An integrated approach to incorporating climate uncertainties into urban land-use change modelling

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An integrated approach to incorporating climate uncertainties into urban land-use change modelling

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An electronic version of this thesis is available at http://repository.tudelft.nl/.

The codes used by this thesis is available at https://github.com/feifeiyuzhuzhu/Master_thesis

TU Delft

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Executive Summary

Urbanization makes cities more vulnerable in the face of climate change risks. Understanding urban growth under climate change can help planners optimize land allocation and development strategies that are resilient to the impacts of climate change. However, the complexity and uncertainty of climate change hinder the urban growth projections and make it hard to form local climate adaptation plans. Therefore, this research aims to develop a methodology to incorporate climate uncertainties into land-use models to explore plausible futures.

The literature review results indicate the lack of a methodology to quantitatively link climate change effects with land-use models and to systematically explore the full parameter space of the climate uncertainties. Hence, our main research question becomes

"How can an integrated land-use modelling methodology be developed to help systematically explore the impacts of climate uncertainties on urban growth?"

This research question is answered by integrating Metronamica, a cellular-automata-based land-use modelling framework with Exploratory Modelling. The Metropolitan Region of Amsterdam (MRA) is selected as the case city to demonstrate the proposed methodology, and the research scope focuses on flooding, a typical and important climate impact.

Specifically, we include the flooding probability maps into the "suitability" section under Metronamica, based on the principle that the higher the flooding risk of an area, the lower the suitability value. These flooding suitability values are deemed as uncertain in our research and they are not given fixed values but certain uncertainty ranges.

The flooding factors and their defined uncertainty ranges are added to a model established for the case city. The establishment and calibration of the basic MRA Metronamica model are in collaboration with Supriya Krishnan and Aarthi Meenakshi Sundaram. Then this model is connected with the Exploratory Modelling Analysis (EMA) workbench and generates 2000 experiments by the random samplings and combinations of the uncertainties.

In the result analysis step, we use clustering algorithms to select 34 representative maps, followed by the comparisons between them and the base map where no flooding factor is included. The 34 representative maps show some land-use change characteristics because of the introduction of the flooding suitability variables and the uncertainties. These characteristics of the projected land-use outcomes are extracted and the reasons behind these observations are explored. Finally, the land-use changes from 2015 to 2050 with the flooding risk considerations are summarized.

Based on the summarized changes, we formulate some policy implications for urban planning under climate uncertainties. We first overlay the land-use map with the flooding map of 2050 to identify the potential high-risk areas where some other flooding mitigation and adaptation measures are needed. Next, we compare the housing plans from the local government with our model results, and some disagreements are identified and some more suitable housing sites are recommended. We also provide suggestions on the areas for developing public amenities and recreation lands.

This research presents a complete workflow of dealing with climate uncertainties in land-use analysis, including the selection of methods, the model conceptualization to include climate variables, the model implementation to set up a Metronamica model for the case city, and the connection between the Metronamica and the Exploratory modelling techniques. In the last step, we carry out result analysis and interpretation, finding out the land-use changes caused by the inclusion of flooding into urban dynamics. This integrated framework could be further applied and improved in the intersections of climate change and urban development, to provide insights into climate adaptation and urban climate resilience.

1. Introduction

This chapter introduces the research topic. In section 1.1, the background information is provided, which highlights the problem gap and shows the necessity and urgency to carry out this research. Next, Section 1.2 and 1.3 clarifies the research objectives and research scope respectively. The last section 1.4 argues why this is a research topic for the master program.

1.1. Background

1.1.1. Coupling effects of urbanization and climate change

According to the United Nations, around 68% of the global population will reside in urban areas by 2050 (UNDESA, 2018). This rapid urbanization process means there will be a growing population, denser use of space, unprecedented demands on resources and infrastructures, and a higher amount of greenhouse emissions, which poses challenges for planners to allocate the resources, deliver services and attain sustainable development goals (World Bank, 2015).

In the meanwhile, cities are experiencing accelerating climate change impacts. A landmark report released by the United Nations shows that climate systems are changing at an unprecedented rate (IPCC, 2021). Extreme weather is an accompanying effect of this global warming (Mitchell et al., 2006). The observed extreme weather events, including heatwaves, flooding, droughts are taking place at a higher frequency. During the summer of 2021, serious flooding events have impacted some European and Chinese cities, causing catastrophic damages and losses to the people and assets. The disasters signify the importance and urgency for urban areas to be prepared for the potential climate hazards.

1.1.2. Climate change adaptations

Two types of strategies are available for the cities to reduce the climate risks. Mitigation aims to reduce greenhouse emissions, whereas adaptation means to enhance the capability for dealing with the observed or projected climate effects (IPCC, 2007). Mitigation actions have been widely introduced and implemented in many cities, but the adaptation strategies that focus on improving urban resilience are still lacking (Carmin, Anguelovski, & Roberts, 2012). However, the cities need to consider adaptations as the climate systems are already interfered with by human-induced greenhouse emissions and climate change is expected to continue in the upcoming decades (Füssel, 2007).

One important part of climate adaptation and urban resilience is to incorporate climate change impacts into the local development plans. If planning is not managed properly, urbanization will expose substantial population and assets to climate hazards, bringing adverse effects to the local economic, social and environmental developments.

1.1.3. Barriers to making climate adaptation plans

The difficulty of making a climate adaptation plan lies in the inherent uncertainties of climate change projections and the complexity of urban systems (da Silva, Kernaghan, & Luque, 2012). The projections of climate change are plagued by uncertain model assumptions and parameters, and it is unknown to which extent climate change will impact the cities. In addition, it is extremely hard to know how the urban system will respond to climate change.

Since the effects of climate change are uncertain and distant, most decision-makers tend to give it lower priority compared to other certain and immediate issues, like housing, transport, and provision of basic urban service. Both climate and planning are wicked problems that involve a great degree of complexity, it is not always easy or straightforward for decision-makers to translate uncertainty information into urban planning implications, which is why climate uncertainties cannot be effectively incorporated into decision-making processes (Wardekker, de Jong, Knoop, & van der Sluijs, 2010).

Hence, when dealing with urban climate adaptations, some traditional planning methods fail to recognise the uncertainty of climate change data or the complexity of cities (da Silva et al., 2012). If we ignore the uncertainty of climate change in the urban planning process, the cities will risk locking in future risks that may prove irreversible or expensive and difficult to rectify (Ranger, 2011). For example, existing zoning regulations may not be resilient to intensive rainfall and would increase the vulnerability of the residents and properties. This implies the importance for decision-makers to improve understanding of climate uncertainties and to investigate the uncertainty space for setting out actions ahead of time.

Societal challenge recognized by this thesis
To be prepared for urban planning under climate change, cities need to consider adaptations and incorporate climate impacts into the local development plans. But the uncertainties of climate change projections and the complexity of urban dynamics have posed challenges to make climate change adaptation plans.

1.2. Research objective

It is an inevitable choice for cities to adapt to the changing and uncertain climate, and to become resilient to the potential climate hazards. Local decision-makers need to integrate the climate considerations with the development plans and to recognize climate uncertainty as one important aspect of decision-making.

In this research, we decide to use land-use change as a way to explore urban dynamics. Land-use planning is a key aspect of urban planning. The way that land resources are allocated plays a key role in a region's ecological, environmental, economic, and social development (Wu, 2008). Hence, understanding future land-use changes and characteristics will help urban planners to make more effective and sustainable land allocation and development strategies.

To facilitate decision-makers to fully investigate climate uncertainties, and understand how climate change factors would influence urban land-use changes, this research aims **to develop a methodology to incorporate climate uncertainties into urban land-use change analysis**. More specifically, the methodology is expected to achieve the following objectives:

1. To incorporate climate change variables and some necessary urban factors into the simulations of urban land-use dynamics.
2. To enable systematic exploration over the uncertainty space in climate variables by using a case city

1.3. The relevance to Engineering and Policy Analysis (EPA) program

Climate change and urbanization are two grand challenges faced by the world today. This research aims to understand the impacts of uncertain climate variables on urban growth over the upcoming decades. Modeling and simulation techniques are employed in this research to explore the uncertainty of climate projections and the complexity of urban systems. In the end, the technical results are transformed into policy recommendations that enable urban planners to form long-term planning strategies that account for the climate risks, while meeting other development goals. All these points make this research a typical EPA topic.

2. Literature Review

Chapter 1 identifies the problem gap in incorporating climate uncertainties into the urban planning process when making climate adaptation plans. Based on this topic, a detailed literature review is carried out in this section to extract some further insights into intersections of climate change impacts and land-use dynamics.

This first section elaborates on the potential impacts of climate change on urban land-use change. Section 2.2 discusses land-use modelling, including comparisons among different land-use models. Section 2.3 investigates the approach that deals with uncertainty in land-use modelling. Lastly, section 2.4 summaries knowledge gaps derived from the literature review.

2.1. The impacts of climate change on land-use changes

Land-use change is a result of complex interactions among socio-economic, cultural, political, technological, and ecological factors within the urban system (Turner & Meyer, 1991; Hersperger et al., 2018). Land-use change is caused by certain driving forces (Bürgi, Hersperger & Schneeberger, 2005). According to Kim, Newman and Güneralp (2020), the driving forces of urban land-use changes can be mainly categorized into the natural environment, built environment, and socio-economic factors. The natural environmental factors are associated with topography, climatic conditions, ecology, and some hazards like flood risks. Built environmental variables include transportation, jobs, services, and housing. For the socio-economic side, it accounts for population, policy, and some other economic-related factors such as GDP, income, and employment rate. In the face of urbanization and climate change, population growth and economic development induced by urbanization will bring drastic changes in land-use patterns. Climate change can influence land-use patterns via altering the driving forces (Dale, 1997).

2.1.1. <u>The relationships between climate impacts and urban growth</u>

In order to have a comprehensive understanding of how climate change will influence urban dynamics, a systematic literature survey is performed. Table 2-1 shows the search terms and search strategies we adopt for this part.

Most relevant studies reveal the impacts of climate change on the urban systems from a qualitative and implicit way. Zondag and Borsboom (2008) discuss that climate change effects such as drought and heavier rainfall could affect the biotopes and agricultural productions, and then indirectly drive land-use changes. In their research, they also mention the adaptation and mitigation strategies of climate change such as energy transition policies, will play a role in determining land-use changes. Van Aalst (2006) points out the extreme precipitation events would increase soil erosion and increase flood risks, whereas increased summer drying and drought bring damages to agriculture production, building foundations, and water quality. Blakely (2007) states that the rise in temperature could result in road material degradation, infrastructure relocation, and high water and energy demand, all of which exert influences on land-use. Some other types of influences could be found in Annex 1.

Table 2-1: The Search terms and search strategies for the comprehensive literature study on the relationships between climate change and urban growth

Search terms (within each column, " OR" is applied)			
keyword 0	**keyword 1**	**keyword 2**	**keyword 3**
climate	risk	land*	dynamics
climat*	effect*	land-use	growth
climate change	impact*	landuse	development
	resilien*	urban	expansion
		urban growth	conversion
		metropoli*	shift*
		cit*	transformation*
		Metronamica	transition*
		sleuth	simulation
		cellular automata	model*
			scenario*
			prediction*
Search strategy			
1	keyword 0 AND keyword 2		
2	keyword 0 AND keyword 2 AND keyword 3		
3	keyword 0 AND keyword 2 AND keyword 3 AND keyword 1		

A small portion of papers integrates climatic variables in land-use change from a specific and quantitative way. Koomen, Loonen and Hilferink (2008) acknowledge that climate change modifies the demand-supply mechanism of lands, as well as the physical suitability of lands in certain areas. In their research, they translate different climate scenarios into the land-use demand parameters of the Land-use Scanner Model. One previous study tries to evaluate climate change effects on land-use via CA-based models such as incorporating flood and increased temperature into a CA-based Metronamica model by modifying the suitability inputs (van Delden & Hagen-Zanker, 2009). Lu et al. (2018) define "the distance to flood area" and "distance to sea-level rise area" as two factors of climate change influencing land suitability and further use a Markov Chain-based cellular automata model to simulate the land-use changes for London. He et al. (2015) argue that climate change influences water resources and then alters the demands for urban lands. Specifically, they first use the system dynamics method to determine the demand per land and then develop a CA model to allocate these demands. However, these studies ignore the uncertain and dynamic characteristics of climate change and do not investigate the impacts of climate uncertainties.

2.1.2. Flooding impacts on urban growth

Much research has been done to explore the impacts of land-use changes on urban flood vulnerability (Saghafian et al., 2008; Liu & Shi, 2017; Liu et al., 2005). The research regarding how flood factors could influence land-use is relatively lacking. Some research has evaluated the urban areas that are impacted by future flooding risk (Zhao, Song & Peng, 2017; Kim & Newman, 2019). Typically, such research generates the projected land-use maps and overlays them with the estimated flooding risk maps, to exam if future urban growth will occur in flood-prone areas. But this kind of research does not really regard flooding-relevant factors as one driving force of land-use change and does not incorporate flooding variables in the land-use projections. Hence, the previous research does not present urban climate resilience solutions but only state the need for flooding control and management.

2.2. Land-use modelling

land-use modelling and simulation is an approach to help deal with the complex urban land-use dynamics, so it is necessary to familiarize with some fundamental knowledge on land-use modelling.

Land-use change models are used as (1) to understand and analyse the complex linkages and feedbacks among different drivers of land-use change (Van Soesbergen, 2016; Verburg et al., 2006); (2) to explore alternative futures with a combination of scenario planning. Land-cover change models generally consist of 3 parts: a demand change part, a transition potential part, and an allocation change part, which determines the amount and spatiotemporal location of the changing land-use types (Eastman et al., 2005).

2.2.1. Overview of different land-use models

Many types of land-use change models have been created and developed to facilitate land-use-related studies. These land-use change models use different modelling approaches and are grounded by different theories (Verburg et al., 2006). A summary of the most common land-use models is shown in Table 2-2.

Among all the land-use models, the ability of a cellular automata (CA)-based model to deal with the extremely complex factors of urban dynamics and behaviour makes it a popular choice of modelers. The spatial explicitness of CA models makes it easy to convey spatial information among modelers and decision-makers. In the meanwhile, transitional rules in CA models are flexible to change by users, such that the complex interaction patterns among urban components could be easily captured. Another strength of CA models is the convenience to integrate them with other techniques, such as fuzzy theory, Markov chain and artificial neural networks (Navarro Cerrillo et al., 2020).

Table 2-2 The overview of different land-use models

Model type	Modelling approach	Main function	Advantages	Disadvantages
Empirical/ Statistical based	Logistic regression analysis, Artificial neural networks (ANNs)-based model	To establish functional relationships between LUC and the possible driving forces (Huang et al., 2009)	Easily obtained	- Heavily rely on comprehensive historic time-series census data; - Less suitable for quantification of change and temporal analysis (Moghadam, H. S., & Helbich, M. (2013))
	Marchov chain (MC) models	To describe the temporal change among the land use types based on transition matrices	Can predict the amount of land-use change (Yang, Zheng & Lv, 2012)	- Cannot simulate the change in the spatial distribution (Yang et al, 2012)
Spatial transition-based	Cellular automata (CA) models	To simulate the spatial pattern change based on the interactions of local conditions and surrounding subsystems	- Spatial explicitness, flexible transitional rules, and compatibility with large data sets (Wagner, 1997; Song et al. 2017) - Can be integrated with other techniques like MC and statistical models	- Heavily rely on the previous land-use research and data (i.e., land-use maps, demand, transition rules, etc) (Du et al., 2010)
	Agent-based models (ABM)	To incorporate human decision making into the LUC process by replacing transition probabilities or differential equations at one level (e.g., populations) with decision rules of entities at a lower level (individual or groups) (Matthews et al., 2007)	Able to explore social interaction, adaptation, and decision-making at different levels. (Matthews et al., 2007)	- Data demanding - The specification of realistic agent behaviour and diversity is challenging (Verburg, 2006)

2.3. Uncertainty exploration in land-use modelling

In a typical land-use analysis, the land-use model is simulated under few fixed scenarios to show different possibilities of future land-use patterns. This is the common way for land-use modelling to deal with uncertainty. Scenarios refer to "coherent and plausible stories, told in words and numbers, about the possible co-evolutionary pathways of combined human and environmental systems" (Swart, Raskin, & Robinson, 2004). Scenarios do not need to represent the true future, but plausible possible future visions (Carter, 2018; Mallampalli et al., 2016). Therefore, the scenarios could entail and communicate the uncertainties in the decision-making process. There are many approaches to develop the scenarios, including the school *La Prospective*, the Probabilistic Modified Trends school and the intuitive logics (Bryant & Lempert,2010).

2.3.1. Story and simulation (SAS) approach

Most land-use analysis and literature follow the intuitive logics school to develop scenarios. The scenarios here are usually composed of a series of 'drivers of change' from different sectors (Carter, 2018). Hence, a series of driving forces are identified in the beginning, of which the uncertain factors are determined. And then the scenarios are created based on the key uncertain factors. Using the intuitive logics helps decision-makers to build up understandable scenarios and broaden their minds to more possible futures (Bryant & Lempert,2010).

The story and simulation (SAS) approach is one typical method from the intuitive logics school that combines qualitative and quantitative scenario developments. The scenarios are interpreted not only in storylines that are easily understood by the stakeholders but also the numerical results that are fed to the models further. As suggested by Figure 2-2, there is a step named "scenario translation" to connect the narrative storylines originally defined by experts and/or stakeholders with the quantitative land-use simulation models. Van Delden and Hagen-Zanker (2009) explain in detail how the narratives are translated into model inputs for Metronamica by implementing the SAS approach.

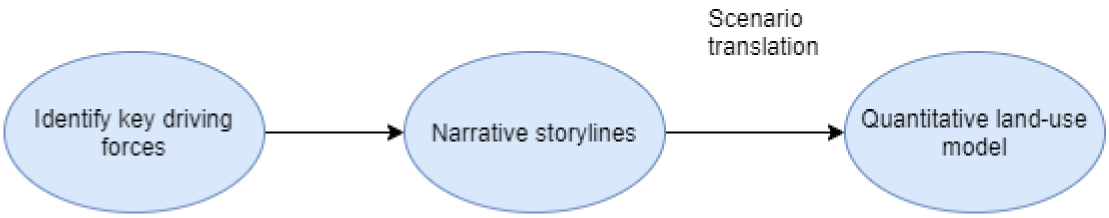


Figure 2-1: SAS-based scenario development process

Regarding the narrative storylines, some shared community (qualitative) scenarios are available in the domain of climate change. The Intergovernmental Panel on Climate Change (IPCC) has identified four emission storylines to assist climate analysis across different disciplines (Scenarios, 2020). Some studies have quantified the IPCC scenarios and applied them to land-use modelling (Yan et al., 2013; Han et al., 2015). Solecki and Oliveri (2004) downscale two IPCC scenarios by a set of future growth parameters, and then set the corresponding values for the parameters in a cellular automata model.

Although there are wide applications of the SAS approach, some limitations surround it. Bryant and Lempert (2010) argued that it is difficult and even impossible to summarise the whole breadth of uncertainty in a small number of scenarios, and additionally, the scenarios are only represented by the interests of the small groups of clients. In the same paper, they discuss the feasibility to use exploratory modelling and scenario discovery in determining the possible futures.

2.4. Knowledge gaps

The literature review investigates the relationships between climate change and urban growth, and the land-use modelling approaches. In addition, the scenario analysis, as a way to deal with uncertainty in land-use modelling, is also checked.

Some previous studies acknowledge the impacts of climate change on land-use and urban growth, but the relationships indicated by them are rather generalized or qualitative. The mechanisms that link climate change effects with land-use dynamics need to be clarified in more detail. For example, some literature suggests that intensive flooding will turn some urban locations untenable (Blakely, 2007), but it remains unclear in which specific way flooding alters the driving forces of land-use changes and further changes the landscapes. Land-use models are proven useful in the explorations of land-use change or urban dynamics. But most studies do not account well for climate change variables and their uncertainties through the simulations of urban landscapes. This is a result of the complexity and uncertainty of quantifying climate change effects through urban growth. Therefore, the literature review results indicate the current linkage between climate change and land-use modelling are rather weak, such that the impacts of climate change on urban growth cannot be well understood.

Knowledge gaps addressed by this thesis

- Lack of quantitative linkages of climate change effects with land-use change modelling.
- Lack of a systematic way to explore full parameter space of the climate uncertainties in land-use change modelling.

Another gap is related to the uncertainty exploration approach. The Story-And-Simulation (SAS) approach is mostly used in the land-use or urban planning relevant studies, but this approach shows some weakness in dealing with deep uncertainty: 1) only a limited number of scenarios are considered; 2) the selections of the important uncertain factors are highly dependent on the involved stakeholders. As a result, the SAS approach could not effectively take account of the entire bandwidth of the uncertainties and fully inform the decision-makers of the possible futures. Climate change in our case is characterized as uncertain, dynamic, and evolving, applying the SAS approach on it may lead to biased and outdated land-use projections. Hence, we need a more systematic and effective technique to help explore the climate uncertainties.

3. Research Questions

This section clarifies the main research question based on the research objective and the research gaps identified in the last two sections. Five sub-research questions are formed in order to answer the main research question. Finally, the thesis structure is presented.

3.1. The research questions

The research objective is to develop a methodology that incorporates climate uncertainties into the urban land-use change analysis, but the knowledge gaps indicate that the quantitative linkages between the climate change effects and the land-use models are lacking, and the climate uncertainties and their impacts are not systematically investigated.

Therefore, the main research question of this research is proposed as:

How can an integrated land-use modelling methodology be developed to help systematically explore the impacts of climate uncertainties on urban growth?

In order to answer the main research question, firstly some literature review work will be conducted to find out the appropriate land-use modelling framework and the uncertainty exploration techniques. Therefore, the first two questions are formed as:

- *Q1: Which land-use modelling framework is suitable for investigating the climate impacts on urban growth?*
- *Q2: Which modelling techniques can be used to help systematically explore the climate uncertainties?*

Secondly, the two kinds of modelling approaches need to be integrated and implemented in a case city. Therefore, the question regarding the model application is formulated:

- *Q3: How can the studied climate variables and their uncertainties be linked with the parameters of the selected land-use modelling framework?*

Once the model is implemented, the model results of the case city are analysed and translated into urban planning implications. In this way, the impacts of the climate uncertainties on urban developments are investigated. Therefore, the last two sub-research questions are:

- *Q4: Based on the modelling results, what are the possible land-use changes if the climate variables and their uncertainties are considered?*
- *Q5: What urban planning implications can be obtained from the projected land-use changes?*

3.2. Thesis structure

Phase	Chapter	Main Contents	Sub-research questions
Thesis Definition	1	Introduction	Propose research questions
	2	Literature review	
	3	Research questions	
Methodology	4	Selected methods	Q1,Q2
Application	5	Model conceptualization	Q3
	6	Model implementation	Implement ideas on the model
Analysis	7	Result analysis	Q4
	8	Policy implications	Q5
Conclusion	9	Conclusion and discussion	Synthesize the findings

Figure 3-1: Thesis structure

In the following chapters, the questions are answered sequentially. Chapter 4 focuses on the methods used by this thesis and answers the sub-research question 1 and 2. The development of the conceptual model is explained in Chapter 5 and it shows how the climate variables and their uncertainties can be incorporated into the proposed methodology. Chapter 6 elaborates on the model implementation process. The result analysis and the policy recommendation formulation process are described in Chapter 7 and 8 respectively, where the answers to research question 4 and 5 can be found.

4. Methodology

This chapter demonstrates the methods that are selected to help address the research gaps and it gives answers to sub-research questions 1 and 2:

- *Q1: Which land-use modelling framework is suitable for investigating the climate impacts on urban growth?*
- *Q2: Which modelling techniques can be used to help systematically explore the climate uncertainties?*

First of all, the research scope needs to be clarified. One case city is selected to demonstrate the proposed methodology. Next, we determine one land-use modelling framework to help explore urban dynamics and one uncertainty exploration technique for fully investigating the impacts of climate uncertainties.

4.1. Research scope: flooding

To narrow down the scope of this research, only one type of climate change impact will be fully investigated. This research focuses on flooding to explore its influences on urban planning. Over the last few decades, urban flood risk has obtained increasing attention, as the flooding frequency and damages have increased (Ashley, Balmfort, Saul, & Blanskby, 2005). The accelerated urbanization has given rise to increased buildings in unsuitable areas, which causes the expansion of impervious areas leading to a higher probability of flooding. Heavier rainfall events and sea-level rise brought by climate change add more pressure to urban flooding mitigation and adaptation.

Land-use changes could be perceived to show a dual nature, in that it is a major influential factor to urban flooding but is also under the impact of flooding. The common consequences of flooding include property damages, traffic disruptions, and agricultural yield reduction. These negative effects could influence the suitability, accessibility and zoning of urban land-use. Hence, flooding plays an important role in urban developments and it will be used as a starting point for this research to understand the effects of climate change on urban land-use dynamics.

4.2. Case study introduction: MRA

To demonstrate the developed methodology of climate uncertainty-based land-use modelling, we need a case city. The Metropolitan Region of Amsterdam is selected by this research.

4.2.1. Introduction on Metropolitan Region of Amsterdam (MRA)

The Amsterdam Metropolitan Area is the informal partnership of 32 municipalities, the provinces of Noord-Holland and Flevoland and the Amsterdam Transport Region, which extends from Zandvoort to Lelystad and from Beemster to Haarlemmermeer. The region includes two airports, seaports, the financial centre of the Netherlands, Media Valley in Hilversum and Greenport Aalsmeer (Metropool

Regioamsterdam, 2021). More than 14% of the Dutch population live within the MRA and it is the country's most robust economic region (Over de metropoolregio Amsterdam, 2021)

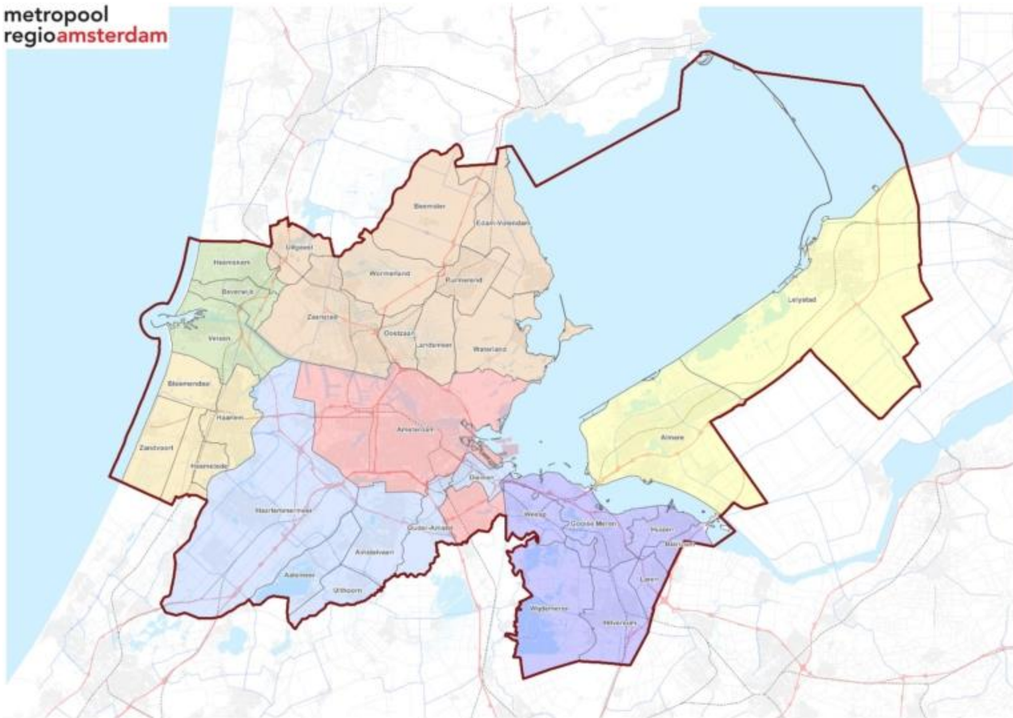


Figure 3-1: Overview of the Metropolitan Region Amsterdam in map [1]

Many of the urban challenges requires a regional approach. This is why the municipalities of MRA are connected. The authorities within MRA address the urban challenges jointly and try to strengthen the quality of life of the entire region through growth.

4.2.2. <u>Motivations for selecting MRA as a case city</u>

MRA is representative in the context of climate change since it faces accelerated threats from heatwaves, stormy weather, flooding, and projected sea-level variations. According to Amsterdam Institute for Advanced Metropolitan Solutions (AMS Institute), there are four to five storms causing 50 million damages per year in the Netherlands. And the government's Delta Programme estimates that 60% of the country could be flooded, given that the sea level is rising at an average of about 3mm a year (Postma & de Wit, 2021). Moreover, current urbanization makes the Great Amsterdam area susceptible and vulnerable to climate hazards. The urban area is experiencing rapid growth, which is expected to bring pressure for land-use planning under climate change.

MRA also places emphasis on climate adaptations. As a low-lying area, safety from the flooding hazards and other adverse climate effects is a national agenda for the Netherlands (Kim & Newman, 2019). There are acknowledgments on the necessity to combine spatial planning with flood management (Dai, Wörner, & van Rijswick, 2018). The local government of Amsterdam has been dedicated to improving urban climate resilience and the city's structural vision plan (to 2040)

1: Image source: https://www.metropoolregioamsterdam.nl/over-mra/

pointed out that far more attention will be given to climate change adaptation and sustainable growth.

The last motivation for choosing MRA is about the data availability for our modelling work. This work is based on an integrative framework, which requires high-quality datasets regarding land use and climate change factors. These types of data for MRA could be collected from different sources. Hence, we decide to apply MRA to our methodology.

4.3. Cellular automata land-use modelling framework: Metronamica

4.3.1. Cellular automata (CA) models

CA modelling is a bottom-up approach using local interactions to reflect the evolution of a system, where space and time are considered as discrete units (He et al., 2015). In a basic CA model, there are usually five essential components: 1) the cells; 2) the state of each cell, specifically in a land-use context, the states represent certain land-use types; 3) the transition rules that define how the states of the cells will shift; 4) the neighbourhood types that may influence the transition potential of the cells 5) and the time steps (He et al., 2015).

CA models have the advantages of spatial explicitness, flexible transitional rules, and compatibility with large data sets (Wagner, 1997; Song et al. 2017). Previous studies have proved the power of CA in successfully simulating urban growth and change processes (Kim & Batty, 2011). Clarke, Hoppen and Gaydos (1997) develop a CA simulation model to predict urban growth for estimating the regional and broader impact of urbanization on the San Francisco Bay area. Bihamta et al. (2015) simulate future urban expansion of a metropolitan area in Iran from 2010 to 2050, by making use of CA modelling.

4.3.2. Metronamica

Metronamica is a constrained CA-based land-use modelling framework, developed and managed by the Research Institute for Knowledge Systems (RIKS). This framework has been widely applied in various urban contexts and proved to have many advantages. First, Metronamica is able to simulate a wide range of urban land-use functions (the current limit set to 26 classes), whereas other CA applications like Sleuth are only able to demonstrate binary distinctions between urban and non-urban uses. Second, the graphical user interface (GUI) of Metronamica makes it possible to update model inputs interactively and explore the model behaviour visually within a short time. (Stanilov & Batty, 2011; Van Delden & Vanhout, 2018). This capacity enables Metronamica to function as a decision-making support tool to carry out experimentation, exploratory analysis, and impact analysis under different scenarios.

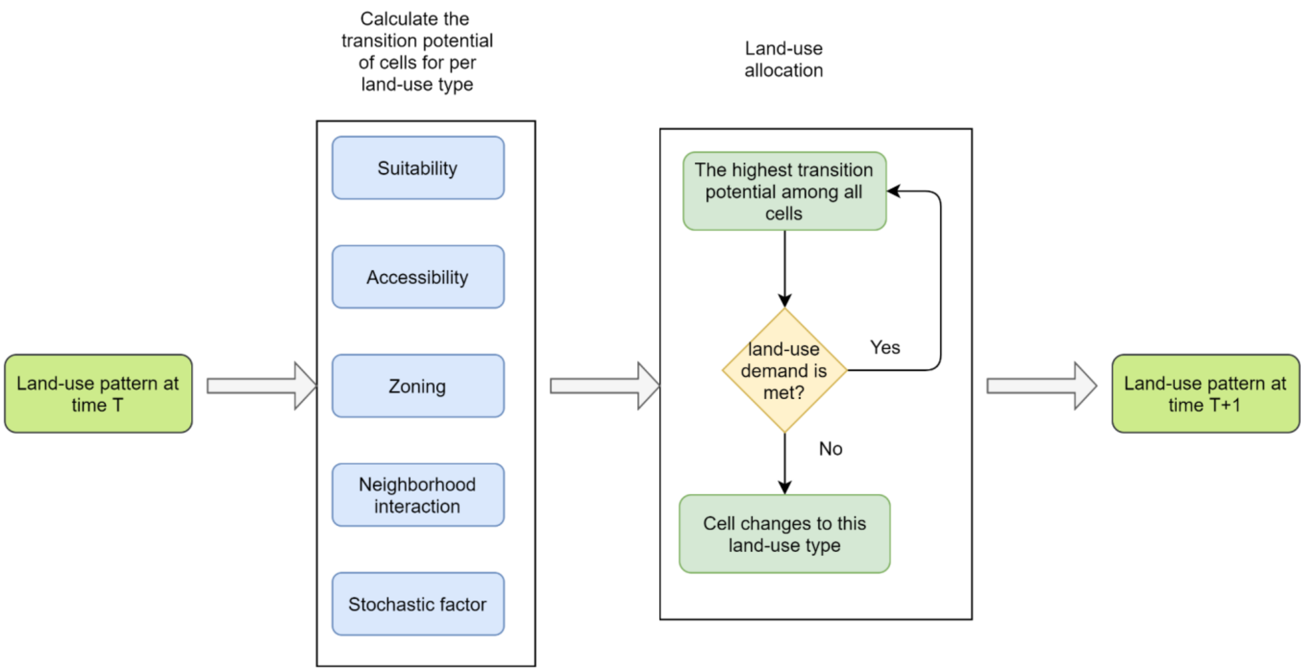


Figure 3-1: The working flow of Metronamica modelling. Adapted from van Delden et al. (2005)

The core idea of Metronamica is "competition for space", where land-use functions will be able to occupy the locations which are most desirable for them. As shown in Figure 3-2, land use demands will be allocated to grid cells based on their transition potential for different land-use types.

To calculate the attractiveness of each land-use function to the cells, four important elements will be considered. They are introduced in Table 3-1. The local ecological, physical, and socio-economic influences could be incorporated into these elements.

4.3.3. Why Metronamica

Cellular automata (CA)-based modelling introduces a disaggregate and dynamic approach to explore the self-organized and non-linear urban transition process in both spatial and temporal aspects (Kim & Batty, 2011). Building a CA-based model will provide us the opportunity to understand the spatial and temporal land-use dynamics and be able to project future land-use patterns, which makes it a suitable modelling choice for us. Metronamica as a CA-based modelling framework allows for simulations over a wide range of urban land-use functions, and the interactive interface enables the users to update the inputs and explore the resulting maps visually. Therefore, this research employs Metronamica to simulate the land-use changes.

4.4. Uncertainty exploration technique: Exploratory Modelling

Exploratory modelling is a way to reason about the uncertain system by assembling a large number of plausible futures (Bankes, 1993; Kwakkel, 2017). With the assistance of computers to run hundreds or thousands of simulations, one could obtain more various and comprehensive outcomes.

Cox (2020) adopted exploratory modelling to analyse the uncertainties existing in the Land User Scanner Model. Specifically in this research, large amounts of experiments are generated by combinations of values for the uncertain parameters. and then the author analyses the experiment results and then uses some algorithms to find which uncertain parameters led to these outcomes.

During the result analysis, the maps need to be clustered by clustering algorithms and some representative maps are selected from each cluster to manifest the characteristics within this cluster.

Table 3-1 The important elements determining transition potential in Metronamica. Adapted from van Delden et al. (2005)

Element	Introduction	Needed inputs	Outputs	Associated model parameters
Suitability	Suitability is defined as the degree to which a cell is fit to support a particular land use function in terms of physical, ecological, and environmental appropriateness.	Maps for each suitability factor (e.g., soil quality, erosion, etc)	A composite map containing suitability values for the cells per land-use type	suitability transformation rule for each suitability factor
Zoning	A measure based on master plans and planning documents to specify which cells can or cannot be taken in by the particular land use	Zoning maps	A composite map containing zoning values for the cells per function land-use type	The zoning state values (i.e., actively allowed, restricted)
Accessibility	A measure of how easy a particular cell can fulfil its needs for transportation and mobility	Maps for the transportation network (e.g., road, railways, waterways)	A composite map containing accessibility values for cells per land-use type	The distance decay values and weights of each accessibility factor
Spatial interactions (or Neighbourhood influence)	A measure to determine the degree to which it is attracted to, or repelled by, the other functions present in the neighbourhood	The defined neighbourhood interaction rules	The values of neighbourhood influences for cells per land-use type	The inertia/conversion and neighbourhood effects values for each land-use type

Based on the observations from the representative maps, the land-use changes are identified and the plausible futures could be defined.

Therefore, compared to other uncertainty exploration approaches (i.e., story and simulation approach), this research contains larger coverages over the uncertainty space. The storylines can be formed in the end rather than defined at the beginning. As a result, the decision-makers will be informed what kind of changes are likely to take place. Figure 3-2 displays the concepts of the two scenario development approaches.

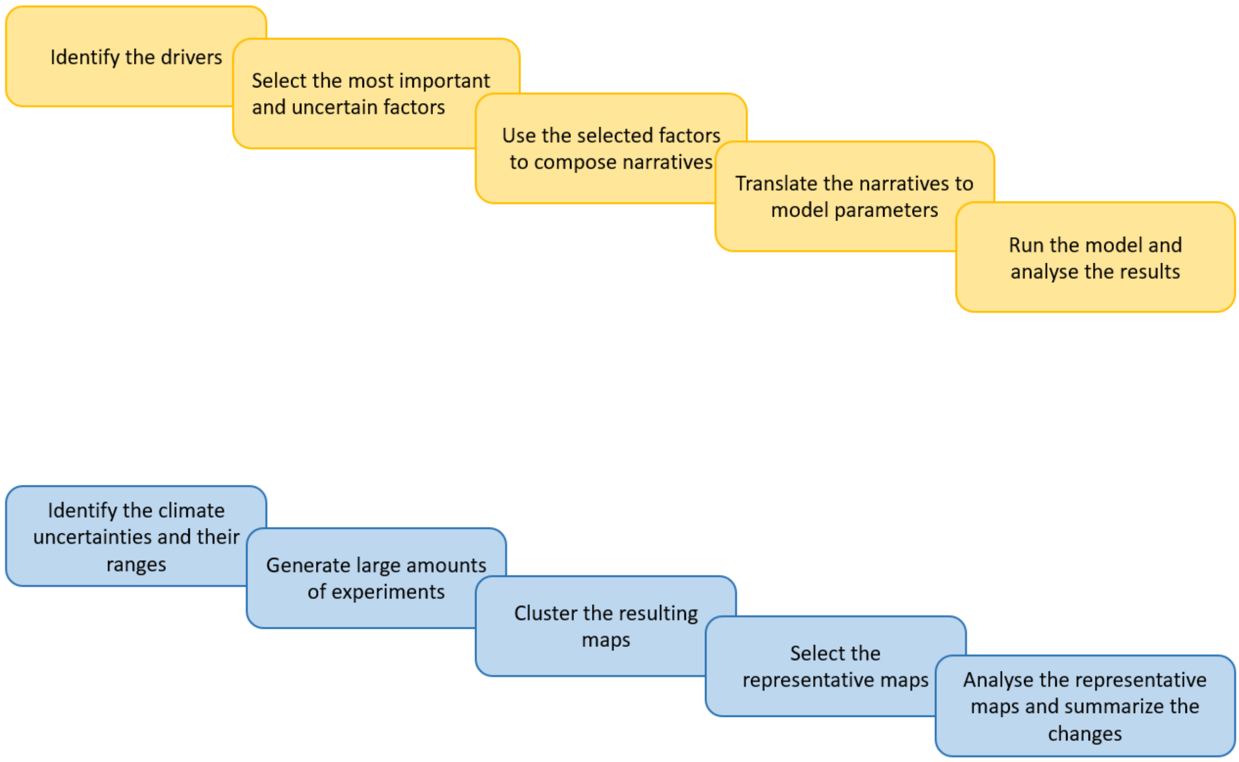


Figure 3-2: The traditional story and simulation way of developing the scenarios (in yellow), and the proposed pathway for uncertainty exploration (blue) in this research.

4.4.1. Why Exploratory modelling

Exploratory modelling addresses some weaknesses of the SAS approach in tackling uncertainties. First, there is no need to define the plausible scenarios before model simulations. In this case, the bias from modelers and planners is reduced (Cox, 2020). Also, it uses broad samplings over the uncertain parameter space and generates several possible outcomes, which largely capture the breadth of uncertainty. The Exploratory Modelling and Analysis (EMA) Workbench is an open-source workbench of Python which enables modelers to implement Exploratory Modelling in various models (Kwakkel, 2020). This research adopts the EMA workbench to systematically explore the climate uncertainties.

4.5. The Integrated Approach

Having decided on Metronamica and exploratory modelling as research methods, we need to integrate them and create a complete workflow to analyse the impacts of climate uncertainties on land-use modelling of MRA. Firstly, the conceptual climate-embedded Metronamica model is expected to be formed. In particular, this conceptualization decides on what types of climate variables (i.e., flooding variables) to be input and specifies where and how to include the climate variables under the Metronamica modelling framework. Second, a Metronamica model is needed for the Metropolitan Region Amsterdam (i.e., MRA), which is expected to reflect the basic land-use change patterns of MRA. And then the previous conceptual ideas are added to this MRA Metronamica model. The next step is to connect this Metronamica with the EMA workbench to perform a large number of experiments. EMA workbench enables the sampling and combinations uncertain climate variables through large amounts of experiments. By this exploratory modelling, many maps are generated and we need to analyse them by clustering based on their similarity. The analysis results can help to form some policy recommendations. Figure 3-3 demonstrates how Metronamica and exploratory modelling are integrated and how the entire research flow looks like.

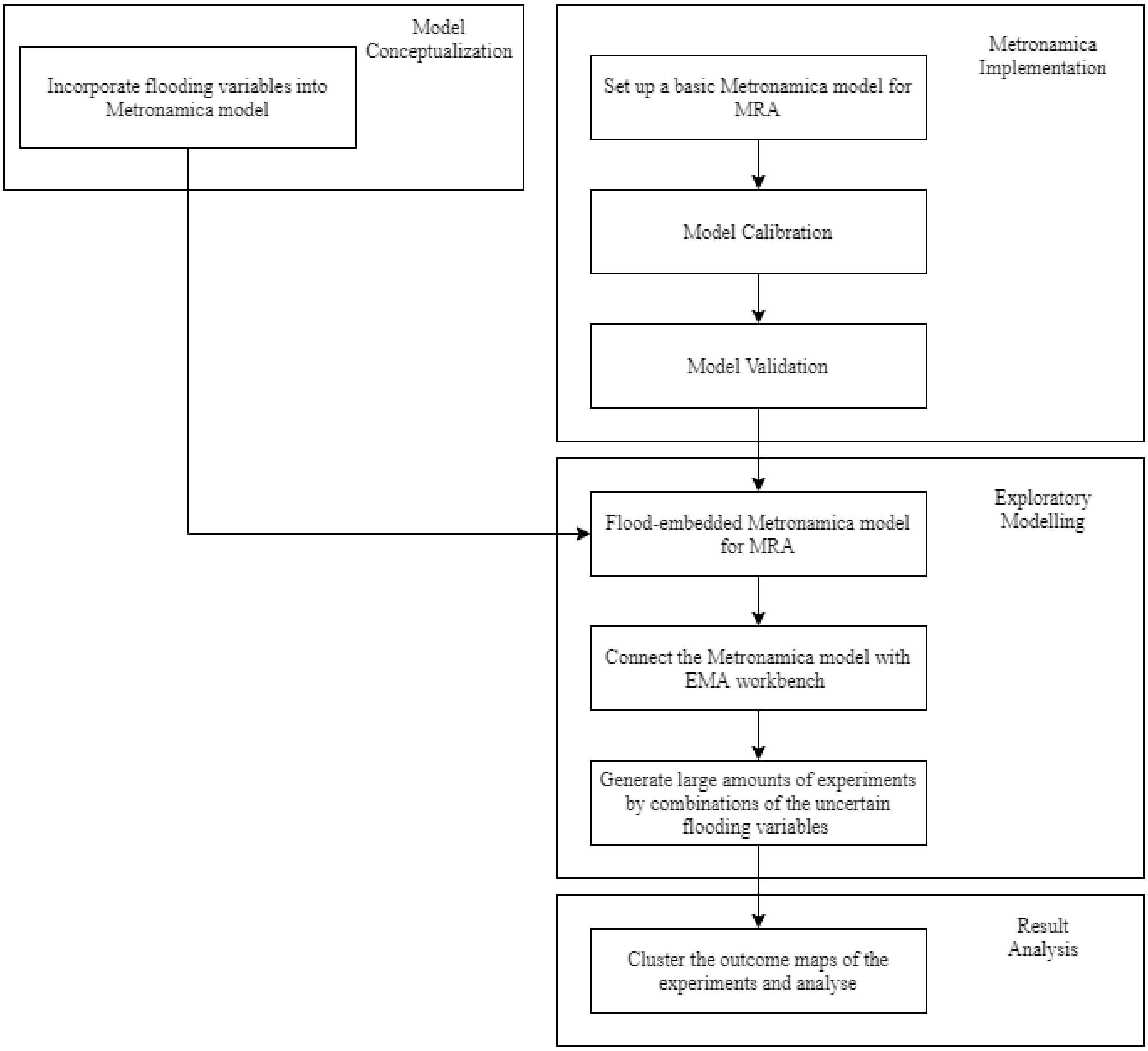


Figure 3-3: Overview of the research flow

5. Model Conceptualization

This chapter answers sub-research questions 3 and 4:

- *Q3: How can the studied climate variables and their uncertainties be linked with the parameters of the selected land-use modelling framework?*

It points out in which way the flooding variables could be incorporated into the Metronamica modelling framework and how we can process the flooding uncertainties.

5.1. Core idea of the inclusion of flooding impacts

In this research, we use the simulation of land-use changes to provide insights on how land resources could be utilized optimally and try to protect urban areas against incompatible growth. The main purpose of using Metronamica in this research is not to predict the future but to inform the policymakers of the options of land-use allocation to reduce flooding risk and improve climate resilience. From the point of view of resilience, flooding cannot be completely prevented from happening, such that flooding management needs to emphasize more on how to reduce the disruptions to flood-prone areas (Schelfaut et al., 2011). Land-use planning is a way to reduce the potential unwanted flooding consequences and the developments in high flooding risk areas should be controlled. Therefore, when simulating land-use changes in our research, it is assumed that flooding risk will be managed through land-use dynamics, and the areas with higher risks should have low potential to get developed.

5.2. Include the flooding variables under one Metronamica section

In Metronamica, there are four sections that determine the final transition potential of the land cells: suitability, accessibility, zoning and the neighbourhood interaction rules. Flooding variables are expected to be included in one of the four sections and to modify the parameters under that section.

The accessibility and the neighbourhood interaction sections are not considered by flooding impacts in this research. Firstly, as flooding is not a common event, transportation is disrupted by floods at a low frequency. Therefore, this kind of accessibility disruption is hard to influence the general accessibility index of the transportation networks in making land-use decisions. Neighbourhood interaction rules mainly reflect the attraction or the repulsion among different land-use classes, and flooding impacts are not able to exert influences in this aspect.

5.2.1. Decision over suitability and zoning

Land suitability assesses the appropriateness of one cell to function as a specific land-use type based on its physical and climatic characteristics. The most common suitability factors are slope, elevation, and soil quality. If flooding is considered as one of the suitability factors, the flooding-prone areas will be assigned with low suitability values for some land-use types, meaning it is not suitable to allocate these land resources there. Based on the overlay of different factors, the suitability map is generated, and the citizens and the government would consider relocating the land resource in order to minimize the loss of human life and reduce the economic consequences and social disruptions caused by flood hazards.

Some may argue the feasibility to consider flooding impacts under the zoning sections. In this case, we already assume that the government will take action on flooding control via zoning regulations. Specifically, the developments of certain land-use types such as residential and commercial in the flood-prone areas would be strictly or slightly restricted. Then the land-use outcomes will indicate how such flooding zoning policies shape the future urban landscape.

The two conceptualization approaches both prevent the developments in flood-prone areas, but through some experiments and reasoning, we decide on including flooding impacts under suitability.

- **The experiment results**

An experiment is carried out on a demo model to figure out where (i.e., suitability or zoning) to include the flooding map could produce the most variability. The one with the most variability could provide more insights into land-use changes, and will hence become more ideal to be adopted in the MRA case.

In this experiment, the flooding map has been added to 1) the suitability section, 2) the zoning section with a high hierarchy, and 3) the zoning section with a low hierarchy respectively. The simulated maps are compared with the base scenario where no flooding factor is considered. The detailed information of this experiment is available in Annex 2. Figure 5-1 shows the amounts of cells that are changed from the initial year to the end year in the four scenarios.

The results indicate that there are insignificant differences between the suitability and the zoning conceptualization approach in terms of the outcome variability, meaning that including the flood probability map into suitability or zoning leads to a similar land-use change pattern. Therefore, from the perspective of result variability, it is acceptable to choose either approach.

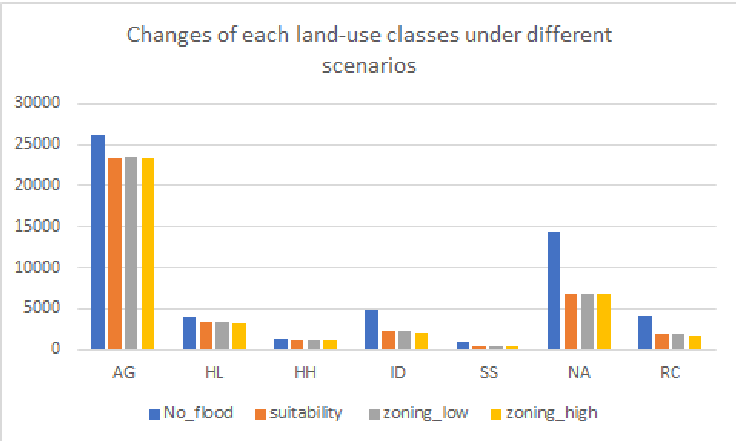


Figure 5-1 The changed cell amounts for each land-use class under the four scenarios. Except for the baseline (the blue bar), the other three scenarios show similar outcomes.

- **The reasoning**

Our research focus is to inform the decision-makers how land resources could be utilized optimally to make cities more climate-resilient. By including the flooding map into the suitability, the decision-makers will understand from the simulated maps how the future land-use patterns look like if the flooding uncertainties are considered, such that they can formulate policies accordingly. These policies are not limited to the restrictions on flood-prone areas. However, if the flooding map is added to zoning, it is already assumed that the restriction rules will be applied to the studied city and the influences of the restriction policy are investigated. Since the flooding management policy is not determined yet in our case, and we need the model and the simulated results to find out the policy recommendations for land-use planning, it is more reasonable to include the flooding map under suitability.

5.3. Link flooding variables with Metronamica

This section is trying to find out how the selected flooding map can be linked with the suitability parameters.

Figure 5-2: The Metronamica interface of transforming a flooding probability map to a land suitability map, taking the example of the Residential (H) land

5.3.1. Introductions on the Metronamica "Suitability" interface

To include the flooding impacts into suitability, either a categorical or numeric map that represents the flooding conditions in the Metropolitan Region of Amsterdam (MRA) is wanted. In this flooding map, each cell belongs to certain flooding categories (in our case, the different flooding probability categories) or contains a certain number. Once the map is imported to suitability, we have to transform these categories or the numbers into suitability values for each land-use class. Figure 5-2 displays an example of transforming a flooding map into a suitability map in the Metronamica interface. The transformation rules should be defined based on the appropriateness of each category or number to function as different land-use classes. In this research, the suitability range is set from 0 to 1. A zero means it is completely unsuitable to allocate a certain land-use class to this land cell.

5.3.2. The available flooding maps

The map imported to Metronamica is the localized probability map with a flooding depth above 0.5 meters (original data source: Climate Impact Atlas). Specifically, this map indicates the probability of each area to experience a flooding event that has a depth of more than 0.5 meters. The reason for selecting the probability map with > 0.5m depth is because we assume that only if a flooding event reaches such severity will people consider relocating and will the government decide to plan for the flooding. The probability is categorized into 5 levels: extremely small (< 30,000 per year), very small (1/3000 to 1/30,000 per year), small (1/300 to 1/3000 per year), middle (1/30 to 1/300 per year), and high (>1/30 per year).

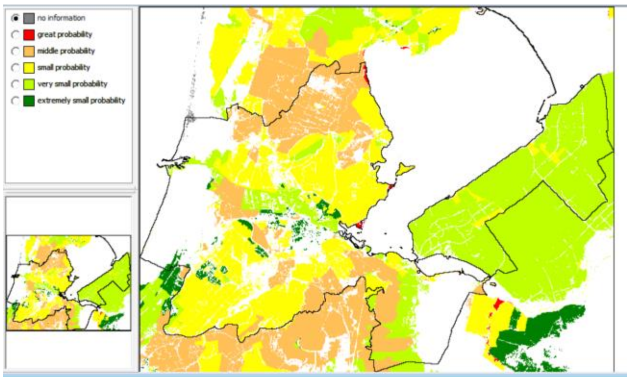


Figure 5-3: The localized flooding probability map for MRA in 2050 [1]

The localized flooding depth map with different probabilities is also available. But once the depth maps are rasterized, the depth values of the map range from 0cm to 50cm. Since one assumption we make for the flooding impacts on urban growth is, the flooding depth will not take an effect on the urban system until the severity is deemed as high (above 50cm) and the depths below this threshold are not able to drive people to move away. Therefore, the flooding depth map is excluded from Metronamica.

We take account of the flood depth by including it as a part of the uncertainties within the flooding probability map. The flooding hazards are co-represented by the flooding probability and the depth. In the selected flooding map, although there are some low probability areas, they may bear the high risk as the flooding depth is uncertain and become unsuitable for living and commercial activities. Consequently, the low probability areas have some chances to be assigned low suitability values due to the uncertainty of flooding depth.

5.3.3. Principles of flooding-probability and suitability transformation

The transition rules between the flooding probability and the land suitability derive from the concept of risk. If allocating one land-use class to one area results in high flooding risk, the suitability value of this area for this land-use class will become low. Therefore, for flooding suitability, a value of 0 implies a very high flooding risk, whereas a 1 means the least flooding risk.

The flood risk is estimated based on the following equation:

1. Map source: https://www.klimaateffectatlas.nl/en/, the map is developed by Rijkswaterstaat.

Flood risk = flood hazard * consequences

In this research, we use the flooding risk to link climate variables with the land-use modelling parameters (see Figure 5-4). Flood hazard can be represented by the flood probability and flood depth, but as the only proper map to be imported to the model is the flooding probability map, flooding depth is internalized as a part of the uncertainties that will be analysed in the following steps. The other dimension of flooding consequences is deemed to be relevant with the land-use types.

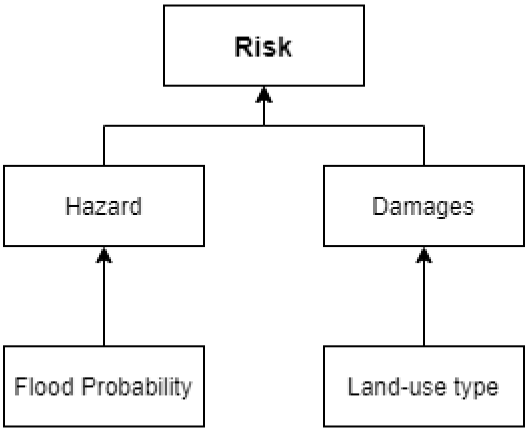


Figure 5-4: The way to determine flood risk in this thesis

Following the concept of flooding risk, the consequences of each land-use type in the case of facing a flooding event with a depth above 50 cm need to be evaluated. The severity of the damage combined with the flooding probability of each area determines the flooding risks of that place, based on which the land suitability values are formed. These land suitability values play a role in the further determination of the uncertainty ranges of the flooding variables. Figure 5-5 demonstrates the workflow of transforming flooding variables into suitability parameters.

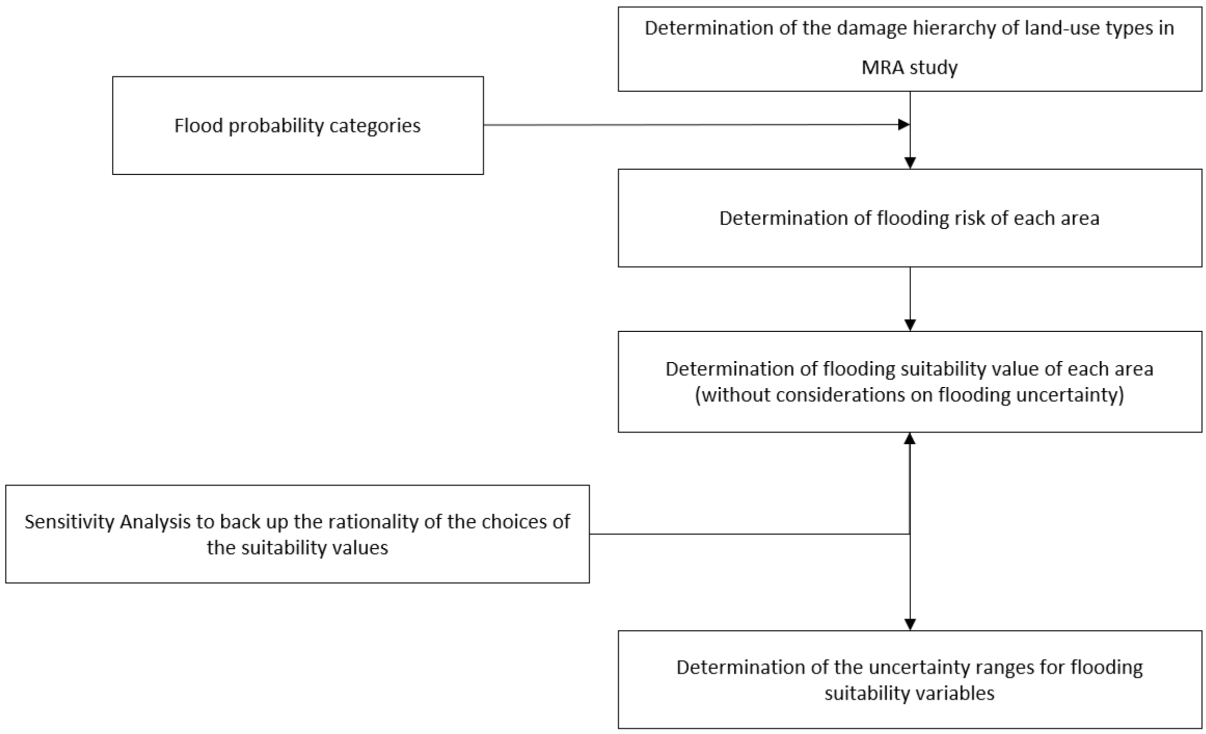


Figure 5-5: the workflow of transforming flooding variables into suitability parameters.

5.3.4. Determination of the damage hierarchy for the land-use types

Generally, the high density of built-up areas has a higher exposure rate than the open space areas regarding the amounts of people and properties, and therefore it tends to cause higher damages than the latter if a flood event happens. Table 5-1 shows the estimated maximum damages for different land-use classes in a case study of the Netherlands (Koks, De Moel, & Koomen, 2012). Table 5-2 demonstrates the land-use categorization adopted for the case city and it could be found which sub-categories are included under each defined land-use type. Since the land-use categorization in this case study is different from that in our research, we adapt a damage hierarchy for MRA from this literature.

Recreation in our research is composed of parks, public gardens and other open spaces, so its exposure rate of assets and people is rather low and the damage costs are in between Nature and Greenhouses. Regarding Public Amenities where the public facilities and the socio-cultural sites are included, it is reasonable to be grouped with the low-density residential areas. The damage hierarchy is shown in Table 5-3.

Table 5-1: The estimated maximum damages for different land-use classes in a case study of the Netherlands. Adapted from Koks, De Moel, & Koomen (2012)

Land-use types	Million euro per hectare
Urban- high density	9.9
Commerce	7.9
Urban- low density	5.3
Infrastructure	1.4
Greenhouses	0.65
Pastures	0.015
Forest	0
Other nature	0

Table 5-2: The land-use categorization adopted for MRA in this research

Land-use types	Included sub-categories
Agriculture	Other agricultural land
Greenhouses	Terrain for greenhouse horticulture
Mineral/Industry	Dump, Wreck Depot, Mineral Extraction Place, Inland water for mineral extraction, Fluid/Sludge Field, Semi-paved
Public Amenities	Grounds for public facilities, Site for socio-cultural facilities, Cemetery
Commercial	Terrain for retail and catering, Business park, Building site
Residential (L)	Low density residential lands
Residential (M)	Medium density residential lands
Residential (H)	High density residential lands
Recreation	Park and public garden, Sports Field, Allotment Garden, Day recreation area, Recreational Area for Stay, Recreational Inland Water
Nature	Forest, Open dry natural terrain, Open wet natural terrain

Figure 5-3: The adapted damage hierarchy for MRA. A higher rank indicates higher damage costs.

Damage costs (From low to high)	Land use class
1	Nature
2	Agriculture
3	Recreation/Industry
4	Greenhouses
5	Residential (L) / Public amenities
6	Commercial / Residential (M)

5.3.5. Determination of suitability values in the normal scenario

The suitability values derive from the flooding risk of each area. Specifically, the higher the flooding risk of an area, the lower the suitability value. In our case, the flooding probability of each area and its potential land-use function jointly determine its flooding risk. As the probability increases, the flooding risk will increase accordingly. Besides, the risk goes up with the damages caused by each land-use type. Therefore, to allocate high-density residential lands in high probability areas results in the highest risk. The suitability always negatively relates to the risk. Figure 5-4 illustrates the transformation from flooding risk to flooding suitability.

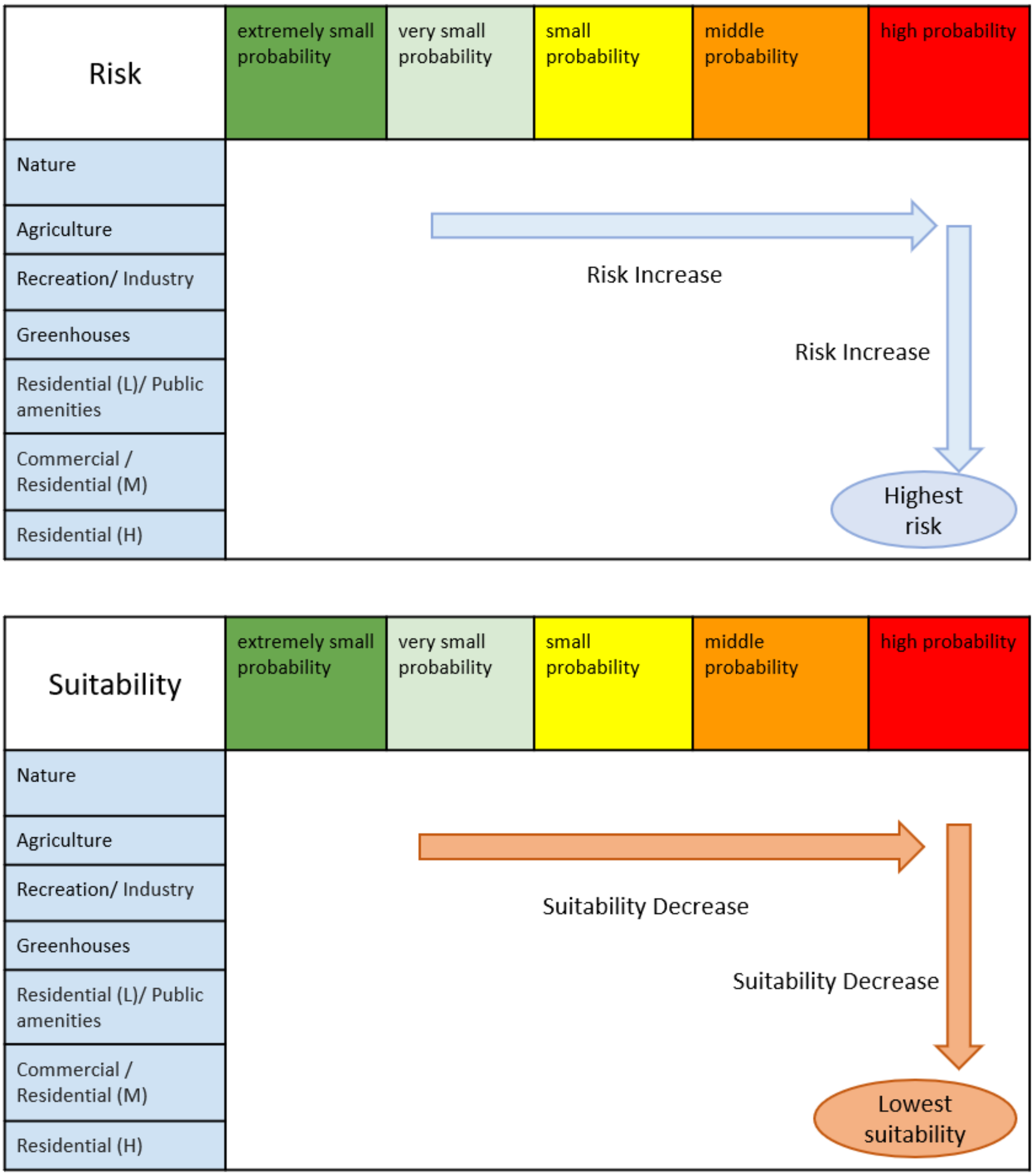


Figure 5-6: The concept of transformation of the flooding risk (the upper table) to the flooding suitability (the lower table)

Based on the transformation concepts, the suitability value of each flooding probability area is determined. Nature has the ability to reduce the rate and volume of stormwater runoff and eliminate flooding impact (Dwyer et al., 1992; Lu et al., 2018). Therefore, it is also suitable to be accommodated in flood-prone areas for better response and recovery and its suitability values are 1 at all the probability areas. On the other side, the extremely small probability areas are preferred by all the land types because it leads to a nearly “risk-free” environment, so the suitability value of 1 is given at “the extremely small probability” area for every land-use class.

As the flooding probability increases, the suitability value decreases. But the land-use classes decrease their suitability values by different “step lengths”, due to the different damage costs of different land-use types.

Table 5-4: The flood probability—land suitability table. It shows for each land-use class the suitability values at different flooding probability areas.

	extremely small probability	very small probability	small probability	middle probability	high probability
Nature	1	1	1	1	1
Agriculture	1	1	0.9	0.9	0.8
Recreation/ Industry	1	0.9	0.9	0.8	0.7
Greenhouses	1	0.9	0.8	0.7	0.6
Residential (L) / Public amenities	1	0.8	0.6	0.4	0.2
Commercial / Residential (M)	1	0.8	0.5	0.3	0.1
Residential (H)	1	0.7	0.4	0.2	0

For the land-use classes that have low damage costs like Agriculture, even though the risk will increase along with the flooding probability, the risk at high probability area remains at a low level. This is why a suitability value of 0.8 is assigned to the high probability area. In contrast, the suitability value of Residential (H) land decreases much when shifting from a lower probability area to a higher one. This is because Residential (H) land is expected to be completely discouraged from the high probability areas, and to remove this land-use type from a low probability area to a high one makes a significant difference. When shifting it from the extremely small probability areas to the high ones, its suitability values will decrease from 1 to 0, and it is why its “step length” is longer than that of the agriculture land. This “step length” is extended as the damage costs of the land-use classes increase. For example, the suitability values from left to right in Table 5-4 decrease at a step length of 0 or 0.1 for Agriculture, but 0.2 for Residential (L) and 0.3 for Residential (H).

5.3.6. Sensitivity analysis of the flooding suitability values

In the course of creating the flooding probability- land suitability table (see Table 5-4), some choices of the numbers involve arbitrariness (e.g., the suitability value of Residential (H) at the very small probability area is 0.7 rather than 0.6). It remains unclear how the slight differences in these suitable values (e.g., increase or decrease by 0.1) will influence the final land-use outcomes. Hence, to investigate the decisions of these values and to validate the further use of this table, a sensitivity analysis is carried out.

- **Experiment Design**

All the suitability values in Table 5-1 except those related to the Nature land are explored, and all the experiments are conducted by using EMA workbench and the MRA Metronamica model from 1996 to 2006 (with flooding suitability added).

The values in the table are considered as base values, and the range of each parameter is from 0.1 higher to 0.1 lower than the base value. For example, the base suitability value of residential land (high density) is 0.4, and hence it will be sampled between 0.3 and 0.5 in the experiments. 200 experiments are performed in which all the suitability values are randomly generated within the defined ranges and combined to run the simulations. The 200 resulting maps will be crossly compared to see how much one map differs from the other, such that it could be figured out how the slight changes of the suitability values will impact the final land-use outcomes.

- **Experiment Result**

The similarity of the land-use maps is evaluated by the Kappa index. The cross-comparison leads to 200x200 Kappa values in total and the average number of these Kappa values reaches 0.93. Figure 5-7 displays parts of the comparison matrix.

The comparison results indicate that the model could generate highly similar maps, even if the differences of one suitability parameter could maximally reach 0.2. Therefore, it can be concluded that the values from the flooding probability-land suitability table are not very sensitive. The choices of the base suitability values in the table are valid. Since the slight changes in the suitability values will not make significant differences to the final land-use outcomes, wide uncertainty ranges are recommended to define in the following climate uncertainty explorations.

	0	1	2	3	4	5	6	7	8	9	...	190	191
0	1.000000	0.931601	0.930600	0.931137	0.930680	0.931788	0.932690	0.932176	0.929045	0.931811	...	0.930275	0.930448
1	0.931601	1.000000	0.931776	0.933114	0.931256	0.931060	0.930695	0.931218	0.932104	0.932247	...	0.931178	0.932870
2	0.930600	0.931776	1.000000	0.931897	0.931492	0.931889	0.931057	0.930461	0.931110	0.931408	...	0.932096	0.932661
3	0.931137	0.933114	0.931897	1.000000	0.931200	0.930751	0.930616	0.931488	0.931565	0.931886	...	0.930632	0.931864
4	0.930680	0.931256	0.931492	0.931200	1.000000	0.930598	0.928840	0.931261	0.930419	0.930984	...	0.932376	0.930792
...	...	...	...	...	...	...	...	...	...	...	...	...	...
195	0.931804	0.932255	0.931720	0.932747	0.932564	0.932027	0.931654	0.933037	0.931314	0.931227	...	0.932515	0.931665
196	0.930993	0.931718	0.931287	0.932299	0.931360	0.932653	0.930932	0.932189	0.929858	0.930490	...	0.931830	0.930476
197	0.929276	0.931772	0.932334	0.932026	0.932192	0.930373	0.929904	0.930361	0.931757	0.930507	...	0.931832	0.932731
198	0.931163	0.932480	0.930419	0.930964	0.931233	0.931193	0.931316	0.931210	0.931495	0.932913	...	0.932229	0.931142
199	0.931179	0.931681	0.932770	0.932047	0.932272	0.933225	0.932355	0.931434	0.931311	0.930824	...	0.932386	0.931899

Figure 5-7: A part of the map similarity comparison results. A value of 1 means the 100% similarity between the two maps.

5.4. Uncertainties of the flooding suitability variables

Since flooding is the only climate effect we consider in this research and the flooding probability map is included in the suitability section to help determine the land suitability of each cell, this climate uncertainty exploration focuses mainly on the suitability values of the flooding factor.

5.4.1. Climate uncertainty identification

Throughout the process of incorporating flooding impacts into Metronamica, the climate uncertainties exist in the following aspects.

a) The flooding probability map itself is uncertain. The estimated flooding probability of each area could be uncertain because:

- The estimation process contains some errors, including measurement errors and model limitations.
- The natural processes within the climate system have some unpredictable variability, for example, the future rainfall amount cannot be predicted precisely.
- The estimation is mainly based on historical experience, but there could be some unexpected events. (e.g., the area with extremely small probability may also experience heavier flooding).

b) The flooding depth of each area is uncertain. The flooding probability map covers all the scenarios with depths above 50m, but the severity of a 200m flooding event is not the same as that of a 50m flooding event.

c) The vulnerability of each area is uncertain, as it is unclear how the social, economic, and environmental systems are prepared for climate change. The vulnerability could influence the flooding consequences and further determines the risk in one area.

5.4.2. Determination of the uncertainty ranges

To manifest these uncertainties in our model, the suitability values of the flooding factors are replaced by certain uncertainty ranges.

Table 5-4 sets up each suitability value in the normal scenario and the uncertainty ranges are determined based on these normal values. Since the sensitivity results suggest that a wider range would produce higher variability, we bunch the probability categorizes in order to broaden the ranges of the uncertain parameters. High probability is still set as the category mostly likely to happen. New "middle" probability is formed by the previous "middle" and "small" probability. And the former "very small" and "extremely small" are bunched into the new "small" probability. By re-categorizing the flooding probabilities, the uncertain factors have reduced to 18.

Table 5-5: the newly defined flooding probability categories

Former flooding probability categories	New flooding probability category
High	High
Middle, Small	Middle
Very small, extremely small	Small

In our uncertainty analysis, we keep the suitability in an ascending order per land class as the probability decreases. For the high probability, there is no uncertainty considered as it already contains the worst scenario. The suitability value of the high probability is used as the lower bound for the middle probability, as we assume in the worst situation the middle probability area could reach the severity of the high probability ones. The normal suitability value of the previous "small" probability decides the upper bound of the uncertain range for the new "middle" probability. For example, in the normal case. the old 5-category map assigns the small probability and high probability with a suitability value of 0.5 and 0.1 respectively, which determines the uncertainty ranges for the new "middle" probability as (0.1, 0.5).

This rule applies to the new "small probability" as well. Its upper bound could reach the lower bound of the "middle" probability, and the best scenario is to have an "extremely low probability" case. Hence, the lower bounds for all the land types in this category are 1. The specific uncertain range of each parameter is specified in Table 5-6.

Table 5-6: the uncertain ranges of the uncertain parameters

Land-use class	Flooding probability	
Agriculture	High	0.8
	Middle	(0.8, 0.9)
	Small	(0.9, 1)
Greenhouses	High	0.6
	Middle	(0.6, 0.8)
	Small	(0.8, 1)
Mineral/ Industry	High	0.7
	Middle	(0.7, 0.9)
	Small	(0.9, 1)
Public Amenities	High	0.2
	Middle	(0.2 0.6)
	Small	(0.6 ,1)
Commercial	High	0.1
	Middle	(0.1 ,0.5)
	Small	(0.5,1)
Residential(L)	High	0.2
	Middle	(0.2 0.6)
	Small	(0.6 ,1)
Residential(M)	High	0.1
	Middle	(0.1 ,0.5)
	Small	(0.5,1)
Residential(H)	High	0
	Middle	(0,0.4)
	Small	(0.4, 1)
Recreation	High	0.7
	Middle	(0.7, 0.9)
	Small	(0.9, 1)

6. Model implementation

This chapter describes the model implementation process. In section 6.1, it first describes the establishment of the basic MRA Metronamica model, including the model calibration and validation. Section 6.2 implements the conceptual ideas and adapts the model settings for the studied period. Next, the connection between Metronamica and EMA workbench as well as the experiment is explained in Section 6.3.

6.1. The Basic Metronamica model for MRA*

The basic Metronamica model refers to the model where no flooding variables are added. It should contain all the fundamental factors that drive the urban land-use changes of the Metropolitan Region of Amsterdam (i.e., MRA). Given the considerations on the data availability, the model is built up and calibrated based on the datasets of 1996 and 2005. The period from 2006 to 2015 is used for validation.

6.1.1. Introduction to the MRA Metronamica model

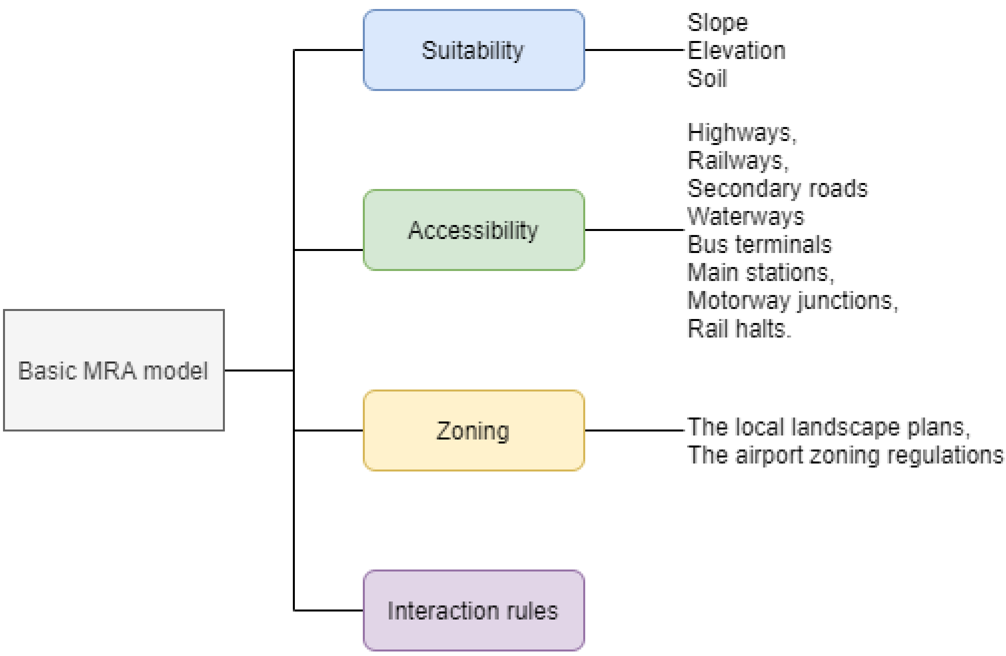


Figure 6-1: The overview of the basic MRA Metronamica model

* The establishment of the basic MRA, including model set up and calibration, is completed by the calibration of Supriya Krishnan and Aarthi Sundaram.

To set up a basic Metronamica model, the fundamental factors determining suitability, accessibility and zoning are added and their influences on the final transition potential are specified. In addition, the interactions among different land-use types are manifested via the input interactions rules. Specifically, in our case of MRA, the basic Metronamica model is composed of the factors shown in Figure 5-1.

- **Rasterized maps and Land-use classes**

Land use maps for the MRA region are input as raster maps (original data source: https://cbs.nl/). A choice of 100 by 100 meters resolution was used as we want to strike the balance between the model granularity and the computation resources. This resolution is deemed suitable for modelling the dynamics of the Amsterdam region.

13 Land use classes (LUC) are classified and input to Metronamica, as shown in Table 6-1.

- **Suitability**

Suitability is defined as the degree to which a cell is fit to support a particular land use function in terms of physical, ecological, and environmental appropriateness (van Delden et al., 2005). The basic model considers three fundamental factors for suitability: 1) slope; 2) elevation and 3) soil quality.

The soil quality imported to Metronamica is categorized into 10 soil classes, and their suitability for the different land types needs to be determined first by literature review, and then we overlay existing land-use maps of 1996 and 2005 with the soil map to observe how land-use classes change in reality. In this way, we can ensure the suitability values are consistent with both the theory and the practice of land-use changes for MRA.

Regarding slope and elevation suitability, the relevant literature mostly indicates qualitative relationships between slope/DEM and land suitability. Hence, we rely more on the previous land-use patterns to determine the quantitative suitability values.

More detailed explanations on determinations of these suitability values are available via the two links: soil and slope/elevation.

- **Accessibility, Zoning and Neighbourhood interactions**

Different infrastructure layers are added to the accessibility of Metronamica model to reflect the multiple influences of transportations infrastructures and other networks and nodes on the urban dynamics. The accessibility networks considered in the basic MRA model include highways, railways, secondary roads and waterways. The considered nodes are bus terminals, main stations, motorway junctions and rail halts.

The zoning maps in the basic MRA model take account of the local landscape plans and the zoning regulations around the airport. The neighbourhood interactions are determined by the literature review and the enrichment curves. The elaborations of these factors can be found here.

Table 6-1: the land-use classes overview in the established Metronamica model

	Description	Included land-use classes	Number of classes
Vacant	These are classes that can be taken over by the functional LUCs if the latter expand in growth in future years	Outside area, Agriculture	2
Function	These are dynamic classes and the most important from an urban growth perspective	Greenhouses, Mineral/Industry, Public amenities, Commercial, Residential (Low density), Residential (Middle density), Residential (High density), Recreation, Nature	9
Feature	These are LUCs that remain more or less fixed over time and have the least potential for changes	Water, Airport, Transport	3

6.1.2. Calibration

Calibration involves tuning the model inputs to have the land use simulation patterns behave as close to the historical reality as possible. We use manual calibration methods for the model with support from computational indicators used to improve the quality of the calibration. The manual calibration procedure uses a visual comparison between Observed changes (the Reality) and Simulated changes (the Model).

- **Assessment of the calibration quality**

In this part, we evaluate the calibration quality of our model. The quality of the calibration is assessed by checking 'predictive accuracy' (how exactly is the model predicting changes) and 'process accuracy' (are the simulations in line with reality). We assess the calibration from 4 aspects: (1) Visual map comparison; (2) Kappa Statistics; (3) Clumpiness Index; (4) Comparison with neutral models. All the assessments were done using the Map Comparison Kit (MCK).

[1] Visual Map Comparison:

We use the MCK's Map Comparison algorithm to visualize the differences in the allocation of Land Use Classes between two maps - in our case Observed and Simulated changes. This allows us to inspect obvious dissonances in the allocation of LUCs and focus on fixing them. The detailed results are attached in Annex 3-1.

[2] Kappa Statistics

Kappa is the goodness of fit between 2 maps. Kappa statistics are widely applied in geographical problems to assess the similarity between observed and simulated results. It is a cell-to-cell comparison approach that checks each pair of cells on the simulated map and actual maps if they are equal.

Table 6-2: Descriptions of the three adopted Kappa statistics

Kappa Index	Kappa Index shows the proportion of cells that are equal in the simulated map and the actual map (Visser & De Nijs, 2006). Kappa is classified into Khisto (similarity of quantity) and Klocation (similarity of spatial allocation). Kappa index is the multiply of the two measures.
Kappa Index	The issue with Kappa Index is that if there is little change in the simulations, the Kappa index will be high despite the quality of the model. Hence, we use Kappa Simulation to compare the cell-to-cell consistency of the two maps by correcting for the amount of change (van Vliet et al., 2013). Kappa Simulation is based on the distribution of "class transitions", which is regarded as one kind of conditional probability: the chance of finding a certain class at a location will depend on the class that was originally there. The Kappa Simulation value is used to indicate how accurate the land-use change process itself is, and reduces the pitfall caused by the high Kappa index due to the small changes (van Vliet, Bregt & Hagen-Zanker, 2011).
Fuzzy Kappa	Fuzzy Kappa considers the two kinds of fuzziness: 1) the vague distinctions of land use categories and 2) the proximity of similar cells (Hagen, 2002). For example, in our land-use classes, there are high, middle and low residential areas, but the boundaries of these categories may contain some vagueness. Also, one cell is not necessarily occupied by one land-use type and the neighbourhood cells around one cell could add some fuzziness to it. Therefore, in Fuzzy Kappa, instead of giving one single category or value for every cell, a membership vector is adopted. After the cell-by-cell comparison, a similarity map is generated, in which value 0 indicates completely distinct and 1 means fully identical. The results of this similarity map will finally be aggregated into one overall Fuzzy Kappa index.

[3] Clumpiness index

Clumpiness Index is a widely used landscape pattern metric (McGarigal, 2002) that has been applied in land-use modelling studies (Van Delden et al., 2012). It is a measure of adjacency indicating the extent of clumped or fragmentations in urban growth. These values range from -1 (complete disaggregation) to 1 (maximal aggregation) and values near 0 indicate the random distribution of patches. The index values must be as close as possible between Observed and Simulated maps - which means the clumpiness matches. The detailed results are available in Annex 3-2.

[4] Comparison with neutral models

Arriving at a Kappa index by comparing the Observed and Simulated maps does not present a benchmark for how well the model is performing. For example, a Kappa index of 0.8 may appear to be excellent but visually the map may not be performing as expected. Therefore, we need to set a benchmark against the goodness-of-fit of the simulated model that can be compared. In order to do this, we compared the simulated model with two types of neutral models: (1) Random Constraint Match; and (2) Null Model. The Simulated model must outperform the Kappa indices of both these neutral models.

Random Constraint Match (RCM) will introduce the same quantity of errors as in the Simulated model - but at random locations. It will first calculate how many cells have changed from the initial map to the end condition, and then randomly distribute these cells on the initial map (Hagen-Zanker & Lajoie, 2008). As a result, the Random Constraint Match model creates a new map by minimally adjusting the initial map, giving it the same frequency distribution of the categories as the simulated map (RIKS, 2010).

Null calibration is an almost uncalibrated version of our model that only contains very basic neighbourhood rules. Specifically, the inertia of all the functional land-use classes will be set to 100, whereas all the conversion is to 1. When distance is more than 0, the influence will also be reduced to zero, which means there is no attraction or repulsion and most places will stay in their current location (van Vliet et al., 2013). No other input layers are added.

Table 6-3: Comparisons between the manually calibrated model with the two neutral models (Random Constraint Match and Null Calibration).

	Kappa	Kappa Simulation	Fuzzy Kappa
Calibrated model	**0.853**	**0.078**	**0.888**
Random Constraint Match	0.831	0.035	0.827
Null Calibration	0.810	0.035	0.836

MCK allows us to generate reference maps for both neutral models that can be compared with the simulated map to see if our manually calibrated model outperforms the two neutral models. Three indicators are chosen to evaluate the performance: Kappa, Kappa Simulation, and Fuzzy kappa (Table 6-3). We see that the values of the manually calibrated model outperform both the neutral models, indicating that the model could be used for validation. The detailed information of each indicator, such as the Khisto and Klocation is available in Annex 3-3. It may be noted that the indices Kappa and Fuzzy Kappa do not outperform by a wide margin - hence there is room for fine-tuning the calibration.

6.1.3. Validation

Validation is the process to assess the model's prediction capability over a separate dataset that has not been applied to the calibration. Thus, the model validation time is set from 2006 and 2015. The simulated maps and actual maps of 2015 are compared to check if the high agreements are satisfied.

The two neutral models, Random Constraint Match and Null calibration, are also adapted to the validation time and simulated. The Kappa index, Kappa simulations and Fuzzy Kappa are used to quantify the similarity between the simulated maps and the actual maps for the three models. Table 6-4 provides the comparison results and detailed information is available at Annex 4.

An overall Kappa index of 0.882 and a Fuzzy Kappa value of 0.908 suggest a high level of agreement between the simulation results and the reality. Additionally, it can be observed that the performance of the working model is better than the two neutral models in the validation process in terms of the Kappa statistics, meaning the current model can be applied to further uses.

Table 6-4: Performance evaluation for the validated model and the two neutral models

	Kappa	Kappa Simulation	Fuzzy Kappa
Validated model	**0.882**	**0.035**	**0.908**
Random Constraint Match	0.859	0.028	0.891
Null Calibration	0.863	0.019	0.887

6.2. Adapt the model for 2050

Once the basic model has been set up and the calibration and validation assessments suggest the valid performance of this model, it can be adapted for the simulations. The localized flooding probability map of 2019 and 2050 are added to the suitability section. One important assumption is that climate change effects will only be considered since 2015. This is why we include the flood probability maps from 2015 instead of in the calibration and the validation periods.

Since the climate data beyond 2050 is currently not available, the simulation time for the flood-embedded Metronamica model is set from 2015 to 2050. Simulating the land-use changes beyond 2050 will involve a great degree of unknowns and uncertainties. The flooding probability maps may be very different from the current ones, and it is not valid to estimate the uncertainty ranges based on the proposed way. On the other side, it is believed simulations till 2050 could already provide many insights into the urban plans for the local decision-makers.

6.2.1. Land demands of 2050

In addition to adding the flooding suitability factors to the model, the land demand of each type is required. The demands are preliminary input variables for this Metronamica model, as they largely determine the total amount of each land cell in the resulting maps and hence, would make big differences to the final landscape outcomes.

Consistent population growth is projected to come in the upcoming decades across Metropolitan Amsterdam, and an increase of 20% in the population is expected by 2040 (OECD, 2017). According to MRA's Structure Vision (2012-2040), the city plans to increase its density to provide 250,000 homes from 2016 to 2040 (OECD, 2017).

We approximate the demands for the residential lands based on the housing demand projections from the above-mentioned policy documents and the historical land change patterns. The historical population reveals that the total number of people residing in MRA will increase by 10% every decade, and this number is consistent with the number projected by the local officials in 2040 for a total 20% growth. Therefore, the total population in 2050 is approximated as 3.02 million.

With more people migrating to the region, the population per cell rises up. The fraction (i.e., changed population /changed the number of cells) is increasing and we estimate it via the historical increasing rate, such that the expected number of the total cells in 2050 can be calculated.

The portion of each residential land to the total residential lands of the three previous years are shown in Table 6-5. As indicated by this table, while the population keeps climbing from 2006, the Residential (M) stops increasing but converts to the Residential (H). This means the portion of residential (H) would keep climbing but that for Residential (M) and Residential (L) would decrease accordingly. Therefore, for the projections in 2050, the percentage becomes 2%, 18% and 80% for the low-, middle- and high-density residential land respectively. Having calculated the total residential land cells and the portions of the different kinds, we can estimate the exact number of cells for the three residential lands.

Table 6-5： The portion of each residential land to the total residential lands

Cells/ total residential cells	Residential (L)	Residential (M)	Residential (H)	Population
1996	76.8%	20.4%	2.7%	1.96 million
2006	5.4%	31.9%	62.7%	2.15 million
2015	3.5%	28.7%	67.7%	2.32 million
2050 (estimated)	2%	18%	80%	3.02 million

Table 6-6 The estimated land demands for 2050

	Greenhouses	Mineral/Industry	Public Amenities	Commercial	Residential(L)
Demand for 2050	988	529	2769	15404	588
	Residential(M)	Residential(H)	Recreation	Nature	
	5920	23486	16511	23960	

In addition to meeting the growing housing demands, MRA is ambitious to improve its "spatial quality", which includes the preservation of socio-cultural sites and the investment of public space (OECD, 2017). Therefore, there are increased projections for public amenities. We assume that there would be an extra 20 % increase in the cells for public amenities in addition to its expected changes based on the historical trend extrapolation. For all the other land types, the trend of the year 2006 to 2015 is assumed to continue. The demands imported to the Metronamica model are displayed in Table 6-6.

6.3. Connect EMA workbench with Metronamica

Having prepared the Metronamica model for simulations, it can be coupled with the EMA workbench. While the EMA workbench is instructed by Python, the Metronamica model file (.

geoproj file) is compiled by the XML language. To make the two parts talk to each other, some specific functions are created to ensure the Metronamica model can be edited and executed by the Python codes. Figure 6-2 presents the overview of the connected Metronamica-EMA working framework.

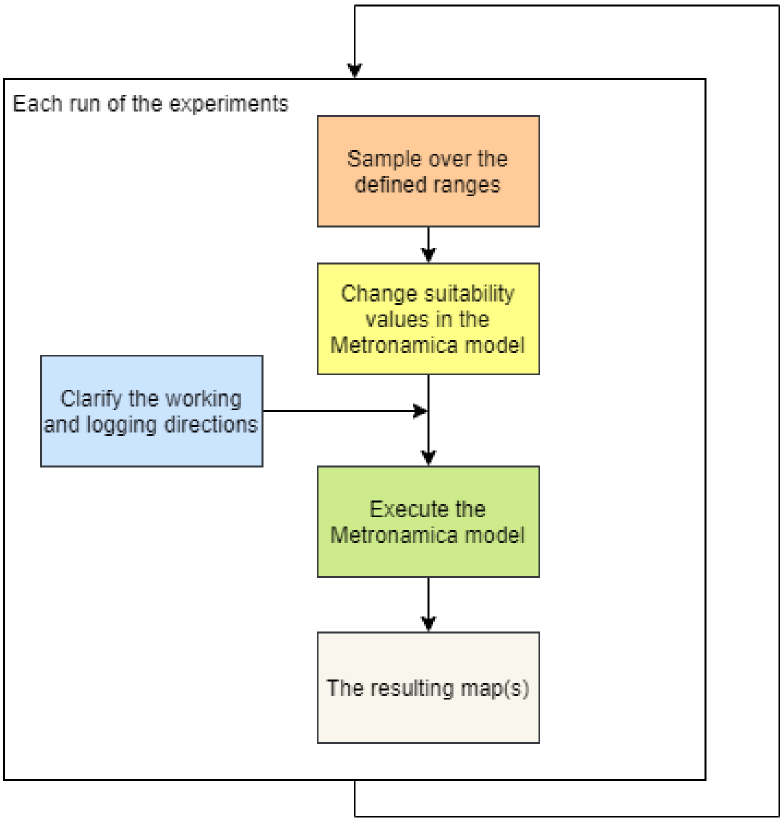


Figure 6-2: The Overview of the "Metronamica-EMA" working flow

Since the uncertainty factors in our research are the flooding suitability values, we need Python to change the suitability values in the *.geoporj* file. The *.geoproj* associated with the Metronamica model is stored in tree structures. Figure 6-3 demonstrates the structure of the MRA Metronamica model studied by the research. Specifically, the python codes access the locations where suitability variables are and treat them as uncertainties. Then the EMA workbench samples values over the defined ranges for these variables by using the LHS algorithm and changes the flooding suitability values in the model. Before the running of the model, the working and logging directions need to be specified such that the outcome maps could be found easily. Next, Python codes send commands to the Metronamica model to run and simulate the land-use map for 2050. This process is carried out iteratively until the experiment numbers are met. In this case, 2000 experiments are performed, producing 2000 resulting maps.

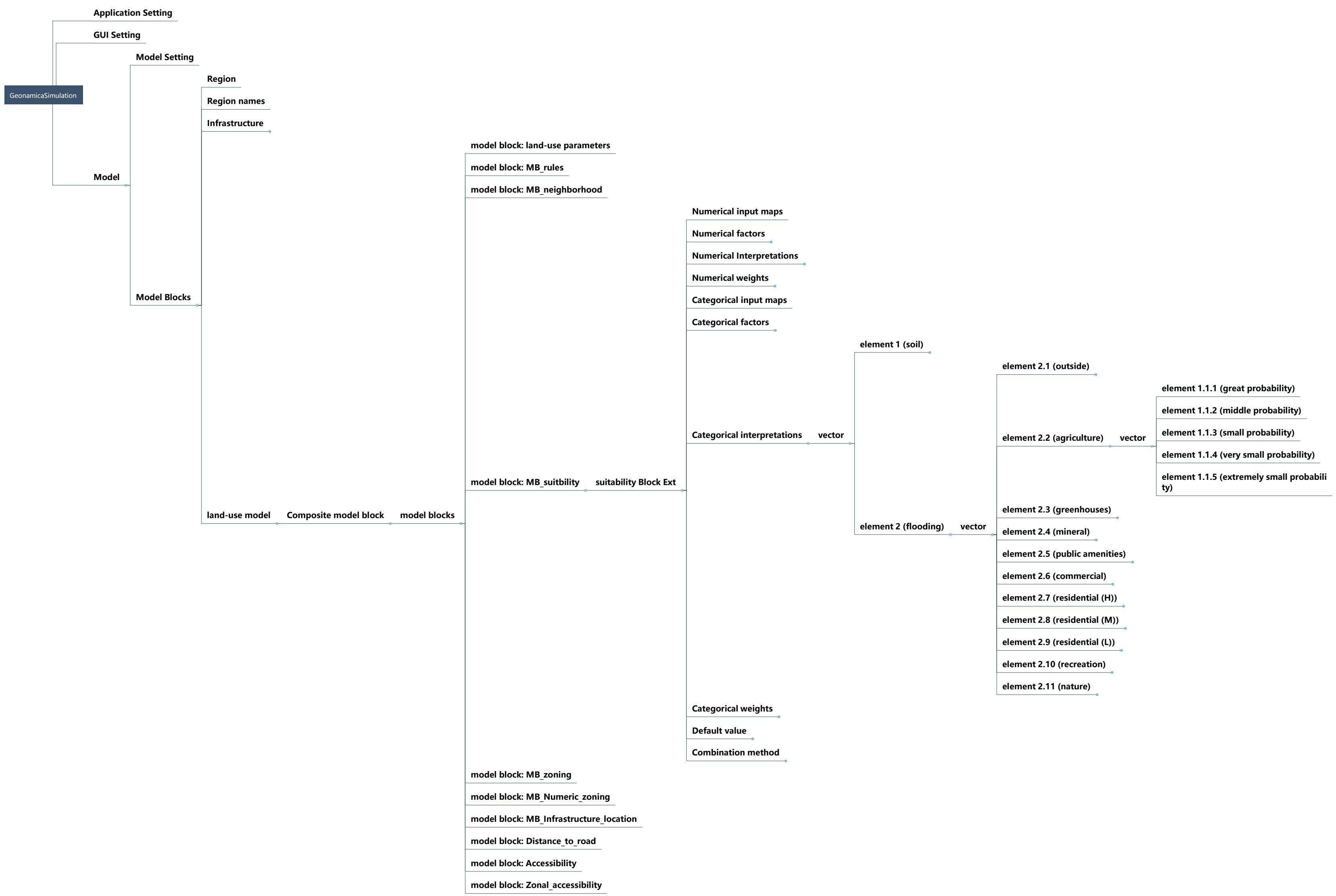


Figure 6-3: The tree structures of the .geoporj file for the MRA Metronamica model., The python codes finds and access to the locations of the uncertain factor

7. Result Analysis

This chapter describes the results analysis process, which answers sub-research questions 5 and 6:

- *Q4: Based on the modelling results, what are the possible land-use changes if the climate variables and their uncertainties are considered?*

The 2000 resulting maps are first clustered by some clustering algorithms, which is introduced in Section 7.1. Then, Section 7.2 explains the selections of some representative maps. After that in Section 7.3, we have analysed the representative maps by comparing them with the base map that considers no flooding factor.

7.1. Determination of the clustering algorithms

By using the LHS algorithm, the experiments sample over the defined uncertainty ranges for every uncertain parameter. Each run of the experiments results in one map, and finally 2000 experiments are generated. The output maps are stored as array forms, and the numbers on the arrays indicate the specific land-use types.

In order to analyse the uncertainties, the first step is to determine the "outcome of interests". When dealing with maps, the "outcome of interests" becomes the map clusters. Specifically, the simulated land-use maps are clustered based on their similarity and then the analysis on each cluster will be performed.

Kappa statistics are used as "distance matrix" in this research to help measure the similarity among the maps. The Kappa value shows the percentage of the cells that are consistent in both the compared maps. The Kappa index is calculated for every pair of the 2000 simulated maps, which leads to a 2000x2000 Kappa matrix.

7.1.1. Comparisons on the different clustering algorithms

Proper clustering algorithms are employed for clustering the maps. Four clustering algorithms are checked in this research, which are introduced in Table 7-1.

Each of the four clustering algorithms is tested with the possible number of clusters varying from 2 to 10. Three indicators are adopted to evaluate the performances of the algorithms and the appropriateness of the number of clusters:

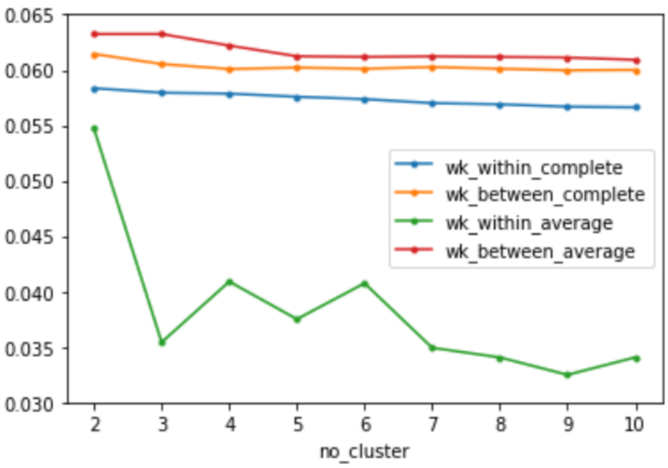
- High similarity within each cluster;
- High dissimilarity between the clusters;
- The even distribution of the number of maps in the clusters.

Table 7-1: The introductions of the four used clustering algorithm

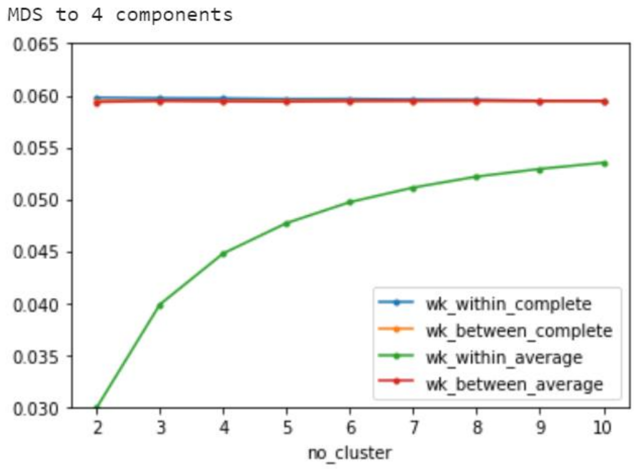
Agglomerative clustering	It is a bottom-up algorithm which treats each data as a singleton cluster at the outset and then every cluster calculate its distance with others and successively agglomerates pairs of clusters, until one big cluster is formed which contains all the datasets. The cut-off point depends on the required number of clusters. The "linkage method" of this algorithm decided how the distance is measured. The method of "completed" checks proximity between two clusters by using their two most distant objects, whereas "average" method refers to the arithmetic mean of all the proximities in their joint cluster.
Agglomerative combined with Multi-Dimensional Scaling	Multi-Dimensional Scaling is a data reduction technique, as we import the distance matrix, it could return lower-dimension distance matrix based on the information of the imported one. Then clustering is performed on the lower dimensional space.
K-means	K-means algorithm identifies the number of centroids according to the number of clusters we define, and then allocates the data to the nearest cluster, while keeping the centroids as small as possible.
K-medoids	K-medoids is similar to K-means. But it finds the cluster centroids by medoids whose dissimilarities with all the other points in the cluster is minimum.

The similarity and dissimilarity are calculated by averaging the Kappa values of the pairs within the same clusters or between two different clusters. The overview of the performances of the four clustering algorithms is shown in Table 7-2.

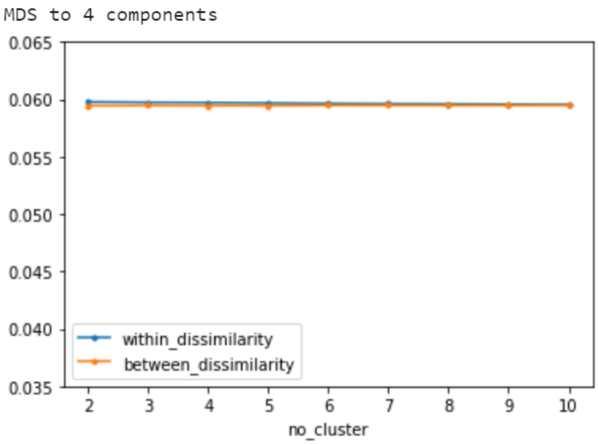
Table 7-2: The performances of the four testing clustering algorithms. The large gaps of the "between_dissimilarity" and "within_dissimilarity" is preferred.

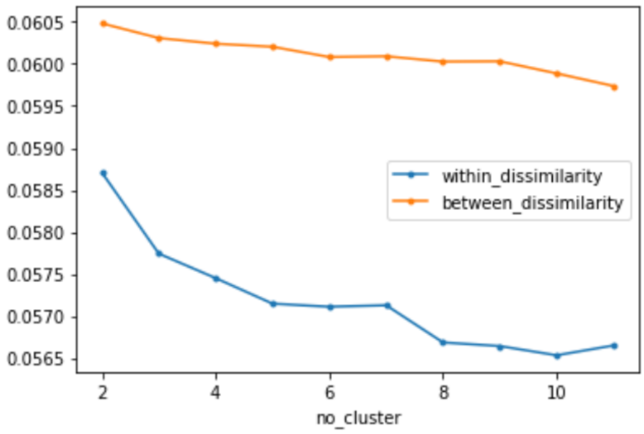


Agglomerative



Agglomerative + MDS





K-Mean + MDS K-Medoids + MDS

As indicated by the algorithm comparison results, K-Means and K-Matroids have very narrow gaps between the dissimilarity within clusters and between clusters, hence they are not proper for further uses. For the Agglomerative algorithms, it generates relatively more significant differences between the inter-and intra- dissimilarity, but there are some trade-offs for choosing the linkage methods. The "average" linkage method produces much higher similarity within the clusters, but it leads to very skewed distributions in terms of the number of maps in each cluster. For example, when the number of clusters is set as 3, the maps categorized in each cluster are 1994, 5 and 1 respectively.

To deal with the uneven distributions caused by the "average" linkage methods, the maps that result in the skewness are treated as "outliers" and are removed from the map set. After that, the same clustering algorithm is performed again on the cleaned map set until an even distribution is met. But the high similarity within the clusters and high dissimilarity between the clusters are compromised.

Since the performances of the "complete" and the "average" (after removing the outliers) linkage methods are rather close, we considered both methods for the further investigations. In addition, we also account for two kinds of Multidimensional Scaling settings (i.e., MDS = 4 and MDS = 9) coupled with an agglomerative algorithm, as the indicator results suggest relatively good clustering outcomes from them, as shown in Figure 7-1.

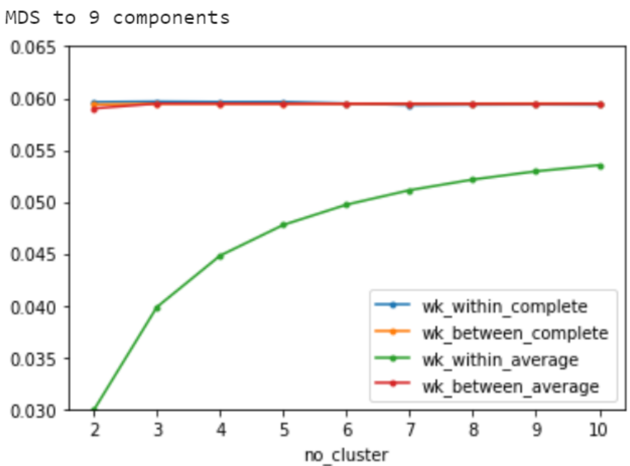


Figure 7-1: The performances of the agglomerative algorithm coupled with MDS=9. The performance is considered as good by comparing with other algorithm settings.

7.2. Selection of the representative maps

Ideally, one algorithm promising the best clustering outcomes is expected. And one representative map should be selected from each of the resulting cluster, to represent the characteristics of that cluster. However, in our case, as the similarity within and between the resulting clusters are quite close, it is hard to select one representative map to summarize the land-use change patterns for every cluster.

Under this condition, in order to capture the plausible land-use outcomes as much as possible, we decide to select multiple representation maps. Instead of using one “best” clustering algorithm and selecting one representative map from each resulting cluster, the four selected clustering algorithms are all applied for the representative map collection. Specifically, the representative maps come from the three sources:

1. **The maps with the highest and lowest variations in each cluster of the four proposed distributions.** Each of the proposed clustering algorithm settings (from section 4.1) results in 3 or 4 clusters. Within each cluster, we calculate the closeness of each map to all the rest maps by summing up the pair-wise Kappa statistics. The one with the highest value represents the lowest variations, whereas the lowest Kappa sum indicates the highest variation.
2. **The randomly selected maps from the clusters.** The map variation results show that some clusters share the same highest or lowest variation map. For instance, the first cluster of the first distribution has Map 906 as its lowest variation map, but cluster 1 from the second distribution also deems this map as one of its representative maps. Since Map 906 is already included in our representative map sets that are analysed further, we replace it by randomly selecting another map from the same map (e.g., Map 906 is replaced by Map 992 by the cluster in the distribution 2).
3. **The outliers**. Although the outliers are excluded from the clustering process to obtain even clustering distributions, we believe the outliers contain some variability which could provide insights into the potential land-use changes. Thus, 8 outliers are collected as representative maps.

The above-mentioned sources have collected 34 representative maps in total and the map’s information is shown in Table 7-3. The selection process of the representative maps considers the representativeness, randomness, and exceptionality; hence the 34 maps are sufficient for summarizing the most characteristics of the 2000 maps. The outlooks of the 34 representative maps are attached in Annex 5.

Table 7-3: the sources and information of the 34 representative maps

Clustering method	The distribution of map amounts	The representative maps (the numbers are the ids of the maps)
Agglomerative + “complete” linkage method + 3 clusters	[1029, 297, 674]	Cluster 1: MAP 1349, MAP 906
		Cluster 2: MAP 1382, MAP 335
		Cluster 3: MAP 531, MAP 883
Agglomerative + “average” linkage method (after removing 8 outliers) + 3 clusters	[962,428,602]	Cluster 1: MAP 1726, MAP 906 (Map 992)
		Cluster 2: MAP 1382 (MAP 783) MAP 335 (MAP1846)
		Cluster 3: MAP 1110, MAP 883 (MAP 1646)
	Outliers	MAP 178, MAP1195, MAP 1366, MAP1467, MAP 1649 MAP 1737 MAP 577 MAP 1584
MDS (4) + Agglomerative + “average” linkage method + 4 clusters	[697, 423, 879, 1]	Cluster 1: MAP 208, MAP 909
		Cluster 2: MAP 1414, MAP 1171
		Cluster 3: MAP 1382 (MAP 938), MAP 1131
	Outliers	Cluster 4: Map 1995
MDS (10) + Agglomerative + “average” linkage method + 4 clusters	[870,619,510,1]	Cluster 1: MAP 1382 (MAP 708), MAP 1338
		Cluster 1: MAP 785, MAP 909 (MAP 1875)
		Cluster 1: MAP 1949, MAP 1131 (MAP 1951)
	Outliers	Cluster 4: Map 1964

7.3. Comparisons of the representative maps with the base map

In order to analyse the characteristics of the land-use changes and provide evidence for urban planning recommendations, the 34 selected representative maps are compared with the base map where no flooding suitability factor is considered.

First, the cell amount of every land type is compared to the base map. Figure 7-3 shows the variations of the cells in each representative map, which indicates there are no differences between the base map and the map with flooding suitability in terms of the cell amounts of the "function" lands. Some increases or decreases are observed within the "vacant" lands (i.e., *Outside* and *Agriculture*). All the "function" lands in the representative maps and the base maps have met their predefined land demands, and the amount of each land cell is not interfered with by adding the suitability factor.

For all the 34 selected representative maps, we compare them with the base map where no flooding suitability factor is considered. The cells that are different in the base map and the representative maps are visualized. Specifically, for all the inconsistent cells, their original land types in the base map and the emerged land types in the simulations are displayed in the left and right respectively (see Figure 7-4). As a result, the changes caused by flooding suitability and its uncertainties are shown. All the comparisons of the 34 maps are available in Annex 6.

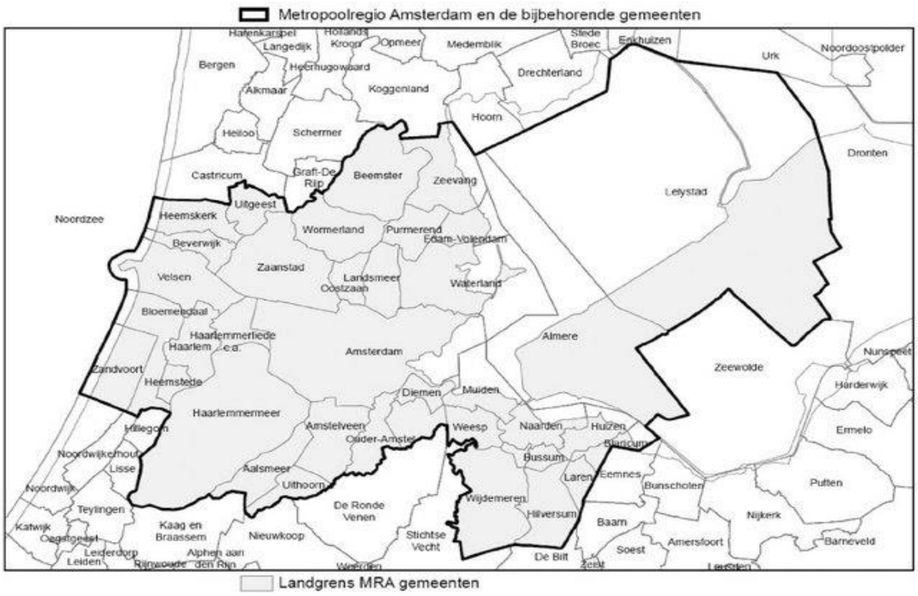


Figure 7-2: The perimeter of Metropolitan Region of Amsterdam (Savini et al.,2016)

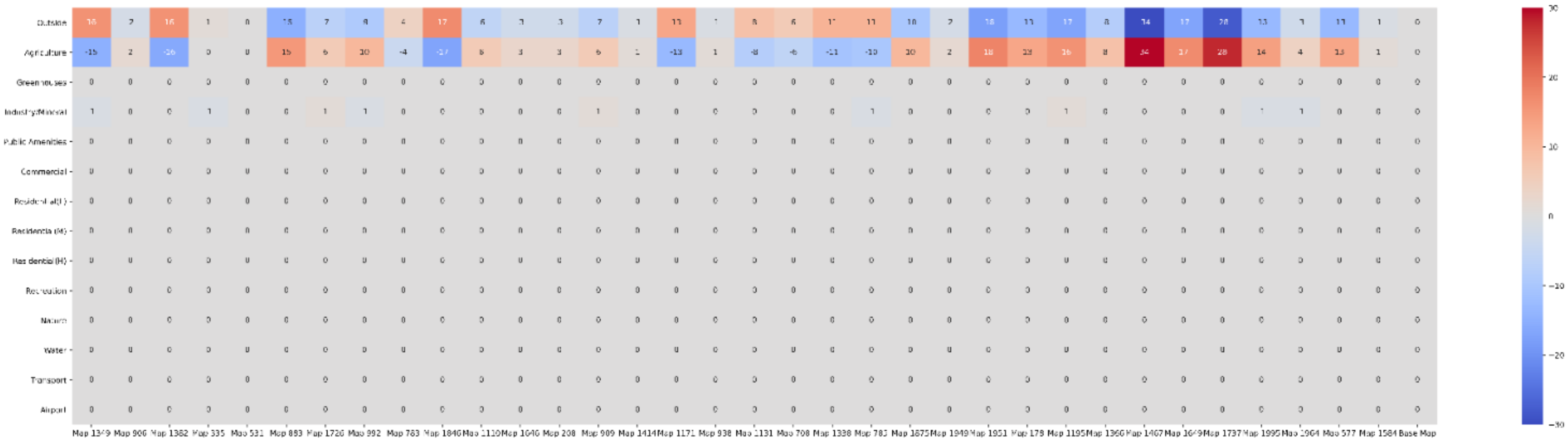


Figure 7-3 The amount comparison between the simulated maps to the base map. A blue square means less cell amount of certain land in the simulated map, and a red square implies more cells in the simulated map.

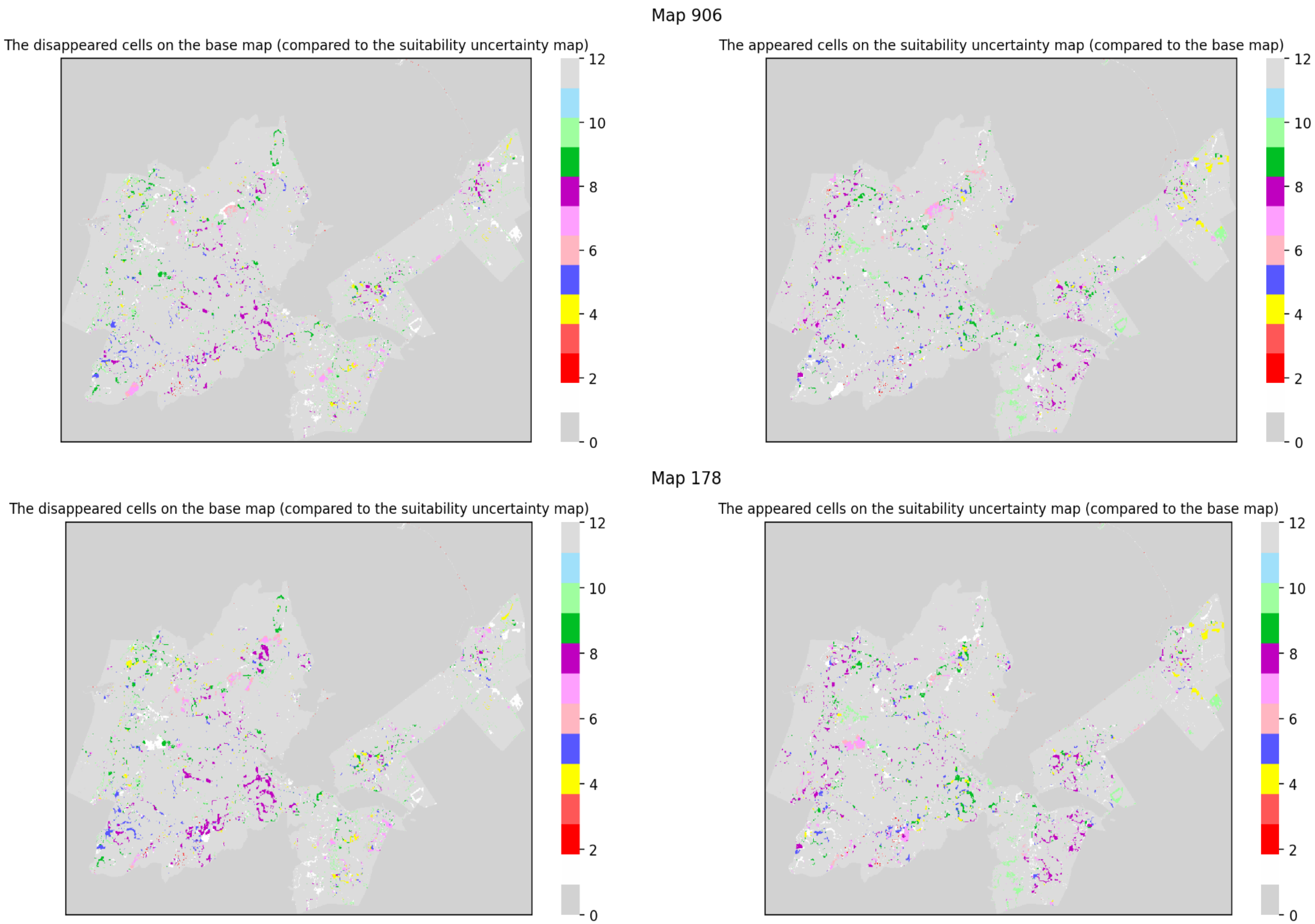


Figure 7-4: Two examples of the land-use change comparisons between the base map (no flood added) and one map resulted by suitability uncertainty. The colour indicates the land-use types (0 = "outside"; 1 = "agriculture"; 2= 'greenhouses"; 4= "public amenities"; 5= "commercial"; 6='residential (L)'; 7= "residential(M)"; 8= "residential(H)"; 9= "recreation", 10="nature", 12="all the unchanged cells")

It is interesting to see that these 34 representatives share common characteristics, which could be attributed to adding the flooding suitability factor. Even if no uncertainty is considered, these characteristics can still be observed. There are also diverged characteristics among these 34 representative maps, which are brought by the suitability uncertainties and the randomness of each simulation. The common and diverged characteristics and the possible reasons are discussed below.

7.3.1. The common characteristics

When comparing the representative maps with the base map, some common land-use change patterns are observed in all the 34 maps. These characteristics originate from the introduction of the flooding suitability factor and the reasons behind these changes are explored.

1) More Public Amenity Cells in south-eastern Lelystad (the upper right part of MRA)

A similar pattern of change is seen for the *Public Amenities* lands: some public amenities cells appear on the upper right part of the region. These public amenities resources could be deemed as transitions from either the southern regions or the western regions of the base map.

In the base scenario, soil quality is the only factor that determines the suitability values for Public Amenities and there are some areas that are restricted due to the soil types. However, once the flooding factor is included, the model averages the suitability values of soil quality and flooding. Consequently, the flooding suitability improves the overall suitability value. Due to the other existing Public Amenities cells in the area, the other ones are soon gathered there and form into larger patches.

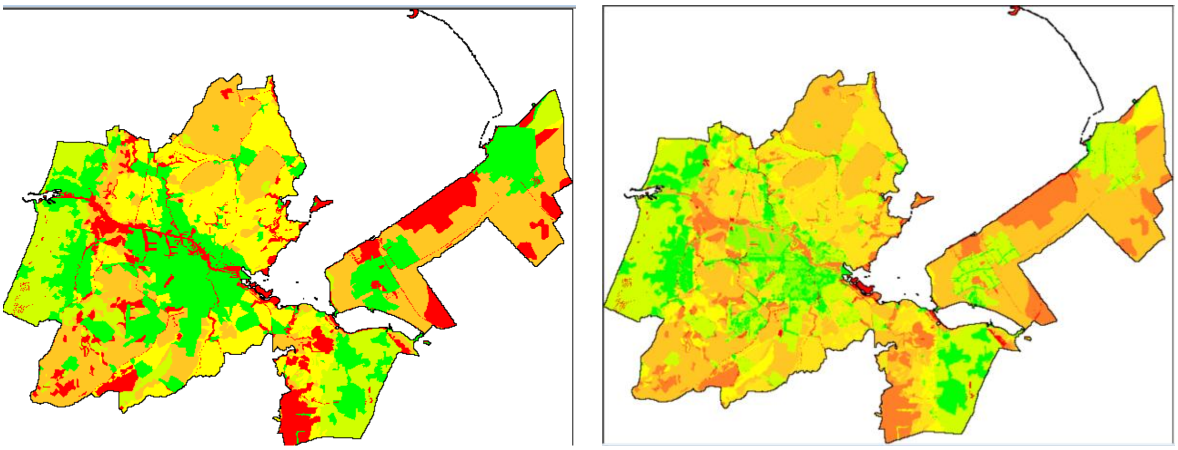


Figure 7-5: The suitability map for Public Amenities before (left) and after (right) including flooding suitability factors. The bright red implies the lowest suitability level and the bright green means the highest suitability.

2) The conversion from Residential (H) lands to Recreation in the north-western and south-western regions

The dark purple patches representing Residential (H) lands in the north-western (Purmerend-Zeevang) and south-western regions (South Amsterdam-Amstelveen) decrease by some amounts of the recreation lands. And some new high-density Residential areas are observed in the east of Hilversum (the lower south-eastern regions) and the west of Almere (the upper south-eastern regions of the map).

The transition from Residential (H) to Recreation could be explained by the fact that Recreation is more suitable for staying in flood-prone areas. As can be seen from Figure 7-6, in the base map the places where the residential (H) occupies (the north-western patches) are taken by the Recreation. As no flooding factor is considered in the base scenario, the suitability is 1 for all this area. The high attractions of Residential (H) cells to its same kind brings this land type high transition potential. In contrast, once the flooding factors are added, this area is deemed as susceptible to flooding. Hence, the suitability of Recreation land exceeds that of Residential (H), which increases the total transition potential of Recreation lands and makes them win the land competitions.

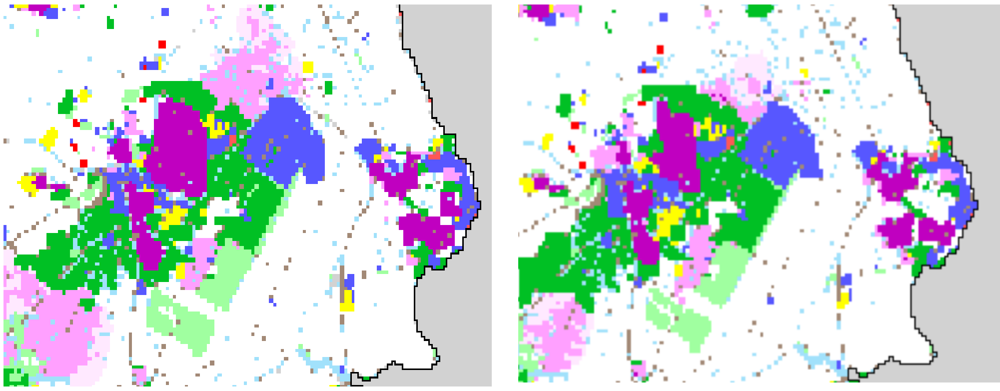


Figure 7-6: The north-western part of the base map (left) and the same region for the representative maps. Some Residential (H) lands in the base map are taken over by the Nature lands.

Residential (H) lands seek for the areas that maximize their transition potential and this is why the newly appeared Residential (H) cells are located at the east of Hilversum (the lower south-eastern regions) and the west of Almere (the upper south-eastern regions of the map). Figure 7-7 shows the suitability map of the Residential (H) land and the map where new land types are converted due to flooding suitability. The areas where new Residential (H) lands appear correspond with those of the highest suitability. This implies Residential (H) cells are located in some flood-prone areas and if the flooding factor is considered, this land type tends to remove to the flood-safe areas.

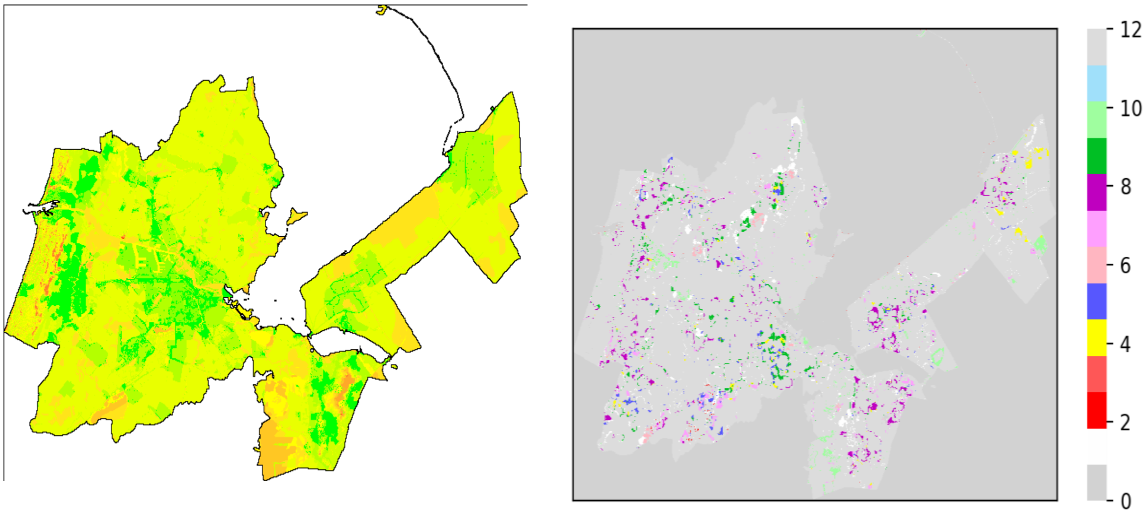


Figure 7-7: The newly appeared Residential (H) land cells (dark purple patches in the right) correspond exactly with the highest suitable areas (the light green areas on the left)

3) The emerging Nature patches on the west, south-east, and the east of MRA

The newly appeared Nature patches are observed in all the 34 representative maps, and the corresponding locations in the base map function as "vacant" because of either the low suitability or the low neighbourhood rules. The base map assigns low suitability to these areas because their soil type is "heavy clay", which is regarded as unsuitable for grass and plant development.

However, *Nature* is the most ideal land type to cope with flooding events and hence it has the highest flooding suitability at all the map locations. Figure 7-8 is the localized flooding probability map imported to the Metronamica model, and it could be seen that the locations where emerging *Nature* lands occupy are within the flood-prone areas (i.e., with a middle or high probability). Under this condition, flooding suitability is a more significant factor than grass development for these areas and high flooding suitability increases the overall transition potential there.

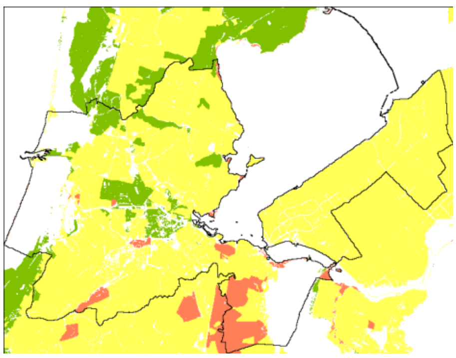


Figure 7-8: the localized flooding probability map imported to the Metronamica model, and the emerging Nature patches are within the middle or high flooding probability areas

4) A small portion of Commercial lands are replaced by Residential(H) along the south-western boundaries

Some previous locations for the Commercial patches along the south-western are replaced by the Residential (H) cells in the representative maps compared to the base map and these blue cells start to move to lower places, as indicated by Figure 7-9.

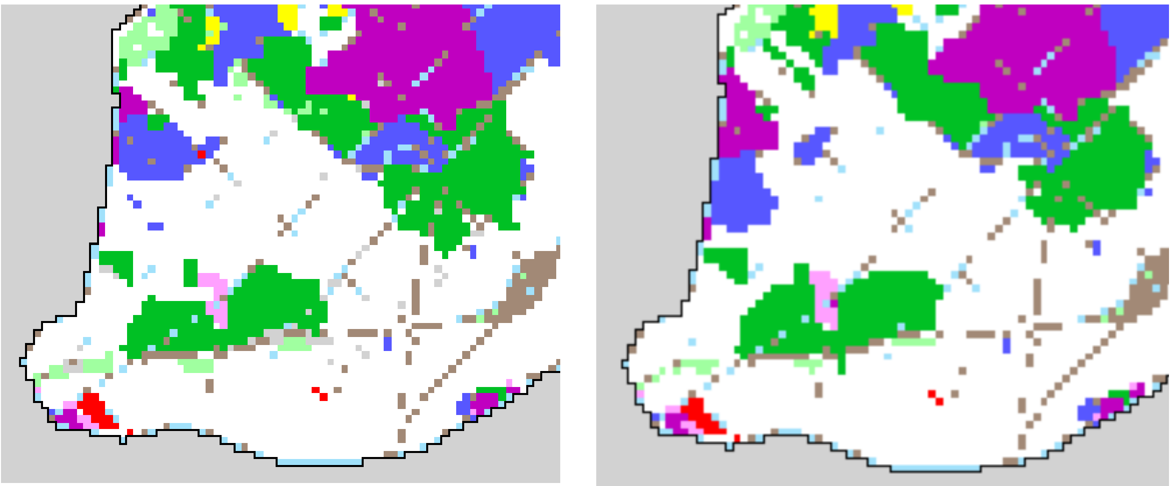


Figure 7-9: the south-western regions of MRA in the base map (left) and one representative map (right). The commercial lands (in blue) shift downwards along the left region boundary

This phenomenon could be explained by the low suitability of Residential (H) lands in flooding-prone areas. In the base map where no flooding suitability is considered, these purple cells are allowed to settle at some flood-prone areas. In contrast, after low flooding suitability is assigned, the residential cells are no longer selected for these areas, and hence, they start to relocate in some flood-safe areas which guarantee the highest transition potential for them. There is one minor patch along the south-western boundary which attracted these Residential (H) cells. Due to the strong neighbourhood interactions for the Residential lands, they soon gather together and occupy the areas owned by the Commercial before, as the neighbourhood effects of the Commercial are lower than that of the Residential (H). This is why the Commercial lands have to move downwards or to somewhere else.

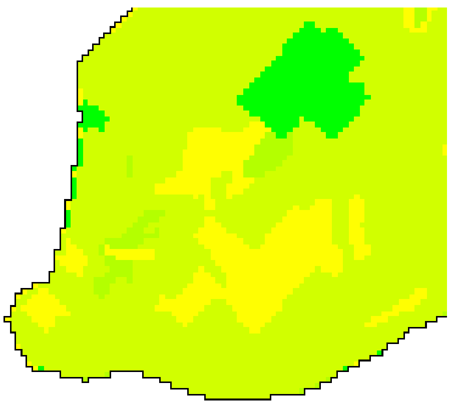


Figure 7-10: The suitability map of the south-western MRA region. The green patches along the boundary attract some Residential (H) areas to be located here.

7.3.2. The diverged characteristics

The common characteristics are explained by the introduction of the flooding suitability factor, but as the different suitability values are assigned to the flooding factor, some distinctions are expected between the representative maps.

1) Residential (M) land cells in the north-west of the region

In some representative maps, the amounts of the middle-density residential lands in the west (i.e., the Landsmeer) are reduced if compared to the base map, as shown in Figure 7-11. This change can be attributed to the suitability uncertainties.

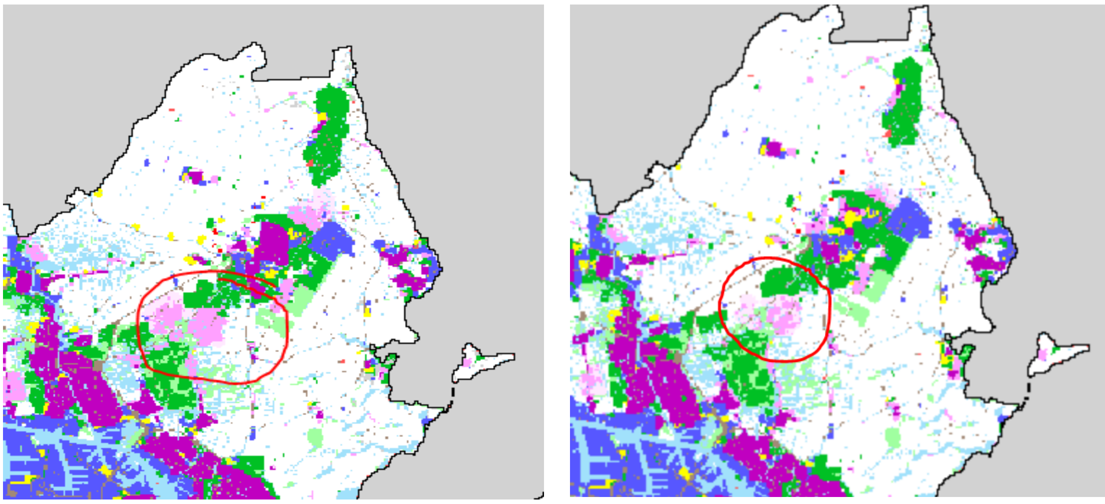


Figure 7-11: The Residential (M) cells have reduced when accounting for flooding suitability uncertainty (right) compared to the base map (left).

In 2015 this region was occupied by some scattered Residential (L) and Residential (M) lands. The expansion of Residential (M) is easier to be observed than Residential (L) because it has stronger neighbourhood attractions. However, one zoning regulation has halved the transition potential of the Residential (M) cells, making suitability values play a key role in deciding the competitiveness of the two residential lands.

In the case where the Residential (M) patch shrinks, a much lower flooding suitability value is assigned to Residential (M) than Residential (L), which limits the potential of these middle-density cells to develop. To confirm this reasoning, we check the parameter settings of the maps that share this characteristic (see Figure 7-13). Since this area is categorized as a "middle probability area", the values of "*mid_rl*" (i.e., the suitability for Residential (L)) and "*mid_rm*" (i.e., the suitability for Residential (M)) should be checked. Similarly, all the Residential (M) lands have lower suitability than Residential (L), with 7 out 9 cases having a suitability value lower than 0.2. In contrast, Residential (L) lands are given with far higher suitability values, with 8 out 9 exceeding 0.5.

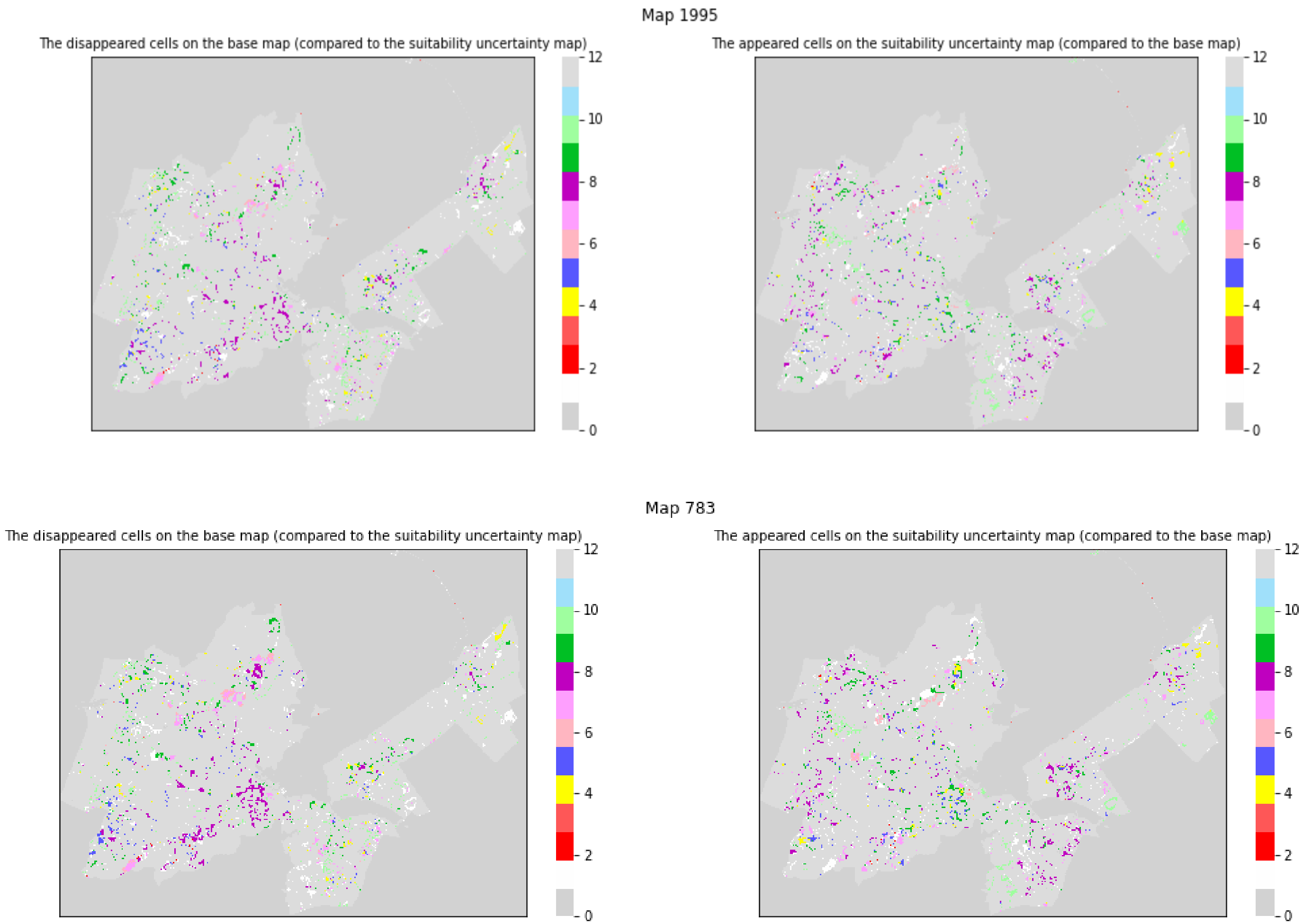


Figure 7-12: Two examples of the representative maps that experience the Residential (M) reduction in the north-western region. This change is observed only in some representative maps. (0 = "outside"; 1 = "agriculture"; 2= 'greenhouses"; 4= "public amenities"; 5= "commercial"; 6='residential (L)'; 7= "residential(M") ; 8= "residential(H); 9= 'recreation", 10="nature", 12="all the unchanged cells")

	mid_agri	mid_comm	mid_gh	mid_min	mid_pa	mid_rec	mid_rh	mid_rl	mid_rm	small_agri	...	small_gh	small_min	small_pa	small_rec	small_rh	small_rl	small_rm
1382	0.864129	0.308969	0.600434	0.746963	0.487930	0.883382	0.032622	0.491932	0.116855	0.903869	...	0.909861	0.962362	0.735076	0.960444	0.996104	0.935212	0.593334
335	0.810241	0.180136	0.602463	0.893175	0.421316	0.738350	0.268515	0.550414	0.183947	0.938404	...	0.862512	0.976664	0.790443	0.951206	0.618496	0.710495	0.671683
326	0.805780	0.494941	0.628466	0.793166	0.398898	0.833383	0.075093	0.570384	0.355486	0.902838	...	0.846079	0.936480	0.942979	0.914057	0.897760	0.919714	0.503447
783	0.800164	0.477499	0.668714	0.750672	0.541352	0.888095	0.046425	0.592476	0.133030	0.961106	...	0.822722	0.993185	0.680313	0.921573	0.786489	0.982380	0.973590
446	0.823235	0.173817	0.771384	0.820929	0.428850	0.835278	0.386955	0.394117	0.110182	0.937027	...	0.961607	0.963436	0.691354	0.956412	0.967479	0.772141	0.745007
1171	0.848637	0.108295	0.647655	0.721251	0.251568	0.779562	0.142830	0.532631	0.119310	0.989984	...	0.920040	0.921755	0.763399	0.907694	0.903511	0.892286	0.572974
785	0.808199	0.151636	0.664913	0.762074	0.227928	0.715779	0.374358	0.574119	0.188170	0.949363	...	0.992442	0.903960	0.920214	0.999972	0.999556	0.995908	0.513171
549	0.811403	0.421332	0.726831	0.744611	0.333448	0.733733	0.018785	0.594951	0.119985	0.989409	...	0.888386	0.995646	0.898074	0.906134	0.956176	0.843140	0.710967
595	0.803442	0.234122	0.665173	0.751238	0.286386	0.893176	0.269600	0.591461	0.284234	0.974670	...	0.850073	0.970702	0.614981	0.936168	0.585318	0.692017	0.624787

Figure 7-13: The parameter settings of the representative maps that share this characteristic. The large difference between the "mid_rl" and"mid_rm" parameters cause this land change pattern.

These large differences in the suitability values between Residential (M) and Residential (L) result in the gaps of the ultimate transition potential and restrict the growth of the Residential (M) cells. This explains why the patches in some presentative maps are smaller than those in the base map.

In contrast, in some cases, the amounts of the middle-density residential lands in the west are more than those from the base map. Two example representative maps are shown in Figure 7-15. This land-use change phenomenon can be interpreted by the small differences between the "*mid_rl*" and "*mid_rm*" values. The two parameter settings are displayed in Figure 7-14.

There are small differences between the suitability values of the "*mid_rl*" and "*mid_rm*". In this case, the middle density's advantage of the high neighbourhood interactions manifests and it takes over the land, pushing the Residential (L) cells which lose the land competition to move outwards. This is why visually these residential blocks are higher than those in the base map.

	mid_agri	mid_comm	mid_gh	mid_min	mid_pa	mid_rec	mid_rh	mid_rl	mid_rm	small_agri	...	small_gh	small_min	small_pa	small_rec	small_rh	small_rl	small_rm	s
906	0.882008	0.493880	0.676939	0.824358	0.270900	0.702206	0.283832	0.287933	0.194105	0.919597	...	0.884937	0.996785	0.854031	0.971684	0.559526	0.620420	0.749589	
883	0.840158	0.464627	0.737701	0.744541	0.218906	0.861662	0.020166	0.369982	0.357028	0.978099	...	0.987269	0.993762	0.820976	0.918075	0.755889	0.774719	0.962631	
909	0.883172	0.280042	0.793040	0.876937	0.378243	0.724223	0.138916	0.362908	0.179349	0.975601	...	0.824475	0.984498	0.662229	0.939084	0.568940	0.834350	0.792350	
14	0.861168	0.358391	0.698103	0.883863	0.246988	0.702847	0.164678	0.332537	0.229238	0.999151	...	0.854942	0.984467	0.767344	0.997092	0.611905	0.808341	0.876431	
1131	0.881553	0.417565	0.768396	0.837319	0.237361	0.738557	0.216788	0.303119	0.164154	0.993538	...	0.927709	0.996937	0.745470	0.985923	0.661285	0.967310	0.722246	
708	0.817047	0.310667	0.769063	0.719311	0.285964	0.871732	0.330771	0.262825	0.189800	0.919803	...	0.918844	0.938430	0.763998	0.934425	0.405265	0.776573	0.709034	
1338	0.869578	0.470579	0.699245	0.718770	0.248806	0.865990	0.186277	0.368668	0.158825	0.935497	...	0.881080	0.921172	0.714253	0.989778	0.603945	0.688369	0.580894	
475	0.808319	0.115872	0.617471	0.791753	0.588175	0.729009	0.239007	0.285630	0.496469	0.939159	...	0.863528	0.961261	0.872846	0.922233	0.700430	0.729501	0.515871	
551	0.875513	0.111891	0.673017	0.858564	0.534655	0.817327	0.064910	0.525128	0.455728	0.954431	...	0.997434	0.994898	0.815083	0.958930	0.704176	0.821658	0.990842	
337	0.855709	0.354056	0.776958	0.766926	0.458677	0.855868	0.118771	0.256833	0.480852	0.968463	...	0.913789	0.978801	0.849301	0.952476	0.972077	0.814274	0.898558	
564	0.856556	0.317565	0.777441	0.852595	0.499189	0.714055	0.331434	0.397964	0.373918	0.910987	...	0.889069	0.932757	0.779968	0.997866	0.727975	0.880490	0.620604	

Figure 7-14: The parameter settings of the representative maps that share this characteristic. The suitability values of "mid_rl" and"mid_rm" are closer compared to those forming the first diverged characteristic

2）Residential(H) cells in north-eastern Lelystad (the upper right part of MRA)

There are some distinctions with the change patterns of the Residential (H) cells in the north-eastern MRA. An increased or decreased number of Residential (H) cells could be seen in this region, depending on the suitability of the small probability areas for Residential (H) lands.

This area is a good destination for Residential (H) lands due to the many blocks of middle-density residential lands. But as this is also home to many public amenities facilities which also tend to expand, the competition between these two land types is determined by the suitability values to some extent.

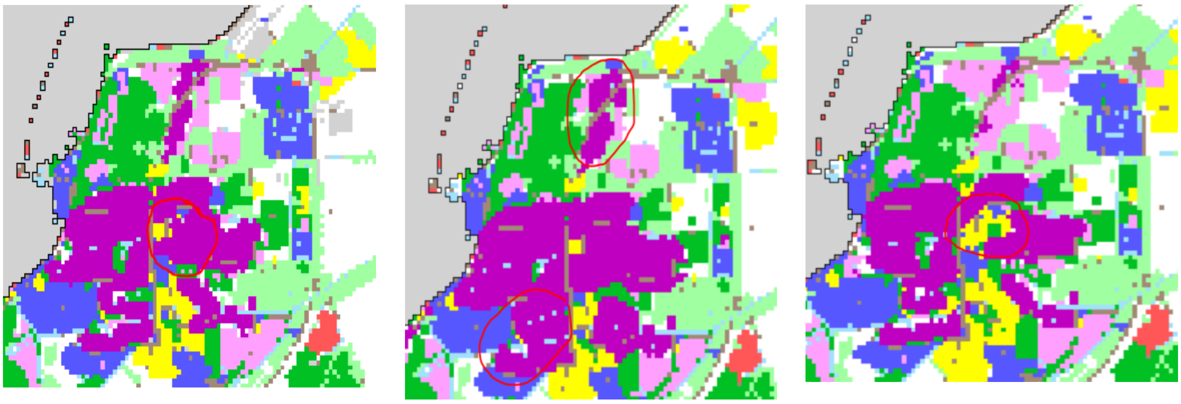


Figure 7-15: From the left to right: the base map, the case where more Residential (H) cells are located, and the case where the Residential (H) are reduced

If the suitability of Residential (H) is low, especially when compared to that of the public amenities, the high-density lands are not likely to grow largely due to the compromised overall transition potential. And the increase of the Residential (H) lands is replaced by the public amenities. But if these suitability values are relatively high, expansions of the purple are observed. We compare the parameter settings of the maps representing the two different change modes. The uncertainty range of the "*samll_rh*" is defined from 0.4 to 1, and in the case where more Residential (H) cells are gathered in the north-eastern region, the suitability values mostly vary from 0.7 to 1. By contrast, for another situation, this suitability parameter is associated with much lower values from 0.4 to 0.7 (see Table 7-4). Combined with our logical reasoning with these experiment datasets, we could conclude that the two different land-use change patterns are relevant to the suitability values of Residential (H) land.

Table 7-4: the comparisons of the suitability values for the Residential (H) in the small probability for two different cases

The increase of the Residential (H) cells	The decrease of the Residential (H) cells
0.831796	0.4900605
0.992025	0.439341
0.688229	0.609927
0.771156	0.729732
0.981152	0.492544
0.989349	
0.895399	

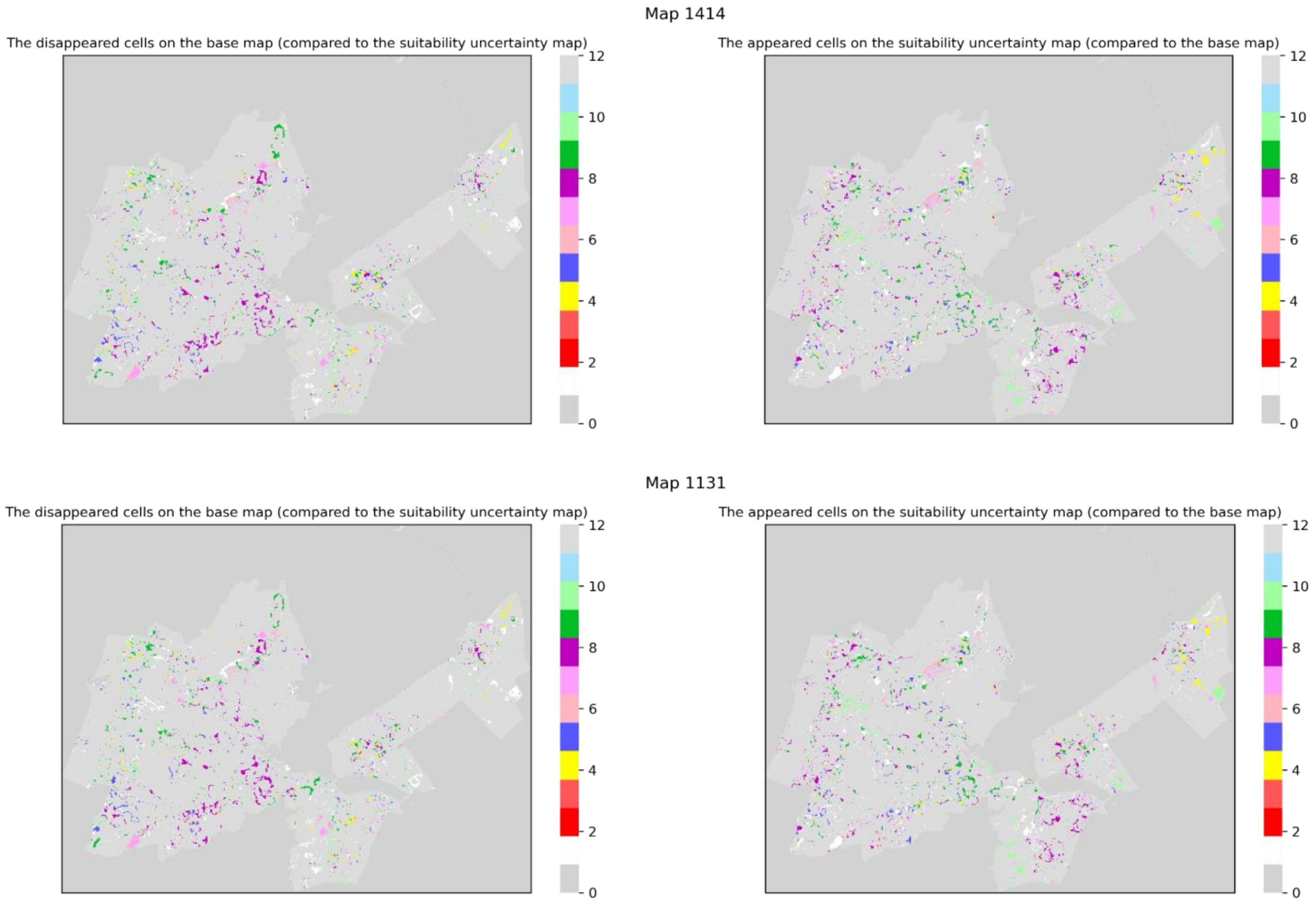


Figure 7-15: Two examples of the representative maps that experience the Residential (M) increase in the north-western region. This change is observed only in some representative map. (0 = "outside"; 1 = "agriculture"; 2= 'greenhouses"; 4= "public amenities"; 5= "commercial"; 6='residential (L)'; 7= "residential(M") ; 8= "residential(H); 9= 'recreation", 10="nature", 12="all the unchanged cells")

7.4. Summary: Land-use changes from 2015 to 2050

Figure 7-16 demonstrates the land-use pattern of 2015 and that of 2050 which contains all the characteristics of the 34 representative maps. Based on the comparison, the land-use changes from 2015 to 2050 can be summarized.

The amount of Residential (H) lands increase significantly during the decades, especially in the Amsterdam-Amstelveen-Haarlem areas. The residential communities grow larger and more connected and compacted. Some portions of low- and middle-density areas have transformed into high-density ones. Because of the inclusion of flooding risks, residential growth is observed in the east of Hilversum (the lower south-eastern regions) and the west of Almere (the upper south-eastern regions of the map) as well as the Beverwijk-Haarlem areas (the west side of MRA). Residential (H) lands in the north-western (Purmerend-Zeevang) area are decreased compared to the base scenario where no flooding factor is added. The lands are replaced by some recreation lands which are more suitable for confronting flooding events. Our model projections also indicate, in some cases, the north-eastern part of Lelystad will also experience the increase of high-density residential areas. But this change will be affected by the climate uncertainty. If the flooding probability of this area rises up, the residential cells are not supposed to locate there.

This urban area still has some portions of the low- and middle-density residential blocks. Our model projections suggest some low- and middle-density residential cells will be situated around the Landsmeer area. But this change is determined by the flood uncertainty. If the probability increases, it will become less suitable for middle-density residential cells to grow there.

To achieve Amsterdam's strategic plan of improving the city's spatial quality, many public amenities are allocated in the north-eastern corner of Lelystad. Compared to the base scenario, nature lands also emerge in the east of Lelystad and the western Almere. In the base scenario, this region is deemed as unsuitable for these land sources due to the soil quality. However, the two land types play a role in responding to flooding events, so once the flooding risk is considered the suitability of public amenities and nature lands in this area is manifested.

The south-western region (i.e., Haarlemmermeer) sees the greatest expansion of commercial lands and many previously scattered commercial cells are moved to this area. Many recreation zones are formed in the northwest (i.e., Zeevang) and the southeast part of the region (i.e., Hilversum-Almere). In contrast, the mineral and industry patch at the lower south-western MRA shrinks as the demand for this land type drops during these years.

The observations are consistent with the socio-economic projections and strategic plans of MRA, in which the housing demands rise up and more public facilities are expected.

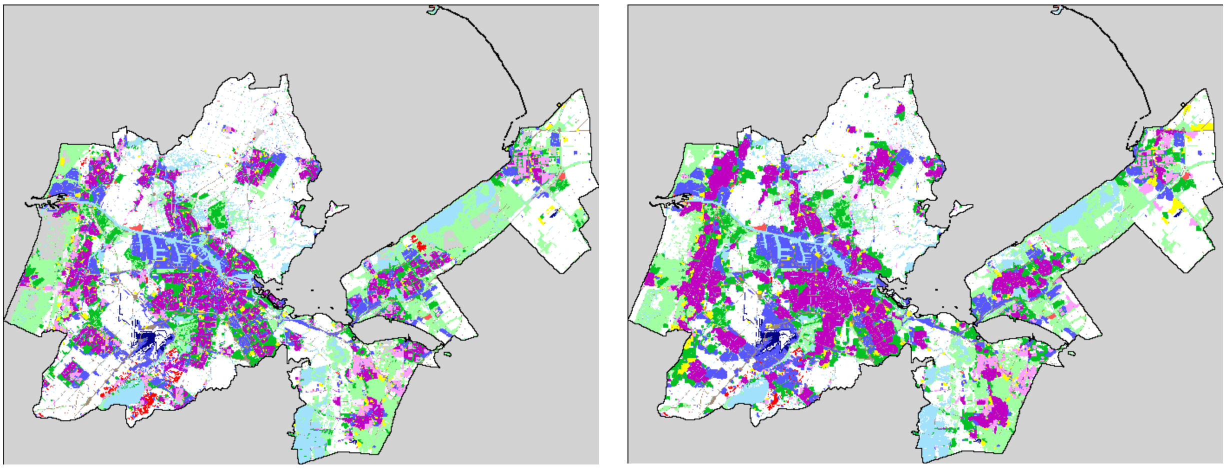


Figure 7-16: The map comparison between the map of 2015 (left) and the map of 2050 for the base scenario (right)

8. Urban planning implications

The last section investigates the land-use change projections from 2015 to 2050 with flooding risks considered, this section does some further analysis on the impacts of these land-use changes and tries to find the answers for the last sub-research question:

Q5: What urban planning implications can be obtained from the projected land-use changes?

First, we check the flood risk situation of 2050 and identify the potential high flood risk areas which needs specific attention in urban planning. Then in Section 8.2, we compare the development plans proposed by the government with our model results, trying to see if there is any conflict or incompatible growth.

8.1. High flood risk areas

In this section, we overlay the estimated flooding probability map of 2050 with the projection of the land-use pattern in 2050. By coupling the flooding probability with the projected developments of each area, the high-risk areas are identified. The flooding risks of these areas are high despite the incorporation of flooding factors in the urban planning process. Therefore, some flooding mitigation and adaptation measures are expected to be implemented in the upcoming decades.

8.1.1. Overlay of the flooding map

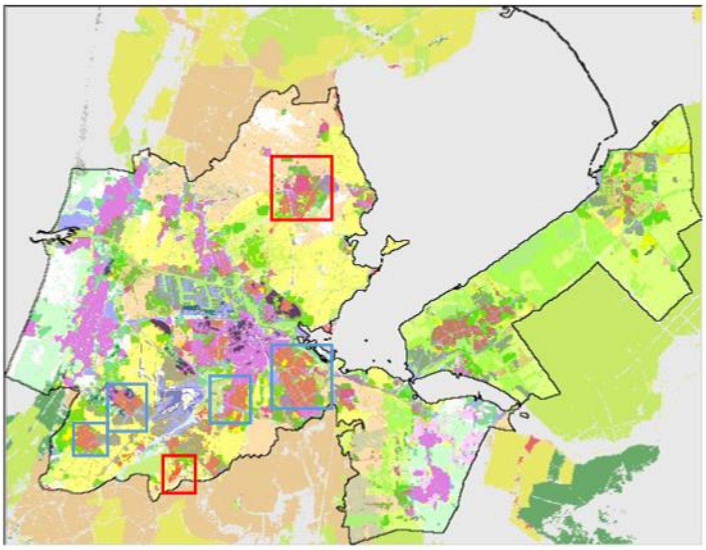


Figure 8-1: The overlaid map of the flooding probability map and the land-use map of 2050. The red squares are high-risk areas and the blue ones are middle-risk areas.

The overlaid maps indicate that the developments in Purmerend and the south of Uithoorn (i.e., the red circles) are still exposure to high flood probability, leading to high potential flooding risks to the neighbourhoods. Although the inclusion of flood risks in our model has reduced the amount of high-density residential development in the Purmerend area, but the rest residential blocks are still there facing with high flooding risks.

Some regions including the two high-density residential blocks in the southwestern Almere, the south-eastern part of Amsterdam and Diemen (i.e., blue squares) are located in the middle probability areas. These neighbourhoods are deemed as facing middle flooding risks in 2050.

8.1.2. Urban planning implications

The land-use projection of 2050 has taken account of flooding risk in the land planning process, but some areas are still under high or middle flooding risks. This implies some extra flooding mitigations or adaptions are needed for these areas, for example, to enhance the capability of local community in the face of flooding events through some training programs.

The local government is advised to set agendas and make efforts on the flooding control and management of the high-risk area (i.e., the centre of Purmerend and the south of Uithoorn). For the middle risk areas (i.e., the high-density residential blocks in the southwestern and the south-eastern part of Amsterdam and Diemen), the local government is also advised to pay some attention these zones, and keep an eye on the local weather conditions and become prepared for some extreme flooding events.

8.2. The current development plans for 2050

The document *Urbanization concept Amsterdam Metropolitan Area 2030/2050* * has revealed some plans for MRA to become a sustainable multicore city.

8.2.1. Comparisons between the urban plans and the model results

MRA plans to locate its housing demands in these locations: Haven-Stad, Achtersluispolder in Zaanstad, Hoofddorp centrum and westflank Haarlemmermeer, Almere-Pampus, and Amsterdam Southeast/Duivendrecht, as indicated by the red polygons in Figure 8-2.

Our projection results also predict the housing increase in the south-eastern Amsterdam and in Haarlemmermeer. But for the developments in Almere, we would argue more residential resources are expected in the middle part rather than in the Almere-Pampus, because of the attractiveness of the existing high-density residential cells and it is easier for housing resources to develop here. For Haven-Stad of Amsterdam, we would recommend to function it as commercial instead of the residential-use. Given the considerations on flooding resilience, the middle of Hilversum, the south of Gooise Meren, Haarlem and the east of Heemskerk-Beverijk-Velsen are more suitable for accommodating the increasing housing demands.

*The urbanization concept document is available at https://www.metropoolregioamsterdam.nl/wp-content/uploads/2021/05/MRA_Verstedelijkingsconcept-Versie-2_mei-2021.pdf

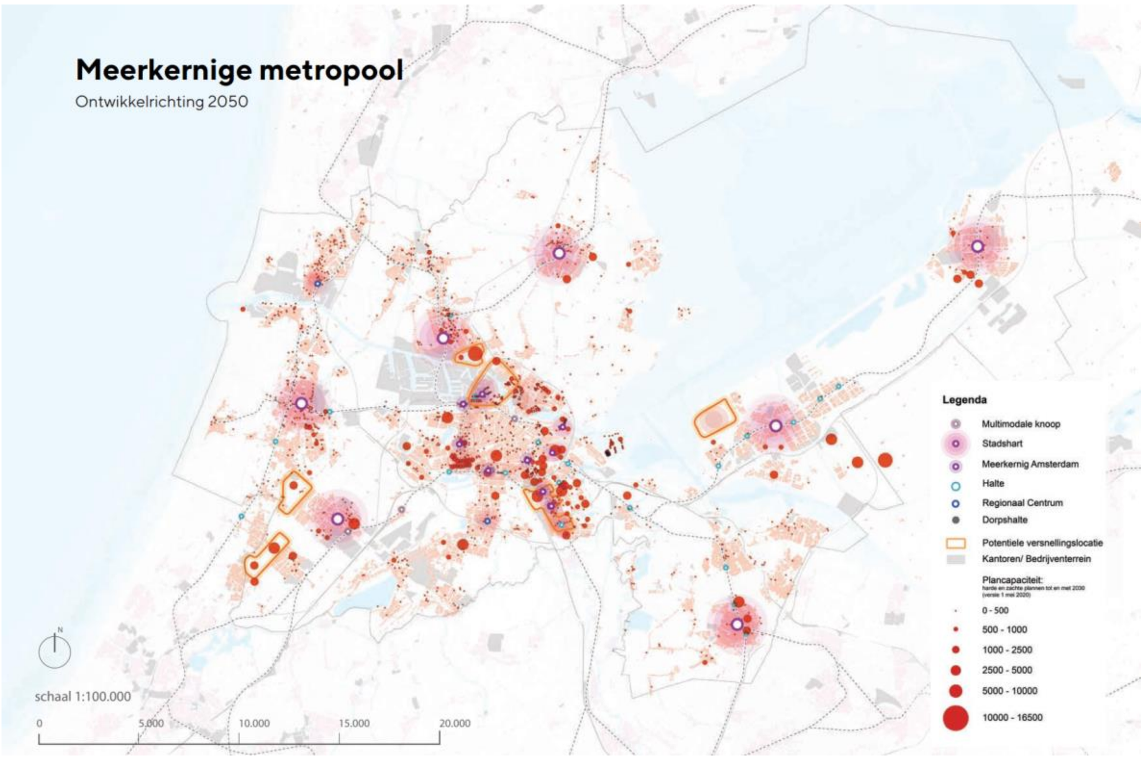


*Figure 8-2: The multi-core plan of MRA. The red polygons are the planned housing blocks and the pink circles are the projected local city centres **

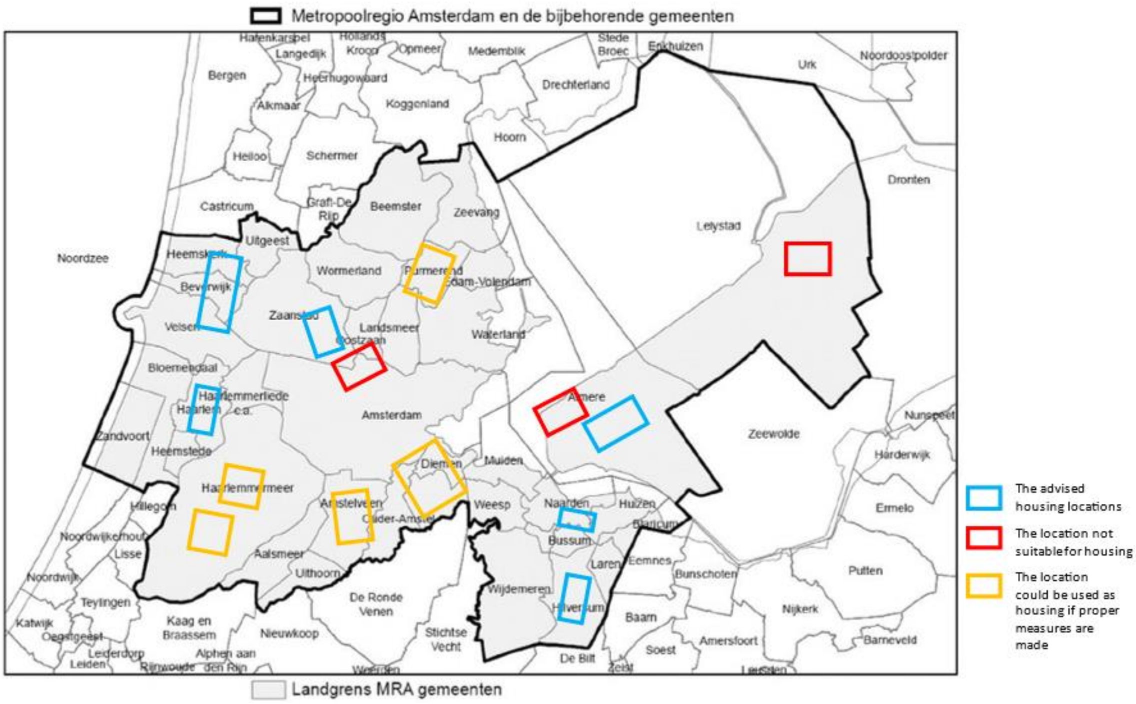


Figure 8-3: The housing plans indicated by the model results. The foundation map is from Savini et al. (2016)

*The map is from https://www.metropoolregioamsterdam.nl/wp-content/uploads/2021/05/MRA_Verstedelijkingsconcept-Versie-2_mei-2021.pdf

Another point focuses on the densification strategy of MRA. Densification is used by MRA as part of its area-oriented approach that enhances the quality of life in some neighbourhoods and the socio-economic conditions of the current residents. Lelystad East is selected as one of the areas where densification efforts will be made. However, our modelling results suggest that the developments in Lelystad East are sensitive to the flooding probability and it would not function for residential use once the actual flooding probability is more serious than the estimation. The flooding estimation indicates there is only a small probability for this area to suffer a flooding event of more than 50cm, given that appropriate climate mitigation and flood control measures are implemented. However, as the climate and socio-economic variables involve a great degree of uncertainties, no one could guarantee the low probability of this area. Therefore, from a climate resilience perspective, there are more suitable places for developing into high-density residential blocks than Lelystad East.

8.2.2. Urban planning implications

To meet the increasing housing demands and to make MRA more resilient to climate impacts, the way to locate the future residential blocks are essential.

Our model results recommend to develop some high-density community in the middle of Hilversum, the south of Gooise Meren, Haarlem, the middle of Almere, and the east of Heemskerk-Beverijk-Velsen (i.e., the blue squares in Figure 8-3). For Hoofddorp centre, westflank Haarlemmermeer, Amsterdam Southeast, Purmerend and the south of Uithoorn (i.e., the orange squares), as they are estimated to be faced by high or middle flooding risks in 2050, some flooding management measures are expected together with the allocation of housing resources.

The current development plan of MRA tends to turn Haven-Stad, Almere-Pampus and Lelystad East (i.e., the red squares) into high-density residential areas. However, our modelling results show the inappropriateness of these sites to be used for residential use. Instead, the housing resources are recommended to allocate in the blue squares.

8.2.3.Other urban planning implications

In apart from housing locations, the MRA government can optimize the land resources to be prepared for the future flooding disasters by allocating some other land-use types.

Some public amenities lands including the public facilities and some socio-cultural sites are recommended to invest in the south-eastern Lelystad and the southwestern Haarlemmermeer. The recreations lands such as parks and gardens are advised to be located at the northwest part and the southeast part of MRA, they can contribute to the flooding control and recovery. Figure 8-4 demonstrates the recommended sites for the developments of recreation and public amenities.

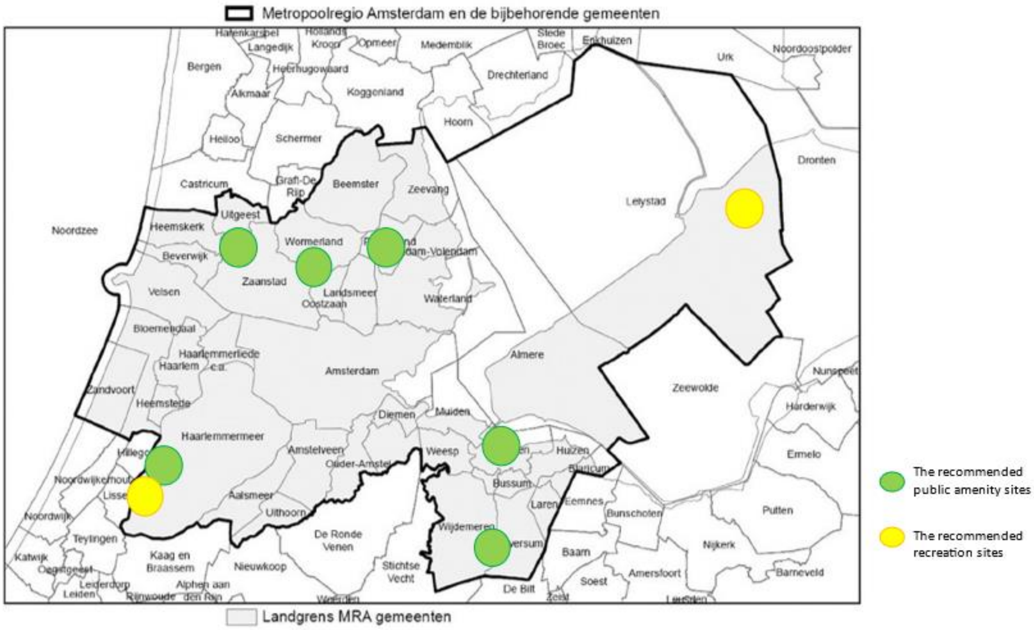


Figure 8-4: The recommends sites for public amenities (yellow) and recreation (green). The foundation map is from Savini et al. (2016)

9. Conclusions

This research is initiated by the coupled challenges of the intensifying climate change and urbanizations. The complexity and uncertainty of both climate change and urban systems are the barriers for cities to make adaptation plans. Therefore, to facilitate the understanding among decision-makers on the climate uncertainty implications for urban dynamics, the research aims to develop a methodology to incorporate climate uncertainties into the urban growth analysis. Based on this, this research combines Metronamica, as a cellular automata-based land-use modelling framework, with the exploratory modelling to systematically investigate the impacts of the uncertain climate factors over their full ranges.

This chapter concludes the research by first revisiting the research questions, and then its scientific and societal contributions are pointed out. In the end, some limitations of this research are discussed, which helps to form future research suggestions.

9.1. Answering the research questions

The main research question is proposed as:

How can an integrated land-use modelling methodology be developed to help systematically explore the impacts of climate uncertainties on urban growth?

To answer this question, we first break down it into five sub-research questions. The first two questions focussing on the research approaches, and the third one is about how to incorporate the climate variables and their uncertainties in our proposed mythology and implement it. The last two questions are to analyse the results and form some policy implications for urban planning under climate uncertainties.

- *Q1: Which land-use modelling framework is suitable for investigating the climate impacts on urban growth?*
- *Q2: Which modelling techniques can be used to help systematically explore the climate uncertainties?*

Regarding the methods to explore urban dynamics, Metronamica is selected as the land-use change model framework due to its capacity of dealing with complex land-use changes, the convenience to explore many land-use types and carry out scenario analysis.

Unlike the traditional way to address uncertainty by forming storylines and simulate only a few scenarios, this research adopts exploratory modelling to explore large amounts of “possible futures”, such that the impacts of the climate uncertainties can be systematically explored.

Therefore, the main research focus of this thesis is to integrate Metronamica with exploratory modelling. Flooding is chosen as the representative climate variables in our analysis because of its important role in city developments. Metropolitan Region of Amsterdam (MRA) is selected as the case study to demonstrate the proposed methodology.

- *Q3: How can the studied climate variables and their uncertainties be linked with the parameters of the selected land-use modelling framework?*

To develop a Metronamica-Exploratory modelling methodology for the investigation of climate uncertainties, we need to consider how to incorporate climate variables and their uncertainties in the modelling process.

First of all, the conceptual climate-embedded Metronamica model is expected to be formed. In particular, this conceptualization decides on where and how to include the climate variables under the Metronamica modelling framework. The inclusion of the climate variables in this thesis follows the “low risk” idea, which means that the allocations of people, assets, and valuable property should be avoided in the high flooding risk areas.

Inspired by this resilience planning idea, we have decided to link the flooding risk with the suitability section under the Metronamica model - the higher the flooding risk of one area when it is coupled with one land type, the lower the suitability value has. The suitability values for each land-use class at each flooding probability zone are determined. However, this research identifies the flooding suitability parameters as uncertain and we further determine the uncertainty ranges for these uncertain suitability parameters.

Once the conceptual model is ready, we implement our ideas to the MRA model. A basic Metronamica model is established for the Metropolitan Region Amsterdam (i.e., MRA), which is expected to reflect the basic land-use change patterns of MRA. The basic Metronamica model of MRA contains the fundamental factors that drive the urban dynamics. The calibration and validation results indicate the valid performances of the basic model and it is used further with our climate uncertainties.

Having set up climate maps and parameters in the MRA model, we have successfully connected it with the EMA workbench and generated 2000 experiments by random sampling and combinations of the uncertainties, through which 2000 outcome maps are generated.

- *Q4: Based on the modelling results, what are the possible land-use changes if the climate variables and their uncertainties are considered?*
- *Q5: What urban planning implications can be obtained from the projected land-use changes?*

In the result analysis step, we use some clustering algorithms to select 34 representative maps, followed by the comparisons between them and the base map where no flooding factor is included. The 34 representative maps show some similar land-use change characteristics because of the introduction of the flooding suitability factor. These characteristics can be observed as long as the flooding factors are added to Metronamica and are not dependent on the suitability values. Some variations are also observed in these 34 maps in terms of their land-use change patterns, which could be attributed to the differences in the flooding suitability values, especially the suitability values associated with the residential lands. Since the climate uncertainties are considered, the suitability values are different in the experiments, leading to different land-use change characteristics in the outcome maps. These characteristics of land outcomes are extracted and the reasons behind these observations are explored. Finally, the land-use changes from 2015 to 2050 with the flooding risk considerations are summarized.

Based on the summarized changes, we formulate some policy implications for urban planning under climate uncertainties. First, we overlay the estimated flooding probability map of 2050 with the projection of the land-use pattern in 2050. By coupling the flooding probability with the projected developments of each area, the high-risk areas are identified. The flooding risks of these areas are high despite the incorporation of flooding factors in the urban planning process. Therefore, some flooding mitigation and adaptation measures are expected to be implemented in the upcoming decades. In addition, we compare the development plans proposed by the government with our model results, trying to see if there is any conflict or incompatible growth. Specifically, we compare the housing plans from the local government with our model results, and some disagreements are identified and some more suitable housing sites are recommended.

The urban planning implications are not limited to the housing aspect. We also provide the suggested areas for developing public amenities and recreation lands.

By answering each sub-research question, we present a complete workflow of dealing with climate uncertainties in land-use change modelling, including the selection of methods, the model conceptualization to include climate variables, the model implementation to set up a Metronamica model for the case city and the connection between the Metronamica and the Exploratory modelling techniques. In the last step, we carry out result analysis and interpretation, finding out the land-use changes caused by the inclusion of flooding into urban dynamics. Therefore, the integrated methodology of systematically exploring the impacts of climate uncertainties on urban growth is developed and could play a role in informing the policymakers about the optimized options of land-use allocations in order to reduce flooding risk and improve climate resilience.

9.2. Scientific and societal contributions

9.2.1. Scientific contributions

This research proposed an integrated modelling methodology that incorporates the climate impacts into one land-use change model and then explores the climate uncertainties systematically.

First, a small portion of the existing literature has linked the climate impacts with urban dynamics. This research presents a way to quantitatively link the climate variables with the driving factors of land-use changes. It also provides spatially explicit outcomes of how climate variables could impact the lands. The approach used by this research to incorporate climate factors can be introduced to other work relevant to urban growth and urban land dynamics.

Second, this research connects the EMA workbench with the cellular-automata-based land-use model to carry out systematic explorations over the uncertain factors. Climate projection uncertainties are always a challenge and are not fully investigated by many studies. Some studies try to use the traditional story-and-simulation approach to picture plausible futures, but this approach is not effective in dealing with deep uncertainties. Using exploratory modelling provides another way to develop many possible scenarios and well address the deep uncertainty issue.

Thirdly, the proposed methodology integrates some specific characteristics of Amsterdam, but it also retains the generality to other spatial contexts in studying climate change influences. This framework can be applied to other cities as well to systematically investigate the impacts of climate uncertainties on urban developments.

9.2.2. Societal relevance

Climate change is one of the biggest challenges faced by cities and to be prepared for potential climate hazards, cities have to adapt and incorporate climate change considerations in urban planning. But the urban planning process is always hindered by uncertainties and complexity, such that the decision-makers are not aware of the future landscapes under a series of uncertainties.

This research incorporates the climate uncertainties into the land-use modelling process, making it possible to know what the plausible futures are if the climate variables are taken into account. The results have linked the future urban land-use outcomes with the climate uncertainty information. And the urban planning implications are made by overlaying the resulting land-use map with the flooding maps and comparing the current development plan with the model results. In this way, the decision-makers could understand the influences of the climate uncertainties and adjust and optimize their urban planning-relevant policies and plans accordingly. This would facilitate the formulation and implementation of urban climate adaptations.

9.3. Limitations and suggestions for further research

This study has developed a methodology to address to investigate the impacts of climate uncertainties on urban growth, which is a new field that little research has ever done before. Since the study had to be completed within a limited time frame, some simplifications had to be made in order to present a complete workflow in the end. The limitations of this research exist in the following aspects:

1) The long-term climate effects

Many consequences of climate change will not take effect until a long time period. This research is intended for a long-term investigation. However, due to the data availability, we can only set the time horizon till 2050 and there may be some other insights by extending the simulation time, given some flooding probability data beyond 2050 is available or can be created based on some stationary data (i.e., rainfall amount) by collaboration with some climate experts.

2) The calibration and validation results

Although our calibration and validation assessment results suggest our basic Metronamica model can proceed for further uses, its current performances could be improved, especially for the residential (L) and residential (M) lands, which shows the most variability with the historical datasets. The input neighbourhood rules can be calibrated further because the current performances indicate that neighbourhood interactions are the most powerful driving factors in our working Metronamica model.

Once the basic model is calibrated to a more sophisticated level, it could be connected to the EMA workbench again and perform the experiments and analysis by following the workflow presented in this thesis. This may lead to more reliable outcomes and valid policy implications for improving the urban climate resilience of MRA.

3) Only one type of climate impact is included

This research selects flooding as a representative climate impact to explore and presents the workflow to deal with it under our proposed "Metronamica and EMA" framework as it is very essential to the developments of the case city. But research is limited to flooding variables, and from the perspective of climate-resilience-based urban planning, there are many other climate factors to consider, including heatwave, sea-level rise, and land subsidence.

It is advised to add some other types of climate variables into the studied land-use model, in this way more comprehensive understandings can be formed regarding the impacts of climate uncertainties on growth. It should be noted that some other model parameters may need to change when adapting to the new climate variables.

4) the socio-economic and other types of uncertainties are untouched

In this research, the demands for the land types as preliminary inputs are treated as fixed numbers. We approximate their values for 2050 by integrating the local projections and plans with the historical development trends. However, as there are many plausible scenarios for the future, the demands thereby involve a great degree of uncertainty. The demand uncertainty ranges could derive from either the local plans or the globally shared pathways (e.g., the IPCC storylines). However, determinations of the uncertainty range for these demands require some other efforts if we aim to link the demands with socio-economic factors like population and economic growth. Two approaches may work for this focus:

- Regression

Regression models establish the relationships between many driving factors and land demands (Batista e Silva et al., 2014). The selection of driving factors is subject to theory or some exploratory analysis results. Another prerequisite for carrying out regression analysis is the large amounts of input data; hence, more efforts are needed for the data collection and processing step.

- System dynamics

System dynamics models are integrated with CA models in some studies to specify the relationships of many socio-economic and physical factors and on the land demand-supply side. In contrast with regression analysis, this is a model-driven approach and therefore, it requires a clear understanding of the causal interrelations between population, economic growth, human behaviour, and land developments (Lauf et al., 2012).

It should be noted that linking socio-economic factors to the demand parameters is only one way of incorporating socioeconomic factors into the Metronamica framework. It could be possible to include these factors into zoning, neighbourhood interaction rules, and accessibility.

5） Only one combination method is considered for integrating the different suitability factors

The suitability value of one cell is determined by multiple factors in most cases and the combination method of these factors plays an important role in the final suitability outcomes. However, in this research, we only calculate the overall suitability values by “Arithmetic mean” with the same weight. while ignoring other methods such as “weighted arithmetic means” and “Minimum”. The influences of different combination methods on the final simulated maps are unexplored. Based on our results, the suitability values are changed as the flooding factor is added and consequently, some variations are observed between the base map and the representative maps that account for flooding suitability. Therefore, it is worth further research to investigate how the decisions of the combination methods would affect the land-use change patterns. In addition, some extra efforts could be made to test the uncertainties of the weights assigned to the suitability factors by further using the developed “Metronamica-Exploratory modelling” framework.

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Annex 1

The main results of the comprehensive literature study on the relationships between climate change impacts and urban growth

Climate variables	Impacts on urban (land) systems	Sources
Increased temperature	• Increased water use/demand • Forest/non-forest shifts • Increased attendance at festivals and outdoor events. • Habitat and food resource loss • Road material degradation • Increased incidence of death and serious illness in older age groups and urban poor • Increased heat stress in livestock and wildlife • Increased risk of damage to a number of crops • Increased electric cooling demand	Van Aalst (2006); Blakely (2007)
Precipitation	• Influences the risks of flood, landslide, avalanche and mudslide, and further impacts the location choices. • Affects soil erosion • Change flood runoff	Van Aalst (2006); Patwardhan et al. (2007)
Heatwave (or increased hot days)	• Increased fire risks • Decreased outdoor tourist activity • Increased tourism at indoor centers • Increased water demand • Increased energy demand • Some locations become untenable without changes in infrastructures.	Patwardhan et al. (2007); Blakely (2007)
drought	• Decreased crop yields • Increased damage to building foundations caused by ground shrinkage • Decreased water resource quantity and quality • Increased risk of forest fire	Van Aalst (2006); Li et al.(2009)
Storm Surge/ Tide	• Change the siting of a residential area • Prone to regular flooding • Affect public transportation choices • Damage to public facilities like schools and churches • Impact on water quality	Blakely (2007)
Sea-level rise	• Communities in low-lying and arid areas are threatened and might be abandoned.	Patwardhan et al. (2007);

For the detailed recordings of this literature study, please check here.

Annex 2

The variability comparisons between adding flooding in suitability and zoning sections

- Experiment Objective

This experiment aims to figure out where (i.e., suitability, zoning, or accessibility) to include the flood hazard map could produce the most variability. The one with the most variability could provide more insights into land-use changes, and will be more ideal to be adopted in the Amsterdam case.

- Experiment Design

Simulated area: Randstad (including most of the MRA area)
Simulation time: 30 years (2000 to 2030
Time step: 1 year
Scenarios:

1. **Baseline**: No flood hazard map included
2. **Normal scenario:** Add flood probability map under suitability, zoning, and accessibility section.

Suitability

MRA model	Randstad model	Suitability value (great/middle/small/very small/extremely small)
Agricultural	Greenhouses Pasture Arable land Other agriculture	0.6/0.7/0.8/0.9/1
Housing high density	Housing high density	0.1/0.3/0.5/0.7/0.9
Housing low density	Housing low density	0.2/0.4/0.6/0.8/0.9
Industry (Feature)	Industry (Function)	0.4/0.6/0.7/0.8/0.9
Public amenities	Services	0.2/0.4/0.6/0.8/0.9
	Socio-cultural uses	0.2/0.4/0.6/0.8/0.9
Nature Natura 2000	Nature Forest Extensive grasslands	0.6/0.7/0.8/0.9/1
Recreation	Recreational areas	0.5/0.6/0.7/0.8/0.9

*For areas where there is no flood information, we assume no significant flood is involved and the suitability is 1

Zoning
Strictly restricted = SR
Weakly restricted = WR
Allowed= AL
Actively simulated = AS

MRA model	Randstad model	Suitability value (great/middle/small/very small/extremely small)

Agricultural	Greenhouses Pasture Arable land Other agriculture	A/A/AS/AS/AS
Housing high density	Housing high density	SR/SR/WR/A/AS
Housing low density	Housing low density	SR/WR/A/A/AS
Industry (Feature)	Industry (Function)	WR/A/A/AS/AS
Public amenities	Services	SR/WR/A/A/AS
	Socio-cultural uses	SR/WR/A/A/AS
Nature Natura 2000	Nature Forest Extensive grasslands	A/A/AS/AS/AS
Recreation	Recreational areas	A/A/A/AS/AS

* Only function lands are considered by zoning
* There are other zoning policies in the Randstad Metronamica model. The flood management policy is tested with the highest and lowest priority respectively.

- Experiment Results

Agriculture = AG; Housing_low = HL; Housing_high= HH; Industry=ID;
Services + Socio-cultural uses = SS; Nature+Forest+Recreation= NA; Recreation = RC

Outcome 1: Include flood hazard map in suitability

No flood/ flood suitability	AG	HL	HH	ID	SS	NA	RC	SUM_No hazards
AG	23414	204	0	145	4	912	196	
HL	107	3297	60	9	24	3	162	
HH	1	55	1172	3	5	0	7	
ID	106	18	1	2277	7	11	44	
SS	5	22	5	4	453	0	21	
NA	922	4	0	5	1	6678	45	
RC	319	62	5	21	16	52	1785	
SUM_flood_suitability								

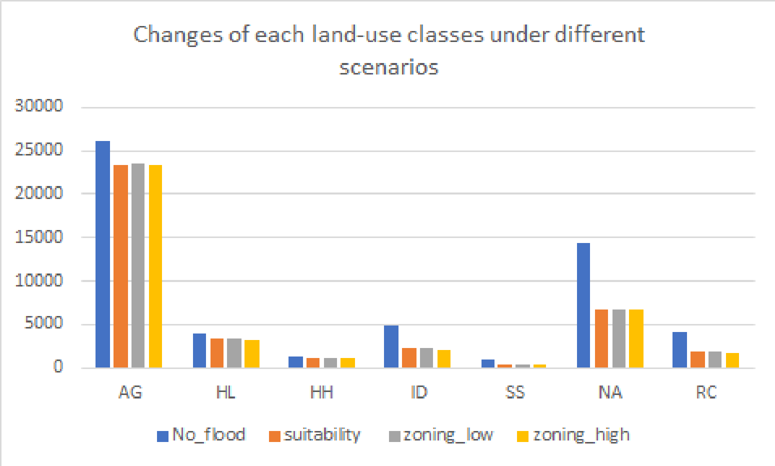
Outcome 2: Include flood hazard map in zoning (with the lowest priority compared to other zoning policies)

No flood/ flood _zoning_low	AG	HL	HH	ID	SS	NA	RC	SUM_No hazards
AG	23489	193	1	131	5	833	223	
HL	112	3318	65	15	22	3	124	
HH	0	58	1172	3	6	0	4	
ID	111	15	0	2283	6	17	32	
SS	2	19	1	7	460	0	21	
NA	849	4	0	3	0	6734	66	
RC	312	55	4	22	11	66	1790	
SUM_flood_suitability								

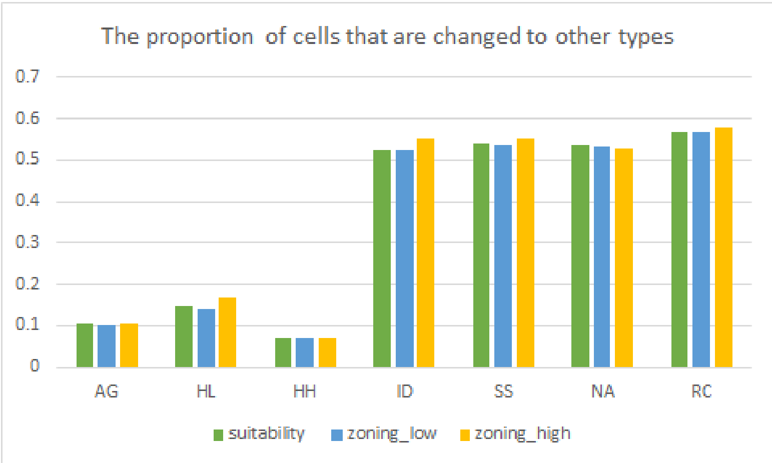
Outcome 3: Include flood hazard map in zoning (with the highest priority compared to other zoning policies)

No flood/ flood_zoning_high	AG	HL	HH	ID	SS	NA	RC	SUM_No hazards
AG	23365	260	5	253	9	776	206	
HL	145	3220	62	6	24	20	185	
HH	1	58	1168	3	7	1	9	
ID	229	10	1	2149	8	29	38	
SS	2	17	3	7	445	1	35	
NA	801	17	1	25	3	6761	48	
RC	331	85	3	21	14	67	1739	
SUM_flood_suitability								

- Results Analysis



The gap between each scenario and the base scenario (no_flood) is larger, the results have more variability.



The figure above indicates that there are insignificant differences among the three kinds of ways, in terms of their variability with the base scenario (no flood included).

- Conclusion and implication

The experimentation shows that including the flood probability map into suitability or zoning will not differ a lot in terms of the amount of land-use cells that are changed. The patterns of land-use change are similar for each modeling approach.

Annex 3-1: Visual Comparisons in the calibration assessment process

The detailed statistics of cell-to-cell comparisons are presented in Table 6-2. The consistency index calculates the portion of cells that are in the both maps to the total cells.

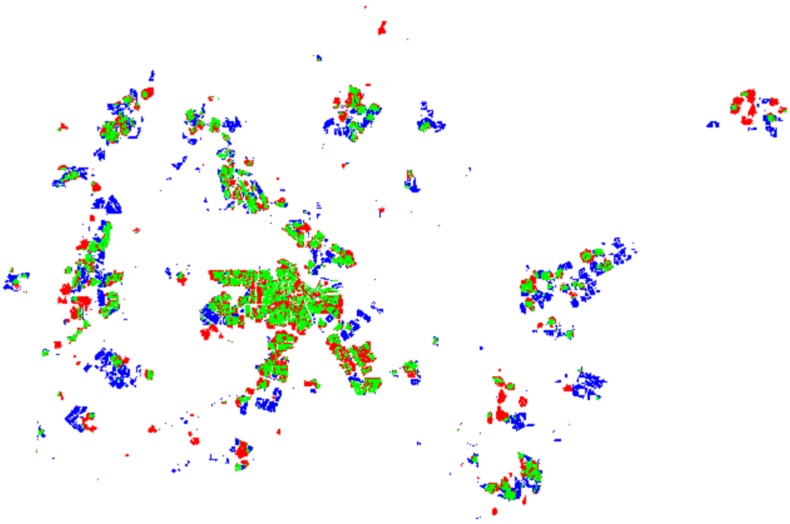


Figure 6-2: A sample map indicating a comparison of the Observed (blue) and Simulated (red) changes for Residential (high density). The green patches refer to nature cells consistent in both maps. (Maps for all other LUCs are here)

Table 6-2: detailed statistics of cell-to-cell comparison for each Land-use category. The 'consistency' indicates the percentage of cells in the simulated map that have the same location as the actual map.

Land-use class	In both maps	Only in the simulated map	Only in the actual map	Consistency
Agriculture	65005	12980	4578	80%
Greenhouses	866	258	258	79%
Mineral/Industry	395	266	266	38%
Public amenities	1847	1311	1311	72%
Commercial	9616	4062	4062	73%
Residential (L)	147	1076	1076	8%
Residential (M)	2626	4567	4567	17%
Residential (H)	7724	6394	6394	57%
Recreation	9521	3514	3514	78%
Nature	20928	2871	2871	87%

Annex 3-2 Performance of clumpiness index in the calibration process

To assess the landscape pattern structure, the average of the absolute category level clumpiness error between Observed and Simulated maps is used. MCK has an inbuilt algorithm to calculate Clumpiness Index and visually illustrate the values and the specific clumpiness index values of all the land-use classes are shown in Table 6-5.

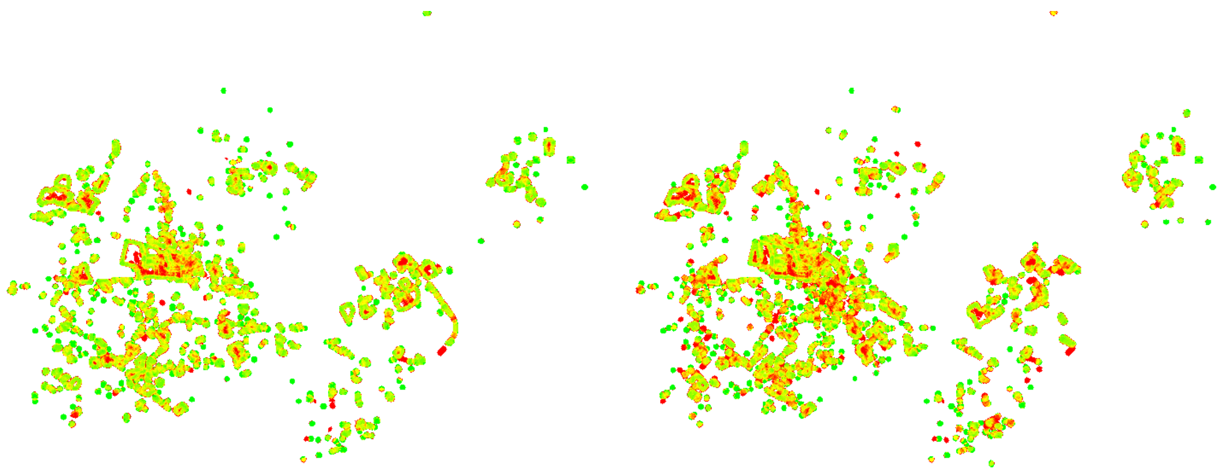


Figure 6-3: The clumpiness of commercial land-use in the Simulated map (left) and Observed Map (right). The colours from red to green correspond to clumpiness index values from 0 to 1.

Table 6-5: Clumpiness indices for each land-use class in Observed and Simulated maps. The differences in values must be as low as possible. The clumpiness maps for other land categories can be found here.

Land-use class	Map 1 (simulated changes)	Map 2 (Observed changes)	Differences
Agriculture	0.844857	0.845025	**-0.0001**
Greenhouses	0.598982	0.573689	**0.0253**
Mineral/Industry	0.32892	0.416452	**-0.0875**
Public amenities	0.591314	0.495191	**0.0961**
Commercial	0.739997	0.676955	**0.06374**
Residential (L)	0.183773	0.690222	**-0.5064**
Residential (M)	0.530357	0.663427	**-0.13307**
Residential (H)	0.833645	0.71799	**0.115475**
Recreation	0.596577	0.59789	**-0.00132**
Nature	0.763518	0.745744	**0.01774**

While most land-use categories perform quite well on this index, the categories that need improvement are Residential (L) and Residential (M). These are currently being fixed. However, based on the results from other indicators, the model is deemed fit to proceed to the next step for Validation.

Annex 3-3: Kappa statistics in the calibration Process

Manually calibrated model

Kappa:

Method: Kappa
Map 1: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica_Aug23\Log\Land_use\23rdAugust\Land use map_2006-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica_Aug23\MCK\Land_use\normal\MRA_2006.rst

Statistics
Kappa: 0.853 Fraction correct: 0.912
KLocation: 0.878 KHisto: 0.972

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_	Water	Tra
Kappa	0.851	0.770	0.597	0.582	0.694	0.118	0.355	0.532	0.722	0.873	0.938	0.8
KLoc	0.906	0.770	0.597	0.582	0.694	0.118	0.355	0.532	0.722	0.873	0.955	0.8
KHisto	0.939	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.982	0.9

Kappa Simulation:

Method: Kappa Simulation
Map 1: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica_Aug23\Log\Land_use\23rdAugust\Land use map_2006-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica_Aug23\MCK\Land_use\normal\MRA_2006.rst
Original map: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica_Aug23\MCK\Land_use\normal\Land use map_1996-Jan-01.rst

Statistics
Kappa Simulation: 0.078 Fraction correct: 0.912
KTransLoc: 0.148 KTransition: 0.525

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature
Kappa Simulation	0.127	0.063	-0.036	0.009	0.066	0.082	0.088	0.106	0.012	0.054
KTransLoc	0.224	0.120	-0.048	0.042	0.106	0.131	0.102	0.176	0.033	0.081
KTransition	0.565	0.520	0.751	0.214	0.624	0.631	0.855	0.600	0.370	0.670

Fuzzy Kappa:

Result statistics: Fuzzy Kappa (2009 version)

Method: Fuzzy Kappa (2009 version)
Map 1: C:\Users\teres\Documents\Master...\Land use map_2006-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base mod...\MRA_2006.rst

Statistics
Fuzzy kappa: 0.888 Average similarity: 0.935

Fuzzy kappa not calculated per category

Comparison with Neutral Models: Random Constraint Match

Kappa:

Method: Kappa
Map 1: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\rcm\reference_map0.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\normal\MRA_2006.rst

Statistics
Kappa: 0.799 Fraction correct:
KLocation: 0.866 KHisto:

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_
Kappa	0.792	0.776	0.537	0.603	0.681	0.045	0.139	0.041	0.775	0.866
KLoc	0.828	0.792	0.665	0.612	0.723	0.326	0.189	0.552	0.804	0.872

Kappa Simulation

Map 1: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\rcm\reference_map0.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\normal\MRA_2006.rst
Original map: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\normal\Land use map_1996-Jan-01.rst

Statistics

Kappa Simulation:	0.035	Fraction correct:	0.881
KTransLoc:	0.127	KTransition:	0.278

Per category

	Greenhouses	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_
Kappa Simulation	0.086	0.099	0.033	0.042	-0.006	0.041	0.006	0.027

Fuzzy Kappa

Result statistics: Fuzzy Kappa (2009 version)

Method: Fuzzy Kappa (2009 version)
Map 1: C:\Users\teres\Documents\MasterThesis\Base...\reference_map0.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base mod...\MRA_2006.rst

Statistics

Fuzzy kappa: 0.827 Average similarity: 0.901

Fuzzy kappa not calculated per category

Comparison with Neutral Model: Null Calibration

Kappa

Method: Kappa
Map 1: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\null\Land use map_2006-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\normal\MRA_2006.rst

Statistics

Kappa:	0.810	Fraction correct:	0.890
KLocation:	0.847	KHisto:	0.956

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_	Water
Kappa	0.847	0.470	0.092	0.682	0.611	0.026	0.062	0.204	0.592	0.935	0.938
KLoc	0.934	0.470	0.092	0.682	0.611	0.026	0.062	0.204	0.592	0.935	0.955

Kappa Simulation

Method: Kappa Simulation
Map 1: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\null\Land use map_2006-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\normal\MRA_2006.rst
Original map: C:\Users\teres\Documents\MasterThesis\Base model_Metronamica\MCK\Land_use\normal\Land use map_1996-Jan-01.rst

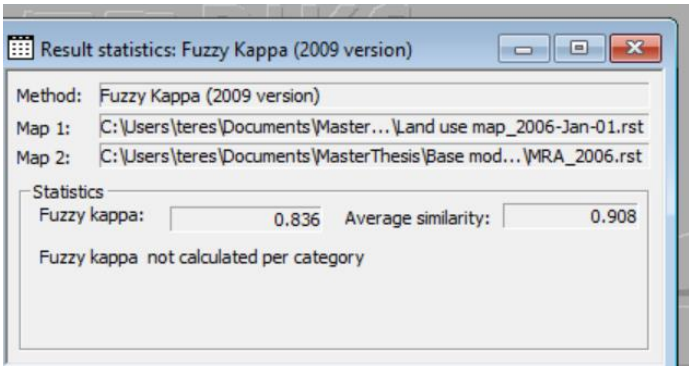
Statistics

Kappa Simulation:	0.035	Fraction correct:	0.890
KTransLoc:	0.111	KTransition:	0.313

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreati
Kappa Simulation	0.152	-0.022	-0.036	-0.015	-0.021	-0.039	0.005	0.032	0.003

Fuzzy Kappa


Result statistics: Fuzzy Kappa (2009 version)
Method: Fuzzy Kappa (2009 version)
Map 1: C:\Users\teres\Documents\Master...\Land use map_2006-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Base mod...\MRA_2006.rst
Statistics
Fuzzy kappa: 0.836
Average similarity: 0.908
Fuzzy kappa not calculated per category

Annex 4: Validation Process

Working Model

Kappa

Method: Kappa
Map 1: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\Land_use\validation_year2015\Land use map_2015-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\Actual_Map_2015\mra_2015\Log\Land_use\mra_2015\Land use map_2015-Jan-01.rst

Statistics
Kappa: 0.882 Fraction correct: 0.930
KLocation: 0.912 KHisto: 0.968

Per category

	Outside	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_	Water	Transport	Airport
Kappa	0.967	0.843	0.777	0.923	0.677	0.750	0.018	0.695	0.707	0.788	0.882	0.972	0.925	0.973
KLoc	0.999	0.908	0.778	0.923	0.678	0.752	0.018	0.696	0.726	0.789	0.884	0.981	0.961	0.997
KHisto	0.968	0.929	0.999	1.000	0.999	0.998	0.999	0.998	0.974	0.999	0.998	0.991	0.963	0.975

Kappa Simulation

Method: Kappa Simulation
Map 1: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\Land_use\validation_year2015\Land use map_2015-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\Actual_Map_2015\mra_2015\Log\Land_use\mra_2015\Land use map_2015-Jan-01.rst
Original map: C:\Users\teres\Documents\MasterThesis\ams_calibration_lastworking_hierarchy\MCK\Land_use\normal\MRA_2006.rst

Statistics
Kappa Simulation: 0.035 Fraction correct: 0.930
KTransLoc: 0.092 KTransition: 0.383

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_
Kappa Simulation	0.054	-0.060	-0.043	0.016	0.030	0.003	0.078	0.053	-0.001	0.025
KTransLoc	0.134	-0.116	-0.080	0.079	0.059	0.071	0.124	0.120	-0.003	0.046
KTransition	0.405	0.519	0.532	0.202	0.516	0.039	0.626	0.442	0.418	0.557

RCM

Kappa

Method: Kappa
Map 1: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\rcm\reference_map0.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\actual_map_2015\mra_2015\log\land_use\mra_...\land use map_2015-jan-01.rst

Statistics
Kappa: 0.859 Fraction correct: 0.916
KLocation: 0.872 KHisto: 0.985

Per category

	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_
Kappa	0.807	0.727	0.903	0.669	0.741	0.013	0.672	0.683	0.766	0.882
KLoc	0.828	0.777	0.923	0.677	0.753	0.017	0.694	0.727	0.788	0.884
KHisto	0.975	0.936	0.979	0.989	0.984	0.805	0.968	0.940	0.972	0.997

Kappa Simulation

Method: Kappa Simulation
Map 1: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\RCM\reference_map0.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\actual_map_2015\mra_2015\log\land_use\mra_2015\land use map_2015-jan-01.rst
Original map: C:\Users\teres\Documents\MasterThesis\ams_calibration_lastworking_hierarchy\mck\land_use\normal\mra_2006.rst

Statistics
Kappa Simulation: 0.028 Fraction correct: 0.916
KTransLoc: 0.084 KTransition: 0.334

Per category

	Outside	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_
Kappa Simulation	0.000	0.042	-0.046	-0.033	0.015	0.030	0.002	0.070	0.048	-0.002	0.025
KTransLoc	0.013	0.132	-0.061	-0.069	0.075	0.053	0.040	0.115	0.113	-0.006	0.045
KTransition	0.034	0.321	0.744	0.479	0.204	0.571	0.053	0.608	0.422	0.380	0.554

Contingency table

Null Calibration

Kappa

Method: Kappa
Map 1: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\Land_use\null_calibration\Land use map_2015-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\actual_map_2015\mra_2015\log\land_use\mra_2015\land use map_2015-jan-01.rst

Statistics

Kappa:	0.863	Fraction correct:	0.920
KLocation:	0.889	KHisto:	0.971

Per category

	Outside	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_
Kappa	0.962	0.905	0.247	0.038	0.648	0.618	0.082	0.468	0.481	0.663	0.954
KLoc	0.998	0.955	0.247	0.038	0.649	0.620	0.082	0.469	0.494	0.663	0.956
KHisto	0.964	0.948	0.999	1.000	0.999	0.998	0.999	0.998	0.974	0.999	0.998

Kappa Simulation

Method: Kappa Simulation
Map 1: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\Land_use\null_calibration\Land use map_2015-Jan-01.rst
Map 2: C:\Users\teres\Documents\MasterThesis\Validation\Validation_model_2006_2015\validation_version3\actual_map_2015\mra_2015\log\land_use\mra_2015\land use map_2015-jan-01.rst
Original map: C:\Users\teres\Documents\MasterThesis\ams_calibration_lastworking_hierarchy\mck\land_use\normal\mra_2006.rst

Statistics

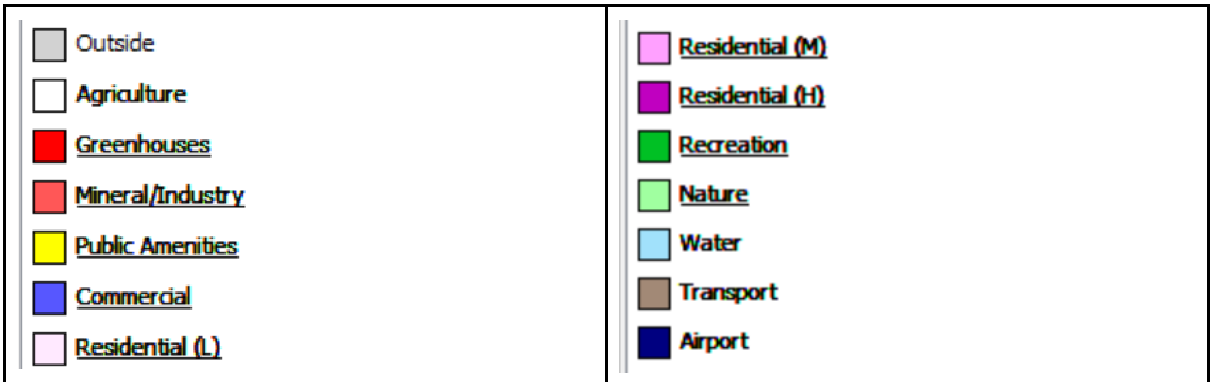
Kappa Simulation:	0.019	Fraction correct:	0.920
KTransLoc:	0.068	KTransition:	0.278

Per category

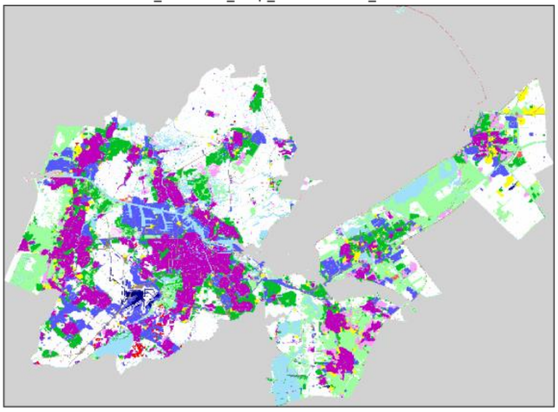
	Outside	Agriculture	_Greenhouses_	_Mineral/Industry_	_Public Amenities_	_Commercial_	_Residential (L)_	_Residential (M)_	_Residential (H)_	_Recreation_	_Nature_
Kappa Simulation	0.001	0.149	-0.056	0.001	-0.004	0.010	-0.084	-0.039	-0.007	-0.002	0.001
KTransLoc	0.052	0.282	-0.284	0.056	-0.018	0.018	-0.438	-0.111	-0.055	-0.008	0.068
KTransition	0.027	0.529	0.198	0.026	0.243	0.545	0.191	0.354	0.127	0.234	0.011

Annex 5 The representative maps

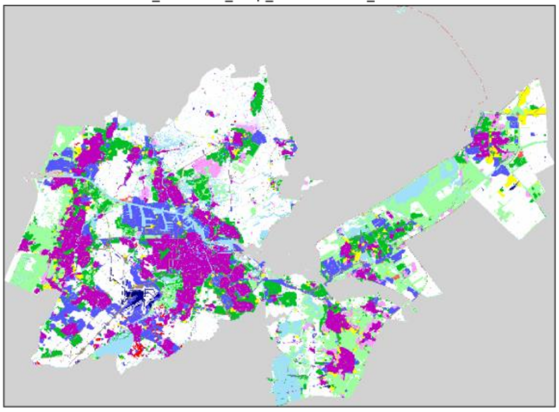
The representative maps selected from the clusters by using different clustering algorithms



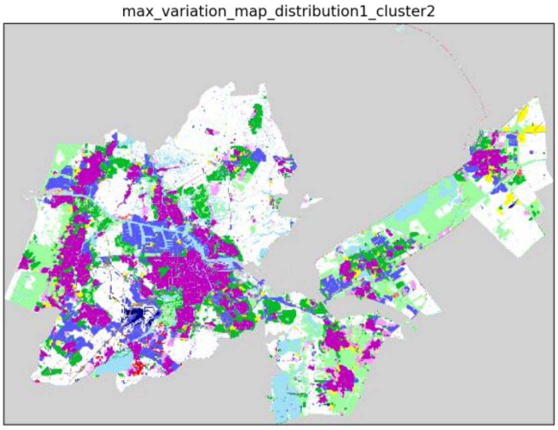
max_variation_map_distribution1_cluster1



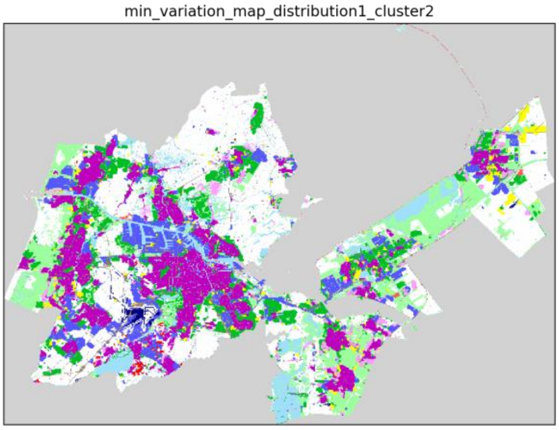
min_variation_map_distribution1_cluster1



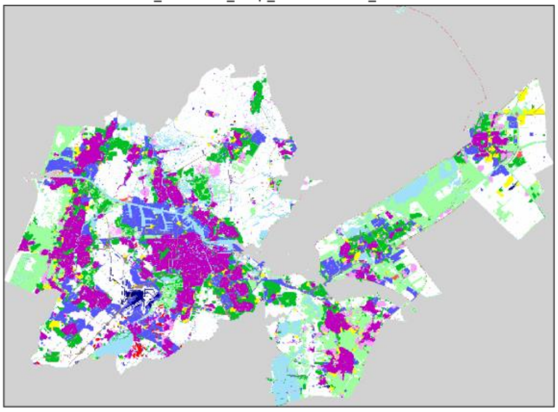
max_variation_map_distribution1_cluster2



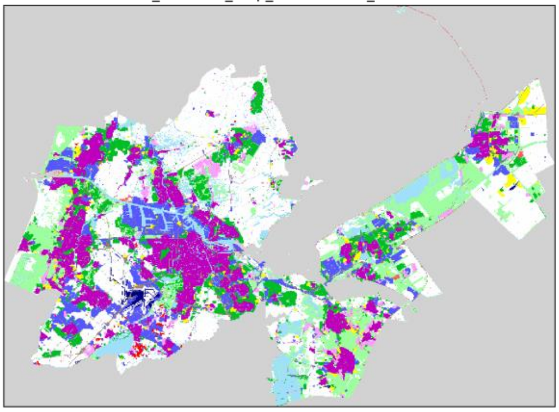
min_variation_map_distribution1_cluster2



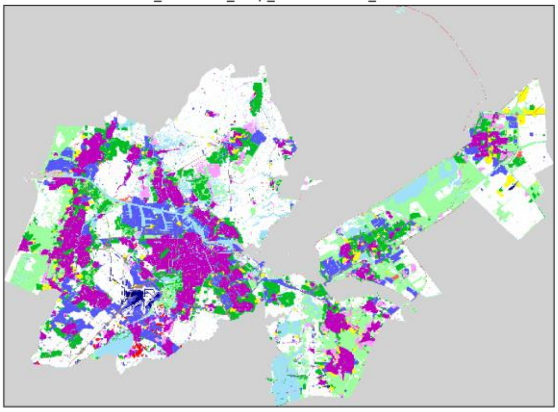
max_variation_map_distribution1_cluster3



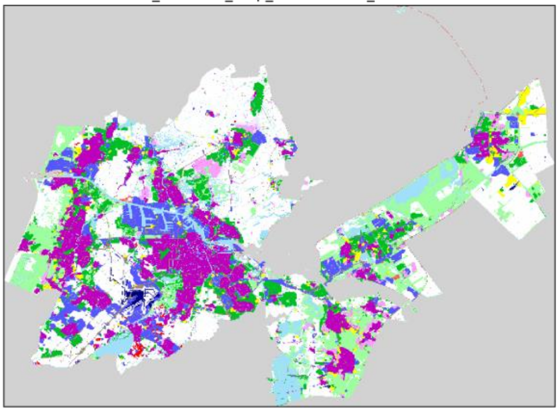
min_variation_map_distribution1_cluster3



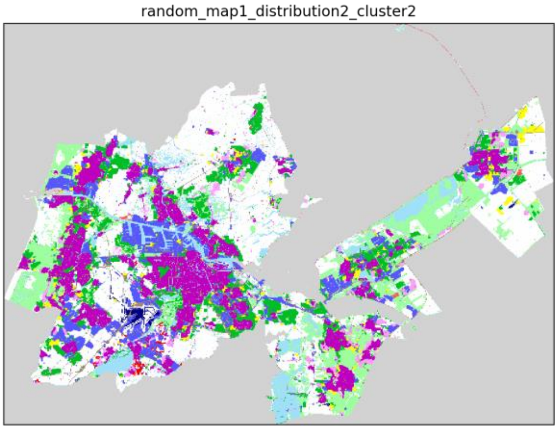
max_variation_map_distribution2_cluster1



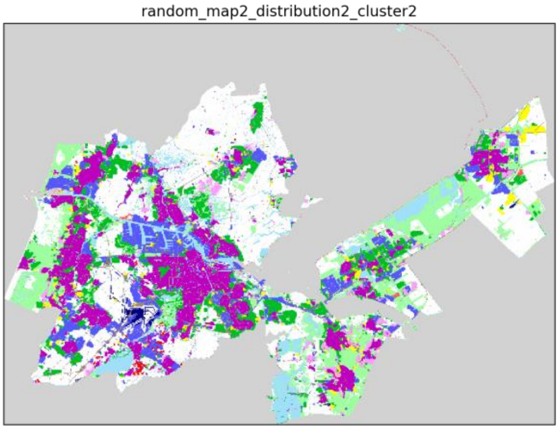
min_variation_map_distribution2_cluster1



random_map1_distribution2_cluster2



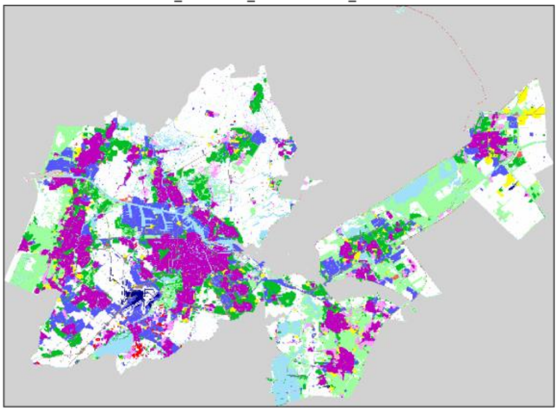
random_map2_distribution2_cluster2



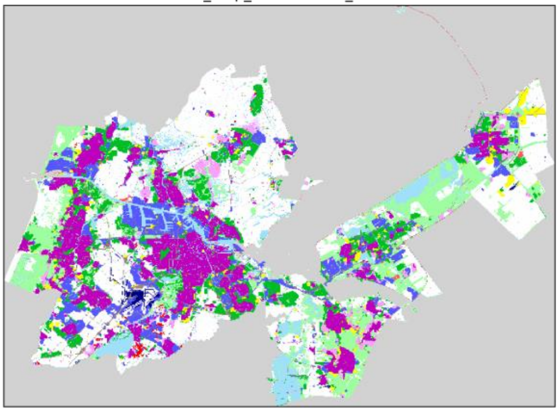

max_variation_distribution2_cluster3
random_map_distribution2_cluster3
max_variation_distribution3_cluster1
min_variation_distribution3_cluster1
max_variation_distribution3_cluster2
min_variation_distribution3_cluster2


random_map_distribution3_cluster3
min_variation_distribution3_cluster3
random_map_distribution4_cluster1
min_variation_distribution4_cluster1
max_variation_distribution4_cluster2
random_map_distribution4_cluster2

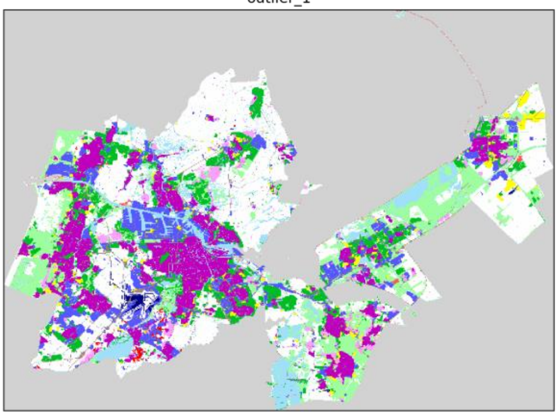
max_variation_distribution4_cluster3



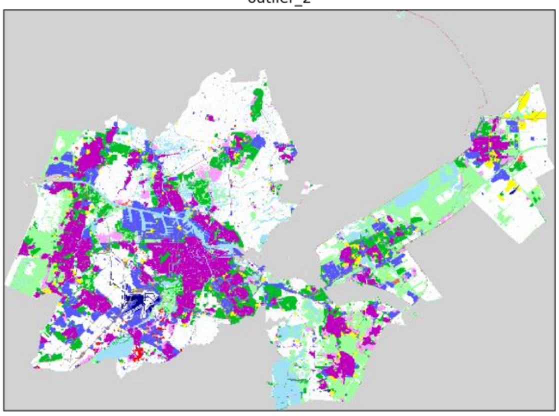
random_map_distribution4_cluster3



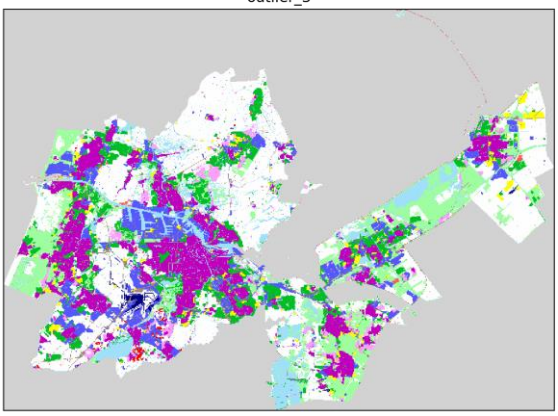
outlier_1



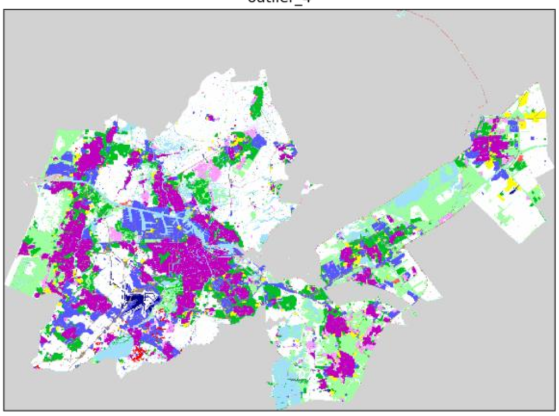
outlier_2



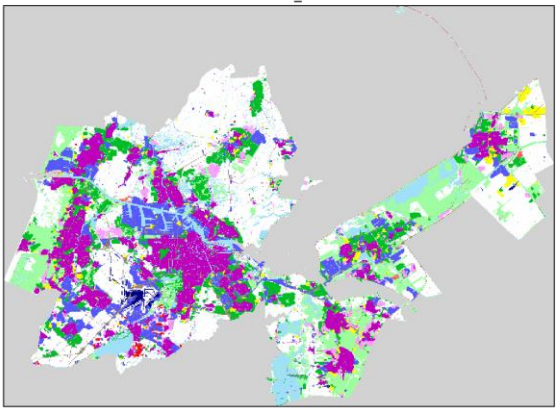
outlier_3



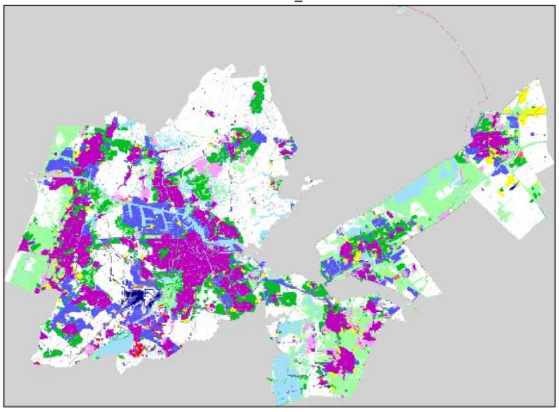
outlier_4



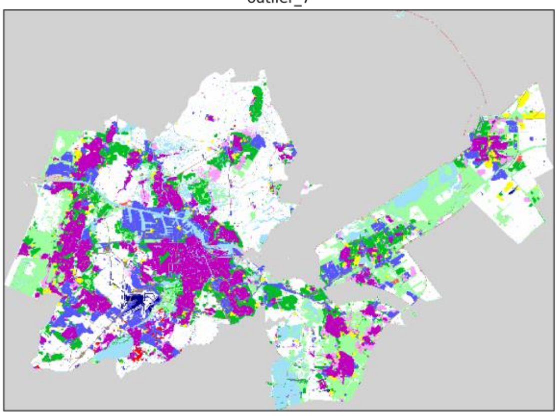
outlier_5



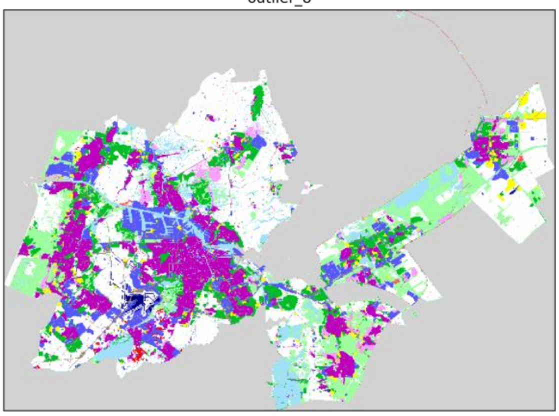
outlier_6



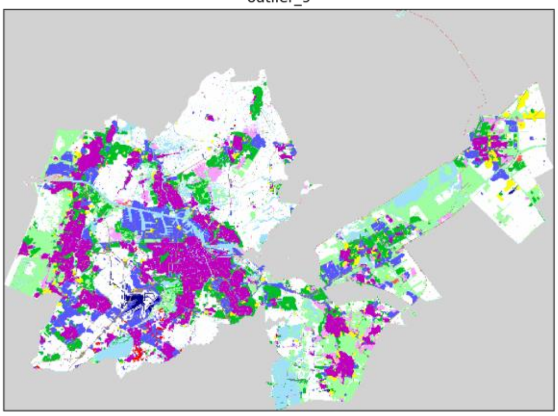
outlier_7



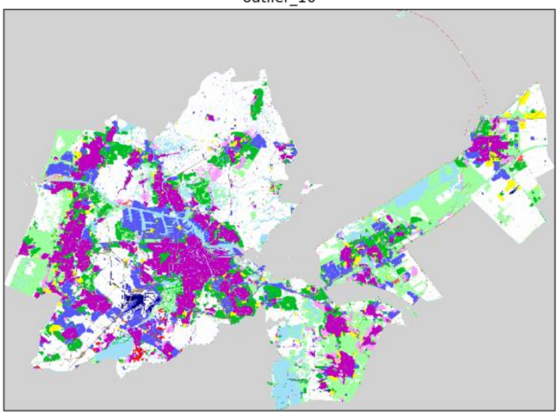
outlier_8



outlier_9

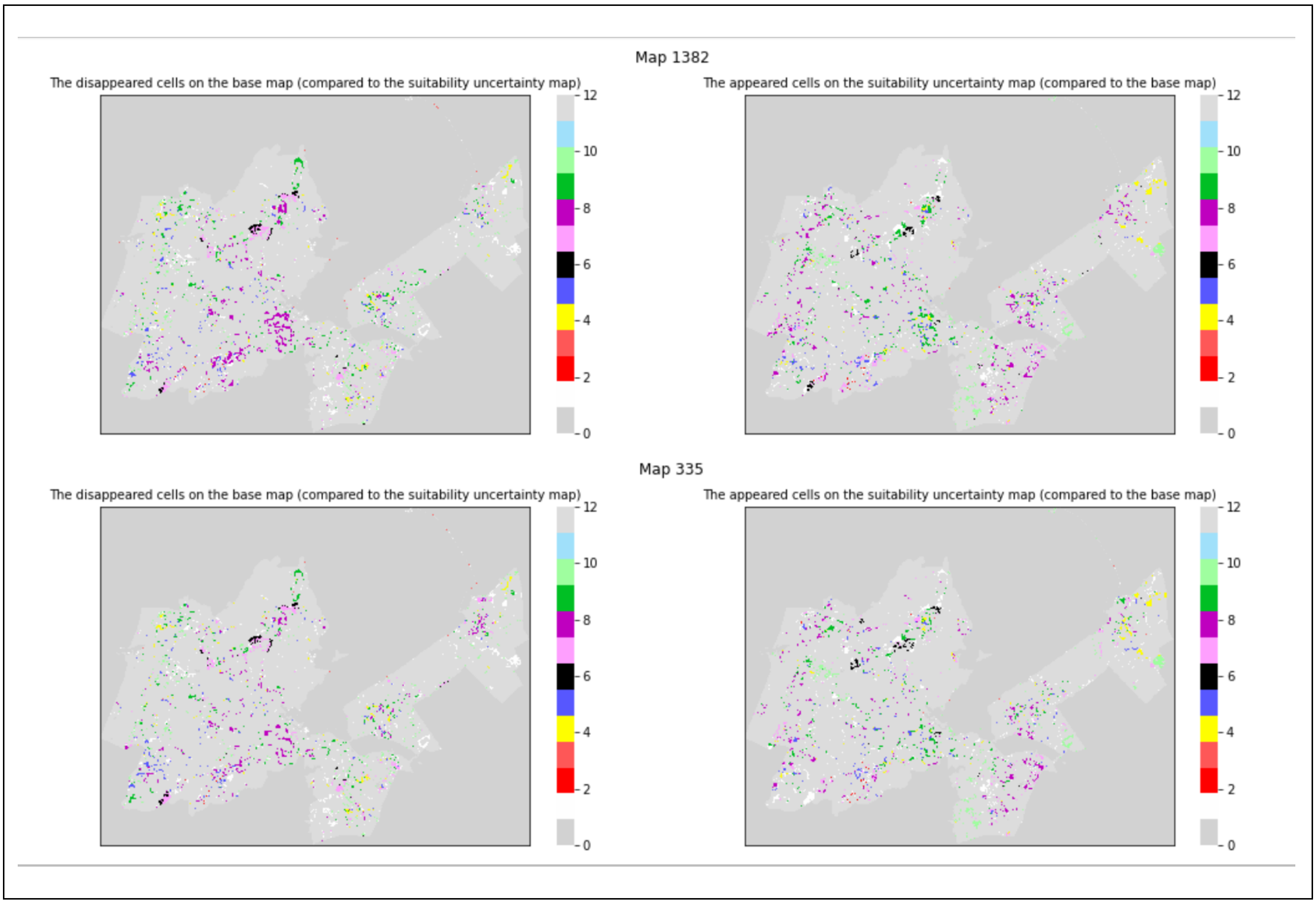


outlier_10

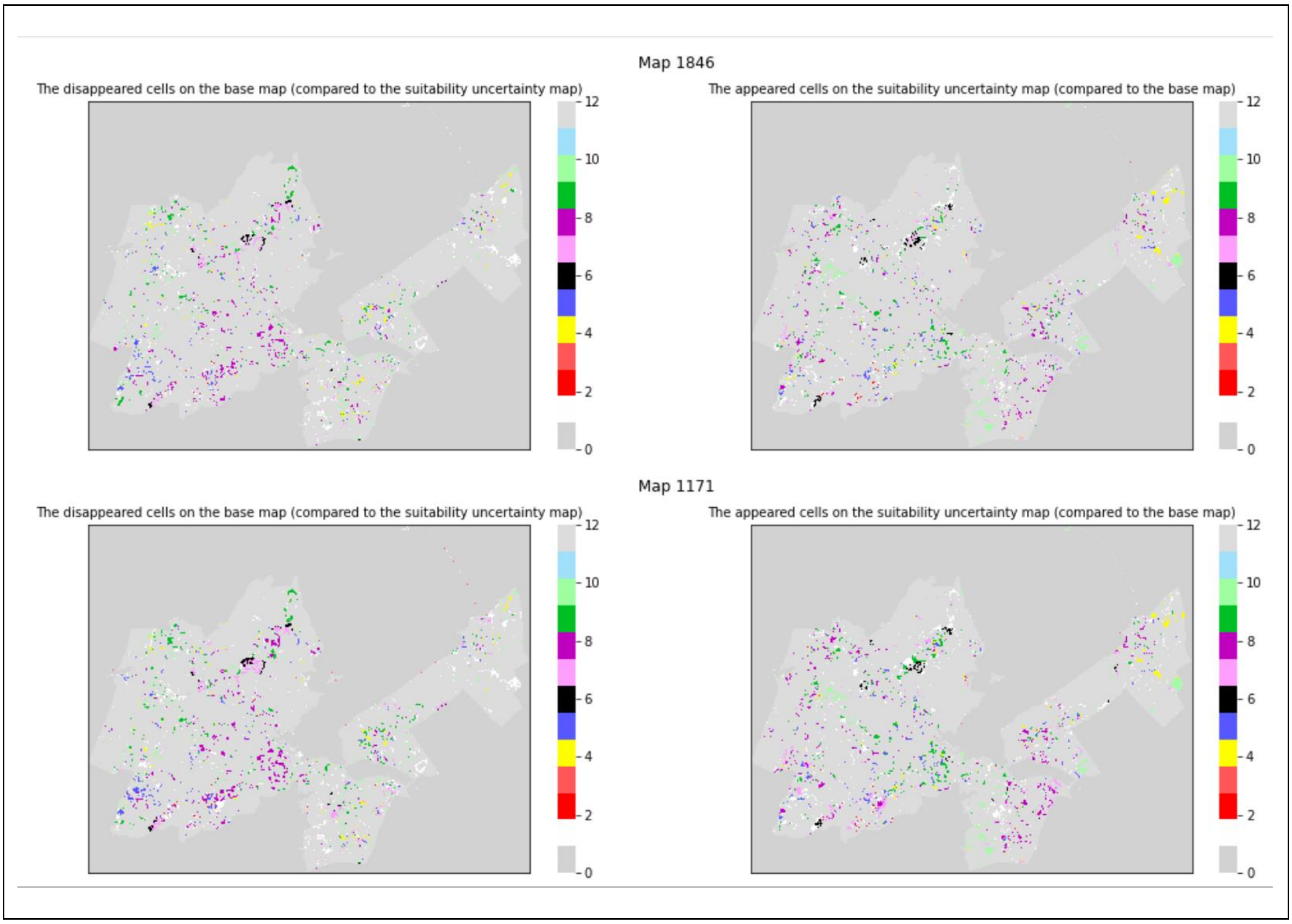


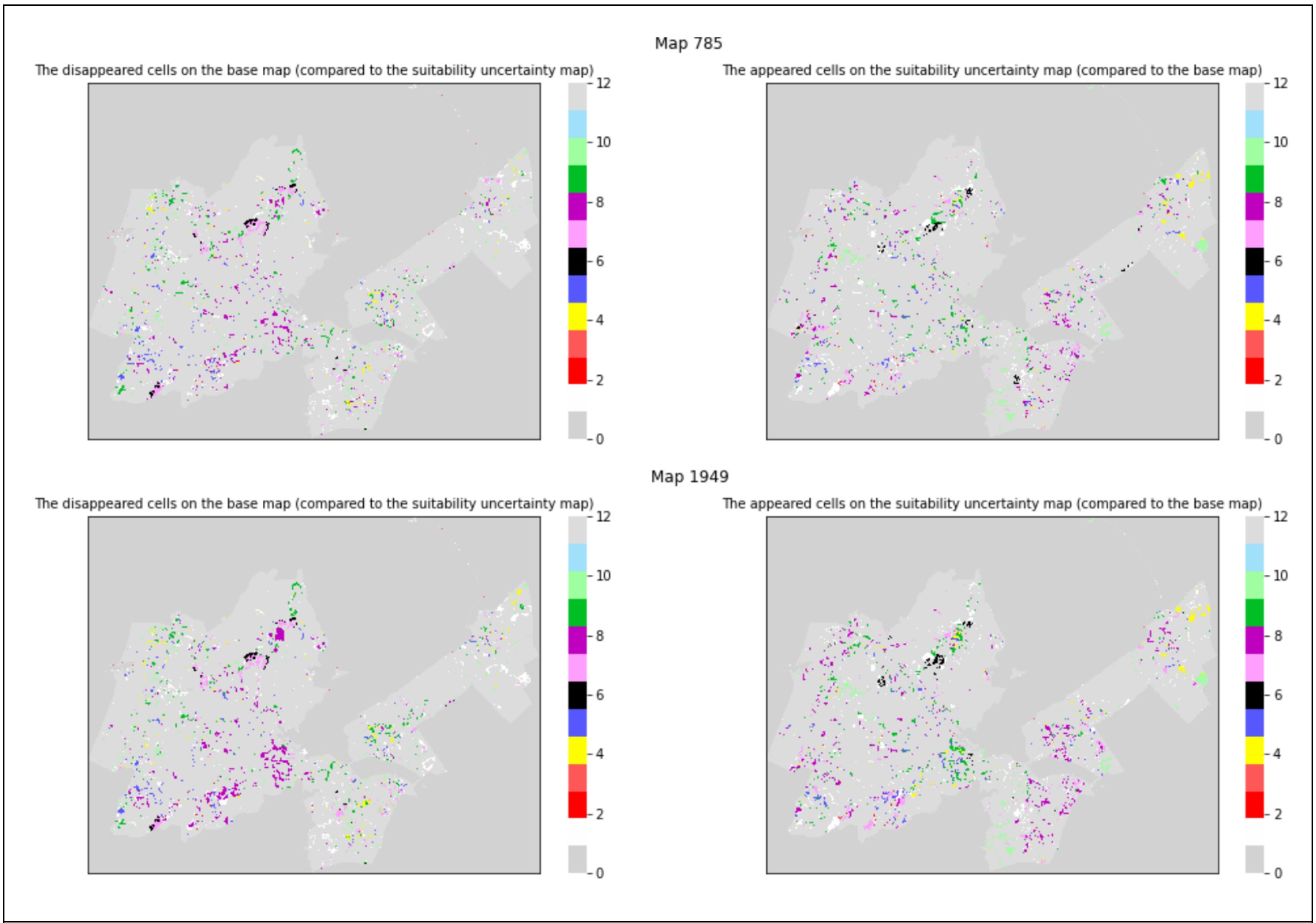
Annex 6 Comparison results of the representative maps with the base map

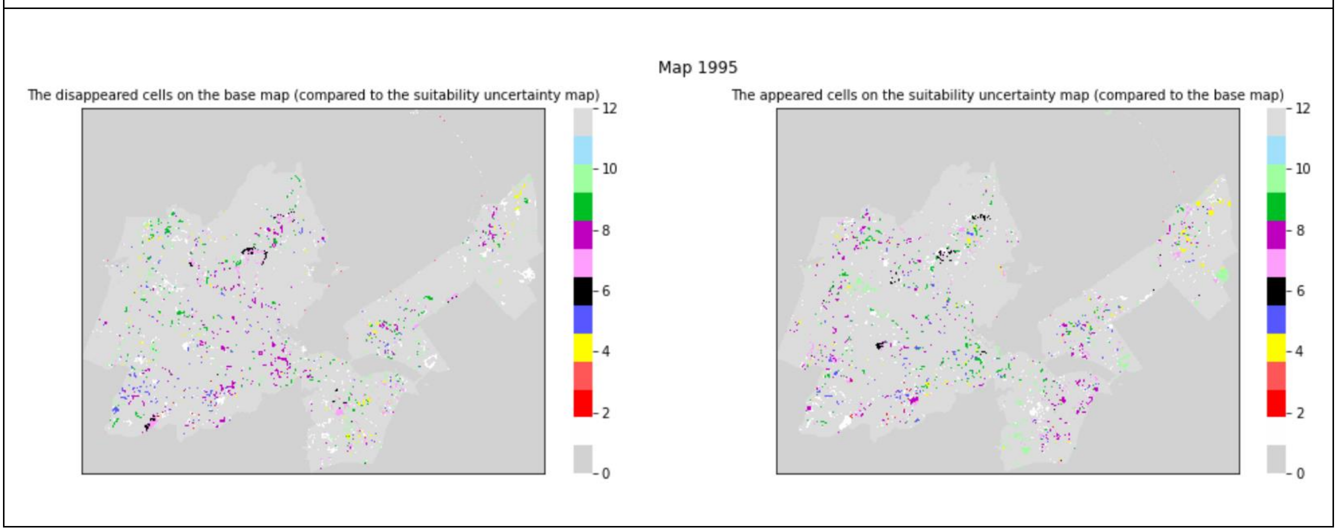
(0 = “outside”; 1 = “agriculture”; 2= ‘greenhouses”; 4= “public amenities”; 5= “commercial”; 6=’residential (L)’; 7= “residential(M”) ; 8= “residential(H); 9= ‘recreation”, 10=”nature”, 12=”all the unchanged cells”)

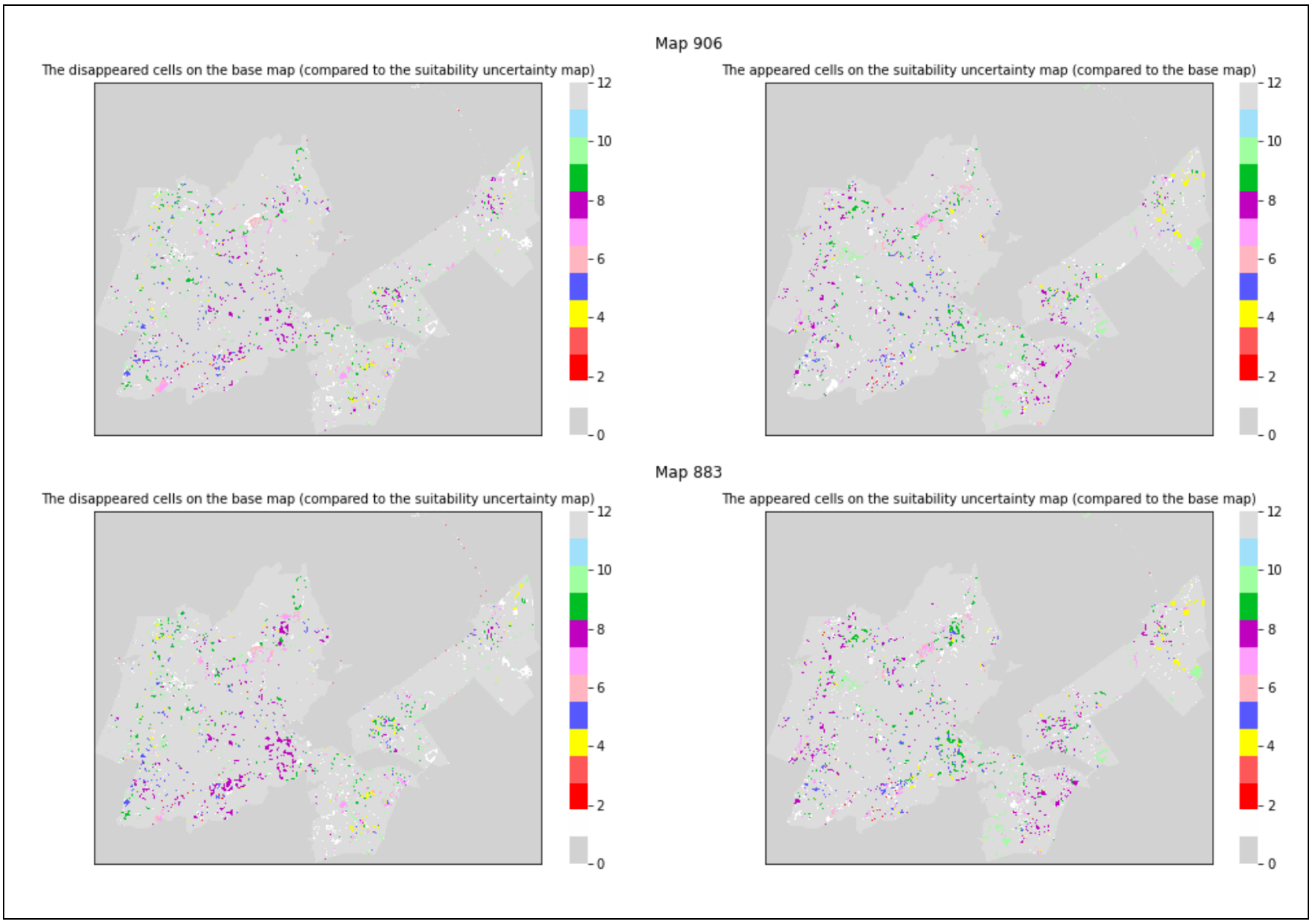


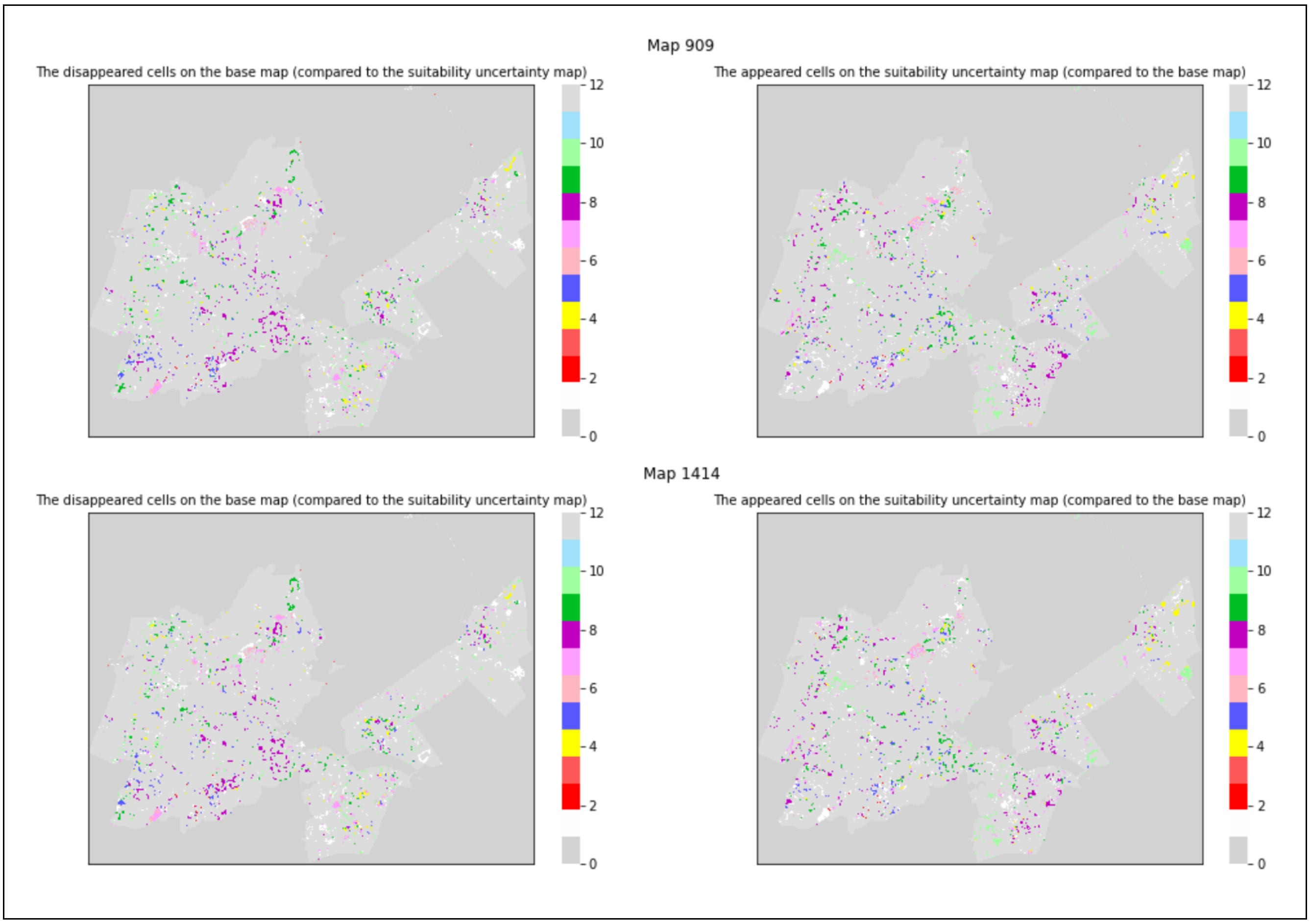

Map 1726
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0
Map 783
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)


Map 1846
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0
Map 1171
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0

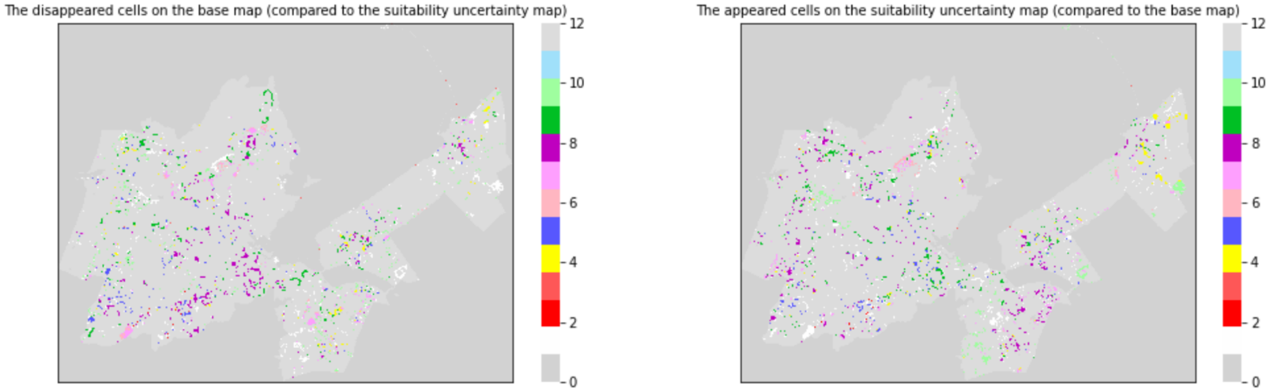

Map 785
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0
Map 1949
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0


Map 1995
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0

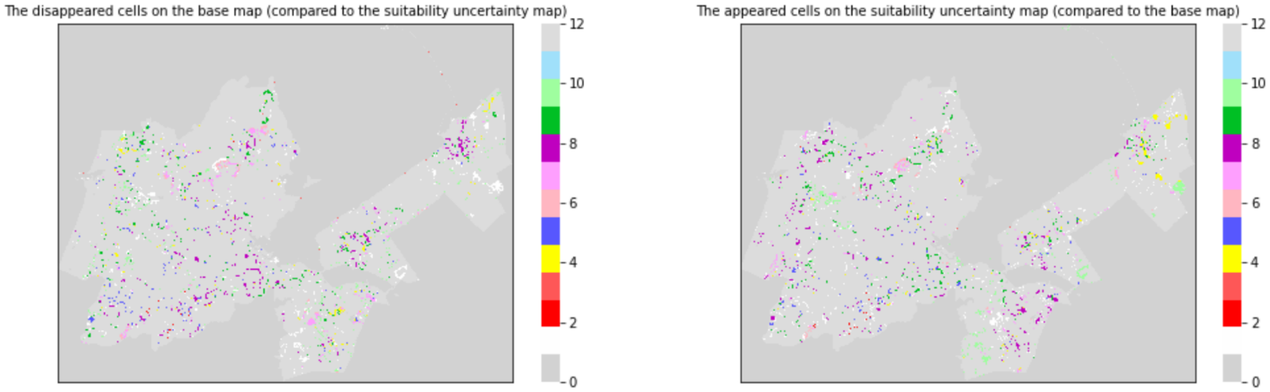

Map 906
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0
Map 883
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0


Map 909
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)
12
10
8
6
4
2
0
Map 1414
The disappeared cells on the base map (compared to the suitability uncertainty map)
The appeared cells on the suitability uncertainty map (compared to the base map)

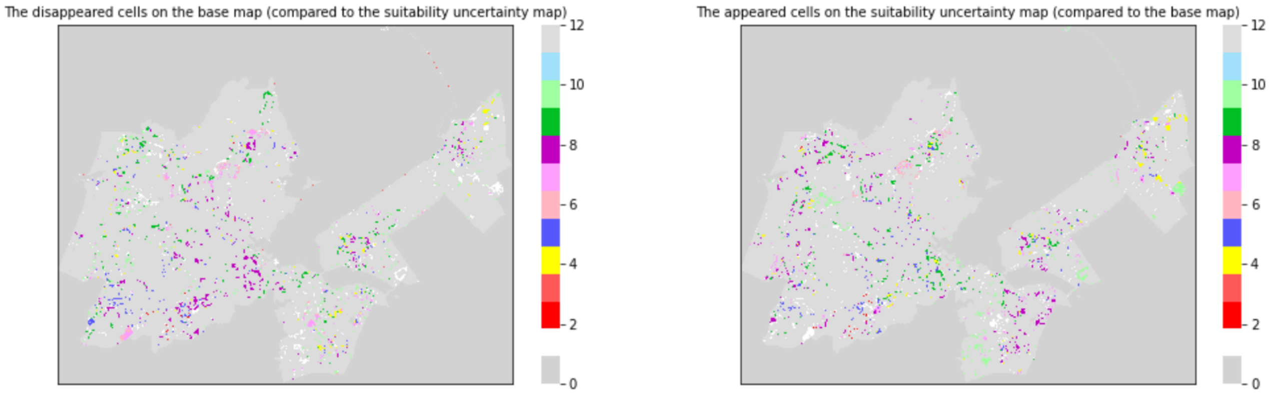
Map 1131



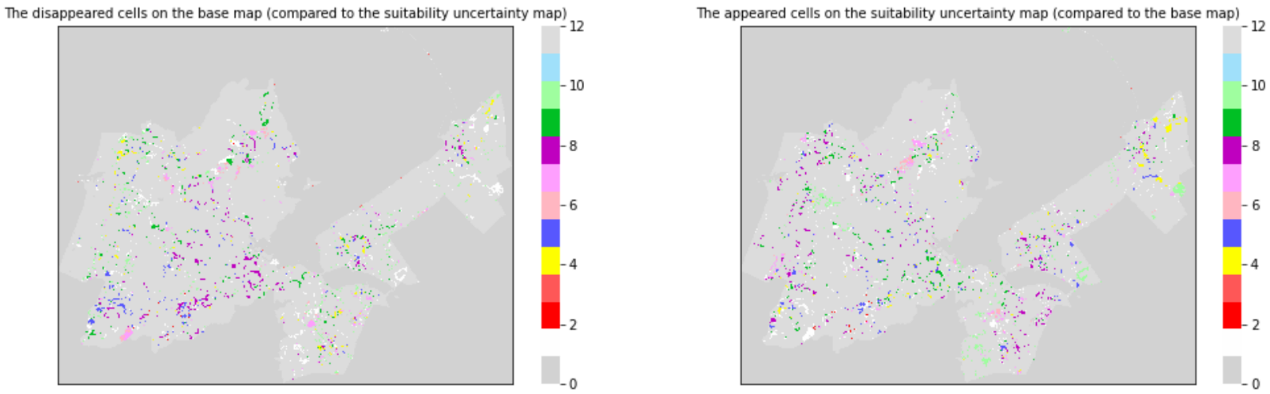
Map 708



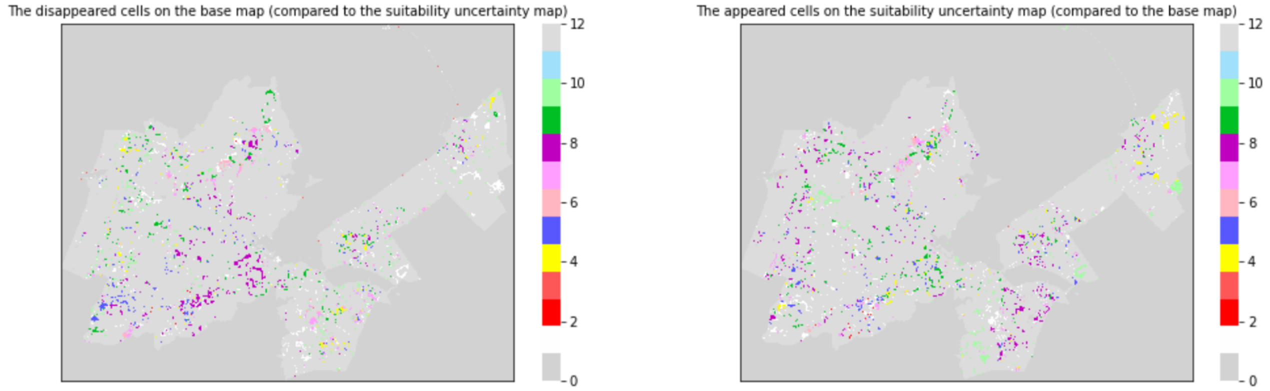
Map 1338



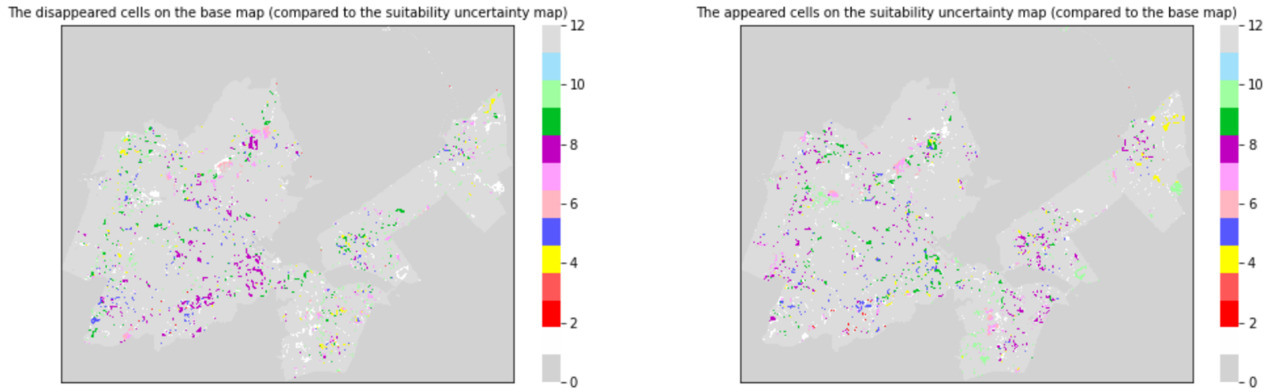
Map 1875



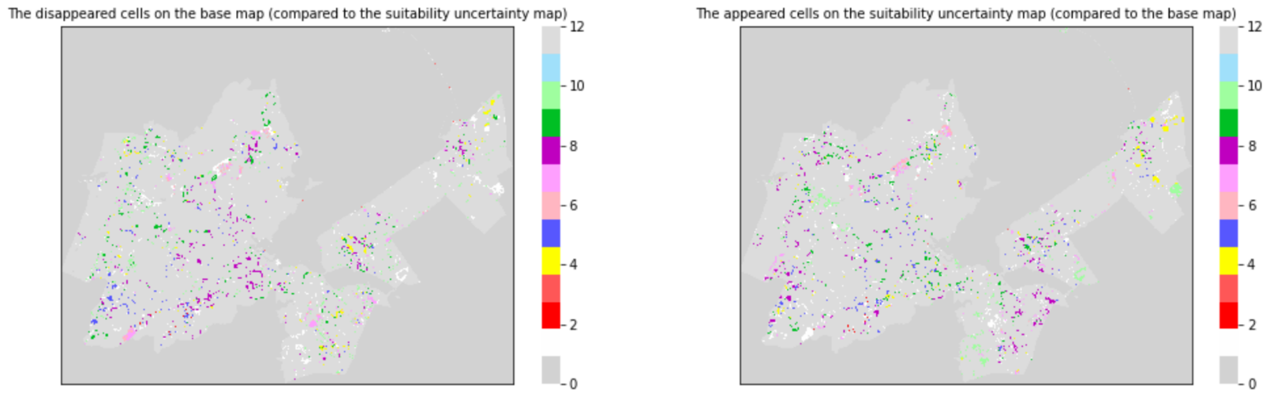
Map 1951



Map 1737

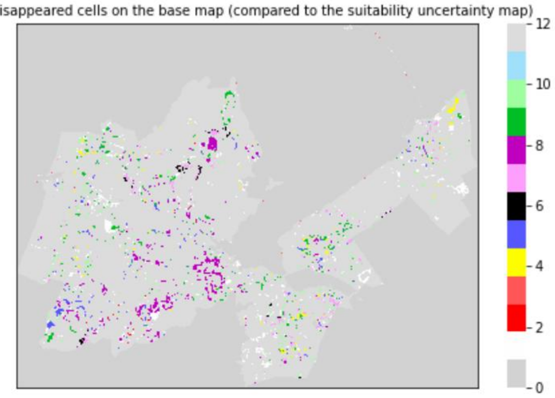


Map 1964

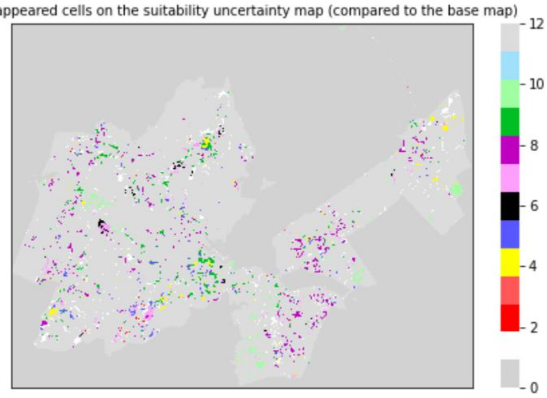


Map 1366

The disappeared cells on the base map (compared to the suitability uncertainty map)

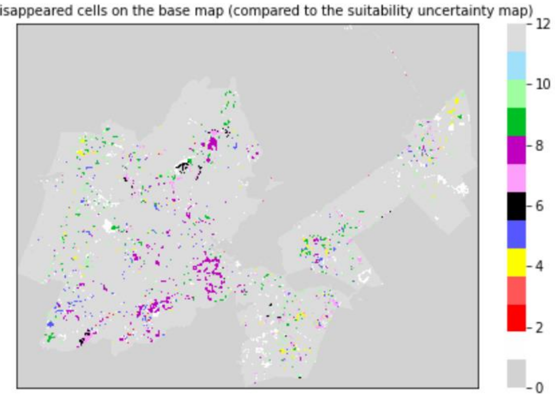


The appeared cells on the suitability uncertainty map (compared to the base map)

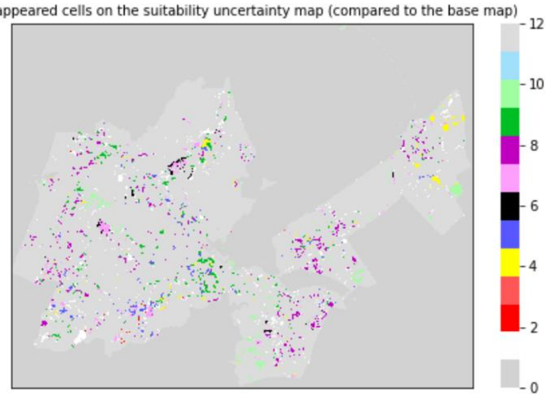


Map 1467

The disappeared cells on the base map (compared to the suitability uncertainty map)

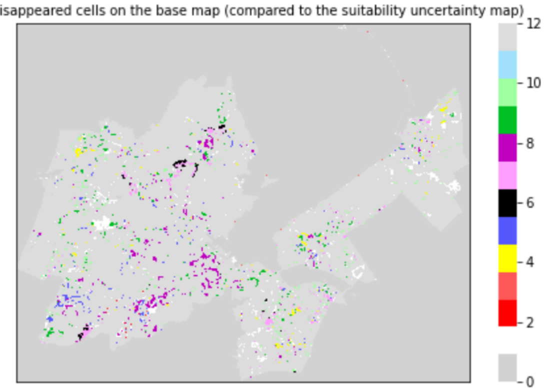


The appeared cells on the suitability uncertainty map (compared to the base map)

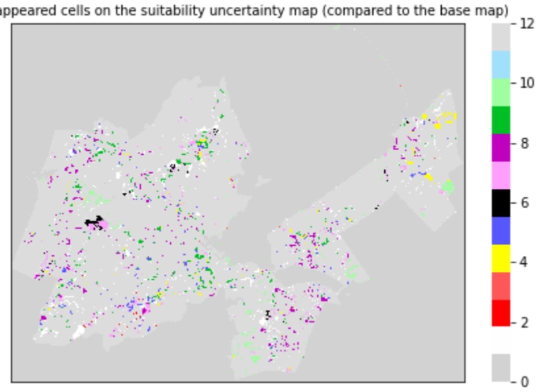


Map 1649

The disappeared cells on the base map (compared to the suitability uncertainty map)

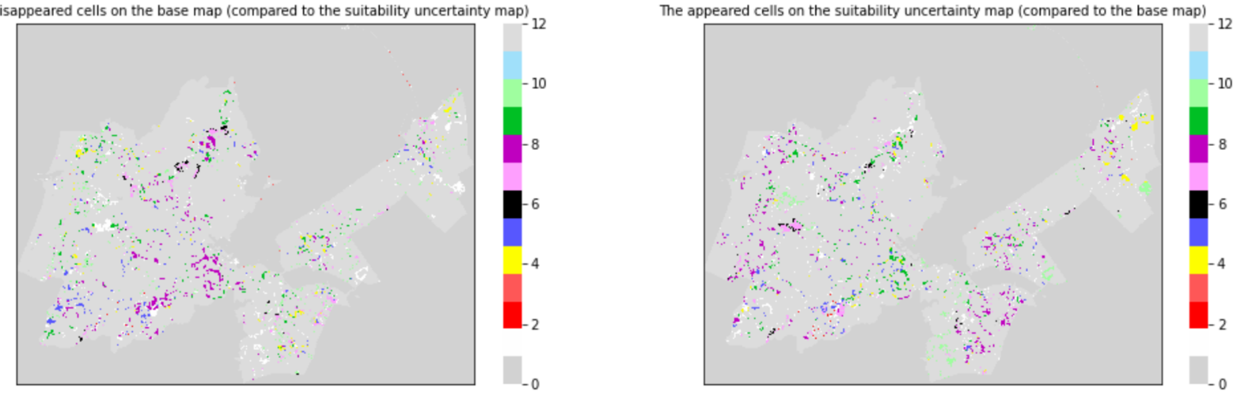


The appeared cells on the suitability uncertainty map (compared to the base map)



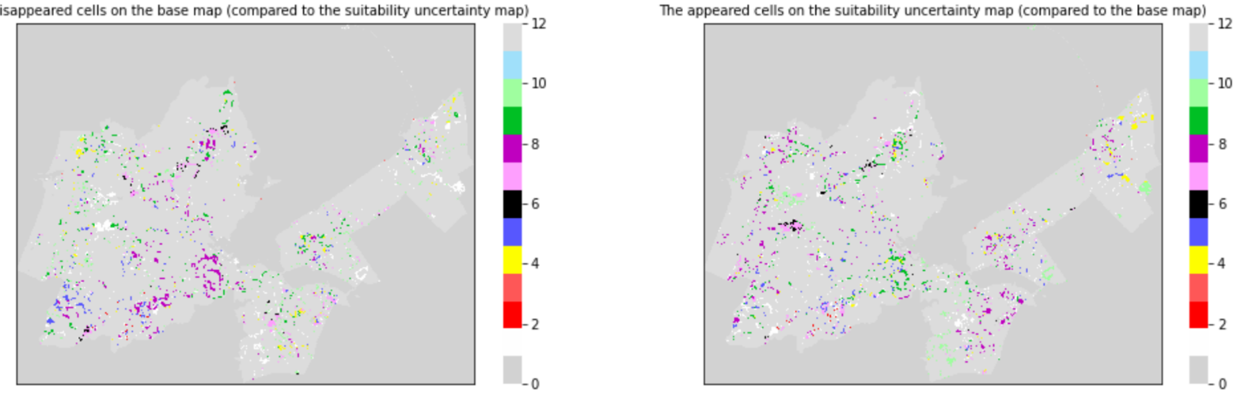
Map 178

The disappeared cells on the base map (compared to the suitability uncertainty map) | The appeared cells on the suitability uncertainty map (compared to the base map)



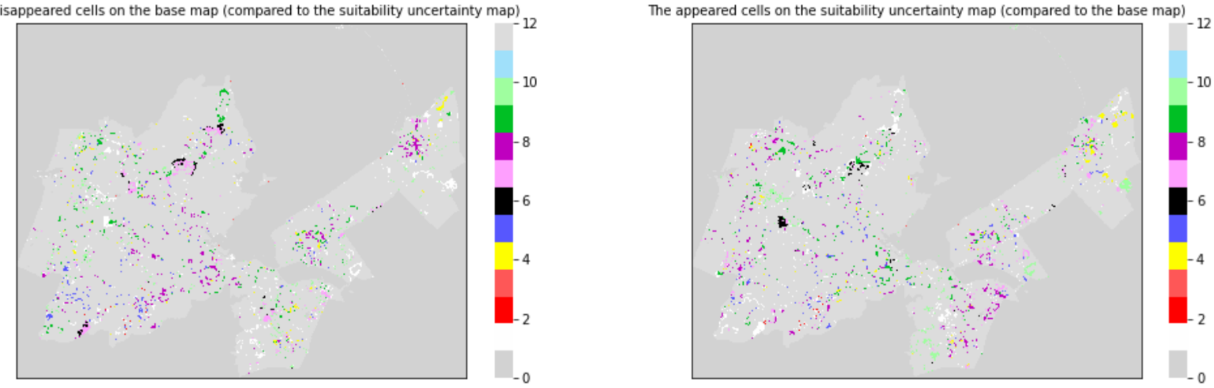
Map 1195

The disappeared cells on the base map (compared to the suitability uncertainty map) | The appeared cells on the suitability uncertainty map (compared to the base map)



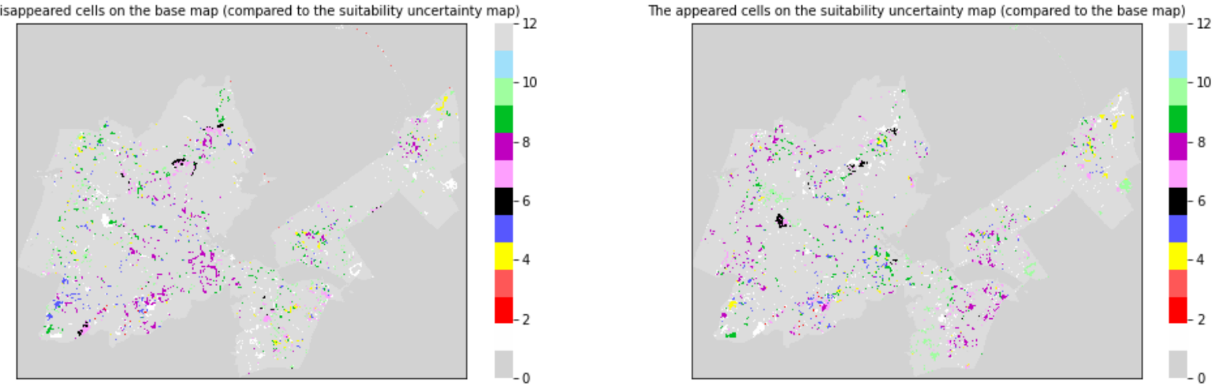
Map 1349

The disappeared cells on the base map (compared to the suitability uncertainty map) | The appeared cells on the suitability uncertainty map (compared to the base map)

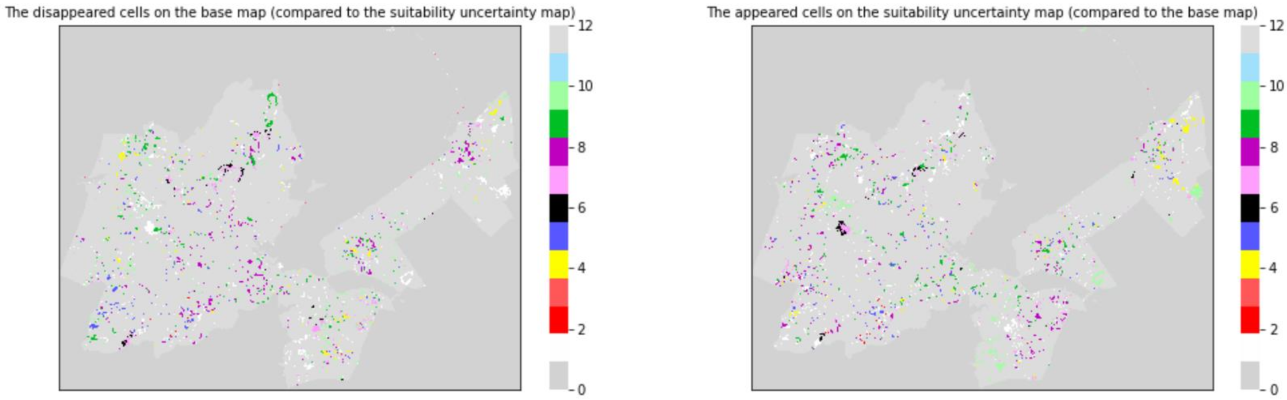


Map 531

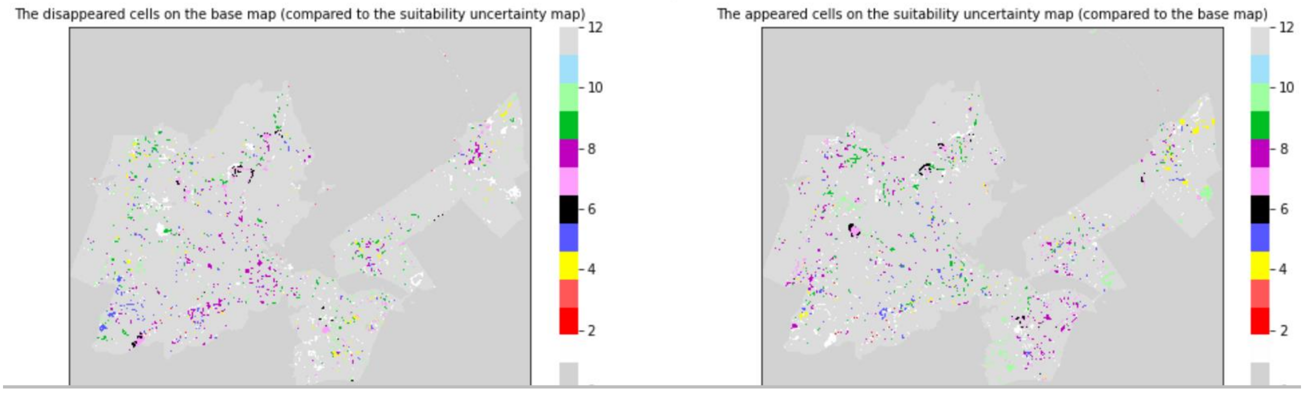
The disappeared cells on the base map (compared to the suitability uncertainty map) | The appeared cells on the suitability uncertainty map (compared to the base map)



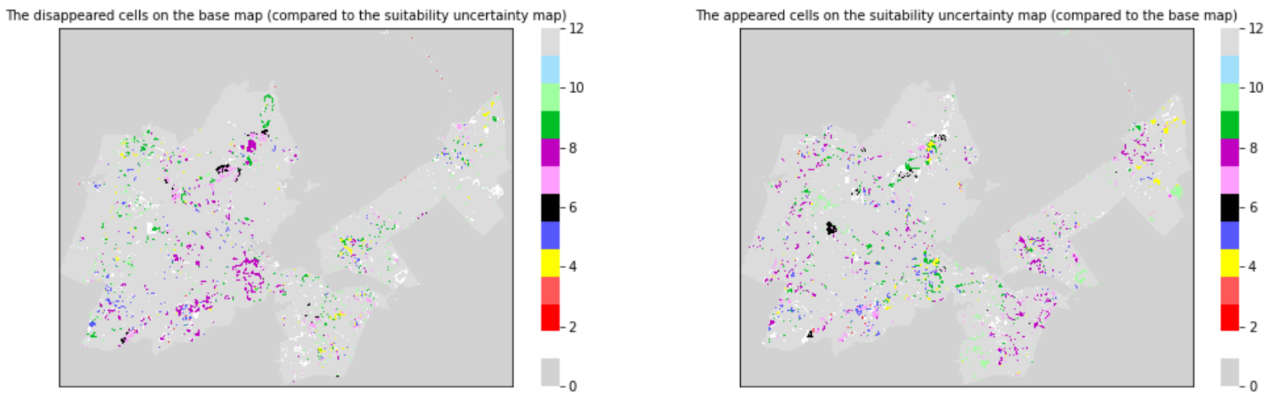
Map 1110



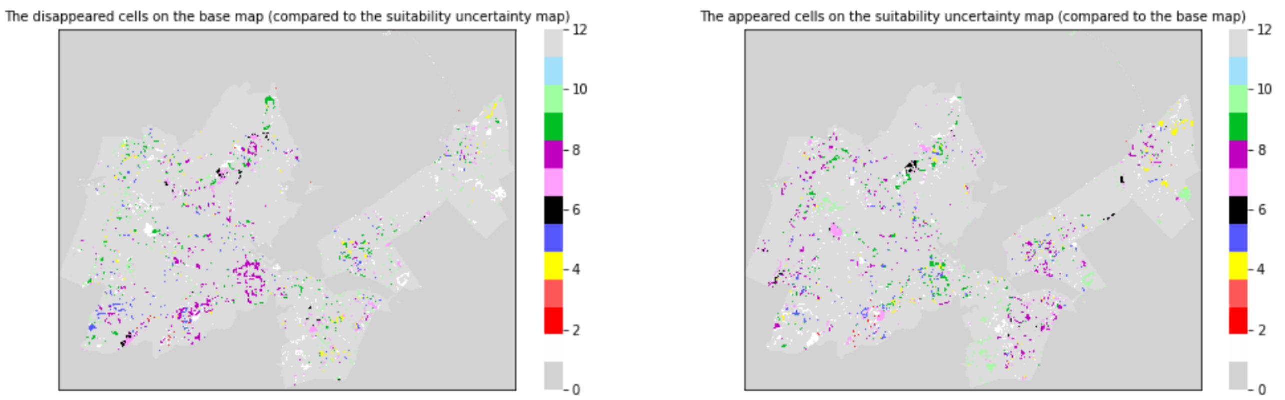
Map 938



Map 208

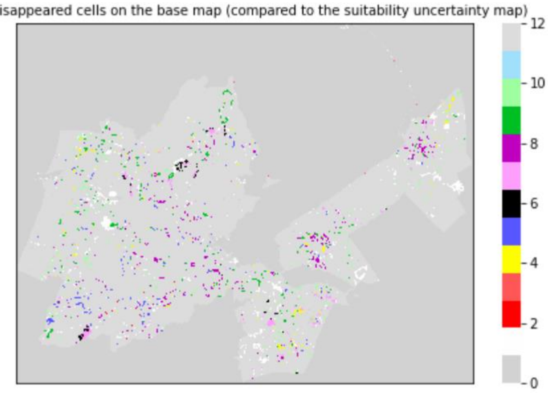


Map 1646



Map 577

The disappeared cells on the base map (compared to the suitability uncertainty map)



The appeared cells on the suitability uncertainty map (compared to the base map)