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Master's Programme in Geoinformatics

A geospatial data-driven approach to assess transport-related carbon emissions: Case Otaniemi, Finland

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Ngoc Chau

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Author Ngoc Chau

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Abstract

The transport sector has not been able to show a downward trend in emissions that sets it apart as the sole sector in the EU necessitating immediate transformation. Urgent action is crucial to bring the transport sector aligned with climate targets. To address this pressing issue, this thesis introduces a proof-of-concept aimed at estimating carbon emissions from transportation while incorporating modal share scenario testing capabilities.

By understanding the potential for carbon reduction, this tool can encourage employers to promote a sustainable mobility culture. For instance, employers could be motivated to offer incentives that support environmentally friendly commuting options. In addition, this tool can support the planning of low-carbon transportation systems.

To demonstrate the practical application of the proposed proof-of-concept, the study focused on assessing the carbon emissions resulting from daily trips to Otaniemi. The information regarding daily trips was obtained from Telia Crowd Insight, which utilizes mobile phone data. Different modal share scenarios, both pre- and post-COVID, were examined to provide insights into emissions.

The main finding of this research was that using existing open source tools with a bottom-up GIS approach made it possible to model the carbon footprint associated with travel.

Keywords CO_2 emissions, GIS, LCA, Mobile phone data, Open-source, Routing, Scenario testing, Sustainable mobility, Transportation

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Tiivistelmä

Liikennesektori erottuu muista sektoreista siten, että se on ainoa, joka ei ole onnistunut kääntämään hiilidioksidipäästöjä laskusuuntaan EU:ssa. Liikennesektorilla on tehtävä välittömiä ja merkittäviä muutoksia ilmastotavoitteiden saavuttamiseksi. Tästä motivaatiosta tämä työ esittelee menetelmän, joka arvioi liikenteen hiilidioksidipäästöt liikennemuoto osuuksien skenaariotestauksen avulla.

Tämä työkalu pyrkii lisäämään ymmärrystä hiilidioksidipäästöjen vähentämispotentiaalista, jolloin se voi kannustaa työnantajia edistämään kestävää liikennekulttuuria. Työnantajat voivat tarjota työntekijöilleen etuja tai kannustimia, jotka tukevat kestävämpää liikkumista. Lisäksi työkalu voi olla tukemassa vähähiilisten liikennejärjestelmien suunnittelussa.

Ehdotettua menetelmää sovellettiin arvioimaan Otaniemeen suuntautuvien päivittäisten matkojen aiheuttamat hiilidioksidipäästöt. Päivittäisiä matkoja koskevia tietoja saatiin Telia Crowd Insight -palvelusta, joka hyödyntää matkapuhelindataa. Päästöjen selvittämiseksi tarkasteltiin erilaisia liikennemuotojen osuuksien skenaarioita sekä ennen että jälkeen koronapandemian.

Työ osoittaa, että on mahdollista mallintaa liikenteen hiilijalanjälkeä GIS-menetelmin bottom-up-periaatteella avoimen lähdekoodin työkaluja hyödyntäen.

Avainsanat Avoin lähdekoodi, CO_2-päästöt, GIS, Kestävä liikkuvuus, Elinkaariarviointi (LCA), Liikenne, Matkapuhelindata, Reititys, Skenaariotestaus

Table of contents

Preface

I would like to thank everyone who helped me complete this thesis. I would like to thank Telia for providing the Telia Crowd Insight service, and Aapo Pihkala and Aalto ACRE for their support in sharing materials. I want to express my gratitude to my supervisor, Henrikki Tenkanen, for his guidance and encouragement throughout this journey. I am grateful for his expertise and for entrusting me with such an interesting thesis topic. Finally, I would like to thank Miloš Mladenović and GIST Lab for the insightful discussions and support.

Otaniemi, 29 July 2023
Ngoc Chau

Abbreviations

API	Application Programming Interface
CO_2-eq	Carbon dioxide equivalent
CPU	Central Processing Unit
CSV	Comma-Separated Values
E-bike	Electric bicycle
EU	European Union
GDPR	General Data Protection Regulation
GHG	Greenhouse Gas
GIS	Geographic Information System
GPRS	General Packet Radio Service
HSL	Helsinki Regional Transport Authority
ITF	International Transport Forum
LBS	Location-Based Services
LCA	Life Cycle Assessment
ODM	Origin-destination matrix
PT	Public transport
RAPTOR	Round-Based Public Transit Optimized Router
r5r	R package for rapid realistic routing on multimodal transport networks
SSP	Shared Socioeconomic Pathways

1 Introduction

1.1 Background

The transport sector causes significant environmental stress. It is the second largest contributor to greenhouse gas emissions in Finland and the EU (Lounasheimo et al., 2021; European Environment Agency, 2022). All sectors have demonstrated a downward trend in greenhouse gas emissions, except for transport. The transport sector is a challenging sector to decarbonize due to its high reliance on fossil fuels and the increasing demand for transportation (European Environment Agency, 2022b).

Car is the most common means of travel in Finland and it constitutes 60 % of overall domestic travel. Most car travels are relatively short (Liikennevirasto, 2018). The potential for carbon reduction lies in substituting short motorized travels with active transport such as walking and cycling. However, there is currently a lack of empirical evidence regarding the extent of carbon reduction achieved through the shift to active transportation (Neves and Brand, 2019).

Technology and infrastructure investments alone will not be enough to tackle the environmental challenges in the transport sector. Cultural change is also needed in addressing climate mitigation. Around two-thirds of Finland's consumption-based carbon emissions are generated by households, and transportation represents 30 % of the Finnish household carbon footprint (Nissinen and Savolainen, 2019). Lifestyle changes can play an essential role in achieving climate targets (Lettenmeier et al., 2019).

Most countries have ratified the Paris Agreement which commits the countries to limit the Earth's average temperature rise to well below 2 °C and preferably to 1.5 °C compared to pre-industrial levels (United Nations, 2015). Based on the agreement, the European Council adopted the European Climate Law, which sets out the net zero greenhouse gas emissions target by 2050 (European Union, 2021). The Parliament of Finland passed the new Climate Change Act in 2022. The new Act commits Finland to reach net zero by 2035 and net negative by 2040 (Climate Act 423/2022). The Ministry of Education and Culture has set a more ambitious target for universities to be carbon-neutral by 2030 (Opetus- ja kulttuuriministeriö, 2021). The universities are among the largest employers and they play an important role in leading climate action through education and research. In addition, employers can promote sustainable commuting culture in their workplaces and shift their employees' commuting habits towards greener modes of transport.

To achieve sustainable mobility, it is important to understand the climate impact of various transportation modes, considering both their direct and indirect emissions. By quantifying carbon emissions through the application of life cycle analysis (LCA) in accordance with ISO (2006) standards, a

comprehensive comparison of transportation modes can be conducted to support the shift towards low-carbon transport.

While LCA is a key methodology for evaluating the emissions associated with travel, it alone does not provide guidance on how these emissions could be reduced. To address this limitation, coupling LCA with modeling techniques specifically focused on travel-related emissions can provide valuable insights. This thesis proposes a model that incorporates travel patterns, modes of transport and other relevant factors into the modeling process to provide a more comprehensive understanding of the emissions associated with different travel scenarios. Scenario-based modeling is crucial as it enables the exploration and understanding of potential outcomes and impacts in different future scenarios. This kind of tool with high spatial resolution big data enables high-resolution mapping of emissions which adds value to informing and shaping climate change policy. The detailed insight into emissions helps in strategic planning and facilitates targeted mitigation efforts. The proposed model is used, for example, to assess the potential of electric vehicles, such as electric bicycles, to reduce emissions.

There is a growing interest in e-bikes as sales of e-bikes reach record levels (CONEBI, 2022). According to the European Cyclists' Federation (n.d.), there are hundreds of incentive schemes across Europe to encourage cycling, and most of these include electric bikes. The Finnish government introduced a tax-exempt benefit for employer-provided bicycles in 2021 (Valtion liikuntaneuvosto, 2020; Verohallinto, 2022). The benefit can encourage employees to get an e-bike since they are more expensive than conventional bikes. Behind the promotion of e-bikes, there are hopes for e-bikes to have a role in decarbonizing road transportation by replacing short motorized travel.

Nevertheless, addressing climate mitigation in the transport sector goes beyond environmental concerns alone. It requires the simultaneous consideration of social and environmental objectives. While increased mobility can offer significant benefits to individuals, it also poses environmental challenges. Achieving a sustainable balance of the two objectives requires identifying a space where basic needs can be met without depleting natural resources excessively. In this regard, Willberg et al. (2023) have proposed a conceptual framework that measures just accessibility within planetary boundaries, outlining the integration of environmental and social goals into the concept of accessibility. This thesis serves as a step towards further development of tools to support the implementation of the framework.

1.2 Research questions and scope

The objective of the thesis is to create a method that would allow testing alternative modal share scenarios to quantify the carbon emission reduction potential, and to understand where the emissions are high with high spatial resolution. This thesis will study how much carbon emissions could be reduced if commuters swapped combustion engines for electric bikes at Otaniemi. Understanding the carbon reduction potential could encourage employers to promote a sustainable mobility culture, for example by offering incentives. In addition, understanding where the greatest carbon reduction potential is and targeting climate mitigation policies accordingly.

The research questions of the thesis are as follows:

- How can commute-related carbon footprint be modeled using bottom-up GIS approaches?
- What is the carbon footprint of commuting at Otaniemi?
- How does the carbon footprint of commuting at Otaniemi change in the post-COVID era?
- What is the carbon reduction potential of replacing short car travel with e-bikes?

1.3 Study area

Otaniemi is a district located along the shore of the Baltic Sea in the city of Espoo, Finland (Figure 1). It is situated approximately 10 kilometers west of the capital city of Helsinki. The area covers a total of approximately 2 square kilometers, excluding the sea areas, and is primarily known for being home to the campus of Aalto University, which brings together the School of Science, School of Engineering, School of Arts, Design and Architecture, and the School of Business. There are almost 12 000 students and 4 000 staff members. As a result, the demography of the area is reflected by the university campus (Aalto University, 2018; Tilastokeskus, 2023). Otaniemi has a long history of research and innovation, dating back to the establishment of the Helsinki University of Technology in the 1950s (Aalto University, 2018). The area is a hub for technology, design, and research, with numerous start-ups and established companies. In addition, there are two upper secondary schools in Otaniemi and a daycare.

Otaniemi is well-connected to the rest of the Helsinki metropolitan area by bus and metro, making transportation convenient for its 4300 inhabitants, visitors, and the Aalto University community (Tilastokeskus, 2023). The district offers a variety of local services, including markets, restaurants, cafes, and other amenities. The characteristics of Otaniemi generate significant demand for travel and have a profound impact on how transportation is

planned and provided in the area. In addition, the Raide-Jokeri tramline is expected to begin operations in fall 2023, further improving transportation options in Otaniemi and the surrounding areas (Raide-Jokeri, n.d.).

In this work, the analysis focuses on travels originating from a particular area of the Helsinki region, as highlighted in Figure 1 on the upper right map, using data from Telia Crowd Insight. Their data is based on mobile network data and allows analyzing crowd behavior and movement patterns. The same figure also includes an orthophoto map of the Otaniemi district, with a black line outlining the area of interest.

Figure 1. Study area

1.4 Previous research

1.4.1 Sustainable mobility in the Universities

In recent years, Finnish higher education institutions have calculated their carbon footprint as part of their sustainability reporting due to the target to be carbon-neutral by 2030 (Opetus- ja kulttuuriministeriö, 2021). Currently, the calculation of the carbon footprint between different institutions is not harmonized. Some universities do not include the emissions from travel between home and campus in their calculations (Helsingin yliopisto, 2022; LUT University, 2022). Travel mode choices can be thought to be the result of personal and independent decisions from the university. Nevertheless, there is an increasing interest in conducting inventories of greenhouse gas emissions. It is crucial to monitor emissions in any effort to cut them down.

It has long been recognized that commuting is one of the significant contributors to universities' carbon footprint. Tolley (1996), stated over 25 years ago that car commuting needs to be drastically reduced for its negative environmental impact. However, the subject is still very relevant to this day. The modal share of university communities and the resulting greenhouse gas emissions of commuting have been well studied in an effort to shift into sustainable mobility. The common workflow for calculating the carbon footprint of commuting is to gather information through a survey, for example, about the demographics, location of residence and mode of transport. The commuting distance can be obtained from the surveys (Ozawa-Meida et al., 2013; Clabeaux et al., 2020; Alvarez Franco, 2021; Sobrino and Arce, 2021) or estimated with routing analysis with a GIS program based on the origin and destination locations (Pérez-Neira et al., 2020; Ribeiro and Fonseca, 2022). The greenhouse gas emissions are derived from applying the defined emission factors by mode of transport with the commuting distances.

1.4.2 Roadmap to a fossil-free transport

The Ministry of Transport and Communications of Finland has developed a Roadmap for fossil-free transport which presents 33 actions to decarbonize domestic transport. The roadmap has been prepared as part of the government programme to achieve its set climate targets. By 2030, the emissions of domestic transport should be halved compared with the year 2005 levels. The ultimate goal is to achieve decarbonized transport by 2045 (Jääskeläinen, 2021). The decarbonization main pathways of the roadmap includes offering subsidies that support replacing fossil fuels, renewing the vehicle stock and improving the efficiency of the transport system (Jääskeläinen, 2021).

In addition, as part of the roadmap, there have been studies to assess how much working from home can reduce carbon emissions by avoiding commutes and what is the carbon emission reduction potential of the new

transport services that people have started to adopt in the urban areas (Metsäranta et al., 2021; Sihvola et al., 2021). The COVID-19 pandemic has impacted the practices of our daily lives. Although the restrictions have been all lifted, the public transport passenger levels have not returned to pre-pandemic levels (HSL, 2022). The pandemic has increased the trend of remote working but at the same time highlighted the importance of active transport (International Transport Forum, 2020).

New transport services have gained significant interest globally in recent years, the implementation of mobility as a service and shared mobility are hoped to lower car ownership. In the study of Sihvola et al. (2021), they predicted that the carbon reduction potential of new transport services is around 0,080 $MtCO_2$ by 2030. The annual reduction could be considerably higher, around 0,260–0,300 $MtCO_2$, if the vehicles of the mobility services electrified faster than private motoring. In the longer-term prediction, the carbon reduction could be around 0,580 $MtCO_2$ annually with the power of autonomous transport in 2045. These results include many uncertainties since it is difficult to predict the development rate of the new transport services, such as, the automatisation of the transport.

Active transport has a role in the roadmap in reducing annually 0,004–0,015 $MtCO_2$ by investing in the national programme for the promotion of walking and cycling. Finnish Cyclists' Federation have pointed out that the impact assessment of Traficom does not consider the increasing use of electric bicycles (Pyöräliitto ry, 2020; Jääskeläinen, 2021).

1.4.3 The role of electric bicycles in decarbonising transportation

Studies support that electric bikes have the potential to shift transportation away from carbon-intensive transport to reduce carbon emissions (Blondel et al., 2011; Lettenmeier et al., 2019). Philips et al. (2022), conducted a national-level study of estimating the maximum capability of carbon reduction by replacing car travel with electric bikes in England. They found that electric bikes have a greater carbon reduction capability than conventional bikes both in urban and rural areas.

Electric bicycles have been found to increase daily trip ranges and offer benefits such as higher speeds and less effort compared to traditional bicycles. They have the greatest potential for replacing car travel within the 5–15 km range (Fyhri and Sundfør, 2020; Sun et al., 2020). E-bikes have demonstrated the ability to replace car trips and make cycling more attractive in the winter months (Naturvårdsverket, 2019; de Haas et al., 2022).

The impact of electric bicycles on transport substitution patterns varies across regions, as demonstrated by a meta-analysis conducted by Bigazzi and Wong (2020), which showed that e-bikes replace 33 % of public transport, 27 % of conventional bicycles, 24 % of cars, and 10 % of walking. Additionally,

the Swedish Environmental Protection Agency found that e-bikes replaced approximately 50 % of car journeys (Naturvårdsverket, 2019).

Electric bicycles have a potential to enhance the sustainability of commuting, which is one of the most common reasons for travel, especially considering that the average one-way commute for Finns is 16 kilometers. The average distance of the commute is not too long for an electric bicycle. Although, the commuting distance varies significantly according to area density. Inhabitants of the sparsely populated region tend to have a longer commute distance. On the other hand, the inhabitants of the capital region commute more frequently (Liikennevirasto, 2018). Half of the commuters in Finland could cycle (with a conventional bicycle) to work in under 30 minutes, and overall cycling is often faster than public transport (Piela, 2017). Cycling constitutes only 10 % of all commute trips which leaves room for improvement in increasing the share of cycling (Liikennevirasto, 2018).

Electric bicycles have shown potential in substituting motorized travel, but there is limited empirical evidence on the carbon reduction achieved through active transportation. A study conducted in Cardiff, Wales by Neves and Brand (2019) used GPS devices and travel diaries to observe the travel patterns of local residents. The findings suggested that walking and cycling could realistically replace a significant portion of short car trips and result in carbon emission reductions from car travel.

Decarbonisation of transport relies heavily on electrification. Fully electric vehicles are considered as zero-emission vehicles since they do not produce any emissions during use. Even so, the production of the vehicles, energy supply, infrastructure and maintenance require resources. It is important to assess these compositions of emission to have a comprehensive understanding of the environmental impact of transport types.

1.4.4 GIS for sustainable transportation

As part of a sustainable urban planning promoting project of the City of Oulu, Määttä-Juntunen et al. (2013) have developed a GIS-based approach to estimate carbon dioxide emissions of private cars that are generated by different solutions of land use planning. They built their carbon dioxide emissions estimation workflow using ArcGIS software for conducting two case studies of land use planning. The calculation of the emissions is based on the assigned emission values to the road links of the network. The tool determines the route and accumulates the emission values of the links of the route.

The first case study was the Hiukkavaara residential area in Oulu. They compared three different structural plans to estimate which plan generated the least carbon dioxide emissions from private car travels to access several local services. The structural plans determine the location of the roads, residential building areas, workplaces, and local services.

The second case study estimated how the potential carbon dioxide emissions develop in three stages in the new residential areas in the Oulu region. In addition, to estimate the new area's carbon-based accessibility differences where the travel impedance is environmental cost. In the first stage, potential emissions have been calculated for existing retail stores and workplaces. For the second stage, they added planned retail stores and a bridge for the third stage. The tool determined the travel from the new residential areas to retail stores and workplaces and calculated the carbon dioxide emissions from the travels.

Kinigadner et al. (2020) have also studied carbon-based accessibility, but in the context of carbon budget. They conducted a case study of a business park in Munich and analyzed how the different scenarios of transport conditions affected the carbon-based accessibility of the case study area. There were two carbon budgets used in the scenarios. The default budget was derived from the total GHG emissions of Germany in 2016 which was divided into the share of one commuting trip. The reduced carbon budget was a half of the default budget to meet the 2030 climate target. Moreover, the scenarios included other feature variations such as increased occupancy rate, electrification, improved electricity generation mix. These scenarios were modeled for travel modes of private car and public transport. The private car model was implemented in ArcGIS and the public transport model in PTV Visum. In the models, the passenger emissions were assigned to the links of the network to calculate the service area according to the selected scenarios. The most common travel impedances used in accessibility measures are distance, time, and monetary cost. Considering that transport is one of the major emitters, it is essential to consider environmental costs as a travel impedance. This method enables the assessment of the accessibility-related environmental impacts based on the urban form and transport supply of the study area.

GIS coupled with scenario building capabilities help to make better decisions by enabling the exploration of the different solutions while understanding their environmental impacts. In both previously mentioned studies, commercial software (ArcGIS and PTV Visum) were used for the models. These kinds of models would be valuable to implement in open-source tools.

2 Theoretical background

2.1 Climate change mitigation

Climate change is an ongoing global reality characterized by observable impacts that affect nations and ecosystems. These impacts, resulting from the rise in the planet's global temperature by 1.1 °C compared to pre-industrial levels, are primarily caused by anthropogenic activities, including the combustion of fossil fuels, deforestation, and agricultural practices (IPCC, 2022).

The most visible impacts of a warming planet include the increased frequency and intensity of extreme weather events, such as heatwaves, along with changes in precipitation patterns that manifest as heavy rainfalls and severe droughts. These impacts have resulted in loss and damage to both people and ecosystems. For instance, the extreme weather further intensifies the occurrence of disasters and poses challenges to the availability and quality of water resources. Consequently, these challenges disrupt food production and threaten food security. The increased stress on biodiversity caused by a warming planet increases the risk of extinction by directly threatening the survival of many species. Without a change in the current trajectory, the situation is projected to deteriorate, with increasingly severe consequences for the planet and its inhabitants (IPCC, 2022).

Figure 2 shows a rapid increase in annual global CO_2 emissions since 1900, leading to a significant increase in global warming of 1.1 °C. The upward trend in global annual carbon emissions is deeply concerning, as the direction of the trend should be in the opposite direction to achieve significant carbon reductions to truly address the climate crisis. Although there was a temporary decline of 5.3 % in global fossil CO_2 emissions in 2020 compared to 2019, largely due to the impact of the COVID-19 pandemic, emissions rebounded in 2021 to reach nearly the same level as in 2019 (Crippa et al., 2022). Therefore, the reduction in global carbon emissions from the pandemic is negligible in terms of climate mitigation.

While the carbon reduction resulting from the pandemic may have been negligible, it has provided valuable lessons for reflection. Despite the challenges it presented, the pandemic also revealed opportunities for change. One notable aspect is the rapid implementation of emergency measures, including the enforcement of new regulations. A similar level of urgency and determination is needed to address climate change.

Nearly every nation has committed to the Paris Agreement, which aims to limit the rise in global average temperature to well below 2 °C, and preferably 1.5 °C, above pre-industrial levels (United Nations 2015). However, if current policies continue, the world is projected to fall short of its climate targets. This means that the goal of limiting warming to close to 1.5 °C or even 2 °C will be out of reach (IPCC, 2022). Urgent and more ambitious action is

needed to reverse this concerning trend and transition towards a sustainable and net-zero future, as continuing on the current path will take the world beyond the carbon budget.

To explore possible climate futures, the Intergovernmental Panel on Climate Change (IPCC) has created Shared Socioeconomic Pathways (SSPs) which are used as inputs to climate models, projecting future greenhouse gas emissions and climate change based on different societal development assumptions. In the pathway models with no or limited 1.5 °C overshoot, global net anthropogenic CO_2 emissions need to be almost halved by 2030 from 2010 levels and eventually reach net zero around 2050.

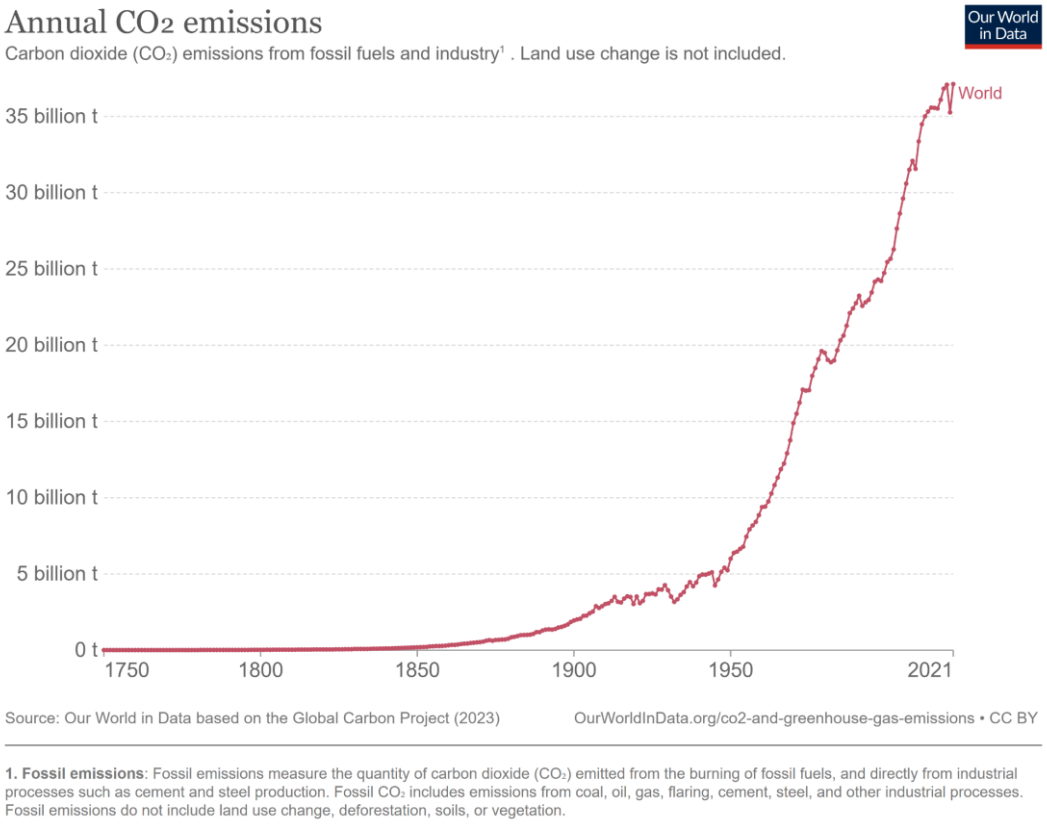

Figure 2. Global annual CO_2 emissions from fossil fuels and industry (1900–2021). Data obtained from Our World in Data (Ritchie et al., 2020).

The transport sector is a major contributor to global greenhouse gas emissions, with road traffic being the largest source, accounting for 70 % of emissions. The sector generated 8.7 gigatons of carbon dioxide equivalent (GtCO2-eq) in 2019, up from 5 GtCO2-eq in 1990. In addition, the transport sector is responsible for 23 % of global energy-related CO_2 emissions. Achieving climate change mitigation targets will therefore require transformative and systemic changes in the transport sector (IPCC, 2022).

2.2 Greenhouse gas accounting

2.2.1 GHG Protocol

The Greenhouse Gas Protocol (Barrow et al., 2013) is the most widely used standard for calculating the environmental impact of companies and organizations. The standard classifies emissions into three categories: Scope 1, Scope 2, and Scope 3. The first scope is for direct GHG emissions, the second is for indirect electricity GHG emissions, and the third is for other GHG indirect emissions. Consequently, commuting belongs to Scope 3. There are three different methods for calculating emissions from commuting: 1) Fuel-based method, 2) Distance-based method, and 3) Average-data method.

Universities are most likely to use the distance-based or average-data method. The distance-based method is more accurate than the average-data method since the distance-based method is based on collected survey data from employees (distance, transit mode, number of commuting days per week, car occupancy) and the average-data method is based on average secondary data. Once the data is collected, the calculation of the CO_2 equivalent emissions is straightforward. First, all distances traveled by employees are totaled for each vehicle type. Then, the sum of the traveled distance for each vehicle type is then used to determine the total emissions. The protocol is used to monitor emissions and it does not guide how to reduce the emissions.

2.2.2 Life cycle assessment

Life cycle assessment (LCA) is an ISO standardized framework (ISO 14040) to assess the environmental impact of a system (product or service). The methodology considers all the stages associated with the product from the cradle to the grave, e.g., manufacturing (including raw material and energy acquisition and logistics), usage, maintenance and repair, and end-of-life processing. The holistic assessment approach provides an opportunity to identify the activities that contribute significantly to the overall environmental impact. Therefore, LCA can help with making better decisions or improving systems based on gained knowledge to support climate change mitigation (ISO, 2006).

The framework consists of four main steps as follows (ISO, 2006):

1. The goal and scope definition, includes defining the system boundary and the degree of detail.
2. The life cycle inventory analysis (LCI) is a data collection of all the resource inputs and emitted outputs of the defined studied system.
3. The life cycle impact assessment (LCIA) provides quantitative and qualitative information of the environmental impact based on the inventory analysis.

4. The interpretation of the results in terms of uncertainties

In the application of LCA to transport modes, the three main components of the inventory analysis are the vehicle component, fuel component, and infrastructure component. First, the vehicle component includes manufacturing, maintenance (e.g., replacing worn vehicle parts), and end-of-life processing such as recycling or final disposal. Second, the fuel component includes emissions from processes of the production, processing, and distribution of fuel or energy, also known as the well-to-tank phase. In addition, there is also the tank-to-wheel phase that covers the emissions from using the fuel. Well-to-wheel includes the two previously mentioned phases of the fuel's life cycle (Cazzola and Crist, 2020). Electric transportation is not seen to contribute greenhouse gas emissions to the atmosphere on the road due to having zero tank-to-wheel emissions. However, it does have an environmental impact, and well-to-tank emissions are included in the power sector instead of the transportation sector (Jääskeläinen, 2021). Finally, the infrastructure component includes the life cycle of infrastructure that is similar to the vehicle component from raw material extraction for construction, and maintenance, to end-of-life processing (Cazzola and Crist, 2020).

2.2.3 The characterization of the transport modes' environmental impacts as emission factors

The sustainability of different transport modes is compared with each other by the LCA emission factor which can be described as grams of CO2-equivalent per passenger kilometer. The unit describes how much carbon dioxide equivalent it takes for one passenger to travel one kilometer by the mode of travel in question.

In a comprehensive LCA study on different transport modes, the energy inputs and emission outputs of the LCA emission factors are included by attributing the previously mentioned three main components of the inventory analysis which were the vehicle, fuel, and infrastructure components. The results of transport mode emission factors vary in the LCA studies due to the accounting method and technical assumptions. The technical assumptions regarding the vehicle can be for example the estimations of lifespan in kilometers, the capacity, and occupancy rate. For the fuel component, the used energy mix can have a significant difference, and the energy efficiency of the vehicle also depends on the vehicle's capacity and occupancy rate. The impacts of infrastructure such as rail and road are divided by the length of the network and then attributed to the emission factor of the transport mode (Cazzola and Crist, 2020).

2.3 Big data for transportation and mobility

The information age, which we are currently experiencing, is characterized by the rise of computers and the internet, transforming the way information is accessed and communication takes place (Castells, 2010). This era has witnessed the rapid growth of data, also referred to as "data explosion", with various types of real-world data being stored in computer applications. The development of computer performance has facilitated the storage and utilization of data, leading to the emergence of big data, including real-time data streams. Although there is no universally accepted definition for big data (Ylijoki and Porras, 2016), one widely recognized framework is the 3V's definition. This definition highlights three essential characteristics of big data: Volume, Variety, and Velocity (Laney, 2001). Volume refers to the vast amount of data being generated and collected, Variety refers to the diverse types and sources of data and Velocity refers to the high speed at which data is being generated, processed, and transmitted.

Traditional methods of studying human mobility and travel behavior often rely on surveys, which can pose challenges due to potential of under-/over-reporting, outdatedness, and cost constraints (Wang et al., 2018; Neves and Brand, 2019). Surveys have been used by researchers to identify and characterize various aspects of human travel patterns, e.g., trip frequency, trip purposes, trip datetime, trip duration, trip distance, travel modes, and so on.

Big data has the potential to support and, in some cases, replace traditional methods of studying human mobility and travel behavior. Mobile phones, being an important source of big data, play an important role in this shift. Mobile phones have become integral to our daily lives and are one of the most owned devices, which is why there is substantial potential for extracting valuable geographical information from them.

By harnessing Big Data, researchers can tap into a wide range of valuable information derived from sources such as social media platforms, mobile phone data, and GPS data. This abundance of data enables them to achieve broader coverage in terms of time, population, and geographic representation. This means that researchers can gather insights from larger and more diverse datasets, leading to a more comprehensive understanding of human mobility and travel behavior.

Furthermore, location-based big data can enhance the quantification and mapping of emissions by utilizing real-time monitoring, high spatial and temporal resolution, integration of diverse data sources, and facilitating predictive modeling. The high spatial and temporal resolution of big data allows researchers to zoom in on specific areas or time periods, identify emissions hotspots and understand variations in emissions across different regions.

2.3.1 Mobile phone data

This study aims to utilize mobile phone data to estimate travel demand to Otaniemi district. The focus will be on one specific positioning method: cellular network-based positioning. The other main positioning method, GPS-enabled smartphones, will not be discussed in detail as it is outside the scope of this thesis. Cellular network-based positioning utilizes the infrastructure established by telecommunication operators to provide mobile communication services and it can be further categorized into two types: passive mobile positioning and active mobile positioning (Silm et al., 2020).

Passive mobile positioning involves the automatic collection of data by mobile network operators, encompassing a range of activities including calls, SMSs, internet usage, GPRS (General Packet Radio Service), and LBS (Location-Based Services). This data can contain the following information: a unique code for phone, start datetime of the mobile communication activity and its associated geographical coordinate from the antenna which provided the network that enabled the activity. Passive mobile positioning is limited by the coverage area of network cells. In addition, the distribution of network cells is not uniform, resulting in varying accuracy in different areas. Naturally, accuracy is higher in densely populated areas (Ahas et al., 2008). However, the application of advanced interpolation methods can enhance the overall accuracy of passive mobile positioning. Passive mobile positioning offers the advantages of long-term data collection and large sample sizes since it includes all subscribers. The weaknesses of passive mobile positioning include its inability to capture data from non-mobile phone users and the variation in mobile phone usage patterns among individuals (Silm et al., 2020).

Active mobile positioning also relies on the existing telecommunications infrastructure to determine the location of mobile devices. In contrast to passive mobile positioning, active mobile positioning is a method initiated by the mobile network operator with the user's consent. It uses specific queries to determine the location of a mobile phone, typically using signal triangulation. This method achieves a higher precision compared to passive mobile positioning. The advantage of active mobile positioning is that it allows researchers to supplement location data with questionnaires, providing additional context and insight into mobility patterns. However, the sample size is typically smaller compared to passive mobile positioning due to the requirement of obtaining consent from subscribers (Silm et al., 2020).

Mobile phone data obtained through network-based positioning provides valuable insights into human mobility patterns, with an accuracy of up to 100 meters in urban areas. However, accuracy decreases significantly in rural and water areas. It is important to note that coverage is always network dependent (Ahas et al., 2008). If the data is obtained from a major operator, there is a possibility to extrapolate and reflect the country's population. The data used in this study was extrapolated by the operator.

2.4 Graph theory

Graph theory is a branch of mathematics that studies the characteristics and connections of networks represented by a graph (Figure 3), where a graph is defined as a collection of vertices (v) and edges (e), mathematically denoted as G = (V, E). A graph can also be seen as a data structure that organizes and represents relationships between various elements (Bondy and Murty, 2008).

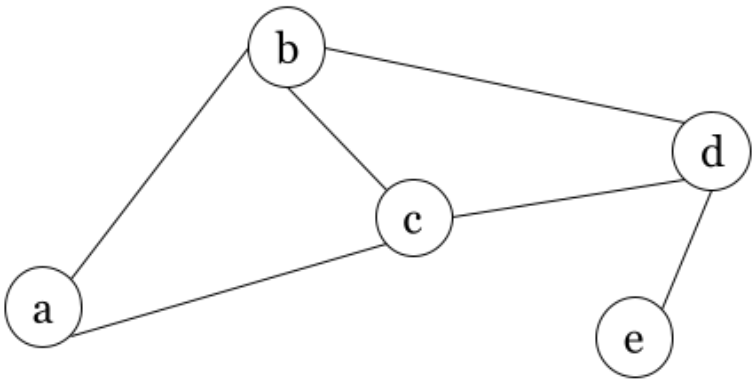

Figure 3. Visual representation of a graph

Graph theory encompasses different types of graphs, including directed and weighted graphs. In a directed graph, the edges have a specific direction or flow, indicating a one-way relationship between vertices. A weighted graph incorporates attributes or costs associated with the edges, providing a way to represent and quantify various characteristics or measures within the graph structure. Graphs can possess both directed edges and weighted edges. For example, a road network can be modeled as a directed and weighted graph. In this representation, the directed edges denote the flow of traffic in specific directions, while the weights assigned to the edges can represent attributes such as travel time, distance, or capacity (Bondy and Murty, 2008).

This mathematical discipline is important in numerous GIS applications because it enables the representation and analysis of real-world structures as graphs. To address issues related to real-world networks represented as graphs, a diverse set of algorithms has been developed. For example, graph theory provides valuable tools for calculating the shortest path between two points within a network, enabling efficient navigation and optimization in various domains. A popular algorithm used for this purpose is the Dijkstra algorithm which was created by Edsger Dijkstra in 1956 (Dijkstra, 2022). The Dijkstra algorithm efficiently determines the shortest path between two vertices in a graph, considering the weights or costs associated with the edges. The basics of Dijkstra's algorithm involve iteratively selecting the node with the lowest cost, calculating the cost of its neighboring nodes, and continuing

this process until the destination is reached. By doing so, the algorithm determines the optimal route.

Graph theory, along with routing algorithms, can be employed as a geospatial approach to assess transport-related carbon emissions. In addition to the mentioned traditional weights, environmental costs can be assigned as weights of the edges in the analysis of transportation networks. Connectivity and accessibility within these networks can be analyzed, providing insights into the spatial distribution of carbon emissions. As a result, graph theory provides a framework for understanding and addressing the environmental impact of transportation systems.

3 Data

3.1 Telia Crowd Insight

Telia is one of the biggest network operators in the Baltic and most of the Nordic countries. Telia offers Telia Crowd Insight service for businesses and municipalities. The service provides information about the movement of people through mobile traffic data, such as where people start and end their trips and where people spend their time. There are endless possibilities in the application of people's mobility data. For example, comprehensive information about population flows and their changes are a vital part of urban and transport planning.

The data of Telia Crowd Insight complies with GDPR and has been anonymized and aggregated. Telia's data processing method excludes observations that have less than five individuals for one radio cell in an hour. In addition, the data has been extrapolated to be representative of the entire population using a mobile phone. However, the extrapolation does not include the population aged 0-6 years (Telia Company, 2021c). If a customer of Telia wishes to opt out of the Telia Crowd Insight analysis and prevent the utilization of their own information, they can do so by contacting the operator and expressing their refusal.

The data is available in four different spatial resolutions: county, municipality, postal code, and grid level. The size of the grid is typically 500 m x 500 meters in the urban areas and larger elsewhere. The grid size 500 m x 500 m is the smallest grid size available.

Telia generates data from its cellular mobile network every day throughout the year. The network stores information about the mobile device when it connects to a base station. The size of the radio cell coverage area affects the accuracy of the observations. Telia produces travel patterns by identifying the time series of cellular signaling data points as stationary or moving points (Telia Company, 2021c).

3.1.1 Trip

The proposed model is using a data product called Trip from Telia Crowd Insight to obtain the origin-destination data for estimating the greenhouse gas emissions from the travels to Otaniemi. The data is provided as an Origin-Destination Matrix (ODM).

A trip is defined by two key parameters that determine its ending. The two parameters are a dynamic pause time and a direction change. The ending of a trip depends on two parameters which are a dynamic break time and a directional change. Trip can have dwell time for various reasons, such as switching transport modes or pumping fuel in a vehicle. The further the

distance of a trip is the longer the allowed break time is without splitting the trip into two trips. For short trips of 2 kilometers or less, the shortest break parameter is 10 minutes of dwelling time, while for longer trips over 200 kilometers, the allowed dwelling time can be up to 70 minutes (Telia Company, 2021b).

The directional change parameter will end the trip when the directional change between the furthest waypoints by more than 155 degrees since it would form a round trip. For example, picking up a friend from a station back home would constitute two trips (Telia Company, 2021a).

The data for the trips was obtained from their web data service, as a CSV file accessed through a dashboard user interface. The origin for the trips covered all postal code areas in Finland, except for Otaniemi, while the destination was set to Otaniemi. The data covered two time periods: 01.01.2019—30.06.2019 (pre-COVID) and 01.01.2022—30.06.2022 (post-COVID). The data was extracted at the grid level of geographic resolution. Therefore, it was aggregated at the monthly level.

The trip data contains information on the month and year of the trip, unique identifiers and names of the origin and destination grids, unique identifiers and names of the municipalities, signal quality ratings, and the number of trips between origin and destination grids (Table 1). This data will be used to route trips from the centroids of the origin and destination grids to obtain the travel distances required for calculating the greenhouse gas emissions.

Table 1: The explanation of the attributes from the trips report

Attributes	**Type**	**Description**
date_month	DATE	Month and year
origin_area_code	INT	Unique identifier of every grid
origin_grid_name	STR	Name of the grid (not unique)
origin_admin_level_2_code	INT	Unique identifier of every municipality
origin_admin_level_2	STR	Municipality name
destination_area_code	INT	Unique identifier of every grid
destination_grid_name	STR	Name of the grid
rating	STR	Alphabetic rating scale from A to D. Rating A being the best signal quality and rating D being the poorest signal quality
people	FLOAT	Number of trips between origin and destination areas.

3.2 Questionnaire data

The information of the modal share was gathered from the Leesman Campus Survey of the Aalto University staff, conducted in February 2020. The Leesman model provides a tool for employers for measuring the employee experience in their workplace by conducting a survey. The campus survey covers questions about the environment, work activities and campus features. The tool generates key performance indicators from the responses from which the Leesman index is derived. The scale of the index is from 0 to 100, and the score is then benchmarked against other workplaces from Leesman's database (Leesman, 2020).

The survey is conducted at Aalto University approximately annually. In 2020, the response rate was 34 % which is 1536 responses in total. In the following year, the Leesman Home survey was conducted instead of the Leesman Campus survey which had 1411 responses. Both surveys include information of employees' commutes, such as the transport mode choice (winter and other seasons), the duration, and the satisfaction level with the daily commute (Leesman, 2020, 2021).

3.3 Transportation network

The model used to estimate greenhouse gas emissions is based on routing, which requires a network and additional General Transit Feed Specification (GTFS) data for public transport routing. GTFS data are necessary since they provide information on public transport schedules, stops and routes. This information allows in the GHG emissions estimation to determine which public transport vehicles are used for specific origin-destination pairs, as well as the duration and distance of the possible different transport mode segments.

The required GTFS data was obtained from transitfeeds.com using the HSL provider. The data covers the period between September 30th and November 13th, 2019. For extracting the network, the BBBIKE extract service (https://extract.bbbike.org/) was used, which is a suitable option for extracting data for smaller areas of interest rather than whole countries.

4 Method

4.1 Proposed model

Figure 4 shows the process of the proposed scenario-based model for estimating greenhouse gas emissions from travel, with the different modal shares serving as distinct scenarios. To model travel-related greenhouse gas emissions, the process begins by obtaining travel demand information through Telia Crowd Insights service, which covers origin-destination and frequency. Next, all origin-destination pairs are routed across different transport modes (see Chapter 4.3. and Chapter 4.4.). Following the routing, the model assigns trips according to the modal share scenario and applies the carbon factors derived from the LCA tool for each respective transport mode (see Chapter 4.2.). Multiple simulations are then conducted to determine the emissions of the trips for the specific scenario (see Chapter 4.5.)

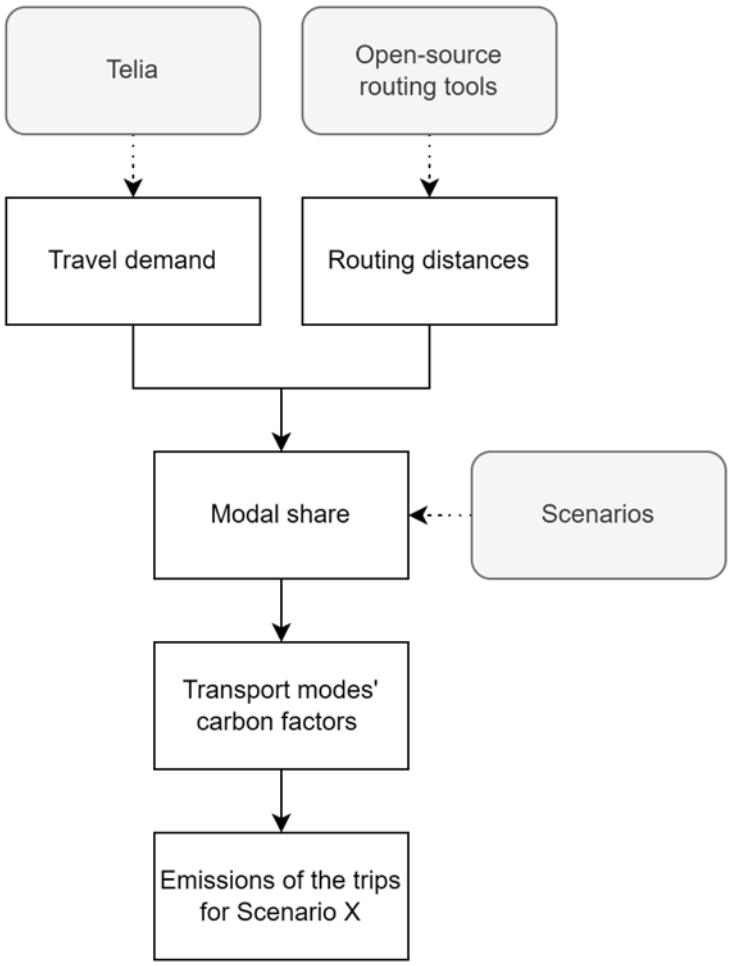

Figure 4. Workflow of emission modeling

4.2 GHG emission factors by transport mode

In the transportation emissions inventory, electric energy is calculated as zero emissions during use (VTT Technical Research Centre of Finland, 2021). The emissions associated with this energy are considered in relation to energy production and the carbon intensity of the energy depends on how it is produced. For instance, carbon dioxide emissions may be high if the electricity is generated using fossil fuels, whereas emissions may be low if the electricity is generated using renewable sources.

To truly understand the environmental impact of various forms of transportation, it's important to take a comprehensive, cradle-to-grave approach that examines their entire life cycle. This approach provides a more complete understanding of their environmental impact and allows for informed decisions about sustainable transportation. This is especially important for new sharing services such as dockless electric scooters, which may have zero tailpipe emissions, but require operational services to reposition and charge the electric scooters.

To this end, the International Transport Forum (ITF) has developed a Life Cycle Assessment Excel-based LCA tool to gain insights into the greenhouse gas emissions of urban transport, including the role that new mobility services play in mitigating climate change. The tool was developed as part of the ITF project "Good to Go? Assessing the Environmental Performance of New Mobility" (ITF, 2020).

Figure 5, shows estimated greenhouse gas emissions per passenger kilometer for various urban transportation modes, calculated using the LCA tool discussed above. In this work, only the direct emission factors are utilized, which means only the fuel component is taken into account. This is in line with common practice in the transport sector, which focuses primarily on quantifying direct emissions from fuel combustion and typically does not include indirect emissions or emissions from the electricity grid used to charge electric vehicles. However, it is important to note that the figure also shows that the other components can make up a significant portion of the emission factor. Therefore, the emission factor, which includes both direct and indirect emissions, can be many times higher, especially for electric vehicles.

It is worth noting that LCAs rely on certain assumptions during the estimation process, such as vehicle occupancy, lifetime, and energy consumption during the use phase. For this study, default inputs were utilized, except for energy production, which was updated to reflect Finland's 2020 energy mix (Table 2).

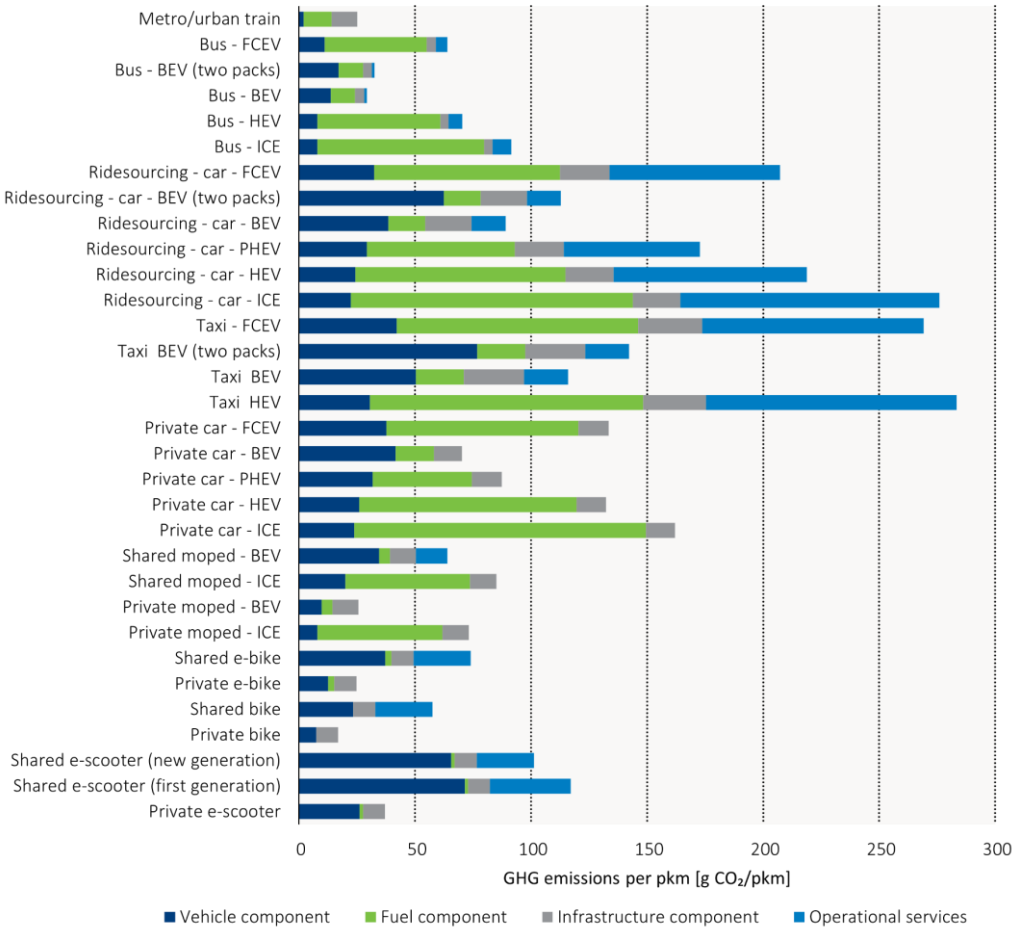

Figure 5. Estimates of the greenhouse gas emissions throughout the life cycle of urban transportation modes per unit of passenger-kilometer. The estimates were derived from the LCA Excel-based tool developed by the International Transport Forum and adjusted using Finnish electricity production data from 2020.

Table 2. The electricity production of Finland 2020 (International Energy Agency, n.d.)

Source	GWh
Coal	5489
Oil	266
Natural gas	3702
Biofuels	10996
Waste	892
Nuclear	23291
Hydro	15856
Solar PV	256
Wind	7938
Total	68686

4.3 Routing with r5r

Routing of the origin-destination pairs in this model was carried out using the r5r package, which is a routing software package in the R programming language. The package was developed by Pereira et al. (2021) and is designed to be a simple interface to R5, which stands for Rapid Realistic Routing on Real-world and reimagined networks. R5 is an open-source Java-based routing engine developed by Conveyal (Conway et al., 2017). The r5r package allows users to perform locally detailed route analysis, as well as the calculation of travel time matrices and accessibility measures. The r5r package contains six fundamental functions, two of which were used in the current work:

1. `setup_r5()`: To utilize the capabilities of the r5r package, it is necessary to first call the function setup_r5(). The objective of this function is to establish a multimodal transport network that can be used for routing purposes. The function combines several data inputs that are located in the directory where the network is to be saved, in order to create the multimodal transport network. The input data must include a single street network file in osm.pbf format. If routing public transit is desired, a GTFS feed should also be included. Additionally, elevation data can also be incorporated into the network creation process. However, this feature was not utilized in the work being discussed. The resulting network is saved in .dat format. If a file named 'network.dat' already exists in the directory where the function is executed, the function will simply load the existing file instead of creating a new one.
2. `detailed_itineraries()`: The function generates travel plans for trips from one or multiple origin to destination as a data frame containing sf LINESTRING objects. The results include the duration spent waiting and in transit for each leg of the trip, in addition to the distance covered, the routes taken, and the geometry of each segment. It can also generate possible alternate routes for origin and destination. The trip planning is available for a variety of transport mode combinations, including transit modes such as tram, subway, rail, bus, ferry, cable car, gondola, and funicular. If the transit option is selected, it includes all the transit modes listed. There are also non-transit modes, which are walking, bicycling, renting a bike. and driving. When routing public transit, the mode of transportation for the final leg of a journey after egress from the last public transport can be selected as either walking, cycling, or driving, with walking being the default mode. This function is more time and memory intensive than other functions in the r5r package.

The code snippet (Code 1) shows how the `detailed_itineraries()` function is used in this work for public transit. The function is called with several arguments, including the `r5r_core` object which represents the routable network. The `origins` and `destinations` data frames input contain columns for `id`, `lat`, and `lon`. The `mode` vector is defined as a character vector containing the modes of transportation to be used in this case, "WALK" and "TRANSIT". The `departure_datetime` variable is defined as a POSIXct object representing the desired departure time for the trip. The `time_window` parameter determines the duration in minutes for which multiple itineraries are computed. If a similar route appears in different minutes, only the quickest itinerary is preserved in the output. The `time_window` is set to 60 minutes to cover infrequent transit connections and ensure that there is a transit option. The `max_trip_duration` parameter limits the total duration of a trip and the `shortest_path` parameter is set to `TRUE` to obtain only one result for the fastest itinerary.

The parameter values were chosen in such a way that every origin-destination pair would receive a route plan while still ensuring that the process would not become too computationally heavy. The same logic was applied to routing for walking and cycling as well. There are several other arguments that can be adjusted in the routing process, but in this work, default values were used for most of them.

```
mode <- c("WALK","TRANSIT")
departure_datetime <- as.POSIXct("02-10-2019 08:00:00",
                                 format = "%d-%m-%Y %H:%M:%S")
det <- detailed_itineraries(r5r_core=r5r_core,
                            origins=origins,
                            destinations=destinations,
                            mode=mode,
                            departure_datetime=departure_datetime,
                            time_window=60L,
                            shortest_path=TRUE,
                            max_trip_duration=180L
```

Code 1: Setting up routable network and generating route plans for sets of origins and destinations.

4.3.1 RAPTOR algorithm

Delling et al. (2015) developed RAPTOR (Round-Based Public Transit Optimized Router), a routing algorithm specifically designed for public transit, which is used in the R5 routing engine. The need for more efficient public transit routing algorithms arose due to the limitations of traditional algorithms such as Dijkstra, which led to the development of RAPTOR.

RAPTOR is a graph algorithm that efficiently computes all Pareto-optimal journeys between given origin and destination points. It does this by working in rounds, starting from a list of access stops and arrival times known as the initial stop-arrivals. In each round, RAPTOR explores all trips from these stops, as well as transfers from all stops reached, resulting in the discovery of a new list of stop-arrivals. By doing so, RAPTOR finds solutions that optimize both minimizing the arrival time and minimizing the number of transfers made between the points, achieving a balance between these two objectives. Due to its lack of dependence on priority queues, RAPTOR can compute optimal routes faster than Dijkstra-based algorithms. In addition, RAPTOR's ability to distribute independent routes across multiple CPU cores allows for efficient parallel processing, which can greatly improve its processing speed, a task that is challenging for Dijkstra-based algorithms (Delling, Pajor and Werneck, 2015).

The `detailed_itineraries()` function in the r5r R package is based on the McRAPTOR extension to the RAPTOR routing algorithm. McRAPTOR is designed to take into account a wider range of factors than just arrival time and transfers, making it capable of handling multiple criteria for optimization (Delling, Pajor and Werneck, 2015).

4.4 Routing with OSMnx

OSMnx is a Python package that was developed by Boeing (2017). It provides a range of functions that allow users to download and extract street networks and other geospatial data from OpenStreetMap, as well as build, analyze, and visualize them. Moreover, OSMnx also includes routing algorithms that enable users to compute the shortest path between origin and destination on a street network for walking, cycling, and driving. This package is built on top of the GeoPandas, Matplotlib, NetworkX Python packages and interacts with the OpenStreetMap APIs. OSMnx utilizes NetworkX to calculate routes on street networks. NetworkX implements Dijkstra's algorithm for finding the shortest path between two points on a graph.

In the previous chapter, routing was explored using the r5r package in R, using different modes of transportation such as walking, biking, and public transit. Routing for driving was also done using r5r, but it was found that

OSMnx produced better routes when the network was preprocessed. As part of the modification process, the network was updated by filling in missing road attributes based on their road class, which helped optimize the driving routes. The criteria applied for filling in the missing speed limits were based on a general rule for urban areas in Finland, although it should be noted that this is not entirely accurate, as the study area covers other regions beyond just urban areas.

4.5 Selected scenarios

The study used five different scenarios for modal share and here I analyze the impact on direct carbon emissions. The scenarios are described below:

- **Scenario 1**: This scenario uses a modal share that reflects the winter season when the ratio of active transport mode is lower compared to the non-winter season. The modal share is applied to the trips made to Otaniemi, using Telia Crowd Insight data for the period between 1.1.2019 and 30.6.2019.

- **Scenario 2**: This uses the same trip data from 2019 and applies the modal share of the non-winter season, which has a higher ratio of active transport mode compared to the winter season.

- **Scenario 3**: Similar to Scenario 2, this scenario uses the non-winter season modal share but replaces all car trips that are under 5 km with e-bikes. This scenario also uses the same trip data as scenarios 1 and 2.
- **Scenario 4**: This scenario uses the winter season modal share, but with trips data from a different period than the previous scenarios. The modal share is applied to the 2022 trips, covering the period of 1.1.2022-30.6.2022.

- **Scenario 5**: This scenario also uses the 2022 trips but applies the non-winter season modal share.

The modal share of each scenario is shown in Table 3. The modal share values were derived from the Leesman survey conducted in February 2020 and based on Aalto University employees. Except for scenario 3, the modal shares for e-bikes and cars are different because all car trips under 5 km were replaced by e-bikes.

These scenarios were defined to compare the differences in carbon emissions between winter and non-winter season modal shares. Furthermore, the aim was to assess the difference in carbon emissions before and after the

COVID-19 pandemic, which had a significant impact on the number of trips. The categorization of the mobile phone data into winter and non-winter months was not performed in this study. The focus was solely on highlighting the differences in carbon emissions between these two different modal shares.

Table 3. Modal share by scenarios

Mode	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Walk	0.09	0.07	0.07	0.09	0.07
Bike	0.06	0.027	0.027	0.06	0.027
E-bike	0.00	0.00	0.07	0.00	0.00
PT	0.55	0.42	0.42	0.55	0.42
Car	0.30	0.24	0.17	0.30	0.24

5 Results

5.1 Modal share emission model implementation in Python

In the thesis, most of the modeling work was conducted using the Python programming language within the Jupyter Notebook environment. The decision to employ the R language for routing was primarily influenced by the availability of the r5r package, known for its transit routing capabilities. Consequently, the R language and r5r package were utilized for routing across all transport modes except for driving. For driving routes, the OSMnx Python package was employed as an alternative solution as it produced better routes when the network was preprocessed (see Chapter 4.4.). Data processing tasks primarily relied on the pandas and GeoPandas libraries, while the creation of plots was accomplished using the matplotlib library. The code of the model can be found in Github (https://github.com/AaltoGIS/lowcarbonmodel/).

The process of carbon emission modeling consists of several steps. The first step was to prepare the network topologies. The next step was to obtain the origin-destination pairs from the Telia Crowd Insight data. This information was used for routing to obtain distance and time data. Routing has been done based on centroids, which were extracted from Telia's grid-based origin-destination matrix.

As a result, a data frame was created containing all unique origin-destination pairs and their corresponding information for walking, biking, transit and driving. After generating the data frame, the next step in the carbon emission modeling process was to create LCA coefficients for different urban transport modes, which enables the assignment of emission factors to individual trips for estimating emissions. These emission factors were derived from the LCA tool developed by the International Transport Forum.

The generated data frame is combined with the Telia Crowd Insight to add the information of the number of trips and the month in which the trips were taken. The Telia Crowd Insight data is combined with the generated data frame to provide the information of duration and distance between the origin-destination pair. As a result, each row of the data frame represents one trip and contains all the relevant information for estimating daily emissions. This data frame is then used in the scenario testing capability. The main concept behind this approach is to allow the user to specify the modal share for walking, cycling, transit, and driving. Afterwards, the trips are randomly assigned to each mode of transportation based on the specified modal share. After assigning the trips to different modes of transportation, the model estimates the emissions for each trip according to the assigned transport mode. Then, the emissions are summed by grid to obtain the daily emissions for each grid cell. Since the model randomly assigns trips, multiple simulations

can be run to minimize sensitivity. These multiple simulations are then aggregated by taking the average of the daily emissions for each grid cell.

5.2 The number of daily trips to Otaniemi in pre-COVID and post-COVID

The bar chart in Figure 6 shows the number of daily trips to Otaniemi in each of the months January to June for the years 2019, 2022, and 2023, aggregated to a monthly level. This provides a clear visual representation of the impact of COVID-19 on travel.

The results show that there is a clear decline in the number of daily trips taken in 2022 and 2023 compared to 2019. In January 2019, the number of daily trips taken was nearly four times greater than the number of daily trips taken in January 2022. However, as the other months of 2022 progress, the gap between the number of daily trips taken in the other months begins to narrow. Nevertheless, in the months of February through June, the number of daily trips is still about half of what it was in the previous year. There are signs of recovery in travel activity when comparing daily trips taken in 2022 to those taken in 2023, as the number of daily trips taken in January, February, and March of 2023 exceeded the number of daily trips taken in the same months of 2022. The year 2023 has only been included in Figure 6 to show the trend in the number of trips over time and is not analyzed further.

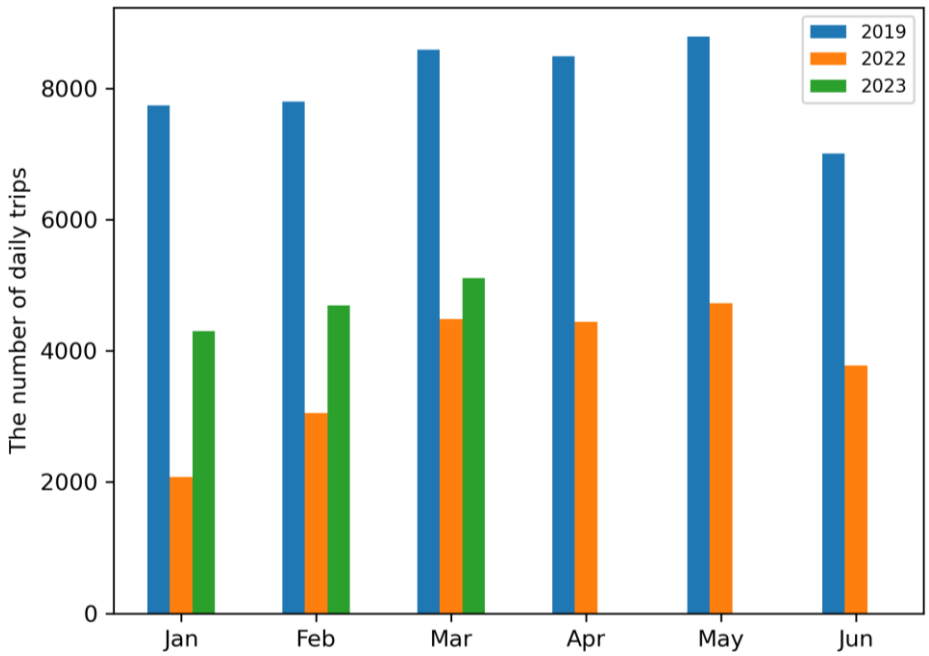

Figure 6. Comparison of monthly aggregated daily trips to Otaniemi during the first six months of 2019, 2022, and 2023, showing the number of trips based on data obtained from Telia Crowd Insight.

5.3 The carbon footprint of the daily trips to Otaniemi in pre-COVID and post-COVID

Figure 7 shows the direct emissions per day resulting from the different scenarios. As shown earlier in the figure showing the number of daily trips, direct emissions are directly proportional to the number of trips made. As Scenarios 1 and 2 involve a higher number of trips, it is not surprising that they have significantly higher daily direct emissions than Scenarios 4 and 5, due to the fact that they have the same winter/non-winter season modal share.

According to the analysis, Scenario 1 (winter season) has higher daily direct carbon emissions compared to Scenario 2 (non-winter season), with an average difference of approximately 25 %. This result can be attributed to the fact that Scenario 2 has a higher proportion of active transport, such as cycling and walking, which do not produce direct emissions. In Scenario 3, replacing car trips of less than 5 km from Scenario 2 with e-bikes can result in a carbon reduction of about 9 %.

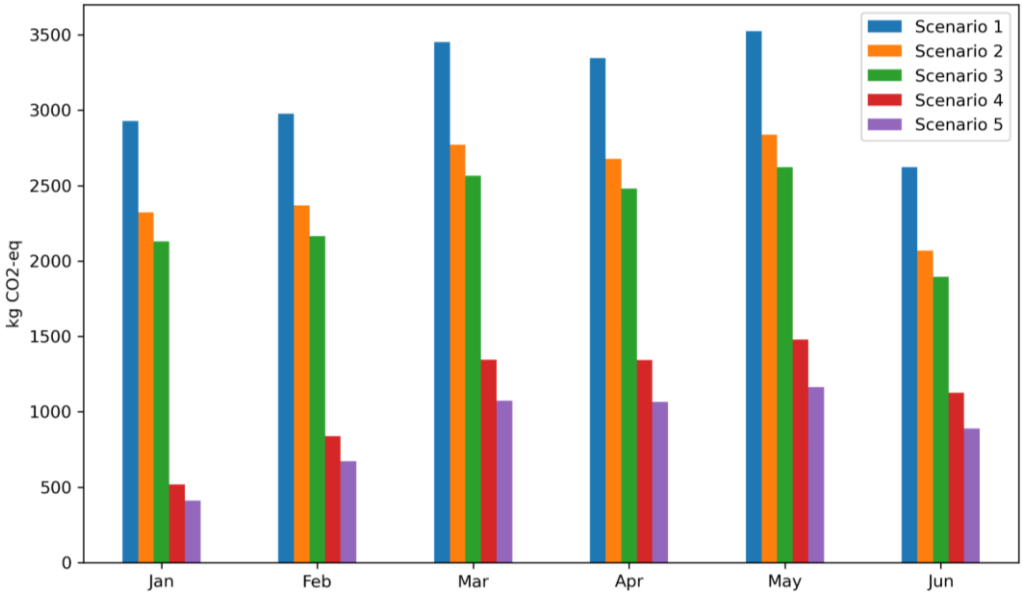

Figure 7. Direct emissions per day from trips by scenarios.

Figure 8 shows data similar to the previous bar chart, but with the months aggregated to show the average from January to June. The stacked bar chart also shows the ratio of emissions between public transport and driving in each scenario. As the figure shows, the ratio of emissions from driving is higher than the ratio of emissions from public transport in all scenarios.

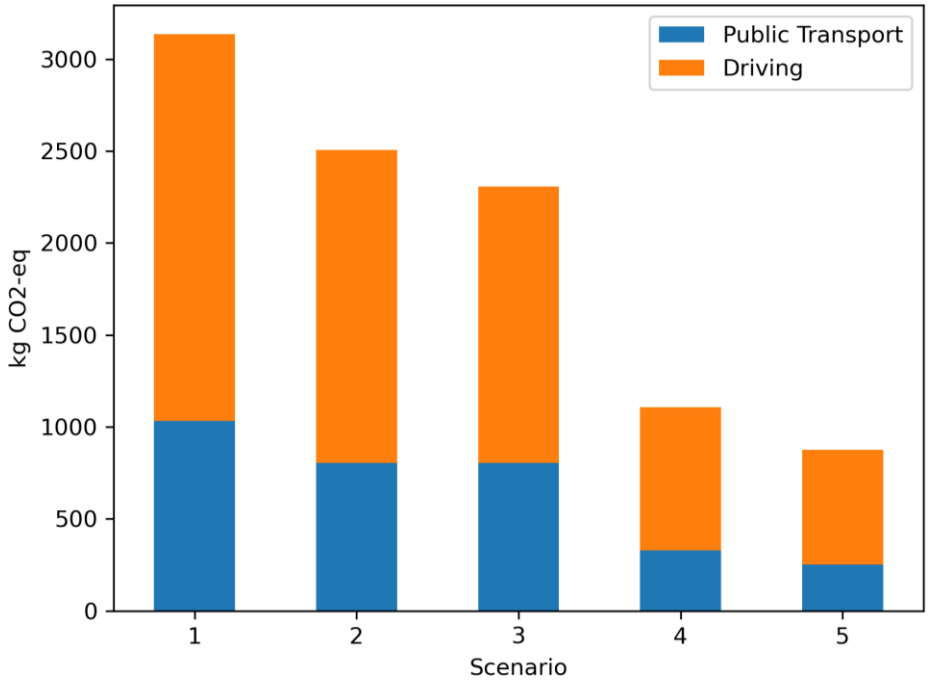

Figure 8. Comparison of average daily direct emissions by scenarios. The stacked barplot shows the average daily direct emissions of the five scenarios, with each bar representing the composition of public transport and driving emissions.

Figure 9 is a map showing the difference in daily direct carbon emissions in kilograms between Scenarios 1 and 2. The largest differences (in kg) can be seen in Matinkylä and Leppävaara, which are located in Espoo and central Helsinki. This can be explained by the higher number of daily trips in these areas. In addition to the map showing the differences in carbon emissions in kilograms between the two scenarios, Figure 10 shows the same information as a percentage difference, providing another perspective on the changes between Scenarios 1 and 2. The map also shows that there are many areas where direct carbon emissions are 30 % lower in the non-winter season compared to the winter season.

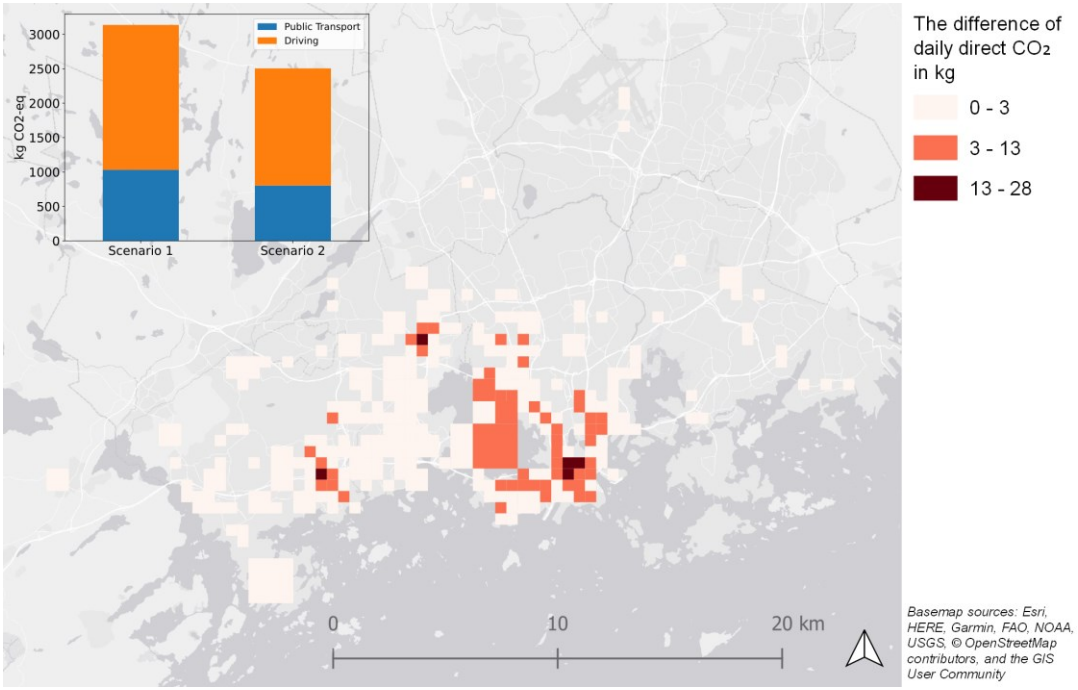

Figure 9. Comparison of daily direct emissions between Scenario 1 and Scenario 2. The map illustrates the difference in daily direct emissions between the winter and non-winter seasons in 2019. The color scale indicates the magnitude of the difference in emissions (in kg). In addition, the emission difference is also shown as a bar plot in the upper left corner of the figure.

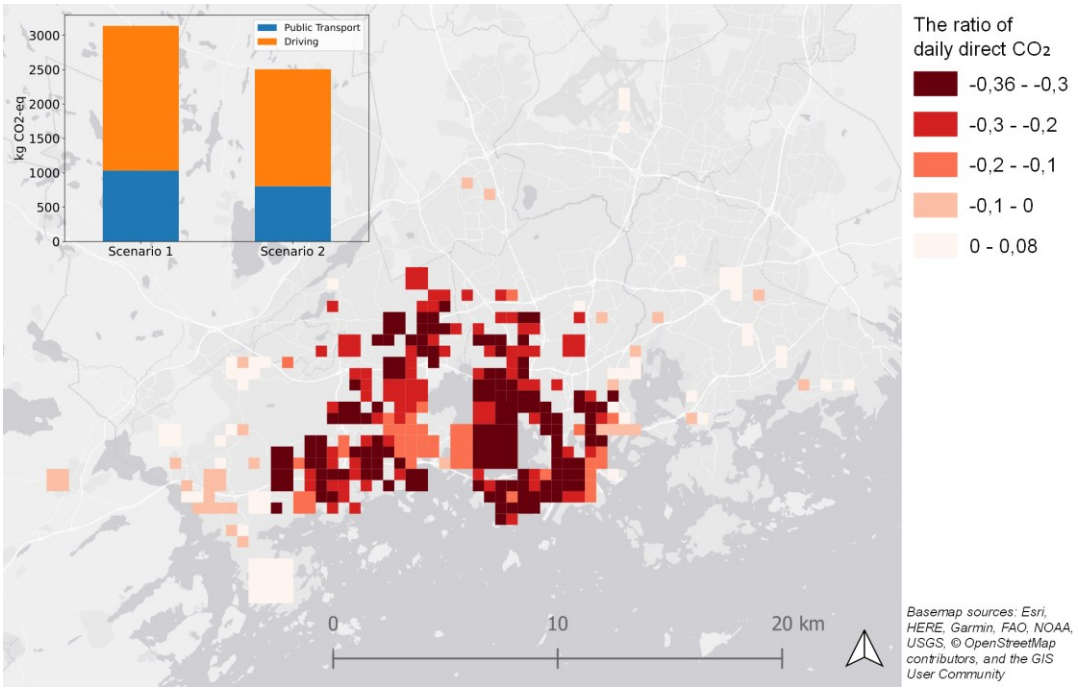

Figure 10. Comparison of daily direct emissions between Scenario 1 and Scenario 2. The map illustrates the difference in daily direct emissions

between the winter and non-winter seasons in 2019. A ratio of 0 represents Scenario 1. In addition, the emission difference is also shown as a bar plot in the upper left corner of the figure.

Figure 11 consists of five maps that show the spatial distribution of daily direct emissions trips per km^2 across the five scenarios. The map shows three distinct areas, namely Matinkylä and Leppävaara in Espoo and the center of Helsinki. These areas are also associated with the highest number of trips, while Tapiola, which also has a high number of trips, do not have such high emissions due to its proximity to Otaniemi.

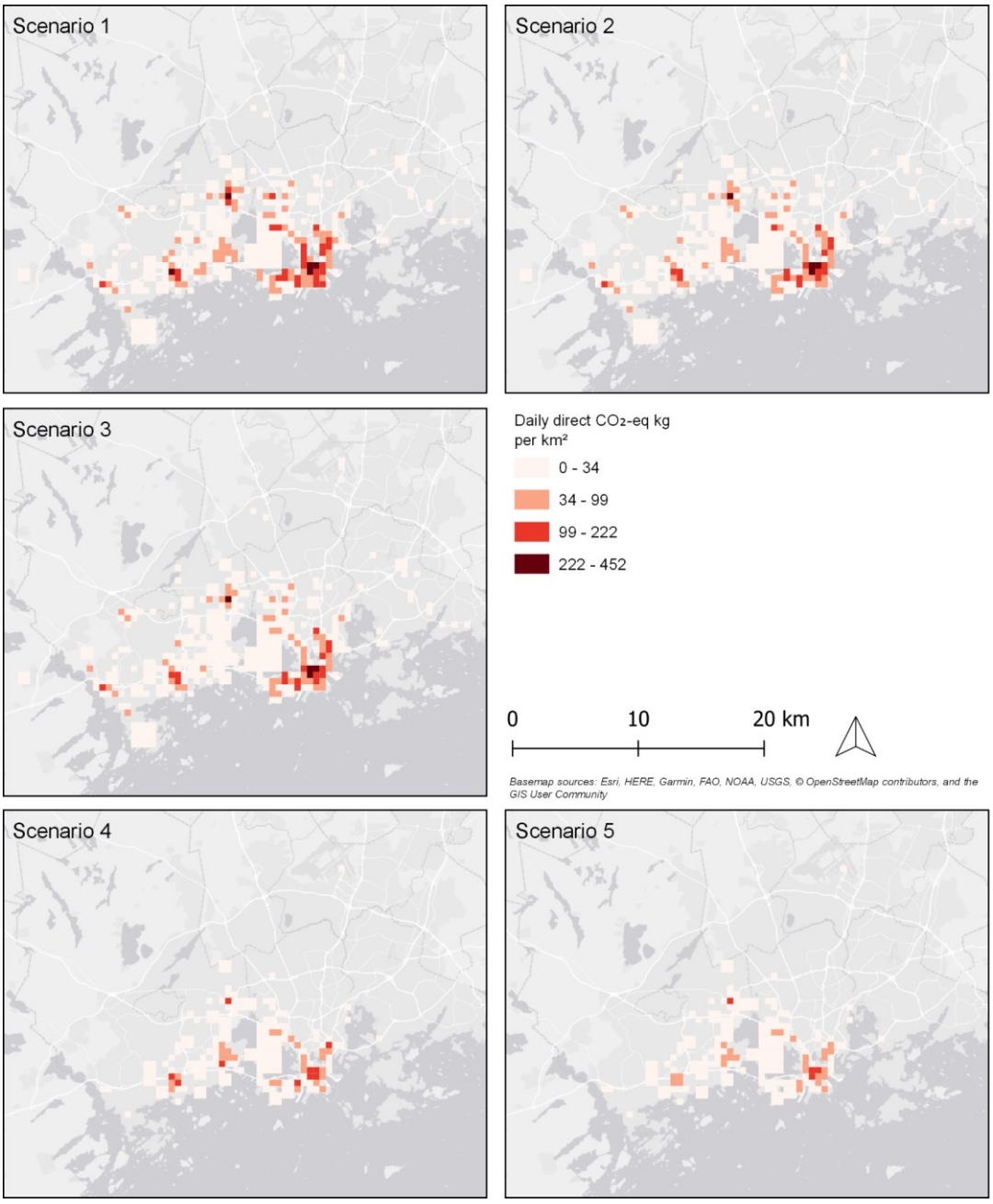

Figure 11. Spatial distribution of daily direct emissions from trips per km^2 in five scenarios.

6 Discussion and conclusion

6.1 The estimation of carbon reduction potential in shifting modal share towards sustainable transportation

This thesis demonstrates how the commute-related footprint can be modeled with bottom-up GIS approaches. By utilizing the available data and current open-source tools in developing a tool for estimating emissions in different modal share scenarios. As a result, this tool provided insights into the differences in emissions between the scenarios, suggesting the possibility of emission reductions.

When planning the scenarios, Leesman's 2020 survey was utilized, which asked about the primary mode of transportation to Aalto University campus. Modal share data for the post-pandemic period was not available, so all comparisons were based on the survey conducted in the same year, using the actual number of trips taken. The aim of the scenarios was to compare the emissions difference between winter and non-winter seasons, as well as to understand the carbon footprint associated with commuting to Otaniemi. The interest in this setup stems from the idea of maintaining the popularity of sustainable modes of transportation regardless of the season. For instance, Oulu is known as a city promoting winter cycling.

The modal share of the winter season resulted in a carbon footprint of 3100 kg CO_2-eq per day for commuting to Otaniemi. In comparison, the modal share of the non-winter season, the carbon footprint decreased to 2500 kg CO_2-eq per day. These values were based on pre-COVID daily trip numbers. In the post-COVID period, the carbon footprint of the commuting to Otaniemi witnessed a significant decrease, reaching approximately 60 % reduction.

The scenarios also examined the emission reduction potential of e-bikes by replacing car trips under 5 kilometers. The scenario comparison showed that implementing this substitution would result in a 9 % reduction in carbon emissions. It would have been possible to increase the share of e-bikes even more, given their greater potential for longer distances beyond 5 km. This would have resulted in a greater carbon reduction potential. However, for the sake of clarity, this choice was made to reflect their potential.

In the proposed model, mobile phone data is utilized to determine travel distances. The mobile phone data does not provide information about mode of transport. Therefore, the proposed model is designed to randomly assign travel modes to trips under certain conditions and is run 100 times to enhance its robustness by reducing fluctuations and improving the reliability of the results. The assignment to transport mode includes different maximum and minimum distances for various modes of transportation. Walking has a maximum distance of 3 km, cycling has 10 km, and electric cycling has 15 km.

Public transportation has a minimum distance of 1 km, and there is no threshold for driving. The specific trip distances were not weighted by mode, which could be a useful addition. For example, while a maximum distance of 10 km has been defined for cycling, it would be a good idea to consider that within this range, trips under 5 km may be more popular than those over 5 km.

If the proposed model were to consider transport accessibility, it would lead to more comprehensive and accurate travel mode assignments. By factoring in the proximity and availability of different transportation options within the origin's area, such as considering the presence of a nearby metro station, the model could better reflect real-world travel patterns and improve the reliability of its results.

The advantage of the method in this thesis is that it introduces a novel approach by utilizing open-source tools and big data together, deviating from the conventional practice of relying on commercial software and the survey of the number of trips.

6.2 Methodology and data reliability

6.2.1 Mobile phone data

Mobile phone data was utilized to estimate people's travel to Otaniemi by routing the origin-destination pairs. Within the study area, the grid sizes ranged from the smallest at 500 x 500 meters to the largest at 2000 x 2000 meters. The relatively low spatial resolution, along with the reliance on grid centroids for routing, causes inherent inaccuracies in the results. The use of an origin-destination matrix does not provide an understanding of individuals' actual mobility. The way people choose their routes is not as simple as travel time alone, which is how the routing was mainly done.

The methods used to collect and process cell phone data often operate as black boxes, making it difficult to evaluate the data. The lack of transparency can impose limitations and raise concerns when analyzing and drawing conclusions from mobile phone data. In the case study, a considerable number of daily trips originated from the city center of Helsinki. This location serves as a hub where different modes of transportation intersect, facilitating transfers for people moving between various transport options. However, it becomes challenging to evaluate whether the city center is the true origin of these trips or if they are the result of a split trip, with the actual origin being elsewhere.

The mobile phone data product used in the study was aggregated and anonymized by Telia, which means that there were no unique IDs to differentiate between trips made with the same ID. Consequently, the data does not provide the possibility to obtain individual-level information.

This study specifically utilized the smallest spatial resolution available, which was at the grid level. There were other spatial levels available such as postcode area, municipality, and county. Due to GDPR regulations, data representing fewer than 5 individuals were excluded. Consequently, if the postcode level was used, it is expected that there would be a higher number of daily trips, as there would be less data exclusion. However, the lower spatial resolution levels were not suitable for this study.

6.2.2 Questionnaire

The Leesman campus survey was not specifically designed to inquire about people's modes of transportation, but rather included additional questions in the survey. The survey included two questions regarding how people generally commute to the campus during winter and other seasons. This survey does not allow for obtaining an accurate picture of people's travel habits, as individuals can often have multiple modes of transportation depending on the environment. The options for answers did not include, for example, multimodal ways of commuting, nor did it specify how frequently each mode of transportation is used. The survey does not represent the entire Aalto University or Otaniemi, as it was targeted towards staff members of the university. The survey responses may emphasize the proportion of sustainable modes of transportation, as universities are centers of knowledge and learning with a central mission to promote a sustainable present and future. However, the university reflects the character of Otaniemi well, as the area is described as a hub of science and technology. The survey would serve its purpose better in this context if it were tied to mobile phone data.

6.2.3 Emission factors for different modes of transport

In this work, emission factors for different modes of transportation were calculated using the LCA tool. The tool covered a wide range of new mobility options, such as shared electric kick-scooters, bicycles, e-bikes, electric mopeds, as well as car-based ride-sharing services. However, only a small portion of these emission factors was utilized in the actual analyses. Within the tool, rail transportation was combined into a single emission factor, based on trains and subways. In fact, one of the subway models used is the one currently operating in the capital region in Finland. Although the tool considers various modes of transportation, it does not account for trams in the life cycle assessment. It would be beneficial for the tool to include trams, as they are less carbon intensive than other forms of rail transport and are an essential part of urban transport (TNMT, 2021). There are also ferry connections in the Helsinki Regional Transport Authority (HSL) region, and the LCA tool does not have emission factors for ferries.

Among the emission factors considered for the entire life cycle, the lowest coefficients are associated with private bicycles and electric bicycles, while taxis and ridesourcing have the highest emission factors. This is due to the inclusion of overhead and cruising associated with these modes of transportation. Furthermore, the need for drivers to travel to areas with demand for taxis and return home adds to their overall higher emission levels (Cazzola and Crist, 2020).

When comparing private car usage to public transportation, it is expected that public transportation has lower emission factors than private cars. The emission factor of a fuel-powered bus is more than half of that of a fuel-powered car. Furthermore, when comparing a fully electric bus to a fully electric car, the emission factor is nearly half. Among these forms of public transportation, the metro and suburban trains have the lowest emission factors.

In comparing new modes of micro mobility to traditional public transportation, considering the complete life cycle becomes crucial. For example, when considering the entire life cycle, the emission factor of dockless shared e-scooters is higher than that of a fossil fuel-powered bus. However, if we compare only the "fuel component," the emission factor of the shared e-scooter is expected to be lower than that of a fossil fuel-powered bus. The manufacturing phase contributes significantly to the emissions of shared e-scooters, as they have a relatively short lifespan. The second-largest contributor is their operational services. Shared bikes and e-bikes are more sustainable options compared to a fossil fuel-powered bus. However, electric buses are still lower in carbon emissions compared to different shared micro mobility transport modes.

From this, we can see that the entire life cycle must be considered to compare different modes of transportation. There is a strong push to electrify transportation because electric vehicles have no emissions during operation. However, it is important to note that the manufacturing process of electric vehicles typically involves a higher consumption of natural resources when compared to vehicles powered by internal combustion engines. The reasoning behind the promotion of electric vehicles is their potential to offset emissions through the absence of tailpipe emissions compared to fossil fuel vehicles. Nonetheless, the carbon intensity of the electricity used depends on the source of electricity production.

The LCA tool utilizes a default global power generation mix, comprising the EU28 and 11 major countries worldwide. Several of these countries have significant coal consumption. As a result, the emission factors used in the tool's study are higher compared to those in this study. It is important to note that this study used the Finnish electricity generation mix, which does not include imported electricity, which may affect the emission factors of the electricity.

Furthermore, in this study, no other assumptions were modified when using the tool. The tool's assumptions aim to provide global estimates. If one

wishes to use the tool while taking their own geographical context into better account, the default parameters should be modified to better align with the specific area of interest. The associated report of the tool effectively illustrates how changes in key input parameters impact emission factors. These assumptions can encompass various factors, such as vehicle occupancy, smaller battery size, reduced deadheading, and more (Cazzola and Crist, 2020).

6.3 Future prospects

This thesis presents a proof-of-concept by demonstrating the feasibility and potential of developing a model utilizing bottom-up GIS approaches and open-source tools. It is important to acknowledge that the work has inherent uncertainties, and further refinement is necessary to enhance the reliability of the results. Nevertheless, the scenario-based approach employed in estimating carbon emissions offers valuable insights into the potential benefits and practical applications of integrating such a model into climate change mitigation planning and related initiatives.

If the proposed model is further developed, several possibilities arise for its expansion and improvement. An important aspect to consider would be the incorporation of carbon budgets into the model, as solely quantifying carbon emissions does not provide sufficient information to determine their impact. By referencing carbon budgets derived from climate targets, the model can assess whether emissions are within or exceed the carbon budget.

The implementation of carbon budgets in practice, even at the country level, poses challenges due to their complexity and the ethical and political questions they raise. It is important to note that countries have self-determined their climate targets based on the Paris Agreement (van den Berg et al., 2020). However, this approach may not necessarily result in a fair allocation of carbon budgets. There are studies about fair carbon budget allocations. For example, the Finnish Climate Change Panel has calculated three carbon budgets per capita for Finland with three different principles which are the equality principle, the ability to pay principle, and the historic responsibility principle (Ollikainen et al., 2019).

In addition to deriving the carbon budget from the climate targets, there is also a new approach to linking the environmental impact to planetary boundaries. Rockström et al. (2009) introduced the concept of nine Planetary Boundaries which are global limits for safe operating space for humanity. Since planetary boundaries are limits for the environment, Meyer and Newman (2018) created Planetary Accounting Framework to translate the planetary boundaries into scalable budgets for different human activity levels (e.g., nation, sector, organization, city, and individual). Further exploration is necessary to address this aspect and strive for a more equitable distribution of scalable carbon budgets.

Furthermore, as stated earlier in this thesis, this research serves as a step towards the development of a tool that aligns with the conceptual framework proposed by Willberg et al. (2023) for measuring just accessibility within planetary boundaries. By further refining and expanding upon the proposed model, it could become feasible to assess the extent to which social and environmental objectives are realized in the context of accessibility, both in current scenarios and future projections.

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