the traffic network and the nodes nearest to each of the 70 facilities. Then we calculated the minimum time between each center node and each facility node using Dijkstra's algorithm, where cost was the time it took to travel down each edge.

Due to inconsistencies in the traffic network data, such as disconnected nodes or closed street loops, we ended up with a small number(.4%) of missing values, which were interpolated using simple kriging. This resulted in raster for each facility that contained travel times to that facility.

To examine the percentage of the population within a certain travel time of a facility, we aggregated the Afripop population dataset to be the same size squares as our sample grid. Then we resampled to align the grids, and scaled to maintain the same overall population total. We followed a similar process for the percent of the population below the poverty line (see figure 2 for the resulting rasters). Combined, these two rasters allowed us to calculate number of people living in each section of the grid, and the number of them living below the poverty line.

Results

We calculated congested and uncongested driving times to facilities level 4 and above for 2903 points across the city of Nairobi, disaggregated by facility type. Results from this analysis are presented in Figure 3. In the text we will refer to facilities 4 and above as L4+, facilities level 5 and above as L5+ facilities, and level 6 facilities as L6 facilities. We examined the distribution of travel times over the population, disaggregated by poverty status (see Figure 6). Because there are fewer facilities at KEPH levels 5 and 6, travel times were faster to L4+ facilities than they were to L5+, and L6 facilities. We also found that those in poverty had to travel slightly longer to reach facilities for all facility levels. In congested conditions, the average person would travel 9.2 minutes to reach a L4+ facility, increasing to 14.7 minutes for a L5+ facility, and

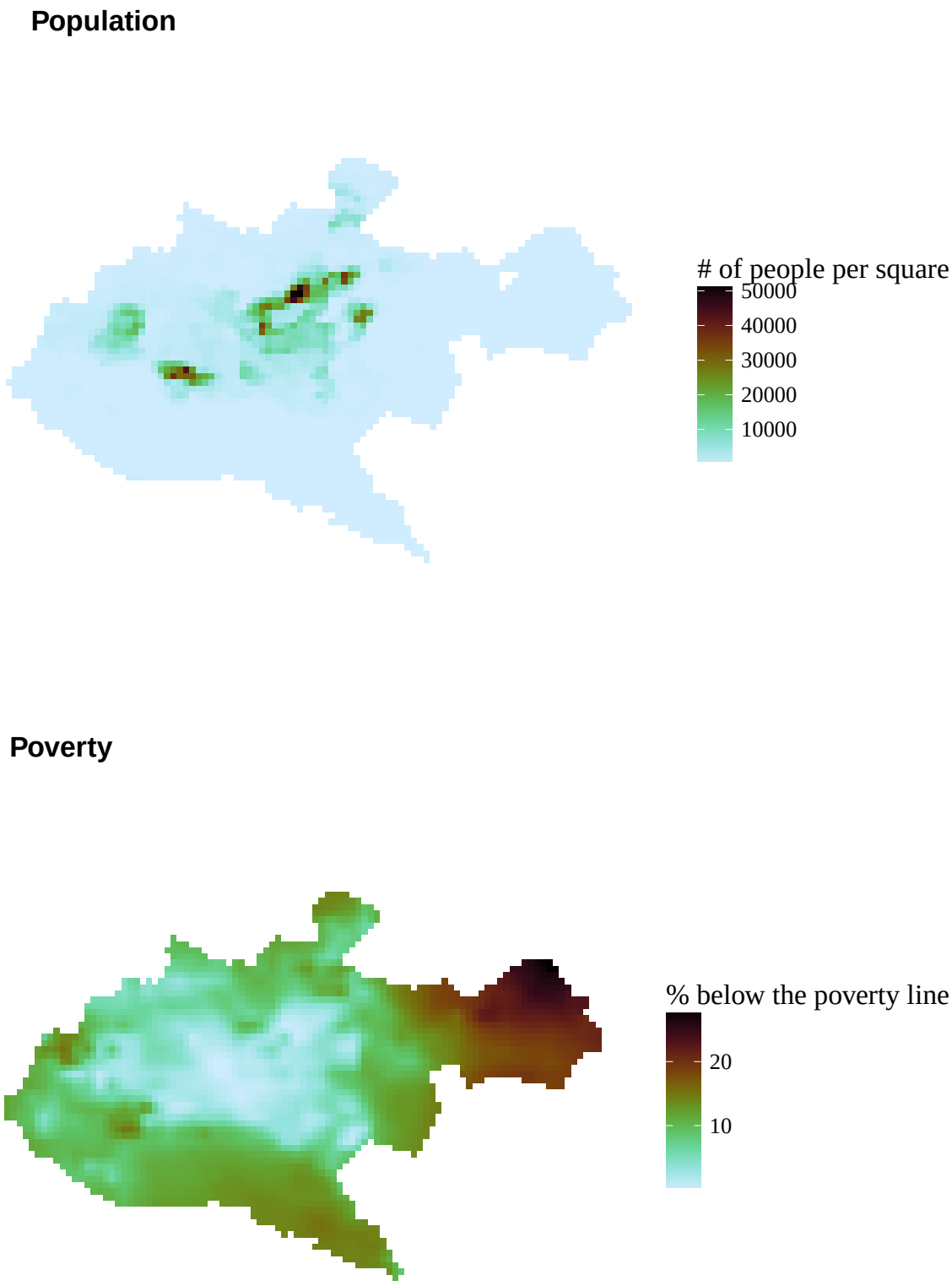

Figure 2: Raster data of population and poverty, sampled to travel time raster

22.7 minutes to reach the L6 facility. For those in poverty, the average travel time to reach a facility was 11.1 for L4+, 17.5minutes for L5+, and 25.3 minutes for L6.

We also disaggregated by owner of facility (public or religious, and private) and found that it takes longer for people to get to public and religious facilities as compared to all facilities. This comparison is only make for L4+ and L5+ facilities because there is only one L6 facility (public). Though the difference is relatively modest, the effect is compounded for those in poverty (see figure 4). While an average person in the population would travel an average of 12.4 minutes to reach a public or religious L4+ facility, someone in poverty who can only afford to go to a public or religious facility would travel an average of 15.2 minutes. This average travel time for a person in poverty going to public and religious facilities represents an increase of 65% over an average member of the population who could travel to private L4+ facilities. For people traveling to public/religious L5+ facilities, the average time is 16 minutes for the population overall and 19.5 minutes for those in poverty, making an increase of 51.3% over someone not in poverty who can visit any L5+ facility.

Most locations in Nairobi are within a half hour drive of a facility in uncongested conditions, with a maximum drive time of 33.9 minutes for L4+ facilities, and 41.9 minutes for both L5+ facilities and L6+ facilities. Across the area of the city, 68.7% of sample points were within 10 minutes of a L4+ facility, 88.6% were within 20 minutes, and 95% were within half an hour. For the L6 facility, 15% of sample points were within 10 minutes, 70.5% were within 20 minutes, and 88.8% were within half an hour.

Under congested conditions times were longer, with 34.6% of points within 10 minutes, 71.3% within 20 minutes, 86% within half an hour, and 94% within an hour for L4+ facilities. Travel times under congested conditions for the L6 facility were significantly longer, with only1.7% of points within 10 minutes of the facility, 16.7% within 20 minutes, 51.7% within half an hour, and 89.2% within an hour. Figure 5 shows the difference between congested travel and uncongested travel for each square. Across the sample points, congestion slowed traffic by an average of 9 minutes for L4+ facilities, 13.1 minutes for L5+ facilities, and 16.3 minutes for the L6 facility.

Discussion

We created a raster of minimum travel times to facilities across the city of Nairobi by finding optimized routes through the road network from Open Street Maps. A very similar approach was used by Lee et. al for a study of travel times to eye care in the United States Medicare population[25]. There are alternative methods for doing such an analysis, including a raster-based method, where the area of study is broken into squares, and each square takes a certain amount of time to cross. Delamater et. al compared raster-based and network-based methods and recommended that network-based methods be used for travel times for vehicles, which must travel on the road network, as opposed to foot travel[26]. Due to our interests in travel by vehicle and a small geographic area, we decided to use a network-based approach. For more work on travel times using raster based data, see the work of Dan Weiss with the Malaria Atlas Project[27].

Our results show a wide variation in travel times within the city. While most people are able to reach lower level facilities in a relatively short amount of time, this is not true for the higher-level facilities that have the capacity to treat severe emergencies. These results should be viewed as the *minimum* total travel time because people do not always travel to the facility with the lowest travel time, and they may not take the most efficient route. Our findings are consistent with the Access, Bottlenecks, Costs, and Equity (ABCE) Kenya report, which found that for national/provincial hospitals, around 40% of patients traveled less than an hour and about 38% traveled between half an hour and an hour[11].Though our study was limited to estimating travel times for those living within the confines of Nairobi, their study was not, which explains why a small minority traveled more than 2 hours to reach care.

These travel times are much longer than those in developed countries. A meta-analysis of prehospital times, defined as all time spent before reaching the hospital, in the US found a an average of 30.96 minutes in urban areas for the entire prehospital time, including response time, time at the scene, and travel time[28]. Travel times themselves were an average of 10.77 minutes for urban areas. In our study, the average *minimum* travel

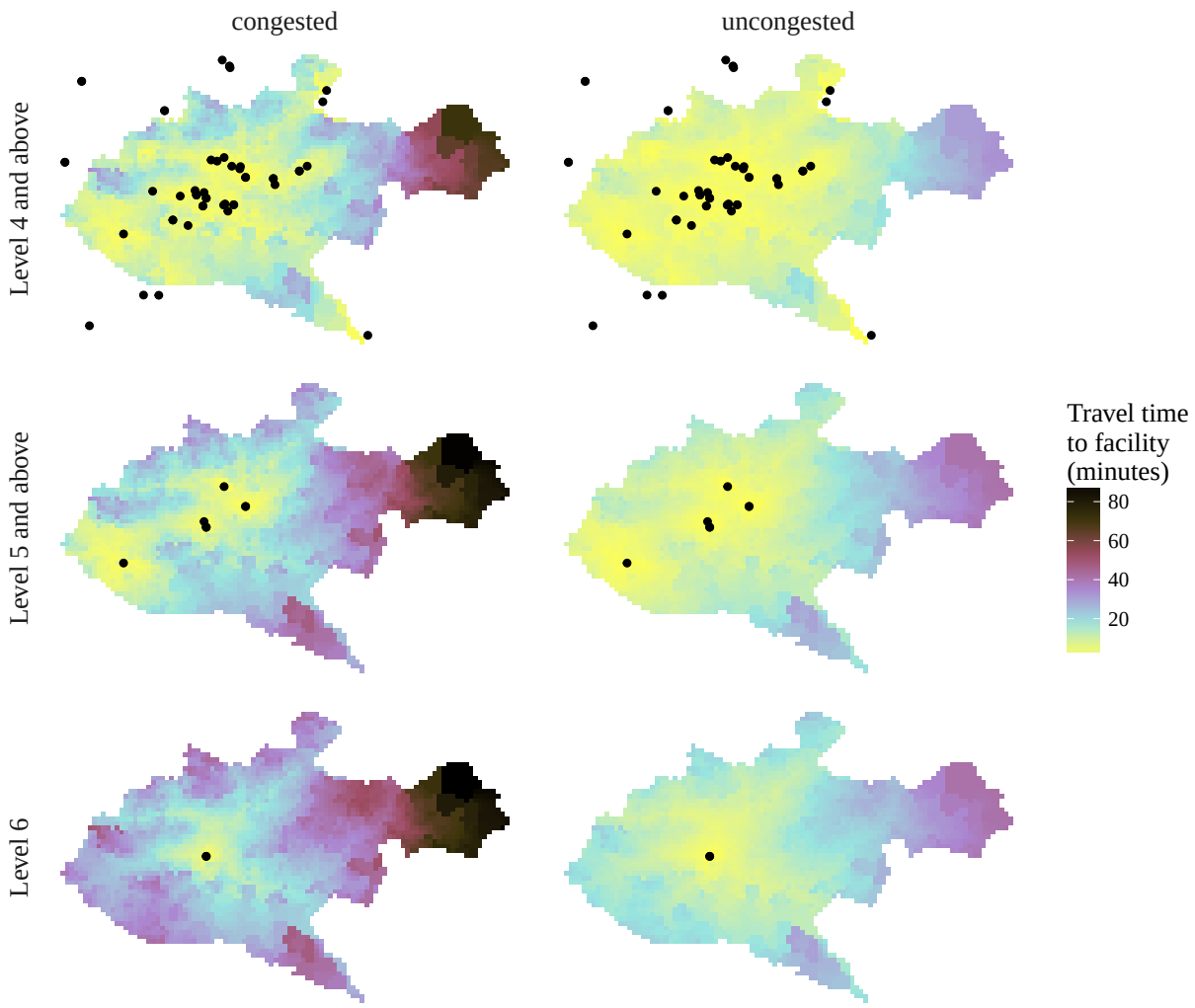

Figure 3: Time to a facility by type of facility under congested and uncongested conditions

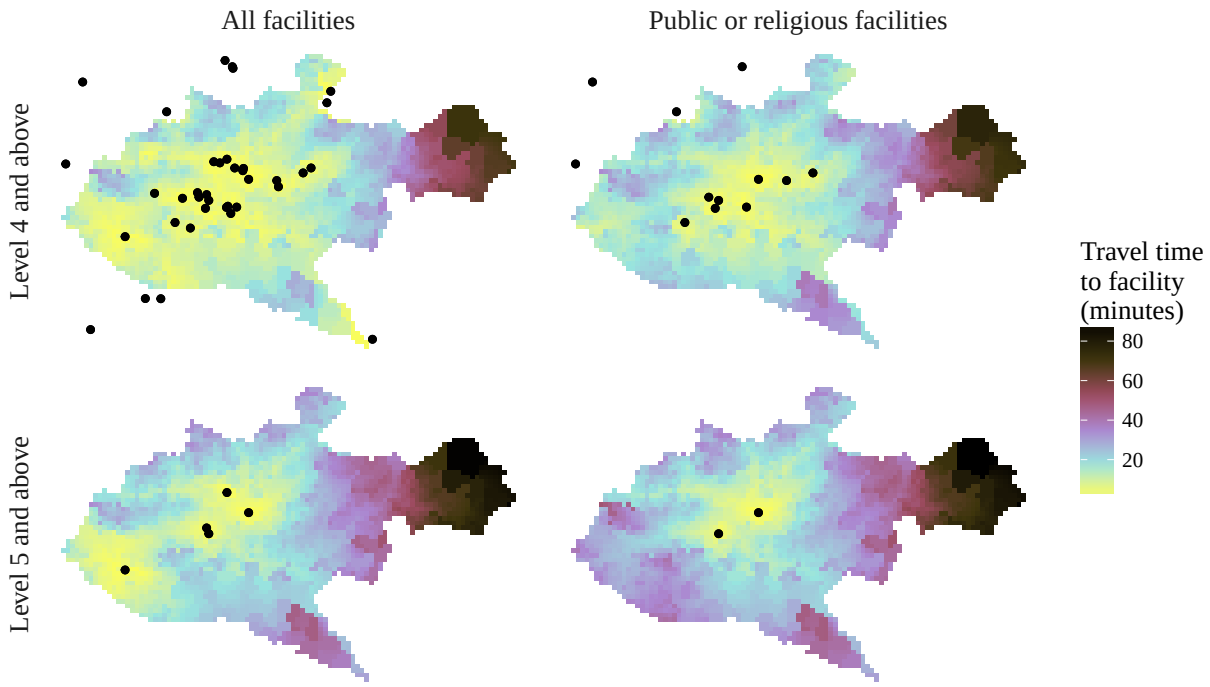

Figure 4: Time to a facility under congested conditions, by facility owner

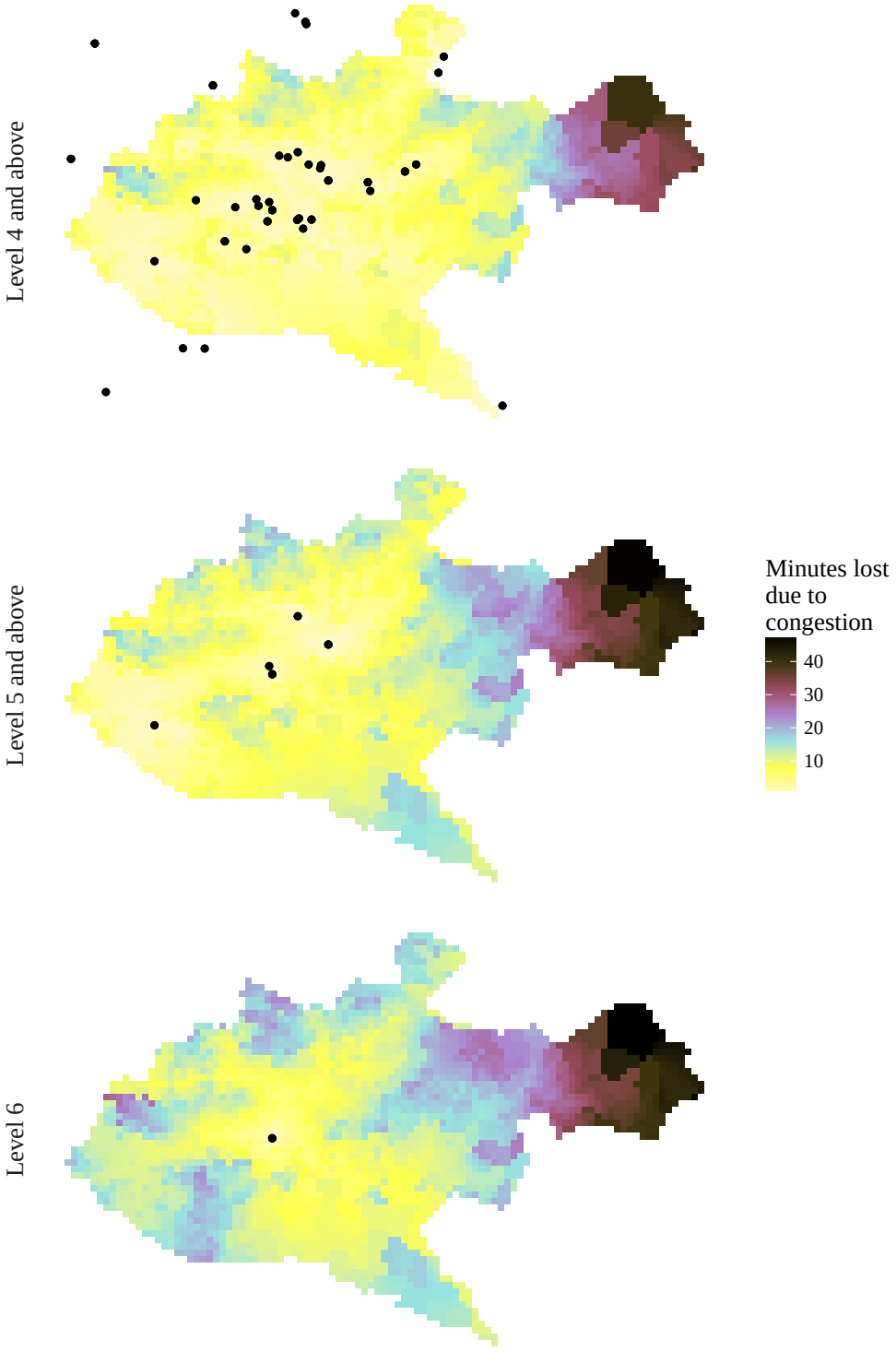

Figure 5: Minutes lost due to congestion by type of facility

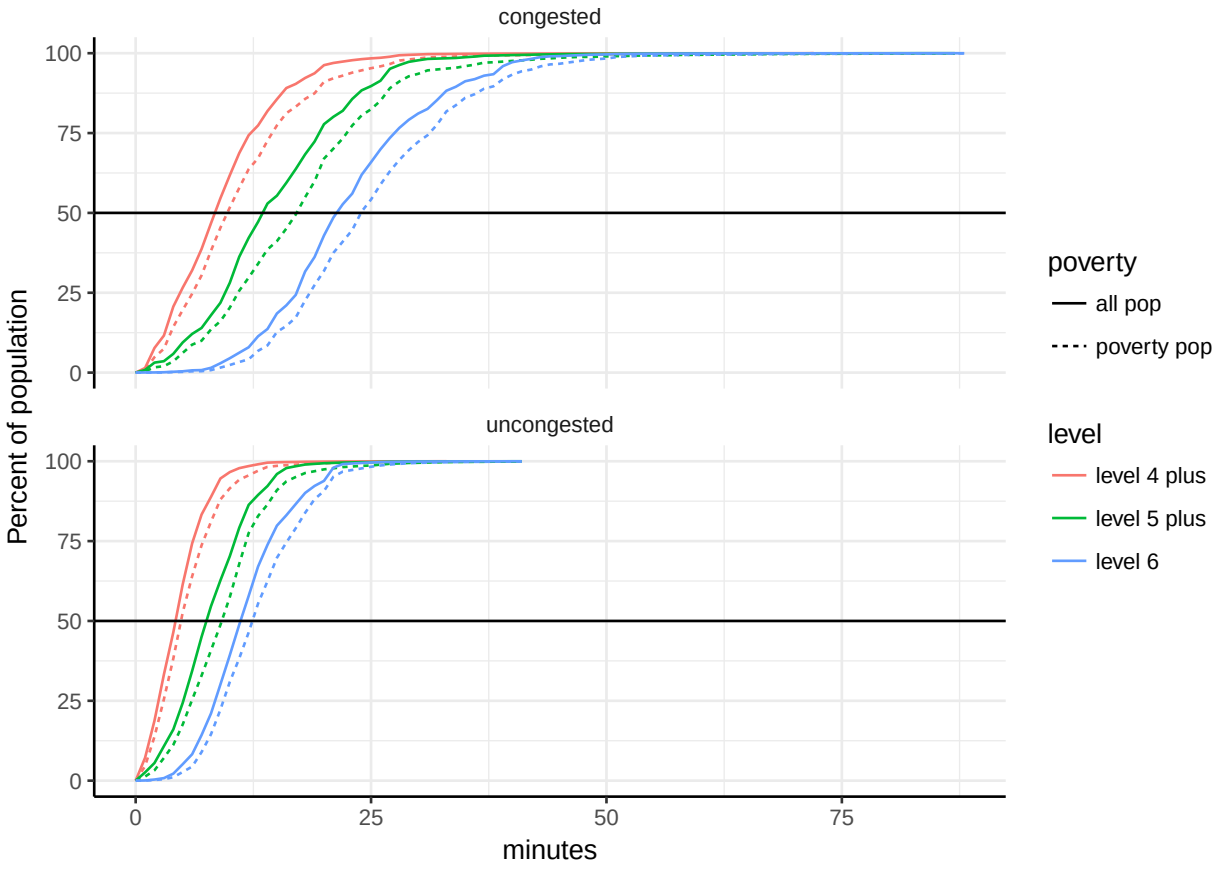

Figure 6: Percent of population living within X minutes of a facilitiy, by type of facility, poverty status, and congestion

time under uncongested conditions to the L6 facility, was 11.6 in uncongested traffic and 22.7 in congested, over twice that of those observed in the US. However, we do see shorter travel times to get to L4+ facilities. Under congested conditions, patients had an average minimum travel time of 9.2 minutes, and without congestion this was reduced to only 4.5 4.5 minutes.

We also found that there were differences in travel times between public or religious and all facilities, especially among those in poverty. Previous research suggests that Kenyans are more likely to seek care at public facilities due to cost considerations, despite the fact that they are less likely to have emergency capacity and have longer wait times[14]. The poor face a double burden of living further away from facilities and not being able to afford facilities that may be close by. This means that the poor may have to travel 50-60% longer on average than a wealthy person who could go to any facility. This is unsurprising given previous evidence that they poor often lack basic access to services[2].

Thes long estimated travel times have potential to cause excess mortality due to the delay of care, though the magnitude of this effect is difficult to determine. Much of the current literature on prehospital time was conducted in developed settings and is concerned with comparing treatment on the scene to immediate transport to a facility. Prehospital time in developed countries often includes medical care in some form, while prehospital time in developing countries does not. However, a recent article that examined the effect of delays in time to care due to road closures for marathons in the United States could give a possible lower bound[29]. The authors analyzed the mortality from patients with cardiac arrest or myocardial infarction on marathon and non-marathon days. They found that mortality rates on marathon days were 13.3% higher than mortality rates on non-marathon days. Though travel times in ambulances were only 4.4 minutes shorter on marathon days, delays were much more substantial for those patients who arrived in private vehicles, approximately 23% of the sample. Those who arrived in private vehicles are in some ways a good proxy to understand those with emergencies in Kenya, though they on average would have access to better treatment when they did arrive at an emergency facility.

Outcomes after trauma may also be affected by time to treatment, though direct evidence is sparse. A recent meta-analysis of the effects of pre-hospital time for trauma patients concluded that shorter response and transit times were probably beneficial, but that longer on-scene time was associated with better survival[30]. This study highlights the fact that it is difficult to compare the effects of prehospital time in developed and developing settings, as most of the studies included were conducted in the United States. In Nairobi, there is little opportunity for treatment during the prehospital period, so the study findings might not be very applicable. An older study of severely injured trauma patients in the Canada found an odds ratio of 3.0 associated with prehospital times greater than 60 minutes[31]. The lack of relevant literature underscores the need for more research examining the relationship between travel times and outcomes in a developing setting.

Several different interventions could reduce the burden of long travel times. Potentially the most effective would be a centralized ambulance system that is available to all. This approach would allow people of all socio-economic classes to access care quickly. It would also be advantageous from a systems perspective, as drivers could communicate with hospitals about where to take patients. Currently, people must make a choice of where to go even if they plan to use an ambulance service from a private facility. Smaller facilities especially may have very little information available online, as we discovered during our process of geolocating facilities. Thus, patients may not know what the most appropriate facility is for their type of emergency, and they certainly do not know if there are long wait times or stock-outs. Having a coordinated ambulance system would allow patients to make more informed decisions and get the care that they need.

Such a system could also be implemented with controls to reduce traffic congestion around the ambulance. In the United States, "move over" laws require drivers to clear a path for ambulances, allowing them to travel faster. Though such an approach may not be feasible in the Kenyan context, it might be possible to use police officers in key positions to stop traffic and let ambulances through, which has been used in other urban contexts. Though there are many benefits of an ambulance system, it is unclear how cost-effective it would be. Both the cost of the system and the health benefits are under-studied. One study estimated that such a system would cost upwards of one million USD per year[32].

Though time spent in traffic can be a significant barrier to accessing care, it is important to remember that it is but one among many. In the qualitative study of community views of emergency medicine in Kenya by the

African Federation for Emergency Medicine, the low quality of the emergency care system was cited the most times as an obstacle, with transportation difficulties being cited the second-most[14].Other barriers included the attitudes and quality of healthcare workers, and poor care at the scene of an accident. The top three changes participants would make in the emergency care system were improving health care providers, better transportation/more available clinics, and emergency training for the community. Because our results showed that most people had quick access to L4+ facilities, one option would be to strengthen the capacity of these facilities to handle emergencies or to stabilize patients for transfer to hospitals with a higher level of care. Some countries have experimented with training laypeople to act as emergency first responders, or simply educating them on what steps to take in an emergency, including who to call for help. While this would not reduce travel times, it would help to stabilize people with some conditions before travel, and reduce the amount of time before someone receives any medical care. It could also be a cost-effective intervention, with an estimated 600 USD cost per life saved[32].

Limitations

This study is subject to several limitations in terms of data availability and methods used. Most important was the lack of real data on traffic speeds on individual roads. Without such data, our estimates are based on an assumed distribution of speeds during uncongested and congested periods. Traffic conditions are constantly changing, so it seems likely that at some points in time speeds could be lower than in our congested scenario. We also assumed speeds based on types of road in the Open Street Maps database, though Nairobi has a specific pattern of traffic where certain streets are often more congested than others. For example, certain locations, such as the Pushorttam Place, Barclays Plaza, and other act as common choke-points, but our model did not give special consideration to these edges and nodes[5].

Though we had originally planned to use a directed graph, where one-way streets are taken into account, poor data quality in local streets meant that many routes had no solution, causing the algorithm to get "trapped" in a circle of one way streets. Due to this limitation in the data quality, we chose to use an undirected graph, where all streets could be traveled in either direction. This most likely led to an underestimate in travel time because our algorithm could always use the most convenient streets, even if they were one-way. Finally, we did not take into account time taken at stoplights or slowing down to turn. As such, the estimates in this paper should be considered to be minimum possible travel times.

Conclusion and directions for the future

This study estimated travel times to facilities in Nairobi using a network approach. We found that congestion caused major delays in arriving at a facility, with times ranging up to half an hour under uncongested conditions and more than an hour under congested conditions. Parts of the city not on major highways gained up to 20-30 minutes of travel time when traffic was congested. Low-level facilities were much more accessible than high-level facilities, with a lower mean travel time across the population. We also found that poor people were slightly further away from facilities than the population overall.

These findings demonstrate a need for faster transportation to emergency services. Potential solutions include a centralized ambulance system, providing lower level facilities with more emergency capacity, and using policemen to stop traffic on crowded streets. Because previous studies suggest that time before treatment has an important impact on outcome in many emergency conditions, these interventions have the potential to save many lives.

Future evidence is needed on the role of pre-hospital time on health outcomes in a developing setting. Because little research exists, it is difficult to determine the cost-effectiveness of our suggested interventions. Combining that data with the results of our study would allow researcher to quantify both the human toll of long traffic times and the cost-effectiveness of improving access.

Finally, more data collection concerning road speed would allow further calibration of these models to achieve better time estimates. Working with private companies, such as Google, who have traffic speed data for different times of the day and levels of congestion, would show the full range of travel times. To aid in further use of our method, either in Nairobi or elsewhere, we have provided full access to our code, data, and database setup, along with a technical appendix (See Appendix B) describing the implementation. As the interest in emergency services in developing countries grows, we hope that this will be a useful tool in bringing access to more people.

Appendix A: Additional figures

Table 1: Open Street Maps road types and assigned speeds

OSM road type	Speed uncongested (km/hour)	Speed congested (km/hr)	Percent of edges
unclassified	50	33	40.26
residential	30	12	35.41
service	50	33	7.25
tertiary	30	12	6.69
road	50	33	5.22
secondary	40	16	4.9
living_street	20	13	1.83
trunk	110	73	1.5
primary	60	30	0.99
motorway	110	73	0.42
trunk_link	110	73	0.26
motorway_link	110	73	0.21
tertiary_link	30	12	0.1
primary_link	60	30	0.1
secondary_link	40	16	0.08
motorway_junction	110	73	0

Table 2: Facilities used in the analysis

Name	KEPH level	Facility type	Owner	Beds	Cots	County	Lat	Long
Radiant Group of Hospital (Kiambu)	Level 4	Primary care hospitals	Private Practice - General Practitioner	13	2	KIAMBU	-1.165	36.82
Nazareth Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	184	84	KIAMBU	-1.136	36.73
Eddiana Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	0	0	KIAMBU	-1.206	36.92
Central Memorial Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	31	2	KIAMBU	-1.035	37.08
Immaculate Heart of Mary Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	0	0	KIAMBU	-1.04	37.09
Plainsview Nursing Home	Level 4	Basic primary health care facility	Private Practice - General Practitioner	0	0	KIAMBU	-1.155	36.96

Name	KEPH level	Facility type	Owner	Beds	Cots	County	Lat	Long
Kihara Sub-District Hospital	Level 4	Primary care hospitals	Ministry of Health	84	0	KIAMBU	-1.215	36.77
Caritas community hospital (Hospital)	Level 4	Secondary care hospitals	Private Practice - General Practitioner	25	5	KIAMBU	-1.04	37.09
Holy Family Mission Hospital Githunguri	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	45	3	KIAMBU	-1.059	36.77
St Judes Nursing Hospital	Level 4	Primary care hospitals	Private Practice - Medical Specialist	10	0	KIAMBU	-1.017	36.91
Mercylight Hospital	Level 4	Primary care hospitals	Private Practice - General Practitioner	16	3	KIAMBU	-1.173	36.83
Naidu Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	55	55	KIAMBU	-1.029	37.07
Jkuat Hospital	Level 4	Primary care hospitals	Ministry of Health	12	0	KIAMBU	-1.097	37.01
Mary Help of The Sick Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	60	22	KIAMBU	-1.04	37.09
Kikuyu (PCEA) Hospital	Level 4	Primary care hospitals	Other Faith Based	218	6	KIAMBU	-1.266	36.67
Kahawa Wendani Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	12	2	KIAMBU	-1.195	36.93
St Mulumba Mission Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	80	0	KIAMBU	-1.055	37.1
Nyathuna Sub District Hospital	Level 4	Primary care hospitals	Ministry of Health	10	3	KIAMBU	-1.186	36.68
Igegania Sub-District Hospital	Level 4	Primary care hospitals	Ministry of Health	14	2	KIAMBU	-0.9739	36.93
Gatundu District Hospital	Level 4	Secondary care hospitals	Ministry of Health	162	11	KIAMBU	-1.015	36.91

Name	KEPH level	Facility type	Owner	Beds	Cots	County	Lat	Long
Kalimoni Hospital (Thika)	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	29	6	KIAMBU	-1.144	36.96
Tigoni District Hospital	Level 4	Secondary care hospitals	Ministry of Health	62	20	KIAMBU	-1.128	36.67
Thika Nursing Home	Level 4	Primary care hospitals	Private Enterprise (Institution)	35	6	KIAMBU	-1.04	37.07
Ruiru Sub-County Hospital	Level 4	Hospitals	Ministry of Health	46	0	KIAMBU	-1.145	36.96
Kiambu District Hospital	Level 4	Secondary care hospitals	Ministry of Health	289	33	KIAMBU	-1.171	36.83
Universal Family Health Services(Machakos)	Level 4	Secondary care hospitals	Private Practice - General Practitioner	0	0	MACHAKOS	-1.525	37.27
Shalom Community Hospital (Athi River)	Level 4	Primary care hospitals	Private Practice - General Practitioner	150	10	MACHAKOS	-1.436	36.97
Shalom Community Hospital (Machakos)	Level 4	Primary care hospitals	Private Practice - General Practitioner	170	0	MACHAKOS	-1.561	37.29
Kathiani District Hospital	Level 4	Secondary care hospitals	Ministry of Health	188	3	MACHAKOS	-1.413	37.33
Mwala Subcounty Hospital	Level 4	Secondary care hospitals	Ministry of Health	18	2	MACHAKOS	-1.349	37.45
Kangundo District Hospital	Level 4	Secondary care hospitals	Ministry of Health	174	32	MACHAKOS	-1.299	37.35
Bishop Kioko Catholic Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	125	13	MACHAKOS	-1.527	37.26
Matuu District Hospital	Level 4	Secondary care hospitals	Ministry of Health	40	10	MACHAKOS	-1.152	37.54
Masinga Sub County Hospital	Level 4	Secondary care hospitals	Ministry of Health	24	8	MACHAKOS	0.9772	37.61
Nairobi Womens Hospital Adams	Level 4	Primary care hospitals	Private Enterprise (Institution)	0	0	NAIROBI	-1.299	36.78

Name	KEPH level	Facility type	Owner	Beds	Cots	County	Lat	Long
Guru Nanak Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	38	0	NAIROBI	-1.27	36.83
St Mary's Mission Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	299	0	NAIROBI	-1.323	36.77
KOMAROCK MODERN HOSPITAL UTAWALA	Level 4	Primary care hospitals	Private Enterprise (Institution)	50	18	NAIROBI	-1.27	36.91
Juja Road Hospital (Nairobi)	Level 4	Primary care hospitals	Private Enterprise (Institution)	6	0	NAIROBI	-1.272	36.84
Lad Nan Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	8	0	NAIROBI	-1.27	36.84
Mama Lucy Kibaki Hospital - Embakasi	Level 4	Secondary care hospitals	Ministry of Health	112	12	NAIROBI	-1.274	36.9
Metropolitan Hospital Nairobi	Level 4	Primary care hospitals	Private Enterprise (Institution)	46	8	NAIROBI	-1.288	36.87
Melchezedek Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	20	4	NAIROBI	-1.294	36.75
Langata Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	20	0	NAIROBI	-1.328	36.79
Meridian Equator Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	54	0	NAIROBI	-1.308	36.82
Nairobi West Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	152	0	NAIROBI	-1.307	36.83
Mp Shah Hospital (Westlands)	Level 4	Primary care hospitals	Private Enterprise (Institution)	0	0	NAIROBI	-1.263	36.81
The Mater Hospital Mukuru	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	166	42	NAIROBI	-1.308	36.83
Jamaa Mission Hospital	Level 4	Primary care hospitals	Kenya Episcopal Conference-Catholic Secretariat	63	8	NAIROBI	-1.282	36.87

Name	KEPH level	Facility type	Owner	Beds	Cots	County	Lat	Long
Nairobi South Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	23	0	NAIROBI	-1.314	36.83
Mbagathi District Hospital	Level 4	Secondary care hospitals	Ministry of Health	200	10	NAIROBI	-1.309	36.8
Avenue Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	65	10	NAIROBI	-1.265	36.82
Nairobi Womens Hospital (Hurlingham)	Level 4	Primary care hospitals	Private Enterprise (Institution)	0	0	NAIROBI	-1.294	36.8
Coptic Hospital (Ngong Road)	Level 4	Primary care hospitals	Christian Health Association of Kenya	60	0	NAIROBI	-1.298	36.8
Thika Level 5 Hospital	Level 5	Comprehensive Teaching &Referral	Ministry of Health	265	24	KIAMBU	-1.042	37.08
Machakos Level 5 Hospital	Level 5	Comprehensive Teaching &Referral	Ministry of Health	375	57	MACHAKOS	-1.524	37.27
The Karen Hospital	Level 5	Primary care hospitals	Private Practice - General Practitioner	102	0	NAIROBI	-1.336	36.73
Pumwani Maternity Hospital	Level 5	Primary care hospitals	Ministry of Health	350	150	NAIROBI	-1.281	36.85
Aga Khan Hospital	Level 5	Primary care hospitals	Private Practice - General Practitioner	243	0	NAIROBI	-1.261	36.82
Nairobi Hospital	Level 5	Primary care hospitals	Private Enterprise (Institution)	350	100	NAIROBI	-1.295	36.81
Kenyatta National Hospital	Level 6	Comprehensive Teaching &Referral	Ministry of Health	1455	427	NAIROBI	-1.301	36.81
AIC Kijabe Hospital	Level 5			NA	NA		-0.9476	36.59
Clay Hill Hospital	Level 4	Primary care hospitals	Private Enterprise (Institution)	30	0	KAJIADO	-1.427	36.69
Nairobi Women Hospital Ongata Rongai	Level 4	Primary care hospitals	Private Practice - General Practitioner	77	20	KAJIADO	-1.396	36.75

Name	KEPH level	Facility type	Owner	Beds	Cots	County	Lat	Long
St Paul's Hospital	Level 4	Primary care hospitals	Private Practice - General Practitioner	5	0	KAJIADO	-1.487	36.96
Mariakani Cottage Hospital Ongatta Rongai	Level 4	Primary care hospitals	Private Enterprise (Institution)	10	1	KAJIADO	-1.397	36.76
Magadi Hospital	Level 4	Primary care hospitals	Company Medical Service	40	0	KAJIADO	-1.903	36.29
Loitokitok District Hospital	Level 4	Secondary care hospitals	Ministry of Health	75	10	KAJIADO	-2.925	37.5
Ngong Sub-District Hospital	Level 4	Primary care hospitals	Ministry of Health	25	3	KAJIADO	-1.365	36.65
Kajiado District Hospital	Level 4	Secondary care hospitals	Ministry of Health	138	4	KAJIADO	-1.842	36.79

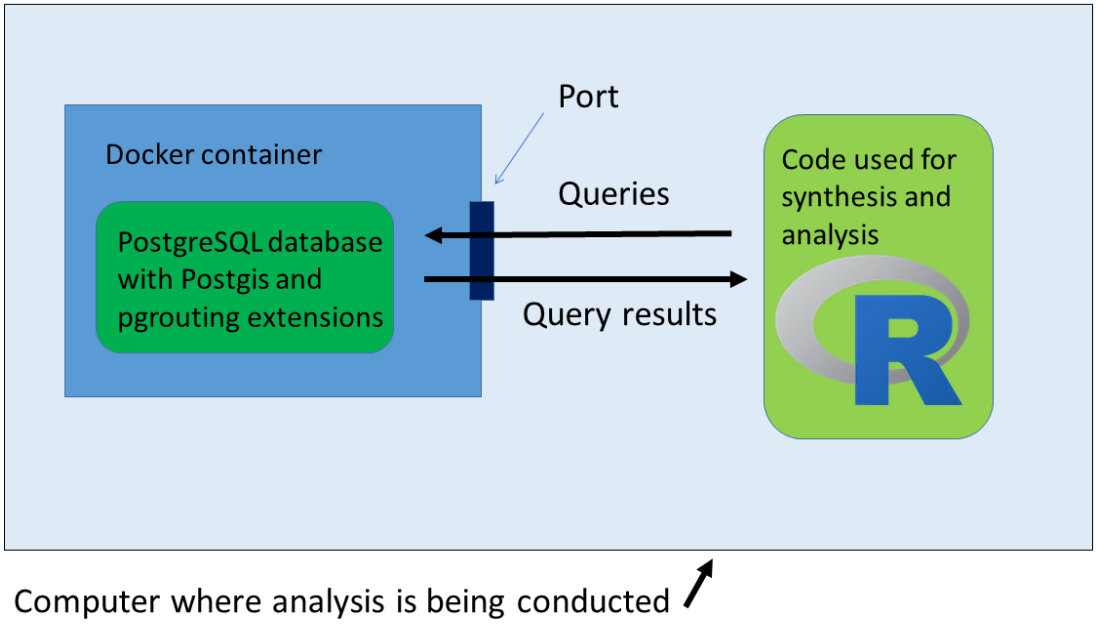

Figure 7: Components of the analysis set-up

Appendix B: Technical details of the network analysis set-up

This technical appendix will discuss how to reproduce our results, or modify our set-up for other analyses.

Schema

We hosted a PostgreSQL database in a Docker container to store our geographic data. A Docker container is a lightweight virtual machine that is usually created for a particular purpose. Docker is desirable in this situation because it allows anyone to use the same set-up, regardless of operating system. It is also easy to share Docker set-ups through Dockerhub, allowing complete replicability of the environment. Once set up correctly, the system should operate as in Figure 5. The database will be hosted in a Docker container on your computer. You can then connect to the container through a port and query the database using SQL commands. We used R to pass in commands, but you could also use another language, such as Python, or interact directly with the database using a database management program such as pgAdmin.

Setting up the Docker container

The first step is to download Docker. You could host the Docker container on a server if you want, but these instructions go over how to set one up on your local machine. On Windows, you will either use Docker for Windows or Docker Toolkit, based on the age of your operating system. Though these should operate in mostly the same way, how you connect to them via a port is different - more on this later. Download whichever program you are using and go through the install process. The default set-up is fine. When you have installed Docker, open either the program or a terminal (Mac). It may take a few minutes for it to set up.

Download the code associated with this project and clone it into a directory. This will be referred to as CODE_DIR. It also contains a configuration file "mapconfig_for_cars_custom.xml", which provides default speeds for when the Open Street Maps data is converted into a database. Changing this file is one way to change the speeds that people can travel down edges in the street map.

Download the Open Street Map data we used, or use your own road network file. In this tutorial we will use the file "Nairobi_final.osm". The folder these are stored in will be referred to as DATA_DIR. We based our set-up on a Docker image created by user pamtrak06. The Docker container is created using the following command, where we create a container named "your_container" and copy over our data and code functions into that directory. We tell it that we the password for the PostgreSQL database is "mysecretpassword" and that we want to use port 5432 to connect to the container. Finally, we tell it that we want to use pamtrak06's postgis-pgrouting-osm container as our image.

```
docker run --name your_container -v DATA_DIR:/data -v \
    CODE_DIR/open_street_maps/sql_functions:/functions \
    -e POSTGRES_PASSWORD=mysecretpassword -d -p 5432:5432 \
    pamtrak06/postgis-pgrouting-osm
```

Once you run that line, you should have a container called "your_container". You can check this by running the following command in the Docker command line:

```
docker ps -a
```

You should see output with your container listed.

Setting up the database

Once you have successfully created a container, you can create the database. The image automatically creates a database called "postgres", but we will create our own with a different name for the sake of clarity. The following line creates a database called "your_db". In general "docker exec" executes a command within an existing container. In this case, we are using psql, the command line utility for PostgreSQL, to create the database.

```
docker exec your_container psql -U postgres -c 'CREATE DATABASE your_db'
```

Once the database is created, you can run the following commands to add PostGIS and pgrouting capabilities to the database and load in our custom SQL functions:

```
docker exec your_container psql -U \
      postgres your_db -c 'CREATE EXTENSION postgis'
docker exec your_container psql -U \
      postgres your_db -c 'CREATE EXTENSION pgrouting'
docker exec your_container psql -U \
      postgres your_db -c "\i '/functions/geog_functions.sql'"
```

Then we convert our Open Street Map data into the "your_db" database that we just created. pgRouting has a utility, "osm2pgrouting", that makes this very easy to do. It uses a configuration file, "mapcon-

fig_for_cars_custom.xml", that determines how speeds are assigned when they are not present in the original dataset. In our scenario, these are the speeds that are used for uncongested conditions. It will take about 30 seconds for the dataset to be converted and put into the database if you are using the Nairobi file.

```
docker exec your_container osm2pgrouting -f /data/Nairobi_final.osm -d your_db -U \
    postgres -c /functions/mapconfig_for_cars_custom.xml #
```

To create congested speeds, we create new congestion costs (seconds it takes to travel down that edge) variable and update it so that it is 50% higher than the uncongested speeds. We then set custom congested speeds for specific categories discussed in the literature.

```
docker exec your_container psql -U postgres your_db -c \
    'UPDATE ways SET cost_s_cong = length_m/1000*3600/30 WHERE maxspeed_forward=60'
docker exec your_container psql -U postgres your_db -c \
    'UPDATE ways SET cost_s_cong = length_m/1000*3600/16 WHERE maxspeed_forward=40'
docker exec your_container psql -U postgres your_db -c \
    'UPDATE ways SET cost_s_cong = length_m/1000*3600/12 WHERE maxspeed_forward=30'
```

Querying from the database

The database should now be set up for you to query. If you are using Docker for Windows or Docker for Mac, you can connect using the address "localhost". If you are using Docker Toolkit, the Docker container has its own IP address that you must use to connect. You can use the following command to find the IP address:

```
docker-machine ip
```

Set the port to 5432, and you should be connect using the password "mysecretpassword" that was set above. To see the code we used to query the database in this study, please see the code 02_query_postgres_db.R. See the README included in the code for more information.

References

1 Chang CY, Abujaber S, Reynolds TA, Camargo CA, Obermeyer Z. Burden of emergency conditions and emergency care usage: New estimates from 40 countries. *Emergency medicine journal: EMJ* 2016; **33**: 794–800.

2 Peters DH, Garg A, Bloom G, Walker DG, Brieger WR, Hafizur Rahman M. Poverty and Access to Health Care in Developing Countries. *Annals of the New York Academy of Sciences* 2008; **1136**: 161–71.

3 Barnes-Josiah D, Myntti C, Augustin A. The 'three delays' as a framework for examining maternal mortality in Haiti. *Social Science & Medicine (1982)* 1998; **46**: 981–93.

4 Munjanja SP, Magure T, Kandawasvika G. Geographical Access, Transport and Referral Systems. In: Hussein J, McCaw-Binns A, Weber R, eds. Maternal and Perinatal Health in Developing Countries. CAB International, 2012.

5 Jain V, Sharma A, Subramanian L. Road Traffic Congestion in the Developing World. In: Proceedings of the 2Nd ACM Symposium on Computing for Development. New York, NY, USA: ACM, 2012: 11:1–11:10.

6 Kobusingye OC, Hyder AA, Bishai D, Hicks ER, Mock C, Joshipura M. Emergency medical systems in low- and middle-income countries: Recommendations for action. *Bulletin of the World Health Organization* 2005; **83**: 626–31.

7 Munene E. County Statistical Abstract 2015. Kenya National Bureau of Statistics. 2017; published online June. https://www.knbs.or.ke/county-statistical-abstract/ (accessed June 13, 2017).

8 Poon L. You Don't Want to Be Stuck in Kenya's 3-Day, 30-Mile Traffic Jam. CityLab. http://www.citylab.

com/commute/2015/11/a-3-day-30-mile-traffic-jam-stalls-kenya/417060/ (accessed June 28, 2017).

9 Mombasa Road Traffic Jam. https://www.facebook.com/pages/Mombasa-Road-Traffic-Jam/392020814164517 (accessed June 28, 2017).

10 Wachira B, Martin IBK. The state of emergency care in the Republic of Kenya. *African Journal of Emergency Medicine* 2011; **1**: 160–5.

11 Fullman N. Health Service Provision in Kenya: Assessing Facility Capacity, Costs of Care, and Patient Perspectives. The Institute for Health Metrics; Evaluation; Action Africa Help-International, 2014 http://www.healthdata.org/policy-report/health-service-provision-kenya-assessing-facility-capacity-costs-care-and-patient (accessed Aug 5, 2017).

12 Kenya Master Health Facility List: Find all the health facilities in Kenya. http://kmhfl.health.go.ke/#/facility_filter/results (accessed March 10, 2017).

13 Nairobi Region. St John Ambulance Kenya. 2015; published online Aug. http://stjohnkenya.org/index.php/nairobi-region/ (accessed March 21, 2017).

14 Broccoli M, Calvello E, Skog A, Wachira B, Wallis L. Community-based perceptions of emergency care in Kenya: The African Federation for Emergency Medicine, 2015 https://www.umaryland.edu/media/umb/global-local/documents/Kenya-Report_Final_paper.pdf (accessed Aug 7, 2017).

15 OpenStreetMap. OpenStreetMap. https://www.openstreetmap.org/ (accessed July 25, 2017).

16 Tatem A, Gething P, Bhatt S, Weiss D, Pezzulo C. Pilot high resolution poverty maps. 2013.

17 Tatem AJ. AfriPop Africa Under-Five Year Old Population Distribution Data 2015. 2013; published online July.

18 pamtrack06. Postgis-pgrouting-osm. Docker Hub. https://hub.docker.com/r/pamtrak06/postgis-pgrouting-osm/ (accessed July 25, 2017).

19 Docker Toolkit. Docker. https://www.docker.com/ (accessed July 20, 2017).

20 PostgreSQL. https://www.postgresql.org/about/ (accessed July 29, 2017).

21 pgRouting. http://pgrouting.org/ (accessed July 20, 2017).

22 PostGIS: Spatial and Geographic objects for PostgreSQL. http://postgis.net/ (accessed July 20, 2017).

23 Kenya Admin Boundaries - Election Polling stations - Humanitarian Data Exchange. https://data.humdata.org/dataset/kenya-elections (accessed April 10, 2017).

24 Avner P, Lall S. Matchmaking in Nairobi: The Role of Land Use. 2016; published online Dec.

25 Lee CS, Morris A, Van Gelder RN, Lee AY. Evaluating Access to Eye Care in the Contiguous United States by Calculated Driving Time in the United States Medicare Population. *Ophthalmology* 2016; **123**: 2456–61.

26 Delamater PL, Messina JP, Shortridge AM, Grady SC. Measuring geographic access to health care: Raster and network-based methods. *International Journal of Health Geographics* 2012; **11**: 15.

27 Weiss DJ, Nelson A, Gibson H *et al.* Mapping inequalities in accessibility: A global assessment of travel time to population centers in 2015. *(In Review).*

28 Carr BG, Caplan JM, Pryor JP, Branas CC. A Meta-Analysis of Prehospital Care Times for Trauma. *Prehospital Emergency Care* 2006; **10**: 198–206.

29 Jena AB, Mann NC, Wedlund LN, Olenski A. Delays in Emergency Care and Mortality during Major U.S. Marathons. *New England Journal of Medicine* 2017; **376**: 1441–50.

30 Harmsen AMK, Giannakopoulos GF, Moerbeek PR, Jansma EP, Bonjer HJ, Bloemers FW. The influence

of prehospital time on trauma patients outcome: A systematic review. *Injury* 2015; **46**: 602–9.

31 Js S, A L, Ji W, Ds M, M K. Impact of on-site care, prehospital time, and level of in-hospital care on survival in severely injured patients. *The Journal of trauma* 1993; **34**: 252–61.

32 Hsia RY, Thind A, Zakariah A, Hicks ER, Mock C. Prehospital and Emergency Care: Updates from the Disease Control Priorities, Version 3. *World Journal of Surgery* 2015; **39**: 2161–7.