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Geospatial evaluation of trade-offs between equity in physical access to healthcare and health systems efficiency

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ABSTRACT

Introduction Decisions regarding the geographical placement of healthcare services require consideration of trade-offs between equity and efficiency, but few empirical assessments are available. We applied a novel geospatial framework to study these trade-offs in four African countries.

Methods Geolocation data on population density (a surrogate for efficiency), health centres and cancer referral centres in Kenya, Malawi, Tanzania and Rwanda were obtained from online databases. Travel time to the closest facility (a surrogate for equity) was estimated with 1 km resolution using the Access Mod 5 least cost distance algorithm. We studied associations between district-level average population density and travel time to closest facility for each country using Pearson's correlation, and spatial autocorrelation using the Global Moran's I statistic. Geographical clusters of districts with inefficient resource allocation were identified using the bivariate local indicator of spatial autocorrelation.

Results Population density was inversely associated with travel time for all countries and levels of the health system (Pearson's correlation range, health centres: −0.89 to −0.71; cancer referral centres: −0.92 to −0.43), favouring efficiency. For health centres, negative spatial autocorrelation (geographical clustering of dissimilar values of population density and travel time) was weaker in Rwanda (−0.310) and Tanzania (−0.292), countries with explicit policies supporting equitable access to rural healthcare, relative to Kenya (−0.579) and Malawi (−0.543). Stronger spatial autocorrelation was observed for cancer referral centres (Rwanda: −0.341; Tanzania: −0.259; Kenya: −0.595; Malawi: −0.666). Significant geographical clusters of sparsely populated districts with long travel times to care were identified across countries.

Conclusion Negative spatial correlations suggested that the geographical distribution of health services favoured efficiency over equity, but spatial autocorrelation measures revealed more equitable geographical distribution of facilities in certain countries. These findings suggest that even when prioritising efficiency, thoughtful decisions regarding geographical allocation could increase equitable physical access to services.

Key questions

What is already known?

- Few prior evaluations of equity-efficiency trade-offs using travel time and population density have been conducted.
- Policy-makers would benefit from simple measures that can be readily estimated using existing data. These measures could help inform debates regarding the geographical placement of new facilities and health services, and enable monitoring of progress towards equity and/or efficiency goals.

What are the new findings?

- We studied associations between district-level population density (as a proxy for efficiency) and travel time (proxy for equitable physical access) using Pearson's correlations and the Global Moran's I test for spatial autocorrelation (geographical clustering of similar or dissimilar values of variables) in four African countries (Kenya, Malawi, Rwanda and Tanzania).
- While negative Pearson's correlations between population density and travel time were observed across countries and health systems levels, there was variability in negative spatial autocorrelation (geographical clustering of dissimilar values of population density and travel time). Weakest spatial autocorrelation was observed in Rwanda and Tanzania, countries with explicit policies supporting equitable access to rural healthcare.

What do the new findings imply?

- Applying this geospatial analytical approach could help policy-makers understand the trade-offs made between efficiency and equity in geographical access to health services across levels of the health system, and study how these decisions impact service delivery and population health.
- Geospatial data and analytical software are available for all countries around the world, facilitating consistent comparisons across countries.
- This approach can be adopted by health planners and policy-makers to monitor progress towards health systems goals, and identify geographical subregions with inefficient resource allocation to motivate an appropriate policy response.

INTRODUCTION

Achieving health equity through optimal allocation of healthcare resources is a priority for

health systems worldwide.[1] Increasing equitable access to health services is one means of reducing health inequities.[2] Access can be defined using four dimensions[3 4]: availability, geographical accessibility, affordability and acceptability. Geographical accessibility depends on decisions made by healthcare policy-makers about where to build healthcare facilities and how to distribute services throughout their coverage areas. Consequently, a better understanding of geographical accessibility to healthcare resources could inform policy decisions concerning the spatial distribution of services in ways that reduce health disparities. Decisions about where to place health services must balance trade-offs between equity of access versus efficiency of placement to leverage economies of scale.[4–6]

Urban and rural patients experience different barriers to accessing care. Geographical accessibility is often limited for rural patients, particularly in low-resource settings.[7 8] As the global burden of disease shifts towards non-communicable diseases that require more complex and specialised diagnosis and treatment (eg, pathology, chemotherapy and radiotherapy for cancer), urban–rural disparities may be exacerbated if services are preferentially deployed in urban areas.[9–12] Policy-makers often decide to place diagnostic services in urban areas to benefit from economies of scale, because these specialised approaches may rely on efficiencies arising from concentrations of highly skilled workers, infrastructure and financial resources. However, placing services in urban areas could introduce geographical, financial and social barriers for rural patients that result in inequitable access to healthcare.[13] Policy-makers may, therefore, choose to sacrifice some efficiency in favour of more equitable geographical access to healthcare services. Scientists have modelled the costs and benefits of these trade-offs when choosing testing options for HIV and tuberculosis. Their models account for the degree of economies of scale, availability of systems to transport specimens, timely return of results and costs incurred when patients are lost to follow-up.[14 15] Policy-makers could benefit from knowing where their health systems lie along the equity versus efficiency spectrum as they decide where to place new healthcare services. Empirical assessment of the relationship between travel time as a proxy for equity and population density as a proxy for efficiency arising from economies of scale could provide useful information to policymakers hoping to evaluate the implications of these trade-offs.[16]

We propose the Geographic-Population Services Access (Geo-PSA) model, a novel conceptual framework and analytical approach to evaluate trade-offs between urban–rural equity in geographical access to health services and health systems efficiency. We illustrate how geospatial analytical approaches can be used within this framework to identify inefficient geographical allocation of health services and motivate appropriate public health responses. Finally, we demonstrate the flexibility of the Geo-PSA model to evaluate urban–rural disparities in access to (1) primary care services and (2) specialised oncology centres in four sub-Saharan African countries.

METHODS

The Geo-PSA model

Geo-PSA is a data-driven framework for evaluating trade-offs between equitable geographical access and health systems efficiency when making decisions about placement of healthcare services. Geo-PSA links a conceptual framework for understanding and interpreting the relationship between equity and efficiency within the context of geographical distribution of health services with a geospatial analytical approach to empirically assess these trade-offs.

Conceptual framework

Travel time to the nearest health facility was chosen as a measure of equity because geographical access to health services is known to be a major barrier to accessing care, particularly for rural patients in low-resource settings.[8 13 17–19] We chose high-resolution population density as a surrogate measure of efficiency arising from economies of scale. Population density reflects urbanicity, and thus, may provide an estimate of economies of scale and expected patient volume. In choosing population density as a proxy for efficiency and travel time as a proxy for equity, we selected metrics that could be readily acquired in diverse geographical contexts over a wide range of spatial scales. However, these measures do not account for other important dimensions of access, such as healthcare quality, which may lead patients to bypass nearby facilities for higher levels of care.[19 20] Local knowledge regarding the relative importance of physical access compared with other barriers preventing patients from accessing care in a given geographical context is critical for interpreting and acting on Geo-PSA model results. The spatial scale chosen should be that which most closely aligns with the level of the health system where decisions regarding programmes and resources are made. In most countries, this will occur at district level.

We propose that plotting the relationship between travel time to nearest facility (vertical axis) and population density (horizontal axis) may reveal geographical distributions of facilities that reveal trade-offs between equity versus efficiency in healthcare systems, as well as identify settings that are inefficient (figure 1). Health systems that prioritise efficiency would be expected to have districts falling along a steeper line from the upper left quadrant (low-population density, long travel time) to the lower right quadrant (high-population density, short travel time). Health systems that favoured equity would be expected to have districts falling on a flatter line. Inefficient quadrants (upper right: high-population density, long travel time; lower left: low-population density, short travel time) can be used to understand how geographical allocation of resources might be improved. Online supplemental appendix table 1 provides examples of

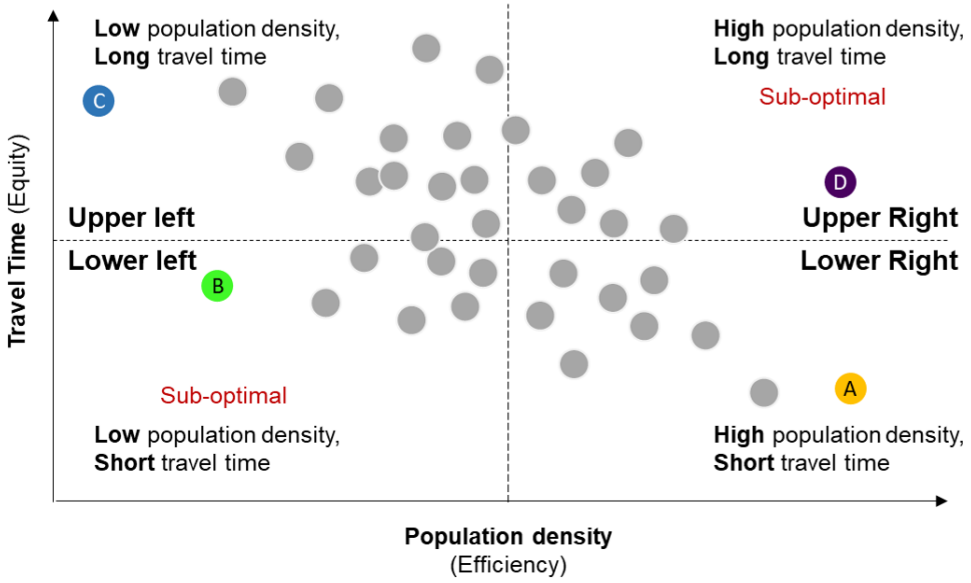

Figure 1 The Geographic-Population services access model: a conceptual framework and analytical approach to inform policies for geographical allocation of health services that Optimise equity and efficiency. Note**:** the model provides a visual display of geographical data that captures proxies for efficiency (population density, x-axis) and equitable geographical access (travel time, y-axis). Efficient quadrants (upper left: low population density, long travel time; lower right: high population density, short travel time) and inefficient quadrants (lower left: low population density, short travel time; upper right: high population density, long travel time) can be visualised. Significant outliers (A–D) can be detected using spatial statistical methods.

policy responses to respond to suboptimal geographical allocation of services relative to population.

Study setting and geospatial data sources

We chose to evaluate data from four sub-Saharan African countries: Kenya, Malawi, Rwanda and Tanzania. These countries were chosen because though they have majority rural populations and similar levels of life expectancy, they vary with respect to population density, economic development. The countries have also adopted different approaches to implementing government health policies addressed towards achieving equitable health service delivery. [21–24] Finally, questions regarding trade-offs between equity and efficiency are particularly pertinent as they expand access to care for cancer and other chronic diseases.[25–27] In order to empirically evaluate the association between population density and travel time, we obtained multiple geospatial data inputs described in online supplemental file 1. These geospatial data are generated from administrative government databases and satellite imagery, and are available for most countries around the world for varying time periods. Governance of the public health system in Kenya, Malawi, Rwanda and Tanzania is decentralised, with decision making occurring at lower administrative levels. In order to reflect this in our analysis, we specifically chose to implement our method at district level in Malawi, Rwanda and Tanzania, and at county level in Kenya. Going forward, we refer to the geographical unit across countries as district level for clarity.

Descriptive characteristics for each of the four African countries are presented in table 1 using data from the World Bank Development Indicators[28] and the International Agency for Research on Cancer obtained in 2018.[29] The total population ranged from 12.3 million (Rwanda) to 51.3 million (Kenya). Gross Domestic Product per capita in current US$ ranged from US$1311 (Malawi) to US$3468 (Kenya). Life expectancy was similar for all countries, though Rwanda reported the highest (69 years). Estimated age-specific cancer mortality rates ranged from 94.6 (Tanzania) to 129.2 (Kenya) per 100 000. Population density was lowest in Tanzania (63.6 persons per km^2 and highest in Rwanda (498.7 persons per km^2. Over half of the population was reported to reside in rural settings for all countries.

Estimating travel time to closest health facility for patients in low-resource settings requires a different set of assumptions and geographical data than in high-resource settings. This is because motorised transport via road networks, assumed to be the primary means of travel by patients in high-resource settings, may not always apply in more rural, low-resource settings. For this reason, geographical scientists proposed use of more detailed raster (gridded cell-based) methods that incorporate geographical datasets, including rivers and lakes, elevation and land cover classes. Incorporating these data enables more accurate consideration of the environment and modes of transport used patients in these contexts.[30]

For raster (gridded) image files (land cover, elevation), we reprojected data using the Universal Transverse Mercator projection in metres corresponding to each country. We then applied a resampling algorithm using ArcMap V.10.2 to change the cell size of all rasters to 500 m to enable consistent spatial contributions of elevation and land cover to travel time estimates. Vector

Table 1 Characteristics of sub-Saharan Africa countries included in case study to evaluate urban–rural access to cancer referral centres

Country	Kenya	Tanzania	Rwanda	Malawi
Total population (thousands)*	51 393	56 318	12 302	18 143
GDP per capita (US$ current)*	3468	3240	2252	1311
Life expectancy (years)*	66	65	69	64
Population density (persons per km^2)*	90.3	63.6	498.7	192.4
% Rural*	73	66	83	83
Districts (no)	47	171	30	27
Health centres (no)†	1038	675	486	457
Average population per health centre†	49 512	83 434	25 313	39 700
Median district-level travel time to health centre (min, median (IQR))†	44.8 (20.0–74.5)	84.9 (53.2–132.7)	19.5 (14.4–26.9)	55.7 (49.2–67.2)
Top five most frequent cancers‡	Breast, cervix, oesophagus, prostate, colorectum	Cervix, prostate, breast, colorectum, Kaposi sarcoma	Cervix, breast, colorectum, stomach, liver	Cervix, Kaposi sarcoma, oesophagus, non-Hodgkin's lymphoma, breast
Total cancer deaths‡	32 987	28 610	7662	13 779
Age-standardised cancer mortality rate per 100 000‡	129.2	94.6	104.8	123.7
Cancer referral centres (no)§	12	10	6	6
Median district-level travel time to cancer research centre (min, median (IQR))†	127.7 (73.2–220.4)	356.0 (211.3–647.1)	59.9 (44.7–92.8)	296.2 (238.1–520.1)

*World Bank Development Indicators (2018).[28]
†Authors' analysis of Maina *et al*. Geospatial Database of Health Facilities in sub-Saharan Africa (2019) (see text).[30]
‡International Agency for Research on Cancer, Cancer Today Country Factsheets (2018).[29]
§Global Oncology Project Map (2020).[32]
GDP, gross domestic product.

datasets (roads, lakes, rivers, healthcare facilities) were acquired from public databases. We examined both geographical distribution of primary care facilities (ie, health centres) as well as tertiary care facilities (ie, cancer hospitals), hypothesising that countries might make different choices at different levels of care. Primary care health centre location data were acquired from a recently published database of government-run health facilities in sub-Saharan Africa.[31] Lists of cancer hospitals and affiliated clinical research centres for each country were obtained from the Global Oncology online map of African cancer research and clinical centres.[32] We obtained latitude and longitude for each cancer research centre by entering the name of the research centre for each country into Google Maps and extracting these coordinates. In sub-Saharan African settings, academic cancer centres often have greater availability of technical experts, training programmes and investments in supply chains, infrastructure and equipment needed to provide high-quality cancer care.[33 34] We reviewed the list of Global Oncology cancer research and clinical centres and excluded those that corresponded to non-profit or national government agency headquarters, because these were not the locations where cancer care was being delivered. We assumed that the remaining cancer referral centres would represent higher quality of care than other cancer care facilities and retained them for our analysis.

Estimating travel time to the nearest facility using geographical information systems

We estimated travel time to the nearest health facility using Access Mod 5, a WHO sponsored web-based tool.[30 35] Briefly, the Access Mod 5 algorithm exploits high-resolution geospatial datasets and the spatial relationships between geographical features in neighbouring areas.[30] We assigned a travel speed and mode of transit to each land cover type (online supplemental appendix table 3). Access Mod 5 merges elevation, land cover, water bodies and road network databases into a single raster file, assigning user-defined speeds to each cell in a grid covering the entire geographical area. Next, we used the Access Mod 5 least cost distance algorithm to calculate the fastest route through a given area by minimising the time spent travelling between adjacent cells.[30] This analysis is augmented with information about elevation, accelerating or decelerating travel speeds depending on whether travel is uphill or downhill. This method produces a raster file that stores and displays estimated travel times for a specified geographical area as a grid, with each cell representing a 500 m by 500 m area. We ran

this analysis separately for each country and for each list of facilities (primary health centres and cancer referral centres.

Statistical analysis

In order to estimate district-level averages for population density and travel time, we calculated zonal statistics for population density and travel time, specifying the district as the geographical zone and taking the average population density and travel time over all cells in the district. District-level averages were log-transformed before conducting correlation analysis to correct the skewed distribution of these variables. We calculated Pearson correlation coefficients and 95% CIs between variables in each country, separately for travel time to closest health centre and travel time to closest cancer referral centre.

In order to evaluate geographical patterns in the relationship between our measures of equity and efficiency, we performed tests for spatial autocorrelation and cluster detection. Spatial autocorrelation arises when values of a variable in geographical space are positively or negatively correlated with values of another variable in neighbouring areas.[36] In our study, negative spatial autocorrelation would arise if densely populated districts were surrounded by districts with short travel time, or if sparsely populated districts were surrounded by districts with long travel time. This would produce clusters in the upper left to lower right quadrants of our conceptual model (figure 1), favouring efficiency. Conversely, positive spatial autocorrelation would arise if most districts clustered in the inefficient lower left to upper right quadrants. The magnitude of the spatial autocorrelation provides evidence regarding trade-offs between equity and efficiency—comparing spatial autocorrelation between countries and health system levels could reveal instances where equity was favoured.

We specified a queen's contiguity matrix to define neighbouring districts. The queen's contiguity matrix is used to classify districts based on their spatial relationships with one another. For a given district, using the queen's contiguity means that a bordering district in any direction would be considered a neighbour. The Global Moran's I[36] was calculated to determine whether positive or negative spatial autocorrelation between district-level population density and travel time was observed at national level. The bivariate local indicator of spatial autocorrelation (LISA)[37] was used to identify four types of geographical clusters of districts: (1) high population density, short travel time (high/short); (2) high population density, long travel time (high/long); (3) low population density, short travel time (low/short); (4) low population density, long travel time (low/long). Since the spatial weighting relies on neighbours, we excluded islands from our analysis. These four categories align with the efficient and inefficient quadrants in our conceptual framework (figure 1). Technical details about the geospatial analysis procedures are provided in the online supplemental methods appendix.

Permutation tests with 999 simulations were used for spatial statistical hypothesis tests. Global Moran's I and bivariate LISA analyses were conducted using GeoDa software.[38] We applied the Benjamini-Hochberg False Discovery Rate to our alpha level of 0.05 to correct for multiple testing across all of the districts.[39] As a sensitivity analysis, we also included results without correcting for multiple testing. In order to facilitate uptake of this analytical approach among government, non-profit or other healthcare organisations, we have included a data sharing appendix containing further information regarding the workflow and links to specific data elements and code used to generate the major figures in this paper.

Patient and public involvement

There was no patient or public involvement in the study.

RESULTS

Primary care at health centres

The number of health centres reported in the database used for this analysis ranged from 457 (Malawi) to 1038 (Kenya) (table 1). On average, each health centre served a population ranging from 25 313 (Rwanda) to 83 434 (Tanzania). The median district-level average travel time to the nearest health centre was shortest for Rwanda (19.5 min, IQR: 14.4–26.9 min) and longest for Tanzania (84.9 min, IQR: 53.2–132.7 min).

The bivariate LISA scatter plots may reflect differences in national priorities when balancing equitable geographical access and efficiency of health service delivery (figure 2). Average travel times to closest health centre were below 120 min for most districts across countries. Correlations between population density and travel time were strongest in Kenya (r = −0.89, 95% CI −0.94 to -0.81) and weaker in Malawi (r=−0.80, 95% CI −0.91 to -0.61), Rwanda (r=−0.76, 95% CI −0.88 to -0.54) and Tanzania (r=−0.71, 95% CI −0.78 to -0.62). The Moran's I was statistically significant (permutation p<0.001), and negative for all countries, favouring efficiency (spatial clusters in the upper left and lower right quadrants of our framework). However, there was stronger evidence of negative spatial autocorrelation in Kenya (−0.579) and Malawi (−0.543) compared with Tanzania (−0.292) and Rwanda (−0.310), suggesting the placement of primary health centres may have favoured equity over efficiency in those countries. Maps revealed the geographical locations of clusters corresponding to the four quadrants in our conceptual framework (online supplemental appendix figure 1). Several significant clusters in the upper left quadrant (low population density, unusually long travel time), particularly near country borders were observed in all countries. Analyses without multiple testing correction revealed greater numbers of inefficient geographical clusters in Tanzania and Rwanda (online supplemental appendix figure 2).

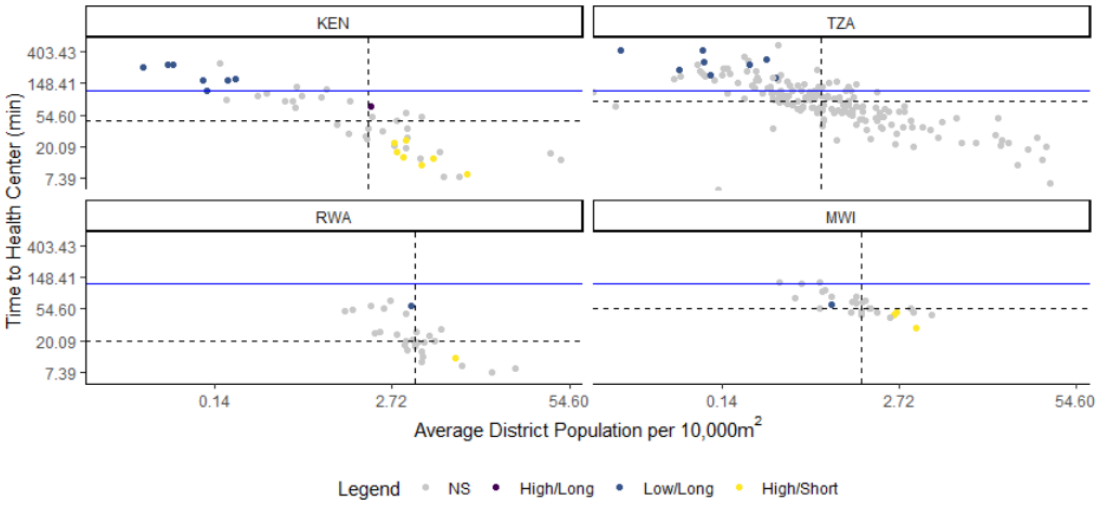

Figure 2 Pearson correlation between district-level travel time to the nearest primary care health centre and population per 10 000 m^2 in Kenya (KEN), Tanzania (TZA), Rwanda (RWA) and Malawi (MWI). Colours correspond to districts with statistically significant bivariate local indicator of spatial autocorrelation clusters of (1): high population density/long travel time, (2): low population density/short travel time, (3): low population density/long travel time and (4): high population density/short travel time. Significance tests for district clusters were conducted using 999 permutation tests with an alpha=0.05. The Benjamini-Hochberg false discovery rate was applied to correct for multiple testing of clusters. Blue horizontal line denotes 120 min travel time. Dotted lines intersect at the median travel time and population density for each country. NS, non-significant.

Cancer referral centres

We applied the same model as for primary healthcare centres using locations of cancer referral and research centres in Kenya (n=12), Tanzania (n=10), Rwanda (n=6) and Malawi (n=6) (table 1). The median district-level average travel time to the nearest facility was shortest for Rwanda (59.9 min, IQR: 44.7–92.8 min) and longest for Tanzania (356.0 min, IQR: 211.3–647.1 min).

Figure 3 presents bivariate LISA plots for each country. The correlations between district-level travel time to cancer referral centres and population density were strongest for Kenya (r=−0.92, 95% CI −0.96 to -0.86) and Malawi (r=−0.87, 95% CI −0.94 to -0.74), and weaker for Rwanda (r=−0.78, 95% CI −0.89 to -0.59) and Tanzania (r=−0.43, 95% CI −0.55 to -0.30). The Moran's I statistic was significant and negative for all countries, favouring efficiency over equity (permutation p<0.001). Kenya (Moran's I: −0.595) and Malawi (−0.666) displayed stronger spatial autocorrelation than Rwanda (−0.341) and Tanzania (−0.259), again suggesting that Rwanda and Tanzania's health systems may have favoured equity in placement of their cancer services over efficiency.

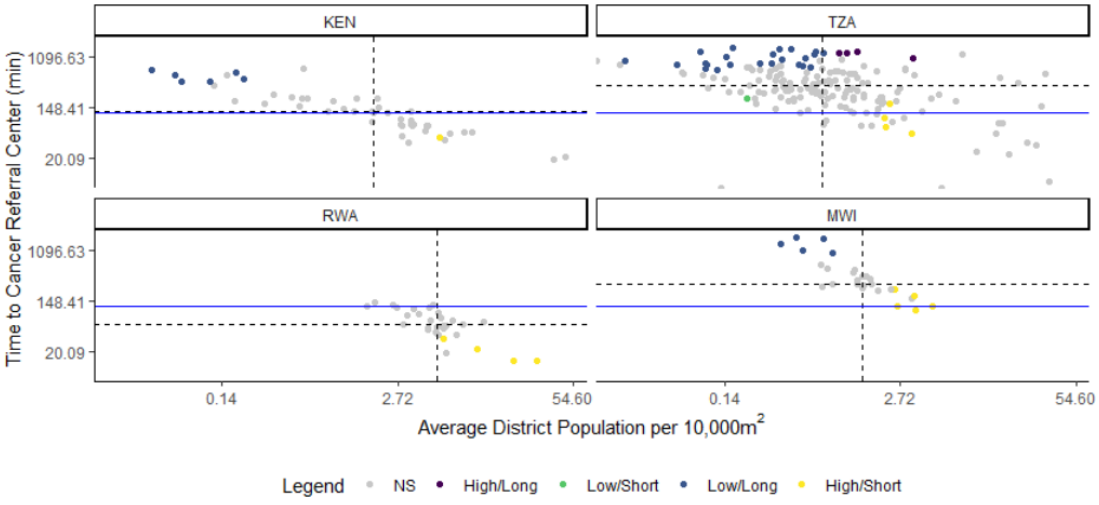

Figure 3 Pearson correlation between district-level travel time to nearest cancer centre and population per 10 000 m^2 in Kenya (KEN), Tanzania (TZA), Rwanda (RWA) and Malawi (MWI). Colours correspond to districts with statistically significant bivariate local indicator of spatial autocorrelation clusters of (1): high population density/long travel time, (2): low population density/short travel time, (3): low population density/long travel time and (4): high population density/short travel time. Significance tests for district clusters were conducted using 999 permutation tests with an alpha=0.05. The Benjamini-Hochberg false discovery rate was applied to correct for multiple testing of clusters. Blue horizontal line denotes 120 min travel time. Dotted lines intersect at the median travel time and population density for each country. NS, non-significant.

Significant district clusters were mostly identified in efficient quadrants (upper left and lower right), except for Tanzania which displayed some clusters in inefficient quadrants (online supplemental appendix figure 3). In analyses not correcting for multiple testing, three countries had at least one district with inefficient allocation (online supplemental appendix figure 4). Though Tanzania's correlation and spatial autocorrelation measures favoured equity, most districts had average travel times exceeding 120 min. Malawi also displayed travel times over 120 min for most districts, with stronger negative correlation and spatial autocorrelation measures than Tanzania. All countries but Rwanda displayed significant clusters of low population density and long travel times, which may require innovations in diagnostics or referral systems that reduce travel burden for rural patients.

DISCUSSION

Applying the Geo-PSA model in four African countries revealed trade-offs between urban–rural equity in geographical access and efficiency in health service delivery. Pearson correlation coefficients were uniformly negative, suggesting favouring of efficiency across all countries and health system levels. There were modest differences in the strength of the association between travel time and population density between countries, with Kenya and Malawi reporting stronger correlations than Rwanda and Tanzania at health centre level and cancer referral centre level. Tests for spatial autocorrelation within the Geo-PSA model allowed us to formally investigate geographical clustering of similar and dissimilar patterns of association between district-level population density and travel time. All tests for spatial autocorrelation were negative, implying that across countries, predominant geographical patterns were of regions exhibiting high population density with neighbours experiencing short travel time, and regions of low population density with neighbours experiencing long travel time. However, the magnitude of this spatial autocorrelation varied between countries, with Rwanda and Tanzania displaying weaker spatial autocorrelation than Kenya and Malawi. Given that all countries displayed strong negative aspatial correlations between population density and travel time that favour efficiency, spatial autocorrelation revealed how the geographical placement of facilities favoured equity more in some countries than others.

This study demonstrates how the Geo-PSA model can be used to monitor progress towards equitable urban–rural access across multiple countries. The governments of Rwanda and Tanzania have historically prioritised health equity through propoor healthcare financing and decentralised primary care services.[21 24 40–42] Kenya's health system has focused on efficiency, and the placement of its facilities have been associated with rural–urban disparities in geographical access to primary care services.[22 43] The health system in Malawi has pursued propoor policies, but its level of economic development has hampered efforts to address urban–rural inequities in accessing primary care services for maternal and child health.[23] In the Geo-PSA model, strong Moran's I correlations between travel time to the closest facility and population density, like those observed in Kenya and Malawi, suggest that the placement of facilities favoured efficiency over equity compared with countries with weaker correlations (Rwanda and Tanzania). This relationship is independent of the overall population density, as Rwanda is the most densely populated of the four countries, while Tanzania is the least. These patterns may reflect differences in healthcare policy implementation in each country. Rwanda and Tanzania have taken steps towards equitable healthcare coverage in their respective countries, which have resulted in a greater rural orientation to cancer care delivery.[25 41 44] Though national policy-making in Rwanda is centralised, implementation of healthcare delivery is decentralised and relies on evidence-based decision making to guide policies and planning.[24 40 41] Since independence, Tanzania's government has pursued policies to ensure equitable access to healthcare and other public services, which prompted the country to build the necessary dispensaries, health centres and hospitals to reach rural populations.[21] In contrast, the Government of Malawi faces resource constraints that limit its ability to apportion funds to increase the geographical extent of its health system.[23 45] In Kenya, Barasa *et al* reported that although universal health coverage increased from 44% in 2003 to 52% in 2013, increases in service coverage and financial risk protection were largely concentrated among the wealthy, suggesting an urban bias in locations where health services are scaled up.[46]

Policy implications

The framework presented here could support healthcare planning in a few important ways. First, the approach can be applied over time as countries increase coverage of healthcare services and introduce new facilities in a population. Countries can compare the Global Moran's I measure of negative spatial autocorrelation between population density and physical accessibility over time and across levels of the health system to monitor progress towards achieving equitable access to services.

Second, the proposed framework enables policymakers to identify locations with inefficient resource allocation (clusters in the lower left or upper right quadrants, reflecting low population density, short travel times or high population density, long travel times, respectively). Prior research in this area focused on modelling the impact of shifting hospital locations on socioeconomic inequities in geographical access to health services to find an optimal balance between efficiency and equity. Our approach offers a simple analytical model for evaluating trade-offs between equity and efficiency. Policy-makers can decide how best to respond to these inefficiencies based on the level of the health system and their resource constraints[6] (box 1).

Box 1 Applications of Geographic-Population Services Access (Geo-PSA) model in other health services research settings

- A high-income country seeking to reduce health disparities has resources to deploy a limited number of decentralised clinical breast examination screening centres. Using the Geo-PSA model, the national task force is able to identify clusters of low population density, high travel time clusters where such a test would increase equitable access to testing.
- An international task force is assembled to study the geographical distribution of laboratory diagnostics around the world. Using the Geo-PSA model, countries can be compared based on their trade-offs between efficiency and urban–rural equity of access to specific laboratory services.
- The national government in a low-income country is rapidly scaling up testing in the wake of a global pandemic, and seeks to determine how best to leverage existing laboratories as well as new tools to identify the disease. Using the Geo-PSA model allows the government to evaluate the current geographical accessibility of its laboratories, areas where new laboratories may need to be built (high population, long travel time), and areas where point-of-care diagnostics or specimen transport should be deployed (low population density, long travel time). Armed with this information, the government can work with other partners to develop a plan for increasing coverage of its testing services.

For primary care services, policy-makers may be willing to sacrifice efficiency to increase access to infectious disease tests, under-5 care and maternal care. For cancer diagnostics, innovations that leverage technology or improved referral systems may be needed to reduce geographical barriers for rural patients. Based on this analysis, programmes in Kenya and Malawi may favour strategies to help rural patients access urban cancer centres, through transport subsidies or patient waiting homes. Tanzania and Rwanda, which already have more geographically accessible health services, may instead introduce systems improvements and technology to lower levels of the health system. Several novel technologies have already been piloted to overcome geographical access barriers for rural populations. For example, GeneXpert devices, which have already been deployed for diagnosis of tuberculosis and other infectious diseases, are being adapted to diagnose breast cancer.[47] Some global oncology programmes have begun experimenting with telepathology services.[48 49] As more researchers test novel approaches to deliver cancer care in sparsely populated rural areas, the solutions will benefit rural cancer patients everywhere.

Some limitations should be considered when applying the Geo-PSA model. First, the geographical analysis used to estimate travel time relies heavily on assumptions regarding the mode of transportation and travel speeds and may underestimate the travel times for individual patients.[50] Analysts should take care to consider the appropriate spatial scale for their analysis, and use high-quality road network data and to the extent they are able, verify the speeds of transit and mode of transit of the population under study. A strength of geographical analytical estimates of travel time is objective measurement, incorporation of elevation and land cover, and ability to conduct cross-country, macrolevel analyses. Even if exact times for individual patients are estimated with error, the method still enables ranking of places with longer or shorter travel times to reach facilities. Caution may be needed when interpreting results from geographical cluster analysis for regions that do not have neighbours or occur at national borders. The Geo-PSA model does not account for availability of specific equipment and tests, quality of services or health outcomes. However, these limitations are offset by several strengths. Growing government and non-profit databases contain harmonised geographical datasets to capture the various geographical inputs required to estimate travel time for countries around the world.[51–53] Furthermore, the availability of data at multiple administrative levels[54] and remote sensing data provide far more flexibility in terms of defining spatial scales and characterising the specific geographical area of interest.[30 52 53] The ability to rapidly estimate travel times for multiple countries, apply spatial statistical analysis to evaluate efficiency and equity in varied contexts, and application of geospatial analysis to locate clusters of inefficient allocation of services to motivate an appropriate policy response. Urban–rural disparities in physical access to healthcare services have been observed within both high-income[55–58] and low-income and middle-income[59–62] countries around the world, suggesting that questions regarding trade-offs between physical accessibility and efficiency may apply to other settings outside of sub-Saharan Africa.

CONCLUSION

In summary, we introduce a novel geospatial analytical model, Geo-PSA, to evaluate trade-offs between equity in geographical access to healthcare and efficiency in four African countries. This flexible model can be applied by health policy and services researchers across different disease areas and geographical contexts. The model can be used to monitor progress towards equitable access to healthcare services at national level, compare countries' trade-offs between equity and efficiency, and inform local policies to respond to inefficient geographical allocation of health services.

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Supplementary Appendix

Geospatial Statistical Analysis

In order to evaluate trade-offs between efficiency and geographic equity in access to health services, we sought to both describe geographic correlations between measures across different countries, and identify geographic clusters of efficient and inefficient allocation of health facilities within countries. Doing so required the use of spatial statistical procedures that are commonly used in fields of geography, demography, and ecology [1–3]. A brief description of these procedures is provided below, along with justification for using these methods to answer our research question.

Testing for global spatial autocorrelation between district-level population density and travel time

We chose to consider spatial autocorrelation in our statistical analysis because unmeasured spatial processes, such as social and political factors, are likely to influence health service distribution and access [4,5]. Spatial autocorrelation refers to the extent to which values of a variable in geographic space vary based on proximity between neighboring units [3]. Positive spatial autocorrelation indicates that neighboring values are more likely to be similarly high or similarly low (high surrounded by high, low surrounded by low). Negative spatial autocorrelation indicates that neighboring values are more likely to exhibit an inverse correlation (high surrounded by low, low surrounded by high). These ideas can be extended to bivariate settings, in which the value of variable x covaries with values of another variable y based on proximity.

Hypothesis tests for geospatial statistics compare observed values in geographic space to those which would have been observed under the null hypothesis of spatial randomness (no spatial ordering to values in space) [3,6]. Implementing these spatial analysis procedures requires neighboring units to be defined using a weights matrix. This weights matrix is often denoted using the notation w_{ij} with equal rows i and columns j, where both i and j are equal to n, the total number of districts in the analysis. Each cell in w_{ij} contains a binary (1/0) element indicating if district j is or is not a neighbor of district i. In our study, we defined neighbors using the "queen" contiguity matrix, in which neighboring districts in any geographic direction would be considered neighbors because we assumed that spatial processes that drive population density and travel times would be expected to be shared across all neighboring regions [6]. Districts without neighbors were excluded from the analysis because they would not contribute to the weights matrix or spatial statistical calculations. Permutation tests were used to determine statistical significance, and we specified 999 permutations [1,2].

We applied the Global Moran's I statistic (Equation 1) to test for global spatial autocorrelation:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(y_j - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Equation 1: Global Moran's I Statistic

Where n is the total number of districts, w_{ij} is the neighborhood weights matrix, x_i is the value of population density for district i, $\bar{x}$ is the global average district-level population density, y_j is the value of travel time in neighboring district j, and $\bar{y}$ is the global average district-level travel time.

Identifying local clusters of positive and negative spatial autocorrelation between district-level population density and travel time

While the global Moran's I test provides evidence of spatial autocorrelation (whether or not the magnitude of population density and travel covary in space in the total study region), it does not allow investigation of the four patterns of correlation between district-level population density and travel time that we were interested in investigating, and that drive the global association. For policy recommendations and planning, local officials must identify where clusters of sub-optimal allocation (high population density, long travel time; low population density, short travel time) are located. Note that these are examples of negative spatial autocorrelation (values of population

density are inversely correlated with values of neighboring travel time). Efficient clusters (high population density, short travel time; low population density, long travel time) are examples are positive spatial autocorrelation.

The Local Indicator of Spatial Autocorrelation (LISA) statistic can be used to identify geographic clusters (Equation 2):

$$I_i = \frac{(x_i - \bar{x})}{\sum_i \frac{(x_i - \bar{x})^2}{n}} \sum_j w_{ij} (y_j - \bar{y})$$

Formula 2: Local Moran's I Statistic

All notation is the same as previously specified. The major difference between equation 1 and 2 is that in equation 2, we obtain a statistic for each district *i*. Heuristically, this method can be interpreted as a regression where district-level population density is the independent variable, and district-level travel time is a spatially smoothed estimate of travel time in its neighboring areas [2]. This method can be used to identify statistically significant clusters in efficient and inefficient quadrants within the Geo-PSA conceptual framework that can be further investigated to inform policy. Because each district *i* through *n* generates its own test statistic, we applied the Benjamini Hochberg False Discovery Rate correction for multiple testing in our primary analysis [7]. As a sensitivity analysis for exploration, we included analyses using the less stringent traditional alpha=0.05 cut-off and have included those results in Supplementary Figures S1 and S2.

Interpretation of geospatial analysis and relevance to evaluating trade-offs between equity and efficiency

In summary, these geospatial statistical procedures made two important contributions to our evaluations of trade-offs between equity and efficiency in the spatial allocation of health services with respect to populations in need. First, tests for global spatial autocorrelation revealed whether the magnitude of district-level population density and travel time tracked together in space. A priori, we hypothesized there would be lower spatial autocorrelation when evaluating primary care services compared to cancer services. Investments in equitable geographic coverage of services could limit the variability in district-level travel times for the whole country, leading to lower spatial autocorrelation between population density and travel time. However, for cancer referral centers, we expected to observe stronger negative spatial autocorrelation because services are more likely to be found in highly populated areas, where shorter travel times would be expected to be found. Regions far from urban centers would be sparsely populated and exhibit longer average travel times to reach cancer care. Second, identifying local clusters of positive (inefficient) or negative (efficient) would allow policymakers to direct resources to those areas to address these imbalances – information to drive action. LISA clusters indicate the specific spatial relationships (efficient or inefficient) between population density and travel time that drive the global correlations, allowing for more rigorous investigation of causes for those imbalances.

Data Sharing Appendix. Analytic Workflow and Data Repository.

In order to enable policymakers and analysts to implement the Geographic-Population Services Access (Geo-PSA) analytic approach, we include additional information regarding specific software and data requirements, as well as a link to data elements and R code used to generate the maps and scatter plots presented in this article.

Analytic Workflow

The analysis presented here includes five main steps:

1. **Preparation of geographic data inputs (administrative boundaries, land cover, elevation, road networks, population density, facility locations).** Sources for these data elements have been provided in Appendix Table 2 below. Particular care should be taken to ensure that all raster data sources use the same projection and resolution. In addition, assumptions regarding travel time and mode of transit for different land cover classes should be informed by local knowledge provided by patients directly, or health care providers with experience working with patients.

2. **Estimating travel time using Access Mod 5**. Users should upload all relevant geographic datasets to Access Mod 5 and perform the geographic accessibility analysis tool. Tutorial videos and documentation are available on their website [8].

3. **Calculating zonal statistics for the average population density and travel time within the administrative boundary of interest**. This can be done directly in Access Mod 5 using the zonal statistics tool, or in ArcMap or QGIS using the zonal statistics as table command.

4. **Estimating the bivariate local indicator of spatial autocorrelation (LISA) and creating indicator variables corresponding to each cluster**. (1: high population density/short travel time, 2: high population density, long travel time, 3: low population density, short travel time, 4: low population density, long travel time). We used the publicly available GeoDa software package developed by Dr. Luc Anselin and currently supported by the University of Chicago. The user can specify application of the Benjamini-Hochberg False Discovery Rate correction for multiple testing when performing the bivariate LISA analysis. The package can be downloaded at their website [9].

5. **Generating summary statistics, maps and scatter plots**. This can be done using any statistical software package of choice. We have chosen to use R because of its superior data visualization capabilities, reproducibility, and ability to work with both geospatial and aspatial data.

Data Repository

We have posted datasets and code used to generate the key results in the main manuscript. Specifically, we have created a GitHub repository containing the travel time raster datasets and the R code used to generate the bivariate LISA scatter plots and maps evaluating associations between population density and travel time to health centers and hospitals. [10]

Appendix Table 1. Using the Geographic-Population Services Access conceptual framework to guide policy response

Quadrant	County Classification	Policy Response
Lower right	High Population Density, Short Travel Time	Efficient, centralized services that serve many people
Lower left	Low Population Density, Short Travel Time	Inefficient, placing resources in poorly populated areas will drive up costs of tests. Consider shifting resources to more populated areas.
Upper left	Low Population Density, Long Travel Time	Efficient but inequitable, policymakers may consider introducing point-of-care testing, telepathology, outreach interventions to facilitate referrals to reduce excessive travel times
Upper right	High Population Density, Long Travel Time	Inefficient, too few resources for high population. If resources are available, centralized health services should be placed in these areas

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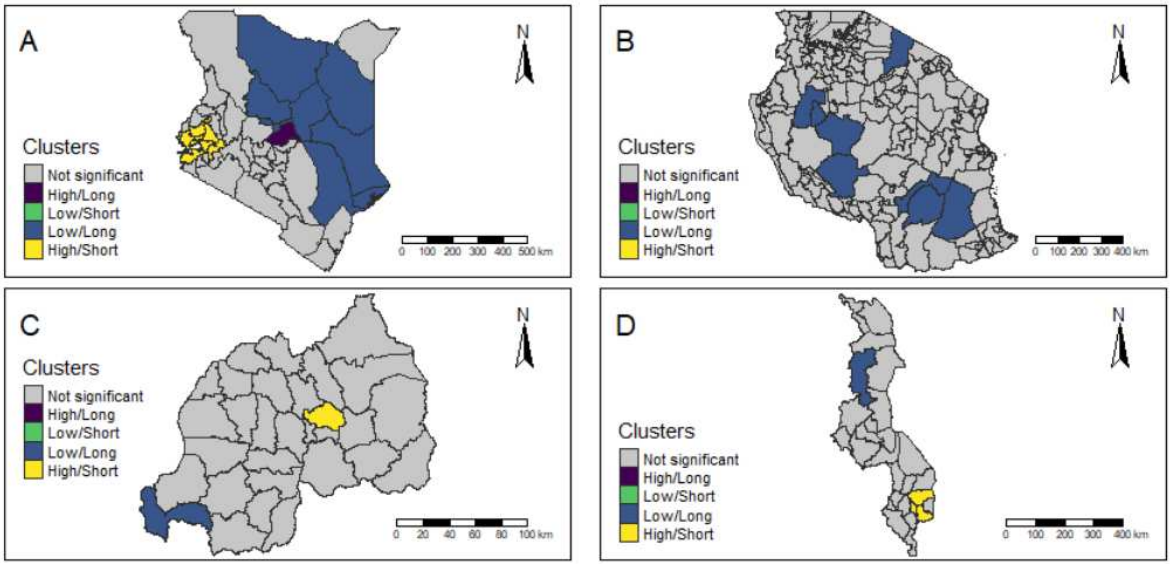
Appendix Table 2. Geospatial data required for evaluating spatial relationships between population density and travel time

Database name	Description	Time	Resolution	Specific analytic input	Source/citation
MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid (MCD12Q1 v006)	Satellite image database that provides global land cover types at annual intervals from 2001 to 2018.	2014	500m	Land cover (forest, shrubland, wetland, savannah, croplands, urban, barren, water, permanent snow)	USGS Friedl & Sulla-Menashe 2019. Available through Google Earth Engine.[11]
Columbia SEDAC gROADSv1	Global database of road networks harmonized across countries.	1980-2010		Roads	Center for International Earth Science Information Network (CIESIN)/Columbia University, and Information Technology Outreach Services (ITOS)/University of Georgia. 2013. Global Roads Open Access Data Set, Version 1 (gROADSv1). [12]
World Pop Project	Modeled high-resolution population estimates available from 2000 to 2019	2015	100m	Population per 100m^2	World Pop Project Population Counts [13,14]
GMTED 2010: Global Multi-resolution Terrain Elevation Data	Elevation measured using multiple sources, primarily NASA digital terrain elevation data	2010	225m	Elevation in 2010	Global Multi-resolution Terrain Elevation Data 2010 courtesy of the U.S. Geological Survey [15]
ESRI hydrolines and hydropolys	River and Lake boundaries			Line files for rivers and lake boundaries for each country	ESRI ArcGIS catalog [16]
Health facility locations (e.g., all facilities in sub-Saharan Africa)	Listing of government-run health facilities in sub-Saharan Africa	2019		Provides details about level of health system and latitude and longitude coordinates	Maina et al. 2019 [17]

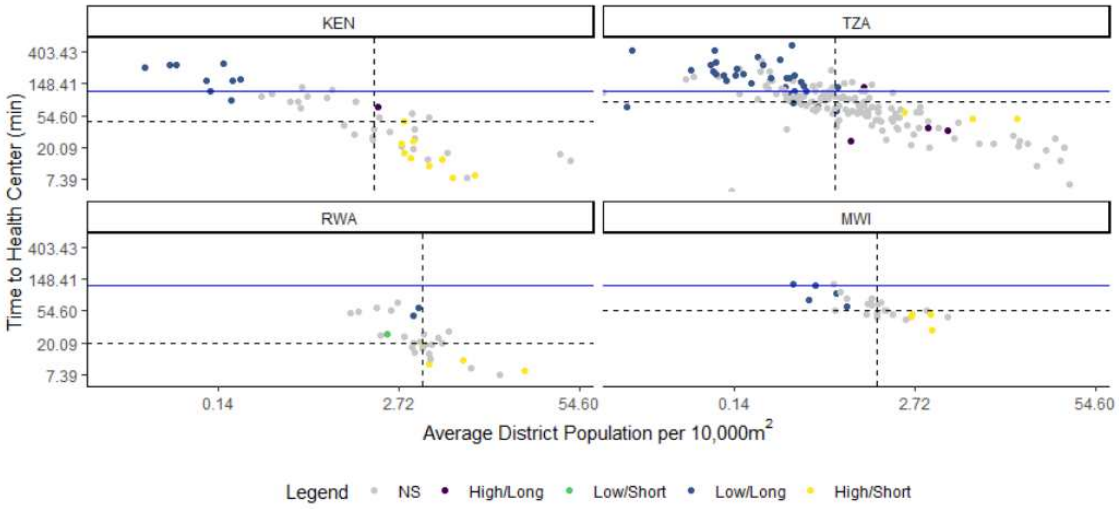
Appendix Table 3. Travel speed and modes of transport for different land cover types specified in the Access Mod 5 algorithm

Label	Speed (kilometers/hour)	Mode
Evergreen Needle Leaf Forests	2	Walking
Evergreen Broad Leaf Forests	2	Walking
Deciduous Needle Leaf Forests	2	Walking
Deciduous Broad Leaf Forests	2	Walking
Mixed Forests	2	Walking
Closed Shrublands	4	Walking
Open Shrublands	4	Walking
Woody Savannas	2	Walking
Savannas	6	Walking
Grasslands	6	Walking
Permanent Wetlands	2	Walking
Croplands	6	Walking
Urban and Built up Lands	15	Bicycle
Croplands Natural Vegetation	6	Walking
Permanent snow and ice	0	Walking
Barren	6	Walking
Water bodies	0	Nothing
Unspecified	20	Motorized
Highway	100	Motorized
Primary	100	Motorized
Local/Urban (Malawi)	40	Motorized
Secondary	60	Motorized
Tertiary	40	Motorized
Trail	20	Motorized



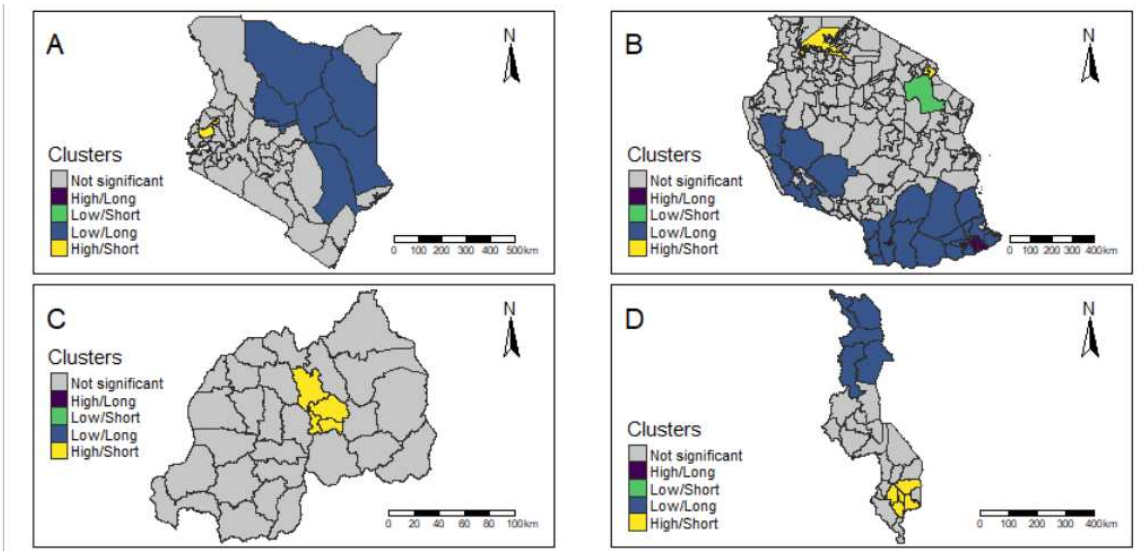
Appendix Figure 1. Maps of bivariate Local Indicator of Spatial Autocorrelation (LISA) plots depicting locations of clusters of four different categories of association between district-level population density and travel time to nearest health center.

Note: The Benjamini-Hochberg False Discovery Rate was applied to correct for multiple testing of clusters. Panel A: Kenya, Panel B: Tanzania, Panel C: Rwanda, Panel D: Malawi. Colors correspond to districts with statistically significant clusters of (1): High population density/long travel time, (2): Low population density/short travel time, (3): Low population density/long travel time, and (4): High population density/short travel time.



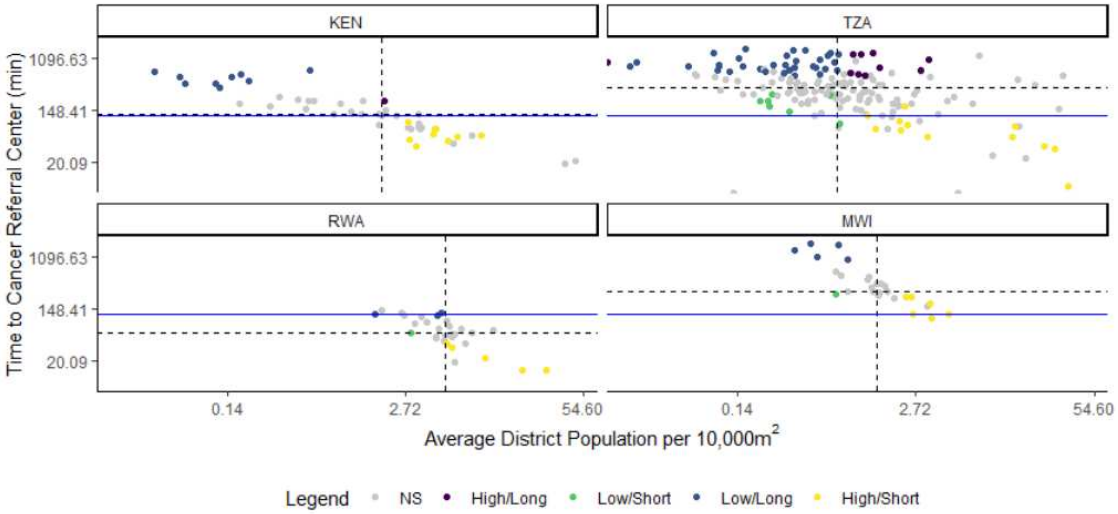
Appendix Figure 2. Pearson correlation between district-level travel time to the nearest primary care health center and population per 10,000m^2 in Kenya, Tanzania, Rwanda, and Malawi.

Note: Abbreviation: NS=Non-significant cluster. Colors correspond to districts with statistically significant bivariate Local Indicator of Spatial Autocorrelation clusters of (1): High population density/long travel time, (2): Low population density/short travel time, (3): Low population density/long travel time, and (4): High population density/short travel time. Significance tests for district clusters were conducted using 999 permutation tests with an alpha=0.05. Blue horizontal line denotes 120 minute travel time. Dotted lines intersect at the median travel time and population density for each country.



Appendix Figure 3. Maps of bivariate Local Indicator of Spatial Autocorrelation (LISA) plots depicting locations of clusters of four different categories of association between district-level population density and travel time to nearest cancer center.

Note: The Benjamini-Hochberg False Discovery Rate was applied to correct for multiple testing of clusters. Panel A: Kenya, Panel B: Tanzania, Panel C: Rwanda, Panel D: Malawi. Colors correspond to districts with statistically significant clusters of (1): High population density/long travel time, (2): Low population density/short travel time, (3): Low population density/long travel time, and (4): High population density/short travel time.



Appendix Figure 4. Pearson correlation between district-level travel time to nearest cancer center and population per 10,000m^2 in Kenya (KEN), Tanzania (TZA), Rwanda (RWA), and Malawi (MWI).

Note: Abbreviation: NS=Non-significant cluster. Colors correspond to districts with statistically significant bivariate Local Indicator of Spatial Autocorrelation clusters of (1): High population density/long travel time, (2): Low population density/short travel time, (3): Low population density/long travel time, and (4): High population density/short travel time. Significance tests for district clusters were conducted using 999 permutation tests with an alpha=0.05. Blue horizontal line denotes 120 minute travel time. Dotted lines intersect at the median travel time and population density for each country.

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