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Theoretical foundations of human decision-making in agent-based land use models – A review

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A B S T R A C T

Recent reviews stated that the complex and context-dependent nature of human decision-making resulted in ad-hoc representations of human decision in agent-based land use change models (LUCC ABMs) and that these representations are often not explicitly grounded in theory. However, a systematic survey on the characteristics (e.g. uncertainty, adaptation, learning, interactions and heterogeneities of agents) of representing human decision-making in LUCC ABMs is missing. Therefore, the aim of this study is to inform this debate by reviewing 134 LUCC ABM papers. We show that most human decision sub-models are not explicitly based on a specific theory and if so they are mostly based on economic theories, such as the rational actor, and mainly ignoring other relevant disciplines. Consolidating and enlarging the theoretical basis for modelling human decision-making may be achieved by using a structural framework for modellers, re-using published decision models, learning from other disciplines and fostering collaboration with social scientists.

Contents

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1. Introduction

Agent-based models (ABMs) have been suggested as powerful tools to investigate land use and land cover change (LUCC) (Parker et al., 2003; Matthews et al., 2007; Rounsevell et al., 2014). This is due to the fact that human decision-making in ABMs can be represented in a very flexible and context-dependent way (An, 2012). Such flexibility is needed to describe human decisions beyond neo-classical assumptions of the fully rational and self-interested *Homo economicus* (Parker et al., 2003; Balke and Gilbert, 2014) to reflect that laboratory economic experiments show the departure of human decision makers from rational or fully informed behaviour (Heckbert et al., 2010). Apart from that, land use systems behave as complex adaptive systems (CAS) (Rindfuss et al., 2008). ABMs offer the possibility to address issues relevant in CAS like learning, adaptation, heterogeneity, interactions and uncertainty in/of human behaviour (Nolan et al., 2009; Milner-Gulland, 2012). To adequately represent human decision-making is not only an academic issue, but crucial for models in order to provide reliable policy recommendations and avoid unintended consequences (Milner-Gulland, 2012; World Bank Report, 2015).

Within the last few years, a substantial number of studies of agent-based land use models (LUCC ABMs) have been published which represent human decision-making explicitly. However, review studies have criticised that the strength of ABMs as a flexible tool to implement different theories comes along with a plethora of independent ad hoc assumptions of the decision process without being grounded on established theories from economics, psychology or sociology (Crooks et al., 2008; Ekasingh and Letcher, 2008). This indicates a mismatch between the availability of numerous decision theories and their limited usage in LUCC ABMs (Parker et al., 2003; Levine et al., 2015; World Bank Report, 2015). Using behavioural models that are based on theory has substantial advantages compared to ad hoc implementations (Rai and Henry, 2016). First of all, communication between scientists of different disciplines would be fostered, for instance between modellers and theoretically and/or empirically working scientists. Second, re-use of models could be improved if models were grounded on established theories. Re-using models is not only sensible from a practical perspective in order to save time for conceptualising and implementing a new model. More importantly, re-using models can lead to consolidation of findings and more rapid scientific advancements (Bell et al., 2015). Third, Klabunde and Willekens (2016) state also that models which are grounded in theory can be used beyond simple extrapolation, but also for predictions when conditions change substantially. Also when data is sparse or completely missing, theoretical models can be used to test alternative theories and their implications which can be confronted with empirical data (Klabunde and Willekins, 2016; Silverman et al., 2011). Overall theory is a way to explain complex phenomena. Verifying and falsifying a theory through models in different contexts can advance theory development.

The most prominent economic theory of human decision-making is Expected Utility Theory (EUT), a theory of choice under risk where a decision maker chooses the option that promises the highest expected utility (Bernoulli, 1954 – which is a translation from the original published in 1738, von Neumann and Morgenstern, 1944, Machina, 2008). Numerous ABMs assume rational decision makers that maximise their utility or profit (see for example Monticino et al., 2007). Rational decision-making in neoclassical economic theory assumes that actors have perfect and complete knowledge and unlimited computational processing powers. These assumptions have been challenged by the concept of bounded rationality. A prominent theory of bounded rationality is Satisficing developed by Simon (1956). It assumes that the decision makers have a so-called aspiration level. They sequentially assess their choice options and stop the search for better options as soon as they have found one that meets their aspiration level. Satisficing has also successfully been implemented in ABMs (e.g. Gotts et al., 2003). Another branch of theories are stochastic modifications of EUT. The general idea is that the inconsistencies of EUT are explained by incorporating stochastic elements, e.g. a random error term added to the utility function. Stochastic theories were promoted by Hey and Orme (1994), and Becker et al. (1963). An ABM that includes a stochastic theory can be found in Liu et al. (2006).

There is also a rich body of psychological theories concerning human decision-making. One prominent example is the theory of planned behaviour (TPB) developed by Ajzen (1985, 1991). TPB explicitly considers subjective norms defined as “perceived social pressure to perform or not perform the behaviour” (Ajzen, 1991, p. 188) and perceived behavioural control defined as „ … the perceived ease or difficulty of performing the behaviour reflecting past experiences as well as anticipated impediments and obstacles” (Ajzen, 1991, p. 188) which has been successfully exploited in an ABM describing the diffusion of technology (Schwarz and Ernst, 2009). In our view, TPB is a relevant theory for LUCC-ABMs as decision makers act under social influence (subjective norms) and multiple restriction factors exist for land use decisions (perceived behavioural control).

The diversity of implementations of human decision-making in LUCC ABMs may be an obstacle to better understand how human decisions affect land use change (Filatova et al., 2013), since it may be difficult to choose the appropriate decision model for a specific application. Attempts to structure decision models and to put them in a framework that may guide modellers in their choice of the most appropriate model have just started (Balke and Gilbert, 2014). To inform this debate about how to model human decision-making and to reflect the current practice and use of theories in LUCC

ABMs, we conducted a quantitative review of 134 studies assessed by a standard questionnaire investigating the way human decisions are implemented and whether they are based on existing theories. We address the following research questions:

1) What are the basic characteristics of LUCC ABMs including human decision-making for instance regarding their purpose, the implementation of the decision-making process and its data basis?
2) Is the modelling of human decision-making in current LUCC ABMs based on theories? If yes, what are the dominant schools of thought (e.g. economics, psychology)? Which influence factors are incorporated in the human decision model (such as economic, social, environmental)?
3) Has the application of theories and behavioural paradigms changed over time?
4) Have the current LUCC ABMs addressed the key challenges of modelling human decision-making in land use change, namely heterogeneity, interaction, uncertainty, adaption and learning, also without theoretical background?

2. Materials and methods

Before we present the process of paper selection and details how we assessed the papers, we will provide working definitions of key terms to avoid misunderstandings.

2.1. Definitions

2.1.1. Behavioural paradigms

Apart from specific theories, behavioural paradigms such as rationality, bounded rationality and non-rationality were mentioned frequently in the reviewed research articles. Therefore, we have introduced the concept of behavioural paradigms into our assessment. Each of these behavioural paradigms consists of specific theories from different fields of research.

Rationality: The actor has (1) consistent and well-defined preferences across all available decision options and (2) chooses the option that meets its preferences best, (3) taking into account all relevant information. In order to obtain a definition of 'all relevant information' that is useful in the context of ABMs, we deviate from its standard economic definition and use it in the sense of all information that the model can provide (Tesfatsion, 2006). In particular this means that we define the decision of an agent rational if it is based on all information that can be extracted from the model but ignoring unforeseeable future conditions or strategic behaviour of other agents.

Bounded Rationality: Actors pursue some objective, but by doing so they deviate from one or more of the above stated assumptions of rationality (1–3), e.g. the actor's decision could be based on limited information due to accessibility restrictions, limited cognitive capabilities or limited processing time.

Non-Rationality: We define decisions as non-rational if actors do not actively pursue any explicit or implicit goal in their decision-making, e.g. choosing an option at random, independent of the outcome of the decision. The non-rationality paradigm is not meant to capture theories that include emotions.

2.1.2. Influence factors

We define influence factors as aspects that influence the agents' decision-making, regardless of the specific evaluation procedure. We distinguish six categories: 1) economic (financial benefit, e.g. income), 2) social influence (driven by social groups), 3) social impact (consideration of impact of own behaviour on others), 4) environmental – altruistic (aiming e.g. at species conservation that not necessarily increases or even decreases individuals' utility), 5) environmental – non-economic benefits (non-financial benefits that increase individuals utility (e.g. aesthetic values or recreation)), and 6) spatial accessibility (distances to locations).

2.1.3. Multiple levels of decision-making

Multiple levels of decision-making apply when the decisions of one agent type constrain the decisions of another agent type due to different power (e.g. formal institutions and private homeowners in a residential development process, Prunetti et al., 2010). Two agent types competing for the same resource or trading goods with similar power are understood as single level of decision-making.

2.1.4. Learning & adaptation

We follow the definition given by Dibble (2006, p. 1526): Adaptation "is generally distinguished from learning by being passive and biological rather than active and cognitive" and operationalize this definition in the way Müller et al. (2013, p. 40) do: "Agents' decision rules are prone to adaptation, where the information used by the rules to generate a decision changes, and learning, where the rules themselves change over time." For instance, in a simulation model by Polhill et al. (2013) agents could adapt by changing a certain parameter while they learned by storing new cases that provided them with options they did not have before (also known as case-based reasoning).

2.1.5. Uncertainty

Here, we follow the understanding of Müller et al. (2013) and evaluate whether agents have limited knowledge about future developments in the model and explicitly consider this uncertainty in their decision process. This is in accordance with the definition of Knightian uncertainty that is widely used in economics, that uncertainty is a risk for which the probabilities are not known (Knight, 1921).

2.2. Paper selection, assessment and analysis

We have selected the publications analysed for this review based on a Web of Science search to obtain a thorough and unbiased literature selection. We conducted a Web of Science Topic Search (TS) with the search term "TS = (((agent AND based AND model*) OR (multi AND agent)) AND land). Of course, there are other relevant sources that are not listed in the Web of Science, for instance the Journal of Land Use Science, that we have scanned separately due to its visibility in the field (see Online Appendix 2). The Web of Science search was limited to document type "Article" (excluding reviews or book chapters) and publication years 2000–2013. Initially, we obtained 479 search results (see Table 1 for details of the selection process). Each publication was evaluated by two persons by title and abstract to determine which articles did not match our general criteria (i.e. a modelling study, but not related to land use research) and which we therefore excluded beforehand. This resulted in 267 publications that were then evaluated in more detail following a standard questionnaire (Table 2). During this second, more detailed evaluation we filtered 134 publications that fit the scope of our review, i.e. agent-based land use models which explicitly

Table 1
Overview of literature selection steps and resulting number of articles in review based on a topic search (TS) using the Web of Science.

Literature selection and evaluation steps		
Source	Step	# articles
Web of Science	TS=(((agent AND based AND model*) OR (multi AND agent)) AND land)	701
	- Publication years: 2000–2013	554
	- Document type: Article	479
Literature database	First scan: Title and Abstract	267
	Detailed evaluation: 23 review criteria	134

Table 2
Overview of review categories (model characteristics) and their values.

General	Study overview	Purpose of the study (multiple matches possible)	System understanding, Prediction, Management or decision support, Communication, Theory development, Hypothesis testing
		Object of decision-making (multiple matches possible)	Agriculture, Urban, Conservation area
		Subject of decision-making (multiple matches possible)	Individual/Household, Formal institution, Informal institution
		Case study	Yes/No/Context specific[a]Where?
		Scale	Local, Regional, Global
Decision model	General	Influence factors for decision (multiple matches possible)	Economic, Social influence, Social impact, Environmental – altruistic, Environmental – non-economic benefits, Accessibility
		Sensitivity analysis carried out?	Yes/No
		Uncertainty analysis carried out?	Yes/No
	Theory	Behavioural paradigm (multiple matches possible[b])	Rationality, Bounded Rationality, Non-Rationality
		Decision theory used?	Yes/No Theory name
		Reasoning behind theory choice	
	Methodology	Technique that is used in decision-making (multiple matches possible)	Optimization, Heuristics, Stochastics
	Empirical Basis	Decision based on empirical data?	Yes/No
		Kind of data	Qualitative, Quantitative
	Individual Decision-making (based on ODD + D protocol (Müller et al., 2013), part II) Design concepts)	Learning	Yes/No
		Interaction	No/Direct/Indirect
		Heterogeneity	Yes/No
		Adaptation	Yes/No
		Prediction	Yes/No
		Sensing	Yes/No
		Uncertainty	Yes/No
		Space	Yes/No
		Time	Yes/No

[a] A context-specific ABM is not based on geographic data but model processes are based on data or expert knowledge specific to a case study.
[b] Multiple matches are only possible if different agent types exist or different decision models are implemented.

address decision-making and that provided a model description. Additionally, we carried out a cross-check of articles between the groups that led to a further standardisation of the assessment across the groups.

The questionnaire that we have used to assess the paper captures general aspects of the reviewed studies and models, as well as details of the decision-making sub-model. Here, we put emphasis on behavioural theories used in the decision process, influence factors of the decision, key characteristics (heterogeneity, interactions, adaptation, learning, and uncertainty) as well as methodology and empirical basis. For that, we adopted parts of the ODD + D model description protocol explicitly tailored to describe human decisions in ABMs (Müller et al., 2013). Furthermore, the group of authors of this study met on a regular basis to discuss open questions and ambiguities. We tried to follow the statements of the authors if they followed the same working definitions that we provided above. However, if we differ in the understanding of terms (e.g. bounded rationality) we deviated from the author's statement to stay consistent between studies. If information was not stated explicitly in the text, we tried to conclude from our own reading. If this did not result in a clear answer we entered 'NA' for the respective category. In cases where several papers have used the same model without major modifications, we selected one paper that had the most extensive model description available. In Online Appendix 1 all 134 papers are listed together with an overview of the most important categories.

Further evaluations were carried out using the R Statistical Computing Environment (R Core Team, 2013). All review criteria were transformed into binary variables by splitting up criteria with more than two levels into separate binary variables each.

3. Results and discussion

3.1. Overview

In total, 134 studies were included in our review from 58 journals, of which three journals were dominant: Environmental Modelling and Software, Environment and Planning B – Planning and Design, and Ecological Modelling (Fig. 1). The model purpose for the majority of reviewed studies has been "system understanding" ($N = 125$) in contrast to "prediction" ($N = 20$) (Fig. 2). This reflects the fact that in LUCC science ABMs are hardly used for prediction. Up to now, prediction purposes have rather been pursued with statistical models (Couclelis, 2001). However, even if

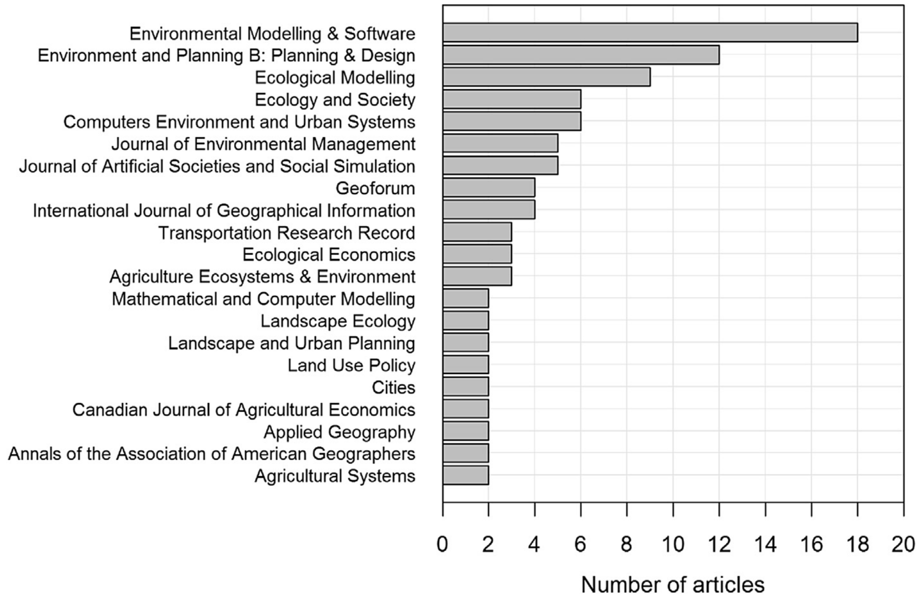

Fig. 1. Distribution of the reviewed studies across journals. Journals featuring only one relevant study are not included in the figure.

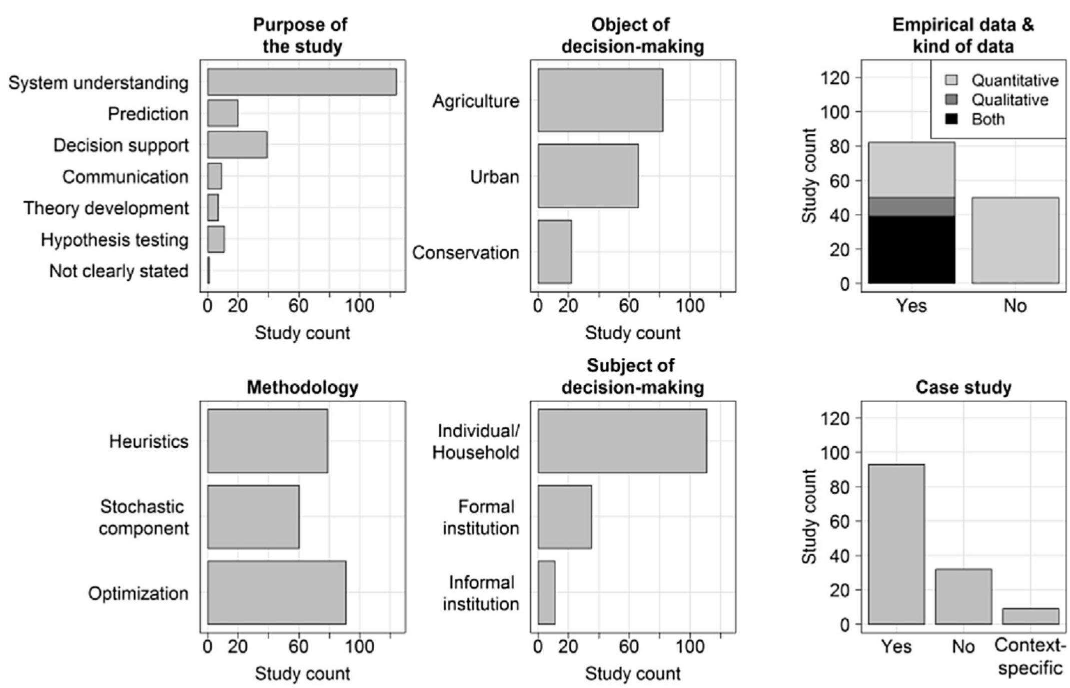

Fig. 2. Overview of characteristics and purposes of the reviewed human decision sub-models. Numbers do not have to add up to the total numbers of reviewed papers ($N = 134$) because multiple entries (e.g. multiple study purposes) are possible. Histograms of all characteristics of our survey can be found in the Appendix (Fig. A1).

models are not meant to be predictive, a substantial number of studies ($N = 39$) is designed to provide management or decision support (Fig. 2).

In 75% of the studies the subject of decision-making are either individuals or households in contrast to formal or informal institutions. In our assessment we kept track of three methodological aspects: 1) heuristics, 2) optimization, and 3) whether the selection process had a stochastic component. Our results showed that optimization was most often used ($N = 91$) compared to heuristics ($N = 77$). Please note that the sum of papers using heuristics vs. optimization is larger than the total number of studies which is consistent since both methods can be implemented in the same study for example comparing different agent types (e.g. Jager et al., 2000). In a substantial number of studies ($N = 60$) the selection process had a stochastic component. Interestingly the decision model of the majority of studies ($N = 82$) was based at least

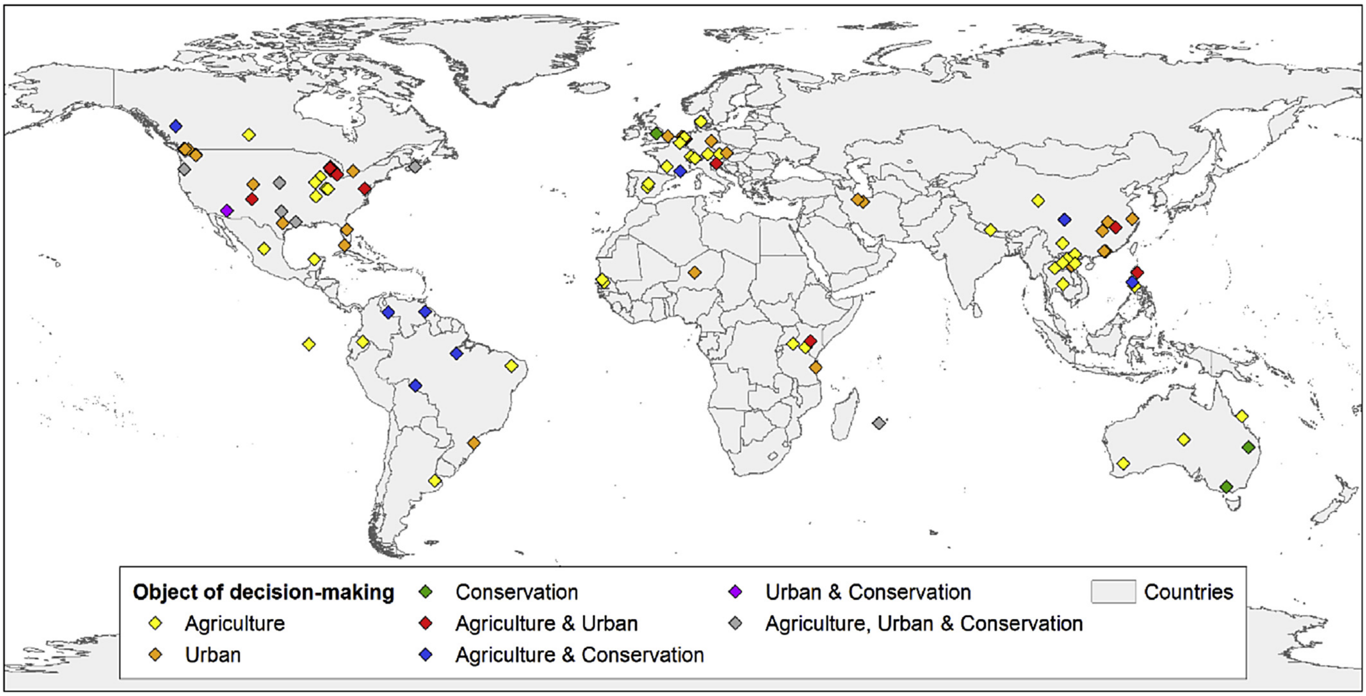

Fig. 3. Global distribution of case studies and information on the object of decision-making. Not all reviewed papers were based on study sites.

partially on empirical data (from quantitative sources $N = 70$ and qualitative sources e.g. expert knowledge $N = 49$). The overwhelming number of studies treated space explicitly ($N = 118$).

The global distribution of 100 case studies that can be geographically located is presented in Fig. 3. The object of decision-making is also shown on the map. Case studies cover all continents, with the highest density in Europe, South East Asia and North America and thus covering both developing and highly developed countries. In Europe, the majority of studies are located in West and Central Europe. In Asia, many case studies are located in China and Southeast Asia. In Africa, the number of case studies is limited to a few studies in West and East Africa. In the Americas most studies have been performed in the US. There are some regions were ABMs have not been used to study land use: most of Scandinavia, the. Baltic states and Eastern Europe, Russia, Central Asia, India, the Arabian peninsula, North Africa, Mesoamerica and the Caribbean.

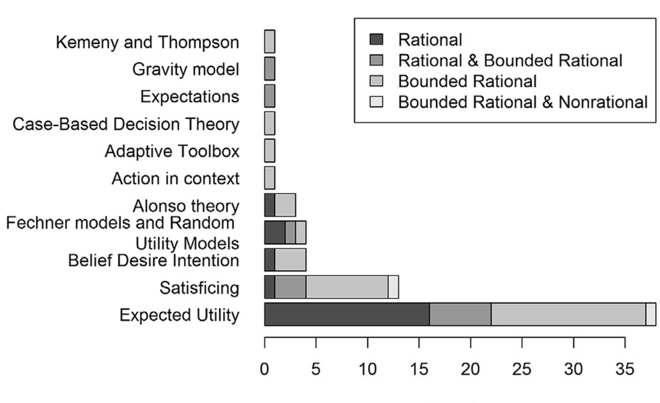

Fig. 4. Frequency of used theories. A theory can be used in the context of a behavioural paradigm, i.e. the most often used theory (Expected Utility) was used in studies that used Rational, Bounded rational, Non-rational actors respectively.

3.2. Use of theories in LUCC-ABMs

In the majority of studies the human decision model has not explicitly been based on a theory ($N = 83$ out of 134). This finding is a strong empirical backup for the statement by Crooks et al. (2008) that the field is dominated by independent ad hoc implementations of the decision process without reference to theories. The single most frequently applied theory.

was EUT ($N = 35$), followed by Satisficing ($N = 13$) (Fig. 4). In our framework EUT can be used in simulation models that use bounded rationality as their behavioural paradigm, for example in cases where agents maximize their expected utility on a subset of all possible options. Most other theories were applied only once or twice (Fig. 4). This certainly reflects the dominance of economics compared to psychology in the field of LUCC ABMs. Furthermore,

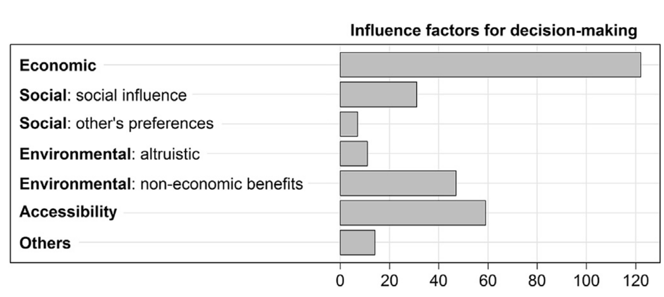

Fig. 5. Influence factors for decision-making.

the 11 theories that have been applied do not reflect the richness provided in the literature, although it is somewhat subjective what to define as a theory. For instance we have not listed the consumat approach by Jager e al. (2000) as a theory following the terminology of the authors, although it provides a detailed framework to operationalize human behaviour in ABMs.

The role of emotions is highlighted in reviews and acknowledged by fields such as behavioural economics (DellaVigna, 2009; Levine et al., 2015) or neuroeconomics (Rangel et al., 2008). However, emotions are widely overlooked in LUCC ABMs, although emotions and 'sense of place' are well known factors for land use and environmental management (Eisenhauer et al., 2000).

Additionally, we have grouped studies into behavioural paradigms, i.e. rational, bounded-rational and non-rational (see method section for our working definitions, Fig. 4). Overall, bounded rationality was the dominating applied behavioural paradigm ($N = 87$) which matches the specific recommendations of prominent reviews in the field to address limits of accessible information and cognitive abilities (Parker et al., 2003). Nevertheless, a substantial body of literature still relied on the rationality paradigm ($N = 57$). However, some of the studies considered the rational actor only as one of many agent types (e.g. Manson and Evans, 2007).

Looking at the influence factors for decision-making (Fig. 5), it is even more striking that economic factors are dominating. In 123 cases, economic influence factors such as income or prices were considered. Economic influence factors were followed by accessibility and environmental factors, leaving social influences and altruistic environmental influence factors (e.g. conservation of a species that does not provide any known ecosystem service) the least important factors.

3.3. Use of decision theories in time

The literature we have reviewed spans an interval of 14 years (2000–2013). At the beginning of this period, Parker et al. (2003) suggested that LUCC ABMs should leave the behavioural paradigms of neoclassical economics behind and take the limitation of

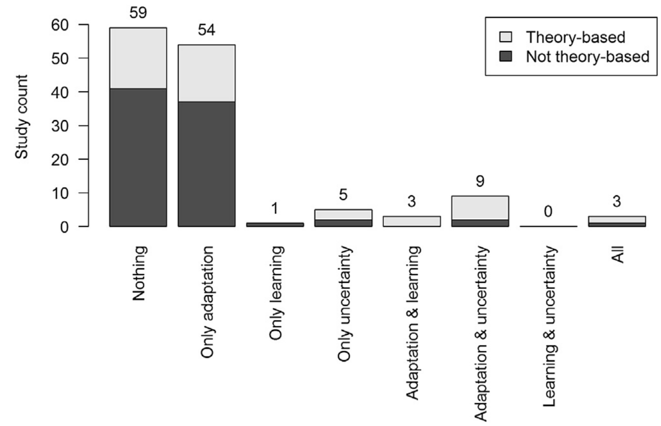

Fig. 7. Number of models that implemented adaptation, learning and uncertainty as well as combinations of those.

available information, cognitive power, adaption, learning and interaction into consideration. Therefore, we have investigated the temporal trends, i.e. whether ABMs are based on theory and which behavioural paradigm has been used (Fig. 6). Due to the small number of observations we present both the absolute and relative number per year. In the case of the relative plots we included additionally a moving average for a simpler detection of any trend. Overall, we found that LUCC ABMs got more popular from two published LUCC ABMs per year in the years 2001–2003 up to 16 LUCC ABMs in the years 2011–2013. Apart from the early years (before 2006), where not many LUCC ABMs have been published, the majority of studies is not explicitly theory based (Fig. 6). The use of behavioural paradigms has only changed slightly over the years. Studies using bounded rationality are dominating over the whole period, whereas the gap between the rational and bounded rational studies is getting smaller. We did not expect this given the explicit calls for using more bounded rational frameworks at the beginning of the study period (Parker et al., 2003). Regarding the influence factors we could not detect a temporal trend (not shown here).

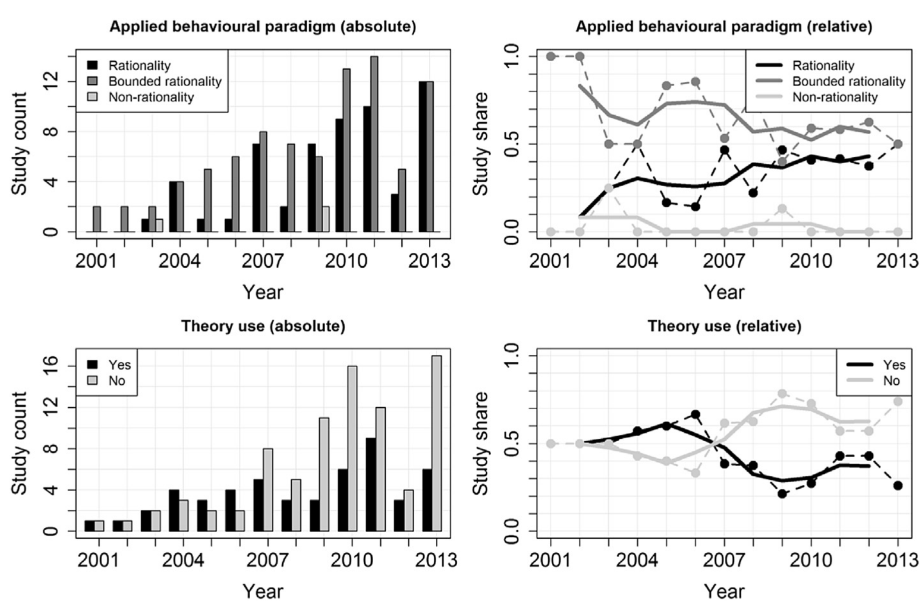

Fig. 6. Temporal trends in the use of three behavioural paradigms (rational, bounded-rational, non-rational) and whether the human decision sub-model has been grounded on theory. Left column shows absolute counts and left column shows fractions.

3.4. Meeting challenges without theoretical background?

We have shown that decision models are often not based on theory. Those decision models that are based on a theory, are dominated by EUT. The following section explores for all models under review, including the ones that were not rooted in theory, if the main challenges (interactions, heterogeneity of agents, uncertainty, adaption and learning) have been addressed. Only 17 out of 134 reviewed human decision models explicitly included uncertainty in the decision-making of the agents. For these 17 applications, there was no clear trend in the decision-making algorithm used (optimization, heuristics, stochastic component) visible. More models had adaptation incorporated (69 with vs. 65 without). Again, no specific decision method such as optimization or heuristics could be associated with adaptation. In our study, only seven human decision models are listed that consider learning. This low number is to some extent caused by our strict definition that we define learning by a change in the decision rule. Surprisingly 16 out of our 134 reviewed studies did not include interactions and 26 (including 2 publications where we could not extract information on this category) studies did not have heterogeneous agents.

Regarding the relations between three of the five main challenges (Fig. 7), we found that only three models incorporated learning, adaptation and uncertainty together. 59 models did not address any of the three major challenges, and 54 only tackled adaptation. Out of the 7 models that include learning, 3 additionally include adaptation. Out of those 15 models that combine adaptation with at least one other challenge, 12 are based on theory.

3.5. Limitations of the study

One limitation of the study is closely connected to the fact that models are different from each other and that they are incompletely described which makes them difficult to compare: Models are neither described in the same way nor do the authors use the same terminology and quite often authors do not directly provide us with the answers we were looking for in our template. Certainly it would help enormously if all authors followed a common protocol in their model description that also would act as a check list (e.g. Müller et al., 2013, 2014). We have tried to assess the papers in the same way among groups but of course there may be biases.

4. Conclusions and ways ahead

Our study confirms that the majority of human decision submodels in LUCC ABMs are not explicitly based on theory. And if so most often Expected Utility Theory has been applied ignoring alternative theories from behavioural economics and other disciplines such as social psychology and artificial intelligence. This is in line with Crooks et al. (2008) stating that the flexibility of ABMs comes along with ad hoc assumptions of the decision process. However, in order to make use of the full potential of ABMs for understanding land use change in the real world and to inform policy makers, this deficit of lacking theory needs to be overcome. Explicitly including theories of human decision-making into LUCC ABMs cannot only foster communication, but also increase re-use of existing models and thus lead to more robust and faster scientific progress.

For those ABMs with a theoretical background, it is detectable that bounded rationality is the dominating behavioural paradigm in the field with only a weak temporal decreasing trend, and that economic theories are dominating the models. In contrast, psychological theories which model human decisions in a more comprehensible manner are the exception. Thus, when selecting theories for incorporating them into LUCC ABMs, psychological theories should explicitly be considered, too.

We propose four directions to fill the mentioned research gaps and to advance in this field:

(1) To develop a structured guided framework which enables modellers to make informed decisions about what decision model to use and which factors to include (see for instance the framework MoHuB (**Mo**delling **Hu**man **B**ehavior) presented in Schlüter et al., 2017). Using such a framework should ease implementing theories in LUCC ABMs.
(2) There is also the plea to establish a culture to publish decision models to foster reuse (Bell et al., 2015) and software platforms exist that provide already several implemented decision models (e.g. www.openabm.org). These may allow the researcher to focus more on the choice of the appropriate decision model (e.g. Fearlus such as in Gotts et al. (2003)).
(3) To build upon experiences of including psychological theories in ABMs gained in other fields: One taxonomy of selected theories can be found in Balke and Gilbert (2014). Our results reflect the state of the art only for the limited domain of LUCC ABMs. It may be most useful in a joined effort to synthesize how human decision models are designed in ABMs across disciplines. Studies from cognitive sciences, artificial intelligence and social psychology show promising attempts in this regard (see Smith and Conrey, 2007; Richetin et al., 2010; Edmonds and Meyer, 2013; Kennedy, 2012).
(4) To foster collaboration between modellers and social scientists/psychologists to find and implement the appropriate psychological theories. Here we argue in the same line as Fischer et al. (2011, p.348) who point out the importance to involve social scientists in building ABMs with a focus on human behaviour. Furthermore, empirical research and participative approaches such as role playing games can deepen our understanding of how humans make decisions in LUCC and thus can help to integrate human decisions in a more plausible manner into such models.

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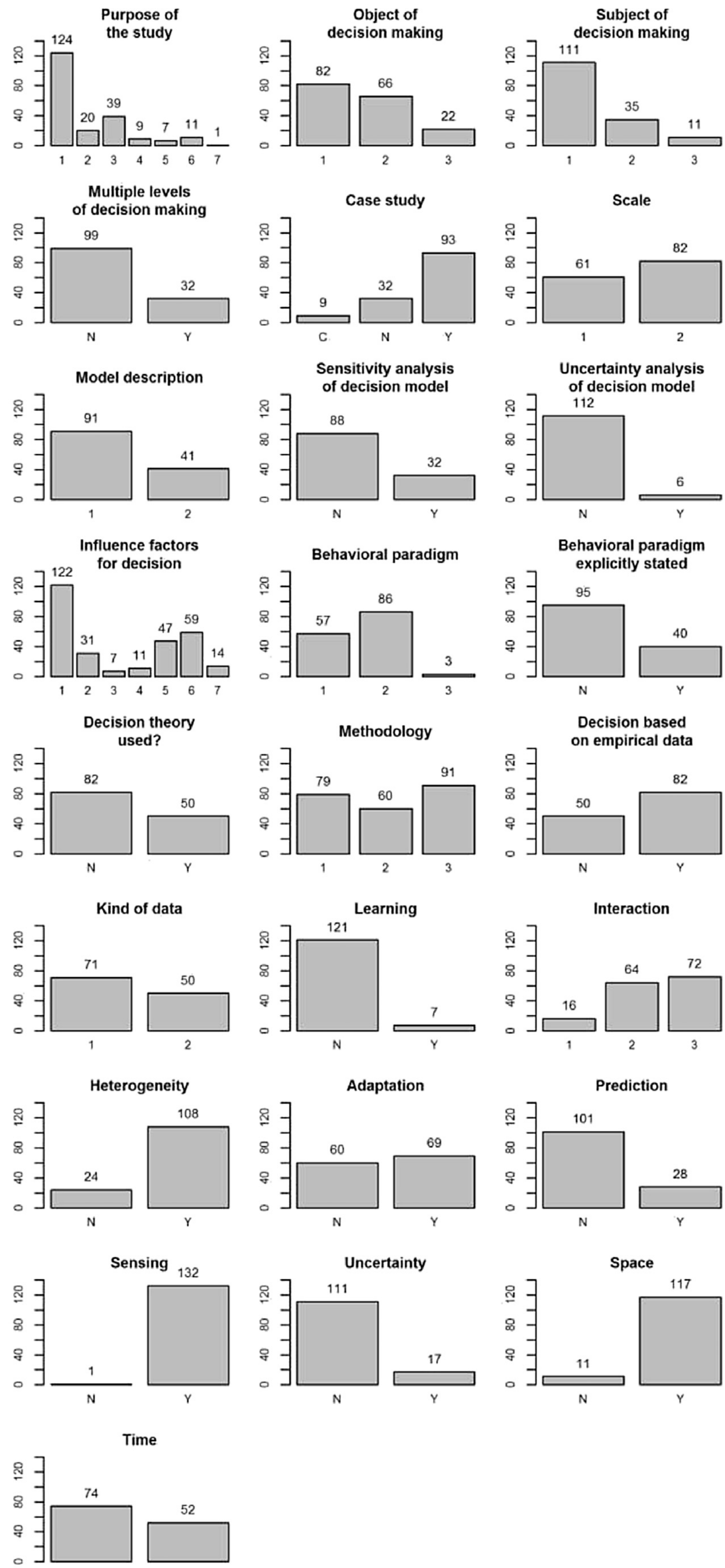
Appendix A



	Review Categories
	General
*	**Purpose of the study** 1 System understanding 2 Prediction 3 Management / decision support 4 Communication 5 Theory development 6 Hypothesis testing 7 Not clearly stated
*	**Object of decision making** 1 Agriculture 2 Urban 3 Conservation area
*	**Subject of decision making** 1 Individual/Household 2 Formal institution 3 Informal institution
	Case study [Y]es / [N]o / [C]ontext specific
	Scale 1 Local 2 Regional 3 Global
	Decision model
*	**Influence factors for decision** 1 Economic 2 Social influence 3 Social impact 4 Environmental – altruistic 5 Environmental – non economic benefits 6 Accessibility 7 Other
	Sensitivity / uncertainty analysis of decision model [Y]es / [N]o
*	**Behavioural paradigm** 1 Rationality 2 Bounded Rationality 3 Non-Rationality …explicitly stated? [Y]es / [N]o
	Decision theory used? [Y]es / [N]o
*	**Methodology used in decision making** 1 Heuristics 2 Stochastics 3 Optimization
	Decision based on empirical data? [Y]es / [N]o
*	**Kind of data** 1 Qualitative 2 Quantitative
	Learning [Y]es / [N]o
	Interaction 1 No 2 Direct 3 Indirect
	Heterogeneity, Adaptation, Prediction, Sensing, Uncertainty, Space, Time [Y]es / [N]o

* multiple matches possible

Fig. A.1. Complete overview of all categories for all 134 papers. Numbers do not necessarily have to add up to 134, since one paper may use several categories at the same time or for some papers an assessment has not been possible.

Appendix B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2016.10.008.

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