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Article

Estimating Demand for Healthcare Facilities in Rural Developing Countries

Brent Lloyd

Nez Perce Tribe, Land Services Department, Lapwai, ID 83540, USA; brentl@nezperce.org

Abstract: Spatial analysis provides decision support for numerous public health issues such as determining locations of healthcare facilities for a given population. With limited population health data available for developing countries, spatial data analysis provides limited benefit in this regard. This paper attempts to assist public health practitioners in overcoming the health information gaps common to developing countries for determining health-related demand locations. We introduce methodologies that use generally available information from Demographic and Health Surveys (DHS). Burkina Faso, a developing country with poor health quality, is used in this paper as a case study to show how DHS data, not generally used for spatial analysis, can be used to estimate multiple area demand locations for healthcare facilities. Factors used to locate demand per administrative province included population density, proximity to major road networks, economic wealth index, birth rate, childhood stunting, and malaria rates. Major health issues in populated areas along access routes ultimately determined the estimated area demand for healthcare facility locations in this analysis.

Keywords: spatial analysis; cluster analysis; weighted factors; Getis-Ord Gi; Demographic Health Surveys; rural health; developing countries; health demand; health access; spatial accessibility

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1. Introduction

Millions of people die in developing countries due to healthcare needs not being met (Harrison, 2009). Developing countries have higher disease rates than first world countries and also have more severe resource constraints and limited access to healthcare (Adeyeye et al., 2023; Hjortserg & Mwikisa, 2002; World Bank, 2008). Multiple studies have analyzed healthcare demand in populations that are considered in need (Comber et al., 2011; Peters et al., 2008; Schoeps et al., 2011). Identifying access to health resources is crucial in caring for disadvantaged populations in areas with high health demand (Faye et al., 2020; Yao & Murray, 2014). Defining access and demand for healthcare can be a vague concept when it comes to decision support analysis for the placement of healthcare facilities (Khan & Bhardwai, 1994; Penchansky and Thomas, 1981). Penchansky and Thomas (1981) describe a broad definition of access in five dimensions including availability, accessibility, accommodation, affordability, and acceptability. Defining access can also include the ability to receive care when needed and desired (Ricketts & Goldsmith, 2005). Rutherford et al. (2010) expands on this idea in terms of influencing factors that can impair access resulting from any intra- or extra-household influences that may hinder health service uptake.

Access to healthcare relates to the availability of healthcare resources relative to the demands of the population for services (Munoz & Källestål, 2012; Ouma et al., 2021). Availability and accessibility can be spatial in nature and it is common to refer to these dimensions as "spatial accessibility" (SA) (Delamater, 2013; Guagliardo, 2004; Luo & Wang, 2003). Spatial data related to demand and accessibility can support the process of determining the location of a healthcare facility. The placement of healthcare facilities depends on multiple factors including accessibility, population densities, and demand from major health issues (Yao & Murray, 2014). Another factor that is considered with demand is the utilization of a healthcare facility. Kiwanuka et al. (2008) observed that the poorer households utilized healthcare facilities less because of the cost. The type of health need can also determine the utilization of a healthcare facility (Kitui et al., 2013; Schellenberg et al., 2003).

The concept of a demand area, as associated with healthcare facilities, has been defined by the population within a given catchment area serviced by a healthcare facility (Munoz & Källestål, 2012; Rahman & Smith, 2000; Tanser, 2006). Studies by Guagliardo (2004) and Joseph & Bantock (1982) focus on population density using a population demand factor to spatially adjust where to locate a facility based on the population density of an area. In addition to using population density as demand, other studies have focused on a health issue of the population in correlation to distance to healthcare facilities such as areas of infant mortality (Becher et al., 2004) or malaria (Beiersmann et al., 2007); these studies were able to examine how distance to a healthcare facility negatively affected the health of the population. Demand can also refer to the severity or potential for healthcare issues in the population. This definition supports that demand should be weighted based on the severity of the health issues and the potential usage of a healthcare facility for a population catchment area. Spatial weights between observations reflect the intensity of the geographic relationship within a certain area (Jerrett et al., 2003). Weighted spatial data for a healthcare facility from health and wealth data can provide important information about the needs of a population.

Spatial analysis has proven to be beneficial for facility site selection. Such applications as location analysis, modeling central themes, locating areas of high demand, spatial weights, distances, and SA can be completed with spatial analysis (Curtin & Church, 2006; Murray, 2010). Spatial analysis provides effective tools for measuring sample data representative of a larger population in a geographic area by performing spatial interpolation (Childs, 2004). Spatial interpolation for studies such as this provides an understanding of spatial health issues in developing countries where data may be sparse or have spatial data holes. Health risk factors, such as malaria, can be given a spatial dimension to help determine spatial patterns of high and low incidences. Spatial cluster analysis can also provide important information for finding statistically significant spatial patterns.

The purpose of this paper is to demonstrate a methodology for locating area demand for a healthcare facility in an administrative boundary by factoring in population density and other factors relative in Burkina Faso including proximity to major road networks, wealth, and health factors. This paper utilizes health data with limited geographic density from a developing country to demonstrate how spatial analysis can be used to identify areas of demand for healthcare facilities. Two exercises presented here examine areas of demand for healthcare facilities in the administrative provinces of Burkina Faso, Africa. The first analysis finds the area of demand for each healthcare facility based solely on population density. This method has common usage in the field of healthcare facility demand location research (Guagliardo, 2004; Langford & Higgs 2006; Munoz & Källestål, 2012; Rahman & Smith, 2000; Tanser, 2006). The second analysis locates an area of demand for a healthcare facility per province based on the population density outputs created from the first analysis and incorporating the additional criteria of local wealth and health factors. Including wealth and health factors in the analysis will help to better estimate the demand of healthcare facilities.

2. Methods

Healthcare facilities can provide education, resources, and preventative measures to protect against diseases, health issues, and provide medical care for communities in need (Robert et al., 2003; World Health Organization[WHO], 2020). Understanding the major health concerns in an area can help find the best location(s) that will serve the greatest portion of the population that is in demand. Spatial analysis methodologies can be utilized to assist as decision support for locating demand site selections. The process described in this section was conducted using Environmental Systems Research Institutes' (ESRI) ArcGIS software suite inclusive of ArcDesktop for the application and geo-visualization of the data. Figure 1 provides an overview of the processes used in this methodology.

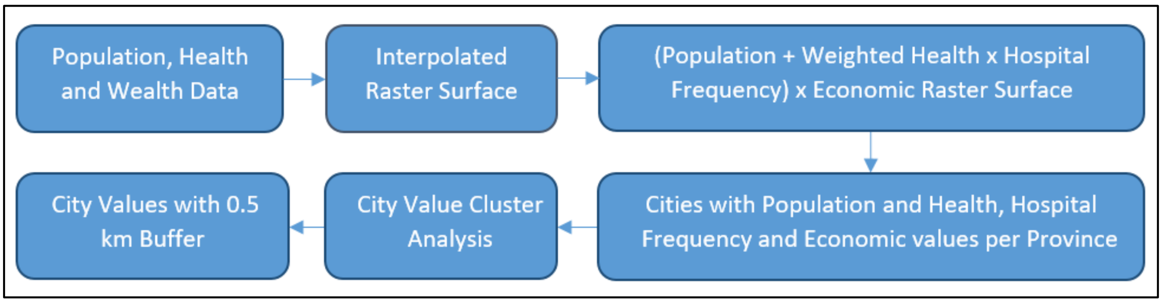

Figure 1. Workflow diagram for locating areas of demand based on the weighted population and health factors.

Burkina Faso has an estimated 19 million inhabitants with approximately 70% of Burkinabé living in rural areas (World Bank, 2015). The country has few medical professionals, with a reported 1 doctor practicing medicine per 1,000 people in the country as of 2010 (IHME, 2010). According to the WHO, Burkina Faso allocated 13% of government expenditures to health care spending, which represented three percent of the GDP for 2010. Both figures rank low even among African countries (WHO, 2010).

2.1. Data

The Demographic and Health Surveys (DHS) collect a variety of information on the health, well-being and a variety of socioeconomic and cultural characteristics of households in most developing countries. These data provide the most comprehensive and detailed information on individual- and household-level health and well-being throughout the 45 provinces in Burkina Faso. In 2010 the DHS collected over 17,000 surveys for households clustered into 540 spatially referenced locations within Burkina Faso (Figure 2). The DHS data were sampled based on a stratified two-stage cluster design drawing first from census files, and then in each census file, a sample of households was selected (DHS, 2012). Data from households participating in the survey were grouped together into clusters and georeferenced to point locations. The cluster point locations are scattered throughout the country (Figure 2) and are randomly shifted 0–2 km in urban areas, 0–5 km in rural areas, with 1% of rural cluster locations displaced 0–10 km, to protect the privacy of respondents (DHS, 2012).

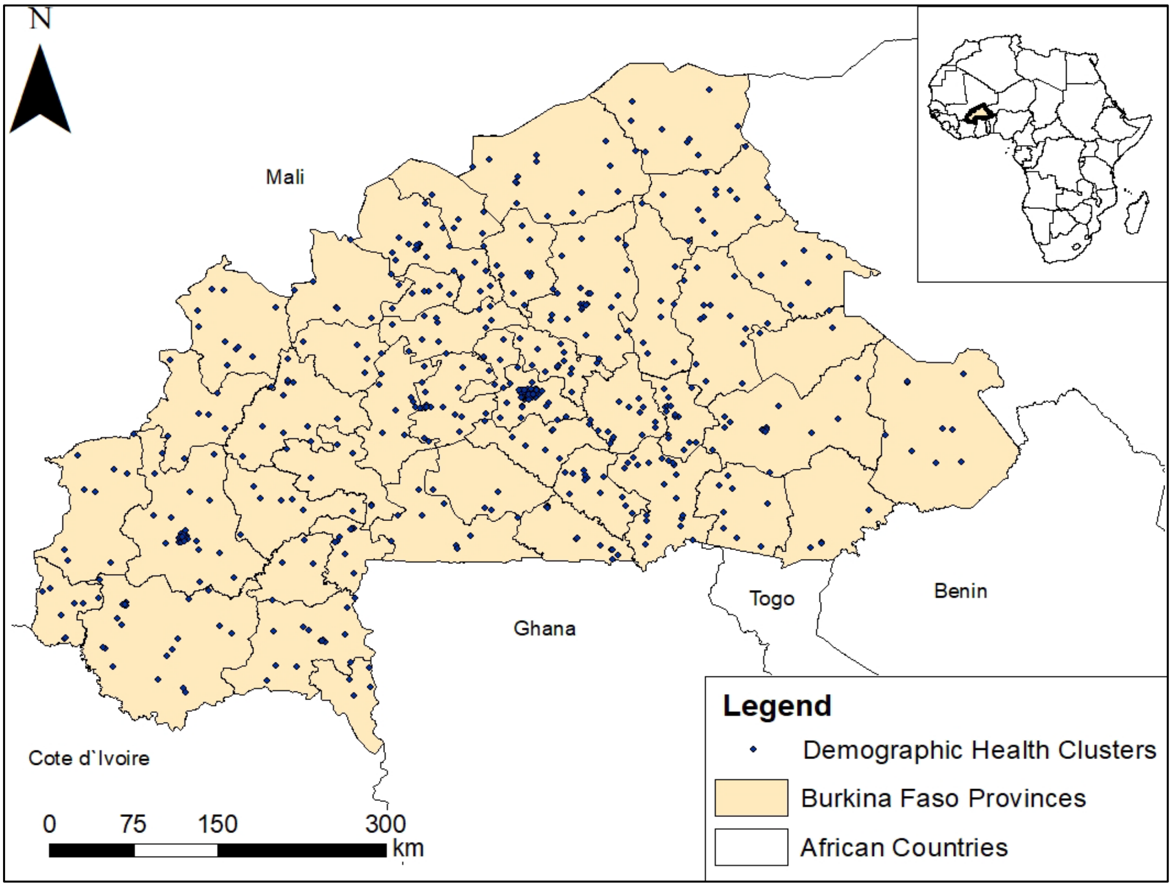

Figure 2. Burkina Faso demographic health cluster locations based on 2010 DHS data.

Factors used in this research to locate area demand per administrative province in Burkina Faso included population density, proximity to major road networks, economic wealth index, birth rate, childhood stunting, and malaria rates. These health risk factors are some of the major indicators of health and preventative care in Burkina Faso and also in Sub-Saharan Africa (SSA) (Kanamori & Pullman, 2013; Lingani et al., 2022; Tessema et al., 2022; World Bank, 2008).

Population density estimates used in this study were extracted from the WorldPop dataset (WorldPop, 2013). WorldPop works with national statistic and remote sensing satellite agencies, ministries of health, and other organizations for the construction of spatially mapped population densities. WorldPop population data is provided as a raster dataset based upon 2010 population estimates using a spatial square grid resolution of 100m.

Access to healthcare facilities in villages near a road network provides the ability for villagers to access a facility and for the provider to facilitate the healthcare facility (Kumar, 2007). Road networks are integral for transport and foot traffic in Burkina Faso (Bigman, 2000). Locations of health facilities were selected at villages in proximity of roads providing greater access to patients and supplies in the surrounding area. Road network data were available in digital format and applied in this study as a criterion for a demand site selection (World Food Program [WFP], 2016). Road network data have been applied in previous studies of healthcare access in developing countries (Moran et al., 2006; Simarro et al., 2014).

Burkina Faso has a birth rate of 5.87 births per woman as of 2010 (Central Intelligence Agency [CIA], 2010). Developing countries in SSA see a high rate of problems related to maternal health and young children (Diallo et al., 2012). In SSA the maternal mortality ratio is ~500 per 100,000 live births, compared to 16 per 100,000 for developed countries in 2010 (WHO, 2012). Regular prenatal care checkups have shown to reduce complications with women's maternal health and increase the healthiness of children born (Bhutta et al., 2010; Moran et al., 2006; Yimer, 2000).

Malnutrition is a lack of adequate energy, protein, and micronutrients to meet basic requirements for body maintenance, growth, and development (FAO, 2014). Infants and children are most vulnerable to malnutrition because of their high nutritional requirements for growth and development (Blössner & De Onis, 2005). Stunting is often used as an indicator of malnutrition for children; when the natural growth trajectory is negatively impacted due to unmet nutritional and caloric needs (WHO, 2010). The stunting metric is the percentage of children (1–5 years of age) that are < -2 standard deviations below average in a height-for-age standard. Approximately 35% of children are stunted in Burkina Faso (DHS, 2012).

DHS data also capture the rate of malaria occurrence. Malaria is a common disease in SSA spread by mosquitos. The parasitic infectious disease causes the death of approximately 40,000 individuals every year in Burkina Faso (Murray et al., 2012). Malaria is highly endemic but is also highly seasonal in Burkina Faso based on the rainy season or shortly afterward which lasts from June to October (Müller et al, 2001). Malaria can be treated by vaccinations and antimalarial drugs. Many people use home remedies to cure fevers and other symptoms caused by malaria (Beiersmann et al., 2007). Healthcare facilities and healthcare workers provide medicine and treatments such as artemisinin-based combination therapy (ACT) and mosquito-treated nets as preventative measures. Mosquito treated nets play an important role in reducing vector-borne diseases such as malaria, yellow fever, and dengue fever (Hemingway et al., 2006; Odhiambo et al., 2013; Okrah et al., 2002).

The DHS includes survey information on the 'wealth' for each household that is used in this analysis. The 'wealth index' comprises a composite measure of selected assets by the household such as televisions, bicycles, and water access (Rutstein & Johnson, 2004). The wealth index is generated using principal component analysis and is relative to the rural areas in Burkina Faso (DHS, 2012). The wealth index reflects the assets of households and the ability to access healthcare based on transportation. The assets or wealth of households has shown to be significant in determining the utilization of healthcare facilities in multiple health studies (Fagbamigbe et al., 2015; Mugisha et al., 2002; Ononokpono & Odimegwu, 2014). Overall, Burkina Faso has a very low wealth index and is one of the poorest countries in the world (United States Department of Labor [DOL], 2014).

2.2. Interpolation

Interpolation is a method that predicts values of a surface based upon surrounding sample data points and provides a viable option based upon the assumption that spatially distributed objects are correlated (Li & Heap, 2008). DHS survey data was not collected at each of the thousands of villages in Burkina Faso resulting in unknown health and wealth information throughout most areas in Burkina Faso. Wealth and health risk factors were available at 540 geolocated point location values throughout Burkina Faso. The surveys at each clustered location were averaged for each health demand factor allowing an estimation of risk per health demand factor.

Each factor was given a value or percentage based upon survey information collected from household interviews. A wealth index percentage was based upon a composite measure of a household's cumulative living standard. The stunting metric is the percentage of children (1–5 years of age) that are < -2 standard deviations below average in a height-for-age standard. Malaria rate was based on those in the past year having symptoms of malaria. Maternity values were based upon birth rates. Each health factor was scaled as an ordinal measurement from one to three; one representing low rates while three represent high rates based upon Jenks natural breaks optimization classification method.

Due to the nature and distribution of the Burkina Faso dataset, interpolation is a suitable method for deriving a suitability weighted surface composed of the interpolated cell values for the population, wealth and health risk factors. The random shift in the geolocated DHS cluster areas should have little effect on predicting cell values as the offset is minimal and the interpolation method accounts for multiple surrounding values. The factors were interpolated using empirical Bayesian kriging (EBK). EBK is a common geostatistical interpolation algorithm for scattered point data and has been used in multiple DHS data studies (Gemperli et al., 2004; Gosoniu &

Vounatsou, 2010; Gosoniu et al., 2012). The EBK method uses an intrinsic random function accounting for the error introduced by estimating the underlying semivariogram model (Krivoruchko, 2012). The parameters chosen for the EBK model include using a k-Bessel semivariogram model with a maximum search neighborhood parameter of 10. The k-Bessel semivariogram model provides the most accurate way to interpolate data and having a small search neighborhood parameter insured health and wealth values closest to the prediction location have more influence on the predicted value than those farther away (Johnston et al., 2001). These parameters provide a way to identify local trends from the inserted DHS data while providing prediction surfaces from the interpolated values.

2.3. Weighting Values

A weighted value of the interpolated fields was created to define a field identifying the total risk. The weights were adjusted to account for each health demand, hospital frequency, and a wealth index. The first analysis of this paper was to estimate area demand for healthcare facilities based on population density. A population density map scaled from 1 to 6 using the Jenks optimization method (Jenks, 1967) was used, reducing the variance within classes and maximizing the variance between classes. The second analysis also factored in population density and included health demand variables, hospital frequency related to each health variable and wealth.

Each health factor was set to a scale value (1–3) based upon severity at each DHS cluster location. The health factors were then multiplied by the weighted frequency of survey applicants with a health risk factor accessing care in a healthcare facility based on DHS surveys collected in 2010 (DHS, 2012; Rutstein & Rojas, 2006). Each scaled demand factor was multiplied by the frequency of patients attending healthcare facilities as an approximation of healthcare facility usage recorded by DHS data (DHS, 2012). This information was collected from DHS data and literature based in SSA (Table 1). Malaria patients were those who went to a doctor to receive antimalarial treatments (DHS, 2012).

Table 1. List of demand variables and weighted frequency used as an approximation of usage of healthcare facilities for each demand variable in Burkina Faso.

Demand Variable	Weighted Frequency
Malaria	0.8
Stunting	0.67
Maternity	0.8
Wealth Index	1–0.75

Approximately two-thirds of children suffering from stunting in households seek medical attention (DHS, 2012). A maternity frequency of 0.8 refers to 80% of women who gave birth in a healthcare facility (DHS, 2012). A wealth index frequency was multiplied by the health risk factors; poorer households have been shown to attend healthcare facilities less frequently (~25%) than wealthier households (DHS, 2012).

The economic and health factor raster cells were added to the population density weighted raster value cells for all areas in Burkina Faso. The second analysis in this paper included the demand factors in the analysis and the equation is as follows:

$$D_{hi} = (D_{pi} + (\sum(H_{wi} * H_{ui}) / (\sum_i H_i))) * E_i \tag{1}$$

Where i is each individual cell value, H_i is each health factor, H_{wi} is the weight of each health value at each raster cell location, H_u is the frequency or utilization of each health demand of likelihood of using a healthcare facility, E_i is the economic wealth index for each location and D_{pi} is the population density demand from the results of the first analysis. An example of this equation is given for the village of Bondoukuy in the Mouhoun province in Table 2. This village has high stunting but a low wealth index. The village will be evaluated with the other villages in the Mouhoun province providing a weighted demand area for a healthcare facility.

Table 2. A demonstration of how population, health and wealth weighted values were assigned for the city of Bondouky, Mouhoun.

Bondoukuy, Mouhoun	Potential Values	Actual Wealth and Health Values	Frequency to hospitals	Health x Frequency Value	Value
Population	1–6	3			3
Stunting	1–3	3	0.67	2.01	2.01
Maternity	1–3	1	0.67	0.67	0.67
Malaria	1–3	2	0.8	1.6	1.6
Wealth Index	0.75–1	.75			0.75
Sum of Health Factors Weighted					4.28
Average of Health Factors					1.42
Sum of Population and Health Factors					4.42
Combined Population and Health Factors multiplied by Wealth Index					3.32

2.4. Identifying Village Values

To narrow the demand site location potential, locations of villages that fell along the road network were selected as a criterion as well. The road network data for Burkina Faso is extensive for a developing country. A road distance buffer of 0.5 km was created to narrow locational access to villages. This level of data made the analysis process easier to narrow potential healthcare demand site locations as villages within the 0.5 km distance were used as a criterion.

Villages situated in proximity to the road network each had a weight based upon population density, wealth, and health factors. Multiple villages with equally high values in each province prompted a further refinement of demand site locations. A cluster analysis using Getis-Ord Gi* statistic was applied to the village locations in each of the 45 administrative provinces to geographically identify a cluster of highest weighted demand site locations.

2.5. Getis-Ord Cluster Analysis

The population density single layer contiguous surface combined with the weighted wealth and health factor surfaces provide a way to identify areas of greatest demand based on the criteria in this paper. The calculated raster layers were then converted to geographic vector features. The vector features were then localized as weighted vector data within administrative provinces. The intersection of village data points and the newly created weighted vector polygons provided a new potential area demand site selection that identified weights with villages falling along the road network. The point data were further analyzed statistically for spatial clustering of the highest weighted locations using the Getis-Ord Gi* statistic using an inverse distance spatial relationship between points. Essentially the statistic identifies the greatest weighted points clustered in a region of each province. Getis-Ord is a spatial clustering statistic tool employed in spatial analysis as a pattern recognition tool (Chaney & Rojas-Guyler, 2016). The Getis-Ord z-score values per village displayed clustering of high demand locations where the population, wealth, and health risk factors were high. Criteria data utilized in the analysis identified each cluster point of high weight as a potential demand area for a healthcare facility. Each village along the buffer road was identified with its weighted cell output. The highest clustered cells included areas that were high in population, malaria rate, childhood stunting, and birthrate while having a high wealth index.

2.6. Weighted Measurement Tools

The Getis-Ord cluster analysis provided spatial locations of high clustering weighted points for demand site locations. Numerous clusters with statistically significant point locations were available to choose from among the final demand site choices in each province. Rather than a random selection or stopping the demand site selection process at this juncture, a Central Feature analysis using a Euclidean distance method identified a central point location within each high-value cluster dataset. Distances from each location to every other location in the province were calculated and summed. The location associated with the shortest cumulative distance to all other locations was selected as the central weighted feature. The highest weighted points captured the intersection of population density and the economic wealth and health weighted factors. The results of this process provided the most central, highest weighted demand site point for each province.

The directional distribution is another way to measure the spatial trends in the distribution and weight of demand. The directional distribution calculates the geographic dispersion and directional trend of weighted locations within a given area. The method calculates the deviation of the x- and y-coordinates from the weighted mean center to define the axis of an ellipse. The measurement provides information on the concentration of demand through the province and the general trend of direction and shape of demand by creating a spatial ellipse covering one standard deviation, capturing approximately 68% of the weighted features. The directional weighted distribution in this analysis was able to examine the clustering of demand areas within each province by providing the spatial breadth of clustering demand of weighted locations and also the trend of direction for demand in each province.

3. Results

The inclusion of economic wealth and health factors with the population density impacted the resulting demand area site selection for many of the provinces in Burkina Faso. The Getis-Ord spatial statistic analyzed the local sum for each weighted demand village location and its neighboring weighted villages were proportionally compared to the sum of all features to find areas where population and health demand areas are the highest. Differences of significant clustered areas represented areas where Getis-Ord z-score values were significantly high compared to the proportional sum of all the villages in the province. The clustering of high z-scores using the Getis-Ord statistic provided statistically significant areas of villages where population and health risk factors are the highest in each province. The wealth and health factors resulted in percent change of 50.5% variation in scale values for 95% of the cities in each province compared to using only population data. Approximately 71% of the provinces had a change in central demand location from using only population to including wealth and health factors (Figure 3). The average distance of the health risk central feature from the population demand site was ~17 km. Most of the outcomes including the health factors displayed only a small shift to a neighboring village location from the population demand area.

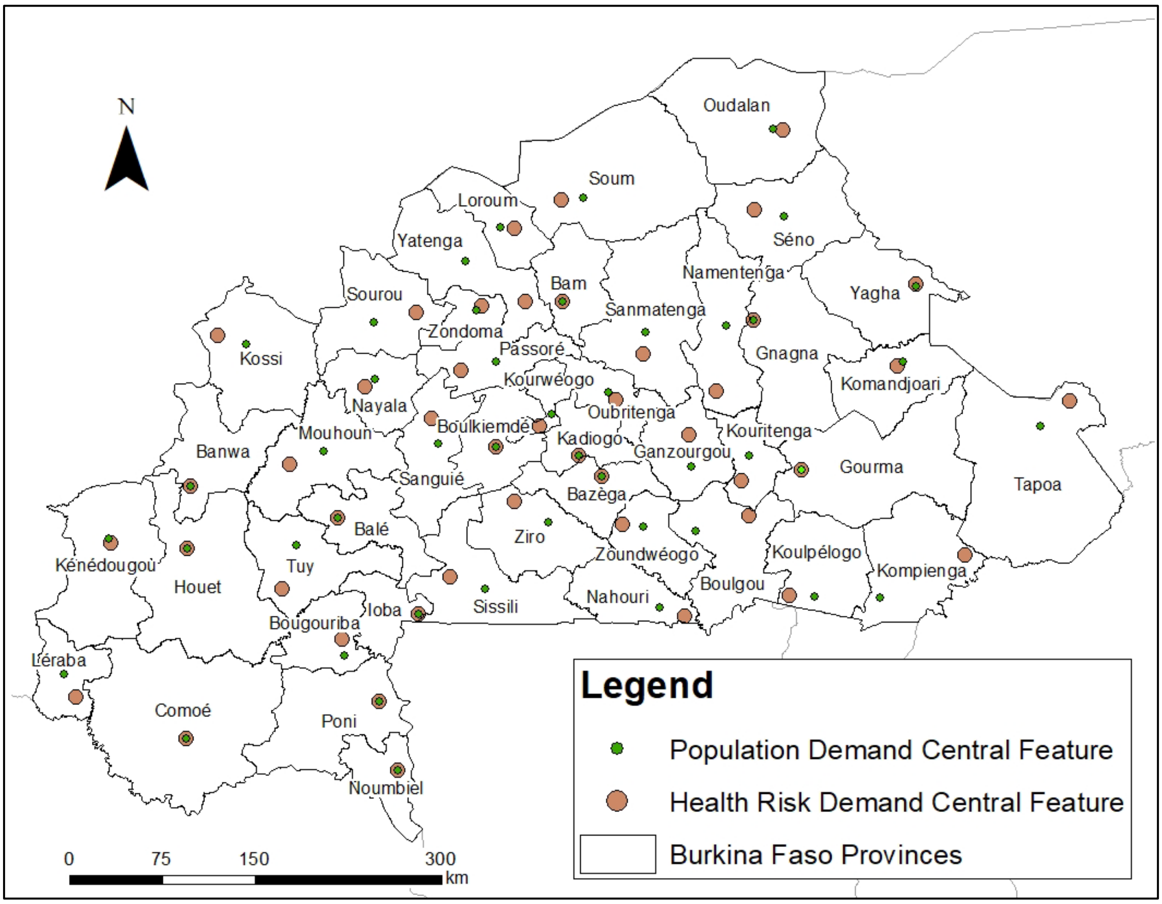

Figure 3. Central feature spatial distributions of population demand and areas that include health risk factors for provinces in Burkina Faso.

The example in the Mouhoun province in Figure 4 shows significant clustering for both population and health risk factors demand in the east of the province. Wealth and health risk factors with population further influenced demand in the Mouhoun province. Including wealth and health risk factors increased the areas of low/high clustering Getis-Ord statistical z-score ranges from -2.72-2.79 to -3.51-2.86. Including health risk factors for demand also affected the weighted directional distribution of data. In the example of the Mouhoun province, the spatial standard deviation of the distribution increased due to including areas of lower population density but high health demands. The variance of the directional distribution varied for each province and allowed the ability to quantify the spatial standard deviation and directional of demand for population and the inclusion of wealth and health factors in this analysis.

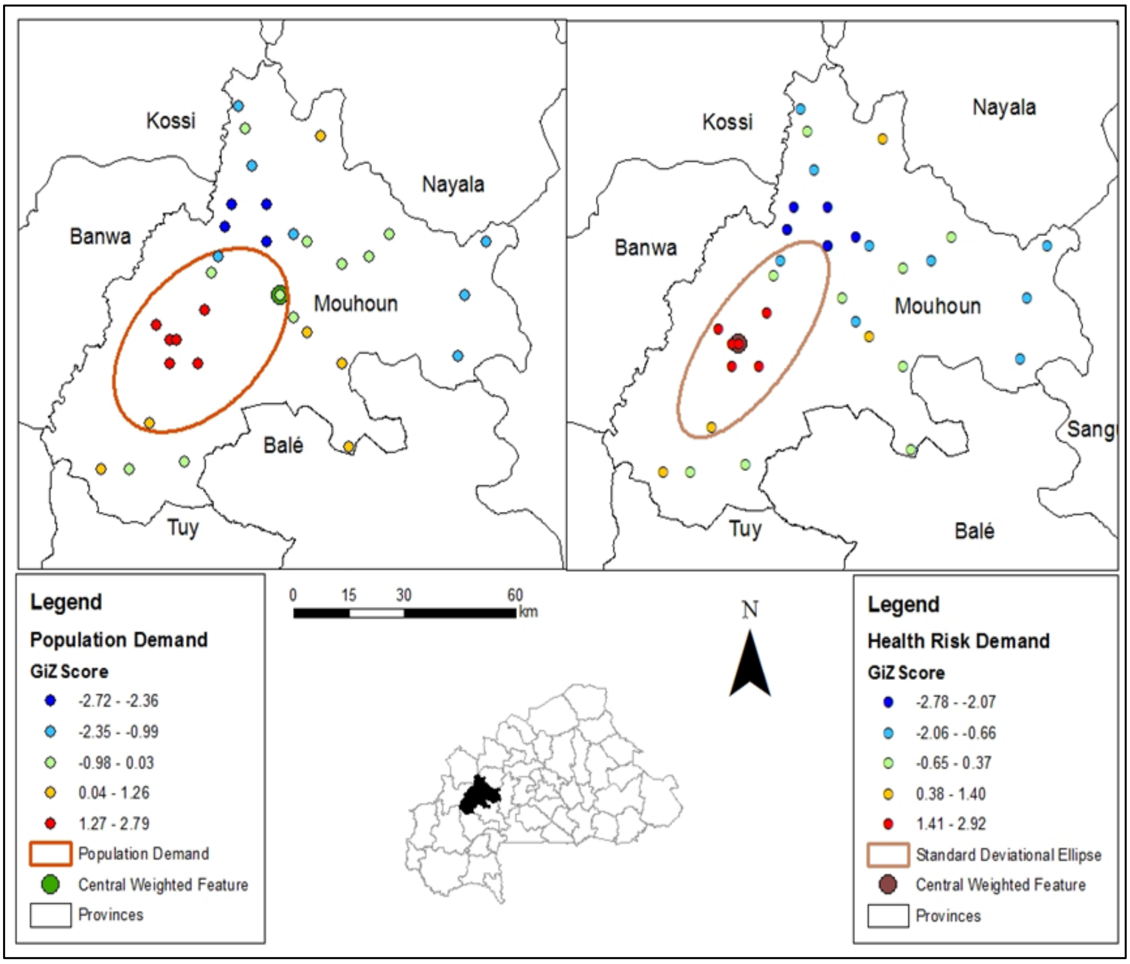

Figure 4. Comparison of population demand distribution areas (left) and areas that include wealth and health risk factors (right) in Mouhoun Province.

Demand based on population and health risk factors varied throughout Burkina Faso in each province. The three health risk factors and wealth index used for this analysis proved to be influential in locating areas of demand for healthcare facilities. The highest rates of demand based only on health risk factors were found in three main clusters located in the northern central provinces, southeast provinces and in the southwest provinces. Overall, low economic wealth and health values were found on the edges of the country while higher economic wealth and health risk values were prevalent around Ouagadougou, the capital city of Burkina Faso located in the center of the country.

Using multiple factors besides population that were included in this analysis drastically changed the demand area in a geographical region. Health factors had a greater influence in locating demand in areas of homogenous population. Including wealth and health risk factors in the methodology provided a more serviceable way to allow the disadvantaged population to access to healthcare facilities.

4. Discussion

This study considered multiple factors including population density, wealth, and health indicators to identify areas of high demand for healthcare facilities in rural Burkina Faso. The data utilized in this study can be obtained and applied, using the same methodologies outlined here, for many developing countries. A challenge for researchers and healthcare workers attempting to locate healthcare facilities in developing countries is accessing spatial data related to health and development for decision support. Few data are available on locations of current healthcare facilities in Burkina Faso. Including locations of current healthcare facilities would likely improve estimation of unmet demand in our analysis.

One concern for locating areas of demand is how to aggregate geographic data which will change where demand locations should be located. In this study, there were different types of administrative boundaries that could have been used to find the best representative location for healthcare facilities. Provinces were selected as they represent generally similar lifestyles, agricultural use, and ethnicity. The methods used in this study can easily be related to any administrative boundary as well as siting multiple healthcare facilities needed within a certain area.

Using the weights based on the percentage of those who were at risk and the probability of someone with a health risk using a healthcare facility in this paper was believed to be an effective way of balancing the demand of population with wealth and health factors. In the example of Mouhoun province, the wealth and health factors for 95% of the cities (2 standard deviations) caused approximately a percent change of 50.5% change in scale value from the average mean when added with the population scale values. The inclusion of weighted economic wealth and health factors caused the area of demand to shift from its original location in the first analysis only using population. The results indicate that even small changes when factoring spatial weights when locating a healthcare facility can cause a spatial displacement in population area demand.

The methodology used in this paper for this study area provided a greater in-depth understanding pertaining to how weighted factors can influence a health demand area. The spatial weights provided a displacement of area demand based solely on population throughout Burkina Faso, but more particularly in the outskirt provinces of the country. Areas of high stunting in the eastern provinces and in pockets throughout the country were prevalent in causing a change in demand area. The spatial pattern of malaria based on DHS survey data in 2010 was severe in the southern areas of the country where precipitation is more abundant and also around bodies of water where there is a greater chance to be bitten by malaria-infected anopheles mosquitos (Karthe et al., 2012).

Different factors may be used based on the specific needs of a country or administrative boundary, and the severity of different health issues will likely differ by region. Education levels have shown to be an important socioeconomic factor in relation to overall health and use healthcare facilities (Fotso, 2007; Heck & Parker, 2002), however in this rural study area, there is little formal education. Similar methods can be used to understand the spatial accessibility of urban areas for both developed and undeveloped countries. Census tracts with health data available on the population in developed countries or urban areas can assist health planners in understanding the distribution of health risks and can be used to locate facilities to assist disadvantaged populations. A growing factor in this region is caring for the aging population and fulfilling specialized medical services and long-term care for the elderly but was beyond the scope of this paper.

5. Conclusion

Geographic analysis is a widespread tool used for many decision support scenarios. Methods outlined in this report demonstrate a technique to determine health-related demand locations with limited information. The inclusion of economic wealth and health factors with the population density impacted the resulting demand site selection for many of the provinces in Burkina Faso. Demand for healthcare facilities was altered from the first analysis to the second analysis for each province in this chapter where the population of villages were homogenous and could be influenced based on weighted economic wealth and health factors. Understanding the spatial accessibility is an important facet to consider when locating and allocating healthcare facilities. The information used in this analysis is publicly available data from open-source GIS data outlets. The ability for healthcare planners to weigh factors that were once thought to be nonspatial with the use of GIScience can be supportive in assisting the disadvantaged population receive healthcare needs to live healthier lives.

CRediT Author Statement: This is a single author paper and the author was solely responsible for the content, including the concept, design, analysis, writing, and revision of the manuscript.

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: http://dhsprogram.com/What-We-Do/Survey-Types/DHS-Methodology.cfm and https://www.worldpop.org.uk.

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