Developing open source tools to estimate accessibility to healthcare

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1. Summary

One of the primary ways in which population access to healthcare can be evaluated is through the calculation of travel time required to reach available health facilities. Here, we have developed an R script that constructs customisable and high-resolution friction surfaces capable of estimating travel times required to traverse any given landscape. We then constructed a friction surface using a ~64 km^2 rural area of Northern Malawi, south-eastern Africa, and carried out a number of cost-distance analyses to calculate minimum travel times required to reach available health facility locations according to open source health facility data. Proportions of the population within this area residing within pre-defined time-boundaries (e.g., < 30 minutes, < 1 hour, etc) of the closest-proximity health facility were then quantified using open source human population density data and estimated proportions were compared depending on where health facility data was obtained. In addition, we also compared estimated proportions to those generated when using an alternative friction surface within the same geographical area.

2. Introduction

To progress toward universal health coverage throughout sub-Saharan Africa, health systems must be optimised through rigorous evaluation and modification. One of the primary ways in which population access to healthcare can be evaluated is through the calculation of travel time required to reach available health facilities[1]. This can be done by downloading or constructing friction surfaces that contain estimates of travel costs (time) required to travel through gridded cells of a given spatial resolution, e.g., 1 km x 1 km, within a Cartesian plane[2].

Using friction surfaces, cost-distance analyses can be carried out that calculate the 'least-cost' (i.e., shortest time) to reach each cell within the friction surface from a point of origin (e.g., the closest-proximity health facility). By then incorporating human population data, proportions of the population residing within pre-defined time-boundaries (e.g., < 30 minutes, < 1 hour, etc) of the closest-proximity health facility can be quantified.

Here, we have developed an R script that uses open source data to construct friction surfaces at a high spatial resolution of 30 m × 30 m that also allows the end user to define on- and off-road (on-foot) travel speeds according to expected travel conditions and circumstances. Our objective is to provide an open source, straightforward-to-use and customisable means of constructing high-resolution friction surfaces capable of estimating travel times required to traverse any given landscape with a high degree of accuracy.

To demonstrate our approach, we constructed a friction surface using a ~64 km^2 rural area of Northern Malawi (Figure 1). Using our friction surface, we then carried out cost-distance analyses to calculate minimum travel times required to reach available health facility locations according to open source health facility data obtained from three independent databases. Proportions of the population residing within pre-defined time-boundaries of the closest-proximity health facility were then quantified using open source human population data and estimated proportions were compared depending on where health facility data was obtained. In addition, we also compared estimated proportions to those generated when using an alternative friction surface developed by the Malaria Atlas Project.

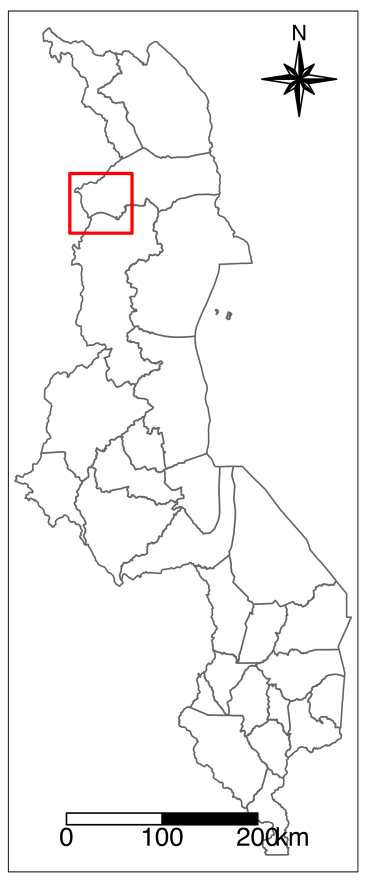

Figure 1. Study area of interest highlighted in red: a ~64 km^2 rural area of Northern Malawi.

3. Methods

Construction of friction surface

- Using R[3], the area of interest is defined
- Open source road network data (major and minor roads) are obtained from OpenStreetMap[4] database
- Landsat-8 satellite data[5] (obtained using Google Earth Engine[6]) is then used to create a Normalised Difference Vegetation Index (NDVI)[7]
- Expected on-road travel speeds are specified for major and minor road types
- Expected off-road (on-foot) travel speeds are specified according to type and density of vegetation (as estimated using NDVI values)
- Using these data, the friction surface is constructed

Cost-distance analyses and human population data

- Health facility location data obtained from a WHO database[8], the healthsites.io database[9] and the Master Health Facility Registry of Malawi database[10]
- Each independently overlayed onto friction surface
- Cost-distance analyses carried out to calculate cumulative travel time to closest-proximity health facility
- Proportions of the population residing within pre-defined travel time boundaries estimated using open source population data obtained from the WorldPop database[11]

Comparison

- Population estimates according to each health facility dataset compared
- Population estimates also compared to those generated using an alternative friction surface developed by the Malaria Atlas Project[12]

4. Results

No health facility data was obtained from the healthsites.io database, whereas health facility location data for 8 and 13 health facilities was obtained from the WHO and Master Health Facility Registry of Malawi databases, respectively.

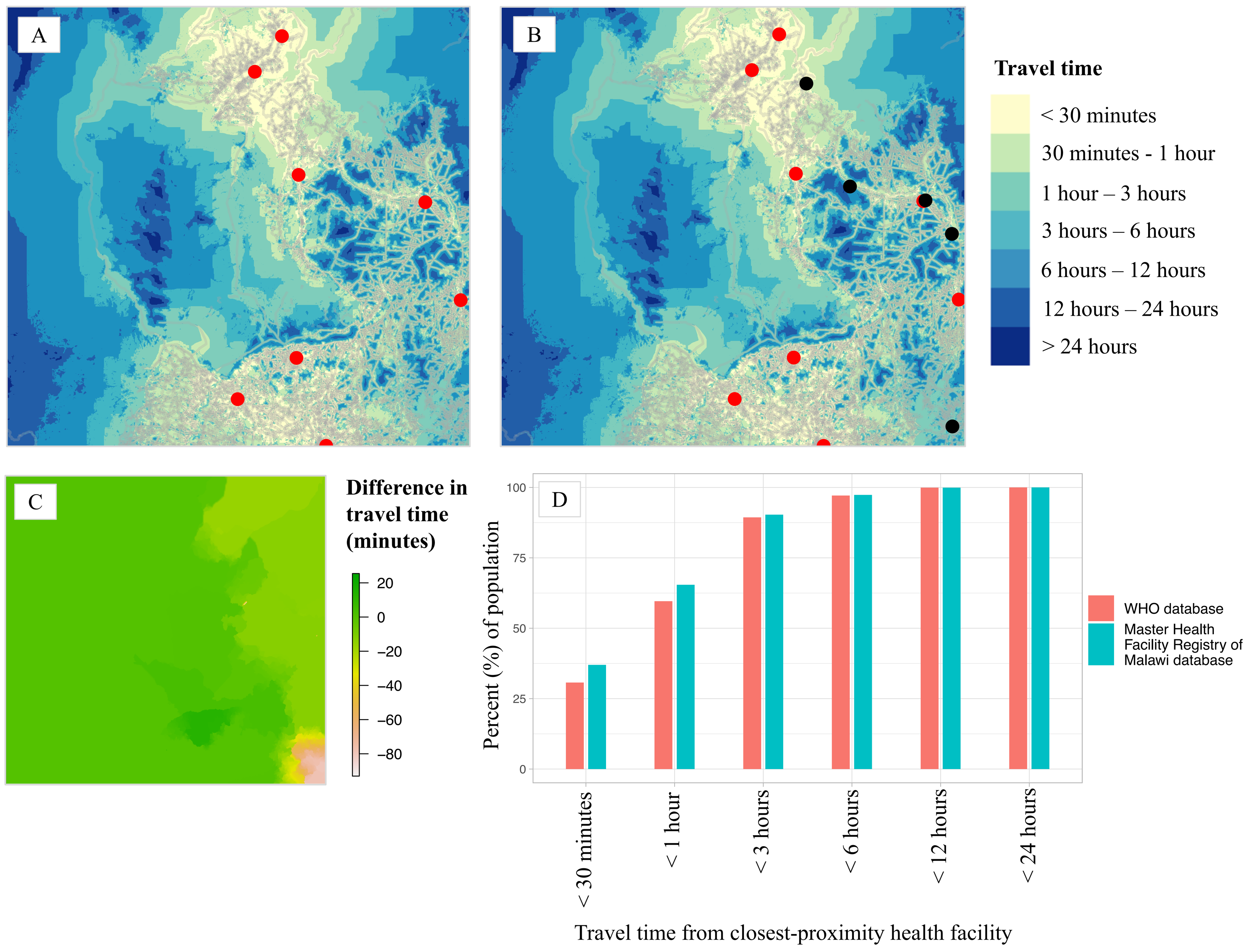

Figure 2. Cost-distance analyses generated using health facility data obtained from a WHO database (A) and the Master Health Facility Registry of Malawi database (B). Both plots show estimated travel times required to reach the closest-proximity health centre as calculated using our friction surface. Health facility location data obtained from both databases are mapped using red dots (A & B). Health facility location data obtained from the Master Health Facility Registry of Malawi database but not from the WHO database are mapped using black dots (B). Road data is coloured grey (A & B). A plot showing the difference in estimated travel times (minutes) for all gridded cells between both cost-distance analyses is shown (C). Proportions of the population residing within specified time-travel boundaries of the closest-proximity health centre as quantified using these data are also shown (D).

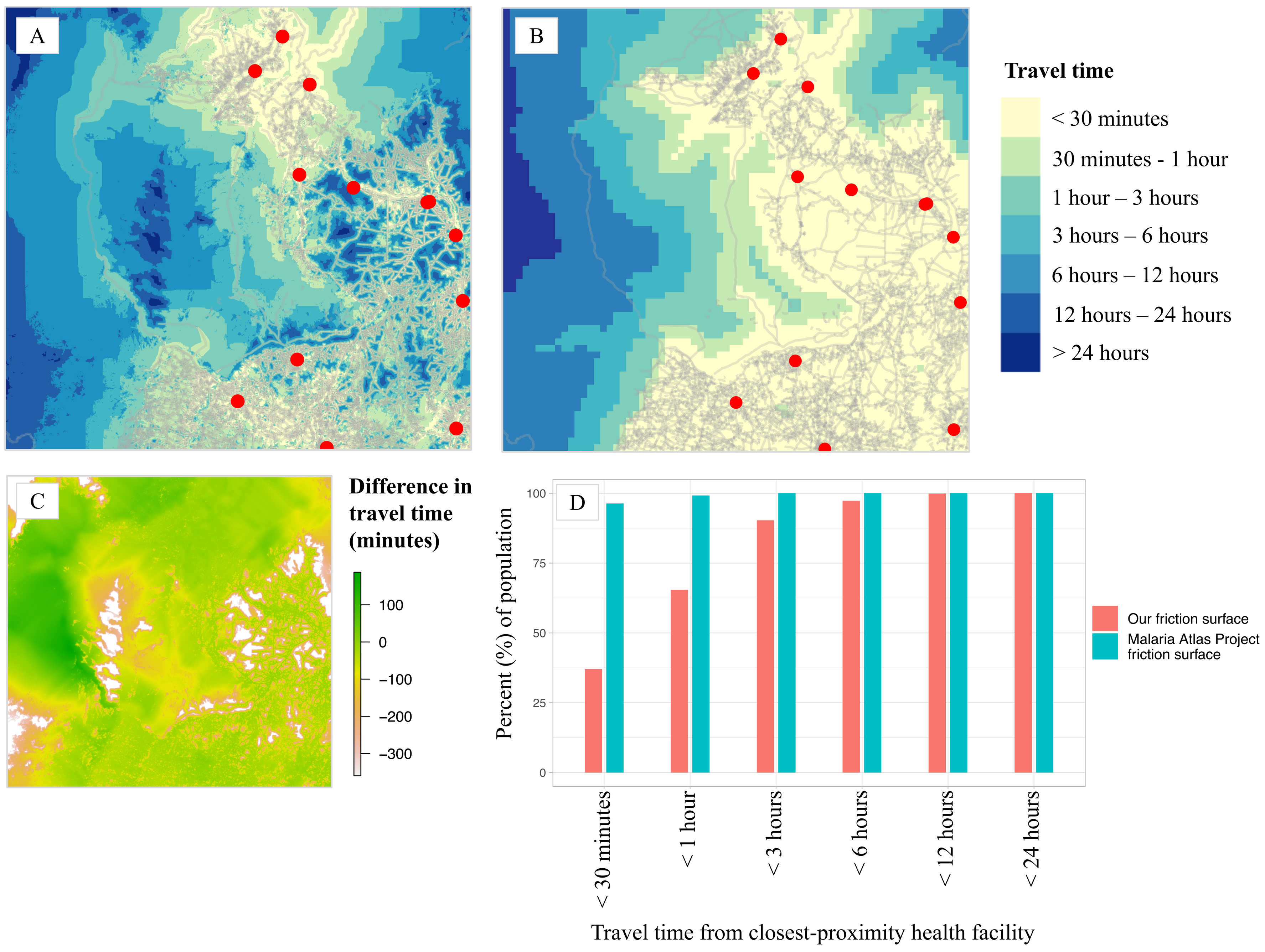

Figure 3. Cost-distance analyses generated using our friction surface and the Malaria Atlas Project friction surface (with health facility data obtained from the Master Health Facility Registry of Malawi), (A & B). Both plots show estimated travel times required to reach the closest-proximity health centre. Health facility location data are mapped using red dots (A & B). A plot showing the difference in estimated travel times (minutes) for all gridded cells between both cost-distance analyses is shown (C). Proportions of the population residing within specified time-travel boundaries of the closest-proximity health centre as quantified using these data are also shown (D).

5. Discussion

- The number of documented health facilities within our area of interest varied considerably depending on which database was used; highlighting the need for one database from which accurate, up-to-date and definitive health facility data can be obtained[13].
- These data demonstrate that a greater number of health facilities does not necessarily result in a proportionate increase in access to healthcare, whilst also illustrating the importance of spatial optimisation with regards to health facility locations[14].
- Friction surfaces constructed at a high spatial-resolution using customisable travel speeds that account for environmental conditions and circumstances may provide a more accurate estimation of travel time required to traverse a given landscape than might be estimated using alternative and lower-resolution friction surfaces that use single and fixed travel speeds.

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