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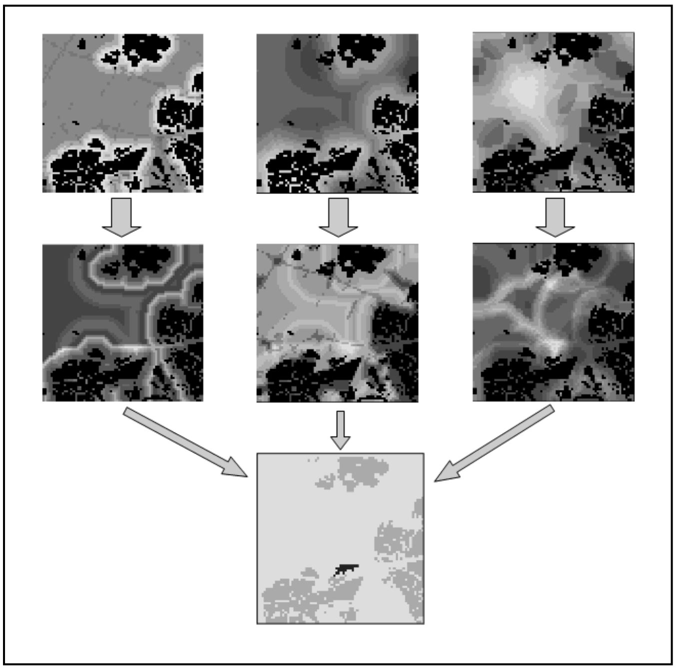
Start with an Ideal and end up with a Deal

Agent-based simulation of joint decision making in spatial planning using Bayesian Networks

Judith Anne Verstegen

March 4th 2010



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Start with an Ideal and end up with a Deal[1]

Agent-based simulation of joint decision making in spatial planning using Bayesian Networks

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[1] Quote by Karl Albrecht (http://www.karlalbrecht.com/)

Preface

This report is written as a part of my thesis for the Master in Geo-Information Science at Wageningen University. Already at secondary school I've learned that the central question in geography is: What, where and why there? This was the first as well as the last thing I learned from that teacher, because she was unable to cope with teenagers and thus she got fired after half a year, but the lesson turned out to be inspiring enough for me to start this master. A few weeks ago I realized that my interest may have been enhanced by my passion for a certain computer game I used to play at that time. This insight appeared when I was reading an interesting article by Oswald Devisch (2008), titled 'Should Planners Start Playing Computer Games? Arguments from SimCity and Second Life'. SimCity is a game in which a new build-up area has to be created in an environment in such a way that it returns the investment, preferably with interest. The game requires strategy and especially patience. My friends, who liked shooting and adventure games, could never understand why I liked it, but they were unable to convince me of their point of view. So now, everything has come together: I've built my own application, in which new urbanization is allocated, thereby focusing on the question 'What, where and why there?'. The minor difference with playing SimCity is that it's on a scientific basis. As a result no giant monsters appear from time to time, to demolish all the new build-up areas. But in return, you get other creatures, just as frustrating: bugs. But, playing SimCity has taught me to have patience and conquer the monsters. This report is a result of that patience, some hard work and a lot of fun, because science can be just as exciting as playing games.

Acknowledgements

Most of this research I've carried out at home with my laptop. Therefore, the weekly meetings with my supervisors, Arend Ligtenberg and Monica Wachowicz, were of great value to me; in a research related as well as in a social way. To Arend my special thanks for providing me his model, a sound starting point for my research. I want to thank both my supervisors a lot for their support, information, comments and the nice discussions we've had. I couldn't have done this without them. In addition, I was very pleased that they came up with the idea to write a paper for the Agile conference. Working on this paper with my supervisors made me realize that I profoundly like to conduct research and that I want to continue doing it after this thesis. I hope the paper gets accepted, so that we can add a grant final piece to our cooperation.

I also want to thank my fellow master students, who were in the same boat as I was and with whom I could share my victories and frustrations at the coffee machine. They were, together with my other friends and family members, especially good at pointing me at the fact that the world does not only consist of rational agents and people should have fun from time to time. Although I was not easily persuaded, I do really appreciate their efforts.

Finally, I want to thank my colleagues at TNO, for giving me the opportunity to turn my brains in the stand-by mode one day a week. This recovery day of simple, repetitive copy-paste tasks, non-science conversations and football matches was a crucial break in my week.

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Summary

This research explores the use of Bayesian Networks to improve on the representation of decision making in an agent based multi-actor spatial planning model. The problem in spatial planning comprises a consensus conflict: actors have different desires, often concealed, but aiming at the same goal, namely to produce a plan for a certain environment. Current agent-based spatial modeling approaches lack a sound decision making framework that can handle learning and adaptation in order to find mutual gain. A Bayesian Network provides a general framework, consisting of variables and their interrelations, of which the case-specific parameters can be easily set according to the considered case. In this thesis, a Bayesian Network is coupled with every agent in an agent-based spatial planning model, in such a way that the network can represent the different beliefs and make them dynamic. This approach allows the agents to learn about each others' desires by taking into account experience acquired throughout their cooperation. The agents adapt their spatial beliefs, using this information, in order to anticipate the optimum between reciprocity and fulfillment of their own desires. The learning and adaptation capabilities of the Bayesian networks thus make the agents proactive. A simulation of a regional spatial planning case illustrates the evolution of the networks during the decision making process and the resulting convergence of their beliefs. When the agents concentrate on a certain area for too long, this convergence becomes too extreme. As a result the agents become 'narrow-minded' and fail to find new solutions. Despite this, the decision making is more effective with added Bayesian functionalities, since the consensus is established faster and the area agreed on becomes larger. The Bayesian Networks have proved to provide a sound general decision making framework that is independent of the case specific parameters and includes the interdependencies of social complexity. Although a complete representation of multi-actor negotiation is still lacking, the added learning and self-adaptation functionalities of the agents offer a more accurate representation of the decision making process in spatial planning.

1. Introduction

This thesis brings together the domains of spatial planning, Multi-Agent Systems, decision making and Bayesian Networks. The current chapter introduces the research by defining the problem, objective and structure of the thesis.

1.1 Problem definition

Spatial planning aims at adjusting the environment to the needs of society. ‘Planning’ is not just producing a plan, but also the process of gaining an understanding of the current and future problems, and the nature of the process, in order to make better decisions (Faludi, 2000). Spatial panning is a complex process due to the involvement of various spatial levels, temporal scales and multiple actors (Ligtenberg, 2006). The number of involved tasks and people in spatial planning has increased in the last decade (Geertman, 2006) which in turn has made decision making more difficult. The actors all have their own semantics, strategies and desires regarding the environment. Since the interactions between the actors are the main element of a spatial planning process, it is convenient to start building a computer model by defining those actors. A modeling concept therefore under interest in the spatial modeling community, is the Agent Based Model (ABM) or Multi-Agent System (MAS) (O'Sullivan, 2008, Parker et al., 2003, Sengupta and Sieber, 2007). Such a model draws on computational entities, agents, with their own characteristics, to represent humans in a social process (Weiss, 1999). An agent can autonomously observe and perceive its environment and decide how to behave accordingly. Multiple agents can interact with each other. This interaction ranges from simple, like passing on a message, to complex, like negotiating to solve a common problem (O'Sullivan, 2008). A MAS is suitable for gaining an understanding of the spatial planning process, since different decision making scenarios can be analyzed, something not usually possible with human experiments (Holland and Miller, 1991, Batty and Torrens, 2005).

Many current spatial MASs maintain a decision making mechanism based on expert systems, often combined with cellular automata, distance decay functions and utility functions (Bousquet and Le Page, 2004, Parker et al., 2003). The main drivers behind these approaches are maximization of utility and minimization of risk. Utilities in this context represent an agent-specific value for an environmental aspect. Communication and negotiation among agents require common understanding of these values and a constant representation of the environment. During interactive spatial planning however, decision making is often based on a highly subjective valuation of the environmental aspects (Ligtenberg et al., 2009). Moreover, in most models agents have either complete information of other agents’ value or no information at all, while in reality the development of knowledge about the beliefs of others is a dynamic process. Through observing other agents’ actions additional information is gained and included into the decision making process. A related problem is that spatial beliefs of agents are static in current models, i.e. their beliefs do not change as a result of gaining experiences over time. But concessions are needed to reach consensus (Choi et al., 2001). Faludi (2000, p. 304) points out that ‘Only after learning has taken place, after consensus has been established, can the switch be made to formulating plans for selected projects’. So, for a realistic depiction of decision making, the learning about other agents’ behavior and the simultaneous adaptation of their actions for anticipating cooperation need to be implemented. Various researchers stress the importance of improving the representation of human processes in spatial models (e.g. Agarwal et al., 2002, Ligtenberg, 2006). This thesis aims at including learning and adaptation into the multi-actor spatial planning decision making process.

A technique capable of learning and adapting is a Bayesian Network (BN), also called Belief network, knowledge map or probabilistic causal network (Charniak, 1991). Simply put, it models variables and their causal relationships into a network. The causal relationships are encoded with probabilities that represent the extent to which one variable is likely to affect another. A Bayesian Network allows the change of the state of those parameters every time new evidence is presented. Therefore, it is expected that Bayesian Networks provide a suitable technique for modeling a learning and feedback mechanism in the spatial planning decision making process.

Bayesian Networks have been applied in spatial modeling, for example to maximize utility (Lei *et al.*, 2005) or calibrate cellular automata transition rules (Kocabas and Dragicevic, 2007); but not yet to add a learning component to spatial decision making. BNs have been used to simulate decision making and negotiation among agents in non-spatial models, primarily in the domain of Artificial Intelligence (e.g. Nielsen and Parsons, 2007, Ren et al., 2002, Zeng and Sycara, 1998). But communication, negotiation and decision making in these cases have assumed a common understanding of the negotiated objects. However, as it has been mentioned before, during decision making within an interactive spatial planning process the perception of the environment is highly subjective and thus requires a different modeling approach. So, although the concept of using BNs to simulate decision making is not new, it will be a challenge to apply it in a spatial planning context.

1.2 Research objective and research questions

The main objective of this research is to explore the use of Bayesian Networks as a means to improve on the representation of the decision making process in an agent based multi-actor spatial planning model.

A Multi-Agent System for multi-actor spatial planning has already been developed by Ligtenberg (2006). The actors have different perceptions of the current environment and different desires about the future environment. He asserts however that 'techniques to describe and implement forms of communication, strategies of negotiation and attitudes of decision-makers are still lacking' (Ligtenberg, 2006, p. 58). This model will therefore be extended with Bayesian Networks to reduce this limitation.

The research assumption is that the use of BNs can assist in improving the representation of the agents' decision making, so that it comes closer to the complex behavior of actual decision making actors. In the previously developed model, their behavior is described by deterministic rules that remain the same throughout the run-time of the simulation. This ignores the fact that in reality humans gain knowledge during a cooperation process and adapt their beliefs as a result. The static behavior impedes the achievement of a consensus. Therefore, agent behavior and planning outcomes could both profit from a more dynamic and self-adaptive representation of beliefs. A Bayesian Network will be implemented in the agent based multi-actor spatial planning model as a proof-of-concept. A case study will demonstrate the model.

The following research questions are defined to achieve the main objective:

I. What are the limitations in current approaches of decision making in multi-agent spatial models?
II. How are Bayesian Networks currently used in computer models?
III. How can decision making among spatial planning actors be modeled using BNs?
IV. What is the added value of BNs in a multi-actor spatial planning model?

Four main research domains emerge from these questions: spatial planning, Multi-Agent Systems, decision making, and Bayesian Networks. The utility of MASs to model spatial processes is already acknowledged; this will be discussed briefly. But the application of Bayesian Networks to implement learning and self-adaptation within such a model is the new challenge. The focus of this thesis is therefore on coupling the existing multi-agent spatial planning model with a Bayesian Network structure.

1.3 Structure of the thesis

The structure of this thesis follows the research questions posed in the previous section. The first two questions are answered by a literature review in Chapter 2, the theoretical background. First, descriptions of spatial planning, Multi-Agent Systems and decision making are provided in three subsequent sections. These three sections are brought together by a discussion on the limitations of current actor representations in agent based spatial models in section 2.4. Section 2.5 presents an explanation of Bayesian Networks and explains why they are expected to be able to improve on the representation of decision making among agents. Section 2.6 shows how Bayesian Networks have been used in other models, especially ABMs and what can be learned from those implementations. The final section of this chapter synthesizes the information on the different theory topics and draws conclusions for the required modeling concepts, contents and methods.

Chapter 3 provides the modeling methodology and thereby aims to answer the third research question. First, the multi-actor spatial planning model that was developed by Ligtenberg (2006) is described. Then the adaptations are presented in relation to the existing framework. Next, the implementation of the model is explained, thereby focusing on the Bayesian part, which is the newly added component. Some scenarios are carried out for a spatial planning case in the 'Land van Maas en Waal', a region in the Netherlands, for the assessment of the model. The scenarios are outlined in the final section of Chapter 3.

In Chapter 4 the results of these scenarios are presented. The results are discussed in relation with the theory and the model behavior in the first section of Chapter 5. This section thereby also provides an answer to the final research question, related to the added value of the Bayesian Networks to the model. Based on this discussion the answers to all research questions are summarized and suggestions for further research are posed in section 5.2.

2. Theoretical background

In order to integrate spatial planning, Multi-Agent Systems, decision making, and Bayesian Networks, a more detailed scope, definition and description of those domains is needed. This chapter provides the concepts within those domains and the tangencies between them to provide a sound basis for the conceptual model in the subsequent chapter. The starting point is the broader scope of the process to be modeled, spatial planning, and the general framework it is modeled in, a Multi-Agent System. The second part of the chapter concentrates on the focal part of this process being decision making, and its aimed modeling concept, Bayesian Networks.

2.1 Spatial Planning

Spatial planning is the search for modifications of the environment that meet the needs of society. It takes place at various spatial scales, ranging from international to local, and at various temporal scales, ranging from less than one year to more than thirty years (Ligtenberg, 2006). The traditional practice of land-use planning, centralized and controlling, has changed into a more decentralized and managing process in the last decades, often referred to as participatory planning or communicative planning (Geertman, 2006). Spatial planning is a perpetual process, since both the physical environment and the requirements of society change continuously. Therefore 'planning' is not just producing a plan, but also gaining an understanding of the current and future problems in order to make better decisions (Faludi, 2000). The decision making process has changed along with the decentralization: the role of governments of the only or primary actor transformed to that of planning team member or even an observer (Wegener, 2001). The tasks and involved people in the process have grown both in number and diversity (Geertman, 2006). This more pronounced involvement of multiple actors, also referred to as stakeholders, has made the planning process more democratic, but also more difficult, because of their diversity (see Ligtenberg, 2006, Samsura et al., 2010):

- Actors have different intentions, usually based on more than one goal.
- Semantics vary among actors, leading to different perceptions of spatial objects.
- Actors hold different strategies for achieving their goals.

Despite all these differences, actors involved in interactive spatial planning have the joint objective to produce a spatial plan. In a consensus building approach planning ends when all participating actors consider this plan as righteous (Cammen van der and Lange de, 1998, in Ligtenberg, 2006). Or, as put by Innes and Booher (1999, p. 414), such a result is 'more likely not only to *be* fair, but also to *be regarded* as fair'. Simon (1996) stresses that the purpose of planning should be to 'satisfy instead of optimize'. Both quotes signify that a satisfactory result for all actors is more important than finding the optimum result, because a satisfactory plan is more sustainable[2].

Due to the complexity of and interdependencies between the above described processes spatial planning can be regarded as a Complex Adaptive System (CAS) (Ligtenberg, 2006, Innes and Booher, 1999). Such a system shows 'emergence', meaning that patterns arise from a multiplicity of interactions.

2 The word 'sustainable' here does not refer to environmental sustainability, but to feasibility, solidity and achievability of the plan depending on the support of the stakeholders

According to Holland (2006), a CAS has the following properties:

- *Parallelism* – multiple processes taking place simultaneously.
- *Conditionality* – processes depending on each other
- *Modularity* – different coupled components at different levels
- *Adaptation and evolution* – changes over time, usually to increase performance

Spatial planning is embedded in society's ongoing stream of political and social action, collective learning and change (Innes and Booher, 1999). It can never be tracked precisely how one action results in another. To give some specific examples of the CAS properties in spatial planning, parallelism is found in the various physical changes in the environment as well as in the social processes of reasoning and anticipation continuously taking place in the minds of the actors. Both conditionality and modularity can be seen in the many interconnected factors influencing the planning process, like policy model, characteristics of the available information, political context and actor characteristics (Geertman, 2006). At a more evident level, conditionality is at hand in the actors' actions and reactions on each other. Modularity is caused by the different spatial, temporal and organizational scales involved. Adaptation and evolution of the actors are experienced in the above described feedback of converging or diverging beliefs. Now, only a few examples of CAS properties in spatial planning are given, but many more can be thought of and even more will be present unidentified. All the mentioned CAS properties of the spatial planning process are somehow related to the environment and the actors. Emergence arises from the interaction between these actors and their interaction with the environment. Therefore, a modeling technique that starts with the definition of the individual participants and their environment could assist in gaining a better understanding of the complexity of the spatial planning decision making process.

2.2 Multi-Agent Systems

Spatial planning, or, more broadly defined, land use change has been simulated within a variety of modeling approaches, including regression, econometric, linear planning, and discrete finite state (Agarwal et al., 2002). Those approaches, however, all somehow fit a function through changes in land use states. If enough data are available (which is usually a problem in the first place), this function fitting might yield adequate results, especially at a large scale. The great disadvantage of this approach is that the separate entities of the Complex Adaptive System which are the forces behind the changes remain hidden. The effects of the decisions of a single spatial planning actor cannot be derived from those kinds of models, which makes the model of limited use for simulation of the process in a different setting. If the process is to be studied at the individual actor level, a function through the emergent patterns of land use change is thus not sufficient. Therefore, a bottom-up approach is needed, that models the CAS by the interaction (parallelism and conditionality) of the entities (modularity) in the system and their development (adaptation and evolution) throughout the process.

A model that uses computational entities, called agents (Weiss, 1999), to fulfill this criterion is an Agent Based Model (ABM) or a Multi-Agent System (MAS). The two terms have a similar meaning, but MAS is used in the remaining of this thesis, because it stresses the interaction between different agents, required for decision making. An agent can autonomously view and perceive its environment and decide how to behave accordingly. The term 'autonomously' refers to the agent's ability to control its behavior without intervention of humans or other systems. This behavior consists of executing some kind of task given a certain performance measure. To accomplish this, agents should be 'intelligent' (Weiss, 1999). This does not mean that they are omniscient or omnipotent, but that they are flexible and rational.

To make agents perform actions various architectures are developed, mainly in the domain of Artificial Intelligence. Four agent architectures can be distinguished (Weiss, 1999):

- *Logic based*
- *Reactive*
- *Belief-Desire-Intention (BDI)*
- *Layered architectures*

The behavior of logic based agents is related to the environment by logical deduction rules. The rules are given by formulae. Furthermore, axioms are used for theorem proving and a model theory for provision of the semantics. The behavior of reactive agents results directly from their perception of the environment. This method is less complex, faster and more flexible than the logic approach. BDI agents have predefined desires about their environment. They relate these to their perceptions to form beliefs that result in intentional behavior (tasks). So, where the first two architectures only respond to the environment (*reactiveness*), BDI agents make a plan and thus anticipate (*proactiveness*). Layered architectures combine these two approaches, using different software layers to simulate both reactiveness and proactiveness. A problem of the layers is that the actions resulting from them can be conflicting. And as humans are often unable to cope with a conflict between intuition and ratio, agents have even more trouble with it. A more extensive explanation of agent architectures and their advantages and disadvantages can be found in Weiss (1999).

Spatial planning was explained before as 'gaining an understanding of the current and future problems'. This learning from the past and anticipating on the future indicates that a proactive architecture is needed to model the process. This fact, together with the different semantics, goals and strategies held by the actors, matches best with the Belief-Desire-Intention (BDI) architecture.

MASs are used for many applications, ranging from managing human-computer interaction to simulating social interactions (Sengupta and Sieber, 2007). The ability to couple social and environmental interactions has made agent-based modeling a popular technology in Geographic Information Science (Hare and Deadman, 2004). In spatial planning the actors, modeled as agents, together form a MAS, where cooperation must take place to resolve some planning issue. To be able to find a framework for this focal part of the process, decision making in real life spatial planning and in current models are discussed in more detail in the next section.

2.3 Decision making

Planning with multiple actors can be seen as a social conflict. There are two major types of social conflict: consensus conflict and scarce resource competition (Aubert, 1962, in Thompson and Hastie, 1990). Consensus conflict arises when persons trying to reach an agreement have incompatible beliefs, while scarce resource competition occurs when persons compete for the same limited resource. Multi-actor spatial planning is an example of a consensus conflict, because the actors have multiple different beliefs about the future state of the environment, but they must decide on a plan together. They have to agree on locations for certain land use type, so, in fact, they have to allocate resources together, instead of competing for them. The funding behind it could be considered scarce resource competition, but funding issues are not within the scope of this research. Therefore, spatial planning is seen as solemnly a consensus conflict.

A framework developed to describe the interactive multi-actor spatial planning process at a regional scale is the ‘regional dialogue approach’ (Mansfeld, 2003). It distinguishes four phases: socialization, externalization, internalization, and combination (te Brömmelstroet and Bertolini, 2008, Nonaka and Takeuchi, 1995). Socialization serves to create trust among the participating actors as well as to get some insight in the desires, beliefs and preferences of each participating actor. Externalization refers to the process of making implicit (or tacit) knowledge explicit, while internalization refers to the process of accepting explicit knowledge as part of the joint stock of knowledge of participating actors. Combination means using internalized information to build new concepts together. The regional dialogue approach thus clearly defines the phases of decision making in spatial planning and shows that knowledge develops throughout the process. This learning process influences the decisions of the actors (Samsura et al., 2010). A positive atmosphere, characterized by trust among the actors, results in convergence of opinions so that in the end the actors reach consensus (Laurian, 2009). But if the differences among actors are too strong, the feedback can also enhance division, so that a consensus becomes out of reach (Laurian, 2009).

The decision on a plan, within the spatial planning procedure, consists of two components: the individual[3] decisions of the actors and the model that determines the result of a certain configuration of individual decisions, the joint decision (Nyerges and Jankowski, 1997). This model is usually determined by the power structure among the cooperating actors. It can be hierarchical, the decisions of the actors have an unequal effect on the joint decision, or democratic, all decisions have equal weight. Actors know this structure on forehand and will therefore take it into account when doing proposals or taking decisions, so that they can estimate whether the total result is agreement or disagreement. The learning process, described by the regional dialogue approach, facilitates a better estimation of the joint outcome as the decision making process develops. And even if no plan is produced, the process can be a success. Or, as put by Innes and Booher (1999), intangible products can be more important than the tangible ones. They mean by this that the change in the attitudes and the knowledge gained by the actors are in itself important long-term results of spatial planning.

Individual decision making in spatial MAS is usually based on maximization of a utility function (Parker et al., 2003). The function describes the preference of an actor, based on his multiple desires and their relative weights. The construction of such a utility function is ambiguous in the first place, since the attributes have different units and their interrelations are often non-linear (Lai et al., 2006). Those interrelations determine which attribute might be ‘given up’ in exchange for another in the negotiation process. But the function characterizes only personal preferences and does not include any anticipation on the joint outcome. In addition, desires and beliefs are in reality not static. One reason for this is the learning throughout the process, as described by the regional dialogue approach. Another is that actors have to do concessions in order to reach consensus. These concessions are often modeled by the concept of bargaining, where a seller tries to maximize his earnings and a buyer tries to minimize his costs. This concept is straightforward and is often used in MAS (e.g. Arentze and Timmermans, 2003, Choi et al., 2001, Moulet and Rouchier, 2008). However, for the spatial planning problem this concept is this not suitable, because spatial planning is a consensus conflict and thus not only one’s own gain should be considered, but also the joint outcome. The ‘best’ consensus can be calculated, based on all utility functions; this is called a *Pareto optimal* solution (Weiss, 1999). The total utility is maximized, i.e. it is not possible to make one player better without making any other worse. This Pareto optimum can be calculated when all utility functions are known, while in reality desires often remain concealed to the other actors. In addition, it was already argued before that it is more important that all participating actors consider the plan

[3] Note that the individual mentioned here can also represent a group, like an organization, a company or a political party. The decision making in fact consists of two levels: first agreement within the group, then agreement between the groups. The fist level is not modeled; it is assumed that the within-group agreement is already reached and can not be deviated from.

as satisfying or righteous, than that the optimum is reached. So, utility maximization alone is not sufficient to represent individual decision making, because it does not account for concealed, dynamic beliefs and the objective to satisfy instead of optimize.

Therefore, another approach for individual decision making is needed, taking into account the joint result. The study of joint decision making in social conflict situations is captured in two main theories: game theory and behavior theory (Hausken, 1997). Because the theories are developed by computer scientists and social scientists respectively, who come from quite distinct research branches, they show a very different approach. Game theory assumes that participants in the game are fully rational, and thus always chose what seems to be the best strategy to them. But in reality, people are never fully rational. Social aspects, like trust, stereotypes and emotions, can be just as important in decision making as rational arguments (Pruyn and Wilke, 2001).These social aspects are the domain of the behavior theory. Behavior theory is not discussed within this thesis, firstly because it is descriptive and thus very hard to capture in an algorithm, and secondly because it is focused on the influence of the individual personality on decision making, while the agents modeled in this research represent groups rather than single persons.

The game theory approach applies a mathematical description of behavior and is thus relatively easy to implement in models. The theory states that all types of social conflict situations can be conceptualized as different kinds of games with three basic elements: a set of courses of action, preferences for the players among the possible outcomes and relationships between those two, i.e. how actions lead to certain outcomes (Anumba et al., 2003). The games are based on three assumptions: players are rational (and expect others to be), they try to maximize their own gain and have complete information of their own and each other's possibilities to do so (Anumba et al., 2003).

Games can be divided into zero sum and non-zero sum games, depending on whether there is a predetermined set of available payoffs, i.e. a fixed treasury (Anumba et al., 2003). A simple example of a zero sum game is cutting a cake; if one player takes a larger piece, the amount of cake available for the others reduces. This illustrates that any result of a zero-sum situation is Pareto optimal. Zero sum games are strictly competitive, no strategic interaction is involved, in contrast to non-zero sum games where the size of the treasury depends on the choices of the players. Spatial planning is a non-zero sum situation; there is no predefined set of available plans on forehand.

The most famous example of a non-zero sum game is the Prisoner's dilemma. In its simplest version, the Prisoner's dilemma involves two players, representing two prisoners arrested together for a crime and separated so that they cannot communicate. Each prisoner has two options: remain tacit (cooperate with the other prisoner) or testify against the other (defect). If one testifies and the other remains silent, the betrayer goes free and the other receives a five year sentence. If both remain silent or both defect, they get the same sentence: one and three years for the respective cases. An overview of all combinations is given in Table 1. In contrast to a utility function, a payoff matrix takes into account the effect of the decisions of others on the result. In the Prisoner's dilemma, defecting is for each individual the most safe option (zero or three years), but if both cooperate they are better off together (one year per prisoner results in a total of two years instead of six). An eminent work on the Prisoner's dilemma is the Robert Axelrod tournament (Axelrod, 1984). He and after him many others have studied what the best strategy is when the game is played iteratively.

Table 1: Payoff matrix for prisoners A and B

	B cooperates	**B defects**
A cooperates	A = 1, B = 1	A = 5, B = 0
A defects	A = 0, B = 5	A = 3, B = 3

Although some result of studies about the Prisoner's dilemma can be used to explain strategies for spatial decision making, there is a clear difference. In the iterated Prisoner's dilemma the behavior of the others is studied in order to improve one's own gain, while in spatial planning gaining information about the others' desires helps to find the best mutual plan, satisfactory for all actors. In other words, the Prisoner's dilemma is a scarce resource competition, whereas spatial planning is a consensus conflict. If only one's own gain is considered no consensus will be reached or the resulting plan will not be sustainable. So, in contrast with the prisoners, spatial planning actors aim at balancing their own interest with the common interest. In addition to this deficit learning is not simulated; the same problem as encountered with the use of utility functions. Finally, the payoff matrix is not very suitable to handle multiple issues, since it would become very large. Although including multiple issues is possible, it would be better if a different approach could be found to divide the total payoff matrix into multiple separate ones, being somehow interlinked.

In summary, a payoff representation is needed, in which multiple issues can be considered. Individual decision making should be based on the combined outcome of this representation and the anticipation on decisions of the other actors and a mutually acceptable solution (compromise). Since the beliefs of other actors are not known at the start of the process, they should develop through socialization. This indicates that learning should be implemented. In Table 2 it is summarized whether the required decision making aspects are present (+) or lacking (-) in the utility maximization (by bargaining or Pareto optimization) and the game theory approach. The utility maximization approach can handle multiple issues, but lacks anticipation capacity, while with game theory it is the other way around. The best approach for this research would therefore be a combined utilization of utility functions and game theory with an additional learning mechanism and search for a compromise.

Table 2: Required decision making aspects

	multiple issues	anticipation others	search compromise	learning
Utility maximization	+	-	-	-
Game theory	-	+	-	-

2.4 Lessons learned from existing spatial MAS

The former three sections have described three main subjects of this thesis: spatial planning, MAS and decision making. Fusion of those three components is not new, and lessons learned from past attempts should be taken into account. This section investigates spatial MAS reviews and summarizes important limitations and recommendations.

Several authors have already carried out assessments of multi-agent spatial models (e.g. Hare and Deadman, 2004, O'Sullivan, 2008, Parker et al., 2003, Sengupta and Sieber, 2007). They have classified the models in different ways. O'Sullivan (2008) identifies three classes of environmental MASs based on increasing realism. The first is defined as 'simple, abstract models as thought experiments'. These models are used 'as a vehicle for exploring the implications of assumptions about the ways in which actors in a social setting behave and interact' (O'Sullivan, 2008, p. 543). The second class contains 'mid-range regionally or locally specific models'. In these models the agents as well as the environment are more realistic. Agents employ more advanced reasoning about geospatial data representing real places and landscapes. The final class comprises 'highly detailed, realistic simulations', very large scale models that represent interactions among many agents. At the moment, such models are mainly used in the domain of big-budget, policy driven projects (O'Sullivan, 2008).

Such a detailed and realistic representation is not the aim of this research. This research specifically focuses on the decision making process in spatial planning, instead of trying to represent a full, realistic spatial planning situation. Parker et al. (2003, p. 325) have found a suitable metaphor to clarify these two different approaches, which draws on the difference between a photographic portrait and a Picasso portrait: 'one attempts to mimic reality; the other, while capturing parts of reality, focuses on particular aspects in the hopes of emphasizing fundamental features'. In addition to this argument, the followed spatial planning approach, the regional dialogue approach, embodies a regional and not a global process (Mansfeld, 2003, Valk van der, 2002), in which real places and landscapes are to be considered, so the second category is the one of interest for this thesis. The problem with this category, according to O'Sullivan, is how to draw general lessons from those regional models, with their location and process specific foci. The model framework should therefore exist of *general* economic, interpersonal and intrapersonal relationships. These relationships are namely comparable at different places and scales. The case specific variables, varying at different places and scales, must be included in such a way that they can be set according to the situation to be modeled. In this way, general lessons can be learned by using the model for different case studies.

A similar complexity study of multi-agent land use change models is carried out by Agarwal et al. (2002). They have, however, defined complexity much more precisely. A framework was developed in which models are evaluated in three dimensions: space, time and human decision making. Especially the last dimension is interesting, because it is the aspect that is to be revised in the spatial planning process for this thesis. Six levels of human decision making are distinguished by Agarwal et al. (2002), as shown in Table 3.

Table 3: Human decision making complexity levels (adopted from Agarwal et al., 2002)

Level	Explanation
1	No human decision making — only biophysical variables in the model
2	Human decision making assumed to be related determinately to population size, change, or density
3	Human decision making seen as a probability function depending on socioeconomic and/or biophysical variables beyond population variables without feedback from the environment to the choice function
4	Human decision making seen as a probability function depending on socioeconomic and/or biophysical variables beyond population variables with feedback from the environment to the choice function
5	One type of agent whose decisions are modeled overtly in regard to choices made about variables that affect other processes and outcomes
6	Multiple types of agents whose decisions are modeled overtly in regard to choices made about variables that affect other processes and outcomes; the model might also be able to handle changes in the shape of domains as time steps are processed or interaction between decision making agents at multiple human decision making scales

Since decision making is the main focus in this research, it is aimed to reach complexity level six, but only by fulfilling the main requirement to include multiple agents and feedbacks; modeling decision making among multiple scales is not the objective in this research. Out of the nineteen models examined by Agarwal et al. (2002), only one was found to exhibit human decision making at complexity level six. A high spatial and temporal complexity was respectively found in 79% and 31% of the examined models. Although this research report considers only land use change models and was conducted already eight years ago, it points to the focus of environmental scientists on the representation of the environment, which is understandable because of their background. But, the human component in this environment is also important and should not be underestimated.

It can be concluded from this section that a general decision making framework is needed, valid independently of the case specific parameters. To simulate the decision making process at an advanced level of social complexity multiple agents should make decisions thereby taking into account their own and others' past decisions and related outcomes. A Bayesian Network is a general framework, consisting of variables and their interrelations, of which the case specific parameters (i.e. the states of the variables) can be easily set according to the considered case. A BN learns from experience and is therefore expected to be able to improve agent reasoning and thus social complexity. This research explores whether the summarized expected improvements can be achieved by the implementation of Bayesian Networks in a MAS. The next sections examine Bayesian Networks and their current applications more closely to get a better understanding of their capabilities.

2.5 Bayesian Networks

The usage of Bayesian Networks to represent Complex Adaptive Systems (e.g. Potgieter, 2004) and learning agents (e.g. Zeng and Sycara, 1998, Lei et al., 2005) has been previously defended by other authors. Still, a justification for the application of BNs within this research is convenient. Therefore, this section explains Bayesian Networks in more detail and provides arguments for their expected added value to spatial planning decision making by agents.

A Bayesian Network (BN), also called Belief network, knowledge map or probabilistic causal network (Charniak, 1991), is a graphical representation of set of variables, *nodes*, and their cause-effect relationships, *links*. These cause-effect relationships are encoded with probabilities that represent the extent to which one variable is likely to affect another. The statistical rule behind this probability is what the network is named after. Thomas Bayes (1702–1761) proved a special case of this rule, which is now called Bayes' theorem. However, it was Pierre-Simon Laplace (1749–1827) who introduced a general version of the theorem and used it to approach problems in several scientific domains (Malakov, 1999).

Before going deeper into the statistics, the following example illustrates the usage of Bayes' theorem. One of the most famous examples to teach someone about probability theory is the jar with black and white balls. The ratio between the two colors is known and one has to depict the probability that a black will be drawn. In contrast, Bayes reasons the other way around. If the ratio between black and white balls in a jar is unknown, what can be said about it when some balls are drawn? Those balls provide evidence for what the ratio in the jar could be. The reasoning thus infers the causes (ratio) from the effects (balls that are drawn). The more balls are drawn, the more one gets to know about the ratio.

A probability (P), on an event (A) given some evidence or condition (B), can be depicted as P(A|B). This is called a *conditional* probability. Sometimes one wants to know it the other way around, the chance on a condition, given an event, P(B|A). The two are related by the following formula (Freund, 2004):

$$P(B|A) = P\frac{(B) * P(A|B)}{P(A)}$$

This notation is only meaningful when there is a (causal) relation between A and B. If not so, P(A) would be same as P(A|B), i.e. condition B tells noting about A; the two are independent and P(B|A) equals P(B). *Undirected* graphical models, also called Markov Random Fields or Markov networks, have a simple definition of independence: two (sets of) nodes A and B are conditionally independent given a third set, C, if all paths between the nodes in A and B are separated by a node in C (Murphy, 2001). By contrast, Bayesian Networks, which are *directed* graphical models, have a more complicated notion of independence, which takes into account the directionality of the arcs, as explained below.

In a directed graphical model, an arc from A to B can be interpreted as ‘A causes B’. Consider the example of the Bayesian Network in Figure 1 with four nodes and four links. In this BN all nodes show two different situations, called *states*. A node can hold more than two states, but the states must always be separate categories; a continuous scale is not possible. One of the nodes is ‘WetGrass’ with two states: ‘True’ and ‘False’. The fact that the grass is wet (W=true) has two possible causes: either the water sprinkler is on (S=true) or it is raining (R=true). R and S are referred to as the *parents* of *child* W. The strength of this relationship is shown in the table belonging to W, it’s *Conditional Probability Table* (CPT) (Murphy, 2001). The probabilities in a row of the CPT must sum to one, because it is assumed that the linked causes are the only possible causes for the grass to be wet. The probability on a certain state, when no information is available about which state a node is currently in, is called the *prior probability*.

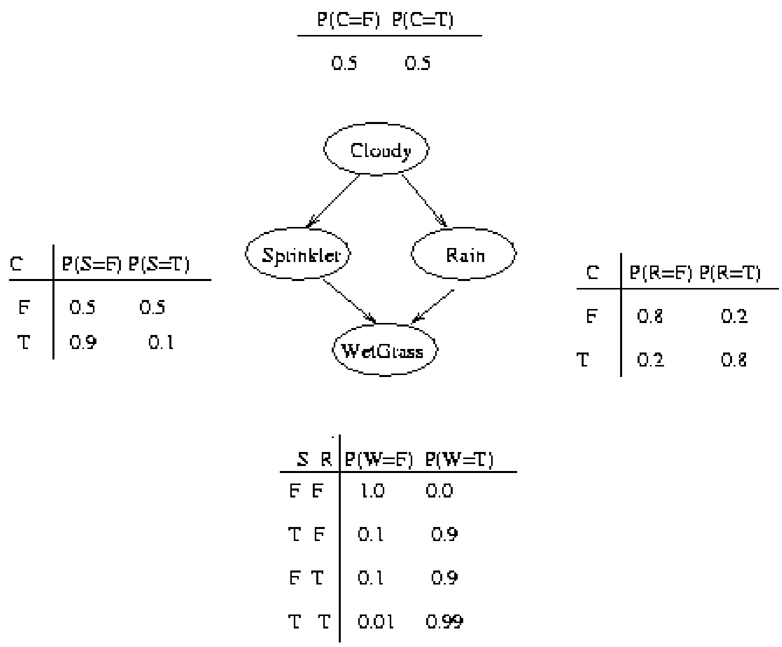

Figure 1: Example of a Bayesian Network (adopted from Murphy, 2001)

By the use of the CPTs it can be calculated how likely it is that wet grass is caused by rain. In this case, the wetness of the grass is the *evidence* and rain is the *event* the probability is required for. If Equation 1 is to fill in, first the total probability that the grass is wet, P(W=true), has to be known. This can be calculated by summing the probabilities belonging to all single ‘paths’, i.e. combinations of states, that lead to wet grass. These are given in Table 4. True and false are denoted as 1 and 0 respectively.

Table 4: All paths resulting in wet grass

C	R	S	W	Calculation	Result
0	0	0	1	0.5*0.8*0.5*0.0	0
0	0	1	1	0.5*0.8*0.5*0.9	0.1800
0	1	0	1	0.5*0.2*0.5*0.9	0.0450
0	1	1	1	0.5*0.2*0.5*0.99	0.0495
1	0	0	1	0.5*0.2*0.9*0.0	0
1	0	1	1	0.5*0.2*0.1*0.9	0.0090
1	1	0	1	0.5*0.8*0.9*0.9	0.3240
1	1	1	1	0.5*0.8*0.1*0.99	0.3726
				Sum	0,6471

From the same table the numerator of Equation 1 can derived, i.e. all cases in which the wet grass is (at least partly) caused by rain (W=1 and R=1). The sum of the probabilities belonging to these cases is 0.4581. Thus:

$$P(R = 1|W = 1) = \frac{P(R = 1) * P(W = 1|R = 1)}{P(W = 1)} = \frac{0.4581}{0.6471} = 0.7079$$

The probability that the wetness of the grass is caused by rain is thus 0.71. This is called a *posterior probability*, because the state of the grass is already known (Murphy, 2001) and the calculation is called *inference* (Heckerman, 1996). When the posterior probability for the sprinkler is calculated, it appears to be 0.43; hence, the two do not sum up to one. The reason for this is that the sprinkler can also be on when it rains. Thus the two are not mutually exclusive, but they do depend on each other, given their common child W.

This dependence is caused by conditionality, the difference between a directed and undirected graph, mentioned before. It is clear that conditionality is required in modeling a Complex Adaptive System, because it is one of the four CAS properties, explained in section 2.1. More of the explained Bayesian Network properties give arguments why they provide a suitable way to model decision making in a spatial planning context.

Two types of data are used by the spatial planning actors: data about the environment they are supposed to produce a plan for (spatial data), and data about each other (perceptions). Spatial data are often continuous (e.g. distances and elevations), while information on actors (e.g. cooperation among them) is Boolean (they do or do not agree). Continuous input data are only possible in a Bayesian Network when they are discretized, i.e. grouped into separate ranges that represent the states of the node. Anticipating on the model set up, discussed in the next chapter, presume that the Bayesian Network will be the interpretation of the events encountered by the agent. The agent represents a human and humans happen to categorize information according to preset schemas (Pruyn and Wilke, 2001). So, the discretization of information by the Bayesian Network is not a drawback in this case.

The combination of prior probabilities and evidence facilitates the fusion of domain knowledge and data (Heckerman, 1996). But this is also the most often encountered critic about Bayesian Networks; two people analyzing the same evidence can arrive at different answers if they start with different prior probabilities (Malakov, 1999). The method is subjective. Heckerman (1996, p. 3) states that 'Whereas a classical probability is a physical property of the world, a Bayesian [prior] probability is a property of the person who assigns the probability'. But in this research, that is exactly the reason why Bayesian Networks are used. Two collaborating spatial planning actors, examining a map of the area under interest, will have different proposals for change, because they have different perceptions and desires, i.e. different prior probabilities. A distinct feature of Bayesian analysis is that it does not yield a single prediction but a distribution of probabilities over a set of states. If a simple 'yes' or 'no' decision is required, this can be a drawback. But in less deterministic situations these probabilities can be used to generate expected utilities associated with various possible issues.

The spatial data are likely to be completely available from the start of the decision making process, because the current state of the environment is known. Perceptions of the actors however, are uncertain or unavailable at the beginning, since these data are learnt from the interaction, for example what the other actor puts forward over time. A Bayesian network can start with prior probabilities (predefined knowledge) and adapt the relations (CPTs) during the process when new data arrives (experience). It can thus start without data, and learn continuously, along with the arrival of data; a process not many other techniques facilitate (Malakov, 1999). In addition, a BN can anticipate on a certain event (e.g. cooperation) using *evidence*. The more data comes in, the more established the CPTs get, the better the BN will become in inferring the effects from the causes or the other way around. Actors learning the results of their actions and thereby developing the ability to anticipate on the results of their future actions can be simulated in this way.

In summary, the possibility to incorporate prior probabilities, handle uncertainty, facilitate continuous learning and cope with both continuous and discrete data are the desired features that together give reason for using BNs to improve on the representation of the decision making process in an agent-based spatial planning model. However, no structure for this representation has been found yet. Different applications of Bayesian Networks are examined in the next section in order to obtain a suitable structure.

2.6 Applications of Bayesian Networks

The probably most omnipresent Bayesian application in everyday life is Microsoft's animated paperclip, which offers help to users of its Office software. It is designed to predict what users will ask next by keeping track of prior questions. Eric Horvitz of Microsoft Research in Redmond, Washington, claims that they even could have avoided that problem the paperclip pops up when it isn't wanted if they 'went all the way with Bayesian' (Malakov, 1999, p. 8). The paperclip is an example of the use of a Bayesian Network for continuous learning, since every time the user poses a question it will learn about his or her interests and become better at anticipating on the next question.

Bayesian Networks are often applied to discern patterns in large datasets where many variables may be influencing an observed result. Genomics researchers, for instance, use prior knowledge about a DNA sequence to identify other sequences that have a high probability of coding for proteins with similar functions (Malakov, 1999). The resulting networks are commonly used as a decision tree, in order to infer the causes from the observed effects by the learnt relations. The most common application field of Bayesian decision nets is medical diagnosis (Charniak, 1991). An example is PATHFINDER (Heckerman, 1990), developed to diagnose diseases of the lymph node (a small organ of the immune system). A patient suspected of having a lymph node disease has a lymph node removed, which is then examined under a microscope. The information gained thereby, possibly together with information from other tests, is entered into PATHFINDER. The network provides the probabilities of the diseases given the evidence so far. Based on this it can be decided which test to perform next (which has the highest probability to give more certainty about the possible disease) when the current tests are not sufficient. However, these Bayesian decision net applications are static. When an effect is encountered, the probable cause can be derived. But the network is not updated when the truth comes about, e.g. the DNA sequence does or does not turn out to have the expected property or the medical diagnosis was found to be right or wrong. This feedback can improve the Bayesian Network. It might not be done in the examples mentioned above, because the users of the network are not the developers.

Bayesian Networks in Multi-Agent Systems provide an excellent framework to include this feedback and thus continuous learning. Both evidence and network persist in the same 'world', being the MAS. The experience of an agent can automatically be incorporated in the network as a new case, like the paperclip's (agent's) experience with the questions (evidence) of the user. Bayesian Networks for agent learning are for example already applied to simulate bargaining (Zeng and Sycara, 1998) and argumentation schemes (Nielsen and Parsons, 2007). However, the approaches of those researches cannot be used, because they assume common semantics for the objects under negotiation.

The use of Bayesian Networks in environmental models is quite limited (Alexanderidis and Pijanowski, 2005). They have been applied in remote sensing (Qin et al., 2006), watershed management (Borsuk et al., 2001), land-use change (Kocabas and Dragicevic, 2009) and urban development (Arentze and Timmermans, 2003). But, the only environmental model found in the literature that uses a continuously learning Bayesian Network for agents is the Multi-Agent-Based Behavioral Economic Landscape Model (MABEL) (Lei et al., 2005). It is a land-use change model driven by BDI agents that can buy sell or keep land. The Bayesian Network is a decision network that calculates the transaction utility based on biophysical (comparable to 'spatial' in this thesis), economic and social attributes. An example of a decision net from MABEL is given in Figure 2. The social attributes are only attributes of the agent itself, thus the Bayesian Network does not contain perceptions of other agents. A transaction takes place when one agent decides to buy a certain type of land and another decides to sell it and the buyer finds the seller via a list. The transaction result is fed back into the BN.

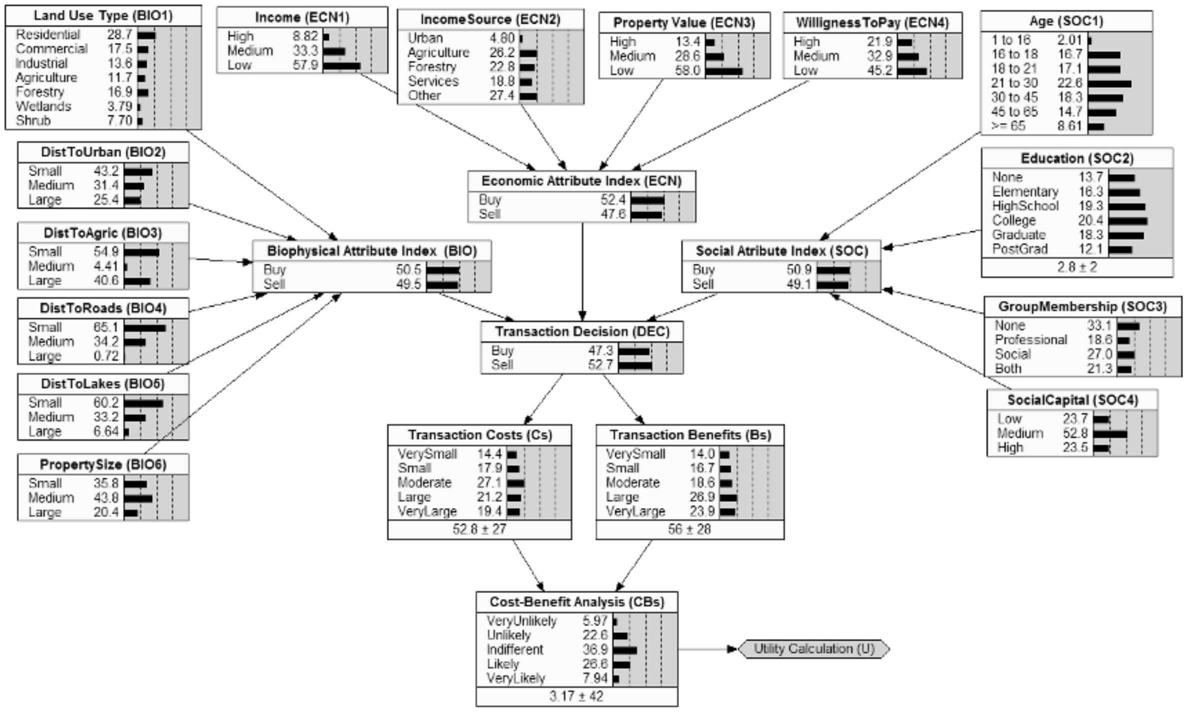

Figure 2: Bayesian decision network from MABEL (adopted from Lei et al., 2005)

There are several similarities between MABEL and the spatial planning model required in this research. In both a Bayesian Network makes the desires related to the environment and other attributes dynamic. The other attributes differ in the two approaches. MABEL agents have economic and social attributes. The first is not really relevant for spatial planning actors, because they do not always own or attempt to buy the concerned land. It is about assigning a new functionality of the land in need of the society. The second attribute is not relevant because the spatial planning actors primarily represent groups of people (e.g. companies) which as a result cannot be assigned a single age, gender or education level. In addition not much is known about the influence of such attributes on the decision making process. What does matter in the decision making process, and is not included in MABEL, is the behavior of the other actors. It is not only important to feed the agent's own actions back into the network, but also the actions (reactions) of the others, in order to be able to find mutual gain. So, the Bayesian Network in MABEL is a good start to realize the objective in this thesis, but its methodology needs some additional functionality like the ones found in the Microsoft Paperclip or Bayesian bargaining and argumentation frameworks.

2.7 Conclusions

Several subjects have been discussed in this chapter, resulting in many concepts and requirements for the model contents and modeling techniques. The spatial planning process is found to comprise a Complex Adaptive System. In this system, with multiple interdependencies and feedbacks, actors try to find a mutually acceptable plan for the environment, despite their multiple different desires, semantics and tactics. In addition to the problem that these differences result in disagreement, the desires are usually concealed and thus difficult to work out. This situation is best represented by Belief-Desire-Intention agents, linked together in a Multi-Agent System. The problem they face is a consensus conflict: they have different desires, but aim at the same goal, to produce a sustainable plan for the considered environment. The agents must formulate beliefs and make proposals about the future state of the environment, thereby taking into account the expected reactions of the other agents. In addition they must account for their original desires; otherwise the result will not be satisfactory for them. The decision making structure herein consists of two components: the individual decisions of the agents and the model that relates them into the joint result. In order to be able to anticipate on the joint outcome, thus to exhibit proactiveness, the agents must know this model and must learn each others' concealed beliefs by experience. Two commonly used decision making approaches were revised: utility maximization and game theory. The first can handle multiple issues, but lacks anticipation capacity, while for the second it is the other way around. The best approach for this research would therefore be a combined implementation of utility maximization and game theory with an additional learning mechanism and search for a compromise instead of individual gain. From previous research on spatial MAS, it was recognized that a general decision making framework is needed, that is valid independently of the case specific parameters, but at the same time able to include the interdependencies of social complexity.

A Bayesian Network is a general framework, consisting of variables (nodes) and their interrelations (links), of which the case specific parameters (states) can be easily set according to the considered case. It is able to combine prior knowledge with data gathered later on and to handle the uncertainty resulting from the lack of data at the start. The spatial planning decision making process is therefore expected to be represented in a suitable way by the synergy of Bayesian Networks and MASs. A BN learns from experience and could therefore improve agent reasoning and thus social complexity. An example of a fusion of BNs and a MAS, in which the network is implemented as the 'mind' of the agent, has been found to be a suitable approach, because it can represent the different beliefs and make them dynamic. The advantages of utility maximization and game theory, consideration of both multiple issues and the behavior of the others, can be implemented within this BN structure. The links between those two can facilitate learning and anticipation on the joint outcome as explained in the next chapter.

3. Methodology

This chapter explains how a model is created from the gained knowledge, presented in the former chapter. First, the conceptual model is outlined, to show the general ideas behind and procedures within the model. Next, the used software and model implementation are explained, to give a better insight in the simulation procedures and the learning mechanisms of the agents. Finally a case study, used to demonstrate the model, is outlined.

3.1 Conceptual model

To explore the application of a BN to improve on the representation of decision making an agent based spatial planning model, MASSA, of Ligtenberg (2006) was extended. This model simulates an interactive multi-actor spatial planning process at a regional scale, inspired by the regional dialogue approach (Mansfeld, 2003), as previously described in section 2.3. MASSA mimics a number of actors, representing groups rather than individuals, who have to allocate new urbanization in an environment. They have the common goal to produce a mutually acceptable spatial plan. However, they have different desires about the location of this new urbanization. MASSA did, until now, not allow any updating of those desires, meaning there was no feedback between the result and the drivers of agents' actions. For more detailed information on the original decision making procedures see Ligtenberg (2006, 2009).

MASSA was previously focused on externalization, internalization and combination phases (te Brömmelstroet and Bertolini, 2008, Nonaka and Takeuchi, 1995). The Bayesian Networks aim to add to the socialization component, which serves to create trust among the participating actors as well as to get insight in the desires, beliefs and preferences of each participating actor. In section 2.3 two approaches that represent decision making in a situation with belief conflicts were described; utility maximization and game theory. Utility maximization was originally used in MASSA. This approach is able to handle multiple issues, but lacks anticipation capacity, or, in agent jargon, proactiveness. This anticipation was implemented, inspired by game theory and adapted for consensus conflict, which means that cooperation is desired. A learning mechanism was added to simulate the development of knowledge about each other's beliefs. While the planning process advances through time the actors become better at anticipating reciprocity. Both the knowledge development and anticipation are provided by Bayesian Networks, which were proved to be very suitable for learning and inference in section 2.5.

In section 2.6 an example of a fusion of BNs and a MAS by Lei et al. (2005) was reviewed. The use of the network as the 'mind' of the agent, such as the one employed in MABEL, is a good approach because it can represent the different beliefs. So, every agent will have its own BN, with its own beliefs and semantics. However, if only the actors own beliefs are considered, the consensus conflict will not be resolved. And, since the actors usually don't reveal their beliefs, they must be learned. Accordingly, the actors adapt their beliefs towards those of the others. Nevertheless, they will not let their beliefs shift too much from their original ones, i.e. they will not completely let go their desires. Therefore, the fulfillment of the original desires, thus satisfaction, is also important. To include both its own and the others' beliefs in individual decision making, the actor's 'mind' should also contain its perceptions of the other actors. These perceptions should become more accurate throughout the planning process, so that the agent can find locations that exhibit the best equilibrium between its own desires and those of the others. While the things to be learned are thus different than in MABEL, the feedback loop between the agents´ beliefs and their actions has the same conceptualization. The main conceptual elements of the BDI decision model of MABEL, displayed in Figure 3, are therefore used as a framework. The BDI level and the cognitive level were already present in MASSA: desires are translated into beliefs by a utility function and the optimization of this function with respect to the environment leads to intentions (proposals), which in turn, lead to decisions. What needed to be implemented was the recording of experience (learning) and feedback (adaptation) of this experience into the beliefs of the agent. The experience box in Figure 3 is implemented using Bayesian Networks.

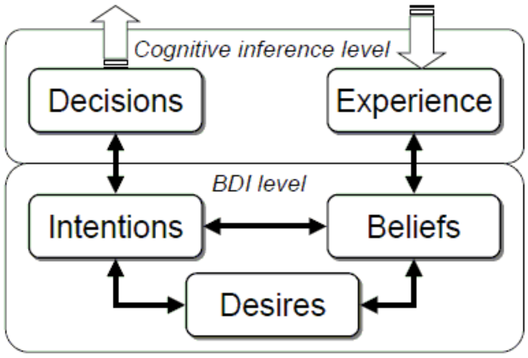

Figure 3: The main conceptual elements the MABEL BDI decision model (adopted from Lei et al., 2005)

In the proposed BN structure, the nodes represent on the one hand the agents' beliefs, thereby comprising the inputs for the utility function, and on the other hand the cooperation of the other agents and their own satisfaction. Cooperation is, like in the Prisoner's dilemma, simply whether an agent says 'yes' or 'no' to a proposal. This decision is based on comparison of their *initial* utility for the proposed cell, with their threshold, the lowest acceptable utility. Satisfaction is also a Boolean property. It indicates if the *initial* utility of the proposed cell is above the threshold. Initial utilities are used here, because if the new utilities were used, the BN would not be able to learn. It would then have to learn a changing parameter and would thus always be 'one step behind'. Cooperation and satisfaction are related to the beliefs by CPTs. Those CPTs denote components that together are forming the payoff matrix as found in the game theory approach. This separated representation solves the problem of a large payoff matrix when multiple issues are considered. A feedback loop between the BN and the agents' behavior facilitates learning and adaptation to find a possible consensus by revision of the beliefs. An example of the network structure and this feedback loop will be given in the next section.

The adapted conceptual framework of Ligtenberg (2006) of multi-actor spatial planning is shown in Figure 4 in order to make the connection between the previous MASSA version and the framework of Figure 3 more comprehensible. Two systems are represented: the spatial and the social system. Between them is the represented spatial system, which is a simplified version of the environment that is easier to interpret (it can be thought of as a geographic map). In the social system the actors are present. They observe and perceive the environment and formulate proposals regarding its desired future state. In the previous version of MASSA, a proposal consisted of several cells, while in the new model a proposal is a single cell. This is done, because deriving characteristics from a group of cells is more difficult, since every cell has its own properties. All actors decide whether they want to accept or reject the proposed cell. The model that relates their individual decisions into the joint result is indicated as 'joint fact finding'. That is the moment when actors learn in order to become able to make proposals in the next round that are satisfactory for all of them, so that an agreement becomes more likely. A cooperative attitude is assumed, meaning that agents are willing to learn from each other and find solutions with mutual gain. Thus inside the social system, a feedback loop is included between the joint fact finding and the actors (adapt arrow in Figure 4), which represents the learning and resulting anticipation on cooperation in the consensus conflict.

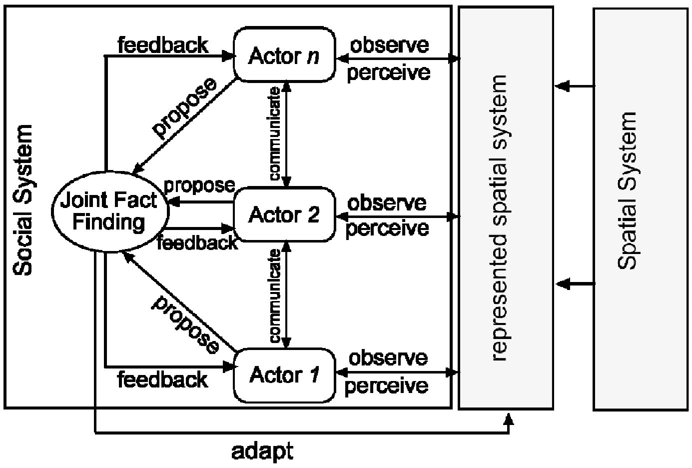

Figure 4: Conceptual framework of multi-actor spatial planning

The main inputs for the multi-actor spatial planning model are a cell-based representation of the current environment and the desires of the actors regarding the future state of this environment. The desires, made explicit in utility functions, are the basic elements that drive the decision making process. Based on the concepts illustrated in Figure 4, the model is implemented according to the following sequence, as shown in Figure 5:

1. Agents generate beliefs about the current state of the environment based on their perception of it. They observe the environment and acquire information about its aspects related to a specific desire ('observe and perceive' arrow in Figure 5). This results in a set of beliefs accounting for the current state of the environment according to an individual agent. For example, a desire to realize new urbanization near existing urbanization requires information about the distance of each location (cell) to existing urbanization (object). This, in its turn, requires information on the areas that are regarded as urbanized by the agent (semantics).
2. The set of beliefs is evaluated by the agents using a utility function ('apply utility function' arrow in Figure 5). This utility function combines the values of each cell (for the distances to all considered objects) with the attached weight of the desire.
3. The agents take turns in proposing a cell they want to be changed into a new urbanization cell. They accomplish this by selecting the cell with the highest utility ('select cell with maximum utility' arrow in Figure 5), given that is was not accepted before or already proposed in the former round. If more cells hold this maximum utility, one of them is randomly picked. This proposal is communicated to the other agents.
4. The proposer examines his initial utility for the proposal (before the beliefs were changed by the BNs) to assess his satisfaction. All other agents decide whether they accept this proposal by examining their own initial utility for that cell and comparing it with their threshold, the lowest acceptable utility ('compare initial utility with threshold' arrow in Figure 5). These decisions are brought forward and the proposal is agreed on when all agents decide to cooperate.
5. The reactions on and characteristics of the proposed cell serve together as a new case for the BN of the agents ('evaluate reactions' and 'evaluate characteristics' arrows in Figure 5). The CPTs of the nodes in the BN are updated, so that the relation between the values and the decisions becomes clearer throughout the simulation.
6. The Boolean nodes are set to the desired state, the situation in which everyone cooperates and the agent itself is satisfied. The utility functions are updated using the new beliefs (again the 'apply utility function' arrow Figure 5). Utilities of the agents will now be higher in areas

where cooperation is anticipated. Additionally utilities for the neighboring cells are increased by 10% to favor a clustered over a scattered pattern. Steps two to six are repeated every round as illustrated by the loop in Figure 5.

7. The simulation stops when the objective is reached, i.e. the required area of new urbanization is allocated, or when a deadlock is reached, i.e. in a predefined number of subsequent rounds no proposal is unanimously accepted.

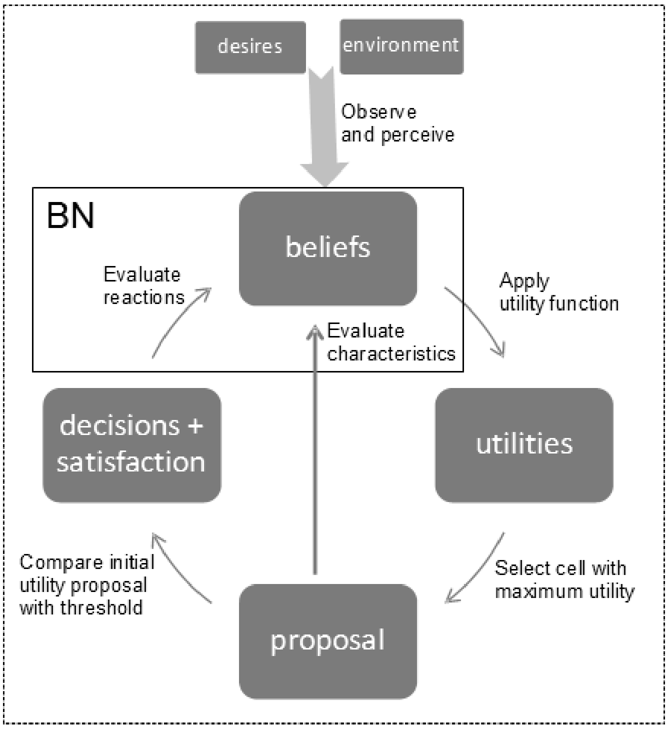

Figure 5: Model sequence

The above described MAS was implemented in Repast (Repast, 2010). The BNs were implemented in Netica (Norsys Software Corp., 2010) and coupled with the MAS via Netica Java-APIs. The utilized software and implementation are discussed in more detail in the next section.

3.2 Implementation

The main modeling platform used in MASSA was the Repast, which stands for Recursive Porous Agent Simulation Toolkit (Repast, 2010). This is a Java-based open source toolkit created at the University of Chicago. Repast was used to implement the agents with their available behaviors and a schedule that states the sequence in which the agents execute their actions. The environment was also created in Repast, using a grid representation in which each cell consists of a Java object that can store information about that location, for example land use type and distances to other spatial objects. The desires of the agents, concerning this environment, were stored in an Access database that communicates with Repast via a JDBC-ODBC bridge. Since this part of the model already existed in the previous model version, it will not be further elaborated on.

The newly added features to MASSA are the Bayesian Networks. Those were not implemented directly by mathematical rules in Repast, since the construction of large networks by hand is very time consuming and prone to errors. Several software packages are available that overcome these problems. Some examples include Bayesia (www.bayesia.com), Netica (www.norsys.com) and Hugin (www.hugin.com). An additional advantage of these software tools is that the graphical construction of the network is straightforward and thus easy to learn also for users without much knowledge of the statistics behind it. This can, however, also be a drawback, since a network can 'look nice' but that does not mean it gives valuable information. The Netica software was chosen to implement the BNs because it provides a clear tutorial and is operational via a graphical interface as well as with Application Program Interfaces (APIs), which are available for several programming languages, including Java. This last functionality is a profound advantage, as the existing MASSA model was programmed in Java.

For all agents a separate Bayesian Network is created. Bayes' theorem is originally developed to handle discrete variables. In Netica however, it is possible to use continuous variables. To be able to work with them, they have to be discretized into ranges, so that they resemble discrete variables. The difference with true discrete variables is that the input data can be continuous. So, the beliefs of the agents, which are preferred distances to certain spatial object and thus continuous, are best represented by continuous nodes. The cooperation of the other agents, which is a Boolean property (they do agree or they do not), is represented by discrete nodes. The CPTs between those two types of nodes represent the relation between proposal characteristics and the reactions of the agents on this proposal. These relations will be learned throughout the simulation (recall the BN box in Figure 5).

The continuous and Boolean nodes and the links between them were 'drawn' with Netica's graphical interface. The CPTs were not filled in, because they should be calculated automatically in every round, as described above. Figure 6 shows an example of the initial configuration of one of the Bayesian Networks used in the case study, which will be outlined in section 3.3. In this case, the agents have belief nodes about roughly the same objects, but with different semantics. If one agent considers very distinct objects from the others, this would complicate learning. It would be interesting to study this complication, but this first implementation of the BN concept is kept straightforward, in order to prove the learning concept. So, three different spatial objects were considered: urbanization, nature and villages. All agents have the method to infer those objects, but they have different semantics and desires regarding them. The structure of the network can easily be altered for another case study by adding or removing nodes.

The network in Figure 6 belongs to an agent representing farmers involved in a spatial planning procedure with two other agents (i.e. citizens and nature-culture conservationists). The lower three nodes, which are the continuous nodes, show the values of the Framers agent attached to certain distance ranges from a spatial object, i.e. the beliefs. The node 'DistanceVillages' for example indicates that the farmers prefer new urbanization to be located far away from patches regarded as villages. The upper three nodes, which are discrete, relate the distance distributions to the satisfaction of the network owner (Farmers agent), and the level of cooperation by the other agents (Citizens and NatureCulture). The possibilities for these nodes are a-priori evenly distributed, since the simulation has not started yet, so the agent has no data available yet about the rates of cooperation and satisfaction.

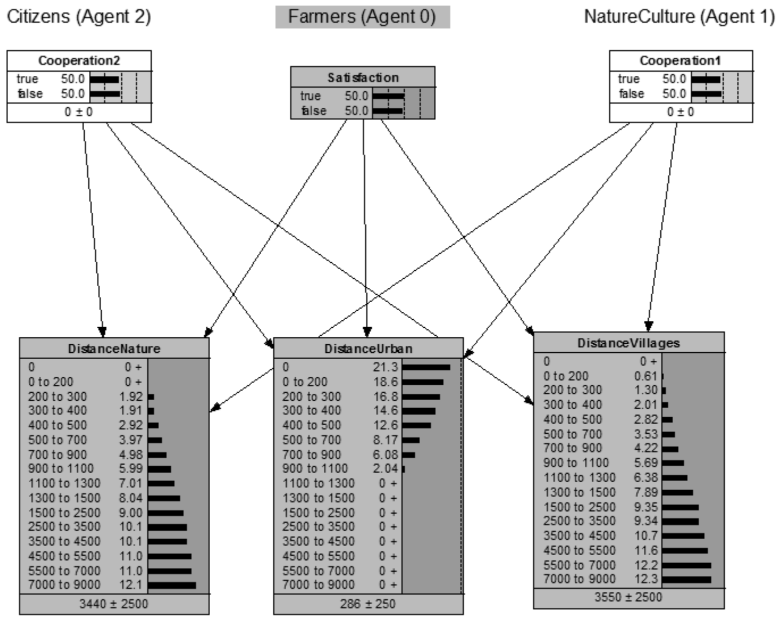

Figure 6: Initial Bayesian Network of the farmer agent

The network is updated when a proposal is made by an agent. The reactions of all agents and the characteristics of the proposed cell together form a *case*. A case, in this denotation, consists of several pieces of evidence of a certain place and time for the variables in a network. In Netica, several cases can be fed to the network at once, in one large case file, or case by case. In the second approach the Bayesian Network starts off with presumed CPTs as prior probabilities and every time a case is encountered, the network becomes more consistent. So, one uses the network in parallel with the data collection. In this way the network is dynamic, because it learns continuously. This approach is used in this research. In every round a case is recorded for every agent. Separate cases are needed for the agents, because they have different semantics and thus derive different characteristics from the proposal. The cases are saved by Repast in CAS files, which are ASCII files structured in a way Netica accepts. An example of how such a file is structured is given in Figure 7. The first line contains the string '// ~->[CASE-1]->~'. This informs Netica that the format is in Netica Case file format #1. This is currently the only possible format, but in the future there might be more advanced formats possible (Norsys Software Corp., 2009). The second line contains the names of the nodes for which evidence is provided in the file, and the third line contains those evidences (the actual case). When more cases are included in one file, the subsequent lines can also contain evidence.

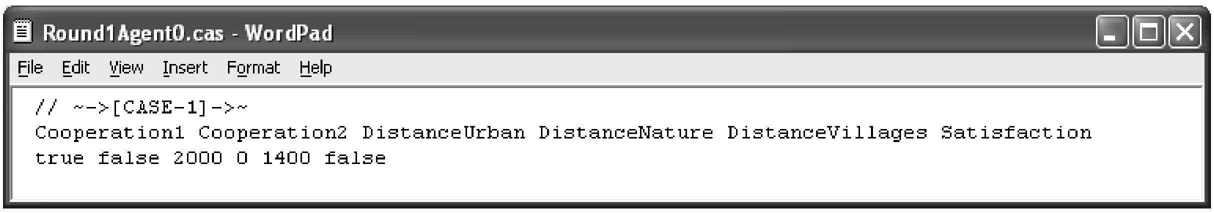

Figure 7: Case file of round 1 for the farmers

When the case files are saved, Repast calls Netica via APIs to incorporate them and to recalculate the CPTs. This means that the characteristics of the proposed cell (the distances to the considered spatial objects) are related to the decisions and satisfaction regarding that proposal. Consequently, the CPTs change. The Bayesian Network for the farmers from Figure 6 with incorporation of the case from Figure 7 is shown in Figure 8. By default the initial configuration counts as one case. This is why, for example, satisfaction is now 25% true, which is the average between the initial 50% and the 'false' case (0% true). The probabilities for the distances encountered in the case file have increased. However, from the displayed network in Figure 8, the new beliefs cannot be derived.

For the new beliefs, posterior probabilities are required, so the evidence has to be set in the network. The upper three nodes are set to the desired situation, i.e. the agent itself is satisfied and the others cooperate. In this occurrence, the evidence does not come from an encountered (present) situation, but from an anticipated (future) situation. The distance distributions, i.e. the event, belonging to that situation are calculated by Netica using Bayesian inference. The mean and standard deviation of these posterior distributions, which can be seen in Figure 8 at the bottom of the nodes, are recorded every round and displayed in graphs, so that the change in beliefs throughout the simulation can be visualized. The probabilities for the states are imported by Repast via a Netica API and exported to the Access database via the JDBC-ODBC bridge. Then, they are used to calculate the new utility maps. These utilities represent values for the optimum between reciprocity and fulfillment of their own desires, thus mutual gain. The inference of this optimum becomes better when more cases are incorporated.

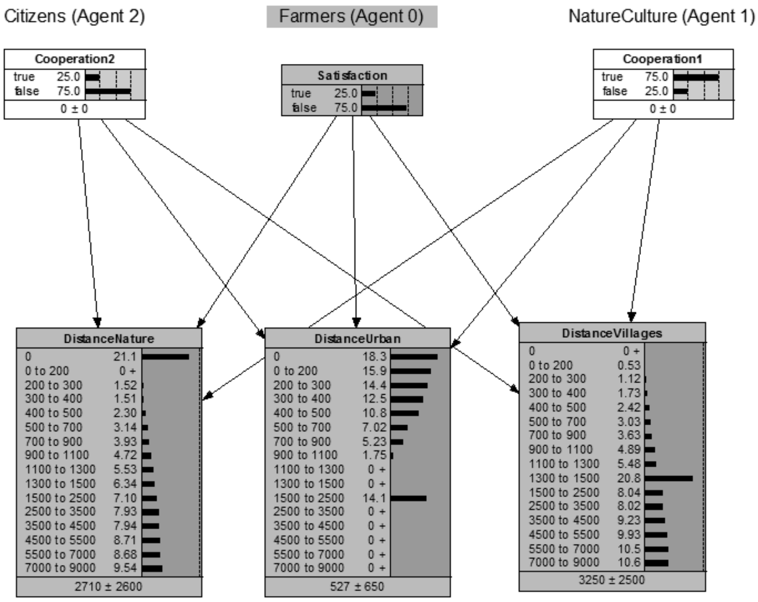

Figure 8: Bayesian Network of the farmers after one round

An additional functionality in Netica with learning case by case is *fading* (Norsys Software Corp., 2009). Fading means that the Bayesian Network excludes cases learnt long ago. As a result, the CPTs have a bias towards the most recent cases. A fading degree from zero to one can be set; where a degree of zero has no effect, whereas a degree of one results in CPTs with no experience, thereby showing only the most recent case. This feature was implemented in MASSA, but it was turned off for the case study in order to be able to clearly show the effects of gaining experience in the BNs on the model output. In future research, fading might be used.

3.3 Case study

A hypothetical planning process is simulated for a study area in the 'Land van Maas en Waal', which is located in the Eastern part of the Netherlands (Figure 9). The area roughly consists of 66% pasture and 26% agriculture. In addition, orchards are a prominent feature in the area. The 'Land van Maas and Waal' has a number of small towns. Part of the 'Land van Maas en Waal' belongs to the nodal point 'Arnhem-Nijmegen'. This generates pressure to supply new urban areas. Therefore, the question where to locate new urbanization is relevant. For the simulation a land use raster map with cells of 100 by 100 meter is used.

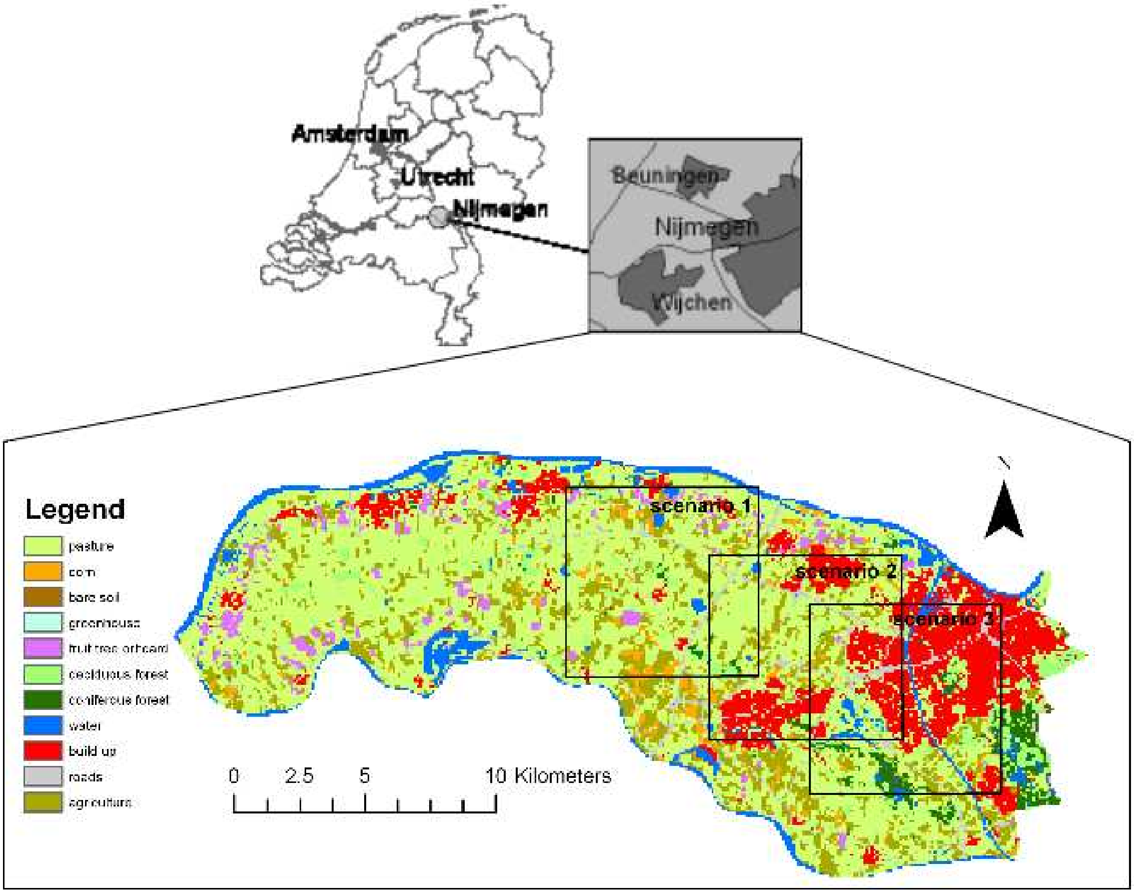

Figure 9: Study area

In this case study, three agents have been implemented, representing farmers, citizens and nature-culture conservation organizations. The agents' votes have equal effects on the joint decision, and proposals are only accepted unanimously. Table 5 shows the desires that have been assigned to each agent. Based on these desires the agent observes and specifies its beliefs for new urbanization makes them explicit on the environment using its utility function. In the Bayesian Network the beliefs are represented in three generalized classes about which can be learned (Table 5), as explained in the previous section. A simulation is carried out in which these three agents have the objective to allocate 200 cells (representing 200 hectares) of new urbanization. A deadlock is assumed to occur when the agents are unable to accept a proposal in 30 subsequent rounds. These 'rounds' do not have an concrete time dimension; they are just iterations without a temporal scale.

Table 5: Desires of the agents

Role	**Desires**	**Category**
citizens	new urbanization around present urbanized areas near forest and nature	urban nature
farmers	new urbanization around existing urbanized areas not near present agriculture not near small villages	urban nature villages
nature-culture conservationists	new urbanization not near nature areas new urbanization as less as possible around 'historical' villages	nature villages

The agents are presented three different parts of the Land van Maas en Waal (Figure 9) to see the effect of different land use settings on the decision making process. The parts are equal in size, approximately 5300 hectares, and vary mainly in current urbanization degree. The first scenario (*Rural*) concerns a rural area with only some small villages. The second (*Intermediate*) has some moderate size towns (including a small part of a larger town). The third scenario (*Urbanized*) encloses the city of Nijmegen, the ninth city in the Netherlands, with 150.850 inhabitants (Wikipedia, 2010). The three scenarios were carried out twice, once with and once without the Bayesian Networks (with and without coupling with Netica) in order to assess the BN impact on the results.

In addition, the second scenario was run 100 times for the assessment of the uncertainty in the model. The resulting maps were summed on a cell by cell basis. This means that a cell that is never selected will get a value of zero, and a cell always selected will get a value of one hundred. For the display of this and all other maps the software ArcMap was used, a component of ArcGIS (ESRI, 2010), which is an integrated collection of geo-information software products.

4. Results

This chapter provides the simulation results for a case study area in the 'Land van Maas en Waal', located in the Netherlands. The spatial plans, utility maps and Bayesian Networks are presented and described. Next, the result of the uncertainty assessment is presented.

4.1 Scenarios

Only in the first scenario, the agents were able to reach the objective to assign 200 new urbanization cells. In the other two scenarios a deadlock was reached. This counts for both the situation with and without agent learning by Bayesian Networks, but the conditions for the consensus and deadlock were different (Table 6). Without Netica it has always taken more rounds to reach the end situation (which is either the objective or a deadlock). The number of cells agreed on without BNs is higher in scenario 2 and lower in scenario 3. The resulting maps for the three scenarios are displayed in Figure 10, Figure 11 and Figure 12. It is apparent that the new urbanization is chosen in approximately the same areas with and without BNs. In scenarios 2 and 3 the simulations without BNs have resulted in a scattered urbanization pattern, while in the simulations with BNs all new urbanization cells were grouped together in one cluster (Figure 11 and Figure 12). In scenario 3 this cluster is interceded by existing urbanization, but the result is still one large urban cluster. In the scenario 1 the result map consists of several small and somewhat larger urbanization clusters (Figure 10). In this scenario, the result for the simulation with BNs is more scattered than the simulation without BNs, which is opposing to the other two scenarios.

Table 6: Conditions in end situations for the three scenarios

Scenario	BN	Agreed Cells	Nr of Rounds
1. Rural	without	200	201
	with	200	215
2. Intermediate	without	19	143
	with	25	107
3. Urbanized	without	46	157
	with	43	109

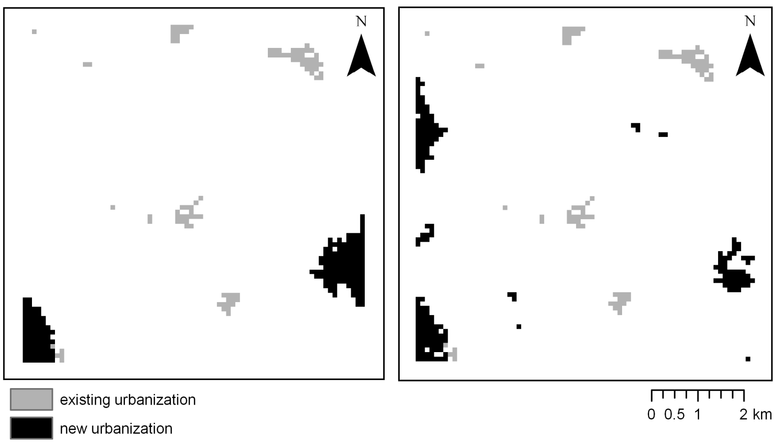

Figure 10: New situation for the rural area (scenario 1) without (left) and with (right) Bayesian Networks

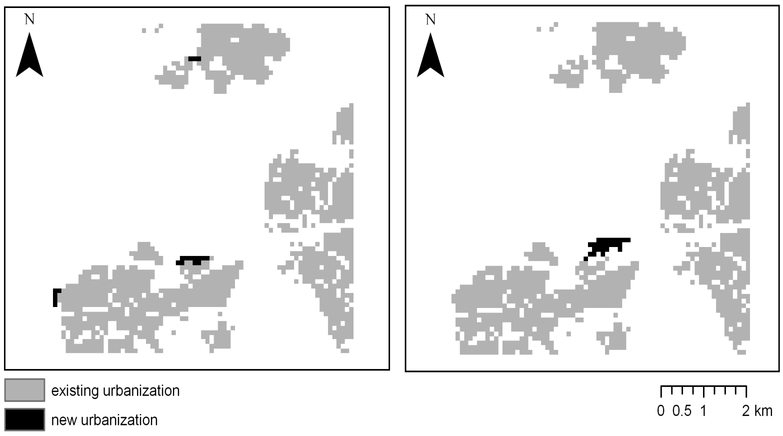

Figure 11: New situation for the intermediately urbanized area (scenario 2) without (left) and with (right) Bayesian Networks

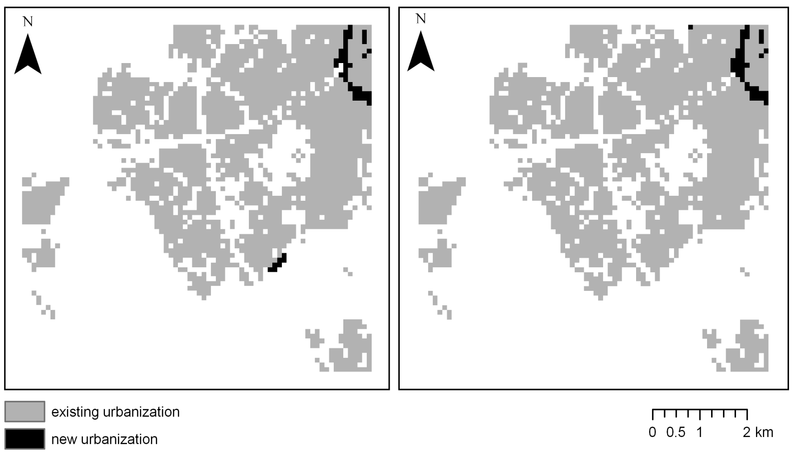

Figure 12: New situation for the urbanized area (scenario 3) without (left) and with (right) Bayesian Networks

In the following the initial and final utility maps of the three agents are displayed in separate figures for the three scenarios. The differences between the initial and final utility maps illustrate the effect of the learning process in the Bayesian Networks. The utility maps are only shown for the situation with Bayesian Networks; without them the utilities do not change throughout the simulation. The initial utility map with Bayesian Networks is the same as the initial and final utility map of the same simulation without BNs, which makes it useless to show them all.

The difference between the upper (a, b, c) and the lower (d, e, f) utility maps of Figure 13 illustrates that the citizens have learned that the others do not like new urbanization to be allocated close to existing villages. The utilities around the villages have decreased for them. The farmers, on the contrary have softened in regard of this desire, thereby coming closer to the citizens desires. Figure 14 shows a similar effect regarding the desire category urban. The citizens have become less determined to allocate cells directly alongside existing urbanization, while the nature-culture conservationists have learned this desire. Concerning the nature category, new urbanization on agriculture (primarily located in the centre of the study area) is now more negotiable for the farmers than at first. When in Figure 15 the initial utilities (a, b, c) are compared to the final utilities (d, e, f) a focusing, i.e. a cluster of high utilities, on the area in the North-East corner is evident for all three agents. This effect could also be found in the other two scenarios, but not as profound. Utilities on the rest of the map have become very low. Agreement on more cells in the area under interest, however, is not possible, because it is enclosed by existing urbanization.

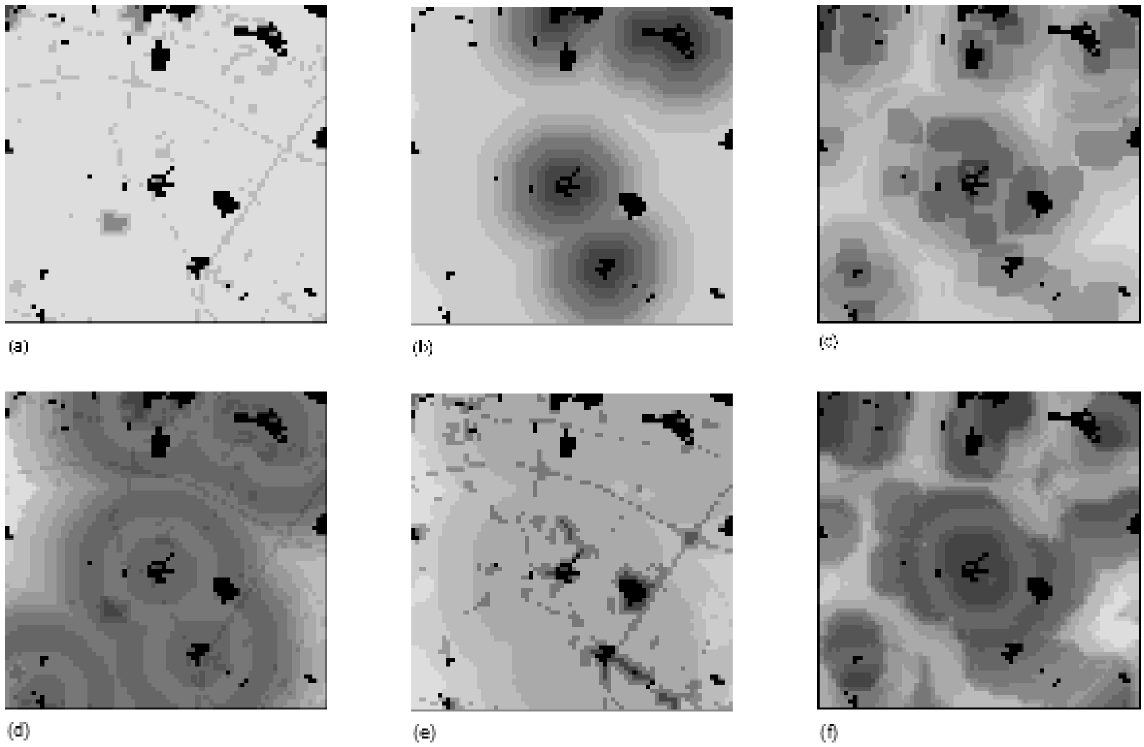

Figure 13: The rural area (scenario 1). Initial utilities (t = 1) for the citizens (a), farmers (b) and nature-culture conservationists (c). And final utilities (t = 201) the citizens (d), farmers (e) and nature-culture conservationists (f). Values range from zero (dark grey) to one (light grey). Black indicates existing urbanization.

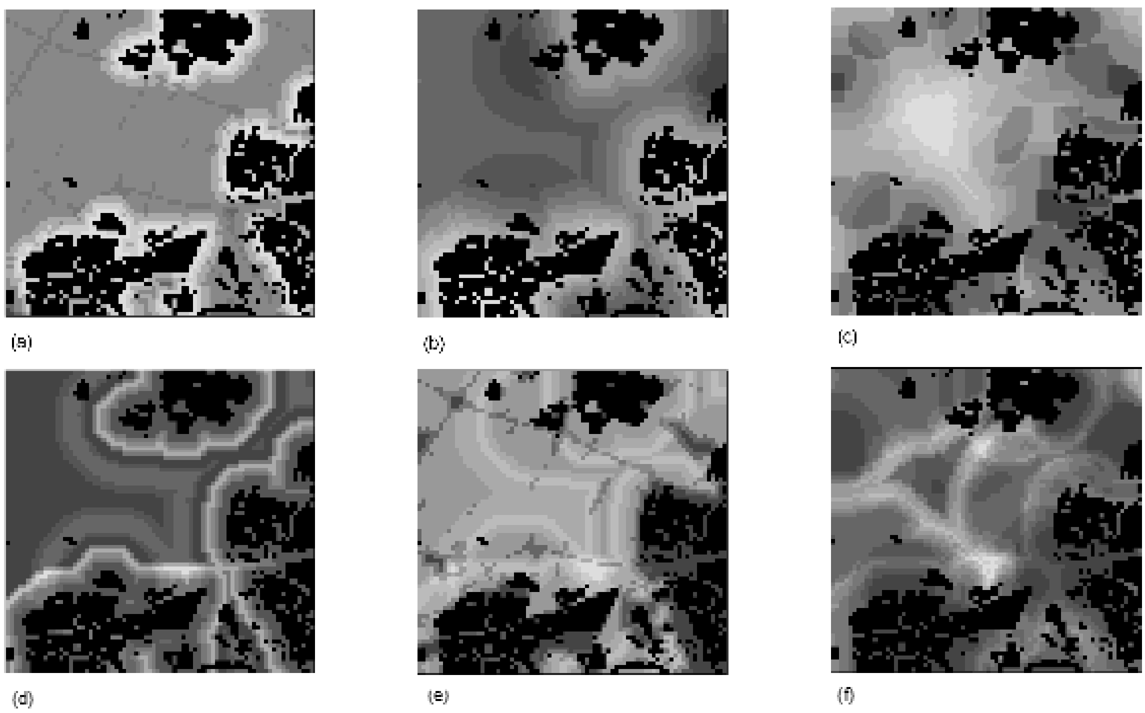

Figure 14: The intermediately urbanized area (scenario 2). Initial utilities (t = 1) for the citizens (a), farmers (b) and nature-culture conservationists (c). And final utilities (t = 107) the citizens (d), farmers (e) and nature-culture conservationists (f). Values range from zero (dark grey) to one (light grey). Black indicates existing urbanization.

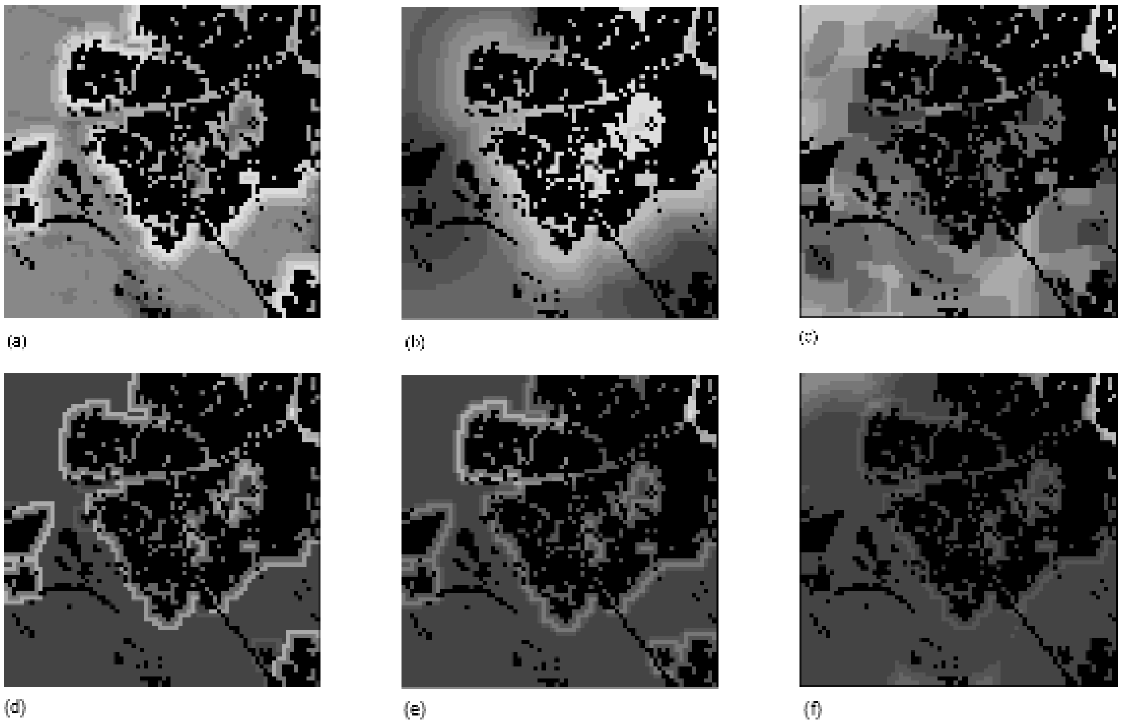

Figure 15: The urbanized area (scenario 3). Initial utilities (t = 1) for the citizens (a), farmers (b) and nature-culture conservationists (c). And final utilities (t = 107) the citizens (d), farmers (e) and nature-culture conservationists (f). Values range from zero (dark grey) to one (light grey). Black indicates existing urbanization.

All described phenomena can be observed in all scenarios when looking at the maps more closely. The reasons behind the utility changes can be derived from the resulting Bayesian Networks. They show the cooperation and satisfaction of the agents averaged over the total simulation time and the belief distributions resulting from that. As an example, the networks of scenario 2 are examined in Figure 16; the networks for the other two scenarios are given in Appendix 1. From the networks in Figure 16 it can be derived that the farmers and nature- culture conservationists often cooperate with each other and with the citizens (67% and 82% of the time), while the citizens are less cooperative towards them (47% for both), which denotes that the citizens were not willing to accept their proposals. This is also indicated by the fact that the citizens are on average 46.5% less satisfied with the generated proposals than the other actors. The inferred distance distributions are comparable for the three agents, meaning that they have learned to generate proposals with similar spatial characteristics. Cells that exhibit the combination of the distances with the highest possibilities are considered most probable to be agreed on.

One prominent difference between the nature-culture conservationists' and the other agents' networks can be seen in the 'DistanceNature' node. For the nature-culture conservationists it shows, in addition to the peak for the short distance, a peak at the range 700 to 1100 meter away from nature. The reason for this can only be seen when the nodes for satisfaction and cooperation are set to their desired state, which is 'true', since agents want to be satisfied with the proposal themselves and want others to accept it. From Figure 17, in which the satisfaction and cooperation nodes are separately set to the desired states, it appears that this second peak is a result of the large inconsistency between the beliefs fulfilling the agent's own satisfaction and the beliefs resulting in cooperation of the other agents. If the difference in belief distributions for the two situations is smaller, the effect becomes less evident; the 'DistanceUrban' node of the nature-culture conservationists also exhibits different distributions for the two situations, but since the distance state with the highest probability is the same for both, this effect disappears in the combined situation. The appearance of a second peak can be discerned at a less evident level in the 'DistanceVillages' nodes for all three agents in Figure 16.

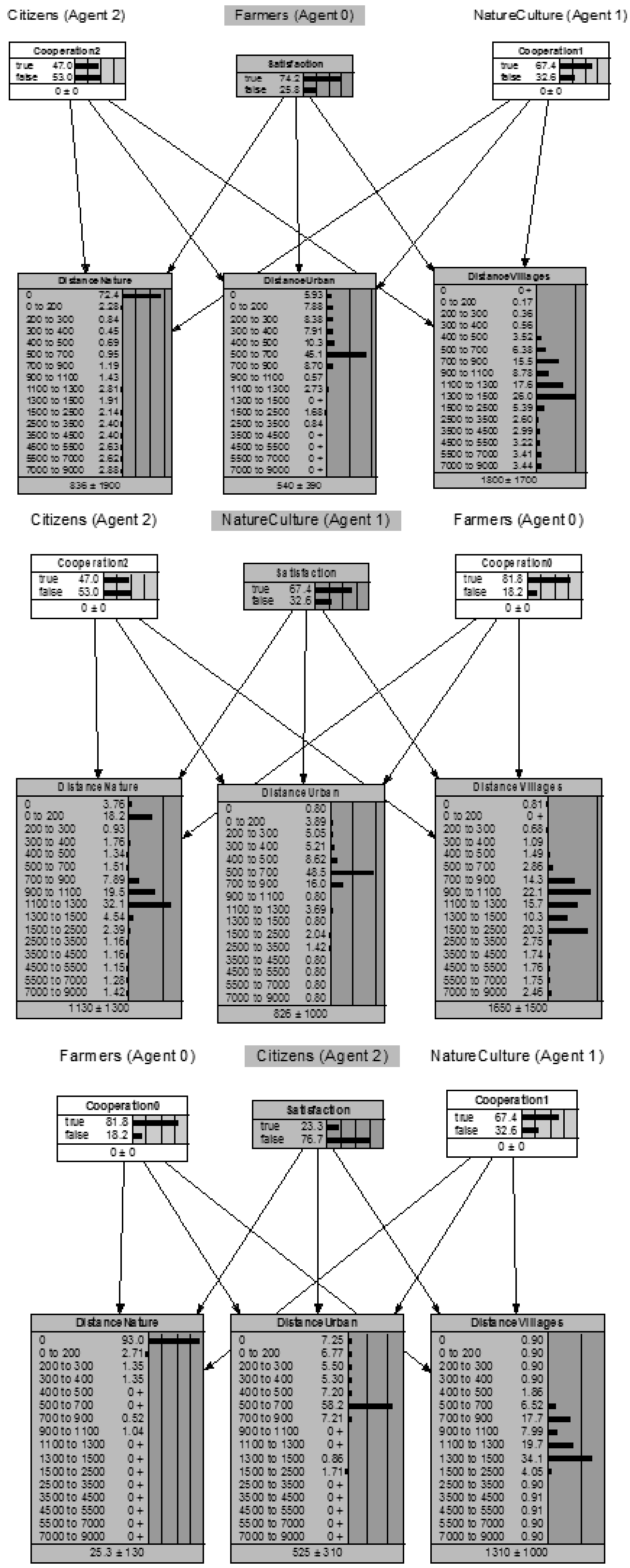

Figure 16: Final Bayesian Network for the intermediately urbanized area (scenario 2) for, from top to bottom, the farmers, the citizens and nature-culture conservationists.

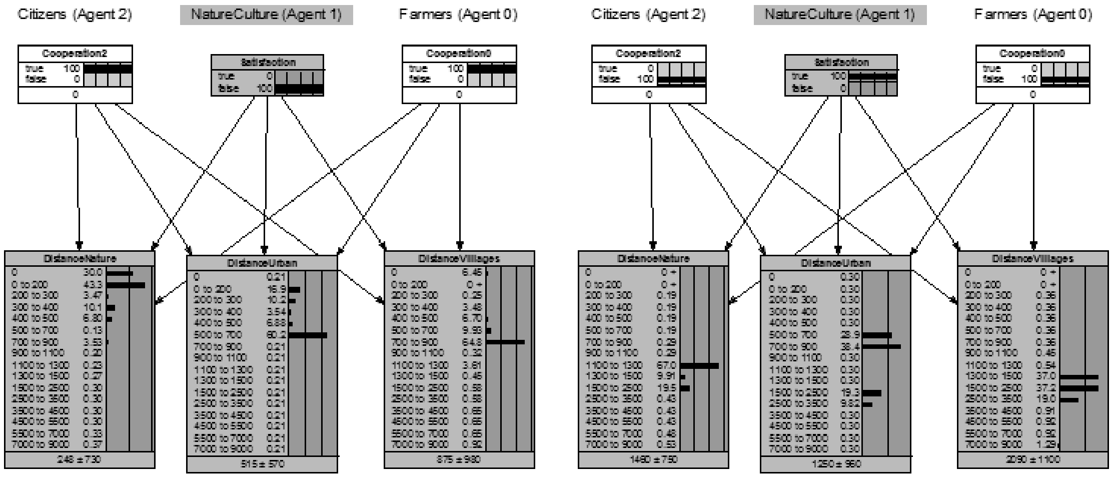

Figure 17: Bayesian Networks for the nature-culture conservationists set to 'true' for cooperation (left) and satisfaction (right).

4.2 Uncertainty

The map that is the result of the cell by cell summation of 100 runs of scenario 2 is displayed in Figure 18. The current urbanization is left out. It appears that the result from Figure 11 is an often obtained result; it is within the lightest colored area of Figure 18. The most frequently chosen cell is selected in 88% of the runs. Beside the commonly selected area above the city of Wijchen, an area below the city of Beuningen is sometimes selected. The row of grey cells East of Nijmegen, is the result of only one run, and thus an exception. What cannot be derived from this map, but was observed additionally in the 100 separate maps, is that the result most often consisted of one cluster of cells. When the agents start 'building' somewhere, they extend the area until expansion is somehow restricted. The result from this path-dependency is that the average number of cells selected around Beuningen is much larger than that the average number of cells selected around Wijchen: 48 against 19. The location of the first cell, thus effect on the outcome location as well as on the outcome cluster size.

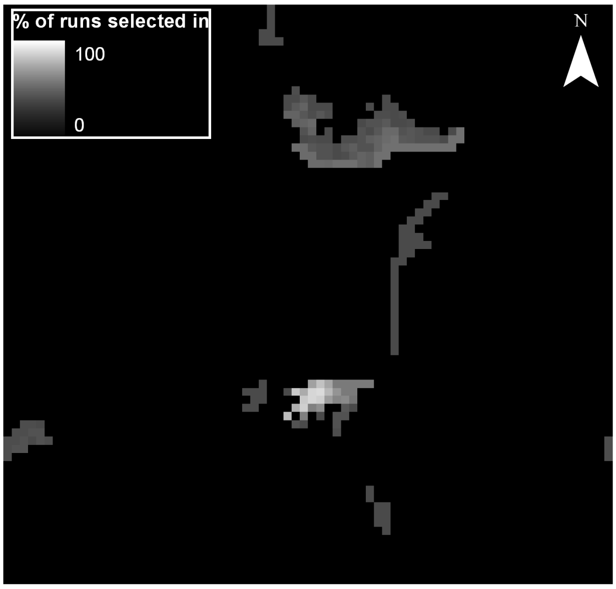

Figure 18: Summation of 100 simulation results

5 Discussion and conclusions

In the preceding chapters the use of Bayesian Networks to improve on the representation of decision making in a Multi-Agent System of an interactive spatial planning process was explored. The results of the developed model, presented in the former chapter, are discussed in this chapter. The advantages as well as the problems and shortcomings of the model are described. Finally, the conclusions are summarized in relation to the research questions.

5.1 Discussion

The initial and final utility maps illustrate that the agents have learned each others' beliefs and that their utilities converge, as they do concessions. This conclusion is supported by the mean values of the distributions of the three belief nodes. Graphs with the evolution of those mean values throughout the simulation for scenario 2 are shown in Figure 19 for the nature nodes, in Figure 20 for the urban nodes, and in Figure 21 for the village nodes. The graphs for the other scenarios have similar characteristics and thus only the curves for scenario 2 are elaborated on. It can be seen that the curves are saw tooth shaped at the beginning of the simulation. This has two reasons. The steepness results from new cases having much influence on the average since not much evidence was gained yet. And, the curve jumps up and down, because proposals with different characteristics are 'tried out' before some insight is gained in the beliefs of each participating agent. When those become more evident, the curves slowly converge, indicating that the agents gradually find a way to generate proposals that satisfy themselves as well as the others. In this process they do some concessions towards each other. When the desires of the others and the agents own desires are too far apart, convergence is impeded. This happens for the distance to nature (Figure 19) of the nature-culture conservationists. The large discrepancy between the distances fulfilling the agent's own satisfaction and the distances resulting in cooperation of the other agents, supporting this statement, was already shown in Figure 17. The fact that the mean distance values of the agents diverge again at the end of the simulation (for example evident in the farmer's curve in the 'Villages' graph going up at the end) is a result of their incompetence to agree in the last 30 rounds. This makes the agents search for new possibilities, thereby returning to their original beliefs. In the networks the following happens: proposals with characteristics (distances) that were found to result in a high degree of cooperation are now continuously turned down, which diminishes the percentage of cooperation connected with those distances and thereby increases the possibilities of cooperation for other distances. The agents return to their original beliefs in this case by the influence of the satisfaction node.

Although the actors reach an agreement on a new urban area, the objective of allocation of 200 hectare is only reached in the scenario 1, given the current set of desires. The implemented topology rule, which accomplishes that neighbors of already selected cells get a higher probability of being selected, makes the agents concentrate on a certain area. When the agents concentrate one area for a number of rounds, the networks converge towards the characteristics this area exhibits. The standard deviation becomes very low, which results in a narrow distribution over the distance states of nodes. This could be metaphorically explained as the agents becoming 'narrow-minded'. Consequently, all cells in the study area that do not have those particular characteristics obtain a very low utility. When expansion of the cluster is for some reason restricted, the allocation of new urbanization in a different place has become almost impossible. It was tested whether it was better to turn off the topology rule, but then a deadlock was reached after agreement on only a few cells, since the beliefs had not converged yet. At least in the beginning, the rule is thus needed to ‘get the networks going’. Turning it off when enough experience is gained, would be a solution. Creating topology rules by means of links between the belief nodes would also be an interesting attempt. Another solution for the narrow-mindedness would be resetting the network when a deadlock tends to be reached, or making the networks gradually forget some of what they have learned by use of the fade function.

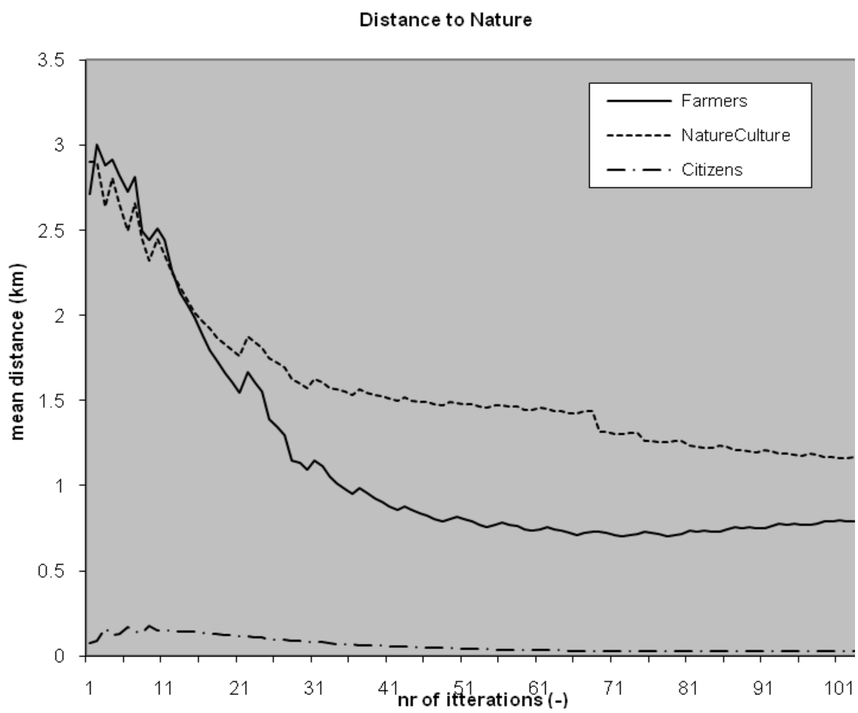

Figure 19: Mean distances of nature nodes throughout scenario 2

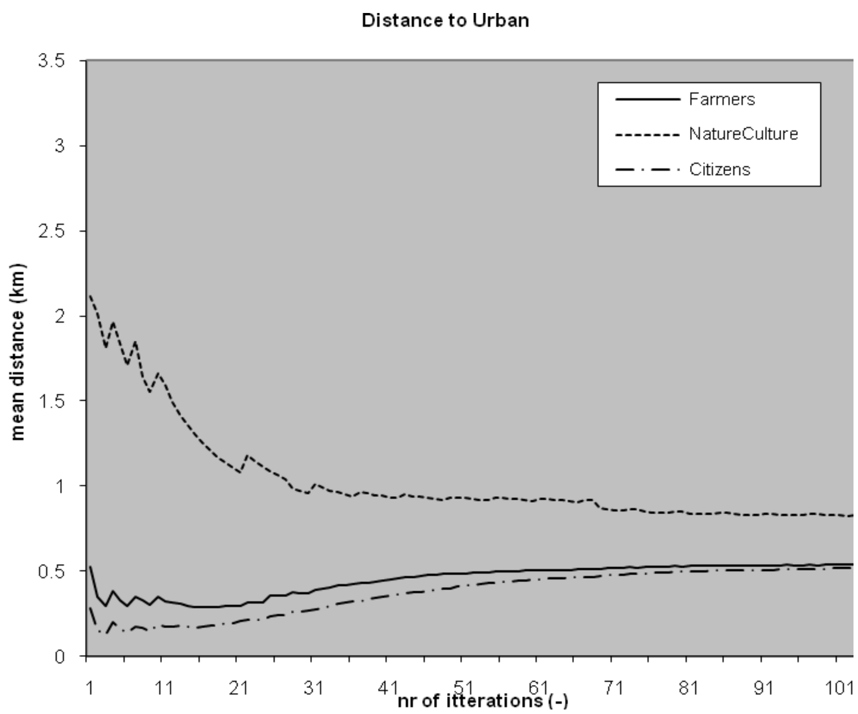

Figure 20: Mean distances of urban nodes throughout scenario 2

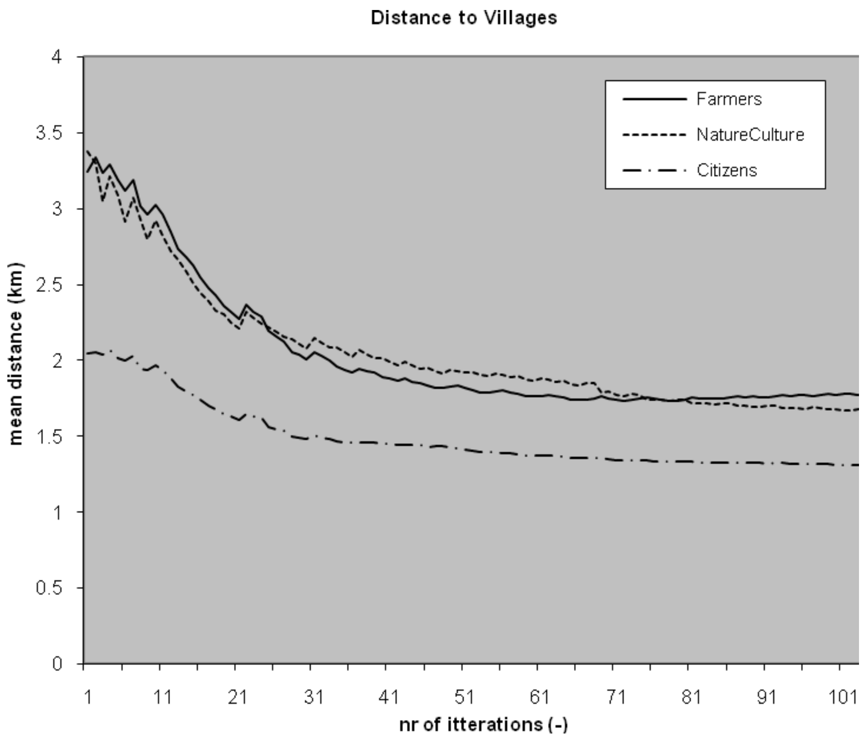

Figure 21: Mean distances of village nodes throughout scenario 2

The fact that a consensus is reached in scenario 1 can be explained by the fact that in the rural area no urbanization is present. As a result, the distribution in this node does not change throughout the simulation (see Figure 22 in Appendix 1), because nothing is learned about this desire. Since there was no disagreement about the desire in the first place, (both the farmers and the citizens prefer new urbanization close to existing urbanization and the nature-culture conservationists have no opinion about it,) the inertness of this node is an advantage. Only two of the three node distributions become narrow, which places fewer restrictions on the location of agreeable cells. This conclusion is supported by the fact that the agreed cells on the result map (Figure 10) are grouped into several clusters, instead of the one urbanization cluster found in the other two scenarios. From this observation it can be concluded that it will become even more difficult to reach a consensus, when more desires are implemented (which would be more realistic). In future research, it is important to find a sound solution for the narrow-mindedness problem.

The innovation of the presented approach is the incorporation of Bayesian Networks in an agent based spatial planning model. This incorporation has resulted in a more natural representation of the decision making process. The beliefs of the agents are not static, but dynamic, and not deterministic, but probabilistic, thus allowing for uncertainty. A solution has been found for the problem of the opponent's payoff openness in game theory. In the concerned games the payoffs of the other agents are always known on forehand (Anumba et al., 2003). In this research agents have no information about each other's beliefs at the start of the simulation. A method was developed in which the agents learn by taking into account experiences from the past. Consequently they adapt their spatial beliefs in such a way that the optimum between reciprocity and fulfillment of their own desires is anticipated. So, the agents have become self-adaptive. This adaptation capacity accounts better for the Complex Adaptive System they are part of. This conclusion is supported by the fact that the social complexity of the model is now upgraded to what Agarwal et al. (2002) refer to as level 6, the highest level. This means that multiple types of agents are modeled, whose decisions are influenced by choices made in the past by themselves and others. To be more specific about the modeled planning process, it can be said that the socialization component of the regional dialogue approach (Mansfeld, 2003) is added to an existing spatial planning model, that already contained the other components of this approach. This is accomplished by the incorporation of learning and anticipation on reciprocity using Bayesian Networks. Now, all four components of the regional dialogue approach are present, so that the full spatial planning process is modeled. The developed BN decision framework is general and flexible, and can thus easily be applied to different planning cases.

Another positive result of the Bayesian networks is the effectiveness of the decision making process, appearing from two observations (see Table 6). First, it took fewer rounds to reach the end situation in all three scenarios with the BNs. Second, the total number of cells agreed on is larger. The reason for these two observations can be found when studying the model products additional to the result maps, BNs and graphs more closely. Two additional products are the case files, in which the reactions on all proposals are stored and intermediate result maps. Those two products proved that, in the simulation of scenario 2 and 3 without the BNs, whenever proposals were accepted, they were always posed by the citizens; proposals of the others were constantly rejected. In reality, it is not plausible an actor will continue to cooperate if his proposals are continuously rejected, while he himself does accept the proposals of another. This means one actor doing concessions and the other being rigid. Such a situation would be regarded unfair, especially in even power settings, and thus be unsustainable. The Bayesian Networks made the other agents learn how their proposals could be accepted, by incorporating the successful proposals and their characteristics in the networks. The result is that in the simulations with Bayesian networks proposals of all agents were regularly accepted and thus a more sustainable situation is created.

However, when comparing the new model with the previous MASSA version (Ligtenberg et al., 2009), the decision-making process has not become more effective. This results from a change in the proposal method. Previously, a proposal consisting of a group of cells was possible, while the current model does not allow this. This change was made, because the characteristics of the proposal, needed as an input for the BN, are more easily derived from a single cell. For a group characteristics would need to be averaged. Nevertheless, the previous way of proposing was more realistic as well as more effective. This approach should thus be made suitable for the BN model.

Effects of the Bayesian Networks are now mainly descriptive. To assess the influence of the BNs numerically additional steps have to be taken. The batch run, of which the combined results are presented in Figure 18, proves the uncertainty and path-dependency of the model. It was explained that these two features have effect on the outcome location as well as on the outcome cluster size. The uncertainty partly results from the method of Bayesian inference and partly from the fact that if more cells have the same utility, one is chosen randomly as a proposal. Bayesian inference introduces one path-dependency by the learning functionality. The implemented topology rule, that neighbors of already selected cells get a higher probability to be chosen, enhances this path-dependency. Thus, a different proposal at the beginning of the simulation can have a pronounced effect on the result. An additional batch run of the model without the Bayesian Networks could give more insight in the individual effects of the BN and the rest of the model in both phenomena. Subtraction of the batch result without BNs from the batch result with BNs, would give the percentual influence of the BNs on the total model uncertainty. Additionally, assessment of the networks themselves can be carried out. It is possible to let Netica calculate the relative effect of a new piece of evidence on a certain node. This hereby gathered information from several moments during the simulation could assist in giving insight in the possible 'saturation point' of the network, i.e. the moment when new evidence loses effect on the state distributions. This is the moment to reset the network or implement forgetting.

Even though the model has implemented learning and anticipation, and social complexity is increased, the social processes in the model are still far from realistic. The agents only learn 'silently' as they do not communicate about what they want and cannot give arguments for their proposals. In addition they will never be able to infer each others' desires completely, because they hold different semantics (for example, from which size onwards becomes a village a city). The agents' behavior is completely rational, while in reality actors' decisions are sometimes based on irrational things, such as trust, impatience and anger (Laurian, 2009). Abrupt changes, like bringing concessions to a halt or even terminating cooperation entirely, do also not appear in the model. A suitable concept for and realistic model of a multi-actor negotiation process is thus still lacking and is a topic for further research.

The spatial reasoning of the agents within the Bayesian Network could be improved by facilitating the creation of new nodes when a new type of information becomes available. This is, however, a far more difficult kind of learning, since the agents would not have the methods to reason about the new feature and will therefore need an adapted modeling approach. Another way to improve the reasoning is to calculate the total utility for certain distance combinations within the network. The advantage of this is that utility functions are not needed anymore, which resolves the issue that the weights for the different desires are now still static.

Due to the explorative character of the research, the use of hypothetical actor stereotypes and an invented case objective, validation of the proposed model was not accomplished. When the model is further developed, calibration and validation against an existing spatial planning case will become necessary. It is demonstrated however, that the use of Bayesian Networks offers an interesting and innovative approach to represent learning and anticipation in a spatial planning decision making process.

5.2 Conclusions and further research

The main objective of this research was to explore the use of Bayesian Networks as a means to improve on the representation of the decision making process in an agent based multi-actor spatial planning model. In section 1.2 the following research questions were posed to structure this exploration:

I. What are the limitations in current approaches of decision making in multi-agent spatial models?
II. How are Bayesian Networks currently used in computer models?
III. How can decision making among spatial planning actors be modeled using BNs?
IV. What is the added value of BNs in a multi-actor spatial planning model?

The answers to these questions, which were presented throughout this report, are summarized below. In addition some guidelines for further research are given.

What are the limitations in current approaches of decision making in multi-agent spatial models?
Two commonly used decision making approaches were revised: utility maximization and game theory. The first can handle multiple issues, but lacks anticipation capacity, while for the second it is the other way around. Both methods lack the ability to handle two important characteristics of the Complex Adaptive System spatial planning is represented by: to learn and adapt to find mutual gain, in agent terminology referred to as proactiveness. The fact that common decision making approaches are unable to cope with those features, results in a lack of social complexity in spatial

models. A framework is required that exhibits those features and has a general form, so that it is applicable for different cases.

How are Bayesian Networks currently used in computer models?
Bayesian Networks were found to serve mainly as a data mining method, with the objective to find relations between measured variables. The use of Bayesian Networks in environmental models is limited. They are for example applied in remote sensing, watershed management, land-use change and urban development. But, only one spatial model was found to use Bayesian Networks as a learning method for agents. In this model, networks serve as the 'minds' of agents. They learn about the effectiveness of their actions, which fulfils the first requirement for the decision making framework as outlined in the previous question. However, adaptation is needed in order to include the second required feature of finding mutual gain instead of only personal gain.

How can decision making among spatial planning actors be modeled using BNs?
The Bayesian Networks are implemented in the model as the 'minds' of the agents, so that the nodes can represent the different beliefs, concerning the future state of the environment, and make them dynamic. The combination of the advantages of utility maximization and game theory, consideration of both multiple issues and the behavior of the others, is implemented within this structure. The links between those two facilitate learning and anticipation on the joint outcome. By taking into account experience gained throughout their cooperation agents learn about each others' desires. Accordingly, the agents adapt their spatial beliefs to anticipate the optimum between reciprocity and fulfillment of their own desires.

What is the added value of BNs in a multi-actor spatial planning model?
The incorporation of Bayesian Networks in an agent based spatial planning model has resulted in a more natural representation the actors' behavior. The beliefs of the agents are not static anymore, but have become dynamic. The agents learn by taking into account experiences from the past and adapt their spatial beliefs in such a way that the optimum between reciprocity and satisfaction with their own desires is anticipated. As a result, the decision making procedure has become more effective, because all agents have learned to generate acceptable proposals. This self-adaptive behavior of the agents accounts better for the Complex Adaptive System they are part of. The social complexity of the model has increased and the addition of socialization makes that now all four components of the regional dialogue approach are present, so that the entire spatial planning process is modeled.

Based on the above, a number of issues were identified requiring improvement. First, a problem in the decision making process occurs when the agents concentrate on a certain area for a number of rounds. The Bayesian Networks converge towards the characteristics this area exhibits, which results in a narrow distribution over the states of the concerning nodes. This 'narrow-mindedness' strongly limits the number of agreeable locations. The importance of this problem becomes clearer when focusing on the second issue: the limited spatial reasoning capacity of the agents. More advanced spatial reasoning, for example additional reasoning about topological relations and shapes, would also result in more desires. More desires further limit the possible solution space and thus enhances the narrow-mindedness problem. A third issue, also related to the behavior of the agents, is that a suitable representation of the full negotiation process is still lacking. In addition to decision making, negotiation requires communication with arguments and a larger range of possible actions and tactics. Further research should find a way to include those aspects. And last, but not least, validation of the proposed model was not accomplished. This is a common problem with Multi-Agent Systems, since their complex behavior and emergent properties are by definition hard to validate. This is, however, more an argument in favor of than against undertaking an effort to tackle this problem, because finding a solution would be a major scientific breakthrough.

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Appendix 1: Resulting Bayesian Networks

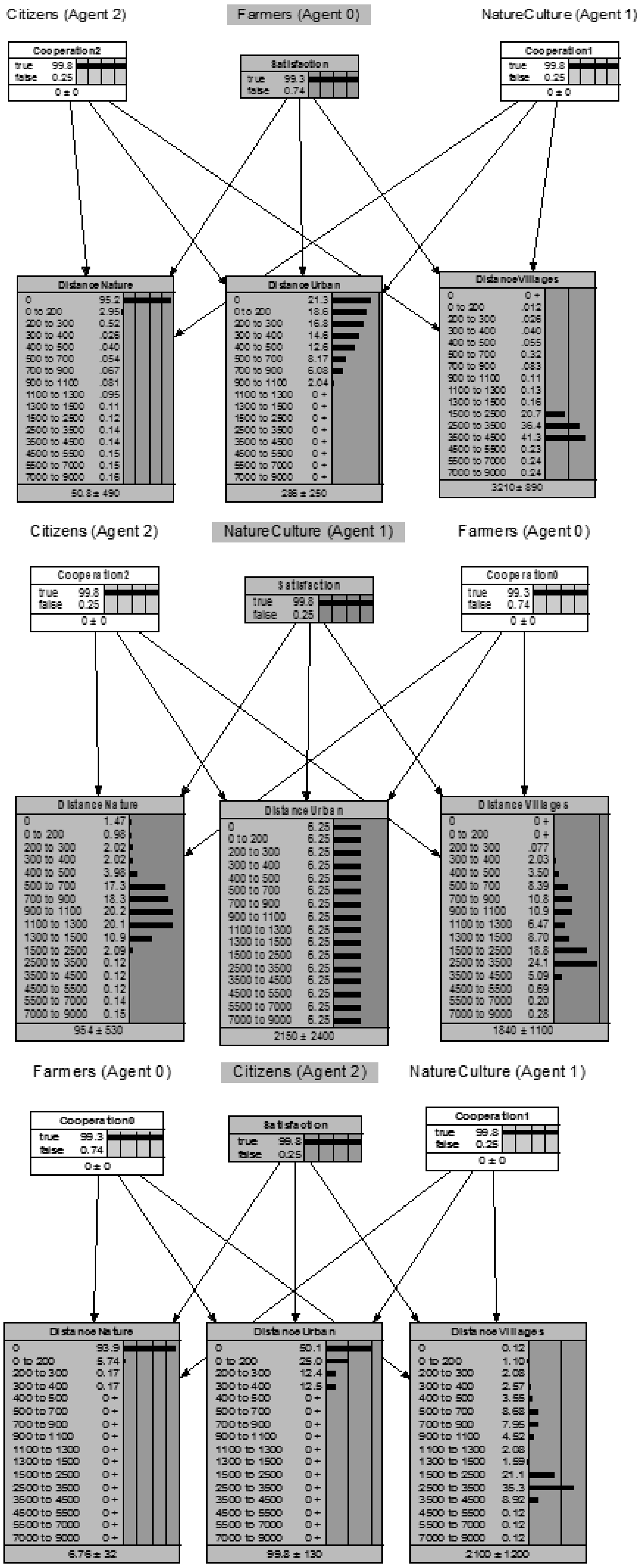

Figure 22: Resulting Bayesian Network for the rural area (scenario 1) for, from top to bottom, the farmers, the citizens and nature-culture conservationists.

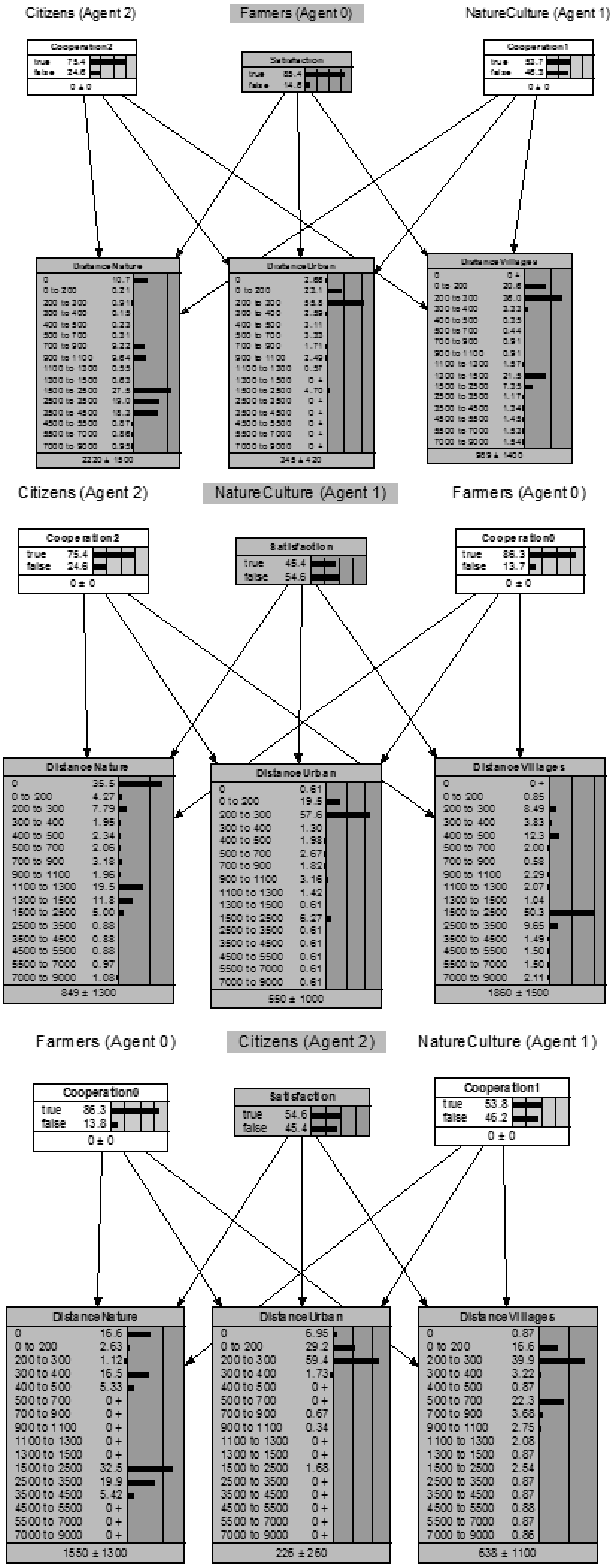

Figure 23: Resulting Bayesian Networks for the urbanized area (scenario 3) for, from top to bottom, the farmers, the citizens and nature-culture conservationists.