INSTITUTE OF GEOGRAPHICAL SCIENCES

B. Sc. Geographical Sciences

Bachelor's Thesis

Spatial Accessibility to Healthcare Facilities in the Tri-Border of the Alto Paraná Atlantic Forest

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June 23, 2024

Declaration of Academic Integrity

I hereby declare to the Freie Universität Berlin that I have completed the following Bachelor's Thesis independently and without the use of sources and aids other than those cited.

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No entire section or full paragraph of this thesis was written with the help of an AI. If an AI was used, it was only to improve my own writing.

Further, I declare that this work has not been submitted to any other university as part of an examination attempt, either in identical or similar form, nor has it been published elsewhere.

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June 23, 2024

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Abstract

This thesis analyses the spatial accessibility of healthcare facilities in the tri-border area of the Alto Paraná Atlantic Forest, which includes municipalities in Paraguay, Brazil and Argentina. The study aims to provide a comprehensive analysis of the differences in accessibility between different regions and population groups in this area.
Using data from OpenStreetMap, official government sources and the Global Human Settlement Layer, the study combines a friction surface and a cost distance algorithm to model the cost of movement through space and calculate travel time to healthcare facilities as an indicator for accessibility.
The analyses revealed notable disparities in healthcare accessibility between the three countries with Brazil and Argentina having the highest accessibility, followed by Paraguay with the lowest accessibility. A strong correlation between population density and accessibility revealed that urban regions exhibit the highest accessibility, while rural and peripheral areas, particularly in Paraguay, face much lower accessibility. It was also revealed that indigenous communities are negatively influenced greater by these disparities in accessibility.

Chapter 1

Introduction

1.1 Agenda for Sustainable Development

This thesis is rooted in the third goal of the global Agenda for Sustainable Development (United Nations, 2015b). This Agenda defines 17 sustainable development goals as a comprehensive plan of action, which is a collective commitment to addressing these most pressing global challenges like elevating societal well-being, protecting our planet, creating lasting prosperity and particularly healthcare accessibility.
Goal 3 specifically calls for equal access to healthcare and education regardless of background, stating: "Ensure healthy lives and promote well-being for all at all ages" (United Nations, 2015b). It emphasises the need for universal healthcare coverage, equitable healthcare services, and improved health outcomes worldwide. This goal is crucial for sustainable development as it improves overall health and increases productivity, which in turn contributes to poverty reduction and economic growth (Zhao, Vemuri, & Arya, 2016). It also promotes equality for marginalised groups (Davy, Harfield, McArthur, Munn, & Brown, 2016).
Achieving this goal requires a concerted effort from various actors, including governments, international organisations, and non-governmental organisations (NGOs) (Sanadgol, Doshmangir, Majdzadeh, & Gordeev, 2021). Key initiatives such as the Universal Health Coverage Partnership of the World Health Organisation (WHO) (UHC-Partnership, 2021), and the Global Fund to Fight AIDS, Tuberculosis, and Malaria (The Global Fund, 2024), illustrate the global commitment to improving healthcare accessibility. These initiatives focus on strengthening healthcare systems, improving service delivery, and ensuring that healthcare is accessible to all, especially the most vulnerable (Syed, Gerber, & Sharp, 2013).
One indicator the United Nations uses to measure the progress of the third goal is, for example the Universal Health Coverage indicator (World Health Organization & World Bank, 2023). This indicator tracks various aspects of healthcare accessibility, including the availability of essential healthcare services, patient satisfaction, and reduced travel times to healthcare facilities.

1.2 Access to Healthcare

While the Universal Health Coverage indicator provides a broad overview of healthcare accessibility, a deeper understanding of access to healthcare is necessary. Access to healthcare is complex to define and measure (Aday & Andersen, 1974). Aday and Andersen (1974) suggest that it is perhaps most meaningful to consider access in terms of whether those who need care receive it. Gulliford et al. (2002) similarly define access to healthcare as the ability to obtain appropriate health care resources to maintain or improve health. Both Aday and Andersen (1974) and Gulliford et al. (2002) emphasise the importance of viewing healthcare accessibility as a multidimensional concept. They identified three primary barriers to healthcare access: the personal barrier, which involves patients' recognition of their need for healthcare and their decisions to seek it; the financial barrier, which pertains to the cost of healthcare services and how it influences patients' decisions to obtain care; and the organisational, also called structural barrier, which encompasses all aspects related to the provision and ease of access to healthcare services. In detail, organisational barriers to healthcare access include structural and systemic barriers such as insufficient resources, inefficient processes, long waiting times, lack of coordination and integration of healthcare services, as well as geographical barriers that make access to medical facilities difficult, for example, the travel time to healthcare facilities (Carrillo et al., 2011).
According to Wang and Luo (2005), organisational barriers can arise from spatial variability due to the uneven distribution of healthcare providers and consumers, as well as differences among population groups based on socioeconomic and demographic characteristics, which then causes variability in travel time.
The consequences of these organisational barriers to healthcare access are examined by Syed et al. (2013). They conclude that such barriers can lead to rescheduled or missed appointments, delayed care, and missed or delayed medication use, ultimately resulting in poorer management of chronic illnesses and poorer health outcomes.

1.3 Travel Time

A critical factor in understanding the variability in travel time to healthcare services as an organisational barrier is spatial accessibility. It is determined by the barriers or friction of space, which are influenced by the time and physical distance needed to access the services (Aday & Andersen, 1974).
To calculate travel time to health care facilities and therefore the accessibility for a region, Weiss et al. (2018) proposed a method that integrates different datasets and geo-spatial modelling techniques to quantify travel time to urban centres. Nelson et al. (2019) and European Commission Joint Research Centre (2021) first developed this methodology, which Weiss et al. (2018) developed further. The authors used data from Open Street Map (OSM) and Google Roads to create a comprehensive road network, supplemented by rail and waterway networks as well as topographic and land cover data. This information was converted into a "friction surface" that represents the speed of movement through each pixel of the earth's surface. A least-cost path algorithm was applied to calculate the travel time from each point to the nearest city. The results were validated by comparing them with travel times from the Google Maps API, where a high level of agreement was found. They further proposed a method for investigating the travel time to healthcare facilities in Weiss et al. (2020), which expands on their previous research by adding healthcare

facilities to the model.

1.4 Study Area

As mentioned in the Sustainable Development Goals the most vulnerable countries like low and middle income countries are facing special challenges (United Nations, 2015b). For a better understanding and to identify barriers of access to healthcare, like travel time, it is especially important to look at these countries.
Border regions especially are of interest because of their similar physical conditions but sometimes very different governance policies and land use and planing. Because of that, the impact of different kinds of governance on spatial indicators like travel time and following that, also sustainable development can be investigated. Border regions can also serve as a natural experiment for studying how each country influences the others with the spillover effect (Piquer-Rodríguez, Gasparri, Zarbá, Aráoz, & Grau, 2021), where policies and developments are copied by the neighbouring states. The tri-border of the Alto Paraná Atlantic Forest in South America displays such features and is optimal for such research on differences in accessibility to healthcare and was therefore the study area. It lies at 55° West and 25.5° and covers an area of 36854 km^2 (Figure 1.1).
The tri-border is also of interest through its high level of inter-connectivity. For example, as Marques, Rodrigues, de Almeida Rezende, Soares, and Vélez (2013) and Cardelli and Muñoz (2021) found, many people regularly move between the border town for healthcare services, shopping, and work. This movement promotes economic growth and regional cooperation among the countries (Arsentyeva, 2020). The historical development of these countries has also significantly shaped the current dynamics of this area (Lisboa & Morínigo Martínez, 2021). However, this inter-connectivity is not without its drawbacks. As Martens and Veloso (2019) noted, the region also experiences cross-border theft, often driven by poor financial conditions.

1.4.1 Alto Paraná Atlantic Forest

The Alto Paraná Atlantic Forest, in which the study area lies, is an important eco-region. This forest extends across the southern part of Brazil, northeastern Argentina and eastern Paraguay. It covers an area of approximately 485,000 km^2 (Schipper, 2018). The geographical extent of this forest ranges from the coastal forest of the Serra do Mar to the basins of the Paraná River (Schipper, 2018). The Alto Paraná Atlantic Forest is of great ecological importance as it has have a remarkable biodiversity and endemism (de Lima et al., 2020). Despite this, the Alto Paraná Atlantic forest is highly endangered (de Lima et al., 2020). Up to 42% of the original biodiversity and biomass has already been lost in the Atlantic Forest, mainly due to human influence (de Lima et al., 2020). These activities have led to significant fragmentation of the forest, affecting the habitats of many species and endangering biodiversity (Gennerich, 2024). The conservation and restoration of the Alto Paraná Atlantic Forest is of crucial importance, not only for the protection of biodiversity but also for the sustainable development of the region. This also extends to the health care of the local population. The loss of forest areas and the associated degradation of ecosystems have a direct impact on the availability and quality of health and well-being through heat stress (Palmer, 2022), (Hedin, Hahs, Mata, & Lee,

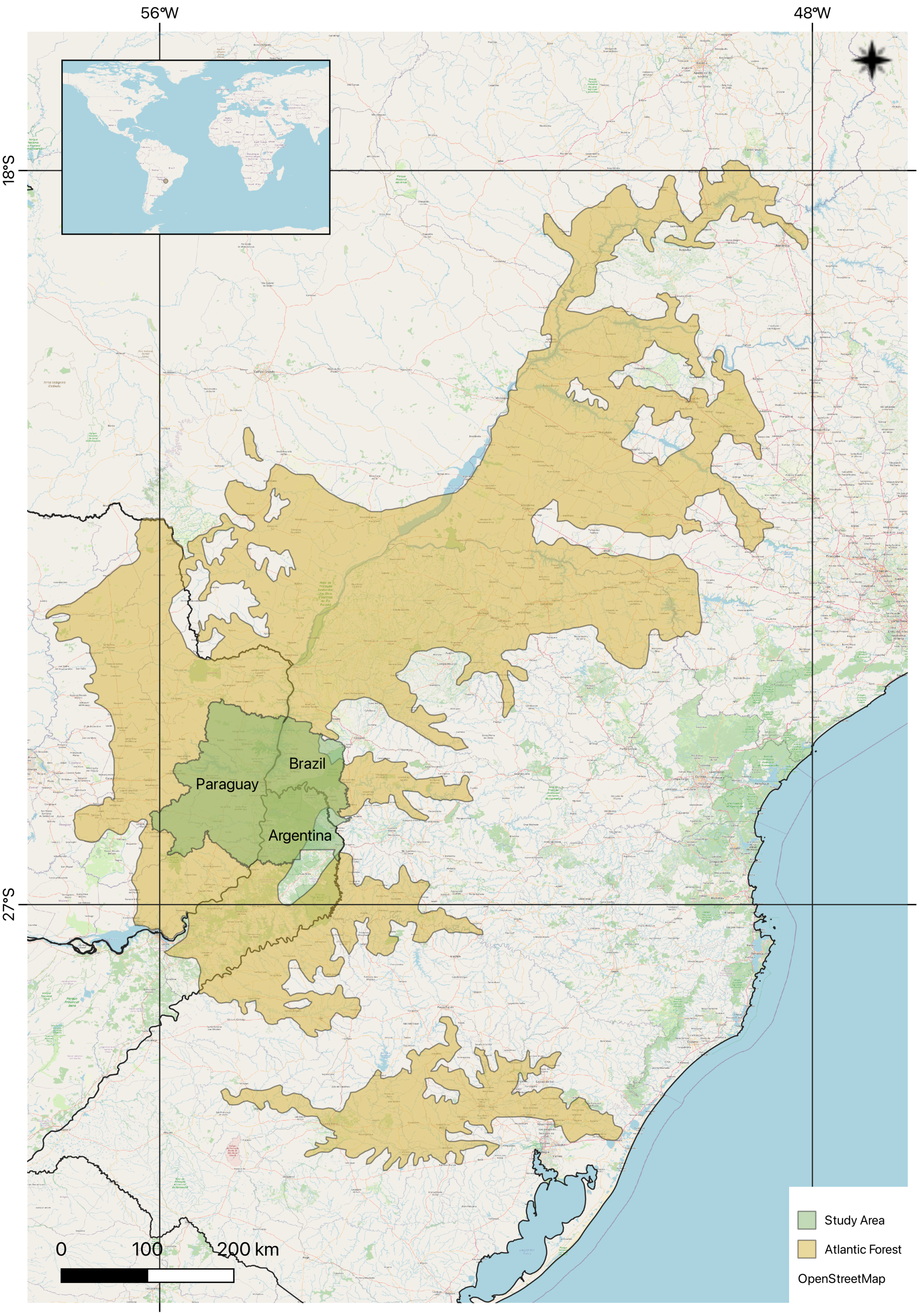

Figure 1.1: Study Region

2022), (Deivanayagam & Osborne, 2023). It is therefore important to develop sustainable solutions that ensure both the protection of nature and access to health services.

1.4.2 Argentina

Argentina's part of the study area consists of three municipalities and covers an area of approximately 7940 km^2. Its border city is Puerto Iguazú. This specific region forms a small part of Argentina's extensive and varied landscape.

The country, located in the southern half of South America, is the eighth-largest in the world by land area, covering approximately 2.78 million square kilometres (Runfola et al., 2020), with over 46 million inhabitants (United Nations, 2022). It shares borders with Chile, Bolivia, Paraguay, Brazil, and Uruguay (Runfola et al., 2020). The country has a diverse geography that includes the Andes mountain range, fertile Pampas plains, and extensive Atlantic coastline.
Argentina's population density is approximately 16 people per square kilometre (United Nations, 2022). The country has a high life expectancy of 76 years (World Bank, 2022a). Argentina is classified as an upper-middle-income country (World Bank, 2022b). Its economic instability, characterised by high inflation and fiscal deficits, poses significant challenges to healthcare accessibility, particularly for low-income and vulnerable populations (World Bank, 2024). Healthcare accessibility in Argentina is also influenced by regional disparities. The healthcare system is divided into public, private, and social security sectors, with the public sector providing free healthcare to all citizens and residents (Belló & Becerril-Montekio, 2011). However, there are significant differences in the quality and availability of healthcare services between urban and rural areas (Vacarezza & Cruz, 2023), (Palacios, Espinola, & Rojas-Roque, 2020). The Northwest and Northeast regions, in particular, face challenges in healthcare accessibility due to fewer facilities and healthcare professionals compared to more developed regions like the Pampas (Gilardino, Cabra, & Zanela, 2016). Government initiatives such as the Primary Health Care Centres and the Nacer/SUMAR Program aim to improve healthcare access, especially for vulnerable populations (Palacios et al., 2020).
In 2022, Argentina had approximately 955,032 indigenous people, which represents 2.03% of the total population (Berger et al., 2024). The indigenous population in Argentina faces significant barriers to healthcare access, such as communication and cultural differences, and a lack of essential services like clean water and sanitation (Quintana et al., 2021). Initiatives to improve healthcare access for these communities include training community health workers and integrating traditional practices with biomedical care (Quintana et al., 2021).

1.4.3 Brazil

Brazil's part of the study area consists of 18 municipalities and covers an area of approximately 8020 km^2. Its border city is Foz do Iguaçu. This area is a small segment of Brazil's vast and varied territory.

It is the largest country in South America, spanning an area of 8.5 million square kilometres (Runfola et al., 2020), and is the world's fifth-largest country by both area and population,

with over 217 million inhabitants (United Nations, 2022). The country is characterised by diverse geographical features, including the Amazon rain forest, Pantanal wetlands, and extensive Atlantic coastline. Brazil's population is heavily concentrated in the southeastern and northeastern regions, with significant urbanisation (Agência de Notícias - IBGE, 2023). Brazil's population density is approximately 26 people per square kilometre (United Nations, 2022). The country has a life expectancy of 73 years (World Bank, 2022a).
Brazil is classified as an upper-middle-income country (World Bank, 2022b). Its economic disparities, coupled with regional inequalities, significantly impact healthcare accessibility, particularly in under-served and remote areas (Hone et al., 2019).
Brazil's healthcare system, known as the Unified Health System (SUS), provides universal healthcare to all residents (Oliveira, Gabriel, Poz, & Dussault, 2017). Despite this, there are significant disparities in healthcare access and quality, particularly in rural and remote areas (Palmeira et al., 2022). The distribution of healthcare facilities and professionals is uneven, with the North and Northeast regions facing greater challenges in accessing healthcare services compared to the more developed southeast (Silva et al., 2021). Initiatives such as the Mais Médicos (More Doctors) Program aim to address these disparities by improving the distribution of healthcare professionals across the country (Oliveira et al., 2017).
The indigenous population in all of Brazil consisted in 2022 of 1,693,535 people, which represents approximately 0.83% of the total population (Berger et al., 2024). The indigenous population includes numerous ethnic groups and faces significant health inequities, including higher infant mortality rates, lower life expectancy, and a high burden of infectious diseases (Berger et al., 2024), (Santos et al., 2022), (Mendes, Leite, Langdon, & Grisotti, 2018). The Indigenous Healthcare Subsystem (SASI) and the National Policy for the Care of Indigenous Peoples (PNASPI) aim to provide differentiated healthcare that respects socio-cultural diversity (de M Pontes & Santos, 2020).

1.4.4 Paraguay

Paraguay's part of the study area consists of 29 municipalities and covers an area of approximately 20894 km^2. Its border city is Ciudad del Este. This region represents a portion of Paraguay's diverse landscape and population distribution.

Paraguay, a landlocked country in central South America, covers an area of approximately 400 thousand square kilometres (Runfola et al., 2020). It is bordered by Argentina, Brazil, and Bolivia. The country has a population of around 7 million people, with a significant proportion living in rural areas (United Nations, 2022). Paraguay's population density is approximately 7 people per square kilometre (United Nations, 2022). The country has a life expectancy of 70 years (World Bank, 2022a).
Paraguay is classified as a lower-middle-income country (World Bank, 2022b), and its economic constraints, including high poverty rates and limited public spending on healthcare, exacerbate challenges in healthcare accessibility, particularly for rural and indigenous populations (World Health Organization, 2024).
Paraguay faces significant healthcare challenges, including a high burden of both communicable and non-communicable diseases (Amnesty International USA, 2024). The healthcare system is fragmented, with public, private, and social security sectors providing services (OECD, 2018). The public sector, managed by the Ministry of Public Health and Social Welfare, is the primary provider of healthcare for the majority of the population,

especially those without health insurance (OECD, 2018). However, there are severe and unequal gaps in access to healthcare, particularly in rural areas where medical facilities and qualified personnel are scarce (Capurro & Harper, 2022). The Paraguayan government has undertaken several reforms to improve healthcare access and quality, including the establishment of family health units and the implementation of a national health policy aimed at achieving universal health coverage (OECD, 2019). Despite these efforts, significant challenges remain, including under-funding, inefficient resource allocation, and the need for better integration of healthcare services (OECD, 2019). The indigenous population in Paraguay represents approximately 2.29% of Paraguay's total population, comprising around 140,206 individuals (Berger et al., 2024). They face significant barriers to healthcare access, including discrimination, cultural barriers, and poor infrastructure (Berger et al., 2024). Initiatives such as the partnership between the Ministry of Public Health and Social Welfare (MSPyBS) and PAHO/WHO aim to improve vaccine coverage and healthcare access for indigenous communities, particularly in remote areas (World Health Organization, 2024).

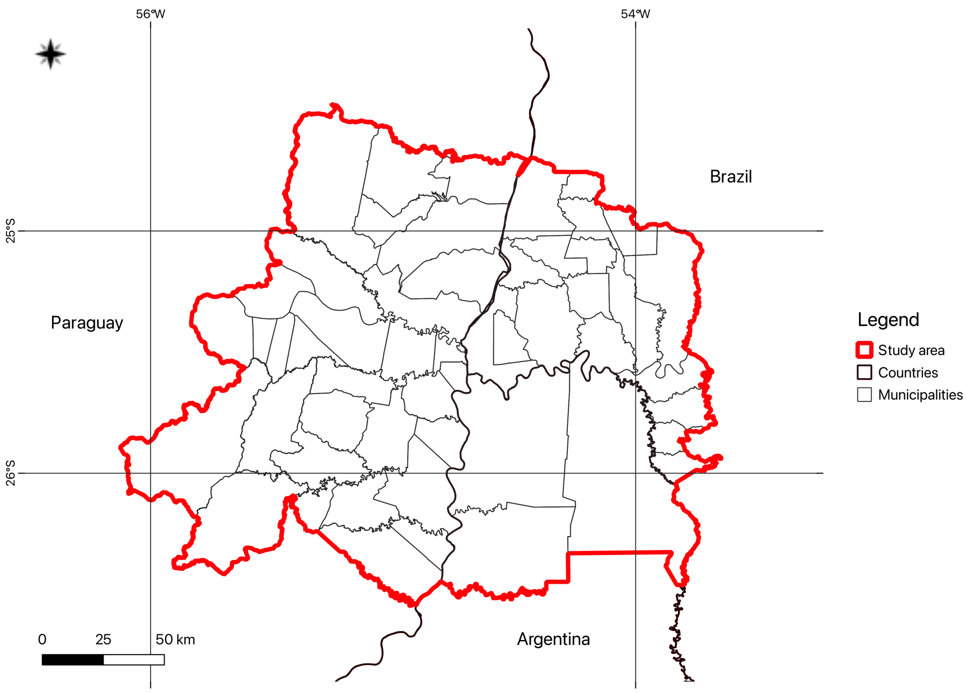

Figure 1.2: Study Area

1.5 Research Questions and Objectives

The general focus of this thesis was to investigate the spatial accessibility to healthcare facilities in the tri-border area of the Alto Paraná Atlantic Forest, encompassing regions in Paraguay, Brazil, and Argentina. This study aims to provide a comprehensive analysis of the current distribution of healthcare facilities and to understand the disparities in accessibility across different regions and populations within the study area. The following research questions and objectives were developed.

RQ1: What are the differences in accessibility to healthcare facilities between Paraguay, Brazil, and Argentina and their states?
OB1: Compare the accessibility to healthcare facilities between Paraguay, Brazil, and Argentina, as well as their respective states.
This comparison will highlight the differences in healthcare accessibility among the three countries and within their internal regions, providing insights into regional disparities and potential areas for improvement.

RQ2: How does population density influence accessibility?
OB2: Analyse the influence of population density on accessibility to healthcare facilities by examining the correlation between population density and the availability of healthcare services.
This aims to identify whether densely populated areas have better or worse access to healthcare compared to less populated regions.

RQ3: What are the differences in accessibility to healthcare facilities between the overall population and indigenous communities?
OB3: Investigate the differences in accessibility to healthcare facilities between the overall population and indigenous communities within the tri-border area.
This aspect of the research is crucial for understanding the specific challenges faced by indigenous populations in accessing healthcare and for identifying any significant disparities that may exist.

Chapter 2

Methodology

In the context of healthcare, several accessibility metrics are commonly used. The most prominent include the "Floating Catchment Area," "Minimum Travel Time," and "Minimum Network Distance," as reviewed by Neutens (2015) and Mark F. Guagliardo and Guagliardo (2004). These metrics can be calculated through various methods, such as Euclidean distance methods, network-based methods, and raster-based methods, also reviewed by Neutens (2015). This thesis employs the "Minimum Travel Time" metric using a raster-based cost distance approach due to its demonstrated effectiveness by Neutens (2015) and Fortney, Rost, and Warren (2000), and because it consistently identifies more areas and people with limited accessibility compared to the network-based method and is more sensitive to travel speed settings identified by Delamater, Messina, Shortridge, and Grady (2012). Notable earlier works utilising a similar method include Tanser, Gijsbertsen, and Herbst (2006), Brabyn and Skelly (2002) and Weiss et al. (2020).
This thesis updates and refines the methodology for calculating travel times from Weiss et al. (2020) to address the specified research questions. Humanitarian mapping and volunteered geographic information have been validated as reliable sources by Goodchild (2007), Barron, Neis, and Zipf (2014), and Herfort, Lautenbach, Porto de Albuquerque, Anderson, and Zipf (2021). Consequently, data sources such as OpenStreetMap for roads, healthcare facilities, and the Global Human Settlement Layer from the European Commission Joint Research Centre (2021) were utilised, supplemented by official governmental sources. Additionally, this thesis incorporated official governmental data on indigenous communities and their locations. The objective of this approach is to simplify and automate the process of generating travel time maps, making them easier to replicate and more accessible. This addresses the issues highlighted by Weiss et al. (2020), who conducted detailed calculations involving numerous factors that may not always be necessary for answering these specific questions.

2.1 Overview of the Approach

The main idea of this methodology was to combine a friction surface map that models the cost of movement through space to the healthcare facilities. With a cost distance algorithm, the least cost path to these facilities can be calculated. A high level visualisation of the created model is visible in figure 2.1.

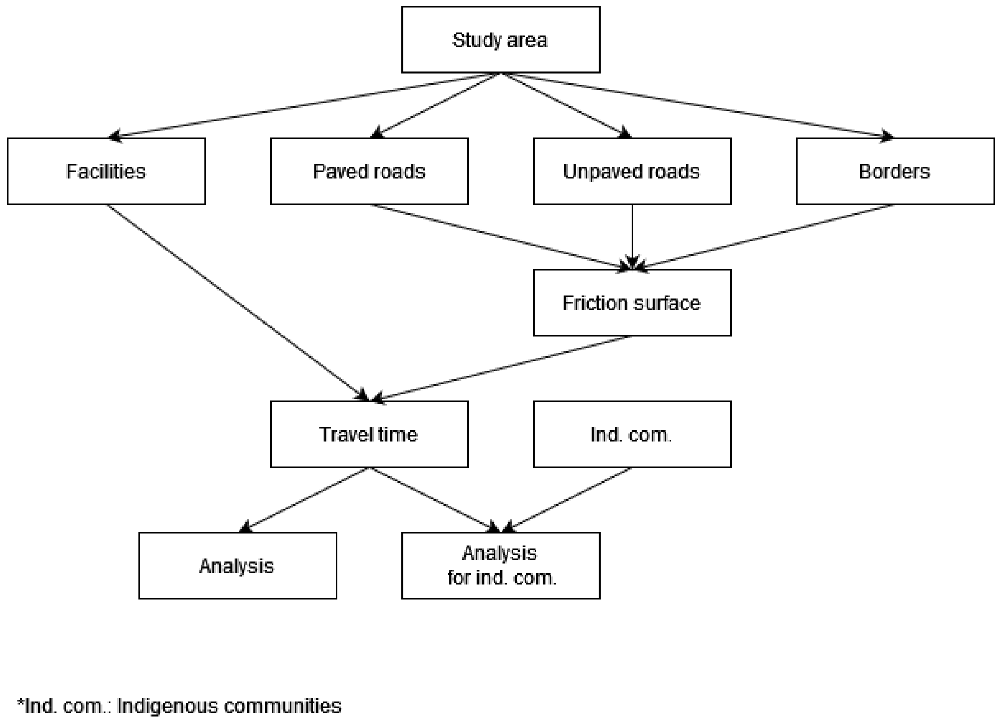

Figure 2.1: Overview Workflow

2.1.1 Software and Tools

This methodology was developed using the QGIS Geographic Information System (QGIS Development Team, 2024). This software includes many algorithms and tools for basic geographic data processing and it also includes a model builder which was also used to automate the creation of the results. The model itself was not available from earlier work and needed to be re-implemented with this model builder. Libraries for geographic data processing that were used include the GDAL (Geospatial Data Abstraction Library) from Rouault et al. (2024) for basic raster processing and the System for Automated Geoscientific Analyses (SAGA) by Conrad et al. (2015), mostly for the cost distance calculation. Utility tools were developed with Python by Python Software Foundation (2024). For plotting the libraries NumPy by Harris et al. (2020), SciPy by Virtanen et al. (2020), Geopandas by Jordahl et al. (2020) and Matplotlib by Hunter (2007) were used.

2.1.2 The Dijkstra Algorithm

The most important algorithm is the cost distance calculation, which was first developed by Dijkstra and is based on graph theory (Dijkstra, 1959). It is a well-known algorithm for solving the single-source shortest-path problem in weighted graphs with non-negative edge weights. The algorithm finds the shortest path from a start node to all other nodes in the graph, generating a shortest path tree. The methodology of Dijkstra's algorithm begins by initialising the distances of all nodes. The start node is marked with a distance of zero, while all other nodes are initially assigned an infinite distance. The algorithm uses a priority queue to manage the nodes that have not yet been visited. At the beginning, the start node is inserted into the queue. The algorithm works iteratively by selecting the node with the smallest known distance from the queue in each step. This node is marked as "visited" and its neighbours are examined. The distance across the current node is calculated for each neighbouring node. If this new distance is smaller than the previously known distance of the neighbouring node, the distance is updated and the neighbouring node is added to the queue or its priority in the queue is adjusted. This process continues until all nodes have been visited or the shortest distances to all reachable nodes have been calculated. The Dijkstra algorithm guarantees that the shortest distances are correct, as it selects the node with the smallest distance in each step.

2.1.3 Reference System

Since the result was a travel time map, a projected coordinate system was necessary for the calculations. Otherwise, the values for calculation would be in *min/degree* instead of *min/km*. The Coordinate Reference System WGS 84 / Pseudo-Mercator with the Authority ID EPSG:3857 was chosen because of its units in meters, an accuracy of 2 meters, and its coverage of the whole world (International Association of Oil & Gas Producers (IOGP), 2024). It is also used in services like Google Maps, Open Street Maps, etc. which are also used for travel time calculation. All input data which is discussed further were re-projected to this coordinate reference system.

2.2 Administrative Data Pre-Processing

The study area for this thesis was the tri-border of the Alto Paraná Atlantic Forest, as described in 1.4. The three cities Ciudad del Este, Foz do Iguaçu and Puerto Iguazú lie in the centre of this frontier and were chosen as the main point of interest. It was assumed that the greater the distance from the city into the countries, the greater the differences in travel time.

To include as much information as possible a circular buffer with a radius of 200 km around the main point of interest was created. The size of the buffer was determined by visual examination of the population density layer of the GHSL (European Commission Joint Research Centre, 2021) (Figure 2.3). A big enough buffer was needed so rural areas are included, and it also needed to be small enough so it does not enter the next populated area. Another buffer of 100 km was used to crop the results to minimise boundary conditions, that can arise when a region is cut off a populated area and would otherwise have a higher travel time. For most of the calculations the 200 km buffer was used.

To not cut off any municipalities, which were necessary for the analysis, these buffers were intersected with all municipality polygons of each country. This municipality boundary data and the country boundary data were made openly available by Runfola et al. (2020). More information in section A. The input data also needed pre-processing like fixing the geometries.

The result of the administrative data pre-processing was one study area with a radius of 200 km, one with a radius of 100 km (Figure 2.3). Both were produced for the municipality level and the country level and an overall level with all information dissolved for calculation (Figure 1.2). And another result were the hexagonal grid of 10 km diameter. A high level visualisation of the workflow is visible in figure 2.2.

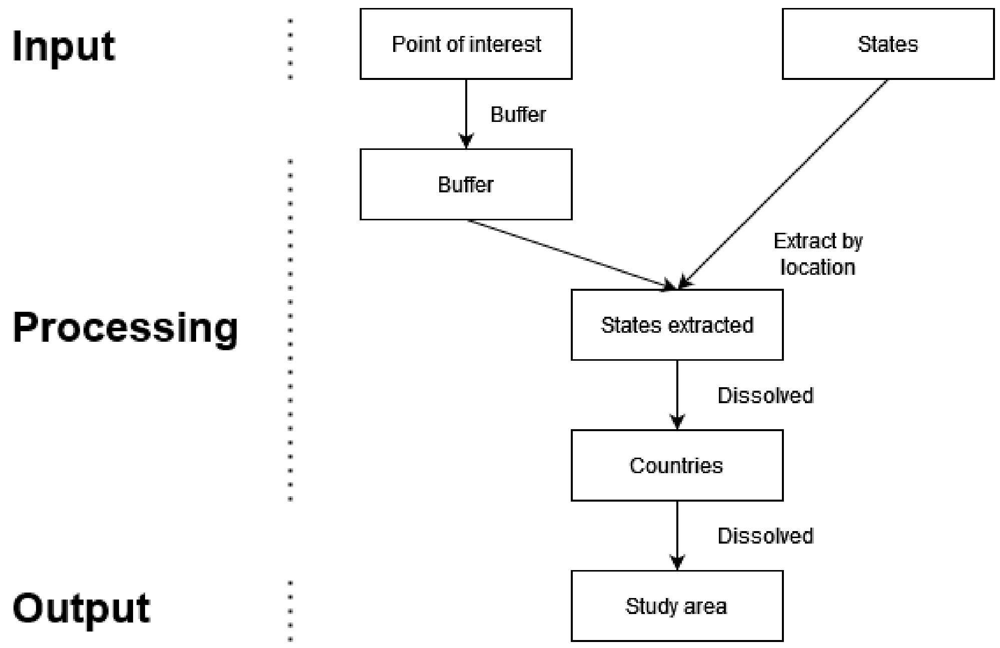

Figure 2.2: Administrative Data Pre-Processing Workflow

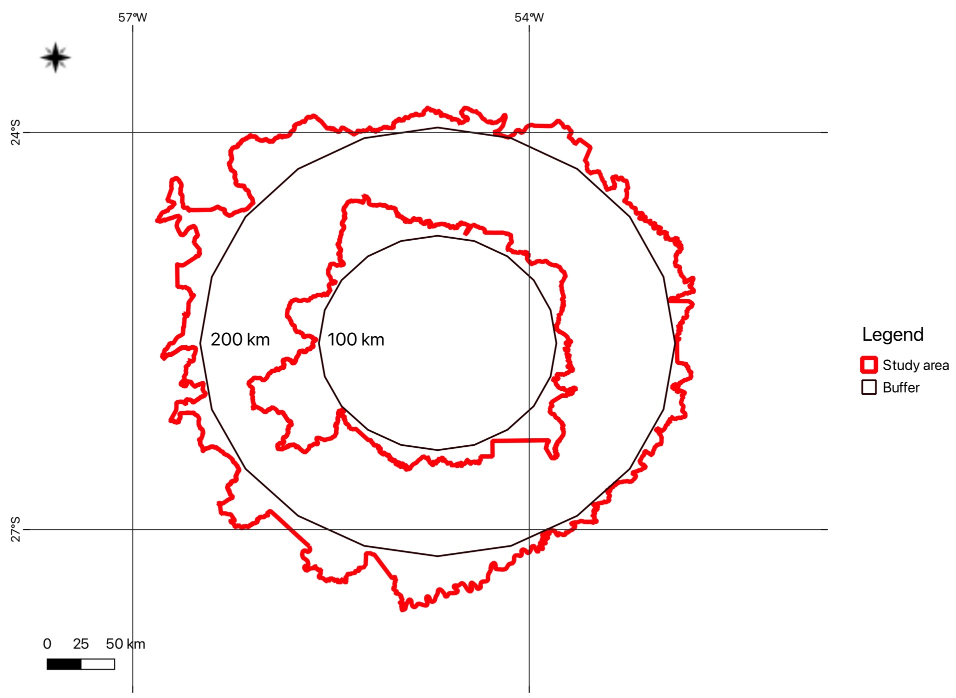

Figure 2.3: Administrative Data Pre-Processing Buffers

2.3 Facilities Data Pre-Processing

The workflow of the facilities data pre-processing is shown in figure 2.4. There are many sources of geo-referenced healthcare facilities. For example, crowd-sourced data like that of Open Street Map are a good starting point.
But the first observation showed that this data was not sufficient as a standalone dataset. This was due to the objectives of this study. This data varies heavily in accuracy due to different usages in different regions and also accessibility to these tools to generate data (Haklay, 2010). Since this study looks at three different countries in comparison, this dataset alone would introduce biases through different use in these countries. Using official governmental data suffers from these same shortcomings. The primary limitation of this work was the varying levels of completeness in the healthcare facility database across different countries. To combat these it was decided that all available data was used to mitigate these biases and get a more accurate representation of reality.
The data that was used from Open Street Map was fetched from providers like Healthsite.io and HOTOSM who are specialised in processing OSM healthcare data and providing them to the public. Governmental data were gathered from MSPBS from the Paraguayan government and from CNES from the Brazilian government, more information about the datasets in the appendix A. Data from the Argentinian government was more incomplete than the data found on OSM, so OSM data was used instead.
The usage of overlapping datasets introduced duplications which were removed. This was achieved by merging overlapping facilities with a radius of 1 km^2 into one facility. For the use in the calculations a few pre-processing steps were necessary, like refactoring of fields to the same datatype.
To create a more homogeneous dataset, the healthcare facilities were filtered by the tags "hospital" and "doctors". Other healthcare facilities like pharmacies were removed because they do not suffice to our classification of healthcare and were not part of the objectives. Data from official government sources needed to be translated and reclassified to fit the overall classification. All pre-processed data were merged into one dataset. At last, the dataset were clipped to the study area. To remove duplicates, a grid of 1 km by 1 km rectangle grid was created. The diameter was decided based on the resolution of the final travel time map. Every polygon that intersected a facility was extracted. For each remaining polygon the centroid point was calculated which results in the facilities. Through that processing, the facility number was reduced by 75%. The final dataset is visible in figure 2.5.

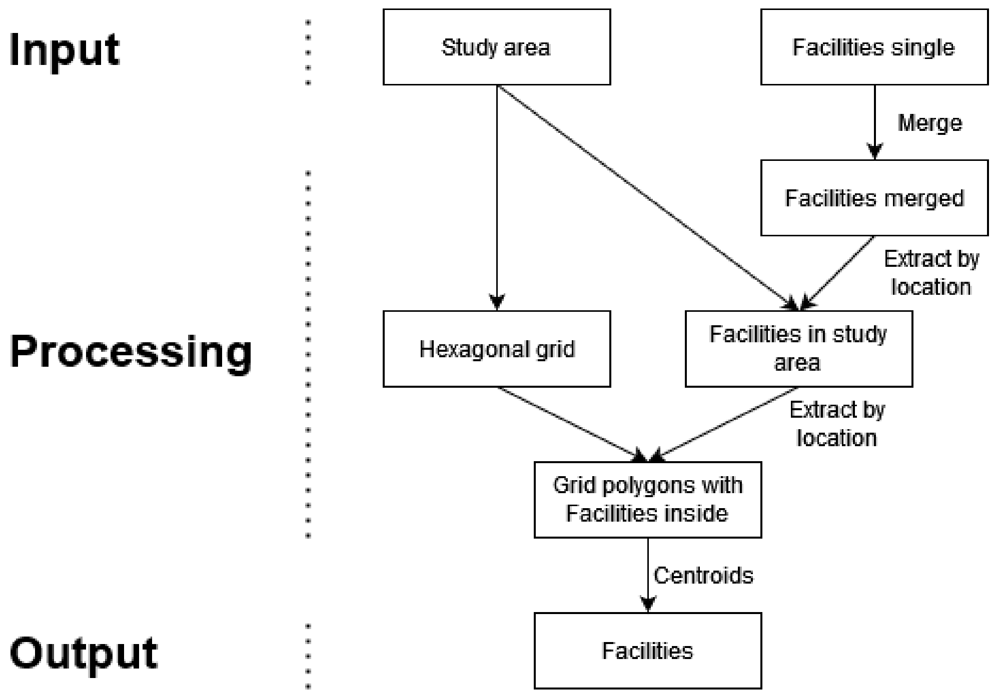

Figure 2.4: Facilities Data Pre-Processing Workflow

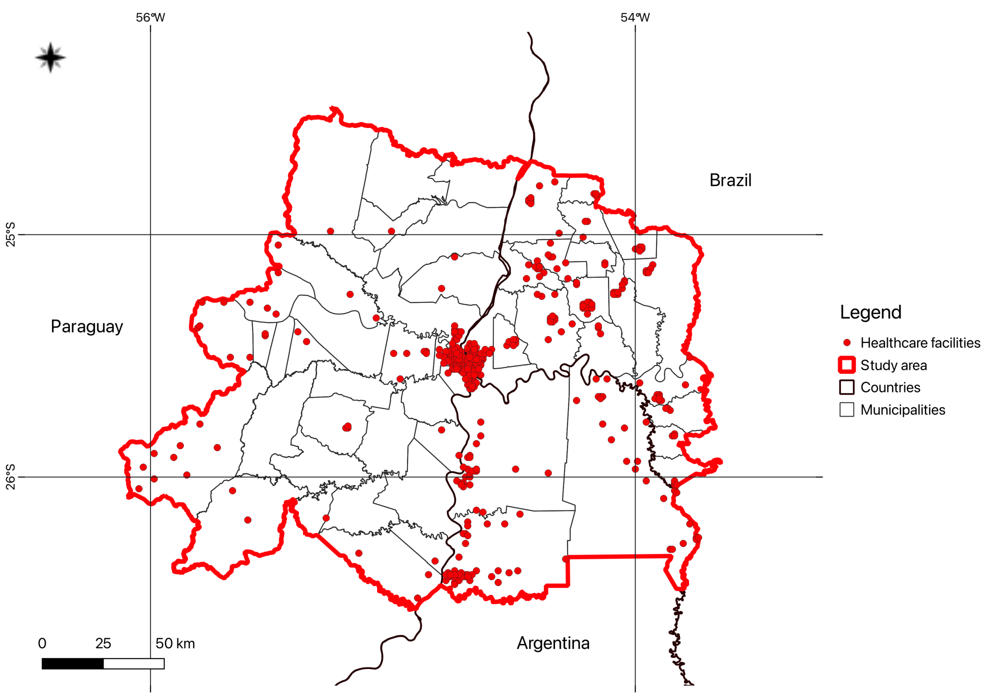

Figure 2.5: Healthcare Facilities

2.4 Friction Surface Creation

A friction surface represents the cost associated with moving through a given space (Carrothers, 1956). There are multiple methods for creating such a surface. One approach, suggested by Weiss et al. (2020), involves layering various cost factors, such as road types and borders, and integrating them into a single, comprehensive raster.
For what to include in the friction surface this thesis took a few assumptions. The first assumption was that people move through space at an optimal speed. This was assumed to simplify the calculation and reduce the factors in human travel. The second assumption was that road transport is the mean transport form in my study area. The third assumption was that the impact of road travel outweighs the short distance walking transport travel times the longer the travel takes.
Because of that, and in addition to that accessibility in urban areas is far more influenced on non-spatial factors which are not in the scope of this thesis, walking transport was not considered in the friction surface. Weather conditions and seasonality were also not considered due to their variability. And slope was also not considered due to the relief of the study area which is mostly shallow which effects road transport only minimal.
The following describes the pre-processing workflow for the roads of the study area (Figure 2.6). The road network was accessed through OSM with the help of the Overpass API (Olbricht, 2024), which is a web-based service that allows users to access and query OSM data programmatically. More information about the sources are in section A. All roads with the key "highway" where extracted from the study area. Road regulations and traffic were not included, due to unavailability of data. Roads were differentiated between paved and unpaved categories, due to their different influences on travel time (Weiss et al., 2018). The following attribute values were categorised as paved roads: "asfalto_pavimentado, asphalt, cobblestone, cobblestone:flattened, compacted, concrete, concrete:plates, fine_gravel, grass_paver, gravel, paved, paving_stones, paving_stones:30, pebblestone, sett, unpaved;paved, metal, Elevada_em_comcreto, gate". Every other attribute value were categorised as unpaved. For the use in the calculations a few pre-processing steps were necessary like refactoring of fields to the same datatype and dissolving for faster processing speeds and a more homogeneous end result.

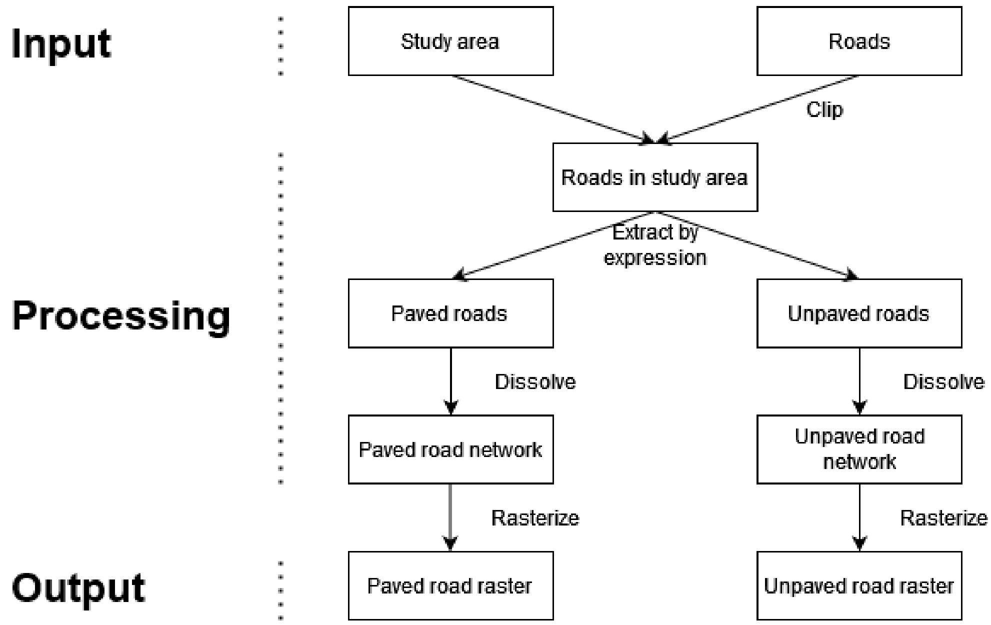

Figure 2.6: Road Data Pre-Processing Workflow

Given that the study area is transnational, considering borders as a reducing factor in travel time was essential. For the creation of the border layer, the country polygons where converted to lines. The study area was subtracted to avoid having false borders around the study area that are not existent in the layer (Figure 2.7).

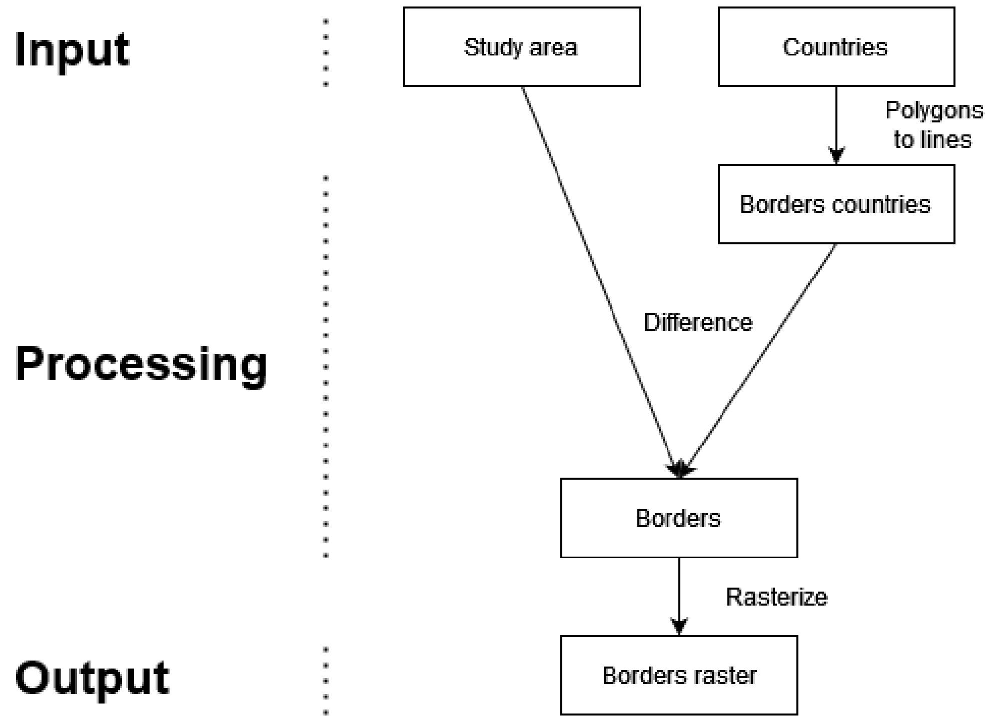

Figure 2.7: Border Data Pre-Processing Workflow

After the friction layers were chosen, it was necessary to weigh each layer with their corresponding movement speed. This creates the friction surface with different values of friction in the end. In the following table 2.1, the given movement speeds with their corresponding layers are presented. The values are based on earlier work from European Commission Joint Research Centre (2021).

Friction	Movement Speed (min/km)	(km/hr)
Unpaved	1	60
Paved	6	10
Borders	120	0.125

Table 2.1: Friction Type and Movement Speed

To have a reasonable outcome value for the result, the resolution of all layers of the friction surface was set to the same resolution. A resolution of 1 km by 1 km was chosen. This resolution was a good middle-ground between high resolution calculation and coverage of the whole study area. It was also recommended by European Commission Joint Research Centre (2021). The assumption was made that the calculated travel time of an area of 1 km^2 would have a similar travel distance because of the possibility of moving to the next road in between this 1 km^2 area.

It also makes things easier in the calculation of the results units. For example, given that an entity moves with a movement speed of 1 min/km through 10 pixel or kilometres it would take him 10 minutes to traverse this distance (Equation 2.1). This requires that the chosen cost distance algorithm calculates the diagonal traversal of a pixel in the same way as the horizontal and vertical traversal.

$$1\ \frac{\text{min}}{\text{km}} \cdot 10\ \text{km} = 10\ \text{min} \tag{2.1}$$

Each layer influencing the friction was converted from a polygon to a raster. Pixels with an intersecting polygon are burned in with their corresponding movement speed value. For every other pixel, a null value was assigned. The GDAL algorithm "Rasterize (vector to raster)" was used for that. Finally, all layers where merged to one friction surface (Figure 2.8). Overlaying pixels were overwritten in the order of input, which determined the precedence. This ensures that the most likely friction was assigned. The order was "Unpaved < Paved < Borders". It was assumed that if the actor had both types of roads available it chose the faster one, so paved roads come before unpaved. Further it was assumed that if an actor faced crossing a border the border travel time was before all else. The GDAL algorithm "Merge" was used for that.

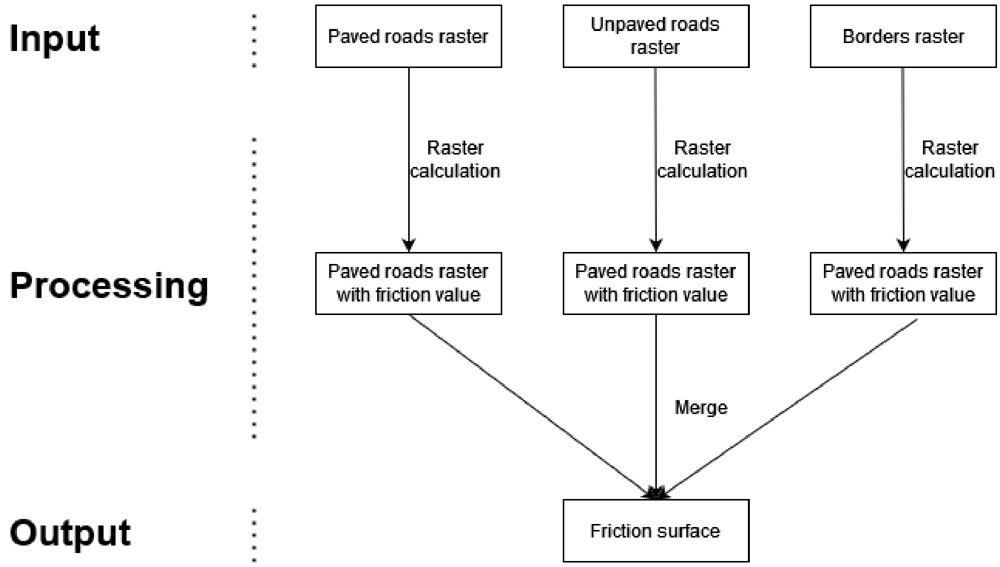

Figure 2.8: Friction Surface Workflow

2.5 Travel Time Analysis

The last step in the methodology was to apply a cost-distance analysis. The workflow for the cost-distance analysis is shown in figure 2.9. The friction surface was used as it was, serving as the starting location for every pixel. The facilities were used as the target location (Section 2.3). The SAGA algorithm "Accumulated cost" was used for that (Conrad et al., 2015).

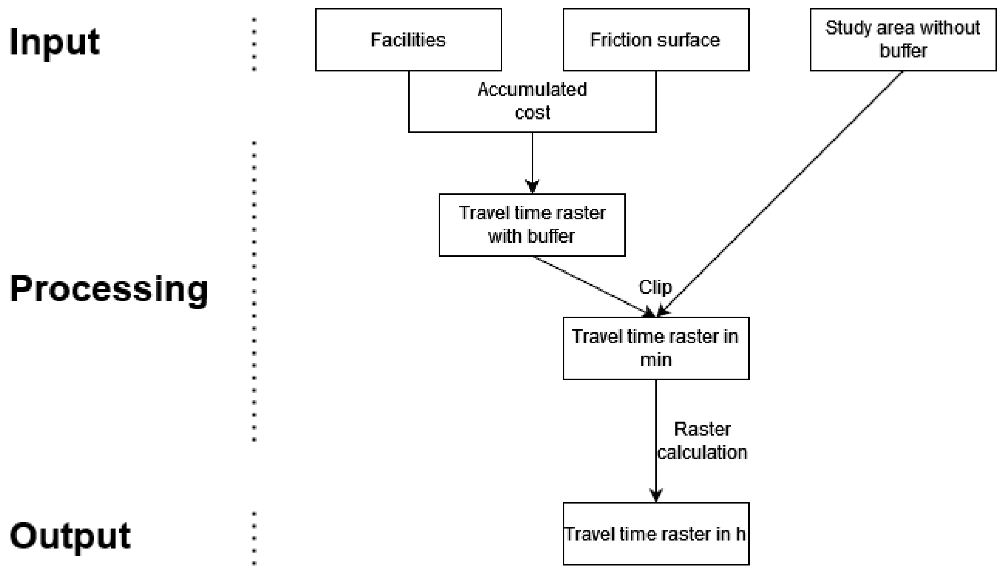

Figure 2.9: Travel Time Workflow

2.6 Accessibility between Countries

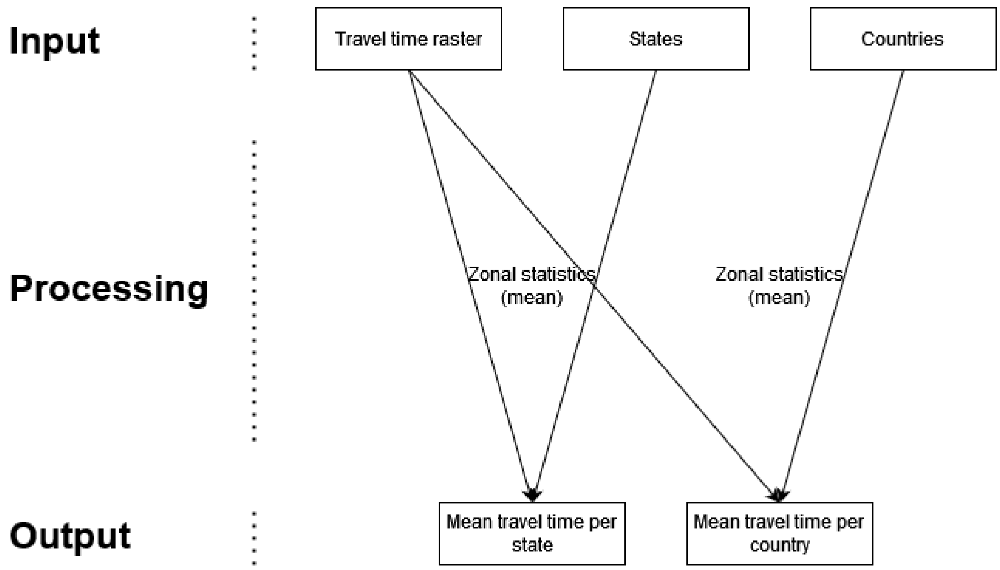

Figure 2.10: Analysis Workflow

The spatial analysis was separated into two levels: the municipality level and the country level (Figure 2.10). The travel time raster was combined with each level's layer and processed with the "Zonal Statistics" tool to gather a mean travel time value for each polygon.

2.7 Accessibility for Indigenous Communities

For the third research question, the earlier created data from indigenous communities was used to identify the travel time for them. For this, a hexagonal grid was used. Every hexagon that intersected a indigenous community was extracted. All remaining hexagons were used in a similar calculation from the previous analysis for the municipalities and the country. The symbology was also very important for the visualisation of the map here classification by quantile was chosen due to the good representation of distribution of travel times. Because lower travel times were less common in the data but more common visually ,a quantile classification was used. Higher values are represented more homogeneously than lower values. For further visualisation purposes, every map was also created as a plot. For this, self developed utility tools were used that streamline the workflow between QGIS and the library Matplotlib.

To answer the third research question data from a part of the population was needed. Since the study area shows a high accumulation of indigenous people, it was decided to gather such data to examine the behaviour of travel time for this part of the population (Berger et al., 2024). Data was made available from the Brazilian and Argentinian government. For the Paraguayan government, only a map was available. This map and its containing points for the indigenous communities needed to be geo-referenced to use for further processing (Figure 2.13). Here, also duplicates were removed. At last, all the data were merged (Figure 2.11). The analysis of this dataset is presented in figure 2.12, which closely resembles the workflow in figure 2.10. The final dataset is shown in figure 2.13.

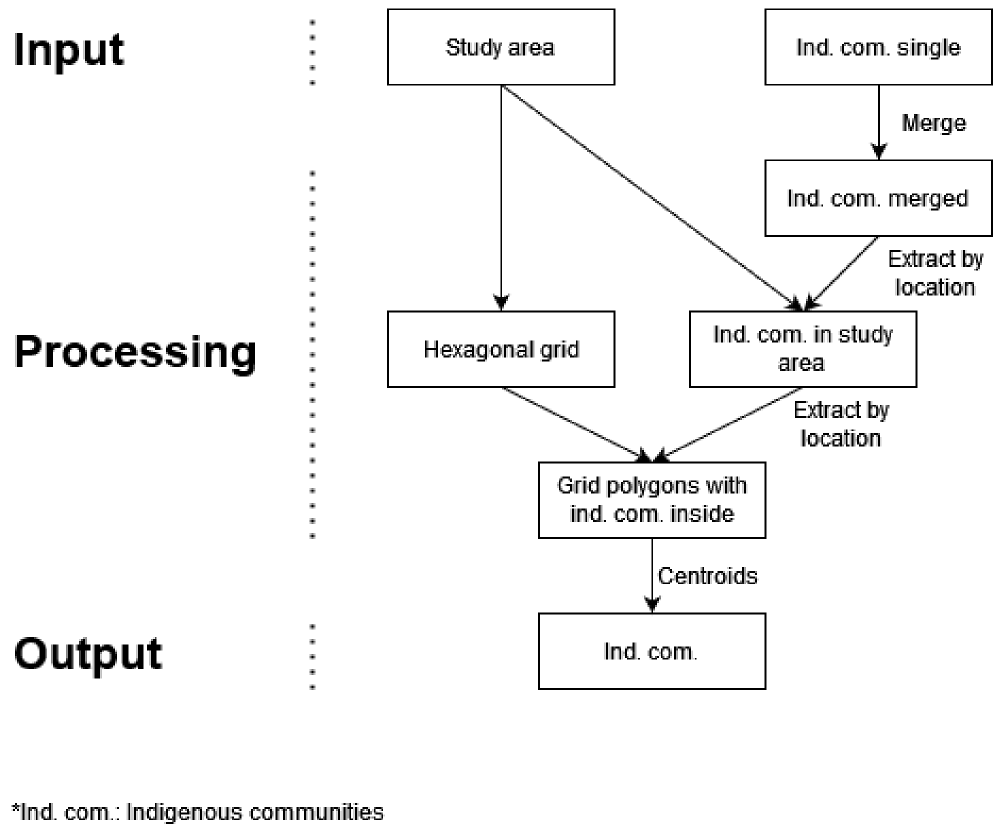

Figure 2.11: Indigenous Communities Workflow

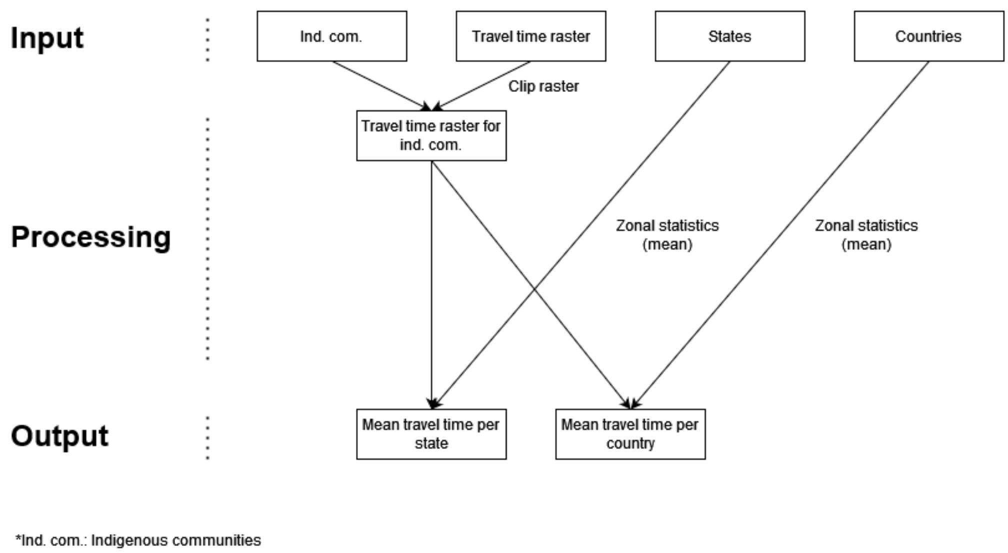

Figure 2.12: Analysis for Indigenous Communities Workflow

Figure 2.13: Indigenous Communities

2.8 Sensitivity Analysis

As suggested by Frew, Higgs, Harding, and Langford (2017), a sensitivity analysis can assess the usability geo-spatial data. Because of that, the sensitivity of all factors were observed during the development process. It became clear, that the availability of roads and facilities is the most influential in determining travel time to healthcare facilities. They are connected in that many facilities without road connectivity would have the same impact on travel time in the region as high road availability with faster roads but fewer facilities to reach. This also includes the parameters of road types that influenced the travel time. All three factors need to be considered. Secondary parameters are parameters of resolution. These parameters influenced the result only in that they refine the outcome. They enrich or diminish the results. Parameters like the resolution of the rasters, the size of the buffer which facilities get excluded and which roads get excluded. These parameters affected the results only in that they specialise them to answer specific questions.

Chapter 3

Results

This chapter presents the results of this study, which tried to analyse travel times to healthcare facilities in the tri-border of the Alto Paraná Atlantic Forest. A friction surface was created to include different factors influencing travel time, like road types and borders (Figure 3.1). A travel time map was created with the use of this healthcare facility dataset (Figure 3.2). Following that, the travel time map is used to analyse differences in travel time between jurisdictions (Figure 3.4 and Figure 3.5) and populations (Figure 3.6), including indigenous communities (Figure 3.7 and Figure 3.8).

3.1 Distribution of Healthcare Facilities

Table 3.1: Healthcare Facilities in the Study Area, Argentina, Brazil, and Paraguay

	Study Area	**Argentina**	**Brazil**	**Paraguay**
Hospitals	112 / 4%	28	35	49
Other Healthcare Facilities	2533 / 96%	519	1432	582
Total	2645 / 100%	547	1467	631

To investigate the current distribution of healthcare facilities in the study area, various datasets of healthcare facilities were collected, merged and filtered, as described in 2.3. Healthcare facilities are represented in figure 2.5 by red dots, clearly indicating their locations. The boundaries of the study area are outlined in red, distinguishing it from the surrounding regions. Borders are outlined in thick black lines and municipalities in thin black lines.
There is a dense concentration of healthcare facilities around central urban regions, especially around the tri-border cities which shows the highest density in the entire region. In contrast, the peripheral regions, especially those closer to the borders with Paraguay and Argentina, exhibit a sparser distribution of healthcare facilities.
The density of healthcare facilities in Paraguay is more evenly distributed within their part of the region but is overall lower in comparison to Brazil and Argentina. Brazil shows the highest density of healthcare facilities, which are also the most equally distributed across the region. In comparison, Argentina exhibits a greater disparity in the distribution of healthcare facilities between rural and urban areas. Despite this disparity, Argentina still

has a denser distribution of healthcare facilities compared to Paraguay.
Overall, the distribution of healthcare facilities highlights significant regional disparities, with Brazil leading in both density and equitable distribution, followed by Argentina and then Paraguay.
To analyse the results quantitatively, statistics were calculated seen in table 3.1. The dataset included a total of 2645 facilities. 112, or 4%, of these were entries with "hospital" in their attributes. 2533 or 96% were other Healthcare facilities. Paraguay had the most hospitals with 49 and Brazil 35 and Argentina 28. For other healthcare facilities, Brazil had the most with 1432, followed by Paraguay with 582 and Argentina with 519.

3.2 Analysis of the Friction Surface

To analyse the travel time to healthcare facilities, a friction surface for the study area was created, as described in section 2.4.
The analysis of the friction surface in the study area visible in figure 3.1 showed a high variability of the friction depending on the surface type. Paved roads, which are shown in blue, were the fastest surface type and were concentrated around city centres and connecting roads between cities. The highest concentration was in the centre of the tri-border. Unpaved roads, which are shown in yellow, on the other hand, extended over the whole study area. Borders which are shown in red cross the study area from north to south and separated Paraguay in the west from Brazil and Argentina in the east. Those on the other hand were separated again through a border from the centre to the east.
Noticeable over the whole study area are regions which are not categorised in the friction surface; they usually lie outside of the fishbone pattern of the roads, especially unpaved roads. This pattern also differs between the countries. In Paraguay the density of paved and unpaved roads is less which results in a fuzzier coverage. In comparison, the density of Brazil and Argentina is greater than in Paraguay, as is visible through larger unpaved areas with fewer un-categorised regions. Also the paved roads are more established which are predominant in the north of Brazil and the east of Argentina. And lastly another difference are the big empty areas in Brazil and Argentina which were analysed in Appendix B. They mostly consist of forests and national parks, and that is why there are less roads there in the dataset.
The differences in road condition and border areas that are visible are important for the understanding of the differences in friction in this region. The friction surface suggests that there is a connection between road condition and friction. This is due to the graduated change from paved to unpaved and at finally to no road coverage. This can be translated to a gradient for friction from urban areas with low friction to rural areas with high friction. This means residents in rural areas have a greater cost of movement than residents of urban areas.

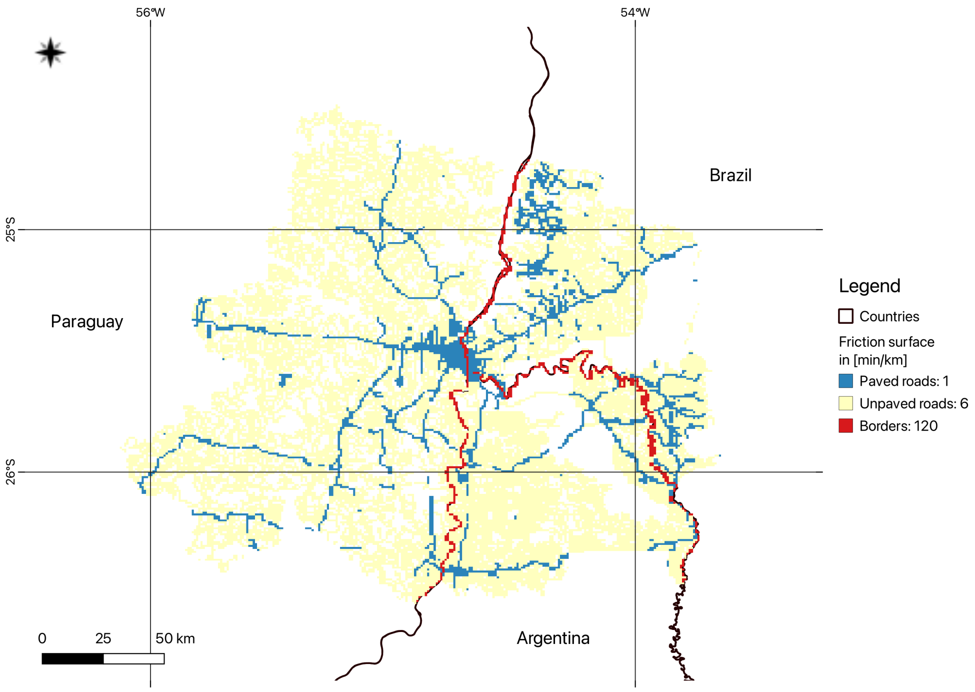

Figure 3.1: Friction Surface

3.3 Assessment of Travel Time

To analyse the travel time to healthcare facilities the accumulated cost in travel time to the nearest healthcare facilities for the study area was calculated as described in section 2.5. The results suggest significant differences within the study area. The travel time map shows a clear gradient in accessibility to healthcare facilities, from blue areas of short travel time over yellow areas with average travel time and red areas with long travel time (Figure 3.2). The average travel time ranges from zero to over two hours. Two hours was chosen as a cap since 90% of the data as visible in figure 3.3, was lying under two hours and clipping the outliers gives a better visualisation of the real results.
The centre of the study area with the tri-border and the population centre has the best travel time in the whole study area. It is also very homogeneous for around a 25 km radius. Going from the centre, you see a distribution from short travel times to long travel time especially when you deviate from big roads and closing in on uncovered areas.
In Argentina, the south-east part of the study area, the travel time decreases with distance from the border areas, which are also the areas with the best road infrastructure, to the centre of the country area, with poorer road types but still a well established network. The areas of short travel time are also much bigger compared to the west of the border in Paraguay.
The Brazilian part of the study area in the north-east is the most well established part. Most of this area has a short travel time with only a few areas with average travel time and a handful of areas with long travel time.
The Paraguayan part of the study area, located in the east and also the largest section, is the most diverse in terms of travel time. There are regions similar to Brazil and Argentina,

primarily in the centre of the study area. Beyond this point, travel time decreases more rapidly than in the other countries when transitioning from urban to rural areas. This is evident in the thickness of the blue short-travel-time areas, which transition quickly to yellow average-travel-time areas and then to large red long-travel-time areas. Long travel times are concentrated in the north and in the areas between the main connecting paved roads.

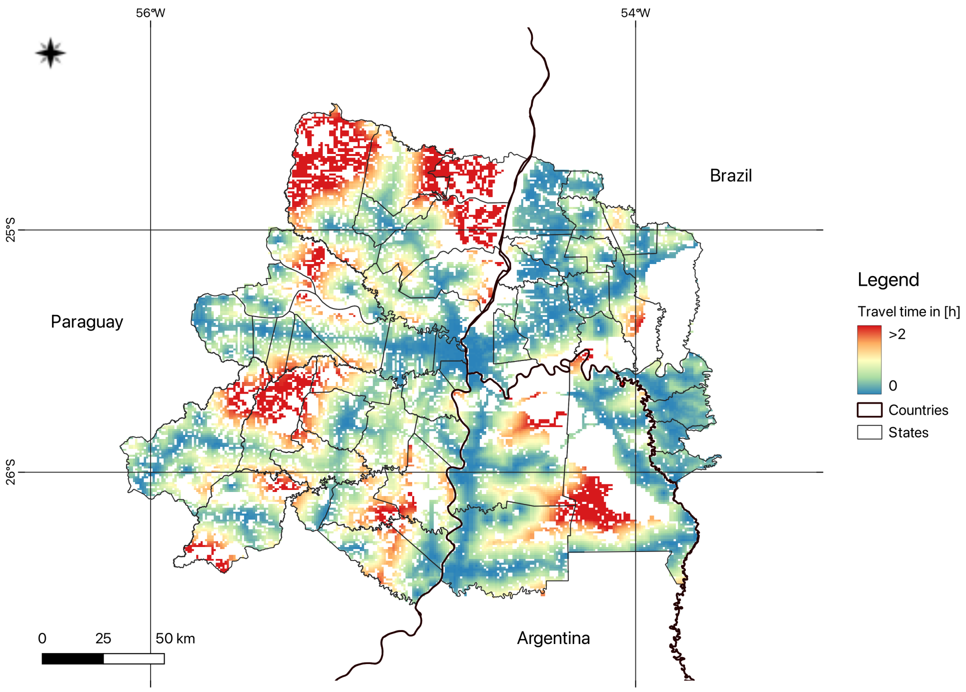

Figure 3.2: Travel Time

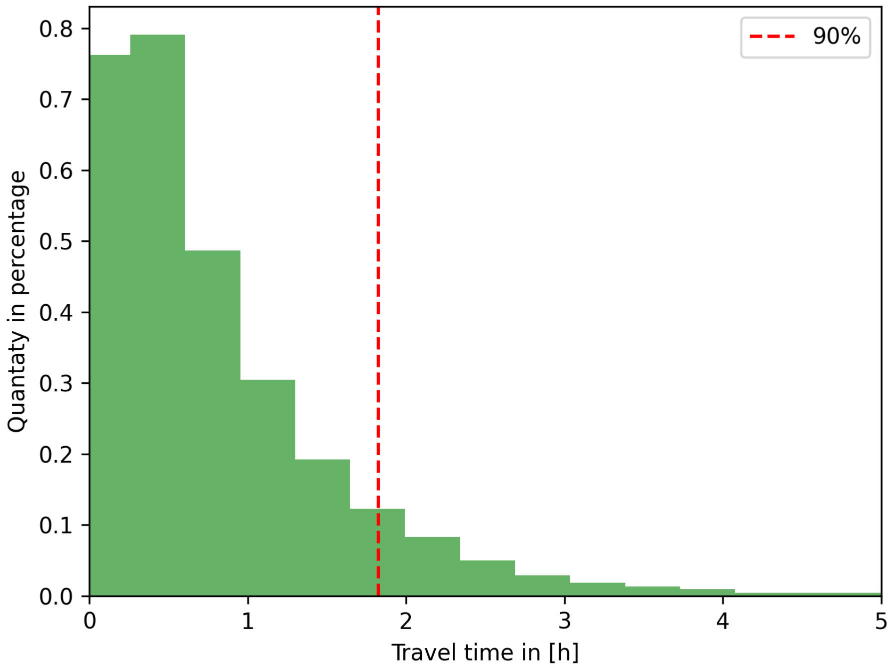

Figure 3.3: Travel Time Distribution

3.4 Accessibility between Countries

To analyse the differences in accessibility of healthcare for jurisdiction, a spatial analysis was made as described in 2.6. The results of this are visible in figure 3.4. A quantitative overview of average travel time supplements the spatial analysis. The bar plot allows for a comparative analysis of all average travel times per municipality and also between the countries of each municipality of the tri-border: Argentina in blue, Brazil in yellow, and Paraguay in red. The data shows a strong variability between the municipalities.
San Alberto in Paraguay has the longest average travel time in the whole study area compared to the other countries, with over three hours. Ciudad Del Este, also in Paraguay, shows the shortest average travel time in the whole study area compared to the other countries, with under 15 minutes. This again highlights the high variability in travel time which were also visible in figure 3.2.
The municipalities of Brazil show a similar variability in average travel time to Paraguay but not so drastic. The average travel time in the Brazilian municipalities ranges from over two and a half hours to half an hour.
The municipalities of Argentina are grouped in the middle of the distribution and are ranging from one hour to half an hour average travel time. This signifies a lower variability than in Paraguay. It is to note here that there are only three municipalities of Argentina included, so the data might not be representative in comparison to the data from Brazil and Paraguay, which have more municipalities included in the study area.

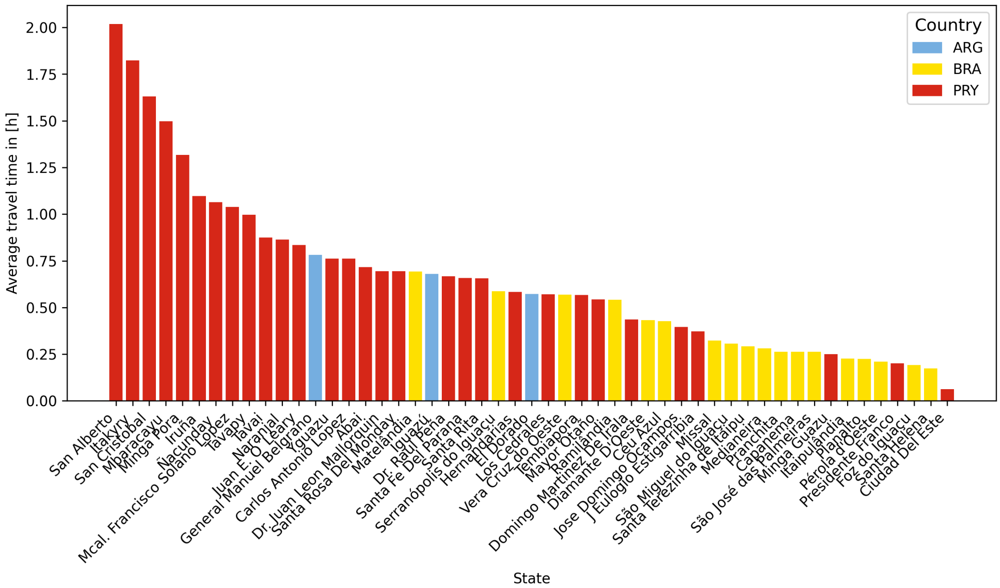

Figure 3.4: Average Travel Time per Municipality

In figure 3.5, the average travel time to healthcare facilities of the three countries in the triple-border is visible. The data shows that Paraguay has the longest average travel time of the three countries, with over an hour. Argentina has the shortest average travel time, under 50 minutes, and Brazil is in the middle with over 50 minutes. It is to note here that on average the travel time does not vary significantly between each country. The differences are less than 10 minutes.

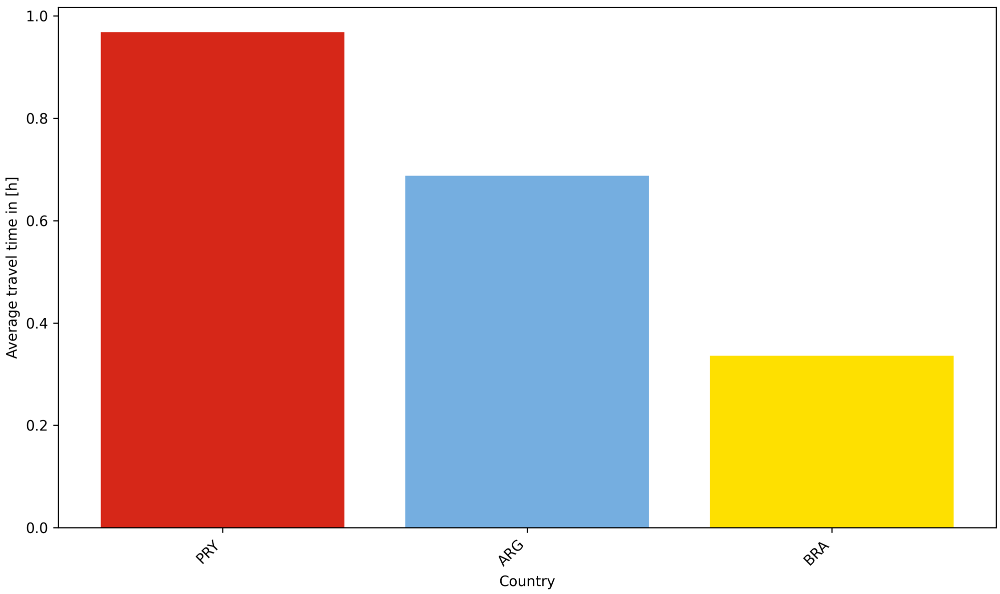

Figure 3.5: Average Travel Time per Country

3.5 Population Density and Accessibility

To analyse the differences in accessibility of healthcare for populations, the population was first analysed in total. For that, the maximum travel time in hours was plotted against the population density in percentage (Figure 3.6). The scatter plot shows the relationship between these two datasets. Every point represents a location on the map. For visualisation, only the maximum travel times for every 1% bin were plotted, since the travel time can also be very high in low population areas where the distance to the facility is very close. The red line is an exponential fit of the data, suggesting an exponential decay trend in the relationship, where maximum travel times are significantly higher in areas of low population density. As population density increases, the maximum travel time rapidly decreases, levelling off as density continues to increase. The initial steep decline of the exponential fit indicates that even small increases in population density can significantly reduce maximum travel time to healthcare facilities. In areas of medium to high population density, the curve flattens, suggesting that beyond a certain threshold, increases in population density have a lower positive impact on maximum travel time.

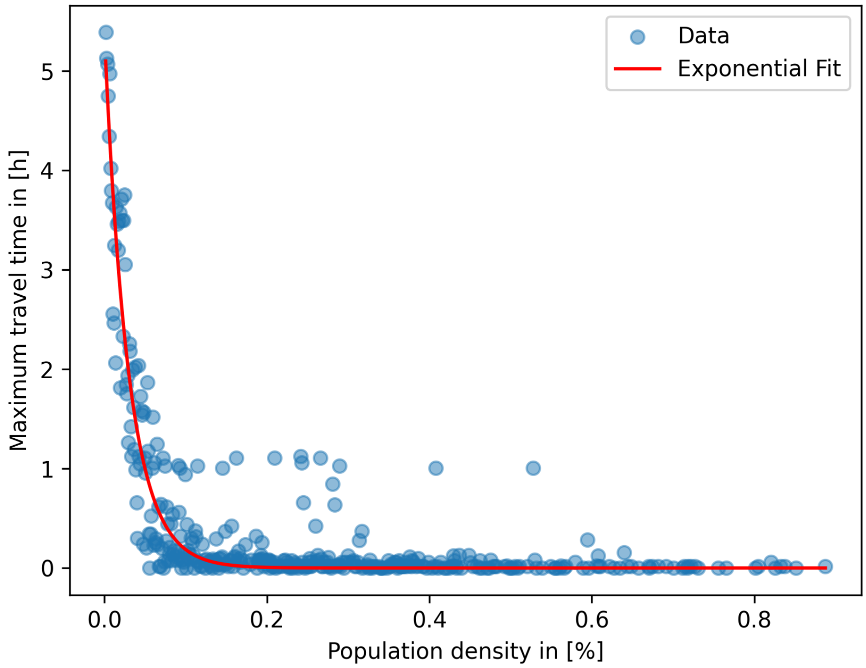

Figure 3.6: Correlation of Travel Time and Population Density

3.6 Accessibility for Indigenous Communities

Table 3.2: Indigenous Communities in the Study Area, Argentina, Brazil, and Paraguay

	Study Area	**Argentina**	**Brazil**	**Paraguay**
Indigenous Communities	100	20	5	75

To analyse the average travel time for a part of the population, the method of section 2.7 was used. The distribution of Indigenous Communities was 100 in total, in the study area (Table 3.2). Most of the communities were in Paraguay with 75, followed by Argentina with 20 and 5 in Brazil (Table 3.2). The bar plot shows the average travel time to healthcare facilities for indigenous communities within the tri-border, grouped by state and country (Figure 3.7). Paraguay is represented in red, Brazil in yellow, and Argentina in blue. The chart ranks states from the longest average travel time to the shortest. The state San Cristobal, in Paraguay shows the highest average travel time with over two hours. The shortest average travel time shows Foz do Iguacu in Brazil with under 10 min. Compared to the figure 3.4, the distribution of Brazil and Argentina is less spread out and groups on the right side of the plot, which means that these countries show a shorter average travel time to healthcare facilities for indigenous communities than for the whole population. The maximum average travel time for Brazil and Argentina is under half an hour. This is a deviation of 20 minutes. For Paraguay, the results look similar to the whole population with an overall slight increase of average travel time visible in the higher average travel time in the Paraguayan states that had the shortest travel time. In Paraguay, the average travel time ranges from over 15 minutes to over two hours. This is a deviation of 1.75 hours.

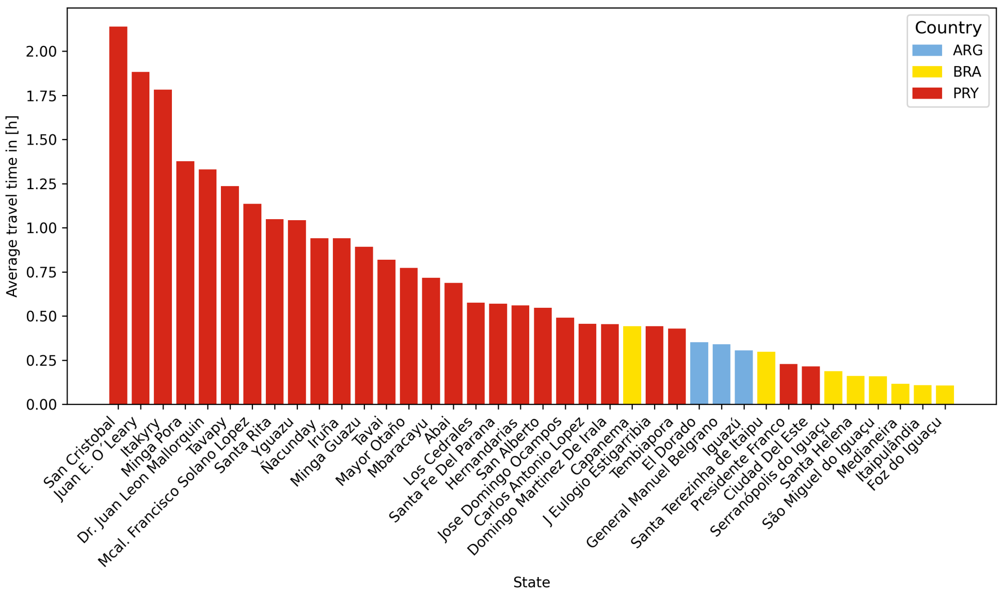

Figure 3.7: Average Travel Time per Municipality for Indigenous Communities

These results are mirrored in the plotting of the overall average travel time of each country, in figure 3.8. Paraguay shows an average travel time of under one hour. With over half an hour less, Argentina shows an average travel time of under 25 minutes and Brazil shows the shortest travel time with under 15 minutes. Here again, Argentina and Brazil show a similar average travel time with a difference of 10 minutes.

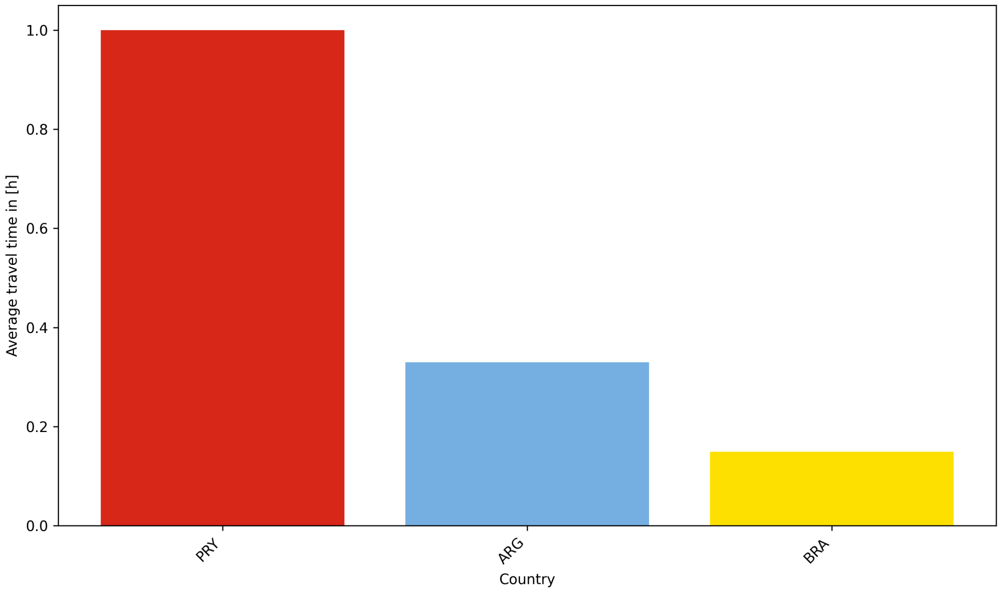

Figure 3.8: Average Travel Time per Country for Indigenous Communities

Chapter 4

Discussion

In the following chapter, each research question is discussed in detail. First, results and their interpretation of the differences in accessibility to healthcare facilities between Paraguay, Brazil and Argentina and their respective states are examined. Next, the correlation between the population density and accessibility is discussed. Finally, the results and interpretation of differences in accessibility to healthcare facilities between the overall population and indigenous communities are compared.

4.1 Accessibility between Countries

To investigate the differences in accessibility to healthcare facilities between Paraguay, Brazil, and Argentina and their respective states, a spatial analysis was done as described in 2.6. The goal was to find out the accessibility of healthcare facilities within each country and their states and to compare these differences.
The analyses revealed visible differences in travel times between countries visible in figure 3.5 and 3.4. There are significant differences in travel times to healthcare facilities between Paraguay, Brazil and Argentina with Paraguay experiencing the longest travel times, which aligns with Collaborators (2018). This disparity can be attributed to Paraguay's different developmental status compared to Brazil and Argentina, as described in section 1.4 by World Bank (2022b). The longer average travel time in Paraguay could be due to lower population density, as indicated in European Commission Joint Research Centre (2021) and United Nations (2022), or a low density distribution of healthcare facilities, as seen in the data 2.5. In Brazil, the shorter average travel times might indicate a broader and more homogeneous distribution of healthcare facilities, as also seen in the data 2.5.
Paraguay as a low-income country, has shown poorer accessibility than Brazil and Argentina, which are higher income, as highlighted by World Bank (2022b). This aligns with existing literature, highlighting the disparities in healthcare accessibility in developing versus more developed regions, like Mcintyre, Thiede, and Birch (2009) and De Siqueira Filha et al. (2022).
The study provides a comprehensive spatial analysis of healthcare accessibility across three countries, highlighting significant disparities and areas for improvement. However, the analysis does not account for other barriers of healthcare access as described in section 1.2 by Wang and Luo (2005) and Carrillo et al. (2011). For example, the quality of

healthcare services, which are critical factor in assessing the overall healthcare provision. Patient preferences were also not considered. For example, it might be preferable to travel a greater distance or cross borders to access better treatment, even if a closer hospital is available. A further limitation of the study is that the transition times were estimated across the borders and were set equally across all transitions. In reality, however, these could deviate considerably. In addition, only the regions of the countries located in the study region were analysed. However, as there are also major differences in the level of development and healthcare provision within the countries, as described in section 1.4 by Gilardino et al. (2016), Palacios et al. (2020), and Vacarezza and Cruz (2023) for Argentina, by Palmeira et al. (2022), Santos et al. (2022), and Silva et al. (2021) for Brazil, and by Amnesty International USA (2024), Capurro and Harper (2022), and World Health Organization (2024) for Paraguay, generalisations from the regions to the countries should be viewed critically. This was due to methodological limitations, such as differences in data collection methods and the definition of healthcare facilities across countries. For example, for Paraguay and Brazil, official government data were used to enrich the dataset because of incompleteness, as described in section 2.3. This was skipped for Argentina due to the significant overlap of the OSM dataset and official sources. Secondly, these datasets showed different definitions of healthcare facilities. Facilities with the "Doctor" tag might be hospitals or local clinics. These inconsistencies may affect the comparability and accuracy of the results. This highlights the need for standardising healthcare facility definitions and data collection methods.

The observed inter-municipality and cross-country variations reflect the complexity of healthcare accessibility and emphasise the need for better regional policies and planning. The significant range within Paraguay calls for a focused policy, particularly in states like San Pedro, where the mean travel time exceeds two hours. For Argentina and Brazil, while the situations seem less critical, there is still a clear indication that policies could further reduce travel times in rural areas, thereby increasing healthcare accessibility. The municipalities closer to the lower end of the travel time spectrum can serve as benchmarks for policy development in other regions like the spillover effect described in Piquer-Rodríguez et al. (2021).

Future research should focus on addressing the data inconsistencies. Additionally, research should include more comprehensive data on healthcare facilities, including quality and patient preferences, and expand the analysis to cover entire countries. Temporal studies analysing changes over time could also offer insights into the effectiveness of policies and evolving healthcare needs.

In conclusion, the accessibility of healthcare facilities showed notable disparities between Paraguay, Brazil, Argentina, with Paraguay experiencing the longest travel times, which aligns with literature like Collaborators (2018). This part also highlights the need for policy actions to improve healthcare, particularly in under-served regions, to ensure equitable access.

4.2 Population Density and Accessibility

For investigating how the population density influences accessibility, the population density was correlated with travel time, as described in 3.5.

Analysing the results of this revealed that there is a strong correlation between population density and travel times to healthcare facilities, with higher population density areas generally having shorter travel times, which aligns with Obubu et al. (2023) and Shi, Yang, and Shen (2020). The analysis of the plot 3.6 showed an initial steep decline of the exponential fit, indicating that even small increases in population density can significantly reduce travel times to healthcare facilities. This is likely due to the fact that higher population densities can justify the establishment of more healthcare facilities, thus reducing the distance individuals need to travel. In areas of medium to high population density, the curve flattens, meaning travel time is low, suggesting that beyond a certain threshold, increases in population density have a negligible impact on travel time. This could be because once a sufficient number of healthcare facilities is reached to serve a denser population, additional increases in density do not require proportional increases in facilities.

Travel times in low-density areas like rural areas are probably longer because of the distribution and concentration of healthcare facilities in urban centres, as visible in 2.5, and also the infrastructure quality like road conditions and road types in rural areas that are worse than near city centres, as visible in 3.1. Continuing, there are greater disparities in accessibility within Argentina and Brazil between rural and urban areas, which aligns with Gilardino et al. (2016), Palacios et al. (2020), Vacarezza and Cruz (2023), Hone et al. (2019), Silva et al. (2021) and Palmeira et al. (2022). This can be interpreted as a result of further urbanisation during the development of these countries, as described in section 1.4.

The study does not account for other barriers to healthcare access, which are described in section 1.2 by Wang and Luo (2005) and Carrillo et al. (2011). These factors that might influence the calculated travel time, such as transportation availability in rural areas, traffic jams, and socioeconomic factors. This might lead to an overestimation or underestimation of travel times, indicating caution in interpretation. While the findings are notable, they should be interpreted with caution when generalising to different regions with varying infrastructure and geographic characteristics.

The study contributes to the theoretical understanding of how population density correlates with service accessibility, highlighting an exponential decay relationship. Practically, the findings suggest that improving accessibility in low-density areas would be visible with relatively small increases in population density or could be achieved through strategic placement of healthcare facilities to minimise travel times. Improving healthcare infrastructure in these rural regions could lead to better health outcomes and reduced inequities, as discussed in Syed et al. (2013), Davy et al. (2016) and Zhao et al. (2016).

Future research should explore the impact and correlation of other variables on travel time, such as transportation infrastructure and socioeconomic factors. Longitudinal studies could provide insights into how changes in population density over time affect accessibility. Further, expanding the geographical scope of the research could help in understanding regional differences in the population density-accessibility relationship.

The findings also suggest the need for targeted infrastructure developments, particularly in rural areas, to enhance healthcare accessibility and equity.

4.3 Accessibility for Indigenous Communities

To determine the differences in accessibility to healthcare facilities between the overall population and indigenous communities, travel times were analysed through the filter of

indigenous communities, as described in 2.7.
The analysis in section 3.6 revealed visible differences in travel times between population groups, highlighting that indigenous communities face worse travel times compared to the overall population, which align with Quintana et al. (2021), World Health Organization (2024) and Santos et al. (2022). In Paraguay, the disparity in travel time is particularly pronounced. This discrepancy is likely due to systemic issues such as segregation or displacement, as identified by the United Nations (2015a). Because of that, many communities are situated in rural areas, which tend to have poorer accessibility to healthcare facilities. Also notable are the differences between the countries in the accessibility of indigenous communities, which show a lower disparity in higher-income countries like Argentina and Brazil in comparison to Paraguay, as described in 1.4 (Figure 3.7). That indicates a connection between income of the country and disparities in accessibility between general and indigenous population.
The findings align with existing literature Davy et al. (2016), Quintana et al. (2021), Santos et al. (2022), World Health Organization (2024), which document the challenges faced by indigenous communities in accessing healthcare.
The analysis does not account for other healthcare accessibility barriers. Especially for the indigenous population, additional barriers such as communication, cultural differences and discrimination should be taken into account. Further, no distinction was made between private and public healthcare facilities. This financial barrier could have a strong impact on access for the local population, who often have less money at their disposal.
While the general trend observed is likely robust, findings should be interpreted cautiously when generalising to different regions with varying infrastructure and geographic characteristics. Additionally, findings about indigenous communities might not be applicable to the whole community or others.
With that, this part of the study contributes to the understanding of how population characteristics influence service accessibility, highlighting systematic disparities. It highlights the need for targeted healthcare policies for indigenous communities, who are disproportionately affected by longer travel times.
Following that future research should explore the impact of other variables on travel time, such as healthcare quality and different forms of barriers. Additionally, studies could examine the accessibility of other essential services beyond healthcare, like education. Conducting temporal studies could provide insights into how changes in population characteristics over time affect accessibility.

4.4 Conclusion

To summarise, this study provides a comprehensive analysis of healthcare accessibility in the tri-border of the Alto Paraná Atlantic Forest including Paraguay, Brazil and Argentina. It highlights the notable disparities in accessibility on the regional and societal level. The findings underscore the need for policy actions to improve healthcare accessibility, particularly in under-served regions and communities. Future research should address data refinement, consider additional barriers to healthcare access, and expand the geographical and temporal scope to provide a more comprehensive understanding of healthcare accessibility in different regions. By addressing these issues, policymakers can develop more effective strategies to ensure equitable access to healthcare for all and promote goal three of the agenda for sustainable development: ”ensure healthy lives and promote well-being for all at all ages.” (United Nations, 2015b).

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Appendix A

Data sets

A.1 Countries and Borders

Name	Source
Administrative boundaries provided by geoBoundaries	(Runfola et al., 2020)

A.2 Healthcare Facilities

Sources used for the creation of the healthcare facilities dataset.

Name	Source
Healthcare facilities provided by the Brazilian government	(Ministério da Saúde, 2024)
Healthcare facilities provided by the Paraguayan government	(Ministerio de Salud Pública, 2024)
Healthcare facilities provided by the Humanitarian OpenStreetMap Team	(Humanitatiran OpenStreetMap Team, 2024)
Healthcare facilities provided by Healthsites.io	(Saameli, Kalubi, Herringer, Sutton, & De Roodenbeke, 2018)

A.3 Road Network

Name	Source
Roads provided by OpenStreetMap	(Olbricht, 2024)

Appendix B

Validation

To validate the results of the friction surface as described in 3.2, all unclassified surfaces between roads and borders outside of city centres, shown as white areas in 3.1, needed to be evaluated. After looking at the difference raster of the friction surface and the MapBIOMAS land-cover raster (Souza et al., 2020), it is clear that these areas were mostly water bodies, national parks and forests (Figure B1).

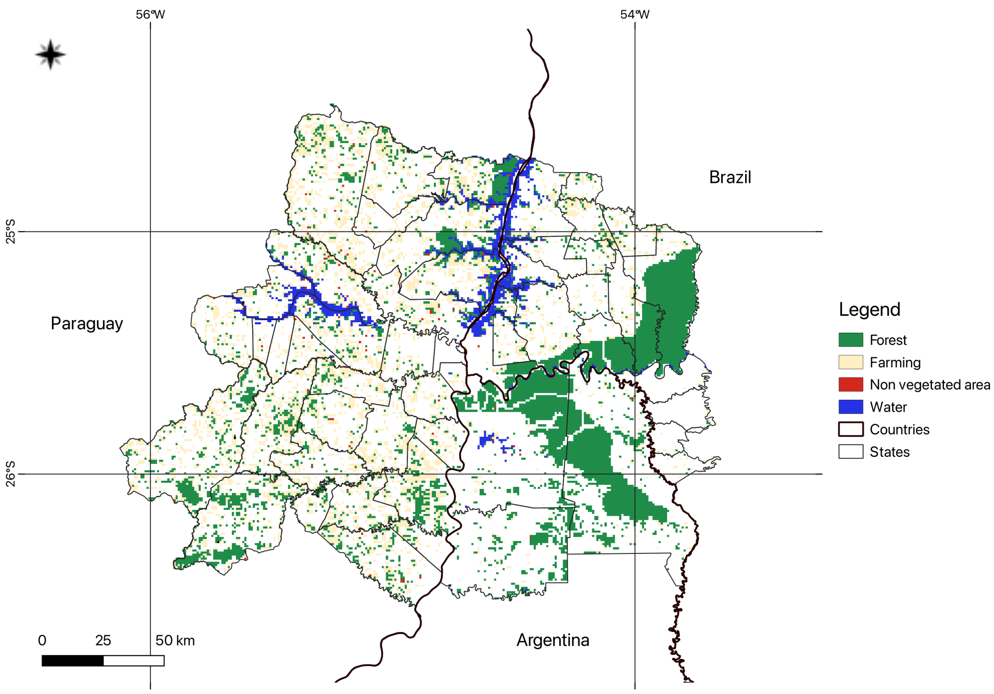

Figure B1: Friction Surface with Land Cover Source: (Souza et al., 2020) & (Runfola et al., 2020)

To further validate, the percentage of population inside and outside the study area was examined. This was achieved with the population density raster by the EU (Figure B2).

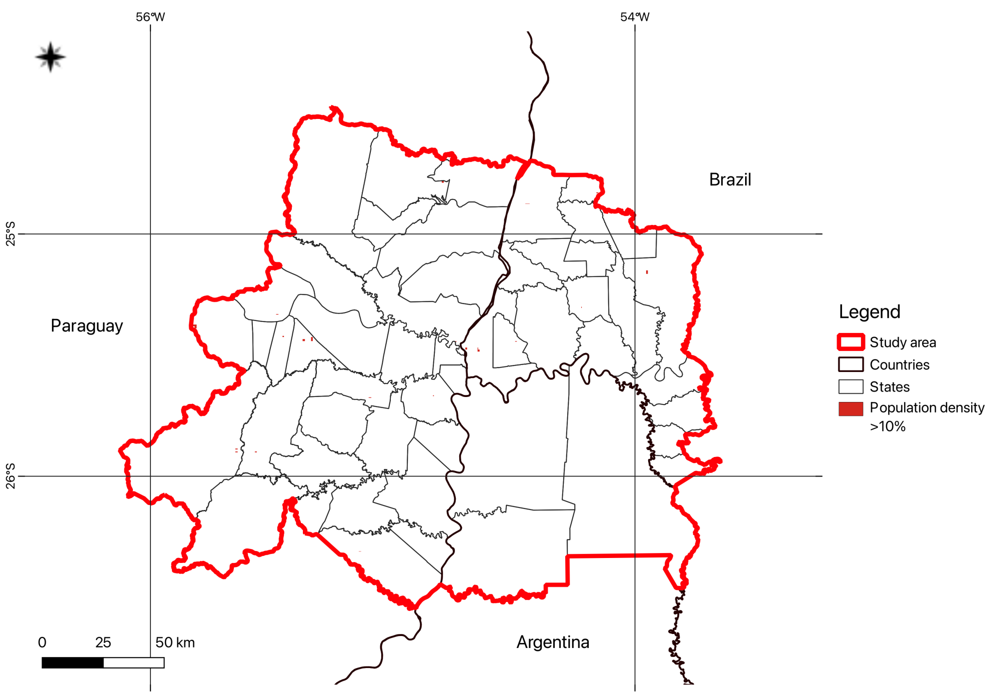

Figure B2: Friction Surface with Population Density

An earlier validation of these types of results was conducted by Haynes, Jones, Sauerzapf, and Zhao (2006). They concluded that travel times calculated with GIS methods were moderately close approximations to reported travel times and also may be superior to reported travel times because reported travel times may contain errors or can reflect unusual circumstances.

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Hiermit erkläre ich, dass ich meine Bachelorarbeit selbstständig und ohne unerlaubte Hilfe angefertigt habe.

23.06.2024

Datum Unterschrift

Hiermit erkläre ich mich einverstanden mit der Veröffentlichung meiner Bachelorarbeit in der Universitätsbibliothek.

23.06.2024

Datum Unterschrift