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Optimising locations for future return carsharing services: case study of the Swiss carsharing cooperative Mobility

GEO 511 Master's Thesis

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Abstract

As carsharing services are a relatively new mobility mode, most operators tend to establish stations in any available location or based on experience, especially in the beginning, as they do not possess the necessary means or power to impose themselves. In order to expand and increase their attractiveness and accessibility, carsharing services have to develop a strategy to implement when choosing locations for future stations. Recent literature on optimising carsharing networks tends to concentrate on the new driving modes developed, one-way and free-floating, even if the round-trip driving mode and the interactions it has are not yet completely understood. The present project is a case study of the carsharing operator Mobility in Switzerland that aimed to identify the factors that drive carsharing performance and discover new locations for future return carsharing stations. Significant carsharing drivers were selected by using multiple regression models. A multi-criteria decision analysis was then carried out to integrate the significant factors, and suitable locations for future stations were established. The analytical hierarchical process was used to weigh the importance of the factors. Subsequently, areas of interest for new carsharing stations were proposed by allocating demand to suitable locations through location-allocation models. The research findings showed that the success of carsharing stations is driven by different factors depending on the level of urbanisation of their location. The presence of existing members and shopping centres, as well as the station being close to a train station, were among the most important factors identified. Although urban areas had larger concentrations of high suitability scores, the study revealed that suburban and rural areas also exhibit moderate to high suitability scores for carsharing. Thus, when allocating demand, the model suggests that carsharing operators should concentrate on suburban and rural areas where the network is scarce, and the demand is not met. Despite from being highly suitable, urban areas had a considerable number of already existing stations that covered the demand. The present work can serve as a base for carsharing operators to build or expand their network while minimising the risk of placing stations with low operational efficiency.

Keywords: carsharing utilisation drivers, return driving mode, multi-criteria decision analysis, location-allocation models, Geographic Information Systems

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Abbreviations

AHP	Analytical Hierarchical Process
AIC	Akaike Information Criteria
CI	Consistency Index
CR	Consistency Ratio
FLP	Facility Location Problem
GHG	Greenhouse gas
GIS	Geographic Information System
OSM	OpenStreetMap
MCDA	Multi-Criteria Decision Analysis
POI	Point of Interest
SAW	Simple Additive Weighting
SBB	Schweizerische Bundesbahnen
VKT	Vehicle kilometres travelled

1. Introduction

1.1 Background and Motivation

In the last couple of years, traffic volumes have become a great disruptor for people living in urban agglomerations. Poorly designed infrastructure, together with inefficient public transport systems and the increased attractiveness and accessibility towards private vehicle ownership have critical implications, such as atmospheric and noise pollution, traffic congestion and excessive occupation of public land by cars. In Europe, transport is accountable for 27% of the total greenhouse gas emissions, 72% of which comes from road transportation (European Environment Agency, 2019). Moreover, private vehicles are responsible for as much as 44% of the total greenhouse gas emissions from the road transport (European Environment Agency, 2019). Considering a different perspective, in the most congested cities globally, a person can lose up to 130 hours per year waiting in traffic (INRIX, 2020). Although specialists and policymakers have thoroughly discussed these impacts, unfortunately, the solutions implemented to reverse these trends have had no significant impact so far.

Altering or building new infrastructure to accommodate the high number of vehicles on the road can be very time-consuming, requires an abundance of resources and some cities cannot sustain a change like this. For example, old historical cities that have crowded city centres with narrow and complex road networks cannot be adapted to the increasing volume of traffic, nor are they suitable for it. Private vehicles are the leading actor when it comes to traffic congestion, parking pressure and pollution. The principal asset of a private car is that it is always available, does not need any scheduling, personal belongings can be stored inside and can be used to transport goods (Neumann, 2021). Unlike public transport, where station locations, pre-settled routes and timetables constrain people, a private vehicle gives individuals all the freedom one could want. Seeking an alternative sustainable mobility solution (Baptista et al., 2014) and wishing to preserve part of the freedom offered by a private vehicle gave rise to the idea of carsharing.

The concept behind carsharing is that multiple users can share between themselves a fleet of cars. As opposed to car rental, carsharing has the advantage of being more flexible, more straightforward, and for short periods of time, often being charged by the hour and by kilometre. There are two different types of carsharing (Figure 1.1): business-to-peer or peer-to-peer. Business-to-peer carsharing means that an organisation has a fleet of cars and makes them available for customers. It can have three different driving types: *return, one-way* and *free-floating*. Return and one-way are station-based driving modes where the customer must either return the car to its original station or drive it to a station of their choosing. For the free-floating driving mode cars can be picked up and dropped off at arbitrary locations in a designated area. For peer-to-peer carsharing, there exist platforms (such as Turo or Getaround) where individuals can advertise their personal car for other people to reserve and drive, without involving an organisation.

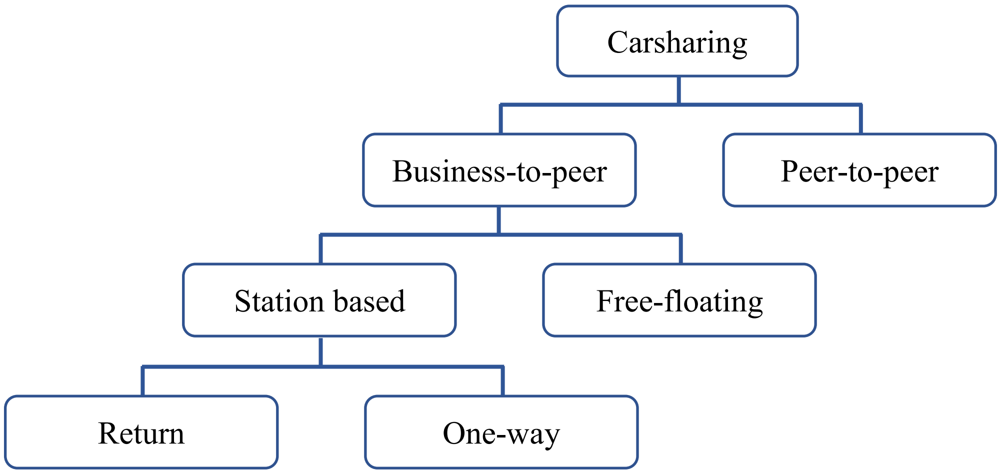

Figure 1.1: Classification of carsharing driving modes.

Carsharing helps the environment by lowering greenhouse gas (GHG) emissions produced by road transportation sector, through minimising the number of vehicle kilometres travelled (VKT) and by removing vehicles off the road. A study made by Nijland and van Meerkerk (2017) in the Netherlands shows that carsharing members are responsible for around 240-390 fewer kilograms of CO_2 emitted per person per year. Another study by Martin and Shaheen (2011), done in North America, finds a reduction of 580 kg GHG per year and household. Moreover, the vehicles that operators have in their fleet are newer vehicles with better technology than the average private cars on the road and thus, they consume less fuel (Martin and Shaheen, 2011). After joining a carsharing programme, different case studies have shown that a share of customers gets rid of their cars: ranging between 10% and 29% (Katzev, 2003; Lane, 2005; Millard-Ball et al., 2005; Cervero et al., 2007); with an even more significant proportion forgoing buying a new car due to carsharing (Katzev, 2003; Millard-Ball et al., 2005; Nijland and van Meerkerk, 2017). In terms of VKT, because driving a shared vehicle requires reservation and planning, customers are more inclined to drive only when it is necessary, thus reducing its percentage by 20-25% per year (Martin and Shaheen, 2011; Nijland and van Meerkerk, 2017).

One should also consider the emissions and VKT added through carsharing by people who do not own a vehicle. However, since carsharing removes vehicles from the roads, the emissions and VKT reductions counterbalance the increase by people who would typically not have access to a car (Martin and Shaheen, 2011). Cohen et al. (2008) state that in North America, each carsharing vehicle removes an average of 15 privately owned cars from the community. In addition, a study done in Europe reveals that, on average, a carsharing vehicle replaces four to eight private cars (Loose, 2010).

Besides environmental benefits, carsharing also has social, economic and health impacts. Firstly, it helps increase equitable access to vehicles for people who cannot afford a car of their own (Litman, 2000). Secondly, it helps people save money by not supporting the fixed and maintenance costs associated with a private vehicle (Litman, 2000; Lane, 2005). Lastly, carsharing increases physical activity by making customers integrate other active mobility modes, such as walking and biking, which in turn leads to less pollution and thus less impact on their respiratory and cardiovascular systems (Kent, 2014).

1.2 Mobility Cooperative

The Mobility Cooperative (short: Mobility) is the largest business-to-peer carsharing scheme in Switzerland, with 1'530 stations throughout the country and 3'120 vehicles available for any occasion. In terms of spatial coverage, Mobility is present in 100% of the Swiss municipalities with a population over 10'000 (Mobility Cooperative, 2019). Each Mobility car replaces at least 11 privately owned vehicles, and the fleet consumes on average 20% less fuel than all the new vehicles sold in Switzerland (Mobility Cooperative, 2019). Thus, Mobility saves 31'000 tonnes of CO_2 each year and keeps free 54'000 parking spaces (Mobility Cooperative, 2019). Mobility customers manage to save more than 4'000 CHF/year because they are carsharing, compared to privately owned cars (Mobility Cooperative, 2019). The renting process is easy, fast, entirely online, and tailored to one's needs using their app or online portal. The cooperative offers the following driving modes: return and one-way. The one-way driving mode is limited to specific stations, meaning not all stations offer this option, but all stations offer the return driving mode. Having a highly developed market that can provide many insights for carsharing expansion, Mobility Cooperative makes the perfect study case for this project and a strong advantage to test the feasibility of the work.

1.3 Aim of this Thesis

Although Mobility Cooperative has a strong presence in Switzerland, their distribution of carsharing stations appears like the network was developed in a rather opportunistic way, that is, there are a lot of stations present in dense urban agglomerations and very few stations in smaller municipalities (Figure 1.2). Therefore, they are present but maybe not sufficient. Naturally, Mobility aims to expand and reach more people, but this requires, besides market knowledge and instinct, a strategy. Finding the best locations to place carsharing stations depends on different combinations of various parameters such as the socio-economic parameters for a specific area, accessibility to public transport and available space for a station. Hence, this study will seek to propose optimal locations for future return stations based on a modelled demand and a combination of key features that a successful station should have. This project aims to look at the already existing Mobility stations, highlight the factors that make a station successful, and search for new places within Switzerland with the same characteristics to expand the network and place new stations. The focus of this master's thesis will be on the return driving mode and the stations that offer this service, as this is the widest and most developed service Mobility offers.

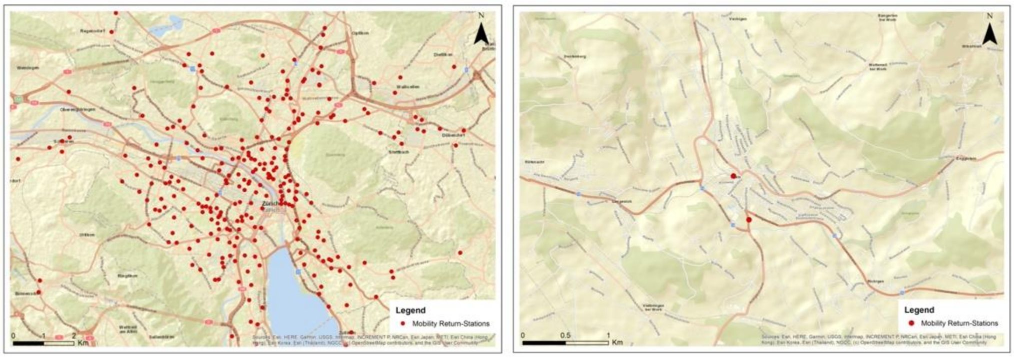

Figure 1.2: Difference in return carsharing stations distribution between an urban area and a smaller municipality. In the map on the left there is the city of Zürich and on the right Worb municipality in canton Bern.

1.4 Structure of this Thesis

This work is structured as follows. Chapter 2 provides an overview of the related work, presenting important background information on supply network optimisation and facility location problems along with summarising the most important themes in the carsharing literature field. Additionally, studies regarding success factors of carsharing station locations are outlined and interesting findings along with suitable methods are highlighted. Chapter 3 presents the research questions and hypotheses of this project. In Chapter 4, the datasets used for the project along with their data sources will be discussed. Chapter 5 introduces and explains the different methods used to detect suitable locations for new carsharing stations, starting from the regression analysis to the multi-criteria analysis and, lastly, the location-allocation models. The results of these three individual methodological parts, as well as the final optimal locations found, are presented in Chapter 6. Chapter 7 puts the findings into perspective, discussing the results with respect to the research questions and hypotheses. Furthermore, possible points for improvements are discussed. Finally, the most important results and findings are highlighted in Chapter 8, together with the limitations of this study and ideas for future work.

2. Background and Related Research

Within this chapter, a broad overview of the state of the art about research in carsharing is given. First, basic principles of supply optimisation and facility location problems are introduced (Section 2.1). Subsequently, a closer look will be taken at carsharing research (Section 2.2) and studies on optimising carsharing networks will be presented, along with the methods used (Section 2.3). Furthermore, socio-demographic and built environment factors that drive carsharing utilisation will be introduced (Section 2.4). Lastly, the research gaps that this study aims to fill will be presented (Section 2.5).

2.1 Background

2.1.1 Supply Optimisation

In today's world, the service industry is a crucial player for the economy, contributing more to the GDP than the manufacturing industries (Baltacioglu et al., 2007). For example, buying a car refers to the manufacturing industries, while using carsharing, the service to drive a car, refers to the service industry. Within this setting, supply and demand are the two forces that are driving the economy. Demand is the need customers have for a good or service. Supply is the total amount of a goods or services made available for customers. Having a higher demand than supply leads to a shortage of that good or service, while the opposite leads to a surplus. An equilibrium point, where the two are balanced, is desired but hard to attain as these entities dynamically change all the time, and with respect to them, so does the equilibrium point. Nonetheless, adjusting the supply according to the demand is very important for a successful business.

A supply chain consists of the route from the earliest developments to the end-user that goods and services need to take (Papageorgiou, 2009). Managing correctly and efficient the supply chain is very important to businesses as it can help them attain certain advantages such as reduced costs or improved service quality (Baltacioglu et al., 2007). If a business does not give enough attention to its supply chain, this can result in a multitude of problems that ultimately would affect the delivery of goods or services to the customers. Supply chain optimisation focuses on the changes needed in the design phase of an existing chain that improve its performance (Papageorgiou, 2009). Examples of these adjustments can be where to locate the warehouses, where and how to adjust the stock or personnel taking into consideration the demand and how to minimise operation costs. Melo et al., (2009) conclude in their review that *facility location* is a decisive characteristic in the supply chain network.

2.1.2 Facility Location

Location modelling is a field addressed by operations research, concerned with searching for the best location for any type of facility, such as public buildings, retail stores, hospitals, bus stops, carsharing stations, power plants, and more. Depending on the application for which location modelling is used or the goal set, there are different variables that can be taken into consideration when wanting to find optimal locations for new facilities, such as cost, service area or market coverage (Bowling et al., 2011).

Needing to place a set of facilities in order to serve a set of customers is a problem studied extensively in the literature and is commonly referred to as the facility location problem (FLP) (Melo et al., 2009). Three components define facility location problems: customers, facilities that need to be located, and the distance, time or cost between the customers and the facilities. Facility location problems can be very different based on what distance function is applied between customers and the facilities that need to be located, based on the number of facilities that need to be located and if the capacity of the facilities is taken into consideration and, based on the objective of the problem, if the facilities need to be reached by the customers or if the customers need to be reached from the facility (Farahani and Hekmatfar, 2009). Therefore, the resulting location model depends on the different decisions made, the specific application for which it is used and the inclusion or not of specific indices (Farahani and Hekmatfar, 2009).

Almost all location models can be categorised into four general classes (Figure 2.1): median, covering, capacitated, or competitive (Church, 1999). The median models aim to minimise the total cost between demand points and the facilities to which they are assigned to (Church, 1999). In the covering models, each facility has a pre-determined catchment area, and so the facilities must be placed such that the catchment area covers all or most of the demand (Church, 1999). When the capacity of each potential facility is considered (i.e., the maximum demand it can supply) the problem is called the capacitated facility location problem. Otherwise, if the capacity is not of importance, we have the simple or the uncapacitated facility location problem. As markets and businesses evolve, more complex models are being developed, such as the competitive facility location problem, where competition and interaction between the businesses is considered when placing new facilities (Church, 1999; Aboolian et al., 2007). Moreover, other models that, for example, place facilities away from demand nodes (i.e., prisons, power plants, solid waste facilities) have been developed (Current et al., 2002).

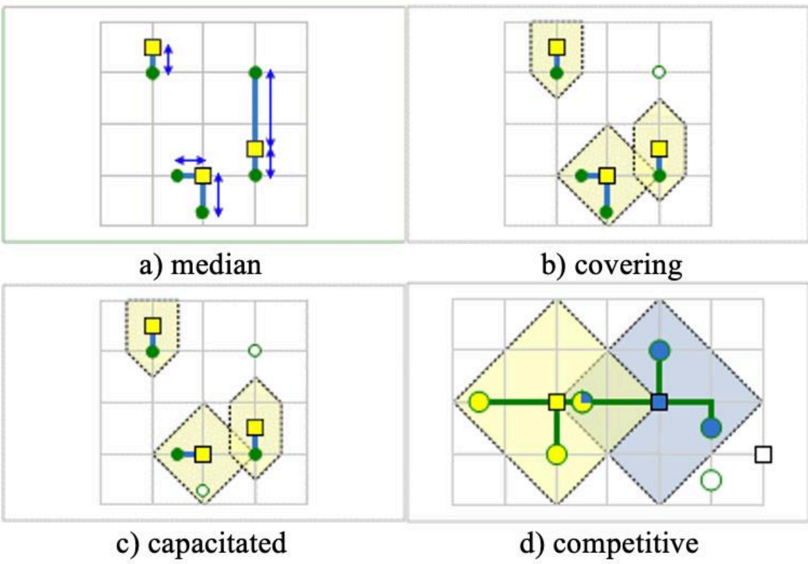

Figure 2.1: Representation of the four general facility location problems with a) median class, b) covering class, c) capacitated class and d) competitive class. The squares represent the facilities to which demand is allocated. The circles represent the demand points that need to be allocated to a facility, having the filled circles as demand points that were allocated to a facility and the hollow circles demand points that were not allocated to a facility. A line from a demand point to a facility means that the demand point was allocated to that facility. The yellow area around the facilities symbolises the service area of the facility and means that only demand points inside the service area can be served by that facility. For the fourth picture, lower right corner, the two different colours represent two facilities from different competitors. (from ESRI, 2020a).

The applications of facility location models are vast and can be found in a variety of industries. One example is the healthcare industry, where these models help place hospitals in optimal locations such that the whole population is within a reasonable distance from at least one facility (Ahmadi-Javid et al., 2017). The same principle can be applied to emergency services like fire stations (Tali et al., 2017). Furthermore, facility location models can also be used for placing food delivery restaurants that have a fixed coverage area and need to cover as much demand as possible in their catchment (Current et al., 2002) or placing warehouses for a distribution business such that the average travel time is minimised (Jayaraman, 1998). Other examples can include placing bus stops, retail stores, public buildings, power plants, or waste management sites (Current et al., 2002; Erkut et al., 2008; Serra and Marianov, 2011; Delmelle et al., 2012).

Geographic Information Systems (GIS) play an essential role in location modelling and solving the FLP by aiding with data structure and integration, aggregation, analysis, and visualisation (Church, 1999). Due to the multiple criteria that need to be integrated and different decisions that need to be taken when solving a FLP, this problem is often considered a multiple-criteria decision problem (Bowling et al., 2011). Thus, location-allocation models and multi-criteria decision analysis (MCDA) are two of the methods that have been extensively used in site selection for facility planning. With the help of MCDA, possible facility locations that satisfy a given set of spatially explicit criteria can be found. However, this method does not actually place the facilities, nor does it consider the travel distance or time from demand locations to supply locations. Location-allocation models allocate demand locations to supply locations, based on the facility location problem that needs to be solved, and do take into account the travel component between locations, thus finding optimal locations for facilities. Hence, MCDA can be used to reduce the possible search space of the facility placement and determine candidate locations for location-allocation models.

GIS applications are well documented in areas of literature such as site selection for hospitals, fire stations, retail stores, and public facilities planning (Goodchild, 1984; Yeh and Chow, 1996; Vahidnia et al., 2009; Gorsevski et al., 2012; Dehe and Bamford, 2015). For instance, Rikalovic et al. (2014) developed a decision-making process that combines GIS and MCDA for industrial site selection. Their process consists of 10 steps that generate and assess alternatives to find the optimal locations and assure the success of the industrial system. The result they generate is a suitability map of recommended sites and a list of sites ranked according to their scores. Based on these, a decision can be made as to where to place the industrial site. Alternatively, Zhao et al. (2017) use location-allocation models to plan a network of emergency shelters for urban disaster resilience, with the goal of minimising the total evacuation distance. In their method, they assume that the population of a given community is concentrated at its central point and take that as the demand points for the analysis. Moreover, they define a maximum distance between each community and its assigned shelter, as the shelters need to be able to be reached in a short time, and also define a shelter's maximum capacity, to avoid crowded and unsuitable shelters. Similarly, Uddin and Warnitchai (2020) and Tali et al. (2020) are both optimising fire station networks through the use of GIS and location-allocation models. Moreover, Uddin and Warnitchai (2020) combine these methods with MCDA too. In their study, they first selected the criteria based on literature and experts' opinions. Then they integrated all constraints in order to find available spaces for development. The optimal locations were selected based on site suitability for construction of new fire stations criteria, fire protection assessment criteria and existing demand in the service area. Sánchez-Lozano et al. (2013) combine GIS and MCDA to find the optimal placement for solar power plants in southeast Spain. According to them, this combination of tools is beneficial for cases involving different types of criteria, such as restrictive criteria and criteria that need to be weighted based on their importance to the goal.

2.2 Carsharing Research

The field of carsharing research is in continuous development and change as it is a relatively novel idea. There are three main groups in which the existing research in this field can be categorised: (1) demand and supply analyses; (2) impact of carsharing; and (3) service optimisation. The first category focuses on building profiles of the existing carsharing customers (Becker et al., 2016; Luan et al., 2018), identifying potential demand based on those profiles (Ciari et al., 2016; Juschten et al., 2019), analysing the relationships between supply and demand (Balac et al., 2015; Chen et al., 2018), and identifying factors that impact carsharing usage (Millard-Ball et al., 2005; Celsor and Millard-Ball, 2007; Stillwater et al., 2009; Kang et al., 2016; Tiejiao and Agrawal Weinstein, 2016; Willing et al., 2017). The second category examines the impacts carsharing has and their magnitude on users and the environment (Litman, 2000; Martin and Shaheen, 2011; Sioui et al., 2012; Baptista et al., 2014; Zhou et al., 2020; Roblek et al., 2021). Underlying themes of this category are studies on the changed travel behaviour of members; the consequences carsharing has on vehicle ownership, and vehicle kilometres travelled (VKT); studies on the environmental benefits, the degree of sustainability of carsharing and GHG emissions associated; and lastly, studies regarding the health and social impact of this travel mode. The third category concentrates on how carsharing networks can be made more efficient and optimal (Uesugi et al., 2007; Correia and Antunes, 2012; Kumar and Bierlaire, 2012; Gavalas et al., 2016; Cheng et al., 2019). The interest in this area increased recently as driving modes, such as one-way and free-floating were developed and gained popularity. New research topics, such as relocation algorithms to solve the supply and demand imbalance are the focus of these studies.

2.3 Optimisation of carsharing networks

The central argument as to why carsharing is important and feasible is that the number of cars required in order to satisfy the needs of a group of individuals is less than each individual having his own private vehicle (Kumar and Bierlaire, 2012). Therefore, through carsharing less vehicles can be used to accomplish the same number of tasks. In fact, individuals generally actively use their private cars for only a small portion of the day (Kumar and Bierlaire, 2012), thus, making sharing a single vehicle between several individuals with different schedules practical.

In order to convince the population that carsharing is a feasible alternative to private vehicle ownership, operators must highlight the advantages that this service has together with trying to attain the advantages that private vehicles have. Carsharing operators must adjust their supply networks to make sure the stations and vehicles are accessible for users. The two definitory aspects that can influence the attractiveness of carsharing systems are: (1) the location of stations and (2) the availability of vehicles at stations (Boyaci et al., 2015). Moreover, the supply of cars must be adjusted, taking into consideration demand. When analysing the demand for carsharing, besides taking into consideration the spatial and temporal distribution of the population, one has to also consider the purpose for which carsharing is used (Willing et al., 2017).

As the one-way and free-floating driving modes become more and more popular in the carsharing business, a vast portion of the literature concerning optimisation concentrates on these modes. The fact that the cars do not have to be returned at a specific location unfolds a number of problems, such as, having the supply unequally distributed because users shift vehicles in a certain area and operators do not have a good relocation strategy. Thus, predicting movement patterns to adjust the supply for each individual location, making sure no station is left too empty or too full, looking for the best locations for one-way stations and designated areas for free-floating vehicles are only just a couple of the main themes in carsharing studies (Correia and Antunes, 2012; Boyaci et al., 2015; Willing et al., 2017; Chen et al., 2018; Chen et al., 2019; Cheng et al., 2019).

The majority of the study cases aiming to optimise carsharing networks and propose future stations use different types of mathematical/statistical models and methods, such as multiple linear regression models, kernel density estimation, and generalised linear models (Kumar and Bierlaire, 2012; Willing et al., 2017; Chen et al., 2018; Cheng et al., 2019; Juschten et al., 2019). Besides these, Balac et al., (2015) use multi-agent simulation tools to investigate the relationship between the supply side on the demand side of carsharing in order to provide optimisation advice for the operators.

Some carsharing studies combine statistical methods with GIS in order to reach optimised networks. For example, Celsor and Millard-Ball (2007) use GIS to integrate different data sources and determine a set of characteristics that a neighbourhood needs to have so that carsharing is likely to flourish within it. They evaluate where carsharing works in terms of the demographic characteristics of the customers but also the characteristics of the neighbourhood as a whole. A similar case study using statistical analysis and spatial analysis was conducted by Stillwater et al. (2009) on return stations for a US carsharing operator. Their study is particularly interested in the relationship between the success of carsharing stations and built environment measures, including household density, sidewalk width, roads characteristics, and transit services, such as bus routes. Additionally, in order to help urban communities in California to identify new locations where carsharing will be successful, Tiejiao and Agrawal Weinstein (2016) built a GIS-based model that calculates a “carshare suitability score” for every neighbourhood within a city, taking into account both socio-demographic and urban form factors. de Oliveira Lage et al. (2019) use GIS to apply location-allocation models in order to determine the best place to settle carsharing stations in the City of Sao Paulo, Brazil.

Other vehicle sharing services

Apart from the literature on carsharing, studies regarding the analysis of bike sharing networks and stations are also worth mentioning. Similar to carsharing, researchers have developed methods to optimise bike sharing networks using GIS (Rybarczyk and Wu, 2010; Vogel et al., 2011; García-Palomares et al., 2012). García-Palomares et al. (2012), for example, use location-allocation models to determine optimal locations for bike-sharing programs and their capacity based on potential demand for trips. Likewise, Vogel et al. (2011) use geographical information technology and data mining methods to propose new station locations based on usage patterns of already existing stations and their locations. Although not for bike sharing but for bike infrastructure, Larsen et al. (2013) create a GIS-based grid-cell model that ranks all the cells in the study area, with high ranking cells being locations where new bicycle infrastructure is most needed.

2.4 Success Factors of Carsharing Station Locations

The location of carsharing stations is believed to have a considerable impact on their performance (Kumar and Bierlaire, 2012), and thus, it is important to understand and quantify what makes a location more successful. As mentioned before, a decent part of carsharing literature gives attention to the characteristics of the locations where service usage is high. By developing a list of such characteristics, locations where carsharing would presumably flourish can be found and thus networks can become more efficient and optimised.

The ‘attractiveness’ of different station locations is based on a combination of various criteria. There are two categories in which these criteria can fall: socio-demographic factors or built environment factors. Several studies have explored how these categories are correlated with carsharing usage. The next two subsections briefly summarise the findings regarding this correlation for each factor.

2.4.1 Socio-demographic factors

The literature has explored quite extensively how socio-demographic factors correlate with carsharing utilisation (Table 2.1).

Table 2.1: Socio-demographic factors linked with carsharing utilisation.

Factor	Literature
Age	*Millard-Ball et al. (2005);Ciari et al. (2016); Luan et al. (2018); Juschten et al. (2019)*
Income	*J Millard-Ball et al. (2005); Kumar and Bierlaire (2012); Luan et al. (2018); Juschten et al. (2019)*
Education	*Millard-Ball et al. (2005); Celsor and Millard-Ball (2007); Kumar and Bierlaire (2012); Luan et al. (2018); Juschten et al. (2019)*
Household Size	*Millard-Ball et al. (2005); Celsor and Millard-Ball (2007); Luan et al. (2018)*
Vehicle Ownership	*Millard-Ball et al. (2005); Celsor and Millard-Ball (2007); Stillwater et al. (2009); Luan et al. (2018); Juschten et al. (2019)*
Population Density	*Millard-Ball et al. (2005); Stillwater et al. (2009); Correia and Antunes (2012); Kumar and Bierlaire (2012)*
Gender	*Millard-Ball et al. (2005); Kumar and Bierlaire (2012); Luan et al. (2018)*
Public Transport Subscription Ownership	*Ciari et al. (2016); Juschten et al. (2019)*
Bike Ownership	*Juschten et al. (2019)*
Commute Mode	*Millard-Ball et al. (2005)*

Age

Although each study analysed and tested different age groups, almost all of them concluded that younger people are more likely to use carsharing services than older people (Millard-Ball et al., 2005; Ciari et al., 2016; Luan et al., 2018; Juschten et al., 2019;). The approximate range of 25-45 years old is found to correlate the strongest (Millard-Ball et al., 2005; Luan et al., 2018), having one study stating that the probability of using carsharing reaches maximum at the age of 35 years (Juschten et al., 2019) and another study stating that people under 30 years old and people above 60 years old are less likely to be carsharing members (Ciari et al., 2016).

Income

Many studies have concluded that carsharing users are typically from above-average income households (Millard-Ball et al., 2005; Kumar and Bierlaire, 2012; Luan et al., 2018; Juschten et al., 2019).

Level of Education

Surveying existing members of carsharing schemes, several studies have concluded that carsharing users generally have a form of higher education completed, having obtained a bachelor's degree or higher (Millard-Ball et al., 2005; Celsor and Millard-Ball, 2007; Kumar and Bierlaire, 2012; Luan et al., 2018; Juschten et al., 2019).

Even though these socio-demographic factors correlated strongly with carsharing usage, it must be taken into consideration that these characteristics cannot be extended to describe the neighbourhoods where carsharing is present (Millard-Ball et al., 2005). For example, in the study of Millard-Ball et al. (2005), 83% of the carsharing members surveyed had a Bachelor's or higher degree, but only 55% of residents living close to carsharing stations had a Bachelor's degree. This difference is a consequence of the small proportion of residents that participate in carsharing schemes, and thus being a small sample, it cannot be representative of the whole population (Millard-Ball et al., 2005).

Household Size

Several studies concluded that carsharing users typically come from small households (Millard-Ball et al., 2005; Celsor and Millard-Ball, 2007; Luan et al., 2018). The most common type of household amongst existing members is the one-person household (Millard-Ball et al., 2005). This is because, as the number of people in a household increases, the likelihood of being carsharing users decreases.

Vehicle Ownership

Vehicle ownership is one of the factors most strongly correlated with carsharing usage (Millard-Ball et al., 2005; Stillwater et al., 2009). Studies uniformly agreed that households/people with low vehicle ownership rates (zero or one vehicle) are more likely to use carsharing services (Millard-Ball et al., 2005; Celsor and Millard-Ball, 2007; Stillwater et al., 2009; Luan et al., 2018; Juschten et al., 2019). Although this makes sense because a person that already owns a vehicle will not need a carsharing service (Ciari et al., 2016), there are arguments supporting that car availability does not have a purely negative correlation with carsharing usage. The study of Ciari et al. (2016) found that having a car available occasionally was a stronger predictor than never having a car available because individuals without access to a car are more probable to live a car-free life.

Population Density

There are conflicting opinions in the literature regarding the importance of population density on carsharing usage. While most studies agree that high population density brings a larger customer basis and correlates positively with high carsharing usage (Correia and Antunes, 2012; Kumar and Bierlaire, 2012), some studies question its importance or find no correlation at all. Millard-Ball et al. (2005) suggest that residential density might not be a strong predictor for carsharing usage and that the relationship between the two is not as simple and straightforward. Their study explains that carsharing stations located in mixed-use centres or near rail stations, locations with low residential population but large daytime population, tend to have higher observed usage. Therefore, this suggests shifting the focus of the analysis from finding neighbourhoods that match the individual demographic characteristics of carsharing members to giving more attention to the built environment factors of the neighbourhood that encourage carsharing (Stillwater et al., 2009).

2.4.2 Built Environment Factors

As with socio-demographic factors, studies have found links between built environment factors and carsharing success as well. All the built environment factors reviewed can be found in Table 2.2.

Table 2.2: Built environment factors linked with carsharing usage.

Factor	Literature
Distance to Carsharing Station	*Katzev (2003); Kumar and Bierlaire (2012); Ciari et al. (2016); Luan et al. (2018);*
Parking Pressure	*Stillwater et al. (2009); Chen et al. (2018)*
Proximity to Transit Stops	*Celsor and Millard-Ball (2007); Kumar and Bierlaire (2012); Chen et al. (2018); Luan et al. (2018)*
Intersection Density	*Millard-Ball et al. (2005); Celsor and Millard-Ball (2007); Chen et al. (2018)*
Proximity to Points of Interest	*Kumar and Bierlaire (2012); Wagner et al. (2016); Willing et al. (2017); Chen et al. (2018)*
Land-Use	*Millard-Ball et al. (2005); Awasthi et al. (2007); Correia and Antunes (2012); Kang et al. (2016)*
Good Pedestrian and Bicycle Environment	*Millard-Ball et al. (2005); Celsor and Millard-Ball (2007)*

Distance to Carsharing Station

Case studies surveying existing members of carsharing schemes show that one essential aspect for users is the distance from their house or place of work to carsharing stations (Ciari et al., 2016). Thus, accessibility to the station decreases as the distance to the station increases (Katzev, 2003; Ciari et al., 2016; Luan et al., 2018). Kumar and Bierlaire (2012) observed that 58% of customers tend to use the closest carsharing station to their home, and 88% choose a station that is within walking distance.

Parking Pressure

As more space is allocated for public parking, it becomes easier and more convenient for people to use their own car and thus this generates more private vehicle trips. Public parking space was discovered to have a significantly negative impact on carsharing usage (Stillwater et al., 2009; Chen et al., 2018). Neighbourhoods and cities where parking pressure already exists are more likely to be successful locations for carsharing stations as using this service would save people the time, effort, and money to find an empty parking spot.

Proximity to transit stops

As most of the carsharing users do not have a car always available, studies have found a strong correlation between the usage of carsharing stations and public transport locations, deeming it important for the two to be close to one another (Celsor and Millard-Ball, 2007; Kumar and Bierlaire 2012; Chen et al., 2018; Luan et al., 2018). Therefore, studies concluded that carsharing performance increases in the presence of developed public transport systems (Luan et al., 2018). Locations where carsharing would flourish need to be locations where walking, biking and the use of the public transport system are realistic alternatives to private vehicles (Celsor and Millard-Ball, 2007).

Intersection Density
As stated above, good pedestrian environments are crucial for the success of carsharing. Intersection density is considered a good indicator of pedestrian friendliness (Tiejiao and Agrawal Weinstein, 2016), with neighbourhoods with a higher intersection density being considered more walkable and thus attracting more carsharing users. Moreover, three studies found this factor to be correlated with neighbourhoods that have high carsharing use (Millard-Ball et al., 2005; Celsor and Millard-Ball, 2007; Chen et al., 2018).

Proximity to points of interest
Carsharing stations that are close to points of interest (POIs), such as shopping centres, hotels, universities, medical services, attractions, and recreation spots were found to attract more customers and have a higher usage (Kumar and Bierlaire, 2012; Willing et al., 2017; Chen et al., 2018; Cheng et al., 2019). Studies are not consistent in testing the same categories of POIs, but those most often correlated with the success of carsharing stations are shopping centres, hotels, medical services, and universities. The correlation with POIs is strongly related to one of the most influential parts of the carsharing demand: trip purpose (Loose, 2010; Becker et al., 2016; Willing et al., 2017). Thus, locations with a high density of amenities that drivers want to reach are naturally more attractive for carsharing (Willing et al., 2017). In a study done by Wagner et al. (2016) in the City of Berlin, the authors prove to be successful in using POIs as a proxy for the attractiveness of various areas within the city and use them to explain the spatial variation in carsharing activity.

Land-Use
Land-use, or the mix of land-use, is another factor used to describe the build environment (Millard-Ball et al., 2005). This factor is taken into consideration in multiple carsharing studies and correlated with carsharing usage (Awasthi et al., 2007; Correia and Antunes, 2012; Kang et al., 2016). While some studies test the land-use types individually (i.e., % of residential use/ % of commercial use/ % of business use in a carsharing district) (Kang et al., 2016), some studies take into consideration the mix of land-use, as different trip purposes can be coupled together (Correia and Antunes, 2012).

Indicators particularly strong in Switzerland
Ciari et al. (2016) and Juschten et al. (2019) are two case studies that showcase specifically carsharing in Switzerland, highlighting the country's specific demand and supply characteristics. In contrast with other countries where carsharing usage is correlated negatively with regional rail and long-distance travel (Stillwater et al., 2009), Mobility has a partnership with SBB (Schweizerische Bundesbahnen / Swiss Federal Railway), meaning that most train stations are hosts for carsharing stations, and carsharing is viewed as a complement to the rail system, serving as the last leg of the journey.

Regarding the socio-demographic factors, studies have found that not only the proximity to public transit stops is important for carsharing usage, but also the public transport/rail subscription ownership is a strong predictor for new carsharing memberships (Balac et al., 2015; Becker et al., 2016; Ciari et al., 2016; Juschten et al., 2019). Moreover, as Switzerland is a tri-lingual country, the study done by Ciari et al. (2016) observed that residents in the German-speaking part of the country are more inclined to be carsharing members, compared to the French and Italian speaking regions.

2.5 Research Gaps

Following from the literature review presented above, three research gaps can be identified that this work is trying to fill.

Firstly, as presented in Section 2.2 and Section 2.3, there is a lack of research and study cases looking into optimising return carsharing networks. The return driving mode is the first carsharing service that has been developed and is considered the easiest from an operational point of view. When compared to the newly developed modes, station-based one-way and free-floating, the return driving mode does not require sophisticated algorithms for establishing relocating strategies and predicting how the demand patterns will change to ensure availability of cars. Moreover, Balac et al. (2015) found that the return carsharing mode still could have great potential if the service is optimised, despite the gaining popularity of one-way and free-floating driving modes.

Secondly, in the already scarce literature on optimising return stations networks there is a real absence of studies using a GIS-based approach. In most of the cases, GIS methods are used to discover and integrate different success factors associated with carsharing stations and their particular location (Celsor and Millard-Ball, 2007; Willing et al., 2017), or serve as a tool to map and present the results (Juschten et al., 2019). In fact, there is only a small portion of studies that use GIS as a spatial analysis tool (Stillwater et al., 2009; Tiejiao and Agrawal Weinstein, 2016; de Oliveira Lage et al., 2019). A GIS-based model is a powerful tool as it not only allows to map and better visualise the data and integrate different datasets from different sources but also model, explore, analyse spatial patterns and relationships inherent to the data.

Thirdly, there is a need for creating clear frameworks in choosing new locations for carsharing services to develop an optimal and efficient station network. As carsharing services are a relatively new mobility mode, most carsharing organisations tend to establish stations in any available locations or based on experience, especially in the beginning, as they are not wealthy enough to place stations in desired locations or are unable to obtain approbations from public authorities (Kumar and Bierlaire, 2012; Ciari et al., 2016). This unplanned approach can have clear disadvantages as it can cause significant losses for the operators and can result in stations with low operational efficiency (Cheng et al., 2019).

Therefore, this study aims to fill the aforesaid research gaps by using real carsharing usage data, and applying GIS-based methods, in order to find new locations for return stations and optimise the carsharing network.

3. Research Questions and Hypotheses

This study aims to develop a framework that would enable optimal placing of new carsharing return stations by taking into consideration the demand and the different factors making the station location favourable. In doing so, an attempt is made to help carsharing operators develop their station network, keeping in mind the drivers in their market. Depending on the goal a carsharing operator has, different factors that characterise the location of carsharing stations can be used. As suggested by Millard-Ball et al. (2005), Kumar and Bierlaire (2012) and Ciari et al. (2016), for various reasons listed in the last chapter, carsharing organisations are more inclined to place stations based on availability, rather than relying on a modelling and analysis of carsharing usage, demand and supply. More stations placed does not necessarily mean more usage and more members. Since the demand influences the supply, and vice versa, both are analysed with a focus on what role the location of the station plays in their relationship.

In other words, the focus is on analysing the performance of the existing Mobility return stations throughout Switzerland and estimate the key features that make a station successful. The overall objective is to understand what drives carsharing usage at a particular location and find locations with similar characteristics, where carsharing is not established yet.

Research Question 1: *What are the factors that make a return station successful? Are there some factors more important than others?*

As discussed in the last chapter, there are a variety of factors that drive the success of a station (Celsor and Millard-Ball, 2007; Kumar and Bierlaire, 2012; Ciari et al., 2016; Chen et al., 2018; Luan et al., 2018). To answer this question, the characteristics and performance indicators of the return stations were linked to data on the built environment and socio-demographic data. Moreover, all available factors are statistically tested against the carsharing usage indicator number of bookings per station and, thus, significant factors are distinguished that can be used as criteria in the site selection process.

Hypotheses:
1. The factors that are presented as crucial for carsharing in the literature will also be significant for the particular case of Mobility.
2. There will be some factors that correlate significantly with carsharing in Switzerland that in the literature are not considered so important (i.e., proximity to train stations).
3. Depending on the level of urbanisation of the given location, carsharing usage has different drivers.

Research Question 2: *What are optimal locations for new return stations from a geographic point of view?*

All significant factors identified from the first research question are integrated as criteria in an MCDA and candidate locations that have the same characteristics as existing carsharing locations are identified. Subsequently, demand is allocated to these candidate sites, taking into consideration the already existing carsharing network, and final return station locations are chosen in a location-allocation model.

4. Data

4.1 Mobility Cooperative Carsharing Data

The main dataset used for this thesis was provided by the Mobility Cooperative. The cooperative has agreed provide their support in this project by allowing access to their database for relevant information, such as the stations' performance and utilisation, customers, and reservations. Access to the company's database was made through the business analytic service offered by Microsoft, Power BI (Microsoft, 2021).

Time Span of the Study

Through Power BI, data on stations' performance such as reservation count, number of hours vehicles were used, number of hours vehicles were available, and revenue, could be viewed from the database, downloaded, and used for analysis. First, the stations data was filtered to contain only return stations. As the cooperative adjusts its network continuously, closing, and opening stations each year, for this project only stations that were open and active in the year 2019 were taken into consideration. Because weekly, monthly, and seasonal trends can occur, the dataset was taken over the span of a whole year to avoid their influence over the stations' performance. The year 2019 was selected as it was the last full year available that had no extraordinary events (i.e., the Coronavirus pandemic in 2020 that had an enormous impact on people's mobility behaviour).

Geography of Return Stations

There were data available for 1'551 return stations during the year 2019. Out of these, 132 stations were further excluded from the analysis as they were stations that had only one vehicle available, and that vehicle was available for less than 90% of the year.

In Figure 4.1, the distribution of Mobility return stations can be seen. At first glance, distinct clusters can be observed around major cities in Switzerland i.e., Zürich, Bern, Basel, Geneva, Lausanne, Lucerne. Moreover, almost all stations are placed in municipalities that have some urban character. In Table 4.1 the attributes that were extracted from the database and were available for each station are listed.

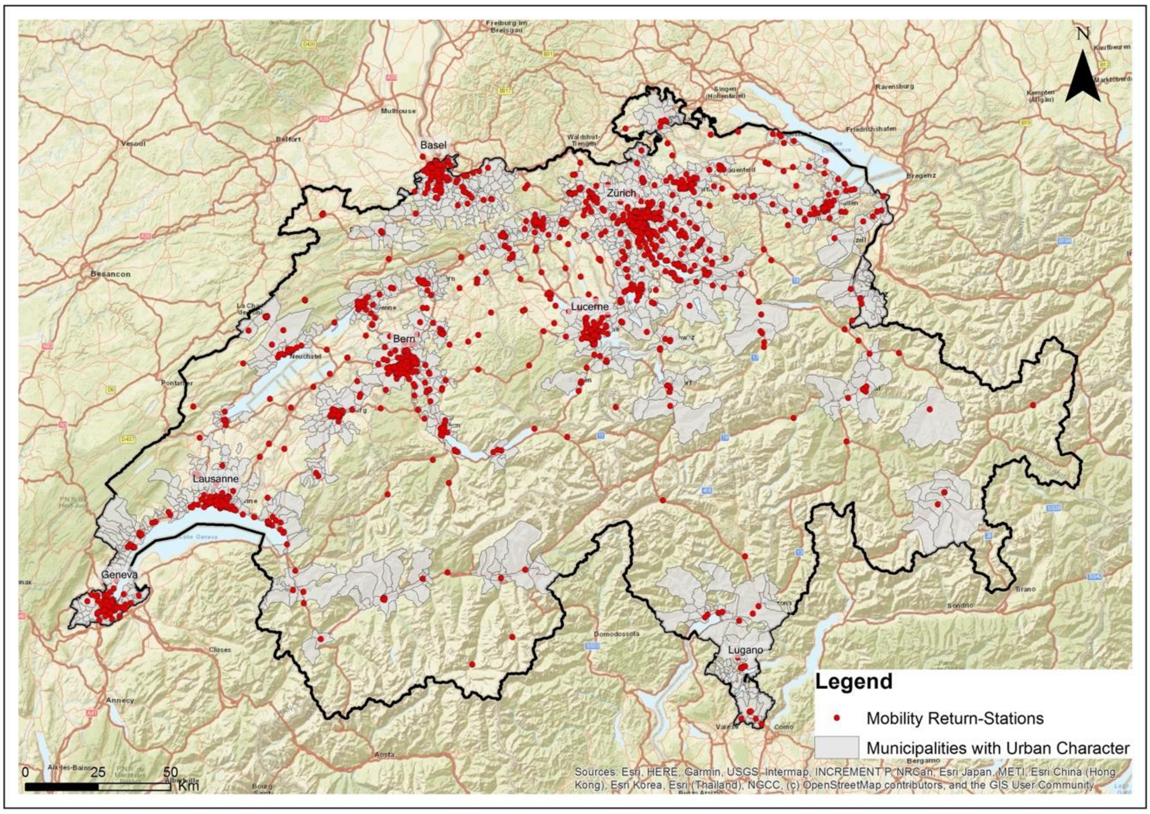

Figure 4.1: Spatial distribution of Mobility return stations in Switzerland in 2019. The grey areas represent municipalities in Switzerland that are considered to have an urban character according to the classification done by the Federal Office of Statistics (Federal Office of Statistics, 2012).

Table 4.1: The attributes available for each station in the dataset.

Attribute	**Description**
Base Number	Unique number of the return station
Base Name	Name of the return station
Reservation Count	Number of reservations recorded in 2019
Net Vehicles Supplied	Number of vehicles available to customers, average quantity in 2019
IsTrainStation	If the station is next to a train station or not
Latitude	Latitude coordinate of the return station
Longitude	Longitude coordinate of the return station

4.2 Auxiliary Data

Besides the main dataset offered by Mobility, further datasets for socio-demographic and built environment factors were used in the analysis. Following the literature review and extensive search of available open-source data, the full list of data used with their associated source can be found in Table 4.2.

Table 4.2: List of auxiliary datasets used, their data source, format, and year.

Data	**Data Source**	**Format**	**Year**
Public Transport Stops	Swisstopo	CSV	2015
Train Stations	SBB	Shapefile	2017
Points of Interest (i.e., hotels, shopping centres, universities, etc.)	OpenStreetMap	Shapefile	2021
Road Data, Road Intersection Density, and Administrative Boundaries	Swisstopo	Shapefile	2021
Population Data (i.e., age, household size)	Federal Office of Statistics	CSV	2019
Land-Use Data	OpenStreetMap	Shapefile	2021
Municipality Classification based on Urban Agglomeration Type	Federal Office of Statistics	CSV	2012

Public Transport Stops

The dataset containing the locations of public transport stops was retrieved from Swisstopo. Swisstopo is the short name for the Swiss Federal Office of Topography (Swisstopo, 2021a). Through an interactive map portal, it offers a collection of thematic maps and geographic datasets that are available as open data (https://map.geo.admin.ch/).

The original dataset contains stops for all public transport modes available in Switzerland (lift, bus, gondola, metro, boat, chairlift, funicular, tram, rack railway, train). For the purpose of this project, the dataset was filtered to contain only bus, tram, and metro stops. Throughout this thesis the term “public transport stops” will be used to refer only to the above-mentioned modes of transportation. There were 22’976 public transport stops considered after filtering the dataset.

Train Stations

As short-distance travel modes and long-distance travel modes can impact carsharing performance in different ways, locations of train stations are considered separately from public transport stops. The dataset used for train station locations was retrieved from the SBB open data portal (Swiss Federal Railways, 2021). The dataset contained 832 train stations.

Points of Interest

The data used for the locations of Points of Interest (POIs) was retrieved from OpenStreetMap (OSM). OSM is a crowd-sourced project, that allows anyone to take part, map features and complete the global map in order to make detailed geographical data available for everyone (OpenStreetMap Wiki contributors, 2021a). In order to have access and use this data, one can easily download the entire database or extract specific parts through APIs. The data for Switzerland is updated frequently and only the latest, up-to-date version is available for download. The OSM datasets used in this project were downloaded through Geofabrik (Geofabrik, 2021).

For the POIs, a dataset containing all categories of POIs in Switzerland was downloaded. It was then filtered for the categories of interest: *accommodation* (i.e., hotels, motels, hostels), *shopping centres* and *universities.* The number of points in each layer were: accommodation – 2637 points; shopping centres – 6030 points; and universities – 186 points. Accommodations were taken into consideration based on the hypothesis that tourism/overnight stays attract customers that do not travel with a car. Shopping locations were taken into consideration based on the hypothesis that a car is needed for transporting goods, and universities were taken into consideration based on the hypothesis that students are not usually vehicle owners. Other POI categories such as bars, pubs, restaurants, cinemas, were not taken into consideration for the analysis, as for the return driving mode it would not be plausible to book and pick up a car in the vicinity of a restaurant, for example, drive it and then return it to its station.

Road Data, Road Intersection Density and Administrative Boundaries

The datasets containing the roads, road intersections and administrative boundaries of Switzerland were retrieved from Swisstopo. The road and road intersection datasets used are part of the swissTLM3D model created by Swisstopo. The swissTLM3D model is a large-scale topographic landscape model of Switzerland that includes both natural and artificial features (Swisstopo, 2021b). The road dataset contained the whole road network present in Switzerland, including all road types, from walking paths to highways. The road intersections were filtered from the roads feature class present in the swissTLM3D model. The administrative boundaries datasets are part of the swissBOUNDARIES3D model, which is a landscape model that contains all administrative units and national boundaries of Switzerland: national, cantonal, district and municipal boundaries (Swisstopo, 2021c).

Population Data

For the population variables, the STATPOP dataset was used. STATPOP is short for Population and Households Statistics, and it is a national register survey created by the Federal Office of Statistics (Federal Office of Statistics, 2019). This dataset includes 69 individual population variables and 8 household variables. The individual population variables include total permanent resident population; permanent resident population by nationality, by place of birth, by age group and gender, according to length of presence in the municipality and by place of residence one year ago. The household statistics variables include the number of households of a certain size (1 person households, 2 person households, …, 6+ person households). The statistical variables on the population and households are aggregated by hectare and have the south-west coordinates as an identifier. For this project, the survey done in 2019 was used. The variables used from the dataset are present in Table 4.3.

Table 4.3: Variables used from the STATPOP 2019 dataset aggregated by hectare.

Variable	Description
Permanent resident population by age group	
20 – 39 years old	Population count in the respective age group
40 – 64 years old	
65 + years old	
Household statistics – Total private households	
with 1 person	Count of households of the respective dimension
with 2 persons	
with 3 persons	

As the data come in a CSV format, it was first pre-processed in ArcMap 10.6.1. There, the point data were transformed into a raster by using the Point to Raster command from the Raster toolset. Rasters for all individual population variables and household variables were created. As the variables were from the same data sources, the raster layers were aligned.

Land-Use Data

The land-use data were retrieved from OSM. A dataset containing all land-use types was downloaded for Switzerland. Then, the dataset was filtered for the commercial, residential, industrial, and retail land-use types. The structure of this dataset was as polygons, so in order to associate it with the dataset of stations' locations, each station was mapped to the nearest land-use polygon. Further, to be able to test this factor against carsharing utilisation, dummy columns were created taking the value 1 if the land-use polygon contains the respective station and 0 for the other polygons.

Municipality Classification based on Urban Agglomeration Type

A dataset that classifies the municipalities of Switzerland by the type of urban character was used in order to subdivide the stations based on different levels of urbanisation (Table 4.4). This dataset registered the urban agglomerations present in Switzerland and then divided the municipalities present in these urban agglomerations in different subdivisions. The classification was based on population density, job density, area, and more. The dataset used is from the Federal Office of Statistics and represents a classification done in 2012 (Federal Office of Statistics, 2012). This dataset comes in the form of an Excel file that states each type of municipality. For pre-processing, the dataset was joined in R, with the spatial dataset representing the boundaries of the municipalities in Switzerland, based on the unique number of the municipality.

Table 4.4: The classification of the municipalities based on their urban character.

<table>
<tr><th>Grouping done for this project</th><th>Classification done by the FSO</th><th>Description</th></tr>
<tr><td rowspan="2">Urban</td><td>Agglomerationskerngemeinde (Kernstadt)</td><td>Principal core city of the urban agglomeration</td></tr>
<tr><td>Agglomerationskerngemeinde (Nebenkern)</td><td>Secondary core of the urban agglomeration</td></tr>
<tr><td rowspan="2">Suburban</td><td>Agglomerationskerngemeinde (Hauptkern)</td><td rowspan="2">These are municipalities that are considered a main core on their own or municipalities surrounding the cores of the urban agglomeration</td></tr>
<tr><td>Agglomerationsgürtelgemeinde</td></tr>
<tr><td>Rural</td><td>-</td><td>The remainder of the municipalities that have no urban character</td></tr>
</table>

5. Methodology

5.1 Overview

The general workflow for this master's thesis can be divided into three parts: (1) discovering the significant factors that make a return station successful, (2) integrating those factors to find all locations with similar characteristics that will serve as candidate locations for future return stations, and (3) allocating demand to candidate locations to find new locations for carsharing stations. The general framework of this thesis can be seen in Figure 5.1.

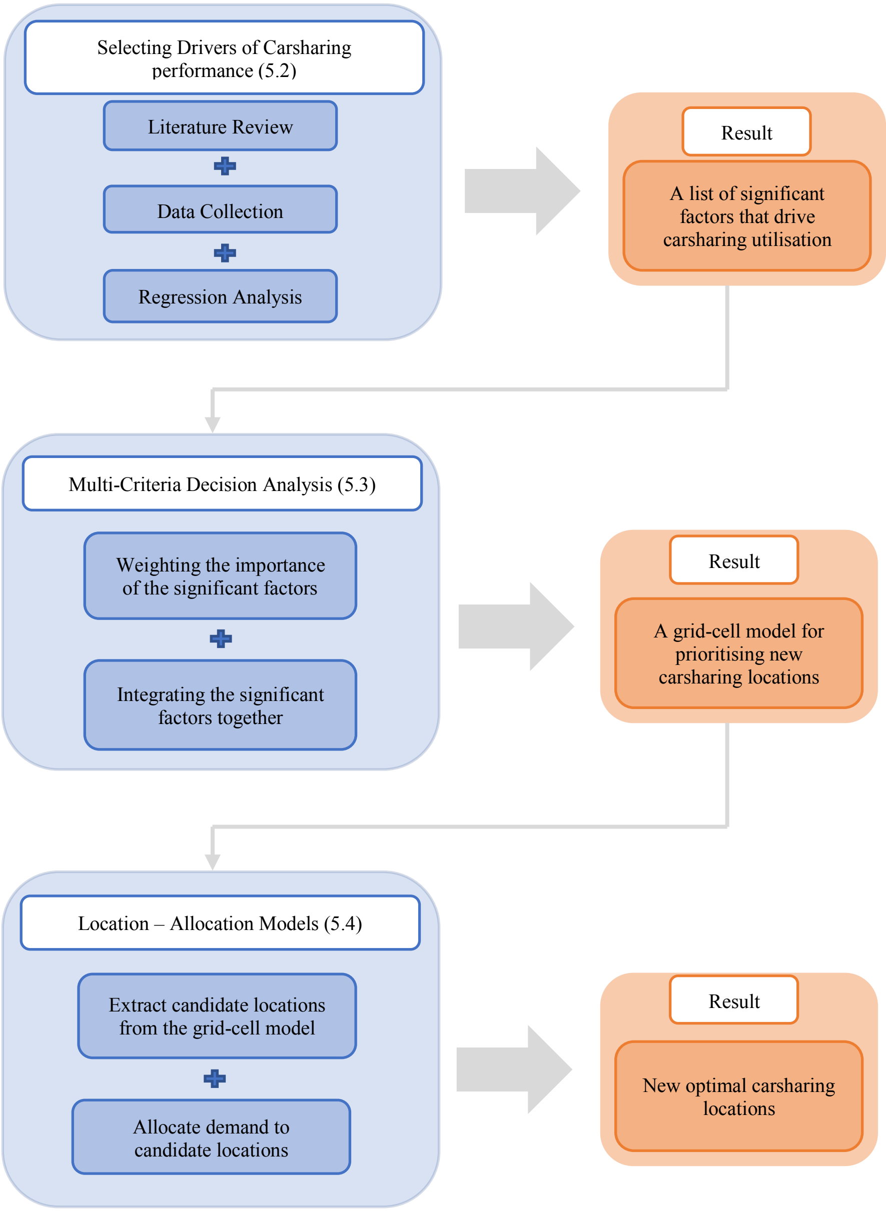

Figure 5.1: The workflow of this study. The numbers in brackets refer to the corresponding sections.

As presented in Section 2.4, the first step of Part 1 consisted of gathering and filtering the factors used in the analysis. A list of factors that are correlated with carsharing utilisation in literature was comprised. This list was then edited based on what data was available for the different factors for Switzerland, and a new list of potential key features of a station was created. These potential key features were then statistically tested against return stations' performance, to determine whether they were significant or not in the location placement of the station. This first part resulted in a list of criteria that a return station needed to have to be considered successful. Second, all criteria discovered significant were integrated together with the constraints. Some characteristics were more important than others (for example: the return station being close to a train station might be more important that it being close to a shopping centre or university) and so depending on their influence, each criterion was weighted differently. After the integration, every candidate location was assigned a suitability score i.e., how suitable was the location for carsharing based on this analysis. Lastly, demand was allocated to the candidate locations, in order to select optimal new carsharing stations.

A large part of the analysis, the regression model and MCDA, together with most of the data preparation and integration steps, were done in R version 4.0.5 (R Core Team, 2021). The last step of the analysis was done in the ArcMap software (ESRI, 2020b) version 10.6.1, together with data pre-processing for the population variables. The QGIS software (QGIS Development Team, 2021) version 3.4 was used during the analysis to visualise and inspect different datasets as well as intermediary steps.

5.2 Selecting Drivers of Carsharing Performance

An extensive literature review was done in order to assemble a list of factors that drive carsharing performance. Factors that were found significant in other carsharing studies were all taken into consideration. The list was then adjusted based on what data was available for Switzerland for those factors. During this step, some factors had to be discarded because of unavailability or incompleteness of the data. After searching for and collecting all necessary data, the list was complete and significant drivers of carsharing performance were ready to be analysed.

To identify the drivers of carsharing performance, a multiple regression model was built. Multiple regression analysis is a technique used for modelling and analysing the relationship between an outcome (i.e., the dependent variable) and several predictor variables (i.e., the independent variables), as well as the contribution of each of the predictors to the relationship.

This model assumes that there is a linear relationship between the dependent variable and the independent variables. The formula for a multiple regression model is:

$$y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \qquad \text{(Equation 5.1)}$$

where:
y = is the dependent variable
$X_1 \ldots X_n$ = are the independent variables
β_0 = is the intercept i.e., the value of y when all other parameters are set to 0
β_k = is the k^{th} regression coefficient representing the change in y relative to a one-unit change in X_k; also representing the slope coefficient for each independent variable
ε = is the models' random error, residual term

The best regression model was chosen in a backward stepwise selection manner where first all the variables were inputted in the model and then the term with the highest p-value was systematically removed one-by-one until only significant predictors remained. The models were also compared based on their Akaike Information Criteria (AIC) value. Moreover, attention was paid to the adjusted and predicted R-squared values.

This method is a popular technique in carsharing literature for exploring the relationship between carsharing utilisation or demand and different spatial attributes. Both the studies of Kumar and Bierlaire (2012) and of Kang et al. (2016) use linear regression models in order to identify factors that influence the performance of carsharing stations. Stillwater et al. (2009) created a carsharing demand model using a GIS-based multivariate regression and looked at the relationship between the activity of carsharing locations and different factors. Lastly, Cheng et al. (2019) applied different statistical models in order to compare their results and find the best method that would help carsharing operators to choose new optimal locations for carsharing stations. Amongst others they used logistic regressions in order to estimate the probability of existence of demand at a certain location based on different carsharing drivers.

For this project, the depended variable refers to the return station performance and is measured by *the total number of bookings per station*. There were several candidate indicators to measure a station's performance: total number of bookings, total number of bookings per vehicle, total revenue, or total hours the vehicles were used at a station. Depending on how a carsharing operator defines its success and performance a different indicator can be chosen. Although being strongly correlated, each individual performance indicator can tell its own different story.

The independent variables used were based on the set of factors gathered from the literature and on the available datasets, presented in Table 5.1. A circular buffer of 500 m was created around the stations' location to correlate the variables with the stations' performance. For each factor, its density inside the 500 m buffer was calculated and associated with the specific station. Firstly, this distance was chosen for the buffer because the 500m distance was found in literature to be the service area of a public transport stop (El-Geneidy et al., 2014). Secondly, members usually prefer having a carsharing station within 500m from their house or place of work in carsharing studies (Luan et al., 2018). Lastly, 500 m is a convenient distance for walking. Moreover, Kumar and Bierlaire (2012) also use a 500 m buffer around carsharing stations in order to associate values of various parameters with the stations. All variables were normalized to a range of [0-1] using the min-max normalization method.

Table 5.1: Variables tested in the regression analysis. The outcome variable is the dependent variable used. The built environment factors and the socio-demographic factors are the independent variables used.

Variable Description	**Value calculated in buffer**
Outcome Variable	
Total number of reservations per station	Count
Built Environment Factors	
Total number of public transports stops	Count
IsTrainStation	Dummy Variable
Total number of accommodations	Count
Total number of shopping centres	Count
Total number of universities	Count
Total number of road intersections	Count
Land-use type: Residential	Dummy Variable
Land-use type: Commercial	Dummy Variable
Land-use type: Retail	Dummy Variable
Land-use type: Industrial	Dummy Variable
Total number of carsharing stations	Count
Socio-demographic Factors	
Total number of already existing members	Count
Population between 20 and 39 years old	Count
Population between 40 and 64 years old	Count
Population above 65+	Count
Total number of 1 person households	Count
Total number of 2 person households	Count
Total number of 3 person households	Count

For the variable IsTrainStation, instead of using the number of train stations in the 500m buffer area, a dummy variable was used with a value of 0 – the carsharing station is not placed near a train station and 1 – the carsharing station is placed near a train station. This is because firstly, in the Mobility dataset it was registered if a station is placed at a train station (due to the partnership between Mobility Cooperative and SBB) and secondly, if the counting method was chosen, the variable would have looked almost the same, as usually train stations are not within 500 m from each other. For each land-use type considered, a dummy variable was used with the value of 0 – the carsharing station was not assigned to that particular land-use type and 1 – the carsharing station was assigned to that particular land-use type.

Besides the factors discussed in Section 2.4, the total number of carsharing stations within the 500 m buffer of a station was added to the regression analysis in order to determine if short distances between stations affect their performance. Kumar and Bierlaire (2012) found in their study that a small distance between stations impacts their performance in a negative way, as their service area has a big overlap and even if more stations are added, they are not bringing any new customers.

In order to discover how the influence of carsharing utilisation drivers may vary in different levels of urbanisation and improve the prediction of regression models, three different models were created for each urbanisation level. The fact that carsharing performance is different based on the level of urbanisation of the location is a detail identified and discussed in the literature. In their study, Kumar and Bierlaire (2012) also created two different models for carsharing stations situated in the city versus carsharing stations situated in suburban areas, as the drivers for demand change based on the different demographic characteristics and travel behaviour patterns. Based on the classification of municipalities done by the Federal Office of Statistics presented in Section 4.2, the three models created contained: stations that are located in municipalities that are considered the primary and secondary core of an urban agglomeration, stations that are located in municipalities around the core of an urban agglomeration and stations that are located in municipalities with no urban character (i.e., rural municipalities). After this division, there were 854 carsharing stations in urban areas, 405 stations in suburban areas and 160 stations in rural areas.

5.3 Multi-Criteria Decision Analysis

The second part of the analysis was to perform a multi-criteria decision analysis (MCDA). The advantage of using an MCDA in the decision making process is given by its capability of simultaneously evaluating and comparing multiple criteria, that can be contrasting or conflicting, and of classifying the alternative solutions generated (Malczewski, 1999). This type of analysis can be used in any field to look at a wide range of problems where there may be multiple favourable solutions. Examples of its application can be found in the healthcare industry, environmental decision making, risk assessment, resource management, land use planning, and site selection.

There were two studies found in the literature that used the MCDA method in order to select optimal new locations for carsharing stations: Awasthi et al. (2007) establish a decision system consisting of 15 evaluation indicators which are calculated from big data, and through using MCDA, a synthetic score is calculated to evaluate the candidate sites available for carsharing stations. In the study of Li et al. (2017) the analysis is structured into three main parts. Firstly, criteria for selecting carsharing stations are identified using the literature and experts opinions. Secondly, the criteria and the stations are weighted on a ratio scale using pairwise comparison and lastly, stations whose overall weights exceed the threshold limit are selected.

Based on the theory presented by Malczewski (1999), the main elements that form a MCDA are (1) a goal; (2) the decision makers involved in the process; (3) a set of objectives and attributes; (4) a set of decision alternatives; (5) the decision environment; and (6) the set of outcomes. The relationships between the elements of MCDA are shown in Figure 5.2.

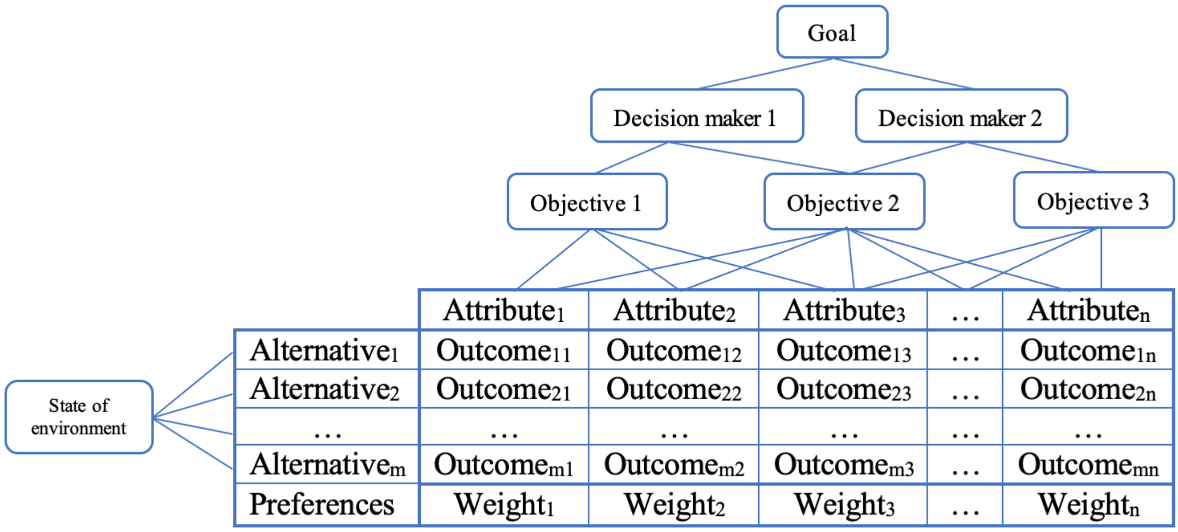

Figure 5.2: Framework for MCDA showing the relationships between all the components (based on Malczewski, 1999, p. 82).

Through a GIS-based MCDA, spatial data is combined and transformed in order to generate new information based on which decisions can be made (Drobne and Lisec, 2009). Several approaches exist to develop a framework for spatial decision making. Drobne and Lisec (2009) describe two of them: *the alternative-focus approach* that is aiming to generate as many alternative solutions as possible at first and then evaluate them, and *the value-focus approach* that is focusing more on the criteria used in the analysis and how they influence the outcome. This study takes a value-focus approach, as the drivers of carsharing utilisation are the centre of the analysis. Figure 5.3 shows a simple workflow of the approach followed.

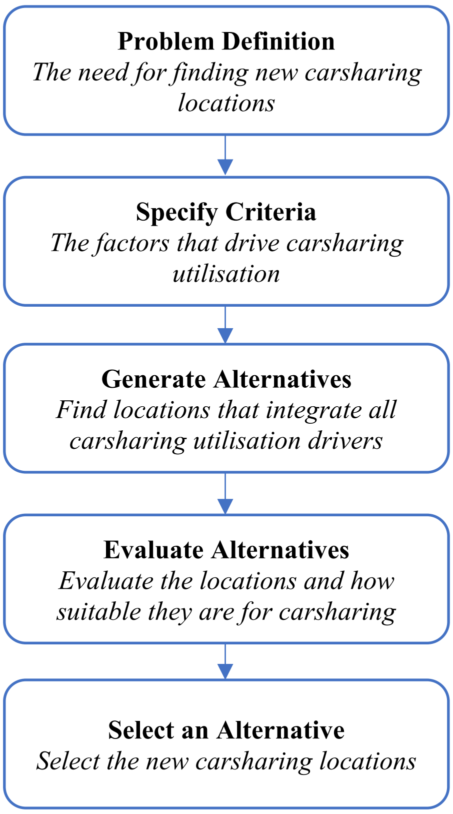

Figure 5.3: Workflow of the value-focus approach taken in this project (based on Drobne and Lisec, 2009, p. 461).

A GIS-based MCDA can be implemented both with raster and vector data models. For this project, a raster data model was used. Each raster cell on the map has attached a suitability score that is a result of combining multiple criteria together (simple visualisation of the process in Figure 5.4). Firstly, an empty raster grid was created over the study area (i.e., the whole Switzerland). The resolution of the grid is 500x500 m. Then, for all the factors the *rasterize* function from the *raster* package in R was used to combine the factor data with the empty raster and count the frequency of each variable in each cell, thus generating new rasters. For the land-use data, presence-absence rasters were created for each land-use type. The last pre-processing step was to use the *mask* function from the same R package to mask all the factors into the three different urbanisation level categories. Because each urbanisation level has its own model and significant drivers, the MCDA was calculated separately for each of the three groups. In the end, the resulting rasters were merged into one final raster.

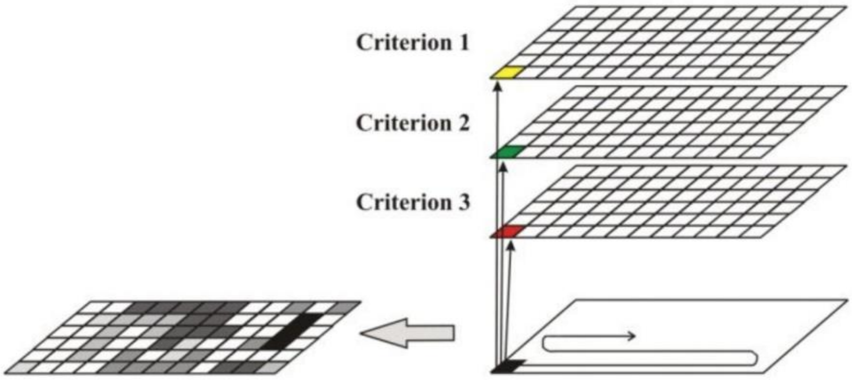

Figure 5.4: Visualisation of the GIS-based MCDA process. Each criterion is represented by a raster. From each raster, pixels in the same position are combined for the final result (figure taken form Drobne and Lisec, 2009, p. 462).

This study used the simple additive weighting (SAW) method and the Analytical Hierarchy Process (AHP) developed by Saaty (1990) in order to combine the significant factors associated with carsharing utilisation that were discovered in the regression analysis. The simple additive weighting method represents a weighted average where the criteria are first standardised, then get assigned their respective weight and lastly the products are summed (Drobne and Lisec, 2009). Any constraints that need to be taken into consideration are applied outside the summation. After the scores are calculated for each raster cell, a suitability map is created. The suitability score is a synthetic score created. The higher the score the more suitable is the raster cell. The formula used for the SAW is the following:

$$s = \left(\Sigma_{i=1}^{n} w_i x_i\right) \times c \qquad \text{(Equation 5.2)}$$

where s = suitability score
w_i = weight attributed to factor x_i
x_i = value of the ith factor
c = any constrain needed to be applied

Before calculating the suitability scores, the weights for each factor were determined. The ranking of the factors for each urbanisation level group was established based on the importance of the regression coefficients. Following this, the AHP was used to derive the weights associated with each criterion. The AHP is a weighting technique in which the factors are arranged in a hierarchical structure and the weights are based on pair-wise comparisons between the criteria (Saaty, 1990; Drobne and Lisec, 2009). The comparisons indicate the relative importance that the criteria have towards the goal. Saaty (1990) also created a scale for these comparisons, present below in Table 5.2.

Table 5.2: Pairwise comparison values for AHP (after Saaty 1990).

Intensity of importance on an absolute scale	**Definition**
1	Equal importance
3	Moderate importance of one over another
5	Essential or strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values between the two judgements

In order to develop weights, a pairwise comparison matrix is used, where every criteria is compared to one another (Table 5.3). Then, the principal eigenvector of the matrix is computed to produce the weights for each criterion.

Table 5.3: Pairwise comparison matrix, where C1-Cn are the criteria and rij are the comparison values.

	C_1	C_2	…	C_n
C_1	1	r_{12}	…	r_{1n}
C_2	r_{21}	1	…	r_{2n}
…	…	…	1	…
C_n	r_{n1}	r_{n2}	…	1

Because the process involves numerous comparisons, Saaty (1990) also developed a procedure to calculate the degree of consistency that has been used in developing the weighting: *a consistency ratio* (CR). Saaty (1990) suggested that matrices that have a CR greater than 0.1 are found to be inconsistent in their comparisons and should be re-evaluated. The formula for the CR is:

$$CR = \frac{CI}{RI} \qquad \text{(Equation 5.3)}$$

where CI is the consistency index:

$$CI = \frac{\lambda - n}{n - 1} \qquad \text{(Equation 5.4)}$$

where λ = the average value of the consistency vector
n = the number of criteria

and RI is the random index that is fixed and given by Saaty (1990), shown in the Table 5.4.

Table 5.4: Random inconsistency indexes for different number of criteria.

Size of matrix	1	2	3	4	5	6	7	8	9	10
Random consistency	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The average value of the consistency vector (λ) in Equation 5.4 is obtained by first calculating the weighted sum vector. This is calculated by multiplying the weight of each criterion with its respective column from matrix and summing the resulting values over each row. Then, by dividing the weighted sum vector by the criteria weights, the consistency vector is determined.

Therefore, for this second part of the analysis, Figure 5.5 exhibits a flowchart of all the steps taken. Each raster layer created for the different significant factors determined by the regression models in Section 5.2 was divided into 3 different raster layers. Each of them represented an urbanisation level group and had non-zero values only in the municipalities that are part of that group and 0 outside of the municipalities. Secondly, respective weights were calculated using the AHP method illustrated above, for each raster layer. The results from these two steps were combined by using Equation 5.2 and suitability scores were calculated. This resulted in three different rasters as the calculation was done once for every urbanisation level group. In the end, they were combined, forming the final raster. In this raster, every raster cell symbolised a potential location for new carsharing stations, with cells that have a higher score being more suitable. Thus, it is a grid-cell model for prioritizing locations for carsharing. This raster served as the basis for the last part of the analysis.

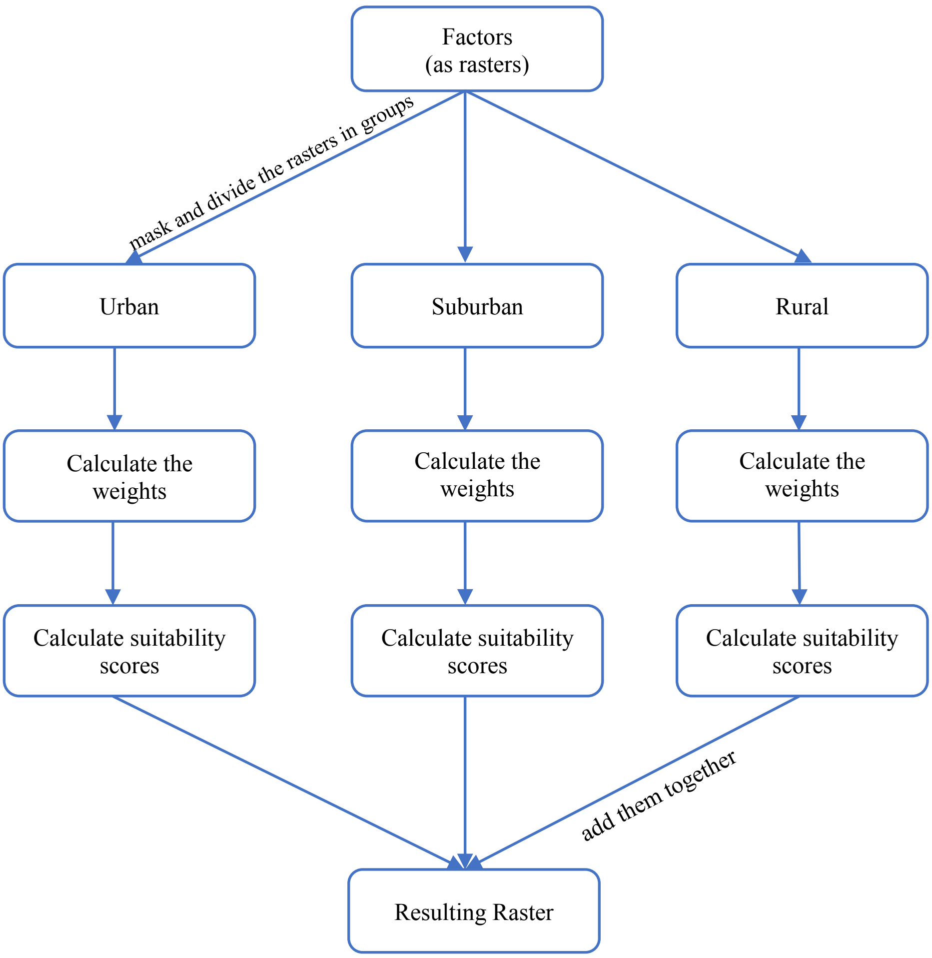

Figure 5.5: Flowchart representing the steps taken in the second part of the analysis.

5.4 Location – Allocation Models

For the final part of the overall workflow, the choice of new optimal locations for carsharing stations was made using location-allocation models. Location-allocation models determine simultaneously the locations of facilities and who is served by which facility, having the goal to create an optimal and efficient network (ESRI, 2020a). A classic and general representation of the location-allocation model can be seen below in Figure 5.6. The demand points are allocated to facilities and connected to them through allocation lines. Depending on the optimisation goal (i.e., minimising the distance from the demand point to the facility, maximizing the number of demand points allocated to one facility or minimising the total number of facilities chosen so that all demand points are allocated to one facility), there can be different analyses computed.

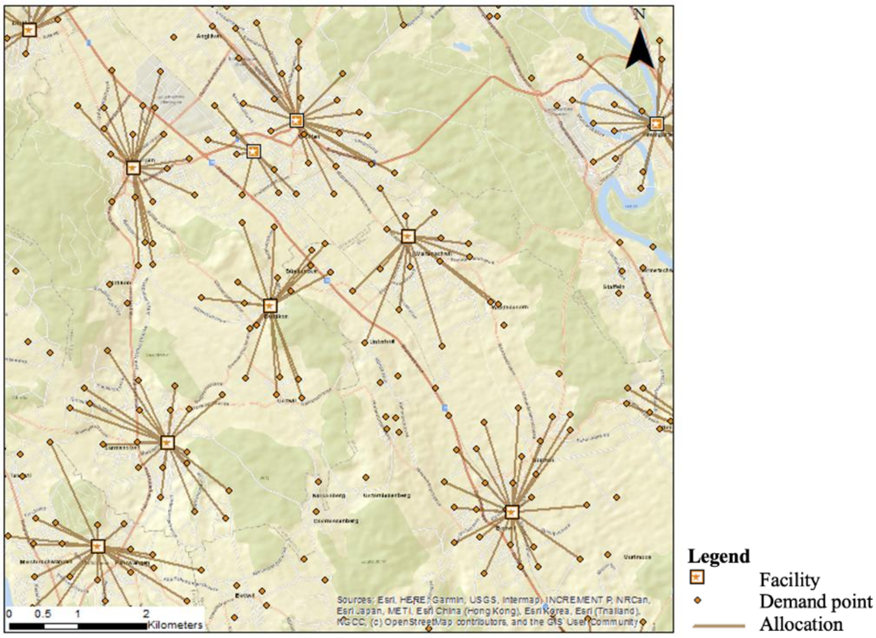

Figure 5.6: General visualisation of location-allocation models. The squares represent the facilities that were chosen by the location-allocation model. The orange points represent the demand points that need to be allocated. The orange lines display which demand point was allocated to which facility.

In the carsharing literature, one study was found to use a location-allocation model in order to place carsharing stations. In their study, de Oliveira Lage et al. (2019) are looking at identifying types of economic activities that could support carsharing utilisation. They apply a location-allocation model to find the best places for placing carsharing stations so that possible partnerships with several types of commercial establishments could flourish their performance.

The location-allocation analysis was performed in the ArcMap software. The ArcMap software was favoured instead of running the analysis in R, because of its broader spectrum of options offered. The ArcMap software contains seven problem types that allow to answer specific kinds of questions: *minimize impedance, maximize coverage, maximize capacitated coverage, minimize facilities, maximize attendance, maximize market share, and target market share* (ESRI, 2020a). For this analysis, the Maximise Attendance problem type was used. This problem type has the goal to choose the facilities such that the amount of demand points a facility can cover is maximised, while also specifying an impedance cut-off and implementing a distance decay function. The underlying assumption is that the chance of interaction between the facility locations and the demand locations decreases with an increasing distance (ESRI, 2020a). This model is useful for the carsharing field as the literature has shown that the majority of carsharing users are located near stations (Juschten et al., 2019) and because this type of problem is particularly beneficial for businesses that have no competitors (ESRI, 2020a), which is the case of this study.

For the implementation of the model and for finding a solution to the Maximise Attendance problem, 3 elements were required. First, a set of candidate locations was needed. This was obtained from the resulting raster in the second part of the analysis. The raster dataset was pre-processed and converted to point features in ArcMap using the *Raster to Point* tool. The new point layer represented the centroid of each raster cell in the dataset, each point having associated the suitability score of that cell. Second, a set of demand points was needed. This was obtained from the census population dataset. As mentioned in Section 4.2, the population data were aggregated by hectare, i.e., 100x100 m. In order to aggregate it on a scale comparable with the raster, i.e., 500x500 m, a weighted mean centre was calculated for the population layer in R, using the total population registered at each point. Last, a network dataset was needed to be built in order to connect the candidate facilities and demand points. This network dataset was built in ArcMap using the roads dataset for the whole Switzerland.

In the location-allocation models, the already existing return carsharing stations were taken into consideration. These stations were marked as required facilities, and their original raw location was used. Therefore, when demand was allocated, it was first allocated to already existing stations and then to candidate locations. Additionally, the candidate facilities were weighted based on the suitability scores developed in the second step of the analysis. Therefore, a candidate facility point that had a higher suitability score was considered more important and demand was first allocated to it. The impedance cut-off value for the Maximise Attendance problem was set at 1 km. The number of locations that end up being chosen from the candidate locations can be chosen depending on the needs of the carsharing operator.

6. Results

This chapter presents the results of applying the developed framework and its methods, presented in Chapter 5, to the carsharing dataset and the factors considered. Following the workflow illustrated in Figure 5.1, this chapter will be divided into three subsections, each showcasing the results of the three methods used. Firstly, the results of the regression analysis are presented (Section 6.1). The factors that drive carsharing utilisation in the different levels of urbanisation are displayed and factors present in all three models are highlighted. Secondly, the results of the MCDA are shown (Section 6.2). Following the AHP process, the developed weights for the significant factors that drive carsharing usage are displayed. Subsequently, maps of the final raster with suitability scores for carsharing locations are shown. Lastly, maps displaying potential future locations for carsharing return stations, chosen with the help of location-allocation models are presented (Section 6.3).

6.1 Regression Analysis

In order to identify the factors that affect carsharing utilisation, linear regression modelling was performed as described in Section 5.2. The dependent variable selected was the total number of reservations per station that occurred in the year 2019, and the independent variables selected were the ones present in Table 5.1. The stations were divided based on the level of urbanisation of the municipality they are in, and thus three groups were created: urban, suburban, and rural. For each group a different model was run using the *stats* R package. The variables that entered the best-fitting models, chosen in a stepwise manner by backward elimination, are shown in Table 6.1, Table 6.2, and Table 6.3, respectively. First, the model was fitted with all candidate variables, and by using the *stepAIC* function in the R package *MASS*, variables that were statistically insignificant were excluded.

Table 6.1: Regression model estimating the effect of the independent variables on carsharing utilisation for stations located in municipalities within the *urban group*. The significance level is shown in brackets for each variable.

Variables	**Estimate**	**Standard Error**	***t*-Ratio**	**Prob > | *t* |**
Intercept	-40.06	119.98	-0.334	0.739
IsTrainStation (***)	1466.53	105.18	13.943	0.000
Total number of public transport stops (**)	746.58	267.04	2.796	0.005
Total number of already existing members (***)	3533.48	516.20	6.845	0.000
Total number of accommodations (.)	574.26	323.99	1.772	0.077
Total number of shopping centres (***)	1103.97	270.22	4.086	0.000
Total number of 2 person households (**)	-4896.61	1484.89	-3.298	0.001
Population between 20 and 39 years old (*)	2413.61	1135.69	2.125	0.034
Population above 65+ (**)	1672.15	624.07	2.679	0.008
Total number of carsharing stations (***)	-1895.14	345.89	-5.479	0.000
Summary Statistic:				
Number of observations		854		
R-squared		0.315		
Adjusted R-squared		0.308		
F-statistic (Probability)		43.21 (0.00)		

(.) Significant at the 0.10 alpha level; (*) Significant at the 0.05 alpha level; (**) Significant at the 0.01 alpha level; (***) Significant at the 0.001 alpha level

Table 6.2: Regression model estimating the effect of the independent variables on carsharing utilisation for stations located in municipalities within the *suburban group*. The significance level is shown in brackets for each variable.

Variables	**Estimate**	**Standard Error**	***t*-Ratio**	**Prob > | *t* |**
Intercept	-23.12	73.50	-0.315	0.7533
IsTrainStation (***)	291.07	48.56	5.994	0.000
Total number of road intersections (*)	504.85	204.47	2.469	0.014
Total number of already existing members (***)	4827.27	613.79	7.865	0.000
Total number of accommodations (***)	2396.14	608.81	3.936	0.000
Total number of shopping centres (***)	1177.70	265.32	4.439	0.000
Land-use type: Commercial (.)	186.72	100.84	1.852	0.065
Total number of carsharing stations (.)	-649.12	367.79	-1.765	0.078
Summary Statistic:				
Number of observations		405		
R-squared		0.402		
Adjusted R-squared		0.392		
F-statistic (Probability)		38.18 (0.00)		

(.) Significant at the 0.10 alpha level; (*) Significant at the 0.05 alpha level; (**) Significant at the 0.01 alpha level; (***) Significant at the 0.001 alpha level

Table 6.3: Regression model estimating the effect of the independent variables on carsharing utilisation for stations located in municipalities within the *rural group*. The significance level is shown in brackets for each variable.

Variables	**Estimate**	**Standard Error**	***t*-Ratio**	**Prob > | *t* |**
Intercept	-34.95	103.95	-0.336	0.737
IsTrainStation (***)	322.33	71.89	4.483	0.000
Total number of already existing members (***)	16344.19	2823.21	5.789	0.000
Total number of shopping centres (***)	2067.54	447.56	4.620	0.000
Total number of universities (*)	12014.20	6074.59	1.978	0.050
Land-use type: Industrial (**)	278.61	94.20	2.958	0.004
Total number of 2 person households (**)	7346.64	2536.40	2.896	0.004
Population between 40 and 64 years old (**)	-8126.52	2444.22	-3.325	0.001
Total number of carsharing stations (*)	-2664.88	1271.74	-2.095	0.038
Summary Statistic:				
Number of observations		160		
R-squared		0.555		
Adjusted R-squared		0.531		
F-statistic (Probability)		23.54 (0.000)		

(.) Significant at the 0.10 alpha level; (*) Significant at the 0.05 alpha level; (**) Significant at the 0.01 alpha level; (***) Significant at the 0.001 alpha level

For the first model, the R-squared value was 0.315, meaning that the 9 independent variables collectively accounted for 31.5% of the variance observed in the carsharing usage data for the stations associated in the urban group. For the suburban group model, the R-squared value was slightly bigger, 0.402, meaning that the 7 independent variables accounted for 40.2% of the variance observed in the data. The last model, for carsharing stations in the rural group, had the highest R-squared value, 0.555, meaning that the 8 independent variables accounted for 55.5% of the variance in the data.

From the three linear models, it can be observed that carsharing utilisation can be explained and predicted by very different significant factors, depending on the level of urbanisation that the stations are in. However, there are some key factors identified that remain significant across all three models: whether it is a carsharing station associated with a train station; the number of already existing carsharing members; the number of shopping centres; and the number of carsharing stations that are in the vicinity.

6.2 Multi-Criteria Decision Analysis

An MCDA was used in order to integrate the significant factors found to drive carsharing utilisation and to find suitable locations for new carsharing return stations. Before combining the variables by using the simple additive weighting method, the factors were weighted in accordance with their importance to the goal, using the AHP process. Table 6.4, Table 6.5, and Table 6.6 reveal the pairwise comparison matrices, where each factor is compared to each other with the help of the scale showed in Table 5.2. The resulting weight for each factor, together with the consistency ratio (CR) and the average value of the consistency vector (λ), are also present in the tables below.

The initial ranking for the factors is based on their importance in each of the regression models. Thus, the relationships between two factors can be different across the tables if their importance in the regression model changes. Moreover, the weights of the factors that are found significant in more than one model are different based on their ranking and the comparisons within that group. For example, the presence of train stations and shopping centres have the second highest weight in the urban group, while in the suburban group the second highest weight is attributed to the presence of accommodations, and in the rural group it is corresponding to the presence of universities.

Table 6.4: Pairwise comparison matrix for the factors found to drive carsharing utilisation for the stations in the urban group. C1-C5 are notations used for the factors to calculate the matrix more easily.

		C1	C2	C3	C4	C5	Weights
IsTrainStation	C1	1	3	1/3	5	1	0.200
Total number of public transport stops	C2	1/3	1	1/5	3	1/3	0.087
Total number of already existing members	C3	3	5	1	7	3	0.470
Total number of accommodations	C4	1/5	1/3	1/7	1	1/5	0.043
Total number of shopping centres	C5	1	3	1/3	5	1	0.200

$\lambda = 5.127$; CR = 0.03

Table 6.5: Pairwise comparison matrix for the factors found to drive carsharing utilisation for the stations in the suburban group. C1-C6 are notations used for the factors to calculate the matrix more easily.

		C1	C2	C3	C4	C5	C6	Weights
IsTrainStation	C1	1	1	1/7	1/5	1/3	3	0.059
Total number of road intersections	C2	1	1	1/7	1/5	1/3	3	0.059
Total number of already existing members	C3	7	7	1	3	5	9	0.472
Total number of accommodations	C4	5	5	1/3	1	3	7	0.253
Total number of shopping centres	C5	3	3	1/5	1/3	1	5	0.128
Land-use type: Commercial	C6	1/3	1/3	1/9	1/7	1/5	1	0.029

$\lambda = 6.255$; CR = 0.05

Table 6.6: Pairwise comparison matrix for the factors found to drive carsharing utilisation for the stations in the rural group. C1-C5 are notations used for the factors to calculate the matrix more easily.

		C1	C2	C3	C4	C5	Weights
IsTrainStation	C1	1	1/7	1/5	1/7	1	0.050
Total number of already existing members	C2	7	1	3	1	7	0.380
Total number of shopping centres	C3	5	1/3	1	1/5	5	0.179
Total number of universities	C4	7	1	5	1	5	0.341
Land-use type: Industrial	C5	1	1/7	1/5	1/5	1	0.050

$\lambda = 5.154$; CR = 0.03

Thus, all factors were multiplied by their respective weight and added together. This created a suitability score for each raster cell and thus a final raster could be constructed, shown in Figure 6.1. After calculating the suitability scores, one constraint was applied. As the regression analysis showed a negative association between carsharing utilisation performance and having a higher number of stations in the 500 m buffer area around a station, all raster cells that contained an already existing station were assigned the suitability score 0. This step was done to avoid placing new stations in the vicinity of already existing stations. The difference in the suitability scores raster before and after applying this constrain is visible in Figure 6.1, Figure 6.2, and Figure 6.3 below. Moreover, after the calculation, the scores were normalised.

Figure 6.1 displays the resulting suitability raster after weighting and integrating all factors. Areas with high suitability scores can immediately be observed around the big cities of Switzerland: Zürich, Bern, Basel, Lucerne, Lausanne, Geneva, and Lugano. Moreover, the areas surrounding these big cities are observed to have low to moderate suitability scores.

In the zoomed-in visualisation of the city of Zürich (Figure 6.2), besides the high suitability scores inside the city, small clusters of high suitability scores cells can be noticed in the areas surrounding it. In addition, although there is a strong presence of already existing carsharing stations in the city, the lower map still shows several locations with high suitability scores where new stations could be placed.

In Figure 6.3 a zoomed-in visualisation of a rural area is shown. It can be noted that in the rural areas the variability in suitability scores is much lower, as there are cells exhibiting medium to high scores neighbouring cells with no suitability at all.

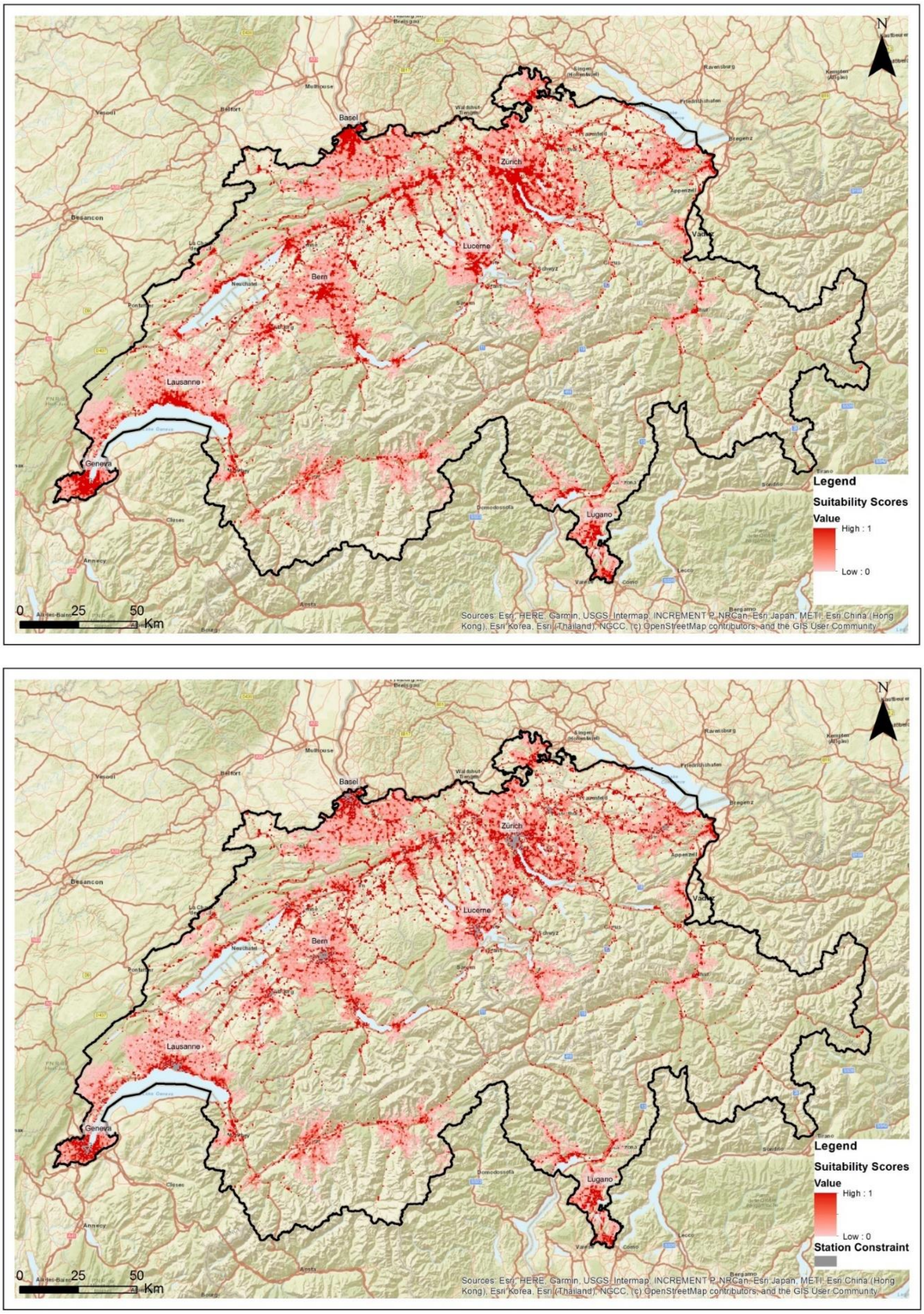

Figure 6.1: Visualisation of the entire suitability raster. The top image displays the suitability raster before applying the constraint that all cells that contain at least one already existing carsharing station are attributed the value 0. The bottom image displays image displays the suitability raster after applying this constraint. Cells that had a suitability score of 0 due to this constraint were assigned the colour grey.

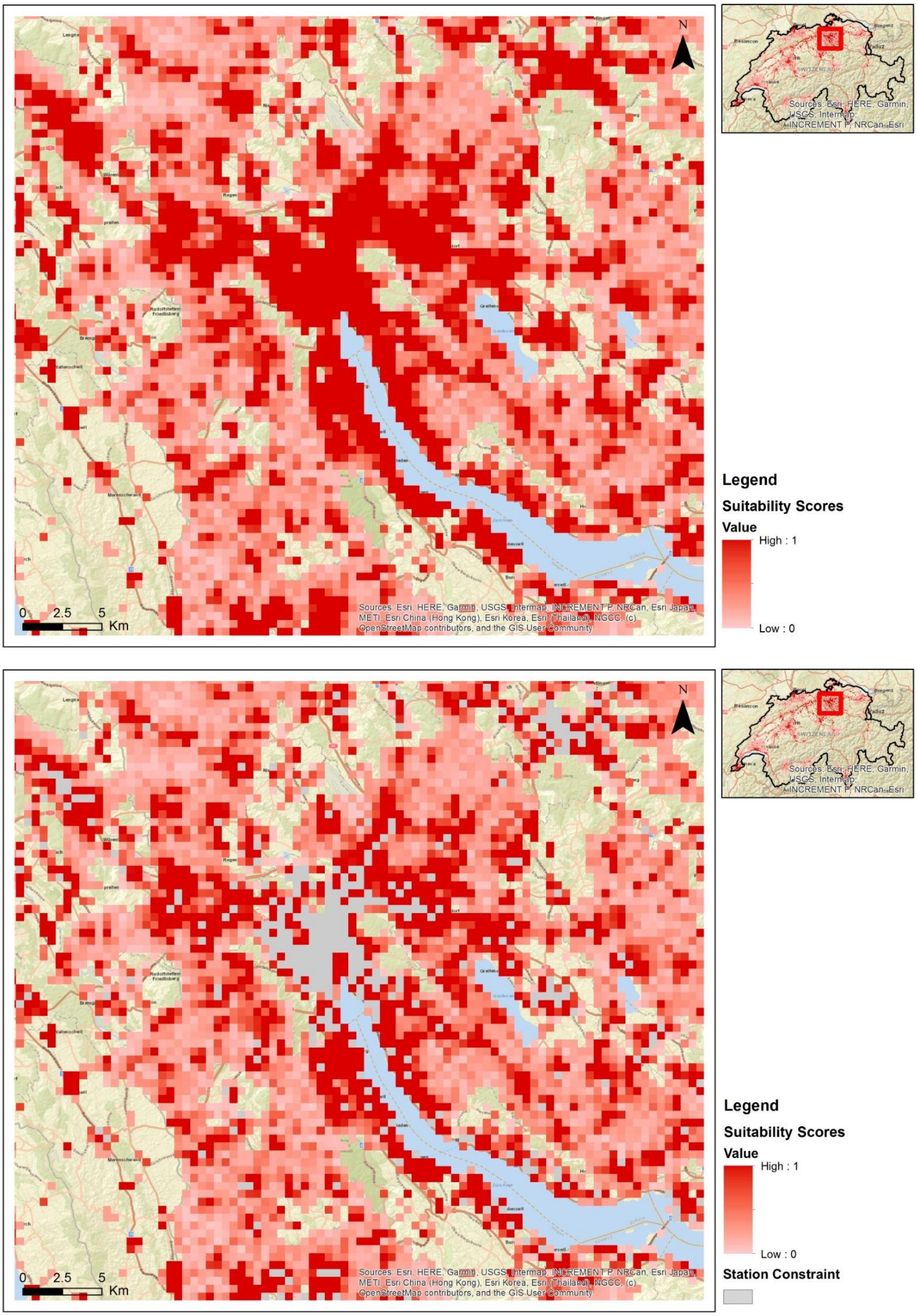

Figure 6.2: Zoomed-in visualisation of the suitability raster. The area displayed in this figure is the city of Zürich and its surrounding area. The exact extent of the display can be visualised on the locator map in the corner. The top image displays the suitability raster before applying the constraint that all cells that contain at least one already existing carsharing station are attributed the value 0. The bottom image displays the suitability raster after applying this constraint. Cells that had a suitability score of 0 due to this constraint were assigned the colour grey.

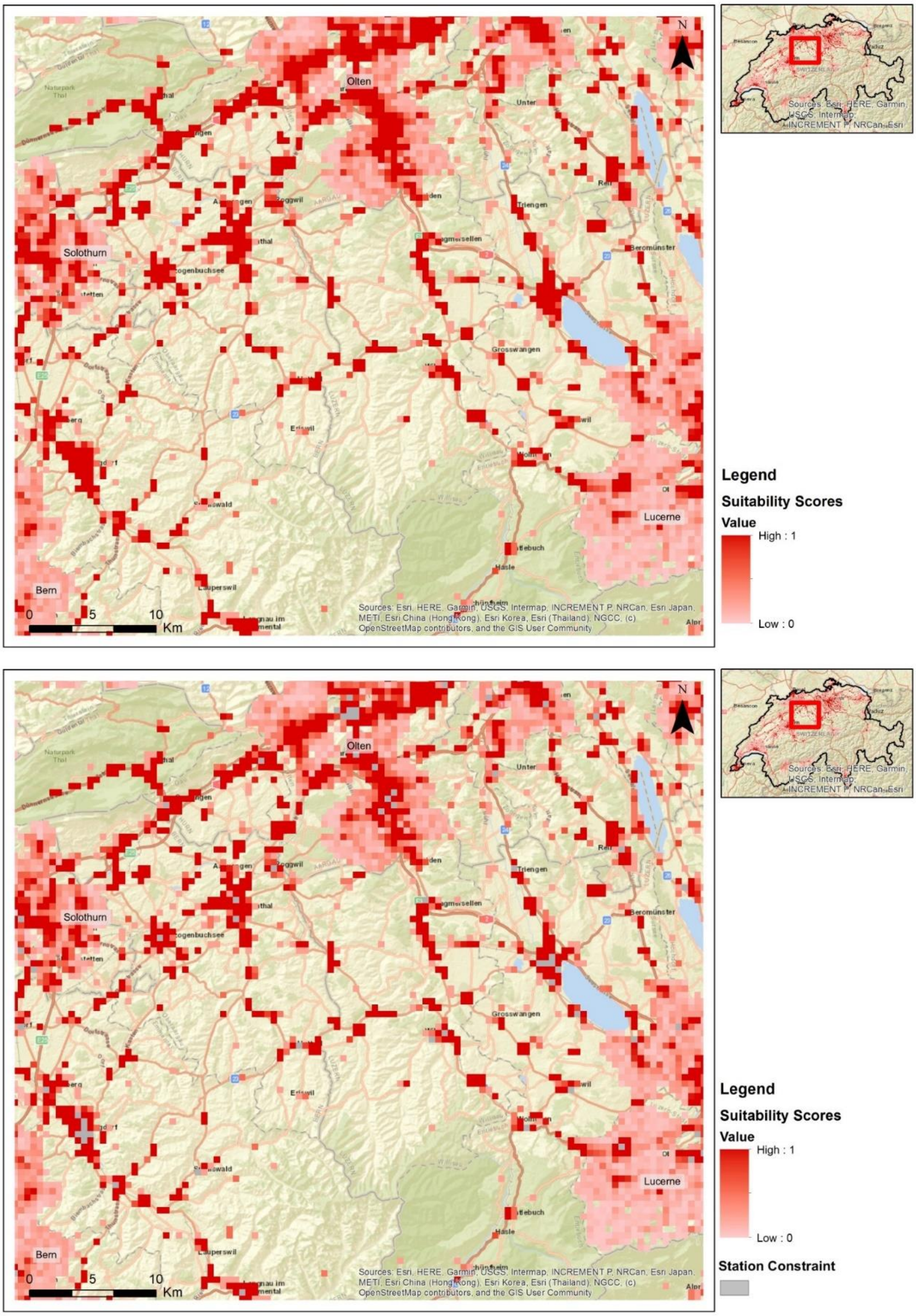

Figure 6.3: Zoomed-in visualisation of the suitability raster. The area displayed in this figure is a rural area between the cities of Lucerne (South-East), Olten (North), Solothurn (North-West), and the city of Bern (South-West). The exact extent of the display can be visualised on the locator map in the corner. The top image displays the suitability raster before applying the constraint that all cells that contain at least one already existing carsharing station are attributed the value 0. The bottom image displays the suitability raster after applying this constraint. Cells that had a suitability score of 0 due to this constraint were assigned the colour grey.

6.3 Location – Allocation Models

By using the suitability raster and applying location-allocation models, new potential locations for carsharing stations were found. The models were run in ArcMap 10.6 using the Network Analyst extension and were chosen to solve the Maximum Attendance problem. There were multiple models developed depending on the desired number of locations to be selected. The list of models is presented in Table 6.7 below. Model 1 represents a baseline model that assessed the situation as it is at present. For this model only the already existing carsharing stations were loaded and designated as required facilities to be placed. For Models 2-5, apart from loading the already existing carsharing stations as required facilities, the candidate locations were loaded as well as candidate facilities. From there, by allocating demand points to the required facilities and candidate facilities the model chose the *n* most optimal locations (*n* being the desired number of facilities to be placed). The same demand points dataset was used for all models.

Table 6.7: A list of all the models run and their description.

	Description of model
Model 1	Allocate demand only to the already existing stations
Model 2	Choose 100 new facilities from the candidate list
Model 3	Choose 250 new facilities from the candidate list
Model 4	Choose 500 new facilities from the candidate list
Model 5	Choose 1000 new facilities from the candidate list

Although in the initial dataset of Mobility stations there were 1'551 return stations, which were all categorised as required facilities, in the solution for Model 1, only 1'330 were chosen. At the end of the solution calculation the software displayed a warning stating that only 1'330 facilities are present in the solution set, as locating all 1'551 facilities would not result in a better solution because some facilities have locations that are redundant. This means that in some areas, for the demand model used, fewer stations could serve the same number of demand points and thus some locations could be inefficient. Upon inspection, the redundant locations were observed to concentrate in the big cities where there is already a high density of existing stations (Figure 6.4). The Maximum Attendance problem does not take into account the capacity of a facility, as it is an uncapacitated facility location problem, and therefore there is no limit for how many demand points can be allocated to a facility. This could be one of the reasons why the locations were considered, by the model, redundant when in fact they might not be.

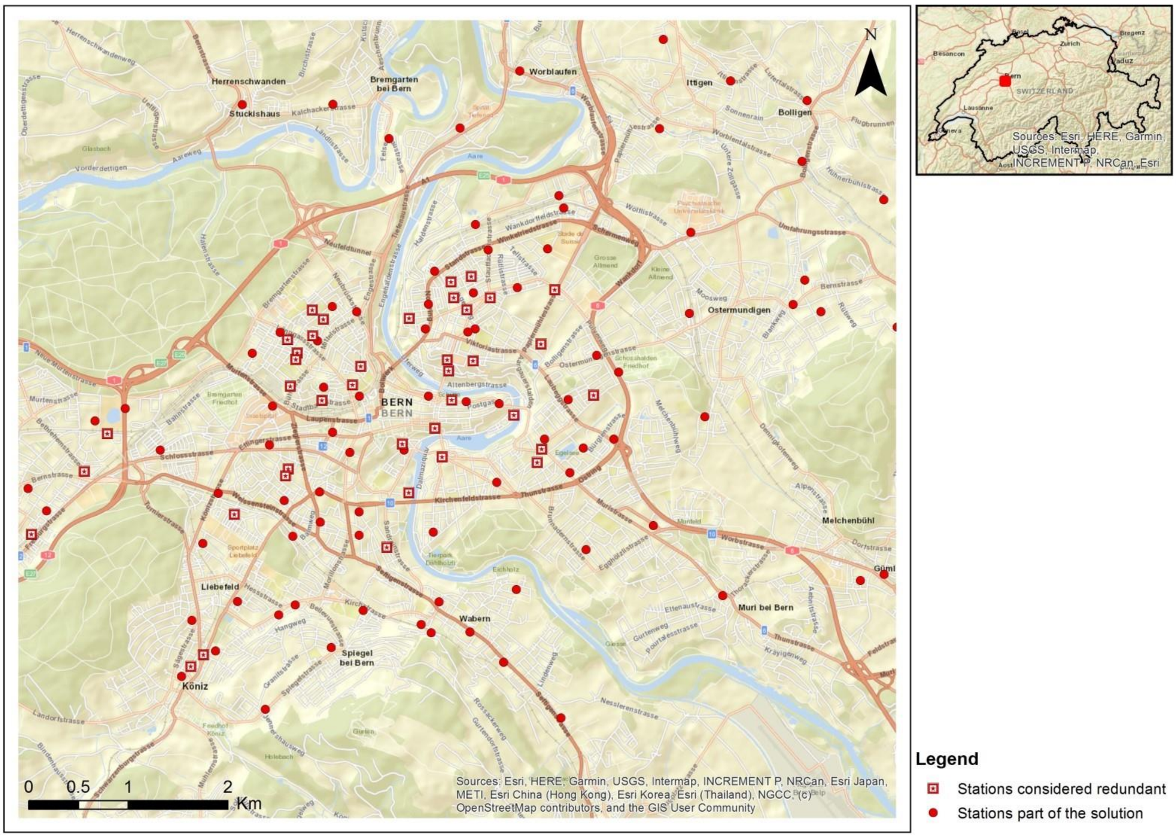

Figure 6.4: Zoomed-in visualisation of the city of Bern. In this map a subset of the facility locations that were considered redundant by Model 1 can be observed. It can be seen that almost each redundant location is in the immediate vicinity of other stations that where allocated demand to by the model.

When running the other 4 models and adding candidate facilities to the model, the solutions included all existing carsharing stations as required facilities, but the stations considered redundant by Model 1 had no demand allocated to them. Nevertheless, the data and locations of those stations were kept in all the models as they represent the current state of the network. The number of demand points served by the solutions of the models, the mean distance travelled between demand points and facilities, and the total area covered by the facilities were calculated and can be found in Table 6.8.

Table 6.8: List of performance variables for each model.

	Number of facilities in the solution	Share of demand points served (%)	Total area covered (km^2)	Mean distance travelled (m)
Model 1	1’330	9.66	2’065	588
Model 2	1’651	11.19	2’369	581
Model 3	1’801	13.37	2’825	577
Model 4	2’051	16.81	3’568	574
Model 5	2’551	23.15	4’979	573
Total number of demand points = 55’577; Total number of candidate facilities = 38’269				

The trends of the indicators against the increase in the number of stations can also be seen in Figure 6.5. As more facilities were added to the solution the share of demand points covered increased significantly. Moreover, the total area covered also increased while the mean distance travelled gradually decreases.

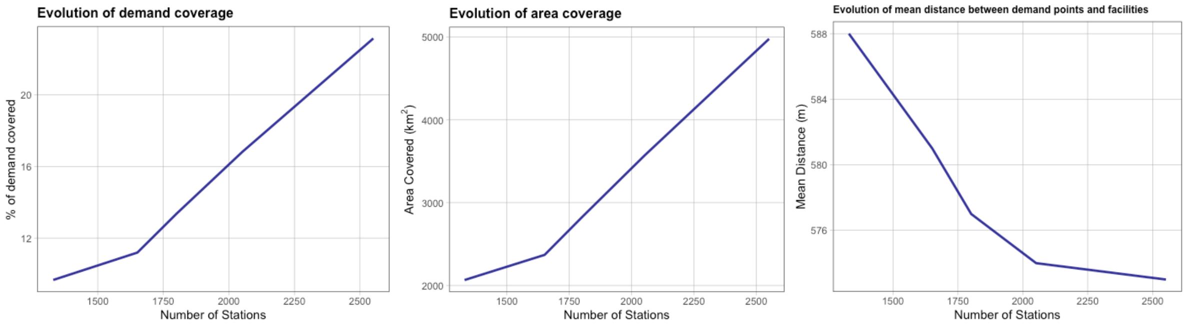

Figure 6.5: Three graphs that display the trends in the indicators of the location-allocation models against the increase in the number of stations.

The locations of the candidate facilities chosen in each solution dataset of Model 2, Model 3, Model 4, and Model 5 can be seen in Figure 6.6, Figure 6.7, Figure 6.8, and Figure 6.9, respectively. As each successive model was set to choose more facilities from the candidate list, it can be seen that the models still chose as optimal new locations the locations proposed by their predecessor model, adding as many new locations as required to the solution. The proposed new locations for return carsharing stations tend to be placed outside the big cities.

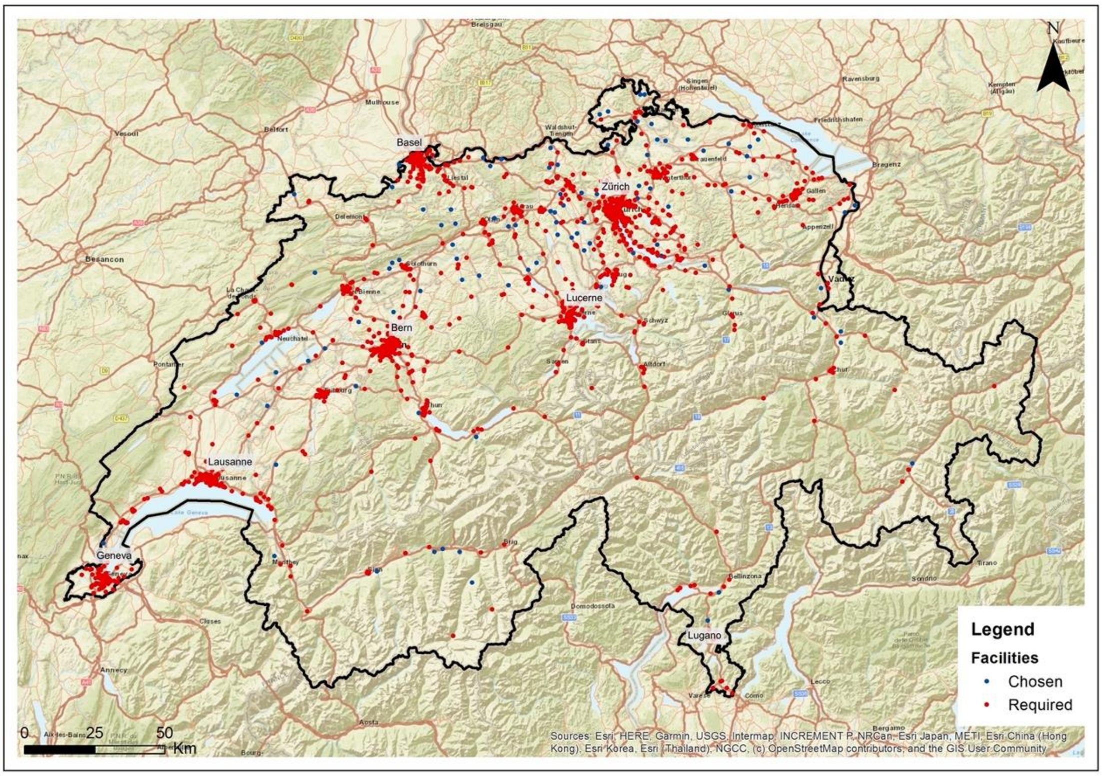

Figure 6.6: Map of the facility locations determined by Model 2. In red, the already existing carsharing stations are represented while in blue, the 100 new locations chosen by the model are represented. The cut-off impedance for each facility was set at 1 km. Demand points beyond this distance cannot be allocated to a facility.

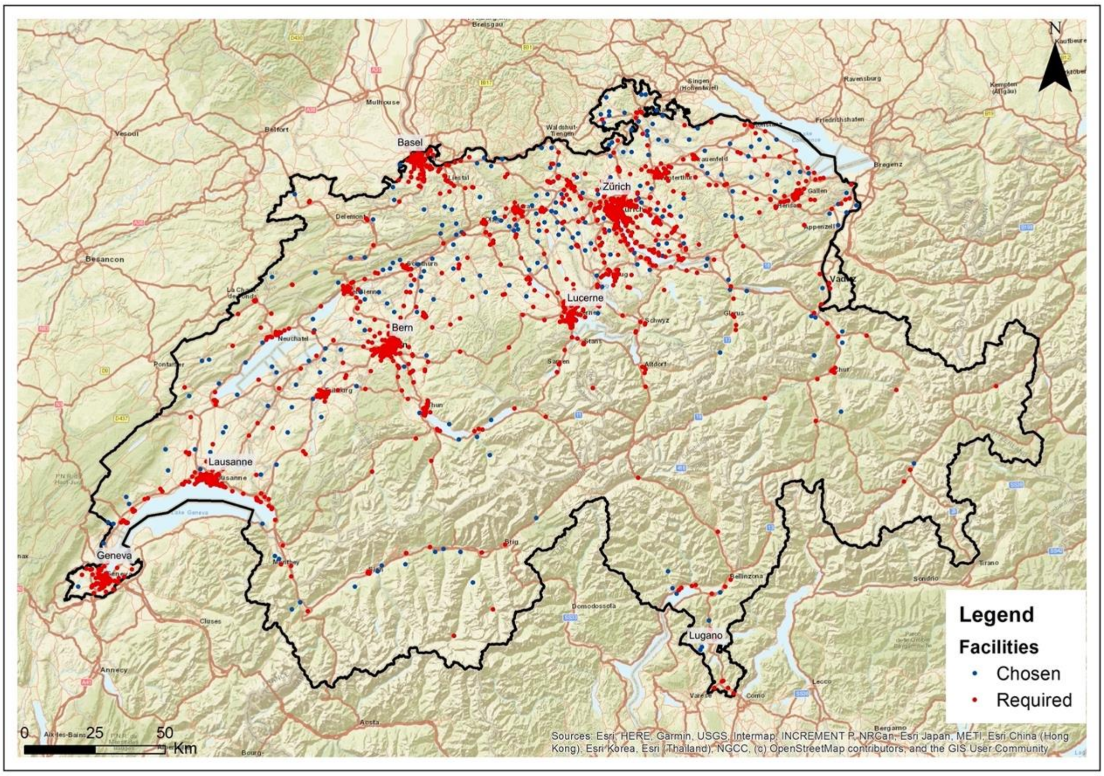

Figure 6.7: Map of the facility locations determined by Model 3. In red, the already existing carsharing stations are represented while in blue, the 250 new locations chosen by the model are represented. The cut-off impedance for each facility was set at 1 km. Demand points beyond this distance cannot be allocated to a facility.

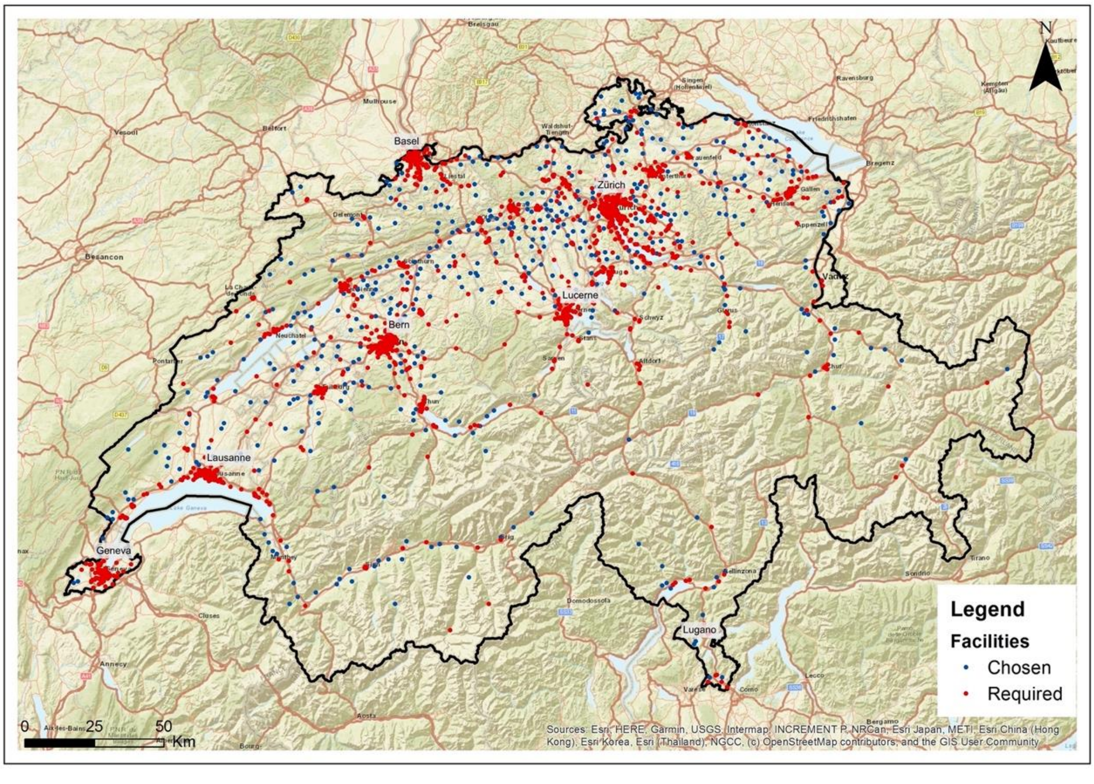

Figure 6.8: Map of the facility locations determined by Model 4. In red, the already existing carsharing stations are represented while in blue, the 500 new locations chosen by the model are represented. The cut-off impedance for each facility was set at 1 km. Demand points beyond this distance cannot be allocated to a facility.

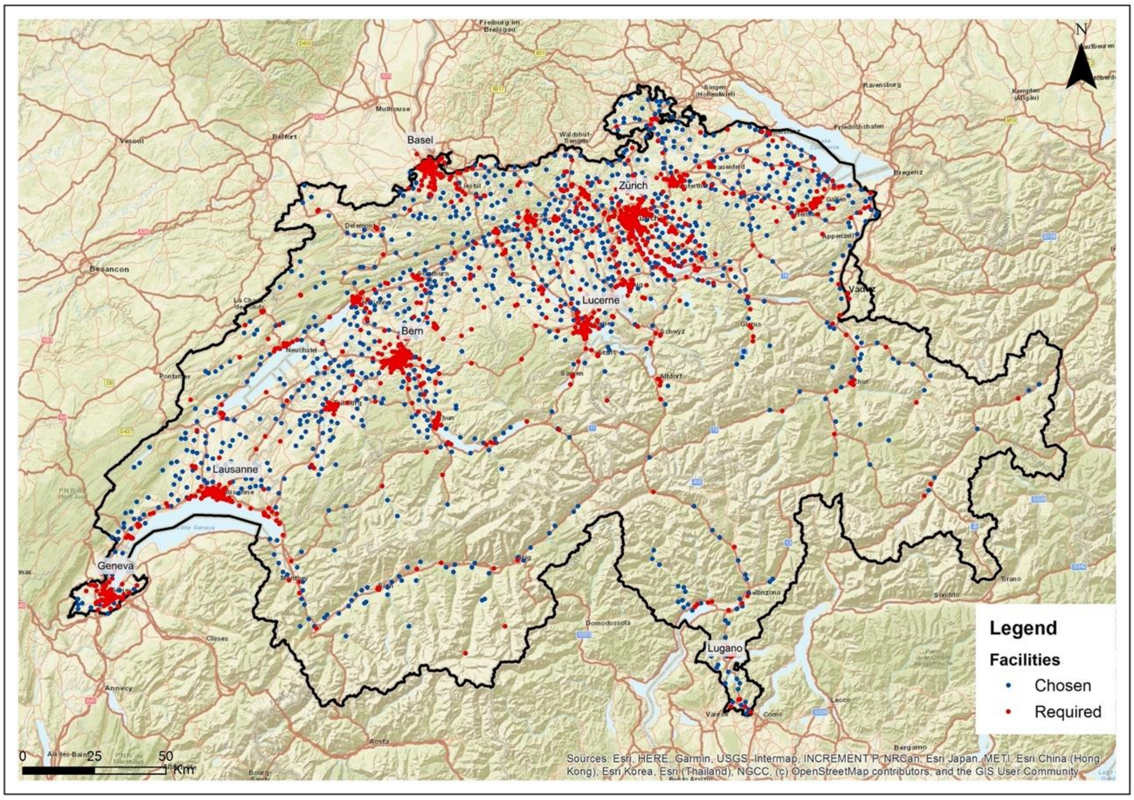

Figure 6.9: Map of the facility locations determined by Model 5. In red, the already existing carsharing stations are represented while in blue, the 1000 new locations chosen by the model are represented. The cut-off impedance for each facility was set at 1 km. Demand points beyond this distance cannot be allocated to a facility.

7. Discussion

The goal of this thesis was to find new optimal locations for carsharing return-stations to be placed. For this, locations that share the same characteristics as locations with already existing high-performing carsharing stations were searched for. The search has been accomplished by taking into consideration what are the factors that drive carsharing performance and integrating them in order to identify new optimal locations. In this chapter, the results presented in Chapter 6 will be discussed in regard to the research questions and hypotheses formulated in Chapter 3, as well as with respect to the previous research in the field presented in Chapter 2.

7.1 Research Question 1: *What are the factors that make a return station successful? Are there some factors more important than others?*

The first research question seeks to determine what are the factors that make a return station successful. This question is answered by creating a multiple linear regression model in order to test if and how the different factors chosen explain carsharing performance. Three models were created based on the different level of urbanisation that the stations were in: urban, suburban, and rural. The results of the regression models were presented in Section 6.1. Regarding the hypotheses established in Chapter 3, the analysis showed that indeed most of the carsharing factors that are presented as crucial in the literature are also significant for the case of Mobility, although unique factors were discovered. Moreover, the three models created found that depending on the level of urbanisation of the given location, carsharing usage has different drivers, even though there are a number of factors that remain consistent irrespective of the level of urbanisation.

Train Stations

Whether or not the carsharing station is associated with a train station was expected to be a significant predictor for carsharing performance in Switzerland. The first reason for this is that Mobility has a strong partnership with SBB, the Swiss Federal Railways. Following this association, Mobility is able to place carsharing stations in the parking area of train stations. In literature, it has been documented that regional transit agencies are hesitant to carsharing companies and restrict them from establishing stations in their parking lots due to fear of competition (Stillwater et al., 2009). However, in Switzerland, carsharing vehicles present at train stations are thought to complete the customers' journey. Moreover, Mobility cars can be booked directly on the SBB website and the SwissPass card (a chip card issued by SBB) can be used as a key to access the Mobility vehicles once registered. In addition, train stations are locations with high daytime population and their locations are placed in a way to serve as much of the population as possible. Thus, there is strong evidence to say that train stations represent a significant factor that drives carsharing, irrespective of the level of urbanisation, and indeed this can be seen also across all three models constructed in this study (Section 6.1).

Public Transport Stops

The presence of public transport stops (bus, tram, metro) was another variable that was highly correlated with carsharing performance in literature and is also found significant in this study for the urban group model. In accordance with the present results, previous studies have demonstrated that carsharing performance increases in the presence of a developed public transport system (Celsor and Millard-Ball, 2007; Kumar and Bierlaire, 2012; Chen et al., 2018; Luan et al., 2018). The relationship between carsharing performance and the presence of public transport stops may partially be explained by people who do not have a car always available deliberately choosing to live in an area with high accessibility to public transport. Moreover, prior studies have noted that people who own a public transport subscription, are more likely to use carsharing services, when public transport is less suitable for their needs (Ciari et al., 2016). Thus, the results suggest that areas with high public transport accessibility and connectivity are flourishing areas for carsharing. A possible explanation as to why the total number of public transport stops is only significant in the urban area but not in the suburban and rural areas might be given by the distribution of the public transport network itself. In rural and suburban areas, where population density is low and sparse, public transport networks face numerous challenges, as it is difficult to provide high frequency quality services without having them run with low occupancy (Petersen, 2016). Due to this, rural and suburban areas are sometimes largely car-dependent. This is also supported by the proportion of Swiss population (above 16 years old) that has a public transport season ticket being 45.1% in areas outside the influence of urban centres compared to 61.5% in urban centre areas (FSO/ARE, 2017).

Mobility Members

The number of already existing mobility members surrounding the carsharing stations is a variable that correlated highly with carsharing performance across all three models. As stated in the literature review, this finding is consistent with several reports in the carsharing literature, where authors found that customers concentrate close to a carsharing stations (Ciari et al., 2016) and that accessibility to a carsharing station is thought to decrease as the distance to the station increases (Kumar and Bierlaire, 2012; Luan et al., 2018). The results of the regression models show that carsharing membership has a substantial impact on stations' performance and that stations that have a high density of members surrounding them have a higher performance. On the one hand, this could be due to people becoming members because of having a carsharing station in the vicinity of their residence or place of work and thus having greater accessibility to the service. Therefore, in principle, high-density urban areas should be key areas to place new carsharing stations as the probability of having a higher membership density is greater. On the other hand, carsharing stations could be placed in an area where a high density of members is already observed. In the study of Juschten et al. (2019), the authors are identifying two "deviator" groups from the expected impact that the accessibility to a carsharing station has on becoming a member: (1) people who are not carsharing members despite having high accessibility to multiple carsharing stations and (2) people who are carsharing members despite having low accessibility to carsharing stations. From their point of view, the interest should be centred on the second group, as they are considered "early adopters" and their characteristics should be examined in order to achieve further growth in areas where the supply is limited, such as the suburban and rural areas (Juschten et al., 2019). Thus, the models in this study suggest that potential areas to expand are those where there are already existing members but where the supply is scarce and cannot meet the demand.

Points of Interest

Among the POIs variables, the presence of shopping centres in the vicinity of carsharing stations showed a statistically significant influence on carsharing utilisation across all levels of urbanisation. This result reflects those of Kumar and Bierlaire (2012) who also found that the presence of commercial centres increases carsharing usage. Furthermore, the study of Becker et al. (2016) explains the reason for this significant correlation by identifying that one of the frequent trip purposes of station-based carsharing users is shopping and transporting items. Shopping centres represent an essential location for people to acquire goods and groceries. Moreover, usually grocery stores tend to be placed near a multitude of other types of retail stores. Thus, these locations attract an extensive daytime population that could potentially influence carsharing performance for the stations in the vicinity.

The presence of accommodations (i.e., hotels, motels, and hostels) was a significant predictor for carsharing performance only for stations existent in the urban and suburban groups. This finding is consistent with that of Kumar and Bierlaire (2012) who also found that the presence of hotels has a positive effect on carsharing performance in both urban and suburban areas. Accommodations bring additional overnight stays, the majority of which could have travelled without their private vehicle, especially in urban areas where access is easily made by plane or train. These could then be potential carsharing users. Moreover, the result that a higher number of accommodations is correlated with a higher performance for carsharing stations can also be impacted by the distribution of accommodations in urban areas. Hotels choose to locate close to one another in order to improve their occupancy levels by getting positive spill over effects from their neighbours (Barros, 2005; Canina et al., 2005; Yang et al., 2012). One explanation for the variable not being significant for the rural group could be that for overnight stays in the rural area, people would need a private vehicle to reach it, as the public transport network might be limited, thus not needing to use a carsharing service. In urban and suburban areas, tourists and visitors can rely much more on the public transport and therefore, a lot of their trips might not be made with their private vehicle. This study however does not take into account the locations of short-term rented apartments and other accommodation types, as there was no data available for this.

The total number of universities was found to be a statistically significant predictor for carsharing performance in the rural group. In literature, this variable was tested among a number of different studies, but there was only one study, Kumar and Bierlaire (2012), that found a significant positive relationship between universities and carsharing usage. However, their study found the relationship to be significant in urban and suburban areas. Upon inspection, 5 out of the 186 points that were considered in this analysis for the universities locations datasets were in municipalities with no urban character. Moreover, 3 out of the 5 university locations had a carsharing station near them with moderate performance. A possible explanation could be that, as rural municipalities can be highly car-dependent, and levels of car ownership are low amongst students. Therefore, students in rural areas use carsharing more than the ones in urban areas where there is a more developed public transport system. In addition, another possible reason for the high performance can be the placement of student accommodations that concentrate near universities.

Land-Use

Out of the land-use types considered in this study, the commercial land-use type showed significant correlation with carsharing performance in the suburban group. The description of the commercial land-use type from OSM is referring to predominantly commercial businesses and their offices (OpenStreetMap Wiki contributors, 2021b). Large business and commercial centres tend to cluster in suburban areas as there is no available area in the city to build them. The result supports arguments from previous studies that also found that the ratio of area for business use has a positive influence of carsharing performance (Kang et al., 2016). These locations bring a large daytime population that is found in literature to be a strong predictor for carsharing performance (Millard-Ball et al., 2005). A reason why this variable was not found to be significant for the urban group could be that in urban areas different land-use types are placed very close to one another. There could be commercial neighbourhoods that are also seen as residential or industrial neighbourhoods and, in the dataset, they would be recorded only under one type. Therefore, a higher resolution dataset would be needed to investigate this relationship further and also taking in consideration the mix of land-use in an area, like the studies of Awasthi et al. (2007) and Correia and Antunes (2012). Further, Kang et al. (2016) uses percentage of building floor area instead of land-use because of the vertical mix for activities in the city of interest, method which could improve the accuracy of the analysis.

The industrial land-use type showed significant correlation with carsharing performance in the rural group. The description of the industrial land-use type from OSM is referring to predominantly workshops, factories, or warehouses (OpenStreetMap Wiki contributors, 2021b). Therefore, these are areas of high activity that bring a big daytime population that could potentially drive carsharing usage. Moreover, industrial land-use areas tend to appear more in rural than urban and suburban areas due to the space required.

Intersection Density
The total number of intersections present around carsharing stations showed significant correlation with carsharing performance only in the suburban group. Swiss urban areas are usually considered highly pedestrian friendly, which is also supported by highly developed public transport networks, thus there might be no difference between the pedestrian friendliness and the performance of carsharing stations. In the suburban areas, where the public transport network and the road network are not very dense, intersection density might be more important for people who do not have a car always available.

Demographic Variables
In the model created for stations in the urban group, the demographic variables that were found to be statistically significant predictors of carsharing performance were population between 20 and 39 years old and population above 65 years. Although customers can use Mobility services form an age as early as 17 years old, the data for the population between 17 and 20 was not integrated in the analysis due to the structure of the STATPOP data that is recording the population in age groups of 5 (i.e., 15-19 age group). The result that population between 20 and 39 years old is a significant predictor for carsharing performance is consistent with other studies within the carsharing literature (Millard-Ball et al., 2005; Kang et al., 2016; Luan et al., 2018). The result of the present study suggests that younger people in Switzerland are less likely to own a private vehicle. This could be due to the high costs associated with owning a car, since apart from having to pay for the vehicle itself, insurance and other associated costs are higher for young people.

Contrary to the expectations and findings in other studies, the model created for stations in the urban group also found the population above 65 years old as a significant predictor. The result implies that population over the age of 65 tends to use carsharing more which further suggest that this population is also less likely to own a private vehicle. There is no public data available on vehicle ownership by age group in Switzerland but in the Mobility and Transport microcensus that is conducted every 5 years, the average daily distance per person for people with ages between 65 and 79 was 27.2 km and for people with ages of 80 years and over was 13.3 km, which is more than 50% less than the average distance travelled by younger age groups (FSO/ARE, 2017). Thus, one explanation for the result could be that, in Switzerland, elderly people tend to travel less and therefore give up their private vehicle, using carsharing when needed.

In the model created for stations in the rural group, population between 40 and 64 years old was found to negatively correlate with carsharing performance. A possible cause of this could be that people in this age group are more likely to be car owners, especially in rural areas, where in the absence of a reliable public transport system they might be dependent on their private vehicle and thus, are less likely to use carsharing.

Household Variables

The only household variable that was found to be a statistically significant predictor was the number of 2-person households, that correlated negatively with carsharing performance in the model for the stations assigned in the urban group and correlated positively in the model for the rural group. For the urban group, the result is somewhat in accordance with the findings in other carsharing studies, which conclude that as the number of people in a household increases, the likelihood of being carsharing users decreases, with one person household being the most frequent household type of carsharing members (Millard-Ball et al., 2005; Celsor and Millard-Ball, 2007; Luan et al., 2018). However, in all three models constructed, one person households are found to be an insignificant predictor for carsharing performance. Moreover, the number of 3-person households was not found to be statistically significant in predicting carsharing usage at all. Further, the spatial distribution of households by dimension could also play an important role, as more 2-person households might mean a denser residential area, thus implying that dense residential areas in urban environments negatively impact carsharing.

Contrary to the results from the urban group, the number of 2-person households correlated positively with carsharing performance in the rural area. This result may be explained by the fact that in rural areas households tend to be bigger, with one-person households being less common in a rural environment. Another possible explanation could be that in rural areas that are car-dependent, for bigger households, carsharing could substitute the second vehicle in the household.

Carsharing Stations

Across all three models, the presence of clusters of carsharing stations correlated negatively with stations' performance. This result is in accordance with a previous study done by Kumar and Bierlaire (2012) which suggested that as the distance between stations gets smaller, the catchment area of the stations gets impacted. Despite the fact that new stations are established, no new customers are added. If two carsharing stations are too close to each other, their service area becomes almost identical and thus no new customers can be reached. However, the small distance between stations can be a result of unavailable parking space to increase the capacity of an already existing carsharing station in order to match the demand at that location. In this case, a possible solution would be to move the station to a location that permits its expansion, when needed.

7.2 Research Question 2: *What are optimal locations for new return stations from a geographic point of view?*

The second research question seeks to determine what optimal new locations for carsharing return stations are based on the carsharing drivers identified in the first part of this study. This question is answered by integrating the significant factors that influence carsharing performance and performing an MCDA in order to determine candidate locations for new stations. Through this, the possible search space of the facility placement is reduced. Afterwards, location-allocation models are used to allocate demand to candidate facilities and thus choose optimal new locations for return stations. The results of the analysis indicate that new optimal locations for return stations concentrate in suburban and rural areas, which are highly suitable for carsharing and where demand is also present.

Before integrating the resulting significant factors, weights needed to be assigned to each one, in order to show and establish their importance towards the goal, the suitability score. For this the AHP process developed by Saaty (1990) was used. This process was also used in previous carsharing studies for weighting different criteria (Awasthi et al., 2007; Li et al., 2017). The advantages of using the AHP process are that the factors are arranged in a hierarchical structure, by using a relative scale to compare their importance with respect to the goal (Saaty, 1990; Awasthi et al., 2007). Through AHP the relative priorities given for a set of factors are quantified.

For this study, the initial relative priorities of the factors considered were extracted from the regression models. Further, the factors were compared to each other using the pairwise comparison and relative scale developed by Saaty (1990) and described in Table 5.2. As different factors drive carsharing performance based on the level of urbanisation, the process was calculated individually for each group. The results of applying the AHP process for all three groups (urban, suburban, and rural) were presented in Table 6.4, Table 6.5, and Table 6.6, respectively. For all three models, the factor with the highest weight is the total number of existing members. This finding is consistent with the study of Li et al. (2017) where the density of members had also the highest weight in their calculation for placing carsharing stations using the MCDA method. The rest of the factors that are present in all three groups had different importance relative to the factors in that group and thus resulted different weightings. For example, the presence of train stations had the second highest weight in the urban group, the fourth highest weight in the suburban group and the smallest weight in the rural group. One possible explanation for this could be the population that commutes by train on a daily basis for work. As urban centres have higher job densities, usually people commute form rural and suburban areas into the city, thus bringing in more daily population that could represent more potential carsharing users. The presence of shopping centres is weighted similar across the three groups having the second highest weight in the urban group and the third highest weight in the suburban and rural groups. This might be explained by the fact that the influence of shopping centres on carsharing stations remains mainly the same, having the same relationship across all levels of urbanisation However, a reason why it is considered a more important factor in urban areas could be due to the higher population density. Therefore, apart from demonstrating that carsharing performance is driven by different factors depending on the level of urbanisation, the present study also found evidence that even for the factors that are significant across all levels of urbanisation, the level of their importance might vary.

The first three figures of Chapter 6 reveal the final raster layer that presents how suitable the locations for carsharing stations are, based on the performed analysis. The resolution of the raster is 500x500 m and hence the decision unit of the analysis is also made up of 500x500 m grid cells. The results show that the majority of cells with high scores are distributed in urban centres, especially in the big cities in Switzerland. Moreover, a vast majority of the cells with suitable scores are present on the Swiss Central Plateau, one of Switzerland's three geographical regions (Figure 7.1), that covers 30% of its area and is home for more than 75% of the countries' population (FDFA, 2019). In addition, the majority of the factors used in this analysis are also concentrated within this area, thus resulting in higher scores. The already existing mobility stations are also located mainly on the Swiss Central Plateau. However, the results also suggest that suitable locations for carsharing stations exist beyond areas of and influenced by the big cities and that carsharing stations could be distributed more dispersed, expanding the coverage, and improving the accessibility to carsharing.

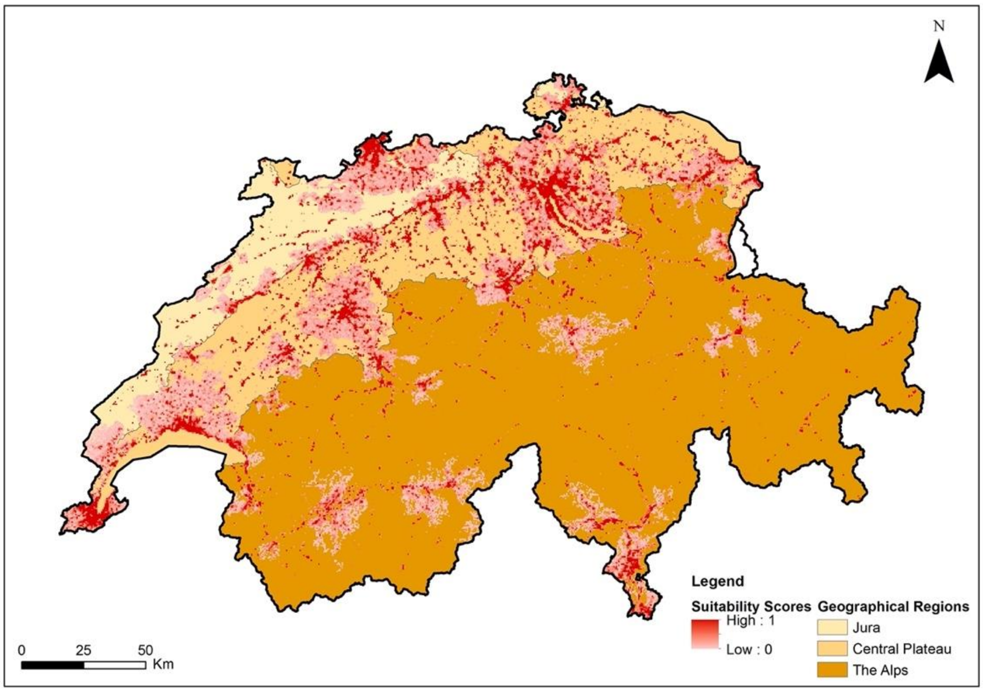

Figure 7.1: The carsharing suitability raster and the three main geographical regions of Switzerland. Data for the geographical regions from FOEN (2020).

When looking at the resulting raster, in rural areas it can be observed that the suitability scores exhibited are high and the variety in scores is quite small. A reason for this could be that rural settlements usually have a small area of anthropogenic land cover, being surrounded by other land cover types such as agricultural fields and forests or having a restrictive topography such as narrow valleys. On the other hand, rural settlements are also quite dispersed, with low population and buildings density. Thus, the density of factors considered concentrates in the centre of the rural municipality and that is where high scores were observed. The resolution at which the analysis is done also had an impact on the results. The MCDA analysis was done using rasters whose resolution was 500x500 m, and therefore, all factors were aggregated to this resolution. One repercussion of this could be that structures and patterns in the data can get lost with lower resolution. As urban areas are denser, they get more impacted by a lower resolution, making it hard to detect any areas that could potentially not be suitable for carsharing.

The suitability of a location should not be the only thing taken into consideration when placing new carsharing stations, or any type of facility. There might be a lot of suitable locations, but if there is no demand to allocate to that facility, the location does not bring any value to the network. For this reason, after suitable areas for carsharing stations were found, location-allocation models were used in order to allocate demand to candidate facilities and select the optimal ones.

The aim of this project was to determine an optimal location configuration of a fixed number of facilities that maximizes accessibility to carsharing services. Thus, the location-allocation model implemented was the *Maximise Attendance* model. The choice of this model was done for several reasons. One of the most used and known location-allocation model is the minimize impedance (p-median). However, this problem did not suit the aim of this analysis as the goal is not to minimise the costs between demand points and the chosen facilities. Carsharing members would not travel any distance to reach carsharing station just because this is the closest. Therefore, an impedance cut-off around the facility was needed. Maximize coverage problems locate facilities such that they serve as many demand points as possible within a specified maximum distance. However, this model is more suitable for emergency services such as fire stations and police stations that need to cover as much of the population as possible within a certain distance and time (ESRO, 2021a). Thus, beyond needing an impedance cut-off, the model applied needed to also take into consideration that the demand is traveling to the facilities, not vice versa. For this, the maximise attendance model is better suited. This is because apart from implementing a service area for the facility through having an impedance cut-off, it also implements a distance decay function, assuming that the demand weight allocated to the facility is inversely proportional with the distance between the demand point and the facility (ESRI, 2020a). Therefore, it was concluded that this was the most appropriate model to be used for the analysis as the probability of a customer to use a carsharing station decreases with the increase of the distance to the station.

The candidate locations for the location-allocation models were extracted from the MCDA raster, as the centroid of the raster cells. Moreover, the suitability score of each cell was attributed to the points. No threshold value was set for the suitability scores of the candidate locations. Because of the ability to set weights for candidate locations in the location-allocation model, the suitability score of each location was used to represent this weight. Candidate locations with higher suitability scores had a greater weight associated with them and thus were considered more attractive to allocate demand to. Applying no threshold is useful in situations where a candidate location has a lower suitability score but the demand in the area is high. One downside of applying no threshold is that there is no elimination of candidate locations, and the computation time of the model increases. If the same framework were applied for another country with a bigger area, a threshold could be considered to be applied in order to avoid high computation times.

In the solution for Model 1, out of 1’551 already existent stations, only 1’331 were part of the solution of the model, the rest being considered to have redundant locations, although all stations were characterised as required. Taking a closer look at the stations performance that were considered redundant by the model, no obvious pattern was observed. This group includes both high- and low-performance stations. However, taking a look at their spatial distribution showed that almost all redundant locations were in the immediate vicinity of a station that was part of the solution. This result supported the findings from the regression analysis that a small inter-distance between stations has a negative impact on the performance of the stations and the service areas overlap. On the other hand, this result could also be explained by the resolution of the analysis and the way the demand was aggregated. In order to aggregate the population to the same level of aggregation as the factors used, a weighted mean of the population was done, and the resulting demand points locations were “skewed” towards the points that had higher registered population. However, by doing this, the size of the population at that point was no longer registered, the demand point representing the location where there is the highest population density within the 500 m^2. Therefore, in urban areas this is an oversimplification of the demand locations and magnitude, which can lead to the assumption that there is less demand to be served, and thus some already existing locations were considered redundant. Furthermore, the current models did not take into consideration the capacity a carsharing station has.

The results from Models 2-5 support the findings from the MCDA analysis that suburban and rural areas have great potential for carsharing services expansion. Areas as such not only exhibited high suitability scores but also exhibited potential demand for carsharing. Moreover, even if urban areas exhibited high suitability scores, with the demand model used it appears that the areas were saturated with carsharing stations. Although, the demand model used was quite simplistic, using the population density, several studies concluded that population density can be a driver for carsharing performance (Correia and Antunes, 2012; Kumar and Bierlaire, 2012) and the probability of having more carsharing members increases with denser population. In accordance with the present results, the previous study of Juschten et al. (2019) has also established that, in Switzerland, areas with low levels of carsharing supply, like the suburban and rural areas identified in this study, exhibit high potential in terms of carsharing attractiveness. All of the aforementioned lead to the conclusion that when thinking of expanding the carsharing network, suburban and rural area show great potential and even though urban areas are the intuitive choice, other areas should be investigated too.

Regarding the performance variables of the models, the trends of both the share of demand points and total area covered were very similar. As the number of stations placed increased, both the share of demand and the area covered increased. For the number of models run and the maximum number of stations added (1’000) no trade-off curve could be observed (Figure 6.5). It is evident that infinite stations cannot be added to the network, but a point where the growth in demand or area covered by the number of facilities becomes less substantial has not been observed. These results suggest that there is enough room for Mobility to expand from the point of view of demand and area available only without concerning additional costs of the new facilities and management. A possible reason for the increasing trend could be that carsharing is a young business with a lot of potential and room for expansion. The trend of the mean distance indicator, between demand points and facilities, displays a decreasing trend. A smaller mean distance travelled means that stations are added closer to the demand, thus providing better accessibility. However, after the network reaches 2’000 stations, the decrease in the mean distance travelled becomes very small.

In sum, this chapter has provided the main findings of this study, answering to the two research questions established in Chapter 3. The density of already existing members, the presence of train stations and shopping centres were factors that were discovered to drive carsharing performance irrespective of the level of urbanisation. Further, locations suitable for carsharing were identified by integrating all drivers of carsharing. Locations for future carsharing stations were chosen not only based on their suitability but also by allocating demand to them and detecting a need for this service in that area. Although urban areas exhibited the highest suitability scores, they are areas with a high number of already existing stations, and the demand was allocated to those. Thus, suburban and rural areas were detected as attractive areas for carsharing expansion.

8. Conclusion

8.1 Summary and Main Findings

This project is a case study of Mobility, a carsharing service in Switzerland. In need for another transportation mode that can be more flexible than public transport but less problematic than owning a private car, the idea of carsharing appeared, where multiple users can share between themselves a fleet of cars. Beyond the environmental benefits that this transportation mode has, by reducing VKT and vehicle ownership, carsharing also provides social, economic and health impacts. The aim of this project was to reveal what surrounding factors make a carsharing station successful and determine new locations for carsharing stations based on these factors. For this, a framework based on identifying the drivers of carsharing performance and combining MCDA and location-allocation models was proposed.

In response to the first research question, factors surrounding the stations that might drive carsharing utilisation were analysed. This was achieved by using multiple regression linear models. The list of variables that were tested against carsharing performance was constructed from literature and the variables used in other carsharing studies. There were 18 independent variables tested against one dependent variable: the number of reservations at each carsharing station. In the interest of observing if there is any variation in the drivers based on the different levels of urbanisation, the stations were divided in three groups: urban, suburban, and rural. The results showed that while there are several factors that are significant across all three groups, in general the performance of carsharing stations can be explained by different factors depending on the level of urbanisation.

Responding to the second research question, new locations for carsharing stations were identified. Firstly, an MCDA was used to integrate the factors discovered in the first part of the analysis and find locations with similar characteristics as locations where successful carsharing stations already exist. The AHP method was used to determine the weights of the significant factors. The density of members turned out to be the most important indicator determining the location of a station, irrespective of the level of urbanisation. The rest of the factors present in all three groups had different importance based on pairwise comparisons and relative to the factors present in the group. The resulting raster shows that urban areas have the largest concentration of high suitability scores, but after applying the constraint associated with already existing carsharing stations, this is eliminated. Moreover, suburban and rural areas also exhibit moderate to high suitability for placing carsharing stations. Thus, based on the performed analysis there are favourable locations for carsharing expansion beyond urban areas. Secondly, location-allocations models were used to allocate demand to candidate locations that were extracted from the MCDA raster. The models placed new carsharing stations mainly in suburban and rural areas, suggesting that the urban areas are saturated with supply. Thus, rural and suburban areas are found to be attractive locations for placing new carsharing services, having good suitability scores and demand for this service.

8.2 Limitations

The main limitation of this study is the data availability for particular factors. As the list of factors that were tested against carsharing performance was created after an extensive literature research, where all studies tested and considered different factors, some of them could not be considered in the present study due to lack of data availability. For instance, there were a lot of factors that were discovered to be significant drivers in certain carsharing studies but could not be used in the present analysis because no data was available for them. These latter include data on vehicle ownership, on driving licence ownership, on public transport subscription ownership, on income and on the level of education of the population. Moreover, the amount of parking space is also a variable often included in the analysis of carsharing studies, but for this study only one dataset was found from OSM which in the end could not be used because of its low quality. Having these data available could potentially improve the percentage of explained variance in the regression models. Nevertheless, this work has put in place a workflow that could be extended by including more predictor variables, if more data becomes available.

Another limitation of the study is that it is not taking into consideration any aspect regarding the actual placement of the proposed new carsharing stations, such as land availability and the costs associated with its opening. Moreover, although the methodological workflow can be in principle applied to any study area, the results and the conclusions that can be drawn from this study are limited to Switzerland, as it was proven by this study and other studies in literature that the factors that influence carsharing performance can be particular from one study area to another.

8.3 Future work

Due to the multiple disadvantages associated with owning a private vehicle and the rapid growth of the sharing economy concept, carsharing is promising to gain increased popularity in the future. In order to be successful and benefit the entire network, developing frameworks for choosing new locations for return carsharing stations is a subject on which further studies should be conducted.

Beyond focusing on the location of the stations, it would be essential for future studies to take into consideration the capacity of the return stations and analyse how it can be adjusted with respect to the demand in that area. Hence, certain guidelines could be developed for carsharing services in order to determine the size of future stations. Moreover, studies focusing on the type of vehicles present at a station could provide insights into what certain vehicle types are used for and where these types are used the most. This would help carsharing services provide a better and more attractive service for their customers.

For future studies that are concerned with optimising carsharing networks, a more refined demand model used would be essential. Constructing a demand model that is built on the characteristics of already existing members or the target population for carsharing will increase the accuracy of the location and of the magnitude of potential demand.

Finally, conducting studies on optimising carsharing networks on a smaller scale, would improve the accuracy of the analysis and of the locations proposed. While a large-scale analysis can help by minimising the search area for where the next expansion of the network is most needed, a smaller scale analysis would help capture the particularities and variations in travel patterns and usage for which carsharing is used.

9. References

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10. Personal Declaration

I hereby declare that the submitted Thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the Thesis.

Place and date: Signature:

Zürich, 30.09.2021 Alexandra Ioana Georgescu