An Evaluation of the Spatial Accessibility of Mental Healthcare Facilities in The Netherlands

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Abstract

Background: Throughout life, 43% of the Dutch population experiences at least one psychological disorder. In the Netherlands, mental healthcare is regulated by the Mental Healthcare Initiative (Geestelijke Gezondheidszorg, GGZ). The Dutch government wants these mental healthcare facilities to be accessible to everyone. Given that longer distances to (mental) healthcare locations have been recognised as a disabling factor in healthcare utilisation, it is of great importance to make the differences in geographical accessibility visible. Furthermore, it is critical to investigate whether socioeconomically vulnerable groups are being more affected by the lack of access.

However, studies examining the association between socioeconomic status and mental healthcare accessibility are rare. On top of that, no research in the Netherlands has been done looking at the spatial accessibility of mental healthcare facilities. In general, studies determining mental healthcare accessibility often focus on small study areas and deploy oversimplified accessibility measurement methods.

Objectives: The main objective of this study is to investigate differences in the socio-spatial accessibility of mental healthcare facilities in the Netherlands with the help of the Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) method.

Methods: The Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) method is used to examine the accessibility for each population square (100x100m) in the Netherlands. MH3SFCA is an improved variation of the Floating Catchment Area (FCA) approach. Among the main advantages of the MH3SFCA method is the incorporation of competition among service providers based on demand probability according to the Huff model. Furthermore, it considers the influence of distance both relatively and absolutely.

Within this research, the MH3SFCA method is executed with the help of Geographical Information Systems (GIS). The result from this analysis is an immediately meaningful index score (SPAI), which can be compared within the Netherlands. Next, a statistical analysis is performed to explain the possible association between socioeconomic variables and the accessibility scores.

Results: As a consequence of the high density of mental healthcare facilities in the Netherlands, almost all population hectares (99.35% of population hectares with at least 10 people) are located within a 12-minute driving range by car to a mental healthcare facility. The highest accessibility scores were not only found in the big cities in the Netherlands, but also medium and smaller-sized cities experienced high mental healthcare accessibility scores. The lowest accessibility scores were found around the Dutch-German border in Drenthe, the rural parts of the Randstad (het 'Groene Hart'), large parts of Noord-Brabant, and some parts of the provinces of Friesland and Noord-Holland.

A regression analysis revealed that population locations with a high percentage of non-Western migrants do not experience lower accessibility to mental healthcare facilities. The percentage of owner-occupied property is negatively associated with the SPAI. Also, the percentage of people receiving unemployment benefits is positively associated with the accessibility to mental healthcare facilities. The percentage of houses owned by housing associations is negatively associated with the accessibility scores. All associations were significant except for the null association found between the WOZ value (value of immovable property) and the SPAI scores in the spatial lag model. Finally, both observed age groups (those aged under 15 and over 65) were negatively associated with the SPAI.

Conclusions: Regional and small-scale differences were found in the spatial accessibility of mental healthcare facilities. Socioeconomically disadvantaged groups are not disproportionally affected by the lack of access.

Keywords: Mental Healthcare Accessibility, Floating Catchment Area, MH3SFCA, GIS, Healthcare Inequality

Contents

List of Abbreviations

2SFCA	Two-Step Floating Catchment Area
3SFCA	Three-Step Floating Catchment Area
AIC	Akaike Information Criterion
CBS	Centraal Bureau voor de Statistiek (Statistics Netherlands)
E2SFCA	Enhanced Two-Step Floating Catchment Area
E3SFCA	Enhanced Three-Step Floating Catchment Area
FCA	Floating Catchment Area
GGZ	Geestelijke Gezondheidszorg
GIS	Geographic Information System
GP	General Practitioner
LM test	Lagrange Multiplier test
M2SFCA	Modified Two-Step Floating Catchment Area
MH3SFCA	Modified Huff Model Three-Step Floating Catchment Area
MLR	Multiple Linear Regression
OD-matrix	Origin-Destination matrix
OLS	Ordinary Least Squares
POH GGZ	Praktijkondersteuner GGZ (general practice supporter)
SPAI	Spatial Accessibility Index
VIF	Variance Inflation Factor

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Introduction

1.1 Mental Healthcare Accessibility in the Netherlands

1.1.1 Mental health in the Netherlands

Throughout life, 43% of the Dutch population experiences at least one psychological disorder (Nederlandse ggz, 2022a). Adolescents experience the highest number of psychological disorders. More than 25% of adults experience either mood disorders or anxiety disorders. Less common are substance use disorders, with 17% of adults experiencing them at some point in their lives (Trimbos Instituut, 2022).

The percentage of adults having a psychological disorder has grown tremendously over the past 12 years (Trimbos Instituut, 2022). In 2019-2022, 26% of the adult Dutch population had a psychological disorder, compared to 17% in 2007-2009. The increase in mental disorders was greater among 18 to 34 year-olds compared to those aged 35 and older, students compared to those who were employed, and urban residents compared to rural residents (Ten Have et al., 2022). In this context, one of the main challenges is how to ensure adequate accessibility to mental healthcare for the entire Dutch population.

1.1.2 Dutch structure of mental healthcare

The Dutch government wants people with mental health problems to receive proper help. For this reason, the governmental mental healthcare initiative called the Geestelijke Gezondheidszorg (GGZ) receives a great deal of attention. The GGZ expenditures on mental healthcare increased to 4.6 billion euros in 2022, which exceeded the costs of primary healthcare (Zorginstituut Nederland, 2022).

The organisation of mental healthcare in the Netherlands is regulated by two laws: the Health Insurance Act and the Youth Act. The GGZ in the Netherlands is divided into four main parts. Mental healthcare provided by the general practitioner (GP), basic mental healthcare (basis GGZ), specialised mental healthcare (gespecialiseerde GGZ), and long-term mental healthcare (langdurige GGZ). Figure **1.1** shows an overview of the structure of the GGZ within the Netherlands.

For basic mental healthcare, services are provided by, among others, general practitioners, social workers, and primary care psychologists. This primary care is general, fast, and easily accessible. Primary care providers can seek advice from specialised mental healthcare institutions (Zorgwijzer Nederland, n.d). In 2021, 642,700 people received help from, what is also called the 'praktijkondersteuner huisarts GGZ' (POH GGZ) (Nederlandse Zorgautoriteit, 2023). The 'praktijkondersteuner huisarts GGZ' (POH GGZ) – which can be translated as general practice supporter – can prescribe medication, self-care modules, and e-health modules (internet treatments).

If further or more specialised treatment is needed, the general practitioner or a medical specialist refers the patient to a second-line treatment: basic or specialised mental healthcare. Mental healthcare institutions provide this care. The difference between the basic and specialised GGZ is that the basic GGZ is intended for individuals with mild to moderate psychological issues. This care is often more short-term and focused on addressing specific complaints. Specialised mental healthcare treats individuals with severe, complex, or frequently recurring issues. In the case of youth care (patients under 18), in addition to locally organised access to assistance, there is also direct referral by the general practitioner, medical specialist, and youth doctor possible. In total, 752,997 people received basic and specialised GGZ combined in 2021 (Nederlandse Zorgautoriteit, 2023).

Finally, long-term GGZ is for people who have been in treatment and/or residence at a GGZ institution for over three years. In 2021, there were 2364 long-term GGZ patients (Nederlandse Zorgautoriteit, 2023).

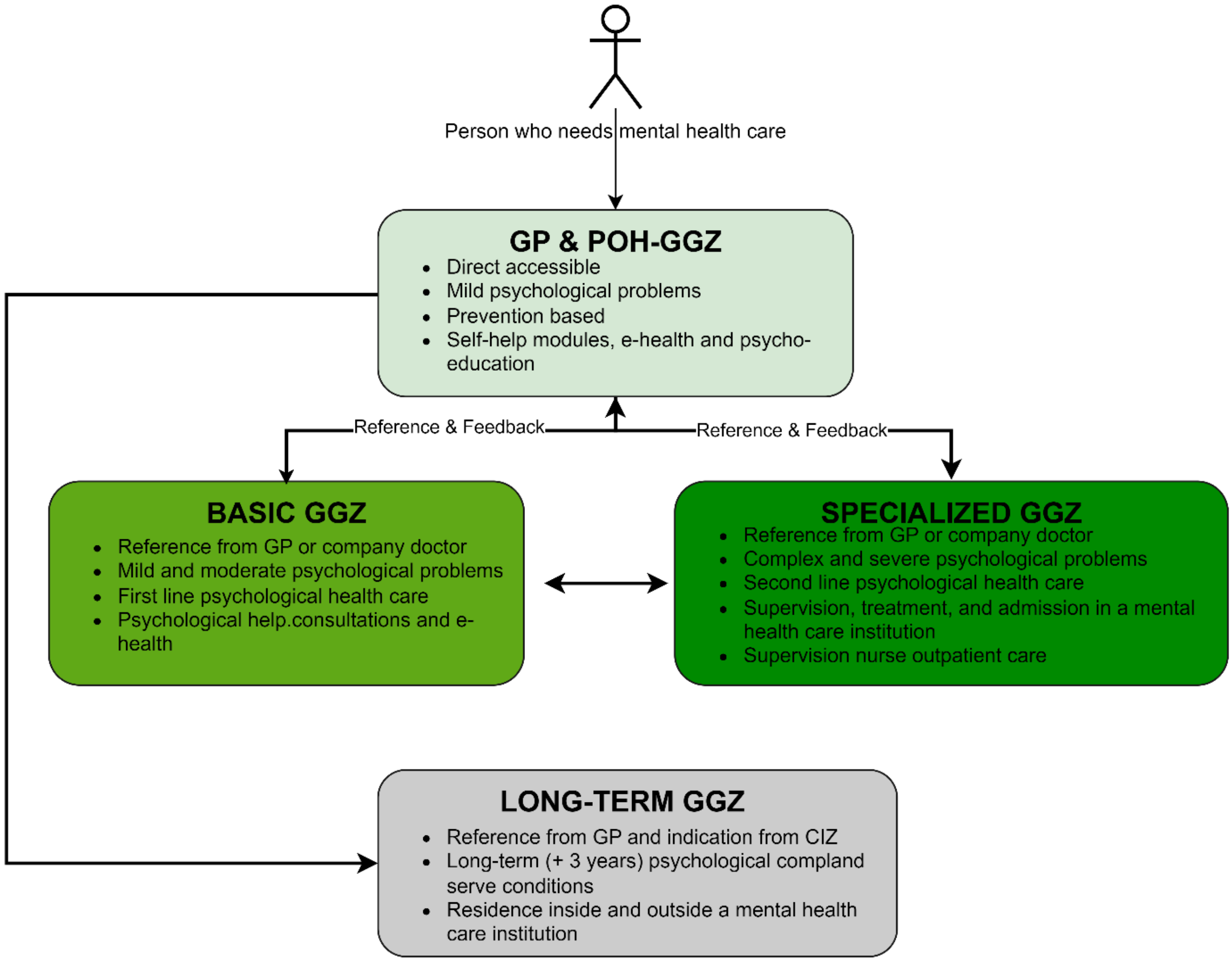

Figure 1.1 Mental healthcare structure in the Netherlands. Adapted from Zorgwijzer Nederland (n.d.).

1.1.3 Importance of mental healthcare accessibility

In general, both the mental healthcare services and the people who demand these services are unevenly distributed over space. In addition, transportation networks are also irregularly distributed within a country. For this reason, there will always be some disparity in geographical accessibility in any specified study area. However, despite this concern, evaluating potential geographical access to healthcare facilities is of significant interest due to the following reasons (Langford et al., 2016):

- To assess the efficiency and reach of the current services.
- To contribute to the development of policies and strategies for future services to maximise accessibility while minimising travel costs.
- To ensure that there is equal access for everyone and maintain the required minimum national guidelines.

In the Netherlands, health equity has become a fundamental priority for policymakers and the rest of the healthcare industry. Health equity implies that each individual has an equitable and morally justifiable chance to achieve the greatest possible state of well-being (Ma et al., 2023). Health equity is also included in the Universal Declaration of Human Rights (UDHR) of the United Nations. Article 25.1 states: “Everyone has the right to a standard of living adequate for the health and well-being of himself and his family, including […] medical care […]” (UN, 1948). Furthermore, the Dutch constitution states that: “Everyone has the right to access preventive healthcare and medical treatment under the conditions established by national laws and practises. In determining and implementing any policy and action of the Union, a high level of protection of human health is ensured" (De Nederlandse Grondwet, 2003). Given the ever-growing importance of mental healthcare, a main challenge for the Dutch government will be to ensure adequate accessibility to mental healthcare facilities within the entire country.

It can thus be concluded that equal access for everyone is the most important incentive for healthcare accessibility within the Netherlands. More equal accessibility to healthcare facilities will lead to fewer inequalities in the health of the Dutch population (Van den Berg et al., 2014). This stresses the importance of examining the differences in healthcare accessibility in the Netherlands.

1.2 Research Gaps

Ongoing developments in geospatial analysis have led to numerous articles exploring the accessibility of healthcare, see for example Luo & Wang (2003), Luo (2014, 2016), Wan et al. (2012), and Delamater (2013). Taking a closer look at these studies, a large part is focused on the accessibility of primary healthcare facilities. This is because primary healthcare is seen as the most important form of healthcare to keep a society healthy and to prevent diseases. Another substantial number of studies focus on the accessibility of hospitals and emergency locations, quite often in rural areas (Guagliardo, 2004).

Nevertheless, the accessibility of mental healthcare facilities is also of great importance, as long travel times can form a potential barrier to the use of mental healthcare facilities, which can lead to higher disparities in the degree of health (Lankila et al., 2022). Moreover, research from the Netherlands (MIND, 2017) shows that a factor for patients when using (preventative) mental healthcare facilities is the travel distance. People should be able to easily go to the facilities independently.

Studies examining socioeconomic inequalities in access to healthcare can be found, for example, the research focused on Brazilian cities by Tomasiello et al. (2024). They found that individuals with a low income have greater access to primary care units, whereas individuals with a high income have better access to more specialised healthcare. A similar study was executed for the Santiago Metropolitan region by Contreras et al. (2023), but here low-income and rural districts had a significantly lower coverage of healthcare facilities. Furthermore, Lee (2022) researched the spatial and socioeconomic inequalities in accessibility to healthcare services in South Korea. These are just a few examples of studies examining the association between the spatial accessibility of healthcare facilities and the socioeconomic characteristics of the population. However, almost all these studies focus on primary healthcare or other forms of healthcare and not on mental healthcare facilities.

Most studies concerned with the accessibility of mental healthcare locations view spatial barriers as a contributing factor in lower mental health service utilisation. This indicates that people living further away from mental healthcare locations are less likely to use them (Lara et al., 2012). However, the characteristics and effects of geographic proximity to these mental health services are understudied because most studies focus on primary healthcare facilities or ambulatory care (Fleury et al., 2012). Furthermore, only a limited number of studies have discussed the relationship between the spatial accessibility of mental healthcare services and the socioeconomic and demographic characteristics of the population.

For example, Ghorbanzadeh et al. (2020) conducted a Geographic Information System (GIS) based analysis to evaluate the accessibility of mental healthcare services in Florida. Furthermore, they assessed how this accessibility differs between different age groups. However, they consider accessibility only by using the shortest path between residential and mental healthcare locations. Using a (variant) of Two-Step Floating Catchment Area (2SFCA) will take both supply and demand into consideration and thus provide a more thorough accessibility measure compared to only using the shortest path between population and mental healthcare locations.

Wang and Ariwi (2021) conducted a study on the spatial accessibility of mental healthcare facilities in the City of Toronto. In contrast to Ghorbanzadeh et al. (2020), they do use a variant of the 2SFCA approach. This can be seen as an improvement because in examining the spatial access of mental healthcare facilities, this method takes both accessibility and availability into account. Furthermore, they explore the relationship between poor socioeconomic circumstances and the spatial accessibility of mental healthcare facilities. A distinction is made between mental healthcare community services and mental healthcare specialists They found that neighbourhoods with higher socioeconomic status enjoy better spatial access to mental healthcare specialists compared to mental health community services. On the other hand, less affluent neighbourhoods had easier access to mental health community services compared to mental healthcare specialists.

Another Canadian study by Ngui and Vanasse (2012), uses the 2SFCA method to assess the variety of accessibility scores for different regions in Montreal. High levels of unequal accessibility to mental healthcare facilities were found in Montreal. The authors note that in the areas with low accessibility scores, this is especially concerning because these are mostly deprived neighbourhoods with a lot of unemployed inhabitants and recent immigrants. However, no further statistical evaluation of how the variation of accessibility corresponds to the distribution of the population with various socioeconomic characteristics was conducted.

Most studies about the spatial accessibility of mental healthcare facilities, are focused on parts of Canada or the United States and are conducted on a smaller scale (city or state). For example, Wang and Ariwi (2021) focus on the City of Toronto and Ngui and Vanasse (2012) on the City of Montreal. However, in the Netherlands, the GGZ is a national initiative with the focus of providing mental healthcare for the entire country and adequate spatial accessibility throughout the whole country (Rijksoverheid, 2023). By implementing a nationwide approach, the regional differences in accessibility within the Netherlands can be identified. Enforcing a nationwide approach to map the accessibility of healthcare facilities will be helpful for the Dutch government in identifying underserviced regions. Finally, plenty of city-based studies struggle with the edge effect, where the study area is defined by a border which does not prevent travel across the border (Gao et al., 2017). The edge effect will be negligible in this study, as there are high financial and cultural barriers to receiving mental healthcare outside of the Netherlands.

In addition, studies such as CBS (2022a) and (Van den Berg et al., 2014) concerned with the spatial accessibility of healthcare facilities in the Netherlands implement a distance-based approach. These methods are often easy to calculate and interpret. However, distance-based approaches do not account for the fact that areas often offer a variety of provider options at a similar distance. Floating Catchment Area (FCA) based methods can offer a more comprehensive and realistic assessment of mental healthcare accessibility by considering both supply and demand factors.

To the best of the author’s knowledge, there are no studies done using (a variation of) the FCA method to calculate the spatial accessibility of (mental) healthcare facilities in the Netherlands. Only a report is available that shows the shortest driving time from each postal area to the GGZ crisis centres. There are 30 GGZ crisis centres in the Netherlands. These crisis centres are only for acute, severe psychological problems where people are a potential danger to themselves or their surroundings (Giesbers & Kommer, 2018).

Finally, as explained above, limited research has been done combining the spatial accessibility of mental healthcare facilities with socioeconomic variables. Some economically vulnerable and socially unprivileged groups in society may be disproportionately affected by the lack of access to mental healthcare facilities. Having more insight into the relationship between the spatial accessibility of these facilities and socioeconomic characteristics within a neighbourhood is essential for policymaking and the resource allocation of mental health services. This will give valuable insights into the less visible inequalities within the Netherlands.

1.3 Research Objectives and Research Questions

The overall aim of this research is to assess the differences in spatial accessibility of Dutch mental healthcare facilities and to see if they can be explained by socioeconomic characteristics. By combining a nationwide approach, an FCA-based method, and a statistical analysis to see whether differences in accessibility can be explained by socioeconomic differences, this study contributes to the research on mental healthcare accessibility.

The main objective of this study is to investigate differences in the socio-spatial accessibility of mental healthcare facilities in the Netherlands with the help of the Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) method. This main objective can be broken down into the following research questions:

1. **Research Question: What are the regional differences in mental healthcare accessibility within the Netherlands?**
   Considering the present repository of knowledge (Ghorbanzadeh et al. 2020; Tadmon & Bearman, 2023) the hypothesis is that the more densely populated, urban parts of the Netherlands will experience better access to mental healthcare facilities compared to less densely populated, rural parts.

2. **Research Question: What is the association between accessibility scores and the socioeconomic and demographic composition of the population area?**
   Looking at the current knowledge base (Ngui & Vanasse, 2012), the expectation is that population locations with a high percentage of people with a non-Western migration background experience lower accessibility to mental healthcare facilities. Furthermore, socioeconomically disadvantaged population locations are expected to have lower accessibility (Vallée et al., 2021). Population cells with a high percentage of elderly people are expected to have lower access too (Ghorbanzadeh et al., 2020).

1.4 Outline of the Thesis

The structure of this thesis is as follows. First, in the literature review, the definition of healthcare accessibility will be discussed. Also, different measurements of accessibility (focusing on location-based measurements) are introduced. Thereafter, the characteristics of Floating Catchment Area (FCA) methods are explained, and the different variants of these methods are compared. The second part of the literature review focuses on inequality in healthcare accessibility in the Netherlands and the impact of distance on mental healthcare utilisation.

Next, in the methods and materials section, the study area and the used data will be discussed in detail. Furthermore, the preprocessing and software are described. In the methods section, both the details of the MH3SFCA method and the statistical analysis will be explained. The result section shows the results of both research questions. Finally, there will be a reflection on the results and the research in general.

2. Literature Review

2.1 Concept of Accessibility

Accessibility is a broad concept, which has been the subject of many discussions, and which can have various meanings depending on the context. A well-known definition is for example from Hansen (1959): “The potential of opportunities for interaction.” Another often-practised definition is “The benefits provided by a transportation or land/use system” (Ben-Akiva & Lerman, 1979). Or “The measure of the capacity of a location to be reached from, or to be reached by, different locations” (Rosenberg, 2018).

Focusing on the accessibility of healthcare, the literature distinguishes between potential access and realized access. Potential access means the availability or distribution of health facilities. The realized access is the actual use of the services (Shah et al., 2016). This idea derives from the work of Khan (1992) who divided between potential and realized access, and spatial and non-spatial accessibility (see Table **2.1**). While having potential access to healthcare facilities may increase the likelihood of utilizing available services, it does not guarantee that they will be used. The actual, realized utilization of services relies on various barriers and facilitators both dependent on the users and the healthcare system.

Table 2.1 Typology of access based on different dimensions of access. Adapted from Khan (1992).

	Spatial (geographic)	**Aspatial (social)**
Potential	Potential spatial/geographic access	Potential aspatial/social access
Realized	Realized spatial/geographic access	Realized aspatial/social access

Another significant study in the field of healthcare access is the work of Penchansky and Thomas (1981). They focus in their study on the concept of healthcare as being multidimensional and based on five types of accessibility. These five types are availability and accessibility (also called reachability) (spatial dimensions), and accommodation, affordability, and acceptability (non-spatial dimensions). Availability is the relation between the supply of health services and the demand from the population. Reachability (also called accessibility) focuses on geographic accessibility. Accommodation means the way in which the healthcare provider meets the preferences of the population. Affordability is related to the costs and the willingness and ability of the clients to pay. Finally, acceptability focuses on the cultural characteristics of people, which can determine the level of acceptability of a specific health service (Jörg & Haldimann, 2023). In other words, access can be defined as the degree of fit between healthcare systems and users/customers (Penchansky & Thomas, 1981). Greater fit means better access (Saurman, 2016). Table **2.2** shows an overview of these different dimensions of accessibility.

Table 2.2 Five dimensions of healthcare accessibility. Adapted from Penchansky and Thomas (1981), Obrist et al. (2007) and Georgia Tech (n.d.).

	Dimension of healthcare accessibility	**Description**	**Aspects to consider**
Spatial Dimensions	*Accessibility (also called reachability)*	The location of the supply is in line with the location of the users.	Proximity, means of transportation, travel time and travel barriers.
	Availability	The existing health services meet the needs of the users.	Volume and type of services and resources. Availability of sufficient skilled human resources, goods, and facilities.
Non-spatial Dimensions	*Affordability*	The prices of services fit the user's income and ability to pay.	Direct and indirect costs of assessing healthcare.
	Accommodation	The delivery of healthcare accommodates the user's needs.	Organisation of services and the expectations from the users. Cultural and language barriers.
	Acceptability	The characteristics of the providers match those of the users.	Ethical standards, cultural and gender differences, life-cycle requirements, ethnicity, type of insurance, etc.

The framework from Penchansky and Thomas is used to define access in a large number of healthcare accessibility studies. Even though this framework encompasses a broad definition of healthcare accessibility, the main criticism is that in healthcare accessibility research, the dimensions are not always practised as they were conceptualized (Saurman, 2016). Furthermore, Saurman argues to add a sixth dimension: awareness. Awareness focuses on the communication and information from both service providers and users. Providing healthcare services that are tailored to the specific needs of the local population can result in more efficient and effective healthcare. On the other hand, it would be easier for patients to access and utilize the services if they were initially informed about their existence and aware of the possibilities.

Another adaptation from the original Penchansky and Thomas framework is formulated by Lévesque et al. (2013). They conceptualise access as a convergence of the characteristics of health systems and the characteristics of the population. Next to the five dimensions of accessibility introduced by Penchansky and Thomas (1981), they propose five corresponding abilities of people. These abilities enable individuals to interact with the various aspects of accessibility in order to create access. These five abilities are: the ability to reach, the ability to seek, the ability to pay, the ability to engage and the ability to perceive (Lévesque et al., 2013).

The Lévesque et al. (2013) framework has been widely used in healthcare accessibility research around the world. The main advantage in comparison to the original Penchansky and Thomas framework is the ability to take both the users and the health systems' perspectives into equal account. Furthermore, the framework does not only focus on failures within the health system but also on barriers to access that patients can face (Cu et al., 2021). However, the main challenge with both the Penchansky and Thomas (1981) framework and the Lévesque et al. (2013) framework is still the difficulty of categorizing between the different dimensions. Some questions related to healthcare access may not neatly fit within a single dimension or ability.

2.2 Measurement of Accessibility

2.2.1 Types of accessibility measurements

The previous section focused on the different characteristics of accessibility. The following chapters concentrate on how to measure accessibility, in particular, accessibility to (mental) healthcare facilities. Accessibility measures can indicate the extent to which progress in transportation infrastructure, land-use and policy plans affect the working of society (Geurs & Van Wee, 2004). A highly cited article by Geurs & Van Wee (2004) describes the following four types of accessibility measures:

1. **Infrastructure-based measures.** Infrastructure-based measures are primarily used in the field of transport planning to assess the performance of the service level of the transport infrastructure.
2. **Location-based measures.** Location-based measures assess the availability of services across different locations on a macro level. These measurements show the extent of accessibility to geographically dispersed activities, such as the number of jobs reachable within a 15-minute travel radius from a point. Advanced location-based metrics take into account competitive factors by incorporating service capacity limitations.
3. **Person-based measures.** Person-based measures originated from Hägerstrand's space-time geography. The focus is here on the activities an individual can participate in at a certain time (Hägerstrand, 1970).
4. **Utility-based measures.** These types of measures analyse the economic benefits individuals gain from their ability to reach activities in different locations, originally based on economic studies.

The focus of this research is to analyse the accessibility of mental healthcare facilities on a nationwide scale. Location-based measures are most suitable for this task. In the following section, different location-based measures will be discussed.

2.2.2 Accessibility measurements for healthcare

In section 2.1, healthcare access is defined based on five different dimensions. Two of these dimensions, availability, and accessibility, are considered spatial dimensions. Accommodation, affordability, and acceptability are considered non-spatial dimensions (Jörg & Haldimann, 2023). The focus here will be on the measurement of the spatial dimensions of accessibility, which can be measured with location-based measures.

Different metrics can be used to quantify the spatial accessibility of (healthcare) facilities. Apparicio et al. (2017) and Guagliardo (2024) classify the measurements of spatial accessibility into five categories. These five categories are provider-to-population ratios, distance to the nearest provider, contour measurements, gravity models, and FCA-based approaches. Table **2.3** shows an overview of the different measurement types. Because of the many variations, FCA-based approaches will be extensively discussed in the next chapter. The other methods will now be explained.

Table 2.3 Overview of most often used measurements for healthcare accessibility.

Measurement type	Description
Provider-to-population ratio	Ratio which shows the amount of healthcare providers within a specific geographic area or population.
Distance to the nearest provider	Euclidean, Manhattan or network distance from a population centre to a healthcare location.
Contour measures	Number of healthcare providers within a set distance or average distance to a set of providers.
Gravity models	Showing the possible connections between a particular population point and all nearby healthcare locations. The probability of interaction decreases as the distance or other travel obstacles increase.
FCA-based approaches	Use of (circular) buffers around population centres to calculate the provider-to-population ratio and compute an immediately meaningful index score.

Provider-to-population ratio

Provider-to-population ratio (PPR) measurements are also called container-based measurements (Delamater, 2013). Another name for these measurements is the regional availability model (Ma et al., 2018). This is because they focus only on a specific area and do not account for population flows over this area. Guagliardo (2004) states that these types of measurements are popular because they are highly intuitive, the data sources are readily available, and they do not require GIS tools or specific technological knowledge to calculate. In these ratios, the numerator represents a measure of healthcare capacity, which could include factors like the number of doctors, facilities, or hospital beds. The denominator represents the size of the population in that specific area.

However, the container-based approaches are vulnerable to the effects of the well-known Modifiable Areal Unit Problem (MAUP) as first described by Openshaw and Taylor (1981). This problem arises because the results of the analysis can be influenced by the scale of the container object (i.e. the size of the geographical unit used) and the specific location of tract boundaries, which are often arbitrarily demarcated. Both of these factors can affect the consistency of the spatial patterns and cause changes in the significance level of correlations when the units of analysis change (Chen et al., 2022).

Distance to the nearest provider

Another often-used accessibility indicator is the distance to the nearest provider, also called the travel impedance to the nearest provider. The development of GIS software with transportation modules, such as the ESRI Network Analyst Extension or the QNEAT3 plugin in QGIS, has greatly contributed to the popularity of this type of measurement (Apparicio et al., 2008).

The distance to the nearest provider is typically determined based on the location of a person or a central measure point within the population. This central point can be the geometric centroid of the unit of analysis, such as a neighbourhood or population square. The choice of the measurement location depends on the available data resolution for a research. To minimize aggregation errors, the smallest area unit possible should be used (Apparicio et al., 2008).

Travel impedance, also known as travel cost, can be expressed in various ways, such as Euclidean (straight-line) distance, Manhattan distance, travel distance along road and rail networks, or estimated travel time (Guagliardo, 2004). Figure **2.1** shows an overview of the different types of distance. Figure **2.1a** shows the Euclidean distance and the Manhattan distance. Figure **2.1b** shows different types of network distances, by public transport, on foot, by car and by bike.

Figure 2.1 Types of distance (Apparicio et al., 2017).

Various studies have been done to compare these different types of measurement. Apparicio et al. (2008) found that the Euclidean and Manhattan distances closely resembled the network distances in urban areas. However, in more suburban areas local differences between Euclidean and network distance were greater, so network distance is the preferred choice.

The main advantage of using distance to the nearest provider as an accessibility indicator is that it is very intuitive and relatively easy to calculate with modern GIS technologies (Guagliardo, 2004). Mostly in rural areas, the distance to the nearest provider can be seen as a reliable measure of accessibility. This is because the closest provider is often the most likely choice here. However, research suggests (Fryer et al., 1999) that this measure is not adequate for urban environments. This is because urban areas tend to have a variety of provider options at a similar distance from a population point. For this reason, spatial accessibility measures should take into account all feasible options available for the potential users (Guagliardo, 2004).

Contour measures

Examples of contour measures are the number of providers within a set distance or the average distance to a set of providers. These types of measurements are also known as isochronic measures, cumulative opportunity, proximity distance or proximity count. These measures refer to the number of potential opportunities within a predetermined travel time or distance. The accessibility improves if more opportunities can be reached within the same distance or time (Geurs & Ritsema van Eck, 2001). An example of this measure is the amount of health services within 15 minutes of driving time.

An advantage of this method is that it is relatively easy to compute with modern-day GIS technologies and simple to interpret (El-Geneidy & Levinson, 2006). Moreover, the data needed for this kind of analysis are often available, making it possible to study various kinds of accessibility to different facilities (Geurs & Ritsema van Eck, 2001). However, this measurement method has received criticism due to its simplistic approach. Contour measures rely on a single threshold and treat all opportunities as equally important in a fixed, binary manner. In reality, not all opportunities are equally desirable for the users. Furthermore, the selection of the isochrone distance (the maximum travel time or distance) is arbitrary (Geurs & Ritsema van Eck, 2001).

Gravity models

The first three measures described above only look at the supply of services (accessibility). However, the potential spatial access to healthcare facilities depends on both accessibility and availability. For this reason, gravity models can be seen as a better indicator of the accessibility of healthcare facilities.

The gravity-based measure is grounded in the work of Hansen (1959). This model is called after Newton's Law of Gravitation. Initially, gravity models were developed to support land use planning and to predict travel to retail facilities. Gravity models show the possible connections between a particular population point and all nearby healthcare locations. The probability of interaction decreases as the distance or other travel obstacles increase (Guagliardo, 2004). Box 1 below shows the basic form of the gravity model.

Box 1. The basic form of the gravity model

$$A_i = \sum_j \frac{S_j}{d_{ij}^{\beta}}$$

- A_i = Spatial accessibility from population point *i*
- S_j = Service capacity at supply location *j*
- β = Gravity decay coefficient/travel friction coefficient
- d_{ij} = Travel impedance (travel time or distance between point *i* and *j*

Despite the strong theoretical soundness of the gravity model, there are two main problems with this type of measurement. First, the value of A_i is not intuitive for policymakers and the population, especially compared to other measurements such as the PPR or distance to the nearest provider. Second, only the supply is measured, not the demand (Guagliardo, 2004). This implies that the value of A_i at any distance will be the same, even if the providers serve different amounts of people in their catchment area. For example, the result from the gravity model A_i for a population location at a certain distance from two providers would be the same, also when one provider serves 50 people in the catchment area and the other 500. In reality, these two providers are not equally accessible. For this reason, improved gravity models were developed as well as Floating Catchment Area (FCA) methods.

It is important to realize that all the FCA methods (which will be discussed in the next section) are based on the ideas of the gravity model (Luo, 2014). A main difference between the gravity model and the FCA method is that the index resulting from FCA analyses is an easy to interpret, container-based measure (Subal et al., 2021). In other words, FCA methods keep the advantages of a gravity model, while at the same time representing a final indicator comparable and intuitive as the provider-to-population ratio (Bauer & Groneberg, 2016).

2.3 Measuring Accessibility: Floating Catchment Area

2.3.1 Characteristics and variants of FCA

To overcome the disadvantages of the above methods, Floating Catchment Area (FCA) methods were introduced as a more suitable method of examining the spatial accessibility of health facilities. These methods address the limitations of other healthcare accessibility metrics and take advantage of the ever-increasing availability of geographic data and GIS tools. FCA-based techniques help in calculating the relationship between healthcare supply and potential demand while also considering the distances between healthcare supply locations and population locations. Flexible catchment areas are calculated for each point of demand and do not rely on fixed regions of analysis (Jörg & Haldimann, 2023).

Different variations of the FCA method exist. One of the earliest versions of the FCA is developed by Wang (2000) for the assessment of job accessibility. This approach shares similarities with kernel density. In order to represent density in a study area, a window is moved across it and the observations within the window are used to estimate the density at the centre of the window. To estimate the density, a gravity model can be used to assign weights to events based on the proximity to the centre by using inverse distances (Luo & Wang, 2003).

Based on the FCA, the 2SFCA method by Luo and Wang (2003) became the most popular and widespread variant (Subal et al., 2021). Based on this method, various other alternatives were developed. The methods that will be discussed in this section are the ones that are all related to the MH3SFCA method (which will be used in this study): the Two-Step Floating Catchment Area (2SFCA), Enhanced Two-Step Floating Catchment Area (E2SFCA), Modified Two-Step Floating Catchment Area (M2SFCA), Three-Step Floating Catchment Area (3SFCA) and the Enhanced Three-Step Floating Catchment Area (E3SFCA).

Despite the differences between these methods (which will be discussed in more detail below), they do have some similarities (Subal et al., 2021):

- Quantification of the relationship between supply and demand (availability).
- Quantification of the spatial relationship in terms of accessibility while considering distance independently of administrative and/or fixed boundaries.
- Incorporation of supply and demand locations and using information from both.

Two-Step Floating Catchment Area (2SFCA)

The widely used method Two-Step Floating Catchment Area (2SFCA) is based on the advanced gravity-based method by Weibull (1976) and the spatial decomposition method of Radke & Mu (2000). The central principle of this method is that the potential access to healthcare facilities depends on both the location of the supply (the healthcare facilities) and the location of the demand (the potential users) (Luo & Wang, 2003).

As the name suggests, the 2SFCA method consists of two steps (Luo & Wang, 2003). First, the number of people near each healthcare facility is determined within a pre-defined search radius. In the second step, the Spatial Accessibility Index is calculated. For each population area, the healthcare facilities that are located within the threshold travel time/distance are considered to determine the supply-demand ratio and the final accessibility score (Liu et al., 2022). Box 2 on the following page shows how to calculate the 2SFCA.

Over the past twenty years, 2SFCA has been extensively used for the assessment of the accessibility of a wide range of (public service) facilities, General Practitioners (GPs), hospitals, schools, green spaces, and elderly care facilities (Liu et al., 2022). One of the main advantages is the intuitive interpretation of this method (Luo & Qi, 2009). However, several authors have pointed out this method has certain shortcomings (Jörg & Haldeman, 2023). First, this method assumes that all population locations within a catchment area have equal access to the facilities, which might not be the case. Second, the 2SFCA is a dichotomous measure, meaning that any locations outside of the catchment area are assumed to have no access whatsoever.

Enhanced Two-Step Floating Catchment Area (E2SFCA)

To address the limitations of the 2SFCA, Luo and Qi (2009) developed the Enhanced Two-Step Floating Catchment Area (E2SFCA) method. This method assigns weights to different travel time zones within a particular catchment area to account for the distance decay effect. Subsequently, others used continuous functions to calculate the weights, for example, kernel density or Gaussian function (Liu et al., 2022). The difference between the 2SFCA and the E2SFCA can be seen in the addition of the distance-decay function $f(d_{ij})$, see box 2.

The main advancement of the E2SFCA method in comparison to the 2SFCA method, is the distance-decay weight making different levels of accessibility to healthcare locations within a catchment area possible. However, within this method, some issues remained. These are for example the choice of appropriate functional form for the distance decay function $f(d_{ij})$ and the arbitrary choice of the maximum catchment size. The size of the catchment can for example differ between rural and urban areas (Luo & Qi, 2009).

Box 2. Calculation of 2SFCA & E2SFCA

	2SFCA	E2SFCA
STEP 1 Calculate the service-demand ratio (R_j)	$R_j = \frac{S_j}{\sum_{i\epsilon\{d_{ij}\leq d_{max}\}} P_i}$	$R_j = \frac{S_j}{\sum_{i\epsilon\{d_{ij}\leq d_{max}\}} P_i\, f(d_{ij})}$
STEP 2 Calculate the Spatial Accessibility Index ($SPAI_i$)	$SPAI_i = \sum_{j\in\{d_{ij}\leq d_{max}\}} R_j$	$SPAI_i = \sum_{j\in\{d_{ij}\leq d_{max}\}} R_j\ f(d_{ij})$

- S_j = Service capacity at offer j
- D_{ij} = Distance between i and j
- D_{max} = Maximum radius/maximum catchment area
- P_i = Population at location i
- $f(d_{ij})$ = Distance decay function

Three-Step Floating Catchment Area (3SFCA)

Next to the E2SFCA method, different modifications are made to the classic 2SFCA method. The Three-Step Floating Catchment Area (3SFCA) focuses on the problem of demand overestimation, as experienced within the 2SFCA and E2SFCA methods. Within the 2SFCA and the E2SFCA methods, the demand of the population for a certain provider is namely independent of the number of providers.

Originally developed by Wan et al. (2012), 3SFCA adds an extra step to the calculation. In this first step, the probability of the population *i* requesting services from provider *j* is calculated. This is called the selection weight, which is based on the distance between the population location and a specific provider as well as on the distance between the population location to all other reachable service providers. This selection weight is then used in the next two steps of the 3FCA method. Box **3** on the following page shows how this method works.

The main advantage of this method compared to the Two-Step approach is the more reasonable display of competition between different healthcare facilities. However, some challenges from earlier discussed methods remain. For example, the rigid determination of the catchment area size. Wan et al. (2012) suggested that this catchment size should vary according to neighbourhood characteristics.

Enhanced Three-Step Floating Catchment Area (E3SFCA)

Comparable to the 3FCA method is the E3FCA method (Luo, 2014; 2016). The general concept of these two methods is the same, however, instead of using selection weights, the model relies on the Huff model to consider supply competition. In short, the Huff model is based on the idea that the probability of a consumer visiting a specific site is a function of the distance to the site, the attractiveness, and the distance and attractiveness of competing sites (Huff, 1963).

The major advantage of this method is that both the 'costs' of travelling to a healthcare facility and the capacity/attractiveness of the healthcare facility are considered. So, it takes into account the effects of service competition on the spatial accessibility (Luo, 2016). However, the choice of the correct distance decay function remains a challenge. Luo (2016) suggests that the distance decay coefficient should be calibrated based on actual interaction data between residents and healthcare providers.

Next to the E3FCA, other variations of the 3SFCA method exist, with increasingly longer and more difficult names. For example, the Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) by Jörg et al. (2019), a similar variant by Subal et al. (2021) and the Modified Huff-based Variable Three-Step Floating Catchment Area (MHV3SFCA) by Jörg and Haldimann (2023). All these variants follow the general outline of the (E)3SFCA, however, they differ mostly in how they determine the catchment of a population location in the first step.

Box 3. Calculation of 3SFCA & E3SFCA

	3SFCA	**E3SFCA**
STEP 1 Calculate the selection weight (3SFCA) or the Huff probability (E3SFCA)	$G_{ij} = \frac{f(d_{ij})}{\sum_{i\epsilon\{d_{ij}\leq d_{max}\}} f(d_{ij})}$	$Huff_{ij} = \frac{S_j\, f(d_{ij})}{\sum_{i\epsilon\{d_{ij}\leq d_{max}\}} S_j\, f(d_{ij})}$
STEP 2 Calculate the service-demand ratio (R_j)	$R_j = \frac{S_j}{\sum_{i\epsilon\{d_{ij}\leq d_{max}\}} G_{ij}\, P_i\, f(d_{ij})}$	$R_j = \frac{S_j}{\sum_{i\epsilon\{d_{ij}\leq d_{max}\}} Huff_{ij}\, P_i\, f(d_{ij})}$
STEP 3 Calculate the Spatial Accessibility Index ($SPAI_i$)	$SPAI_i = \sum_{j\in\{d_{ij}\leq d_{max}\}} G_{ij}\ R_j\ f(d_{ij})$	$SPAI_i = \sum_{j\in\{d_{ij}\leq d_{max}\}} Huff_{ij}\ R_j\ f(d_{ij})$

- S_j = Service capacity at offer j
- D_{ij} = Distance between i and j
- D_{max} = Maximum radius/maximum catchment area
- P_i = Population at location i
- $f(d_{ij})$ = Distance decay function
- G_{ij} = Selection weight
- $Huff_{ij}$ = Huff probability

Modified Two-Step Floating Catchment Area

Delamater (2013) developed a methodology called Modified Two-Step Floating Catchment Area (M2SFCA). Box **4** shows how to calculate this indicator. Delamater argues that this method brings significant improvements compared to other FCA variants. The M2SFCA builds upon the E2SFCA method by adding an additional distance weight into the calculation of the first step. This added weight ensures that the distances between healthcare facilities and population locations are not only considered in relative terms but also in absolute terms. By including absolute distances, the M2SFCA makes it possible to evaluate the spatial accessibility of the overall system (Delamater, 2013). Unlike the 3SFCA and E3SFCA methods, the M2SFCA does not make corrections for demand probabilities based on supply competition. This means that competition between service providers is not considered within this method.

Box 4. Calculation of M2SFCA

	MSFCA
STEP 1 Calculate the service-demand ratio (R_{ij})	$R_{ij} = \frac{S_j\, f(d_{ij})}{\sum_{i\epsilon\{d_{ij} \le d_{max}\}} P_i}$
STEP 2 Calculate the Spatial Accessibility Index ($SPAI_i$)	$SPAI_i = \sum_{j\in\{d_{ij} \le d_{max}\}} R_j\, f(d_{ij})$

- S_j = Service capacity at offer j
- D_{ij} = Distance between i and j
- D_{max} = Maximum radius/maximum catchment area
- P_i = Population at location i
- $f(d_{ij})$ = Distance decay function

2.3.2 Comparison of different methods

The main choice here is to choose for (a variant of) the 2SFCA or the 3SFCA method. Both methods are found appropriate for the assessment of healthcare accessibility. The 3SFCA can be seen as an upgraded version of the 2SFCA because it also accounts for competition effects between service suppliers within the catchment area (Wu et al., 2020). Wan et al. (2012) have demonstrated that the 2SFCA and E2SFCA methods tend to overestimate the demand of the population on service locations. This is especially the case when there are multiple service sites within a catchment area, and these sites compete with each other, which affects the population demand.

The M2SFCA method by Delamater (2013) brings significant improvements compared to earlier methods, however, is not the most suitable for this research because of the overestimation of the distance effects as argued by Jörg & Haldimann (2023). Also, unlike the 3SFCA (via the selection weight) and the E3SFCA (via the Huff model), the M2SFCA does not include a correction of the demand due to supply competition.

Next to the E3SFCA, plenty of other variations of the 3SFCA method exist. The following 3SFCA-based studies are analysed to see which would be the best fit for this study: 3SFCA by Wan et al. (2012), E3SFCA by Luo (2014; 2016), Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) by Jörg et al. (2019) and Subal et al. (2021) with a slightly different version of MH3SFCA.

All these five studies implement a (variant of) the Three-Step Floating Catchment Area approach. The main difference between these studies is the way they calculate the distance-decay effect in the first step of the method. Jörg et al. (2019) and Wan et al. (2012) divide the catchment into several sub-zones. In contrast, Luo (2014), Luo (2016), and Subal et al. (2021) implement a continuous approach. Instead of calculating the Gaussian weights for each subzone, each pair of population location and residential location gets their own individual weight (Subal et al., 2021). Another difference is the type of the distance-decay function. Luo (2014) implements a negative power distance function, whereas Wan et al. (2012) use the Gaussian weight. Luo (2016), Jörg et al. (2019) and Subal et al. (2021) use the Huff model in combination with the Gaussian function.

By using a continuous approach, Subal et al. (2021) move away from the subzone-based weights. This is based on the ideas of Luo (2016), who also implemented a continuous approach. Using a continuous Gaussian function can be seen as a more realistic way of modelling the distance-decay effect compared to using subzones. Furthermore, the choice of the number and size of the subzones is arbitrary and will affect the outcomes. Next, integrating the Huff model into the methodology can help in reducing the overestimation of demand, which is a problem in many previous FCA methods. For this reason, the Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) method as described by Subal et al. (2021) will be used in this research.

Subal et al. (2021) use the MH3SFCA method in the same context as this research; by quantifying the spatial accessibility of health facilities (in their case, GPs). However, it is important to realize that methods consisting of the elements used here (integration of the Three-Step Floating Catchment Area method, continuous Gaussian function, and the Huff model) are also used for accessibility studies in other domains. For example, to assess the accessibility of green spaces by Liang et al. (2023) and Zeng et al. (2024, under review). Or for examining the spatial accessibility of schools by Han et al. (2023).

In short, the MH3SFCA is a good fit for this research because:

- It takes into account competition among service providers based on demand probability according to the Huff model (similar to E3SFCA). This helps avoid overestimating demand.
- It evaluates distances relatively and absolutely, similar to M2SFCA. As a result, MH3SFCA allows for an evaluation of the overall system.

It could be argued that the MH3SFCA method has some advantages compared to the other methods. Table **2.4** on the following page shows an overview of the different characteristics of the different methods.

Table 2.4 Comparing the main variants of the FCA. Adapted from Jörg et al. (2019).

Characteristic	2SFCA	E2SFCA	3SFCA	E3SFCA	M2SFCA	MH3SFCA
Consideration of demand competition	✓	✓	✓	✓	✓	✓
Results are independent of the analysis unit (e.g. administrative boundaries)	✓	✓	✓	✓	✓	✓
Dependencies among the analysis regions are reflected in the results	✓	✓	✓	✓	✓	✓
Consideration of multiple supply options	✓	✓	✓	✓	✓	✓
Consideration of relative distance differences (within the max. radius)	✗	✓	✓	✓	✓	✓
Supply competition is considered	✗	✗	✓	✓	✗	✓
Consideration of relative and absolute distances	✗	✗	✗	✗	✓	✓
Constant total demand per population	✗	✗	✗	✗	✗	✓

2.4 Inequality in (Mental) Healthcare Accessibility in the Netherlands

2.4.1 Background health inequalities

In an international context, people in the Netherlands enjoy generally good health. However, the inequalities in health have rather increased than decreased in the recent decades in the Netherlands (Raad voor Volksgezondheid en Samenleving, 2020). The higher the income, the higher the life expectancy and healthy life expectancy (Knoops & Van den Brakel, 2010). For example, the life expectancy is 7.3 years higher for men and 6.4 years higher for women, between the lowest and highest educated groups in the Netherlands. Although, the differences in healthy life expectancy show even more striking differences: 19.2 years for men and 20.6 years for women (Van Bon-Martens et al., 2012). An example of the inequalities in access to healthcare in the Netherlands is for example that low-income households (mostly ethnic minorities) have more difficulties with paying their monthly health insurance. These difficulties are for those groups a reason to refrain from medical healthcare (Anderson, 2018).

Two main explanations for socioeconomic health inequalities that have been proposed in the literature are social causation and health selection (Hoffmann et al., 2018). Social causation suggests that someone's level of education can affect their health because education can increase awareness about healthy behaviours. Also, someone's job can impact their health because of the risks associated with their occupation. Finally, their level of income can impact their health by giving people the ability to afford healthcare.

On the other hand, health selection suggests that someone's health during childhood can have an impact on their level of education. This could be due to their ability to invest in education or due to factors such as mental health conditions. Poor health can also affect a person's job opportunities and income, as it can make it difficult to invest in a career and can lead to medical expenses (Hoffmann et al., 2018). Finally, a third model suggests that there may be other factors that are not yet identified, such as family background or individual characteristics, which can indirectly influence someone's socioeconomic status and health.

The level of health is caused by the social determinants of health, for example living and working conditions, poverty, and stress. Moreover, different expectations of care, healthcare facilities that are not aligned with patients' expectations, or are less accessible, and low health literacy also contribute to this. People with limited health literacy skills find it challenging to manage their health and illness at home and have difficulties with navigating within the healthcare system and actively participating in healthcare consultations (Andrus & Roth, 2002).

2.4.2 Inequality in mental healthcare accessibility

In the Netherlands, structural socioeconomic inequality has a significant influence on the mental health of the inhabitants. Individuals with a lower income, lower level of education, housing problems, financial difficulties or limited language proficiency have a higher chance of developing mental health issues. On the other hand, mental health problems increase the likelihood of quitting school and work, and socioeconomic disparities can lead to stress and problems (Wijma et al., 2023).

Recalling from Chapter 2.1, the five different dimensions of health accessibility are affordability, (spatial) accessibility, availability, accommodation, and acceptability. Regarding mental healthcare, most research, see Wijma et al. (2023), Lopes (2022) and Lopes et al. (2023) for the Netherlands has been done focused on the dimensions of availability and affordability. Studies focusing on availability mostly focus on the high number of people (84,000) who are currently on the waiting list to receive a GGZ treatment (Wijma et al., 2023). More than half of these 84,000 people are already waiting longer than 14 weeks. Further complicating is the fact that the waiting lists are the longest for people with complex mental problems. This concerns a diverse group of vulnerable individuals with combinations of issues. This can lead to an increase in the inequalities in mental healthcare availability in the Netherlands (Wijma et al., 2023).

Looking at mental healthcare affordability, research suggests that income inequalities are apparent among different stages of specialist mental healthcare treatment. People with low socioeconomic status require more treatment minutes to get the same outcome compared to people with a higher income. It can be the case that financial barriers are preventing low-income people from receiving sufficient treatment. Additionally, it might be the case that the effects of the treatment are lower for low-income people (Lopes et al., 2023).

Furthermore, Lopes (2022) reported that when the price of mental healthcare in the Netherlands becomes higher (because of a higher number of deductibles), some groups are less likely to use mental healthcare facilities. This is especially the case for young women from households with lower incomes, leading to an increase in inequality in access to mental healthcare.

However, on the spatial dimensions of mental healthcare accessibility, in the Netherlands, little to no research is yet available. Especially not on the possible relation between reduced spatial accessibility of mental healthcare facilities and poor socioeconomic conditions. In the next section, various studies from different countries emphasizing the importance of equal spatial accessibility to mental healthcare facilities will be discussed.

2.5 Accessibility of Mental Healthcare Facilities

Over recent years, quite a few articles - see for example Luo & Wang (2003), Luo (2014, 2016), Wan et al. (2012) and Delamater (2013) - have explored the geographical accessibility of (mental) healthcare. The research on the accessibility of mental healthcare facilities can be roughly divided into two types: articles focusing on the realized and the potential accessibility of mental healthcare facilities. As explained earlier, the realized access describes the actual use of mental healthcare facilities. It researches patient behaviour based on observed data. On the other hand, potential access solely takes into account the needs of a specific population and does not consider the effective utilization of services (Jörg & Haldimann, 2023). Given the topic of this research, the focus will be on the potential access. However, first, some studies discussing the realized access will be reviewed because they will demonstrate the importance of accessible mental healthcare facilities.

2.5.1 Impact of distance on mental healthcare utilization

There has been a persistent interest from researchers in the relationship between healthcare accessibility and the use of healthcare facilities. Additionally, for mental healthcare facilities, this has also been a topic of research since the 19th century. Already in 1866, Edward Jarvis wrote *The Influence of Distance from and nearness to an insane hospital on its use by the people*. In his study, he focused on the association between the admission rates and the home-to-hospital distance for the Oneida County Hospital of New York and the Kentucky Lunatic Asylum in Fayette County. Jarvis concluded that how farther away people lived from the ‘insane hospital’, the less likely they were to use this facility.

The location of mental healthcare services is critical due to the nature of mental disorders. Increased travel times to medical services are connected to a higher risk of mental disorders. Individuals with severe mental disorders may have to move to a different city or town to receive mental healthcare. Being away from their familiar surroundings can negatively impact their recovery progress (López-Lara et al., 2012).

Across the globe, studies found a negative impact of distance on the use of mental healthcare facilities. For example, a study from Switzerland found that for outpatient mental healthcare locations, travel time (by public transport) negatively predicted the utilization of these services. Interestingly, for inpatient mental healthcare locations, no distance-decay effect was found (Stulz et al., 2018).

Additionally, a study on the impact of socioeconomic position and distance to mental healthcare in Denmark found that a greater distance to service providers may increase differences in mental healthcare use between patients with high and low socioeconomic positions (Packness et al., 2017). They found that for the lowest income group, the contact with a psychologist decreased when the travel distance increased. Interestingly, this was also the only researched group which was significantly affected by distance (when adjusting for other factors such as age, gender, and country of origin).

Moreover, research from Australia suggests that people outside metropolitan cities in Australia face greater barriers to mental healthcare. Amos et al. (2023) found that the incidence/duration of public mental health unit admissions was correlated with distance from the hospital (providing mental healthcare facilities) and socioeconomic disadvantages. In a similar respect, Lankila et al. (2022) found that distance is negatively associated with the use of mental health services in Finland.

2.5.2 Accessibility of mental healthcare facilities

In the previous section, the focus was on the realized accessibility of mental healthcare facilities, in other words: the actual use. However, it is also important to map the so-called potential accessibility in order to identify regions that are (potentially) underserved and where the accessibility can be improved (Ngui & Vanasse, 2012).

Ngui and Vanasse (2012) use the 2SFCA method to assess to probable utilization of services in the urban environment in the southwest of Montreal. They found that the mental healthcare facilities were clustered in the southwest of Montreal, causing unequal accessibility. The authors note that in these areas this is especially concerning because these are neighbourhoods with a lot of recent immigrants and unemployed inhabitants. However, besides this remark, Ngui and Vanasse do not evaluate statistically how the variation in accessibility scores correlates with socioeconomic characteristics.

Ghorbanzadeh et al. (2020) use GIS analysis to evaluate the accessibility of mental healthcare services in the state of Florida, United States. They use distance to the nearest mental healthcare provider as an accessibility measure. Furthermore, a statistical analysis was done to see how the accessibility for each county differs between the different age groups. However, they consider accessibility only by using the shortest path between residential and mental healthcare locations.

Wang and Ariwi (2021) conducted a study on the spatial accessibility to mental healthcare facilities in the City of Toronto. In contrast to Ghorbanzadeh et al. (2020), they do use an E2SFCA approach. They compare the number of mental health crisis events per dissemination area (DA) with the accessibility of both community mental health services and psychiatrists. Interestingly, neighbourhoods in the City of Toronto with high mental crisis rates and low spatial access to mental healthcare facilities are mostly middle and high-income. This is in contrast with most studies, which view income as an enabling factor of healthcare accessibility (Wang & Ariwi, 2021).

Finally, a recent study by Tadmon & Bearman (2023) takes it one step further, as they found a strong association between the spatial-social accessibility of mental healthcare facilities and heightened suicide risk in the USA. They implemented a 3SFCA method and found a correlation between the number of suicides in a county and the accessibility of mental healthcare facilities.

It is concerning if socioeconomically disadvantaged population groups experience lower access to mental healthcare facilities. This is because lack of access to such facilities can have a greater impact on these groups, who may already face several disadvantages. For example, they experience smaller areas around their activity locations and have less flexibility in spatial behaviour compared to those socioeconomically advantaged. Additionally, they often encounter limitations in effectively using nearby services. This indicates that such individuals are more likely to face financial, cultural, and organizational barriers when trying to access services that are located close to them. In short, not all groups in the society have equal abilities to deal with an 'objective' absence of services near the places they live (Vallée et al., 2022).

In short, plenty of studies have examined the association between geographical mental healthcare accessibility and utilization of these services. However, the relation between healthcare accessibility and spatial-socio characteristics on a large (nationwide) scale is insufficiently researched.

3. Methods and Materials

3.1 Study Area

The study area is the country of the Netherlands, see Figure **3.1**. The Netherlands is the second most densely populated country in Europe with 17,933,41 inhabitants (CBS, 2023a). The population density is 507 persons per square kilometre. The country consists of 12 provinces. The most densely populated part of the country is the Randstad. This is a conglomerate of large and midsize cities in the western part of the Netherlands, see Figure **3.1**.

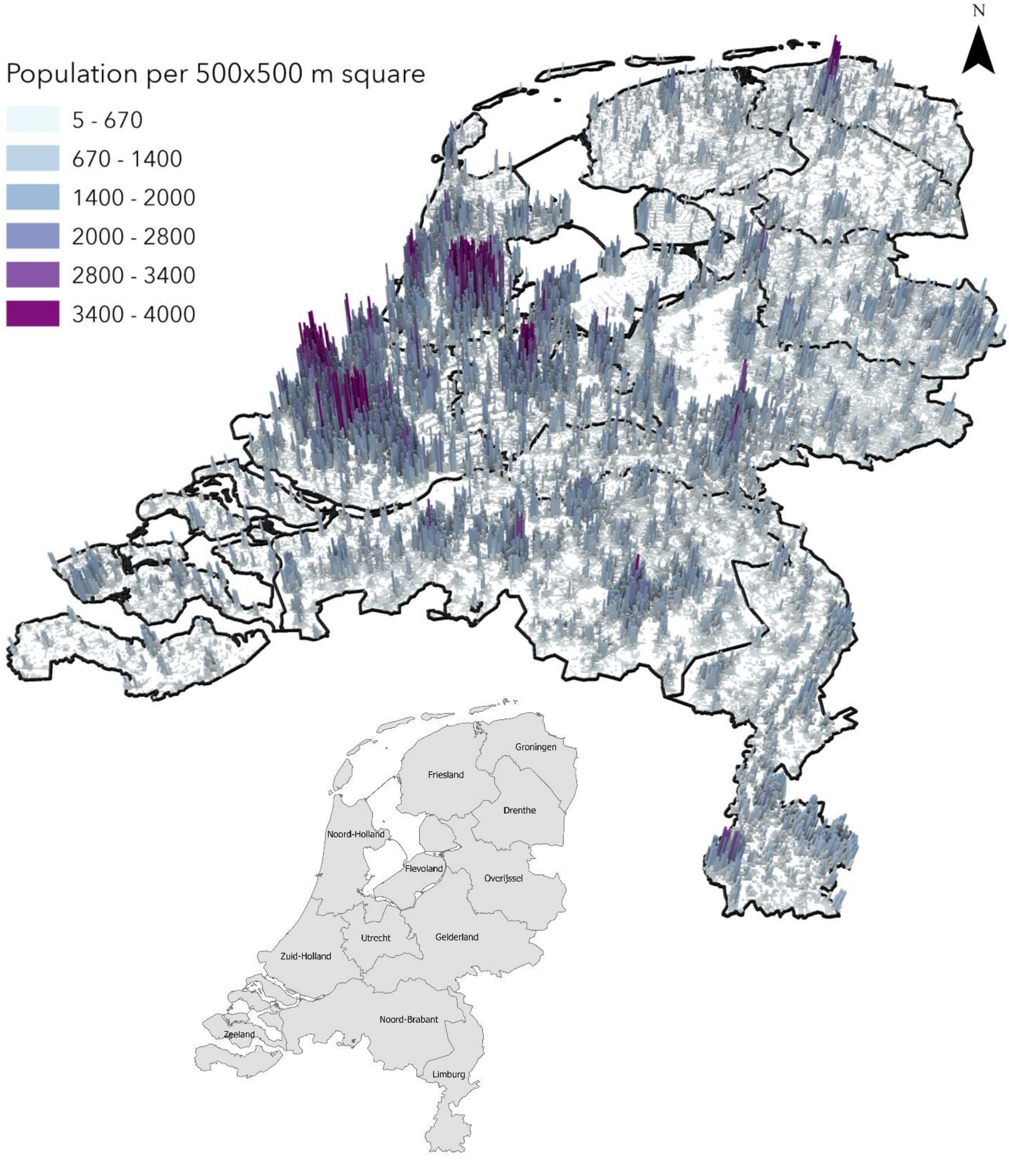

Figure 3.1 Map of population density in the study area (CBS, 2021) and a map showing the 12 provinces.

The Netherlands is a densely populated country with, compared internationally, short travel times to healthcare facilities (Weiss et al., 2020). To illustrate, Dutch people live an average of 1.0 kilometres from a general practitioner's office. In 2022, less than 0.10% of the population had a travel time longer than 10 minutes to the nearest GP office (Kommer et al., 2023).

For hospitals, the differences between the provinces are bigger. Dutch people live on average 5.3 kilometres from the nearest hospital. Residents from Friesland travel the longest, with an average of 9 kilometres. Residents from Zuid-Holland have the shortest travel distance, they live on average less than 4 kilometres from a hospital. Residents in the Randstad not only live close to a hospital but also have the most available options. One in ten Dutch people, however, lives in a neighbourhood located over 20 kilometres away from the closest hospital. These neighbourhoods are mainly in the northern part of the Netherlands, Flevoland, and Zeeland (CBS, 2009).

One of the goals of this research is to get more insight into the differences in the accessibility of mental healthcare facilities within the Netherlands. The Dutch context is interesting because of the GGZ initiative, which is, as explained earlier in the introduction, regulated on a national scale and embedded into the Dutch law. Furthermore, no research has been done on assessing the spatial accessibility of mental healthcare facilities in the Netherlands.

3.2 Data

To assess spatial accessibility with FCA methods, three datasets are needed: population data, service data, and network data (Hong et al., 2023). Table **3.1** shows an overview of the data that is used in this research.

Table 3.1 Overview of main data sources.

Description Dataset	Type of Dataset	Source
Mental healthcare (GGZ) facilities in the Netherlands 1	Website	https://www.zorgkaartnederland.nl/ggz
Mental healthcare (GGZ) facilities in the Netherlands 2	CSV	https://www.zorginzicht.nl/openbare-data/open-data-geestelijke-gezondheidszorg-kwaliteitsstatuut
CBS squares of the Netherlands 100x100m	Available as ESRI shapefile and GeoPackage	https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/kaart-van-100-meter-bij-100-meter-met-statistieken
Network Dataset of the Netherlands	ESRI OpenStreetMap Network	https://www.esri.nl/nl-nl/producten/data/premium-data/netwerkanalyse-met-openstreetmap

The data needs to be preprocessed and cleaned in order to be used within the MH3SFCA method. Figure **3.2** shows an overview of the data preprocessing. In the next section, the data sources and preprocessing will be explained in detail.

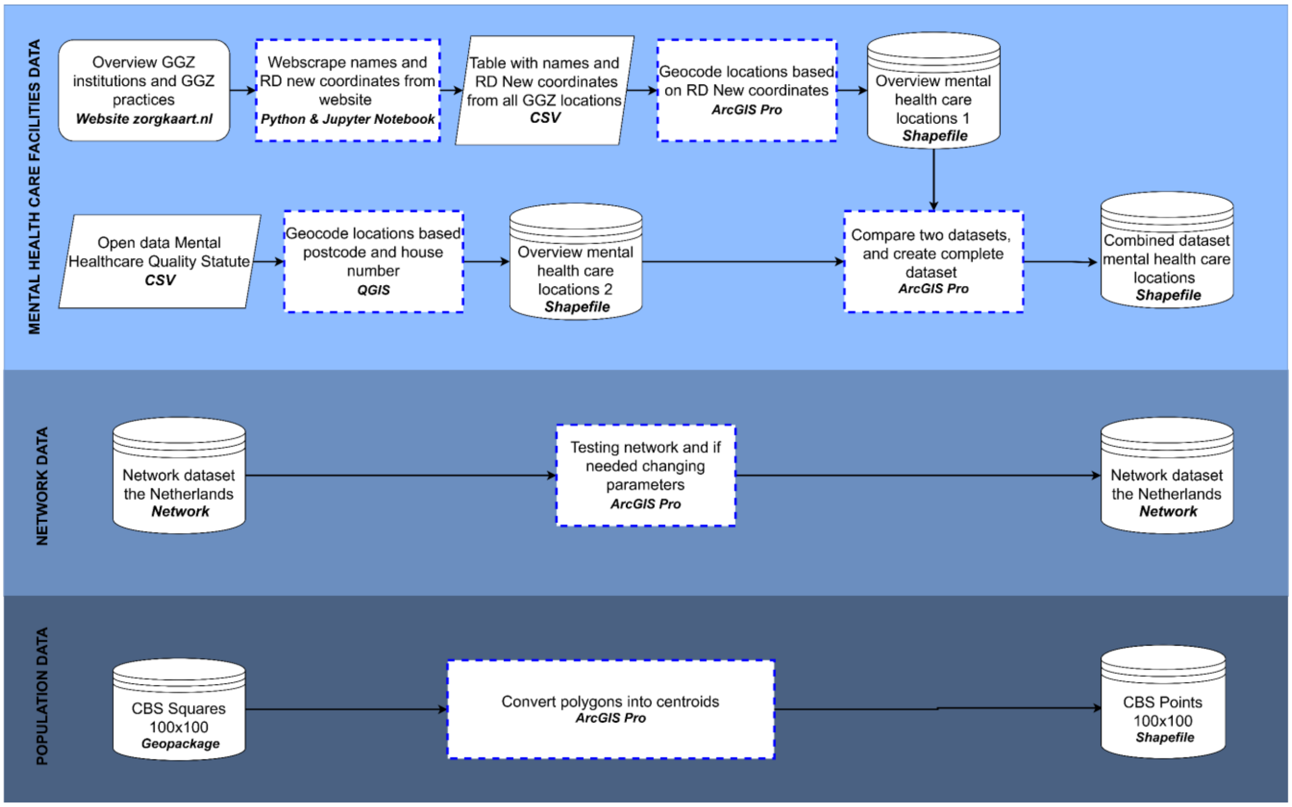

Figure 3.2 Overview of preprocessing steps.

3.2.1 Mental healthcare facilities data

In order to examine the geographic accessibility of mental healthcare facilities, it is necessary to know where they are located. As described in the introduction, the Dutch healthcare initiative is called the Geestelijke Gezondheidszorg (GGZ). As explained earlier, some (mostly preventative) treatments are given by the POH-GGZ in the GP office. However, most mental healthcare in the Netherlands is provided by professional carers who work in basic or specialised GGZ. For this reason, this is the focus of this research.

There are two different kinds of GGZ mental healthcare locations: institutions and independent practises. In an institution, multiple therapists collaborate. Often, various therapeutic approaches and specialists can be found in one institution. On the other hand, in an independent practice, usually, one or a few therapists work (Nederlandse Vereniging voor Psychotherapie, n.d.)

Unfortunately, no geographical database is available/accessible for these institutions. For this reason, two different data sources were consulted. First, the website www.zorgkaartnederland.nl was used. This website is an initiative of the Dutch Patient Federation. Zorgkaart Nederland is independent and operates without a profit motive. This website lists all BIG (Beroepen in Individuele Gezondheidszorg, translation: Professions in Individual Healthcare) registered healthcare professionals in the Netherlands. If a profession has a protected title, the healthcare provider is obligated to register in the BIG register before being able to practice their profession.

The second dataset used is from the National Quality Status GGZ (Zorginstituut Nederland, n.d.). Since January 1, 2017, all providers of curative mental healthcare (GGZ) under the Health Insurance Act (Zvw) are required to have a quality status. This applies to both institutions (section III) and independent practises (section II).

The Dutch Healthcare Institute publishes a monthly public database. This is called the Openbaar databestand GGZ Kwaliteitsstatuut (ODB), which can be translated as the Public Data File Mental Healthcare Quality Statute. This dataset contains all healthcare providers with an approved quality status and consent declaration. If a GGZ healthcare provider is not listed in the ODB, it may imply that their claims are not approved by health insurers. Therefore, all providers of curative GGZ must be visible in the ODB. The Dutch Healthcare Institute assumes that the ODB includes a large portion of GGZ healthcare providers (Zorginstituut Nederland, 2023).

By combining these two datasets, a largely complete view of GGZ locations was created. However, it is still possible that some mental healthcare providers are missing. Consequently, this study will overestimate the distance to the nearest mental healthcare facility.

Both datasets were preprocessed differently. See Figure **3.2** for a complete overview of the data preprocessing. First, the information from the Zorgkaart Nederland website was web scraped from the website. With the help of web scraping in Python, the addresses of these mental healthcare locations were obtained. This Jupyter Notebook (*JupyterNotebook_Webscraping.*) is added as an extra file next to the thesis. Furthermore, the code can be found in Appendix **8.1**. The web scraping consists of the following steps (Hiremath, 2023).

First, the page was inspected, as the data is nested in tags. The HTML code of the website was explored. Within the Zorgkaart Nederland website, the name of the mental healthcare institution and the address are stored in tags. The address is also stored in a tag as an RD new coordinate (projected coordinate system for the Netherlands). Next, a Python file was created, and the necessary libraries were downloaded ('*requests'* and '*BeautifulSoup'*). The data that needed to be extracted from the website is nested in <div> tags. The div tags with those respective class names were integrated within the Python code. The data was extracted and stored in a variable. On the website, the mental healthcare facilities are displayed on different pages. A loop was used to web scrape all the pages. Finally, the data was stored in a CSV format.

Next, through geocoding, these coordinates were converted into geographic coordinates and mapped. The ArcGIS Pro Tool '*Coordinate conversion*' is used for this task (ESRI, n.d.-a). 2059 of the 2073 GGZ institutions on this website could be mapped. The coordinates that could not be mapped had all the value of '0.0000000;0.0000000'.

Secondly, the Mental Healthcare Quality Statute dataset is preprocessed. This database already comes in CSV format. After cleaning the database, with the help of QGIS the addresses (based on postal codes and house numbers) were geocoded. The '*PDOK Location Server*' is used for this. The PDOK Location Server is an open and free geocoding service that allows searching for data from various government registrations (PDOK, n.d.). 5569 of the 5616 locations could be mapped.

After geocoding both datasets, they needed to be compared and combined, and the duplicate mental healthcare facilities had to be removed. This is done with the intersect tool in ArcGIS Pro and the duplicate facilities were removed. Furthermore, different mental healthcare facilities had the same location. For example, two psychiatrists have their practises in the same building. For this reason, the attribute 'capacity' was added. This attribute gives a value of the capacity of the mental healthcare locations. In general, there is one mental healthcare professional working in an independent GGZ practice. In these cases, this number is included in the capacity attribute. For independent practises where this information is unknown, the capacity value was set to 1.

As a general rule, in a GGZ institution, works more than one mental healthcare professional. For this reason, when no information was available on the capacity of these institutions, these institutions were given an estimated capacity value of 10. In total, the final dataset with GGZ locations consists of 5389 mental healthcare locations with varying capacities between 1 and 60. Figure **3.3** below shows an overview of the mental healthcare locations in the Netherlands. A division is made between the GGZ independent practises and GGZ institutions.

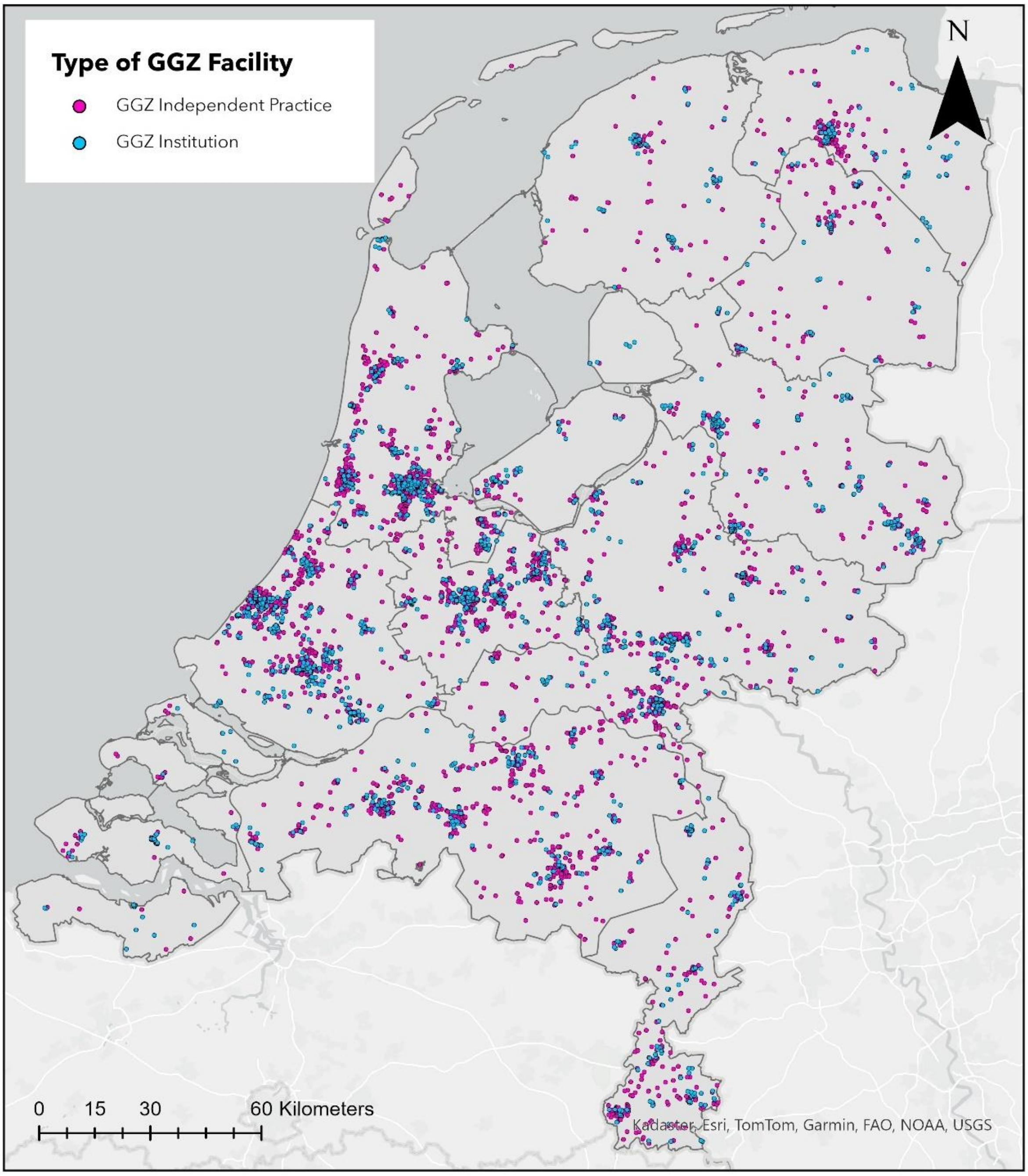

Figure 3.3 Overview of mental healthcare facilities within the Netherlands (Zorgkaart Nederland, 2023; Zorginzicht, 2023).

3.2.2 Network data

For the network data, the ESRI Premium Open Street Map (OSM) network of the Netherlands was used (ESRI, n.d.-b). As the name suggests, this network is based on OSM data, which is a free open geographic database updated and maintained by volunteers. The Dutch cadastre researched the quality of OSM as a data source and compared it to their base registration: the Basisregistratie Topografie (BRT). They conclude that despite the fact you always have quality issues with crowd-sourced data, the dataset contains a way more diverse set of objects at a higher granularity level compared to the BRT. Also, the data in OSM is more up-to-date compared to the BRT data (Beek et al., 2022). The data in the ESRI Premium OSM network is updated two times a year (ESRI Nederland Content, 2023).

OSM uses ‘tags’ to add attribute values to geographic objects. A tag consists of two items: a key and a value. The key is used to describe a subject or category, for example, highway or the name of an object. The value provides details about the key. The dataset contains of three feature classes: streets (including roads and walking and cycling paths), ferries, and nodes (ESRI Nederland Content, 2023). Also, different modes of transport are defined within this network, among which are car travel time, bike travel time, and walking travel time. This network does not account for traffic.

A big advantage of this network is that it can be directly used for all kinds of network analysis within ArcGIS Pro. Another benefit is the fact that this network is updated frequently (two times a year) (ESRI Nederland Content, 2023). In addition, using a local network has a lower computation time than using an online network. This is an important factor for this research as there is a large number of input destinations and origins. Finally, by using a local network (unlike using an online network), no limits to the number of origins and destinations are set. When using the online network, there is a limit of 1000 origins and 1000 destinations per run (ESRI, n.d.-c).

The network was used to calculate the service area for each mental healthcare facility, based on a pre-determined maximum radius. Furthermore, with the use of the network and the Dijkstra shortest path algorithm, the driving time between population locations and mental health facilities was calculated. This information was stored in an Origin-Destination (OD) matrix, which is needed to calculate the MH3SFCA. It is important to note that travel time instead of travel distance was used. Wang (2006) explored that if travel speeds vary and roads are unevenly distributed, travel distance is not a good measure of travel impedance and travel time should be used. Figure **3.4** shows an example of a part of the study area (part of Zeeland, the Netherlands) in which the network dataset is used to determine the service area of the mental healthcare facilities in this region.

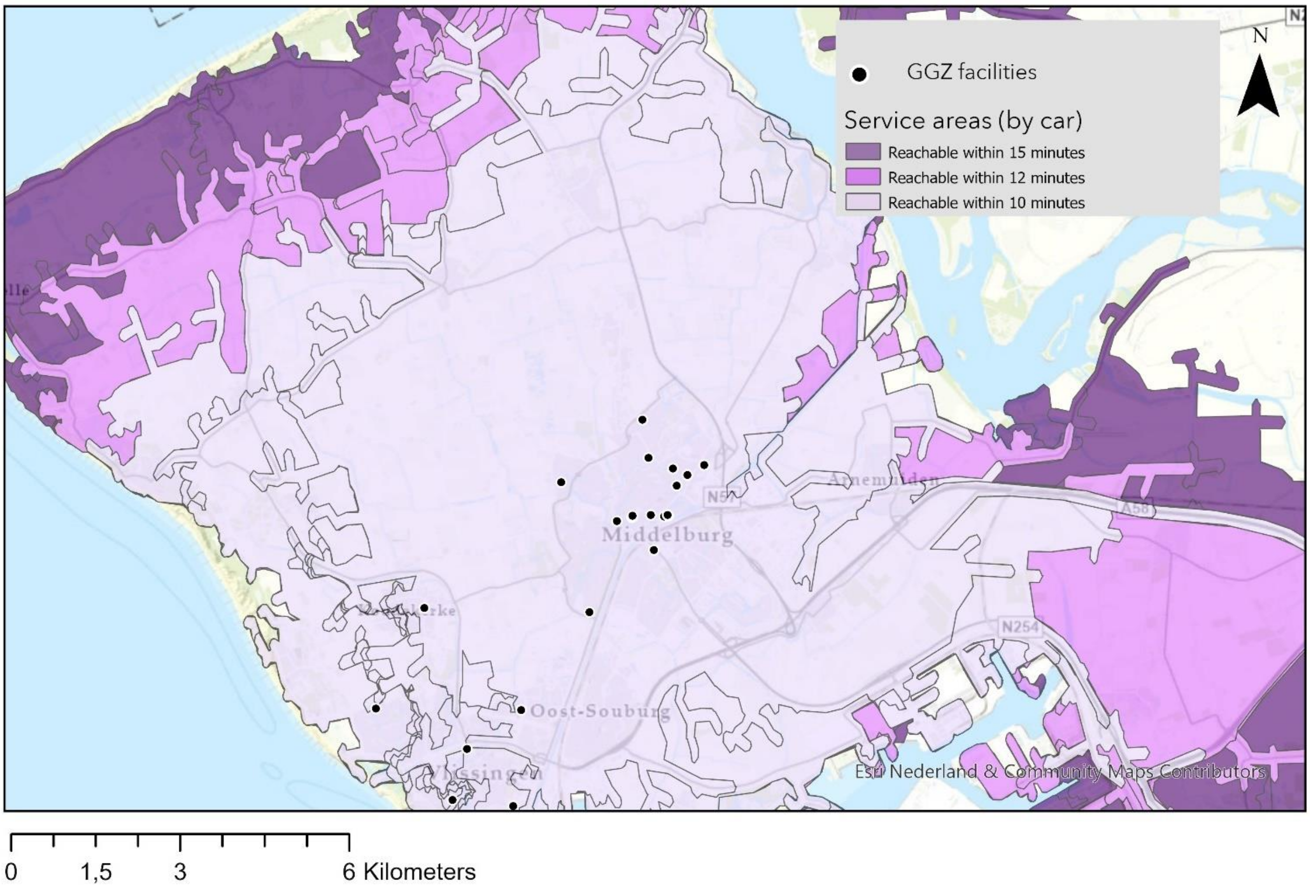

Figure 3.4 Example of service area calculation with the network (ESRI Nederland Content, 2023).

3.2.3 Population data

Detailed population data is needed to review the availability and accessibility of mental healthcare facilities. The Central Agency of Statistics (CBS) is the main statistics office in the Netherlands. Every year, CBS publishes the CBS squares population data. The CBS squares is a shapefile, that consists of squares of the Netherlands, the dataset is available for 100x100 meter squares and 500x500 meters. Other detailed population data is available in the CBS postal code 5 and postal code 6 datasets.

The CBS postal code 5 and CBS postal code 6 are not grid systems but are based on unique postal code areas in the Netherlands. However, those datasets are less suitable for this research. This is because the CBS postal code 5 consists of areas that are too large for a correct examination of accessibility. On the other hand, the number of polygons in the CBS postal code 6 is too large (almost 500,000) given the computational limits of the hardware and software. Furthermore, a lot of the postal code areas are multipart polygons. These are objects made up of multiple physical parts but referred to as a single unit (ESRI, n.d.-d). To calculate the distance from population locations to mental healthcare facilities, the centroid of the population location needs to be used, which can give a confusing and distorted view for multipart polygons. For these reasons, the CBS squares 100x100 meters dataset was used in this research.

Due to the size of the file to be published for the Netherlands, only those squares in which there are at least 5 residents or 5 houses located will be published (Van Leeuwen & Venema, 2023). This implies that for some areas, no squares are available. Attribute information is given about the total number of inhabitants, age, gender, country of origin, household size and type, housing characteristics, social security, energy consumption, and distance to facilities. These socioeconomic and demographic characteristics were used in the second part of this research, the statistical analysis.

The CBS squares dataset 100x100m consists of 383,061 polygons. Due to the size of this research project and computation costs, all cells with a population value of ‘null’ and all cells with a value lower than 10 people were removed. This means that 323,744 population cells remain, resulting in N = 323,744 for the spatial accessibility analysis of mental healthcare facilities.

For this research, the CBS squares dataset from 2021 was used. The dataset is also available for 2022 and 2023, however, the attribute information from these two datasets is less complete. For example, the 2021 dataset has fewer null values. In addition, the 2021 dataset also shows distance variables for each population location (distance to nearest hospital, distance to nearest GP, distance to nearest school etc.) (Van Leeuwen & Venema, 2023).

This dataset was downloaded from the CBS website as GeoPackage. After downloading the data, with the help of ArcGIS Pro, the centroid of these 100x100m polygons was calculated. This is done with the tool ‘*Feature to Point’*. Determining the centroids is necessary to calculate the Origin-Destination matrix. Figure **3.5** shows a zoomed-in view of the CBS 100x100m dataset (converted into points) displaying the City of Utrecht. The population hectares where more than 5 residents or 5 houses are located are shown.

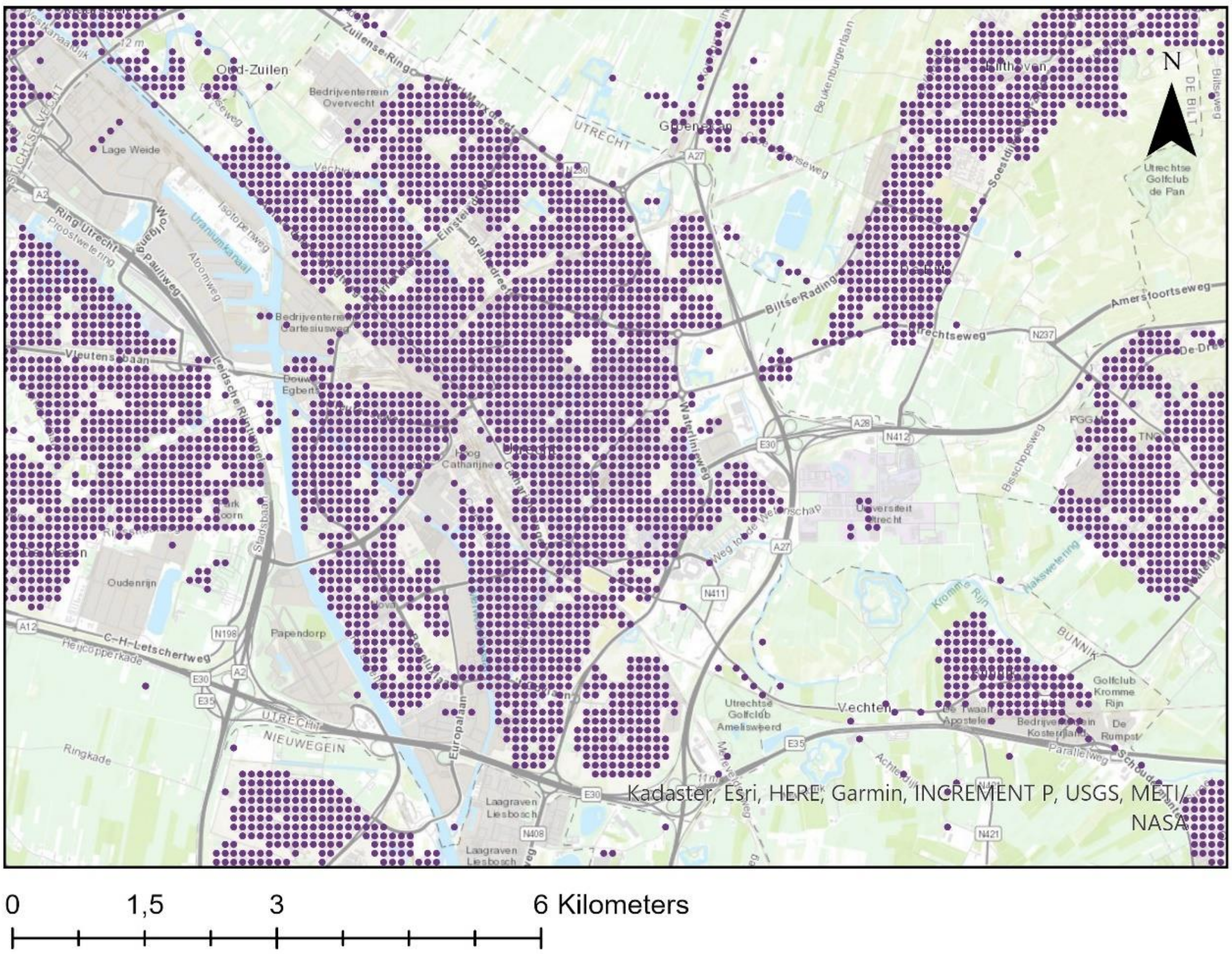

Figure 3.5 CBS population data 100x100 meter cells (CBS, 2021).

3.3 Software

Different software packages were used to execute this research. Python (version 2023.22.1) and Jupyter Notebook (version 2023.11.1100101639) were used for the web scraping of the mental healthcare locations. Furthermore, ArcGIS Pro (version 3.2.1) and QGIS (version 3.22.12) were used for the geocoding of the addresses and the coordinates.

With the help of the network analyst, a network dataset, a population dataset, and a mental healthcare facilities dataset, an OD-matrix was calculated. The MH3SFCA method can be executed fully within ArcGIS Pro (Zeng, 2023). Nevertheless, given the very large size of the OD-matrix in this research, this was not possible as ArcGIS Pro is not appropriately designed to work well with attribute tables with over 20 million rows. As a consequence, the MH3SFCA (see steps below) is implemented within a Jupyter Notebook. Next to the way faster computation times, this increases the reproducibility of this research. ArcGIS Pro was used for the geographic visualisation of the results. Finally, R software (version 4.3.1) was used for the statistical part of the research. The packages '*spdep*' and '*spatialreg*' were used for the model fitting (Bivand, 2022).

3.4 Methods

The method consists of roughly two steps: a Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) analysis and a regression analysis. Figure **3.6** shows an overview of the method.

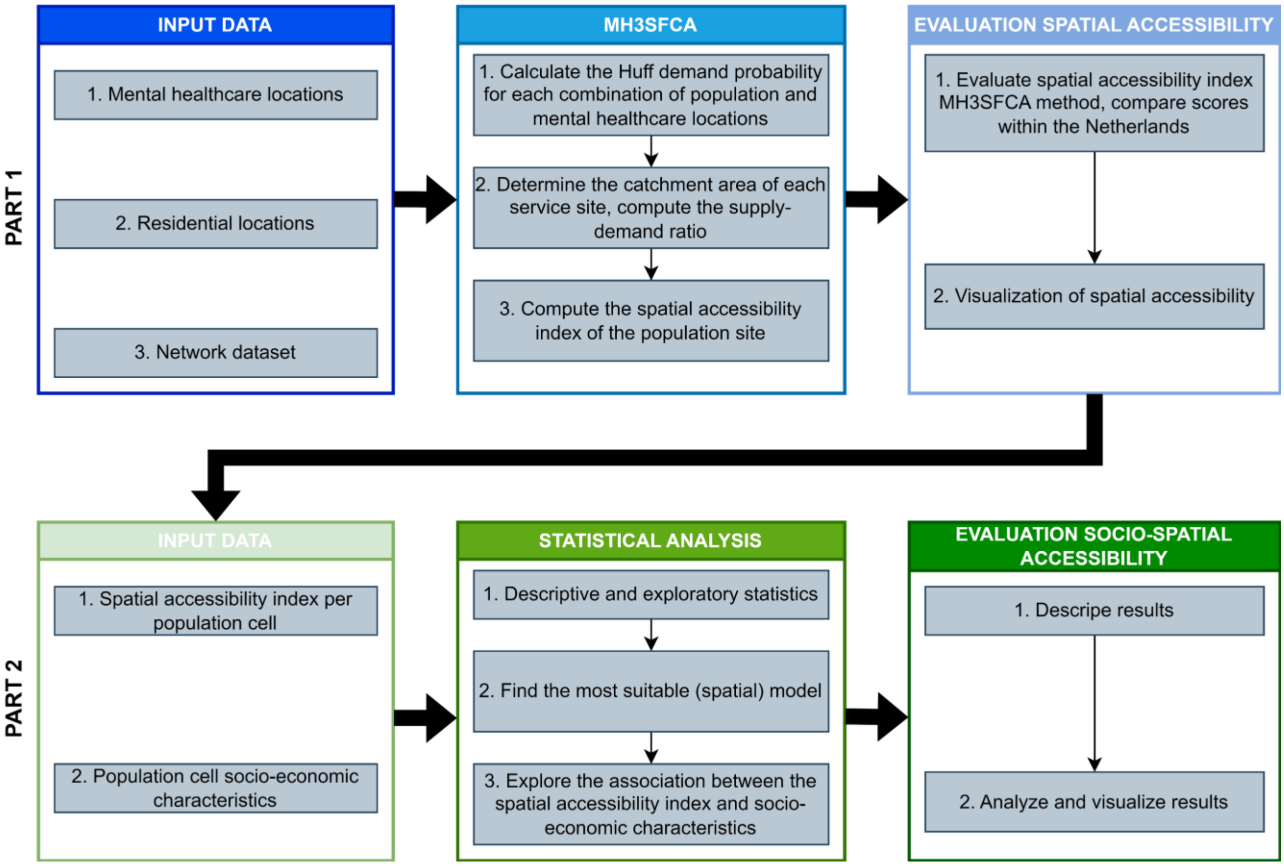

Figure 3.6 Simplified view of the methodology in this research.

3.4.1 MH3SFCA

The Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) method used in this study is based on the work of Subal et al. (2019). This method is a variation of the 2-Step Floating Catchment Area Method (2SFCA) by Luo and Wang (2003). The MH3SFCA is suitable for this study given that this model is appropriate to use for large study areas, as it is also used by Jörg et al. (2019) for the entire Switzerland. Furthermore, it considers the influence of distances both relatively and absolutely (Subal et al., 2021). As the name suggests, this method consists of three main steps which will be explained below after the explanation of the OD-matrix, and the catchment area and transportation mode.

Origin-Destination matrix

Before performing the MH3SFCA method, an OD-matrix was calculated. This is done with the help of the three datasets (population locations, mental healthcare locations and network) as described in section 3.2. This OD-matrix forms the foundation for the other steps of the MH3SFCA.

Some population and mental healthcare locations may not be located on a line element of the network dataset. For this reason, the search tolerance was set at 20 meters. The search tolerance is the maximum search distance from a population or mental healthcare location used when pinpointing the features on the network (ESRI, n.d.-e).

For each supply location, catchment areas were calculated based on the defined radius. For all combinations of supply and population locations where the population is reachable within a certain travel time radius, the corresponding travel times were stored in a table, the OD-matrix. This output OD-matrix served as the basis for further calculations (Jörg et al., 2019).

Catchment area and transportation mode

When creating the OD-matrix an important parameter is the maximum radius/maximum catchment area (d_{max}). Various studies implement different thresholds for the maximum radius. For example, Subal et al. (2021) and Luo and Wang (2003) implement a 30-minute timeframe for primary healthcare services. Jörg et al. (2019) use a maximum radius of 20-minutes driving distance to GPs. Looking at studies focused on the accessibility of mental healthcare facilities, Wang and Ariwi (2021) use a maximum driving radius of 10 minutes. Ngui and Vanasse (2021) use driving distance instead of driving time and chose for a maximum distance of 3 kilometres.

In this study, the maximum catchment area was set at a 12-minute timeframe. This is based on similar studies on the accessibility of mental health facilities and Dutch policy and government documents that define what an acceptable travel time to healthcare facilities should be. For example, the maximum distance to the GP in the Netherlands should be under 15 minutes (Landelijke Huisartsenvereniging, 2021).

Using a maximum catchment radius of 15 minutes was also examined for this research. However, using a 15-minute catchment radius demanded high computational requirements. This is because for all population hectares in the Netherlands, the distance to all mental healthcare locations within a 15-minute travel time needed to be calculated. This led to an OD-matrix with over 40 million rows, which exceeded what the utilised GIS software packages could handle effectively.

Finally, due to the small-scale structure and well-developed transportation network in the Netherlands, choosing a maximum radius of 12 minutes for the analysis of mental healthcare is deemed appropriate. Furthermore, this 12-minute maximum catchment area is the driving time by car, which implies that frequently the travel time walking, cycling, or taking public transport would be longer.

Another important choice when building the OD-matrix is the mode of transport. In this research, this is driving time by car. Looking at all movements in the Netherlands, the car is still the dominant mode of travel (CBS, 2021). In addition, an examination is done to see if the travel times by car are correlated with the travel times by bike. Appendix **8.2** shows the details of these tests. For all three researched areas, a positive linear correlation between car and bike travel times was found. Significant, positive, and high correlation coefficients were found for all three areas. For the Amsterdam area, a significant positive correlation was found ($r = 0.744$, $p < 0.01$). For the Hilversum-Enkhuizen area and the Drenthe West area, even stronger correlations ($r = 0.920$, $p < 0.01$) and ($r = 0.953$, $p < 0.01$) were found. This implies that the final accessibility scores resulting from this thesis can also be applied to biking as a mode of transport, especially in moderately to sparsely populated areas.

Step 1

In the first step, the demand probability $Huff_{ij}$ for each combination of population (i) and mental healthcare locations (j) is calculated with the help of the Huff model. The following formula is used (Subal et al., 2021):

$$Huff_{ij} = \frac{S_j\, W_{ij}}{\sum_{k\epsilon\{d_{ij}<d_{max}\}} S_k W_{ik}}$$

S_j refers to the capacity of mental healthcare location j. d_{max} is the maximum travel time by car. k are all mental healthcare locations within the catchment of i ($d_{ik} \leq d_{max}$). W_{ij} and W_{ik} are the Gaussian distance weights for the distance between i-j and between i-k.

The distance decay coefficient W_{ij} based on the Gaussian function was calculated with the following equation (Zeng et al., 2024, under review):

$$W(d_{ij},\, d_{max}) = \begin{cases} \dfrac{e^{-0.5\times(d_{ij}/d_{max})^2} - e^{-0.5}}{1 - e^{-0.5}}, & d_{ij} \leq d_{max}\,, \\ 0, & d_{ij} > d_{max} \end{cases}$$

d_{ij} is the travel time from population location i to mental healthcare location j, d_{max} is the maximum travel time.

Step 2

In the second step, the Huff demand probability from step 1 is used. In this step, the supply-demand ratio (R_j) is calculated.

$$R_j = \frac{S_j}{\sum_{i\epsilon\{d_{ij}<d_{max}\}} Huff_{ij} P_i}$$

$Huff_{ij}$ is the interaction probability according to the Huff model (describes the probability that population i selects service j) calculated in the first step. S_j refers to the capacity of mental healthcare location j. P_i is the number of people in the cellular population grid i.

Step 3

For the final step, the Spatial Accessibility Index ($SPAI_i$) for each population location i is calculated by summing the service-demand ratios (R_j) of all accessible services for i, weighted by distance (W_{ij}) and demand probability ($Huff_{ij}$).

$$SPAI_i = \sum_{j\in\{d_{ij} \leq dmax\}} Huff_{ij}\ \ R_j\ \ W_{ij}$$

Finally, the Spatial Accessibility Indices were visualised and mapped for all of the Netherlands to get an overview.

3.4.2 Implementation of the MH3SFCA method

Because of the large size of the study area of this research, the MH3SFCA was implemented in a Jupyter Notebook, which can be found in a separate file called *JupyterNotebook_MH3SFCA*. Also, this code is added to Appendix **8.3**.

The input for this script is an OD-matrix in CSV format. This matrix consists of all possible connections between the population locations and destination locations, given a defined maximum catchment area. Furthermore, the OD-matrix should contain information on the capacity of the destination location as well as the population count at the origin location.

The notebook was built using the same Three-Step structure as the MH3SFCA method. It was built in such a way that you can check the output of each step and go back to a previous step as needed. The output of the script is a CSV file with for each population location a unique Spatial Accessibility Index ($SPAI_i$).

3.4.3 Statistical analysis

The goal of the regression analysis is to explore the association between the socioeconomic and demographic decomposition of the cell and the spatial accessibility of mental healthcare facilities in the Netherlands. The dependent variable of this study is the SPAI (Spatial Accessibility Index) calculated with the MH3SFCA method.

Descriptive and exploratory analysis

First, the data is summarised and the number of final observations in the statistical analysis is explained. The most commonly used test to see if the SPAI levels are autocorrelated is called the Moran's *I* test. Positive spatial autocorrelation emerges when units that are close to each other are more similar than units that are far apart (Arbia, 2014). As opposed to negative spatial autocorrelation, where dissimilar values are spatially close by. Moran's *I* inspects for global spatial autocorrelation and generally has a value between -1 (negative spatial autocorrelation) and 1 (positive spatial autocorrelation). The Moran's *I* score based on a k-nearest neighbour matrix was used to evaluate the patterns of the dependent variable SPAI. The statistical significance was tested with 999 Monte Carlo simulations. In the Monte Carlo method, random patterns are created by reassigning the observed values among the areas. Moran's *I* is calculated for each of the patterns, which provides a randomization distribution of the Moran's *I.* The assumption of independence among the observations can be rejected when the value of Moran's *I* falls within the tails of the distribution (Moraga, 2023). In addition, by using Spearman's correlation coefficients, the bivariate correlations between the variables were calculated.

Regression analysis

As a starting point, ordinary least squares (OLS) regression was used in this research (Lee, 2022). Multiple linear regression (MLR) is an extension of the OLS. The MLR calculation considers multiple independent variables that are possibly associated with the dependent variable. MLR was used to assess the association between the SPAI scores and the socioeconomic composition of the population cell. The independent variables should not correlate too much with each other (Chen, 2016). This assumption was tested by the means of calculating the Variance Inflation Factors (VIF) for each dependent variable (Craney & Surles, 2002).

Because of the explicit spatial character of the data, it is important to realise that this spatial data has unique properties (Fotheringham et al., 2000). For instance, spatial autocorrelation can be observed within the data. The residuals of the regression should be without spatial autocorrelation. Spatial autocorrelation can be a problem because it violates the assumption that the residuals in the regression are independent. As a result, the standard error or parameters can be biased (Hawkins, 2011).

Given the OLS regression's assumption of residual independence, Moran's *I* with the k-nearest neighbours weight matrix was used to examine potential spatial dependency in the residuals. K-nearest neighbours was used to prevent isolated observations lacking any neighbours (Anselin, 2005). The statistical significance was again tested with 999 Monte Carlo simulations. The Moran's *I* score was significant, which violated the assumption of no spatial residual autocorrelation.

For this reason, the Lagrange Multiplier test statistics were consulted (Anselin, 2005). The LM test statistics were used because this test provides guidance on which alternative spatial model – spatial lag model or spatial error model – is suitable. The diagnostic output includes four Lagrange Multiplier test statistics. The LM-Lag and Robust LM-Lag are associated with the spatial lag model as the alternative. The LM-Error and Robust LM-Error test statistic may suggest the spatial error model as suitable model. The spatial regression model selection decision rule as displayed in Anselin (2005) was followed here.

During the analysis, different variations of the k-nearest neighbour matrix (k = 4 up to and including k = 10) were tested to determine the best model fit. To assess the model's goodness of fit, the Akaike

Information Criterion (AIC) of different model specifications was compared. When the AIC is lower, this indicates a better fit (Hayward & Helbich, 2024).

Independent variables

Several characteristics can be considered indicators of socioeconomic position, such as housing tenure, unemployment benefits, and occupation-based measures (Galobardes et al., 2006). Based on the literature and availability in the CBS dataset, seven different independent variables were considered in this research, see Table **3.2**.

First, having a non-Western migration background can be seen as an important socioeconomic factor in the Netherlands (Centraal Planbureau, 2019). Additionally, the percentage of people owning a house/houses was also considered. Next, the percentage of houses owned by housing associations was also included. These are primarily social housing homes, for which a specific income limit is set (Rijksoverheid, n.d.). The fourth independent variable is the WOZ (property valuation) value of the houses. Next, the number of people receiving unemployment benefits is also an important socioeconomic indicator (Van Echtelt et al., 2023). Finally, demographic factors were considered by adding two vulnerable age groups: people under the age of 15 and people over the age of 65. These age groups might experience more difficulties in visiting mental healthcare facilities and might be disproportionately affected by the lack of access (Kang et al., 2023).

The variables that were used are available in the CBS (Statistics Netherlands) 2021 squares dataset for each hectare. The variables migrants from a non-Western background and owner-occupied houses were already given as percentages in the CBS dataset. The variables houses owned by housing associations, people receiving unemployment benefits, population aged under 15 and population aged over 65 were converted to percentages to make the values better comparable (Van Leeuwen & Venema, 2023).

Table 3.2 Overview of variables used (CBS, 2022b).

Variable	Measurement type	Description
Non-Western migration background	% of total people	The percentage of residents of whom at least one parent is born abroad in Africa, Latin America, or Asia (excluding the countries of Indonesia and Japan) or in Turkey.
Owner-occupied properties	% of total houses	Houses owned by the (future) occupant(s) or used as a second residence.
Houses owned by housing association	% of total houses	Rental properties owned by accredited housing corporations. This refers to the number of rental homes for which it has been determined that the owner is an accredited housing corporation.
WOZ value houses	Value in € x1000	The calculated WOZ (Value of Immovable Property Act) value is the average of the number of properties with at least one residential function in the BAG (Basisregistraties Adressen en Gebouwen) and an assigned WOZ value greater than zero.
Unemployment benefits (WW)	% of total people	Residents receiving unemployment benefits, social assistance or related benefits, as well as disability benefits. These concern benefits provided to residents up to the retirement age (AOW-leeftijd).
Population aged under 15	% of total people	The number of residents younger than 15 years old on January 1st.
Population aged 65+	% of total people	The number of residents aged 65 or older on January 1st.

4. Results

4.1 Results MH3SFCA

4.1.1 Service area

First, to get some insight into the accessibility of mental healthcare services in the Netherlands with a maximum catchment area of 12 minutes of driving time by car, we can look at the service area. As stated in section 3.3.3, after preprocessing, the number of population squares in the CBS dataset is 323,744. For the MH3SFCA method, a maximum driving time of 12 minutes was used. It is interesting to compare this with a slightly larger (15 minutes) and a slightly smaller (10 minutes) service area, to see what the differences in accessibility are and to get more information about the accessibility of mental healthcare facilities in the Netherlands. Due to the high density of mental healthcare facilities in the Netherlands (and services in general), a high percentage of population cells can be reached within only 10 minutes of travel time by car towards mental healthcare facilities. Table **4.1** shows an overview of the number of population cells that can be reached from mental healthcare facilities given different driving times by car.

Table 4.1 Service area results of mental healthcare facilities.

Maximum travel range	Number of population cells outside travel range	Number of population cells within travel range but not connected to the network	Total number of cells
Driving time 15 minutes	260 (0.08%)	1510 (0.46%)	323,744
Driving time 12 minutes	901 (0.28%)	1207 (0.37%)	323,744
Driving time 10 minutes	2750 (0.85%)	1207 (0.37%)	323,744

Table **4.1** shows that there are two reasons why some population cells have no access to mental healthcare services. First, no service may be accessible within 15, 12 or 10 minutes driving time from the population location (see second column in Table **4.1**). In these cases, it would be appropriate to give these hectares the spatial accessibility value of zero (SPAI = 0) (Jörg et al., 2019). The 901 cells which are located outside the travel range were given a SPAI of 0. Figure **4.1** shows an overview of the locations of these population cells outside the different travel ranges. These cells are mostly located on the Wadden Islands, Midden-Zeeland, Friesland, along the Belgium border in Noord-Brabant, and a small cluster of cells in Drenthe.

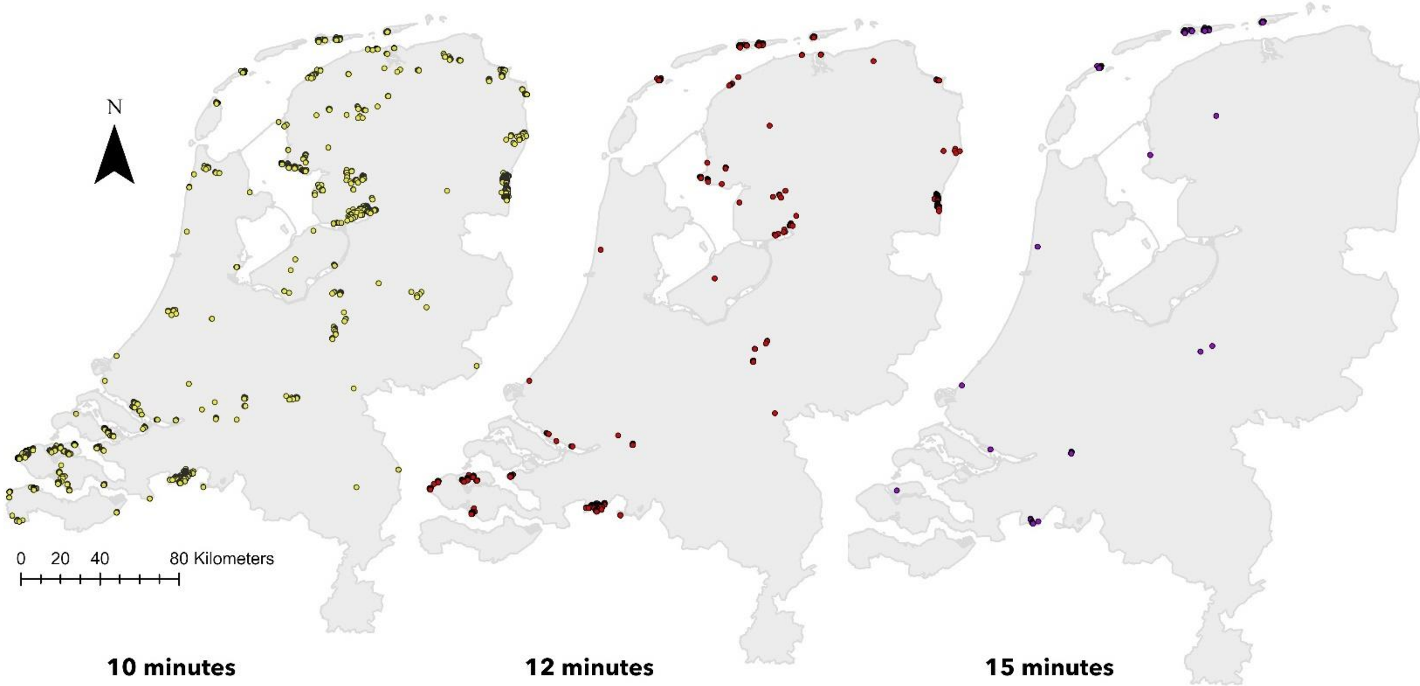

Figure 4.1 Population hectares outside 10, 12 and 15 minutes driving time of mental healthcare locations.

Second, it is possible that, during the accessibility analysis based on the underlying road network, erroneously no connection between population and service was identified (see the third column in Table **4.1**). To overcome this problem, for the population locations an offset distance of 20 meters around the population location was already used. This implies that if the population point was not coincident with the network feature, within a distance of 20 meters a network edge was searched (ESRI, n.d.-e). However, even with this parameter, some population points (within areas with nearby mental healthcare services) had no access to a service. This could occur because the hectares were located using their centroids and these centroids can be located within a body of water or too far from a road. In addition, this can also be caused by errors in the network dataset. It would be appropriate to view these values as missing data, as they are very likely accessible within the chosen range. The 12-minute driving time scenario was executed in this research.

4.1.2 SPAI scores

The first step of the MH3SFCA analysis – creating an Origin-Destination (OD) matrix, resulted in 23,828,962 OD-pairs. Based on this matrix, the capacity of each mental healthcare location, and the population of each hectare, a SPAI (Spatial Accessibility Index) score was calculated. In order to approve the readability, the scores were multiplied by 1000. The boxplot in Figure **4.2** shows the distribution of the scores. Only six population cells had a SPAI over 60 (while all other SPAI scores were below 6.5). Further examination revealed that these population locations were located very close (under 5 meters) to a mental healthcare facility. It might be the case that some errors occurred while calculating the OD-matrix for these population cells. For this reason, those six scores were removed.

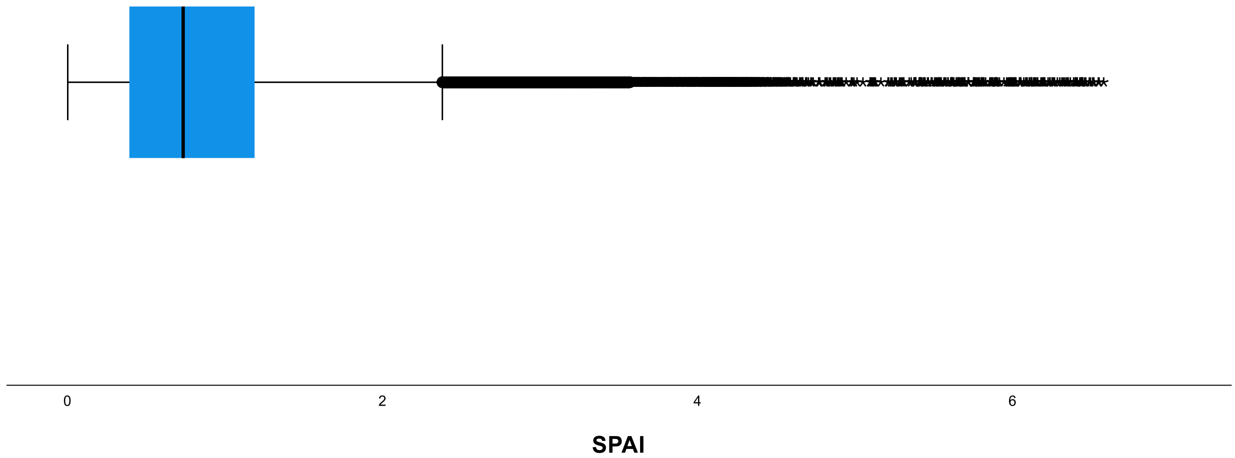

Figure 4.2 Distribution of the SPAI scores.

The mean SPAI score is 0.863. There are 1213 missing values, which are those population locations for which no routes to mental health locations could be found plus the removed scores (see above and section 4.1.1). There are also population locations with a SPAI value of 0. These are locations where there are no mental health facilities within a 12-minute drive.

Next, a spatial representation of the data is made. Following the studies of Subal et al. (2021) and Jörg et al. (2019), quantiles were used as the classification method. This method was selected because it allows for comparison of the tendencies of the index values (Subal et al., 2019). Different possibilities (points, polygons) were tested to visualise the results for the entire Netherlands. Using the centroid points of the polygons seemed to be the most useful way to visualise the results.

Figure **4.3** shows the spatial accessibility of mental healthcare locations in the Netherlands. As a reminder, a higher SPAI indicates higher accessibility. In general, the SPAI scores are distributed in a polycentric pattern. Furthermore, the differences between rural and urban areas are visible. In most urban areas, higher accessibility indices were found compared to rural areas. This can be caused by the fact that people in rural areas have longer travel times to mental healthcare locations, or that the capacities of mental healthcare locations are higher in urban areas compared to rural ones. The lowest accessibility scores were found around the Dutch-German border in Drenthe, the rural parts of the Randstad (het ‘Groene Hart’), large parts of Noord-Brabant, and some parts of the provinces of Friesland and Noord-Holland. The highest accessibility scores were found in the cities.

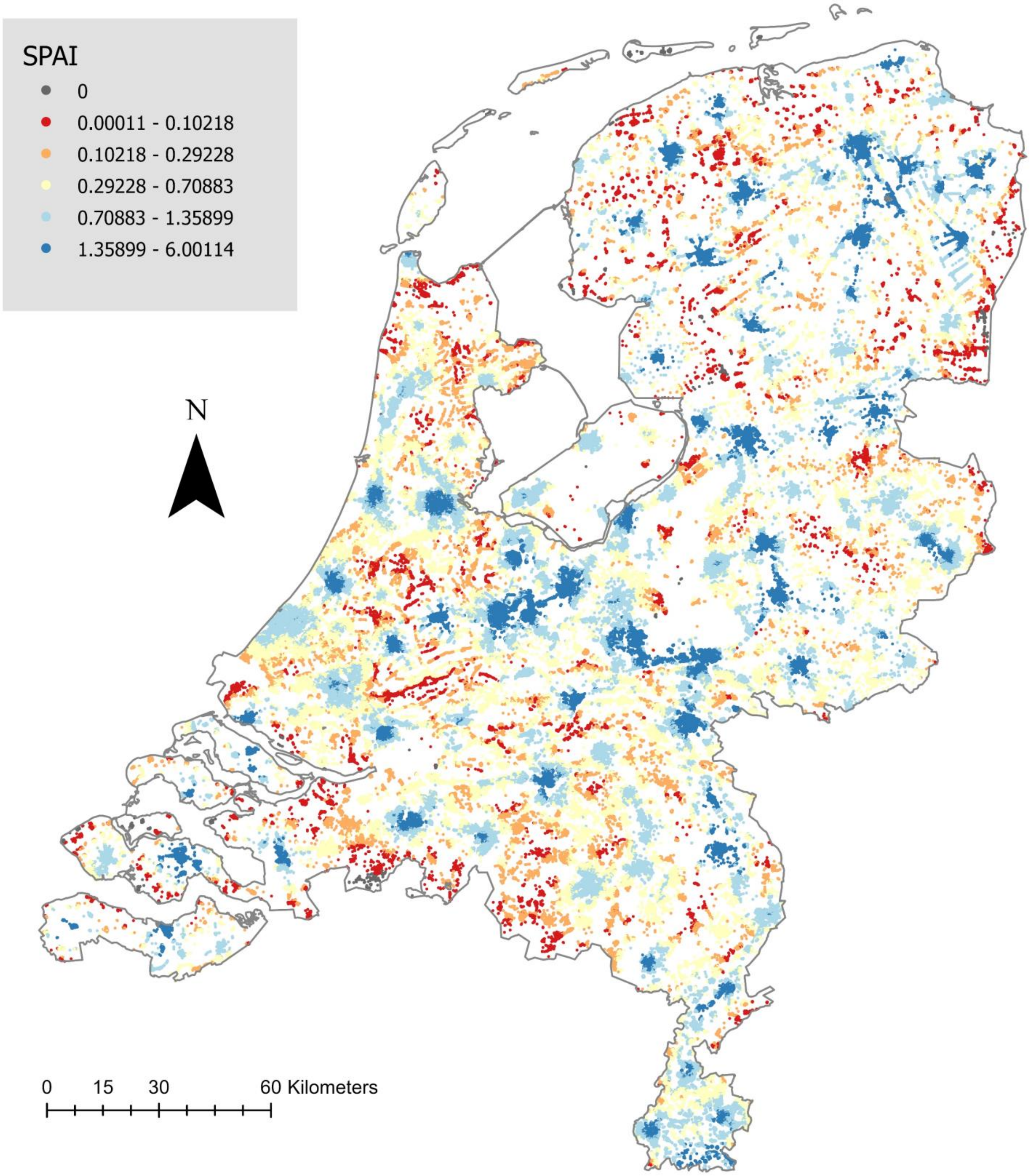

Figure 4.3 Spatial accessibility of mental healthcare facilities per hectare.

Figure 4.3 shows some clear differences between rural and urban areas. However, also some less densely populated areas seem to experience very high accessibility scores, see for example, the area around Goes (Zeeland), along the Groningen-Drenthe border, and in the south of Zuid-Limburg. Therefore, an analysis of the correlation between surrounding address density and the SPAI scores is performed.

The address density is a measure of the CBS, which calculates the average number of addresses within a 1 kilometre radius. The address density aims to represent the level of concentration of human activities, for example residing, working, attending school, shopping, going out, etc. CBS uses the address density to determine the degree of urbanisation of a specific area (CBS, n.d.).

The address density variable is only available for the 500x500 meter squares dataset and not for the 100x100 meter used in this research. For this reason, the mean SPAI scores per 500x500 meter square were calculated. Next, Spearman’s correlation coefficient was used to assess the correlation between the SPAI scores and the address density. A correlation was found of $r = 0.426$, $p < 0.01$. This means that there is a significant, moderate positive relationship between the SPAI scores and the address density.

4.1.3 Municipality comparison

Just because population cells of 100x100 meters were used as a unit of analysis, does not imply that the results can only be interpreted at this level. On the contrary, the accessibility indices calculated in this study can be aggregated at any higher regional level, depending on what is suitable for the research. When visualising the results on a higher level, the underlying calculations are still based on the hectare data, which is independent of administrative boundaries (Jörg et al., 2019).

The SPAI scores can thus also be displayed at the municipality level. The reason why municipalities were chosen as units of visualisation is that in 2022 all Dutch municipalities signed the Comprehensive Healthcare Agreement. As per this agreement, municipalities have to ensure that the mental healthcare infrastructure, including people and resources, remains available and sufficient. Therefore, municipalities play a crucial role in the provision of GGZ (Nederlandse ggz, 2022b).

Appendix **8.4** shows the mean accessibility score for all Dutch municipalities. As expected, cities with a high number of mental healthcare locations generally received high mean scores. The highest mean accessibility scores can be found in medium-sized cities. These are cities such as Goes, Venray, Zwolle, Zutphen, and Assen. This can be explained by the relatively lower number of inhabitants in these areas being assigned to high-capacity mental healthcare locations in the surrounding areas.

The lowest scores were found in the Wadden Islands municipalities of Ameland, Schiermonnikoog and Vlieland. No mental healthcare facilities are located on these islands. On the Wadden Island Vlieland, only one mental healthcare service is available, also resulting in a low accessibility score. Other clusters of low-scoring municipalities were found in the western and southern parts of Noord-Brabant, as well as the northern part of Noord-Holland. These low scores can be explained by the fact that the number of mental healthcare facilities is quite low in these municipalities and the travel times are relatively high.

4.2 Results Statistical Analysis

In this second part of the analysis, the SPAI scores calculated in the first part were used. After running the descriptive statistics, initially, a linear regression using ordinary least squares is executed to assess the associations between the SPAI scores and the covariates. VIF, Moran's *I*, LM, and AIC test statistics were assessed to evaluate the model fits and to find the best-fitting model.

4.2.1 Descriptive statistics

Not all CBS squares were included in the statistical analysis. This can be caused by one of the following reasons: less than 10 people live in a square, no accessibility score could be calculated for the square, or the independent variables were not available for this square. Figure **4.4** shows an overview of the number of observations in the statistical analysis. The locations of the observations in the statistical analysis are evenly distributed over the Netherlands, see Appendix **8.5**.

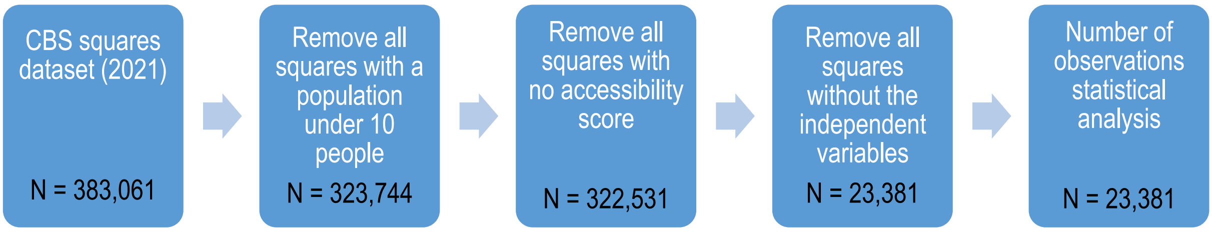

Figure 4.4 Number of observations in the statistical analysis.

Minimum, maximum, mean, and standard deviation scores were created to summarise the data, see Table **4.2**. Because the value of the SPAI and the other variables are skewed, a log transformation was applied to all variables before they entered the model, and a value of 0.1 was added to the variables with a minimum of zero (West, 2021).

Table 4.2 Descriptive statistics.

Variable	Abbreviation	Minimum	Maximum	Mean	Std. Deviation
SPAI	SPAI	0	6.577	0.863	0.648
Non-Western migrants (%)	NWEST	10	100	23.560	16.514
Owner-occupied properties (%)	OCUP	0	190	73.300	26.805
Houses owned by housing association (%)	HOUS	1,60	136.364	51.429	23.859
WOZ value houses	WOZV	4	4479	289.9	156.043
Unemployment benefits (WW) (%)	UNEM	0.435	100	14.585	10.462
Population aged under 15 (%)	UN15	0.719	100	19.803	9.055
Population aged 65+ (%)	OV65	0.487	100	27.513	19.074

The Moran’s *I* test statistic is used to assess the patterns of the response variable SPAI (Arbia, 2014). To calculate Moran’s *I*, a spatial weights matrix (W) had to be calculated. A spatial weights matrix based on k-nearest neighbours is calculated. As to be expected based on Figure **4.3**, the pattern of the SPAI scores indicated positive spatial autocorrelation. The statistical significance of the Moran’s *I* score was assessed using 999 Monte Carlo simulations. A very high positive and significant spatial autocorrelation was found for the SPAI scores (Moran’s $I = 0.893$ $p < 0.001$).

4.2.2 Bivariate statistics

Figure **4.5** shows the pairwise correlation coefficients. Almost all correlations were significant at the $p < 0.01$ level. In general, only weak correlations were found between the SPAI scores and socioeconomic and demographic factors. Significant and positive associations were found with the percentage of non-Western migrants ($r = 0.047$, $p < 0.01$), houses owned by housing associations ($r = 0.049$, $p < 0.01$) and the percentage of people receiving unemployment benefits ($r = 0.068$, $p < 0.01$). Significant and negative associations were observed with the number of owner-occupied properties ($r = -0.102$, $p < 0.01$), the average WOZ value of the houses ($r = -0.065$, $p < 0.01$), population aged under 15 ($r = -0.088$, $p < 0.01$) and the population aged over 65 ($r = -0.117$, $p < 0.01$). A correlation coefficient that stands out is $r = -0.788$, $p < 0.01$ for the owner-occupied properties and houses owned by a housing association. It was expected that these two variables would have a strong negative correlation.

	SPAI	NWEST	OCUP	HOUS	WOZV	UNEM	UN15	OV65
SPAI	1							
NWEST	0.047	1						
OCUP	-0.102	-0.272	1					
HOUS	0.049	0.278	-0.788	1				
WOZV	-0.065	-0.196	0.467	-0.308	1			
UNEM	0.068	0.323	-0.426	0.453	-0.468	1		
UN15	-0.088	-0.243	0.212	~~0.002~~	0.202	0.017	1	
OV65	-0.117	-0.211	0.067	0.141	0.076	0.084	-0.243	1

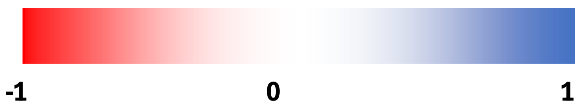

Figure 4.5 Results of the Spearman correlation analysis. All correlations are significant at the 0.01 level (2-tailed) except for the population aged under 15/houses owned by housing associations (crossed out).

4.2.3 Regression analysis

Variance inflation factors (VIF) were computed for each explanatory variable. This score measures the contribution of each variable to multicollinearity. The threshold factor of VIF is set at 5 (Craney & Surles, 2002). The following VIF scores were found: 1.257 (non-Western migration background), 1.656, (owner-occupied properties), 1.273 (houses owned by a housing association), 1.649 (WOZ value houses), 1.388 (unemployment benefits), 1.289 (population aged under 15) and 1.309 (population aged over 65). The highest VIF score is 1.656, which is well below the critical value of 5. This assumes that there is no indication of multicollinearity.

First, an OLS regression was executed, see Table **4.3** for the results. An adjusted R^2 of 0.100 was found. When examining the OLS residuals, significant autocorrelation among the residuals was discovered (Moran's $I = 0.881$, $p < 0.001$), suggesting a probable bias in inference. The values of the k-nearest neighbour weight matrix were tested between 4 and 10. The Moran's *I* of all the attempted specifications indicated the presence of residual spatial dependency.

A downside of the Moran's *I* test is that it does not provide guidance regarding alternative specifications that may be more suitable for the given data. For this reason, the Lagrange Multiplier test statistics were consulted. Both the LM-Error and LM-Lag test statistics were significant. Following the Anselin (2005) decision rule, the robust LM test statistics were consulted. Both robust statistics were also highly significant ($p < 0.001$). However, the spatial lag model had a higher value (2369.38) compared to the error model (138.78).

For this reason, the spatial lag model was applied. Values between k = 4 and k = 10 for the weight matrix were tested to find the best model fit based on the AIC scores. K = 4 resulted in the best AIC score (-57684.84). An adjusted R^2 of 0.916 was found. The results of the spatial lag model can also be found in Table **4.3**.

Table 4.3 Results of the OLS and spatial lag model. The variables entered the model log transformed.

	OLS	Spatial lag model			
	Estimate (Std. error)	Estimate (Std. error)	Direct effect	Indirect effect	Total effect
NWEST	0.091 (0.006) ***	0.014 (0.002) ***	0.029 ***	0.156 ***	0.188 ***
OCUP	-0.111 (0.006) ***	-0.010 (0.002) ***	-0.020 ***	-0.111 ***	-0.131 ***
HOUS	-0.168 (0.008) ***	-0.016 (0.002) ***	-0.031 ***	-0.174 ***	-0.205 ***
WOZV	0.113 (0.011) ***	0.006 (0.004)	0.012	0.066	0.077
UNEM	0.142 (0.009) ***	0.009 (0.002) ***	0.0181 ***	0.101 ***	0.119 ***
UN15	-0.211 (0.009) ***	-0.022 (0.002) ***	-0.043 ***	-0.237 ***	-0.280 ***
OV65	-0.111 (0.006) ***	-0.005 (0.001) ***	-0.010 ***	-0.056 ***	-0.066 ***
Constant	0.298***	0.031 (0.009) ***			
Rho		0.929 ***			
Observations	23 381	23 381			
Adj. R^2/Nagelk. R^2	0.100	0.916			
AIC	-2321.9	-57684.84			
F statistic	373, $p < 0.001$				
LR test		55 365, $p < 0.001$			
Moran's *I* resid.	0.881, $p < 0.001$	-0.065, $p = 0.999$			

Note: *** $p < 0.001$

The Moran's *I* (-0.065, $p = 0.999$) of the spatial lag model shows that this model properly incorporates the residual autocorrelation. Furthermore, the significant value of Rho (0.929, $p < 0.001$) provides additional support for the superiority of this model over the OLS regression specification (Brazil, 2023).

Table **4.3** shows the direct, indirect, and total effects of the spatial lag model. It is encountered with difficulty to interpret the regression effects in spatial lag models. Unlike in OLS, each observation in the spatial lag model is impacted by both its predictors and the information from its neighbouring observations. To address this issue, three key quantities are displayed: average total impact, average direct impact, and average indirect impact. Average total impact represents the combined effect of both direct and indirect impacts of a predictor on the outcome. Average direct impact resembles a conventional interpretation. Average indirect impact is the average influence of one's neighbours on the outcome (Sparks, 2015).

To compare the results of the OLS and spatial lag model, the associations can be compared in a graph (see Figure **4.6**). The logged population with a non-Western migration background and the logged population receiving unemployment benefits are significantly and positively associated with the SPAI levels. The logged population possessing houses, the logged percentage of houses from housing associations, the logged population over 65, and the logged population under 15 are negatively associated with the SPAI levels. All these associations were found to be significant at the $p < 0.001$ level. Considering the logged WOZ value of the houses, no significant association was found. The regression results of the spatial lag model were found to be robust to a different number of nearest neighbours in the weight matrix.

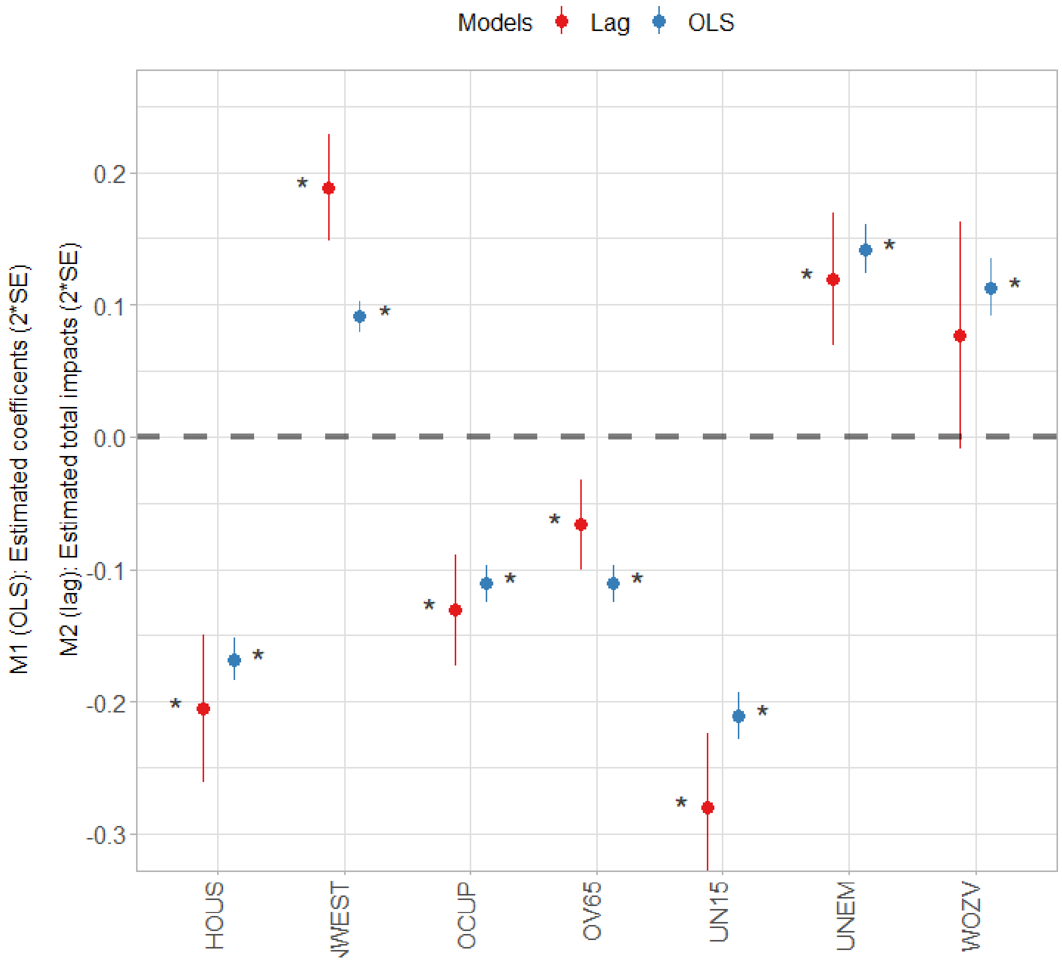

Figure 4.6 Estimations of associations were conducted using both the OLS model (Model 1) and the spatial lag model (Model 2). The lag model estimates refer to total impacts. The estimates are reported with double the standard error. Variables achieving statistical significance at the 1% level are marked with an asterisk (*).

5. Discussion

Receiving accessible mental healthcare is of vital importance for the Dutch population. In this nationwide study, the differences in mental healthcare accessibility were visualised. Furthermore, the associations between those accessibility scores and the socioeconomic and demographic composition of the population were assessed.

5.1 Main Findings

In general, there is a high density and a good distribution of mental healthcare facilities in the Netherlands. As a consequence, almost all population hectares (99.35% of population hectares with at least 10 people) are located within a 12-minute driving range by car to a mental healthcare facility. The unreachable population locations are mostly located on the Wadden Islands, Midden-Zeeland, Friesland, along the Belgium border in Noord-Brabant, and a small cluster of cells in Drenthe.

The results of the Spatial Accessibility Index (SPAI) score for each hectare support the first hypothesis that the accessibility scores are lower in more rural areas. A moderate positive relationship was found between the SPAI scores and the address density. The highest accessibility scores were found to be clustered in medium-sized cities and villages: Goes, Zwolle, Venray, and Zutphen. A possible explanation for the high scores in these areas is that relatively fewer residents are assigned to the high capacities of mental healthcare locations surrounding them. Also in the Randstad area, generally high accessibility scores were found.

The lowest accessibility scores were found around the Dutch-German border in Drenthe, the rural parts of the Randstad (het 'Groene Hart'), large parts of Noord-Brabant, and some parts of the provinces of Friesland and Noord-Holland. Furthermore, small clusters of low accessibility scores can be found everywhere around the country. Using the MH3SFCA method, it is possible to identify variations in accessibility on a small scale.

The second research question focuses on the association between accessibility scores and the socioeconomic and demographic composition of the population cell. Contrary to the hypothesis, population locations with a high percentage of non-Western migrants do not experience lower accessibility to mental healthcare facilities. Instead, a significant positive effect was found between these two variables. Moreover, contrary to the exception, the percentage of owner-occupied property is significantly negatively associated with the SPAI. Also, the percentage of people receiving unemployment benefits is against expectations significant and positively associated.

In line with the hypothesis, the percentage of houses owned by housing associations is significantly negatively associated with the accessibility scores. Furthermore, a null association was found between the WOZ value and the SPAI scores in the spatial lag model. Finally, both vulnerable age groups (under 15 and over 65) are significantly and negatively associated with the SPAI. The latter confirming the hypothesis.

5.2 Interpretation

To the author's knowledge, this is the first study that specifically quantifies the spatial accessibility of mental healthcare facilities in the Netherlands. For this reason, it is thus difficult to compare the results of the accessibility analysis. However, Lopez et al. (2023) acknowledge that there is an extensive network of Dutch mental healthcare facilities, resulting in high spatial accessibility. This is in line with the findings of this research. Furthermore, the high spatial accessibility of mental healthcare facilities is comparable to the accessibility of GPs in the Netherlands. Only 0.1% of the Dutch population travels longer than 10 minutes to a GP (Van den Berg et al., 2014).

The accessibility patterns found in this study (higher accessibility in more densely populated areas) are in line with the findings of Amos et al. (2023), Lankila et al. (2022) and Tadmon & Bearman

(2023) for mental healthcare accessibility in other parts of the world. In contrast to this study, higher differences in mental healthcare accessibility in those study areas were found. However, this can be explained by the fact that these authors focus respectively on Australia, Finland, and the United States, which are on average less densely populated than the Netherlands. The most rural parts of the Netherlands are still densely populated in an international context.

Population cells with a high percentage of non-Western migrants are associated with higher accessibility scores. These results contradict the results of Ngui and Vanasse (2012) for Montreal. They found that disadvantaged neighbourhoods with a lot of recent immigrants and unemployed inhabitants showed the lowest accessibility scores. These different findings might be explained by the fact that most people with a non-Western migration background in the Netherlands live in cities (CBS, 2016). As stated above, in general, more densely populated areas enjoy higher accessibility scores.

The percentage of owner-occupied property and the percentage of people receiving unemployment benefits are two socioeconomic factors that are negatively associated with the SPAI. None of the other studies explicitly use these variables. A possible explanation for this is that these are from the CBS dataset, and there are no Dutch studies that examine the association between mental health accessibility and socioeconomic factors.

Wang & Ariwi (2021) use only household income as an indicator of the socioeconomic status of the Toronto population. Their findings are in line with this study. They found less affluent neighbourhoods had easier access to mental health community services compared to high income neighbourhoods. However, on the other hand, high income neighbourhoods experienced better access to mental healthcare specialists. This distinction between community and specialist services is not in such a manner present in the Netherlands. All the GGZ institutions considered in this research have the characteristic that claims can be approved by health insurance companies (Zorginstituut Nederland, 2023).

Following Ghorbanzadeh et al. (2020), the percentage of elderly people in this study is negatively associated with the SPAI scores. They found that some counties in Florida with poor accessibility scores to mental healthcare facilities have a high proportion of elderly people. Results from this study reveal that the same negative relationship is found with people under the age of 15. Nevertheless, it is not possible to compare these results with the study of Ghorbanzadeh et al. (2020) as they only consider age groups over 18 years old.

So far, only studies analysing the association between accessibility scores and mental healthcare facilities have been considered. This number of such studies is limited. Consequently, studies assessing the relationship between accessibility scores and other healthcare facilities (GPs for example) can also be examined.

Tomasiello et al. (2024) reported that individuals with high income, regardless of race, have greater access to primary healthcare units in cities in Brazil. This corresponds with the findings of this study, where also a positive relationship between a non-Western migration background and the SPAI scores was found. Also, the percentage of owner-occupied property and people receiving unemployment benefits being negatively associated with the SPAI is in line with the study of Tomasiello et al. (2024). On the other hand, in Brazil, individuals with a high income, mostly white, have better access to high-complexity units. Such a distinction between primary and complex healthcare is not made in this study for mental healthcare facilities in the Netherlands.

In accordance with this study, Lee (2022) found that elderly people had significantly lower accessibility scores to healthcare facilities in South Korea. However, the finding of Lee (2022) that the migrant population experienced unequal access to healthcare facilities contradicts the findings in this study. This can be explained by the fact that this inequality is primarily evident by looking at public transport as a mode of transport, which is not considered in this study.

5.3 Policy Advice

As revealed in this study, spatial inequalities across the Netherlands in the accessibility of mental healthcare facilities are evident. This knowledge could be useful for policymakers to see which areas need future improvement and to help formulate strategies. In addition, it can enhance the understanding of regional differences in accessibility. It may also improve planning by pointing at suitable locations for potential mental healthcare facilities.

The Dutch government and the trade association Nederlandse ggz should take the lead in overseeing and appointing the locations of GGZ facilities. The government should take a more proactive role in defining constraints on what an acceptable travel time to a mental healthcare facility should be. Especially for independent practises, it is difficult to control the location, as these are mostly individuals choosing for themselves where to provide their services. For the GGZ institutions, a more centrally managed approach is possible where underserved areas are identified and improved. Regarding the allocation of those services, new services should be located in areas with lower accessibility scores.

The results from this study do not imply socioeconomic inequalities in mental healthcare accessibility in the Netherlands. However, more research is needed to see if this is actually the case, see the next section. Both age groups under 15 and over 65 suffer lower accessibility to mental healthcare facilities. This is especially concerning as over the past years a decline in mental health has been observed for both adolescents (age 12-18) and young adults (age 18-25) (Nederlands Jeugdinstituut, 2023).

Elderly people in the Netherlands face relatively the lowest number of mental problems. However, research suggests that mental health issues in the elderly are often recognised late or not at all (NOS, 2022). Furthermore, both the 65+ groups and the adolescents often depend on others or public transportation as they are not able to move around by car or bike alone. This implies that these groups are disproportionally affected by the lack of access. For this reason, it is important in areas with low accessibility scores and a high percentage of elderly people or adolescents to increase the variety of transportation options, among which are community transport and local access initiatives (Lee, 2022). In addition, enhancing the public transport network, focusing on train and bus transport in the Netherlands can improve the accessibility for these groups.

5.4 Strengths

This study has several different strengths. First, it is, to the author's knowledge, the first study in the Netherlands focusing on the spatial accessibility of mental healthcare facilities. Furthermore, it moves away from the city-based approach, as few existing studies have conducted a nationwide analysis of mental healthcare accessibility.

Next, by using units of analysis of 100x100 meters, accessibility scores are calculated on a very small scale so local differences can become clear. The MH3SFCA used in this study is a sophisticated accessibility indicator as both the accessibility (distance) of healthcare services and their availability (in terms of the relationship between supply and demand) are considered. This makes it possible to compare between different regions as well as to compare within regions to improve decision making. Using individual Gaussian weights to represent driving times in this research improves the accessibility score compared to a binary or subzone approach.

Another notable strength is the examination of mental healthcare accessibility in relationship with socioeconomic and demographic factors. By implementing various socioeconomic and demographic variables a distinction is made between the current studies assessing mental healthcare accessibility and socioeconomic factors, which only look at one or two variables (Wang & Ariwi, 2021). To conclude, this study uses spatial models in order to overcome the challenges of spatial autocorrelation.

5.5 Limitations and Suggestions for Future Research

Despite these strengths, this study also has some shortcomings. First, regarding the data collection, no distinction was available for different types of mental healthcare facilities. Some patients with particular diseases need to visit an institution with a specific specialisation. As a result, they might not be able to access the facilities in their neighbourhood. Furthermore, for the GGZ institutions, the capacity number is sometimes an estimated value, if the data on the capacity is missing.

Regarding the network analysis in this study, a small number of cells were not accessible due to errors in the network. Another limitation of the network is that traffic is not included. This can increase travel time and result in lower accessibility scores, especially in densely populated areas. Future research should use a network that includes traffic. Also, using grid cells for transport network analysis has some disadvantages for example the fact that some population cells are not connected to the transport network. Furthermore, the population might be unevenly distributed along the cell, and using the centroid of the grid is an oversimplification. Van Wee & De Jong (2022) describe the importance of spatial scale when measuring the accessibility of health services. This implies that the accessibility scores should be compared with accessibility scores measured on another spatial scale.

Other limitations are related to the MH3FCA model. One limitation of this model is the difficulty in interpreting why there are certain outcome patterns. Because this model takes a high number of factors into account, compared to other accessibility measures, it can be difficult to explain why certain differences were found. Also, the choice of the parameter values in the MH3FCA can impose limitations. The travel time threshold and the coefficient of fraction have a big influence on the outcomes of the results. As there are no official guidelines or advice on what the travel time threshold should be for mental healthcare facilities in the Netherlands, this parameter is partly arbitrarily chosen.

Also, the statistical analysis has its limitations. First, due to privacy reasons and the detailed level of the analysis, the final number of observations in the statistical analysis comprises a small amount of the entire CBS dataset. Furthermore, some important socioeconomic variables such as income were not available in the used dataset. The variables chosen in this study are based on the literature, but certain variables may be missing in the analysis.

This study outlines various directions for further research. The same method may be executed to see what the accessibility scores are using public transport. Individuals with lower socioeconomic status may not have a car and thus depend on public transport (Amaddeo & Jones, 2007). It is known that the quality of public transportation is worse in the countryside in the Netherlands (Jorritsma et al., 2023). Further research should investigate to what extent this will influence the accessibility scores.

This study only focuses on spatial accessibility. However, a very important factor in the comprehensive accessibility picture is the fact that GGZ institutions generally have long waiting lists. This has to do with the accessibility dimensions of availability, accommodation, and acceptability. Ideally, in future research, spatial and non-spatial factors of accessibility should be combined to create a complete accessibility score (Lévesque et al., 2013).

Another suggestion for further research is to focus on the accessibility scores of the group of people aged between 16 and 25. This group has experienced an increase in mental health disorders over the past years (CBS, 2023c). Research should find out if this group also experiences less access to mental healthcare facilities, such as the groups of people aged under 15 and over 65.

To conclude, further research should focus on the development of digital mental healthcare facilities and the implications for accessibility indices. Especially since the COVID pandemic, increasingly more people are engaged in digital mental healthcare. In 2021, therapeutic conversations were conducted online approximately thirty percent more often in the Netherlands compared to a year earlier (VGZ, 2023). This type of care is also called telehealth and has the potential to overcome spatial barriers and make mental healthcare more accessible. However, research has shown that the use of telehealth often replicates existing barriers, which can disadvantage older, rural, and lower-income population groups (Tadmon & Bearman, 2023). This suggests that online and offline accessibility patterns may be similar. Future research is needed to see if this is also the case in the Netherlands and to investigate the relationship of telehealth on the association between the spatial accessibility of mental healthcare and socioeconomic characteristics.

6. Conclusions

Over a quarter of Dutch adults have experienced a mental disorder in the past year. The Dutch GGZ struggles to accommodate all those people. In this study, the focus was explicitly on the spatial accessibility of mental healthcare facilities in the Netherlands. With the help of the MH3FCA method, for each populated hectare in the Netherlands, a Spatial Accessibility Index (SPAI) was calculated. Due to the high density of those facilities, most populated locations in the Netherlands are in close proximity to a mental healthcare institution. However, some areas along the Dutch-German border in Drenthe, the rural parts of the Randstad (het 'Groene Hart'), large parts of Noord-Brabant, and some parts of the provinces of Friesland and Noord-Holland showed lower accessibility scores. Also, some regional and small areas with poor accessibility scores could be detected due to the MH3SFCA method. These regions should be a focus for the GGZ institutions and the Dutch government when building new locations or relocating facilities.

With this SPAI, both an OLS and a spatial lag model were executed. The models underscored the importance of taking spatial effects into account when analysing differences between population cells. Socioeconomically disadvantaged groups were not disproportionally affected by the lack of access. Instead, non-Western migrants were positively associated with the SPAI. In addition, the percentage of owner-occupied property and the percentage of people receiving unemployment benefits are two socioeconomic factors which are negatively associated with the SPAI.

Both considered age groups (under 15 and over 65) were negatively associated with the SPAI. This is especially concerning because there has been an increase in mental healthcare problems among adolescents, and mental health issues by elderly people are often recognized late or not at all. Besides, these two groups often depend on others or public transportation, so they might be disproportionately affected by the lack of access.

7. References

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8. Appendices

8.1 Code Web Scraping Mental Healthcare Locations

This code is used for webscraping names and coordinates from [*https://www.zorgkaartnederland.nl/ggz*](https://www.zorgkaartnederland.nl/ggz)

This first section describes how the names from the GGZ institutions can be web scraped

```
import requests
from bs4 import BeautifulSoup
import csv

# Base URL and URL structure for pagination
base_url = "https://www.zorgkaartnederland.nl/ggz"
page_number = 1

# Initialize a list to store scraped data
all_data = []

# Specify the number of pages you want to scrape
total_pages = 104

# Loop through the pages
for _ in range(total_pages):

    # Generate the URL for the current page
    current_url = f"{base_url}/pagina{page_number}"

    # Send a GET request to the current page
    response = requests.get(current_url)

    if response.status_code == 200:
        soup = BeautifulSoup(response.text, 'html.parser')

        # Scrape data (Names) from the current page and add it to the list
        data_elements = soup.find_all("a", class_="filter-result__name")
        data = [element.text.strip() for element in data_elements]
        all_data.extend(data)

        # Increment the page number for the next iteration
        page_number += 1
    else:
        print(f"Failed to retrieve the page at {current_url}")

# Specify the CSV file name
csv_filename = "scrapedGGZ_names.csv"

# Print the collected data
with open(csv_filename, mode='w', newline='') as csv_file:
    csv_writer = csv.writer(csv_file)
    csv_writer.writerow(['Index', 'Data'])

    for i, data in enumerate(all_data, start=1):
        csv_writer.writerow([i, data])
        print(f"{i}. Data: {data}")

print(f"Names data exported to {csv_filename}")
```

This second section describes how the coordinates of the GGZ institutions can be extracted

```
import requests
from bs4 import BeautifulSoup

# Function to scrape coordinates from a single page
def scrape_coordinates(url):
    response = requests.get(url)
    if response.status_code == 200:
        soup = BeautifulSoup(response.text, 'html.parser')
        coordinates = []

        # Find and extract coordinates from the page
        elements = soup.find_all("div", class_="filter-result")
        for element in elements:
            data_location = element.get('data-location')
            if data_location:
                coordinates.append(data_location)

        return coordinates
    else:
        print(f"Failed to retrieve the page at {url}")
        return []

# Base URL for pagination
base_url = "https://www.zorgkaartnederland.nl/ggz/pagina"

# Number of pages to scrape
total_pages = 104

# Initialize a list to store all coordinates
all_coordinates = []

# Scrape coordinates from each page
for page_num in range(1, total_pages + 1):
    page_url = f"{base_url}{page_num}"
    page_coordinates = scrape_coordinates(page_url)
    all_coordinates.extend(page_coordinates)

# Specify the CSV file name
csv_filename = "scrapedGGZ_coordinates.csv"

# Print the collected coordinates
with open(csv_filename, mode='w', newline='') as csv_file:
    csv_writer = csv.writer(csv_file)
    csv_writer.writerow(['Index', 'Coordinates'])
    for i, coordinates in enumerate(all_coordinates, start=1):
        csv_writer.writerow([i, coordinates])
        print(f"{i}. Coordinates: {coordinates}")

print(f"Coordinates data exported to {csv_filename}")
```

8.2 Correlation Car and Bike Travel Times

For this research, travel times by car are used. However, it is interesting to see to which degree the travel times by car and bike correlate and whether this result of the accessibility analysis is also applicable to cycling as a transport mode. Cycling is one of the main modes of transport in the Netherlands. The average Dutch person uses the bike 232 times a year to cycle a total distance of 979 979 kilometres (CBS, 2023b).

Three different areas of the Netherlands are used to compare the travel times by bike and by car, see Figure **8.1**. These areas are a highly densely populated area (Amsterdam, see A), a medium densely populated area (Hilversum-Enkhuizen area, see B) and a sparsely populated area (West of Drenthe, see C). For each of these areas, the shortest travel time from the population location to the nearest mental healthcare location is calculated for both car and bike. It is important to realize that this network does not account for traffic. Next, for each of the areas, the Pearson correlation coefficient between bike and car travel times is calculated.

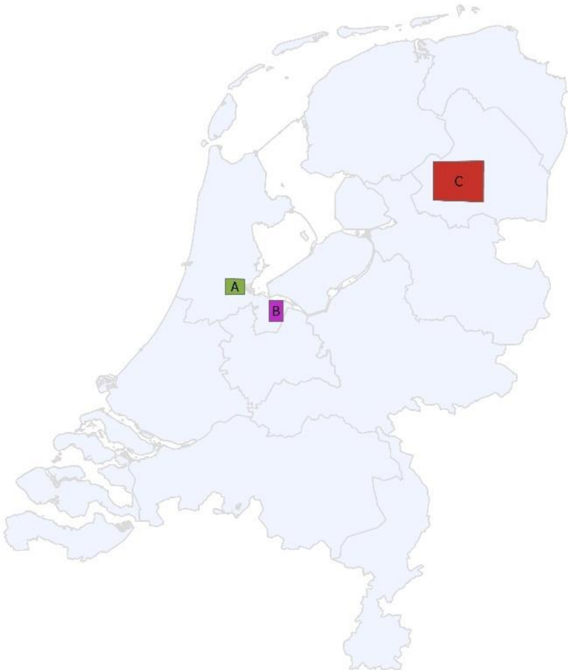

Figure 8.1 Researched areas correlation bike and car travel times.

The results are displayed below. For all three areas, a positive linear correlation between car and bike travel times was found. Significant and high correlation coefficients were found for all three areas. For the Amsterdam area, a correlation was found of r = 0.744. For the Hilversum-Enkhuizen area and the Drenthe West area, an even stronger correlation (r = 0.920) and (r = 0.953) was found. This implies that the final accessibility scores resulting from this thesis can also be applied to cycling as a mode of transport, especially in moderate to sparsely populated areas.

8.2.1 Amsterdam area

N = 3551. r = 0.744, p < 0.01

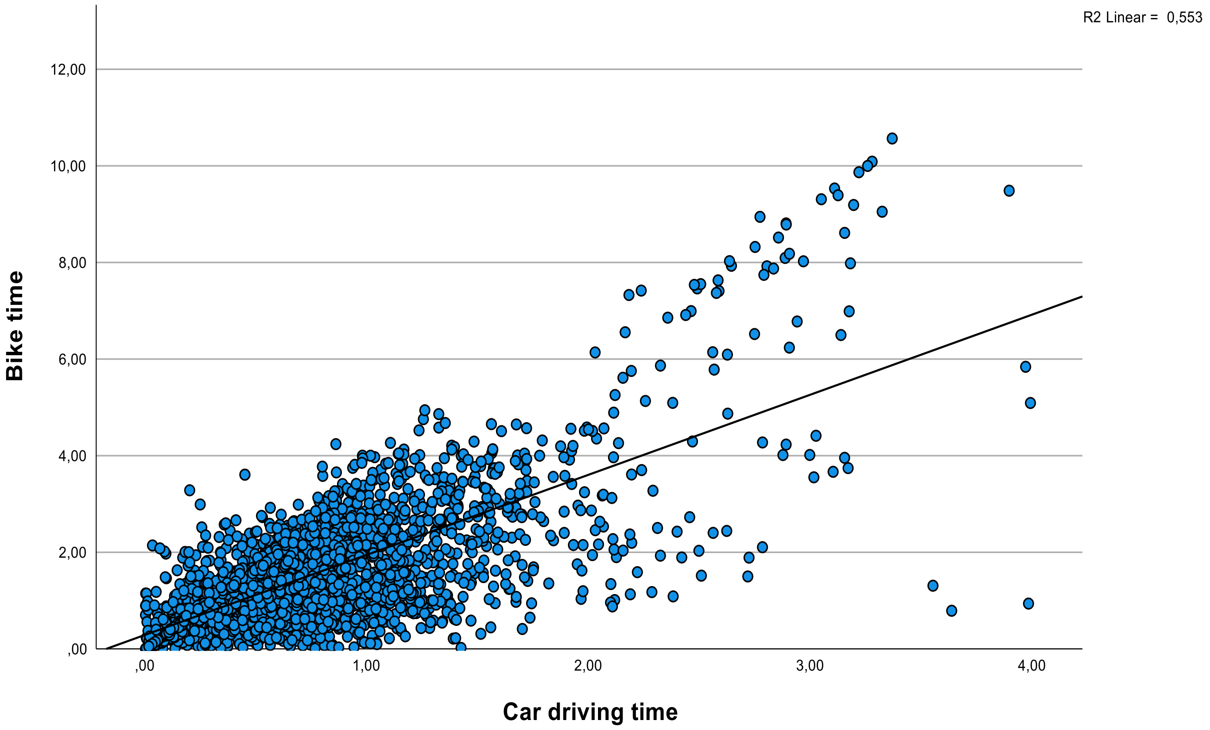

Figure 8.2 Scatter diagram car and bike driving time Amsterdam area.

8.2.2 Hilversum-Enkhuizen area

N = 2127. r = 0.920, p < 0.01

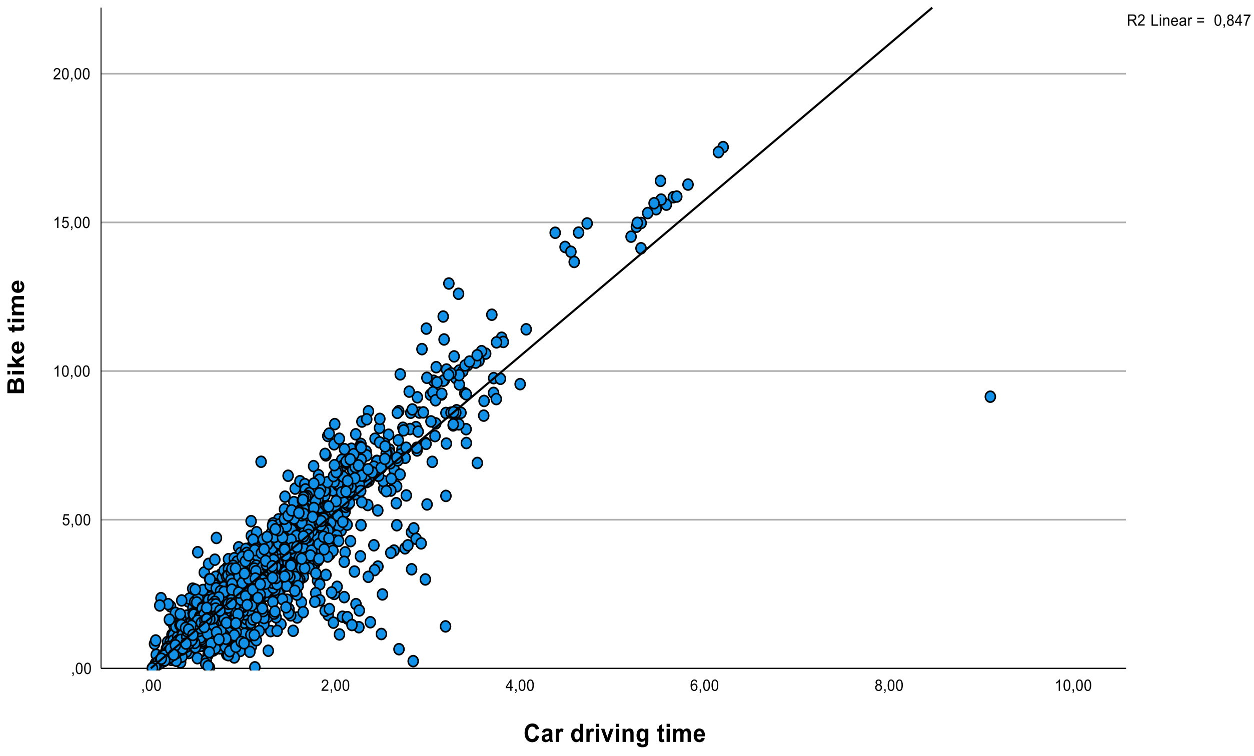

Figure 8.3 Scatter diagram car and bike driving time Hilversum-Enkhuizen area.

8.2.3 West-Drenthe

N = 1367. $r = 0.953$, $p < 0.01$

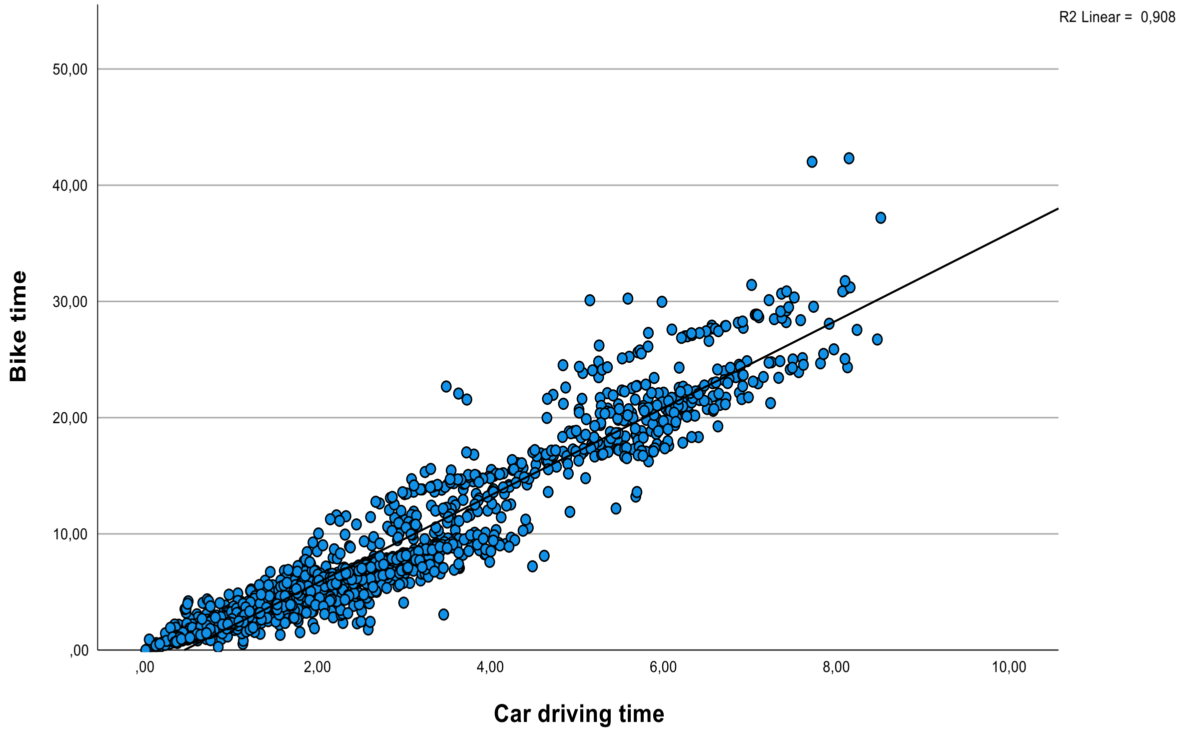

Figure 8.4 Scatter diagram car and bike driving time West-Drenthe area.

8.3 Code for Calculation of MH3SFCA

Created by Marjon van Dijke, 14-01-2024. Based on the work of Subal et al. (2021), Jörg et al. (2019) and Zeng et al. (2024).

For more background information on the Modified Huff Model Three-Step Floating Catchment Area (MH3SFCA) method and research, please see my thesis: An Evaluation of Spatial Accessibility of Mental Healthcare Services in The Netherlands.

This notebook assumes that you have an Origin-Destination (OD-Matrix) as a CSV format as input. This matrix should consist of all possible connections between your population locations and your destination locations given a defined maximum catchment area. Furthermore, the OD-Matrix should contain (for each OD combination) information on the capacity of the destination location, as well as the population count at the origin location. The OD-matrix can be created in ArcGIS Pro or with the help of other GIS software.

This notebook is based on the idea that you can check the output of each step (as a CSV file) and you can go back to a previous step if needed. The MH3SFCA method consists of 3 main steps, which are also used within this notebook.

Load the necessary libraries

```
import pandas as pd
import numpy as np
```

Load your CSV into a dataframe and load a part of the CSV to inspect data

```
# Replace 'input.csv' with your CSV file path
file_path = "C:/Users/input.csv"

# Load the CSV data into a DataFrame
df = pd.read_csv(file_path, sep=';')

# Display the first few rows of the DataFrame
df.head(50)
```

STEP 1A: Calculate the distance weight W from each population point to each accessible facility point, based on the Gaussian function

If required, some values, needed to be converted to numeric and commas should be replaced by dots. The following attributes are needed in this first step:

1. Total_Car_Time: for each OD-link, this gives the travel time by car in minutes
2. Capacity: Capacity of the destination location

With the help of the Gaussian function, the DistanceWeight can be calculated. Next with this distance weight, the individual Huff score (also known as the Huff numerator: HuffNum) can be calculated.

```
# Replace 'input.csv' and 'output01.csv' with your file paths
input_csv_path = "C:/Users/input.csv"
output_csv_path = "C:/Users/output01.csv"

# Read the CSV file into a DataFrame
df = pd.read_csv(input_csv_path, sep = ';')

# Convert 'Total_Car_Time' to numeric, replacing commas with dots
df['Total_Car_Time'] = pd.to_numeric(df['Total_Car_Time'].str.replace(',', '.'), 
errors='coerce')

# Calculate DistanceWeight and create a new column
df['DistanceWeight'] = (np.exp((-1/2) * (df['Total_Car_Time'] / 12) * (df['Total_Car_Time'] 
/ 12)) - np.exp(-1/2)) / (1 - np.exp(-1/2))

# Calculate HuffNum and create a new column
df['HuffNum'] = df['Capacity'] * df['DistanceWeight']
```

```
# Write the DataFrame with the new field back to a new CSV file
df.to_csv(output_csv_path, index=False)
```

STEP 1B: Calculate the denominator of the Huff formula and join this field back to the table

To calculate the denominator of the Huff formula, you need to summarize all HuffNum values based on the field DestinationID For this, use your output01.csv from the previous step. Next, you need to join the field HuffNum back to the table based on the field 'DestinationID'.

```
# Replace 'output01.csv' and 'output02.csv' with your file paths
input_csv_path = "C:/Users/output01.csv"
output_csv_path = "C:/Users/output02.csv"

# Summarize 'HuffNum' based on 'DestinationID'
summary_df = df.groupby('DestinationID')['HuffNum'].sum().reset_index()

# Write the summarized DataFrame to a new CSV file
summary_df.to_csv(output_csv_path, index=False)

# Replace 'output01.csv' and ''output02.csv'' with actual file paths
output_csv_path_01 = "C:/Users/output01.csv"
output_csv_path_02 = "C:/Users/output02.csv"
output_merged_path = "C:/Users/output03.csv"

# Read the CSV files into DataFrames
df_01 = pd.read_csv(output_csv_path_01)
df_02 = pd.read_csv(output_csv_path_02)

# Merge DataFrames based on 'DestinationID'
merged_df = pd.merge(df_01, df_02, on='DestinationID', how='left')

# Write the merged DataFrame to a new CSV file
merged_df.to_csv(output_merged_path, index=False)
```

STEP 1C: Calculate the final Huff Probability score

The last part of the first step is to calculate the final Huff score (HuffTot).

```
# Replace 'output03.csv' with your file path
csv_path = "C:/Users/output03.csv"

# Check if the columns 'HuffNum_x' and 'HuffNum_y' exist in the DataFrame
if 'HuffNum_x' in df.columns and 'HuffNum_y' in df.columns:

    # Add a new column 'HuffTot' by dividing 'HuffNum_x' by 'HuffNum_y'
    df['HuffTot'] = df['HuffNum_x'] / df['HuffNum_y']

    # Save the updated DataFrame to a new CSV file
    output_csv_path = "C:/Users/output04.csv"
    df.to_csv(output_csv_path, index=False)
    print(f"DataFrame with 'HuffTot' field saved to {output_csv_path}")
else:
    print("Columns 'HuffNum_x' and 'HuffNum_y' not found in the DataFrame.")
```

STEP 2A: Calculate the Service-Supply ratio

The second step of the MH3SFCA is to calculate the Service-Supply ratio. First, the corrected served population for each population location needs to be calculated. The variables 'HuffTot' and 'Population' are needed for this step.

```
# Replace 'output04.csv' with your file path
csv_path = "C:/Users/output04.csv"

# Read the CSV file into a DataFrame
df = pd.read_csv(csv_path)

# Check if the columns 'HuffTot' and 'Population' exist in the DataFrame
```

```python
if 'HuffTot' in df.columns and 'Population' in df.columns:

    # Add a new column 'HuffPop' by multiplying 'HuffTot' by 'Population'
    df['HuffPop'] = df['HuffTot'] * df['Population']

    # Save the updated DataFrame to a new CSV file
    output_csv_path = "C:/Users/output05.csv"
    df.to_csv(output_csv_path, index=False)
    print(f"DataFrame with 'HuffPop' field saved to {output_csv_path}")
else:
    print("Columns 'HuffTot' and 'Population' not found in the DataFrame.")
```

STEP 2B: Summarize results HuffPop

```python
# Replace 'output05.csv' and 'output06.csv' with file paths
input_csv_path = "C:/Users/output05.csv"
output_csv_path = "C:/Users/output06.csv"

# Summarize 'HuffPop' based on 'DestinationID'
summary_df = df.groupby('DestinationID')['HuffPop'].sum().reset_index()

# Write the summarized DataFrame to a new CSV file
summary_df.to_csv(output_csv_path, index=False)
```

STEP 2C: Join HuffPop back to the table and calculate Supply-Demand Ratio Rj

```python
# Replace 'output05.csv' and 'output06.csv' with your file paths
output_csv_path_05 = "C:/Users/output05.csv"
output_csv_path_06 = "C:/Users/output06.csv"
output_merged_path = "C:/Users/output07.csv"

# Read the CSV files into DataFrames
df_01 = pd.read_csv(output_csv_path_05)
df_02 = pd.read_csv(output_csv_path_06)

# Merge DataFrames based on 'DestinationID'
merged_df = pd.merge(df_01, df_02, on='DestinationID', how='left')

# Write the merged DataFrame to a new CSV file
merged_df.to_csv(output_merged_path, index=False)

# Replace 'output07.csv' with your file path
csv_path = "C:/Users/output07.csv"

# Read the CSV file into a DataFrame
df = pd.read_csv(csv_path)

# Check if the columns 'Capacity' and 'HuffPop_y' exist in the DataFrame
if 'Capacity' in df.columns and 'HuffPop_y' in df.columns:

    # Add a new column 'Rj' by dividing 'Capacity 3' by 'HuffPop_y'
    df['Rj'] = df['Capacity'] / df['HuffPop_y']

    # Save the updated DataFrame to a new CSV file
    output_csv_path = "C:/Users/output08.csv"
    df.to_csv(output_csv_path, index=False)
    print(f"DataFrame with 'Rj' field saved to {output_csv_path}")
else:
    print("Columns 'Capacity' and 'HuffPop_y' not found in the DataFrame.")
```

STEP 3A: Calculate the final accessibility score for each OD link

The final step of the MH3SFCA method is to calculate a final accessibility score for each population location.

```
# Replace 'output08.csv' with your file path
csv_path = "C:/Users/output08.csv"

# Read the CSV file into a DataFrame
df = pd.read_csv(csv_path)

# Check if the columns 'Rj', 'DistanceWeight' and 'HuffTot' exist in the DataFrame
if 'Rj' in df.columns and 'DistanceWeight' in df.columns and 'HuffTot' in df.columns:

    # Add a new column 'HuffRj' by dividing 'Capacity 3' by 'HuffNum_y'
    df['HuffRj'] = df['Rj'] * df['DistanceWeight'] * df['HuffTot']

    # Save the updated DataFrame to a new CSV file
    output_csv_path = "C:/Users/output09.csv"
    df.to_csv(output_csv_path, index=False)
    print(f"DataFrame with 'HuffRj' field saved to {output_csv_path}")
else:
    print("Columns 'DistanceWeight', 'Rj' and 'HuffTot' not found in the DataFrame.")
```

STEP 3B: Summarize the results of the previous step

```
# Replace 'output09.csv' and 'output10.csv' with your file paths
input_csv_path = "C:/Users/output09.csv"
output_csv_path = "C:/Users/output10.csv"

# Summarize 'HuffRj' based on 'OriginID'
summary_df = df.groupby('OriginID')['HuffRj'].sum().reset_index()

# Write the summarized DataFrame to a new CSV file
summary_df.to_csv(output_csv_path, index=False)
```

Final result and next steps

The final result is a CSV file with a spatial accessibility score for each population location. It is possible to multiply all these scores by 1000 in order to improve the readability. This CSV can be joined to a shapefile of the population locations in GIS software to visualize the results.

8.4 SPAI Scores per Municipality

Figure **8.5** shows the main SPAI score per municipality and the locations of the mental healthcare facilities. On the following pages a table is shown with the municipality name, the population count, the number of mental healthcare facilities and the mean SPAI score.

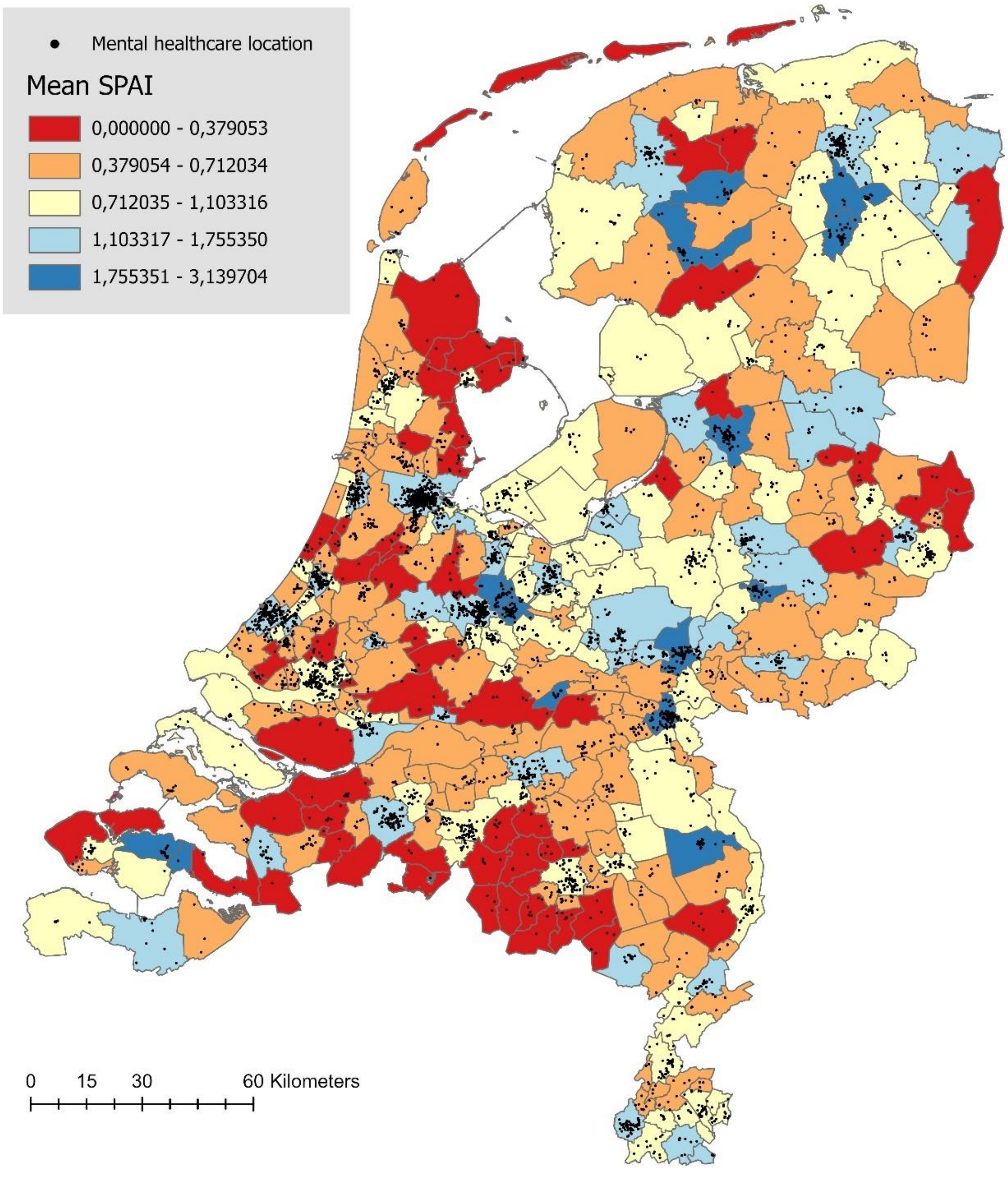

Figure 8.5 Mean SPAI scores per municipality.

Table 8.1 Mean SPAI scores per municipality.

Municipality code	Municipality name	Mean SPAI score	Population count	Population density (per km2)	Number of mental healthcare locations
GM0014	Groningen	1.650404	238147	1284	148
GM0034	Almere	0.855402	222825	1725	51
GM0037	Stadskanaal	1.374501	32135	273	5
GM0047	Veendam	1.224935	27616	364	7
GM0050	Zeewolde	1.077798	23692	96	7
GM0059	Achtkarspelen	0.283012	28149	275	4
GM0060	Ameland	0.000000	3840	68	0
GM0072	Harlingen	1.041130	16188	649	2
GM0074	Heerenveen	1.973365	51637	272	24
GM0080	Leeuwarden	1.481590	127073	535	49
GM0085	Ooststellingwerf	0.536137	25837	116	6
GM0086	Opsterland	0.511933	30054	134	3
GM0088	Schiermonnikoog	0.000000	982	23	0
GM0090	Smallingerland	2.119284	56098	479	14
GM0093	Terschelling	0.196842	4928	57	1
GM0096	Vlieland	0.000000	1291	31	0
GM0098	Weststellingwerf	0.369160	26467	120	3
GM0106	Assen	2.055162	69414	848	34
GM0109	Coevorden	0.643938	35700	121	6
GM0114	Emmen	0.420269	108765	324	11
GM0118	Hoogeveen	0.807828	56433	442	10
GM0119	Meppel	1.007261	35464	639	9
GM0141	Almelo	1.103316	73949	1101	17
GM0147	Borne	0.772179	24524	944	3
GM0148	Dalfsen	0.548621	29612	179	6
GM0150	Deventer	1.429910	102781	787	45
GM0153	Enschede	1.086483	161235	1146	48
GM0158	Haaksbergen	0.427990	24502	234	3
GM0160	Hardenberg	1.422557	62509	200	15
GM0163	Hellendoorn	0.540354	36261	263	5
GM0164	Hengelo	1.241348	82311	1353	32
GM0166	Kampen	1.374319	55614	394	12
GM0168	Losser	0.148220	23362	237	1
GM0171	Noordoostpolder	1.048081	49729	109	3
GM0173	Oldenzaal	0.432442	31925	1481	8
GM0175	Ommen	1.717562	18955	105	7
GM0177	Raalte	0.783917	38500	225	7
GM0180	Staphorst	0.397667	17628	132	1
GM0183	Tubbergen	0.467079	21408	146	3
GM0184	Urk	0.873999	21829	1661	4
GM0189	Wierden	0.637648	24862	263	4
GM0193	Zwolle	2.507199	132411	1196	72
GM0197	Aalten	0.656892	27244	282	2
GM0200	Apeldoorn	0.932256	167191	492	46

GM0202	Arnhem	1.869685	165770	1696	82
GM0203	Barneveld	0.872140	61655	351	14
GM0209	Beuningen	0.657038	26573	609	10
GM0213	Brummen	1.052738	21105	252	7
GM0214	Buren	0.525898	27725	208	4
GM0216	Culemborg	0.886041	29729	1016	14
GM0221	Doesburg	0.460815	11081	959	3
GM0222	Doetinchem	1.398173	59195	749	22
GM0225	Druten	0.454473	19505	520	2
GM0226	Duiven	0.568053	24937	736	6
GM0228	Ede	1.453512	122012	384	45
GM0230	Elburg	0.235349	24037	377	2
GM0232	Epe	0.407193	33283	213	6
GM0233	Ermelo	1.432606	27496	321	9
GM0243	Harderwijk	1.515566	48906	1256	19
GM0244	Hattem	1.308292	12563	545	1
GM0246	Heerde	0.867346	19214	245	7
GM0252	Heumen	0.914130	16824	423	10
GM0262	Lochem	1.259614	34314	161	18
GM0263	Maasdriel	0.420323	26020	395	2
GM0267	Nijkerk	0.880798	44975	649	9
GM0268	Nijmegen	1.844407	182480	3456	125
GM0269	Oldebroek	0.646108	24264	248	6
GM0273	Putten	0.873635	24904	292	5
GM0274	Renkum	1.705639	31461	685	25
GM0275	Rheden	1.161662	43570	533	15
GM0277	Rozendaal	1.493455	1754	63	0
GM0279	Scherpenzeel	0.788264	10386	753	2
GM0281	Tiel	1.834186	42604	1299	11
GM0285	Voorst	0.880193	25215	205	7
GM0289	Wageningen	1.494009	40960	1347	14
GM0293	Westervoort	0.765906	15114	2155	1
GM0294	Winterswijk	0.948883	29253	212	5
GM0296	Wijchen	0.521459	41537	629	19
GM0297	Zaltbommel	0.539951	30349	386	10
GM0299	Zevenaar	0.614603	45042	486	7
GM0301	Zutphen	2.362252	48510	1186	33
GM0302	Nunspeet	0.743261	28731	223	4
GM0303	Dronten	0.456426	43593	131	4
GM0307	Amersfoort	1.755350	160759	2572	94
GM0308	Baarn	0.946602	25008	769	5
GM0310	De Bilt	1.871486	43884	663	32
GM0312	Bunnik	0.879887	16026	434	3
GM0313	Bunschoten	0.452706	22500	740	4
GM0317	Eemnes	0.761419	9598	309	2
GM0321	Houten	0.820334	50581	921	27
GM0327	Leusden	1.092652	31467	538	12
GM0331	Lopik	0.284362	14704	195	2

GM0335	Montfoort	1.022498	13929	371	3
GM0339	Renswoude	0.973973	5747	313	0
GM0340	Rhenen	0.825253	20329	484	1
GM0342	Soest	1.014832	47439	1026	17
GM0344	Utrecht	1.707663	367947	3924	237
GM0345	Veenendaal	1.372433	68525	3528	20
GM0351	Woudenberg	0.638335	14358	393	3
GM0352	Wijk bij Duurstede	0.633592	23995	504	4
GM0353	IJsselstein	0.541321	33492	1594	6
GM0355	Zeist	1.986355	66629	1374	64
GM0356	Nieuwegein	1.047534	65426	2794	20
GM0358	Aalsmeer	0.339559	33063	1645	5
GM0361	Alkmaar	0.894967	111834	1014	48
GM0362	Amstelveen	0.682384	94418	2297	41
GM0363	Amsterdam	1.246067	918117	4880	518
GM0373	Bergen (NH.)	0.448439	30138	304	13
GM0375	Beverwijk	0.574229	42711	2327	4
GM0376	Blaricum	0.822768	12490	1128	1
GM0377	Bloemendaal	0.913000	23922	602	23
GM0383	Castricum	0.983127	36345	732	16
GM0384	Diemen	0.952180	32785	2744	12
GM0385	Edam-Volendam	0.262570	36760	677	5
GM0388	Enkhuizen	0.290541	18885	1491	2
GM0392	Haarlem	1.381746	165396	5662	86
GM0394	Haarlemmermeer	0.579335	162300	823	32
GM0396	Heemskerk	0.581135	39431	1446	4
GM0397	Heemstede	1.288958	27778	3029	17
GM0399	Heiloo	0.996580	24319	1300	11
GM0400	Den Helder	0.926737	56539	1254	11
GM0402	Hilversum	1.512701	93327	2046	47
GM0405	Hoorn	0.742881	75216	3692	19
GM0406	Huizen	0.631306	41252	2609	10
GM0415	Landsmeer	0.456192	11705	522	2
GM0417	Laren	1.274623	11712	944	8
GM0420	Medemblik	0.252862	46031	380	4
GM0431	Oostzaan	0.620876	9720	841	2
GM0432	Opmeer	0.102664	12180	294	1
GM0437	Ouder-Amstel	0.790810	14276	596	3
GM0439	Purmerend	0.680473	93992	1004	14
GM0441	Schagen	0.405210	47450	282	9
GM0448	Texel	0.512558	13979	86	7
GM0450	Uitgeest	0.663768	13472	703	2
GM0451	Uithoorn	0.376443	31442	1735	5
GM0453	Velsen	0.522540	68790	1528	13
GM0473	Zandvoort	0.512682	17542	547	2
GM0479	Zaanstad	0.541081	159618	2165	34
GM0482	Alblasserdam	0.547056	20356	2320	1
GM0484	Alphen aan den Rijn	0.439757	114182	907	21

GM0489	Barendrecht	0.514749	48812	2493	6
GM0498	Drechterland	0.219951	20385	346	2
GM0502	Capelle aan den IJssel	0.730481	67552	4777	22
GM0503	Delft	0.570608	106086	4681	30
GM0505	Dordrecht	1.408698	121434	1566	36
GM0512	Gorinchem	1.167483	38461	2055	14
GM0513	Gouda	1.619368	75316	4565	30
GM0518	's-Gravenhage	1.654633	562839	6827	205
GM0523	Hardinxveld-Giessendam	0.441807	18681	1108	0
GM0531	Hendrik-Ido-Ambacht	0.785497	32183	3159	7
GM0532	Stede Broec	0.216888	22138	1529	2
GM0534	Hillegom	0.317519	22453	1747	1
GM0537	Katwijk	0.875618	66607	2685	13
GM0542	Krimpen aan den IJssel	0.320349	29504	3845	3
GM0546	Leiden	1.581330	127089	5816	80
GM0547	Leiderdorp	1.082312	27657	2406	7
GM0553	Lisse	0.306896	23390	1490	4
GM0556	Maassluis	0.288040	35303	4180	6
GM0569	Nieuwkoop	0.110372	29463	375	3
GM0575	Noordwijk	0.379053	45179	774	13
GM0579	Oegstgeest	1.405258	25746	3530	17
GM0589	Oudewater	0.271975	10232	263	2
GM0590	Papendrecht	1.014274	32277	3428	5
GM0597	Ridderkerk	0.491576	47477	2022	6
GM0599	Rotterdam	0.872154	663900	3040	175
GM0603	Rijswijk	0.862082	57997	4150	12
GM0606	Schiedam	0.501488	80628	4528	13
GM0610	Sliedrecht	0.788447	26184	2038	4
GM0613	Albrandswaard	0.524839	26357	1217	4
GM0622	Vlaardingen	0.429866	75079	3214	10
GM0626	Voorschoten	0.919204	25665	2309	13
GM0627	Waddinxveen	0.485061	32601	1175	2
GM0629	Wassenaar	0.621982	27093	529	10
GM0632	Woerden	1.660915	53244	601	25
GM0637	Zoetermeer	0.618564	126998	3689	24
GM0638	Zoeterwoude	0.710977	9443	446	2
GM0642	Zwijndrecht	0.911494	45018	2217	5
GM0654	Borsele	0.867113	23159	164	1
GM0664	Goes	3.139704	39433	426	23
GM0668	West Maas en Waal	0.353085	20065	263	2
GM0677	Hulst	0.668771	27596	137	3
GM0678	Kapelle	1.826412	13051	351	1
GM0687	Middelburg	1.013066	49956	1033	15
GM0703	Reimerswaal	0.315960	23255	229	2
GM0715	Terneuzen	1.241072	54993	220	12
GM0716	Tholen	0.510670	26825	183	5
GM0717	Veere	0.213774	22045	166	1
GM0718	Vlissingen	0.686805	45150	1314	5

GM0736	De Ronde Venen	0.399342	45572	457	13
GM0737	Tytsjerksteradiel	0.106610	32408	218	2
GM0743	Asten	0.632037	17242	246	5
GM0744	Baarle-Nassau	0.103142	7071	93	1
GM0748	Bergen op Zoom	1.345139	68864	861	18
GM0753	Best	0.267945	30897	912	5
GM0755	Boekel	0.966630	11163	324	4
GM0757	Boxtel	0.324224	33748	489	3
GM0758	Breda	1.326396	186438	1483	82
GM0762	Deurne	0.460390	32977	282	5
GM0765	Pekela	1.070210	12404	253	1
GM0766	Dongen	0.428426	27200	930	6
GM0770	Eersel	0.176256	20004	243	6
GM0772	Eindhoven	0.861598	243730	2769	70
GM0777	Etten-Leur	0.456758	44578	806	5
GM0779	Geertruidenberg	0.473592	22099	831	2
GM0784	Gilze en Rijen	0.513148	26815	410	6
GM0785	Goirle	0.884325	24177	563	8
GM0794	Helmond	0.875123	94898	1785	24
GM0796	's-Hertogenbosch	1.167796	158753	1450	58
GM0797	Heusden	0.712034	45830	581	10
GM0798	Hilvarenbeek	0.280880	15949	168	5
GM0809	Loon op Zand	0.415210	23797	477	3
GM0820	Nuenen en Nederwetten	0.484731	24015	714	6
GM0823	Oirschot	0.120222	19217	189	3
GM0824	Oisterwijk	0.209466	32941	411	7
GM0826	Oosterhout	0.855580	57425	804	17
GM0828	Oss	0.709651	94437	583	25
GM0840	Rucphen	0.170095	23636	367	2
GM0845	Sint-Michielsgestel	0.653648	30135	516	10
GM0847	Someren	0.511081	20061	250	1
GM0848	Son en Breugel	0.168621	18010	694	2
GM0851	Steenbergen	0.127930	24610	168	1
GM0852	Waterland	0.261276	17609	339	11
GM0855	Tilburg	0.918634	227707	1809	70
GM0858	Valkenswaard	0.376709	31527	574	6
GM0861	Veldhoven	0.611707	46417	1465	8
GM0865	Vught	0.967203	32113	535	17
GM0866	Waalre	0.644495	17980	803	10
GM0867	Waalwijk	0.591927	49952	774	10
GM0873	Woensdrecht	0.277917	22191	242	1
GM0879	Zundert	0.047336	22518	187	0
GM0880	Wormerland	0.305602	16612	431	2
GM0882	Landgraaf	0.833790	37175	1512	3
GM0888	Beek	0.602467	16132	766	3
GM0889	Beesel	0.672855	13449	482	3
GM0893	Bergen (L.)	0.740967	13119	127	3
GM0899	Brunssum	0.520986	27682	1606	4

GM0907	Gennep	0.387858	17764	373	3
GM0917	Heerlen	1.094510	87122	1940	28
GM0928	Kerkrade	0.855826	45620	2082	13
GM0935	Maastricht	1.246408	122734	2200	60
GM0938	Meerssen	0.664101	18600	696	8
GM0944	Mook en Middelaar	0.493560	8043	463	3
GM0946	Nederweert	0.634327	17499	175	2
GM0957	Roermond	1.352203	59981	989	22
GM0965	Simpelveld	0.787245	10396	649	0
GM0971	Stein	0.526472	24772	1184	5
GM0981	Vaals	1.564092	10190	427	3
GM0983	Venlo	0.973494	103328	832	32
GM0984	Venray	3.115652	44628	273	22
GM0986	Voerendaal	0.980276	12405	394	6
GM0988	Weert	1.249349	50872	488	14
GM0994	Valkenburg aan de Geul	0.837567	16423	447	6
GM0995	Lelystad	0.872439	83033	363	11
GM1507	Horst aan de Maas	0.606712	43641	231	7
GM1509	Oude IJsselstreek	0.518491	39613	291	6
GM1525	Teylingen	0.603511	38510	1360	9
GM1581	Utrechtse Heuvelrug	0.725137	50429	382	18
GM1586	Oost Gelre	0.761028	29846	271	9
GM1598	Koggenland	0.259278	23509	293	1
GM1621	Lansingerland	0.294801	64754	1216	9
GM1640	Leudal	0.457859	36141	222	7
GM1641	Maasgouw	1.069276	24305	532	8
GM1652	Gemert-Bakel	0.808106	31383	257	8
GM1655	Halderberge	0.189585	31041	417	7
GM1658	Heeze-Leende	0.170303	16627	160	3
GM1659	Laarbeek	0.407723	23260	420	3
GM1667	Reusel-De Mierden	0.111492	13542	174	3
GM1669	Roerdalen	0.453550	20702	235	6
GM1674	Roosendaal	0.426856	77613	729	12
GM1676	Schouwen-Duiveland	0.663490	34561	151	8
GM1680	Aa en Hunze	0.921759	25724	93	11
GM1681	Borger-Odoorn	0.754697	25919	94	4
GM1690	De Wolden	0.463861	24602	110	9
GM1695	Noord-Beveland	0.025447	7857	91	0
GM1696	Wijdemeren	0.427784	24659	519	2
GM1699	Noordenveld	0.934751	31591	159	12
GM1700	Twenterand	0.325684	33867	319	6
GM1701	Westerveld	0.499704	19860	71	5
GM1705	Lingewaard	0.729558	47220	762	13
GM1706	Cranendonck	0.270049	20851	273	5
GM1708	Steenwijkerland	0.866241	45376	157	7
GM1709	Moerdijk	0.224966	37711	237	8
GM1711	Echt-Susteren	0.788101	31967	310	8
GM1714	Sluis	0.791968	23243	83	5

GM1719	Drimmelen	0.419233	27994	295	9
GM1721	Bernheze	0.441333	32263	360	1
GM1723	Alphen-Chaam	0.103703	10463	113	2
GM1724	Bergeijk	0.107142	19092	189	2
GM1728	Bladel	0.095308	21009	279	1
GM1729	Gulpen-Wittem	1.227536	14210	194	8
GM1730	Tynaarlo	2.386365	34592	242	24
GM1731	Midden-Drenthe	0.887382	33987	100	6
GM1734	Overbetuwe	0.650621	48707	447	12
GM1735	Hof van Twente	0.240236	35455	167	5
GM1740	Neder-Betuwe	0.686027	25448	424	5
GM1742	Rijssen-Holten	0.673196	38493	409	5
GM1771	Geldrop-Mierlo	0.395135	40441	1304	7
GM1773	Olst-Wijhe	0.445972	18682	164	4
GM1774	Dinkelland	0.207129	26743	152	4
GM1783	Westland	0.504096	114887	1423	15
GM1842	Midden-Delfland	0.315073	19472	413	2
GM1859	Berkelland	0.630253	44022	171	7
GM1876	Bronckhorst	0.620402	36277	128	11
GM1883	Sittard-Geleen	1.042129	92234	1173	40
GM1884	Kaag en Braassem	0.147190	28573	453	2
GM1891	Dantumadiel	0.842285	19194	227	2
GM1892	Zuidplas	0.466500	46981	811	4
GM1894	Peel en Maas	0.340594	45276	284	5
GM1895	Oldambt	1.515805	39044	172	8
GM1896	Zwartewaterland	0.359449	23368	284	1
GM1900	Súdwest-Fryslân	0.836815	90883	174	14
GM1901	Bodegraven-Reeuwijk	0.523401	36308	482	1
GM1903	Eijsden-Margraten	0.805292	25991	335	12
GM1904	Stichtse Vecht	0.358582	65771	685	20
GM1911	Hollands Kroon	0.129398	49431	138	4
GM1916	Leidschendam-Voorburg	0.843211	77753	2384	28
GM1924	Goeree-Overflakkee	1.071867	51590	197	9
GM1926	Pijnacker-Nootdorp	0.395682	57672	1564	6
GM1930	Nissewaard	0.576003	86833	1184	9
GM1931	Krimpenerwaard	0.393115	57700	389	9
GM1940	De Fryske Marren	0.619436	51992	148	7
GM1942	Gooise Meren	0.945107	60359	1457	31
GM1945	Berg en Dal	1.081078	35420	410	12
GM1948	Meierijstad	0.448618	83715	455	20
GM1949	Waadhoeke	0.395491	46718	164	5
GM1950	Westerwolde	0.272500	26537	96	4
GM1952	Midden-Groningen	1.078922	61554	221	13
GM1954	Beekdaelen	0.575738	35966	459	8
GM1955	Montferland	0.557356	36882	349	7
GM1959	Altena	0.423700	57726	289	7
GM1960	West Betuwe	0.323595	52720	244	7
GM1961	Vijfheerenlanden	0.438469	60052	411	6

GM1963	Hoeksche Waard	0.299602	89760	334	8
GM1966	Het Hogeland	0.751215	48298	101	16
GM1969	Westerkwartier	0.454219	64946	179	12
GM1970	Noardeast-Fryslân	0.640391	45812	121	7
GM1978	Molenlanden	0.265393	45158	249	4
GM1979	Eemsdelta	0.687828	45394	169	4
GM1980	Dijk en Waard	0.659310	88985	1438	21
GM1982	Land van Cuijk	0.772675	91423	268	21
GM1991	Maashorst	0.582532	58934	429	16
GM1992	Voorne aan Zee	0.851645	73945	607	9

8.5 Distribution of Observations Statistical Analysis

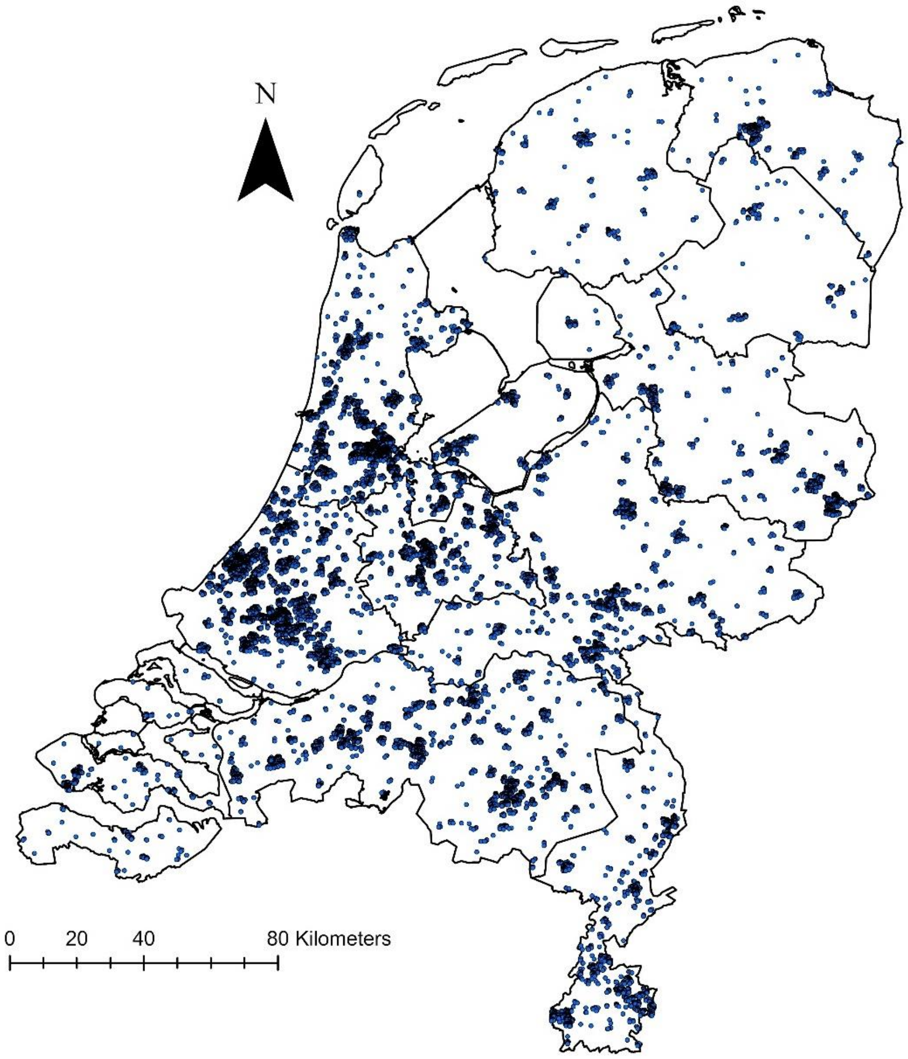

Figure 8.6 Distribution of the observations used in in the statistical analysis (N = 23,381).