EXAMINING THE SPATIAL MISMATCH IN THE SUPPLY AND DEMAND FOR MATERNAL AND CHILD HEALTH SERVICES IN BANGLADESH

by

Priyanka D. Vyas

APPROVED BY SUPERVISORY COMMITTEE:

____
Dohyeong Kim, Chair

____
Brian J. L. Berry

____
Michael Tiefelsdorf

____
Richard K. Scotch

To Himanshu

EXAMINING THE SPATIAL MISMATCH IN THE SUPPLY AND DEMAND FOR MATERNAL AND CHILD HEALTH SERVICES IN BANGLADESH

by

PRIYANKA D. VYAS, BA, MPA

DISSERTATION

Presented to the Faculty of

The University of Texas at Dallas

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY IN

PUBLIC POLICY AND POLITICAL ECONOMY

THE UNIVERSITY OF TEXAS AT DALLAS

December 2017

ACKNOWLEDGMENTS

I cannot believe that five years of academic life are almost getting over and very soon I will have to learn to stand on my own feet, making decisions on my own, and professors whom I could readily turn to for their advice may not be available. This journey would have been incomplete without mentors who provided their intellectual support and family and friends for their moral support. Firstly, I would like to thank my academic advisor Dohyeong Kim for introducing me to this fascinating country, Bangladesh, about which I knew very little until I had an opportunity to travel there for a research project. Many ideas and thoughts have been inspired from a series of collaborative papers we worked on together and which influenced my thinking while writing this dissertation. Some of the GIS data used in this research were collected from government agencies during this trip, and I owe Dr. Kim several of the connections I made with local scholars and the data I was able to gather during this visit. He has provided me the intellectual freedom and support to explore ideas, while providing inspiration to learn about major theories about which I had very limited understanding until he introduced me to them. The roots of this dissertation were sown when I took a dissertation proposal seminar with Brian Berry. A substantial part of this research rests on some of the most influential work by Dr. Berry and the theory propounded by him. Since then his intellectual support has been central to shaping this research. I do not know whether I have done justice to his work, but the long conversations we had were instrumental in shaping a major part of this research. I thank him for all his time and effort. I took two classes with Michael Tiefelsdorf and his style of teaching inspired me to continue a part of this journey under his guidance. He graciously accepted to serve on my committee. I express my deepest gratitude to Michael Tiefelsdorf for his intellectual contribution to this research. I wish to thank him for his unconditional time and support in getting through a major part of this research. Conversations with him have always been thought provoking and I will certainly miss them once I leave. I would like to express my most sincere gratitude to Richard Scotch for being willing to serve on my committee. A seminar class I attended one summer that he offered deepened my understanding of social and structural barriers that affect disparities. He has always been someone I could count on for support and guidance whenever needed. And he lent his ear to me readily whenever I needed to whet my ideas and know that I was on the right track. I thank him for his generosity and guidance. I would like to thank the School of Economic, Political, and Policy Sciences for the financial support, without which it would have been impossible to attain this degree. Special thanks to Jennifer Holmes for her continued financial support through the program. I also thank Simon Fass and Euel Elliott for providing me research and teaching opportunities, which has broadened my horizons, and will ultimately help me in being successful in my future academic career. I also thank the graduate program administrator Betsy Albritton for always going out of her way to help students. I am most grateful to my family for giving me the financial support when I did not have scholarship. I owe the opportunity I had for this education to my dad. He has given me an education beyond his means that he could never dream of. I will always remember him for stretching beyond his financial means to give me a good education. My father-in-law, Mr. Umesh Shukla and my brother-in-law, Mr. Paarth Shukla and Mr. Yatin Bhatt also contributed towards my education. My mother, Mrs Bhavana Vyas and my sister, Mrs Brinda Bhatt have always provided me their moral support when the going got tough. I also thank my mother-in-law Mrs Amita Shukla and my youngest brother-in-law Mr. Ronak Shukla. I am extremely grateful to my husband as without his optimism and faith in me, this journey would have not been completed. A special thanks to my friends and colleagues from the geospatial information science program, Muna Shah, Vaishnavi Thakkar, Parmanand Sinha, and Monghyeong Lee. I thank my friends Louis Burns, Rekha Burns, Cheng Nie from the Jindal School of Management Toastmasters without whom graduate school would have been a very lonely experience. I am also indebted to my mentors and teachers from India. My deepest gratitude to Sudhakar Solomonraj who inspired me to get a PhD from the US and who believed in me more than I could in myself. He pushed me and inspired me to challenge myself no matter what the circumstances were. His faith in me has culminated in this journey. I cannot forget my colleague and mentor, Harish Damodaran, who has been a major source of inspiration for undertaking this academic journey.

June 2017

EXAMINING THE SPATIAL MISMATCH IN THE SUPPLY AND DEMAND FOR MATERNAL AND CHILD HEALTH SERVICES IN BANGLADESH

Priyanka D. Vyas, PhD
The University of Texas at Dallas, 2017

Supervising Professor: Dohyeong Kim, Chair

Over the past decades countries have made remarkable progress in improving population health. Yet gaps in service provision and differences in service utilization often result in within-country disparities in health outcomes. This poses a formidable challenge in the equitable delivery of health care for governments in developing countries. Poor availability of geographic data also attenuates the ability of researchers to examine equity in the spatial distribution of health facilities in relation to the population demand. This dissertation examines spatial equity in access to health services and in the utilization of maternal and reproductive health services in the context of Bangladesh. By examining the spatial distribution of public health facilities in Bangladesh, this research seeks to answer policy relevant questions on factors influencing differencing within regions, which in turn can help the government respond better to the challenges of disparities. This research consists of two components. The first component examines spatial equity in the distribution of tertiary and secondary level health facilities using the lens of central place theory and urban hierarchy, while the second section examines mismatch in the supply and demand for primary health care services. In order to examine spatial equity in the distribution of tertiary and secondary public health services, this research uses geo-spatial data from the Government of Bangladesh in combination with the Demographic and Health Survey data from 2011 for

Barisal and Sylhet Division of Bangladesh. Contrary to the assumption of urban hierarchy and central place theory which suggests market areas to be homogeneous for the same type of goods and services, this research finds substantial amount of within region variation in travel distance for the same type of health services. This research finds that inequality in access to public health facilities is influenced by the heterogeneous size of the administrative units to which they are linked. To test the spatial mismatch hypothesis, this dissertation used bivariate kernel density estimation technique to examine whether the distribution of the clinics followed population distribution. This analysis finds a greater concentration of clinics in rural areas than urban areas. This implies lower access to primary health care for the urban population. This methodology to assess spatial inequity can be useful in the context of developing countries where covariate data may not be reliable or available. This research provides recommendation to the Government of Bangladesh to capitalize on its vast distribution of primary health care facilities, with services aimed at improving the overall population health. Overall, it was found that with regard to hospital services, urban consumers in the city corporation had better access while communities living further from the city corporations and district centers were at a disadvantage; whereas in the case of primary health care, rural consumers had better access while urban consumers in the most densely populated places had limited access.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Background

Globally, urban population is expected to double by 2050 while the rural population is projected to drop during this same period. Most of the population growth is projected to occur in cities that are located in developing countries. Annual rate of population growth in cities is anticipated to increase at a rate of 4 percent for the next three decades (World Health Organization, 2010). Specifically, South Asia alone accounts for about 23 percent of the world's population, with nearly 14 percent of them living in urban areas. Cities in South Asia like Dhaka, Mumbai, Delhi, and Karachi rank among the world's most densely populated places. Rapid urbanization and globalization poses an enormous policy challenge for governments in terms of delivering essential services to meet the growing population demand (Ellis and Roberts, 2015). Migration from the rural areas to the urban areas increases the demand for infrastructure and government services and creates an imbalance between the supply of services and increased population demand.

While the traditional policy discourse has focussed on bridging rural-urban disparities, urbanization has shifted the policy focus on bridging the gap between the urban poor and the urban rich population. Across countries in Africa, Asia, and Americas, richest 20 percent of the population had a much lower rate of under-five mortality in comparison to the poorest 20 percent of the population living in urban areas in the period 1990 to 2007. Similar trend persisted in access to skilled birth attendance between the rich and the poor living in the urban areas (World Health Organization, 2010).

This shift in the demographic landscape requires an examination of the traditional model of health infrastructure model that was inherited by countries from the colonial period and whether it can service adequately the population needs (Watson, 2009). Equity in health facilities planning and delivery can be achieved by understanding not just the overall population distribution and growth, but also spatial distribution and knowing geographic pockets where population growth is most likely to occur in order to meet the population demand. Spatial equity in health facility planning requires understanding of population distribution in terms of rural-urban trends and geographic distribution within these urban and rural landscapes to better target service delivery (Streatfield and Karar, 2008).

Studies testing the spatial mismatch hypothesis became popular in the 1970's and 1980's, mostly in the context of examining the spatial distribution of jobs with regard to commuting pattern from residential locations and assessing whether or not specific socio-economic groups were at a disadvantage (Gordon et al., 1989; Holzer, 1991). Many of these studies examine spatial disparities in the context of employment opportunity in relation to commuting time to work place from where people live or examine job accessibility based on average travel time within a neighborhood or census tract (Houston, 2005; Holzer, 1991). Studies that have examined spatial disparities at an aggregated level such as census tract often use a single measure such as spatial dissimilarity or an accessibility index. A weakness of such an approach is it fails to take into consideration intra and inter metropolitan area variation in travel time (Hu, 2015). In the context of GIS-based studies that have examined access to health facilities have used floating catchment method, network based travel time, or location-allocation modeling to explain disparities in access and coverage (Wang and Luo, 2005; Yang et al., 2006; Munoz and Kallestal, 2012; Oppong and Hodgson, 1994). But most of these studies are conducted at a district level or at a city level and do not examine intra-regional or intra and inter-district variation in access or the factors that influence inequitable spatial access.

Several countries have taken initiative to better understand the geographic distribution of their health facilities to assess the renewed demand. The World Health Organization recently led an initiative towards creating a master health facility list under which countries are encouraged to create a database of all their public and private health facilities along with infrastructure capacity and related indicators as well as the location coordinates for each of the health facility stored in a geographic information systems database. According to the WHO, knowledge of the spatial distribution of the health facilities in terms of the supply of health infrastructure is key to improving the quality and the delivery of health services. Countries like Kenya, Nigeria, and Haiti have also been successful in creating a master level health facility list and have made it available for public access (Makinde et al., 2014; Rose-Wood et al., 2014). Even in Bangladesh geovisualization of health facilities and projects examining spatial access for specific services and distribution of health facilities have been led by the research and the non-profit organizations in some of the geographic areas. However, a few of these projects are descriptive as they map the health facilities locations and their characteristics while some others perform network analysis in terms of travel time to assess disparities in coverage and service use (Adams et al., 2015; Panciera et al., 2016). Lack of availability of GIS data and trained personnel are additional barriers towards applying a spatial approach for health policy planning (Kim et al., 2016).

In light of the growing thrust to deliver equitable health care, this dissertation seeks to answer the following research questions:

1. What factors influence spatial variation in access to public health facilities?

2. Do differences in access influence service utilization?

3. Does the distribution of public health facilities match the spatially varying population demand?

Based on the above research questions, Chapter 2 provides insights into different theories that are related to the spatial distribution of health facilities. The chapter begins with the theories of urban hierarchy and central place in explaining the distribution of goods and services based on the population served. It then proceeds into providing the theoretical arguments around the notion of equity and access by referring to scholarly work and also discusses the prevailing literature on the various methodological approaches and challenges associated in modeling spatial access and service utilization.

After discussing the general theories and various methodological approaches, Chapter 3 pertains specifically to health policy in Bangladesh and provides an overview of the nature of the spatial planning of health facilities and service delivery. The chapter discusses the country's health policy landscape since the colonial era and highlights recent studies that have examined the challenges of equity in delivery of health care in Bangladesh. By providing descriptive data which highlight regional differences in the distances traveled to health facilities and the variation in service utilization, the chapter sets the context for the above research question and selection of appropriate data and research design to answer them.

Chapter 4 discusses the survey data and the GIS data that were used in this research and provides a detailed justification into the research design and the rationale for the selection of the two study areas. Since this research used the Demographic and Health Survey of Bangladesh, the chapter provides a thorough description into the strengths and the limitations of the sampling methodology that was used for conducting the survey. It also describes the methodology for processing GIS data and the descriptive statistics for the data that were generated.

After discussing the data and the justification for the research design, Chapter 5 dives into answering the first and the second research question. By examining distances traveled to hospitals in Bangladesh for two regions, this chapter finds that factors influencing intra and inter district variation are similar for both the study areas, thereby increasing the generalizability of the findings to other regions of Bangladesh. This chapter finds that geographical variation in the districts influence uneven size of the hospital service area, which in turn influence inter-district variation in the travel distance to the nearest hospital.

Another finding is that intra-district variation is governed by the size and the number of upazillas nested within the districts due to which communities that are situated in upazillas that are further away from the district centers are likely to have to travel more in comparison to those that live in the the sub-districts that are in immediate neighborhood of the district center.

Chapter 6 shows results from multivariate analysis on factors influencing distances to the district and the sub-district hospital as well as travel time to these health facilities. Time to the district and the sub-district hospital was significantly associated with the travel time to the district and the sub-district administrative headquarter. This confirms the underlying assumptions about hierarchy and the nature of association between spatial planning of health facilities to their administrative structure of governance. The chapter finds that average distance to both the district and sub-district hospital was negatively associated with the district area.

After investigating inequitable access to higher level facilities, Chapter 7 proceeds into the third and the final research question pertaining to examining the distribution of health facilities in relation to population distribution. While health facilities of higher order are tied to administrative units, this does not apply in the case of primary health services. Hence, this chapter applies bivariate kernel density estimation technique to examine whether the distribution of clinics match the population demand. This chapter finds that the density of primary schools exceeded clinics for both the regions, suggesting that the Government of Bangladesh favors a larger service area for clinics than schools. The chapter finds that for both the study areas, rural areas remain consistently well-served when it comes to primary heath care, which confirms empirically the policy that the country has been following for several decades. The chapter finds that contrary to one's expectations, spatial distribution of community clinics does not match the population distribution, suggesting densely populated urban areas as highly under-served areas when it comes to primary and preventive health care.

The last chapter provides the concluding remarks by highlighting the major findings of this research in the context of both primary and tertiary level services. It provides insights into the overall policy implications of this dissertation for health policy planning in Bangladesh and provides recommendations that can lower disparities in service provision in the context of the findings of this research.

CHAPTER 2

URBAN HIERARCHIES IN THEORY AND PRACTICE

Since the nature of spatial planning for health facilities in Bangladesh resembles the structure of urban hierarchy, this chapter proceeds with explaining the concepts of hierarchy and the central place theory. This chapter begins with a general overview of the theory and then moves into giving specific applications of the theory in different sectors, including health. Since the central place theory and urban hierarchy has implications on health equity and access to services in terms of travel time, the chapter proceeds forward with defining the different strands from the literature with regard to health access and equity and its relationship with place in theory; it then moves on to the practical and methodological approaches to measure these concepts

2.1 Central Place Theory

In examining the geographical distribution of retail locations and their market areas, central place theory gained prominence in the 1960's and 1970's, especially in economic geography. On a general note, the theory sought to explain the market areas for different goods and services and the relation between higher order goods and services to the point locations of lower order goods and service providers (Berry and Berry, 1967). Urban hierarchy refers to the concept of a class structure under which the different types of services that are provided are nested within each other based on their functionality. The following can be regarded as the key principles of urban hierarchy and central place system as stated by (Berry and Garrison, 1958a,b):

1. Different types of goods and services that are provided in the economic system have a rank or a position based on the services they provide.

2. All lower order goods and services are nested within the market area of a higher level good or a service. In the context of health facility planning, a lower order good means services provided at shorter distances and higher order goods imply services which require longer distances to be traveled. Therefore, services provided at the highest level include market areas for all lower level goods and services.

3. Ranking of each level of services provided is inversely proportional to the frequency of the centers that exist to serve the same type of services. Therefore, a service that is at the top of the hierarchy has only 1 center or the fewest centers. The services provided one level below, and which has a second rank in the system contains more number of market centers than the level above it. Similarly, the goods or the service provided at the lowest level have the maximum number of centers that provide the service.

4. Each higher level provides all goods and services that are available at the lower level in addition to services that are unique to its level

5. Consumers travel the least to avail goods and services that are at the lowest level as they are most frequently used and therefore have the maximum number of centers in the system; whereas consumers travel the most to access a specialized good or a service that is at the top of the hierarchy and has the fewest centers

Figure 2.1 shows the hexagon based market structure, consisting of uniform market areas and population distribution as propounded by the theory. In the context of health facility planning, a hospital or a specialized medical college is at the top of the medical hierarchy and on average consumers are willing to travel a lot more distances to access these services. In contrast a lower-order goods and services, which are more frequently availed such as visiting a doctor for fever, cough, cold, are located at much shorter distances (Meade and Emch, 2010).

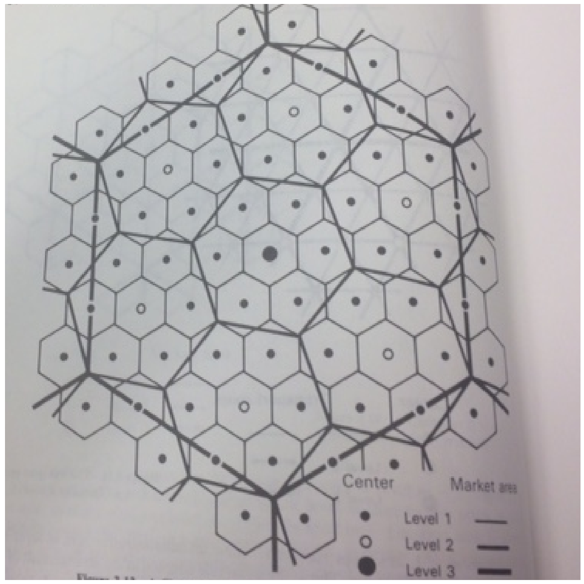


Figure 2.1. Hexagon-based market areas under the central place theory based on (Berry et al., 1987). Reprinted by permission from Pearson Education, Inc.

.

Berry empirically shows how the ranking of each type of service was associated with its function, type of services provided, and the distances traveled by people to access those services. Services at each level have a specific threshold in terms of the minimum and the maximum distance that consumers must travel to access a range of services at that level (Berry et al., 1970, 1987). Thus the theory also sought to explain the travel pattern of consumers based on distance to the nearest center and the conditions under which consumers would be willing to travel and surpass a lower order service for a more specialized good and services located at farther distances (Rushton, 1971; Clark and Rushton, 1970). In the context of health services usage, this implies that consumers may not use the nearest health facility or a lower order service that is available at shorter distances; instead they would surpass the nearest facility and may travel farther distances to acquire services at a higher order facility as the latter may provide better quality of services.

The theory holds a great relevance in the context of public health planning since government health services are uniquely associated at each level; this is unlike financial services where there may be multiple firms at the same center providing the same range of services or even in case of manufacturing where competition prevents any single firm from providing unique services in a market area (Parr and Budd, 2000). It also helps in understanding economies of scale and the structure of the hierarchies as the basis for defining market areas even when the assumptions of homogeneous population as postulated by the theory may not be met in reality (Rushton, 1971).

Since the original theory that was developed by Christaller and Lösch sought to delineate market areas based on hexagon structure that were homogeneous in terms of population distribution and purchasing power, even when these assumptions are met closely, certain consumers may not be able to afford traveling longer distances and may also lack the transportation networks to access centers that are at the top of the hierarchy. This has implications on equity as certain consumers may not have access to public health services as they may be out of the range of the threshold of these services (Nakamura, 2014).

2.2 Defining Access and Equity

Equity in health is regarded as the absence of disparities associated with social advantages or disadvantages. It refers to the just distribution of resources and providing equal opportunities to the disadvantaged groups to move forward (Braveman and Gruskin, 2003). Inequitable access to health care within a country is usually attributed to socio-demographic factors such as wealth, education, ethnicity, race, among other factors. These factors give rise to within country variation as those who are well educated and can afford are able to use services and also have the necessary transport to get to a facility, which may not be the case for others (McIntyre and Mooney, 2007; Marmot et al., 2007). While theories of social determinants of health emphasize on social and demographic factors, a cultural perspective attributes much of this variation to community and social institutions that can possibly explain why some communities behave differently than others, causing variation in health utilization and outcomes (McIntyre and Mooney, 2007).

Even when public health services are free in developing countries, access can be limited due to user fees at government clinics, which poses financial barriers for poor and vulnerable groups(Killingsworth et al., 1999). From an economist's view point barriers to access could also mean supply side factors such as having availability of doctors and trained medical personnel, supply of essential drugs and other medical equipments and any other aspects that ensure a certain quality of services in order for people to be able to use these services(Balarajan et al., 2011; Jacobs et al., 2012). In medical geography, access could refer to physical access or distance to the health facility or actual travel time. Potential access refers to availability of services, usually measured in terms of distance to the health facility (Nesbitt et al., 2014), while realized access refers to the use of services. Potential access is measured in several different ways such as container approach which examines the density or availability of facilities in a geographic area; coverage approach which measures equity in access based on the population covered by each facility; and some other ways to measure potential access include distances to nearest or closest 4 nearest health facilities, average travel time and similar measures. Realized access, on the other hand, examines spatial access in relation to service utilization.

2.3 Relation between Access and Equity in Service Utilization

Even when government funded public health services are free or when households are located in close proximity to the services, there remains wide variation in the use of services among the different socio-economic groups due to various demand side factors. Two cross-sectional studies based on DHS data in Namibia and Bangladesh found that service utilization indicators such as access to skilled birth attendance, number of antenatal care services, institutional deliveries,and use of cesarean services was high among wealthier and well-educated women (Zere et al., 2007, 2013). However, the evidence is somewhat mixed as to whether inequities in use of services among different socio-economic group reduces over time. In Cambodia, based on three rounds of DHS survey, it was found that inequities reduced over time (Dingle et al., 2013), another study in India found that the gain in the use of services among the poor remained much smaller (Sanneving et al., 2013). Apart from education and wealth related differentials in service utilization, rural-urban differences have been found to have a statistically significant relationship across several studies (Sanneving et al., 2013; Asamoah et al., 2014).

2.4 Place Effects on Access and Service Utilization:

Several scholars have pointed to the relation between health and place. Spatial variation in terms of where communities live and the individuals who make up that community affects individual behavior and health. The assumption is that people who live close to each other are likely to be similar with regard to their income, race, ethnicity, life style, and similar other measures. Furthermore they may also share common geographic advantages or constraints depending on where they live, which can explain similarities or differences among communities. Geographic characteristics that are perhaps commonly shared by a community could include physical barriers such as rivers, lack of transportation, and lack of accessibility, among other issues which could hinder their utilization of services. Non-geographic barriers that could be common among a community could include institutional barriers which are related to supply of provision of services and quality in those local regions. It pertains to how local governments promote availability, quality, and accessibility of services in their jurisdictions. Scholars call these geographic traits shared by community as contextual effect while individual and socio-demographic characteristics of the population are referred to as compositional effect. Thus context deals with place while composition refers to the characteristics of people (Bernard et al., 2007).

Several other authors have also examined the debate between the compositional and contextual effect (Macintyre et al., 2002; Curtis and Rees Jones, 1998). But even when scholars agree that both individual and contextual factors affect utilization of health services and outcomes, there continues to be a debate as to what constitutes a place and at what geographic unit can these contextual factors that affect individual level variation can be modeled. Several authors have criticized the approach of capturing the place effect on health at a particular geographic unit based on several grounds, one of them being that health inequality at geographic unit is often scale dependent, which means inequalities that manifest at larger geographic units may look very different when examined at a smaller spatial scale or lower administrative units. Some authors point out that in most cases the choice of researchers to examine inequality at a particular geographic unit of analysis is guided by the availability of data and convenience than anything else. However, several authors have criticized this approach of analyzing the place effect on health (Macintyre et al., 2002; Meade and Emch, 2010). Another important theoretical debate in this area is the construct of place itself. Some view place as a social construct because individuals who share similar identities and culture may be even geographically or spatially located close to each other and communities that are socially distinct (wealthier communities from relatively poor communities) may also be located physically apart. In this context while place can be regarded as a social construct shaped by individuals that make up a community, others may view place as an absolute location on the earths surface or a region that can be identified by certain physical and social characteristics (Curtis and Rees Jones, 1998; Kearns and Moon, 2002). Another debate in this area on the empirical grounds is what constitutes endogenous and exogenous factors in studying the linkages between health and place. Several scholars, as discussed above, argue that this is a two way process as place or the physical environment has an effect on individual behavior; at the same time people shape the place where they live based on their habits, social customs, and practices.

Within the larger framework of the DHS surveys, on which this research is based upon, even after accounting for individual and community level factors, studies have shown intra-cluster correlation at the community level up to 17-35 percent (Yebyo et al., 2015; Ononokpono and Odimegwu, 2014; Aremu et al., 2011). This suggests a powerful relationship between individual choices of health behavior and the community in which they reside. Another study based in Ghana found strong differences within ecological zones in which women lives in addition to rural-urban differences (Johnson et al., 2009).

2.5 Methodological Approaches to Measure Spatial Access and Integrating it with Population Demand

Since the distribution of health resources is not even and the population distribution also varies across the geographic landscape (Wang and Luo, 2005), sometimes certain socio-economic groups are at a disadvantage in getting access to certain services. Anselin defines spatial equity in access as comparing the locational distribution of facilities or services to the locational distribution of different socio-economic groups. A simple measure of access is a count of facilities in some geographic unit, without taking into consideration the transportation network and the effect of distance (Talen and Anselin, 1998). However, several scholars have criticized the container view because of its sensitivity to the type of measurement used, scale of analysis, and lack of consideration for cross-boundary flows (Higgs, 2004; Talen and Anselin, 1998; Langford and Higgs, 2006). In a literature review summarizing different methods for measuring spatial access, Higgs describes the following main methods: a) container approach under which number of facilities in a given unit is estimated b) coverage approach under which number of facilities within a given distance is calculated c) travel cost based on distance and network analysis methods d) gravity models examine the interaction between the supply and the demand side factors. Problem with some of the methods is they do not account for cross flow between regions.

The most common approach is to compare accessibility based on travel time and different modes of transportation. One such study based in a province in Rwanda created a raster-based travel time to assess the coverage of primary health care services (Munoz and Kallestal, 2012). Another study used a similar approach but compared differences in accessibility between rural and urban areas and disparities in travel time arising due to such differences (Jin et al., 2015). Other approaches that examine proximity and coverage include location allocation modeling (Hodgson, 1988; Khan et al., 2001; Rahman and Smith, 2000) and assessing consumer's preference to travel based on the availability of the facility and the type of services provided (Oppong and Hodgson, 1994; Ayeni et al., 1987).

A popular method to examine spatial access in relation to the population is a floating catchment in which a drive time is generated within a threshold of each service area and then it searches for population location within the catchments. The index accounts for the supply capacity at a medical facility distance between the facility and the population location or the travel cost, and the population size in the area. Thus demand is estimated for each medical site and a physician to a population ratio is calculated for each medical facility in the study area. However, the three step floating catchment involves estimating the catchments based on the population location and differing drive time distances in the first step, then searching for all service sites within each catchment in step 2, and finally computing physician to population ratio (Wang and Luo, 2005; Yang et al., 2006). This method requires access to lot rich information such as hospital infrastructure capacity and related information. In the absence of such detailed data for developing countries where spatial data and attribute data is not easily available, such methods may not be easy to implement. Another study combined the information on the location of health facilities with the population demand based on census data to map geographic inequities and identify regions where the government should target resources(Rosero-Bixby, 2004). In examining the relation between location of health facilities and consumers travel pattern, studies have found that in the context of health services consumers are often willing to surpass the closest or a lower order facility and go to a higher order facility the assumption here being that the latter provides a better quality of service (Noor et al., 2006).

Since the distribution of health facilities is a point pattern data, several papers have approached the problem using models for point pattern analysis either based on a road network or based on Euclidean distance. One approach to model the distribution of health facilities is to use kernel density estimation using fixed and adaptive bandwidths to examine relative risk based on high and low density areas (Davies et al., 2011). Quite a few papers have used kernel density estimation with fixed and adaptive bandwidths to generate a smooth surface of varying intensity of point data, especially in spatial epidemiology and in modeling ecology (Lemke et al., 2015; Zhang et al., 2013; Buck et al., 2015). One study used K function methods to test spatial pattern of road traffic injuries to examine burden of accidents at specific locations (Jones et al., 1996; Okabe et al., 2008). Another approach with point pattern data is to use network voronoi diagrams or weighted network voronoi diagrams as proposed by Okabe (Okabe et al., 2008).

CHAPTER 3

HEALTH POLICY LANDSCAPE IN BANGLADESH

3.1 Health Facility Planning

In Bangladesh, spatial planning of government health facilities builds on the country's administrative structure. The country is divided into distinct levels, with the 7 Divisions divided into 64 Districts, which are divided into 545 Thanas, which are in turn split into Unions and then the Mauzas . The organization of health facilities corresponds to its administrative structure. At the top of the medical services hierarchy are the district government hospitals, specialized medical colleges, and other tertiary care institutions that are located at this administrative level of governance. Thanas – also known as Upazillas – form the next level of administrative hierarchy. The Thana Health Centers (THC) or the Upazilla Health Complexes (UHC) serve at the second level of health services planning. Unions form the third level of health services and the facilities which serve at this level are known as the Health and Family Welfare Center. The Unions are further split into Mauzas – the smallest level of administrative unit for urban areas or Mohallas in case of rural areas. Health facilities at this level are known as community and satellite clinics. These mainly provide primary care and have been set up to serve on average a population of about 6000, residing in the radius of 1-2 kilometers. Figure 3.1 on the next page depicts the hierarchy of the spatial planning system in Bangladesh. This structure of spatial planning also influences travel distances to health facilities at each administrative unit as revealed in figure 3.2. The figure shows that consumers have to travel the most to the nearest hospital and maternal and child welfare center. The Thana Health Center or the Upazilla Health Complex holds the second rank in the administrative hierarchy as per figure 3.1 and even in travel distances as gets reflected in figure 3.2. The figure shows that while 90 percent of consumers travel up to 40 kilometers to access the nearest hospital, 10 percent of them have to travel beyond 100 kilometers to

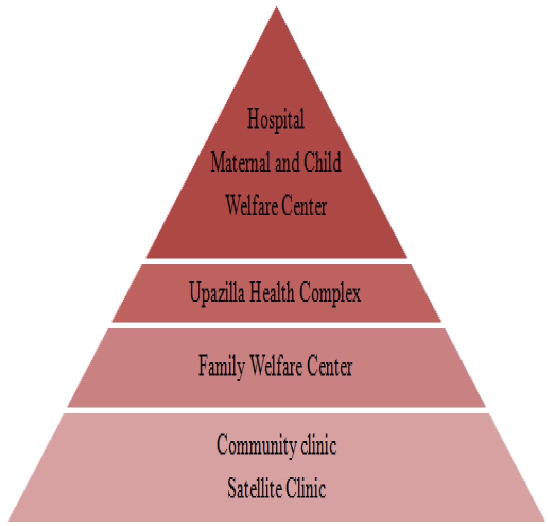


Figure 3.1. Administrative hierarchy of the organization of health facilities

get access, whereas in case of sub-district hospitals 90 percent of the consumers travel up to 20 kilometer and 10 percent of them have to travel up to 50 kilometers. The Family Welfare Centers and Community Clinic have a lower rank in the hierarchy and this gets manifested as consumers travel shorter distances to these centers as the figure demonstrates.

3.2 Expansion of Health Infrastructure under 5 Year Plans

Since 1980s the Government of Bangladesh (GOB) has made several efforts to improve the provision of health services. Under the second five year plan from 1980 to 1985, the government set up a policy to introduce health and family welfare centers at the Union-level. Under the third five year plan, the government made efforts to expand satellite and community clinics in the villages. Apart from expanding health infrastructure, GOB also expanded the provision of services at the UHC and worked towards modernization of facilities at the district level (MOHFW, 2014, 2011). The government and large non-profit organizations have also increased the number of community health workers, family welfare visitors, and skilled birth attendants to promote utilization of services and provide essential care at the

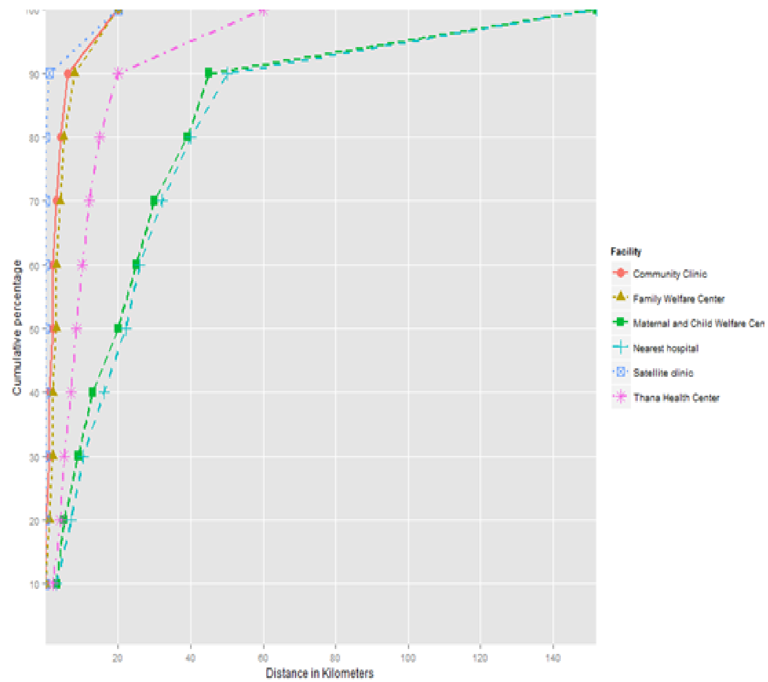


Figure 3.2. Self reported distance in kilometers to the nearest health facility for all consumers based on type of facility

grassroots level and reach under-served communities (El Arifeen et al. 2013). The district hospital or a medical college hospital has a capacity of 100-250 bed and provides a range of maternal and child health services, and is generally equipped to provide emergency and obstetric care service. In contrast, the sub-district level hospitals, also known as the Upazilla Health Complex (UHC) are smaller, with a bed capacity of 30-50, and differ widely in the provision of emergency and obstetric care services (MOHFW, 2014, 2011). District hospitals and teaching hospitals remain overcrowded due to high population demand while health facilities at the upazilla level and below remain under-utilized due to lack of skilled human resources and poor services. A study which examined provision of emergency and obstetric care services in 24 districts of Bangladesh, comprising of both public and private providers, found that the public health facilities in the selected had about 1.2 comprehensive emergency obstetric and New Born Care (CEmoNC) per 500,000 population, but public EmONC facilities stood at only about 2.5, below the minimum requirement. According to the UN guidelines, countries are required to have at least 1 CEmoNC and 5 EmONC facilities serving a population of 500,000. The report pointed out that the UHC's faced greater challenge of having adequate staff in comparison to the hospitals that are based at the district level. Several facility level surveys have shared a concern about shortage of staff at public health facilities. As per the UN guidelines, countries are required to have at least 1 CEmoNC and 5 EmONC facilities serving a population of 500,000. Private health facilities also offer emergency and obstetrics care services but most of them are located in urban areas (Chowdhury et al., 2014).

Based on the 1996-2001 five year plan, the GOB has enacted a policy of providing a Community Clinic (CC) for every six thousand population. These CC's are organized at the grassroots level and are expected to provide basic health facilities. Located at the ward level, they are the lowest level static health facilities with referral linkages with higher level health facilities. Between 1998 and 2003, 10,723 CCs were constructed of which 8000 were made functional. The Government started a project titled "Revitalization of community-based health care in Bangladesh". As of 2014, 13,094 independent community clinics were made functional. These CCs are managed by a 13-17 member management committee. By April 2014 all the community clinics received internet connection and laptop. While these clinics are mostly in rural areas, they are available in selected urban corporations. A growing population density in some of the city corporations is widening the gap in the availability of government funded primary care services between rural and urban areas, between the city corporations and the non-city corporations urban areas and between the regions. The problem of urban population and lack of access in the context of Bangladesh becomes very acute due to heavily skewed population in the urban areas and lack of availability of services. Since tertiary-level services are mostly located in the urban areas, it is mostly the urban population that has access to hospitals. Often hospitals are very crowded and there are long waiting lines. However, in the absence of availability of primary health facilities, most people have to go to government hospitals even for basic services, which further exacerbate the problem. Yet there is no systematic evidence on equity in the distribution of primary health care services in Bangladesh. Fortunately, primary health care in Bangladesh received a renewed focus under the Bangladesh Urban Primary Health Care Project, which was funded by several donors. Under the project the government contracted services through non-profit organizations to run community clinics. The lowest level services that are available in the urban areas are delivered through NGO field workers. Another project that was being operated in the urban areas included the Smiling Sun clinics , donor assisted project to improve primary health care in urban areas whereas the Urban Community Health Program was specifically designed for the population living in urban slums (Ahmed et al., 2007).

3.3 Regional Differences in Travel Distance to Health Facilities

Given that spatial planning of the health system is such that each type of health facility is unique in the services it provides at that particular administrative unit, it seems plausible that differences in the size of administrative units and population density could influence travel distances between and within districts for the same type of health service. A direct policy implication of this type of planning system is inequities in access to health services. This poses a formidable challenge for the government and health planners in delivering and improving the coverage of services. Tables 3.1 and 3.2 suggest the relation between the spatial extent of the administrative region and inequities in service area for the health facility at that administrative unit. Based on table 3.1 , Dhaka, Chittagong and Khulna Division consist of the largest number of districts and also have the largest area at the division level according to table 3.2. Among these 3 regions, Dhaka Division has the largest number of districts and the average district area is the smallest, while Chittagong has the least number of districts given its large size and as result the districts areas tend to be large. This implies that larger divisions with fewer districts have on average a larger service area for district

Table 3.1. Administrative inequalities

Level	Barisal	Chittagong	Khulna	Sylhet	Dhaka	Rangpur	Rajshahi
Districts	6	11	10	4	17	8	8
Upazillas	40	112	64	38	163	58	70
Unions	349	947	574	333	1256	539	564
Mauzas	2920	7561	6564	5108	15517	6523	10134
Villages	4097	15219	9287	10250	25243	9050	14075

Table 3.2. Geographic inequalities

Area	Barisal	Chittagong	Khulna	Sylhet	Dhaka	Rangpur	Rajshahi
Division	10234	33908	22284	12635	31178	16184	18152
Avg district area	1705	3082	2228	3158	1834	2023	2269
Avg Thana area	243	308	371	315	183	289	252
Avg. Union area	27	38	41	35	22	28	31

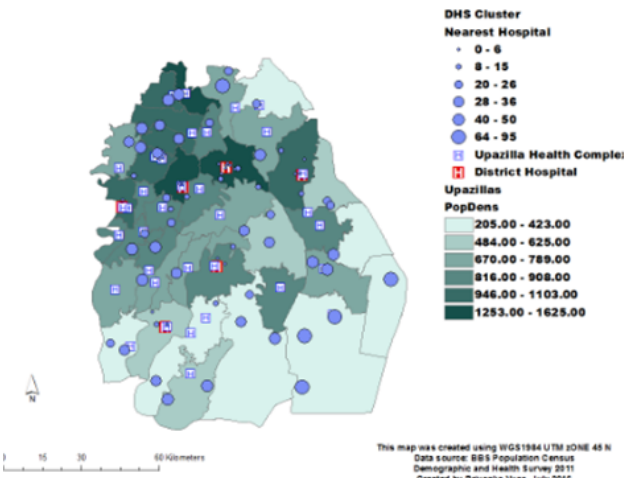
hospital and vice-versa. Similarly, a comparison of tables 3.1 and 3.2 also suggests that Rangpur Division and Rajashahi Division have the same number of districts contained in them and have a similar area due to which there is not much difference in the service area of the district level health facility. At the same time Barisal and Sylhet Division have a similar spatial extent but lesser number of districts in case of latter doubles the district hospital service area than the former. A similar pattern could also be found at the sub-district or the Upazilla level. Since Dhaka Division has maximum number of sub-districts, average area of the Upazilla is the smallest. Chittagong's larger number of Upazillas in comparison to Khulna decreases the size of the service area for the sub-district level health facility.

A comparison of regions based on the spatial extent and their service areas leads into examination on the effect of geographical inequalities on travel distances to health facilities. Table 3.3 confirms this relationship. It can be observed that while mean distance to the nearest hospital was in the range of 21-28 kilometers, some communities in Barisal had to travel as far as 95 kilometers , some in Chittagong had to travel as much as 150 kilometers, and few

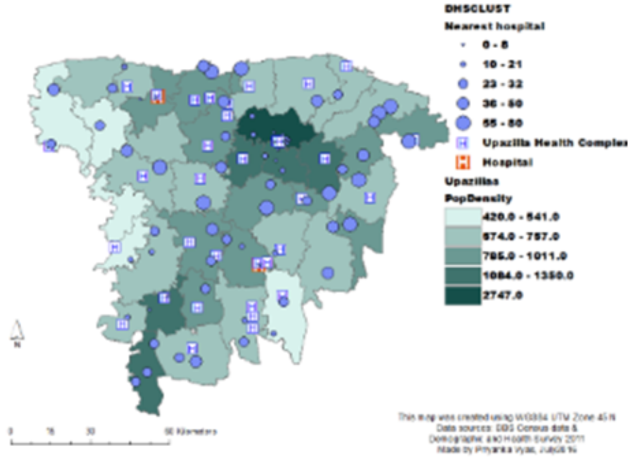
Table 3.3. Self reported travel time to different health facilities in 2011

Distance to nearest hospital	**Barisal**	**Chittagong**	**Dhaka**	**Khulna**	**Rajshahi**	**Rangpur**	**Sylhet**
Mean	25.6	28.2	21.5	21.0	22.1	26.5	27.9
Std Deviation	21.9	25.0	16.8	16.7	14.9	19.04	20.2
Percentiles							
5	2	3	3	2	1	1	1
25	6.4	8	8	10	10	14	12
50	22	25	16	17	22	25	25
75	40	40	33	30	32	35	40
95	72	72	50	50	50	65	62
99	95	152	65	90	60	87	80
Distance to the nearest THC	**Barisal**	**Chittagong**	**Dhaka**	**Khulna**	**Rajshahi**	**Rangpur**	**Sylhet**
Mean	10.73	11.28	10.05	9.35	9.47	9.5	10.87
Std. Deviation	9.01	11.09	7.05	6.93	6.33	6.73	8.98
Percentiles							
5	1	1	2	0	1	1	0
25	5	5	4.5	4	5	4	5
50	9.5	8	10	8	8	9	9
75	13.5	12	14.5	12	12	13	15
95	27	40	22	20	24	26	26
99	45	60	35	42	30	28	40
Distance to the nearest FWC	**Barisal**	**Chittagong**	**Dhaka**	**Khulna**	**Rajshahi**	**Rangpur**	**Sylhet**
Mean	3.66	3.15	3.38	2.91	3.23	4.22	4.55
Std. Deviation	3.02	3.22	3.2	2.19	3.11	4	3.94
Percentiles 5	0	0	0	0	0	0	0
25	1	1	1	1.6	1	2	1
50	3	3	3	2	3	3	4
75	5	4	5	4	4	5	7.5
95	8	9	9	8	10	13	12
99	15	20	20	10	15	20	15

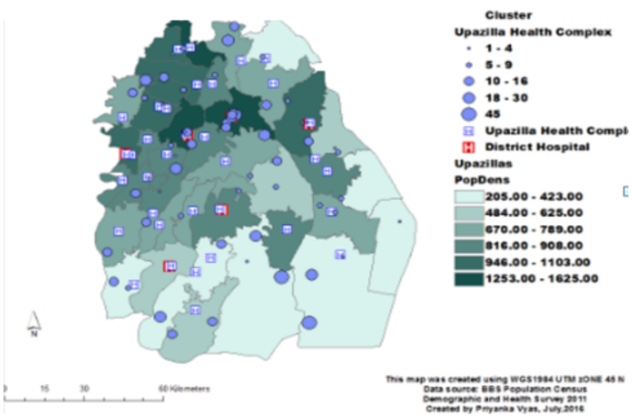
communities in Khulna, Rangpur, and Sylhet had to traverse between 80-90 kilometers for the same type of service. This suggests that across regions, while the average travel distances are similar there seems to a lot of variation within regions due to which some communities have to travel much more to access the nearest hospital. While the average distances traveled to the nearest hospital is similar for all the Divisions, Chittagong and Khulna Divisions, which are the largest, report the maximum travel distance. Even though Dhaka Division is much larger than Rajshahi, its smaller average hospital service makes the range of its travel distance comparable with Rajshahi. For both the Divisions, the maximum travel distance in the range of 60-65 kilometers It shows that mean travel time to access the nearest hospital is lowest in Rajshahi and highest for those communities residing in Chittagong. This seems to be the case even for sub-district hospitals. While the mean distance was between 9 and 11 kilometers for all communities to access the sub-district level health facility, within different administrative regions, the range of the maximum distances for this level of health facility shows lot of variation. Take the case of Barisal where some communities have to travel as much as 45 kilometers to access a sub-district level health facility in contrast to Rangpur where the maximum travel time for all communities was 28 kilometers. Both Chittagong and Khulna Division have the largest service area at the Upazilla level and the maximum reported travel distance for the community is longer than other regions. Rangpur and Rajshahi being the smallest regions report the maximum range of the distances traveled to the nearest Upazilla Health Complex to be the lowest at 28 and 30 kilometers respectively, and it is farthest for those living in Chittagong Hill Tracts. Figure 3.3 displays the variation in travel pattern at the community level or for the DHS sampled clusters. Each dot on the map corresponds to a self reported distance from the sampled clusters. It can be observed that while distances remain longer in sparsely populated areas as one would expect, in case of Bangladesh even some sub-districts remain densely populated even at the periphery. As a result communities living at the periphery of the sub-districts report longer travel distances.



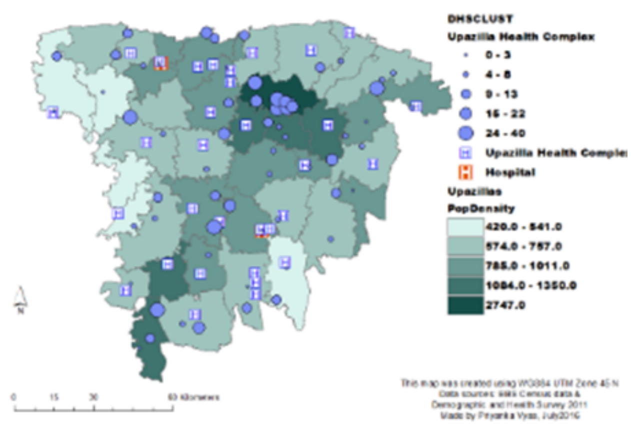
(a) Distance to the nearest hospital in Barisal



(b) Distance to the nearest sub-district hospital in Sylhet



(c) Distance to the nearest sub-district hospital in Barisal



(d) Distance to the nearest sub-district hospital in Sylhet

Figure 3.3. Within region variation in travel distances for district and sub-district hospitals in two Divisions

This raises the question on why some communities within the same region have to travel so much in comparison to others, and why is there so much variation when it comes to getting access to the nearest public health facility. It seems plausible that differences in access to health facilities may also influence service utilization pattern.

3.4 Regional Differences in Service Utilization

Similarly, regional variation is also found in the government service delivery programs and in the utilization of such services. While at a national level there have been impressive gains on health outcomes and several health indicators, some regions continue to be lag behind while others consistently outperform on several of the millennium development goals. For example, institutional deliveries remain highest in Khulna and worst for Sylhet. With regard to other measures of antenatal care, women who received no anc were highest in Sylhet and the least in Khulna. Among the women who had at least 1 anc visit, Rajshahi and Khulna had the highest share, whereas Sylhet remained the worst. Tables 3.4, 3.5, and 3.6 highlight these regional differences in service utilization indicator. And among those who completed 4 or more ANC visits, Rangpur and Khulna had the highest proportion of such women while Sylhet had the lowest share. Similar divergence also exists in vaccination coverage. While for BCG vaccination the coverage looks more equitable between the regions, for DPT 3 dose, Khulna had the highest coverage of 97.2 percent while Sylhet had 89 percent coverage. For Polio 3, Khulna's coverage stood at 94.2 in contrast to Sylhet's 87.2 percent coverage. Based on total vaccination coverage for all doses, only Khulna and Rangpur had over 90 percent coverage, while Rajshahi was close to 90 percent, and all other regions having a coverage in the range of 80-85 percent. Yet, there is limited evidence investigating factors influencing these regional differences.

3.5 Conclusion

In view of the tables presented in this chapter, it is evident that geographical inequalities influence inequity in the health facilities service area, which in turn affects the travel distances and service utilization within regions. In order to assess factors influencing regional differences in travel distance and service usage, this dissertation examines two regions that

Table 3.4. Regional variation in institution-based deliveries

Division	2007	2011	2014
Barisal	13.1	23.3	29.9
Chittagong	15.1	22.4	35.2
Dhaka	19.4	28	40.5
Khulna	27.3	42.8	54.5
Rajshahi	18.3	30.2	39.1
Rangpur	NA	27.3	34.3
Sylhet	10.6	21.9	22.6

Table 3.5. Regional variation in home-based deliveries

Division	2007	2011	2014
Division	2007	2011	2014
Barisal	86.9	76.4	69
Chittagong	84	77.3	64.4
Dhaka	80.2	71.8	59.1
Khulna	72.4	57.1	45
Rajshahi	81.4	69.5	60.7
Rangpur	NA	72.4	65.3
Sylhet	88.8	77.6	76.6

Table 3.6. Regional variation in the use of antenatal care

Division	None	At least 1 visit	4 or more visits	Total
Barisal	33.9	38.6	27.5	100
Chittagong	37.5	41.1	21.4	100
Dhaka	35.2	38.1	26.7	100
Khulna	25.1	42.2	32.7	100
Rajshahi	27.9	47.2	24.9	100
Rangpur	24.2	39.5	36.3	100
Sylhet	45.7	35.2	19.1	100

share a similar spatial extent but differ in the size of the administrative units and population density. A comparison of travel distances by district in each of the two regions provides an opportunity to validate the above hypothesis on the effect of differences in geographical area on hospital service area and travel pattern. The next chapter discusses the methodology of the survey data and the steps involved in processing spatial data that were used in this dissertation.

CHAPTER 4

MATERNAL AND CHILD HEALTH IN BANGLADESH; SURVEY AND GIS DATA

4.1 Research Design

Since this dissertation is concerned with examining the influence of geographic inequalities on consumer's travel pattern to health facilities, two regions with similar geographic area but having a different population distributions were chosen for analysis. Even though in terms of area per sq kilometer, the two regions are fairly similar,yet they differ in terms of the size of the administrative units that are nested within each higher level geographical unit. Selection of two regions which are homogeneous on certain characteristics but are heterogeneous on other is an excellent opportunity to test the theory and validate the findings by having a comparison group.

For the purpose of this research, Barisal and Sylhet Division were chosen. Figure 4.1 shows the upazilla map for both the divisions with an inset map of the divisions by districts. The figure demonstrates that Sylhet Division with 4 districts have a much larger area while Barisal Division consists of 6 districts that are heterogeneous. In Barisal Division, Bhola, Patuakhali, and Barisal District have the largest area while Jhalokati, Pirojpur, and Barguna are relatively small. As discussed in the earlier chapter, a similar variation in the size of the upazilla is also found based on the district to which they belong to. Upazillas in Bhola and Patuakhali are much larger while smaller districts such as Jhalokati, Pirojpur also have smaller sub-districts. A similar pattern also exists for the upazillas in Sylhet Division.

Table 4.1 shows the administrative divisions for Barisal and Sylhet region and the corresponding difference in the size of the service areas. It can be observed that Barisal Division has 6 districts while Sylhet Division has four districts. Based on this, it can be assumed that the average area of the sub-districts or the upazillas that are nested within the districts is

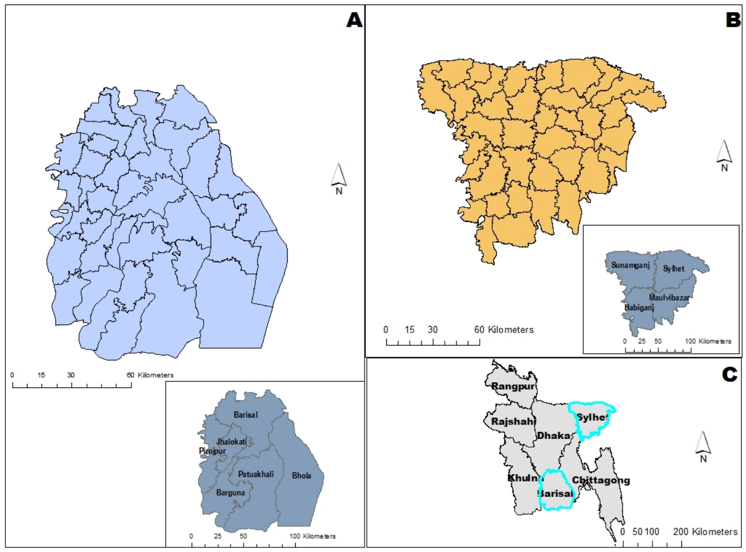


Figure 4.1. Sub-districts in Barisal and Sylhet Division

Table 4.1. Study Area

	Barisal	**Sylhet**
Total Geographical extent	10234.86 sq km	12635 sq km
Population density per sq km at the Division Level	8121	3132
Number of Districts	6	4
Number of Upazillas	40	38
Number of Unions	349	333
Number of Mauzas	2920	5108
Number of villages	4097	10250

likely to be smaller than for Sylhet. This provides an opportunity to examine the influence of the varying size of the geographic areas of the administrative units, which influences differences in the market areas of the health facilities, and thus affects the distances consumers travel to access services.

4.2 Survey Data

This research uses data from the Demographic and Health Survey for Bangladesh for 2011 (BDHS 2011) to examine variation in distances travelled to health facilities and service utilization indicators. Since several low and middle-income countries do not have the data or lack capacity to undertake nationally representative surveys that can track key trends in births, fertility, and mortality among children and women, the demographic and health surveys are designed to monitor changes in basic health indicators of maternal and child health and changes in attitude and preferences towards issues of marriage, child birth, contraceptives, among others. USAID has been conducting and implementing these surveys in more than 90 low and middle income countries since 1984. Due to the large sample size, these surveys are generally conducted once every three or five year in a target country.

The DHS data is based on a two-stage stratified cluster sampling procedure, under which in the first stage cluster or an enumeration area (EAs) are drawn from a sampling frame consisting of all EAs in the country. In the next stage, individuals or households are randomly drawn from these clusters. Here a cluster, community, or an EA is used interchangeably though they essentially refer to the same geographic unit. An EA refers to a small geographic area in which the country has already been divided for the purpose of census. In Bangladesh, an EA usually comprises of about 100-120 households. Hence these EAs were pre-defined for all the 7 Divisions and the sampling frame consisted of all the EAs for the entire country. The EAs are classified as urban/rural, and urban EAs are further categorized into City Corporation and Non-city Corporation. For BDHS 2011, a total of 600 EAs were selected, and at the next stage, 30 households were randomly chosen from each of the EA. The final sample consisted of 207 urban EAs and 393 rural EAs and a total of 18,000 households. The sampling design used in BDHS 2011 was defined as follows:

Let p_{jk} be the probability of selecting the j^{th} cluster in stratum k at the first stage

Let p_{ij} be the probability of selecting the i^{th} household in the cluster j at the second stage

Thus the probability of selecting the $j^{l}th$ cluster in stratum k was obtained using the formula below:

$$p_{jk} = \frac{c_k H_j}{\Sigma H_k} \tag{4.1}$$

where c_k is the number of clusters selected for the stratum k
H_j is the total number of households in the sampling frame of the j^{th} cluster
ΣH_k is the total number of households in stratum
and the probability of i^{th} household in the cluster j was obtained as follows:

$$p_{ijk} = \frac{N_h j}{H_{jk}} \tag{4.2}$$

where H_{jk} is the total number of households in the jth cluster of stratum k
$N_h j$ is the number of households that are selected for the jth cluster.

Thus the total probability was obtained by taking a product of the first and second stage probability and the sampling weight was inverse of the overall household selection probability. The survey data provided sampling weights to account for the non-response biases (BDHS, 2011)

4.3 Geomasking Procedure of EAs

DHS surveys provide geo-location of the EAs or the communities that were sampled. In order to protect confidentiality of the survey respondents, households within the same EA are aggregated and assigned coordinates of the EA. This ensures that the households cannot be identified. At the second stage, the GPS coordinates of the EAs are randomly displaced using a random direction random distance algorithm using a python tool in Arcgis. In this process, the location coordinates are randomly displaced between 0 to 2 km if it is an urban

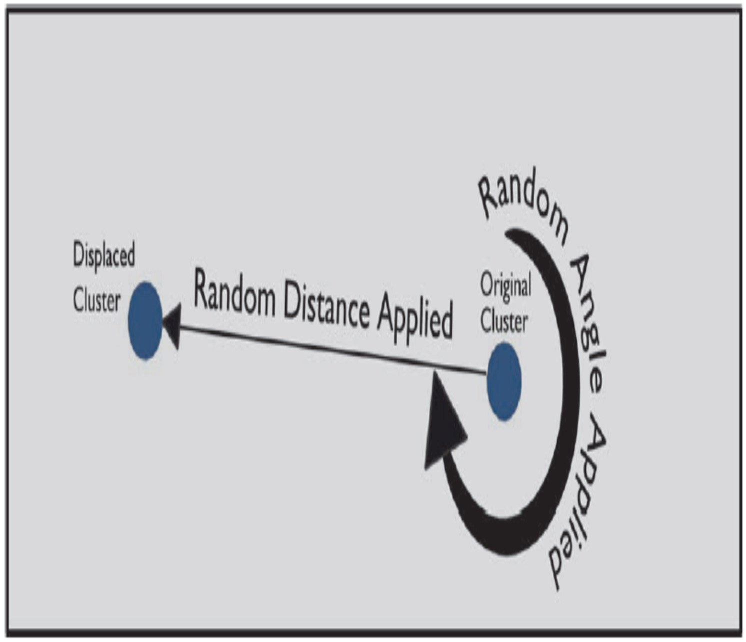


Figure 4.2. Random angle and random displacement procedure for DHS cluster location. Adapted with permission from (Burgert et al., 2013)

cluster, between 0 and 5 km if it is a rural cluster, and 1 percent of the sampled rural EAs are displaced anywhere in the range of 10 km. Figure 4.2 illustrates the displacement procedure described here. The EAs can be displaced in any direction between 0 and 360 degrees. However, if any of the EAs get displaced to an adjacent sub-district, then the algorithm is reiterated until it is assigned coordinates within the same administrative unit. While this ensures that EAs are not moved out of the sub-district, the displacement procedure used is a major limitation to do spatial analysis at smaller scale or administrative units below the sub-district unit. A comparison of DHS raw data and simulation reveals that the displaced coordinates of GPS follow a uniform distribution (Skiles et al., 2013; Burgert-Brucker and Prosnitz, 2014).

4.4 Survey Questionnaire and Key Methodological Considerations for DHS Data

The survey data asked several questions at the household level and at the community level to answer research questions pertaining to access and service utilization. The following are some of the survey questions that were used in the analysis:

1. Where is the nearest district hospital from where you live?

2. How far is the nearest Upazilla Health Complex?

3. Where is the nearest Family Welfare Center?

4. Where did you deliver your most recent child?

5. Was it a public or a private health facility?

Furthermore, the community survey also included other attributes such as whether the EA was rural or urban, the type of road access that was available from the EA, distance and time to closest primary school for boys and girls, and related variables that can serve as a proxy to the environment or neighborhood effects in explaining individual level access to care or variation in utilization of public health services. Information was recorded both in distance and time to four closest health facility of each type based on these six experts. Thus information on service utilization and distance to different types of health facility from the community.

Several approaches exist to measure spatial access for the DHS sampled clusters. One approach could be based on using self-reported distance or time to the nearest health facility, as recorded in the community survey. The problem with this approach is that often in case of health services individuals may skip the nearest health facility and are willing to travel to a higher order facility under the assumption that the latter provides more qualified doctors and professional staff. Thus using the average distance or travel time to the four closest facilities is another approach to examine spatial access to health facility. Other common approaches to examine spatial access to the health facility from an EA include buffer, road network distances, linking the EA to closest facility, or to the four nearest facilities. While the availability of geographic locations of the survey clusters provides a rich opportunity to examine spatial variation in access to health services and pockets of low and high service utilization indicators, random displacement of the survey clusters requires several methodological considerations before performing any analysis (Skiles et al., 2013; Burgert-Brucker and Prosnitz, 2014; Burgert, 2013; Burgert et al., 2013).Geographic displacement of the cluster locations makes it challenging to link the EA with actual health facility locations. The problem becomes more acute in urban areas due to high population density and thus displacement of 2 kilometers can affect the reliability of the results (Burgert-Brucker and Prosnitz, 2014). A study has shown that linking DHS cluster to the closest facility or to even a sample of health facility biases the result, and hence should be avoided. In the absence of reliable spatial data and population information, several authors who have accounted for some spatial factors in explaining individual and household behavior with DHS data used multilevel models. On the other hand, in situations where SPA (Service Provision Assessment) data was available, population raster, or actual facility information through some other source, more sophisticated modelling approaches could be employed.

4.5 Strengths and Limitations of the Survey Data

In developing countries where governments may lack financial resources and in certain cases even technical capacity to implement nationally representative survey, DHS survey is an important source of reliable data for maternal and child health services. A major advantage of the survey is that it provides individual or household level variables as well as community or cluster level variables that are sampled at a fine geographical scale. This allows investigation

Table 4.2. GIS data prepared for two Divisions

	Barisal	**Sylhet**
Total number of schools	2180	2850
Total number of clinics	615	579
Total number of Family Welfare Centers	175	132
Total number of THC's	35	34

into the relationship between neighborhoods level characteristics such as distance to the nearest hospital from the community and individual level service utilization indicator such as home and institutional births. A major criticism of the DHS data is that the geolocation of the communities are displaced, which limits the application of GIS based models to accurately measure travel distance. Even though the clusters are displaced, they still remain within the same sub-district. This provides an opportunity to examine district or sub-district level variation.

4.6 GIS Data Preparation

Survey data were combined with GIS data obtained from the Local Government Engineering Division of Bangladesh. Shapefiles of the administrative boundaries were obtained from the Bangladesh Bureau of Statistics. Since the maps of health facilities and administrative units were only available as JPEG maps from the government website, layers of administrative headquarters, Upazilla Health Complex, Family Welfare Centers, and Community Clinics were digitized for both the regions. Layer for the district hospital was obtained from web maps on the website of Director General of Health Services (DGHS) and the KML file was converted to shapefile. Figures 4.3 and 4.4 show the GIS data of health facilities up to 3 administrative boundaries. Additionally, roads upto union level, rivers, primary schools were also digitized from the LGED maps for both the divisions. Primary schools were digitized to reflect the locally varying population distribution. Figures 4.5 and 4.6 show the distribution

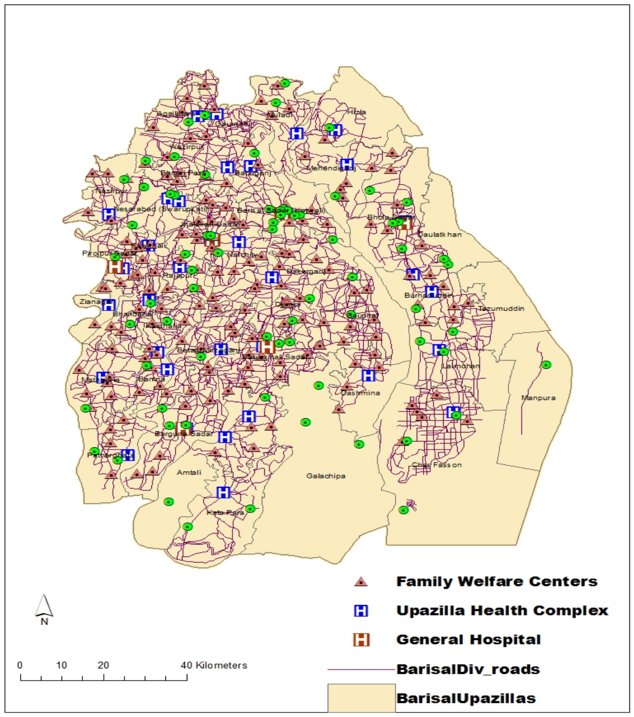


Figure 4.3. Distribution of public health facilities in Barisal Division

of primary schools and clinics. In both the figures, the primary schools mask the clinics, suggesting a substantial difference between their numbers. Table 4.2 summarizes the GIS data that were prepared for the two divisions. It can be seen that the number of Upazilla Health Complex are similar for both the study areas.

4.7 Strengths and Limitations of the GIS Data

Since most of the spatial data layers were generated from a single government source, it improves the reliability of the data and any bias that results from missed locations during the GPS data collection can be assumed to be similar for both the study area and for all the layers. The temporal period when the maps were field verified was also the same for all the layers and matched with the data collection period for the survey data. Hence it does not raise any issue regarding merging of the survey and GIS data if they were collected

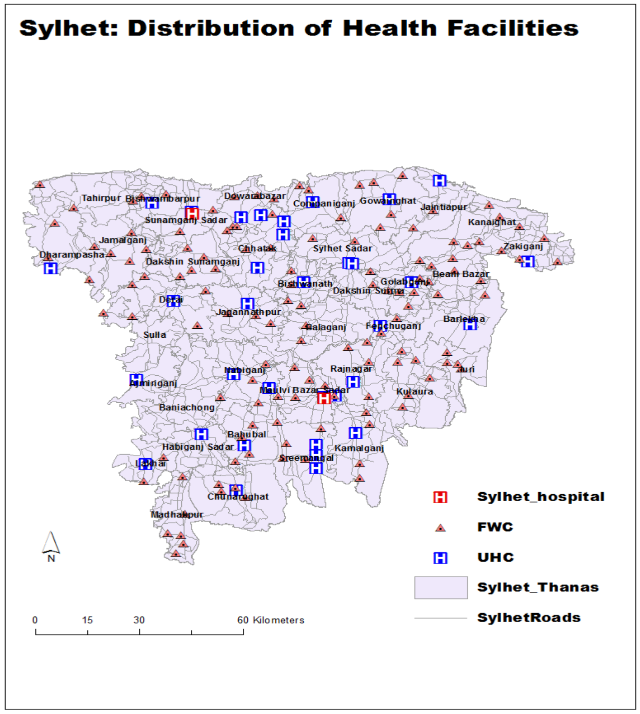


Figure 4.4. Distribution of public health facilities in Sylhet Division

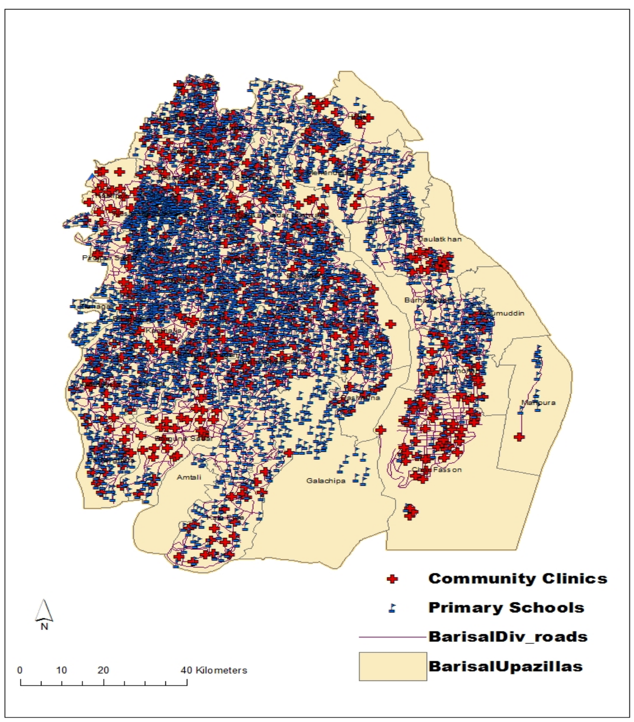


Figure 4.5. Distribution of community clinics and primary schools in Barisal Division

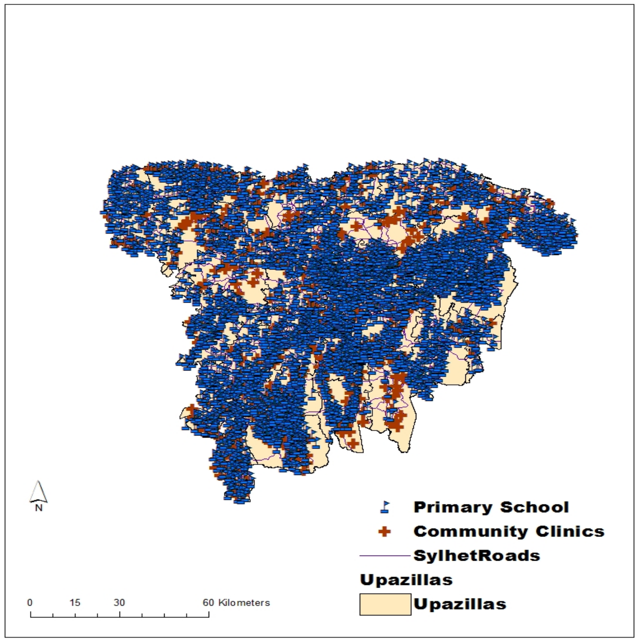


Figure 4.6. Distribution of community clinics and primary schools in Barisal Division

at different time periods. While high resolution population data from satellite imagery facilitates a more sophisticated analysis, combining population and GIS data from different sources can bias the results, especially if they were collected during different time periods. Given these challenges, the GIS data obtained from LGED seemed the most suitable for this analysis in spite of its limitations. One limitation of the GIS data from LGED were it only included layers for government health facilities, and excluded any information on private or non-government organization facilities. But given the research questions that this dissertation seeks to examine, this was not a major concern. Even though road up to the village level were available in the JPEG maps, it is almost impossible to digitize such a large spatial extent accurately without any human errors. Given some of the limitations of the survey and the GIS data, the analysis presented in the subsequent chapters must be viewed in the light of these limitations and challenges.

CHAPTER 5

MARKET AREAS FOR PUBLIC HOSPITALS AND IMPLICATIONS FOR CONSUMER'S TRAVEL

Chapter 2 highlighted the underyling principles of central place theory and urban hierarchy. This chapter examines inequity in the geographical distribution of health facilities and market areas based on the following key postulates:

1. Lower order goods and services are nested in higher order goods and services

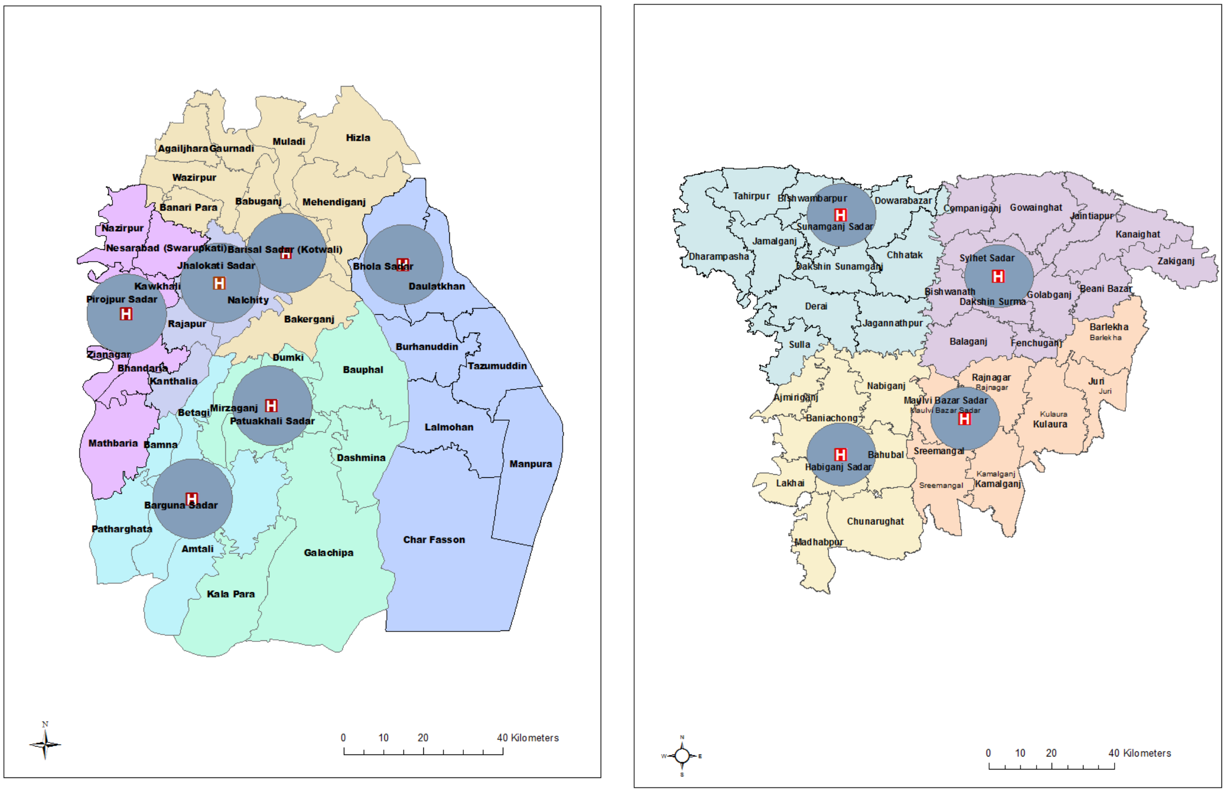
2. Market areas for each center are homogeneous in terms of size

3. Population distribution within each market area is uniformly distributed

4. Each center has a rank based on its function and the size of the population served.

Since each district has a hospital that is uniquely set up to service population in that specific administrative unit, on the face it appears that there is equitable distribution. However, when one takes into consideration the market areas for the same type of service, then this distribution suggest inequities in the service area and therefore the travel distances to access the nearest hospital. In the context of health facility planning, a lower order good or service would imply a clinic or a service that is provided at the shortest distance while a higher order good would be a hospital for which the range in terms of travel distance would be the furthest. By using self-reported distances traveled to the nearest hospital and the actual location of district hospitals, the following analysis is an exploratory analysis on the inequalities in the size of the districts and its effect on distances traveled by consumers to access the same level of good or a service. Based on the research questions raised in the introductory chapter, the specific research objectives for this chapter are:

1. What factors influence the distances traveled to health facilities in Bangladesh?



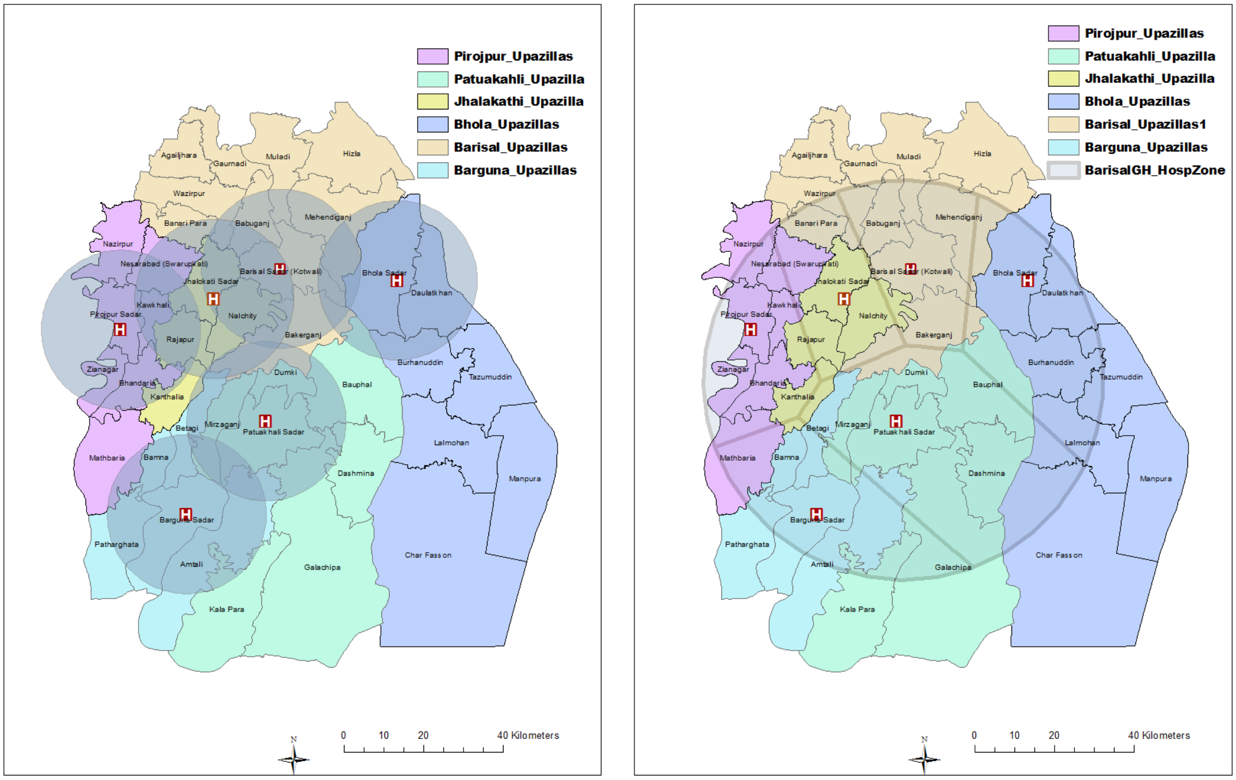
(a) (b)

Figure 5.1. Service areas of district hospital based on 10 kilometer buffer in Barisal and Sylhet Division. Polygons of the same color belong to the same district.

2. Are these differences in travel pattern linked to geographic inequalities in the administrative units, which in turn influence the heterogeneous size of the hospital service areas?

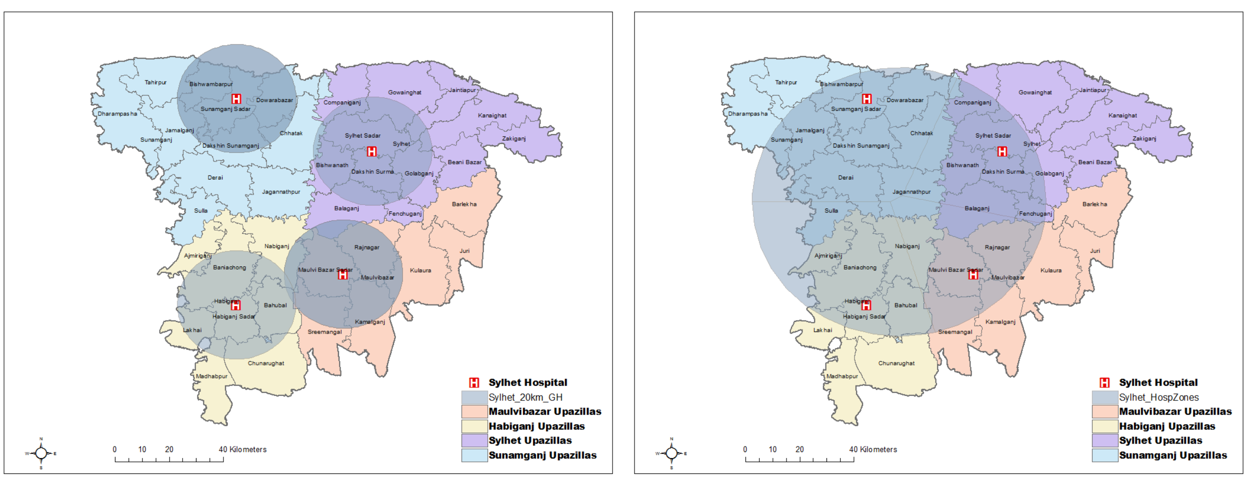
3. Does access to hospital services influence health service usage?

4. Which geographical areas and communities remain well-served and which remain out of the hospital service areas?



(a) (b)

Figure 5.2. Service areas of district hospital based on 20 kilometers buffer and straight line distance partitioning in Barisal. Polygons of the same color belong to the same district.



(a) (b)

Figure 5.3. Service areas of district hospital based on 20 kilometers buffer and straight line distance partitioning in Sylhet. Polygons of the same color belong to the same district.

5.1 Examining Regional Variation in Hospital Service Areas

In order to illustrate the size of the districts and its effect on the market areas of hospital, buffers of 10 and 20 kilometers were constructed around each district hospital for both the Divisions. It is plausible that larger districts have a larger hospital service area and vice-versa. Figure 5.1 shows the hospital service areas based on a radius of 10 kilometers for both Barisal and Sylhet Division. Within Barisal Division, Pirojpur and Jhalokati Districts are smaller and as the figure illustrates the hospital service areas do overlap each other, while for larger districts such as Bhola, Barisal, and Patuakhali the hospital service areas do not overlap. But in Sylhet Division due to the large size of the districts relative to the area, there is no overlap between 10 kilometer buffers. This contrast is even more evident for 20 kilometers buffer around the hospitals for both the divisions. A comparison of figure 5.2a and 5.3a on the previous page reveals that the hospital service areas overlap for smaller districts for Barisal but in Sylhet the service areas remain very distinct for each district. In case of Sylhet, for larger districts such as Habiganj and Maulvi Bazar they tend to be much closer in comparison to larger districts such as Sylhet and Sunamganj figure 5.3a suggests.

Both figures 5.4 and 5.5 depict an alternative approach to estimate market areas, which is based on voronoi polygons or road network partitioning. Voronoi polygons or thiessen polygons are constructed such that each polygon is generated around a point such that it includes only one generator point and the distance from this generator point is the shortest than any other point. Therefore, areas where there are more number of points the voronoi polygons are small and tightly packed and areas where there are fewer points the polygons are larger and more spread out. This unique property makes them useful in examining market areas in several different scenarios. While road network partitioning is a more sophisticated approach, availability of high quality and updated road network data for a large scale study area in a developing country is challenging. Considering the large spatial extent of the study area and limited availability of accurate street network layers for the two study areas, an

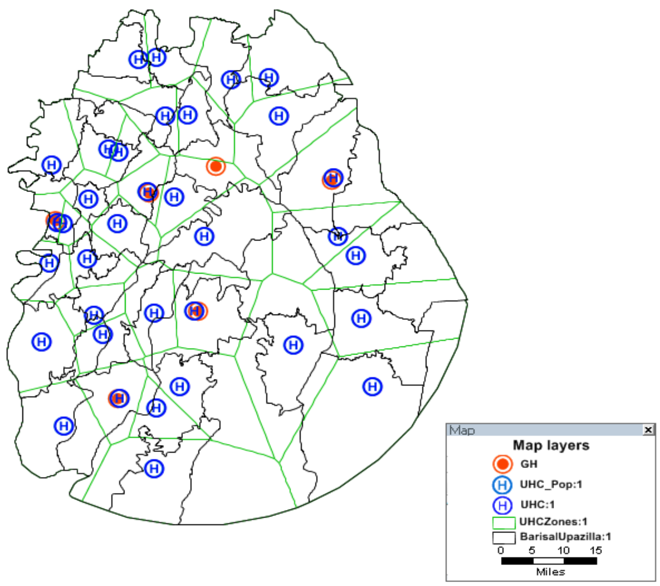


Figure 5.4. Service area of the sub-district hospitals based on straight line distances in Barisal Division

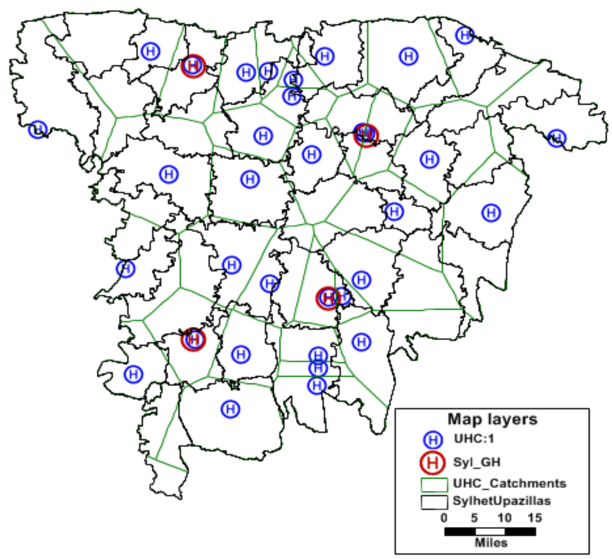


Figure 5.5. Service area of the sub-district hospitals based on straight line distances in Sylhet Division

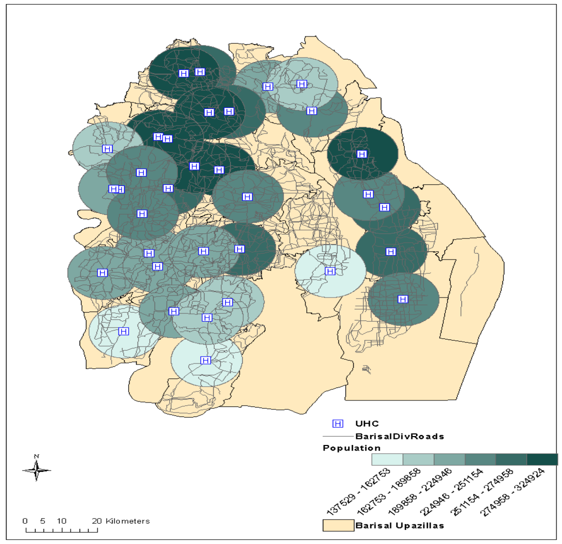


Figure 5.6. Population serviced in a radius of 10 kilometers of each sub-district hospitals of Barisal Division

approach based on voronoi polygons was chosen to create market areas. This was done using Maptitude software. In the absence of good quality street network data, the software creates a circle that encompasses all the points and then creates market areas based on straight line distances around the point features. Results based on straight line influence area confirm to the pattern for 10 and 20 kilometer buffers. Market areas are smaller for Barisal, Jhalokati, and Pirojpur and larger for Bhola and Patuakhali. In both the Divisions, the figures suggest areas at the border excluded from these influence areas though this difference appears larger for Sylhet than Barisal Division. Partly this is also due to the very few points for district hospitals due to which this approach does not encompass the entire study area. This exercise was repeated even for sub-district hospitals. Figures 5.4 and 5.5 show the irregular sizes of market areas of sub-district hospital or the UHC superimposed on the administrative boundaries for the sub-districts.

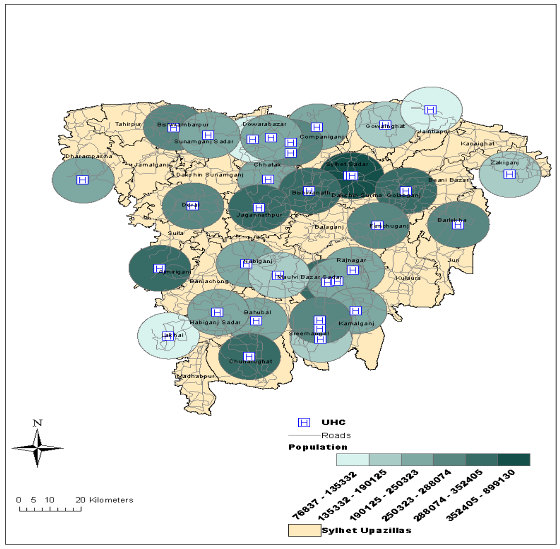
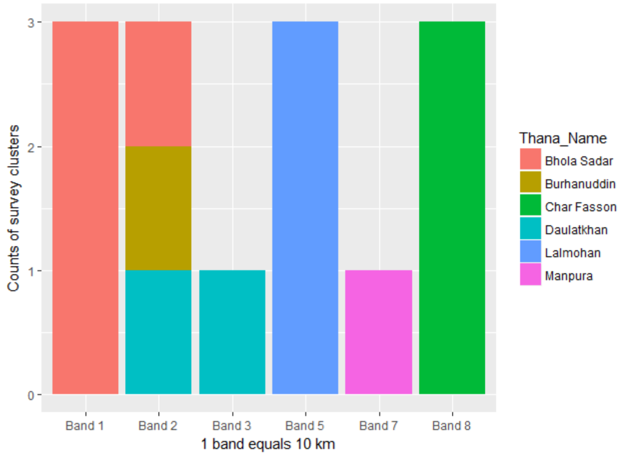


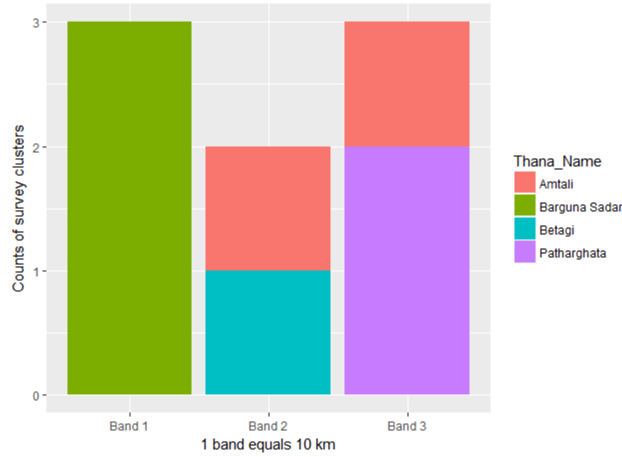
Figure 5.7. Population serviced in a radius of 10 kilometers of each sub-district hospital in Sylhet Division

5.2 Population Partitioning

While buffers are constructed based on fixed radius, an alternative approach to examine service areas is based on population serviced within a specific radius of a health facility. This pertains directly to the second and the third postulate of the theory with regard to homogeneous distribution of the population within market areas. Figures 5.6 and 5.7 show the population serviced within 10 kilometers or 6 mile radius of a sub-district hospital. It is evident that the population served by the same level of health facility is very different from one sub-district hospital to another within a fixed distance. This is different from a container approach which examines population serviced in a specific administrative unit and relies on the assumption that people use services strictly within that administrative boundary, without any cross-border flow in the use of services. An alternative approach would be to estimate the population serviced within a specific radius by estimating the demand from all the lower-level administrative units that fall within this distance. This approach can account for population from different administrative units that overlap within a hospital service areas. Specifically,



(a) Bhola District



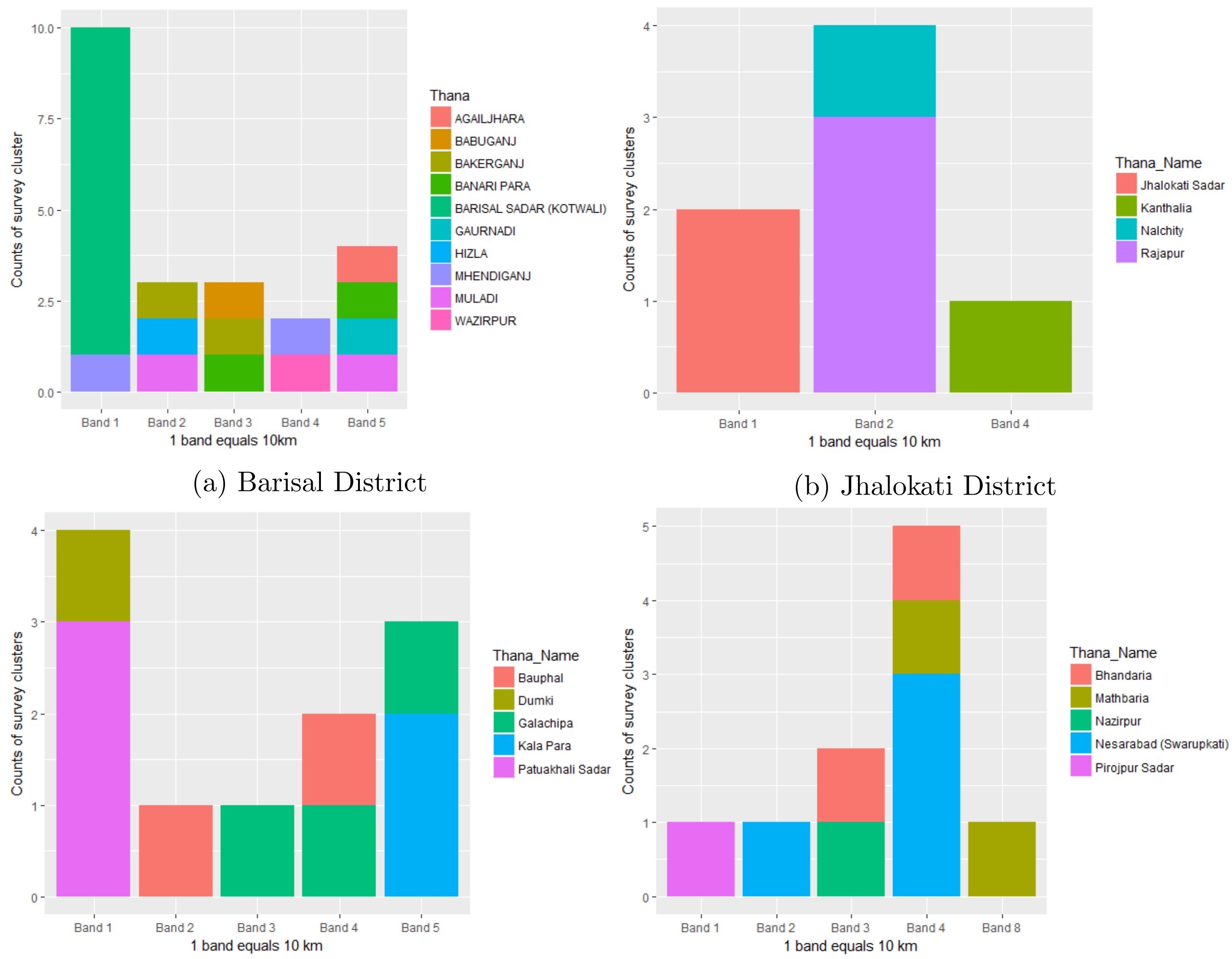
(b) Barguna District

Figure 5.8. Distance to the nearest hospital by sub-districts in two districts of Barisal Division

this can be accomplished in Maptitude by overlaying a hospital service area on lowest level administrative boundaries. The lowest level administrative boundaries have an assigned population based on census data. Therefore, when a hospital service area is superimposed on these administrative boundaries, the population that gets assigned is proportional to the area of the administrative unit that falls within a higher level service area. For example, if 70 percent of town A area and 30 percent of the area of town B fall within a hospital service area, then the software will sum the population from these two towns based on the area of each individual town that falls within it. As revealed in figures 5.6 and 5.7, there is a huge variation in the population distribution within a 10 km range of each sub-district hospital service area. This confirms that allocation of fixed number of health facility based on administrative units does not take into consideration the population demand.

5.3 Intra-district Variation in Travel Pattern

As established in the previous section on the effect of district size on hospital service area, this section examines intra and inter district variation in travel distances by comparing two



(a) Barisal District

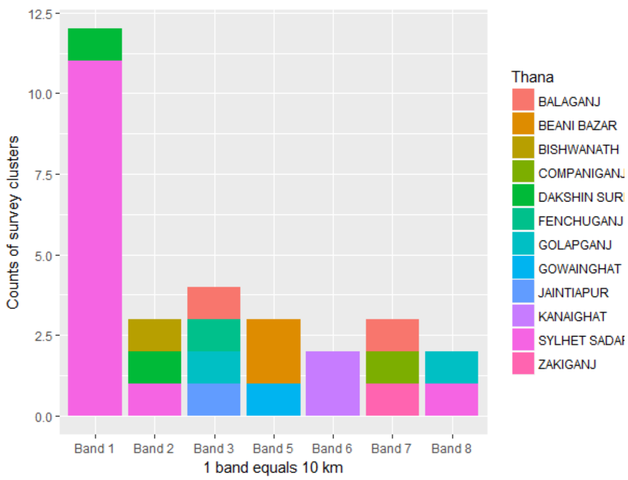
(b) Jhalokati District

(c) Patuakhali District

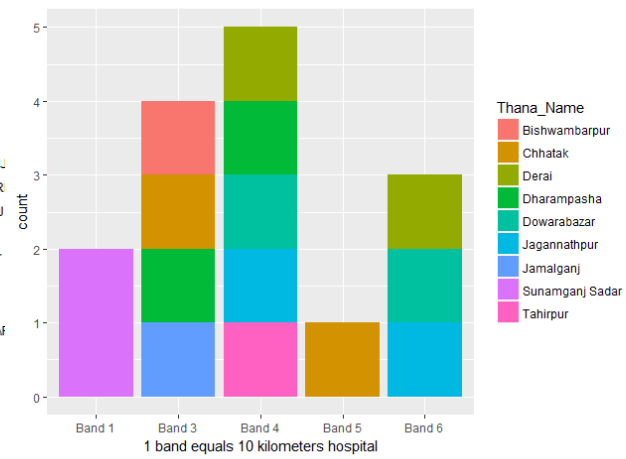
(d) Pirojpur District

Figure 5.9. Self-reported distance to the nearest hospital by sub-districts within Barisal Division

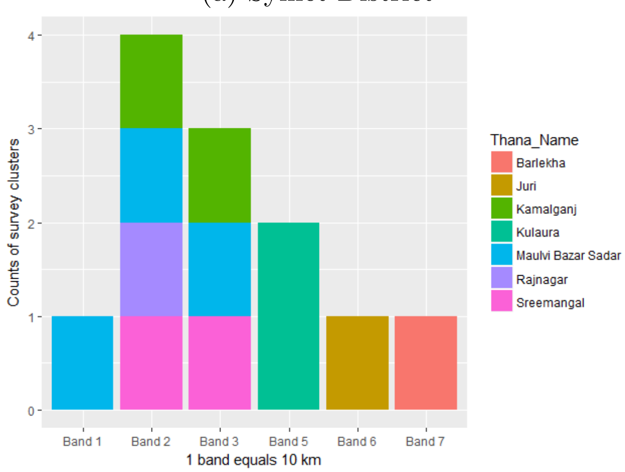
districts to begin with. To examine spatial variation in access to the nearest hospital based on the area of the sub-districts and their relative location from the district centers, DHS clusters sampled within each sub-district were classified into distance bands of 10 kilometers. Sampled clusters in each district were grouped based on the distance bands that each cluster belonged to. Therefore, all sampled clusters in a district that were 10 kilometers away from the nearest hospital were aggregated, without losing any information on the sub-districts. Figure 5.8 compares travel distances to the nearest hospital in one of the largest and the



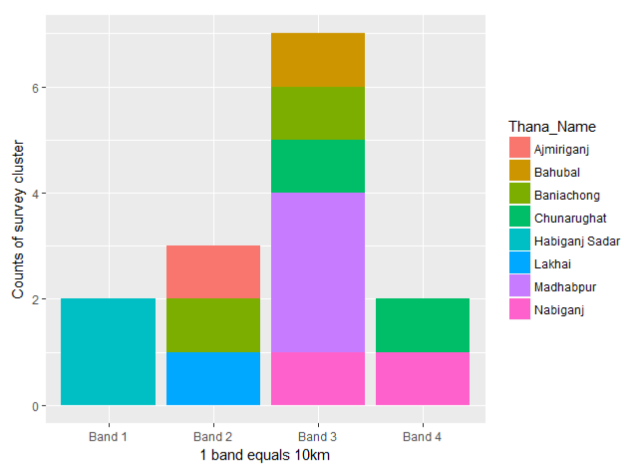
(a) Sylhet District



(b) Sunamganj District



(c) Maulvi Bazar District



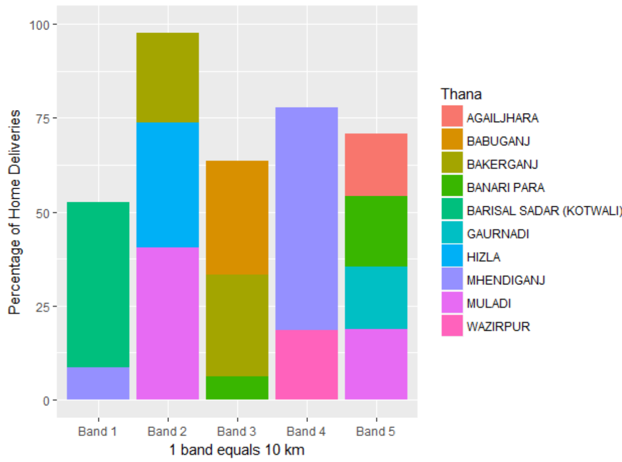
(d) Habiganj District

Figure 5.10. Self-reported distance to the nearest hospital by sub-districts within Sylhet Division

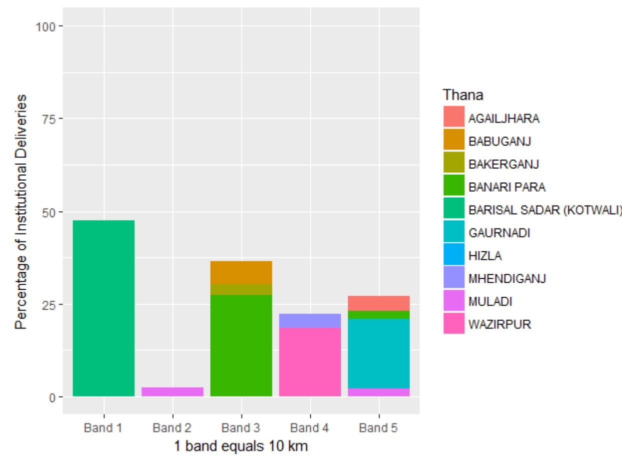
smallest district in Barisal Division. In the figure 5.8a each color represents the distance to the nearest hospital based on the sub-district in which the community lived. It can be observed that Bhola District has 6 sub-districts and the range of the self-reported distance stretches up to 80 kilometers for some of the communities. Contrast this with figure 5.8b where the district only consist of 3 sub-districts and the range for the hospital service area has shrunk to 30 kilometers.

A similar pattern can be observed for other districts in Barisal Division. Take the case of Barisal District. Figure 5.9a shows that Barisal district has a large number of sub-districts nested within them in comparison to figure 5.9b for Jhalokati District. As a result the range of the distances to the nearest hospital are also different. In case of former, some communities in Muladi Upazilla of Barisal District travel up to 50 kilometers, while some communities in the same upazilla live in the fourth ring. But Jhalokati District, with its relatively small size and fewer upazillas suggests that the maximum self reported distance is 40 kilometers for the nearest hospital. In Patuakhali District, figure 5.9c demonstrate that communities in the Bauphal commuted in the range of 20 to 40 kilometers while communities in the upazilla of Galachipa reported a distance of 30,40,and 50 kilometers respectively. This suggests a larger intra-district variation due to the size of the sub-districts. By the same logic, in Pirojpur District as represented in figure 5.9d sub-districts located away from the Pirojpur Sadar or the City Corporation had the maximum travel distance. Since the upazilla of Mathbaria is located furthest from the district hospital, distance varied in the range of 40 to 80 kilometers.

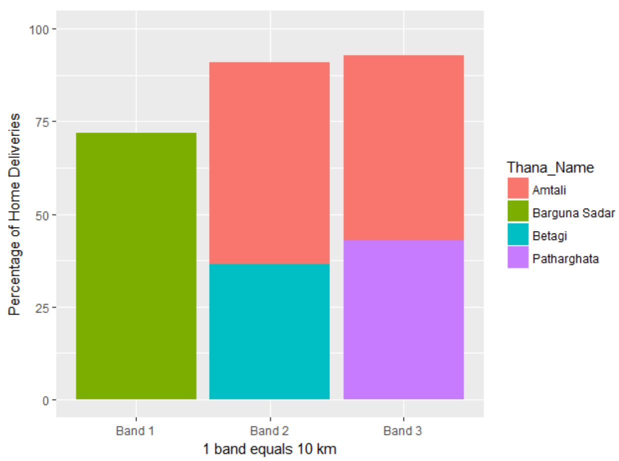
For Sylhet Division, communities belonging to the same sub-district fell in different distance bands, suggesting the larger areas of the Upazillas. Figure 5.10a shows that in Sylhet district, with 12 Upazillas, the service area for few communities stretches up to 70 and 80 kilometers due to its large area. However, figure 5.10b suggests that Sunamganj district the hospital service area shrinks to 60 kilometers due to its relatively smaller area compared to Sylhet District. For Maulvi Bazar district, figure 5.10c points large distances for communities living in Upazillas at the periphery such as Juri, Kamalganj and Barlekha as the service area extends in the range of 50 to 70 kilometers Again, this confirms that hospital service areas are linked to the administrative units contained within them. Interestingly, among all the four districts, communities in the Habiganj District had the shortest distance as the maximum self-reported distance was 40 kilometers as revealed in the 5.10d.



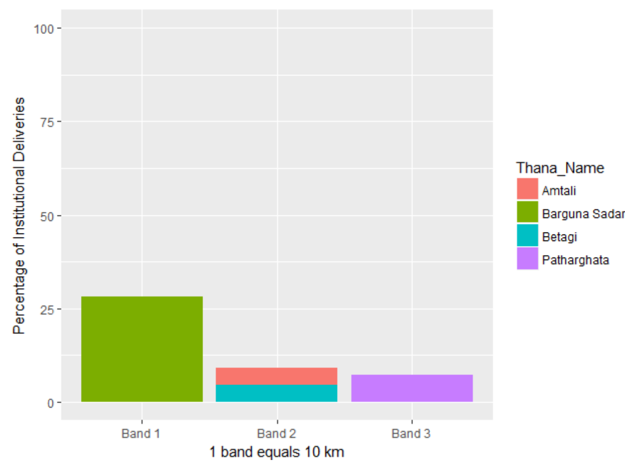
(a) Home Births in Barisal



(b) Institutional Births in Barisal



(c) Home Births in Barguna

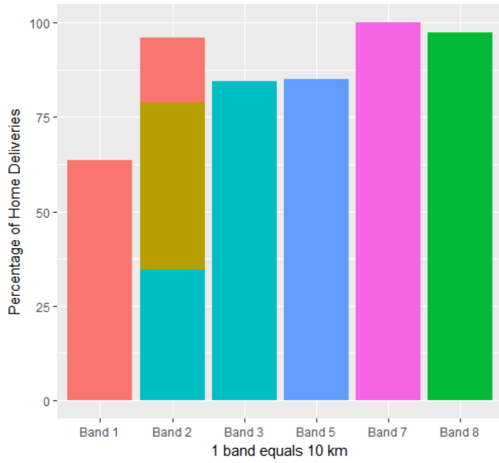


(d) Institutional Births in Barguna

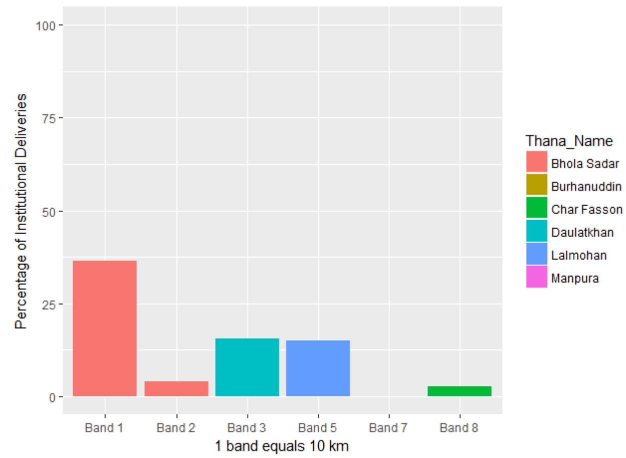
Figure 5.11. Home and institutional deliveries in Barisal and Barguna district of Barisal Division

5.4 Intra-district Variation in Service Utilization

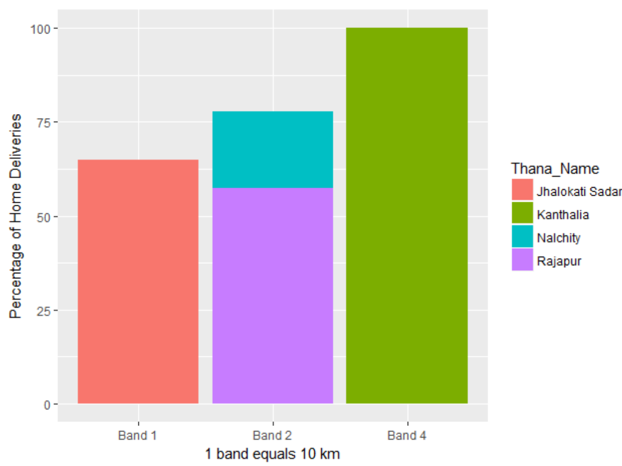
In examining the relation between the distances traveled and service usage,figure 5.11a shows that home deliveries were reported the lowest for communities that lived in the first band of the hospital service area while it peaked to 100 percent in the second band and then declined from the third band onwards. At the same time institutional deliveries, as figure 5.11b suggests stood at 50 percent for communities that lived within the first band, and as communities live further away, the proportion of home births rises while institutional



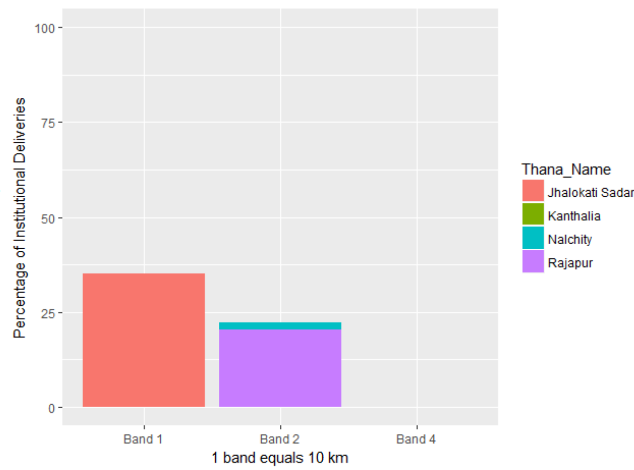
(a) Home Births in Bhola



(b) Institutional Births in Bhola



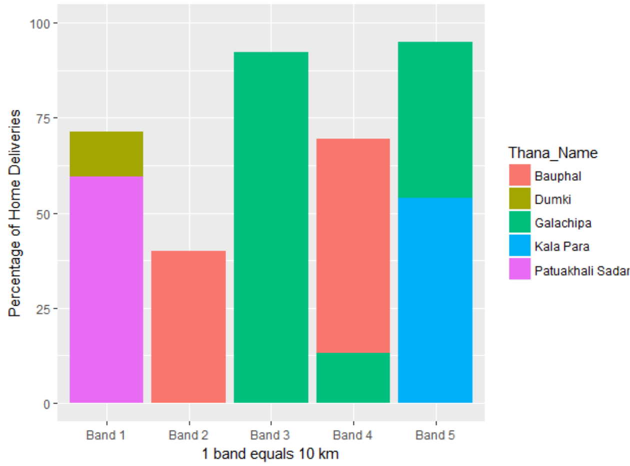
(c) Home Births in Jhalokati



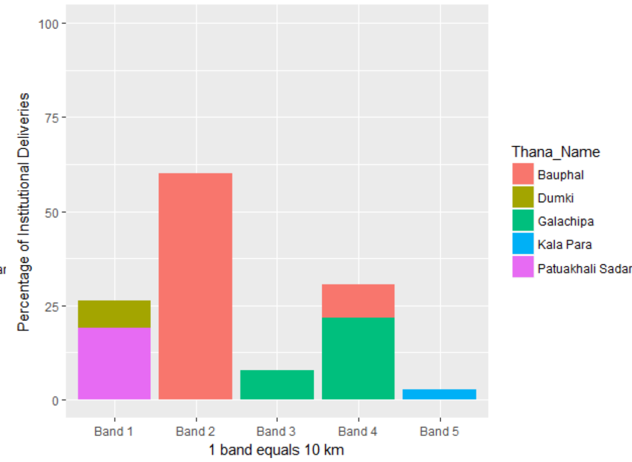
(d) Institutional Births in Jhalokati

Figure 5.12. Home and institutional deliveries in Bhola and Jhalokati district of Barisal Division

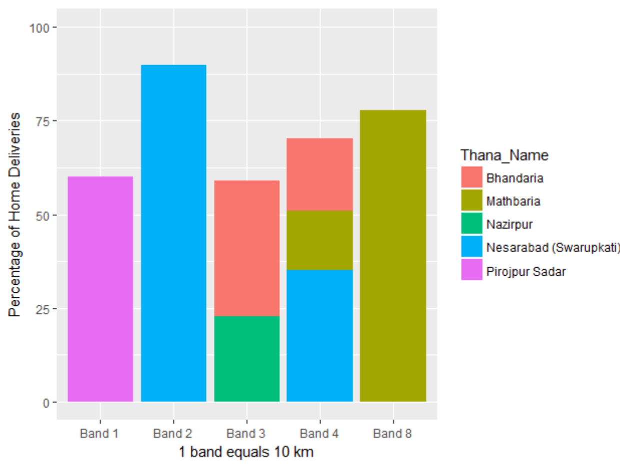
deliveries decline. The steep increase in the home deliveries from the second band could be explained by the relatively low levels of urbanizations and perhaps poorer socio-economic background of the women in those rural communities. A similar pattern can be seen for Bhola too. Figures 5.12a and 5.12b illustrate a lower rate of home births in the first band while they are similar for all the communities that live in the sub-districts that belong to the second band onwards. This is because Bhola is relatively a poorer district. Similarly, institutional births are reported the highest in the first distance band though it accounts



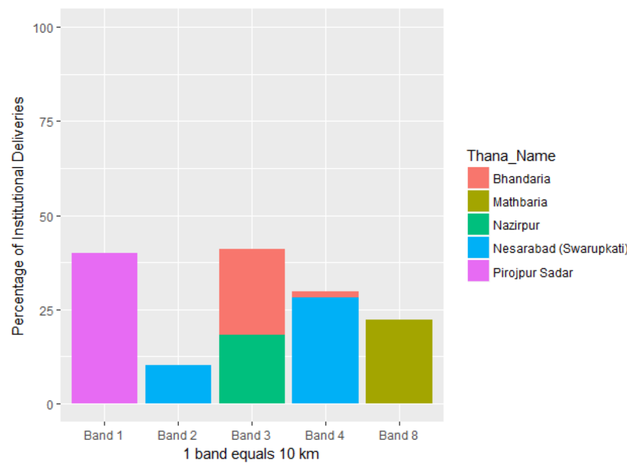
(a) Home Births in Patuakhali



(b) Institutional Births in Patuakhali



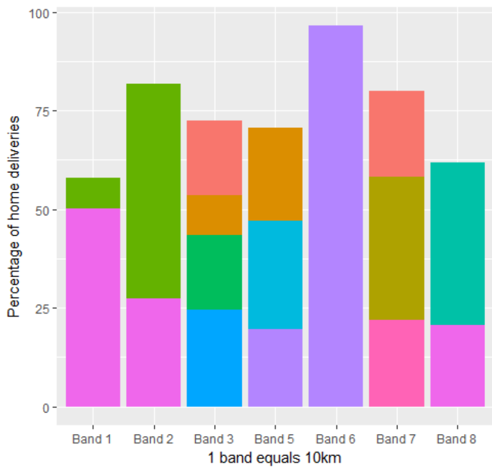
(c) Home Births in Pirojpur



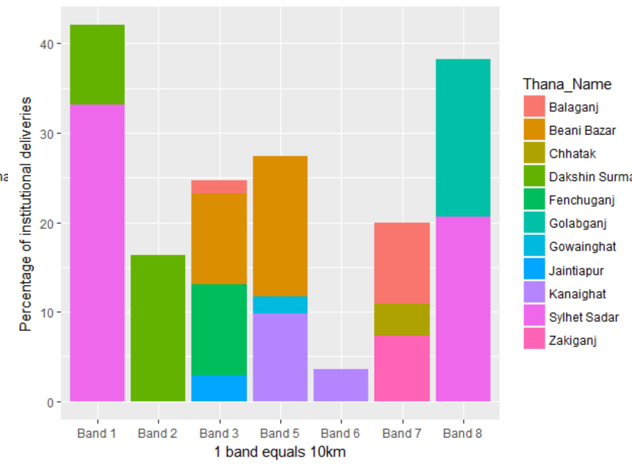
(d) Institutional Births in Pirojpur

Figure 5.13. Home and institutional deliveries in Patuakhali and Pirojpuri district of Barisal Division

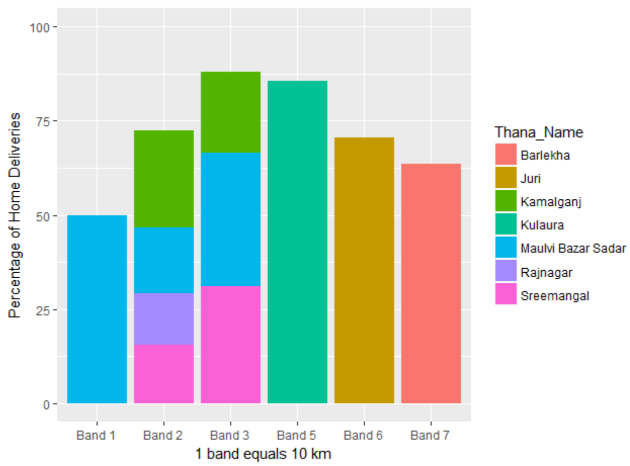
for only about 30 percent while the rest of the communities reported less than 20 percent of institutional deliveries. It can be noted from the figures 5.12c , 5.12d, 5.11c and 5.11d that both Jhalokati and Barguna districts comprise of a similar number of Upazillas and share a similar range of hospital service area, and interestingly, the pattern of the home and institutional births is similar. For both the districts, the distances are much shorter and the share of home births is the lowest in the first band, while it shows a steady increase in the second and third distance band, suggesting a clear pattern of distance decay. At the same



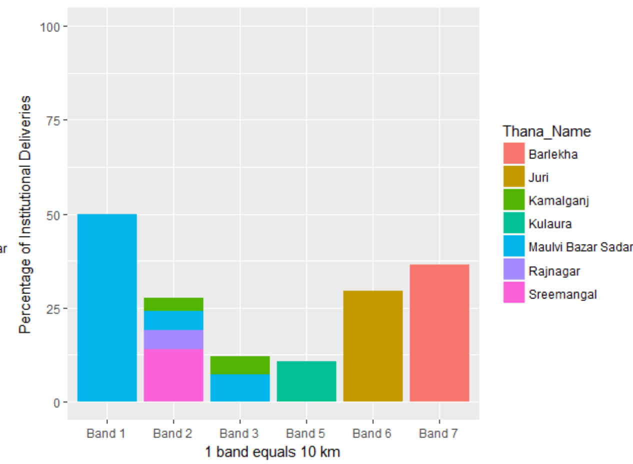
(a) Home Births in Sylhet



(b) Institutional Births in Sylhet



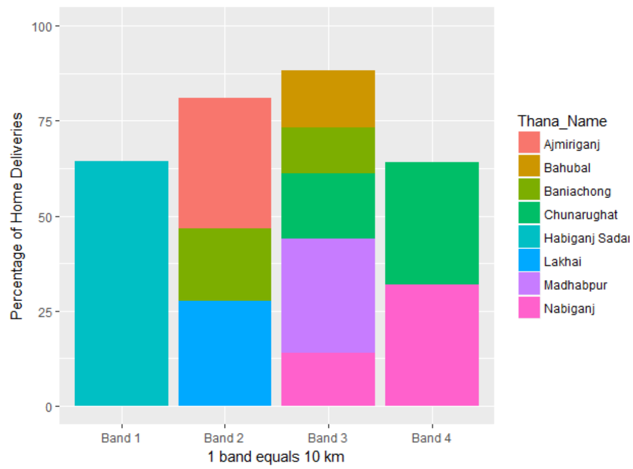
(c) Home Births in Maulvibazar



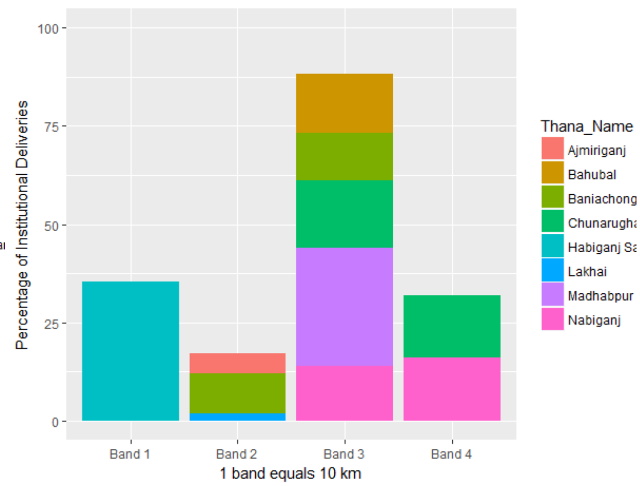
(d) Institutional Births in Maulvibazar

Figure 5.14. Home and institutional deliveries in Sylhet and Maulvibazar district of Sylhet Division

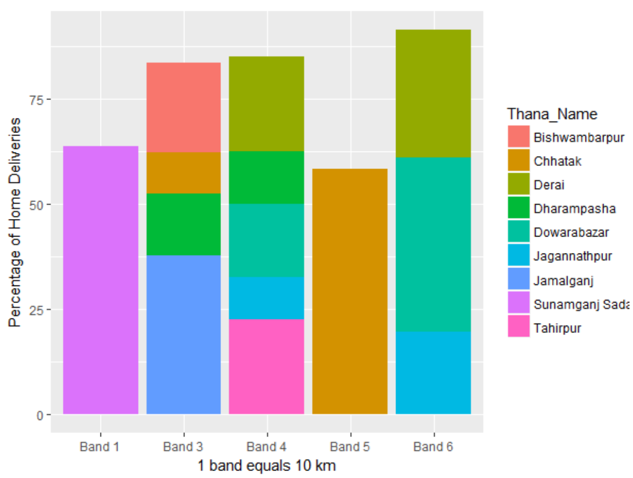
time institutional births remain higher in the first band and decline in the second band. In Pirojpur, institutional births are similar in the first and the third distance band while remain low in the second and the fourth band as can be seen in 5.13d. This anomaly can be explained by the rural urban differences as communities that are rural may have a lower rate of institutional births even though they may be living in the second band. With regard to urban-rural differences, most clusters were rural in Bhola District due to which share of home deliveries remain almost similar for communities living in Upazillas at shorter distance



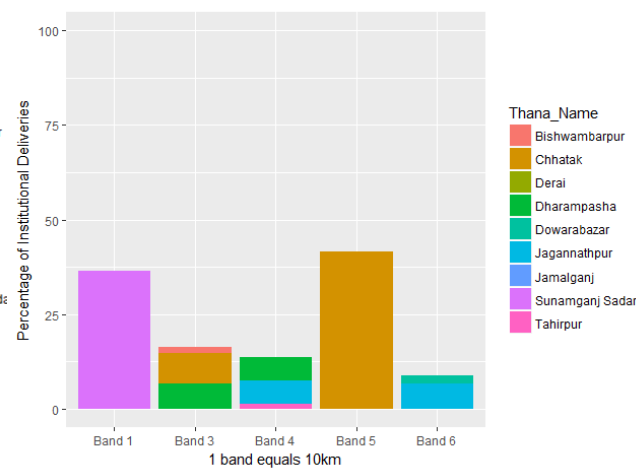
(a) Home Births in Habiganj



(b) Institutional Births in Habiganj



(c) Home Births in Sunamganj



(d) Institutional Births in Sunamganj

Figure 5.15. Home and institutional deliveries in Habiganj and Sunamganj district of Sylhet Division

bands and for those living in sub-districts that are further away. Similarly, Patuakhali is also predominantly rural due to which the proportion of home births are nearly 70 percent in the first distance band and peak to 100 percent in the third and the fifth band, while the share of institutional deliveries remain marginal even in the first band. Both Jhalokati and Barguna District have high proportion of home deliveries in rural clusters of the first distance band and institutional deliveries that are mainly due to women living in the urban clusters of the city corporations for both the districts.

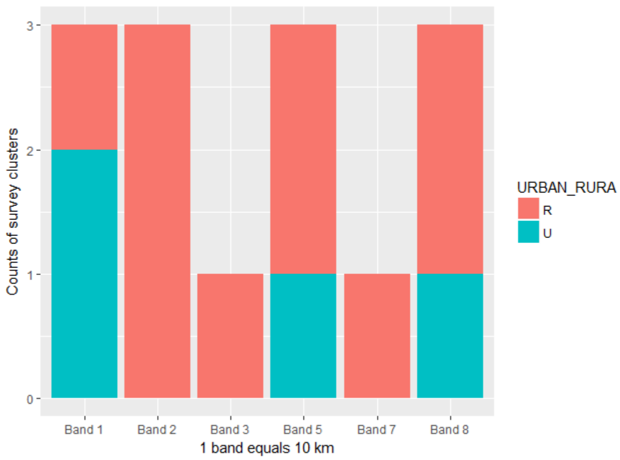
Within Sylhet District, figure 5.14a and 5.14b suggests that communities living in the first distance band of Dakshin Surma accounted for a much smaller share of home births in comparison to communities that belonged to the same Upazilla but lived in the second band. For communities that lived in the first distance band of Sylhet Sadar, the share of institutional births remained higher while showed a decline in the next band. Also, a large number of surveyed communities were in the first distance band were urban while most clusters in the subsequent rings were mainly rural. Again, this explains the high proportion of home deliveries in the second band and their high rate even in the subsequent bands led by rural clusters. Even for Maulvi Bazar, figures 5.14c and 5.14d shows that the share of home births is substantially high for communities in the first and the third band while much lower in the second band. This is because of the rural clusters that the high rate of home births is observed in the second distance band. In Sreemangal, home births are lesser for communities in the second band while higher for those in the third band. For those Upazillas where all communities belonged to the fifth, sixth, and seventh distance band, the proportion of home births were substantially higher. In terms of institutional births, the share of communities living the first distance band of Maulvi Bazar Sadar was the highest while other Upazillas accounted for a negligible proportion of institutional births. For Sunamganj District, it can be noted from figure 5.15cand 5.15d that communities in the sixth distance band of Dowarabazar Uapzilla accounted for much larger share of home births in comparison to communities that belonged to the fourth distance band of the same sub-district In Sunamganj, even though the clusters are predominantly rural in the first distance band, they belong to the city corporation and unlike some densely populated city corporations in Barisal Division such as Bhola Sadar, Sunamganj Sadar has a relatively low population density, which implies lesser competition to access health facilities. In both Habiganj and Maulvibazar urban clusters account for a high proportion of institutional births at the short distances.

5.5 Rural-Urban Variation in Travel Pattern and Service Usage

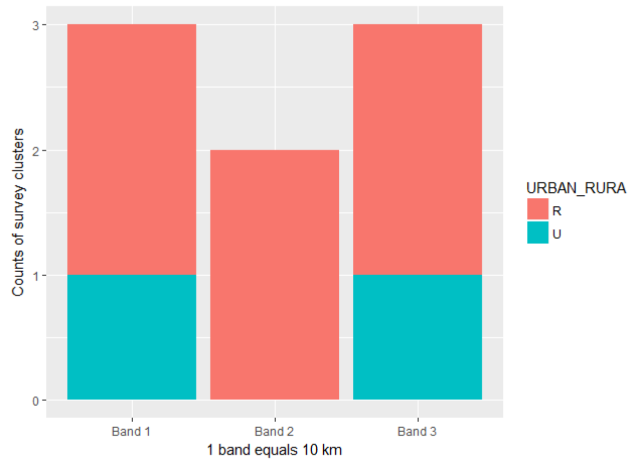
Another anomaly that can be observed is the distribution of the rural and urban clusters with regard to the distances to the district hospital. While the theory suggests that urban consumers travel less than rural consumer for the same type of good or service, figure 5.16 shows that even at short distances there are some rural communities while some communities at further distances are urban. A plausible explanation for this is the high poverty and population density due to which the conventional belief about rural-urban differences on travel distances may not necessarily hold true in case of Bangladesh. Figure 5.17 reveals a similar pattern for Sylhet where some urban communities are found as far as in the eighth distance band. In other districts such as Habiganj and Maulvibazar, some urban communities are up to 30 kilometers away.

5.6 Conclusion

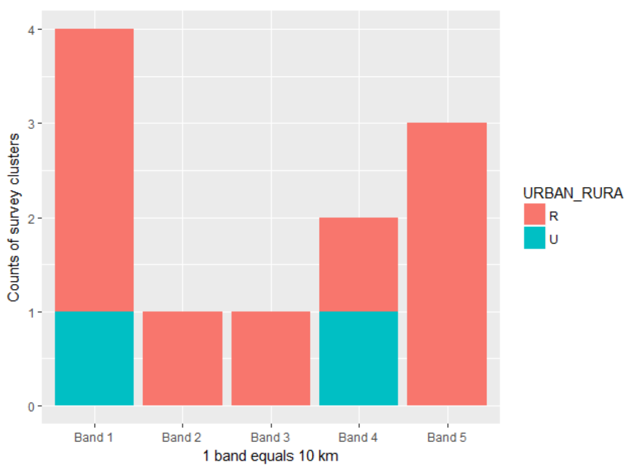
Based on the maps and the figures for both the divisions, it was evident that district hospitals are situated in the city corporations of Bangladesh where the administrative headquarters are located. Therefore, in terms of spatial access, communities living in the city corporations had the most access to public hospitals while the further the communities lived in sub-districts that were away from the city corporations, the distances increased. However, within city



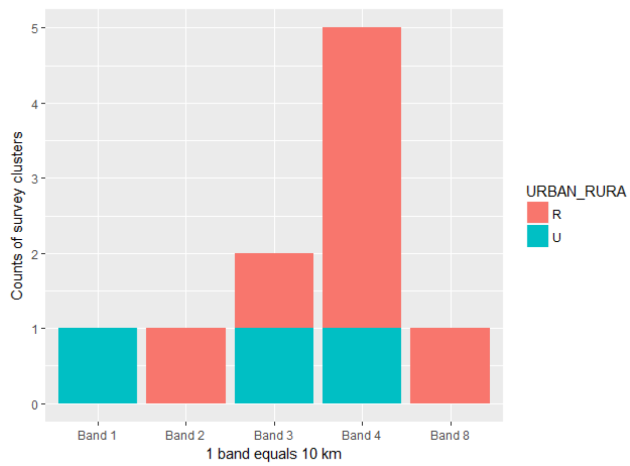
(a) Bholа District



(b) Barguna District



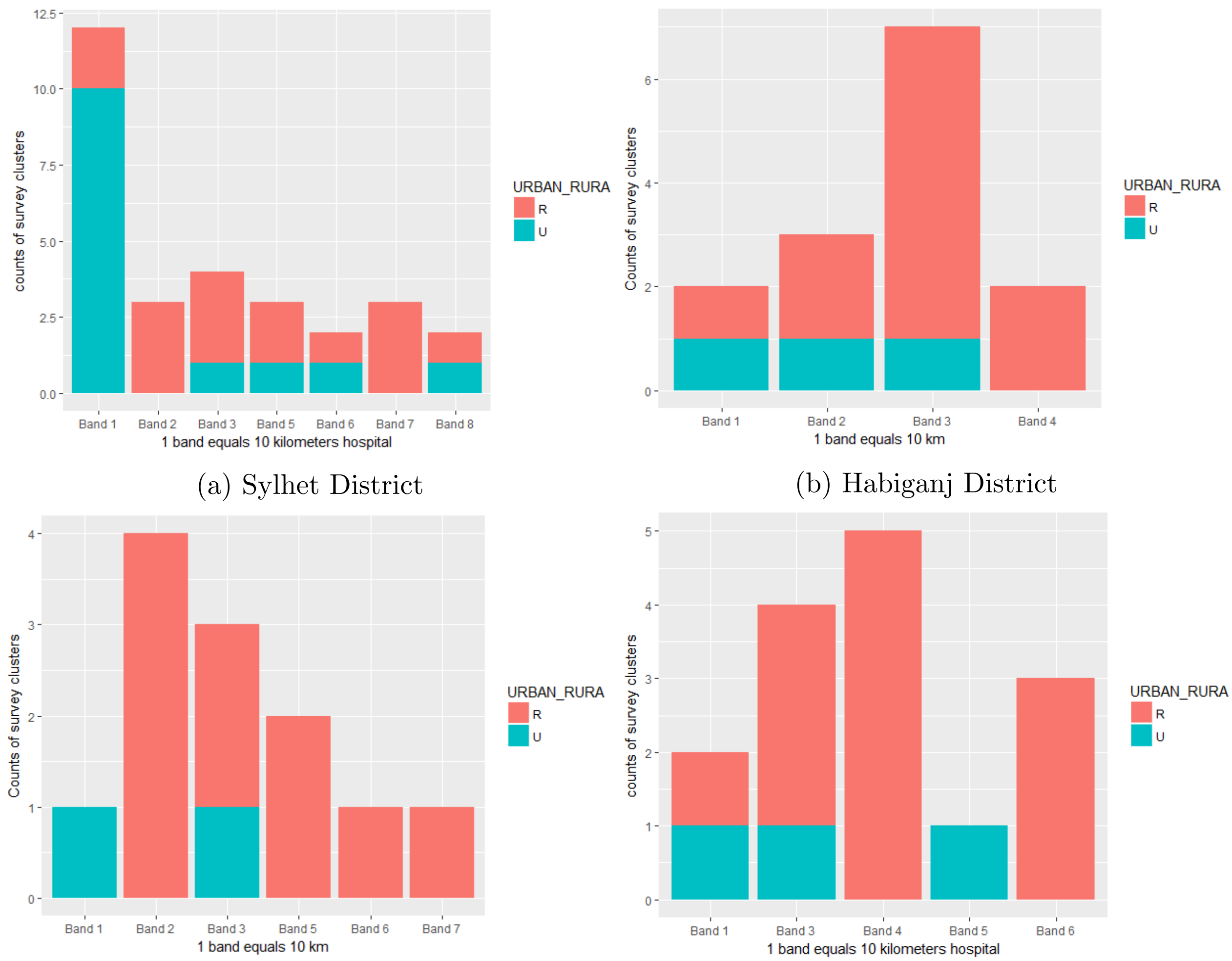
(c) Patuakhali District



(d) Pirojpur District

Figure 5.16. Distance to the nearest hospital by rural-urban differences in Barisal Division

corporations the pattern was not homogeneous in terms of distance and service usage. City corporations where most clusters were urban accounted for a larger share of institutional births while rural communities in some of these areas were responsible for a higher share of home births. While some city corporations had all or majority of the surveyed clusters living in the first distance band, in case of others it was found that some communities lived in the second distance band. This suggest that city corporations are heterogeneous and differ in their sizes, which influences the hospital service areas. They are also very heterogeneous on the population density front, which makes the competition intense to access public health



(a) Sylhet District

(b) Habiganj District

(c) Maulvibazar District

(d) Sunamganj District

Figure 5.17. Distance to the nearest hospital by rural-urban differences in Sylhet Division

services for certain city corporations in the Barisal Division while it makes the resources more available in some of these areas in Sylhet Division that are less densely populated. Within Sylhet Division, the exception is Sylhet City Corporation because its population density is double than its most densely populated counterparts in Barisal Division and is much higher compared to any other sub-district in the Sylhet Division. The high proportion of home births in the city corporations of both the Divisions manifests the problem of urban poor in these areas. With regard to the influence of the varying size of the district and the hospital service areas on the commuting pattern, it was observed that in both the divisions distances to the nearest hospital stretched up to 50, 60, 70, and 80 kilometers while for districts that were smaller in terms of their geographical area and had fewer number of sub-districts, distances to access the nearest hospital shrank to 50 or less kilometers. It is also possible that in smaller districts accessibility from neighboring Upazillas of the city corporation may be better due to their relatively smaller size. This confirms that the range of the hospital service areas is linked to the variation in the spatial extent of the administrative units. Both the divisions had districts that were relatively large and the range of the distances were substantially higher and both had districts that were relatively smaller and the radius of the service area was much smaller. Even though the traditional policy discourse views Sylhet as the worst performing region, this analysis confirms that differences in access to public health facilities and service usage are more influenced by the geographic inequalities in the size of the administrative units than any specific regional differences.

CHAPTER 6

MODELLING DISTANCES AS A FUNCTION OF COVARIATES AND WOMAN'S CHOICE FOR DELIVERY

After an exploratory analysis in the previous chapter, this chapter models distances and travel time for district and sub-district hospital as a function of covariates. This would help validate the findings from the previous chapter. It should be noted that all the variables were only for the two selected study areas. Even though the survey data is nationally representative, some of the variables were constructed from the GIS data that were processed for the two Divisions. As a result the sample size was restricted only to these two regions. However, for the purpose of this analysis data were pooled from both the divisions and analysis was run on these combined data.

Table 6.1 and Table 6.2 describe the individual, community and area level covariates that were used from multiple data sources and provides descriptive statistics for the data respectively. Table 6.3 displays the results for travel time to the nearest hospital from where a community lived and the self-reported travel time to the nearest district headquarter. It is evident that majority of the variation is explained by time to the administrative headquarter. Even though the survey questionnaire did not explicitly ask for whether this was a public or a private hospital, it can be assumed that while district hospitals are in close vicinity of administrative headquarters, private hospitals are also likely to be concentrated in these areas. This is because city corporations are the most densely and relatively better off areas in comparison to other sub-districts. District area has a negative and a significant relationship. This meets the initial expectations and the arguments made in the previous chapter. Having access to just a seasonal road or a waterway significantly increased travel time to the nearest hospital. Road density is positively associated with travel time. While one would expect that an increase in the road density should lower travel time, the positive sign on the coefficient

Table 6.1. Individual and Area Variables

Individual-level variable	**Measure**
Place of delivery	Coded as 1 for an institutional delivery and 0 otherwise
Household Wealth Index	Variable available from BDHS2011. Constructed using principal component analysis based on survey questions on household wealth assets
Age of mother	Age in years
ANC visits	Number of antenatal care visits
Place of ANC	Coded as 1 if a women availed care at a private clinic or a hospital, coded as 2 for government, 3 for home
Urban cluster	Whether the EA was urban or rural based on the community questionnaire
Area-level variables	**Measure**
Time to Thana Health Center	Self-reported travel time in minutes from an EA
Time to Thana headquarter	Self-reported travel time in minutes from an EA
Distance to Thana Health Center	Self-reported travel distance from an EA
Time to nearest hospital	Self-reported travel time in minutes from an EA
Time to District headquarter	Self-reported travel time in minutes from an EA
Distance to nearest hospital	Self-reported travel distance from an EA
School Density in Thana	Primary schools digitized in each sub-district divided by the area
Clinics Density in Thana	Clinics digitized in each sub-district divided by the area
Population Density in Thana	Based on census data for 2011 obtained from Bangladesh Bureau of Statistics
Area of Thana	Measured in kilometers in ArcGIS
Road Density in Thana	Road length of the sub-district divided by the area
All Weather Road Access	Self-reported measure on type of road access from EA
Seasonal Road Access	Self-reported measure on type of road access from EA
Waterway Access	Self-reported measure on type of road access from EA
Unpaved Road Access	Self-reported measure on type of road access from EA
Percent of Urbanization in Thana	Based on census data
District Area in Sq km	Based on census data
Population Density in District	Based on census data

Table 6.2. Descriptive Statistics

Individual-level variables	**N**	**Mean**	**sd**
Place of delivery (Home)	1447		
Place of delivery (Institutional)	461		
Household Wealth Index	4154	4474.961	101886.1
Age of mother	4154	31	9
ANC visits	1914	2.12	2.70
Place of ANC (Private)	360		
Place of ANC (Government)	457		
Place of ANC (Home)	85		
Area-level variable	**N**	**Mean**	**sd**
Time to Thana Health Center	123	59.27	47.56
Time to Thana headquarter	98	66.75	60.05
Distance to Thana Health Center	123	10	9
Time to nearest hospital	140	96.92	76.36
Time to District headquarter	98	121	84.69
Distance to nearest hospital	140	26.4	20.82
School Density in Thana	142	.24	.14
Clinics Density in Thana	129	.06	.03
Population Density in Thana		1018	610
Area of Thana		355	217
Road Density in Thana	142	8.148	5.36
All Weather Road Access	96		
Seasonal Road Access	36		
Waterway Access	9		
Unpaved Road Access	1		
Percent of Urbanization in Thana			
District Area in Sq km	142	2453	1082
Population Density in District	142	780	203
Urban cluster	44		
Rural cluster	98		

Table 6.3. Time to the nearest hospital

Time to the Hospital	**Model**
Variable	Coefficient
Time to District Headquarters	0.858***
	(0.0414)
School Density in Thana	-16.21
	(23.28)
Clinics Density in Thana	-30.69
	(121.8)
Population Density in District	0.0365
	(0.0186)
District Area in Sq Km	-0.0105**
	(0.00396)
Seasonal Road Access	16.99*
	(6.853)
Waterway Access	42.74***
	(11.77)
Unpaved Road Access	-73.72*
	(31.31)
Road Density	1.700*
	(0.709)
Constant	-0.981
	(24.35)
R^2	0.887
$AdjR^2$	0.874
F	67.36
df_m	9
df_r	77
$Number of Communities$	87

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

could in part be explained by the country's humongous population density due to which even if there is increased availability of roads travel time may not necessarily reduce.

Table 6.4 compares three different models with regard to the average distance to two closest district hospitals. Average distance was calculated by first obtaining estimates from the EA to the two closest district hospital using near tool in ArcGIS. These two distances were combined to obtain average distance from the EA or the community. School density is negatively related and remains a statistically significant predictor across three models. This relationship makes sense as school density is highest in the city corporations and that is where the public hospitals are usually situated. So as density increases, average distance decreases. As the distance to the hospital increases, the population density also increases. Interestingly, as the district area increases, the average distance also increases in all three models. The positive relation between road density and average distance could be explained by better availability of road in urban areas and more densely populated areas and further one goes from the urban centers the road density also declines. Distance to the nearest hospital and average distance to the hospital are positively related. If the average distance to two closest THC increases, average distance to the hospital also increases. But if the average distance to four closest THC increases, the average distance to the hospital reduces.

Table 6.5 shows the results from a linear regression for the travel time to the nearest Thana Health Center (THC) or the sub-district hospital. The outcome variable in the model was based on the self-reported travel time from the sampled EA and was chosen from the community questionnaire of BDHS 2011. Time to the nearest THC was most explained by the travel time to the nearest Thana Headquarters and the relationship is statistically significant. This makes sense as most public health facilities are situated in close vicinity of the administrative headquarters. Having access to a waterway from where a community lives increased travel time to the nearest THC. Together these variables explained about 75 percent of the variation in getting access to the nearest THC. Table 6.6 shows the results for average distance to four closest THC's as a function of several covariates. Across all the three model, the average distance to two closest THC's is significant predictor. This makes sense as sub-districts that are smaller in size are likely to have shorter average distance to two or even four closest THC's. Several sub-districts that have a small area are likley to have THC in close vicinity, which reduces the overall distances to the neighboring THC's. As population density at the district level increases, the average distance to the closest THC's reduces. This could be explained by urbanization and better accessibility to provision of goods and services. Area of the district is a consistent predictor and the relationship is inverse. As road length increases, so does the average distance. If the community was accessible mostly by waterway, then the average distance to THC also increased. Overall , these three models explain about roughly 60 percent of the variation in the average distances to THC's.

Table 6.7 shows results from logistic regression, with a women's choice for delivery as an outcome variable. It is modeled as 1 if a women gave birth at an institutional facility and 0 if the place was home. Among individual level covariates, wealth index and the number of antenatal care visits a woman had are significant predictors. The odds of institutional delivery greatly increase when a women seeks antenatal care from a private source such as private clinic or hospital. With regard to availing antenatal care at a government hospital there is no significant relationship, suggesting perhaps the poor quality of government services. Since results from the previous chapter showed a distance decay effect for home and institutional births within the first distance band on a consistent basis for most sub-districts, a distance of 10 kilometers was used to assess the effect of proximity to the hospital. Based on the self-reported distance to the nearest hospital from the community questionnaire, hospital within 10 kilometers was created as an indicator variable with the value 1 if the sampled community was within 10 kilometers of the nearest hospital and 0 otherwise. In the first model, this relationship is a significant and the odds increase for women as they live in proximity to 10 kilometers of the hospital. However, in model 2 this relationship becomes insignificant as

Table 6.4. Average Distance to Two Nearest District Hospital

Avg Distance to Hospital	**Model1**	**Model2**	**Model3**
Variable	Coefficient	Coefficient	Coefficient
School Density in Thana	-24.04*	-19.09*	-17.63*
	(9.331)	(8.977)	(7.561)
Clinics Density in Thana	45.92	63.81	40.91
	(48.95)	(46.93)	(39.17)
District Population Density	0.0462***	0.0415 ***	0.0325***
	(0.00681)	(0.00662)	(0.00576)
District Area in Sq Km	0.00727***	0.00903***	0.00536***
	(0.00140)	(0.00142)	(0.00133)
Road Density	1.431***	0.959***	-0.450
	(0.241)	(0.262)	(0.284)
Seasonal Road Access	2.046	-1.094	-5.075
	(5.319)	(5.132)	(4.388)
Waterway Access	-2.267	-7.863	-2.710
	(14.08)	(13.50)	(11.12)
Nearest Hospital		0.251***	0.256***
		(0.0642)	(0.0554)
Avg Distance to Two closest THC			1.848***
			(0.247)
Avg Distance to Four closest THC			-1.394***
			(0.276)
Constant	-23.95**	-29.46***	-8.338
	(8.354)	(8.098)	(9.125)
R^2	0.585	0.632	0.755
$AdjR^2$	0.557	0.603	0.732
F	21.12	22.29	32.30
df_m	8	9	11
df_r	129	127	127
$NumberofCommunities$	129	129	129

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6.5. Time to the Nearest Thana Health Center

Time to the nearest Thana Health Center	**Model1**
Variable	Coefficient
Time to the nearest Thana Headquarters	0.675 ***
	(0.0590)
School Density in Thana	-32.01
	(27.00)
Clinics Density in Thana	29.70
	(118.1)
Population Density in Thana	0.00811
	(0.0140)
Area of Thana	0.00426
	(0.0188)
Road Density in Thana	0.0915
	(0.611)
Seasonal Road Access from the Community	-2.375
	(7.470)
Waterway Access from the Community	31.17 *
	(12.22)
Unpaved Road Access from the Community	8.614
	(31.21)
Percent of Urbanization in Thana	0.328
	(0.507)
Constant	12.91
	(17.45)
R^2	0.749
$Adj R^2$	0.712
F	20.55
df_m	10
df_r	69
$Number of Communities$	80

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6.6. Average Distance to the four nearest Thana health Centers

Avg Distance to THC	**Model1**	**Model2**	**Model3**
Variable	Coefficient	Coefficient	Coefficient
School Density in Thana	-10.923 ***	-6.578 ***	-4.411
	(2.338)	(2.45)	(2.398)
District Population Density	-0.004 *	-0.0031	-0.00409*
	(0.001)	(0.0018)	(0.00175)
District Area in Sq Km	-0.001***	-0.0022***	-0.00257***
	(0.0003)	(0.00035)	(0.000350)
Road Length for Thana	0.00001***	0.0000249***	0.0000220 ***
	(0.00000356)	(0.00000347)	(0.00000332)
Seasonal Road Access	-.315	0.111	-0.900
	(0.803)	(0.749)	(0.713)
Waterway Access	4.454*	4.182*	2.803*
	(1.408)	(1.420)	(1.377)
Unpaved Road Access	4.567	4.84	3.905
	(4.07)	(3.712)	(3.549)
Urbanization in Thana	0.013	0.029	
	(0.017)	(0.160)	
Avg Distance to two closest THC			0.210***
			(0.0537)
Clinics Density in Thana		-24.516	-22.69
		(12.96)	(12.39)
Constant	15.02***	15.02***	16.62***
	(2.447)	(2.447)	(2.440)
R^2	0.502	0.584	0.621
$AdjR^2$	0.472	0.552	0.592
F	16.82	18.58	21.67
df_m	8	9	9
df_r	133	119	119
$Number of Communities$	142	129	129

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6.7. Women choice for place of delivery

Place of birth	**Model1**	**Model2**
Variable	Odds Ratio	Odds Ratio
Wealth Index	1.000 ***	1.000***
	(0.00000105)	(0.00000107)
Age of mother	0.993	0.991
	(0.0154)	(0.0154)
Number of ANC visits	1.152***	1.153***
	(0.0367)	(0.0367)
Pvt ANC	3.251**	3.388 **
	(1.227)	(1.297)
Govt Inst ANC	1.949	1.966
	(0.731)	(0.748)
Hospital within 10 km	1.794*	1.518
	(0.446)	(0.397)
Upazilla Area	0.998*	0.998*
	(0.000938)	(0.000921)
Upazilla Population Density	1.000	1.000*
	(0.000197)	(0.000206)
Upazilla Road Density	1.034	1.031
	(0.0364)	(0.0363)
Clinics Density	2980.8*	897.2*
	(9399.0)	(2884.6)
Urban cluster		1.847**
		(0.408)
Constant	0.151*	0.178*
	(0.113)	(0.133)
N	812	812

Exponentiated coefficients; Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

urban-rural variable was included in the model. The community survey questionnaire included a variable if the EA or the community was urban or rural. As upazilla or thana area increases, the odds of women's choosing an institutional delivery decreases. The density of clinics remained a consistent predictor of institutional deliveries. While women may not go directly to avail services at a clinic during or after pregnancy, high density of clinics should reflect a better overall service environment, with the possibility that non-government organization funded services and other private services may also be in tandem with government services.

CHAPTER 7

EXAMINING SUPPLY AND DEMAND FOR PRIMARY HEALTH CARE IN BANGLADESH

7.1 Primary Health Care in Developing Countries

The previous chapter showed spatial inequity in the service area of health facility is tied to the inequality in the administrative units. The only exception to this norm are primary health care clinics because they are assigned based on a fixed population and are not allocated by village or mauza. This provides an excellent opportunity to assess whether the supply of clinics matches the population demand.

In the wake of rapid urbanization, globalization, and emergence of new forms of communicable and chronic diseases, primary health care has received a renewed focus. Even though it has been several decades since the Alma Ata declaration was signed, when for the first time countries pledged their commitment to health equity and recognized health as a right, countries have achieved a varied level of success in their ability to provide primary health care services. In the absence of a large network of primary health care centers, promises made by governments of low and middle-income countries with regard to universal health care would remain ineffective. Primary health care offers an opportunity for universal access to care, especially when they are funded by government and are free to the public. It's close vicinity to where people live offers opportunity even to poor people to access essential services, without facing any barriers related to transportation costs and time (Van Lerberghe, 2008). When physical access to primary health care is supplemented with adequate logistics and supply chain system to ensure the availability of drugs and essential medicines, it can have a major improvement. Several countries have been successful in improving health indicators based on the provision of services under primary health care. In Kenya, availability of insecticide treated bednets through local services has been attributed to lower incidence of malaria

(Van Lerberghe, 2008). China's rural health care system, managed by the barefoot doctors helped address the gaps in health disparity through equitable distribution of resources even in rural areas and by focusing on preventive care, health education and promotion activities, maternal and child health issues and in performing disease surveillance related activities. While the country suffered when the system was dismantled and more people were forced to spend out-of-pocket, the government recognized this problem and increased health spending under the Rural Medical Cooperative Scheme (Zhaoyang, 2008). Similar to the success of China's barefoot doctors, Thailand has used Buddhist monks and network of temples to promote health promotion activities within the community. Thailand's primary health care program that relies on a network of volunteer doctors and nurses helped the country reduce new HIV incidents to about 13,936 cases in 2007, from 100,000 in 1995 (Treerutkuarkul, 2008).

Brazil, which recognizes health as a constitutional right since 1988, follows a decentralized system of universal health care under which each individual is provided comprehensive and free primary health care. The country's flagship program, Family Health Program, is organized in teams comprising of doctors, nurses, and staff. The system is used by roughly 70 percent of the country's population as they cannot afford private care (Tomassini, 2008). Just like Brazil, Portugal also recognizes the right to health as a constitutional right. The country, introduced a new primary health care program in 2005, under which group of family doctors, nurses, and administrative staff work together in units known as the Family Health Units. Portugal is working on a series of reforms to provide integrated and community based health care that is comprehensive, free, and responsive to the needs of the local people. The country's infant mortality rate has reached almost at par with European countries, an impressive gain since the 1970s. Portugal, which established a comprehensive network of primary health care services along with a hospital network between 1979-1983 also witnessed a major reduction in perinatal mortality, infant mortality, and maternal mortality (Waddington, 2008; Van Lerberghe, 2008).

Primary health care services can also reduce waiting time at the hospitals and help improve health outcomes by delivering essential services. In Oman, a rapid expansion of district hospitals and regional health facilities along with an increase in the number of health workers enabled the country to achieve 90 percent of births attended by trained personnel. In contrast, prior to this expansion in Oman, patients traveled up to 4 days to reach a hospital and had to wait in a long queue to see a physician. It can also bridge rural-urban disparities. In Iran, under-5 mortality in rural areas was twice than the urban areas, but a gradual expansion in primary health care network enabled the country to sharply narrow this gap by 2000 and the service utilization rates are almost the same (Van Lerberghe, 2008). On the other hand, Nigeria, which had not been successful in instituting successful PHC reforms, saw a steady increase in infant mortality rates between 1982 to 2007 (Reid, 2008).

7.2 Primary Health Care Policy in Bangladesh

Based on the 1996-2001 five year plan, the Government of Bangladesh has enacted a policy of providing a community clinic for every six thousand population. Community clinics (CC's) are organized at the grassroots level and are expected to provide basic health facilities. Located at the ward level, CC's are the lowest level static health facilities with referral linkages with higher level health facilities. Between 1998 and 2003, 10,723 CCs were constructed of which 8000 were made functional. The Government started a project titled "Revitalization of community-based health care in Bangladesh". As of 2014, 13,094 independent community clinics were made functional. These CC's are managed by a 13-17 member management committee. By April 2014 all the CC's received internet connection and laptop. While these clinics are mostly in rural areas, they are available in selected urban corporations. A growing population density in some of the city corporations is widening the gap in the availability of government funded primary care services between rural and urban areas, between the city corporations and the non-city corporations urban areas and between the regions. The problem of urban population and lack of access in the context of Bangladesh becomes very acute due to heavily skewed population in the urban areas and lack of availability of services. Since tertiary-level services are mostly located in the urban areas, it is mostly the urban population that has access to hospitals. Often hospitals are very crowded and there are long waiting lines. However, in the absence of availability of primary health facilities, most people have to go to government hospitals even for basic services, which further exacerbate the problem. Yet there is no systematic evidence on equity in the distribution of primary health care services in Bangladesh.

Fortunately, primary health care in Bangladesh received a renewed focus under the Bangladesh Urban Primary Health Care Project, which was funded by several donors. Under the project the government contracted services through non-profit organizations to run community clinics. The lowest level services that are available in the urban areas are delivered through NGO field workers. Another project that was being operated in the urban areas included the Smiling Sun clinics another donor assisted project to improve population health in the urban areas. The Urban Community Health Program was specifically designed for the population living in urban slums (Ahmed et al., 2007).

7.3 Research Objectives

Given the evidence on the role of primary health care in improving population health, this research seeks to examine spatial equity in the distribution of primary health care by examining the geographical distribution of community clinics. However, any assessment of equity in coverage would be incomplete without knowing the underlying population distribution. Common approaches to measure underlying population distribution include areal interpolation or dyasmetric mapping. However these are also prone to error. The goal of dyasmetric mapping is to identify populated areas vis--vis areas which are not inhabited by population settlements due to geographic barriers such as rivers, mountains, forests. It classifies the population into homogeneous areas based on the data and creates a smooth surface. This is a different in comparison to a polygon based approach under which information about population distribution is aggregated at an administrative unit. A major disadvantage of this approach is that any variation in the underlying population density gets masked due to aggregation.

In the absence of availability of population data based on satellite imagery, this research used the distribution of primary schools as a proxy for the underlying population distribution. In terms of hierarchy of services, both primary schools and clinics offer services in close proximity to the population. Hence, the use of primary schools can be considered as a proxy for population distribution. Furthermore, both primary schools and clinics would be where population settlements exist as one would not expect a primary school to be at a location where there are no settlements. This gives an additional reason to hypothesize that the distribution mirrors the underlying population. Thus it was hypothesized that if the supply of clinics matched the population demand it would be regarded as spatial equity. In contrast if the supply of the clinics did not follow the demand, it would be regarded as a spatial mismatch.

In this research, the clinics were treated as cases and the primary schools were treated as controls. In geographical epidemiology, it is a common method to compare two distributions by treating one as cases and the other as controls. For instance, by comparing the spatial distribution of two diseases, one could ascertain whether the risk for a disease is uniform across the study area; whether it follows the underlying population distribution; or whether there are specific areas where the risk may be greater for the occurrence or spread of a disease. Generally, one would expect that two distributions would match because the incidence rates of a specific disease are likely to be higher where the underlying population distribution is also high and lower where the population is sparsely populated. Several applications can be found in epidemiology where these techniques were used to assess if the incidents were unusually higher at any specific locations and identify disease clusters. The most famous application was the lung and larynx cancer incidence rates, with the former being treated as case and the latter being used as a control (Kelsall and Diggle, 1995). Another noted example is the geographic distribution of primary bilary cirhosis modelled by (Prince et al., 2001). (Waller and Gotway, 2004) demonstrate a similar application through the use of medieval grave data and in the context of childhood asthma in San Diego county based on an original paper published by (English et al., 1999). More recent examples examining spatial variation in risk by comparing the intensities of two distributions include (Zhang et al., 2013) and (Lemke et al., 2015). (Lawson, 2013) argues modeling the distribution of cases and controls as a binary logistic regression, conditional on the location. However, a major disadvantage of such a technique is that it requires covariate data at each of the point locations in the study area, which may not be available easily, especially in the context of developing countries. Some other alternative techniques include application of the spatial SCAN statistic, as demonstrated by as demonstrated by (Rushton and Lolonis, 1996), in the context of birth defects. The authors examine proportion of cases that fall within a specific radius around the controls and identify statistically significant clusters. To assess the spatial mismatch in the supply and the demand for primary health care, the following assumptions were made:

1. The supply of clinics follow the population distribution. Hence, places with higher population density should have more clinics than places with lower population density

2. It was assumed that the distribution of primary schools reflects a higher proportion of population of mothers and young children since primary schools are usually set up in close proximity to where children can go to school. Thus the locations of the primary schools were used as a proxy for population distribution

3. Since primary health care is related to offering basic and preventive services at the grassroot level and the distribution of primary schools should reflect the age and the demographic structure of young population, it can be assumed that the distribution of one should follow the other. Therefore, it was assumed that the distribution of the clinics follow the distribution of primary schools

4. It can be assumed that in densely populated areas the density of primary schools would be higher, therefore one would also expect to see a higher density of clinics. In contrast in sparsely populated areas the density of primary schools and clinics should be lower as fewer people live in such areas and hence lower should be the demand. Similarly, places where nobody lives such as forests and rivers and hills, one would not expect to see any school or a clinic at such a location.

5. Furthmore, it was assumed that the service area of the clinics and the schools should be homogeneous. Thus the population serviced by each clinic should be similar to the average number of children served by each primary school

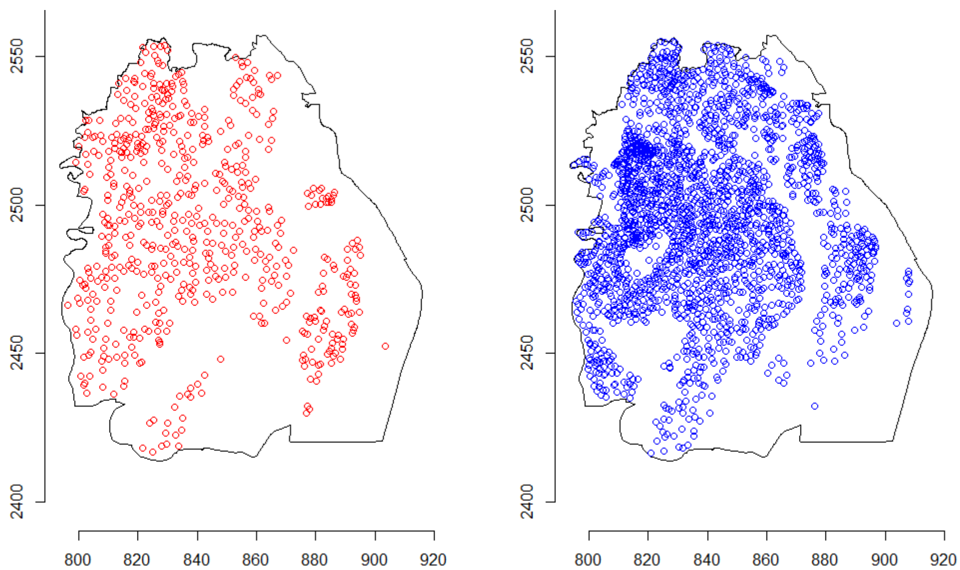
Based on the assumptions stated above, the specific research objectives were as follows:

1. Does the distribution of clinics follow the distribution of schools?

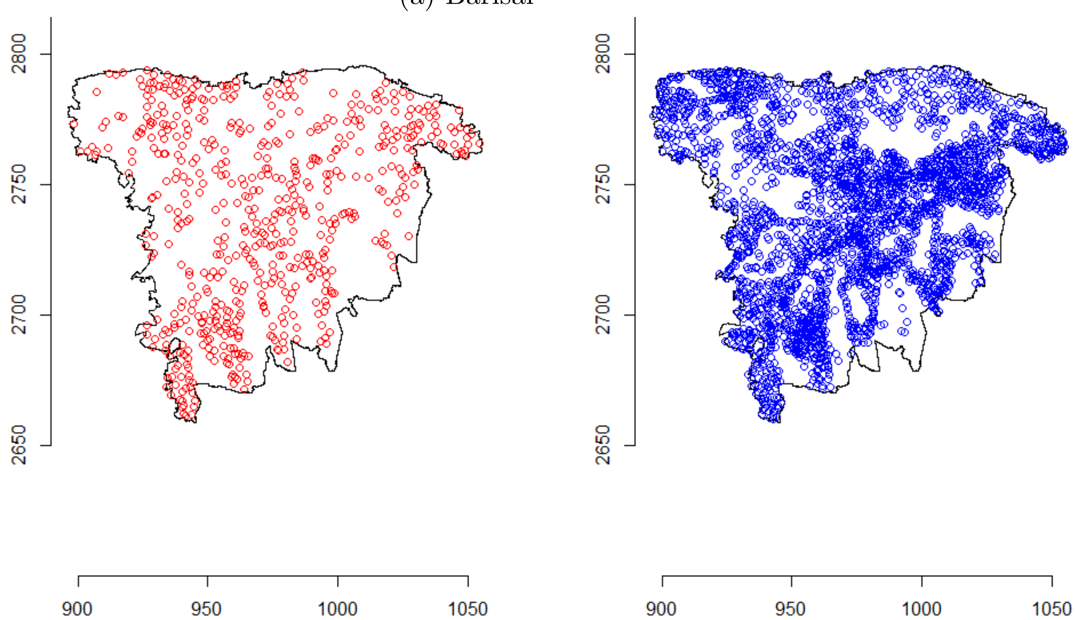
2. Does this distribution of clinics match the population demand in both urban and rural areas?

3. Identify under-served and over-served areas

In order to examine whether the distribution of clinics match the distribution of schools, the ratio of two intensities will be compared. Areas where the intensity of the clinics exceed to that of primary schools would suggest that supply exceeds the demand whereas in areas where this ratio is lower would imply that the population demand exceeds than the available supply of primary health care through clinics.



(a) Barisal



(b) Sylhet

Figure 7.1. Point pattern for Barisal and Sylhet Divisions. The top row shows the distribution of the clinics and primary schools for Barisal Division and the bottom row shows the two distributions for Sylhet Division

Table 7.1. Comparison of the two point patterns

Clinics	**Barisal Division**	**Sylhet Division**
Frequency	615	578
Proportions	0.22	0.16
Intensity	0.0476	0.0465
Window Area	12932.3 sq km	12429.9
Schools	**Barisal Division**	**Sylhet Division**
Frequency	2180	2850
Proportions	0.78	0.83
Intensity	0.16	0.23
Window Area	12932.3 sq km	12429.9

7.4 Data

To test the spatial mismatch hypothesis, the distribution of clinics was compared in a densely population and in a sparsely populated region of Bangladesh. A comparison of two regions that are very similar in their area and only differ in their population distribution offers an opportunity to test not just how the distribution of the clinics compare to the population distribution within a region, but also how this distribution varies in a densely populated areas versus sparsely populated areas and the distances at which one would expect them to be accessible for the population. For example, in a densely populated areas, one would expect a higher intensity as the clinics should be closely located to each other if they are set up based on the government policy of serving a specific size of the population. In contrast, in a sparsely populated areas, one would expect the population to be more dispersed in sparsely populated areas, and therefore the intensity of the points should be lower. Furthermore, one would also expect that in areas with lower population density, the distances at which the services are available are likely to be larger in comparison to densely populated areas.

Figure 7.1a and 7.1b shows the distribution of the clinics and schools in Barisal and Sylhet Division. The figure shows that visually the distribution of the clinics and the primary school seem to be following one another. In places where there are no primary schools, one can assume that nobody lives there and one would not find any clinic at such a location. Table 7.1 compares the summary statistic for the two point patterns in the study area. The intensity refers to the average number of points per unit area of the study region, which is usually referred as a window area by the software package. The window area was rescaled to kilometers from meters to reflect accurately the spatial extent of the study area in its original units. Frequency refers to the total number of points of each type in the window area, while the proportion refers to the contribution of one type of points in the overall point pattern. For both the study area, the clinics account for a much smaller proportion than the schools, with the latter having a much higher intensity than the former. Descriptive statistics from the table suggest differences in the intensity of the two processes. A question which then arises is to assess whether the two intensities match or not. In other words, it would be of interest to know whether areas with high intensity of clinics also have a high intensity of schools and vice-versa.

7.5 Methodological Approaches in Point Pattern Analysis

Given the distribution of the clinics and primary schools is in the format of a point pattern data, it provides an opportunity to examine the above stated research objectives using a variety of methods that have been developed to compare two distributions. While the first study that used the most basic form of point pattern analysis was conducted by John Snow to examine the distribution of the incidents of cholera around the Broad Street Pump, in recent years these techniques have become popular to model the distribution of diseases. The assumptions stated above are consistent with the popular methods in spatial epidemiology where the geographic distribution of another disease is used as a proxy for population distribution.

Statistical methods to model the spatial distribution of point locations are usually based on the first and the second order properties of a point process. The first order property pertains to the homogeneity assumption by which the intensity of the points is uniform for the entire study area. These tests allow to investigate whether the point pattern is completely random or it deviates from complete randomness, thereby providing insights into specific places where the points may be more or less likely to occur. Tests of complete spatial randomness allow investigation into the first order properties of the point process i.e whether the mean or the intensity is constant over the study area. The second order property assesses dependence or the spatial scale at which there is any evidence of clustering (Bailey and Gatrell, 1995).

Two key properties of the point patterns are:

1. The expected number of points in the region A follows a poisson distribution with the mean $\lambda|A|$
2. The points are independent and have a uniform distribution

A popular technique to assess the first order property is the use of kernel density estimation. In case of point data of a single type, kernel density estimation technique creates a radius of a specific distance around a point, known as smoothing bandwidth, and sums the points that falls within this disc. Hence, in areas where the density of points is more, it creates a peak and in areas where there are fewer points, the density estimates show a rough or a spiky surface. Mathematically, the function is specified in (Baddeley et al., 2015) as follows:

$$\lambda^{\tilde{0}}(u) = \sum_{i=1}^{n} K(u - x_i) \tag{7.1}$$

where the function $K(u - x_i)$ represents the probability density at a location x_i such that $k(u) \geq 0$ and the $\int_{R^2} K(u) = 1$. The formula stated above is without edge correction. Since the points at the boundary of the study area contribute less, different edge correction techniques exist to correct for this bias. In spatstat, by default the correction is done based on the techniques recommended by Diggle. Two commonly used edge correction techniques that is available in the software include uniform correction and Diggle's correction technique and are specified respectively in (Baddeley et al., 2015) as follows:

$$\lambda^{U}\tilde{(}u) = \frac{1}{e(u)} \sum_{i=1}^{n} K(u - x_i) \tag{7.2}$$

$$\lambda^{D}\tilde{(}u) = \sum_{i=1}^{n} \frac{1}{e(x_i)} \sum_{i=1}^{n} K(u - x_i) \tag{7.3}$$

Similar to estimating the kernel density for univariate data, the approach can be extended to bivariate distribution. In recent years comparison of bivariate distribution of point data has emerged as popular, especially in spatial epidemiology to detect disease cases relative to the controls or the population distribution. This is also known as a case-control method where the point location of incidents are considered as cases and a comparison is made to the point distribution of another disease that can serve as a control or reflects the spatially varying population. However, bivariate kernel density estimation requires taking into consideration several issues. A common issue is the choice of bandwidth since the cases and the controls have different intensities, so the question arises as to whether one should choose a case-based bandwidth or based on the controls. (Davies et al., 2016) recommends a choice of a common bandwidth for the case and controls to avoid any artifact that arises by choosing different bandwidths. Similarly, (Bailey and Gatrell, 1995) warns against simply taking the ratios of the numerator and denominator as the resulting ratios may be sensitive to small changes in the denominator; instead they recommend over- smoothing, especially when is interested in examining ratios of intensities. Since the controls or the population at risk is generally much larger than the cases, in certain situations it is recommended to use a larger bandwidth for the controls (Bailey and Gatrell, 1995). In a study examining ratios of birth defects to all births in Des Moines Iowa, (Rushton and Lolonis, 1996) recommended expanding search radius wide enough to ensure each case and control gets included in the computation of the ratios. (Waller and Gotway, 2004) also cite a similar concern as in areas where the cases or the controls might be too small, it may lead to numerical instability that arises due to division by zero. Therefore, there seems to be a consensus that the most sensible bandwidth for cases and controls may not be the best choice when taking their ratios.

When taking ratios of two kernel intensities, a common and a recommended approach is to take a log transformation of these ratios to stabilize the variance. As a result most software packages provide log ratios of kernel densities by default. If $\lambda_1(s)$ denotes the intensity of cases and $\lambda_0(s)$ is the intensity of the controls, then assuming that the distribution of the cases and the controls arise from two independent random samples, then the density function is estimated as follows: (Waller and Gotway, 2004)

$$f(s) = \lambda_1(s) \Big/ \int_D \lambda_1(u)du \tag{7.4}$$

where f(s) is the function for cases

$$g(s) = \lambda_0(s) \Big/ \int_D \lambda_0(u)du \tag{7.5}$$

where g(s) is the function estimating the intensity of the controls. Then it is suggested to take a natural logarithm of the ratio of the two densities based on

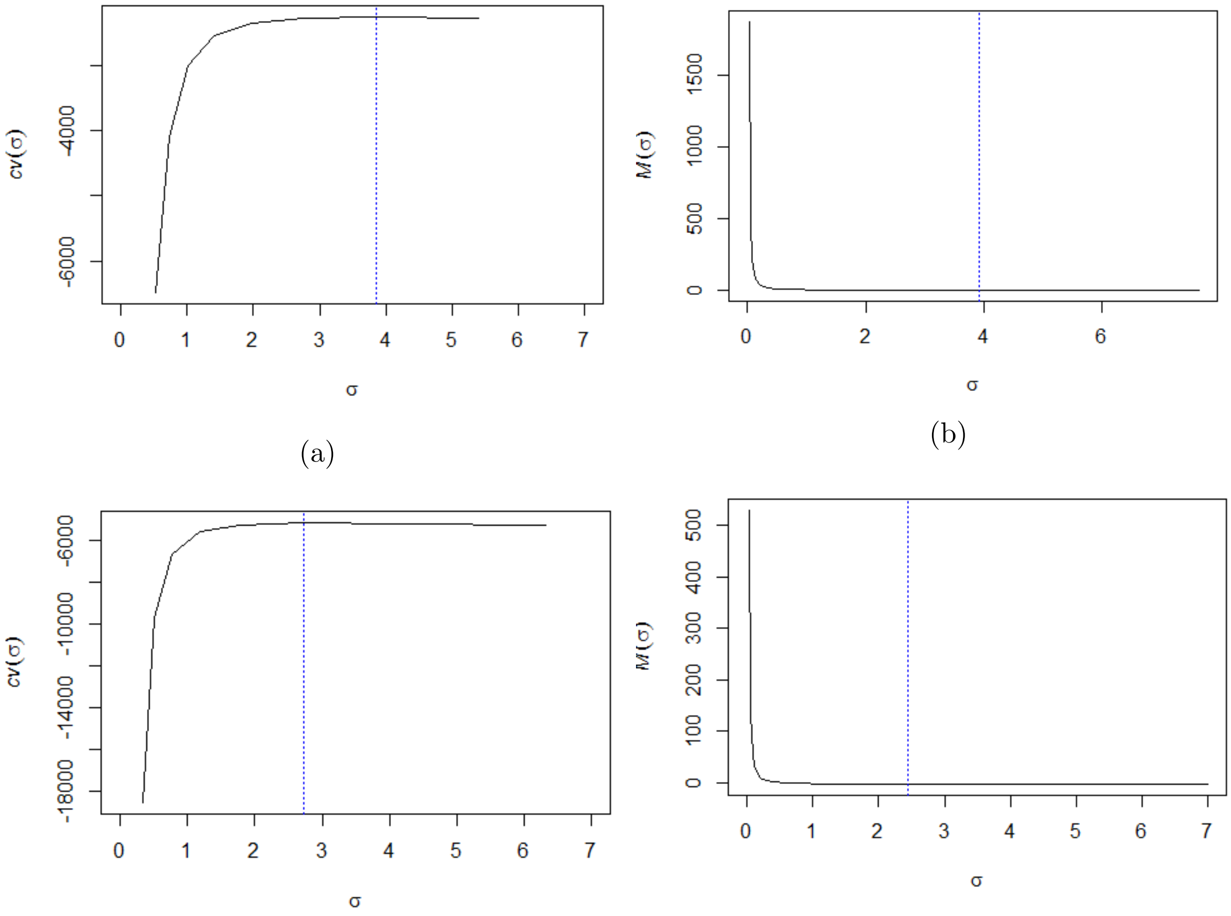
$$r(s) = log\{f(s)/g(s)\} \tag{7.6}$$

where r(s) is the log of relative risk of observing a point as a case instead of a control at a given location. This allows identification of the areas where risk r(s) exceeds 0.

The equation discussed above uses a fixed bandwidth. The assumption, therefore, is based on the intensity of the cases and controls being constant across the study area. However, some scholars argue that this assumption may not always make sense since the population distribution is heterogeneous and recommend using adaptive bandwidths. Unlike fixed bandwidths that use the same smoothing parameter for the entire study area, adaptive bandwidths expands in sparsely populated areas, taking a larger number of points, and shrinks in densely populated areas (Davies et al., 2011). This approach has found wide applications in spatial epidemiology in recent years (Zhang et al., 2013; Lemke et al., 2015). An elaborate discussion of the results will follow in the next section. The R package spatstat and smacpod are based on fixed bandwidths even though spatstat has the functionality to implement adaptive bandwidths based on univariate data. The most commonly used software for adaptive bandwidths is sparr package written by (Davies et al., 2011). In spatstat the raw intensity i.e number of points per unit area is standardized by multiplying it with the window area.

7.6 Regional Variation in the Distribution of Cases and Controls

Based on the figure 7.2 it can be noted that even though the intensities of the clinics and the schools differ substantially, the suggested bandwidths for the two point pattern based on maximum likelihood and cross-validation approach only differ by one kilometer. However, the two approaches do provide a different result in case of Sylhet as evident from the figure 7.3. The bandwidth for the clinics suggested by the maximum likelihood approach is larger than one kilometer as opposed to the suggested bandwidth for Diggle. The rural-urban divide can be observed in the suggested bandwidths for the two regions. Since Sylhet is more rural than Barisal, the bandwidth for clinics is larger as one would expect. However, the difference appears marginal when it comes to the bandwidths for schools in Sylhet. A plausible explanation for this anomaly could be that while most of the region is predominantly rural, population in Sylhet City Corporation is more than twice than the most densely populated places in Barisal. This could be a reason why the intensity of schools is more in Sylhet than Barisal even though on a regional level, the former is less densely populated in comparison to the latter. The bandwidths recommended based on the two approaches can inform into the possible choice of bandwidths, however there is no compulsion as to use the theoretically suggested bandwidths, especially when one is primarily interested in taking the ratios of two

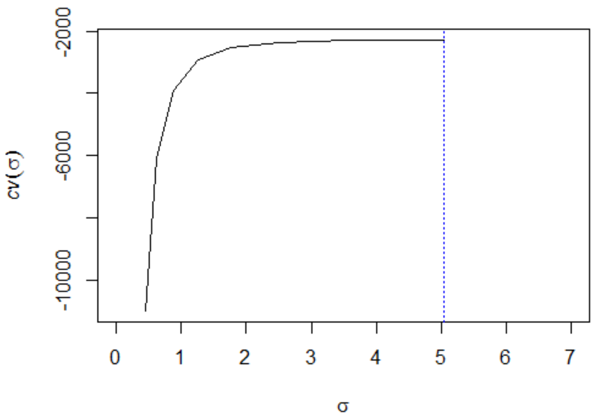


(a) (b)

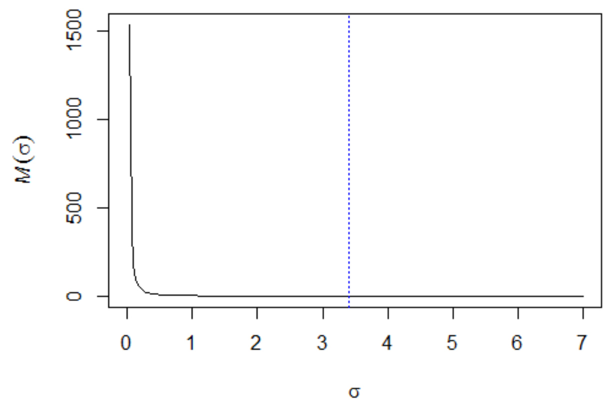
(c) (d)

Figure 7.2. Bandwidth for clinics and schools in Barisal based on maximum likelihood and cross-validation approach. The top row shows the suggested bandwidths for clinics based on the two approaches and the bottom row displays for schools.

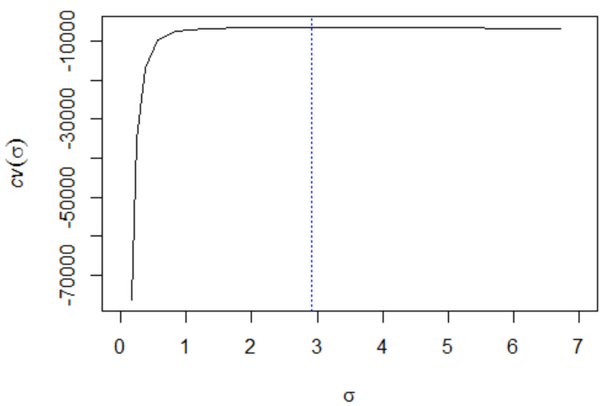
kernel densities. While there is no agreement on the choice of bandwidths in the literature, there is broadly a consensus that it should make sense based on the data as taking a very large bandwidth would over-smooth the data and mask variation whereas having too small a bandwidth would under-smooth the data and result in a very patchy pattern, without providing any meaningful results. Therefore, in case of Barisal Division, the fixed bandwidths was chosen at 5 kilometers as choosing a bandwidth less than that was resulting in numerical



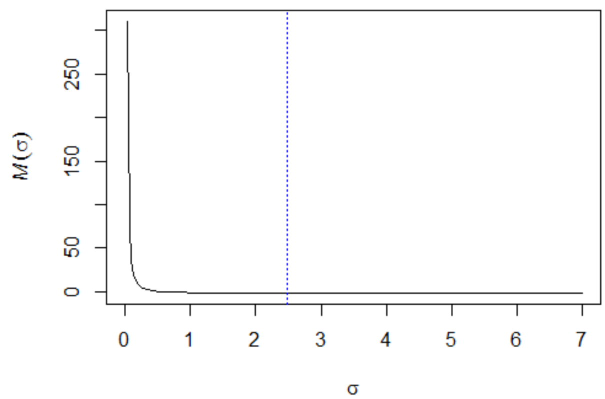
(a)



(b)



(c)

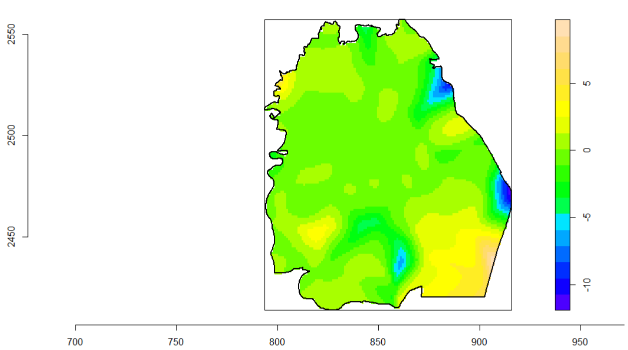


(d)

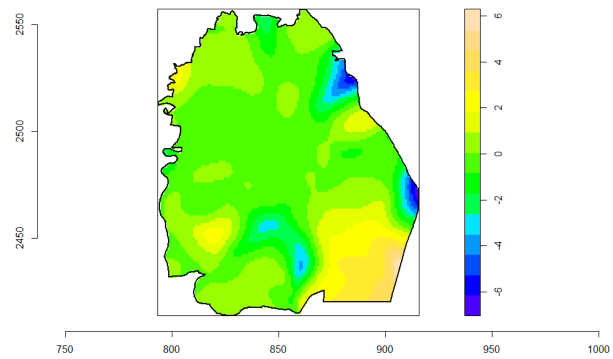
Figure 7.3. Bandwidth for clinics and schools in Sylhet based on maximum likelihood and cross-validation approach. The top row shows the suggested bandwidths for clinics based on the two approaches and the bottom row displays for schools.

instability. In case of Sylhet Division, the fixed bandwidth was run for 4 and 5 kilometers, and this did not create any problems.

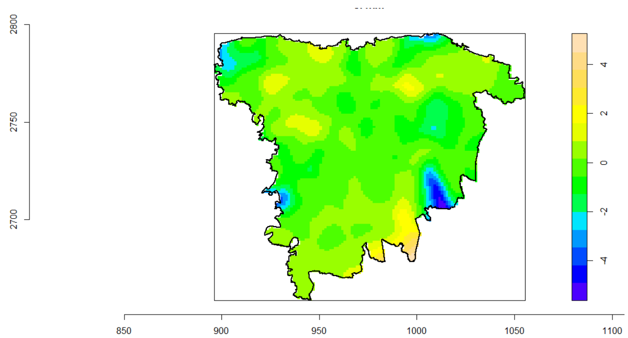
Figures 7.4 and 7.5 shows the relative risk surface based on the ratios of two intensities using fixed bandwidth and adaptive bandwidths respectively. While fixed bandwidth standardizes the density based on area, adaptive densities work under slightly different assumption. If the distribution of the cases vary over the study area, then the distribution of the controls should also vary, and the intensity of the cases should mostly mirror the process



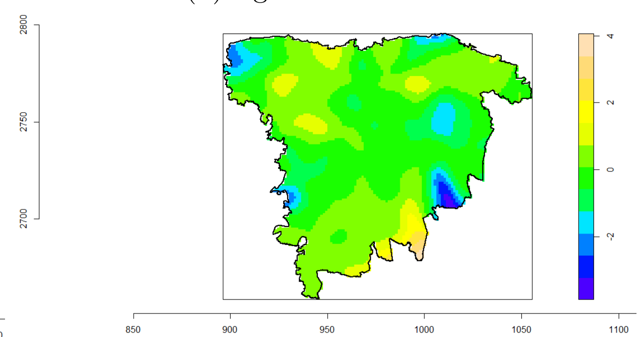
(a) sigma= 4 km fixed



(b) sigma=5 km fixed



(c) sigma= 4 km fixed

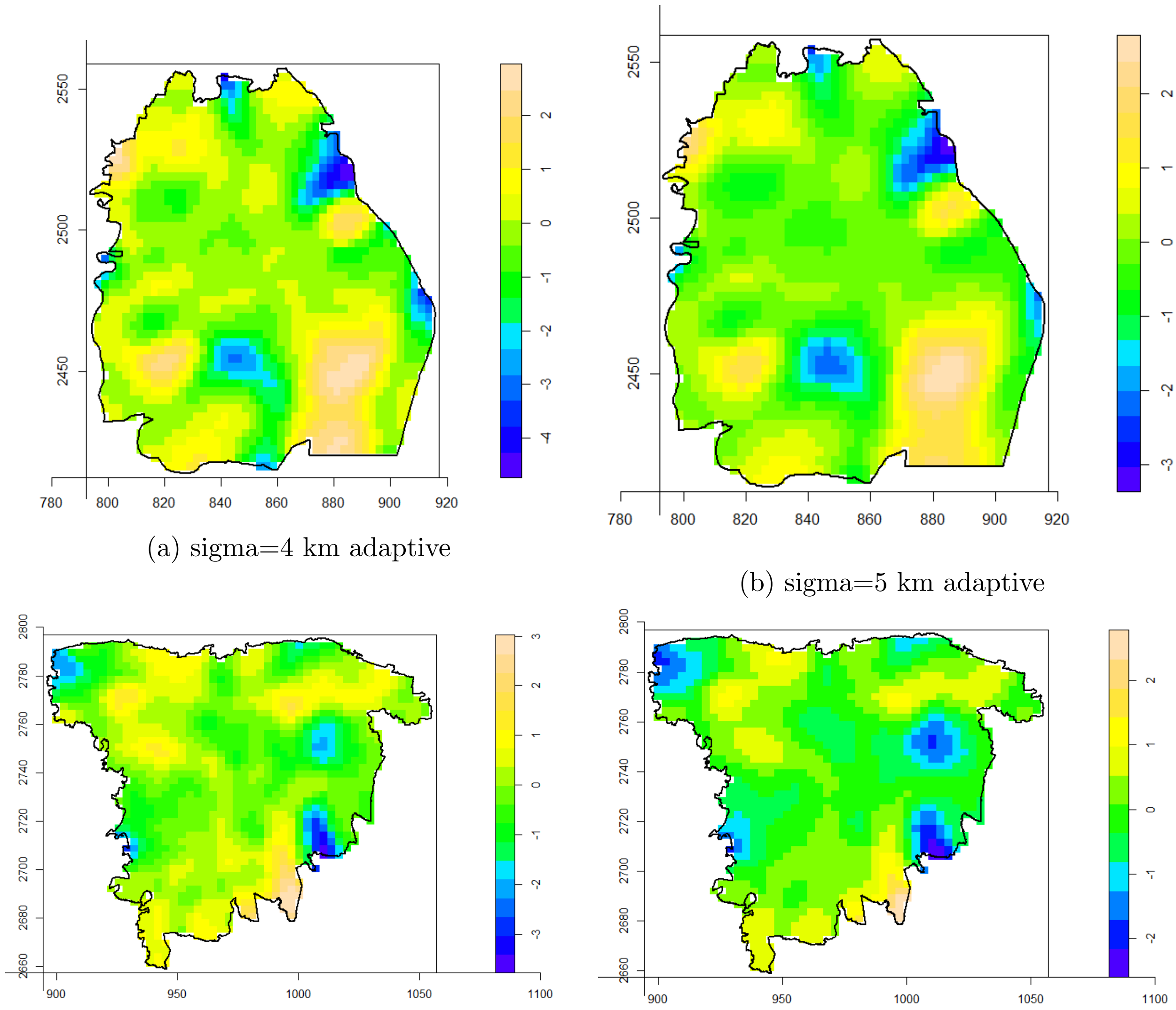


(d) sigma=5 km fixed

Figure 7.4. Log relative risk surface for Barisal and Sylhet based on a fixed bandwidth of 4 and 5 kilometers.

that is underlying the controls. So adaptive bandwidths expands in sparsely populated areas as the number of points is more dispersed in comparison to densely populated areas.

Figures 7.6 and 7.7 displays the distribution of the probability densities computed from the log risk function based on the bivariate kernel densities. As pointed out earlier, the use of logarithms is a common practice in the ratio of two kernel densities as it imparts symmetry and stabilizes the variance. The log ratios also provide a useful interpretation as areas with the value zero detect neutral risk and areas where the ratios exceeds zero or one indicate a higher presence of clinics than schools and vice-versa. Based on the histograms, it can be observed that the range of density values stretch much more for fixed bandwidths as opposed to adaptive bandwidths for both the Divisions. However, the results for the fixed and the adaptive bandwidths show more similarity for Sylhet Division than Barisal. This



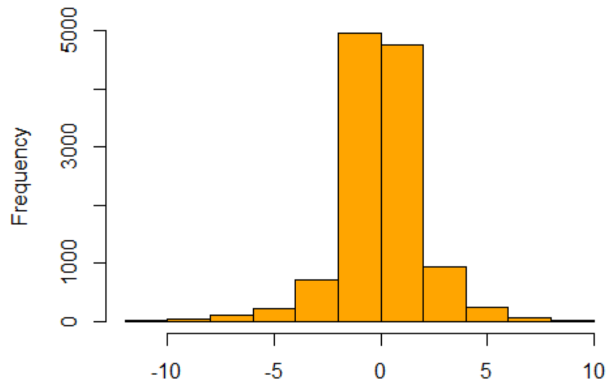
(a) sigma=4 km adaptive

(b) sigma=5 km adaptive

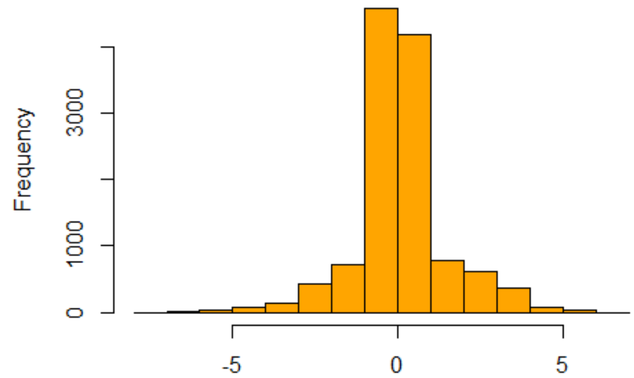
(c) sigma=4 km adaptive

(d) sigma=5 km adaptive

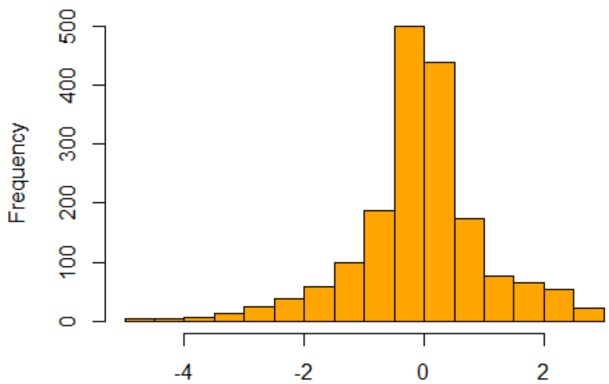
Figure 7.5. Log relative risk surface for Barisal and Sylhet based on adaptive bandwidths of 4 and 5 kilometers



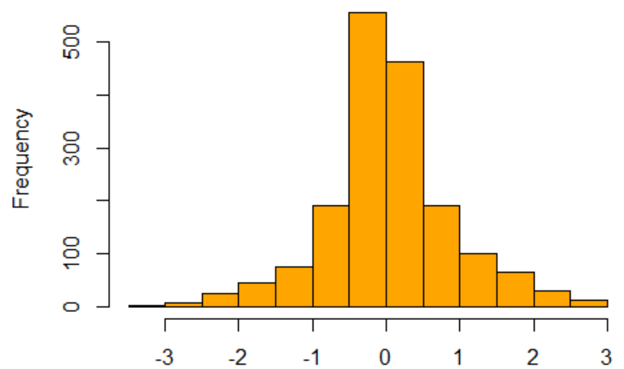
(a) sigma=4 km fixed



(b) sigma=5 km fixed



(c) sigma=4 km adaptive

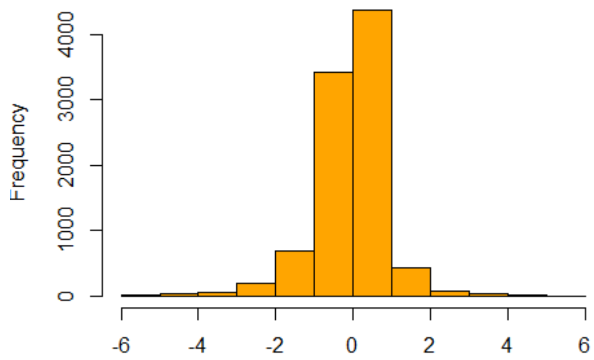


(d) sigma=5 km adaptive

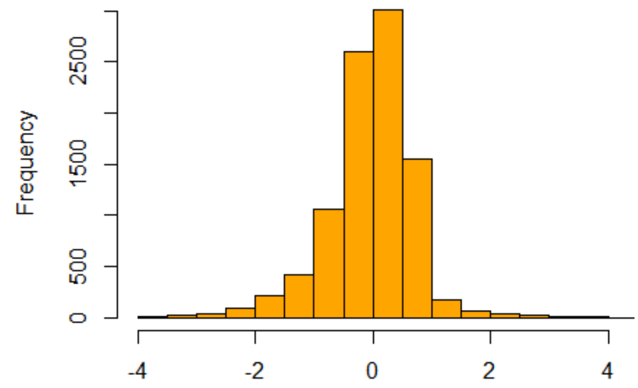
Figure 7.6. Histogram of the ratios of spatial densities for Barisal

suggests that even though Sylhet is relatively sparsely populated, the ratio of the clinics to the schools is less skewed as compared to Barisal.

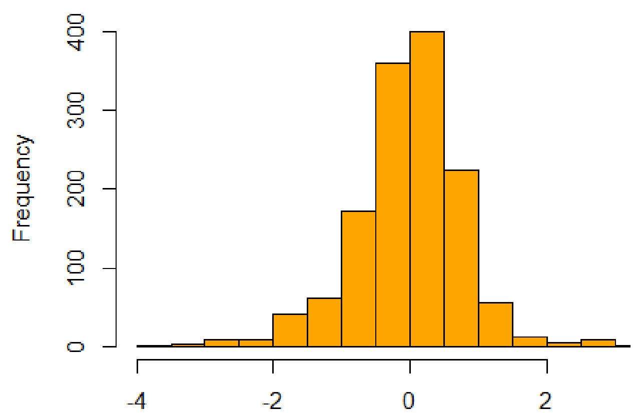
Figures 7.8, and 7.9 demonstrates the log relative risk surface constructed from 999 simulations using Monte Carlo. The manner in which this simulation works is that it randomly assigns the label of a case or a control conditional on the location for each simulated pattern. The process is repeated based on a pre-specified number of simulations and then values obtained from the simulations are compared to the observed value to detect areas of statistical significance where the controls exceed the cases and vice-versa. The light green and yellow areas detect well-served areas or areas where the ratio of clinics exceed to that of schools, whereas areas in dark green and different shades of blue indicate under-served



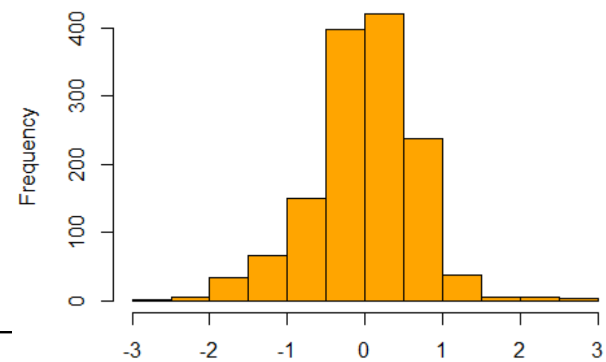
(a) sigma=4 km fixed



(b) sigma=5 km fixed



(c) sigma=4 km adaptive



(d) sigma=5 km adaptive

Figure 7.7. Histogram of the ratios of spatial densities for Sylhet

areas or areas where the ratio of the schools exceed to that of clinics. In both the Divisions, urban areas get detected as under-served areas and most over-served areas get detected on the boundaries. In Barisal Division, Barisal City Corporation and Bhola City Corporation are extremely densely populated while Char Fasson, which is close to the Bay of Bengal, is predominantly a rural area. Results show these urban centers as under-served areas while the rural areas in Char Fasson, DaulatKhan, Agailjhara, Nesarabad are identified as well-served regions. In Sylhet Division, the Sylhet City Corporation is the most densely populated while the rest of the region is mostly rural and sparsely populated. Ironically, the Sylhet City Corporation, is identified as under-served area and rural areas at the periphery show as reasonably well-served. Results for both the divisions show a consistent pattern.

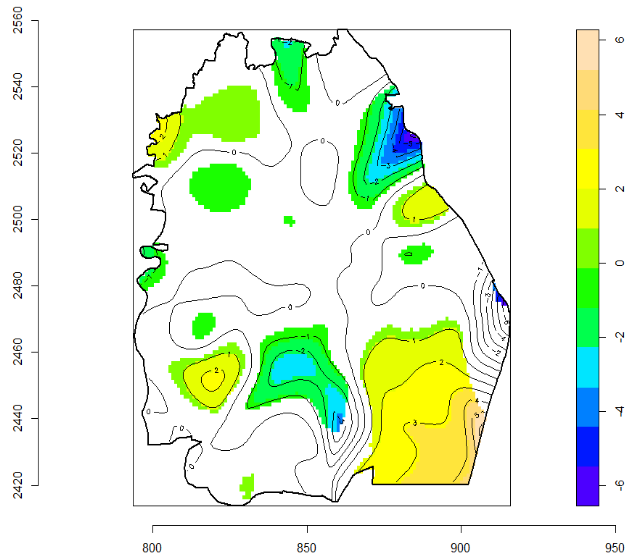
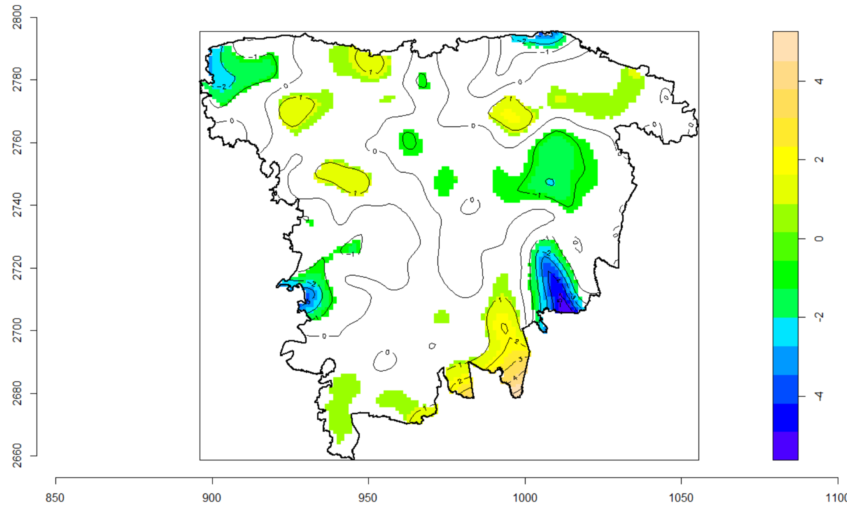


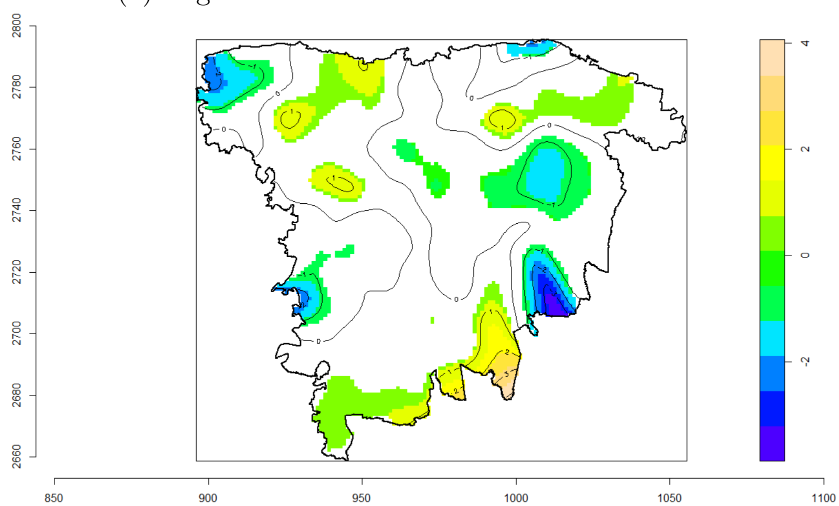
Figure 7.8. Log relative risk surface for Barisal Division based on 999 simulations with a 5 km bandwidth

7.7 Limitations and Delimitations

This analysis is limited by the fact that the data were not available for the non-profit organizations and private organizations that deliver primary health care. In Bangladesh, several non-profit organizations led by BRAC, USAID operate programs that work towards providing primary health services in selected urban areas. As a result findings are biased to the degree that the analysis only accounted for clinics exclusively run by government and could not account for alternative delivery mechanisms. However, lack of availability of private providers for primary care was not much of a concern because the focus of the analysis was mostly on government led primary health care services. Another limitation of the study was lack of any information on any difference in the capacity of the clinics or the primary schools in the urban versus rural areas. But if there was any difference in the population served by the clinics or schools in urban areas versus rural areas, then these effects would cancel out each other while estimating the ratios. A major delimitation of this study lies in its approach to estimate spatial inequity in the absence of population information at a disaggregate scale.



(a) Log relative risk based on a bandwidth of 4km



(b) Log relative risk based on a bandwidth of 5km

Figure 7.9. Log relative risk based on a bandwidth for Sylhet

CHAPTER 8

CONCLUSION

In Bangladesh, the traditional policy discourse has focused on regional differences that influence poor health outcomes in certain areas. This study is the first to compare two regions of the country and examine factors influencing equity in the distribution of health services. By understanding factors that drive the current distribution of health facility in terms of spatial access, one can understand consumers who have the most access to public health facilities and those that are the most deprived from the reach of government services , this research identifies the over-served and under-served areas for two regions of Bangladesh for both primary health care services and for public hospitals. While most geo-spatial studies are conducted for a small geographic area, this is the first study to compare two regions of the country. By comparing and contrasting two regions, this research finds that factors influencing intra and inter-district variation are similar across the divisions of Bangladesh. A unique contribution of this research is that it examines factors influencing inequity for both tertiary level facilities such as public hospitals and for primary health care. In Bangladesh the administrative hierarchy becomes more unequal as one moves from the division level to the mauza level. While some divisions have the optimal number of lower order units nested in them, some other divisions have too many administrative units under their control. This affects access and service delivery. The allocation of the health facilities is found not to be consistent with the homogeneous service areas and the market areas principles as recommended under the principles of urban hierarchy and central place theory. With regard to access to hospital level services, this research finds that that district-level spatial variation in the distances traveled to public health facilities, such as hospitals, is influenced by the size of the districts and the administrative units nested within them. As a result, districts that are smaller in size have a smaller hospital service area and therefore shorter commuting distance while communities in larger districts have longer distances to traverse to access the nearest hospital. Another factor influencing intra-district variation is also the number of administrative units that are nested within each district. Therefore, communities that live in sub-districts that are at the periphery of the district center are likely to have to travel the most while communities that live in sub-districts that are situated at the core of the administrative center are likely to have to commute the least. This research finds that district hospitals in Bangladesh are situated in the city corporations, hence communities living in the city corporations had the least distance to commute while further the communities lived from the city corporation, distanced increased. This has an important implication in terms of the spatial mismatch problem in the context of Bangladesh because the country small land size and high population density has resulted into some densely populated urban clusters even at the periphery of certain districts. As a result densely populated communities living on the periphery of the district get excluded from government services.

An examination into the relation between the distances to the nearest hospital and service utilization, this research finds that at shorter distances institutional births were higher while they declined at longer distances and vice-versa in most cases. However, in some districts rural-urban differences in the communities masked the influence of distance on service usage. Among rural and urban clusters, there appeared to be heterogeneity on the influence of distance on service utilization. Communities in some of the districts showed a lower rate of institutional births in spite of being located at short distances, suggesting the high population density in some of the urban clusters that increases the competition for public health services for the poorer population in the proximity to hospitals.

This research is the first to examine empirically the problem of access for primary health care services in Bangladesh. While recent debates in the literature have focused on the problem of urban poor, this dissertation is the first to understand factors driving the spatial distribution of clinics and assess the mismatch between the supply and demand for primary health services. This research finds that population is mostly concentrated in urban areas whereas clinics are most concentrated in the rural areas, suggesting a mismatch between the availability of services and the population demand. Across the two regions, rural areas at the periphery and within the core areas get identified as well served but urban areas are identified as under-served.

This research has a few policy implications for health policy delivery and provides recommendations to the Government of Bangladesh that influences intra-regional differences. Given that population growth is likely to be in the urban areas, an important policy implication of this research is the need for expansion of primary care services in the urban areas, especially in the city corporations which remain the most densely populated places. Bangladesh's high population density in the regions periphery excludes certain population from hospital service areas. This increases intra-urban disparities. Bangladesh's topography also makes some of the areas away from the city corporation less connected by road and transportation network. This exacerbates the problem of spatial equity. Therefore, to improve service utilization indicators such as institutional births in these most deprived areas, the Government of Bangladesh must improve connectivity and provide free ambulance or transportation services to communities living in the most deprived area. Another alternative would be to harness the river network and develop a ferry network that connects communities that are currently excluded from government health services and make these areas more accessible.

8.1 Limitations and Delimitations

In spite of the usefulness of the findings of this research for policy purposes, this research was confronted with several limitations. Firstly, while the survey data provided the geolocation of the communities, displacement of the survey locations limited the scope of spatial analysis. Secondly, the individual and the community survey questionnaire consisted of several variables that provided an opportunity to examine spatial access and service utilization within the communities. However, the survey data was not a geographic sample and was population representative at the regional level. Therefore, utmost care was taken to ensure that any methodology that was chosen for analysis doesn't violate the data collection procedure for the survey data. Furthermore, the GIS data that were obtained lacked information on private providers and non-profit organizations. Therefore, the analysis was restricted towards examining government health facilities only. The analysis was limited to distances and could not account for travel time using multiple modes of transportation. In a densely populated country like Bangladesh it is possible that even at short distances travel time to a nearby hospital could be much more in comparison to a hospital that is situated much further away in a sparsely populated area with good road conditions. Unfortunately, this research could not take into account differences in travel time due to lack of availability of accurate street network data. Apart from disparities that differ by travel distance and time to the health facility, this research did not control for any social and cultural barriers that affect women's choice in utilizing health services or even quality of services. However, it was beyond the scope of this research to address those issues.

A major strength of this research is supplementing the survey data with ancillary GIS data. While the DHS survey is a standardized questionnaire that is implemented in several countries, GIS data allowed construction of several additional covariates that were combined with the survey data. This allowed investigation into the spatial context of the communities within the sub-districts and examining the effect of covariates at the sub-district level on overall access and service utilization behavior. Another delimitation of this research is that the temporal period of the survey data and the field verification of the GIS data were similar. This made the study less biased. A novel contribution of this research is applying the prevailing methods in spatial epidemiology to examine the distribution of primary health care. This is an important contribution, especially in the context of developing countries where covariate data may not be easily available.

REFERENCES

Adams, A. M., R. Islam, and T. Ahmed (2015). Who serves the urban poor? a geospatial and descriptive analysis of health services in slum settlements in dhaka, bangladesh. *Health policy and planning 30*(suppl 1), i32–i45.

Ahmed, S. M., H. A. Begum, and K. Afsana (2007). Maternal, neonatal and child health programmes in bangladesh.

Aremu, O., S. Lawoko, and K. Dalal (2011). Neighborhood socioeconomic disadvantage, individual wealth status and patterns of delivery care utilization in nigeria: a multilevel discrete choice analysis. *International journal of women's health 3*, 167.

Asamoah, B. O., A. Agardh, K. O. Pettersson, and P.-O. Östergren (2014). Magnitude and trends of inequalities in antenatal care and delivery under skilled care among different socio-demographic groups in ghana from 1988-2008. *BMC pregnancy and childbirth 14*(1), 295.

Ayeni, B., G. Rushton, and M. L. McNulty (1987). Improving the geographical accessibility of health care in rural areas: A nigerian case study. *Social Science & Medicine 25*(10), 1083–1094.

Baddeley, A., E. Rubak, and R. Turner (2015). *Spatial point patterns: methodology and applications with R.* CRC Press.

Bailey, T. C. and A. C. Gatrell (1995). *Interactive spatial data analysis*, Volume 413. Longman Scientific & Technical Essex.

Balarajan, Y., S. Selvaraj, and S. Subramanian (2011). Health care and equity in india. *The Lancet 377*(9764), 505–515.

BDHS (2011). Bangladesh demographic and health survey. Technical report.

Bernard, P., R. Charafeddine, K. L. Frohlich, M. Daniel, Y. Kestens, and L. Potvin (2007). Health inequalities and place: a theoretical conception of neighbourhood. *Social science & medicine 65*(9), 1839–1852.

Berry, B. J. and W. L. Garrison (1958a). The functional bases of the central place hierarchy. *Economic Geography 34*(2), 145–154.

Berry, B. J. and W. L. Garrison (1958b). A note on central place theory and the range of a good. *Economic Geography 34*(4), 304–311.

Berry, B. J. L. and B. J. Berry (1967). *Geography of market centers and retail distribution.* Prentice-Hall Englewood Cliffs, NJ.

Berry, B. J. L., E. C. Conkling, and D. M. Ray (1987). *Economic geography: Resource use, locational choices, and regional specialization in the global economy.* Prentice Hall.

Berry, B. J. L., F. E. Horton, and J. O. Abiodun (1970). *Geographic perspectives on urban systems: with integrated readings.* Prentice Hall.

Braveman, P. and S. Gruskin (2003). Defining equity in health. *Journal of epidemiology and community health 57*(4), 254–258.

Buck, C., T. Kneib, T. Tkaczick, K. Konstabel, and I. Pigeot (2015). Assessing opportunities for physical activity in the built environment of children: interrelation between kernel density and neighborhood scale. *International journal of health geographics 14*(1), 35.

Burgert, C. (2013). Spatial interpolation with demographic and health survey data: Key considerations, dhs spatial analysis reports no 9. *United States Agency for International Development, Calverton, MD*.

Burgert, C. R., J. Colston, T. Roy, and B. Zachary (2013). Geographic displacement procedure and georeferenced data release policy for the demographic and health surveys.

Burgert-Brucker, C. R. and D. Prosnitz (2014). *Linking DHS household and SPA facility surveys: Data considerations and Geospatial Methods.* ICF International.

Chowdhury, M., L. Roy, T. Biswas, M. Rahman, S. Akther, and A. Al-Sabir (2014). needs assessment study for emergency obstetric and newborn care (emonc) services in 24 districts of bangladesh. *Dhaka: International Centre for Diarrhoeal Disease Research, Bangladesh*.

Clark, W. and G. Rushton (1970). Models of intra urban consumer behavior and their implications for central place theory. *Economic Geography 46*(3), 486–497.

Curtis, S. and I. Rees Jones (1998). Is there a place for geography in the analysis of health inequality? *Sociology of health & illness 20*(5), 645–672.

Davies, T. M., M. L. Hazelton, J. C. Marshall, et al. (2011). Sparr: analyzing spatial relative risk using fixed and adaptive kernel density estimation in r. *Journal of Statistical Software 39*(i01).

Davies, T. M., K. Jones, and M. L. Hazelton (2016). Symmetric adaptive smoothing regimens for estimation of the spatial relative risk function. *Computational Statistics & Data Analysis 101*, 12–28.

Dingle, A., T. Powell-Jackson, and C. Goodman (2013). A decade of improvements in equity of access to reproductive and maternal health services in cambodia, 2000–2010. *Int J Equity Health 12*(1), 51.

Ellis, P. and M. Roberts (2015). *Leveraging Urbanization in South Asia: Managing Spatial Transformation for Prosperity and Livability.* World Bank Publications.

English, P., R. Neutra, R. Scalf, M. Sullivan, L. Waller, and L. Zhu (1999). Examining associations between childhood asthma and traffic flow using a geographic information system. *Environmental health perspectives 107*(9), 761.

Gordon, P., A. Kumar, and H. W. Richardson (1989). The spatial mismatch hypothesis: Some new evidence. *Urban Studies 26*(3), 315–326.

Higgs, G. (2004). A literature review of the use of gis-based measures of access to health care services. *Health Services and Outcomes Research Methodology 5*(2), 119–139.

Hodgson, M. (1988). An hierarchical location-allocation model for primary health care delivery in a developing area. *Social Science & Medicine 26*(1), 153–161.

Holzer, H. J. (1991). The spatial mismatch hypothesis: What has the evidence shown? *Urban Studies 28*(1), 105–122.

Houston, D. S. (2005). Methods to test the spatial mismatch hypothesis. *Economic Geography 81*(4), 407–434.

Hu, L. (2015). Job accessibility of the poor in los angeles: Has suburbanization affected spatial mismatch? *Journal of the American Planning Association 81*(1), 30–45.

Jacobs, B., P. Ir, M. Bigdeli, P. L. Annear, and W. Van Damme (2012). Addressing access barriers to health services: an analytical framework for selecting appropriate interventions in low-income asian countries. *Health Policy and Planning 27*(4), 288–300.

Jin, C., J. Cheng, Y. Lu, Z. Huang, and F. Cao (2015). Spatial inequity in access to healthcare facilities at a county level in a developing country: a case study of deqing county, zhejiang, china. *International journal for equity in health 14*(1), 67.

Johnson, F. A., S. S. Padmadas, and J. J. Brown (2009). On the spatial inequalities of institutional versus home births in ghana: a multilevel analysis. *Journal of community health 34*(1), 64–72.

Jones, A. P., I. H. Langford, and G. Bentham (1996). The application of k-function analysis to the geographical distribution of road traffic accident outcomes in norfolk, england. *Social Science & Medicine 42*(6), 879–885.

Kearns, R. and G. Moon (2002). From medical to health geography: novelty, place and theory after a decade of change. *Progress in Human Geography 26*(5), 605–625.

Kelsall, J. E. and P. J. Diggle (1995). Non-parametric estimation of spatial variation in relative risk. *Statistics in medicine 14*(21-22), 2335–2342.

Khan, M. M., D. Ali, Z. Ferdousy, and A. Al-Mamun (2001). A cost-minimization approach to planning the geographical distribution of health facilities. *Health Policy and Planning 16*(3), 264–272.

Killingsworth, J. R., N. Hossain, Y. Hedrick-Wong, S. D. Thomas, A. Rahman, and T. Begum (1999). Unofficial fees in bangladesh: price, equity and institutional issues. *Health Policy and Planning 14*(2), 152–163.

Kim, D., M. Sarker, and P. Vyas (2016). Role of spatial tools in public health policymaking of bangladesh: opportunities and challenges. *Journal of Health, Population and Nutrition 35*(1), 8.

Langford, M. and G. Higgs (2006). Measuring potential access to primary healthcare services: the influence of alternative spatial representations of population. *The Professional Geographer 58*(3), 294–306.

Lawson, A. B. (2013). *Bayesian disease mapping: hierarchical modeling in spatial epidemiology.* CRC press.

Lemke, D., V. Mattauch, O. Heidinger, E. Pebesma, and H.-W. Hense (2015). Comparing adaptive and fixed bandwidth-based kernel density estimates in spatial cancer epidemiology. *International journal of health geographics 14*(1), 15.

Macintyre, S., A. Ellaway, and S. Cummins (2002). Place effects on health: how can we conceptualise, operationalise and measure them? *Social science & medicine 55*(1), 125–139.

Makinde, O. A., A. Azeez, S. Bamidele, A. Oyemakinde, K. A. Oyediran, W. Adebayo, B. Fapohunda, A. Abioye, and S. Mullen (2014). Development of a master health facility list in nigeria. *Online journal of public health informatics 6*(2).

Marmot, M., C. on Social Determinants of Health, et al. (2007). Achieving health equity: from root causes to fair outcomes. *The Lancet 370*(9593), 1153–1163.

McIntyre, D. and G. Mooney (2007). *The economics of health equity.* Cambridge University Press.

Meade, M. S. and M. Emch (2010). *Medical Geography.* Guilford Press.

MOHFW (2011). Health, population and nutrition sector development program. Technical report.

MOHFW (2014). Background paper on health strategy for the 7th five year plan.

Munoz, U. H. and C. Kallestal (2012). Geographical accessibility and spatial coverage modeling of the primary health care network in the western province of rwanda. *Int J Health Geogr 11*, 40.

Nakamura, D. (2014). Social participation and social capital with equity and efficiency: An approach from central-place theory. *Applied Geography 49*, 54–57.

Nesbitt, R. C., S. Gabrysch, A. Laub, S. Soremekun, A. Manu, B. R. Kirkwood, S. Amenga-Etego, K. Wiru, B. Höfle, and C. Grundy (2014). Methods to measure potential spatial access to delivery care in low-and middle-income countries: a case study in rural ghana. *International journal of health geographics 13*(1), 25.

Noor, A. M., A. A. Amin, P. W. Gething, P. M. Atkinson, S. I. Hay, and R. W. Snow (2006). Modelling distances travelled to government health services in kenya. *Tropical Medicine & International Health 11*(2), 188–196.

Okabe, A., T. Satoh, T. Furuta, A. Suzuki, and K. Okano (2008). Generalized network voronoi diagrams: Concepts, computational methods, and applications. *International Journal of Geographical Information Science 22*(9), 965–994.

Ononokpono, D. N. and C. O. Odimegwu (2014). Determinants of maternal health care utilization in nigeria: a multilevel approach. *The Pan African medical journal 17*(Suppl 1).

Oppong, J. R. and M. J. Hodgson (1994). Spatial accessibility to health care facilities in suhum district, ghana. *The Professional Geographer 46*(2), 199–209.

Panciera, R., A. Khan, S. J. R. Rizvi, S. Ahmed, T. Ahmed, R. Islam, and A. M. Adams (2016). The influence of travel time on emergency obstetric care seeking behavior in the urban poor of bangladesh: a gis study. *BMC pregnancy and childbirth 16*(1), 240.

Parr, J. B. and L. Budd (2000). Financial services and the urban system: an exploration. *Urban studies 37*(3), 593–610.

Prince, M. I., A. Chetwynd, P. Diggle, M. Jarner, J. V. Metcalf, and O. F. James (2001). The geographical distribution of primary biliary cirrhosis in a well-defined cohort. *Hepatology 34*(6), 1083–1088.

Rahman, S.-u. and D. K. Smith (2000). Use of location-allocation models in health service development planning in developing nations. *European Journal of Operational Research 123*(3), 437–452.

Reid, M. (2008). Nigeria still searching for right formula: despite several attempts at reform over the past 30 years, nigeria still lacks a clear and coordinated approach to primary health care. *Bulletin of the World Health Organization 86*(9), 663–666.

Rose-Wood, A., N. Heard, R. Thermidor, J. Chan, F. Joseph, G. Lerebours, A. Zugaldia, K. Konkel, M. Edwards, B. Lang, et al. (2014). Development and use of a master health facility list: Haiti's experience during the 2010 earthquake response. *Global Health: Science and Practice 2*(3), 357–365.

Rosero-Bixby, L. (2004). Spatial access to health care in costa rica and its equity: a gis-based study. *Social Science & Medicine 58*(7), 1271–1284.

Rushton, G. (1971). Postulates of central-place theory and the properties of central-place systems. *Geographical Analysis 3*(2), 140–156.

Rushton, G. and P. Lolonis (1996). Exploratory spatial analysis of birth defect rates in an urban population. *Statistics in Medicine 15*(7-9), 717–726.

Sanneving, L., N. Trygg, D. Saxena, D. Mavalankar, and S. Thomsen (2013). Inequity in india: the case of maternal and reproductive health. *Global health action 6*.

Skiles, M. P., C. R. Burgert, S. L. Curtis, and J. Spencer (2013). Geographically linking population and facility surveys: methodological considerations. *Population health metrics 11*(1), 14.

Streatfield, P. K. and Z. A. Karar (2008). Population challenges for bangladesh in the coming decades. *Journal of Health, Population and Nutrition*, 261–272.

Talen, E. and L. Anselin (1998). Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. *Environment and Planning a 30*(4), 595–613.

Tomassini, H. C. B. (2008). Flawed but fair: Brazils health system reaches out to the poor. *Bulletin of the World Health Organization 86*(4).

Treerutkuarkul, A. (2008). Thailand's unsung heroes. *Bulletin of the World Health Organization 86*(1), 5–6.

Van Lerberghe, W. (2008). *The world health report 2008: primary health care: now more than ever*. World Health Organization.

Waddington, R. (2008). Portugal's rapid progress through primary health care.

Waller, L. A. and C. A. Gotway (2004). *Applied spatial statistics for public health data*, Volume 368. John Wiley & Sons.

Wang, F. and W. Luo (2005). Assessing spatial and nonspatial factors for healthcare access: towards an integrated approach to defining health professional shortage areas. *Health & place 11*(2), 131–146.

Watson, V. (2009). Seeing from the south: Refocusing urban planning on the globes central urban issues. *Urban Studies 46*(11), 2259–2275.

World Health Organization (2010). *Hidden Cities: unmasking and overcoming health inequities in urban settings.*

Yang, D.-H., R. Goerge, and R. Mullner (2006). Comparing gis-based methods of measuring spatial accessibility to health services. *Journal of Medical Systems 30*(1), 23–32.

Yebyo, H., M. Alemayehu, and A. Kahsay (2015). Why do women deliver at home? multilevel modeling of ethiopian national demographic and health survey data. *PloS one 10*(4).

Zere, E., Y. Suehiro, A. Arifeen, L. Moonesinghe, S. K. Chanda, and J. M. Kirigia (2013). Equity in reproductive and maternal health services in bangladesh. *Int J Equity Health 12*(1), 90.

Zere, E., P. Tumusiime, O. Walker, J. Kirigia, C. Mwikisa, and T. Mbeeli (2007). Research inequities in utilization of maternal health interventions in namibia: implications for progress towards mdg 5 targets. *Hospital 2000*, 31.

Zhang, Z.-J., T. M. Davies, J. Gao, Z. Wang, and Q.-W. Jiang (2013). Identification of high-risk regions for schistosomiasis in the guichi region of china: an adaptive kernel density estimation-based approach. *Parasitology 140*(07), 868–875.

Zhaoyang, Z. (2008). Chinas village doctors take great strides. *Bulletin of the World Health Organization 86*(12).

BIOGRAPHICAL SKETCH

Priyanka Vyas, started her career as a journalist in New Delhi, after completing her BA in political science from Wilson College, Mumbai. During her stint as a reporter covering trade and policy issues, she became interested in how policies could be better analyzed and implemented. This single most desire to influence policy decisions led her to move to the US for further education. She earned her Masters in public management and policy from North Carolina State University and moved to The University of Texas, Dallas, to pursue her doctorate in public policy and political economy. During her doctoral studies, her research has focused on maternal and child health outcomes in the context of low and middle income countries and applying geospatial techniques to target health intervention. Her research has been featured in local media and newspapers such as the Daily Sun and The Business Line newspaper. She was also featured twice on the UT Dallas News Center for her publication in the field of occupational health and on the use of spatial approach towards improving health policy in developing countries. Upon the completion of her Ph.D.,Priyanka will be joining as a post-doctoral scholar at the University of California, San Francisco, School of Medicine, where she will be applying her policy and methodological background towards solving problems in public health, both on the domestic and international front.

CURRICULUM VITAE

Priyanka D. Vyas

June, 2017

Contact Information:

Public Policy and Political Economy
The University of Texas at Dallas
800 W. Campbell Rd.
Richardson, TX 75080-3021, U.S.A.

Email: `priyanka.vyas@utdallas.edu`

Educational History:

Ph.D., Public Policy and Political Economy, University of Texas, Dallas, 2017
M.P.A., North Carolina State University, 2011
B.A.,Wilson College, Mumbai, India, 2006

Additional Training:

Certificate in Geospatial Information Science, The University of Texas at Dallas, 2017 .

Bayesian Disease Mapping with Andrew Lawson, Consultant for the World Health Orgnanization on Disease Modelling and par Professor at Medical University of South Carolina, 2017

Published Research:

Dohyeong Kim, Malabika Sarkar, Priyanka Vyas, Role of spatial tools for the purpose of public health decision-making in Bangladesh, *Journal of Health, Population, and Nutrition*, 2016.

Simon Fass, Divakaran Lal, Rami Youssef, Priyanka Vyas, Understanding the causes of Fall and Struck-by related incidents: What differentiates Construction Safety in the Arabian Gulf Region? , *Journal of Applied Ergonomics*,2016.

Professional Experience:

Post-doctoral Scholar, University of California, San Francisco, School of Medicine, July 2017 - present
Instructor of Record, EPPS Research Design, Spring 2017
Program Assistant, EPPS SACS Assessment and Accreditation, August 2015 - June 2017
Graduate Teaching Assistant, Undergraduate Statistics, Fall 2013-Spring 2015
Policy Research Intern, Public School Forum of North Carolina, Raleigh, May-July 2010
Senior Reporter, The Hindu Business Line Newspaper, July 2006 - July 2009

Proficiency in Software and Statistical Packages:

STATA (Data management and statistical analysis)
R (Statistical packages and spatial analysis)
HLM 7 (Multilevel Modelling)
ArcGIS Desktop and Online, Geoda, Maptittude
Nvivo, QDA Miner (Content Analysis)
LaTEX (Professional reports, manuscripts, and publication preparation)

Media Highlights of Published Work:

Contributed opinion piece on editorial page of a financial daily on Geospatial Information Regulation Bill: July, 2016
Interview with Mohammed Arju featured in the Daily Sun on public health and GIS, July 2016
Interview with Kim Horner on GIS and Public Health, July 2016: