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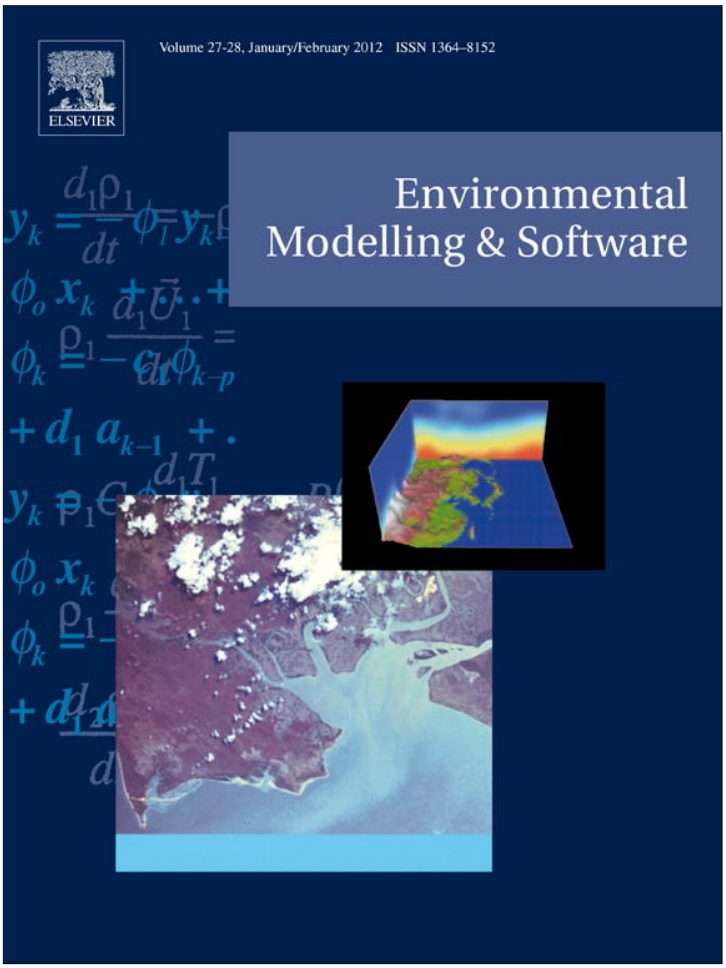

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Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol

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ABSTRACT

Representing human decisions is of fundamental importance in agent-based models. However, the rationale for choosing a particular human decision model is often not sufficiently empirically or theoretically substantiated in the model documentation. Furthermore, it is difficult to compare models because the model descriptions are often incomplete, not transparent and difficult to understand. Therefore, we expand and refine the 'ODD' (Overview, Design Concepts and Details) protocol to establish a standard for describing ABMs that includes human decision-making (ODD + D). Because the ODD protocol originates mainly from an ecological perspective, some adaptations are necessary to better capture human decision-making. We extended and rearranged the design concepts and related guiding questions to differentiate and describe decision-making, adaptation and learning of the agents in a comprehensive and clearly structured way. The ODD + D protocol also incorporates a section on 'Theoretical and Empirical Background' to encourage model designs and model assumptions that are more closely related to theory. The application of the ODD + D protocol is illustrated with a description of a social–ecological ABM on water use. Although the ODD + D protocol was developed on the basis of example implementations within the socio-ecological scientific community, we believe that the ODD + D protocol may prove helpful for describing ABMs in general when human decisions are included.

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1. Introduction

It is widely acknowledged that process-based models, and in particular agent-based models (ABMs), can play an important role in fostering understanding of the dynamics of complex systems (see Matthews et al., 2007; Clifford, 2008; Polasky et al., 2011; Schlüter et al., 2012 with respect to coupled human–environmental systems). A number of studies have demonstrated that the appropriate inclusion of human decision-making in models is of fundamental importance (Parker et al., 2003; Bousquet and Le Page, 2004; Jager and Mosler, 2007; Parker et al., 2008b; Le et al., 2012). This is supported by the fact that, in many modelling studies, macro-level patterns are strongly influenced by the assumed human decisions and behaviour at the micro-level (Hare and Deadman, 2004; Rounsevell and Arneth, 2011). However, current modelling practice has two substantial shortcomings: (1) The reasoning behind the choice of a certain human decision model is often not well documented; insufficient empirical or theoretical foundations are given; or the decision model is only assumed on an ad-hoc basis (Feola and Binder, 2010). (2) Often the model is not described in a transparent manner (clear and complete) that would allow for reproducibility and facilitate the communication of the model and its results (Polhill et al., 2008). Consequently, model comparison and advancement is hampered to a large extent.

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Referring to first shortcoming, one has to take into account that decision-making in ABMs can be based on various theories (for an introduction see Baron, 2000): A widely used approach for modelling decision-making in general, especially in economics, is rational-choice theory (Sen, 2008). However, rational-choice theory has been criticised for being overly simplistic (Camerer and Loewenstein, 2004). Various alternative theories of how decision-making is in reality based on a more bounded rationality have been proposed (Simon, 2008; Kahneman, 2003; Gigerenzer and Selten, 2001). For implementation in ABMs, rational choice theory is often represented by an optimisation routine, whereas models based on bounded rationality rely on condition-action rules or on a combination of both approaches (Schreinemachers and Berger, 2006). New opportunities to model bounded rationality are considered to be one of the major advantages of using an ABM approach (Epstein, 2006, p. 6), and there are by now many examples of ABMs that make use of bounded rationality (Jager et al., 2000; Duffy, 2001; Pahl-Wostl and Ebenhöh, 2004).

Referring to the second shortcoming mentioned above, several attempts have been made in the social sciences and land-use sciences to develop frameworks, classification schemes or protocols to represent and communicate ABMs. Hare and Deadman (2004) presented a taxonomic structure to help modellers choose the appropriate model type based on three requirements for social–ecological ABMs: Different specifications for (1) the coupling of social and environmental models, (2) social interactions and (3) the intrinsic adaptation of the agents. Richiardi et al. (2006) criticised the lack of a methodological standard for social ABMs and proposed a three-stage process that could lead to the establishment of such standards in social and economic simulations. The proposed process was based on the development of a questionnaire that includes specific questions on the model structure (including decision-making mechanisms), model analysis and replicability. According to the authors, the evaluation of the questionnaire can then provide the input for a methodological protocol. The MR POTATOHEAD framework, "Model Representing Potential Objects That Appear in The Ontology of Human–Environmental Actions & Decisions", represents key elements of standard ABM and LUCC (Land Use and Cover Change) models in a structured and comprehensive way (Parker et al., 2008a). This "conceptual design pattern" aims first to facilitate a comparison of the structure and functioning of different models and second to assist scholars new to the field with designing their models. Certain facets of human decisions are discussed in all three of these classification schemes and frameworks. However, these studies differ in terms of purpose and none of them puts the main focus on human decisions or elaborates on this topic in a comprehensive way.

Modelling in general, not only the modelling of human decisions, has to address the challenge of providing transparent and complete model descriptions (Richiardi et al., 2006; Parker et al., 2008a). Standardised protocols for (agent-based) model descriptions and especially the ODD (Overview, Design Concepts and Details) protocol (Grimm et al., 2006, 2010) have been well received by the scientific community. The ODD protocol consists of three parts: First, it provides an 'Overview' on the purpose and main processes of the model. Second, in the 'Design Concepts' block, the general concepts underlying the model design are depicted and third, in the 'Details', all of the necessary information is given that would allow for a reimplementation of the model. However, the original ODD protocol focuses primarily on ecological dynamics (Grimm et al., 2006). The first revision of the ODD protocol has attempted to open the standard for all ABMs (Grimm et al., 2010). Nevertheless, a comprehensive description of the human decision process was not a focal point until now.

First attempts have been made to determine the usefulness of the ODD protocol for describing social–ecological models. Polhill et al. (2008) investigated to which extent the ODD protocol can be applied to LUCC models, considering three ABMs that include human agents as examples. They concluded that the ODD protocol could provide a useful standard to facilitate communication and model comparison. However, refinements are required concerning the definition of terms (such as entities, state variables and parameters). An (2012) took the same line and concluded in his review on modelling and understanding human decisions that the development of protocols similar to the ODD protocol for social–ecological models aimed at modelling human decisions must be put on the future research agenda.

We want to address this gap. The aim of this paper is to provide an extension of the ODD protocol, termed ODD + D (ODD + Decision) which facilitates a clear and comprehensive description of ABMs in a standardised way, with an emphasis on human decisions and which includes the empirical and theoretical foundations for the choice of decision model. The paper is structured as follows: In the next section, the main shortcomings of the ODD protocol, in particular with respect to describing human decisions, are summarised. Then, important terms are defined. The terms *decision-making*, *adaptation* and *learning* are clarified and distinguished. Furthermore, general structural changes in the ODD + D protocol (mainly in the Design Concepts block), as compared to the ODD protocol, are delineated and discussed. Afterwards, we present a detailed description of the revised and new design concepts with an emphasis on human decision-making. In Section 4, we illustrate the application of the extended protocol ODD + D by describing a social–ecological ABM on water use as an example. Given our background in social–ecological modelling, we refer for illustrative purposes in Sections 3 and 4 to examples from that domain, but we believe that the ODD + D protocol may prove to be a helpful protocol for describing ABMs that include human decisions in general. The discussion section focuses on the expected benefits and the efforts required while applying the protocol. The section closes with open challenges for the future. Online Appendix provides a standardised form of the ODD + D protocol that can be used as template to fill in the necessary information about the model to support a transparent and complete model description.

2. Shortcomings of the ODD protocol for describing human decision-making

The ODD protocol is not fully suited to describe how human decision-making has been modelled for the following reasons: (1) Central aspects of modelling human decision-making are not explicitly addressed, such as decision algorithms, the formation of expectation, the temporal characteristics of decision-making and cultural values, amongst others. (2) The theoretical and empirical basis for the chosen decision submodel is not sufficiently emphasised. (3) The Design concepts section does not provide a suitable structure for describing human decision-making.

(1) Central aspects of human decision-making are addressed in related frameworks: In their checklist-type summary, Richiardi et al. (2006) mention the type of agent behaviour (optimising, satisficing, …), the interaction structure, the coordination structure, the formation of expectations and learning with respect to decision-making. In their MR POTATOHEAD framework, Parker et al. (2008a) use the decision algorithm of the agents, their characteristics and cultural values, and the temporal aspects in decision-making and the like as general aspects of decision-making. While the ODD protocol includes some of these aspects (e.g. interaction), other aspects such as coordination, the temporal aspects in decision-making and

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Table 1
The ODD + D protocol including the guiding questions. (We provide both the original questions (Grimm et al., 2010) and the newly proposed questions (in bold print) to present a comprehensive model description.)

Structural elements		Guiding questions
I) **Overview**	I.i Purpose	I.i.a What is the purpose of the study? **I.i.b For whom is the model designed?**
	I.ii Entities, state variables and scales	I.ii.a What kinds of entities are in the model? I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterised? **I.ii.c What are the exogenous factors/drivers of the model?** **I.ii.d If applicable, how is space included in the model?** I.ii.e What are the temporal and spatial resolutions and extents of the model?
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?
II) **Design Concepts**	**II.i Theoretical and Empirical Background**	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level**(s)** of the submodel**(s) (apart from the decision model)?** What is the link to complexity and the purpose of the model? **II.i.b On what assumptions is/are the agents' decision model(s) based?** **II.i.c Why is/are certain decision model(s) chosen?** **II.i.d If the model/submodel (e.g. the decision model) is based on empirical data, where do the data come from?** **II.i.e At which level of aggregation were the data available?**
	II.ii Individual Decision-Making	**II.ii.a What are the subjects and objects of the decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included**? **II.ii.b What is the basic rationality behind agent decision-making in the model?** Do agents pursue an explicit objective or have other success criteria? **II.ii.c How do agents make their decisions?** **II.ii.d Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?** **II.ii.e Do social norms or cultural values play a role in the decision-making process?** **II.ii.f Do spatial aspects play a role in the decision process?** **II.ii.g Do temporal aspects play a role in the decision process?** **II.ii.h To which extent and how is uncertainty included in the agents' decision rules?**
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience? **II.iii.b Is collective learning implemented in the model?**
	II.iv **Individual** Sensing	II.iv.a What **endogenous** and **exogenous** state variables are individuals assumed to sense and consider in their decisions? **Is the sensing process erroneous?** II.iv.b What state variables of which other individuals can an individual perceive? **Is the sensing process erroneous?** II.iv.c What is the spatial scale of sensing? II.iv.d Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables? **II.iv.e Are the costs for cognition and the costs for gathering information explicitly included in the model?**
	II.v **Individual** Prediction	**II.v.a Which data do the agents use to predict future conditions?** II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions? **II.v.c Might agents be erroneous in the prediction process, and how is it implemented?**
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect? **II.vi.b On what do the interactions depend?** II.vi.c If the interactions involve communication, how are such communications represented? **II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?**
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation? II.vii.b How are collectives represented?
	II.viii Heterogeneity	**II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?** **II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?**
	II.ix Stochasticity	II.ix.a What processes (including initialisation) are modelled by assuming they are random or partly random?
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected? II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)
III) **Details**	**III.i Implementation Details**	**III.i.a How has the model been implemented?** **III.i.b Is the model accessible, and if so where?**
	III.ii Initialisation	III.ii.a What is the initial state of the model world, i.e. at time $t = 0$ of a simulation run? III.ii.b Is the initialisation always the same, or is it allowed to vary among simulations? III.ii.c Are the initial values chosen arbitrarily or based on data?
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'? III.iv.b What are the model parameters, their dimensions and reference values? III.iv.c How were the submodels designed or chosen, and how were they parameterised and then tested?

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cultural values are not explicitly mentioned (see Table 1 Section II.ii of ODD + D).

(2) Different scientific disciplines use a variety of approaches for conceptualising human decision-making. Even within a single discipline, different schools of thought have specific, often implicit assumptions about decision-making. Without knowing the exact theoretical or conceptual background, scholars from different disciplines or schools might interpret the same model description in a totally different way and come to different conclusions. Such guessing might lead to metaphorical and theoretical plasticity (Hare and Deadman, 2004, p. 38) if the same implementation of a model can be explained and justified by the use of more than one metaphor or theory. In the ODD protocol, the basic principles ask for general concepts, theories, hypotheses, or modelling approaches that are underlying the design of a model. The guiding questions do not include the assumptions that underlie the decision-making in particular and the reasons for choosing a certain concept or theory. Apart from a theoretical basis, the choice of decision model may be based on empirical observations/data. This is crucial information for the reader of a model description and should be mentioned explicitly. This was not accounted for in the ODD section on basic principles.

(3) In part, the structure of the design concepts in the ODD protocol does not follow a logical order when it is used to describe human decision-making. For example, the ODD protocol foresees that prediction shall be explained before sensing, although agents usually sense their environment before they predict possible outcomes of their decision-making.

Finally, some minor aspects of the ODD protocol might be elaborated that could also be relevant for models that do not include human decision-making: (a) Stating the target group of a model makes its influence on model design transparent, but is not asked for in the ODD protocol. (b) In the ODD protocol, internal and environmental state variables are not clearly defined; thus, Polhill et al., 2008, suggested using the terms 'endogenous' and 'exogenous' instead. (c) Space is included in the ODD protocol, but its importance could be highlighted. (d) Heterogeneity, a very important issue for ABMs, was not discussed in a separate design concept. (e) The published attempts to replicate ABMs have shown that model results often cannot be reproduced or are based on assumptions that differ from the ones stated in the publication. Therefore, implementation details that are lacking in the ODD protocol, including where to find possibly available source code, need to be added.

3. The ODD + D protocol: adapting ODD for describing decisions in ABMs

3.1. Definitions of terms

The consideration of human decisions is a crucial aspect of agent-based complex models and an important issue in various disciplines. However, the definitions of terms vary widely. In this section, we specify our definitions of the most ambiguous terms.

Because we are considering ABMs, our first task is to clarify our definition of the term "agent": Following the definition given in Tesfatsion (2006), we define an agent as "bundled data and behavioural methods representing an entity constituting part of a computationally constructed world". This allows for the consideration of human beings, social groupings and institutions or biological and physical entities as agents (Tesfatsion, 2006). The ODD + D extension is designed for human decision-making. However, it may also be applied to non-human agents to describe their simulated actions in a detailed way without any limitations.

With "decision-making", we refer to "the methods agents use to make decisions about their behaviour" (Dibble, 2006). Two important concepts are often confused: adaptation and learning. For "adaptation", we adopt the definition given by Dibble (2006): Adaptation "is generally distinguished from learning by being passive and biological rather than active and cognitive". We operationalise this distinction in the following way: 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.

Any confusion that resulted from the application of the original ODD protocol concerning the definition of the terms "entities" and "state variables" has already been addressed in the updated ODD protocol (Grimm et al., 2010). Here, we will follow the proposed definitions: "An entity is a distinct or separate object or actor that behaves as a unit and may interact with other entities or be affected by exogenous factors (drivers). Its current state is characterised by its state variables […]. A state variable […] is a variable that distinguishes an entity from other entities […], or traces how the entity changes over time". Therefore, the above-defined agent is one specific type of entity. Furthermore, Polhill et al. (2008) criticise the lack of delineation between state variables and parameters. According to our understanding, state variables are the minimal set of variables that completely describe the system and are dynamic. Parameters are static but can vary between simulations, scenarios or agents.

A further lack of clarity refers to the understanding of internal and environmental state variables in the ODD protocol. Environmental variables could also be internal, e.g. rain depending on the evapotranspiration calculated within the model. Therefore, we follow the proposition of Polhill et al. (2008), and use the terms endogenous and exogenous instead. Variables that can be influenced by other variables of the model should be referred to as endogenous, whereas those that cannot be influenced by other variables should be referred to as exogenous. From our point of view, the usefulness of the ODD protocol for ABMs can be enlarged if these exogenous factors, also called drivers, are explicitly listed separately, which has not been the case up to now. In land-use science, a driver is defined as an exogenous variable that influences actors and/or changes in land use but is not influenced by them (see also Turner et al., 1995).

3.2. Structural changes between the ODD protocol and the ODD + D protocol

The main idea behind the ODD + D protocol is to preserve the basic structure of the ODD protocol to foster the establishment of the ODD protocol as a standard. Hence, changes were mainly made to the Design concepts block (cf. Fig. 1). It is more difficult to standardise this block across different disciplines and Grimm et al. (2010) already anticipated that the list of design concepts may need to be enlarged. Note: "The block …"Design concepts" does not describe the model itself, but rather describes the general concepts underlying the design of the model" (Grimm et al., 2006).

The ODD protocol was structurally changed as follows for the ODD + D protocol: The design concept "Basic Principles" was renamed "Theoretical and Empirical Background" and expanded to emphasise the importance of information regarding the sources of the assumptions and data used in a model. The ODD design concept "Objectives" was merged into the new design concept "Individual decision-making", which summarises the conceptual background of the decision model (see the right side of Fig. 1). We deleted "Adaptation" as separate design concept because we see adaptation as part of "Individual decision-making" (see Section 3.1, Definition of terms). "Sensing" and "Prediction" were expanded, and their order was reversed to reflect the characteristics and timeline of

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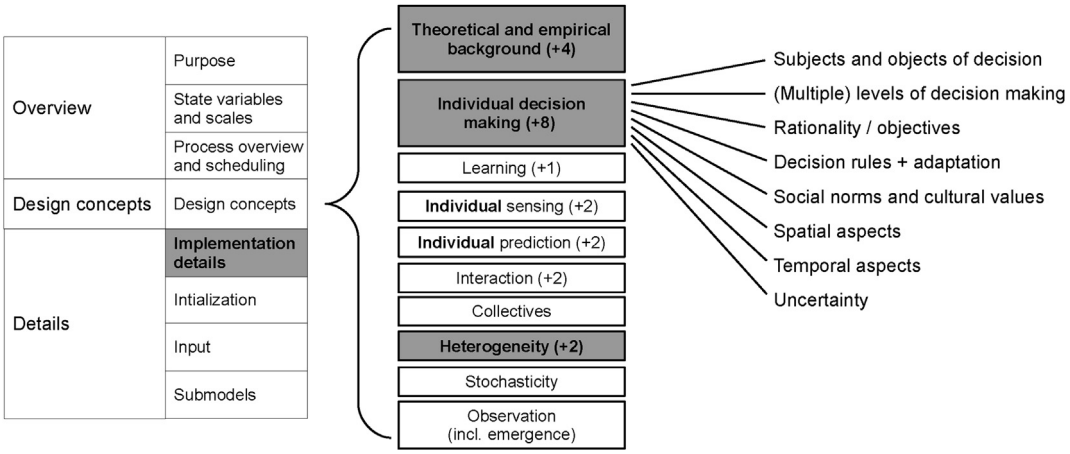

Fig. 1. The structure of the ODD + D protocol. Grey boxes indicate new design concepts/categories compared to the ODD protocol. The numbers of added new questions are noted in parentheses. The different aspects of the new design concept "Individual decision-making" are displayed on the right.

human decision-making. For the same reason, "Interaction" was expanded. A new design concept, "Heterogeneity", was introduced as it is a property that often distinguishes ABMs from other models, and can, therefore, provide crucial insights into their characteristics. Despite its undisputed importance for ABM modelling, the design concept "Emergence" was moved into "Observation" to reduce the risk that users might mistake it for a feature to be constructed rather than an outcome of the interplay of the model entities. By including "Emergence" in "Observation", the forms of stochasticity that were put into the model and the patterns that emerge in the model's results can be clearly distinguished. Finally, the category "Implementation Details" was included in the Details block because we believe that this information will improve comparability and reproducibility (see also Ince et al., 2012).

3.3. Usage of the ODD + D protocol

Beyond the requirements formulated in the ODD protocol (Grimm et al., 2006, 2010), we strongly encourage that all questions be answered to avoid an incomplete model description. If the model description is very long, we recommend the following: The complete ODD + D description including the submodels could be published in an Online Appendix using the template provided. Using the template makes the creation of an ODD + D description easier, since some categories can be answered by keywords such as "yes" or "no" instead of full sentences (see Online Appendices A and B). The use of this tabular form simplifies the comparison of models applied in different studies to a large extent. In the main text, the overview and the design concepts should be copied and, if necessary, shortened. One concern about the ODD protocol is the potential redundancy between the purpose, design concepts and the submodels description. This redundancy can be reduced by not repeating the details already given as design concepts in the submodel description (see Grimm et al., 2010). However, this drawback is outweighed by the benefits of a hierarchical model description that first gives an overview and afterwards provides the details with regard to comprehensibility and clarity.

3.4. The ODD + D protocol in detail: guiding questions and examples for describing human decisions in models

Table 1 provides a complete list of the guiding questions for each element of the extended ODD + D protocol. A template for using the ODD + D protocol, including examples for possible answers to the guiding questions, is available at as Online Appendix and on the website http://www.ufz.de/index.php?de=10464.

The questions that have been added are displayed in bold. In the following paragraphs, the questions are explained more in detail and examples and literature references are given. In the examples and literature references, emphasis is put on the new part for describing the decision model. In this part, the guiding questions are mentioned again to facilitate orientation.

I **Overview**

The overview section consists of the subsections i) purpose, ii) state variables and scales, and iii) process overview and scheduling. In the following, we summarise the original description of the ODD protocol (see Grimm et al., 2010) and our extensions. The citations from the original ODD protocol are given in double quotes.

I.i *Purpose*

Grimm et al. (2010) state "…ODD starts with a concise summary of the overall objective(s) for which the model was developed. Do not describe anything about how the model works here…" We suggest adding to this subsection some meta information that will facilitate understanding of the study, particularly whether the study was mainly designed for hypothesis testing, theory development, quantitative predictions, management and decision support, or communication and learning (e.g. Simon and Etienne, 2010). For whom is the model developed: scientists, students/teachers, stakeholders, or decision-makers?

I.ii *Entities, state variables and scales*

The intention of this section is well summarised by the guiding questions: "What kinds of entities are in the model? By what attributes (i.e. state variables and parameters) are these entities characterised? What are the temporal and spatial resolutions and extents of the model?" In social–ecological models, the entities will mainly be agents (e.g. humans, households, institutions), spatial units (e.g. grid cells), environments and collectives (list of agents). The different types of agents should only be mentioned here, as the detailed description will follow in the context of the Design Concept "Heterogeneity". In addition to the mentioned state variables in Grimm et al. (2010), state variables such as land ownership and memory are frequently used in social–ecological ABMs. In addition to the original ODD protocol, we suggest the inclusion of the

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question 'If applicable, how is space included in the model?' at this point in the protocol. To avoid wrong expectations, the authors should explicitly mention if they do not consider space at all. We think it is of special interest whether space is represented in models implicitly or explicitly, and if explicitly, to specify by which spatial dynamics the landscape is linked and whether the modelled space is based on real landscapes (e.g. based on GIS data). Additionally, all exogenous factors/drivers should be listed in this section because this will inform the reader from the outset whether the factors/drivers (e.g. precipitation or prices) are influenced by processes or other state variables during a model run or whether they are assumed to be exogenous.

I.iii *Process overview and scheduling*

Invaluable information for reimplementing the described model is given in this subsection. Such a description may be substantially facilitated by a graphical representation or a pseudo-code representation of the scheduling (Richiardi et al., 2006). Self-explanatory names for the model's processes foster a clear and concise description of the process overview. The authors should also inform the reader as to how the update process is implemented in the model (e.g. synchronous vs. asynchronous updates).

II **Design concepts**

In the following section, we introduce ten design concepts that are partly based on the previous ODD protocol (Grimm et al., 2010), extended and ordered from general to detailed information. There is a gradient from the overall view (the theoretical and empirical background, individual decision-making and learning) to the details (e.g. individual sensing and prediction). The stochasticity and observation relate to more technical questions and were therefore placed at the end of the section. Details of the implementation, such as the underlying equations, should, however, not be mentioned here but should appear in the submodels section. We provide guiding questions that should be answered by the model description and examples that help writers to give precise answers. This will give readers of the description a more profound understanding of the simulated decision-making process.

II.i *Theoretical and empirical background*

II.i.a The aim of this section is to describe the general concepts, theories or hypotheses that underlie the model's design. The answer should provide more precise information on the underlying theories; for example, the population dynamics theory and resilience thinking in Schlüter and Pahl-Wostl (2007), see the example description below. In contrast to Grimm et al. (2006), we do not ask for the modelling approach because the focus of the ODD + D protocol is only ABM.

II.i.b To compare the different models regarding the assumptions on which their representation of decision-making is based, it is important to note whether specific behavioural theories (such as profit maximisation, bounded rationality, cognitive models, social psychology approaches and mental models) real-world observations (mechanistic or process-based explanation, statistical regression methods and heuristics), ad-hoc rules (dummy rules and assumptions) or their combinations were used (see Johnson and Busemeyer, 2010 for a recent review of the theoretical approaches for modelling decision-making under risk and uncertainty).

II.i.c There may be many reasons behind the motivation for choosing a certain decision model, e.g. data (non)availability, reference to previous studies, theoretical reasons, or pattern-oriented modelling (Grimm et al., 2005). We believe that the choice of the decision model is often not only based on theory but is (co)determined by such practical factors. While these reasons should be dealt with in more detail in the discussions section of a paper, this question ensures that not only the choice for a certain decision model but also the practical constraints under which it was made can be compared.

II.i.d This section does not ask for the data input into the model in general, but specifically for the empirical data on which the decision submodel within the model is based (e.g. with regards to parameterisation, heuristics used, etc.). Such empirical data may stem from participatory approaches (role playing games, e.g. Castella et al., 2005), household surveys, interviews, direct observations, statistical census, archives, field or lab experiments, GIS products (see Smajgl et al., 2011, for an overview of empirical methods to parameterise ABMs).

II.i.e Information on the level of aggregation of the empirical data would be helpful for comparing the model with other models in terms of the data. Data levels might, for example, be at the individual, household or group level or there may be different resolutions of input data.

II.ii *Individual decision-making*

The following questions represent an important part of the extension of the ODD protocol with regards to the representation of decision-making in a model, as they explicitly address the basic design concepts behind it.

II.ii.a The documentation of the decision-making processes included in a model requires, first of all, that the subjects and objects of these processes are made explicit. The subjects are necessarily agents according to the definition above (see Section 3.1) and might belong to several different types, whereas the objects might be other elements of the model or may also be agents. As an example, farm household agents (subjects) might decide about the land-use state of land parcels they own (objects). The questions regarding multiple levels address models in which the decisions made on one level affect decisions made on higher or lower levels of aggregation; for example, farmer and government agents (Schlüter and Pahl-Wostl, 2007).

II.ii.b In this section, we focus the more general "Objectives" block from the ODD protocol on the specific characteristics of human decision-making. The rationality behind decision-making is crucial for understanding the role of decision-making in a model. It includes, for example, whether agents optimise according to an explicit objective, whether they have other types of success criteria, such as meeting aspiration thresholds, or whether they have no explicit objectives at all, as might be the case when decision-making heuristics are used. If agents have some type of success criterion, it should also be mentioned, whether they pursue it in a perfectly rational manner or whether their rationality is in some respects bounded, for example by limited information, limited cognitive capabilities, or limited decision-making time.

II.ii.c The question on how agents make their decisions refers to the way in which the rationality behind decision-making is translated into specific decision-making rules. For example, the pursuit of an objective might be implemented through the optimisation of an objective function via mathematical programming, whereas decision-making heuristics might be represented in a decision tree (Schreinemachers and Berger, 2006).

II.ii.d In this section, information shall be given on how agents adapt their behaviour to changing state variables, both endogenous and exogenous. Examples of agents adapting their behaviour is the adaptation of the number of irrigated fields to budget constraints and water inflow (see the example in Section 4) and of the mobility pattern of pastoralists to multiple stressors such as climate and policies (Boone et al., 2011). Because there is no universal agreement in the relevant literature on how to distinguish adaptation

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from learning, we have decided to use the one provided above in the "Definitions of terms" section (Section 3.1). According to this definition, adaptation occurs within given decision rules, whereas learning changes those rules.

II.ii.e Because real-world decision-making often takes place in relation to an individual's social environment, it can be argued that social norms or cultural values should be reflected in models of decision-making (Van den Bergh et al., 2000). For example, trust between agents can be a basis for cooperation (Janssen et al., 2006), or traditional perspectives can represent an alternative strategy to purely economic profit maximisation (Millington et al., 2008).

II.ii.f Space plays a role in an agent's decision-making process if the decision is influenced by the absolute or relative position of the agent or another entity in the model space. McAllister et al. (2006) investigated the role of spatial (and temporal) variations on the efficiency of the agistment networks in Australia using an ABM. Further examples can be found in An (2012).

II.ii.g Temporal aspects enter the decision process if agents' decision-making takes into account past experiences or expectations for the future. Past experiences might be incorporated in some representation of the agent's memory, which might also be related to agent learning (see Section II.iii below). The formation of expectations about the future depends on the ability of the agents to make predictions (see Section II.v below).

II.ii.h The information that the agents obtain may be characterised by uncertainty because, for example, agents have limited knowledge about future developments in the model. Thus, this section asks for a summary of the reactions to this uncertainty used in the model, which might enter the agents' decision-making process at different points. Uncertainty might, for example, be included in different learning processes (see Section II.iii below), such as Bayesian learning, which seeks to gradually reduce uncertainty, or it might be directly manifested in the decision-making process, e.g. in the form of a satisficing rule (Gotts et al., 2003) or in the form of risk aversion (Quaas et al., 2007).

II.iii *Learning*

II.iii.a Learning is defined on the level of the individual by changes in each one's decision-making rules. This is the part of the model documentation where different types of established learning representations can be cited (Brenner, 2006) or where the general idea behind the learning model can be described, e.g. reinforcement learning or belief-based learning. II.iii.b Learning does not only take place on an individual level but also takes place on a collective level, when agents are able to exchange information. For example, different types of evolutionary algorithms can be used to represent how land-owner agents collectively "learn to interact, cooperate, and compromise" to decide about the use of common resources (Bennett and Tang, 2009) or how researchers collectively learn to improve their publication practices (Watts and Gilbert, 2011).

II.iv *Individual sensing*

Compared to ecological sensing, where organisms or populations perceive their local environment, sensing becomes more complex in the context of human decision-making. Using societal structures, information may be transported on the global level. The following questions help to reflect on what information is exactly available before an agent has to decide. Thereby, all sensing processes may be erroneous.

II.iv.a In this section, the endogenous and exogenous state variables that agents are assumed to sense and consider in their decisions are summarised. Land managers may perceive the availability of (multiple) resources which include working power, monetary resources and different sources of income (e.g. Smajgl and Bohensky, 2013). Further, they may perceive the behaviour and actions of other agents (as opposed to the characteristics of other agents, see the following question) or market conditions. Additionally, the observation of the state of the natural resources can be erroneous (cf. Milner-Gulland, 2011, for a modelling study applying the management strategy evaluation approach).

II.iv.b This question refers to direct or indirect contact between agents that enables them to exchange information on their individual state. Signals may be sent between agents intentionally (e.g. Matthews, 2006) or unintentionally. Furthermore, it is asked whether the sensing process is erroneous.

II.iv.c The spatial scale of information flow may be local, global or via a network in the model space.

II.iv.d Sensing may be implemented via mechanisms by which agents obtain information explicitly, or via the assumption that agents simply know these variables. In the former case, signals or messages may be sent between agents (e.g. Matthews, 2006), which takes a certain amount of time within the model space so that information may not be available at once in every time step and may not be available to every agent.

II.iv.e This section asks whether the costs for cognition and costs for gathering information are included in the model. If the resources for gathering information are limited, it may be useful to include costs for different types of information acquisition, as e.g. motivated by the critique of rational choice (Simon, 1957).

II.v *Individual prediction*

The first question asks for data used by the agents for prediction, the second for their internal model and the last for their prediction error. The information used by the agent can be based on actual (spatial) observation, on experience or on a mixture of both. The agents' internal model describes how the agent processes the collected data to get predictions. This could be influenced by mental models such as a pessimistic versus optimistic view of the agents (e.g. Lux and Marchesi, 1999). The prediction error can, for instance, result from limited information processing capabilities of the agents or from unknown consequences of interactions with other resource users (e.g. unknown water extraction of upstream agents in Schlüter and Pahl-Wostl, 2007).

II.vi *Interaction*

We explicitly add the interactions between agents and entities in addition to the interactions among agents. Both can be mediated by the environment (Schlüter and Pahl-Wostl, 2007), by markets (Deadman et al., 2004) or auctions (Schreinemachers and Berger, 2011). The interaction itself depends on conditions (e.g. spatial distance, access to a resource). Additionally, we introduce a question about whether a (de)centralised or group-based coordination structure of the agents exists.

II.vii *Collectives*

Agents can belong to aggregations such as social groups, human networks or other organisations. These collectives can either emerge during the simulation or be defined by the modeller.

II.viii *Heterogeneity*

Agent heterogeneity is one of the characteristic features of ABMs. Agents may differ in parameters (e.g. managerial abilities,

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Happe et al., 2006; or preferences, Filatova et al., 2011). They can also be heterogeneous in their decision-making in terms of the different decision models (e.g. Jager et al., 2000, applied in Acosta-Michlik and Espaldon, 2008 and in Murray-Rust et al., 2011) or in their decision objects. If agents only differ in their state variables e.g. the location in space or financial budget, but are the same otherwise, we do not consider this population to be heterogeneous because exchanging an agent at the beginning of the simulation would not change the outputs of the simulation.

II.ix *Stochasticity*

To understand the model, it is crucial to know which processes include randomisation. Examples for coincidence in models can be the random initialisation of the values of agents' state variables (e.g. Balmann, 1997; Matthews, 2006), location of households on a map (e.g. Castella et al., 2005) or market-prices that influence agent decisions (e.g. Janssen et al., 2000).

II.x *Observation*

The questions asked in this paragraph aim to clarify which model output is collected at what time point in the simulation. It should also be stated which of the model results are a result of emergence.

III **Details**

The technical information that is needed to replicate the model and the experiments should be provided in this block (Grimm et al., 2006). This includes information on model implementation, availability of the model's source code, model input data and a detailed (mathematical) description of the submodels.

III.i *Implementation details*

Information on the model implementation should be delivered in this section. This includes stating the programming language or modelling platform in which the model was implemented. For a list of further important implementation details, we refer to the "Guide for Authors" of the journal Environmental Modelling and Software and/or the data availability section (cf. EMS, 2012). Authors are encouraged to make the model code accessible (Janssen, 2009; Ince et al., 2012). If the model code was published, for example, in an open model library such as openabm.org, please state where it can be downloaded.

III.ii *Initialisation*

III.iii *Input data*

III.iv *Submodels*

We adopted the initialisation, input data and submodels elements almost as-given by Grimm et al. (2010). However, in the element 'Initialisation', we added the case that the data could be based on stakeholder choice.

4. Sample application of ODD + D

We present a sample application of the ODD + D protocol for describing an ABM of water use (Schlüter and Pahl-Wostl, 2007). The model has been used to compare the performance and resilience of a centralised and decentralised water governance system with single or multi-purpose water use in the face of uncertain water flows. The centralised version is a stylised representation of water management in the Amudarya river basin in Central Asia.

I **Overview**

I.i *Purpose*

The purpose of the model is to understand how different governance structures (centralised versus decentralised) and diversity of water use affect the resilience of a farming community to variable and uncertain water flows. The model has been designed for scientists, particularly those interested in natural resource governance and resilience, with the aim of testing hypotheses about resilience mechanisms.

I.ii *Entities, state variables and scales*

The model consists of two types of human agents, individual farmers and a regulator such as a national government authority, and one animal agent, an age-structured fish population. A fourth entity is the water resource. Water is modelled as the units of water that enter the river stretch upstream and are then distributed downstream along the river onto the fields and into a terminal fishing lake. Farmers are characterised by their location along the river and hence the distance to the water inflow and the fishing lake, the number of fields they irrigate, their individual expectation of the water available each season, their memory of past water deliveries, the yield they receive from cultivating their fields, the catch from fishing, and the financial budget that is determined by their net returns from agriculture and fishing activities. The national authority is characterised by the total number of fields irrigated in the area, its expectation of water availability each season, its memory of past water flows and a budget that is the sum of all of the farmers' net incomes from irrigation.

The fish population is composed of 12 age classes. Age 0 is larvae that are born in the lake or migrate to the lake from upstream, ages 1–4 are juveniles and ages 5–12 are adult. Each age group is characterised by specific density-dependent and density-independent mortalities, birth and reproductive rates and, in the case of the age 0 class, a migration rate. The water entity is characterised by a unidirectional flow that is reduced by irrigation uptakes by the farmers. The remaining water at the downstream end of the river stretch enters the lake where the fish population is located. Water inflow into the river stretch from upstream is an exogenous variable. The parameters of the model are given in Table B.2 of Online Appendix.

The governance structure is represented by two different model structures, a centralised and a decentralised version, that differ in terms of which type of agent (farmer or national authority) makes the decisions on the number of fields to irrigate in a season and hence the amount of water to withdraw from the river.

Space is implicitly included through the location of each farm along the river stretch, which determines the farm's access to water and to the fish resources as well as the information each farmer has on the water flows. There are nine farms along the river. The model runs with monthly time steps over a period of 200 years. Decisions about the number of fields to irrigate in a season are taken at the beginning of a season.

I.iii *Process overview and scheduling*

Within each year, a sequence of activities takes place in the following order. In the centralised version at the beginning of the season (April), the national authority predicts the expected water inflow to the river stretch and decides on the number of fields to irrigate. The farmers calculate their water demand and irrigate the

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fields each month with the water actually available. Crops experience water stress when they do not receive the required amount of water. The remaining water after all fields have been irrigated, if any, flows into the lake. At the end of the year, the fish population grows, the farmers fish and harvest, and the national authority calculates its budget.

In the decentralised version, all farmers make their individual prediction of the expected water availability at their location along the river stretch at the beginning of the season, and decide on the number of fields to irrigate. They calculate the water needed to irrigate their fields each month. They irrigate the fields each month with the actually available water. Crops experience water stress when they do not receive the required amount of water. The water remaining after all fields have been irrigated, if any, flows into the lake. At the end of the year, the fish population grows and the farmers fish, harvest and calculate their individual budgets. Each agent is updated in the sequence determined by its location along the river stretch.

II Design concepts

II.i *Theoretical and empirical background*

The hypothesis that this model was designed to test was informed by resilience thinking (Folke et al., 2010). The modelling of the fish population growth is based on population dynamics theory, in particular, the Ricker model (Ricker, 1954). The water distribution and the impact of water stress on crop yield are modelled based on standard hydrological and agricultural approaches. The agents' decision model is based on the assumption that their information processing capacity is limited and that they have only partial information on water availability, hence they are boundedly rational (Simon, 1957). The agents use a form of inductive reasoning (Deadman et al., 2000) and rely on heuristics that guide their behaviour (Ostrom et al., 1994). They have no foresight. They are satisficers who, once they are above a certain minimum income threshold, engage in a process of trial and error to determine their best irrigation strategy based on their experience with past strategies. It is also assumed that the agents have different memory strengths with respect to past water flows. The memory strength affects their prediction of future water availability. The decision model of the national authority is based on real-world heuristics of water allocation. It is a simplified caricature of decision-making in the case study.

The ad-hoc decision model for the decentralised version was chosen because a decentralised setting does not exist in the case study and hence there are no data. The calculation of the expected water availability is based on the assumption that agents have different memories of past events and value this past experience differently. The method is based on a discounting approach used before in models of agent past memory (e.g. Satake et al., 2007). A 15-year runoff time series for a gauging station at the entrance to the Amudarya river has been used to determine the exogenous inflow to the river stretch (Schlüter et al., 2005).

II.ii *Individual decision-making*

Decision-making is modelled on two different levels, the national and the local. In the centralised version, the national authority decides the number of fields to be irrigated by the farmers along the entire river stretch. Farmers only execute the decisions. In the decentralised version, each individual farmer decides on the number of fields to irrigate on the farm. The number of fields determines the amount of water diverted to the farm (if available).

The agents pursue the objective of finding the number of fields they can irrigate with the uncertain water supply and a limited budget. They try to find the best strategy by adapting the number of fields based on an evaluation of their past performance. They do so by adapting their behaviour to changes in expected water availability, experienced water flows, yields and budget. The heuristics the agents use to make a decision on how many fields to irrigate are represented in a decision tree.

Social norms or cultural values and spatial aspects do not play a role in decision-making; however, the latter influence the outcome of the decision. The decision on how many fields to irrigate is influenced by the memory of past water availability. Agents can have different memory strengths, i.e. they weigh the experience from past years more or less strongly. Note, however, that within a simulation run, the agents do not differ in their memory strength.

Uncertainty is not explicitly included in the agent's decision rule; however, agents try to address the uncertainty of water flows by taking past flows as a predictor of future ones. The willingness of individual farmers to change their irrigation strategy and hence take the risk of losing their investment depends on their past income level. If the level is below a minimum value, the farmers take more risks.

II.iii *Learning*

No individual or collective learning is included in the decision process.

II.iv *Individual sensing*

The national authority knows about the realised water flows into the river stretch (note that this happens after the decision on the number of fields to prepare for irrigation has been made), the total agricultural budget available and the total irrigation costs. The farmers know in hindsight the amount of water delivered to their fields, their own budget, the costs of irrigation and the crop yields. Hence for the national authority, the spatial scale of sensing is global; for the farmers, the spatial scale is local. The agents receive this information for the on-going year without error. Farmers do not know any of the state variables for other farmers, but the national authority knows the net returns from irrigation of each farmer in the centralised version. In the model implementation, agents are assumed to simply know the values of the relevant variables, i.e. they do not carry out any activities to receive this information. The costs for cognition or for gathering information are also not explicitly included.

II.v *Individual prediction*

The national authority uses the information on past inflow to the river stretch to predict future water flows; the farmers use the information about past water deliveries to their fields to assess how much water they can expect in the next year. The agents make their prediction based on their memory of those past water flows. The prediction process is implemented through a weighted average of past water flows, where the weights are determined by the memory strength. The prediction is erroneous because of the variability of water inflows between years that is not known to the agents and the loss of memory of the agents. The downstream agents also do not know the water extraction of the upstream agents.

II.vi *Interaction*

Interactions among agents are indirect through their water and fish extraction (the resource extracted by one agent is no longer available for the other agents); the interactions are thus a consequence of the resources being common pool resources. The

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interactions depend on the location of the agent in relation to the water flow and distance from the fishing lake. In the centralised version, the national agency coordinates water use. Here, coordination affects the water extraction decision of each agent. In the decentralised scenario, no coordination mechanism exists.

II.vii *Collectives*

Agents do not belong to or form any collectives.

II.viii *Heterogeneity*

There is no heterogeneity of agents. Agents are not heterogeneous in their decision-making.

II.ix *Stochasticity*

Within the catchable age classes of the fish population, the actual age class from which a fish is caught is modelled randomly.

II.x *Observation*

The annual yields and catch of each farmer, accumulated total returns and abundance of the fish population are collected at the end of each year to compare the two model versions and the different scenarios of memory capacity and diversity of water use and for sensitivity analysis. A distinct pattern of distribution of yields along the upstream–downstream gradient emerges.

III **Details**

The model was implemented in Java using the Repast platform. The source code can be made available upon request.

The model world is initialised with nine farmers that all have the same initial budget, number of irrigated fields, yields and memory capacity but differ in their location along the river. The national authority in the centralised scenario has an initial budget, an initial number of fields and a memory capacity. The initial values for the agents and the fish population have been determined through calibration. The initial number of fields is varied among simulations to reflect scenarios with a strong focus on agriculture or fisheries. The inflow to the river stretch is provided by a data file of the observed characteristic runoff time series for the Amudarya River.

The model has a main part that models the actions of the two types of agents (the farmers and the national agency) and two submodels that represent the two resources (water and fish). The model parameters, their dimensions and default values are given in Table B.2 of Online Appendix.

The remaining details section is described in Online Appendix. There, the completed template for the ODD + D protocol for this example can also be found.

5. Discussion

The documentations of ABMs that include human decision-making often do not describe the details that are needed to understand and replicate the decision-making part, particularly with respect to the underlying assumptions and theories on which the agent's decision making is based. Using standardised protocols can help to provide model descriptions that meet this need. The ODD protocol is now widely used for describing agent- or individual-based models in general, but lacks the details relating to decision-making. Therefore, we have introduced an extension for the ODD protocol to describe human decision-making in ABMs: ODD + D.

5.1. Expected benefits from ODD + D

Using standardised protocols to describe simulation models offers many advantages (see also Grimm et al., 2010): The experienced scientific audience can understand the models described with a standardised protocol more easily, and meta-analyses on existing models is facilitated. Our protocol also eases the use of the taxonomy of ABMs suggested by Hare and Deadman (2004): The three taxonomy levels (coupling social and environmental model, social interaction and intrinsic adaptation) are covered in Sections I.ii, II.vi and II.ii.d of the ODD + D protocol, respectively. Referees of scientific articles may find it easier to review a manuscript that draws upon such a protocol. Modellers do not have to decide upon the structure of their model description, as the structure is already given by the protocol. And finally, modellers-to-be seeking guidance on and thinking about what aspects of a model have to be conceptualised before implementing the model, might use the ODD + D protocol as a checklist for the model development process.

5.2. The added value of the ODD + D protocol compared to the ODD protocol

The ODD + D protocol enhances the original ODD protocol in three ways: First, it incorporates the central aspects of human decision-making into the design concepts section resulting in a considerable re-organization of this section. New components on individual decision-making and heterogeneity were added, and numerous questions regarding concepts that are missing in the ODD protocol were included, i.e. coordination, temporal aspects in decision-making, cultural values and the like. Second, greater emphasis has been placed on the theoretical and empirical basis by renaming the "basic principles" section and adding more detailed questions regarding the background of the model in general and the decision-making algorithms in particular. Third, the design concepts were organised (including a reversed order) in a hierarchical fashion. Finally, minor aspects have been revised, such as adding questions regarding target groups, exogenous factors, space and implementation details.

By implementing these alterations, the ODD + D protocol allows for a concise and well-structured documentation of human decision-making in a more straightforward way than the original ODD protocol. In the example description, the ODD + D protocol helped to make the theoretical foundations of the decision-making algorithms more explicit, which would not have been possible with the ODD protocol. This makes it easier to link the model results to the results of other models that are based on similar assumptions about the decision-making process. It also facilitates the assessment of model results in view of the underlying assumptions and thus promotes a better understanding of the robustness and scope of the results. The ODD + D protocol also provides for the specification of the empirical data used as input to the model, which would not have been mentioned in the ODD protocol. This allows for a better understanding of how the model relates to a real-world setting. Finally, the questions about individual decision-making specify the details of the decision making process that would not be revealed in the ODD protocol but are relevant for assessing model outcomes, e.g. how the memory of past water flows affects the performance of individual farmers and the overall system in the face of inflow uncertainty.

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5.3. The effort required to use the ODD + D protocol

The ODD + D protocol requires answering a variety of questions, which is inevitably time consuming. Compared to the ODD protocol, the ODD + D protocol, especially the Design concepts section, includes more questions and thus leads to a more lengthy documentation. Therefore, we provide a template that guides the user through the questions. Some of the questions can be answered simply using keywords instead of full-length descriptions. Thus, we think that the additional effort required when using the ODD + D compared to ODD is negligible. The wide usage of the ODD protocol shows that a detailed protocol is currently well received by the scientific community. We believe that the ODD + D protocol will make the documentation of human decision-making easier.

For users who have not described their simulation model before, applying the ODD + D protocol definitely requires effort to answer all of the questions. However, the structure provided in the ODD + D protocol will very likely facilitate the whole documentation process, as users do not have to decide upon the structure of their description. Users who already have a model description in the ODD protocol need to consider the additions made by the ODD + D protocol (see Fig. 1 and Table 1 for a comparison of the ODD and ODD + D protocols). In sum, they need to (1) describe the spatial aspects in the overview section, (2) re-arrange the design concepts section into the ODD + D structure and answer the supplemented guiding questions of the copied design concepts, (3) add (3a) the theoretical and empirical background, (3b) individual decision-making and (3c) heterogeneity in the Design Concepts section and finally (4) provide implementation details in the Details section.

5.4. Future work

This first version of the ODD + D protocol was developed based on experiences gained in the social–ecological scientific community. We believe that the ODD + D protocol may prove to be helpful for describing ABMs in general. However, describing models with other thematic foci such as economic, sociological or political research questions might reveal blind spots in the ODD + D protocol. Furthermore, a wider application will show if the current structure of the ODD + D protocol constrains modellers and if model descriptions become very lengthy. Such issues should be addressed in updates of the protocol. This first version is meant as a starting point for a participatory discourse on describing ABMs including human decision-making. The scientific community is invited to try out the ODD + D protocol and participate in discussions on the protocol by contacting the authors of this article. Updates to the ODD + D protocol will be published on the website mentioned in Section 3.4.

A further challenge is the development of a ΔODD protocol to describe different model variants (Polhill et al., 2008) and its usage in the ODD + D protocol. This is especially relevant for describing human decisions, as testing the influence of different decision algorithms in a single overall model is often a part of ABM studies. Apart from that, the usability of the ODD + D protocol in the model development part of the TRACE modelling process documentation (Schmolke et al., 2010) still has to be tested. Finally, the current version of the ODD + D protocol draws solely on written text for describing the model concept and implementation. It might be useful to also provide templates for visualising individual aspects of the model, for instance using UML or the Web Ontology Language (Polhill and Gotts, 2009).

In sum, the ODD + D protocol shall foster the explicit description of the theoretical background of ABMs incorporating human decisions and important details of the model implementation. This enables the scientific community to reproduce simulation results and to further develop already existing models. As the ODD + D protocol also explicitly asks for the underlying theories, the ability of a theory or hypothesis to replicate patterns found in the real world can be assessed more easily. Furthermore, widespread usage of a protocol such as ODD + D would clearly facilitate model comparisons focused on human decisions. The ODD + D protocol might address the "particular need for research that compares these decision making models to extant theory, practice, and observation of the real world" (Parker et al., 2003) by facilitating model comparisons related to specific theories.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2013.06.003.

References

Acosta-Michlik, L., Espaldon, V., 2008. Assessing vulnerability of selected farming communities in the Philippines based on a behavioural model of agent's adaptation to global environmental change. Global Environmental Change 18 (4), 554–563.
An, L., 2012. Modeling human decisions in coupled human and natural systems: review of agent-based models. Ecological Modelling 29, 25–36.
Balmann, A., 1997. Farm-based modelling of regional structural change: a cellular automata approach. European Review of Agricultural Economics 24 (1–2), 85–108.
Baron, J., 2000. Thinking and Deciding. Cambridge University Press, Cambridge, MA.
Bennett, D.A., Tang, W., 2009. GAIA-RM: a geographically aware intelligent agents framework for rangeland management. In: Proceedings of the 10th International Conference on GeoComputation. Sydney, Australia.
Boone, R.B., Galvin, K., BurnSilver, S.B., Thornton, P.K., Ojima, D.S., Jawson, J.R., 2011. Using coupled simulation models to link pastoral decision making and ecosystem services. Ecology and Society 16 (2). Art. no. 6 (online).
Bousquet, F., Le Page, C., 2004. Multi-agent simulations and ecosystem management: a review. Ecological Modelling 176 (3–4), 313–332.
Brenner, T., 2006. Agent learning representation – advice in modelling economic learning. In: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics, Agent-based Computational Economics, Handbooks in Economics, vol. 2. North-Holland, Oxford, pp. 895–947.
Camerer, C.F., Loewenstein, G., 2004. Behavioral economics: past, present, future. In: Camerer, C.F., Loewenstein, G., Rabin, M. (Eds.), Advances in Behavioral Economics. Princeton UP, Princeton, pp. 3–51.
Castella, J.C., Trung, T.N., Boissau, S., 2005. Participatory simulation of land-use changes in the northern mountains of Vietnam: the combined use of an agent-based model, a role-playing game, and a geographic information system. Ecology and Society 10 (1). Art. no. 27 (online).
Clifford, N.J., 2008. Models in geography revisited. Geoforum 39, 675–686.
Deadman, P., Robinson, D., Moran, E., Brondizio, E., 2004. Colonist household decision making and land-use change in the Amazon rainforest: an agent-based simulation. Environment and Planning B-planning & Design 31 (5), 693–709.
Deadman, P., Schlager, E., Gimblett, R., 2000. Simulating common pool resource management experiments with adaptive agents employing alternate communication routines. Journal of Artificial Societies and Social Simulation 3 (2), 2.
Dibble, C., 2006. Computational laboratories for spatial agent-based models. In: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics, Agent-

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based Computational Economics, Handbooks in Economics, vol. 2. North-Holland, Oxford, pp. 1511–1548.
Duffy, J., 2001. Learning to speculate: experiments with artificial and real agents. Journal of Economic Dynamics and Control 25 (3–4), 295–319.
EMS, 2012. Guide for Authors of the Journal Environmental Modeling and Software. http://www.elsevier.com/journals/environmental-modelling-and-software/1364-8152/guide-for-authors#68000 (accessed 05.11.12.).
Epstein, J.M., 2006. Agent-based computational models and generative social science. In: Epstein, J.M. (Ed.), Generative Social Science – Studies in Agent-based Computational Modeling. Princeton UP, Princeton, pp. 4–46.
Feola, G., Binder, C.R., 2010. Towards an improved understanding of farmers' behaviour: the integrative agent-centred (IAC) framework. Ecological Economics 69 (12), 2323–2333.
Filatova, T., Voinov, A., van der Veen, A., 2011. Land market mechanisms for preservation of space for coastal ecosystems: an agent-based analysis. Environmental Modelling & Software 64 (1), 179–190.
Folke, C., Carpenter, S.R., Walker, B., Scheffer, M., Chapin, T., Rockström, J., 2010. Resilience thinking: integrating resilience, adaptability and transformability. Ecology and Society 15 (4). Art. no. 20 (online).
Gigerenzer, G., Selten, R., 2001. Bounded Rationality – the Adaptive Toolbox. MIT Press, Cambridge.
Gotts, N.M., Polhill, J.G., Law, A.N.R., 2003. Agent-based simulation in the study of social dilemmas. Artificial Intelligence Review 19 (1), 3–92.
Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser, U., DeAngelis, D.L., 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling 198 (1–2), 115–126.
Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F., 2010. The ODD protocol: a review and first update. Ecological Modelling 221 (23), 2760–2768.
Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H.H., Weiner, J., Wiegand, T., DeAngelis, D.L., 2005. Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science 310, 987–991.
Happe, K., Kellermann, K., Balmann, A., 2006. Agent-based analysis of agricultural policies: an illustration of the agricultural policy simulator AgriPoliS, its adaptation and behavior. Ecology and Society 11 (1). Art. no. 49 (online).
Hare, M., Deadman, P., 2004. Further towards a taxonomy of agent-based simulation models in environmental management. Mathematics and Computers in Simulation 64 (1), 25–40.
Ince, D.C., Hatton, L., Graham-Cumming, J., 2012. The case for open computer programs. Nature 482 (7386), 485–488.
Jager, W., Janssen, M.A., De Vries, H.J.M., De Greef, J., Vlek, C.A.J., 2000. Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model. Ecological Economics 35 (3), 357–379.
Jager, W., Mosler, H.J., 2007. Simulating human behavior for understanding and managing environmental resource use. Journal of Social Issues 63 (1), 97–116.
Janssen, M.A., 2009. Understanding artificial Anasazi. Jasss-the Journal of Artificial Societies and Social Simulation 12 (4), 13.
Janssen, M.A., Bodin, Ö., Anderies, J.M., Elmqvist, T., Ernstson, H., McAllister, R.R.J., Olsson, P., Ryan, P., 2006. Toward a network perspective of the study of resilience in social-ecological systems. Ecology and Society 11 (2). (Art.15).
Janssen, M.A., Walker, B.H., Langridge, J., Abel, N., 2000. An adaptive agent model for analysing co-evolution of management and policies in a complex rangeland system. Ecological Modelling 131 (2–3), 249–268.
Johnson, J.G., Busemeyer, J.R., 2010. Decision making under risk and uncertainty. Wiley Interdisciplinary Reviews: Cognitive Science 1 (5), 736–749.
Kahneman, D., 2003. A perspective on judgment and choice – mapping bounded rationality. American Psychologist 58 (9), 697–720.
Le, Q.B., Seidl, R., Scholz, R.W., 2012. Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation. Environmental Modelling & Software 27-28, 83–96.
Lux, T., Marchesi, M., 1999. Scaling and criticality in a stochastic multi-agent model of a financial market. Nature 397 (6719), 498–500.
Matthews, R., 2006. The People and Landscape Model (PALM): towards full integration of human decision-making and biophysical simulation models. Ecological Modelling 194 (4), 329–343.
Matthews, R.B., Gilbert, N.G., Roach, A., Polhill, J.G., Gotts, N.M., 2007. Agent-based land-use models: a review of applications. Landscape Ecology 22 (10), 1447–1459.
McAllister, R.R.J., Gordon, I.J., Janssen, M.A., Abel, N., 2006. Pastoralists' responses to variation of rangeland resources in time and space. Ecological Applications 16 (2), 572–583.
Millington, J.D.A., Romero-Calcerrada, R., Wainwright, J., Perry, G., 2008. An agent-based model of Mediterranean agricultural land-use/cover change for examining wildfire risk. Journal of Artificial Societies and Social Simulation 11 (4), 4.
Milner-Gulland, E.J., 2011. Integrating fisheries approaches and household utility models for improved resource management. Proceedings of the National Academy of Sciences of the United States of America 108 (4), 1741–1746.
Murray-Rust, D., Dendoncker, N., Dawson, T.P., Acosta-Michlik, L., Karali, E., Guillem, E., Rounsevell, M., 2011. Conceptualising the analysis of socio-ecological systems through ecosystem services and agent-based modelling. Journal of Land Use Science 6 (2–3), 83–99.
Ostrom, E., Gardner, R.H., Walker, J., 1994. Rules, Games and Common Pool Resources. University of Michigan Press, Ann Arbor, Michigan, USA.
Pahl-Wostl, C., Ebenhöh, E., 2004. An adaptive toolbox model: a pluralistic modelling approach for human behaviour based on observation. Journal of Artificial Societies and Social Simulation 7 (1), 3.
Parker, D.C., Brown, D.G., Polhill, J.G., Deadman, P.J., Manson, S.M., 2008a. Illustrating a new 'conceptual design pattern' for agent-based models and land use via five case studies: the MR POTATOHEAD framework. In: Paredes, A.L., Iglesias, C.H. (Eds.), Agent-based Modelling in Natural Resource Management. Universidad de Valladolid, Valladolid, Spain, pp. 23–51.
Parker, D.C., Hessl, A., Davis, S.C., 2008b. Complexity, land-use modeling, and the human dimension: fundamental challenges for mapping unknown outcome spaces. Geoforum 39 (2), 789–804.
Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Annals of the Association of American Geographers 93 (2), 314–337.
Polasky, S., Carpenter, S.R., Folke, C., Keeler, B., 2011. Decision-making under great uncertainty: environmental management in an era of global change. Trends in Ecology & Evolution (Personal Edition) 26 (8), 398–404.
Polhill, J.G., Brown, D.G., Grimm, V., 2008. Using the ODD protocol for describing three agent-based social simulation models of land use change. Journal of Artificial Societies and Social Simulation 11 (2), 3.
Polhill, J.G., Gotts, N., 2009. Ontologies for transparent integrated human-natural system modelling. Landscape Ecology 24 (9), 1255–1267.
Quaas, M.F., Baumgärtner, S., Becker, C., Frank, K., Müller, B., 2007. Uncertainty and sustainability in the management of semi-arid rangelands. Ecological Economics 62 (2), 251–266.
Richiardi, M., Leombruni, R., Saam, N.J., Sonnessa, M., 2006. A common protocol for agent-based social simulation. Journal of Artificial Societies and Social Simulation 9 (1), 15.
Ricker, W.E., 1954. Stock and recruitment. Journal of the Fisheries Research Board of Canada 11 (5), 559–623.
Rounsevell, M.D.A., Arneth, A., 2011. Representing human behaviour and decisional processes in land system models as an integral component of the earth system. Global Environmental Change 21 (3), 840–843.
Satake, A., Janssen, M.A., Levin, S.A., Iwasa, Y., 2007. Synchronized deforestation induced by social learning under uncertainty of forest-use value. Ecological Economics 63 (2–3), 452–462.
Schlüter, M., McAllister, R.R.J., Arlinghaus, R., Bunnefeld, N., Eisenack, K., Hölker, F., Milner-Gulland, E.J., Müller, B., Nicholson, E., Quaas, M., Stöven, M., 2012. New horizons for managing the environment: a review of coupled social-ecological systems modeling. Natural Resource Modeling 25 (1), 219–272.
Schlüter, M., Pahl-Wostl, C., 2007. Mechanisms of resilience in common-pool resource management systems: an agent-based model of water use in a river basin. Ecology and Society 12 (2). Art. no. 4 (online).
Schlüter, M., Savitsky, A.G., McKinney, D.C., Lieth, H., 2005. Optimizing long-term water allocation in the Amudarya River delta: a water management model for ecological impact assessment. Environmental Modelling & Software 20 (5), 529–545.
Schmolke, A., Thorbek, P., Chapman, P., Grimm, V., 2010. Ecological models and pesticide risk assessment: current modeling practice. Environmental Toxicology and Chemistry 29 (4), 1006–1012.
Schreinemachers, P., Berger, T., 2011. An agent-based simulation model of human-environment interactions in agricultural systems. Environmental Modelling & Software 26 (7), 845–859.
Schreinemachers, P., Berger, T., 2006. Land-use decisions in developing countries and their representation in multi-agent systems. Journal of Land Use Science 1, 29–44.
Sen, A., 2008. Rational behaviour. In: Durlauf, S.N., Blume, L.E. (Eds.), The New Palgrave Dictionary of Economics, second ed., Palgrave Macmillan. The New Palgrave Dictionary of Economics Online Palgrave Macmillan. http://dx.doi.org/10.1057/9780230226203.1385. Available at (last visited October 25 2012): http://www.dictionaryofeconomics.com/article?id=pde2008_R000022.
Simon, C., Etienne, M., 2010. A companion modelling approach applied to forest management planning. Environmental Modelling & Software 25 (11), 1371–1384.
Simon, H., 1957. Models of Man. John Wiley, New York, USA.
Simon, H.A., 2008. Rationality, bounded. In: Durlauf, S.N., Blume, L.E. (Eds.), The New Palgrave Dictionary of Economics, second ed., Palgrave Macmillan. The New Palgrave Dictionary of Economics Online Palgrave Macmillan. http://dx.doi.org/10.1057/9780230226203.1391. Available at (last visited October 25 2012): http://www.dictionaryofeconomics.com/article?id=pde2008_B000176.
Smajgl, A., Bohensky, E., 2013. Behaviour and space in agent-based modelling: poverty patterns in East Kalimantan, Indonesia. Environmental Modelling & Software 45, 8–14.
Smajgl, A., Brown, D.G., Valbuena, D., Huigen, M.G.A., 2011. Empirical characterisation of agent behaviours in socio-ecological systems. Environmental Modelling & Software 26 (7), 837–844.
Tesfatsion, L., 2006. Agent-based computational economics: a constructive approach to economic theory. In: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics, Agent-based Computational Economics, Handbooks in Economics, vol. 2. North-Holland, Oxford, pp. 831–880.
Turner, M.G., Arthaud, G.J., Engstrom, R.T., Hejl, S.J., Liu, J., 1995. Usefulness of spatially explicit population models in land management. Ecological Applications 5 (1), 12–16.
Van den Bergh, J.C.J.M., Carbonell, A., Munda, G., 2000. Alternative models of individual behaviour and implications for environmental policy. Ecological Economics 32 (1), 43–61.
Watts, C., Gilbert, N., 2011. Does cumulative advantage affect collective learning in science? An agent-based simulation. Scientometrics 89 (1), 437–463.