Responses to referee comments on the manuscript by Müller-Hansen et al.

Referee Comment #1

We thank the referee for his valuable comments. Although we do not agree with all the points, we think that they raise important issues that could be clarified in the paper. Furthermore, a productive ongoing discussion about these issues could help in aligning forces for the important goal of gaining a more holistic understanding of global human-nature interactions by developing Earth system models that include important social and economic dynamics. In the following, we respond point by point to the comments of the referee.

This paper provides an overview of a broad range of representations of human behaviours that might be considered when attempting to 'people' Earth System Models (ESMs). I found the paper to be well researched and written on the whole and if the aim was to inform the reader as to the range of options on offer in this space it did a relatively good job (with one or two notable exceptions which I detail below). However, the title suggests something more, with the stated aim to also offer some guidance over the way forward in this space. This is very much needed given the likely expansion of research this area will experience. Unfortunately, I found this aspect of the paper a

little disappointing given it was rather passive, reserved or limited in any guidance it offered. This was not helped by the structure of the paper which separated out the extensive review of potential methods and the critique of these methods which was largely relegated to the Discussion. If the authors really want to be faithful to their title and stated aims I would suggest some editorial changes. I would start by offering a strong steer on the guiding principles of model framework selection in this space. I would then combine the description of the options with a more hard-hitting critique of the various options assessed against your guiding principles. My reading of the current

paper suggest the author team would be more than able to achieve this and the product would be far more valuable than the largely descriptive review currently tabled. The alternative would be to dilute the title and aims to being those of a review of options as I believe this is what is currently being offered. I would like to encourage the former but providing the title and aims were adjusted the paper could go forward without this reediting. I've ticked the 'major revisions' box but only because I couldn't simultaneously tick the 'minor revisions' box. This depends on which way you chose to jump.

We appreciate the critique of the referee and agree that this work did not deliver on the promise of a general guideline for building ESMs with explicit human decision and behavior components. This is for a specific reason: Such a guideline depends a lot on the concrete research questions that a modeler wants to tackle with the model. Therefore we argue that rather than a concrete guideline, some general principles have to be considered by the modelers and they have to be aware of the various possibilities from the toolbox that the literature provides and we aim to give an overview over. This approach is much in line what researchers from sociology have termed theory of the middle range (Merton, 1957). This approach does not aim at an all-encompassing theory of whole societies, but rather argues for using elements of different theories tailored to a specific problem. The selection of assumptions underlying the modeling approach has to be on the ground of good reasons and empirical evidence. In case of doubt, the validity of assumptions have to be tested for the specific context. Furthermore, we note that an extensive critique of all the different methods would be beyond the scope of a single paper. Where we were aware of such critiques, we provided some references for the readers. However, due to the huge variety of methods, there may be relevant strands of critique which we were not aware of and therefore did not include into the paper. In line with the above considerations, we will change the title and make the aim of the paper clearer in the introduction to avoid misunderstandings. Furthermore, we will make the general point more

prominent, that there is not one method and theory that will fit all relevant research questions, which are interesting in the context of global human-nature interactions. Therefore the approach most appropriate for the question at hand has to be selected taking into account various general considerations as listed in the Discussion part of the paper.

Specific points (in no particular order)

1. I would like to see a full discussion over when ESM peopling might be useful, when it might not and when it might be actively discouraged. Given the huge uncertainties this activity can/will open up researchers need dissuading from the illegitimate and unnecessary hybridisation of social and natural systems models. This paper could offer some guiding principles. For example, although the chosen example of land surface/use parameterisation suggest a useful role for microscopic representations of people, ultimately we are only interested in the structural social dynamics when exploring Earth (i.e. global) scale feedbacks, even if these dynamics arise from the act of an individual. Therefore, at the ESM scale you would have to have a really powerful justification of a highly disaggregated representation of people and there should always be a presumption in favour of the macroscopic representation. The fact that ESMs are spatially disaggregated and therefore we should naturally entertain representations of people at this scale is not sufficient in my view.

We agree with the referee that a discussion about when a "peopling" of ESMs is useful should be added to the paper. We will add some corresponding paragraphs to the paper discussing that this is only relevant if there is a closed loop of interactions with the outcome of relevant decision processes and behaviors changing over the relevant time scales. However, we think that a full-blown discussion of this question could be well suited for a follow-up paper as suggested by the editor.

Regarding the example of the macro- vs. micro-description of a human component in ESMs, we want to note that we do not argue that human behavior always has to be included at a micro-level and on the basis of single actors. But, as we are arguing in the paper, a complete picture of humans in ESMs should be well founded in micro-models of decision making, behavior and interaction. Especially when large societal and institutional changes are considered, models purely based on observed macro-dynamics might not be able to rightly capture these changes (this is referred to as the Lucas-critique in the economic literature). Of course, here again, it depends on the research questions whether a macro model of societal dynamics suffices (assuming that major societal dynamics will not change fundamentally over time) or if a more micro-founded model is needed.

2. The opening text made a big play of the distinction between 'explicit decisions' and 'implicit behaviours'. Close inspection suggests this is a largely arbitrary distinction and some critique of this divide would be a useful addition. Is me typing this response an explicit decision or an implicit behaviour? I'm not sure.

If the question is based on the reading of our definition that decisions are only explicit and there are no implicit processes involved, then we regret the misunderstanding. We reformulated the corresponding paragraph to make it clear that decision-making can be influenced by implicit, unconscious and intuitive processes. In this understanding, the result of a decision process is usually a certain type of behavior.

However, not every behavior has to be the outcome of a decision process, and this is why we have to insist that the distinction between decision making and behavior is analytically useful and not arbitrary. Although in the end, only the behavior of humans may be observable, many behaviors are highly influenced by semantic considerations as well as inscribed social and individual norms and values. For complex cultural settings, it is therefore often not helpful to reduce humans to a reflexresponse scheme as in behaviorist approaches. The only alternative to modeling behavior without explicitly using theory about the decision processes would be to model behavior statistically or at the basis of physiological processes in the brain. Concerning the latter, the science is still in its infancy and it is at least questionable whether such a description is possible at all. Regarding statistical approaches, as explained in the previous point, when looking at strong social changes, statistical correlations might break down calling for the explicit modeling of decision processes.

Apart from these more pragmatic considerations, there is a philosophical argument to be made: From introspection the distinction between behavior as an event of the physical world (i.e., the body) and the decision-making process as at least being influenced by the mind should be clear to every human making conscious decisions. How these different processes interact has been the subject of the age-old debate called the mind-body problem in philosophy. Solving this problem by simply denying the existence of the mind altogether leads to even more serious problems: If we would assume that me typing this response is only a behavioral reaction to a very complex stimulus without any involvement of semantic processing, why should anybody of us care about the semantic content of want we are writing here anyways?

3. Surely the most important distinction in normative framing involving any ESM is whether they adhere to the current socio-economic norm or they represent transitional/ transformative dynamics. Everything else is simply detail. This is not developed at all and yet practically all applications of peopled ESMs will revolve around exploring and contrasting alternatives to business-as-usual. This review is very constrained in this regard, and hardly mentions alternative (and potentially indispensable) economic framings required when investigating, for example, implementation of the Paris Agreement.

We are well aware of the debate between the economic mainstream dominated by neoclassical theory and heterodox schools of economic thought and the different economic framings they involve (see publications of the lead author). To come up with new models of the economy that build on the work done in heterodox branches such as ecological and institutional economics is actually one of the main challenges when building social dynamics into ESMs. Thus, we agree that such models have to go beyond the currently dominant socio-economic framing. However, we tried to avoid an extensive discussion of this debate in the paper. The main goal of this paper is to compare different approaches to modeling human decision making that could be potentially useful to Earth system modeling. Therefore, the paper only considers those economic approaches that use mathematical modeling. Because many of the heterodox economic schools are not much engaged with modeling or event reject mathematical modeling as a valid tool to advance knowledge about social processes, this collection, unfortunately, is much biased towards mainstream economic thinking. If we omitted important and formalized economic modeling approaches in the literature, this is only due to our limited knowledge.

4. Other than discussion of flow consistent approaches, this review makes little or no mention of (bio)physical frameworks as covered in say ecological economics. I appreciate they are not mainstream but I think this is a critical omission because perhaps the most consistent scheme for peopling of ESMs is where both the Earth and social systems are both on a sympathetic '(bio)physical' footing. This could be nicely contrasted against the fact that the standard macroeconomic framings are flow/physically inconsistent. Perhaps it's time for the natural sciences to call the macroeconomic emperor on their lack of physically defensible clothing and peopling ESMs appears to be a great place to start. ESD has been central to getting these alternatives into the literature and it is anomalous that they are not considered here.

A discussion of purely biophysical models is neither the goal nor the focus of our article. We agree that a biophysical description of human activities is crucial for linking classical ESMs and social

science approaches and that physically consistent stock-flow or similar models should be an essential part of ESMs with explicit human dynamics. Therefore, we will improve our account of physical stock-flow consistent modeling and add references to the important work of Nicholas Georgescu-Roegen in this area. We also agree that models of the social metabolism have to take thermodynamic limits into account. However, we doubt that thermodynamic laws alone can account for the complex dynamics of social-metabolic processes as some recent work of the referee and others in this special issue suggest (Garrett, 2014; Garrett, 2015; Jarvis et al., 2016).

5. Much of the problem space that peopled ESMs would explore would be around precautionary Command and Control type policy such as that offered in the Paris Agreement. Here a formal control representation of 'people' is much more appropriate given it is about compliance or non-compliance with a stated environmental objective such as keeping below 2 K. I would like to see some discussion of this.

Actually, a lot of economic reasoning for environmental policy recommendations builds strongly on the control perspective. But as the failure of some of these policies shows, it is not only important to have the formal framework right but also the micro-model of human behavior and decision making to judge how people will react to changes in institutional frameworks. For example, in some settings monetary incentives for environmental behavior might be counterproductive because they can lead to crowding out effects when moral rules are replaced by economic considerations. Therefore, a successful policy assessment needs to select correct micro-models to identify the right approaches for adjustments that influences individual behavior in the right direction. This applies equally to command and control type policies as to other (e.g., market-based) solutions. As suggested by the referee we will add these considerations to the paper.

Referee Comment #2

This paper provides a very comprehensive review of the application of human behavior in earth system models. I was impressed with the coverage and extensive literature review. The paper is well written and will make a valuable contribution to the field. My main concern, which perhaps is unavoidable for such a review, is that the paper is very long, bordering on overwhelming. There are parts that are redundant such as page six, which takes three paragraphs to restate a Table. I suggest the authors search for other places to streamline the paper. The table in the Discussion is an excellent summary. I would recommend publication following minor revision.

We thank the referee for the positive response. We will revise the paper, shorten the suggested parts, and aim at an overall reduction of the text.

List of changes in the manuscript

Important note: The co-author Rainer Hegselmann withdraw his authorship because he was not able to take part in the revision process and held that his contribution to the paper would not justify a co-authorship.

We included all the changes as promised in the above response to the reviewers comments. These include:

- We changed the title.
- We changed the introduction, discussion and abstract to make the goals of the paper clearer.
- We included a part in the introduction explaining that there is no single approach/technique usable for all relevant questions regarding human-nature interactions on a global scale and that researchers have to choose the techniques to model decision making and behavior appropriate for the specific context.
- We added some brief discussion of the question when modeling of human decision making explicitly is useful.
- We extended the discussion of models from the field of ecological economics.
- We made it clear in the introduction that a micro-based approach to human behavior is important for exploring the impact of environmental policies (even from a control-theory perspective).
- We shortened the paper as much as possible, given the requests by the first referee to extend some parts of the introduction, discussion and some subsections of the main parts.

Furthermore, we made the following changes:

- We moved the discussion of the methodological question how to model social systems (methodological individualism vs. structuralist approaches) from the introduction to the second section because it fits there much better.
- We corrected typos in the former version of the paper, changed wording that caused misunderstanding with some readers of the discussion paper and updated the references. A detailed comparison of the original submission and the resubmitted version of the paper can be found below.

%% Copernicus Publications Manuscript Preparation Template for LaTeX Submissions %% ------%% This template should be used for copernicus.cls %% The class file and some style files are bundled in the Copernicus Latex Package, which can be downloaded from the different journal webpages. %% For further assistance please contact Copernicus Publications at: production@copernicus.org %% http://publications.copernicus.org/for_authors/manuscript_preparation.html

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%% 2-column papers and discussion papers
\documentclass[esd]{copernicus}
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%% \usepackage commands included in the copernicus.cls: %\usepackage[german, english]{babel} %\usepackage{tabularx} %\usepackage{cancel} %\usepackage{multirow} %\usepackage{supertabular} %\usepackage{algorithmic} %\usepackage{algorithm} %\usepackage{algorithm} %\usepackage{float} %\usepackage{subfig} %\usepackage{rotating}

\begin{document}

\title{Towards representing human behavior and decision making in Earth system
models - an overview of techniques and approaches}

\Author[1,2]{Finn}{M\"{u}ller-Hansen} \Author[3]{Maja}{Schl\"{u}ter} \Author[4]{Michael}{M\"{a}s} \Author[5, 6]{Rainer}{Hegselmann} \Author[1,3]{Jonathan F.}{Donges} \Author[1,2]{Jakob J.}{Kolb} \Author[1]{Kirsten}{Thonicke} \Author[1]{Jobst}{Heitzig}

\affil[1]{Potsdam Institute for Climate Impact Research, Telegrafenberg A31, 14473 Potsdam, Germany} \affil[2]{Department of Physics, Humboldt University Berlin, Newtonstra{\ss}e 15, 12489 Berlin, Germany} \affil[3]{Stockholm Resilience Center, Stockholm University, Kr\"{a}ftriket 2B, 114 19 Stockholm, Sweden} \affil[4]{Department of Sociology and ICS, University of Groningen, Grote Rozenstraat 31, 9712 TG Groningen, The Netherlands}

```
\affil[5]{Frankfurt School of Finance \& Manangement, Sonnemannstraße 9-11
60314 Frankfurt am Main, Germany}
\affil[6]{Bayreuth Research Center for Modeling and Simulation, Bayreuth
University, Universit\"{a}tsstrasse 30, 95440 Bayreuth, Germany}
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\runningtitle{Approaches to represent human behavior in ESM}

\runningauthor{M\"{u}ller-Hansen et al.}

\correspondence{Finn M\"{u}ller-Hansen (mhansen@pik-potsdam.de)}

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\begin{abstract}

In the AnthropoceneToday, humans have a critical impact on the Earth system and vice versa, which can generate complex feedback processes between social and ecological dynamics. Integrating human behavior into formal Earth System Models (ESMs), however, requires crucial modeling assumptions about actors and their goals, behavioral options and decision rules, as well as modeling decisions regarding human social interactions and the aggregation of individuals' behavior. In this tutorial Here, we review, we compare existing modeling approaches and techniques from differentvarious disciplines and schools of thought dealing with human behavior at variousdifferent levels of decision making. Providing an overview over social-scientific modeling approaches, wewe demonstrate modelers' often vast degrees of freedom but also seek to make modelers aware of the often crucial consequences of seemingly innocent modeling assumptions.

After discussing which <u>socio-economicsocioeconomic</u> units are potentially important for <u>ESMs</u>, we <u>reviewcompare</u> models of individual decision making that correspond to alternative behavioral theories and that make diverse modeling assumptions about individuals' preferences, beliefs, decision rules, and foresight. We <u>discussreview</u> approaches to model social interaction, covering game theoretic frameworks, models of social influence and network models. Finally, we <u>elaboratediscuss</u> approaches to <u>studystudying</u> how the behavior of individuals, groups and organizations can aggregate to complex collective phenomena, discussing agent-based, statistical and representative-agent modeling and economic macro-dynamics. We illustrate the main ingredients of modeling techniques with examples from land-use dynamics as one of the main drivers of environmental change bridging local to global scales. \end{abstract}

\introduction %% \introduction[modified heading if necessary]

Even though Earth system models (<u>ESMs</u>) are used to study <u>and project the</u> human <u>impactimpacts</u> on the complex interdependencies between various compartments of the Earth, humans are not represented <u>explicitly</u> in these models. <u>ESMs</u> consider <u>the</u> human influence usually in terms of scenarios, comparing <u>the impact of</u> <u>alternative narratives about the</u> future <u>developmentdevelopments</u> of key <u>socio-</u> <u>economicsocioeconomic</u> characteristics <u>of</u> human societies. For instance, the <u>IPCC scenario approachprocess</u> uses <u>economic</u> integrated assessment models to compute plausible future emission pathways <u>forfrom</u> energy and land use (<u>RCPs</u>, <u>SSPs</u>).for different scenarios of climate mitigation. These <u>emission</u> projections are thendetermine the radiative forcing used as external input in <u>Earth system</u> <u>modelsESMs</u> to study <u>changes in climate and the consequentits</u> natural impacts \citep{Moss2010, IPCC2014b}. These natural impactsThe latter can, however, have <u>socioeconomic</u> consequences that may be translatedfed back to <u>socio-economic</u> <u>impacts and fed again</u> into the scenario process, leading to an iterative <u>process</u>. However, the <u>dynamic and potentially</u> complex interplay of dynamics of the natural Earth system and <u>human</u> social, cultural and economic responses <u>to</u> them are not captured.

Studying feedback loops between human behavior and the Earth system, projecting its consequences, and developing interventions to manage human impact on the Earth system requires a suitable dynamic representation of human behavior and decision making.

In fact, even a very accurate statistical description of human behavior may be insufficient for several reasons. First, in a closed loop, humans constantly respond to changes in the Earth system, facing novel environmental conditions and decision problems. Hence, their response cannot be predicted with a statistical model. Second, for a correct assessment of different policy options (e.g., command and control policy vs. market-based solutions) a sound theoretical and empirical account of the principles underlying decision making in the relevant context is needed, because they guide the development of intervention programs, such as incentives schemes, social institutions, and nudges \citep{Ostrom1990, Schelling1978, Thaler2009}. A statistical model would not help decision makers identifying handles to influence human behavior.

Incorporating human behavior in <u>ESMs</u> is a <u>complex endeavor</u>. Modeling the <u>interaction between various nonlinear components of the Earth system is already</u> a <u>huge challenge, even though</u>challenging. In contrast to physical laws that traditional <u>ESMs</u> rely on precise natural laws. In order to capture feedbacks between biophysical and social dynamics, it is necessary to explicitly model human decision making and behavior, which can be very heterogeneous. Accordingly, scientificuse as a basis, there is no single theory of human behavior that can be taken as a general law \citep{Rosenberg2012}. The understanding of the determinants of individuals' behavior as well as its collective consequenceshuman behavior is still_limited.

Furthermore, human action is influenced by its determinants often being contingent and socially formed by norms and institutions. This allows a view on social systems as socially constructed realities, which is in stark contrast to the positivist epistemology of one objective reality prevalent in the natural sciences. These epistemological questions may cause misunderstandings between natural and social scientists and show to the fundamental difference between rules in social systems and natural laws.

In the past decades, technological advances and the Internet have brought about unprecedented amounts of data about individual behavior and have led to a rapid growth in computational power. With these advances, new models that include human decision making and behavior could move beyond current approaches and describe for example changes in social norms and preferences, consumer behavior and/or social structure besides purely economic relationships. Contrary to conventional approaches, such coupled models would allow exploring possible complex nonlinear dynamics in the Earth system and reveal potential socialenvironmental tipping points and regime shifts \citep{Filatova2016}. Here, we provide a guide for Earth system modelers to existing modeling approaches describing human behavior and decision making.

Following \citet{Weber1978}, weIn fact, past attempts to develop grand theories have been criticized for being too remote from reality and, as a consequence, hard if not impossible to test empirically \citep{Boudon1981, Hedstrom2009, Hedstrom2010, Merton1957}. Accordingly, many social scientists favor a so-called ``middle-range approach'',

Accordingly, many social scientists favor a so-called `middle-range approach', trying to tailor theoretical models to specific contexts rather than developing overarching, general theories. This acknowledges, for instance, that individuals act in some contexts egoistically and based on rational calculus, while in other contexts they may act altruistically and according to simple heuristics. The principles that determine human decisions depend on, e.g., whether the decision maker has faced the decision problem before, the complexity of the decision, the amount of time and information available to the individual, and whether the decision affects others or is framed in a specific social situation. Likewise, different actor types might apply different decision principles. Furthermore, the decision determinants of agents can be affected by others through social interactions or aggregate outcomes of collective processes.

Here, we give an overview over existing approaches to model human behavior and decision making to provide readers with a toolbox of model ingredients. Rather than promoting one theory and dismissing another, we list decisions that modelers face when modeling humans, point to important modeling options, and discuss methodological principles that help developing the best model for a given purpose.

We define decision making as the cognitive process of <u>deliberately</u> choosing <u>consciously</u> between alternative actions, <u>which may involve analytic as well as</u> <u>intuitive modes of thinking</u>. Actions are intentional and subjectively meaningful activities of an agent. Behavior, in contrast, is a broader concept that also includes unconscious and <u>reflexiveautomatic</u> activities, such as habits <u>and</u> <u>reflexes</u>. The outcome of a decision is therefore a certain type of behavior, which might be explained by a decision-making theory</u>.

In Earth system modelsESMs, only those human decisions and responses behaviors are relevant that have considerable impacts impact on the Earth system. They result from, i.e. primarily behavior towards the environment of a large number of individuals or decisions amplified decisions, e.g. through the social position of the decision-maker or technology. Therefore, this paper also covercovers techniques to model individuals' interactions between agents and to aggregate individual's behavior and interactions to a macro-level. On the micro-level, relevant decisions include for instance reproduction, consumption and production of energy- and material-intensive products, place of living and land use. These decisions lead to aggregate and long-term dynamics in population of populations, production and consumption patterns and migration between countries as well as urban and rural areas.

There are diverse social-science theories explaining human behavior and decision making in environmental and ecological contexts, for example in environmental economics, sociology and psychology. In this paper, we focus on mathematical and computational models of human decision making and behavior. Here, we understand the terms `modeling approach' and `modeling technique' as a class of mathematical or computational structures that can be interpreted as a simplified representation of physical objects and actors or collections thereof, events and processes, causal relations or information flows. Modeling approaches draw on theories of human behavior that make -- often contested -- assumptions about the structure of decision processes. Furthermore, modeling approaches can have different purposes: The objective of descriptive models is to explore empirical questions (e.g., which components and processes can explain the system's dynamics), while normative models aim at answering ethical questions (e.g., which policy we should choose to reach a certain goal). Recent reviews focus on existing modeling approaches and theories that are applied in the context of environmental management and change: For example, \citet{Verburg2016} assess existing modeling approaches and identify challenges for improving these models in order to better understand Anthropocene dynamics. \citet{An2012}, \citet{Meyfroidt2013} and \citet{Schlueter2017} focus on cognitive and behavioral theories in ecological contexts, providing an overview for developers of agent-based land-use and social-ecological models. \citet{Cooke2009} and \citet{Balint2017} review different micro- and macroapproaches with applications to agro-ecology and the economics of climate change, respectively.

The present paper complements this literature by reviewing modeling approaches of (1) individual agent behavior, (2) agent interactions and (3) aggregation of individual behaviors with the aim to support the integration of human decision making and behavior into Earth system models. The combination of these three different categories is crucial to describe human behavior at scales relevant for Earth system dynamics. Furthermore, this review highlights strengths and limitations of different approaches by connecting the modeling techniques and their underlying assumptions about human behavior and discusses criteria to guide modeling choices.

Our survey of techniques has a bias towards economic modeling techniques for two simple reasons: First, economics is the social science discipline that has the longest and strongest tradition in formal modeling of human decision making. Second, economics focuses on the study of production and consumption as well as the allocation of scarce resources. In most industrialized countries today, a major part of human interactions with the environment is mediated through markets, central in economic analyses.

This review aims to go beyond the often narrow framing of economic approaches while at the same time not ignoring important economic insights. For instance, consumption and production decisions do not only follow purely economic calculations but are deeply influenced for instance by behavioral patterns, traditions and social norms \citep{TheWorldBank2015}.

Because we discuss different approaches to model decision making and behavior from various disciplinary or sub-disciplinary scientific fields, there are considerable differences in terminology that make a harmonized presentation of the material challenging. For example, the same terms are used to describe quite separate varieties of an approach in different fields and different terms from separate fields may refer to very similar approaches. We adopt a terminology that aims to a better interdisciplinary understanding and point out different understandings of contested terms where we are aware of them.

This paper works with land-use change as a guiding and illustrative example. Land use and land-cover change is the second largest source of greenhouse gases -- besides the burning of fossil fuels -- and thus contributes strongly to climate change. Behavioral responses related to land use will play a crucial role for successful mitigation and adaptation to projected climatic changes, challenging modelers to represent decision making in models of land-use change \citep{Brown2017}. The complexity of land-use change provides various examples how collective and individual decision making interacts with the environment across spatial scales and organizational levels. Land-use models consider environmental conditions as important factors in decision-making processes, giving rise to feedbacks between environmental and socioeconomic dynamics \citep{Brown2016}.

<u>However, this paper does not provide an exhaustive overview over existing land-use models. For this purpose, the reader is referred to the various reviews in the literature \citep[e.g.,][]{Baker1989, Brown2004, Michetti2012, Groeneveld2017}.</u>

The remainder of the paper is organized as follows. In Section~\ref{sec:levels}, we give an overview over different levels of description of social systems and the socioeconomic units or agents associated with them. Sections \ref{sec:individual_behavior}--\ref{sec:aggregation} form the main part of the paper, presenting different modeling techniques and their underlying assumptions about human decision making and behavior. First, Section \ref{sec:individual_behavior} introduces approaches to model

individual decisions and behavior from rational choice to learning theories. Many of these techniques can be used to also model higher-level social entities. Second, Section \ref{sec:interaction} puts the focus on techniques for modeling interactions between agents. Strategic interactions and social influence are significant determinants of individual decisions and therefore important for long-term changes in collective behavior, i.e. the group outcome of mutually dependent individual decisions. Third, Section \ref{sec:aggregation} reviews different aggregation techniques that allow describing human activities at the level of social collectives or systems. These approaches allow making simplifications so that theories about individual decision making can be scaled up. Figure~\ref{fig:assumptions} summarizes these main parts of the paper, the corresponding modeling approaches and important considerations for model selection, which we discuss in detail in Section~\ref{sec:discussion}. The discussion also reflects on important distinctions between models of natural and social systems that are crucial to consider when including human behavior into ESMs. The paper concludes with remarks on the remaining challenges for this endeavor.

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<u>\section{The challenge: Modeling decision making and behavior across different</u> <u>levels of organization}</u> \label{sec:levels}

Decision making and behavior of humans can be described and analyzed at different levels of social systems. While decisions are made and behavior is performed by individual humans, it is often useful to not represent individual humans in a model but to treat social collectives, such as households, neighborhoods, cities, political and economic organizations, and states, as decision makers or agents.

Figure~\ref{fig:levels} shows a hierarchy of socioeconomic_units, i.e., groups, organizations and structures of individuals that play a crucial role in human interactions with the Earth system. We consider a broad scheme of levels ranging from the micro-level across intermediate levels to the global level. This hierarchy of socioeconomic units is not only distinguishable by level of complexity but also by the different spatial scales involved. However, there is no one-to-one correspondence: For instance, some individuals have impacts at the global level, while many transnational organizations operate at specific local levels. Especially in the context of human-environment interactions in ESMs, scaling and spatial extent are therefore important issues \citep{Gibson2000}. Furthermore, we note that the strict separation between a micro- and macro-level may result in treating very different phenomena alike. For instance, many economic models describe both small businesses and transnational corporations as actors on the micro-level and model their decision processes with the same set of assumptions, even though they operate very differently.

<u>%f</u>

<u>begin{figure*}[t]</u> <u>includegraphics[width=12cm]{fig1.png}</u> <u>caption{Overview of modeling categories, corresponding modeling approaches and</u> <u>techniques discussed in this paper and important considerations for model choice</u> <u>and assumptions about human behavior and decision making.}</u> <u>label{fig:assumptions}</u> <u>lend{figure*}</u> One major challenge for modeling humans in the Earth system is therefore to bridge the diverse levels between individuals and the global scale and integrate different levels of social organization and spatial as well as temporal scales.

The relation between individual agents and social collectives and structures has been the reason forsubject of considerable debate in the social sciences: In the social-scientific tradition of methodological individualism\footnote{We notethough, that there are different accounts of methodological individualism and it often remains unclear to what extend structural and interactionist elements can be part of an explanation, <u>\citep[see \citet{][]{Hodgson2007, Udehn2002</u>}.}, the analysis aims to explain social macro-phenomena, e.g., phenomena at the level of social collectives such as groups, organizations, andor societies, with theories of individual behavior \citep{Coleman1994, Udehn2002, Homans1951} This approach deviates from structuralist traditions, which claim that collective phenomena are of their own kind and can, thus, not be traced back to the behavior of individuals <a href="https://citepforcement.citepf extremes emphasize the interdependency of individual agents and social structure. Structure, which is understood as an emerging phenomenon emerging from the interactions between agents and that stabilizes particular behaviors \citep{Giddens1984}. Coleman1994, Homans1951}.

While it very much depends on the purpose of the given modeling exercise whether the model should represent individuals or collectives (e.g. households, neighborhoods, cities, countries),, we mainly focus here on athe research tradition that acknowledges that complex and unexpected collective phenomena can arise from the interplay of individual behavior.

There are diverse social science theories explaining human behavior and decision making in environmental and ecological contexts, for example in the fields In Table~\ref{tab:levels}, we provide an overview of environmental and ecological economics \citep{Perman2003, VandenBergh2001}, environmental sociology and psychology \citep{Pellow2013}, and many others.

In this paper, we focus on mathematical and computational models of human decision making and behavior. Here, we understand the terms `modeling approach' and `modeling technique' as a class of mathematical or computational structures that can be interpreted as a simplified representation of physical objects and actors or collections thereof, events and processes, causal relations or information flows. Modeling approaches may differ for instance according to (i) variables and parameters that they use to describe the entities of the modeled system, (ii) the logical or functional relationships between modeled entities, (iii) the representation of space and time, if any, and (iv) the kinds of mathématical and computational solution techniques applied to find a solution of the model. The modeling approaches that we review often draw upon theories of human behavior that make -- often contested -- assumptions about the structure of decision processes and the resulting behavior. Furthermore, we want to point out that models of social systems can have socioeconomic units at different purposes, which is levels that are potentially important for the choice of modeling approach. The purpose can be either descriptive (helping to answer empirical questions, e.g., which components can explain the system's dynamics) or normative (helping to answer ethical questions, e.g., how should we act or which policy should we choose to reach a certain goal).

Recent reviews focus on existing modeling approaches and theories that are applied in the context of environmental change: For example, \citet{Verburg2016} assess existing modeling approaches and identify challenges for improving these models in order to better understand the <u>Anthropocene</u>. \citet{<u>Meyfroidt2013</u>} and \citet{<u>Schlueter2017</u>} focus on cognitive and behavioral theories in ecological contexts, providing an overview for developers of agent-based land-use and social-ecological models. \citet{<u>Cooke2009</u>} also classify micro- and macroapproaches and review their applications in <u>agro</u>-ecology. The present paper complements this literature, reviewing modeling approaches of

The present paper complements this literature, reviewing modeling approaches of individual agent behavior, agent interactions and aggregation. The combination of these three different categories is crucial to describe human behavior at a level relevant for ESMs. Furthermore, this review highlight connections between modeling techniques and their underlying assumptions about human behavior and discuss criteria to guide modeling choices. The presented composition and classification of approaches into categories was guided by an iterative process that aims at an interdisciplinary understanding.

This paper works with land-use change as a guiding and illustrative example. Land use and land-cover change is the second largest source of greenhouse gases <u>besides the burning of fossil fuels -- and thus contributes strongly to</u> climate change, one of the most challenging environmental problems of our time. Behavioral responses in the land based sector will play a crucial role for successful mitigation and adaptation to projected climatic changes, challenging modelers to represent decision making in models of land-use change \citep{Brown2017}. The complexity of land-use change provides various examples how collective and individual decision making interacts with the environment across spatial scales and organizational levels. Land-use models consider environmental conditions as important factors in decision-making processes, giving rise to feedbacks between environmental and socio-economic dynamics \citep{Brown2016}. Furthermore, there are first attempts to integrate diverse human decision making explicitly into global models by the use of agent functional types in the context of land-use science \citep[Arneth2014]. However, this paper does not provide an exhaustive overview over existing landuse models. For this purpose, the reader is referred to the various reviews in the literature \citep[e.g.,][]{Baker1989, Brown2004, Michetti2012, Groeneveld2017

The rest of the paper is organized as follows. In Section~\ref{sec:levels}, we give an overview over different levels of description of social systems, the socio-economic units or agents associated with them and the research communities that study them. Sections \ref{sec:<u>individual_behavior</u>}--\ref{sec:aggregation} form the main part of the paper. There, we review the different modeling techniques and their underlying assumptions about human decision making and behavior in detail, following a simple tripartition:

First, Section \ref{sec:individual_behavior} introduces approaches to model individual decisions and behavior. Second, Section \ref{sec:interaction} puts the focus on techniques for modeling interactions between agents. Third, Section \ref{sec:aggregation} reviews different aggregation techniques that allow describing human activities at the system level. Examples from the land-use context are used throughout these sections to illustrate the modeling techniques in a relevant context. Section~\ref{sec:discussion} provides a discussion of criteria and questions for guiding model selection and important distinctions between models of natural and social systems. The paper concludes with remarks on the many remaining challenges for incorporating human behavior into Earth system models.

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\section{The challenge: Modeling decision making and behavior across different levels of organization} \label{sec:levels}

Decision making and behavior of humans can be described and analyzed at different levels of social systems. While decisions are made and behavior is performed by individual humans, it is often useful to not represent individual humans in a model but to treat social collectives, such as households, neighborhoods, cities, organizations and states, as decision makers or agents. However, we argue below that independent of the level of analysis the following main questions are useful to guide the modeling choices regarding decision making of agents: Which goals do individual agents follow? Which constraints restrict the pursuit of these goals? And finally, according to which decision rules do the agents choose an action? Furthermore, when thinking about how to integrate human decision making into Earth system models, we are generally interested in the outcome of aggregate and collective behavior, i.e. the group outcome of mutually interdependent individual decisions, possibly leading to a joint decision. Therefore, a considerable part of this paper will be devoted to providing guidelines to modeling approaches that are organized around two additional questions: In which way do individual agents interact? How are individual decisions and interactions aggregated to phenomena at the level of social collectives? Figure~\ref{fig:assumptions} gives an overview of the modeling approaches that we introduce in detail in Sections~\ref{sec:<u>individual_behavior}--</u> \ref{sec:aggregation} and important considerations for model choice and

assumptions about human behavior and decision making.

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\begin{figure*}[t]

\includegraphics[width=12cm]{fig1.png}

\caption{Overview of modeling categories, corresponding modeling approaches and techniques discussed in this paper and important considerations for model choice and assumptions about human behavior and decision making.} \label{fig:assumptions}

\end{figure*}

A central challenge for integrating human decision making into Earth system models is the bridging of several levels of social organization and collectives as well as across spatial and temporal scales.

Figure~\ref{fig:levels} shows a hierarchy of socio economic units, i.e., groups, organizations and structures of individuals that play a crucial role in human interactions with the Earth system. modeling. We consider a broad scheme of levels ranging from the individual and micro-level across intermediate levels to the macro- and global level. This hierarchy of socio-economic units is not only distinguishable by level of complexity but also by the different spatial scales involved: For instance, some individuals may also operate at the global level while transnational organizations may also have impacts on the local level. Because some socio-economic units span various scales there is no canonical mapping. Especially in the context of human environment interactions in Earth system models, scaling and spatial extent are important issues \citep{Gibson2000}.

Furthermore, we note that the clear distinction between a micro- and macro-level may result in neglecting intermediate levels and treating very different phenomena alike.

For instance, many economic models describe both small businesses and transnational corporations as actors on the micro-level and model their decision processes with the same set of assumptions, even though they operate very differently.

One of the major difficulties for modeling humans in the Earth system is therefore to bridge these diverse levels between individuals and the global population with all its structural complexities.

In Table~\ref{tab:levels}, we summarize the socio-economic units found in Fig~\ref{fig:levels} and connect them to traditional scientific disciplines and fields that focus on them. Additionally, we name some_list common theories, frameworks and assumptions that are made about decision making and human behavior for these socioeconomic units and link them to scientific fields that focus on them.

At the micro-level, models consider individuals, households, families and small businesses. <u>Individuals For instance, individuals</u> can make decisions as policy makers, investors, business managers, consumers, <u>or</u> resource users, or in various other contexts. Communities and disciplines focusing on this level are the cognitive and behavioral sciences, and related fields. More specifically in the context of human-nature interactions interdisciplinary fields like natural resource management, resource and institutional economics, social-ecological and land systems research. At this level, decisions about lifestyle, consumption, individual natural resource use, migration and reproduction are particularly relevant in the environmental context. Individual decisions have to be takenmade by a large number of individuals or have to be multipliedreinforced by organizations, institutions or technology to become relevant at the level of the Earth system. ParticipationIndividuals' participation in collective decision processes, such as voting, may also has potentialhave consequences for the environment at higher levelsa global level.

At various intermediate levels, communities and organizations like firms, political parties, labor unions, educational institutions, non-governmental and lobby organizations play a crucial role in shaping <u>national</u> economic and <u>policypolitical</u> decisions and therefore have a huge impact on aggregate behavior. Governments at different levels and representing different territories, from cities to nation states, enact laws that strongly frame the <u>condition for</u> economic and social activities of their citizens. Fields that are <u>concerned with this level include sociology</u>, <u>political science</u>, <u>economics</u>, <u>management science and anthropology</u>. Important decisions for the Earth system context include environmental regulations and standards, production and distribution of commodities and assets, trade, extraction and use of natural resources (e.g., mining, forestry, burning of fossil fuels) and the development and building of physical infrastructures (e.g., roads, dams, power and telecommunication networks).

At the global level, multinational companies and intergovernmental organizations negotiate decisions. This level <u>may be remote from most individuals</u>, <u>but it</u> has <u>nevertheless hugeconsiderable</u> impacts on policy and business decisions <u>even</u> <u>though it is remote from the daily life of most individuals</u>. Often this level provides framing for activities on lower organizational levels and thus strongly influences the problem statements and perceived solutions for instance regarding environmental issues. <u>Disciplines that focus on this level include</u> <u>macroeconomics, international relations, as well as most of the disciplines</u> <u>important for</u> the Earth system at this level are for instance international climate and trade agreements, decisions of internationally operating corporations and financial institutions, and the adoption of global frameworks like the UN Sustainable Development Goals \citep{UnitedNations2015}.

An overarching question that has triggered considerable debate between different disciplines is the allocation of agency at different levels of description. Even if individuals can decide between numerous options, the perception of options and decisions between them are shaped by social context and institutional embedding. Institutions\footnote{The notion of institution is used in the literature with slightly different meanings: (1) formal and informal rules that shape behavior, (2) informal social order, i.e. regular patterns of behavior, and (3) organizations. Here, we adopt an understanding of institutions as formal (e.g., law, property rights) or informal rules (e.g., norms, religion). However, formal rules often manifest in social, political and economic organizations and informal rules may be shaped by them.} and organizations can display their own dynamics and lead to outcomes unintended by the individuals. On the other hand, theresocial movements can beinitiate disruptive changes in institutional development brought on by social movements. This. The attribution and perception of agency for a specific problem is therefore important to bear in mind when choosing a for the choice of a suitable level of model description for. The following section starts our discussion of different modeling a given problem techniques at the level of individual decision making and behavior.

\begin{figure*}[t]
\includegraphics[width=12cm]{fig2.png}
\caption{Socio-economicSocioeconomic units and their corresponding level and
scales.}
\label{fig:levels}

%f

\end{figure*}

% separating theories and assumptions whould be nice but is hardly practical: most of the discussed theories include techniques as well as assumtions about human behavior and how to aggregate it %t \newcolumntype{L}[1]{>{\raggedright}p{#1}} \begin{table*}[t] \caption{Overview of particular levels of description of socioeconomic socioeconomic units, associated scientific fields/communities and some common approaches and assumptions about decisions and behavior. The list gives a broad overview but is far from being exhaustive.} \label{tab:levels} \begin{tabular}{p{1.5cm} L{3cm} L{3cm} p{4cm} p{4cm}} \tophline Level & Socio-economic unit & Field/CommunitySocioeconomic units & Fields/Communities & Common approaches and theories & Common assumptions about decision making \\ \middlehline \multirow{2}{1.5cm}{Micro} & Individual humans & Psychology, <u>neuroscience</u>, sociology, economics, anthropology & Rational choice, bounded rationality, heuristics, learning theory, complex cognitive architectures & [All assumptions presented in this collumncolumn] $\boldsymbol{\Lambda}$ & Households, families, small businesses & Economics, anthropology & Rational choice, heuristics, social influence & Maximization of consumption, leisure, profits $\backslash \backslash$ \middlehline Intermediate & Communities (villages, neighborhoods), cities & Sociology, anthropology, urban studies & Social influence, networks & Transmission and evolution of cultural traits and traditions $\backslash \backslash$ & Political parties, NGOs, lobby organizations, educational institutions & Political science, sociology & Social influence on networks, strategicStrategic decision making, public/social choice, social influence and evolutionary interactions & Influenced by beliefs and opinions of others, agents Agents form coalitions (and cooperate) to achieve goals, influenced by beliefs and opinions of others $\backslash \backslash$ & Governments & Political science, operations research & Strategic decision making, cost-benefit and welfare analysis, multi-criteria decision making & Agents choose for the common good $\backslash \backslash$ & Nation states, societies & Economics, political science, sociology & welfare maximization, social choice & Majority vote $\boldsymbol{\Lambda}$

\middlehline

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Global & Multinational firms, trade networks &
Economics, management science &
Rational choice &
Maximization of profits or shareholder value
\boldsymbol{\Lambda}
& Intergovernmental organizations &
Political science (international relations) &
Strategic decision making, cost-benefit analysis &
Coalition formation
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In the following three sections, we introduce the modeling techniques that are
used in the literature to describe human behavior, interactions between
individuals, and to aggregate them between the different levels. We start this
overview at the level of individual behavior.
\section{Modeling individual behavior and decision making}
\label{sec:individual_behavior}
In a nutshell, models of individual decision making and behavior differ with
regard to their assumptions about three crucial determinants of human choices:
goals, restrictions and decision rules \citep{Hedstrom2005, Lindenberg2001,
Lindenberg1990, Lindenberg1985}.
First, allthe models assume that individuals have motives-or, goals or
preferences. That is, agents rank goods or outcomes in terms of their
desirability and seek to realize highly ranked outcomes. For instance, learning
theories assume that actors evaluate the outcome of their choices and that
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satisficing decisions are reinforced. Other models, such as rational choice theory, make more complex assumptions about preference relations \citep{Neumann1944}. Another prominent but debated assumption is that motivesA prominent but debated assumption of many models is that preferences or goals are assumed to be stable over time. Stable preferences are included to prevent researchers from developing trivial explanations, as a theory that models a given change in behavior only based on changed motivespreferences does not have explanatory power. However, empirical research shows that preferences can change even in relatively short time frames \citep{Ackermann2016}. Furthermore, changingChanging individuals' goals or preferences is an important waymechanism to affect their behavior, e.g., through policies, making flexible preferences particularly interesting for Earth SystemSystem modelers.

Second, alldecision models make assumptions about restrictions and opportunities that constrain or help the agents to follow the motives or pursue their goals. For instance, each behavioral option comes with certain costs (e.g., money and time) and decision makers form more or less accurate beliefs about these costs and how likely they are to occur, depending on the information available to the agent.

Third, actorsmodels assume that agents apply some decision rule that translates their preferences and restrictions into a choice. Although decision rules differ very much in their complexity, they can be categorized into three types. First, there are decision rules that are forward looking. Rational choice theory, for

instance, assumes that individuals list all positive and negative future consequences of a decision and choose the optimal option. Alternatively, backwards looking approaches, such as classical reinforcement learning, assume that actors remember the satisfaction experienced when they chose a given behavior in the past and tend to choose thea behavior that felt bestwith a high satisfaction again. Finally, there are sideward-looking decision rules, which assume that actors adopt the behavior of others, for instance because they imitate successful others \citep{Kandori1993}. DecisionTheories assume different degrees of context-dependency of rules are interlinked withand make different implicit assumptions about the agent'sunderlying cognitive capabilities of agents.

In the remainder of this section, we describe in more detail three important models of approaches to individual decision making: models of rational choice, models of bounded rationality and learning models. For each model we discuss, pointing out typical assumptions about motives, restrictions and decision rules. In Section-\ref{sec:discussion} we provide general guidelines for the choice of model assumptions.

\subsection{Optimal decisions and utility theory in rational choice models} \label{sec:rational_choice}

\emph{Rational choice theory},
a standard model in many social sciences including economics and

widely studied in mathematics,

assumes that decision making is an approach to model goal-oriented decision making. Rational choice models assume that :

rational agents have \emph{preferences}, representing goals that they try to pursue } and choose the strategy whose expected outcome is

most preferred,

given a number of some external \emph{constraints}. Agents choose the action that brings about the most preferred outcome.}

Some versions of rational choice theory also take into account that agents form and potentially based on their \emph{beliefs} about external constraints on their decision options

\citep[represented by subjective

probability distributions, see beliefs, preferences, constraints (BPC) model,][]{Gintis2009}. Beliefs are subjective priors that can be shared among agents, but contrary to external constraints they can be wrong. Rational choice theory is a standard model in various social sciences, especially in economics, and has been widely studied also in mathematics.

The qualification of a decision or action as being rational It can either be used to represent actual behavior or serve as a

normative benchmark for other theories of behavior.

How to judge the ``rationality'' of individual decisions
subject to ongoing debates. For example,

\citet{Opp1999} distinguishes between—a

strong and weak version of rational choice theory. While the strong version (often referred to as rationality (``homo economicus) describeseconomicus''), assuming purely self-interested agents that have full control and knowledge of theirwith unlimited cognitive

capacities knowing all possible actions, information about the and probabilities of possible consequences-<u>,</u>

and unlimited capacities to compute the optimal decision to take, a weaker version relaxes theseweak rationality that makes less strong assumptions. Other authors like \citet{Rabin2002} further distinguishdistinguishes between standard and non-standard

assumptions regarding preferences, beliefs and decision-making rules. In the remainder of this

Before discussing non-optimal decision making in subsection, \ref{sec:bounded_rationality}, we discuss the differentreview here common assumptions regardingon preferences and beliefs, while in the next subsection (\ref{sec:bounded_rationality}) we introduce decision-making rules that deviate from the standard that agents always choose the optimal action.

Usually <u>individual preferences</u>, <u>agents</u> are assumed to be fixed over the relevant time scales, to regard possible outcomes of actions and <u>mainly self</u><u>interested</u>,

having fixed preferences regarding their personal consequences for the agent (self-interest or even ``selfishness'', in particularly assumed by economics scholars), and to take into account risk in some way (see below).of

In general, however, preferences are completely neutral with regard to their contentpossible futures and

being indifferent to how a decision was taken and, for example, can also concern features of collective decision processes \citep[to consequences for others.

Exceptions are procedural preferences, e.g.,][]{\citep{Hansson1996, Fehr1999}}
and consequences for others \citep[

other-regarding preferences and altruism, e.g.,][]{\citep{Mueller2003, Fehr2003}.

In the broadest version, preferences are Preferences can be modeled as binary \emph{preference relations}, e.g. $x \$

 $P_i \setminus y_{\frac{5}{2}}$ denoting that individual \$i\$ prefers $\frac{5}{2}$ to $\frac{5}{2}$, where $\frac{5}{2}$ and $\frac{5}{2}$ represent outcomes, consequences, processes, combinations thereof, or probability distributions of such.situation or outcome $\frac{5}{2}$ to $\frac{5}{2}$. Standard versions of rational choice theoryMost authors assume that the binary relations $\frac{5}{2}$ are is complete (for every pair $\frac{5}{2}$ then $\frac{5}{2}$ either $\frac{5}{2}$ or $\frac{5}{2}$ $P_i x_s$) and transitive (if $\frac{5}{2}$ P_i y_s and $\frac{5}{2}$ P_i z_s then $\frac{5}{2}$, although more general preference relations are possible $\frac{1}{2}$ then $\frac{5}{2}$. Heitzig2012]. These properties allow it to be represented by which allows representing the preferences with a $\frac{1}{2}$

 $\frac{(x)^{2} - (x)^{2} + (x$

Some authors also allow incomplete or cyclic preferences \citep{Fishburn1968, Heitzig2012}.

In the context of land use context, \$i\$ could be a farmer and, \$x\$ might denote a state of affairs, where \$i\$ grows growing

some traditional crops generating a moderate profit. In addition,, and \$y\$ could denote an alternative state of affairs where \$i\$ instead grows some genetically modifiedgrowing hybrid seeds generatingfor more profit but puttingmaking \$i\$ into a strong dependencydependent on the seed supplier. Then, $$x \ P_i \ y$$ would denote \$i\$'s preference of \$x\$ over \$y\$ because he If \$i\$ considers independence valuable enough to make up for the lower profit. $$x \ P_i \ y$$ would denote \$i\$'s preference of \$x\$ over \$y\$.

Utility functions are particularly useful in the context of \emph{decision making under uncertainty}\footnote{We note that some authors make the distinction between risk as unknown events with measurable probabilities (``known unknowns'') as opposed to (fundamental) uncertainty as such events without any knowledge about their probabilities \citep[``unknown unknowns'', cp.][]{Knight2006}. Although fundamental uncertainty may be important in human decision making, we only consider risk here because some forms of fundamental uncertainty cannot be represented in models.}.

To determine the optimal decision under probabilistic uncertainty, the standard \emph{expected utility theory} is usually applied to calculate the utility $u_i(p)$ of a \emph{lottery} or \emph{risky prospect} (i.e. a probabilistic outcome) \$p\$ represented by probabilities p(x) as the linear combination $u_i(p) = \sum_{n decision making under uncertainty, agents have to choose between$ $different \emph{risky prospects} modeled as probability distributions$

\$p(x)\$ over outcomes \$x\$. In \emph{expected utility theory}, \$p\$ is preferred to $\frac{p'\$}{if and only if \$\sum_x p(x) u_i(x)\$.} > \sum_x p'(x) u_i(x)\$.$ Empirical research however shows that only a minority of people evaluate lotteries uncertainty in this \emph{risk-neutral} way \citep{Kahneman1979}. The vast majority, however, overestimates \emph{Prospect theory} therefore models agents that overestimate small probabilities and showsand evaluate outcomes relative to a reference point, which leads to \emph{risk-aversionaverse} or \emph{risk-seeking} with respect to behavior regarding losses or gains in comparison with expected utility theory. Such decisions are described by \emph{prospect theory}, using the non-linear formula $u_i(p) = \sum w_p(x) v(u_i(x))$ respectively. \citep{Kahneman1979}, or by the slightly more complex \emph{cumulative prospect theory} \citep[e.g.,][]{, Bruhin2010}. A conceptual example from the land-use context illustrates decision making under risk: A farmer \$i\$ might face the choice whether to stick to her current crop-(\$ \$x\$)\$ or switch to a differentnew crop (\$\$y\$).. \$. She may think that with 20\% probability the switch will turn out badly, resulting in only a quarter as much yield as with \$x\$, result in a 50\% reduction in her profits, while with 80\% probability, the yieldprofits would double. If her utility depends logarithmically on yield is proportional to the profits and she evaluates this uncertain prospect as described by expected utility theory, her gain from switching to \$y\$ would be positive. If, however, she is averse to losses and thus conforms to prospect theory, she might evaluate the switch as negative and prefer to stick to x. If behavior and its consequences involve several time points \$t\$, then \emph{time \$ are involved in a decision, agents are typically assumed to \emph{discount} future consequences by using utility weights that decay in time and reflect the agent's time preferences} and \emph{patience} are often taken into account via \emph{discounting}... Discounted utility quantifies the present desirability of some utility obtained in the future. Therefore, discounting can be used to measure the utility that an individual derives at a given point in time from future consequences of her current decisions. Exponential discounting is often used in models Most authors use exponentially decaying weights of the form \$e^{-rt}\$ with a \emph{discounting rate} \$r>0\$ because it is mathematically convenient and \emph{time-consistent}, meaning that itthis makes no difference at which point in time the evaluation is made. independent of its time point. However, empirical research findsstudies suggest that people seem to discount hyperbolically, meaning that their valuation in the short-term declines much faster thanoften use slower decaying weights (e.g., hyperbolic discounting), especially in the long term. This is \emph{time inconsistent} because people might prefer getting one dollar today over two dollars tomorrow but two dollars in a month and a day over one dollar in a month presence of uncertainty \citep{Ainslie1992, Jamison2011}.\footnote{For exponential discounting, future (expected) utility is depreciated with an exponentially decaying factor \$u_i(x) = $\sum_{x,y} \frac{1}{x,t}$, while for hyperbolic discounting the factor decays slower in the far future $u_i(x) = u_i(x,t) / (1 + r t)^{s}$ Consider as an example from the land-use context aalthough this might lead to \emph{time-inconsistent} choices that appear suboptimal at a later time. A farmer \$i\$ who comparesmay compare different crops not only by next year's expected profit \$u_i(x,1)\$ but, due to the various crops' different effects on future soil quality, also by future years' profits $u_i(x,t)$ for t > 1. Crop \$y\$ might promise higher yields than \$x\$ in the short run but lower

ones in the long run due to faster soil depletion, so that although $u_i(x,1) > u_i(y,1)$, it might still be that her evaluation of this utility stream is $u_i(x) < u_i(y)$, but only if .

 $\frac{1}{(x)} < u_i(y)$, but only if ______. If \$i\$ is ``patient'' enough, i.e., if the discounting rate \$r\$ is, having small enough. Enough \$\frac{1}{x}\$, she might prefer \$y\,P_i\,x\$

In addition, preference aggregation even though $u_i(x,1) > u_i(y,1)$.

<u>Preferences</u> can <u>also</u> be <u>necessary</u>aggregated not only in time but</u> across <u>independent or coupled decisions dealing with</u> several interrelated issues or types of consequences.

For example, in the modeling of preferences over \emph{consumption bundles} in consumer theory \citep{Varian2010}, models preferences over \emph{consumption bundles},

combining the utility derived from consuming \$n\$ apples, \$u_{i,a}(n)\$ and \$m\$ pears, \$u_{i,p}(m)\$, may be combined different products

into a total consumption utility by means of an \emph{additively separable}
utility function \$u_i(n,m) = u_{i,a}(n) + u_{i,p}(m)\$, a \emph{Cobb-Douglas}
utility function \$u_i(n,m) = u_{i,a}(n)^\alpha u_{i,p}(m)^{1 - \alpha}\$, or a
\emph{constant elasticity of substitution} (CES) utility function \$(u_{i,a}(n)^r
+ u_{i,p}(m)^r)^{1/r}\$ representing different forms of

by simply adding-up these utilities or by combining them in some nonlinear way

with imperfect \emph{substitutability of goods}. In the land-use context,}
(\emph{Leontieff}, \emph{Cobb-Douglas}, or \emph{CES} utility functions).
A farmers' utility from leisure time \$h_x\$ and consumption enabled by work in

the field that increases and crop yield \$y_x\$-(1)\$ depending on working time \$1\$ might for example be combined in a similar way (e.g. via ausing the Cobb-Douglas utility function

 $u_i(x) = y_x^a(alpha (12-h_xl)^{1-alpha})$ for some $emph{elasticity}$ Given constraints by the environment, the available information and the evaluation by utility resulting from each possible action, rational choice theory assumes that the agent chooses the action with the maximal utility. In models, the resulting optimization problem is alpha(0,1).

<u>Complex optimization problems arising from rational choice theory</u> <u>can be</u> solved <u>using tools such as \emph{by</u> mathematical programming} (e.g. <u>linear programming) or \emph{,</u> calculus of variations} and similar methods \citep[see, e.g.,][]{<u>Kamien2012</u>, <u>Chong2013</u>}. Optimal decisions under constraints are not only discussed as a description of human behavior, but are often taken as the normative benchmark for comparison with other

non-optimal approaches that we discuss in the following section. Section~\ref{sec:bounded_rationality}.

Regarding decision-_modeling in Earth system modelsESMs, rational choice theory is useful for contexts in which the agents' when agents have clear goals are sufficiently clear, agents can be assumed to posses and possess enough information, time and cognitive resources to assess all available options for action. the optimality of strategies. For instance, individuals' decisions regarding long-term investments or decisions of organizations such as firms or governments in competitive situations can often be assumed to follow reasonably well a rational action model. However, rational choice model. It can also be a useful assumption when actors make the same decision many times and get immediaterepeated similar decisions and can learn optimal strategies from fast feedback, so that they learn to choose the optimal option. Thus, they making them behave <u>``</u>`as if''if' they were rational decision makers.

\subsection{Bounded rationality and heuristic decision making}

\label{sec:bounded_rationality}

Empirical research on human decision making finds that individual behavior depends on the framing and context of the decision \citep{Tversky1974}. Human decision making is characterized by deviations from the normative standards of the rational choice model, so-called \emph{cognitive biases}, challenging the understanding that rational choice theory serves not only as a normative benchmark, but also as a descriptive model of individual decision making. Biases can be the result of time-limited information processing \citep{Hilbert2012}, heuristic decision making \citep{Simon1956}, or emotional influences influences.com influences.com Loewenstein2003 Loewenstein2003 Loewenstein2003 **\emph{Bounded rationality theory} assumes that human decision making is** constrained by \emph{cognitive} and computational capabilities of the agents, additionally to the constraints imposed by the environment and the available information about it \citep{Simon1956, Simon1997}. In the economic literature, non-transitive preferences, time-inconsistent discounting and deviations from expected utility that we already introduced in the previous subsection are often also considered as boundedly rational citepfointis2009}. Boundedly rational agents can be considered as \emph{satisficers} that try to find a satisfying action in a situation given their available information and cognitive capabilities \citep{Gigerenzer2002}.

Constraints on information processing imply that agents do not <u>integrate all the</u> <u>available information to</u> compute the utility of every possible option in complex decision situations and choose <u>the onean action</u> with maximal utility. Instead, <u>agent decisionsagents</u> use \emph{heuristics} for judging the available information and choosing actions that lead to the more preferred outcome over less preferred ones. \citet{<u>Gigerenzer2011</u>} <u>definesdefine</u> heuristics in decision making as a ``strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods.''-<u>In contrast to so-called `as if' models of human decision making that</u> <u>mathematically integrate all available information to mimic the outcome of the</u> <u>decision process</u>, <u>heuristic decision making taps into the process of information</u> <u>gathering and processing and describes it in the form of simple algorithmic</u> <u>rules.</u>

Heuristics are considered to be \emph{fast and frugal} in the sense that they do not solve algebraic or optimization problems and evaluate only part of the available information. Consequently, they are well suited for computationally efficient implementations of human decision making in models.

Furthermore, \citet{Gigerenzer1999} argue that many of the decision theories being used as a benchmark for rationality are not designed for so called `large worlds' where information relevant for the decision process is either unknown or has to be estimated from small samples. They question the usefulness of rational choice theory as the normative standard and try to relieve heuristic decision making of its stigma of cognitive laziness, bias and irrationality. In many real world situations, especially when high uncertainties are involved, some decision heuristics perform equally good or even better than more elaborated decision strategies \citep{Dhami2001a, Dhami2001b, Keller2014}. Therefore, it is argued that instead of an all-purpose tool the mind carries an 'adaptive toolbox' of different heuristic decision schemes, that are ecologically rational\footnote{Ecological rationality claims that rational decisions should not be made based on rules that are independent of the circumstances (as for example in rational choice theory) but on context-specific ones such as heuristics, making heuristic decision making also a normative choice model.} in particular environments \citep{Gigerenzer2002, Todd2007}.

It is argued that instead of an all-purpose tool the mind carries an ``adaptive toolbox'' of different heuristic decision schemes applicable in particular environments \citep{Gigerenzer2002, Todd2007}.

In general, heuristic rules are formalized either as **\emph**{decision trees} or **\emph**{flowcharts} and consist of three building blocks: one for information

search, one for stopping information search and one to derive a decision from the information found. They evaluate a number of pieces of information -- socalled cues -- to either categorize a certain object or to choose between several options. Many heuristics evaluate these cues in a certain order and make a decision as soon as a cue value allows classification or discriminates between options. This is illustrated by means of the \emph{Take the Best heuristic}: Pieces of information (cues) are compared between alternatives according to a prescribed order until one cue discriminates between the alternatives under consideration. At each step in the cue order of the decision process, some information is searched and evaluated. If it allows discriminating between the options, the option with the higher cue value is chosen. Else the process moves on to the next cue. This repeats as the process moves down the cue order until a cue is reached where the differentiation between options is possible. For the 'Take the Best' heuristic, the order in which the cues are evaluated is crucial for the result.

OtherThis is illustrated by means of the \emph{Take the Best heuristic}: Pieces of information (cues) are compared between alternatives according to a prescribed order, which is crucial for the decision process. At each step in the cue order, some information is searched and evaluated. If the information does not allow discriminating between the options, the process moves on to the next cue. This repeats as the process moves down the cue order until a cue is reached where the differentiation between options is possible and the option with the higher cue value is chosen.

Another notable examples are \emph{Fast and Frugal Trees} and example is the \emph{satisficing heuristics}. The latterheuristic} that evaluates information sequentially and chooses the first option satisfying certain criteria. An everview and explanation of numerous other decision heuristics can be found in the recent review paper by \citet{Gigerenzer2011}.

Heuristics, especially cue orders, can also be interpreted as encoding norms and preferences in individual decision making as they prioritize features of different options over others and hierarchically structure the evaluation of available information.

<u>An overview and explanation of numerous other decision heuristics can be found</u> <u>in the recent review paper by \citet{Gigerenzer2011}</u>.

\citet{Gigerenzer1999} question the usefulness of rational choice theory as the normative benchmark because it is not designed for so-called `large worlds' where information relevant for the decision process is either unknown or has to be estimated from small samples. Instead, they want to relieve heuristic decision making of its stigma of cognitive laziness, bias and irrationality. With their account of ecological rationality, they suggest that heuristics can also serve as a normative choice model providing context-specific rules for normative questions. This is motivated by the observation that in many real world situations, especially when high uncertainties are involved, some decision heuristics perform equally good or even better than more elaborated decision strategies \citep{Dhami2001a, Dhami2001b, Keller2014}.

So far, heuristics have primarily been studied for inferences rather than preferences. Nevertheless, the same frameworks can also be used to describe decisions based on preferences, such as for instance in consumer choice \citep{Hauser2009}, voter behavior \citep{Lau2006}, or and organizational behavior \citep{Loock2015, Simon1997}.

Also, recent findings suggest that cue orders can spread via social learning and social influence \citep{Gigerenzer2008, Hertwig2009} analogously to norm and opinion spreading in social networks (see Sections \ref{sec:social_influence} and \ref{sec:networks}). Therefore, heuristics might be used to shed light on the implications of changing norms and values for individual and collective behavior.

Despite the many upsides of However, Fast and Frugal decision heuristics, they are not yet commonly applied in dynamic modeling of social-ecological systemshuman-nature interactions. One exception is the description of farmer and pastoralist behavior in a study of origins of conflict in east Africa \citep{Kennedy2011}. However, as the following example shows, similar decision trees can behave been used to model decision making in agent-based simulations of land-use change \citep. The model by \citet{Deadman2004}. The model} describes colonist household decisions in the Amazon rainforest. Each household is a potential farmer who first checks whether a subsistence requirement is met. If this is not the case, the household farms annual plantscrops. If the subsistence requirement is met, the household checks the quality of the soil. In the case of acidic soil, it_eventually plants perennials. In the case of nonacidic soil, it plants pasture and breed or breeds livestock. If the activities are not affordable, the household does not farm at all, depending on the soil quality.

The model shows how <u>simple</u> heuristic decision trees can be used to simplify complex decision processes and represent them in an intelligible way. However, the example also shows the many degrees of freedom in the construction of heuristics, pointing at the difficulty to obtain these structures from empirical research.

Heuristics are a promising tool for including individual human decision making at the micro-level into Earth system modelsinto ESMs because they can capture basic crucial choices in a computationally efficient way. In order to describe the long-term evolution of preferences, norms and values, which might play an important role relevant for human influences on interactions with the Earth system, heuristics could also be used to model meta-decisiondecisions of preference andor value adoption. Recent findings suggest that cue orders can spread via social learning and social influence \citep{Gigerenzer2008, Hertwig2009} analogously to norm and opinion spreading in social networks (see Sections \ref{sec:social_influence} and \ref{sec:networks}), which could be an promising approach to model social change.

However, in contrast to fully rational decision making, it can be very challenging to aggregate heuristic decision making <u>analytically</u> to higher organizational levels. Therefore, <u>computational methodsapproaches</u> like agentbased modeling are <u>neededsuitable</u> to explore the aggregate outcomes of <u>many</u> <u>agents with</u> such decision <u>processes</u>, <u>which has implications for the possible</u> <u>analysesrules</u> (see Section~\ref{sec:<u>abm</u>}).

\subsection{Learning theory} \label{sec:learning}

The approaches discussed in the previous two subsections mainly took the perspective of a forward-looking agent. Rational or <u>boundedly</u> rational actors optimize future payoffs based on information or beliefs about how their behavior affects future payoffs, while the procedures to optimize may be more or less bounded.

However, these techniques do not specify how the information is acquired and how the beliefs are formed. Therefore, another branch of modeling

\emph{Computational learning theory} focuses on behavior from a backward-looking behaviorperspective: an agent learned in the past that a certain action gives a reward (or, feels good) or is satisfying and is therefore the agent repeats itsmore likely to repeat this behavior. It can describe the adaptivity of agent behavior to a changing environment and is particularly suited for modeling behavior under limited information. To model the learning of agents unsupervised learning techniques are mostly used because they do not require a training with an external correction.

Computational learning theory focuses on this narrow understanding of learning. It can help to capture the adaptivity of agent behavior and is particularly suited for modeling behavior under limited information.

\emph{Reinforcement learning} is such a modeling approachtechnique that capturesmodels how an agent maps- environmental conditions to desirable actions in a way that optimizes a stream of rewards (and/or punishments). The obtained reward depends on the state of the environment and the chosen action, but may also be influenced by chosen actions and environmental conditions in the past. According to citet{Macy2013}, reinforcement learning differs from forwardlooking behavioral models regarding three key aspects: $(\frac{1}{2})$ Because agents explore the likely consequences and learn from outcomes that actually occurred rather than those which are intended to occur but only with a certain probability, reinforcement learning does not need to assume that the consequences are intended. (ii2) Decisions are guided by rewards fosteringthat foster approach or punishment leadingand lead to avoidance rather than by static utilities. (iii) Rather than optimization, decisions rules are(3) Learning is characterized by stepwise melioration and models the dynamic search for an optimum rather than assuming that the optimal strategy can be determined right away.

The learning process is modeled via a learning algorithm that operationalizes different strategies of trial and error, (e.g. by a simple., Q-Learning, SARSA-Learning, Actor-Critic-Learning), based on iteratively evaluating the current value function or of the environmental state utilizing a temporal difference (Qlearning) algorithms or artificial neural network approacheserror of expected value and experience value \citep{Sutton1998}. Some learningArtificial neural network algorithms can explore very high dimensional state and action spaces. Genetic algorithms have also been, which are inspired by the process of naturalevolutionary mechanisms such as mutation and selection (\emph{genetic algorithms})., are also applied to learning problems. The learning algorithm has to balance a trade-off between the exploration of actions with unknown consequences and the exploitation of current knowledge. In order to not having to explore all possible actions by brute forceexploit only the currently learned strategy, many algorithms use randomness to includeinduce deviations from already learned behavior.

The environment in reinforcement learning problems is often modeled as awith Markovian transition probabilities. The special case of a single agent is called Markov decision process \citep{Bellman1957}. In each of the discrete states of the environment the agent can choose from a set of possible actions. The choice then influences the transition probabilities to the next state and the reward. Reinforcement learning is an unsupervised learning technique as opposed to supervised learning, which requires that optimal responses are presented and therefore trained with an external correction. Therefore, it is suitable to model the learning of agents. As an illustration from the land-use context, consider a farmer adapting her planting and irrigation practices to new climatic conditions by adjusting the timing. The environment could be modeled by a Markov process with different states of soil fertility and moisture, where transitions between states reflect the influence of sowing, irrigation and harvesting.stochastic weather events. Without the possibility to acquire knowledge through other channels, she would experiment in some way with theexplore different possible adjustments actions and evaluate how they change the yield (her reward). Eventually, by a trial-and-error process her yield would on average increase.

A <u>standard_common</u> approach to model the acquisition of \emph{subjective probabilities} associated with the consequences of actions is \emph{Bayesian learning}, which has also been applied to reinforcement learning problems \citep{Vlassis2012}. Starting with some prior probability (e.g. from some highentropy ``uninformative'' distribution) $P(h_i)$ that some hypothesis h_i about the relation of actions and outcomes is true, new information or evidence P(E) is used to update the subjective probability with the posterior $P(E|h_i)$ calculated with Bayes' theorem: $P(h_i|E) = P(E|h_i) P(h_i) / P(E)$ P(E) \citep{Puga2015}. The most probable hypothesis can then be chosen to determine further action. Combining various approaches to model the acquisition of beliefs through learning, the formation of preferences and different decision rules <u>discussed in</u> <u>the previous sections</u> with further insights from psychology and <u>neuroscience</u> has led to the development of very diverse and detailed behavioral theories which are often formalized in \emph{complex cognitive architectures} \citep{<u>Balke2014</u>}. These approaches can <u>also</u> be used to <u>modeldescribe</u> human behavior <u>in computational models</u>, but <u>we will notare too complex and complex and diverse to</u> discuss them <u>here</u> in detail <u>here because of their complexity and</u> <u>diverse formalization</u>.

Learning and related theories that emphasize the adaptability of human behavior might be important building blocks to model on the one hand the long-term evolution of human interactions with the Earth system from an individual perspective. On the other hand, they can capture also short-term responses to drastically changing natural environments, which might give insights on behavioral transformations relevant for instance in the future context of tipping elements in the Earth system.

Table~\ref{tab:individual} summarizes the approaches that focus on individual human behavior. However, besidesBesides the forward- and backward-looking behavior that we introduced in this section, agents may exhibit sideways-looking behavior: agents can copy the behavior of successful others, thereby contributing to a \emph{social learning} process. For this kind of behavior, interactions between different agents are crucial. This will be the focus of the next section.

%t

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\begin{table*}[t]
\caption{Summary table for individual behavior and decision making}
\label{tab:individual}
\begin{tabular}{L{4cm}p{4cm}p{4cm}p{4cm}}
\tophline
Theories & Key considerations & Strengths & Limitations \\
\middlehline
Optimal decisions in rational choice: Individuals take the decision that
maximizes their expected utility given economic, social and environmental
constraints &
What are agent's preferences? Which information (and beliefs) do they have? &
Highly researched theory with strong theoretical foundation and many
applications &
Individuals assumed to have strong capabilities for information processing and
perfect self-control
\boldsymbol{\Lambda}
\middlehline
Bounded rationality and heuristic decision making:
Individuals have biases and heuristic decision rules that help them navigate
complex environments effectively &
Which cue order is used to gather and evaluate information?
When do agents stop gathering more information and decide? &
Simple decision processes that capture observed biases in decision making &
Suitable decision rules highly context dependent
\backslash \backslash
\middlehline
Learning: Agents explore possible actions through repeated learning from similar
past eventsexperience &
```

How do agents interact with their environment?

What is the trade-off between exploitation of knowledge and exploration of new options? & Captures information and belief acquisition process & High degree of randomness in behavioral changes

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\\
\bottomhline
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\end{tabular}
\belowtable{} % Table Footnotes
\end{table*}
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\section{Modeling interactions between agents} \label{sec:interaction}

In the previous section, we discussed modeling approaches that focus on the choices of individuals that are confronted with a decision in a specified situation. In contrast, this section focuses on interaction between individuals or groups of agents, decisions where reviews techniques to model how actors interact with each other and influence or respond to each other. We review different kinds of direct interactions and techniques to model them. Direct interactions are usually local and take place between two (or sometimes a few) agents. Indirect interactions other's decisions. Interactions at the system level that can happen at broader scales, for instance mediated through priceare also aggregation mechanisms on (e.g., voting procedures and markets₇) will be discussed as part of Section~\ref{sec:aggregation}.

The section starts with reviewing strategic interactions as modeled in classical game theory and dynamic interactions withinin evolutionary approaches and social learning. Then, we address models of social influence that are used to study opinion and preference formation or the transmission of cultural traits, i.e. culturally significant behaviors.

Finally, we discuss how interaction structures can be modeled <u>onas dynamic</u> networks.

\subsection{Strategic interactions between rational agents: classical game theory} \label{sec:game_theory}

Game theory focuses on <u>situations</u> <u>decision problems</u> of ``strategic interdependence'', <u>decision problems wherein which</u> the utility that a decisionmaker (called player) gets does not only depend on her own decision but also on the choices of others. These are often situations of conflict or cooperation. Players choose an action (behavioral option, control) based on a \emph{strategy}, i.e. a rule specifying which action to take in a given situation. \emph{Classical game theory} explores how rational actors identify strategies, usually assuming the rationality of other players. However, rational players can also base their choices on beliefs about others players' decisions, which can lead to an infinite regress of mutual beliefs about each others' decisions.

Formally, a game is described by what game-theorists call a \emph{game form} or \emph{mechanism}. The game form specifies the actions $a_i(t)$ that agents can choose at well-defined time points t from an \emph{action set} $A_i(t)$ that may vary over time, having to respect all kinds of situation-dependent rules. The game form may furthermore allow for communication with the other agent(s) (\emph{signaling}) or binding agreements (\emph{commitment power}). Simple social situations are typicallyformalized in so-called normal-form games represented as ``normal form games'' by a \emph{payoff matrix} specifying the individual utilities are unexplained attributes of the agents and need not have a relation to monetary quantities.} for all possible action combinations, while more complex situations are modeled as a stepwise movement through the nodes of a decision tree or game tree \citep{Gintis2009}.

In particular, classicalClassical game theory assumes that players form consistent beliefs about each others' unobservable behavior. They assumestrategies, in particular that the other's behavior results itself from an optimal strategy. Because theHowever, multi-player inter-temporalinteraction and optimization often leads to recursive relationships between beliefs and strategies, which makes solving complex classical games becomes quiteoften very difficult. SuchMany problems often have several solutions, called \emph{equilibria} (not to be confused with the steady-state meaning of the word) and call for sophisticated nonlinear fixed-point solvers \citep{Harsanyi1988}. Only in special cases, e.g. where players have complete information and moves are not simultaneous but alternating, game-theoretic equilibria can easily be predicted by simple solution concepts such as backwards induction \citep{Gintis2009}.

In other cases, one can identify strategies and belief combinations consistent with the following two assumptions. First, each player eventually chooses a strategy that is optimal given her beliefs about all other players' strategies (rational behavior). Second, each player's eventual beliefs about other players' strategies are correct (\emph{rational expectations}). The solutions are called \emph{Nash equilibria}. However, many games have multiple Nash equilibria, and the question of which equilibrium will be selected arises.

Therefore, game theorists try to narrow down the likely strategy combinations by assuming additional forms of consistency and rationality \citep[see][]{{Aumann2006} such as consistency over time {\emph{(sequential and subgame perfect equilibria}), stationarity over time {\emph{Markov equilibria}), and stability against small deviations \citep[\emph{[stable equilibria]][],][]{Foster1990, Maes2016}, coordinated deviations by groups {\emph{correlated, coalition-proof, and strong equilibria}), }, or small random mistakes \citep[\emph{[trembling-hand-perfect] and \emph{proper equilibria},][]{Harsanyi1988}. After a plausible strategic equilibrium has been identified, it can then be used in a simulation of the actual behavior resulting from these strategies over time, possibly including noise and mistakes.

As an example **infrom** the land—use context, consider two farmers living on the same road. They get their irrigation water from the same stream. A dispute over the use of water emerges. Both may react to the actions of the other in several turns. The upstream farmer located at the end of the road may increase or decrease her water use and/or pay compensation for using too much water to the other. The downstream farmer at the entrance of the road may demand compensation or block the road and thereby cut the access of the upstream farmer to other supplies. Either of them may appeal to the magistrate or apologize to the other and the magistrate may set quotas or impose fines. This results in a complex game tree that A complex game tree encodes which actions are feasible at which moment and what are the consequences on players' utilities. The magistrate in the example might not know about the farmers' actions before one of them appeals to him and the other farmer might not know about the appeal until the magistrate acts. If these are the only relevant constraints and it is possible to explicitly model specify the information and options of available to the players at each time point, then a classical game theoretical analysis makes sense, allows determining the rational equilibrium strategies that the farmers

Classical game theory is widely applied to interactions in market settings in economics (see also Section~\ref{sec:macroeconomics}), but increasingly also in the social and political sciences to political and voting behavior in \emph{public and social choice theory} \citep[see, e.g.,][and Section~\ref{sec:social_welfare}]{Ordeshook1986, Mueller2003}. For example, public choice theory studies strategic interactions between groups of politicians, bureaucrats and voters with potentially completely different preferences and action sets under constraints by existing law.

would follow.

While many simple models of strategic interactions between rational and selfish agents will predict only low levels of \emph{cooperation}, more complex models can well explain how bilateral and multilateral cooperation, \emph{consensus}, and stable social structure emerges \citep{Kurths2015}. This has been shown in diverse contexts such as individual bilateral interactions in large groups \citep[e.g.,][]{Helbing2009}, bilateral international relations \citep[e.g.,][]{Helbing2009}, multiplayer public goods problems \citep[e.g.,][]{Heitzig2011}, group decision making \citep{Heitzig2012}, coalition formation on networks \citep{Auer2015}, and international climate policy \citep[e.g.,][]{Heitzig2011, Heitzig2013}.

To model relevant decision processes in the Earth system, classical game theoretic analysis could be used for describing strategic interactions between agents which could be assumed highly rational and well informed, i.e. international negotiations of climate agreements between governments, bargaining between social partners or monopolistic competition between firms. Similarly, international negotiations and their interactions with domestic policy can also be framed as two- or multilevel games <citep[as in some models of political science, e.g.,][]{Putnam1988, Lisowski2002}. Furthermore, social choice theory could be used to simulate simple voting procedures that (to a certain extent) determine the goals of regional or national governments.

\subsection{Interactions with dynamic strategies: evolutionary approaches and learning in game theory} \label{sec:evolutionary_approaches}

In game theoretic settings, complex individual behavioral rules are typically modeled as \emph{strategies} specifying a behavioran action for each node in the game tree. Consider as an example the repeated version of the Prisoners' Dilemma in which each of two players can either ``cooperate'' or ``defect'' in each period \citep[e.g.,][]{{Aumann2006}}. A typical complex strategy in this game could involve reciprocity (defect temporarily after a defection of your opponent), forgiveness (everevery so often not reciprocate), and making up (don't defect again after being punished by a defection of your opponent after your own defection).

Many or even most nodes of a game tree will not be visited in the eventual realization of the game and strategies may involve deliberate randomization of actions (e.g. tossing a coin). Therefore, strategies are (like preferences), unlike actual behavior, principally unobservable (only actual behavior is), and assumptions about preferences and strategies them are unfalsifiable and hard to validate.

For this and other reasons, often several kinds of additional assumptions are often made that constrain the set of strategies further that a player can choose, e.g., assuming only very short memory or low farsightedness (``myopic''(myopic behavior) and disallowing randomization, or allowing only strategies of a specific formal structure such as heuristics (see Section~\ref{sec:bounded_rationality}).

The above-mentioned water conflict example (seefrom

Section~\ref{sec:game_theory}} bears some similarity to the repeated prisoners' dilemma in that the farmers' possible actions can be interpreted as either defective (using too much water, blocking the road, appealing to the magistrate) or cooperative (not do any of this, compensate for past defections). Assuming different levels of farsightedness may thus lead to radically different predictions sinceactions because myopic players would much more likely get trapped in a cycle of alternating defections than farsighted players. The latter would recognize some degree of forgiveness asbecause that maximizes long-term payoff and would thus desist from defection with some probability. In any case, both farmers' choices maycan be modeled as depending on what they believe the other will likely do or how she will react to the last action.

Evolutionary approaches in game theory study the interaction of different strategies and analyze which strategies prevail on a population level as a result of selection mechanisms. Thus, in contrast to classical game theory, evolutionary approaches focus on the dynamics of strategy selection in populations. The agent's strategies may be either hardwired, acquired or adapted by learning \citep[e.g.,][]{{Fudenberg1998}, Macy2002b}.

Although many evolutionary techniques in game theory are used in biology to study biological evolution (variation through mutation, selection by fitness and reproduction with inheritance), \emph{evolutionary game theory} can be used to study all kinds of strategy changes in game theoretic settings, for instance cultural evolution (transmission of memes), social learning through imitation of successful strategies or the emergence of cooperation \citep{Axelrod1984, Axelrod1997}.

In an evolutionary game, a population of agents is divided into factions with different strategies. They interact in a formal game (given e.g. by a payoff matrix or game tree, see Section~\ref{sec:game_theory}), in which their strategy results in a fitness (or payoff/utility). The factions change according to some replicator rules that depend on the acquired fitness. This can be modeled using different techniques. Simple evolutionary games on well-mixed large populations can be described with replicator equations. The dynamics describing the relative change in the factions of with a particular strategy \$i\$ is proportional to the deviation of the fitness of this faction from the average fitness \citep{Nowak2006a}.

Alternatively, the behavior resulting from evolutionary interactions is often easy to simulate numerically as a discrete-time dynamical system even for large numbers of players if the individual action sets are finite or low-dimensional and only certain simple types of strategies are considered. This type of agentbased model (see Section~\ref{sec:abm}) simply implements features such as mutation or experimentation and replication via strategy transfer (e.g., imitation and inheritance) at the micro-level. Combined with (adaptive network approaches (see Section~\ref{sec:networks}), the influence of interaction structure can also be studied \citep{Szabo2007, Perc2010}. The steady states of evolutionary games are usually Strategies can be characterized by so-calledas \emph{evolutionary stable strategies} or \emph{stochastically stable equilibria}. A} if a population which adopts an evolutionary stablewith this strategy cannot be invaded by otheranother, initially rare strategies. strategy. If the steady statea strategy is furthermore stable for finite populations or noisy dynamics, stable equilibria areit is called stochastic.\emph{stochastically stable}.

In our water conflict example, the farmers could use a heuristic strategy (see Section~\ref{sec:bounded_rationality}) that determines how much water they extract given the actions of the other. The evolution of the strategies could either be modeled with a learning algorithm, repeating the game again and again. Alternatively, to determine feasible strategies in an evolutionary setting, a meta-model could consider an ensemble of similar villages consisting of two farmers and a magistrater. The strategies of the farmers would then be the result of either an imitation process between the villages, or of an evolutionary process, assuming that less successful villages die out over time.

Evolutionary approaches to game theory are a promising framework to better understand the prevalence of certain human behaviors regarding interaction with the Earth system. This is especially interesting regarding the modeling of longterm cultural evolution and changes in individual's goals, beliefs and decision strategies or the transmission of endogenous preferences \citep{Bowles1998}.

\subsection{Modeling social influence}
\label{sec:social_influence}

Another strong force in human interaction is Human behavior and its determinants (beliefs, goals, and preferences) are strongly shaped by social influence, a process in which individuals adjust their opinions, beliefs, preferences, or behavior after interacting with others. Humans exert influence on each other forcan result from various reasons. Theycognitive processes. Individuals may be convinced by persuasive arguments \citep{Myers1982}, may aim to be similar to esteemed others \citep{Akers1979}, arebe unsure about what is the best behavior in a given situation \citep{Bikhchandani1992}, or perceive social pressure to conform with others \citep{Wood2000, Festinger1950, Homans1951}.

\emph{Models of social influence} allow studying the outcomes of repeated influence in social networks and have been used to explain the formation of consensus, the development of mono-culture, the emergence of clustered opinion distributions, and the emergence of opinion polarization, for instance. Models of social influence are very general and can be applied to any setting where individuals exert some form of influence on each other. However, seemingly innocent differences in the formal implementation of social influence in models can have decisive effects on the model outcomes. In, as the following, we list of important modeling decisions that have been shown to have significant implicationsdocuments.

A first question is \emph{how} agentsocial influence changes individual attributes are influenced by interactions. For example, a farmer deciding when to till his field might either choose the date which most of his neighbors think is best, take the average of the proposed dates, or even try to counter coordinate with others. disliked farmers.

Classical models incorporate influence as averaging, which meansimplies that interacting individuals becomealways grow more similar over time \citep{Friedkin2011}. \emph{Averaging} is an accepted and empirically supported model of influence resulting, for instance, from social pressure that an actor exerts on someone else \citep{Takacs2016}. In other contexts, averaging is debated \citep{Myers1982, Maes2013a, Maes2013b, Myers1976, Vinokur1978}. For instance, some models of opinion influence assume that opinion influence results from argument communication \citep{Maes2013a, Maes2013b}. When actors with similar opinions interact in these models, their opinions do not always converge. Instead, they turn more extreme as the interaction partner provides them with new arguments that support the own opinion. Likewise, some models Models assume different forms of averaging: Rather than following the arithmetic average of all opinions, actors might only consider the majority view (mode) in their network \citep{Nowak1990}. For example, a farmer considering on which date to best till his field might either take the date which most of his neighbors think is best or simply take the average of all the proposed dates.\citep{Nowak1990}.
In other models, social influence can lead to polarization \citep{Myers1982}.

In other models, social influence can lead to polarization \citep{Myers1982}. For instance, in models of argument communication, actor's opinions can turn more extreme when the interaction partners provide them with new arguments that support their own opinion \citep{Maes2013a, Maes2013b}.

Second, <u>one could askmodelers need to decide</u> whether there <u>areis</u> just one or <u>severalmultiple</u> \emph{dimensions of influence}. For instance, it is often argued that political opinions are multi-dimensional and cannot be captured by the onedimensional left-right spectrum. Explaining dynamics of opinion polarization and clustering turned out to be often more difficult when multiple dimensions are taken into account \citep{Axelrod1997}. Additionally, model predictions often depend on whether the influence dimension is a \emph{discrete} \<u>citep[see e.g.,][]{Axelrod1997</u>, <u>Mark1998</u>, <u>Carley1991</u>, <u>Galam2005</u>, <u>Nowak1990</u>] or a \emph{continuous variable} \citep[see e.g.,][]{ <u>DeGroot1974</u>, <u>French1956</u>, <u>Lehrer1975</u>, <u>Friedkin2011</u>}.

Models of individuals' decisions about certain policies often model the decisions as binary choices <u>\citep{Sznajd-Weron2000</u>, <u>Martins2008</u>}. However, binary scales fail to capture that many opinions vary on a continuous scale and that differences between individuals can therefore increase also on a single dimension <u>\citep{Barker2006, Dalton1998, Feldman2011</u>, Jones2002, <u>Maes2013a</u>,

<u>Stroud2010</u>}. Therefore, models that describe opinion polarization usually treat opinions as continuous attributes. The opinion on a land reform can, for instance, be modeled as a binary variable (approval or rejection) whereas the willingness to support it could be better described by a continuous variable from strong support to strong opposition.

A nextthird critical question is whether agents' characteristics can travel in different directions from one person to another, i.e. if how the influenceinteraction process is directionalmodeled. In models of opinion dynamics, for example, influence is often \emph{bi-directional}, in the sense that an actor who exerts influence on someone else iscan also be influenced by the other \citep{Macy2013, Maes2010}. ButIn diffusion models, in contrast, the effective influence is directed. For instance, information can spread only from informed to uninformed individuals, not the influence can also be only possible in one direction or the strength of influence can be asymmetric.other way around.

Furthermore, the influence actors may be influenced \emph{multilateraldyadically} or \emph{dyadic}, i.e. only between two interaction partners.multilaterally}. Model outcomes often depend on whether the influence that a group exerts on an actor is modeled as an eventa sequence of events involving a dyaddyads of actors or multiple contacts foras a single opinion update where the actor considers all contacts' influences at once \citep{Parisi2003, Flache2011, Lorenz2005, Huckfeldt2004}. In models that assume binary influence dimensions, for instance, dyadic influence implies that an agent copies a trait from her interaction partner. When influence is multilateral, agents aggregate the influence exerted by multiple interaction partners (using e.g. the mode of the neighbors' opinions), which can imply that agents with rare traits are not considered even though they would have an influence in the case of dyadic influence events. It has been demonstrated that this can have important consequences on equilibrium predictions \citep{Flache2011, Huckfeldt2004}. For example, a farmer seeking advice whether

to adopt a new technology can either consult his friends one after another or all together, likely leading to different outcomes if they have different opinions on the matter.

Social influence is a strong force but it is not plausible to assume thatFourth, agents nevermay slightly deviate from the influence of their contacts. The exact modeltype of these \emph{deviations} affects model outcomes and can introduce a source of diversity into the modelmodels of social influence \citep{Maes2010, Pineda2009, Kurahashi-Nakamura2016}. For instance, some models of continuous opinion dynamics include deviations as Gaussian noise, i.e. random values drawn from a normal distribution. In such a model, noise implies that opinions in homogeneous subgroups will fluctuate randomly fluctuate, which aggregates to collective random walks of subgroup members through the opinion space. When twoand subgroups happen to adoptwith similar opinions, influence will lead to a fusion of subgroups can merge that would have remained split in a model without deviations \citep{Maes2010}.

In other contexts, deviations are better modeled by uniformly distributed noise, assuming that big deviations are as likely as small ones. This can help to explain for instance the emergence and stability of subgroups with different opinions, that do not emerge in settings with Gaussian noise\footnote{Gaussian noise needs to be very strong to generate enough diversity for the emergence of subgroups with different opinions. However, when noise is strong, subgroups will not be stable.} \citep{Pineda2009}. In the context of land use, the opinion dynamics regarding a land reform may not only be determined by the interactions between individual agents but may also be influenced by mass media that randomly shifts individual's opinions.

To model Finally, the effects of social influence depend on the structure of the network that determines who influences whom. Complex dynamics can arise when this interaction network is dynamic and depends on the attributes of the agents, as we discuss in the following section.

<u>Models of social influence are a promising approach to explore how social</u> transitions interact with the Earth system, e.g., transitions of norms regarding norms and lifestyle changes to sustainable consumption, admissible resource use and emissions, as well as technology adoption at a micro-level, models of social influence are an important tool. These mechanisms can furthermore be combined with changes in social structure and be modeled via adaptive networks, as we show in the next sectionlifestyle changes, and adoption of new technology. For instance, they can be used to model under which conditions social learning enables groups of agents to adopt sustainable management practices.

\subsection{Modeling the evolution of interaction structure: (adaptive) network modelsapproaches \label{sec:networks}

In most of the models discussed in the previous section, the social network <u>can</u> <u>beis</u> formally modeled as a <u>\emph{graph}</u> (the mathematical notion for a network): a collection of nodes that are connected by <u>a collection of</u> links. In this mathematical framework, nodes (<u>vertices</u>) represent agents and links (edges) <u>between the agents</u> indicate <u>that agents</u> interact by communicating and exchanging <u>informationinteraction</u>, communication, or <u>forma</u> social <u>relationships</u> relationship. Agents can only interact and thus influence each other if they are connected by a link in the underlying network. Note that network models of agents can be understood as a special case of agent based models, which we discuss in more detail in Section~\ref{sec:abm}.

Classical social-_influence models study the dynamics of influence on <u>\emph{</u>static networks₇}, assuming that agents are always <u>influencedaffected</u> by the same subset of interaction partners \citep{<u>Abelson1964</u>, [e.g.,][]{DeGroot1974, French1956, <u>Harary1959</u>, Friedkin2011}. As discussed above, theseThese networks can be directed or undirected or directed, possibly restricting the direction of influence, but their structure does not change over time. Furthermore, the topology of the network, i.e. the arrangement of links, can be more or less random or regular, clustered and hierarchical. In social influence models on static networks, fully-connected populations will usually reach perfect-consensus in the long run. However, it depends on the duration of the modeled processes whether the assumption of flexible network ties is plausible. For instance, in an organization where individuals have fixed position in organizational subunits networks appear to be less flexible than in on-line social networks.

Especially when modeling social processes over longer time scales, it is reasonable to assume that the social network is dynamic, i.e. that its structure evolves over time. This time evolution can be independent of the dynamics on the network and encoded in a \emph{temporal networksnetwork} \citep{Holme2012}. However, for many social processes, it can be assumed that the structure of the social network and the dynamics on the network (e.g., social influence) interact. \emph{Adaptive network models} make the removal of existing and the formation of new links between agents dependent on attributes of the agents. Thus they build, building on the insight that the social structure influences the behavior, opinionopinions or value systemsbeliefs of individual actors, which in turn drives changes in social structure \citep{Gross2008}.

Local update rules for the social network structure and the agent behavior can be chosen very flexibly. The rules can be deterministic or stochastic and described for example by discrete maps, ordinary differential equations or logical operations (related to cellular <u>automata</u>). Changes in agent behaviors may be governed by rules such as random or <u>boundedly</u> rational imitation of the behavior of network neighbors (see above). Relevant update rules for network structure describe processes such as <u>homophily</u>, where agents with similar states tend to form new links between each other while breaking links with agents having diverging states \citep[<u>Wimmer2010</u>, <u>McPherson2001</u>, <u>Lazarsfeld1954</u>].Update rules for the network structure are often based on the insight that This common assumption is based on the insight that agents tend to be influenced by similar others and ignore those sources who hold too distant views \citep{Axelrod1997, Carley1991Wimmer2010, McPherson2001, Lazarsfeld1954}.
Many models assume that agents with similar characteristics tend to form new
links between each other (homophily), while breaking links with agents having
diverging characteristics \citep{Axelrod1997, Hegselmann2002, Deffuant2005}.
In adaptive network models, homophily in combination with social influence
generates a positive feed back loop influence increases a positive feed back loop. generates a positive feed-back loop: influence increases similarity, which leads to more influence and so on. Such models can explain for instance the emergence and stability of multiple internally homogeneous but mutually different subgroups. Other applications of co-evolutionary network models allow to understand the presence of social tipping points in opinion formation \citep{Holme2006}, epidemic spreading \citep{Gross2006} in systems of networked agents, the emergence of cooperation in social dilemmas on co-evolutionary networks \citep{Perc2010} and the co-evolution of multilateral cooperation (interdependence of coalition formation) with social networks \citep{Auer2015}. The dynamical interaction inSuch adaptive network models can give rise toexhibit complex and nonlinear co-evolutionary dynamics such as phase transitions \citep{Holme2006, Auer2015}, multi-stability \citep{Wiedermann2015}, oscillations in both agent states and network structure \citep{Gross2006}, and subtle but robust structural changes in social structurenetwork properties \citep{Schleussner2016}.

While adaptive networks have so far mostly been applied to networks of agents representing individuals, the framework can in principle be used to model coevolutionary dynamics on various levels of social interaction as introduced in Table~\ref{tab:levels}.

For instance, global complex network structures such as financial risk networks between banks, trade networks between countries, transportation networks between cities and other communication, organizational and infrastructure networks can be modeled citep{Currarini2016}. Furthermore, approaches such as multi-layer and hierarchical networks or networks of networks allow modeling the interactions between different levels of a system citep{Boccaletti2014}.

As an illustration for an application in the land-use context, consider a community of farmers described byagents each harvesting a renewable resource, e.g., wood from a forest. The agents interact on a social network, imitating the harvesting effort of social relations. The farmers are faced with the choice to adopt a new agricultural technology which is potentially neighbors that harvest more productive, but this is uncertain. If the social acquaintances and may drop links to neighbors that use another effort. The interaction of a farmer successfully test the new technology, she is more likely to adopt it herself. However, if the adoption is not successful, she might form relationships with other farmers that have not yet adopted the new technology. In this way, rich model the resource dynamics can emerge, that may with the network dynamics either leadleads to a full adoption convergence of the new technology harvest efforts or a segregation of the -community into a group with and another without the new technology higher and a lower effort, depending on the model parameters. \citep{Wiedermann2015, Barfuss2017}.

In the context of long time scales in the Earth system, the time evolution of social structures that determine interactions with the environment are particularly important. Adaptive networks offer an interestinga promising approach to modeling <u>transformative</u> change with deep structural imprints onchange of the internal connectivity of a complex system \citep{Lade2016} such as an alleged great transformation}. For example, this could be applied to sustainability \citep{WBGU2011} that may involve the transition from explore mechanisms behind transitions between centralized to and decentralized infrastructure network structures and organizational networks.

Table~\ref{tab:interaction} summarizes the different modeling approaches that focus on agent interactions in human decision making and behavior. These interactions occur between two or several agents. For including the effect of

these interactions into <u>Earth system modelsESMs</u>, their aggregate effects need to be taken into account as well. Therefore, we introduce in the next section approaches that allow to aggregate individual behavior and local interactions and to study the resulting macro-level dynamics.

%t \begin{table*}[t] \caption{Summary table for agent interactions.} **\label{tab:interaction}** \begin{tabular}{L{3cm}p{4cm}p{4cm}p{4cm}} \tophline Approaches and frameworks & Key considerations & Strengths & Limitations \\ \middlehline Classical game theory: strategic interactions between rational agents & What is the game structure (options, possible outcomes, timing, information flow) and what are the players' preferences? & Elegant solutions for low-complexity problems & Agents Difficult to solve for complex games, agents cannot change the rules of the game $\boldsymbol{\Lambda}$ \middlehline Evolutionary game theory: competition and selection between hardwired strategies Which competition and selection mechanisms are there? & Can explain how dominant strategies come about & Agent strategies are modeled as hard-wired (no conscious strategy change) $\backslash \backslash$ \middlehline Social influence: agents change theirinfluence each other's beliefs, preferences and opinions or behaviors & WhatHow do influence mechanisms are dominantchange agent attributes? Is social the influence multilateral or, dyadic, directed? How large are deviations? & Allows to model social learning, preference formation, and hearding behavior & Local dynamics are often stylized // \middlehline Network theory: changing social interaction structures & Is the social network static or adaptive? How do agents find new neighbors? How much randomness and hierarchy is in the structure? How do agents form new links? & Mathematical formalization to model co-evolution of social structure with agent attributes & Micro-interactions mostly diadic and schematic $\boldsymbol{\Lambda}$ \bottomhline \end{tabular} \belowtable{} % Table Footnotes \end{table*} % %

\section{Aggregating behavior and decision making and modeling dynamics at the
system level}
\label{sec:aggregation}

So far, we focused on theories and modeling techniques that describe decision processes and behavior of single actors, their interactions and the interaction

structure. This section builds on the previously discussed approaches and highlights different <u>aggregation</u> methods <u>howfor</u> the behavior of an ensemble or group of agents <u>might be aggregated</u>. This is an important step if models shall describe <u>system level outcomes or</u> collective decision making and behavior in the context of Earth system modeling.

In general, aggregation can take place on all levels introduced in

Section~\ref{sec:levels} and summarized in Table~\ref{tab:levels}. Aggregation techniques link modeling assumptions at one level (often called the micro-level) to a higher level (the macro-level). They therefore enable the analysis of emergent macro-level outcomes and help to transfer models from one scale to another.

They enable the analysis of macro-level outcomes and help to transfer models from one scale to another.

In general, this could link all levels introduced in Section~\ref{sec:levels}.

In this section, we describe different approaches that are used to make this connection: On the one hand, analytical tools allow representingAnalytical approaches generally represent groups of individual agents through some macro-level or average characteristic, often using simplifying assumptions regarding the range of individual agents' characteristics. On the other hand, simulationsSimulation approaches describe individual behavior and interactions and computational methods allow to study then compute the resulting aggregate macroscopic dynamics.

The question how to aggregate micro-processes to macro-phenomena is not specific to modeling human decision making and behavior. Aggregation of individual behavior and the resulting description of collective action, such as collective motion, is also an ongoing challenge in the natural sciences \citep[see e.g.,][]{{Couzin2009}.

Specific assumptions about the individual behavior and agent interactions have consequences for the degree of complexity of the macro-level description. For instance, if agent goals and means do not interact, the properties of single agents can often be added up. If, on the contrary, agents influence each other's goals or interact via the environment, complex aggregate dynamics can arise.

The following sections discuss the specificities for aggregating human decision making and behavior and notable applications in models in the global environmental change context.different aggregation techniques, their underlying assumptions and how these reflect specific aggregation mechanisms. They are summarized in Table~\ref{tab:aggregation}.

As some aggregate dynamics are difficult to reduce to micro-behavior and interactions, the section concludes with discussing important macro-level approaches with applications in Earth system modeling.

\subsection{Aggregation of preferences: social welfare and voting}
\label{sec:social_welfare}

The original micro-level framework of rationalRational choice is often appliedapproaches can also be used to model the behaviordecision making by agents on higher levels from Table~\ref{tab:levels}, e.g., firms or countries.

higher levels from Table~\ref{tab:levels}, e.g., firms or countries. The ``preferences'' of such groups of individuals at all levels introduced in Table~\ref{tab:levels}. are often represented

\emph{Social choice theory} explores how individual preferences can be
aggregated to social welfare, a measure of collective desirability of an
outcome. Furthermore, it analyzes how group choices can be determined best in
voting procedures, in which group members choose between different options and
the collective choice is determined by some formal rules.

As in Section~\ref{sec:rational_choice}, utility functions can form the basis for modeling \emph{preferences of groups} by a ``social utility''. Individual utilities can be aggregated into a \emph{social welfare function} by making the assumption that individual agents have a common scale measurable unit of utility (``<u>util</u>''), which represents an amount of satisfaction, happiness or sometimes simply a monetary value.

Most often, modelers use the linear and inequality-neutral utilitarian welfare function, taking the average over the N individuals in the group, $U(x) = \frac{x_{i}(x) / N}{S}$. Sometimes this is motivated by the assumption that groups may redistribute utility internally to mitigate inequality (\emph{transferable utility}).

by using as the optimization target a \emph{social welfare function},

which aggregates the members' utility functions, either additively (``utilitarian'' welfare)

or in some nonlinear way to represent inequality aversion \citep[e.g., the

Gini-Sen, Atkinson-Theil-Foster, or egalitarian welfare

functions;][]{Dagum1990}.

To do so, a common scale of utility must be assumed.

For example, individual utility in many economic models equals the logarithm of the total monetary value of the individual's consumption.

In reality, social welfare functions are indeed used to find optimal

policy, e.g. in \emph{cost-benefit analysis} \citep{Feldman2006}.

For example, consider a village of farmers growing crops, which need different amounts of water,

so that water management policies affect farmers' incomes.

The effects of a water policy could then be evaluated using either the

average, minimal or average-logarithmic income of farmers as

a measure of social welfare.

The policy option maximizing the chosen indicator should be implemented.

However, it is highly debated that utilities of different individuals can really be compared and substituted

in the sense that a drop in collective welfare resulting from an actor's decrease in utility can be compensated by increasing the utility of another actor. Though, when only considering ordinal preference relations instead of cardinal (scale-measurable) utility into account, general statements about aggregated preferences are very limited $\citep[Arrow1950]$. Inequality-averse groups can be modeled using $U(x) = \sum_i f(u_i(x)) / N$ for some concave function \$f\$, or via welfare functions based on inequality measures

some concave function \$1\$, of Via weifare functions based on inequality measure such as the <u>Gini</u>-Sen welfare function, \$U(x) = \sum_{i,j} min(u_i(x),u_j(x)) / N^2\$ \citep{Dagum1990}, the Atkinson-Theil-Foster welfare function

 $\frac{\text{Locitep}[\underline{Dagum1990}]}{\text{Context}} \text{ or, in the extreme case, the egalitarian welfare function} \\ \frac{\text{Locitep}[\underline{Dagum1990}]}{\text{SU}(x) = \min_i u_i(x)$. In economic contexts, welfare functions are often based on monetary values such as wealth, income or total value of consumption. Defining suitable group preferences <u>becomesis</u> especially <u>complicated</u> when the group

composition or size \$N\$ changes over time as in intergenerational models \<u>citep[e.g.,][]{Millner2013}</u>.

Once a social welfare function is constructed, one may identify the social welfare associated with different collective actions and choose the one with the maximal value. The social welfare is used for instance as a criterion to evaluate which policy in a bundle of options leads to the social optimum. Welfare maximization reduces to \emph{cost-benefit analysis} if the utilities are simply added up and are equated with monetary values \citep{Feldman2006}. An alternative to such policy evaluation tools is multi-criteria decision making \citep{Huang2011}. However, cost benefit analysis remains one of the most applied decision models to normatively evaluate policies and can therefore also be used to model government decisions descriptively.

An example from the land-use context illustrates the concept of ``social utility''. In a village farmers grow crops that each need specific amounts of water. Water management policies thus affect the incomes of the farmers in different ways. The effect of a policy on the village can be evaluated using either the average or the minimal income of the farmers or some more complex aggregation. Then, the policy should be taken that maximizes this indicator of social welfare. Analogous criteria might be used in policy making on higher levels of social organization from towns to countries. In complex organizations, however, the actual decision might be non-optimal and a more explicit modeling approach of actual decision procedures might describe the decisions better, e.g. using a game theoretical model with voting or bargaining procedures.

In \emph{voting theory}, a set of \emph{voters} partitioned into factions with similar preferences can decide over the group's joint actions by means of a formal bargaining or voting protocol. The protocol is designed to find a compromise between the factions' preferences (\emph{cooperative game theory}). \citep{Millner2013}.

Also, in complex organizations, real decisions might be non-optimal for the group and more explicit models of actual decision procedures may be needed.

Models in subfields of game theory (bargaining, voting, or social choice theory) explore the outcomes of formal protocols that are designed to aggregate the group member's heterogeneous preferences.

Under different voting <u>methods</u> or <u>bargaining protocols</u>, subgroups may dominate the decision or the group may be able to reach a compromise

\citep[<u>cp.][]{{Heitzig2012}, also depending on the individual's strategies.</u>
Voting methods can be seen as an aggregation mechanism for individual (and
possibly heterogeneous) preferences.}.

In the above example, the farmers may not agree on a social welfare measure that a policy should optimize but instead on a formal protocol that would allow them to determine a policy for water usage that is acceptable for all.

\subsection{Aggregation via markets: economic models and representative agents}
\label{sec:macroeconomics}

Nowadays, aA major part of the relevant interaction of contemporary societies with the Earth system is closely linkedrelated to the organization of production and consumption organized on markets. Markets do not only mediate between the spheres of production and consumption, they can also be seen as a mechanism to aggregate agents' decisions and behavior. Economic theory builds on rational choice theory to askexplores how goods and services are allocated and distributed among the various activities (sectors of the economyproduction) and agents (firms, households, governments) in an economy. Goods and services may be consumed or can be the input factors to economic production. Input factors for production are usually labor and physical capital, but can also include financial capital, land, energy, natural resources and intermediate goods. In markets, the coordination between \emph{demand} and \emph{supply} of goods is mediated through \emph{prices} that are assumed to reflect information about the abundance or scarcity and production costs of goods. Economics compares different kinds of market setting (e.g., auctions, stock exchanges, international trade) with respect to different criteria such as allocative efficiency criteria.

MicroeconomicBuilding on rational choice theory for modeling the decisions of individual agents, microeconomic models in the tradition of neoclassical economics analyze the conditions for an equilibrium between supply and demand on a-single marketmarkets (\emph{partial equilibrium theory}) and between all markets in an economy. (\emph{general equilibrium theory}). The behavior of households and firms is usually modeled as utility maximization under budget constraints and profit maximization under technological constraints in the production, respectively. A central ideaassumption is that an economy is characterized by \emph{decreasing

A central ideaassumption is that an economy is characterized by \emph{decreasing marginal utility} and production\emph{diminishing returns}: The additional individual utility derived from the consumption of one additional unit of some good (or of one additional hour of leisure) is declining. Similarly, it is

assumed that the additional amount of a production derived from one additional unit of some input factor is declining with its absolute amount. The output of the production process is described as a \emph{production function} that has input factors as arguments is declining.

Decreasing marginal utility andSimilarly, the additional production implies that utility andderived from an additional unit of a single input factor is declining with its absolute amount when holding other input factors fixed. Accordingly, the output of the production functions areprocess is described as a

<u>\emph{production function}, which is concave in theirits input factor arguments</u> (i.e., they have a negative second derivative)..

Assuming that there is \emph{perfect competition}, between producers, resources and goods would beare allocated in a \emph{Pareto-efficient} way so that no further redistribution is possible that benefits somebody without making somebody else worse off \citep{Varian2010}. It has been shown that this leads to the emergence of an equilibrium price for each good as the market is cleared and supply meets demand \citep{Arrow1954}.

The idea of this \emph{market equilibrium} can be understood by the associated prices: The rational market participants trade goods as long as there is somebody who is willing to offer some good at a lower price than what somebody else is willing to pay for it.

However, in markets dominated by only a few or very heterogeneous agents perfect competition cannot be assumed, and price wars, hoarding, and cartel formation can occur. Such situations can be described in models of oligopoly, bargaining or monopolistic competition but are sometimes difficult to integrate into macroeconomic frameworks.

The idea of the \emph{market equilibrium} can most easily be understood by the associated prices: The rational market participants trade goods as long as there is somebody who is willing to offer a unit of some good at a lower price than what somebody else is willing to pay for it (bid price). In a competitive setting, offer prices will go up and bid prices down after each trade because of decreasing marginal utility that the agents can derive from obtaining more of the same products. Under some conditions, one can show that this leads to the emergence of an equilibrium price for each good to which all local offer and bid prices converge as the market is cleared and supply meets demand. %\red{[Arrow-Debreu]}

Macroeconomic models are often builtbuild on this micro-economicmicroeconomic theory incorporatingby modeling decision making of firms and households with the representative agent approach. A representative agent stands for an ensemble of identical agents or an average agent of a population that can be heterogeneous to some degree. However, an. An underlying assumption is that heterogeneities and local interactions cancel out for large numbers of agents. The behavior of theseWhile representative households and firms is usually modeled as utility and profit maximization, respectively. Furthermore, theymodel the supply of different sectors, the demand is determined by one or several representative households. Representative firms and households are assumed to act as if there would be perfect competition and they had no \emph{market power}, i.e. that they takeoptimize their production or consumption taking the prices of inputsgoods and outputsproduction factors as given and cannot influence them.. The dynamicsprices of the economy is then the result of the optimizing behavior under various constraints.

In simple \emph{general equilibrium} (GE) models, different sectors of the economy are modeled by representative firms and the demand is determined by one or several representative household. The representative agents interact on perfect markets for all factors of production and consumer goods. In other words, it is assumed that all sectors pay the same wage for an hour of some type of labor, the same interest on financial capital, and the same price for any other input factor. These pricesproduction factors are assumed to value of what they are able to produce additionally by using one more hour of labor or one moreadditional unit of the respective input factor, i.e. their

\emph{marginal product}. The household can consume goods worth the capital and labor income it receives. This leads to In simple macroeconomic models, representative agents interact on perfect markets for all production factors and goods. The solution of the associated optimization problem (with constraints given by a system of nonlinear algebraic equations in prices and quantities that may be solved by convex optimization, resulting an allocation of input factors, their prices and the resulting output from it. The implication of these equilibrium arguments are full employment of labor and capital in models that allow for substitution of production factors.

As an example from land use, consider the effect of the introduction of a new technology which requires more capital and less labor for the same production of the same good: In a general equilibrium framework, this could be modeled by a closed agrarian sector with two representative agents and a fixed amount of labor and capital. When the representative agent using the old technology has to compete against the one with the new technology, the wages would fall and interest rates would rise until an equilibrium is reached. In this equilibrium, the prices) specifies the quantity and allocation of input factors are such that the producer with the old technology can produce at the same price as the producer with the new one. An interpretation of this model at the micro-level is that farmers would switch to the new technology until the prices of input factors adjust to the new demand, their prices (wages and interest rates), and the production and allocation of consumer goods. A change in one constraint therefore can lead to adjustments in all sectors and

new equilibrium prices.

For example, in an economy with only two sectors, industry and agriculture, modeled by two representative firms and a representative household, increases in agricultural productivity may lead to the reallocation labor into the industrial sector and changes in wages.

In reality, prices can undergo rapid fluctuations, which challenges the validity of equilibrium assumptions at least in the short run. Models captureFurthermore, production factors may not be fully employed as general equilibrium considerations suggest. Other deviations from equilibrium by efficient equilibria are discussed as \emph{market imperfections} such as transaction costs, asymmetries in available information and stochastic shocks due to new information as well as changes of production functions due to technological change. non-competitive market structures.

\emph{Dynamic stochastic general equilibrium} (DSGE) models account for imperfections by applying stochastic shocks to technological developments and prices. They model the expectations of economic agents and the corresponding consumption and investment decisions of economic agents under uncertainty. Most and explore the consequences of stochastic shocks on public information or technology for macroeconomic indicators.

Many modern DSGE models also incorporate short-term market frictions such as barriers to nominal price adjustments (``sticky'' prices, which have consequences for inflation) and imperfect competition) or other market imperfections \citep{Wickens2008}. However, these models still build on the key concept of general equilibrium because they assume that the state of the economy is always near such an equilibrium and market clearance is fast.

In the land-use context, a DSGE approach was used to model land-price dynamics \citep{Liu2013}. The investment decision of the representative firm in the model is not unconstrained as in a general equilibrium framework but constrained by having to provide security in the form of physical capital and land when borrowing financial capital for investment. When subject to several types of shocks (in housing demand, labor supply, or credit availability), the dynamics describes off-equilibrium land price evolution.

In addition to the equilibration between supply and demand through prices, the dynamical evolution of economic quantities, as captured in \emph{Economic growth models}, is important for modeling aggregate human impacts in the Earth system. For example, economic growth is an important driver of energy and resource } are

used to study the long-term dynamics of production and consumption as well as changes in the agricultural sector \citep{Mundlak2000}. In standard and are therefore an important approach for Earth system modeling.

<u>In standard and are therefore an important approach for Earth system modeling.</u> <u>In simple growth models</u>, a quantity \$Y(t)\$ of a homogeneous product is produced per time unit according to an aggregate production function depending on productive physical capital \$K(t)\$, labor and possibly some other inputs\footnote{Standard aggregate production functions are characterized by decreasing marginal productivity and constant returns to scale (i.e., if all the inputs are doubled, the output also doubles).}.

<u>. A part of the output is can be</u> saved and invested into as new capital, while the rest can be remaining output is consumed.

The evolution of the capital stock K is <u>describedgiven</u> by a differential equation, e.g., dK / dt = s Y(t) - delta K(t). Here, the fraction ss of the output is as new capital and the capital depreciates with a rate delta. taking into account investments and capital depreciation.

In the typical \emph{standard neoclassical growth model} \citep{Ramsey1928, Cass1965, Koopmans1965}, the fraction of saving \$s(t)\$ is, the savings are endogenously determined by inter-temporal optimization of a representative household. It is assumed that the and equal investments.

The household maximizes an exponentially discounted utility stream \$U(t)\$ (compare Section~\ref{sec:rational_choice}), which is a function of its consumption \$C(t) = \left(1 - s(t) \right) Y(t)\$ \citep{Acemoglu2009}. The central decision of the representative household is thus how much of the produced output it saves and invests at each point in timeto increase production in the future and therefore cannot consume and enjoy directly. The Such intertemporal optimization problemproblems can be solved either computationally by discretization in time or analytically by applying variational calculus (techniques from optimal control theory\footnote{Optimal control theory deals with the problem of finding thean optimal choice for some control variables (often called policy) given by a set of differential equations for the control variables that optimizeof a dynamical system that optimizes a certain objective function of a (dynamical) system (under constraints), see, using for example \citetvariational calculus \citep{Kamien2012}.}.

Besides population growth, the only long-term drivers of growth in the standard neoclassical growth model are changes in the production function representing technological changes, i.e. model are exogenously modeled increases in factor productivity. While through technological change is exogenous in standard growth models, it is modeled explicitly in. In contrast, so-called endogenous growth models exhibit long-run growth and endogenously account for increases in productivity, for example through innovation, human capital or knowledge accumulation _\citep{Romer1986, Aghion1998}.

The assumptionuse of representative agents in macroeconomic models has theoretical implications that stem from the implicit assumption that the representative agent has the same properties as an individual of the underlying group \citep{Kirman1992, Rizvi1994}: First, the approach neglects that single agents in the represented group have to coordinate themselves, leaving out problems that arise due to incomplete and asymmetric information. Second, a group of individual maximizers does not necessarily imply collective maximization, challenging the equivalence of the equilibrium outcome. Finally, the representative agent approach may neglect emergent phenomena from heterogeneous micro-interactions \citep{Kirman2011}.

In spite of the deficiencies of the representative agent approach, its application to markets allows to aggregate behavior in simple and analytically tractable forms. Modelers who wish to describe economic dynamics at an aggregate level can rely on a well developed theory that <u>describedescribes many</u> economic <u>growthphenomena</u> in a <u>plausible way.good approximation</u>. In the following section, we will discuss how this approach is used <u>in combination with the to analyze</u> impacts of <u>this</u> economic <u>engineactivities</u> on <u>Earth system</u>the environment.

\subsection{Modeling of decisions in integrated assessment models: social planner and economic policy}

Starting from economic growth and equilibrium models discussed above, environmental economics developed models to account for various environmental externalities in the economy \citep[see e.g.,][]{Perman2003}. Externalities are defined as benefits from and damages to the natural system that are not reflected in prices. Such models allow evaluating\emph{Integrated assessment models} (IAMs) comprise a large modeling family that combine economic with environmental dynamics. However, the majority of currently used IAMs draws on ideas from environmental economics. Using the concept of environmental \emph{externality}, they evaluate the extraction of exhaustible resources, environmental pollution and overexploitation of ecosystems economically. They alsoExternalities are benefits from or damages to the environment that are not reflected in prices and affect other agents in the economy \citep[see, e.g.,][]{Perman2003}. These models therefore help to designassess economic policies tothat tackle the associated environmental problems.

\emph{Integrated assessment models} (IAMs) draw on these ideas and State-of-theart global IAMs combine macroeconomic models with detailed representations of sectors that are closely linked to the environment. They arelike the most commonenergy and land system with models that combine both a micro-of the biophysical bases and a macro-description of human activities at a scales with relevant consequences for the global environment. IAMs couple economic activities to environmental variables by incorporating material flows explicitly impacts of these sectors. For example, CO\$_2\$ emitted from burning fossil fuels is linked to economic production by carbon intensities and energy efficiencyefficiencies in different production technologies. <u>IAMs</u> usually<u>IAMs</u> often model technological change endogenously, for example with investments in R\&D or learning-by-doing (i.e., decreasing costs with increasing utilization of a technology). Because of the possibility to induce technological change, the models capture path-dependencies of investment decisions. Many IAMs take the perspective of a social planner, who makes decisions on behalf of society by optimizing a social welfare function (see Section~\ref{sec: social_welfare}). It is assumed that the social optimum equals the perfect market outcome with a policyeconomic regulations that internalizesinternalize all external effects... (e.g., emission trading schemes).\footnote{This argument is based on the second fundamental theorem of welfare economics, see for example citet[][pp. 63--70]{Feldman2006}.}

<u>IAMs</u> are often<u>mostly</u> computational (general or partial) equilibrium models, using large data sets for parametrization and calibration of initial conditions. Regarding modeling technique, <u>IAMs</u> can be broadly categorized with respect to (1) their scope of representation and (2) their inter-temporal modeling. (1) General equilibrium models represent the whole economy and assume simultaneousdescribing market- clearing between all sectors. They often combine a top-down macroeconomic model with bottom-up sectoral models. Partial equilibrium models, on the other hand, only incorporate parts of the economy explicitly, such as the land and energy system. Projections or using exogenous projections of macroeconomic variables (interest rates, wages, etc.) then drive these sectoral models exogenously. (2) Intercp. Section~\ref{sec:macroeconomics}).

They also differ with respect to inter-temporal allocation: While inter-temporal optimization models use discounted social welfare functions to allocate investments and consumption optimally over time. They use discounted social welfare functions as discussed above as objective functions in an optimization procedure. Recursive dynamics, recursive dynamic models solve an equilibrium for every time step. The dynamics is usually prescribed by difference equations that are derived from considerations about optimal allocation. In these models the inter-temporal allocation is generally non-optimal \citep{Krey2014, Babiker2009}.

Furthermore, IAMs differ with respect to the representation of technological change, model flexibility in capital reallocation between sectors and regions, and the implementation of trade between subregions. Investment choices between different technology options have long term effects because the relative prices of technologies can be reduced by induced technological change. Models typically

use \emph{constant elasticity of substitution} (<u>CES</u>) production functions that allow for shifts between different (intermediate) products. <u>IAMs</u> represent technological change in different ways: technological parameters such as energy efficiencies or production costs are given as model input or are represented for example by learning by doing effects on costs with increasing installation or endogenous investments in R\&D. The implementation of trade between subregions depends on the model type: If the model is solved by global optimization, trade between regions emerges endogenously. Other models determine the trade between regions exogenously.

With respect to their objectives, it is common to distinguish between two categories of IAMs \citep{Weyant1996}: First, are designed for (1) either determining optimal environmental outcomes of a policy optimization models (POM) makeby making a complete cost benefitwelfare analysis between the costs of mitigation policies in terms of consumption or welfare losses and the costs of climate change impacts and adaptation. Thereby, they determine the optimal emission target. The costs are usually represented in highly aggregated damage functions and have led to extensive discussion about the validity of such models. Second, different policy evaluation models (PEMs) assess policy options and socio economicor (2) evaluating different paths to reach a political target with respect to their cost-effectiveness to achieve certain emission targets. They usually \citep{Weyant1996}. In the context of climate change for example, many IAMs have emission targets as constraints in thetheir optimization procedure and determine the best way to reach them \citep[see for instance the most recent IPCC report,][]{{Clarke2014}.

For the analysis of global land-use, <u>IAMs</u> combine geographical and economic modeling frameworks \citep{<u>Darwin1996</u>, <u>Lotze-Campen2008</u>, <u>Hertel2009</u>, <u>Havlik2011</u>}. These models are used for example to investigate <u>interactions</u> <u>between land allocation and price mechanisms, the</u> competition between different land uses (<u>forestry</u>, <u>bioenergy</u> and food production) and trade-offs between agricultural expansion and intensification. They often assume thatWith the <u>optimization</u>, land- uses <u>can beare</u> instantaneously and globally allocated, only constrained by environmental factors such as soil quality and water availability, as well as climate and protection policies.

IAMs differ from ESMs not only inregarding their modeling technique (mostly optimization) but also inregarding their purpose from Earth system models: They help policy advisors to assess normative paths that the economy could take to reach environmental policy goals. Because IAMs represent While the supply side in much detail, they are used to evaluate investment decisions under different policy choices, for instance between different energy production technologies. Thus, while decision about the policy decision is exogenous to the model, the investmentsinvestment decisions within and between sectors are only modeled as a reaction to the political constraints. It would be a promising exercise to couple the policy decision in an IAM with some opinion dynamics that depends on the development of the economy. Furthermore, there is already a continuing effort to couple approaches from However, most IAMs do not account for possible changes on the demand side, e.g., through changes in consumer's preferences for green products. A better cooperation between the IAM and ESM communities, as called for by \citet{vanVuuren2016} in this Special Issue, is certainly desirable because some of the problems that arise when including human decision making into ESMs have already been dealt with in IAMs. However, when considering the coupling of IAMs and ESMs with different methods \citep{vanVuuren2012}. However, this could prove very difficult due to the incompatible modeling approaches, especially}, modelers have to keep in mind not only technical compatibility (e.g. regarding the treatment of time in inter-temporal optimization models) but also the possibly conflicting modeling purposes.

\subsection{Modeling agent heterogeneity via distributions and moments}

As discussed in Section~\ref{sec:macroeconomics}, the representative agent approach can hardly capture heterogeneity in human behavior and interaction. In this section we describe analytical techniques that allow to capture at least some forms of thisagent heterogeneity.

An ensemble of similar agents can be modeled via statistical distributions if the agents are heterogeneous regarding only some quantitative properties. Such properties could for example becharacteristics, e.g. endowments such as income or wealth or parameters in utility functions. In simple models, techniques from \emph{statistical physics} and theoretical ecology can be used to derive a macro-description from micro-decision processes and interactions. For instance, the distribution of agent properties representing an ensemble of agents can be described via a small number of statistics such as mean, variance and other moments or <u>cumulants</u>. The dynamics in form of difference or differential equations of such statistical parameters can be derived by different kinds of approximations. A common technique is \emph{moment closure} that expresses the dynamics of lower moments in terms of higher order moments or approximating them by functions of lower-order ones \citep[see, e.g.,][]{Goodman1953, Keeling2000, Gillespie2009}.

To aggregate simple interactions between single nodes in network models, similar techniques can be used to describe <u>the frequencies of particular simple</u> <u>subgraphs</u> with differential equations how the occurrence of simple sub-graphs (motifs) changes with the dynamics on and of the network. In network theory, these approaches are <u>often</u> also called moment closure, although the closure <u>here</u> refers <u>here</u> to neglecting more complicated subgraphs <u>\citep[see e.g.,][]{Do2009, Rogers2012, Demirel2014</u>}. For example, the simple <u>\emph{pair approximation} only considers different subgraphs consisting of two vertices</u> (agents) and one link. To abstract from the finite-size effects of fluctuations at the micro-level in stochastic modeling approaches and arrive at deterministic equations, analytical calculations often take the limit of the agent number going to infinity <u>\citep[in statistical physics called the thermodynamic limit</u>, <u>see e.g.,][]{cp.][]{Reif1965</u>, <u>Castellano2009a</u>}.

The following illustration shows how these techniques could be applied in the land-use context: Consider a model that describes the interaction between farmers who can decide on the amount of fire clearing on their land depending its soil quality and policy choices by a government. The farmers interact on a social network and imitate actions that are profitable under an imposed policy. Such a system can be described by a continuous variable measuring the fraction of farmers that apply fire clearing. The dynamics of this variable would depend on of the success of the different types of farmers, which in turn would depend on the soil quality of the farmers' land. The latter could be described by the mean and variance of the soil qualities of the two factions of farmers. The resulting system would describe the dynamics of the statistical measures and could be analyzed analytically with methods from statistical physics.

Techniques based on moment closure and network approximations <u>can beare</u> used<u>in</u> order to aggregate the dynamics of processes like opinion formation on networks. This This might be especially useful to reduce computational complexity when modeling social processes at intermediate levels of aggregation and could allow to investigate investigating the interplay of <u>suchmeso-scale</u> social processes with natural dynamics of the Earth system, <u>e.g. coupled through resource</u> extraction or emissions \citep[cp.][]{Wiedermann2015}.

\subsection{Aggregation in agent-based models}
\label{sec:abm}

Agent-based modeling (ABM) is a computational approach to modeling the emergence of macro- or system-level outcomes from micro-level interactions between individual, autonomous agents and between agents and their social and/or

biophysical environment and studying their emergent macro-level outcomes environments https://www.environments https://www.environments https://www.environments https://www.environments https://www.environments https://www.environments https://www.environments https://www.environments-citepstein1999, Gilbert2008, Https://www.environments-citepstein1999, Gilbert2008, Https://www.environments-citepstein1999, https://www.environments-citepstein1999, Gilbert2008, Https://www.environments-citepstein1999, https://www.environments-citepstein1999, Gilbert2008, Https://www.environments-citepstein1999, <a href behavioral diversity can be represented by a single representative agent as in many macroeconomic models (cp. Section~\ref{sec:macroeconomics}). Instead, population level dynammics emerge from the interactions of heterogeneous agents. ABMInstead, the behavior of heterogeneous agents or groups of agents is explicitly simulated to study the resulting aggregate outcomes. As each action of an individual agent is interdependent, i.e. it depends on the decisions or actions of other agents within structures such as networks or space, local interactions can give rise to complex, emergent patterns of aggregate behavior at the macro-level \citep{Page2015}. ABMs allow exploring such non-linear behavior in order to understand possible future developments of the system or assess possible unexpected outcomes of disturbances or policy interventions. Agent-based modeling is widely used to study complex systems in computational social science \citep{Conte2014}, land-use science \citep{Matthews2007}, political science \citep{deMarchi2014}, computational economics \citep{Tesfatsion2006}, for the study of, Heckbert2010, Hamill2016}, socialecological systems research \citep{Schlueter2012, An2012}, as well as inand ecology \citep[where it is often called individual-based modeling,][]{{Grimm2005}...}, among others...footnote{Note that in some scientific communities, this class of modeling approaches is also known as multi-agent simulations \citep[MAS,][]{Bousquet2004} or individual-based modeling \citep{Grimm2005}.}

Agents in ABMs can be individuals, households, firms or other collective actors as well as elements of the biophysical environment, for example other entities or groups thereof, such as fish, fish populations. Agent behavior can be modeled at the individual level with any of the approaches introduced in Section~\ref{sec:individual_behavior} or other theories that can be formalized in equations, decision trees or rules. or plant functional types. Agents are assumed to be diverse and heterogeneous, i.e. representing they can belong to different types of agents that are and can vary within one type, respectively. Agent types can be characterized by specificdifferent attributes and decision making models (e.g., large and commercial versus small and traditional farms). AgentsHeterogeneity within a type areis often also quantitatively heterogeneous represented through quantitative differences in that they possess varying_values of these attributes (e.g. regarding market access, social or financial capital). Agents interact on structures such as networks and their behavior is interdependent. They can adapt their behavior and learn. Together these characteristics can give rise to complex, often unpredictable aggregate behavior, patterns or functions \citep{Page2015}.

Because ABMs integrate individual The decision making, heterogeneity and interactions between agents as well as between social and environmental processes, they are particularly suitable to study social-ecological systems as \emph{complex_adaptive_systems} \citep{Levin1998, Miller2007}, which are characterized by self-organization, adaptation, non-linear behavior and crossscale emergence. \emph{Self-organization} refers to the lack of a central control and the path-dependent evolution of patterns within the model (e.g. of groups of similar agents) through micro-level interactions over time. The system evolves through adaptations of heterogeneous and diverse agents and their behavioral strategies to the endogenously changing conditions of their social and ecological environment. ABMs therefore allow exploring non-linear behavior at the system level that emerges from interactions of micro-level structures and studying unexpected outcomes of micro- or macro-level disturbances or interventions in the system. In this way, ABM helps to develop a mechanismbehavior of the agents can be modeled with any of the approaches introduced in Section~\ref{sec:individual_behavior} or be based understanding of system-level phenomena \citep{Epstein1999, Hedstrom2010}. However, because of their potentially high complexity and dimensionality in state and parameter space,

ABMs are often difficult to analyze and may require high computational capacities to understand their dynamics beyond single trajectories.

In addition to the behavior of the agents, ABMs of social-ecological systems
incorporate the dynamics of the environment resulting from natural processes and
human action insofar as it is relevant for the agents' behavior or for answering
a research question about its environmental and social consequences.
For example, the decision to intensively use a land plot as pasture may lead to
overgrazing and change the nutrient content of soils. This can ultimately make
the land unusable and may force the agent to adapt a new strategy.
Most ABMs of social ecological systems describe agents as boundedly rational
decision makers (see Section~\ref{sec:bounded_rationality}) or profit maximizers
that take into account information from the environment and other agents or
social learners that imitate other agents (see Section~\ref{sec:interaction}).

In ABMs that describe systems at the local and regional level, agent behavior is
often modeled through on data or observations that are formalized in equations,
decision trees or other formal rules. In empirical ABMs agents are often
classified into empirically-based agent types \citep{Smajgl2014} or described
by, which are characterized by attributes and decision heuristics based on
empirical observations ofderived from empirical data obtained through interviews
or surveys \citep{Smajgl2014}. Increasingly, social science theories of human
behavior beyond the rational actor are being used in ABMs to represent more
realistic human behaviordecision making. However, many challenges remain to
translate these theories for usage in specific situationsABMs \citep{Conte2014}.

<u>Probabilistic and</u> stochastic processes are <u>often</u> used to capture uncertainty in and the impact of random events on human decision making and assess the consequences for macro-level outcomes. For example, random events at the local level such as a random <u>encounter between two agents that results in a</u> strategy change <u>by an individual of one agent</u> or <u>a system-level</u> environmental variation can give rise to non-linear macro-dynamics such as a sudden shift into a different system state <u>\citep{Schlueter2016</u>}.

In the context of land-use science, ABMs are mostly In addition to the behavior of the agents, ABMs of human-environment systems incorporate the dynamics of the biophysical environment resulting from natural processes and human actions insofar as it is relevant for the agents' behavior and to understand feedbacks between human behavior and environmental processes. For example, in an ABM by \citet{Martin2016}, a number of cattle ranchers can move their livestock between grassland patches in a landscape. Overgrazing in one year decreases feed availability in the following year because of the underlying biomass regrowth dynamics. Agents decide how many cattle to graze on a particular land patch based on their individual goals or needs, information on the state of the grassland, beliefs about the future and interactions with other ranchers. The model can reveal the interplay and success of different land-use strategies on common land and assess their vulnerability to shocks such as droughts. Most ABMs in the context of land-use science have so far been developed for local or regional study areas, taking into account local specificities and fitting behavioral patterns to data acquired in the field \citep{Parker2003, Parker2008a, Matthews2007, Groeneveld2017}. They are often combined with cellular automaton models that describe the dynamics and state of the physical land system \citep[e.g.,][]{Heckbert2013}. In these ABMs, the spatial embedding of agents usually plays an important role \citep{Stanilov2012}.

The following example from the literature illustrates the ABM approach in the context of land-use science: \citet{Martin2016} model a number of cattle ranchers on a landscape that have to decide how to move their livestock on grassland patches. The patches are described by equations for biomass regrowth depending on the precipitation in the area. Therefore, overgrazing in one year decreases feed availability in the following year. Agents decide when, where and how many cattle to graze on a particular land patch based on their individual

goals or needs, information on the state of the grassland, beliefs about the future and interactions with other ranchers. Such a model can reveal the interplay of different land-use strategies on common land and help to assess the vulnerability of land-use strategies to shocks such as droughts.

Because ABMs can integrate a diversity of individual decision making, heterogeneity of actors and interactions between agents constrained by social networks or space as well as social and environmental processes, they are particularly suitable to study feedbacks between human action and biophysical processes. In the context of ESM these may include human adaptive responses to environmental change such as effects of climate change on agriculture and water availability, to policies such as bioenergy production or the global consequences of shifts in diets in particular regions. Agent-based modeling is also a useful tool to unravel the causal mechanisms underlying system-level phenomena \citep{Epstein1999, Hedstrom2010} and thus enhance understanding of key human-environment interactions that may give rise to observed Earth system dynamics. However, because of their potentially high complexity and dimensionality in state and parameter space, ABMs are often difficult to analyze and may require high computational capacities and sophisticated model analysis techniques to understand their dynamics beyond single trajectories.

Agent-based approaches can be applied without modeling each individual agent explicitly. It suffices to model a representative statistical sample of agents that depictdepicts the important heterogeneities of the underlying population. To capture major types of human behavior, a recent proposal are \emph{agent functional types <a>href="https://footnote{\citet{Arneth2014">https://footnote{\citet{Arneth2014} make the analogy to plant functional types in vegetation models.] based on a based on a theoretically derived typology of agent attributes, interactions and roles \citep{Arneth2014}. This proposal is explored for modeling the adaptation of land-use practices to climate change impacts \citep{Murray-Rust2014a}. Agent-functional types represent a typology that is theoretically constructed instead of an empirically derived data-driven typology, which is common in empirically-based ABMs. Such agentAgent-based approaches are promising for Earth system modeling with respect tobecause they allow addressing questions of interactions across levels, for instance how regional or global patterns of land use emerge from interdependent regional and local or regional land-use decisions that which are in turn constrained by the results of local interactions atemerging global patterns. Furthermore, they would allow the respective level. integration of uncertainty, agent heterogeneity and aggregation of detailed technological and environmental changes \citep{Farmer2015}.

\subsection{Dynamics at the system level: System dynamics, stock-flow consistent and input-output models}

This final subsection discusses modeling approaches without explicit microfoundations. Decisions in such models are not modeled <u>directlyexplicitly with</u> <u>one of the options discussed in Section~\ref{sec:individual_behavior}</u> but, as policy decisions in integrated assessment models, through the construction of different scenarios for the evolution of crucial exogenous parameters in the model. Because the dynamics are not explained by decisions of individual agents, such approaches deviate from the standards of methodological individualism.

Global \emph{System_system dynamics} models describe the economy, population and crucial parts of the Earth system as well as their dynamic interactions at the level of aggregate dynamic variables, usually modeling the dynamics as ordinary differential equations or difference equations to mapproject future developments. The equations are often built on stylized facts about the dynamics of the underlying subsystems and are linked by functions with typically many parameters. Modelers employ systemssystem dynamics models to develop scenarios based on different sets of model parameters and assess system stability and transient dynamics of a system. In comparison to equilibrium approaches, systemssystem dynamics models capture the inertia of socio-economicsocioeconomic systems at the cost of a higher dimensional parameter space. This can lead to more complex dynamics, e.g. oscillatory., oscillations or overshooting, dynamics. Systems. System dynamics models can be very detailed, like the World3 model commissioned by the Club of Rome for their famous report on ``Limits to Growth'' \citep{Meadows1972, Meadows2004}, the GUMBO model \citep{Boumans2002a}, or the International Futures model \citep{Hughes1999}. Subsystems of such models comprise human population (sometimes disaggregated between regions and age groups), the agricultural and industrial sector, as well as the state of the environment (e.g. pollution and resource availability). Simpler models describe the dynamics of only a few aggregated variables at the global level \citep{Kellie-Smith2011} or confined to a region \citep{Brander1998b}.

SystemOther system-level approaches to macroeconomic modeling-often emphasize self-reinforcing processes in the economy and point at positive feedback mechanisms, resulting in multi-stability or even instability (e.g., increasing returns to scale in capital accumulationproduction and self-amplification of expectations during economic bubbles).

For example, post-Keynesian and ecological economists use <u>\emph{stock-flow</u> consistent models} to <u>describe a circulartrack the complete monetary flows in an</u> economy in which low aggregate demand can lead to underutilization of production factors and the state plays an active role to stabilize the economy <u>\citep{Godley2007}.</u> In these models, a social accounting matrix provides a detailed framework of transactions (<u>e.g., monetary flows, i.e. per-time</u> <u>quantities</u>) between <u>representative agents in the economy such as</u> households, firms and the government, which hold stocks of <u>financial and physical</u> assets and commodities <u>\citep{Godley2007</u>}.

While stock-flow models often focus on the monetary dimension of capital and goods, ecological modeling approaches focus on material accounting or try to integrate material with financial stocks and flows in one framework \citep[e.g.,][]{Berg2015}.\\emph{Input-output modeling} focuses on the material side of economic models} track flows to much more detail between different industries or sectors of production \citep{Leontief1986, TenRaa2005, Miller2009} and can be extended to analyze the industrial metabolism, i.e. }. Each industry the material and energy flows and its environmental impacts in modern economies \citep{FischerKowalski1997, Ayres2002, Suh2009}._Input-output models consider different sectors or production sites of the economy and the material inputs that are needed to produce a desired good together with unwanted side-products such as waste and pollution. Each sector or production siteprocess is modeled by a fixed proportions (``Leontief'') production function, which is characterized by linear factors that depend on the available technology. Given a final demand, the required production of all intermediate goods and the resulting environmental footprint can be calculated by linear programming techniques. Regional input-output models also account for spatial heterogeneity and are used for example to estimate the environmental footprints of industrialized countries in other regions \citep{Wiedmann2009} or to evaluate possible impacts of extreme climate events on the global supply chain \citep{Bierkandt2014}.

In the context of land-use changeFor example, an input-output model couldcan describe which primary input factors such as land, fertilizer, machinery, irrigation water and labor are required for satisfying the demand of an agricultural commodity by a specificmix of production technique. Sometechniques. The model would consider that some of these primary inputs have to be produced themselves, using other inputs. Outputs and outputs may also include be unwanted side-products such as manure in cattle production or externalities such as environmental degradation. The model could be used to compare different technologies or. Such models are used for instance to explore how changes in demand would lead to higher-order effects along the supply chain. Regional input-output models also account for spatial heterogeneity and are used for example to evaluate possible impacts of extreme climate events on the global supply chain \citep{Bierkandt2014}.

<u>While the approaches discussed above focus on the monetary dimension of capital</u> and goods, models from ecological economics \citep{vandenBergh2001} track material flows or integrate material with financial accounting. For example, input-output modeling has been extended to analyze the industrial metabolism, i.e. the material and energy flows and its environmental impacts in modern economies \citep{FischerKowalski1997, Ayres2002, Suh2009}. , for instance differences between intensive agriculture (mono-cultures for animal feed) and extensive land-use such as cattle ranching.

Regionalized versions of such models can for instance be used to estimate the environmental footprint that industrialized countries have in other regions \citep{Wiedmann2009}.

In the emerging field of ecological macroeconomics \citep[see][for a detailed review of modeling approaches]{Hardt2017}, stock-flow consistent and inputoutput models have been combined into one framework tracking financial as well as material flows \citep{Berg2015}.

Other ecological models use the flow-fund approach by \citet{Georgescu-Roegen1971} or combine it with stock-flow consistent modeling approaches \citep{Dafermos2017}. While the flow concept refers to a stock per time, a fund is the potentiality of a system to provide a service. The important difference lies in the observation that a stock can be depleted or accumulated in one time step while a fund can provide its service only once per time step. This distinction reflects physical constraints on the production process that have important consequences for modeling the social metabolism. \citet{Garrett2015} and \citet{Jarvis2015} in this Special Issue provide an extreme view on the dynamics of social metabolism based only on thermodynamic considerations without taking human decision making or agency into account.

In order to make these techniquesapproaches that only consider the system level useful for modeling the impact of humans on the Earth system, they could be combined with approaches that model the development of new production technologies and how they are the deployment of new technologies is affected by decisions at different levels (consumers, firms and governments). Even if this integration with decision models may prove difficult, the approaches discussed in this section can help linking social and environmental dynamics in new ways, providing an important methodology to policy makers). include humans into ESMs.

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\begin{table*}[t]
\caption{Summary table for aggregation and system level descriptions}
\label{tab:aggregation}
\begin{tabular}{p{4cm}p{4cm}p{4cm}p{4cm}}
\tophline
Approaches and frameworks & Key considerations & Strengths & Limitations \\

\middlehline
Social utility and welfare: Aggregate individual utility, possibly taking
inequalities into account &
How is inequality evaluated?
How is welfare compared between societies and generations? &
Base for cost-benefit analysis, a widely applied decision model for policy
evaluation &
Assumes that individual utility can be compared on a common scale
\\

\middlehline

Aggregation via markets: Representative agents in economic models & Which goals or preferences do representative agents have? Which How efficient do market mechanisms allocate on which spatial and temporal scales do price mechanisms span? Which market imperfections are there? & Well developed formalism that makes the connection between micro- and macroeconomics analytically traceable & Assumes that aggregated agent properties are similar to individual ones to derive economic equilibrium, coordination effort between agents neglected

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\middlehline Social planner and economic policy in integrated assessment models: Model possibilitiesways to internalize environmental externalities & Which economic policy instruments internalize environmental externalities best? What are plausible scenarios for policy implementation? How do agents react to changes in policy? & Allows to determine optimal paths for reaching societal goals & Models focus on production and investment in the economy $\boldsymbol{\Lambda}$ \middlehline Distributions and moments: Model heterogeneous agent attributes via statistical properties of distributions & Which heterogeneities are most important for the macro-outcome? & Systematic way to analytically treat heterogeneities & Only applicable for rather simple behaviors and interactions $\boldsymbol{\Lambda}$ \middlehline Agent-based models: Simulate agent behavior and interactions explicitly to study emergent macro-dynamics computationally & Which kind of agents types are important? How do they make decisions? How do the agents interact with each other and the environment? & Very flexible framework regarding assumptions about decision rules and interactions & Models often with many unknown parameters, difficult to analyze mathematically $\backslash \backslash$ \middlehline Dvnamics at the system level & Which crucial parameters in the model can be influenced by decision makers? & Allows to explore possible dynamical properties of the system based on macromechanisms & No explicit micro-foundation $\boldsymbol{\Lambda}$ \bottomhline \end{tabular} \belowtable{} % Table Footnotes \end{table*} % % _____ \section{Discussion} \label{sec:discussion}

In the previous three sections, we <u>reviewed different showed that there is a</u> <u>diversity of approaches to model _individual human decision making and behavior,</u> <u>to describe interactions between agents and to aggregate these processes. We</u> <u>illustrated them with examples from the land-use context and discussed their</u> <u>potential application in Earth system modeling with the aim of modeling complex</u> <u>feedback dynamics between natural and social components.</u>

One intention The discussion of this review is to draw the attention strengths and limitations of the reader to the different modeling approaches showed possible underlying assumptions and connections to theories about human decision making

and behavior that are possible to describe with specific modeling approaches and point to their strengths and limitations.

Some of human behavior. While some modeling techniques are compatible with almost any theorymany theories of human behavior or decision making that can be formalized and can thus be used with manya variety of assumptions about human behavior. Other modeling, other techniques significantly constrain possible assumptions about human behavior and decision making.

Therefore it is important to first decide on <u>%</u> paragraph: when is it useful to model humans dynamically

For many relevant questions in global environmental change research, a dynamical representation of humans in ESMs may not be necessary. If behavioral patterns are not expected to change over the relevant time scales or feedbacks between natural and social dynamics are sufficiently weak, modelers can simply use conventional scenario approaches.

However, if behavioral patterns are expected to change over time and give rise to strong feedbacks with the environment, then an explicit representation of human decision making will provide new insights into the joint dynamics. In this case, modelers have to choose carefully which assumptions about human behavior and decision making are reasonable in the context of a research question and then choose the techniques accordingly.

To put it the other way around, the choice of aplausible for their specific modeling technique may have considerable consequences for the types of meaningfully answerable research questions and kinds of analysis that they can providepurpose.

Modeling choices require a constant interplay between model development and the research questions that drive it. <u>In Table~\ref{tab:summary}</u>, we summarized the approaches we discussed in this paper and collected important questions regarding the different categories. We think a modeler who needs to make decisions on which approaches and techniques to use in order to include humans into Earth system models should be aware of the questions and considerations, which we discuss in the following.

RegardingBecause there is no general theory of human decision making and behavior, especially not for social collectives, we cannot provide a specific recipe for including humans into ESMs.

In Table~\ref{tab:summary}, we summarize the approaches we discussed in this paper and collect important questions to guide the choice of appropriate model assumptions and approaches.

To find the right assumptions for a specific context, modelers can furthermore build on and consult existing social-scientific research, even though ambiguities due to a fragmentation of the literature between opposing schools of thought and difficulties to generalize single case studies from their local or cultural specificities can make some of the research difficult to access. In case of doubt, modelers can team up with social scientists to conduct empirical research in the specific context needed to select the appropriate approach.

The selection of a modeling technique compatible with the chosen assumptions also has to consider its limitations for meaningfully answerable research questions and analyses that it can provide. In the following, we discuss some important considerations regarding individual decision making, interactions and aggregation.

<u>% discussion of individual decisions</u>

<u>Concerning</u> individual agents, we identified three important determinants in decision models: motives, restrictions and decision rules. Assumptions about each of these three determinants <u>Modelers</u> need to be made with great care, as there are take the many factors into account that <u>might</u> influence which motives, restrictions, and decision rules are relevant assumptions about each of these three determinants are applicable in a given context. For instance, modelers <u>can</u> make different assumptions about whether <u>decision makersagents</u> only consider financial incentives or whether also <u>soft incentives</u>take into account other <u>criteria</u>, such as a desire for fair outcome distributions \citep{<u>Fehr2002</u>}, are <u>relevant \citep{0pp1999}.</u>}, depending, e.g., on whether a situation is more or <u>less competitive or cooperative</u>. Research shows that the relevance of motives and goals can vary over time and that surprisingly subtle cues can change <u>thetheir</u> importance<u>of motives</u> \citep{Lindenberg1990, <u>Tversky1985</u>}. Likewise, the choice of a plausible decision rule depends on the studied context. For instance, a decision rule that requires complex <u>calculationscomputations</u> may be relatively plausible in contexts where <u>individualsagents</u> make decisions with important consequences and where they have the information and time needed to compare alternatives. When stakes are low and time to decide is limited, however, more simple decision rules are certainly more plausible. Cognitively demanding decision rules are also more plausible when decision makers are collectives, such as companies and governments. Sometimes, it may even be reasonable to assume that <u>actorsagents</u> use combinations of<u>the</u> different decision models \citep{Camerer1999}.

When focusing on the interaction of agents, important<u>%</u> discussion of interactions

<u>Important</u> criteria for choosing an appropriate model <u>of agent interactions</u> are the type and setting of interactions, the assumptions that agents make about each other, the influence they may exert on each other and <u>the</u> structure of interactions. For example, interactions in competitive environments will only lead to cooperation if this is individually beneficial. In such environments, agents may assume that the <u>others'others</u> form their strategies rationally. In less competitive settings, where social norms and traditions play a crucial role, however, behavior may not be strategically chosen but rather adaptively, e.g., by imitating other agents. This might also be important on time scales at which cultural evolution happens.

Furthermore, social settings might favor that agents influence each others' characteristics and primarily interact by exchanging opinions or sharing beliefs and influence each others' decisions in this way.

% interaction structure

Finally, an important criterion% discussion of aggregation

<u>Crucial criteria for the choice of how to model an appropriate aggregation</u> <u>technique for behavior and interactions of single elements</u> the properties of relevant economic and political institutions (e.g., market mechanisms or voting procedures), decision criteria for collective agents, heterogeneity of modeled agents, availability of data to evaluate the model and relevant time and spatial scales of macro-descriptions.

Depending on the specific research questions, modelers have to choose the aggregation method that fits the real-world systems of interest and describes their aggregation mechanisms and aggregate behavior reasonably. Whether the aggregate behavior of many agents is whether better represented by a representative agent as in macroeconomic models, a distribution of agent characteristics, or many diverse individuals as in ABMs depends on the importance of agent heterogeneity and interaction structures such as networks or spatial embeddedness.

The choice of an aggregation technique then determines which characteristics and processes of the system are modeled explicitly and which assumptions influence the form of the model only implicitly.

% interaction structure

If the local structure of interaction matters. If it does, this would require a
gridded or networked approach, otherwise a mean field approximation is
justified. Similar choices have to be made in classical Earth system modelsESMs:
For example, the interaction of ocean and atmosphere temperature near the
surface on a spatial grid could be modeled either by only taking interactions
between neighboring grid points into account or by coupling the ocean
temperature to the atmospheric mean field. Analogously, the interactions between
groups of two types of agents may be modeled explicitly on a social network.
However, it might also suffice to only consider interactions between two agents
representing the mean of each group respectively. The question whether the

interaction structure matters can often not be answered a priori but <u>canmay</u> be the result of a comparison between an approximation and an explicit simulation.

For the aggregation of individual decision making and interactions, crucial criteria for modeling choices are the properties of relevant societal aggregation mechanisms, decision criteria for collective agents, heterogeneity of modeled agents and relevant time and spatial scales of macro descriptions. We introduced different approaches to model political and economic institutions (markets, voting protocols) that aggregate individual decisions. Depending on the specific research questions, such modeling approaches can be adopted to fit particular real world system and describe their aggregation.

To model decisions between economic or environmental policies, normative decision models can sometimes also be used to describe such decisions if they take into account actual and perceived controls of policy makers and consider the effect of compromises between different interest groups.

Furthermore, there are interesting parallels in choices of modeling techniques between classical Earth system modeling and socio-economic models at the macrolevel. We discuss here two examples:

% heterogeneity

First, the choice between different aggregation techniques to connect a microto the system level% heterogeneity / level of detail and aggregation For the choice of an appropriate aggregation technique, modelers also have to decide on the level of detail to describe the system and whether the modeling of individuals or intermediate levels of the system is necessary or an aggregate

description suffices.

This choice depends on the expected importance of interactions and heterogeneity in an assumed set of agents. Take asAs an example from classical Earth system modeling consider vegetation models, in which modelers may considerchoose between the simulation of representative plant functional types or ensembles of individual adaptive plants depending on whether they consider the interaction and heterogeneity important for the macro-dynamics. Analogously, a model of social dynamics may choose for instance betweenuse a representative agent approach or model heterogeneous agents explicitly in an agent-based model. Of course the choice between a coarse-grained and a fine-grained description crucially depends, depending on the properties of the system and the research questionsquestion.

The choice between a detailed and aggregated description depend strongly on the model purpose. For example, if the goal is to predict the future development of a system, a system-level description could already suffice, while a more detailed model (e.g., ABM) would be needed for understanding the mechanisms that explain these outcomes in terms of underlying heterogeneous responses of individuals. Likewise, for a normative model aiming to identify the action that maximizes social welfare an intermediate level of detail could suffice, taking only specific agent heterogeneities into account.

% time scales

Second, In general, the evaluation of time scales <u>can</u> help <u>in many of the above-</u> <u>mentioned modeling choices</u> to decide whether <u>elements and social</u> processes <u>and</u> <u>properties of socioeconomic units</u> should be <u>modeled</u>represented as evolving <u>inover</u> time, <u>can be</u> fixed or need not be <u>considered</u>modeled explicitly at all for a macro-level description of the system. <u>As an</u>

For example, <u>consider the propagation of increased</u> CO\$_2\$ concentration in global circulation models. The relatively quick convection of CO\$_2\$ in the atmosphere may not be of interest on longer time scales and the

<u>COS_2S concentration can be</u> <u>can be</u> assumed to be well-mixed. <u>But when</u> <u>modeling COS_2S concentrations in the oceans</u> for the atmosphere, while assuming this for the ocean with its slow convection would distort results on politically relevant time scales, the assumption that COS_2S is well-mixed might distort the <u>results</u>_considerably <u>because convection</u> between ocean layers is comparatively <u>slow</u>\citep{Mathesius2015}.

Similarly, general equilibrium models can be a good description if the convergence of prices happens on fast time scales and market imperfections are

negligible. Dynamical systems models, on the contrary aremay be more appropriate to describe systems with a high inertia that—may operate far from equilibrium due to continuous changes in system parameters and slow convergence. Questions about the relevant spatial scales and the importance of the location of entities can be similarly related to modeling decisions in classical Earth system models.

A decisive question is therefore if the time scales of processes in the system allow a separation of scales. For instance, this is possible if the microinteractions are some orders of magnitude faster that changes in system parameters or boundary conditions. Similar considerations apply for spatial scales.

<u>% differences to natural science models</u>

As we have shown in the examples above, there are somemany similarities regarding the choice of modeling techniques and assumptions in Earth systemESMs and models and models of socio-economic socioeconomic systems. However, fundamental differences between the modeled systems pose a big challenge for an informed choice of modeling techniques. Earth system modelsESMs can often build on fundamental scientificphysical laws describing micro-interactions that can be tested and scrutinized. Of course this can result in very complex macroscopic system behavior with high uncertainties. But models including human behavior on the other hand have to draw on a variety of accounts of basic motivations in of human decision making. And these motivations may change over time while societies evolve and humans change their actions because of new available knowledge.

At this point, there is This can lead to a crucial feedback between the real world and models: Agents (e.g., policy makers) may decide differently when they take the information provided by model projections into account. Therefore, $\frac{1}{11}$ is important to keep in mind that modeling activities including humans choices regarding human behavior might eventually change thethis behavior of agents because. This aspect of human reflexivity. This makes models of human dominated systems societies fundamentally different from natural science models-This also points and is closely linked to the important difference in social modeling between normative and descriptive model purposes. We highlighted For example, models that optimize social welfare usually reflect the goal that a government should pursue, and therefore have a normative purpose. But if this difference throughout the paper but want to point outmodel is used to guide policy making while taking into account the actual and perceived controls of policy makers and considers the effect of compromises between different interest groups, it could also describe its importance here again: The purpose of a model is crucial for the choice of suitable modeling techniques, e.g. choosing a maximization technique or a set of differential equations to tackle the research question. Or to put it the other way around: The choice of a modeling approach may_behavior.

This example already <u>imply basic</u>shows the often intricate interconnections between normative and descriptive assumptions although the modeler may not in decision modeling that modelers should be aware of them and just choose.

This is further complicated by the observation that the same assumption may be understood in one model as a descriptive (positive) statement whereas in another model it may be meant as a prescriptive (normative) one. For example, in a model of agricultural markets, the assumption that big commercial farms maximize their profits might be a reasonable descriptive approximation. for pragmatic reasonsHowever, in a model that asks how small-holder farms could survive under competitive market conditions, the same assumption gets a strong normative content.

AAnother difficulty that we encountered in the classification and presentation of the material is that it is not always clear which parts of a theory is that model choices are important often not only based on the most plausible assumptions regardingabout human behavior and which modeling decisions decision making but are taken because of strongly influenced by considerations about the assumption's mathematical convenience. Choosing assumptions for technical reasons, e.g., mathematical simplicity and tractability, may be problematic because it remains unexplained how they are related to the real world. Additionally, assumptions in one model may be understood as descriptive (positive) statements whereas in another model they may be meant as prescriptive (normative) ones, depending on the application of the modelBut because not all assumptions can be easily implemented in formal models, often a trade-off has to be found between plausibility and technical practicality of assumptions. For example, in a model of agricultural markets, the assumption that big commercial farms maximize their profits might be a reasonable descriptive approximation. However, in a model that asks how small-holder farms could survive under such market conditions, the same assumption gets a strong normative content.

Another important insight from the reviewing effort is that the terminology sometimes differs between disciplinary or sub-disciplinary scientific fields. Therefore, different terms from two separate fields could refer to very similar theories whereas the same term might be used to describe quite separate varieties of a theory in different fields. We tried to use our terminology as clearly as possible and thus hope to contribute to a better understanding between different fields. But not only the terminology differs between fields, there are also important differences in focus and consequent limitations between different schools in the social sciences.

We also want to point out that our survey of techniques has a bias towards oconomic modeling techniques for two simple reasons: First, oconomics is the social science discipline that has the longest and strongest tradition in formal modeling of human decision making. Second, economics focuses on the study of production and consumption as well as the allocation of scarce resources. In most industrialized countries today, a major part of human interactions with the environment is mediated through markets, central in economic analyses. This review goes beyond the often narrow framing of economic approaches while at the same time not ignoring important economic insights. For instance, consumption and production decisions do not only follow purely economic calculations but are deeply influenced for instance by behavioral patterns, traditions and social norms \citep{TheWorldBank2015}.

However, many theories in the social sciences are building on verbal models rather than mathematical formalizations. A major part of the theoretical work in the social sciences is very context specific and some sub-disciplines reject that their findings can be meaningfully generalized \citep{Williams2012, <u>Rosenberg2012</u>}. However, including human decisions into Earth system models requires such generalizations. Without them, the modeling of futures that are potentially very different from the past would not be possible. This makes many approaches in the social sciences incompatible with natural science and therefore difficult to include into Earth system models. It is therefore important to put effort into formalizing such theories, making them scalable and testing the consequences of their different assumptions about human behavior, interactions and its aggregation at different levels.

Most global models that describe human interactions with the Earth system <u>and</u> we <u>found in the literature reviewed here</u> are based on economic assumptions about the behavior of <u>humans and</u> societies <u>and</u>. They are often only linked in a one-way fashion to the <u>biogeophysical</u> part of the Earth system. <u>It</u>

Including closed feedback loops between social and environmental dynamics into ESMs is thus an ongoingstill a big challenge. To advance this endeavor, more work is needed to include co-evolutionary

To advance this endeavor, more work is needed to include co-evolutionary dynamical interactions synthesize modeling approaches that can represent various aspects of human societies with other Earth system components into behavior in the context of global models. modeling, even if the need for generalizations and formalization of human behavior is sometimes met with skepticism or rejection by social scientists who emphasize the context dependence and idiosyncrasy of human behavior. Of course, models <u>includingthat use simple theories of</u> human decision making and <u>social dynamics can notbehavior to describe human-environment interactions in</u> <u>the global context cannot claim to describecapture all real-world social</u> interactions. However, they could include formal descriptions of idealized social mechanisms so far not considered explicitly in global models that are regarded as being important to explain driving forces for environmental impacts such as land-use change. Even though more realistic models would have to be much more complex if they If models considered the heterogeneity of agents in all relevant aspects, <u>they</u> would have to be much more complex than all models that have been developed to date. But in many real-life settings even simple conceptual models of social mechanisms are good descriptions of key features of the dynamics at work, as we have highlighted throughout this review. One the one hand, modeling human behavior comes with many degrees of freedom. On the other hand, modelers need to choose assumptions that are plausible in the

context of their study, consulting existing social-scientific research, exploring whether alternative assumptions about the three determinants are crucial in the sense that they affect the predictions of the ESM, and conducting the empirical research needed to select the appropriate model.

Including such formal descriptions of idealized social mechanisms can therefore be a good starting point for understanding feedbacks in the Earth system and their qualitative consequences so far not considered explicitly in global models.

%t
\begin{table*}[t]
\caption{Collection of questions that may guide the choice of modeling
approaches and assumptions.}
\label{tab:summary}
\begin{tabular}{p{4cm}p{10cm12cm}}

\tophline
Category & Important modeling questions \\

\middlehline
Modeling individual decision making and behavior
& Which goals do agents pursue?

Which constraints do they have?

Which decision rules are useddo agents use?

How do agents acquire information and beliefs about their environment?

Modeling interactions between agents & Do agents interact in a competitive environment or are interactions primarily governed by social norms?

What do agents assume about each other's rationality?

Do agents choose actions strategically or adaptively?

How are agents influenced by others regarding their beliefs and norms?

Which structure do the interactions have and how does the structure evolve?

Aggregating behavior and modeling dynamics at the system level &

Are <u>agent</u> decisions aggregated through political institutions (e.g., voting procedures) or markets?

According to which criteria do policy makers decide and which controls do they have?

Is the heterogeneity of agent characteristics and interactions important?

Which macro-level measures are dynamic and which can be assumed to be fixed? $\verb|||$

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\end{tabular}
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\conclusions[Summary and Conclusion]
\label{sec:conclusion}

In this review, we discussed common modeling techniques and theories that could be potentially used to include human decision making and the resulting responsesfeedbacks with environmental dynamics into Earth system models. (ESMs). Although we could only discuss basic aspects of the presented modeling techniques, it is apparent that modelers who want to include humans into Earth system modelsESMs are confronted with crucial choices of which assumptions to make about human behavior and which appropriate techniques to use.

As Table~\ref{tab:summary} summarizes, we discussed techniques and modeling assumptions in three different categories. First, the modeling of individual decision makingmodeling focuses on decision processes and the resulting behavior of single agents and therefore has to make assumptions about how the determinants of choices between possible behavior comes about.behavioral options. Second, modelsmodel of interactions of two or several between agents capture how decisions depend upon each other and how agents influence are influencedeach other regarding different decision criteria. Third, modeling techniques that aggregate individualagent behavior and interactions to a system level description. The third category is are crucial for being able to model human behavior at scales relevant for the Earth system butand requires key elementsingredients of the first and the second categories. To include human decision making into ESMs, techniques and assumptions from these three categories have to be combined. Finally, we discussed important questions regarding the choice of modeling approaches and their interrelation with assumptions about human behavior and decision making, e.g-., regarding the level of description, the relevant time scales but also difficulties that can arise due to human reflexivity and the amalgamation of normative and descriptive assumptions in models.

The<u>Most</u> formal models <u>used in various disciplines to that</u> describe human behavior in <u>global</u> environmental contexts <u>have a bias towardare based on</u> economic approaches. This is not surprising because <u>most of the modeling</u> techniques applied in the context of global environmental change today follow economic approaches and many human interactions with the environment are driven by economic forces, and economics has a stronger focus on formal models than <u>other social sciences</u>. However, we think that it is necessary to advance research that <u>alsobuilds on insights from other social sciences and</u> applies social modeling and simulation in the context of global environmental change. One important aim of such research would be to provide a theoretical basis for including processes of social evolution and institutional development into Earth system models.ESMs. If we want to explore the possible futures of the Earth, we need to get a better understanding of how the long-term dynamics of the Earth system in the <u>Anthropocene</u> is shaped by these <u>cultural and</u> social processes.

A new generation of Earth system modelsESMs can build on various approaches, some of which we reviewed here, to include human decision making and behavior explicitly into Earth system dynamics. However, ambitious endeavors like this have to take into account that modeling of human behavior and social processes is a contested topic and the assumptions and corresponding modeling techniques need to be chosen carefully being aware of their strengths and limitations for the specific modeling purpose.

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%\authorcontribution{TEXT}

\competinginterests{The authors declare that they have no conflict of interest.}

%\disclaimer{TEXT}

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