Department of Spatial Sciences

Spatio-temporal modelling and analysis of spatial accessibility to primary health care - a case study of Bhutan

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

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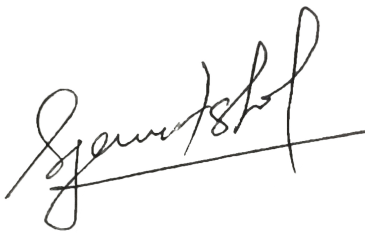
Signature:  Date: **June 10, 2016**

Abstract

One of the most important aspects of primary health care is related to the ease of access to health care providers. It is a challenging task in most countries to adequately and equitably provide basic health infrastructure and services across a spatially distributed population. This entails the need for an evidence-based method of measuring spatial accessibility to these services.

Spatial accessibility models such as the floating catchment area models can be used to measure or assess spatial access to health care services between regions or countries. These models suffer from a number of modelling uncertainties ranging from the availability of different computational methods to the use of a different distance decay function. Because of these uncertainties there is no consensus amongst researchers on a single unified model. Without a common model, there is no basis to compare spatial accessibility to health care services between regions or countries. This study proposes the nearest neighbour method of delineating service and population catchment areas within an augmented version of the modified two-step floating catchment area model for measuring spatial accessibility to PHC services. As far as possible, the proposed model minimizes the modelling uncertainties by defining a theoretically-determined Gaussian decay function, using a finite number of closest service centres and employing two different weighting functions within the existing floating catchment area model.

This study has developed an open-source based application for aiding in planning of allocation of health resources within a country. The system can be used for computing spatial accessibility scores, visualizing and analysing spatial data, and conducting 'what-if' scenario analysis. Accessibility values from 2010 to 2013 in Bhutan were analysed both spatially and temporally by producing accessibility ranking maps, plotting Lorenz curves and conducting spatial clustering analysis. The spatial accessibility indices of the 205 subdistricts showed great disparities in healthcare accessibility in the country, with the highest-ranked subdistrict having a hundred times better accessibility than the lowest ranked subdistrict. Furthermore, such accessibility indicators can be incorporated within the existing gross national happiness measurement system of this country to evaluate spatial accessibility to health, education and agricultural service centres.

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*...to my daughter, **Lasem Tshogyal**, who is a source of immense joy and inspiration in both good and bad times...*

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Abbreviations

2SFCA Two-Step Floating Catchment Area
3SFCA Three-Step Floating Catchment Area
AM2SFCA Augmented Modified Two-Step Floating Catchment Area
ARIA Accessibility/Remoteness Index of Australia
BHU Basic Health Unit
BR Buffer Ring
CI Confidence Interval
DEM Digital Elevation Model
DHHS Department of Health and Human Services
E2SFCA Enhanced Two-Step Floating Catchment Area
FCA Floating Catchment Area
Gc Gini Coefficient
GDP Gross Domestic Product
GIS Geographic Information System
GNH Gross National Happiness
GNHC Gross National Happiness Commission
GPS Global Positioning System
GRASS Geographic Resources Analysis Support System
GUI Graphical User Interface
HA Health Assistant
HAPSS Health Accessibility Planning Support System
HPSA Health Professional Shortage Area
JDWNRH Jigme Dorji Wangchuck National Referral Hospital
JUMP Java Unified Mapping Platform
Km Kilometres
KDE Kernel Density Estimation
KD2SFCA Kernel Density Two-Step Floating Catchment Area

MAPE Mean Absolute Percentage Error
MAUP Modifiable Areal Unit Problem
M2SFCA Modified Two-Step Floating Catchment Area
MoF Ministry of Finance
MoH Ministry of Health
MoAF Ministry of Agriculture and Forests
NHP National Health Policy
NHS National Health Survey
NLC National Land Commission
NN Nearest Neighbour
NSB National Statistical Bureau
OECD Organization for Economic Cooperation and Development
ORC Out-reach Clinic
PHC Primary Health Care
PHCB Population and Housing Census of Bhutan
PPA Potential Path Area
QGIS Qantum GIS
DPPA Daily Potential Path Area
PDF Population Density Fraction
PPR Provider-to-Population Ratio
PSS Planning Support System
RA Remoteness Area
RAM Random Access Memory
RGoB Royal Government of Bhutan
RMSE Root Mean Square Error
RNR Renewable Natural Resources
SDSS Spatial Decision Support System
UNGA United Nation General Assembly
WHO World Health Organization

Chapter 1

Introduction

Primary health care (PHC) is one of the most important aspects of healthcare in Bhutan. However, as yet there is no reliable method established to assess accurately the spatial accessibility to PHC services in the country. This research develops a suitable methodology for evaluating spatio-temporal changes in spatial accessibility to healthcare services in this country.

Section 1.1 presents the background information on the PHC service system in Bhutan. The motivation for conducting the study on spatial accessibility to PHC services in this country is briefly presented in Section 1.2. Section 1.3 defines the research problem pertaining to the measurement of spatial accessibility and Section 1.4 presents the overall objectives of the research. Section 1.6 briefly outlines the chapters included in this thesis.

1.1 Background

Health is generally defined as the "state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (World Health Organization (WHO), 1948, p. 2). Besides jobs, education, housing, cultural and spiritual needs; health is an important measure of quality of life, and refers to overall happiness and satisfaction with life (Centre for Disease Control and Prevention, 2000). Brodie et al. (2007) reported that people from across the world have consistently rated health as one of their highest priorities, closely following economic needs related to unemployment, low wages and the high cost of living. Because health is a core aspect of human life, more than six decades ago in 1948, the world came together and instituted the WHO solely to promote and safeguard population health through collective effort. Since the 1970s, the WHO has been at the forefront in promoting the "Health for All" programme throughout the world by providing technical guidance and financial support, especially in developing countries where both technical and financial resources are scarce. Equitable access to health care was finally enshrined in the Alma Ata Declaration of 1978, which mandated the member states to establish primary health care services.

PHC is the "first level of contact of individuals, the family and community with the national health system bringing health care as close as possible to where people live and work". "Scientifically sound and socially acceptable methods made universally accessible", need to be provided by proficient healthcare service providers in "fostering equitable access to promotive, preventive, curative, palliative and rehabilitative health services" (WHO, 1978, p.1). PHC has been further strengthened by the resolution of the World Health Assembly in 2005 which specifically urged member countries to plan for instituting universal coverage of the population to meet the quality health care needs of all people, to reduce poverty and to achieve collectively agreed development goals. The World Health Report 2008 reiterated the importance of PHC in the health care system (WHO, 2008) and the World Health Report 2010 proposed the development of sustainable health financing system based on the principle of universal health coverage (WHO, 2010). In 2012, the United Nation General Assembly (UNGA), through a global health and foreign policy resolution, reaffirmed "universal health coverage, including social protection and sustainable financing" besides also recognizing the importance of relationships between health, environment, natural disasters and social factors (UNGA, 2012, p.2). The World Health Report 2013 highlighted the importance of conducting evidence-based scientific research for assessing universal health coverage (WHO, 2013).

Bhutan established a modern health system only in 1962 and the PHC approach to the health care delivery system started in 1979. Since then, this country has been progressively working towards fully state-sponsored universal health coverage in both traditional and modern medicine. The provision of free access to basic health coverage to all the citizens of Bhutan is guaranteed by its Constitution, which states, "The State shall provide free access to basic public health services in both modern and traditional medicines". Besides providing free access to primary level care, the Royal Government of Bhutan (RGoB) also provides free access to specialised medical care within the country and bears medical expenses for out-country referrals of patients who need special medical services that are not available in-country. Providing free health care services to the general population comes at a high cost, which constituted about 8 % of the annual budget for the fiscal years 2014-2015 (MoF, 2014) or about 3 % of the total Gross Domestic Product (GDP). Bhutan's annual GDP is about US$ 2 Billion. Like any other developing country, the sustainable financing of health services in Bhutan is also a challenging task, with continuously increasing costs due to increases in non-communicable diseases that account for more than 70 % of the recently reported disease burden in the country (WHO, 2014). The Ministry of Health (MoH) is the apex health organization in the country that bears the responsibility for planning and management of health resources and delivery of health services across the country towards achieving Gross National Happiness (GNH) of the general populace. GNH is the fundamental philosophical guide and developmental yardstick employed by RGoB to measure the overall progress of the country. Health constitutes one of the nine domains of GNH which contribute effectively to building a happy society, which is its main objective.

According to the national health policy guidelines, Bhutan will "pursue the comprehensive approach of primary health care, provide universal access with emphasis on disease prevention, health promotion, community participation and inter-sectoral collaboration" (MoH, 2011, p.5). PHC services were progressively rolled out to far-flung rural regions from urban centres through the establishment of three-tiered health centres, with basic health units (BHUs) and out-reach clinics (ORCs) at the primary level, district hospitals at the secondary level and regional referral hospitals and national referral hospitals at the tertiary level. Owing to the lack of specialised medical practitioners, PHC in the peripheral health centres was serviced by health assistants (HAs) who were proficiently trained at the national health centre to provide primary level care. Bhutan has so far achieved about 90% coverage of primary level health care services (MoH, 2008) i.e. 90% of population lives within 3 hours walking distance of their nearest health facility. It is important to note that current accessibility to health care centres is crudely measured from survey questionnaire response to the question which asks about the travelling time to the nearest health centre from the resident's location. The importance of travelling distance proximity to health care is clearly stated in MoH (2011, p.5), "the health care coverage shall be sustained with at least 90% of the population living within 3 hour walking distance from a health facility".

1.2 Motivation

Bhutan's developmental activities are guided by five-year developmental plans. Two of the important goals of the MoH in the 10^{th} Five-Year Plan (2008-2012) was to "improve quality and accessibility of health services" and "promote sustainability and equity in a health care delivery system" (MoH, 2012*a*, p.2). Geographic accessibility to health services is an important aspect of health care delivery systems in many countries, which can often act as a barrier to accessing primary health care services. Studies on geographic accessibility have demonstrated a high correlation between physical proximity of health service centres and the utilization of primary health care services in many countries (Stock, 1983; Müller et al., 1998; Goddard and Smith, 2001; Buor, 2003; Noor et al., 2003; Cloutier-Fisher et al., 2006; French et al., 2006; Feikin et al., 2009).

There are however very few evidence-based studies using geographic information system (GIS) conducted by the Bhutanese health sector. The only specific activity related to geographic accessibility and spatial planning has been the mapping of health facilities and a survey questionnaire enquiring about the travel-time proximity to the nearest health centres during the national health survey (NHS) in 2012. Although GIS planning has been widely used for health resource allocation and planning in other parts of the world, it has not been effectively used in Bhutan because of the lack of human and technical resources in this area. Two of the main objectives of the MoH in the current 11^{th} Five-Year Plan are to "improve access to quality and equitable health services" and "promote efficiency and effectiveness in financing and delivery of health services" (MoH, 2014*b*, p.1). This demands the need for "evidence-based planning to effect improvements in the quality and scope of health-service delivery" (WHO, 2014, p.51). Thus, there is a need for the development of an evidence-based spatial accessibility measurement system using GIS technology, which can be specifically utilized to conduct spatio-temporal analysis and modelling of spatial accessibility to health care services at the regional and national level.

1.3 Research problem

Spatial accessibility refers to the integration of regional availability and regional accessibility (Joseph and Phillips, 1984). In a computational sense, spatial accessibility refers to the integration of availability of health care providers within a service catchment area, demand for health care services within a population catchment area and physical separation between the location of the population and healthcare providers (Jamtsho et al., 2015). Spatial accessibility indices were used to assess spatial and temporal changes in spatial accessibility to healthcare services in other countries (Luo and Wang, 2003; Yang et al., 2006; Unal et al., 2007; Luo and Qi, 2009; Wan et al., 2012a; Delamater, 2013). Such measures can also be used for planning health resources allocation to facilitate the equitable establishment of health centres and distribution of healthcare services within a nation. Although Bhutanese people are guaranteed by the Constitution for free and fair access to primary healthcare services, there have been very few evidence-based studies conducted on measuring equity of spatial access to healthcare services in the country.

Previous studies on spatial accessibility indicated that the floating catchment area (FCA) based computational models have been more widely used than the gravity model because they incorporate variable and overlapping population catchment areas for each service centre in contrast to the single catchment area employed in the gravity model (Luo and Wang, 2003; Wan et al., 2012a; Delamater, 2013). These studies were also conducted using the travel-time measure within a FCA-based computational model where road transportation is readily available across the region and road network data are comprehensively available yet such studies were mostly confined to a small region of a country. There are very few accessibility modelling studies conducted at the national-level, such as that by McGrail and Humphreys (2014), where spatial accessibility to PHC services was modelled for the whole of Australia using travel-time measures within a two-step FCA computational model. The FCA-based computational method using travel-time measure is ideally suited to regions where travel times can be accurately derived from comprehensive route network data. Therefore, an alternative approach to measuring spatial accessibility at the regional and national level is necessary for regions where road transportation is not readily available nor are route network data comprehensibly mapped.

The FCA accessibility model suffers from a number of modelling uncertainties, such as the modifiable areal unit problem (MAUP) caused by the aggregation level of population cluster data (Handy and Niemeier, 1997), the use of a distance or travel-time measure, the use of a computational method with different weighting schemes, the use of a decay function with different patterns of the decay rate, and the use of different methods of delineating service and population catchment areas that lead to a difference in the association between service centres and population clusters. Although the measurement of spatial accessibility is biased with a number of modelling uncertainties, most or all of the variants of the FCA computational models are differentiated by the use of a weighting scheme. Other uncertainties, such as the availability of multiple decay functions or availability of other forms of delineation method have not been adequately evaluated. Using the difference in the weighting scheme, the FCA models are classified as the two-step floating catchment area (2SFCA) (Luo and Wang, 2003), enhanced two-step floating catchment area (E2SFCA) (Luo and Qi, 2009), kernel density two-step floating catchment area (KD2SFCA) (Dai and Wang, 2011), three-step floating catchment area (3SFCA) (Wan et al., 2012a) and modified two-step floating catchment area (M2SFCA) (Delamater, 2013). Delamater (2013) has computationally analysed these models and found that the M2SFCA model is based on a theoretically sound framework and computationally more reliable than the other models. However, the M2SFCA model tends to increase the differences of accessibility values between the lowest and the highest ranked population clusters within a given study region thereby leading to unrealistic comparisons of accessibility outcomes between different regions. So the M2SFCA model has to be augmented to mitigate the effect of computational biases prevailing in this method.

There is also a need to explore uncertainty problems caused by ambiguity in the delineation of service and population catchment areas. Past studies have delineated service and population catchment areas based on the buffer ring (BR) method whereby buffer rings with certain radii of travel-time centred at the computation point were used to identify potential service centres for each population cluster (Luo and Wang, 2003; Yang et al., 2006; Dai and Wang, 2011; Langford et al., 2012; Wan et al., 2012a; Delamater, 2013). For instance, in a travel-time based computation approach, buffer rings of 30, 45 or 60 minutes from the location of the population units have been defined to identify potential service centres for each population cluster. This method has some theoretical and practical problems. Firstly, it introduces accessibility differences by the inclusion of a variable number of service centres for each population cluster as accessibility is the sum of individual components due to the number of associated service centres. Secondly, the buffer rings can be theoretically defined by an infinite number of real values between the shortest and the longest travel times within a study area so the selection of a certain travel-time buffer ring is highly arbitrary. Thirdly, in a real-world scenario people tend to seek services from few service centres that are in closest proximity to their location rather than engaging with a large number of service centres that happen to fall within a specified distance or travel-time. Owing to these limitations of the BR method, there is a need to explore other methods of delineating service and population catchment areas. One such method based on the selection of a finite number of nearest neighbours (NN) is proposed in this study.

One of the other important issues in spatial accessibility modelling is the choice of a particular decay function, which is used to model distance impedance effects by computing relative distance weights to reflect the physical separation between locations of the service centres and population clusters. Eight different distance decay functions have been reported in past studies on spatial accessibility modelling - inverse-power (Unal et al., 2007), linear (Langford et al., 2012), Gaussian (Langford et al., 2012), logistic (Delamater et al., 2013), exponential (McGrail, 2012), Epanechnikov-kernel (Dai and Wang, 2011), Butterworth-filter (Langford et al., 2012) and step (Luo and Qi, 2009) functions. Nevertheless, there were no studies conducted on evaluating the spatial accessibility outcome using different decay functions. Therefore, there is a specific need to assess the differences in computational outcome of accessibility values between different distance decay functions, and this forms one of the objectives of this study.

1.4 Research objectives

The main objective of this thesis is to conduct spatio-temporal modelling and analysis of spatial accessibility to primary health care services in Bhutan. It can be achieved by developing a robust computational model with as few uncertainties as possible and by developing an application system to calculate accessibility values of population clusters, subdistricts and districts within a GIS framework. Key objectives of this thesis are:

- To conduct population mapping in Bhutan at disaggregated level using a population dasymetric mapping technique
- To use the NN method of delineating population and service catchment areas for modelling spatial accessibility to healthcare services
- To assess the computational outcome of accessibility values using different distance decay functions
- To improve the M2SFCA method of computing spatial accessibility indices

- To develop an open-source GIS-based health accessibility planning tool for modelling and analysing spatial accessibility indices
- To conduct the spatio-temporal analysis of spatial accessibility to healthcare services at the regional and national level in Bhutan
- To develop spatial accessibility indicators for the GNH measurement system

1.5 Contributions

The work reported in this thesis has led to the following publications.

- Jamtsho, S, Corner, R and Dewan, A 2015, 'Spatio-temporal analysis of spatial accessibility to primary health care in Bhutan', *ISPRS Int J Geo-Inf*, vol. 4, no. 3, pp. 1584-1604.
- Jamtsho S, Corner RJ 2014, Evaluation of spatial accessibility to primary healthcare using GIS, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2014; II-2: 79-86.
- Jamtsho S, Corner RJ 2015, An objective method of defining spatial accessibility indicators for GNH measurement system, International Conference on GNH: From GNH Philosophy to Praxis and Policy, November 4 - 6, Paro, Bhutan.

1.6 Outline

This thesis deals with many important aspects of spatial accessibility modelling in the context of Bhutan, namely the review and evaluation of the spatial accessibility measurement approaches, population modelling at the disaggregated level, augmentation of the existing M2SFCA model for measuring spatial accessibility to healthcare services, development of a GIS-based open source application system, spatial and temporal analysis of accessibility indices and development of the GNH accessibility indicators. The structure of this thesis is as follows.

Chapter 2 presents a comprehensive review of spatial accessibility measurement approaches, which include both the gravity model and the floating catchment area models. It includes a comprehensive evaluation of different FCA models based on the computational outcome of their accessibility values using simulated data.

Chapter 3 describes the scope, data requirements for measuring spatial accessibility and areal interpolation method of disaggregating population data. Disaggregated population data is needed for measuring spatial accessibility indices, but population data for Bhutan is only available at the subdistrict level which is too aggregated to be reliably used for computing accessibility values. Therefore, a specialised form of areal interpolation method using only housing data is proposed to distribute population data from subdistrict level to a village level.

Chapter 4 outlines the methodology used in the computation of spatial accessibility indices. Owing to the lack of comprehensive road network data in Bhutan, the use of travel-time based computational modelling is not appropriate. Instead, a straight-line or 'crow-fly' distance based computational model using the nearest neighbourhood selection method for delineation of population catchment areas within the augmented version of the existing M2SFCA model is proposed for computing accessibility indices. Given the availability of many distance decay functions, this study also examines the differences in accessibility outcome between different decay functions using the existing M2SFCA model.

Chapter 5 describes the development of an open source GIS application system for calculating spatial accessibility indices at the regional and national level. One of the drawbacks of GIS technology is that the proprietary software products are very expensive and often beyond the budget available for health organizations in countries like Bhutan. The development of an open source system for accessibility measurement in this study should encourage health planners and managers across the country to use such freely available application system for conducting basic GIS planning for resource allocation within their regions. It would also foster the development of a comprehensive spatial health decision support system in the country.

Chapter 6 presents the accessibility results and spatio-temporal analysis of spatial accessibility to primary health care in Bhutan. In particular, the spatial and temporal changes in spatial accessibility to primary health care services from 2010 and 2013 are analysed using accessibility indices of population clusters, subdistricts and districts.

Chapter 7 proposes the development of GNH accessibility indicators for Bhutan. The absence of any spatial-based indicators in the current GNH measurement system makes this holistic model incomplete for spatial planning purposes in Bhutan. This study presents an evidence-based approach to measure road accessibility, remoteness accessibility and spatial accessibility indices of the whole country based on spatial distribution of road network and various service centres, which can be potentially used as an indicator to facilitate spatial planning and allocation of service centres in the country.

Chapter 8 discusses some limitations of this study, and **Chapter 9** presents conclusions and recommendations for future work.

Chapter 2

Literature Review

PHC is considered to be an important aspect of the health care system in any country, with a direct impact in improving the overall health of the population. Access to health care providers is a critical component of a primary health care system. One technique in evaluating spatial accessibility to healthcare services is by computing gravity or FCA based measures using a GIS approach. This chapter presents a comprehensive review of the location-based spatial accessibility measures available for measuring spatial accessibility to primary health care services.

Section 2.1 describes the primary health care system in Bhutan, where a primary care approach was established to promote population health and well-being. Some health statistics pertaining to important health outcomes are also presented. Section 2.2 defines the fundamental concepts of spatial accessibility and its relationship with equity of access to health care services. Section 2.3 which constitutes the main body of the text in this chapter describes different types of spatial accessibility measures that have been, to date, used for health accessibility modelling. Most of the accessibility models used in health applications are associated with location-based measures such as the travel-impedance measure, provider-to-population ratios (PPR), gravity models, kernel density estimation (KDE) methods and FCA models. The last section of this chapter describes the methodological uncertainties associated with the FCA-based accessibility models.

2.1 Primary health care in Bhutan

Bhutan's modern health care development started with the implementation of five-year developmental plans in 1961. Up to this point, people of Bhutan had relied exclusively on traditional medicine, which still continues to play a pivotal role in the overall health care system. In 1961 there was no modern health infrastructure in this country. Today it has 1 national referral hospital, 2 regional referral hospitals, 28 district hospitals, and 206 BHUs and more than 500 ORCs located across the country. These hierarchical health facilities form the three-tiered primary health care delivery system providing basic health care services to the general population within the country. The PHC services encompass a broad range of health care services such as health promotion, prevention, treatment and rehabilitation. This is an important aspect of a health care system which has helped in building a healthy population in many countries. It is inexpensive and can be effectively distributed to many places unlike speciality and inpatient hospitalization care (Guagliardo, 2004). In Bhutan, PHC services are provided by general practitioners or doctors and specially trained health assistants and nurses. Due to a massive shortage of doctors in the country, the health diagnostic services in peripheral BHUs and ORCs are provided by health assistants. Unlike in many developed countries where doctors are located in private clinics, almost all health care providers in Bhutan are stationed within the state-owned health facilities.

Bhutan provides almost free health care services to its citizens. A national health survey conducted in 2012 indicated that 88 % of the overall medical expenses were government's expenditure whereas only about 11 % of the medical expenses were private expenditure. According to the World Bank's statistical report on public health expenditure, Bhutan's public finances on health expenditure accounts for about 73.8 % whereas public health expenses in neighbouring countries such as India, Bangledesh, Pakistan, Nepal, Sri Lanka and Maldives are only about 32.2, 35.3, 36.8, 43.3, 43.9 and 57.6 percent, respectively. It is important to note that the public expenditure figures between the World bank and the NHS results differ by about 10 %. In comparison with the neighbouring countries, the Bhutanese people enjoy the lowest relative out-of-pocket health care expenses (World Bank, 2014). This is a testament to the Government's endeavour towards providing universal health care coverage and quality health care services as enshrined in the Constitution. The Constitution mandates the government of the day to "provide free access to basic public health services" and "provide security in the event of sickness and disability or lack of adequate means of livelihood for reasons beyond one's control" (Bhutan, 2008, p.20). In addition, health is one of the nine domains of GNH, which recognizes health as one of the prerequisites for the economic and spiritual development of Bhutanese people to achieve personal well-being and happiness. Bhutan's public expenditure on health care accounts for about eight percent of the annual budget, which is roughly 3% of GDP. Like most developing countries, Bhutan also largely depends on external aid to finance its development activities. The annual budget of 2014 indicates that 23% of the total budget was financed through external grants. Of the eight percent of annual budget apportioned for the health sector, it is estimated that about 18% of this budget has been provided by donor countries (MoH, 2014*a*).

The MoH is mandated at a decadal interval to obtain information on health-related indicators and to monitor changes in population health using a survey questionnaire and interviews. The sampled population comprises both genders and ages ranging from 10 to 70 years, ethnically diverse with different socio-economic status, and is distributed across both rural and urban regions. The result of the NHS conducted in 2012 indicated a considerable increase in health coverage, an increase in accessibility to safe drinking water and a decrease in the infant and under-five mortality rate in the country (MoH, 2012*b*). Infant and under-five mortality rates improved from 70.6 and 96.9 to 30 and 37.3 deaths per 1000 live births respectively between 1994 and 2012. The proportion of births attended by skilled health personnel increased from 10.9 to 74.6 % between 1994 and 2012. Delivery of children in a proper health centre increased from 19.8 to 73.7 % between 2000 and 2012. Access to safe drinking water also increased from 88% to 97.7% of households between 2000 and 2012. Other health related indicators that have no basis for comparison are noted as follows. Only about 63% of the households in the country had access to proper sanitation facilities (modern toilet facility or latrine). All these health indicators suggest that there is a marked improvement in health-related outcome which can be directly or indirectly attributed to robust development and distribution of PHC services across the country through gradual establishment of health centres and deployment of well-trained health care providers in the peripheral rural regions.

The NHS 2012 also collected extensive information on utilization and access to health care services across the country (MoH, 2012*b*). About 54 % of the surveyed households in 2012 reported having BHU as their nearest health facility and 46% as having hospitals as their nearest facility. With respect to seeking healthcare services, about 53% of the surveyed households reported having visited a hospital and 47% having visited BHU for health concerns. The majority of people who visited health centres cited closeness to the health centre as the reason for visiting that facility. About 39 % of the Bhutanese people live within half-hour distance to the nearest health facility, 33% live within half to one-hour distance, 23% live within 1 to 3 hours of travelling distance. Only 4.6% of the population live more than 3 hours away from their nearest health facility. The travel-time statistics indicate that about 95% of the surveyed population in 2012 was found to be living within 3 hours proximity to the nearest health service centre. This 3 hour travel-time distance statistic is used by the MoH to gauge the spatial coverage of the PHC services within the country. The mode of transportation used varied between walking, bi-cycling and travelling by vehicles. About 67% of the rural population walked to the nearest health facility as opposed to only about 49% of the urban population. This indicates that walking has been the main form of transportation mode used by Bhutanese people to travel to health centres, indicative of under development in the road transportation infrastructure in the country.

Responding to the need for health-policy development guidelines, Bhutan's government had framed the national health policy (NHP) in 2012 to guide the health sector towards improving the health of the general populace. A key aspect of the NHP 2012 is to strengthen the existing health care system by pursuing "the comprehensive approach of primary health care", with an "emphasis on disease prevention, health promotion and community participation" by making it freely accessible to all citizens (MoH, 2012*b*, p.5). Despite the fact that the modern health system in Bhutan has progressively improved after the institution of PHC services in 1979, there are still many health-related challenges remaining and new challenges evolving. These require a concerted effort from both the government and general public to successfully confront these challenges. One of the challenges still remaining at the end of the 10^{th} Five-Year Plan is the lack of proper "monitoring and evaluation processes, outcomes and impacts, as well as the use of data and evidence for planning and implementation" in the health system of this country (WHO, 2014, p.33). This has been further identified in the WHO's country strategy document for Bhutan (for 2014 to 2018) as an area of critical need for the development of a "comprehensive national health management information system to better monitor health trends, and undertake health impact/health-equity assessments to strengthen the development of public policies, and evidence-based planning to effect improvements in the quality and scope of health-service delivery" (WHO, 2014, p.51). To consolidate health management and information system in facilitating 'health impact/health-equity assessments' and 'evidence-based planning', one approach available is to integrate GIS-based spatial system with the traditional non-spatial information system. A GIS-based health information system can be used for integrating spatial aspects of the public health system such as health accessibility, disease incidence or mortality rate mapping and epidemiological analysis between health outcomes and other variables, such as demographic, social, economic or environmental variables (Nobre et al., 1997).

A geographical information system is a computerised system whereby capture, storage, management, analysis and visualization of a geographically referenced data can be achieved in an integrated environment. The use of spatial data and GIS technology in the health system is ever increasing with various applications ranging from data visualization to epidemiological analysis. GIS-based evidence has been extensively used for decision-making process by policy makers in the planning and allocation of health resources (Cromley and McLafferty, 2002; Boulos, 2004; Williams et al., 2011). GIS has been used extensively to assess the equity of spatial access to PHC services (Luo and Wang, 2003; Yang et al., 2006; Unal et al., 2007; Luo and Qi, 2009; Wan et al., 2012a; Delamater, 2013; McGrail and Humphreys, 2014; Jamtsho et al., 2015). Other GIS-based applications for public health assessment and monitoring largely deal with epidemiologic studies that include the development of predictive disease outbreak models (Rogers and Randolph, 2003), GIS modelling techniques that correlate ambient air pollution with mortality (Scoggins et al., 2004), investigation of the cattle-human transmission of the Escherichia coli bacteria (Kistemann et al., 2004), etc. These GIS based applications can be either developed independently or integrated with the existing decision support system to realize the full benefits of GIS technology. Boulos (2004) has developed an online-based spatial accessibility system for the province of British Columbia in Canada to assist health policy makers and administrators in conducting evidence-based decision making for allocating health resources to rural regions. Yi et al. (2008) have developed the 'EpiVue' web-based platform for health users to upload spatially linked health data for visualization and analysis purpose. Nobre et al. (1997) developed a simple standalone GIS-based application to visualize disease incidence data and conduct elementary epidemiological analysis for disease surveillance purpose. Bedard et al. (2002) developed a spatial decision support system using GIS and on-line analytical processing technologies to support decision-making in the field of environmental health. Kelly et al. (2012) have presented a conceptual framework for the development of spatial decision support system for malaria elimination and control programs using proprietary MapInfo technologies. Kulldorff

(1997) developed a standalone software application called SaTScan to conduct disease cluster analysis using spatial scan statistics method.

GIS technologies have been widely used by many health organizations around the world for various health-related applications. However, the Bhutanese health system has not embraced GIS potentialities fully, save for limited usage in visualization and mapping purposes. There are few GIS-based spatial accessibility to PHC services research studies conducted in Bhutan (Jamtsho and Corner, 2014; Jamtsho et al., 2015).

2.2 Spatial accessibility - concepts and definitions

Following Whitehead (1990, p.5), the phrase “inequity in health care” generally refers to differences in health care or health outcomes resulting from “unnecessary and avoidable” action which are generally considered “unjust and unfair”. To understand the concept of equity in health care more vividly, few examples from Whitehead (1990) are reproduced as follows. Owing to biological or genetic differences, each person differs from others with respect to their physiological susceptibility to diseases or defensive immunity of fighting the diseases. Therefore, inequalities in health attribute arising due to genetic disposition are inevitable rather than inequitable. Similarly, older men are more susceptible to coronary heart disease than younger men. This case would also not instil feelings of injustice as the health outcome is due to the natural process of ageing. These two examples cannot be associated with ‘inequity in health care’ rather it is associated with ‘inequality in health status’. In contrast, there are other health outcomes and implications that are directly or indirectly influenced by social, economic, demographic, environmental and geographical barriers or facilitators. For example, poor people in many countries have no choice but to live in unsafe and overcrowded places where access to proper sanitation and safe drinking water are not available. The higher outbreak of diseases in such places is certainly due to environmental factors and clearly represent a case of inequity in health care. In such cases, people living in these places need better health care than people living in other places thus leading to the notion of equality of treatment based on need. So equity in health care concerns with “creating equal opportunities for health and bringing health differentials down to the lowest level possible” (Whitehead, 1990, p.7), in order to uplift even the disadvantaged group of people to attain “a level of health that will permit them to work productively and to participate actively in the social life of the community in which they live” (WHO, 1984, p.9). This resonates very well with the technical definition adopted by the WHO: "equity means fairness" and "equity in health means that people's needs guide the distribution of opportunities for well-being" (WHO, 1998, p.7), which promotes "both horizontal and vertical equity treating alike all those who face the same health need, and treating preferentially those with the greatest needs" (WHO, 2000, p.55).

The phrase 'access to health care' is also an ill-defined concept as stated in Aday and Anderson (1974), Penchansky and Thomas (1981), Gulliford et al. (2002) and United Nations Research for Social Development (2006). It has been defined with respect to supply of services, demand for services, integration between supply and demand, geographic separation, health outcome and effectiveness of services, and its meaning has evolved through time. Fox (1972) and Salkever (1975) referred it to as entry into or use of the health care system and Aday and Anderson (1981) defined it as potential or actual entry of people into the health care system, which are both based on the barriers posed by availability of services. Donabedian (1973) defined access to health care as the ease with which potential users can seek health care services, where utilization may be limited due to organizational or geographical barriers. Penchansky and Thomas (1981, p.128) extended the concept of access to health care to represent "specific areas of fit between the patient and the health care system". The specific areas were segregated into five dimensions of access to health care, namely availability, accessibility, accommodation, affordability and acceptability. Availability refers to the provision of health care facilities and providers with specialized programs and services. Accessibility implies the physical separation between location of health care providers and the location of residents with respect to distance, time and costs. Accommodation means the manner in which health resources are organized to provide health care services as deemed appropriate by the recipients. Affordability refers to the cost of health care services and its relationship to the patients' ability to pay for these services. Acceptability refers to personal prejudices and preferences of providers or patients which may hinder providing or receiving health care services (Penchansky and Thomas, 1981). Access to health care is also defined as providing appropriate service to the needy population at the right time in the right place (Rogers et al., 1999) or the appropriate use of personal health services to achieve the best possible health outcome (Institute of Medicine, 1993). Luo and Wang (2003) define access to health care as the relative ease by which a given health centre can be reached from a particular location, which echoes Donabedian (1973)'s definition pertaining to only geographical barriers. Even today there is no consensus amongst the health care community on the definition of access to health care. It has been reported by the United Nations Research for Social Development that the existence of multiple definition of access to health care creates confusion, leading to a hampering of the "progress in generating and applying knowledge to identify and strengthen pathways between access and health outcomes, especially in low-income countries"(United Nations Research for Social Development, 2006, p.1).

From a measurement perspective, Penchansky and Thomas (1981)'s five dimensions of access to health care simplify the measurement of various determinants of accessibility to health care. It appears that these five dimensions of access to health care were broadened to encompass more determinants of access and renamed as the four elements of 'Right to Health' (WHO, 2015). This is a fundamental right of citizens of the member states of WHO as enshrined in its Constitution. 'Right to Health' means that those member states around the world must work towards creating conditions in which every citizen of their country can live a healthy life. Such conditions may range from providing sufficient number of health care providers to creating safe neighbourhood and working conditions which would enable everyone to live a healthy and happy life. These conditions are defined exclusively within the context of the four elements: availability, accessibility, acceptability and quality. Affordability and accommodation dimensions in Penchansky and Thomas (1981) are included within the accessibility element group, which includes non-discrimination, physical accessibility, economic accessibility and information accessibility. Quality of care implies that the health care providers need to maintain sufficiently good quality equipment and provide a high standard of care to patients.

In a computational sense, these dimensions or elements can be dichotomously segregated into spatial or non-spatial components. If these dimensions of access deals with geographic facilitators or barriers then it is known as spatial access, otherwise, it is termed as non-spatial or aspatial access (Khan and Bhardwaj, 2002). Furthermore, access to health care is also dichotomously referred to as potential and realized access (or accessibility): potential access to health care refers to the supply of health care resources relative to the potential demand of the population; and realized access refers to the actual utilization of health care resources by the needy population (Aday and Anderson, 1981). Following Geurs and van Wee (2004, p.128), access implies "person's perspective" whereas accessibility implies "location's perspective". Realized accessibility is often also called revealed accessibility (Joseph and Phillips, 1984). Since revealed accessibility deals with the actual utilization of health resources, it has not been used for measuring the equity of spatial accessibility to health care. On the other hand, potential access to health care deals with the potential demand for health care services so it has been generally adopted for measuring equity to spatial access to health care services. When spatial accessibility deals with the potential access to health care, it is called the spatial potential accessibility. The availability of health care services and physical accessibility are spatial in nature whereas the other dimensions are aspatial in nature. This means that the availability (or supply) of health care services and population demand for services can be distinctly represented by location information thus forming a provider-population configuration network in a given health care delivery system, where differences in distance between locations of providers and population creates inequities in access to health care services.

Measurement or modelling of spatial accessibility to health care services can be conducted in a GIS framework using various data which may include some or all of the following dataset: population and health facilities data, road network data, digital elevation model, land use and land cover data and physician database (Makuc et al., 1991; Kohli et al., 1995; Parker and Campbell, 1998; Cromley and McLafferty, 2002; Luo and Wang, 2003; Guagliardo, 2004). On the other hand, the quantification of non-spatial access to health care will have to be done by means of a qualitative or quantitative based survey questionnaire. This thesis will exclusively deal with the measurement of spatial accessibility indices and spatio-temporal analysis of spatial accessibility to primary health care services in Bhutan, which in itself is a broad research area that has attracted many health geographers across the world.

Past studies on spatial accessibility have shown that the increased availability of primary care providers and easy accessibility to health care facilities has a significant positive impact on the health of the population (Frankenberg, 1995; Lavy et al., 1996; Perry and Gesler, 2000; Starfield et al., 2005; Cloutier-Fisher et al., 2006; French et al., 2006). Field and Briggs (2001) argued that a person living close to health facilities may likely to enjoy better health outcome because people living in close proximity to health centres are more likely to utilize health care services when needed. Travelling distance or time between population and health care providers is an important spatial barriers to health care services (Aday and Anderson, 1981; Penchansky and Thomas, 1981; McLafferty, 2003). It has been generally observed that the utilization of health care services is inversely related to the distance proximity to the health care centres

(Goddard and Smith, 2001; Cloutier-Fisher et al., 2006). Fortney et al. (1995) and Fortney et al. (1999) observed that the travel distance between the health centre and the patient's location affected the utilization of mental health and alcoholism treatment, respectively. Similarly, a decrease in the utilization of breast cancer treatment was observed as a result of the increasing distance to the treatment centre (Athas et al., 2000; Nattinger et al., 2001). Goodman et al. (1994) and Goodman et al. (1997) reported that the greater distance to hospital was likely to decrease hospitalization for discretionary conditions. Furthermore, the impact of the distance to the health care facilities on utilization of health care services were studied by Lovetta et al. (2002), O'Neill (2003) and Hadley and Cunningham (2004). Anderson and Morrison (1989) concluded that the primary medical care provided by the state may not impact the overall mortality but it may influence mortality and morbidity of some population groups and preventative health behaviours of such groups. Skinner (2006) and Chan et al. (2006) also observed the existence of relationship between health accessibility and health care outcomes. Travel time and distance proximity to health centres are also crucial in responding to an emergency as indicated by Blackwell and Kaufman (2002) study where they observed strong correlation between emergency medical service response time and morbidity. All the aforementioned studies suggest that the physical separation between locations of providers and population is very important in utilization of health care services. This implies that an equitable geographic distribution of health care providers and facilities can promote population health and even contain the cost of health services by minimizing oversupply and increasing equity in health services to medically underserved areas (Yang et al., 2006; Waldorf and Chen, 2010).

2.3 Review of spatial accessibility measures

According to Hansen (1959, p.73), accessibility is defined as the "potential of opportunities for interaction", which is a measure of the "intensity of the possibility of interaction rather than a measure of the ease of interaction". From a mathematical perspective, accessibility is simply a generalization of the concept of "potential of population" or population potential, which is analogous to physical concepts such as gravitational potential or electrostatic potential (Stewart, 1947, p.471). On the other hand, Dalvi (1979) specifically defined it as the ease with which a particular destination (such as location of a service provider) can be reached from a location, using a specific mode of transportation. This means that accessibility is determined by a network or configuration of locations between supply of service centres and demand for services due to population that are spatially connected by means of some transportation network. In a computational sense, accessibility is generally referred to as physical accessibility, geographical accessibility or spatial accessibility.

Many different spatial accessibility measures for health care services have evolved during the course of time such as the isochronic measure, opportunity-based models, travel-impedance based models, regional availability measure or provider-to-population ratio, gravity model, FCA models, KDE models and space-time models. Accessibility models have been used to measure accessibility to services in several areas of study such as "urban geography, rural geography, health geography, time geography, spatial economics and transport engineering" (Geurs et al., 2015, p.82). The isochronic or contour measure is simply a count of opportunities (service providers) available within a certain travel distance or time (Ingram, 1971; Wachs and Kumagai, 1973) whereas the opportunity-based measure is a contour measure weighted by an impedance decay function, a decreasing function of travel distance or time (Dalvi, 1979; Koenig, 1980). The travel-impedance based measure is defined simply by travel-time or distance to the nearest service facility from a resident's location (Dutt et al., 1986; Brabyn and Skelly, 2002; Lovetta et al., 2002). The container-based regional availability measure is a distribution of supply of health care provider and the population demand in the given region, often expressed as a provider-to-population ratio (Brabyn and Skelly, 2002; Starfield et al., 2005). This measure is the most commonly used indicator around the world as it is relatively easy to compute at any level of population aggregation, and is easy to interpret and intuitively understand. Gravity models are based on the concept of population of potential which account for supply of service providers, population demand for services, and travel impedance costs - due to geographical separation between service providers and population units (Weibull, 1976; Knox, 1978; Joseph and Bantock, 1982). The FCA models are a special derivative of the gravity model which uses a variable population catchment area instead of a single catchment area (Luo and Wang, 2003). This model has often been applied in computing spatial accessibility measure for health care services (Guagliardo, 2004; Luo and Qi, 2009; Dai and Wang, 2011; Langford et al., 2012; Wan et al., 2012a; Delamater, 2013; Jamtsho and Corner, 2014; McGrail and Humphreys, 2014). Kernel density models are a non-parametric technique which generate smooth density surfaces from point events of supply and demand locations using a kernel density function (Silverman, 1986).

A more detail review on travel-impedance measures, provider-to-population ratios, gravity model, FCA models, KDE model and space-time model are described in the following sections.

2.3.1 Travel-impedance measure

Travel impedance between locations of health care providers and the residents can be simply measured by calculating distance between two locations, time taken to travel to health care centres or monetary costs incurred to reach the health centre from a resident location. A typical distance or travel-time measures include Euclidean distance, Manhattan distance, the shortest travel distance or the shortest travel-time via a transportation network (Apparicio et al., 2008). Often such simple and direct measures are used to assess health accessibility within a country. For instance, a travel-time based impedance measure has been used to assess the health coverage in Bhutan. The last nationwide health survey in 2012 uses a survey questionnaire to collect accessibility data, where respondents were asked to recall the time taken to reach to the nearest health centre from their location. According to this survey report, about 94.8% of the population surveyed lives within a travelling time of 3 hours to their nearest health facility. This crude measure of health accessibility has been used to assess the health coverage in the country. Travel-impedance measures are relatively simple to use and also readily understood, however, they do not capture either the supply of health care providers or the population demand for health care services (Fortney et al., 2000). In addition, the travel-time measure to the nearest health facility is accurate only in rural areas where very few health facilities are located because people in urban areas do not necessarily uses the service of the nearest health facility given there are usually more choices available in their locality (Goodman et al., 2003).

2.3.2 Provider-to-population ratio

A container-based accessibility indicator, such as the PPR, is the most popularly used health care accessibility measure (Luo and Wang, 2003; Guagliardo, 2004; Luo and Qi, 2009). PPR is calculated as the proportion of the number of health care providers to the population within a given region. This index characterizes both the supply and demand of services by considering equal access to all the opportunities available within a certain region by all of the population in that region, irrespective of their geographic location. It excludes geographic aspects of population distribution which are one of the barriers in access to health care. Nevertheless, the simplicity and intuitive comprehensibility of this indicator has popularised it so much that it has been widely adopted across the world for identifying medically under-served areas, underpinning both policies and allocation of health resources. This unit of measure can be represented by computing number of physicians per 1000 or 10000 people within a predefined region. Table 2.1 shows the number of doctors per 10000 people in twenty districts of Bhutan in 2013. At the national level, there were two doctors for every 10000 people. Thimphu district had the highest number of doctors in the country with 6.65 doctors available per 10000 people in its district whereas Wangdiphodrang district reported the lowest with only 0.28 doctors available for every 10000 people in its jurisdiction.

TABLE 2.1: Provider-to-population ratio for doctors in 2013

Districts	**Population**	**No. of Doctors**	**Doctor-to-Population**	**Doctors (per 10000 population)**
Bumthang	18416	2	1-to-9208	1.09
Chukha	85615	8	1-to-10702	0.93
Dagana	26550	1	1-to-26550	0.38
Gasa	3578	1	1-to-3578	2.79
Haa	13147	1	1-to-13147	0.76
Lhuntse	17207	2	1-to-8604	1.16
Mongar	42843	13	1-to-3296	3.03
Paro	41848	5	1-to-8370	1.19
Pemagatshel	24648	3	1-to-8216	1.22
Punakha	26982	2	1-to-13491	0.74
Samtse	68582	4	1-to-17146	0.58
Sarpang	43920	10	1-to-4392	2.28
Thimphu	111312	74	1-to-1504	6.65
Trashigang	54766	5	1-to-10953	0.91
Trashiyangtse	20264	2	1-to-10132	0.99
Trongsa	15502	1	1-to-15502	0.65
Tsirang	21215	1	1-to-21215	0.47
Wangdiphodrang	36278	1	1-to-36278	0.28
Zhemgang	20950	3	1-to-6983	1.43
Samdrupjongkhar	38599	5	1-to-7720	1.30
National	732222	144	1-to-5084	1.97

Despite their popularity, PPR indicators have two limitations (Joseph and Phillips, 1984), which can bias the accessibility measurement at the regional level. Firstly, container-based indicators are based on the assumption that all opportunities are available to all population within that region. This is generally unrealistic in the real world. Owing to physical separation between service provider and population cluster, especially in rural areas, access to service providers is frequently limited to a small part of the container region. Secondly, the container-based accessibility measure assumes that regions are bounded by an impermeable boundary. In reality, regions within a nation are not separated by such artificial boundaries and people are free to move around to seek services from any health centre. The effect of constraining the free movement of people between regions affects for the most part those populations living near the boundaries of the regions in accessing health services from a health facility located close-by in the adjoining region.

Therefore the assumption of any boundary between regions does not reflect the propensity of people to seek health care services across such boundaries if a near-by facility is available. These assumptions of the provider-to-population ratios challenges the integrity of this spatial accessibility measure because it does not truly reflect the actual relationship between providers and population.

2.3.3 Gravity models

Following Stewart (1947), population potential (N/d) is expressed as the number of people (N) divided by the distance (d) between a service centre and the population unit, which is analogous to a gravitational potential (mass of the planet(m)/distance to the planet(d)). Therefore, gravity models are also synonymously known as potential accessibility models. A simple gravity model for measuring accessibility at resident location(i) was proposed by Hansen (1959), which is given by

$$A_i = \sum_{j=1}^{n} S_j d_{ij}^{-\beta}, \tag{2.1}$$

where A_i is the accessibility index at the population cluster location i, n is the total number of health service provider locations, S_j is the service capacity offered at location j and $d_{ij}^{-\beta}$ is the distance or travel impedance function and β represents the decaying parameter or impedance coefficient. For measuring health accessibility, service capacity is generally measured as number of physicians or beds available at the given health facility. The impedance coefficient is defined in such a way that the nearby service providers are weighted higher as these locations are deemed more accessible than the farther ones. It also depends on numerous other factors such as socio-economic status of the patient, demographic characteristics and road accessibility (Lovetta et al., 2002). However, the value of β is mostly obtained by an ad-hoc choice or by a trial-and-error method. Luo and Wang (2003) have tested for range of β values from 1.0 to 2.2 for computing health accessibility measures and Wang (2000) used β value of 1.85 for measuring job accessibility in Chicago.

Other forms of distance impedance function associated with the gravity model include variants of exponential functions such as $e^{-\beta d_{ij}}$ (Wilson, 1971) and $e^{-d_{ij}^2/\beta}$ (Ingram, 1971). Wachs and Kumagai (1973) used dichotomous values, 1 for all distances less than a certain threshold distance (d_0) and 0 for all distances greater than the threshold distance, to moderate the available opportunities. With the availability of different decay functions, the original gravity model has been modified to represent a generic model. Following Weibull (1976), the reformulated gravity model is given by

$$A_i = \sum_{j=1}^{n} S_j f(d_{ij}), \tag{2.2}$$

where $f(d_{ij})$ represents a generic decay function that is unity for zero distance and tends to zero as distance approaches to infinity. Equation 2.2 computes spatial accessibility at location i by accounting for the total service capacity of all the potential providers within the computation region while discounting the service capacity offered at the given location by the travel impedance factor between locations i and j. Although this gravity model considers the effect of the proximity of the location of the health service providers, it only accounts for the supply side of health care services without considering population demand for the health services. Owing to this deficiency in this model, the spatial accessibility scores in urban areas will always be higher than the rural areas because the majority of health service providers are located in the urban areas. By accounting for the higher population demand for health services in urban areas, the rural-urban discrepancies can be reduced or eliminated completely. Weibull (1976) modified Equation 2.2 by including the population parameter to form the modified gravity model:

$$A_i = \sum_{j=1}^{n} \frac{S_j f(d_{ij})}{D_j}, \tag{2.3}$$

where D_j is the demand for services at location j and other variables are same as in Equations 2.2. The demand for the health service at location j comes from the whole population in the computation region, which can be computed by

$$D_j = \sum_{i=1}^{k} P_i f(d_{ij}), \tag{2.4}$$

where P_i is the population at the location i, k is the the total number of population locations and d_{ij} is the distance between the population location i and the provider location j. Equation 2.3 can be applied for both areal and point data. Other variants of the gravity model are described in Wilson (1971) and Breheny (1978).

Geurs and van Wee (2004) observed a number of advantages of gravity or potential measures. The gravity-based accessibility measures overcome some of the theoretical shortcomings of travel-impedance measures (see Section 2.3.1) by evaluating the supply and demand effect of service centres and population respectively, and by accommodating people's travelling differences using a distance impedance function. It can be used to assess accessibility to social and economic opportunities (e.g. health and job accessibility) for various population groups. Knox (1978), Joseph and Bantock (1982), Unal et al. (2007), Waldorf and Chen (2010), Xu and Cui (2012) and Jamtsho and Corner (2014) used the modified gravity model to assess accessibility to general practitioners in rural areas, Shen (1998), van Wee et al. (2001) and Wang and Minor (2002) used it for assessing job accessibility. It may also be used to evaluate spatial and economic aspects of transportation projects. Fürst et al. (2000) have used the potential measure as an explanatory variable for regional GDP and evaluated the impact of investment on transport infrastructure on economic growth in the European Union.

One of the important advantages of the gravity model is that the data required for computation are readily available: population census data, available opportunities in service centres and transportation network data. The theoretical framework of the gravity model is similar to the Newton's gravitational model where all population and health service centres are interacting simultaneously within a single catchment area and thereby influencing the demand and supply of health services at all locations: for instance, in the case of the gravitational field where all objects within the field contribute to the computation of the gravitational field at any given location. This proven theoretical basis of the gravity model has led to the popularity of this method of computation for spatial accessibility in various fields of social sciences. However, the inclusion of all the population clusters and service providers within a large computation area (regional and national level) may not be realistic given that not all health service centres are either accessible nor used by all the population in a given region. In addition, the unit of the gravity measure is also not intuitively comprehensible because of the inclusion of three interacting variables causing confusion in the interpretation of this measure (Luo and Wang, 2003; Guagliardo, 2004; Luo and Qi, 2009; Delamater, 2013). (Luo and Wang,

2003) observed that the gravity model overemphasizes the decay function resulting into a highly spatially smooth concentric pattern of accessibility with higher accessibility regions located around the urban areas and lower accessibility regions around rural areas thereby failing to reflect the spatial variability of accessibility within rural or urban regions. In addition, they also observed that the gravity model overestimated accessibility values for underserved regions. Nonetheless, this criticism may have to be viewed sceptically as their study exclusively used the inverse power function with a certain value for the decay parameter. There are other decay functions available such as exponential function, Gaussian function, Butterworth function, etc. These drawbacks of the gravity models have led to the development of numerous variants of the floating catchment area metrics and these are described in the following sections.

2.3.4 Floating catchment area models

FCA models are special derivatives of the gravity model where the computation of the spatial accessibility is carried out by using a number of floating catchment areas rather than only one catchment area. Generally, the catchment areas (or buffer rings) are defined based on a threshold value of distance or travel time. For example, Peng (1997) and Wang (2000) used a floating catchment area technique in computing the job-housing ratio, which is often used as a job accessibility measure. Unlike the gravity model, the FCA method does not use all the population clusters and service centres in a gravitational way for the computation of spatial accessibility measures. It uses service centres and population units falling only within the associated catchment area to compute the accessibility at the location of the given population cluster. There are a number of variants of the FCA models developed so far, such as the 2SFCA, E2SFCA, KD2SFCA, 3SFCA and M2SFCA methods, which are described in the following sub-sections.

2.3.4.1 2SFCA method

Radke and Mu (2000) developed the spatial decomposition method to measure accessibility to social services, where the accessibility measure for residents living exclusively in non-overlapping catchment areas is computed as the ratio of providers to population within that service catchment area centred at the supplier's location, and the accessibility measure for resident's falling in overlapping service areas is computed as the sum of the ratios of all service centres associated with it. So a progressive model of accessibility in close relation to the provider-to-population measure was developed using a floating catchment area technique by incorporating both the supply and demand components underpinning the theoretical aspects of the accessibility measure. The spatial decomposition technique was used by Luo and Wang (2003) to develop the two-step floating catchment area (2SFCA) method. The 2SFCA method commonly uses distance or travel time to define the catchment area and is implemented in two steps. Firstly, the provider-to-population ratio at the provider location (R_j) is computed using Equation 2.5,

$$R_j = \frac{S_j}{\sum\limits_{i \in \{d_{ij} \leq d_0\}} P_i} \tag{2.5}$$

where P_i is the population at location i which falls within the catchment area of the service provider location j, S_j is the number of service providers available at location j, d_{ij} is the distance or travel time between location k and j, and d_0 is the user specified threshold distance or travel time for defining service catchment areas. The catchment area of the service provider can be defined using a user specified distance or travel time centred at the provider's location. Luo and Wang (2003) used a travel time of 30 min to define the catchment area. This step generally corresponds to computing the provider-to-population ratios at all the service provider locations. Figure 2.1 shows an illustration of the 2SFCA method, which is used for describing the computational steps.

Following the rationale of Luo and Wang (2003), it has been assumed that there is only one person residing at each population location represented by a black dot, and only one physician at the provider location represented by a cross in Figure 2.1. A journey time of 30 min is used to define a catchment area at the location of each physician. The catchment area of physician A has one physician and six residents, so the PPR of this catchment is 1:6. Similarly, the PPR of the catchment area B is 1:5. Therefore, the PPR of the overlapping area is the sum of the physician-to-population ratios of both the catchment areas.

Secondly, the accessibility at the population or resident location, A_i is computed using Equation 2.6,

$$A_i = \sum_{j \in \{d_{ij} \leq d_0\}} R_j = \sum_{j \in \{d_{ij} \leq d_0\}} \frac{S_j}{\sum\limits_{i \in \{d_{ij} \leq d_0\}} P_i} \tag{2.6}$$

where R_j is the provider-to-population ratio at provider location j which falls within the catchment area centered at location i, d_{ij} is the travel time between location i and j

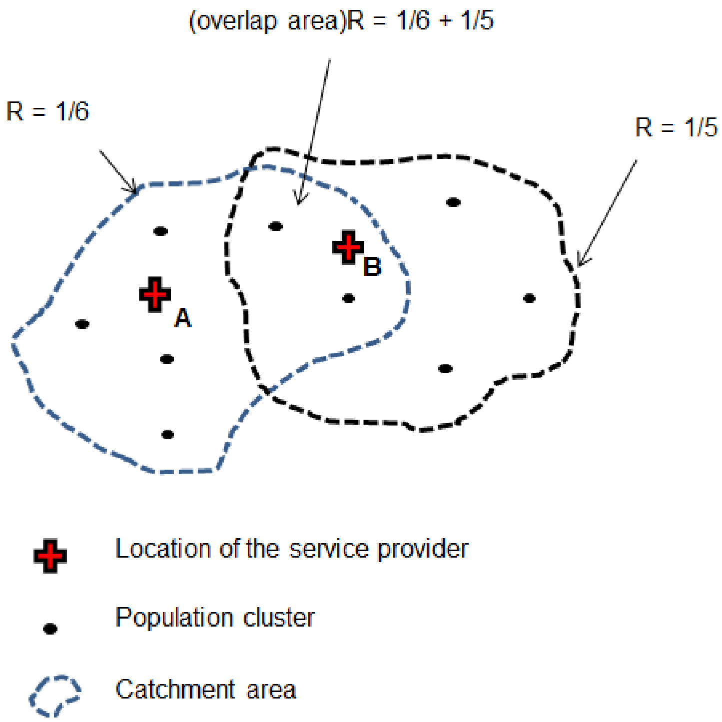


FIGURE 2.1: A simple provider-population configuration of the 2SFCA method

and d_0 is the threshold distance. This step corresponds to computing the accessibility measure at each population locations by summing up the provider-to-population ratio of the associated service providers computed in the first step. The region for summation can now be defined using the travel or distance threshold centred at the population cluster's location, i.

Luo and Wang (2003, p.879) proved that the 2SFCA method is a specialised case of the gravity model. The difference between the two models lies with respect to the use of the distance impedance function whereby the gravity model computes accessibility by applying impedance function as a continuous measure for the whole computational region whereas the 2SFCA model computes accessibility by applying the distance impedance function as a dichotomous measure by segregating the computational region into two regions. In other words, it means that the gravity method uses a continuous function within a single catchment area whereas the 2SFCA method implicitly uses a distance impedance value of 1 within the region defined with a buffer distance and 0 for outside regions. Equations 2.3 and 2.6 are equivalent because the former model explicitly includes a continuous decay function whereas the later model implicitly defines a binary function.

It is important to note that weights are unitless. Equation 2.6 represents a ratio of supply to demand because the numerator of the ratio is equal to the supply of medical services and the denominator is equal to the population demand for health services. The output unit of the 2SFCA method is thus service opportunities per person which can be interpreted for practical purposes (Wan et al., 2012a; Delamater, 2013). In contrast the gravity measure has a cumbersome unit, whereas, the 2SFCA measure possesses a simple intuitive unit akin to a PPR measure. If the gravity and 2SFCA models are geometrically the same when considering a weighting function then it can be argued that the gravity measure has similar units to the 2SFCA measure. In a mathematical sense, the only difference between the two models is that the gravity model uses a single catchment area for all computational regions whereas the FCA model uses a variable catchment area.

The 2SFCA model has been widely applied, particularly in measuring health accessibility as reported by Wang and Luo (2005), Scott et al. (2006), Cervigni et al. (2008), McGrail and Humphreys (2009a), Schuurman et al. (2010), Dai and Wang (2011), Ngui and Apparicio (2011), Langford et al. (2012), Wan et al. (2012b), Liang and Nekorchuk (2013) and McGrail and Humphreys (2014). Luo and Wang (2003) observed that the 2SFCA model clearly identified spatial variability in accessibility within a region while the gravity model highly smoothed the accessibility values. Yang et al. (2006) noted that the KDE method produced volatile and deflated accessibility ratios whereas the 2SFCA method produced relatively stable accessibility values. Although the 2SFCA method is popularly used and has certain advantages over other accessibility models, it has two limitations (Luo and Qi, 2009; Wan et al., 2012a). Firstly, it creates an arbitrary boundary which segregates service providers as being accessible or inaccessible. In the example shown in Figure 2.1, it means that physicians within 30 min are accessible but beyond that time are inaccessible, arbitrarily creating two regions separated by an imaginary impermeable barrier to health services. This so called permeability problem exists in all the variants of the floating catchment area metric system and have to be accommodated by realistically formulating a suitable travel-time or distance threshold value. Secondly, this method does not take account of the distance variation between a resident living at 1 minute travel time and the 29 min travel time as both the cases falls within the limit of the catchment area so it is possible for these two cases to have the same accessibility measure despite the nearby resident having a better access to the health services than more distant one. This second problem of the 2SFCA method have been tackled by introducing number of different distance weighting mechanisms, which are described in Section 2.3.4.2. Further improvements to the 2SFCA model have been proposed to include dynamic sizes of catchment areas to reflect the size of the population and availability of effective service opportunities, for instance, a small town will not have as many service providers as would be available in larger town or indeed city (McGrail and Humphreys, 2009b; Luo and Qi, 2009).

2.3.4.2 E2SFCA AND KD2SFCA methods

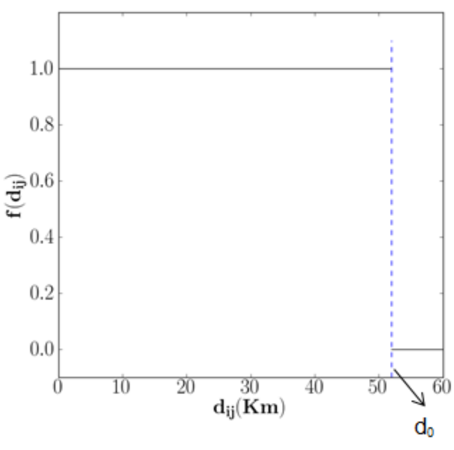
In Equations 2.5 and 2.6, there are no weighting functions explicitly included. However it can be stated that the distance based segregation of the computation region forms dichotomous regions where the parameters for the inner region are weighted 1 and the parameters for the outside region 0. This dichotomous weighting mechanism causes the problem of unbalanced weighting between the closer regions and the farther away regions within a catchment area thereby affecting the computation of their accessibility measures. To address this problem, two distinct weighting schemes based on a distance decay function have been developed: the E2SFCA method weights the parameters in the 2SFCA equations by a distance-based step decay function (Luo and Qi, 2009; Hu et al., 2013); and the KD2SFCA method uses a continuous distance decay function(Dai, 2010; Dai and Wang, 2011; Langford et al., 2012).

The mathematical model for both the E2SFCA and KD2SFCA are given by Equations 2.7 and 2.8 for the first and second step of computation, respectively,

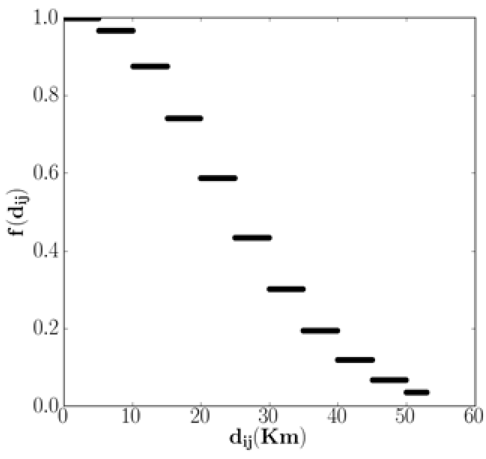
$$R_j = \frac{S_j}{\sum\limits_{i \in \{d_{ij} \leq d_0\}} P_i f(d_{ij})} \tag{2.7}$$

$$A_i^e = \sum_{j \in \{d_{ij} \leq d_0\}} R_j f(d_{ij}) \tag{2.8}$$

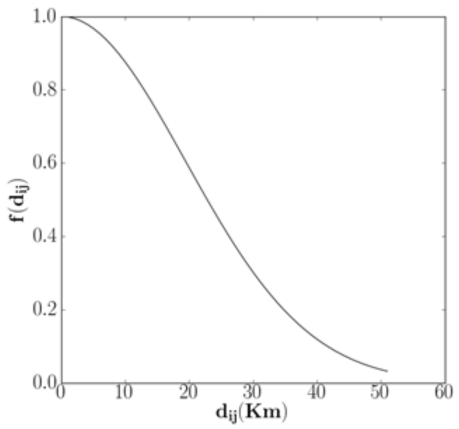
where $f(d_{ij})$ is a weighting function. Closer inspection of the two equations above indicate that these equations together constitute the gravity model equation given in Equation 2.3 where all the different parameters involved in the equations are exactly the same. The only difference between this method and the gravity method is that this method uses variable floating catchment areas for computation purposes instead of the single catchment area used in the gravity model. Figures 2.2(a) to 2.2(c) shows the different weighting scheme used in the 2SFCA, E2SFCA and KD2SFCA metric system.



(a) 2SFCA



(b) E2SFCA



(c) KD2SFCA

FIGURE 2.2: FCA weighting methods

Luo and Qi (2009) compared the health professional shortage areas of a few counties designated by the Department of Health and Human Services (DHHS) of the United States with the results obtained from the 2SFCA and E2SFCA methods. They observed that both the 2SFCA and E2SFCA methods identified shortage areas at a finer spatial resolution within the bounds of the health professional shortage areas (HPSAs) identified by the DHHS method. Furthermore, they observed that these FCA methods identified shortage areas unidentified by the DHHS method at a finer spatial resolution. The DHHS method used a physician-to-population ratio threshold value of 1:3000 within a health service area as an indicator for defining HPSAs (Wang, 2012). The difference between the 2SFCA and E2SFCA methods cannot be explicitly known through accessibility outcome but the later method has a theoretical advantage owing to its consideration of continuous distance weighting values. Luo and Qi (2009) suggested the use of different sizes catchment areas in rural and urban areas and in the first and second computational steps of the 2SFCA method, in order to accommodate the differences in available opportunities and size of population across regions and differences in the dynamics of the supply-demand interactions between step 1 and 2.

2.3.4.3 3SFCA method

The three-step floating catchment area method was developed on the assumption that the demand for service at a given service centre is not only influenced by the population demand to this service site but also by the population demand at other close-by service centres (Wan et al., 2012a). This competition effect between service providers which is unaccounted in the 2SFCA, E2SFCA and KD2SFCA methods would potentially cause overestimation of the accessibility at locations where there are many service centres available. In order to accommodate this effect, Wan et al. (2012a) modified the E2SFCA model by introducing an additional weighting parameter (H_{ij}) as given by Equations 2.9, 2.10 and 2.11.

$$H_{ij} = \frac{f(d_{ij})}{\sum\limits_{j \in \{d_{ij} \leq d_0\}} f(d_{ij})} \tag{2.9}$$

$$R_j = \frac{S_j}{\sum\limits_{i \in \{d_{ij} \leq d_0\}} P_i f(d_{ij}) H_{ij}} \tag{2.10}$$

$$A_i^{3sfca} = \sum_{j \in \{d_{ij} \leq d_0\}} R_j f(d_{ij}) H_{ij} \tag{2.11}$$

2.3.4.4 M2SFCA method

Delamater (2013) proposed another modification to the original 2SFCA method and named it the modified two-step floating catchment area method, M2SFCA, to combat the computational issues of the aforementioned FCA models. For instance, consider two arbitrary data configuration systems having three population clusters each located 2 and 7 kilometres away from the sole health provider, respectively. The 2SFCA, KD2SFCA,E2SFCA and 3SFCA methods produces same accessibility values for all three population clusters, irrespective of the absolute distance separation between the population and provider locations in both the configuration systems. This limitation of the aforementioned FCA models can potentially bias the accessibility outcome of some regions by over-estimating their accessibility values as illustrated in these scenarios. Such bias in the accessibility models can potentially increase the accessibility score for poorly served regions thereby failing to identify the underserved regions accurately, which is often referred to as the problem of over-estimation (Wan et al., 2012a; Delamater, 2013). In addition, Delamater (2013) also observed that within other FCA systems, all the available opportunities to population clusters were relatively distributed based on their relative distance separation from the health provider. He argued that in a single provider system the optimality condition would be reached only when both the provider and population clusters are collocated, i.e. when all the providers are available to all the population clusters. In any other scenarios, especially with multiple locations of providers, the optimality condition is never reached and less total opportunities in the system become available. Total opportunities refer to the total number of service providers in the provider-population system.

Following Delamater (2013), the optimal and sub-optimal characteristics of the FCA metric systems can be explained by revisiting the gravity model from which the FCA metric systems are constructed. For a system consisting of only one provider and one population unit, the gravity-model (Equation 2.3) reduces to Equation 2.12.

$$A_i = \frac{S_j f(d_{ij})}{P_i f(d_{ij})} = \frac{S_j}{P_i} * \omega, \qquad \omega = \frac{f(d_{ij})}{f(d_{ij})} = 1 \tag{2.12}$$

The implication of Equation 2.12 is that the accessibility values in a single provider and population unit system will always remain the same for all distance separations because the value of ω is always 1. This effect is also true for single provider and multiple population unit system, however, it cannot be generalized to a system consisting multiple providers as only collocated providers would satisfy the optimality condition, which is not prevalent in real-world systems. Nonetheless, this implicit assumption of the optimality condition ($\omega = 1$) in FCA metrics poses the problem of over-estimation. In response to this, Delamater (2013) has added an additional weighting term in the numerator component of the modified gravity model. Equation 2.13 formulates the M2SFCA model,

$$A_i^m = \sum_{j=1}^{k} \frac{S_j f(d_{ij}) f(d_{ij})}{\sum_{i=1}^{m} P_i f(d_{ij})}, \tag{2.13}$$

which can be computationally realised by following similar computation steps to the E2SFCA method except that the second step of the computation is augmented with an additional weighting parameter as shown in Equation 2.14.

$$A_i^m = A_i^e f(d_{ij}) \tag{2.14}$$

Equation 2.13 indicates that the optimal configuration ($\omega = 1$) of the system of providers and the population clusters is reached when all the entities are collocated (i.e. $d_{ij} = 0$). In all other configuration system, ω varies between 0 and 1 which is a realistic approximation of real world systems. Therefore, in practice, the total available opportunities are not completely accessible owing to the sub-optimal condition of the provider-population configuration system. This means that the sum of the opportunities of individual population clusters only add up to a value less than the actual total opportunities. A computational example for a hypothetical system is presented in Section 4.4.

2.3.5 Kernel density estimation model

Kernel density models are non-parametric techniques which generates smooth density surfaces using a kernel density function (Silverman, 1986). Guagliardo (2004) has used KDE method to compute a physicians-to-children ratio in Washington, DC. Yang et al. (2006) have compared 2SFCA and KDE methods by computing accessibility measures for dialysis service centres in Chicago. Normally, the computation is done using raster data, which represents spatial data with an equal size grid cells arranged in rows and columns. The integral part of the KDE method is the kernel estimator, which is mathematically defined as given in Equation 2.15:

$$\hat{f}(x) = \frac{1}{nh} \sum_{j=1}^{n} K(\frac{x - x_i}{h}) \tag{2.15}$$

where $\hat{f}(x)$ is a density estimator,$(x_1, x_2, ..., x_n)$ is a sample drawn from unknown density function, n is the number of sample data, h is the bandwidth or smoothing parameter and K is the kernel function. The kernel estimator is literally understood as sum of 'bumps' stacked at the data point where K determines the shape of the bumps and the h determines their width (Silverman, 1986). The choice of h is critical in defining the kernel estimator because if h is too small then noisy fine structure is evidently visible whereas if h is too big then the probability density function is too smooth. A kernel function can be defined using functions such as the uniform, triangular, bi-weight, tri-weight, Epanechnikov, cosine, Gaussian, etc. A further explanation of kernel density estimation can be found in (McLafferty et al., 1979; Silverman, 1986).

There are three steps involved in KDE technique of computing health accessibility ratios. First, a physician density surface has to be created using its grid data available at individual or group level using a kernel estimator. Guagliardo (2004) used a Gaussian kernel function as the kernel estimator. This kernel estimates a smooth conic surface centred at the location of the point of computation, the providers' location, where the density value decreases outward from the point of computation and reaches 0 at the search radius distance or bandwidth. Guagliardo (2004) used 3.9 miles while Yang et al. (2006) used 1 mile as the search radius, which limits the extent of each kernel surface computed at different locations. The volume of the conic surface equals the magnitude of the field value associated with the service location (e.g. number of hospital beds, number of physicians, etc), otherwise it is simply assumed to be 1 to reflect the single entity of the providers' location. The density estimate at each raster cell is the sum of all the estimates obtained from different kernel surfaces overlapping at that cell centre. Second, a similar kernel estimation approach is used to obtain a density surface for the population clusters with same cell size and extent as the provider density layer. Third, a provider-to-population ratio at each cell location can be computed by dividing the provider density estimate at that location by the population density estimate at the corresponding location. Then the health accessibility ratio at the census tract level or any higher geographical aggregation level can be computed as a mean of the accessibility ratios falling within a given region.

Compared with the accessibility outcome from the 2SFCA method, the KDE method produced volatile and significantly lower accessibility ratios, which are also considerably dependent on the size of the search radius or bandwidth used in the kernel function Yang et al. (2006). Hence, the KDE method is not as good as the 2SFCA method for identifying poor access areas. Furthermore, the selection of the bandwidth is largely arbitrary which can hugely effect the accessibility outcome (Neutens, 2015). Neutens (2015) cautioned that the presence of uninhabited areas like forest and water bodies might distort the density estimates for both the service providers and the population clusters. In addition, the density estimates for the population clusters could be biased if the actual population density were not towards the zonal centroid because the kernel function assumes that population is evenly concentrated around the centroid and decreases towards the end of the search radius (Neutens, 2015). The KDE method is rarely used for health accessibility measurement, although it is routinely applied in disease incidence and risk mapping in epidemiological studies (Neutens, 2015).

2.3.6 Space-time accessibility model

Ren et al. (2014) and Neutens (2015) have observed that location-based health care accessibility measures such as the travel-impedance, gravity, FCA and KDE models do not consider the travel behaviour patterns of individuals during daytime where multiple activities occurs posing contextual problems with respect to location of the individuals and timing of visits to health service centres, rather the location-based models that are all based on a static population assumed to be generating demand at a fixed location. In addition, these models also suffer from the modifiable areal unit problem due to individuals being grouped into population clusters at the census tract level (Neutens, 2015). So there is a need for more sophisticated geocomputational techniques such as the person-based space-time accessibility model (Kim and Kwan, 2003; Neutens, 2015).

Space-time accessibility modelling is based on the framework of space-time geography, as proposed by Hägerstrand (1970). Hägerstrand observed that an individual's movements in spatial and temporal domains is limited by coupling, capability and authority constraints. Coupling constraints refer to "where, when and for how long, an individual has to join other individuals, tools, and materials to produce, consume and transact", capability constraints are "those which limit the activities of the individual" such as sleeping and eating activities, and authority constraints refer to a "time-space entity within which things and events are under the control of a given individual or a given group" (Hägerstrand, 1970, p.14-16). It is therefore pertinent to consider people's daily activities in mapping an individual's mobility patterns and other discretionary choices while modelling accessibility measures, because individual activity such as a visit to a health centre may be constrained by the spatio-temporal availability of other competing destinations. Activity-travel research studies have shown that people can include various activities in their daily schedule thus leading to a notion of dynamic demand of population distribution instead of a static demand, which is incorrectly assumed by existing location-based accessibility models (Chen and Kwan, 2012).

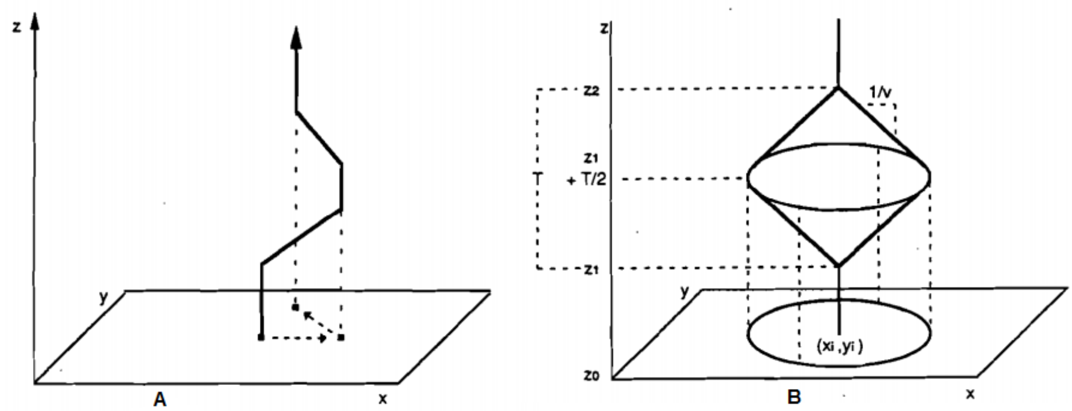


FIGURE 2.3: Schematic representation of space-time path (A) and space time prism (B) (Miller, 1991, p.290)

The conceptual framework of a space-time accessibility measure is premised on the mathematical construct of a space-time prism. This determines an individual's possibility to participate in a set of locations bounded within a finite spatial region and limited time interval (Miller, 1991). Figure 2.3 (A), reproduced as in Miller (1991), shows a schematic representation of a space-time path. The triad axes represent two spatial dimensions (x- and y-axis) and time dimension (z-axis). If an individual does not move in space then the space path is parallel to the z-axis; if the slope of the space path becomes more horizontal then the individual is moving at greater velocities. Projection of the space path on a two-dimensional x-y plane is shown by dotted lines in Figure 2.3(A). Figure 2.3 (B) shows a schematic representation of the space-time prism developed with a coincident starting and ending point and without stop points (Miller, 1991). As time progresses (positive z-axis), an individual at a given location (xi, yi) starts the journey at time z1 and returns to the same location at time z2 after spending time at various travel destinations. The space-path deviates from parallel to the z-axis in all spatial directions to a slope of 1/v. This slope is positive along the z-axis starting at time z1 and away from the travel origin, and negative along the z-axis starting at time z2 away from the travel destination, until the two cones meet at time z1 + T/2. Overall space-time paths of an individual from starting time (z1) to ending time (z2) create the space-time prism or potential path space. The potential path space becomes more complex when stoppage time and non-coincident starting and ending points are considered. This complexity limits the practical application of space-time modeling, but it can be circumvented by considering potential path area (PPA), which is simply a projection of potential path space on to two-dimensional planar surface. The PPA is the circular area on the x-y plane shown in Figure 2.3 (B). A set-theoretical construct of the space-time prism model is elaborately described in Kim and Hong (1998) and Neuten et al. (2010).

Miller (1991) presented the operational aspects of PPA using GIS technology by considering a transportation network analysis at the individual level. Since an individual PPA can be constructed on the basis of a point representation of locations of travel origin and destination, it can be modelled within the framework of a transportation network by considering a number of factors affecting a street network. This may include traffic congestion, speed limits, peak times, traffic stoppage times or some other attributes associated with the connecting streets. There may also exist multiple routes between two locations in a transportation network which can also be modelled using either shortest distance or shortest travel-time route. Even stoppage time at different travel destinations can be included in PPAs to reflect time spent by individuals in different activities. A network based PPA can also incorporate other space-time constraints that relate to an individual choices. If a certain number of travel activities are carried out by an individual within the stipulated time interval and on a given day then the same number of PPAs or daily PPA (DPPA) for each individual within the study area can be derived. GIS technology can facilitate the combination of these DPPAs to derive aggregate accessibility measures for various applications. For instance, the network based PPAs of a specified number of individuals within a given region can be aggregated, based on a certain time budget to determine composite accessibility indices. Ren et al. (2014) have incorporated the DPPAs space-time constructs of 376 individuals to modify the travel-impedance measure of accessibility to hospitals within a travel time budget of 5 or 10 min. Other variants of DPPA-based space-time measures are presented in Kim and Hong (1998), Neuten et al. (2010) and Ren et al. (2014).

Person-based space-time accessibility models have the potential to eliminate the modifiable areal unit problem given they model accessibility at the individual level. Potentially they can also solve the uncertain geographical context problem (Kwan,

2012) by modelling the dynamic demand of population distribution using an individual's mobility pattern data and spatio-temporal constraints within the study area (Neutens, 2015). In doing so there is the potential to refine the current method of determining perceived health coverage, which was generally conducted through questionnaires where respondents were asked to estimate the travel time to their nearest health facility.

However, conducting a comprehensive survey to collect individual travel data at the national level would be prohibitively expensive, especially in developing countries like Bhutan where financial resources are constrained. Individual travel data surveys cannot be incorporated with the 10 yearly national health survey because individual travel data survey questionnaire comprises a large number of space-time related questions that have to be captured for a duration of one or two weeks. Currently, this model is generally applied only in small study regions (Kim and Hong, 1998; Neuten et al., 2010; Ren et al., 2014). Space-time models are also very complex as they deal with the travel behavioural patterns of individuals. So far it has not been possible to develop an operational algorithm inclusive of all spatio-temporal constraints (Geurs and van Wee, 2004). Unlike the location-based models such as the gravity, FCA or KDE models, the space-time model does not account for competition effects caused by the 'attractiveness' factor in service centres such as number of health care providers or hospital beds, and it is thus ineffective in analysing job accessibility or accessibility to primary health care providers where competition between individuals or groups occurs (Geurs and van Wee, 2004).

2.4 Uncertainties in FCA modelling

The PPR method is the health service availability indicator most widely used by health institutions across the world to practically evaluate the regional availability of health services within a certain geographic region. Travel-impedance measures such as the fixed distance or travel-time between locations of provider and population are the most commonly used indicator for defining physical accessibility to health care services. These two indicators when combined together are known as the spatial accessibility measure and form a more robust measure of spatial accessibility to health care services. This accounts for the supply and demand components of health services and as well as the geographical separation between the location of a provider and population cluster. The review of the literature on health accessibility suggests that all recent publications have directly or indirectly used the FCA metric system to compute spatial accessibility measure for various applications (Luo and Wang, 2003; Wang and Luo, 2005; Scott et al., 2006; Cervigni et al., 2008; McGrail and Humphreys, 2009a; Luo and Qi, 2009; Schuurman et al., 2010; Dai, 2010; Ngui and Apparicio, 2011; Dai and Wang, 2011; Wan et al., 2012a; Langford et al., 2012; Wan et al., 2012b; Delamater, 2013; McGrail and Humphreys, 2014). The numerous uncertainties associated with the spatial accessibility models have led to a lack of consensus amongst researchers on a single viable spatial accessibility model, often deterring health professionals from embracing this potential measure of spatial accessibility or using it for practical purposes. As research on this subject continues more vigorously, it is only a matter of time before a pragmatic and viable solution is achieved. Other variants of the accessibility measures such as person-based space-time methods are too sophisticated and cumbersome to measure accurately and the KDE method is too inaccurate to be used as an accessibility measure. In consequence, these measures are not considered as a pragmatic alternative to the traditional health accessibility indicators, and therefore a further analysis of the location-based FCA methods is outlined below.

Handy and Niemeier (1997) identified a number of methodological issues relating to accessibility modelling. Two such problems are spatial aggregation errors and measurement of travel impedances due to availability of a number of decay functions. In addition to these, the FCA modelling is affected by the use of travel-time or distance measure, computational method and the size of service and population catchment areas. The evaluation of spatial accessibility is likely to be affected by the choice of the these parameters (Handy and Niemeier, 1997; Hewko et al., 2002; Apparicio et al., 2008) which are discussed in the following sections.

2.4.1 Computational method

All the FCA methods are derivatives of the modified gravity model and the variants of the FCA methods differ only by their respective weighting mechanisms. The only difference between the FCA model and the gravity model is that the later model computes accessibility by considering a single catchment area whereas the former model uses a variable floating catchment area.

More specifically, the 2SFCA model closely mirrors the modified gravity model except that it uses a weight value of 1 for all distances less than a given threshold distance and 0 for all other distances. The E2SFCA model uses a discretised continuous function whereas the KD2SFCA model uses a continuous decay function. On the other hand, the mathematical framework of the 3SFCA model differs from the modified gravity model by the addition of extra weighting parameter,G_{ij} or G_{kj} in the numerator and denominator components of the later model (see Equations 2.10 and 2.11), respectively. The M2SFCA model differ from the modified gravity model by the inclusion of additional weighting function, $f(d_{ij})$, in the numerator component of the later function (see Equation 2.13). In all these location-based accessibility models, the unit of the accessibility measure is simply opportunities per person (S/P) because the weighting parameter (W) only serves as a normalizing factor. Therefore, both the modified gravity model and its range of derivative models produce accessibility measures that are intuitively comprehensible and readily interpretable.

The advantages and disadvantages of the FCA computational methods were described in Section 2.3.4. A comparative study between spatial accessibility models was also carried out by Guagliardo (2004), Yang et al. (2006), Luo and Qi (2009),Wan et al. (2012a) and Delamater (2013). Delamater (2013) has proposed the M2SFCA model, which has a sound theoretical framework and calculates more realistic accessibility indices than other FCA models.

2.4.2 Population aggregation level

When a point based feature is aggregated or clustered at a higher level of representation, then the analysis is subject to the MAUP (Openshaw, 1984). In order to limit the effect of the MAUP on the computation of spatial accessibility indices, the population cluster has to be aggregated at the smallest spatial unit. Most previous work has used census tract or Zip Code population data, represented by either the population-weighted centroid or the centroid of the census tract polygon (Guagliardo, 2004; Luo and Qi, 2009; Dai and Wang, 2011; Wan et al., 2012a; Delamater, 2013; McGrail and Humphreys, 2014).

Apparicio et al. (2008) computed a travel impedance based accessibility measure using three different population aggregation methods, namely, the census tract centroid, the population-weighted mean of the dissemination areas within census tracts and the population-weighted mean of the blocks within census tracts. Figure 2.4 shows these three population disaggregation methods. Their accessibility results indicated a high correlation (> 0.9) for the majority of accessibility measures between the three aggregation methods except for the number of services within 500, 1000 and 2000

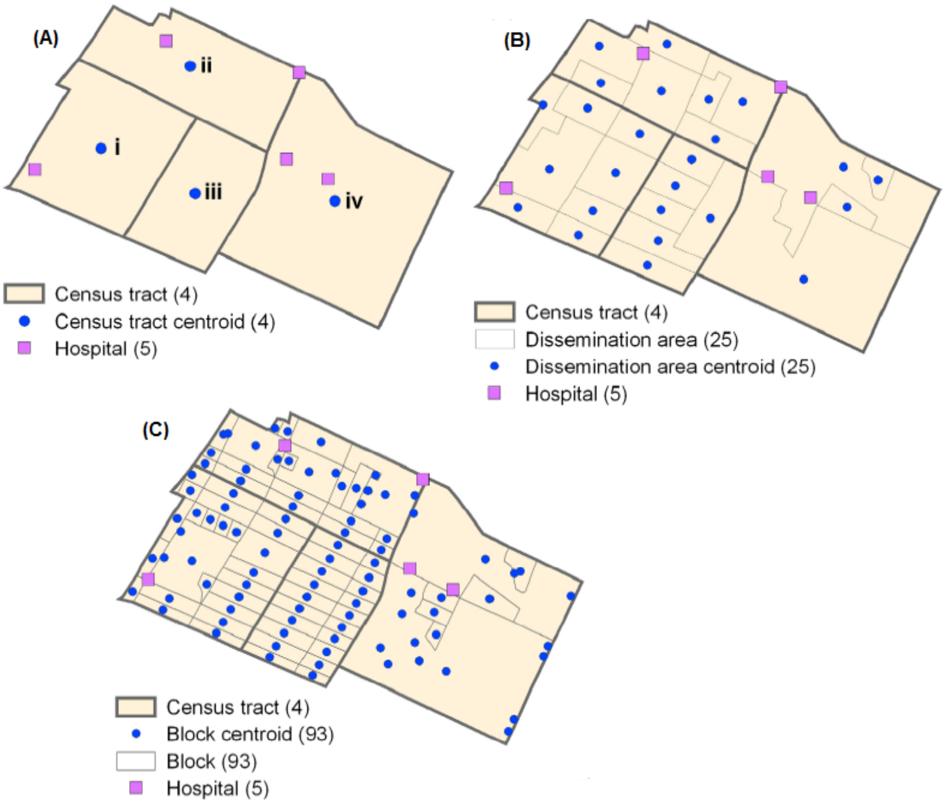


FIGURE 2.4: Population disaggregation method: census tract (A), dissemination area (B) and census block (C)(Apparicio et al., 2008)

metres. The various measures of accessibility used include minimum network distance, average distance to three, five or all closest services, number of services within 500,1000 or 2000 metres, and a gravity model with decay parameters 1, 1.5 or 2. Furthermore, the accessibility measures obtained from census tract and dissemination area were compared with the result from the block method, which is the most accurate method of the three disaggregation techniques. It was observed that at local neighbourhood levels the least accurate population aggregation method, the census tract centroid method, wrongly estimated the distance to the closest hospital with an average distance error of 365 metres and about 5% of cases the distance error was larger than 1.5 kilometres and in 10% of cases the error was larger than 948 metres. Although the correlations between different population aggregation methods are as high as 0.9, the relative distance error between different methods significantly affected the measurement of accessibility at the neighbourhood level.

The general rule of thumb is to use population data at the most disaggregated level to minimize the effect of the modifiable areal unit problem. The issue of data aggregation is not going to be solved in the near future because population data is rarely mapped at the individual level. Even if individual data is physically collected or spatially modelled, it will only reflect accuracy for a short period because of the high mobility of people. Therefore, the population data at the higher aggregation level such as at the household level, village level or census tract level may prove to be a viable alternative for accessibility modelling.

2.4.3 Travel-time or distance measure

The travel impedance is measured by distance or time measure, which can be estimated by 'crow-fly' or straight-line distance measurement, network route analysis as a fastest travel time route or shortest distance route between origin and destination points, field surveys of respondents' perceived distance or travel time (Handy and Niemeier, 1997). Most commonly, the computation of spatial accessibility measure is done by either using a straight-line distance (Love and Lindquist, 1995; Haynes et al., 1999; Hewko et al., 2002; Guagliardo, 2004; Yang et al., 2006; Fone et al., 2006; Jamtsho and Corner, 2014; Nesbitt et al., 2014) or a network-based distance (Bamford et al., 1999; Witten et al., 2003; Apparicio et al., 2007) or travel-time (Luo and Wang, 2003; Luo and Qi, 2009; Dai and Wang, 2011; Delamater, 2013; McGrail and Humphreys, 2014) to define the distance impedance function. The choice of any one of these impedance measures can affect the outcome of spatial accessibility measurement. Straight-line distances can be computed between two points quite easily whereas the computation of the network-based time or distance requires comprehensive route network data with accurate street information such as the speed limit, traffic congestion, single or double carriageways, etc.

The accessibility measures computed from straight-line distance and vehicle-based travel-time measure in rural areas have been found to be highly correlated with correlation coefficient values above 0.8 between crow-fly distance and bus time, 0.9 between the crow-fly distance and car time and also 0.9 between the crow-fly distance and combined bus and car times (Martin et al., 2002). Apparicio et al. (2008) juxtaposed four different types of distance or time measure, namely Euclidean distance, Manhattan distance, shortest network distance and network travel time. Their study produced three important outcomes. Firstly, at the global metropolitan level of their study region, these four measures were found to exhibit high similarity with correlation coefficient values between any two of the measures exceeding 0.95. Secondly, the

Euclidean distance measure exhibited stronger correlation than the Manhattan distance when compared with the network-based measures. Thirdly, the correlation between the two network-based measures was almost perfect with correlation coefficient value of 0.99. Fone et al. (2006) conducted a questionnaire based accessibility survey with a sample population of over 11,000 people in the county of Caerphilly in the United Kingdom, and their study found a positive correlation between the public's perception of accessibility and actual GIS derived accessibility. Furthermore, they found a positive correlation between straight-line and network-based time measures. Nesbitt et al. (2014) conducted a comparative study on accessibility in Ghana's Brong Ahafo region using six different measures such as the Euclidean distance, network distance (combination of road distance and Euclidean distance), mechanised network time (network distance multiplied by respective driving or walking speed limit), non-mechanised network time (network distance multiplied by only walking speed limit for both road and footpath), mechanised raster time (same as mechanised network time but computed using grid cells) and non-mechanised raster time (same as non-mechanised network time but computed using grid cells). With the exception of the mechanised raster time measure, their study showed that the spatial potential accessibility measure obtained from the use of the other five impedance measures were highly correlated and also identified the same healthcare facility as the closest facility for over 80 % of the village centroids. In developing countries in particular, where researchers are faced with a lack of complete and accurate road transportation data, they have suggested the use of the Euclidean measure to define an impedance function that can produce reasonably acceptable accessibility results when taking into account of errors associated with all the assumptions needed in the computation of a network-based travel time measure.

However, the use of the network based distance or time measure will certainly reflect a more accurate travel pattern of population in modern times. With GIS technology, more sophisticated computation in network analysis is possible. Therefore, wherever transportation data is completely and accurately available, the network time measure can be used for modelling accessibility instead of the straight-line measure.

2.4.4 Size of service and population catchment areas

One of the other uncertainties in the spatial accessibility modelling is caused by the variability in the method of delineating service and population catchment areas.

Population catchment area is an area defined for a given population cluster, in order to search for potential service providers within that region. The service catchment area is the area defined for a given service provider by including all the population clusters that are associated to this service provider. From a computational perspective, the service catchment areas are explicitly defined in the first step of the FCA method and population catchment areas are defined in the second step of the computational method. In a theoretical sense, such catchment size is the whole region of the country because every citizen can access any service provider within their country. However, in practice, people only tend to access nearby service providers. In order to actually model the catchment sizes, a general survey of the population must be conducted to find out the spatial association between providers and populace. Such an extensive survey of population would be too expensive and time consuming, so most health organizations would not consider field surveys for accessibility modelling. Despite the huge importance of catchment sizes in FCA modelling of spatial accessibility, there is not much research activity focussed on modelling approaches to determine the size of catchment areas.

Luo and Wang (2003) used a 30 min buffer ring to uniformly define both service and population catchment areas, Dai and Wang (2011) experimented with 15 to 90 min catchment size incremented at 15 min interval and McGrail and Humphreys (2009a) used 15 to 60 min catchment size at an interval of 15 min to compute FCA-based accessibility measure. Most other studies dealing with the FCA-based accessibility modelling have used the BR method for delineating catchment areas (Guagliardo, 2004; Luo and Qi, 2009; Langford et al., 2012; Wan et al., 2012a,b; Delamater, 2013). Yang et al. (2006) emphasized the need for variable catchment size to account for differences in provider or neighbourhood types because one provider location may be more popularly used compared to another and demand for service also varies by gender, race, and age groups. One such variable size catchment area technique was incorporated in the 2SFCA model by Luo and Whippo (2012). They defined a variable size service catchment area at each provider location by searching all population locations within the proximity of that provider's location and adding up the population until a certain threshold value was reached (e.g. PPRs of 1:3,500) with the search radius starting from an initial limit of 10 min extending up to 60 min, if the population threshold value was not reached. A base population threshold value of 500,000 was used to limit the population aggregation while defining the service catchment areas. Similarly, the size of the population catchment areas were defined at each population cluster's location by searching all providers within its proximity and then adding up the PPRs until the threshold value was reached. In both the case, the travel time at which the threshold values have been reached was considered as the size of the catchment areas. McGrail and Humphreys (2009b) also pointed out that the fixed size catchment areas would produce a high accessibility score for some small towns because such a method tends to incorporate physicians located in nearby towns, although these physicians may not be actually accessed by people from the other town. According to Luo and Whippo (2012), the variable 2SFCA (V2SFCA) method addresses the problem of overestimation and is also closely related with the current practices used by the DHHS to identify health professional shortage areas in the U.S. as it uses the base population and PPRs to compute health accessibility.

McGrail and Humphreys (2009a) have varied the catchment sizes by capping the number of service providers within a catchment area to the 100 nearest service centres by applying a search radius of minimum of 10 min and maximum of 60 min. Their method is based on three different assumptions: firstly, service providers located within the core urban regions are only likely to provide services within their local neighbourhood; secondly, service providers located in urban-fringes or large rural towns are likely to provide services well beyond their locality; and thirdly, service providers in small rural communities are generally confined to providing services to their immediate locality (McGrail, 2012). This method will greatly affect the definition of catchment areas in urban regions because of the availability of a large number of service providers and their uneven variation in distribution within the search zone of 60 min. However, it may not affect much in the rural regions because it is unlikely to have 100 providers within a 60 min search zone. According to McGrail (2012), their method distinguishes between geographical regions (rural and urban settings) whereas Luo and Whippo (2012)'s method is confined to the immediate locality which only considers extending the catchment size if a minimum access threshold value (with PPR of 1:3,500 or BP of 500,000) is not reached. In very sparsely populated rural regions, these threshold values are too high to noticeably make a difference in catchment sizes thereby leading to the measurement of a redundant choice of providers rather than actual accessibility.

McGrail and Humphreys (2014) have dynamically increased the catchment size with increased remoteness of a region based on the geographical remoteness index for national-level health accessibility modelling in Australia. Inland Australia has been divided into five different remoteness regions based on the remoteness index, which is defined by the

Australian Statistical Geography Standard-Remoteness Area (ASGS-RA) classification method – primarily measuring the physical distance of a location from a few different service centres (Australian Bureau of Statistics, 2011). The accessibility trial at the national level using the 2SFCA model by incorporating five different catchment sizes (30,45,70,120 and 200 min) corresponding to the five RAs (major towns, inner regional, outer regional, remote and very remote areas) produced erratic accessibility scores at the bordering regions between different RAs because of the sudden change in the catchment sizes at the border areas. An alternative accessibility trial using the same computational model by adding a 3-level catchment subtype in each of the five RA produced a smoother accessibility outcome. The 3-level subtypes introduce new catchment sizes for those population clusters located in the border areas based on the degree to which their nearby services are located in the lower RA. If most (or greater than 50%) of nearby services of a given population cluster are from the same or higher RA, then the catchment size of that cluster remains same as the original catchment size of that RA. If some (or 25 to 50%) nearby services of a given cluster are from the same or higher RA then the catchment size of that cluster is reduced moderately by 33% of the difference in catchment size between the two adjoining RAs, and if few (less than 25%) nearby services of a given cluster are from the same or higher remoteness level then the catchment size of that cluster is reduced more substantially by 66% of the difference in catchment size between the two adjoining RAs. Further detail of this method of defining catchment size is elucidated in (McGrail and Humphreys, 2014).

It is important to note that, to date, there have been very few studies on health accessibility modelling conducted at a national-level (McGrail and Humphreys, 2014; Jamtsho et al., 2015). Almost all other past studies on health accessibility modelling were confined to small regions such as a state, metropolitan or rural region. The advantage of health accessibility modelling at the national-level is that such accessibility outcome can be directly applied for the whole country because most health policies related to health accessibility are framed and applied at the national level rather than small areas (McGrail and Humphreys, 2014).

2.4.5 Distance decay functions

The gravity model and the variants of the FCA metric systems are also affected by the choice of the distance or travel-time decay function, which explicitly models the distance separation between the service providers and the service seekers. There are a number of different distance-based weighting functions available which can be used in the measurement of spatial accessibility. Joseph and Bantock (1982) used gravity models to measure spatial accessibility to healthcare services where the distance weights were defined by an inverse-power function with an arbitrarily defined impedance coefficient (β) value of 2. Similarly, Luo and Wang (2003) used a gravity model with the impedance coefficient (β) value of 1.8. This coefficient value was empirically identified from a set of values (β = 1 to 2.2) by arbitrarily comparing with the accessibility outcome from the 2SFCA method with a catchment size of 30 min. Schuurman et al. (2010) also used an inverse-power function within a gravity model with an arbitrarily defined coefficient value of 1.0. Shen (1998) used an exponential function with an arbitrarily defined impedance coefficient value of 0.1 for measuring employment accessibility. McGrail (2012) also used an exponential function with an arbitrarily defined impedance coefficient value of 1.5. Wan et al. (2012b) tested a range of impedance coefficient values using the Gaussian model for evaluating spatial accessibility to colorectal cancer services in Texas. Delamater (2013) also used a continuous Gaussian function to derive distance weights while evaluating differences in the FCA-based computational models. Langford et al. (2012) used a Butterworth-filter function with arbitrarily defined parameters for measuring spatial accessibility to public bus services in South Wales, United Kingdom while Dai and Wang (2011) used the Epanechnikov-kernel function to measure disparities in accessibility to food stores in southwest Mississippi in the U.S. In all the studies cited, the decay function and their parameters were arbitrarily or subjectively defined. There have been no or very few closely related studies conducted on the effect of spatial accessibility outcome using different distance decay functions.

Instead of applying a continuously decaying weight values, the weighting values can also be uniformly applied within a certain zone. This can be achieved by forming a step-like function using any of the aforementioned continuous decay function or by arbitrarily defining weights for different distance or travel-time zones. Luo and Qi (2009) arbitrarily defined travel-time weights for 0-10 min, 10-20 min and 20 to 30 min driving zones. Luo and Wang (2003) and McGrail and Humphreys (2014) used the 2SFCA method of computing spatial accessibility where distance weights are implicitly defined as 1 for regions within the catchment area and 0 for regions outside the catchment area. McGrail (2012) tested fast-step, slow-step and continuous decay weighting methods in conjunction with a variable population catchment size while evaluating spatial accessibility to primary healthcare services in the state of Victoria, Australia. Four different time zones were used; first three zones as defined by Luo and Qi (2009) and the fourth zone, 30-60 min, as extended by Wan et al. (2012b). The weights for all the decay methods were arbitrarily defined. It was found that the accessibility scores obtained from the three distance-decay methods only slightly differed with the scores obtained from the original 2SFCA method across the rural regions. However, their results were noticeably different in urban regions with population of more than 100,000. A concentric pattern of accessibility scores, which decreases from urban-fringes to rural regions, was observed whilst using just a distance decay function without considering the variable population catchment sizes. Wan et al. (2012b) compared the accessibility outcomes from seven different Gaussian functions with different impedance coefficient values from 440 to 1040 with an increment of 100. It was observed that the spatial pattern of the spatial accessibility indices for different coefficient values differed substantially from one another with larger coefficients producing more homogeneous spatial distributions, whereas the spatial pattern of spatial accessibility ratios (spatial accessibility index divided by the mean value) for different coefficient values were almost similar. Their results indicate that the accessibility ratio values are less sensitive to the use of a different coefficient values in the decay function than the spatial accessibility indices.

In a theoretical sense the decay function is chosen based on the characteristics of the patient-provider interaction or socio-economic aspects of the regions, in order to accurately represent the degree of difficulty of accessing the services (Luo and Wang, 2003; Luo and Qi, 2009; McGrail, 2012). McGrail (2012) pointed out that the key limitation of their study and others concerned with the use of different catchment size or distance decay function was the lack of provider-population interaction data and its relationship to geography. Hence, the choice of different distance or travel-time weighting function and the size of the catchment areas cannot be resolved without surveying the actual health care utilization behaviour of the target population (Wang, 2012). Delamater et al. (2013) analysed spatial accessibility to hospital beds in Michigan by fitting the hospitalization inpatient data with a downward log-logistic function, whose parameters were determined by non-linear least squares estimation method. Jia et al. (2013) evaluated spatio-temporal variation of hospital service areas using the Huff model, where the distance impedance effect was modelled by an inverse-power function with its impedance coefficient value determined by the root mean square error (RMSE) analysis of the estimated and actual number of patients in each postal zone. Such analysis can only be done if the inpatient hospitalization data are available. Often due to confidentiality issues, personal data may not be available for public use. The other way of obtaining travel behaviour data is through a survey. However, the collection of travel behaviour data for a country using this method remains costly. Therefore, it is understandable that much of the study done on spatial accessibility modelling has been conducted using an arbitrarily defined distance- or time-decay function.

2.5 Summary

This chapter presented the concept of spatial accessibility to primary health care and the different mathematical models which have been used for measuring spatial accessibility. Spatial potential accessibility to health care measures only the availability and accessibility component of the health care system by interacting supply of health services, population demand for health services and distance impedance between the locations of the health service providers and the population. The gravity model is the fundamental mathematical model that led to the development of other accessibility models such as the most commonly used FCA metric systems. The FCA metric system is popularly used for computing spatial accessibility for various social services because of its adaptability to larger study regions by realistically modelling the population demand for health services by using a variable service catchment area instead of using a single container system like in the gravity model. The FCA metric system constitutes the 2SFCA, E2SFCA, KD2SFCA, 3SFCA and M2SFCA methods. Of these FCA methods, the M2SFCA method is theoretically sound and more robust than the other methods. This method appears to outperform the other methods as it accurately computes the accessibility indices by considering the absolute separation of distances between the locations of the providers and the populations unlike the other methods which only considers the relative distances whereby all service opportunities are distributed based on summed weights. There are five uncertainties involved in the FCA modelling of accessibility that could potentially affect the outcome, namely the aggregation level of population cluster data, the measurement of travel impedance, the computational method, the choice of decay functions and the size of population catchment area of each service centre. The uncertainties of population data modelling are presented in Chapter 3.

Chapter 3

Data Modelling

This chapter presents the data required for the computation of spatial accessibility for primary healthcare services in Bhutan. One of the important datasets required for this study is population cluster data at a lower level of aggregation. However, it is not available so there is a need for modelling population data from larger areal units to smaller areal units using some form of areal interpolation technique. An areal interpolation technique using only settlement data of the whole country is proposed for distributing population from subdistrict and town census blocks to regular grid cells at finer resolution.

Sections 3.1 and 3.2 describe the scope and data requirements for measuring spatial accessibility to PHC services, respectively. Section 3.3 reviews some of the population distribution modelling techniques available to disaggregate aggregated data from larger areal units to smaller areal units. Section 3.4 deals exclusively with the modelling of population data of Bhutan. The mathematical and processing framework of the existing dasymetric mapping technique, the proposed areal interpolation method and the randomization technique are presented in Sections 3.4.1, 3.4.2 and 3.4.3, respectively. Section 3.4.4 presents the population distribution results of different dasymetric methods and the assessment of these methods using mean absolute percentage errors and root mean square error statistics. Section 3.4.5 describes the computational process for clustering of disaggregated population data at the village level using a distanced-based proximity method of integration and collection of population point features.

3.1 Study area

Bhutan is a developing country with a population of about 730,000 people. It is a small landlocked country with a geographical area of about 38,000 square kilometres. It is located in the eastern part of the Himalayas, with China bordering from the north and regions of India bordering from east, west and south. This country is predominantly mountainous with altitudes ranging from 150 to 7,500 metres above sea level. The

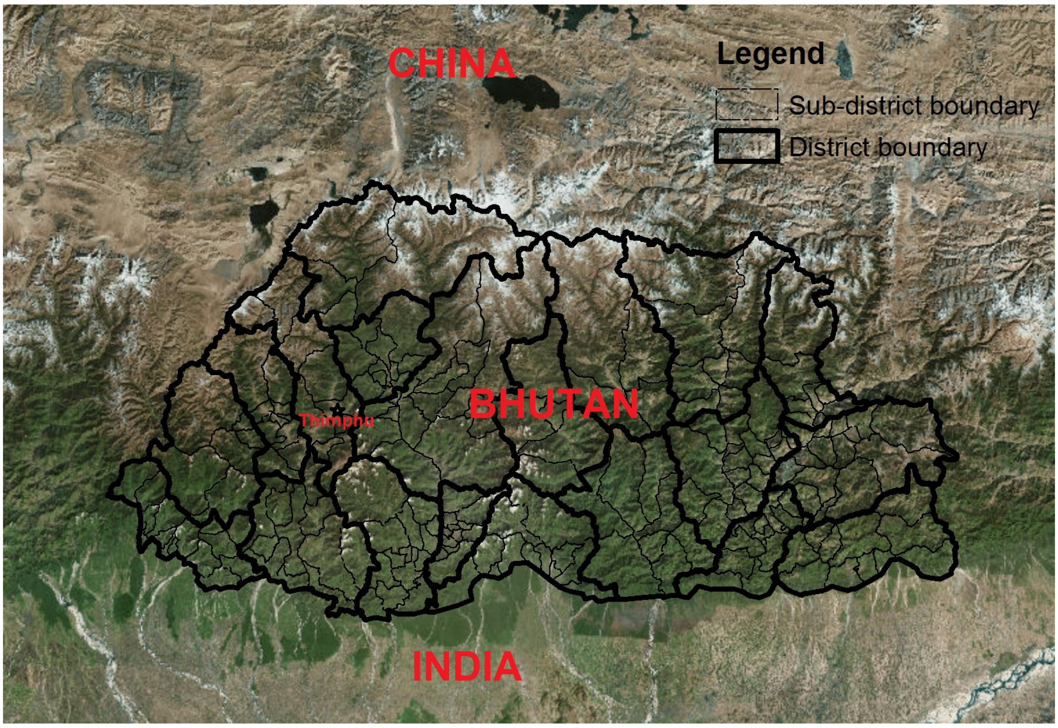


FIGURE 3.1: Study area

capital city of Bhutan, Thimphu is located at an altitude of 2300 metres. Bhutan is divided into twenty districts, locally known as *Dzongkhag*. Each district is divided into number of subdistricts, known as *Gewogs*. There are 205 subdistricts in the country. A few subdistricts are further divided into rural and urban administration regions. The rural regions are governed by the subdistrict administration whereas the urban regions are governed by the city or town administration. The geographical location of Bhutan and its administrative regions are shown in Figure 3.1. The majority of the 60 percent of population of this country who dwells in rural regions do not have access to road transportation. Bhutan was chosen as the case study area because the data for the entire country can be readily collected from few organizations. Furthermore, its regions are predominantly rural, making geographic accessibility to primary health care very relevant.

3.2 Data requirements

GIS needs both spatial and non-spatial data for visualization, analysis and modelling purposes. Spatial data refers to the representation of physical objects with geographic coordinates that may describe the location, size and shape of the object, whereas non-spatial data represents the attribute information of that object. Two of the important

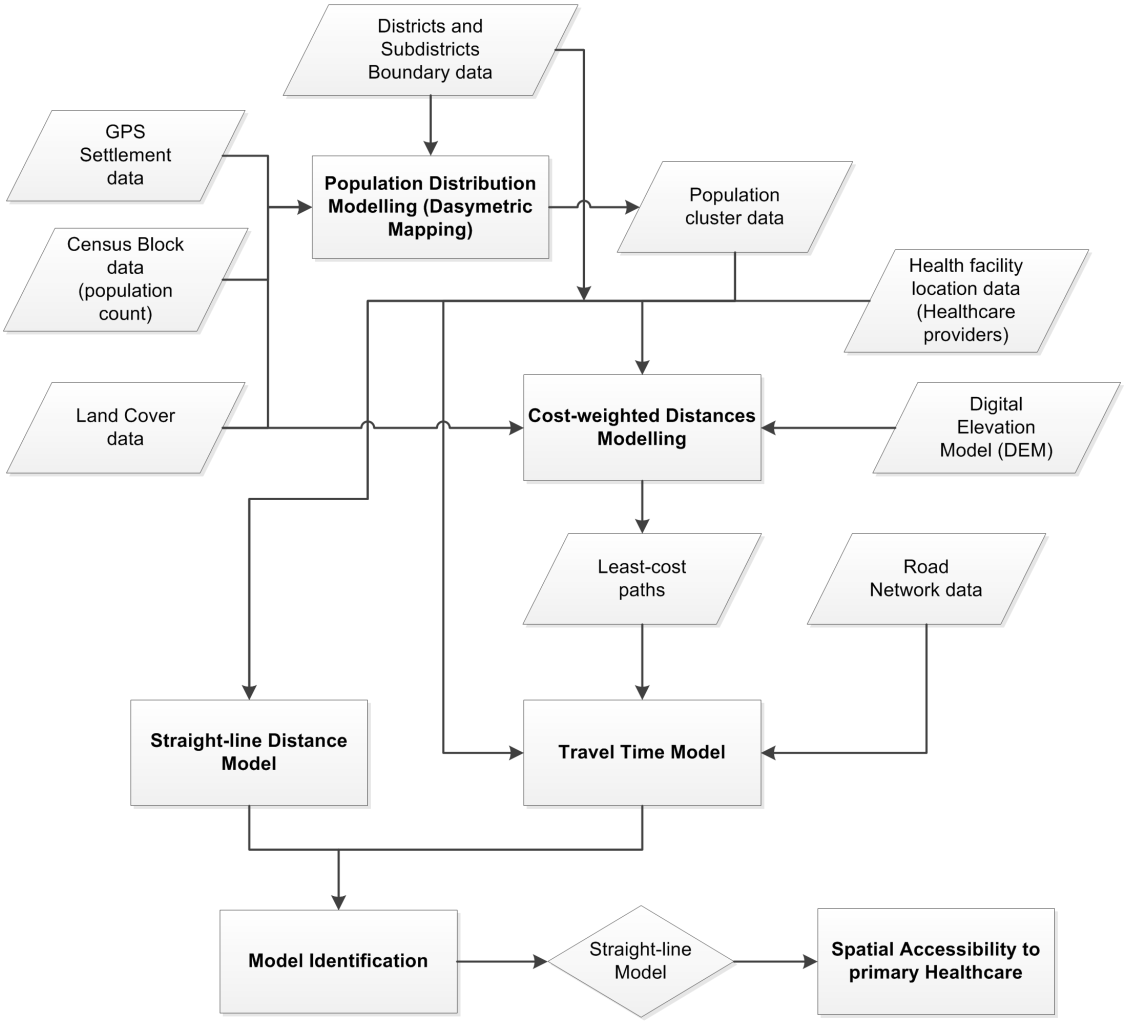


FIGURE 3.2: Data required for various modelling processes

datasets require for calculating spatial accessibility indices are disaggregated population clusters data at the village level and the location data of healthcare centres with an attractiveness component such as the number of healthcare providers in each healthcare centre. Since the village level population cluster data is not available, there is a need to simulate or model the population cluster data at this lowest aggregation level. There are also other spatial and aspatial data needed for conducting an extensive evaluation of spatial accessibility models. Figure 3.2 shows the overview of the spatial accessibility computational process indicating the requirements for various types of data for various modelling processes. Population modelling requires data on the location of settlements or dwelling houses, population data and land cover data to estimate village-level population cluster data. Cost-weighted distance modelling requires population cluster data, a digital elevation model, health facility and land cover data to model least-cost paths between origin and destination points. Road network data, least-cost paths, population clusters and health facilities with a count of the healthcare providers are needed to compute travel-time based spatial accessibility indices. On the contrary, only population clusters and health facilities with a count of the healthcare providers are needed to compute straight-line based accessibility indices.

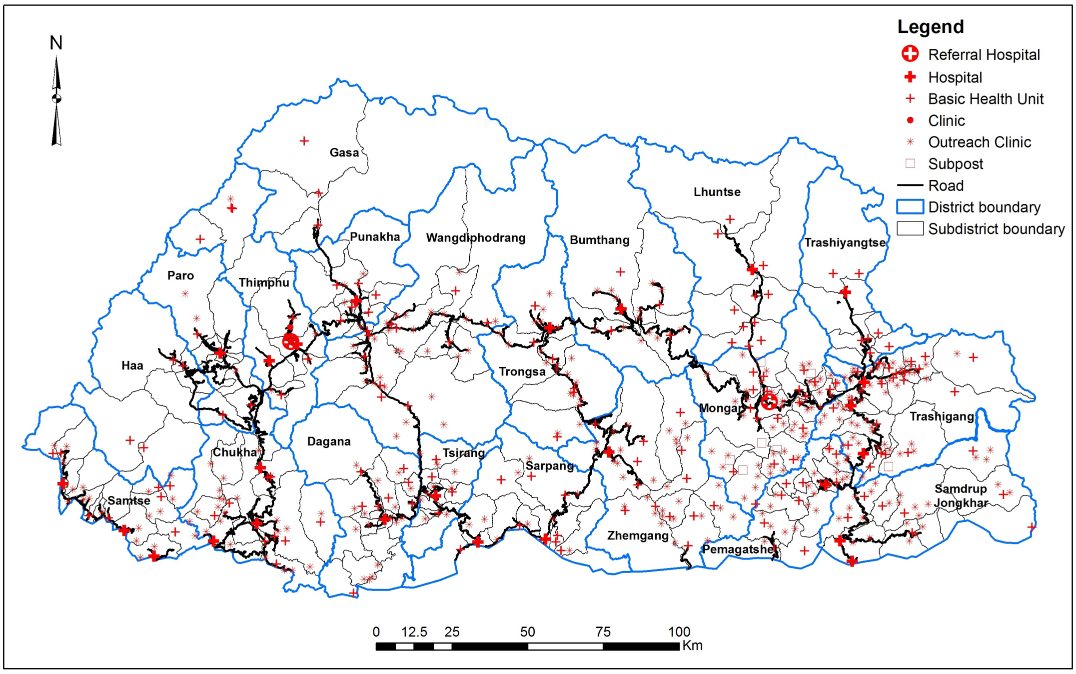


FIGURE 3.3: Distribution of health facilities in Bhutan

Figure 3.3 shows the distribution of health facilities across the country. Health spatial data consists of the GPS (Global Positioning System) locations of the health facilities along with information about the number of health personnel and number of beds available in these facilities. Today, there are three referral hospitals, 28 general hospitals, over 200 BHUs, more than 500 ORCs and several sub-posts in the country. Referral hospitals provide specialized services to the whole population of the country. In addition, they also provide general primary care services to the population within the vicinity. General hospitals provide primary care services and some specialized services including minor surgery to the population within the district. BHUs are the lowest level health facilities. These facilities were established in a subdistrict to provide primary care services to the population within that subdistrict. Clinics are like BHUs which are mostly established in major cities in order to share the burden of referral hospitals where people tend to visit unnecessarily often for a minor illness. Outreach clinics are semi-permanent or temporary facilities established in villages to provide immunization services to the rural population. Sub-posts are generally established to provide basic health services to military personnel who are posted in the border areas. Basic health diagnostic services in Bhutan are provided by doctors and health assistants. Due to the acute shortage of doctors in the country these service providers are only available in hospitals and some higher grade BHUs, whereas health assistants are available in all the health centres. For evaluating spatial accessibility to primary health care services in Bhutan, doctors and health assistants were separately used as the service providers for the computation of the spatial accessibility values.

Population and settlement data were obtained from the National Statistical Bureau (NSB) which houses the Population and Housing Census of Bhutan (PHCB) database. PHCB 2005 is the first ever nationwide census survey undertaken in Bhutan where a population and housing census was conducted in addition to collecting other socio-economic data. The locations of all forms of man-made structures were captured using handheld GPS devices. GPS point settlement data comprises of stone stupas, animal sheds, huts and buildings in the rural regions. For the urban regions, the location of huts and buildings were obtained from cadastral surveys conducted by the Ministry of Work and Human Settlements. Other data such as administrative boundaries, digital elevation model and road network data were obtained from the National Land Commission (NLC), the national mapping organization of Bhutan. The land cover data of the whole country was obtained from the Ministry of Agriculture and Forests (MoAF). The MoAF conducted nationwide land cover mapping from 2010 to 2011 using satellite imagery. Figure A.2 in Appendix A shows the data model framework of the aforementioned spatial and textual data required for this study. This data model specifically reflects the geodatabase architecture in ArcGIS 10.2 system. All the feature classes and tables have the attribute named SourceProduct, which indicates the original source of the data. Since this field has multiple values, it is defined using a domain coded values as indicated in the DOSourceProduct box. Likewise, any field in the other feature classes which have multiple sub-types can be defined using domain codes in the ArcGIS system.

With respect to the quality assurance of the data sources, it is difficult to precisely define the completeness, accuracy and consistencies of the spatial data because there are no formal documents available for most of the aforementioned data sources. However, it is possible to approximately calculate the positional accuracy of the spatial data as the data collection devices are known. GPS settlement point and health facility location data were collected using hand-held GPS receivers which measure with a positional accuracy of about 10 to 15 meters. The road network data was collected using Differential GPS receivers which measure with a positional accuracy of about 3 to 5 meters. Land cover maps were produced using 10 metres resolution multispectral ALOS (Advanced Land Observing Satellite) images collected from 2006 to 2009 during the winter season. An unsupervised classification method was used to classify 29 different land cover classes

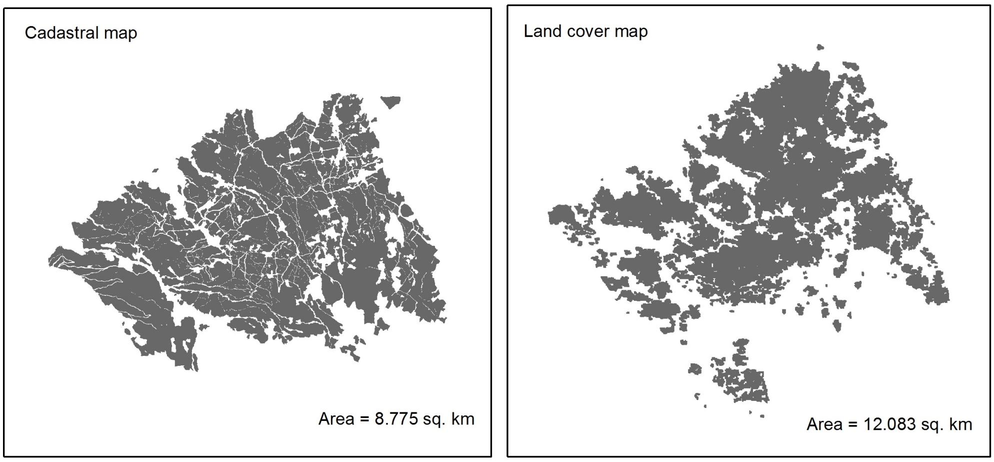


Figure 3.4: Agricultural land use data from two sources

ranging from different types of forests to agricultural land. It has been reported that the average total accuracy of classification at the national level is 97.91% with a minimum total accuracy of 95.67% and maximum of 100% at 95% confidence level (MoAF, 2011). However, it has been found that the area of agricultural land cover derived from the MoAF data is about 38% larger than the actual area obtained from the cadastral survey. Figure 3.4 shows the total acreage of agricultural land use region in the subdistrict of Radhi in

Trashigang district obtained from the MoAF and cadastral data, respectively. A digital elevation model (DEM) of Bhutan was created using ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) ortho-images with a relative DEM product having a spatial resolution of 15 meters (Fujita et al., 2008). Fujita et al. (2008) have reported a relative accuracy in the vertical position with root mean square errors of between 10 to 15 meters for the ASTER DEM when compared with the results obtained from the Differential GPS ground survey.

In order to study the spatio-temporal characteristics and trend of spatial accessibility to health care services in Bhutan, temporal data is necessary. However, reliable health data are available only from 2010 onwards. At the time of data collection in July 2014, health data from 2010 to 2013 were obtained from the Ministry of Health of Bhutan. Tables B.1 to B.4 in Appendix B show a summary of health data information from 2010 to 2013, respectively. On the other hand population data for 2010 to 2013 are predicted populations based on the population census of 2005 (NSB, 2005).

3.3 Review of population distribution models

Most population census data are aggregated at some areal unit. Population data in the U.S. is aggregated at census tract level (U.S. Department of Commerce, 2013), population data in Australia is published for areal units called mesh blocks (Australian Bureau of Statistics, 2011) and the population data of Bhutan is aggregated at the subdistrict level (NSB, 2005). Although the actual census survey gathers data at the household level, the population data is generally published at an aggregated level because of data confidentiality issues. Traditionally, population distribution maps are produced as homogenous choropleth maps. Figure 3.5 shows the choropleth map of population of Bhutan developed using the population data of the subdistricts and town census blocks which are shown in Tables B.6 and B.7 in Appendix B. Such representations of population suffer from mapping and analytical problems.

The most commonly encountered issue with the aggregated data is the MAUP. MAUP is a statistical bias caused by the use of the actual point data treated as aggregated data at the larger areal unit. It alters the results of the spatial data analysis due to modifying boundaries or aggregation of data from the smaller unit to the larger unit (Openshaw, 1983). In addition to the MAUP issue, the aggregated census data

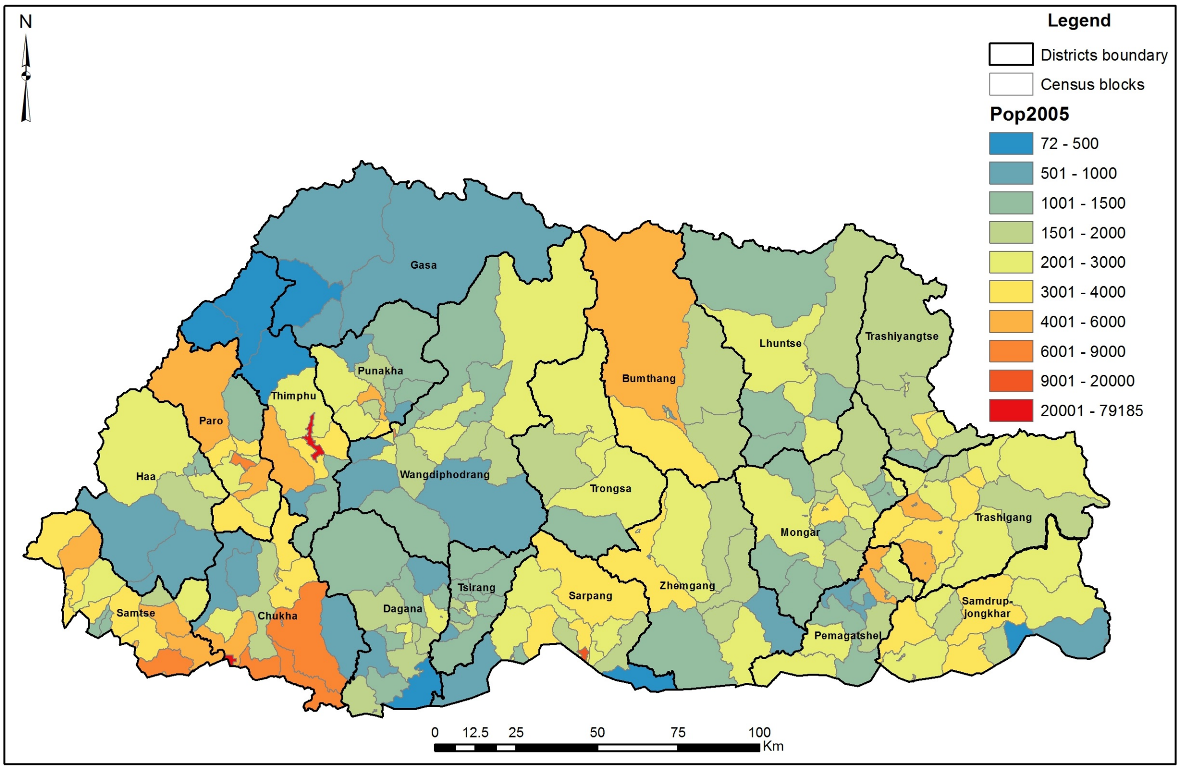


FIGURE 3.5: Choropleth population distribution map of Bhutan

represent population homogenously across the areal unit which is a misrepresentation given the actual population distribution varies heterogeneously within a region (Fotheringham and Wong, 1991; Bracken, 1993; Dorling, 1993; Mennis, 2003). Most census data do not coincide with the other zone-based data such as land use pattern in urban areas which makes spatio-temporal analysis difficult (Luo, 2005). The aggregated census data is often erroneously interpreted because of the confusion of whether the census data represents individuals living in that modified region or a function of the areal unit used for aggregation (Openshaw, 1984)

MAUP can be minimized to a certain extent by disaggregating the population data to a lower aggregation level. There are a number of different methods available for estimating population using GIS and remote sensing technologies. Following Wu et al. (2005), population modelling methods can be grouped into areal interpolation and statistical modelling methods. Areal interpolation refers to the transformation of data from one spatial unit to the other (Goodchild and Lam, 1980). Lam (1983) referred these spatial units as the source and target zones. The statistical modelling method makes use of morphological factors or socio-economic variables to indirectly estimate population using some theory of urban geography and population. The areal interpolation methods can be further divided into those with or without the use of ancillary information, whereas, the statistical modelling methods can be classified by the correlation between populations and urban areas, land uses, dwelling units, image pixel characteristics or other socio-economic variables (Wu et al., 2005).

Areal interpolation methods without ancillary information are grouped into point-based and area-based methods (Lam, 1983). The point-based method uses an arbitrarily defined control point to represent source zones with gridded data generated from these control points. The source zone population is then distributed to grid cells either by including all of the grid cells at once or by including a certain number of nearest neighbours using some form of distance-based interpolation function. The interpolation functions can be defined precisely by using polynomials or any of the distance-based weighting functions. It can also be defined by using kriging, spline functions, finite difference methods, power-series trend models, fourier series or distance-weighted least squares. The kernel-based interpolation method was widely used in the UK for disaggregating census data (Bracken and Martin, 1989; Martin, 1989; Martin and Bracken, 1991). This method uses a centroid of the source zone as the control point. A moving window kernel is positioned at each control point whereby the source population value is distributed to grid cells falling inside the window using a distance decay function.

Other forms of areal weighting techniques include maximally smooth estimation, radially symmetric kernel functions (Parr, 1985; Bracken and Martin, 1989), piecewise approximation (Flowerdew et al., 1991), uniform target-zone densities (Goodchild and Lam, 1980; Goodchild et al., 1993), and uniform control-zone densities (Flowerdew and Green, 1989, 1992). There are a few notable problems associated with point-based methods (Lam, 1983). Firstly, the use of a centroid of the source zone as the control point often introduces errors due to the asymmetrical shape of the source zone. Secondly, the use of an interpolation function assumes some form of mathematical model underpinning the population distribution which may not actually represent the population geography of the real world. Finally, point-based methods do not always preserve the population value of the source zone, which is tantamount to people being "destroyed" or "manufactured" during the distribution of population value from source unit to target units (Langford and Unwin, 1994).

Area-based interpolation methods preserve the total population value of the source zone during transformation to the target zones. The overlay method is one of the simplest forms of the area-based methods which can be achieved by computing proportional weighting between the target and the source zones to transform the population value to various target units. However, such homogeneity of population distribution rarely reflects the real world distribution of population. Pycnophylactic interpolation is also a form of area-based method. This method generates a smooth population density surface by considering the effect of the neighbouring source zones while at the same time preserving the volume of the source unit (Tobler, 1979). The interpolation process is conducted iteratively by smoothing the values of the source units with the weighted average values of the neighbouring lattice grid cells. In each iteration, smaller target units are created from a parent unit where the sum of the value of the target units is constrained to be equal to the value of the parent unit. The iterative process ends when the desired smoothing is achieved or maximum iteration is reached. Rase (2001) extended the pycnophylactic method to a surface configuration represented by a triangular irregular network.

One of the most commonly used areal interpolation methods is the dasymetric mapping technique which uses some ancillary information to estimate population at target units from the source unit. Dasymetric mapping is an extension of the area-based method where ancillary information is used to refine the interpolation process. Wright (1936) produced a population density map of Cape Cod by iteratively partitioning the source zones into two subsidiary zones of varying population densities while preserving the population value of the source zone. The population densities of the sub-zones were crudely estimated by relying on knowledge of the local areas. Langford and Unwin (1994) and Holt et al. (2004) also used a binary method of dasymetric mapping. The binary method is the simplest form of dasymetric mapping technique where land use is classified to either inhabitable or uninhabitable regions. Others have extended the binary method by including a greater number of land use classes where population densities for each class were determined by using pre-defined statistics, empirical methods or some form of statistical regression methods. Eicher and Brewer (2001) presented a three-tier grid method of dasymetric mapping where population is distributed non-uniformly across three land use classes such as urban, agriculture or woodland and forested areas. They used pre-defined population densities for the three different classes. The binary and the three-tier methods are often known as limiting variable methods because population is distributed iteratively by constraining population density over less inhabitable regions like the forested areas in the first iteration and then over the agriculture areas in the next iteration. Yuan et al. (1997) applied multivariate regression analysis to estimate the population densities of different land use classes. Mennis (2003) used areal weighting and empirical sampling techniques to determine relative densities between different land use classes, which has been referred to as intelligent dasymetric mapping (Mennis and Hultgren, 2006). The different land uses classes were mostly derived from remote sensing imageries (Yuan et al., 1997; Eicher and Brewer, 2001; Mennis, 2003). Although dasymetric mapping distributes populations non-uniformly between different land use classes, this method still suffers from the problem of even distribution within each land use class. Harvey (2002) used regression analysis to iteratively update the population densities at the pixel level for different land use classes, which in a theoretical sense is supposed to solve the problem of homogeneity within land use classes. He argued that the pixel level dasymetric method is better than zone-level dasymetric methods because individual dwelling units where people live are best represented by pixels.

There are other forms of areal interpolation with ancillary information method such as the street weighted, address weighted and parcel distribution methods. Riebel and Buffalino (2005) developed a population distribution algorithm to estimate people living along each street segment by combining the population distribution weight of the street segment and the population of the census tract in which the street segment is located. The address weighting method is an extension of the street weighting method where computation of the relative weights for street segment is enhanced by including the actual geocoded addresses of dwelling units along the street segment. The parcel distribution method is a form of dasymetric mapping where fine-resolution parcel information is used instead of the coarse-resolution land use classes derived from satellite images (Tapp, 2010). Dasymetric mapping is further enhanced by including multiple ancillary data to improve the interpolation process. The LandScan Global Population database and LandScan USA are the global and regional population distribution models, respectively, which represent an average daytime and nighttime population developed using multi-dimensional data (Bhaduri et al., 2007).

Statistical modelling methods are primarily focussed on estimating population counts rather than population density, which is required for modelling population distribution (Tapp, 2010). Nevertheless, population and population density are related by the size of the area so both these parameters can be used for mapping population distribution. These methods are rarely used nowadays. Tobler (1969) was the first to use satellite imagery from the Gemini space flight program to study the relationship between population and urban areas in different cities around the world, where he obtained a correlation coefficient of 0.87 or higher between the radius of a circle of the built-up areas and populations. Lo and Welch (1977) used Landsat multi-spectral images from 1972 to 1974 to study major cities in China, where they obtained correlation coefficients of about 0.82 or higher between population and size of the built-up areas. Besides size of the built-up areas, some researchers have also used light volumes from night-time images and populations to determine their correlation coefficients (Prosperie and Eyton, 2000; Lo, 2002).

Population estimation can also be carried out by correlating population counts with different areas of land use classes where population densities were determined from regression analysis (Lo, 2003) or sample surveys (Kraus et al., 1974). Counts of housing units can also be used to estimate population by multiplying the total number of housing units with the number of people living in a housing unit (Tapp, 2010). A number of population estimation studies have been conducted by obtaining individual housing data from aerial photographs or satellite images and deriving a persons-per-dwelling unit ratio from census data or ground surveys (Hsu, 1971; Lo and Chan, 1980; Lo, 1989). Besides physical objects derived from remotely sensed images, the spectral properties of pixels can also be directly correlated with population density (Hsu, 1973). Iisaka and Hegedus (1982), Lo (1995) and Harvey (2002) have all used spectral properties of pixels to estimate populations by correlating with population densities. Some researchers have also conducted population estimation studies by correlating population with socio-economic or other physical characteristics (Dobson et al., 2000; Liu and Clarke, 2002).

3.4 Modelling of population data

The population and housing census data of Bhutan consists of GPS housing data and socio-economic household information. However, the link between the settlement and household data has not been published or the census data collection was not properly conducted and this may have resulted in the failure of linking the two datasets. Therefore there is a need to disaggregate the aggregated population data from the subdistrict level to a lower level in order to be used for the computation of spatial accessibility to health care services. Three different forms of spatial decomposition method were tested to evaluate the efficacy of these methods for disaggregating population data from census block to a finer resolution at 100 meter cell size. An areal interpolation method using settlement data is thus recommended for modelling population distribution within Bhutan, as this outperforms the traditional dasymetric mapping method using the land use information.

3.4.1 Dasymetric mapping method

In most dasymetric mapping methods, land use or land cover information is used to aid the interpolation process (Langford and Unwin, 1994; Holloway et al., 1999; Eicher and Brewer, 2001; Mennis, 2003; Mennis and Hultgren, 2006). The fundamental mathematical framework of the dasymetric mapping model is that the population is equal to the product of the population density and the area of the given unit of analysis. So the important aspect of this model is to compute the relative population densities of each target cell for different land use classes within a given census block as the area of each target cell is a known quantity. One form of the mathematical model for the grid-based dasymetric mapping is presented in Holloway et al. (1999), and is given by

$$P_{cell} = \frac{R_c \times P_b}{T_b \times E_b} \times A_{cell} \tag{3.1}$$

$$T_b = \sum_{c=1}^{m} N_c \tag{3.2}$$

$$Q_c = \frac{N_c}{T_b} \tag{3.3}$$

$$E_b = \sum_{c=1}^{m} R_c \times Q_c \tag{3.4}$$

where P_{cell} is the population value estimated at the target cell, R_c is the relative density of a cell for land use class c, P_b is the population value of the census block which contains this cell,A_{cell} is the area of the cell, T_b is the total number of cells in the census block that contains this cell as computed by Equation 3.2, Q_c is the proportion of number of cells of a land use class c in a parent census block (N_c) to the total number of cells in that block, E_b is the expected population of the census block as computed by Equation 3.4 and m is the number of land use classes.

A similar type of dasymetric model is also described in Mennis (2003). Mennis (2003) used population density (persons /10000 square metres) within a county (or district) to compute the relative densities for different urbanization classes as given in Equation 3.5, where d_{cd} is the population density fraction (PDF) of land cover class c in district d and m is the number of land cover classes. In the case of Bhutan, R_c was computed for each district block for different land cover classes using the GPS settlement data based on the variation in their distribution between different land cover classes, as given by Equation 3.5

$$R_c = \frac{d_{cd}}{\sum_{c=1}^{m} d_{cd}} \tag{3.5}$$

The implementation of Holloway's dasymetric mapping process using the ArcGIS 10.2 system is shown in Figure 3.6. The first step of this method is to compute the relative population density (R_c) for various land cover classes at the district level. GPS settlement data was used to compute the relative weights based on its variation in the distribution between different land cover regions. The proportionate relative weight of each of the land cover classes is equal to the number of settlement features located in that region divided by the total number of features. It can be seen in Table 3.1 that the relative population distribution weights for land cover classes varied among districts. Steps 2 and 4 simply convert polygonal census block data to different raster data with 100 meter resolution grid cells using population and block identifier fields respectively. In Step 3, the relative weights obtained from Step 1 were used to reclassify the land cover raster data. The variables such as T_b, Q_c and E_b of Equations 3.2, 3.3 and 3.4 respectively are computed in Step 5 and 6 using reclassified land cover and census block identification raster data. Step 7 and 8 joins the aforementioned parameters table with the census block polygon data and creates raster data of T_b and E_b attributes respectively. GPS settlement data is also used to create the locations of the target grid cells for population distribution as people are expected to live in huts and buildings. So all the raster data used in this computation were defined by setting null values to all other cells except those locations occupied by the GPS settlement features. Step 9 defines the extent and the locations of the target cells of all the input raster data. The final step is to distribute the source population to each target cell using Equation 3.1.

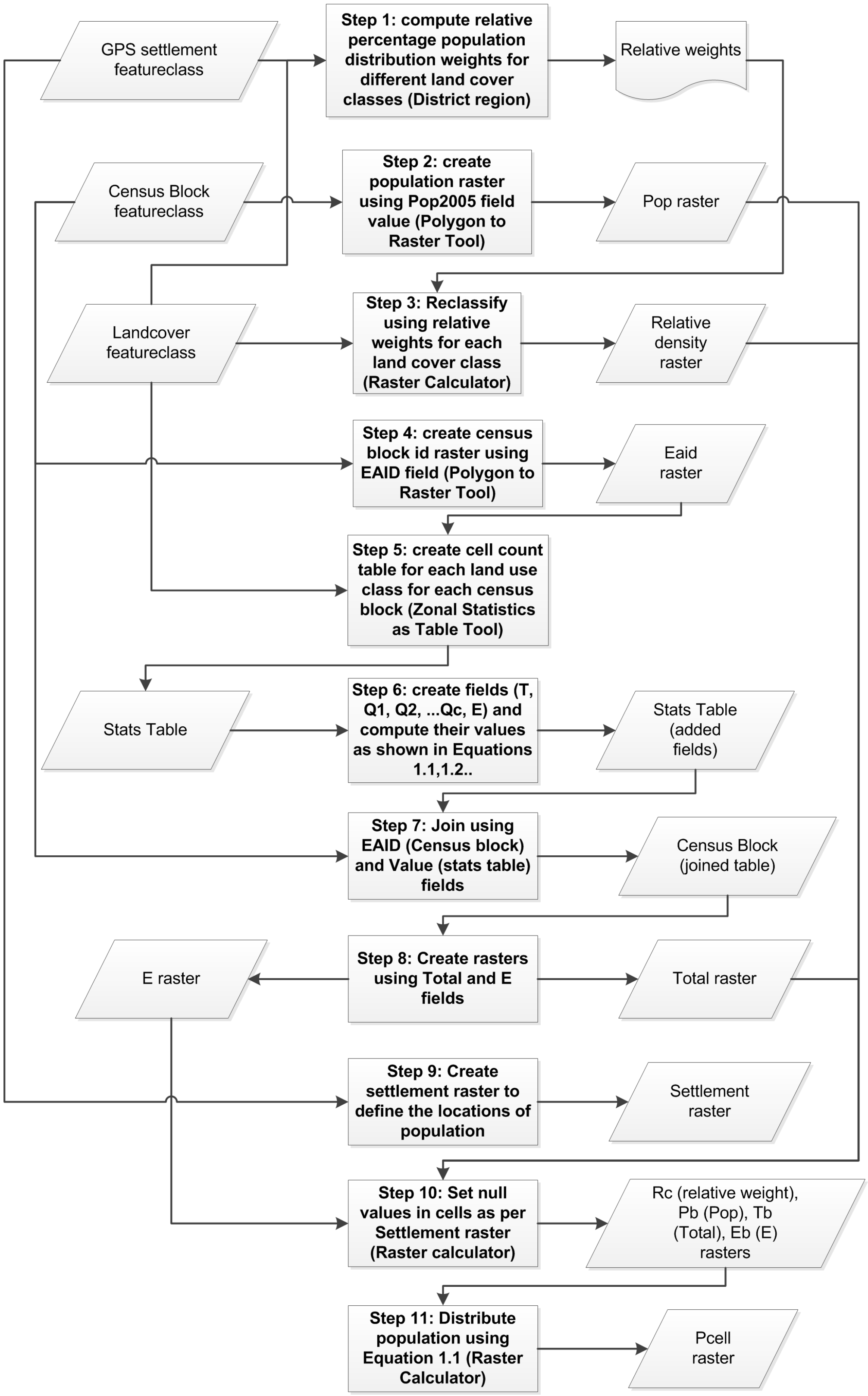


Figure 3.6: Processing steps for Holloway model

TABLE 3.1: Relative population distribution weights for different land covers within a district region

Districts	**Agri. Land**	**Forest Area**	**Built-up Area**	**Others**	**Total**
Bumthang	0.36	0.20	0.11	0.33	1
Chukha	0.36	0.26	0.28	0.10	1
Dagana	0.58	0.33	0.05	0.04	1
Gasa	0.47	0.24	0.01	0.28	1
Haa	0.55	0.14	0.19	0.12	1
Lhuntse	0.61	0.21	0.05	0.13	1
Mongar	0.41	0.40	0.07	0.12	1
Paro	0.60	0.10	0.18	0.12	1
Pemagatshel	0.62	0.24	0.03	0.11	1
Punakha	0.56	0.22	0.05	0.17	1
Samtse	0.60	0.27	0.09	0.04	1
Sarpang	0.38	0.23	0.11	0.28	1
Samdrupjongkhar	0.55	0.24	0.10	0.11	1
Thimphu	0.17	0.07	0.67	0.09	1
Trashigang	0.42	0.35	0.05	0.18	1
Trashiyangtse	0.49	0.29	0.04	0.18	1
Trongsa	0.31	0.27	0.13	0.29	1
Tsirang	0.59	0.26	0.10	0.05	1
Wangdiphodrang	0.44	0.15	0.07	0.34	1
Zhemgang	0.44	0.36	0.05	0.15	1

3.4.2 Areal interpolation with housing data

Unlike the dasymetric mapping techniques where land use data is used for disaggregation of population data, the proposed method is based on areal interpolation using only GPS housing data. This method assumes that the housing density is proportional to the density of the population. Therefore the relative population distribution weight of a target cell is computed as the proportion of the number of housing features within a target cell to the total number of housing features within the census block which contains that cell. The census block represents the subdistrict or town administrative regions whose population values are published by the NSB. The resolution of the target cell was chosen at 100 meters because there is no improvement in the accuracy of the proposed population distribution method at a finer resolution than this.

$$P_{cell} = \frac{N_{cell}}{N_{block}} \times P_{block} \tag{3.6}$$

Equation 3.6 shows the mathematical model of the proposed pupulation distribution method, where P_{cell} is the population estimated at the target cell, N_{cell} is the count of the settlement features within the target cell, N_{block} is the count of the settlement features within the parent census block which contains the target cell and P_{block} is the population value of the parent census block.

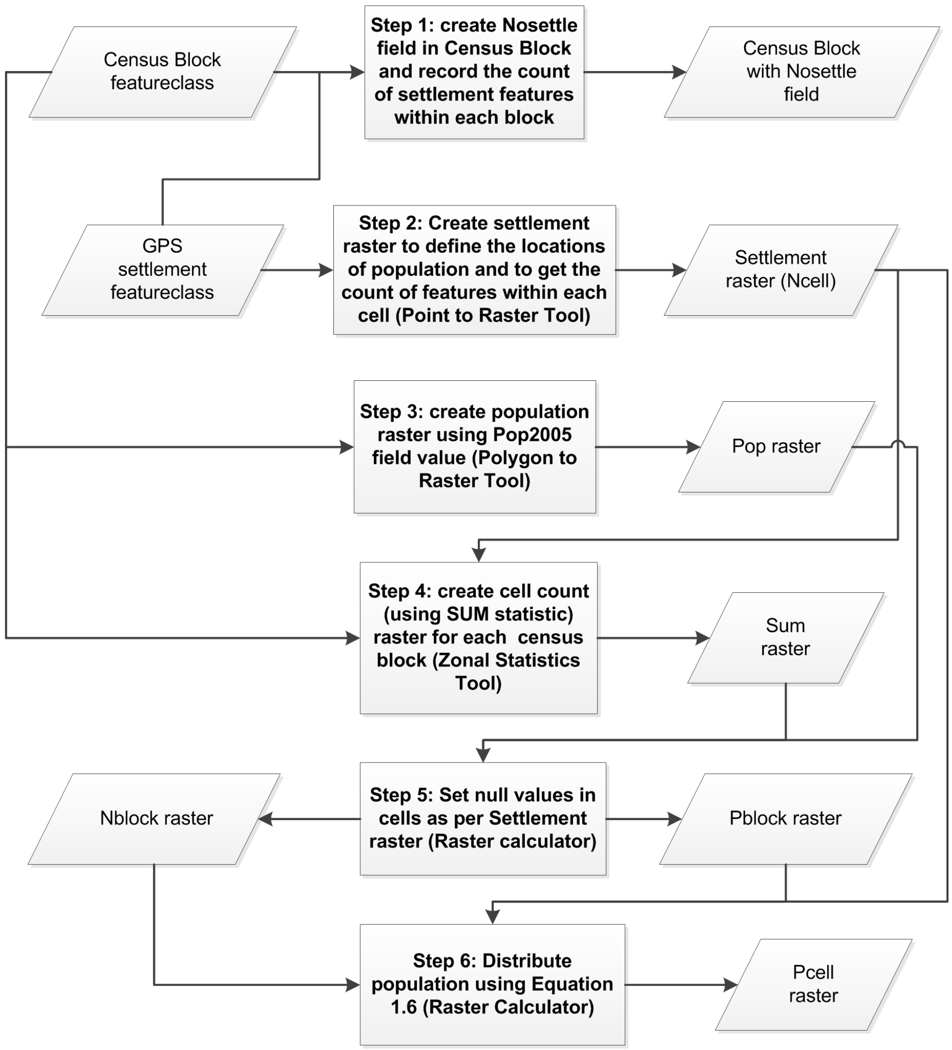


FIGURE 3.7: Processing steps for the proposed model

The processing steps for the proposed model are shown in Figure 3.7. The difference between this and the dasymetric model is that the proposed model do not use land use class as settlement data is directly used to compute the relative population distribution weights of each cell. In addition, the computational process is greatly simplified as there is no need to compute the area ratio and other parameters for different land use classes in each census block unlike the case in the dasymetric mapping methods.

3.4.3 Random disaggregation method

The aforementioned population distribution models are based on a systematic approach of population disaggregation using an areal interpolation method. On the other hand, population disaggregation can also be achieved by randomly generating population point features using the population count data. The randomization hypothesis postulates that there are infinite ways of defining spatial pattern of population data so there are infinite ways to generate population point features using a randomization method. People are constantly moving from one place to the other so a given population data represents only one static instance out of infinite possibilities of spatial arrangement of population data. That is why the population mapping of individual person is neither possible nor a sensible task to undertake. However, individual population data may be required for spatial modelling of disease outbreaks or for an accessibility measurement at the individual level. The accessibility measurement should be thus done at the individual level because accessibility is physically related to an individual accessing certain services rather than a group of individuals as represented by an aggregated population data.

Any areal interpolation method should be better than a random method. There has been no study so far to indicate that the population distribution models are better than a random method. Therefore, a randomization method of mapping individuals as a point features is proposed herein. Based on the randomization hypothesis, the randomly generated population point features may represent an instance of the dynamic population so such randomly generated population data at the individual level can be used for modelling spatial processes. The proposed randomization method was developed to suit the structure of population and housing data of Bhutan collected in 2005, described in the following two sections. It is important to note that all the processes from defining various count parameters to generating individual point features are random processes.

3.4.3.1 Defining independent and apartment households

In the real world, houses have one or more than one household occupants. In order to populate the houses, each one needs to be classified as an independent house with one household occupant or apartment building with multiple household occupants. PHCB household data do not have any variables defining whether the household lives in an independent house or apartment building. In the absence of such housing characteristics it was assumed that the house with less than or equal to four number of rooms – an apartment building, and the house with more than or equal to five rooms – an independent house.

3.4.3.2 Random generation of household and population point features

GPS settlement point data consists of many kinds of natural and man-made structures. It has attributes such as type of structures, name of the owners and name of the district and subdistricts. There is no variable indicating whether it is an independent house or apartment building. In the case of PHCB socio-economic data, the household cases were segregated based on the variable, number of rooms in the house, whereas the settlement data do not have any variable that could be used to classify as independent house or apartment building. Therefore, the independent household and apartment household point features were randomly generated by using the approximated count variables computed in Section 3.4.3.1. Both the household point features were created using the settlement point features. Independent household point features were randomly selected from the settlement point features using the independent household count value and the apartment household point features were generated in the proximity of the remaining settlement features using randomization technique. Figure A.1 in Appendix A shows the flow diagram of the randomization technique used in generating household and population point features. Then the household point features were randomly linked with the PHCB household data within specific census enumeration area. The PHCB data has a variable indicating the size of the household and the gender of the household members. Using these variables, male and female point features were generated for each household. For each household point, a rectangular bounding extent was formed using an offset length of 3.5 meters. Each male and female point feature were generated within this spatial extent. A population point feature was obtained by combining both males and females point features within each enumeration area.

3.4.4 Accuracy assessment of different methods

The population disaggregation was conducted at the subdistrict or town enumeration levels so the total count of the population at the subdistrict or town enumeration levels are preserved for all the aforementioned population distribution methods save for the random method because this method generates random population point features based on a randomly calculated household size. In order to assess the accuracy of a population distribution model the actual village level population count data is required but it is not available for Bhutan. In the absence of population census data at the village level, the quality control assessment of these models were crudely done by comparing the population distribution results obtained from aggregated and disaggregated census blocks of a certain test area. Since Thimphu district has a large number of town enumeration blocks (66 census blocks), this district's town was used for evaluating the accuracy of the dasymetric mapping models. Figure 3.8 shows the aggregated and disaggregated Thimphu town blocks that were used as a parent census block to distribute population to a 100 metres resolution grid cells.

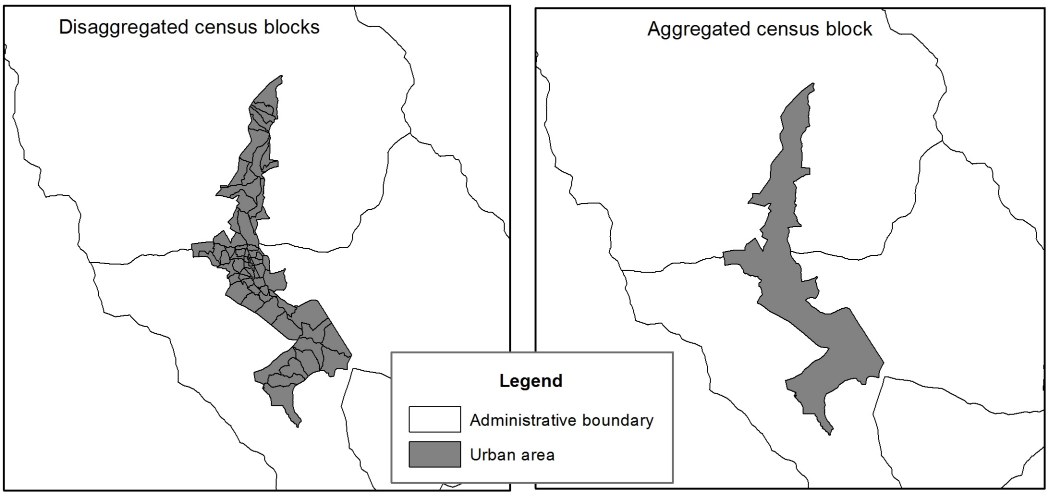


FIGURE 3.8: Aggregated and disaggregated Thimphu town census blocks

Six different types of areal interpolation methods were evaluated to identify the best model for disaggregating aggregated population data of Bhutan. Two classes, four classes, seven classes and population density fractions methods are based on the traditional dasymetric models as elucidated in Section 3.4.1, whereas the cell proportionate methods (50 and 100 metres cell size) are based on the proposed model described in Section 3.4.2. The first three dasymetric mapping methods differ only in the usage of the number of land cover classes, and the relative population density (R_c) for different land cover classes were derived from the GPS settlement data. The dasymetric mapping by the PDF method uses seven land cover classes and its relative population density (R_c) at the district level was computed using pre-defined population density (persons /10000 meter squares) instead of using the GPS settlement data. The areal interpolation methods with 50 and 100 meters cell size only differs in the resolution of the grid cells. All other modelling approaches except for the random method used 100 meter cell resolution. The random method is a vector-based modelling method whereas all other mapping techniques are raster-based modelling methods.

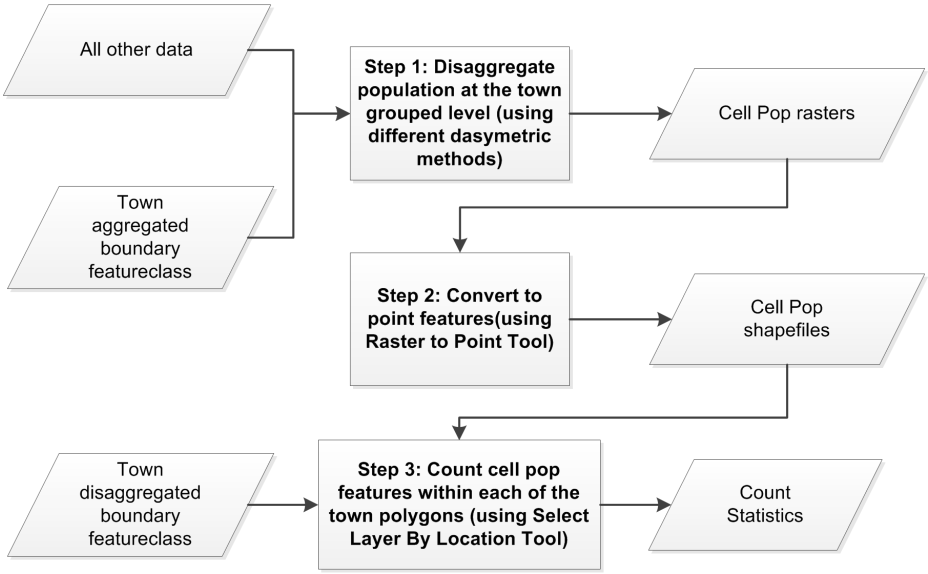


FIGURE 3.9: Processing steps for evaluating accuracy of dasymetric methods

Figure 3.9 shows the processing steps for evaluating relative accuracy between different population distribution methods. The first step is to estimate population at the cellular level by using processing models outlined in Section 3.4.1 or 3.4.2 in accordance to their types by using the town grouped census block population data. The estimated population values are real numbers. The next step is to convert the raster data into a point features, with the final step being to add up the estimated populations falling within each of the town enumeration census blocks by using a proximity-based clustering process.

Table 3.2 shows the summary statistics for the seven different methods. The total population field values of the six methods vary slightly because of rounding errors in adding up the real values of population point features. The Underestimation columns contain fields whose statistics were computed for census blocks that have a lower estimated population value than the actual value, and vice-versa for the Overestimation columns. The mean absolute percentage error (MAPE) values of the percent less and percent more attributes were computed using Equation 3.7, where P_i is the actual population value, $\hat{P}_i$ is the estimated value and N is the total number of census blocks. The mean error field value is the average of the mean percent less and more field values,

Table 3.2: Summary of statistics for different dasymetric mapping methods

Methods	**Total Pop. Est.**	**Underestimation (%)**			**Overestimation (%)**			**MAPE (%)**	**RMSE**
		Min.	**Max.**	**Mean**	**Min.**	**Max.**	**Mean**		
Dasymetric (2 classes)	79157	3.53	85.97	41.61	1.65	659.68	123.94	82.77	996.59
Dasymetric (4 classes)	79156	0.67	80.91	36.01	5.49	269.92	84.25	60.13	814.47
Dasymetric (7 classes)	79153	3.96	80.46	37.31	0.30	276.79	80.36	58.84	806.52
Dasymetric (7 classes,PDF)	79153	0.54	82.58	36.35	3.47	306.54	95.86	66.10	852.911
Areal interpolation with housing data(50m cell size)	79155	2.33	70.93	30.76	5.69	276.44	57.63	44.19	621.04
Areal interpolation with housing data(100m cell size)	79150	0.44	65.08	34.19	5.42	284.29	55.49	44.84	618.06
Random method	82534	0.97	69.97	28.95	2.71	306.02	61.56	45.25	605.60

which roughly indicates the percentage errors of the corresponding population estimation methods. The RMSE values were computed using Equation 3.8.

$$MAPE = \frac{\sum_{i=1}^{N} \frac{\left|\hat{P}_i - P_i)\right|}{P_i}}{N} \tag{3.7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{P}_i - P_i)^2}{N}} \tag{3.8}$$

MAPE and RMSE statistics are commonly used to evaluate the relative accuracy of areal weighting and dasymetric mapping techniques (Eicher and Brewer, 2001; Mennis, 2003; Kim and Yao, 2010). In general, a model that produces lower MAPE and RMSE values is relatively more accurate than one with higher values. Amongst the dasymetric methods, the method with seven land cover classes is better than the one using two and four land cover classes. The two land cover classes method is the least desirable method as it produced the highest MAPE and RMSE values.

This study shows that dasymetric methods which use a larger number of land use or land cover classes produce better estimation of population than the ones that uses few classes. The dasymetric method using PDF as the relative population densities of different land use classes produced poorer results than the method that used GPS settlement data to compute relative densities. Therefore, it can be plausibly inferred that the density of the settlement features can be positively correlated with the density of the population. It has been also found that the resolution of the target cells do not influence the accuracy of the computational methods as the MAPE and RMSE values of the methods with 50 and 100 meters cell sizes are almost equal.

One of the main finding of this study is that the proposed method of areal interpolation with housing data outperforms the dasymetric modelling approaches as the former model produced lower MAPE and RMSE values than the later model. The proposed method did not use any land use classes to compute area ratios as done with the dasymetric mapping techniques which may have introduced additional biases. The areal interpolation with settlement data is simple to execute as it directly computes population at the cellular level without having to compute area ratios of different land use classes, unlike in the case of the dasymetric mapping methods. With respect to both the MAPE and RMSE values, the random method produced better population estimates for individual enumeration blocks than the dasymetric mapping methods. The random method also produced similar results as the proposed method with the later method having a slightly better MAPE value and the former method having a better RMSE value. It can be surmised that in the case of Bhutan, the dasymetric model is only up to 40% accurate whereas both the random and proposed methods are about 55% accurate. However, the use of random household sizes have affected in the total population estimates for the random method with overestimation error of about 4.3% whereas such an error is non-existent or negligible for all other modelling methods.

3.4.5 Population data clustering

The spatial accessibility measurement system requires population cluster data at the village level in order to maintain data consistency for temporal analysis of spatial accessibility to health care services. Since the location of villages, or suburbs in a town remains the same for a long period of time, it is a reliable unit on which to base the clustering of population data for evaluating spatial accessibility to healthcare services in Bhutan. NLC has compiled a partial list of village location data using the cadastral database. These village location data were used as anchor points for clustering the population estimates obtained from the population modelling method described in Section 3.4.2. There are only 3020 georeferenced village locations available. In regions

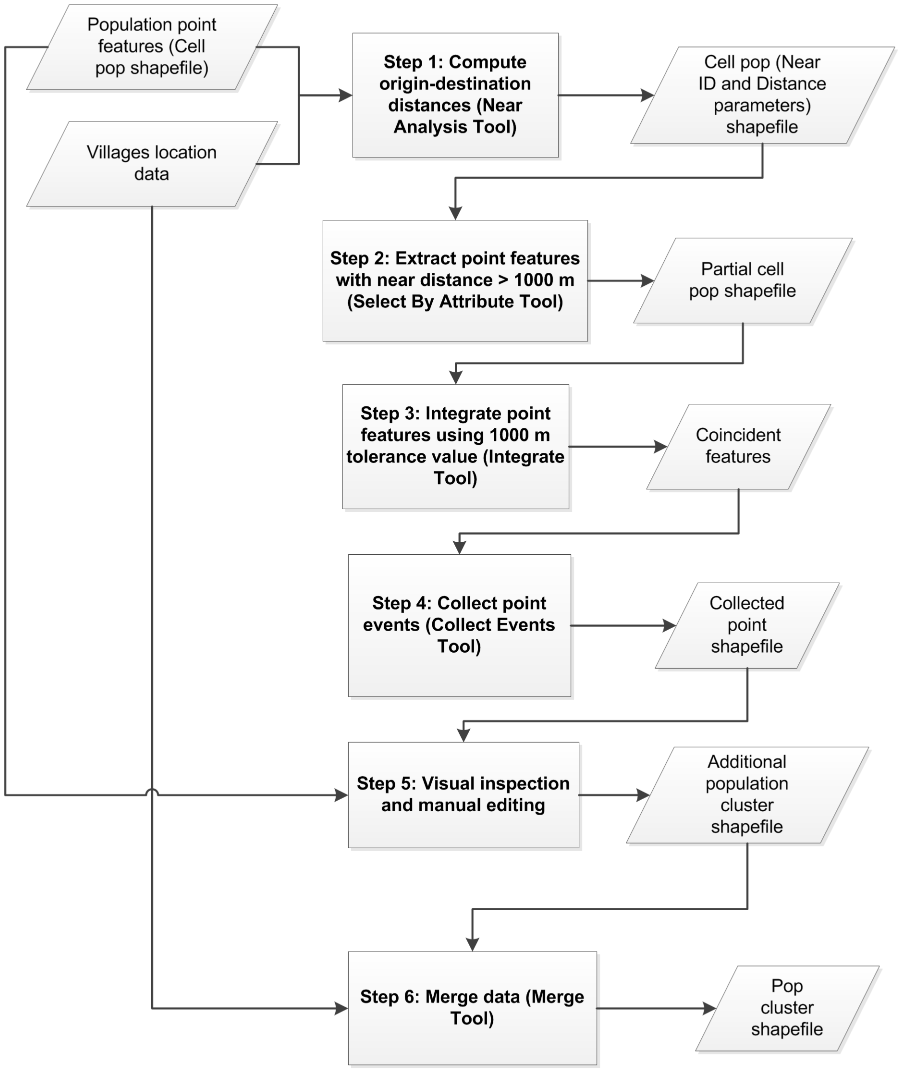


FIGURE 3.10: Processing steps for creating population cluster points

where there are no village location points and where the population density is relatively high then additional points were created by spatially integrating and collecting population point features within 1000 meters, which is a distance tolerance value used to search nearest neighbours at each computational point.

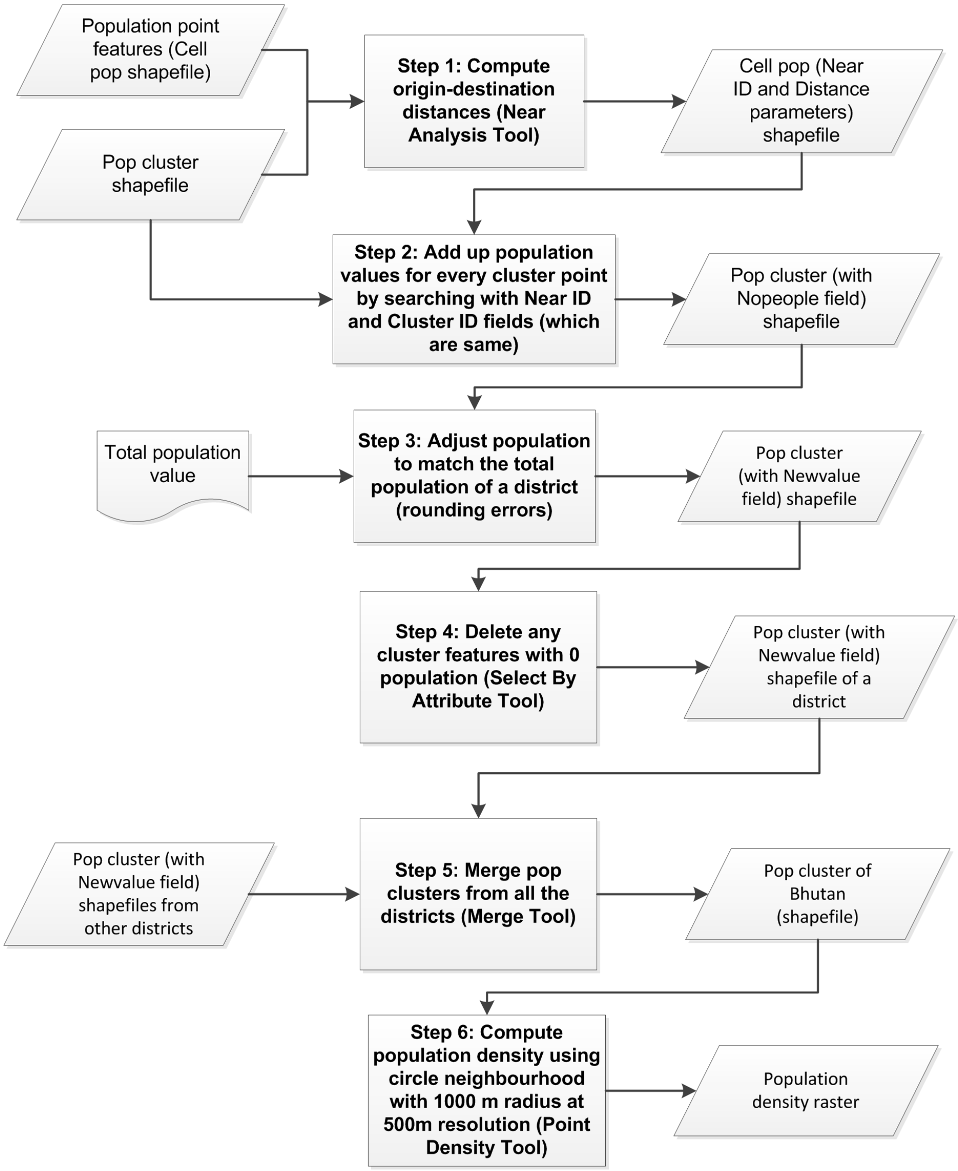


FIGURE 3.11: Processing steps for assigning population to a cluster points

Figure 3.10 shows the steps for creating population cluster points in the ArcGIS 10.2 system. Population point features were obtained by transforming each raster cell with their population estimate into vector points using a simple raster to vector conversion tool. The integration process makes the point features coincident or identical if the point features are falling within a distance tolerance value of 1000 metres, and the collection process creates coincident features into weighted point data. The location of the population cluster is the mean spatial position of all points falling within the tolerance value. These additional cluster points were visually verified and manually edited to position them as closely as possible within the bounds of the population point features as sometimes the aforementioned clustering method generates points at a location away from the extent of the clustered point features. There were 1075 cluster points created using the integration and collection clustering method.

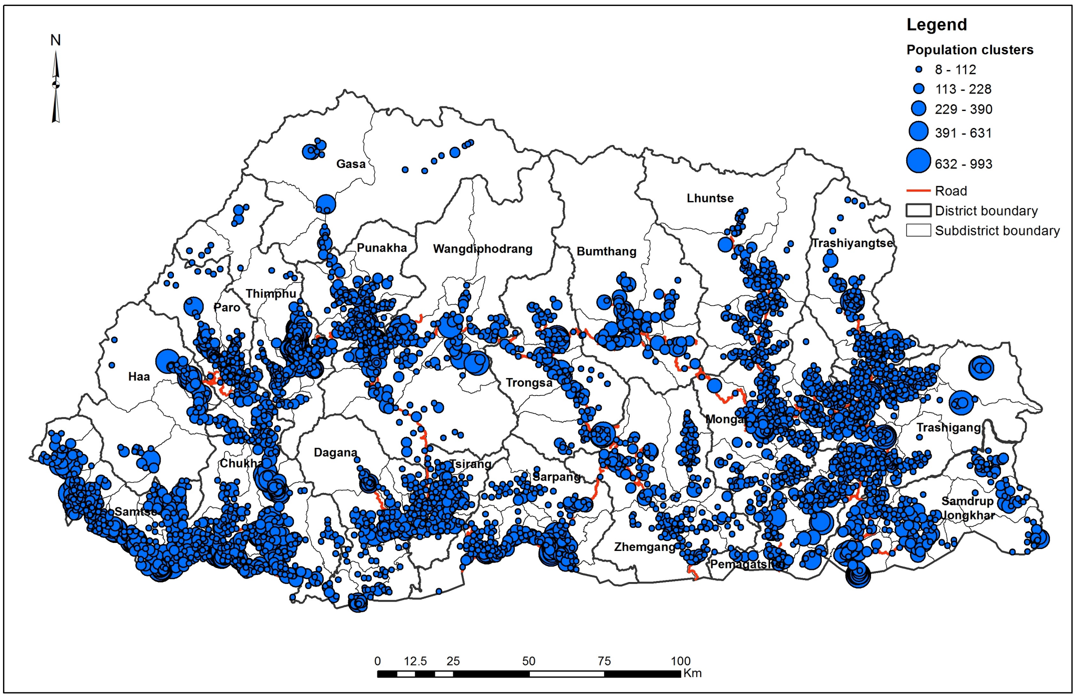


FIGURE 3.12: Distribution of population clusters in Bhutan

Figure 3.11 shows the steps for assigning population value to a cluster points. Each population point feature was associated with its nearest cluster point. The estimated population value of each cluster point being the sum of the estimated values of its associated population point features. As the estimated population values of the population point features are real numbers, the addition of real values to get the whole number of population causes rounding errors. This leads to mismatch in the total population of the computational region, which in this case was a district. The rounding error is uniformly distributed serially to all the clusters as the rounding errors do not exceed more than one actual person per cluster thereby preserving the total population of a district. Any cluster points that recorded zero population were removed from the population cluster points. Figure 3.12 shows the population cluster points data obtained from the proposed population distribution model and Figure 3.13 shows the population density map of Bhutan at 500 metres cell resolution created using the estimated cluster data.

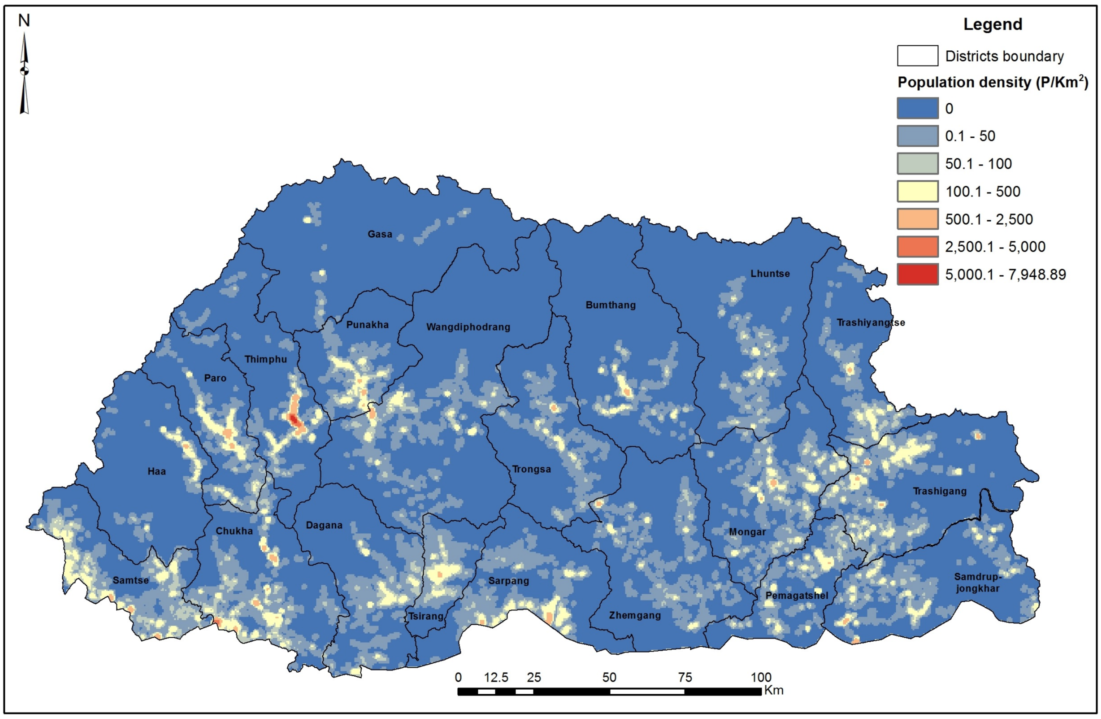


FIGURE 3.13: Population density map of Bhutan

3.5 Summary

This chapter has presented the data requirements for the computation of spatial accessibility to primary healthcare services in Bhutan. A number of spatial and non-spatial data are required such as the population clusters data at the village level, health facilities location data of all the healthcare service centres along with the number of healthcare professionals available in each centres, a digital elevation model, land cover and transportation network data of the whole country. Most of the data are partially or fully available except the population clusters data at the village level, which is only available as aggregated data at the subdistrict and town enumeration levels. The internal quality of the data was not able to be precisely evaluated because of the unavailability of metadata information of these data. Nevertheless some form of accuracy evaluation was carried out based on the form of data collection devices used for collecting these data.

This chapter identified a simple model of areal interpolation using only settlement data to distribute population values from source units to cellular target units. It is a cellular based population distribution model which does not require that population densities be computed at the district or county level because of the direct computation of relative densities at the target cells using variation in the density of the settlement features between the target cells. The proposed method was used to calculate population estimates at a particular cell resolution using population and housing census data of 2005 and then these estimates were relatively compared with the population estimates obtained from a number of dasymetric methods that used land use data to aid the interpolation process. It was found that the proposed method, areal interpolation using only housing data, produced more accurate population estimates than the dasymetric models using land use data as both the MAPE and RMSE values of the proposed method were comparatively less than the other models. The estimated population at 100 metres cell resolution was used to create population cluster data at the village level using villages location data by clustering the population point features to the village location data based on the near-distance analysis. In regions where the actual village location data were not available, new cluster points were created by integrating and collecting the population point features in that vicinity.

The modelled population cluster data at the village level was used for the computation of spatial accessibility in succeeding chapters such as for evaluation of straight-line distance or travel-time based computational models, different FCA-based computational models and various distance decay functions.

Chapter 4

Methodology

Of the many accessibility models available for measuring spatial accessibility, the FCA methods are most commonly used in evaluating health accessibility. Although these models are used by various researchers across the globe for modelling spatial accessibility to health care services, there is no consensus amongst researchers on a single model because of the numerous questions associated with FCA modelling. A number of these uncertainties of spatial accessibility modelling were presented in Chapter 2. In Chapter 3, the issue of population cluster modelling was specifically addressed for Bhutan by developing an areal interpolation method using housing data to estimate population data at the village level. This chapter will tackle other uncertainties such as the delineation of service and population catchment sizes, distance impedance measures, the computational aspects of modelling spatial accessibility and distance decay functions.

Section 4.1 describes the BR and the NN methods of defining service and population catchment areas for the FCA-based modelling of spatial accessibility. All the current approaches of defining catchment areas are based on a buffer ring method using a certain threshold distance or travel-time value. The nearest neighbours method of delineating catchment areas is proposed in this study. Section 4.2 compares straight-line and cost-weighted distance measures. Section 4.3 describes the mathematical models of eight different distance decay functions, and compares their accessibility outcome using a simple simulated data configuration system. Section 4.4 evaluates accessibility outcome between different FCA-based computational models using a simple data configuration system. An AM2SFCA model, which is based on the existing M2SFCA model, is proposed for measuring spatial accessibility to primary health care services in Bhutan. Section 4.5

describes the processing steps for computing spatial accessibility indices of population clusters, subdistricts and districts.

4.1 Delineation of service and population catchment areas

The FCA measurement system consists of service and population catchment areas. That is, each service centre has a population catchment area and each population cluster has a service catchment area, which are generally finite and overlapping with the neighbouring catchment areas. The actual delineation of population catchment areas is supposed to be performed by modelling the spatial relationships between the service centre and the residents living within the vicinity of the service centre (Luo and Wang, 2003). However, it is not practically feasible to accurately model the provider-population interaction since this would require extensive and costly surveys throughout the country. Therefore, the service and population catchment areas may be defined by developing a sound theoretical framework underpinning the spatial accessibility model. This study proposes a new variant of the FCA computational model based on a NN method of delineating the service and population catchment areas (Jamtsho et al., 2015).

4.1.1 The NN method

As discussed in Section 2.4.4, most of the FCA-based studies have used a BR method for delineating service and population catchment areas in which the buffer rings are defined by a radial measure either with a uniform or variable size distance or travel-time value. This method may seem very intuitive but it is very far from reflecting the real world because there is no absolute single distance or time threshold value that people would adhere to when selecting the service centres such as health facility. In most of the past studies on FCA modelling, researchers have used a range of time values from 5 minutes to 90 minutes at a certain interval. These threshold values are either conveniently or arbitrarily chosen. Any real value, for instance 5.912 minutes, is hypothetically possible in defining a buffer ring. The theoretical ambiguity of the BR method is obvious, so its usage is very questionable. In addition, the method does not apply the distance decay effect by considering all relative differences in distances between locations of population clusters and service providers within the study region because the decay function is truncated beyond the threshold distance or time value. Finally, this method introduces 'choice' bias in accessibility scores between different population clusters because population clusters are associated with a variable number of health facilities. The accessibility score of a given population cluster is equal to the sum of the individual components due to each of its associated service centres (see Equations 2.3, 2.6 or 2.13).

The principle of 'nearest neighbours' algorithms are simple and also closely relate to human cognitive phenomenon (Smith and Medin, 1981). On this premise, the concept of nearest neighbour is often used in measuring physical accessibility to health care services. For example, the nearest distance or travel-time between two locations is a simple measure of physical accessibility to health care, which has been widely used by health organization across the world. The MoH in Bhutan uses travel-time to nearest health facility from respondent's location as a health accessibility indicator to evaluate health coverage in the country (MoH, 2012*b*). Furthermore, spatial relationship between entities follow Tobler's "first law of geography" which states, "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p.236). This theoretical concept is also well reflected in spatial interaction models such as the FCA-based accessibility model which is a derivative of the gravity model in which the entities involved within a spatial system interact in a gravitational way. The NN method is based on sound theoretical concepts, therefore, it can also be used for delineating catchment sizes in spatial accessibility modelling. In the NN method, the delineation of catchment areas is performed by associating a fixed or variable number of neighbouring service centres to each population cluster.

There are three main advantages of the NN method. Firstly, it closely reflects the spatial relationship between people and surrounding spatial objects with respect to their spatial cognitive process of associating with landmark places. For instance, a person can linguistically describe neighbouring entities as "by less than 3000 miles" (Landau and Jackendoff, 1993) or 'less than 30 minutes'. However, it is impractical to spatially interact with an unknown number of service centres available within 3000 miles or 30 minutes from their location. Following Tobler (1970), it can be safely assumed that a person would choose to visit a few close service centres rather than those located farther away, which are included as the potential service centres by the BR method. By selecting just the few closest service centres, those redundant service centres can be excluded from the computation thereby effectively eliminating the accessibility 'choice bias' contributed by those centres. For instance, McGrail and Humphreys (2009a) have used a maximum of 100 nearest service centres found within a 60 minutes search radius to compute a 2SFCA-based accessibility measure. Obviously, people would not access these many service centres so the majority of those are redundant. This only contributes accessibility bias by largely measuring "choice" in urban areas rather than actual accessibility, as observed by McGrail (2012, p.6). Secondly, the NN method defines variable-size service and population catchment areas whereby the smallest to largest distance separation between the location of providers and population are captured. Hence, the distance decay effect is effectively applied across the regions whereby longer distances in rural regions and shorter distances in urban regions can be relatively weighted to produce accurate accessibility scores. Finally, health planning and allocation of GP services should be done with an objective to provide few services as close as possible to the location of all population clusters. Therefore, the evaluation of accessibility should be done by comparing the service availability at few closest locations rather than by including a redundant number of service centres located within 30, 45, or 60 min.

However, there remains one major question related to the proposed method. This is the ambiguity in the selection of an optimal number of nearest health centres for each population cluster. However, even the range of this whole number ambiguity is small compared to the real number ambiguity associated with the BR method where the selection range is theoretically defined by an infinite number of real values.

4.1.2 Optimal number of nearest neighbours

The NN method was originally developed to accommodate large variations in distances between some population clusters from their nearest health facilities while evaluating spatial accessibility for the entire nation (Jamtsho and Corner, 2014). For Bhutan, no particular distance cut-off value can be used since it has been observed from the health centres and population clusters network data that some of the population clusters (located in Lunana sub-district of Gas district) are located 53 kilometres away from their nearest health facilities. If this largest distance is chosen as the threshold value then the urban population would be associated with the population catchment areas of the health centres located in farther rural regions and vice versa. In practice, it is very unlikely that the urban population would seek healthcare services from the rural regions when there are better services available within the urban regions. If a threshold distance smaller than the largest distance is chosen then some population clusters in rural regions will have no health facilities assigned to them as all the health facilities would fall outside the threshold distance. Therefore, in order to associate all population clusters with some health facilities, each population cluster was associated to a finite number of nearest health centres.

The selection of the closest health facilities was considered based on the following reasons. Firstly, it was observed from the health system network data that most of the regions have more than one health facility located in a close proximity to another. It is also possible for many population clusters to have almost equidistant health facilities located within their vicinity. In such instances, it is quite inaccurate to choose just one health facility as the only likely target facility. Secondly, the third-nearest health facility for the majority of the population clusters are located relatively much further away as the majority of sub-districts have only one or two health facilities. For instance, the national average distance between population clusters and their third-nearest health facility for doctor services is about 30 kilometres whereas it is about 22 kilometres to the second-nearest facility. Table B.8 in Appendix B shows minimum, maximum and average distances between population clusters and their first-, second- and third-nearest health facilities for both HA and doctor services. To choose more than the two nearest health facilities is quite redundant and impractical because it is unlikely that people would travel there if there are two nearer health facilities located within their vicinity. Even in a densely populated region, such as Thimphu city, there are only five health centres available and two nearest neighbours accommodate about half of all the available opportunities. Therefore, the choice of two nearest health facilities was considered as optimal to define a realistic configuration of the healthcare delivery system for Bhutan. However, the value 2 is not absolute in the NN method because it can be adapted uniformly or variably in accordance with the health network data of a particular region.

The NN method of delineating catchment areas can be carried out as follows. Each population cluster is associated with its two nearest health centres based on distance proximity – defined as the population catchment area of each population cluster. The service catchment area of each health centre is delineated by including all the population clusters (both first- and second-nearest clusters) that are associated with the respective health centres. Figure 4.1 shows the distribution of the first- and

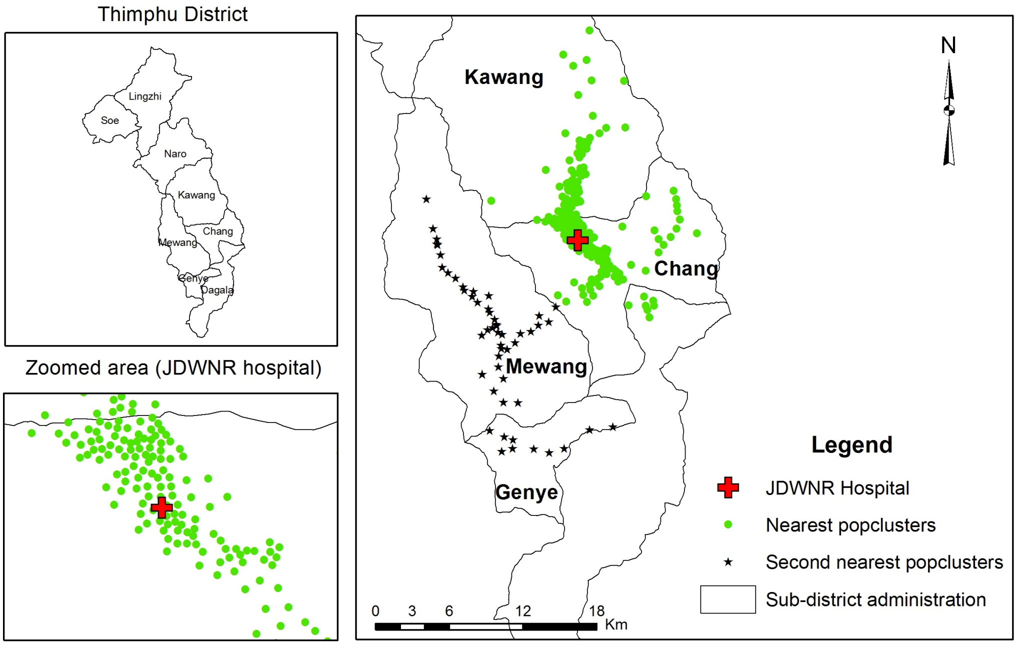


FIGURE 4.1: Health service catchment area of JDWNR Hospital (Jamtsho et al., 2015)

second-nearest population clusters that were associated with Jigme Dorji Wangchuck National Referral Hospital (JDWNRH). The population clusters represented by circular markers are the clusters for which JDWNRH is the first-nearest health facility, and the population clusters represented by star markers are those clusters for which JDWNRH is the second-closest health facility. Thus, the service catchment area of JDWNRH is formed by combining all first- and second-nearest population clusters associated to this health centre.

The other issue in the computation of the spatial accessibility is the definition of the computation region. For this study, the whole country has been considered as the single computation region in order to facilitate the association of provider sites and population clusters based on the first-two nearest distance condition. This means that people from one subdistrict or district can be associated to health facilities located in another subdistrict or district solely based on the distance proximity condition.

4.2 Distance impedance measure

In most developed countries where road network data are readily and comprehensibly available, network-based distance or travel time data are used for computing spatial accessibility to primary health care services. However, it is not always possible to use network-based data to compute spatial accessibility in third world countries because of the lack of road accessibility in most parts of the country and also due to the unavailability of comprehensive transportation network data.

On the one hand, as Bhutan has more than 60 percent of its population living in rural areas (NSB, 2005) the road transportation system is sparsely available. In rural areas, the primary mode of travel to health care facilities is walking (MoH, 2012*b*). Furthermore, in the absence of road and footpath data for the whole country, it is not possible to accurately develop a transportation database for the computation of spatial accessibility using a network-based distance or time data. Therefore, the straight-line (or Euclidean) and cost-weighted distance measures were evaluated for measuring spatial accessibility to health care services. Straight-line distance is the simplest form of distance measure which can be computed between two points, $p(x_1, y_1)$ and $q(x_2, y_2)$ using Equation 4.1.

$$d_{pq} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{4.1}$$

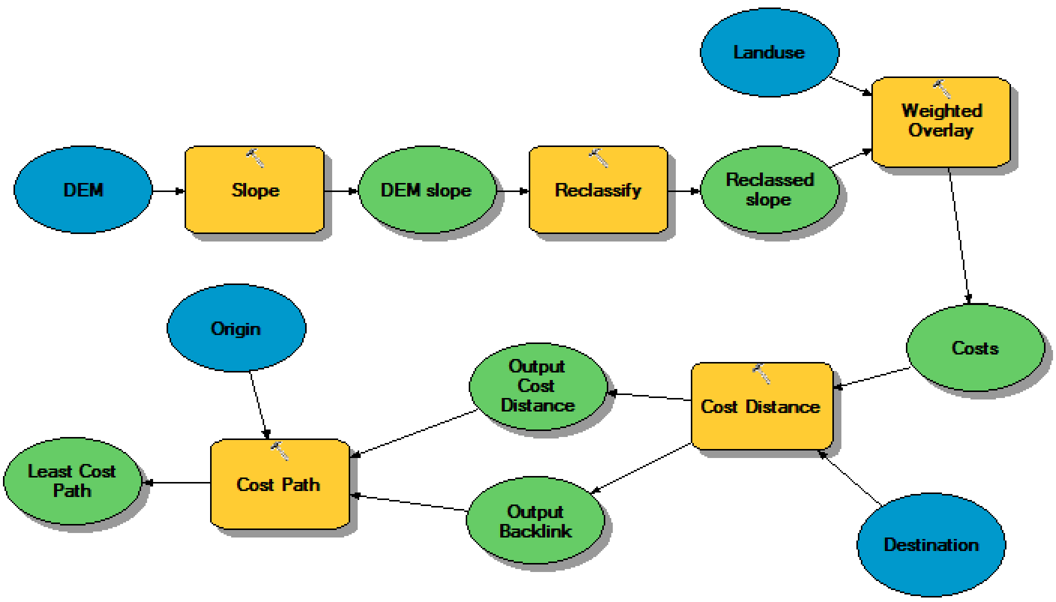


FIGURE 4.2: Process model for computing cost-weighted distances

On the other hand, the cost-weighted distance measure can be more accurate than the straight-line distance (Sander et al., 2010). Figure 4.2 shows the flowchart for computing cost-weighted distance using Spatial Analyst tools in the ArcGIS 10.2

system. In the computation of the cost-weighted or least-cost path, the optimal path between the origin and destination points can be based on numerous evaluation criteria (Lee and Stucky, 1998). Each criterion represents a friction surface and all of these friction surfaces are optimized to generate the least-cost path. One way of computing a least-cost path between two points involves the use of a digital elevation model and land use data, which are used for creating friction surfaces. For instance, a least cost path can be modelled between an origin (health facility) and a destination point (population cluster) based on travel impedance costs due to the slope of the area and the type of land use of the area. Higher slopes can be weighted as being more costly than lower slopes and human intervened land use areas as less costly than non-intervened areas.

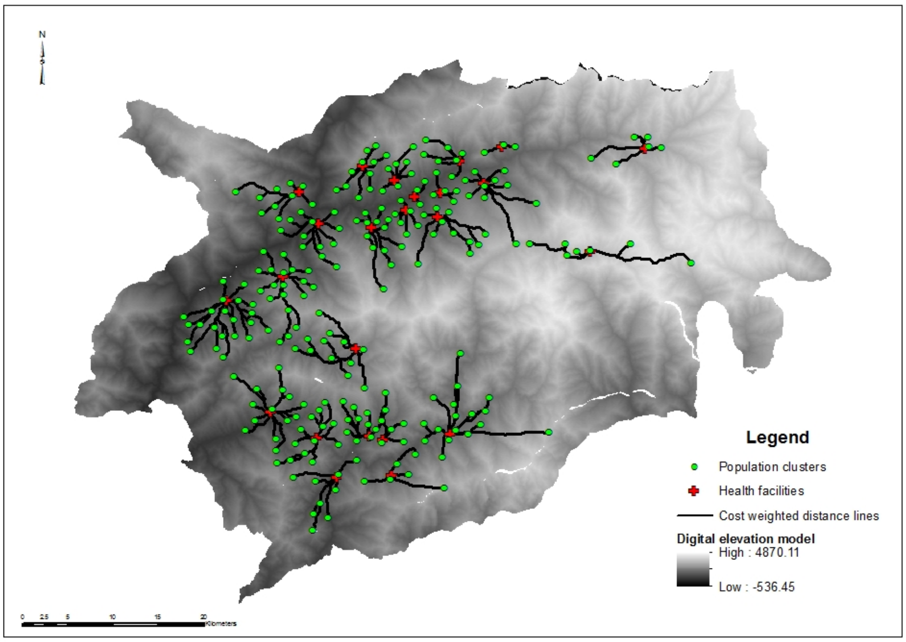


FIGURE 4.3: Cost weighted distance lines for Trashigang district

Figure 4.3 shows the cost-weighted distance lines for the Trashigang district, which was used as the case study area. It took about 2 hours, using a 3.30 GHz and 8 GB RAM computer, to compute 240 cost-weighted distances. On the contrary, the computation of straight-line distances took only a couple of seconds. This indicates that the computation of the straight-line distance measure is less intensive and time-consuming than the computation of the cost-weighted distances. Figure 4.4 shows the difference between the cost-weighted and the straight-line distances. The average difference between the two measures is 374 meters with maximum and minimum difference of

2411.01 and .0008 meters respectively. Cost-weighted distances were highly correlated with the straight-line distances with a Pearson correlation coefficient of 0.99 which indicates that these two distance measures are very similar.

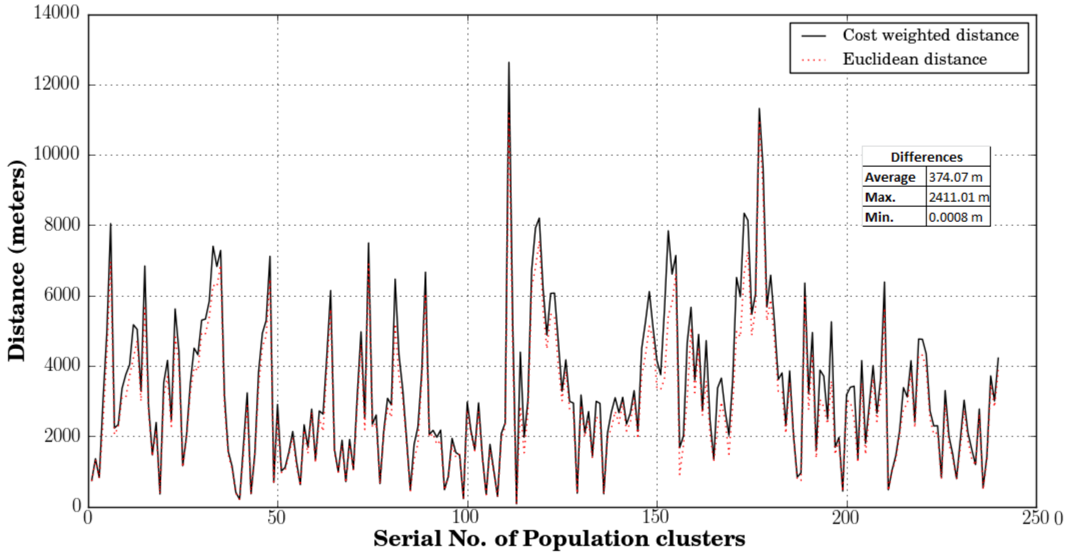


FIGURE 4.4: Differences between Euclidean and cost weighted distances for Trashigang district

Although the cost-weighted distance measure is theoretically more accurate than the straight-line distance, it was not selected for measuring spatial accessibility for two reasons. Firstly, the difference between the straight-line distance and the cost weighted distance was not very high as observed with the Trashigang district data and also these two distances were highly correlated. Secondly, the computational process of the cost-weighted distance is very time consuming. Furthermore, the computational outcomes of spatial accessibility between straight-line and travel-time models were also positively correlated, which is presented in Section 6.1. Therefore, the choice of one distance over other would not make a substantial difference in the computation of spatial accessibility to health care services in Bhutan.

4.3 Evaluation of distance decay functions

Section 2.4.5 discussed about the distance or travel-time decay function, $f(d_{ij})$, which explicitly models the distance separation between the location of service providers and the residents. McGrail (2012) and Wang (2012) have expressed the need for a comprehensive health utilization dataset to accurately model distance decay function based on the characteristics of the patient-provider interaction in order to accurately represent the degree of difficulty of accessing the health care services. In the absence of such data, the selection of the distance function is generally based on personal convenience or ad-hoc choice. There have been no studies undertaken so far to evaluate the effect of the different distance decay functions on the outcome of the accessibility measures. Therefore, the best way forward is to identify optimal decay functions heuristically by comparing their accessibility outcomes with the result from a control function, which can be defined based on a sound theoretical framework. This study has evaluated eight different distance decay functions by computing spatial accessibility values using the NN-M2SFCA method. Only results obtained from the simulated data system are described in the following sections. The results obtained from the actual population and health data is presented in Section 6.2.

4.3.1 Selection of the control function

The control function can be identified based on a sound theoretical framework describing the travel behaviour of people. Thorsen et al. (1999) defined a logistic function or S-shaped curve as the distance-deterrence function based on a hypothesis on commuting behaviour of people in urban areas. The general idea behind this concept is that people tend to select destinations randomly for short distances whereas travelling to long distances are governed by the principle of minimum cost. It means that the distance weights for short distances remains constant or increases minimally, then the weights gradually increases with distance and finally approaches 1 at infinity. A positive logistic function reasonably satisfies "a-priori postulates on spatial interaction behaviour" (Thorsen et al., 1999, p.80). Equation 4.2 represents one form of a logistic function,

$$f(d_{ij}) = \frac{1}{1 + e^{-k(d_{ij} - x_0)}} \tag{4.2}$$

$$x_0 = \frac{d_0 + d_\infty}{2}$$

$$k = \frac{2ln(\frac{1}{\alpha} - 1)}{d_\infty - d_0},$$

where d_0 is the extent of the short distance where weights remain constant (say 5 or 10 Km), d_∞ is the maximum distance between the locations of service provider and residents within the study region and α is the functional decay rate. Geurs and

Ritsema van Eck (2003) and Johansson et al. (2002) used log-logistic or S-shaped decay function for modelling of commuting pattern in Netherlands and Sweden, respectively. A negative or downward logistic function was fitted to log trip data of home-to-work journeys between municipalities in Denmark (De Vries et al., 2009). They observed that the logistic model fitted better than the exponential or power distance-decay functions. For accessibility modelling, a negative logistic function (with positive k value in Equation 4.2) can be adopted because accessibility scores should be weighted with high values for short distances and vice-versa.

Elsewhere, exponential and inverse-power functions were commonly used for modelling healthcare accessibility (Wilson, 1971; Joseph and Bantock, 1982; Shen, 1998; Luo and Wang, 2003; McGrail, 2012). The model parameters were mostly defined subjectively. However, these functions tend to produce unrealistic accessibility patterns at shorter distances because of the steep decline of the curve near the trip origin (Kwan, 1998). In addition, the power-decay function exhibits constant elasticity which can potentially cause overestimation of accessibility at long distances and underestimation at short distances (De Vries et al., 2009). There are very few studies, such as by Jia et al. (2013) and Delamater et al. (2013), where decay function was determined by analysing actual health utilization data. Delamater et al. (2013) in particular, estimated distance weights for computing E2SFCA-based accessibility scores by fitting log-logistic function to actual hospital utilization data of Michigan residents. Their study supports the applicability of a logistic function, an optimal model based on the theoretical framework of Thorsen et al. (1999), for modelling spatial accessibility. In contrast, Kwan (1998) suggested that the Gaussian curve, which portrays a gradual descent at the first and end part of the curve and somewhat rapid descent in the middle section, is a more appropriate distance impedance function for measuring health accessibility in urban areas. The general characteristics of this curve also closely resemble to the logistic function. Therefore, either a logistic or the Gaussian function can be used as a control function because both of these functions exhibit similar decay characteristics and were found to fit well to health utilization data. Nevertheless, the Gaussian function was chosen as the control function because of its simpler mathematical form. The mathematical form of the Gaussian function, as per Langford et al. (2012), is given by

$$f(d_{ij}) = e^{-\left[\frac{d_{ij}}{d_{pass}}\right]^{\beta}}, \quad \beta = 2.0, \quad d_{pass} = \frac{d_{\infty}}{R}; \tag{4.3}$$

where d_{pass} is a distance bandwidth, which is equal to some fraction $(1/R)$ of the maximum distance (d_{∞}).

The other issue with the distance impedance function is the ambiguity in the choice of the model parameter values because potentially there are a wide range of real values which can fit the functional form. This ambiguity can be drastically minimized by evaluating different forms of a particular distance decay function in two steps. Firstly, the distance-based weight values for the whole study region can be constrained to close or equal to 1 for the closest distance and close to 0 for the farthest distance in order to apply smoothly decaying weights for all distances. For instance, the Gaussian function can be defined with different values for parameter β and w, which is defined as a ratio of the maximum distance and some real value, R. Figure 4.5 shows various forms of the Gaussian function

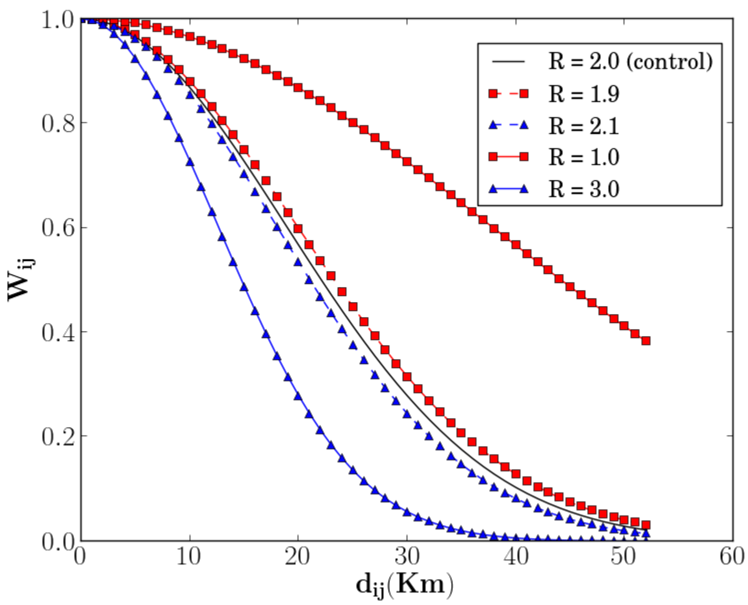


FIGURE 4.5: Gaussian function with different R values

with different values for the R parameter while the β value is 2.0 for all curves. The functional curves with the R value of 1.0 or 3.0 can be rejected outright because the curve with the R value of 3.0 has a steep decay pattern and also prematurely flattens at a lower distance (30 Km), whereas, the curve with the R value of 1.0 has a very slow decay pattern with a very high weights for larger distances instead of an expected value of close to 0. So the curves with the R value of 1.9 or 2.1 remains as a potential alternative to the curve with the R value of 2.0, arbitrarily considered the control function. Furthermore, the Gaussian function can also take different forms with different values for the impedance coefficient, β. Figure 4.6 shows three different forms with different values for β parameter while the value for the R parameter is fixed to 2.0. In this case, it is not possible to reject any of the curves by examining their weighting values because all three curves appear to be fulfilling the theoretical definition of the control function, suggesting all curves with a different impedance coefficient value remain a potential decay function.

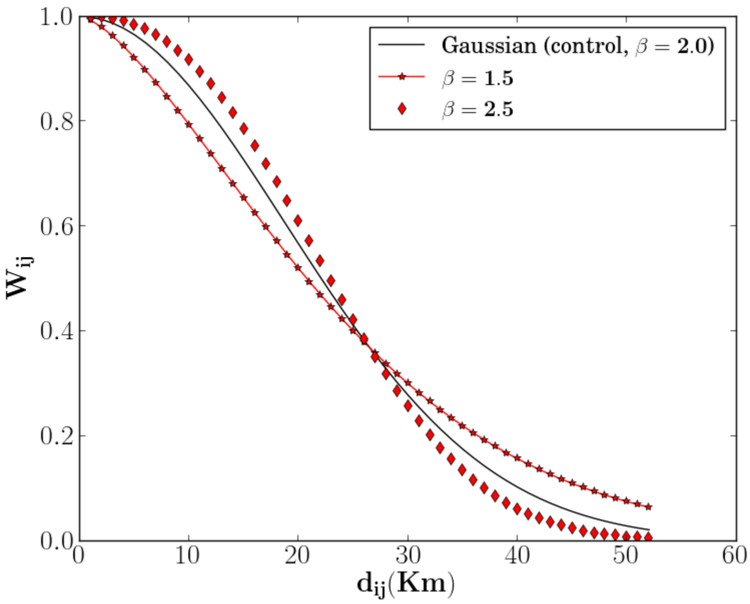
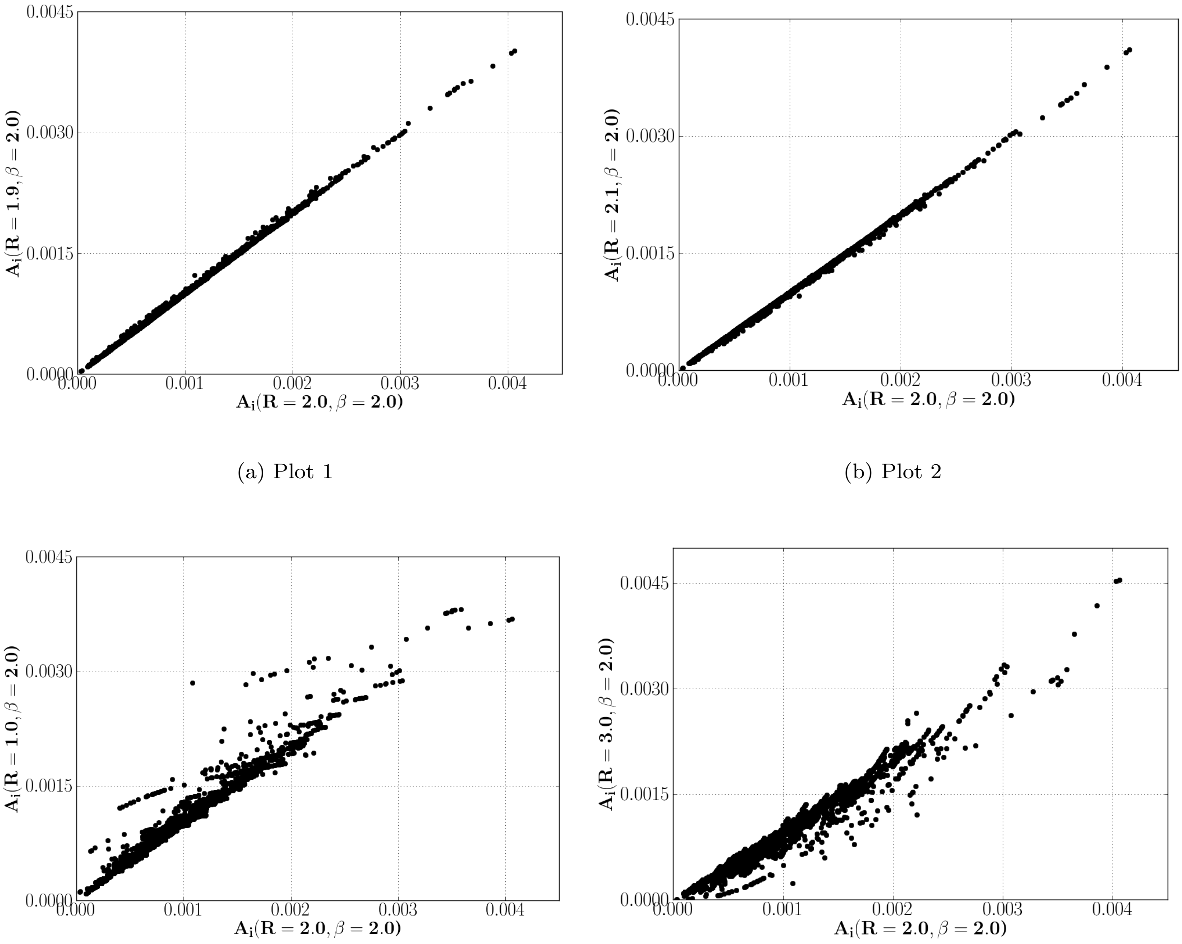


FIGURE 4.6: Gaussian function with different β values

Secondly, the remaining potential curves can be evaluated by computing their respective accessibility values using one of the computational methods. The NN-M2SFCA method was employed to calculate actual accessibility values using health facilities and population clusters data of Bhutan. Figures 4.7(b) to 4.7(d) show the scatter plots of accessibility values between Gaussian curves with different R values. It can be clearly observed that the plots of the accessibility values between Gaussian curves with the R value of 1.9 or 2.1 and the control curve with the R value of 2 portrays a strong positive correlation. The Pearson correlation values between these curves are effectively equal to 1 which indicates that their accessibility values are very similar. The correlation coefficients between different pairs of the Gaussian curves are shown in Table B.5 in Appendix B. On the other hand, the scatter plots of the accessibility values between curves with the R value of 1.0 or 3.0 and the control curve do not exhibit as strong dependency as the one observed between the aforementioned curves. Since the actual accessibility scores between the potential Gaussian curves (with the R values of 1.9, 2.0 or 2.1) do not differ significantly between



(a) Plot 1

(b) Plot 2

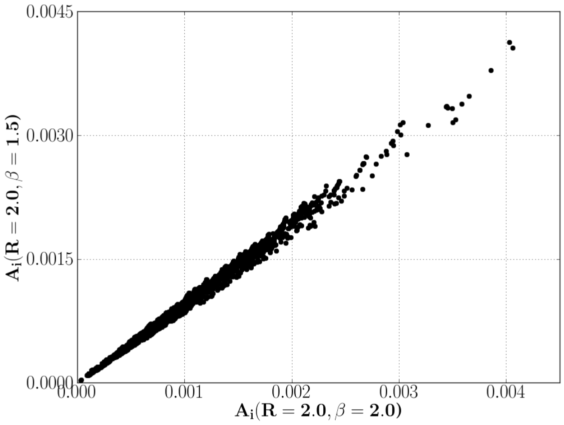
(c) Plot 3

(d) Plot 4

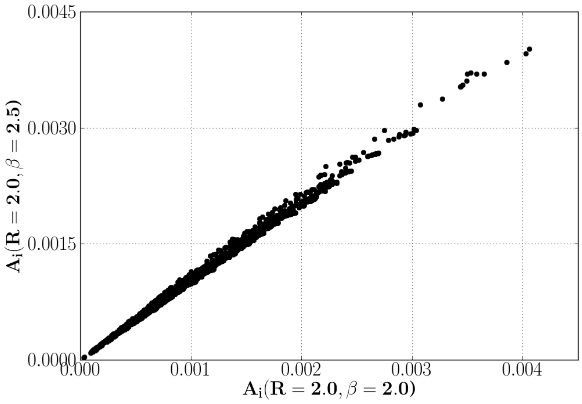
FIGURE 4.7: Scatter plots of accessibility values with different R values of the Gaussian curve

each other, any of these values can be selected as the value of R for the control curve. The R value of 2 was chosen for the control curve.

By keeping a constant R value of 2 within the Gaussian model, the effect of the change of values of β parameter was also evaluated by computing the M2SFCA-based accessibility values. Figures 4.8(a) and 4.8(b) show the scatter plots of accessibility values for the control curve ($\beta = 2$) and curve with β values of 1.5 and 2.5, respectively. These plots clearly show a strong linear dependency between the control curve and the other two curves. The high Pearson correlation values of 0.997 and 0.999 for the control curve and curve with β values of 1.5 and 2.5, respectively, indicate a strong positive correlation. This means that their accessibility values are significantly similar to each other. The use of β value of 2 for the control curve is thus acceptable as this particular curve not



(a) Plot 5



(b) Plot 6

FIGURE 4.8: Scatter plots of accessibility scores between Gaussian curves with different β values

only fulfils the theoretical expectation of a decaying pattern but also there is no further improvement or differences while using a similar curve with slightly different parameter values for the impedance coefficient. Past studies have also generally used the impedance parameter values of between 1.5 and 2.0. Hence, the Gaussian curve with R value of 2 and β value of 2 was considered as the control curve in this study.

4.3.2 Other distance-decay functions

There are a number of other distance-decay functions available for modelling distance impedance effects which have been used in previous studies or can be used for modelling spatial accessibility. Besides the Gaussian and logistic functions described in Section 4.3.1, the other decay functions are inverse-power, linear, exponential, Epanechnikov-kernel, Butterworth-filter and piecewise step functions. Figures 4.9 and 4.10 show a schematic representation of the aforementioned decay functions.

The mathematical models of these functions are given below:

Exponential function (as defined in McGrail (2012)),

$$f(d_{ij}) = a^{-\beta}, \qquad a = \frac{d_\infty - d_{ij}}{d_\infty}; \tag{4.4}$$

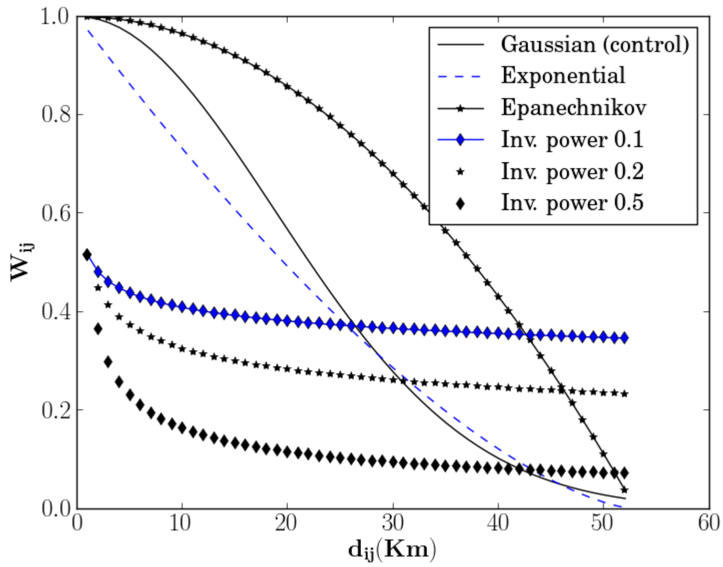


FIGURE 4.9: Logistic, Gaussian, Epanechnikov and Inverse power functions with relative to the control function

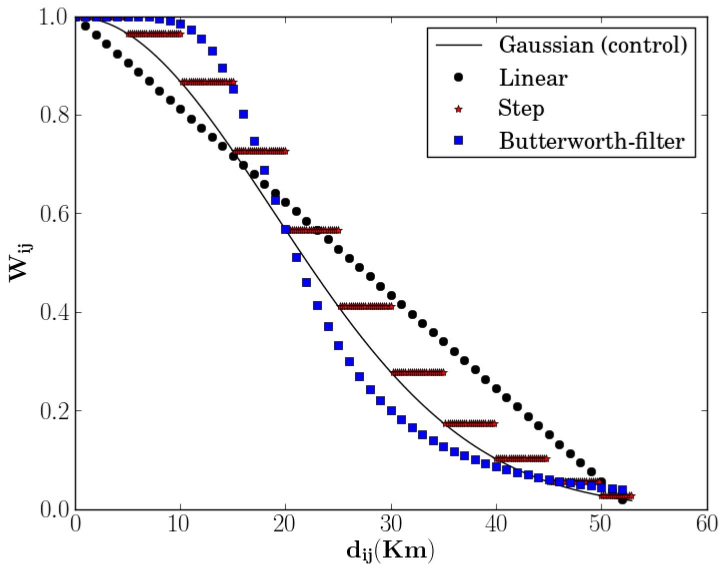


FIGURE 4.10: Linear, step and Butterworth-filter functions with relative to the control function

Epanechnikov-kernel function (as defined in Dai and Wang (2011)),

$$f(d_{ij}) = \gamma\Big[1 - \Big(\frac{d_{ij}}{h}\Big)^2\Big], \qquad h = \text{catchment size}; \tag{4.5}$$

Inverse-power function ,

$$f(d_{ij}) = d_{ij}^{\beta}; \tag{4.6}$$

Linear function (as defined in Langford et al. (2012)),

$$f(d_{ij}) = -\Big(\frac{1}{d_\infty}\Big)d_{ij} + 1; \tag{4.7}$$

Butterworth-filter function(as defined in Langford et al. (2012)),

$$f(d_{ij}) = \sqrt{\frac{1}{1 + \big[\frac{d_{ij}}{d_{pass}}\big]^6}}, \qquad d_{pass} = \frac{d_\infty}{R}; \tag{4.8}$$

and a step-function can be defined with constant arbitrary weight values for certain intervals or by using any of the other decay functions. In this study, it was defined using the Gaussian function at an interval range of 5 Km.

Similar to that concerning the control function, the ambiguity of the model parameters of the other functions were solved in a similar way by constraining the weight values between 0 and 1 before analysing actual accessibility values between potential alternative curves. To begin with, the logistic function has only one unknown parameter, α, which is normally defined as equal to 5% of the extreme distance values within the study region. Based on this proposed value for the α parameter (Thorsen et al., 1999), three real values of 0.025, 0.05 and 0.1 were tested. Figure 4.11 shows the three different curves of the

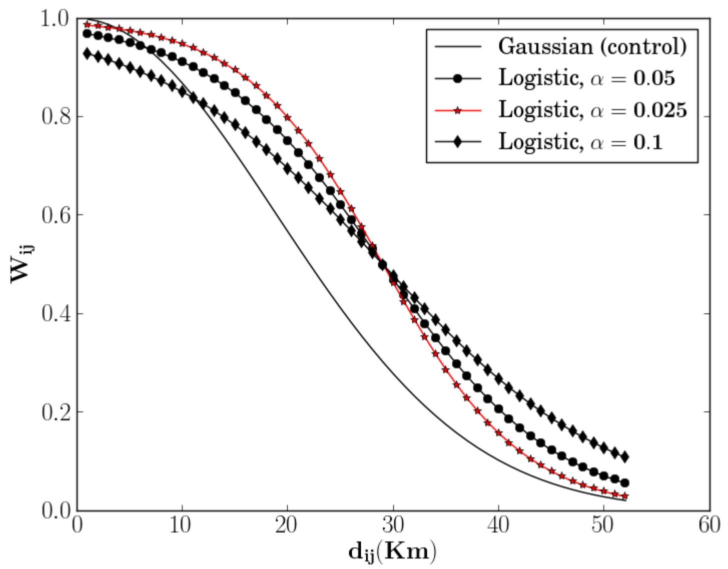
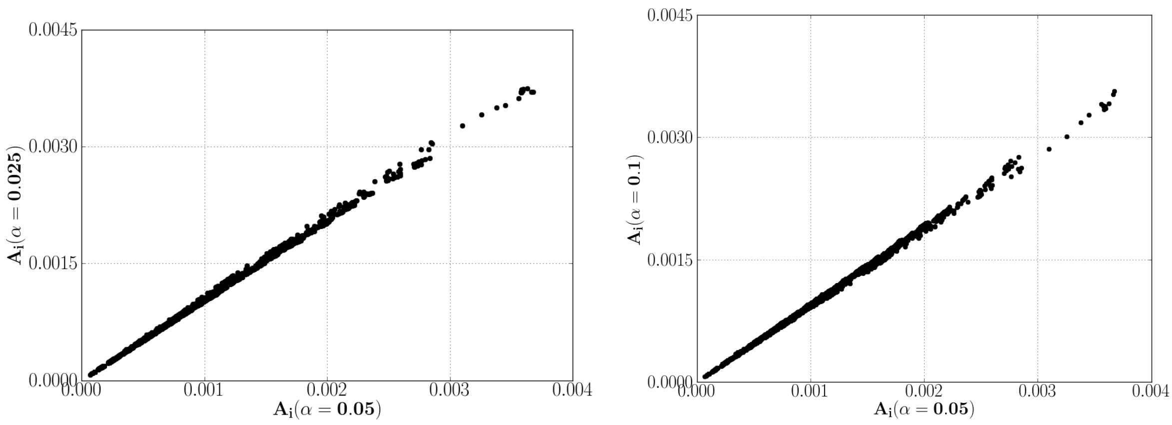


FIGURE 4.11: Logistic curves with relative to the control function

logistic function with relative to the control function. The extreme weight values of the



(a) Plot 7

(b) Plot 8

FIGURE 4.12: Scatter plots of accessibility values with different α values of the logistic function

curve with the α value of 0.1 falls a bit short of the standard value of close to 0 and close or equal to 1, whereas the other two curves very much fulfil this criteria. Figures 4.12(a) and 4.12(b) show the scatter plots between different variants of the logistic function. These plots clearly show a strong positive linear relationship between the three variants of the logistic curves. Despite the differences in the extreme weight values and decaying pattern between the three curves, the M2SFCA-based accessibility outcomes from these curves are very similar. The curve with the α value of 0.05 was selected for evaluation purpose.

With respect to the exponential function, β values of 1,1.5 and 2 were tested. The β value of 1.5 was used by McGrail (2012) in defining their weights using an exponential function. Figure 4.13 shows three different curves of the exponential function, and Figures 4.14(a) and 4.14(b) show the scatter plots of the accessibility values between curves with different β values. The data points between the exponential curves are laterally spread within a larger envelope than observed between the curves for the Gaussian or logistic function. This larger size of the envelope indicates a greater difference in their accessibility values when compared with the outcome between the curves for the other two functions. Although there are substantial differences in their accessibility values, the curve with the β value of 1.5 was selected for evaluation purpose because this impedance coefficient value was commonly used in the past studies.

The parameter values for the Epanechnikov and Butterworth functions were also selected on the basis of their expected weighting outcome within close proximity to the control

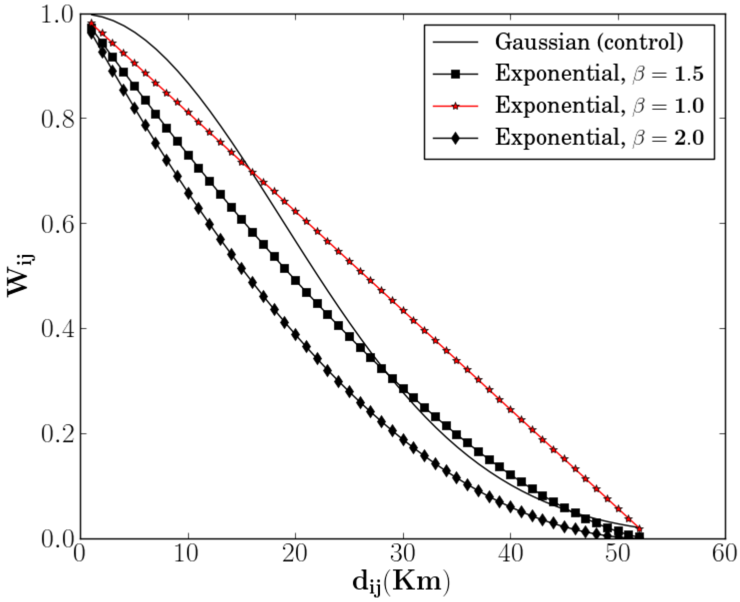
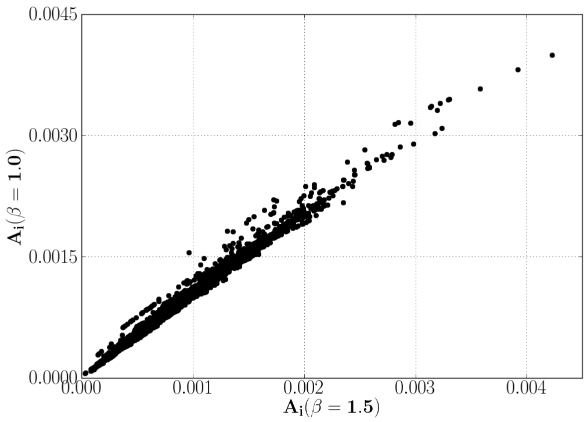
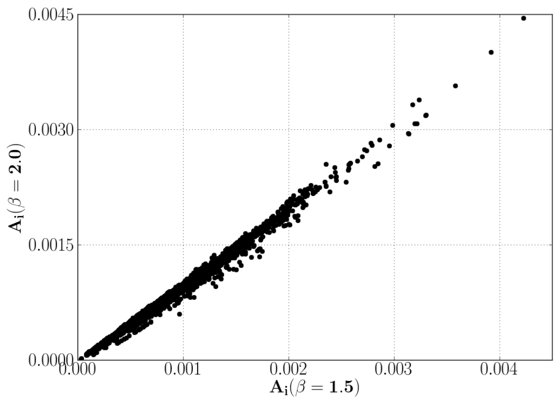


FIGURE 4.13: Exponential curves with relative to the control function



(a) Plot 9



(b) Plot 10

FIGURE 4.14: Scatter plots of accessibility values with different β values of the exponential function

function. Figures 4.15 and 4.16 show curves with different parameter values for the Epanechnikov and Butterworth functions, respectively. For example, the Epanechnikov curve with the γ value of 0.75, as used by Dai and Wang (2011), produced weighting values between 0 and 0.75. These weighting values are very different to the weighting outcome of the control function. The curve with the γ value of 1 and with larger bandwidth size($1.5 * d_{\infty}$) produced weights between 0.6 and 1, which is also significantly different from the weights produced by the control function. On the contrary, the curve with the γ

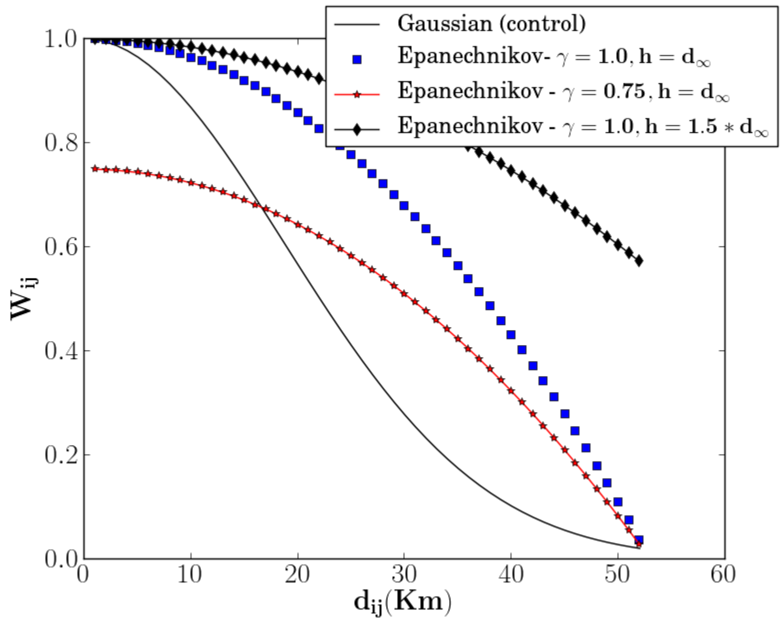


FIGURE 4.15: Epanechnikov curves with relative to the control function

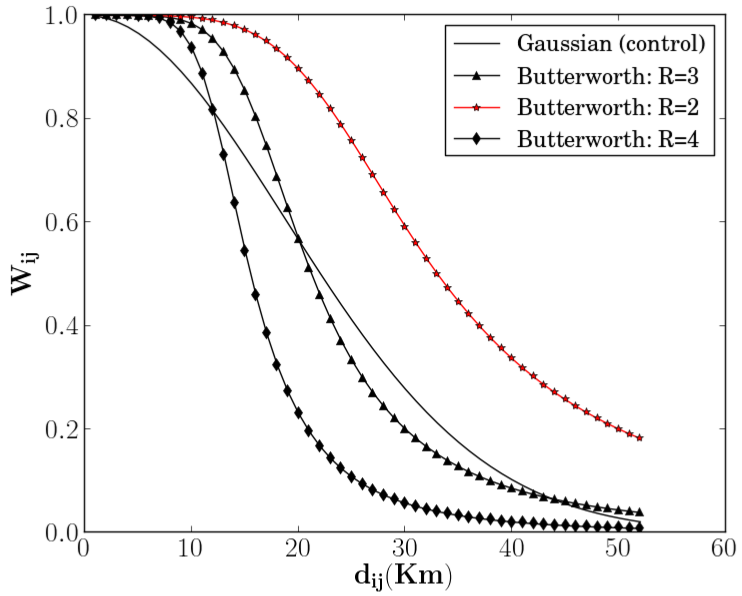


FIGURE 4.16: Butterworth curves with relative to the control function

value of 1 with the bandwidth size of maximum distance (d_∞) produces weighting values between 0 and 1, and its decaying pattern portrays an almost similar trend to the one for the control function. Therefore, the parameter values of this Epanechnikov curve were chosen. It can be noted that there are other parameter values, such as real numbers very close to γ and d_∞ that would have almost similar weighting outcome and decay pattern as the selected curve, however a very small difference in weighting outcome would not greatly affect the calculation of accessibility values as observed for the Gaussian curves with very close R values of 1.9, 2.0 or 2.1. Using a similar approach as the one used for the selection of the Epanechnikov curve, the curve with the R value of 2 was chosen for the Butterworth function.

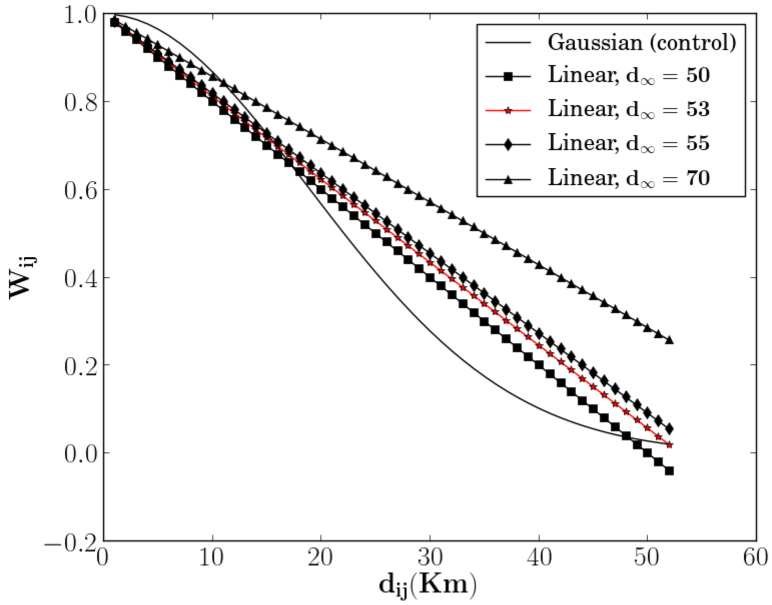


FIGURE 4.17: Linear curves with relative to the control function

With respect to the inverse-power function, there is not a single β parameter values that would produce weighting values similar or closely similar to the values of the control function. Thus, three different β values of 0.1, 0.2 and 0.5 were tested. The linear and step functions can also have numerous forms with different parameter values. Figure 4.17 shows four linear curves with different d_∞ values. Were the curve with the d_∞ values less than the maximum distance within the study area, 53 Km, or the slope of the line increase from -1/53 to -1/50, then the later curve would produce a negative weight values for some distances which cannot be reliably used for calculating accessibility values. On the other hand, the linear curves with lower gradients than -1/53 such as a slope value of -1/70 would produce weighting values between ranges other than 0 and 1. If the slope of the line is closer to -1/53 such as -1/55 then such curves would effectively produce almost similar weighting values which would result in similar accessibility outcome. Therefore, the curve with slope value of -1/53 was selected for the linear function because this curve would produce weights close to 0 and 1 for the minimum and maximum distances, respectively.

As regards the step-function, the constant weight values for different intervals were derived using another decay function. Figure 4.18 shows three variants of the step-function whose weight values were defined using the linear, Gaussian and Butterworth functions. For evaluation purpose, the Gaussian based step function was selected as its weights are similar to the control function.

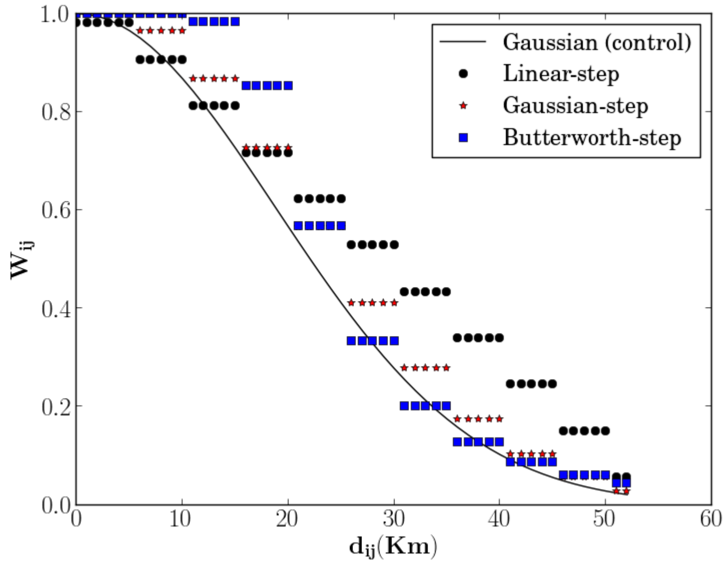


FIGURE 4.18: Step curves with relative to the control function

4.3.3 Simulated data analysis

Often real-world data is too complex due to the presence of multiple service centres and population clusters which complicate interpretation of the results. A simple data system can provide a better insight into understanding the effect of decay function on accessibility scores. Figure 4.19 shows a simple simulated system of provider-population configuration. Consider two service centres at A and B with 10 physicians each and six locations of population clusters at p, q, r, x, y and z with 100 people each. Only two service centres were used so that both the providers are seen as accessible to all population clusters as per the NN method. The location of the population clusters p and z are symmetrically opposite to the locations of r and x clusters, respectively, with respect to the positions of the two service centres. Similarly, q and y clusters are also positioned in such a way to have same distances to their closest and farthest service centres. Such a simple arrangement of providers-population configuration facilitates interpretation of the accessibility outcome because the competition effect of one cluster on the other for services can be intuitively interpreted. All the distances in Figure 4.19 are in kilometres.

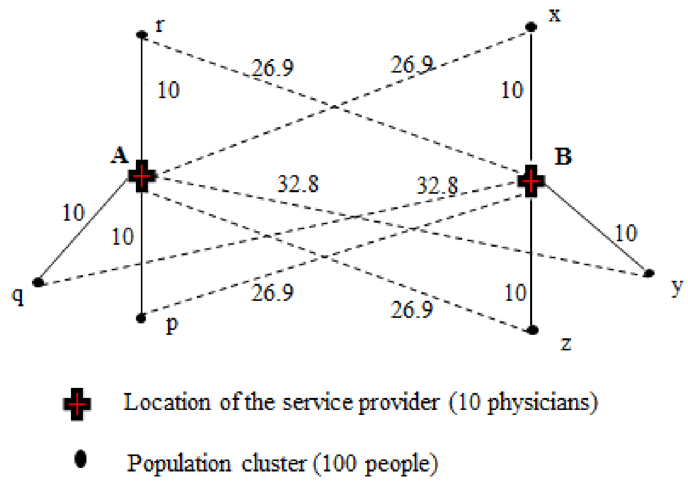


FIGURE 4.19: Provider-population configuration system (System 1)

The simulated data system of provider-population network configuration shown in System 1 was used to calculate the NN-M2SFCA based accessibility scores at six locations of population clusters using eight different decay functions. The selection of parameter values for the eight decay functions was described in Sections 4.3.1 and 4.3.2. Figure 4.20 shows the plot of the accessibility values for different functions. The point-based accessibility values are represented as a line to distinguish the outcome between different functions. As expected, due to the symmetrical structure of the data configuration, the accessibility scores for p, r, x and z clusters are same and scores for q and y are same too. It can be seen that the inverse-power functions with the power value of 0.5 produced the lowest accessibility values followed by the exponential and linear functions. It is interesting to observe that the inverse-power function with the power value of 0.1 produced accessibility scores within close proximity to the control function, when compared with the other two inverse-power functions, despite their decay patterns differing significantly from one another. Also, the logistic, linear and Gaussian-step functions produced accessibility scores similar to the control function. The Butterworth and Epanechnikov functions produced the highest accessibility values, and their scores were not as similar as the scores of the linear or logistic functions. It can also be observed that the variability in accessibility scores between different population clusters for inverse-power functions are small when compared with the variability of scores for the other functions. The small

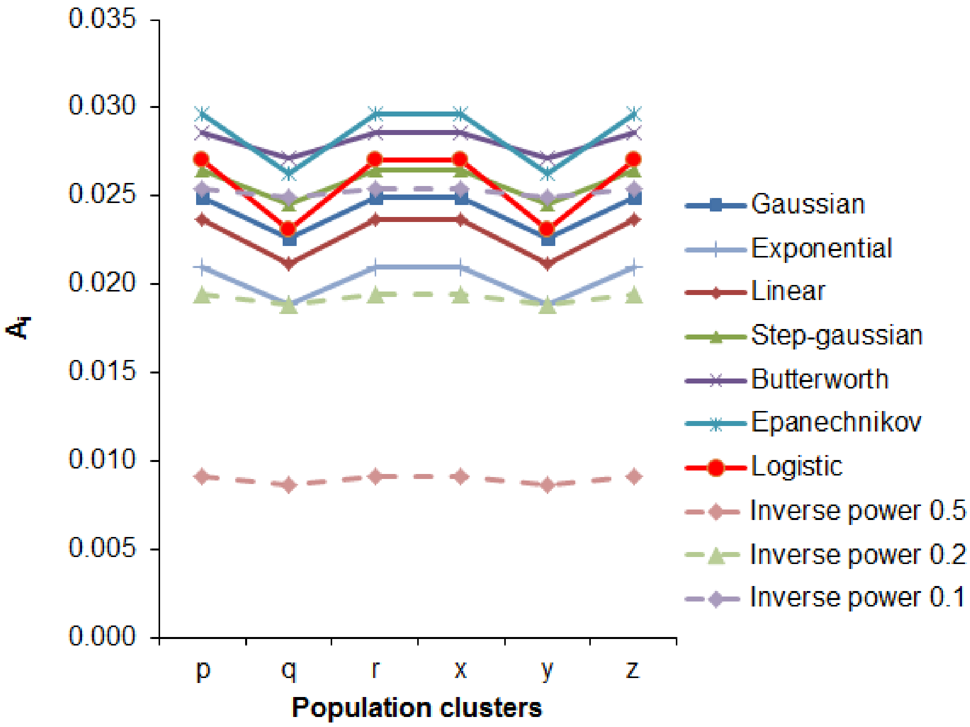


FIGURE 4.20: Accessibility plot for points in System 1

difference in scores between six population clusters for the inverse-power functions is because their weights almost flattens or negligibly increases after a certain distance as shown in Figure 4.9, unlike the weights of the other functions whose weights gradually increases with the increase of distance. Due to this flattening effect, it is quite possible that the accessibility scores from inverse-power functions may be failing to differentiate accessibility between regions which are located at a longer distance from the service centres.

Figure 4.21 shows the actual total opportunities distributed between different population clusters within the simulated data system for various decay functions. The total opportunities in a system is equal to the sum of the product of the accessibility score of each population cluster and its population. One of the salient features of the M2SFCA model is that it does not distribute all available opportunities because this model assumes that provider-population configuration system is almost always sub-optimal as the entities are not collocated with each other (Delamater, 2013). Therefore, the actual total opportunities available in the system are always less than the theoretically available opportunities (20 providers in System 1). It can be seen in Figure 4.21 that the Epanechnikov function has distributed 17.11 providers within the system

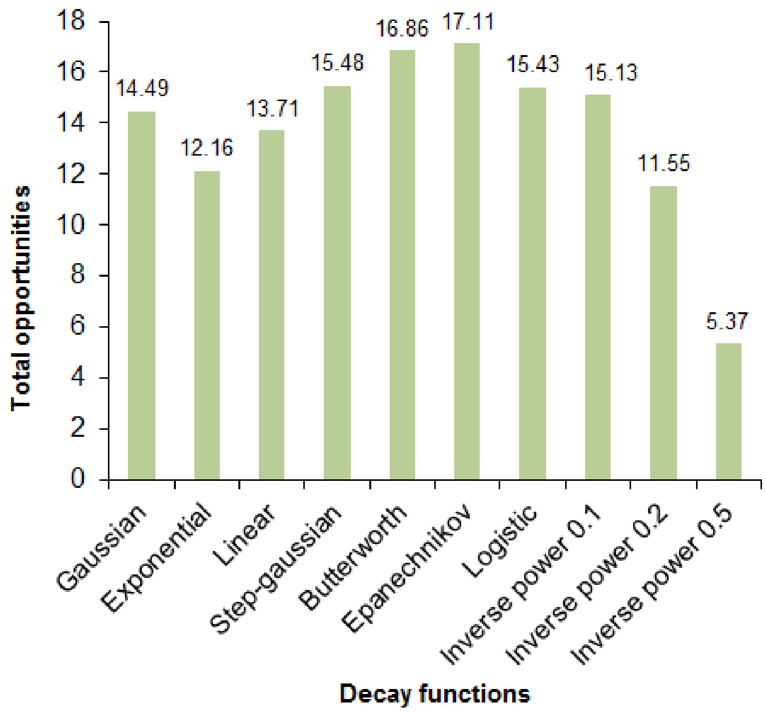


FIGURE 4.21: Actual total opportunities distributed in System 1

as opposed to the inverse-power 0.5 function, which has only distributed 5.37 providers out of 20. The control function has distributed about 14.49 opportunities between the six population clusters. This can also be interpreted as the distance impedance cost of the inverse-power 0.5 function being 14.63 (20-5.37), which is more than three times higher than the control function that only incurred a cost of 4.51 (20-14.49) opportunities. In practical terms, the impedance cost of inverse-power 0.2 and 0.5 functions are quite large because of the greater loss of service opportunities when compared with the loss incurred by the control function. All other functions have incurred an impedance cost within ±3 opportunities with respect to the cost incurred by the control function. Although it is not possible to be absolutely certain about the actual cost of total opportunities in an optimal system, as a rule of thumb, any decay functions which cause excessive cost or very low cost of total opportunities should be generally avoided because of their potential to cause either under-estimation or over-estimation of the accessibility scores.

4.4 Evaluation of FCA-based accessibility models

Generally, a spatial accessibility measurement system is defined by a gravity model or a FCA model. Recent research on spatial accessibility indicates that the FCA models are more widely used than the gravity model because they are intuitively interpretable and use variable-sized population catchment areas for each of the service centres instead of using a single catchment area for all the service centres as used in the gravity model (Wan et al., 2012a; Delamater, 2013; McGrail and Humphreys, 2014). One of the uncertainties of spatial accessibility modelling is caused by the availability of a number of FCA models such as the 2SFCA , KD2SFCA , E2SFCA , 3SFCA and M2SFCA models. Delamater (2013) carried out an extensive analysis of the aforementioned FCA models and found that the M2SFCA model is computationally more robust than the other models. A detailed description of these FCA methods has been presented in Chapter 2. The following sections only present the data configuration and accessibility outcomes of a simulated system. The accessibility results from real-world data is presented in Section 6.3.

4.4.1 Simulated data analysis of different FCA models

In order to understand the computational framework of different FCA models, following Delamater (2013), a simulated system of service providers and population clusters as shown in Figure 4.22 was designed to evaluate these models. System 2 has a similar configuration to System 1 except that the distances between any two points in System 2 are given different weights from System 1. The accessibility values were computed for all of the population clusters using different FCA models. Table 4.1 shows the accessibility values of six clusters obtained from different methods. As expected, the accessibility values of all population clusters computed using 2SFCA, E2SFCA, KD2SFCA and M2SFCA methods logically conform to the theoretical expectation of their respective models. However, the 3SFCA method produces dubiously larger accessibility values for population clusters q and y when compared with the other clusters which don't conform to their theoretically expected value – that of lower values than the other clusters. On careful scrutiny of the 3SFCA mathematical model, it can be seen that the weighting parameter (H_{ij}) has been incorporated in both Equations 2.10 and 2.11, which may have biased the accessibility outcome. Including this once in Equation 2.10 would be sufficient to model the competition effect as desired – accessibility score is also shown in Table 4.1 (see Modified 3SFCA). However, even this modification would not produce

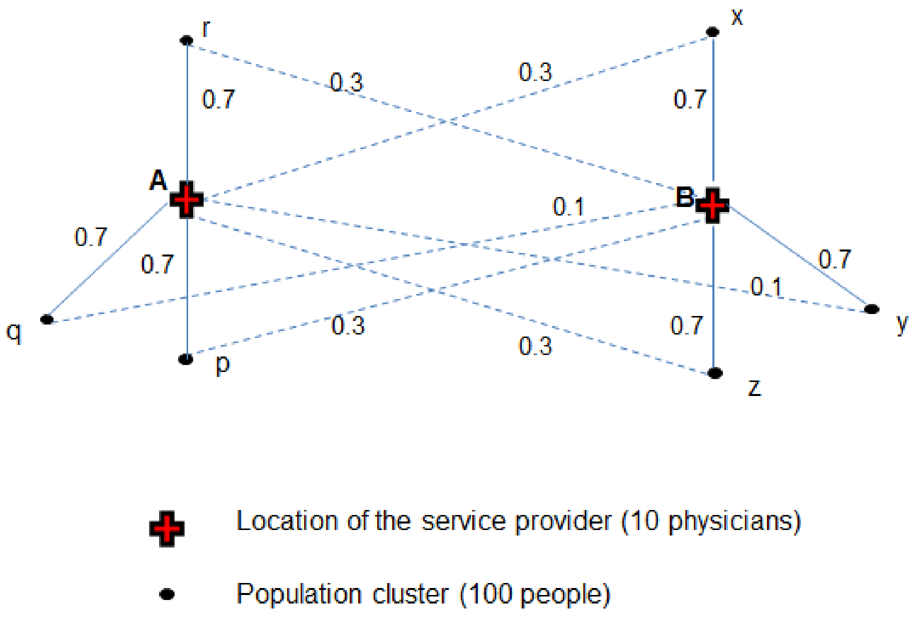


FIGURE 4.22: Provider-population configuration system (System 2)

any significant difference in relative accessibility outcome because the accessibility ratio between cluster p and q would be same as the ratio obtained from the E2SFCA method thereby making the 3SFCA model redundant.

TABLE 4.1: Results from the simulated System 2

FCA methods	**Accessibility (A_i)**						**Ratio (p/q)**
	p	**q**	**r**	**x**	**y**	**z**	
2SFCA	0.03333	0.03333	0.03333	0.03333	0.03333	0.03333	1
E2SFCA	0.03571	0.02857	0.03571	0.03571	0.02857	0.03571	1.25
3SFCA	0.03249	**0.03501**	0.03249	0.03249	**0.03501**	0.03249	0.92
Modified 3SFCA	0.05602	0.04481	0.05602	0.05602	0.04481	0.05602	1.25
M2SFCA	0.02071	0.01786	0.02071	0.02071	0.01786	0.02071	1.16

An additional illustration may be needed to fully expose the mathematical deficiencies of the 2SFCA, E2SFCA, KD2SFCA and 3SFCA models. Following Delamater (2013), two similar types of imaginary provider-population configuration systems (System 3 and 4) were framed as shown in Figure 4.23, where equal distance weights were assigned between all the population clusters and its sole service provider except that the absolute magnitude of weight for the two systems are different.

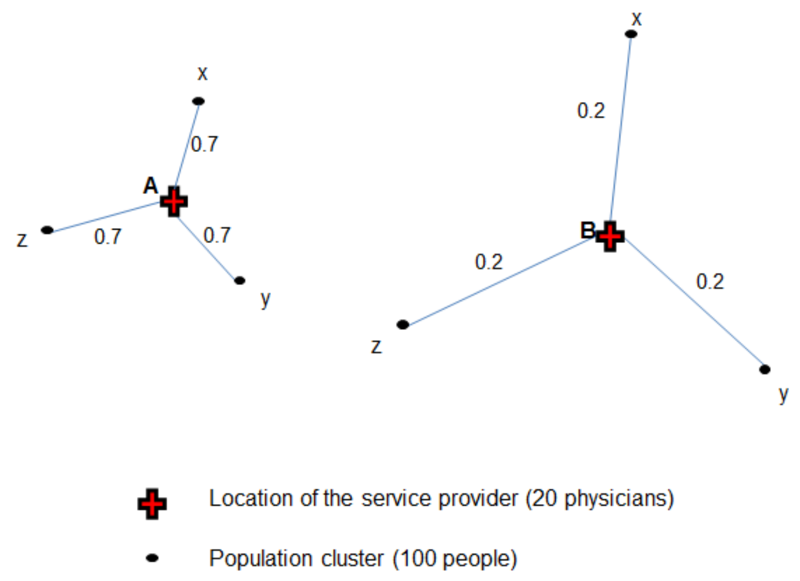


FIGURE 4.23: Provider-population configuration systems (Left: System 3, Right: System 4)

The accessibility results of the different FCA methods are shown in Table 4.2, where O(x), O(y) and O(z) values represents individual total opportunities of respective population clusters which were computed by multiplying its accessibility value by the population (100), and total opportunities in the system are equal to sum of all the individual opportunities. A full spectrum of accessibility outcome with respect to all weights between 0 and 1 for different FCA methods is shown in Figure 4.24. It can be observed that the spatial accessibility of all population clusters for the 2SFCA, E2SFCA, KD2SFCA and 3SFCA methods for both System 3 and 4 have same scores in spite of the population clusters in the two systems have different absolute distance

TABLE 4.2: Results from the simulated System 3 and 4

System	**2SFCA, E2SFCA, KD2SFCA, 3SFCA methods**						
	$A_i(x)$	**O(x)**	$A_i(y)$	**O(y)**	$A_i(z)$	**O(z)**	**Total Opportunities**
3	0.0667	6.67	0.0667	6.67	0.0667	6.67	20
4	0.0667	6.67	0.0667	6.67	0.0667	6.67	20
	M2SFCA method						
3	0.0467	4.67	0.0467	4.67	0.0467	4.67	14.1
4	0.0133	1.33	0.0133	1.33	0.0133	1.33	3.99

weights. Only the M2SFCA method produced a different accessibility scores between the two systems whereby the accessibility value decreases with the increase in the distance between the locations of the provider and population cluster. Furthermore, in

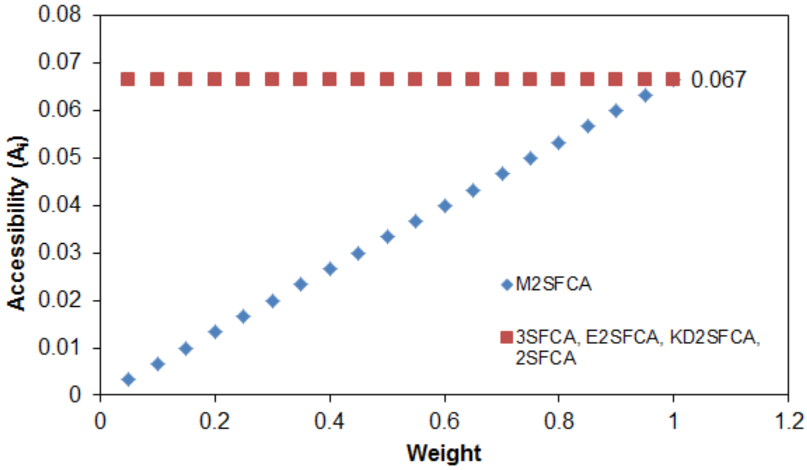


FIGURE 4.24: Accessibility outcome w.r.t weights for different FCA methods

the case of the 2SFCA, E2SFCA, KD2SFCA and 3SFCA methods, the total opportunities are completely preserved and relatively distributed in accordance to the weighting values associated with the population clusters. For instance, the total opportunities available (20) in both the systems were equally distributed to all three population units as their relative weights are same irrespective of the difference in the absolute weights between the two system.

On the contrary, the M2SFCA method only distributed some available opportunities which also decreased with the increase in the distance between the location of a provider and population cluster. This indicates that the 2SFCA, E2SFCA, KD2SFCA and 3SFCA metric system evaluates accessibility by considering the full optimality condition of the configuration system where all the entities (both service centres and population clusters) are collocated at a single point (Delamater, 2013). However, in the real-world scenario, it is very unlikely that the locations of the service providers and populations are optimally configured due to both relative and absolute distance separation between various entities within the healthcare delivery system. Consequently, there is a possibility of over-estimating the accessibility values as in System 4, where the accessibility values of its population clusters are same as the accessibility values of clusters in System 3 although the absolute distance separation between providers and population clusters in System 4 is larger than in System 3. Such over-estimation effect associated with the 2SFCA, E2SFCA, KD2SFCA and 3SFCA methods is of great concern especially for regions with sub-optimal configuration of the service providers and the population clusters (Delamater, 2013). Moreover, the real world data configuration usually portrays highly sub-optimal conditions because of the availability of multiple providers providing services to multiple locations of populations.

4.4.2 Problem of the M2SFCA model

From a theoretical perspective, the M2SFCA model appears to be more mathematically robust than other FCA models. However, there is one issue with the M2SFCA model with respect to its weighting mechanism. Since it uses the same weighting function twice to normalize the accessibility score of a population cluster, the unwanted consequence of such multiplication by the square of a weighting value is that the accessibility scores increasingly deflate as a function of distance. This effect is referred to, in this study, as the small number squaring bias. For instance, consider two accessibility scores of 0.3 and 0.03, which indicate that the first value is ten times larger than the second value. On weighting these values respectively by their individual scores, the resulting scores are 0.09 and 0.0009 respectively. The new ratio between the two scores is 100, which is ten times larger than the original ratio. Similarly, the M2SFCA model introduces unwanted small number squaring bias, which increasingly deflates the accessibility score of a population cluster with the increase of the distance from the service centre. This deflation effect causes underestimation of accessibility scores for the lowest ranked population clusters thereby inflating the differences between the lowest and highest accessibility ranked population clusters within the study region. Hence, the accessibility outcome between population clusters cannot be reliably juxtaposed.

An illustration of the small number squaring bias in the M2SFCA model can be demonstrated using a fictitious provider-population configuration system, System 5, which is shown in Figure 4.25. Consider a system with two health service centres with 20 providers each and six different locations of population clusters with 100 people in each cluster. Points 2 to 5 are fixed while Point 1 is moved incrementally towards the health centres. Point 1 is located equidistance from both the service centres, so the distance weights of Point 1 to both the service centres are same. As the distance between Point 1 and the service centres decreases, the corresponding weights increases in accordance with a decay function, the exponential function was used in this study. At each new location of Point 1, the M2SFCA-based accessibility score for all of the population clusters were computed.

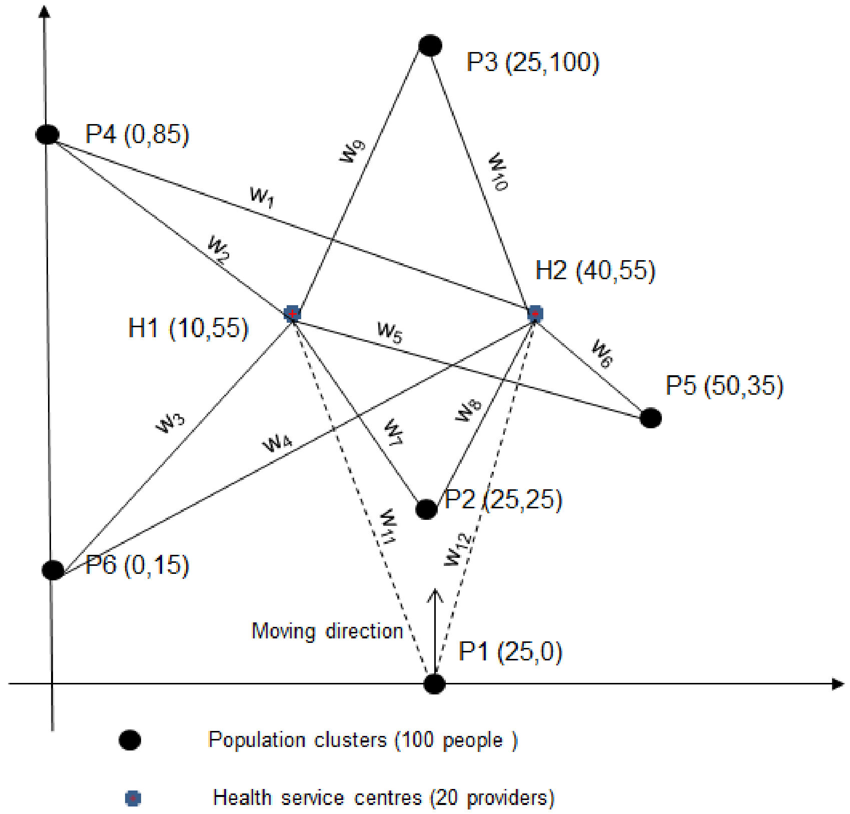


FIGURE 4.25: Provider-population configuration system (System 5)

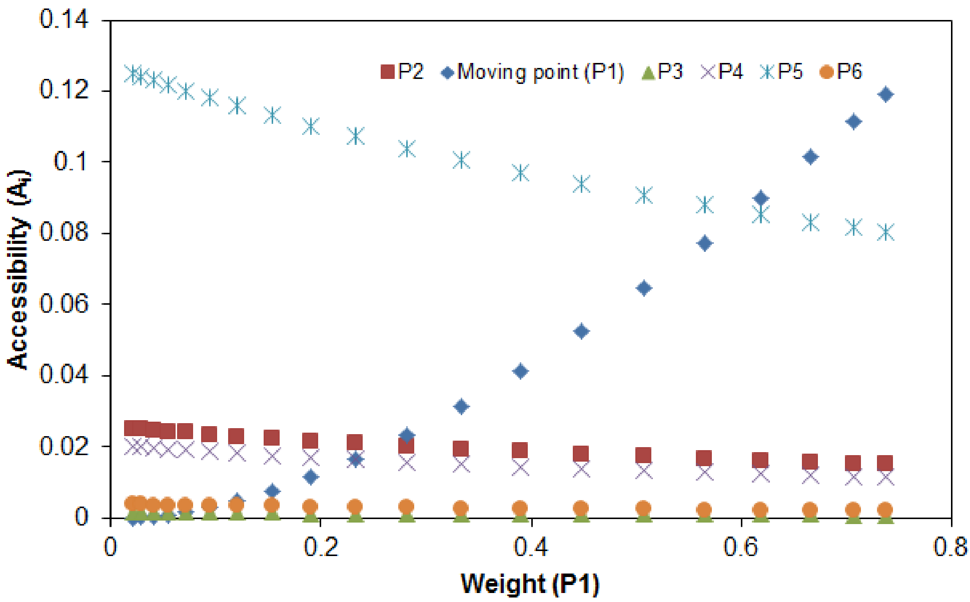
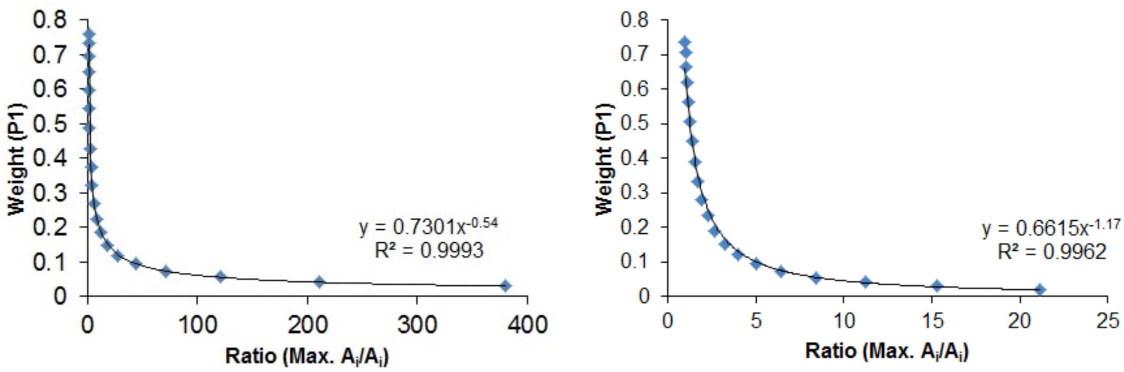


FIGURE 4.26: M2SFCA accessibility scores for System 5

Figure 4.26 shows the plot of the M2SFCA-based accessibility scores of Point 1 to Point 6 with respect to distance weight between Point 1 and service centres. As expected, the accessibility score of Point 1 increases rapidly with the decrease of the distance between its location and the health centres and accessibility scores of Point 2 to 5 decreases at a slower rate than the accessibility score of Point 1. The ratio between the accessibility scores at the first location and the last location of Point 1 cluster is about 380 which indicates that the highest ranked region is about 380 times having better accessibility than the lowest ranked region. This ratio value is so large that it cannot be intuitively or meaningfully interpreted to reflect the actual scenario of provider-population configuration in System 5. Figure 4.27(a) shows all the ratio values between the accessibility score of Point 1 at the final position and other locations. These ratio values can be precisely fitted with an inverse power function, which indicate that the ratio values between the highest and other scores considerably increase with the increase in the distance between Point 1 and service centres.



(a) M2SFCA (b) E2SFCA

FIGURE 4.27: Accessibility ratio versus distance weights of Point 1

In this scenario, only the distance between Point 1 and the service centres were changed. Therefore, only the second weighting parameter in the M2SFCA model could have influenced the accessibility score of the population clusters. If this weighting parameter is removed then no such inflation of accessibility ratio between the highest and smallest scores is observed which can be demonstrated by computing the E2SFCA-based accessibility scores. Figures 4.28 and 4.27(b) show the accessibility scores and ratios between the highest and other scores obtained from the E2SFCA model, respectively. The highest ratio is only about 21 which is a very acceptable outcome when compared with the highest ratio value of 380 for the M2SFCA model. Therefore, it is ascertained

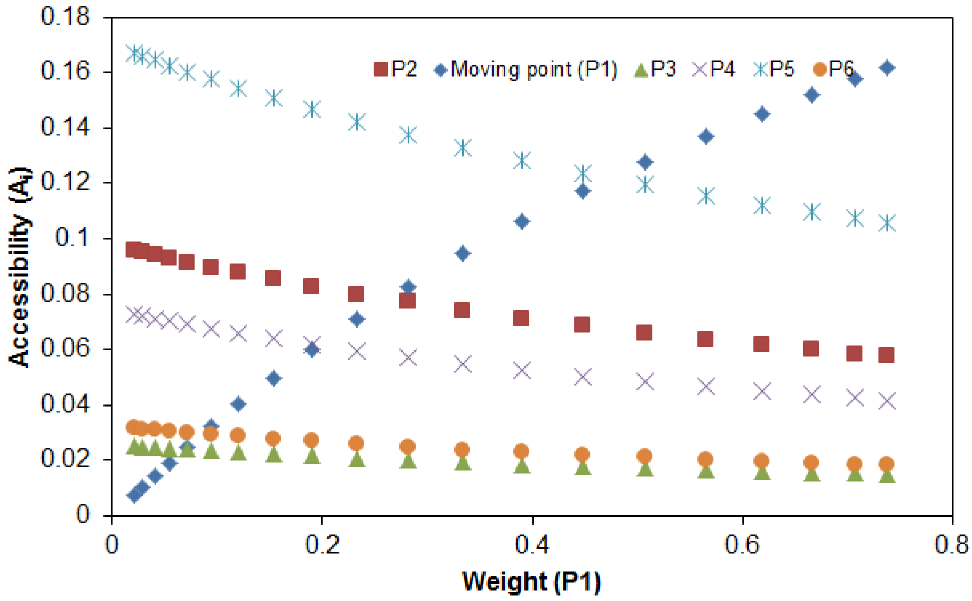


FIGURE 4.28: E2SFCA accessibility scores for System 5

from the test that the large value of accessibility ratio between the highest and lowest accessibility scores for the M2SFCA model is caused by the small number squaring bias rather than by actual differences in accessibility between regions. Such computational bias in the M2SFCA model limits its usage for practical application because of the high possibility of misinterpreting the accessibility outcome.

4.4.3 AM2SFCA model

The problem of underestimation of accessibility score for the poorly served regions or the problem of inflation of differences in accessibility ratios between the largest and the lowest accessibility scores due to the M2SFCA method can be solved by modifying one of the weighting variable, $f(d_{ij})$, in Equation 2.13. For the purposes of clarity, the two weighting variables in the numerator of the M2SFCA model will be referred for clarity sake as the first and second weighting functions. In the M2SFCA model, both the first and second weighting parameter values are derived from the same distance decay function. Instead of using the same decay function, a different second decay function is proposed with a slower decaying rate than the first function. The proposed AM2SFCA model is given by

$$A_i^a = \sum_{j=1}^{n} \frac{S_j W_{ij} G_{ij}}{\sum_{i=1}^{m} P_i W_{kj}}, \tag{4.9}$$

where W_{ij} and W_{kj} values are derived from the first distance decay function, $f(d)$, G_{ij} is derived from a second distance decay function, $g(d)$, and all other variables remain the same as in Equation 2.13.

The second weighting parameter has to balance the effect of normalization on the accessibility scores by preserving the same or minimal increase or decrease in weighting value for population clusters located closer to the service centre and by drastically increasing the weighting value for population clusters located farther away from the service centre when compared to the corresponding weighting values obtained from the first distance decay function. One such second function can be achieved by using a similar function to the first function with its decaying rate decreasing slower than the first function such that the distance weight for the longer distances are several times higher than the value obtained from the first function.

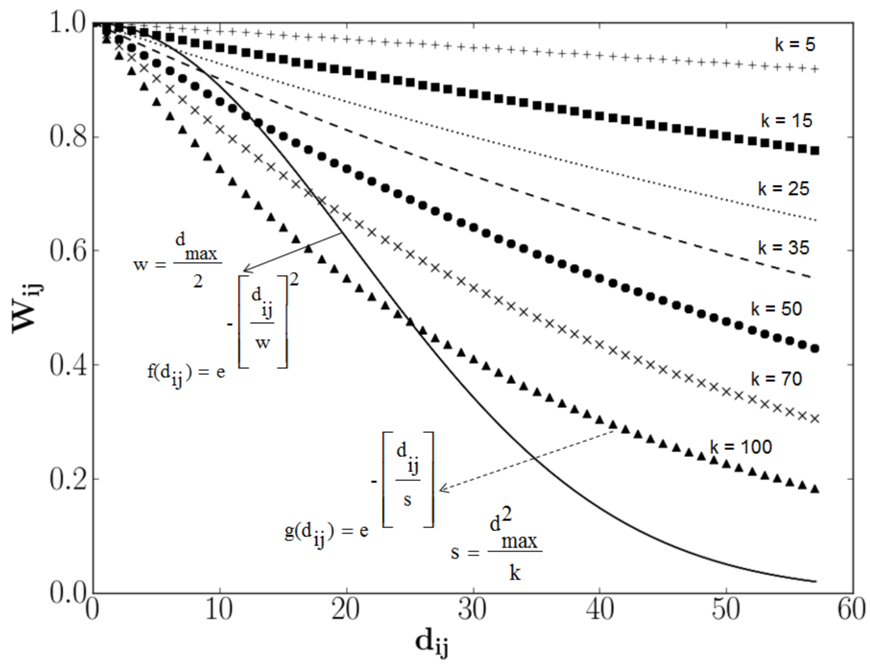
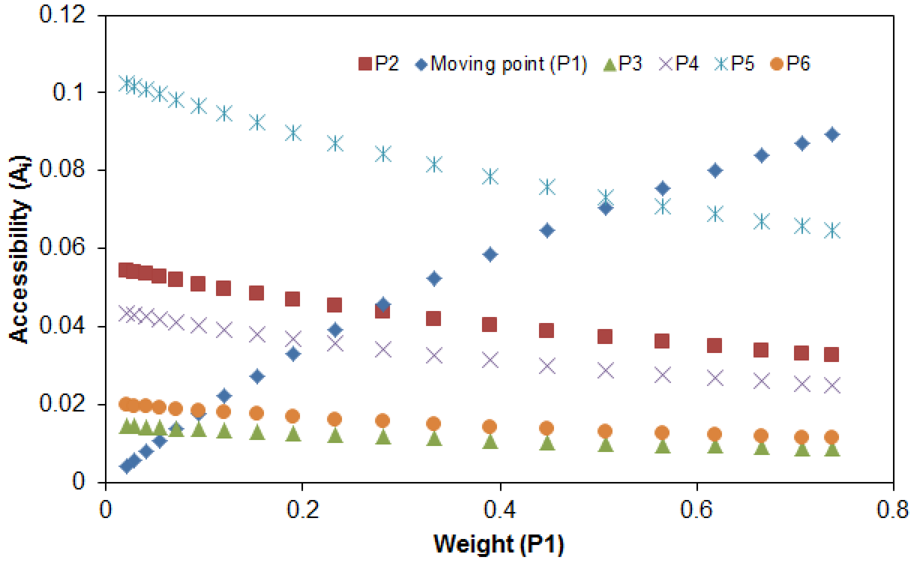
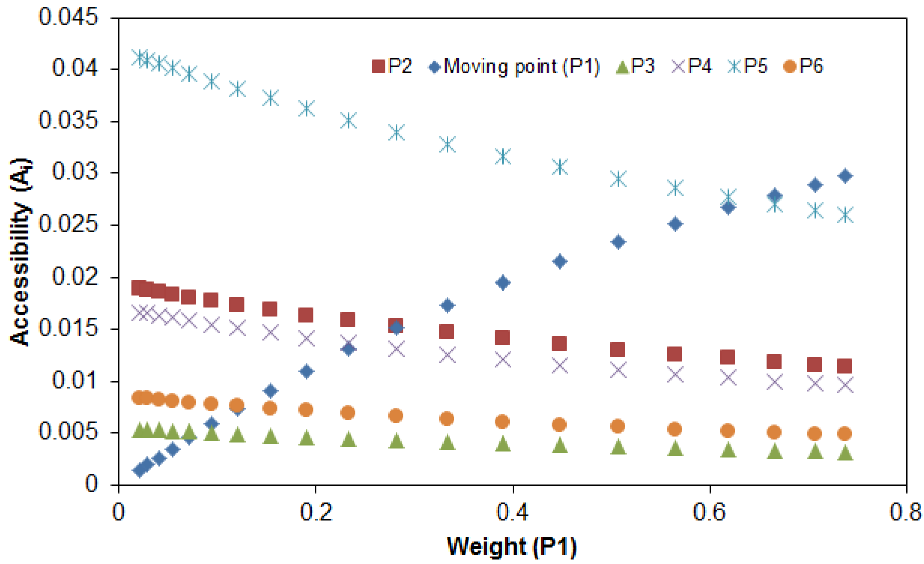


FIGURE 4.29: An example of first and second weighting functions

Figure 4.29 shows an example of the first decay function and several options for the second decay function that were both defined using the Gaussian function. The example



(a) $k = 35$ in $g(d_{ij})$



(b) $k = 100$ in $g(d_{ij})$

FIGURE 4.30: AM2SFCA scores obtained using different second weighting functions for System 5

of a provider-population configuration system of System 5 is used to test the accessibility outcome from the AM2SFCA model. A range of k values from 5 to 100 for the second decay function can be used for the AM2SFCA method. Figures 4.30(a) and 4.30(b) show the accessibility scores of points P1 to P6 for a k value of 35 and 100, respectively. It was observed that the only difference in the accessibility scores between second decay functions with different k values is the magnitude of their absolute accessibility value, which was seen to be gradually decreasing with the increase of the k value. The result of the M2SFCA method for System 5 has been presented in Section 4.4.2. Like the accessibility outcome from the M2SFCA method, the AM2SFCA method also produces logical and consistent accessibility values such that the actual total opportunities available within the system is always less than the available opportunities. In System 5, there are a total of 40 service providers. Owing to the costs incurred by distance separation between providers and populations, the actual opportunities available in the system is less than 40. For all k values of the second weighting function, the actual total opportunities available are all less than 40 and decrease with the increase of the k value. Figure 4.31 shows the actual

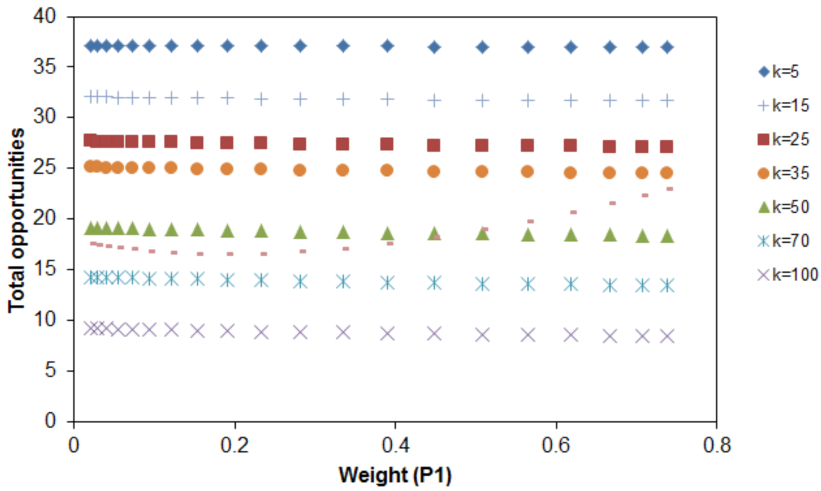
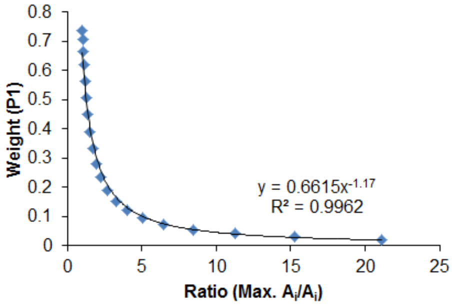
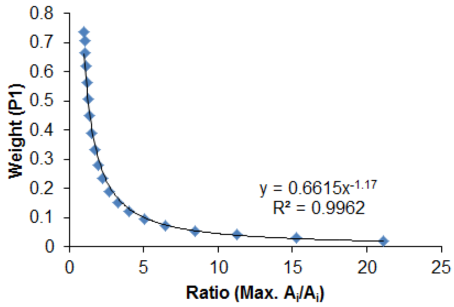


FIGURE 4.31: Actual total opportunities available in System 5 using different second weighting functions

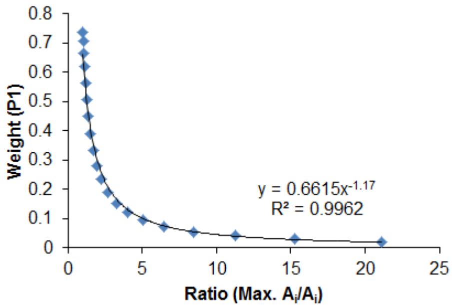
total opportunities computed at each location of moving Point 1 for all different second weighting functions used in the AM2SFCA method. On the other hand, the accessibility ratios between the highest score and other scores of Point 1 for all k values were exactly same with the highest ratio of about 21 which is very much comparable with the ratio outcome of 16 from the E2SFCA method (see Figure 4.27(b)). Figures 4.32(b) to 4.32(d) show accessibility ratios of four different second weighting function with k values of 15, 35, 70 and 100 respectively. These results indicate that the use of different k values in the second weighting function has no effect on the accessibility ratio outcome. However, the accessibility ratio results do not indicate the efficacy of any of the second decay function with a particular k value.



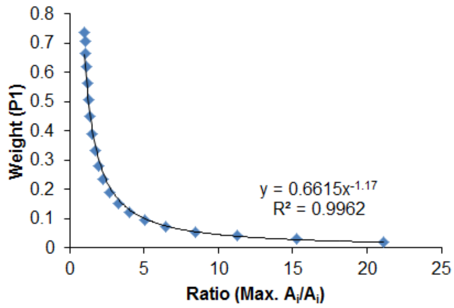
(a) $k = 15$ in $g(d_{ij})$



(b) $k = 35$ in $g(d_{ij})$



(c) $k = 70$ in $g(d_{ij})$



(d) $k = 100$ in $g(d_{ij})$

FIGURE 4.32: Accessibility ratios obtained from the AM2SFCA model using different second weighting functions

In order to further evaluate the efficacy of the M2SFCA and AM2SFCA methods, a fictitious data system with a single service centre surrounded by four population clusters located at equidistance from the service centre was used. Figure 4.33 shows the provider-population configuration in System 6. All the clusters were moved incrementally towards the service centre. At each location of the population clusters, the M2SFCA-based accessibility scores and the AM2SFCA-based scores, using different k values in the second decay function were computed. Figures 4.34 and 4.35 show the absolute accessibility scores and actual total opportunities, respectively, at different locations of population clusters obtained from the M2SFCA and AM2SFCA methods. Since all the population clusters were located equidistant from the sole service centre, their accessibility scores are identical at a particular computational point. Both the figures show a decreasing trend with the increase in the distance of the population clusters from the service centre. It can be observed that the trend for the M2SFCA method linearly decreases towards zero whereas the trend for the AM2SFCA method is non-linear and approaches some constant value other than zero. There are 20 providers available in System 6. Owing to the accessibility costs incurred due to the distance separation between the providers and population, the actual total opportunities

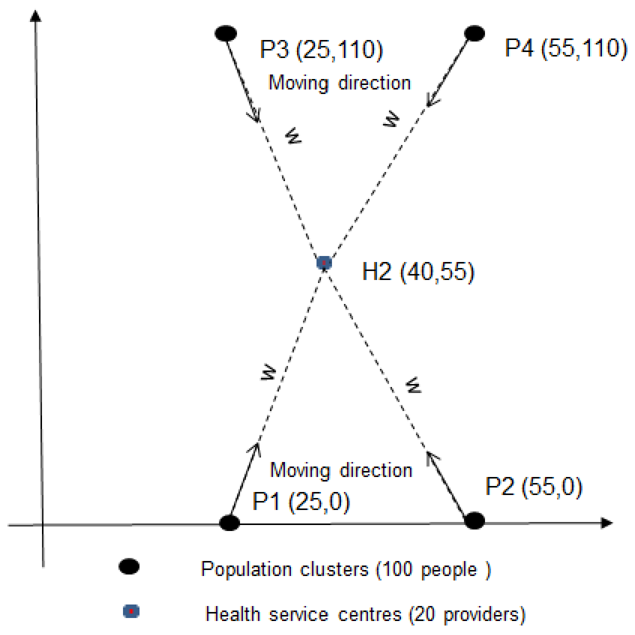


FIGURE 4.33: Provider-population configuration system (System 6)

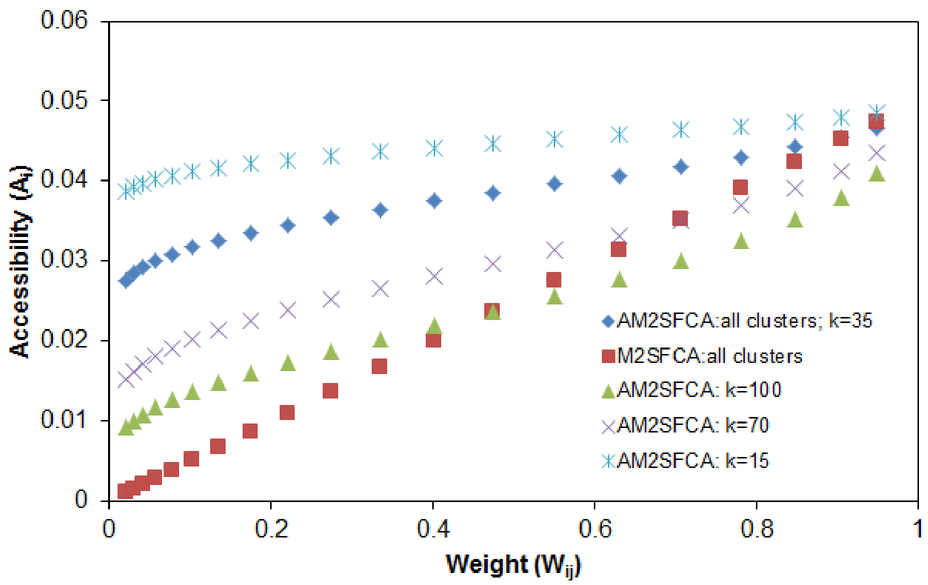


FIGURE 4.34: Accessibility scores between the M2SFCA and AM2SFCA methods for System 6

available in the system is less than 20 for both the M2SFCA and AM2SFCA methods. For all k values of the second decay function within the AM2SFCA method, the actual

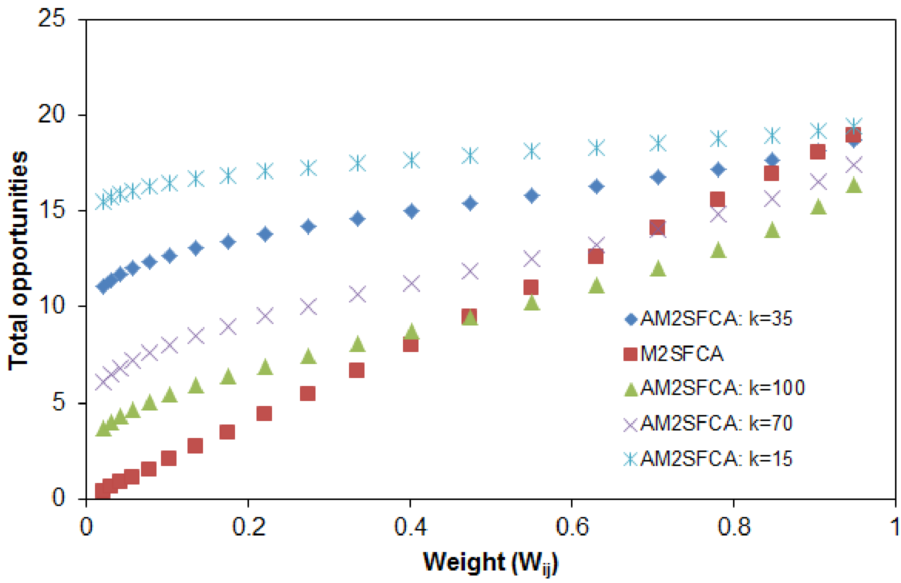


FIGURE 4.35: Total opportunities available in System 6 for different M2SFCA and AM2SFCA methods

total opportunities available are less than 20, which also decrease with the increase of the k value.

Accessibility to any service centres is not just a function of distance but depends on many other factors including both spatial and non-spatial components (Penchansky and Thomas, 1981). Therefore, it is theoretically wrong to consider actual total opportunities available in the system reducing to zero solely based on the accessibility costs due to distance parameter. The total costs incurred by geographic separation should only partially contribute rather than entirely as indicated by the computational outcome of the M2SFCA method. Thus, the M2SFCA method is biased because of the use of the same function for both the first and second weighting parameters. However, all the variants of the AM2SFCA method with different k values only incurred partial costs on accessibility as indicated by the actual total opportunities reducing to some constant value instead of zero which conforms to the theoretical framework underpinning the spatial accessibility model. Nonetheless, the exact identification of the second decay function with a specific k value is hard to determine without knowing the actual costs incurred by different factors affecting accessibility. The second weighting function with k values in the range between 15 to 35 seems logical for use when computing accessibility measures because this range of k values would not cause travel impedance costs to increase rapidly but rather increases slowly and converge to neither a very small value nor a very big value. Therefore, in this study, a k value of 35 was chosen.

4.5 Processing steps

The general processing steps for the computation of spatial accessibility using the NN-AM2SFCA method is shown in Figure 4.36. In Process 1, all folders for districts and subdistricts required for the whole computation processes were created using a standard district and subdistrict names. These names were also used to match the geometric features in the following processing. Process 2 dealt with the computation of distances between the location of a provider and population cluster at the national level. The distances between all possible combinations of origin (provider location) and destination (population cluster location) points were computed and then the first- and second-nearest health facilities of each population clusters were identified based on the straight-line distance measure. Figure 4.37 shows straight-lines and the associated pair between the few provider sites and the population clusters for one of the subdistrict. Population cluster P125 is associated to first- and second-nearest health facilities, H80 and H84 respectively.

Process 3 dealt with the computation of the spatial accessibility measure at the location of population clusters using the proposed computational method. There are two steps in this process. Initially, the service catchment area of each health facility was formed by associating all the population clusters associated to the given facility (j) based on the two-nearest distance condition which was then used to compute the denominator component of Equation 4.9 for both the first- and second-nearest facilities. The accessibility at location i was then computed using Equation 4.9. Process 4 and 5 dealt with the clipping of districts and subdistricts data from the national-level health and population data into respective folders. In Process 6, the subdistrict accessibility indices (G_k) were computed by averaging the accessibility indices of all population clusters falling within the subdistrict (k) using the Equation 4.10,

$$G_k = \frac{\sum_{i=1}^{p} A_i}{q}, \tag{4.10}$$

where A_i is the accessibility value of a population cluster at location i and q represents the number of population clusters within the sub-district, k. Process 7 dealt with the computation of relative accessibility indices (RA_k) for subdistricts. The relative

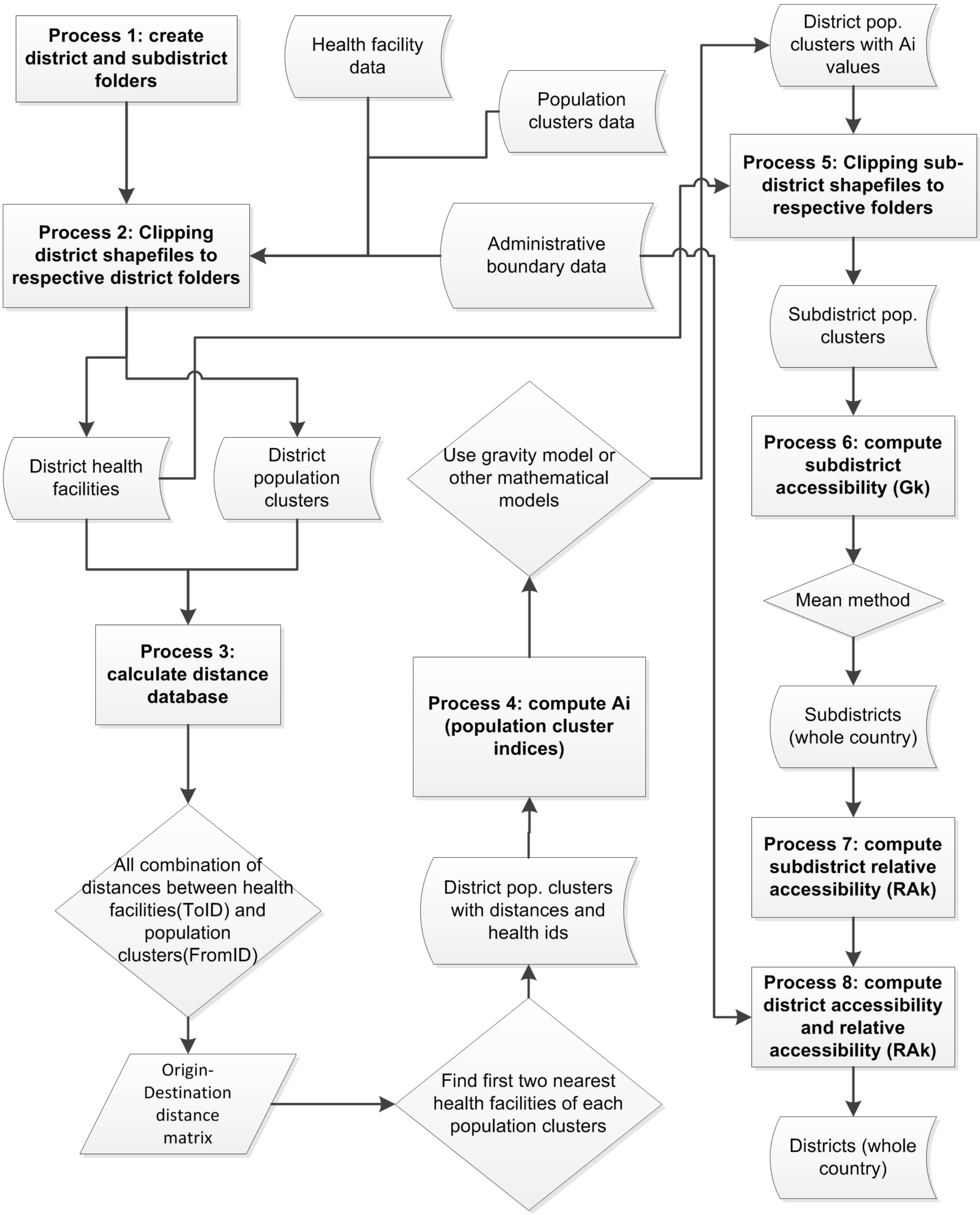


FIGURE 4.36: Processing steps for calculating spatial accessibility values

accessibility values can be computed by,

$$RA_k = \frac{G_k - \min\limits_{k=1,,,,p} G_k}{\max\limits_{k=1,,,,p} G_k - \min\limits_{i=1,,,,p} G_k}, \tag{4.11}$$

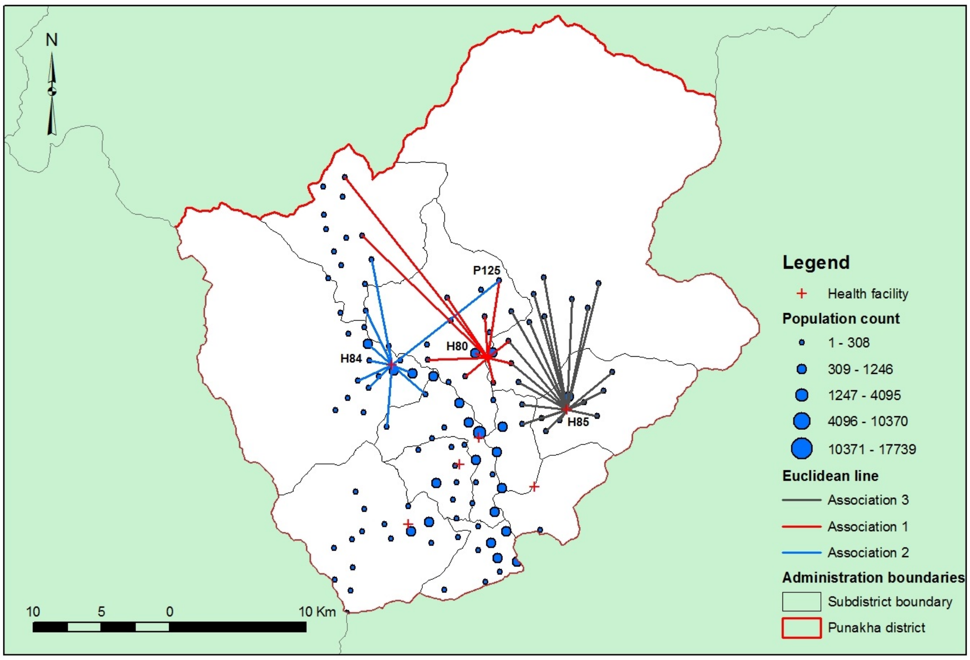


FIGURE 4.37: Health service centres and their associated population clusters

where p is the number of subdistricts within the country. This process ensured that the re-scaled values were between 0 and 1, where 1 refers to the highest health care accessibility score and 0 refers to the lowest accessibility score within the country. The accessibility ranking of the subdistricts were obtained by arranging the relative accessibility values in ascending order. Using the similar method of Process 6 and 7, the absolute and relative accessibility indices of districts were computed in Process 8.

4.6 Summary

There are three important outcomes of this chapter. Firstly, the NN method of delineating service and population catchment areas were presented. Particularly, the advantages of this method over the BR method has been analysed theoretically. Secondly, the NN-M2SFCA was used to calculate accessibility values for eight different distance-decay functions on a simulated data system. The inverse-power function with power value of 0.5 produced the lowest accessibility values followed by the exponential function and the inverse-power function with the power value of 0.2. All the other functions produced accessibility values within close proximity to the values obtained from the control function. As there was no conclusive outcome from the simulated data results, further analysis of different decay functions were conducted using real-world data. Finally, the deficiencies of the existing FCA models were analysed using the simulated data system. Like Delamater (2013), this study found that the M2SFCA method produces more logical and consistent accessibility scores than the 2SFCA, E2SFCA, KD2SFCA and 3SFCA models. However, the M2SFCA method also suffers from the small number squaring bias due to the use of a similar decay function for both the first and second weighting parameters. As the accessibility values are all less than 1, this bias affected more significantly for those underserved regions by deflating accessibility scores when using the M2SFCA method. In order to lessen the effect of such computational bias, the M2SFCA model was augmented by including two separate decay functions with the second decay function having a slower decay rate than the first function. The simulated data processing results indicate that the AM2SFCA method would substantially reduce the differences in accessibility ratio between the highest and the lowest scores within a given region thereby facilitating a realistic comparison of accessibility rankings between different regions. More results and analysis between the M2SFCA and AM2SFCA methods are presented in Chapter 6.

Chapter 5

Data Processing

This chapter describes the data processing aspects of calculating spatial accessibility indices using an open-source GIS application system. In order to deploy the proposed health accessibility measurement system at the regional level, it is very important to develop a standalone map-based software application so that the health planners at the district and subdistrict level can readily use the system during the planning process. It is crucial to develop an open source GIS-based system as the local health organizations in developing countries are unable to procure expensive proprietary software due to budget constraints. A geographical information system can be used to develop a health accessibility planning support system (HAPSS) for aiding planning of allocation of health resources across the country.

Section 5.1 presents a brief review of open-source GIS systems. Section 5.2 presents a framework for the health accessibility planning support system. Sections 5.3, 5.4 and 5.5 describe the functional specification, technical specification and graphical user interface (GUI) of the HAPSS software application.

5.1 Review of free and open source GIS applications and libraries

Any commonly used proprietary GIS system such as ArcGIS and MapInfo can be used to build spatial health accessibility plug-ins or extensions using any of the supported programming languages such as python, .NET, C/C++ and java. However, these systems are very costly. In developing countries most peripheral health institutions will not have the budget to procure proprietary software. Therefore, it is of paramount importance to develop a GIS-based system using open-source libraries and platforms to facilitate the use of the proposed spatial health accessibility measurement system.

Free software is technically referred to software that a user can use for any purpose, copy and share with others, study and change as needed, and modify or improve by accessing the source codes (Free Software Foundation, 2014). Often free software is exclusively referred to as free and open source software. There are many free GIS-based systems available online such as GRASS (GRASS Development Team, 2014), Qantum GIS (QGIS Development Team, 2014), MapWindow GIS (MapWindow Development Team, 2014), uDig (uDig Development Team, 2014), JUMP (JUMP Development Team, 2014), etc. These desktop GIS applications commonly support storage and management of spatial data, manipulation and analysis of the data and visualization of the spatial product. The productivity and efficiency of free software depends on the level of documentation, modularity of the source codes, diverse composition and transparency of the development team and the user base (Ramsey, 2007). Quantum GIS is technically the most successful free GIS desktop software because its GUI is very much user-friendly, it includes a comprehensive set of spatial processing tools, it can facilitate modular customizations using simple programming languages such as Python scripting, and it can be run on different operating system like Windows, Linux, Unix and Android.

Free GIS software can be loosely classified into different groups based on the use of programming language for their development (Ramsey, 2007). For instance, the C/C++ group includes GRASS, Mapserver, PostGIS, QGIS and etcetera. The Java group consist of software such as GeoTools, uDig, gvSig, GeoServer, JUMP, etc. The .Net group include software such as WorldWind, SharpMap, MapWindow and etcetera. The Web group includes OpenLayers, MapBuilder, Geoserver, etc. By combining a number of these free software applications, it is possible to build a comprehensive GIS-based system as an alternative to standard proprietary software.

The core components of most free GIS applications are the shared libraries. Figure 5.1 shows some of the shared libraries used by different applications. For instance, the Java group applications uses GeoTools and the JTS library and the C group uses GEOS, Proj4, FDO, OGR/GDAL, etc. and the .Net group uses Proj4.Net, JTS and a wrapped version of the GDAL/OGR libraries to build basic spatial functionalities such as representation of geometries, conversion of data formats, coordinate projection and topological computations. All these shared libraries are freely available in the public domain. A more detailed description of these libraries and applications can be found in Ramsey (2007) and the various web sites.

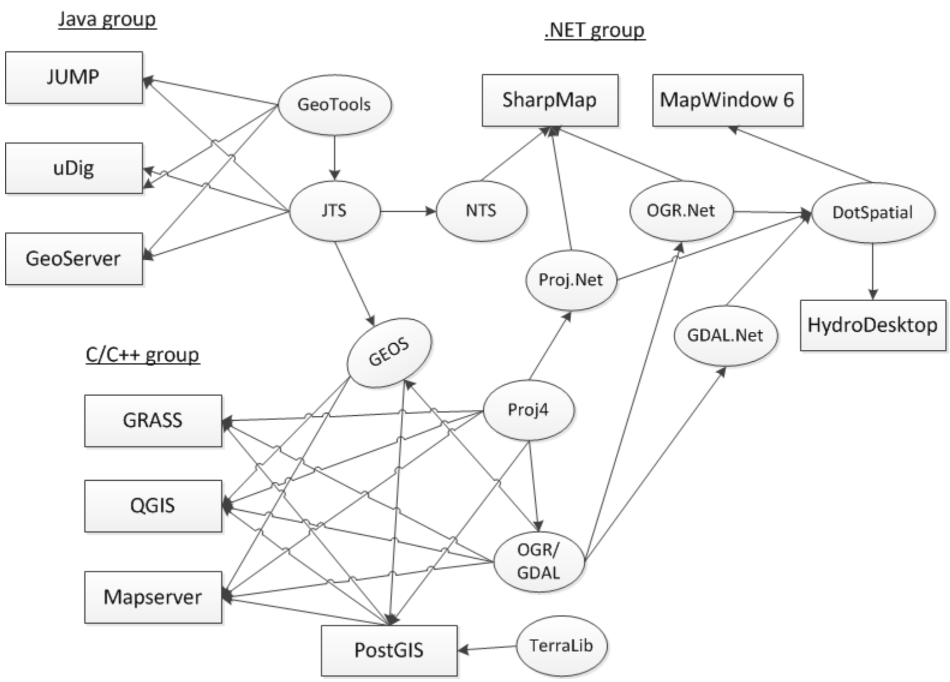


FIGURE 5.1: Use of shared libraries for developing GIS applications

Free and open source GIS applications may have large numbers of GIS tools for various applications, yet the usage of these free software are generally confined to expert GIS users because of the unavailability of basic GIS tools in any one system and the complexity in using these tools as compared to most proprietary systems. For instance, the ArcGIS system has almost all the basic GIS tools available in one package which are arranged systematically and can be implemented by a novice GIS user with ease. On the one hand, a novice user may find it hard to locate a simple manipulation tool in QGIS or other free software as most of the functionalities are available as open source modular extensions which are often more difficult to implement too. On the other hand, an advanced GIS user may benefit more using open source software due to the availability of a large number of specialized modelling tools which can be modified using the source code as desired. One convenient aspect of the proprietary systems is the availability of a wide variety of printing and visualization tools for producing high quality maps often lacking in most of the free GIS software system. The major advantage of the free software is that it is freely available online from sources such as SourceForge.net, CodePlex.com, etc.

Any of the aforementioned free desktop applications can be used for developing a GIS functionality or tool for the desired project depending on the preference of the programming language and availability of existing spatial and modelling tools. For landscape ecological applications, GRASS software is predominantly used because of the availability of large number of landscape modelling tools (Ramsey, 2007). Microsoft .NET programmers tend to choose the framework of MapWindow or HydroDesktop to build a GIS applications, which has been adopted for this study.

MapWindow is a free and open source GIS application written in C#.NET using DotSpatial libraries. It is a GUI based application which has basic GIS functionalities to create, display and manipulate spatial data. Either by using a MapWindow desktop framework or by using the DotSpatial libraries, it is possible to build customized GIS applications. DotSpatial libraries are written in C#.NET for .NET 4.0 framework which can then be used to build a GIS desktop. There are fourteen major DotSpatial library packages (Table B.9 in Appendix B) which support the design of the GIS application framework. One such customization is the HydroDesktop, which deals with searching, downloading, visualizing and analysing of hydrologic and climatic data obtained from the online data centers (Ames et al., 2012). The HydroDesktop application has used a number of APIs (Application Programming Interfaces) besides DotSpatial assemblies to construct a comprehensive standalone GIS system for retrieving data from the clearinghouses using a robust search algorithm. It also provides an interface to analyse data using other programming tools like R and Matlab within the system. Other important components include a Graph module which is developed using the Zed Graph package. The GUI of the HydroDesktop is designed by using core DotSpatial libraries in a plugin architectural setup with extensible ribbon-style menus, a legend or time series window and application windows (Map, Graph, Table, Edit) configured in a tabbed interface with movable and dockable panels (Ames et al., 2012). Figure 5.2 shows the different design components of GUI of a DotSpatial-based application. Because of the presence of many functionalities in HydroDesktop, this open source software was chosen as the framework to build the HAPSS for Bhutan. The customization of the HydroDesktop to HAPSS can be done by building specific plugins needed for the later system and by removing the redundant tools and extensions from the HydroDesktop framework.

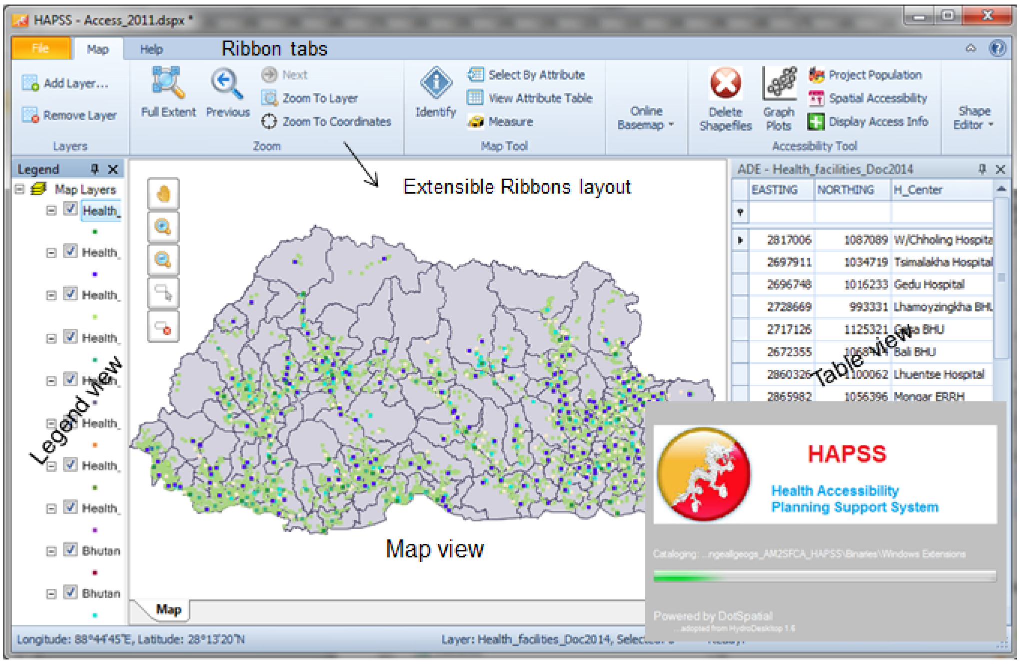


FIGURE 5.2: GUI of the HAPSS

5.2 HAPSS framework

Planning support systems (PSS) are defined as integrated computer systems specifically used for supporting planning processes (Harris and Batty, 1993), information technologies that are used by planners to undertake their planning responsibilities (Klosterman, 1997, 1999) or integrated technologies with a common interface to specifically support the whole or part of a unique planning task (Geertman and Stillwell, 2003). According to Harris and Batty (1993), PSSs are formed by combining three components of the planning process. To begin with, the PSS specifies the problems for which planning aims to resolve. Next, it incorporates system models which are used to aid the planning process through analysis, prediction and prescription. Finally, it transforms primary data into information which can be used to drive the modelling and design of the planning process. Some of the characteristics of a PSS are shown in Figure 5.3. These are capable of managing both spatial and non-spatial data including analysis of such data, both spatially and temporally. They also have a simple and interactive graphical user interface which can be readily used by non-technical personnel such as the planners and policy makers for spatial data modelling and analysis, report generation and data visualization. They need to have the capacity to formulate plans, build scenarios and conduct scenarios evaluation for aiding the recursive decision-making process. In addition, they may offer avenues in

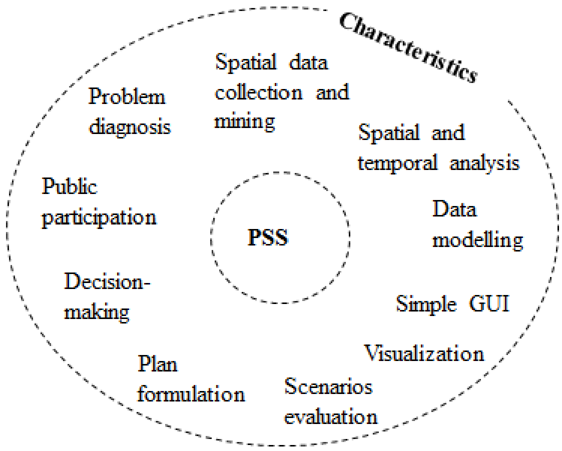


FIGURE 5.3: PSS characteristics

supporting public participation. There is little difference technically between PSS and SDSS (Spatial Decision Support System) except that the former is specifically dedicated to long-term and strategic planning activities (Geertman and Stillwell, 2003). GIS is an integral part of both PSS and SDSS, which provide the capability to capture, manage, analyse, process and visualize spatial data to transform basic data into useful information.

The health planners and policy-makers in Bhutan are faced with the semi or ill-structured decision problems in allocating health resources equitably across the country. The standard approach of decision-making in establishing new health centres is at best done through public consultation. This decision-making process is often mired in controversy due to personal favouritism and nepotism. Even the allocation of health care providers is carried out by assessing written requests made by respective health centres. In the absence of evidence-based approach to decision-making, it is possible that the establishment of a new health centre or allocation of health care providers in one region can potentially leave another region with greater need. Therefore, it is vital to supplement the current decision-making process by developing a PSS to aid long-term strategic planning activities and to provide a check and balance mechanism for management of health resources by decision-makers. The HAPSS is proposed for Bhutan, which can be used by the planners and health resources personnel to plan for the establishment of a new health centre and allocation of health care providers – by conducting 'what if' scenario analysis. A simple framework for the HAPSS was designed by incorporating data and model management systems within a shared graphical user interface as shown in Figure 5.4. Using this basic framework, the HAPSS was developed by customizing the HydroDesktop 1.6 system using C#.Net in Visual Studio 2013.

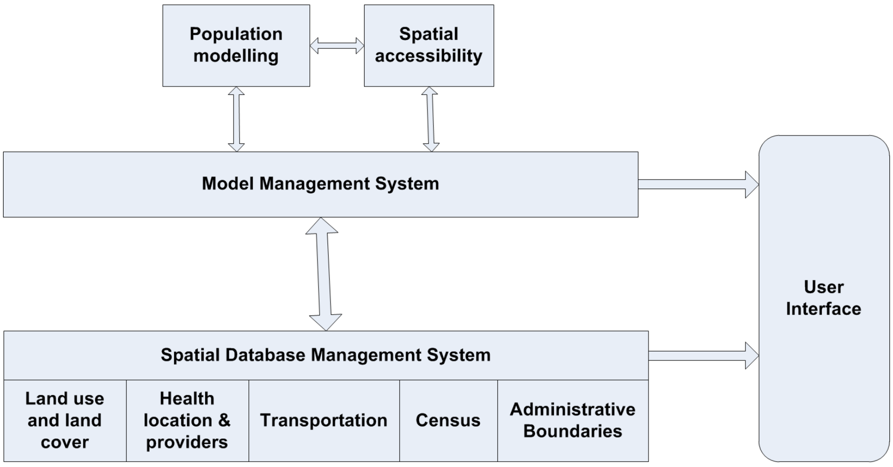


FIGURE 5.4: HAPSS framework

5.3 Functional specification of the software

A desktop GIS system needs basic functionality to create, view, edit and store geometric data objects as shapefiles which is the most commonly used data type in the GIS world. In addition, the desktop GIS must include basic layout, design and printing of maps. Most of these GIS functionalities are included in the HydroDesktop system as an independent plugin or embedded with some other modules. In cases where general GIS functionalities are embedded with other functionalities, then those functionalities were modified to suit the need of the proposed system. In the absence of some GIS modules, new tools were developed using DotSpatial.Plugins packages, which supports the development of a diverse range of processing tools. For instance, the Measure tool can be implemented by including the DotSpatial.Plugins.Measure package as an independent plugin. This plugin can be used for both linear and areal measurements. Similarly the Shape Editor tool can be implemented using the DotSpatial.Plugins.ShapeEditor package which can be used for editing geometric objects. Other functions of the proposed system can be realized by building independent plugins. As this system is in the initial phase of the development, only the spatial accessibility component is fully built and functional. Figure 5.5 shows the functionalities required for the proposed accessibility system of Bhutan. The main component of the proposed system is the spatial accessibility component which initiates the process of computing spatial accessibility independently for two primary health care providers at different level of spatial aggregation in accordance to the processing framework shown in Figure 4.36. This module has been constructed to independently process the spatial

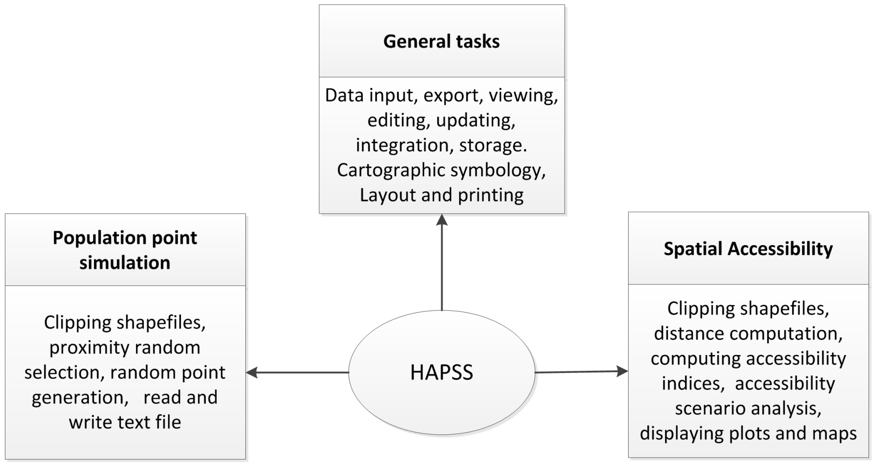


Figure 5.5: Some functionalities required in HAPSS

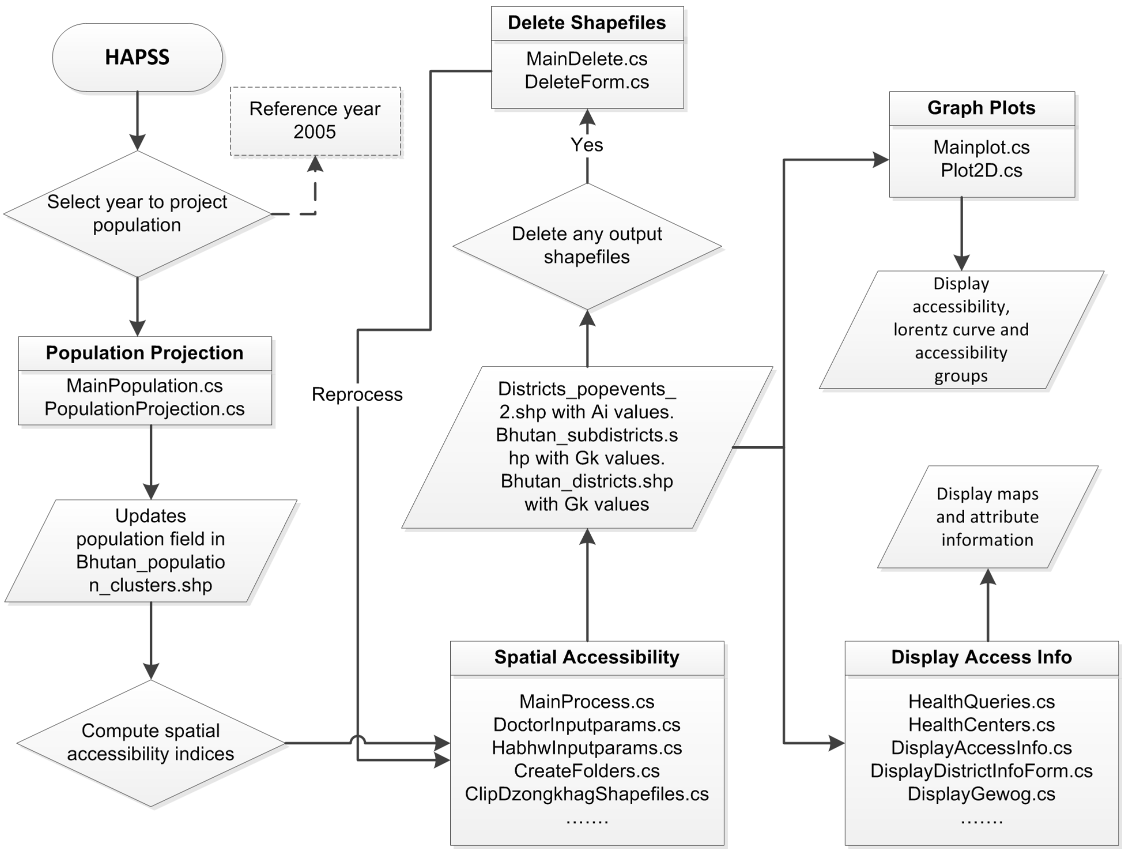


Figure 5.6: Functional relationships between custom-built plugins of the HAPSS

accessibility for one district or all districts simultaneously. The other customised tools in the proposed system include Display Access Info, Population Projection, Graph Plots and Delete Shapefiles ribbon plugins. The Display Access Info plugin is used to display attribute and map information of the health centres, sub-districts and districts. The Population Projection tool estimates population figures of subsequent years based on population of 2005 by using a simple exponential function, which defines the population growth rates in each district. The Graph Plots plugin has been added to plot accessibility values. The Delete Shapefiles plugin was added to delete specific shapefiles simultaneously from subdistricts, districts or national folders as warranted. Figure 5.6 shows the functional relationship between custom-built plugins of the proposed system.

5.4 Technical specification of the software

The technical design of the HAPSS application is very similar to the design of the HydroDesktop 1.6 system as the proposed system is developed by incorporating the main project component plugins of the later system, which were developed using DotSpatial assemblies. Like the HydroDesktop application, the proposed system also accesses the main application through the plugin architecture route using .NET assemblies. All the technical designs and programming was carried out in Visual Studio 2013 system. Figure 5.7 shows the technical components of the HAPSS.

A number of custom-built plugin extensions have been added into the system using plugin architecture technology, which carry out the main functions of the proposed system. The Spatial Accessibility plugin is the main program component of the proposed system which deals with the computation of spatial accessibility. This plugin was built using number of classes and methods as shown in Figure A.4 in Appendix A. Most of the methods involved in this plugin required manipulation of shapefiles which was performed using GDAL (Geospatial Data Abstraction Library) .NET assemblies and the ogr2ogr operation of FWTools (open source GIS binary kit). GDAL assemblies were used to directly access and edit the geometric and attribute properties of the shapefiles. FWTools's ogr2ogr function was used specifically for conducting clipping operations on shapefiles using a single line SQL (Structured Query Language) command. The use of different open source programs was necessary because of the unavailability of specific mapping tools within the DotSpatial domain. Other supporting plugins such as Population Projection, Display Access Info, etc. were developed and added into the system in a similar way. Figure A.3 Appendix A shows the classes and method of the Display Access Info plugin.

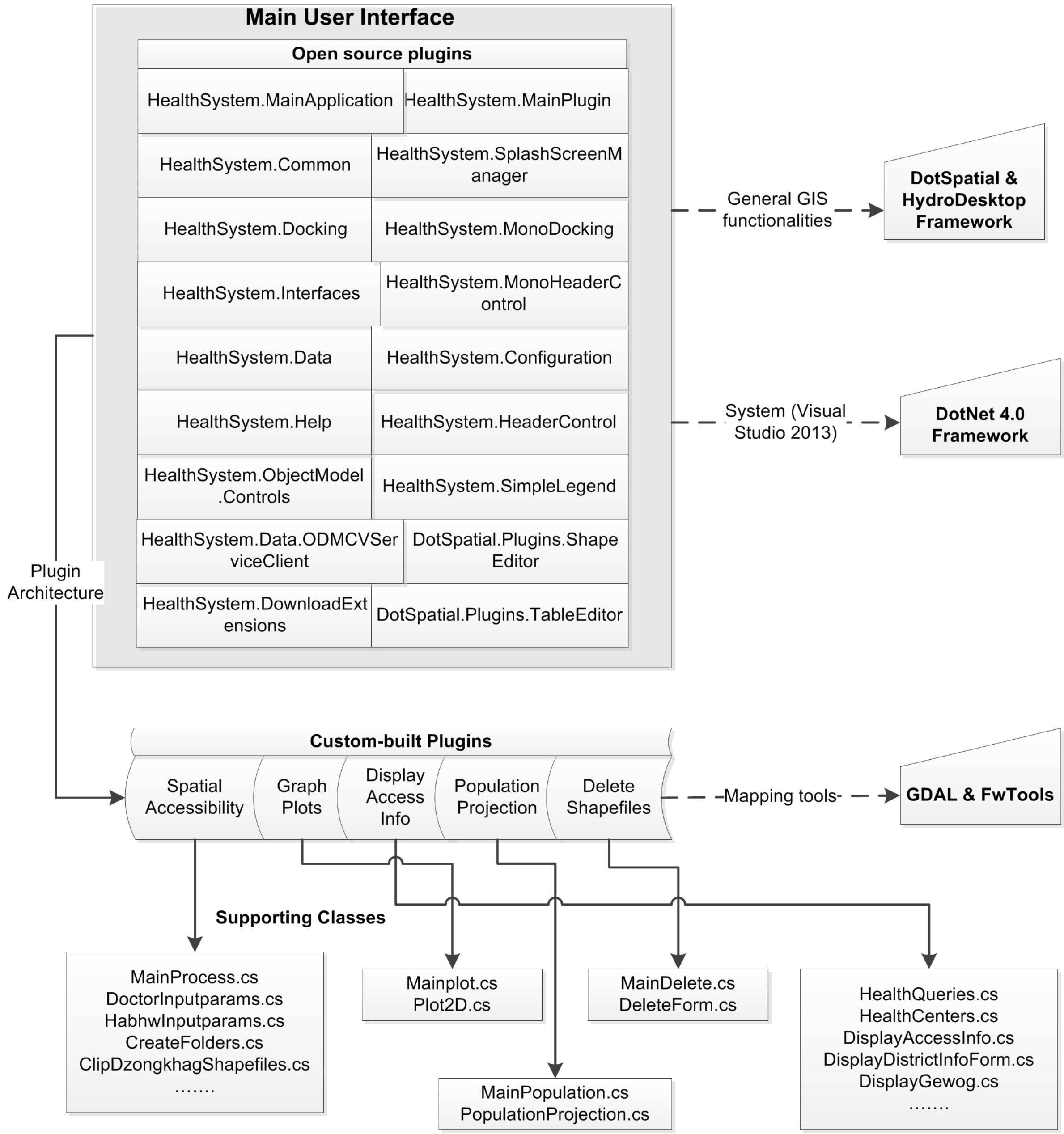


FIGURE 5.7: Program components of the HAPSS application

5.5 GUI design of the software

The GUI design is the most important part of any application development as it is the medium from which application users can interact with the software. The GUI of the HydroDesktop application is like any other desktop applications consisting of forms, ribbon buttons, data grid view controls, labels, command buttons, combo boxes, list boxes, radio-buttons, etc. Even a basic GIS user can immediately get used to this software as its plugins and functionalities are well structured within a simple GUI framework. Similarly, the custom-built plugins for the proposed health planning system were also designed by including user-friendly GUI forms with most processing tasks accomplished by prompting one or two input and selection forms with which the users can interact easily.

The application starts with the display of the welcome screen followed by the selection prompt which asks the user to select default or existing projects. Figure 5.2 shows the welcome screen and the main GUI of the proposed health application system which contains a number of GIS layers used in the computation of the spatial accessibility indices. The extensible ribbons are clustered into a number of groups in accordance to their functionalities. For instance, all the custom-built plugins for the proposed system are grouped under the Accessibility Tool group.

On selecting the ribbon button named Spatial Accessibility, the software will prompt the user with the selection form to choose the type of health care providers followed by the input selection parameters form where a user is required to select an appropriate input for different parameters. The districts, subdistricts, population clusters and health facilities shapefiles used for this processing have to be pre-stored under the project's directory. This data arrangement will create a list of shapefiles available in the root directoy, which can be selected from the drop down combo boxes. The other parameters required for this processing are the file path to the location of the ogr2ogr function of the FWTools application, and the computation method that can be selected from the list available in the drop down combo box. The Process All button initiates the processing which will immediately prompt a progress form that keep tracks of the progress of the processing. This processing takes a few minutes to complete the whole process. Figure 5.8 shows the GUIs involved in the processing of the spatial accessibility indices.

The Display Access Info plugin was developed to assist the users with viewing the health catchment areas and accessibility information at various spatial aggregation levels with the click of a button. This plugin begins by prompting the user to choose either District, National, Subdistrict or Health Center Info buttons. District Info will show the map of the particular district with its accessibility information. National Info will show the accessibility ranking map at the national level for subdistricts and districts aggregation. Subdistrict Info will show the map and accessibility information at the subdistrict level. Health Centre Info will show the population catchment map and other statistics of a particular health centre. Figure 5.9 shows the GUIs and outcomes involved in the selection

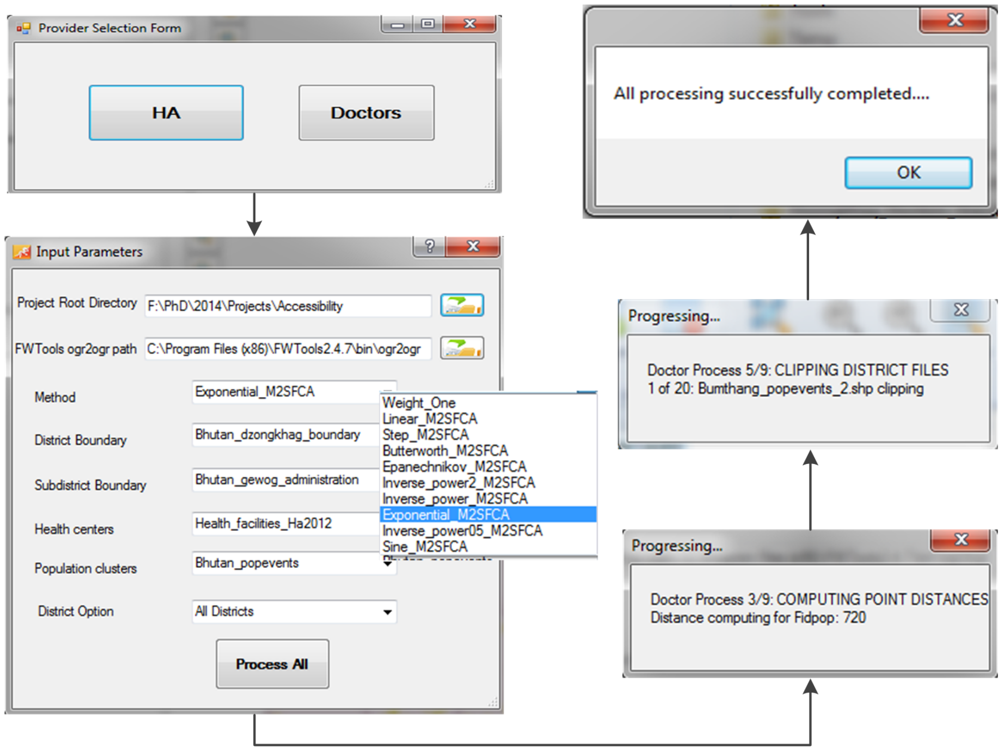


FIGURE 5.8: GUIs involved in Spatial Accessibility plugin

of the Health Centre Info option. The second form in Figure 5.9 enables the user to choose the district and the particular health centre which can be easily selected from the drop down lists. The health centres list is populated based on the facilities available within the selected district. The user can then view the population catchment map for the different providers or view the statistical information of that particular health facility.

The other important supporting plugin in the proposed system is the Graph Plots plugin, which was developed using the ZedGraph C#.NET class library. This library has its own user control to draw points, lines, bar graph and charts. Graph Plots is specifically used in this system to plot the accessibility groups, which are defined by comparing the subdistrict accessibility indices of the existing scenario or scenario in question to the reference scenario. Figure A.5 in Appendix A shows the GUI of the Graph Plots. This process requires the user to select the shapefiles containing subdistricts accessibility at the national level for both the providers and define the file path to the reference shapefiles which is prompted just prior to the display of this GUI. On pressing the Plot 2D command button, this plugin computes the median and mean values of all the scenarios and display the grouping results based on a grouping criteria described in Section 6.6.

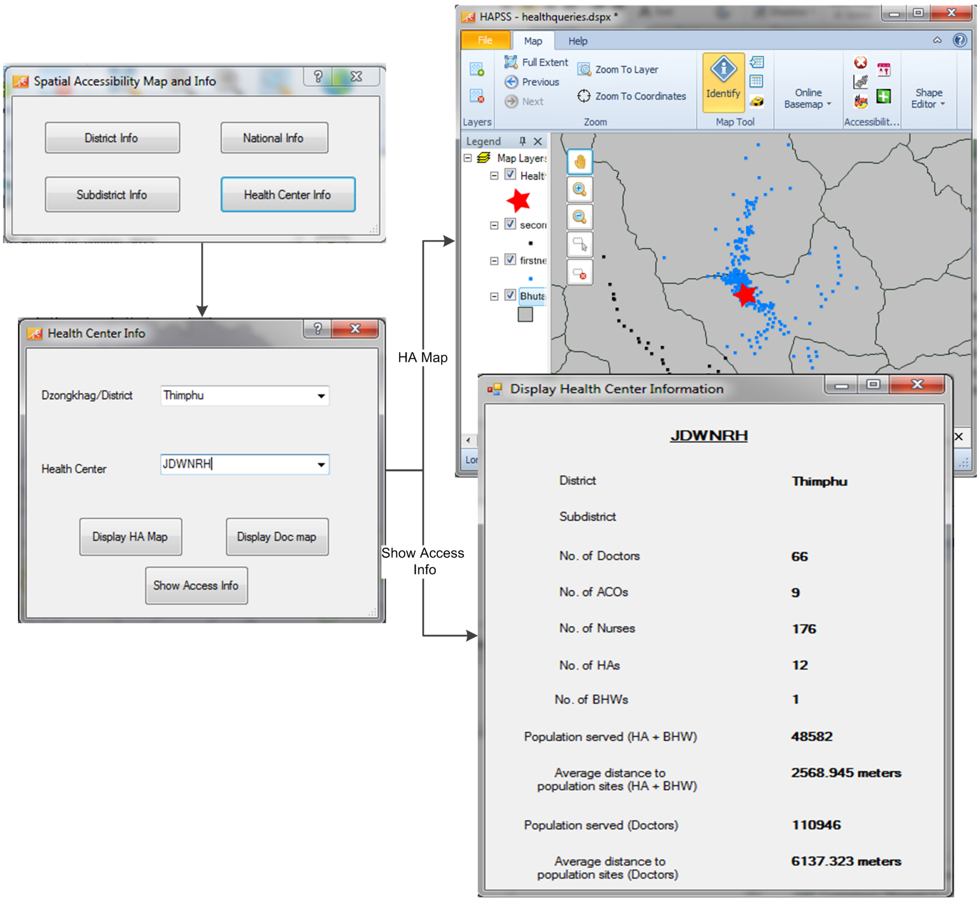


FIGURE 5.9: GUIs involved in Display Access Info plugin

5.6 Summary

An open-source standalone GIS application has been developed as a planning support system to aid health planners and policy-makers in the decision-making process - specifically for the allocation of health resources across the country. The HAPSS can be used for evaluating the distribution of health care providers with respect to population catchment areas of each health centre. It can also be used to evaluate average travelling distances between locations of health service centres and its associated population clusters. Most importantly, this system combines parameters for supply of health care providers, population demand within catchment areas and distance separation between service centres and population clusters using a FCA-based spatial accessibility model to quantify accessibility scores of population clusters, sub-districts and districts.

Chapter 6

Results and Analysis

The data required for the spatial accessibility computation and the population clusters data modelling were presented in detail in Chapter 3. In Chapter 4, the NN-AM2SFCA computational method using a straight-line distance measure and the Gaussian decay function was proposed for computing spatial accessibility to primary health care services. The data processing application system, the HAPSS, was described in Chapter 5. This chapter presents the results obtained from real-world data processing and its analysis in evaluating spatio-temporal changes to spatial accessibility for primary health care services in Bhutan.

Section 6.1 presents the real-world data processing and analysis for the straight-line and travel-time based computational models. Section 6.2 presents the results and analysis for the M2SFCA-based accessibility outcome between different decay functions, Section 6.3 presents the accessibility outcome between different FCA models and Section 6.4 presents the differences in accessibility outcome between the M2SFCA and AM2SFCA methods. Sections 6.5 and 6.6 present the AM2SFCA-based accessibility results and analysis for the individual healthcare providers and combined healthcare providers, respectively. Section 6.7 presents the spatial and temporal changes in spatial accessibility from 2010 to 2013 and Section 6.8 presents the results and analysis of spatial accessibility outcomes for different hypothetical scenarios.

6.1 Comparison between the travel-time and straight-line methods

The NN-M2SFCA model was used to compare the accessibility outcome between the travel-time and straight-line methods. Sections 6.1.1 and 6.1.2 describe the methodology of computing travel-time and straight-line measures between two points, respectively. Either the M2SFCA or the AM2SFCA model can be used for evaluating the differences between the two distance measures. The M2SFCA model was chosen because of its greater ease of computational process over the AM2SFCA model. Section 6.1.3 presents the comparison of accessibility results between these two methods for the Trashigang district.

6.1.1 Travel-time computation method

In the NN method of computing spatial accessibility for Bhutan, the two closest facilities were associated with each of the population clusters. The closest entities can be determined based on a distance or travel-time measure. Travel-time data can be formed by using road and footpath data. As there was no actual footpath data in the study region, the footpath tracks between two points were modelled using the cost-weighted method as described in Section 4.2. Figure 6.1 shows the distribution of road network, health facilities and population clusters in the district of Trashigang.

The transportation network data was built using the ArcGIS 10.2 Network Analyst Extension tool. It is the primary input data for computing the fastest travel-time route between origin and destination points. Figure 6.2 shows the processing steps for computing the fastest route between two points using the Network Analyst tool. In order to evaluate the travel time during the computation of the fastest route, the variable named Minutes in the transportation network data was used to accumulate the total travel time accrued between the two points due to the involvement of mixed travel modes such as main highway (50 Km/hr), farm roads (30 Km/hr) and footpaths (2 Km/hr). The travel time between two nodes of the transportation line segment is given by the ratio between the distance and the speed associated to that line segment. The straight-line distances database was formed by computing all possible combinations between the provider and the population sites. The five shortest distances for all population clusters were then used to determine the fastest route between the associated

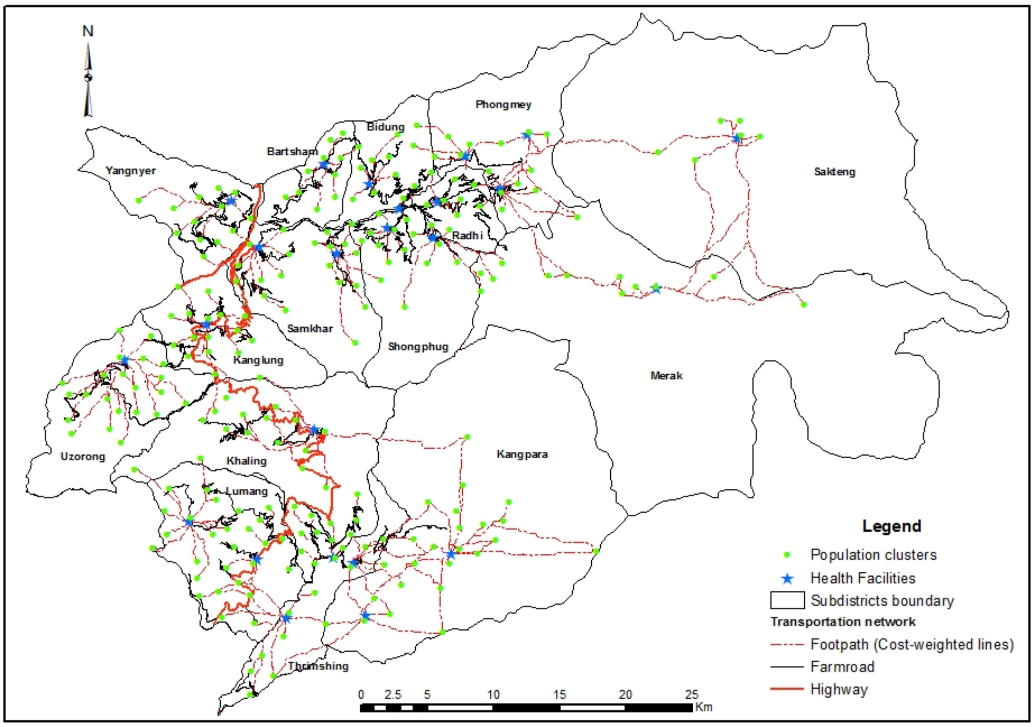


Figure 6.1: Distribution of population clusters, health facilities and transportation network in Trashigang district

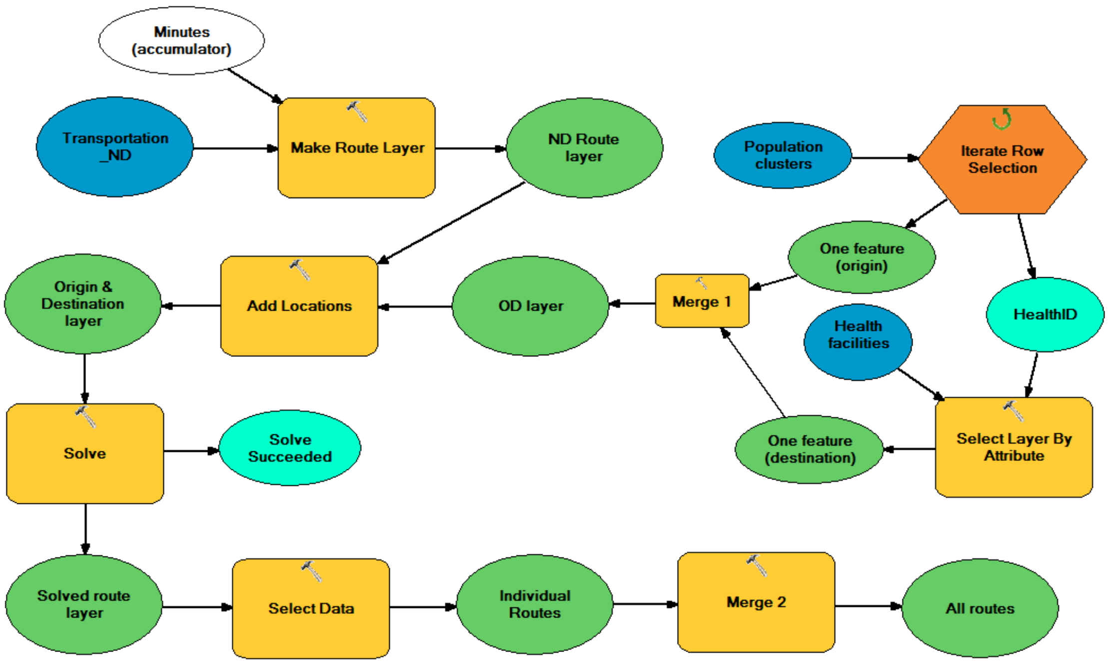


Figure 6.2: Processing steps for solving fastest routes

pairs using the route solver of the Network Analyst tool. All the fastest routes between the provider and population sites were iteratively computed one by one using only the origin (population cluster) and destination (health facility) points which were selected using unique indices stored in the population cluster data. Figure 6.3 shows an example of the fastest route computed for one provider-population pair. All single fastest route layers between associated population cluster and service centres were merged to form a single layer data. This iterative process was repeated for the second to the fifth nearest association data. The two nearest facilities for all population clusters can then be obtained by sorting the five route segments. The use of five route segments was needed in order to accurately define the first two nearest facilities for each population cluster because the first two nearest facilities obtained by comparing just the straight line distances are not necessarily the first two nearest facilities based on travel-time.

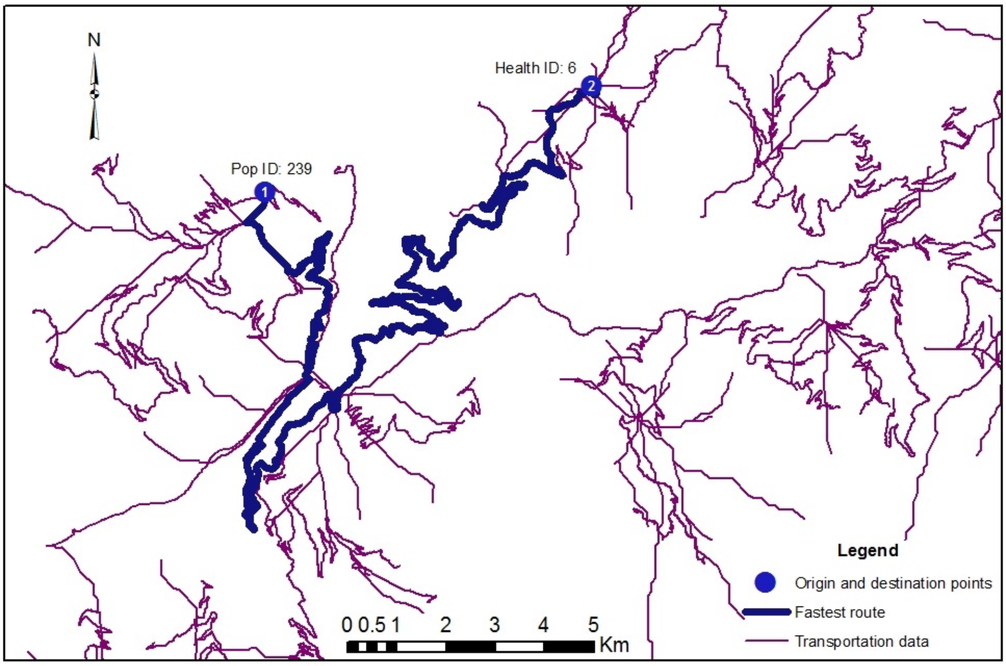


FIGURE 6.3: An example of fastest route between two points

6.1.2 Straight-line distance computation method

The computation of straight-line distances does not require any transportation data as the distance can be directly measured between the origin and the destination point using Equation 4.1. The first two nearest neighbours of each population cluster were identified by computing a straight-line distance between the given population cluster and a number of nearest service centres. Then all these distances were arranged in ascending order to identify the first and second nearest neighbours. Figure 6.4 shows the first two nearest distances lines between all of the provider and population sites in Trashigang district.

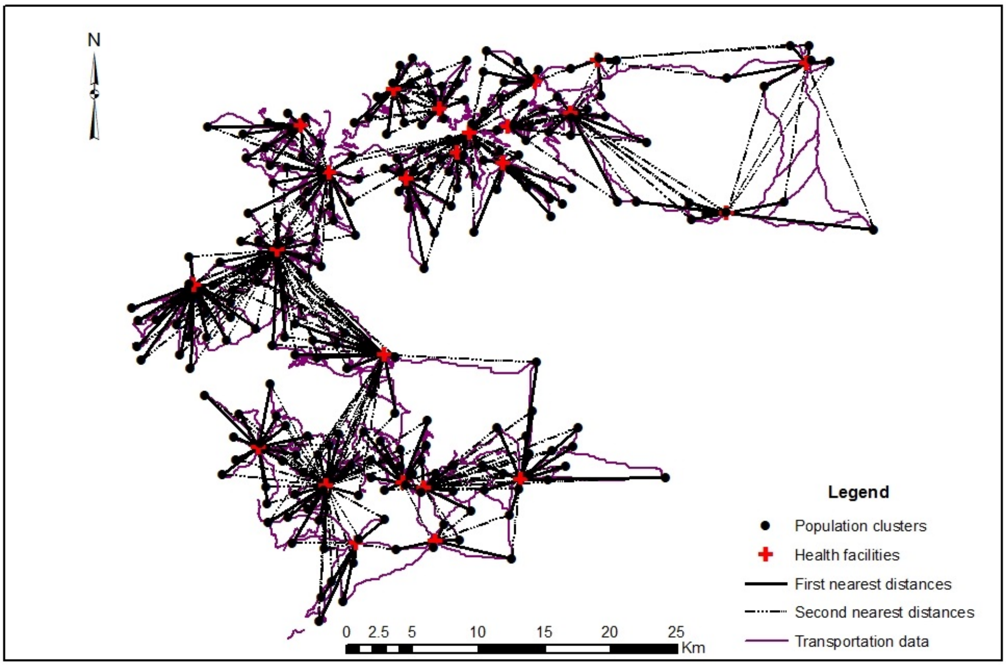


Figure 6.4: First two nearest distances based on straight-line distance measure

6.1.3 Accessibility outcome

The processing steps outlined in Section 4.5 was used to compute spatial accessibility indices of population clusters in Trashigang district using straight-line distance and the travel-time measures. Figure 6.5 shows the plot of the accessibility values obtained from the straight-line distance and travel-time methods. It can be observed that the accessibility values of the two methods are not completely different as they tend to follow a similar pattern. Regression analysis of the two methods indicates a high positive correlation with a Pearson correlation value of 0.71.

Even at the subdistrict level, the accessibility values from the two methods are quite similar with a correlation value of 0.80. Figure 6.6 shows the plot of the subdistrict accessibility values of the two methods. These results indicate that the straight-line and travel-time computation method produces almost similar results for the Trashigang

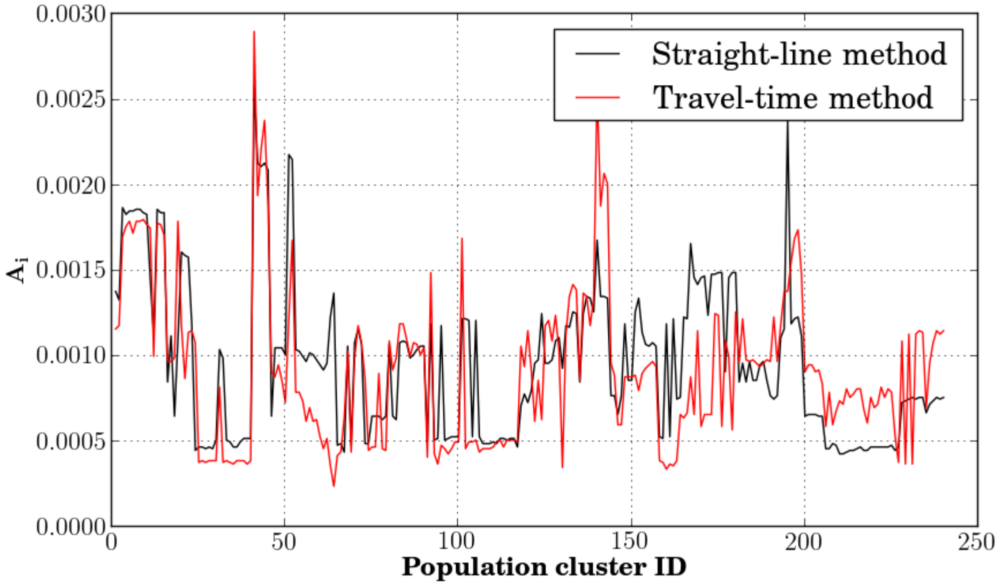


FIGURE 6.5: Plot of A_i for the straight-line and travel-time methods

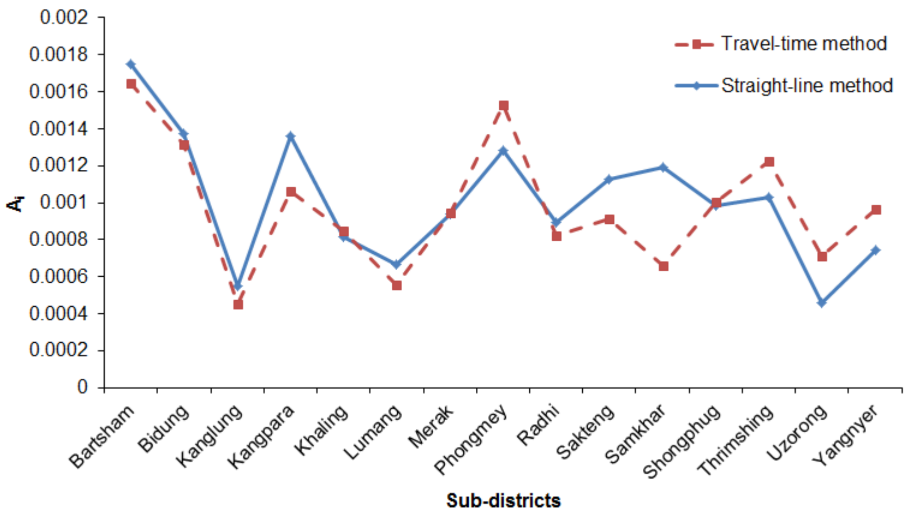


FIGURE 6.6: Subdistricts accessibility indices for two different methods

district. Generally, the travel-time measure is more accurate than the straight-line distance measure. However, in the absence of reliable transportation network data the travel-time method does not produce significantly different results from the straight-line distance method. On the other hand, the travel-time method is very intensive and time-consuming due to the need for modelling least-cost paths and for computing the fastest route between the provider and population locations. Therefore, the use of the travel-time method is not recommended at this time for Bhutan because of the unavailability of comprehensive transportation network data. So the straight-line distance measure was used for evaluating spatial accessibility to primary healthcare services in this country.

6.2 Comparison between different decay functions

The accessibility outcomes from different distance-decay functions using the simulated data configuration systems are presented in Section 4.3. This section presents the real-world data processing results for different decay functions. Figure 6.7 shows accessibility values of individual population clusters obtained from actual data processing for the Gasa district and Figure 6.8 shows the moving average scores computed from individual accessibility scores of population clusters in the entire country. A sample of 100 clusters was serially used in the same order for all decay functions to compute moving average scores. Moving average scores are only used to show a general trend of the accessibility values of different decay functions. The accessibility curves, in both these figures, depict an almost identical trend between different decay functions as observed for the simulated data system shown in Figure 4.20.

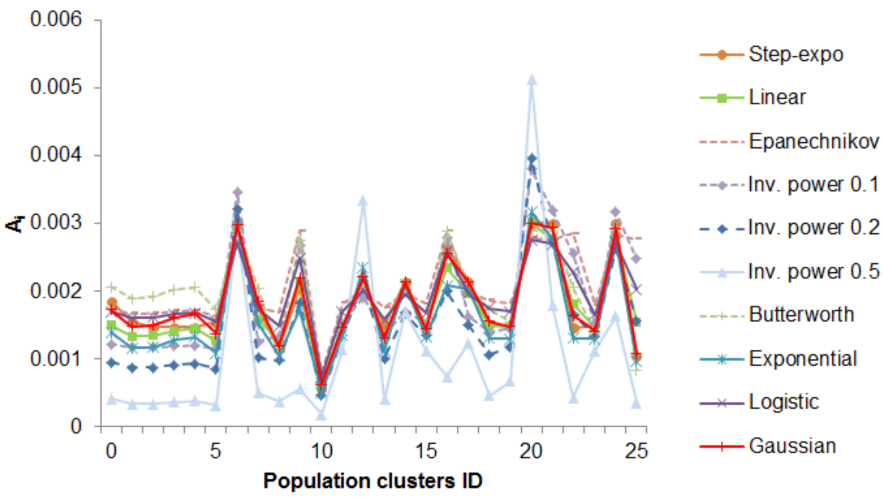


FIGURE 6.7: Accessibility scores of population clusters in Gasa district for different decay functions

The accessibility scores of population clusters can be used to calculate the mean score at the district or national level for different decay functions. For instance, the mean of

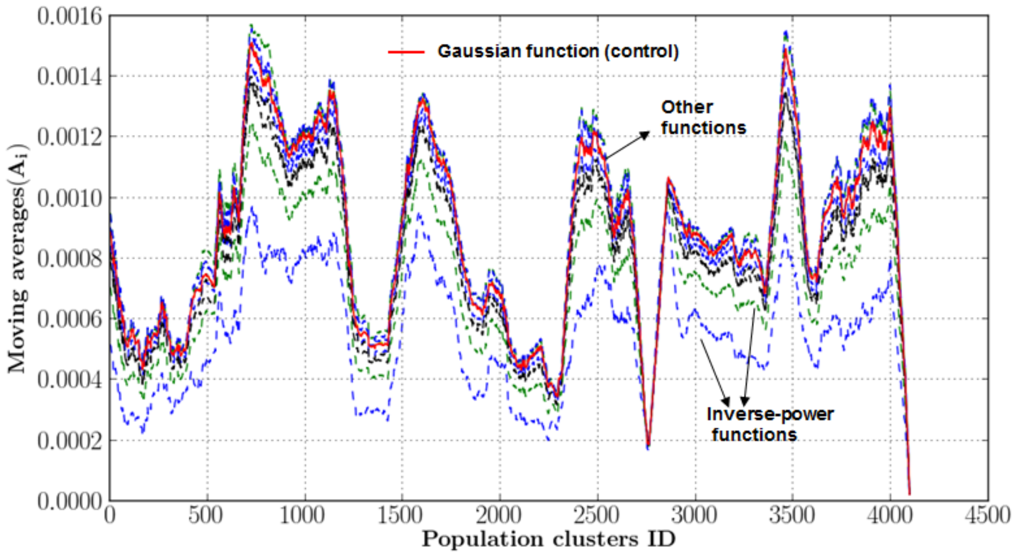


FIGURE 6.8: Moving average scores of population clusters for different decay functions

accessibility scores for all population clusters within the country is the accessibility score of the nation, which can be used to compare spatial accessibility to healthcare services between countries. Therefore, the accessibility outcome from different decay functions can be statistically tested for the equality of means using an independent-samples t-test or an analysis of variance (ANOVA) test. The equality of means testing requires homogeneity of variances between different groups, which can be tested using Levine's test or an F-test. Figure 6.9 shows the error bars representing mean and standard deviation of accessibility outcome from various decay functions. A variance is equal to the square of the standard deviation. The hypothesis test for the equality of means or equality of variances is based on the null hypothesis, which states that the difference in the mean or variances between the control (Gaussian function) and other function is equal to zero. The alternative hypothesis states that their differences are not equal to zero. An independent t-test between a different function and the control function was done at the 95% CI using SPSS Statistics.

Table 6.1 shows the statistical results of the Levine's and t-tests. The two-tailed p-values for the Gaussian-Logistic pair are 0.606 and 0.830 for the F-test and t-test, respectively, which are larger than the test value of 0.05 at the 95% CI. These large p-values indicate that the variance and mean of the Logistic function are not statistically significantly different from the corresponding values of the control function. Similarly, the step-function also has larger p-values than the test value which means

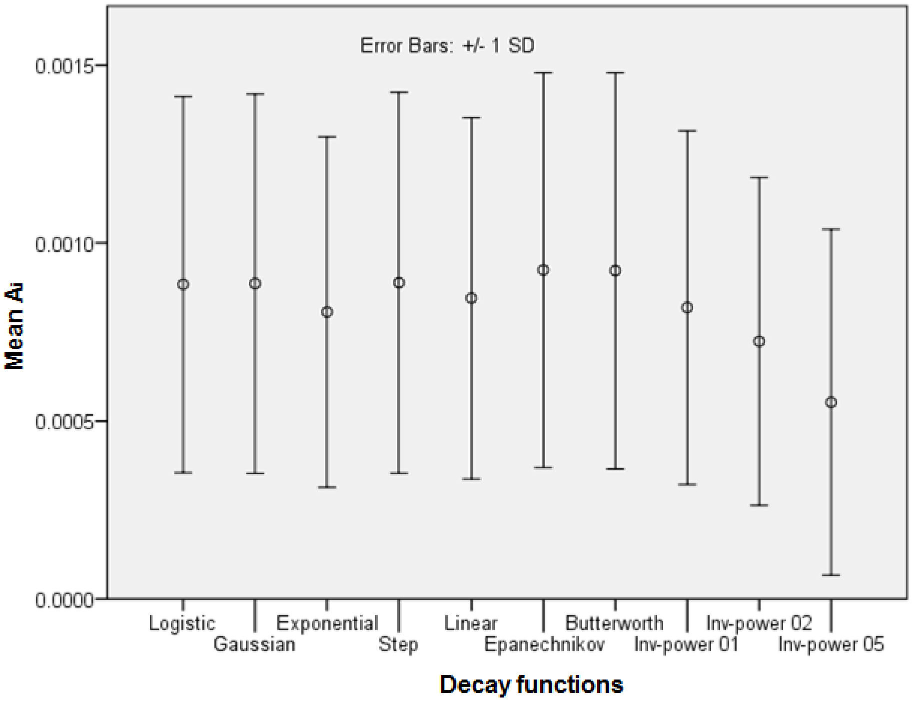


FIGURE 6.9: Box plot of accessibility values for different decay functions

TABLE 6.1: Results of Levine's test and t-test at 95% confidence interval

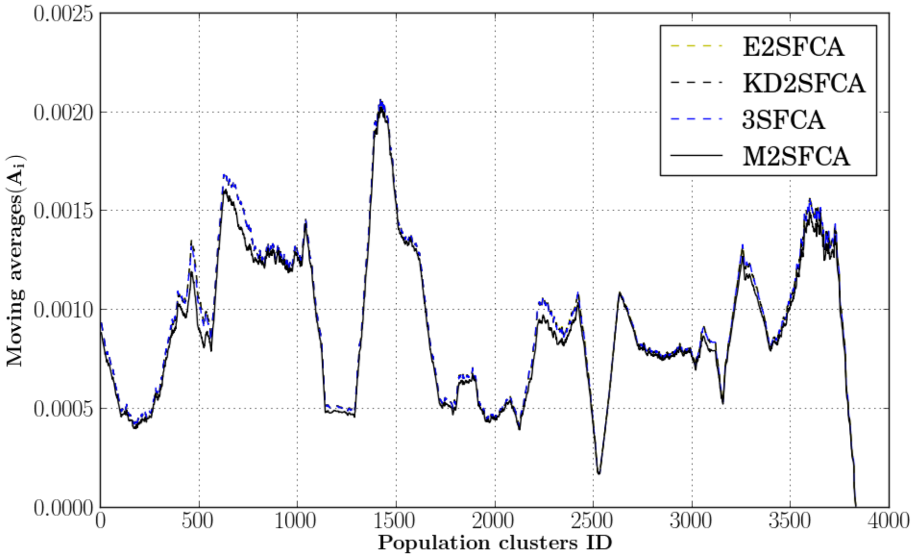
Decay Functions	**Levine's Test**		**t-test**		
	F	**Sig.(2-tailed)**	**t**	**Sig.(2-tailed)**	**Equality of variances**
Gaussian - Logistic	0.266	0.606	0.215	0.830	Assumed
Gaussian - Step	0.023	0.0.879	-0.208	0.835	Assumed
Gaussian - Exponential	19.816	0.000	7.048	0.000	Not Assumed
Gaussian - Linear	7.304	0.007	3.591	0.000	Not Assumed
Gaussian - Epanechnikov	4.138	0.042	-3.177	0.001	Not Assumed
Gaussian - Butterworth	4.764	0.029	-3.022	0.003	Not Assumed
Gaussian-Inv. Power 0.1	17.258	0.000	5.934	0.000	Not Assumed
Gaussian-Inv. Power 0.2	76.896	0.000	14.762	0.000	Not Assumed
Gaussian-Inv. Power 0.5	73.452	0.000	29.539	0.000	Not Assumed

that its mean and variance are also not statistically significantly different from the mean and variance of the control function. As with the step-function, this result is expected because its constant weighting values were derived from the control function. On the other hand, the p-values for all other functions for both the F- and t-test are smaller than the test value of 0.05. These results indicate that their means and variances are statistically significantly different from the corresponding values of the control function at the 95% CI. Based on the hypothesis test results, it can be surmised that the use of either the Gaussian, logistic or Gaussian-based step functions would not change the mean accessibility value significantly. In this study, the Gaussian function was selected over the other two functions because it has a simpler mathematical form than the logistic function and the weighting values of the step-function was derived from the Gaussian function.

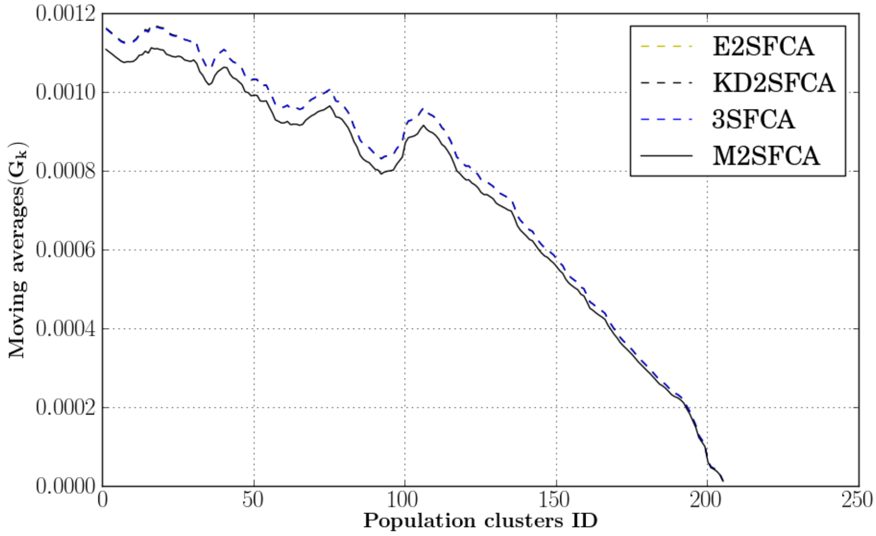
6.3 Comparison between the existing FCA models

A simple simulated data configuration system, described in Section 4.4.1, may not truly reflect the real world system where the provider-population configuration is more complex. Therefore, the accessibility outcome from the E2SFCA, KD2SFCA, 3SFCA and M2SFCA methods were compared using the actual data for Bhutan.

In Section 4.4.1, it was found that the accessibility values obtained from the simulated data processing for the E2SFCA, KD2SFCA and 3SFCA models were comparatively larger than the M2SFCA methods as these three computational methods calculate accessibility values by considering only the relative distance separation unlike the M2SFCA method, which calculates accessibility values by considering both the relative and absolute distance separation between the population clusters and service providers. This computational bias causes an over-estimation of accessibility values by the three aforementioned methods which have the potential to affect the underserved regions by increasing their accessibility values. An over-estimation of accessibility values by the E2SFCA, KD2SFCA and 3SFCA models was also observed with the real-world data when compared with the accessibility outcome from the M2SFCA method. Figures 6.10(a) and 6.10(b) show the moving averages of accessibility values of population clusters and subdistricts for the four different FCA models, respectively. It can be clearly seen in these figures that the M2SFCA method produces lower values than the other three methods whereas the other three methods produced almost similar accessibility values. Furthermore, it can be seen that the accessibility outcome from the E2SFCA, KD2SFCA and 3SFCA models were similar. The accessibility values between any two methods are significantly correlated at the 0.01 significance level with correlation values portraying greater than 0.998 between E2SFCA, KD2SFCA and 3SFCA methods and correlation values ranging from 0.992 to 0.994 between any of the aforementioned three FCA methods with the M2SFCA method. Table 6.2 shows the



(a) Population clusters



(b) Subdistricts

FIGURE 6.10: Accessibility plot between different FCA methods

correlation values between pairs of the FCA methods. Although the correlation coefficients are very high for all the pairs, the M2SFCA method produced a significantly different accessibility scores when compared with the other three methods. Like the results from the simulated data processing (see Section 4.4.1), the results from real data processing also indicate that the M2SFCA method is uniquely robust than the other FCA methods. Therefore, the M2SFCA method was used as a basis for developing the AM2SFCA method which was used for calculating spatial accessibility to healthcare services in Bhutan.

Table 6.2: Pearson correlation values between different FCA methods

Methods	**E2SFCA**	**KD2SFCA**	**3SFCA**	**M2SFCA**
E2SFCA	1.0	0.999	0.998	0.992
KD2SFCA	0.999	1.0	0.999	0.993
3SFCA	0.998	0.999	1.0	0.994
M2SFCA	0.992	0.993	0.994	1.0

6.4 Comparison between the M2SFCA and AM2SFCA models

Recall from Section 4.4.2 that the original M2SFCA method with the same first and second decay functions produced excessively large difference in scores between the lowest and highest ranked accessibility scores because of the small number squaring bias, which has the potential for causing misinterpretation of accessibility outcomes between different population clusters within a region. The AM2SFCA method was proposed to mitigate this computational bias so that the difference in scores between the highest and lowest scores is modified to a realistic level.

Figures 6.11 and 6.12 show the moving averages accessibility values of population clusters in the entire country for HA and doctor services, respectively. The high correlation coefficients of larger than 0.99 indicate that the accessibility values for these two methods are significantly correlated, which is expected because of the use of a similar mathematical model except for the different usage of the second decay function. Nevertheless, closer scrutiny of the accessibility values at the district level indicates a substantial difference in the maximum and minimum accessibility values between the two models. Table 6.3 shows the minimum and maximum scores of different districts obtained from the M2SFCA and AM2SFCA methods for HA services. It can be clearly seen in all districts that the ratio of maximum and minimum scores of population clusters has substantially decreased or remained the same in the AM2SFCA method when comparing with the results obtained from the M2SFCA method. The maximum decrease in the ratio value is clearly observed

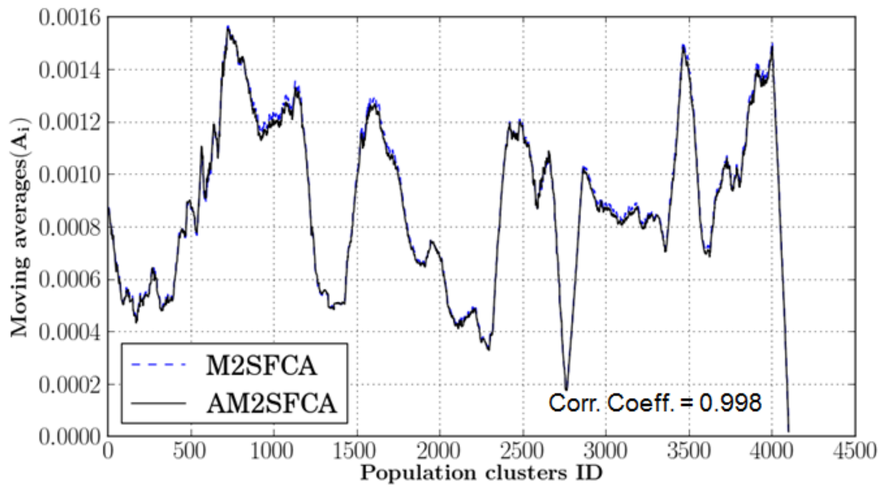


FIGURE 6.11: Accessibility values from the M2SFCA and AM2SFCA methods for HA services

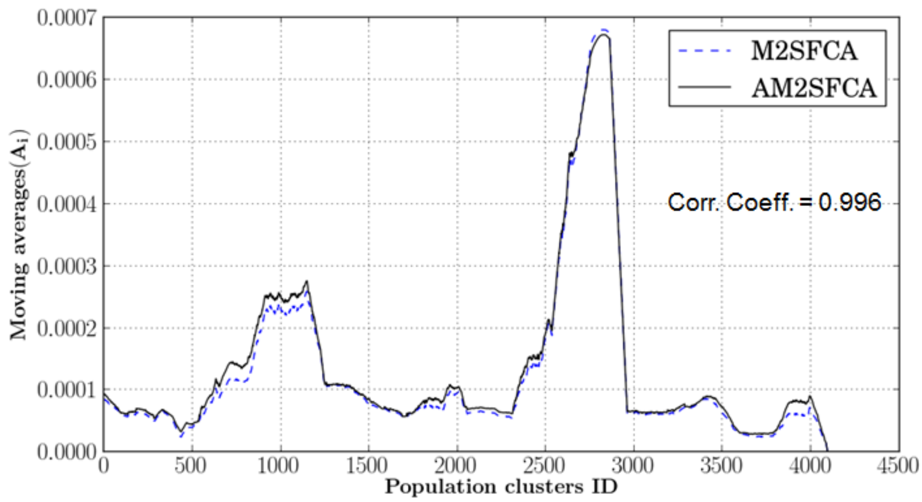


FIGURE 6.12: Accessibility values from the M2SFCA and AM2SFCA methods for doctor services

for Haa district where the ratio value decreased from 96 for the M2SFCA method to 57 for the AM2SFCA method.

Table 6.4 shows the minimum and maximum scores of different districts obtained from the M2SFCA and AM2SFCA methods for doctor services. Likewise for HA services, the ratio of maximum and minimum scores for population clusters within a district has decreased in the AM2SFCA method when compared with the results obtained from the M2SFCA method, except for the Pemagatshel district which has same value for both the methods. Unlike the accessibility results of HA services where only Haa district has a

Table 6.3: Summary statistics of two computational methods for HA services

Districts	M2SFCA method			AM2SFCA method		
	Min.	**Max.**	**Max./Min.**	**Min.**	**Max.**	**Max./Min.**
Bumthang	0.000547	0.002022	4	0.000545	0.002006	4
Chukha	0.000125	0.002626	21	0.000125	0.002597	21
Dagana	0.000339	0.002176	6	0.000330	0.002175	7
Gasa	0.000630	0.002894	5	0.000659	0.002907	4
Haa	0.000035	0.003398	96	0.000059	0.003341	57
Lhuntse	0.000526	0.002364	4	0.000799	0.002294	3
Mongar	0.000441	0.002726	6	0.000429	0.002653	6
Paro	0.000101	0.002719	27	0.000114	0.003103	27
Pemagatshel	0.000539	0.002783	5	0.000527	0.002766	5
Punakha	0.000620	0.001780	3	0.000602	0.001765	3
Samtse	0.000110	0.001419	13	0.000118	0.001401	12
Sarpang	0.000356	0.002120	6	0.000463	0.002095	5
Thimphu	0.000089	0.005016	56	0.000087	0.005025	58
Trashigang	0.000440	0.001625	4	0.000431	0.001587	4
T/yangtse	0.000160	0.001673	10	0.000306	0.001635	5
Trongsa	0.000325	0.003508	11	0.000327	0.003461	11
Tsirang	0.000412	0.002146	5	0.000400	0.002209	6
W/phodrang	0.000345	0.002920	8	0.000352	0.002903	8
Zhemgang	0.000785	0.003056	4	0.000827	0.003006	4
S/jongkhar	0.000374	0.001482	4	0.000401	0.001487	4

Table 6.4: Summary statistics of two computational methods for doctor services

Districts	M2SFCA method			AM2SFCA method		
	Min.	**Max.**	**Max./Min.**	**Min.**	**Max.**	**Max./Min.**
Bumthang	0.0000327	0.0001113	3	0.000057	0.000115	2
Chukha	0.0000127	0.0002552	20	0.000020	0.000328	16
Dagana	0.0000059	0.0000932	16	0.000014	0.000094	7
Gasa	0.0000003	0.0003349	1080	0.000005	0.000337	63
Haa	0.0000074	0.0001120	15	0.000020	0.000114	6
Lhuntse	0.0000317	0.0002196	7	0.000051	0.000260	5
Mongar	0.0000329	0.0003774	11	0.000050	0.000384	8
Paro	0.0000065	0.0001350	21	0.000020	0.000135	7
Pemagatshel	0.0000469	0.0001409	3	0.000055	0.000147	3
Punakha	0.0000317	0.0004828	15	0.000036	0.000498	14
Samtse	0.0000200	0.0000883	4	0.000029	0.000090	3
Sarpang	0.0000112	0.0002891	26	0.000017	0.000292	17
Thimphu	0.0000024	0.0006839	289	0.000011	0.000683	61
Trashigang	0.0000037	0.0002043	55	0.000010	0.000241	24
T/yangtse	0.0000062	0.0001090	18	0.000022	0.000111	5
Trongsa	0.0000232	0.0001522	7	0.000032	0.000155	5
Tsirang	0.0000095	0.0000375	4	0.000014	0.000038	3
W/phodrang	0.0000035	0.0000563	16	0.000008	0.000055	7
Zhemgang	0.0000092	0.0001844	20	0.000028	0.000181	7
S/jongkhar	0.0000037	0.0002040	55	0.000010	0.000204	20

large difference in the ratio values between the two models, the accessibility results for doctor services has a number of districts with an inflated ratio value. The largest ratio value was observed for the Gasa district with a value of 1080 for the M2SFCA method. This value is considerably decreased to 63 with the AM2SFCA method. Thimphu district has the second largest ratio value of 289 for the M2SFCA method, which has decreased to 61 with the AM2SFCA method. Similarly, all other districts with high ratio values for the M2SFCA method have decreased by 1 to 35 with the AM2SFCA method. Such a large difference in ratio value obtained from the M2SFCA method, like in the case of Gasa district with a value of 1080, does not make practical sense because the accessibility scores between the lowest and highest ranked regions cannot be realistically juxtaposed. Therefore, the accessibility outcome from the AM2SFCA method clearly appears to be more credible than the M2SFCA method.

6.5 Individual healthcare providers

This section presents individual results for spatial accessibility to doctor and HA services. The AM2SFCA-based spatial accessibility for both services were computed using population and health data of the entire country.

6.5.1 PPR and distance proximity analysis

The district-wise PPR statistics for doctor and HA services in 2013 are shown in Tables 6.5 and 6.6, respectively. Generally, the PPR of a district is directly computed as a ratio of the number of health care providers to the population of a district, which is shown in the last column of the tables. This ratio is referred as the simple PPR. Thimphu district had the highest number of doctors in the country because the majority of doctors worked at the national referral hospital, which is located in this district. Even though the Gasa district is located in the remotest region of the country, it ranked third in the country with respect to simple PPR because of its small population size. With respect to the simple PPR indicator the national average for doctors and health assistants were 1-to-5091 and 1-to-1175, respectively. Thirteen of the twenty districts had better simple PPR than the national average of accessibility for HA services whereas only five districts had better accessibility for doctor services. A large number of districts had a lower PPR than the national average for doctor services because more doctors were placed in few major hospitals such as the general referral hospital in Thimphu and secondary referral hospitals in Mongar and Sarpang districts. Wangdiphodrang district with only one doctor for every

Table 6.5: Provider-to-population ratio for doctor services in 2013

Districts	**Population**	**No. of Doctors**	G_k	$1/G_k$	**Modified PPR**	**Simple PPR**
Bumthang	18416	2	0.0000927	10785	1-to-10785	1-to-9208
Chukha	85615	8	0.0000586	17052	1-to-17052	1-to-10702
Dagana	26550	1	0.0000425	23517	1-to-23517	1-to-26550
Gasa	3578	1	0.0001955	5115	1-to-5115	1-to-3578
Haa	13147	1	0.0000727	13747	1-to-13747	1-to-13147
Lhuntse	17207	2	0.0001406	7111	1-to-7111	1-to-8604
Mongar	42843	13	0.0002439	4099	1-to-4099	1-to-3296
Paro	41848	5	0.0001022	9781	1-to-9781	1-to-8370
Pemagatshel	24648	3	0.0000779	12840	1-to-12840	1-to-8216
Punakha	26982	2	0.0000678	14739	1-to-14739	1-to-13491
Samtse	68582	4	0.0000664	15059	1-to-15059	1-to-17146
Sarpang	43920	10	0.0001824	5481	1-to-5481	1-to-4392
Thimphu	111312	74	0.0003916	2553	1-to-2553	1-to-1504
Trashigang	54766	5	0.0000616	16241	1-to-16241	1-to-10953
Trashiyangtse	20264	2	0.0000829	12067	1-to-12067	1-to-10132
Trongsa	15502	1	0.0000795	12573	1-to-12573	1-to-15502
Tsirang	21215	1	0.0000321	31199	1-to-31199	1-to-21215
Wangdiphodrang	36278	1	0.0000305	32816	1-to-32816	1-to-36278
Zhemgang	20950	3	0.0000811	12331	1-to-12331	1-to-6983
Samdrupjongkhar	39409	5	0.0000928	10770	1-to-10770	1-to-7882
Average	733032	144	0.0001098	9109	1-to-9109	1-to-5091

Table 6.6: Provider-to-population ratio for HA services in 2013

Districts	**Population**	**No. of HAs**	G_k	$1/G_k$	**Modified PPR**	**Simple PPR**
Bumthang	18416	17	0.001009	991	1-to-991	1-to-1083
Chukha	85615	42	0.000785	1273	1-to-1273	1-to-2038
Dagana	26550	23	0.000775	1291	1-to-1291	1-to-1154
Gasa	3578	7	0.001921	521	1-to-521	1-to-511
Haa	13147	7	0.001185	844	1-to-844	1-to-1878
Lhuntse	17207	29	0.001504	665	1-to-665	1-to-593
Mongar	42843	56	0.001205	830	1-to-830	1-to-765
Paro	41848	20	0.000529	1891	1-to-1891	1-to-2092
Pemagatshel	24648	31	0.001284	779	1-to-779	1-to-795
Punakha	26982	26	0.000992	1009	1-to-1009	1-to-1038
Samtse	68582	33	0.000456	2191	1-to-2191	1-to-2078
Sarpang	43920	46	0.001179	848	1-to-848	1-to-955
Thimphu	111312	82	0.001514	660	1-to-660	1-to-1357
Trashigang	54766	47	0.000840	1190	1-to-1190	1-to-1165
Trashiyangtse	20264	19	0.000861	1162	1-to-1162	1-to-1067
Trongsa	15502	20	0.001483	674	1-to-674	1-to-775
Tsirang	21215	17	0.000688	1453	1-to-1453	1-to-1248
Wangdiphodrang	36278	36	0.001040	962	1-to-962	1-to-1008
Zhemgang	20950	36	0.001433	698	1-to-698	1-to-582
Samdrupjongkhar	39409	30	0.000694	1440	1-to-1440	1-to-1314
Average	733032	624	0.001068	936	1-to-936	1-to-1175

36278 people had the worst accessibility to doctor services and Paro district with one HA for every 2092 people had the lowest accessibility for HA services in 2013.

The problem with the simple PPR is that it does not take into account the issue of difficulty of accessibility to health care providers due to the physical separation between the location of the providers and residents. Some residents are located in remote inaccessible areas of the country where they have to travel for several hours to secure services from the nearest health facility. Although the Gasa district ranks third in the country based on the simple PPR (1: 3578), there were many residents living in some parts of its subdistrict who had to travel for several days to seek a doctor's services. This factor of physical accessibility is not considered in the calculation of a simple PPR. On the other hand, the modified PPR accounts for the supply of health care providers, demand of population for healthcare services and the distance separation between locations of the providers and populations. In this case the modified PPR is derived from spatial accessibility indices of districts. The unit of the spatial accessibility indices is opportunities per person. Therefore, the reciprocal of such index represents a finite population served by a single provider. The modified PPR of the Gasa district is 1: 5115 which is worsened by about 40% when compared with the simple PPR. Indeed this value may be truly reflecting the actual accessibility score of this district because it explicitly includes physical accessibility factor. In the case of HA services in 2013, the modified mean PPR of 1:936 is better than the simple mean PPR of 1:1175 by about 20%. This means that the inclusion of distance impedances has positively affected the indicator value of accessibility for HA services. For doctor services, the modified mean PPR of 1:9109 is worsened by about 79% when compared with the simple mean PPR of 1:5091, which means that the inclusion of distance impedances have negatively affected the indicator value of accessibility for doctor services. So it can be inferred that the spatial accessibility would positively or negatively alter the provider-to-population ratio in accordance with the provider-population data configuration system.

Figures 6.13 and 6.14 show maps of population clusters and the subdistricts classified based on national average distance threshold for HA and doctor services in 2013, respectively. The average distance between the population clusters and the nearest health facility to access HA services was 3.3 kilometres. About 27 percent of Bhutanese population had to travel farther than 3.3 Km to seek HA services from the nearest health facility. Some people living in the Bumdelling subdistrict of the Trashiyangtse district had to travel more than 26 km to the nearest health facility. For 125 of the 205

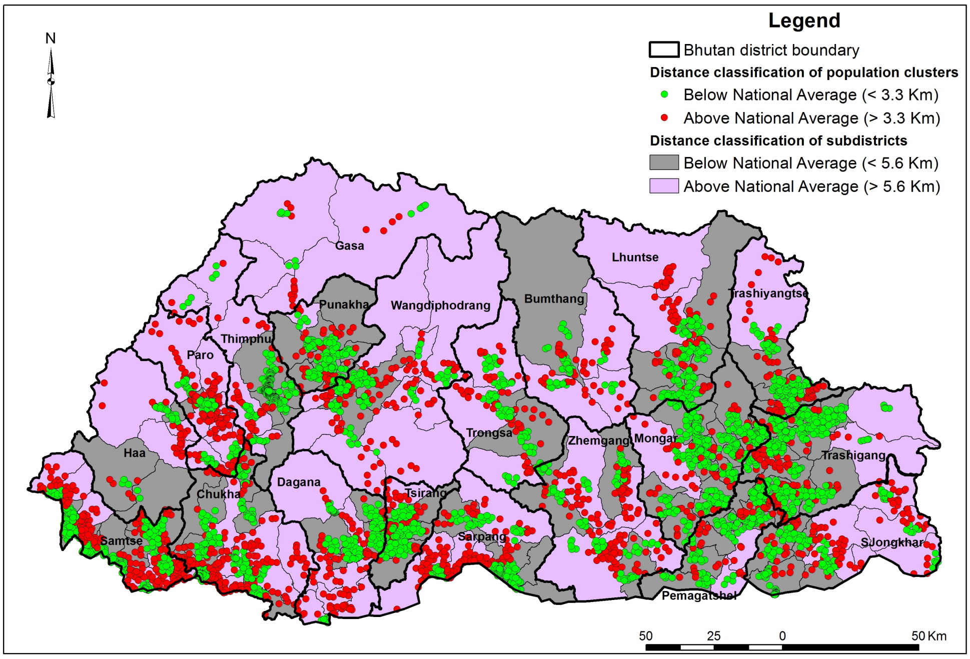


FIGURE 6.13: Distance-based classification of population clusters and subdistricts for HA services

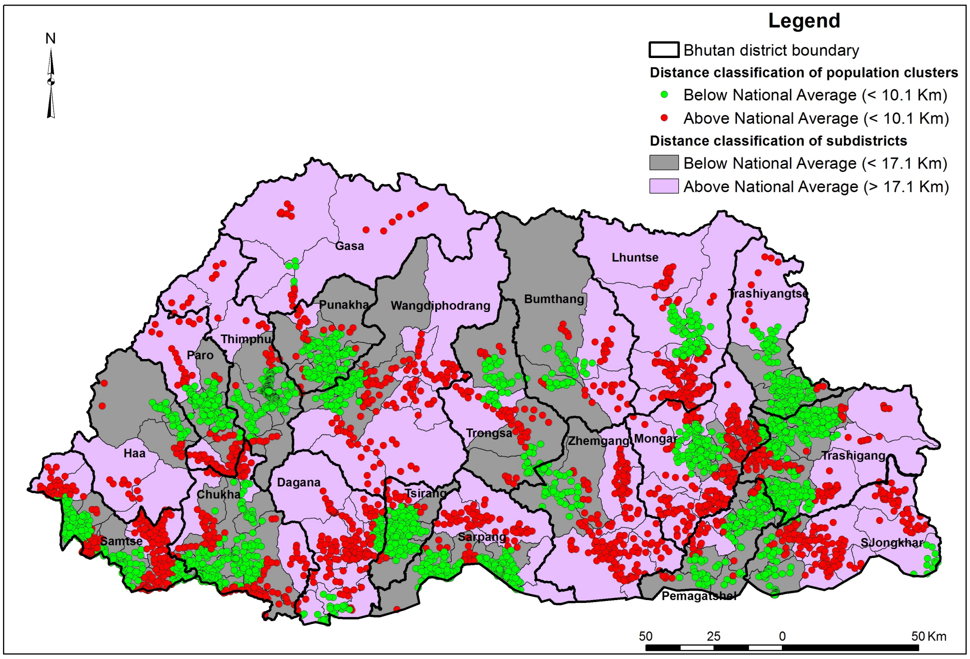


FIGURE 6.14: Distance-based classification of population clusters and subdistricts for doctor services

subdistricts in the country, their nearest health facility providing HA services was located within the subdistricts' national average distance of 5.6 kilometres. With respect to doctors services, the average distance between the population clusters and the nearest health facility was about 10.1 kilometres. The average travel distance to access doctors was thrice the average distance to access HA services because doctors were generally not available in the peripheral health facilities due to the shortage of doctors in the country. About 29 percent of the population had to travel farther than the national average distance to access doctors services. Some residents of the Gasa district had to travel the furthest distance of about 53 Km to access doctors services. In 118 of the 205 subdistricts, their health facilities providing doctor services was located within subdistrict's national average distance of 17.1 kilometres.

6.5.2 Spatial accessibility of population clusters

The accessibility values of population clusters can be used to produce spatial accessibility plots. NB: Any figures or tables will refer to the year 2013 if the year is not specifically mentioned.

Figure 6.15 shows the accessibility scores for both the service providers of all population clusters within the country in 2013. This plot clearly indicates that the spatial accessibility for doctor services is considerably lower than HA services across the country with a mean scores of about 0.0009 and 0.0001 for HAs and doctors, respectively. This accessibility plot can be further segregated to observe the general trend of scores of population clusters between different districts. Figure 6.16 show the accessibility scores for HA services of all population clusters within different districts. It

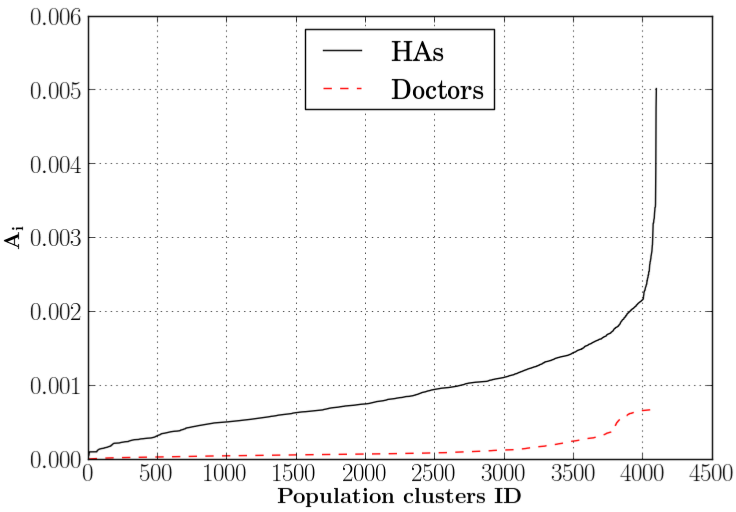


FIGURE 6.15: Accessibility scores of all population clusters for doctor and HA services in 2013

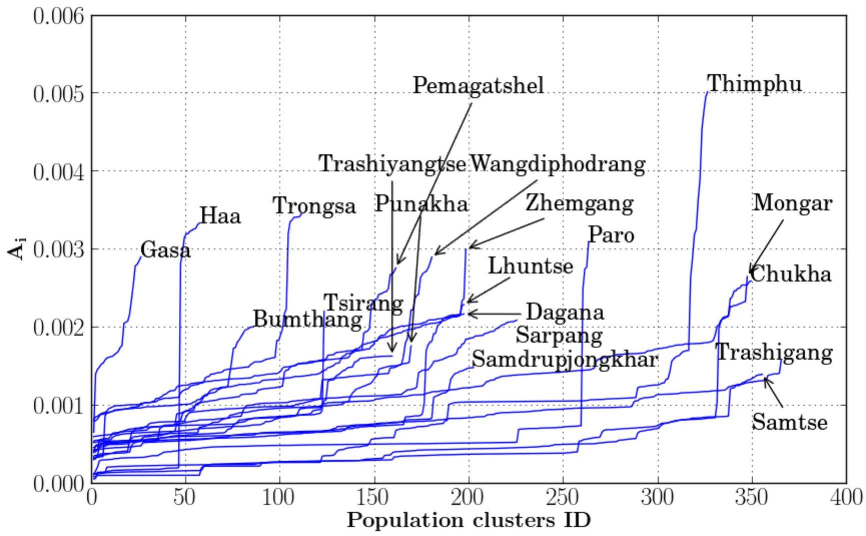


Figure 6.16: Accessibility scores of all districts for HA services in 2013

can be observed that the majority of the population clusters had scores less than 0.002 for HA services. The spikes observed for a number of districts are due to having few clusters with high accessibility scores. For instance, the Thimphu district had 10 clusters with accessibility for HA services greater than 0.002 which barely constitute less than 1% of its population having very high accessibility. Whilst comparing the minimum and maximum scores within each district, the highest ranked population cluster in the Thimphu district had 58 times better accessibility for HA services than its lowest ranked cluster (see Table 6.3). On the other hand, Bumthang, Gasa, Lhuntse, Punakha, Trashigang, Zhemgang and Samdrupjongkhar portrayed a minimum ratio difference of less than 4 between their highest and lowest ranked clusters. With respect to mean scores, the Gasa district had the highest value of 0.0019, which is about 5 times larger than the lowest mean score of Samtse district with a value of .0004.

Figure 6.17 show the accessibility scores for doctor services of all population clusters within different districts. All population clusters within each district had accessibility scores of less than 0.0007. The majority of population clusters had scores less than 0.0003 except for the clusters of Thimphu district. It can be clearly observed that the population clusters of Thimphu district had the highest accessibility to doctor services followed by Mongar district with only about half the scores of clusters of Thimphu district. Chukha, Punakha, Samtse and Trashigang districts had similar average scores of 0.00006, which is about 10 times less than the mean score of population clusters of Thimphu district with a value of 0.00068. Tsirang, Dagana and Wangdiphodrang districts had the lowest

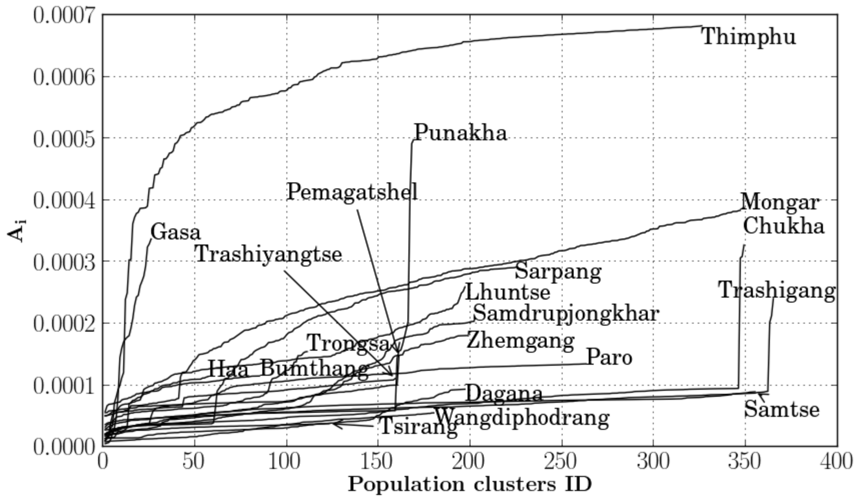


FIGURE 6.17: Accessibility scores of all districts for doctor services in 2013

scores with a mean value of about 0.00004. With respect to the ratio of maximum and minimum scores within each district, the Gasa district portrayed the largest difference with a ratio value of 63, which indicates that its lowest ranked population cluster had 63 times worse accessibility for doctor services than the highest ranked cluster (see Table 6.4). Bumthang, Pemagatshel, Tsirang, Samtse, Lhuntse, Trashiyangtse and Trongsa districts portrayed smaller difference between their maximum and minimum scores with a ratio value of less than 5. Table B.10 in Appendix B shows the accessibility statistics of districts for both the health care providers.

6.5.3 Spatial accessibility ranking of subdistricts and districts

The relative accessibility values of the subdistricts and districts were used to rank these administrative regions within the country. Figures 6.18 and 6.19 show districts and subdistricts accessibility rankings for HA and doctor services in 2013. The ranking maps for the years 2010 to 2012 are shown in Figures A.6 to A.11 in Appendix A. Bold numbers refer to the districts ranking while the non-bold numbers represent the ranking of the subdistricts.

In 2013, Lingzhi subdistrict of the Thimphu district had the highest rank (Rank 1) and the Bara subdistrict of the Samtse district had the lowest rank (Rank 205). The ranking of Lingzhi and Bara subdistricts can be explained based on the three parameters used for computing spatial accessibility, namely distance proximity between the population

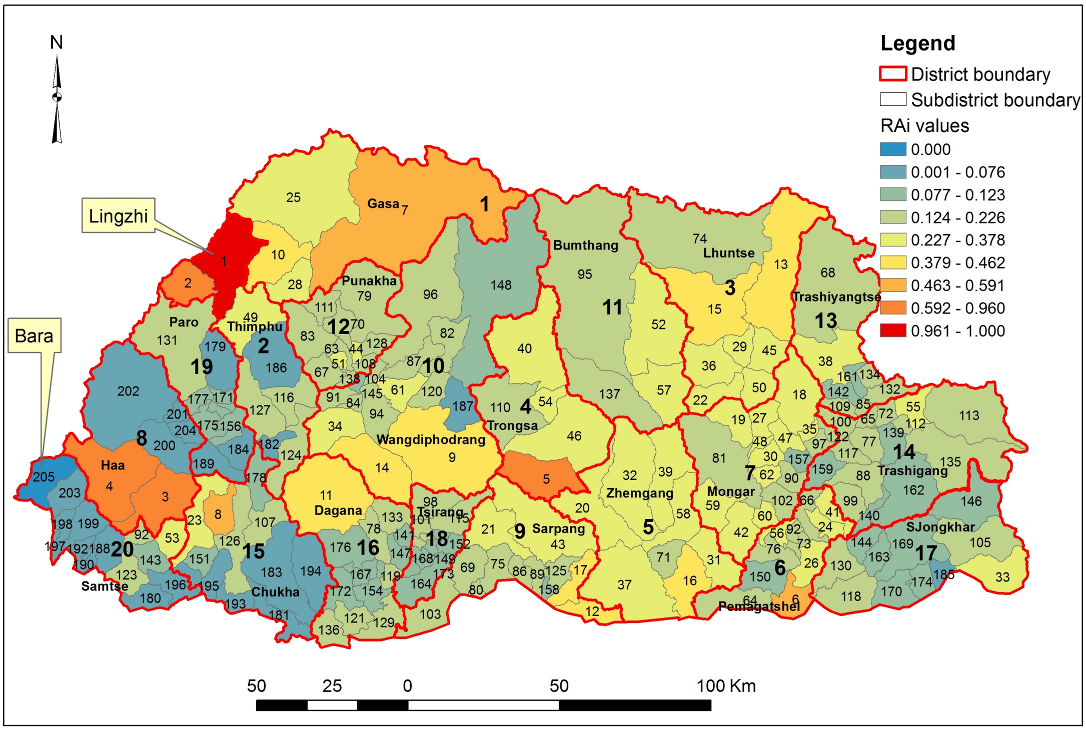


FIGURE 6.18: SA ranking map for HA services in 2013

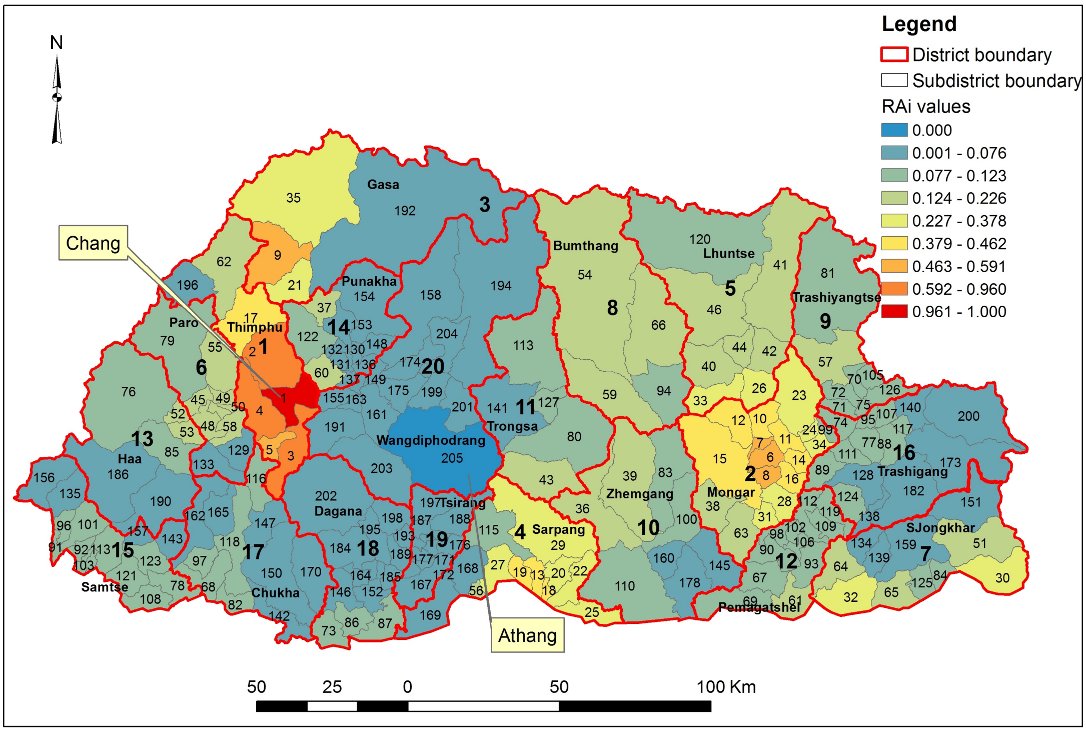


FIGURE 6.19: SA ranking map for doctor services in 2013

clusters and the associated health facilities, size of the population and the number of health care providers in the respective population catchment areas. Figure 6.20 shows the distribution of population clusters and health facilities in the two subdistricts and

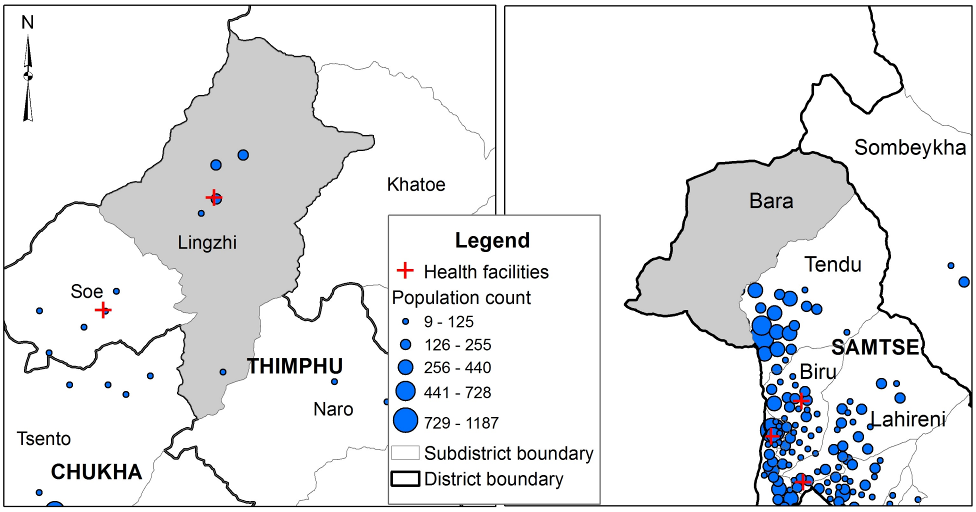


FIGURE 6.20: Distribution of population clusters and health facilities with HAs in Lingzhi and Bara subdistricts

TABLE 6.7: Summary statistics of the first and last ranking subdistricts in 2013

HA + BHW case					
Subdistricts	**Districts**	**Pop.**	**Avg. Distances(m)**	G_k	**No. of health care providers in the two nearest health facilities**
Lingzhi	Thimphu	597	10207	0.004496	5
Bara	Samtse	3962	8790	0.000149	2
Doctors case					
Chang	Thimphu	75663	6291	0.000657	76
Athang	W/phodrang	974	31132	0.000010	5

Table 6.7 shows the summary statistics of the first and last ranking subdistricts. The average distance column indicates the average distance between all the population clusters and their two associated health facilities. It can be seen in Table 6.7 that the average distance for the Bara subdistrict was lower than the Lingzhi subdistrict by about 2 Km, however, in terms of weights used in the computation there was no significant difference between these values as 10.2 Km and 8.8 Km would have a weight values of 0.87 and 0.9 respectively. Therefore, the distance parameter may not have been affected the calculation of accessibility values of population clusters within these districts. Lingzhi subdistrict had four population clusters with their first-nearest health facility located in close proximity

and their second-nearest health facility located in the neighbouring subdistrict, Soe. In addition, Lingzhi subdistrict had a population of 597 people who had access to five health care providers located in the two associated health facilities, with the first health facility having four health providers and the second one with only one provider. In contrast, Bara subdistrict had a total population of 3962 people with access to only two health care providers, one provider each in the two associated health facilities. Thus, it can be inferred that the accessibility values for the Lingzhi and Bara subdistricts differed substantially due to the number of health care providers in their associated health facilities and the size of the population of the respective subdistricts. The spatial health accessibility of Lingzhi subdistrict was about 30 times better than the Bara subdistrict. At the district level for HA services, Gasa district ranked highest (Rank 1) and the Samtse district ranked the lowest (Rank 20) in the country.

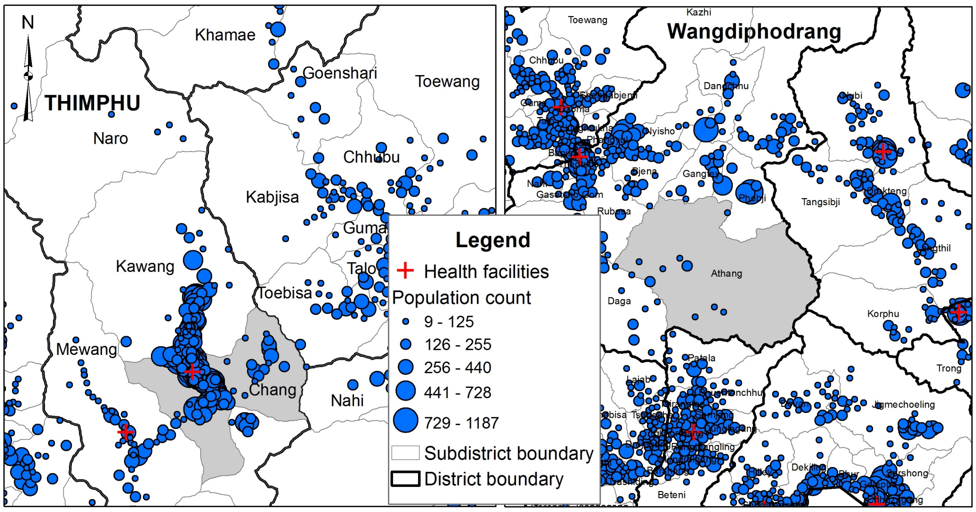


FIGURE 6.21: Distribution of population clusters and health facilities with doctors in Athang and Chang subdistricts

For doctor services, the Chang subdistrict in the Thimphu district was ranked as having the highest accessibility (Rank 1) and the Athang subdistrict in the Wangdiphodrang district was ranked as having the lowest (Rank 205). Figure 6.21 shows the distribution of health facilities and population clusters in the vicinity of the Chang and Athang subdistricts. It can be observed that the health facilities providing doctor services were located far from the population clusters in the Athang subdistrict but the population clusters in the Chang subdistrict had relatively easy access to doctor services. Table 6.7 shows that the average travelling distance to the two nearest health facilities for the Chang subdistrict was about 6 Km whereas it was about 31 Km for the other district.

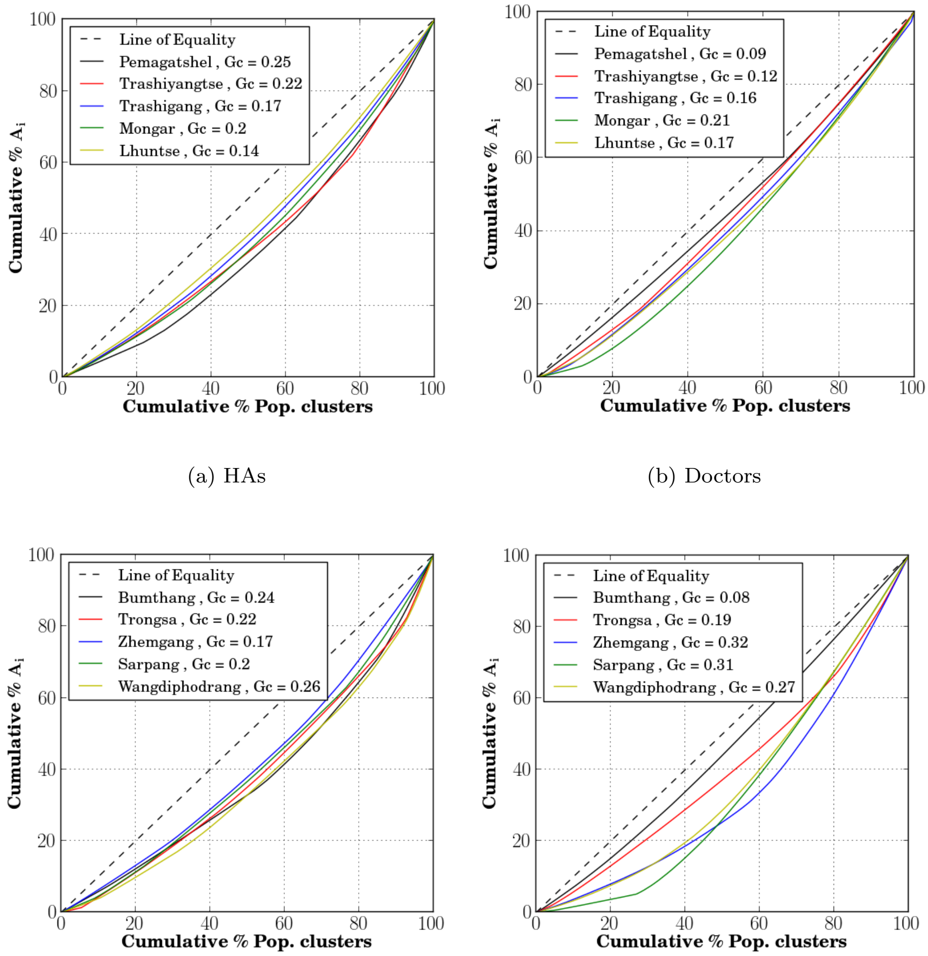
In terms of distance weights, 6 and 31 Km represents 0.95 and 0.29 respectively, which indicates a considerable difference between their distance weights. Furthermore, the Chang subdistrict had access to about 76 doctors whereas the Athang district had access to only 5 doctors. Therefore, the large difference of accessibility between the Chang and the Athang subdistricts was because the former subdistrict had more doctors and also its population had greater ease of distance accessibility to doctor services. The spatial accessibility to doctor services of Chang subdistrict is about 64 times better than the Athang subdistrict even though the population of the former subdistrict is six times more than the later subdistrict. In this case the two computational parameters, travelling distance and the number of health care providers had lessened the negative impact of the population parameter in the computation of the spatial accessibility indices. At the district level for doctor services, Thimphu district ranked the highest and the Wangdiphodrang district ranked the lowest in the country because the population clusters in Thimphu district had better accessibility to doctor services than population clusters in other districts.

6.5.4 Equality of distribution of spatial accessibility

The Gini coefficient (Gc) is most commonly used for measuring the evenness of wealth or income distribution within a region. Similarly, this measure can be used to assess the evenness of distribution of spatial accessibility to health care services within a region using the spatial accessibility indices. Generally, the Gini coefficient is calculated by plotting a Lorenz curve. The mathematical measure for the equality of distribution is the Gini coefficient, which is defined as a ratio of the area between the Lorenz curve and the line of equality and the total area under the line of equality. A Gini coefficient value of 0 represents perfect equality and 1 represents perfect inequality. There are more than a dozen ways of computing the Gini coefficient (Yitzhaki, 1998). One form of the Gini coefficient is computed using Equation 6.1

$$Gc = \frac{Gi}{100}, \;\; Gi = 100 + (100 - 2S)/n, \;\; S = \sum_{i=1}^{n+1} y_i, \;\; y_i = 100 * \frac{c_i}{c_{n+1}}, \tag{6.1}$$

where G_i is the Gini Index, n is the total count of the population clusters used in the computation, c_i is the cumulative totals for the spatial accessibility values and $n+1$ items describe the Lorenz curve as the (0,0) coordinate has to be included.



(a) HAs

(b) Doctors

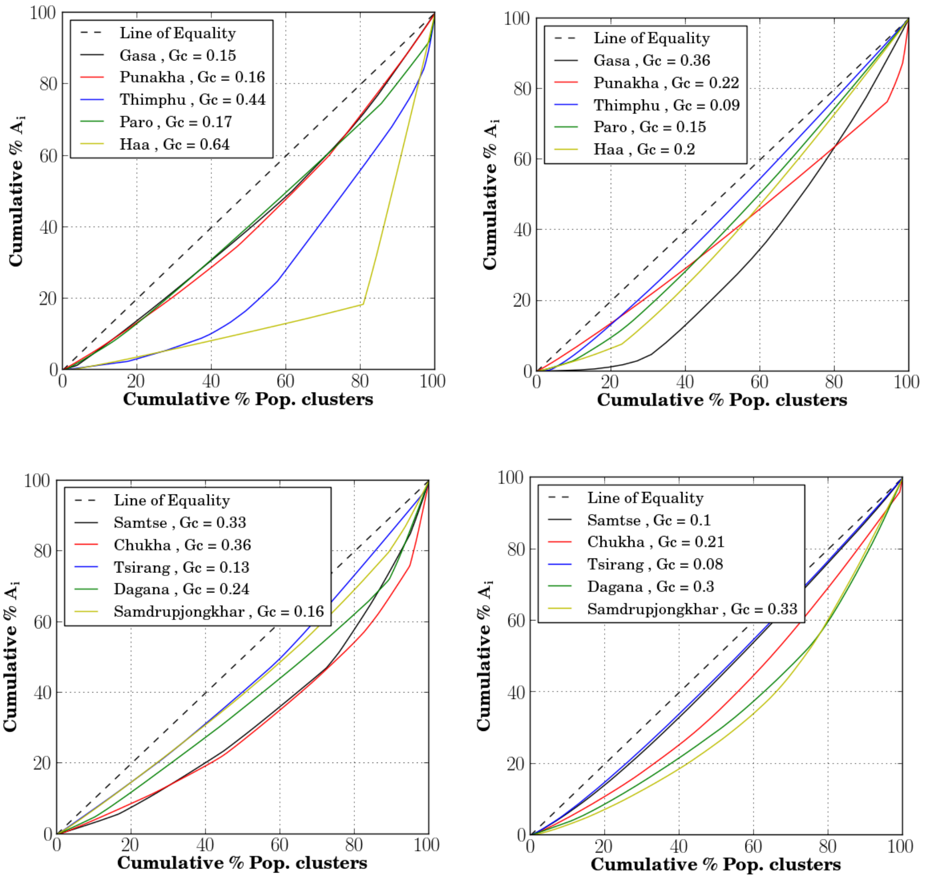
(c) HAs

(d) Doctors

FIGURE 6.22: Gini plots of the eastern and central districts in 2013

For the spatial accessibility case, a Lorenz curve can be obtained by plotting the cumulative percentage of spatial units (population clusters or subdistricts) against the cumulative percentage of spatial accessibility values of the corresponding spatial unit. Figures 6.22(a) to 6.22(d) and 6.23(a) to 6.23(d) show the plot of the Lorenz curves for different districts using the spatial accessibility indices of their population clusters. The dashed lines in these figures represent the line of equality, which indicates perfect equality of distribution. A Lorenz curve closer to the line of equality has a better equality in distribution of health care services than the ones further away from the line of equality.

The Gini coefficients of the twenty districts indicates that the Tsirang district had the best equality of distribution of health resources with a value of 0.13 for HA services and



(c) HAs (d) Doctors

FIGURE 6.23: Gini plots of of the southern and western districts in 2013

Tsirang and Bumthang districts had the best equality of distribution with a value of 0.08 for doctor services. Haa district with the Gini coefficient of 0.64 had the worst inequality of distribution of health assistants's services and Gasa district with a Gini coefficient of 0.36 had the worst inequality of distribution of doctor services in the country in 2013.

6.5.5 Clustering analysis of spatial accessibility indices

One of the important aspects of spatial data analysis is to determine the existence of identifiable spatial patterns by using either location or both the location and attribute information of the incident data points (Ord and Getis, 1995). There are a number of statistical tests available such as global statistics like Geary's C and global Moran's I to detect cluster occurrences at the global level, and local statistics like Getis-Ord Gi* (Ord and Getis, 1995), Local Indicators of Spatial Autocorrelation (Anselin, 1995) and local Moran's I (Moran, 1950) to determine the cluster at the local level. More complex methods for cluster detection include Besag and Newell's method (Besag and Newell, 1991) and spatial scan statistics (Kulldorff, 1997). In this study, Getis-Ord Gi* was used to produce hot spots (high value clusters) and cold spots (low value clusters) using the spatial accessibility indices of the population clusters. Equation 6.2 shows the mathematical formula to compute the Getis-Ord Gi* statistic:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - \left[\sum_{j=1}^{n} w_{i,j}\right]^2}{n-1}}} \tag{6.2}$$

where x_j is the spatial accessibility index for population cluster j, $w_{i,j}$ is the spatial weight between population clusters i and j, and n is the total number of population clusters, and $\bar{X}$ and S are the population mean and standard deviation, respectively (Equation 6.3).

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}, \quad S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2} \tag{6.3}$$

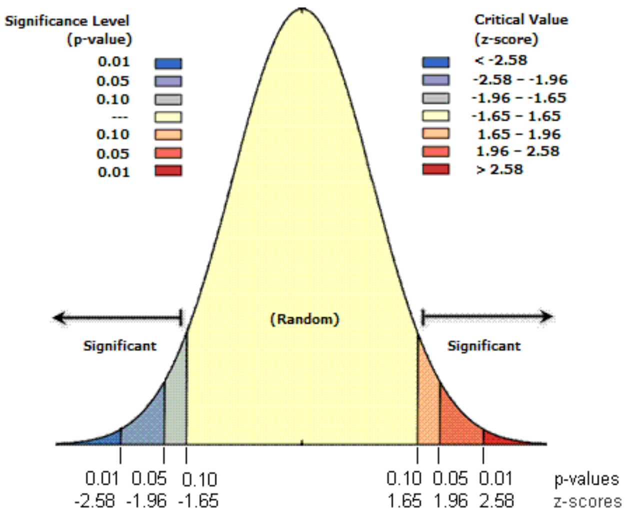


FIGURE 6.24: Normal distribution curve (ArcGIS, 2014)

A fixed distance band threshold value of 20000 metres was used to conceptualize the spatial relationship between the neighbouring points. Hot Spot Analysis tool in ArcGIS 10.2 was used to compute the p-values and z-scores (Getis-Ord Gi* statistic) of each of the population clusters. The p-value is the probability and the z-score is the standard deviation, which are associated with the normal distribution curve as shown in Figure 6.24. In this test, the null hypothesis states that the spatial accessibility values associated to those population clusters exhibits spatial randomness. A very high positive z-score or very low negative z-score with small p-value indicates that the observed spatial pattern is not due to random spatial processes as represented by the null hypothesis, hence leading to the rejection of the null hypothesis.

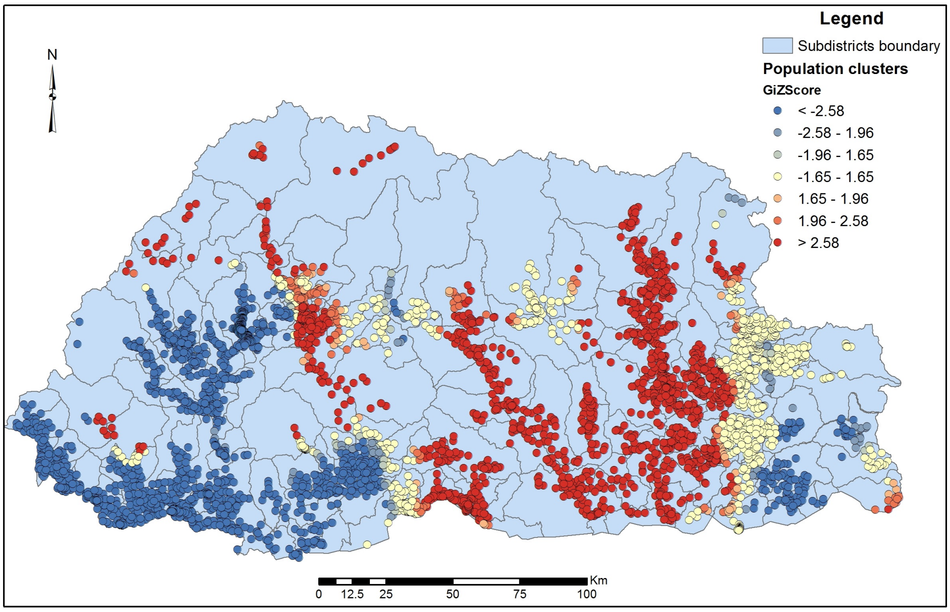


Figure 6.25: Hot spots and cold spots for HA services

Figures 6.25 and 6.26 show the spatial clusters for the HA and doctors services in 2013, respectively. At the 95% confidence level, the features with z-score values greater than +1.96 with low p-values were categorised as hot spots and features with z-score values less than -1.96 with low p-values were categorised as cold spots. Spatial accessibility hot spots refer to statistically significant features with high accessibility values which are surrounded by other features with high accessibility values whereas cold spots refers to statistically significant features with low accessibility values surrounded by other features with low accessibility values. In general, the pattern analysis outcome can be used for investigating the underlying hidden spatial processes that has caused the rejection of the

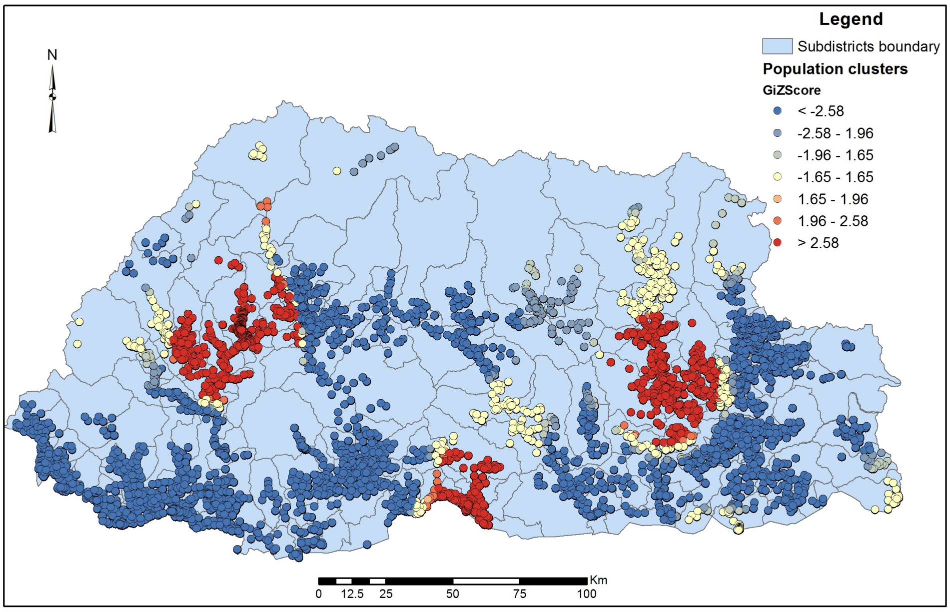


Figure 6.26: Hot spots and cold spots for doctor services

null hypothesis. In this study the hot spots and cold spots can be used to identify the under-served or over-served regions in order to allocate or reallocate the limited health care resources towards achieving an equitable health care delivery system in the country.

6.6 Combined healthcare providers

Using classification method proposed by Unal et al. (2007), the subdistricts of Bhutan were classified into good, medium and poor spatial accessibility groups using accessibility indices of both the health care providers. Figure 6.27 shows the histogram distribution plots of relative accessibility indices for the two different service providers. The histogram plots indicate a skewed distribution where mean values exceeded the median values for both the service providers. Median and mean values of the accessibility measures were used to classify subdistricts into three accessibility groups. A poor status indicates that the G_k value of a subdistrict is lower than the national median values of both the health care providers. A medium status indicates that the G_k value of a subdistrict is greater than the national median values but less than the national mean values. A good status indicates that the G_k value of a subdistrict is larger than the national mean values of both the health care providers.

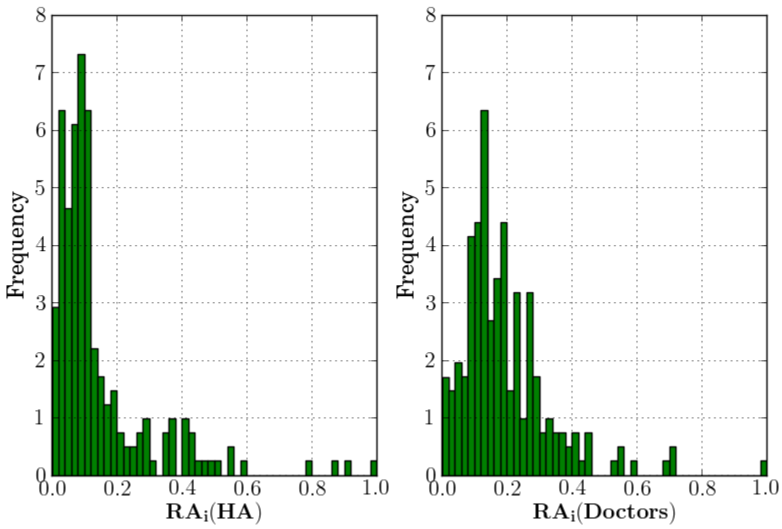


FIGURE 6.27: Histogram distribution plots of G_k values

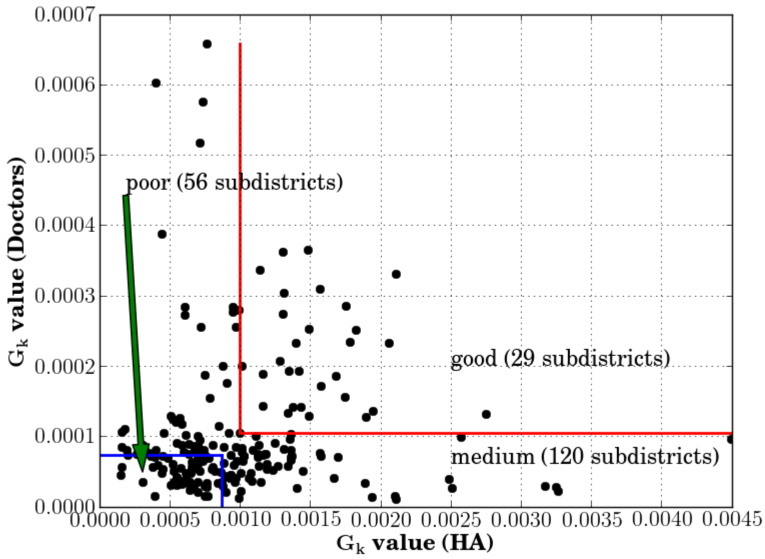


FIGURE 6.28: Classification of subdistricts using G_k values for both providers

Figure 6.28 shows the schematic representation of the subdistricts classified into three health care accessibility categories. There were 56 subdistricts which had poor access to both the service providers, 120 subdistricts that had medium level access and 29 subdistricts which had good access to both the providers in 2013. In terms of population 26 percent of the population had fallen under poor access category, 64 percent under medium access category and 10 percent under good access category. Table B.11 in Appendix B shows the district-wise classification status for the year 2013. Bumthang, Chukha, Dagana, Haa, Paro, Pemagatshel, Punakha,Samtse, Trashigang, Trashiyangtse, Tsirang and Wangdiphodrang had no good accessibility ranking subdistricts but these districts had one or more subdistricts under the medium or poor accessibility category. Bumthang, Gasa, Haa, Lhuntse, Mongar, Pemagatshel, Sarpang, Thimphu and Zhemgang districts did not have subdistricts which fell under the poor access category but they had one or more subdistricts achieving good or medium accessibility rankings. Tsirang, Dagana and Samtse districts had 10, 9 and 7 subdistricts with poor accessibility rankings, respectively, followed by Chukha and Trashigang with 6 poor-ranked subdistricts each.

6.7 Temporal changes of spatial accessibility

The spatial accessibility indices at different levels were computed for both the health care providers. Figure 6.29 shows the temporal variation in the districts spatial accessibility

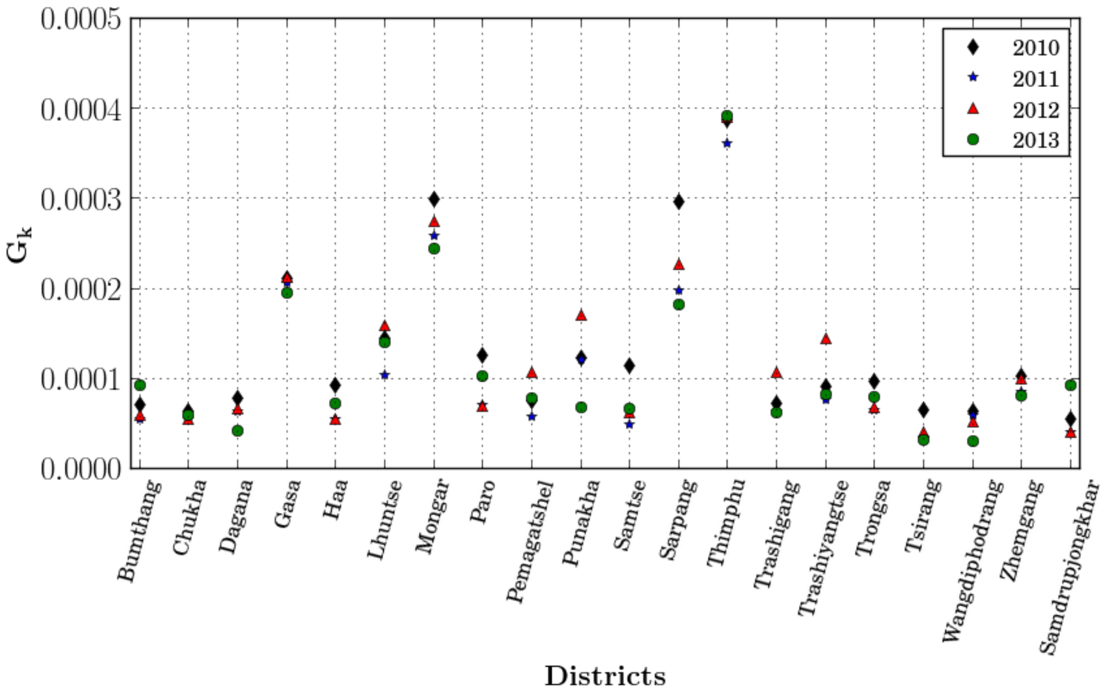


FIGURE 6.29: Districts' accessibility to doctor services from 2010 to 2013

indices for doctor services from 2010 to 2013. Since the district accessibility index is computed as an average of all the spatial accessibility indices of the population clusters within the district, the accessibility indices of a population cluster directly affects the value of the district's index. For instance, it can be seen in Figure 6.29 that the accessibility

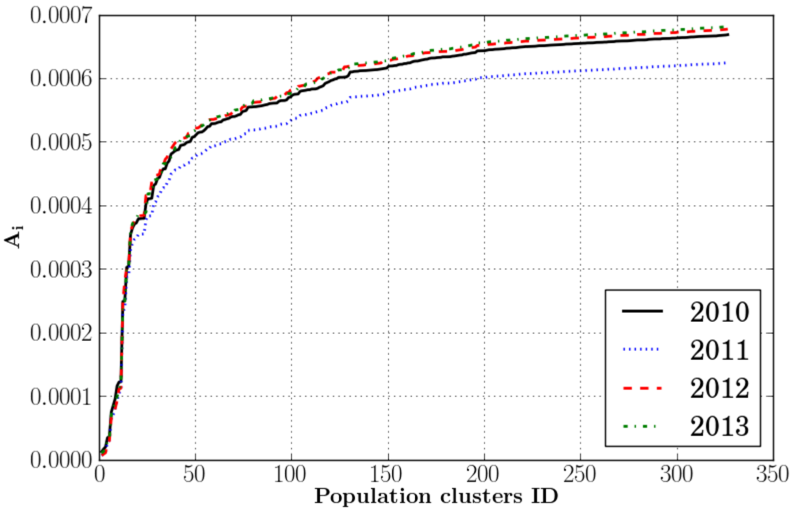


FIGURE 6.30: Accessibility scores for doctor services in Thimphu district from 2010 to 2013

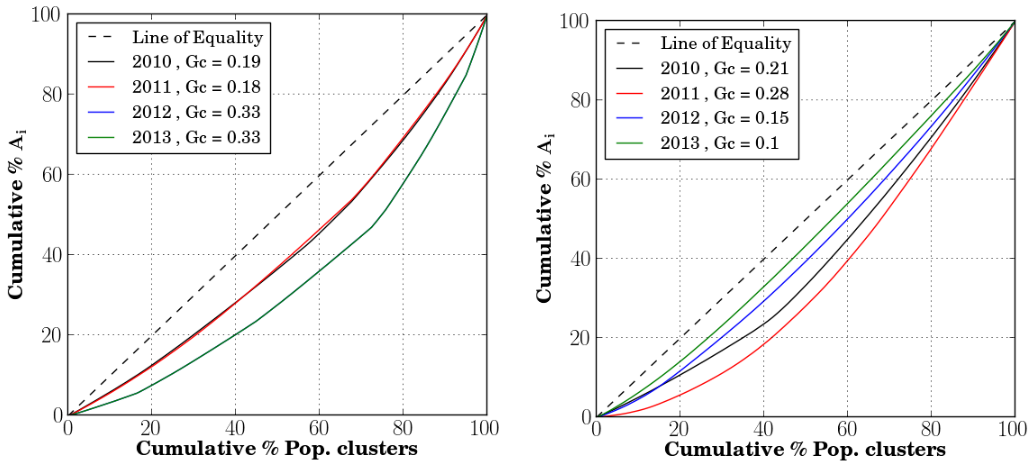
trend observed for the district's indices is similar to the trend observed for the population cluster's index in Thimphu district from 2010 to 2013, which is shown in Figure 6.30.

TABLE 6.8: Statistics for Thimphu district for doctor services from 2010 to 2013

Years	**Pop.**	**Avg. Distance**	G_k	**No. of Doctors**	**National Rank**	**Decreased or Increased By(%)**
2010	104202	18873.528	0.000387	68	1	0.00
2011	106569	18873.528	0.000361	65	1	-6.5
2012	108941	18873.528	0.000391	72	1	1.03
2013	111312	18873.528	0.000392	74	1	1.29

Table 6.8 shows the summary of the results for the Thimphu district from 2010 to 2013 for doctor services. The last field in the aforementioned table represents the percentage increase or decrease in the accessibility score with respect to the base year, 2010. The accessibility for doctor services in the Thimphu district decreased by 6% in 2011 and then increased by merely 1% in 2012 and 2013. This trend can be plausibly explained as follows. As the computation of the spatial accessibility index for the population cluster depends on distance, the number of the providers and population parameters, the same average distance values observed in Table 6.8 for all the years indicate the configuration of the population clusters and the health facilities remained unaltered from 2010 to 2013. Thus the distance parameter has not caused the variation of the Thimphu district's accessibility indices between these four years. The population of the Thimphu district had gradually increased from 2010 to 2013 so the population parameter would decrease the accessibility values in the same order because this parameter is being used to normalize the accessibility

index. On the other hand, the number of doctors available from 2010 to 2013 follows a similar trend as their district's accessibility indices. This indicates that the number of provider parameter had impacted considerably on the computation of Thimphu district's accessibility indices. Using similar logic and analysis, the spatio-temporal changes of subdistrict's or district's accessibility indices can be explained for other cases too.



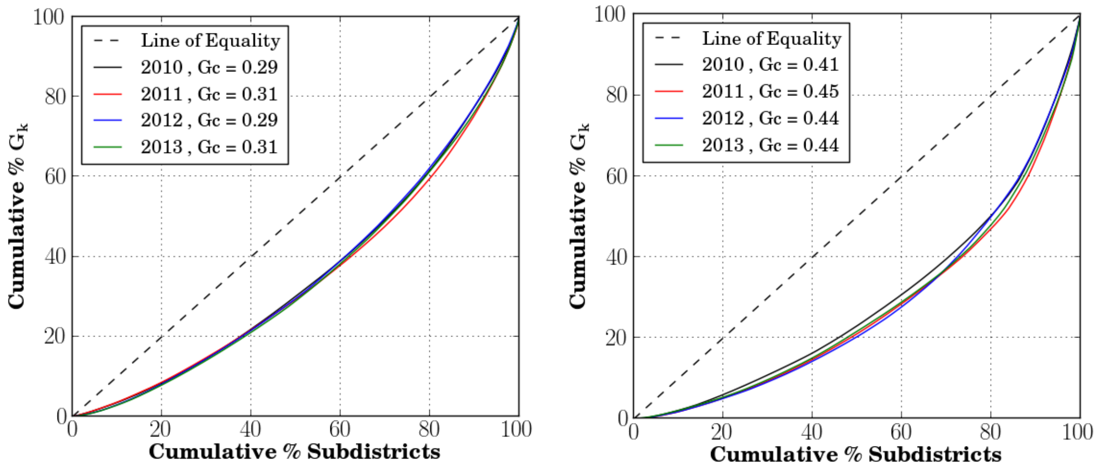
(a) HAs

(b) Doctors

FIGURE 6.31: Gini plots of Samtse district from 2010 to 2013

In order to study the variation in the equality or inequality in distribution of the spatial accessibility to primary health care services between 2010 to 2013, the Gini curves were plotted at the district and national levels using population cluster accessibility indices and subdistrict accessibility indices, respectively. Figures 6.31(a) and 6.31(b) show the Lorenz curves of the Samtse district for the two health care providers, obtained by plotting the cumulative percentage of accessibility scores of population clusters (A_i) against the cumulative percentages of the number of population clusters within the district. It can be clearly observed in Figure 6.31(a) that the Lorentz curves for 2010 and 2011 almost overlap, and also for the HA services for 2012 and 2013. This indicates that the equality distribution of spatial accessibility to HA services are the same for both 2010 and 2011, and 2012 and 2013. Their Gini coefficient values also confirm the similarity between 2010 and 2011, and 2012 and 2013. The Lorentz curve closer to the line of equality represents a much fairer distribution of spatial accessibility than the curve further away from the line of equality. However, the Lorentz curves for doctor services from 2010 to 2013 portrayed different distribution than the one observed for HA services. With Gini Coefficients of

0.10, 0.15, 0.21 and 0.28 for the years 2013, 2012, 2010 and 2011 respectively, the fairness of the distribution of spatial accessibility to doctor services in Samtse is in the same order.

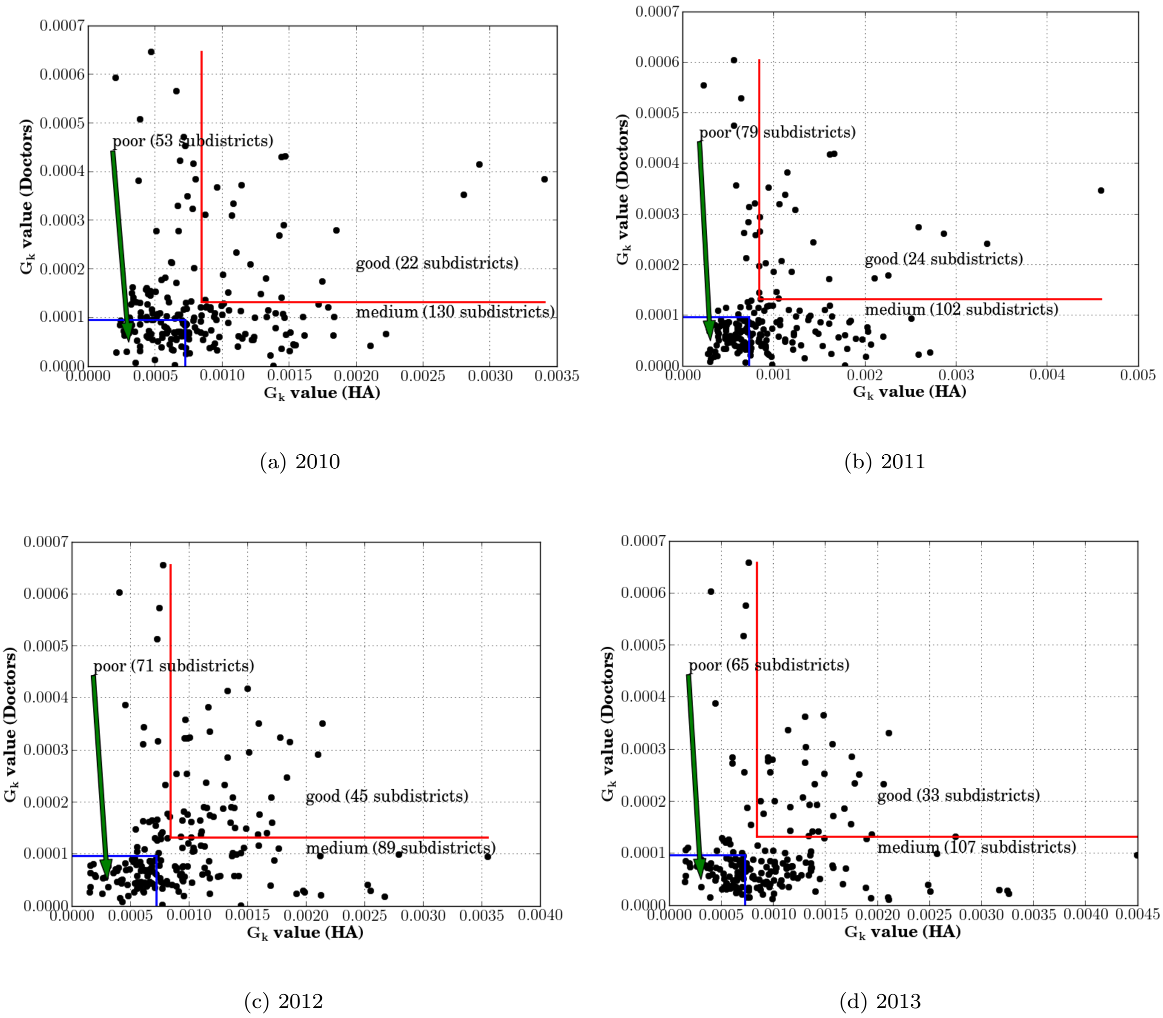


(a) HAs (b) Doctors

FIGURE 6.32: Gini plots of the two health care providers from 2010 to 2013

Figures 6.32(a) to 6.32(b) show the Gini plots of the HA and doctor services for the whole country from 2010 to 2013. The Lorenz curves were plotted using the cumulative percentage of accessibility indices of subdistricts (G_k) against the cumulative percentages of the number of subdistricts in the country. At the national level, the equality distribution of spatial accessibility to HA services (Gc $\approx$ 0.3) is slightly better than the equality distribution of spatial accessibility for doctor services (Gc $\approx$ 0.45) as indicated by their respective Gini Coefficients for all the years. For both the health care providers, there were no significant differences in the temporal changes of the spatial accessibility between 2010 to 2013 as their Gini Coefficients only differed by less than 0.002 for HA services and less than 0.004 for doctors services.

Figures 6.33(a) to 6.33(d) show the temporal change in the number of subdistricts classified into three groups from 2010 to 2013, respectively. The classification was done by comparing the subdistricts accessibility indices in a given year with the mean and median accessibility values of the base year, 2010. As per the combined classification method, there were 53 poor-ranked subdistricts, 130 medium-ranked subdistricts and 22 good-ranked subdistricts in 2010. The results from 2011 to 2013 indicate an increase of the number of poor-ranked subdistricts by 26, 18 and 12 respectively. With respect to the medium category group, the number of subdistricts classified into this group decreased by 28, 41 and 23 in 2011, 2012 and 2013 respectively whilst the number of good-ranked subdistricts increased by 2, 23 and 11 in 2011, 2012 and 2013, respectively.



(a) 2010

(b) 2011

(c) 2012

(d) 2013

FIGURE 6.33: Classification of subdistricts from 2010 to 2013 with reference to 2010

6.8 "What If" scenarios analysis

Two hypothetical scenarios were formulated to evaluate the change of accessibility outcome based on the different values of input parameters within a spatial accessibility model. The first scenario investigated the implication of health accessibility across the country when more providers are added into the health care system. The second scenario evaluated the implication of health accessibility when both health facilities and providers are simultaneously increased in the health care system. Such 'What If' scenario analysis can be effectively used to develop evidence-based policies to facilitate the establishment of new health facilities or distribution of health care providers equitably across the country.

6.8.1 Scenario 1: Increasing health care professionals in the health care system

For both the health care providers, two different scenarios were examined by increasing the number of providers to have a minimum of three or five health care providers in each of the health facilities. The actual health and population data was used to develop these scenarios. The minimum three and five providers method is termed as Scenario

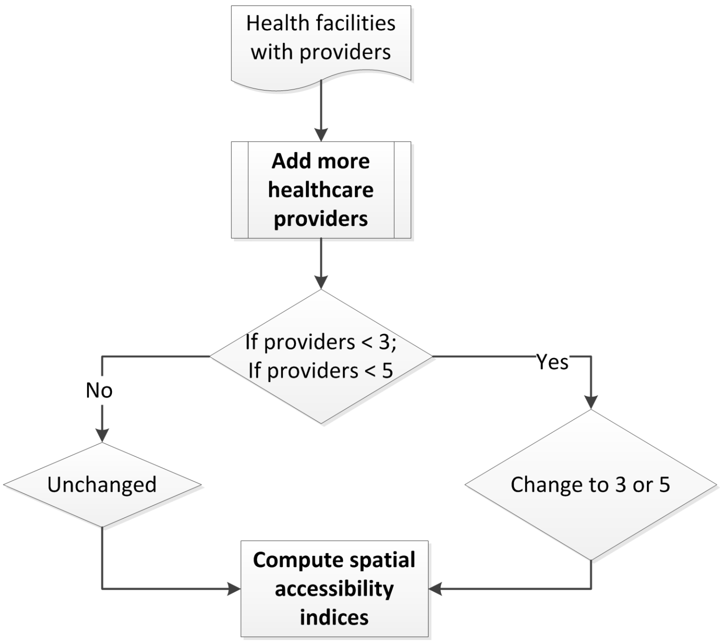


FIGURE 6.34: Additional processing steps for Scenario 1

1 - Minimum 3 Providers and Minimum 5 Providers methods, respectively. Figure 6.34 shows the additional processing step required for both the HAs and doctors services to evaluate Scenario 1. The computation of the spatial accessibility indices was done using the method described in Section 4.5.

Table B.12 in Appendix B shows the result of the combined analysis for the Scenario 1 - Minimum 3 Providers method when compared with the accessibility results from 2013. For this method, the number of subdistricts ranked under good category increases to 80 from 31, medium-ranked and poor-ranked subdistricts decreased to 120 and 5 from 121 and 53, respectively. In terms of population about 31 percent of the population would fall in the good accessibility group, 67 percent in the medium accessibility group and only 2 percent in the poor accessibility group. To achieve this accessibility outcome, it would require a total of 186 doctors in 32 health facilities with doctor services and 809 HAs in 210 health facilities with HA services across the country.

Table B.13 in Appendix B shows the results of the combined analysis for the Scenario 1 - Minimum 5 Providers method when compared with the results from 2013. For this method, the number of good-ranked subdistricts increases to 134 from 31, medium-ranked and poor-ranked subdistricts decreases to 71 and 0 from 121 and 53, respectively. In terms of population about 51 percent of population would fall in the good accessibility group, 49 percent in the medium accessibility group and none in the poor accessibility group. In order to achieve this outcome, there is a need for a total of 240 doctors and 1165 HAs respectively allocated to 210 health facilities with HA services and 32 health facilities with doctor services across the country.

6.8.2 Scenario 2: Increasing health facilities and providers in the health care system

In Scenario 2, the number of health facilities and health care providers were increased by allocating new health facilities to the under-served regions. Well-served population clusters were defined as those clusters having spatial accessibility values higher than the national average value, and the under-served clusters were those with lower values than the national average value. Allocation of new health facilities to the under-served regions were carried out as described in Figure 6.35. New health facilities were created using the population clusters of the underserved areas by integrating and collecting the point clusters using 5000 and 15000 meters cell size for HA and doctor services respectively. This integration and collection process creates point clusters at the spatial mean position of the collected point events. In some instances these newly created point clusters were created farther away from the settlement areas, so those point clusters were manually repositioned near the settlement areas. Figures A.12 and A.13 in Appendix A show the well-served and under-served accessibility regions along with the distribution of the existing and new health facility sites across the country for HA and doctor services, respectively.

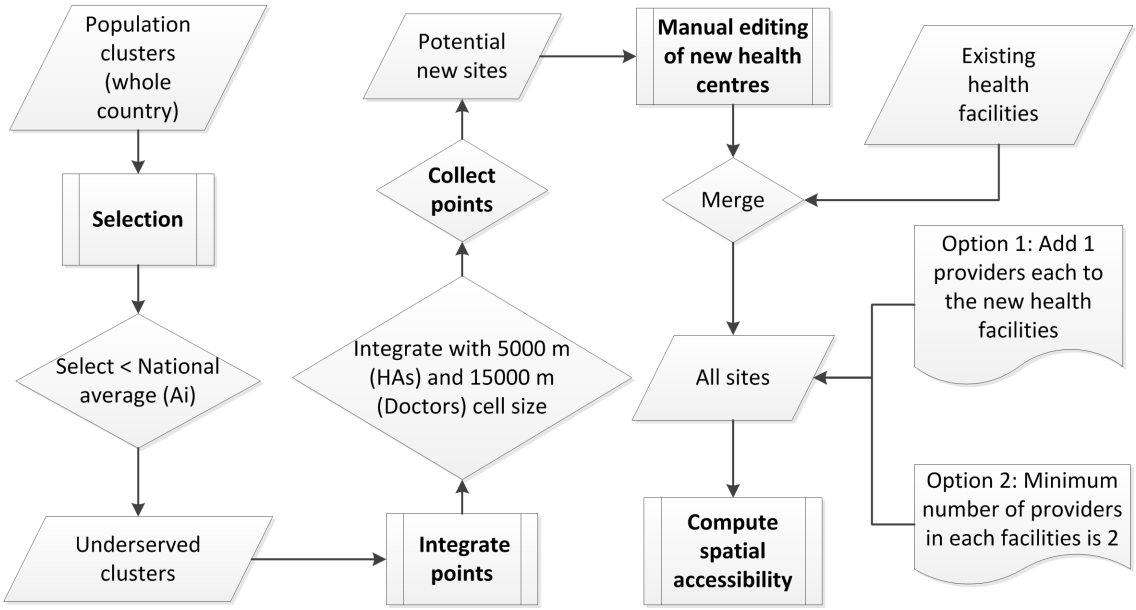


Figure 6.35: Processing steps for Scenario 2

Two different methods of processing were done for Scenario 2. Option 1 involved using 65 new health facilities for HA services and 19 additional facilities for doctor services with one health care provider in each of the new facilities in addition to the existing facilities and providers. Option 2 also involved using the same number of additional health care facilities in addition to the existing facilities, with at least having a minimum of two health care providers in each of the health facilities.

Table B.14 in Appendix B shows the results from combined analysis for the Scenario 2 - Option 1 method when compared with the results from 2013. For this method, the number of good and medium-ranked subdistricts increased to 56 and 130 from 31 and 121, respectively, and poor-ranked subdistricts decreased to 19 from 53. In terms of population about 20.5 percent of population would fall in the good accessibility group, 69 percent in the medium accessibility group and 10.5 in the poor accessibility group. In order to achieve this outcome, some 163 doctors in 51 health facilities with doctor services and 689 HAs in 275 health facilities with HA services would be needed.

Table B.15 in Appendix B shows the results of the combined analysis for the Scenario 2 - Option 2 method when compared with the results from 2013. For this method, the number of good-ranked subdistricts increased to 120 from 31 and the number of medium and poor-ranked subdistricts decreased to 85 and 0 from 121 and 53, respectively. In terms of population about 59 percent of the population would fall in the good accessibility group, 41 percent in the medium accessibility group and none in the poor accessibility group. 199 doctors in 51 health facilities with doctor services and 814 HAs in 275 health facilities with HA services would be needed to achieve this outcome.

6.8.3 Analysis of the two scenarios

Though the analyses are based on hypothetical scenarios, such analysis can be incorporated in health care accessibility planning for efficient distribution of health resources to different subdistricts in the country. Scenario 1 deals exclusively with the increase in the number of providers while Scenario 2 deals with the increase in the health facilities as well as the health providers. By increasing only the number of providers as in the case of Scenario 1 would considerably improve the spatial accessibility to health care services, however travelling distance between the locations of the residents and the health facilities would not change. Therefore, Scenario 2 health policies offered a better alternative towards improving the spatial accessibility to primary health care services as such policy alternative would greatly reduce the travelling distances to health facilities besides increasing the supply of health care providers in the population catchment areas.

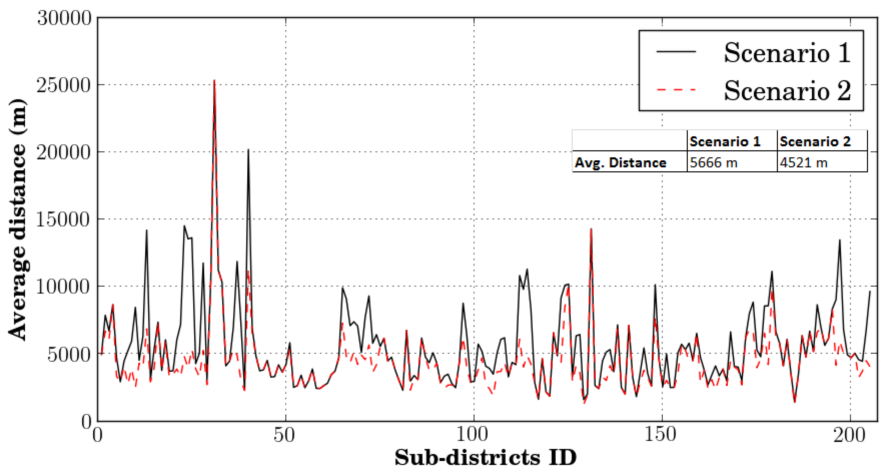


Figure 6.36: Average distances between health facilities and population clusters within subdistricts for Scenarios 1 and 2 for HA services

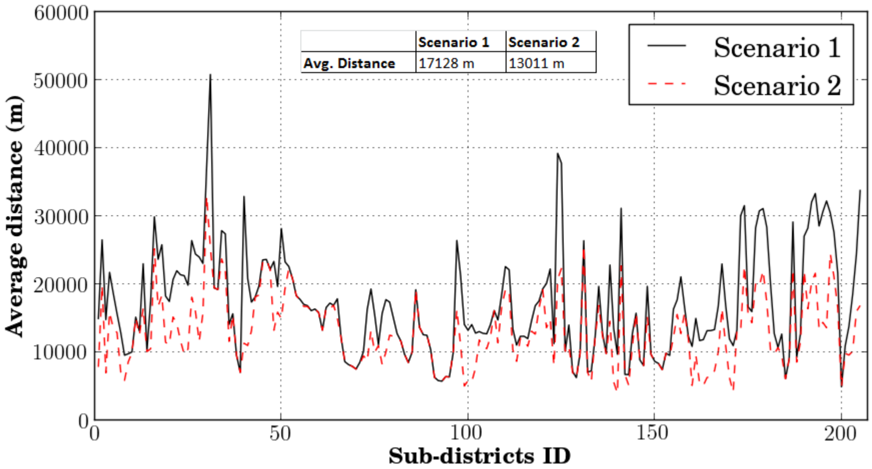


FIGURE 6.37: Average distances between health facilities and population clusters within subdistricts for Scenarios 1 and 2 for doctor services

Figures 6.36 and 6.37 show the average distances between the population clusters and the health facilities within subdistricts between Scenarios 1 and 2 for HA and doctor services, respectively. These figures clearly show that the travelling distances between the resident location and the health facilities have decreased when additional health facilities were introduced into the health care system. For HA services, the average travelling distance of the whole country is 5.6 Km for Scenario 1 while it is 4.5 Km for Scenario 2. For doctor services, the average travelling distance of the whole country is 17.13 Km for Scenario 1 while it is 13.01 Km for Scenario 2.

Figures A.14(a) to A.17(b) in Appendix A show a classification of subdistricts based on G_k values obtained by combining the results from HA and doctor services of Scenarios 1 and 2. The criteria for classification into good, medium and poor category was carried out using the average and median values of the base reference year, 2013. Only eight possible combinations between the two providers were shown in these figures out of many possible combinations. In accordance with the number of subdistricts for good, medium and poor categories, Scenario 1 Minimum 5 providers method for doctor services with Scenario 2 Option 2 for HA services produced the best accessibility outcome amongst the eight combinations shown.

All these analyses were carried out only to show that spatial accessibility to primary health care can be planned by formulating potential scenarios and then identifying the best possible outcome, by assessing their spatial accessibility indices using individual and combined analysis method. In this way, health planners can effectively conduct evidence-based planning in the allocation of limited health resources equitably to various subdistricts in the country.

6.9 Summary

This chapter presented the spatial accessibility results and different methods of analysis by using the spatial accessibility indices. It has been demonstrated using various analytical techniques that the spatial accessibility measure can be used for identifying the medically under-served and over-served regions, for measuring the equality of distribution of health resources across the regions as well as studying the temporal changes in the distribution of the health resources in the country. The spatial accessibility results of 2013 show that there were huge disparities in the distribution of the health resources in the country with the best-ranked Lingzhi subdistrict of Thimphu district having 30 times better accessibility to HA services than the lowest-ranked Bara subdistrict of Samtse district, with Chang subdistrict of Thimphu district having 64 times better accessibility to doctor services than the Athang subdistrict of Wangdiphodrang district. The Gini coefficients of the twenty districts indicate that the Thimphu and Tsirang districts had the best equality of distribution for doctor services and the later district also had the best equality of distribution for HA services. Haa district had the worst inequality of distribution for HA services and Zhemgang district had the worst inequality of distribution for doctor services in the country in 2013.

A number of hypothetical policy scenarios were formulated to study the implication of increasing the health facilities and the health care providers. Even by merely increasing the number of health care providers by one or two per health facility, this would increase the number of subdistricts in good accessibility group considerably. Increasing only the number of health care providers will not address the travelling distance between locations of the residents and the health facilities. Therefore, there is a need to design policy scenarios by simultaneously increasing both the number of health care providers and the health facilities. In the hypothetical scenario formulated in this study, Scenario 1 Minimum 5 providers method for doctor services with Scenario 2 Option 2 method for HA services produced the best accessibility outcome.

In the following chapter, the spatial accessibility indices are used for calculating composite accessibility index for Bhutan's gross national happiness measurement system.

Chapter 7

Future Application

This chapter presents a potential application of spatial accessibility indicators in consolidating accessibility component of the GNH measurement system. In doing so, three different accessibility indices which are relevant to Bhutan are discussed and compared to each other. Firstly, the equity of access to road transportation within the country was measured by calculating a simple straight-line distance separation between the closest road point and the dwelling location of the residents. Secondly, the remoteness accessibility index of a population cluster was calculated based on the straight-line distance proximity of a population cluster to its nearest major and minor towns, health and educational centres and nearest road access point. Thirdly, spatial accessibility to education, health and agriculture service centres within the country was modelled using the AM2SFCA model.

The structure of this chapter is as follows. Section 7.1 presents background on GNH philosophy and measurement system, and Section 7.2 presents the need for including the (spatial) accessibility indicators in the current GNH measurement system. Sections 7.3, 7.4 and 7.5 present the computational aspects, data analysis and results for road accessibility, remoteness accessibility and spatial accessibility to educational, health and RNR (renewable natural resources) services in Bhutan, respectively. Section 7.6 analyses the similarities between different accessibility indices.

7.1 Background on GNH

The beginning of the GNH developmental paradigm dates back to 1986 when the fourth King of Bhutan, Jigme Singye Wangchuck stated in an interview in London conducted by the Financial Times, that gross national happiness is more important than gross domestic product (Brahm, 2009). This new developmental paradigm sought for a middle path approach by balancing material and spiritual development. The former prime minister of Bhutan stated that GNH places equal emphasis on all aspects of development which includes social, economic, environmental, spiritual, cultural and emotional needs of the people (Thinley, 1998). In GNH, economic growth is not seen as a dominating force in development but only as a subsidiary part of socio-economic needs of the people in order to bring happiness in their lives.

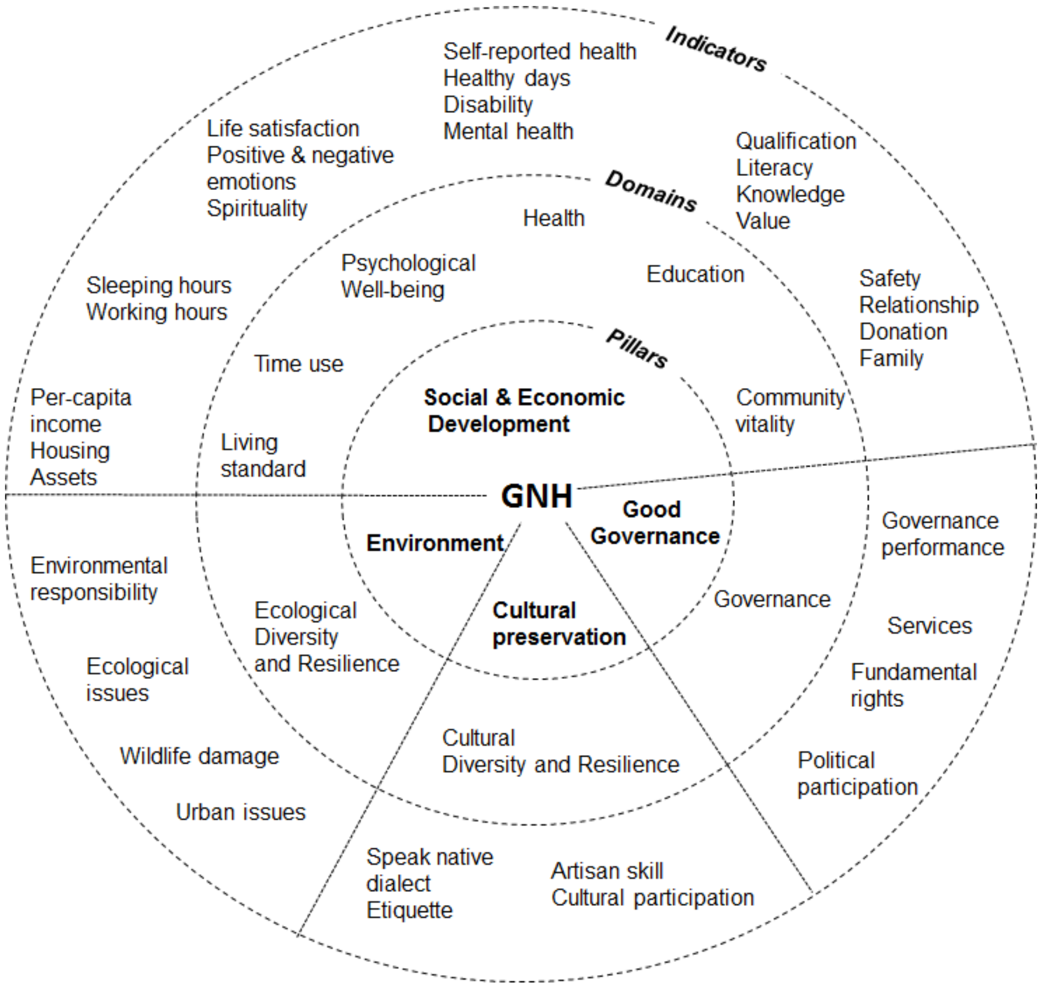


Figure 7.1: Components of the GNH system

Figure 7.1 shows the pillars, domains and indicators of the GNH measurement system. There are four main pillars of GNH, namely sustainable and equitable socio-economic development, conservation of environment, preservation and promotion of culture and promotion of good governance (Ura et al., 2012). These in turn are further divided into nine domains, namely, psychological well-being, health, time use, education, cultural diversity and resilience, good governance, community vitality, ecological diversity and resilience and living standard. Each domain is measured by some number of indicators which are in turn measured from several sub-indicators or variables. Each sub-indicator represents a specific survey question used for collecting data from the respondents. A total of 33 GNH indicators encompassing nine domains were proposed for calculating the GNH index using Alkire-Foster methodology, a multidimensional approach for measuring poverty or wellbeing indices (Alkire and Foster, 2011). The ultimate goal of the GNH measurement system is to use the GNH index for framing developmental policies, planning and allocation of resources, measuring happiness and well-being of people and gauging the developmental progress of subdistricts, districts and nation as a whole (Ura et al., 2012). Based on these indicators, GNH became the developmental guide for policy making process in Bhutan.

7.2 Why spatial-based GNH accessibility indicators?

The absence of any spatial-based indicators in the current Gross National Happiness (GNH) measurement system makes this holistic model incomplete for spatial planning purposes in Bhutan. Spatial indicators are generally related to geographic space where the location, distance or area of a spatial object is measured to capture the outcome of a spatial relationship or phenomenon. For instance, spatial indicators are essential in capturing the separation of human settlements from the nearest road point and in measuring the loss of forests cover due to human activities. An evidence-based approach to measuring road and remoteness accessibility indices of population clusters and spatial accessibility indices of health, education and agriculture service centres for the whole country can be potentially used as an indicator to facilitate proper planning of allocation of social service centres and road infrastructure in the country.

According to the results of the 2008 GNH survey, twenty different sources of happiness for the Bhutanese people were identified as shown in Figure 7.2 (Centre for Bhutan Studies, 2008). It indicated that access to roads, education, good health and agricultural productivity are within the top six sources of happiness for the Bhutanese people. Access to roads can be simply understood as the closeness of roads to a particular settlement such that people within that settlement can travel by a vehicle from one place to the other. It is possible to spatially quantify access to roads by measuring the distance to the nearest road point from a particular dwelling location of the residents. Nevertheless, there is no indicator included in the current GNH system to measure road accessibility despite it is being perceived as the second most important source of happiness by the people of Bhutan. However, education, health and agricultural productivity may very well depend on a number of factors. One key factor impacting on these three variables could be spatial accessibility to the respective service centres.

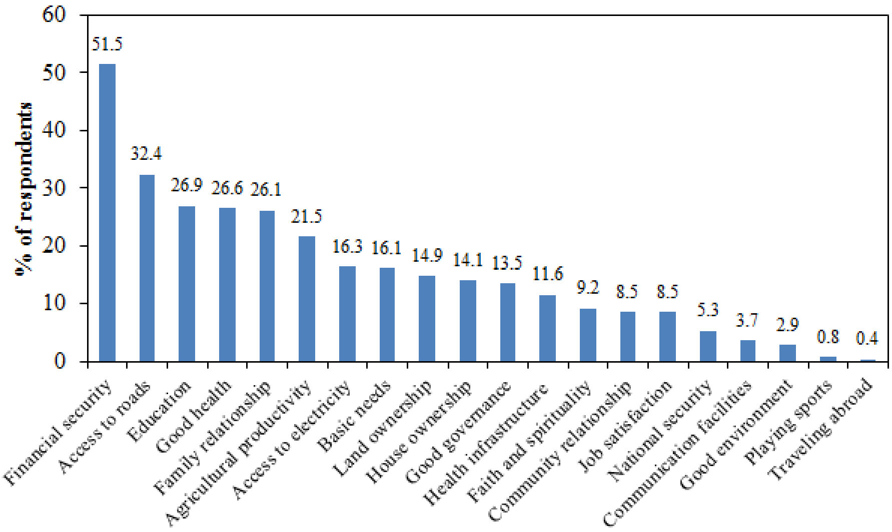


FIGURE 7.2: Priority sources of happiness for the Bhutanese people

Spatial accessibility measures the availability of service centres and accessibility to these centres based on the potential demand for services (Weibull, 1976). By measuring spatial accessibility to certain service centres, it is possible to identify spatial patterns of accessibility to various services and equity of distribution of service centres within a given region (Talen and Anselin, 1998). Spatial accessibility has been widely used for policy making purposes in the field of transport, urban, land use and infrastructural planning (Geurs and van Wee, 2004). Most notably, the importance of spatial accessibility to health services had been widely reported in literature (Weibull, 1976; Aday and Anderson, 1981; Joseph and Bantock, 1982; Khan and Bhardwaj, 2002; Fortney et al., 2000; Luo and Wang, 2003; Luo and Qi, 2009; McGrail and Humphreys, 2014; Jamtsho et al., 2015).

Other studies on accessibility include equity of distribution of public amenities (Talen and Anselin, 1998; Talen, 2002; Smoyer-Tomic et al., 2004; Wolch et al., 2005), food stores (Dai and Wang, 2011) and transportation networks (Geurs and van Wee, 2004). Often accessibility measure can be used as an economic indicator to assess the economic benefits of changes in land-use and transport planning and as a social indicator to evaluate access to various social and economic services for a disaggregated population (Geurs et al., 2015). There are a number of non-spatial indicators included in the GNH system to measure different aspects of education, health and agricultural services within the country, however, there is no indicator defined to measure the spatial distribution of these important social service centres within the country.

The GNH policies guided the development of the Ninth and Tenth Five Year Plans of Bhutan (GNHC, 2009, 2013). In doing so, the ministries and autonomous institutions around the country were required to formulate plans and activities and gauge those activities based on GNH indicators. There were no meaningful indicators available in the current GNH system to gauge the progress of technically-related activities. For instance, the change in the coverage of forest area in the country can only be measured by actually calculating the acreage of the forest cover in certain time intervals. Similarly, the universal coverage of health care services can only be effectively determined by measuring the physical distances between the service centres and the dwelling locations of the populations. The current practice of measuring the progress of technical activities with the existing GNH indicators by indirect comparison is flawed because the relationship between the technical variables and the GNH variables cannot be ascertained. Therefore, there is a need to include specific technical variables, such as the accessibility indicators for measuring road accessibility and spatial accessibility indices for measuring spatial access to healthcare services, within the GNH measurement framework, in order to accurately gauge the progress of technical activities in various organizations.

7.3 Road accessibility indices

A simple measure of road accessibility can be computed as the distance to the nearest road point from the population cluster. In urban areas where multiple access roads are available this distance is very small, whereas, the distance to the nearest road point in rural areas may vary by up to tens of kilometres. Figure 7.3 shows the distance to the nearest road point from individual population clusters of the whole country. The distance to the nearest road point from the population cluster was measured as the straight-line distance between that population cluster and its nearest road point. Table 7.1 shows the summary of population falling in different distance ranges. About 40 percent of the

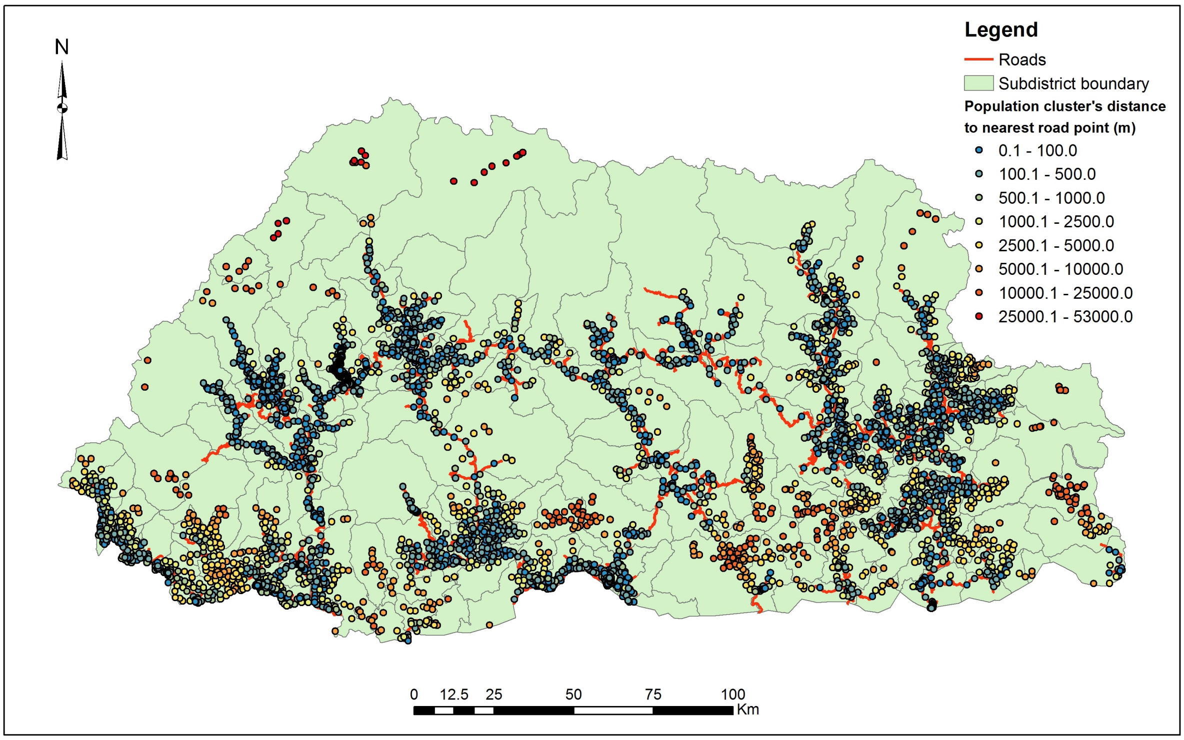


FIGURE 7.3: Distances between population clusters and nearest road points

TABLE 7.1: Summary of distances between population clusters and nearest road points

Distance to nearest road point	**Population**	**Percentage**
< 100 m	292952	39.96
100 to 500 m	263660	35.97
500 to 1000 m	48395	6.60
1 to 2.5 Km	47952	6.54
2.5 to 5 Km	35357	4.82
5 to 10 Km	24901	3.40
10 to 25 km	17438	2.38
25 to 53 Km	2377	0.32
Total	**733032**	**100**

population lived within 100 metres of a road point, 80 percent of the population lived within 1 kilometre and 87 percent of the population lived within 2.5 kilometres. About 13 percent of the population were living more than 2.5 kilometres away from the nearest road point with only 2.6 percent of that population living farther than 10 kilometres. The longest distance to the nearest road point was about 53 kilometres recorded for one of the population clusters in Lunana subdistrict of Gasa district.

TABLE 7.2: Average distances between population clusters and nearest road points at the district level

		Distance to road point (Km)		
Districts	**Population**	**Mean**	**Max.**	**Min.**
Bumthang	18416	0.28146	0.41829	0.17816
Chukha	85615	2.36880	9.41667	0.10850
Dagana	26550	1.82380	4.30153	0.16870
Gasa	3578	19.92821	45.13637	0.31443
Haa	13147	4.23128	11.53817	0.15243
Lhuntse	17207	0.86125	1.85014	0.29472
Mongar	42843	1.98418	10.21517	0.16915
Paro	41848	0.39421	2.58957	0.08790
Pemagatshel	24648	2.23764	6.61539	0.18792
Punakha	26982	0.28286	0.61336	0.12364
Samtse	68582	1.89279	6.33535	0.20113
Sarpang	43920	1.89205	11.97089	0.07553
Thimphu	111312	7.14249	26.35024	0.16273
Trashigang	54766	2.29992	16.86389	0.18411
Trashiyangtse	20264	1.87917	5.78789	0.35896
Trongsa	15502	0.78794	1.79877	0.21167
Tsirang	21215	0.54605	1.95145	0.13980
Wangdiphodrang	36278	0.94471	3.05095	0.07156
Zhemgang	20950	5.59447	9.95943	0.28258
Samdrupjongkhar	39409	4.24695	19.18066	0.22866

At the sub-district level, the longest mean distance to nearest road points from resident locations was about 45 kilometres as recorded for Lunana subdistrict of Gasa district followed by Laya subdistrict of Gasa district and Lingzhi subdistrict of Thimphu district with a mean distances of 26 kilometres. Gasetsho Wom subdistrict of Wangdiphodrang district and Taklai subdistrict of Sarpang district had the least mean distance to nearest road points from their population clusters measuring at about 70 metres. Table 7.2 shows the average distance to nearest road points from population cluster at the district level. Paro district had the least mean distance to the nearest road points of about 400 metres, with a maximum distance of 2.5 kilometres for Tsento subdistrict and minimum distance of about 80 metres for Dopshari subdistrict. Gasa district had the longest mean distance to nearest road points of about 19 kilometres and minimum distance of about 300 metres for Khamae subdistrict.

7.4 Remoteness accessibility indices

Faulkner and French (1983, p. 3) defined remote communities as "spatially defined communities which are distant from urban centres where supplies of goods and services, and opportunities for social interaction are concentrated". They proposed a geographical approach of computing remoteness accessibility based on distances to a number of different levels of urban hierarchy, which can be classified based on population size. Following a similar measurement approach of Faulkner and French (1983), Department of Health and Aged Care & National Key Centre for Social Applications of Geographic Information Systems (2001) developed a geographic measure of remoteness for the whole region of Australia, called the Accessibility/Remoteness Index of Australia (ARIA). The remoteness accessibility index of Bhutan can also be computed by adopting the ARIA model with some modification in the usage of service centres. In the case of Bhutan, five different service centres were used for measuring remoteness indices, namely major towns (comprises of only Thimphu and Phuntsholing cities where major economic activities occur in the country), minor towns (all other towns in the country with relatively low economic activities), nearest road point, hospitals (districts and referral hospitals) and education centres (primary and secondary level schools). For computational purposes, towns were represented by polygon features, roads by line features, and health and educational centres by point features.

The computation of accessibility indices was as follows. The straight-line distance between each population cluster and its five nearest service centres were computed. In the case of towns, if a distance to the nearest minor town of a given population cluster is longer than the distance to the nearest major town of that cluster then the distance to the major town was used for both the towns because major town is at the higher level of hierarchical structure than the minor town, following the computational process of the ARIA model. The distances obtained for the other three service centres remained unchanged because of their exclusion from the hierarchical structure of towns. Then these distances were standardised by dividing each distance value by the mean value for the country for that service centre category. Each standardised value is curtailed to a maximum value of 4.0 in order to limit the effect of the extreme values on the computation of the overall remoteness index of a population cluster, which is equal to the sum of all the indices obtained from different service categories. The maximum remoteness index is 20, which is equal to the sum of all possible maximum values in each service category.

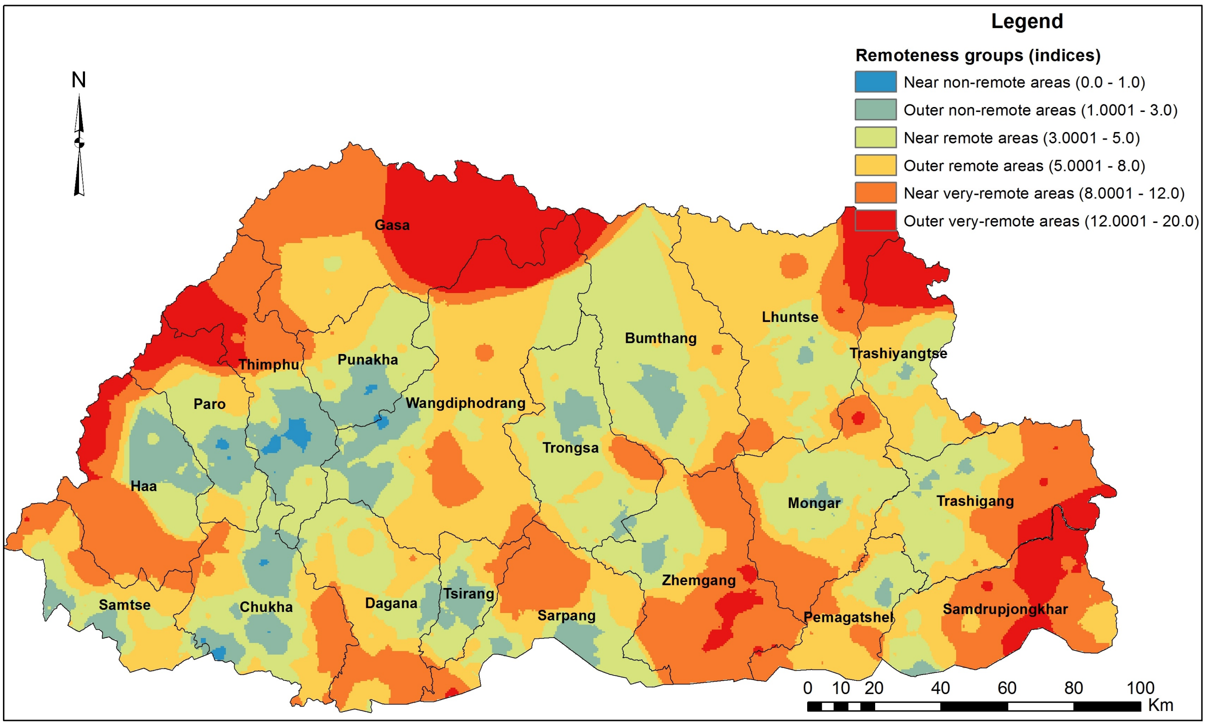


FIGURE 7.4: Remoteness accessibility indices map of Bhutan

The remoteness accessibility indices were calculated only at the location of population clusters. Therefore, the remoteness accessibility values of all regions across Bhutan were spatially interpolated using inverse-distance squared weighting method at 500 metres cell resolution using 6 nearest neighbours. These remoteness indices were arbitrarily classified into six different groups. Figure 7.4 shows the remoteness accessibility indices map of Bhutan. Table 7.3 shows the distribution of population between different remoteness groups. About 52% of the population lived in non-remote areas, 41% in remote areas and only 7% in very-remote areas.

TABLE 7.3: Population distribution between different remoteness groups

Groups	**Population**	**Percentage**
Near non-remote areas	122729	17.03
Outer non-remote areas	250649	34.78
Near remote areas	195950	27.19
Outer remote areas	97507	13.53
Near very-remote areas	47420	6.58
Outer very-remote areas	6414	0.89
Total	**720669**	**100**

7.5 Spatial accessibility indices

The simple road accessibility measure described in Section 7.3 only considers the physical closeness of the population clusters to the road network. A better measure of accessibility to social service centres can be computed using the spatial accessibility model presented in Chapter 4 where relative attractiveness of the service centres and their population catchment regions are considered exclusively. For the computation of the GNH accessibility indices primary and secondary level educational centres, primary healthcare centres and RNR centres were used as the basic service centres that are predominantly used by the majority of the population. RNR centres provide agricultural, forestry and livestock services to the general farming community. Figure 7.5 shows the locations of the education, health and RNR service centres. There were 356 primary and secondary level educational facilities, 208 health facilities and 236 RNR facilities in the country in 2012 as per the database obtained from the NSB. More service centres could be included in the computation of spatial accessibility measure if the spatial and attribute information of other social or business service centres were available. In this study, it was restricted to only three different service centres due to the availability of the data.

Recall that the spatial accessibility model includes the attractiveness component of the facilities, represented by S_j in Equation 4.9. In the computation of the spatial accessibility to primary healthcare services, the number of doctors or health assistants was used to define the attractiveness variable. Similarly, the attractiveness variable for the educational and agricultural services can also be defined using the number of professionals available in each of these centres. However, due to the unavailability of comprehensive human resource data in either educational or agricultural centres, the attractiveness component could not be consistently defined amongst the three service centres using the number of service providers. Therefore, the attractiveness component was based on their sole existence as a unitary service centre within a region irrespective of the number of professionals available in the centres (i.e. $S_j = 1$). The use of the same value for the attractiveness component had an added benefit as it would ensure that only the distance and population variables influenced the computational results, necessary for GNH's accessibility indices. The computation of the spatial accessibility to three different service centres were carried out individually as described in Section 4.5.

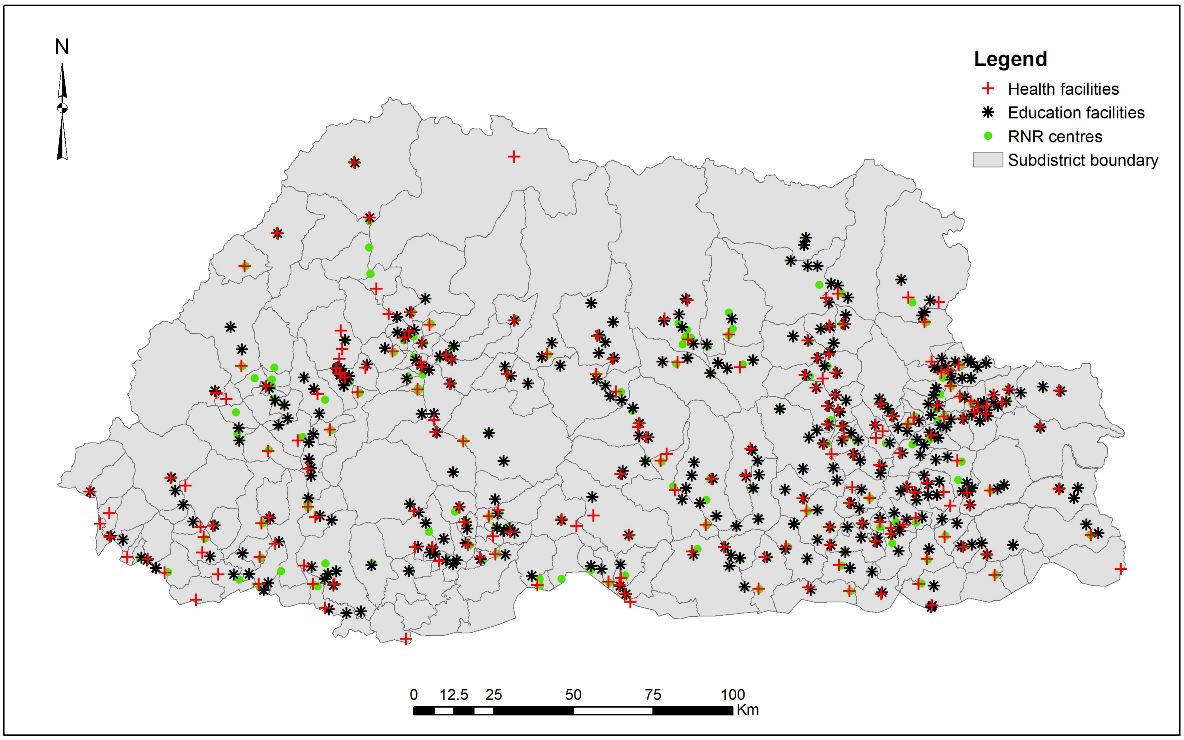


FIGURE 7.5: Locations of education, health and RNR service centres

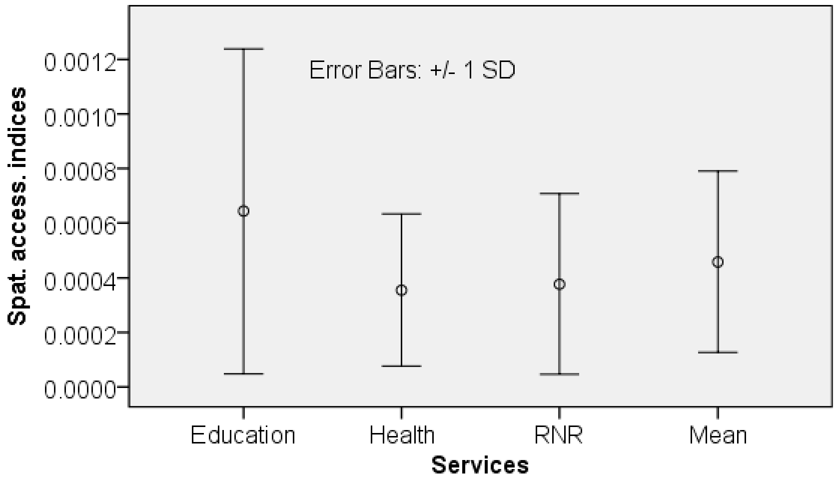


FIGURE 7.6: Error bars of spatial accessibility scores of population clusters for different services

Figure 7.6 shows a schematic plot of error bars representing the mean and standard deviations of spatial accessibility indices of all population clusters in the country. The people of Bhutan had better access to educational services with a mean value of 0.000643 when compared with spatial accessibility to the health and RNR services, which had mean scores of 0.000355 and 0.000377, respectively. However, the spread of accessibility scores for individual population clusters from the mean value was almost double for the educational service than the other two services, indicated by the length of the error bars. The large variation of accessibility scores of population clusters for all three services was due to the presence of a number of population clusters with high values outside the 75^{th} percentile of the box-plots shown in Figure 7.7. These values were not outliers because spatial accessibility values could have been affected by the population count and distance values associated with each population cluster.

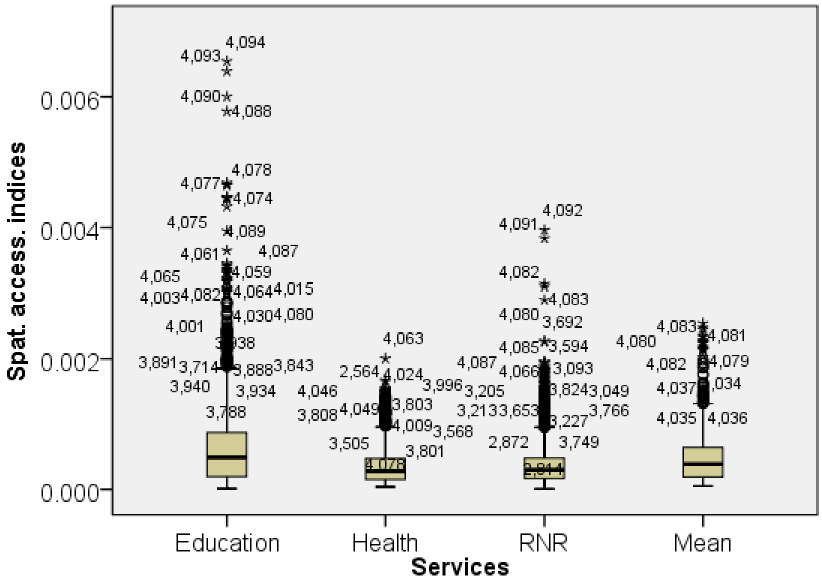


FIGURE 7.7: Box-plot of spatial accessibility scores of population clusters for different services

Figure 7.8 shows the subdistricts accessibility indices of education, health and RNR services along with the mean accessibility indices. The subdistrict accessibility index is computed as the average value of all the accessibility indices of the population clusters located within that subdistrict. The line marker was used only to connect the point data for aiding in visual identification of different data. Overall the spatial accessibility to educational services was higher than the accessibility to health and agricultural services, and was mainly attributed to the availability of more educational facilities. Table 7.4 shows the minimum and maximum accessibility indices of subdistricts for education, health and RNR services. For educational services, Chimung subdistrict of Pemagatshel had the highest accessibility index and Lunana subdistrict of Gasa district had the lowest accessibility index with the highest ranking subdistrict having about 34 times better accessibility to educational services than the lowest ranking subdistrict. Lingzhi subdistrict of Thimphu district and Doteng subdistrict of Paro district were the highest and lowest ranked subdistricts for spatial accessibility to healthcare services with and the highest ranked subdistrict having about 25 times better accessibility than the lowest ranked subdistrict.

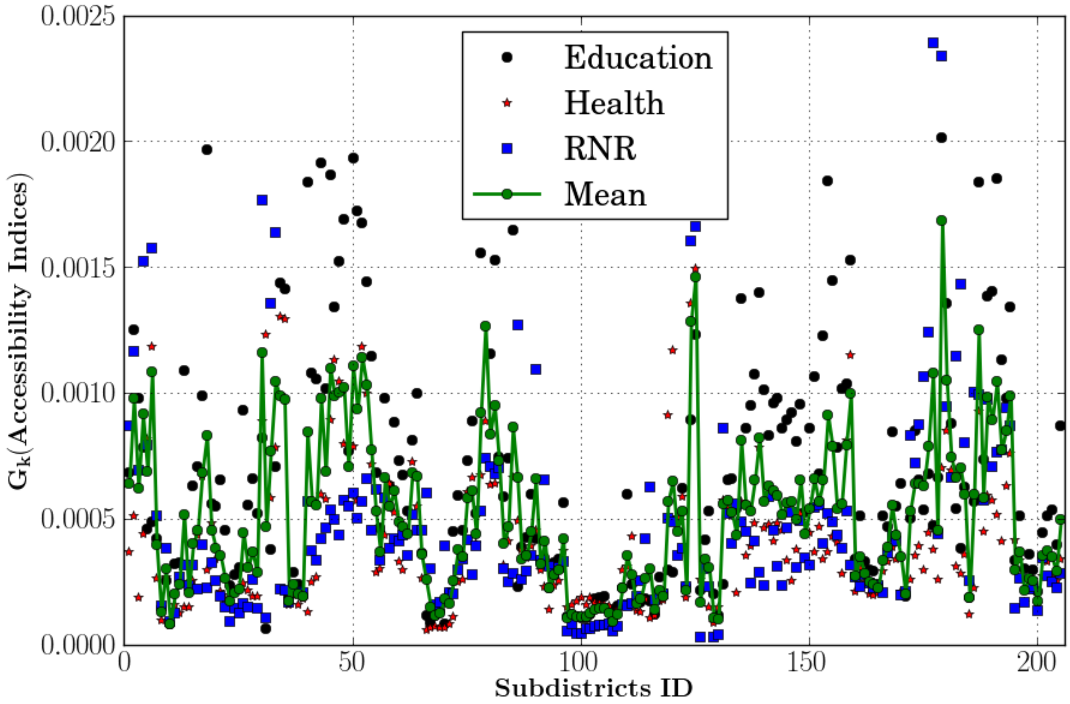


FIGURE 7.8: Subdistrict's accessibility indices of education, health and RNR services

TABLE 7.4: Maximum and minimum accessibility indices of subdistricts for education, health and RNR services

	G_k		Subdistricts(Districts)		
Services	**Max.**	**Min.**	**Max.**	**Min.**	**Max./Min.**
Education	0.002175	0.000064	Chimung (Pemagatshel)	Lunana (Gasa)	34
Health	0.001497	0.0000596	Lingzhi (Thimphu)	Doteng (Paro)	25
RNR	0.0023916	0.0000295	Gangtey (Wangdiphodrang)	Dagala (Thimphu)	81
Mean (GNH)	0.001686	0.0000845	Athang (Wangdiphodrang)	Sampheling (Chukha)	20

Gantey subdistrict of Wangdiphodrang district and Dagala subdistrict of Thimphu district were the highest and lowest ranked subdistricts for spatial accessibility to RNR services with the highest ranked subdistrict having about 81 times better accessibility than the lowest ranked subdistrict. The mean accessibility indices indicated that

Athang subdistrict of Wangdiphodrang district and Sampheling subdistrict of Chukha district as the highest and lowest ranked subdistricts for spatial accessibility to the combined services of the three centres with the highest ranked subdistrict having about 20 times better accessibility than the lowest ranked subdistrict.

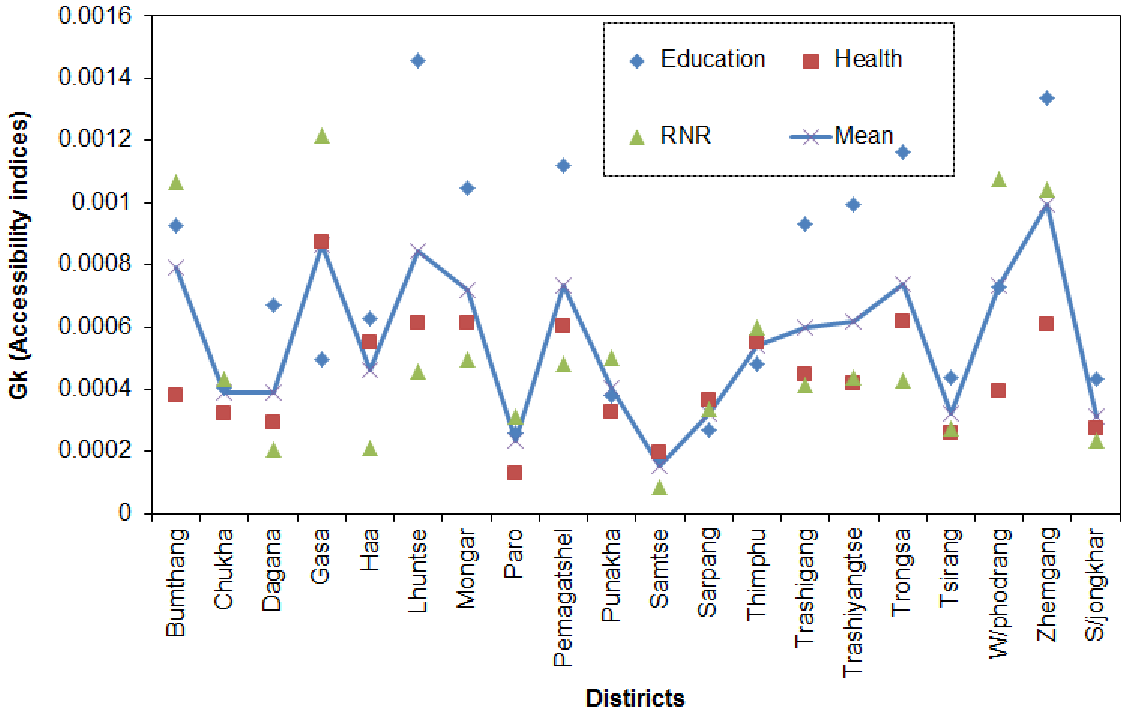


FIGURE 7.9: Districts' accessibility indices of education, health and RNR services

The district-level accessibility indices were computed by averaging the subdistricts' accessibility indices for all the subdistricts within a district. Figure 7.9 shows the accessibility indices of the districts for education, health and RNR services along with the GNH accessibility indices. The district accessibility index was computed as the average value of all the accessibility indices of the population clusters located within that district. Table 7.5 shows the maximum and minimum accessibility indices of districts for education, health and RNR services. Lhuntse and Samtse districts had the highest and lowest accessibility indices with the former district having about 8 times better accessibility to educational services than the later district. Gasa district was ranked highest and Paro district the lowest for spatial accessibility to healthcare services with the highest-ranked district having about 7 times better accessibility than the lowest-ranked district. Gasa district was also ranked highest for spatial accessibility to RNR services while Samtse district was ranked lowest for this service with the former

TABLE 7.5: Maximum and minimum accessibility indices of districts for education, health and RNR services

	G_k		Districts		
Services	**Max.**	**Min.**	**Max.**	**Min.**	**Max/Min**
Education	0.001456	0.000181	Lhuntse	Samtse	8
Health	0.000873	0.00013	Gasa	Paro	7
RNR	0.001217	0.000086	Gasa	Samtse	14
Mean	0.000995	0.000155	Zhemgang	Samtse	6

district having about 14 times better accessibility than the later district. The mean accessibility values of the combined services of education, health and RNR indicates Zhemgang as the highest ranked district and Samtse the lowest ranked district with the highest-ranked district having about 6 times better accessibility than the lowest-ranked district.

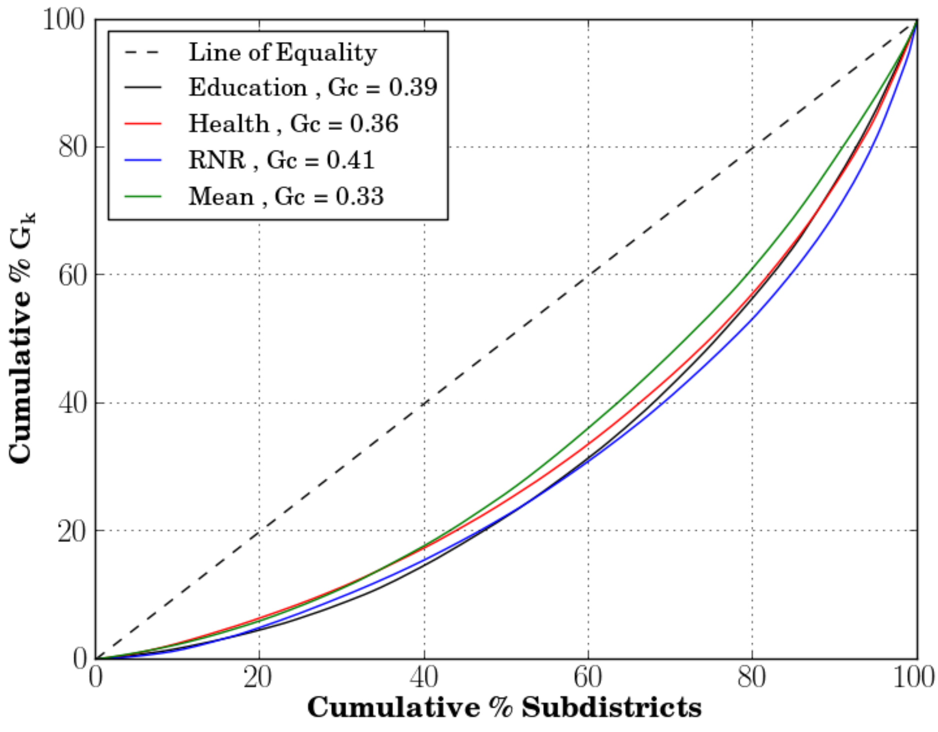
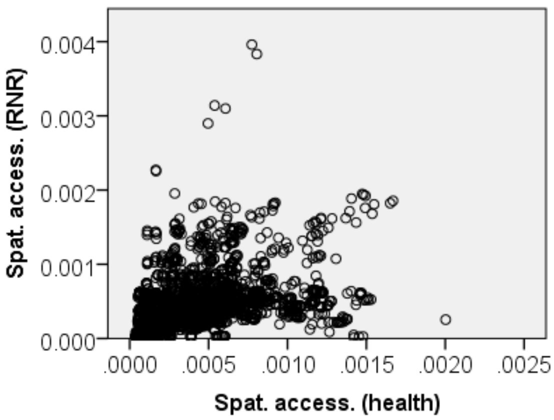
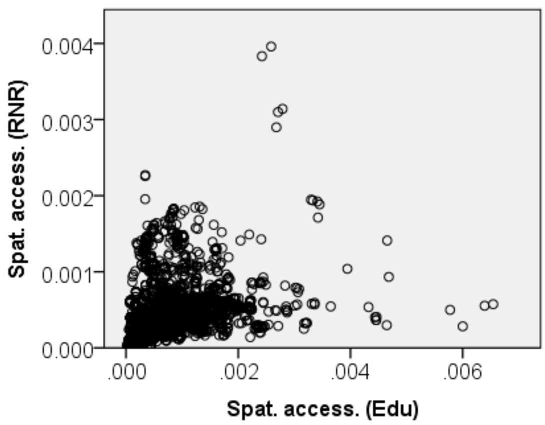


FIGURE 7.10: Gini plot of education, health and RNR services

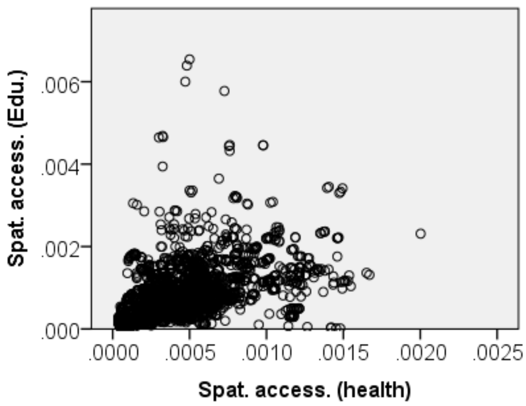
Figure 7.10 shows the Lorentz curves and Gini coefficients of the education, health and RNR services computed using the subdistricts accessibility indices. There were no significant differences in the equality of distribution of the three service centres within the country as their Gini coefficients varied only by small values from 0.03 to 0.05. Figures A.18(a) to A.19(b) in Appendix A show the Lorentz curves and Gini coefficients of districts for the combined services computed using the mean accessibility indices. Trashigang district with a Gini coefficient value of 0.15 had the best equality of distribution of these three service centres across the country whereas Thimphu district with Gini coefficient value of 0.46 had the worst equality of distribution of these service centres.



(a) RNR vs Health



(b) RNR vs Education



(c) Education vs Health

Figure 7.11: Scatter plots of spatial accessibility values of population clusters

Figures 7.11(a) to 7.11(c) show the scatter plots of spatial accessibility indices between pairs of different services. The Pearson correlation values between different services indicate a moderate positive correlation between RNR-Health, RNR-Education and Health-Education with correlation values of 0.476, 0.419 and 0.594, respectively. It also indicates that the correlation is significant at the 0.01 significance level. This means that the correlations between any two services were not caused merely by chance but by some other factors. However, there is no visible trend observed in the scatter plots that can be fitted with a well-defined functional curve. Therefore, the accessibility scores between any two services can be safely assumed to be independent of each other. This is true because the geographic locations of these three service centres are not clustered within a small region across the country. Only in few places were these three service centres located in close proximity to each other.

7.6 Correlation between different accessibility indicators

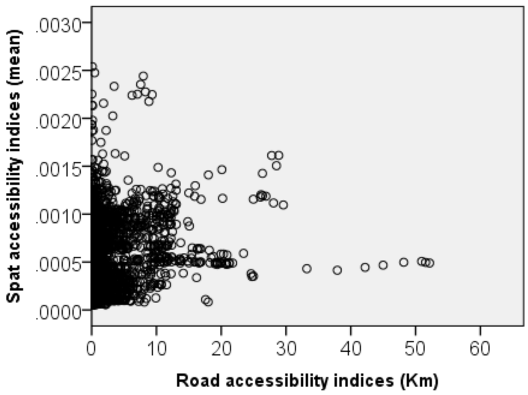
The road, remoteness and spatial accessibility indices were computed using different methods. In order to evaluate the relationship between the three different indices,

Table 7.6: Pearson correlation coefficients between different accessibility indices

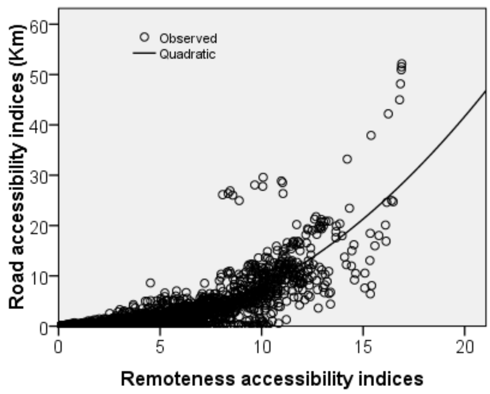
	Parameters	**Road accessibility indices**	**Spatial accessibility indices (mean)**	**Remote accessibility indices**
Road accessibility indices	Correlation	1	.247**	.741**
	Sig. (2-tailed)		.000	0.000
	N	4094	4094	4094
Spatial accessibility indices (mean)	Correlation	.247**	1	.441**
	Sig. (2-tailed)	.000		.000
	N	4094	4094	4094
Remote accessibility indices	Correlation	.741**	.441**	1
	Sig. (2-tailed)	0.000	.000	
	N	4095	4094	4094
**. Correlation is significant at the 0.01 level (2-tailed)				

Pearson correlation coefficients were computed for different pairs of indicators. Table 7.6 shows the correlation coefficients and the result of the hypothesis test for correlation between different indicators obtained from the SPSS Statistics. The mean spatial accessibility indices were used instead of the three separate spatial accessibility indices for education, health and RNR services. The correlation coefficient value of 0.247 between spatial accessibility and road accessibility indices indicate a weak positive correlation between these two variables. The spatial and remoteness accessibility indices portray a moderate positive correlation with a correlation value of 0.441.

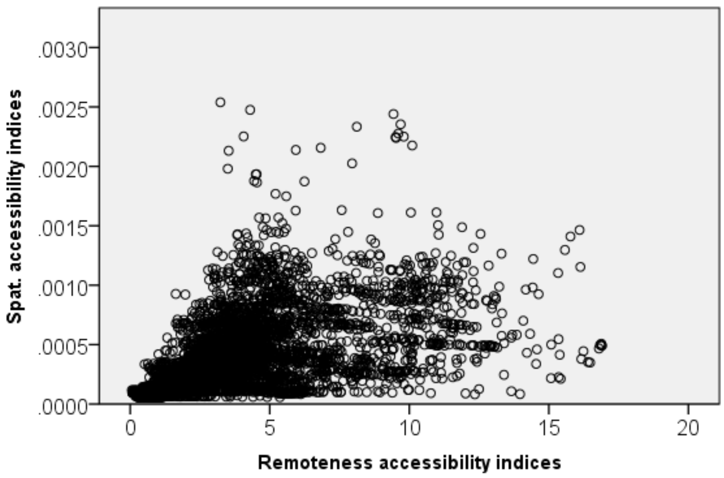
On the other hand, the road and remoteness accessibility indices exhibit a strong positive correlation with a correlation value of 0.741, which is relatively larger than the other two coefficients.



(a) Spat. access vs Road access.



(b) Road access. vs Remote access.



(c) Spat. access. vs Remote access.

Figure 7.12: Scatter plots of different combination of accessibility indices

Although the hypothesis test at a confidence level of 99% suggested that all the three coefficients were high enough to be considered that the corresponding indicator-pairs were significantly correlated, this test result cannot be taken at face value for the spatial-road and spatial-remoteness accessibility pairs because the test value may have been biased by the large sample size of 4094. Figures 7.12(a), 7.12(b) and 7.12(c) show scatter plots of spatial-road, road-remoteness and spatial-remoteness accessibility pairs, respectively. It can be clearly observed that the spatial-road and spatial-remoteness indices pairs do not appears to portray significant correlation due to other factors but by chance alone. On the contrary, the road-remoteness indicators pair exhibits a strong relationship that can be almost perfectly modelled by a quadratic curve. This result suggests that the correlation between these two indicators were not caused by chance alone. The strong relationship may be because one of the ratio component for remoteness indices is derived using the nearest distance measure to the road access point, which also defines the road accessibility index.

7.7 Summary

The result of the first GNH survey conducted in 2008 indicates access to roads, education, good health and agricultural productivity as some of the important sources of happiness for the Bhutanese people. The ease of accessibility to road transportation, health services, educational and agricultural services can positively affect sources of happiness. Nonetheless, the existing pool of GNH indicators do not contain any spatial indicators, which are essential in quantifying spatial distribution of road network and social service infrastructure such as education, health and agricultural service centres. This study has proposed straight-line distance-based accessibility indicator to quantify road accessibility, standardised distance-based remoteness accessibility to define degree of remoteness of a place within a country, and spatial accessibility indices to measure the equity of distribution of social service centres across the country.

Distance-based road accessibility indices of the whole country show that about 40% of the population lived within 100 metres from the nearest road point, 36% of the population lived within 500 m to 1 kilometre and 20% of the population lived beyond 1 kilometre. Only about 2.6% of the population were living farther than 10 kilometres from the nearest road point. As per the remoteness accessibility classification, about 52% of the Bhutanese population lived in non-remote areas where accessibility to road transportation, towns, hospital and educational centres were better than for the 48% of the population living in the remote areas. Based on the mean spatial accessibility indicator of health, education and agriculture services, Athang subdistrict of Wangdiphodrang district and Sampheling subdistrict of Chukha district were the highest and lowest ranked subdistricts in 2012, respectively, with the former subdistrict having about 20 times better accessibility than the later subdistrict. Trashigang district with a Gini coefficient value of 0.15 had the best equality of distribution of these three service centres across the country whereas Thimphu district with a Gini coefficient value of 0.46 had the worst equality of distribution of these service centres.

Chapter 8

Discussions

This chapter discusses the limitations of this study in the context of data constraints, methodology of identifying the optimal model for calculating spatial accessibility values, development of planning support system for modelling spatial accessibility and potential use of spatial accessibility indicators in GNH measurement system. Section 8.1 discusses the limitation of data used in this study and Section 8.2 discusses some constraints about the BR and NN method of delineating service and population catchment areas. Section 8.3 discusses the need for a theoretically-defined distance-decay function over an empirically-defined decay function. Section 8.4 discusses about the limitations of the open-source based HAPSS application, followed by the discussion on the existing GNH measurement system in Section 8.5.

8.1 Data constraints

One of the drawbacks of the proposed accessibility measurement approach for the computation of road, remoteness and spatial accessibility indices is the use of a simple straight-line distance measure between two locations instead of computing actual travel-time or distance from road transportation network data. Most of the urban-based studies on accessibility in developed countries have been done using travel-time measures. This is computed from transportation network data as places within their study region were well connected by road networks (Luo and Wang, 2003; Luo and Qi, 2009; Dai and Wang, 2011; McGrail, 2012; McGrail and Humphreys, 2014). However, in developing countries like Bhutan, road connection in most part of the rural areas is limited to a few places. Therefore, the computation of travel-time measures from road network data cannot be uniformly conducted throughout the country. Until road transportation is readily available in all regions of Bhutan, accessibility measurements can only be undertaken using a straight-line distance measure. If the simple straight-line distance measure is used uniformly across the country then it would provide an unbiased basis for comparing spatial accessibility between different regions.

Only Bhutanese data were used in this study to substantiate the theoretical development of the NN method of delineating catchment areas and the AM2SFCA model for computing accessibility values. It is expected that the difference in the data characteristics between different countries would not greatly affect the accuracy and logical consistency of accessibility outcome from the aforementioned computational methods. However, if actual travel data is used to model the distance impedance effects then the accessibility outcome for different countries would vary significantly because travel behaviour of people may considerably vary from one country to the other because of differences in transportation system and configuration of population clusters and health facilities. Therefore, the use of a theoretically-defined distance-decay function which is common for all regions or countries would partially or completely eliminate the measurement uncertainties caused by the use of a different weighting function between regions or countries.

8.2 The NN method

In a theoretical sense, it appears that only the modified gravity model (Equation 2.3) solves the problems of the BR method. It uses a single catchment size for all computations so there is no requirement for threshold values to define catchment sizes and uses all population clusters and service providers to compute an accessibility score. Thus there is no introduction of accessibility bias due to the difference in the number of associated service centres. It also effectively applies the distance decay effect by considering the smallest to largest distance separation between locations of population units and service providers within the study region by the virtue of using a single catchment size. Nonetheless, the gravity model is flawed in the sense that it does not reflect the real world. All service centres are neither physically accessible to all population nor being used by everyone within the study region. The deficiency of the single catchment size of the gravity model has led to the development of numerous variants of FCA models based on the BR method, which define variable or floating catchment sizes that closely reflect the real world.

In the BR method the number of service centres associated to each population cluster varies from one cluster to the other. These differences in the number of service centres between population clusters inherently introduce accessibility differences between different clusters because the spatial accessibility index of a population cluster is computed as the sum of accessibility components due to all the service centres associated with the given cluster. If the variation in the number of associated service centres between population clusters is large, then the difference in the accessibility outcome between respective clusters will also vary considerably. Such large variation in the number of associated service centres between population clusters can cause choice biases. The choice bias may be necessary in order to reflect the potential accessibility of each population clusters. However, it becomes unrealistic when tens and hundreds of service centres are associated with each service centre, especially in urban areas where a high density of health facilities are located, where people generally tend to seek healthcare services from a few service centres which are located in close proximity to their locations. Moreover, the planning of health resources allocation should be done with the aim of allocating few closest health facilities to each population cluster rather than a large number of service centres for each cluster. These two aspects of the catchment areas can be achieved using the NN method because with this method it would only be deemed necessary to associate a minimum of 2 and a maximum of five or ten service centres with each population cluster depending on the variation in the density of health facilities across the region. It is redundant to associate more than 10 service centres with each population cluster even in urban regions because there is no practical need to access more than one primary level care physician so nine is more than enough to include as potential alternatives. Nonetheless, the actual comparison of accessibility scores between the BR and NN methods is unlikely to produce any sensible outcome because there are an infinite range of values for the size of the rings for the BR method and quite a lot of whole numbers for the NN method to be tested. These two methods can be, at best, effectively resolved by assessing the theoretical basis of their methodology.

There is no exact solution to all of the uncertainties involved in the computation of spatial accessibility indices. The accommodation of these uncertainties in the spatial accessibility model depends on the nature of the data availability and the method of defining population catchment areas. In the context of Bhutan, the proposed NN-AM2SFCA spatial accessibility model was developed to minimize the burden of these uncertainties, where a variable-sized population catchment area of each service centre was defined by assigning the first- and second-nearest health facilities to each population cluster. The absolute accuracy of these accessibility values may never be known because a perfect accessibility model does not yet exist whereby uncertainties could be completely eliminated through modelling. Nonetheless, as long as the spatial accessibility model is consistently defined by a robust model with the same parameters, then they can be effectively utilized for assessing the spatio-temporal changes of spatial accessibility to PHC in different regions across the country.

8.3 Distance-decay functions

It is very important to consolidate the use of distance decay functions for spatial accessibility modelling by standardising the decay function based on a theoretical framework rather than by an empirical approach. There are five main reasons for doing this. Firstly, it is very difficult to identify a specific decay function based on modelling distance impedance effects using health utilization or travel diaries data. The health utilization or travel diary data from one particular region or country may not match with the travel diary data from another region or country because of the differences in population health, transportation network system or distribution of healthcare resources. Secondly, there are numerous ways of fitting some form of a functional curve (by using different parameter values or a combination of parameter values) to the health utilization or travel diaries data at the local level. Thirdly, the health utilization data are not available for public use due to confidentiality issues and the collection of survey data is very expensive. Fourthly, it is not absolutely necessary to model the exact functional form of distance impedance effects for measuring spatial accessibility indices. Because the measurement of the spatial accessibility indices is affected by a number of modelling uncertainties, such as the aggregation level of population clusters, delineation of catchment areas and selection of inaccurate distance measures, which cannot be completely eliminated through modelling. A small achievement in overall accuracy of accessibility values by using a very expensive data collection method to model an exact functional form becomes useless, if other modelling uncertainties are not eliminated. In addition, a certain level of accuracy of accessibility indices is enough to meet the objectives for developing health policies on resource allocation. Finally, spatial accessibility measures were developed as an alternative indicator to container-based PPR indicator because the former measure explicitly considers physical accessibility whereas the later measure does not. If a different region or country uses a different distance impedance function based on the fitting of an actual travel pattern data, then it is theoretically impossible to measure the differences of spatial accessibility to healthcare services between different regions or countries because of the inherent differences between the computational models, defeating the very purpose of the spatial accessibility modelling.

Both the Gaussian and logistic functions portray a decay characteristic that fits very well with the theoretical curve suitable for modelling distance impedance effects. Added to which, these functions were fitted to the health utilization data in past studies. Nevertheless, the Gaussian function was chosen as the control function over the logistic function because of its simple mathematical form. The selection of either the Gaussian or logistic function as the control function would not greatly affect the comparative study conducted with the other decay functions. This is because the hypothesis tests on the mean accessibility values of these two functions indicate that their mean values are not statistically significantly different from each other. Since the control function was defined based on a theoretical framework, there is no other way but to arbitrarily select parameter values for both the control and testing functions. It is even impossible to test or identify exact parameters for each model as there are infinite numbers of real values available for each of the functional models. In this study, the parameters of each decay function were arbitrarily determined by constraining weighting values of each function between 0 and 1 and by comparing the accessibility outcome between competing curves (with different parameter values) of a particular decay function. Such a crude method of model identification may be one of the limitations of this study but there is no other viable method available in this case as the control function was theoretically determined.

8.4 The HAPSS application

The proposed planning support system for health planners and decision-makers was not constructed to provide them with concrete solutions but as a tool to support evidence-based decision making in the planning and allocation of health resources. It is quite difficult to make a correct decision on allocation of health care providers or establishment of health centre if there are no scientific methods of evaluating the existing scenario of a health care delivery system. The HAPSS is specifically developed to compute spatial accessibility scores at different levels of population aggregation that can be used for assessing spatial and temporal variability of health care services across the country with respect to supply of health care providers, population demand for services and geographic separation between the locations of health care providers and population. For instance, knowing only the population catchment areas of different health centres would help decision-makers to calculate the provider-population ratio of each health facility. The average travelling distances between population clusters and health centres can be used as supplementary information along with the provider-to-population ratio of health centres. Such information can aid in making decisions related to the allocation of health care providers to health centres.

The classification of sub-districts into different accessibility groups can be used to evaluate different scenarios of health data configuration for long-term planning of health resources allocation. Different scenarios of health system configuration of service centres and population clusters can be tested based upon the existing system with spatial accessibility scores computed for each scenario. The trend analysis of accessibility scores of population clusters, classification of sub-districts into different accessibility groups, spatial cluster analysis of accessibility scores of population clusters and plot of Lorentz curves with sub-districts or districts accessibility scores can be used to identify the best candidate scenario from amongst many alternative scenarios. Such evidence-based quantitative methods can be used in conjunction with other qualitative information obtained through public consultation to make an unbiased decision on identifying the optimal location for the establishment of new health centres.

With respect to scenario modelling, the alternative scenarios were intuitively designed with few possible values for the unconstrained parameters of the model rather than automatically developing scenarios for a range of parameter values. Because there is no need of testing either for every possible locations of prospective service centre or for every range of numbers for the attractiveness parameter (S_j) in Equation 4.9. This logic is based on the fact that the health planners would have only limited options available for both parameters of location of service centres and number of service providers. For instance, there would be only few possible village locations within a subdistrict or district that could be used for constructing a new service centre. Similarly, the number of health service providers that can be trained within a given period is also limited to certain numbers. Therefore, scenario modelling can be effectively done without using a complex optimization technique. The scenario optimization technique of finding an optimal solution from a large number of scenarios is beyond the scope of this research, however, it could be a possible area of interests for further study.

The development of the HAPSS is still at a preliminary stage, so the statistical and spatial analysis capability of this software is limited to the computation of means and display of simple maps. The majority of this spatio-temporal analysis of accessibility scores has to be done using other software. Nevertheless, this standalone software application can be reliably used for computing accessibility scores using straight-line based computational models, which is the most time-consuming operation in the proposed system. This application can be easily customised for other developing countries, where comprehensive transportation network data are not available. For most of the developed countries where transportation network data is used to compute network-based travel time or distance, this application can be customised to incorporate a transportation network module or by introducing network-based time or distance measures directly into the system.

8.5 GNH measurement system

Although the GNH measurement system has been fully embraced by the Bhutanese government, the efficacy of the existing GNH measurement system of indicators is questionable because they are measured from data which represents a small percentage (1 to 5%) of the population. The questionnaire based data collection is also often biased with subjective non-quantifiable responses. Like the GDP indicator that measures overall goods and services produced in the country, the GNH indicators have to capture as much as possible of the whole system. It is also noteworthy to mention that the proposed accessibility indicators were computed objectively from administratively gathered data for the whole country. The use of objective data country-wide indicates a gross representation of the population, unlike the current GNH indices which are subject to sampling bias as these indices are derived from survey questionnaire responses from a sampled population.

Undertaking a general survey of the whole population would be prohibitively expensive if not unnecessary as there are other viable methods available to define indicators. For instance, as in the computation of proposed road, remoteness and spatial accessibility indicators, there is no need to conduct a survey to find out the distance measurement between two locations given the distance metrics can be computed using locations of the modelled population clusters and the road network data of the whole country. This study has highlighted the potential of objectively quantifying accessibility indicators using both spatial and non-spatial data of the whole country. These evidence-based indicators can be incorporated into the GNH measurement system. However, there is a need to restructure the measurement system of the GNH system and realign it closely to methods used by other countries. One viable way of measuring indicators is to use a causal framework, such as the pressure-state-response (PSR) system, similar to the ones used for defining sustainability indicators by the OECD countries (OECD, 2001, 2008). Only through the integration of GNH indicators with internationally adopted indicators would the GNH measurement system become a viable alternative for measuring the social, economic and environmental progress of a nation.

Chapter 9

Conclusions and Recommendations

This chapter summarizes the research activities and outcome of modelling spatial accessibility to health care services in Bhutan, which was presented in detail in preceding chapters. Although, the study is primarily focussed on Bhutan because of the availability of data for this country, the substantial portion of this thesis deals with the methodology and evaluation of spatial accessibility modelling, which is very relevant to other parts of the world. In addition, it would provide a future course in addressing any related problems that have remained unanswered or created in this study during the course of the research on spatial accessibility modelling.

9.1 Conclusions

The main objective of this thesis was to conduct spatio-temporal analysis of spatial accessibility to primary healthcare services using Bhutan as the case study. This research activity entailed the evaluation of methodological aspects of spatial accessibility modelling, which is affected by a number of computational uncertainties. The spatial accessibility modelling was explicitly focussed on the availability of healthcare services and physical accessibility between the locations of the service providers and populations, following the commonly used definition for spatial accessibility in the health research community (Joseph and Phillips, 1984; Luo and Wang, 2003). Although this model comprised just three parameters, namely: the number of healthcare providers, size of population at each location of population cluster and distance separation between the locations of the populations and service providers, there have been quite a number of uncertainties associated with the measurement of spatial accessibility values. These uncertainties range from the aggregation level of the population clusters to the selection of parameters for the distance-decay function for calculating relative weighting values. As far as possible, these uncertainties were defined clearly and examined thoroughly to determine a viable or practical approach of measuring spatial accessibility to healthcare services within a region or country with special reference to Bhutan. A chapter summary is presented as follows.

In Chapter 2 an extensive review of spatial accessibility modelling and its uncertainties were presented. Currently, health accessibility is typically measured by a simple indicator such as the provider-to-population ratio, which is a container-based measure of accessibility that does not take into consideration physical accessibility. A GIS-based indicator such as the spatial accessibility measure proved to be a better measure for health accessibility because it realistically models spatial accessibility by including availability of healthcare services, population demand for services and physical accessibility to service centres. The FCA method is predominantly used in modelling spatial accessibility because this method relates closely with the real-world scenario of the healthcare system. This method suffers from a number of modelling uncertainties which are caused by many factors such as the aggregation level of population clusters, the availability of a number of computational methods, use of the travel-time or distance measure, size of the service and population catchment areas, and availability of a number of distance- or time-decay functions. Firstly, the modifiable areal unit problem caused by aggregation level of population clusters can be minimised by using clusters at the lowest aggregation level. Secondly, there are different variants of the FCA methods available for computing accessibility indices, such as the 2SFCA, KD2SFCA, E2SFCA, 3SFCA and M2SFCA methods. The use of any of these models will alter the outcome of accessibility indices. Delamater (2013) evaluated the aforementioned models using both simulated and real-world data and found that the M2SFCA model is better than the other models both in terms of the theoretical framework and computational outcome. Thirdly, the travel-time or distance measure between two locations of service providers and populations can also affect the outcome of spatial accessibility indices because there are different ways of calculating distances such as straight-line or Euclidean distance, Manhattan distance, network-based distance, fastest or shortest routes, etc. Fourthly, the delineation of service and population catchment areas is an important aspect of spatial accessibility modelling. All the past studies have used the buffer-ring method to define the catchment areas. This approach creates modelling uncertainties by associating unequal numbers of service centres with each population cluster and arbitrarily defining distance or time threshold values of 15, 30, 60 or 90 min. Finally, the choice of a particular distance-decay function can also affect the accessibility outcome because the relative weighting values which represents distance measures can be significantly different between different decay functions. Distance-decay functions such as the logistic, exponential, Gaussian, inverse-power, linear, Butterworth-filter and Epanechnikov-kernel functions were used for modelling spatial accessibility in past studies. Due to these uncertainties, it has been not possible to identify an optimal model for spatial accessibility modelling. In the absence of the optimal FCA-based model, it is not possible to replace the simple container-based accessibility measure because the use of a different FCA-based model by different countries around the world will only create unequal basis of comparison of accessibility values between regions or countries. This suggests a need for consolidating spatial accessibility model by partially or completely eliminating these uncertainties.

Chapter 3 outlined the data requirements for modelling spatial accessibility to healthcare services and for defining spatial accessibility indicators. With respect to population data, it is essential to model population data at the lowest aggregation level, where the cluster's locations would not change much in the due course of time. This stability of locations would ensure accurate temporal comparisons of accessibility values between population clusters. In the case of Bhutan, villages locations were chosen to represent population clusters because the geographic boundaries of villages remain generally unchanged for many years. However, there was no population data available at this level of aggregation. Therefore, population at the village level were estimated from areal interpolation method using GPS settlement and subdistrict's population data. A number of areal interpolation methods aided by ancillary data sources such as the settlement and land use data were tested. It was found that the areal interpolation method aided by only settlement data produced better population estimates at the village level than the other variants of the dasymetric methods.

Chapter 4 presented a specific solution to a number of uncertainties associated with the FCA models. Firstly, the uncertainty due to the use of either straight-line distance or travel-time measure has been evaluated in the context of Bhutan. If comprehensive transportation network data are available then the travel-time between two locations can be computed accurately and thus prove to be a better parameter than the distance measure. However, in the absence of transportation network data, the modelling of travel-time measures using cost-weighted distances between two locations does not have significant benefit over using straight-line distances between two locations for the computation of spatial accessibility. In the case of Bhutan where highly accurate DEM and land use data are lacking, the differences between the straight-line and cost-weighted distances are not great. The correlation coefficient value of 0.99 between the two distance measures suggests that these two distance measures are very similar. So there is no significant benefit in using the travel-time measures derived from the cost-weighted distances. Therefore, a straight-line distance measure can competitively produce similar accessibility results, especially in developing countries where there is a lack of comprehensive transportation network data.

Secondly, the FCA modelling systems are also biased by the use of the BR method of defining service and population catchment areas. Currently, almost all health accessibility studies uses some threshold travel-time values such as 15, 30, 45, 60 or 90 minutes to define the catchment areas. A seemingly less ambiguous method of delineating catchment areas based on a NN method is proposed in this thesis. The NN method uses a finite number of nearest health facilities as potential target facilities for each population cluster rather than associating tens and hundreds of facilities to each population clusters falling within a search radius defined by some threshold travel-time value. In the case of Bhutan, first- and second-nearest health facilities were deemed sufficient to be used as the potential sites which people would generally tend to visit to seek primary health care services. Hence, such a delineation method effectively measures actual accessibility rather than measuring accessibility due to 'choice' of health facilities as largely measured by the BR method.

Thirdly, the uncertainty in the FCA modelling is also posed by the availability of a number of distance decay functions such as the inverse power function, linear, step and exponential functions, Epanechnikov kernel function, Butterworth filter function, etc. In this study, the Gaussian function was chosen as the control function because its decay function exhibits a similar decay characteristic as the theoretically-defined function and its mathematical form is simpler than the logistic function, which also produces weighting outcome as expected from a theoretically-defined decay function. The model parameters for the control function and other functions were crudely obtained by constraining the extreme weighting values between close to 0 and close or equal to 1 for the largest and smallest distances of the study region, respectively. If there exists a number of competing curves of a given function with similar weighting outcome, then the model parameters for that function were chosen by analysing their actual accessibility outcome.

Fourthly, the accessibility outcome of the FCA metric systems are also influenced by the use the 2SFCA, E2SFCA, KD2SFCA, 3SFCA or M2SFCA models. From a theoretical perspective, all of these models are built on a sound framework, however, the mathematical outcome of the 3SFCA method produced illogical accessibility scores for some population units thereby making it an inefficient model. On the contrary, all other FCA models produced consistent accessibility scores as per the expectation from their respective mathematical frameworks. On further evaluation using a simple system with a single provider and multiple population clusters located equidistance from the provider's location, it has been found that the accessibility scores from the 2SFCA, E2SFCA, KD2SFCA and 3SFCA models remained unchanged for all absolute distance separations between the location of a provider and population cluster, which suggests that these models only account for relative distance separation between the location of a provider and population cluster. Furthermore, these models also distribute all the available opportunities relatively to all population clusters within the system as if the system is completely efficient with all the entities collocated at a single point. In the real world, all health systems consist of multiple providers and population clusters, so the system would always be suboptimal where all opportunities will not be available due to accessibility costs incurred by physical separation between the location of a provider and population cluster. In contrast, the M2SFCA model corrected both problems associated with the other FCA methods.

However, the M2SFCA model also deflates accessibility scores for the poorly served regions leading to an exponential increase of accessibility ratios between the largest score and other scores within the study region. This problem would potentially lead to inaccurate juxtaposition of absolute accessibility scores between higher and lower accessibility regions. In order to solve the aforementioned problem of the M2SFCA method, the original M2SFCA method is augmented with two separate weighting functions in order to balance the accessibility scores between the higher and lower accessibility regions. The augmented model is called the NN-AM2SFCA method, which has been proposed for measuring spatial accessibility to primary health care services in Bhutan.

Chapter 5 described the architecture of a standalone application system, the HAPSS, which was developed using open-source C#.NET GIS libraries. More specifically, this system was developed on the application framework of HydroDesktop 6.1 by customizing specific modules required for calculating spatial accessibility scores of population clusters, subdistricts and districts.

Chapter 6 presented the spatial and temporal results and analysis of spatial accessibility scores of population clusters, subdistricts and districts in Bhutan. The analysis of the accessibility scores was conducted on the outcome from real-data processing. Some of the important results are given as follows. Firstly, the spatial accessibility outcome between the straight-line and travel-time methods produced high positively correlated scores, which indicates that there was no additional benefit of using cost-weighted distances for computing spatial accessibility scores for Bhutan because the computation of cost-weighted lines is a very time-consuming operation. Secondly, the accessibility scores between different FCA-based computational methods were highly and positively correlated, with correlation values exceeding 0.99. Nevertheless, the correlation of the 2SFCA, 3SFCA, E2SFCA and KD2SFCA methods with the M2SFCA method have lower values than the correlation between any of the two methods from the former group. Although the real-data processing did not indicate a huge difference in scores between these models, the accessibility outcome from the simulated-data processing using a simple configuration indicates that the M2SFCA model produced a more consistent and logical scores than the other models. Hence, Delamater (2013)'s results were validated by this study as well.

Thirdly, the effect of different distance decay functions on the outcome of spatial accessibility to healthcare services was evaluated on the basis of a theoretically-defined control function. The accessibility results from both the simulated and real data processing indicate a similar pattern for the eight different decay functions used in this study. The hypothetical test of the means and variances on accessibility scores of all population clusters indicates that the accessibility scores of the logistic and Gaussian-derived step-function are as good as the scores of the control function whereas the accessibility scores of the inverse-power, exponential, linear, Butterworth-filter and Epanechnikov-kernel functions are significantly different from the scores of the control function. Finally, this study has demonstrated that spatial accessibility indices can be used for identifying medically under-served and over-served regions, for measuring the equality of distribution of health resources across the regions and for studying spatial and temporal changes in the distribution of the health resources in the country.

The spatial accessibility results for Bhutan in 2013 showed that there is a huge disparity in the distribution of the health resources in the country. The best-ranked Lingzhi sub-district of Thimphu district had about 30 times better accessibility to HA's services than the lowest-ranked Bara sub-district of Samtse district, and Chang sub-district of Thimphu district had about 64 times better accessibility to doctor's services than Athang sub-district of Wangdiphodrang district. The Gini coefficients of the twenty districts indicates that Thimphu and Tsirang districts had the best and worst equality of distribution for doctor's services, respectively, and the later district also had the best equality of distribution for HA's services in 2013. Haa district had the worst inequality of distribution for HA's services and Zhemgang district had the worst inequality of distribution for doctor's services. In addition, a number of alternative scenarios were formulated to study the implication of increasing the number of health care providers and service centres. Such scenario analysis can be utilized for planning of resource allocation because it is possible to identify the best candidate scenario from amongst many possible scenarios based on the analysis of their spatial accessibility values.

In Chapter 7, three different accessibility indicators were proposed, namely road accessibility, remoteness accessibility and spatial accessibility indices. These three indices were compared with each other and it was found that there is a significant correlation between the road and remoteness accessibility indices, which can be closely fitted with a quadratic curve. However, there were no similar dependencies observed between spatial accessibility indices of health, education and RNR services. The road accessibility outcome indicates that about 75% of the Bhutanese population are living within 1 kilometre from their nearest road access point and only about 6% of the population are living farther than 5 kilometres from their nearest road point. The remoteness accessibility outcome indicated that about 52% of the population lived in non-remote areas and only about 7% of the population lived in very-remote areas. The sub-districts and districts spatial accessibility indices of the three different social service centres indicated a large disparity in the distribution of these service centres in the country in 2013 where the distribution of service centres for the best ranked sub-district was several times better than the worst ranked subdistrict. This large disparity in the spatial distribution of social service centres and road infrastructure within the country may potentially cause dissatisfaction of population living in the underserved regions. More importantly, it can adversely hinder the developmental progress of the underserved regions. From a GNH perspective, it is essential to achieve equitable distribution of various social service centres and road infrastructure in the country in order to optimize the overall happiness of the Bhutanese people. One way of gauging the equity of spatial distribution of social service centres and road infrastructure is to use the proposed accessibility indicators.

9.2 Recommendations

Owing to data constraints and methodological complexities of spatial accessibility modelling, there is scope to consolidate and enhance the findings of this study by undertaking further studies in following subject matter.

The proposed NN method may be theoretically more sound than the BR method but the efficacy of this model cannot be ascertained in this study because of the lack of absolute accessibility scores. It is also unreliable to compare the accessibility outcome between the NN and BR methods which is unlike the comparative study done between different FCA models, where parameters remain the same except for the weighting parameter. This is because the parameters involved in both these methods can be ambiguously defined with a range of values. For instance, the NN method can be defined with a range of nearest neighbours (1, 2, 3,) whereas the BR method can be defined with a range of radial values of buffer rings (5, 10, 15, 30, 60 min,). It is meaningless to compare one value of the NN method with another value of the BR method. So a comparative study cannot absolutely ascertain their differences in accessibility outcome. However, there is a scope to conduct a comparative study between these methods by including a number of values for both the methods and this could be a possible area of future investigation.

Although this study has rigorously tested the accessibility outcome from different decay functions with respect to a theoretically determined control function, such a study can be further consolidated by incorporating actual health utilization data. It can be very difficult to obtain health utilization data due to confidentiality issues or the need to conduct expensive surveys. Nevertheless, the availability of such data can be used to validate the efficacy of the theoretically-defined control function. There is a scope in future to carry out a study on decay functions using health utilization data.

The choice of the Gaussian function as the control function was made purely on the basis of a theoretical expectation of weighting outcome of a decay function rather than by modelling distance impedance effects using actual health utilization or travel diaries data. Also, the values of model parameters for different decay functions were arbitrarily selected based on a trial and error approach rather than on a sound mathematical process of model identification. In both the cases, the methodological approach undertaken in this study was found to be appropriate in the context of theoretical modelling of a decay function, which is the main objective. However, there are opportunities in future to consolidate this kind of study by enhancing the model identification process. In addition, this study exclusively used the nearest-neighbours method of delineation of catchment areas, so there is also an opportunity to conduct studies on the effect of distance decay function using the buffer-ring method.

The HAPSS application is at the early stage of development and offers some functionalities to calculate accessibility values using straight-line distances. It cannot compute travelling time between service centres and population clusters using transportation network data as it was designed to process straight-line based computational models. It also does not have most of the spatial and statistical analysis tools that can be used for spatio-temporal analysis of spatial accessibility scores. Furthermore, it does not have the capability to incorporate knowledge-based models. There are thus opportunities for future work to consolidate this system by developing into a full-fledged SDSS. This application can be further enhanced by incorporating non-spatial components of various dimensions of the health care delivery system such as the availability, accessibility, affordability, acceptability and adequacy.

This study has exclusively looked into the computational aspects of accessibility indices. It has not undertaken analysis of spatial or non-spatial relationships between accessibility indices and other socio-economic or cultural variables underpinning the developmental aspects of a country. For policy and planning purposes, it is crucial to understand the variation in spatial accessibility between different regions based on their socio-economic status. Therefore, one of the future tasks is to conduct exploratory analysis between various accessibility indices and other variables.

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Appendix A

Additional Figures

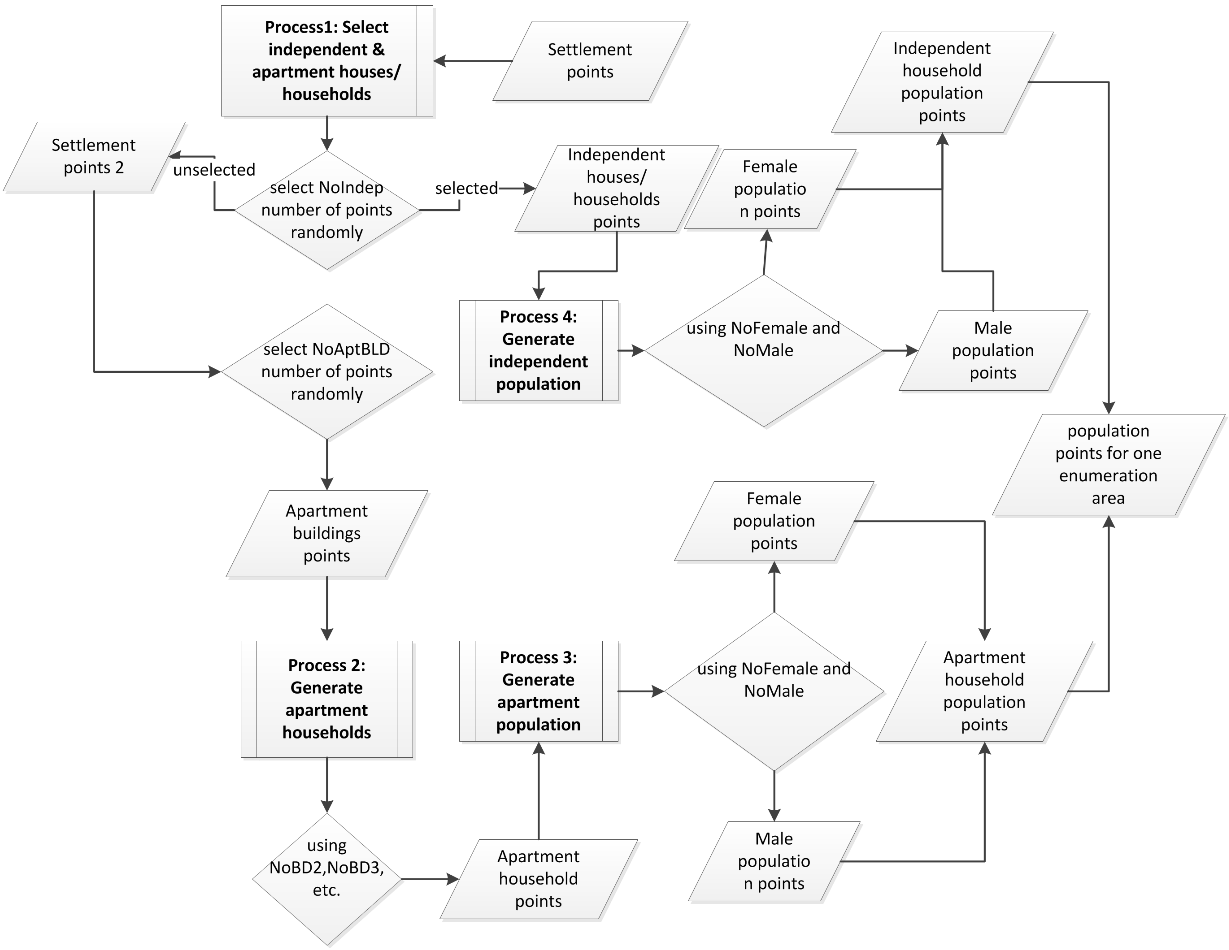


FIGURE A.1: Random selection and generation of point features

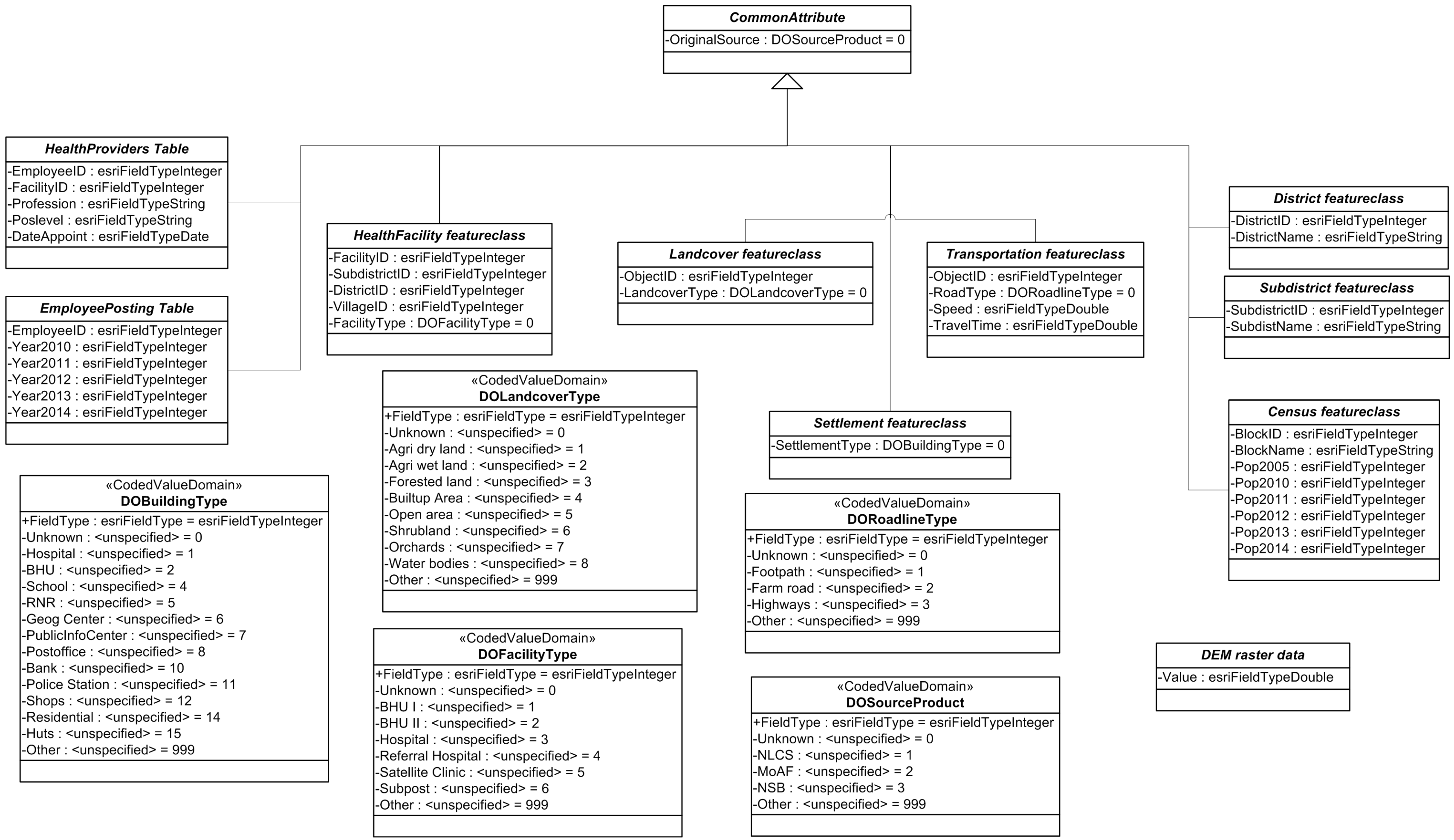


FIGURE A.2: Health accessibility data model

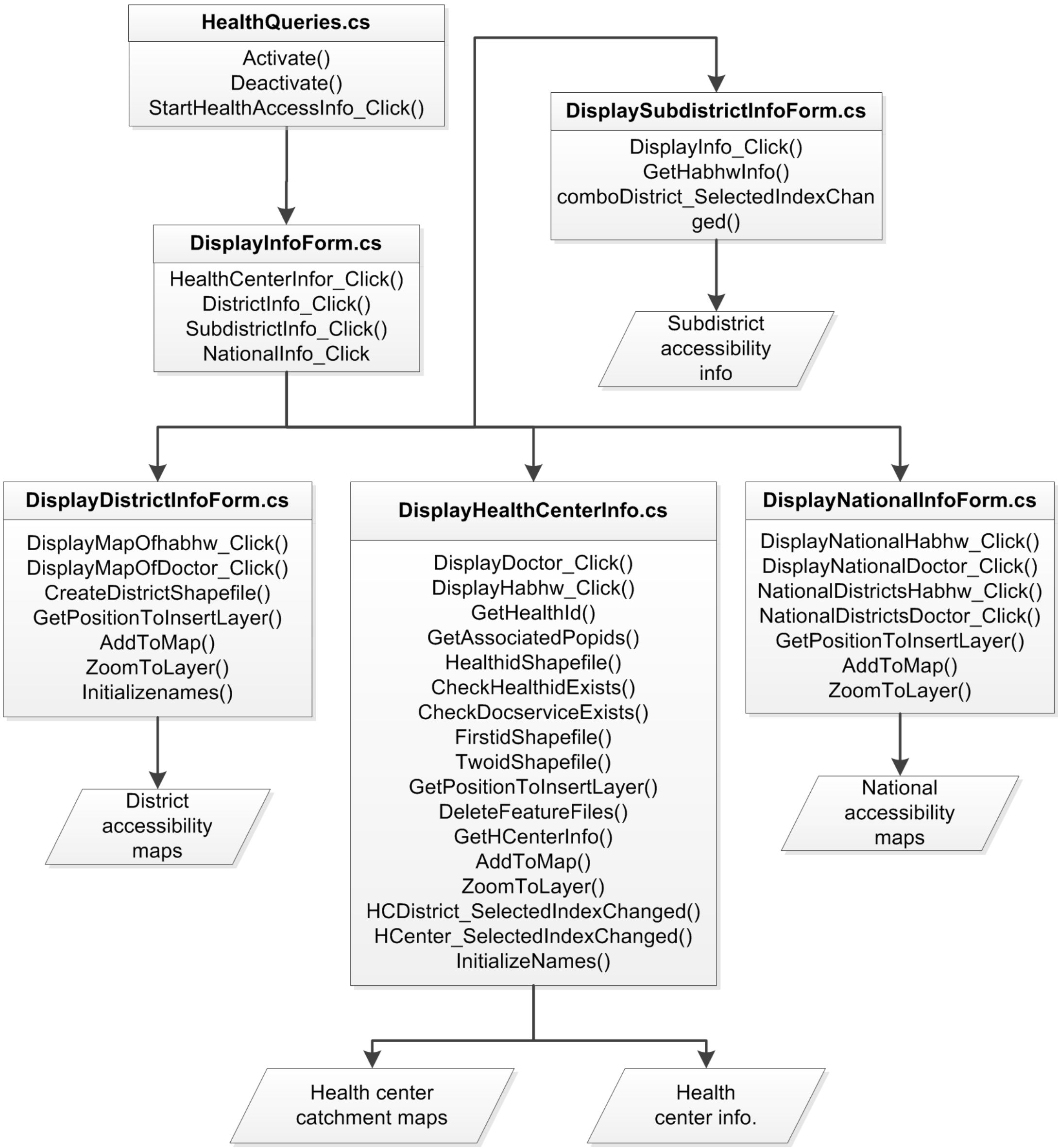


Figure A.3: Classes and methods of Display Access Info plugin

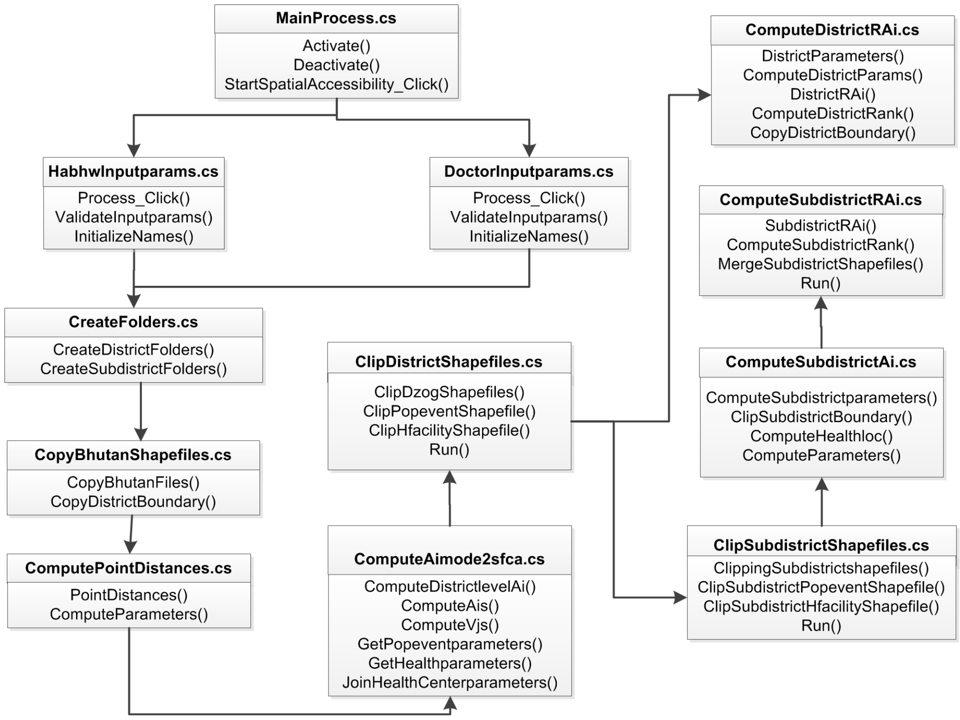


FIGURE A.4: Classes and methods of Spatial Accessibility plugin

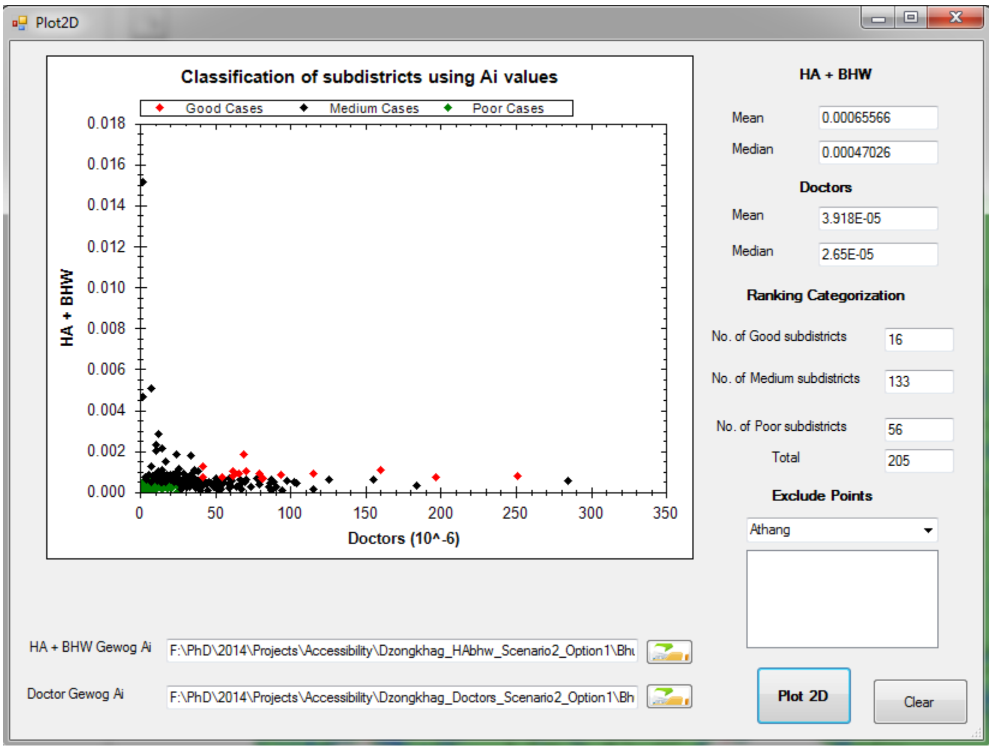


FIGURE A.5: GUI of Graph Plots

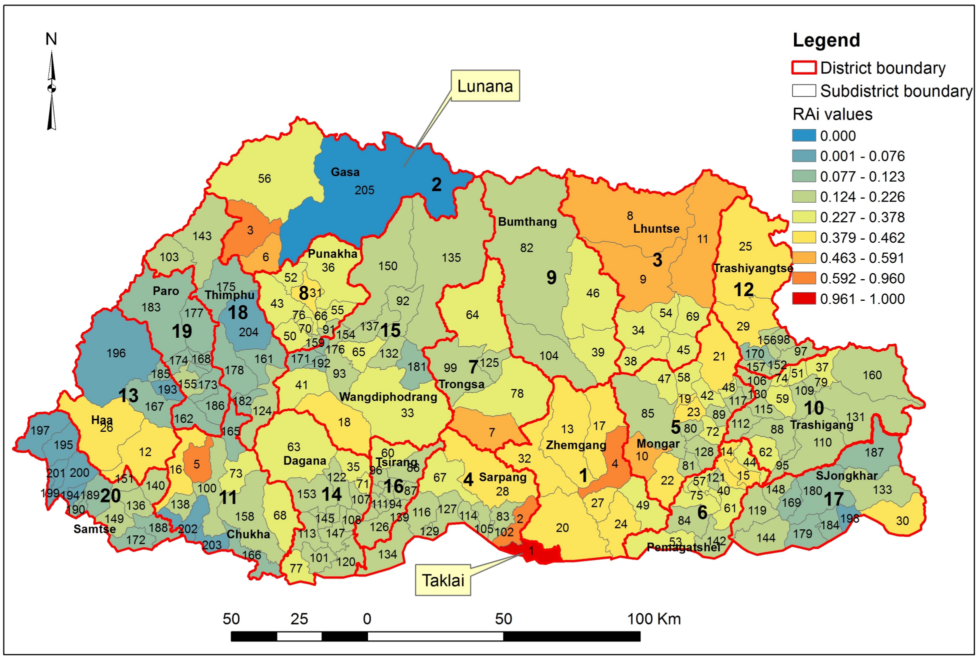


FIGURE A.6: Spatial accessibility ranking map for HA's services in 2010

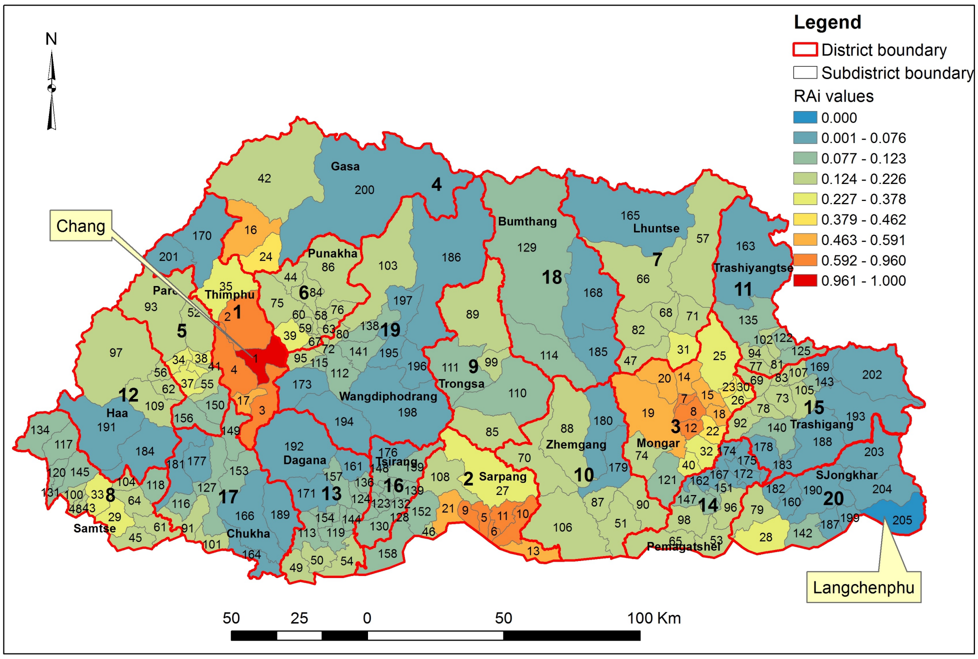


FIGURE A.7: Spatial accessibility ranking map for doctors' services in 2010

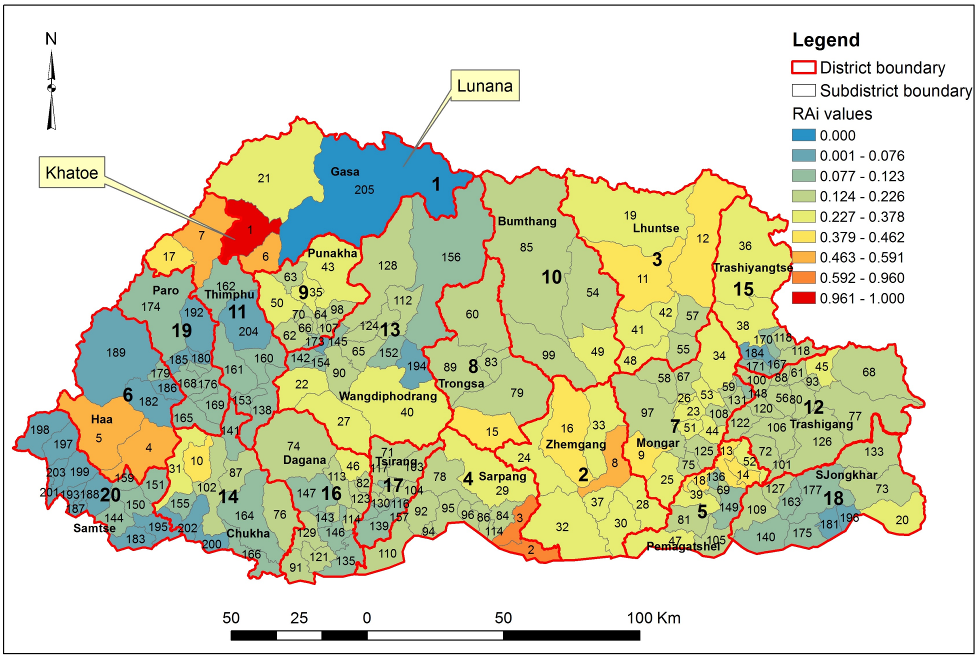


FIGURE A.8: Spatial accessibility ranking map for HA's services in 2011

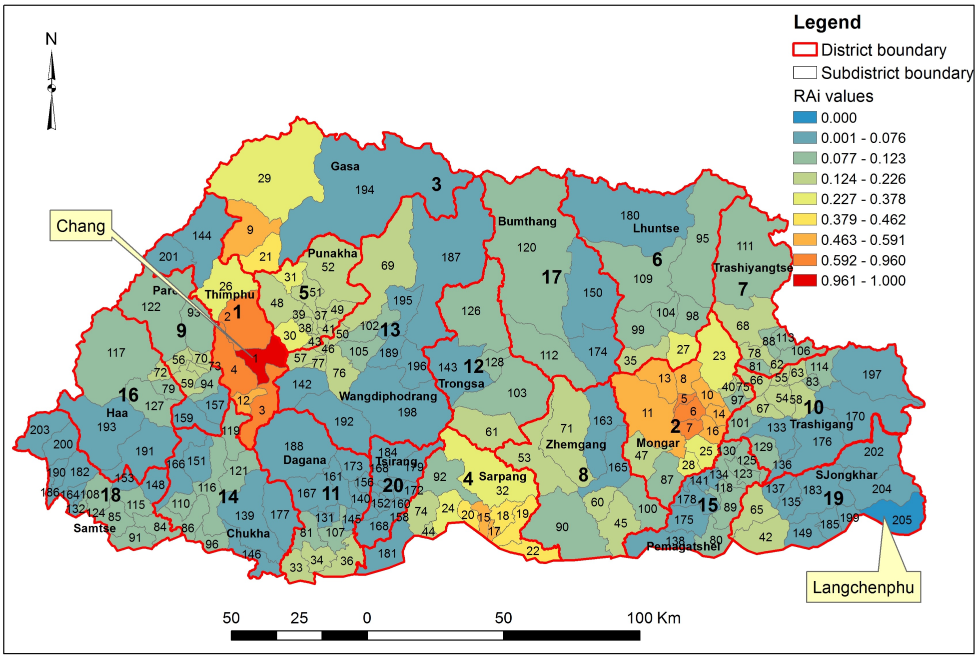


FIGURE A.9: Spatial accessibility ranking map for doctors' services in 2011

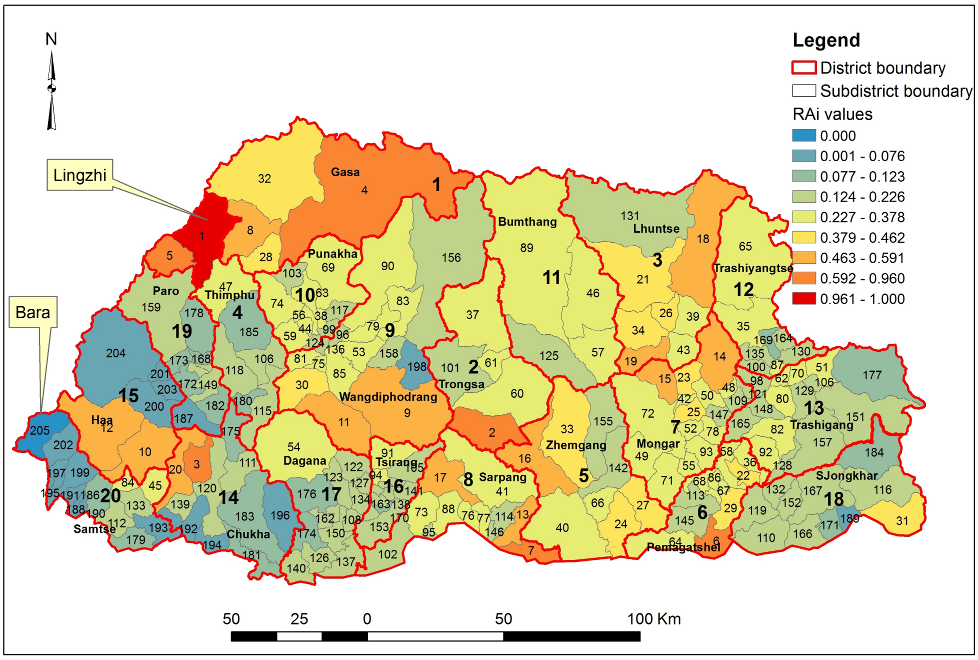


FIGURE A.10: Spatial accessibility ranking map for HA's services in 2012

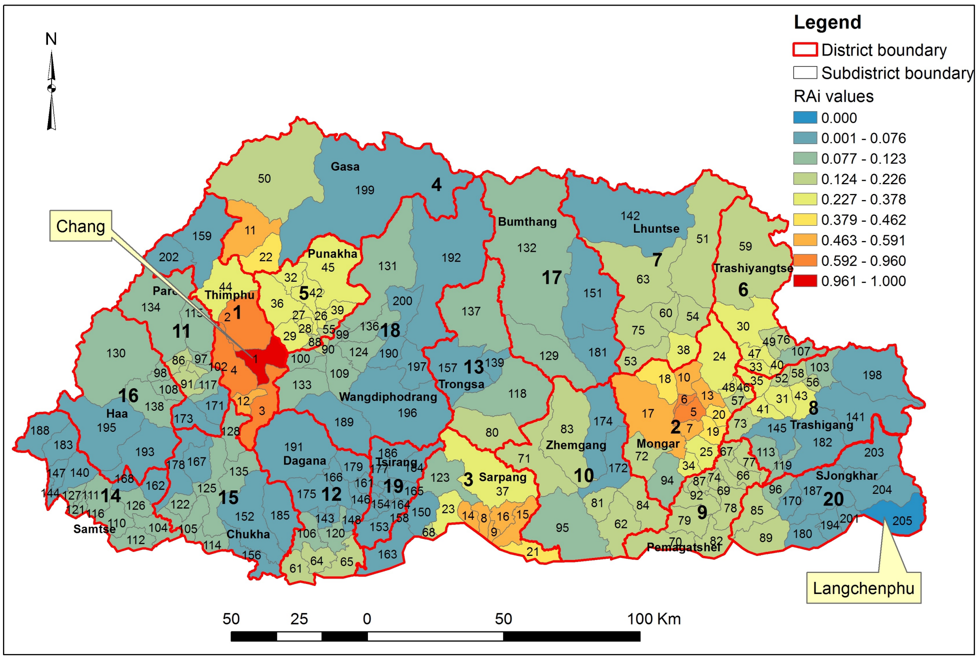


FIGURE A.11: Spatial accessibility ranking map for doctors' services in 2012

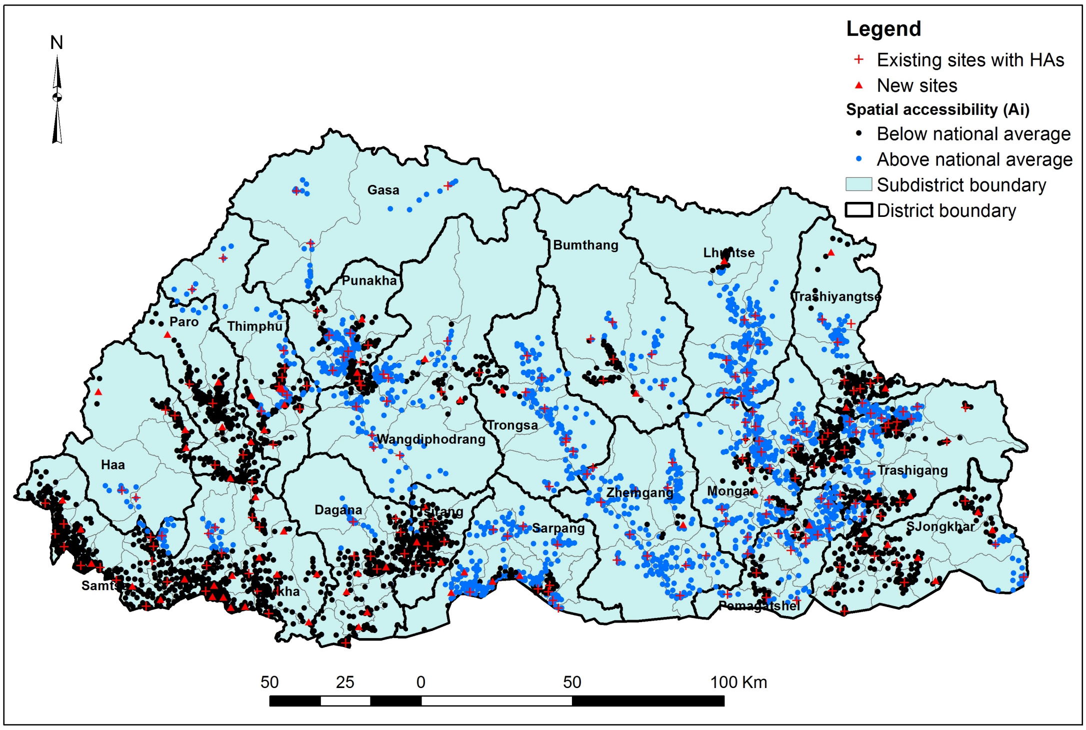


FIGURE A.12: Locations of new health facilities with HA services for Scenario 2

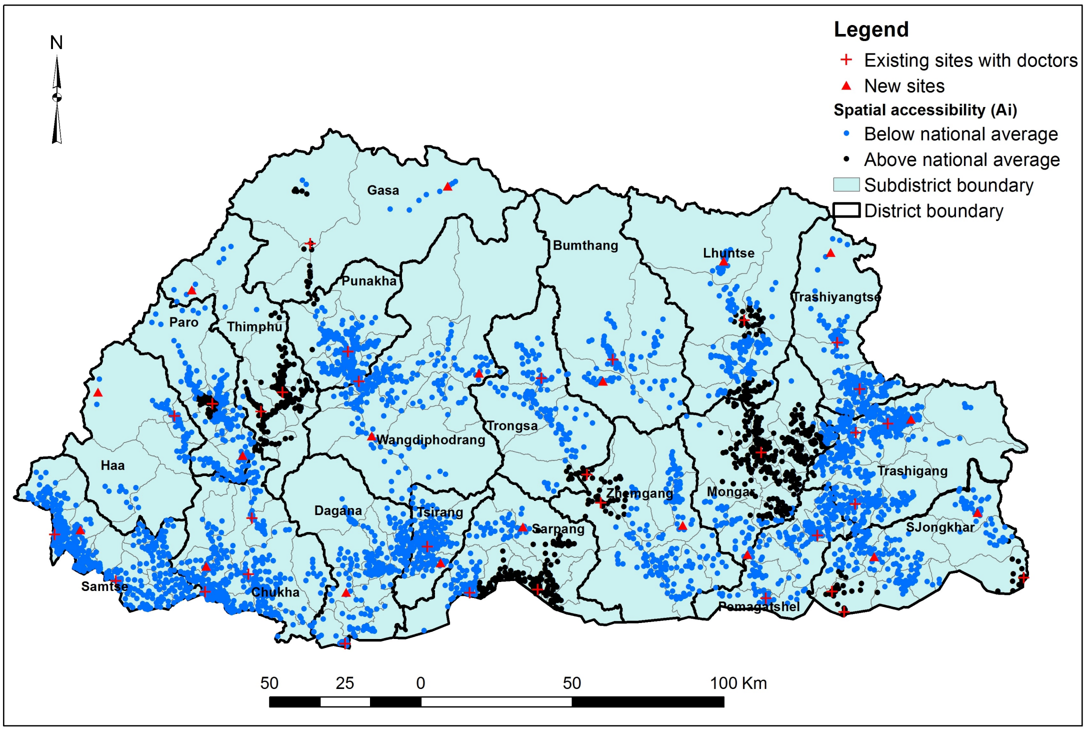
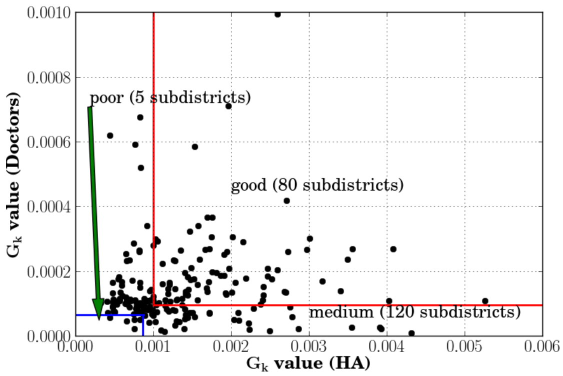
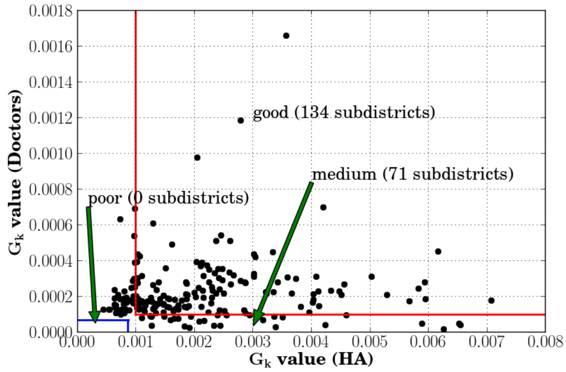


FIGURE A.13: Locations of new health facilities with doctor services for Scenario 2

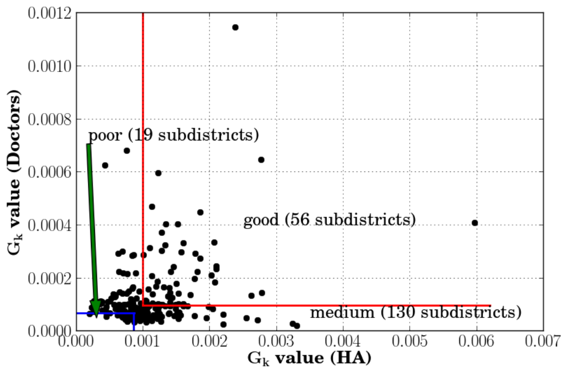


(a) Scenario 1 Minimum 3 Providers method

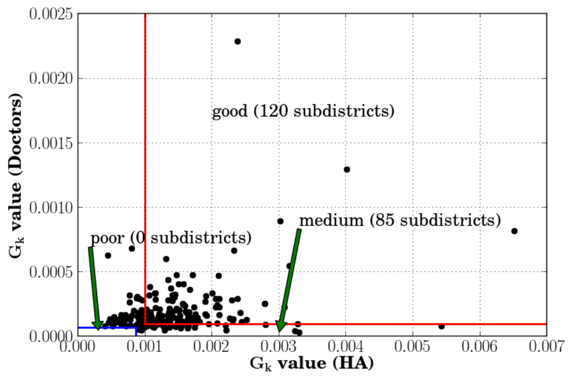


(b) Scenario 1 Minimum 5 Providers method

Figure A.14: Scenarios 1 - individual classification results

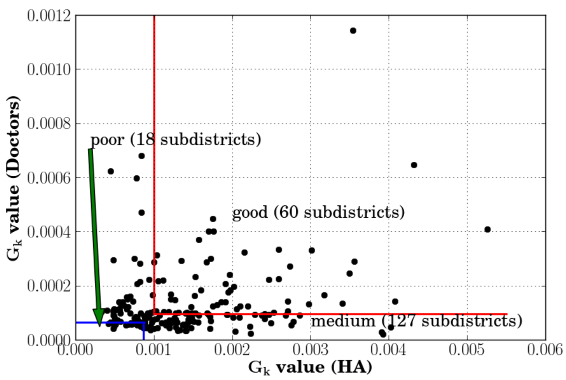


(a) Scenario 2 Option 1 method

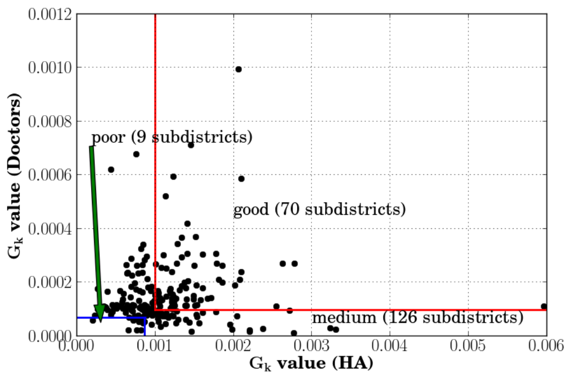


(b) Scenario 2 Option 2 method

Figure A.15: Scenarios 2 - individual classification results

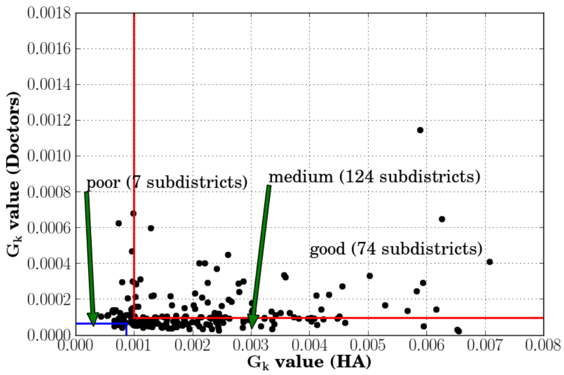


(a) Scenario 1 Minimum 3(HA) vs Scenario 2 Option 1(doctors)

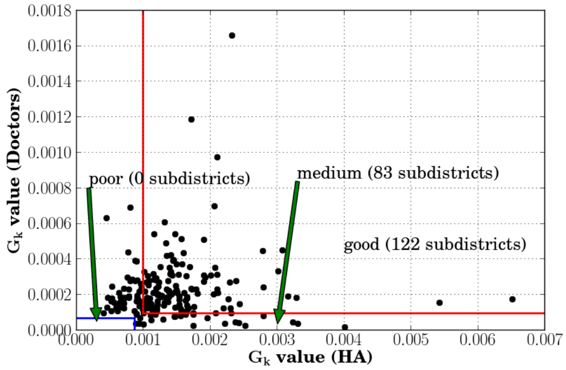


(b) Scenario 2 Option 1(HA) vs Scenario 1 Minimum 3(doctors)

Figure A.16: Part 1: Scenarios 1 and 2 - combined classification results

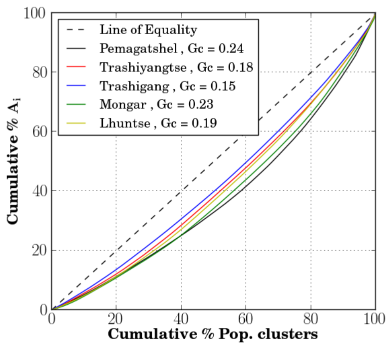


(a) Scenario 1 Minimum 5(HA) vs Scenario 2 Option 1(doctors)

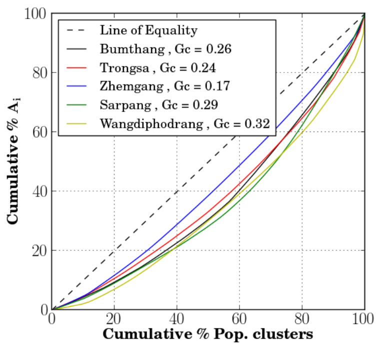


(b) Scenario 2 Option 2(HA) vs Scenario 1 Minimum 5(doctors)

FIGURE A.17: Part 2: Scenarios 1 and 2 - combined classification results

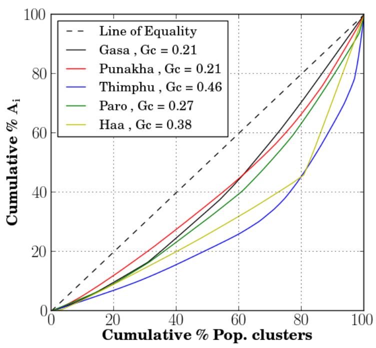


(a) Eastern Districts

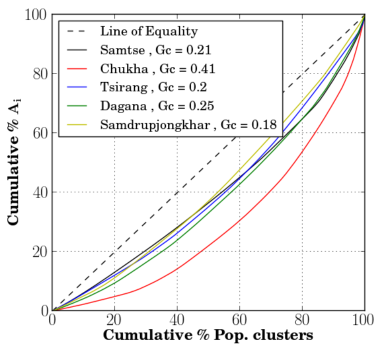


(b) Central Districts

FIGURE A.18: Part 1: Gini plots of the mean spatial accessibility scores



(a) Western Districts



(b) Southern Districts

FIGURE A.19: Part 2: Gini plots of the mean spatial accessibility scores

Appendix B

Additional Tables

Table B.1: Population and number of health care providers in districts in 2010

Districts	Population	No. of Doctors	No. of health facilities with doctors	No. of HA	No. of health facilities with health assistants
Bumthang	17550	1	1	16	5
Chukha	81355	8	3	39	13
Dagana	25076	2	2	19	9
Gasa	3406	1	1	6	2
Haa	12585	1	1	6	3
Lhuntse	16534	2	1	24	11
Mongar	40651	15	1	47	22
Paro	39801	6	1	17	4
Pemagatshel	23779	2	2	28	9
Punakha	25648	4	1	23	7
Samtse	65393	8	3	28	12
Sarpang	41302	15	2	36	9
Thimphu	104202	68	2	46	10
Trashigang	52538	7	2	44	23
Trashiyangtse	19319	1	1	18	8
Trongsa	14711	2	1	14	7
Tsirang	20255	2	1	17	6
Wangdiphodrang	34324	2	1	23	12
Zhemgang	20089	3	3	31	15
Samdrupjongkhar	36535	4	2	22	10
Total	695053	154	32	504	197

Table B.2: Population and number of health care providers in districts in 2011

Districts	**Population**	**No. of Doctors**	**No. of health facilities with doctors**	**No. of HA**	**No. of health facilities with health assistants**
Bumthang	17838	1	1	17	5
Chukha	82778	7	3	44	13
Dagana	25566	2	2	20	9
Gasa	3464	1	1	9	2
Haa	12776	1	1	9	4
Lhuntse	16753	1	1	27	11
Mongar	41383	14	1	52	22
Paro	40481	3	1	17	4
Pemagatshel	24074	1	1	33	11
Punakha	26098	4	1	24	8
Samtse	66467	3	1	30	12
Sarpang	42160	10	1	42	9
Thimphu	106569	65	2	59	11
Trashigang	53307	6	4	48	23
Trashiyangtse	19635	1	1	18	8
Trongsa	14974	1	1	16	7
Tsirang	20574	1	1	17	6
Wangdiphodrang	34978	2	1	26	12
Zhemgang	20377	3	3	35	15
Samdrupjongkhar	37227	3	2	28	10
Total	707479	130	30	571	202

Table B.3: Population and number of health care providers in districts in 2012

Districts	**Population**	**No. of Doctors**	**No. of health facilities with doctors**	**No. of HA**	**No. of health facilities with health assistants**
Bumthang	18119	1	1	17	6
Chukha	84210	7	3	40	12
Dagana	26053	2	2	20	8
Gasa	3521	1	1	7	3
Haa	12963	1	1	5	4
Lhuntse	16987	2	1	27	10
Mongar	42126	14	1	54	25
Paro	41168	3	1	20	4
Pemagatshel	24360	4	2	30	13
Punakha	26535	4	1	26	8
Samtse	67521	4	2	33	13
Sarpang	43039	12	2	45	10
Thimphu	108941	72	2	81	13
Trashigang	54037	9	4	44	23
Trashiyangtse	19942	3	2	18	8
Trongsa	15242	1	1	19	8
Tsirang	20895	1	1	17	6
Wangdiphodrang	35627	3	2	35	12
Zhemgang	20668	3	3	32	12
Samdrupjongkhar	37919	2	2	29	10
Total	719873	149	35	599	208

Table B.4: Population and number of health care providers in districts in 2013

Districts	Population	No. of Doctors	No. of health facilities with doctors	No. of HA	No. of health facilities with health assistants
Bumthang	18416	2	1	17	6
Chukha	85615	8	3	42	12
Dagana	26550	1	1	23	8
Gasa	3578	1	1	7	3
Haa	13147	1	1	7	4
Lhuntse	17207	2	1	29	10
Mongar	42843	13	1	56	26
Paro	41848	5	1	20	4
Pemagatshel	24648	3	2	31	13
Punakha	26982	2	1	26	8
Samtse	68582	4	2	33	13
Sarpang	43920	10	2	46	10
Thimphu	111312	74	2	82	13
Trashigang	54766	5	3	47	23
Trashiyangtse	20264	2	2	19	9
Trongsa	15502	1	1	20	8
Tsirang	21215	1	1	17	6
Wangdiphodrang	36278	1	1	36	12
Zhemgang	20950	3	2	36	12
Samdrupjongkhar	38599	5	3	30	10
Total	732222	144	32	624	210

Table B.5: Pearson correlation coefficients between accessibility scores of different Gaussian curves

	R=2.0, β=2.0	**R=2.0, β=1.5**	**R=2.0, β=2.5**	**R=1.0, β=2.0**	**R=1.9, β=2.0**	**R=2.1, β=2.0**	**R=3.0, β=2.0**
R=2.0, β=2.0	1	0.997	0.999	0.981	1	1	0.982
R=2.0, β=1.5	0.997	1	0.992	0.969	0.996	0.998	0.992
R=2.0, β=2.5	0.999	0.992	1	0.988	0.999	0.997	0.971
R=1.0, β=2.0	0.981	0.969	0.988	1	0.985	0.977	0.931
R=1.9, β=2.0	1	0.996	0.999	0.985	1	0.999	0.978
R=2.1, β=2.0	1	0.998	0.997	0.977	0.999	1	0.986
R=3.0, β=2.0	0.982	0.992	0.971	0.931	0.978	0.986	1

Table B.6: Population in subdistricts and towns of Bhutan in 2005 - Part 1

S.No	Dzongkhag	Census Block	Pop. 2005	S.No	Dzongkhag	Census Block	Pop. 2005
1	Bumthang	Chhoekhor	4866	66	Lhuntse	Lhuntshi town	1175
2	Bumthang	Ura	1953	67	Mongar	Gongdue	1329
3	Bumthang	Chhume	3591	68	Mongar	Jurmey	1449
4	Bumthang	Tang	1816	69	Mongar	Silambi	1458
5	Bumthang	Wangdicholing	1045	70	Mongar	Saling	2110
6	Bumthang	Bathpalathang	100	71	Mongar	Tsamang	1204
7	Bumthang	Jakar	80	72	Mongar	Tsakaling	1596
8	Bumthang	Jalkhar	548	73	Mongar	Shermung	1830
9	Bumthang	Chamkhar	2117	74	Mongar	Chhali	1620
10	Chukha	Dungna	731	75	Mongar	Mongar	3421
11	Chukha	Metakha	539	76	Mongar	Drepung	1094
12	Chukha	Logchina	2672	77	Mongar	Ngatshang	2109
13	Chukha	Phuentsholing	5183	78	Mongar	Balam	1092
14	Chukha	Geling	1856	79	Mongar	Narang	1239
15	Chukha	Sampheling	7310	80	Mongar	Drametse	2130
16	Chukha	Dala	8566	81	Mongar	Chaskhar	2376
17	Chukha	Bongo	6870	82	Mongar	Kengkhar	1996
18	Chukha	Getana	903	83	Mongar	Thangrong	1863
19	Chukha	Bjachho	3583	84	Mongar	Dremtse town	541
20	Chukha	Chapchha	3248	85	Mongar	Gyelpozhing town	2291
21	Chukha	Chukha	2855	86	Mongar	Lingmithang town	819
22	Chukha	Gedu	4288	87	Mongar	Mongar town	3502
23	Chukha	Phuntsholing	20537	88	Paro	Tsento	5253
24	Chukha	Tala	1652	89	Paro	Doteng	1149
25	Chukha	Tsimasham	1233	90	Paro	Dopshari	3180
26	Chukha	Tsimalakha	2361	91	Paro	Hungrel	2016
27	Dagana	Tseza	1106	92	Paro	Wangchang	6425
28	Dagana	Lajab	863	93	Paro	Lango	3336
29	Dagana	Khebisa	1212	94	Paro	Lungnyi	2543
30	Dagana	Tsangkha	1352	95	Paro	Shaba	4072
31	Dagana	Drujegang	2121	96	Paro	Dogar	2273
32	Dagana	Trashiding	1636	97	Paro	Naja	3254
33	Dagana	Tsendagang	1874	98	Paro	Bondey town	570
34	Dagana	Nichula	479	99	Paro	Tshogdue town	2362
35	Dagana	Deorali	1315	100	Pemagatshel	Norbugang	2948
36	Dagana	Lhamoizingkha	1876	101	Pemagatshel	Choekhorling	1052
37	Dagana	Kalidzingkha	1964	102	Pemagatshel	Dechheling	2072
38	Dagana	Gesarling	1340	103	Pemagatshel	Dungmin	1470
39	Dagana	Dorona	754	104	Pemagatshel	Chimung	749
40	Dagana	Gozhi	2187	105	Pemagatshel	Yurung	1313
41	Dagana	Daga town	1146	106	Pemagatshel	Chongshing	934
42	Dagana	Drujegang town	552	107	Pemagatshel	Khar	1846
43	Dagana	Lhamoizingkha town	778	108	Pemagatshel	Shumar	4648
44	Dagana	Sunkosh town	115	109	Pemagatshel	Zobel	1697
45	Gasa	Laya	949	110	Pemagatshel	Nanong	2351
46	Gasa	Lunana	693	111	Pemagatshel	Kherigonpa town	141
47	Gasa	Khamae	906	112	Pemagatshel	Pemagatshel town	1066
48	Gasa	Khatoe	166	113	Punakha	Goenshari	622
49	Gasa	Gasa town	402	114	Punakha	Kabjisa	2361
50	Haa	Gakiling	552	115	Punakha	Chhubu	1991
51	Haa	Sombeykha	758	116	Punakha	Toewang	1363
52	Haa	Bji	2675	117	Punakha	Shengabjemi	1257
53	Haa	Samar	1568	118	Punakha	Dzoma	1350
54	Haa	Eusu	2485	119	Punakha	Lingmukha	597
55	Haa	Katsho	1115	120	Punakha	Bapisa	3326
56	Haa	Haa town	2495	121	Punakha	Guma	4288
57	Lhuntse	Kurtoe	1005	122	Punakha	Talo	1594
58	Lhuntse	Gangzur	2690	123	Punakha	Toebisa	2421
59	Lhuntse	Khoma	1819	124	Punakha	Khuru town	2292
60	Lhuntse	Menji	1382	125	Samdrupjongkhar	Langchenphu	934
61	Lhuntse	Menbi	2528	126	Samdrupjongkhar	Serthi	2004
62	Lhuntse	Metsho	1210	127	Samdrupjongkhar	Samrang	106
63	Lhuntse	Jaray	1143	128	Samdrupjongkhar	Pemathang	1504
64	Lhuntse	Tsenkhar	2142	129	Samdrupjongkhar	Phuntshothang	3144
65	Lhuntse	Autsho town	301	130	Samdrupjongkhar	Dewathang	2992

Table B.7: Population in subdistricts and towns of Bhutan in 2005 - Part 2

S.No	Dzongkhag	Census Block	Pop. 2005	S.No	Dzongkhag	Census Block	Pop. 2005
131	Samdrupjongkhar	Orong	3144	196	Trashigang	Khaling town	1349
132	Samdrupjongkhar	Gomdar	2751	197	Trashigang	Rangjung town	633
133	Samdrupjongkhar	Wangphu	1932	198	Trashigang	Riserboo town	153
134	Samdrupjongkhar	Martshala	3022	199	Trashigang	Tashigang town	2383
135	Samdrupjongkhar	Lauri	2803	200	Trashigang	Wamrong town	581
136	Samdrupjongkhar	Deothang	2644	201	Trashiyangtse	Khamdang	3297
137	Samdrupjongkhar	Sjongkhar town	5952	202	Trashiyangtse	Bumdeling	1988
138	Samdrupjongkhar	Jomotsangkha town	957	203	Trashiyangtse	Yangtse	1546
139	Samtse	Bara	3403	204	Trashiyangtse	Tongzhang	1555
140	Samtse	Tendu	4587	205	Trashiyangtse	Jamkhar	1228
141	Samtse	Biru	3026	206	Trashiyangtse	Ramjar	1275
142	Samtse	Sipsu	3170	207	Trashiyangtse	Toetsho	2128
143	Samtse	Lahireni	2904	208	Trashiyangtse	Yalang	1705
144	Samtse	Chargharay	3155	209	Trashiyangtse	Duksum town	283
145	Samtse	Yoeseltse	1342	210	Trashiyangtse	Yangtse town	2735
146	Samtse	Ugentse	1467	211	Trongsa	Nubi	2451
147	Samtse	Chengmari	3877	212	Trongsa	Drakteng	2697
148	Samtse	Samtse	3263	213	Trongsa	Tangsibji	1848
149	Samtse	Pagli	6593	214	Trongsa	Langthil	2637
150	Samtse	Tading	4115	215	Trongsa	Korphu	1091
151	Samtse	Dorokha	4419	216	Trongsa	Trongsa town	2695
152	Samtse	Dungtoe	1839	217	Tsirang	Beteni	1203
153	Samtse	Denchhukha	2801	218	Tsirang	Barshong	759
154	Samtse	Gomtu	4254	219	Tsirang	Mendrelgang	1510
155	Samtse	Samtse town	4981	220	Tsirang	Rangthangling	1447
156	Samtse	Sibsoo	904	221	Tsirang	Tsholingkhor	1670
157	Sarpang	Singhi	742	222	Tsirang	Gosarling	1428
158	Sarpang	Shompangkha	1130	223	Tsirang	Semjong	1318
159	Sarpang	Dekiling	3835	224	Tsirang	Tsirangtoe	1153
160	Sarpang	Bhur	1517	225	Tsirang	Patala	1352
161	Sarpang	Gelephu	3975	226	Tsirang	Phuentenchhu	1157
162	Sarpang	Chhuzagang	2426	227	Tsirang	Dunglegang	1135
163	Sarpang	Sershong	2045	228	Tsirang	Kikhorthang	2869
164	Sarpang	Umling	1546	229	Tsirang	Damphu town	1666
165	Sarpang	Taklai	72	230	Wangdiphodrang	Kazhi	1284
166	Sarpang	Jigmechoeling	3414	231	Wangdiphodrang	Sephu	2011
167	Sarpang	Dovan	2064	232	Wangdiphodrang	Dangchhu	1299
168	Sarpang	Hilley	2517	233	Wangdiphodrang	Nyisho	2304
169	Sarpang	Gelephu town	9199	234	Wangdiphodrang	Bjena	2110
170	Sarpang	Sarpang town	2619	235	Wangdiphodrang	Gangtey	1677
171	Thimphu	Thimphu town	79185	236	Wangdiphodrang	Phobji	1929
172	Thimphu	Soe	183	237	Wangdiphodrang	Athang	808
173	Thimphu	Lingzhi	495	238	Wangdiphodrang	Daga	1347
174	Thimphu	Dagala	1497	239	Wangdiphodrang	Gasetsho Wom	722
175	Thimphu	Genye	918	240	Wangdiphodrang	Gasetsho Gom	2241
176	Thimphu	Mewang	4743	241	Wangdiphodrang	Nahi	823
177	Thimphu	Chang	3137	242	Wangdiphodrang	Rubesa	1709
178	Thimphu	Kawang	2582	243	Wangdiphodrang	Thedtsho	2222
179	Thimphu	Naro	189	244	Wangdiphodrang	Phangyul	1127
180	Trashigang	Bartsham	1807	245	Wangdiphodrang	Nobding town	473
181	Trashigang	Bidung	1929	246	Wangdiphodrang	Rurichhu town	335
182	Trashigang	Kanglung	4749	247	Wangdiphodrang	Wangdue town	6714
183	Trashigang	Kangpara	2217	248	Zhemgang	Pangkhar	1367
184	Trashigang	Khaling	3046	249	Zhemgang	Trong	3314
185	Trashigang	Lumang	4754	250	Zhemgang	Nangkor	2527
186	Trashigang	Merak	1621	251	Zhemgang	Shingkhar	1546
187	Trashigang	Phongmey	2427	252	Zhemgang	Bardo	1997
188	Trashigang	Radhi	3303	253	Zhemgang	Goshing	1533
189	Trashigang	Sakteng	2072	254	Zhemgang	Ngangla	2396
190	Trashigang	Samkhar	2681	255	Zhemgang	Bjoka	949
191	Trashigang	Shongphug	3463	256	Zhemgang	Tingtibi town	675
192	Trashigang	Thrimshing	2435	257	Zhemgang	Zhemgang town	2332
193	Trashigang	Uzorong	3148				
194	Trashigang	Yangnyer	2315				
195	Trashigang	Kanglung town	1717				
Total							**634982**

Table B.8: Statistics for distances between population clusters and health facilities

Facility	Doctor services			HA services		
	Min. (Km)	**Max. (Km)**	**Mean (Km)**	**Min. (Km)**	**Max. (Km)**	**Mean (Km)**
First-nearest	0.046	59.602	12.560	0.012	51.819	12.697
Second-nearest	2.916	66.232	22.368	1.205	52.401	8.891
Third-nearest	9.022	71.033	29.776	2.248	57.012	12.697

Table B.9: Description of the core DotSpatial packages

SL.NO	Namespaces	Description
1	DotSpatial.Analysis	GIS Analysis tools such as clipping, overlay and etc.
2	DotSpatial.Controls	Windows Forms controls includes a map control,legend control, plugin control and etc.
3	DotSpatial.Data	Deals with GIS Data objects.
4	DotSpatial.Data.Rasters .GdalExtension	Deals with raster data
5	DotSpatial.Data.Forms	Windows Forms controls for GIS objects.
6	DotSpatial.Extensions	Interfaces to facilitate extensibility in DotSpatial.
7	DotSpatial.Modeling	Place holder for non-GUI modeling code.
8	DotSpatial.Modeling.Forms	Windows Forms elements for tools and the modeler.
9	DotSpatial.Projections	Deals with projections and coordinate systems. Conversion of the proj4 C++ library to C#.
10	DotSpatial.Projections.Forms	Windows Forms elements for working with projections and coordinate systems.
11	DotSpatial.Serialization	Helper assembly to save DotSpatial objects to XML file.
12	DotSpatial.Symbology	For customizing cartographic symbology.
13	DotSpatial.Symbology.Forms	Windows forms elements for customizing cartographic symbology.
14	DotSpatial.Topology	Deals with the topology of the geometric objects which is derived from the Java Topology Suite (JTS).

Table B.10: Summary statistics for both the service providers in 2013

	HA services			Doctor services		
Districts	**Min.**	**Mean**	**Max.**	**Min.**	**Mean**	**Max.**
Bumthang	0.0005451	0.00201	0.0009544	0.0000575	0.000115	0.0000972
Chukha	0.0001252	0.00260	0.0005103	0.0000202	0.000328	0.0000664
Dagana	0.0003300	0.00217	0.0007834	0.0000137	0.000094	0.0000403
Gasa	0.0006591	0.00291	0.0018984	0.0000054	0.000337	0.0001705
Haa	0.0000589	0.00334	0.0007532	0.0000198	0.000114	0.0000818
Lhuntse	0.0007992	0.00229	0.0014984	0.0000508	0.000260	0.0001460
Mongar	0.0004289	0.00265	0.0012092	0.0000505	0.000384	0.0002523
Paro	0.0001135	0.00310	0.0005322	0.0000199	0.000135	0.0001041
P/gatshel	0.0005270	0.00277	0.0012336	0.0000555	0.000147	0.0000767
Punakha	0.0006018	0.00177	0.0010090	0.0000364	0.000498	0.0000647
Samtse	0.0001181	0.00140	0.0004416	0.0000291	0.000090	0.0000680
Sarpang	0.0004634	0.00210	0.0011320	0.0000174	0.000292	0.0001737
Thimphu	0.0000870	0.00503	0.0007530	0.0000112	0.000683	0.0005914
Trashigang	0.0004307	0.00159	0.0008413	0.0000101	0.000241	0.0000652
T/yangtse	0.0003065	0.00163	0.0008911	0.0000218	0.000111	0.0000842
Trongsa	0.0003274	0.00346	0.0013916	0.0000325	0.000155	0.0000758
Tsirang	0.0004002	0.00221	0.0006997	0.0000138	0.000038	0.0000317
W/phodrang	0.0003525	0.00290	0.0010081	0.0000084	0.000055	0.0000317
Zhemgang	0.0008271	0.00301	0.0014419	0.0000275	0.000181	0.0000866
S/jongkhar	0.0004011	0.00149	0.0007081	0.0000101	0.000204	0.0000971

Table B.11: Classification results in 2013

	Number of Subdistricts				Population count			
Districts	**Good**	**Medium**	**Poor**	**Total**	**Good**	**Medium**	**Poor**	**Total**
Bumthang	0	4	0	4	0	18416	0	18416
Chukha	0	5	6	11	0	42638	42977	85615
Dagana	0	5	9	14	0	9155	17395	26550
Gasa	3	1	0	4	2811	767	0	3578
Haa	0	6	0	6	0	13147	0	13147
Lhuntse	7	1	0	8	16085	1122	0	17207
Mongar	10	7	0	17	25981	16862	0	42843
Paro	0	8	2	10	0	35687	6161	41848
Pemagatshel	0	11	0	11	0	24648	0	24648
Punakha	0	8	3	11	0	21069	5913	26982
Samtse	0	8	7	15	0	26485	42097	68582
Sarpang	4	8	0	12	10455	33465	0	43920
Thimphu	1	7	0	8	229	111083	0	111312
Trashigang	0	9	6	15	0	34454	20312	54766
Trashiyangtse	0	6	2	8	0	15894	4370	20264
Trongsa	1	3	1	5	1296	12021	2185	15502
Tsirang	0	2	10	12	0	2865	18350	21215
Wangdiphodrang	0	10	5	15	0	18149	18129	36278
Zhemgang	2	6	0	8	9943	11007	0	20950
Samdrupjongkhar	1	5	5	11	2195	23089	14125	39409
Total	29	120	56	205	68995	472023	192014	733032
Percent	14.15	58.54	27.32		9.41	64.39	26.19	

Table B.12: Classification results for Scenario 1 - Minimum 3 Providers method

	Number of Subdistricts				Population count			
Districts	**Good**	**Medium**	**Poor**	**Total**	**Good**	**Medium**	**Poor**	**Total**
Bumthang	2	2	0	4	12085	6331	0	18416
Chukha	1	10	0	11	623	84992	0	85615
Dagana	0	13	1	14	0	24256	2294	26550
Gasa	3	1	0	4	2811	767	0	3578
Haa	0	6	0	6	0	13147	0	13147
Lhuntse	7	1	0	8	16085	1122	0	17207
Mongar	16	1	0	17	40381	2462	0	42843
Paro	0	10	0	10	0	41848	0	41848
Pemagatshel	11	0	0	11	24648	0	0	24648
Punakha	5	6	0	11	14731	12251	0	26982
Samtse	0	14	1	15	0	64620	3962	68582
Sarpang	6	6	0	12	28998	14922	0	43920
Thimphu	2	6	0	8	826	110486	0	111312
Trashigang	10	5	0	15	38250	16516	0	54766
Trashiyangtse	8	0	0	8	20264	0	0	20264
Trongsa	5	0	0	5	15502	0	0	15502
Tsirang	0	12	0	12	0	21215	0	21215
Wangdiphodrang	0	14	1	15	0	33924	2354	36278
Zhemgang	2	6	0	8	9943	11007	0	20950
Samdrupjongkhar	2	7	2	11	4523	28895	5181	38599
Total	80	120	5	205	229670	488761	13791	732222
Percent	39.02	58.54	2.44		31.37	66.75	1.88	

Table B.13: Classification results for Scenario 1 - Minimum 5 Providers method

	Number of Subdistricts				Population count			
Districts	**Good**	**Medium**	**Poor**	**Total**	**Good**	**Medium**	**Poor**	**Total**
Bumthang	3	1	0	4	14304	4112	0	18416
Chukha	5	6	0	11	10736	74879	0	85615
Dagana	7	7	0	14	15407	11143	0	26550
Gasa	3	1	0	4	2811	767	0	3578
Haa	0	6	0	6	0	13147	0	13147
Lhuntse	7	1	0	8	16085	1122	0	17207
Mongar	17	0	0	17	42843	0	0	42843
Paro	2	8	0	10	9693	32155	0	41848
Pemagatshel	11	0	0	11	24648	0	0	24648
Punakha	10	1	0	11	23167	3815	0	26982
Samtse	1	14	0	15	9644	58938	0	68582
Sarpang	9	3	0	12	37930	5990	0	43920
Thimphu	4	4	0	8	3755	107557	0	111312
Trashigang	13	2	0	15	50624	4142	0	54766
Trashiyangtse	8	0	0	8	20264	0	0	20264
Trongsa	5	0	0	5	15502	0	0	15502
Tsirang	10	2	0	12	14514	6701	0	21215
Wangdiphodrang	7	8	0	15	14558	21720	0	36278
Zhemgang	4	4	0	8	12757	8193	0	20950
Samdrupjongkhar	8	3	0	11	33304	5295	0	38599
Total	134	71	0	205	372546	359676	0	732222
Percent	65.37	34.63	0.00		50.88	49.12	0	

Table B.14: Classification results for Scenario 2 - Option 1 method

	Number of Subdistricts				Population count			
Districts	**Good**	**Medium**	**Poor**	**Total**	**Good**	**Medium**	**Poor**	**Total**
Bumthang	1	3	0	4	2080	16336	0	18416
Chukha	0	8	3	11	0	58935	26680	85615
Dagana	2	8	4	14	3959	13593	8998	26550
Gasa	4	0	0	4	3578	0	0	3578
Haa	1	5	0	6	2982	10165	0	13147
Lhuntse	8	0	0	8	17207	0	0	17207
Mongar	11	6	0	17	30506	12337	0	42843
Paro	0	10	0	10	0	41848	0	41848
Pemagatshel	4	7	0	11	7957	16691	0	24648
Punakha	1	8	2	11	2722	19762	4498	26982
Samtse	0	13	2	15	0	59547	9035	68582
Sarpang	5	7	0	12	25844	18076	0	43920
Thimphu	5	3	0	8	8731	102581	0	111312
Trashigang	3	11	1	15	11040	41403	2323	54766
Trashiyangtse	3	5	0	8	8593	11671	0	20264
Trongsa	2	3	0	5	7248	8254	0	15502
Tsirang	0	8	4	12	0	11124	10091	21215
Wangdiphodrang	2	11	2	15	3107	21700	11471	36278
Zhemgang	3	5	0	8	12194	8756	0	20950
Samdrupjongkhar	1	9	1	11	2195	32908	3496	38599
Total	56	130	19	205	149943	505687	76592	732222
Percent	27.32	63.41	9.27		20.48	69.06	10.46	

Table B.15: Classification results for Scenario 2 - Option 2 method

	Number of Subdistricts				Population count			
Districts	**Good**	**Medium**	**Poor**	**Total**	**Good**	**Medium**	**Poor**	**Total**
Bumthang	2	2	0	4	12085	6331	0	18416
Chukha	5	6	0	11	20248	65367	0	85615
Dagana	8	6	0	14	14745	11805	0	26550
Gasa	4	0	0	4	3578	0	0	3578
Haa	1	5	0	6	2982	10165	0	13147
Lhuntse	8	0	0	8	17207	0	0	17207
Mongar	16	1	0	17	40123	2720	0	42843
Paro	2	8	0	10	9693	32155	0	41848
Pemagatshel	10	1	0	11	22357	2291	0	24648
Punakha	2	9	0	11	3558	23424	0	26982
Samtse	0	15	0	15	0	68582	0	68582
Sarpang	9	3	0	12	34031	9889	0	43920
Thimphu	6	2	0	8	9840	101472	0	111312
Trashigang	8	7	0	15	25937	28829	0	54766
Trashiyangtse	7	1	0	8	16156	4108	0	20264
Trongsa	5	0	0	5	15502	0	0	15502
Tsirang	5	7	0	12	6907	14308	0	21215
Wangdiphodrang	9	6	0	15	18086	18192	0	36278
Zhemgang	8	0	0	8	20950	0	0	20950
Samdrupjongkhar	5	6	0	11	13458	25141	0	38599
Total	120	85	0	205	307443	424779	0	732222
Percent	58.54	41.46	0.00		41.99	58.01	0.00	