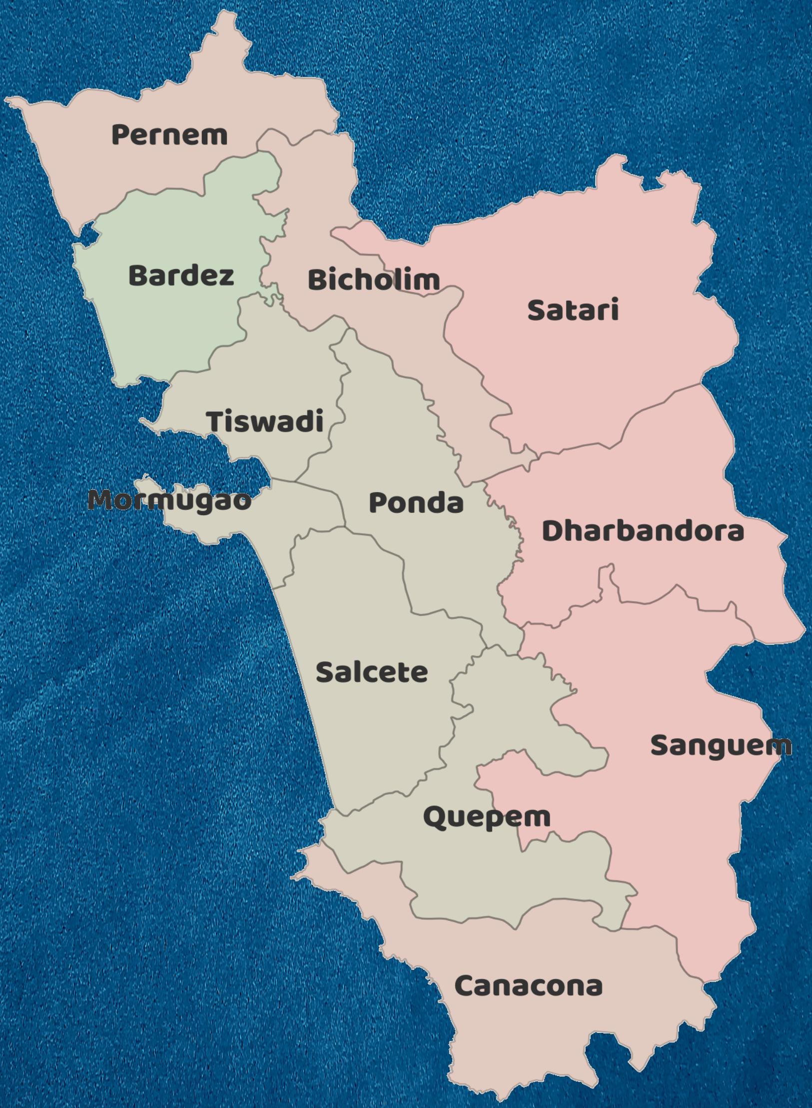
Evaluating the relation between spatial healthcare access and mortality during the COVID pandemic: Case Study from GOA State, India

Sercinho Banda

CASE STUDY GOA



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DELFT UNIVERSITY OF TECHNOLOGY

EVALUATING THE RELATION BETWEEN SPATIAL HEALTHCARE ACCESS AND MORTALITY DURING THE COVID PANDEMIC: CASE STUDY FROM GOA STATE, INDIA

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PREFACE

This thesis was written in fulfilment of the graduation requirements for the degree of Master of Science in Engineering and Policy Analysis (EPA) at the faculty of Technology, Policy & Management at the Delft University of Technology. As my time at the EPA program comes to an end, short as it may be, I can look back at a few remarkable years that have provided me with great memories, friends and all manner of accomplishments. This thesis serves as the final test of my academic skills. Therefore, I proudly present the final product of my work.

The research presented in this master thesis addresses the impact that policy and the spatial distribution of healthcare resources can have on the healthcare accessibility during a health crisis. The journey was challenging, but pushing on and conducting extensive research has resulted in me being able to answer my research question and achieving my research goal.

To that end, I would like to express my gratitude to the Centre for Urban Science & Policy (CUSP) for providing me the opportunity to work on a master project that helped developed my skills as a researcher and allowed me to be part of a community that shares my passion for sustainable urban planning. Secondly, I would like to thank my First Supervisor Dr.ir. Trivik Verma for the guidance and support he gave me during our bi-weekly sessions. I also want to thank my Chair Person Prof.dr. Cees van Beers and my Second Supervisor Dr. Saba Hinrichs-Krapels for the guidance and constructive feedback that helped guide the direction of my research. Lastly, I want to thank my family and friends who supported me during the writing of this research paper: your kind words and wise counsel have always served me well and kept me motivated during the writing of this research paper.

I hope you enjoy your reading!

Sercinho Banda
Delft, September 2022

ABSTRACT

In India the COVID-19 pandemic resulted in a nationwide lockdown from March 25, 2020 till the end of May 2020. During this time public and private transportation activities were limited, economic activities came to a standstill and healthcare resources were redistributed. India's healthcare system faced problems prior to the COVID-19 pandemic such as insufficient availability, suboptimal healthcare services and high out-of-pocket expenditures. The exponential rise in patient care during the COVID-19 pandemic exacerbated existing problems in the Indian healthcare system while introducing new ones. Realizing optimal care during the health crisis became more challenging as the focus was on mitigating the spread of the virus. The absent of public transportation and the pressure on healthcare resources impacted the healthcare accessibility of different demographic groups. During this study we assessed how access to healthcare was influenced due to the policy interventions that were meant to mitigate the spread of COVID-19. The hypothesis is that healthcare access for different demographic groups was negatively impacted by the policies meant to curb the spread. In order to analyse the impact, we performed a case study in the state of Goa using the Network-based Health Accessibility Index Method (NHAIM). This gravitational model allows us to study the spatial distribution of healthcare resources in the state of Goa. Based on our findings we can conclude that healthcare access is unevenly distributed in the state of Goa. Furthermore, we concluded that there is no significant correlation between healthcare availability and the urban and rural mortality rate for the state of Goa. However, there is a significantly strong positive correlation between geographical healthcare access and the urban and rural mortality for the state of Goa.

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ACRONYMS

CHC Community Healthcare Centre

CHE Catastrophic Health Expenditure

CVD Cardiovascular disease

GeoView Geographic visualizations for HoloView

GIS Geographic Information System

HAv High Availability

HAc High Accessibility

HDX Humanitarian Data Exchange

LAc Low Accessibility

LAv Low Availability

NHAIM Network-based Health Accessibility Index Method

NPI Non-pharmaceutical intervention

NCRC National Clinical Registry for COVID-19

OGD Open Government Data platform India

OSM OpenStreetMap

PHC Primary Healthcare Centre

QGIS Quantum Geographic Information System

REM Relevant Excess Mortality

SARS-CoV-2 Severe Acute Respiratory Syndrome Coronavirus-2

SDRF State Disaster Response Fund

SEDAC Socioeconomic Data and Applications Center

SPSS Statistical Analysis Software

UHC Urban Healthcare Centre

WHO World Health Organisation

1 INTRODUCTION

1.1 BACKGROUND

Located in South Asia, India is the Seventh largest country in the world [7] with approximately 65 per cent of its population living in rural areas [8]. Furthermore, the Indian economy is among the fastest growing economies in the world [9]. However, with an estimated population of more than 1.3 billion people [10], India is still considered a developing country based on factors such as gross national income (GNI) per capita [11]. Near the end of January 2020, the first case of COVID-19 was registered in India. Since then, India has experienced multiple waves of the COVID-19 pandemic. As of September 2022, more then 44 million COVID-19 cases have been confirmed in India, with an estimated death toll surpassing half a million people [12].

In December 2019, cases of pneumonia of unknown aetiology started to emerge in Wuhan city, Hubei Province, China [13]. According to the World Health Organization (WHO), this outbreak was caused by Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) [14]. The Coronavirus SARS-CoV-2 is a new type of Coronavirus which causes the disease COVID-19 [15]. On January 30th, 2020, the WHO went on to declare the virus outbreak a public health emergency of international concern [16]. Since then, the Coronavirus has rapidly spread worldwide with an estimated global death toll surpassing 6 million as of September 2022 [17].

COVID-19 has a median incubation period of three days (range 0-24 days). However, the disease course of Covid-19 and the way it presents itself is unpredictable. Currently, individuals infected with Covid-19 experience mild illnesses to severe acute respiratory symptoms which require immediate medical attention [18]. At the same time, some COVID-19 infected individuals remain asymptomatic, but contagious like symptomatic patients [19].

Furthermore, effective and affordable treatment against COVID-19 is still being developed [20][21], because vaccinated individuals and immunocompromised patients can still get infected with SARS-CoV-2 [22]. Regardless, vaccination campaigns are ongoing as current COVID-19 vaccinations have proven to be effective in reducing the mortality rate among COVID-19 infected patients [23][24].

In addition to the rapid spread, SARS-CoV-2 is also capable of genetic evolution. The results are mutant variants that have different characteristic than their ancestral strain. Since the beginning of the pandemic, five SARS-CoV-2 variants of concern have emerged, namely [25]:

- Alpha (B.1.1.7): emerged late December 2020
- Beta (B.1.351): emerged December 2020
- Gamma (P.1): emerged early January 2021
- Delta (B.1.617.2): emerged December 2020
- Omicron (B.1.1.529): emerged November 2021

The emergence of SARS-CoV-2 mutant variants are becoming a growing public health threat. The reason being that emerging variants can influence the severity of the symptoms, the transmissibility of the virus and the effectiveness of current vaccines [26].

At the start of the COVID-19 pandemic as the global number of infected persons continued to rise and different COVID-19 strains started to emerge, government efforts were concentrated on preventing and slowing down transmission. The absence of vaccines at the start of the pandemic made non-pharmaceutical interventions by government entities the primary means to combat this disease. In India non-pharmaceutical measures to curb the spread of infection included a nationwide lockdown which first went in effect on March 25th, 2020, closure of non-essential services, travel restrictions, social distancing, quarantine and self-isolation [27] [28]. Because COVID-19 has the potential to overwhelm India's healthcare resources, interventions that could slow down economic growth were mandatory [29]. However, these interventions had adverse effects on the socioeconomic wellbeing of the population [30] [31][32]. Furthermore, the economic decline and the restrictions on movement had cascading effects on India's healthcare system [33].

1.2 PROBLEM ANALYSIS

Prior to the COVID-19 pandemic, insufficient availability, suboptimal healthcare services and high out-of-pocket expenditures were among the key challenges faced by the Indian healthcare system [34]. According to the 75th round of the National Sample Survey (NSS), which was conducted from July 2017 to June 2018, 80 per cent of rural households and 84 per cent of urban households depended on their income and savings to finance their hospitalization expenses. While thirteen per cent of rural households and nine per cent of urban households had to borrow from various sources to finance their hospitalization expenses [35]. During the same period, only 37,2 per cent of the total Indian population was covered by insurance, with at least 80 per cent of the insured population falling under a government sponsored scheme [36]. Lastly, out-of-pocket expenses in India accounted for about 62,6 per cent of total health expenditures in the year 2018 [37].

At the start of the COVID-19 pandemic, at least 45 per cent of households in India reported a fall in income as a result of the lockdown policy, compared to nine percent in late February 2020 [38]. A fall in income leaves Indian households more exposed to health-related financial shock. First, because of their high dependency on income and saving to cover their health expenses. Second, because only a small percentage of households has some form of health insurance. However, even households that are insured under a government sponsored scheme were forced to make high hospitalization debt to secure treatment for their Covid infected family members [39]. Some household reported that it took them days to secure a hospital bed because of the limited capacity and availability of government and private hospitals in certain areas and the distance between them [39]. The travel restriction imposed by the government created travel impedance for those trying to reach primary healthcare facilities [40]. Furthermore, to increase the supply of hospital beds for COVID-19 patients, government policy mandated that certain private hospitals had to be converted to Covid-only healthcare facilities [41]. Meaning that non-Covid infected patients were left with fewer options to choose from. The government intervention has also led to increasing regional disparity amongst different states [42]. These disparities, pose a problem to India's healthcare system because they make it challenging to offer healthcare to the socially disadvantaged, the economically challenged, and the systemically marginalized [43].

As India's healthcare system adopts new means to provide healthcare to both Covid and non-Covid infected patients, equitable distribution of healthcare resources remains a challenge [44]. Handling other (deadly) diseases will become more difficult as healthcare resources are diverted away due to the Coronavirus [45]. Furthermore, physically accessing local healthcare facilities becomes challenging if more space is allocated to COVID-19 infected patients [46] [47].

1.3 KNOWLEDGE GAP

The COVID-19 pandemic has created new challenges and exacerbated existing challenges faced by the Indian healthcare system. In order to determine what knowledge is lacking to help mitigate these challenges we will explore the current state of knowledge that exists on the factors that influence the COVID-19 health outcomes in India.

The spatial distribution of the COVID-19 mortality rate is uneven across the different states in India [4]. The variability in the spatial distribution of the COVID-19 health outcomes in India can be related to numerous underlying factors, but for now our knowledge about the determinants of the unequal distribution remains limited. In order to mitigate this knowledge gap recent studies have focused on person specific determinants that relate to the COVID-19 health outcomes. While other studies explored the relationship between the COVID-19 health outcomes and different demographic, socioeconomic and environmental factors.

Evidence from East Asia and Europe suggest that individuals over 70 years of age and those with cardiovascular disease (CVD), diabetes, chronic respiratory disease, hypertension or cancer are most vulnerable to sever COVID-19 infection or death [48] [49]. Hence, a risk assessment study found that districts in northern, southern and western Indian states are at the highest health risk from severe COVID-19. The reason being that they are comprised of a population with higher proportions of elderly and higher rates of chronic diseases compared to the rest of India [50].

The influence of age structure on the COVID-19 mortality was further explored in seven Indian states (Maharashtra, Karnataka, Tamil Nadu, Haryana, West Bengal and Kerala), and one union territory (Delhi) from January to November 2020. The research found a high mortality rate among the elderly, but there was also a high mortality rate among the working population (age group 45-59 years) [51]. Furthermore, data collected between September 2020 and May 2021 under the National Clinical Registry for COVID-19 (NCRC) reveals that there is a difference between the demographic and clinical features of individuals infected during the first and second wave of COVID-19 in India. According to the data COVID-19 patients during the second wave consisted of a younger demography, had fewer comorbidities, a higher proportion had trouble breathing and the mortality rate increased in all age groups except for those younger than twenty [52].

Since SARS-CoV-2 spreads via human contact it is hypothesised that the COVID-19 infection rate will be higher in densely populated areas [53]. Hence, numerous studies exploring the relation between COVID-19 and the population density found a positive correlation between population density and the COVID-19 health outcomes [54] [55] [56] [57] [58]. Research performed in India at the district level using data up till September 10th, 2020 found similar results [59]. However, there were variations in the strength of the correlation between population density and COVID-19 compared to Japan [54], Italy [55], China [56] and the United States [57] [58]. Geo-statistical research performed on the district level in five South Indian states (Andhra Pradesh, Kerala, Tamil Nadu, Karnataka and Telangana) using COVID-19 data as on July 20, 2020 also found a positive correlation between population density and COVID-19 health outcomes, but with variation in the strength of the correlation among the different states [60]. The reason for the difference in correlation strength is unclear and could be related to different factors such as adherence to social distancing policies and the health care infrastructure in densely populated areas. Nevertheless, there is still a research gap in the literature about assessing the access to healthcare services during a global pandemic such as COVID-19 and to our knowledge no comprehensive study has been performed in India on a sub-district level to investigate the spatial relationship between healthcare access and the COVID-19 health outcomes [61].

1.4 RESEARCH QUESTION

In September 2022, SARS-CoV-2 continues to wreak havoc and the relative shortage of healthcare resources remains a growing concern. During the previous COVID-19 waves it became apparent that a sudden surge in COVID-19 cases could deplete hospital resources, hinder physicians in their ability to provide consistent and quality care which could contribute to a high disease burden and death [62] [63]. Hence, there remains an unprecedented need to investigate the major determinants that are related to the COVID-19 health outcomes in India.

The disease burden of COVID-19 is unpredictable and requires a variety of healthcare resources to treat COVID-19 infected patients such as hospital beds, ICU beds with ventilator and qualified hospital staffing. Because physical access to healthcare facilities became challenging as a result of the imposed policy measures in India. Identifying areas with limited healthcare accessibility could enable policymakers to understand and optimize the distribution of healthcare resources during a health crisis [64]. Also, understanding the impact of government intervention on the health outcomes of the COVID-19 pandemic could help guide the implementation of future policy efforts to control the spread during a pandemic. Therefore, the research objective of this thesis is to identify areas with limited healthcare access in India, understand the impact of government intervention on healthcare access during the COVID-19 healthcare crisis and analyse how this relates to the COVID-19 health outcomes.

Based on the identified problem and our research objective, the following main research question and sub-research questions were formulated.

Main research question:

"How does spatial healthcare access to inpatient care during the COVID-19 health crisis relate to the mortality rate for different demographic groups in India?"

Sub-research questions:

1. *"How do we define and measure healthcare access?"*
2. *"How did government intervention impact mobility during the COVID-19 health crisis?"*
3. *"How is healthcare access to inpatient care distributed?"*
4. *"How has COVID-19 impacted the mortality rate?"*

Study area
For this thesis, the state of Goa, which is located on the southwest coast of India, is considered as the study area. In the North the state of Goa borders the state of Maharashtra, in the East and South Goa borders the state of Karnataka and in the West the Arabian Sea. The State of Goa consist of two districts (North Goa

and South Goa) and twelve subdistricts (Pernem, Bardez, Bicholim, Tiswadi, Satari, Ponda, Mormugao, Salcete, Dharbandora, Quepem, Sanguem and Canacona) with its state capital Panaji located in North Goa. The state of Goa with a population size of 1.46 million according to the 2011 census, covers an area of approximately 3702 square kilometres, which makes it the smallest state in India [65]. The demographic data of the state of Goa are summarised in Table 1.1. Furthermore, Goa has an estimated bed strength of 3060 beds in the public domain and 2743 beds in the private domain. The strength of Goa's health infrastructure is summarised in Table 1.2. Since the start of the COVID-19 pandemic over three thousand COVID-19 infected patients have lost their lives in the State of Goa. The estimated lives lost is relatively low compared to the other 36 territories in India (28 states and 8 union territories). However, with an estimated COVID-19 death ratio of 1.54 per cent, the state of GOA has a relatively high death rate [4]. The COVID-19 status of the state of GOA is summarised in Table 1.3.

Table 1.1: Goa state demographic data based on 2011 census [3]

	North Goa	South Goa	Goa State
Total population	8,18,008	6,40,537	14,58,545
Density per Sq.Km.	466	329	394
Total No. of household	1,91,766	1,51,845	3,43,611
Rural population	3,24,927	2,26,804	5,51,731
Urban population	4,93,081	4,13,733	9,06,814
Total literacy rate (percent)	89.57	87.59	88.70

Table 1.2: Goa state health infrastructure data based on 2018-2019 survey data [3]

	North Goa	South Goa	Goa State
No. of specialised and general hospitals (Govt.)	5	8	13
No. of community/Primary Health Centres (including attached hospitals)	14	15	29
No. of beds in Government Hospitals	1996	1064	3060
No. of private hospitals (Private)	49	63	112
No. of beds in private hospitals (Private)	1325	1418	2743

Table 1.3: Goa state Covid-19 status as of July 2022 [4]

	Status
Total COVID-19 cases	2,48,849
Active cases	1,033
Active ratio	0.42%
Discharged	2,43,978
Discharge ratio	98.04%
Death	3,838
Death ratio	1.54%

1.5 RESEARCH APPROACH

To evaluate the relation between healthcare access and the COVID-19 mortality rate in India we rely on data from several databases such as the Development Data Lab and Open Government Data (OGD) platform India. Given the spatial dependency of healthcare access, the open source Geographic Information System (GIS) tool QGIS will be used to identify areas with limited healthcare resources and visualize this in a manner that supports the decision-making process.

Firstly, a qualitative approach in the form of a literature study will be used to assess research findings related to the evaluation of healthcare access and the non-pharmaceutical COVID-19 government intervention in India. Furthermore, data from the literature review will be gathered using the Scopus, Google Scholar and PubMed search engine. Secondly, a quantitative approach will be used to assess the distribution of healthcare access in India. This research will use the Network-based Health Accessibility Index Method (NHAIM) which complements the popular 2SFCA gravitational model by considering the patient border crossing problem [2]. Lastly, statistical analysis will be performed to determine if there is a relation between healthcare access and the mortality rate in the state of Goa.

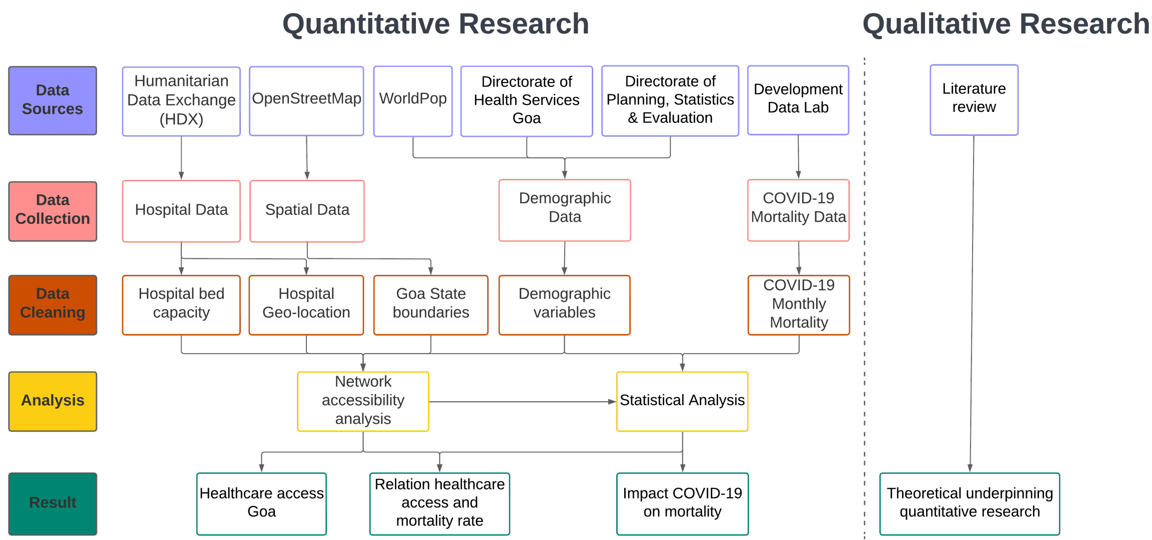


Figure 1.1: Methodology

1.6 THESIS OUTLINE

This thesis is structured as follows. Chapter 2 reviews existing literature about healthcare accessibility and how to measure this. It also evaluates the impact of government intervention on mobility. Chapter 3 provides an overview of the methodology and explains how the research method is applied. Chapter 3 also explains how the data was acquisitioned and pre-processed for further analysis. Chapter 4 provides an overview of the main research findings. Chapter 5 discusses the main research findings, limitations of the study and provides recommendation for future research. Finally, chapter 6 concludes by answering the main research question.

2 LITERATURE REVIEW

The literature review aims to provide the theoretical underpinnings for the quantitative research that will be performed to explore the relation between healthcare access and the COVID-19 health outcomes. First, sub-research question 1 will be addressed by exploring the meaning of the concept healthcare access and the available methods to evaluate this concept. Second, sub-research question 2 will be addressed by exploring the government interventions that were implemented at the start of the COVID-19 pandemic in India.

2.1 DEFINING AND MEASURING HEALTHCARE ACCESS

2.1.1 Defining Healthcare Access

The term health is multifaceted and according to the WHO defined as the *"state of complete physical, mental and social well-being and not merely the absence of disease or infirmity"* [66]. This definition of health includes both physical, mental and social well-being. Therefore, when measuring healthcare access, a choice will have to be made on the variable that will be considered. Furthermore, the WHO definition of health is based on societal norms regarding aspiration and needs which means it is prone to evolve over time [67].

The term healthcare access is a complex term for which there is no commonly agreed upon definition or measurement approach. Regardless, based on the study of Levesque et al.[1] we define healthcare access as *"the opportunity to identify healthcare needs, to seek healthcare services, to reach, to obtain or use healthcare services and to actually have the need for services fulfilled"*. Healthcare access can further be classified in potential access and effective access. Effective access to healthcare reflects an individual's ability, mobility and time to reach a healthcare service once the need has been established, while potential access reflects the existence of a service independent of whether this is effectively accessible [68]. Furthermore, healthcare access has been conceptualised using different frameworks [69][70]. For this research we will used the most recent conceptualisation by Levesque et al. [1] which takes into account the ability of individuals and the population to perceive, to seek, to reach, to pay, and to engage, in healthcare. The framework as illustrated in Figure 2.1 allows us to look beyond the failures of a health system and into the barriers that an individual or population faces when accessing healthcare. Based on the framework of Levesque et al. [1] healthcare access can be conceptualised in five dimensions that capture both the supply as well as the demand side determinants of access. Further, these dimensions are both spatial and non-spatial in nature:

1. Approachability (non-spatial dimension)
2. Acceptability (non-spatial dimension)
3. Availability and accommodation (spatial dimension)
4. Affordability (non-spatial dimension)
5. Appropriateness (non-spatial dimension)

Approachability, the first dimension of healthcare access, concerns the ability of people with healthcare needs to identify that healthcare services exist, are reachable and capable of having an impact on one's health. In this regard the ability to perceive healthcare needs among different social or geographical population groups is imperative and influenced by factors such as health literacy and beliefs about health and sickness.

Acceptability, the second dimension of healthcare access, concerns the social and cultural perceptions that influences the ability of people to accept healthcare services and judge its appropriateness. Meaning that healthcare services need to be culturally mindful and locally relevant. Furthermore, the ability to seek healthcare relates to factors such as personal autonomy and knowledge about individual rights that may influence one's intention to obtain healthcare.

Availability and accommodation, the third dimension of healthcare access, relates to the ability to physically reach healthcare services and if this can be achieved in a timely manner. Availability reflects the geographical access to healthcare services and the existence of a required type of service. It takes into account the characteristics of healthcare facilities (e.g. density, concentration, distribution), urban contexts (e.g. urban spread and transportation system), the characteristics of individuals (e.g. duration and flexibility of working hours), the characteristics of providers (e.g. qualification of healthcare provider) and healthcare provision modes (e.g. physical or virtual consultations). Furthermore, the ability to reach healthcare services relates to the availability of transportation, occupational flexibility and spatial knowledge that enables one to physically reach a service provider.

Affordability, the fourth dimension of healthcare access, relates to the economic capacity of an individual to spend resources and time to use appropriate healthcare services. It concerns the direct (price of healthcare service and related expenses) and indirect prices (opportunity cost related to income losses) of healthcare services. Also, it varies by service type and is dependent on the capacity to produce the payment resources (e.g. mode of payment). Lastly, the ability to pay for healthcare describes the capacity to produce economic resources (e.g. through income, savings, borrowing or loans) to finance healthcare services without catastrophic health expenditures (CHE). Factors restricting the ability to pay include poverty, social isolation and indebtedness.

Appropriateness, the fifth dimension of healthcare access, concerns the match between the available healthcare services and the healthcare needs, the timeliness, the time spent assessing healthcare problems, determining the correct treatment and both the technical and interpersonal quality of the provided service. Furthermore, the ability to engage in healthcare is related to the participation and involvement of an individual in the healthcare treatment decision making process. This process is influenced by the capacity and motivation to participate in the healthcare process and one's commitment to its completion.

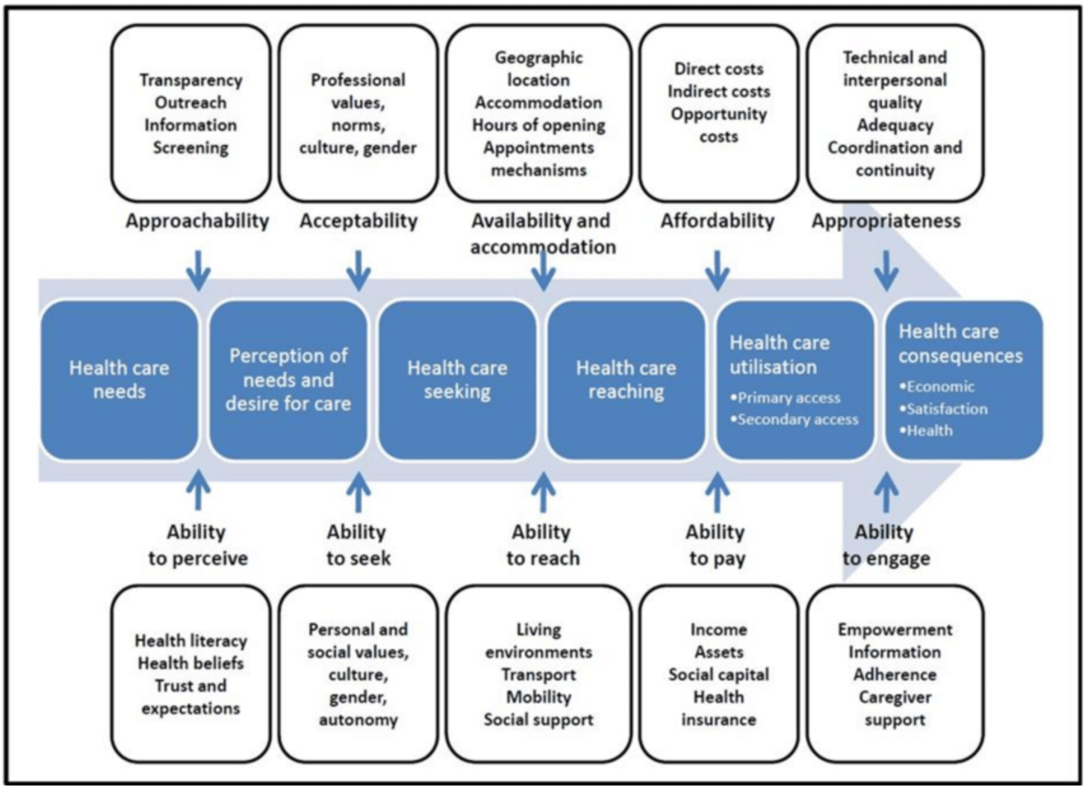


Figure 2.1: Healthcare access conceptual framework by Levesque et al. [1]

2.1.2 Measuring Healthcare Access

Availability and accommodation, the third dimension of healthcare access, is spatial in nature and reflect the geographical access to healthcare services (accessibility) and the existence of a required type of service (availability). Geographic accessibility has been identified as an important determinant of (or major barrier to) healthcare utilization in low- and middle-income countries [71]. Regarding the quantification of geographic accessibility, opinions vary between travel time units and distance [72]. However, the WHO recommends the use of travel time units for the quantification of physical access because geographic and transport impedance which can cause time delays could be present and differ per location [72].

To measure spatial accessibility, previous research has suggested a variety of Geographic Information System (GIS) techniques. These GIS techniques can be classified in four categories namely: provider-to-population ratio, distance to nearest provider, average distance to a set of providers, and gravitational models of provider influence [73].

Provider-to-population ratio
The provider-to-population ratio method calculates the ratio between an indicator of health service capacity and the population size within a certain area. After which inferences can be made about the relation between the calculated provider-to-population ratio value and an indicator of healthcare utilization or health status [74]. The provider-to-population ratio method is limited in the sense that it does not account for distance and travel impedance, patient border crossing and variations in accessibility within the research area [73].

Distance to nearest provider
The distance to nearest provider techniques calculates the distance from a reference point such as a patient's residence or population centre to a health service

provider. This technique is suitable for measuring spatial accessibility in rural areas, but less for urban settings because it does not account for multiple healthcare service providers that can be present at a similar distance from a reference point [73].

Average distance to a set of providers
The average distance to a set of providers technique is a measurement for both accessibility and availability. This technique calculates the average distance from a reference point such as a patient's residence or population centre to all health service provider within an area such as a city or a country. The average distance to a set of providers technique is limited because it does not account for patient border crossing and it tends to overestimate the influence of service providers located near the periphery of the research area [73].

Gravitational models
Gravitational models are capable of measuring accessibility and availability in both an urban and rural setting. Gravitational models represent the potential interaction between a reference point and all service providers within a certain distance of that reference point, taking into account that the potential interaction is reduced with increasing distance or travel impedance [73]. Frequently used gravitational models are the Simple gravity-based accessibility model, the Two-step floating catchment area method (2SFCA), Enhanced two-step floating catchment area method (E2SFCA) and the Three-step floating catchment area method (3SFCA). Limitations of the gravitational model vary depending on the model being implemented.

Affordability is the fourth dimension of healthcare access. A report of the National Commission on Macroeconomics and Health estimated that yearly 3,3 per cent of Indians are driven to poverty due to catastrophic health expenditures. High OOP expenditures are the major source of total health expenditures in India [75]. Most OOP expenditures in India are related to the high cost of private healthcare, which India's healthcare system has come to rely on. Despite, the higher cost for private healthcare in India, this option remains the preferred chose because of the perceived higher quality of private healthcare [76]. Also, in India, approximately 80 per cent of outpatient and 60 per cent of inpatient healthcare services are provided by private healthcare facilities [77].

2.2 GOVERNMENT INTERVENTION

The first case of COVID-19 in India was detected on January 27, 2020 in the state Kerala [78]. Since then, both national and state government have taken steps to mitigate the spread of COVID-19.

On March 14, 2020, after the WHO declared COVID-19 a pandemic, the Central Government of India declared COVID-19 a notified disaster under the Disaster Management Act of 2005 by way of a special one-time dispensation [79]. The goal of this policy intervention is to provide state governments with limited financial aid under the State Disaster Response Fund (SDRF). The financial assistance provided are to be used towards the following COVID-19 containment measures:

- Measures for quarantine, sample collection and screening [80]
- Procurement of essential equipment's/labs for response to COVID-19 [80]
- Arranging relief camps for and providing food to the homeless and stranded migrant workers due to the national lockdown measures (as of March 28, 2020) [79].

- Arranging oxygen generation and storage plants in hospitals, the strengthening of ambulance services for transport of patients, setting up containment zones and COVID-19 care centres (as of September 23, 2020) [79].

The SDRF was established to ensure that state governments have sufficient financial resources to provide relief during one of the notified disasters (cyclone, drought, earthquake, fire, flood, tsunami, hailstorm, landslide, avalanche, cloudburst, pest attack, frost and cold waves) [81]. Therefore, state governments were only allowed to spend the following percentages on COVID-19 containment measures [79]:

- 35% of the SDRF annual allocation during the financial year 2019-2020
- 50% of the SDRF annual allocation during the financial year 2020-2021
- 50% of the SDRF annual allocation during the financial year 2021-2022

The annual contribution from the central government to the SDRF is released in two equal instalments [81] and in the financial year 2021-2022 the first instalment amounted to Rs. 8873.60 crore (1 crore equals 10 million rupees) [82].

On March 22rd the state government of India announced a nationwide curfew from 7 AM to 9 PM known as the *"Janta Curfew"* [83][84]. The goal of this lockdown was to mitigate the spread of COVID-19 at the start of the pandemic. The Janta Curfew was subsequently replaced by a nationwide lockdown that went into effect from the 25th of March, 2020 till the 31th of May, 2020 [5]. Furthermore, the nationwide lockdown was divided in different phases with different measurements per phase. The start and end date of each phase is summarised in Table 2.1. During phase one of

Table 2.1: COVID-19 lockdown phases [5]

Policy	**Start date**	**End date**
Janata Curfew	March 22, 2020	March 24, 2020
National lockdown phase 1	March 25, 2020	April 14, 2020
National lockdown phase 2	April 15, 2020	May 3, 2020
National lockdown phase 3	May 4, 2020	May 17, 2020
National lockdown phase 4	May 18, 2020	May 31, 2020

the national lockdown citizens were urged to remain indoors with many activities being prohibited. Also, non-essential transport was suspended, and only healthcare and other essential services were allowed to remain operational [85].

During phase two the different states in India were divided in red, orange and green zones depending on the number of active COVID-19 cases and the spread of the virus.
In areas identified as red zones all forms of public transport were suspended and both public and private gatherings were prohibited. Also, only healthcare and other essential services were allowed to remain operational.
In areas identified as orange zones, outpatient healthcare services were allowed to operate with social distancing norms and safety precautions in mind. Also, inter district movement for permitted activities was sanctioned as well as limited movement for taxis.
Lasty, areas identified as a green zone had some of their restriction uplifted in a phased manner. At the start of April 2020 both districts in the state of Goa were considered non-hotspot districts [86]. Therefore, on April 20, 2020 the State of Goa

was allowed to restart economic activities listed in the Ministry of Health and Family Welfare guidelines [86].

During phase three of the national lockdown areas identified as red zones remained in lockdown. In orange zone areas public transportation was still inactive and in green zone areas public transport operated with a 50 per cent capacity. At the start of phase three the state of Goa was still considered a green zone area [87].
During phase four of the national lockdown state government were given more authority over the implementation of lockdown procedures including the categorization of different zones.

Lastly, it should be noted that during calendar year 2020 no pharmaceutical interventions were used to mitigate the spread of COVID-19. However, this changed after the launch of the nationwide COVID-19 vaccination campaign. In the state of Goa, the COVID-19 vaccination campaign was launched at the start of calendar year 2021 [88][89].

3 METHODOLOGY

The methodology elaborates on the methods used for this thesis. First, the quantitative and qualitative approach for answering the sub-research questions are discussed. After which the data collection strategy and data processing steps are described.

3.1 METHODOLOGY OVERVIEW

3.1.1 Strategy

The study utilized data obtained through multiple sources, namely:

- Literature
- The Development Data Lab
  The Development Data Lab is an open data platform that collects socioeconomic data of India from government and non-government sources. The data from the different sources our merge with the purpose of offering a high-resolution geographic framework for socioeconomic analysis [90].
- Open Government Data (OGD) Platform India
  The Open Government Data Platform India is designed, developed and hosted by the National Informatics Centre (NIC), the Ministry of Electronics Information Technology and the Government of India. With this platform the Government of India hopes to increase transparency in governmental functioning and promote the reuse of government data [91].
- OpenStreetMap (OSM)
  OpenStreetMap is a free and participatory geographic database, specializing in the creation of editable maps of the world. The maps in the OSM database are maintained by the OSM community and created from local knowledge and other free sources [92].
  One of the main advantages of using OSM is that it is open source data which allows its users to create large and complex datasets. Achieving similar results would be difficult with a small group or with limited funding.
  As the OSM database is a community-driven collection of global geospatial data, representativeness of the data remains an area of concern. Compared to proprietary data, OSM is limited because of its inconsistent data quality [93]. Geographic locations with and active community tend to have more accurate and detailed information than areas with a limited amount of participant adding and updating the data. Another limitation of OSM is the accuracy of its data [93]. The OSM community consist of both skilled and unskilled contributors. Combined with the lack of standards or methods for data entry, the OSM data can sometimes be less accurate than proprietary data. Regardless of its limitations, OSM remains a viable source for spatial information.
- Humanitarian Data Exchange (HDX)
  The Humanitarian Data Exchange is an open platform for sharing data in the humanitarian sector. The HDX is managed by the United Nations Office for

the Coordination of Humanitarian Affairs (OCHA's), Centre for Humanitarian Data [94].

- WorldPop hup
  The WorldPop hup is an open platform that develops peer reviewed research and methods for the construction of open and high-resolution geospatial demographic data, with the focus being low and middle income countries [95].

- Government of Goa, Directorate of Planning, Statistics & Evaluation (DPSE)
  The Directorate of Planning, Statistics & Evaluation is concerned with the collection, compilation, tabulation and publication of socio-economic data for the state of Goa [96].

Furthermore, to evaluate the relation between healthcare access and the mortality rate in the state of Goa, we conducted both qualitative and quantitative research as illustrated in Figure 3.1.

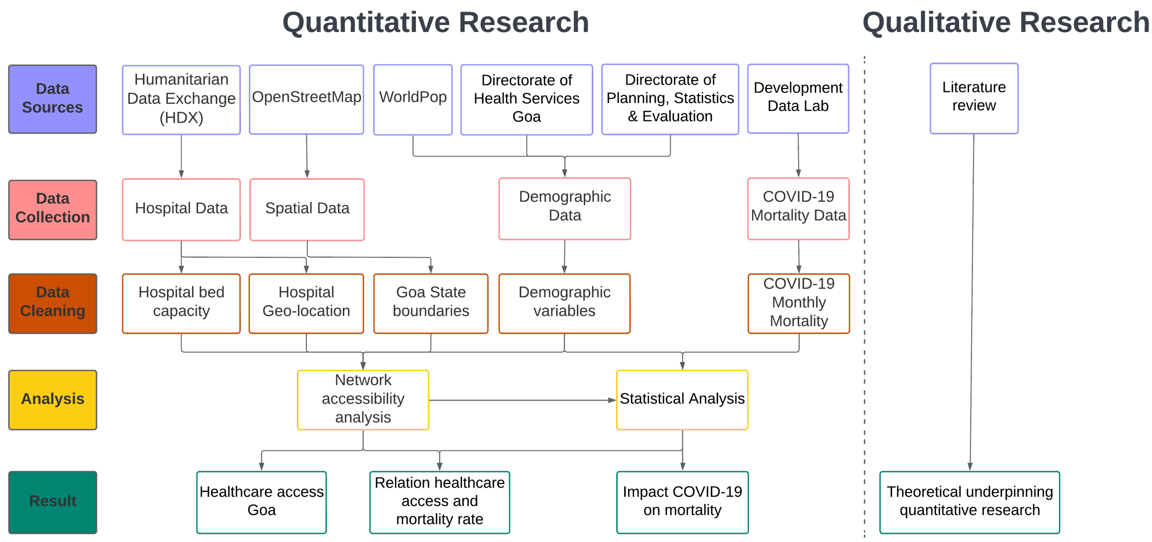


Figure 3.1: Methodology

First, a qualitative approach in the form of a literature study was used to assess research findings related to the evaluation of healthcare access and the COVID-19 government intervention in India. The data from the literature review was gathered using the Scopus, Google Scholar and PubMed search engine. The findings from the literature review, which were discussed in Chapter 2, served as the theoretical underpinning for the chosen method in the quantitative approach.

The quantitative approach was used to access the distribution of healthcare access in the State of Goa. Based on the findings from the literature review this study used the Network-based Health Accessibility Index Method (NHAIM) which complements the popular 2SFCA gravitational model by considering the patient border crossing problem [2]. Lastly, statistical analysis was performed to determine if there is a relation between healthcare access and the COVID-19 mortality rate in the state of Goa and whether this relation is statistically significant.

3.1.2 Network-based Health Accessibility Index Method (NHAIM)

As previously mentioned, healthcare access is a complex term that spans over multiple dimensions. In order to measure the Availability and accommodation dimension, this research used the Network-based Health Accessibility Index Method

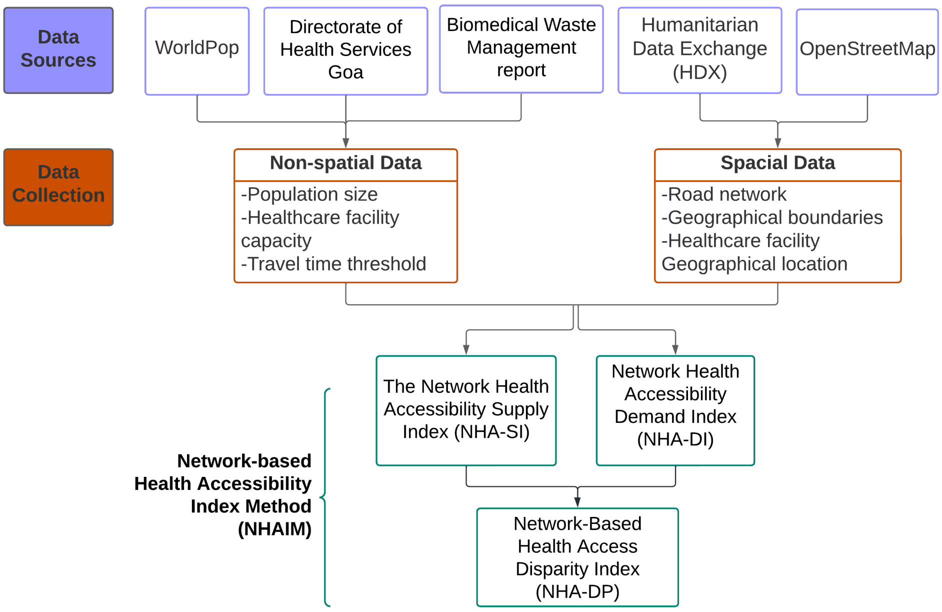


Figure 3.2: Network-based Health Accessibility Index Method (NHAIM)

(NHAIM) which complements the popular 2SFCA gravitational model by taking into account the patient border crossing problem [2]. The required data and data sources for performing the NHAIM are illustrated in Figure 3.2. The Availability and accommodation dimension acknowledges that healthcare access is spatial in nature. Furthermore, spatial accessibility is dependent on the geographical location of healthcare providers and healthcare seekers, together with the travel time or travel distance between them. The NHAIM took this into account by considering the ease with which healthcare services could be reached from the demand side and the choices of healthcare services from the supply side. Like other GIS techniques, the NHAIM has both strengths and limitations.

Strength of NHAIM

- The NHAIM measures geographic accessibility as well as availability of healthcare resources and evaluates the interaction between them [2].
- The NHAIM applies Network distance instead of Euclidean distance or Manhattan distance [2] which is a more accurate measurement for real travel time and travel distance.
- Compared to other gravity models, the results of NHAIM are easy to interpret.

Limitations of NHAIM

- The NHAIM only includes spatial determinants of healthcare access. Meaning, aspatial factors such as socioeconomic status are excluded.
- The NHAIM does not account for variability in traffic conditions [2]. In densely populated areas, the traffic flow and speed are significantly impacted by traffic conditions and can therefore affect geographic accessibility measurements [97].

The NHAIM represent the spatial dimension of healthcare in three sub-indexes: the Network-Based Health Accessibility Supply Index (NHA-SI), the Network-Based Health Accessibility Demand Index (NHA-DI) and the Network-Based Health Access Disparity Index (NHA-DP) [2]. Characteristics of the indexes and the calculation procedures can be described as follows.

Network-Based Health Accessibility Supply Index (NHA-SI)

The NHA-SI explores healthcare accessibility problems from the supply side by quantifying the availability of healthcare providers within a chosen spatial unit.

- Reflects health care access from the supply side.
- Measures service availability in terms of healthcare facilities.

The NHA-SI was executed in four steps which are illustrated in Figure 3.3.

1. Step 1: we represented the aggregated demand for healthcare in each spatial unit using population centroids. The demand aggregation method reduces the complexities of location problems. However, it can result in an over- or underestimation of the true distance to healthcare and the coverage of healthcare providers. The aggregation error increases when larger spatial units are selected, but can be mitigated when accessibility is measured over smaller spatial units.

2. Step 2: we calculated the network demand area of healthcare for each population centroid from step 1. The healthcare demand area can be described as the network-distance travel zone from the population centroid within each spatial unit. Further, the size of the healthcare demand area is dependent on the travel distance threshold of the type of health service. Because there are different types of healthcare services, the travel distance threshold can be adapted to reflect the chosen healthcare service. Lastly, the size of the healthcare demand area increases when a larger travel distance threshold is chosen.

3. Step 3: we calculated the population P_i within each healthcare demand area i, which was generated in step 2. Next, we determined how many demand areas n were being served by healthcare facility j ($n \geq 0$; n = the number of healthcare demand areas covering healthcare facility j). Finally, we calculated the total population residing in n demand areas that healthcare facility j was serving. This is expressed by

$$P_j = \sum_{i}^{n} P_i \tag{3.1}$$

   In order to get the most accurate results for P_j, the population residing within overlapping healthcare demand areas should be counted only once.

4. Step 4: we calculated the NHA-SI for each spatial unit i. First, we calculated the healthcare accessibility for each healthcare facility j. As a result, each spatial unit i contained the healthcare accessibility of n ($n \geq 0$) healthcare facilities j. This is expressed by

$$S_j = k\frac{C_j}{P_j}, \quad 0 < S_j < 1, \quad \forall j \tag{3.2}$$

   Where:
   C_j = the capacity of healthcare facility j (the number of hospital beds is chosen as a proxy for the supply capacity)
   P_j = the total population residing within n demand areas that are being served by healthcare facility j.
   k = is the scalar to adjust the (hospital bed) ratio.
   Next, we calculated the NHA-SI for each spatial unit i. This is expressed by

$$S_i = \sum_{j=1}^{n} S_j, \quad j \in R \tag{3.3}$$

   Where:
   R = the set of healthcare facilities j located within spatial unit i.

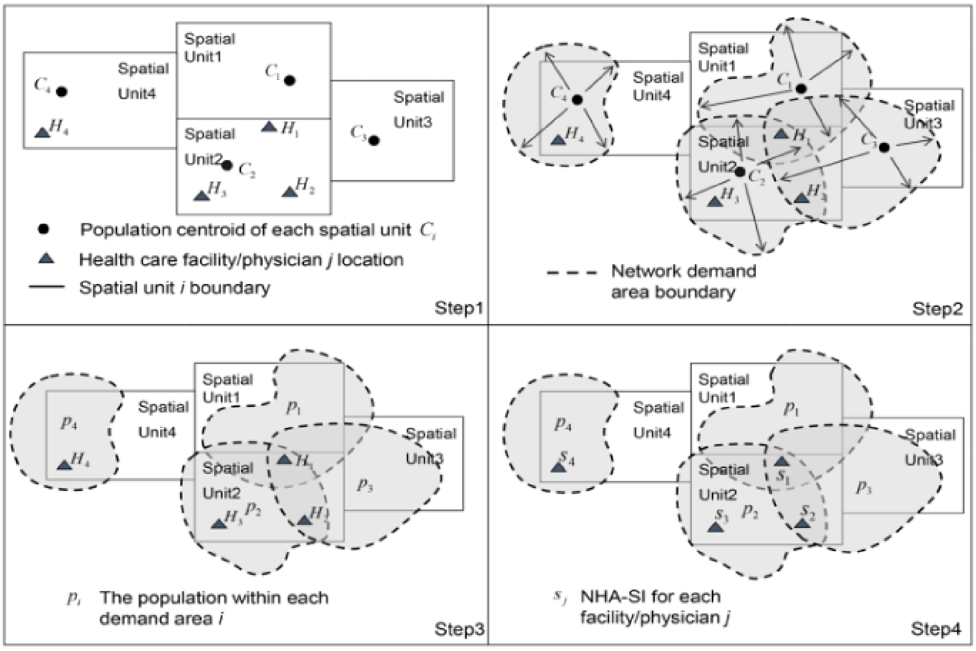


Figure 3.3: Steps for executing the Network-Based Health Accessibility Supply Index (NHA-SI) [2]

Network-Based Health Accessibility Demand Index (NHA-DI)

The NHA-DI explores healthcare accessibility problems from the demand side by calculating the total population within the service area of the healthcare facilities in each spatial unit, while also considering the capacity of healthcare facilities in each spatial unit.

- Reflects health care access from the demand side.
- Measures overall healthcare accessibility for the population in demand.

The NHA-DI was executed in four steps which are illustrated in Figure 3.4.

1. Step 1: we identified the geographic locations of healthcare facilities within each spatial unit.
2. Step 2: we calculated the network service area for each healthcare facility j. The network service area can be described as the network distance travel zone from each healthcare facility j in spatial unit i. The size of the network distance travel zone is dependent on the travel time threshold, just like the healthcare demand area. Meaning that the size of the network distance travel zone also varies depending on the healthcare service. Furthermore, the size of the network distance travel zone is adaptable to the healthcare service offered and increases if a larger travel time threshold is chosen.
3. Step 3: we calculated the population ratio covered by the network service area of healthcare facility j in spatial unit i. The formula to achieve this is as follows:

$$\frac{P_i^j}{P_i}, \qquad (P_i^j \leq P_i) \tag{3.4}$$

Where:
P_i^j = The population in spatial unit i, that is within the network service area of healthcare facility j.
P_i = The total population residing within spatial unit i.

4. Step 4: we calculated the NHA-DI index D_i for each spatial unit. This is expressed by

$$D_i = k \sum_{i=1}^{n} C_j \frac{P_i^j}{P_i}, \quad 0 \leq D_i \leq 1, \quad \forall i \tag{3.5}$$

Where:
P_i^j = The ratio of the population that is within the network service area of healthcare facility j to the total population in spatial unit i.
C_j = the capacity of healthcare facility j (the number of hospital beds is chosen as a proxy for the capacity)
k = The scalar to adjust the ratio

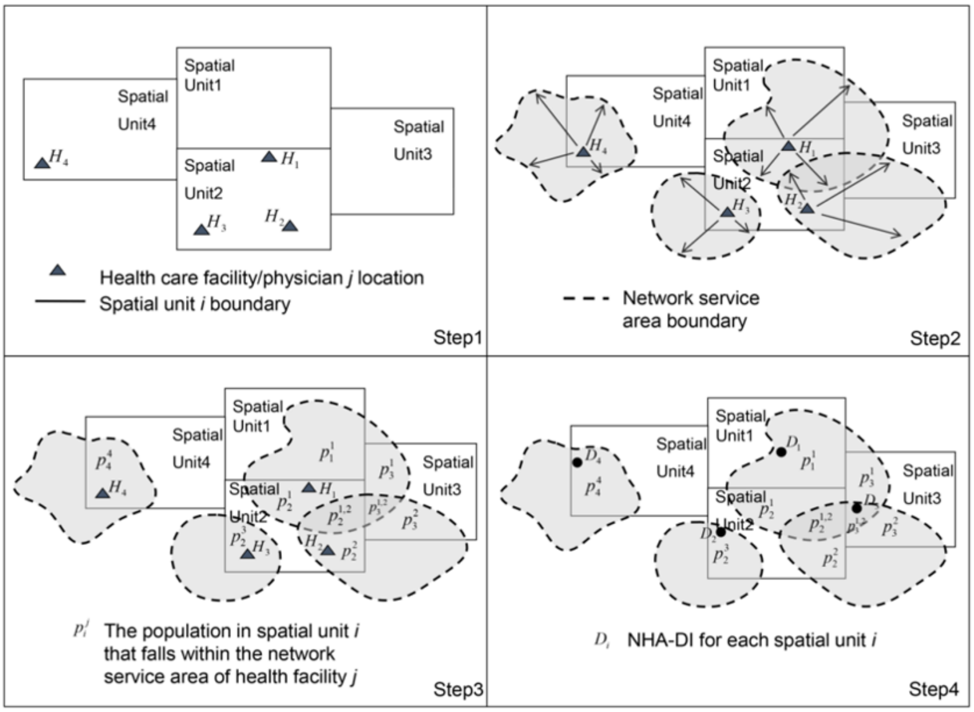


Figure 3.4: Steps for executing Network-Based Health Accessibility Demand Index (NHA-DI) [2]

Network-Based Health Access Disparity Index (NHA-DP)

The NHA-DP is a global index that summarizes the interaction between healthcare accessibility and healthcare availability at each spatial unit i, by evaluating the NHA-SI and the NHA-DI.

- Combines both the NHA-SI and NHA-DI.
- Measures both healthcare accessibility and healthcare availability.

Each spatial unit i contained a population centroid with attribute D_i and n healthcare facilities with summed up attribute S_i. Therefore, we expressed the level of spatial disparity A_i for each spatial unit i as follows:

$$A_i = [NHA - SI, NHA - DI] = [D_i, S_i], \quad \forall i \tag{3.6}$$

The NHA-DP can be categorised in four quadrants which are illustrated in Figure 3.5.

1. The first quadrant includes spatial units for High Accessibility (HAc) and High Availability (HAv). This quadrant indicates that a high portion of the population has access to a high capacity of healthcare services.

2. The second quadrant includes spatial units for Low Accessibility (LAc) and High Availability (HAv). This quadrant indicates that only a small percentage of the population is being served by the healthcare facilities in the service area.

3. The third quadrant includes spatial units for Low Accessibility (LAc) and Low Availability (LAv). This quadrant indicates that population has limited accessibility to the healthcare services within travel range. Healthcare demands in this quadrant are unsatisfied and supply is limited.

4. The fourth quadrant includes spatial units for High Accessibility (HAc) and Low Availability (LAv). This quadrant indicates that healthcare services in the spatial unit are scarce or over capacitated. Regardless, the available healthcare services are well within traveling range.

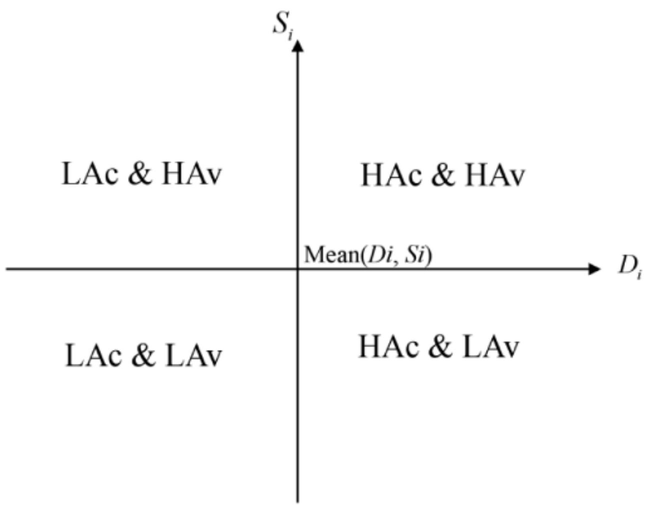


Figure 3.5: Classification of special units using the NHA-DP quadrants (Note: H=High, L=Low, Av=Availability, Ac=Accessibility). [2]

3.1.3 Statistical Analysis

The absence of COVID-19 mortality data on the sub-district level made it difficult to determine the correlation between spatial healthcare access and the COVID-19 mortality for the state of Goa. Therefore, we determined the correlation between spatial healthcare access and the urban and rural mortality on the sub-district level for the year 2020.

Correlation analysis is a statistical measure that tests if a relationship exists between two or more variables by measuring the direction and strength of their relationship [98]. A positive correlation means that the variables are moving in the same direction (increasing or decreasing together) while a negative correlation means that the variables are moving in an opposite direction (increasing while the other variable is decreasing and vice versa). There are three commonly used correlation analysis namely Pearson correlation, Spearman correlation and Kendall Rank correlation. Each correlation method makes assumptions about the data in order to prove causality. Therefore, we explored the data to see if it meets the conditions for assuming causality.

During the national lockdown, the state of Goa was registered as a green area. Furthermore, COVID-19 data retrieved from the Development Data Lab showed that the COVID-19 mortality in the state of Goa was relatively low during the lockdown. During the lockdown spatial access to the different healthcare facilities was limited. In order to estimate if the low COVID-19 mortality rate was due to the limited access to different healthcare facilities for testing, we estimated the Relevant Excess Mortality (REM).

We assessed the impact of COVID-19 on the monthly mortality for the state of Goa for the calendar year 2020. The impact of COVID-19 on mortality was determined by estimating the Relevant Excess Mortality in the state of Goa for the year 2020. The reported COVID-19 cases and deaths can be affected by the available testing capacity and the COVID-19 reporting policies. Hence, excess mortality which is defined as the increase in all-cause mortality relative to the expected mortality, is recognised as a more objective indicator of the COVID-19 health outcomes [99]. The Relevant Excess Mortality method was used in similar studies [100][101] and the process was achieved by the following steps:

- First, we determined the monthly expected mortality for all-cause mortality of the year 2020 for the state of Goa by calculating the historical average.
- Second, we determined the Standard Deviation (SD) of the historical average. After which we calculated the 2 standard deviations confidence limit for all-cause mortality.
- Third, we calculated an upper threshold which consist of the historical average plus the 2 standard deviations confidence limit for all-cause mortality.
- Fourth, we considered the Relevant Excess Mortality when the observed mortality surpasses the historical average plus the 2 standard deviations confidence limit for all-cause mortality.
- Lastly, we determined the observed mortality for calendar year 2020 minus the monthly COVID-19 mortality for 2020. After which we determined what percentage of the monthly Relevant Excess Mortality is determined by the COVID-19 mortality.

3.1.4 Materials

Maps and spatial analyses are commonly used to provide a geographical perspective on health data. To that end Geographic Information Systems (GIS) and geomatics tools were used to inform on the distribution of diseases and healthcare resources.
Currently, there is no commonly agreed upon definition for a Geographic Information System. Regardless, this study defined GIS as *"a computerized system for capture, storage, retrieval, analysis and display of spatial data describing the land attributes and environmental features for a given geographic region, by using modem information technology"* [102]. Meaning, GIS provides the means to easily connect geographic dependent data to a map and display this in an understandable visual format. Given the spatial dependency of healthcare access, the open-source Geographic Information System tool Quantum-GIS (QGIS) version 3.24.3-Tisler was used to identify areas with limited healthcare resources and visualize this in a manner that supports the decision-making process. The QGIS tool was chosen for this study because of the following:

- QGIS is a professional free and open source community-driven software.
- QGIS is a user friendly GIS application.

- QGIS runs on multiple operating systems such as Linux, Unix, Mac OSX and Windows.
- QGIS supports the use of plugins that extend its capabilities beyond the core functions. This feature made it possible to directly access and edit OpenStreetMap data from QGIS.

Furthermore, Python version 3.9.12.final.0 with the Geographic visualizations for HoloViews (GeoViews) library was used to explore and perform the data analysis on the geographical datasets. Lastly, statistical analysis were performed using Statistical Analysis Software (SPSS) version 28.0.1.1 (14).

3.2 DATA COLLECTION

The study area of this thesis is the state of Goa located on the southwest coast of India. We collected spatial and non-spatial data from the aforementioned data sources. A complete overview of the datasets utilized for this study is summarised in Table 3.1.

COVID-19 mortality data
The COVID-19 mortality data from January 30, 2020 till December 31, 2020 of the State of Goa was collected from the Development Data Lab. The dataset covid-infected-deaths contains the number of confirmed COVID-19 cases and deaths on the district level [6]. However, India has no standardised method for reporting COVID-19 health data. As a result, different states in India report COVID-19 health data on different geographical levels. In the case of the state of Goa COVID-19 mortality data is reported on a state level. The variables that were extracted from this dataset are *total-cases* and *total-deaths*.

Healthcare facility spatial data
The gravitational model NHAIM allows us to investigate spatial healthcare accessibility on different geographical levels. In order to achieve these results, the NHAIM requires the geographical location of the healthcare facilities within the investigated area as an input variable. However, in India the total number of hospitals in the private sector are largely unknown, but estimated at 44.000 in 2020 [103].

On August 10, 2017, the Open Government Data platform India published the *National Hospital Directory with Geo Code and additional parameters (updated till last month)* which was contributed by the Ministry of Health and Family Welfare (MoHFW), Department of Health and Family Welfare and the National Institute of Health and Family Welfare (NIHFW) [104]. The open government dataset contains information on healthcare facilities in India such as their geolocation. However, the dataset is incomplete and, in a few cases, inaccurate because some healthcare facilities are located on a different continent.

Nevertheless, the hospital records form the available directories were improved and added to the OSM by individual local users. Further, additional healthcare facilities were added to the dataset based on local knowledge. Finally, the OSM data on healthcare facilities in India was retrieved from HDX. The dataset is a shapefile named *hotosm_ind_south_health_facilities_points_shp* from which the geolocation of the healthcare facilities were imported into QGIS [105].

Road network data
The road network data for India, HOTOSM India South Roads (OpenStreetMap Export), was retrieved from HDX. The dataset is a shapefile titled *hotosm_ind_south_roads_lines_shp* which contains the road network from OSM for the State of Goa and was last up-

dated in 2020 [106].
Even though the road network dataset from OSM for the State of Goa contains all the mayor roads, the dataset is still limited in the sense that it does not provide information about the speed limit. The available variables make it possible to deduct forward and backward roads, but information about the lanes and surface is mostly missing. This makes it difficult to estimate the speed limit.

Hospital resource data
The hospital bed capacity was used as an indicator to reflect the availability of healthcare services. The total number of hospital beds in India is estimated at around 19.00.000 [103]. Finding the bed capacity of healthcare facilities proved to be quite challenging because the data was either unavailable or outdated. The National Hospital Directory published by the OGD has limited to no data on the bed capacity in India. Different states had limited to no information on the private or public bed capacity in their region. Furthermore, there was little means to verify the data as often the data would be published without date. Therefore, the state of Goa was selected based on the availability of both private and public bed capacity. Information on the bed capacity of private healthcare facilities was not published on the government website, but could be extracted from the Biomedical Waste Management reports. Public health data was extracted from the Directorate of Health Services Goa [107] and the Biomedical Waste Management report of 2019 [108].

Goa state boundaries
The state boundaries from the state of Goa were extracted from OSM using the QuickOSM plugin in QGIS. QuickOSM makes it possible to easily download OSM data and integrate this into QGIS. OSM uses mapping values to categorize different features in the OSM database. In order to extract data from the OSM database you require a primary key and a value key for further search refinement. The chosen query values in QuickOSM were:

- Key: boundary
- Value: administrative
- In: Goa

De resulting data was a Thiessen polygon map of the state of Goa which contains the district and sub-district boundaries.

Population density
The 2020 United Nation (UN) adjusted population density for India was retrieved from the WorldPop Hup. The dataset was download in Geotiff format at a resolution of 30 arc (approximately 1km at the equator). The projection is Geographic Coordinate System, WGS84 [109]. Each data point represents the number of people per square kilometre based on country totals adjusted to match the UN 2019 revision of world population prospects. Based on the 2020 UN adjusted population density, Goa has an estimated population size of 1.8 million.

Goa mortality data
The mortality data for the state of Goa is published in the annual report on registration of births and deaths which is produced by the government of Goa, Directorate of Planning, Statistics Evaluation, Office of the Chief registrar of births and deaths. The annual report on registration of births and deaths contains the monthly mortality data for the state of Goa and the yearly mortality data for the sub-districts in the state Goa from 2007 till 2020 [110].

Table 3.1: Variables, definitions and data sources

Variable	Definition	Data Source	Data year
total-cases	Number of confirmed COVID-19 cases	Development Data Lab [6]	COVID-19 data from the states of Goa up to December 31, 2020.
total-deaths	Number of confirmed COVID-19 deaths	Development Data Lab [6]	COVID-19 data from the states of Goa up to December 31, 2020.
Goa state monthly mortality	Number of monthly registered deaths on the state level	Directorate of Planning, Statistics & Evaluation [110]	Goa Mortality data from 2007 till 2020.
Goa sub-district yearly mortality	Yearly registered deaths on the sub-district level	Directorate of Planning, Statistics & Evaluation [110]	Goa Mortality data from 2007 till 2020.
Healthcare facility Geographic data	Latitude and Longitude of facility	Humanitarian Data Exchange [105]	2020
Road network	Road networks data	Humanitarian Data Exchange [106]	2020
Goa state boundary	District and sub-district boundary of Goa	OSM database	2022
Number of hospital beds	Total beds in public/private facilities	Biomedical Waste Management report [108]	2019
		Directorate of Health Services Goa [107]	2022
2020 UN-adjusted population density	Estimated population per grid-cell	WorldPop Hup [109]	2020

3.3 DATA PREPARATION

3.3.1 NHAIM

The NHAIM represent the spatial dimension of healthcare in three sub-indexes. The Network-Based Health Accessibility Supply Index (NHA-SI), the Network-Based Health Accessibility Demand Index (NHA-DI) and the Network-Based Health Access Disparity Index (NHA-DP).

The Network-Based Health Accessibility Supply Index (NHA-SI)
Step 1 NHA-SI: Represent the demand for healthcare using population centroids

In order to determine the population centroid, the 2020 UN-adjusted population density dataset had to be transformed.

- The dataset was downloaded in Geotiff format and imported to QGIS. The dataset contained population density information for all of India. Therefore, the raster was clipped to the Goa state Thiessen polygon map using the Clip raster by mask Layer function in QGIS.
- The clipped raster was then converted into a vector point layer using the Raster pixels to points algorithm in QGIS. This made it possible to explore the data in Python.
- The vector point layer was than merged with the Goa state Thiessen polygon map using the Join attributes by location function in QGIS. This step was necessary to determine the population centroid.
- The population centroid was than determine using the Mean coordinate(s) algorithm in QGIS.
- The sub-districts were used as the spatial unite for which to determine the population centroid.

Step 2 NHA-SI: Calculate the network demand area of health care for each population centroid
The OSM road network was initially used to determine the service area from the population centroid. However, the OSM road network did not provide information on the speed limit and the missing data about the surface of the road and the number of lanes made it difficult to deduct. The Openrouteservice (ORS) plugin from QGIS was considered seeing as this plugin was used in similar studies. However, ORS had the tendency to overestimate the service area compared to Google Maps. Therefore, the TravelTime QGIS plugin was considered. A travel time threshold of 30 minutes was considered, and the travel mode was set to driving. The result was a Thiessen polygon that was more realistic in size compared to ORS.

Step 3 NHA-SI: Calculate the population within each demand area generated in the previous step

- The 2020 UN-adjusted population density vector point layer was merged with the demand area Thiessen polygon by performing a spatial join using the join attributes by location algorithm in QGIS. However, the population in overlapping demand areas is counted only once. Therefore, the spatial join was performed using a one-to-one relation as illustrated in Figure 3.6.
- Next, we needed to calculate how many demand areas were served by each healthcare facility. This was achieved by performing a spatial join with the geolocation of the healthcare facilities. Each healthcare facility was linked with the total population of n demand areas.

Step 4 NHA-SI: Calculate the healthcare accessibility for each healthcare facility in the demand area.
The health care accessibility for each facility was calculated using QGIS Open Field Calculator.

The Network-Based Health Accessibility Demand Index (NHA-DI)
Step 1 NHA-DI: Identify the locations of health care facilities within each spatial unit.
A shapefile containing the geolocation of private and public healthcare facilities in Goa was used.

Step 2 NHA-DI: Calculate the network service area for each healthcare facility
The service area was generated using the TravelTime QGIS plugin. Seeing as we

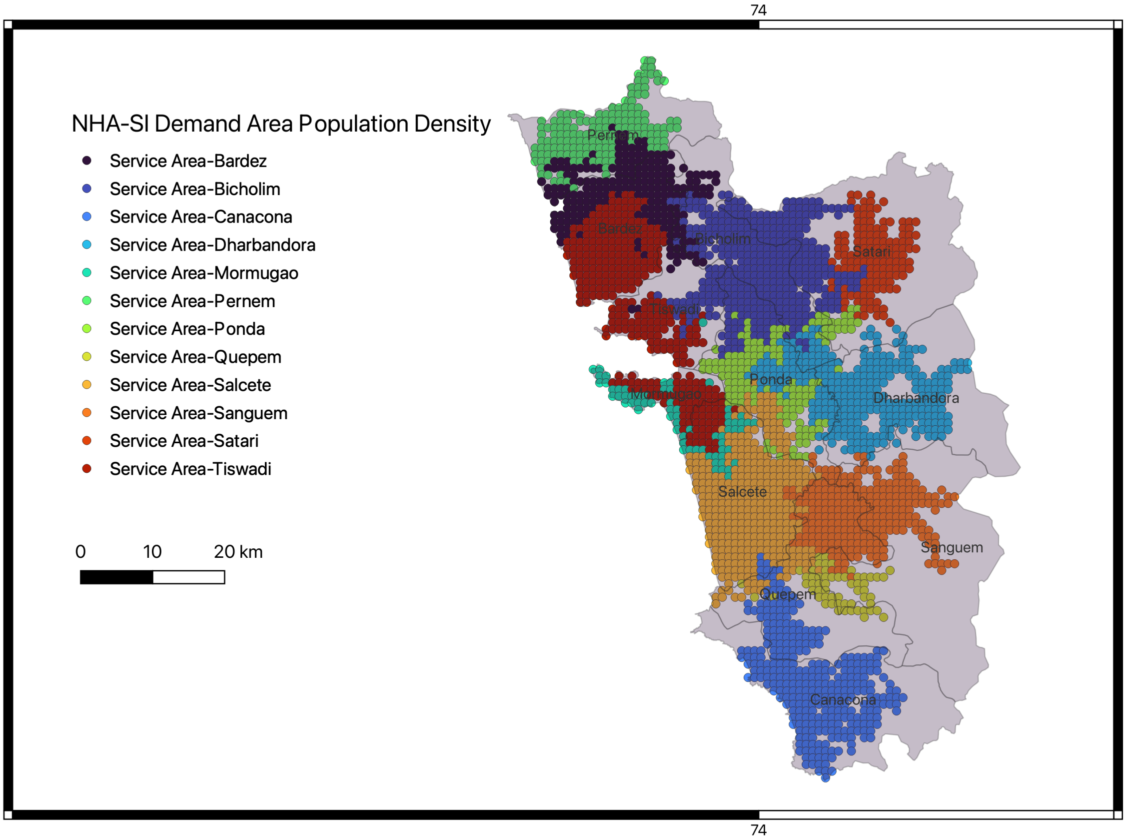


Figure 3.6: NHA-SI Population Demand Area

were using the free version of the TravelTime we were restricted to calculating 2 hours of service area per minute. Therefore, the service area was calculated in batches and then later merged using the merge vector layer algorithm in QGIS. Furthermore, a travel time threshold of 30 minutes was considered, and the travel mode was set to driving. The result was a Thiessen polygon containing all the service areas as illustrated in Figure 3.7.

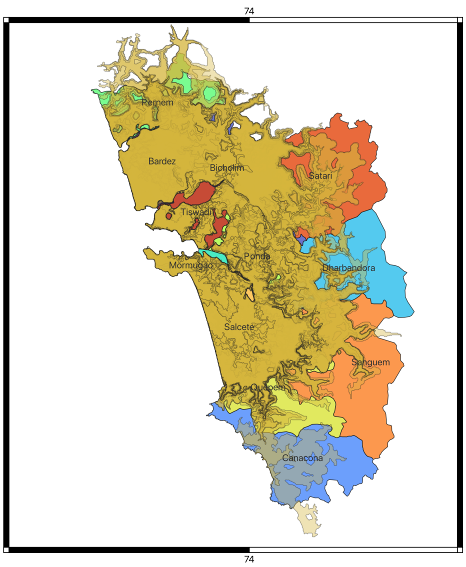


Figure 3.7: NHA-DI-Service Area

Step 3 NHA-DI: Calculate the population ratio covered by the network service area of healthcare facility j in spatial unit i
The 2020 UN-adjusted population density vector point layer was merged with the service area Thiessen polygon by performing a spatial join using the join attributes by location algorithm in QGIS. The spatial join was performed using a one-to-many relation. The Population was than calculated using the Open Field Calculator in QGIS.

Step 4 NHA-DI: Calculate the NHA-DI index for each spatial unit.
The NHA-DI index was calculated in Python and imported to QGIS as a shapefile.

The Network-Based Health Access Disparity Index (NHA-DP)
First, the average of the NHA-SI and the NHA-DI respectively were calculated. After which accessibility labels were assigned to the different spatial unites or in our case the different sub-districts. The results are summarised in Table 3.2 and illustrated in Figure 3.8.

Table 3.2: Spatial Healthcare accessibility Goa

Sub-district	Spatial healthcare accessibility
Bardez	HAc & HAv Area
Mormugao	HAc & LAv Area
Ponda	HAc & LAv Area
Quepem	HAc & LAv Area
Salcete	HAc & LAv Area
Tiswadi	HAc & LAv Area
Bicholim	LAc & HAv Area
Canacona	LAc & HAv Area
Pernem	LAc & HAv Area
Dharbandora	LAc & LAv Area
Sanguem	LAc & LAv Area
Satari	LAc & LAv Area

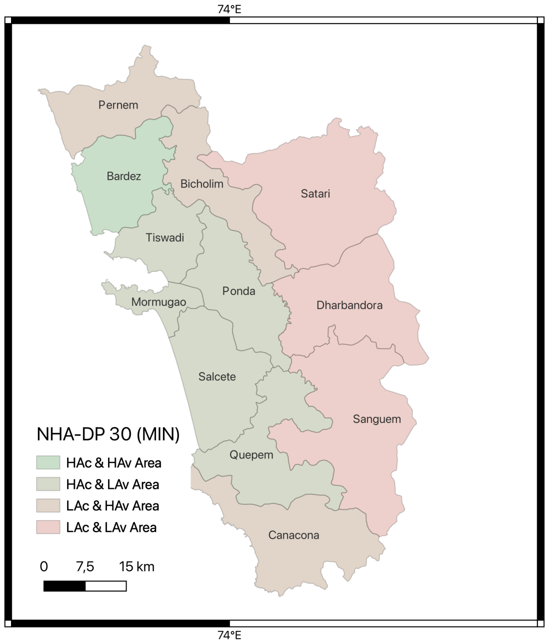


Figure 3.8: NHA-DP GOA

3.3.2 Correlation Analysis

The correlation analysis was performed in order to determine the correlation between spatial healthcare access and the COVID-19 mortality data for the calendar year 2020. The state of Goa consists of two districts and twelve sub-districts. The spatial healthcare accessibility was measured on the sub-district level. Therefore, we retrieved the sub-district mortality data for the state of Goa which was only available on the yearly basis. The yearly data per sub-district was available for Urban towns with population 30.000 and above, All other urban areas and Rural areas. The Urban towns with population 30.000 and above were Panaji, Margao, Vasco and Mapusa. All other urban areas represents the urban areas with a population less than 30.000. Lastly, the datasets described the mortality by type of medical attention received. The available datasets for the yearly mortality data for the different sub-districts are summarised in Table 3.3.

Table 3.3: Available sub-district mortality data

Category	Dataset
Urban town with population 30.000 and above	Institutional
	Medical attention other than institution
	No medical attention
All other Urban areas	Institutional
	Medical attention other than institution
	No medical attention
Rural	Institutional
	Medical attention other than institution
	No medical attention

In order to determine the total mortality for the urban areas the categorical data for Urban towns with population 30.000 and above and All other urban areas was aggregated. Similarly, the total mortality for the rural areas was determined by aggregating the data in the rural datasets. The data used for the correlation analysis is summarised in Table 3.4.

Table 3.4: Data for correlation analysis

Sub-District	NHA-DI (Geo Access)	NHA-SI (Availability)	Total_Urban_Death 2020	Total_Rural_Death 2020
Pernem	0,1756	0,004723853	33	607
Bardez	0,1624	0,23318793	632	1367
Tiswadi	0,0172	0,07556838	413	4490
Bicholim	0,0424	0,127485628	256	403
Sattari	0,0189	0,015728422	74	302
Mormugao	0,0791	0,001130303	336	547
Salcete	0,0137	0,019298728	1693	1184
Quepem	0,0171	0,01038261	238	275
Sanguem	0,0068	0,096688063	45	183
Canacona	0,0775	0,006721768	87	203
Dharbandora	0,1483	0,002866049	0	182
Ponda	0,1253	0,001015333	170	881

Before performing the correlation analysis, we explored our data and analysed which statistical test could be used to prove causality. First, we checked if our data meets the criteria for performing the widely used Pearson correlation. In order to perform the Pearson correlation, certain assumptions about the data have to be met.

Assumptions about data for performing the Pearson correlation [98]

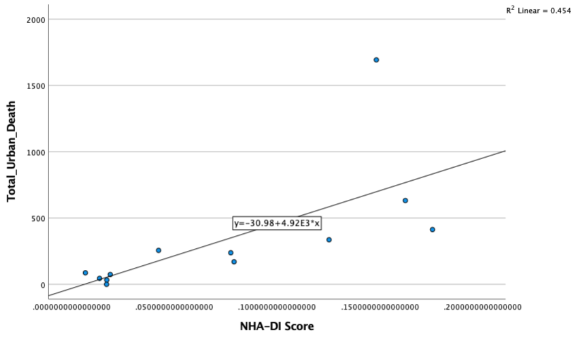
- The variables are scaled data and not ordinal or normal.
- There exists a linear relationship between the variables.
- Both variables are normally distributed.

The data used for the correlation analysis is scaled data, which can be seen in Table 3.4. Furthermore, we tested the linearity assumption which states that the relationship between each pair of correlated variables is linear. Testing for linearity can be achieved by looking at the bivariate scatter plots of the variables to be used for the correlation analysis [98]. The test for linearity was performed in SPSS by creating bivariate scatter plots of each pair of variables used for the correlation analysis. In order to assume linearity, the observations should be plotted in the shape of a straight line [98]. The variables that were tested are:

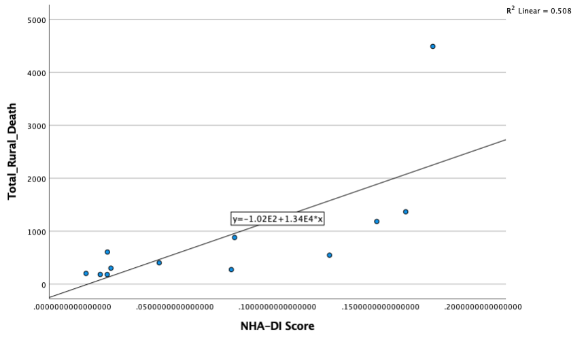
- NHA-DI (Geo Access)
- NHA-SI (Availability)
- Total Urban Death 2020
- Total Rural Death 2020

The results of the linearity test are illustrated in Figure 3.9. By looking at the resulting scatter plots we can see that perfect linearity is not achieved because all the observations are not aligned around a straight line.

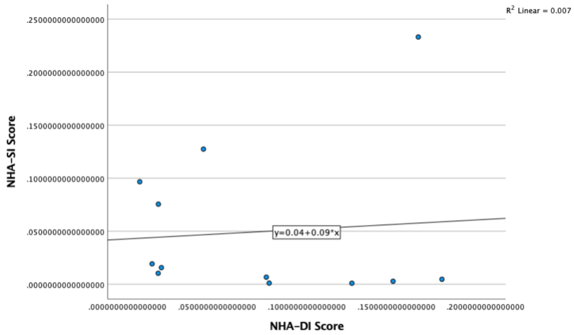
After testing for linearity, we performed a normality test on the different datasets and a visual inspection on their histograms and normal Q-Q plots. The histograms and normal Q-Q plots are graphical means of showing normality of the data. The normal Q-Q plot compares two probability distributions: the observed sample data and a generated standard normal data. The points of the Q-Q plots will lie on the line or close to it, indicating a normal distribution, if the observed sample data is similar to the generated standard normal data [98].
The normality assumption was tested in SPSS. Common statistical tests used for testing the normality assumption are Kolmogorov Smirnov test, which is preferable when using large sample sizes, and Shapiro Wilk test, when using small to medium samples ($N \leqslant 50$) [98][111]. Given our small sample size we used the Shapiro-Wilk test which is commonly used for testing normality with the following hypothesis:



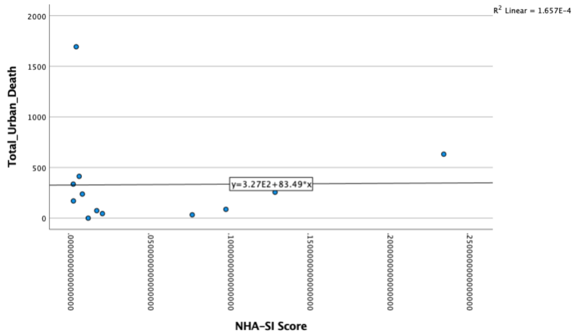
(a) fig 1



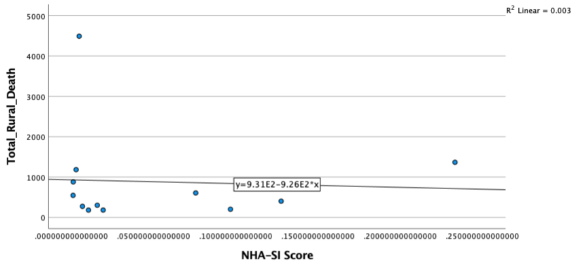
(b) fig 2



(c) fig 3



(d) fig 4

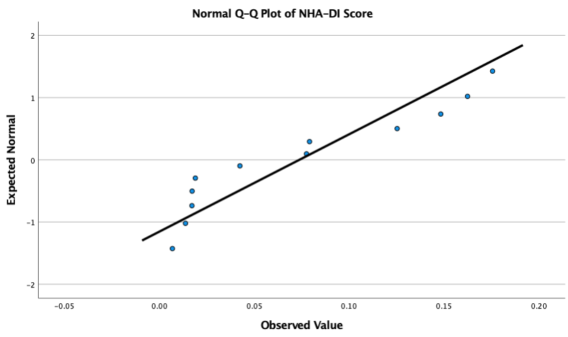


(e) fig 5

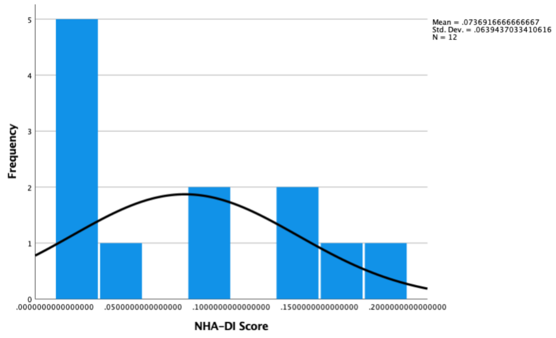
Figure 3.9: Testing for linearity

- H0: The data is normally distributed.
- H1: The data is not normality distributed.

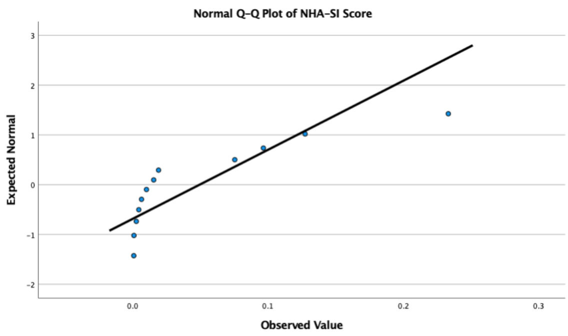
The null-hypothesis is rejected if the p-value is below 0.05. Further, the resulting p-values were below 0.05 for all the datasets. Based on the Shapiro-Wilk test ($p < 0.05$), and a visual inspection on the histograms and normal Q-Q plots of the different datasets, we concluded that the datasets are not normally distributed. Therefore, when performing bivariate analysis, we cannot perform the Pearson Correlation analysis because of the normality assumption [112]. Instead, we used the Spearman rank correlation analysis because our data does not adhere to the criteria for the Pearson corelation analysis. Lastly, the results of the Shapiro-Wilk test are illustrated in Figure 3.11.



(a) fig 1



(b) fig 2



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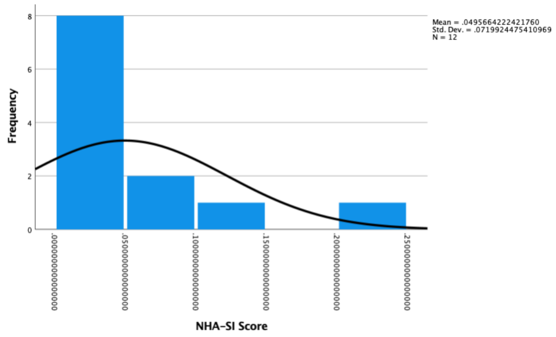

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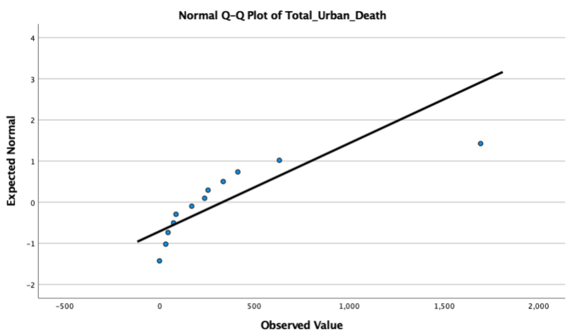

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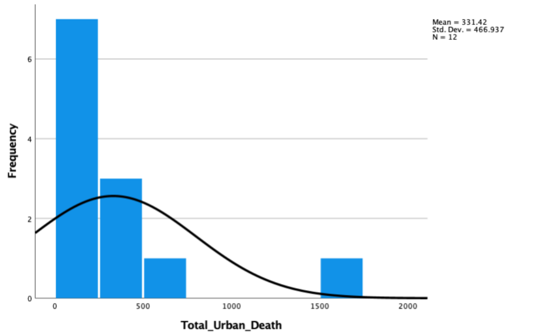
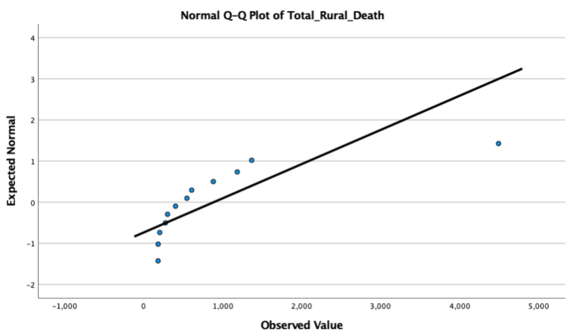
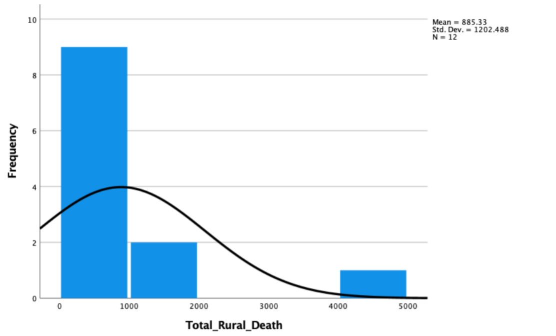


(f) fig 6



(g) fig 7



(h) fig 8

Figure 3.10: Testing for Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Accessibility_score	.221	12	.109	.858	12	.046
Availibility_score	.330	12	<.001	.728	12	.002
Total_Urban_Death	.264	12	.021	.674	12	<.001
Total_Rural_Death	.279	12	.010	.608	12	<.001

a. Lilliefors Significance Correction

Figure 3.11: Normality test

3.3.3 REM Method

The monthly mortality data for the state of Goa was retrieved from the government of GOA, Directorate of Planning, Statistics & Evaluation. The monthly mortality data for the state of Goa was available from 2007 till 2020 (13 years) and contained mortality data for both male and females. After retrieving the historical mortality data of the past thirteen years, we calculated the total monthly state mortality by summarizing the total mortality for males and females. After which we calculated the average monthly mortality data of the past decade. We also calculated the standard deviation of the average monthly mortality data and the 2SD-limit. The 2SD-limit was then added to the average monthly mortality data of the past decade. The retrieved monthly averages and standard deviation are summarised in Table 3.5.

Table 3.5: Average monthly mortality Goa (2007-2020)

Month	Total Death (Female & Male)	Std. Deviation (SD)	2SD-limit
January	1169	150,595	301,19
February	1056	81,149	162,298
March	943	146,094	292,188
April	984	90,968	181,936
May	998	78,729	157,458
June	963	66,781	133,562
July	1078	78,252	156,504
August	1112	137,674	275,348
September	1115	187,232	374,464
October	1135	148,553	297,106
November	1030	117,628	235,256
December	1042	130,954	261,908

Secondly, we retrieved the COVID-19 data from the Development Data Lab. The COVID-19 mortality and case data were available on the state level. Furthermore, the dataset contained daily historical data for calendar year 2020 and 2021. The COVID-19 data for 2020 was retrieved and aggregated to monthly COVID-19 data.

Lastly, we retrieved the observed monthly mortality data for the state of Goa for the calendar year 2020. After which we subtracted the aggregated monthly COVID-19 data from the observed monthly mortality data for the state of Goa for the calendar year 2020.

4 ANALYSIS RESULTS

In this chapter we eleborate on the results from our quantitative analysis. First we look at the results from the NHAIM method and than we elaborate on our statistical findings.

4.1 RESULTS NETWORK-BASED HEALTH ACCESSIBILITY INDEX METHOD (NHAIM)

In this study we primarily focused on availability and reachability of healthcare services in the state of Goa. In the public domain, the state of Goa houses the following healthcare facilities: Primary Healthcare Centre (PHC), Community Healthcare Centre (CHC), Urban Healthcare centre (UHC) and Tertiary Healthcare (Medical College, district and sub-district hospitals). The role of PHC at the start of the COVID-19 pandemic were as followed: [113]

- Finding of COVID-19 cases and referral for COVID-19 testing.
- Providing essential non-COVID-19 healthcare services.
- Facility preparedness in response to COVID-19. Meaning that measure should be taken to minimize the spread at the healthcare facility.

The role of CHC and UHC at the start of the COVID-19 pandemic was to monitor the clinical severity of the COVID-19 infected patient and refer to Tertiary Healthcare where they would be treated based on their clinal assessment [113]. Furthermore, the location and capacity of the healthcare facilities in the public domain are dictated by health policy. Also, the services offered at these facilities are usually free of charge. Private healthcare facilities on the other hand are not govern by institutional policies that dictate the number or level of service. The total bed capacity that was identified in the state of Goa is summarised in Table 4.1. In order to determine if unavailability of healthcare facilities or insufficient capacity of healthcare facilities is the major concern, we performed the NHAIM. In Figure 4.1 we show the NHA-SI indexes for the 30-minute threshold. The NHA-SI addresses the healthcare access problem from the supply side by evaluating the population that is being served in the healthcare demand area. Meaning that a higher healthcare facility capacity and a smaller population in need will result in a larger NHA-SI index. In our study we used fixed capacities for the healthcare facilities. Meaning that the NHA-SI index will be smaller if the healthcare demand increases. The state of Goa consists of twelve sub-districts that were used to calculate the population centroid from which the demand area for healthcare services was determined. A travel time threshold of 30 minutes was used during our analysis for this is an optimal travel time for both primary healthcare and hospital emergency care which ranges between 31-80 minutes [114]. Given the travel time threshold and the size of the study area, twelve demand areas were created that overlapped each other. The overlap meant that health seekers can cross the sub-district borders (spatial unit) in order to fulfil their health needs in another sub-district. Therefore, a healthcare facility is not bound to serve only the population of its own sub-district, but neighbouring sub-districts as well. This means that the capacity of a healthcare facility is under more pressure

Table 4.1: Healthcare facilities in Goa

Sub-district	Total population (2011 census)[3]	Population density per Sq.Km. (2011 census)[3]	Total bed capacity
Bardez	2,37,440	899	629
Mormugao	1,54,561	1406	341
Ponda	1,65,830	566	424
Quepem	81,193	255	108
Salcete	2,94,464	1005	1059
Tiswadi	1,77,219	830	1880
Bicholim	97,955	410	169
Canacona	45,172	128	70
Pernem	75,747	301	68
Dharbandora	Not Availible	Not Availible	15
Sanguem	65,147	75	20
Satari	63,817	129	43

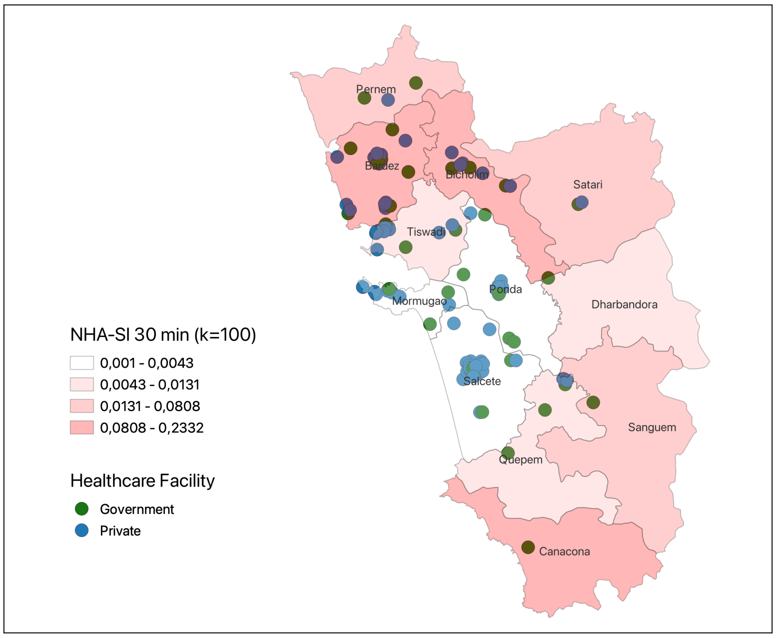


Figure 4.1: NHA-SI GOA

if it lays within multiple demand areas. The scenario in which health seekers can cross borders to fulfil their health needs is a better representation of reality. Especially during the COVID-19 health crisis.

Based on our analysis the sub-district Ponda, Marmugoa and Salcete have the lowest NHA-SI values which means that the healthcare capacity in those sub-districts has trouble keeping up with the healthcare demand from the population. It should be noted that Sub-district Ponda, Marmugoa and Salcete are areas with high population densities based on the 2011 census. Furthermore, these are areas with an urban population of at least 60 per cent as summarised in Table 4.2. The sub-district Bardez, Bicholim and Canacona have the highest NHA-SI values which means there is a better balance between the healthcare supply and demand.

The NHA-DI addresses healthcare access from the demand side by calculating the percentage of population within the service area of the healthcare facilities in each sub-district while also taking the capacity of the healthcare facility into consideration. The NHA-DI index increases, if the percentage of the population ratio covered by the service area of a healthcare facility or the capacity of the healthcare facility increases. Should the NHA-DI index increase, than this means that more people have access to higher capacity healthcare facilities. In our analysis we used a travel time threshold of 30 minutes for the healthcare service area. The findings as illustrated in Figure 4.2 show that Sub-district Canacona, Sanquem and Dharbandora have the lowest NHA-DI values. Meaning that these areas are unable to satisfy the healthcare needs from the demand-side. For the sub-district Bardez, Tiswadi and Salcete the opposite is true because they have the highest NHA-DI values. The

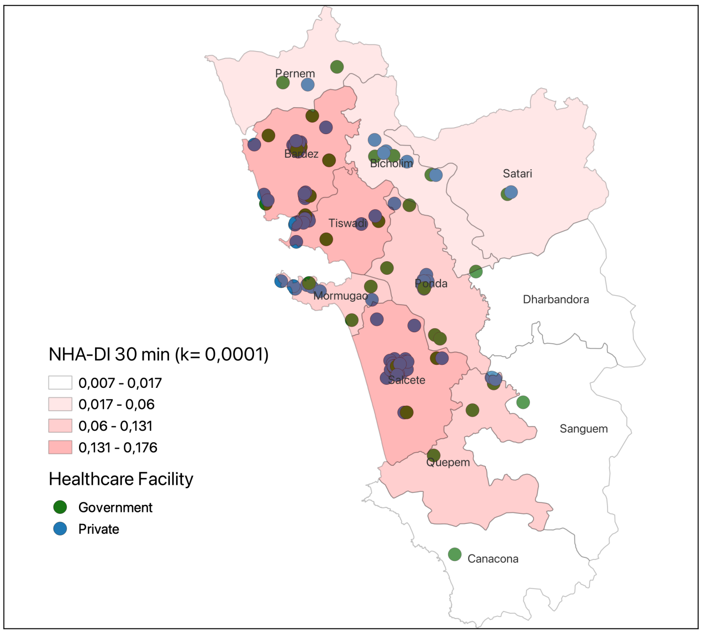


Figure 4.2: NHA-DI GOA

NHA-DP addresses both the geographical accessibility as well as the availability of the healthcare facilities in each sub-district. The NHA-DP achieves this by categorizing the NHA-SI index and NHA-DI index in four quadrants. Each sub-district now contains an NHA-SI index and NHA-DI index. In order to determine its relative position, we calculate the average NHA-SI index and NHA-DI index for all sub-districts. Areas with NHA-SI value and NHA-DI values below the mean are categorised as Low Availability (LAv) and Low Accessibility (LAc). Areas with NHA-SI value and NHA-DI values greater than the mean are categorised as High Availability (HAv) and High Accessibility (HAc). The results are shown in Figure 4.3 and summarised in Table 4.2.

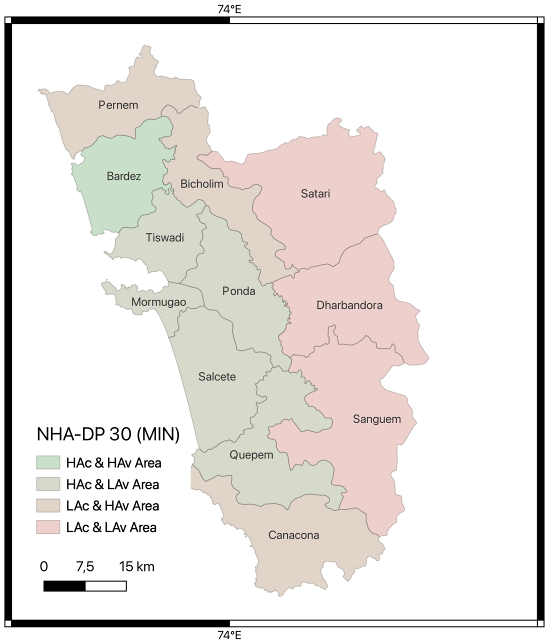


Figure 4.3: NHA-DP GOA

Table 4.2: Results NHA-DP GOA

District	Sub-district	%Urban Population 2011 census [3]	%Rural Population 2011 census [3]	Accessibility (NHA-DI)	Availability (NHA-SI)
North Goa					
	Bardez	68,7	31,3	HAc	HAv
	Ponda	62,5	37,5	HAc	LAv
	Tiswadi	78,81	21,19	HAc	LAv
	Bicholim	43,06	56,94	LAc	HAv
	Pernem	39,69	60,31	LAc	HAv
	Satari	22,56	77,44	LAc	LAv
South Goa					
	Mormugao	85,62	14,38	HAc	LAv
	Quepem	55,37	44,63	HAc	LAv
	Salcete	72,15	27,85	HAc	LAv
	Canacona	27,53	72,47	LAc	HAv
	Dharbandora	Not Available	Not Available	LAc	LAv
	Sanguem	17,72	82,28	LAc	LAv

Quadrant 1: HAc & HAv
In the state of Goa, sub-district Bardez is the only area identified as to be well accessible with a high proportion of its population having access to high-capacity healthcare facilities. The high accessibility of sub-district Bardez is related to the presence of a road network that connects the population of Bardez with healthcare facilities within and outside of its borders.

Quadrant 2: LAc & HAv
Sub-districts Pernem, Bicholim and Canacona are areas with a poor road network which makes it difficult to reach the Healthcare facilities. As a result, only a small percentage of the population is covered by the service area of the available healthcare facilities.

Quadrant 3: LAc & LAv
Sub-district Satari, Dharbandora and Sanquem are areas with a poor road network and a population that consist mostly out of a rural class. The available healthcare facilities are difficult to reach and unable to keep up with the healthcare demand.

Quadrant 4: HAc & LAv
Sub-districts Tiswadi, Salcete, Ponda, Mormugoa and Quepem are areas with a mature road network, but limited healthcare capacity to keep up with the demand. The healthcare facilities are over constrained because their service area covers a large population. The high accessible road network makes it possible for the local population to cross borders and access neighbouring healthcare facilities.

4.2 RESULTS STATISTICAL ANALYSIS

4.2.1 Correlation Analysis

In order to determine the correlation between Spatial healthcare access and the sub-district mortality for 2020, we used the Spearman rank correlation analysis. The following hypothesis were tested and the null-hypothesis is rejected if the p-value is below 0.05:

- H0: There is no correlation between Accessibility scores and the Total Urban Death.
- H1: There is a correlation between Accessibility scores and the Total Urban Death.
- H0: There is no correlation between Accessibility scores and the Total Rural Death.
- H1: There is a correlation between Accessibility scores and the Total Rural Death.
- H0: There is no correlation between Availability scores and the Total Urban Death.
- H1: There is a correlation between Availability scores and the Total Urban Death.
- H0: There is no correlation between Availability scores and the Total Rural Death.
- H1: There is a correlation between Availability scores and the Total Rural Death.

The results reveal that there is a significantly strong positive correlation ($P < 0.05$) between geographic accessibility and total urban ($r = 0.853$, $p < 0.001$) and rural death ($r = 0.867$, $p < 0.01$) for the calendar year 2020. Meaning that a higher accessibility score could increase the yearly total urban and rural death.

Furthermore, the correlation analysis suggests a negative correlation between the availability score and the total urban ($r = -0.203$, $p > 0.05$) and rural death ($r = -0.189$, $p > 0.05$). However, the correlation is not statistically significant because the p-values are above 0.05. Therefore, the null hypothesis is accepted. Meaning that there is no significant correlation between the availability score and the total urban and rural deaths. The results of the Spearman rank correlation analysis are displayed in Figure 4.4.

Correlations

			Accessibility_score	Availibility_score	Total_Urban_Death	Total_Rural_Death
Spearman's rho	Accessibility_score	Correlation Coefficient	1.000	-.392	.853**	.867**
		Sig. (2-tailed)	.	.208	<.001	<.001
		N	12	12	12	12
	Availibility_score	Correlation Coefficient	-.392	1.000	-.203	-.189
		Sig. (2-tailed)	.208	.	.527	.557
		N	12	12	12	12
	Total_Urban_Death	Correlation Coefficient	.853**	-.203	1.000	.734**
		Sig. (2-tailed)	<.001	.527	.	.007
		N	12	12	12	12
	Total_Rural_Death	Correlation Coefficient	.867**	-.189	.734**	1.000
		Sig. (2-tailed)	<.001	.557	.007	.
		N	12	12	12	12

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 4.4: Results Spearman Rank correlation

4.2.2 Relevant Excess Mortality (REM)

The monthly COVID-19 data based on the dataset of the Development Data Lab for the calendar year 2020 are summarised in Table 4.3 and displayed in Figure 4.5. Based on the result there was a relevant access mortality for all cause mortality in the months September (180), October (106) and November (32). During the month May, last month of the national lockdown, the REM was zero. Lastly, the analysis shows that 100 per cent of the REM could be explained by COVID-19 when the monthly COVID-19 values are subtracted from the REM values.

Table 4.3: Goa state COVID-19 data 2020 [6]

Month	New COVID-19 Cases	New COVID-19 Death
January	0	0
February	0	0
March	2	0
April	5	0
May	64	0
June	1244	3
July	4598	42
August	11505	147
September	16000	236
October	10208	176
November	4337	84
December	3103	51

Table 4.4: Goa Relevant Excess Mortality 2020

Month	Expected Death	Observed Deaths 2020	Excess Death	Expected Death+2SD	Relevent Excess Deaths
January	1169	1259	90	1470	-211
February	1056	1099	43	1218	-119
March	943	905	-38	1235	-330
April	984	1056	72	1166	-110
May	998	1155	157	1155	**0**
June	963	1006	43	1097	-91
July	1078	1097	19	1234	-137
August	1112	1217	105	1387	-170
September	1115	1670	555	1490	**180**
October	1135	1538	403	1432	**106**
November	1030	1297	267	1265	**32**
December	1042	1302	260	1304	-2

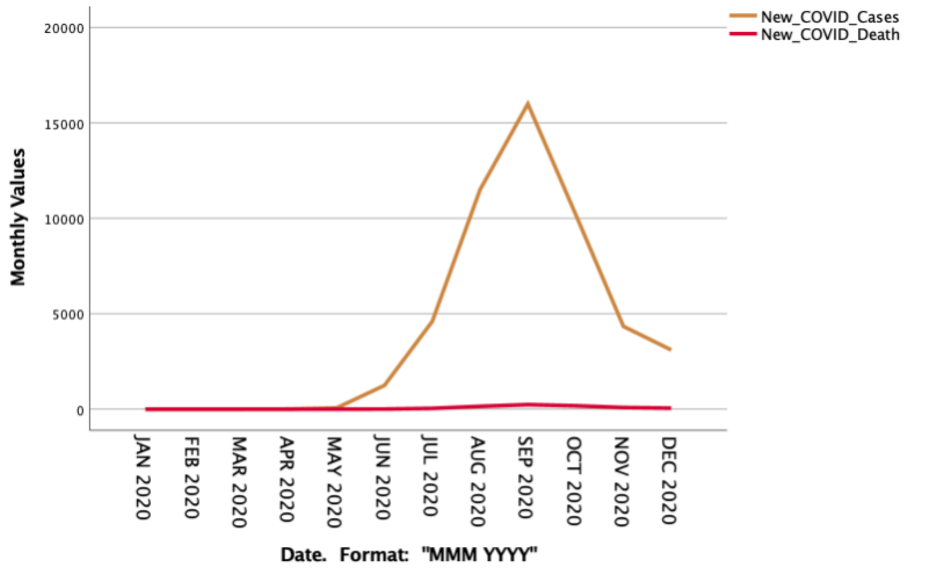


Figure 4.5: Goa state COVID-19 monthly data 2020

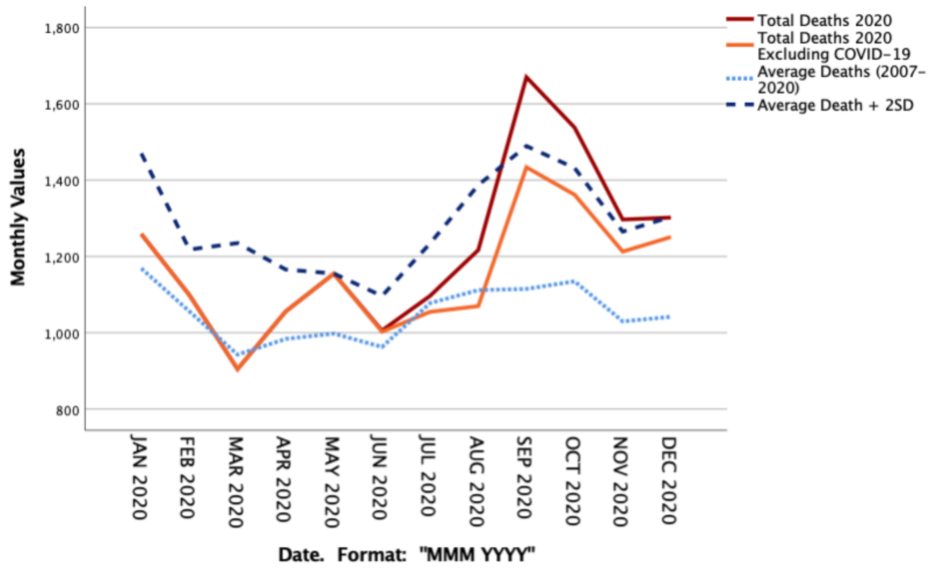


Figure 4.6: Goa state Excess Mortality

5 DISCUSSION

In this chapter we discuss the key findings of our analysis. Secondly, we highlight the strength and limitations of our approach. Lastly, we discuss the implications of our work and provide recommendations.

5.1 DISCUSSION OF KEY RESULTS

At the start of the COVID-19 pandemic the national government of India introduced several non-pharmaceutical interventions to limit the spread of COVID-19 with the nationwide lockdown from March 25, 2020 till May 31, 2020 being the most severe. During the lockdown the different states and union territories in India were categorized in different zones depending on the number of active COVID-19 cases. Even though the state of Goa was categorised as a green zone area, the lockdown still created travel impedance because of the limited public transportation available. Other researchers found similar results regarding the travel behaviour during the lockdown, which comes as no surprise because economic activities are directly or indirectly linked with the transportation system [115][116].

Prior to the nationwide lockdown, the period from January 2020 till March 2020, there was a decline in the monthly mortality rate for the state of Goa. During this period there were no registered COVID-19 mortalities and the number of registered COVID-19 cases was less than five. Based on the historical all-cause mortality data for the state of Goa, this type of behaviour was to be expected. Furthermore, similar research on excess mortality in India (13 states and two union territories) during the COVID-19 pandemic found similar results for the same period [117]. Our results combined with previous research suggest a seasonal drop in the all-cause mortality rate in India for the period from January till March.

The absence of COVID-19 mortalities remained till the end of the lockdown period in May 2020. During the lockdown from March 2020 till May 2020 there were also a limited number of new COVID-19 cases reported. However, the all-cause mortality rate rose exponentially during the lockdown, but remained below the upper bounds of the REM. Based on the historical all-cause mortality data, we expected to see a slightly to moderate increase in all-cause mortality. A possible explanation could be the low COVID-19 test rate in India (0.28 per 1000 people as of April 20) during the lockdown [118]. However, during the lockdown we measured no REM for the state of Goa. Therefore, the exponential increase in all-cause mortality cannot be attributed to COVID-19. Prior research on 13 states and two union territories in India found a different behaviour of the all-cause mortality during the lockdown. The findings suggest that other states experienced a decrease in all-cause mortality from January 2020 till April 2020, and a moderate increase till September 2020 [117]. However, an observational study of all-cause mortality performed in the Chennai district found its first peak between May 2020 and July 2020 [119].

After the nationwide lockdown was uplifted, there was a drop between May 2020 and June 2020, in the all-cause mortality. After June 2020, the data shows an exponential increase in the number of COVID-19 cases and mortality. This development reached its peak in September 2020. As a result, in the months September, October and November the monthly mortality surpassed the upper threshold. The data also shows that the relevant excess mortality in this period could be attributed to the COVID-19 mortality. Meaning that in the year 2020, the state of Goa had two all-cause mortality peaks, with the REM in the second peak being due to the COVID-19 mortality. Our correlation analysis also revealed a significantly strong positive correlation between geographical healthcare access and the mortality rate in both urban and rural areas. Meaning that the exponential increase in all-cause mortality during the different peaks could also be attributed to the unequal spatial healthcare access in the state of Goa.

Our findings also revealed the inequalities in the spatial healthcare access between the different sub-districts in the state of Goa. Individuals residing in sub-districts with a mature road network benefit from good geographical access to different healthcare facilities. It was also noticeable that sub-districts with an urban population of more than 50 per cent were identified as high accessible areas while sub-districts with an urban population below 50 per cent were identified as areas with low geographical accessibility.

Availability of healthcare resouces was also unequally distributed between the different sub-districts in Goa. High accessible areas, with the exception being sub-district Bardez, experienced increasing pressure on the available healthcare capacity. The supply was unable to keep up with the demand. The demand area was not restricted to the boundaries of a sub-district, but allowed inhabitants of neighbouring sub-districts to compete over the available healthcare capacity. Meaning that areas that have good access to their neighbouring sub-districts, had to share their healthcare capacity.

Furthermore, certain low accessible areas were unable to meet the healthcare demand because they did not have the healthcare capacity to achieve this. However, there were also areas that serviced a smaller population and had just enough capacity to meet the demands.

5.2 STRENGTH AND LIMITATIONS

Strength of our findings
The spatial distribution of healthcare resources was researched using the NHAIM gravitational model. This approach allows for the analysis of healthcare resources from both the demand and the supply side. By taking into consideration the patient border crossing, we were able to represent the health behaviour of health seekers in a more realistic manner.

Another strength of our work is our ability to identify areas with limited spatial healthcare access at a much lower geographical scale (sub-district level) than previous work and in a more realistic manner. The geographical level at which the research was performed created insights that would otherwise be overlooked.

Limitation of our findings
Data availability
Analysis on the distribution of spatial healthcare access in the state of Goa was performed using the NHAIM method. This research method requires both non-spatial and spatial data as illustrated in Figure 3.2.

One of the non-spatial input variables required by the NHAIM is the capacity of the healthcare facility. The Indian healthcare system is reliant on both public and private healthcare services. However, during the data collection process it was noticeable that there was no standardized manner for reporting the number of healthcare facilities and their capacity.

The national government provides an estimate about the total number of public healthcare facilities and their total capacity on the state level, but fails to provide any information about the private healthcare facilities. Also, the National Hospital Directory published by the OGD with the goal of providing information about the public and private healthcare facilities in India had limited to no data about their bed capacity.

While exploring the public health data made available by the different state governments and union territories in India, it was noticeable that data about the different public and private healthcare facilities and their capacity was either missing, outdated or fragmented across different websites. It was also noticeable that the available data about the healthcare facilities and their capacity differed between districts within the same state. Also, governments on the state and district level rarely report any information about the private healthcare facilities within their areas.

The state of Goa provided the necessary non-spatial health data for the public facilities in a clear and structured manner, but information about the private healthcare facilities had to be retrieved from the published Biomedical Waste Management reports. The Biomedical Waste Management reports published by the state of Goa provide information about the public and private healthcare facilities and their capacity. However, the reported data is not machine readable. Meaning that human error could result in an under- or overestimation of the healthcare capacity. Regardless, every effort was made to mitigate this error.

One of the spatial input variables required by the NHAIM is the geographical location of the public and private healthcare facilities. The only government entity that reported this information was the OGD. However, the geographical information published in the National Hospital Directory was incomplete and sometimes invalid. Therefore, we used the OSM data on healthcare facilities in India. This dataset complements the dataset published by the OGD, but the information was retrieved through local knowledge. As a result, there were instances when the OSM dataset on healthcare facilities in India contained information for which we were unable to find the healthcare capacity. Healthcare facilities whose existents could not be verified were excluded from our research. Hence, there is a possibility that we underestimated the available healthcare capacity. The healthcare facilities that were excluded were private healthcare facilities and their number was limited. Therefore, we are confident that our findings remain relevant.

Data validity
Non-spatial data about the public healthcare facilities in the state of Goa was retrieved from the Directorate of Health Services Goa. The available data did not have a time stamp, hence there is a possibility that this data is outdated. Information from the Directorate of Health Services Goa was compared with the Biomedical Waste Management report of 2019, published by the state of Goa. Comparison found a limited instance when the data did not match. Therefore, we assumed that the available data posted by the Directorate of Health Services Goa was up to date.

Furthermore, spatial data about the geographical locations of the public and private healthcare facilities was extracted from the OSM dataset on healthcare facilities in India. Provided this dataset was created by adding information from local knowledge to the OGD dataset, the resulting work could be prone to human error. Regardless, this dataset was used due to the limited alternatives.

Another spatial input variable required by the NHAIM is the road network necessary to perform the network analyses. The state of Goa, our case study area, includes both rural and urban areas. Rural areas are known to have both paved and unpaved roads. Further, it is common for the unpaved roads in rural areas to be unregister. Therefore, accessibility in rural areas may be underestimated.

Research method
One of the limitations of the NHAIM research method is that it does not account for variability in traffic conditions. However, this may be overlooked during the lockdown period as citizens were instructed to stay at home, most public activities were prohibited and public transportation was limited.

5.3 RESEARCH IMPLICATIONS

Academic contribution
The COVID-19 health outcomes are unevenly distributed among the different states and union territories in India. Currently there is limited understanding about the determinants that influence the unequal COVID-19 health outcomes. Previous research focused on person specific, demographic, socioeconomic and environmental factors that relate to the COVID-19 health outcomes in India. However, that research was performed on the state and district geographical level [50][60]. Furthermore, there is limited understanding about how healthcare access was distributed during the COVID-19 health crisis.

Our research analyzed the spatial distribution of healthcare resources on the sub-district level for the state of Goa in India. With our findings we were able to identify the disparity in the available healthcare services on a lower geographical level than previously researched in India. We were also able to identify a strong positive correlation between the geographical access and the mortality of different demographic groups during the COVID-19 pandemic. Meaning our research added to the understanding about the spatial healthcare access during the COVID-19 pandemic and its correlation with the excess mortality at the start of the pandemic.

Societal contribution
The societal contribution lies in the identified disparity in the spatial distribution of healthcare resources between the different sub-districts in the state of Goa. The unequal distribution of spatial healthcare access hinders an effective response to the COVID-19 pandemic. Capacity building efforts of the Indian government is focused on strengthening its bed capacity and ICU units without taking into account the underlying inequalities of healthcare access [120][121]. By identifying the areas with limited spatial healthcare accessibility, policy makers can strategically strengthen its healthcare infrastructure.

5.4 POLICY RECOMMENDATIONS AND FUTURE WORK

Further research on spatial healthcare access in India requires the availability of spatial and non-spatial data about the different healthcare facilities. However, during our research we recognised the disparity in the available healthcare data between different states and among districts within a state. Effective decision-making can be achieved by improving access to public health data [122]. Therefore, we will make recommendation that can improve the accuracy of the decision-making process during a health crisis.

Currently public health data provides information about the bed capacity of the different public healthcare facilities. However, the data does not specify what type of beds are available (ICU beds with or without ventilation). Furthermore, information about the available healthcare services and the operation times of those healthcare services is limited. Lastly, information about the available health staff at the different healthcare facilities and the number of ambulances present is often unavailable. Therefore, we recommend an extension of the current public health data that is being measured by the state government. In order to mitigate the available data disparity, we recommend that the national government creates legislation and provides guidelines for the measurement of public health data.

At present, there is no policy for the measurement of health resources within the private sector. Data about the private healthcare facilities in the state of Goa was retrieved from the Biomedical Waste Management report of 2019. However, we were unable to retrieve private healthcare data from other states in a similar manner because not all states provided the most recent biomedical waste management report and especially not in such an elaborate manner. This limited our ability to include and verify private healthcare data in our research. Therefore, we recommend that policies regarding the measurement of public health resources extends to the private sector.

Lastly, COVID-19 mortality data in India is measured on different geographical scales. Most states report this data on the state and district level, but COVID-19 data on the sub-district level is unavailable. This hindered our ability to directly analyse the impact of spatial healthcare access on the COVID-19 mortality rate on the sub-district level. Therefore, we recommend that the national government provides guidelines for the measurement of COVID-19 mortality data on different geographical levels.

Spatial data about the geographic location of the different healthcare facilities was available, but not verifiable. The absence of private healthcare resource data made this task more challenging. Therefore, we recommend that the national government continues its effort in collecting this spatial data and collaborates with private non-profit actors such as OSM to improve the quality of the published spatial healthcare data. Furthermore, road network data for India is freely available on OSM, but the quality differs per state [123]. The available road network of some states and union territories has a lot of missing roads when compared to google maps. Also, detailed government road network data is not freely available which makes it difficult to verify the data of private actors. Therefore, we recommend that the national government makes road network data freely accessible.

Healthcare access has both spatial and non-spatial dimensions. During our research we focused on the spatial dimension of healthcare access. However, the different dimensions are interrelated. Meaning that they influence each other at different times during the course of an illness or care [124]. Therefore, future research could expand our current findings by taking into account the non-spatial dimensions of healthcare access and how they influence mortality over time during the COVID-19 health crisis.

6 CONCLUSION

This chapter concludes on the main research question that was formulated in Chapter 1.4. First, we revisit the sub-research questions used to answer the main research question and describe how our research has answered them. Secondly, we describe how our research has answered the main research question. Finally, we discuss the link between our thesis and the Master program Engineering and Policy Analysis for which it was conducted.

Sub-Research Question 1

How do we define and measure healthcare access?

Based on our literature review findings healthcare access is a complex term for which there is no commonly agreed upon definition or measurement approach. Nevertheless, we defined healthcare access as *"the opportunity to identify healthcare needs, to seek healthcare services, to reach, to obtain or use healthcare services and to actually have the need for services fulfilled"* based on the study of Levesque et al.

Furthermore, healthcare access can be classified in potential access and effective access. Effective access to healthcare reflects an individual's ability, mobility and time to reach a healthcare service once the need has been established, while potential access reflects the existence of a service independent of whether this is effectively accessible. Our research was based on the potential access to healthcare for inhabitants of the state of Goa.
Also, healthcare access can be conceptualised in five dimensions which are either spatial or non-spatial in nature. During our research we focused on the spatial dimension of healthcare access.

Spatial dimension
Availability and accommodation: reflects the geographical access to healthcare services and the existence of a required type of service.

Non-spatial dimension

- Approachability: reflects the ability of health seekers to identify that healthcare services exist, are reachable and capable of having an impact on one's health.
- Acceptability: reflects the social and cultural perceptions that influences the ability of health seekers to accept healthcare services and judge its appropriateness.
- Affordability: reflects an individual's economic capacity to spend resources and time to use appropriate healthcare services.
- Appropriateness: reflects the match between the available healthcare services and the healthcare needs, the timeliness, the time spent assessing healthcare problems, determining the correct treatment and both the technical and interpersonal quality of the provided service.

Lastly, measuring the spatial dimension of healthcare access can be achieved through a variety of Geographic Information System techniques. These GIS techniques can be classified in four categories, namely: provider-to-population ratio, distance to nearest provider, average distance to a set of providers, and gravitational models of provider influence. Each GIS technique comes with a set of strengths and limitations. Based on these strengths and limitations, the Network-based Health Accessibility Index Method which complements the popular 2SFCA gravitational model was chosen for our research. The NHAIM was deemed appropriate for our research because it measures geographic accessibility as well as the availability of healthcare resources while accounting for the patient border crossing problem.

Sub-Research Question 2

How did government intervention impact mobility during the COVID-19 health crisis?

At the start of the COVID-19 pandemic government intervention was aimed at mitigating the spread of the virus. Pharmaceutical interventions in the form of vaccinations only became available at the start of calendar year 2021 for the citizens of the state of Goa. Therefore, prior to the start of the vaccination campaign, non-pharmaceutical measures were the main government instruments for limiting the spread. These non-pharmaceutical interventions resulted in a nationwide lockdown that created travel impedance because non-essential transportation was prohibited while public transportation was either suspended or operated at limited capacity.

Sub-Research Question 3

How is spatial healthcare access to inpatient care distributed?

Based on our research findings, spatial healthcare access is unequally distributed between the different sub-districts in the state of Goa. Sub-districts with an urban population of more than 50 per cent (Bardez, Tiswadi, Salcete, Ponda, Mormugoa and Quepem) were categorised as high accessible areas and those with less (Pernem, Bicholim, Canacona, Satari, Dharbandora and Sanquem) were categorised as low accessible areas. The geographical healthcare accessibility of a sub-district was influenced by the available road network. Sub-districts with a mature road network offered its inhabitants good access to the local healthcare facilities and the healthcare facilities of neighbouring sub-districts.

Furthermore, the distribution of healthcare resources was influenced by the available bed capacity and the geographical healthcare access. Areas with a poor road network were categorised as low accessible areas. Areas with low geographic accessibility served a smaller demand area. Meaning that a lower percentage of the population had access to the available healthcare facilities. Nonetheless, there were sub-districts that had the bed capacity to keep up with the smaller population demand (Pernem, Bicholim and Canacona) and those who were unable to achieve this (Satari, Dharbandora and Sanquem).
Also, areas with a mature road network were categorised as high accessible areas. Areas with high geographic accessibility served a larger demand area. Meaning that both the local population and that of neighbouring sub-districts had access to the available healthcare facilities. As a result, the local population and that of the neighbouring sub-districts competed over the available healthcare resources. There were sub-districts (Tiswadi, Salcete, Ponda, Mormugoa and Quepem) that did not have enough bed capacity to serve the larger demand area while there was only one sub-district (Bardez) capable of achieving this.

Sub-Research Question 4

How has COVID-19 impacted the mortality rate?

Based on our research findings the monthly mortality rate of the state of Goa for the calendar year 2020 had two peaks. The first peak was during the national lockdown period and the second peak was during the last two quarters of 2020. During the first peak we did not measure any relevant excess mortality. Meaning that the exponential increase in all-cause mortality could not be attributed to the registered COVID-19 mortality. However, during the second peak we measured a relevant excess mortality for the months September, October and November. Meaning that the excess mortality during the second all-cause mortality peak could be attributed to the registered COVID-19 mortality.

Main Research Question: How does spatial healthcare access to inpatient care during the COVID-19 health crisis relate to the mortality rate for different demographic groups?

The purpose of this thesis was to explore the relation between spatial healthcare access and the mortality rate for different demographic groups during the COVID-19 pandemic for the state of Goa. Based on our research findings we conclude that there is no significant correlation between healthcare availability and the urban and rural mortality rate for the state of Goa. However, there is a significantly strong positive correlation between geographical healthcare access and the urban and rural mortality for the state of Goa. This correlation suggests that the two all-cause mortality peaks for the calendar year 2020 were partly influenced by the spatial healthcare accessibility of the different sub-districts.

Link to EPA program
The central focus of the Engineering and Policy Analysis program is on analysing and solving complex problems within a multi-actor system. The fundamental themes include system understanding, modelling, simulation, policy and politics. During the EPA program students are taught that solving complex problems requires solutions that not only address the technological aspects, but focus on the societal and political aspects as well.

The complexity surrounding the COVID-19 health crisis is reflected by the number of countries impacted, the millions of lives lost and the added global debt. Both government and private actors were forced to make decisions with limited information and unpredictable outcomes. In order to limit the research gap and inform policy our analysis addressed both the social and political aspects surrounding spatial healthcare access during the COVID-19 health crisis. We also used a method that is technical in nature and provided policy advice. Therefore, our research has fulfilled the requirements of an EPA thesis by using a technical solution on a societal problem to inform the decision-making process.

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A LIST OF PUBLIC HEALTHCARE FACILITIES

District	Healthcare Facility	No. of Beds	Type
North GOA	Asilo District Hospital, Mapusa	240	DH
South GOA	Community Health Center, Canacona	70	CHC
South GOA	Community Health Center, Curchorem	30	CHC
North GOA	Community Health Center, Pernem	40	CHC
North GOA	Community Health Centre Sankhalim-Bicholim	46	CHC
North GOA	Community Health Centre Valpoi	35	CHC
North GOA	Community Health Centre, Tuem	40	CHC
South GOA	Urban Health Centre, Margoa	0	UHC
North GOA	Primary Health Centre, ponda	0	PHC
North GOA	Goa Medical College & Hospital	1155	Hospital
South GOA	Primary Health Centre Cortalim	0	PHC
South GOA	Employee State Insurance Dispensary, Vasco	0	Clinic
North GOA	UHC Mapusa	0	UHC
South GOA	Primary Health Centre Loutolim	0	PHC
South GOA	Hospicio District Hospital, Margoa	212	DH
North GOA	Primary Health Center, Colvale	0	PHC
South GOA	Primary Health Center, Navelim	0	PHC
South GOA	Primary Health Centre, Chinchinim	0	PHC
North GOA	Urban Health Centre, Panaji	0	UHC
South GOA	Primary Health Centre, Chimbel	0	PHC
North GOA	Primary Health Center, Cansarvarnem	12	PHC
South GOA	Primary Health Centre Marcaim	12	PHC
North GOA	Primary Health Centre Mayem, Bicholim	30	PHC
South GOA	Primary Health Centre Pillem, Dharbandora	15	PHC
North GOA	Primary Health Centre, Aldona	12	PHC
South GOA	Primary Health Centre, Bali	24	PHC
North GOA	Primary Health Centre, Betki	12	PHC
North GOA	Primary Health Centre, Candolim	10	PHC
South GOA	Primary Health Centre, Cansaulim	12	PHC
South GOA	Primary Health Centre, Curtorim	12	PHC
South GOA	Primary Health Centre, Quepem	24	PHC
South GOA	Primary Health Centre, Sanguem	20	PHC
North GOA	Primary Health Centre, Shiroda	24	PHC
North GOA	Primary Health Centre, Siolim	12	PHC
North GOA	Shri Kamaakshidevi Homeopathic Medical College	25	Hospital
South GOA	Sub District Hospital, Chicalim (Cottage Hospital)	120	SDH
North GOA	Sub District Hospital, Ponda	220	SDH
South GOA	TB Hospital, Margao	66	Hospital
North GOA	Primary Health Center, Corlim	0	PHC
North GOA	Sub-Health Centre, Gaune	0	SHC
South GOA	Sub-health Centre, Verlem	0	SHC
South GOA	Sub-health Centre, Curpem	0	SHC
South GOA	Sub-Health Centre, Ambaulim	0	SHC

B | LIST OF PRIVATE HEALTHCARE FACILITIES

District	Healthcare Facility	No. of Beds
South GOA	Adarsh Family Hospital	10
North GOA	Adhar Hospital	10
North GOA	Amshekar Hospital, Valpoi	8
North GOA	Anandi Nursing Home & Maternity Hospital	9
South GOA	Antonio Vicante Da Costa Memorial Clinic / A.V. Da Costa Hospital	10
South GOA	Ashirwad Urology and Laparoscopy hospital	6
South GOA	Aster Hospital Pvt Ltd	35
South GOA	Baracho Hospital and Maternity Home	10
North GOA	Bhagyoday Hospital	19
North GOA	Bosio Hospital	18
North GOA	Campal Clinic	30
North GOA	Chaitanya Hospital	10
South GOA	Chikitsa Hospital, Verna	10
North GOA	Chodanker Nursing Home	24
North GOA	Desai Nursing Home, Ponda	4
South GOA	Dr A G Borkar Memorial Borkar Nursing Home	23
North GOA	Dr Barbosa Eye Clinic and Hospital	2
South GOA	Dr Buvaji's Family Welfare Centre	10
North GOA	Dr Caeiros Bichollm Polyclinic	17
South GOA	Dr Panandikar Eye Care Clinic & Hospital	4
North GOA	Dr Paresh Borkar Clinic And Nursing Home, Ponda	5
South GOA	Dr Rebello Clinic and Hospital, Margoa	10
South GOA	Dr. Correia Afonso Hospital	10
North GOA	Dr. Dukie's Hospital & Research Centre	18
North GOA	Dr. Juwarkar's Hospital	8
North GOA	Dr. Kamat's Nursing Home/ Dr. Ajit Kamat Hospital	10
North GOA	Dr. Kedar Hospital, Panji	30
North GOA	Dr. Kolwalkar's Galaxy Hospital	44
South GOA	Dr. Lawande's Hospital & Medical Research Center	25
South GOA	Dr. Menezes Nursing Home	20
North GOA	Dr. Mopkar's Ankur nursing home	9
North GOA	Dr. Prabhu Nursing Home	4
South GOA	Dr. Subodh Maternity Home	12
North GOA	Drishti Eye Hospital & Laser center	5
South GOA	E.S.I. Hospital	100
North GOA	Gauns Child Care Hospital, Mapusa	16
North GOA	Ghanashyam Govind Kamat Memorial Hospital	18
South GOA	Grace Intensive Cardiac Care Centre	62
South GOA	Grace Nursing Home	30
South GOA	Gracias Maternity Hospital	24
North GOA	Healthway Hospital, Mala	40
North GOA	Healthway Hospitals Pvt Ltd, Kadamba Plateau	240
North GOA	Hirabai Parsekar Memorial Hospital	10
North GOA	Holy Cross General Remanso Hospital, Mapusa	30

District	Healthcare Facility	No. of Beds
South GOA	Horizon ICU & Hospital	35
North GOA	Dhumaskar General Hospital	16
South GOA	Infant Jesus Nursing Home	10
South GOA	Jeevodaya Nursing Home, Savordem	8
North GOA	Kaisare Eye and Dental Hospital	10
North GOA	Kalangutkar Nursing Home	12
North GOA	Kamakshi Arogya Dham	100
North GOA	Kamat Maternity & Surgical Hospital	10
South GOA	Kulkarni Eye Clinic and Hospital	6
South GOA	Madkaikar City Hospital	10
North GOA	Mahatme Nursing Home Hospital	10
North GOA	Mandovi Clinic (Hospital)	10
North GOA	Manipal Hospital	280
North GOA	Mardolkar Hospital	10
North GOA	Menezes Polyclinic	27
South GOA	Mothercare Chikitsa Hospitals	30
South GOA	MPT Hospital	60
South GOA	My Eye Hospital	10
South GOA	Nagarsenkars Classic Hospital	40
South GOA	Nagzarkar Hospital & Clinic	12
North GOA	Navjeevan Nursing Home	10
South GOA	Noble Hospital	16
South GOA	Orthopedic hospital for surgery	10
South GOA	Pai Hospital	20
South GOA	Parulekar eye site hospital	5
South GOA	Parulekar Nursing Home Medical-Surgical Maternity	12
North GOA	Platicare Hospital	16
North GOA	Kamat Nursing Home	15
North GOA	Priolkar Surgical/Priolkar Nursing Home	9
North GOA	Raikar Nursing Home	10
North GOA	Redkar Hospital and Research Center	16
North GOA	RG Stone Urology & Laproscopy Hospital, Porvorim	45
South GOA	Roque Fereira Memorial Hospital	25
South GOA	Royal Hospital	48
North GOA	Sankalp Nursing Home	24
North GOA	Savaikar Hospital and Laparoscopy Centre	41
South GOA	Sheldekar Nursing Home	10
North GOA	Sushrusha Nursing Home, Ponda	15
South GOA	Sinai Clinic & Hospital	12
North GOA	Singbal Hospital	20
South GOA	SMRC's V. M. Salgaocar Hospital	86
South GOA	Sonu Kamat Maternity Orthopaedic & Surgical Hospital	10
North GOA	St. Anthony's Hospital and Research Centre	12
South GOA	Sushrushlaya Hospital	14
North GOA	Sushrutzi Dhulapkar's Hospital	20
South GOA	Trimurti General Hospital	50
North GOA	Trinity Healthcare And Research, Esperanca Hospital	20
North GOA	Usgaonkers Children Hospital and iNICU	19
South GOA	Vaatsalya Hospital	16
South GOA	Victor Hospital and Medical Services	150
North GOA	Vision Multispeciality Hospital	40
South GOA	Yashodan Hospital	26