Quantifying the Environmental impact due to resource consumption in cities: Case study of the Hague

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Summary

In the past few decades, we have witnessed unprecedented impacts of climate change. The increase in Green house gas (GHG) emissions due to human activities has disastrous implications for the earth including an increase in global mean temperatures, rise in sea level and melting of polar ice caps. Climate change has impacted all forms of human life on earth and if unchecked, poses a threat to human existence. With more than 50% of global population currently living in the cities and the upward trend of people migrating to the cities expected to increase in the next few decades, cities are one of the major contributors to climate change. Cities consume nearly 80% of global energy and 75% of global resources. There is an urgent need to tackle the environmental impacts of cities. In this research, we develop a methodology to quantify and analyze the environmental impacts of cities by considering the consumption of all resources occurring in a city. The methodology is applied to the city of the Hague in the Netherlands but can be replicated for other cities as well.

Quantifying and analyzing the environmental impacts of cities provide decision makers with insight into the relative environmental impacts of different regions of a city, different resources consumed in a city and of different demographic groups in a city. Based on this, the decision makers can identify potential opportunities for policy interventions to reduce the negative environmental impacts of a city. In literature, there are three main ways to quantify environmental impacts of a city : Population impact model, Ecological footprint and Sustainability assessment (Life cycle assessment). The former two take a more aggregated approach to quantifying the environmental impacts and as a result do not provide much information on the breakdown of resources that contribute the maximum and minimum environmental impact. Sustainability assessment is composed of a number of methods to assess sustainability in terms of social aspect, economic aspect and environmental aspect. Life Cycle assessment (LCA) is chosen in the current research to quantify and analyze the environmental impacts of a city. Of the many impact categories in LCA, Global warming potential (GWP) is chosen to quantify the environmental impact since the main focus of reducing the impacts of climate change is on reducing the overall Green house gas (GHG) emissions.

Quantifying the environmental impacts though strategically important is a very complex endeavour to achieve due to lack of data availability at the local level and the available data being from multiple sources. The resource use behaviour of people is driven by their socioeconomic conditions. Thus, different socioeconomic indicators of the population of city are used to predict their resource consumption of 6 main resource use categories in this research: Food, energy, water, mobility, Basked of Products (BoP) and waste generation.

Based on the quantification of environmental impact of resource consumption data for the city of the Hague, car use was found to have the maximum GWP per capita whereas water use had the minimum GWP per capita. On further analysis, neighbourhoods with smaller household size had higher GWP due to energy compared to neighbourhoods with larger household size and neighbourhoods with larger household size had higher GWP due to mobility compared to neighbourhoods with smaller household size (taking into account household sizes in both cases). Neighbourhoods with relatively higher standards of living had a higher GWP due to energy whereas neighbourhoods in which living standards were relatively lower compared to that of the Hague had high GWP due waste and slightly higher than average GWP due to mobility.

Resource use categories in which intervention by cities is possilble account for nearly 70% of Global warming potential (GWP): 45% mobility, 15% waste,10% energy. Policy interventions related to this resources use categories which have been implemented in cities around the world were modelled for the Hague. The policy intervention related to energy entails investing a fixed amount every year to provide subsidies to households to install solar panels on their rooftop. The policy showed a potential reduction of around 10% GWP on an average for an investment of 10 million €every year. The next policy intervention is related to reducing waste generation by households by charging them based on the amount of waste generated by them. The analysis showed potential reduction of waste by almost 50% in neighbourhoods

which generated the maximum waste. The last intervention was related to reducing GHG emissions in mobility sector by increasing the parking charge of cars and reducing the fare for public transportation. The analysis could not give definitive results since the exact impact of increasing car parking fees could not be quantified. However, based on the assumed relationship between reduction in car use and increase in car parking fees, overall reduction of 30% GWP could be observed in the best case. When all 3 interventions are combined, a potential reduction of net GWP by 25% in the Hague can be achieved. One of the main areas of improvement in this research is on exploring ways to quantify the impacts of policy intervention since many of the assumptions through which currently the interventions are analyzed could completely change the results if a more concrete relation is found between variables.

The developed methodology relying on completely open source data could be particularly useful in down-scaling data to the local level when researchers or analysts do not have access to microdata of individuals. Despite its limitations, this research is one of the few attempts at quantifying the environmental impacts due to use of large number of resources in a city and provide insights into which areas, which resources and which demographics need intervention to reduce negative environmental impacts?

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Chapter 1

Introduction

1.1 Problem Introduction

1.1.1 Urbanization and its current state

Today, around 55% of global population lives in cities with this number expected to rise to 68% in 2050 (UNDESA, 2018). Cities provide a better quality of lifestyle in terms of access to jobs, healthcare, education (Satterthwaite, 2000). While more than 70% population in the developed world lives in large cities, only 40% population in developing countries lives in large cities. With the overall population in developing parts of Africa and Asia expected to increase till 2050 and with the transition from agriculture based economies to industry based economies in some of these countries, a massive influx of population from rural areas to mega cities is expected in the near future (Satterthwaite, 2000). Apart from the definite advantage in terms of increased quality of life, the compactness of cities and concentration of people in large cities has reduced the per capita costs for electricity, water, transport, sewers, etc through economies of scale and proximity (Satterthwaite, 2000). Thus, cities play an important role in enhancing the quality of life through access to opportunities and provision of services.

Increasing Urbanization also has its pitfalls and negative costs. Feng *et al.*(Feng, 2015) argue that increasing urbanization causes urban decay in terms of increasing economic inequality, urban center decline and environmental problems. For example, migrant workers from rural areas who settle in slum areas with limited access to sanitation and clean drinking water leads to vulnerability to communicable diseases and potential to establish a transmission cycle (Kuddus et al., 2020).Apart from the impact on humans, rapid urbanization tends to impact biodiversity since increasing ecological footprint due to urbanization results in habitat clearing, degradation and fragmentation of landscapes. According to *Seto et.al* (Seto et al., 2012), an estimated 200 critically endangered species will be extinct due to rapid urbanization. Finally, the increasing demand for mobility and electricity leads to increase in Green house Gas (GHG) emissions which are a huge health and environmental hazard and are responsible for global warming and climate change. Currently, cities consume 78% of world's energy and account for more than 60% of all Carbon dioxide and significant amounts of other GHG emissions (UN Habit, 2019). While, on one hand, cities are responsible for climate change and GHG emissions, they are also one of the most vulnerable to the impacts of climate change. Cities are witnessing the impact of climate change through induced disasters such as flooding, water shortage, landslides due to intense rainfall (Atta-ur-Rahman et al., 2016). The situation will worsen with increasing urban population accompanied by increasing resource consumption resulting in increase of GHG emissions in urban areas. Coupled with an increasing population, expanding urban areas are also becoming hotspots for increased industrial activities. This results in an increased pressure on cities to sustain the quality of life with limited resources. Therefore, minimizing the detrimental effects of Urban expansion is of utmost importance. It is also clear that cities play a major role in our fight with climate change and towards achieving sustainable development (Gouldson et al., 2016).

1.1.2 Environmental impact of cities

The negative impacts of climate change could be catastrophic for both nature and human kind. Climate change causes sea level rise, increase in global mean temperature and heat waves, droughts and melting of polar ice sheets. All these pose a major threat to all forms of life on earth. By 2050, a sea level rise of between 1 feet to 2 feet could impact around 570 cities and 800 million people (Muggah, 2019). In 2020, the polar ice caps in the Arctic and Antarctic are melting six times faster than in 1990 (Carrington, 2020). While the coastal flooding caused due to rising sea levels as a result of polar ice cap melting will leave millions of people vulnerable, the flora and fauna in the region like polar bears, arctic fox, walruses will bear the major brunt of such a change. The release of GHG emissions causes air temperatures to increase which results in higher evaporation of moisture from rivers, lakes and bodies of water and thus reduces rainfall ultimately resulting in severe drought. Thus, it is extremely important to prevent climate change to safeguard the future generations.

As major hubs of consumption and as population centers, cities are major contributors to climate change and are also highly vulnerable to climate change. Thus, quantifying the environmental impacts of an entire city could be useful to reduce the negative environmental impacts. The environmental impacts of cities are analyzed through three main methods namely : population impact, ecological footprint and sustainability assessment (Newman, 2006). The population impact model is a simple model according to which the total environmental impact is calculated as the product of population of region, the consumption per person and the technological impact per unit of consumption. The ecological footprint model encompasses total resource consumption in a city relative to its population and converts it into a per capita land footprint or the amount of land required per capita to account for all resource use. Finally, Sustainability assessment is an integrative decision making tool that takes into account a range of criteria (both environmental and human) to assess urban development. Life Cycle Assessment is a part of sustainability assessment that is mainly used to quantify the environmental impacts in the entire life cycle of a product or service. However, these models, specifically the population impact and ecological footprint models do not consider specific sources or the resource use which have the maximum environment impact and are rather aggregated to a total environmental impact. Furthermore, the environmental impacts in these models are not quantified in terms of GHG emissions.Thus, these models have limited applicability in terms of analyzing policy interventions to reduce GHG emissions. These models will be discussed in detail in the literature review section.

1.2 Research Objective

To summarize the previous section, rapid urbanization is a cause of concern due to the negative environmental impact it has in terms of GHG emissions and global warming resulting in climate change. Thus, quantifying the environmental impacts of cities could help decision makers identify the main areas where the emissions are high and thus intervene to reduce those emissions. In assessing the environmental impacts of resource use, there are three main perspectives (Carneiro & Arbache, 2000):

1. Production based perspective : Which production processes have the highest environmental impacts? These are focussed more on upstream processes and the policies are aimed at reducing the environmental impacts of production.

2. Final consumption based perspective : These are aimed at identifying which products or resource categories have the most environmental impacts and thus making policies focussed on responsible consumption.

3. Material use perspective : It is aimed at identifying which material have greatest impacts across the life cycle and thus relevant for choosing materials and resources with lower environmental impacts.

For a city, assessment of environmental impacts on a consumption based perspective is most relevant since the actual consumption of resources takes place inside the city through its inhabitants but the actual production processes take place outside the city and decision makers at city level have little control on the production process to reduce the negative environmental impacts of production. Assessing environmental impacts through a consumption based perspective would identify the resource use categories with higher environmental impacts and thus policies at the city level could be implemented to stimulate change in the consumption behaviour related to those resources. Moreover, taking a consumption based perspective is also important to properly account for the entire environmental impacts of city. For example, if some products consumed by inhabitants of a city are imported from another country, in a consumption based perspective, the environmental impacts are still allocated to the final users of the product whereas in a production based perspective, they would simply be allocated to the producer of the product.

Thus, the research focuses on developing a method that could be used to analyze environmental impacts of a city by firstly quantifying the environmental impacts related to different resource use categories from a consumption based perspective and secondly performing exploratory policy analysis to reduce the environmental impacts.

1.2.1 Thesis Outline

The thesis is divided into the following sections:

Table 1.1: Thesis outline

Part	**Function**	**Chapter**
I	Scoping	1)Introduction 2)State of the art
II	Analysis	3)Data computation and exploratory analysis 4)Results 5)Policy analysis
III	Synthesis	6)Discussion 7)Conclusion

Part I deals with scoping out the research problem. The state of the art section deals with existing research on Urban components and identifying the knowledge gap as well as the background knowledge of methods used in this study.

Part II deals with actual operationalization of the research. Chapter 3 deals with analyzing resource use flows in a city and data sources related to obtaining those flows. Chapter 4 deals with quantifying the environmental impacts of resource use categories in through Life Cycle Impact Assessment (LCIA) and further analyzing it. Chapter 5 is related to exploratory policy analysis to reduce environmental impacts related to the reosurce use categories.

Part III deals with the discussion on results, limitations, future work that can take inspiration from current work and current work's applicability to real life cases. Conclusions on the developed framework and directions for further research will be discussed

Chapter 2

State of the art

2.1 Urban system

It is important to understand what an urban system consists of and how an urban system functions in order to analyze the environmental impacts of city . These will allow us to understand the use of different resources that have an environmental impact and factors that drive the use of those resources. According to *Meerow et.al* (Meerow et al., 2016), an urban system is comprised of four subsystems namely : governance networks, networked material and energy flows, urban infrastructure, socioeconomic dynamics.

The governance subsystem is composed of different actors and stakeholders who shape the way an urban system evolves. It is comprised of actors like consumers, policymakers, industry. These actors are interrelated and the actions of one of these actors also decide the action of other actors and the overall fate of urban system not just in terms of environmental impacts but in other factors like economy, healthcare, culture. For example, the policies implemented by the municipalities drive the behaviour of inhabitants and industries in a urban system. For climate change, it is often said "Think globally, act locally" (French et al., 2017). This refers to the difference in efficiency of leadership at the national scale and local scale with regards to implementing policies tackling climate change. Cities are increasingly seen as centers of innovation for sustainability policies and thus the urban governance subsystem plays an important role in tackling climate change. From a climate change perspective, the urban governance subsystem is focussed on issues relating to mitigation and adaptation efforts (Elander & Gustavsson, 2007). The mitigation efforts by local governments focus on reducing the impact of climate change by working on changing human activities in terms of consumption and implementing energy efficient infrastructure in collaboration with citizens. The adaptation efforts are more focussed on adapting to the already visible impacts of climate change. The interest is also on studying if strong efforts towards adaptation block efforts towards mitigation efforts.

The networked energy and material flow subsystem is the subsystem that accounts for the consumption activities of water, food, energy, materials and generation of waste by activities of residents of cities in households, businesses and government activities commonly referred to as urban metabolism (Kennedy et al., 2007). From a consumption perspective, all these activities are responsible for GHG emissions even if the production activity occurs outside the cities. Thus, most of quantitative studies related to analyzing environmental impacts of cities focus on the quantification of flows in these subsystem. According to *Weisz et.al* (Weisz & Steinberger, 2010), an important limitation in most cases is related to the data. Most of the data sets are aggregated exclusively at the national level and thus attempts to study urban metabolism for specific cities are limited by incomplete or uncertain data. Furthermore, there is also a great degree of interconnectedness between difference resource flows especially Water, energy and food thus forming the WEF nexus. However, at the governance subsystems, policies are often implemented in silos meaning there is little interaction between people responsible for management of different resources. Thus, the interactions between different flows including WEF are not taken into account when implementing policies. (Covarrubias et al., 2019) show the interaction of flows in the WEF nexus for the city of Amsterdam and how a greater degree of interaction between different actors in governance subsystem focussing on interconnectedness between WEF flows in energy and material subsystem can achieve meaningful results.

The urban infrastructure subsystem consists of all the public infrastructure and services that are used by residents of a city in their daily life like transportation system, utilities like energy and water. Even though the actual environmental impacts are quantified and analyzed through the networked material and energy subsystem, sustainable policies aiming to reduce negative environmental impacts and GHG emissions are actually realized through the urban infrastructure system. For example, in order to reduce GHG emissions due to energy flows, adoption of renewable electricity systems would change the infrastructure related to utilities. Similarly, in order to reduce emissions related to material flow, they can be transported by energy efficient vehicles for last mile operations in a city (Covarrubias et al., 2019) thus transforming the mobility infrastructure.

The socioeconomic dynamics subsystem consists of socioeconomic and demographic characteristics of residents of a city. Though, this subsystem has no direct relation with environmental impacts, it is well known that the consumption choices of people are driven by their socio-economic characteristics (Vinholes et al., 2012). Thus, the socioeconomic dynamics subsystem plays an important role in shaping the other three systems specifically the networked material and energy subsystem. Furthermore, since disaggregated data related to consumption behaviour for residents is not easily available at local level, the variables in socioeconomic dynamics subsystem could be used as a keying variables to predict the consumption in networked energy and flow subsystem.

2.2 Environmental impacts of cities

The conceptual model of (Meerow et al., 2016) on urban systems helps to understand the intricate interactions between different susbsystems as well as within the subsystems and how they shape the urban landscape. The networked material and energy flow subsystem accounts for the consumption of materials by different actors in a city and thus the environmental impacts and GHG emissions. As mentioned in Ch1, the environmental impacts of these flows can be quantified using 3 models namely : Population impact model, ecological footprint and sustainability assessments (Newman, 2006). Therefore this section will discuss in detail the 3 models and their implications in terms of usage and shortcomings to measure environmental impacts of cities.

2.2.1 Population impact model

The population impact model was first introduced in the 1960s by *Paul Ehrlich et.al* (Ehrlich & Ehrlich, 1970) according to which every human being has an environmental impact and the total environmental impact is given by:

$$I = PAT \tag{2.1}$$

where P= Population, A= Affluence level or consumption per capita and T= Technological impact per unit of consumption. Over the years, due to rapid urbanization, population has been increasing. Similarly, the affluence level or consumption per capita has been increasing with industrialization. The technological impact per unit of consumption has decreased over the years with the increase in production efficiency. However, with exponential increases in population and consumption per capita, the rate of reduction in T has not been able to keep up with the rate of increase in P and A. Thus, the environmental impacts of human consumption both globally and in cities has increased exponentially over the last few centuries. In the late 1980s and 1990s, the population impact model had an enormous appeal since it provided a simple explanation for urban decay and deteriorating environment in cities- Increasing population. This model had been widely used up until now by anti-development groups opposed to development of cities and those who hold apocalyptic view of the future of cities.

The population impact model provides a rather one sided view of the environmental impact of cities. According to the population impact model, larger population of cities is the major cause of environmental impacts of cities. However, curtailing urbanization and increasing ruralization simply redistributes the environmental impacts from cities to rural areas without decreasing the environmental impacts. Furthermore, due to high population density in urban areas, there is an endogenous factor of economies of scale which leads to better management of natural resources like energy and waste in cities. The population impact model also does not distinguish between global impact and local impact. Many cities in the western world import consumption products from other countries, thus their local impact is minimized while the overall global impact is not accounted for. Finally, since the model is too simple, it does not provide a detailed explanation behind the flows which have a major environmental impact nor does it take into account differing values of Technology impact in different locations. (Dietz & Rosa, 1997) modified the model to account for cross country effects in the values of technological impact (T) which is a step forward to disaggregate environmental impacts for different geographical regions. However, the model still falls short of analyzing environmental impacts at the geographic level of cities without implying a higher degree of generalization.

2.2.2 Ecological Footprint

Ecological footprint measures the overall impact of human actions into nature by quantifying the total amount of biologically productive land and sea area that is needed to account for human consumption (Wiedmann & Barrett, 2010). According to *Barrett et.al* (Barrett et al., 2002), ecological footprint can be defined as *"The land area required by the people in a defined region to provide continuously all the resources and services they presently consume and to absorb all the waste they presently discharge wherever that land might be."* For example, if a person consumes 100 kg of vegetables in a year and the yield is 500 kg/hectare, the person's contribution to ecological footprint due to vegetables is 0.2 hectares. Energy consumptions are usually accounted for by an energy conversion factor. For example, if 1 kg of product has a Global warming potential (GWP) (in the actual energy required to produce the product) of 20 kg CO_2 equivalent and it is known that 1 kg CO_2 requires 0.0052 hectares of forest to sequester the emissions (Barrett et al., 2002), the total area needed to sequester the emissions is :

$$20kgCO_2 \times 0.0052\frac{ha}{kgCO_2} = 0.104ha \tag{2.2}$$

The ecological footprint is an useful indicator that provides information of overall impact of human activity on the nature aggregated into a single number. According to global footprint network (Global Footprint Network, 2020), an open source tool to measure ecological footprint, the average global footprint per capita is 2.8 hectares/capita while the carrying capacity is only 2.1 hectares/capita implying an overshoot of about 30% . However, a common critique of ecological footprint is that it provides no information about the factors that contribute the most to the environment since it aggregates the impact of different contributing factors (Wiedmann & Barrett, 2010). Since it is a single number, its applicability in terms of policy measures to suggest what can be done to reduce the ecological footprint is limited. Ecological footprint is composed of contributing factors like water, energy, food but as a composite number, ecological footprint falls short of suggesting how can it be reduced and what contributing factors require priority (Newman, 2006). As a result, a number of variations have been proposed to Ecological footprint over the years. For example, (Barrett et al., 2002) use a top down approach on mapping out the ecological footprint of York by considering 5 components of the city namely Energy use, Water, Transport, Built land and building infrastructure. For each component, they further dive into detailed data that is needed to assess the ecological footprint. In order to make the study more extensive, the analysis extends the system boundary to include the geographic area from which raw materials were extracted and transported to York. Similar to the population impact model, Ecological footprint also does not consider linkages between different resource use categories. For example, the land use patterns in a city are shaped by its transport infrastructure. The land use pattern further shape the management of resources related to waste and water since a dense land use pattern is less water intensive (Newman, 2006). Thus, in summary, Ecological footprint can provide insight as to whether consumption pattern in a city has a higher or lower environmental impact compared to a benchmark value but in terms of policies related to reduction of environmental impact, Ecological footprint provides little insight.

2.2.3 Sustainability assessment

The main problem with Population impact model and ecological footprint is that they lack insight related to policies to reduce negative environmental impact. Thus, these models are used by ecologists opposed to development to show the negative effects of urbanization. As a result, Sustainability assessment tools developed from the need to have integrated assessments that take a holistic view on sustainability. Sustainability assessments take into account not only the environmental impacts but also the social and economic aspects of issue and try to reach a solution aggreeable to all the actors involved. Thus Sustainability assessment tools are constructive tools aiming to achieve the best outcome on a variety of issues through identifying trade offs between them as opposed to ecological footprint and population impact model which often present a destructive view of development issues (urbanization for example) on environment.

For conducting a full scale, sustainability assessment, several methods relating to social (Social impact assessment), economic (Cost benefit analysis) apart from environmental issues need to be combined so as to have a holistic view on sustainability. However, since the scope of current study is limited to environmental impacts of cities, we will focus on the environmental aspect of sustainability assessments. In the environmental assessment, the main methods are LCA (Life Cycle Assessment), SEA-EIA (Strategic Environmental assessment-Environmental impact assessment) and Emergy. SEA-EIA is generally a mandatory requirement by governments for large scale development and construction projects. However, its applicability in urban context where the focus is on quantifying environmental impacts related to consumption of resources is limited. *Emergy is the amount of energy consumed in the direct and indirect transformations to make a product* (Odum, Howard, 1996). Emergy is mainly concerned with the production of a product and not the environmental impacts of a product after it has been produced. Thus, in the urban context, LCA is the most relevant methodology to quantify environmental impacts of consumption.

2.2.4 Life Cycle Assessment

Life Cycle Assessment (LCA), is a process to estimate the environmental impacts associated with a product or activity by quantifying the energy and material used in the process right from its formation to demolition and finally to evaluate and implement interventions to reduce the environment impacts (Dewaele, 2018). The environmental impacts can be quantified by 18 impact categories, some of them include climate change impact, eutrophication, ecotoxicity, acidification, land use. LCA studies are usually conducted in a 4 step framework identified by (Jacquemin et al., 2012):

1. Goal and Scope definition: The system boundaries are defined in this step as well as the functional unit is identified. Most of the LCA studies generally consider a cradle to grave system meaning the analysis is considered from procurement of raw materials to post-use or disposal of the finished product.fig. 2.1 shows a conceptual diagram of the phases a generic product (system) encounters in its lifetime. In the first step of LCA, it is important to define the functional unit. Functional unit is the reference unit based on which the environmental impacts are quantified. For example, in the urban context, the environmental impacts could be quantified for all consumption activities in a city for a period of 1 year on per capita basis or a per household basis.

Figure 2.1: *Life phases of a generic product*

2. Inventory Analysis : This step deals with doing an analysis of the inputs and outputs related to the system. The quantity of different inputs (raw materials, energy) and outputs (waste, emissions) in each life phase of the product are calculated.

3. Impact assessment: The inputs and outputs identified in inventory analysis are mapped onto different categories of environmental impact like Global warming potential, toxicity, eutrophication, etc either through modelling or use of standard databases such as ecoinvent (Wernet et al., 2016), GaBi (Spatari et al., 2001).

4. Interpretations: Environmental impacts identified in step 3 are interpreted and conclusions are drawn regarding the use of product

The main advantage of LCA over ecological footprint and population impact model is that it provides information on the exact processes that have maximum environmental impact and thus it provides policy insight into which processes (in case of production or material based perspective) or flows (in case of consumption based perspective) need to be considered to reduce the environmental impacts. Furthermore, multiple indicators in LCA can show the trade offs between different impact categories like global warming, acidification, impact on human life. However, it is still not possible to analyze the linkages between different flows i.e. changes in quantity of one flow impacting another flow. In our opinion, analyzing the linkages between different resource use flows require a modelling approach as compared to the methodological approach provided by LCA or ecological footprint.

Method	**Approach to urbanism**	**Quantify impact in terms of GHG emissions**	**Provides policy relevant insights**	**Possible to analyze resource linkages**
Population impact model	Anti urban	Yes	No	No
Ecological footprint	Anti urban	No	Partially	No
Sustainability assessment (Life Cycle Assessment)	Seeks to achieve trade off and balance between different aspects of urbanism	Yes	Yes	No

Table 2.1: Comparison of different methods used to analyze environmental impacts of cities

Table 2.1 shows the comparison of different methods used to analyze environmental impacts of cities. From the comparison, it is clear that, of the three methods, LCA provides detailed insights into the actual flows that have significant environmental impacts. Thus, for the current study, LCA will be used to analyze the environmental impacts. While most LCA studies do a multi criteria analysis of different impact categories, the environmental impact that is a major concern for cities is climate change. In LCA, the impact category corresponding to climate change is Global Warming Potential (GWP). Emission of different GHG have a different impact on the warming of the earth. Thus, the GWP of a GHG is *the measure of how much energy the emissions of 1 ton of a gas will absorb over a given period of time, relative to the emission of 1 ton of CO* $_2$ (Vallero, 2019). Apart from CO_2, the 2 other major GHG are Methane (CH_4) and Nitrous oxide (N_2O). The GWP for CH_4 is 28 to 36 meaning that 1 ton of CH_4 absorbs between 28 to 36 times more energy than 1 ton of CO_2. Similarly, the GWP for N_2O is 265-298. The GWP of chlorofluorocarbons (CFC) are of the order of 10000 but their emission levels compared to

CO_2 are very low. The net GWP for a LCA flow or product is:

$$\sum x_i GWP_i \tag{2.3}$$

Where x_i is the amount of emission of GHG i and GWP_i is the GWP of GHG i.

2.2.5 Life Cycle Assessment of cities

The previous section described different models used to analyze environmental impacts of consumption in general and their applicability to cities in particular. From the description, it can be seen that LCA is the most effective way to analyze environmental impacts of cities since it provides a detailed perspective on the contributing factors to environmental impacts and thus on areas in which there needs to be policy intervention.

Conducting LCA of cities to assess its environmental impacts is a relatively new area of research in the field of LCA. One of the first attempt at conducting LCA of cities by combining it with urban metabolism is by *Goldstein et.al* (Goldstein et al., 2013).However, the authors suggest that an improvement in data methodology as well as analyzing environmental impacts with more impact categories is required to represent a complete LCA of cities. There are two major issues that researchers face when conducting a full LCA of cities. When LCA is applied to all the activities occurring inside a boundary, it is called territorial LCA (Nitschelm et al., 2016). Thus, LCA of cities falls under territorial LCA. *Loiseau et.al* (Loiseau et al., 2014) provide a 4 step methodology to conduct territorial LCA that includes: 1)Setting functional unit(s) 2)Selecting boundaries of territories 3)Collection of regional data 4)Considering local context in impact evaluation i.e. whether the environmental impact is local or global. The first issue concerning LCA of cities is related to the 2nd point in (Loiseau et al., 2014)'s methodology : Selecting territorial boundary. In scientific literature, a proper definition of city does not exist. Due to a lack of proper definition, it is difficult to set boundaries for cities. Thus, it provides LCA researchers with various choices on how to set boundaries for cities. These include (Mirabella et al., 2019) : 1)Administrative based boundaries- referring to the political or geographical boundaries of the municipality 2)Functional approach, refers to delineating city boundaries based on functions like income per capita, population density, transportation activity 3)Morphological approach- refers to the use of land use or land planning for delineating city boundaries.

The other major issue related to conducting LCA of cities is the allocation of environmental impacts. Existing LCA studies conducted for a product or service assign environmental impacts to the product or services and the aim is often to choose the product or service with least environmental impact which is called comparative LCA. However, since cities are complex systems composed of different subsystems (Meerow et al., 2016) as discussed in section 2.1, there is an intricate flow of products (materials) and energy both within the city as well as with other cities. Thus environmental impacts cannot be simply assigned to individual products or resource. Four different ways of allocating environmental impacts have been studied by (Albertí et al., 2019). They are : 1)Monetary based approach- environmental impacts of product are allocated based on the value added at each location in the life cycle of the product, 2)Production based- environmental impacts are assigned to the location where the product is produced 3)Consumer based allocation-environmental impacts are allocated to the location where the product is consumed 4)Category based allocation-environmental impacts are allocated based on the impact categories and locations at which they occur. For example, impact category corresponding to climate change is GWP and the impact is global so the GWP is allocated to the location at which consumption occurs. However, the water used in the manufacturing of product is generally obtained from local nearby sources. As a result, the water footprint is allocated to the production site and not to the consumption site.

2.3 Research question

Based on the literature review, it can be concluded that Life Cycle Analysis (LCA) as a sustainability assessment tool has been applied to a specific product or specific sector of city. However, its extension to different material and energy flows in a city have not been explored due to the issues of city boundaries and allocation method. LCA of different energy and material flows of a city could provide interesting insights into main contributors of environmental impacts in a city and thus set path to improve the environmental sustainability of a city.

In order to fill the research gap relating to urban sustainability and produce research that can improve sustainability and accelerate transition to circular economy, the research will focus on developing a method to analyze environmental impacts of a city using LCA. We will focus on the consumer based allocation of environmental impacts. The reason for focussing on consumer based allocation are mainly because the decision makers at the city level can directly influence the consumption habits of the consumers through policy interventions or sustainability campaigns. Consumption based allocation of environmental impacts enables us to analyze environmental impacts of different geographical regions of the city or environmental impacts of different demographic groups. Thus, decision makers can direct their policy making efforts considering the regions or groups with high environmental impacts. As opposed to consumption based allocation, production based allocation would require allocating the environmental impacts to the producers of products irrespective of the location of production if the product is consumed in a city. In most cases, industrial facilities are located outside the city limits and there is little that decision makers at the city level can do to influence the production of those products. Thus, for this research, the environmental impacts will be allocated to consumers of products or resources within the city. However, the focus of the analysis will be solely on households. There are two main reasons to focus the analysis on households. The data collected through household surveys represent majority of the resource consumption in the life of resident of a city. Thus, household consumption accounts for majority of the flows in a city. Secondly, data related to consumption behaviour can be mined for households from their socioeconomic characteristics and most of the data collection process occurs at the level of households through surveys and questionnaires whereas for business establishments, data related to consumption activities is not available easily. The entire methodology to analyze environmental impacts of a city will be demonstrated using a case study. The case study is conducted for the city of the Hague, the Netherlands. Firstly, due to a well developed data collection process in the Netherlands through surveys, high quality data relating to resource consumption is available for the Netherlands. Secondly, the research group under which the study is undertaken has regular interactions with policymakers from the municipality from the Hague. Thus, the method developed to analyze environmental impacts would be highly useful for the policymakers from the Hague who can then decide on interventions to reduce the negative environmental impacts. Thus, the main research question (RQ) addressed is:

How can the environmental impacts due to resource consumption in cities be analyzed from consumption based allocation perspective?

The main research question shall be answered with the following sub research questions:

1. How can the household consumption activities by residents of a city be broken down in the form of resource consumption categories? (Conceptualization)
2. How can the consumption data on national level along with socioeconomic indicator data on neighbourhoods of city be used to estimate resource consumption by neighbourhoods in a city? (data)
3. How can the the data on household consumption be quantified into environmental impacts and analyze environmental impacts at the level of neighbourhoods? (LCA modelling)
4. How can commonly implemented urban sustainability policies be modelled as policy interventions and analyzed to see their positive environmental impact? (Exploratory Policy analysis)

Sub RQ 1 deals with breaking down household activities into different categories and further breaking down categories into specific products or resources. Thus, this sub RQ is intended to identify all the resources consumed by residents of a city that have an environmental impact and classifying them into resource use categories.

Sub RQ 2 deals with disaggregating national level resource use data to the neighbourhood level using socioeconomic indicators of neighbourhoods as input variables. In most of the cases, the data on consumption behaviour is generally available in the form of nationwide statistics and not at the level of a city or neighbourhood. To quantify the environmental impacts due to household consumption in a city or neighbourhood, it is important to disaggregate national level data to the level of cities or neighbourhoods. For each of the activities identified in sub RQ 1, a methodology will be laid out to disaggregate national level data to the level of cities or neighbourhoods if it is not available. sub RQ1 and sub RQ2 are interrelated, thus they will be answered together in Chapter 3.

Sub RQ 3 deals with quantifying and analyzing the environmental impacts of household consumption. Once the data on household consumption is available, the environmental impacts due to the consumption have to be modelled using life cycle inventory. This will also allow to allocate the environmental impacts of household consumption to different resource categories or different subsystems identified in sub RQ 1 in the life cycle of the process and further analyze the environmental impacts both spatially at the neighbourhood level and sectorally for different resource use sectors.

Sub RQ 4 deals with a exploratory analysis of different policy interventions that could reduce the negative environmental impacts due to consumption behaviour. Policy interventions that have been implemented in cities around the world to improve urban sustainability are chosen and a quantiative analysis is performed to demonstrate the extent to which implemented policies could reduce overall environmental impacts. This part of research is more exploratory in nature and thus modelling is conducted taking into account different uncertain parameters and policy levers.

Chapter 3

Data computation and exploratory analysis

3.1 Data requirements: Resource use categories

The first step to analyze the environmental impacts of cities is to compute data related to household consumption patterns. However, in most cases, resource consumption data is aggregated to a lower geospatial resolution for an entire country or the province to which the city belongs. Thus, lack of accurate data on resource consumption at the local level of cities poses a major challenge to analyzing environmental impacts of cities. In this chapter, we lay down the methodology to disaggregate the data from aggregated level for the entire Netherlands or for European union countries (for the case of BoP and waste) to the level of neighbourhoods of the Hague. The disaggregation of data at the level of neighbourhoods allows us to analyse the environmental impacts at geographical units at which interventions by the decision makers could have direct impact on reducing negative environmental impacts. Modelling consumption patterns of individual households could not provide information on which areas of cities have maximum negative impact on the environment. Also, it is difficult to intervene on the consumption habits of specific households. For example, it makes sense to implement additional public transports in areas where many people use private transport due to lack of accessibility to public transport.

In the current study, we have divided the household resource use/consumption into 6 major categories based on the household budget survey that is conducted in all the European countries to determine consumer price indices for the EU 28 countries (EU, 2020b). They represent most of the activities by the residents of a city that have an environmental impact. However, we have not considered activities like use of postal services, international travel even though they have an indirect environmental impact. There are multiple reasons for that. Firstly, as mentioned earlier, the current research is limited to household consumption of resources. The use of services, even though contributes to environmental impacts, the major environmental impacts occur not due to household but due to business processes. For example, in case of postal services, the environmental impacts occur due to transportation of post from origin to destination which is not under the control of households. Secondly, data related to use of such services is not available even for the national scale, thus quantifying the environmental impacts due to use of services would require altogether a different approach. Finally, the limited data that is available for the use of services is in the form of amount of money spent by households nationally on those services. To quantify the environmental impacts of monetary use of services would require altogether a different approach of using Environmentally extended input output tables (EEIO). Thus, we have limited the scope of current research to directly observable resource use behaviour by residents of a city. The 6 resource use categories considered are: 1)Food 2)Energy 3)Water 4)Mobility 5)Basket of Products (BoP) 6)Municipal solid waste or household waste.

In order to compute data related to resource use at the neighbourhood level for the city of the Hague, we first provide an overview of the city of the Hague : geographic division into neighbourhoods and the important socioeconomic indicators used in the study. Following that, we provide a conceptual model of the data ecosystem linking different models and methods that were used to disaggregate resource use data to the neighbourhood level for the Hague. Finally, we present detailed methodology to disaggregate data of resource use for each of the six individual resource use categories.

3.2 Case study : City of the Hague

The city of the Hague had a total population of 532,561 in the year 2018. The administrative region of the Hague is divided into 111 neighbourhoods as shown in fig. 3.1. As mentioned in section 2.2.5, one of the major issue in analyzing environmental impacts of cities through LCA is the definition of cities. Researchers face many choices while delineating cities and one of them is based on administrative boundaries. For the current research, the definition based on administrative boundaries is chosen. The main reason for doing so is related to data availability as well as the administrative control by the municipality. Extending the analysis beyond the municipality of the Hague to surrounding municipalities and the encompassing metropolitan region though would provide a more complete picture of the environmental impacts in the metropolitan region, policy interventions to reduce environmental impacts would require the support of multiple governing bodies and decision makers which might be difficult to achieve. Since different socio-economic indicators were used to predict the consumption of resources, table A.1 in appendix A1 provides a descriptive statistics of the indicators for the neighbourhoods of the Hague.

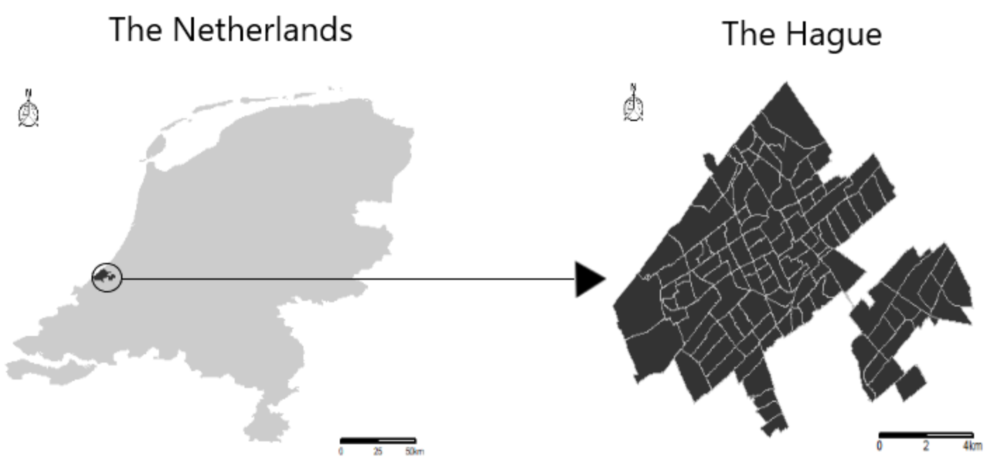

Figure 3.1: *Location of the Hague in the Netherlands and Geographical division of the Hague into 111 neighbourhoods*

3.3 Data computation methodology

3.3.1 Conceptual overview of data computation

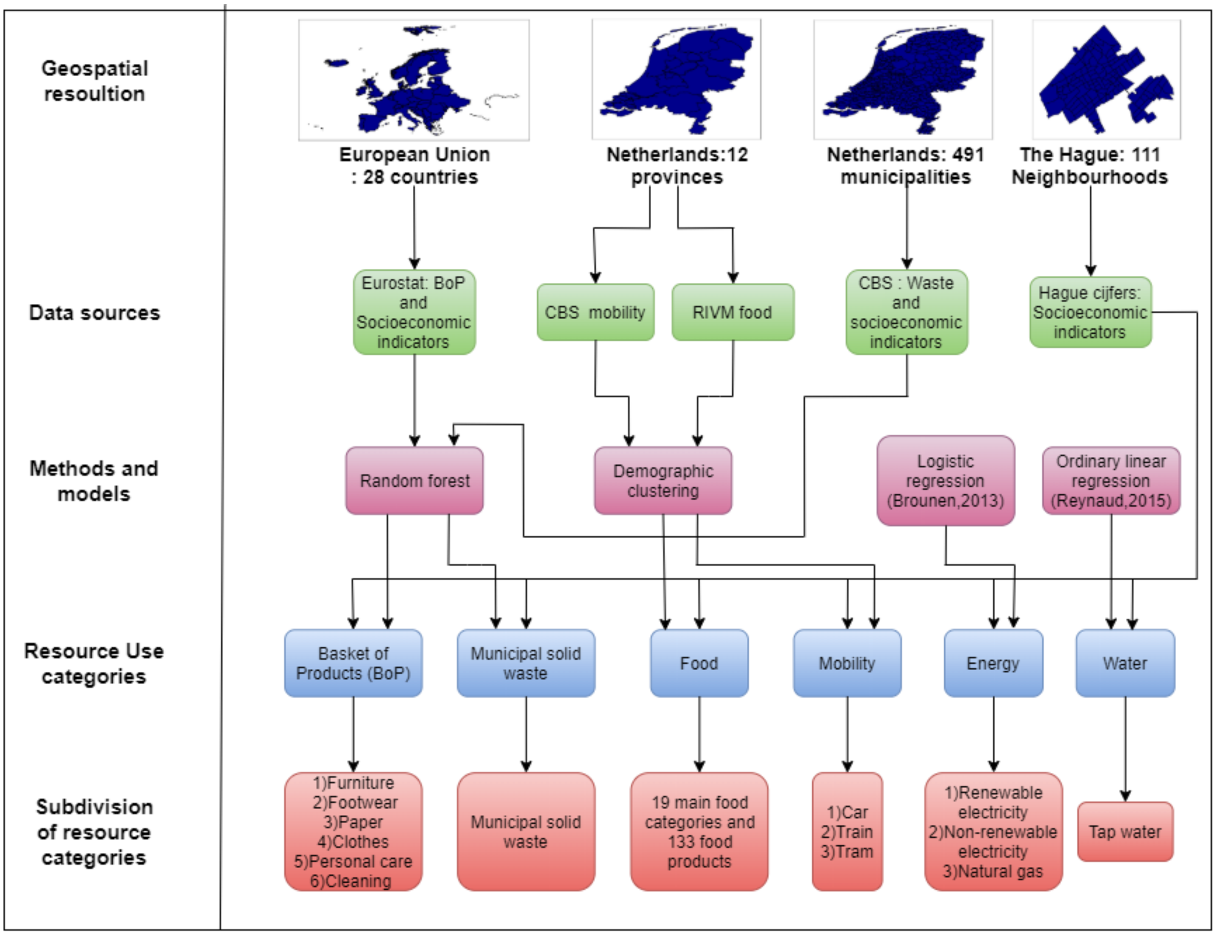

Figure 3.2: *Data computation methodology of the six resource use sectors for the neighbourhoods of the Hague*

Figure 3.2 shows the data ecosystem linking different models, databases that are used to compute resource use data for the 111 neighbourhoods of the Hague. The general idea is either to start with resource use data at lower geospatial resolution, link it through a model or empirically with socioeconomic indicators at lower scale and use the socioeconomic indicators at higher geospatial resolution to predict resource use data at higher geospatial resolution or to directly predict the resource use data at higher geospatial resolution through predictive models available in literature. For the current research, we use the Eurostat database (EU, 2020a) which has aggregated values for socioeconomic indicators and Basket of products for 28 European countries. The dataset is used to fit a random forest model for BoP use by population of European countries which is then used to predict BoP use by residents of different neighbourhoods of the Hague along with the Hague cijfers database. The hague cijfers dataset is central to the research and we have used it to compute resource use for all 6 resource use categories in the Hague based on socioeconomic indicators of different neighbourhoods of the Hague. Energy use is predicted by logistic regression model and water use is predicted by linear regression model of *Brounen et.al* (Brounen et al., 2013) and *Reynaud et.al* (Reynaud, 2015) respectively. We use the Central Bureau of Statistics (CBS) mobility dataset (CBS, 2020) and Rijksinstitut voor Volksgezondheid en Milieu's (RIVM) food dataset (RIVM, 2020) which have aggregated data for the 12 Dutch provinces to calculate mobility behaviour and food consumption respectively by applying the demographic clustering technique. Finally, the CBS dataset on waste has municipal waste generation per capita for each of the 491 municipalities of the Netherlands and random forest model is fit using the CBS waste dataset which is then applied to each neighbourhood of the Hague to calculate waste generation per capita. In the succeeding sections, we explain the detailed methodology used to compute resource use data for each sector. Furthermore, while the data system is unique to the city of the Hague, many elements of the data system can be applied to other European cities too. For example, the socio economic indicators such as sex ratio, income, education and employment rate are available for most of the cities and thus the random forest models can be used to predict their BoP use and waste generation. Similarly, the models of *Reynaud et.al* (Reynaud, 2015) have been specifically customized for every country in the European Union. The main areas where a different approach might be needed is Food consumption and Mobility patterns. Demographic clustering is used to compute the use of food and mobility. In the Netherlands, CBS and RIVM collect data related to mobility and food respectively. However, a similar data collection body might not be present in other European countries, specifically smaller countries, thus a modelling approach might be needed to compute data for food and mobility.

3.3.2 Food

In the Netherlands, RIVM conducts surveys on food consumption known as the Dutch National Food Consumption Survey (DNFCS). The survey asks individuals their daily consumption of 133 types of food.The broad categories of items are:1)Potatoes and tubers 2)Vegetables 3)Legumes 4)Fruits,nuts and olives 5)Dairy products and substitutes 6)Cereals and cereal products 7)Meat, meat products and substitutes 8)Fish and fish products 9)Eggs 10)Fats and oils 11)Sugar and confectionery 12)Cakes and sweet biscuits 13)Non alcoholic beverages 14)Alcoholic beverages 15)Sauces and seasonings 16)Soups and stocks 17)Miscellaneous 18)Savoury snacks

The RIVM DNFCS data set contains information on daily consumption of these 133 food items classified by gender, age and education level. When the datset at lower geospatial resolution is classified by socioeconomic indicators, demographic clustering can be applied to compute resource use data at higher geospatial resolution :

Demographic clustering

Demographic clustering is a simple method in which the population in a smaller geographical unit is divided into clusters based on their socioeconomic attribute such that the data on the variable to be predicted is available for the demographic clusters but on lower geospatial resolution or a higher aggregated level. The variable value at higher geospatial resoultion is then the population weighted mean of variable values for individual clusters. In order to calculate the population of each cluster, the following method is employed: The total number of clusters $\mathrm{n_c}$are,

$$n_c = \prod_{i=1}^{i=n} x_i \tag{3.1}$$

where $\mathrm{x_i}$ is the number of discrete categories for socioeconomic indicator i and n are the total number of socioeconomic indicators. For example, in case education is categorized into primary, secondary and tertiary, $\mathrm{x_i} = 3$.
The population p in a particular cluster is then,

$$p_{a_i b_j \ldots n_k} = P y_{a_i} y_{b_j} \ldots . y_{n_k} \tag{3.2}$$

where P is the population of the geographic area for which variable is to be determined, $\mathrm{a_i}$ is the value of socioeconomic indicators i, $\mathrm{b_j}$ is the value of socioeconomic indicator j and so on. $\mathrm{y_{a_i}}$ is the percentage of population with value $\mathrm{a_i}$ in the geographic region with lower resolution, $\mathrm{y_{b_j}}$ is the percentage of population with value $\mathrm{b_j}$ in the geographic region and so on. Finally, the value of the variable c for the geographic area is given by :

$$c = \frac{\sum_{n_c} p_{a_i b_j \ldots n_k} z_{a_i b_j \ldots n_k}}{P} \tag{3.3}$$

where $z_{a_i b_j \dots n_k}$ is the variable value for that cluster on a lower geospatial resolution.

Since the RIVM DNFCS dataset has data on food consumption for different genders, age groups and education levels, demographic clustering method can be used to compute data on food consumption at the local level for the neighbourhoods of the Hague. Table 3.1 shows the categorical values of different socioeconomic indicators used for clustering. Thus, the consumption of food item b in neighbourhood a in per capita per day terms is given by Equation (3.4),

$$y_{a,b} = \sum_i \sum_j \sum_k p_{a,i} p_{a,j} p_{a,k} y_{ijk,b} \tag{3.4}$$

where i,j,k is the categorical value of gender,age and education level respectively, $p_{a,i}$, $p_{a,j}$ and $p_{a,k}$ is the percentage of population in neighbourhood a with gender i, age group j and education level k respectively. Finally $y_{ijk,b}$ is the per capita consumption of food item b by demographic cluster with sex i, age group j and education level k.

Socioeconomic indicator	**Values**	**Symbol**
Gender	Male	i
	Female	
Age	0 to 18	j
	18 to 79	
Education	Primary	k
	Secondary	
	Tertiary	

Table 3.1: Socioeconomic indicators used in demographic clustering

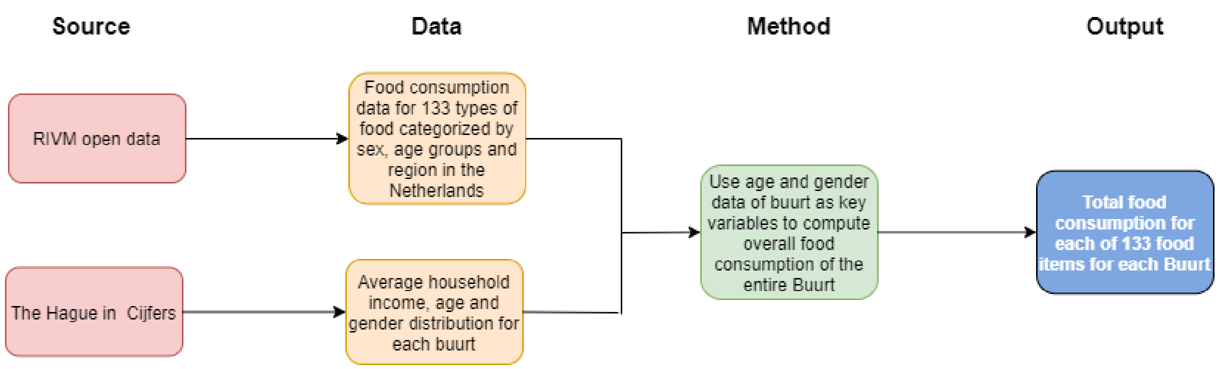

Figure 3.3: *Methodology to compute food consumption data for different neighbourhoods of the Hague*

Figure 3.3 is visual representation of the methodology to compute food consumption of different neighborhoods of the Hague.

3.3.3 Energy

The overall consumption of energy by households is divided into electricity and gas consumption. While the environmental impacts due to consumption of electricity may be different depending on the source from which electricity is produced, *Brounen et.al* (Brounen et al., 2013) performed an empirical study of 1716 households to determine whether they use green electricity (electricity generated from renewable sources of energy) or non-green electricity (electricity generated from fossil fuels) and fit a logistic regression model based on the socio-economic indicators of the respondents. Logistic regressions are specialized cases of linear regression where the model is used to predict the probability of occurrence of binary variables (Robles-Velasco et al., 2020). The probability of occurrence of value of interest is given by Equation (3.5),

$$p_i = \frac{1}{1 + e^{-(\sum a_i x_i + c)}} \tag{3.5}$$

where p_i is the probability of interest, c is a constant, x_i are predictor variables and a_i are the coefficients to be determined.

Thus, in the present study, the socioeconomic indicators in a neighbourhood are used to determine the percentage of households using green energy using the model of *Brounen et.al* (Brounen et al., 2013). The main reason for using this logistic regression model is that since the empirical study was conducted for Dutch households, it accurately reflects the determinant of green electricity by households in the Netherlands due to similar cultural beliefs and economic conditions of the population of the current research and that of the applied model.

Socioeconomic indicator	**Coefficient**	**Value**
Constant	β_0	0.059
Male respondent(yes=1)	β_1	-0.032
Age of respondent(60-70 years)	β_2	-0.5794
Age of respondent(>70 years)	β_3	-0.1892
Tertiary education(yes=1)	β_4	0.1628
Annual Income in €/capita	β_5	$1.813 \times 10^{-}6$

Table 3.2: Parameters of logistic regression model

Based on the socioeconomic indicators mentioned in Table 3.2, for each neighbourhood clusters are created based on sex, age and education. For each of the cluster in each neighbourhood, the probability of using green electricity can be determined using the logistic equation with parameters mentioned in table 3.2. Since the number of people in each of the clusters can also be determined, the expected probability or the percentage of households that use green electricity in a neighborhood can also be determined.

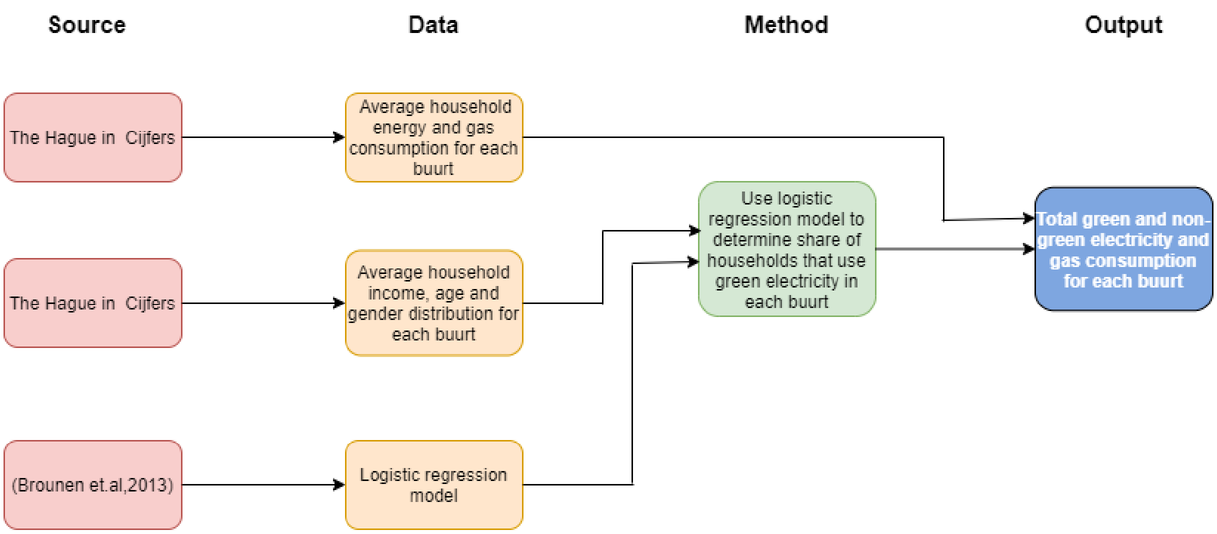

Figure 3.4: *Methodology to compute Energy consumption data for different neighbourhoods of the Hague*

fig. 3.4 is a visual representation of the entire methodology explained above to compute green and non-green electricity as well as gas consumption by households.

3.3.4 Water

Empirical data related to water consumption is not available in any of the centralized repositories of the CBS or RIVM. In the *Reynaud et.al* (Reynaud, 2015) (Report by Joint Research Center EU) study conducted for households in the Netherlands, the main determinants for household water consumption are cost of water, income of households, residential area and average rainfall. In *Wolters et.al* (Wolters, 2014), the main determinants are age, gender, education, political ideology, income, degree of Urbanization, water availability and support for the environment. In the current study, the approach and equation from (Reynaud, 2015) is used since the same socioeconomic indicators are available for each of the Buurt from the Hague cijfers. The Household water consumption obtained from the OLS model of *Reynaud et.al* (Reynaud, 2015) is divided by the average household size (number of people in each house) to obtain per capita water consumption for each neighborhood. Similar to the case of green and non-green electricity, since the OLS model was applied to population in the Netherlands, applying the same model to determine water use by the population of neighbourhoods in the Hague is justified due to similar characteristics of the population in terms of income, water use purpose. Household water consumption is obtained is using the following equation:

$$ln(Householdwaterconsumption) = \beta_0+(\beta_1\times ln(MWP))+(\beta_2\times ln(HHI))+(\beta_3\times ln(HHS))+(\beta_4\times ln(SET)) \tag{3.6}$$

Socioeconomic indicator	Variable	Coefficient	Value
Constant	1	β_0	2.001
Water price (in €/m^3)	MWP	β_1	-0.275
Household income (in €/year)	HHI	β_2	0.201
ln(Household size(in m^2))	HHS	β_3	0.013
summer evapotranspiration	SET	β_4	-0.023

Table 3.3: Parameters of OLS model for household water consumption

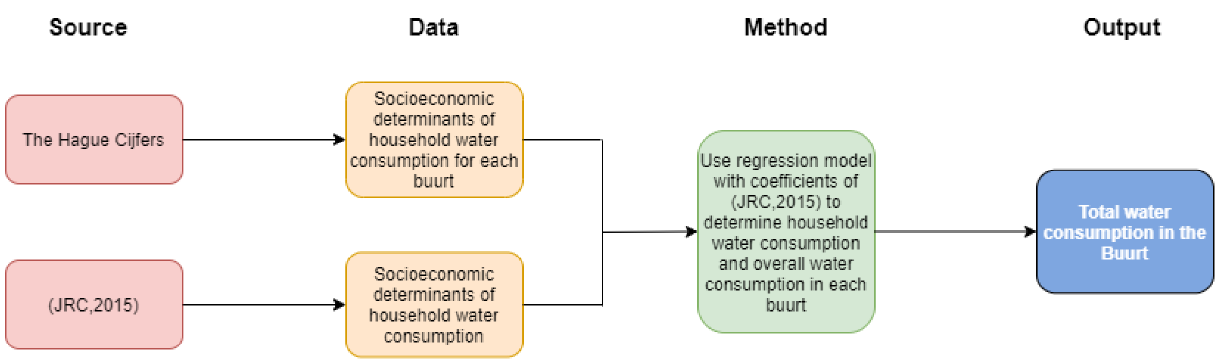

Figure 3.5: *Methodology to compute Water consumption data for different neighbourhoods of the Hague*

Figure 3.5 is a visual representation of the entire methodology explained above to compute Water consumption per household.

3.3.5 Mobility

Environmental impacts due to mobility are classified into three major categories : Private car use, Train use and local public transport use (Bus and tram). The CBS collects mobility pattern data for each of the 12 provinces of the Netherlands. Like the RIVM database on food consumption, the mobility pattern database is further segregated by socieconomic characteristics of gender (Male and Female) and 8 groups of age distribution. Similar to the methodology applied for generating food consumption for each neighborhood in the Hague, clusters of people depending on age and gender are created for each neighborhood. Since the database provided by the CBS is already on provincial level, it provides more accurate data for the Hague. The mobility patterns (distance travelled per day by different modes of transport)of each cluster are known and the number of people in each cluster for each neighborhood can be calculated. Thus, the distance $\mathrm{d_{a,b}}$ travelled per capita per day by a resident of neighbourhood a through mode b is given by,

$$d_{a,b} = \sum_i \sum_j p_{a,i} p_{a,j} d_{ij,b} \tag{3.7}$$

where i is the gender and j is the age group. $\mathrm{p_{a,i}}$ and $\mathrm{p_{a,j}}$ is the percentage of population in neighbourhood with gender i and age group j. Finally $\mathrm{d_{ij,b}}$ is the distance travelled per capita in the province of South Holland by a person of gender i and age group j through mode b.

While currently, the data related to mobility of tram/bus is directly computed from the empirical data provided by CBS, the data taken from GTFS files of HTM (The public transit company that operates bus and tram in the Hague) containing frequencies of all the tram and bus lines as well as the distances travelled by them for each route can be compared with the empirical data to identify the accuracy of the tram/bus mobility patterns provided by the CBS.

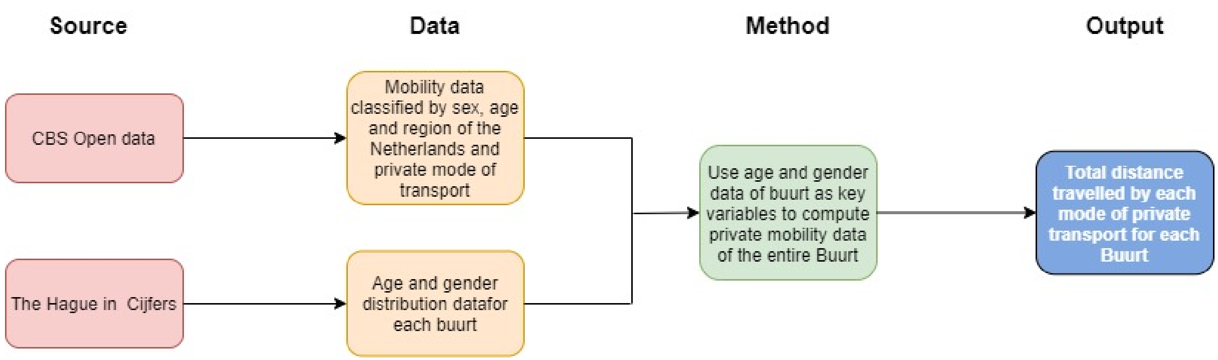

Figure 3.6: *Methodology to compute Mobility pattern data for different neighbourhoods of the Hague*

Figure 3.6 is a visual representation of the methodology explained above to compute distance travelled by residents of the neighborhoods through car, train and bus/tram.

3.3.6 Basket of Products

Baldassarri et.al (Baldassarri et al., 2017) (report by Joint Research center,EU) provides a reference list of household items (other than food, energy and water) that have an environmental impact commonly referred to as Basket of Products (BoP). The items categorized under BoP are Clothing, Household cleaning, Footwear, Furniture, Personal care and paper products. Data on BoP use is not available in any of the Dutch datasets. However, the Eurostat dataset (EU, 2020a) contains data on consumer spending on BoP and cost of BoP from 2009 to 2019 for each of the European countries. The consumption behaviour of daily use items like clothes, footwears, personal care products often depend on the socioeconomic characteristics of the individual. Thus, in the current research, socio-economic indicators of the neighbourhood are employed to predict BoP use in the neighbourhoods. The choice of socio-economic indicators which predict BoP use was based on literature review as well as the indicators for which data is available at the neighbourhood level in the Hague. The studies conducted by (Avery, 2018; Mashao & Sukdeo, 2018; Saleh, 2013) show that consumer spending on BoP is influenced by gender, age and income level. Furthermore, consumer spending is also impacted by the activity rate as shown by (Ganong & Noel, 2019).

Firstly, predictor variables that likely influence the consumption of BoP materials are assumed. These include :Percentage male in the population, Percentage of population in cohorts of : 0-15 years,15-25 years, 25-45 years and 45-65 years, Percentage of population who have obtained tertiary and secondary education, Activity rate of population, Average annual income. Secondy, data for each of this predictor variables is collected for the EU 28 countries from 2010 to 2019 from the Eurostat database (EU, 2020a). The Eurostat database also provides data on the total consumer spending for each of the product in BoP for each of the EU 28 countries from 2010 to 2019. Each of the items mentioned in BoP are further divided into specific products. For example, paper products are divided into Magazine, Newspaper, A4 sheets and novels. The individual prices (in €) of this products are provided by the Eurostat database for each of the EU 28 countries from 2010 to 2019. The individual prices of a specific product in a BoP category are averaged to get the representative price for one unit of that BoP category. Since the total consumer spending on a BoP category in a particular country for a particular year is known, the total cost is divided by the representative price to obtain the total units of that BoP category consumed for a given country and given year. This is further divided by the population of the country to obtain the per capita consumption of products in that BoP category. Thus, the per capita consumption of a BoP category and the input predictor variables for each of the EU 28 countries from 2010 to 2019 are known. Based on the input data set containing information on socioeconomic indicators and output data set containing information on BoP use, a random forest model is fit for each of the BoP category. The random forest model is then applied to each neighbourhood of the Hague to compute its BoP use.

A random forest is a collection of decision trees such that in each tree a subset of predictor variables is randomly chosen to construct the tree. The final value predicted by random forest model is the mean or mode of the values predicted by different decision trees (Liaw & Wiener, 2002). Decision tree is a predictive model which uses a node and leaf structure to predict the output. At each decision node, a condition is set on the input variables to further classify the outgoing branch. The process is repeated until a leaf is reached. Each leaf node contains condition on one input variable that predicts the output variable.

Random forest model is chosen because of two main reasons. Firstly, in a large dataset like Eurostat which has data from multiple countries over multiple years, there is a high likelihood of the presence of outliers in the data. Outliers often affect the performance of regression models like OLS or logistic regression. Random forests are basically made up of multiple decision trees and decision trees are local in nature. In regression models, the fitted equation holds true for entire space whereas in decision trees, the model is fitted locally for a single subspace i.e. every leaf of the tree. Thus, by default, outliers are classified at different leaves and thus random forest is quite robust to outliers. Secondly, random forest models are able to handle non linear relationships between input and output variables well. This is because, fundamentally, decision trees classify classify the data based on nested if-else statements. As a result, a linear relationship is not assumed between the inputs and output variables.

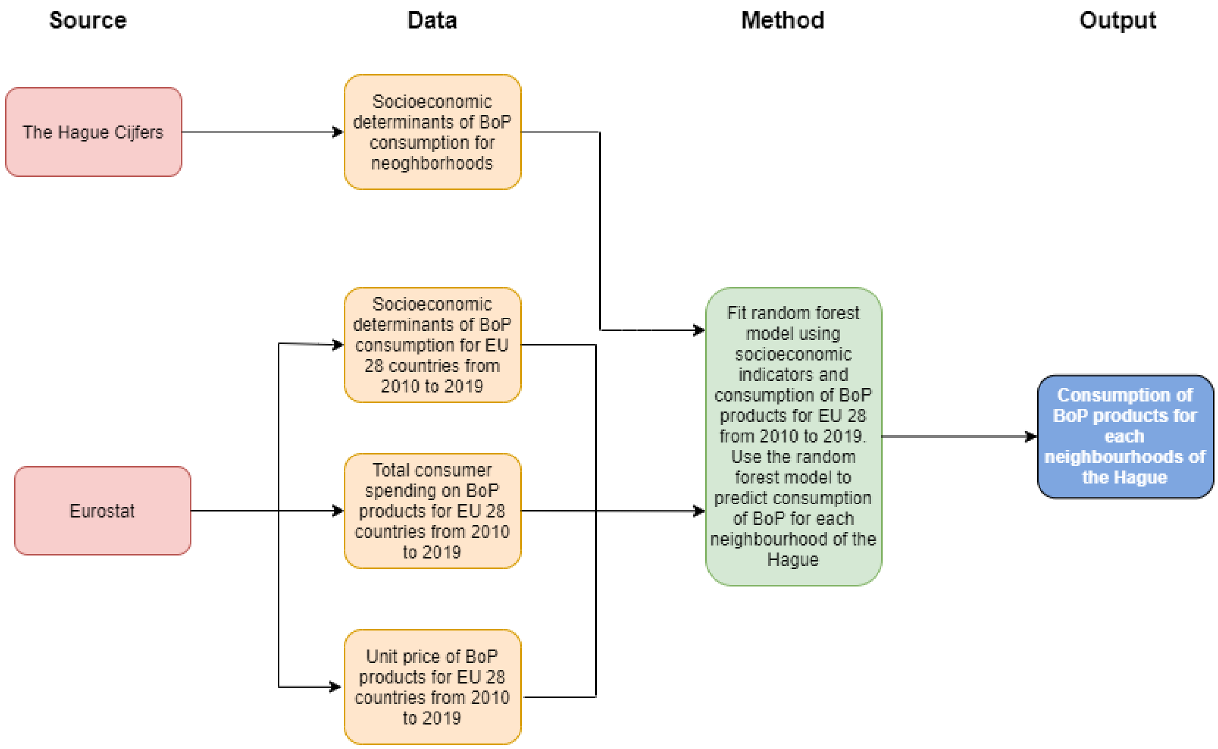

Figure 3.7: *Methodology to compute BoP data for different neighbourhoods of the Hague*

Figure 3.7 is a visual representation of the methodology explained above to compute BoP consumption for each of the neighborhoods of the Hague.

3.3.7 Household Waste

The method used to calculate the household waste generated is the same as the one used to determine the use of BoP. CBS provides data on the average household waste generated per household for each of the municipality in the Netherlands. The data set is further divided into 20 distinct types of waste such as textiles, glass. However, the LCA flow corresponding to waste is "Municipal solid waste" which is the aggregated value of the 20 different types of waste. Hence, for the current research, the focus will be on computing the total household waste. Based on the socioeconomic indicators of these municipalities as predictor variables, random forest model is fit which is then applied to the level of neighborhoods in the Hague to determine the household waste generated per household. The predictor variables include, percentage male, average age of residents in the geographical area, income per household, education level and the household size (number of members per household). The variables are chosen based on (Linderhof et al., 2000) who conducted an empirical study to determine factors that affect the amount of waste generated by households in Oostzaan, the Netherlands. The random forest model predicts household waste per household with a Mean Absolute Percentage Error (MAPE) of 12% while Ordinary Linear Regression (OLS) model also predicts waste generated with the same accuracy on the existing dataset of waste generated by different municipalities of the Netherlands. The random forest model is then used to compute waste generated by each neighbourhood of the Hague based on their input predictor variables.

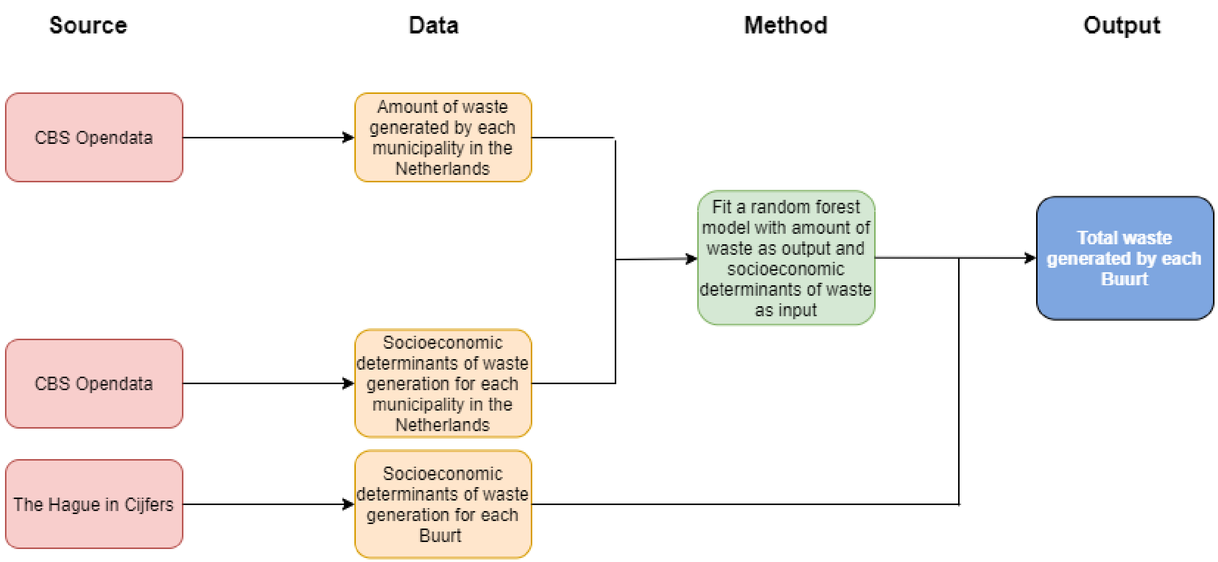

Figure 3.8: *Methodology to compute waste generation data for different neighbourhoods of the Hague*

Figure 3.8 is a visual representation of the methodology explained above to compute waste generation for each of the neighborhoods of the Hague.

3.4 Validation of random forest models and Resource Consumption patterns for the Hague

3.4.1 Validation of random forest models for BoP and Waste

Two different methods were applied to validate the random forest models for each of the six BoP categories as well as waste. In the first method, the entire dataset is split into training and testing set with 75% and 25% split respectively. The random forest model is then trained on the training data set and applied on the testing data set (Witten et al., 2013). The mean absolute percentage error (MAPE) is compared between the actual value in testing data set and the value predicted by the random forest model for inputs in the testing data set. However, this method is sensitive to the training and testing data set. Since the training and testing data set is chosen randomly, the MAPE may be different every time a different training and testing data set is chosen. Thus another validation method known as k-fold cross validation is chosen (Kohavi, 1995). In k-fold cross validation, the dataset is split into k distinct and mutually exclusive data sets.In a iterative process, k-1 data sets are randomly chosen and a model (not necessarily a random forest model) is trained on the union of k-1 data sets. The model is then tested on the data set that is not chosen. Thus this process is repeated k times and each time R squared value based on the performance of the model on the training data set is recorded. The final performance of the model is assessed based on the average of all the R-squared values. In the current research, a 10 fold cross validation method is applied.

Resource	**MAPE random forest**	**MAPE OLS**	**R-squared 10 fold cross validation Random forest**	**R squared 10 fold cross validation linear regression**
Clothing	9.089	20.334	0.9671	0.847
Household cleaning products	13.364	50.3621	0.924	0.4046
Footwear	9.511	22.1927	0.9065	0.5423
Furniture	10.998	24.314	0.9404	0.75408
Personal care products	11.5775	35.573	0.88202	0.20635
Paper products	10.294	24.231	0.9219	0.5806
Waste	12.288	11.437	0.764	0.805

Table 3.4: Validation results for random forest test applied to BoP and household waste generation

Table 3.4 shows the comparison of validation tests applied to the random forest model and OLS model for each of the six BoP resource use categories and waste. The R squared value is a measure of how close the predicted value is compared to the actual value. The closer the R squared value to 1 is, the more accurate a model is.Equation (3.8) and Equation (3.9) show the formula for MAPE and R squared value where 'E' denotes expected value, V denotes variance, y is the value predicted by the model and $\widehat{y}$ is the actual value of the variable. It could be seen that the accuracy of random forest model is much higher compared to the OLS model for all the six BoP resource use categories both in terms of MAPE and R squared values (10 fold cross validation). The MAPE for BoP products is around 10% in case of random forest model and is more than 20% in case of OLS with household cleaning products showing MAPE of 50% which implies the value predicted by OLS model differs by 50% compared to the actual value. Similarly, the R squared value of random forest model is quite close to 1 for BoP categories for a 10 fold cross validation technique. However, for the case household waste both the random forest method and OLS predict waste generated by household with approximately the same and reasonably well accuracy.

$$MAPE = E(100 \times \left|\frac{y-\widehat{y}}{\widehat{y}}\right|) \tag{3.8}$$

$$R^2 = 1 - \frac{E(y-\widehat{y})^2}{V(y)} \tag{3.9}$$

Finally, Figure 3.9 shows the plots for the values predicted by random forest model on test data sets versus the actual values of those variables for each of the six BoP categories as well as household waste. Overall, for the six BoP categories, the models predict values with good amount of accuracy. In the case of personal care products, for values higher than 150, the predicted values show slightly more amount of error. Finally, for household waste, the model does not predict waste generated by households with an accuracy as high as the models for BoP products but overall, the predicted values are within the expected margin of error.

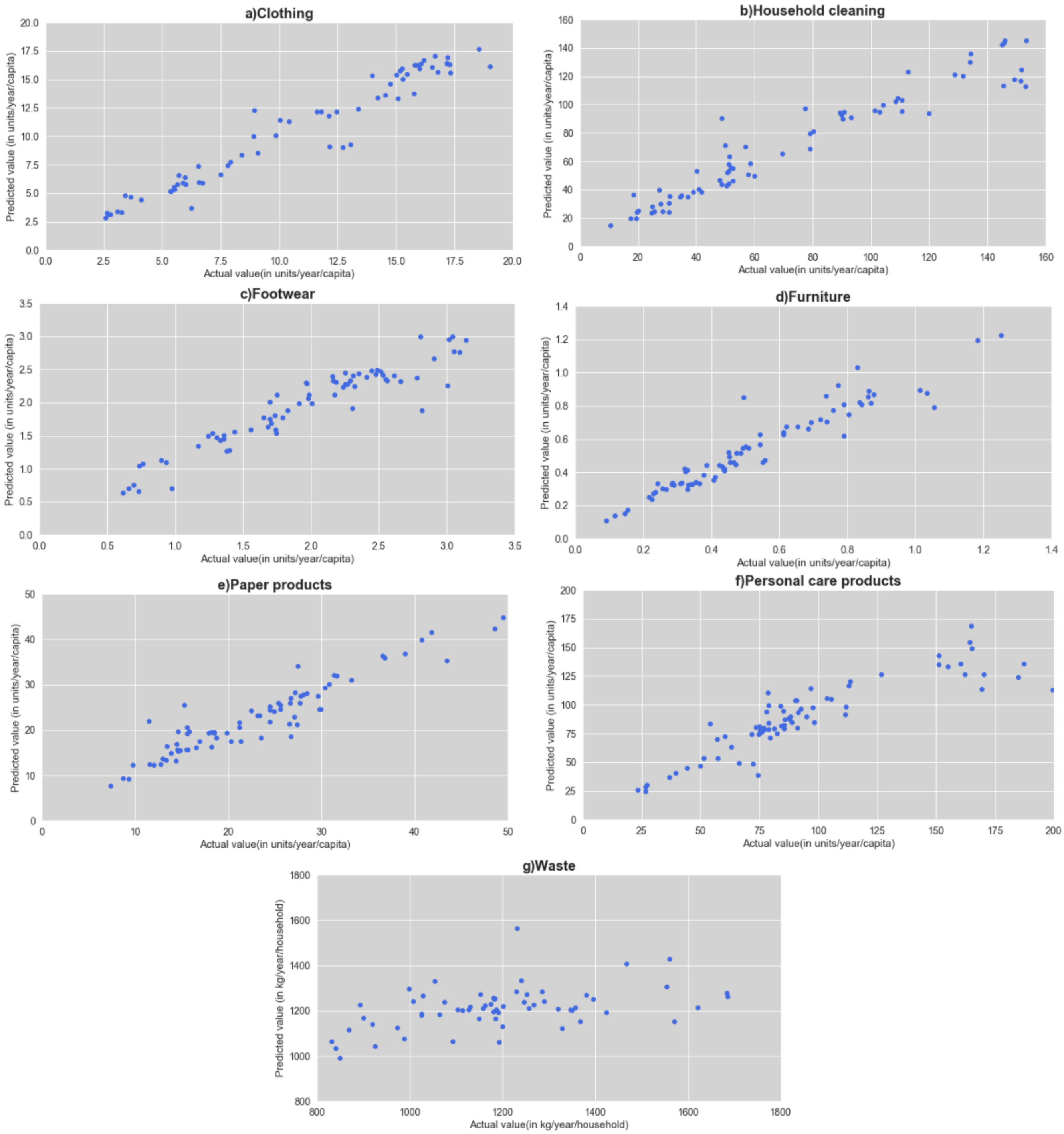

Figure 3.9: *Plots of actual values vs predicted values based on random forest model for BoP use and waste applied on the testing data set: a)Clothes b)Household cleaning c)Footwear d)Furniture e)Paper products f)Personal care products g)Waste*

3.4.2 Resource consumption patterns in the Hague

The different methods and models discussed in section 3.2 for different resource use sectors are applied to each of the neighbourhood in the Hague to calculate the resources consumed per capita for the year 2018. Figure 3.10 shows the geospatial distribution of the consumption/use patterns of key resources of food, water, waste, energy, and travel among different neighbourhoods of the Hague. In fig. 3.10, there is little variance among different neighbourhoods on the amount of food consumed per capita per day which can mostly be accounted to the demographic make up of the neighbourhood. Neighbourhoods with more male and less kids on an average show a higher consumption per capita. For the case of Water consumption, as can be seen in fig 4.6b, the neighbourhood of Binckhorst seems to have extremely low consumption of water per capita as compared to other neighbourhoods. The total population of the neighbourhood is 1790 while there are only 230 households. As a result, even though the water consumption per households in Binckhorst is large, the per capita water consumption is quite small. Similarly, for the case of energy consumption (green electricity, non-green electricity and natural gas), in Binckhorst, on account of lesser households but a large population, the energy consumption per capita is relatively small compared to other neighbourhoods of the Hague. There is a shortcoming in the way in which data for energy use is collected and water use is modelled. The data on energy use is available on a household basis while the water use is also modelled for households. Thus, in cases of large households, the per capita use of resource might not be accurately represented by the data.

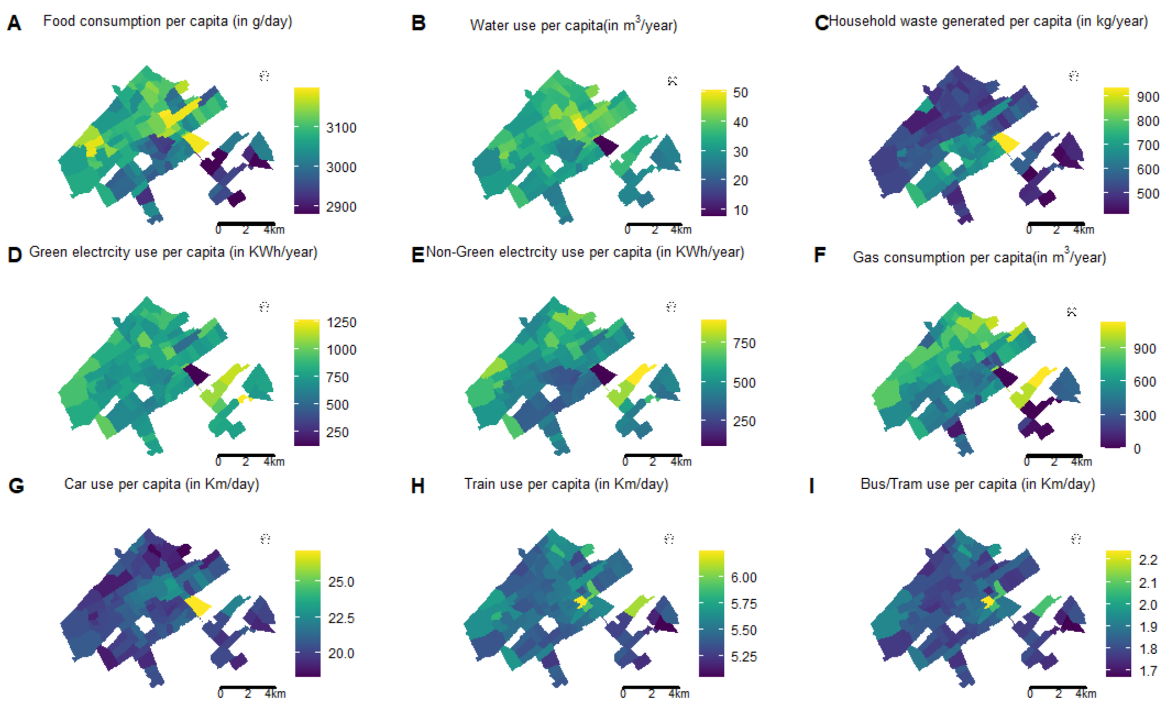

Figure 3.10: *Resource consumption/use per capita for different neighbourhoods in the Hague for the year 2018: a)Food b)Water c)Waste d)Green (Renewable) Electricity e)Non-green (Non-renewable) electricity f)Natural gas g)Travel by car h)Travel by train i)Travel by bus/tram*

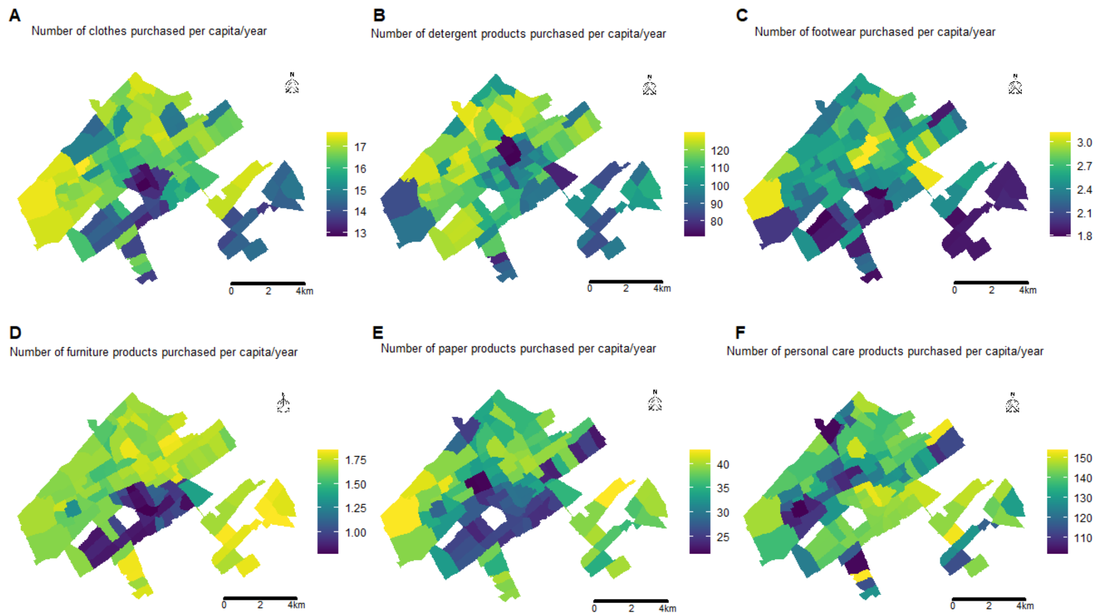

Figure 3.11: *BoP use per capita for different neighbourhoods in the Hague for the year 2018: a)Clothes b)Detergent c)Footwear d)Furniture e)Paper products f)Personal care products*

Figure 3.11 shows a geospatial distribution of different BoP in different neighbourhoods of the Hague. The neighbourhoods on the western region of the Hague along the coast show a proclivity for higher purchase of BoP per capita. These can be attributed to the relatively higher education level as well as income per capita in this regions. Furthermore, it can be seen that the purchase of detergent and personal care products far outweigh the purchase of other BoP in terms of number of units. This can be attributed to the broad variety of products in detergent and personal care. For example, personal care products are composed of shampoo, tooth-paste, soap, shower gel, deodrants and tampons which are purchased on a regular basis compared to other BoP such as furniture or clothes.

Chapter 4

Results

The data related to consumption of resources by neighbourhoods in the Hague is quantified in terms of LCA flows to analyze the environmental impacts due to resource use. The environmental impacts have been quantified in terms of Global Warming Potential (GWP). As explained earlier in Ch 2, the reason for using impact category GWP is that it corresponds to the environmental impact for climate change and GHG emissions and the main priority for cities in terms of environmental impacts is to reduce GHG emissions. Thus, this Chapter analyzes the environmental impacts of different resource use categories for different neighbourhoods of the Hague in terms of GWP.

4.1 Environmental impacts of resource consumption

4.1.1 Analysis of GWP of neighbourhoods of the Hague and its contributing factors

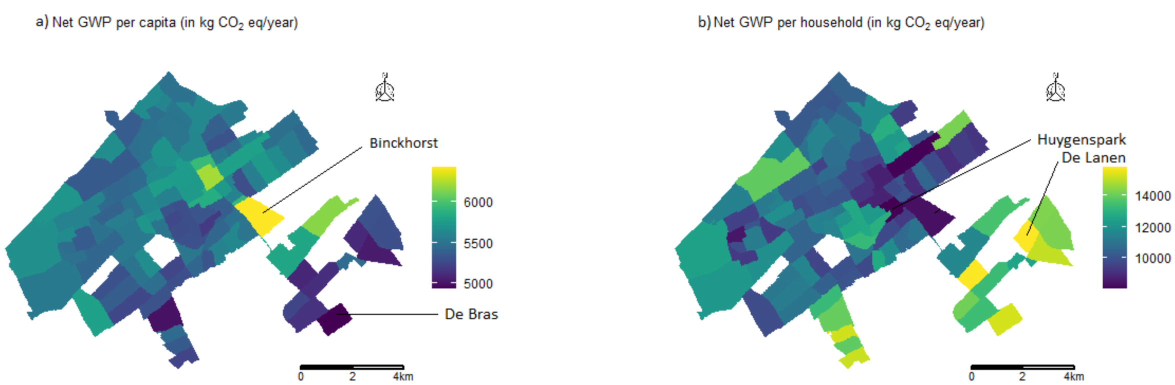

Figure 4.1: *Total GWP for different neighbourhoods of the Hague in the year 2018 on a a) per capita and b)per household basis*

Figure 4.1a and Figure 4.1b show the net GWP per capita and per household for different neighbourhoods of the Hague in 2018 by aggregating all the resource use categories. Binckhorst has the highest GWP per capita at around 6.5 tonnes CO_2 while the neighbourhood of De Bras has the lowest GWP per capita at around 4.9 tonnes CO_2. The values are in line with the national GWP per capita for the Netherlands of 9.4 tonnes CO_2 in 2018. The values for the neighbourhoods are lower than the national average because, we consider the major resource use categories but many of the services like postal services, dining out at a restaurant or the emissions in the construction sector are excluded from the analysis. When we look at GWP per household for different neighbourhoods, the trend is quite reverse with neighbourhoods which had high GWP per capita having some of the lowest GWP per household and the ones with lowest GWP per capita having the highest GWP per household. Huygenspark has the lowest GWP per household and De lannen has the highest GWP per household at 8.1 and 15.8 kg CO_2 respectively. One way to look at the trends is that neighbourhoods which have high GWP per capita tend to have very small household size in terms of number of family members. However, as household size increases and there are more members per household, overall the resource use increases but the marginal increase in resource use is small thus the GWP per capita decreases but GWP per household increases as the size of household increase. As a result, neighbourhoods with large households have a higher GWP per household due to more household members but the GWP per capita is still small because more household members would imply more efficient use of resources compared to smaller households. For example, it can be expected that a 2 person household would not be using twice as much energy or generate twice as much waste compared to a one person household.

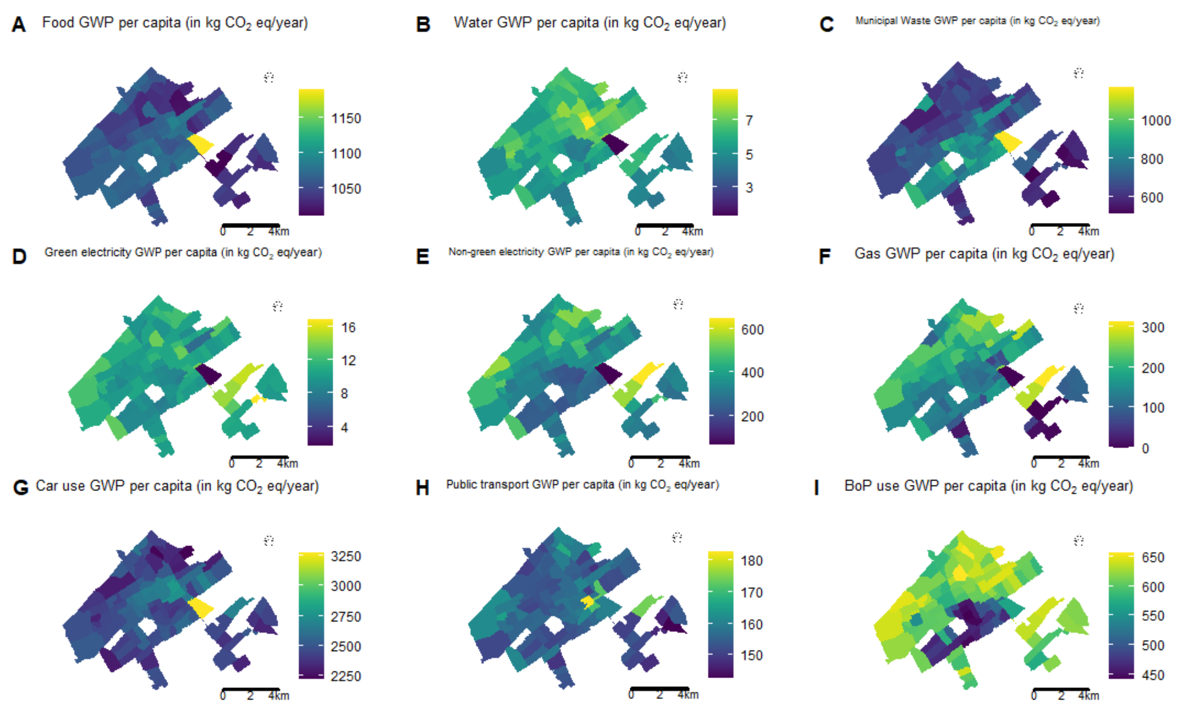

Figure 4.2: *GWP per capita for different neighbourhoods in the Hague for the year 2018: a)Food b)Water c)BoP d)Green (Renewable) Electricity e)Non-green (Non-renewable) electricity f)Natural gas g)Car use h)Public transport use i)BoP use*

While Figure 4.1 gives a broad overview of the environmental impacts of different neighbourhoods of the Hague compared to a certain benchmark (like national value), it is useful to look at the contributing resource use sectors that have the highest environmental impacts and thus enable decision makers to make policies that are oriented towards reducing the impact in those resource use sectors. Figure 4.2 shows the total GWP per capita for different neighbourhoods of the Hague and due to the use/consumption of different resources. The GWP due to energy is further divided into green electricity, non-green electricity and Natural gas use and the GWP due to mobility is divided into car and public transport. Amongst the nine contributing factors to GWP shown in fig. 4.2, the use of car has the maximum GWP while water use has the least GWP. However, the environmental impacts also depends on the impact category used for quantification. For example, even though the GWP due to water use is extremely low compared to use of other resources, the water footprint of water use might be very large compared to the use of other resources. Of particular interest is the district of Binckhorst which has the highest GWP per capita due to food consumption and car use while the lowest GWP per capita due to water, electricity and gas use. The total population of Binckhorst is 1790 out of which 1435 are males and 355 are females with 1255 people in the age range of 15-45 years. Since empirical data suggests that males in this age group have the maximum consumption of food and maximum use of car among the demographic groups, the GWP per capita due to food consumption and car use is relatively high for Binckhorst. Following is a brief analysis of GWP per capita due to each of the resource use sector:

Food

GWP due to food is the aggregated value of GWP due to 133 food items. However, LCI flow corresponding to all 133 food items are not available in the Ecoinvent database. Therefore, in some cases for food items for which LCI flows are not available, the nearest flow is taken. For example, it is expected that the GWP due to Butter is similar to the GWP due to Cheese. Finally, some of the miscellaneous items which are consumed in miniscule amount such as pastries are excluded. Overall, GWP per capita due to food is the second largest among all the resource use categories. As seen in fig. 4.1a, the neighbourhood of Binckhorst is the outlier in terms of GWP per capita. This is attributed to its demographic characteristics which is skewed towards middle aged males (demographic with highest food consumption). Overall, the range of GWP is still quite small compared to other resource use categories and apart from Binckhorst, other nighbourhoods have a very similar GWP per capita. The main contributors GWP due to food are red meat and white meat. Red meat in particular has very high GWP per kilogram and coupled with its high consumption, the overall GWP increases. Thus, in order to reduce GWP due to food consumption, the major focus should be directed towards reducing the consumption of meat. However, food choices are personal and it is difficult to affect food choices unlike other resource use categories like mobility or waste.

Water

The GWP due to water is composed of singular flow of tap water unlike other resource use sectors which are broken down into multiple flows. Overall, the GWP due to water is quite small compared to other resource use sectors. Once again, Binckhorst stands out as an outlier as shown in fig. 4.2b. The low water use in Binckhorst can be attributed to it being one of neighbourhoods with the lowest average income as well as small household sizes.

Waste

Figure 4.2c shows the GWP per capita due to household waste generated by the residents of a city. In the Netherlands, the net effect of household waste on the environment is positive since the heat generated from municipal waste treatment is used to offset the emissions due to electricity generated by coal, oil and natural gas. However, in the current study, the cutoff model is used so that the producer of the waste does not receive credit for the positive environmental impact generated from the recycling of waste. The treatment of waste involves transport of waste to the treatment plant as well as GHG emissions released during the treatment of waste. All these impacts are aggregated in the cut off model and thus the negative impact of household waste in the Netherlands is 1.255 kg CO_2 eq. Overall, the GWP due to waste generation is relatively high compared to other resource use categories. The features which predict high GWP due to waste are household size (less members per household leads to more GWP due to waste) and income per capita (low income per capita leads to more GWP due to waste) as could be seen in neighbourhoods near the south of the Hague.

Energy

Figure 4.2d, e and f show the GWP per capita due to the use of renewable (green) electricity, non-renewable (non-green) electricity and natural gas. In the Netherlands, renewable electricity is generated through solar power, hydroelectric power, wind power, nuclear power, biomass and municipal waste. The overall GWP due to renewable electricity is the weighted average of GWPs due to individual sources with respective weights being the proportion in which the electricity due to each of the individual source is generated in the Netherlands. Similarly, non-renewable electricity in the Netherlands is generated from coal, oil and natural gas. Thus, GWP due to non-renewable electricity is the weighted average of GWP due to the individual sources with weights being their proportions in the total electricity generated through non-renewable sources. The GWP due to non renewable electricity has the highest impact while the GWP due to renewable electricity is quite low. Thus, a transition from non-renewable electricity to renewable electricity could reduce the overall GWP due to energy by more than 60% since the total contribution of non-renewable electricity to GWP due to energy is almost two thirds and due to natural gas is almost one-thirds with renewable electricity having minor impact.

Mobility

The GWP due to mobility is broken down into GWP due to car use and GWP due to public transport as shown in fig. 4.2g and fig. 4.2h. The GWP due to public transport can be further broken down into GWP due to train use and bus/tram use. The GWP due to car use is extremely high compared to the GWP due to public transport. This is due to the compounding effect of high GWP per km of car use combined with high car usage by the residents of the Hague. Thus, encouraging the residents to use public transport could greatly reduce GWP. A number of policies related to stimulating public transport use have been implemented in major cities around the world which will be analyzed in the succeeding chapter. Similar to food, Binckhorst has the highest GWP due to car use primarily due to Binckhorst being a neighbourhood composed of middle aged males who use car frequently.

BoP

Figure 4.2i shows the GWP per capita due to BoP use. The GWP due to BoP is composed of footwear, furniture, clothes, household cleaning, personal cleaning and paper products. Furniture purchase has the highest GWP among the six products. The main feature that leads to higher GWP due BoP products is income (higher income leads to more GWP). Thus neighbourhoods in the western and northern parts of Hague have high GWP compared to neighbourhoods in the south of Hague where the average household income is lower. Similar to food, the use of BoP is a personal choice and it is difficult to change the consumption behaviour of individuals for BoP.

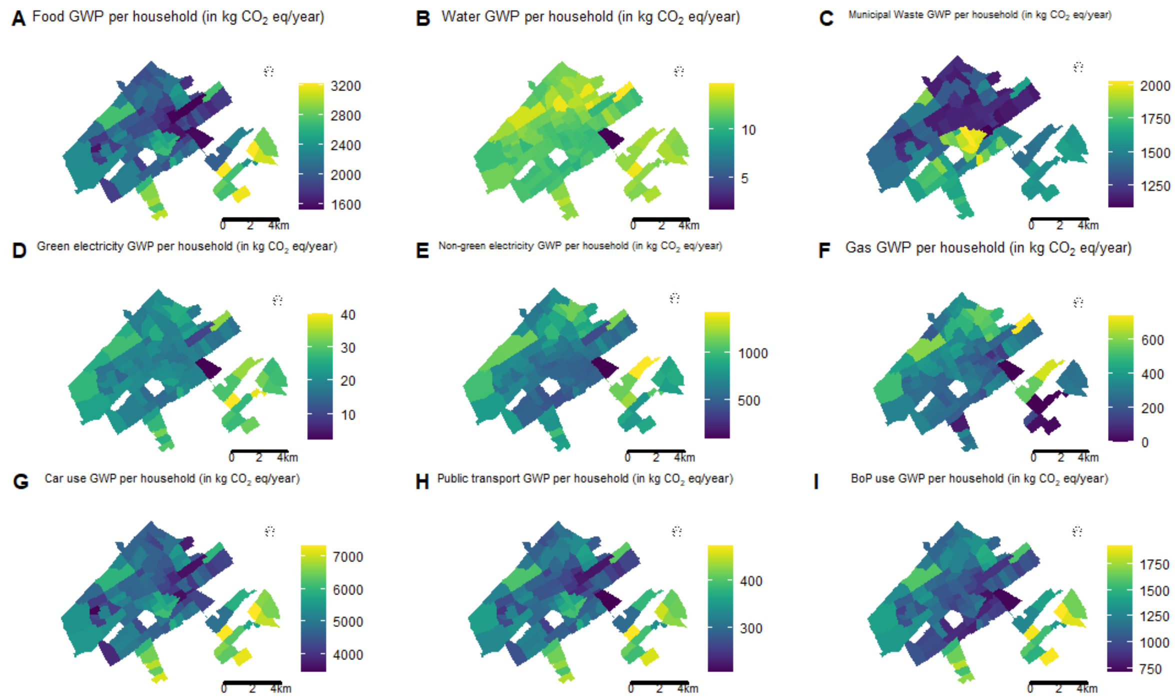

Figure 4.3: *GWP per household for different neighbourhoods in the Hague for the year 2018: a)Food b)Water c)BoP d)Green (Renewable) Electricity e)Non-green (Non-renewable) electricity f)Natural gas g)Car use h)Public transport use i)BoP use*

Figure 4.3 shows the conversion of GWP per capita to GWP per household for different neighbourhoods of the Hague and different resource use sectors. The relative trend for GWP per capita and GWP per household (relative position among different neighbourhoods) remains similar for the neighbourhoods along the northern part and west coast of the Hague but the neighbourhoods along the Eastern boundary of the Hague have a much higher GWP per household but a lower GWP per capita. This is mainly because the neighbourhoods in the eastern part of the Hague have large household sizes with 2.5 to 3 people on an average. In terms of policy implications, it implies that if the resource consumption is driven by individual choices then neighbourhoods with high GWP per capita scattered along the centre and western part of the Hague have a maximum impact and thus policies targetting those neighbourhoods could be used to reduce negative environmental impacts. The resource consumption is also driven by the overall choice of households as a group and in that case, the neighbourhoods along the eastern and southern parts of the Hague have maximum impact and thus policies targetting those neighbourhoods should be used to reduce the negative environmental impacts. The next subsection will discuss the issue of whether consumption is driven by individual choices or household choices.

4.1.2 Relation between GWP per capita and GWP per household

The GWP per capita and GWP per household are inherently related through the household size. Many national and international organizations have started to center their environmental policies around households and to reduce the environmental impacts of households as a whole (Girod et al., 2017; Söderholm, 2011). Since GWP per household is composed of two elements of GWP per capita and household sizes, it is important to look at which factor out of the two dominates in the environmental impacts of households (GWP per household). Figure 4.4a and b show the scatter plot for household size vs total GWP per household and total GWP per capita vs total GWP per household respectively. Household size and GWP per capita have an opposing effect on total GWP per household. Thus, the overall impact of household size and GWP per capita on GWP per household is analyzed using feature scoring to understand the variable having the dominating effect.

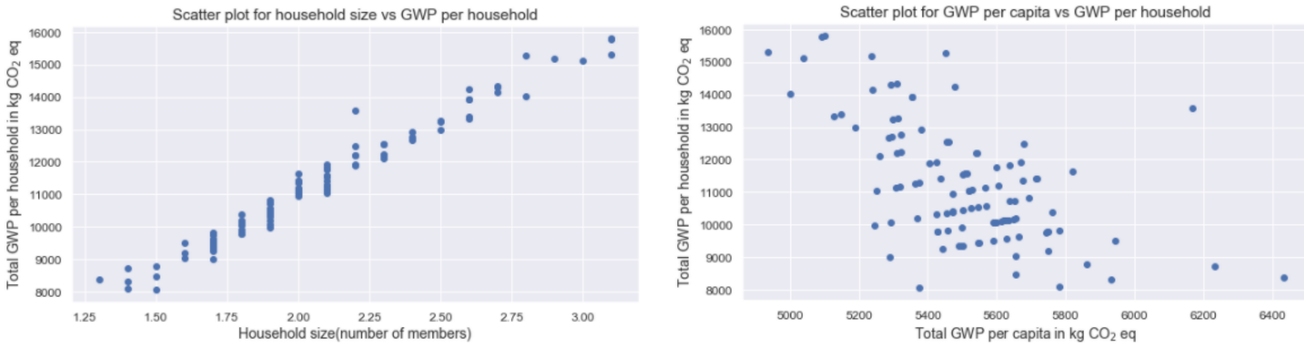

Figure 4.4: *Scatter plots showing correlation between a)Household size vs total GWP per household b)total GWP per capita vs total GWP per household*

Feature score is an an alternative to sensitivity analysis that can be used to assess the relative importance of various input parameters on output parameters (Kwakkel, 2016). Generally a global sensitivity analysis method such as SOBOL is preferred, however, the sample size of 111 neighbourhoods is too small to conduct a global sensitivity analysis. Therefore, feature scoring method was chosen. Figure 4.5 shows the feature scores of household size and GWP per capita of a resource use category on the GWP per household of the corresponding resource use category. It can be seen that except for water, the GWP per household is highly sensitive to household size and less sensitive to GWP per capita. The GWP per household due to food and mobility are highly dominated by the household sizes whereas the GWP per household due to energy, waste and BoP though are more sensitive to household size, they are also sensitive to GWP per capita due to energy, waste and BoP respectively. Thus, overall the GWP per household is more sensitive to household size compared to GWP per capita. As discussed in section 4.1.1, the GWP per capita of larger households is less compared to GWP per capita of smaller households due to increase in resource efficiency in larger households. Taking this factor into account, fig. 4.5 shows that larger households are still likely to have overall more environmental impacts compared to smaller households even after taking into account the greater resource efficiency of larger households.

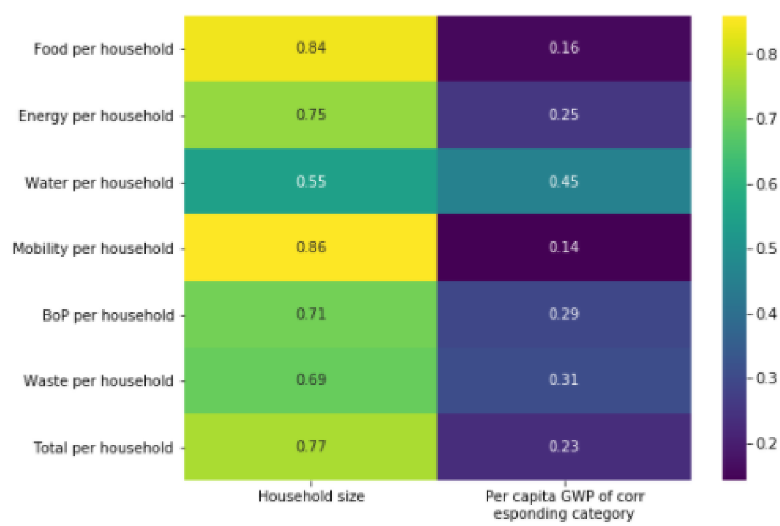

Figure 4.5: *Feature scores of GWP per household for different resource use categories with household size and GWP per capita as features*

The maps from fig. 4.1 to fig. 4.3 show the GWP for differernt neighbourhoods of the Hague and provide information on least polluting and most polluting parts of the Hague. However, they do not provide information on the distribution of GWP due to different resource use categories across the neighbourhoods. The distributions of GWP could provide more information about the variance and skewness of distributions in a particular direction which could be used to decide on which resource use sectors must be intervened on. Figure 4.6 shows the distribution of GWP per capita and GWP per household for the neighbourhoods of the Hague 5 major resource use categories (Water is excluded due to its extremely small GWP) through boxplots. The distribution of GWP per capita exhibits much less variance compared to the GWP per household across all resource use categories. The effect of variance in household size combined with variance in GWP per capita leads to a higher variance in GWP per household. Mobility has the most inequitable distribution of GWP per household even when its distribution of GWP per capita is equitable.This can be interpreted that neighbourhoods with a high GWP per capita, in general also have large household size and as a result, the variance in GWP per capita is large. In practical terms, this can be interpreted as large households have a high GWP per capita probably due to more car use and this results in overall a very high GWP per household due to combined effect of more members in household and higher car use whereas smaller households have low GWP per capita compared to larger household which results in profound differences in GWP per household for smaller and larger households. Contrary to that, the variances for GWP per capita and GWP per household in energy sector are comparable. This means that neighbourhoods with smaller GWP per capita due to energy have large household sizes and neighbourhoods with larger GWP per capita have smaller household size. The opposing effects of high GWP per capita and low household sizes or low GWP per capita and large household sizes results in a lower variance in GWP per household for all neighbourhoods. Thus interventions geared towards energy efficiency could be targetted towards smaller households and interventions directed towards mobility could be directed towards larger households.

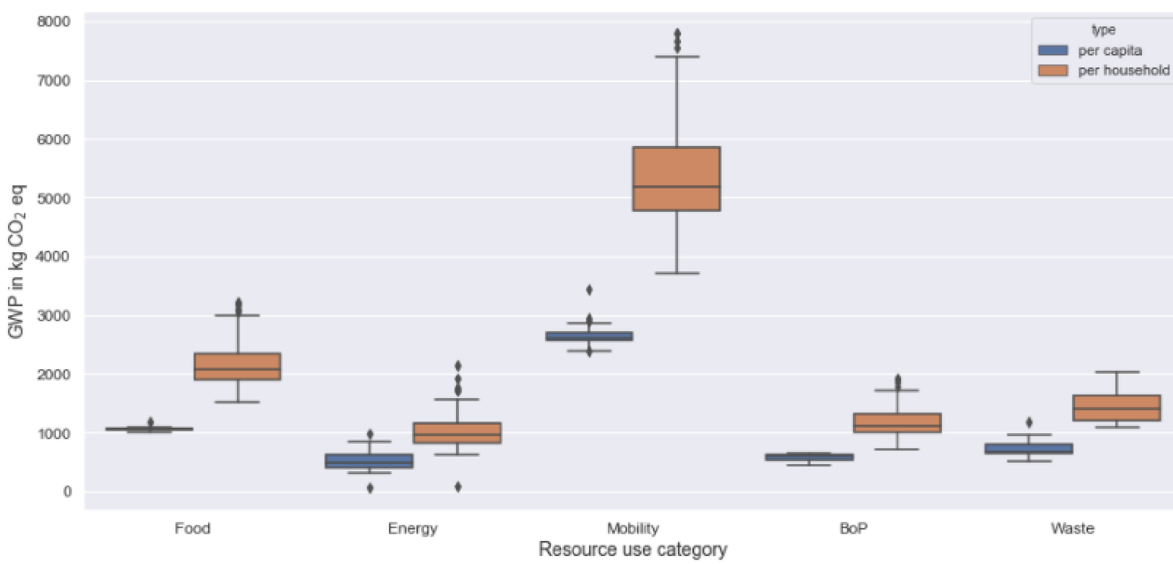

Figure 4.6: *Boxplot for GWP per capita and GWP per household for 5 major resource use categories for the neighbourhoods of the Hague in 2018*

4.1.3 Aggregation of GWP of different neighbourhoods of the Hague

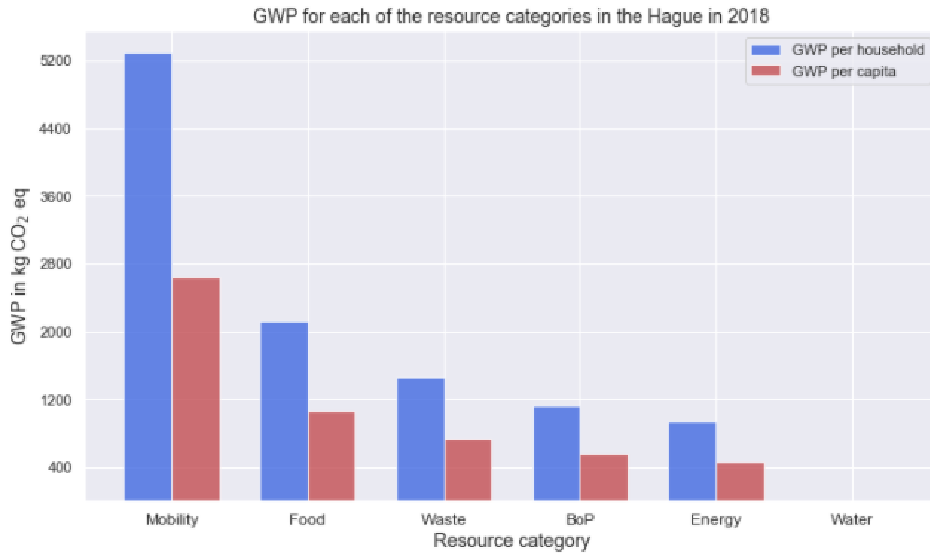

Figure 4.7: *Barplot of GWP for different resource categories for the Hague in 2018*

The previous analysis was focussed on the comparison of GWP between different neighbourhoods of the Hague. It is also useful to look from a broader perspective considering the Hague as a whole and see the contribution of different resource use sectors to overall GWP. Thus we extend the analysis from a neighbourhood level to the city wide environmental impact. The net GWP per capita and per household for a resource use category for the entire Hague is the population weighted and number of household weighted mean of GWPs for a resource use category of different neighbourhoods respectively given by eq. (4.1) and eq. (4.2) respectively.

$$GWP_{i,capita} = \frac{\sum_{j\in n} p_j GWP_{i,j,capita}}{\sum_{j\in n} p_j} \tag{4.1}$$

$$GWP_{i,household} = \frac{\sum_{j\in n} h_j GWP_{i,j,household}}{\sum_{j\in n} h_j} \tag{4.2}$$

where $\mathrm{GWP_{i,capita}}$ is the GWP per capita due to resource use category i, $\mathrm{GWP_{i,household}}$ is GWP per household due to resource use category i for the entire Hague. $\mathrm{p_j}$ and $\mathrm{h_j}$ are the population and number of households in neighbourhood j respectively. n is the set of all neighbourhoods to which j belongs to. $\mathrm{GWP_{i,j,capita}}$ and $\mathrm{GWP_{i,j,household}}$ are GWP per capita and GWP per household for resource use category i in neighbourhood j. Figure 4.7 shows the net GWP per capita and per household for the municipality of the Hague in 2018 for different resource categories. Mobility is the major contributing factor to GWP accounting for almost 45% of net GWP. On an average, residents of the Hague travel by car for 30 km/day accounting for high GWP due to mobility. Thus, policies focussed on stimulating the use of public transport could considerably reduce the negative environmental impacts in a city. The next major resource use which has a considerable negative environmental impact is food consumption which accounts for nearly 20% of total GWP followed by waste and BoP use at 15% and 10% respectively. While the food habits of people cannot be controlled, consumption of organic food products (with lower GWP) can be promoted. For energy use, the majority of GWP is due to the use of electricity generated from non-renewable sources like coal, oil and natural gas. In the Hague, households are given a choice to select the source of their electricity and they can choose green(renewable) or non-green (non-renewable) sources of electricity. Thus promoting green or renewable sources of electricity has a great potential to reduce GWP due to energy. Finally, the use of water contributes to less than 1% to total . Thus, the GWP due to water is quite insignificant compared to the use of other resources.

4.2 Cluster based analysis of Environmental impacts

In the previous section, we analyzed the GWP for different neighbourhoods of the Hague and different resource use categories. It was concluded that larger households have a higher environmental impact due to car use whereas smaller households have more environmental impact due to energy use. In this section, we explore the relation between socioeconomic characteristics and environmental impacts in detail. We analyze how the environmental impacts of households and individuals are impacted by their socio-economic conditions. As discussed in section 2.1, the socioeconomic dynamics subsystem is responsible for the resource consumption behaviour of residents of city and thus the environmental impacts of a city are linked with the socioeconomic conditions of residents. Firstly, different neighbourhoods of the Hague are clustered based on their socioeconomic characteristics and archetypes describing the clusters are created. Secondly, the environmental impacts of the clusters of neighbourhoods are analyzed as a whole: This serves a two fold purpose. Firstly, in allocation of environmental impacts, there is always an issue of equity and efficiency. In the context of city, while the overall consumption based environmental impacts of city should be allocated to the city itself, analyzing environmental impacts based on socio-economic characteristics allows us to understand which socioeconomic groups have the maximum impact and thus provide a systematic approach to allocate environmental impacts to residents of a city based on their socioeconomic conditions. Secondly, the combination of break down of environmental impacts into resource use categories along with information on the environmental impact of socioeconomic groups in different resource use categories helps policymakers target their policies to specific socioeconomic groups (Froemelt et al., 2018). The clustering of neighbourhoods based on socioeconomic characteristics allows us to understand the intrinsic factors that lead to different consumption patterns and enable decision makers to micro target policies and sustainability messages to neighbourhood level that can encourage sustainable behaviour among the residents of a city.

4.2.1 Optimal Clustering method and optimal number of clusters

Clustering is a unsupervised machine learning technique used to group objects which are similar in nature into a number of groups or clusters. For the current research, these objects are neighbourhoods of the Hague and they are grouped together based on their socioeconomic characteristics. The socioeconomic indicators chosen for the neighbourhoods are: 1)Annual income per household 2)Percentage of population with tertiary education 3) Activity rate (1-unemployment rate) 4)Percentage of population younger than 40 years of age 5)Percentage of non-Dutch population 6)Percentage of single person households 7)Percentage of rental houses 8)Number of cars per household. The indicators were chosen based on the assumption that they are the factors that affect the consumption choices of residents. The indicator values were standardized with mean 0 and standard deviation 1 so as to make the scale of indicators uniform. If the indicators are not standardized, indicator like annual income whose value is in thousands would have a dominating effect compared to other indicators.There exist several clustering algorithms in literature, the most common clustering algorithm being the k means clustering algorithm (Jain, 2010). In the current research, we choose the optimal clustering method by firstly comparing the performance of several clustering algorithms across similar performance metrics and then look at the practical implications of obtained neighbourhood clusters through different methods in terms of policy intervention and decision making for the municipality of the Hague.

Two performance metrics are commonly used to assess the performance of clustering algorithms : Silhouette score and Davies-Bouldin index. The silhouette score is given by eq. (4.3) where 'a' is the mean intra cluster distance and 'b' is the mean nearest cluster distance. A larger value of Silhouette score is more preferable since it indicates that a point is closer to its cluster centroid but farther away from the nearest cluster. The Davies-Bouldin index is a measure of similarity of each cluster with its most similar cluster. Similarity is the ratio of within cluster distances to between cluster distances.More information on calculation of the index can be found in (David & Bouldin, 1979). A lower value of Davies-Bouldin index is preferable.

$$\frac{b - a}{max(a, b)} \tag{4.3}$$

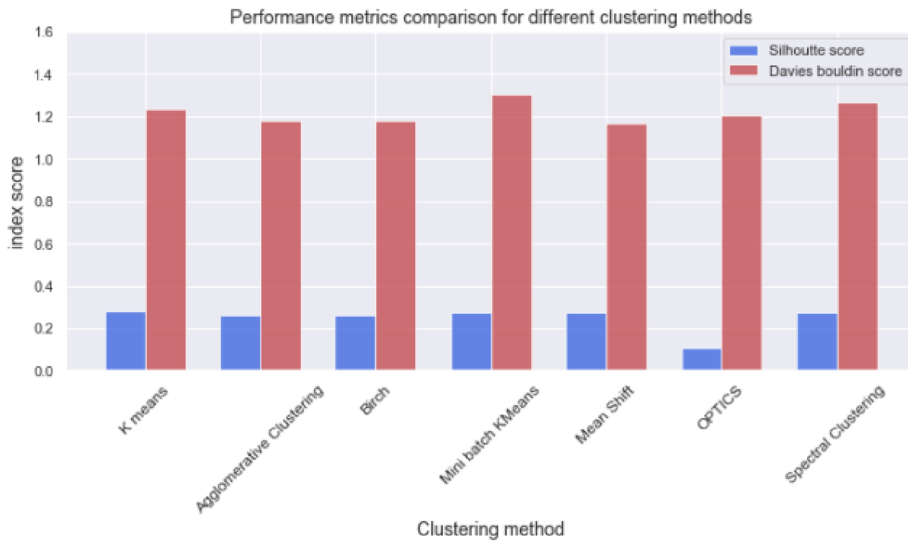

Figure 4.8: *Silhouette scores and Davies-Bouldin index for different clustering methods applied to the neighbourhoods of the Hague*

Figure 4.8 shows the Silhouette scores and Davies-Bouldin index for different clustering algorithms when applied to the neighbourhoods of the Hague. The optimal number of clusters for each algorithm was chosen such that the number of clusters for each method maximized the Silhouette score for that method. As mentioned earlier, higher the Silhouette score and lower the Davies-Bouldin index is, better the clustering algorithm is. There is often a trade off between higher Silhouette score and lower Davies-Bouldin index. OPTICS clustering algorithm has very low Silhouette score whereas mini batch K means algorithm has very high Davies-bouldin score. Thus,we decided to eliminate these 2 algorithms for further analysis. Of the remaining 5 algorithms, K means has a slightly higher Silhouette score compared to the other algorithms and the mean shift algorithm has the lowest Davies-Bouldin index. The main issue with mean shift algorithm is that it divided the neighbourhoods into only 2 clusters. Furthermore, the division into clusters is such that the first cluster contains all the nieghbourhoods except Vlietzoom east and Vlietzoom west and the second cluster contains only the neighbourhoods of Vlietzoom east and Vlietzoom west. Therefore, even though mean shift algorithm has a relatively high Silhouette score and the lowest Davies-Bouldin index, the neighbourhood clusters obtained using mean shift do not provide any practical inference in terms of policy interventions and decision making. Thus, mean shift algorithm is also eliminated. Among the remaining algorithms, the Silhouette scores and Davies-Bouldin index are very similar.All other algorithms except the K means clustering have one dominant cluster which accounts for almost half of the neighbourhoods of the Hague and one cluster with very small number of neighbourhoods. Thus, even if the neighbourhoods have different socioeconomic characteristics, they may be grouped together in a singular big cluster. Owing to these considerations, K means clustering algorithm is chosen as the optimal algorithm for further analysis. The exact distribution of neighbourhoods of the Hague into different clusters through different methods can be found in appendix appendix A.4.1 fig. A.2.

K means clustering algorithm starts with a group of randomly selected k centroids in the n dimensional space of $m \times n$ input vector (m are the number of points in data set and each data point has n attributes). The algorithm performs iterative calculations to optimize the centroid so that the euclidean sum of m points from their assigned centroid is minimized. The number of clusters k are generally determined using elbow method. In the elbow method, the number of clusters are increased iteratively and the sum squared of distances from the centroids is plotted against the number of clusters. The number of cluster k is chosen at the elbow of the plot such that increasing the clusters further results in a minimal decrease in sum squared of distances. The elbow method is applied to the neighbourhoods of the Hague for the 8 indicators mentioned above to determine the optimal number of clusters. Figure 4.9 show the plot for number of clusters versus the sum squared of errors for socio-economic indicators of the neighbourhoods of the Hague. For a smooth and continuous data set, it is often difficult to obtain a clear elbow which is also one of the main disadvantages of the method. At around k=5, the sum squared of error is seen to converge and further increasing the number of cluster also adds complexity to analyzing the environmental impacts. Therefore, 5 clusters are chosen to proceed with the analysis. The other main disadvantage of using K means clustering is that in case of outliers in the data set, the centroid can be dragged to the outlier value. It is recommended to remove the outliers from the data set before clustering.

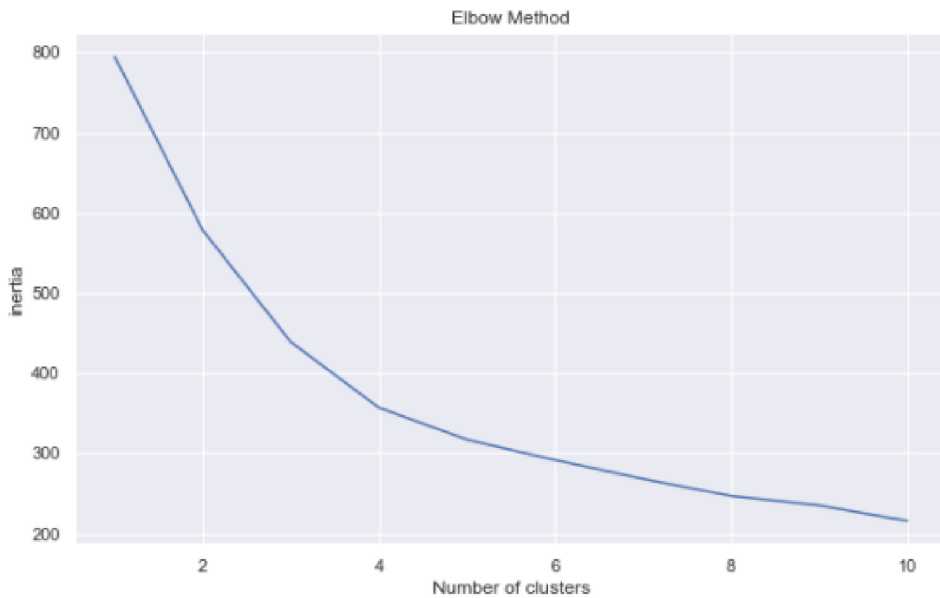

Figure 4.9: *Plot of sum squared of error vs number of clusters for socio-economic indicators of the Hague*

Socioeconomic indicator	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
Defining features	Young, highly active middle class households using a lot of cars	Relatively older, moderately educated, middle class households with average car use	Middle aged, rich, highly educated households with high home and car ownership	Low income, low educated households with high degree of unemployment	Older, middle class single person households with very low car use
Age (0-40) years(%)	67.5	42.2	49.69	58.46	34.8
Income(€/year)	27962	27081	48355	16266	26393
Tertiary Education(%)	32.75	34.36	60.7	13	39.66
Employment rate(%)	66.6	58.38	57.2	47.7	55.1
Expat population(%)	11.4	19.44	29.5	13.1	23.1
One person households(%)	23.22	47.2	45.8	48.4	62.7
Rental houses(%)	34.9	41.4	35.2	74.8	71.1
Number of cars per household	1.242	0.765	0.987	0.566	0.463

Table 4.1: Average socioeconomic indicators of the neighbourhoods in 5 clusters

Table 4.1 shows the centroid values of indicators for the 5 clusters of neighbourhoods along with the defining characteristics for each cluster. Further information on the neighbourhods present in each cluster can be found in appendix appendix A.4.2.Figure 4.10 shows the neighbourhoods of the Hague and their allocated clusters. The neighbourhoods with moderately higher standards of living represented by cluster 2 and 3 are along the northern and western parts of the Hague whereas the neighbourhoods with relatively lower standards of living are present along the eastern and southern parts of the Hague. It is also interesting to see that neighbourhoods in similar cluster are located geographically close to each other barring a few exceptions. This also shows that the clustering algorithm and socioeconomic indicators chosen to cluster neighbourhoods are accurate since the neighbourhoods with similar socioeconomic characteristics are located closer to each other.

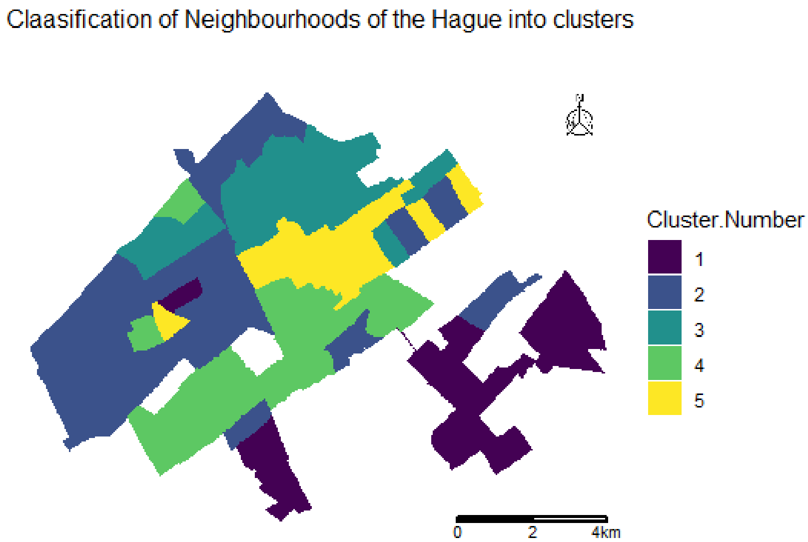

Figure 4.10: *Division of neighbourhoods of the Hague into 5 clusters*

4.2.2 Environmental impacts: clusters

Figure 4.11 shows the GWP per household of different resource use categories for each of the 5 clusters relative to the average GWP per household for the Hague for a specific resource use category. Cluster 1 has the highest GWP in terms of food, mobility, BoP use as well as the total GWP which is 35%, 30%, 45% and 28% compared to the average GWP per household of the Hague respectively. This can primarily be attributed to more members in a household in cluster 1. In cluster 1, only 23% of households are single person households. As a result, the food consumption and BoP use is expected to be higher compared to households belonging to other clusters. Resources like food and BoP often show a strong positive correlation with number of members in a household whereas energy use and waste generation even though increase as the number of members in household increase, the relation might not be strong. As a result,multi member households have a higher GWP due to food and BoP. Another feature of cluster 1 is a very high amount of car ownership along with high activity (employment) rate. As a result, the car use is expected to be high and the corresponding GWP due to mobility is the highest. The combination of more multiperson households and high degree of car ownership results in cluster 1 having the highest GWP per household. Cluster 2, which is characterized by moderate values of most of the features has almost the same GWP per household as the Hague in all the categories. Neighbourhoods in cluster 3 which experience the highest standards of living due to high income, education level along with high degree of home and car ownership would be expected to have high GWP per household. However, it has many one person households and its car ownership level is still significantly less than cluster 1. As a result, GWP due to energy use is the highest for cluster 3 (around 42% more than that of the Hague) but GWP due to mobility is quite low compared to cluster 1. Neighbourhoods in cluster 4 have the lowest income, education level and activity rate have overall high GWP in waste and mobility category. The high GWP in waste could be attributed to low activity rate as a result of which more people stay at home instead of working and thereby resulting in more waste generation. It is also possible that features like young residents, low home ownership rate, low education level whose impact on GWP is not observable directly results in such a behaviour. Finally, cluster 5 is characterized by highest percentage of single person households and lowest car ownership. This factors lead to lowest GWP overall as well as lowest GWP due to mobility. The low GWP due to mobility in neighbourhoods with low car ownership and vice versa shown through the analysis also validates the approach for mining mobility data since it is inherently expected that neighbourhoods with lower car ownership would have a low GWP due to mobility. The absolute GWP per household for each cluste for different resource use categories are shown in fig. A.3 in appendix.

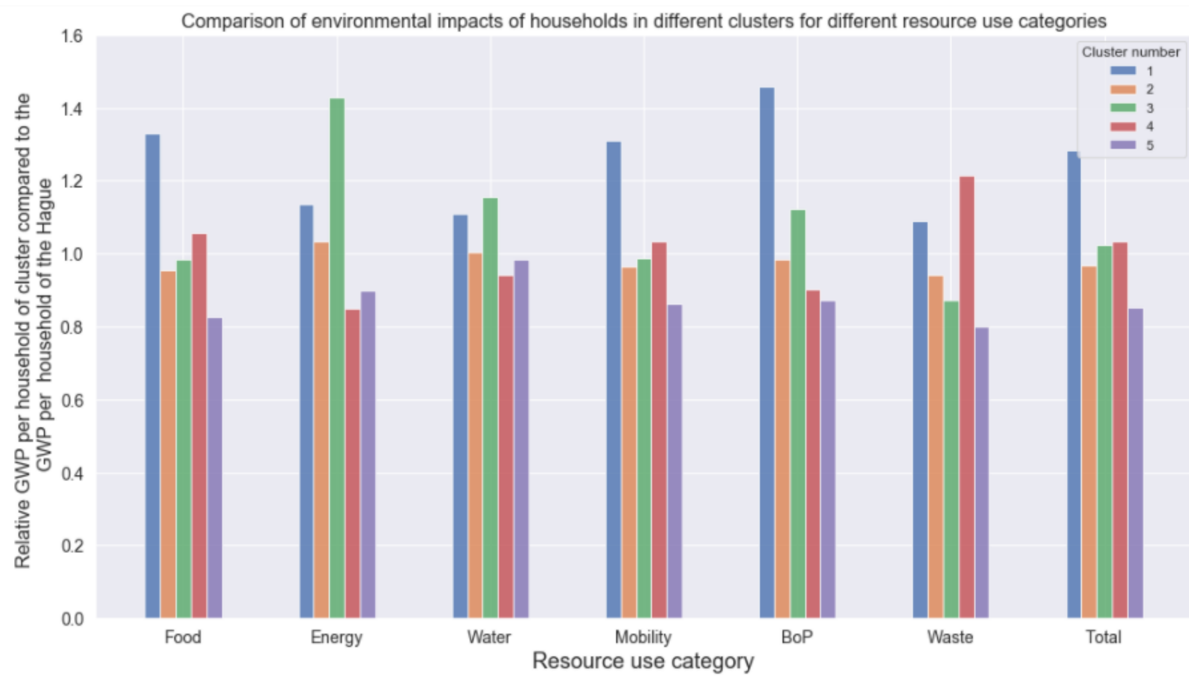

Figure 4.11: *Relative average GWP per household for different clusters compared to the average GWP per household of the Hague for different resource use categories in 2018*

As mentioned earlier, the purpose of clustering neighbourhoods based on their socioeconomic characteristics serve a two fold purpose : Firstly, it provides a basis of allocating environmental impacts to different demographic groups within the city. Secondly, based on the assigned environmental impacts, targetted policy interventions and sustainability campaigns can be used to encourage sustainable behaviour amongst different socioeconomic groups. The exploratory analysis conducted above is quite preliminary in nature and provides a perspective into socioeconomic clustering of neighbourhoods and how they translate into environmental impacts. Further analysis into more archetypes, their consumption habits and corresponding environmental impacts could provide policymakers with more policy reelvant insights into which group can be targetted with a specific policy and how likely they would respond to those policy interventions.

Chapter 5

Policy Analysis

The previous two chapters focussed on computing data related to consumption behaviours of households and quantifying the data to analyse the environmental impacts on a per household and per capita basis. In this chapter, policy interventions that could be implemented by the municipality of the Hague will be analyzed to see their impact on reducing the negative environmental impacts. Specifically, 3 policies related to stimulating the use of green energy (Solar energy), reducing household waste generation and stimulating the use of public transport are analysed. As opposed to sectors like food consumption or BoP consumption, consumption behaviour in sectors like energy, waste and mobility can be modified directly by policy interventions related to these sectors. Food consumption or BoP purchase choices depend on personal preferences of residents of a city and there is not much the municipality can do to affect these choices whereas it can incentivize the residents to travel more by public transport by reducing the fares of tram or take up production of green energy by providing subsidies. While most of the research studies focus on analyzing the environmental impacts of a region, service or a product, they lack in providing concrete evidence based interventions that could reduce the environmental impacts. Thus, we go a step further by analyzing the already implemented policy interventions related to urban sustainability in big cities around the world by applying it to the city of the Hague. The exploratory analysis of policies is not aimed at providing a precise assessment of the performance of policy interventions byt the analysis performed under the presence of uncertain parameters provide insight into the extent to which the policy interventions can reduce the GWP in energy, waste and mobility resource use sectors. The policies related to energy and mobility are analyzed using the XLRM framework which is explained below.

XLRM framework

XLRM framework (Kwakkel, 2016) is used to characterize policy problems in the presence of deep uncertainties. X represents uncertain parameters that are beyond the control of policy makers, L are the policy interventions that can be used to address the problem, R is the quantitative relationship between uncertain parameters X and policy interventions L that result in final metrics M. Thus the combination of uncertainty subspace and policy subspace shape the final metrics M. Using the Exploratory modelling and analysis (EMA) workbench (Kwakkel, 2016) in Python, the XLRM framework can be operationalized by running a number of experiments in the uncertainty and policy subspace to analyze the final performance metric under different combinations of policies and uncertain parameters.

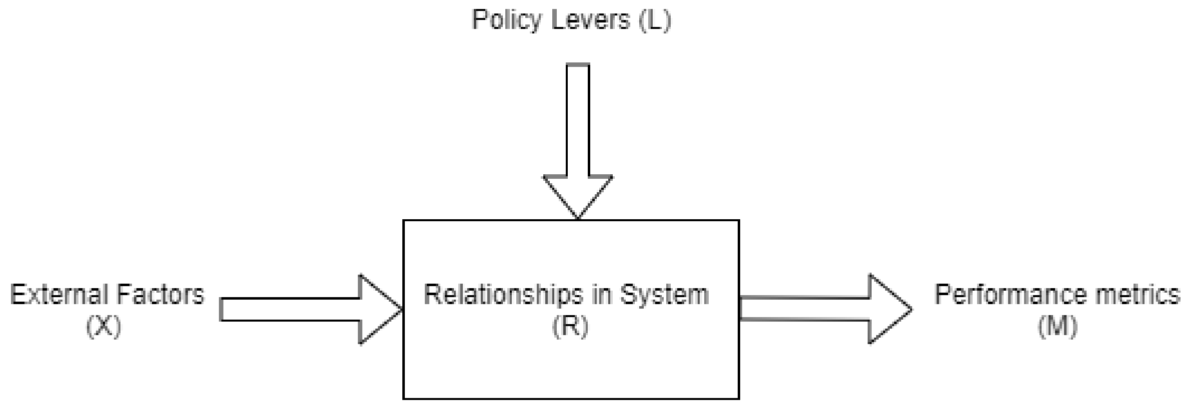

Figure 5.1: *XLRM framework representation (Kwakkel, 2016)*

5.1 Policy 1 : Subsidizing solar energy

In many countries around the world, the national or local governments incentivizes households to produce electricity from solar panels by subsidizing the purchase of solar panels or by purchasing surplus energy directly from the households generating solar electricity. For example, in the UK under the Smart Export Gurantee (SEG), (OFGEM, 2020), small scale low carbon electricity generators receive payments for surplus electricty exported by them to the grid. Similarly, in Gujarat, India, the state government provides a subsidy of upto 40% to households for installing rooftop solar PV. This scheme is aimed at targetting around 1 million households over a period of 3 years (Indianexpress, 2019). The municipality of the Hague can incentivize the residents to produce green electricity through solar energy. A simple exploratory analysis is presented to see the prospects of implementing such a policy and how much of emissions due to non-green electricity can be offset with such a policy. The current exploratory analysis presents a simple model in which municipality provides subsidies to households to install solar panels in their homes. However, it would also be interesting to explore the impact of a 3 way transaction in which the surplus energy generated by households is purchased by utility companies. Furthermore, the current analysis does not take into account seasonal trends since utility companies depend on weather conditions for buying and selling electricity. For example, during summer months, there might be more sunlight hours and correspondingly more electricity can be generated. However, the demand for electricity may not meet excess supply and thus households might not be able to store the excess electricity.

5.1.1 Model formulation

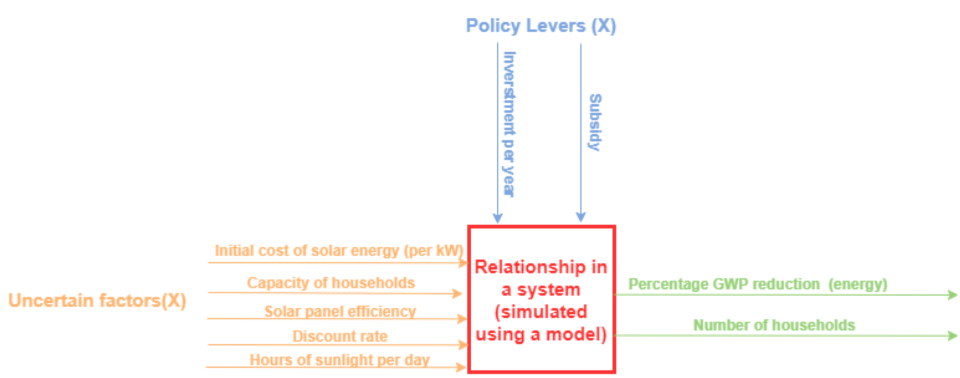

Figure 5.2: *XLRM framework for solar panel policy*

Figure 5.2 shows the XLRM framework for the policy pertaining to subsidizing solar panels for household. Table 5.1 provides a detailed explanation of different variables shown in Figure 5.2 as well as used in the model. A 10 year time frame is considered during which the municipality of the Hague invests a specific amount every year towards providing subsidies to households for purchasing solar panels. Apart from the amount that it invests each year, the municipality can also control the percentage of costs for each panel that it will bear. The combination of this two factors along with the cost per Watt of solar energy directly affects the number of households that will be subsidized through the scheme. The amount of electricity generated by each household depends on the product of capacity of solar panels,efficiency of solar panels and Hours for which sunlight is available. While the capacity of the households does not affect the total electricity generated through solar panels and correspondingly the percentage reduction in emission, it determines the number of households that can benefit from the solar panel subsidy thus ensuring equity in distribution of benefits of the policy. As solar energy becomes cheaper as time progresses (discount factor), more and more households could benefit from subsidy and thus more electricity could be generated with a fixed investment from the municipality. The positive environmental impact of this policy is measured in terms of percentage emission reduction/offset. The difference in emissions due to electricity generated from solar panels and from non-green sources is multiplied with the total electricity generated through solar panels to account for reduction in emissions each year which are then normalized with the total emissions due to non green electricity per household in the Hague in 2018. Thus the final metrics are the percentage reduction in emissions per household per year compared to the emissions in 2018 and the total number of households that can benefit from the subsidy each year.The system can be coneptualized with the following set of equations,

$$P_t = \frac{P_0}{(1+r)^t} \tag{5.1}$$

$$N_t = min(N_1, N_2) \tag{5.2}$$

$$N_1 = \frac{I}{10000 \times S \times C \times P_t} \tag{5.3}$$

$$N_2 = H \times f(S) \times g(C, P_t) \tag{5.4}$$

$$E_t = \frac{365 \times N_t \times C \times \eta \times h_{sunlight}}{H} \tag{5.5}$$

$$Q_t = 100 \times \frac{E_t \times (GWP_{nonrenewable} - GWP_{solar})}{GWP_{household}} \tag{5.6}$$

where $\mathrm{P_t}$ is the price of solar energy in year t, r is the discount rate, $\mathrm{P_0}$ is the initial cost of solar energy, $\mathrm{N_t}$ is the number of households that benefit from the subsidy, $\mathrm{N_1}$ is the maximum number of households that can benefit from the subsidy which is a function of I,the investment by the municipality each year, S, the percentage subsidy provided by the municipality , C, the capacity of solar panels and $\mathrm{P_t}$. Thus $\mathrm{N_1}$ represents the supply of subsidy. $\mathrm{N_2}$ are the number of households that are interested in installing solar panels through the subsidy scheme. Thus, the number of houses $\mathrm{N_t}$ benefitting from subsidy in year t is the minimum of $\mathrm{N_1}$ and $\mathrm{N_2}$. $\mathrm{E_t}$ is the energy generated by solar panels for each household in the Hague which is the product of , η the efficiency of solar panels, $\mathrm{h_{sunlight}}$ the number of hours of sunlight everyday, the capacity C and the numberof households that are benefitted from the policy over H,the total number of households in the Hague. $\mathrm{GWP_{nonrenewable}}$ is the GWP of non renewable electricity, $\mathrm{GWP_{solar}}$ is the GWP of electricity generated by solar panels and $\mathrm{GWP_{household}}$ is the net GWP per household due to use of nonrenewable electricity in the Hague and $\mathrm{Q_t}$ is the percentage reduction in GWP in the energy use sector.

N_2 the number of house who want to avail the benefit of subsidy policy and thus represent the demand and it is dependent on S, the subsidy and the price of solar panel which depends on the cost per kW of solar energy and the capacity of solar panels. Both the functions are modelled using a logarithmic function such that all households want to avail solar panel subsidy when subsidy rate is 100% (practically free solar panels) and only 20% households want to install solar panels when there is no subsidy. Smilarly, of the households that are interested in installing solar panels, 50% house would install solar panels irrespective of the cost and the remaining 50% would install it depending on the cost of the solar panels (modelled logarithmically) as shown in eq. (5.7) and eq. (5.8). The parameters of 0.2 and 0.8 relating to minimum demands are chosen just based on assumption and they could vary. Table 5.1 shows the different model parameters and their ranges.

$$f(S) = 0.2 + 0.8 \times \ln(1 + 1.718S) \tag{5.7}$$

$$g(C, P_t) = 0.5 + 0.5 \times \ln(1 + 1.718(\frac{C_{min} \times P_{t,min}}{C \times P_t})) \tag{5.8}$$

Variable	Explanation	Range	Unit	Source
Initial cost of solar energy(X)	Cost of solar energy is not measured per panel. Rather, the cost of panel is directly proportional to its capacity. So, the cost of a panel is measured in terms of cost per watt	[0.5,2]	€/W	http://solarcellcentral.com/cost_page.html
Capacity of household(X)	Capacity of the solar panel is the maximum power that can be generated by a solar panel. It depends directly on the surface area of panel	[1,5]	kW	https://www.yesenergysolutions.co.uk/advice/how-much-energy-solar-panels-produce-home
Efficiency(X)	Efficiency of Solar panels depend on the type of Silicon used in the panels	[0.15,0.2]	fraction	https://www.greenmatch.co.uk/blog/2014/11/how-efficient-are-solar-panels#:~:text=While%20solar%20panel%20efficiency%20is,is%20measured%20under%20laboratory%20conditions.
Hours of sunlight(X)	The number of hours per day sunlight is available. It is different from daylight hours since in cloudy weather, there is no sunlight	[5,10]	hours/ day	https://www.currentresults.com/Weather/Netherlands/sunshine-annual-average.php
Discount rate for solar energy(X)	As technology progresses, solar energy becomes cheaper. Discount rate is the amount by which price of solar energy decreases every year	[0.03,0.07]	Fraction	https://news.energysage.com/solar-panel-efficiency-cost-over-time/
Subsidy(L)	The fraction of cost for each Solar panel that is borne by the municipality	[0.2,0.6]	Fraction	
Investment per year(L)	The amount of money that municipality invests in provinding solar panel subsidies every year	$[10^6, 10^7]$	€/year	
Percentage emission reduction(M)	The percentage of emissions due to energy use that offset on account of Solar panel use		%	
Number of households benefitted(M)	Number of households that benefit from the subsidy		%	

Table 5.1: Description of variables in the Solar panel model

5.1.2 Results

The Python based model is analyzed using EMA (Exploratory modelling and Analysis) workbench. Firstly 4 policy levers are chosen from the policy subspace and the model is run for multiple uncertain scenarios. This 4 policy levers represent extreme values of the two set of policy levers. In policy 1, the subsidy is set at 20% and the municipality invests 1 million €per year for a period of 10 years. In policy

2, the municipality invests 10 million €per year while subsidy rate stays constant at 20%. In policy 3, the municipality invests 1 million €every year while subsidy is set at 60% and in policy 4, the municipality invests 10 million €per year while providing subsidy at 60%.

Figure 5.3 shows the boxplot for the performance of 4 policies under a number of uncertain scenarios. Policies 2 and 4 are the most effective at both reducing the GWP due to energy and increasing the number of households with solar panels. On an average, around 9% and 8% reduction in GWP due to energy can be achieved with policy 2 and 4 respectively and in the best case a reduction of 20% with policy 2 and 25% with policy 4 can be achieved. In terms of number of households that would be able to take advantage of solar panel subsidies, around 7000 households can take advantage of the subsidies under both the policies. Clearly, policies 2 and 4 outperform policies 1 and 3. The obvious reason for this is the high investments by the municipality each year under policies 2 and 4. Policies 1 and 3 are ten times cheaper compared to policies 2 and 4. Policy 1 is still able to achieve around 3% reduction in GWP emissions every year. Thus, policy 1 with low investments and low subsidies is the most price efficient though not the best performing policy. It is also interesting to note that under the same investment amount by the municipality, lower subsidies achieve a higher reduction in GWP and more households participating in the subsidy scheme. This is because at a lower subsidy rate, even though less number of households are willing to participate in the scheme, all the households that would like to receive subsidy benefit are able to do so because the municipality has more spots for providing subsidy whereas at a higher subsidy rate, even though many households would like to participate in the scheme, the municipality can provide subsidies only to a limited number of households. Thus, when it is assumed that the residents are less sensitive to subsidies and more willing to install solar panels even if they get lower subsidies, the combination of high investment and low subsidy policy (policy 2) is the best alternative.

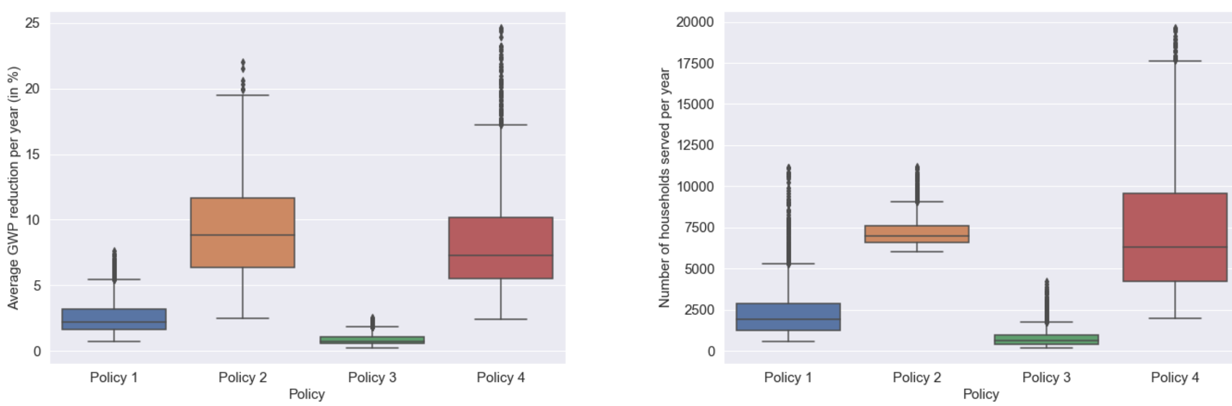

Figure 5.3: *Boxplot showing the performance of subsidy policies under different combination of uncertain parameters: a)average GWP reduction per year (in %)* b)Number of households served

While fig. 5.3 shows the behaviour of policies for different values of policy variables and provides comparison of different policies, it is also useful to understand the relative importance of different input variables (X and L) to understand which variables have the largest impact on final outcome. Figure 5.4 show the feature scores of different input variables on the final metrics (M) of GWP reduction and number of households benefitted from the subsidy. As expected, the investment by the municipality has the largest impact on the percentage reduction in emissions followed by the initial cost of solar power. The total impact of policy levers (investment by municipality and subsidy rate) is around 60% in GWP reductions. While, the initial cost per kW is an uncertain parameter, the municipality can buy cheaper but low quality solar panels. The potential procurement mechanism is beyond the scope of the study and thus it is considered as uncertain factor. The number of households depend equally on the capacity of solar panels and investment by municipality. Capacity depends on the surface area of solar panels that can be installed on rooftops. While the factor does not have much impact on GWP reduction, the number of households served are strongly impacted by capacity since panels with higher capacity are expensive.

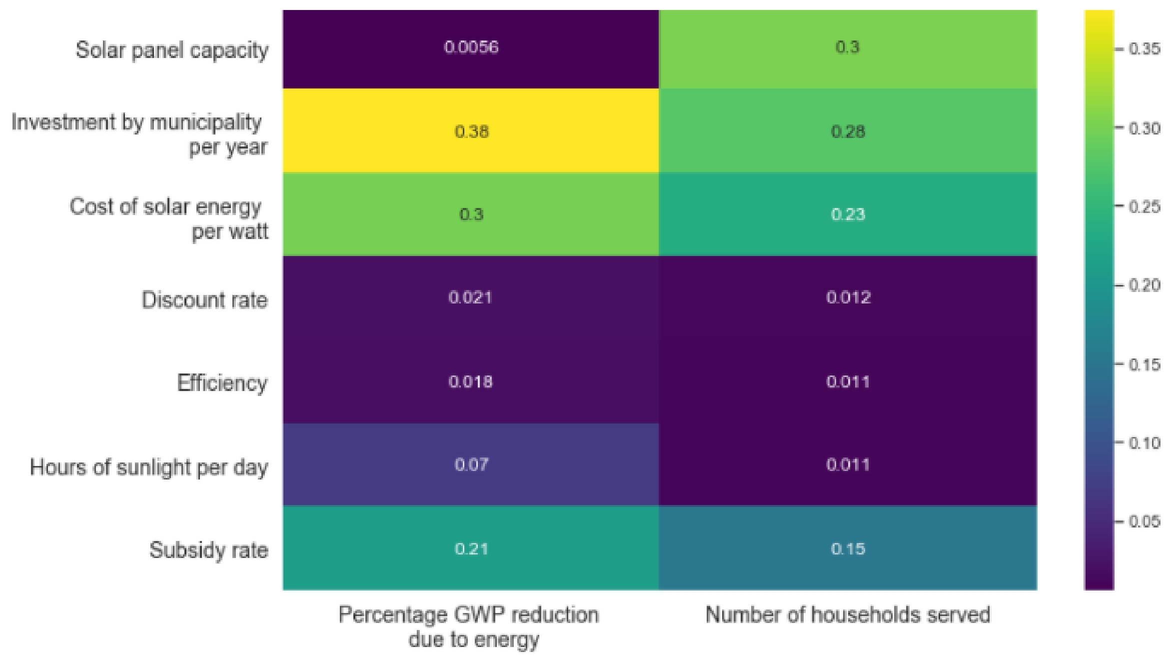

Figure 5.4: *Feature score table of different inputs(X and L) correspondng to GWP reduction percentage and number of households benefitted (M)*

The feature scores for different variables show their relative importance in determining the value of final metrics. With the help of scenario discovery, it is possible to determine the range of these input variables that can give desired values of outputs. The aim of scenario discovery is to identify the scenarios in which worst or best outcomes for final metrics occur. Using Patient rule induction method (PRIM) (Shokri et al., 2018),subspace is partitioned to identify the value of uncertain parameters and policy levers in which the desirable or undesirable outcomes occur. For the case of solar panel subsidy, we perform scenario discovery for 4 cases: 1)Top 10 percentile of GWP reduction 2)Bottom 10 percentile of GWP reduction 1)Top 10 percentile of number of households served 4)Bottom 10 percentile of households served. The reason for choosing percentiles is that for the current case of scenario discovery, we are interested in the range of values of parameters in uncertainty space and thus policy lever chosen is random. Thus percentile based discovery ensures that values of uncertain parameters in partitioned subspace are not affected by randomness in policy lever.

Figure 5.5a to d show the range of uncertain parameters for worst case of GWP reduction, best case of GWP reduction, worst case of number of households benefitted and best case of number of households benefitted. The features or input uncertain parameters with high scores in fig. 5.4 are translated to their respective ranges in Figure 5.5. The worst cases of GWP reduction occur when the solar panels bought initially are very expensive (1.7 €to 2€per Watt), there is less innovation in PV cells and as a result the price of soar energy does not reduce much (by more than 6%) and finally there are very few sunny days with less than 6 hours of sunlight. The combination of all this factors result in worst performance of GWP reduction. Similarly, in order for the policy to succeed in terms of GWP reduction, it requires moderate reduction in price of solar energy every year by more than 4%, high amount of sunlight(more than 7.5 hours) and initially cheap solar panels. Thus, the two points in scenario subspace are quite opposite in nature. The uncertain factors that have maximum impact on number of households benefitted from the solar panel subsidy are the cost of solar energy and capacity. Very small panels with capacity less than 1.6 kW and cost less than 1€/W result in maximum number of houses receiving the subsidy whereas large panels with capacity more than 4 kW and initial cost more than 1.7€/W result in cases in which a very small number of households are enthusiastic about installing solar panels. While, strictly speaking, it is possible to control both the capacity as well as initial cost of solar energy, there are many other factors which impact them such as the quality of solar panels or efficiency of solar panels. For example, cheaper panels might not be of good quality or larger panels with more capacity have a higher efficiency thus they might be preferred. The interrelation between these uncertain factors is not clear and thus in the current research, both initial cost and capacity of solar panels are considered uncertain parameters.

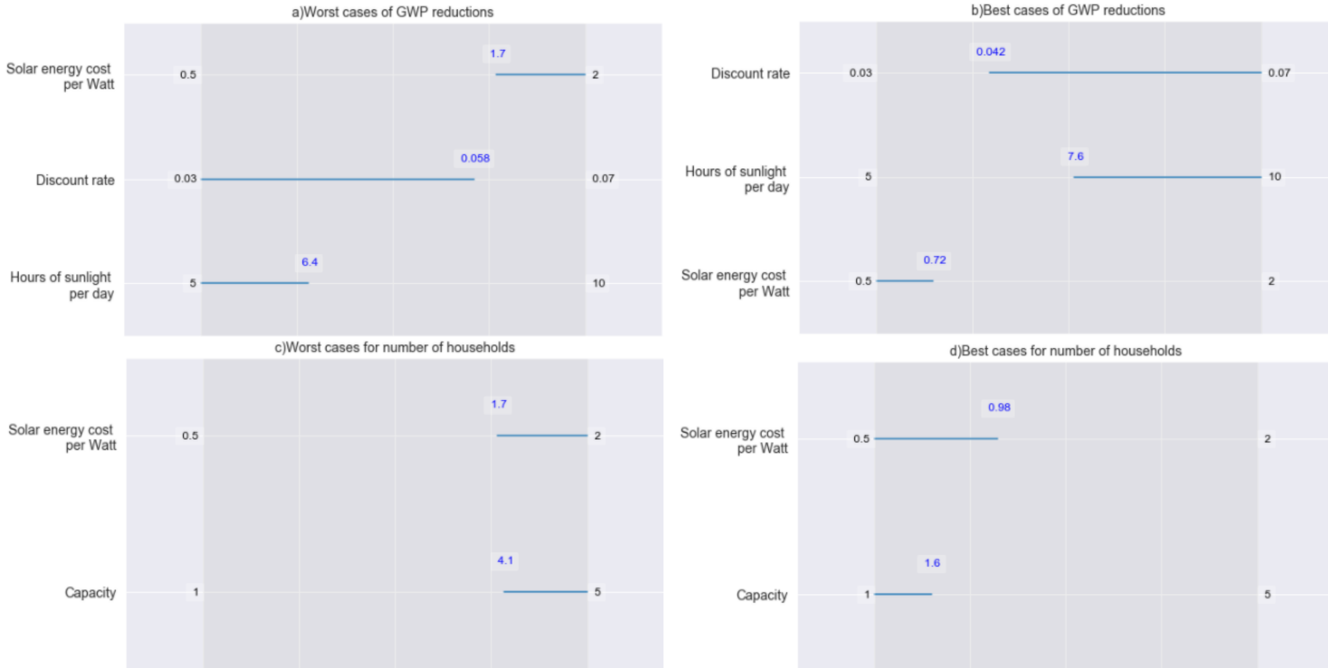

Figure 5.5: *Scenario discovery for : a)Worst cases of GWP reduction b)Best cases of GWP reduction c)Worst cases for number of Households benefitted by subsidy d)Best cases for number of Households benefitted by subsidy*

In conclusion, the most cost efficient policy for the municipality is to invest a small amount every year and provide less subsidies. However, the GWP reduction with such a policy is around 3%. Investing more amount results in GWP reduction of around 10% per year and in the best cases scenario, it even reaches 25%. In terms of uncertain parameters, hours of sunlight available per day and initial cost of solar energy have the highest impact on GWP reduction whereas the capacity of the panels and initial cost of solar panels have the maximum impact on number of households that benefit from the policy.

5.2 Policy 2: Waste charging schemes

Household waste has the third highest emissions among the resource use categories. Many cities around the world, in order to decrease the waste generated by households have introduced a weight based, volume based or frequency based waste charging schemes so that households which generate more waste are subsequently penalized. Cities like Seoul and Taipei have been able to achieve more than 50% reduction in waste with the implementation of quantity based waste charging scheme (Chan, 2013). In the Netherlands, the municipality of Oostzan was the first one to charge residents based on the amount of waste generated by them in 1995 which resulted in significant waste reductions (Linderhof et al., 2000). In the Hague, the municipality charges a fixed amount of 250-300 €per year as afvalstoffenheffing or waste tax depending on number of people in a household. Thus, if the municipality of the Hague shifts to a quantity based waste charging scheme, there could be a big potential to achieve waste reduction. In order to quantify the exact effects of such a policy, the econometric model developed by (Dijkgraaf & Gradus, 2004) is used. The multiple regression model predicts the waste generated by households based on household income, house and flat ownership percentage, whether the house is in a city or village, percentage of foreigners per Dutch person, household size, percentage of population older than 65 years and area of locality per inhabitant. The model is developed based on empirical data collected from over 1300 households in 29 Dutch municipalities. Table 5.2 presents the formulation of the linear regression model used to predict household waste. The main reason for using this regression model is that it has been generated from empirical data and thus provides more accurate data compared to other traditional modelling approaches. Furthermore, since the study was conducted for households in the Netherlands, it reflects similar socioeconomic characteristics as well as cultural beliefs of the people and is likely to provide a good assessment of amount of household waste generated under different policy interventions.

Variable	Explanation	Unit	Coefficient
ln(Waste$_{total}$)	Annual total waste collected in kilograms per inhabitant	kg/year	
UBP$_{weight}$	Dummy = 1 if municipality has a weight-based pricing system	no unit	-0.48
UBP$_{volume}$	Dummy = 1 if municipality has a volume-based pricing system	no unit	-0.07
ln(Retire)	Percentage of inhabitants older than 65 (logged)	%	0.11
ln(Fam size)	Number of inhabitants per household (logged)	#/households	0.24
ln(Foreigner)	Number of non-western foreigners per inhabitant (logged)	#/inhabitants	-0.03
City	Dummy = 1 if municipality has more than 100,000 inhabitants	No unit	-0.05
ln(Density)	Area of municipality per inhabitant	hectare/inhabitants	0.03
Own$_{house}$	Number of houses sold per 1000 inhabitants	#*1000/inhabitants	0.002
Own$_{flat}$	Number of flats sold per 1000 inhabitants	#*1000/inhabitants	-0.007
ln(Income)	Percentage of inhabitant whose income is between 40 and 80 percentile incomes	%	0.24

Table 5.2: Description of variables in the Econometric model to estimate waste generation (Dijkgraaf & Gradus, 2004)

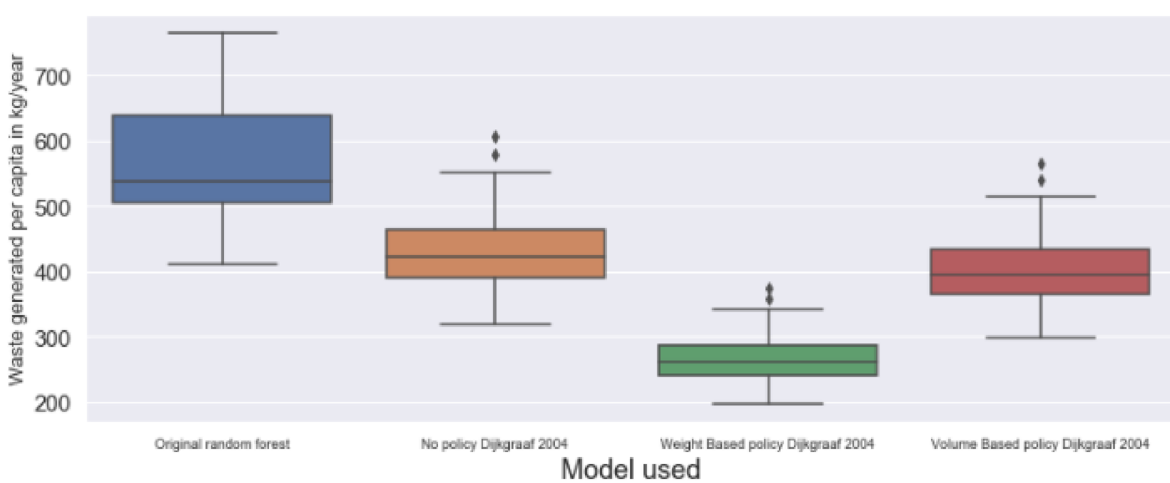

Figure 5.6: *Boxplot showing distribution of waste per capita for different models*

Since Ch 3 already presented methodology related to obtaining data for waste generation by households, it is useful to compare the deviation between the original random forest model and the current multiple linear regression model. Figure 5.6 shows the boxplot comparing the distribution of waste generated per capita for different neighbourhoods in the Hague under different uses of models. The original random forest approach used in Ch 3 predicts on an average 22% higher waste generation compared to (Dijkgraaf & Gradus, 2004) 's model. However, in the model of Dijkgraaf, some variables have been aggregated to a higher spatial level since not all variables in the model were available on the highest level of granularity i.e. Buurts (Neighborhoods). For example, variables relating to density and Ownership of houses and flats were available for the 45 Wijks but not for all 111 Buurts so they have been aggregated accordingly. Similarly, the data for number of foreigners is available only for the entire Hague and not for any of the Wijks or Buurts. Furthermore, the weight based policy scheme seems to be the most effective in reducing waste generated by households. Compared to the weight based scheme, the volume based scheme has little impact in reducing the overall waste generated. The weight based scheme shows overall reduction of 38% and 53% compared to the no policy scheme of Dijkgraaf model and Original random forest model respectively whereas the volume based scheme is shown to reduce waste only by 6.7% and 30% in the corresponding models for no policy scheme of Dijkgaaf and original random forest model.

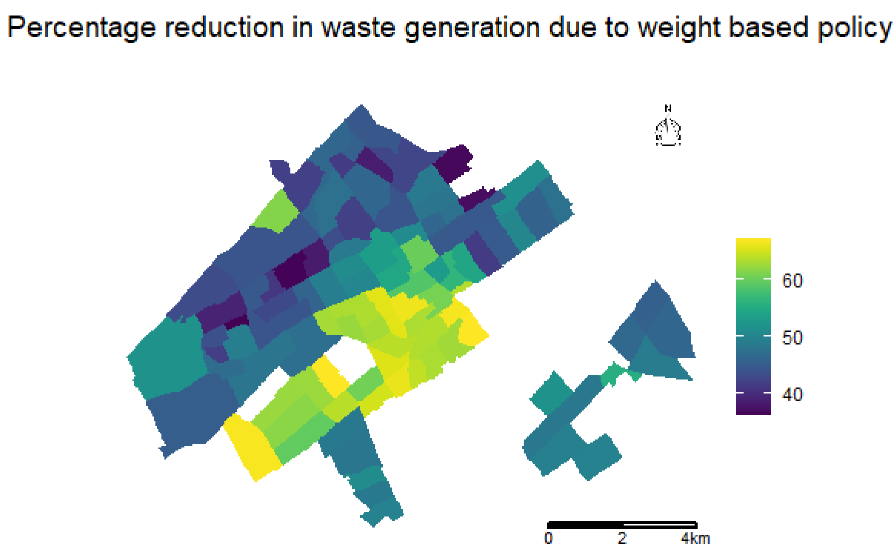

Figure 5.7: *Geospatial representation of percentage reduction in waste achieved in different neighbourhoods of the Hague with a weight based waste charging scheme*

Since the weight based policy shows maximum potential in waste reduction from fig. 5.6, we see the impact of weight based policy on different neighbourhoods of the Hague.Figure 5.7 shows the percentage weight reduction in waste in different neighbourhoods of the Hague for weight based waste charging scheme compared to the original random forest model. Neighbourhoods are able to achieve between 38% to 65% reduction in waste. The high income neighbourhoods in the North and North-West of the Hague are the least affected whereas the neighbourhoods along the centre and east boundary of the Hague achieve maximum reduction in waste generation. The reduction in waste has a strongly negative correlation with the incomes in the neighbourhoods. For example, richer neighbourhoods in the North and North-West show minimum reduction whereas relatively poorer neighbourhoods in the centre and east (belonging to cluster 4 with maximum GWP due to waste as shown in fig. 4.11) show the maximum reduction in waste since poorer households are more severely impacted by the policy. Thus, while the policy might achieve its intended aim of reducing waste generation, there needs to be a governance mechanism which ensures fair and equitable impact of this policy on all sections of the society.

5.3 Policy 3: Stimulating public transport use

From the analysis in Ch4, it is clear that mobility is the main contributor to Environmental impact with car use accounting for more than 40 % of GHG emissions. Furthermore, for the same distance travelled, GHG emissions due to car use are almost 5 times higher compared to GHG emissions due to public transport use. Stimulating the residents to use bus, tram or train as opposed to car could go a long way in reducing the overall GHG emissions and GWP. The Hague has a dense network of tram lines and bus lines, thus accessibility of neighbourhoods to public transport is not an issue. Thus, building a new tram or bus line would not solve the issue of reducing car use. The focus has to be on incentivizing public transport use while discouraging the use of cars. Two specific policy interventions can be implemented that have been tried and tested in cities around the world. The first one is related to reducing the fare of public transport. In many cities around the world, the local or the federal government incentivizes people to take public transport by reducing the fares during a certain period of time. For example, in the Netherlands, the national railway company NS, charges 40% less to passengers using trains during off peak hours. In Luxembourg, from March 2020, public transport (both trains and buses) in the entire country is completely free to reduce congestion and prioritize environment (RTL, 2019). Thus the municipality of the Hague in collaboration with HTM (the public transport company in the Hague that operates tram and buses) can offer to subsidize the public transport. Secondly, a common policy intervention around many cities in the world is to discourage the use of cars by charging exorbitant parking fees. In Copenhagen, the local government, in an effort to reduce congestion due to car use decided to increase the costs of parking in the inner city by 100 times (Kollinger, 2019).

5.3.1 Model formulation

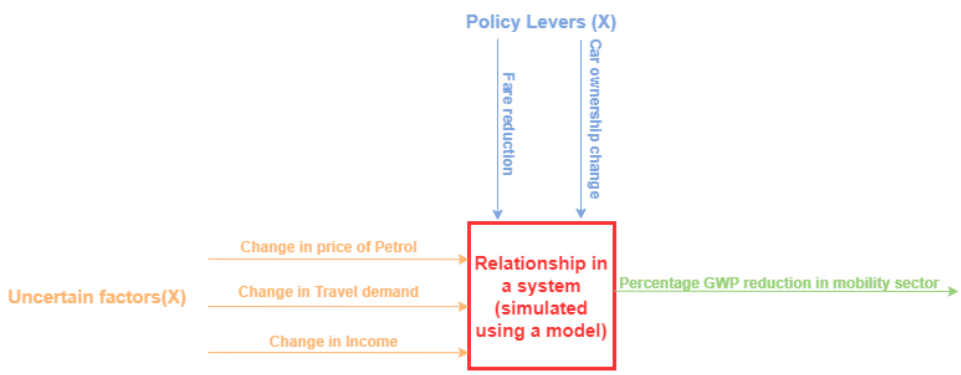

Figure 5.8: *XLRM model for public transportation*

Figure 5.8 shows XLRM model for stimulating public transport use. The policy interventions include reducing fare for public transport by a certain percentage from existing costs and reducing car ownership. While the municipality cannot directly control car ownership, it can indirectly reduce car ownership by charging higher parking fees. Different uncertain factors and policy interventions impacting the change in public transport use are shown in fig. 5.9.Three scenarios are considered in which the municipality charges high, medium and low parking fees. The relation between car ownership and increase in parking fees is such that neighbourhoods with a higher income are least affected by increase in parking fees while poorer neighbourhoods show the highest reduction in car ownership due to increase in parking fees. It is assumed that the poorest neighbourhood in the Hague shows 50%, 33% and 17% reduction in car ownership in cases of high, medium and low increase in parking fees respectively while the richest neighbourhood is unaffected by increase in parking fees in all 3 scenarios. For other neighbourhoods, the trend of car reduction is assumed to be logarithmically decreasing with the increase in income. Figure 5.10 shows the relation between household income and reduction in car ownership under low, medium and high charge of parking scenarios. The sensitivity of public transport use with the change in input variables

(Uncertainties and Policy levers) is modelled using the following equation from (Holmgren, 2013):

$$\Delta \ln(q) = \beta_1 \Delta \ln(F) + \beta_2 \Delta \ln(V) + \beta_3 \Delta \ln(PP) + \beta_4 \Delta \ln(Y) + \beta_5 \Delta \ln(C) \tag{5.9}$$

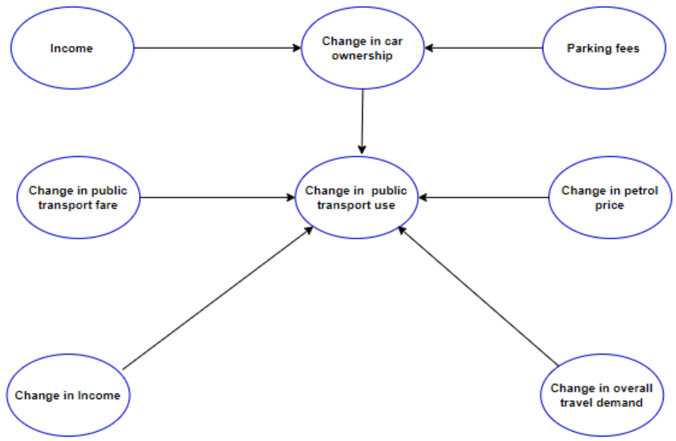

Figure 5.9: *Uncertain Factors and policy levers affecting the total public transport use*

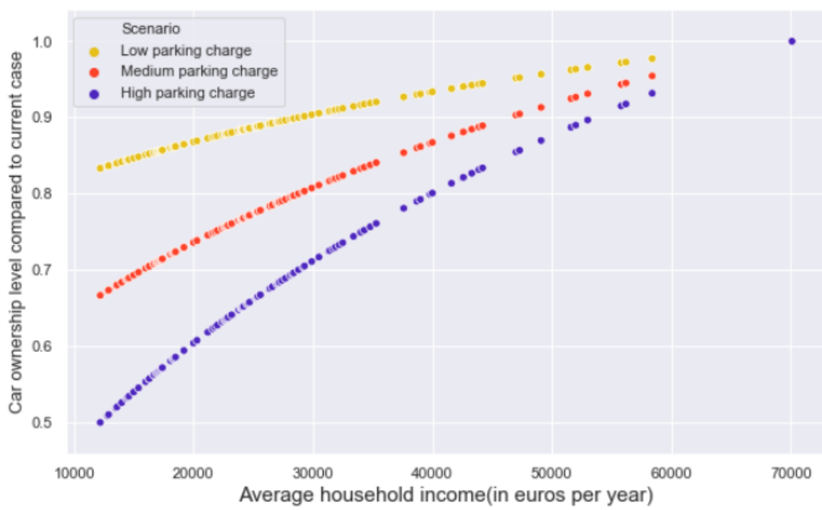

Figure 5.10: *Car ownership reduction and its relation with income per household under different policy scenarios*

Variable	**Range**	**Symbol**	**Coefficient name**	**Coefficient value**
Fractional change in Distance travelled by public transport per capita		Δq		
Fractional change in Public transport fare(L)	[-0.3,-0.05]	ΔF	β_1	-0.4
Fractional change in Travel demand in terms of vehicle kilometres(X)	[0.01,0.2]	ΔV	β_2	0.55
Fractional change in Price of petrol(X)	[-0.3,0.3]	ΔPP	β_3	0.34
Fractional change in Income(X)	[0.03,0.2]	ΔY	β_4	0.34
Fractional change in Car ownership(L)	Depends on policy scenario	ΔC	β_5	-1.37

Table 5.3: Variables of model to predict change in public transport demand (Holmgren, 2013)

Table 5.3 shows the operationalization of the regression model used to predict the change in public transport ridership. EMA workbench is used to analyze the model for different combinations of uncertain parameters and policy levers in each of the neighbourhood. With the change in public transport ridership and overall change in travel demand for each neighbourhood, the new value of car ridership in each neighbourhood can be estimated. The total GWP due to new values of car ridership and public transport are compared to existing GWP values to analyzed the net GWP reduction due to the mobility sector.

5.3.2 Results

Emission reduction

Figure 5.11 shows the fractional reduction in GWP in mobility sector for different values of reduction in public transport fare and parking charge policies for the entire Hague. The model was simulated 100000 times under a fixed scenario of mean value of uncertain parameters. Thus, in this scenario the price of Petrol remains constant while income and overall travel demand increase by around 11.5% and 10.5% respectively. If the price of parking is increased only slightly, there is no reduction in GWP even if the public transit fare is reduced by as large as 30% whereas in the case where public transit fare is reduced only slightly, there is an overall increase of 5% in GWP. When the price of car parking is increased moderately, a reduction of 4% to 9% in GWP can be achieved depending on the reduction in public transit fare. Finally, when the price of parking is increased to a great extent, a GWP reduction between 16% to 23% can be achieved in mobility sector. From Figure 5.11, it is clear that the increasing the car parking charges is more effective compared to reducing the public transport fare. Thus Figure 5.12 shows the reduction in GWP in different neighbourhoods of the Hague for 3 policy scenarios relating to different pricing measures for car parking while holding other parameters constant (ceteris paribus). While the policy seems effective in reducing emissions related to mobility sector, a major drawback is the inequity in the distribution of impact. The policy mainly targets poorer neighbourhoods while richer neighbourhoods are not affected by the increase in car parking.

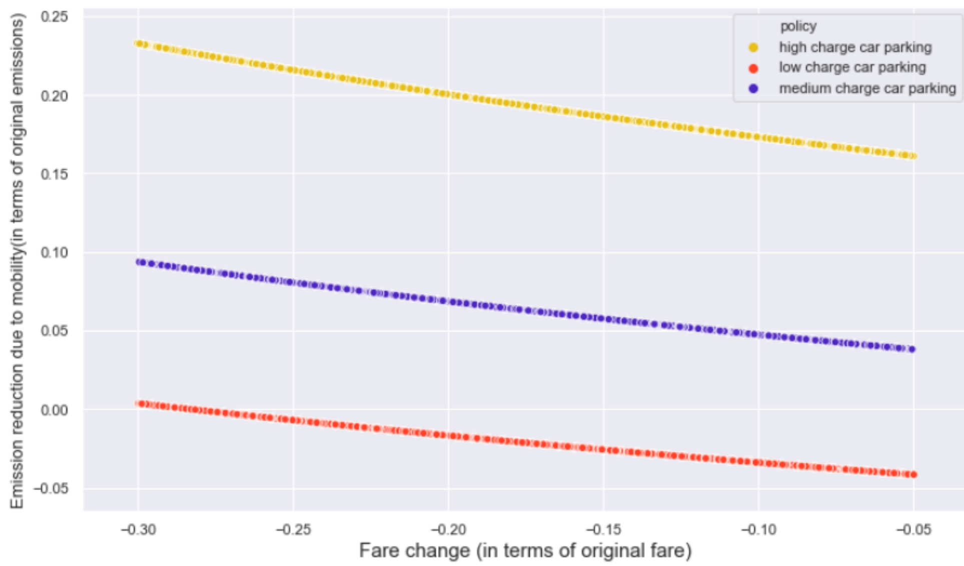

Figure 5.11: *Net emission reduction in the mobility sector under different policy levers for the Hague*

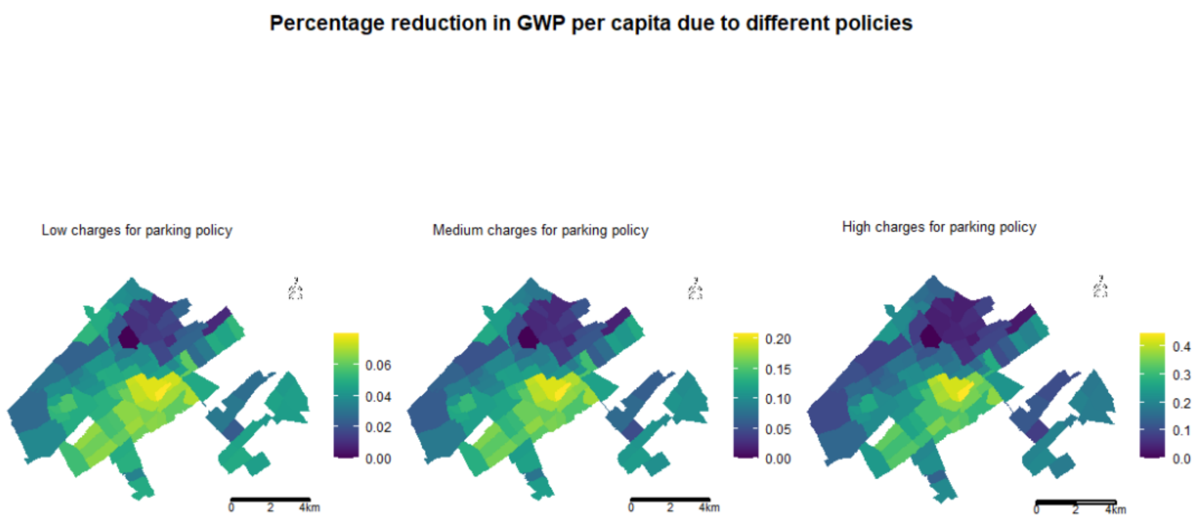

Figure 5.12: *Net emission reduction in the mobility sector for different neighbourhoods of the Hague under different car parking charging policies ceteris paribus*

Scenario Discovery

Similar to the scenario discovery conducted for solar panel subsidy policy, scenario discovery is conducted to identify the worst and best outcomes for different scenarios of uncertain parameters and policy levers. In the current case, worst outcomes are defined as scenarios in which there is an increase in GWP compared to the current case and the best cases are defined as scenarios in which GWP reduces by more than 20% (corresponding to 90 percentile) Figure 5.13 shows the conditions for which the policy will be a failure. When a combination of low increase in parking charges and increase in travel demand by more than 12% occurs there would be a net increase in GWP emissions due to mobility sector. As shown earlier, the policy related to changing the parking fees is more effective compared to the one relating to decrease public transport fare. Thus in the best case scenarios when there is a net reduction of more than 20% in GWP, a high increase in parking fee along with a decrease in public transport fare by more than 15% is needed. In terms of uncertain factors, this would also require a significant increase in petrol prices and an increase in travel demand of less than 9%. Practically, if a short time frame is considered the increase in petrol prices by 9% would have huge global implications in terms of economy and transport and such a steep and permanent increase is unlikely to occur in the near immediate future.

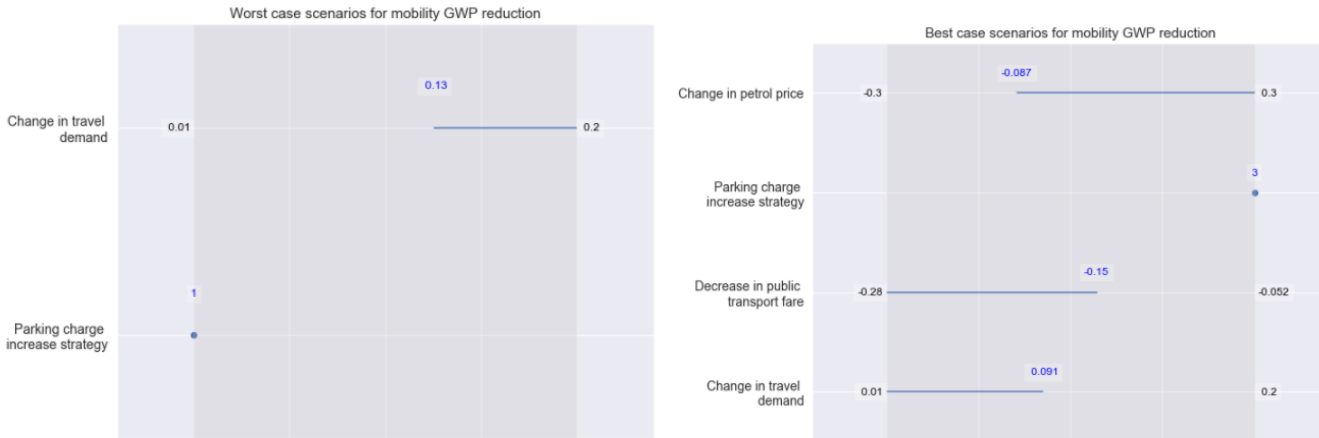

Figure 5.13: *Scenario discovery for : a)Worst cases of GWP reduction b)Best cases of GWP reduction due to mobility policy*

5.4 Policy Analysis: Comparison of interventions and recommendations

There are many factors that affect the feasibility and practical implementation of the analyzed policy interventions. In this section, we aim to qualitatively interpret the advantages and disadvantages associated with the interventions and recommend feasible interventions out of the ones analyzed in the previous sections.

In the Netherlands, Energy related GHG emissions account for nearly 80% of GHG emissions (EEA, 2020). Thus, a large part of environmental policies of the government of the Netherlands are centered on achieving energy transition to renewable sources of energy. However, household energy use is responsible for only a small percentage of these emissions and majority of these emissions occur due to industrial or agricultural activities. In the current study, we analyzed the policy intervention related to solar panel subsidy to stimulate the use of renewable energy by households. The contribution of this policy to overall reduction in GWP achieved is quite less compared to the other two policy interventions related to waste and mobility as observed from the analysis. Apart from potentially less reduction in GWP achievable by solar panel subsidy policy, the uncertain factors are also not favourable for the policy. Firstly, for most parts of the year, the weather in the Netherlands is cloudy and the solar panels can generate electricity only in the presence of sunlight. As seen in fig. 5.5b, maximum reduction in GWP is achieved when there is more than 7.5 hours of sunlight everyday. Thus, this renders the chances for success of this policy low. Secondly, another factor that impacts the reduction in GWP is the discount rate. Discount rate represents the decrease in price of solar power and is dependent on the research and innovation in the field of photovoltaic cells. The innovation of many products follows a S-shaped curve whereby (Kijek, 2015) whereby in the beginning phase, the acceleration in the performance of a product is slow. In the middle phase, there is rapid acceleration in the performance of a product and finally the performance of a product achieves saturation and there is limited improvement in its performance. The research in solar panels has seen rapid acceleration in the 1990s and over the last decade its price has reduced considerably and its expected to decrease in the coming decade. However, the rate of decrease in price decreases with time and thus the discount factor for solar panels is also likely to reduce with time. Lastly, as compared to the other two interventions, solar panel subsidies require a huge amount of investment from the municipality and they achieve quite less reduction in GWP. Thus, overall it would not be feasible to implement the solar panel subsidy policy and policies aimed at achieving energy transition could be better oriented towards industry and other users compared to households.

The other two policy interventions related to reducing waste generation and stimulating public transport use have one main disadvantage. From fig. 5.7 and fig. 5.12, it can be seen that, maximum reduction in waste generation as well car use is achieved in neighbourhoods with lowest income levels. On one hand, these are the also the neighbourhoods that generate the maximum waste and have high car use. However, the policy interventions, irrespective of the households' environmental impacts, have an adverse impact on households with lower income level. There may be a situation in which households which generate a lot of waste or use a lot of car will not be affected by higher waste disposal charge or car parking charges if they have high income. Thus, while the intervention related to solar panel subsidy does not have an inequitable impact on households depending on their income, charging households based on the amount of waste generated by them and car use results in a situation in which lower income households are adversely impacted while higher income households are not impacted even if they generate higher quantity of waste or use more car. It might be difficult to implement the weight based waste charging scheme and the increased car parking charging scheme due to the monetary loss imposed by the policies on the residents of the Hague. However, the potential reduction in GWP that can be achieved with the latter two policy interventions is much higher compared to the solar panel subsidy policy. Furthermore, the additional revenue generated by the weight based weight charging scheme and increased car parking charging scheme can be used to implement other sustainable policies such as providing solar panel subsidies or reducing the fare of public transport in the Hague. Thus, as a first step, the municipality of the Hague can implement the weight based weight charging scheme and increase car parking charging scheme and based on the success of the schemes (revenue generated), the municipality can use the revenue to fund additional interventions related to solar panel subsidies and public transport fare reduction. Finally, between the weight based waste charging scheme and increased car parking charging scheme, in our opinion, the former is a safer choice since it has been implemented in multiple cities around the world and has been able to achieve waste reduction of more than 50% in those cities (current research also showed similar results). While many European cities like Copenhagen have increased the car parking fees, their exact impact on the reduction of car use is not known. Thus, based on prior evidence, implementing weight based waste charging scheme is a better alternative compared to increasing the charges for car parking in the city limits.

Chapter 6

Discussion

The main aim of this research was to systematically quantify and analyze the environmental impacts due to resource consumption by households from a consumption perspective and analyze policy interventions implemented in cities around the world and see to what extent they could reduce the GHG emissions. The research was conducted using a case study for the city of the Hague. However we have tried to make the research reproducible by breaking it down to three main components: Data computation, analysis of environmental impacts and quantitative analysis of policy interventions. This chapter will discuss each of the components considering the results, reproducibility and limitations related to environmental impacts of cities.

6.1 Data Computation framework

One of the major issues faced by researchers while quantifying the environmental impacts of a city is the lack of data available at the local scale. Data related to resource consumption such as food, mobility, water, energy use is often available nationally while data on socioeconomic indicators like income, education, employment is available locally for countries like the Netherlands with a well organized data collection process through surveys. The lack of resource consumption data at the local level presents a barrier to quantify environmental impacts of households but data on their socioeconomic characteristics at the local level presents an opportunity to model the resource consumption of households by linking their socioeconomic characteristics with consumption behaviour. As a first step multiple data sets whose geospatial resolution ranged from the countries in European union to the neighbourhoods of the Hague were chosen. In the second step, either direct models available in literature that were developed using empirical data of Dutch population were applied to the Hague cijfers database or data science models were first built using data sets of lower geospatial resolution and then applied to the neighbourhoods of the Hague to compute their resource consumption behaviour. The combination of different data sets and data science models and methods developed a unique data ecosystem or data toolbox for the city of the Hague, the final output of which was the data related to 6 resource consumption categories for each of the 111 neighbourhoods of the Hague.

While the data ecosystem is specific to the city of the Hague, many elements of it can be easily applied to other European cities and the conceptual data model can be applied to all the Dutch cities since Dutch cities have a similar data collection process. The random forest models built using data on gender, age, employment, education and income level of European countries to predict BoP use and waste can be applied to any European city contingent on data being available related to the predictors mentioned. Demographic clustering method to compute food consumption and mobility patterns can be applied to other major Dutch cities since similar to the Hague cijfers data set, other Dutch cities have their own data sets with data on the same indicators available.

In fig. 6.1, we lay down a general methodology to disaggregate data on resource use from lower geospatial level (country or continents) to higher geospatial level (city or neighbourhood). In our research, we have considered 6 resource use categories : Food, energy, water, mobility, BoP and waste. While this 6 categories account for almost all resource use, their further subdivision may differ from country to country. As a first step, resource use data available at the national level is collected to determine the division of resources into categories and subcategories which determine the final structure of data ecosystem. For a particular resource use whose data at the national level is also available at the local level, the data at the local level is directly chosen for that particular resource use category since direct data at the local level is the most accurate compared to predicting it through other methods. If the data is not available at the local level but if a predictive model is available either at local or even at national level that predict the use of resources based on socioeconomic indicators or other conditions (for example it could be evapotranspiration for water as is the case for Netherlands) and the predictor variables are available at the local level, the predictive model is used to predict the use of resources at local level. For example, this method was used to predict percentage of renewable energy consumption section 3.3.3 and amount of water consumed section 3.3.4 in different neighbourhoods of the Hague. This method has a high predictive accuracy since the model is often fitted based on local level empirical data collected through surveys conducted for a city or country. If a predictive model at local or national level is not available, the next step is to see if a predictive model can be fit based on socioeconomic indicators. The requirements to use this method are that a data set containing data on resource use is available for many sub national regions in the country or for many countries altogether (like EU). Thus, a predictive model is fit based on the data set for resource use categories and socioeconomic indicators at the higher geographic level. After splitting the available data set into training and testing, the model is fit on the training data set and its accuracy is tested on the testing data set. If the fitted model shows high level of accuracy, it implies the model is suitable for predicting the resource consumption at the local level. If the predictor socioeconomic indicators are available at the local level, the model is used to predict the resource consumption at the local level. This method is used because it is possible to validate the model by testing its accuracy. Thus, the model is used only if it has high predictive power. For example this method was used in section 3.3.6 and section 3.3.7 to predict BoP use and waste generation. However, if it is not possible to use this method because the fitted model is not accurate or data related to predictor socioeconomic variables is not available at the local level, the next step is to see if it is possible to apply demographic clustering method as was done in section 3.3.2 and section 3.3.5 to compute food consumption and mobility pattern data respectively. This method requires that data related to resource use is available at the national level but it is split into demographic clusters such as the resource consumption data is available for distinct age groups, genders, education level. If the data on gender distribution, age groups, education level is also available at the local level, the consumption at the local level can be computed by computing the population in each demographic group and taking a population weighted mean of resource use data at the higher level. This method is not robust since the accuracy of this method decreases as the population of a demographic cluster at the local level decreases. If it is not possible to apply demographic clustering, the next step is to see if a predictive model for resource use exists not at the national or local level, but for a specific country other than the country to which the city belongs to. If such a model exists and the input predictor variables for this model are also available at the local level, the model is used to predict resource consumption at the local level. This is one of the least accurate methods of predicting resource use data since the model is not local and used for a different geographic region. As a result, other location related factors are not considered when applying the model to the geographic region for which resource use is being computed. For example, in section 5.3, the model of *Holmgren et.al* (Holmgren, 2013) was applied to the Hague to predict the change in public transport demand even though the model was actually fit based on empirical data in Sweden. Finally, if such a predictive model at the level of other country is also not available, the last step is to simply use national level data for resource consumption at the local level since there is no other choice.

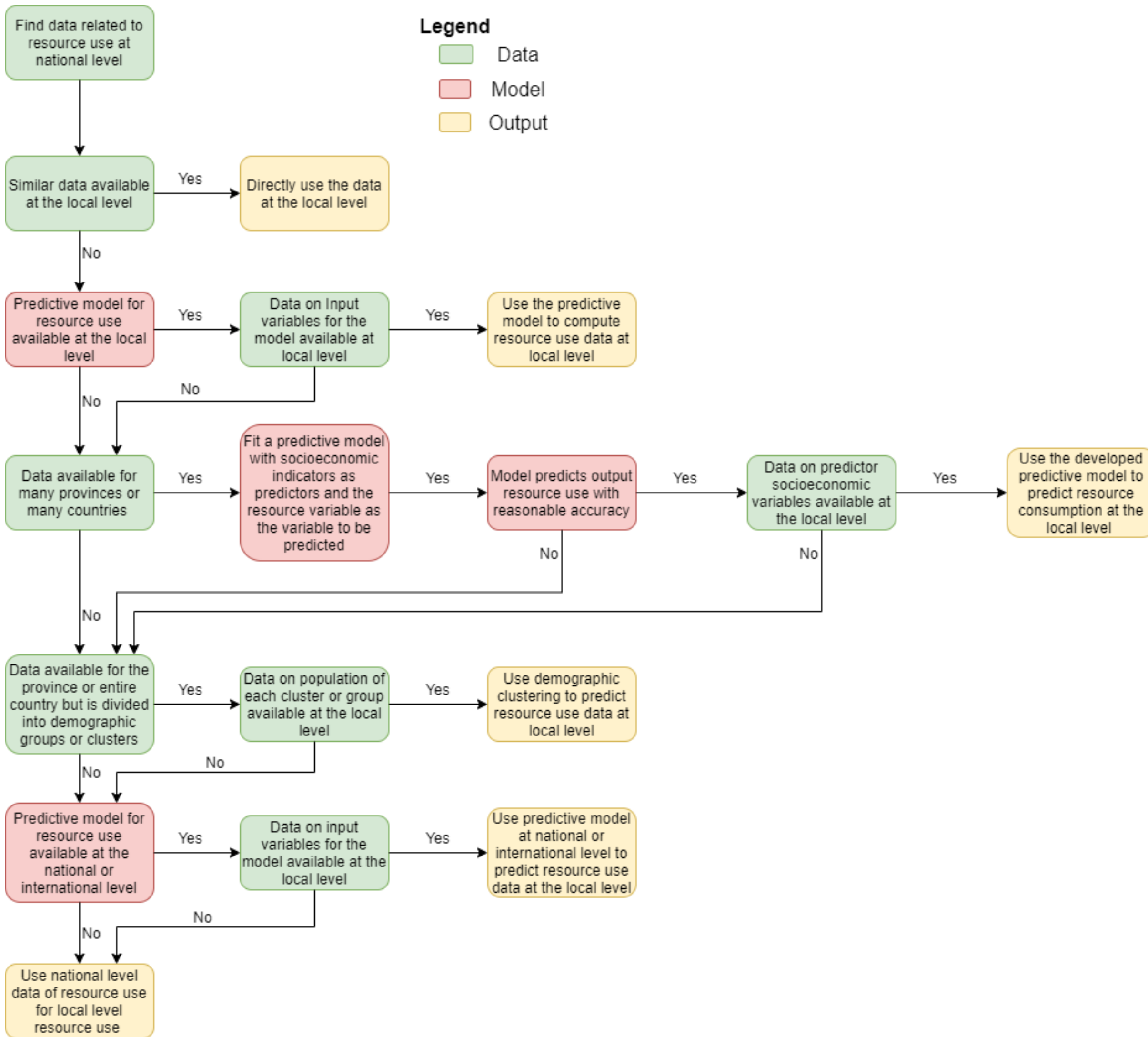

Figure 6.1: *Methodology to disaggregate national level data of resource consumption to local level*

6.2 Environmental impacts of household consumption

The resource consumption data for different resource use categories is quantified into environmental impacts using the Life Cycle Assessment (LCA) method. While the environmental impact can be quantified using a variety of impact categories, the most relevant impact category is "Climate change" since the entire research is based on the premise that cities are major contributors to climate change and a methodology must be developed to analyze the climate change impacts of cities. The climate change is measured with Global Warming Potential (GWP) which in simple language is the overall impact of Green house gas (GHG) emissions quantified in terms of CO_2 equivalent. Based on the quantification of environmental impacts of resource use, we found that the GWP per capita for the neighbourhoods of the Hague range between 4.9 tonnes to 6.5 tonnes kg CO_2 equivalent as shown in fig. 4.1 whereas the average for the Netherlands is 9.4 tonnes CO_2 equivalent. The lower value for neighbourhoods of the Hague is mainly on account of ignoring certain sectors and activities like construction sector or residents taking a vacation or dining out. This is done conveniently so as to focus on consumption activities for which direct intervention by decision makers is possible and thus the GHG emissions can be reduced.

Based on the breakdown of GWP into different resource use categories as shown in fig. 4.7, for the Hague, mobility has the highest GWP at 45% followed by food consumption whose GWP is less than half that of mobility. Food is followed by household waste. Even though, the net impact of waste by incinerating it generates heat and thus offsets GHG emissions. This does not mean that generating waste should be encouraged since waste generation requires consumption of other resources. Following waste are energy and BoP which have almost same GWP. Finally, water has a negligible GWP in comparison to other resource use categories. For the environmental impacts related to mobility, there is a strong debate about how should the environmental impacts be allocated to cities for the case of intercity travellers and daily commuters. Many of the residents of the Hague travel outside the Hague everyday for work or other purposes. Thus, the question arises as to whether the environmental impacts due to travel should be allocated to the Hague or to the city they are travelling to. In our study, we used a consumption based approach. Thus, this would essentially mean allocating the environmental impacts to the city in which the travellers reside (in this case, the Hague) since by travelling to other city they are actually generating utility for themselves and getting added value in terms of money or leisure.

In terms of policy interventions, Food and BoP use are mostly driven by personal choices and the actual environmental impacts occur outside the cities in the upstream processes related to production. Thus, policy intervention by decision makers would have little impact on reducing the GWP due to food and BoP. However, campaigns and messages aimed at encouraging sustainable behaviour could be targeted towards specific demographic groups based on their socioeconomic characteristics. Mobility, waste and energy account for 70% of GWP and interventions in this resource categories are likely to yield results since the supply of these resources is controlled by the municipality to a considerable extent.

A major part of the analysis was focussed on which demographic group or which neighbourhoods have the most environmental impact. Two distinct types of analysis were conducted to identify these groups.

Firstly, the GWP per capita for each neighbourhood and each resource use category was translated to GWP per household by taking the product of GWP per capita and household size in the neighbourhood. Neighbourhoods with high GWP per capita are smaller in size whereas the neighbourhoods with low GWP per capita have household size.This can be explained by the fact that as the number of members in a household increases, the efficiency of resource consumption also increases and thus larger households have lower GWP per capita. However, for mobility, this trend does not hold true as shown in fig. 4.6. There is large variance in GWP per household for mobility compared to GWP per capita. This implies that the effect of the increase in household size resulting in efficient use of resources is not profound in mobility sector since if the GWP per capita would have been small for larger households, the variance in GWP per household would have been small too because of the opposing effects of large household size and corresponding low GWP per capita but that is not the case. Practically, it can be interpreted that households with more members find it convenient to use private transport like cars resulting in a relatively higher GWP per capita whereas smaller households prefer to take public transports resulting in lower GWP per capita. This is also something that can be observed realistically since households with children often use more cars in day to day life compared to single person households. For energy use, the variances in GWP per capita and GWP per household are comparable. This implies that neighbourhoods with high GWP per capita have a smaller size and the combination of these two opposing factors result in comparable variance in GWP per household. This is again what one would expect in real life since larger households are expected to be more energy efficient and would not consume twice or thrice as high energy as a single person household. From the box plots for Waste, a conclusive relationship between GWP per capita, GWP per household and household size cannot be drawn.

Secondly, neighbourhoods in the Hague were clustered into 5 clusters based on their socioeconomic indicators and their GWP per household were analyzed for each resource use category. For each cluster, archetypes are developed describing the socioeconomic characteristics of the neighbourhoods. While the first method showed the relation between GWP per capita and GWP per household for different resource use categories, clustering neighbourhoods based on their socioeconomic characteristics is a more detailed way to identify groups that have higher or lower environmental impacts. For example, in fig. 4.11, neighbourhoods which have households with high car ownership, home ownership, moderate level of incomes and high activity rate (cluster 1) are the groups that have maximum environmental impacts in all resource use categories except waste and energy. Probably, this can be attributed to high car ownership and activity rate which requires the residents to travel more. Neighbourhoods with very high income, high level of education and high home ownership can be considered to have a higher standards of living. Correspondingly, this neighbourhoods have high GWP in the energy sector (cluster 3). Neighbourhoods with lower standard of living (low income, low education, low activity rate and more rental houses) were found to have high GWP due to waste generation.

The two approaches discussed above have their own benefits and shortcomings. While the neighbourhoods provide a way to analyze environmental impacts and compare the environmental impacts of different neighbourhoods across different resource use categories, the policy interventions to reduce GHG emissions should be targeted towards actual households. The actual factors responsible for environmental impacts are the socioeconomic characteristics of individual households. The two methods discussed above provide a way of linking environmental impacts with the attributes of households and intervene based on their environmental impacts. The first method linked GWP per capita and household size with GWP per household. Thus, household size is the only factor that is taken into account while analyzing the environmental impacts and analyzing subsequent interventions. As a result, the policy is intended for a wider group (based on just household size) and might not be received well by everyone from the target audience. However, due to larger intended audience, it is easier to implement it compared to a policy which targets only few households. The other approach involved dividing the neighbourhoods into clusters and computing the environmental impacts of each cluster for each resource use category. Based on the environmental impacts and cluster archetypes, potential intervention opportunities to reduce GWP are identified and households in those clusters are targeted through interventions. Since interventions are targeted for specific groups after identifying intervention opportunities, the policies are intended for smaller audience and are more likely to be received well by the intended audience and thus reduce GWP. Since only small groups are targeted, the overall impact towards reducing GWP might be smaller and the policy might be difficult to implement. As an alternative, instead of direct policy intervention, specific demographic groups can be targeted through advertisements to encourage sustainable behaviour just like political microtargeting.

6.3 Recommendations

Following the analysis of environmental impacts due to household resource consumption, policies implemented in cities around the world to reduce GHG emissions were analyzed by considering scenarios in which they are applied to the city of the Hague. The policies were analyzed using the Exploratory analysis and modelling (EMA) workbench. We provide policy recommendation firstly on the use of developed methodology and secondly recommendations based on exploratory policy analysis specific to the Hague.

6.3.1 Recommendations for researchers and analysts

The research started with the goal of quantifying the environmental impacts of a city. The research narrowed down to the environmental impacts due to household consumption. The developed methodology to quantify environmental impact can be primarily used by researchers and analysts in two main ways.

The first main use of the developed methodology could be in tackling issues related to disaggregation of data from lower geospatial resolution to a higher level. As mentioned earlier, the first issue faced by researchers while quantifying the environmental impacts of cities is that data related to resource use is not available on the local level but on a national level. While some countries like the Netherlands provide an option to access microdata of each households, a simple approach that can be used to obtain data at the disaggregated level is required. Thus, a hierarchical methodology to disaggregate national level resource use data to local level is developed and is shown in fig. 6.1. The methodology has been successfully applied for the city of the Hague to develop a data ecosystem linking different methods, models and datasets and using them to compute resource consumption for the neighbourhoods of the Hague. The method is easily replicable to other cities due to its simplicity. Thus researchers working at the intersection of urban and environmental studies could make use of the methodology to compute data related to resource consumption.

The second main use of the methodology is more oriented towards analysis purpose. For a city, in order to draw a pattern between environmental impacts and household characteristics, it is necessary that data for resource consumption in a city be available at the subdivision of multiple geographic units within the city. In the case of the Hague, it was the 111 neighbourhoods of the Hague. The main recommendation for analysts with regard to the second aspect of methodology would be to conduct the analysis based on the policy requirements from policymakers. The first approach with a wide intended audience mainly computes the environmental impacts of neighbourhoods across different resource use categories on a per capita and per household basis and attempts to find relation between household size and GWP per capita and households. Based on this relation, specific interventions could be identified that target neighbourhoods with small household size and large household size. The second approach is more detailed and its intended audience is small. It relies on clustering the neighbourhoods on socioeconomic characteristics and identifying potential intervention opportunities for each clusters of neighbourhoods. Thus, if policymakers are interested in microtargeting policy interventions or advertisements related to sustainability, analysts should follow this approach and create multiple archetypes of population not only on neighbourhood level (since the number of neighbourhoods in a city may not be high), but also on a higher geospatial resolution (like streets or household itself).

6.3.2 Recommendations for policy makers of the Hague

Since the method to analyze environmental impacts was developed with the Hague as the case study, the results could be useful for the Hague in terms of developing policies that could reduce GHG emissions. Based on the analysis, GWP due to mobility, waste and energy (sectors in which intervention by municipality has direct impact), account for 70% of the total GWP of the Hague. The municipality of the Hague has two options in terms of its intended audience for policy interventions, either to directly target households based on their size or to target clusters of neighbourhoods based on their socioeconomic characteristics. For the first case, it was discovered that smaller households had a high GWP due to energy use while larger households had a high GWP due to mobility. If the policymakers want to focus on interventions that consider a wider population without taking into account socioeconomic characteristics, households with smaller sizes are less energy efficient and households with larger household size have higher GWP due to mobility use. If the decision makers at the municipality of the Hague want to implement policies that have a limited target audience, the neighbourhood clustering approach provided some insightful results. In fig. 4.10, neighbourhoods in cluster 3 with relatively high standards of living are found to have high GWP due to energy and neighbourhoods in cluster 4 with relatively lower standards of living have high GWP due to mobility and very high GWP due to BoP.

The analysis identifies the likely intervention opportunities with the more general approach and the approach of clustering neighbourhoods. In our opinion, policies with a wider target audience might be easier to implement but its penetration level may not be high whereas microtargeted intervention for specific neighbourhoods might be difficult to implement but are likely to be received well by the target audience. The policymakers of the Hague are more experienced and aware of the governance and know-how of each approach and thus are better equipped to make the ideal choice for interventions.

Since it is established that Mobility, waste and energy are the major contributors to GWP for the Hague, specific policies that can be implemented were operationalized using the XLRM framework and analyzed under uncertainty. Firstly, in order to stimulate increase in renewable electricity use by households, policy related to offering households subsidy on solar panels was analyzed. The parameters of the demand function were set such that the demand function exhibited low elasticity with respect to price and subsidy rate. The policy showed best performance under high investment by the municipality and low subsidy rate. (situation resulting in high supply of costly solar panels). Overall, as shown in fig. 5.3, around 10% reduction in GWP due to energy for the entire Hague could be achieved with a policy in which the municipality invests a sum of 10 million €every year and provides subsidy at the rate of 20%. However, if the target households for the policies have higher elasticity of demand with respect to subsidy rate and price of solar panel, the same policy might not be successful as the subsidy rates might have to be increased so that the demand can match the supply. Secondly, the effectiveness of quantity based waste charging policy which has been implemented in Oostazan, the Netherlands was tested for the Hague. It was found that weight based weight charging scheme is the most effective compared to a volume based charging scheme or a constant charge for waste. The regression model of (Dijkgraaf & Gradus, 2004) was applied to each neighbourhood of the Hague. From earlier discussion, neighbourhoods in cluster 4 were found to have maximum GWP due to waste and it was observed that weight based charging policy would have maximum impact on neighbourhoods of cluster 4 reducing waste generation by around 55% on an average as shown in fig. 5.7. This presents an ideal intervention opportunity wherein the analysis shows that a particular demographic group which generates higher waste is likely to generate much lower waste under policy intervention. Finally, the third policy intervention is related to decreasing GHG emissions in the mobility sector by increasing the cost of car parking fees and reducing the fare of public transport. Hypothetical scenarios were assumed in which 3 levels of increase in car parking feed lead to changes in car use in each neighbourhood depending on their income. The analysis showed that the most effective way to reduce GWP due to mobility is to increase car fees. Even by reducing the public transport fare by almost 30%, if the car parking fees are not increased, the reduction in GWP is minimal primarily due to increase in travel demand. In fact, the GWP due to mobility showed an increase if the travel demand increased by more than 13% and there is only a slight increase in parking fees. Thus, the overall recommendation is to increase the parking fees considerably so as to reduce the car fees.

To summarize the interventions, the following three policy interventions showed potential to reduce overall GWP (considering all resource use categories) by almost 25% : Firstly, invest 10 million €in providing solar panel subsidies at a rate of around 20% . Secondly, implement a weight based waste charging scheme so that there is a reduction in total amount of waste generated by households. Finally, increase the car parking rates in parking areas throughout the city to reduce car use and reduce public transport fare to stimulate the use of public transport. The interventions related to mobility alone showed potential to reduce GWP by round 30% in the mobility sector and 14% overall.

6.4 Limitations

In this section, we discuss the main limitations of the methodological analysis.

6.4.1 Data

There are two main issues related to the approach used to disaggregate national level data to local level data. The first limitation is related to the data disaggregation method. Demographic clustering was used to compute data related to food consumption and mobility patterns for the neighbourhoods of the Hague. The accuracy of the method increases as the populations of neighbourhoods increases. With a populous neighbourhood, the chances that all demographic cluster are sufficiently represented is high and the actual average consumption of food and mobility use in the neighbourhood clusters converges to the average food consumption and mobility use for the national level data. When the population of neighbourhoods is smaller, such as the Vlietzoom neighbourhood in the Hague which only has 270 residents in total, the population in the 12 demographic clusters would be extremely small and the food consumption or mobility use for a given demographic cluster in Vlietzoom might not be accurately represented by the national level values for the cluster. Thus, the accuracy of demographic clustering method reduces as the neighbourhood population becomes small. In order to compute percentage of renewable energy use and total water use, a logistic regression model (Brounen et al., 2013) and OLS model (Reynaud, 2015) were used which were designed specifically for the Netherlands. However, the logistic regression model did not take into account some important variables such as political ideologies which also influence the adoption of renewable energy by households. For water use, there exist other models which consider a different set of variables to predict water use. A comparative analysis of different models could increase the robustness of the methodology for both energy and water use. Finally, the implicit assumption in data computation related to resource use in neighbourhoods is that resource use is driven by socioeconomic indicators of the neighbourhoods. Though, the approach has been validated for BoP use and waste generation in fig. 3.9, the validation was done on the same data set. A more robust approach would be to build a model in one data set (eg: Eurostat) and validate it on another data set (eg: Hague Cijfers). However, this is not possible because more often, the resource consumption is often available only for one data set.

The quantification of environmental impacts was limited to household consumption as a whole. However there is a strong debate between what constitutes household consumption and what does not? For the current study, household consumption was decided based on the resource use for which good quality data was available. Activities like dining out or flying out for vacations though occur as businesses and directly it is restaurants and airline companies that are responsible for the environmental impact but it is actually the households that enjoy the benefits of such activities and if missing data related to business activities is available, it would be prudent to consider those activities in environmental impacts as well.

6.4.2 Environmental impacts of resource consumption

Ecoinvent 3 database was used to quantify the environmental impacts of resource consumption. However, the database did not have flows relating to all resource uses. Specifically for the case of food and BoP use, miscellaneous products which are not consumed in high quantities like tea, alcoholic beverages, confectionery items were not available in the ecoinvent database. As a result, environmental impacts of such miscellaneous products was quantified by taking their GWP as a proxy for the closest product available in the database. For example, the GWP related to butter was not available in the database so its GWP was taken as equivalent to the GWP of Cheese since both are similar products. Besides missing flows in the database, the environmental impacts of many flows were aggregated at the European level or global level. The environmental impacts for the same type of product may be different in the Netherlands compared to other countries or the global average. Thus, this adds additional uncertainty in the GWP values of some flows.

The approach to cluster neighbourhoods based on their socioeconomic indicators used the K means clustering algorithm which uses the elbow method to decide the optimal number of clusters. For smooth and continuous data, it is often difficult to achieve a well defined elbow. Thus, the optimal number of clusters chosen was 5. The limitation of this approach can be seen in fig. 4.10 in which some of the neighbourhoods are geographically isolated from other neighbourhoods of their clusters.

6.4.3 Policy Analysis

The main limitations in the exploratory policy analysis are tied to its major assumptions. We look at the assumptions for the 3 policy interventions that were analyzed and how they cause a limitation. Firstly, for the intervention related to solar panel subsidy, the elasticity of demand was assumed to be logarithmically dependent on subsidy rate and cost of the panels as modelled in eq. (5.7) and eq. (5.8). The parameters of the model highly influence the results and it was found the model yielded optimal results under high investment, low subsidy policy. This corresponds to low elasticity of demand among the consumers for solar panels. But by tweaking the model parameters, the optimal policy outcome could shift to a high investment, high subsidy rate. Thus, more research is needed on the exact response of potential solar panel customers to price changes in subsidies. For interventions related to related to reducing waste and reducing car use, the main limitations are related to the models employed to analyze the interventions. For the case of waste reduction, the model of (Dijkgraaf & Gradus, 2004) is local and based on empirical evidence for the Netherlands. The model has not been used by other known studies and thus, there is no way to validate the results obtained from the model.

The model of (Holmgren, 2013), used to analyze intervention related to increase in car parking fees and decreasing public transport fare was based on empirical evidence for 8 Swedish cities. Due to local nature of this models, it is quite difficult to adapt them to other locations since the models have the local conditions and local preferences of the population implicitly embedded in the model. In the absence of any other method to analyze the policy interventions for the Hague, this models were chosen. Finally, for the intervention related to increasing car parking fees to reduce car use, hypothetical scenarios were assumed relating to three different levels of increase in car parking. This is because while the relations relating to income level of neighbourhoods, increase in car parking fees and their impacts on car use hold true, the exact quantitative relation is difficult to determine. The policy intervention will be effective only for car use within the Hague. Thus, with the car parking intervention being focussed on the city limits of the Hague, it does not take into consideration the environmental impacts due to intercity car use.

Finally, the interventions related to mobility and waste reduction do not have the temporal dimension in the analysis. The analysis was conducted so that it showed the difference between current GWP due to mobility and waste and the GWP due to mobility and waste if the policies are implemented. However, the outcome often occurs with a delay and not in a discrete step from the current state to final state. Thus, it is important to consider factors related to governance, implementation and adaptation of these interventions and the evolution of reduction in GWP over this period.

Chapter 7

Conclusion

7.1 Revisiting sub research questions

Sub RQ1 : How can household consumption activities by residents of a city be broken down in the form of resource use categories?

We answered this question by breaking down activities by residents that have a direct environmental impact. Activities that contribute indirectly such as postal services, dining out were excluded. The main activities were divided into 6 resource use categories of food consumption, energy use, water use, mobility activities, BoP use and waste generation. While the 6 resource use categories account for most of the activities if not all the activities, a top down approach is required to further subdivide the activities. The subdivision into specific consumption activities is different for different countries depending on the household survey for data collection. For example, in the Netherlands, data is available related to the consumption of 133 food items while in other countries the data might be more aggregated. Similarly, the electricity used by households comes from multiple sources such as coal, oil, wind, solar. Thus, in this step, researchers must identify specific activities related to a resource consumption category using a top down approach and the data available related to household consumption activities on a national level.

Sub RQ2: How can the consumption data on national level along with socioeconomic indicator data on neighbourhoods of city be used to estimate resource consumption by neighbourhoods in a city?

This research question dealt with the disaggregation of national level or European level data to local level. Different data sets, methods and models were identified that could be used to compute data from the national level to the local level. Combining the methods, models and data sets, a conceptual data ecosystem to compute local level resource consumption data for the neighbourhoods of the Hague was created and applied to the Hague. While some models were specific for the Netherlands, we also laid out a detailed hierarchical methodology that could be used for other cities to compute local level data for resource use. To disaggregate national level data to local level data, the first step is to look if a predictive model to compute resource uses based on socioeconomic conditions at the local level is available. If not, a predictive model is built based on national level data and corresponding national level socioeconomic indicators and the model is then applied to the local level. If such a approach is not possible, next step is to look for empirical data at national level and apply demographic clustering at the local level. If it is not possible to apply demographic clustering because of lack of empirical data in form of clusters, the next step is to rely on national level predictive models that might not be specific for the country or the city being studied. Finally, if all the above approaches fail, the only way is to use national level data for per capita resource use at the local level.

Sub RQ3: How can the the data on household consumption be quantified into environmental impacts and analyze environmental impacts at the level of neighbourhoods?

Firstly, the environmental impacts on resource use for the city of the Hague were quantified with a LCA database. When LCA flows corresponding to resource use are not available, LCA scores of proxy products closest to the desired product were taken. The impacts were then analyzed across different resource use categories as well as different neighbourhoods by taking into account their socioeconomic characteristics and average household sizes. Based on the analysis the highest environmental impacts were for mobility (45%), followed by food (20%), waste(15%), BoP and energy (10% each) and water (close to 0%). Further analysis revealed, households with larger sizes were had a higher contribution in GWP due to mobility whereas households with smaller size had higher contributions in GWP due to energy. Lastly, neighbourhoods were also clustered based on their socioeconomic characteristics. This allowed us to link environmental impacts of neighbourhoods with their socioeconomic characteristics and identify worst and best socioeconomic groups in terms of environmental impacts which can be used to spot potential opportunities for interventions and the groups that could benefit from the interventions. Thus, in conclusion, there are two approaches to analyze environmental impacts, one based on the household size and the other one more extensive and based on the relation between socioeconomic indicators and respective environmental impacts.

Sub RQ4: How can commonly implemented urban sustainability policies be modelled as policy interventions and analyzed to see their positive environmental impact?

In this research, three commonly implemented policy interventions that have been implemented for different cities around the world were modelled for the Hague. The model for intervention 1 related to providing solar panel subsidy is generic in nature and can be applied for other cities by changing the model parameters. However, interventions related to waste reduction and stimulating public transport use were modelled using models which had empirical data and thus it limits validating the analysis. Overall, the analysis shows that a reduction of around 25% can be achieved in terms of total GWP per capita. More robust models are needed to analyze policies related to waste and mobility.

The main research question of the study was **How can the environmental impacts due to resource consumption in cities be analyzed from consumption based allocation perspective?** We can now answer the main research question by following a three step procedure of first identifying the activities contributing to environmental impact by a top down approach, then using the data disaggregation methodology to compute resource use data at the local level and finally quantifying the resource use data with LCA. The environmental impacts can then be analyzed for different resource categories, different geographical areas within the city and different demographic groups. The main research question can thus be answered with the first three sub research questions. The last sub research question related to analyzing the impacts of policy interventions provides further insights into potential improvements in environmental impacts with the implementation of policies under uncertain scenarios.

7.2 Future research avenues

The current approach to computing resource consumption data excludes traditional modelling approaches. They could be especially useful for resource for which scarce data is available : Food and Mobility. In the current study, both food and mobility data were obtained using demographic clustering. However, in countries which do not have a well defined data collection procedure, this may not be an option.Thus, commonly used models like discrete choice model (Greene, 2009) for mobility provide a better alternative to existing methods to compute data related to resource consumption. In most cases, input socioeconomic indicator data needed to model the resource consumption use is available. We recommend integrating modelling approaches to the existing data computation framework. Secondly, the developed method was applied to the Hague as a case study. While we provided recommendations on how to compute data at disaggregated level for other cities, future work could focus on applying the data disaggregation methodology and analyze the environmental impacts due to resource use in other European and specifically Dutch cities. Application of current methodology to other cities will not only reveal to what extent the method can be applied to other cities but will also provide a comparison of how different cities stack up against one another in terms of environmental impacts. Finally, we recommend further research into quantifying the impact of policy interventions. The current approach to analyze policy interventions (except solar panel subsidy) relies on local and specific models based on empirical data which reduces the robustness of analysis. Thus, we suggest a more generic and widely accepted approach to model policy interventions related to waste and car use. In this regard, a modelling approach that takes into account the impact of interventions and socioeconomic conditions of different people in the city and links them with the choices of people to study the evolution of environmental impacts could prove useful to see the impacts of intervention on reducing environmental impacts.

7.3 Societal and Scientific contribution

The main objective of the research was to develop a methodology to analyze the environmental impacts of city. The objective has both societal and scientific contribution. The main societal contribution of the work is towards improving urban sustainability and reducing green house gas emissions. The application of the methodology on middle sized European city - the Hague showed the environmental impacts of different regions of the city, environmental impacts due to different categories of resource use and environmental impact linked to socioeconomic conditions of the population. Thus, the analysis helped to identify which regions in the Hague have the maximum environmental impact, which resources contribute the most to environmental impacts and which demographic groups of the population cause maximum environmental impact? Mobility, waste and energy are responsible for 70% of the GWP. This should draw the attention of policymakers and policy analysts in the Hague to design better urban transport system (both public and private), encourage the use of renewable energy and reduction of waste through policy interventions. We also provided a concrete and quantitative analysis of three specific policy interventions under uncertain conditions. This could provide policymakers with a starting point of how different policy interventions perform under uncertain conditions, how different regions of the Hague would be affected by the intervention in terms of their environmental impacts and what other factors should they take into account when implementing the policy interventions.

The scientific contribution of this study can be discussed in terms of the data disaggregation methodology introduced and the contribution to existing research on urban sustainability. This study is one of the few attempts at quantifying and analyzing the environmental impacts of a city. Quantification of environmental impacts of an entire city is a complex endeavour since firstly it requires large amount of data related to use of different resources which is often not from the same source. Secondly, it requires down scaling national level data to local level data which is possible only through a data modelling approach. The previous studies that studied environmental impacts of city often had access to microdata of individual households (Froemelt et al., 2018) which was then use to analyze environmental impacts. Thus, this study is one of the first attempts to use open source data at national level or higher to downscale it to the local level. The method developed for data disaggregation using different data sources, methods and models could really prove useful for researchers studying cities in general but do not have access to quantitative data on the city level. The second scientific contribution of this study is to the broader field of urban sustainability. The developed methodology is simple, easy to implement and provides important insights with regards to environmental impacts of different resources, different groups and different geographical locations and identifies potential points of policy interventions. Despite its shortcomings, it provides a starting point to analyze environmental impacts in a systematic manner with limited access to local level data. In this era of Internet of things (IoT), the quality of data collected is continuously improving both in terms of quality of data as well as data collected for consumption of different resources. This can be increasingly leveraged to further analyze the environmental impacts of city with the proposed methodology and improve the quality of results.

The thesis project is a clear example of an EPA project since it provides a methodological approach to analyze a grand challenge or wicked problem of climate change. Advanced data modelling techniques were used to generate down scaled data and was used to analyze the pressing problem of climate change with a focus on resource consumption in the cities.

7.4 Environmental impacts of cities and beyond

We began by stressing the catastrophic impacts of climate change and how, if unchecked, it could pose a threat to human existence. The satirical poster in fig. 7.1 perfectly summarizes the necessity to act on climate change. A highly contagious virus caused a global pandemic which brought the world on its feet this year. Decision makers at all levels of governance swiftly swept into action and implemented unprecedented interventions to contain the pandemic and without those interventions, the health impact of the pandemic would have been lot worse. Unfortunately, this sense of emergency is hardly seen in acting towards preventing climate change. This is possibly because the actions taken by humans do not have an immediate impact on nature and the path dependence is not observable directly. Though impact of actions by humans on nature occurs with a delay, the impact is much more severe. Thus, climate change is caused by both human actions and human inactions. We aimed at addressing the environmental impacts due to human actions (activities) in the hope that it could contribute towards reducing human inaction (decision making) by both policy makers and normal citizens.

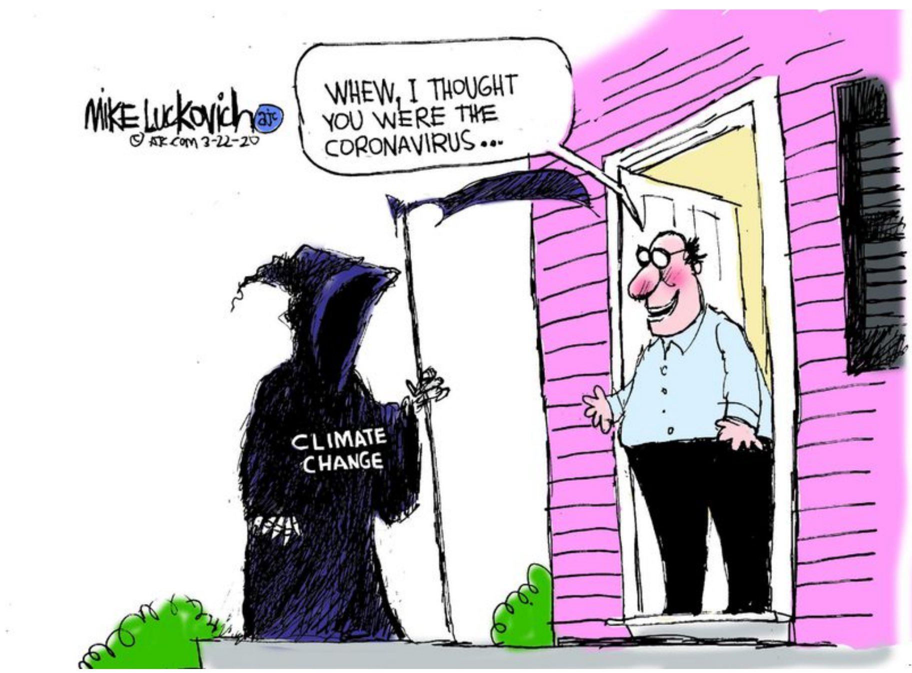

Figure 7.1: *Taken from (Mike Luckovich, 2020)*

Rapid urbanization means that cities have become the center of human activity and are thus responsible for climate change to a big extent. Thus, the scope of this research was narrowed down to cities and since cities are major hubs of consumption (as opposed to production), only consumption based environmental impacts were addressed. The lack of research on quantifying the environmental impacts of cities means that decisionmakers at city level do not have a way of knowing the relative contribution of different resources and different demographic groups to overall environmental impact and thus they have no evidence on what might work and what might not work towards reducing the environmental impact. Thus, we developed a framework to analyze the environmental impacts of any city or neighbourhoods in city in the world (though the framework is likely to provide more accurate results for European and Dutch cities) contingent on basic data related to socioeconomic indicator is available. Quantification is a highly data intensive pursuit. The main barrier to quantifying the environmental impacts of city is the lack of high quality data related to resource use available at the local level of cities. We attempted to remove this barrier with the data disaggregation methodology. Thus, by applying the data disaggregation methodology, resource use data can be computed for any city around the world which can then be quantified to environmental impacts.

The quantified environmental impact of cities could be used by two main stakeholders: Policymakers at the city level and residents of a city through a participatory approach. Cities can disseminate the quantified environmental impacts to its residents in the form of open access dashboards. As discussed in section 6.4.3, the major limitations of policy analysis in this research are the lack of quantifiable relation between policy interventions and their impact on resource use behaviour of residents of city. Policymakers can primarily use the quantified environmental impacts as well as the feedback of residents as an input for generating concrete evidence based policy. Thus, with quantified environmental impacts disseminated to the residents of city, they can inform policymakers how they would respond if specific policy interventions (suggested by policymakers or other fellow residents) are implemented as well as suggest potential policy interventions to the policymakers in the form of citizen initiatives.Environmentally aware residents of a city can also use the disseminated quantified environmental impacts to modify their own resource use behaviour and contribute to reducing the environmental impacts.

Finally, with the advent of sensor technologies, getting access to high volume and high quality data is becoming easier this days. Recently, the UTD19 dataset has been generated (Loder et al., 2019), largest dataset of its kind on traffic generated through sensors in 50 cities over a period of 4 years. This type of innovations could really prove to be gamechanger in the domain of urban data driven decision making. The accuracy of our current methodology could be greatly improved by replacing resource use data for some of the resource use categories with data generated from sensors in the data computation framework.

7.5 Personal reflection

This section discusses the personal development as well as discovery about himself experienced by the author as a result of this research undertaken by him.

7.5.1 Motivation to pursue "Environmental impact of cities"

I pursued my thesis project as a part of internship at Luxembourg Institute of Science and Technology (LIST) in the Environmental Sustainability assessment and circularity unit (SUSTAIN). In my first year of EPA course, I had worked on many modelling and simulation projects and had become fairly proficient with the 3 paradigms of modelling. I wanted to develop holistic skills to tackle societal problems and felt that I lacked data science skills. Therefore, for my thesis I was mainly interested in using data science to tackle societal challenges (not exclusively data science though). I did not have a specific societal challenge in mind and was open to diverse topics. I came across the project at LIST on performing LCA of cities to quantify the environmental impact of cities. On talking with my supervisors at LIST, I learned that a large part of project involved using data science techniques to downscale national level data to local level of cities and then performing LCA on the downscaled data. Thus, I saw this project as a perfect fit since it gave me an opportunity to apply data science on societal challenges alongwith researching on state of the art research on LCA (of cities) independently. Ultimately, though the use of Data science techniques was not extensive, I learned a great deal about methodological aspects of LCA, its application towards sustainability in industry and policy making. I am very grateful for this opportunity as I learn further about advanced techniques in LCA in the next step of my career.

7.5.2 Process: Challenges and Self discovery

In my undergraduation, I studied Mechanical engineering, a very traditional engineering field. As a result, I developed a style of working which involved solving complicated equations, building computational models and performing calculations. I was used to an objective way of working in which I had to come up with a "correct" answer. In the first year of EPA program, students are taught to work with and model complex systems where there is no "correct" answer. Though different from Mechanical engineering, I really enjoyed this way of modelling since it fully utilized my modelling and analytical skills developed during undergraduation along with working on pressing societal problems requiring lots of brainstorming with like minded colleagues. Though I consider myself as a proficient modeller, one area where I lacked skills was communication of results through scientific writing. I also did not make any efforts towards improving this skills in my first year, since, often I was the person who built complex models while contributing minimally to report writing. As a result, my writing skills were not developed. Apart from conducting good quality research contributing towards urban sustainability, I also saw the thesis project as a opportunity for me to develop my writing skills independently and communicate my research with coherently written report. However, it proved to be easier said than done and initially, writing the thesis report proved be a daunting task. In the end, I discovered that writing a good report is a highly intuitive process and is something one learns with practice. Can I say that writing this thesis report has made me a very good writer of policy documents? Maybe not. But I can definitely say that writing this thesis report is a step in that direction and I am confident that with practice, I will develop the skill professionally. In this regard, the initial critical yet constructive feedback from committee members and specific suggestions proved very useful. The hourglass model of writing scientific text (Trivik Verma, 2020) proved to be very useful for me to improve my writing style.

One other problem faced by me during the project is my tendency to try and work on things that are beyond the scope of a 6 month thesis project. Initially, my plan was to include all the industrial activities in the vicinity of cities in addition to activities by residents of a city. Working in a group often results in a brainstorming phase during which such overly ambitious ideas are ruled out. However, the initial proposal was rightfully ruled out by committee members due to time constraint of a master thesis project. As a very result oriented person, I was often concerned about the practical and academic usefulness of my work. Even though I had been warned by one of my supervisors before the starting the project, there were moments when I felt a sense of futility regarding the work and that I am not doing "real research" but simply processing and cleaning data and doing simple numerical calculations using open source data. To be honest, these feelings of "Impostor syndrome" still persist from time to time. However, one thing I have realized is that methodological studies (as opposed to modelling), such as this one are often grounded in simplicity and it takes more collaboration and time to refine them to which I hope to direct my efforts in the next few months. This thesis work also proved to be a great learning experience for me in the field of LCA as well as cities. At the end of this thesis, I can now also confidently say that I can have insightful and thoughtful conversations with urban planners, industrial ecologists and sustainability researchers regarding the benefits and pitfalls of state of the art methods in the aforementioned domains. In the end, based on personal experiences, I would also argue towards making thesis work a larger part of the EPA curriculum like many other TU Delft Masters courses which could allow students to explore their thesis topics in more depth and work towards truly being masters in a particular topic.

Lastly, the research work coincided with the occurrence of a global pandemic : COVID 19. As a result, I had to work from the confines of the four walls of my home. This greatly impacted my efficiency. I discovered that the I require formal settings and the company of colleagues or other students which create an extrinsic motivation for me to work at my full efficiency. The work from home setting also made it difficult to brainstorm with the advisors or seek their feedback on some smaller yet important parts of the project. I believe, currently, I am not suited for the work from home environment at all.

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Appendix A

Appendix

Since the research work is highly data intensive, The appendix contains extra information on different data sources as well as information of flows used in LCI modelling. All the data sources except the Hague cijfers are open source. Finally source code is presented to increase the reproducibility of the work.

A.1 Data Sources

A.1.1 Socioeconomic indicators for different neighbourhoods of the Hague

Indicator	**Minimum**	**Maximum**	**Mean**	**Standard deviation**
Percentage Male	41.48	80.1	49.54	3.87
Percentage Female	19.83	58.31	50.37	3.9
Percentage population 0 to 15 years	2.51	32.12	16.53	5.15
Percentage population 15 to 25 years	3.52	30.96	11.72	4.29
Percentage population 25 to 45 years	10	50.83	28.37	8.73
Percentage population 45 to 65 years	16.21	40	26.3	4.61
Percentage popoulation 65 or older	0.83	54.28	17.16	10.83
Percentage population:Primary education	8	69	30.46	14.39
Percentage population:Secondary education	13	46	34.99	6.41
Percentage population:Tertiary education	6	74	34.38	17.52
Activity rate(in percentage)	36.1	74.5	56.34	8.56
Income per household(€/year)	17200	89900	36475.7	16218.12

Table A.1: Descriptive statistics for socioeconomic indicators of the neighbourhoods of the Hague

A.1.2 Food

The data from Table A.2 and Table A.3 is matched to calculate the food consumption of different types of food for each neighbourhood in the Hague

Geographical region	Netherlands	
Input variables	Sex	Male
		Female
	Age	0-19
		19-79
	Education	Primary
		Secondary
		Tertiary
Output variable	Food consumed (in g/day)	19 main food categories further subdivided into 133 individual food items
Link	https://statline.rivm.nl/portal.html?_la=nl_catalog=RIVMtableId=50038NED_theme=74	

Table A.2: Description of RIVM food consumption database

Geographical region	Neighbourhoods of The Hague	
Variables used	Sex distribution	Number of Male
		Number of Female
	Age distribution	Number of people between ages 0-15
		Number of people between ages 15-25
	Population	Total population of the Neighbourhood
	Education level	Percentage population with Primary education
		Percentage population with Secondary education
		Percentage population with Tertiary education
Link	https://service.openinfo.nl/downloads/informatie-gemeente-den-haag/	

Table A.3: Description of The Hague cijfers database used to calculate food consumption

A.1.3 Energy

Geographical region	Neighbourhoods of The Hague	
Input variables	Sex distribution	Percentage Male
		Percentage Female
	Age distribution	Number of people between ages 60-70
		Number of people more than 70 years of age
	Education level	Percentage population with Tertiary education
	Income level	Average household income per annum
	Gemiddeld elektriciteitsverbruik totaal	Total electricity consumption per year
	Gemiddeld aardgasverbruik totaal	Total gas consumption per year
Output variables	Total electricity consumption from green sources (renewable)	
	Total electricity consumption from non-green sources (non-renewable)	
	Total gas consumption	
Link	https://service.openinfo.nl/downloads/informatie-gemeente-den-haag/	

Table A.4: Description of The Hague cijfers database used to calculate Energy consumption

A.1.4 Water

Geographical region	Neighbourhoods of The Hague	
Input variables	Price of water	Source: https://www.dunea.nl/tarieven-en-voorwaarden
	Household income	Hague cijfers
	Household area	Hague cijfers
	Summer evapotranspiration	Wikipedia
Output variables	Annual water consumption by households	

Table A.5: Description of variables used to calculate annual household water consumption

A.1.5 Mobility

Geographical region	South Holland	
Input variables	Sex	Male
		Female
	Age	6 to 12 years old
		12 to 18 years old
		18 to 25 years old
		25 to 35 years old
		35 to 50 years old
		50 to 65 years old
		65 to 75 years old
		75 years or older
Output variables	Distance travelled by	Car
		Tram /Bus
		Train
Link	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84709NED/table?ts=1595693451720	

Table A.6: Description of CBS mobility behaviour database

Geographical region	Neighbourhoods of The Hague	
Variables used	Sex distribution	Number of Male
		Number of Female
	Age distribution	Number of people between ages 0-15
		Number of people between ages 15-25
	Population	Total population of the Neighbourhood
Link	https://service.openinfo.nl/downloads/informatie-gemeente-den-haag/	

Table A.7: Description of The Hague cijfers database used to compute mobility behaviour

A.1.6 BoP

Geographical region	European Union 28	
Time scale	2010-2019	
Input variables	Sex distribution	Number of males
		Number of Females
	Age distribution	Population aged between 0 to 15 years
		Population aged between 15 to 25 years
		Population aged between 25 to 45 years
		Population aged between 45 to 65 years
		Population older than 65 years
	Education level	Percentage of population with primary education
		Percentage of population with secondary education
		Percentage of population with tertiary education
	Income	Household income per capita
	Activity level	Employment rate for population aged between 18-65
	Amount spent per capita on each of the BoP product categories	6 BoP product categories and amount spent on each of them
	Cost of per unit of BoP product	Cost of per unit of BoP product divided into 6 categories further divided into multiple categories
Output variables	Number of BoP products purchased per capita	Number of BoP products purchased per capita for 6 different BoP product categories
Activity	Fit a random forest model with input variables as predictor and output variables as predicted variables	
Link	https://ec.europa.eu/eurostat/data/database	

Table A.8: Description of data used from Eurostat to fit random forest model

Geographical region	Different Neighbourhoods of the Hague	
Input variables	Sex distribution	Number of males
		Number of Females
	Age distribution	Population aged between 0 to 15 years
		Population aged between 15 to 25 years
		Population aged between 25 to 45 years
		Population aged between 45 to 65 years
		Population older than 65 years
	Education level	Percentage of population with primary education
		Percentage of population with secondary education
		Percentage of population with tertiary education
	Income	Household income per capita
	Activity level	Employment rate for population aged between 18-65
Output variables	Number of BoP products purchased per capita	Number of BoP products purchased per capita for 6 different BoP product categories
Activity	Use the random forest model built earlier and predict BoP use for 6 product categories with input variables as predictors	
Link	https://service.openinfo.nl/downloads/informatie-gemeente-den-haag/	

Table A.9: Hague cijfers data used to predict output BoP use using random forest method

A.1.7 Waste

Geographical region	Different municipalities of the Netherlands	
Input variables	Sex distribution	Number of males
		Number of Females
	Age distribution	Population aged between 0 to 15 years
		Population aged between 15 to 25 years
		Population aged between 25 to 45 years
		Population aged between 45 to 65 years
		Population older than 65 years
	Education level	Percentage of population with primary education
		Percentage of population with secondary education
		Percentage of population with tertiary education
	Income	Household income per capita
	Household size	Average number of people living in a household
Output variables	Household waste per capita generated in each municipality in 2018	
Activity	Build a random forest model with input variables as predictors and out variable as predicted variable	
Link	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83452NED/table?ts=1595727935676	

Table A.10: Input variables to build a predictive model for household waste generation per capita

Geographical region	Different Neighbourhoods of the Hague	
Input variables	Sex distribution	Number of males
		Number of Females
	Age distribution	Population aged between 0 to 15 years
		Population aged between 15 to 25 years
		Population aged between 25 to 45 years
		Population aged between 45 to 65 years
		Population older than 65 years
	Education level	Percentage of population with primary education
		Percentage of population with secondary education
		Percentage of population with tertiary education
	Income	Household income per capita
	Household size	Average number of people living in a household
Output variables	Household waste per capita generated in each neighbourhood of the Hague in 2018	
Activity	Use the random forest model built earlier and predict household waste generation per capita in each neighbourhood with input variables as predictors	
Link	https://service.openinfo.nl/downloads/informatie-gemeente-den-haag/	

Table A.11: Hague cijfers data used to predict output household waste using random forest method

A.2 GWP values

A.2.1 GWP values of products excluding food

Product	Resource category	Resource sub category	Source	GWP	Unit
Tap water	Water	Water	Ecoinvent	0.000344	Cubic meters
Natural gas	Energy	Natural gas	Ecoinvent	0.29786	Cubic meters
Electricty production from Oil	Energy	Non-green electricity	Ecoinvent	0.7695	kW hour
Electricty production from Coal	Energy	Non-green electricity	Ecoinvent	1.008	kW hour
Electricty production from Natural gas	Energy	Non-green electricity	Ecoinvent	0.64291	kW hour
Electricity production from wind power	Energy	Green electricity	Ecoinvent	0.01409	kW hour
Electricity production from nuclear power	Energy	Green electricity	Ecoinvent	0.01071	kW hour
Electricity production from Solar power	Energy	Green electricity	Ecoinvent	0.050136	kW hour
Electricity production from Hydroelectric power	Energy	Green electricity	Ecoinvent	0.0040337	kW hour
Electricity production from municipal waste	Energy	Green electricity	Ecoinvent	0.00512	kW hour
Transport by passenger car	Mobility	Car	Ecoinvent	0.33114	Kilometer
Transport by Train	Mobility	Public transport	Ecoinvent	0.0464	person-kilometer
Transport by Bus/Tram	Mobility	Public transport	Ecoinvent	0.0943	person-kilometer
Solid municipal waste	Waste	Waste	Ecoinvent	1.2549	Kilogram
Clothes	BoP	BoP	Literature search	12.023	1 unit clothing
Detergent products	BoP	BoP	Literature search	0.4985	1 unit detergent
Footwear	BoP	BoP	Literature search	2.572	1 unit footwear
Furniture	BoP	BoP	Literature search	141.692	1 unit furniture
Personal care products	BoP	BoP	Literature search	0.5127	1 unit personal care product
Paper products	BoP	BoP	Literature search	1.44	1 unit paper products

Table A.12: GWP values for different products used in the study(except food)

A.2.2 GWP values of products including food

Product	**Resource category**	**Resource sub category**	**Source**	**GWP**	**Unit**
Leafy vegetables	Food	Vegetables	Ecoinvent	1.3344	kg
Fruity vegetables	Food	Vegetables	Ecoinvent	0.994	kg
Root vegetables	Food	Vegetables	Ecoinvent	3.455339	kg
Stalk vegetables	Food	Vegetables	Ecoinvent	0.541	kg
Cabbage	Food	Vegetables	Ecoinvent	0.3686	kg
Potato	Food	Potato	Ecoinvent	0.9893	kg
Legumes	Food	Legumes	Ecoinvent	0.8065	kg
Pineapple	Food	Fruits	Ecoinvent	0.2144	kg
Apricot	Food	Fruits	Ecoinvent	0.30274	kg
Banand	Food	Fruits	Ecoinvent	0.26713	kg
Pear	Food	Fruits	Ecoinvent	0.27335	kg
Strawberry	Food	Fruits	Ecoinvent	0.43665	kg
Orange	Food	Fruits	Ecoinvent	0.536875	kg
Peach	Food	Fruits	Ecoinvent	0.27198	kg
Lemon	Food	Fruits	Ecoinvent	0.4144	kg
Grape	Food	Fruits	Ecoinvent	0.31012	kg
Mango	Food	Fruits	Ecoinvent	0.26957	kg
Olive	Food	Fruits	Ecoinvent	0.4175	kg
Almond	Food	Nuts	Ecoinvent	1.1424	kg
Milk and Milk products	Food	Milk and Milk products	Ecoinvent	1.701057	kg
Red meat	Food	Meat	Ecoinvent	16.7433	kg
White meat	Food	Meat	Ecoinvent	6.9	kg
Maize flour	Food	Flour	Ecoinvent	0.8146	kg
Wheat flour	Food	Flour	Ecoinvent	0.8465	kg
Basmati rice	Food	Pasta,Rice and other grain	Ecoinvent	3.4918	kg
Non-basmati rice	Food	Pasta,Rice and other grain	Ecoinvent	1.4309	kg
Marine fish	Food	Fish and fish products	Ecoinvent	1.9384	kg
Demersal fish	Food	Fish and fish products	Ecoinvent	2.5646	kg
Fish oil	Food	Fish and fish products	Ecoinvent	1.1828	kg
Butter	Food	Fats	Ecoinvent	7.397	kg
Vegetable oil	Food	Fats	Ecoinvent	5.6303	kg
Tofu	Food	Nuts	Literature search	2	kg
Yoghurt	Food	Milk and Milk products	Literature search	2.2	kg
Eggs	Food	Meat	Literature search	4.8	kg
Peanut butter	Food	Nuts	Literature search	2.5	kg

Table A.13: GWP values for different food products used in the study

A.3 Research Flow Diagram

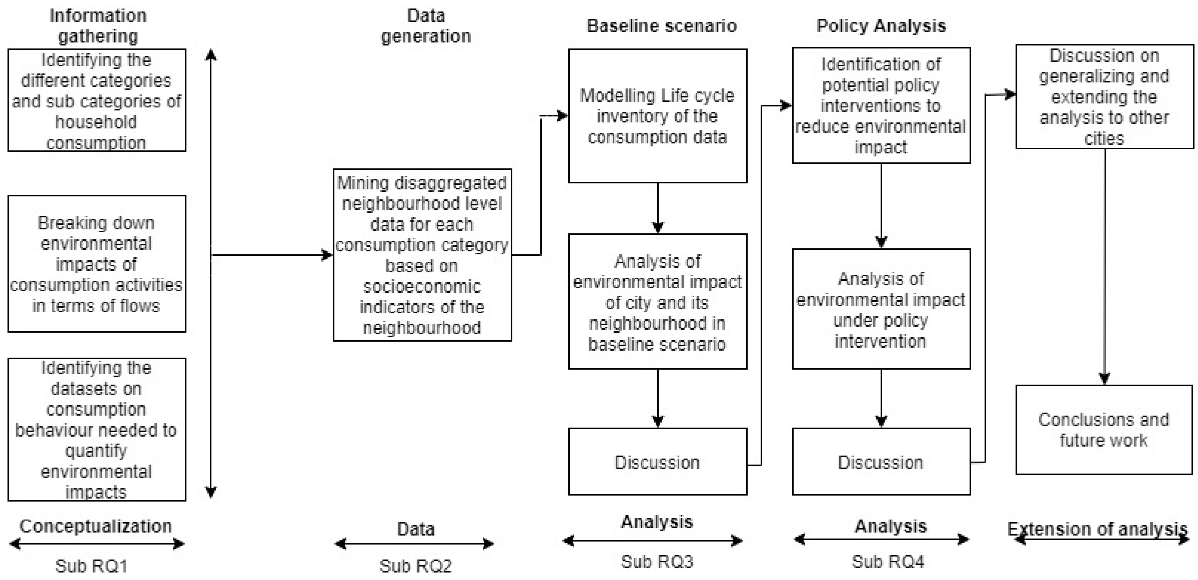

Figure A.1: *Research Flow diagram*

A.4 Supplementary information related to clustering analysis

A.4.1 Neighbourhood clusters obtained through different clustering algorithms

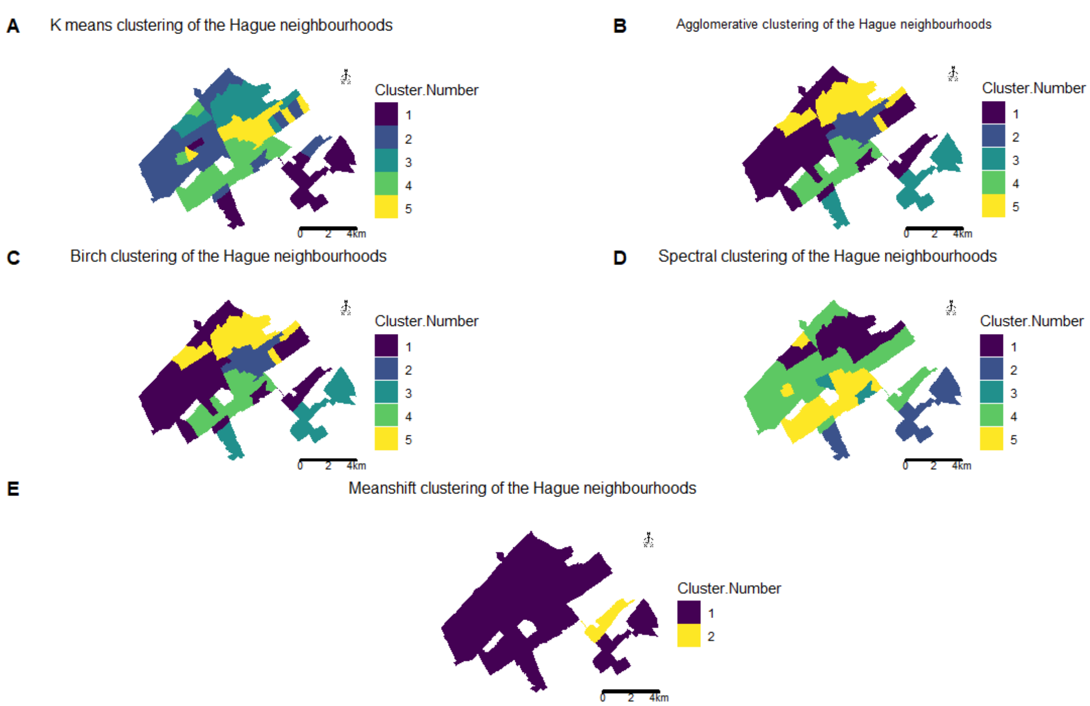

Figure A.2: *Neighbourhood clusters in the Hague obtained through different clustering algorithms*

A.4.2 Neighbourhood clusters obtained through K means clustering algorithm

Cluster 1

Cluster 1 is composed of very young Dutch people with moderate annual income. Mostly of them are employed own a house and the car ownership is high and the homes consist of more than one person. The neighbourhoods in cluster 1 include:Vruchtenbuurt, Hoge Veld, Parkbuurt oosteinde, Lage Veld, Zonne Veld, Vlietzoom-West, Bosweide, De Venen, Morgenweide, Singels, Waterbuurt, De Bras, De Lanen, De Velden, De Vissen and Rietbuurt

Cluster 2

Cluster 2 is composed of Middle aged population with moderate level of income,moderate level of education, moderate level of employment,moderate level of home ownership and moderate car ownership.The neighbourhoods in cluster 2 are: Belgisch Park, Oud Scheveningen, Vissershaven, Scheveningen Badplaats, Visserijbuurt, Rijslag, Geuzenkwartier, Bloemenbuurt-West, Bloemenbuurt-Oost, Bomenbuurt, Bosjes van Pex, Bohemen en Meer en Bos, Ockenburgh, Kijkduin, Kraayenstein, Houtwijk, Kom Loosduinen, Waldeck-Zuid, Componistenbuurt, Waldeck-Noord, Eykenduinen, Heesterbuurt, Valkenboskwartier, Burgen en Horsten, Bezuidenhout-Oost, Rustenburg, Oostbroek-Noord, Oostbroek-Zuid, Leyenburg, Laakkwartier-West, Laakkwartier-Oost, Erasmus Veld and Vlietzoom-Oost

Cluster 3

Cluster 3 is composed of middle aged population with high level of income, high education, many expats, high home ownership and high car ownership. Thus, in a way this cluster represents neighbourhoods with higher standards of living. The neighbourhoods in this cluster include : Westbroekpark, Duttendel, Nassaubuurt, Uilennest, Duinzigt, Waalsdorp, Arendsdorp, Van Hoytemastraat en omgeving, Archipelbuurt, Van Stolkpark en Scheveningse Bosjes, Statenkwartier, Zorgvliet, Stadhoudersplantsoen, Sweelinckplein en omgeving, Vogelwijk, Willemspark, Marlot and Bezuidenhout-Midden

Cluster 4

Cluster 4 is composed of neighbourhoods with Relatively young population, lower income level, lower education level, mostly rental houses and low car ownership. The neighbourhoods in this cluster include: Duindorp, Nieuw Waldeck, Schildersbuurt-West, Schildersbuurt-Noord, Schildersbuurt-Oost, Transvaalkwartier-Noord, Transvaalkwartier-Midden, Transvaalkwartier-Zuid, Venen, Oorden en Raden, Zijden, Steden en Zichten, Dreven en Gaarden, De Uithof, Morgenstond-Zuid, Morgenstond-West, Morgenstond-Oost, Moerwijk-Oost, Moerwijk-West, Moerwijk-Noord, Moerwijk-Zuid, Groente- en Fruitmarkt, Laakhaven-Oost, Laakhaven-West, Spoorwijk, Noordpolderbuurt and Binckhorst

Cluster 5

Cluster 5 includes neighbourhoods with Older population with moderate levels of income, many one person households, low home ownership and extremely low car ownership. The neighbourhoods in this cluster are: Rosenburg, Rond de Energiecentrale, Koningsplein en omgeving, Zeeheldenkwartier, Haagse Bos, Landen, Kampen, Bezuidenhout-West, Huygenspark, Rivierenbuurt-Zuid, Rivierenbuurt-Noord, Kortenbos, Voorhout, Uilebomen and Zuidwal

A.4.3 Environmental impacts of different clusters

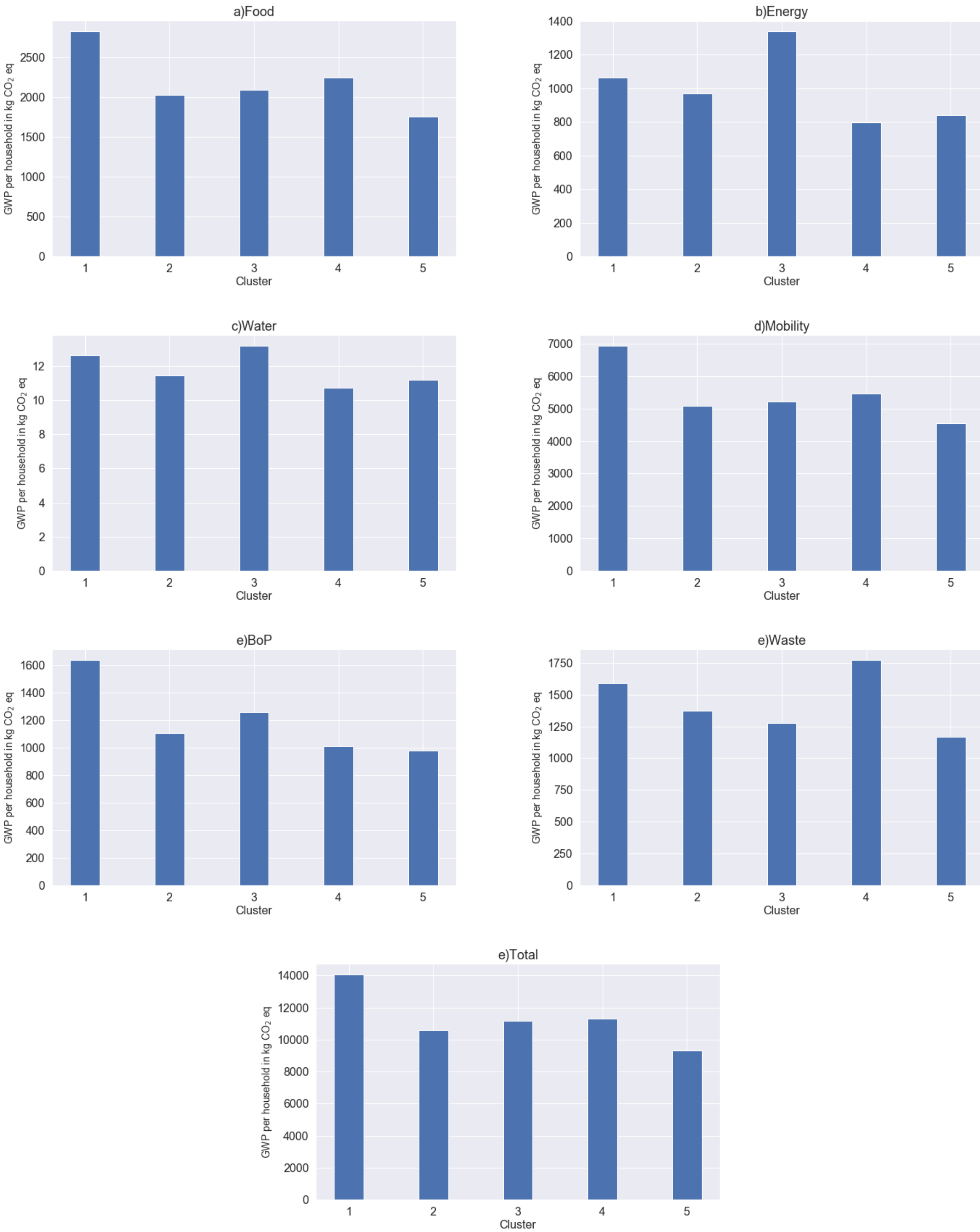

Figure A.3: *Plots for GWP per household of different resource use categories for each of the 5 clusters: a)Food b)Energy c)Water d)Mobility e)BoP f)Waste g)Total*