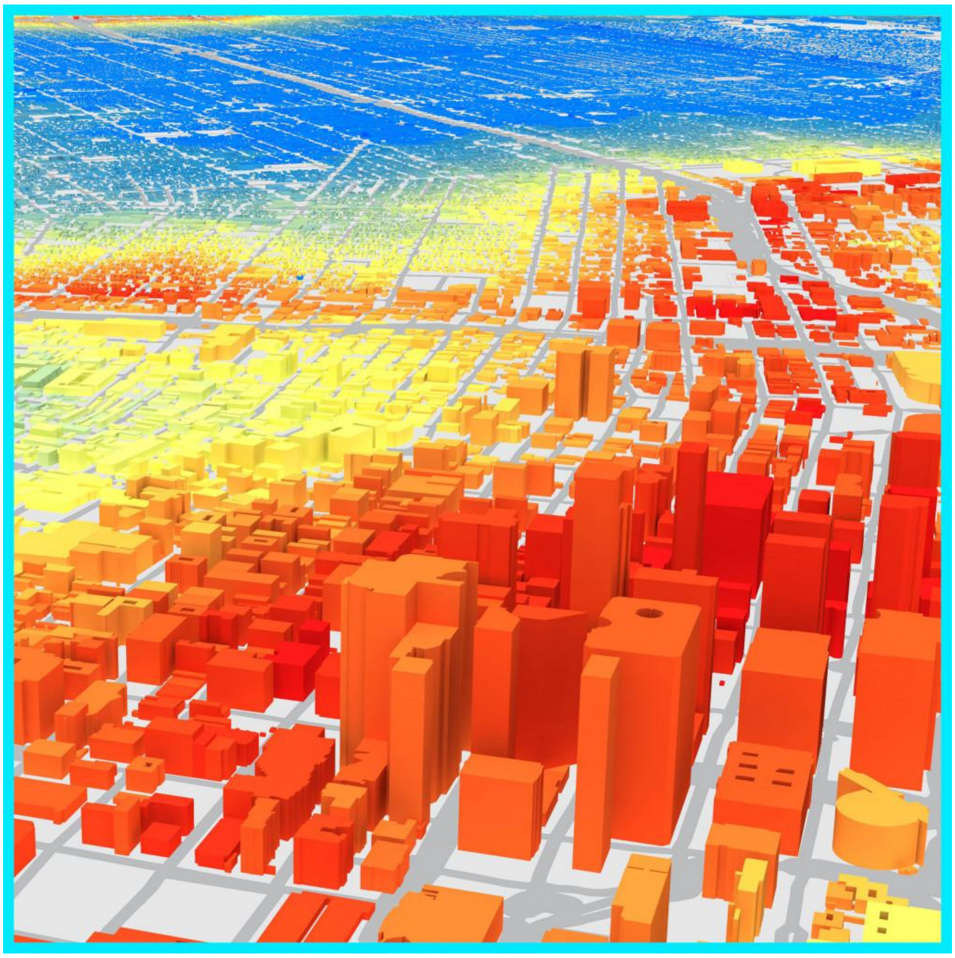
Master thesis

‘Mapping and analysing the impact of spatial data aggregation on Urban Heat Vulnerability maps: A case study on Haarlem, the most petrified city in the Netherlands’



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Author: Beau Verhoef

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Colophon

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Supervisor: Kevin Raaphorst

Second Reader: Lulian Barba-Lata

Author: Beau Verhoef

Identification number: s1151162

E-mail: beau.verhoef@ru.nl

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Abstract

Increasing global temperatures are making the implementation of climate adaptation more crucial than ever before. This is due to the fact that urban areas, in which the majority of earth's population resides, experience much higher temperatures than its surrounding areas, which is known as the Urban Heat Island (UHI) effect. Climate Services containing data on climate change are used to indicate which areas are the most eligible for cooling strategies, with support of vulnerability mapping. However, the way in which data is presented in these maps can affect the interpretation of data and ultimately affect decision making processes amongst stakeholders who are active in climate adaptive spatial planning. One of the problems that arises in the creation of maps with data on climate change is the Modifiable Areal Unit Problem (MAUP). This is a statistical bias resulting in visual and statistical variations depending on the unit of analysis. Therefore, this research aims to create awareness of the effects of spatial data aggregation on vulnerability maps to the UHI effect. With support of multiple mapping scenarios and statistical analyses, indicating the effects of spatial data aggregation, followed by semi-structured interviews with stakeholders in climate adaptive spatial planning, this research contributes to the current social and scientifical gaps on climate adaptation and vulnerability mapping.

Keywords

Urban Heat Island Effect (UHI), Climate Adaptation, Climate Services, Vulnerability Mapping, Modifiable Areal Unit Problem (MAUP), Spatial Data Aggregation

Preface

With this master's thesis I finalise my master's degree in Spatial Planning at the Radboud University in Nijmegen. During the process of writing this thesis I have expanded my experience in mapping the effects of climate change, my skills in gathering and interviewing respondents, and my knowledge on the effects of spatial data aggregation on the visual representation of maps and the resulting statistics. Furthermore, receiving feedback from my supervisor and the insights from respondents has increased my abilities to critically reflect on issues regarding the mapping the effects of climate change. Therefore, I would like to thank my supervisor Kevin Raaphorst for his support and guidance during this process. I would also like to thank the five respondents who have devoted their time and contributed to this research. Finally, I want to thank every reader of this thesis for their interest and their time to read this document.

Beau Verhoef
Nijmegen, August 2025

Summary

Climate change increases the negative health effects of heatwaves. This is especially the case in urban areas, in which the majority of the population on earth resides. Therefore, the so called urban heat island effect needs to be countered with support of climate adaptive spatial planning. This research investigates the usability of climate services which represent data on climate change and climate adaptation. The way in which data is presented in these climate services can influence decision making processes in climate adaptive spatial planning. One factor of influence is the statistical bias known as the Modifiable Areal Unit Problem (MAUP). Therefore, the MAUP, which is a result of spatial data aggregation, will be emphasised. According to the literature, new insights on the effects of spatial data aggregation on urban heat vulnerability could contribute to new insights for stakeholders and decision making processes. As a result, this research tries to answer the following research question:

"How do variations in spatial data aggregation influence the usability of urban heat vulnerability maps?"

The Dutch city of Haarlem, which was classified as the most petrified city in the Netherlands in 2022, was used as a case study. In order to answer the research question, maps which present indicators of vulnerability to the UHI effect have been conducted on different scales. This quantitative method includes spatially aggregating existing data with support of zoning and scaling. The data which has been used concerns exposure, sensitivity, and adaptability, which are the three elements that form vulnerability to urban heat. The outcomes have been assessed on visual representation, statistical validity, and qualitative opinions on the usability. Several semi-structured interviews were held with stakeholders from the municipality of Haarlem and consultancy firms.

The findings confirm that the spatial data aggregation influences the visual representation of the data in maps. Furthermore, the majority of the maps were assessed on statistical validity and turn out to be significant (excluding the largest used scales). The analysis of the interviews focused on validity, readability, and interactivity, which are components of usability. It turns out that the stakeholders found the multiple mapping scenarios to some extent useful for practice. The majority argued that the maps are sufficient for the start of discussions on climate adaptation. However, the usability of the maps depend on the type of stakeholder and the type of the project for which it will be used. Maps conducted with support of larger-scale aggregation simplify the results, however they are useful for budget related municipal projects. Whereas smaller scales are more useful for detailed projects on a local scale. In conclusion, it appears that the possibility to analyse multiple scales at the same time increases the awareness of the effects of MAUP on visual representation and communication.

Finally, this research builds further upon the already existing theories on how MAUP affects vulnerability mapping. Furthermore, it recommends experimenting with presenting data in different types of scales. Additionally, future research should focus on the presentation of data which is independent from units of analysis as a result of municipal boundaries.

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1. Introduction

1.1. Research problem statement

Due to climate change it is likely that the amount of, and the power of heatwaves in cities will increase in the future. The reason for this, is the so-called urban heat island (UHI) effect. According to Oke (1982) the UHI effect can be characterised by the situation in which the temperature in urban areas is significantly higher than the temperature in the surrounding areas. Rapid urbanisation, which has been taking place all over the world, has led to the transformation of pervious land into hard, impermeable, and heat absorbing surfaces in urban areas. Furthermore, the UHI effect is strengthened by the fact that ventilation is blocked by the increasing number of tall buildings in cities (Abrar et al., 2022). The majority of the population on earth is living in urban areas, which is why extreme heat events are a serious threat to human health (Sabrin et al., 2020). The UHI effect is a phenomenon that will further increase the negative effects of extreme heat events. Therefore, policy makers, city governments, and other stakeholders are now facing the task to beat the UHI effect with support of climate adaptation.

1.1.2. Climate services

In order to create climate adaptive policies to beat the UHI effect, stakeholders need to be provided with the right information This will support them in making choices for investing in climate adaptation strategies. Examples of strategies which help cooling down urban areas can be retrieved from nature-based solutions according to Sanchez & Govindarajulu (2012). In their article they mention blue and green infrastructures, which are networks of both natural and designed landscape components. Examples are parks, lakes, rivers, and creeks. They can, besides cooling down urban areas, also contribute to water storage, recreation space, and wildlife habitat (Gofrani et al., 2017). Currently, the development of blue and green infrastructure is taking place in many urban areas in the global north. Information on where to implement such blue and green infrastructures can be provided by climate services (CS). These are tools that can provide people with information about the impacts of climate change and climate adaptation measures. Therefore, CS can support decision-making processes which is done by stakeholders in both governmental and non-governmental organisations. Examples of CS are projections, scenarios, and maps (Raaphorst et al., 2020).

An increase in the use of maps to analyse the effects of climate change has taken place in the past decade. For example, the mapping of social vulnerability as a result of the UHI effect can contribute to decision-making processes in climate adaptive urban planning. This is seen as seriously important due to the increasing threat of human health during heatwaves. However, it should be mentioned that it is crucial to know when specific climate change or climate adaptive information should be used. Furthermore, it is important to consider which audience is provided with the information. The kind of information which is shown in CS and to whom it is shown to can possibly lead to usability gaps according to Lemos et al. (2012). Usability gaps are formed because of the difference in what scientists understand as useful information and what the users regard as useful in their decision-making processes. Besides usability gaps due to different interpretations of the presented information, it can also occur that the visualisation of the data in CS is not suitable for certain types of users (Raaphorst et al., 2020). Furthermore, maps have historically been used to persuade and to influence readers, both intentionally and unintentionally. According to Prestby (2025), maps can lead to a spread of misinformation due to decisions in the design. Data classification, symbology, and colour schemes can contribute to fabricated narratives. Since maps play a dominant role in communicating science, it is therefore important to address the fact that CS can also be persuasive. Therefore, it is crucial to critically reflect on the usability of maps that present information regarding the impacts of climate change and climate adaptation measures.

Examples of CS can be maps which present the social vulnerability to the UHI effect. According to Räsänen et al. (2019) the outcomes of mapping social vulnerability to the UHI effect can depend on many indices, which are combined of indicators such as spatial patterns, population density, and socio-economic characteristics of citizens. The use of so-called index-approaches has been criticised by multiple authors because it is argued that vulnerability is a phenomenon that cannot be measured and generalised easily. Hinkel (2011) argued that the indices which are used to raise awareness on the effects of the UHI and the steering adaptation policies, are ill-fit.

1.1.3. The Modifiable Areal Unit Problem

Besides critiques on vulnerability indicators, another aspect of mapping can also influence the outcomes and presentation of UH vulnerability maps. This is the scale on which the data in maps is presented. Data in maps can be presented in various administrative units or cells with varied sizes. According to Jeffery et al. (2014), usually the data on vulnerability is spatially aggregated, for example to a neighbourhood or district level. The reason for this is the fact that point level socio-economic data is not publicly available. However, Ho et al. (2015) argue that this spatial aggregation of the data can lead to problems, with the modifiable areal unit problem (MAUP) as the most notable one. MAUP refers to "*A statistical bias that arises from the selection of a specific spatial unit of analysis. When geographic data are aggregated into a spatial feature with specific spatial scale (e.g., by census tract, postal code, or county), mean values within the spatial feature are affected by its boundary, which in turn may lead to a zoning effect that affects subsequent analyses*" (Ho et al., 2015, p. 16111).

The authors argue that spatial data aggregation can be performed with two different methods. The first method is scaling, in which grid cells containing certain values, all with the same size, are spatially aggregated into smaller or larger grid cells. The second method is zoning, in which administrative boundaries containing spatial data, such as neighbourhoods and municipalities, are aggregated to smaller or larger administrative boundaries. Also, they argue that MAUP can lead to errors in both communicative and statistical validity of maps in the end.

1.1.4. Earlier research on MAUP

Spatial data aggregation also takes place during the creation of CS which are used to guide stakeholders in decision-making processes in climate adaptative urban planning. According to

Räsänen et al. (2019) the spatial uncertainties that arise due to MAUP in socio economic vulnerability research have only been examined by a few studies. A study on mapping flood exposure in Switzerland by Rothlisberger et al. (2017) compared two diverse ways of data aggregation. They calculated and mapped both the density and the ratio of exposed assets on a municipal scale and per grid cell with approximately the same size as the municipalities. According to them, their study has shown that using two types of data aggregation did influence the results. However, they only focused on exposure to floodings and not on the social vulnerability.

Another study, by Lang et al. (2014), aims to map the spatial distribution of policy relevant phenomena with support of optimal areal units known as geons that are separate from administrative boundaries. These areal units are suitable for regional urban planning due to the fact that the polygons are created based on land use categories. Therefore, the authors argue that geons would minimize the effects of outliers and would be more suitable than administrative units or grid cells. However, more research needs to be done on the conceptual validity and robustness of the geon's method.

Räsänen et al. (2019) researched the socio-economic vulnerability to the UHI effect in Helsinki, the capital of Finland. The outcomes of this research are in line with the other studies mentioned in this paragraph. Five different zoning options were used to map the vulnerability to the UHI effect in Helsinki. The zones were ranging from small administrative areas such as postal code areas, to larger ones such as municipal areas. In stead of one final map, a bunch of maps on vulnerability to UH in Helsinki was presented. According to Räsänen et al. (2019) presenting the data on different scales would increase trustworthiness and credibility of the maps. These maps could be more effective in understanding the actual probability of vulnerability to the UHI effect in urban areas (Räsänen et al., 2019). Therefore, they could contribute to decision-making among stakeholders in adaptive spatial planning.

1.2. Research aim

The aim of this research is to create awareness of the diverse ways in which data can be presented and interpreted from climate services (CS). CS are often used by stakeholders in decision making processes in adaptive spatial planning, therefore they can indirectly influence climate adaptive policies. Hence, it is important to critically analyse the usability of such CS.

The mapping of vulnerability to the UHI effect is an example of a CS that can be used in decision-making processes. Earlier in the research problem statement, MAUP and its influence on the visualisation and statistical validity has been discussed. Furthermore, it was argued that the uncertainties as a result of MAUP have only been included in a limited amount of research (Räsänen et al., 2019). Beating the UHI effect with support of climate adaptative spatial planning has become of critical importance due to climate change. Hence, it is necessary to critically analyse the current methods of presenting the vulnerability to the UHI effect in CS, and to introduce stakeholders to possible alternatives.

This research will analyse the data on vulnerability to the UHI effect in the Dutch city of Haarlem, and how this is presented by CS. In 2022 Haarlem was given the title of most petrified city in the Netherlands. As was claimed in the introduction, petrified surfaces are heat absorbing and contributing to the UHI effect. Therefore, implementing blue and green infrastructures is a top priority. Currently Haarlem is undergoing a rapid process of urban greening. The city is now taking the second place in the “Greening the City Challenge, which is an initiative of architects, and an engineering consultancy firm called Sweco (NH Nieuws, 2024).

1.3. Research questions

The problem statement and research aim have led to the following research question: “How do variations in spatial data aggregation influence the usability of urban heat vulnerability maps?” The following sub-questions will be used to perform a critical analysis and to answer the main research question:

1. What are the current perceptions of usability of climate services presenting vulnerability to the UHI effect?
2. How does spatial data aggregation with support of zoning affect the visual representation of vulnerability to the UHI effect in climate services?
3. How does spatial data aggregation with support of scaling affect the visual representation of vulnerability to the UHI effect in climate services?
4. To what extent does spatial data aggregation with support of zoning affect the statistical validity of maps presenting the vulnerability to the UHI effect?
5. To what extent does spatial data aggregation with support of scaling affect the statistical validity of maps presenting the vulnerability to the UHI effect?
6. How do stakeholders in urban planning and climate adaptation perceive the usability of UHI effect vulnerability maps created at different spatial scales and zoning configurations?

1.4. Relevance of the research

This chapter will emphasise in which ways this research is both socially and scientifically relevant. Firstly, the social relevance will be discussed with support of a perspective on what role this research can play in real-life issues. For example, decision-making processes in climate adaptive spatial planning. Secondly, the scientific relevance will be discussed with a focus on how the research can contribute to academic knowledge. Furthermore, it emphasises what this research can add to narrow down the knowledge gap in vulnerability mapping.

1.4.1. Societal relevance

In the first chapter of the introduction, the UHI effect was introduced. It can be concluded that the UHI effect will be strengthened due to climate change caused by global warming. Urban areas can be characterised by heat-absorbing concrete surfaces, with high density of both buildings and populations. During heatwaves urban areas are more likely to experience higher temperatures. Looking at the patterns of urbanisation across the globe it is estimated that by 2030 approximately 60% of the world’s population will live in these urban areas. Whereas urban areas only occupy around 2% of land surface (The Conversation, 2019). The fact that most of the population on earth lives in the areas where temperatures are likely to increase the most during heatwaves can be seen as problematic. The UHI effect can lead to negative health effects on citizens due to worsening air pollution, a decrease in the quality of water, and finally the direct exposure to increased temperatures can be lethal (Heaviside, 2017). Since the amount of people living in urban areas will not decrease but will only increase in the future according to scientists, climate adaptive measures will need to be implemented.

Presenting maps of vulnerability to the UHI effect in a CS can contribute to decision-making processes. More specifically, in creating policies to beat the urban heat and to reduce the negative health effects. However, the visualisation of these maps will need to be usable, readable, and credible in order to lead to successful interpretation and implementation of policies by stakeholders. Research on the implications for climate action and governance in the UK has analysed the way in which data analysis can affect decision making processes in climate adaptation. This research focused on data on emissions in both local and regional areas (Sudmant, 2023). It turned out that each local area and its government had different priorities in terms of reducing emissions. In one local area, the largest source of emissions was agriculture, whereas in other local areas it was the domestic sector or aviation. In local climate action plans, each area is likely to reduce the emissions of the most dominant source. However, in a regional climate action plan, including multiple local areas, the most dominant source of the region would be combatted. According to Sudmant (2023) this can lead to unequal development of climate action plans due to ineffectiveness for some local areas. Finally, this can lead to environmental justice concerns.

This research presents an example of how the MAUP, in terms of scaling data on emissions from a local to a regional scale, influences decision making processes in climate adaptation. This can indirectly result in increased inequalities amongst populations living in different local areas. Examples like this can also occur in climate adaptive measures to beat the UHI effect. Scaling and zoning data on components of vulnerability to urban heat into certain units of analysis can influence the priorities of stakeholders active in climate adaptive spatial planning. Unintentionally, this can lead to a possible increase of unequal vulnerabilities between populations in urban areas. Therefore, conducting this research on the influence of mapping variations in presenting the vulnerability to the UHI effect can be seen as socially relevant.

1.4.2. Scientifical relevance

The mapping variations that will be considered in this research are focused on the influence of spatial aggregation of data. As mentioned in the problem statement there only have been a few studies which have researched the effects of spatial aggregation (Räsänen et al., 2019). It appears to be the case that some studies have found striking results after the usage of spatial data aggregation. At the same time, it is important to conduct usable, readable, and credible CS which can support climate adaptive stakeholders in decision making processes. Hence, research needs to be done on factors that can influence the visualisation and the statistical validity of CS. Therefore, it can be concluded that conducting this research can contribute to the current limited knowledge of the influence of spatial data aggregation on patterns in vulnerability mapping. Furthermore, some articles on this topic have given research recommendations. This section will build upon these recommendations and will explain how this research can contribute to science.

The research by Sudmant (2023) on the implications for climate actions and governance illustrates the urgency for further research on the effects of data scaling on climate action. The author mentions that exploring data in other geographical context can contribute to our understanding of dealing with climate phenomena. With this argument he advices to experience with presenting data in different scales. This thesis, in which the effects of spatial data aggregation on urban heat vulnerability maps will be analysed, can therefore contribute to the limited amount of research on how to deal with MAUP.

Räsänen et al. (2019), who have researched the effects of zoning and weighting in urban heat island vulnerability in Helsinki, address the need for research on uncertainties in the use of data and the methods of analysis. Besides the visual effects of MAUP, the statistical validity of the use of different units of analysis will also be evaluated in this research. Therefore, this research will contribute to the desired research on uncertainties in the use of specific methods of analysis. Finally, Hot et al. (2015) created a spatial framework for mapping health risks to urban heat on multiple scales in the Greater Vancouver Area, using both scaling and zoning. They argue that in their research outcomes the MAUP issue has changed its nature in stead of being avoided. For them, it is still not clear which mapping scenario presents the vulnerability to urban heat in the most accurate way. However, they argue that the possibility to compare different maps on different scales does in fact give new insights. For example, on the spatial relationships between units of analysis and components of urban heat vulnerability. Therefore, this research can contribute to the knowledge gap in dealing with MAUP. Furthermore, it can increase the awareness of the effects of spatial data aggregation on urban heat vulnerability maps.

2. Theoretical framework

This chapter will provide an overview of all the theories and concepts that are relevant to this research. To finally answer the research question, it is important to reduce it to multiple smaller pieces. The previous chapter already mentioned the sub-research questions. In this chapter all the main concepts which are mentioned in the sub-research questions will be discussed with support of academic literature. Defining the main concepts is crucial since they will be recurring throughout the research.

Firstly, a more detailed description of the Urban Heat Island (UHI) effect will be given. Secondly, the concept of vulnerability, which is a vague concept according to several authors, will be analysed critically. Thirdly, the focus will be on the two diverse types of spatial data aggregation according to Ho et al. (2020). The differences and similarities of these two types will also be discussed. Furthermore, the concept of usability will be discussed, with support of its three dimensions. Finally, the challenges for stakeholders in climate adaptive spatial planning will be analysed with support of theory on usability gaps. Finally, the literature review on the main concepts will be followed by a theoretical framework. This framework will present all the main concepts which are needed in the analysis in an illustrative figure. It will present the relationship between the concepts and how they will be of influence in the research. How they will be used, and what kinds of data and methods are needed to use them will be discussed in the methodology chapter. This will be done with support of a flowchart of the research and a table which shows the operationalisation of the concepts.

2.1. Literature review

2.1.1. Urban heat island effect (UHI)

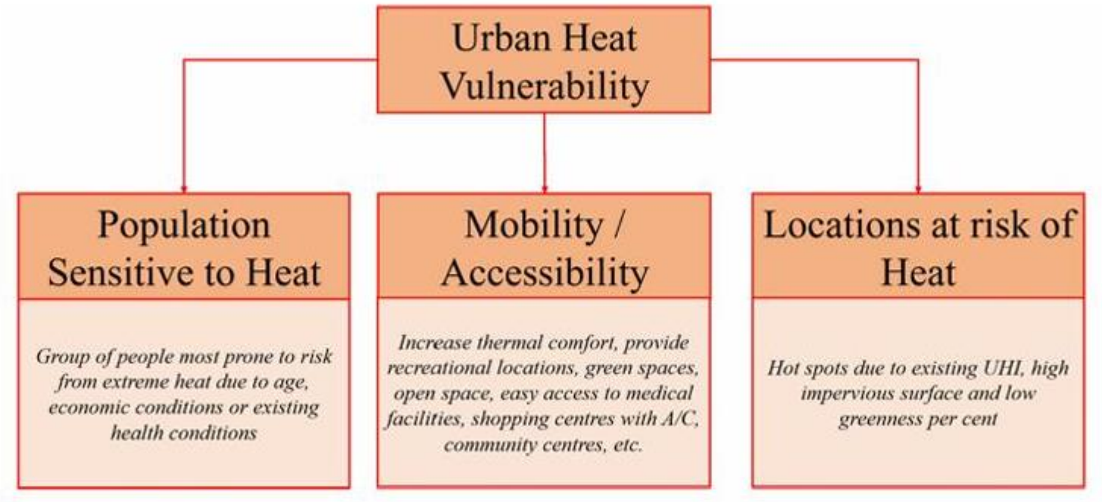
In the introduction chapter, a brief definition of the UHI effect was given according to Oke (1982). According to him, it is the situation in which the temperature in urban areas is significantly higher than the temperature in the surrounding areas. Early in the 19th century the UHI effect was measured and presented for the first time by Lake Howard. After this, much research on the characteristics of the concept was conducted (Yang et al., 2016). It is argued that the UHI effect is caused by human activities such as urban constructions which have resulted in heat-absorbing surfaces in urban areas and the blocking of ventilation (Abrar et al., 2022).

The UHI effect is closely related to population density, vegetation coverage, and urbanization (Yang et al., 2016). Especially the last one, has led to a significant increase of surface temperatures in urban areas. The UHI effect can, in case of hot temperatures, lead to certain hotspots in city areas. These hotspots are formed due to the lack of vegetation cover, and high density of impervious infrastructure (Sidiqui et al., 2022). Heaviside (2017) argues that the UHI effect can negatively affect health of citizens due to worsening air pollution and a decrease in the quality of water. Finally, the direct exposure to increased temperatures can therefore be problematic, especially during heat waves.

2.1.2. Vulnerability

Previously, research on vulnerability to the UHI effect was predominantly focused on using simple temperature maps. These maps identified which areas in a city are exposed to hot temperatures the most. However, such broad-brush approaches leave out information about the relative health risks within city blocks associated with urban heat (Sidiqui et al., 2022). Therefore, more research has been conducted lately on identifying indices and indicators of vulnerability. Sidiqui et al have performed an analysis on UHI vulnerability based on three main indices which are shown in figure 1. The first indice is the sensitivity of the population to the urban heat, which consists of several socio-economic variables that can influence or increase risk factors. Examples are the age and economic conditions. The second indice concerns the mobility or accessibility of populations to adapt to UH. Examples are accessibility to medical facilities, or the mobility to move to thermal comfort zones such as parks. The final indice focuses on the exposure to urban heat and can be characterised by indicators such as the amount of surface which is covered with green space and the physiological equivalent temperature (PET).

Figure 1: Indices and indicators of Urban Heat Vulnerability



Source: Sidiqui et al. (2022)

2.1.3. Spatial data aggregation

Spatial data aggregation refers to combining or summarising geographic data into certain spatial units. So far, spatial data aggregation has been used to map areas which are at a relatively high risk to the UHI effect. The reason that spatial data aggregation is used, is due to the fact that most point level socio-economic data is not publicly available. However, as mentioned in the introduction, spatial data aggregation can lead to the Modifiable Areal Unit Problem (MAUP). Ho et al. (2015) argue that there are two diverse types of spatial data aggregation and refer to the methods of scaling and zoning. Figure 2 gives a schematic representation of MAUP and shows the role of scaling and zoning in this problem.

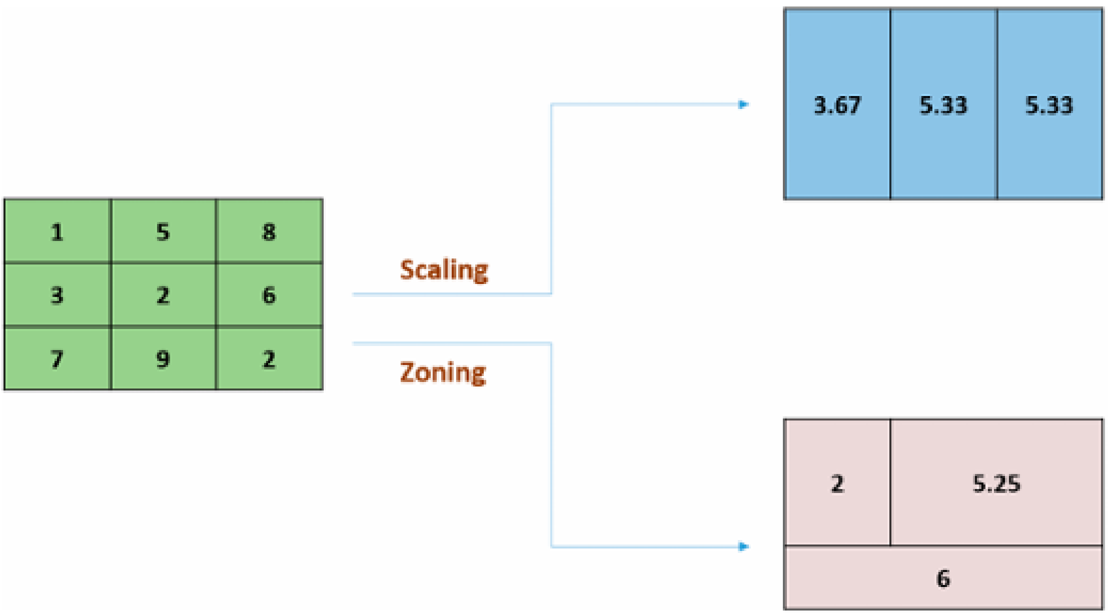
2.1.3.1. Scaling

Figure 2 shows the green grid cells in the left, which are all the same size, and all contain an individual value. Scaling refers to spatial data aggregation from a certain grid level to a smaller or larger resolution. In the top right corner in figure 2 the green grid cells have been spatially aggregated into larger blue grid cells with the same cell size. Aggregating the data from the green grid cells to the larger blue grid cells is done by calculating the average value of three green spatial units. This type of spatial data aggregation leads to the fact that the data from the blue grid cells can be interpreted in a totally different way both statistically and communicative. However, in fact the situation is actually the same as before in the green grid cells. Sobrino et al. (2012) argue that spatial units which are used to quantify socio-economic vulnerability are usually less than one square kilometre, since larger resolutions would not be representative enough.

2.1.3.2. Zoning

In another method, administrative boundaries were used to measure socio-economic vulnerability, this method is referred to as zoning. In the bottom right corner, the green grid cells are spatially aggregated into larger pink administrative units. Examples of administrative units in which geographic data can be presented are postal codes, neighbourhoods, and municipalities. After spatially aggregating the data into administrative boundaries, the values are now dependent on the new boundaries of the pink spatial units. Ho et al. (2015) mention an example of an error that can occur in mapping vulnerability to the UHI effect. This example shows that including a lake in a certain spatial unit can lower the average temperature in that spatial unit. However, if this lake were included in the neighbouring spatial unit the results on the final map would be different.

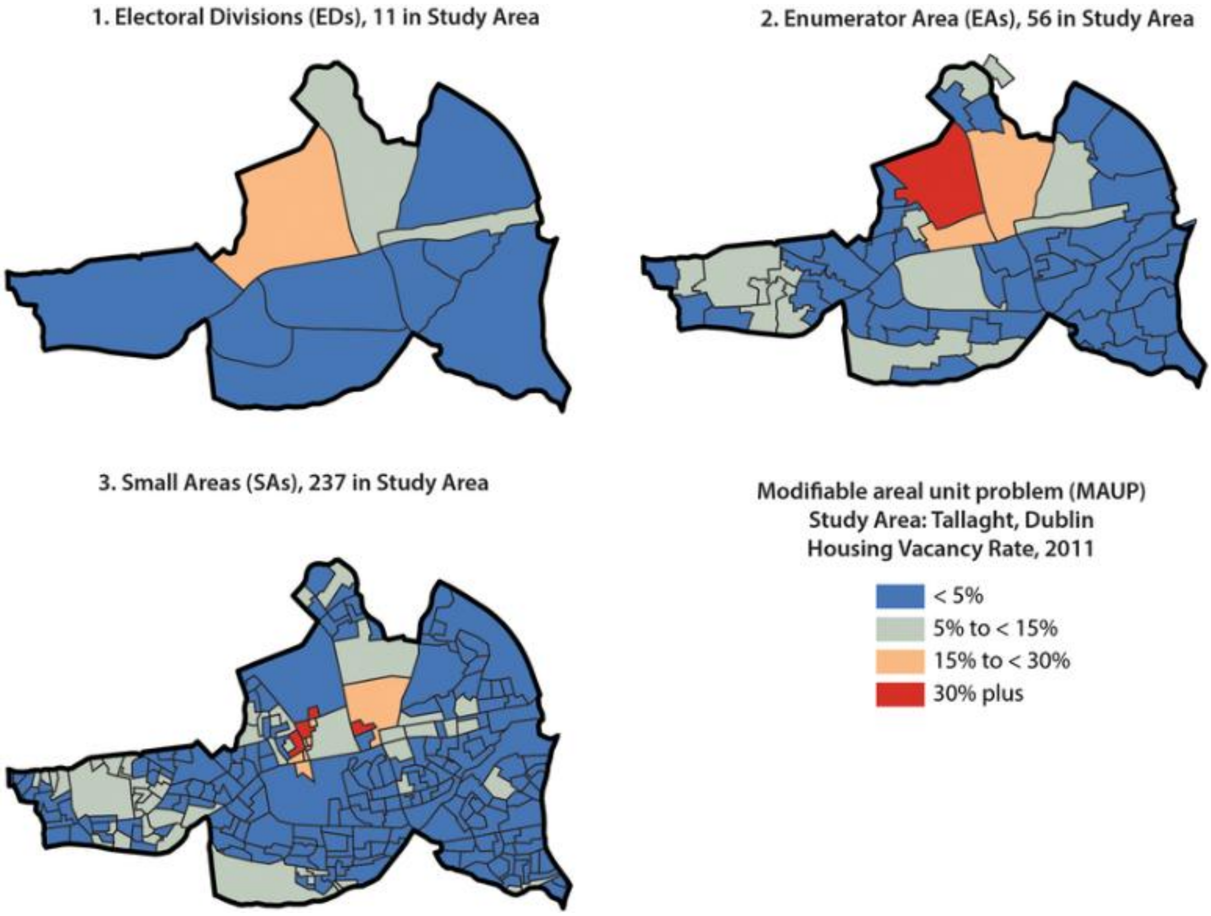
Figure 2: Schematic representation of the Modifiable Areal Unit Problem



Source: Ho et al. (2015)

Figure 3 presents the MAUP in practice and shows the mapping of housing vacancy rate in Tallaght, Dublin in 2011 at three different scales. Map one illustrates the vacancy rate per electoral division, map two per enumerator area, and map three per small area. In each map the same indicator was used to present the vacancy rate per administrative unit. According to the legend of the maps, the vacancy rate is reaching between less than five percent up to more than 30 percent. Blue and green colours present relatively low rates, whereas orange and red colours present relatively high rates. In figure 3, it can be noticed that the patterns of vacancy rates per administrative unit are different in every map, due to the fact that different scales have been used. It presents an example of zoning (Ho et al., 2015). Ho et al. (2015) clearly distinguish the differences between scaling and zoning, whereas Räsänen et al. (2019) use the term zoning for both scaling and zoning in spatial data aggregation. Nevertheless, in this research the distinction according to figure 2 will be used.

Figure 3: Example of MAUP in practice, three maps showing the housing vacancy rate in Dublin in 2011 with the same indicator.



Source: Kitchin et al. (2015)

2.1.4. Usability

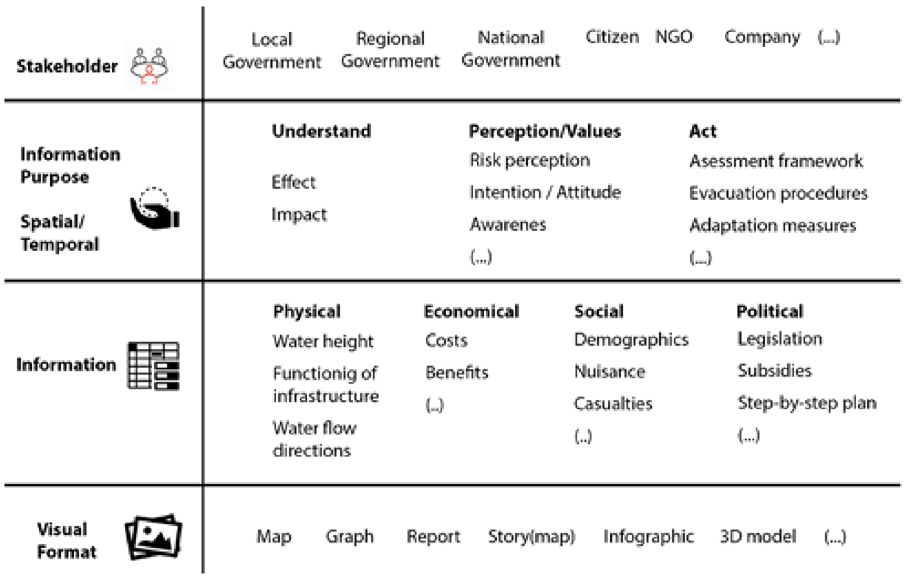
Maps which present the vulnerability of populations to the UHI effect are an example of climate services (CS). As mentioned earlier in this research, CS are tools that can be used to communicate information about climate change or climate adaptation. They can support decision-making processes amongst stakeholders in climate adaptive spatial planning. However, the way these CS are presented can lead to diverse ways of interpretation of information and visualisation of the data. According to Raaphorst et al. (2020) CS need to contain three distinct types of qualities to be usable. These qualities are related to the information itself, the audience it is presented to, and in which format it is presented. The first quality which is mentioned in the article is validity.

Validity is focused on whether the information of a CS is presented to an appropriate audience and whether it affects them. Also, it addresses if the purpose of the CS is suitable for the policy cycle of the institutions/group of stakeholders. Furthermore, it involves if the information on climate change or climate adaptation is presented correctly, and if the type of format in which the data is presented is actually representing the accurate climate situation.

Readability is a concept which emphasises if the visual language is suitable for the interpretative capacity of the audience. Furthermore, it concerns if the purpose of the CS and the information which is presented is clear. And finally, if the way how to read the CS, and how to interpret the information is clear as well since there could be differences between types of CS. The last quality regards interactivity. This relates to the possibility to add or adapt the information that the CS presents, for example by modifying colours or scales which can influence the visualisation.

The concepts of validity, readability, and interactivity are dimensions of the usability of CS. Usability is an overarching concept that can be defined as "*the extent to which a climate service enables stakeholders of climate adaptation processes to access, understand, and use climate data, which can be expressed in relative levels of validity, readability, and interactivity*" (Raaphorst et al., 2020, p. 6). In the same article a climate information design (CID) was presented to illustrate the usability of climate data visualisations, such as CS. The CID, which can be seen in figure 4, presents four visual communication components: involved stakeholders/audience, the purpose of the information, the type of information, and the visual format. The four components are in line with the components of the definitions of validity, readability, and interactivity.

Figure 4: Conceptualisation of usability according to the climate information design



Source: Raaphorst et al. (2020)

2.1.5. Usability gaps

This section will explain the possible challenges that stakeholders may have to deal with during the process of interpreting CS. In the theories on CS certain challenges are referred to as usability gaps. In the introduction the concept of usability gaps was already mentioned briefly: *"Potentially useful climate information which goes unused leads to a gap between what scientists understand as useful information and what users recognize as usable in their decision-making"* (Lemos et al., 2012, p. 789). Usability gaps can also be a result of visualisation. This is the case when the visualisation of data is not suitable for the users

(Raaphorst et al., 2020). It is necessary to reduce the amount of usability gaps occurring in practice, so that decision-makers can make more accurate decisions in climate adaptive spatial planning. Hence, in this chapter the diverse types of usability gaps will be illustrated in figure 5. The usability gaps are related to the level of validity, readability, and interactivity of CS. According to Raaphorst et al. (2020) they can be divided into four categories which are stakeholders, the purpose, the information, and the visual format.

Figure 5: Usability gaps that can occur due to the lack of validity, readability, and interactivity.

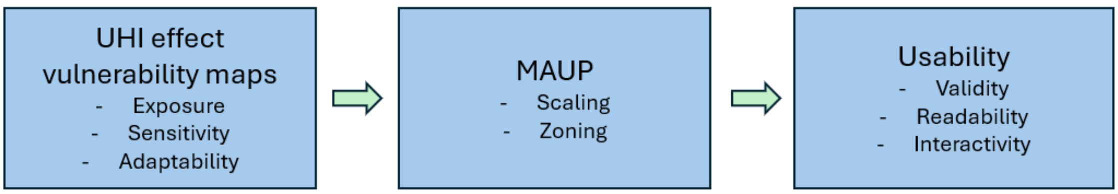
	Validity	Readability	Interactivity
Stakeholder	Is the desired action the responsibility of the targeted audience?	Does the visual language, and its possible connotations, match the interpretive frames of the audience?	Is the visual literacy required for interpreting the CS suitable for the target audience?
Purpose	Is the purpose (understand, feel, act) suitable for the phase in the policy cycle?	Is the purpose of the CS clear? (otherwise people act before understanding)	Can the CS be repurposed by the user?
Information	Is the information shown correct/trustworthy?	Is it clear what information is presented in a CS?	Can the information be modified?
Visual format	Does the visual mode enable an accurate representation of the climate phenomenon?	Is the type of mode, and its way of reading, clear? (a story map requires a different viewing than a standard GIS map)	Can aspects of the mode (zoom level, color scheme, etc.) be modified?

Source: Raaphorst et al. (2020)

2.2. Conceptual model

This section will provide the conceptual model, which includes all the main concepts and the causal relationships between them. The conceptual model, which is presented in figure 6, functions as the backbone for this research. The starting point of the conceptual model is in the blue square in the left of the figure, containing ‘UHI effect vulnerability maps’. Within this blue square, the three components of urban heat vulnerability according to figure 1 are presented. The components are exposure, sensitivity, and adaptability. Firstly, these existing vulnerability maps based on the three components will be analysed with support of my own analysis. Secondly, an analysis on the MAUP with support of spatial data aggregation (scaling and zoning) will be performed. The outcomes of the second analysis will lead to multiple mapping scenarios. The usability of the mapping scenarios will then be analysed according to the literature on usability which is discussed in this chapter.

Figure 6: Conceptual model



Source: Own (2025)

3. Methodology

This chapter will provide information on the following topics, concerning the methodology of the research. Firstly, the research strategy, which will be used to conduct this research will be introduced according to literature on social research methods. Secondly, the different research methods that will be used to conduct this research, followed by information on the data which will be collected, will be emphasised. Thirdly, the chapter will focus on the diverse ways in which the gathered data will be analysed, followed by a paragraph concerning validity, replicability, and reliability of the research. Finally, this chapter will end with a paragraph on ethics in social research.

3.1. Research Strategy

This research contains a mixed methods approach due to the fact that it contains both a quantitative and a qualitative analysis. The quantitative approach is a strategy in which quantification of the collection and analysis of the data is emphasised. One of the core data collection and analysis methods of this research will be the use of Geographic Information Systems (GIS). This is a program that allows you to present quantitative data in geographical units. The outcomes of the quantitative data collection and analysis will be evaluated with support of the opinions of stakeholders. This part of the analysis will be qualitative, which means that the focus lies on the emphasis of words in data collection and analysis.

The two approaches are aligning with two distinct social research doctrines according to Bryman (2012). The quantitative approach of this research fits in the positivist doctrine. In this doctrine “the role of research is to evaluate theories and to provide material for the development of laws” (Bryman, 2012, p. 70). The provided material from positivist research allows the assessment and explanation of laws, which is the exact aim of this research. The qualitative approach of this research fits in the constructivist doctrine. Constructivism can be defined as an approach in which the meanings of social phenomena are created and recreated by social actors. It indicates that the researcher does not present a definitive version of reality but rather focuses on specific versions of social reality in the social world (Bryman, 2012).

It can be concluded that this research strategy is deductive since it is evaluating already existing theories. Whereas an inductive approach aims to create new theories with support of observations and findings (Bryman, 2012). So far, the theories about mapping the vulnerability to the UHI effect, and the possible influence of diverse types of spatial data aggregation have been examined. The collection of these theories has led to the following hypothesis. It states that the spatial aggregation of data on the vulnerability to the UHI effect will lead to different visual and statistical outcomes. The findings of this research will ultimately confirm or reject this hypothesis, which will finally lead to a revision of the existing theories on the influence of spatial data aggregation on mapping the vulnerability to the UHI effect.

3.2. Research methods

This section will present the main research methods. As mentioned in the introduction shortly, this research will focus on the mapping of the UHI vulnerability in the Dutch city of Haarlem. A detailed analysis on a single case, such as Haarlem, is commonly known as a case study design. According to Stake (1995) case studies observe the complexities and nature of a single case in question, furthermore Bryman (2012) argues that some of the best-known social studies have been conducted with support of a single case study design.

In 2022, Haarlem was classified as the most petrified city in the Netherlands compared to other Dutch cities. The city is known for its high density of population and buildings due to the lack of space for expansion which makes it an interesting case. Therefore, an analysis on a local city scale can be useful for climate adaptive spatial planning. Presenting vulnerability to the UHI effect on larger scales (national or regional) might not be useful for climate adaptive spatial planning. Also, blue, and green infrastructures to beat the urban heat are usually implemented based on city, neighbourhood, or even smaller local scales. Furthermore, other urban areas might have different spatial characteristics, which would make a comparison between multiple cases irrelevant. Since most of the world's population lives in urban areas, the case study of this Dutch city was chosen as the unit of analysis. Presenting the phenomenon on a city scale might give insights on which locations in the city will need the most climate adaptive spatial planning compared to other parts of the city.

3.3. Data collection

As mentioned earlier, the analysis for this research consists of both a quantitative and a qualitative part. In order to do this, two diverse types of data will need to be collected with support of different methods. This section will address the different methods of the data collection for this research. The methods are based on the sub-research questions which have been presented in the theoretical framework and are also shown in table 2.

3.3.1 Quantitative data collection

To create multiple mapping scenarios presenting the vulnerability to the UHI effect on different scales, quantitative data will be collected. It will be retrieved from public Dutch sources such as Klimaateffectatlas, Atlas Leefomgeving, and the Municipality of Haarlem. Web maps, story maps, and the data which was used to create these maps on these websites will be analysed. Based on the literature on the components of vulnerability to the UHI effect (exposure, sensitivity, and adaptability), the data of several maps will be chosen for the analysis. It will be requested from CAS, which is an institution that creates CS that can also be found on Klimaateffectatlas and Atlas Leefomgeving. The data which will be retrieved from CAS will consist of specific indicators of exposure, sensitivity, and adaptability.

Table 2 shows the operationalisation of the concepts which are crucial for conducting this research. In this table the sub-research questions, concepts, indices, indicators, and data sources are presented. Data on the exposure to urban heat will be indicated by Physiological equivalent temperature (PET), coming from Klimaateffectatlas, Nelen & Schuurmans (2024). This data was retrieved on the 1st of July in 2015, which was representative as a tropical hot summer day according to (RIVM, 2019). On this day, a maximum temperature of 33,1 degrees Celsius was measured in de Bilt. The PET of that day has been measured with support of air temperature, wind speeds, air humidity, reflected solar radiation, and heat radiation from the environment (Klimaateffectatlas, 2025).

Data on the sensitivity will be indicated by the percentage of vulnerable populations, coming from Klimaateffectatlas & RIVM (2025). It can be concluded that several social groups are more likely to experience negative effects from the UHI effect than other groups. Examples of these groups are infants, disabled people, and people with an age of 65 years or older. In this research this last social group will be used for the analysis of social vulnerability. With support of Kleinenberg-Talsma et al. (2023) an index was created to estimate the amount of vulnerable people with an age of 65+. The index includes physical vulnerability in terms of disabilities. Additionally, it focuses on mental vulnerability in terms of confidence and dealing with tense situations. Finally, the social networks on which a person can rely on have al been included in the index.

Data on the adaptability will be indicated by the average walking distance in meters from a building in Haarlem to a cooling spot. This data is coming from Klimaateffectatlas & Tauw HVA (2025). A cool spot can be indicated by several characteristics, such as a minimum size of 200 square meters and the fact that it should not exceed a temperature of 35 degrees Celsius. Furthermore, it should have a minimum distance from a road. Finally, the area should be spacious in terms of width and should not be a long stretched small stroke of land. The average walking distance from a building to a cool spot has been measured with support of a network analysis, including only walkable roads and pavements (Rucabado Gordo & Keizer, 2025).

The data on social vulnerability will be retrieved on a neighbourhood scale. The data on exposure in both grid cells of two by two meters and on a neighbourhood scale. The data on adaptability will be retrieved on an address scale. Finally, all this data, which presents the vulnerability to the UHI effect in Haarlem, will be aggregated into different units of analysis. As mentioned by Ho et al. (2015) this can be performed with both zoning and scaling. In terms of zoning several layers in Arc GIS Pro, consisting of administrative boundaries will be retrieved from CBS (2025) and the Municipality of Haarlem (2025). In terms of scaling, different self created cell sizes will be used to aggregate the data.

3.3.2. Qualitative data collection

The second part of the data collection consists of qualitative methods. Several stakeholders in climate adaptive spatial planning will be interviewed on the usability of current Climate Services and the generated multiple mapping scenarios from this research. The goal is to ask every stakeholder that will be interviewed the same questions in the same order. However, if significant replies do occur in the interview, the interviewer has the possibility to ask further questions. As a result, this can make the interviews semi-structured. To create insights on the opinions of stakeholders active in climate adaptive spatial planning, respondents from three different institutions were asked to take part in interviews.

Respondent 1 (R1) is working at Sweco, which is one of Europe's largest architectural and engineering firms and active in 14 European countries. The firm engages in consultancy for climate adaptation, sustainable urban design, and heat issues. Furthermore, they both publish and use Climate Services to indicate urban heat and possibilities for blue and green infrastructure. R1 is active in consultancy for climate adaptation and urban water and has taken part in several projects concerning beating urban heat. An intern at Sweco, who is active in projects concerning beating urban heat will also take part in the interview and will be mentioned as respondent 2 (R2).

Respondent 3 (R3) works for Buroboot, which is a Dutch firm that uses landscape architecture and urban design to focus on climate adaptive public spaces. Projects in which Buroboot participates concern reducing the urban heat. This is done with strategies such as implementing green space, shading public spaces, and creating permeable surfaces. R3 is a project manager in climate adaptation and urban water and has been part of multiple project which focus on reducing the impacts of urban heat.

Respondent 4 (R4) and respondent 5 (R5) are both working for the municipality of Haarlem. As mentioned earlier, the city of Haarlem was named the most petrified city in the Netherlands in 2022. Therefore, the city has undertaken action to become greener and more climate resilient. R5 works as a climate policy consultant and gives advice for implementing blue and green infrastructure. R4 is a senior consultant in geo information services and has a lot of experience in translating data into usable climate services, which stakeholders such as R5 use in their work in creating climate adaptive policies.

Table 1: Overview of the respondents from four interviews

Respondent	Institution/company	Type	Function
R1, R2	Sweco	Architectural and engineering consultancy	Consultant in Climate Adaptation and Urban Water, Intern
R3	Buroboot	Consultancy and management services	Project manager Climate Adaptation and Urban Water
R4	Municipality of Haarlem	Municipality	Senior consultant geo-information services
R5	Municipality of Haarlem	Municipality	Policy consultant Water and Climate

Source: Own (2025)

3.4. Operationalisation

This chapter will provide the operationalisation of the main concepts which are needed to answer the sub-questions. The combination of the answers to the sub-questions will finally lead to a conclusion on the main research question. Table 2 shows the six sub-questions in the first column. The second column provides the main concepts which have been discussed in the literature review and have been presented in the conceptual model. The third column provides the indices which emphasise the dimension in which the concept will be researched. In the fourth column the units in which the concepts will be measured are presented as indicators, and finally the fifth column shows which sources have been used for gathering data on the concepts.

Table 2: Operationalisation of the concepts

Sub RQ	Concepts	Indices	Indicators	Sources
1. What are the current perceptions of usability of climate services presenting vulnerability to the UHI effect?	Usability	CID framework	Audience, purpose, information, format	Raaphorst et al. (2020), Sweco, Buroboot, Municipality of Haarlem (2025)
		Opinions of stakeholders	Validity, readability, interactivity	
2. How does spatial data aggregation with support of zoning affect the visual representation of vulnerability to the UHI effect in Climate Services	Spatial data aggregation	Zoning	6-digit postal codes, neighbourhoods, 4-digit postal codes, districts, boroughs	Klimaateffectatlas, CBS (2025)
	Vulnerability to the UHI effect	Exposure	Physiological equivalent temperature (PET)	Klimaateffectlas, Nelen & Schuurmans (2025)
		Sensitivity	Percentage of vulnerable population	Klimaateffectlas & RIVM (2025)
		Adaptability	Average walking distance to a cooling spot	Klimaateffectatlas, Tauw HVA (2025)
3. How does spatial data aggregation with support of scaling affect the visual representation of vulnerability to the UHI effect in Climate Services	Spatial data aggregation	Scaling	Cell sizes of two-by-two, 20X20, 50X50, 100X100, 250X250 meters	Klimaateffectlas, CBS (2025)
	Vulnerability to the UHI effect	Exposure	Physiological equivalent temperature (PET)	Klimaateffectlas, Nelen & Schuurmans (2025)
		Adaptability	Average walking distance to a cooling spot	Klimaateffectatlas, Tauw HVA (2025)
4. To what extent does spatial data aggregation with support of zoning affect the statistical validity of maps presenting the vulnerability to the UHI effect?	Statistical validity	Moran's Index Analysis	Moran's I	Klimaateffectatlas, Nelen & Schuurmans (2025), RIVM (2025), Tauw HVA (2025)
			Z-score	
			P-value	
5. To what extent does spatial data aggregation with support of scaling affect the statistical validity of maps presenting the vulnerability to the UHI effect?	Statistical validity	Moran's Index Analysis	Moran's I	Klimaateffectatlas, Nelen & Schuurmans (2025)
			Z-score	
			P-value	
6. How do stakeholders in urban planning and climate adaptation perceive the usability of UHI vulnerability maps created at different spatial scales and zoning configurations?	Usability	Validity	Interview codes	Sweco, Buroboot, Municipality of Haarlem (2025)
		Readability		
		Interactivity		
	Usability gaps			

3.5. Data analysis

Besides the data collection, the data analysis also consists of two parts. The first part is the quantitative analysis of the multiple mapping scenarios visually and statistically. The second part concerns the qualitative analysis of the interviews with stakeholders in climate adaptive spatial planning. For the quantitative analysis, the collected data on vulnerability to the UHI effect will be spatially aggregated in different administrative units. The units of analysis are 6-digit postal codes, neighbourhoods, 4-digit postal codes, districts, and boroughs. Also, the data will be aggregated into different cell sizes. The different cell sizes are two by two, twenty by twenty, fifty by fifty, one hundred by one hundred, and 250 by 250 meters.

The outcomes of the spatial data aggregation will be presented in multiple maps which can be placed next to, and on top of each other to compare the visualisation. Furthermore, the maps will be evaluated on statistical validity to present to what extent data variations are visible between the multiple maps and whether the results are significant. The qualitative data, which will be received from four interviews with stakeholders from different institutions or companies, will be transcribed, coded, and analysed. The theories on usability and usability gaps, which have been discussed in the theoretical framework, will be used as codes to indicate the opinions of the stakeholders. These codes are presented in table 3.1 and 3.2. The classified results will be used to make conclusions on the interviews.

Table 3.1: Interview codes used to analyse usability of the multiple mapping scenario's, according to the stakeholders.

Validity	**Readability**	**Interactivity**
V1: CS reaches appropriate audience	R1: Visual language is attuned to the intended audience	I1: It is possible to repurpose the CS
V2: Type of information presented in the CS is correct	R2: The purpose of the CS is transparent	I2: It is possible to adapt the CS
V3: Visual format is coherent with the type of audience	R3: The presented information is clearly understandable	I3: It is possible to modify visual modes
	R4: It is clear how the visual format should be read	

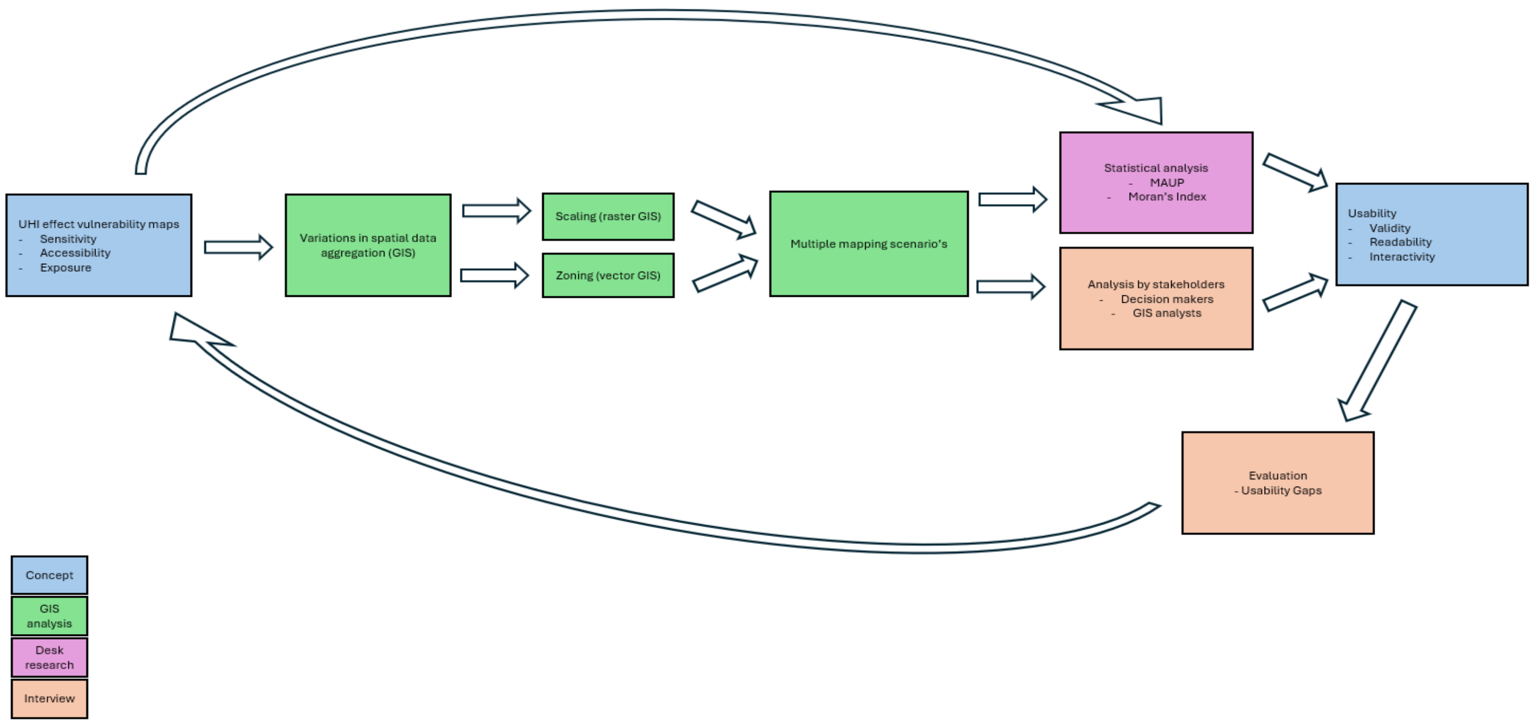
Table 3.2: Interview codes used to analyse the challenges in working with the multiple mapping scenarios, according to the stakeholders.

	Validity	**Readability**	**Interactivity**
Stakeholder	VS1: Desired action is not the responsibility of the targeted audience	SR1: The visual language does not match the interpretive frames of the audience	SI1: Visual literacy required for interpreting the CS is not suitable for the targeted audience
Purpose	PV1: The purpose of the CS is not suitable for the phase in the policy cycle	PR1: The purpose of the CS is not clear	PI1: The CS can not be repurposed by the user
Information	IV1: The information shown in the CS is not correct/Trustworthy	IR1: It is not clear what information is presented in the CS	II1: The information in the CS can not be modified
Visual format	VV1: The visual mode does not enable an accurate representation of the climate phenomenon	VR1: The type of mode, and the way of reading is not clear	VI1: Aspects of the mode (zoom, colour) can not be modified

3.6. Research flowchart

Figure 7 presents a flowchart of the research, in which the concepts, the methods, and the relations between them are illustrated. The flowchart functions as an overview of the methodology of this research. The starting point of the flowchart is the blue square in the left, which contains the concept of existing "UHI effect vulnerability maps." Firstly, these existing vulnerability maps will be analysed with supported with my own analysis. Secondly, an analysis with support of spatial data aggregation (scaling and zoning) will be performed. The outcomes will lead to multiple mapping scenarios. These maps which will be analysed with support of two different methods. Firstly, the statistical validity of the multiple maps will be evaluated with support of Moran's Index, which is a method to calculate spatial autocorrelation. Secondly, the maps will be analysed by both me and different stakeholders such as decision makers and data analysts. With support of these methods, the usability of the maps can be evaluated according to the literature on validity, readability, and interactivity. Possible usability gaps will be illustrated and evaluated, ultimately leading to the contribution to the usability of UHI effect vulnerability maps.

Figure 7: Research Flowchart



Source: Own (2025)

3.7. Research validity, replicability, and reliability

Research validity focuses on whether the indicators are measuring the concepts that they are supposed to measure. In this research, the influence of spatial data aggregation on the usability of UHI effect vulnerability maps will be researched. This will be measured with support of both my own analysis, and the opinions of stakeholders. Since I have conducted this research myself, prior knowledge can be of influence, according to Bryman (2012) this could be an error in implementation which is another aspect of validity. However, since the interviewees will not have prior knowledge and will not need to adapt their behaviour due to circumstances (reactive effect), the research will still meet the needs of research validity.

Reliability concerns whether the same results will be generated when the research is replicated. Firstly, it is important to mention that the research has a high level of replicability, which is common in quantitative research according to Bryman (2012). The fact that the research is replicable is due to the fact that the necessary data for the GIS analysis is publicly available. However, new data updates with possible changes on the data on the same components could lead to different outcomes if the same methods are used. Furthermore, due to new experiences of researchers and data analysts, new components, and indicators of vulnerability to the UHI effect could be added to the data and can possibly influence the validity of this research.

For the analysis that contains the opinions of stakeholders, the researcher needs the cooperation of the same stakeholders, which could be a challenge. To make research reliable, measures of the concepts need to be consistent. However, due to new experiences the opinions of stakeholders can change over time, referring back to the characteristics of constructivism which states that realities are socially constructed. Hence, Bryman (2012) argues that replication in social research is not common. This research can be reliable if the same case study and the same stakeholders will be analysed. However, choosing another case will make it necessary to include other stakeholders who are active in the region of that case. Finally, this can lead to different outcomes due to qualitative differences in stakeholder opinions.

3.8. Ethics

Ethical concerns might arise during the conduction of research. Therefore, they cannot be ignored which is why this chapter will provide information on the ethics. Bryman (2012) mentions four different ethical principles, which will be used to analyse the ethics of this research. The first principle concerns the harm to participants, which will not take place in this research due to the following things. All the data on vulnerability to the UHI effect, which will be used to create multiple mapping scenarios, is publicly available. Furthermore, the participants in the interviews will all be asked permission to share the results. If participants do not give permission, the data will not be analysed in the results of the research. This also argues that the second and third ethical principle, which are the lack of informed consent, and the invasion of privacy. Finally, the fourth principle emphasises the importance of the fact that the work of researchers should not present something else than what was told beforehand. Therefore, the results of this research will only be used to present to stakeholders in decision-making processes on climate adaptive spatial planning.

4. Results

In this chapter the findings from the quantitative GIS analysis, and the qualitative interviews will be presented. Firstly, an analysis on various existing CS on vulnerability to the UHI effect will be analysed according to the earlier described literature on the usability of climate services. The analysis will be supported by opinions from stakeholders in climate adaptive spatial planning, which have been gathered during four semi-structured interviews. Secondly, the visual representation and the statistical validity of the multiple mapping scenarios will be assessed. These sections will be provided with several figures and tables. Finally, an analysis on the usability of the multiple mapping scenarios by the four interview respondents will be presented.

4.1. Analysis of current UHI effect vulnerability Climate Services

This section will provide an analysis of current CS which present vulnerability to the UHI effect. The CS have been found on the internet and are examples retrieved from Klimaateffectatlas. Furthermore, several CS have been mentioned during the interviews with stakeholders in climate adaptive spatial planning. The findings on the usability of these CS will also be discussed in this section.

4.1.1. Own analysis

This section will provide the results according sub research question 1. *"What are the current perceptions of usability of Climate Services presenting vulnerability to the UHI effect?"* This research focuses on three different components of vulnerability to the UHI effect, which are exposure, sensitivity, and adaptability. Therefore, examples of Dutch CS presenting these components will be analysed in this chapter. The analysis will be performed with support of the Climate Information Design (CID) (Raaphorst et al., 2020), which has been discussed in the theoretical framework and figure 4. This design contains four categories of usability. These are the reached audience (stakeholders), the purpose of the CS, the information presented in the CS, and the visual format in which the information is presented. Each of the categories from the CID will be assessed on usability with support of validity, readability, and interactivity for the users of the CS. The results of this analysis have been presented at the end of this section in a Schematic overview of the analysed CS according to the CID in table 4.

4.1.2. The Klimaateffectatlas

An example of a Dutch website which presents CS on vulnerability to the UHI effect is the Klimaateffectatlas. It is commonly known by governments and institutions in the Netherlands. Furthermore, the website is publicly available for citizens, NGOs, and companies. Klimaateffectatlas is a Dutch website which presents data on climate change and climate adaptation in maps. The website has multiple functions, such as an abstract map viewer in which data on various topics can be analysed by both stakeholders in climate adaptive spatial planning and citizens. Furthermore, it also presents climate scenarios which illustrate an estimation of situations in the future. Finally, Klimaateffectatlas also presents several story maps. Story maps are gadgets in which a story on climate change or climate adaptation is written and supported by interactive maps, figures, and images.

There are several examples of CS in the Klimaateffectatlas which present the three different components of vulnerability to the UHI effect. There is a CS which is presenting the number of trees and green space per neighbourhood (adaptability/exposure), and one which presents the average PET per neighbourhood (exposure). Furthermore, there are CS on the average walking distance to a cool spot (adaptability) and the share of vulnerable elderly people per neighbourhood (sensitivity). The Klimaateffectatlas gives the reader the opportunity to zoom in to different cases, such as the case for this research which is the Dutch city of Haarlem.

4.1.3. Audience

The first category of the CID framework focuses on the audience to which the CS are presented. In the case of this research, they can be diverse type of stakeholders who participate in climate adaptive spatial planning. The CS on the exposure, sensitivity, and adaptability to the UHI effect can reach a wide range of audience. The CS are publicly available for national, regional, and local governments. Furthermore, citizens, NGOs, and companies can also access them. Raaphorst et al (2020) address the importance of the selected audience which can influence the desired effects of the CS. It is argued that not every type of information presented in CS is relevant for every type of stakeholder. For example, local and regional governments might interpretate a CS in a different way than a national government would do. Furthermore, it can occur that citizens, NGOs, and companies are less informed about the characteristics of the data in CS. Therefore, they might interpret the presented data in a different way than the more informed readers such as government stakeholders. Such examples indicate gaps in stakeholder validity.

The CS from Klimaateffectatlas do not mention for which types of audience the climate information is the most suitable. This can indirectly lead to distinct kinds of interpretations amongst diverse types of stakeholders. Besides validity, there can also occur gaps in terms of CS readability. This occurs if the way in which the CS are interpreted according to colour schemes and scales differ amongst stakeholders. Figure 8 presents the exposure to urban heat by the average PET in Haarlem on a tropical summer day. The data is presented in a single scale of grid cells with a size of two by two meters. The legend presents the different levels of heat stress and the different numbers of average PET. According to the legend the darker the colour red becomes, the higher is the average PET on that specific spot in the city. However, the colour red can be seen almost across the whole city of Haarlem. The colour red is commonly used for high data values in cartography, especially in the case of data on temperatures. Therefore, this CS indicates that the situation in the whole city is basically problematic, whereas in some parts of the city the average PET is relatively low. Diverse types of stakeholders can interpret this CS in different ways due to this specific colour scheme. This indicates a readability gap amongst different types of stakeholders for this CS.

Another Klimaateffectatlas CS, which is shown by a screenshot in figure 9, presents the level of population sensitivity per neighbourhood in Haarlem. The level of sensitivity is based on both fragility and welfare. A different colour scheme is used for this CS, compared to the CS on the average PET in figure 8. The differences between the values of the neighbourhoods are clearly visible and distinguishable. However, the level of information on the nature of the data is relatively limited. Therefore, less informed stakeholders can face problems regarding the readability of this CS. Furthermore, the fact that two variables (fragility and welfare) are used to present only one component can also decrease the readability of the CS for some stakeholders. In stead, two distinct maps showing one variable each can make reading the CS less complex.

Another Klimaateffectatlas CS is shown in figure 10. This CS presents the average walking distance from a building to a publicly accessible cool spot. The colour scheme which is presented in the legend has a higher level of readability compared to the scheme in figure 8. This is due to the fact that there is a clear flow of the colours ranging from green to red, indicating the different average walking distances. The cool spots are indicated with a dark blue colour. However, the information on the actual characteristics of the cool spots is missing. Readers of this CS can make conclusions based on the average walking distance to a cool spot. Although, due to the lack of information on the characteristics of the cool spots it is unknown if these spots are actually effective for residents in the area.

4.1.4. Purpose

The second category of the CID framework is the purpose of CS. It focuses on the intention of the information which is presented. Raaphorst et al. (2020) mention that some information which is presented in CS can be relatively abstract and therefore not useful for climate adaptive spatial planning. They mention an example of a lack of detail on micro-micro scale in a CS presenting the soil of the surface. This can lead to a lack of information on how and why this CS can be used by stakeholders. On the other hand, if a CS contains too much information, it can occur that stakeholders do not see the purpose of the CS anymore. This is the result of complex readability.

The purpose of the CS presenting the average PET (figure 8) appears to be clear for different types of stakeholders. For climate adaptive spatial planners, the CS illustrates which areas in Haarlem will experience the highest and lowest average PET on a tropical summer day. The information in the CS can support strategies for cooling down the areas with the highest average PET. On the other hand, the CS can provide information for citizens on what will be the hottest places in the city during future heatwaves. With support of this CS, they can influence their behaviour if a heatwave does in fact take place. The data in this CS is gathered on a local and microscale which indicates a relatively high level of validity.

The purpose of the CS which is presenting the population sensitivity (figure 9) is to inform those who can undertake action against urban heat. The CS provides stakeholders in climate adaptive spatial planning with demographic information, which can be useful in decision-making processes. On the other hand, other types of stakeholders who are less informed on the components of urban heat vulnerability might not fully understand the purpose of this CS. These stakeholders would be citizens or companies. The data in this CS is gathered on a larger scale and is therefore less detailed. This results in a lower level of validity.

The third CS presents the average walking distance to a cool spot (figure 10). The data is gathered on a local and micro scale and is therefore relatively detailed. The purpose of this CS can be assessed as clear for a wide range of stakeholders. Climate adaptive spatial planners are informed on where to implement green and blue infrastructures in areas which are lacking cooling spots. Furthermore, citizens are informed about the distance to spots in the cities where they can cool down. This can make them adapt to urban heat during heat waves.

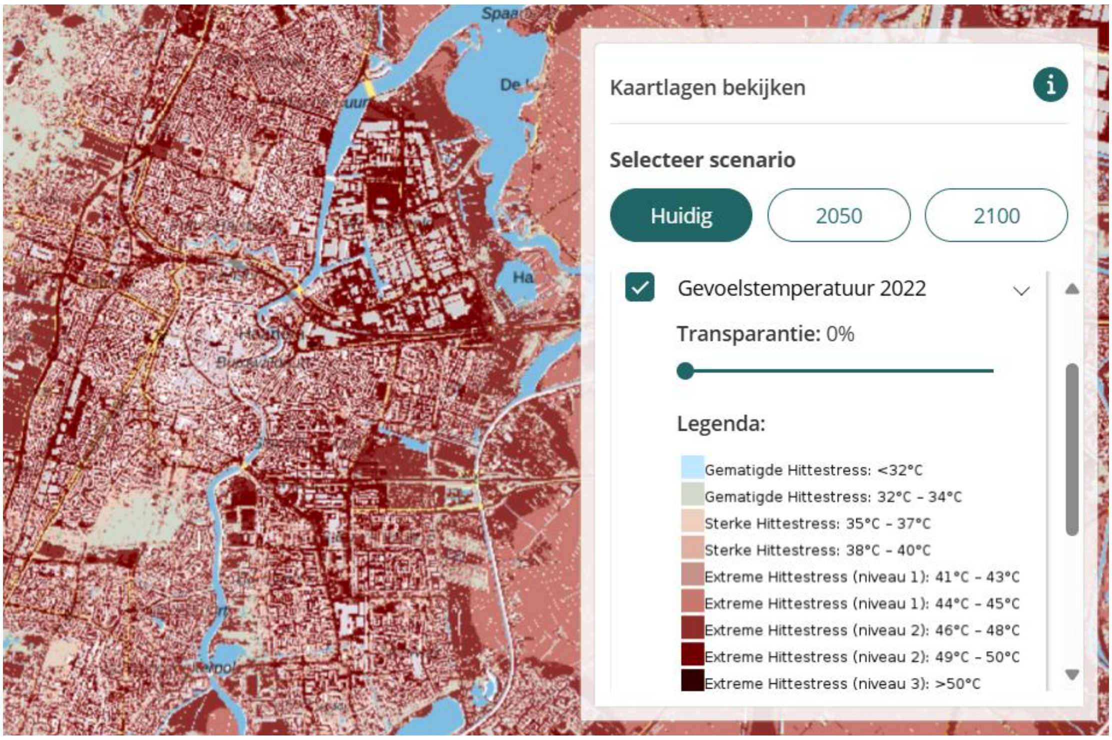
4.1.5. Information

The third category of the CID framework focuses of the presented information in the CS. Clear descriptions and manual explanations of the types of information could benefit the readers according to Raaphorst et al. (2020). However, limited space for information in the legends of CS can influence the readability for stakeholders. Therefore, the Klimaateffectatlas gives the readers an opportunity to open a story map for all the three components (exposure, sensitivity, and adaptability). The story maps give clear descriptions of the components of UHI effect vulnerability, and what types of data have been used to present them. Furthermore, they also explain how the presented information should be interpreted. The story maps address the urgency of implementing blue and green infrastructures to beat the urban heat. Besides that, they also increase the awareness of the impacts of climate change on liveability in urban areas.

4.1.6. Format

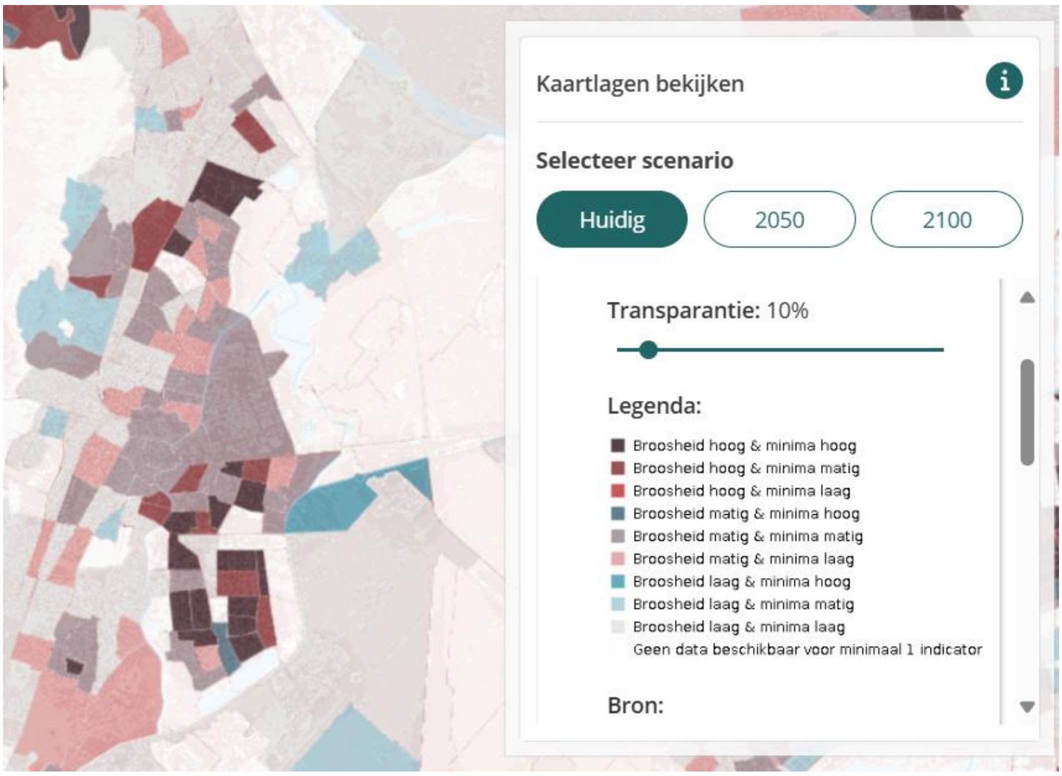
Finally, the fourth category of the CID framework concentrates on the format in which the CS are presented. So far, the three discussed CS (figures 8, 9, and 10), can be assessed as informative and interactive maps. They are supported with options to receive detailed information from corresponding story maps. In terms of interactivity the three CS give the reader the opportunity to zoom in and out to specific areas in the Netherlands. Furthermore, there are possibilities to switch specific layers on and off to compare distinct types of data which present different components of UHI effect vulnerability. For example, the Klimaateffectatlas also provides a map which shows the average PET (figure 8) on a neighbourhood scale. This has resulted in the possibility to compare the visuality of a grid cell pattern and administrative units of analysis. Furthermore, there is the possibility to switch from a layer presenting the average PET on a hot tropical summer day in 2012 to one in 2022. With this function it is possible to illustrate the impacts of climate change in urban areas over a period of ten years.

Figure 8: Screenshot from the Klimaateffectlas, a CS presenting the average PET per grid cell of two by two meters on a tropical summer day in Haarlem in 2022. Taken on the 24th of July in 2025.



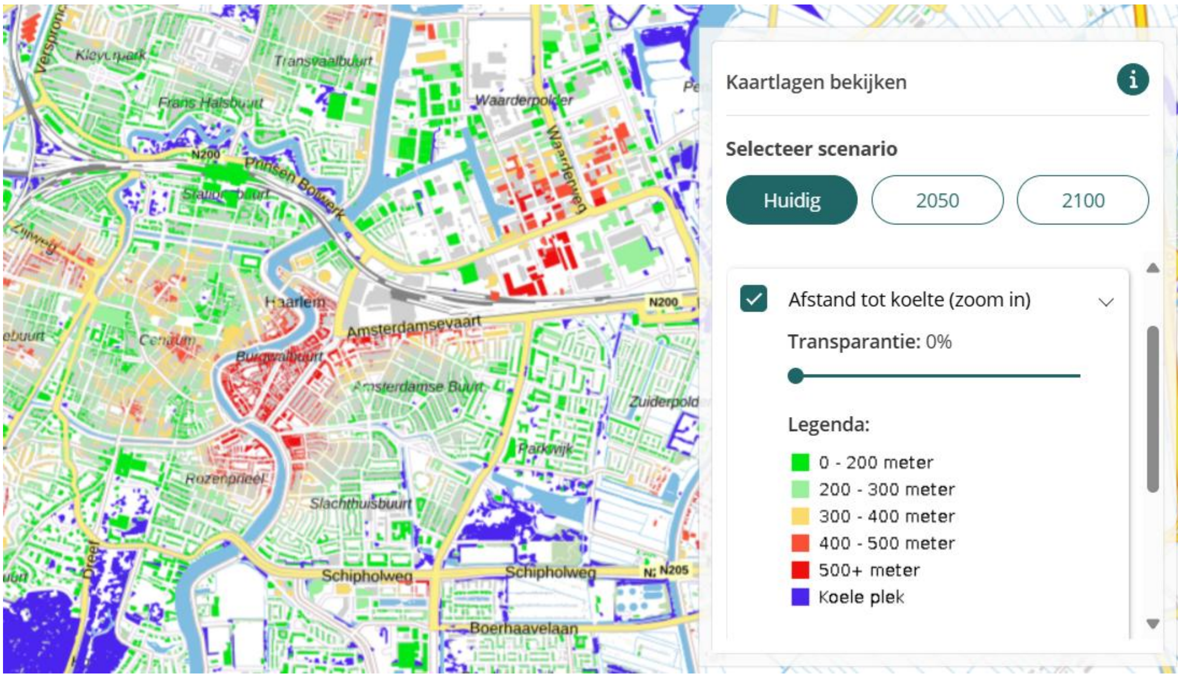
Source: Klimaateffectatlas (2025)

Figure 9: Screenshot from the Klimaateffectatlas, a CS presenting the level of population sensitivity in different neighbourhoods of Haarlem. Taken on the 24th of July in 2025.



Source: Klimaateffectatlas (2025)

Figure 10: Screenshot from the Klimaateffectatlas, a CS presenting the average walking distance from a building to a cool spot in Haarlem. Taken on the 24th of July in 2025.



Source: Klimaateffectatlas (2025)

Table 4: Schematic overview of the analysed CS according to the CID.

	Exposure	Sensitivity	Adaptability
Audience	Local, regional, national governments. Citizens, NGO's, companies	Local, regional, national governments. Citizens, NGO's, companies	Local, regional, national governments. Citizens, NGO's, companies
Purpose	Supporting stakeholders in climate adaptive spatial planning with information on where to implement blue and green infrastructure to beat the urban heat, creating awareness on the effects of climate change in urban areas for citizens	Providing climate adaptive spatial planners with information on populations in urban areas, which can influence their decision-making processes	Supporting stakeholders in climate adaptive planning with information on where to increase the possibilities for adaptivity. Providing citizens with information on locations and distances to cool spots in urban areas
Information	Information on the data presented in the CS is limited, links to story maps have been added to provide readers with detailed information	Information on the data presented in the CS is limited, links to story maps have been added to provide readers with detailed information	Information on the data presented in the CS is limited, links to story maps have been added to provide readers with detailed information
Visual format	Informative and interactive maps, story maps	Informative and interactive maps, story maps	Informative and interactive maps, story maps

Source: own (2025)

4.2. Opinions of stakeholders

This section will provide the extended results according sub research question 1: *"What are the current perceptions of usability of climate services presenting vulnerability to the UHI effect?"* The results have been retrieved from the opinions of the interviewed stakeholders.

This section will build upon the previous section and will further analyse the CS that are currently used in climate adaptive spatial planning. Four interviews with stakeholders from different institutions who are active in climate adaptive spatial planning have been conducted. Table 1 in the chapter on methodology shows an overview of the interview respondents. The stakeholders have been asked on their opinions on the current CS which they are using in decision making processes. With support of questions concerning validity, readability, and interactivity of the CS.

4.2.1. Validity

During the four interviews each respondent was asked several questions on the validity of current CS presenting vulnerability to the UHI effect. It turned out that the respondents were satisfied with the level of validity in general, especially for the CS of the Klimaateffectatlas. Respondent 1 (R1) is a consultant in Climate Adaptation and Urban Water, respondent 2 (R2) is an intern taking part in projects concerning beating urban heat. R1, who is already working for 6 years at Sweco, mentioned that the Klimaateffectlas is commonly used for his and his colleague's work. R1 argued that the strength of the validity is a result of using a single standardised method for presenting urban heat. This increases the usability of the CS for stakeholders active in climate adaptation. *"It is important that it is one single settled method, I think that how we currently work with this method in the Netherlands is seriously effective. For example, on another topic which is the modelling of flood risks, several methods are being used which results in comparing outcomes of different methods with each other. This will make it much more complex"* (R1, 2025).

Respondent 3 (R3), a project manager in climate adaptation and water at Buroboot, also mentioned the Klimaateffectatlas as one of the most dominant CS in his firm. The data from these CS is often used as a starting point for further analysis on a local scale. R3 argued that the CS are effective for the start of conversations with institutions or citizens which are experiencing the negative effects of climate change. The CS presenting the UHI effect with the average PET is an example. On the other hand, R3 argues that he sometimes has doubts in the fact whether such a CS is realistic. He mentioned the recent KNMI maps as an example. *"For example, you might have seen the new maps from KNMI presenting urban heat. These maps have been conducted while data on the wind direction is lacking, resulting in one big baking sheet. As a result, people might think it is more useful to install air conditioning in their houses instead of making the public spaces climate adaptive"* (R3, 2025). He indicates that more details are needed to translate CS into actual strategies for climate adaptation.

Respondent 5 (R5) is a policy consultant on water and climate in Haarlem and Zandvoort. He mentioned the usage of urban heat CS from the metropolitan area of Amsterdam, in which Haarlem is located. The map, which is conducted by Nelen and Schuurmans (2025) is also presented in the Klimaateffectatlas. R5 expressed confidence in the validity of the current CS. However, he suggested that the validity of current CS could be further increased with support of adding more temporal information. An example is presenting the average PET throughout the entire year, so that readers can compare the values on a tropical summer day with a regular day. Respondent 4 (R4) is active as a senior consultant in geo-information sciences. The essence in his work is to create and to analyse CS for the municipality of Haarlem and Zandvoort. R4 argued that the validity of a CS strongly depends on the research question of the user or reader. Therefore, he addressed the importance of analysing the desired information from clients before constructing CS. As a result, stakeholders are less likely to experience gaps in terms of CS validity according to R3.

4.2.2. Readability

Each respondent was also asked to assess the readability of current CS. Whereas the respondents were relatively positive on the level of validity, this turned out not to be the case for the level of readability. R1 and R2 shared their critical perspectives on the readability of CS in the Klimaateffectatlas which present the average PET. According to them, basically all urban areas are marked with a red colour and barely any local differences can be distinguished. This is a result of the current colour scheme and legend which are used in the Klimaateffectatlas. The opinions of R1 and R2 indicate a low level of readability of this CS.

The arguments on the readability according to R3 were in line with R1 and R2. R3 argued that sometimes the scenarios in the CS can be exaggerated. *"Sometimes the scenarios can look relatively extreme, which indicates the urgency of explanation and background information"* (R3, 2025). However, the need for further explanation depends on what is the purpose of the CS. If the purpose is to create awareness amongst urban populations, there would be no problem. Although, when the purpose is to inform stakeholders on which locations should be prioritised for implementing measures the situation is different. In contrast to the other respondents, R5 argued to be content with the scales and colour schemes which are currently being used. *"I do not need the data on a highly detailed scale, this scale indicates the problem, and that is sufficient enough. If I see a large red spot on a map then I know that measures will need to be implemented there"* (R5, 2025).

4.2.3. Interactivity

Asking questions concerning the interactivity of the current CS in the Klimaateffectatlas resulted in generally positive answers. R1 argued that there is the possibility to zoom into certain locations, and to add circles or squares to highlight certain locations of interest. Furthermore, it is possible to add symbols to mark certain relevant provisions such as childcare institutions. Besides that, R1 mentioned that it is possible to download the data from the Klimaateffectatlas itself. This allows the user to change the colour schemes and the legend to get different perspectives on the data. Furthermore, extra features such as buildings or trees can be added to experiment with the influences of such factors. R4 mentioned similar functions of the current CS. He addressed the importance of CS interactivity in terms of switching layer views and satellite backgrounds. Furthermore, he mentioned the opportunity for the user to hatch within a map view and to download the data as a service for other applications.

In table 5 a schematic overview of the stakeholder opinions on the discussed CS from the Klimaateffectatlas is shown. The empty cells in the table indicate that a certain opinion on one of the concepts has not been given during the interview.

Table 5: Schematic overview of the opinions of stakeholders on urban heat CS from the Klimaateffectatlas

	Validity	**Readability**	**Interactivity**
R1	Content with the validity of presented data	Legends and colour schemes reduce readability	Content with the high levels of interactivity
R2	Content with the validity of presented data		Content with the high levels of interactivity
R3	Questions the validity of certain CS	Scenarios can be extreme due to specific colour schemes	
R4	Data from the CS on a local scale (Haarlem) increases validity	Data from the CS on a local scale (Haarlem) increases readability	Content on the interactivity and possibilities to experience with the data from Klimaateffectatlas
R5	Additional information needed to increase validity	Additional information needed to increase readability	

Source: Sweco, BuroBoot, Municipality of Haarlem (2025)

4.3. Multiple mapping scenarios

This section will provide the results according to the following sub research questions. 2: *"How does spatial data aggregation with support of zoning affect the visual representation of vulnerability to the UHI effect in climate services"*. 3: *"How does spatial data aggregation with support of scaling affect the visual representation of vulnerability to the UHI effect in Climate Services?"*

This section will present the multiple mapping scenarios which have been created with support of spatial data aggregation in arc GIS pro. As mentioned in the chapter on methodology, the data which has been used is coming from Klimaateffectatlas and various other sources. The maps present different components of UHI effect vulnerability on different spatial scales. The components that have been used are exposure, sensitivity, and adaptability, as described in the theoretical framework. Firstly, the maps that have been created with support of zoning will be analysed, followed by the multiple maps as a result of scaling.

4.3.1. Zoning

Zoning refers to one of the two methods to aggregate spatial data, which were mentioned in the theoretical framework. Spatial data aggregation can be considered as zoning when different administrative units of varied sizes are used. For example, when data presented on a neighbourhood level is aggregated to larger districts. In the following three figures, data on three different components of UHI effect vulnerability have been spatially aggregated to five different administrative units.

4.3.1.1. Exposure

In figure 11, the average physiological equivalent temperature (PET) has been used to indicate direct exposure to urban heat. The data shows the average PET per administrative unit on a tropical summer day in 2022 in Haarlem. The data was obtained in a raster layer consisting of cells of two by two meters. After this the data has been aggregated into 5 different types of administrative units: six-digit postal codes, neighbourhoods, four-digit postal codes, districts, and boroughs. The average PET has a range between 35 to 50 degrees according to the legend. The data has been divided into different classes and can be read on the maps according to the colours in the legend. Blue and green coloured units indicate relatively low average PET values, whereas orange and red coloured units indicate relatively high values.

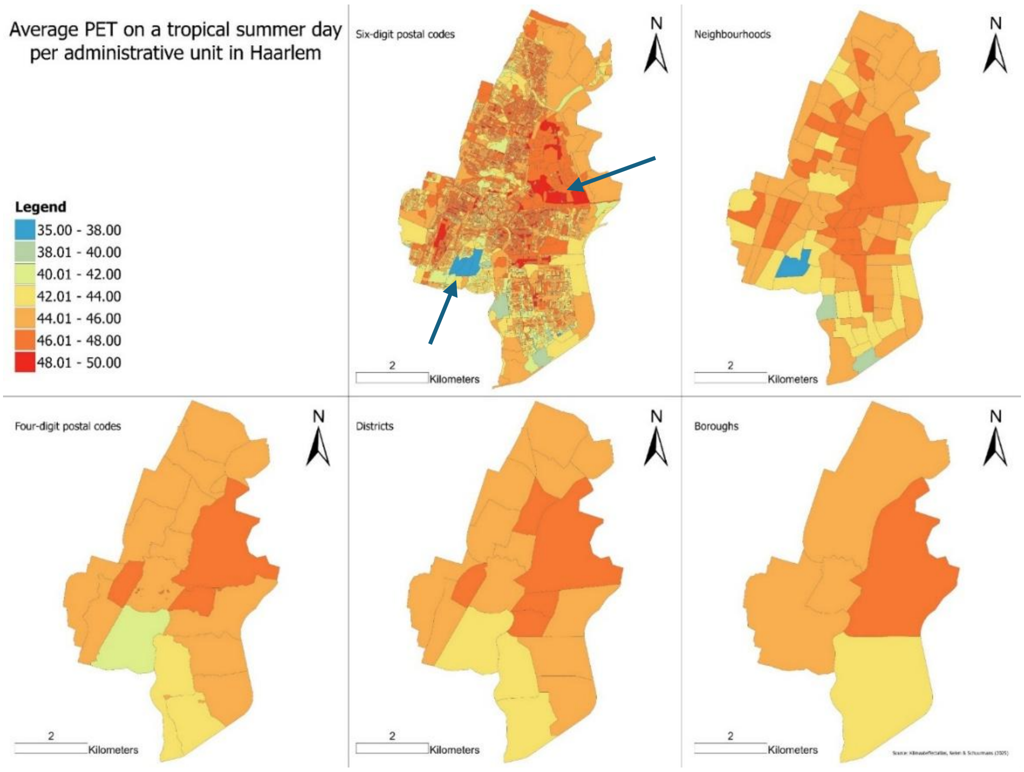
In the theoretical framework the definition of the Modifiable Areal Unit Problem was illustrated with support of academic literature: "*A statistical bias that arises from the selection of a specific spatial unit of analysis. When geographic data are aggregated into a spatial feature with specific spatial scale (e.g., by census tract, postal code, or county), mean values within the spatial feature are affected by its boundary, which in turn may lead to a zoning effect that affects subsequent analyses*" (Ho et al., 2015, p. 16111). Figure 11 indicates that the scale on which the data is aggregated directly influences the colour patterns of the maps. This is a result of summing up and recomputing the average PET values, which takes place during spatial data aggregation.

An example can be found in the bottom left of the six-digit postal codes map. This area of interest which contains the Frederikspark, located in the southwest of Haarlem. It is marked with support of a blue arrow in the map in figure 11 and can furthermore be identified by the blue coloured six-digit postal codes. The administrative units are coloured blue due to the presence of green space and shade. After spatially aggregating the data into larger administrative units, the relatively cool area within and around the Frederikspark can no longer be identified. The low values have been merged with higher surrounding values, which therefore results in higher average values on larger spatial scales.

Another example is marked with a second blue arrow and is located in the east of Haarlem. In the six-digit postal code map many of the administrative units in this area are coloured red. This indicates high average PET values between 48 and 50 degrees Celsius in these units. However, after aggregating the data into neighbourhoods, four-digit postal codes, districts, and boroughs these high values are not presented anymore. In all of these maps the maximum PET value does not exceed 48 degrees Celsius. And therefore, the spatial data aggregation results into a visual presentation of the same data in which the micro-scaled differences are not visible.

Furthermore, there are some examples at the edges of the city in both the north and the south of Haarlem. In the six-digit postal code map, the green coloured units on the edges of the city present an average PET value ranging between 38 and 40 degrees Celsius. The spatial data aggregation results into different patterns on the larger spatial scales. The results leave out the outliers that are in fact visible on a smaller scale.

Figure 11: Data on the Average PET, aggregated to five different administrative units



Source: Klimaateffectatlas, Nelen & Schuurmans (2025)

4.3.1.2. Sensitivity

In Figure 12, the sensitivity to the UHI effect of the population in Haarlem is presented with multiple maps. The sensitivity is indicated with the percentage of frail older adults (Frail and 65 years or older) from the total population per administrative unit. Firstly, data on the absolute amount of frail older adults and the total population per neighbourhood was obtained from the Klimaateffectatlas. The percentage of frail older adults per neighbourhood was then calculated by the following formula: (Amount of frail older adults / total population) *100. After this the data has been aggregated into 4 other types of administrative units: six-digit postal codes, four-digit postal codes, districts, and boroughs.

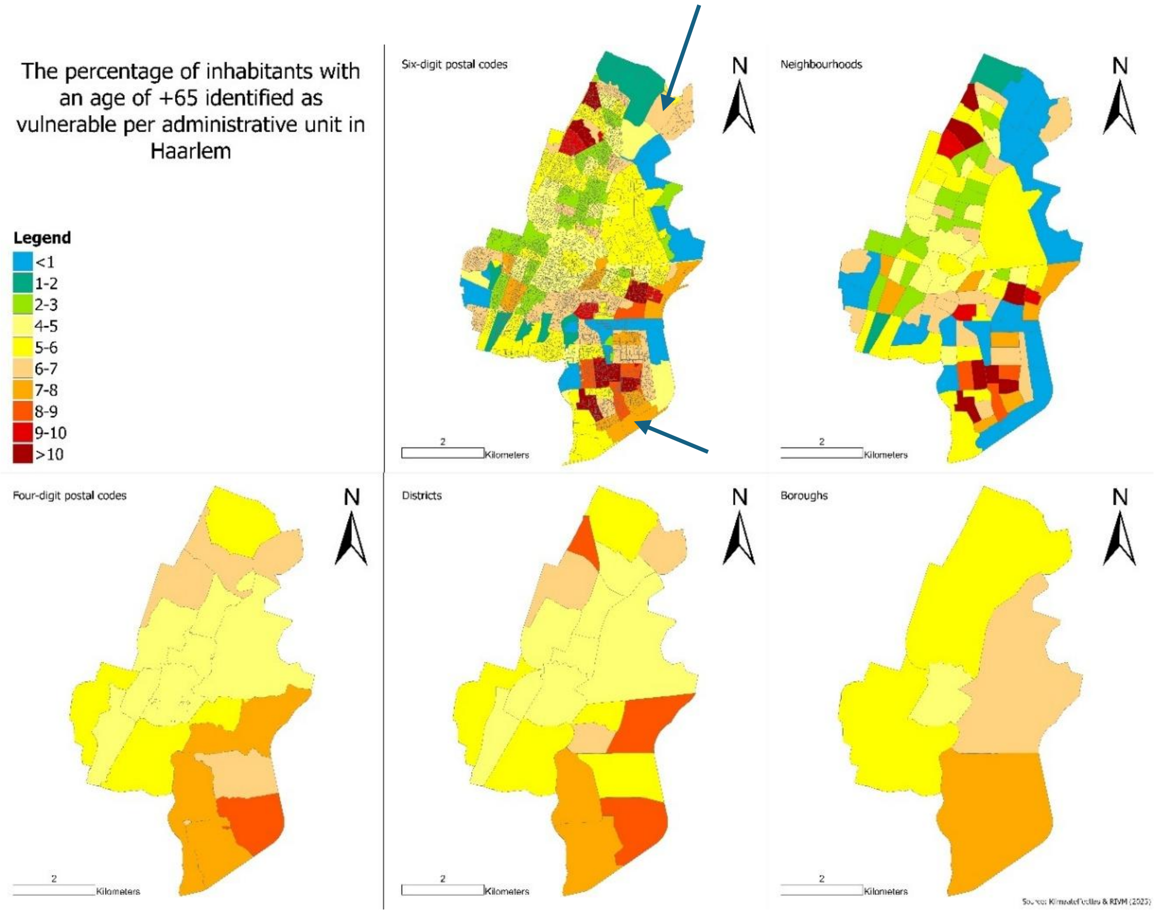
For the spatial data aggregation, the tool "geoprocessing intersect" was used to create a layer of overlaps between different administrative scales. After this a weight factor was created to calculate the share of frail older adults per overlapping unit. This was done with support of data on the surface area of the administrative units in square meters. Finally, all overlapping units were aggregated into larger administrative units with the dissolve tool. This tool allows to recalculate the statistics with support of the created weight factor.

The legend of figure 12 indicates that the percentage of frail older adults has a range between 0 and 10 percent. Although, there are some outlier areas which have percentages that are exceeding 10 percent. However, to maintain a clear and readable legend these outlier areas are classified as “<10”. Administrative units with a relatively low percentage of frail older adults are coloured blue or green. Units with a medium percentage are indicated with a yellow colour, and finally the relatively high percentages are coloured orange, red, and dark red.

Referring back to the literature on the MAUP it can be concluded that there is a similar pattern visible compared to figure 11. The blue and green colours which are present in the six-digit postal code map and the neighbourhood map are not visible anymore after the spatial data aggregation. Furthermore, some changes in the colour patterns are already visible after the first level of spatial data aggregation. The first example can be found in the six-digit postal code map in the north of Haarlem. It is marked with support of a blue arrow. In this area multiple six-digit postal codes are marked with a light orange colour. This indicates a percentage of frail older adults ranging between 6 and 7. After the data is spatially aggregated into neighbourhoods, units in the same area have become blue. This indicates a percentage below 1, which is a relatively large difference compared to the previous range between 6 and 7 percent.

Another example can be found in the south of the six-digit postal codes map and is again marked with support of a blue arrow. In this area some of the units are coloured dark orange, which indicates a percentage ranging between 7 and 8. After aggregating the data into neighbourhoods, this same area is now indicated with a blue colour. This is the result of the fact that the six-digit postal codes with high values have become part of a larger neighbourhood with a relatively low percentage of frail older people. This area becomes of more interest after the data is aggregated from neighbourhoods into larger administrative units. The dark orange and red colours on the four-digit postal codes and districts indicate percentages ranging between 7 and 9 which is differing a lot from the values on a neighbourhood scale. Just as was the case in figure 11, the direct impact of MAUP is clearly visible in figure 12 as well.

Figure 12: Data on the percentage of frail older adults, aggregated to five different administrative units.



Source: Klimaateffectatlas & RIVM (2025)

4.3.1.3. Adaptability

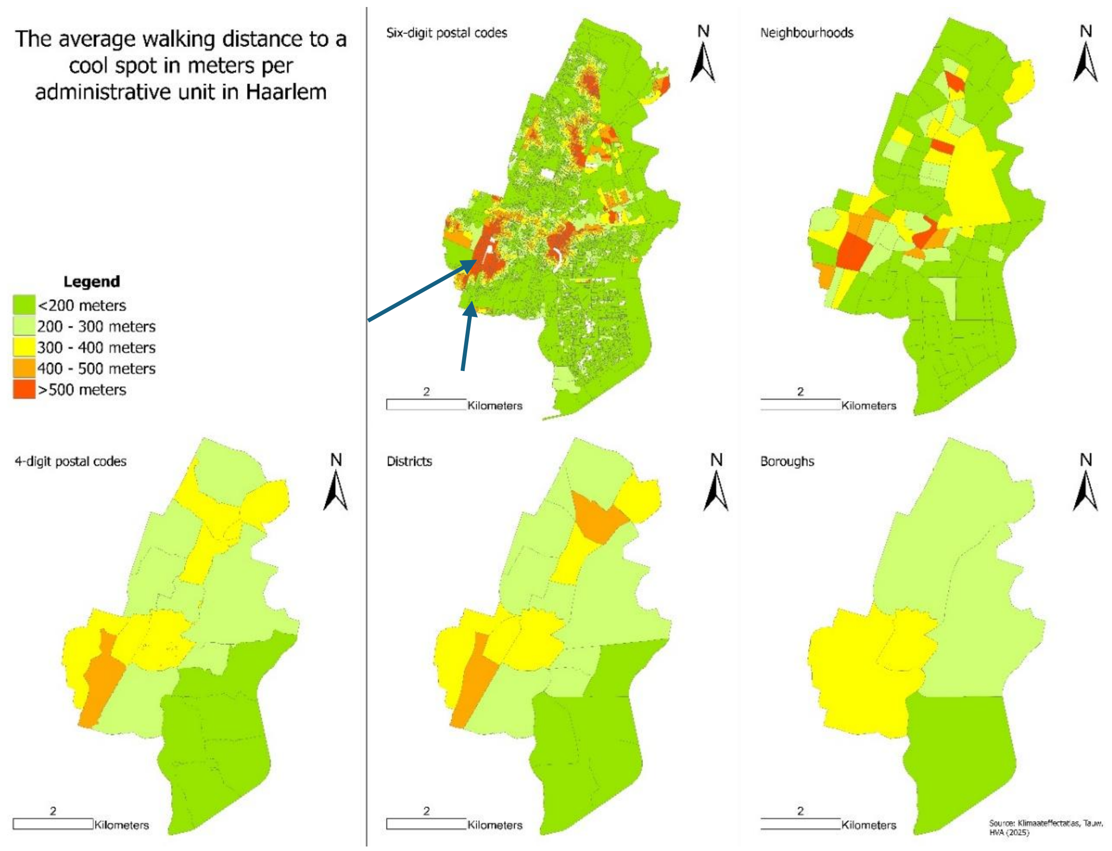
Figure 13 presents data in maps on the average walking distance in meters from a building to a cool spot. The data was obtained from Klimaateffectatlas and Tauw HVA (2025) in a layer file consisting of buildings. Each building contained an average value of walking distance to a cool spot in meters. The buildings have been classified by administrative units, and all the mean values have been summed up and then divided by the number of buildings per administrative unit. The legend indicates that the green areas in the maps have a relatively short average walking distance ranging between 0 and 300 meters. The yellow and orange areas contain a relatively high walking distance to a cool spot with distances ranging between 300 and 500 meters. Some areas are marked with a dark red colour, which indicates that the average walking distance exceeds five hundred meters.

Just as was the case for figures 11 and 12, figure 13 also presents some examples of the influence of spatial data aggregation. Again, two areas of interest have been marked with support of the blue arrows in figure 13. It is noticeable that there are some units in the six-digit postal code map with an average walking distance exceeding 500 meters. An example is located in the southwest of Haarlem and can be identified by a large red hotspot in the six-digit postal code map. After spatially aggregating the data into 4-digit postal codes and districts it is striking to see that the values in the same area have dropped to an average distance between 400 and 500 meters.

Another example is also located in the southwest of Haarlem. However, this area of interest contains the six-digit postal codes which are located south of the large red hotspot. These units are located relatively close to cool spots in the city according to the colour scheme in the legend of figure 13. The reason for this is that some of these administrative units are bordering the Frederikspark which contains a high level of green space, trees, and shade. However, after spatially aggregating the data the low values of <200 meters have merged with units in the same area with higher values. The maps which present the same data on a 4-digit postal code and district scale indicate that the same area of interest has been coloured orange. This indicates that the average walking distance in this unit is between 400 and 500 meters. However, some areas within this unit are in fact located right next to one of the major cooling spots in the city according to the six-digit postal codes map.

Finally, there are several other red hot spots according to the six-digit postal code map which are not identifiable anymore after aggregating the data into larger units. There are some red areas in the north for example, which you do not see in the 4-digit postal code, district, and borough map. Figure 13 is another example which presents the influence of spatial data aggregation on the visualisation of UHI effect vulnerability maps.

Figure 13: Data on the average walking distance to a cold spot from a building, aggregated to five different administrative units.



Source: Klimaateffectatlas, Tauw HVA (2025)

4.3.2. Scaling

Scaling refers to the second one of the two methods to spatially aggregate data, which was mentioned in the theoretical framework. Spatial data aggregation can be considered as scaling when grid cells are used in stead of administrative units. The data is often obtained in layers with a grid cell pattern in which all grid cells have the same size, unlike administrative units. In the following figures, a grid cell pattern can be seen in which the same data is aggregated into five different cell sizes: two by two meters, twenty by twenty meters, fifty by fifty meters, one hundred by one hundred meters, 250 by 250 meters.

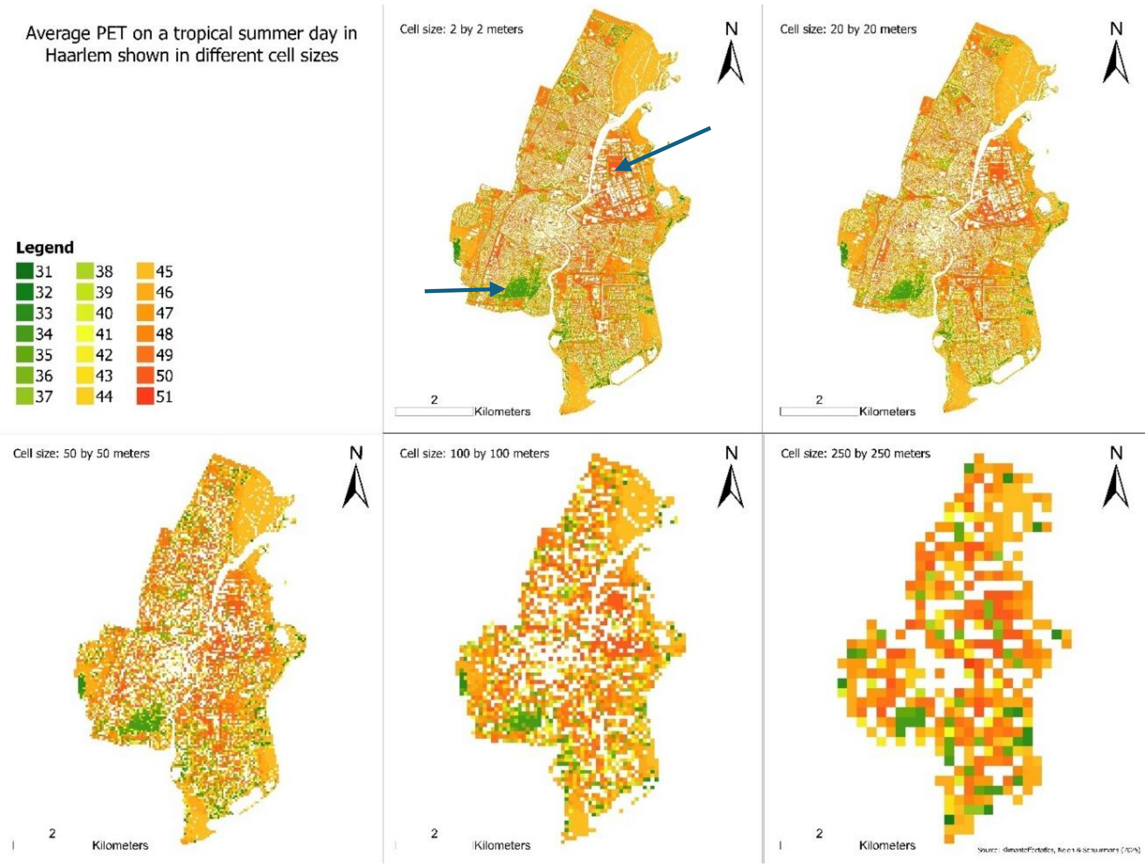
4.3.2.1. Exposure

Figure 14 presents the average physiological equivalent temperature (PET) to indicate direct exposure to urban heat. The data was obtained in cells from two by two meters, and this smallest grid cell pattern is presented in the top left map. From that point the data was aggregated into larger grid cells. The average PET values range between 31 and 51 degrees Celsius according to the legend. The different values have been classified with a colour scheme which flows from dark green to dark red. Green coloured cells identify the relatively cooler areas, whereas orange and red coloured cells represent the relatively hotter average PET values. This colour pattern is in line with the patterns in figure 11 which presents the average PET in different administrative units.

In the two by two meters map in figure 14 there are two major areas of interest which have been marked with support of two blue arrows. The first area of interest is located in the east of Haarlem. This area can be identified as the hottest area in the city in terms of average PET values. In the east of Haarlem there are barely any green coloured cells compared to the orange, red, and dark red cells according to the first four scales. However, after the data is finally aggregated into cells of 250 by 250 meters the situation appears to be different. In fact, there are several green cells visible in this map, which indicate relatively low PET values. In this example the effect of the spatial data aggregation is clearly visible. It is leading to different visualisations of the same area when comparing the data on different scales.

Another example is located in the southwest of Haarlem and can also be identified with support of a blue arrow. This area which includes the Frederikspark was discussed in the previous section as well. The area can be identified with support of the large number of green cells in the two by two meters map. The green coloured cells indicates low average PET values in this area, due to the presence of the park. The cells which are located around the park clearly contain higher average PET values. However, after spatially aggregating the data into larger cell sizes, the situation in the area of interest changes according to figure 14. In the fifty by fifty, and one hundred by one hundred maps some of the cells located in the park have merged with relatively high valued cells surrounding the park. This results in the fact that the average PET values of the cells surrounding the park have dropped. This is a result of merging with low valued cells in the park.

Figure 14: Data on the average PET, aggregated into five different cell sizes.



Source: Klimaateffectatlas, Nelen & Schuurmans (2025)

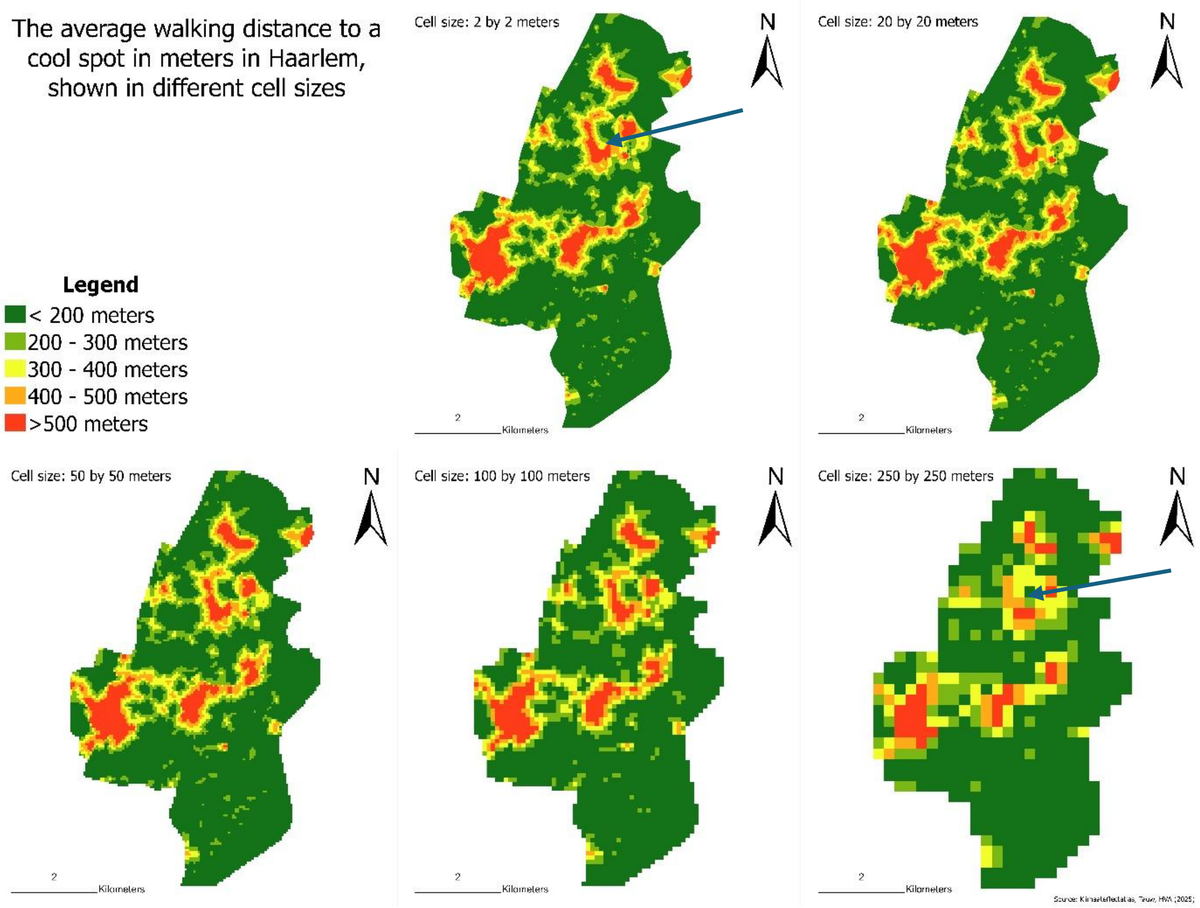
4.3.2.2. Adaptability

Figure 15 shows the average walking distance from a building to a cooling spot in Haarlem, presented in five different patterns with different cell sizes. The classification of the cells in the legend is the same as in figure 13. The cells which are coloured dark green indicate an average walking distance of less than 200 meters. The cells with yellow, orange, and red colours indicate the locations which are relatively far away from the cool spots.

A clear pattern of hotspots which indicate areas relatively far from cool spots is visible in the 2 by 2 meters map in figure 15. This pattern appears to be similar to figure 13, in which the same data was presented in administrative units. For climate adaptive spatial planners these red hotspots in the centre, north, and west of Haarlem would be the areas of interest. However, after spatially aggregating the data into larger grid cells the patterns in the maps are changing. For example, in the 250 by 250 meter map the details have been faded away.

One example in the east of Haarlem is marked with a blue arrow. In the 2 by 2 meter map there are many units which present an average walking distance of more than 500 meters. However. After spatially aggregating the data, these red colours have become less dominant in this area. This is indicated by the presence of light green coloured cells indicating average distances between 400 and 500 meters. Furthermore, similar patterns can be found after analysing the change in shapes of the other red hotspots after spatially aggregating the data.

Figure 15: Data on the average walking distance to a cold spot from a building, aggregated into five different cell sizes.



Source: Klimaateffectatlas, Tauw HVA (2025)

4.4. Statistical validity

This section will provide the results of the following sub research questions. 4: *"To what extent does spatial data aggregation with support of zoning affect the statistical validity of maps presenting the vulnerability to the UHI effect?"* 5: *"To what extent does spatial data aggregation with support of scaling affect the statistical validity of maps presenting the vulnerability to the UHI effect?"*

4.4.1. Global Moran's Index

It will assess the statistical validity of all the maps from figures 11, 12, 13, 14, and 15. The statistical validity has been calculated with support of spatial autocorrelation. This can be conducted with the tool "Global Moran's Index" in Arc GIS Pro. It is an inferential statistical tool which functions as a sampling technique for large populations. In the case of this thesis the population regards to the number of administrative units or cells. With support of this tool, it can be evaluated whether the pattern of features and its values is random, dispersed, or clustered. Clustering means that features with similar values are located close to each other within the pattern, the values can either be relatively high or low. Dispersion means that features with the same values are evenly spread across the pattern, therefore neighbouring features will have dissimilar values. Finally, a randomised pattern indicates that there is no spatial autocorrelation and that the features with relatively high and low patterns are randomly distributed. The Global Moran's Index contains a null hypothesis. It states that the features and its values are randomly distributed (Esri, n.d.).

4.4.2. Interpretation

After conducting the spatial autocorrelation with Global Moran's Index, five values will be given in an output. Firstly, a Moran's Index with a range between -1 and 1 is given which indicates the spatial pattern of the features. A positive number indicates that the pattern is clustered, whereas a negative number indicates dispersion. The further the number is from 0, the stronger the clustering or dispersion is. If the number is relatively close to 0 it can be concluded that the pattern is random.

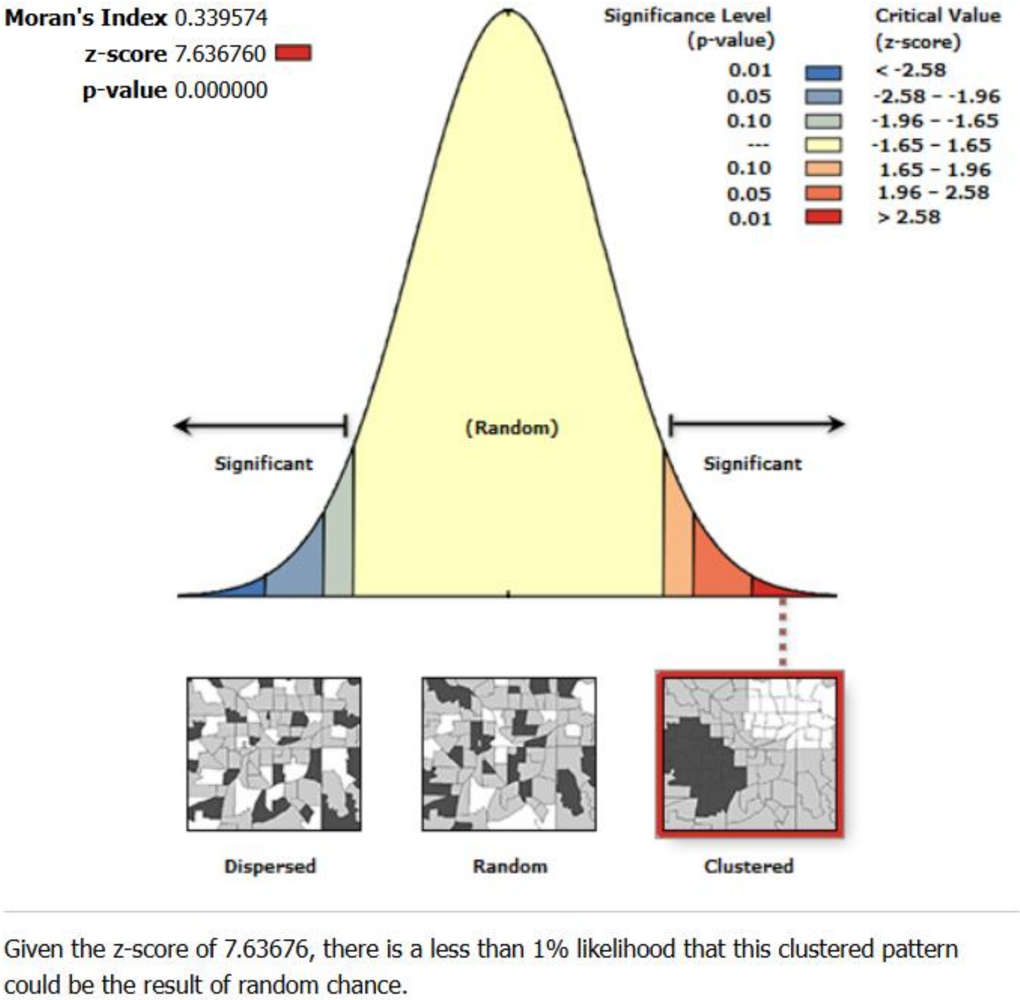
Secondly, an expected index will be given. This indicates what the Moran's Index would have been if the data across the units was randomly spread. The expected index refers to the null hypothesis. Thirdly, the level of variance is given which tells how far each value from a feature is differing from the average of all values. Furthermore, a z-score will be presented which indicates how strong the observed Moran's I Index is compared to the expected index. Basically, the z-score can be seen as a standard deviation.

Finally, a p-value is given which stands for the probability that the observed spatial pattern is random. The lower the p-value is, the less likely is the chance that a spatial pattern is random. Usually, a certain level of probability is chosen before the statistics are conducted. Examples of probability levels are 90, 95 or 99 percent. For this analysis, a probability level of 99 is chosen, this means that the p-value must not exceed 0.01 or it can be concluded that the spatial pattern is random. In practice, the values which are dominant in the analysis are the Moran's Index, the z-value, and the p-value.

4.4.3. Outputs

Figure 16 presents an example of the output of the spatial autocorrelation after it is conducted in Arc Gis Pro. It is an output of the map showing the average PET in Haarlem on a neighbourhood scale, as presented in figure 11. According to the output, the Moran's Index has a value of 0.339574, which indicates clustering of the features with similar values. Therefore, it can be concluded that the cells with similar PET values are bordering each other. This is the case for both the high PET values and the low PET values. The z-score of 7.636760 indicates a strong standard deviation compared to the expected index, which has a value of -0.009091. Finally, the p-value is 0.000000 which is lower than 0.01 and indicates that there is less than 1 percent chance that the clustered pattern could be the result of a random chance. According to figure 16 it can be concluded that the pattern which is visible in the average PET per neighbourhood map in figure 11 is not a coincidence. Therefore, this spatial autocorrelation can be seen as valid.

Figure 16: Example of an output of a spatial autocorrelation, on the average PET on neighbourhood scale



Global Moran's I Summary	
Moran's Index	0.339574
Expected Index	-0.009091
Variance	0.002084
z-score	7.636760
p-value	0.000000

Source: Arc Gis Pro (2025)

Outputs of the spatial autocorrelation, as shown in figure 16, have been created on all the mapping scenarios presented in figures 11, 12, 13, 14, and 15. The results of the spatial autocorrelation for each administrative unit and different size of grid cells have been presented in table 6. The Moran's Index in the first column indicates clustering if the number is positive, a random pattern if the number is 0 or relatively close to 0, and dispersion if the number is negative. The second column indicates the expected index if the pattern would have been random. This usually concentrates around 0 and refers to the null hypothesis. The third column presents the variance, which tells how far the average feature value is differing from the average of all feature values. The z-score in the fourth column presents the standard deviation, which indicates how strong the Moran's I Index is compared to the expected index. The higher the z-score is, the stronger is the spatial autocorrelation. Finally, a p-value is given in the last column which stands for the probability that the observed spatial pattern is random. If the p-value is exceeding 0.01, the result can be defined as invalid. If this is the case the results are marked in bold in table 6.

Table 6: Results of the spatial autocorrelation of the multiple mapping scenarios, with support of Moran's Index, indicating the statistical validity if the p-value does not exceed 0.01. Invalid results are marked in bold.

6.1 Zoning the exposure with the average Physical Equivalent Temperature (PET)

	Moran's Index	Expected Index	Variance	z-score	p-value
6-digit postal codes	0.263097	-0.000243	0.000105	25.702831	0.000000
Neighbourhoods	0.339574	-0.009091	0.002084	7.636760	0.000000
4-digit postal codes	0.540248	-0.023810	0.012576	5.029915	0.000000
Districts	**0.247859**	**-0.050000**	**0.031801**	**1.670278**	**0.094864**
Boroughs	**0.132349**	**-0.250000**	**0.070448**	**1.440539**	**0.149715**

6.2 Zoning the sensitivity with the percentage of frail older adults.

	Moran's Index	Expected Index	Variance	z-score	p-value
6-digit postal codes	0.925003	-0.000243	0.000209	64.058889	0.000000
Neighbourhoods	0.112553	-0.009091	0.001598	3.043213	0.002341
4-digit postal codes	0.615148	-0.023810	0.003498	10.803589	0.000000
Districts	0.186905	-0.050000	0.005852	3.096925	0.001955
Boroughs	**-0.450273**	**-0.250000**	**0.093876**	**-0.653649**	**0.513338**

6.3 Zoning the adaptability with the average walking distance to a cold spot from a building.

	Moran's Index	Expected Index	Variance	z-score	p-value
6-digit postal codes	0.842176	-0.000243	0.000056	113.058445	0.000000
Neighbourhoods	0.377274	-0.009091	0.001872	8.930280	0.000000
4-digit postal codes	0.737755	-0.023810	0.005373	10.389179	0.000000
Districts	0.420484	-0.050000	0.016417	3.671920	0.000241
Boroughs	**-0.385086**	**-0.250000**	**0.057698**	**-0.562381**	**0.573857**

6.4 Scaling the exposure with average Physical Equivalent Temperature (PET)

	Moran's Index	Expected Index	Variance	z-score	p-value
2X2 meter cells	0.479806	-0.000001	0.000000	894.536144	0.000000
20X20 meter cells	0.214430	-0.000031	0.000013	59.599486	0.000000
50X50 meter cells	0.084653	-0.000186	0.000080	9.470511	0.000000
100X100 meter cells	0.100329	-0.000679	0.000300	5.831911	0.000000
250X250 meter cells	**-0.019001**	**-0.003802**	**0.001728**	**-0.365646**	**0.714629**

6.5 Scaling the adaptability with average walking distance to a cold spot to a building.

	Moran's Index	Expected Index	Variance	z-score	p-value
2X2 meter cells	0.999195	-0.000000	0.000000	2309.729151	0.000000
20X20 meter cells	0.982166	-0.000018	0.000009	334.453105	0.000000
50X50 meter cells	0.950711	-0.000091	0.000046	140.954811	0.000000
100X100 meter cells	0.897994	-0.000323	0.000164	70.079297	0.000000
250X250 meter cells	0.740272	-0.001789	0.000952	24.054238	0.000000

Source: Arc Gis Pro (2025)

4.4.4. Table interpretation

According to table 6.1, the spatial pattern of the average PET is clustered on all five scales of administrative units. This can be concluded due to the fact that the Moran' I Index is positive on all the five different scales. However, some of the patterns turn out to have a stronger level of clustering than others. The clustering of the PET in the 4-digit postal codes turns out to be the strongest with a value of 0.540248, whereas the pattern of the districts (0.247859) and boroughs (0.132349) are the weakest. The z-scores of the 6-digit postal codes (25.702831), neighbourhoods (7.636760), and 4-digit postal codes (5.029915) are all relatively high compared to the districts (1.670278) and boroughs (1.440539). This indicates that the spatial pattern of the first three scales has a strong standard deviation from the expected random pattern. The last two scales have a less strong standard deviation and can also be classified as invalid due to the fact that the p-values are both exceeding 0.01.

In table 6.2 the Moran's I Index reveals that the spatial pattern of social vulnerability is clustered on the first four scales, due to the positive numbers. The six-digit postal code map shows the strongest clustering with a value of 0.925003. The boroughs map shows a pattern of dispersion due to the negative value of -0.450273. However, this result can be classified as invalid due to the p-value of 0.513338 which exceeds 0.01. Just as in table 3.1, in this case it also indicates that the spatial pattern of the first four scales has a strong standard deviation from the expected random pattern. All of the four patterns are valid due to the p-values which do not exceed 0.01.

In table 6.3 the Moran's Index indicates that the spatial pattern of adaptability is clustered in the first four scales due to the positive numbers. The six-digit postal codes are given the highest value of 0.479806. They are followed by the four-digit postal codes (0.737755), districts (0.420484), and neighbourhoods (0.377274). The boroughs map appears to have a dispersed pattern due to the negative value of -0.385086, however this result can be classified as invalid due to the p-value of 0.573857 which exceeds 0.01. The rest of the results in table 6.3 are all valid with p-values below 0.01. In terms of z-scores all of the four valid scales have a strong standard deviation compared to the expected index: neighbourhoods (8.930280), 4-digit postal codes (10.389179), and districts (3.671920). The six-digit postal codes map appears to have the strongest standard deviation with a value of 113.058445. As was the case in the previous two tables, the results of the spatial data aggregation of the data on the adaptability indicates strong standard deviations. Furthermore, the results are all valid due to the p-values which do not exceed 0.01.

In table 6.4 and 6.5 the results are focusing on the spatial autocorrelation of grid cell patterns in stead of administrative units. The Moran's I Index of table 5.4 indicates that the spatial pattern of the average PET per grid cell is clustered in the first four maps with different cell sizes. The map with grid cells of two by two meters has an index of 0.479806. The map with cells of twenty by twenty an index of 0.214430, followed by 0.084653 and 0.100329 for cell sizes of fifty by fifty and one hundred by one hundred. Although the pattern of the last two maps is clustered, the numbers are relatively close to 0 which indicates a weak pattern of clustering. The map which shows the average PET in grid cells of 250 by 250 meters appears to have a dispersed pattern with a Moran's I Index of -0.019001. However, due to the fact that the p-value is exceeding 0.01 with a value of 0.714629 this result can be classified as invalid. The z-scores of the one hundred by one hundred meter cell size map (5.831911) and fifty by fifty meters (9.470511) indicate strong standard deviations. This is also the case for the twenty by twenty meters (59.599486) and two by two meters map (894.536144). All of the patterns are valid due to the p-values which are not exceeding 0.01.

Finally, table 6.5 reveals that the pattern of adaptability is clustered for all of the five different maps with different cell sizes. Moran's I Indexes are ranging between 0.740272 and 0.999195 which indicates strong clustering. All of the mapping scenarios can be classified as valid due to the fact that the p-values are 0.000000 for all of the five maps. The z-score of the map with cell sizes of 2 by 2 meters is 2309.729151 and indicates a strong standard deviation from the expected index value. This is also the case for the twenty by twenty meters map (334.453105) and the fifty by fifty meters map (140.954811). Furthermore, the values of the one hundred by one hundred (70.079297), and 250 by 250 meters (24.054238) map also indicate a strong standard deviation.

4.5. Stakeholder opinions on the multiple mapping scenarios

This section will provide the results according to the last sub question. 6: "*How do stakeholders in urban planning and climate adaptation perceive the usability of UHI vulnerability maps created at different spatial scales and zoning configurations?*" The results have been received from the four interviews, as presented in table 4. All the respondents have been asked questions on the validity, readability, interactivity, and usability gaps. Therefore, the results have been classified according to these elements. The codings which have been used to classify the results are presented in table 3.1 and 3.2 in the methodology chapter.

4.5.1. Usability of the multiple mapping scenarios

The usability of the multiple mapping scenarios according to the interviewed stakeholders will be described with support of quotes. These quotes have been selected as a result of matching with the codes presented in table 3.1 and 3.2. Firstly, the opinions of the stakeholders on the validity of the multiple mapping scenarios will be discussed, followed by readability, and finally the interactivity.

4.5.2. Validity

The interviews with the respondents revealed that there are both indicators of confidence and critical perspectives on the validity of the maps. Respondents argued that the maps are well suited as starting points for projects in climate adaptive spatial planning. This indicates that the format in which the information is presented matches the audience of stakeholders in climate adaptive spatial planning. One of the reasons for this is the fact that all of the presented maps are based on trustworthy public data sources. *"Yes, everything is based on public data sources, from which we assume that they are trustworthy. Therefore, this is something which can be used for the start of a project."* (R3, 2025).

Furthermore, R3 argued that a wider spread of audience in terms of civilians would need more detailed information on what the specific numbers in the legends of the maps mean in terms of health risks. He mentions an example which is based on the maps which present the average PET. *"On this map people can see that the PET is 44 degrees Celsius on a certain place, and for me as project manager this indicates if the level of urban heat is high or low, so it depends on who is reading the map. However, policies are created for a wider spread of people and perhaps they might want to know what does dis number 44 actually mean and what are the health risks."* (R3, 2025). This indicates that validity does not only have a technical aspect, but also a communicative one.

According to R3, the possibility to change the scales of the maps can contribute to decision making processes. He argued that municipalities are often struggling with which scale is the most suitable for certain projects. *"I think it is great to have the possibility to compare scales. Often municipalities are struggling with the question on which scale they should set demands. You also see this in national policies, some say on the scale of neighbourhoods, others say districts or projects. Now you can give them a free choice and then municipalities can decide themselves."* (R3, 2025).

Additionally, R5 addresses that the maps are clear for stakeholders in climate adaptive spatial planning. He argued that it is commonly known that the north of Haarlem contains the most petrified areas in the city, which results in higher PET values. However, he would have expected that the level of severity in these areas would have been higher. *"Yes, it seems clear, the industrial area is marked with an orange and red colour, just as some parts of the city centre, we are currently working on these areas. The most petrified areas in the north are marked with orange, and not with red, which is something I would have expected to be different."* (R5, 2025).

Finally, after analysing the map that presents the average PET in grid cells (Figure 14), it appears that R5 thinks some scales are more suitable for climate adaptive spatial planners than others. He argues that the map which presents the data in cell sizes of twenty by twenty meter make certain cool spots disappear. Still, it would give enough sufficient information since it shows that a certain square in Haarlem is too hot according to the PET values in that area. However, after analysing the same data in the map with cell sizes of ten by ten meters, he argued to see some differences in the PET values on the same square. This has to do with the shades as a result of buildings and some trees which are present on the square. The fact that this map gives more detailed information on the relatively cooler spots in the area makes it more useful. *"Look yes, this ten-by-ten scale is much better. This twenty by twenty scale indicates that this is just a square and that the entire square is hot."* (R5, 2025).

4.5.3. Readability

In terms of readability, R1 argued that the presented maps in figures 11, 12, 13, 14, and 15 are relatively easy to read for users. *"This is easy for people to understand. This place is cooler over here, so it is nice to go to this place."* (R1, 2025). He addressed that in most of the climate adaptive projects the smallest possible scales with the most detailed information are used. Therefore, the maps which present the data on exposure, sensitivity, and adaptability on larger scales would have a lower level of readability. However, in some projects larger scales are more useful since often municipalities are working with certain budgets for projects. Therefore, it appears to be more useful to start analysing an urban area on a larger scale at first. *"If you would say, a municipality wants to invest in social aspects of a neighbourhood, such as sports but also green areas, it can be useful to look at larger scales since you are working with budgets then"* (R1, 2025).

Another perspective of readability was mentioned by R3. He argues that he clearly sees the influence of the spatial data aggregation on the visuality of the maps. *"It is interesting and useful to see what different scales are doing with your awareness and what you might communicate."* (R3, 2025). However, according to him most stakeholders in municipalities would know where the most work in terms of climate adaptation would have to be done. *"You can see that there are some red spots in the north, but yes over there the effect appears to be weaker. On that scale it appears to be the case that the problem lies in the centre left area. At least as a municipality, you know where the work needs to be done."* (R3, 2025). This indicates that the readability of the multiple mapping scenarios is in line with the audience.

From a more technical perspective, geo information consultant R4 addressed the readability of the maps with aggregated grid cells. According to him the maps still contain valid and readable information for decision making processes, after being aggregated into larger grid cells. Whereas the maps which present the average PET in administrative units are losing detailed information after the spatial data aggregation. *"It is interesting to see that compared to the previous map in which administrative units have been used, in this map even the cell sizes of 100 by 100 meters provide enough useful information, whereas you lose a lot of detail after aggregating to a larger scale in the previous map."* (R4, 2025).

Furthermore, he enlightened the effects of the spatial data aggregation again according to the multiple maps as a result of scaling. He mentioned that a few cells with a low average PET value are not remarkable in the maps with small grid cells, such as two by two, and twenty by twenty meters. However, these values do have their impacts after the data is spatially aggregated into cells of 250 by 250 meters, which nuances the situation. *"The map with cell sizes of 250 by 250 meters picks up different information than the smaller cell sizes. For example, if you look at the Haarlem-Oost area, you see multiple green cells of 250 by 250 meter, you do not see this colour on the smaller scales. This area is predominantly an industrial area with barely any trees, within this area there are a few housing areas which you* *do not see in the first maps with cell sizes of two by 2 and 20 by twenty. The last map of 250 by 250 meters nuances the situation which is not presented in the smaller scales."* (R4, 2025).

Finally, R5 addressed a problem regarding the readability of maps when administrative units are used for the analysis. In a project in which administrative units with a high number of vulnerable buildings were selected for restauration, several vulnerable buildings bordering the areas of interest were excluded from the project. This was the case due to the fact that they are part of other units with a small number of vulnerable buildings. *"I have an example, we are working on a project in which we analyse if neighbourhoods have enough vulnerable buildings. There are specific norms for a neighbourhood to be eligible for restauration. if you look at the problem on this neighbourhood scale, there might be some neighbourhoods which will be left out due to the fact that there are not enough vulnerable buildings according to the map. As a result, these buildings are not eligible for restauration whereas in fact they should be."* (R5, 2025). Therefore, R5 argued that the possibility of changing the scales in which the data is presented can change the reading perspective of stakeholders.

4.5.4. Interactivity

In terms of interactivity of the multiple mapping scenarios, the respondents were generally positive. R1 mentioned the fact that having multiple maps with different scales in the same portal can be useful for choosing the areas of focus. *"Yes, I think that if you have multiple maps in one portal, it is useful to switch between these maps. For example, as a civil servant you want to know more about a specific neighbourhood because it has a dark colour, and then you can zoom in with support of another scale that shows more smaller administrative units. Such an option could make it easier to make decisions on choosing which areas need more focus."* (R1, 2025). This would especially be the case if municipalities are working with specific budgets for climate adaptive projects. *"It could be the case that you are working with certain budgets for neighbourhoods, for example you have 10 million euros available for the next 10 years and you want to know where to use it, you will start looking at a larger scale."* (R1, 2025).

Furthermore, R2 addressed that switching scales results in a decrease of generalising the characteristics of neighbourhoods. *"In some of the maps you can see that many neighbourhoods have the same colour, whereas if you change the scale to a more detailed level, you can see the differences within a neighbourhood. Here the colour orange is dominant, resulting in the fact that you would place all these neighbourhoods in the same category even if there are differences within the neighbourhoods."* (R2, 2025). R3 also indicates the usability of interactive maps in which scales can be switched. It appears to be the case that the spatial data aggregation influences the visuality of the maps. *"If you look at the 4-digit postal codes here in the north, there are two yellow units, and then if you look at the districts this area becomes a green unit."* (R3, 2025). Analysing multiple scales at the same time can therefore give different insights which can contribute to decision making processes.

Finally, the same observations were mentioned by R4. He presents an example of the scaled data on the average PET. *"The map with cell sizes of 250 by 250 meters picks up different information than the smaller cell sizes. For example, if you look at the Haarlem-Oost area,* *you see multiple green cells of 250 by 250 meter, you do not see this colour on the smaller scales. This area is predominantly an industrial area with barely any trees, within this area there are a few housing areas which you do not see in the first maps with cell sizes of two by 2 and 20 by twenty. The last map of 250 by 250 meters nuances the situation which is not presented in the smaller scales."* (R4, 2025).

4.5.4. Challenges

Besides the positive observations the respondents also identified several usability gaps in terms of validity, readability, and interactivity. Table 7 presents the amount of usability gaps that have been identified. They have been classified according to the usability gap framework of Raaphorst et al. (2020) which has been presented in the theoretical framework. Furthermore, the table presents the four elements of the CID framework. These are stakeholder, purpose, information, and the visual format. To illustrate how the table should be read for example, there have been found two usability gaps in terms of validity which concern the information presented in the multiple mapping scenarios. Empty cells in the table indicate that there have not been identified any usability gaps in that specific category. In total, there have been found twenty-one usability gaps after analysing the interviews. It turns out to be the case that the majority of these usability gaps concern the validity of the CS (15). Only three usability gaps were found concerning both the readability and the interactivity.

Table 7: Amount of usability gaps identified in the four conducted interviews.

	Validity	**Readability**	**Interactivity**
Stakeholder		1	2
Purpose	2		
Information	5	1	
Visual format	8	1	1
Total usability gaps	15	3	3

Source: Own (2025)

4.5.4.1. Challenges in validity

The usability gaps which concern validity are dominantly focused on the visual format and information of the multiple mapping scenarios. Respondents have addressed several challenges regarding the maps in which administrative units of analysis are used. The spatial data aggregation in large units with support of zoning can lead to misinterpretations of the situation. As a result, the severity of climate related problems is reduced according to R1. *"In the end, it appears to be the case that there are few problems, because you lose information on that point. You do not see the red areas anymore, because they have been merged with green areas"* (R1, 2025).

R5 also mentioned his concerns of the effect of spatially aggregating data. He mentioned that according to the maps some areas in the north of Haarlem appear cooler in terms of average PET than it is in reality. *"If you look at the north, which actually contains the most petrified neighbourhoods in the Netherlands, these areas are marked green which is absolutely not the case."* (R5, 2025). R3 also argued that the aggregation of the data can lead to striking values in specific administrative units. This indicates a certain distrust in the validity of some of the mapping scenarios. *"Sometimes I think, is what I see here actually correct? Aren't the values crazy?"* (R3, 2025).

Another aspect which can influence the results of zoning data relies on municipal boundaries according to R4. He mentions relatively cool and green areas such as the dunes west of Haarlem can influence the average PET and the average walking distance to a cool spot. However, these areas are not included in the analysis. *"There are a lot of dunes and green areas bordering Haarlem; however, these areas cannot be included in the analysis due to the fact that they do not belong to the municipality. This is also the case when analysing the average walking distance to a cool area. If you would leave out the boundaries of the municipality, the situation in Haarlem might become less severe"* (R4, 2025).

Additionally, R1 addressed another problem which occurs when grid cells are used in stead of administrative units. Cells which do not contain data are leaving large white areas in the maps after the data is spatially aggregated, which reduces the usability. *"The parts which contain cells with no data, the densest part of the centre, is almost completely useless. At some point you lose the usability of the maps, there is a certain limit of scaling, in the first maps it is useful but on the larger levels it is not."* (R1, 2025). Furthermore, R1 mentioned a usability gap which relates to the validity of the multiple mapping scenarios as a result of scaling. He mentioned an example from practice which concerns the mapping of flood risks. R1 mentioned that large grid cells were used in some of the analyses, which did not include differences in the elevation. This resulted in the fact that in some areas the flood risk was relatively low, whereas in practice this was not the case. *"What we see there is that when you make a model for a polder, the situation does not appear to be that severe, because differences in the height within a cell are not presented. That is something which is familiar to use, and you also see this coming back in your maps."* (R1, 2025).

4.5.4.2. Challenges in readability

The total number of identified usability gaps in terms of readability (3) were relatively limited compared to validity gaps (15). However, the respondents did discover some examples of possible difficulties in reading the maps. R1 mentioned one example which is based on the relatively high average PET values which are shown in the east of Haarlem in figures 11 and 14. He argued that some readers of the maps might lose the focus on which areas are the most problematic in terms of urban heat. Few people are living in the industrial area in the east of Haarlem. Most of the people who visit this area are working there in air conditioning in stead. It might occur that other areas in which more vulnerable people are living are given less attention. *"You know Haarlem, and I know it too, you point out that the average PET in the industrial area of Haarlem is high, which is correct. However, what you have here is that people are comfortably working in air conditioning, so in fact it is not hot in this area. So, if you purely look at these maps you might lose the focus on what are the most important areas."* (R1, 2025).

Furthermore, the assessment of R1 is in line with another usability gap. During a conversation with R3 a discussion on the lack of detailed information on certain PET hotspots in the maps was held. R3 argued that the urgency of solving the problem of urban heat is not clear in figures 11 and 14. According to him this is due to the fact that the high PET values are not supported with information on the level of severity. He suggests that doing this could increase the readability of the maps. *"So, adding the severity in the maps, like hey this specific group of people is in danger with this specific value of PET. This will show the urgency of implementing measures."* (R3, 2025).

4.5.4.3. Interactivity

The number of identified usability gaps in terms of interactivity (3) also appeared to be rather limited. Nevertheless, this section will provide several examples of experienced difficulties amongst the respondents. R5 addresses the limited number of categories in the legend of the average PET maps presented in grid cells. In terms of interactivity and the possibility of switching to different scales, a larger number of categories in the legend could contribute to more perspectives on the relationships between the values of cells. *"There is an ideal relationship between the cell sizes and the number of categories in the legend. If you have more categories, you can see more detailed patterns which include the relationships between units of analysis"* (R5, 2025).

Furthermore, R3 argued that the interactivity of the maps can be improved by adding more features in the map. He mentioned features such as the locations of schools and nursing homes, which are seen as vulnerable locations in terms of health risks. *"The heat maps that you have produced, in combination with the maps presenting the vulnerable population, they could use more urgency in terms of the location of vulnerable places such as nursing homes and schools. That would indicate that for example there are a lot of nursing homes in the centre, and those people there are locked in an urban heat island. We could do that differently, so in terms of communication there is a lot to gain."* (R3, 2025). According to him, combining these features with the maps presenting exposure and sensitivity could be more effective for climate adaptive spatial planning.

5. Conclusion

This chapter addresses the main research question with support of responding to the six sub research questions and reflecting on the hypothesis.

Data on climate change and climate adaptation can be presented in diverse ways. The way data is presented and interpreted in CS can therefore influence decision making processes in climate adaptive spatial planning. According to the literature, presenting data in CS on multiple scales can increase trustworthiness and credibility. Therefore, this research aimed at giving more insights in the effects of spatial data aggregation on the usability of urban heat vulnerability maps. In order to perform this research, the following research question was used.

"How do variations in spatial data aggregation influence the usability of urban heat vulnerability maps?"

5.1. Answering the sub research questions

To answer the main research question, 6 sub research questions were formulated. These questions will be answered first before the conclusions on the main research question will be given.

1. *“What are the current perceptions of usability of climate services presenting vulnerability to the UHI effect?”*

It turns out that the majority of the respondents are using the CS from the Klimaateffectatlas at their companies. These CS can reach a wide audience of governments, companies, and citizens. Therefore, the purpose of most CS is either to create awareness or to get insights in locations eligible for climate adaptation. The respondents argue to have confidence in the validity of the CS, due to the single used methods which are used to create them. However, the CS validity can be increased if more detailed information on the data is added.

Currently, the CS are valid enough to start discussions on climate adaptation. However, there are doubts on whether the CS are actually presenting a valid level of severity of the vulnerability to urban heat. This is due to the influence of colour schemes with dominant red colours. Furthermore, according to one of the respondents it is important to get insights on the research question of the readers of the CS before they are created. This could influence the validity and reduce usability gaps. Finally, the respondents also argue to be content with the levels of interactivity. These findings indicate that the respondents are content with the CS in general. However, there are several aspects of readability and validity which could be improved to make the CS more usable.

2. *“How does spatial data aggregation with support of zoning affect the visual representation of vulnerability to the UHI effect in climate services?”*

Analysing the spatially aggregated data on exposure, sensitivity, and adaptability in different types of administrative units led to the following conclusion. It turns out that the different zoning configurations influence the visual representation of the data. This is visible in figures 11, 12, and 13. Especially in the area around the Frederikspark in the southwest, and the industrial area in the east of Haarlem differences in the patterns of the map can be spotted. After the data is spatially aggregated into larger units (districts and boroughs) the average values decrease, and the details disappear.

3. *“How does spatial data aggregation with support of scaling affect the visual representation of vulnerability to the UHI effect in climate services?”*

Figures 14 and 15 present that different sizes of grid cells influence the visual representation of the data on exposure and adaptability. Cells with relatively low values merge with cells with relatively high values when the data is spatially aggregated. Again, the area around the Frederikspark and the industrial east of Haarlem appear to experience the most differences in visual representation. However, the differences in visual representation due to scaling are less dominant than the differences due to zoning.

4. *"To what extent does spatial data aggregation with support of zoning affect the statistical validity of maps presenting the vulnerability to the UHI effect?"*

After the analysis of the statistical validity of the maps in figures 11, 12, and 13, the following can be concluded on the spatial data aggregation with support of zoning. The majority of the mapping scenarios as a result of zoning are valid in terms of significance. The spatial autocorrelation indicates that the visual patterns in the maps are clustered and not a result of random chance. However, the exposure, sensitivity, and adaptability maps in which the largest administrative units (boroughs) are used turn out not to be significant. Furthermore, this is also the case for the exposure map in which the data is presented in districts. This indicates that the spatial data aggregation in terms of zoning is valid until a certain size and a limited number of administrative units is used for the analysis.

5. *"To what extent does spatial data aggregation with support of scaling affect the statistical validity of maps presenting the vulnerability to the UHI effect?"*

After the analysis of the statistical validity of the maps in figures 14, and 15, the following can be concluded on the spatial data aggregation with support of scaling. As was the case with the maps as a result of zoning, the majority of the scaled maps is also significant. The spatial patterns are clustered and not based on a random chance. However, one map scenario in which the data on exposure was presented in relatively large grid cells (250 by 250 meters) turned out to be not significant. This indicates that the validity of spatial data aggregation is not only dependent on the size of the units of analysis, but also dependent on the variable that is used.

6. *"How do stakeholders in urban planning and climate adaptation perceive the usability of UHI effect vulnerability maps created at different spatial scales and zoning configurations?"*

The analysis of the opinions of the interviewed stakeholders active in climate adaptation has led to the following conclusion. In general, the respondents are positive on the possibilities to swich the scales of the maps. However, they do argue that some scales are more suitable for specific stakeholders than others. The relatively small scales give new insights for climate adaptive spatial planners on the local differences in an area. Therefore, it reduces generalisation of larger units of analysis. On the other hand, the larger scales which are often addressed as less useful appear to be more suitable for municipalities who are working on budget dependent projects. Several respondents also mentioned that the lack of information on certain hotspots according to the multiple mapping scenarios could lead to misinterpretations of the data.

Furthermore, it has been argued by the respondents that the data which has been used is coming from trustworthy sources. However, several usability gaps in terms of validity were identified after analysing the interview transcripts. Respondents mentioned their doubts on whether the maps are presenting the reality of the effects of climate change. This indicates a distrust in the validity of some of the maps. On the other hand, this is, according to the literature, a direct result of the Modifiable Areal Unit Problem and further emphasises the importance of assessing validity of certain scales in maps.

5.2. Answering the main research question

Based on the answers on the six sub research questions, this section will provide the final conclusion on the main research question.

"How do variations in spatial data aggregation influence the usability of urban heat vulnerability maps?"

With support of zoning and scaling multiple mapping scenarios on urban heat vulnerability components have been conducted. The spatial data aggregation results in noticeable differences in visual representation of maps on urban heat vulnerability. Especially the maps in which distinct zonings have been used to aggregate data on exposure, sensitivity, and adaptability exhibit substantial differences in the patterns. The maps as a result of scaling also present noticeable differences between the units of analysis. However, there the results of spatial data aggregation are less noticeable.

As a result, the multiple mapping scenarios are interpreted in different ways according to stakeholders active in climate adaptive spatial planning. According to the respondents, they give new insights on what the use of multiple scales can do with the visual representation of data and decision making processes. Additionally, it appears to be the case that the relatively large scaled maps are more suitable for budget related municipal projects. These can be used as starting points for discussion, whereas the smaller scales will be more useful in later stages of decision making processes. This indicates a certain level of usability in combining multiple mapping scenarios.

However, the respondents also address their concerns on whether specific scales present the actual severity of climate change related problems. Nevertheless, the majority of the mapping scenarios has been assessed as statistically significant, excluding only the maps with the largest units of analysis. This indicates that the usability of conducted maps with support of spatial data aggregation is significant until a certain rough size of the units of analysis is chosen.

In conclusion, the hypothesis which was given in the methodology can not be rejected. The reason for this is that the findings of this research confirm that spatial aggregation of data on vulnerability to the UHI effect will lead to different visual and statistical outcomes. Furthermore, the findings indicate that spatial data aggregation creates awareness of the MAUP and supports stakeholders in comparing and using different representations of data.

6. Discussion

In this chapter the outcomes of the research will be positioned in a discussion section according to the literature in the theoretical framework. Additionally, a reflection on the implications and limitations of the research will follow. Finally, recommendations for future research will be given.

6.1. Reflection on the literature

The following concepts were discussed in the theoretical framework according to academic literature. Firstly, the UHI effect was characterised by hot spots of hot average temperatures in urban areas. The hotspots are a result of lacking vegetation, heat absorbing surfaces, and the blocking of ventilation according (Abrar et al., 2022), (Sidiqui et al., 2022). The hotspots are surrounded by areas with relatively cooler temperatures, which is why they are characterised as islands. The patterns in the maps presenting the average PET in Haarlem on a summer day in 2022 (Figures 11 and 14) are in line with the mentioned characteristics of the UHI effect. Furthermore, this was also confirmed by the interview respondents who are active in climate adaptive spatial planning. Especially the examples of the area around Frederikspark and the industrial east appeared to be familiar hotspots.

The vulnerability to the UHI effect can, according to academic literature, be characterised with support of three indicators. Exposure, sensitivity, and adaptability were all mentioned by the respondents during the interview. This indicates that these components are in fact used in practice when vulnerability to the UHI effect is presented.

Furthermore, the modifiable areal unit problem (MAUP), which was emphasised with support of Ho et al. (2015), appears to be clearly visible in the conducted maps. The MAUP is a result of spatial data aggregation which can be performed with support of zoning and scaling. Räsänen et al. (2019) use the term zoning for both scaled and zoned maps. However, this research indicates the differences in effects of the two methods. Therefore, it can be argued that there should be a distinction between these two different elements of spatial data aggregation.

Finally, the validity, readability, and interactivity were discussed as elements of climate service usability. In practice, not all of the elements of usability were discussed evenly during the interviews. In the discussions on the usability of the conducted maps the validity and the readability were more dominant than the interactivity. Furthermore, the number of usability gaps in validity (15) was much higher than the numbers of gaps on readability (3), and interactivity (3). This could indicate that some of the elements of usability should weigh more in a climate services assessment than others.

6.2. Research implications

The findings of this research contribute to decision making processes in climate adaptive spatial planning due to the following reasons. Firstly, it builds further upon the discussions of the effects of the Modifiable Areal Unit Problem. The research demonstrates that MAUP is more than a statistical bias by addressing the influence of spatial data aggregation on the interpretation of urban heat vulnerability maps. Therefore, the effects of spatial data aggregation should be considered in practice.

Secondly, it appears to be the case that spatial data aggregation with support of zoning and scaling is valid until a certain size and number of the units of analysis is used. Therefore, I recommend that multiple spatial scales of maps should be assessed in terms of statistical validity before conclusions are drawn from them. Therefore, the third reason concerns both the potentials and the risks of using spatial data aggregation to analyse multiple mapping scenarios. It appears that large scales are more suitable for budget related projects than the smaller scales. Nevertheless, using such scales can lead misinterpretations due to the lack of local details. On the other hand, this further indicates the importance of analysing multiple scales which results in new insights of the climate situations.

Finally, according to the identified usability gaps there is room for improvement in terms of validity and readability of the spatially aggregated maps. Where the influence of analysing different scales increases usability to a certain level, more transparency on the presented information is recommended.

6.3. Research limitations

There are also several limitations of this research which could have influenced the results. For example, in this research the exposure, sensitivity, and adaptability to the UHI effect vulnerability were presented with a selection of several indicators. The indicators which have been used are the average PET in Celsius, the percentage of frail older adults, and the average walking distance to a cool spot. There are many other indicators which could have presented the exposure, sensitivity, or adaptability. For example, sensitive populations can be indicated with the amount/percentage of frail children, the number of people with relatively low average incomes, or the physical locations of schools and nursing homes. Furthermore, a data file on the locations of cool spots in Haarlem has been used to calculate the average walking distance to a cool spot in the city. However, it is unknown if these cool spots in the city are actually pleasant to stay, and if these spots are suitable and have enough facilities for large numbers of people.

Furthermore, As presented in table 6 it appears to be the case that not all of the mapping scenarios were significant according to the spatial autocorrelation. Therefore, other scales to present the influences of spatial data aggregation on UHI effect vulnerability could have been used. Finally, in this research the number of respondents in the four interviews was five. More interviews could have been conducted to increase the amount of qualitative data on the usability of the multiple mapping scenarios.

6.4. Suggestions for further research

This research has demonstrated the effects of spatial data aggregation on the usability of urban heat vulnerability maps. The analysis has led to several new insights which require further research. Firstly, one of the respondents argued that the type of scale which is the most suitable for stakeholders in climate adaptive spatial planning depends on the research question of the reader of the map. Research on what stakeholders actually want to know about certain climate change related events can influence the way and in which scale CS should be presented. Therefore, research on what is the gap between the reader and the creator of the CS should be performed to increase the usability of CS to a higher level.

Secondly, case studies are often chosen as a result of predefined lists or abstract findings about specific locations. Haarlem for example was classified as the most petrified city in the Netherlands in 2022. However, as a result of the municipal boundaries of the city, several influential areas around Haarlem such as the coastal dunes were not included in this analysis. Excluding surrounding areas from a case study can distort the representation of data on climate change events. Therefore, future research could investigate the effects of removing spatial boundaries on maps presenting urban heat vulnerability. Perhaps, another city will then be classified as most petrified Dutch City.

7. Library

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