Scenario Discovery in land use change models

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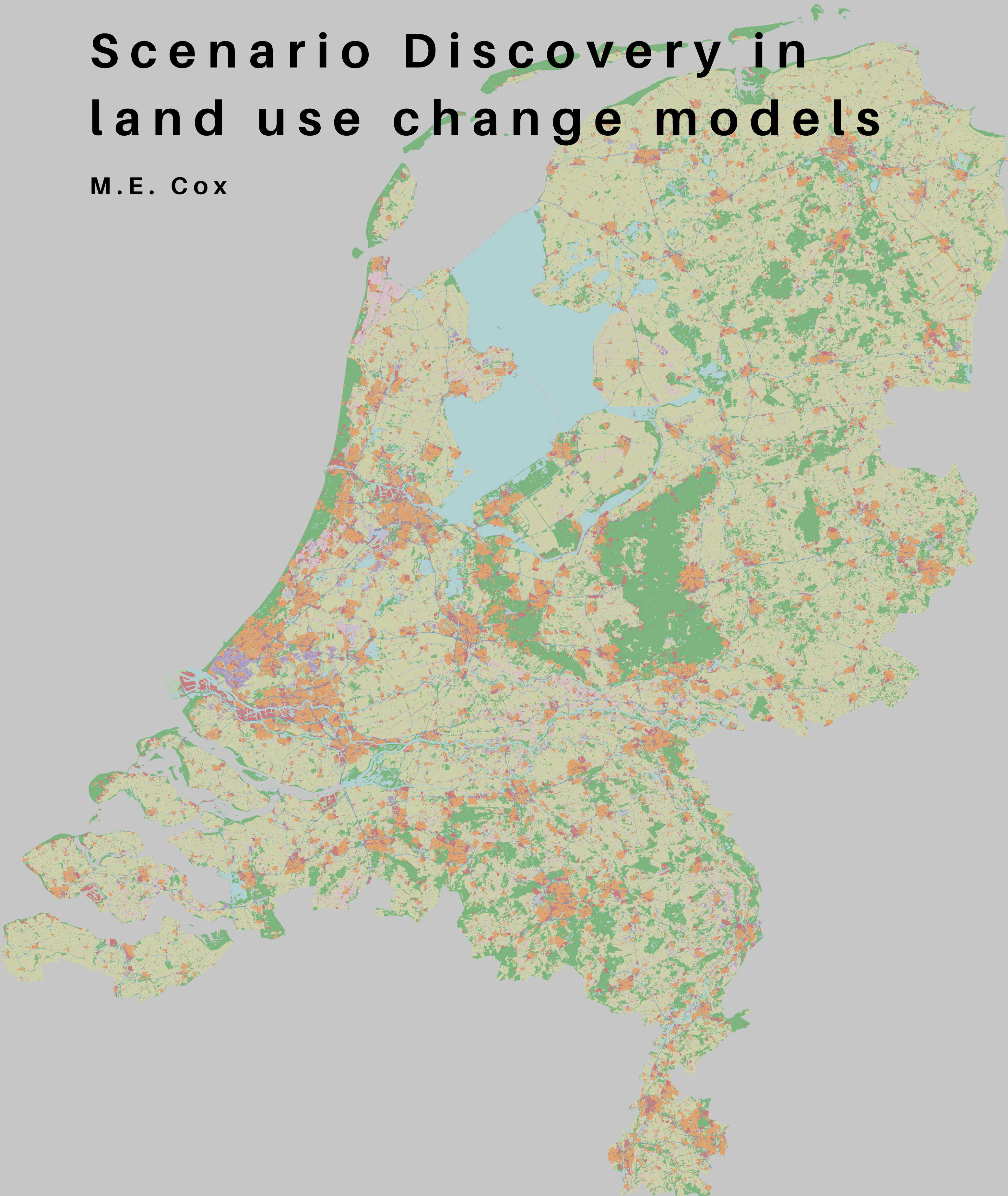
Scenario Discovery in land use change models

M.E. Cox



TU Delft

Executive Summary

The way land is used and how this use changes over time is a complex and dynamic process. Moreover, many grand challenges society faces today are influenced by land use and influences land use as well. Therefore, understanding the relationships between these challenges and land use can support policymakers in dealing with these challenges.

Using land-use change models, policymakers can explore possible developments of land use, the possible causes of these developments, and the consequences. However, understanding the dynamics of land use is a difficult task. Due to assumptions, simplifications, or lack of data when developing such models, many uncertainties remain concerning the driving forces and how they could play out in the future. Currently, to reduce uncertainty, a deductive scenario approach is the main method used in the land-use change modelling field. However, research points out that it remains difficult to deal with uncertainty, even though this intuitive scenario approach is used.

Another, yet less known, method to deal with uncertainties is the Scenario Discovery. In Scenario Discovery, rather than creating two to six scenarios based on the driving forces, statistical or data-mining algorithms are applied to a large number of simulation-model-generated results, generated by sampling over the relevant uncertain variables, to identify policy-relevant regions which are then translated back into comprehensible scenarios. However, this technique has not been implemented in the land-use change modelling field. Therefore, this research aims to compare the currently dominant approach, the deductive scenario approach, to this new approach, Scenario Discovery, when used in the land use modelling field. To do this, the Land Use Scanner model is used to identify scenarios with the usage of Scenario Discovery, as this model has been validated and applied in various fields. This model was used in earlier research in the simulation of future land use patterns using the so-called Delta Scenarios. These Delta Scenarios and their corresponding future land use patterns simulated with the Land Use Scanner model are used to compare to the results of this research.

The main research question is:

In which ways are scenarios identified with Scenario Discovery different from, or similar to, the Delta Scenarios, when generated with the aid of land-use change models?

To implement Scenario Discovery, the Exploratory Modelling and Analysis (EMA) Workbench is used. This open-source workbench is a tool in Python which enables modellers to implement Scenario Discovery in various models. The EMA workbench enables the generation and analysis of experiments. Using the EMA Workbench, one is able to use a sampling algorithm which systematically samples over the defined input variables and their provided value ranges.

Together with the Land Use Scanner model and the EMA workbench, 2000 experiments were generated, which were clustered into six clusters. With the CART subspace portioning algorithm, the important driving forces behind each cluster are identified. These clusters and their corresponding driving forces formed the base for scenario development. Thus, six scenarios were developed.

This research has demonstrated the use of an alternative way for scenario development, namely, Scenario Discovery. The results indicate that this approach is capable of generating a number of model-driven scenarios in a way that provides additional insights into the complex system of land-use change, which were otherwise overlooked. The six Scenario Discovery scenarios have different land-use patterns than

the Delta Scenarios. Although some land-use classes show similar land-use patterns, not one Delta Scenario is the exact same as the Scenario Discovery scenarios and vice versa. Looking at the driving forces characterising the Delta Scenarios and Scenario Discovery scenarios, the source of the differences in land use patterns can be identified. Moreover, both sets of scenarios also differ in which driving forces are considered as important. While all the important driving forces in the Scenario Discovery scenarios are also considered as important in the Delta Scenarios, not all important driving forces of the Delta Scenarios are considered as important for the Scenario Discovery scenarios. Only the demand for houses and jobs, spatial development policy, nature policy and policy stimuli, and the importance of nature location factors are considered as important driving forces in both sets of scenarios.

Another interesting difference is the fact that whereas each Delta Scenario emerges from one unique scenario narrative, each Scenario Discovery scenario has multiple possible combinations of driving forces leading to the land-use patterns of that specific scenario. Also, some of the Scenario Discovery scenarios have similar driving forces, while still resulting in different land-use patterns. In contrast, the driving forces characterising the Delta Scenarios hardly show any similarities at all.

This research resulted in six scenarios which differ from the Delta Scenarios in the narrative and the corresponding land-use patterns. However, the Scenario Discovery scenarios differ in other ways as well. Firstly, the development of the Scenario Discovery scenarios makes the analyst aware of under which conditions a combination of similar driving forces lead to different land-use patterns. Also, this approach makes the analyst aware under which conditions combinations of different driving forces still yield similar land-use patterns. Next to this, the Scenario Discovery scenarios show which driving forces are most important. Overall, this means that the scenarios identified with Scenario Discovery differ from the Delta Scenarios in the way that they provide analysts and policymakers with several insights, which can support sufficient informed decision making, which are overlooked when with the development and use of the Delta Scenarios.

As this research demonstrated the potential of Scenario Discovery in the land-use change modelling field, it is recommended for land-use change model users, such as LUS model users, to use Scenario Discovery for the development of scenarios. To do so, it is also recommended to increase research into the necessary steps of Scenario Discovery in the land-use change modelling field, such as the calculation of land use map similarity, the clustering process and the identification of driving forces. As for the decision-makers in spatial planning, it is recommended to involve land-use change models more into the decision-making process by increasing research into the use of different scenario development approaches namely Scenario Discovery. Instead of only using the land-use change models for the simulation of pre-defined scenarios, these models should be used as scenario generators, using Scenario Discovery, in order to use these models up to their full potential. Lastly, on a more general note, the use of story and simulation approaches in model-based decision making should be reconsidered, and instead, it is recommended to research the possibilities of Scenario Discovery in various modelling fields.

Preface

This thesis has been written to fulfil the graduation requirements for my master, Engineering and Policy Analysis at Delft University of Technology. I am happy to have received the opportunity to work on this subject, as it combined many of my interests such as spatial planning, societal challenges, and model-based decision making. I also feel lucky to have been able to work with the Land Use Scanner model, which has been made available to me by the VU University Amsterdam.

Firstly, I would like to thank Jip Claassens, who prepared the Land Use Scanner model for the use of this thesis. Without his help, I would still be lost in in the maze that is the Land Use Scanner model.

Next, I would like to thank Bramka Arga Jafino for his guidance and unending support during this research. I really appreciate all the time he spent on providing me with the necessary elements of this research, clear explanations on just about anything, running the experiments (twice), and critical feedback. Even for the smallest questions, he found time to help me out.

I also would like to thank Jan Kwakkel, who was my thesis supervisor. Although, due to the current circumstances, we have seen less from each other than expected during this process, the meetings were to the point and very helpful. I would also like to thank Jaco Quist for his critical questions and help in structuring my thesis report.

Lastly, I want to thank my family and friends who always, even from a distance, were there to support and motivate me.

Margriet Cox

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Chapter 1

Introduction

The way land is used and how this use changes over time is a complex and dynamic process (Koomen & Stillwell, 2007). This process has direct impacts on soil, water and atmosphere and therefore affects many aspects of life (Turner & Meyer, 1994). For example, one could imagine that replacing forests with agriculture influences the biodiversity of that area. Moreover, many grand challenges society faces today are influenced by land use and influences land use as well. Examples of such challenges are climate change, water management, food production and urbanisation (Dale, 1997; Koomen & Stillwell, 2007; Watson et al., 2000). Therefore, understanding the relationships between these challenges and land use can support policymakers in dealing with these challenges (Verburg et al., 2004).

To understand the dynamics of land use, the driving forces which drive these dynamics must be identified and understood. When policymakers understand these driving forces and dynamics, it could support them in planning and policy development. This is where land-use change models come into play, as a tool to support decision making in spatial planning (Verburg, Tabeau & Hatna, 2013). With land-use change models, policymakers can explore possible developments of land use, the possible causes of these developments, and the consequences (Verburg et al., 2004). However, understanding the dynamics of land use is a difficult task. Due to assumptions, simplifications, or lack of data when developing such models, many uncertainties remain concerning these driving forces and how they could play out in the future (Verburg, Tabeau & Harna, 2013).

Currently, to reduce uncertainty, a deductive scenario approach is the primary method used in the land-use change modelling field (Koomen, Hilferink & Borsboom-van Beurden, 2011; Rounsevel et al., 2006; Verburg, Tabeau & Hatna, 2013; Dekkers, Koomen, Jacobs-Crisioni & Rijken, 2012; Mallampalli et al., 2016). One example is the Land Use Scanner model (LUS model), a GIS-based model which simulates future land use using a deductive scenario approach (Koomen, Hilferink & Borsboom-van Beurden, 2011). More specifically, this LUS model simulates future spatial development using the Dutch Delta Scenarios, developed by Deltares. These scenarios, containing four scenario narratives, were developed to gain more insight into future water-related developments (Bruggemann et al., 2013).

However, research points out that even with this intuitive scenario approach, it remains difficult to deal with uncertainty. Firstly, developed scenarios are often biased due to the specific interests and goals of the analyst (Bryson, piper & Rounsevell, 2010; Parson, Burkett, Fisher- Vanden, Keith, Meams, Pitcher & Webster, 2007). Also, using only a few scenarios leaves large parts of the total uncertainty space undiscovered (Bryant & Lempert, 2010; Kwakkel & Pruyt, 2013; Lamontagne et al., 2018; Schweizer, 2018). Both bias and the reduction of uncertainty can leave policy-relevant futures undetected.

Another, yet less known, method to deal with uncertainties is the Scenario Discovery (Bryant & Lempert, 2010; Kwakkel & Pruyt, 2013; Lempert, Bryant & Bankes, 2008). In Scenario Discovery, rather than creating two to six scenarios based on the driving forces, statistical or data-mining algorithms are applied to a large number of simulation-model-generated results, generated by sampling over the relevant uncertain variables, to identify policy-relevant regions which are then translated back into comprehensible scenarios (Bryant & Lempert, 2010; Kwakkel & Pruyt, 2013). However, this technique has not been implemented in the land-use change modelling field. Therefore, this research aims to compare the currently dominant approach, the deductive scenario approach, to this new approach, Scenario Discovery, when used in the land use modelling field. The main research question is:

In which ways are scenarios identified with Scenario Discovery different from, or similar to, the Delta Scenarios, when generated with the aid of land use change models?

To answer this research question, the LUS model is used to identify scenarios with the usage of Scenario Discovery, as this model has been validated and applied in various fields (Koomen, Hilferink & Borsboom-van Beurden, 2011). Previous research by the "Vrije Universiteit Amsterdam" (VU Amsterdam), a university in Amsterdam, has used this LUS model to simulate the previously mentioned Delta Scenarios (Claassens, Koomen & Rijken, 2017). This research by VU Amsterdam, and the resulting simulated Delta Scenarios with the LUS model, is used to compare with scenarios generated with the LUS model using Scenario Discovery.

Considering the research gap and research aim, three sub-questions are formulated in order to answer the main research question:

1. *What uncertainties exist in the Land Use Scanner model?*
2. *Given a selection of uncertainties, what are possible future land use patterns and their conditions for occurring?*
3. *What are the main similarities and differences between the Delta Scenarios and the scenarios developed with Scenario Discovery?*

The first sub-question serves to gain more insight into which uncertainties exist in the Delta Scenarios and the LUS model. Here, it is also identified how these uncertainties are, or are not, implemented in the LUS model. From these identified uncertainties, a selection is made of uncertainties which are considered in this research. Based on the selected uncertainties and using Scenario Discovery, sub-question 2 will provide more insight into possible future land use patterns and what their conditions are for occurring. In other words, this sub-question aims to gain more insight into which combinations of uncertainties lead to what kind of future land use patterns. Lastly, sub-question 3 will compare the scenarios identified with the use of Scenario Discovery with the original Delta Scenarios. To do this, the findings from sub-question 2 are used to formulate new scenario narratives. These new scenario narratives are compared to the Delta Scenarios. This comparison will look into the similarities and differences between these scenario narratives by comparing the driving forces behind the resulting land-use patterns and the resulting future land use patterns themselves.

To allow fair comparison, the scope of this research is similar to the scope of the VU Amsterdam research. Firstly, this means the LUS model is used to model Dutch future land use patterns with a time horizon from 2012 to 2050. Moreover, the LUS model is originally part of a larger model chain, existing out of four main models (Rijken et al., 2013). Similar to the VU Amsterdam research, only the LUS model itself is within the scope of this research, although the output of models located earlier in this model chain is used as input for the LUS model. Also, the selection of uncertainties is limited to the uncertainties already recognised as uncertainties in the LUS model. Thus, the model is not altered by adding new parameters or changing the model structure. Lastly, the main focus of comparison is on comparing the results of the two approaches, rather than the comparison of the approaches itself.

In the following report, chapter 2 contains a literature review on the topics discussed in this introduction. Next, chapter 3 will discuss the methods used for this research. In chapter 4, the uncertainty identification and classification will be discussed, answering the first sub research question. Chapter 5 will follow the steps of Scenario Discovery and elaborate on the results of this process. Then, chapter 6 will introduce the Scenario Discovery scenarios and compare the results of Scenario Discovery to the Delta Scenarios. Chapter 7 contains the discussion and, lastly, chapter 8 contains the conclusion.

Chapter 2

Literature overview

This chapter firstly elaborates on the meaning of land-use change and will discuss land-use change models. Next, section 2.2 discusses uncertainty in model-based decision making, and different scenario development approaches. Lastly, section 2.3 summarises the key findings of the literature overview.

2.1 Land use change and land use change models

Literature often makes the distinction between land use and land cover. Land use represents the actual use of lands, such as agriculture or residential use, whereas land cover is what can be observed, such as grass or buildings (Lambin et al., 2001). In this research, the term land use covers both land use and land cover.

Land-use change is the process that links together natural and human systems (Koomen & Stillwell, 2007). The relationship between natural and human systems is interdependent. This means that human decisions have impacts on the environment, and the environment has impacts on human decisions (Turner & Meyer, 1994). Land-use change is caused by certain driving forces (Bürgi, Hersperger & Schneeberger, 2005). Five major categories of driving forces are distinguished, namely socioeconomic, political, technological, natural, and cultural driving forces (Brandt, Primdahl & Reenberg, 1999). Economic driving forces are, for example, consumer demands or governmental subsidies and incentives. Political driving forces are the policies relevant to a specific area. Technological driving forces include not only human-made artefacts but also the knowledge of different processes. Natural driving forces include current land use and other land characteristics, such as type of soil and general topography. Lastly, cultural driving forces address societal developments and the way people live. These driving forces do not act independently but form a complex system of dependencies and interactions which drive land use in different ways (Hersperger & Bürgi, 2007).

Land use is related to many environmental issues. Firstly, land use affects climate change and human-induced climate change affects land use (Dale, 1997; Likens & Cronon, 2012; Watson et al., 2000). For example, land used for industrial manufacturing emits CO2, which increases climate change. In turn, sea levels rise due to climate change, which influences the way land is used in delta areas in order to adapt to the new circumstances. Another example is how urbanisation pressures existing areas which fulfil essential roles such as the conservation of biodiversity (Koomen & Stillwell, 2007).

Land-use change models are used to simulate the complex interaction between natural and social systems. According to Verburg et al. (2004), land-use change models are tools to support the analysis of the causes and consequences of land-use change. Currently, different operational land-use change models exist (Koomen & Stillwell, 2007). These land-use change models use different modelling approaches and vary in theoretical backgrounds (Verburg et al., 2004).

Different land-use models use different scales. Scale refers to the extent and resolution of a land-use change model. In this case, the extent is the magnitude of a dimension used in measuring, and the resolution refers to the precision used for this measuring (Verburg et al., 2004). It is possible to build multi-scale land-use models, which is useful since some features in land-use change, such as the driving factors, are scale-dependent. However, most models are based on one scale due to practical reasons (Verburg et al., 2004). Next to scale, land-use models can also differ in temporal dynamics as land-use models are static or dynamic. Where static models directly calculate the land use at a certain point in time, dynamic models use time-steps and take initial land use into account (Koomen & Stillwell, 2007; Verburg et al., 2004).

Another feature of land-use change models is the driving forces and spatial interactions (Verburg et al., 2004). In land-use change modelling, driving forces are often considered exogenous to the land-use system (Verburg et al., 2004). These driving forces thus often relate to the input parameters of land-use change models. Apart from driving forces, land use pattern changes are also influenced by the current land use, and surrounding land uses due to the so-called neighbourhood effect (van Vliet et al., 2016). More land-use models are implementing these neighbourhood effects (Verburg et al., 2004).

2.2 Dealing with uncertainty

Outcomes of models representing this complex world are misleading (Kwakkel & Pruyt, 2013). Models, including land-use change models, are built upon assumptions and know many uncertainties (Koomen, Hilferink & Borsboom-van Beurden, 2011). Land-use change models represent complex socio-ecological systems. As a result, land-use models suffer from high levels of uncertainty due to incomplete knowledge and lack of data, strong simplifications and assumptions (Mallampalli et al., 2016; Rounsevell et al., 2006; Verburg, Tabeau & Hatna, 2013). Moreover, it is not possible to decrease the level of uncertainty by gathering more data and information, as inherent uncertainty remains in demographic, economic and political developments (Koomen, Hilferink & Borsboom-van Beurden, 2011; Verburg, Tabeau & Hatna, 2013).

Thus, analysts in the land-use change modelling field should be aware of and deal with uncertainty in one way or another. If uncertainties are ignored, the use of land-use change models leads to misleading conclusions or prevents the use of these models in the decision-making processes all together (García-Álvarez et al., 2019). This is to be prevented, as land-use change models have the potential to improve decision making in spatial planning.

A common approach to handle uncertainties is scenario development and scenario planning (Bishop, Hines & Collins, 2007; Bradfield et al., 2005). Many definitions and methodologies exist for scenario development and planning, which are categorised into three main schools of thoughts, namely: La prospective school, the probabilistic modified trends school and the intuitive logics school (Huss & Honton, 1987; Bradfield et al., 2005). Section 2.3.1 will elaborate more on the different scenario development approaches. Next, section 2.3.2 will discuss the use of scenario development in the land-use change modelling field.

2.2.1 Scenario development approaches

La Prospective emerged as a consequence of the failure of classical forecasting approaches and is developed by Gaston Berger and Michel Godet (Godet, 2012). The objective is generally to determine the most likely development of a particular phenomenon as to improve the effectiveness of policies (Bradfield et al., 2005). La Prospective school shares certain features of the Intuitive logic school but makes often use of computer-based mathematical models, comparable with the probabilistic modified trends school (Bradfield et al., 2005).

The probabilistic modified trends school exists out of two distinct methodologies, namely Trend Impact Analysis and Cross Impact Analysis (Huss & Honton, 1987). Trend-Impact Analysis uses historical data to create an independent forecast of the variable of interest. Next, this forecast is adjusted based on a list of unprecedented future events, their probability of occurrence and their expected impact(Huss & Honton, 1987; Bradfield et al., 2005). Cross-Impact Analysis was later developed due to the belief that a forecast based on one event in isolation of other possible events generated unrealistic outcomes (Huss & Honton, 1987). Therefore, Cross-Impact Analysis was developed to consider other relevant events when creating a forecast.

The methodology of the Intuitive logic school was proposed by Herman Kahn at the Rand Corporation and was implemented by Pierre Wack at Royal Dutch Shell (Bradfield et al., 2005; Wack, 1985). The intuitive scenario development approach is mostly applied in practice (Bishop, Hines & Collins, 2007). Scenarios developed using intuitive logic approaches can offer significant benefits for decision-makers who are dealing with deep uncertainty (Bryant & Lempert, 2010). The general belief of this approach is that policy decision is based on a wide variety of external factors. Consequently, to improve decision making a company must understand these external factors (Huss & Honton, 1987). Often the intuitive logic school is called the scenario axis approach (Bryant and Lempert, 2010). To develop scenarios, the first step is to identify key driving forces in the system (Bradfield et al., 2005). Next, the most uncertain and important driving forces are selected, which will form the axes necessary to develop scenarios (Bryant & Lempert, 2010; Groves & Lempert, 2007; Schwartz, 1991). Next, an internally consistent scenario narrative is created for each case (Bryant & Lempert, 2010). Lastly, the scenario outcomes should be assessed in terms of implications or potential impacts of the scenario assumptions (Swartz, 1991). An overview of this scenario approach is represented in Figure 2.1.

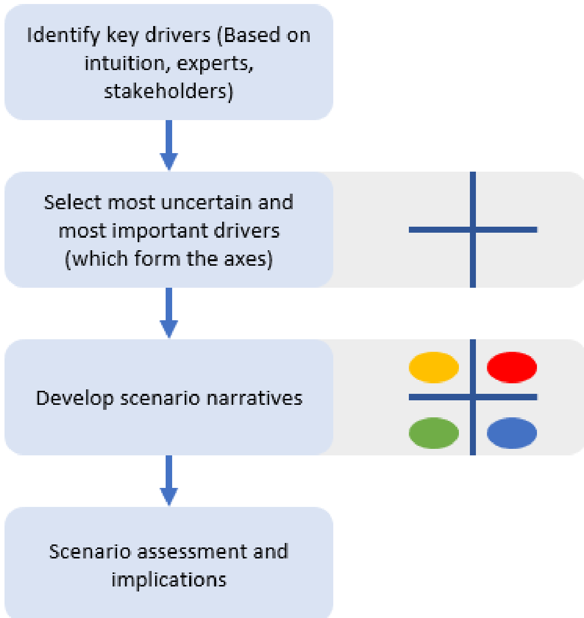


Figure 2.1: Intuitive scenario development approach

2.2.2 Scenario development in land use change modelling

The scenario development approaches described by the intuitive logics school are most discussed in the literature and applied in practice (Bradfield et al., 2005). Analysis of future land use patterns also often take this approach to deal with uncertainties (Mallampalli et al., 2016; Rounsevell et al., 2006; Verburg, Tabeau & Hatna, 2013). A distinction is often made between qualitative and quantitative scenario development approaches (Alcamo, 2008; van Delden & Hagen-Zanker, 2009; Kok & van Delden, 2009; Mallampalli et al., 2016). Qualitative scenarios are presented as written storylines which are understandable and interesting for readers, whereas quantitative scenarios, usually based on computer models, provide scenarios in numerical results (Alcamo, 2008). Both qualitative and quantitative scenario approaches have their benefits and, consequently, the two approaches are often combined in various fields, including the land-use change modelling field.

The story and simulation approach has been mostly applied to combine these two approaches (Alcamo, 2008; van Delden & Hagen-Zanker, 2009; Mallampalli et al., 2016). Figure 2.2 displays the steps of this story and simulation approach. The first step is to create scenario narratives. Nowadays, shared community scenarios are available, such as the Intergovernmental Panel on Climate Change's (IPCC) emission scenarios (Nakicenovic et al., 2000; Thompson et al., 2012). These shared community scenarios enable inter-study comparison across diverse disciplines (Lamontagne et al., 2018). In the second step, the scenarios narratives are quantified. In the land-use change modelling field, this implies that each scenario is represented by a combination of values of the parameters in the land-use change model (van Delden & Hagen-Zanker, 2009; Mallampalli et al., 2016; Rounsevell et al., 2006). Van Delden and Hagen-Zanker (2009) present a detailed application of the quantification of scenario narratives in land-use modelling. When the scenarios are quantified, the model can run the different simulations, each simulation run corresponding to a scenario. Lastly, the outcome of the simulation runs is assessed.

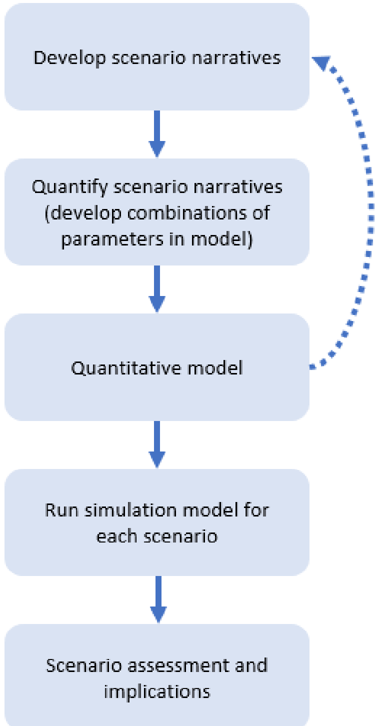


Figure 2.2: Story and simulation approach

Dealing with uncertainty in land-use change models remains difficult. In geospatial analysis, the presence of uncertainty forms one of the largest challenges (García-Álvarez et al., 2019). Although the development and use of scenarios have certain benefits when dealing with uncertainties, this method falls short in some areas. Firstly, the choice and development of scenarios prove to be a difficult task, especially when many parties are involved with different interests and values (Parson et al., 2007). When selecting the most important and uncertain driving factors, which will determine the scenarios, the bias in selection could lead to the exclusion of relevant information needed for the selection of the key driving forces (Parson et al., 2007). Moreover, it is difficult, if not impossible, to summarise the whole breadth of uncertainty in only three to six scenarios (Bryant & Lempert, 2010). By reducing the uncertainty a priori, by choosing the key driving forces, plausible futures could be excluded from the analysis (Lamontagne et al., 2018). Scenario development often systematically exclude surprising or paradoxical developments (Postma & Liebl, 2005). When the key driving forces are selected, it could also still be a difficult task to come to a consensus about what each scenario exactly means. Different parties could interpret the same scenario axes in different ways, therefore leading to different scenario narratives (van 't Klooster & van Asselt, 2006). Also, when quantifying the scenario narratives, this process itself is subject to personal judgements and assumptions (Verburg, Tabeau & Hatna, 2013). This can lead to many different scenario outcomes, even though the same scenario narratives are used (Metzget et al., 2010).

Due to these challenges, land-use models and the findings from such models are often not used in the decision-making process (Timmermans, Batty, Couclelis & Wegener, 2011). This is not the case for only land-use change models; climate models, in general, are often not used to their potential as decision-making support tools (Weaver, 2013). Therefore, this raises the question of whether or not the scenario development approaches as currently applied are sufficient enough.

2.2.3 Scenario Discovery

Scenario discovery builds on the intuitive logics school and addresses the challenges associated with scenario development approaches linked to the intuitive logics school (Bryant & Lempert, 2010). Scenario discovery is a model-driven approach that helps decision-makers to identify scenarios focussing on the futures relevant for policymakers (Bryant & Lempert, 2010; Lempert, Bryant & Bankes, 2008; Groves & Lempert, 2007). Scenario discovery typically starts with a model representation of the system, which is consistent with the available knowledge, data and information (Kwakkel, Auping & Pruyt, 2013). Then, using this model, simulations are run many times, where each simulation run has different combinations of values for the uncertain input parameters (Bryant & Lempert, 2010). Next, looking at the model outputs, subsets of cases of interest are selected. These subsets of cases of interest are selected to keep the focus on those futures most important for decision-makers (Bryant & Lempert, 2010). Statistical or data mining algorithms are applied to find the input space that has led to these subsets of cases of interest. These regions of input space can be considered as scenarios, where the input parameters corresponding to these regions of input become the key driving forces for the scenarios (Bryant & Lempert, 2010; Lempert, Bryant & Bankes, 2008).

Scenario discovery addresses some of the challenges known in scenario development approaches, as discussed in section 2.3.2. Firstly, with scenario discovery, it is not necessary to select the most important and uncertain driving factors before running the simulations (Bryant & Lempert, 2010). This way, bias from the analysts is less likely to interfere with the analysis of future developments. This also means that it is not necessary to reduce the uncertainty space a priori, as scenario discovery covers a much larger part of the uncertainty space. Scenario discovery implements a broad sampling over the uncertainty space (Lamontagne et al., 2018). Lamontagne et al. (2018) show in his research that this could lead to the discovery of policy-relevant simulation outcomes, and the responsible combination of key driving forces responsible for these outcomes, which would otherwise be undetected. Figure 2.3 shows the steps of the intuitive scenario approach, when used in model-based decision making, next to the scenario discovery approach to demonstrate the differences between the two approaches.

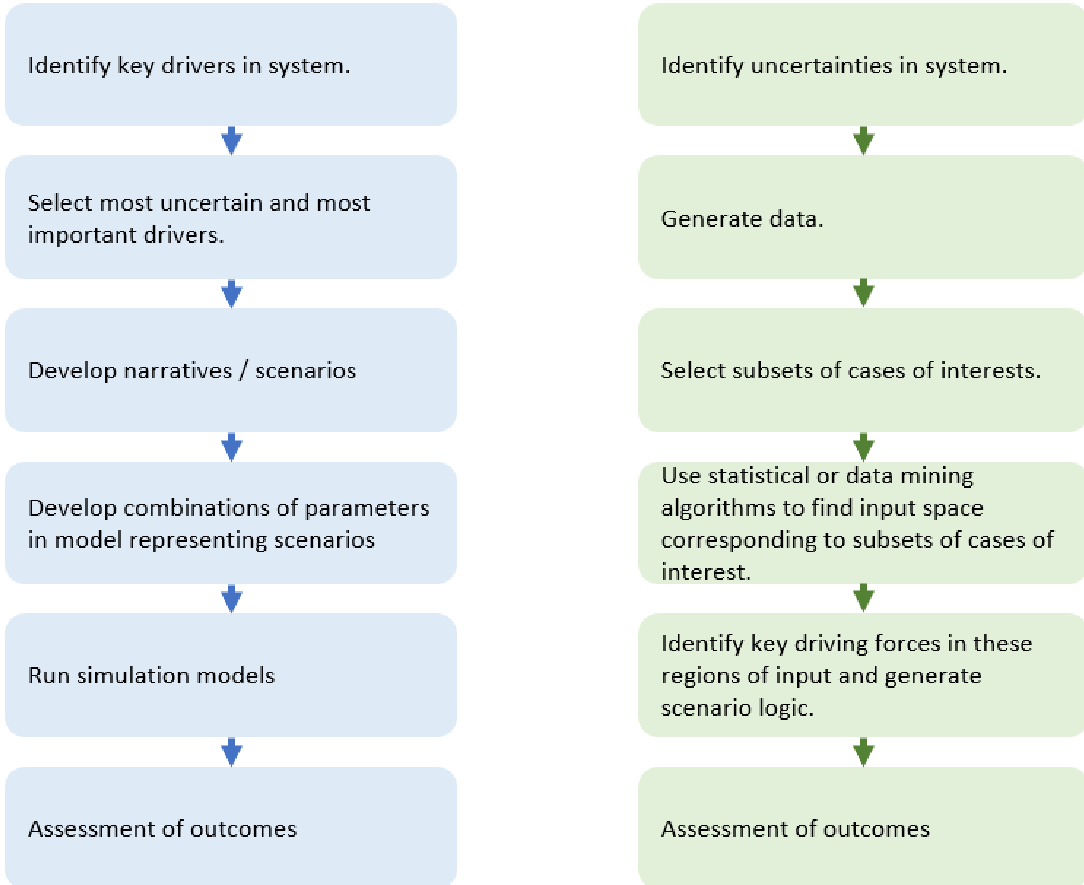


Figure 2.3: Overview intuitive scenario approach (Schwarz, 1991) and Scenario Discovery (Bryant & Lempert, 2010)

2.3 Key findings literature review

As land-use change is related to many environmental issues and challenges, spatial planning plays a vital role in dealing with these challenges. However, spatial planning is not an easy task for policymakers since the interaction between natural and social systems is complex. Land-use change models have the potential to improve policy-making in spatial planning. Although land-use change models increase understanding of the socio-environmental system it simulates, these models deal with high uncertainty. This uncertainty can lead to either misleading conclusions used in decision-making or prevents the use of land-use change models at all. Thus, uncertainty is viewed as one of the biggest geospatial challenges known today.

To deal with uncertainty, the story and simulation approach is commonly used in combination with shared community scenarios. With this approach, analysts can choose from a set of qualitative storylines, which are generated with expert knowledge and covers a range of climatic, socioeconomic and policy uncertainty. Then, using land-use change models, these qualitative storylines form a guideline to simulate future land use patterns and thus develop quantitative projections of the future. The use of these shared community scenarios enables inter-study comparison across diverse disciplines. Moreover, it saves analysts time as they do not have to develop scenarios independently.

However, story and simulation, in combination with the shared community scenarios, may fall short in some areas. With the use of pre-defined scenario narratives, analysts might not focus on the most important driving forces. Moreover, a small number of scenarios cannot cover the whole uncertainty space. As a result, with story and simulation, possible futures could be excluded from the analysis.

Numerous researches have suggested a backwards approach, where, rather than reduce the uncertainty space a priori by selecting a few scenario narratives, analysts begin with a broad uncertainty space and determine a posteriori which driving forces are important. Thus, instead of a story and simulation approach, this becomes a simulation and story approach, which is the main idea of Scenario Discovery.

Chapter 3

Methods

This research aims to compare scenario narratives generated following a story and simulation approach to scenario narratives generated with Scenario Discovery, with the aid of land-use change models. The following sections will discuss the methods used in this research to fulfil this research aim.

3.1 Case selection and description

The Netherlands has a long history in land-use change modelling as the PBL Netherlands Environmental Assessment Agency has been implementing land use modelling for the last 23 years (Koomen, Hilferink & Borsboom-van Beurden, 2011). The PBL manages the Land Use Modelling System (LUMOS), which consists of on the most well-known land-use models, namely the Land Use Scanner model. Next to applications in the Netherlands, the Land Use Scanner has many more international applications, which includes the simulation of various future land-use scenarios (Koomen, Hilferink & Borsboom-van Beurden, 2011). For this reason, an application of this Land Use Scanner model will be selected as the case study for this research, as this model has been validated and applied in various fields (Koomen, Hilferink & Borsboom-van Beurden, 2011).

The case used for this research is the application of the Land Use Scanner model (LUS model) where this model is used to simulate the Dutch Delta Scenarios, developed by Deltares in collaboration with multiple experts and stakeholders. The Delta Scenarios were developed to gain more insight into future water-related developments and based on the shared community scenarios generated by the IPCC (Bruggemann et al., 2013).

The Land Use Scanner is a GIS-based model which simulates future land use (Koomen, Hilferink & Borsboom-van Beurden, 2011). Future land use is simulated based on a demand and supply mechanism for land, where different land use classes compete for land. The demand side consists of the demand for space for each land-use class in acreages. The supply side is based on the land available and the local suitability of this available land. For each area in the Netherlands, the local suitability is calculated for each of the land use classes. The land-use class for which the calculated suitability is highest is allocated to those areas. Figure 3.1 shows an overview of the model structure.

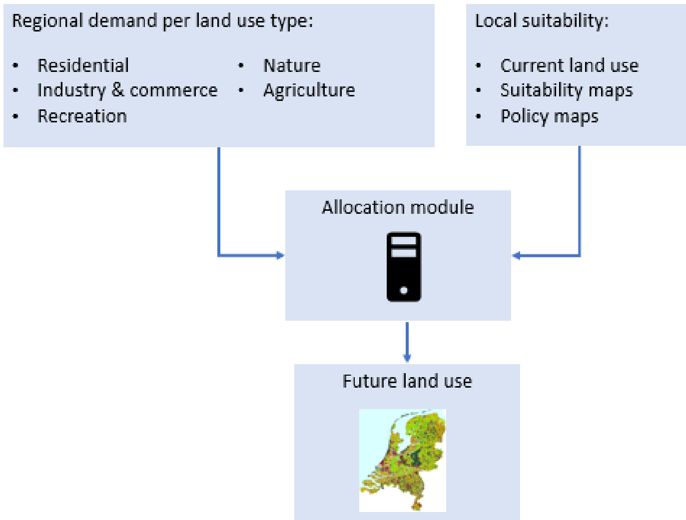


Figure 3.1: Land Use Scanner model structure

Regional demand for land use is used as input for the model and is scenario-specific. The Land Use Scanner is part of a larger model chain where the residential and industry and commerce demand is derived from the Tigris XL model (TXL model), and the agriculture demand is derived from the DRAM model. The demand for the remaining land use classes is based on expert judgement. For a full description of this model chain, see Appendix A.

Local suitability is based on a large number of geo-datasets. Firstly, current land use influences future land use and is the starting point in the simulation. Also, biophysical properties of land, such as soil type, play an important role in the allocation of land use. Next, operative policies, often implemented through so-called policy maps, also play a role in defining suitability. Lastly, market forces also steer the allocation of land use classes. Such market forces are, for example, expressed in distance relations to other land use functions, such as railway stations or other factors that influence location preferences.

3.2 Uncertainty classification

Firstly, the uncertainties addressed in the Delta Scenario narratives are identified. Next, by analysing the LUS model, an overview is created of the uncertainties in the LUS model. To identify the uncertainties considered in the Delta Scenarios, documents explaining the Delta scenarios and documentation on the quantification and modelling of these scenarios in the LUS model are used. For the analysis of the LUS model, documentation on this model and the model itself is analysed. Next, to create a structured overview of the identified uncertainties in the LUS model, the XLRM framework is used. The XLRM framework, as described by Lempert (2003), serves as a bookkeeping mechanism for assembling and categorising uncertainties. The four categories are policy levers (L), exogenous uncertainties (X), Measures (M) and Relationships (R).

Each uncertainty is also classified based on the level and nature of the uncertainty, following the uncertainty matrix framework as defined by Kwakkel, Walker and Marchau (2010). The uncertainty matrix uses a classification scheme to classify uncertainties based on the level and the nature of uncertainty.

Four levels of uncertainty are recognised. Level one, shallow uncertainty, means analysts can enumerate multiple alternatives and provide probabilities. Level two, medium uncertainty, means analysts are also able to enumerate multiple alternatives and rank order these alternatives in terms of perceived likelihood. Uncertainties are considered level three, deep uncertainty, when analysts can enumerate multiple alternatives but are not able to rank order these alternatives in terms of how likely these alternatives are. Lastly, level four uncertainty, or recognised ignorance, means analysts can enumerate multiple alternatives but are aware of the possibility of being surprised.

Following Kwakkel, Walker & Marchau (2010), the nature of uncertainty can be ambiguous, epistemic, and ontic. Ambiguity arises from the simultaneous presence of multiple and alternative frames of reference about a specific phenomenon, thus implying lack of knowledge, epistemology is uncertainty due to the imperfection of our knowledge, and ontology implies inherent variability of the phenomena being described (Walker et al., 2003).

Lastly, this research briefly looks into which uncertainties exist in the LUS model, but are not treated as such. To demonstrate this, another dimension of uncertainty, as defined by Kwakkel, Walker & Marchau (2010), is used as a guideline, namely the location of uncertainty. By looking at the possible locations of uncertainty, it can be determined whether or not this location of uncertainty was considered at all.

Once an overview of the uncertainties is created, uncertainties are selected for the Scenario Discovery approach. Since the comparison between the Delta Scenarios and the scenarios identified with Scenario Discovery is the primary goal of this research, only the uncertainties are selected, which are currently present in the LUS model. This to achieve a level of fairness in comparing the results of the two approaches. Next, a value range is assigned to each of the selected uncertain factors. These value ranges are in line with the current value range considered in the Delta Scenarios.

3.3 Scenario Discovery

To perform Scenario Discovery with the LUS model, this research follows the general steps for Scenario Discovery, as defined by Bryant and Lempert (2010) and Kwakkel, Auping and Pruyt (2013):

1. Generate experiments
2. Find outcomes of interest: cluster the experiments
3. Identify key driving forces
4. Develop scenario narratives

To implement Scenario Discovery, the Exploratory Modelling and Analysis (EMA) Workbench is used. This open-source workbench is a tool in Python which enables modellers to implement Scenario Discovery in various models (Kwakkel, 2017). The EMA workbench enables the generation and analysis of experiments. Using the EMA Workbench, one can use a sampling algorithm which systematically samples over the defined input variables and their provided value ranges. The EMA Workbench supports various sampling algorithms such as Latin Hypercube sampling (LHS) or Monte Carlo sampling. Next to generating the experiments, the EMA workbench also supports the analysis of the resulting experiments.

3.3.1 Generate experiments

Based on the selected uncertainties and their corresponding value ranges, 2000 experiments are generated using the Land Use Scanner model. Each experiment contains a different combination of values of the input variables. To generate the experiments, an experimental design should be defined to sample over the uncertain factors (Bryant & Lempert, 2010). For this research, LHS is the applied sampling algorithm to sample over the different uncertainties and their value ranges. LHS is a suitable sampling algorithm which uses stratified sampling and is easy to implement in cases where the number of variables is large (Reddy, 2011). LHS produces more stable results than random sampling and samples efficiently reducing the computing time needed to generate all the experiments (Reddy, 2011).

3.3.2 Find outcomes of interest: cluster the experiments

Each of the 2000 experiments is a land-use map. These 2000 land use maps are clustered based on how similar they are. To measure the similarity between land use maps, the Kappa statistic is used as a similarity metric. Kappa is a measure of similarity between two maps and is based on the percentage of similarity between two maps and corrected for the level of agreement that could be expected by pure chance (Visser & Nijs, 2006).

The calculation of the Kappa value is based on the contingency table between two land use maps. Such a contingency table is displayed in Table 3.1. In this contingency table, p(a=i ∧ s=j) represents the fraction of cells, of the total number of cells in the land use maps, that have land-use class i in map A and land-use class j in map S. The total p(a=i) is the fraction of cells that have land-use class I in map A, and the total p(s=j) is the fraction of cells that have land-use class j in map S.

Table 3.1: Kappa contingency table (van Vliet, Bregt & Hagen-Zanker, 2011

	Map S categories				
	1	2	…	c	Total map A
Map A categories					
1	P (a=1 ∧ s=1)	P (a=1 ∧ s=2)		P (a=1 ∧ s=c)	P(a=1)
2	P (a=2 ∧ s=1)	P (a=2 ∧ s=2)		P (a=2 ∧ s=c)	P(a=1)
…					
c	P (a=c ∧ s=1)	P (a=c ∧ s=2)		P (a=c ∧ s=c)	P(a=1)
Total map S	P(s=1)	P(s=1)		P(s=c)	1

Using this table, the observed fraction of agreement, p_o, and the expected fraction of agreement p_e are calculated (See equation 1 and 2). Using both p_o and p_e, the Kappa coefficient of agreement is then calculated (See equation 3).

$$p_o = \sum_{i=1}^{c} p(a = i \wedge s = i) \qquad \text{Equation 1}$$

$$p_e = \sum_{i=1}^{c} p(a = i * s = i) \qquad \text{Equation 2}$$

$$Kappa = \frac{p_o - p_e}{1 - p_e} \qquad \text{Equation 3}$$

From the Kappa value, the Kappa location and Kappa histogram are calculated. Kappa location describes the similarity in terms of location of specific land-use classes, and kappa Histogram describes the similarity in terms of the magnitude of specific land-use classes (Hagen, 2002). To calculate Kappa histogram and Kappa location, firstly, the maximum fraction of agreement needs to be calculated (see equation 4).

$$p_{Max} = \sum_{i=1}^{c} \min\,(p(a = i), p(s = 1) \qquad \text{Equation 4}$$

$$K_{histo} = \frac{p_{Max} - p_e}{1 - p_e} \qquad \text{Equation 5}$$

$$K_{location} = \frac{p_o - p_e}{p_{Max} - p_e} \qquad \text{Equation 6}$$

For every combination of two land-use maps from the 2000 experiments, the Kappa coefficient is calculated. To cluster the land use maps, the kappa values are converted into so-called distance values. This is done with a simple computation step: for each cell, the distance value is equal to 1 – kappa, as shown in equation 7.

$$Distance\ value = 1 - Kappa \qquad \text{Equation 7}$$

With the distance value, the 2000 experiments are clustered. Different clustering algorithms are possible to use. However, it is not clear how different clustering algorithms influence the resulting clusters. For this research, the hierarchical agglomerative clustering algorithm is proposed. This is a bottom-up hierarchical clustering approach, which means that each experiment starts in its own cluster. Next, pairs of clusters are successively merged until a desired number of clusters is achieved. The hierarchical agglomerative clustering algorithm has several benefits. Firstly, this algorithm works with a variety of similarity and distance metrics, including the Kappa similarity metric (Abbas, 2008). Also, this clustering algorithm is convenient in use and provides interpretable results. In order to perform agglomerative clustering, the linkage method has to be determined. Linkage indicates the way how the proximity between two clusters is defined. In this case, complete linkage is used, which means the distance between two clusters is defined as the longest distance between two points in each cluster, as shown in Figure 3.2. The benefit of complete linkage is that the resulting clusters are compact.

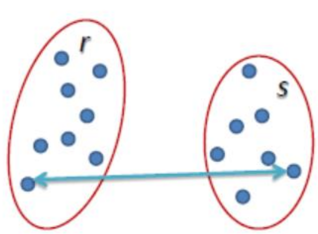


Figure 3.2: Visualisation of complete linkage in agglomerative hierarchical clustering

In order to cluster the experiments, the number of clusters has to be determined. Three criteria are considered, namely high in-cluster similarity, high between-cluster dissimilarity and interpretability. To gain more insight into the level of in-cluster similarity, the average kappa value within each cluster is calculated after clustering with the clustering algorithm. Then, the average kappa value of all average kappa values per cluster is calculated. This process is performed for every possible number of clusters between 2 and 8 clusters, to create a scatter plot indicating the average in-cluster similarity value for each possible number of clusters.

To gain more insight into the between-cluster dissimilarity, a dendrogram is created using the hierarchical agglomerative clustering algorithm. A dendrogram is a diagram in the shape of a tree and shows the hierarchical relationship between objects. On the y-axis of a dendrogram, a distance value is presented which indicates the dissimilarity between the clusters. With this dendrogram, it is possible to derive the average distance value for a specific number of clusters. Based on the dendrogram, a scatter plot is created indicating the average between-cluster dissimilarity value for each possible number of clusters.

Based on the scatter plot depicting the averaging in-cluster similarity and the scatter plot depicting the between-cluster dissimilarity, the number of clusters will be determined. To fulfil the third criterium, interpretability, the number of clusters should not be higher than 6 clusters.

The resulting clusters serve as outcomes of interest and form the base for the development of scenario narratives. To calculate the Kappa coefficient for each combination of land use maps resulting from the experiments and to cluster the land use maps using this coefficient, Python will be used. To perform the hierarchical agglomerative clustering algorithm, the software of Scikit-learn is used in Python (Pedregosa et al., 2011).

3.3.3 Analyse clusters and identify key driving forces

Once clusters are formed, the next step is to analyse these cluster further. It is necessary to identify subspaces in the model input space (the uncertainty ranges) that result in certain land-use patterns. The goal is to identify which combination of uncertain factors in the input space lead to specific outcomes if interest (the clusters). These combinations of uncertain factors will play an important role in scenario development, as these uncertain factors will form the key driving forces for each scenario.

In scenario discovery, two rule induction methods are most often used to find the subspaces in the input space corresponding to certain outcomes of interest: the Patient Rule Induction Method (PRIM) and Classification and Regression Trees (CART) (Lempert, Bryant & Bankes, 2008). PRIM uses a lenient or patient hill-climbing optimization procedure to find combinations of values in the input space that result in similar model outcomes. CART is a tree-based algorithm, where branches of the tree are pruned and ignored when these branches generate uninteresting outputs. PRIM is not suited for dealing with data that is classified in more than two classes, since this would require separate usage of PRIM for each cluster. Since in this research the experiments are classified in more than two classes, CART is preferred over PRIM. CART can be used for both binary and multi-category data (Gerst, Wang & Borsuk, 2013; Kwakkel & Jaxa-Rozen, 2016).

3.3.4 Generate scenarios

Based on the resulting clusters, and the identification of which subset of the input space corresponds with these clusters, scenario narratives are created. The use of scenario narratives supports the communication of scenarios. These narratives explain how certain uncertainties, the driving forces, influence future land use.

Firstly, an overview is created of each cluster and their conditions of occurring. This overview shows which variables and parameters in combination with which values lead to which clusters of land use maps. Each cluster and the corresponding conditions of occurring represents a scenario. It is also possible to identify more scenarios than the number of resulting clusters. For example, when different subsets of the input space result in one cluster, this cluster will translate into two scenario narratives. Based on a certain input which leads to a certain cluster, a scenario narrative is generated in a similar way as in the intuitive logics school. The subset of the input space is interpreted in the same way as to how key driving forces are used in the intuitive logics school to create scenario narratives. To do this, each scenario narrative corresponding to a specific cluster follows three main themes recognised within the land use patterns, namely: Urbanization, Nature and Recreation, and Agriculture. This structure is also followed for the Delta Scenario narratives and will support structured comparison.

As some input variables and parameters are generated by other models or expert judgement, it is necessary to trace back the meaning of these values in order to formulate the narratives. For example, the input values for the housing demand are derived from the TXL model. To formulate a clear narrative, using the insights of the TXL model, the demand for houses is traced back to demographic and social developments, and the economic growth rate.

3.4 Compare Scenario Discovery scenarios with Delta scenarios

For the comparison of the intuitive scenario development approach with the scenario discovery approach in land-use change modelling, the focus is on the comparison of the results. Firstly, the land-use model outcomes of both approaches are compared. Next, the key driving forces for each scenario are compared for both approaches. This means the focus is on the comparison of which uncertainties (driving forces) result in what model outcomes and scenarios.

Chapter 4

Uncertainty identification

Future spatial development knows many uncertainties which are mostly determined by demographic and economic changes, and government intervention (Koomen, Hilferink & Borsboom-van Beurden, 2011). The Land Use Scanner model deals with these uncertainties by implementing a scenario-based approach. The application of the Land Use Scanner model used for this research simulates future spatial development using the Dutch Delta Scenarios, developed by Deltares. These scenarios were developed to gain more insight into future water-related developments (Bruggemann et al., 2013).

Using the Delta scenario narratives and by analysing the Land Use Scanner model, uncertainties addressed by this application of this model will be identified. Firstly, section 4.1 will discuss the Delta Scenarios and provide an overview of the uncertainties within the Delta Scenarios. Next, in section 4.2, an overview will be created of the uncertainties within the LUS model itself. Lastly, section 4.3 will provide an overview of the selected uncertainties, which will be used for Scenario Discovery in this research.

4.1 Uncertainties in the Delta Scenarios

The Delta scenarios are used to simulate future land use. By analysing these Delta scenarios, uncertainties are identified which influence future land use. Firstly, a brief overview of the four Delta scenarios will be provided. Next, an overview will be created of the uncertainties addressed by these Delta scenarios.

4.1.1 The Delta Scenarios

The Delta scenarios are based on two uncertainties which are considered to be the most influential and most uncertain and will form the two axes for scenario development, as shown in Figure 4.1. These two uncertainties are the rate of climate change and economic and demographic growth (Bruggemann et al., 2013). Following these axes, each quadrant represents a scenario narrative, namely *DRUK*, *STOOM*, *RUST* and *WARM*. Table 4.1 provides an overview of the relevant features of each Delta Scenario. A more elaborate description of the Delta Scenarios is located in Appendix B.

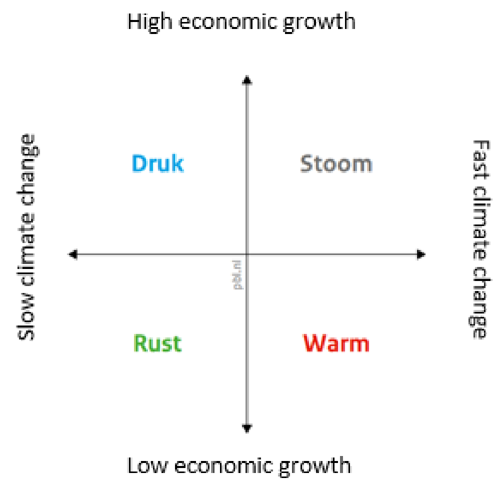


Figure 4.1: Delta Scenario axis

Table 4.1: Description Delta Scenarios

DRUK	STOOM

• High global economic growth
• High national economic growth
• High demographic growth
    ○ Concentrated in Randstad
• Slow climate change rate
• Restrictive spatial development policy
• High concentrated urbanisation
• High technology development
• More large nature areas
• Fresh water supply challenges
• Water safety challenges
	• High global economic growth
	• High national economic growth
	• High demographic growth
	    ○ Less concentrated in Randstad
	• Fast climate change rate
	• Liberal spatial development policy
	• High urbanisation and sub-urbanisation
	• High technology development
	• More buildings in nature areas
	• Big fresh water supply challenges
	• Big water safety challenges

RUST	WARM

• Low global economic growth
• Low national economic growth
• Low demographic growth
    ○ Concentrated in Randstad
• Slow climate change rate
• Restrictive spatial development policy
• Limited concentrated urbanisation
• Slow technology development
• More nature for functional services
• Small fresh water supply challenges
• Limited water safety challenges
	• Low global economic growth
	• Low national economic growth
	• Low demographic growth
	    ○ Less concentrated in Randstad
	• Fast climate change rate
	• Liberal spatial development policy
	• Limited urbanisation and sub-urbanisation
	• Slow technology development
	• More nature for functional services
	• Small fresh water supply challenges
	• Big water safety challenges

4.1.2 Uncertainties in the Delta Scenarios

In this section, the main uncertainties identified in the Delta Scenarios are described. For this identification, reports concerning the Delta Scenarios are used for analysis. The Delta Scenarios present a list of driving forces which are considered highly uncertain. Table 4.2 represents the identified uncertainties.

The most uncertain and important driving forces are climate change rate and economic growth and form the main guidelines along which the four scenarios are built upon. Next to these main uncertainties, more driving forces are considered uncertain and important. Closely related to economic growth is demographic development, as this uncertainty is aligned with economic growth in the Delta Scenarios. High economic growth is always combined with high population growth and increased household growth, whereas low economic growth is always combined with low population growth and fewer households. Although economic growth is strongly related to demographic development, they are here considered as two separate uncertainties, since in reality, demographic development is not solely dependent on economic growth. Next, the Delta Scenarios describe three highly uncertain categories which relate to land use development. Each of these three categories has different sources of uncertainty, as described in the Table below. Lastly, the Delta Scenarios also view several policies as uncertainties, with the focus being on national and regional policies.

Table 4.2: Uncertainties in Delta Scenarios

Uncertainty category	**Uncertainties**
Economic & demographic development	GDP percentage growth per year Natural population development Migration Household composition
Climate change impact	Temperature rise Sea level rise Rainfall Fresh water supply
National policies	Spatial development policy Nature policy
Labour sector development	Employment opportunities per sector and location National and international market forces Availability of resources Technology development
Societal preferences	Societal living location preferences Societal labour sector and labour location preferences Societal nature and recreation preferences
International policies	EU policies
Other international developments	-

4.2 Uncertainties in the Land Use Scanner model

For the simulation of future land-use and the implication of the resulting land use patterns, the PBL introduces a framework of models which are used together. Since only the LUS model is within the scope of this research, the following sections will focus on uncertainties which directly impact the LUS model.

Section 4.2.1 will discuss the identified uncertainties related to the LUS model. Next, section 4.2.2 will discuss possible additional uncertainties in the LUS model, which were not considered as uncertainties in the implementation of the Delta Scenarios.

4.2.1 Identified uncertainties in LUS model

In this section, the parameters and variables which are considered as uncertainties in de LUS model are identified. For the identification of these uncertainties, documentation on the LUS model and the LUS model itself is analysed. The identified uncertainties will be categorised according to the XLRM framework. Next to this, the uncertainties will be classified based on the level and nature of the uncertainty. Table 4.3 represents the identified uncertainties in the LUS model and their corresponding level and nature.

The national nature policy and spatial development policies are perceived as uncertainties (Rijken et al., 2013). In the LUS model, three nature policy maps are defined for the four scenarios. Appendix C.3 provides an explanation of the three nature policies, including the corresponding policy maps (See Figures C.1, C.2 and C.3, Appendix C.3). As for the spatial development policy, most features of this policy are embedded in models outside of the LUS model itself, namely the TXL model, influencing the demand for houses and jobs. The only feature of the spatial development policy implemented in the LUS model itself is the level of restrictiveness of this policy, which is simulated using an infringement percentage and is perceived as an uncertainty in the LUS model (Claassens, Koomen & Rijken, 2017).

The demand for different land use classes is considered to be exogenous uncertainties in the LUS model. Firstly, the demand for houses and jobs, derived from the TXL model, are exogenous uncertainties. These uncertainties relate closely to the Delta Scenario uncertainty category urbanization, economic growth and demographic development as defined in Table 4.3. Next, the demand for nature and recreation are perceived as exogenous uncertainties and are derived from expert judgement (Claassens, Koomen & Rijken, 2017). The demand for horticulture and intensive agriculture are determined with the DRAM model and are also perceived as exogenous uncertainties in the LUS model. Lastly, one physical characteristic of land is implemented in the LUS model as an exogenous uncertainty, as this physical characteristic is scenario dependent. More specifically, it depends on whether or not water levels are controlled by pumping, which influences the suitability of areas for nature development.

The relationship-related uncertainties involve mostly features used to calculate the suitability of a certain area towards a certain land-use class. For nature, the importance of certain location factors and physical factors are perceived as uncertain. Also, the impact of the nature policy in place is scenario dependent. The importance of location factors for residential land use is also considered uncertain. Lastly, the degree to which nature policy restrictions, imposed on other land use classes, influence the suitability of the other land use classes, is also scenario dependent.

Table 4.3: Overview uncertainties in LUS model

Policy levers (L)	
Uncertainty	**Level and nature of uncertainty**
Nature policy: The potential policy maps for nature policies	Level 3: Different ideas, no likelihood

	Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Spatial development policy: Level of restrictiveness Infringement percentage	Level 3: Different ideas, no likelihood, depending on spatial development policies Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Exogenous uncertainties (X)	
Residential demand (# houses): Population and household development Economic growth Spatial development policies Preference for living/work areas	Level 3: Different ideas, no likelihood Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Industry & commerce demand (# jobs): Population and household development Economic growth Spatial development policies Preference for living/work areas	Level 3: Different ideas, no likelihood Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Labour preferences: Location type preference and corresponding terrain coefficient development	Level 3: Different ideas, no likelihood Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Housing density: How many houses are built within a certain areas.	Level 2: Different ideas Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Nature claim: Availability financial resources Appreciation of nature by society	Level 3: Different ideas, no likelihood Nature: Epistemic (lack of knowledge and different ideas) and ontic (Inherent variability and societal variability)
Recreation claim: Economic growth (money available) Personal preferences	Level 3: No likelihood Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Intensive agriculture and horticulture claim: Available space Innovation and adaption possibilities Climate change effects on agriculture	Level 3: No likelihood Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Nature physical suitability: Map depicting the potential areas for nature development, based on potential wet and dry land	Level : Depending on policies related to subsidence Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Relationships (R)	
Nature location factor: Weight of location factors related to suitability of nature land use	Level 3: Depending on nature appreciation, different ideas Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Nature policy stimuli: Degree to which the government encourages the creation of nature with policy stimuli	Level 3: Depending on nature appreciation, different ideas

	Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Nature policy restriction: Weight of policy restriction Relevance of policy restriction to different land use classes	Level 2/3: Different ideas and depending on nature policy Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Residential location factor: Degree to which people want to live in existing residential areas or new residential areas	Level 3: Depending on societal preferences Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)
Measures (M)	
land use classes allocated Residential Industry and commerce Nature Recreation Intensive agriculture Extensive agriculture	Level 3 Nature: Epistemic (lack of knowledge) and ontic (societal variability and behavioural variability)

4.2.2 Additional uncertainties

Table 4.3 provides an overview of uncertainties which are implemented as uncertainties within the LUS model. However, it is important to note that more uncertainties exist within the LUS model, which are not treated as such. To demonstrate this, another dimension of uncertainty, as defined by Kwakkel, Walker & Marchau (2010), will be used as a guideline, namely the location of uncertainty. By looking at the possible locations of uncertainty, it can be determined whether or not this location of uncertainty was considered at all.

As shown in Table 4.4, all identified uncertainties are located in the input data. Therefore, possible additional uncertainties could be found in other locations. For example, the implementation of different temporal and spatial scales often result in different simulation results (Pontius & Spencer, 2005; Verburg & Veldkamp, 2004). Also, uncertainties relating to conceptual model uncertainties are not considered in the Delta Scenarios. All four scenarios are based on the same conceptual model. Looking at uncertainties related to the computer model, it can again be observed that the computer model is similar for each scenario. Lastly, although uncertainties related to input data are considered in the LUS model, many more parameters could be uncertain but are not implemented as uncertainties in the Delta Scenarios. For example, all parameters used for the calculation of suitability could be uncertain, but only a few are scenario dependent.

Table 4.4: Overview of the possible location of uncertainties

Location	**Considered in Delta scenarios or LUS model?**
System boundary: Temporal scale Spatial scale	No

Conceptual model: Selection of variables and relationships chosen to describe the system	No
The computer model: Model structure Parameters	No
Input data	Yes
Model implementation	No
Processes output data	No

4.3 Uncertainty selection

The scope of this research limits the selection of uncertainties to the uncertainties already existing in the LUS model in combination with the value ranges as defined by the Delta Scenarios. The demand for houses and jobs are taken as one dimension, as these demands are highly interdependent and derived from the same output file of the TXL model. To convert the demand for jobs to demand in acreage of the industry and commerce sector, location type preferences and terrain coefficients are used. These two variables either use values corresponding to a high economic growth scenario (high) or a low economic growth scenario (low). The values for nature demand in acreage are based on expert judgement. This also goes for recreation demand, where recreation demand also has two possible values corresponding to either a high economic growth scenario or a low economic growth scenario. Next, the intensive agriculture demand is taken as one dimension containing the demand for each separate intensive agriculture land-use class.

Chapter 5

Scenario Discovery

This chapter will first discuss the process of generating the experiments and clustering these experiments. Section 5.2 will discuss the resulting clusters. Next, section 5.3 will discuss the characteristics of each cluster and the scenario development behind each cluster will take place in section 5.4.

5.1 Generating and clustering the experiments

Based on the uncertainties selected in the previous chapter, an experimental set-up is created for the implementation of Scenario Discovery. For this experimental set-up, the uncertain parameters are defined as Boolean or Categorical parameters. This way, it is easier to handle the large data files derived from the model output of other models in the LUS model chain. Table 5.1 displays an overview of the parameters and their possible values. See Appendix C for a full explanation of the meaning of each parameter and corresponding values.

Using the LHS algorithm to sample over the input space, 2000 experiments were generated. The output of each experiment is a land-use map, stored as an array. Within this array, each value corresponds to a certain land-use class.

Table 5.1: Experimental set-up: Uncertainties and possible values

Name	Description	Possible values			
House and job demand	Demand in number of houses and jobs	Very high	High	Low	Very low
Labour preferences	Location preference and terrain coefficient	In accordance with high economic growth		In accordance with low economic growth	
Nature claim	Nature demand in acreage	106000 (High demand)	75000 (Medium demand)	50000 (Low demand)	
Recreation claim	Recreation acreage	High		Low	
Intensive agriculture and horticulture claim	Demand for intensive agriculture land use classes	High		Low	
Residential location factor	Scatter ratio	0.5		1.0	
Spatial development policy	Infringement fraction reflecting the spatial development policy	0.25 (Liberal spatial development policy)		0.75 (Restrictive spatial development policy)	
Housing density	Housing density	1.33 (High housing density)		1.00 (Low housing density)	
Nature location factor	Location weight	High within 500-meter existing nature	Equal to residential location weight	0.0	
Nature policy stimuli	Policy stimuli weight	5.0 around nature and recreation	5.0 around nature	5.0 around nature	0.0 (no nature policy stimuli)

Nature policy restriction	Restriction weight	30.0 (Policy restriction in place)	0.0 (No policy restriction in place)	
Nature policy	Policy maps	Robust and vital nature policy	EHS nature policy	Functional nature policy
Nature physical factor	Suitability map nature	Both dry as wet land suitable for nature	Only dry land suitable for nature	

For each combination of land use maps, the similarity between these maps is calculated using the Kappa metric. Based on the identified kappa values, a distance matrix is created. This distance matrix is needed to cluster the experiments based on the similarity of the maps.

To determine the number of clusters, three criteria are considered. Firstly, the in-cluster similarity must be high. The scatter plot below, Figure 5.1, shows the number of clusters with the corresponding average in-cluster similarity value. This figure shows that when two clusters are used, the average in-cluster similarity value is the lowest, and when eight clusters are used, the average in-cluster similarity value is the highest. The second criterium is that a number of clusters are desired where the between-cluster dissimilarity is high. The scatter plot in Figure 5.1 shows the number of clusters and their corresponding between-cluster distance value. This figure shows that using two clusters results in the highest between-cluster distance value while using eight clusters produces the lowest distance value. Lastly, the third criterium is interpretability, meaning that the chosen number of clusters should not be too high.

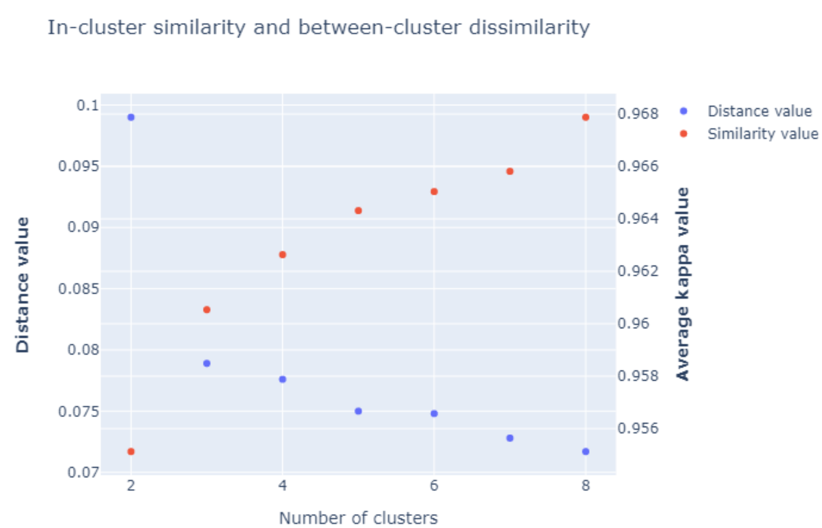


Figure 5.1: Scatter plot in-cluster similarity vs. between-cluster dissimilarity

Figure 5.1 shows that while using two clusters is desirable in terms of between cluster dissimilarity, it is not desirable in terms of in-cluster similarity. On the other hand, whereas the use of eight clusters guarantees high in-cluster similarity, the between-cluster dissimilarity is at its lowest. Thus, it is clear that a trade-off has to be made when selecting the number of clusters. It is decided to cluster the 2000 land use maps into six clusters. Although a high in-cluster similarity is achieved with eight clusters, it is difficult to maintain a clear overview of this number of clusters and thus decreases interpretability. With six clusters, the average in-cluster similarity is as high as possible, while maintaining interpretability. Moreover, using six clusters, the decrease in between-cluster dissimilarity is also limited, as the decrease of the distance value compared to five clusters is quite small. In conclusion, with the use of six clusters, the average in-cluster similarity and between-cluster dissimilarity have desirable values, while maintaining interpretability.

5.2 Introducing the clusters

In the following sections, the clusters will be analysed. Firstly, section 5.2.1 will present an overview of the six clusters and their overall land-use patterns. Next, each section will discuss in more detail specific land use classes for all clusters.

5.2.1 Overall land use patterns

For each cluster, the medoid map within that cluster is retrieved and serves as the representative land use map of that cluster. The medoid map of each cluster is depicted in Figure 5.2. Based on these medoid maps, an overview is created of the amount of acreage per land-use class, as shown in Table 5.2. The percentage change of acreage for each land-use class compared to the base year is visualised in Figure 5.3. Next to changes in the total area of each land-use class, the allocation of each land-use class on the map can also change. Together, the magnitude and location of land use classes determine the overall land-use patterns.

Table 5.2: Acreage per land use class of base year and clusters

Land use class	Base year	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Residential area	317405	330005	428896	428897	351895	354426	354542
Industry & commerce[1]	117227	123949	167727	167542	123268	158467	168357
Recreation[2]	34054	36543	36541	43266	36543	36544	36544
Nature	615483	665483	665483	665483	665482	665481	690483
Horticulture	15873	14366	14366	14366	14366	14366	14366
Intensive agriculture[3]	75224	72211	72211	72211	72211	72211	72211
Extensive agriculture[4]	1914764	1860399	1733705	1727461	1846732	1815529	1781331

1: Industry, services and seaports

2: Recreation and accommodation

3: Corn, potatoes, beets, grain, open vegetables and livestock

4: Flower bulbs, tree orchards, arboriculture

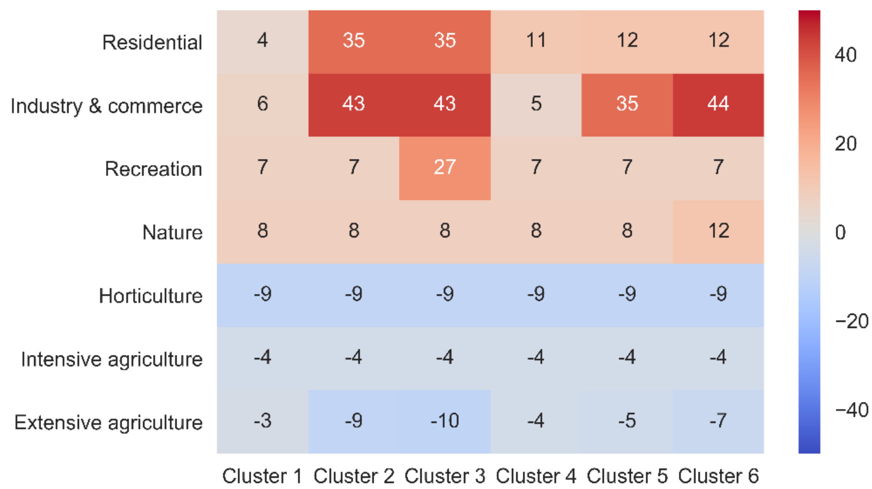


Figure 5.2 Heatmap visualising percentage change compared to base year

Figure 5.4 displays the medoid map of each cluster. To view each medoid map in greater detail, see Appendix D. Figure 5.3 displays the legend of the medoid maps.

Figure 5.3: Legend medoid maps

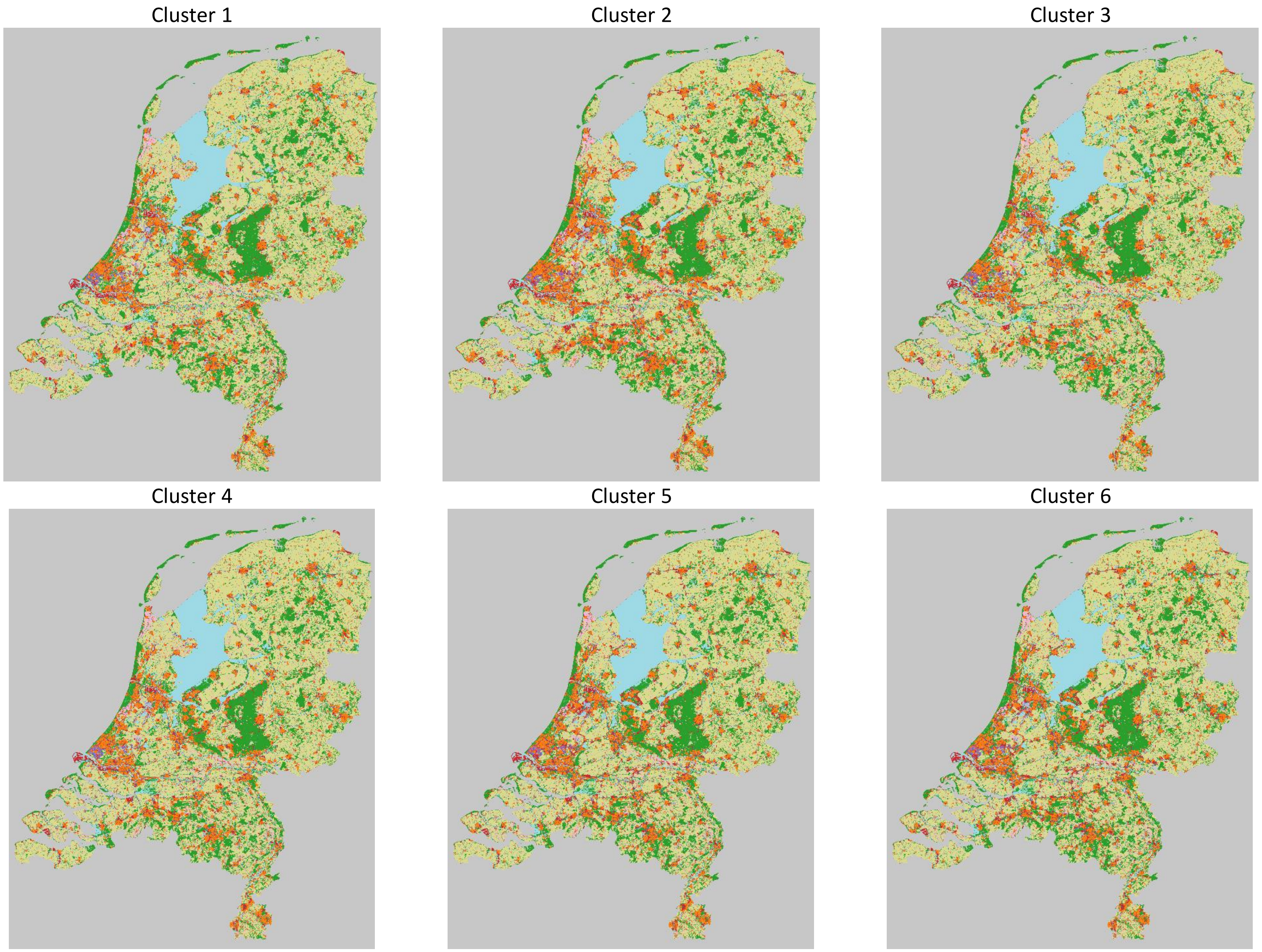


Figure 5.4: Medoid maps

The overall land-use patterns of each cluster are discussed here. As the growth in acreages of one land use class in certain area results in another land-use class giving up acreage in that area, for each cluster, a confusion matrix is created. This matrix compares the changes in the allocation of land-use classes between the medoid maps and the base map in 2012. Specifically, each column shows for a specific land-use class the amount of acreage that previously, in 2012, belonged to either the same land-use class or other land use classes.

Cluster 1

Cluster 1 shows limited growth or decrease in acreage for all land use classes. The residential land use class covers 330005 acreages in the Netherlands, with a concentration in the Randstad. The industry and commerce land-use class covers 123949 acreages and is mainly located around residential areas. For the residential and industry and commerce land use classes, the growth is only 4 and 6 per cent, respectively. Also, the recreation and nature land use classes show limited growth in acreage since 2012, with only 7 and 8 per cent, respectively. The land use classes horticulture and intensive agriculture also have a limited decrease. Lastly, as extensive agriculture is allocated to the areas which remain after allocating all other land use classes, the agriculture land-use class has a limited decrease of only 3 per cent, due to the limited growth in all other land use classes.

The confusion matrix for the base year and cluster 1 is displayed in Table 5.3. The Table shows that both the residential as industry and commerce land use classes did not replace a large amount of other land use classes. As for nature, most new nature areas are at the cost of extensive agriculture. As the Table shows, 49243 acreages of extensive agriculture are allocated to the nature land-use class in 2050. However, since all other land use classes show a limited growth between 2012 and 2050, the overall decrease in the extensive agriculture land-use class is also limited.

Table 5.3: Confusion matrix cluster 1 and base year

	Res.	**I&c**	**Recr.**	**Nat.**	**Hort.**	**Int.**	**Ext.**	**Other**	**Total base year**
Res.	317049	0	0	0	0	0	0	356	**317405**
I&c	7	116603	0	0	0	0	0	617	**117227**
Recr.	0	0	34010	0	0	0	0	44	**34054**
Nat.	34	0	11	614504	0	0	0	934	**615483**
Hort.	105	275	31	176	14366	18	898	4	**15873**
Int. Agr.	109	104	198	998	0	72192	1555	68	**75224**
Ext. Agr.	2161	1823	2278	49243	0	0	1857728	1531	**1914764**
Other	10540	5144	15	562	0	1	218	5668490	**5684970**
Total cluster 1	**330005**	**123949**	**36543**	**665483**	**14366**	**72211**	**1860399**	**5672044**	

Cluster 2

The residential land use class covers 428896 acreage of the Netherlands, which means that since 2012 this land-use class has expanded up to 35 per cent. The industry and commerce land-use class also show strong growth, namely growth of 43 per cent, amounting to 167727 acreages. Nature and recreation have more limited growth, with 8 and 7 per cent, respectively. As for the agriculture land use classes, horticulture and intensive agriculture do not show a significant decrease in acreage, with only 9 and 4 per cent. Due to the more substantial growth in the residential and industry and commerce land use classes, the extensive agriculture land-use class decreases more, with 9 per cent.

Table 5.4 displays the confusion matrix for land use maps from the base year and the medoid map of cluster 2. Looking at the column of the residential land use class, the table shows that the large increase in acreages is at the cost of several other land use classes. For example, 2327 acreages of nature are replaced by residential areas, and this land-use class replaces 79130 acreages of extensive agriculture. As for nature, the table shows that this land-use class regains and adds more acreages from the extensive agriculture land-use class. As a result, the table shows a higher decrease in acreage of the extensive agriculture land-use class.

Table 5.4: Confusion matrix cluster 2 and base year

	Res.	**I&c**	**Recr.**	**Nat.**	**Hort.**	**Int.**	**Ext.**	**Other**	**Total base year**
Res.	317049	0	0	0	0	0	0	356	**317405**
I&c	110	116778	0	0	0	0	0	339	**117227**
Recr.	24	0	33986	0	0	0	0	44	**34054**
Nat.	2327	546	22	611654	0	0	0	934	**615483**
Hort.	1150	351	1	2	14350	0	15	4	**15873**
Int. Agr.	2489	1820	68	328	0	70323	128	68	**75224**
Ext. Agr.	79130	43101	2430	53239	16	1830	1733487	1531	**1914764**
Other	26617	5131	34	260	0	58	75	5652795	**5684970**
Total cluster 2	**428896**	**167727**	**36541**	**665483**	**14366**	**72211**	**1733705**	**5656071**	

Cluster 3

Cluster 3 is characterised by strong urbanisation land use patterns, where the residential and industry and commerce land use classes cover 428897 and 167542 acreages of the Netherlands, respectively. A substantial growth of 27 per cent is also observed for the recreational land-use class, amounting to 43266 acreages. Nature grows with only 8 per cent, amounting to a total of 665483 acreages. As for the agricultural land use classes, horticulture and intensive agriculture show a limited decrease, whereas extensive agriculture decreases more significantly by 10 per cent.

Table 5.5 displays the confusion matrix for the land use maps of the base year and cluster 3. Looking at the column of the residential land use class, the table shows that of the nature areas that disappeared between 2012 and 2050, 2277 acreages were replaced by the residential land use class. Moreover, new residential areas replaced 78745 acreages of extensive agriculture in 2050. Also, the land use classes industry and commerce and nature grew in acreages at the cost of the extensive agricultural land use class. This explains the higher decrease in the extensive agricultural land use class.

Table 5.5: Confusion matrix cluster 3 and base year

	Res.	I&c	Recr.	Nat.	Hort.	Int.	Ext.	Other	Total base year
Res.	317049	0	0	0	0	0	0	356	**317405**
I&c	318	116570	0	0	0	0	0	339	**117227**
Recr.	40	0	33970	0	0	0	0	44	**34054**
Nat.	2277	382	194	611696	0	0	0	934	**615483**
Hort.	1161	342	5	1	14348	0	12	4	**15873**
Int. Agr.	2548	1793	231	1030	0	69428	126	68	**75224**
Ext. Agr.	78745	43311	8818	52372	18	2711	1727258	1531	**1914764**
Other	26759	5144	48	384	0	72	65	5652498	**5684970**
Total cluster 3	**428897**	**167542**	**43266**	**665483**	**14366**	**72211**	**1727461**	**5655774**	

Cluster 4

The residential land use class has increased to 428897 acreage, which indicates a moderate growth of 11 per cent compared to the base year. The industry and commerce land-use class, on the other hand, shows a limited growth of just 5 per cent, amounting to a total of 167542 acreages in 2050. Both the recreation and nature land use classes also show limited growth, with 7 and 8 per cent, respectively. Lastly, the three agriculture land use classes show a limited decrease between 4 and 9 per cent each.

The confusion matrix for the land use maps of the base year and cluster 4 is displayed in Table 5.6. The Table shows that both the residential as industry and commerce land-use class did not replace a large amount of other land use classes. As for nature, most new nature areas are at the cost of the extensive agriculture land-use class. As the Table shows, 50111 acreages of extensive agriculture are allocated to the nature land-use class in 2050. However, since all other land use classes show a limited growth between 2012 and 2050, the overall decrease of the extensive agriculture land-use class is also limited.

Table 5.6: Confusion matrix cluster 4 and base year

	Res.	I&c	Recr.	Nat.	Hort.	Int.	Ext.	Other	Total base year
Res.	317049	0	0	0	0	0	0	356	**317405**
I&c	183	116465	0	0	0	0	0	579	**117227**
Recr.	3	0	34007	0	0	0	0	44	**34054**
Nat.	430	20	22	614077	0	0	0	934	**615483**
Hort.	586	141	6	106	14366	23	641	4	**15873**
Int. Agr.	581	24	209	870	0	72184	1288	68	**75224**
Ext. Agr.	14720	1579	2282	50111	0	4	1844537	1531	**1914764**
Other	18343	5039	17	318	0	0	266	5660987	**5684970**
Total cluster 4	**351895**	**123268**	**36543**	**665482**	**14366**	**72211**	**1846732**	**5664503**	

Cluster 5

The residential land use class has grown since 2012 with 12 per cent, amounting to a total of 354426 acreages. On the other hand, the industry and commerce land-use class show more considerable growth, compared to the base year, of 35 per cent, which corresponds to a total of 158467 acreages. Both the recreation as the nature land-use class show smaller growth, of 7 and 8 per cent, respectively. Lastly, the three agricultural land use classes show a limited decrease in 2050, compared to 2012.

The confusion matrix for the land use maps of the base year and cluster 5 is displayed in Table 5.7. As the table below shows, the residential land use class does not grow strongly and thus does not replace other land use classes between 2012 and 2050. The industry and commerce land-use class does grow more significantly, but this does not go at the cost of the residential, nature or recreation land use classes. Only the three agricultural land use classes, mostly the extensive agriculture land-use class, have to give up acreages for the growth of the industry and commerce land-use class. The nature land-use class grows mostly in areas which were allocated to extensive agricultural areas in 2012.

Table 5.7: Confusion matrix cluster 5 and base year

	Res.	**I&c**	**Recr.**	**Nat.**	**Hort.**	**Int.**	**Ext.**	**Other**	**Total base year**
Res.	317049	0	0	0	0	0	0	356	**317405**
I&c	16	116872	0	0	0	0	0	339	**117227**
Recr.	10	0	34000	0	0	0	0	44	**34054**
Nat.	118	1	26	614404	0	0	0	934	**615483**
Hort.	328	999	4	69	14366	41	62	4	**15873**
Int. Agr.	585	1636	122	1237	0	71284	292	68	**75224**
Ext. Agr.	12918	33365	2370	48644	0	823	1815113	1531	**1914764**
Other	23402	5594	22	1127	0	63	62	5654700	**5684970**
Total cluster 5	**354426**	**158467**	**36544**	**665481**	**14366**	**72211**	**1815529**	**5657976**	

Cluster 6

In this cluster, the residential land use class covers 354542 acreage of the Netherlands, which indicates a growth of 12 per cent since 2012. The industry and commerce land-use class show strong growth of 44 per cent, which amounts to 168357 acreages in total. The land-use class recreation shows a limited growth of only 7 per cent since 2012. However, the nature land-use class, with a total of 690483 acreages, grows moderately with 12 per cent.

As the confusion matrix displayed in Table 5.8 indicates, most of these new nature areas are in former agricultural areas, with 72730 acreages of former extensive agriculture. The strong growth of the industry and commerce land-use class only goes at the cost of the three agricultural land use classes, which means the residential, nature and recreation land use classes do not have to give up acreages to this land-use class.

Table 5.8: Confusion matrix cluster 6 and base year

	Res.	I&c	Recr.	Nat.	Hort.	Int.	Ext.	Other	Total base year
Res.	317049	0	0	0	0	0	0	356	317405
I&c	9	116879	0	0	0	0	0	339	117227
Recr.	0	0	34010	0	0	0	0	44	34054
Nat.	33	0	11	614505	0	0	0	934	615483
Hort.	182	996	3	237	14366	44	41	4	15873
Int. Agr.	568	1834	77	1598	0	70941	138	68	75224
Ext. Agr.	13269	42511	2424	72730	0	1182	1781117	1531	1914764
Other	23432	6137	19	1413	0	44	35	5653890	5684970
Total cluster 6	354542	168357	36544	690483	14366	72211	1781331	5657166	

5.2.2 The residential land use class

Figure 5.5 displays for each cluster the difference compared to the base year for the residential land use class specifically. Cluster 1 has the lowest growth in acreage, with only 4 per cent. This limited growth is concentrated in the Randstad, as is shown in Figure 5.6. Between 2012 and 2050, cluster 4, 5 and 6 grow more significantly, around 11 and 12 per cent. This growth is also concentrated in the Randstad (see Figure 5.6). Cluster 2 and 3 show strong urbanisation patterns, expanding and connection residential areas between 2012 and 2050 amounting to a growth of 43 to 44 per cent compared to the base year. As Figure 5.5 shows, new residential areas emerge throughout the Netherlands in these two clusters, with the highest growth within the Randstad, but also significant growth is visible in other areas such as the province Noord-Brabant.

Figure 5.5: Difference map for the residential land use class

Figure 5.6: Difference map for residential land use class, close up Randstad

5.3.3 The Industry and commerce land use class

Figure 5.7 displays the difference between the industry and commerce land-use class for each cluster. In this land-use class, all clusters have in common that Maasvlakte 2 has been constructed since 2012. In the LUS model, the construction of the Maasvlakte 2 was perceived to be certain, as the plans for this project were as good as fixed in 2012. Other than the Maasvlakte, the clusters show different land-use patterns for the industry and commerce land-use class.

Cluster 2, 3, 5 and 6 show significant growth in the industry and commerce land-use class, with a growth of 35 per cent for cluster 5 and a growth of at least 43 per cent for the clusters 2,3 and 6. The new areas of this land-use class emerge scattered throughout the Netherlands and mainly around residential areas. On the other hand, cluster 1 and 4 show a limited growth between 2012 and 2050 for this land-use class, with 6 and 5 per cent, respectively. For these two clusters, the growth of this land-use class is mainly visible in the Randstad, as shown in Figure 5.8.

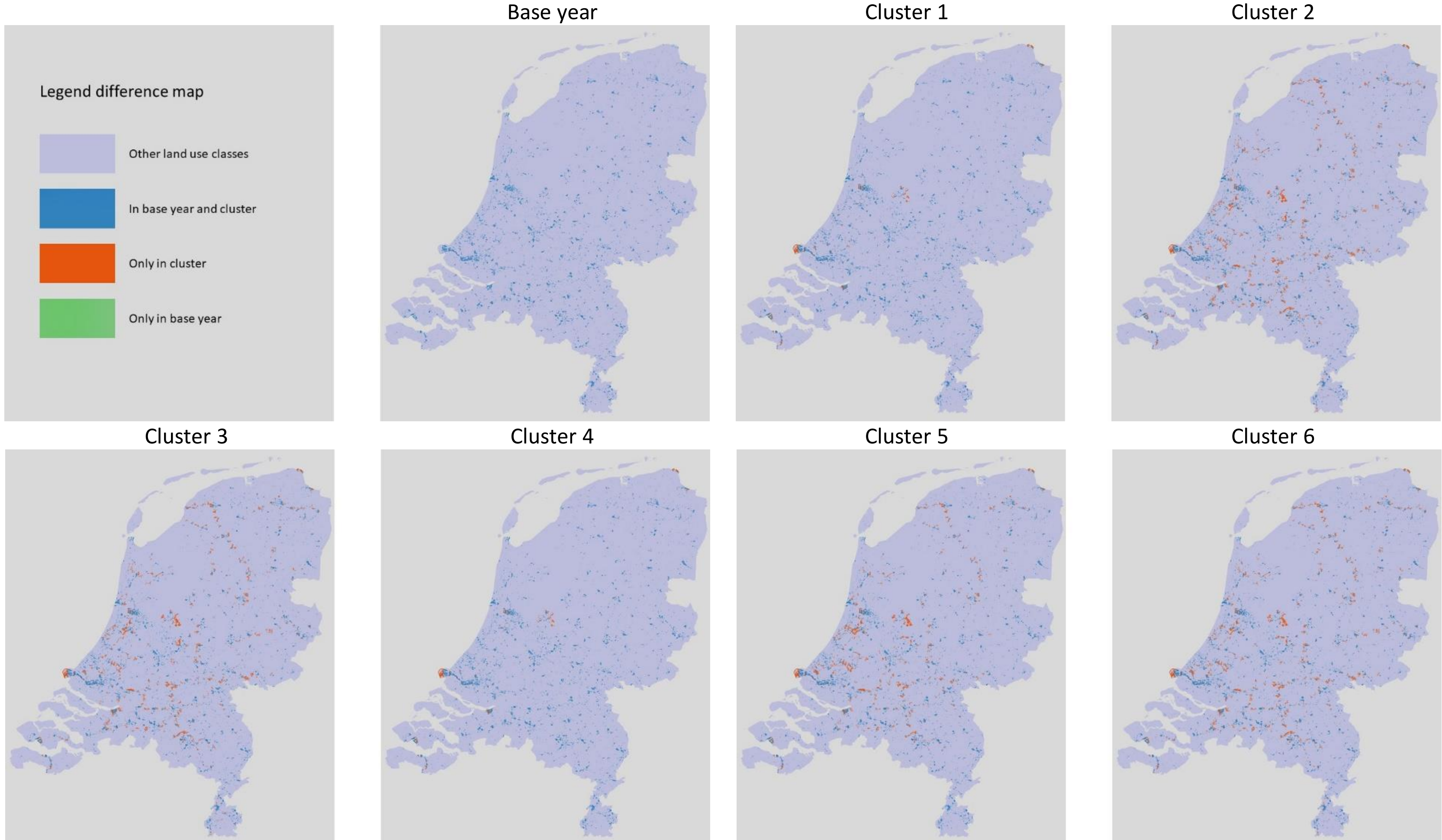


Figure 5.7: Difference map for the industry and commerce land use class

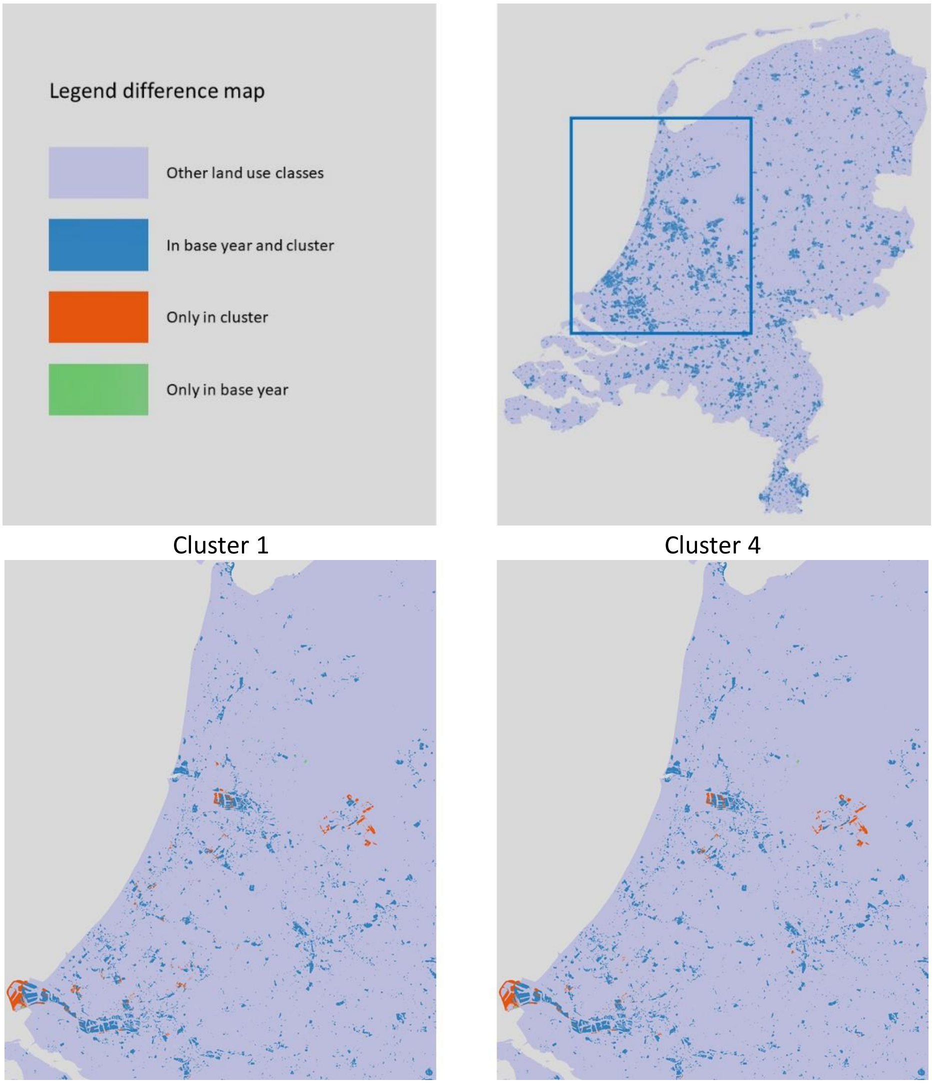


Figure 5.8: Difference map for industry and commerce land use class, close up Randstad

5.2.4 The recreation and nature land use class

Figure 5.9 shows the difference map for the nature land-use class for each cluster compared to the base year. In cluster 1, new nature emerges mainly in the area's part of the ecological main structure, with a concentration of growth in the Randstad.

Due to the growth of residential areas, nature areas are replaced by this land-use class. This is mainly visible in the Randstad, as shown in Figure 5.10. In this figure, nature areas are visible, which disappeared between 2012 and 2050. Both cluster 2 and 3, however, regain nature in other areas. New nature emerges in cluster 2 and 3 also mainly in the Randstad. There are a few differences between the nature land-use patterns of these two clusters. Firstly, new nature in cluster 2 is mainly in agricultural areas scattered throughout the Netherlands, with a concentration in the Randstad. As a result, apart from the concentration of growth in the Randstad, Figure 5.11 shows for cluster 2 new emerged nature areas in Noord-Brabant as well. New nature in cluster 3 also emerges in former agricultural areas, but in a different way. New nature in cluster three increases and connects existing nature areas between 2012 and 2050.

This is, for example, visible in Figure 5.11 for cluster 3, where new nature is visible in Noord Brabant, however, allocated much tighter around existing nature areas in contrast to the more scattered pattern observed for cluster 2.

Cluster 4 shows similar nature land-use patterns compared to cluster 2. New nature areas emerge scattered throughout the Netherlands in former agricultural areas, with a concentration of growth in the Randstad, as shown in Figure 5.10. However, as Figure 5.10 shows, nature does not disappear in the Randstad in cluster 4, as was the case for cluster 2. This is because cluster 4 does not show strong urbanisation patterns, whereas cluster 2 does.

Lastly, although both cluster 5 and 6 also show a slightly concentrated nature growth in the Randstad, nature emerges in these two clusters in a more scattered way compared to the other four clusters. As a result, stronger growth in areas other than the Randstad can be observed, such as in Noord Brabant, as shown in Figure 5.11.

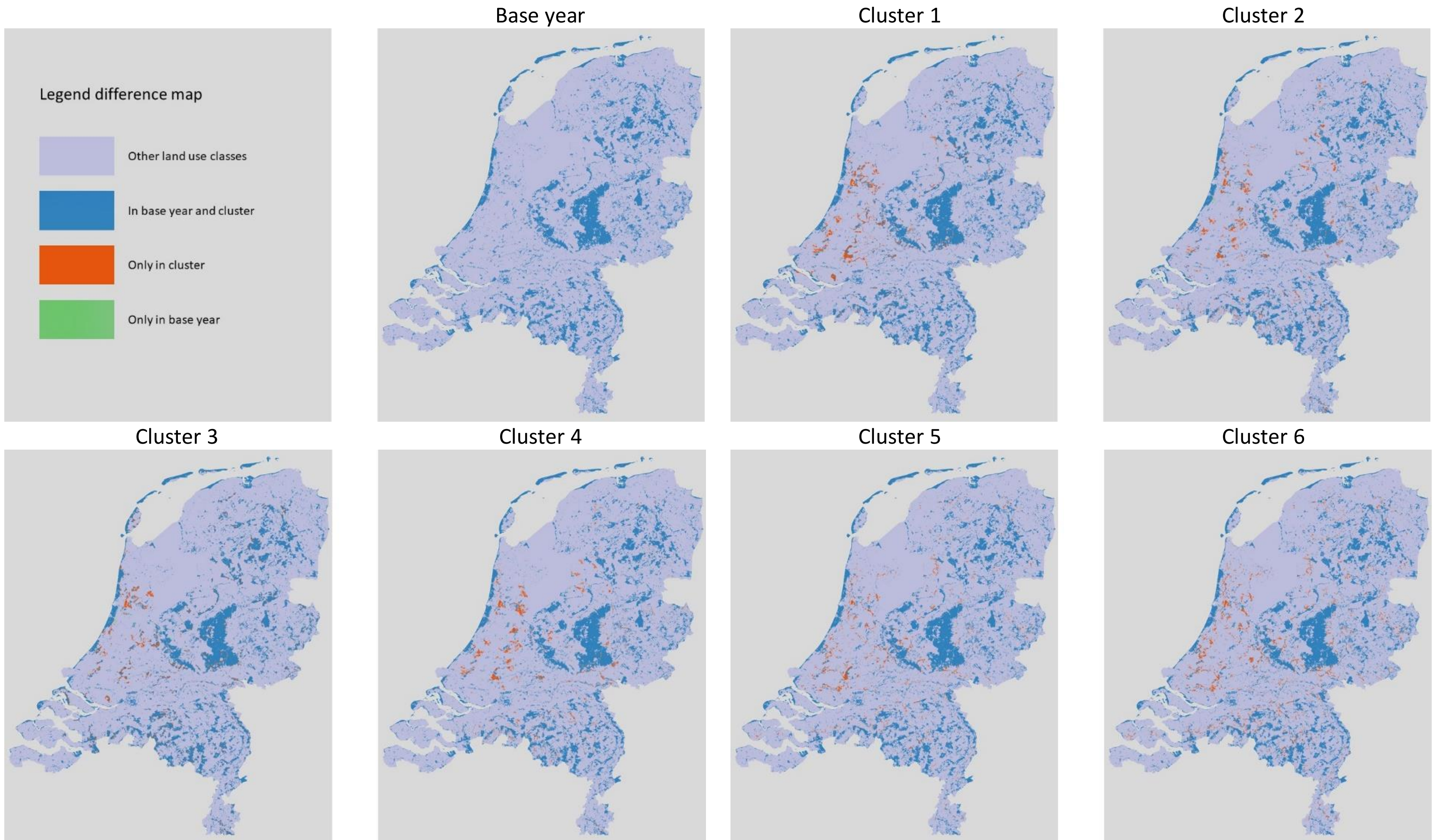


Figure 5.9: Difference map for the nature land use class

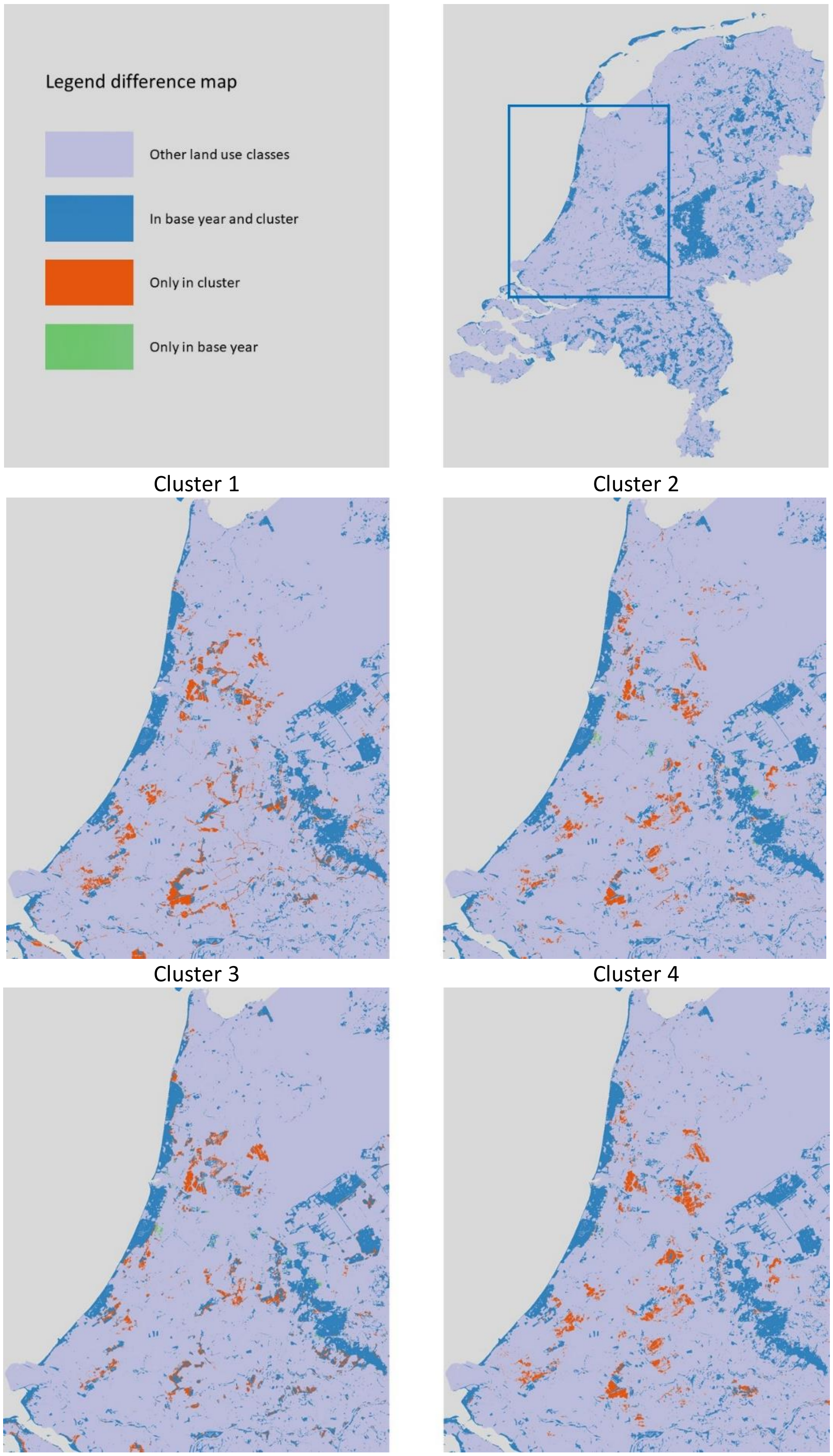


Figure 5.10: Difference map for nature land use class, close up Randstad

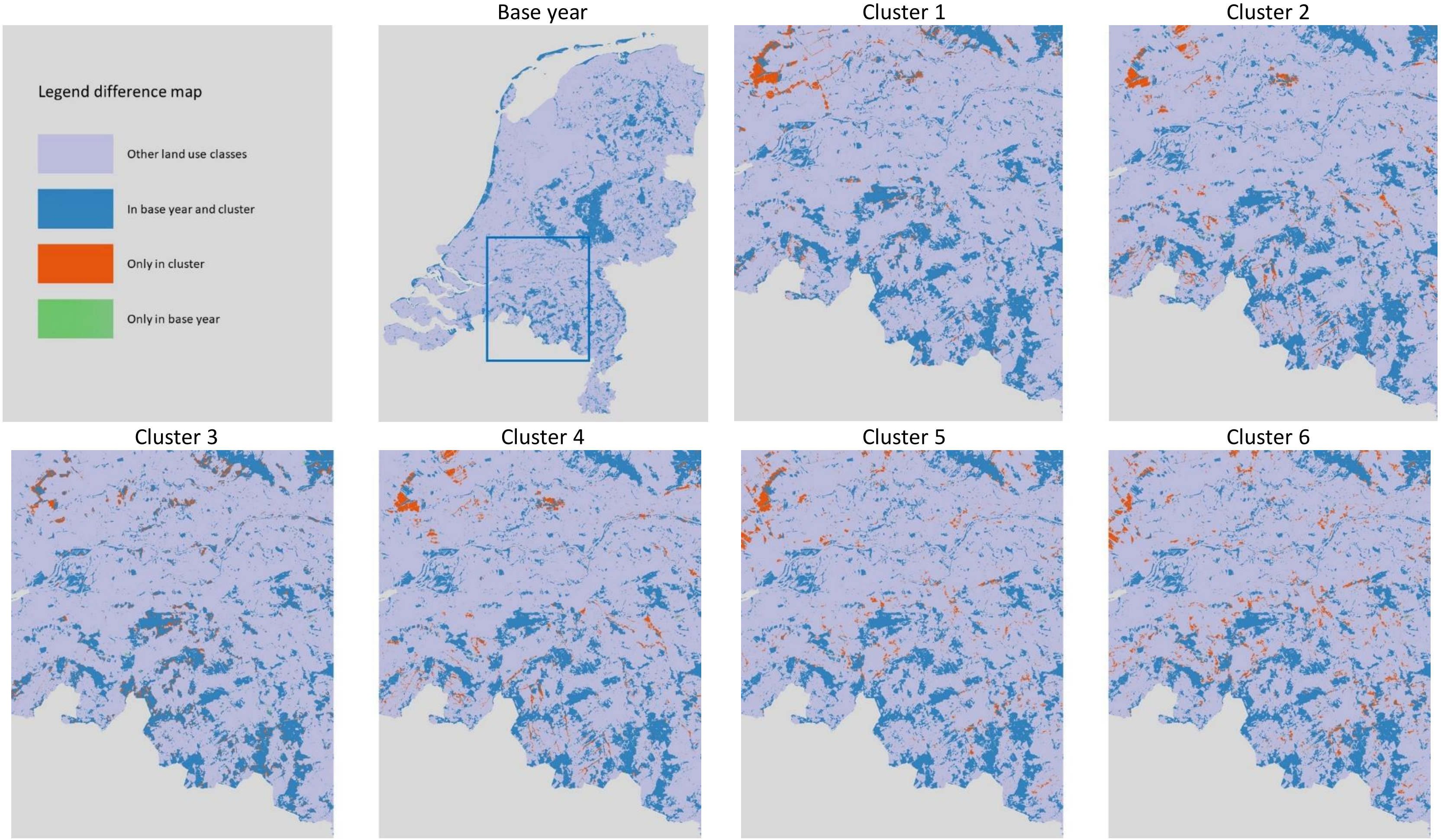


Figure 5.11: Difference map for nature land use class, close up Brabant

5.2.4 The agriculture land use classes

The six clusters all show similar land use patterns for the horticulture and intensive agriculture land use classes. For all clusters, the decrease is limited, with only a 9 per cent decrease of horticulture and a 4 percent decrease of intensive agriculture. The land-use patterns observed for the extensive agriculture land-use class show more diversity between the clusters. The difference maps compared to the base year are displayed in Figure 5.12. Although all cluster shows a decrease in the extensive agriculture land-use class, the clusters that have strong urbanisation land-use patterns show a higher decrease, which is the case for cluster 2 and 3. Cluster 1 and 4 show the lowest decrease in this land-use class, as the increase in other land use classes is also limited. As for cluster 5 and 6, they have a slightly higher decrease in this land-use class because of the strong growth of the industry and commerce land-use class in both clusters. In cluster 6 additional extensive agriculture disappears, as this cluster shows next to strong growth in the industry and commerce land-use class, a medium growth in the nature land-use class.

Figure 5.12: Difference map for the extensive agriculture land use class

5.3 Identification of driving forces

With the CART subspace partitioning algorithm, the underlying driving forces of each cluster are identified. The generated CART tree visualises which driving forces, and their corresponding value, are most predictive for each cluster. A simplified CART tree is created, as shown in Figure 5.13. See D, Figure D.1, for the complete CART tree.

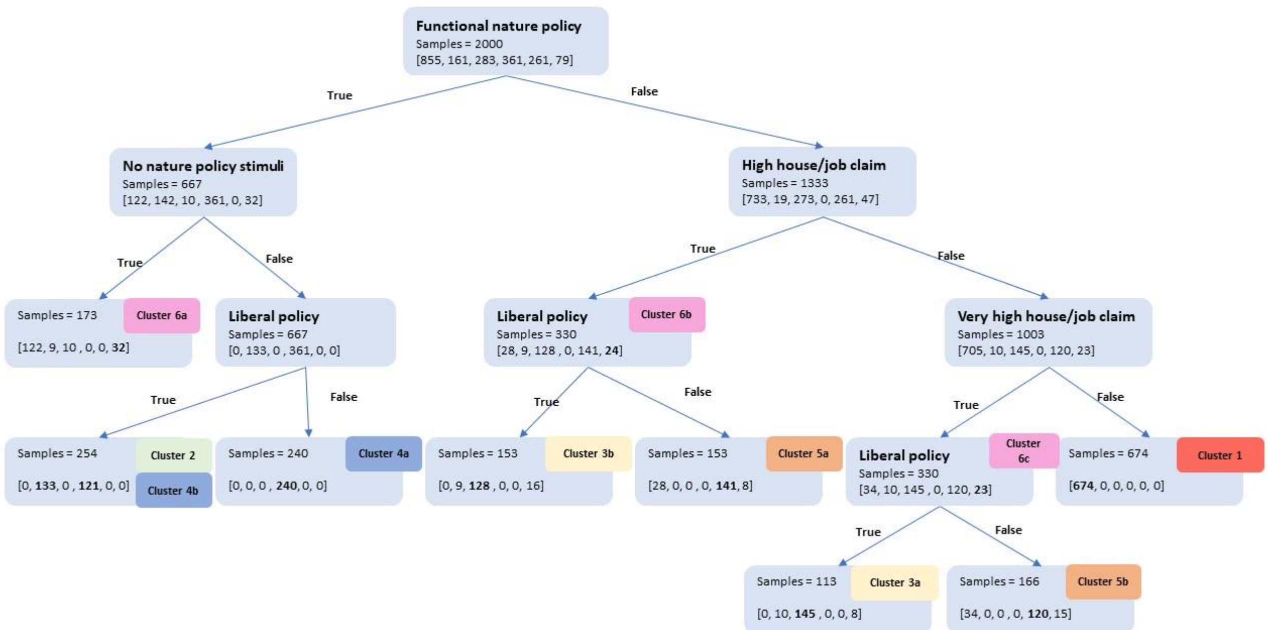


Figure 5.13: Simplified CART tree. The CART tree has been simplified by not displaying the nodes which were not representative for any cluster. In these nodes, the coverage is too low

Table 5.9: Overview important driving forces per cluster, as identified with the CART subspace partitioning algorithm

Cluster	Driving forces	
1	• Robust and Vital nature policy or EHS nature policy • Low or very low house / job claim	
2	• Functional nature policy • Policy stimuli in place • Liberal spatial development policy	
3	• Robust and Vital nature policy or EHS nature policy • High house / job claim • Liberal spatial development policy	• Robust and Vital nature policy or EHS nature policy • ery high house / job claim • Liberal spatial development policy
4	• Functional nature policy • Policy stimuli in place • Restrictive spatial development policy	• Functional nature policy • Policy stimuli in place • Liberal spatial development policy
5	• Robust and Vital nature policy or EHS nature policy • High house/job claim • Restrictive spatial development policy	• Robust and Vital nature policy or EHS nature policy • Very high house/job claim • Restrictive spatial development policy

6	• Functional nature policy • No policy stimuli in place	• Robust and Vital nature policy or EHS nature policy • High house / job claim	• Robust and Vital nature policy or EHS nature policy • Very high house / job claim

As both the CART tree indicates, some clusters have more than one possible sets of driving forces. This becomes even more evident when a parallel axis plot is computed which depicts all possible combinations of driving forces per cluster, as shown in Figure 5.14.

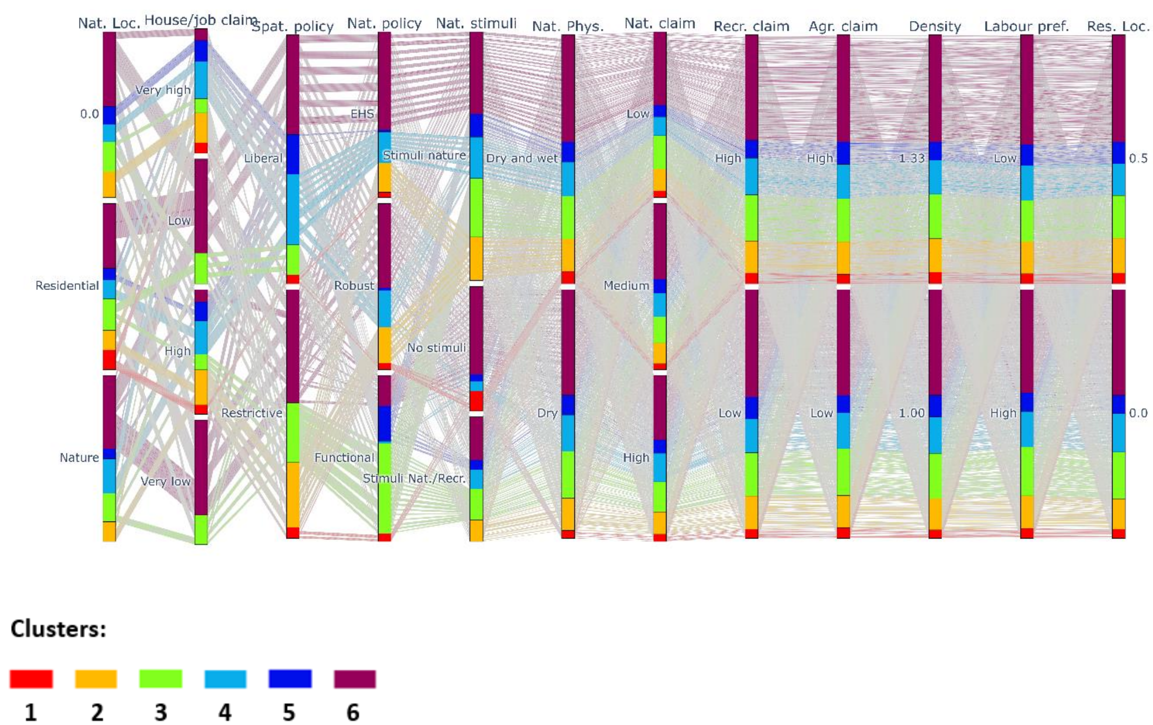


Figure 5.14: Parallel axis plot of clusters and their corresponding driving forces

Based on this parallel axis plot, a number of observations are made. Firstly, the parallel axis plot indicates that all cases within cluster 2 either are characteristic very high or a high house and job claim (house/job claim). Figure 5.15 shows the parallel axis plot solely for cluster 2, which shows that all cases either have indeed a very high or high house and job claim. Interestingly, the CART tree only indicates these specific values for this driving force for 19 cases within cluster 2 (see Figure 5.13). However, since in reality, all cases in this cluster are characterized by a very high or high house and job claim, this driving force will be used for the purpose of scenario development.

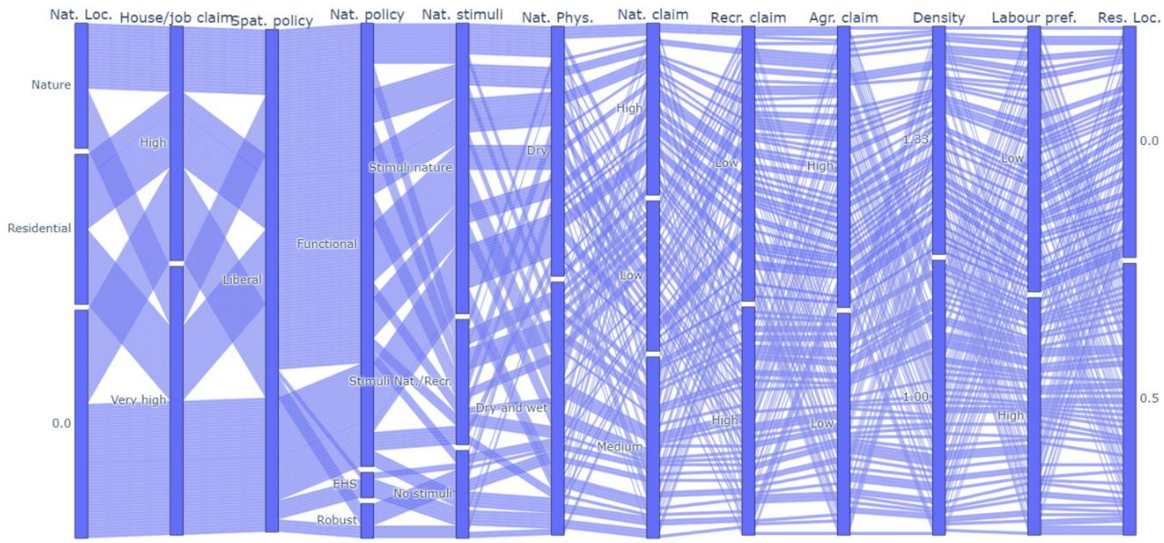


Figure 5.15: Parallel axis plot cluster 2

The parallel axis plot in Figure 5.16 also provides an interesting insight into cluster 6. Namely, all cases are characterised by a nature location value (Nat. Loc.) "equal to residential". However, this driving force was not recognised by the CART tree. To inspect this matter further, an alternative subspace partitioning method is used for this specific cluster, namely PRIM. The resulting plot of PRIM is shown in Figure 5.17 and shows that using this method, the nature location value with the value "equal to residential" is indeed identified as an important driving force. However, the PRIM box also indicates that cluster 6 is characterised by nature policy stimuli value 1, which corresponds to the value "5.0 around nature and recreation", which according to the parallel axis plot in Figure 5.15 is not accurate. The question remains why CART was not able to identify this driving force. This could be due to the fact that cluster 6 is a small cluster, consisting of only 79 cases of the total of 2000 cases. Since the CART algorithm works by maximising the reduction in Gini impurity, which is dependent on the number of members within each cluster, the algorithm fails to identify the nature location suitability as a branching variable due to the fact that it is only relevant for cluster 6, which has a relatively much lower number of members compared to the other clusters. Based on this analysis, it is decided to include this driving force as an important driving force in the scenario development process.

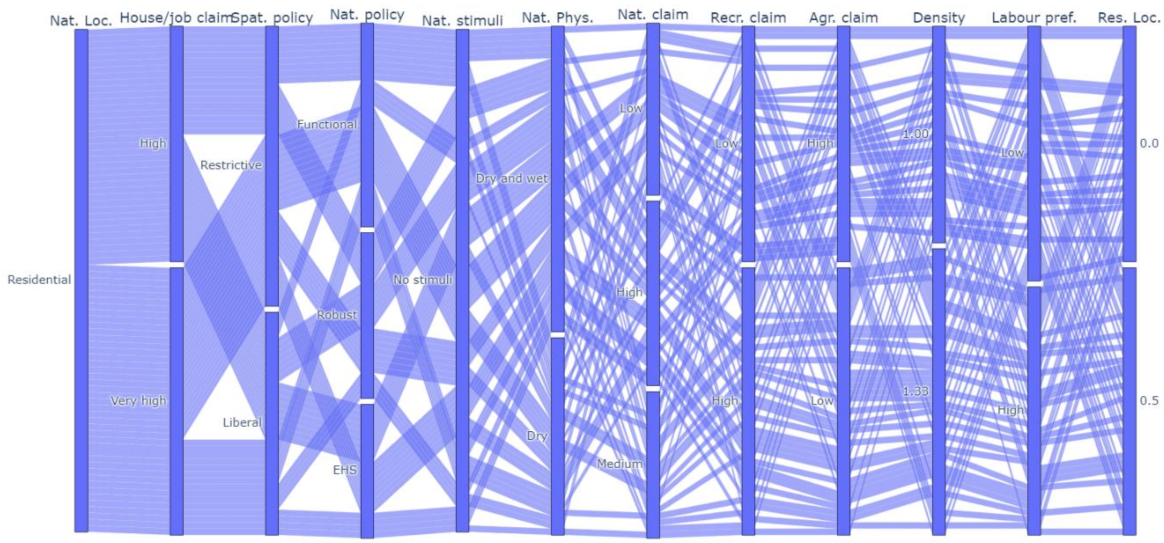


Figure 5.16: Parallel axis plot cluster 6

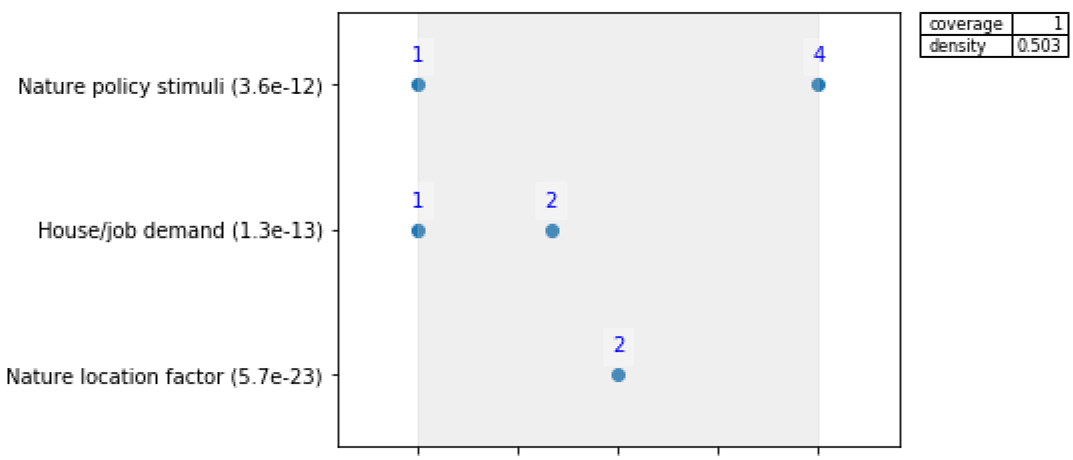


Figure 5.17: PRIM results for cluster 6

Based on above additional analysis, Table 5.9 is updated with this new information, resulting in Table 5.10, as displayed below.

Table 5.10: Clusters and their driving forces, updated Table

Cluster	Driving forces
1	• Robust and Vital nature policy or EHS nature policy • Low or very low demand for houses and jobs
2	• Functional nature policy • Policy stimuli in place

	• Low infringement • High house / job claim, concentrated or scattered		
3	• Robust and Vital nature policy or EHS nature policy • High house / job claim, concentrated • Low infringement	• Robust and Vital nature policy or EHS nature policy • High house / job claim, scattered • Low infringement	
4	• Functional nature policy • Policy stimuli in place • High infringement	• Functional nature policy • Policy stimuli in place • Low infringement	
5	• Robust and Vital nature policy or EHS nature policy • High house / job claim, concentrated • High infringement	• Robust and Vital nature policy or EHS nature policy • High house / job claim, scattered • High infringement	
6	• Functional nature policy • No policy stimuli in place • Increased suitability nature around residential areas	• Robust and Vital nature policy or EHS nature policy • High house / job claim, concentrated • Increased suitability nature around residential areas	• Robust and Vital nature policy or EHS nature policy • High house / job claim, scattered • Increased suitability nature around residential areas

5.4 Cluster discussion

After identifying and introducing the resulting clusters and the driving forces characterizing each cluster, it is noticeable that some clusters can have similar driving forces but different resulting land-use patterns. Also, within several clusters, different combinations of distinctive driving forces are identified. This section will discuss these cases. Firstly, this section will look into cases where similar driving forces result in different land-use patterns. Next, this section will discuss cases where different driving forces result in similar land-use patterns.

5.4.1 Similar driving forces, different land use patterns

Considering the CART tree, cluster 2 and cluster 4b seem to have similar driving forces, while still resulting in two different clusters, thus containing different land-use patterns. However, cluster 2 and 4b do differ in driving forces. As earlier established, all cases in cluster 2 are characterised by high demand in houses and jobs. Looking closely at cluster 4b, however, it can be observed that these cases are characterised by low demand in houses and jobs in combination with a liberal spatial development policy. When the demand in houses and jobs is low, the spatial development policy does not affect the eventual land use patterns greatly. However, when the demand for houses and jobs is high, a liberal spatial development policy results in strong urbanisation patterns, whereas a high infringement percentage strongly reduces the growth of the residential land use class.

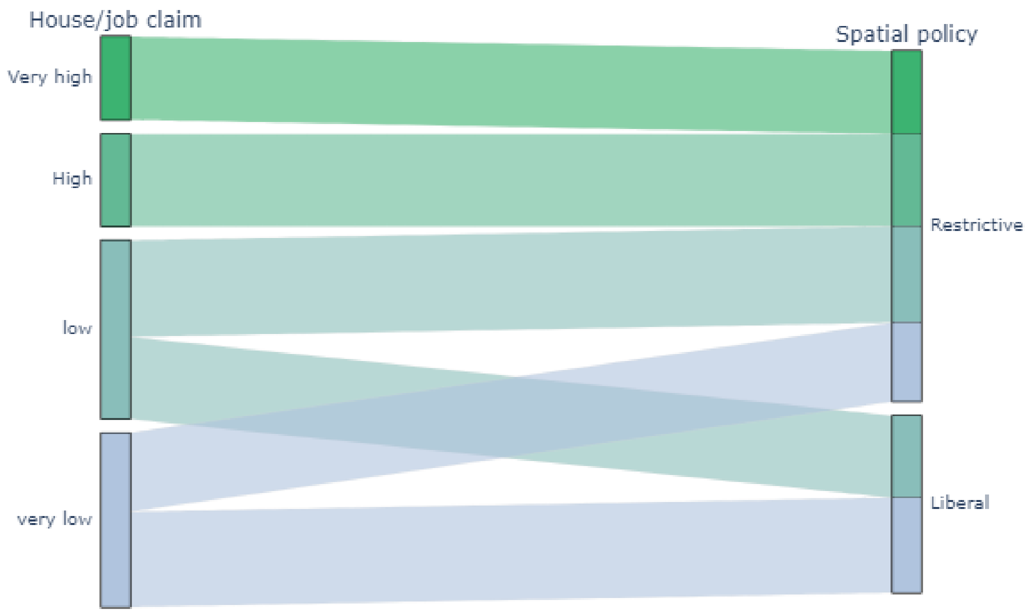


Figure 5.18: Parallel axis plot cluster 4, for demand for houses and jobs, and spatial development policy

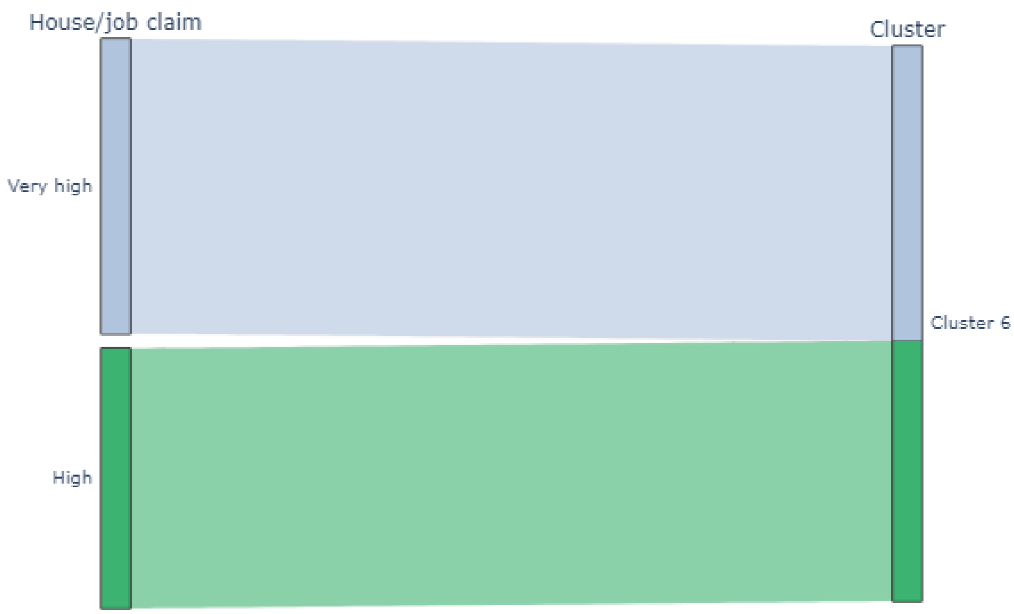


Figure 5.19: Parallel axis plot cluster 2, for demand for houses and jobs, and infringement.

5.4.2 Different driving forces, similar land use patterns

Firstly, the parallel axis plot displaying all clusters and their corresponding driving forces (Figure 5.14) and the CART tree (Figure 5.13) demonstrate that each cluster has at least more than one possible combination of driving forces leading to that certain cluster.

Firstly, considering cluster 1, at the very top of the CART tree it can be observed that 122 of the cases are characterised by a functional nature policy, whereas the other 733 cases are characterised by either a robust and vital nature policy or the EHS nature policy. However, when looking at the parallel axis plot for cluster 1 for the driving forces nature policy and nature stimuli, Figure 5.20 shows that all 122 cases which were characterised by the functional nature policy, are also characterised by no nature policy stimuli which means there are no nature policy stimuli in place. When no nature policy stimuli are in place, the impact of a nature policy map is limited, which could explain why the combination of the functional nature policy with no nature policy stimuli in place still result in similar land-use patterns as when the nature policy map is either map 1 or 2.

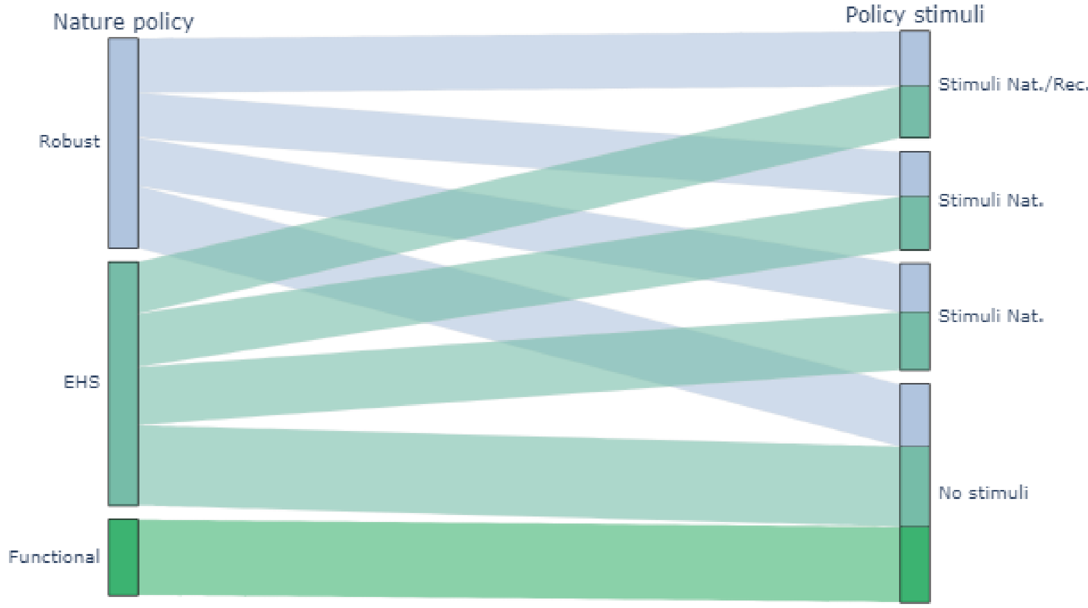


Figure 5.20: Parallel axis plot cluster 1, for nature policy and nature policy stimuli

Considering the driving force demand for houses and jobs, a very high and a high demand does not affect the land use patterns, neither does the difference between a low or very low demand. This is as expected, as earlier research regarding the LUS model indicated that the difference between the two high demand values and the difference between the two low demand values is low (Claassens, Koomen & Rijken, 2017). This explains why for cluster 2 and 3 both a high and very high demand for houses and jobs are important driving forces.

Also, cluster 4 has different combinations of driving forces which lead to similar land-use patterns. As the CART tree indicates, the resulting maps in cluster 4 emerge with both strong and weak infringement. However, as earlier observed in Figure 5.18, weak infringement only occurs in combination with low demand for houses and jobs, whereas a strong infringement of 75 per cent occurs with both high and low demand for houses and jobs, which eventually results in similar land-use patterns.

Lastly, cluster 6 emerges from all three possible nature policy maps, while still resulting in similar land-use patterns. However, as determined earlier, all cases in this cluster are characterised by no nature policy stimuli. This means that the nature policy-map hardly affects the eventual land use patterns at all. Rather, in this cluster, the only driving force which impacts the land use patterns regarding the nature land-use class is the nature location suitability value. For cluster 6, all cases are characterised by nature location suitability value that increases the suitability around residential areas (Figure 5.16). Next to this, cluster 6 is, similar to cluster 2 and 5, characterised by a high and very high demand for houses and jobs. However, this does not affect the eventual land use patterns greatly, thus resulting in similar land-use patterns.

5.4.3 Significance of land use patterns per cluster

Looking at the representative maps of each cluster, and comparing these to the driving forces characterising each cluster, it can be stated that the land use patterns in the medoid map for some land use classes are not necessarily representative for the whole cluster. For example, in all representative maps, the recreation land-use class shows a limited growth of 3 per cent, except in cluster 3 where the growth is 27 per cent. However, in all clusters, both high demand and low demand for recreation are represented in almost equal amounts, as shown in Figure 5.21.

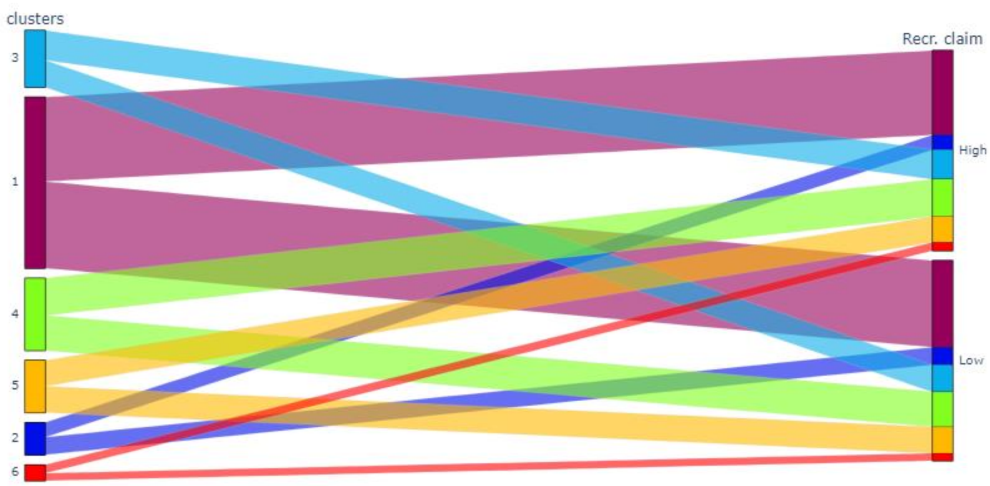


Figure 5.21 Parallel axis plot showing the recreation claim values per cluster

The reason why recreation is not representative for a cluster could be that this land-use class covers only a small fraction of the Netherlands, namely only 0.4 per cent. Thus, for the clustering process used in this research, differences in this land-use class are not significant enough to influence the similarity metric, the Kappa value, used in this research.

The same can be observed for the horticulture and intensive agriculture land use classes, as shown in Figure 5.22.

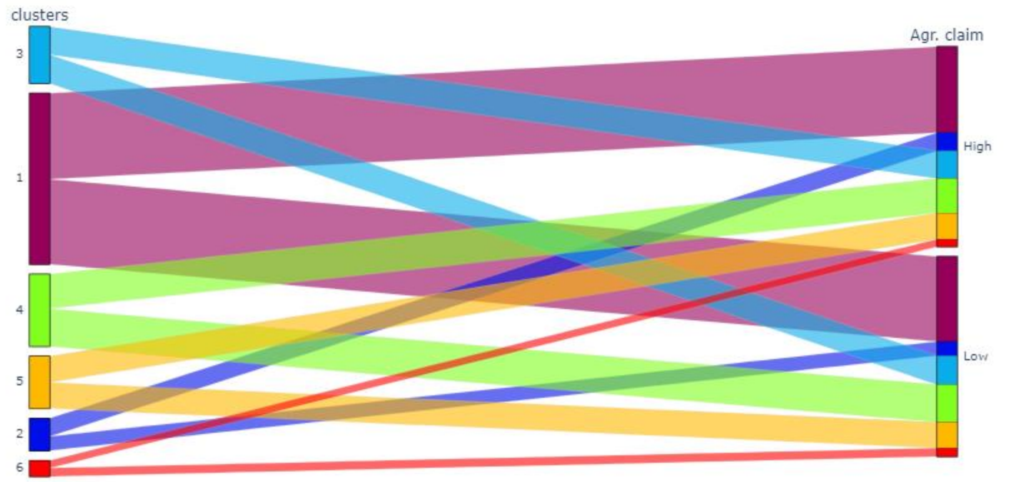


Figure 5.22: Parallel axis plot showing the agriculture claim values per cluster

Moreover, looking at the nature land-use class, it can be stated that for this class the land use patterns in terms of location as observed in the representative map are indeed representative for the whole cluster. However, in terms of magnitude, this is not the case. The magnitude of the nature land-use class directly influences the demand for nature. As the Figure below shows, for each cluster, the number of low, medium and high demand is more or less equal, thus not necessarily unique for a specific cluster.

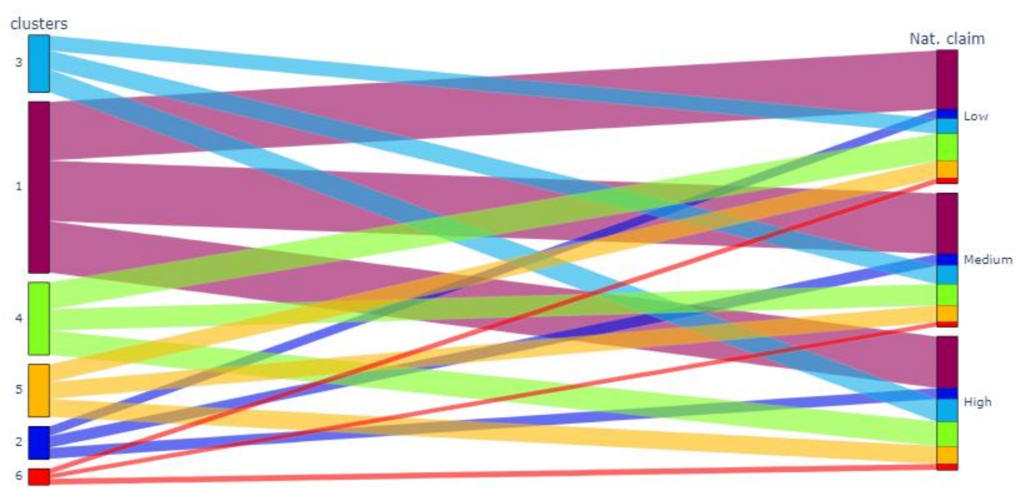


Figure 5.23: Parallel axis plot showing the nature claim values per cluster

5.5 Conclusion

From the 2000 experiments, 6 clusters were formed using the kappa metric and hierarchical agglomerative clustering. For each cluster, a medoid map was selected which serves as the representative map of that cluster. Using CART partitioning, each cluster is characterised based on the driving forces and their corresponding values, resulting in an overview of the combination of driving forces for each cluster. However, upon further analysis, using parallel axis plots and PRIM, this overview is updated. The reason why CART did not identify certain important driving forces could be due to the fact that cluster 6 is a small cluster, consisting of only 79 cases of the total of 2000 cases. Since the CART algorithm works by maximising the reduction in Gini impurity, which is dependent on the number of members within each cluster, the algorithm fails to identify the nature location suitability as a branching variable due to the fact that it is only relevant for cluster 6.

Based on this process, a number of conclusions are made. Firstly, there are no clusters which have the exact same combination of driving forces. Although some clusters show overlap in the driving forces characterising that cluster, by inspecting the parallel axis plots, the source of the difference in the land-use patterns could be identified. This was, for example, the case for cluster 2 and 4b. Secondly, each cluster has at least more than one possible combination of driving forces, while resulting in similar land-use patterns. Lastly, not all land use classes are distinctive to the whole cluster. This is most likely due to the fact that some land use classes, such as recreation, horticulture and intensive agriculture, are too small to impact the kappa value. Thus, the magnitude of this land-use class is not necessarily representative of the whole cluster. This also goes for the nature land-use class, for which the land use patterns in terms of location are representative for the whole cluster, but the magnitude is not. Table 5.11 displays an overview of the clusters and their driving forces and land use patterns.

Table 5.11: Overview of driving forces with corresponding land use patterns for each cluster

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Land use patterns	Urbanisation	No strong urbanisation patterns. Limited growth industry and commerce	Strong urbanization land use patterns. Strong growth in industry and commerce sector.	Strong urbanization land use patterns. Strong growth in industry and commerce sector.	No strong urbanisation patterns. Limited growth industry and commerce.	No strong urbanisation patterns. Strong growth industry and commerce.	No strong urbanisation patterns. Strong growth industry and commerce.
	Nature and recreation	New nature emerges within the ecological main structure.	In Randstad, nature areas are replaced by residential areas. New nature emerges in former agricultural areas.	In Randstad, nature areas are replaced by residential areas. New nature increases and connects existing nature areas.	Limited growth in both recreation and nature areas. New nature areas emerge mainly in agricultural areas.	New nature increases and connects existing nature areas.	New nature emerges throughout the Netherlands, near residential areas.
	Agriculture	Limited decrease in all agricultural land use classes.	Limited decrease in all agricultural land use classes. Only the extensive agriculture land use class shows a slightly larger decrease.	Limited decrease in all agricultural land use classes. Only the extensive agriculture land use class shows a slightly larger decrease.	Limited decrease in all agricultural land use classes.	Limited decrease in all agricultural land use classes.	Limited decrease in all agricultural land use classes.
Driving forces	Urbanisation related	Low or very low house/job claim.	High or very high house/job claim. Low infringement	High or very high house/job claim. Low infringement	High infringement or low infringement	High or very high house/job claim. High infringement	High or very high house/job claim.
	Nature related	Robust and Vital nature policy, or EHS nature policy	Functional nature policy and policy stimuli in place.	Robust and Vital nature policy, or EHS nature policy	Functional nature policy and policy stimuli in place.	Robust and Vital nature policy, or EHS nature policy	No nature policy stimuli in place

Chapter 6

Scenario development and comparison

6.1 Scenario development

In this section, the scenario narratives are formulated. The scenario narratives will be structured similarly to the Delta Scenario narratives. For the sake of scenario development, the scenarios will be matched to the medoid map of each cluster. This will enable the development of complete scenario narratives. Firstly, for each cluster, the scenario elements corresponding to urbanization will be discussed. Next, for each cluster, scenario elements related to nature and recreation are discussed. Lastly, the focus will be on agriculture.

Cluster 1

Urbanisation

The economic growth between 2012 and 2050 is low. Due to the low economic growth, the birth rate within the Netherlands is also low. Moreover, due to the low economic growth, the Netherlands is not necessarily attractive for potential immigrants. All in all, this means the demographic growth is also low. With a low economic and demographic growth, the demand for houses and jobs is limited. As a result, there are no strong urbanisation patterns between 2012 and 2050, which means a low acreage of residential areas emerges over the years.

Nature and recreation

Even though economic growth is low, the government makes money available for the creation and maintenance of nature areas. The goal is to maintain and expand the ecological main structure of the Netherlands in order to improve the connection between nature areas and agriculture areas. However, the overall societal demand for nature is quite low, which means that the actual nature newly created between 2012 and 2050 is limited. Next to nature, the investment in the recreational sector is also limited. Although the recreational sector increases, this increase is limited.

Agriculture

Even though the economic and demographic growth is low, the agricultural sector is performing relatively well. The decrease in demand for horticulture and intensive agriculture products is limited, which means the decrease in acreage is also limited. Overall, this indicates that the agricultural sector is still well functioning.

Cluster 2

Urbanisation

The economic growth between 2012 and 2050 is strong. Both birth rates and immigration rates are high, especially in the Randstad. This results in high demand for housing throughout the Netherlands, with a concentration of demand in the Randstad. Consequently, the labour market is also performing well, which means the demand for jobs has also increased over the years. Due to the liberal spatial development policy, which is in place in the Netherlands, in combination with the increase in households, strong urbanisation land-use patterns occur between 2012 and 2050. Mainly within the Randstad, but also throughout the Netherlands, residential areas are expanded and connected.

Nature and recreation

Due to strong urbanisation, nature areas are replaced by residential areas in some areas, especially in the Randstad. However, new nature areas are also created. Although the Netherlands is doing economically well, the budget for nature development is limited, and the nature policy focusses on functionality and efficiency rather than on the expansion and connection of existing nature areas. This means that newly created nature serves multiple purposes such as recreation, water reserves and biodiversity support. These new nature areas emerge in former agriculture areas, where agriculture landowners receive income for making their land available for these nature purposes.

Agriculture

Although it is expected for intensive agriculture and horticulture to decrease over the years in the Netherlands, the actual decrease between 2012 and 2050 is low. However, the decrease in the extensive agriculture sector is higher. Firstly, this is the result of the strong urbanisation land-use patterns observed in this scenario. Both residential areas as industry and commerce areas replace extensive agriculture areas. On top of that, extensive agriculture is transformed into nature areas, as explained before.

Cluster 3

Urbanisation

The economic growth between 2012 and 2050 is strong. Both birth rates and immigration rates are high, especially in the Randstad. This results in high demand for housing throughout the Netherlands, with a concentration of demand in the Randstad. Consequently, the labour market is also performing well, which means the demand for jobs has also increased over the years. Due to the liberal spatial development policy, which is in place in the Netherlands, in combination with the increase in households, strong urbanisation land-use patterns occur between 2012 and 2050. Mainly within the Randstad, but also throughout the Netherlands, residential areas are expanded and connected.

Nature and recreation

Due to strong urbanisation, nature areas are replaced by residential areas in some areas, especially in the Randstad. New nature areas are created with the purpose of increasing and connecting existing nature areas. This is to maintain and increase biodiversity and create an overall robust and vital nature network throughout the Netherlands. Although the Netherlands experiences strong economic growth, the demand for nature is quite low. Thus, the result is a limited growth of nature between 2012 and 2050.

Agriculture

Although it is expected for intensive agriculture and horticulture to decrease over the years in the Netherlands, the actual decrease between 2012 and 2050 is low. However, the decrease in the extensive agriculture sector is higher. Firstly, this is the result of the strong urbanisation land-use patterns observed in this scenario. Both residential areas as industry and commerce areas replace extensive agriculture areas. On top of that, new nature areas also replace former extensive agricultural areas due to the increase and connection of smaller nature areas.

Cluster 4

Urbanisation

The economic and demographic growth between 2012 and 2050 is low. As a result, this scenario is characterised by weak urbanisation land-use patterns, simply because the demand for houses and *jobs is low.*

Nature and recreation

Both the demand as the budget for nature development is limited. The nature policy focusses on functionality and efficiency and aims at creating new nature areas which fulfil multiple purposes to benefit from this creation in both economic as ecological terms. This means that newly created nature serves multiple purposes such as recreation, water reserves and biodiversity support. These new nature areas emerge in former agriculture areas, where agriculture landowners receive income for making their land available for these nature purposes.

Agriculture

The decrease in demand for agricultural products is limited, resulting in a limited decrease in acreage of all agricultural sectors.

Cluster 5

Urbanisation

The economic growth between 2012 and 2050 is strong. Both birth rates and immigration rates are high, especially in the Randstad. This results in high demand for housing throughout the Netherlands, with a concentration of demand in the Randstad. However, due to the restrictive spatial development policy, this scenario has no strong urbanisation patterns. Although the demand for houses is high, this policy focusses on infringement, which means new houses are mainly built in existing residential areas, rather than creating new residential areas. The reason for this restrictive spatial development policy is to limit urbanisation and to protect National buffer zones, National Landscapes, and nature areas. Young people tend to move towards the Randstad as well, due to the concentration of people and work there (van Gemeren et al., 2016). Due to this, the birth rate within the Randstad will increase and is the main cause of population growth in this area. Outside of the Randstad, population growth is mainly caused by immigration. As a result, within cities, houses are built in higher densities.

Nature

The budget for new nature development allows for the maintenance and creation of new nature with the purpose of maintaining and increasing biodiversity. As a result, new nature areas emerge throughout the Netherlands. The newly created nature areas do not necessarily focus on increasing and connecting existing nature areas, which results in new nature areas rather scattered throughout the Netherlands. However, the overall demand for nature is low, which results in limited growth between 2012 and 2050.

Agriculture

The decrease in demand for agricultural products is limited, resulting in a limited decrease in acreage of all agricultural sectors.

Cluster 6

Urbanisation

The economic growth between 2012 and 2050 is strong. Both birth rates and immigration rates are high, especially in the Randstad. This results in high demand for housing throughout the Netherlands, with a concentration of demand in the Randstad. However, due to the restrictive spatial development policy, this scenario has no strong urbanisation patterns. Although the demand for houses is high, this policy focusses on infringement, which means new houses are mainly built in existing residential areas, rather than creating new residential areas. The reason for this restrictive spatial development policy is to limit urbanisation and to protect National buffer zones, National Landscapes, and nature areas.

Nature

Although economic growth is strong, no policy is in place for the maintenance and creation of nature. In the first place, this results in a relatively random land use pattern of new nature areas. However, society prefers to have nature areas close to their homes. Thus, the new nature areas that do emerge are mainly around residential areas with a concentration in the Randstad.

Agriculture

The decrease in demand for agricultural products is limited, resulting in a limited decrease in acreage of all agricultural sectors.

6.2 Comparison with Delta Scenarios

The heatmap displayed in Figure 6.1 shows the percentage change compared to the base year for the Delta Scenarios and the Scenario Discovery scenarios. Looking at the overall land-use patterns of each scenario, the Figure shows that no scenario is the same as the other. For a detailed comparison of the land use patterns, section 6.2.1 discusses the scenarios for each land use theme. Next, section 6.2.2 will discuss the similarities and differences of the driving forces characterising the Delta Scenarios and the Scenario Discovery scenarios.

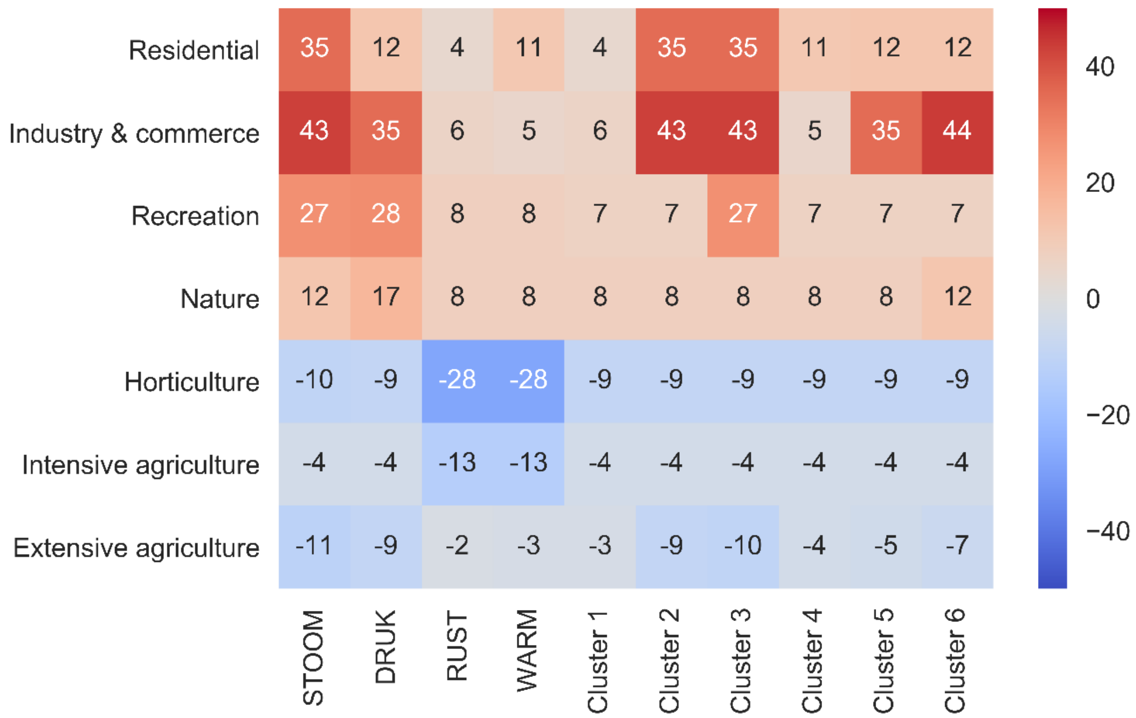


Figure 6.1: Heatmap visualising percentage change compared to base year for Delta Scenarios and scenario Discovery scenarios

6.2.1 Comparison of land use patterns

To compare the scenarios based on their land-use patterns, the scenarios are discussed based on urbanisation, nature and recreation and agriculture land use patterns.

Urbanisation

Strong urbanisation patterns are visible in the Delta Scenario STOOM and cluster 2 and 3. In each of these scenarios, residential areas grow strongly throughout the Netherlands, with a concentration of growth in the Randstad. Next to strong residential growth, the industry and commerce land-use class also grows strongly.

Cluster 5 and 6 are similar to the Delta Scenario DRUK. For these three scenarios, strong growth is visible in the industry and commerce land-use class, while there are no strong urbanisation patterns as the residential land use class grows with only 12 per cent. However, cluster 6 is unique with a growth of 44 per cent in the industry and commerce land-use class, which is the highest growth of all scenarios.

The only scenario that shows similar urbanisation patterns as the Delta Scenario RUST is cluster 1. Both scenarios have limited growth in the residential and industry and commerce land-use class, with only 4 and 6 per cent, respectively. For both these scenarios, this limited growth is concentrated in the Randstad.

Lastly, both the scenarios WARM and cluster 4 have a small growth in the industry and commerce land-use class, with only 5 per cent, but a slightly higher growth in the residential land use class.

Nature and recreation

If only the amount of acreage is considered for the nature land-use class, cluster 6 is similar to STOOM while all other clusters are similar to either the Delta Scenarios WARM or RUST. However, the comparison based on the allocation of this land-use class provides more interesting insights.

Firstly, it can be observed that in both STOOM as cluster 6 new nature emerges in the ecological main structure. However, the nature growth in cluster 6 is more concentrated in the Randstad compared to the nature growth of STOOM. This is partly due to the strong urbanisation land-use patterns in STOOM, which has consequences for the nature land-use class as nature areas are replaced by residential areas in the Randstad. Cluster 6, on the other hand, has no strong urbanisation patterns and thus has more room for nature growth within the Randstad.

STOOM is not the only scenario where nature areas are replaced by residential areas. Both cluster 2 and 3 show similar land-use patterns, as these two scenarios also have strong urbanisation patterns. However, this is where the similarities between STOOM, cluster 2 and cluster 3 end.

In cluster 2, new nature does not emerge within the main ecological structure, but rather in previously agricultural areas which are deemed to be more useful fulfilling multiple functions rather than the agricultural function. The Delta Scenario RUST and cluster 4 follow a similar land use pattern, as new nature also emerges mainly in former agricultural areas. However, as Figure 6.2 shows, each of these three scenarios are still quite unique in their land-use patterns, which is most likely due to the differences in land use pattern in other land use classes.

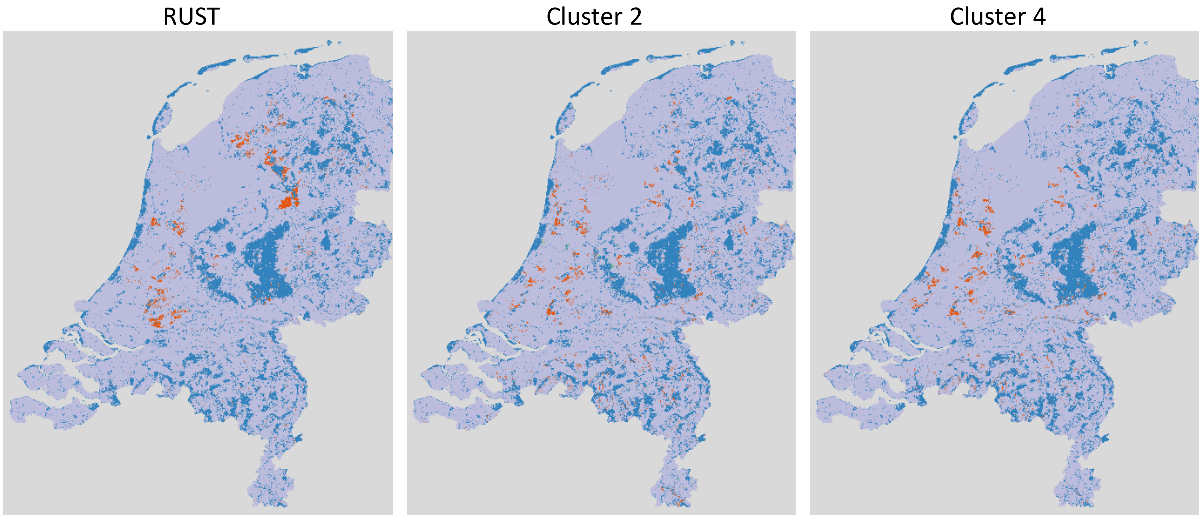
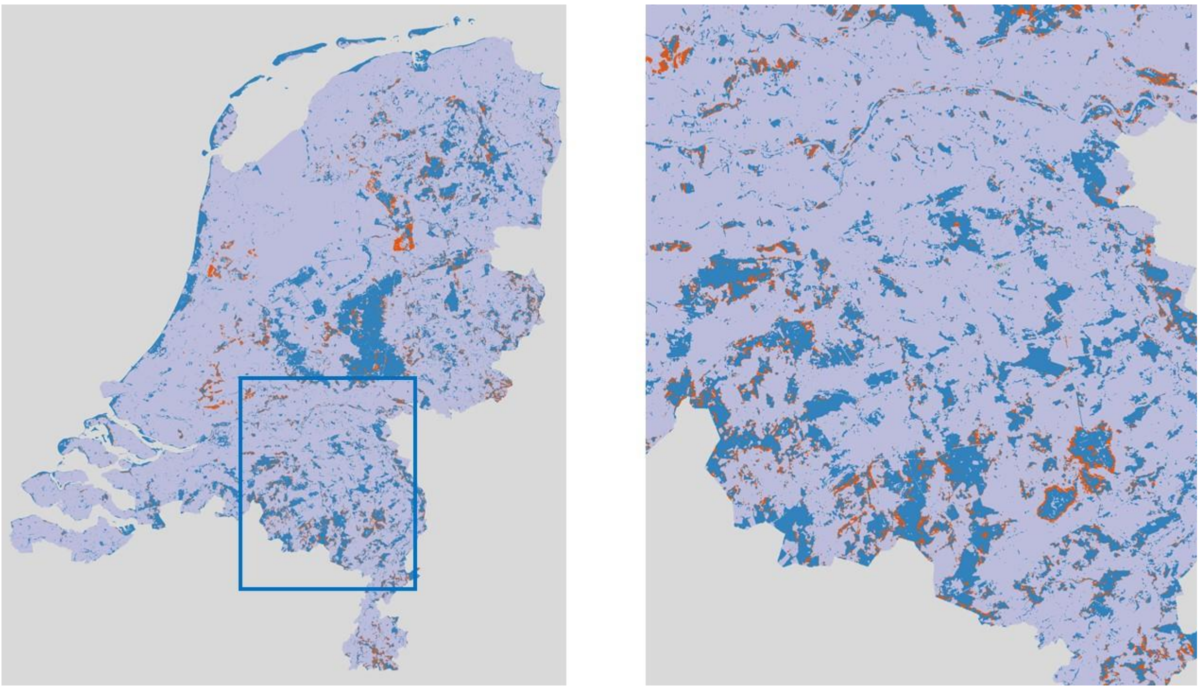


Figure 6.2: Difference map for the nature land use class

As for cluster 3, similar nature land-use patterns are visible in the Delta Scenario DRUK. In both these scenarios, existing nature areas are increased and connected. Looking at the two scenarios, the nature land-use patterns seem quite different, but this is mainly caused by the difference in the amount of acreage. The allocation pattern is more similar, which is demonstrated in Figure 6.3, where it can be observed that new nature areas really cling around existing areas, similar to DRUK. However, since DRUK has a stronger nature growth, this particular land use pattern is more obvious in this scenario.

DRUK



Cluster 3

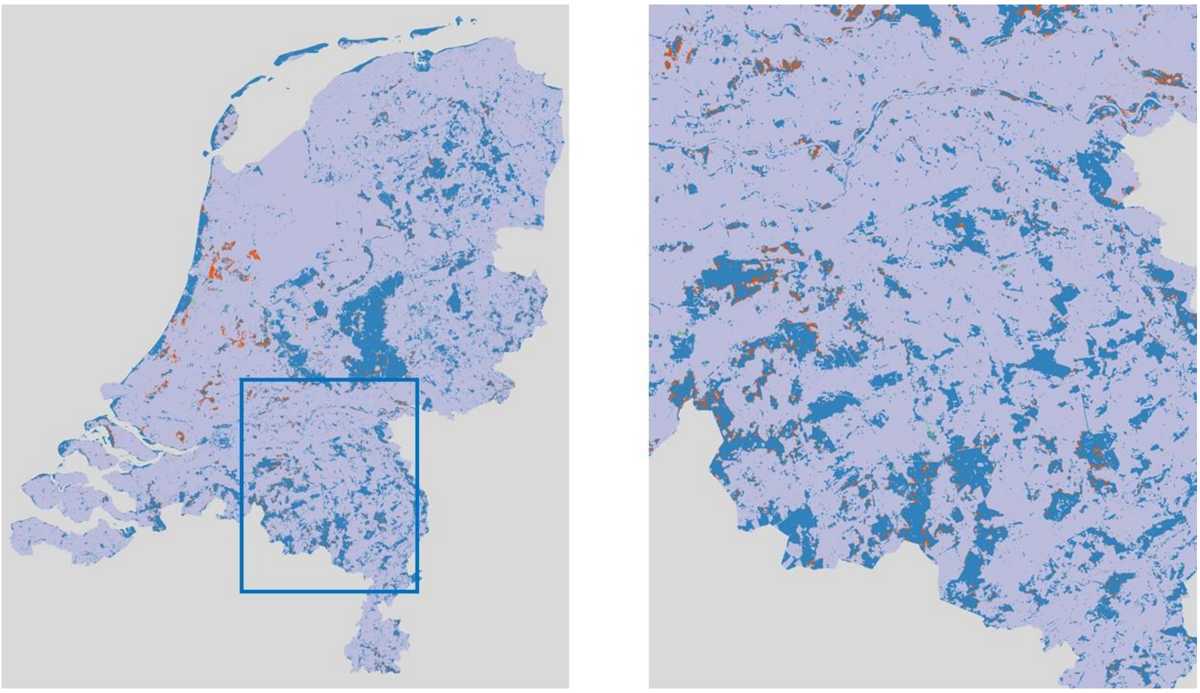


Figure 6.3: Difference map for the nature land use class with close-up

Also, cluster 5 shows similarities with both Delta Scenario DRUK and cluster 3, as new nature in cluster 5 emerges mainly around existing nature areas. However, where both DRUK and cluster 3, this nature emerges clearly within 500 meters of existing nature, new nature in cluster 5 has a more scattered pattern.

The emergence of new nature in a scattered pattern is also a recurring land use pattern in different scenarios. STOOM, WARM, cluster 5 and cluster 6 all have this in common, as shown in Figure 6.4. However, although new nature is more scattered throughout the Netherlands, it is not a random pattern. In reality, this indicated that new nature emerges mainly around residential areas. The Delta Scenario WARM is quite unique, as new nature emerges mainly in the east of the Netherlands.

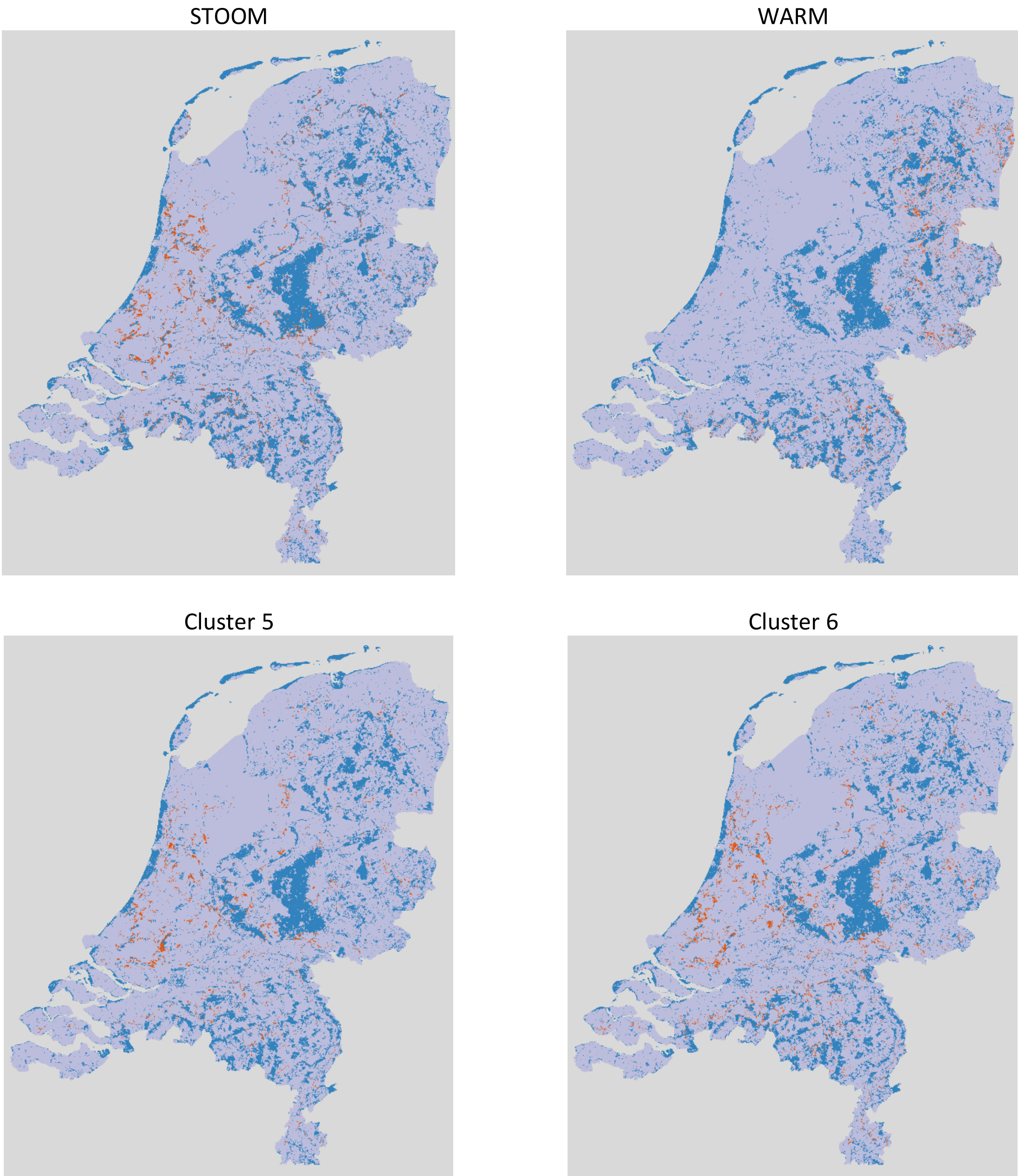


Figure 6.4: Difference map for the nature land use class

Considering the recreation land-use class, all but one cluster show similar land-use patterns compared to the Delta Scenarios WARM and RUST, where the recreation growth is limited to only 7 per cent. Only cluster 3 has a higher growth in this land-use class, namely with 27 per cent, which is similar to the Delta Scenario STOOM.

Agriculture

For both the horticulture as intensive agriculture land use classes, all medoid maps of the clusters have similar land-use patterns as the Delta Scenario DRUK. In this Delta Scenario and all clusters, the decrease of horticulture and intensive agriculture is small. As for extensive agriculture, the decrease of this land-use class depends on how much the other land use classes grow. The Delta Scenarios and Scenario Discovery scenarios show similar land-use patterns. For the scenarios that have strong urbanisation patterns, the decrease of the extensive agricultural land-use class is higher. This is observable in STOOM, cluster 2 and cluster 3. On the other hand, the scenarios with weak urbanisation patterns show a limited decrease in the extensive agricultural land-use class, as is the case for RUST, WARM, cluster 1 and cluster 4.

6.2.2 Comparison of driving forces

For the Delta Scenarios and Scenario Discovery scenarios, not one scenario shows the exact same land-use patterns as the other, although similarities do exist when considering each land-use class separately. It is thus interesting to analyse whether or not the scenarios with similar and different land-use patterns also share the same driving forces, or if they are characterised by different driving forces.

All scenarios with strong urbanisation patterns share a similar set of driving forces, namely a very high demand for houses and jobs in combination with liberal spatial development policy. This is the case for Delta Scenario STOOM and the Scenario Discovery scenarios of cluster 2 and 3. However, whereas the STOOM scenario is only characterised by a very high demand for houses and jobs, cluster 2 and 3 are characterised by either a very high or high demand for houses and jobs. This is also the case for cluster 5 and 6, which share similar urbanisation patterns to the Delta Scenario DRUK. Whereas the scenario DRUK is characterised by a high demand for houses and jobs, cluster 5 and 6 have cases with both high or very high demand for houses and jobs, while still resulting in similar land-use patterns. Figure 6.5 demonstrates this, where for these four clusters, the value for the demand for houses and jobs are visualised. For the Scenario Discovery scenarios which have no strong urbanisation patterns and also a low growth of the industry and commerce land-use class, clusters 1 and 4, a similar phenomenon is observed as these two clusters are characterised by both low and very low demand for houses and jobs, whereas the Delta Scenarios WARM and RUST are characterised by either one of the low demand values. Moreover, although cluster 4 shows similar urbanisation land-use patterns as RUST, some cases of cluster 4 are characterised by a high or very high demand for houses and jobs. However, these cases occur only in combination with restrictive spatial development policy, thus still yielding similar urbanisation land-use patterns as the cases where the demand for houses and jobs is low.

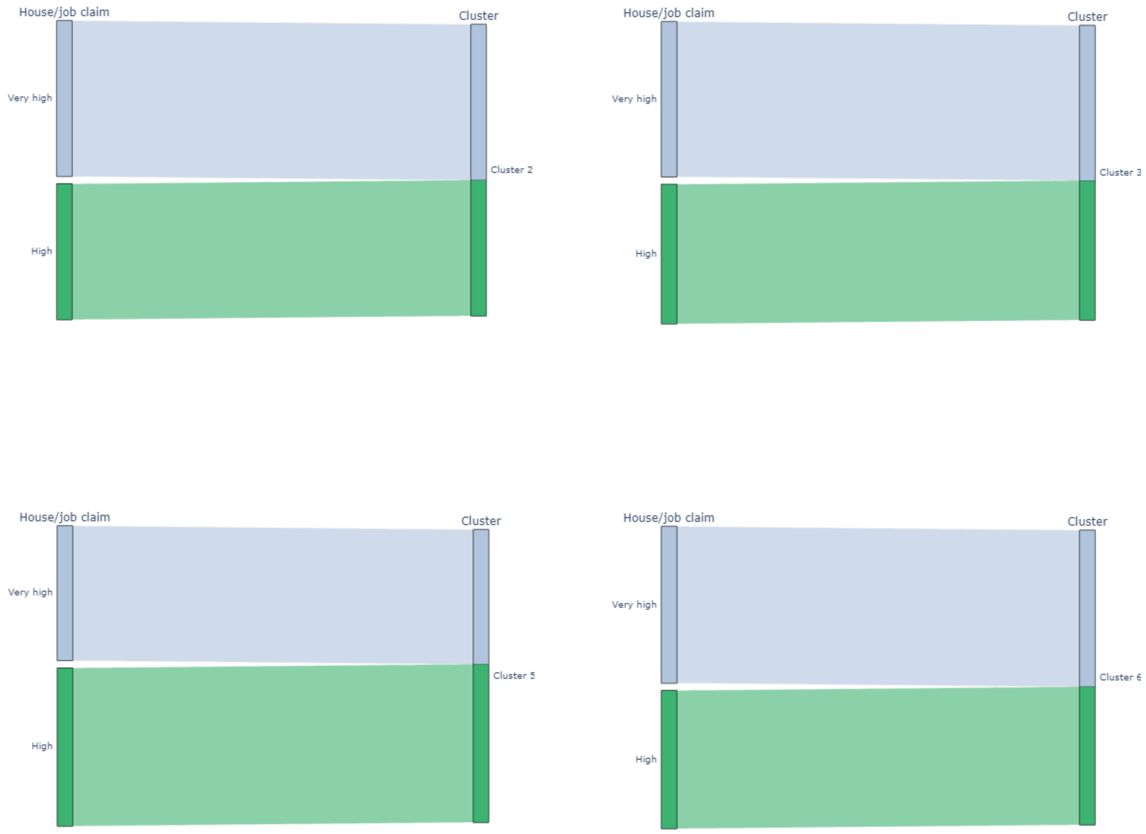


Figure 6.5: Parallel axis plot for house/job demand and the corresponding clusters

The driving forces influencing the nature land-use class are the demand for nature, the nature policy, the nature policy stimuli, and a couple of factors used to calculate the suitability for nature, namely the physical and location factor. The nature land-use patterns observed in the Scenario Discovery scenarios result from different combinations of these driving forces and are hybrids of the Delta Scenarios.

Each Delta Scenario has an almost unique set of driving forces related to the nature land-use patterns. In contrast, the Scenario Discovery scenarios have similarities in their driving forces related to the nature land-use patterns. For example, some cluster shares the same nature policy, as shown in Figure 6.6. Still, due to different combinations with nature-related driving forces other than the nature policy, diverse nature land-use patterns emerge. Moreover, most clusters are characterised by more than one nature policy, while resulting in similar nature land-use patterns.

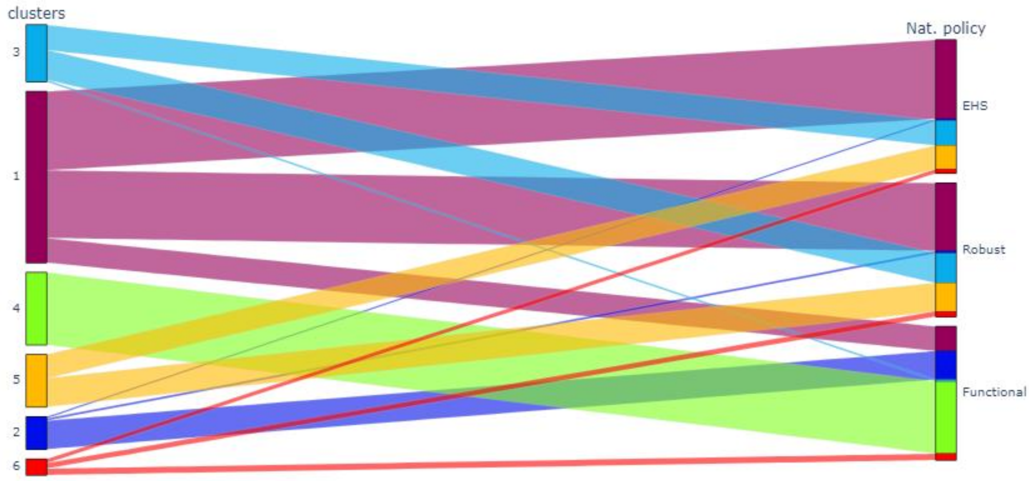


Figure 6.6: Parallel axis plot for clusters and their corresponding nature policy

As an example, the driving forces characterising cluster 1 are shown in Figure 6.7. Most in-cluster cases of cluster 1 are characterised by either the Robust and Vital nature policy, or the EHS nature policy, in combination with different policy stimuli. However, several cases are also characterised by the Functional nature policy. According to this Figure, all in-cluster cases with the functional nature policy are in combination with no policy stimuli in place, which indicates that the Functional nature policy has no influence. Thus, this explains how cluster 1 can contain in-cluster cases characterised by the Functional nature policy, while still resulting in land-use patterns overall similar to the whole of cluster 1.

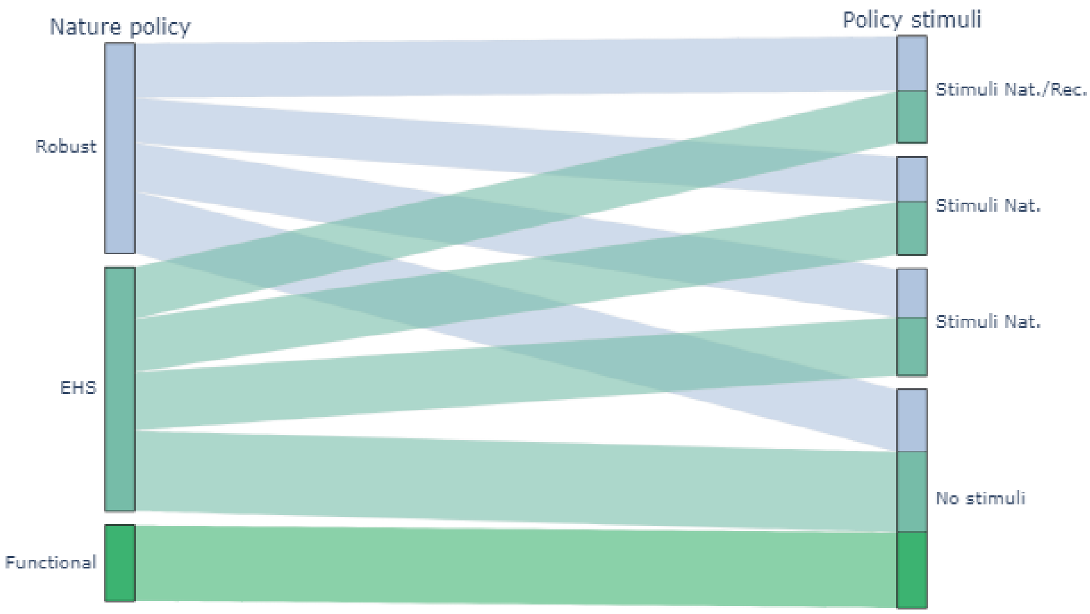


Figure 6.7: Parallel axis plot cluster 1 for the driving forces nature policy and nature policy stimuli

Lastly, the Scenario Discovery scenarios and the Delta Scenarios differ as well in which driving forces are considered as important. All driving forces considered as important by the Scenario Discovery scenarios are also considered as important by the Delta Scenarios. However, not all driving forces considered important by the Delta Scenarios are considered as important by the Scenario Discovery scenarios. The only driving forces considered as important by the Scenario Discovery scenarios are House and job claim, spatial development policy, nature policy, nature policy stimuli and nature location value.

6.3 Conclusion

Several conclusions can be drawn from the comparison between the Delta Scenarios and the Scenario Discovery scenarios. Firstly, the Scenario Discovery scenarios included land-use patterns which were different from the Delta Scenarios. From the comparison of driving forces, it became clear that these new land-use patterns observed in the clusters were the result of combinations of driving forces which were not present in the Delta Scenarios. This means that possibly policy-relevant land-use patterns could emerge from hybrids of the Delta Scenarios. Moreover, whereas each Delta Scenario has one set of driving forces characterising that scenario, the Scenario Discovery Scenarios show that similar land-use patterns emerge from multiple combinations of driving forces, rather than one fixed set. Lastly, the comparison showed that different land-use patterns could emerge, even though the majority of the driving forces is the same. For these cases, it can be interesting to analyse what exactly causes the difference in land use patterns.

Chapter 7

Discussion

Numerous studies have suggested the use of Scenario Discovery, or other similar approaches, rather than the use of a deductive scenario development approach for the development of scenarios (Gerst, Wang & Borsuk, 2013; Lamontagne et al., 2018; McJeon et al., 2011; Rozenberg et al., 2014; Weaver et al., 2013). The key difference between these approaches is that rather than using models to simulate a set of pre-defined scenarios, following a story and simulation approach (Alcamo, 2008), the models itself are used to produce scenarios. However, such story and simulation approaches remain the standard in most modelling fields, including the land use modelling field (Koomen, Hilferink & Borsboom-van Beurden, 2011; Rounsevel et al., 2006; Verburg, Tabeau & Hatna, 2013; Dekkers, Koomen, Jacobs-Crisioni & Rijken, 2012; Mallampalli et al., 2016).

To demonstrate the potential of Scenario Discovery in the land-use change modelling field, this research used Scenario Discovery for scenario development with the aid of land-use change models, as an alternative to the use of a priori specified scenarios. To do this, the Dutch Land Use Scanner model was used. The resulting scenario narratives from the Scenario Discovery approach were then compared to the results of the Land Use Scanner model when used with a priori specified scenarios, namely the Delta Scenarios.

The following sections in this chapter will firstly reflect on the limitations of this research. Next, this chapter will discuss the results and put them in the context of relevant literature. Lastly, this chapter will discuss the implications of the results and proposes research recommendations.

7.1 Limitations

This section will discuss the limitations of this research and the results, to indicate what can and what cannot be concluded from this research.

Firstly, the scoping of this research contributed to the limitations. The modelling and simulation of the Delta Scenarios involve a modelling chain, of which the LUS model is one part. However, within this model chain, only the LUS model is used for this research. Because the LUS model uses the output of models earlier in this model chain as input for its simulation process, some identified uncertainties do not directly affect the LUS model. As a result, these uncertainties could not be analysed individually. For example, one of the most important uncertain driving forces in the Delta Scenarios is economic growth and demographic development. However, these driving forces did not directly influence the Land Use Scanner model, but rather influenced a model earlier in the model chain directly, namely the TXL model. Also, using only the LUS model limits the way the results of this research can be interpreted. Although it is possible to analyse the resulting land-use patterns of each cluster, identifying the exact implications of these land-use patterns for policymakers is usually done using post-processing mechanisms within the LUMOS model chain. These post-processing mechanisms often involve other models or calculation, which make more sense of the resulting land-use patterns.

The next limitations involve the experimental set-up of the Scenario Discovery approach in this research. Firstly, the selected uncertainties were limited to the uncertainties which were already implemented as uncertainties in the LUS model. However, as this research pointed out, more uncertainties exist in the LUS model. Also, in hindsight, the definition of certain uncertainties could have been improved. For example, the uncertainties regarding the nature policy and the nature policy stimuli were treated as two separate uncertainties. However, these uncertainties are closely related could also be seen as one uncertainty. Also, of the four possible values of the nature policy stimuli uncertainty, two of these values have the same effect and should have been considered as one value. This means that the nature policy stimuli uncertainty consists of three possible values, rather than four. Although the use of four separate values did not have a great impact on the results, it does cause the eventual cases as sampled with the LHS algorithm to be out of proportion. Overall, the experimental set-up was not the focus of this research but could benefit from these improvements in future use.

In this research, the Kappa similarity metric is used to calculate the similarity between land use maps. However, more similarity metrics exist which could be better (or worse) suited for calculating the similarity between land use maps. This research did not look into how different similarity metrics possibly influence the clustering process of land use maps. Thus, a limitation of this research is that just one similarity metric was used for the calculation of map similarity, while it is uncertain how this might have affected the outcome. Following this limitation, this research also knows limitations in the clustering process. Also, for clustering, there are multiple clustering algorithms to choose from. Apart from the agglomerative hierarchical clustering algorithm with complete linkage used for this research, another clustering algorithm was also possible to use. For example, the so-called k-medoids clustering algorithm could have been implemented, which is a partitional clustering algorithm in contrast to the hierarchical clustering algorithm used in this research. Consequently, another limitation of this research is that such different clustering algorithms were not compared and how the choice in clustering algorithms affects the results remains unknown. Another limitation of this research, which also relates to the clustering process, is that the clustering was based on all possible land use classes, and did not compare the clusters where only relevant land use classes were considered. As this research showed, some land use classes were so small compared to other land use classes, that they did not play a significant role in the clustering process. As a result, some land use classes, such as the recreational land-use class, were not necessarily representative for their whole cluster. However, although some land use classes are relatively small, this does not mean they are insignificant for policymakers.

While identifying the key driving forces for each cluster with the CART subspace partitioning algorithm, some inconsistencies were brought to light upon further analysis of the driving forces. Firstly, some driving forces which are unique for a specific cluster were not identified by CART as important driving forces. This was the case for a driving force which was only relevant for cluster 6, a relatively small cluster with only 79 members. Since CART works by maximising the reduction in Gini impurity, the algorithm failed to identify this specific driving force, as the Gini impurity is dependent on the number of members within each cluster and cluster 6 has a low number of members compared to the other clusters. Because of this disadvantage of CART, PRIM was used as an additional analysis for cluster 6, where this driving force was indeed identified as an important driving force. Another identified disadvantage of CART was the misrepresentation of the number of members in a cluster in a certain box within the CART tree. Some boxes showed a low coverage for a certain cluster, the fraction of cases in that box of a certain cluster. This was, for example, the case for cluster 6, for which the CART tree showed that only 19 of the 161 in-cluster cases were characterised by high or very high demand for houses and jobs. While, when looking at the parallel axis plot of cluster 2, it shows that all 161 in-cluster cases are characterised by a high or very high demand for houses and jobs. This phenomenon is due to the way the CART tree is formed. Due to an earlier split higher in the CART tree, not all 161 in-cluster cases ended up in the box representing the cases where demand for houses and jobs are high or very high.

Lastly, although the use of Scenario Discovery in this research resulted in five scenario narratives, it is not guaranteed that each scenario narrative is internally consistent. One way to attempt the creation of scenario narratives which are internally consistent is the application of Cross-impact balance analysis (Schweizer & Kurniawan, 2016). With Cross-impact analysis, one records all state-dependent interdependencies of the driving factors considered in scenario development. However, the use of Cross-impact analysis needs more research, as there is not yet a general approach for using this in various modelling fields (Schweizer & Kurniawan, 2016). Thus, the resulting scenarios in this research which were derived using Scenario Discovery might not all be internally consistent.

7.2 Interpretation of results

The use of Scenario Discovery resulted in six scenario narratives and corresponding land-use patterns of which not one is exactly similar to the Delta Scenarios. However, considering the land use classes individually, similarities do exist. On the other hand, some land use classes in the Scenario Discovery scenarios show land use patterns which were not visible in the Delta Scenarios.

Apart from the fact that Scenario Discovery yielded not previously considered scenario narratives and land use patterns, the results of Scenario Discovery differ in other ways as well. Firstly, this research showed that similar driving forces could lead to different land-use patterns. Cluster 2 and 4 share similar driving forces. Namely, both clusters are characterised by a high number of cases with a functional nature policy, nature policy stimuli in place, and liberal spatial development policy. Upon further inspection of these two clusters, the source of the difference in land-use patterns could be identified. Namely, where a liberal spatial development policy in cluster 2 was always combined with a high demand for houses and jobs, resulting in strong urbanisation land-use patterns, liberal spatial development policy in cluster 4 was always combined with low demand for houses and jobs, resulting in no urbanisation. Thus, although the majority of the driving forces between these clusters were similar, specific combinations with other driving forces resulted in two different land-use patterns.

Also, this research showed that similar land-use patterns emerge through different combinations of driving forces. There are several explanations for this occurrence. Firstly, in some cases, a driving force simply does not influence the eventual land use pattern enough. This is, for example, the case for the driving forces nature, recreation and agriculture claim. The difference between land use patterns cause by either a low or high claim value of these driving forces do not influence the Kappa value. This can either be due to the fact that the land-use class that is influenced is too small in acreage to impact the Kappa value or due to the fact that the difference between the values of these driving forces is too small. Another possibility is that certain combinations of driving forces result in similar land-use patterns. For example, the combination of high demand in houses and jobs with a restrictive spatial development policy results in similar urbanisation patterns as low demand in houses and jobs in combination with liberal spatial development policy.

Thus, whereas the Scenario Discovery scenarios show the possibility of similar driving forces and different land-use patterns and vice-versa, the Delta Scenarios exist out of scenario narratives which each have their unique combination driving forces corresponding to on unique land use pattern. In general, studies using a story and simulation approach, often not address this occurrence, while different studies using a Scenario Discovery approach showed similar results. For example, the work of Lamontagne (2018) showed how a set of similar driving forces could be associated with both good and bad outcomes, depending on the policy context and specification of outcomes of interest.

Not all driving forces considered important in the development of the Delta Scenarios were identified as important driving for the Scenario Discovery narratives. In the Delta Scenarios, the complete selection of uncertainties as identified in this research are considered as important driving forces. However, the CART subspace algorithm, and some additional analysis methods, identified only a small number of driving forces as important. Only the spatial development policy, the nature policy, the nature policy stimuli and the demand for houses and jobs are identified as important driving forces. As indicated in the research of Rozenberg (2014), one concern of the story and simulation approach is that the focus is not on the most important driving forces. Scenario Discovery enables analysts to identify those driving forces most relevant to their outcomes of interest. Considering the results in this research, this implies that the use of Scenario Discovery enables policymakers to focus their policies on the most important driving forces, and thus prevent them from focussing on less important factors.

It is important to realise that the identified driving forces depend greatly on how the outcomes of interest are defined. In this research, the 2000 generated land use maps were clustered based on the Kappa value, which represents the overall similarity between land use maps. Consequently, land use classes which cover a relatively small area in the Netherlands do not impact the clustering process much as they do not change the overall land-use patterns much. The recreational land-use class is one of those small land-use classes. As a result, none of the clusters contained a distinctive recreational land use pattern and the driving forces which only influence this specific land use class are not identified as important driving forces. Thus, the use of different similarity metrics or different clustering approaches also results in different important driving forces. This is viewed as one of the perks of Scenario Discovery. Firstly, when diverse stakeholders are involved in the decision-making process, it is often easier to agree upon what defines outcomes of interest than to agree upon which driving forces are most important, as is necessary in story and simulation approaches (Groves and Lempert, 2007). Secondly, it enables policymakers to use models to identify scenarios that are important to the decisions they have to make (Groves and Lempert, 2007).

Lastly, although this research only took the uncertainties into consideration as already identified in the Delta Scenarios, the identification and classification of uncertainties have shown that in the Land Use Scanner model only a part of the all existing uncertainties is covered. This became especially clear when considering the different locations of uncertainties present in model-based decision making. From all seven locations of uncertainties, as defined by Kwakkel, Walker & Marschau (2010), the LUS model only considers one location, namely the input data location. These findings build on the existing evidence that overall, in geospatial research, such as this one, not all potential sources of uncertainties are considered, as suggested by García-Álvarez et al. (2019). It is important for analysts in the land-use modelling field to be aware of the uncertainties from multiple sources and to communicate these uncertainties well, as in present time uncertainties could act as a barrier for decision-makers to take the results from geospatial models, such as the LUS model, into consideration in the decision-making process (García-Álvarez et al., 2019).

7.3 Implications

The Land Use Scanner model has been around for a long period of time and has evolved over the years. This model has been applied in various fields and has the potential to support informed decision making. However, as pointed out by Weaver (2013), many models fall short of their potential as decision-making support tools. This is also the case for the Land Use Scanner model, as this model is currently not actively used in the decision-making process (Timmermans, Batty, Couclelis & Wegener, 2011). One of the reasons for this lack of use of the Land Use Scanner model is that several aspects of uncertainty do not receive the attention it needs (Timmermans, Batty, Couclelis & Wegener, 2011). Although the use of the Delta Scenarios is a good start in handling uncertainties in a systematic way, the use of a number of pre-defined scenarios to simulate with a model still faces many challenges.

This research has demonstrated the use of an alternative way for scenario development, namely, Scenario Discovery. The results indicate that this approach is capable of generating a number of model-driven scenarios in a way that provides additional insights into the complex system of land-use change, which were otherwise overlooked. Therefore, it is recommended for users of the Land Use Scanner model, such as the PBL, to explore alternative ways to utilise this model. Rather than using this model solely for the simulation of pre-defined scenarios, this model itself should be used to generate scenarios. Moreover, as this research pointed out the presence of many more uncertainties other than the ones identified in the Delta Scenarios, it is recommended for users of the Land Use Scanner model to research these uncertainties and acknowledge their existence and even consider including these uncertainties in the implementation of Scenario Discovery.

On a broader level, the findings in this research support the belief that using models in a story and simulation approach alone is not sufficient in its role to support policymaking, which is also suggested in several other studies such as Lamontagne (2018), Rozenberg et al. (2014) and Gerst, Wang & Borsuk (2013). Models, including land-use change models, have the potential to support informed decision-making. To enable decision-makers to do so, it is time to not limit models to the use of a story and simulation approach. Following the two decision-making paradigms as defined by Weaver (2013), instead of using models to solely simulate pre-defined scenarios, in accordance to the "predict-than-act" paradigm, decision-makers should shift to the "seek robust solutions" paradigm. This means that models should be used as scenario generators which provide several insights into complex system behaviour and more sufficiently support informed decision-making (Weaver, 2013).

Moreover, this could affect the way community scenarios are currently used in a variety of research fields. The use of community scenarios poses several challenges. Firstly, it is difficult to create a set of scenarios detailed enough for a wide variety of research fields (van Vuuren, 2012). Consequently, the quantification of such scenarios in sector-specific models is also difficult. However, the idea of community scenarios should not be completely discarded, as they also succeed in several aspects. They allow for integration across different research disciplines and make the assessment and comparison of different studies easier (van Vuuren, 2014). Also, community scenarios form a great resource for studies that cannot, or want not, generate scenarios themselves (van Vuuren, 2014).

Thus based on this research in addition to findings of several other studies, it is recommended to view these community scenarios as a common ground for different studies to start from, which enables studies, such as this one, to perform Scenario Discovery in order to develop model-driven scenarios. This way, existing community scenarios could be enriched with these new data-driven scenarios, creating a large multi-model scenario database, as envisioned by Rozenberg et al. (2014). By doing so, a more diverse scenario database will emerge, which makes it easier for future analysts to find scenarios better suited for their specific research or decision-making field.

7.4 Future research

Based on the above discussion and limitations, recommendations for future research are made. Firstly, for the use of Scenario Discovery and the land use scanner model, it is recommended to conduct further research into:

- The use of different similarity metrics for the calculation of similarity between land use maps. Firstly, future research can look into the usage of the Kappa similarity metric to calculate the similarity between maps based on only certain land use classes, rather than based on all land use classes as in this research. Next to this, the influence of the use of other map similarity metrics could be investigated. For example, an adaption on the Kappa similarity metric is the Fuzzy Kappa (Hagen, 2003) or Kappa Simulation (van Vliet, Bregt & Hagen-Zanker, 2011).

- The use of different clustering algorithms. It is not certain how different clustering algorithms influence the outcome. Therefore, future research could look into the impact of choice in cluster algorithms.

- The improvement of the experimental set-up and the addition of more uncertainties. This research only considered the uncertainties which were already implemented in the LUS model. It would be interesting to see how future land use patterns emerge when additional uncertainties are considered. These additional uncertainties could include other uncertainties located and the input-data location, or consider even uncertainties in other locations such as model structure. Moreover, it is recommended for future researchers to include models earlier in the LUMOS model chain in their research, such as the TXL model.

- The impact of the newly developed scenario narratives. For policymakers to understand the impact of the Scenario Discovery scenarios, the post-processing tools within the LUMOS modelling chain are needed. This is necessary to understand the implications of these new scenario narratives, as in this stage, it is not possible to say in which ways the developed scenarios are policy-relevant.

- Internal consistency of the developed narratives and how such internal consistency could be guaranteed. The use of Cross-impact analysis needs more research, as there is not yet a general approach for using this in various modelling fields (Schweizer & Kurniawan, 2016).

Chapter 8

Conclusion

The main research question of this research was:

In which ways are scenarios identified with Scenario Discovery different from, or similar to, the Delta Scenarios, when generated with the aid of land use change models?

To answer this research question, three sub questions were formulated, which will be answered below.

1. *What uncertainties exist in the Land Use Scanner model?*

The outcomes of models representing complex systems are always built upon assumptions and know many uncertainties. In this respect, the Land Use Scanner model is no different. Uncertainties are located at different locations. Firstly, uncertainties exist in the location System boundary, where uncertainties emerge in the implementation of different temporal or spatial scales. Next, uncertainties are present at the so-called Conceptual model location and the Computer model location. Next, uncertainties are located at the Input data location. Looking specifically at the Land Use Scanner model, the specific application of this model used as the case study for this research was based on the Delta Scenarios. Although the Land Use Scanner model knows uncertainties at all above-described locations, this model only takes into consideration uncertainties at the input data location.

To create an overview of the uncertainties considered within the Land Use Scanner model, the XLRM framework was used to categorise the uncertainties. Firstly, there is two policy lever (L) uncertainties. The choice in nature policy and spatial development policies are considered as uncertainties in the Delta Scenarios. Next, the demand for each land-use class (residential, industry and commerce, recreation, nature and agriculture) is considered as exogenous uncertainties (X). Also, the physical suitability for nature is an exogenous uncertainty. Relationship uncertainties (R) include a number of parameters which influence the total suitability value for a certain land-use class. These parameters influence the importance of location, physical and policy factors when calculating the total suitability. Lastly, Measures (M) include the allocated land use classed in the eventual land-use change map.

2. *Given a selection of uncertainties, what are possible future land use patterns and their conditions for occurring?*

Using the LHS algorithm to sample over the selection of uncertainties, 2000 land use maps were generated. These land-use maps were then clustered into six clusters. With the CART subspace partitioning algorithm and additional analysis, the underlying driving forces of each cluster were identified. This resulted in six scenario narratives.

<u>Cluster 1</u>

No strong urbanisation land use patterns. Residential and industry and commerce areas grow mainly in the Randstad. This limited growth is due to a low demand for houses and jobs, which indicated a low economic and demographic growth between 2012 and 2050. Also, nature shows limited growth. New nature emerges mainly within the ecological main structure, which is due to the EHS nature policy that is in place. As for recreation, the limited growth of this land-use class is due to low demand. Lastly, the agriculture land use classes show a limited decrease. For horticulture and intensive agriculture, this is due to a low decrease in demand. As for extensive agriculture, since the other land use classes did not grow strongly, the decrease is limited.

Cluster 2

Cluster 2 shows strong urbanisation patterns, with a concentration in the Randstad. This is due to high demand for houses and jobs in combination with liberal spatial development policy. Both nature as recreation has a limited growth, which is due to the low demand for these two land-use classes. Due to strong urbanisation, nature areas disappear in the Randstad. New nature emerges mainly in agricultural areas, which is due to the functional nature policy which characterises this cluster.

Cluster 3

Cluster 3 shows strong urbanisation patterns, with a concentration in the Randstad. This is due to high demand for houses and jobs in combination with liberal spatial development policy. Both nature as recreation has a limited growth, which is due to the low demand for these two land-use classes. Due to strong urbanisation, nature areas disappear in the Randstad. New nature emerges mainly around nature areas existing in 2012 and connects separate nature areas, which is due to the Robust and Vital nature policy.

Cluster 4

No strong urbanisation land use patterns. Residential and industry and commerce areas grow mainly in the Randstad. This limited growth is due to a low demand for houses and jobs, which indicated a low economic and demographic growth between 2012 and 2050. Both nature as recreation has a limited growth, which is due to the low demand for these two land-use classes. New nature emerges mainly in agricultural areas, which is due to the functional nature policy which characterises this cluster.

Cluster 5

No strong urbanisation land use patterns. Residential and industry and commerce areas grow mainly in the Randstad. This limited growth is due to high demand for houses and jobs in combination with restrictive spatial development policy. Both nature as recreation has a limited growth, which is due to the low demand for these two land-use classes. The emergence of new nature areas seems to be mostly around nature areas already present in 2012 and around recreation areas, which is due to the Functional nature policy.

Cluster 6

No strong urbanisation land use patterns. Residential and industry and commerce areas grow mainly in the Randstad. This limited growth is due to the high demand for houses and jobs in combination with restrictive spatial development policy. Both nature as recreation has a limited growth, which is due to the low demand for these two land-use classes. New nature areas emerge mainly around existing cities and smaller residential areas, which is due to an increased suitability factor around residential areas. The emergence of new nature does not follow a specific nature policy since there are no nature policy stimuli in place.

3. *What are the main similarities and differences between the Delta Scenarios and the scenarios developed with Scenario Discovery?*

The first difference lies in the resulting scenario narratives. The six Scenario Discovery scenarios have different land-use patterns than the Delta Scenarios. Although some land-use classes show similar land-use patterns, not one Delta Scenario is the same as the Scenario Discovery scenarios and vice versa. Looking at the driving forces characterising the Delta Scenarios and Scenario Discovery scenarios, the source of the differences in land use patterns can be identified. Moreover, both sets of scenarios also differ in which driving forces are considered as important. While all the important driving forces in the Scenario Discovery scenarios are also considered as important in the Delta Scenarios, not all important driving forces of the Delta Scenarios are considered as important for the Scenario Discovery scenarios. Only the demand for houses and jobs, spatial development policy, nature policy and policy stimuli, and the importance of nature location factors are considered as important driving forces in both sets of scenarios.

Another interesting difference is the fact that whereas each Delta Scenario emerges from one unique scenario narrative, each Scenario Discovery scenario has multiple possible combinations of driving forces leading to the land-use patterns of that specific scenario. Also, some of the Scenario Discovery scenarios have similar driving forces, while still resulting in different land-use patterns. In contrast, the driving forces characterising the Delta Scenarios do not overlap at all.

This research aimed to explore the use of Scenario Discovery with the aid of land-use change models and to compare the results with the Delta Scenarios. With the sub-questions answered, the main research question can also be answered:

This research resulted in six scenarios which differ from the Delta Scenarios in the narrative and the corresponding land-use patterns. However, the Scenario Discovery scenarios differ in other ways as well. Firstly, the development of the Scenario Discovery scenarios makes the analyst aware of under which conditions a combination of similar driving forces lead to different land-use patterns. Also, this approach makes the analyst aware under which conditions combinations of different driving forces still yield similar land-use patterns. Next to this, the Scenario Discovery scenarios show which driving forces are most important. Overall, this means that the scenarios identified with Scenario Discovery differ from the Delta Scenarios in the way that they provide analysts and policymakers with several insights, which can support sufficient informed decision making, which is overlooked when with the development and use of the Delta Scenarios.

As this research demonstrated the potential of Scenario Discovery in the land-use change modelling field, it is recommended for land-use change model users, such as LUS model users, to use Scenario Discovery for the development of scenarios. To do so, it is also recommended to increase research into the necessary steps of Scenario Discovery in the land-use change modelling field, such as the calculation of land use map similarity, the clustering process and the identification of driving forces. As for the decision-makers in spatial planning, it is recommended to involve land-use change models more into the decision-making process by increasing research into the use of different scenario development approaches namely Scenario Discovery. Instead of only using the land-use change models for the simulation of pre-defined scenarios, these models should be used as scenario generators, using Scenario Discovery, in order to use these models up to their full potential. Lastly, on a more general note, the use of story and simulation approaches in model-based decision making should be reconsidered, and instead, it is recommended to research the possibilities of Scenario Discovery in various modelling fields.

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Appendix A: Framework spatial modelling and simulation

In the following sections, the integral spatial modelling instruments, a modelling chain for spatial modelling, will be discussed. Firstly, and overview of the whole modelling chain will be presented. The next section will discuss the Land Use Scanner model in more detail.

A.1 The model chain

In practice, the Land Use Scanner model (LUS model) is used within a large modelling chain, called "the integral spatial model instruments". This model chain is used to simulate and interpret scenario narratives, such as the Delta Scenarios. Figure A.1 shows the structure of this modelling chain (Rijken et al., 2013).

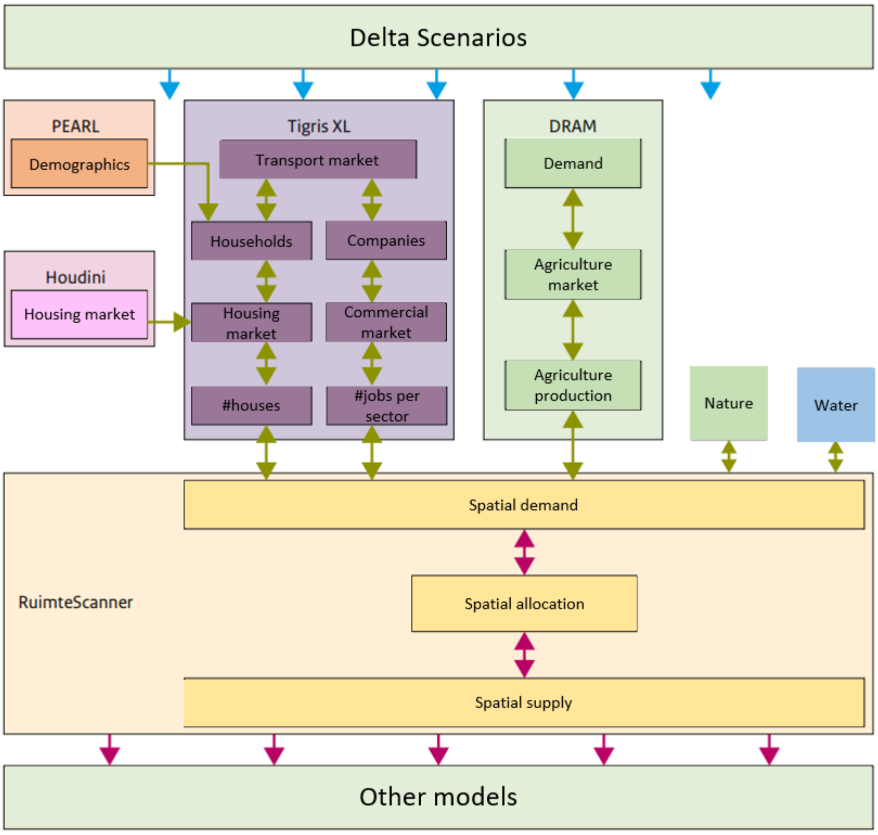

Figure A.1: Model chain for spatial planning and analysis (Rijken et al., 2013)

Firstly, the Tigris XL model (TXL model) simulates the interaction between land use and transport (Rijken et al., 2013). The TXL model itself uses two other models as modules, namely the PEARL model, which simulates the population and household prognosis, and the Houdini model, which simulates the housing market. The output of the TXL model is the demand for houses, in number of houses per year, and the demand for jobs, in number of jobs per sector per year.

The second model in this model chain is the DRAM model. This is a regional-economic agriculture model which simulates the development of agriculture. The relevant output of this model is the demand for agriculture, which is expressed in acreage per agriculture sector (Rijken et al., 2013).

The output of the TXL model and the output of the DRAM model, together with the demand for nature based on expert judgement, forms the input for the LUS model. The next section will discuss the LUS model into more detail.

A.2 The Land Use Scanner model

The LUS model is a GIS-based model that simulated future land use patterns. Within the spatial modelling chain, the LUS model is used to provide more insights into the future of spatial development, or the future land use patterns. The general structure of this model is shown in Figure A.2.

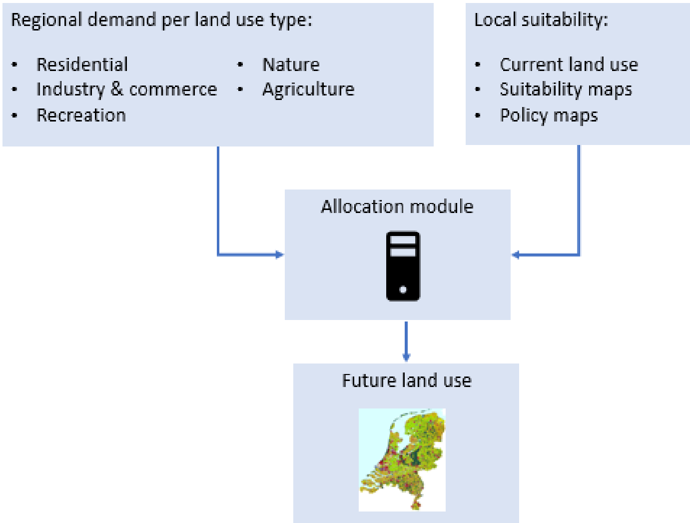

Figure A.2: Model structure Land Use Scanner model (Claassens, Koomen & Rijken, 2017)

The simulation of future land use patterns is based on the Regional demand per land use class and the local suitability for a specific land use class. This demand is expressed as demand in acreage per region, per land use class. The LUS model works with 28 different land use classes, as shown in Table A.1. When analysing the future land use patterns, the focus is generally on the land use classes residential, industry and commerce, recreation, nature and agriculture. The demand for certain land use classes depends on a number of driving forces.

Most of the demand is derived from other models or expert judgement. As explained in the previous section, section A.1, the demand for houses and jobs are derived from the TXL model. The TXL model generated the demand for the land use classes residential and industry and commerce. However, the TXL model defines this demand in number of houses and number of jobs, which means a couple of steps have to be taken to convert this in demand in acreage. For the residential demand, this is done by taking the product of the number of houses and the observed urban densities (Dekkers, Koomen, Jacobs-Crisioni & Rijken, 2012). Next, an infringement percentage is used to calculate the final demand for the residential land use class in acreage per region (Claassens, Koomen & Rijken, 2017). This infringement percentage represents the national spatial development policy in place. For the industry and commerce demand, to convert the demand in number of jobs to demand in acreage, labour preferences are used to calculate this. For the demand in number of jobs the location type preferences per sector per region is determined, also derived from the TXL model. Then, this is used to calculate the acreage needed using the so-called terrain-quotients per sector per region (Dekkers, Koomen, Jacobs-Crisioni & Rijken, 2012).

The demand for agriculture is derived from the DRAM model in combination with expert judgement (Rijken et al., 2013). These numbers are expressed in demand for horticulture and intensive agriculture in acreage per region and do not need further processing. It is important to note that the demand for extensive agriculture is not formulated, as this land use class has no explicit expectations in the Delta Scenarios. The eventual allocation of extensive agriculture is based on what is left after allocation all other land use classes (Claassens, Koomen & Rijken, 2017).

The demand for nature and recreation are based on expert judgement. The demand is expressed in nature acreage, and is mostly based on the WLO scenarios (Claassens, Koomen & Rijken, 2017).

Next to the demand, local suitability is used in the allocation process of the land use classes. Where the demand for land use is, as the name implies, the demand, the local suitability represents the supply side in the allocation process (Rijken et al., 2013). The local suitability represents for each specific area in the Netherlands to which degree that specific area is suitable for a certain land use class. If for a certain land use class the value of the local suitability is highest, this land use class is allocated to that specific location. Local suitability is based on the following aspects (Claassens, Koomen & Rijken, 2017):

- Transition costs
  Which indicates the costs of removing the current land use type in a specific area and rebuilding it. If these costs are high, then it is preferable to keep the current land use type.

- Location factors
  Location factors indicate the suitability of a certain area for a specific land use class based on the location. For example, for the industry and commerce land use class location factors such as distance to public transport or highways play a role. For the residential land use class the distance to already existent residential areas play a role.

- Physical factors
  Physical factors refer to type of soil, water levels and other similar physical land characteristics that might influence the local suitability of a certain area.

- Policy stimuli
  Policy stimuli indicate whether or not it is encouraged, with policies, if a certain land use class is allocated in a specific area.

- Policy restriction
  In contrast to policy stimuli, if policy restrictions are in place for a certain land use class, then the local suitability is decreased making that location less suitable for a specific land use class.

To calculate the local suitability for every area in the Netherlands, for the above described factors so-called suitability maps are often used. For example, physical suitability maps for the calculation of local suitability for the land use class nature depict areas in the Netherlands where the physical aspects of land are in favour for the development for dry or wet nature. Another example, policy stimuli maps used to calculate the local suitability for the residential land use class are maps where spatial plans for future residential areas are specified.

Based on the demand and supply as described here, the LUS model then allocates each land use class and thus simulating future land use patterns. The LUS model simulates in a time horizon from the year 2012 to the year 2050.

Table A.1: Land use classes in the LUS model

ID Land use class	Land use class
0	Railway
1	Roads
2	Airports
3	Residential area
4	Industry and commerce
5	Services
6	Sea ports
7	Building site
8	Semi hardened
9	Recreation
10	Recreation accommodation
11	Gras in residential areas
12	Horticulture
13	Corn
14	Potatoes
15	Beets
16	Grain
17	Open vegetables
18	Flower bulbs
19	Livestock
20	Tree orchard
21	Arboriculture
22	Nature
23	Fresh water
24	Sea
25	Rivers
26	Other water

A.3 Post processing of data

Going back to the whole spatial modelling chain, the last part of this chain is where the maps featuring the future land use patterns are used to interpret the specific implications of these land use patterns. For this, the National Hydrologic Instruments (NHI) are used (Rijken et al., 2013). The NHI provides insights concerning the hydrological consequences of the future land use patterns and the consequences for climate change.

Appendix B: The Delta Scenarios

Each scenario and the corresponding land use patterns will be discussed. For each scenario, a general scenario narrative will be provided, following three main themes in land use patterns, namely: Urbanization, nature and recreation, and agriculture.

Table B.1 shows the percentual change of acreage for each important land use class in each scenario, compared to the base year 2012.

Table B.1: Percentual change Delta Scenario land use patterns compared to the base year

Land use class	2012	STOOM	DRUK	RUST	WARM
Residential area	317405	35%	12%	4%	11%
Industry & commerce[1]	117227	43%	35%	6%	5%
Recreation[2]	34054	27%	28%	8%	8%
Nature	615483	12%	17%	8%	8%
Horticulture	15873	-9%	-9%	-28%	-28%
Intensive agriculture[3]	75224	-4%	-4%	-13%	-13%
Extensive agriculture[4]	1914764	-11%	-9%	-2%	-3%

1: Industry, services and seaports

2: Recreation and accommodation

3: Corn, potatoes, beets, grain, open vegetables and livestock

4: Flower bulbs, tree orchards, arboriculture

B.1 STOOM

Urbanization

The Netherlands experience a high economic growth and strong population growth (Rijken et al., 2013). This is because a high economic growth often goes hand in hand with a wealthier and healthier population, increasing the birth rate (van Gemeren et al., 2016). Also, with the high economic growth more labour opportunities arise within the Netherlands, which often results in higher immigration rates (Kool & Huizinga, 2015).

Due to this population growth, the demand for housing increases. Moreover, the spatial development policies become less restrictive compared to how restrictive these policies were around 2012. Where the spatial development policy used to focus on infringement, thus mainly building in existing residential areas rather than in non-residential areas, the new spatial development policy does allow for this to happen.

Due to the high economic and demographic growth, the demand for houses, thus residential land use, increases strongly as well. With the less restrictive spatial development policy, this results in both urbanization and sub-urbanization, as new residential areas are built around cities. Next to this, with the high economic growth more households are able to afford larger houses and therefore also prefer to live in larger outside of the city where more space is available. Also, society shows high appreciation for nature and agriculture, which also enhances the preference for households to settle outside of the city near such green areas (van Gemeren et al., 2016).

Nature

As for the nature policy, a large amount of money is made available for the creation and maintenance of nature, which is possible due to the high economic growth. However, due to the less restrictive spatial development policy nature areas are not well protected and some nature areas are replaced by other land use functions such as residential areas or industry and commerce (Rijken et al., 2013). For this reason, the nature policy focusses on compensating this decrease in nature areas by searching for nature development opportunities in other areas. The selection of these new nature areas as compensation of nature loss is mostly based on the “Ecological main structure” (Ecologische Hoofd Structuur). Of course, some nature areas stay protected, such as the Natura-2000 areas, which are maintained and protected according to the European Natura-2000 policy. As a result, the total amount of nature in acreage does increase in this scenario.

Agriculture

The demand for most agriculture sectors decreases in this scenario. Firstly, the demand for horticulture decreases with 10 percent. Also, for intensive agriculture, the demand is quite low in this scenario, but due to high economic growth the decrease in demand is limited. This is because with higher economic growth, both private as public agriculture parties have more money to spend (Rijken et al., 2013).

Another reason why in this scenario the overall decrease in agriculture is limited, is that due to higher economic growth, the Netherlands also experiences a strong technology development (Kool & Huizinga, 2015). As a result, although this scenario is characterized by high climate change rates, the agriculture sector is able to deal with the negative consequences of climate change with the help of technology (Rijken et al., 2013).

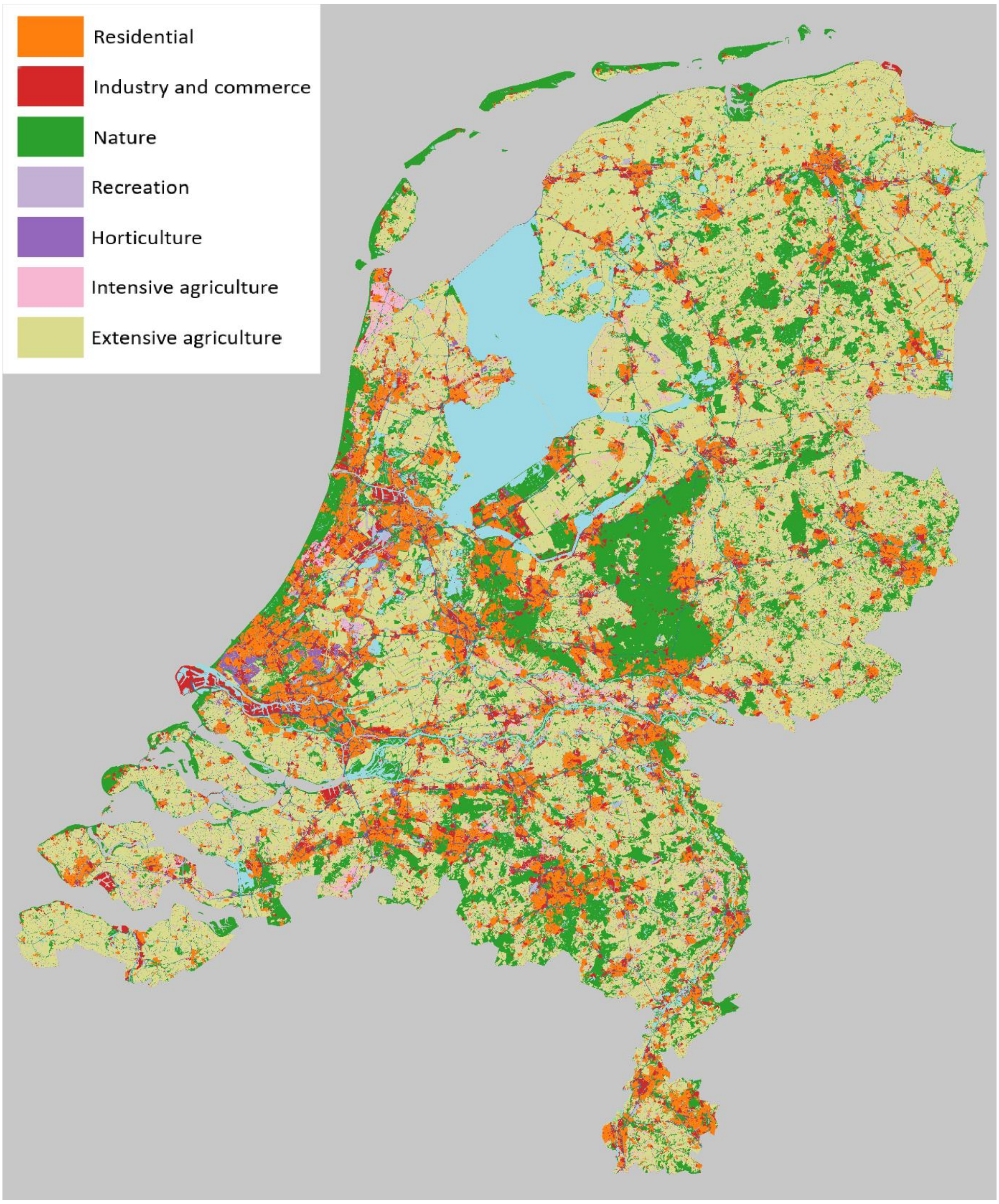

Figure B.1: STOOM land use map

B.2 DRUK

Urbanization

The Netherlands experience a high economic growth and strong population growth (Rijken, et al., 2013). This is because a high economic growth often goes hand in hand with a wealthier and healthier population, increasing the birth rate (van Gemeren et al., 2016). Also, with the high economic growth more labour opportunities arise within the Netherlands, which often results in higher immigration rates (Kool & Huizinga, 2015).

Due to this population growth, the demand for housing increases. However, the spatial development policy in this scenario is of a restrictive nature. This means that spatial policies focus on infringement, thus making sure that new residential areas and industry and commerce areas are mainly built within existing residential areas. This policy is in place to protect National buffer zones, National Landscapes, and nature areas. Young people tend to move towards the Randstad as well, due to the concentration of people and work there (van Gemeren et al., 2016). Due to this, the birth rate within the Randstad will increase and is the main cause for population growth in this area. Outside of the Randstad, population growth is mainly caused by immigration. As a result, within cities houses are built in higher densities, increasing urbanization. However, sub-urbanization is limited (van Gemeren et al., 2016).

Nature

Next to the spatial development policy, the implemented nature policy impacts spatial development as well. With the current nature policy, the main goal is to maintain and restore biodiversity (MNP, 2007; PBL, 2011). To do this, large nature areas are to be created and maintained, rather than scattered nature areas throughout the country. To complete this, a large sum of money is made available for the maintenance and creation of nature (Rijken et al., 2013). On top of that, policy stimuli are in place to encourage nature development. As mentioned before, the spatial development policy protects nature areas to reach this goal. Moreover, this nature policy implements restrictions towards other land uses, such as residential and industry land use.

Agriculture

The demand for most agriculture sectors decreases in this scenario. Firstly, the demand for horticulture decreases with 10 percent. Also, for intensive agriculture, the demand is quite low in this scenario, but due to high economic growth the decrease in demand is limited. This is because with higher economic growth, both private as public agriculture parties have more money to spend (Rijken et al., 2013).

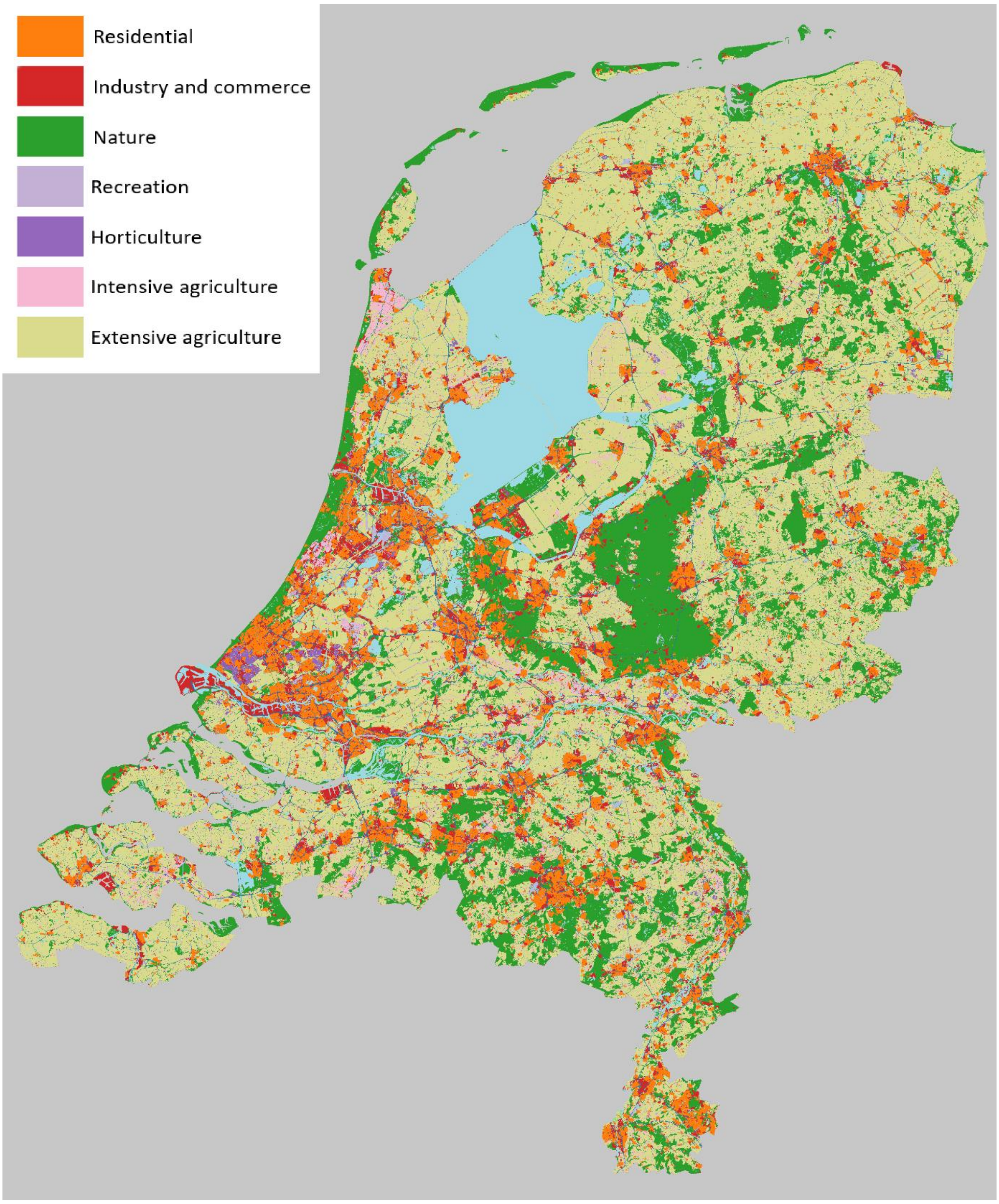

Figure B.2 DRUK land use map

B.3 RUST

Urbanization

Although the economy does grow, the growth rate is low in this scenario (Rijken et al., 2013). Due to this, the Netherlands knows a low birth rate, since the general population is less healthy. Moreover, a low economic growth often goes hand in hand with less labour opportunities, which also results in a lower immigration rate. All in all, this scenario is thus characterized by a low population growth.

The low economic growth is partly due to lack of investment in technology and the lack of international trade (Kool & Huizinga, 2015). As a result, there are strong economic agglomerative effects for companies in this scenario, meaning that companies benefit from being located near each other. These agglomerative effects imply that companies are more productive when concentrated within a city (van Gemeren et al., 2016). Thus, working life benefits from face to face interaction and people prefer to live and work within cities (van Gemeren et al., 2016).. The result is a relatively higher birth rate and lower death rate within cities. Looking at migration patterns, immigration rates in city areas is higher compared to immigration rates in the rest of the country (Kool & Huizinga, 2015).

In this scenario a restrictive spatial development policy is in place. Therefore, National buffer zones, National Landscapes and nature areas are protected and cannot be used for other land use functions. However, due to low population growth, there is also a lower demand for housing. Therefore, housing development rather follows the demand (van Gemeren et al., 2016).

Nature

As for the nature policy, less money is made available for the creation and maintenance of nature areas. Still, the nature policy aims at using nature as functional as possible in order to make the most of the available funds (Rijken et al., 2013). Thus, the policy aims for the creation of new nature areas which has multiple functions. For example, agricultural areas will be used for recreation, water reserves, and simultaneously promote biodiversity (PBL, 2011). This way, agriculture landowners receive income for making their land available for these purposes, people can recreate in these areas, and new nature gets developed.

Agriculture

The demand for most agriculture sectors decreases more strongly than the previous two described scenarios. Firstly, this is due to the low economic growth, which both private as public agriculture parties have less money to invest in agriculture. Also, as described in the nature section, agriculture parties seek alternative ways to earn money, for example to receive income for their land by making their land available for recreation, water reserves, and the preservation of biodiversity (PBL, 2011).

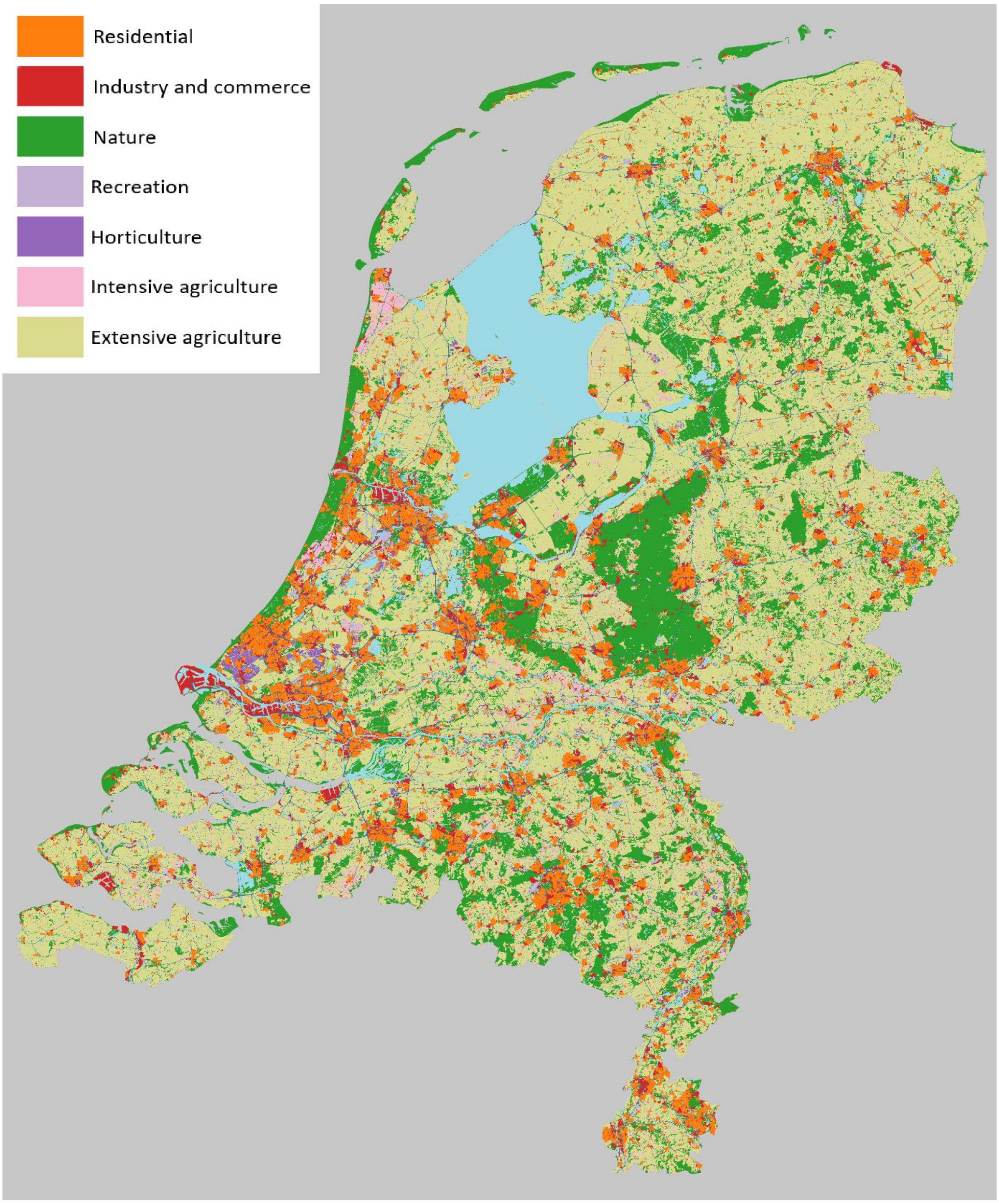

Figure B.3: RUST land use map

B.4 WARM

Urbanization

Although the economy does grow, the growth rate is low in this scenario (Rijken et al., 2013). Due to this, the Netherlands knows a low birth rate, since the general population is less healthy. Moreover, a low economic growth often goes hand in hand with less labour opportunities, which also results in a lower immigration rate. All in all, this scenario is thus characterized by a low population growth.

The birth rate is quite low in this scenario. Although there are young people moving towards the city, it is less than in other scenarios due to the fact that there are fewer young people. Also, immigration is mainly happening in the cities. Therefore, the pattern in demographics is similar to concentration, but less concentrated due to the population decrease.

In this scenario a restrictive spatial development policy is in place. Therefore, National buffer zones, National Landscapes and nature areas are protected and cannot be used for other land use functions. However, due to low population growth, there is also a lower demand for housing. Therefore, housing development rather follows the demand (van Gemeren et al., 2016).

Nature

Not a lot of money is available for the creation and maintenance of nature. Similar to the RUST scenario, the creation of new nature is mainly in areas where other land use classes are not functional anymore. These are mainly agriculture areas which are rendered unproductive due to the high rate of climate change (Rijken et al., 2013). Other than the European nature policies in place, such as the policy regarding the Nature-2000 areas, there are no policies or policy stimuli in place specifically to create new nature or maintain existing nature.

Agriculture

The demand for most agriculture sectors decreases more strongly than the previous two described scenarios. Firstly, this is due to the low economic growth, which both private as public agriculture parties have less money to invest in agriculture. Next to this, due to higher climate rates and lack of technological developments, several agriculture areas cannot function anymore. Similar to the RUST scenario, agriculture parties seek alternative ways to earn money, for example to receive income for their land by making their land available for recreation, water reserves, and the preservation of biodiversity (PBL, 2011).

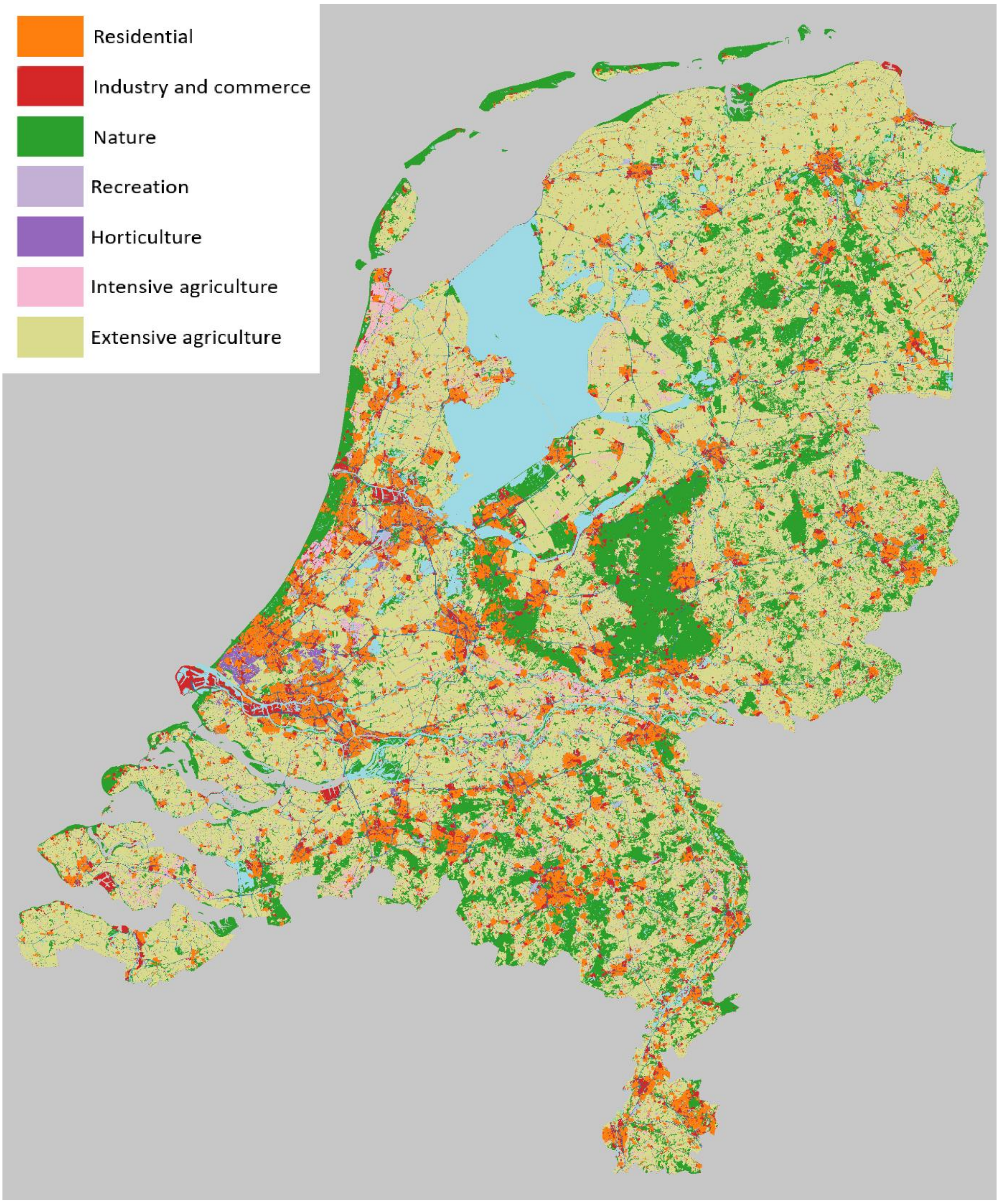

Figure B.4: WARM land use map

Appendix C: Model parameters and values

In the following sections, the model parameters and possible values are discussed. This chapter will also elaborate on how the Python model represents the parameters from the LUS model.

C.1 Residential and industry and commerce demand

The **demand for houses and jobs** is derived from the TXL model, in number of houses per year and number of jobs per year. First, this section discusses the parameters involved for the calculation of the residential demand in acreages, then this section discusses the parameters needed for the calculation of industry and commerce in acreages.

There are four possible values, each on derived from a different file which is the output of the TXL model which contain the demand for houses. The four possible values, and the corresponding value of the accumulated number of houses are:

1. Very high 418775 houses
2. High 365268 houses
3. Low 347624 houses
4. Very low 334128 houses

The difference between very high and high lies in that the TXL model already represents the spatial development policy. Very high is associated with a liberal spatial development policy and high is associated with a restrictive spatial development policy. The same goes for the difference between the values low and very low. However, the difference between these values does not accurately reflect the real world (Claassens, Koomen & Rijken, 2017). For this reason, to calculate residential demand, the **Infringement** parameter was added to represent either a restrictive or liberal spatial development policy. There are two possible values for the infringement parameter:

1. 25%, a liberal spatial development policy
2. 75%, a restrictive spatial development policy

Also, the housing density plays a role for the calculation of the residential demand, which is represented with the **Density** parameter. There are two possible values for Density:

1. 1.33, high density
2. 1.00, low density

For industry and commerce, the **demand for number of jobs** are derived from the same TXL files as from which the demand for houses are derived. The possible values are:

1. Very high 130059 jobs
2. High 122804 jobs
3. Low 84801 jobs
4. Very low 84566 jobs

To calculate the eventual Industry & Commerce demand, the demand of number of jobs is converted to the demand in acreage for the Industry & Commerce sector. This is done using a location type preference value and the average space needed per job, which will be referred to as **labour preferences**. There are two possible values for the parameter labour preferences, where “high” is in accordance with assumptions made in a high economic growth scenario and “low” is in accordance with assumptions made in a low economic growth scenario.

1. High
2. Low

C.2 Nature, recreation and agriculture demand

The **demand for nature** in acreage is derived from expert judgment. The possible values are:

1. High 106000
2. Medium 75000
3. Low 50000

The **demand for recreation** has two possible values:

1. High
2. Low

As for agriculture demand, it is important to note that for extensive agriculture no demand is formulated. The resulting land allocated to extensive agriculture is based on the land left after all other land use classes are allocated. For horticulture and extensive agriculture demand is acreage is derived from expert judgement and the DRAM model.

For **horticulture demand** and **intensive agriculture demand**, the following values are possible:

1. High
   Horticulture: decrease of 10%
   Intensive agriculture: 85100 acreages
2. Low
   Horticulture: decrease of 30%
   Intensive agriculture: 74100 acreages

C.3 Nature related suitability factors

Firstly, the **nature policy** influences the suitability value for nature of an area. The nature policies are represented with nature policy maps. There are three possible nature policies.

1. Robust and Vital nature policy
   The nature policy map is based on the so-called Robust and Vital nature policy. The goal of this nature policy is to increase and connect existing nature areas as to protect the current biodiversity in the Netherland but also stimulate an increase in biodiversity. Figure C.1 depicts this nature policy map.

Figure C.1: Robust and Vital nature policy map

2. EHS nature policy
   The nature policy map is based on the so-called EHS nature policy. This policy map encourages the creation of new nature to guarantee enough nature development in case nature is replaced by other land use classes. In this policy map, areas within the Randstad, and some other larger cities in the Netherlands, are perceived as better suitable for new nature development. This is because households prefer to live among nature and also prefer to recreate in nature areas. New nature emerges mainly in the ecological main structure. The corresponding policy map is shown in Figure C.2.

Figure C.2 EHS nature policy map

3. Functional nature policy
   The nature policy map is based on the so-called functional nature policy. This means that new nature is mainly created in previously agriculture areas. This policy map assumes that these agriculture areas are not functional anymore in agricultural practices, and therefore use their land in a new functional way for nature. In return, these agriculture landowners receive payment. The corresponding policy map is shown in Figure C.3.

Figure C.3: Functional nature policy map

How much the nature policy influences the eventual land use patterns of nature depends on the **Nature policy stimuli**. There are four possible values:

1. 0.0
   This means there is no policy stimuli in place, which makes the nature policy map ineffective.
2. 5.0, where policy map is black
   This indicates that policy stimuli are in place in accordance to the policy map.
3. 5.0, where policy map is black
   This indicates that policy stimuli are in place in accordance to the policy map.
4. 5.0, where policy maps is black and within 500 meters of recreation.
   Location suitability value for nature of an area is always 0.

The suitability value for nature of an area is also influenced by location characteristics of the Netherlands, which is represented by the parameter **Nature Location**. There are three possible Nature Location values:

1. 5.0 around nature
   This indicates a higher suitability value in areas within 500 meters of existing nature.

2. Equal to residential
   This indicates a higher suitability around residential areas.
3. 0.0
   Location suitability value for nature of an area is always 0.

The suitability value for nature of an area is also influenced by physical characteristics, which is represented by the parameter **Nature Physical**. There are two possible values:

1. Dry and wet
   Which indicates both dry and wet land is suitable for nature development, because water is pumped away in case of subsidence.
2. Dry
   Which indicates only dry land is suitable for nature development, because water is not pumped away in case of subsidence.

C.4 Residential suitability

Most features needed to calculate the suitability of a certain area for the residential land use class are not considered as uncertainties in de LUS model. Only the for the calculation of location suitability know uncertainty. This uncertainty depends on the location preference of people for where to live. Either people want to live in concentrated, thus with many houses in one place, or people want to live more scattered throughout the ratio. This preference is quantified with the parameter **Spread ratio**. This spread ratio knows two possible values:

1. 1.0
2. 0.5

Appendix D: Results clustering

For each cluster, the medoid, or middle map, is selected to serve as a representative land use map of the whole cluster. The medoid map is identified as follows:

1. Select for each cluster a subset of the total Distance Matrix, thus ending up with for each cluster a distance matrix containing only the distance values for the combinations of maps within that cluster.
2. Compute for each row the sum.
3. Select row with minimum value to identify the medoid map.

Table D.1 shows the acreage per land use class for each cluster, based on the medoid map corresponding to that cluster.

Table D.1: Acreage per land use class in each cluster

ID	Land use class	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
0	Railway	9117	9117	9117	9117	9117	9117
1	Roads	107928	107928	107928	107928	107928	107928
2	Airports	3229	3229	3229	3229	3229	3229
3	Residential area	330005	428896	428897	351895	354426	354542
4	Industry and commerce	82444	126222	126037	81763	116962	126852
5	Services	26989	26989	26989	26989	26989	26989
6	Sea ports	14516	14516	14516	14516	14516	14516
7	Building site	21549	5576	5279	14008	7481	6671
8	Semi hardened	3820	3820	3820	3820	3820	3820
9	Recreation	11650	11650	11650	11650	11650	11650
10	Recreation accommodation	24893	24891	31616	24893	24894	24894
11	Gras in residential areas	119994	119994	119994	119994	119994	119994
12	Horticulture	14366	14366	14366	14366	14366	14366
13	Corn	265180	242329	241316	259886	256545	248692
14	Potatoes	159046	151039	150864	157493	155826	154035
15	Beets	76596	72605	72344	75903	74907	74186
16	Grain	195778	185487	184065	194810	190302	188469
17	Open vegetables	113178	110383	110177	113202	111600	111571
18	Flower bulbs	27177	27177	27177	27177	27177	27177
19	Live stock	1050621	971862	968695	1045438	1026349	1004378
20	Tree orchard	22584	22584	22584	22584	22584	22584
21	Arboriculture	22450	22450	22450	22450	22450	22450
22	Nature	665483	665483	665483	665482	665481	690483
23	Fresh water	199843	199843	199843	199843	199843	199843
24	Sea	2538619	2538619	2538619	2538619	2538619	2538619
25	Rivers	18193	18193	18193	18193	18193	18193

26	Other water	118399	118399	118399	118399	118399	118399
		2531353	2531353	2531353	2531353	2531353	2531353

For each cluster, the key driving forces are identified using CART analysis. The complete three is shown in Figure D.1.

Figure D.2 to D.7 display the medoid maps of each cluster.

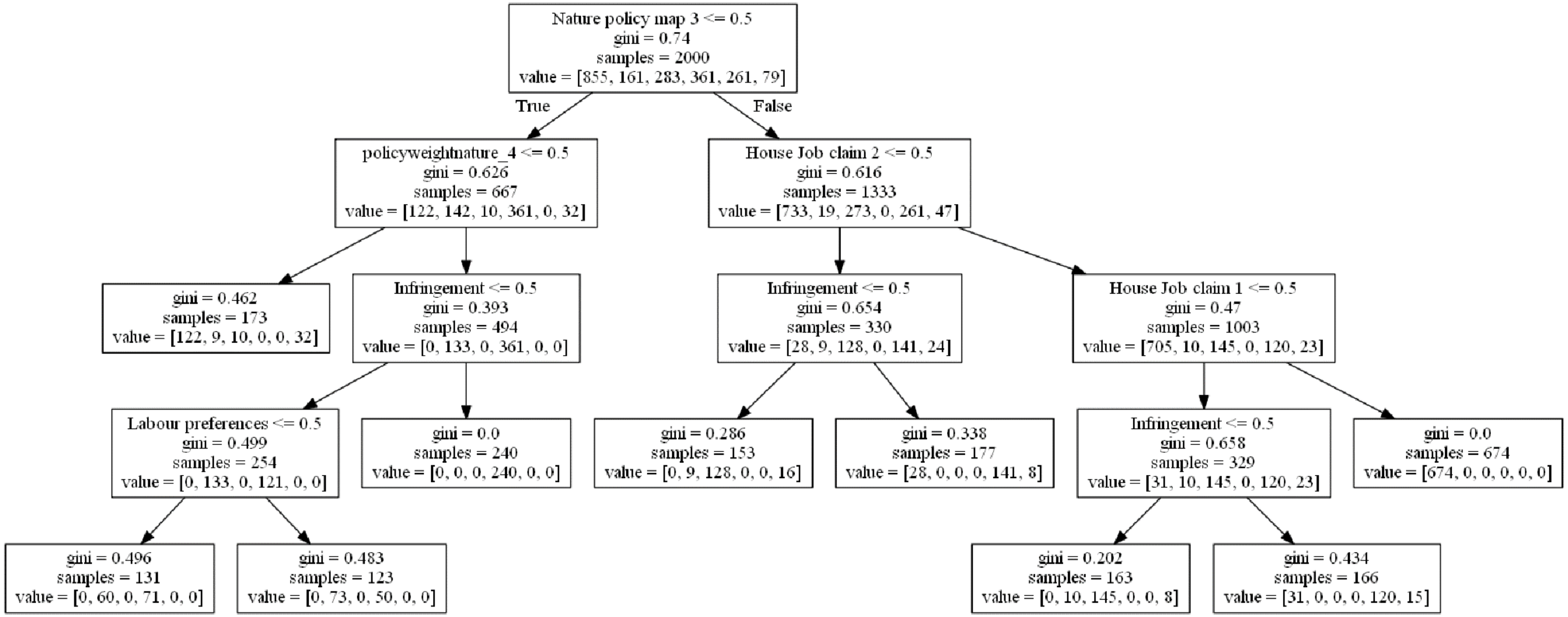

Figure D.1 CART tree

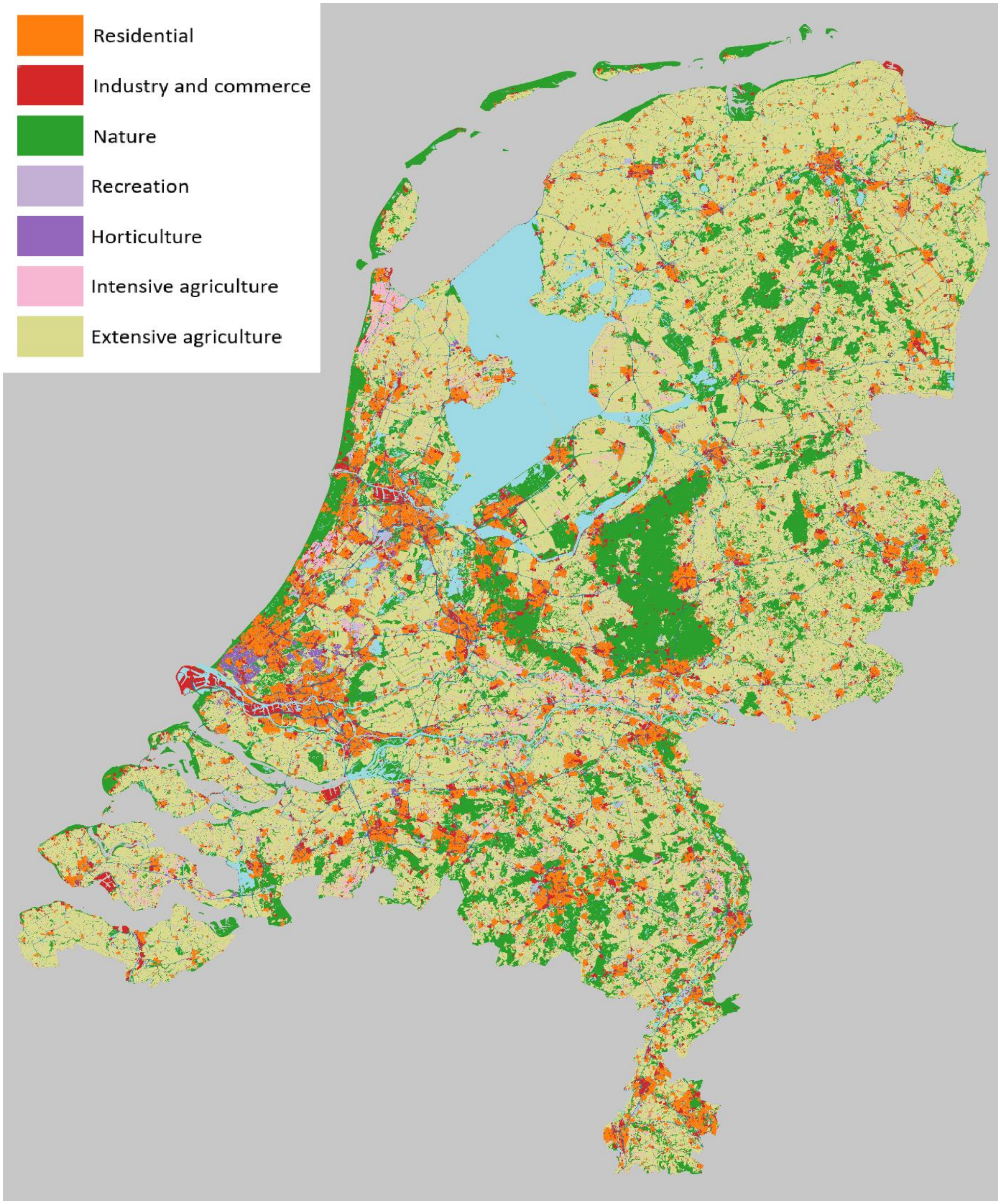

Figure D.2: Cluster 1 medoid map

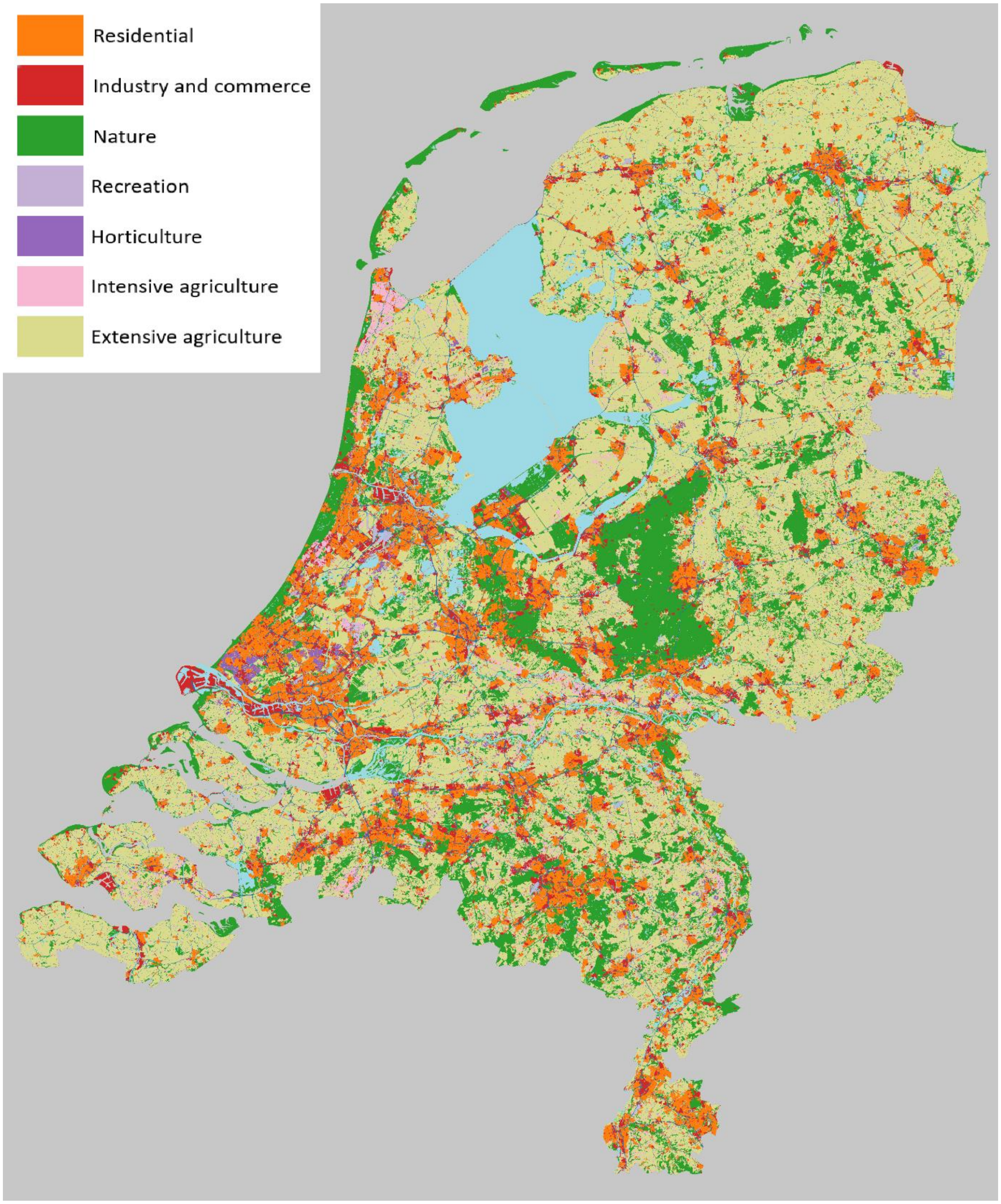

Figure D.3: Cluster 2 medoid map

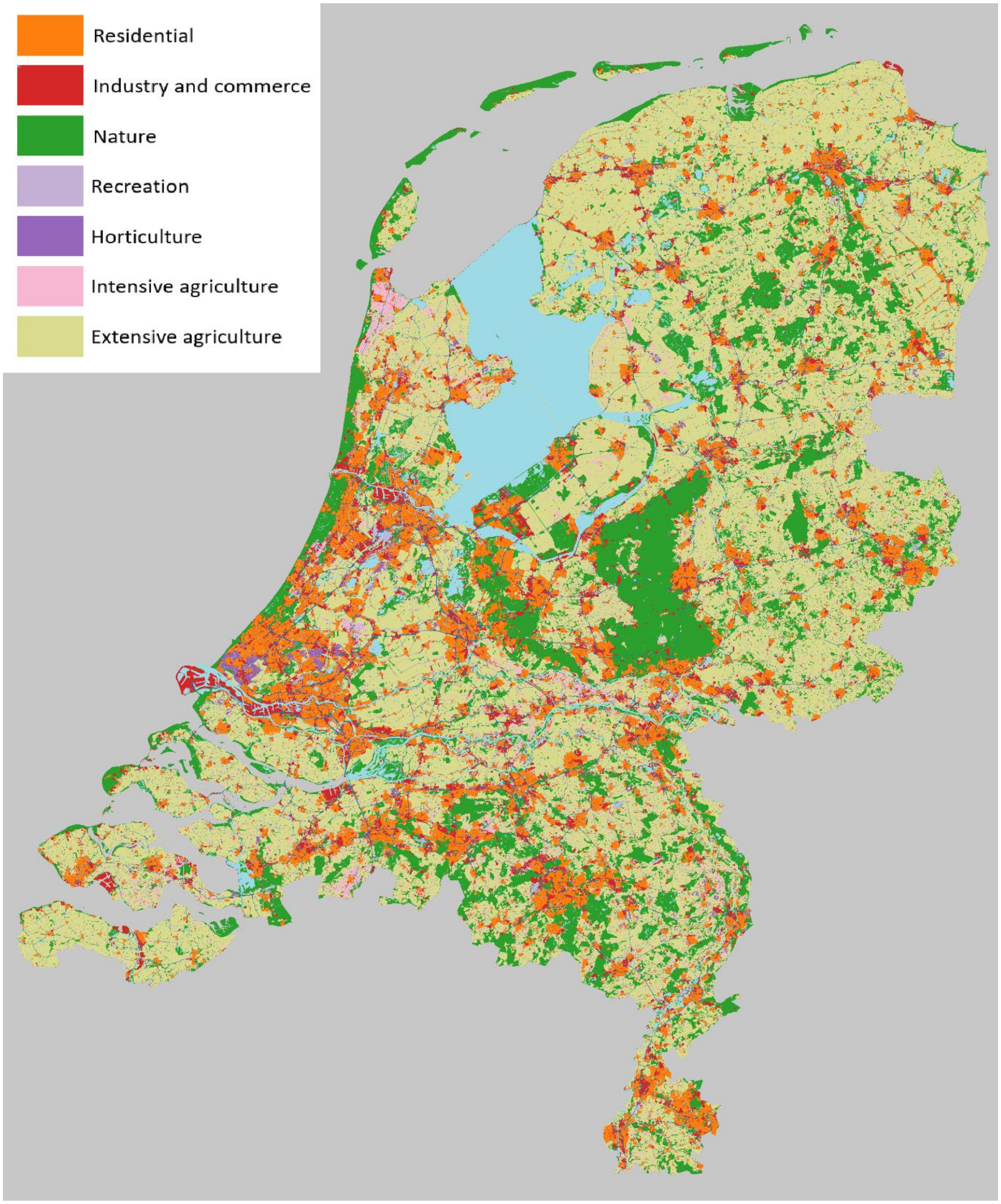

Figure D.4: Cluster 3 medoid map

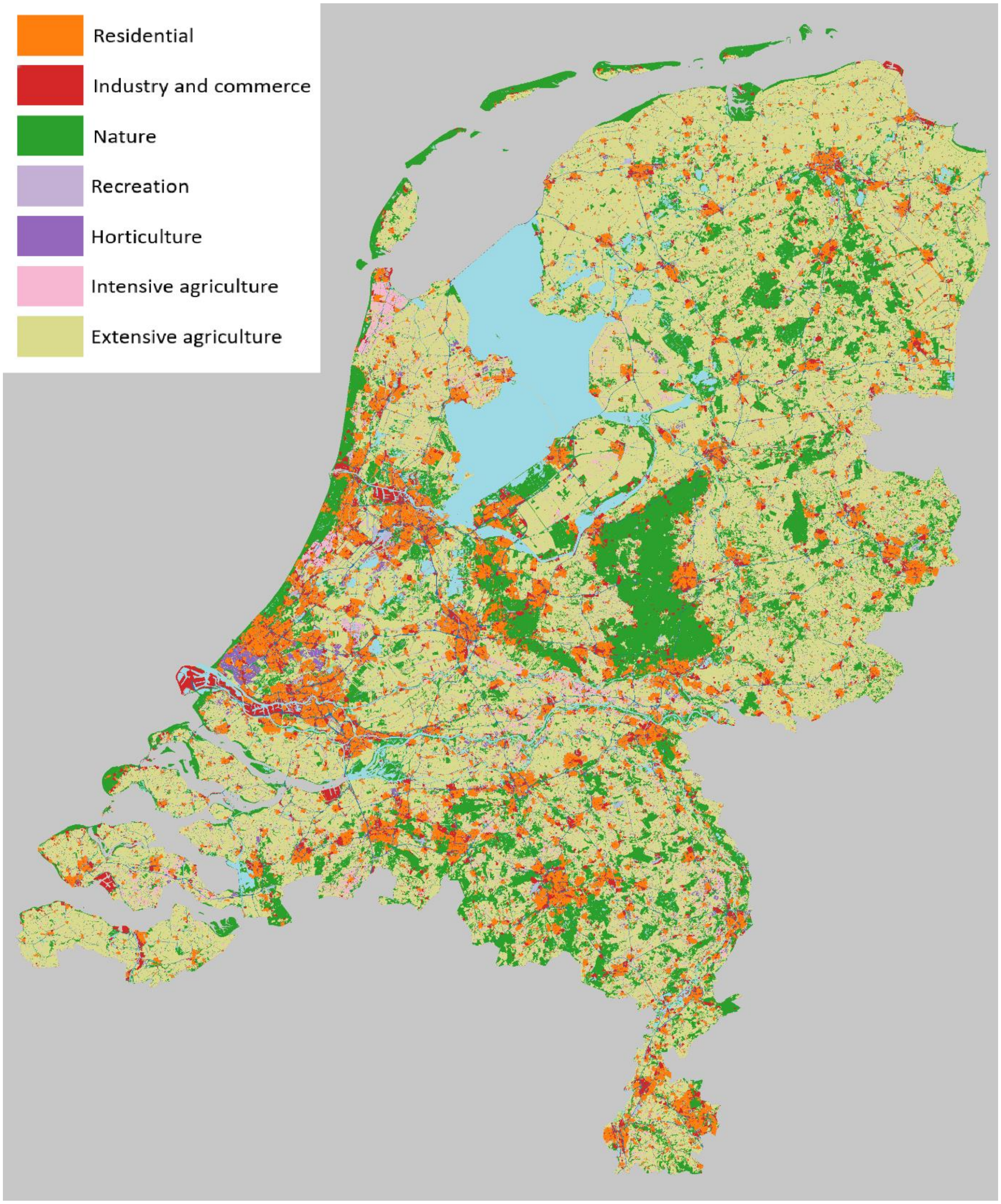

Figure D.5: Cluster 4 medoid map

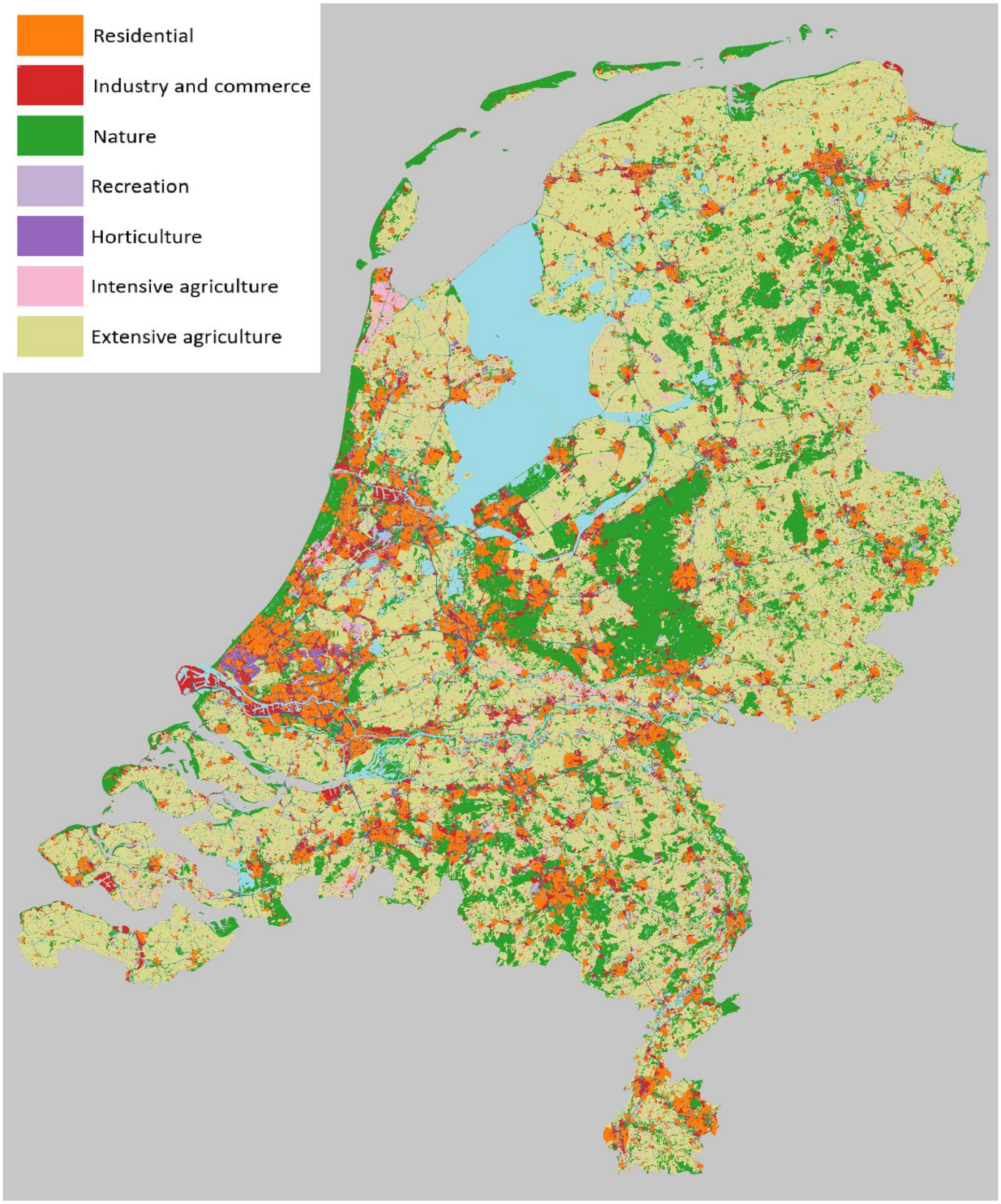

Figure D.6: Cluster 5 medoid map

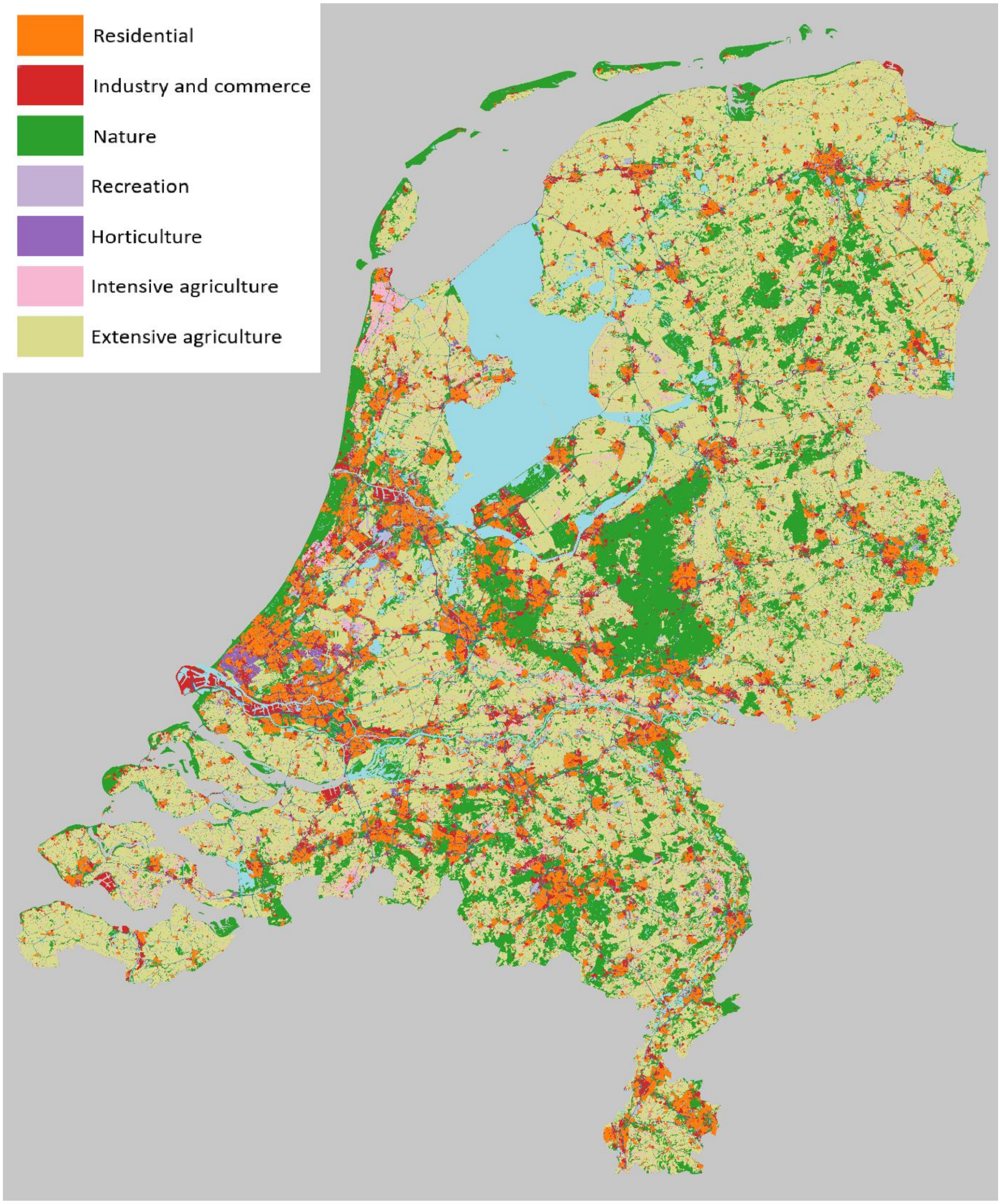

Figure D.7: Cluster 6 medoid map

Appendix E: Python code

The Python code used for this research are located at GitHub:

https://github.com/margrietcox/LUS-scenario-discovery