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Exploring activity spaces and GHG travel emissions in connection to the built environment

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Abstract

The challenge of mitigating the climate impacts of cities will require research in multiple directions such as with activity spaces. The goal of this research was to find connections between activity spaces, neighborhood characteristics, housing characteristics, and GHG travel emissions in the Greater Reykjavík Area; prior to this research, there was a gap in the literature on the relationship between GHG travel emissions and activity spaces. Activity spaces span temporal and spatial scales. They describe an individual's mobility behavior through daily travel locations and provide insights into how inhabitants are using the city. ArcGIS was used to map activity spaces and neighborhood characteristics. Binomial and multiple regression analyses were performed using Jamovi. This study builds on previous research using the survey data from 539 respondents on daily travel locations, GHG travel emissions, and housing characteristics. Results showed inhabitants of the Greater Reykjavík Area are very mobile with an average activity space size of 19.3 km^2. Statistically significant positive relationships were found between activity space size and GHG travel emissions. Although not significant neighborhood characteristics showed negative relationships with AS size. Access to a yard had negative effects on AS size, local emissions, and international travel emissions. Respondents living in neighborhoods closer to the city center on average had smaller activity spaces, thus reducing their impact from local travel emissions. These findings can contribute to future urban planning for Reykjavík, as the city plans to be carbon neutral by 2040.

Útdráttur

Helsta áskorunin verkefnisins við að draga úr áhrifum gróðurhúsalofttegunda í borgum krefst rannsókna úr mörgum áttum og eitt er að skoða athafnasvæði fólks (activity spaces). Markmiðið með þessari ritgerð var að skoða tengsl á milli athafnasvæðis fólks, sérkenna í þéttbýli, gerð húsnæðis og magn útblásturs vegna ferðavenja fólks á höfuðborgarsvæðinu. Í ljós kom við gerð þessarar rannsóknar að skortur var á lesefni varðandi útblástur vegna ferðavenja og daglegra athafna fólks. Þessar daglegu athafnir ná bæði yfir tíma og rými. Þær lýsa hversdagslegri hreyfingu einstaklinga og veita innsýn í það hvernig íbúar nýta borgina sína. Forritið ArcGIS var notað til að kortleggja athafnasvæði fólks og sérkenni í þéttbýli. Marghliða og tvíhliða aðfallsgreining voru framkvæmdar með forritinu Jamovi. Þessi rannsókn byggir á fyrri rannsókn um hversdagslega hreyfingu 539 einstaklinga. Niðurstöður sýndu að einstaklingar í höfuðborgarsvæðinu eru mikið á ferðinni, en meðalaltal fyrir athafnasvæði þeirra var 19.3 km^2. Það fannst jákvætt marktækt samband á milli athafna fólks og útblásturs vegna ferðavenja. Neikvæð ómarktæk tengsl voru á milli athafnasvæðis fólks og sérkenna í þéttbýli. Að hafa aðgang að garði hafði neikvæð áhrif á stærð athafnasvæðis fólks, útblásturs í höfuðborgarsvæðisins og útblástur vegna ferðalaga erlendis. Þátttakendur sem bjuggu nær miðbænum notuðu minna athafnasvæði að meðaltali en aðrir og minnkuðu þannig áhrifin af útblæstri. Þessar niðurstöður geta haft áhrif á framtíðar borgarskipulagi í Reykjavík þar sem borgin hefur það markmið að vera kolefnishlutlaust árið 2040.

Dedication

For my family, Lily Butters, and all the future generations.

Table of Contents

List of Figures

List of Tables

Abbreviations

AS- activity space

Dist. to c.c.- distance to the city center

HC- housing characteristics

IASM- individualized activity space modeler

NC- neighborhood characteristics

Pop. density- population density

OR- odds ratio

GHG- greenhouse gas emissions

GIS- geographical information system

PPGIS- public participation geographic information system

PT- public transportation

SE- standard error

β- standardized beta

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A big thank you to my advisors Dr. Jukka Heinonen and Johanna Raudsepp.

1 Introduction

Climate change poses irreversible threats to Earth's ecosystems and the well-being of civilizations. Since the pre-industrial era, there has been a dramatic increase in GHG emissions causing increased warming. Carbon dioxide concentrations in the atmosphere have nearly doubled since 1750, increasing from 280 ppm to 414 ppm in 2021 (NASA, n.d.). Urbanization trends are on the rise and most of the world's population resides in cities. Cities are a major cause of environmental degradation and urban areas are the highest emitters of greenhouse gas emissions (IPCC, 2014). There is an undeniable need for global action supported by abundant scientific evidence; the IPCC's 6th Assessment report blatantly stressed the urgency for action toward climate change mitigation and adaptation (Pörtner et al., 2022). Globally, urban adaptation measures have been weak and limited (Chow et al., 2022). However, urban centers provide a huge opportunity towards combatting climate change through the development of adaptation and mitigation strategies, since 90% of projected population growth will reside in cities (Chow et al., 2022). City planners are faced with the challenge of mitigation through the development of sustainable cities in which the people and environment can prosperously coexist.

The planet is a finite system with a finite amount of material resources and buildable land. Humans use Earth's resources to satisfy wants, needs, and desires and fundamentally depend on these resources to build civilization. The current operations of the system have proved to be unsustainable (Rees, 2022; Rockström et al., 2009; Steffen et al., 2015). The planetary boundaries concept proposes a safe operating space for human civilization, and if civilization can stay within these boundaries a sustainable system is possible (Rockström et al., 2009). The boundaries are located upstream of thresholds and tipping points (Steffen et al., 2015). The nine planetary boundaries include: biodiversity loss, climate change, ocean acidification, chemical pollution, stratospheric ozone depletion, global freshwater use, biogeochemical nitrogen and phosphorus cycles, atmospheric aerosol loading, and land system change; three of the nine boundaries have already been crossed (Rockström et al., 2009). Earth's systems are complex and there is a "zone of uncertainty", planetary boundaries are interconnected and can affect one another (Steffen et al., 2015). Thus, humanity is stepping into the unknown. Human societies are interdependent on the planet's ecosystem services; climate impacts on the planet's system will affect human systems (Chow et al., 2022). Some of these boundaries are rapidly collapsing, thus the reason for urgent action, since there is a limited time slot to ensure a "sustainable future for all" (Pörtner et al., 2022).

A revised version of the planetary boundaries found climate change and biodiversity as core boundaries, suggesting they have the strongest effect (Steffen et al., 2015). According to Steffen et al. (2015), sustainable development requires the use of a planetary framework in conjunction with social and economic frameworks that prioritize human needs. Together, these frameworks can advance the UN's Sustainable Development goals. It is worth emphasizing that relying solely on the planetary framework may not be sufficient to guide human development effectively. The urban form has a crucial role to play in combatting climate change. Urban structures undeniably can have huge impacts on these boundaries, since they are hotspots of consumption, congestion, and land use change; 60% of greenhouse gas emissions that are contributing to atmospheric warming are created in cities (United Nations, n.d.). The transport sector produces one-fifth of all global emissions and 45 percent of these emissions are produced within the passenger transport sector (Ritchie, 2020). Transportation is an essential component of human civilization and within the urban structure. Transportation fulfills desires, wants, and needs such as workplaces, educational institutions, grocery stores, leisure activities, etc. Dense urban structures host densely populated transportation networks. The way cities are designed affects how this transportation network is used, additionally influencing specific mobility types (Golledge & Garling, 2001). “Private driving and air travel” are the highest contributors to GHG emissions within the passenger transport sector; increased densification can combat private driving, but it has been suggested that inhabitants within dense urban structures tend to fly more (Åkerman, 2012; Brand & Boardman, 2008; Ottelin et al., 2014).

Many propositions for sustainable cities involve increased densification. Research has indicated this could result in rebound effects such as increased long-distance air travel and increased consumption (Holz-Rau et al., 2014). Explanations for such phenomena include the compensation hypothesis, cosmopolitan lifestyles theory, monetary rebound effects, and dispersion of social networks (Czepkiewicz, Heinonen, & Ottelin, 2018). Additionally, dense infrastructure areas are not always as appealing as the infrastructure and environmental quality of suburbs. This had led to the phenomenon of urban sprawl, the outward expansion of a city. Thus, leaving many cities faced with challenges of automobile dependency especially with commuters of the suburbs; this phenomenon is common in many American cities (Angel & Blei, 2016; Kenworthy & Laube, 1999). Densification alone is not a win-win solution in addressing climate change. Other factors come into play when determining the sustainability of a city such as energy efficiency and consumption (Heinonen & Junnila, 2011). Cities are hotspots of consumption. Life cycle assessments have demonstrated the high carbon footprint of high-consumption lifestyles, “life in less dense and less affluent areas is in fact less CO2 intensive due to lower overall consumption” (Heinonen & Junnila, 2011). Reduced living size has been connected to reducing one’s carbon footprint (Lettenmeier et al., 2014; Sandberg, 2018). However, smaller living dwellings are more common in dense areas, where it has been found that individuals contribute to more consumption of goods and services (Heinonen et al., 2013a, 2013b). Further research on human behavior related to consumption could have interesting insights for contributing to a sustainable urban form.

The challenge of mitigating climate impacts of cities will require research in other directions such as activity spaces. An individual’s activity space includes mobility behavior such as daily travel locations. The activity space concept is relevant within various fields of literature such as transportation modeling, mobility behavior, health, and environmental exposure. Activity spaces span temporal and spatial scales; it includes commonly visited locations such as workplace, school, gym, daycare, and vicinities near the home (Chapin Jr, 1968; Golledge, 1997; Hasanzadeh et al., 2019). Activity spaces provide insights into how residents are interacting with the city. Chapin (1968) suggests the city’s spatial organization influences the activity space, in addition lifestyles. Furthermore, Klinger et al. (2013) based the typology of mobility culture on the mode of transportation and highlights how the transportation infrastructure of a city contributes to its mobility culture but is not the only factor. In the 1960s and 70s behavioral geographers in the United States developed the concept of action space to understand an individual’s “perceived utility of places” in the urban form (Golledge, 1997). Golledge (1997) characterizes activity spaces by three major components: movement taking place near the home, directional movement towards an activity location (work, shop, leisure, etc.), and movement that takes place around activity locations. Activity spaces can be used to represent spatial behavior, thus providing key information for transportation and urban planning. Activity spaces enable planners to see the travel patterns of city dwellers, thus helping detect the main areas of traffic. Hasanzadeh et al. (2019) suggest holistically using the activity space concept. This could be beneficial in future urban planning toward sustainability through the connection and comparison to other dimensions such as neighborhood characteristics, housing characteristics, and GHG emissions. Li et al. (2018) suggest the use of activity spaces to provide a more complete representation of environmental exposure beyond the residential neighborhood. Furthermore, providing insights into the connection between land use and travel behavior within the urban form.

Prior to this research, there was a gap in the literature on the relationship between activity spaces and greenhouse gas travel emissions. This research aims to help fill this gap through a single case study within the Greater Reykjavík Area; in addition to looking for insights from the built environment, with comparison to housing and neighborhood characteristics. Research on activity spaces can provide valuable insights into how residents are interacting with the city. This can support city planners and provide them with insights for improving the city's infrastructure. City dwellers are a key component in the development of sustainable cities because cities would not exist without their citizens. Inhabitants provide insights into how the city is being used. Additionally, mitigation strategies of cities should include its inhabitants since some research has suggested that increased densification correlates with increased long-distance air travel and consumption (Czepkiewicz et al., 2019; Czepkiewicz, Heinonen, & Ottelin, 2018; Holz-Rau et al., 2014; Ottelin et al., 2014).

1.1 Research aim

This research aims to fill the literature gap on the relationship between activity spaces and GHG travel emissions. An activity space framework is used to discover more about the relationships between activity spaces, GHG travel emissions, neighborhood characteristics, and housing characteristics, using a case study within the Greater Reykjavík Area. The following research questions were the focus of the study.

- How do activity spaces influence travel emissions?
- How do neighborhood and housing characteristics influence activity spaces and GHG travel emissions?

This study uses PPGIS survey data collected from respondents located in the Greater Reykjavík Area. The data consists of sociodemographic and economic information, geographical points of activity and residential locations, travel emissions, housing characteristics, and neighborhood characteristics. Activity spaces and neighborhood characteristics were mapped and analyzed with spatial data using ArcGIS Pro 3.0. Local travel emissions, domestic leisure travel emissions, and international leisure travel emissions were looked at to provide a complete picture of travel emissions, in addition to providing possible insights into the relationship between neighborhood characteristics, mobility styles, and leisure travel. This thesis uses GHG emissions from the individual's travel-related emissions associated with the burning of fuel. The research starts with a literature review of relevant topics related to the research questions, thus setting the stage by providing background. The following section provides a review of relevant literature related to mobility behavior and urban form in connection to GHG emissions, activity spaces, housing characteristics, and neighborhood characteristics.

2 Literature Review

The first area of literature covered looks at how the urban form influences mobility behavior and emissions, thus, literature on the urban form related to travel behavior (i.e., leisure travel) and consumption is reviewed. The second area focuses on previous literature on activity spaces, but there is a gap in the literature on the relationship between activity spaces and GHG travel emissions. The second area includes two subsections focusing on housing and neighborhood characteristics.

2.1 Urban form and GHG connection

As society is in an age of planetary boundaries, there is much research occurring on the topic of sustainability in the urban form, resulting in various ideas to support a city that can continue to fully provide for future generations. Mobility behavior has been a focus of some of this research, due to its contribution for mitigation in the passenger transport sector. Increased densification has been connected to a sustainable urban form with a large body of literature support. There are various reasons to support densification such as with habitat protection, less land use, and lower transportation emissions from daily travel within the city (Fatone et al., 2012). Compactness and densification have been related to lower emissions from local transportation, energy efficiency (Jenks & Burgess, 2000; VandeWeghe & Kennedy, 2007), and the furtherment of public transportation systems (Fatone et al., 2012). However, many of these studies are only looking at transportation and housing energy which only explains a piece of the picture. Cities are hotspots of consumption. Research from Finland found common lifestyle components connected to the urban form (Heinonen et al., 2013). Another similar study found a positive correlation between density and “consumption of services” (Heinonen & Junnila, 2011). Dense urban structures offer more employment opportunities, thus higher incomes are found in the dense city centers. As income increases, consumption of personal goods increases, subsequently increasing GHG emissions (Heinonen et al., 2013). However, those living in rural areas may consume fewer personal goods lowering their ecological footprint, but tradeoffs include increased emissions from private driving (Heinonen et al., 2013).

Densification has been the common solution to combat urban sprawl (Neuman, 2005). A literature review by Neuman (2005) sought to determine how sustainable the compact form is. Neuman (2005) indicates the literature is conflicting due to the limited focus on one aspect of travel, but overall states that there is a weak correlation. Neuman (2005) highlights how many cities are planned with old theories. In the past these settlements may have been sustainable, but older settlements grew at much slower rates than today’s high-speed urbanization developments; many new challenges have emerged since the past. Neuman (2005) suggests density is insufficient to determine a city's sustainability and claims operations are more important. The creation of high-quality compact cities is a major goal of sustainable development, such as through the enhancement of public transportation systems that promote energy efficiency, reduce travel distances, and limit pollution (Fatone et al., 2012; Neuman, 2005). Fatone et al. (2012) state that even though densification is preferred over urban sprawl it is not an applicable solution in “any context,” and conducted research to develop environmental measures that sustainably guide densification. Fatone et al. (2012) suggest the use of sustainability measures to achieve sustainable development within densification policies, and highlight the importance of improving the quality of the existing environment before further densification occurs, such as by updating old infrastructure. City planners must look beyond densification in their quest for the sustainable city.

Certain researchers suggest the use of three principles to explain urban form's relationship to mobility behavior: "density, diversity, and design" (Cervero & Kockelman, 1997; Klinger et al., 2013). All three D's offer objective insights into mobility behavior, in addition to socioeconomic characteristics, therefore it is important to not overlook one angle. Design refers to how the city is planned and structured. Diversity refers to how the land is used (e.g. land-use mixture). Density refers to the compactness of the city (contrary to urban sprawl), it is usually calculated through the "share of dwellings", or the number of people per hectare of land (Klinger et al., 2013). In addition, socioeconomic characteristics contribute to lifestyles, attitudes, and preferences of (subjective) mobility behavior (Klinger et al., 2013), travel theories that attempt to explain this behavior are presented below.

2.1.1 Travel theories

Many studies have been interested in how the urban form influences city dwellers' travel behavior, specifically with long-distance air travel. Many studies have found connections between densification and an increase in air travel (Czepkiewicz et al., 2019; Czepkiewicz, Heinonen, & Ottelin, 2018; Holz-Rau et al., 2014; Ottelin et al., 2014). There are important connections to be made from mobility behavior to lifestyles, attitudes, and preferences (Klinger et al., 2013). The main emitters of GHG emissions within passenger transport are private driving and air travel (Ottelin et al., 2014). Ottelin et al. (2014) found that air travel forms a major component of GHG emissions of Helsinki city dwellers, thus contradicting the decrease of emissions from local travel within the dense city structure. Several hypothetical explanations are currently used within the literature to explain this travel behavior.

Some studies have found relevant connections between Reykjavík's urban environment and long-distance travel. Czepkiewicz, Heinonen, et al. (2020) found an increase in international trips for those living in Reykjavík's city center. Raudsepp et al. (2021) found that a car-free lifestyle induced international leisure travel of those living in Reykjavík's city center, thus highlighting the monetary rebound effects from car savings (Raudsepp et al., 2021). This means the money saved from not having a car is used elsewhere such as with international travel. Similarly, Ottelin et al. (2014) found that not owning a car resulted in a dramatic increase in flight emissions within the middle class of the Helsinki metropolitan area. Additionally, two other studies found a higher amount of leisure trips abroad with downtown dwellers (Czepkiewicz et al., 2019; Czepkiewicz, Klaas, & Heinonen, 2020), and suggest cosmopolitan attitudes as an explanatory factor. The cosmopolitan attitudes theory suggests flying to be a major lifestyle component of those living in city centers characterized by higher densification (Czepkiewicz, Heinonen, & Ottelin, 2018; Holden & Norland, 2005).

The compensation hypothesis proposes that people residing in dense urban areas want to travel more to compensate for its deficiencies (Czepkiewicz, Klaas, & Heinonen, 2020; Næss, 2006; Raudsepp et al., 2021), thus, dramatically increasing the carbon footprint of city-dwelling individuals. Deficiencies include a lack of green space or urban stressors such as traffic, pollution, and noise (Czepkiewicz, Klaas, & Heinonen, 2020; Næss, 2006). In

Reykjavík, the compensation hypothesis was found to be mainly relevant for domestic travel. Raudsepp et al. (2021) found car commuting stress and lack of quality green space inducing domestic travel trips. Raudsepp et al. (2021) suggest a lack of activities and cultural diversity were push factors for international travel. Iceland is an interesting case due to it being an isolated island, therefore a lot of times a plane is the only way to leave, and air travel forms a major mode of transport; additionally, Iceland is an affluent country, and in general, there is a strong connection between frequency of flying and higher income, however within Iceland high mobility has been reported within all income groups (Raudsepp et al., 2021). This is where the dispersed social connections theory comes in to attempt to explain this behavior, which suggests individuals with a foreign background or a dispersed social network travel further distances to maintain their social network (Czepkiewicz, Heinonen, et al., 2020; Mattioli & Scheiner, 2019).

2.2 Activity spaces

Activity spaces describe an individual's daily travel behavior and include commonly visited locations such as work, childcare, and leisure activities (Chapin Jr, 1968; Golledge, 1997; Hasanzadeh et al., 2019). They provide insights into spatial behavior while describing an individual's mobility behavior. The activity space concept stems from animal migration research within the field of zoology (Burt, 1943). Mobility behavior is complex, and activity spaces provide a practical approach to studying individual mobility behavior. The existing literature on activity spaces is within various fields such as public health and transportation planning, but there is a gap in the activity space and GHG travel emissions relationship. Perchoux et al. (2013) suggest activity spaces can be used to show a complete picture of environmental exposures accounting for space and time behavior, because they show locations of exposure outside of the immediate neighborhood. Space and time behavior can provide a comprehensive understanding of where, how, and why people go where they go. One of the earliest works of literature on activity spaces comes from Chapin Jr. (1968), setting the stage through the introduction of an activity space framework to better understand processes of urban form, with a focus on households. Chapin Jr. (1968) describes urban centers as places of interaction, thus a social system; activities are a central component since they are comprised of interactions. Chapin Jr. (1968) suggests residential selection is influenced by an individual's activities, in addition to socioeconomic factors and lifestyle preferences. (Chapin Jr, 1968).

Järv et al. (2014) used mobile phone tracking data to further the understanding of the complexity of mobility behavior by focusing on the variability of activity spaces. Järv et al. (2014) found an increase of variability in activity locations during winter and summer; the monthly activity space sizes of July were increasingly larger than the rest of the months, and the number of new activity locations. Järv et al. (2014) highlight the seasonal effects on mobility behavior and leisure travel, further highlighting the complexity of mobility behavior. Shareck et al. (2014) suggest activity spaces provide a cognitive interpretation of mobility behavior through mobility potential. Furthermore, Shareck et. al (2014) found that mobility potential is dependent on geographical, personal, social, and authoritative constraints, and highlights the importance of connecting mobility to health.

Li et al. (2018) argue that previous research on the relationship between travel behavior and land use characteristics is "static" and incomplete, since most only study land characteristics of an individual's immediate neighborhood. Li et. al. (2018) suggest the use of activity spaces to provide a more complete understanding of the land-use characteristics that an individual is exposed to, such as going beyond the residential neighborhood, because many services or land that is interacted with are beyond the residential buffer. Li et al. (2018) found land use characteristics of the activity space had a stronger impact on travel behavior than the residential characteristics. Additionally, Li et al. (2018) found that land-use mixture within the activity space had a greater effect on decreased non-work travel distance than land-use mixture within the residential neighborhood. Similarly, Tana et al. (2016) found higher amounts of land use diversity resulting in smaller activity spaces. Li et al. (2018) found stronger effects of land-use diversity on auto-related travel than public transportation for both spatial units (residential and activity space), thus suggesting the use of land use mixture to reduce travel distance. Similarly, Hasanzadeh et al. (2017) and Hasanzadeh et al. (2018) described previous research on mobility behavior as static. Hasanzadeh et al. (2017) presented a method that provides for a more appropriate account of environmental exposure, using an individualized activity space modeler that calculated a home range buffer based on the visited points and home locations.

Many previous studies have mainly focused on "distance traveled and mode of transportation" (Hasanzadeh et al., 2019). Hasanzadeh et al. (2019) suggest the use of activity spaces in a holistic and multidimensional manner to provide a more comprehensive understanding in the connection between urban form and well-being. Hasanzadeh et al. (2019) used seven components to describe activity space: elongation, polycentricity, size, destination type, volume of trips, and intensity of activities. Hasanzadeh et al. (2019) suggest the activity space framework can be used to provide insights into urban mobility. Hasanzadeh et al. (2019) propose the use of the centricity method to better understand activity spaces, and suggest life is commonly centered around activity locations not the home. The centricity measure results in three categories: monocentric, bicentric, and polycentric; monocentric activity spaces are located around the home, and on the contrary, polycentric activity spaces are composed of two or more activity centers located away from the home (Hasanzadeh et al., 2019).

Another study used the proposed centricity method to further the understanding of the relationship between transportation mode, sociodemographic characteristics, neighborhood characteristics, age groups, and well-being (Hasanzadeh et al., 2021). Hasanzadeh et al. (2021) found polycentric activity spaces more common with young adults and a higher amount of monocentric activity spaces with older adults; monocentric activity spaces were more common with individuals residing in denser neighborhoods. In younger adults, Hasanzadeh et al. (2021) found higher income associated with polycentric activity space.

2.2.1 Neighborhood characteristics

The term neighborhood can be defined as a subsection of the larger community and can be seen as "a source of place-identity, an element of urban form, or a unit of decision making" (Balestra & Sultan, 2013). Fundamentally, neighborhoods are the nearby surrounding environment where people live. Examples of characteristics of a neighborhood include walkability, access to services or public facilities, density, land use, green space, and blue space. Characteristics of neighborhoods are largely dependent on land use. Neighborhood characteristics influence mobility behavior, such as through accessibility to transportation, accessibility to services, and land use type (Zhang et al., 2018). Residential satisfaction is largely dependent on socioeconomic factors (Dong & Qin, 2017). Al Mantilla et al. (2018) found connections between urban zones and subjective well-being; respondents in the central pedestrian zone (city center) reported higher quality of life, but respondents in car-oriented zones reported higher happiness.

Neighborhood characteristics can connect into broader dimensions such as with GHG emissions and activity spaces, thus providing city planners with insights for future planning and mitigation strategies. It has been strongly established that neighborhoods characterized by density result in high walkability and accessibility to public transportation, decreasing transportation emissions. Studies have found that city dwellers have “smaller and less dispersed activity spaces” (Hasanzadeh et al., 2019; Tana et al., 2016; Zhang et al., 2018). Contrary, residents in the suburbs were found to have larger, more elongated, and polycentric activity spaces characterized by automobile commuting (Hasanzadeh et al., 2019). Suburbs located on the outskirts of dense city centers are characterized by lower density. Many families with children reside in the suburbs, and transportation tends to be dominated by private cars. Heinonen et al. (2011) found that neighborhoods characterized by density (compared to those in the countryside) have much higher GHG emissions due to higher consumption of personal goods. Zhang et al. (2012) studied the relationship between residential characteristics and travel behavior focusing on automobile dependency. Zhang et al.’s (2012) research showed individuals residing in mixed land use cities drove less distances; however, this was only found in the larger urban cities. Additionally, neighborhoods with higher residential density and shorter block distances resulted in lower distances traveled by vehicles (Næss, 2011; Zhang et al., 2018). A study from Oslo found higher use of public transport within higher-density neighborhoods (Næss et al., 1995). Czepkiewicz, Klaas, and Heinonen (2020) looked at the consonance and dissonance of neighborhood characteristics to compare individuals' preferences with their long-distance travel behavior within Reykjavík and Helsinki. Czepkiewicz, Klaas, and Heinonen (2020) found that individuals in Helsinki who preferred greenness, but whose neighborhoods lacked green space took more domestic leisure travel. Similarly, Klinger et al. (2013) research shows residential spatial preferences mismatching where a respondent resided.

2.2.2 Housing characteristics

Housing characteristics include details about an individual’s home residence and include characteristics such as: bedroom number, distance to the city center, number of inhabitants, and residence type (e.g. apartment or house). The previous literature on the connections between housing characteristics, activity spaces, and GHG emissions is limited. However, there has been consideration over appropriate living sizes in reference to climate change mitigation, as reduced living size has been found to reduce carbon emissions (Lettenmeier et al., 2014; Sandberg, 2018). Tana et al. (2016) found that fewer household inhabitants resulted in smaller AS sizes. A study from Reykjavík found that individuals with a home close to the city center overall drove lower distances, but throughout all of Reykjavík´s Capital Region private car was the dominant mode of travel (Næss et al., 2021). However, Næss et al. (2021) suggest this could be due to a weak public transportation system with bus being the only mode. Similarly, Tana et al. (2016) found that individuals residing further from the city center have larger activity spaces. Another study in Reykjavík found that access to a yard correlated with a decreased motivation for domestic leisure trips (Czepkiewicz, Heinonen et al., 2020), and other researchers (Holden & Linnerud, 2011) reported similar findings in an Oslo study. A study in Finland found differences in the emissions (from housing, transport, and indirect consumption emissions) of those living in low-rise versa high-rise households (Heinonen et al., 2013a, 2013b). High-rise households which were mainly located closer to the city center, overall contributed to more emissions (mainly due to consumption), but low-rise households located outside of the city center contributed to more transportation emissions from private driving (Heinonen et al., 2013a, 2013b).

3 Research design

This thesis takes a quantitative approach with a spatial and statistical analysis through the use of a single case study in the Greater Reykjavík Area. The methods, materials, and details on the area of study used in this thesis are presented below. The resulting maps from this thesis also serve as a form of qualitative visual data.

3.1 Object of research

The main purpose of this research is to map and analyze activity spaces in the Greater Reykjavík Area using an activity space framework to compare to other dimensions: neighborhood characteristics, housing characteristics, and GHG travel emissions. The following neighborhood and housing characteristics are calculated in ArcGIS Pro 3.0: blue space, open space (includes green space), density, distance to the city center, public transportation zoning, and urban zoning. Activity space size and elongation are compared to neighborhood characteristics, housing characteristics, and GHG travel emissions through a regression analysis, further GHG travel emissions are compared to neighborhood and housing characteristics through a regression analysis. Overall, this study is an application of an activity space framework that connects to other dimensions with the goal of providing sustainability insights to urban planners.

3.2 Area of study

The data for this thesis comes from respondents located in the Greater Reykjavík Area which consists of central Reykjavík, Seltjarnarnes, Kópavogur, Mosfellsbær, Garðabær, Hafnarfjörður, and Kjósarhreppur. Iceland is a sparsely populated country categorized by low density and has a total population of 374,776. However, 64% of the population resides in the Greater Reykjavík Area with a population of 240,882 (Statistics Iceland, 2023). Central Reykjavík is located on a peninsula only accessible from one side. The city has a sub-polar oceanic climate, and the weather is prone to great variability. Iceland has a low amount of vegetation due to its close location to the Arctic Circle, thus green space is limited. Reykjavík is currently working on municipal mitigation and adaptation plans, as the city plans to be carbon neutral by 2040.

3.3 Data/Materials

This research builds on a larger research project and uses PPGIS survey data collected in 2017. The data collected consist of quantitative and geographical data. The data was collected for the Sustainable Reykjavík Capital Region Project (SuReCaRe) by a group of researchers at the University of Iceland’s Department of Civil Engineering and Natural Sciences. The survey was sent out to a randomly selected sample of 6000 young adults from ages 24 to 40 residing in the Greater Reykjavík Area (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Data consisted of 735 respondents of which 539 respondents provided complete geographical data for this analysis. The survey collected data on residential location, GHG travel estimates, housing and residential characteristics, daily travel patterns, socioeconomic and demographic characteristics, and life satisfaction measures.

The greenhouse gas travel measures included in this study were from local emissions, national leisure emissions, and international leisure emissions. GHG estimates were calculated for the Sustainable Reykjavík Capital Region Project. They were computed using a life cycle assessment including both direct and indirect emissions (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Only emissions associated with fuel were included in any calculations associated with this thesis to focus on impacts directly associated with the individual's travel behavior. Direct emissions account for travel emissions directly associated with the burning of fuel, and indirect emissions associated with the production of fuel were included in this study. A complete description of the calculations can be found in the Sustainable Reykjavík Capital Region report (Czepkiewicz, Heinonen, & Árnadóttir, 2018).

3.4 Research methods

3.4.1 Case study

The case study methodology is a practical approach for understanding and exploring complex research questions through a context-based setting within a variety of disciplines. A variety of data types and collection methods can be used in a case study both qualitative and quantitative (Yin, 1981). Case studies can be used as a building component in the development of theory (Eisenhardt & Graebner, 2007). Theory which attempts to explain phenomena is a key component in empirical research. One of the main strengths of case studies is that they attempt to explain a phenomenon in a real-world setting (Eisenhardt & Graebner, 2007), further enhancing the connection between deductive and inductive research. However, since case studies take place in a real-world setting the data can be influenced by external factors that are unknown to the researcher (Priya, 2021) According to Priya (2021), bias can be a major challenge for the case study researcher, therefore research needs to maintain objectivity. Replication logic is a key component in the development of theory through case study research, and multiple iterations of case studies can work together to contribute to theory (Eisenhardt & Graebner, 2007). Phenomena discovered within case studies can gain higher credibility through peer review (Priya, 2021). Generalizations cannot be made from a single case study, but through multiple case studies it is possible to find generalizations (Eisenhardt & Graebner, 2007; Flyvbjerg, 2006). For example, a phenomenon found in one place may not exist in another place. The case study method is a useful method for exploring a gap in the literature, such as when there is no existing theory to explain a phenomenon. (Eisenhardt & Graebner, 2007). However, it can be used for both generating and testing hypotheses, in addition to providing further detailed descriptions of observations made from the case study (Eisenhardt, 1989; Flyvbjerg, 2006).

3.4.2 Public participation GIS

The public participation GIS (PPGIS) methodology is an emerging field that furthers accessibility of map integration into greater parts of the population (Obermeyer, 1998), through a variety of applications in which individuals of the public can participate in GIS technology (Brown & Kyttä, 2014). Brown et al. (2014) suggest its use for enhancing the public's involvement in informing future land-use planning. It can be used as a tool for combining the realms of public participation and geographical information systems. For example, it can be used to collect spatial information through a softGIS survey in which the respondent actively presses locations on a map, such as for collecting spatial data for activity space modeling. PPGIS allows for the collection of a ready-to-use large sample of individualized spatial datasets (Hasanzadeh, 2022). The main limitations associated with PPGIS are due to the quality of spatial data being dependent upon the respondent's mapping abilities. Therefore, it can be prone to errors associated with inaccurately marked locations (Hasanzadeh, 2022). In addition, compared to GPS spatial data which includes the temporal aspect of the spatial dataset, PPGIS relies upon the respondent to achieve this information; however, frequency of travel can be used to shed light on temporality (Hasanzadeh, 2022).

3.4.3 Activity space modeling & analysis

The Individualized Activity Space Modeler (IASM) is a ESRI compatible geographic information system toolbox (Hasanzadeh, 2018). Geographical information systems can be used to analyze and manage spatial data. This method of activity space modeling was proposed in research from Hasanzadeh et al. (2017) as a more individualized and home-based approach to studying mobility behavior. IASM can be used on spatial data collected from various methods such as public participation GIS, GPS, and mobile tracking. The IASM provides an individualized based approach to activity space modeling. The toolbox consists of four customizable tools: home range distance identifier, home range modeler, IREModeler, and the maximum exposure area estimator (Hasanzadeh, 2018). All four tools can be used for different types of activity space modeling. The home range distance identifier estimates a home boundary through the Jenks natural breaks optimization method which determines the best arrangement of classes through the Goodness of Variance Fit (Hasanzadeh, 2018). The calculated distance for the home boundary threshold will then be inputted into the optional D3 distance value for the home range modeler. The home range modeler uses three distance parameters: D1, D2, and D3; these parameters are used to make individualized convex polygons (Hasanzadeh, 2018). D1 creates a circular buffer distance of the individual's direct neighborhood, and its value is defaulted at 500m within the literature (Hasanzadeh, 2018; Hasanzadeh et al., 2017). The D2 distance creates circular buffers around activity location points; this distance can be calculated by measuring the data's "average size of spatial clusters" or by measuring the "average block size of study area" (Hasanzadeh, 2018; Hasanzadeh et al., 2017). The D3 threshold defines an optional home range boundary which will decide the points that are included within the activity space modeling (Hasanzadeh, 2018; Hasanzadeh et al., 2017). Hasanzadeh et al. (2017) used the home range distance identifier to define a neighborhood or home boundary to provide an individualized boundary based on the entire dataset. Hasanzadeh et al. (2017) suggested it as a more fluid approach to defining a neighborhood boundary compared to traditional static jurisdictions.

Once activity spaces are modeled further dimensions can be looked at such as size, elongation, and centricity. Size or area has been a common activity space characteristic looked at in previous studies (Hasanzadeh et al., 2021; Järv et al., 2015; Tana et al., 2016), and provides insights on overall travel distances (Hasanzadeh et al., 2021). Centricity creates a typology that categorizes activity spaces into monocentric, bicentric, and polycentric. Centricity looks at the centering of an activity space in relation to the home. A monocentric activity space is centered within a 15–20 minute walking distance from the home, an additional activity space outside this range falls into bicentric, and anything more than two centers outside is polycentric. (Hasanzadeh et al., 2019; Hasanzadeh et al., 2021). Centricity can be used to show an individual's "extra-neighborhood" or a place outside of the home neighborhood that an individual frequently visits for activities (Hasanzadeh et al., 2021). Elongation is a geometrical characteristic that has been used in previous studies (Hasanzadeh et al., 2019; Hasanzadeh et al., 2018; Perchoux et al., 2014). A high value can indicate traveling in one direction such as with commuting, resulting in a bicentric activity space (Hasanzadeh et al., 2019). A low value can indicate omnidirectional travel (Hasanzadeh et al., 2019). It is calculated through a standard deviational ellipse. Elongation should be interpreted with sensitivity since a low value can be representative of a monocentric or polycentric activity space.

3.4.4 Spatial analysis

Spatial analysis is used to examine spatial phenomena with geometry and mathematics through a geographical information system. Hotspot analysis is a type of spatial analysis that identifies areas within a spatial data set that are statistically hot or cold spots. This tool works by doing intra-comparisons between all values within a specific desired feature. The hotspot analysis calculates the Getis-Ord Gi* statistic which provides a p-value and z-value. The z scores can be used to indicate areas of clustering of both high and low values (Esri, n.d.).

3.4.5 Regression analysis

Statistical analysis is a common approach for analyzing quantitative data. Regression analysis is a type of statical analysis for analyzing the relationship between two or more variables through the creation of a linear or nonlinear model. It can be used to see if there is any correlation between variables and the strength of the relationship (Uyanık & Güler, 2013). With multiple linear regression, multiple independent variables can be added into a model for the prediction of a quantitative dependent variable; independent variables can be categorical or quantitative. The following is the formula for multiple linear regression in which variables can be inputted: y = a + b1*x1 + b2*x2 + b3*x3 +…+ e. Whereas y is the dependent variable, x stands for independent variables, and e is the amount of variance. The y-intercept is represented by a in the equation above. The regression coefficient (also referred to as the beta coefficient) which is represented by b1, b2, b3, etc. is the amount of change in y for each unit change in x when holding all other independent or control variables constant. The regression coefficient provides a numerical value for the prediction of the relationship between variables. The standard error is the amount of variance around the beta coefficient, and p-values are used to determine statistical significance. The R^2 and F^2 test values can be used to evaluate how good of a fit the model is and how much error or variance is within the specific model. The r-squared values range from 0 to 1. A value of 1 is an indication that the model is a good predictor of the dependent variable, and a value of 0 indicates that the model is not a good fit. A larger F value (greater than 1) indicates the model is better at predicting the outcome of the dependent variable.

Binomial logistic regression consists of two binary dependent variables such as with categorical variables (e.g., married, not married). Similarly to linear regression, there is a slope coefficient, but it is interpreted differently than in linear regression. The slope coefficient represents a change in odds not in values, meaning how likely it is for the dependent variable to be in "category one and not in category 0" when the independent variable increases by one; the reference level in the above-mentioned example would be 0. The odds ratio is a central component in interpreting a logistic regression model (Field, 2013). A value above one indicates the independent variables increase the chance of the outcome (i.e., category one/ dependent variable), and values under zero indicate a decrease in the odds of an outcome. X^2 and McFadden's R^2 values are used to determine the overall fit of the model.

3.5 Research process

3.5.1 Activity space modeling and analysis

The spatial dataset from the PPGIS survey was inputted into ArcGIS Pro 3.0. The dataset required a cleanup of misplaced points, for example removing points that were placed inaccurately by the respondent. The selection tool was used to limit visited points and home locations to the Greater Reykjavík Area. Activity spaces were mapped and analyzed using the Individualized Activity Space Modeler toolbox published by Kamyar Hasandazeh (Hasandazeh, 2018), and used in the study from Hasandazeh et al. (2017). The individualized home range modeler tool (from the above-mentioned toolbox) was the focus of this study, in order to focus on the influence of the neighborhood on activity space. The following inputs were used with this tool.

A 100m value for D1 and a 500m value for D2 were selected as suggested by previous literature (Hasanzadeh, 2018; Hasanzadeh et al., 2017). The D3 value was not activated so that activity spaces would be fully mapped without a boundary. A selection was done to limit local points to the Greater Reykjavík Area. The home range modeler tool resulted in convex polygons and calculated the area of each polygon in m^2 (overall size); this calculation was converted to km^2. In addition to size, centricity and elongation were calculated using the above-mentioned toolbox. These variables were chosen based on the studies from Hasanzadeh et al. (2017), Hasanzadeh et al. (2019), and Hasanzadeh et al. (2021). Further information on the calculation of variables is presented in Table 1 below.

Table 1: How activity space characteristics were calculated.

AS variable	*ArcGIS calculation*
Area	Area of the polygon including all visited activity points.
Elongation	Standard deviational ellipse major to minor axis ratio.
Centricity	Count of the number of activity centers.

3.5.2 Spatial variable calculations

The following section lists how the variables for neighborhood and housing characteristics were calculated in ArcGIS.

Open space and blue space

Blue spaces are defined as water areas such as rivers, oceans, and lakes (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Open space is defined as publicly accessible areas such as green urban areas, parks, forests, grasslands, wetlands, vegetated areas, areas with little or no vegetation (i.e., beaches, bare rocks, glaciers), sport and leisure facilities, etc. (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Open space can be used as an indication of green space and greenness. The blue space and open space classifications use land classes from GMES Urban Atlas, in addition to ocean water which was added (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Open space and blue space were measured in relation to a respondent's home location and calculate the percentage of green or blue space within a 1 km radius of the circular buffer around the respondents' home location.

Population density

Urban density is commonly measured through population density. Population density was measured as the number of residents per hectare using data from Samtök sveitarfélaga á höfuðborgarsvæðinu (Czepkiewicz, Heinonen, & Árnadóttir, 2018). The population density was measured in relation to a respondent’s home location using a 1 km radius of a circular buffer, and the amount of people residing within this area was measured.

Distance to the city center

Laugavegur, Bankastræti, and Skólavörðustígur were allocated as points to represent the city center as chosen by an expert for the Sustainable Reykjavík Capital Region Project (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Driving distance from the city center was calculated as the distance from these points using the Network Analyst tool from ArcGIS. The distances were calculated in meters and converted into kilometers.

Public transportation and urban zoning

Table 2 and Table 3 describe how the public transportation and urban zoning classifications were calculated (Czepkiewicz, Heinonen, & Árnadóttir, 2018).

Table 2: How urban zones were calculated.

Zone name	*ArcGIS calculation*
Central pedestrian zone	Area that is within 1500 meters distance from the main city center.
Fringe of central pedestrian zone	Area that is within 1500 m-3000 m distance from the main city center.
Intensive public transportation zone	Area with frequent and walkable bus stops: 10 bus departures per hour and 332 meters street network distance to the nearest bus stop.
Basic public transportation zone	Area with 4 bus departures per hour and 332 meters street network distance to the nearest bus stop.
Car-orientated zone	Area where public transport is less than 4 bus departures per hour and no bus stop within 332 meters street network distance.

Table 3: How public transportation zones were calculated.

Zone number	*Criteria*
PT zone 1	Highly accessible public transportation, 10 or more departures per hour within a 5 min walk to a bus stop e.g., Mjódd and Hlemmur.
PT zone 2	Medium accessibility to public transportation around 4-10 departures per hour within a 5-minute walk to a bus stop.
PT zone 3	Limited accessibility to public transportation 4 or fewer departures per hour within a 5-minute walk to a bus stop.
PT zone 4	Low accessibility to public transportation, no bus stop within a 5-minute walk.

3.5.3 Further Assessment

Once all the variables were calculated in ArcGIS Pro 3.0 it was possible to continue with a further assessment. Three variables from the activity space modeling were taken into further assessment (size, elongation, and centricity). The first stage of the assessment was to create hotspot maps with the hotspot analysis tool in ArcGIS. Hotspot analyses were performed on AS size, AS elongation, and travel emissions to see for clustering of high or low spots.

The second stage of the assessment was to take all the calculated variables from ArcGIS, in addition to other variables taken from the survey, and bring them into Jamovi 2.3.21 for the regression analysis. Regression analyses were done to further analyze relationships. The following data was taken from the survey and used as variables: GHG estimates, bedroom number, residence type, inhabitant number, access yard (yes or no), and sociodemographic and economic information. Six models were created, each with different dependent variables. The following dependent variables were placed into multiple linear regression models: activity space size (i.e., area in square kilometers), activity space elongation, GHG national leisure travel emissions (yearly), GHG international leisure travel emissions (yearly), and GHG local travel emissions (yearly). A binomial logistic regression model was created for the centricity variable with the following two categories polycentric and not polycentric (i.e., mono or bicentric). The following variables were included as independent variables to see for their effects on the dependent variables: open space, blue space, population density, distance to the city center, public transportation zoning, access to a yard, residence type, household type (with or without children), inhabitant number, bedroom number, AS size (only for GHG models), and AS elongation (only for GHG models). The setup of the regression models can be seen below in Figure 1.

The following sociodemographic and economic information was controlled for: income, occupation status, gender, age, and education level. Income and education variables were transformed into low, medium, and high categories. Income was recorded as per month's salary. The low income category included 150,000-450,000 ISK and less than 150,000 ISK. The medium income category ranged from 450, 000 ISK to 900, 000 ISK. The high income category was for more than 900,00 ISK per month. The household type was transformed from six categories (single, living with parents, couple with no children, couple with children, single parent, etc.) to two categories mainly to control for the effects that children have on a household's mobility behavior. A log function was performed on the GHG variables (local, national, and international) to normalize the datasets since they were skewed to the right.

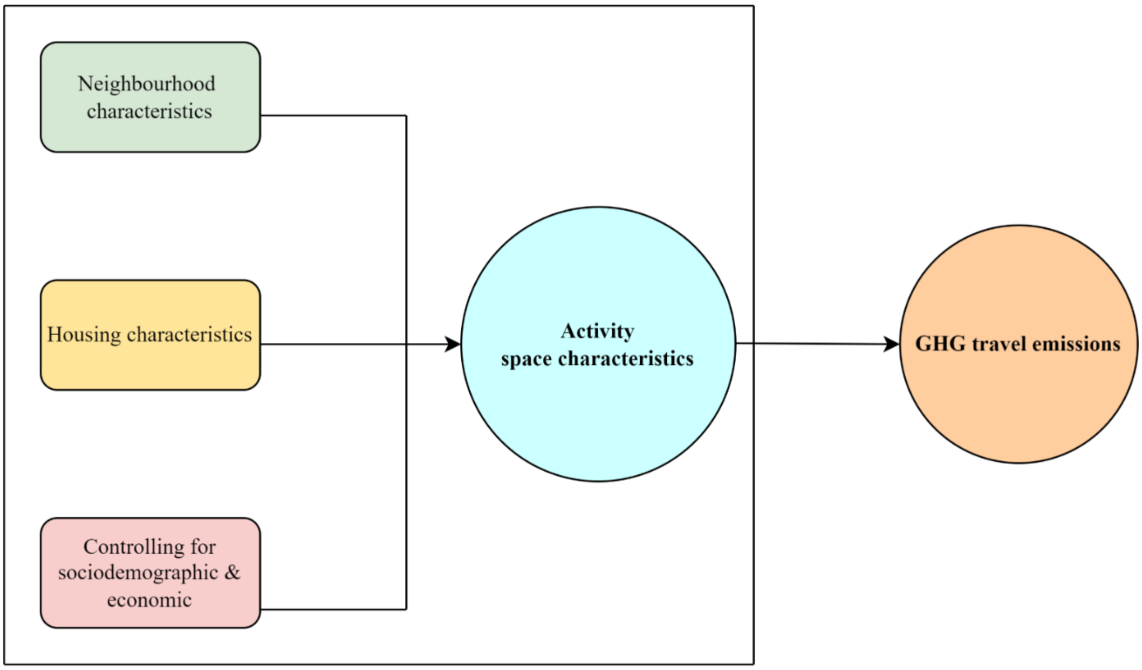

Figure 1: Setup of regression models

4 Results

The first subsection includes results from AS modeling and examples of individually mapped activity spaces in connection to the centricity typology. In addition, the first subsection includes results from the hot spot analyses for AS size, AS elongation, and GHG travel emissions. The second subsection includes results from the regression analyses which includes a total of six statistical models.

4.1 AS modeling and hotspot analysis

Activity space modeling

The average activity space size of the whole sample was 19.3 km^2. The average elongation was 3.38. 82.9 percent of activity spaces were categorized as polycentric meaning most of the respondents had more than two centers of activity locations. The majority of monocentric activity spaces, although few, were located close to the city center. Table 4 and Table 5 provide an overview of descriptives from the mapping of activity spaces. Further below, Figures 2-4 show examples of mapped activity spaces in connection to the centricity typology.

Table 4: Average AS size and elongation by distance to the city center

Distance to the city center	Average AS size (km^2)	Average AS elongation
0-3 km	13.33	3.23
3-6 km	17.85	2.76
6-9 km	17.62	3.09
9-12 km	25.14	3.74
12-15 km	33.54	4.23
15+ km	25.57	8.06

Table 5: Percent of centricity type by the municipality

AS type	**Municipality**	**Counts**	**% of total**
Polycentric	Garðabær	15	2.8 %
	Reykjavík	304	56.5 %
	Kópavogur	56	10.4 %
	Hafnarfjörður	50	9.3 %
	Mosfellsbær	16	3.0 %
	Seltjarnarnes	5	0.9 %
Bicentric	Garðabær	5	0.9 %
	Reykjavík	48	8.9 %
	Kópavogur	10	1.9 %
	Hafnarfjörður	11	2.0 %
	Mosfellsbær	3	0.6 %
	Seltjarnarnes	1	0.2 %
Monocentric	Garðabær	1	0.2 %
	Reykjavík	11	2.0 %
	Kópavogur	1	0.2 %
	Hafnarfjörður	0	0.0 %
	Mosfellsbær	1	0.2 %
	Seltjarnarnes	0	0.0 %

Figure 2: Monocentric activity space example which is categorized by activities near the home vicinity.

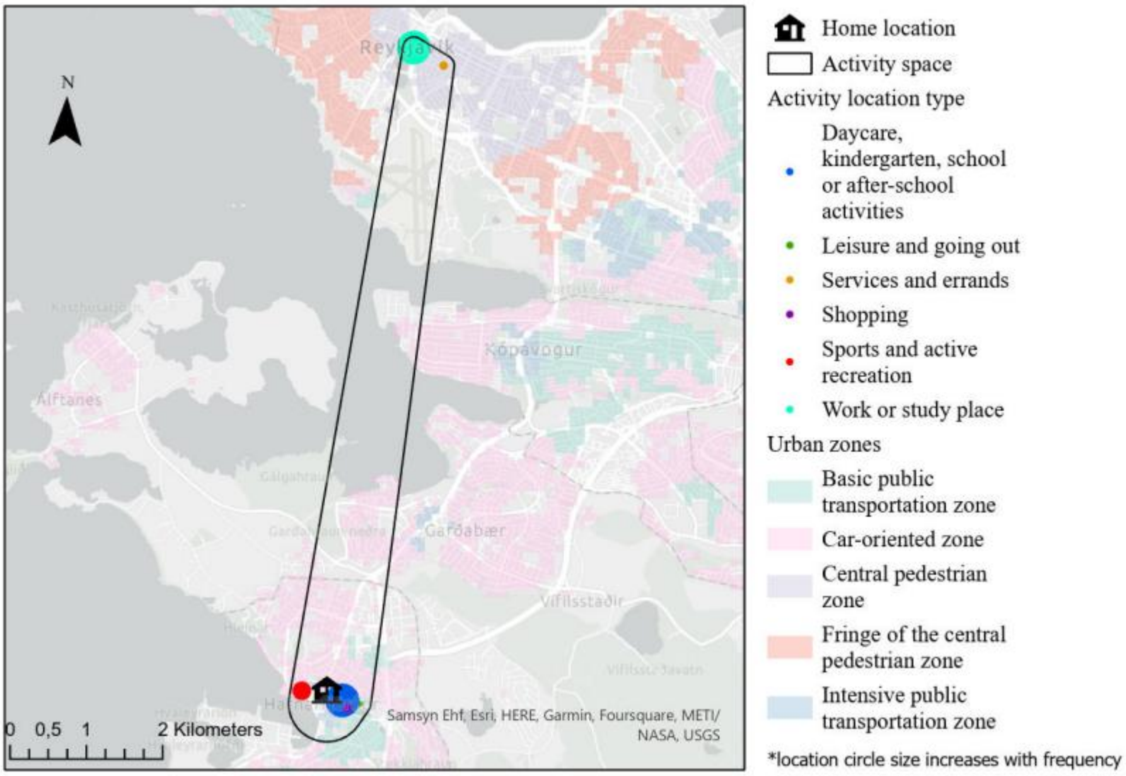

Figure 3: Bicentric activity space example: A bicentric activity space has a cluster of activity locations within the home area, and another cluster is outside of the home range around the city center.

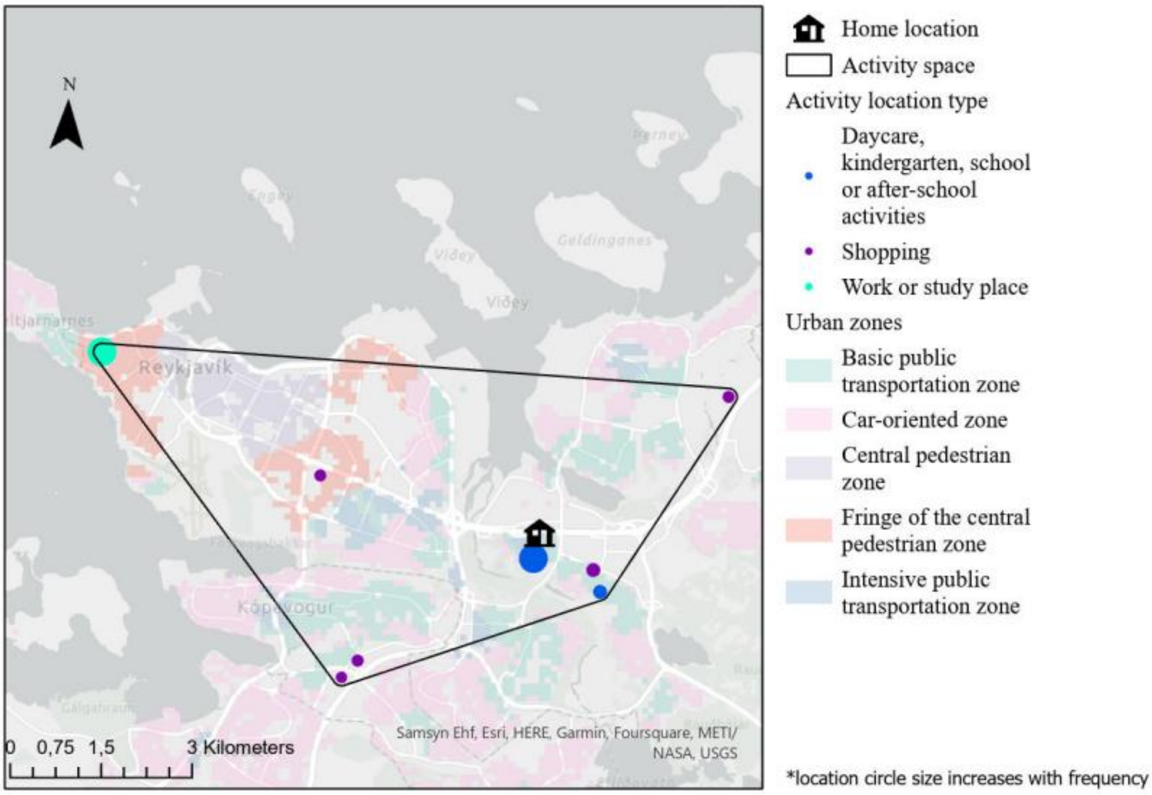

Figure 4: Polycentric activity space example which has more than two activity centers outside of the home range.

ArcGIS hotspot analysis

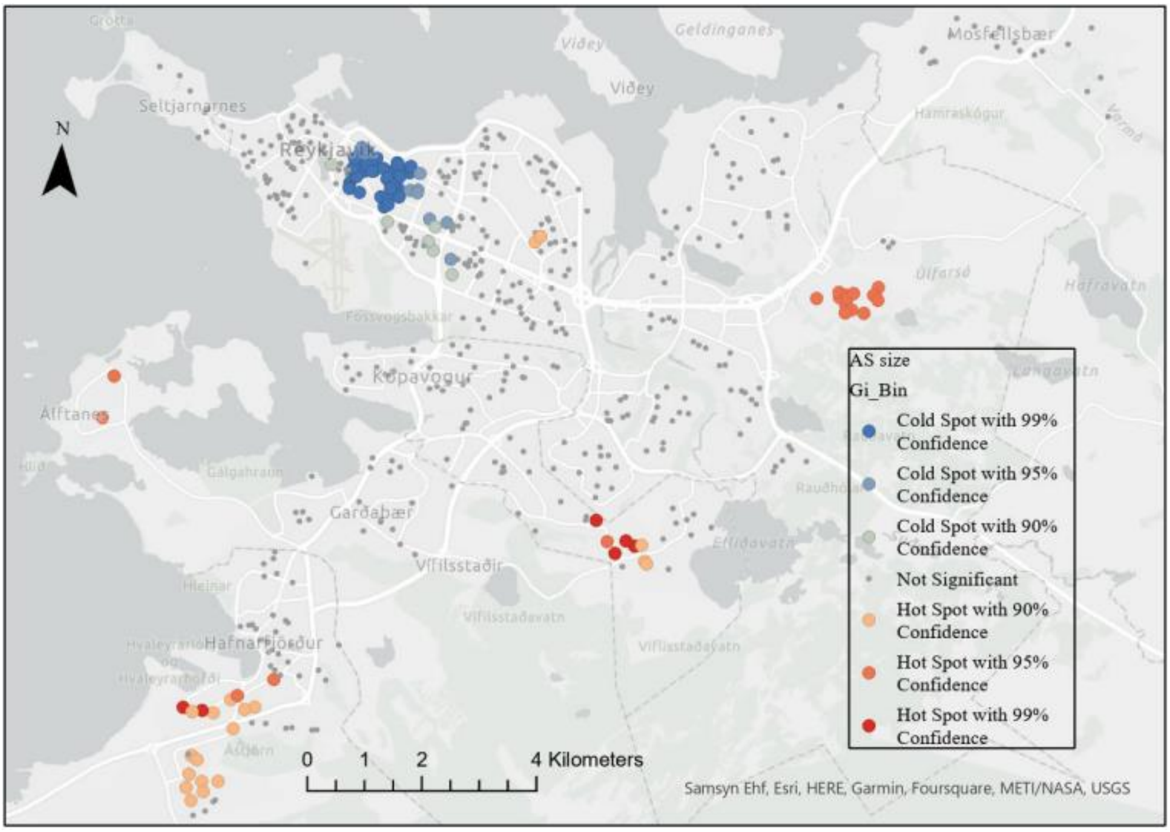

*Figure 5: Hotspot analysis of activity space size based on Getis-Ord Gi**

Figure 5 shows clusters of large activity space size, represented by orange and red spots, which were scattered throughout the outskirts of the city center. Clusters of small activity space size represented by the blue spots were scattered closer to the city center.

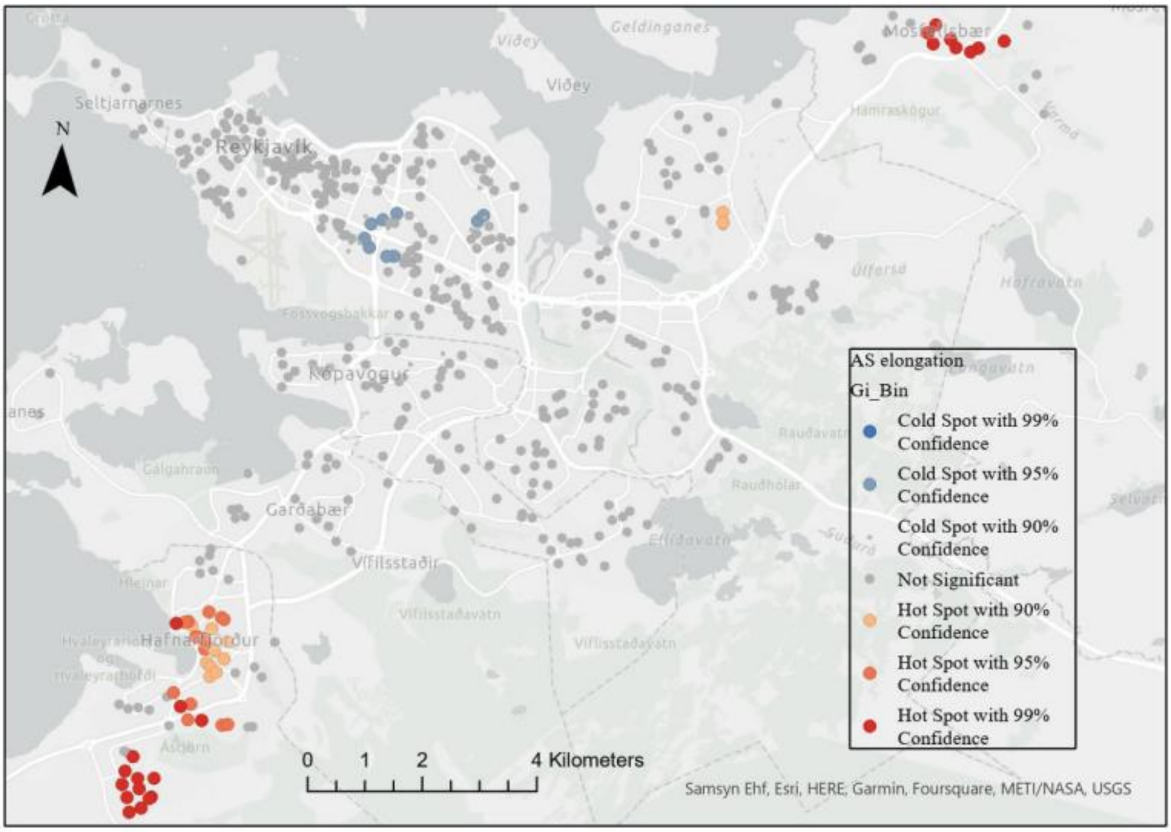

*Figure 6: Hotspot analysis of activity space elongation based on Getis-Ord Gi**

Figure 6 shows clusters of high elongation, represented by orange and red spots, which were scattered towards the outskirts of the city center mainly in Mosfellsbær and Hafnarfjörður. Clusters of low values for elongation represented by blue spots were scattered closer to the city center.

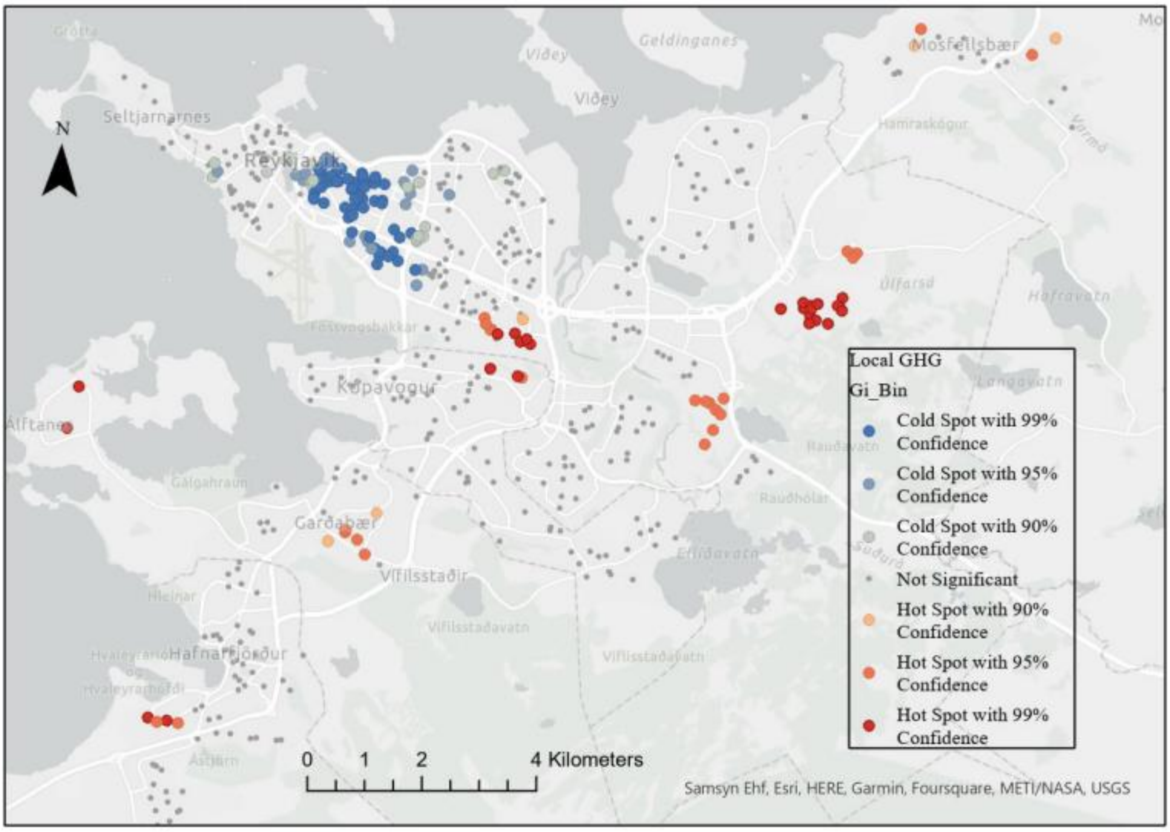

*Figure 7: Hotspot analysis of GHG local travel emissions based on Getis-Ord Gi**

Figure 7 shows clusters of high emissions, represented by orange and red spots, were scattered throughout the outskirts of the city center. Clusters of low emissions represented by the blue spots were scattered closer to the city center.

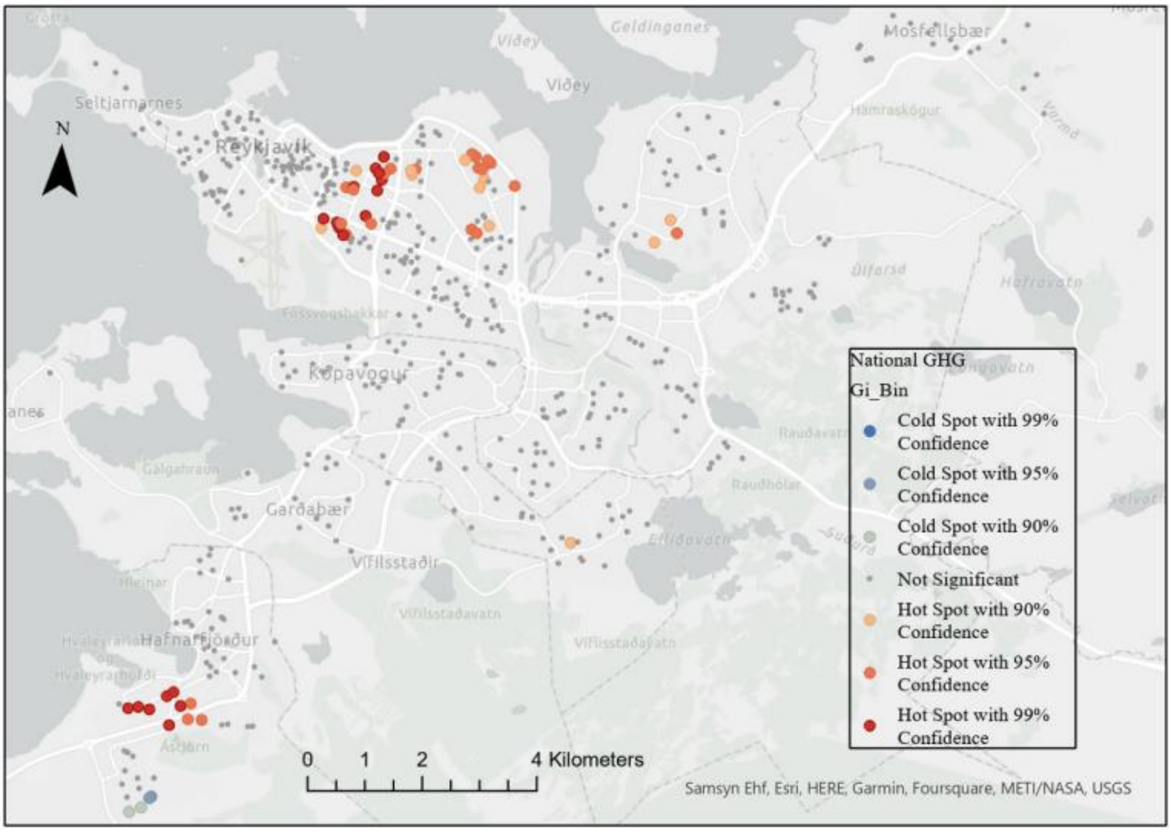

*Figure 8: Hotspot analysis of national GHG leisure travel emissions based on Getis-Ord Gi**

Figure 8 shows clusters of high emissions, represented by orange and red spots, which were mainly scattered closer to the city center. A cluster of high emissions was also found in Hafnarfjörður and a smaller cluster in Grafarvogur. A small cluster of low emissions represented by the blue spots were scattered only by the outskirts of Hafnarfjörður.

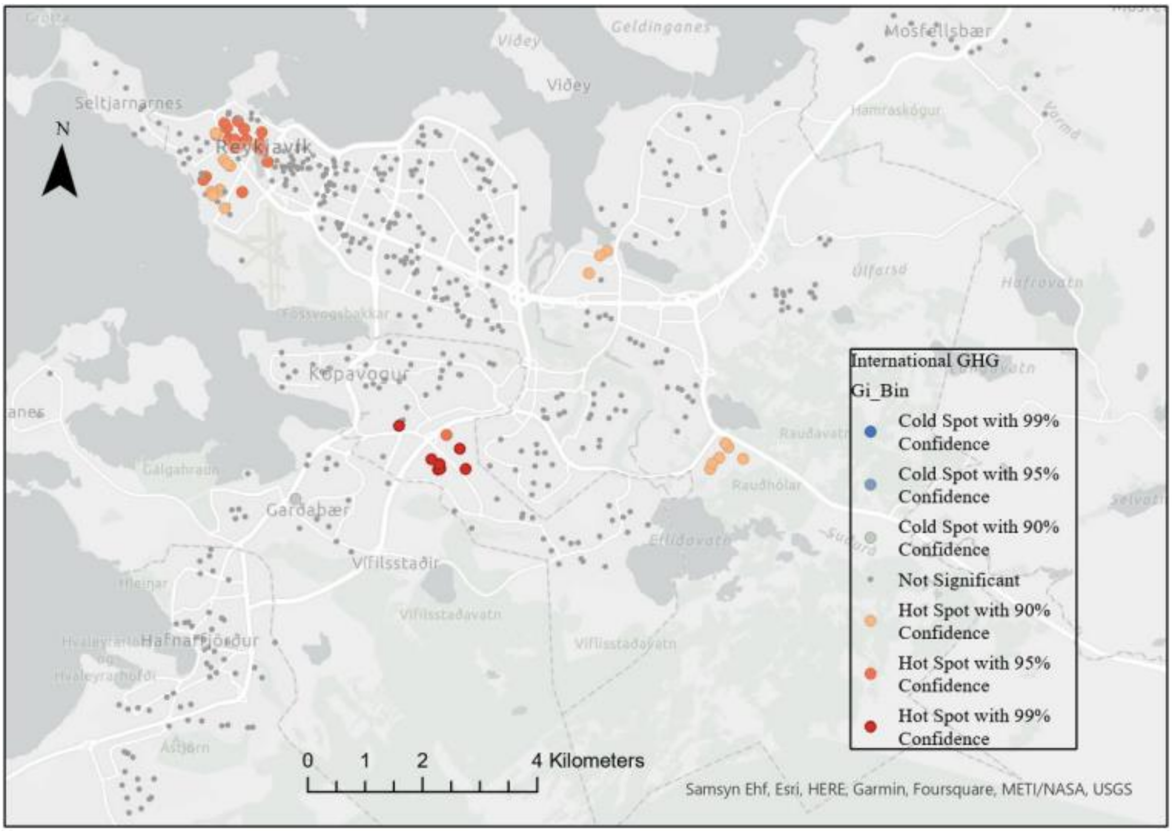

*Figure 9: Hotspot analysis of international GHG leisure travel emissions based on Getis-Ord Gi**

Figure 9 shows clusters of high emissions, represented by orange and red spots, were scattered closer to the city center. Three additional clusters of high emissions were found on the outskirts of the city center near Kópavogur, Árbær, and Grafarholt.

4.2 Regression analysis

This section includes two subsections. The first subsection looks at the effects of housing and neighborhood characteristics on activity spaces using three models with activity space characteristics as dependent variables. The second subsection furthers these models by looking at the effects on GHG travel emissions with connection to activity space characteristics.

Activity space models

The following table (Table 6) includes results from the following models.

- *AS model 1:* Multiple linear regression model on AS size with neighborhood characteristics and housing characteristics as independent variables. Socioeconomic and demographic variables are controlled for.
- *AS model 2:* Multiple linear regression model on AS elongation. Independent and control variables are the same as model 1.
- *AS model 3:* Binomial logistic regression on AS centricity. Independent and control variables are the same as model 1.

Table 6: Multiple linear regression models and binomial logistic regression model with AS size, elongation, and centricity as dependent variables.

AS model	**1**		**2**		**3**	
	Size		**Elongation**		**Centricity** (ref.: polycentric)	
	β	SE	β	SE	OR	SE
	Neighborhood					
Open space	-0.14941	21.294	-0.1332	1.4454	0.00376**	2.3961
Blue space	-0.00851	19.726	0.0353	1.3347	358.46819***	1.9836
Pop. density	-0.15029	0.283	-0.0894	0.0195	0.98083	0.0291
PT zone (ref.: 1)						
2	-0.26030	7.369	0.2378	0.4924	0.67363	0.7558
3	-0.30097	7.524	0.3290	0.5055	0.93103	0.7627
4	-0.46007*	7.914	0.3558	0.5335	2.33496	0.7742
	Household					
Access to yard (ref.: no)						
Yes	-0.33103**	4.307	0.1196	0.2931	1.57865	0.4295
Residence type (ref.: apartment)						
Semi or detached house	0.26226	5.278	0.1802	0.3596	1.09092	0.4792
Dist. to c.c. (ref.: 0-3 km)						
3-6 km	0.06844	6.098	-0.3597*	0.4177	0.66188	0.5984
6-9 km	-0.06681	7.092	-0.0414	0.4871	1.60803	0.6912
9-12 km	0.14805	7.432	0.3167	0.5048	1.95930	0.6678
12-15 km	0.67684**	9.732	0.6112**	0.6708	1.83747	1.0706
15+ km	0.52732	14.737	1.6111****	1.0112	10.96191*	1.3120
Inhabitant number	0.00332	1.826	0.0440	0.1242	1.03902	0.0383
Bedroom number (ref.: 1-2 rooms)						
3-5 rooms	-0.11492	4.577	-0.2263	0.3150	1.49203	0.4583
5 or more	-0.30042	9.668	-0.1535	0.6660	2.31621	0.9038
Household type ref.: Household with children)						
No children	-0.00214	4.760	0.0946	0.3232	1.13428	0.4622
	Controls					
Gender (ref.: female)						
Male	0.22638*	3.759	0.0926	0.2584	1.29374	0.3666
Age	-0.01234	0.449	-0.0251	0.0304	0.97298	0.0440
Income (ref.: high income)						
Middle income	0.09554	4069	0.0166	0.3271	0.79800	0.4053
Low income	-0.16671	6711	0.0658	0.7685	1.22883	0.6224
Education (ref.: basic or secondary)						
Vocational or undergraduate	0.00171	5.089	-0.1876	0.3461	0.60248	0.4582
Graduate or postgraduate	-0.16917	5.231	-0.1806	0.3547	0.45383	0.4920

Occupation (ref.: employed full-time)						
Student	-0.21459	6.194	-0.2435	0.4136	0.58201	0.6935
Employed part-time	-0.04561	7.842	0.2422	0.5204	1.33298	0.7339
Not working	-0.17247	18.990	-0.0526	1.1439	10.27213*	1.4070
Intercept	56.8152**		4.0664***		0.2563	
F	1.57		2.08			
R^2	0.119		0.147			
McFadden's R^2					0.136	
X^2					36.8	

Notes. *p < .1. **p < .05. ***p < .01. ****p < .001.

Neighborhood characteristics did not show many statistically significant relationships with activity space size or elongation, but with centricity the largest odds ratio showed a significant effect (p<.01) with blue space. Respondents with a higher amount of neighborhood blue space were 358 times more likely to not have a polycentric activity space (meaning more likely to have a mono or bicentric AS), meaning these respondents were more likely to have an activity space centered around the home vicinity. Open space also showed a statistically significant (p<.05) effect with centricity, showing open space increases the odds of having a polycentric AS, meaning these respondents were more likely to have 2 or more activity centers outside of the home vicinity. The only significant relationship with the public transportation zones was with PT zone 4 which showed a statistically significant (p<.1) negative relationship with AS size; PT zones are ranked hierarchically with 1 having the most access to public transportation and 4 having the lowest. Although not significant, PT zone 2-3, blue space, population density, and open space had negative effects on AS size. Household characteristics showed more significant effects with AS size and elongation. Access to a yard showed a statistically significant (p<.05) negative relationship with AS size, and the 12-15km distance to the city center showed a statistically significant (p<.05) positive relationship with AS size. This means individuals who had access to a yard had smaller activity spaces, and individuals residing within a 12-15km distance from the city center had larger activity spaces. Similarly, with AS elongation the 3-6km (p<.1), 12-15 km (p<.05), and 15+ km (p<.001) distances to the city center showed a statistically significant positive relationship to AS elongation, meaning respondents within these distances to the city center were more likely to commute in one directional travel. Only two significant relationships were found between AS characteristics, sociodemographic characteristics, and socioeconomic characteristics. Being a male showed a statistically significant (p<.1) positive relationship with AS size, and not working showed a statistically significant relationship (p<.1) of being 10 times more likely to not have a polycentric AS.

GHG with connection to AS models

The following table (Table 7) includes results from the following models.

- *GHG model 1:* Multiple linear regression on the natural logarithm of the amount of yearly emissions from local travel with neighborhood and housing characteristics as independent variables. Socioeconomic and demographic variables are controlled for.
- *GHG model 2:* Multiple linear regression model on the natural logarithm of the amount of yearly emissions from national leisure travel. Independent and control variables are the same as model 1.

- *GHG model 3:* Multiple linear regression model on the natural logarithm of the amount of yearly emissions from international leisure travel. Independent and control variables are the same as model 1.

Table 7: Multiple linear regression models of GHG local, national leisure, and international leisure travel emissions as dependent variables.

GHG Model	**1**		**2**		**3**	
	Local		**National**		**International**	
	β	SE	β	SE	β	SE
	Activity space					
Size (km^2)	0.32047****	1.61e-4	0.15547**	9.87e-4	0.02422	6.99e-4
Elongation	0.02366	0.00228	-0.05345	0.01661	-0.07114	0.01276
	Neighborhood					
Open space	0.20052**	0.05843	0.00513	0.37579	-0.13046	0.26124
Blue space	-0.09639	0.05374	-0.01591	0.34556	0.19711**	0.25094
Pop. density	-0.00203	7.93e-4	-0.14186	0.00509	-0.05604	0.00357
PT zone (ref.: PT zone 1)						
2	0.05795	0.02059	-0.22460	0.13295	0.06704	0.09143
3	0.02373	0.02115	-0.05618	0.13668	-0.11547	0.09201
4	-0.08199	0.02270	-0.30951	0.14670	0.14813	0.09573
	Household					
Access to yard (ref.: no)						
Yes	-0.00958	0.01215	0.05252	0.07639	-0.08927	0.05258
Residence type (ref.: apartment)						
Semi or detached house	-0.09750	0.01476	0.05962	0.09469	-0.35100*	0.06962
Dist. to c.c. (ref.: 0-3 km)						
3-6 km	0.26798	0.01700	-0.18924	0.10978	-0.08770	0.07517
6-9 km	0.52666**	0.01960	-0.53173**	0.12799	0.36060	0.08943
9-12 km	0.42235**	0.02039	-0.27912	0.13139	0.27025	0.09461
12-15 km	0.22643	0.02737	-0.35073	0.18085	-0.00530	0.13044
15+ km	-0.07466	0.04150	-0.58609	0.28038	0.05733	0.23024
Inhabitant number	0.03881	0.00505	-0.22339**	0.03281	-0.23863**	0.02350
Bedroom number (ref.: 1-2 rooms)						
3-5 rooms	0.01834	0.01283	0.01654	0.08377	-0.26748	0.05764
5 or more	0.26554	0.02686	-0.06548	0.18102	0.71425***	0.10921
Household type ref.: Household with children)						
No children	-0.14542	0.01322	-0.00457	0.08465	0.07505	0.06056
	Controls					
Gender (ref.: female)						
Male	-0.07682	0.01064	0.05587	0.06789	-0.02161	0.04776
Age	-0.00533	0.00125	-0.01866	0.00802	0.09598	0.00583
Income (ref. high income)						
Middle income	0.17218	0.01334	0.09553	0.19298	0.00867	0.05962
Low income	0.02402	0.03405	-0.02518	0.19281	0.42136	0.16790

Education (ref. basic or secondary)						
Vocational or undergraduate	0.27835**	0.01397	0.34656**	0.09097	0.26608	0.06312
Graduate or postgraduate	0.37935**	0.01443	0.43725**	0.09522	0.41704**	0.06632
Occupation (ref. employed full-time)						
Student	0.04640	0.01693	0.01123	0.10952	0.22333	0.07389
Employed part-time	-0.28701	0.02095	-0.25305	0.12760	0.06867	0.08832
Not working	-1.18847**	0.04614	-1.05131*	0.31501	-2.72564**	0.38915
Intercept	0.30876****		2.85602****		3.35974****	
F	4.38		1.65		1.30	
R^2	0.289		0.152		0.137	

Notes. *p < .1. **p < .05. ***p < .01. ****p < .001.

Two significant effects were found with AS independent variables. AS size showed statistically significant positive effects with both national (p<.05) and local (p<.001) emissions. Two significant effects were found with neighborhood characteristics. Blue space showed a statistically significant (p<.05) positive relationship with international leisure emissions, and open space showed a statistically significant (p<.05) positive relationship with local travel emissions. Although not significant, blue space and population density had weak negative effects on both local and national travel emissions. Population density also showed a small negative effect on international travel emissions. The 6-9km and 9-12km distance to city center showed a statistically significant (p<.05) positive effect on local travel emissions; this shows that individuals residing between 6-12km to the city center were associated with a higher amount of local travel emissions. The 6-9 km distance to the city center showed a statistically significant (p<.05) negative effect on national travel emissions. Amount of household inhabitants showed a statistically significant negative effect with national (p<.05) and international (p<.05) travel emissions; this shows individuals with more inhabitants in the household participated in less leisure travel. Households with more than 5 rooms showed a statistically significant (p<.01) positive relationship with international travel emissions. There were more statistically significant interactions with socioeconomic characteristics in the GHG models than in the AS models, specifically with higher education and not working.

5 Discussion

Overall, the modeling of activity spaces showed that Greater Reykjavík's residents are highly mobile with an average AS size of 19.3 km^2. Almost all respondents (82.9%) had polycentric activity spaces even though more than half of the respondents resided within 6km or less of the city center. Respondents residing within 0-3km of the city center had the lowest AS size with an average of 13.33 km^2, and respondents residing within a 12-15km distance to city center had the largest average of 33.54 km^2. Although not statistically significant blue space, open space, and population density showed negative relationships with AS size, thus showing weak support that an increase in the above-mentioned neighborhood characteristics could decrease overall local travel size. However, for the centricity model blue space was a statistically significant indicator of not having a polycentric activity space. This was an interesting result but could be due to the sample size. The hotspot analysis maps provided a visual description to compare connections. The connection between activity space characteristics and local travel emissions can be seen through the similar location of hotspots. High and low clusters for local emissions were in relatively similar places on the elongation and size hotspot maps.

In this study, housing characteristics were found to have more significant effects on activity space characteristics, specifically with distance to the city center. The 12-15km distance to city center had a statistically significant positive relationship with AS size and elongation; the 15+ km distance to the city center had a statistically significant positive relationship with AS elongation. These areas could be defined as the suburbs of Reykjavík in which residents are prone to longer commutes. Individuals residing 12+km from the city center were more likely to participate in one-way directional travel. In addition, access to a yard had a statistically significant negative relationship with AS size. Similarly, with the GHG regression models, distance to the city center showed statistically significant relationships with national and local emissions, but in different ways. The 6-9km distance to the city center had a positive effect on local travel emissions, but interestingly a negative effect on national leisure emissions. In addition, although not statistically significant blue space and population density had negative effects on local travel emissions. Open space had a statistically significant positive effect on local emissions. This was an interesting finding for open space since it had a negative effect on AS size, but this could be due to geographical context and sample size.

Although the previous literature for activity spaces was limited. Some of the found results coincided with the previous literature. Hasanzadeh et al., (2019), Tana et al. (2016), and Zhang et al. (2018) found that density correlated with smaller activity spaces. Although not statistically significant, density showed a negative relationship with AS size in this study. Hasanzadeh et al. (2019) suggest high values of elongation as an indication of one-way directional travel such as with commuting. A similar trend was seen in this study. Higher values of elongation were found with respondents living 12+km from the city center, and this could be an indication of traveling in one direction for commuting to the area located around the city center. Hasanzadeh et al. (2021) found polycentricity more common with younger adults and suggested that life commonly takes place outside of the home range. Similarly, in this study, 82.9 percent of respondents had polycentric activity spaces. However, this could be attributed to the young age of the sample, but geographical context is an important consideration when studying mobility behavior. Reykjavík's city center is located on a peninsula only accessible from one side.

Previous research has found connections between the built environment and GHG travel emissions. This study aimed to further this research using an activity space framework. Densification has been connected to lower transportation emissions (Fatone et al., 2012). However, other research has found that individuals living in dense neighborhoods can have higher carbon footprints due to indirect emissions from consumption or leisure travel (Heinonen et al., 2013a, 2013b; Holz-Rau et al., 2014; Ottelin et al., 2014). In this study, local emissions showed a significant negative relationship with AS size, and although not significant density showed a negative relationship with all three categories of GHG travel emissions. However, overall Reykjavík's Capital Region is low density.

Previous studies (Heinonen et. al, 2020; Holden & Linnerud, 2011) showed access to a yard decreased motivation for domestic leisure travel. In this study, access to a yard decreased overall activity space size. Although not significant, access to a yard showed a negative relationship with local and international travel emissions. Raudsepp et al. (2021) found the compensation hypothesis only relevant towards domestic travel in Reykjavík and found that urban stressors (such as traffic) and lack of quality green spaces induced such trips. In this study, an increase in activity space size coincided with an increase in domestic leisure emissions, thus this study showed weak support for the compensation hypothesis, since a larger activity space size could be an indication of being prone to more traffic and needing to compensate.

5.1.1 Limitations and future research directions

This section discusses the limitations and weaknesses of this study. This study used geographical data collected from a PPGIS survey. This type of data can be prone to uncertainty and personal bias since it is dependent on the respondent's mapping skills. In this study, some of the data collected could not be used in the geographical analysis; for example, a respondent inaccurately placed their home location in the ocean. An alternative option is using GPS data which provides for a more complete recollection of an individual's activity space, but also has its limitations such as privacy concerns and higher costs.

This study was a single setting case study which allowed for the exploration of complex research questions. However, generalizations cannot be made from a single case study, but further iterations can allow for the generation of hypotheses. Only emissions associated with the burning and production of fuel were included in this study. Emissions directly associated with fuel only provide a piece of the picture. Indirect emissions include emissions associated with the manufacturing of vehicles and development of infrastructure (Czepkiewicz, Heinonen, & Árnadóttir, 2018). Life cycle assessments have shown that different modes of transportation have different impacts from indirect emissions, and the inclusion of all indirect emissions would generally increase the amount of emissions.

The dataset used for this project only consisted of a selected target age range to focus on the mobility behavior of this group, perhaps future research with less of an age limitation (any resident over 18+) could provide meaningful insights for more of the population. In addition, 54.8 percent of the respondents for the dataset lived within 6 km or less from the city center. It would be useful to have more respondents that live further away from the city center and are prone to longer commutes, such as with Mosfellsbær and Garðabær. Interestingly, income did not show any statistically significant relationships with any of the models. This could be due to the sample size. 46.3 percent of respondents within the sample were within the high income bracket (over 900,00ISK/month). Hasanzadeh et al. (2021) found higher incomes associated with polycentricity, and the majority of activity spaces within this study’s sample were classified as polycentric. Further descriptives of the dataset can be found in the appendix.

Furthermore, this study used a convex polygon method to map activity spaces and relied upon limited layers to describe land use characteristics. The convex polygon method does not consider the road network; thus, it does not accurately describe the paths one takes when traveling. It would have been beneficial to have more descriptive layers of land use characteristics. The exposure to different land-use types and consideration of road networks could be improved by using the residential exposure model when mapping activity space as suggested by Hasanzadeh et al. (2018).

6 Conclusion

This thesis aimed to look for insights using an activity space framework, while filling a gap in the literature on the relationship between activity spaces and GHG travel emissions. An activity space framework is used to discover more on the relationships between activity spaces, GHG travel emissions, neighborhood characteristics, and housing characteristics, using a case study within the Greater Reykjavík region. This thesis used an activity space framework to answer the following questions.

- How do activity spaces influence travel emissions?
- How do neighborhood and housing characteristics influence activity spaces and GHG travel emissions?

In this study as activity space size grew so did local, national, and international travel emissions. Higher values of activity space elongation (an indication of one-way directional travel) also increased local emissions. Homes that were located further away from the city center had higher values for elongation. Although not statistically significant neighborhood characteristics were found to decrease overall activity space size, thus showing that an increase in open space (which includes green space), blue space, and population density decreases overall activity space size. Similarly, blue space and population density showed negative effects on local emissions, but interestingly blue space had a statistically significant positive effect on international travel emissions. Housing characteristics, such as ccess to a yard and distance to the city center, showed statistically significant effects with activity space characteristics and GHG travel emissions. Individuals with homes further away from the city center had larger activity space sizes, and subsequently a higher amount of local travel emissions. Access to a yard decreased overall local travel which was seen with AS size and local emissions; it also showed a negative effect on international emissions. Even though there is not a clear answer to the research questions. This was the first of its kind case study aiming to fill a gap in the literature. The relationship between mobility behavior, GHG travel emissions, and the built environment is complex.

Previous research in Reykjavík has indicated private car as the dominant mode of travel and suggest this could be due to a weak public transportation system consisting of only one mode (Næss et al., 2021). The city is currently working on enhancing the public transportation system with a rapid bus system called Borgalína. It will use separate lanes to connect major parts of the city; this new system will work in a complementary fashion to the current bus system, and is planned to make the public transportation system more efficient (Borgalínan, n.d.). It will be interesting to see how this affects the mobility behavior of Reykjavík residents and contributes to a more sustainable transportation system. Within this study, local emissions and activity space characteristics were connected, thus highlighting that individuals who travel less distance for activities contribute to lower emissions. There are no clear suggestions for policy recommendations, but additional iterations of this study could help with this. However, there seem to be relevant effects occurring between neighborhood characteristics and local travel. In this study, it was found that an increase in population density correlated to lower local emissions and activity space size. Densification can be an indicator of high walkability and access to services. A further investigation of services and land-use types within neighborhoods could provide insights into what people need in their immediate environment without having to travel far.

Overall, this case study found interesting contributions from using an activity space framework. Future research should compare activity spaces to more dimensions such as with well-being, important connections have been found between well-being and mobility behavior. Future research should use the residential exposure modeler when mapping activity space to provide further insights on land-use exposure. Furthermore, the reiteration of this project in a different geographical context would be interesting. Reykjavík is a unique case being that it is an island close to the Arctic with relatively little vegetation, as well as being sparsely populated and categorized by low density. The quest for the sustainable city and climate change mitigation will require urban planners to look in multiple directions for insights on urban planning. Mobility behavior has become a focus due its potential in reducing passenger transport emissions. Densification has been a common solution for reducing transport emissions within the city structure. However, research has shown this may have rebound effects such as with higher consumption or leisure travel. City planners must look beyond densification in the quest for the sustainable city, since there is no clear-cut solution to the complexity of the issues at hand.

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Appendix A

This appendix presents further descriptives on the dataset used in this thesis.

Table 8: Percentage of income type within sample

Income category	Counts	% of total
Low income	49	10.7 %
Middle income	197	43.0 %
High income	212	46.3 %

Table 9: Percentage of respondents within each distance to city center category

Distance to c.c.	Counts	% of total
0-3 km	155	45.5 %
3-6 km	135	70.5 %
6-9 km	90	16.7 %
9-12 km	108	90.5 %
15+ km	13	92.9 %
12-15 km	38	100.0 %

Table 10: Percentage of housing type within sample

Housing type	Counts	% of total
Apartment	349	71.4 %
Semi-detached house	61	12.5 %
Detached house	79	16.2 %