



Integrating Behavioral Theories in Agent-Based Models for Agricultural Drought Risk Assessments

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OPEN ACCESS

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Specialty section:

This article was submitted to
Water and Human Systems,
a section of the journal
Frontiers in Water

Received: 26 March 2021

Accepted: 09 August 2021

Published: 03 September 2021

Citation:

Schrieks T, Botzen WJW, Wens M,
Haer T and Aerts JCJH (2021)
Integrating Behavioral Theories in
Agent-Based Models for Agricultural
Drought Risk Assessments.
Front. Water 3:686329.
doi: 10.3389/frwa.2021.686329

Improving assessments of droughts risk for smallholder farmers requires a better understanding of the interaction between individual adaptation decisions and drought risk. Agent-based modeling is increasingly used to capture the interaction between individual decision-making and the environment. In this paper, we provide a review of drought risk agent-based models with a focus on behavioral rules. This review leads to the conclusion that human decision rules in existing drought risk agent-based models are often based on *ad hoc* assumptions without a solid theoretical and empirical foundation. Subsequently, we review behavioral economic and psychological theories to provide a clear overview of theories that can improve the theoretical foundation of smallholder farmer behavior and we review empirical parameterization, calibration, and validation methods of those theories. Based on these reviews, we provide a conceptual framework that can give guidance for the integration of behavioral theories in agent-based models. We conclude with an agenda to guide future research in this field.

Keywords: agent-based model (ABM), drought risk assessment, behavioral theory, adaptation behavior, human decision-making, smallholder farmer

INTRODUCTION

As a result of climate change, the intensity, and duration of droughts are likely to increase in several regions around the world, particularly in low- and middle-income countries in tropical regions, which are disproportionately affected by climate change (Mendelsohn and Williams, 2006; Morton, 2007; IPCC, 2012; CRED and UNDRR, 2020). One of the most vulnerable groups to the potentially devastating impact of such droughts, are smallholder farmers in the rural areas in these countries. Such smallholder farmers often have a relatively low capacity to adapt, and this capacity to adapt is further hampered by recurring droughts that reduce the agricultural productivity on which they rely for subsistence and income (Morton, 2007; IFAD and UNEP, 2013; Donatti et al., 2018). Despite these disproportionate adverse effects on smallholder farmers, the majority of the research on the impact of climate change on agriculture has been done in industrialized countries (Claessens et al., 2012; van Valkengoed and Steg, 2019). To address this research gap, more knowledge is required on the intertwined evolution of drought risk and smallholder farmer adaptation decisions under climate change in low- and middle-income countries.

Drought risk depends on the interaction between hazard, exposure, and vulnerability (IPCC, 2012). A drought risk assessment, both in general and for smallholder farmers, therefore involves

an analyses of the interactions between physical and societal processes, which requires integration of natural and social sciences (Van Loon et al., 2016). Traditional drought risk models, originated in natural sciences, focus on the hydro-meteorological drought hazard and therefore neglect important influences of human adaptation behavior, such as smallholder farmers changing their land use (Hagenlocher et al., 2019; Wens et al., 2019). The social-hydrological literature aims to improve the realism of hydrological modeling by studying the interactions and feedbacks between natural and human systems (Sivapalan et al., 2012; Blair and Buytaert, 2016). Human behavior is, however, often represented as rational behavior of a homogeneous group in existing social hydrological risk assessment approaches (Di Baldassarre et al., 2015; Wens et al., 2019). Individual adaptation decisions are, in reality, found to be heterogeneous in space and time; they differ widely across regions, leading to different patterns of risk (Gebrehiwot and van der Veen, 2015; Huber et al., 2018). Moreover, multiple empirical studies show that individual adaptation decisions often cannot be explained by economic rational behavior; decisions are influenced by individual perceptions and attitudes and bounded rationality (Keshavarz and Karami, 2016; Malawska and Topping, 2016; Van Duinen et al., 2016; Wens et al., 2020).

An approach that allows to better represent the evolution of drought risk by capturing bounded rationality, differences in individual decision-making and interactions and feedbacks between individuals and their environment is agent-based modeling (An, 2012; Filatova et al., 2013; Aerts et al., 2018; Huber et al., 2018). In recent years, agent-based models (ABMs) have gained popularity in studies on coupled human-natural systems, such as studies on flood risk assessment (Haer et al., 2019; Aerts, 2020), land use change (Groeneveld et al., 2017) or drought risk assessment (see **Table 1**). An ABM explicitly models each individual agent and its (mal-)adaptation decisions. Based on decision rules, each agent responds to environmental states and has the capacity to adapt decisions based on changes in other agents or the environment (Matthews et al., 2007; Wens et al., 2019). A challenge in agent-based modeling is however to select realistic human decision rules (Filatova et al., 2013; Schlüter et al., 2017). Decision rules are often based on *ad hoc* assumptions of human behavior without sufficient empirical and theoretical foundation (Müller et al., 2013; Groeneveld et al., 2017; Schulze et al., 2017; Schwarz et al., 2020). A better representation of the complex human decision-making process can be reached when decision rules are based on behavioral economic and psychological theories that can be calibrated with empirical methods (An, 2012; O'sullivan et al., 2016; Groeneveld et al., 2017; Schulze et al., 2017; Muelder and Filatova, 2018). It can, however, be a challenge for modelers, who often do not have a social science background, to select the relevant theory among the many competing decision-making theories (Filatova et al., 2013; Aerts, 2020).

Several ABMs apply decision theories in the context of adaptation behavior of smallholder farmers (e.g., Van Duinen et al., 2016; Hailegiorgis et al., 2018; Pouladi et al., 2019; Wens et al., 2020), but different modelers have different interpretation of the same theories. Modelers often build their

own models from scratch focusing on specific cases, which makes it difficult to compare studies and to learn general lessons (O'sullivan et al., 2016; Muelder and Filatova, 2018). So far, there has been no clear overview of theories that are suitable to describe adaptation behavior of smallholder farmers in ABM and there are no clear guidelines on the selection, integration, and calibration of the theories. The aim of this paper is to (1) review existing agent-based drought risk models with a focus on human decision rules, to (2) provide an overview of economic and psychological decision-making theories that are suitable to model adaptation behavior, and (3) to guide future research on drought risk assessments for smallholder farmers by developing a conceptual framework for the integration of adaptation behavior, based on decision-making theories and calibrated by empirical observations, in ABMs.

LITERATURE REVIEW ADAPTATION BEHAVIOR IN DROUGHT RISK ABMS

ABMs have been introduced in the coupled human-natural systems literature to better capture the actions, interactions, and feedbacks between individual decision-makers and the environment (Aerts et al., 2018). The ABM approach also gives the possibility to account for more realistic bounded rationality and heterogeneity in individual behavior, in contrast to the commonly used, but less realistic, rational utility maximizing behavior (Filatova et al., 2013; Schlüter et al., 2017).

Acosta-Michlik and Espaldon (2008) are one of the first to apply agent-based modeling to model human adaptation behavior to climate change. They contribute to the advancement of vulnerability concepts by assessing the vulnerability of farmers in the Philippines and assessing adaptation options to reduce vulnerability. Acosta-Michlik and Espaldon (2008) demonstrate that ABM can be a useful tool to simulate the effect of adaptation options on reducing climate change vulnerability. Later studies applied agent-based modeling specifically to drought adaptation behavior. Van Loon et al. (2016), Hailegiorgis et al. (2018), Wens et al. (2020) and Zagaria et al. (2021) combine a human decision making model with an agricultural model that estimates crop yield based on hydrological conditions, meteorological data and farm water management. Van Duinen et al. (2016) and Wens et al. (2020) demonstrate that the selection of the decision rule has a large impact on the model outcome and that decision rules based on bounded rationality better represent actual behavior in their case study areas than decision rules based on rational behavior. Hailegiorgis et al. (2018) and Zagaria et al. (2021) focus on the impact of different climate scenarios on the decision of farmers and demonstrate that climate change expectation and drought risk perceptions are important drivers of adaptation behavior.

Next to the ABMs on drought and climate adaptation, a related group of ABMs focus on water resource management in the context of water scarcity. Berger et al. (2007) demonstrate that ABM can be a useful approach to support water resource management, by coupling an ABM on water use behavior with

TABLE 1 | Overview of drought risk agent-based models.

References	Main output	Agents	Adaptation measures	Theory	Parameterization and Calibration	Output Validation	Location
Wens et al. (2020)	Drought risk	F	Long-term	EUT, PMT	Expert knowledge, social surveys, interviews.	Historical data on average maize yields and poverty	Kitui, Kenya
Van Duinen et al. (2016)	Agricultural income, Water demand	F	Long-term	CM	Interviews, surveys, expert knowledge.	–	Zeeland, The Netherlands
Hailegiorgis et al. (2018)	Adaptive capacity of households	F	Short-term	PMT	Census data and scientific literature	Face-validity tests. Historical data and field visits	South Omo Zone, Ethiopia
Acosta-Michlik and Espaldon (2008)	Vulnerability to global environmental change	F,G	Government policies	CM	Interviews, social surveys and cluster analysis	–	Tanauan City, Philippines
Pouladi et al. (2019)	Amount of water reaching Urmia Lake through Zarrineh river	F	Long-term	TPB	Interviews, social surveys and cluster analysis	Observed time-series of river discharge	Zarrineh River/Urmia lake, Iran
Mehryar et al. (2019)	Impact of policies on groundwater use	F,G	Short-term, long-term and government policies	No	FCM, interviews and cluster analysis	Historical data on groundwater use	Rafsanjan, Iran
Hyun et al. (2019)	Irrigation decisions under future climate scenarios	F	Short-term	TPB	Trial and error	Historical precipitation data	San Juan River Basin, Upper Colorado River Basin, USA.
Zagaría et al. (2021)	Transformational adaptation to water scarcity	F	Short-term and long-term	No	Interviews and Census data	–	Romagna, Italia
Van Oel et al. (2012)	Spatial distribution of water availability and water use	F, G	Short-term	No	Social surveys	Reservoir volumes, land use (remote sensing)	Jaguaribe basin, Brasil
Castilla-Rho et al. (2017)	Groundwater	F, R	Government policies	No	World value survey	Survey data of one basin	Global
Ghoreishi et al. (2021)	Yearly Agricultural Water Demand	F, G	Short-term and long-term	No	Empirical data on water demand and irrigation system area	Empirical data on cropping patterns. Qualitative data from existing reports and interviews	Bow River Basin, Canada

Agents: F, Farmer; G=Government R, Regulator. **Theory:** EUT, Expected Utility Theory; PT, Prospect Theory; PMT, Protection Motivation Theory; TPB, Theory of Planned Behavior; CM, Consumat.

a water run-off and crop growth model. (Schlüter and Pahl-Wostl, 2007) develop an ABM to assess different types of water management regimes. Van Oel et al. (2012) couple an ABM on land use and irrigation decisions with a model on water levels in the river basin of the Jaguaribe River in Brasil, to analyze the feedback mechanisms between water availability and water use under decreasing rain fall scenarios. Their model shows that a decrease in rainfall and runoff leads to a transition of water use from the dry to the wet season which increases water scarcity in the dry season. Other studies that couple an AMB on water use behavior to a model on water levels in a river basin, analyze how water use behavior influences restoration of the environment (Pouladi et al., 2019), study the role of risk perception in water management decisions (Hyun et al., 2019), or research the impact of changes in cropping patters and irrigation systems on agricultural water demand (Ghoreishi et al., 2021). Castilla-Rho et al. (2017) and Mehryar et al. (2019) also model

water use under water scarcity conditions, but instead of water use in a river basin they model groundwater use. The aim of these models is to analyze the impact of ground water conservation policies on groundwater use.

To get a better understanding of human-decision making in drought risk ABMs, we made a more detailed comparison of the components of the human-decision making module in a selection of recent ABMs. All selected papers couple a human decision-making module, describing the behavior of heterogeneous agents, with a hydrological module, which captures the drought hazard. **Table 1** gives an overview of all selected papers.

We start with a description of agents that are involved in the models, followed by a description of adaptation measures, behavioral theories and, parametrization, calibration, and validation methods. To make a comparison, we examined the model descriptions in the papers and, if available, the descriptions

in the ODD (Grimm et al., 2010) and ODD+D (Müller et al., 2013) protocols¹.

Agents

The central agents in the reviewed ABMs are the individual farmers (pastoralist, agro-pastoralists or agriculturalists) who make the final adaptation decisions and interact with other farmers in their social network. The behavior of farmers is, however, also influenced by several other agents. Important agents in the context of drought ABMs can be government officials (e.g., policymakers or regulators), economic and financial institutions (e.g., insurers, banks, and donor organizations) and domestic or industrial water users (Kaiser et al., 2020). While the government is included in several of the reviewed studies (Van Oel et al., 2012; Castilla-Rho et al., 2017; Mehryar et al., 2019; Ghoreishi et al., 2021), the other types of agents are not. The studies that do include a government (policymaker, regulator or allocation committee) generally do not model governments as endogenous agents, but include different scenarios of government policies as exogenous elements that influence the decision making process. The models thus focus on the decision-making of the farmers and do not include a dynamic interaction between farmers and other agent types.

Adaptation Measures

Several different types of adaptation measures are included in the papers in **Table 1**. Some of the papers include short-term managerial adaptation decisions, such as the timing of land preparation, planting, and harvesting (Van Oel et al., 2012; Hailegiorgis et al., 2018), decisions on irrigation area (Hyun et al., 2019; Ghoreishi et al., 2021; Zagaria et al., 2021) and adding purchased water to the land or updating well depth (Mehryar et al., 2019). Most of the reviewed papers focus, however, on longer-term decisions which require investments in new technology, with for example selecting alternative (drought resistant) crop types (Pouladi et al., 2019; Ghoreishi et al., 2021; Zagaria et al., 2021), well deepening (Mehryar et al., 2019; Wens et al., 2020), freshwater storing (Van Duinen et al., 2016; Wens et al., 2020), changing farm size (Mehryar et al., 2019; Zagaria et al., 2021) and investing in irrigation systems (Van Duinen et al., 2016; Mehryar et al., 2019; Wens et al., 2020; Ghoreishi et al., 2021). These longer-term measures require investments that have a long-term impact with an uncertain outcome. Capital availability, risk perception, and risk preferences are therefore important factors in the decision-making process of the farmer. A third type of adaptation measures included in some models involves government policies, such as policies on farm size and irrigation systems (Mehryar et al., 2019), allocation of water rights (Castilla-Rho et al., 2017) and financial support (Acosta-Michlik and Espaldon, 2008).

¹We could not find an ODD or ODD+D protocol for Acosta-Michlik and Espaldon (2008), Ghoreishi et al. (2021) and Pouladi et al. (2019). Mehryar et al. (2019) and Van Oel et al. (2012). followed the ODD (Overview, Design concepts and Details) and all other selected models did use the ODD+D (ODD + Decisions) protocol, which provides a more detailed description of human decision-making.

Behavioral Theories

Some of the reviewed papers have based the human decision-making module on psychological theories that describe the cognitive processes behind the adaptation decisions. Wens et al. (2020), Zagaria et al. (2021) and Hailegiorgis et al. (2018) use the protection motivation theory of Rogers (1983), which assumes that farmers' intention to adapt depends on the threat appraisal and coping appraisal. Pouladi et al. (2019) and Hyun et al. (2019) use the theory of planned behavior (Ajzen, 1991), which assumes that adaptation intentions are influenced by someone's attitude, subjective social norms and perceived control over the situation. Van Duinen et al. (2016) and Acosta-Michlik and Espaldon (2008) build a behavioral module based on the Consumat approach (Jager et al., 2000), a method to classify and describe different types of bounded rational behavior influenced by the social network.

The description of the theory and the argumentation for the selection of the theory is however often limited and there is quite some variation in the interpretation of the theories. Wens et al. (2020), Zagaria et al. (2021) and Hailegiorgis et al. (2018) apply the same theory, but they use different proxy variables for the different elements of the theory and Van Duinen et al. (2016) and Acosta-Michlik and Espaldon (2008) use two different version of the Consumat approach. These differences in interpretation make it difficult to make a comparison between the different models. Wens et al. (2020) and Van Duinen et al. (2016) compare bounded rationality in respectively the protection motivation theory and the Consumat approach with rational choice theory and conclude that these psychological theories with bounded rational behavior provide a more realistic estimation than the models with rational behavior. They however only include the very restrictive rational choice theory that assumes full rationality and do not compare the psychological theories with less restrictive economic theories such as subjective expected utility theory (Fishburn, 1981) or prospect theory (Kahneman and Tversky, 1979).

The papers that do not include a specific behavioral theory develop *ad hoc* decision rules based on simple heuristics. Ghoreishi et al. (2021) emphasize the importance of including bounded rationality instead of rational behavior, but subsequently they only include a few simple decision rules with simple elements of bounded rational behavior without building on established behavioral theories. The main disadvantages of using *ad hoc* decision rules that are not grounded in behavioral theories are that a comparison between different models cannot be made and important elements in the decision-making process, that have been studied extensively in social sciences, may be missed. In Section Behavioral Theories we give a more elaborate description of different behavioral theories and how they can be applied in an ABM.

Parameterization, Calibration and Validation Methods

Parameterization, calibration and validation of the coupled models is one of the main challenges in agent-based modeling (Smajgl et al., 2011; Smajgl and Barreteau, 2017; Venkatramanan

et al., 2018; Aerts, 2020). For parameterization and calibration, most of the reviewed models rely on their own fieldwork with a combination of expert interviews and household surveys. Alternative approaches that have been used are fuzzy cognitive mapping that links important variables (Mehryar et al., 2019), or calibration based on existing data, such as the world value survey (Castilla-Rho et al., 2017), census data (Hailegiorgis et al., 2018) or water demand data (Ghoreishi et al., 2021). Cluster analysis is applied in several of the models to define different agent types based on household characteristics in household surveys or census data (Acosta-Michlik and Espaldon, 2008; Mehryar et al., 2019; Pouladi et al., 2019; Zagaria et al., 2021). For validation, several studies compare the model estimates with historical data on, e.g., average yield (Wens et al., 2020), river discharge (Pouladi et al., 2019) reservoir volumes (Van Oel et al., 2012), or groundwater use (Mehryar et al., 2019). A challenge with output validation with historical data is however that those datasets often only contain aggregated information and therefore cannot capture behavior of heterogeneous individuals (Claessens et al., 2012). In Section Empirical Methods for Parameterization, Calibration, and Validation, we discuss some alternative methods that are more suitable for the calibration and validation of economic and psychological theories.

BEHAVIORAL THEORIES

Some of the reviewed papers have based their behavioral modules on economic or psychological theories, but most of them base their decision rules on empirical observations or *ad hoc* assumptions, without modeling the underlying cognitive process. Improving the integration of human behavior in ABMs requires a more elaborate behavioral module that has a theoretical foundation. A first challenge for a modeler is to select the relevant behavioral theory, among the many theories that have been developed by social scientists (Schlüter et al., 2017). In this section we describe the most relevant economic and psychological theories for modeling drought risk adaptation of smallholder farmers in an ABM. The selection of the theories is based on the review of agent-based models above and a literature search on theories that have been applied in social science literature on adaptation behavior of farmers. We discuss two economic theories: expected utility theory (EUT) and prospect theory (PT), which are the two most prominent theories on decision-making under risk in (behavioral) economics and have been applied in several ABMs (Groeneveld et al., 2017; Schlüter et al., 2017); two psychosocial theories, theory of planned behavior (TPB) and protection motivation theory (PMT), which have also been used in ABMs to model adaptation behavior (e.g., Hailegiorgis et al., 2018; Pouladi et al., 2019; Wens et al., 2020); and the Consumat framework (Jager et al., 2000), which combines elements from several psychological and economic theories, and has been used in two of the reviewed ABMs (Acosta-Michlik and Espaldon, 2008; Van Duinen et al., 2016).

Expected Utility Theory

Expected utility theory (EUT) is the traditional economic theory on decision-making under risk and has been applied in different

contexts (Machina, 2008; Sen, 2008). Several ABMs on coupled human-natural systems make use of EUT to model human behavior (Groeneveld et al., 2017; Aerts, 2020). This theory, developed by Von Neumann and Morgenstern (1947), is based on the assumption that people are rational decision makers who will always select the option that gives them the highest expected utility. People have perfect information on the available decision options, the likelihood of different outcomes, and the corresponding gains and losses (Sen, 2008). In the context of drought risk adaptation, this would mean that farmers have perfect information on the available adaptation options and that they consider the full distribution of risks, meaning that they recognize the existence of different drought events with different degrees of costs and likelihoods (Van Duinen et al., 2015b). Farmers will make a ranking of the different options and select the adaptation strategy that gives the highest expected utility within their budget.

Using EUT in an ABM on drought risk assessment requires to specify one or more adaptation strategies for the agents, with the corresponding costs and benefits under different drought impact scenarios. The agents select the strategy with the highest (discounted) expected utility, within their budget constraint. Expected utility is a function of wealth, the costs and benefits of the adaptation strategy, which can depend on climate change, and potential residual losses. As an example (based on the examples in Haer et al., 2017), consider a farmer who has to make a choice between M adaptation measures (e.g., investing in drought resistant crop types or irrigation) or not adopting a measure. The discounted utility functions for those options are:

$$EU(\text{no adaptation}) = \sum_{t=0}^T \delta^t \sum_{i=1}^I p_i U(W_t - L_{i,t}) \quad (1)$$

$$EU(\text{adaptation } m) = \sum_{t=0}^T \delta^t \sum_{i=1}^I p_i U(W_t - R_{i,m,t} - C_{m,t}) \quad (2)$$

The utility $U(x)$ of the farmer is a function of his wealth which depends on the drought impact and the choice of the adaptation measure m . The expected utility is a summation of the utility of all possible states of the world i that occur with probability p_i . The states of the world in this example are the possible drought events with different magnitudes that can occur and the situation with no drought. W_t is the initial wealth of the farmer at time t and $L_{i,t}$ is the loss of drought event i at time t , when the farmer did not invest in the adaptation measure. $C_{m,t}$ is the net cost of investing in adaptation measure m at time t , and $R_{i,m,t}$ is the residual loss of drought event i when the farmer has invested in adaptation measure m . In general the residual ($R_{i,m,t}$) loss should be smaller than the loss ($L_{i,t}$) without the adaptation measure and both $R_{i,m,t}$ and $L_{i,t}$ should be zero when no drought occurs². The adaptation measures are evaluated over T periods, which represents the lifetime of the adaptation measure. Future

² $R_{m,i,t}$ differs per type of adaptation measure. Some measures only have an effect in extreme drought events, while other also have a positive or negative effect in cases of moderate or no droughts. These differences in adaptation measures at different stages can all be captured in $R_{m,i,t}$. This could then also result in a positive $R_{i,m,t}$ (gain) or a larger loss than without an adaptation measure for specific drought (or non-drought) events.

periods are discounted with discount rate δ , because people are generally assumed to put more weight on current wealth than on future wealth (Frederick et al., 2003). Different agents can have different time-preferences, which can be represented in an ABM by assigning different discount rates to different (groups of) agents. The farmer will select the option that gives the highest expected utility within the following budget constraint:

$$C_{m,0} \leq \sum_{t=0}^T \frac{1}{(1-r)^t} (W_t - \sum_{i=1}^I p_i R_{i,m,t}) \quad (3)$$

With r being the interest rate for loans on the capital market. For farmers that do not have access to the capital market, which might be realistic for smallholder farmers in low- and middle-income countries, the budget constraint just becomes the wealth at time 0 minus the expected loss from droughts ($\sum_{i=1}^I p_i R_{i,m,t}$). The budget constraint can be modeled heterogeneously across farmers, for instance by varying initial wealth levels W_t .

Application of the EUT generally assume that people are slightly risk averse, which is in line with empirical findings (Bombardini and Trebbi, 2012), also in the context of climate risk for smallholder farmers (Jin et al., 2016). A standard function used in EUT is $U(X) = X^{1-\beta}/(1-\beta)$, where the β represents the level of constant relative risk aversion. An often used value for β is 1 (e.g., Haer et al., 2017; Wens et al., 2020), in which case the utility function is written as $U(X) = \ln(X)$. Empirical estimates indicate that the average value for risk aversion is indeed around 1 (e.g., Bombardini and Trebbi, 2012), but the disadvantage of selecting one value for each agent is that heterogeneity in risk aversion is ignored. Research shows that risk aversion over modest stakes is different from risk aversion over large stakes and that risk aversion decreases if wealth increases (Binswanger, 1980; Rabin, 2000; Wik et al., 2004; Bombardini and Trebbi, 2012). A more realistic representation of reality could therefore be to include different values of risk aversion for the different agents, for example by linking risk aversion to household disposable income.

The assumption of perfect information, in the EUT of Von Neumann and Morgenstern (1947), implies that farmers' drought risk perception is identical to the actual drought risk and can therefore be fully predicted with objective drought risk factors (Van Duinen et al., 2015b). Research shows that objective risk factors are important determinants of risk perceptions, but subjective factors such as the experience of previous droughts and farmers' individual sense of control are also important risk perception determinants (Van Duinen et al., 2015b). The influence of those subjective risk perception factors is not included in traditional EUT. Most economic models therefore apply subjective EUT, first developed by Savage (1954), which is a variant of the theory with less strict assumptions on rationality. Subjective EUT assumes that people are uncertain about the probabilities of the occurrence of events and they make their own estimation of those probabilities based on both objective and subjective factors (Fishburn, 1981). This theory still has the assumption that farmers are rational utility maximizers, but they now maximize their utility based on their own subjective estimations of probabilities of drought and drought losses. These

subjective estimates can be included in the model by varying the probabilities p_i per individual agent (Haer et al., 2019). Subjective expected utility therefore includes the influence of risk perception and allows to create heterogeneity between farmers in their estimations of risk probabilities and severity.

Prospect Theory

Prospect theory (PT) is another often used theory in behavioral economic research on decision-making under risk. PT was developed by Kahneman and Tversky (1979) as a critique on the EUT and then further developed by the same authors and renamed into cumulative prospect theory (Tversky and Kahneman, 1992)³. EUT assumes that utility of gains and losses is based on absolute wealth and that individuals put the same weights on gains and losses. PT, however, assumes that people assess the utility of gains and losses as deviations from a reference point and that there are differences in preferences for gains and losses, such as loss aversion by which losses loom larger in individual decisions than equivalent gains. Furthermore, PT accounts for non-linear weighting of probabilities in decision-making about risk (Tversky and Kahneman, 1992).

A farmer who has to make a decision about adaptation measures will, according to PT, take his initial wealth as reference point and assess the gains or losses of these measures by comparing it with this reference point. The expected utility functions for a farmer that has to decide between investing in adaptation measure m and not investing in this measure (see example in Section Expected Utility Theory) are:

$$PT(\text{no adaptation}) = \sum_{t=0}^T \delta^t \sum_{i=1}^I \pi_i V(-L_{i,t}) \quad (4)$$

$$PT(\text{adaptation}) = \sum_{t=0}^T \delta^t \sum_{i=1}^I \pi_i V(-C_{m,t} - R_{m,i,t}) \quad (5)$$

The parameter π_i represent the farmers' subjective weighting of the probability of drought event i . The standard function for probability weighting in PT is (Tversky and Kahneman, 1992):

$$\pi_i = \frac{p_i^\gamma}{(p_i^\gamma + (1-p_i)^\gamma)^{1/\gamma}} \quad (6)$$

The weighted probability π_i would be the same as the actual probability p_i for $\gamma = 1$. Although probability weighting functions can differ between contexts (Barberis, 2013), Tversky and Kahneman (1992) find that people overweight low probabilities and underweight higher probabilities which is represented by a γ smaller than 1. The value for γ can differ per agent to represent heterogeneity in probability weighting. $V(X)$ is the utility of the farmer compared to the reference point. The general utility function in PT is:

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda (-x)^\beta & \text{if } x < 0 \end{cases} \quad (7)$$

³For simplicity we refer to both prospect theory and cumulative prospect theory with PT in this paper.

The x in equation (7) represents the deviation from the reference points, α and β are the utility curvature parameters and λ represents the level of loss aversion. The loss aversion λ should be larger than 1, which means that losses have a bigger impact on the utility than equivalent gains. Investing in adaptation measure m costs $C_{m,t}$ and therefore is considered as a loss of $C_{m,t}$ compared to the reference point. This loss will be $C_{m,t} + R_{m,i,t}$ in case of a drought⁴. In case of no drought and no investment in the adaptation measure, there is no change in wealth compared to the reference point, so there is no gain or loss. The farmer who does not invest, only has a loss of $L_{i,t}$ when a drought occurs. Just like in EUT, the adaptation measure is evaluated over T periods, which is the lifetime of the measure, and future periods are discounted with discount rate δ . The farmer will select the option that gives the highest expected utility within their budget, following the same budget constraint as in EUT (equation 3).

Theory of Planned Behavior

The Theory of Planned Behavior (TPB), developed by Ajzen (1991), is a psychological theory that is regularly applied in ABMs (Muelder and Filatova, 2018). The central factor in the decision making process, according to this theory, is an individual's intention to perform certain behavior, which is influenced by three factors (Ajzen, 1991, 2002b). The first factor is *attitude*, which refers to the degree of personal, positive or negative, evaluation of the behavior. In the contexts of drought adaptations, these are the personal beliefs of the farmer about the importance and usefulness of an adaptation measure for his farm (Arunrat et al., 2016). The second factor is *subjective norm*, which refers to the perceived social pressure to perform the behavior i.e., do friends, neighbors, family or other people who are important for the farmer expect him to invest in the adaptation measure (Yazdanpanah et al., 2014; Arunrat et al., 2016). The last factor is *perceived behavioral control*, which refers to the believe of an individual in his own ability to implement the intended decision i.e., does the farmer believe that he is able to execute the adaptation measure (Yazdanpanah et al., 2014; Arunrat et al., 2016). The stronger the intention, the more likely that the farmer will perform the adaptation behavior. The actual performance depends, however, also on the availability of the required resources and skills, which Ajzen (1991) calls the actual *behavioral control*.

A challenge of implementing TPB in ABMs is that attitudes, subjective norms and intentions are rather subjective model parameters and the original theory does not provide a mathematical formalization (Schlüter et al., 2017; Muelder and Filatova, 2018). Multiple studies have however successfully integrated TPB in mathematical models (Scalco et al., 2018). The basic equation for an individual's intention to perform the behavior (I), in accordance with Ajzen (1991), is a linear function of attitude (A), subjective norm (SN) and perceived behavioral control (PBC):

$$I = \alpha * A + \beta * SN + \gamma * PBC \quad (8)$$

The actual behavior (B) is a function of the intention in equation (8) and actual behavioral control (ABC):

$$B = \delta * I + \varepsilon * ABC \quad (9)$$

Perceived behavioral control can be used as a proxy to measure actual behavioral control as long as a person has realistic expectations about the difficulty of the behavior (Ajzen, 1991, 2002b).

The relative weights of the different factors (α , β , γ , δ , and ε) depend on the behavioral context and can be estimated with survey data and statistical methods such as regression techniques or structural equation modeling (Hankins et al., 2000; Ajzen, 2002a; Scalco et al., 2018). The results of the empirical analysis have to be translated in decision rules to use them in an ABM. An example of the application of TPB in ABM in the context of water conservation behavior can be found in Pouladi et al. (2019) and Koutiva and Makropoulos (2016). In both of those papers the farmer can choose between three conservation levels, that are linked to the TPB value of the behavioral intention, such that people with a high intention are most likely to perform high conservation behavior, people with low intention are most likely to perform no or low conservation behavior and people with intermediate intention are most likely to take the intermediate option.

Protection Motivation Theory

Another psychological theory that has been used in ABMs to model farmer's adaptation behavior (e.g., Hailegiorgis et al., 2018; Wens et al., 2020; Zagaria et al., 2021) is the protection motivation theory (PMT, Rogers, 1983). According to this theory, a person's intention to adapt depends on the threat (or risk) appraisal and coping appraisal (Maddux and Rogers, 1983; Rogers, 1983; Grothmann and Patt, 2005; Gebrehiwot and van der Veen, 2015). The risk appraisal process consists of two sub elements: the perceived probability and the perceived severity of the evaluated events. In the context of a drought, perceived probability refers to a person's expectation of the chance of getting exposed to a drought and perceived severity refers to the expected magnitude of the drought impact if the drought occurs (Keshavarz and Karami, 2016). The coping appraisal process depends on a person's belief in his own ability to carry out the adaptation measure (perceived self-efficacy), the believe in the effectiveness of the adaptation measure (perceived response efficiency) and the perceived costs of the adaptation measure (Van Duinen et al., 2015a; Wens et al., 2020). A persons perceptions of the factors in both threat and coping appraisal are influenced by personal characteristics and experiences and influences from the social network (Rogers, 1983).

Rogers (1983) presents the protection motivation, or intention to adapt, as an additive function of threat appraisal (TA) and coping appraisal (CA), which can be translated into the following linear function of the intention to adapt (I) for adaptation measure m at time t :

$$I_{t,m} = \alpha * TA_t + \beta * CA_{t,m} \quad (10)$$

⁴ $R_{m,i,t}$ differs per type of adaptation measure. Some measures only have an effect in extreme drought events, while other also have a positive or negative effect in cases of moderate or no droughts. This differences in adaptation measures at different stages can all be captured in $R_{m,i,t}$.

A person will only implement a certain adaptation measure when the threat appraisal and coping appraisal are high enough. This can be modeled (a) with probabilities, the higher the intention to adapt the higher the probability that the farmer actually invests in the adaptation measure (e.g., Keshavarz and Karami, 2016), or (b) with thresholds, the farmers only invests if intention to adapt is above a certain threshold (e.g., Hailegiorgis et al., 2018). The threat appraisal is an additive function of perceived probability (PP) and perceived severity (PS) and the coping appraisal of a measure is positively influenced by the perceived self-efficiency (PSE) and perceived response efficiency (PRE) and negatively influenced by the perceived costs (PC) of the measure.

$$TA_t = \gamma * PP_t + \delta * PS_t \quad (11)$$

$$CA_{t,m} = \epsilon * PSE_{t,m} + \zeta * PRE_{t,m} - \eta * PC_{t,m} \quad (12)$$

The weights of the different variables (α , β , γ , δ , ϵ , ζ , η) depend on the contexts of the adaptation decision and can be estimated with statistical analysis of survey data. Applications of PMT in ABMs often include proxy variables for some of the theoretical components if survey data is not available for all components (e.g., Hailegiorgis et al., 2018; Wens et al., 2020).

Consumat

Another approach that is used in a few ABMs on farmers' decision-making is the Consumat approach (e.g., Acosta-Michlik and Espaldon, 2008; Malawska and Topping, 2016; Van Duinen et al., 2016). Consumat (Jager et al., 2000) is a conceptual framework for the simulation of human behavior that combines insights from multiple economic and social psychological theories. An agent's behavior in Consumat is based on the satisfaction of needs and the ability to perform different types of behavior (Jager et al., 2000; Jager and Janssen, 2012; Schaaf et al., 2017). The decision making process is modeled in two steps. In the first step, the level of need satisfaction and level of uncertainty is determined for each agent. Depending on these levels of satisfaction and uncertainty, the agents will select one out of four types of decision rules for their actual adaptation behavior in the second step.

The level of need satisfaction depends on a combination of needs. In an application of Consumat on harvest behavior, Jager et al. (2002) include two needs: subsistence and leisure. In a later version of Consumat (The Consumat II, Jager and Janssen, 2012), they include three needs: existence, social and personality. Each need has a value between 0 and 1, depending on how satisfied the farmers are with this need, and follows a diminishing marginal utility function (Jager et al., 2000, 2002). The value of need y for farmer i at time t is:

$$Ny_{i,t} = 1 - \exp(-\alpha_{y,i}x_{y,i,t}) \quad (13)$$

The value of $\alpha_{y,i}$ indicates the sensitivity of individual i for need y and $x_{y,i,t}$ represent the level of 'consumption' or fulfillment of need y for individual i at time t . The total level of need satisfaction is the product of the satisfaction value of all n different needs.

$$N_{i,t} = \prod_{y=1}^n Ny_{i,t} \quad (14)$$

The level of uncertainty is defined as the difference between the expected value of consumption at time $t - 1$ and the actual value of consumption at time $t - 1$.

$$U_{i,t} = |E[x_{i,t-1}] - x_{i,t-1}| \quad (15)$$

A disadvantage of the Consumat approach is that there are no clear guidelines on which needs should be included and how they should be measured. Applications of Consumat therefore use different proxies to measure need satisfaction. More research is required to test which needs are important to include and to come to standardized formulas. An example of a proxy that can be used in the context of drought risk adaptation behavior of farmers can be found in the model of Van Duinen et al. (2016), in which satisfaction of farmers is a function of current and future income.

Both need satisfaction and uncertainty are modeled as threshold functions. Depending on whether the level of satisfaction and the degree of uncertainty are above or below the threshold, a Consumat agent can have four different types of decision strategies: repetition, imitation, deliberation and social comparison (Jager et al., 2000; Van Duinen et al., 2016; Schaaf et al., 2017). An agent with high satisfaction and low uncertainty will repeat his previous behavior and an agent with high satisfaction and high uncertainty will imitate the behavior of a similar agent. Agents with low satisfaction have to invest more effort in improving the situation. They will engage in deliberation when uncertainty is low, which means that they evaluate the outcome of all possible decisions and select the decision that results in the highest level of need satisfaction. An agent with low satisfaction and high uncertainty will perform social comparison, which involves comparison of their own previous behavior with the behavior of other agents with similar abilities.

The deliberative strategy is equivalent to the traditional economic assumption of rational behavior (e.g., the EUT decision rules 1, 2, 3), while the other strategies describe habitual behavior (i.e., repeating previous behavior) and influence of social networks. The Consumat approach thus allows for switches between rational and bounded rational decision strategies when circumstances change (Jager et al., 2000; Van Duinen et al., 2016). In the context of farmers' decisions on drought adaptation this allows for a more realistic modeling of changes in behavior when drought risk changes. For example, an increase in droughts because of climate change might cause a shift from habitual behavior to deliberation or social comparison, because an increase in droughts can decrease satisfaction and increase uncertainty. The strategies described above are the four basic strategy categories, but it is possible to include more variation in these strategies with, for example, variations in the time-horizon, discount-functions, and effect of expertise (Jager et al., 2000).

Heuristics and Biases

Research on behavioral economics and psychology has also focused on the role of heuristics and biases in decision making (Tversky and Kahneman, 1974; Gilovich et al., 2003; Gigerenzer and Gaissmaier, 2011). People are often not able to analyze all the available information to come to the optimal decision, instead they use simple decision rules (heuristics) based on

limited information, which can lead to biases in their decisions (Tversky and Kahneman, 1974). Climate change and its impact on droughts is characterized with uncertainty and the availability of reliable climate information is often limited especially for smallholder farmers in low- and middle-income countries, which makes it likely that those farmers to some degree base their drought adaptation decision on simple heuristics (Waldman et al., 2020). Decision rules in an ABM can be solely based on simple heuristics (Deadman et al., 2004; Dobbie and Balbi, 2017). Using heuristics in ABMs can be useful when little data is available about the decision making process, but some important elements in the decision making process might be overlooked. Instead of decision rules that are only based on heuristics, it is also possible to combine the heuristics with a certain behavioral theory as we discuss for some of the main decision heuristics in the context of climate change risk (Botzen et al., 2021).

A heuristic that is likely to influence decision making in the context of drought adaptation behavior is the availability heuristic (Tversky and Kahneman, 1973). The availability heuristic implies that people who experienced a severe drought find it easier to imagine that they will be hit by a drought again and therefore they indicate a higher perceived risk than people who did not experience a drought (Waldman et al., 2019). The availability heuristic can be included, for example, in PMT by assuming that threat appraisal is influenced by memory of previous droughts (Hailegiorgis et al., 2018; Wens et al., 2020). It also has been included in SEUT and PT by making risk perceptions dependent on disaster occurrence (Haer et al., 2017, 2019).

Another heuristic related to risk perceptions is the threshold level of concern heuristic (Slovic et al., 1977). Individuals that follow this heuristic do not make a rational assessment of the full risk distribution, but instead only take adaptation measures when their perceived disaster probability comes above a certain threshold. This heuristic has been incorporated in PT by making the probability weighting function of natural hazard risks dependent on this threshold (Robinson and Botzen, 2020) and is indirectly incorporated in some applications of PMT, who assume that people only consider an adaptation measure if the threat appraisal has reached a specific threshold (e.g., Grothmann and Patt, 2005). The threshold level of concern heuristic is also related to the Consumat framework, where agents only decide to apply a more cognitive demanding strategy if the need satisfaction is below a certain threshold (Jager et al., 2000).

Another heuristic that might be relevant to include in the context of adaptation to extreme droughts is myopia, which refers to a short term focus leading to overweighting of upfront costs and underweighting of future benefits of adaptation investments (Gneezy and Potters, 1997). Myopia can be incorporated in the discounted (subjective) EUT and PT frameworks through a high discount rate or short time horizon T . Moreover, herding, which refers to the observation that decision are often influenced by people in their social network (Meyer and Kunreuther, 2017) is a heuristic that is already included in the Consumat framework, where people with high uncertainty will follow either an imitation or social comparison strategy, and indirectly in TPB through subjective norms.

EMPIRICAL METHODS FOR PARAMETERIZATION, CALIBRATION, AND VALIDATION

In this section we discuss the literature on parameterization, calibration, and validation of the above mentioned behavioral theories and we discuss the advantages and disadvantages of these methods in the context of agricultural drought risk ABMs.

The difference between parametrization, calibration and validation is not always clear in the literature, because varying definitions are used. In this paper, parameterization refers to the selection of model parameters and assigning values to those parameters in the early stages of model development (Smajgl et al., 2011; Smajgl and Barreteau, 2017). The calibration process comes after that and involves fine-tuning of the model parameters including those of behavioral rules grounded in decision theories by identifying a range of values that is consistent with input data. The final phase is the validation phase which entails the evaluation of model outcomes with independent data or information (Xiang et al., 2005; Ngo and See, 2012; Smajgl and Barreteau, 2017).

Parameterization and Calibration

The parameterization and calibration of empirical ABMs is often based on a combination of different methods. The first stage, before the actual parameterization is the characterization stage in which the initial setup of the model with the principal agent types and their principle behaviors should be defined (Smajgl et al., 2011; Smajgl and Barreteau, 2014, 2017). The initial model setup is often based on a combination of theory and qualitative information on the local context of the case study region. Suitable qualitative empirical information in this stage can come from key informant interviews and expert knowledge, other suitable techniques that can be used to gather qualitative data are fuzzy cognitive mapping (e.g., Mehryar et al., 2019), focus group discussions (e.g., Nyumba et al., 2018; Palermo and Hernandez, 2020), participant observations (e.g., Yang and Gilbert, 2008) and participatory modeling (e.g., Belem et al., 2018). The initial model setup could be fully derived from such qualitative, empirical data, but we advise to build on an established behavioral theory. The qualitative empirical data can guide the selection or verification of the behavioral theory. The advantage of developing a decision module based on an established behavioral theory is that one can build on an extensive literature. Furthermore, a risk of a model that is fully—and only—designed based on local empirical data is overfitting, which means that the model is over-specified or calibrated on a specific observation (Sun et al., 2016). Such a model performs well to describe the specific case of the input data, but fails in other situations. A model that builds on an established behavioral theory avoids overfitting, which makes it more generally applicable.

Later stages in the parameterization and calibration process often rely more on quantitative data, with a variety of empirical methods suitable for diverse modeling contexts. Three important criteria are (i) size of the modeled population, (ii) the availability

of existing data, and (iii) the possibility to conduct surveys or other types of field work (Janssen and Ostrom, 2006; Smajgl et al., 2011; Smajgl and Barreteau, 2014, 2017). Smallholder farmers are often located in low- and middle-income countries where large longitudinal datasets on farming characteristics are generally not available (Saqalli et al., 2010; Dobbie et al., 2018). In the following sections we therefore first describes which methods can be applied to collect data and how these data can then be used for calibration. Subsequently, we discuss how existing longitudinal datasets can be utilized.

Surveys

Several of the reviewed ABMs in Section Literature Review Adaptation Behavior in Drought Risk ABMS rely on (household) surveys (semi-structured questionnaires) to gather quantitative input data (Acosta-Michlik and Espaldon, 2008; Van Oel et al., 2012; Van Duinen et al., 2016; Pouladi et al., 2019; Wens et al., 2020). With surveys, one can gather quantitative data on implemented risk reduction measures and factors that influence taking these measures, such as characteristics, beliefs and preferences of the relevant agents. Moreover, they can be applied to calibrate behavioral theories (Robinson et al., 2007). A benefit of building a decision making module on an established behavioral theory is that the development of survey questions can build on a large amount of existing studies that have used survey data to test those theories. In the context of climate change adaptation, several empirical studies use surveys to estimate weights of variables and relationships between variables for both PMT (e.g., Grothmann and Patt, 2005; Gebrehiwot and van der Veen, 2015; Truelove et al., 2015; Van Duinen et al., 2015a; Keshavarz and Karami, 2016), TPB (Yazdanpanah et al., 2014; Arunrat et al., 2016) and a comparison between PMT and TPB (Wang et al., 2019). Multiple studies also work with surveys to estimate farmers' risk perception and the influence of risk perceptions on drought risk adaptation (e.g., Fisher and Snapp, 2014; Van Duinen et al., 2015b; van Winsen et al., 2016), which is an important factor in PMT, EUT and PT. A meta-analysis of surveys on climate change adaptation behavior can be found in van Valkengoed and Steg (2019). It is important that a survey is designed in such a way that all components of the theory can be directly measured. In case this is not feasible or when an incomplete existing data set is applied, one can try to proxy components of a theory (e.g., Hailegiorgis et al., 2018; Wens et al., 2020). Using proxies is not the preferred option, because different modelers will have a different interpretation of the same theory which makes a comparison of model results difficult. Furthermore, using proxies or leaving out components of a theory increases the risk of omitted variable bias.

The main advantage of surveys is that they give insights in individual attitudes and perceptions and therefore represents heterogeneity between farmers or other agents (Robinson et al., 2007). A disadvantage is that most surveys applied in empirical ABMs only contain data at one point in time and therefore they are not very suitable to represent temporal variation (Robinson et al., 2007). Because of this snapshot in time, cross-sectional datasets are not suitable to test for causality of behavioral theories.

Applications of PMT, for example, would like to test for the causal relationship between risk perceptions and the intention to implement adaptation measure. It might be the case that someone had a high risk perception in the past, therefore this person has invested in risk reduction measures, which decreases the current risk perception. If the cross-sectional survey takes place after this person has invested in adaptation measures, then a low risk perception will be measured, but based on this survey it is impossible to conclude whether this person has a low risk perception because of the investment in adaptation measures or if this person never had a high risk perception (Bubeck et al., 2012). A solution for this problem is to use longitudinal surveys over multiple years, this is however rarely done (van Valkengoed and Steg, 2019) and most studies will not have the time and budget to do a longitudinal survey. Alternatively elicitation methods can be applied that assess individual intentions to take risk reduction measures, for which contingent valuation methods, choice experiments, and economic experiments have been designed to minimize hypothetical bias in such responses.

Contingent Valuation and Choice Experiments

The individual intentions to implement adaptation measures can be estimated by eliciting willingness to pay for adaptation measure with the contingent valuation method (e.g., De-Graft Acquah, 2011; Arshad et al., 2015) or choice experiments (e.g., Kassie et al., 2017). Both of these methods elicit willingness to pay based on hypothetical questions and can therefore also be used to estimate adaptation intentions in hypothetical policy or climate change scenarios (Logar and van den Bergh, 2013). With the contingent valuation method people are explicitly asked to state how much they are willing to pay for a certain adaptation measure, while in choice experiments people can be asked to make a choice between a set of alternative adaptation measures, where each alternative has several characteristics. Choice experiments can therefore also be applied to elicit preferences on other characteristics of adaptation measures or to elicit preferences on policy scenarios (Holm et al., 2016).

Contingent valuation methods and choice experiments both create an artificial market and results are therefore only hypothetical. Especially open ended contingent valuation questions have been associated with hypothetical bias, meaning that people overestimate the actual willingness to pay. For this purpose closed ended contingent valuation questions have been developed in which respondents state whether or not (yes or no) they are willing to pay a stated amount for a good, and choice experiments that mimic a market setting in which goods are bought with certain characteristics for a given price. However, hypothetical bias cannot be completely eliminated since these question formats do not involve real financial incentives as is the case in economic experiments (Hoyos, 2010; Logar and van den Bergh, 2013).

Economic Experiments

Economic laboratory experiments are experiments in a controlled setting, with students or representative samples of households or specific population groups, where participants get monetary rewards based on their decisions (Robinson

et al., 2007; Falk and Heckman, 2009). These experiments try to estimate causal relations and are often used in behavioral economics to calibrate behavioral theories. A lot of studies have used laboratory experiments to estimate risk attitudes, time preferences, and risk perceptions (Anderhub et al., 2003; Andreoni and Sprenger, 2012; Trautmann and Kuilen van de, 2018). A benefit of using EUT and PT in an ABM is that parameterization can be selected based on these existing studies if there are limited resources to collect data in the specific case study region of the ABM. However, accounting for specific characteristics of farmers in a specific region and heterogeneity of the farmers in that region requires data collection in that region which can be done with economic field-experiments or lab-in-the-field experiments.

Multiple studies use field experiments to measure risk aversion of local farmers (e.g., Binswanger, 1980, 1981; Wik et al., 2004; Holden and Quiggin, 2017). Several economic studies have worked with field-experiments to analyze whether farmer's adaptation decisions under risk are better reflected by PT or EUT. Studies with farmers in Malawi (Holden and Quiggin, 2017), Argentina (Gonzalez-Ramirez et al., 2018), Vietnam (Tanaka et al., 2010), France (Bocquého et al., 2014), and China (Liu, 2013) demonstrate that the average farmer is loss averse and that farmers overweight small probabilities and underweight large probabilities. Individual discount rates are often viewed as being a generic individual trait that is determined by individuals' impatience as well as other contextual factors, such as market interest rates. A large behavioral economics literature exists that has estimated individual discount rates for various population groups and contexts, including farmers in low and middle income countries (e.g., Tanaka et al., 2010).

Other Available Data

Instead of only relying on their own fieldwork, ABMs often also make use of census data or other existing time series data on the population in the case study area if these data are available. Census data or other existing household data are especially useful for the parameterization of ABMs for large populations. Surveys and field experiments can generally only be executed for a sample of the population. Other datasets can therefore be used for up-scaling of the model to a larger population (e.g., Smajgl and Bohensky, 2013). The benefit of Census data is that it provides nationwide information on the whole population for multiple years (Smajgl et al., 2011). Census data does not provide specific data on individual preferences and behavior that can be used for the calibration of theories. Census data or other large household datasets can however be used for cluster analysis, which is a technique where different agent types are identified based on agent attributes (Smajgl et al., 2011). Agent types in census data can be compared with agent types in a selected sample to analyze whether this sample is representative for the population. Subsequently, survey data or field experiments can be applied to identify behavior of agent types in the sample which can be scaled up to the whole population with disproportional upscaling (Smajgl and Bohensky, 2013). Several of the reviewed ABMs on drought risk make use of cluster analysis combined with interviews or surveys (Acosta-Michlik and Espaldon, 2008;

Mehryar et al., 2019; Pouladi et al., 2019). Dobbie et al. (2018) show that even in a scarce data environment, such as their case study area in Southern Malawi, cluster analysis can be a useful method to combine existing regional household data with a small survey for specific information at the village level. Cluster analysis does not necessarily have to be done for upscaling, it is also used to identify agent types in a select sample based on their own survey data.

Validation and Sensitivity Analysis

The aim of parameterization and calibration is to align model process with input data, which might be enough for a study that is interested in understanding these processes. Model simulations, however, always contain some uncertainty, and subjectivity. An ABM that aims to make predictions therefore also requires validation of the model output (Cirillo and Gallegati, 2012; Lee et al., 2015).

Calibration and validation of an ABM is generally an iterative process. Model validation, according to Cirillo and Gallegati (2012), should start with calibration of the model processes with input data (see Section Parameterization and Calibration). Subsequently, the output data of the model can be compared with actual (historical) data for the output validation. If output validation is sufficient, the validation is done. If not, the modelers should go back to the calibration process. Different types of data can be used for validation, but the validation data should always be independent of the calibration data.

The validation of model outputs can be done at different levels. One approach is to validate the macro-outcomes of the whole modeled system. For example, based on input data for parameterization and calibration, an ABM simulates adaptation behavior. This adaptation behavior feeds into a coupled hydrological model and influences the hydrological process. Time series data on these hydrological outcomes can then be used to compare the simulated model outcomes with actual outcomes. Examples of this approach can be found in Pouladi et al. (2019), who validate with data on river discharge, Van Oel et al. (2012), who validate with data on reservoir volumes and Wens et al. (2020), who validate with data on average crop yields. A challenge for the validation of models on adaptation behavior of smallholder farmers is however the fact that suitable datasets for output validation are often not available (Claessens et al., 2012; Brown et al., 2017). Datasets that do exist often only provide aggregated results and therefore do not capture heterogeneity between individuals (Claessens et al., 2012). An alternative approach is to validate specific decision rules with data from household surveys or economic experiments instead of these aggregated datasets (Heckbert et al., 2010). Especially economic experiments can be suitable to test in a controlled setting whether decision rules in an ABM are a realistic representation of actual behavior (Colasante, 2017).

A common approach for calibration and validation in hydrological modeling is to split a dataset and use one part of this dataset for calibration and another part of the same dataset for validation (Biondi et al., 2011). For an ABM coupled to a hydrological model it becomes more complicated, because more complex dynamics between human decision-making and

the hydrological process are involved. Ideally one would have different types of data to validate both the human decision-making processes and the hydrological processes, but these different types of datasets are not always available. Splitting a dataset for the calibration and validation of decision rules is also a possibility. For example, if a questionnaire involves questions on factors that determine adaptation intentions and questions on actual adaptation measures that are implemented, then this first part can be used for the calibration and the second part for the validation. A disadvantage of this method is that a survey often only contains data at one point in time, which makes it difficult to validate the influence of current intentions on future adaptation decisions.

An alternative for (or complement to) historical data validation is a face validity test (Xiang et al., 2005). This can be done with a discussion of modeling results with experts in the field (Valbuena et al., 2010), but an alternative more interactive methods is expert validation with role playing games (Amadou et al., 2018; Dobbie et al., 2018). A more elaborate discussion of validation methods and techniques can be found in Klügl (2008), Cooley and Solano (2011) and Xiang et al. (2005).

Besides validation with empirical data, it is also important to perform a sensitivity analysis as part of the model validation process. With a sensitivity analysis, the modelers test for the impact of variations in parameter values and model assumptions on the outcome of the model (Cooley and Solano, 2011; Muelder and Filatova, 2018). A discussion of different types of sensitivity analysis methods that can be used for an ABM can be found in Ten Broeke et al. (2016).

CONCEPTUAL FRAMEWORK AND DISCUSSION

In the previous sections we discussed decision-making theories and parameterization, calibration and validation of those theories. The questions that remains is how modelers should select the relevant theory. To decide what theory to apply/adopt when developing an agent-based drought risk model, one has to consider the aim of the model and the local context of the modeled case study. In the context of drought risk adaptation, it is important to identify the types of agents that should be included and the behavioral factors that are the drivers of the adaptation behavior of those agents. In this section we discuss the components of a drought risk ABM and make a comparison between the theories which results in a framework that gives an overview of the different theories and can guide the development of a decision-making module for smallholder farmers in an ABM for drought risk assessment.

Drought risk ABM

A drought risk ABM should at least have a component that models the hydrological processes related to the drought hazard and a component on the behavior of stakeholders related to their exposure and/or vulnerability (Wens et al., 2019). The foundation combining these components is the traditional risk framework, where drought risk depends on the product of

hazard, exposure, and vulnerability (Kron, 2005; IPCC, 2012). Time and space dependents estimates for the hazard, exposure, and vulnerability can be provided by existing hydrological, water resources, land use, and economic models (IPCC, 2012). Within a drought risk ABM, these estimates of the traditional risk approach can be linked with a module that accounts for heterogeneous adaptation behavior of interacting agents who implement adaptation measures to reduce drought risk. Doing so also allows for a dynamic, temporally explicit analysis, where each daily, monthly, or yearly decision influences the physical, and behavioral processes in the next time period. **Figure 1** provides a schematic framework of a drought risk ABM in the context of agricultural communities. The framework is developed for application in regional or local case studies, because adaptation behavior of smallholder farmers differs widely across regions, and should therefore be studied at the local or regional level (Gebrehiwot and van der Veen, 2015; Huber et al., 2018). The framework can also be applied in ABMs with another context or scale, but might then miss some important element. Price developments in agricultural markets are, for example, not included in the framework, because of its regional focus⁵.

Agents

The focus of the framework in **Figure 1** is the individual decision-making process of the farmer. Decision of other agents can be modeled exogenously or endogenously depending on the research question. An overview of agent types for drought and water-resource ABMs can be found in Kaiser et al. (2020). Important agent categories in the context of drought in rural areas are included in **Figure 1**. The first important agent type, besides the farmers, is the government (local and national policymakers and regulators) who provides risk information and can implement policies to change adaptation behavior. Other important agents are domestic and industrial water users as the use of water by those groups can influence the water availability of farmers potentially leading to conflicts of interest. The final important group of agents in **Figure 1** are the financial institutions. Loans from banks can be used to finance adaptation measures, but access to credit is often missing for smallholder farmers in low- or middle-income countries (Hertel and Lobell, 2014). Insurance schemes and financial aid from international donor organizations can improve the financial capacity to invest in adaptation measures, and, if well designed, can provide incentives to invest more in adaptation measures (Suarez and Linnerooth-Bayer, 2010; Nnadi et al., 2013; Haer et al., 2019). Insurance schemes and financial aid can also reduce the incentives for adaptation if compensations and premiums do not reflect the risks (Suarez and Linnerooth-Bayer, 2010).

Comparing the Theories

After the relevant agents have been selected, model designers have to select the relevant behavioral theory that captures the cognitive process of the agents and their interaction with the other agents. The relevant theory depends on the context and the

⁵The assumption is that the farmers are price takers and that regional droughts do not affect the world prices, meaning these are exogenous in the regional ABM.

TABLE 2 | Overview of theories.

Theory/framework	Description	Main factors	Advantages	Disadvantages
Expected Utility Theory (EUT)	Economic theory, assuming rational utility maximizing agents. Traditional EUT: perfect information. Subjective EUT: No perfect information, agents make decision based on their own subjective estimates of the risks.	Adaptation costs Adaptation benefits Risk attitudes through utility curvature Time-preferences Risk perceptions Income constraints	Full distribution of risk. Easy to link to natural disaster risk assessments models based on costs and benefits. Calibration can be done with economic lab and field experiments.	Does not include other psychological factors, such as perceived ability to perform, subjective norms and attitudes. No (or limited) bounded rationality in traditional EUT, but risk misperceptions allowed in subjective EUT. Limited heterogeneity between agents in traditional EUT, but more heterogeneity in Subjective EUT.
Prospect Theory (PT)	Introduces psychological elements in EUT. Gains and losses are evaluated based on a reference point and losses loom larger in decisions than equivalent gains. Allows for non-linear probability weighting in decisions.	Adaptation costs Adaptation benefits Risk attitudes through utility curvature and probability weighting Time-preferences Risk perceptions Loss aversion Income constraints	Full distribution of risk. Accounts for loss aversion and bounded rationality in evaluation or risks. Calibration can be done with economic lab and field experiments.	Does not include other psychological factors, such as perceived ability to perform, subjective norms and attitudes.
Protection Motivation Theory (PMT)	Psychological theory, assumes that adaptation behavior depends on intentions to adapt, which is a function of threat appraisal and coping appraisal.	Perceived probability Perceived severity Perceived self-efficacy Perceived response efficacy Perceived response costs	Combines risks perceptions and perceived costs and benefits of economic theories with individual coping perceptions.	Does not include a full distribution or risks and does not include risk attitudes and time preferences.
Theory of Planned Behavior (TPB)	Psychological theory with intention to perform behavior as central factor in decision-making process. ⁴ Intention is influenced by perceived behavioral control, subjective norms and personal attitudes.	Perceived behavioral control Subjective norm Attitude	Includes individual attitudes and subjective norms.	Does not include risk perceptions and attitudes and time preferences.
Consumat Framework	Framework that combines elements of psychological and economic theories. Agents can switch between different types of decision-making strategies depending on level of need satisfaction and uncertainty.	Uncertainty Need satisfaction Social network	Includes elements of both psychological and economic theories. Good to model influence of social networks.	Include a lot of different elements and relatively little empirical applications, and there are no clear guidelines on which needs should be included and how they should be measured. Calibration and validation is therefore complicated.

identical in practice (e.g., Wang et al., 2019). Besides perceived self-efficacy, PMT has quite some overlap with the economic theories, as it accounts for adaptation costs with perceived responses costs and benefits with perceived response-efficacy and it accounts for risk perceptions (perceived probability and perceived severity). A disadvantage of PMT is that it does not account for the full distribution of risk and risk perceptions for different scenarios, but only for perceptions of a single or summed probability and damage. This does not capture that different drought events have different probabilities with varying drought impacts and adaptation measures have different risk reduction effects per event. Moreover, PMT does not account for risk attitudes. This disadvantages also holds for TPB, which neglects risk perceptions which would be important for modeling drought adaptation decisions. However TPB points toward other important personal attitudes that can influence adaptation decisions and subjective norms, influenced

by the social network, that are not included in the other theories⁶.

In conclusion, there is not a single theory that captures all relevant decision variables. It depends on the local context and purpose of the model which one is preferable. An advantage of the economic theories is that they can be better linked to natural disaster risk assessment models and estimate adaptation behavior based on benefits and costs. This approach can also address future climate change (influencing future risk) and policy interventions like subsidies (influencing adaptation). An advantage of the psychological theories is that they can (compared to the economic theories) capture more heterogeneity in bounded rational beliefs, norms, and personal attitudes, but they miss a full distribution of risk and risk perceptions. No

⁶PMT also implicitly assumes that perceptions are influenced by influence from the social network, but social norms are not explicitly included as model variable.

theory perfectly describes the behavior of everyone and even the same person is likely to behave differently in different situations, therefore it might be useful to combine different theories in one model, such as in the Consumat approach in which an agent can follow four different types of behavioral models depending on the level of need satisfaction and uncertainty (Jager et al., 2000; Schwarz et al., 2020).

The decision on the selection of a theory not only influences which factors will be included in simulating the decision-making process of the individual farmer, but also how the interaction of these farmers with other relevant agents can be modeled. Empirical studies show that risk perceptions are influenced by memory of previous drought impact (risk experience) and risk information from the government, the social network or media (Gebrehiwot and van der Veen, 2015; Van Duinen et al., 2015b; Azadi et al., 2019; van Valkengoed and Steg, 2019), which can only be included if risk perceptions are part of the selected theory. Decisions of neighboring farmers that have a monetary impact on the wealth of the farmer can be captured by the economic theories, but impacts through social norms or social comparison are better captured by TPB and the Consumat framework. Financial institutions can influence the capital availability which plays a direct or indirect role in each theory, but in each theory this is modeled in a different way which influences how the role of financial institutions can be integrated in the model.

RECOMMENDATIONS FOR FUTURE RESEARCH

Studies on drought risk assessment increasingly use ABMs to capture the complex dynamics between humans and their environment. ABM has the potential to provide a realistic representation of boundedly rational behavior of heterogeneous individuals, but existing models often apply *ad hoc* decision rules for the human agents or a loose interpretation of existing economic or psychological theories. To improve the representation of human decision-making, the modeler should build on the rich social science literature on human behavior toward risk. This paper aims to contribute to an improved design of drought risk ABMs. This is done by providing a review of existing ABMs on drought risk with a focus on decision rules, followed by an overview of behavioral theories that can be used for these decision rules, and a review of methods for parameterization, calibration and validation of those decision rules. These different review components are combined in a conceptual framework for the integration of hydrological modeling with decision theories from behavioral economics and psychology.

Based on our study we provide the following eight main recommendation for future research:

1. Ground human-decision making in ABMs in an established behavioral theory. These theories have been extensively tested and therefore provide a solid base for capturing decision processes. Models with simple decision rules based on empirical observations or *ad hoc* assumptions may miss important elements in the underlying decision process. Furthermore, comparability of ABM results may

be improved if behavioral rules are based on similar sets of decision theories. This requires collaboration between physical (hydrologic, agronomic) and social scientists in the model development.

2. Select the behavioral theory in an early stage of model development to make sure that all elements of the theory can be integrated in the model. The theory that is most suitable to use depends on the aim and the context of the model. The framework in this paper can be used for a comparison of the theories to guide selection of the relevant theory.
3. Researchers who use the same theory can still make different assumptions about that theory which can lead to large differences in the outcome of an ABM (Muelder and Filatova, 2018). It is important that researchers are transparent about their model assumptions such that a comparison can be made. To improve transparency about decision rules, authors can make use of the ODD+D protocol (Müller et al., 2013).
4. Parameterization and calibration of the behavioral rules, following the selected behavioral theory, is ideally based on micro-data to provide a good fit.
5. Include measurements for all variables of the selected theory. ABMs that build on a behavioral theory sometimes ignore elements of that theory or use simple proxy variables based on own interpretations. It is advisable that all elements of a selected theory are included in the ABM and that measurement of those variables is based on methods developed in social science literature, to make sure that relevant decision processes are adequately represented in the ABM.
6. Rigorous empirical methods have been developed to provide data for calibration of behavioral theories, such as choice-experiments and economic lab-, and field experiments, which are advisable to use for calibrating ABM decision rules that are grounded in these theories.
7. Historical datasets are often not suitable to validate individual processes, because they only contain aggregated information. It is therefore advisable to use data on individual behavior, which can be obtained with household survey and economic experiments, for the validation of decision rules.
8. Most existing models only focus on decision-making of farmers, whilst further research can be done on the interaction between farmers and other agents, such as governments, financial institutions, and domestic and industrial water users.

AUTHOR CONTRIBUTIONS

TS took the lead in writing the manuscript. WB, MW, TH, and JA contributed to the creative process and editing of the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

DOWN2EARTH, HORIZON 2020 EU, Grant Number: 869550. COASTMOVE, ERC Advanced grant, Grant Number: 884442. The Netherlands Organization for Scientific Research (NWO) VICI research project number 453-582 13-006.

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