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Comparing absolute and relative distance and time travel measures of geographic access to healthcare facilities in rural Haiti

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ABSTRACT

Introduction While travel distance and time are important proxies of physical access to health facilities, obtaining valid measures with an appropriate modelling method remains challenging in many settings. We compared five measures of geographic accessibility in Haiti, producing recommendations that consider available analytic resources and geospatial goals.

Methods Eight public hospitals within the ministry of public health and population were included. We estimated distance and time between hospitals and geographic centroids of Haiti's section communes and population-level accessibility. Geographic feature data were obtained from public administrative databases, academic research databases and government satellites. We used validated geographic information system methods to produce five geographic access measures: (1) Euclidean distance (ED), (2) network distance (ND), (3) network travel time (NTT), (4) AccessMod 5 (AM5) distance (AM5D) and (5) AM5 travel time (AM5TT). Relative ranking of section communes across the measures was assessed using Pearson correlation coefficients, while mean differences were assessed using analysis of variance (ANOVA) and pairwise t-tests.

Results All five geographic access measures were highly correlated (range: 0.78–0.99). Of the distance measures, ED values were consistently the shortest, followed by AM5D values, while ND values were the longest. ND values were as high as 2.3 times ED values. NTT models generally produced longer travel time estimates compared with AM5TT models. ED consistently overestimated population coverage within a given threshold compared with ND and AM5D. For example, population-level accessibility within 15 km of the nearest studied hospital in the Center department was estimated at 68% for ED, 50% for AM5D and 34% for ND.

Conclusion While the access measures were highly correlated, there were significant differences in the absolute measures. Consideration of the benefits and limitations of each geospatial measure together with the intended purpose of the estimates, such as relative proximity of patients or service coverage, are key to guiding appropriate use.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ We compared five measures of geographic access based on distance and travel time, using simple models, such as Euclidean distance, and more complex geographic information system models that accounted for geographic features in the study area.
⇒ Our findings highlight that there are significant differences in the absolute estimate values of time and distance produced by each approach, and we provide generalisable recommendations to guide investigators when choosing between measures.
⇒ To our knowledge, this is the first study to provide comparisons between measures of geographic accessibility to healthcare in the Caribbean region, and it provides guidance for conducting similar comparisons in other resource-limited settings.
⇒ By revealing the stark differences in population coverage estimates obtained using different geographic access measures, our study demonstrates the need to carefully consider the geospatial model used to estimate access when considering absolute thresholds.
⇒ This study did not use a true gold standard measurement of travel time; our analysis relied on key assumptions that patients used motorised transport, followed national speed limits and did not account for possible financial barriers.

BACKGROUND

Longer distance to health services has been associated with lower service utilisation rates, increased health expenditure and poor health outcomes across multiple diseases.[1–4] Studies in low-income and middle-income countries (LMICs) have described poor geographic access leading to lower rates of facility-based deliveries, increased childhood mortality and worse outcomes in communicable diseases such as HIV as well as in non-communicable diseases (NCDs) such as cardiovascular disease and breast cancer.[4–16] Hence, distance to health services has been adopted as a population measure of health equity, with travel time a proxy for equitable physical access.[17] Patient travel distance and travel time measures can be used to assess disparity and to describe the trade-offs health systems make between equity of access and efficiency.[18–23] Further, being able to contextualise the accessibility of particular health service in relation to relative disease burden is critical for overall health system efficiency. A 2-hour, one-way travel time threshold has been proposed for hospital services such as emergency care, obstetrics and general surgical interventions and is the threshold often used by policymakers examining population-level access.[24] However, a realistic threshold may vary based on condition or required care, and a lower threshold may be indicated for more basic health services provided at health centres, such as malaria care or immunisations.

Despite the importance of distance and time measurements, there are challenges with obtaining accurate estimates in LMICs. Historically, Euclidean distance (ED), or straight-line distance, has been most commonly used in many LMICs. However, when compared against distance measures from more sophisticated geographic information system (GIS) modelling techniques and patient-reported estimates of travel time, straight-line distances often result in substantial underestimates, inaccurately capturing travel burden and erroneously estimating catching areas of health facilities.[1 7] Increasingly however, health ministries and service providers are adopting GIS across resource-limited settings.[25] Automated platforms such as AccessMod 5 (AM5) use publicly available geographic feature databases including road networks and local topography to produce valid estimates of distance and travel time.[26 27] Additionally, raw worldwide geographic data are becoming more widely available through platforms such as Google Earth Engine and Open Street Map (OSM), which, taken together, allow for more sophisticated modelling techniques to be leveraged by LMICs to accurately measure population-level access and ultimately improve health outcomes.[28–30]

The primary aim of this study is to compare different GIS measures used to estimate the geographic accessibility of services at seven non-governmental organisation (NGO) supported public health facilities and the main national referral hospital in Haiti (figure 1A). The majority of health services in Haiti are concentrated in the capital region and distance is a known access barrier for many Haitians, particularly in rural regions.[31 32] While historically there has been substantial variation in quality of services across the primary care system in Haiti, there is ongoing strengthening of the healthcare system with a national goal of achieving universal health coverage by 2030.[32 33] As previous studies in Haiti have used ED as a measure to estimate patients' physical access to care,[34 35] we sought to compare access measures obtained using different analytic approaches in this setting given the increasing availability and usability of these modelling techniques. This analysis set out to compare increasingly sophisticated models for estimating travel time and distance from patient residence to healthcare facilities, using both raster and vector approaches. Our study highlights the importance of appropriately measuring accessibility and how research questions can inform the choice of methods. We provide empirical estimates of geographic accessibility in Haiti, but more importantly provide guidance to policymakers in other resource-limited settings seeking to estimate geographic access to answer public health questions.

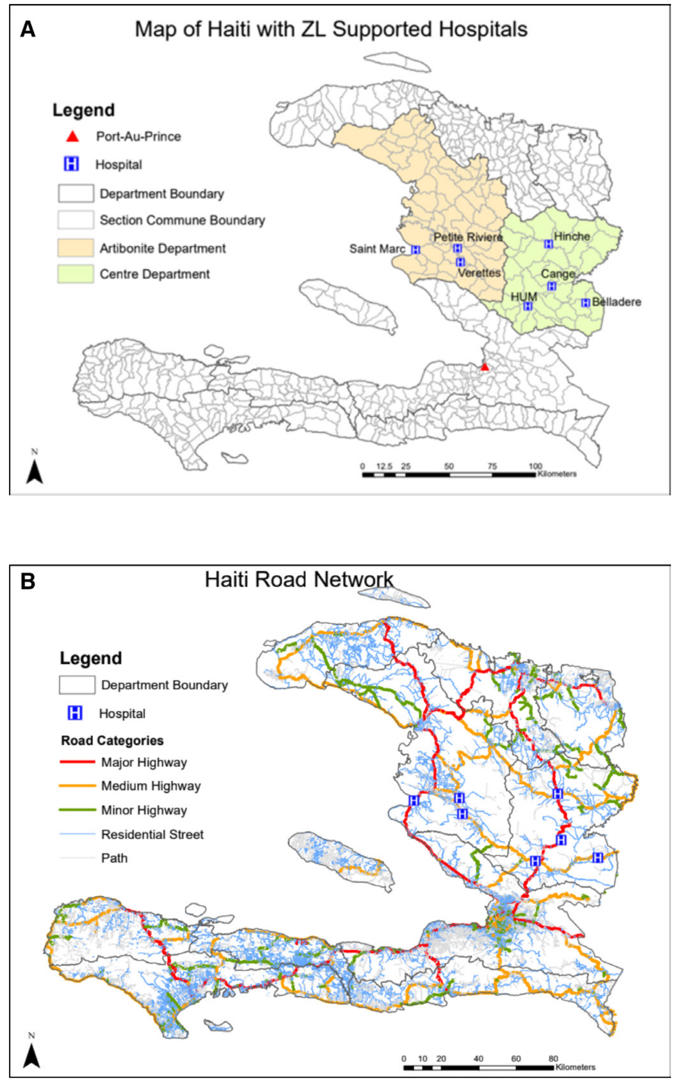

Figure 1 (A) Map of Haiti with seven Zanmi Lasante (ZL)/Partners In Health supported hospitals throughout the Center and Artibonite departments. (B) Map of Haiti with road network by road category and all Zanmi Lasante/Partners In Health supported hospitals included in analysis.

METHODS

Study setting

Haiti is a country in the Caribbean region with a population of nearly 11 million, covering a land area of 27 750^2 km. The country is irregularly shaped and about 80% of the land area is covered by mountains.[36 37] Classified as a low-income country, many Haitians (65%) live below the national poverty line and the country ranks poorly relative to neighbouring countries on many health indicators.[36–39] The healthcare system in Haiti is divided into three levels—primary, secondary and tertiary, managed by the ministry of public health and population (MSPP). Nearly half of the healthcare facilities are located in the capital, Port-Au-Prince, while service coverage is poorer in rural areas where many lack access to essential health and nutrition services.[31] MSPP collaborates with many NGOs to support care delivery and emergency response in these rural areas. Zanmi Lasante (ZL) together with Partners In Health (PIH) has worked closely with MSPP to provide high-quality care in Haiti for over 30 years, helping to establish 16 health centres and public hospitals throughout the country, and serving as one of the largest healthcare providers outside of the government. These health facilities are concentrated within the Center and Artibonite departments, two of the most remote and underprivileged regions in the country.[40] Given the unique geography and topography of the country, comparing the utility of different measures of distance and time may inform selection of the most appropriate measure given available resources and precision required to guide health systems planning efforts.

Data management and data sources

Information regarding geographic and population features was obtained from publicly available databases. The basemap of Haiti's administrative boundaries was obtained from the Humanitarian Data Exchange.[41] Road files were acquired from OSM updated in 2018.[42] Modelled population estimates were obtained from WorldPop database for 2019.[43]

Measures of geographic access

The administrative level used for this analysis was the section commune level, the smallest administrative division in Haiti with consistently available geographic data (online supplemental appendix figure 1). There are a total of 570 section communes ranging in size from 5 to 318 km^2 with a mean area of 53 km^2 and average population of 19 160 individuals. The geographic centroids of each section commune were calculated and represent the 570 origins of our analysis. Two tertiary hospitals, University Hospital Mirebalais (HUM) and State University Hospital (HUEH) and the six hospitals supported by ZL/PIH, were chosen as destinations for our analysis. Geocodes for these hospitals were extracted from Google Maps.[44] We used GIS to produce five different measures of geographic access: (1) ED, (2) network distance (ND), (3) network travel time (NTT), (4) AM5 distance (AM5D) and (5) AM5 travel time (AM5TT).

ED estimation

ED was calculated using geocodes corresponding to the origin (section commune centroids) and destinations (HUM, HUEH and six ZL/PIH hospitals), using the near distance tool in ArcMap V.10.6.1 (Esri, Redlands, California).[45]

ND and time

First, roads were extracted within the Haiti national border from a road shapefile obtained for the entire island of Hispaniola.[46] A topology profile was added to the road file using widely accepted topology rules: must not overlap, must be single part and must not have pseudo nodes. Using this methodology, errors in topology were corrected using the following commands: subtracting shorter road, exploding roads and merging roads.[47 48] Based on Haitian government classification and on prior published studies, roads were reclassified into five categories: pedestrian path, residential streets, minor highways, medium highways and major highways (figure 1B).[49 50] The associated road speeds were based on a previous study by Mathon *et al*[49] and were stored as attributes; they can be found in online supplemental appendix table 1.[49]

A network dataset was built with the road file and accumulation cost attributes were added for length and times. The section commune centroids were added as the origin and the location of the health facilities as the destinations. Using the network dataset an Origin Destination (OD) cost matrix analysis was performed with time as the impedance factor. The resultant network was validated using Google Maps by randomly sampling 30 pairs (5%) of origin and destination points and comparing the distance and times from the OD cost matrix with Google Maps driving directions. Cases which had no connection network found between an origin point and the destination were manually identified (eg, located within a water barrier, located far from road network). After identifying these cases, in order to assign complete road networks to these section communes, a road segment was built connecting centroids located away from existing roads and walking speeds were assumed for those segments. The final resultant OD cost matrix for length and time was exported for data analysis. All spatial data management and adjustments to complete the road network, ED estimations and ND and NTT estimations were done in ArcMap.

AM5 raster model for distance and time

AM5 was developed in 2005 as a suite of GIS tools to allow countries to evaluate health service coverage using an algorithm based on least-cost paths and accumulative cost surface ultimately determining the most efficient path between two points on the surface.[26 51] AM5 enables estimation of a travel time surface that covers a geographic area of interest, assigning travel times to each raster grid cell using the geographic access tool. Using this travel time surface, AM5 also can estimate referral times between lower-level health facilities and hospitals using the referral analysis tool. AM5 uses road networks and travel speeds similar to the network dataset described above; however, AM5 further accounts for surface wide geographic features evaluating the entire study setting which in turn allows for travel off roads. By incorporating additional geographic features beyond just road networks, AM5 estimates may better capture the extent to which physical distance impedes access to care in low-resource settings where private car-based travel is less common.[26 27] The inputs into AM5 consisted of a digital elevation model obtained from DIVA-GIS with a 1000m resolution, a land cover raster file from Google Earth Engine with a 500m resolution, rivers and lakes shapefile obtained from OCHA Services, the road shapefile described previously, hospital locations and section commune centroid locations.[52 53] Speeds for all land cover types can be found in online supplemental appendix table 1. After generating a merged land cover from the input layers listed above in AM5, 61 (11%) section commune centroids were located on top of barriers. Facility locations were corrected in AM5 by using the Interactive Map tool to preview raster layers and manually move facility locations to the nearest cell that did not contain a defined barrier (rivers and lakes). In order to calculate the distance and time from the section communes to the health facilities, we used the referral analysis tool to estimate travel time and distance between section commune geographic centroids and the hospitals. This table was then exported into Microsoft Excel V.16.3 (Microsoft, Redmond, Washington) and the shapefile was exported into ArcMap for visualisations.

Statistical analysis plan

We sought to compare five measures of geographic access representing travel times and distance between section communes to closest hospital. Measures of geographic access are generally used for two purposes in health services research: (1) obtaining estimates of the proportion of population within a given access threshold and (2) ranking participants or geographic areas by how far they are from care.[26] Obtaining accurate measures of coverage proportion requires accurate absolute estimate values, while ranking participants only requires that the relative ordering of estimate values is preserved. Analysis of variance (ANOVA) and pairwise t-tests were used to assess concordance between absolute measures of geographic access and correlations to assess concordance of ranking of geographic access measures assigned to section communes.

After estimating the distance between section commune centroids within the Center and Artibonite departments and the seven ZL/PIH hospitals based on three distance measures: ED, ND and AM5D, one-way ANOVA was used to test for a global difference between means, and then pairwise t-tests with equal variances to determine which measures differed from each other. Similarly, travel time between the section communes and health facilities were summarised based on two measures: NTT and AM5TT and a pairwise t-test was performed to assess differences between the measures. Following an assessment of the distribution of the different measures, ANOVA and t-test were chosen based on the relatively normal distribution of distance and time measurements.

Given that healthcare planners often implement services at varying levels of the healthcare system, with some targeting smaller catchment areas and others rolled out at a national level, we repeated these analyses at the national level. Examining geographic accessibility across Haiti from all section communes to the nearest of the two tertiary hospitals included in our analysis, we were able to compare the correlations and absolute differences between measures at two spatial scales. In our experience, some specialised health services such as cancer treatment may only be available in one facility in the country, and patients of these two hospitals will often travel from every part of the country to reach these specialised services. In addition, the population surrounding these two tertiary hospitals are vastly different with HUM located in a rural mountainous area and HUEH located in the urban capital city. Of note, 15 observations (3%) located on islands off the cost of mainland Haiti were excluded from this analysis since the distance and time for these section communes could not be calculated in AM5. In order to compare relative ranking of section communes across the five measures, we examined correlations between the five geographic access measures of distance and time estimates from section commune centroid nationally to HUM using Pearson correlation coefficients and 95% CIs.

Lastly, we estimated population-level accessibility within the Center and Artibonite departments capturing the proportion of the catchment population that has geographic access to their nearest ZL/PIH supported hospital. We report these findings stratified by time and distance intervals.

All statistical analyses were done in R statistical software (V.4.0.3). All statistical tests were two sided and p values of <0.05 were considered statistically significant.

Patient and public involvement

There was no direct patient involvement in the design and conduct of this analysis. However, the development of the research question was motivated by patient experiences traveling far distances to reach healthcare services in Haiti.

RESULTS

Geographic characteristics

Online supplemental appendix table 2 summarises geographic, health and economic characteristics of each department. The Center department, home to 701 205 individuals, is composed of 35 section communes and has four ZL/PIH hospitals including HUM. The Artibonite department, composed of 63 section communes, has a population of 1 684 599 and has three ZL/PIH hospitals. The Artibonite department is both larger in size and more densely populated than the Center department.

Comparing mean distances and times across geographic access measures

The results of the distance and time estimates from each section commune to selected ZL/PIH-supported hospitals, HUM and Saint Marc Hospital (SM), the largest

Table 1 Comparison of mean distance (in km) and time (in min) from section communes to selected hospitals in Center and Artibonite departments

	Distance and time estimates to HUM (N=35)		Distance and time estimates to SM (N=63)	
Absolute measures				
Measure	**Mean distance (SD)**		**Mean distance (SD)**	
ED	29.4 (15.7)		42.5 (19.4)	
ND	51.7 (30.4)		63.1 (30.1)	
AM5D	43.8 (26.2)		59.1 (28.3)	
Measure	**Mean time (SD)**		**Mean time (SD)**	
NTT	98.7 (61.0)		97.4 (56.8)	
AM5TT	66.2 (33.2)		75.8 (34.8)	
Distance pairwise comparison				
	Mean difference (95% CI)	**T-test p value**	**Mean difference (95% CI)**	**T-test p value**
ND–ED	22.33 (8.19 to 36.47)	<0.001	20.65 (9.57 to 31.73)	<0.001
AM5D–ED	14.44 (0.30 to 28.58)	0.04	16.59 (5.51 to 27.67)	0.001
ND–AM5D	7.89 (–6.25 to 22.02)	0.38	4.06 (–7.02 to 15.14)	0.66
Time pairwise comparison				
	Mean difference (95% CI)	**T-test p value**	**Mean difference (95% CI)**	**T-test p value**
NTT–AM5TT	32.5 (19.7 to 45.3)	<0.001	21.7 (13.8 to 29.5)	<0.001

AM5D, AccessMod 5 distance; AM5TT, AccessMod 5 travel time; ED, Euclidean distance; HUM, University Hospital Mirebalais; ND, network distance; NTT, network travel time; SM, Saint Marc Hospital.

facilities within the Center and Artibonite departments, respectively, are summarised in table 1.

Table 1 shows that within both the Center and Artibonite departments, ED is significantly shorter than both ND and AM5D yet ND and AM5D are comparable. For example, the mean ND to SM was 20.65 km (48%) longer than ED (p=<0.001) and the mean AM5D to SM was 16.59 km (39%) longer than ED (p=0.001). Findings were similar for all ZL/PIH supported hospitals in this study as displayed in online supplemental appendix table 3. The largest absolute difference between distance measures appeared for travel to Belladere hospital, where ED was 33.3 km and ND was 77.4 km (2.3 times ED).

NTT and AM5TT were also different, with AM5 producing significantly shorter estimates than NTT. For example, among section communes in the HUM catchment department, there was a statistically significant 32.5 min (95% CI: 19.7 to 45.3) shorter average time to HUM when using AM5TT compared with NTT. These measures followed a similar pattern in the SM catchment department in addition to the other ZL/PIH supported hospitals (see table 1 and online supplemental appendix table 3).

Figure 2A displays choropleth maps of travel times to the nearest ZL/PIH hospital within the Artibonite and Center departments in 30 min time intervals comparing the NTT and AM5TT estimation techniques. The dark blue colour represents the section communes with the shortest travel time and the dark red represents longest travel times. While the maps are generally consistent, more section communes were classified as having longer travel times with NTT compared with AM5TT.

The nationwide distance and time estimations from section communes to the two referral hospitals are outlined in online supplemental appendix table 4, expanding the spatial scale of the analysis and comparing hospitals in both rural and urban settings. Based on the estimation technique used, the national mean distance to HUM, averaging over all of the section communes in the study, ranged from 111.9 (ED) to 167.3 km (ND) and the national mean distance to HUEH ranged from 108.3 (ED) to 161.6 km (ND). The findings followed a similar pattern to the results from the departmental difference with ED being very different from ND and AM5D; however, in the national analysis, AM5D was also significantly different from ND in a pairwise test (p<0.001).

However, comparing the proportional differences from the national comparison to HUM with the earlier departmental comparison, we see that ND is only 50% longer than ED nationally compared with 76% longer when restricting to the Center department. This analysis also found significant differences in the mean travel time to these referral hospitals between the estimates generated from the two techniques used. On average, NTT was 30.4 min (95% CI: 27.4 to 33.4) longer than AM5TT to HUM (p<0.0001), with a similar pattern observed at HUEH.

Figure 2B displays national choropleth maps of travel times to the nearest tertiary referral hospital in 1-hour

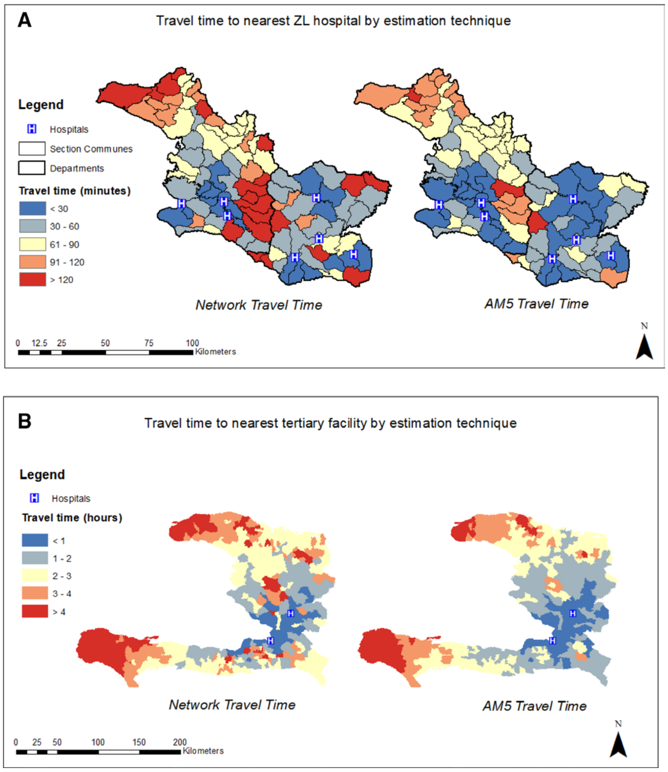

Figure 2 (A) Comparison of NTT and AM5TT to nearest Zanmi Lasante (ZL)/Partners In Health supported hospitals by 30 min intervals throughout the Artibonite and Center departments. (B) National comparison of NTT and AM5TT to nearest tertiary hospitals by 60 min intervals. AM5, AccessMod 5; AM5TT, AM5 travel time; NTT, network travel time.

time intervals comparing the NTT and AM5TT estimation techniques. Similarly, maps are generally consistent, though AM5 produced shorter travel times in the Center and Western departments relative to estimates derived from network calculations.

Correlation between geospatial estimation measures

Table 2 includes Pearson correlations between the five geographic access measures (travel time and distance from each section commune centroid to HUM). We found that the three distance and the two travel time estimation techniques produced values that were all highly correlated (range: 0.78–0.99) meaning that the rank ordering of geographic access by section commune is preserved across most measures.[54] The strongest correlations were between the various distance measures with each of the three correlation coefficients >0.96. The weakest correlation was between ED and NTT (0.78).

Population-level comparison

Online supplemental appendix figure 2 presents population-level accessibility comparisons between the three distance estimation techniques across both the Center and Artibonite departments. The relative percentage of the catchment population living within a particular threshold from the nearest hospital varies based on the estimation technique used, with the differences being more pronounced in the Center department. Population-level accessibility comparisons between the two travel time estimation techniques are also presented in online supplemental appendix figure 3 stratified by 30 min intervals and follow a similar pattern to distance techniques. For example, within the Center department, it was estimated that 54% of the catchment population lives within 30 min of the closest hospital when using AM5TT, while only 33% are estimated to live within this radius when using NTT. In the Artibonite department, 35% of the population lives within 30 min of the closest hospital when using AM5TT, while only 26% are estimated to live within this radius when using NTT.

DISCUSSION

Our results indicate that while distance and travel time estimates were highly correlated, there were differences in absolute measures across the five approaches. ED models estimated significantly shorter distance travelled compared with ND and AM5D models that incorporated roads and other geographic features. AM5D estimates were longer than ED but shorter than ND; this pattern was anticipated as AM5 raster referral analysis allows for travel off roads. The absolute differences between ND and ED were more pronounced when the analysis was restricted to one department as compared with the national analysis; however, we find that patterns are similar regardless of spatial scale. Given the increasing focus on tracking geographic accessibility indicators to reach Universal

Table 2 Matrix of Pearson correlation and 95% CIs of distance and time values to University Hospital Mirebalais by different geospatial estimation techniques

	ED	ND	AM5D	NTT	AM5TT
ED	1.00	–	–	–	–
ND	0.97 (0.97 to 0.97)	1.00	–	–	–
AM5D	0.98 (0.98 to 0.99)	0.99 (0.99 to 0.99)	1.00	–	–
NTT	0.78 (0.75 to 0.81)	0.83 (0.80 to 0.85)	0.81 (0.78 to 0.84)	1.00	–
AM5TT	0.88 (0.86 to 0.90)	0.91 (0.89 to 0.92)	0.91 (0.89 to 0.92)	0.93 (0.92 to 0.94)	1.00

All values are significant at the 0.05 level.
AM5D, AccessMod 5 distance; AM5TT, AccessMod 5 travel time; ED, Euclidean distance; ND, network distance; NTT, network travel time.

Health Coverage and the Sustainable Development Goals, accurate estimates of travel distance and times are crucial to inform progress.[55 56] Recognising we did not present a gold standard of directly observed patient travel times and routes,[57] our analysis highlights possible trade-offs between ED estimates and more sophisticated estimation techniques, providing generalisable lessons regarding the implications for each. These findings contribute to the international literature by demonstrating the feasibility of computing multiple measures of geospatial access in resource-limited settings. Our study showcases the importance of choosing the appropriate accessibility measurement and methods depending on the research question. This work provides empirical estimates of geographic accessibility in Haiti, but more importantly, provides guidance to policymakers in other resource-limited settings seeking to estimate geographic access to answer public health questions.

To our knowledge, no earlier studies have provided comparisons between measures of geographic accessibility to hospitals in Haiti or the Caribbean region. While few studies have assessed the impact of geographic health accessibility, they have all used ED estimation. Wang and Mallick[58] estimated the extent to which women's contraceptive use is associated with the available method choices in the health facilities throughout Haiti using ED to link Demographic and Health Surveys (DHS) clusters with facilities.[59] However, they note that mountainous terrain and road conditions may have led to misclassification of accessibility by inaccurately classifying which facilities were more easily accessed. Kwan *et al*[35] evaluated the poverty distribution among patients with NCD at HUM, using ED to explore the relationship between poverty and distance to HUM. They found that among those who presented at the health facility, those who lived further were less poor than those living closer, speculating that those who live further and are more poor face high barriers to accessing care and therefore were underrepresented in their sample.[35]

Our findings are consistent with other studies from LMICs; they reinforce the concept that the choice of geographic accessibility measure may influence conclusions about absolute accessibility. Noor *et al* illustrated this issue by comparing multiple spatial models in Kenya. Their results revealed that ED models incorrectly classified roughly 6 million individuals as being within 1 hour of government health services.[1] Recently, van Duinen *et al* compared two geospatial models against patient-reported travel times and found that the more conservative travel time estimates, with lower travel speeds, better estimate patient-reported travel times, highlighting how critical the input variables are to producing valuable spatial model outputs.[16] Similarly, Rudolfson *et al* found that standard AM5 generated travel times underestimated patient-reported travel times for emergency obstetric care in Rwanda; however, when the GIS models were adjusted to model patients travel path passing through health centres enroute to the hospital, modelled times were much closer aligned to the patient-reported times.[27] Banke-Thomas *et al* compared modelled travel time to comprehensive emergency obstetric care in Lagos, Nigeria, to measured times from replicated patient journeys. Their findings confirmed that existing geospatial modelling methods underestimate actual travel times when using a gold standard validation, which these authors did through actual replication of travel by two independent drivers.[57] These findings further underscore the importance of understanding true travel patterns of patient populations. It is critical to note this analysis is focused on geographic or physical accessibility to health services and we acknowledge that there are additional dimensions of healthcare access not addressed by this study. Although a region may appear to have geographic access to a health facility, this does not mean services are available, affordable, acceptable or that there is appropriate accommodation—all dimensions that contribute to overall access.[59]

Similar to our findings, Nesbitt *et al* compared a variety of spatial models of delivery care access in Ghana and found that the models were highly correlated with each other including ED.[21] Despite its known limitations, ED may offer a reasonable proxy for other spatial measures, especially when rank preservation rather than coverage estimation is the goal of the analysis. Nonetheless, our findings support growing consensus that ED may severely overestimate health facility coverage within a given threshold distance, and therefore should be used with caution when estimating coverage.

Careful consideration of the benefits and limitations of each measure can help guide appropriate use and are summarised in table 3. Based on our findings, ED is acceptable when estimating the relative proximity of patients, with NTT and AM5TT being preferable. However, when estimating coverage, ED results in underestimates of health services coverage and therefore would be unfavourable, while NTT or AM5TT would be preferred. Furthermore, since ND and NTT estimates use road networks, they would be the preferred options when approximating actual patient travel routes. However, it is key to note that ED requires the least amount of researcher time and effort as well as the least amount of data inputs, while ND and NTT require the most research time and effort and AM5D and AM5TT require the most data inputs.

Given the lack of a true gold standard measure of travel time from a patient's address to their health facility, which would have required greater investments of resources and time than our study allowed such as detailed surveys or GIS trackers, our analysis relied on key assumptions. We assumed that all patients travelled using motorised transport and followed national speed limits, which may not accurately reflect the true transportation patterns used by patients to reach care. Our analysis also assumes uninterrupted travel between two points; however, we recognise patients may use multiple

Table 3 Summary of recommendations on application of geospatial estimation measures based on goals of geospatial analysis and analytic resources

	Goals of geospatial analysis			Analytic resource	
	Relative accessibility/ proximity	Absolute coverage	Estimating patient travel route	Researcher time and effort	Required data inputs
ED	++	+	+	###	###
ND	++	++	+++	#	##
NTT	+++	+++	+++	#	##
AM5D	++	++	+	##	#
AM5TT	+++	+++	++	##	#

+ Unfavorable.
++ Acceptable.
+++ Preferred.
# High requirement.
Medium requirement.
Low requirement.
AM5D, AccessMod 5 distance; AM5TT, AccessMod 5 travel time; ED, Euclidean distance; ND, network distance; NTT, network travel time.

forms of transportation, which may lead to additional waiting times. Further, all estimates are measured from geographic centroids and therefore do not reflect the distribution of the population within each section commune nor capture variation in travel patterns among residents of the same section commune. In addition, we do not account for travel costs which may also influence the routes and mode of transportation. While geospatial estimates may be helpful, assessing the true burden of travel distance and time frequently requires detailed survey of patients and the use of GIS trackers. Future studies in Haiti and beyond should endeavour to validate geospatial estimation techniques using patient-reported methods. Lastly, this analysis focused on a subset of hospitals throughout Haiti focusing predominantly in the Center and Artibonite departments. We recommend that future studies in Haiti and the region explore a wider range of hospitals and resident locations in order to confirm generalisability of our findings.

Producing the geographic measures presented in this study requires specialised geospatial analytic skills. Given the limited published data on healthcare accessibility in Haiti, we have stored the data and analytic files used in a publicly available GitHub repository.[60] This resource will enable researchers at ZL/PIH and other organisations in Haiti and elsewhere to produce their own geographic access measures, identify gaps and underserved areas, inform allocation of resources and strengthen evidence-based policy decisions.

CONCLUSION

Geographic access is a modifiable dimension of accessibility and one where research can inform policy and programmes such as travel support, strengthening referral networks, decentralising care or building additional facilities to improve accessibility. Longer travel times place an increased burden on patients—especially the poorest—and may result in delays in treatment, higher out of pocket expenditures and ultimately increased mortality.[14 15] Understanding and measuring geographic barriers to accessing care is of critical importance, especially in settings like Haiti where care may be inaccessible to many. Our study highlights the advantages and trade-offs of different geographic accessibility measures and provides guidance to researchers and policymakers on choosing between measures when making relative or absolute population comparisons.

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