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COMMENT

Improving the design of climate insurance: combining empirical approaches and modelling

Meike Will [a], Annika Backes[b], Marco Campenni [c], Lee Cronk [d], Gunnar Dressler [a], Christoph Gornott [e,f], Jürgen Groeneveld [a], Lemlem Teklegiorgis Habtemariam[e], Kati Kraehnert [e], Martin Kraus[a], Friederike Lenel [g], Daniel Osgood [h], Masresha Taye [i] and Birgit Müller [a]

[a]Department of Ecological Modelling, Helmholtz Centre for Environmental Research – UFZ, Leipzig, Germany; [b]Halle Institute for Economic Research (IWH), Halle (Saale), Germany; [c]Centre for Ecology and Conservation, Department of Biosciences, University of Exeter, Cornwall, UK; [d]Department of Anthropology, Rutgers University, New Brunswick, NJ, USA; [e]Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Potsdam, Germany; [f]Agroecosystem Analysis and Modelling, Faculty of Organic Agricultural Sciences, University of Kassel, Kassel, Germany; [g]Universität Göttingen, RTG Globalization and Development, Göttingen, Germany; [h]International Research Institute for Climate and Society, Columbia University, Palisades, NY, USA; [i]PASTRES Programme, Institute of Development Studies, University of Sussex, Brighton, UK

ABSTRACT

Extreme weather due to climate change often disproportionately affects the weakest members of society. Agricultural insurance programs designed specifically for smallholders in developing countries are valuable tools that can help farmers to cope with the resulting risks. A broad range of methods including household surveys, experimental games, and agent-based models have been used to assess and improve the effectiveness of such climate insurance products. Furthermore, process-based crop models have been used to derive suitable insurance indices. However, climate change raises specific socioeconomic and environmental challenges that need to be considered when designing insurance schemes. We argue that, in light of these pressing challenges, some of the methodological approaches currently applied to study climate insurance reach their limits when applied independently. This has fundamental implications. On the one hand, not all undesired side effects of insurance can be detected and, on the other hand, insurance indices cannot be derived sufficiently well. We therefore advocate a sound combination of different methods, especially by linking empirical analyses and modelling, and underline the resulting potential with the help of stylized examples. Our study highlights how methodological synergies can make climate insurance products more effective in supporting the most vulnerable households, especially under changing climatic conditions.

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1. Introduction

Climate change is expected to alter the likelihood and severity of extreme weather events such as droughts and floods (IPCC, 2018). This poses a particular threat to poor households in developing countries that are engaged in agriculture (Hallegatte & Rozenberg, 2017; World Bank, 2009). Agricultural insurance products specifically designed for the needs of smallholder farmers, known as microinsurance or inclusive insurance, are seen by many as a promising tool for managing disaster risks. The International Panel on Climate Change (IPCC), for example, has stressed the need for risk-sharing and risk-transfer mechanisms such as insurance as a climate adaptation mechanism (IPCC, 2012). Similarly, the United Nations Framework Convention on Climate Change (UNFCCC) has pointed out the importance of insurance for addressing effects of climate change in their Warsaw International Mechanism for Loss and Damage (UNFCCC, 2013). However, to design climate insurance products effectively from a socioeconomic as well as environmental perspective, unintended side effects must be addressed (Kraehnert et al., 2021; Müller et al., 2017). Furthermore, to avoid low acceptance rates, especially in the case of agricultural index insurance where payouts depend on exceeding or falling below a threshold derived from rainfall or vegetation data (Benami et al., 2021; Brown et al., 2011), the mismatch between actual losses from a weather shock and insurance payouts received, commonly defined as spatial basis risk, must be minimized (Clement et al., 2018).

Researchers currently use a wide range of methods, including household surveys, experimental games, and agent-based models, to assess the demand for and impact of climate insurance and to identify its shortcomings and unintended side effects. These assessments contribute to an understanding of insurance products needed to improve insurance design. In addition, process-based crop models are used to assess crop yields and derive suitable insurance indices. Although these models can offer a variety of insights into climate insurance, they do reach their limits in some respects. The econometric

CONTACT Meike Will meike.will@ufz.de Department of Ecological Modelling, Helmholtz Centre for Environmental Research – UFZ, Permoserstr. 15, 04318 Leipzig, Germany
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analysis of household surveys, for example, allows researchers to draw inferences from large samples representative of the population. However, such surveys, and household panel surveys in particular, from which conclusions can be drawn about the impacts of potentially changing external conditions, are time- and cost-intensive. Potential effects of insurance on behaviour can often become apparent only at a later stage and can thus be taken into account for insurance design only belatedly. Experimental games, on the other hand, are a valuable tool to assess specific behaviour, but they usually include only a small number of individuals and, unless the same experimental design is replicated in different contexts, the results are difficult to generalize. In particular, when the design of insurance policies is assessed based on decisions of a few hundred individuals, one needs to be cautious to make general statements for entire countries or regions. Modelling approaches allow researchers to overcome time and space constraints of household panel surveys and experimental games: Agent-based models that can include human decision-making in detail, however, depend heavily on the availability of data to validate model assumptions. Process-based crop models, which cover biophysical aspects of crop yield dynamics and agronomic management information to derive insurance indices, on the other hand, do not account for human behaviour explicitly.

From our point of view, the potential of each of these methods to contribute to a better understanding of climate insurance products – needed for a more appropriate and sustainable insurance design as well as for direct improvements of insurance indices – could be considerably enhanced by combining them. Mixed-method approaches that link quantitative and qualitative techniques have already been advocated in the context of microinsurance (White, 2014). We reinforce this demand by proposing a combination of modelling and empirical analyses. In this article, we (1) explore strengths and limitations of current approaches to assess the effectiveness of climate insurance products and contribute to the improvement of their design and (2) underline the potential of combining different methods with three stylized examples that address current challenges for insurance products. With these examples, we illustrate how a more holistic approach can be beneficial to advance an appropriate and sustainable insurance design. We conclude with recommendations on how to achieve such methodological synergies.

2. Strengths and limitations of current methods to evaluate insurance design

Below, we provide brief descriptions of four methods used to identify unintended social and environmental side effects of insurance products or to develop appropriate insurance indices. We focus on the econometric analysis of household surveys, experimental games, agent-based models, and process-based crop models, as they illustrate well the range of methods currently being used. Importantly, the methods discussed are not exclusive; analytical models, Bayesian Belief Networks, and qualitative research, for example, may be similarly useful for understanding the effectiveness of insurance and improving its design.

2.1. Econometric analysis of household surveys

The econometric analysis of household surveys has been used to study drivers of the demand for agricultural insurance among farmers in India (Cole et al., 2013; Mobarak & Rosenzweig, 2012, 2013), Ethiopia (Dercon et al., 2014), and Ghana (Karlan et al., 2014). In addition, the impacts of agricultural insurance *ex ante*, i.e. before an extreme weather event occurred, on the investment decisions of farm households were quantified using household survey data (Cai, 2016; Cole et al., 2017; Hill et al., 2019; Hill & Viceisza, 2012). A related field of research assesses whether indemnity payments from index insurance help farmers to recover from losses. Studies quantifying these *ex post* effects of agricultural insurance based on survey data have focused on Kenya (Janzen & Carter, 2019; Jensen et al., 2017), Mongolia (Bertram-Huemmer & Kraehnert, 2018), and Bangladesh (Hill et al., 2019) and cover changes in consumption behaviour, agricultural production practices and livestock sales.

Household surveys are an essential source of information on the well-being and behaviour of individuals. The sample of households surveyed is ideally representative of subgroups and geographical areas of the population of interest and is usually based on census or administrative data. Household surveys may address a variety of different objectives. These range from documenting the living conditions of a target population to estimating the impact of development programs and policies on households' well-being (Grosh & Glewwe, 2000). Cross-sectional surveys that are implemented with similar questionnaire design over several years allow researchers to monitor how living standards change over time. Household panel surveys in which the same households are traced over time are particularly informative for policy design. When analysed with econometric methods, household surveys are a key source for establishing a cause and effect relationship between policy-relevant variables and household-level outcomes.

Despite these major advantages, household surveys are also subject to limitations. Depending on the level of representativeness and, in turn, the sample size, implementing household surveys – and especially panel surveys – can be expensive. Furthermore, the amount of information that can be recorded in household surveys is constrained by the time respondents readily devote to a survey interview. There is also a limit to the level of detail that respondents can be asked to recall. While major events in life are usually remembered well, individuals typically find it more difficult to recall income streams retrospectively (Wooldridge, 2012). Moreover, some information can hardly be recorded at all, such as inherent abilities, skills, or work attitudes. Finally, specific mechanisms that drive behavioural changes are difficult to detect with survey data alone.

2.2. Experimental games

In the context of insurance, experimental games have been used primarily to study whether formal insurance crowds out grassroots risk pooling. Such experiments have been conducted in laboratory settings (Lin et al., 2014) and at field sites in the Philippines (Landmann et al., 2012), Ethiopia (Anderberg & Morsink, 2020), and Cambodia (Lenel & Steiner, 2020). Similarly, at a field site in Uganda, Cecchi et al. (2016) studied whether formal insurance crowds out social capital, operationalized as donations to a public goods game. In addition, to assess the demand for insurance and to adequately design insurance products, researchers have started to adopt an approach known as 'gamification' (Hernandez-Aguilera et al., 2020b), which is the use of game design elements in non-game contexts (Seaborn & Fels, 2015). For instance, Norton et al. (2014) assessed demand for index insurance among farmers in Ethiopia by using a game in which people could allocate money across different risk management options.

Experimental games are used to learn what choices people make in specific, well-defined situations and which factors drive these choices. Games can contribute to our understandings of individuals and groups by mimicking the actual environments where policy interventions will take place (Hernandez-Aguilera et al., 2020a). In most experimental games, participants are first endowed by the experimenter with a fixed amount of money or another easily shared resource, such as small packages of food, and are then asked to decide how to allocate this resource given a specific context. Because experimental games can be conducted in laboratory and field settings located in any society in the world, they can yield useful insights not only into behaviour but also into local cultural models (Henrich et al., 2004).

One weakness of the game method is that a researcher's choice of a game and its usefulness for addressing the research question at hand depends on the researcher's understanding of the local cultural context; in turn, researchers' design choices can interact with the cultural contexts that subjects bring to an experimental game. Indeed, small variations in the game design have been shown to affect results considerably (DellaVigna & Pope, 2019; Landy et al., 2020). Another drawback is that it can be difficult at many field sites to obtain large sample sizes, particularly if the game takes a long time to play or requires participants to play simultaneously. Specific cultural contexts and small sample sizes make it difficult to generalize the findings. Furthermore, although games aim to map realistic situations, participants might not behave as they do in their everyday life, but rather as they think they should (Quidt et al., 2018; Zizzo, 2010).

2.3. Agent-based models

Agent-based models (ABMs) have been used to analyse potential long-term effects of index insurance on the sustainability of rangeland management (Müller et al., 2011) and resulting pasture conditions (John et al., 2019). In other studies, the effectiveness of insurance through informal risk sharing (Aktipis et al., 2011, 2016; Campennì et al., 2021; Hao et al., 2015) and impacts of combining formal and informal insurance (Will et al., 2021) have been investigated.

ABMs are simulation tools that focus on individual actors, such as humans, households, firms or institutions. Interactions among such agents and their interaction with their environments are explicitly modelled (Bonabeau, 2002; Railsback & Grimm, 2012). Agents can differ in their characteristics, i.e. they can be heterogeneous in their attributes and decision rules. Based on the prescribed rules and micro-level properties, emergent temporal dynamics such as the spread of an innovation or collective behaviour can be observed on a macro-level. ABMs can be used to systematically disentangle the influence of different factors by including and excluding environmental features or aspects that impact individual decision-making. Furthermore, they have few time and space constraints: Results can be obtained for large regions, which would require large financial resources if empirical methods were used. In addition, ABMs can simulate long-term effects of new policies or altered climatic conditions on a time scale beyond what can be detected with empirical observations. Apart from such explorative analyses, ABMs can also take a backward perspective and help uncover relations that cannot be fully explained empirically. This so-called pattern-oriented modelling can be used to test assumptions about human behaviour, which can then be compared to observed results (Grimm et al., 2005).

As is true of every other modelling approach, ABMs are only a simplified version of reality, which has to be taken into account when drawing general conclusions. Furthermore, ABMs can easily become complex when many influencing factors are included, which can make it impossible to derive cause and effect relations. In addition, model outcomes crucially depend on assumptions that require careful calibration with real-world data that is often not available. Moreover, although the explicit integration of human behaviour is one of the strengths of ABMs, the theoretical basis of the decision-making frameworks used in such models is often quite simplified (Groeneveld et al., 2017; Schlüter et al., 2017).

2.4. Process-based crop models

So far, mainly weather indexes (Dalhaus & Finger, 2016), remote sensing satellite vegetation indexes (Enenkel et al., 2019), and statistical models (Conradt et al., 2015) have been used to quantify crop yield losses. However, there is a growing interest among governments and insurance companies in process-based model assessments, for instance in India (Arumugam et al., 2020).

Process-based crop models include biophysical plant and soil processes such as the growth of above- and below-ground biomass as well as water and nutrient flows in the plant and the soil to calculate interactions between environment and crop development (Boote et al., 2013; White et al., 2011). Due to their plant physiological algorithm, the models can capture effects such as extreme temperatures, dry spells, or shifts in the growing season that have not been observed in the past. Hence, these models can be used for quantifying yield and environmental effects of adaptation measures and for projecting future periods or other environments, which is particularly interesting in the face of changing climatic conditions (Lobell & Asseng, 2017; Rötter et al., 2018; Wallach et al., 2016). Since process-based crop models can provide information on yield losses immediately after the harvest, they can be used for risk assessments and adaptation planning (Challinor et al., 2018; Webber et al., 2020). This is highly relevant for insurance indices, in particular in developing countries, where crop yield information is not available and/or too expensive to collect because of remotely located fields. Furthermore, the process-based organization of the model allows researchers to distinguish between weather- and management-attributable influences on crop yields, which is crucial for the design of insurance indices because only weather-induced losses should be covered by the insurance product (Arumugam et al., 2020).

To feed process-based models, information about weather, soil and management information is needed. Weather information is available on a global scale informed by weather stations, satellite observations and weather models. Soil data are also widely accessible from global or regional soil maps. However, there is often little information about management practices and underlying drivers of management decisions (Asseng et al., 2013; Folberth et al., 2019; Wang et al., 2019). In particular, responses of farmers to changing environmental and economic conditions are often not known. This lowers the ability of process-based crop models to capture and reproduce accurate crop yields, especially in developing countries where the range of management practices differs highly across space, time, and farmer groups.

3. Synergies between different approaches to improve climate insurance

To overcome some of the individual limitations of the different methods, a holistic approach that couples several approaches could be beneficial. To show how a combination of methods can be used to address pressing challenges of climate insurance design, we provide three examples that focus on unintended (1) social and (2) environmental side effects of insurance uptake and (3) the appropriate derivation of insurance indices. We suggest approaching these challenges by linking empirical analyses that provide grounding in reality and models that reduce this complex reality to a limited number of key variables and processes. We use the first two examples to elaborate on combining household surveys, experimental games, and ABMs, mediated by the use of econometric methods; with the third example, we show the potential benefits of integrating empirically-parameterized ABMs into process-based crop models.

3.1. Interplay between empirical data and ABMs

The general insights from household surveys and specific hypotheses tested using experimental games provide excellent bases for specifying the parameters and decision-making rules in ABMs. While econometric analyses of household surveys can be used to parameterize individual household characteristics such as income, social relationships, insurance status, and environmental conditions (Smajgl et al., 2011), decision-making in ABMs can be based on inferences drawn from small-scale experimental games with the same decision space (Smith & Rand, 2018). The outcome of ABMs can, in return, help refine experimental research if, for example, specific factors are found to have a large influence on the model outcomes and more precise empirical information is needed to further understand these aspects (Chávez-Juárez, 2017). There exist successful examples of such back-and-forth approaches. Cronk et al. (2019), for instance, designed a two-player game to study risk pooling in a laboratory based on earlier ABMs of risk pooling in dyads (Aktipis et al., 2011, 2016). The results from the game and ABMs were then used to inform the design of additional experimental games (Claessens et al., 2021).

In the context of insurance, we suggest that a combination of methods could help determine the interplay between formal and informal risk-coping instruments (Figure 1). An increasing number of covariate shocks due to climate change may threaten existing risk-sharing instruments, for instance, when an entire community is affected by an extreme event and informal safety nets can no longer absorb the losses (Wossen et al., 2016). At the same time, the introduction of insurance may lead to rising social inequality if insured households no longer contribute to traditional risk-sharing arrangements (Anderberg & Morsink, 2020; Lenel & Steiner, 2020). Household surveys can provide information about characteristics that influence insurance uptake. The behaviour of insured households can then be tested in experimental games. Surveys can be used to determine the relevant pool of participants for these games. While participants in experimental games typically are randomly matched to simulate risk-sharing arrangements, in reality the structure of risk-sharing networks is complex, and the effectiveness of individual risk-coping depends on their overall structure. Informal protection varies depending on whether, for example, particularly poor households are linked to rich households or whether there is income segregation. Network structures can be revealed with the help of surveys that include detailed social network modules. Integrating information on household behaviour observed during the games as well as network structures of specific villages in ABMs allows researchers to draw precise conclusions on the long-term welfare effects of potentially altered solidarity norms in a society. By using the results of experimental games and the ABM to refine survey items on, for example, the actual transfer amount between households, the understanding of the potential consequences of the introduction of insurance can be further increased. Incorporating insights on social side effects into insurance design by, for example, offering group insurance (Santos et al., 2021; Trærup, 2012), can help realize the full potential of formal insurance.

A combination of methods is also a promising approach to investigate the potentially unintended consequences of insurance uptake on the environment (Figure 2). In pastoralist communities, insurance coverage may eliminate the need to reduce livestock numbers following a drought (Gebrekidan et al., 2019) or allow herders to quickly restock after an extreme event (Bertram-Huemmer & Kraehnert, 2018). While having a positive impact on households' livelihood in the short-term, this may result in overgrazing and pasture degradation, which increases vulnerability to future extreme events. In agricultural communities, insurance coverage may create incentives to intensify production and, for instance, turn to cash crops or mono-cropping, which yield higher returns but are riskier and potentially less environmentally sustainable due to higher pesticide requirements and lower disease resistance (Cai, 2016; Cole et al., 2017; Jensen et al., 2017; Mobarak & Rosenzweig, 2012, 2013). To grasp the long-term effects of

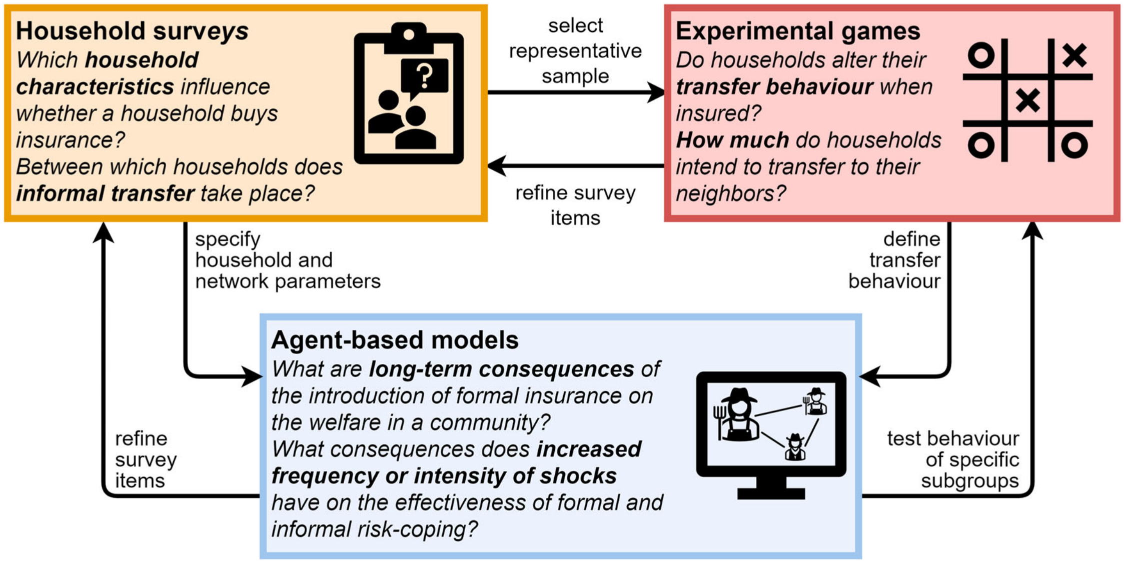

Figure 1. Schematic representation of the interplay between empirical data and ABMs to determine the interplay of formal and informal risk-coping instruments.

insurance uptake on the environment, econometric methods may be used to infer from surveys how households adapt their agricultural practices after purchasing insurance. Here, behavioural changes before a payment-inducing extreme event (*ex ante*) as well as once payments from insurance are made (*ex post*) are of interest. Complementary experimental games, conducted in the same empirical context, may reveal more explicitly how the introduction of agricultural insurance changes households' attitudes towards managing the global commons, e.g. to what extent households shift priorities between maximizing their own utility and communal welfare. Social-ecological agent-based models may be used to extrapolate from the behaviour observed at the micro-level and derive macro-level trends in natural resource use under different scenarios of insurance design and uptake. The information available from household surveys thereby allows researchers to select representative samples for the experimental games and to parameterize household variables in an ABM. Outcomes from the model can be used to further refine survey items and game scenarios when, for example, the model underlines the importance of considering land-use practices in longitudinal studies. Obtaining a precise picture of potential environmental side effects is crucial for designing sustainable insurance products, especially when changing climatic conditions that lead to an increased risk of droughts and other extreme weather events further weaken the state of the natural resource.

3.2. Interplay between ABMs and process-based crop models

In order for insurance products to be effective not only under current conditions but also in the long term, their design must take into account both changes in climate and adjustments in agricultural practices (Siebert, 2016; Surminski et al., 2016). Accurate derivation of insurance indices using process-based crop models requires weather, soil, and management data. Whereas several long-term climate projections exist that can be used in agricultural modelling (Asseng et al., 2013; Folberth et al., 2019; Jones & Thornton, 2013), future management decisions are much more difficult to predict. Agricultural practices are highly dependent on a farmer's individual psychological and socioeconomic characteristics such as risk aversion, habits, and openness to innovations. Furthermore, there is feedback between farming strategies and global change processes. Farmers might adjust their crop portfolios or invest in irrigation to avoid losses due to altered climatic conditions (Collier et al., 2009). In addition, there might be indirect adaptations of farming decisions when insurance uptake incentivizes different management strategies (cf. section 3.1); insurance uptake, in turn, is largely determined by farmers' satisfaction with the product (Shirsath et al., 2019).

Combining process-based crop models with ABMs can help fill this gap. ABMs maybe a powerful tool for the investigation of land use decisions (Matthews et al., 2007; Parker et al., 2003; Rounsevell et al., 2014), especially when they are empirically parameterized (Robinson et al., 2007). Furthermore, insurance uptake can be explicitly modelled as the adoption of innovations (Kiesling et al., 2012). Here, the influence of other farmers, as well as additional factors such as liquidity constraints or education that affect the insurance decision, could be taken into account (Jones et al., 2017). ABMs would make it possible to consider how farmers incorporate various influences into their management and insurance decisions (Brown et al., 2017). Providing these results as input to the process-based crop model would allow researchers to include management decisions explicitly in the derivation of crop yields and insurance indices. The outcome of the process-based model could then again be used as input for the ABM to further refine long-term projections (Figure 3). The combined approach would ultimately improve the design of insurance indices and contribute to ongoing discussions on the reduction of basis risk (see, e.g. Li et al. (2021) for a dynamic factor model to forecast crop yields).

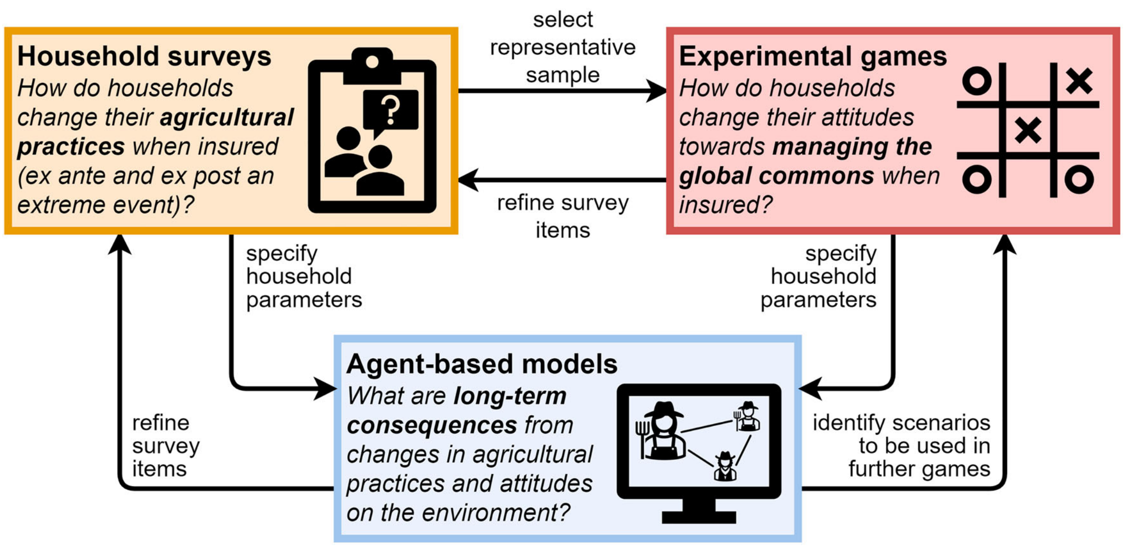

Figure 2. Schematic representation of the interplay between empirical data and ABMs to quantify the side effects of insurance coverage on agricultural practices.

4. Conclusions

In this study, we elaborated on how combining several methodological approaches could help tackle challenges associated with climate insurance product design. We specifically addressed the potential benefits of coupling quantitative empirical and model-based approaches to overcome limitations that arise when applying these methods separately. Of course, these examples show only a subset of possibilities where a combination of methods can make a direct or indirect contribution to insurance design. In addition, there are other problems, such as cash or credit constraints or a lack of education, that cannot be addressed by methodological synergies alone but that nevertheless play a crucial role in the development of appropriate and sustainable insurance products.

To successfully combine different methods, it is important to clearly indicate which contributions can be provided by which methods while keeping the limits of each approach in mind (Jones et al., 2017; Kline et al., 2017; White, 2014). For example, an issue that needs to be addressed in the context of microinsurance is the selection of the most representative time to obtain information on insurance uptake or land use. While this is also crucial for stand-alone empirical studies, it is especially important in combination with agent-based models because the rules of such models that are based on

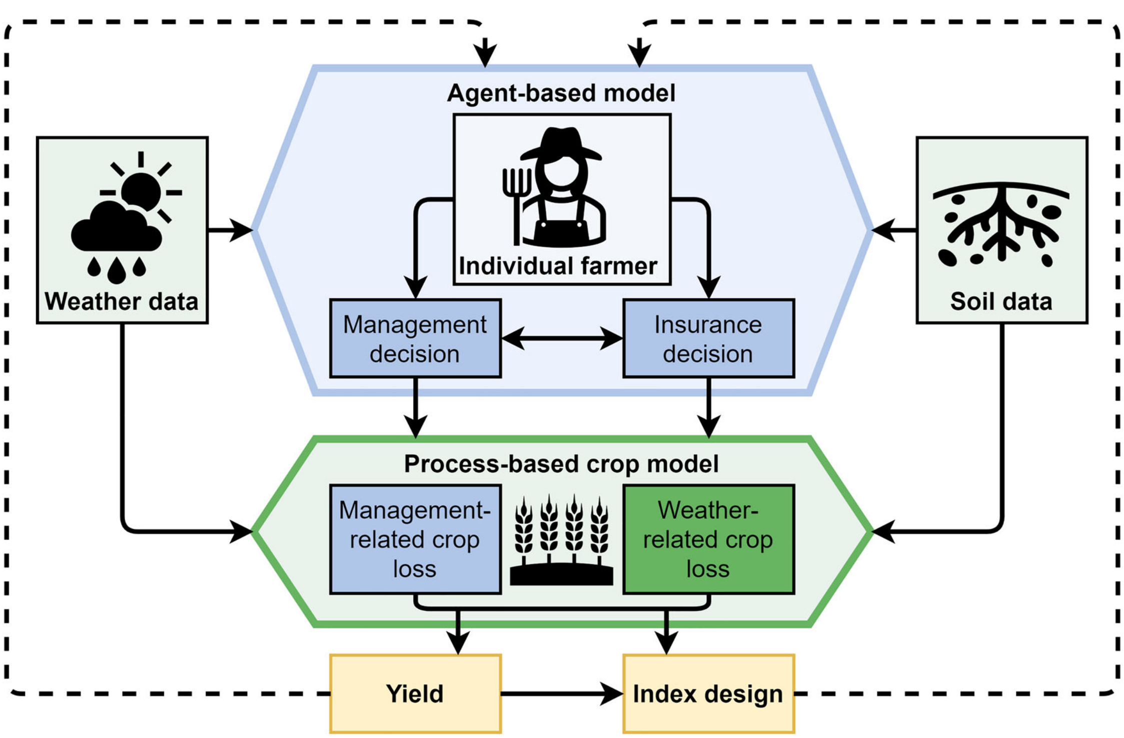

Figure 3. Schematic representation of the interplay between ABMs and process-based crop models to improve index design.

these observations are used to make statements about broad temporal and spatial scales. Furthermore, it must be clearly communicated how much data is needed for the simulations, and uncertainties in empirical observations must be accounted for in the model (Cheong et al., 2012). Additional challenges that arise for interdisciplinary research, such as establishing a common language for exchange and allowing sufficient time for iterative cycles of reflection across all phases of the research process, should also be considered (Kelly et al., 2019).

In this study, we did not focus on the integration of qualitative research, which can add further relevant perspectives (Millington & Wainwright, 2017; Paluck, 2010; White, 2014). Since understanding the local cultural process is crucial to framing specific research questions, the use of quantitative methods should ideally be combined with qualitative ethnographic approaches obtained through interviews and participant observation. For example, Cronk (2007) used trust games to study a Maasai risk pooling system. He selected the game based on what he learned during a first round of interviews and conducted a second round of interviews in light of the results of the game. In the context of microinsurance, qualitative methods could be used to assess risk exposure, risk perceptions, and risk management strategies to gain an overall understanding of vulnerability particularly under conditions of climate change (Turner et al., 2003).

Overall, we believe that the use of complementary methods to evaluate the effectiveness of insurance and to elucidate potential unintended side effects as presented in our study may improve insurance design and make this instrument more powerful in supporting the most vulnerable in a sustainable manner. Future research projects should strive for such methodological synergies to tackle the pressing issue of effectively protecting the poorest against extreme events that will be even more pronounced under climate change.

Disclosure statement

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Notes on contributors

Meike Will is a postdoctoral researcher at the Department of Ecological Modelling of the Helmholtz Centre for Environmental Research. She uses agent-based modelling to analyse the effectiveness of formal and informal risk-coping instruments and implications of agricultural policies on the adoption of environmentally friendly farming practices.

Annika Backes is a doctoral student at Department of Structural Change and Productivity of the Halle Institute for Economic Research (IWH). Her research focuses on economic causes of populism and education economics, using applied microeconometric methods.

Marco Campenni is a postdoctoral researcher working at the University of Exeter. His work is centred on modelling the evolution of cooperation, using different modelling techniques and tools (agent-based modelling, social network analysis, evolutionary game theory, GIS data).

Lee Cronk is a professor of anthropology at Rutgers University in New Brunswick, New Jersey, USA. He has conducted field research in Kenya, Honduras, and the United States. He is also co-director of The Human Generosity Project, a transdisciplinary effort to understand the biological and cultural underpinnings of generosity and other forms of cooperation among humans.

Gunnar Dressler is a postdoctoral researcher at the Department of Ecological Modelling of the Helmholtz Centre for Environmental Research. He is interested in complex dynamics of social-ecological systems with respect to tipping points and regime shifts, the representation of human decision making in agent-based models, and the use of serious games in research together with stakeholders.

Christoph Gornott is an agricultural scientist, leader of the working group Adaptation in Agricultural Systems at the Potsdam Institute for Climate Impact Research and chair of the department Agroecosystem Analysis and Modelling at the University of Kassel. He conducts interdisciplinary research aiming to improve food security and resilience in tropical agricultural systems and investigates climate impacts on agriculture and strategies of how the agricultural sector can respond to changing climatic conditions.

Jürgen Groeneveld is an ecological and socio-ecological modeller at the Department of Ecological Modelling of the Helmholtz Centre for Environmental Research. He uses mainly agent-based simulation models to investigate the development of honeybee colonies, the emergence of mono-dominant stands in tropical forests, the combination of formal and informal risk-coping instruments and the emergence of pastoral property regimes.

Lemlem Teklegiorgis Habtemariam is a postdoctoral researcher at the Potsdam Institute for Climate Impact Research. Her work mainly focuses on assessing the impacts of climate change and adaptation on households' well-being using household surveys and econometric methods.

Kati Kraehnert is a development economist and leads the FutureLab Inequality, Human Well-Being and Development at the Potsdam Institute for Climate Impact Research. Her research quantifies the economic impact of climate change on households in low- and middle-income countries, using an applied microeconomic perspective.

Martin Kraus was a research assistant at the Department of Ecological Modelling of the Helmholtz Centre for Environmental Research. He used Bayesian Belief Networks to investigate factors that affect land use behaviour of farmers.

Friederike Lenel is a Research Associate at the Research Training Group Globalization and Development and postdoctoral researcher at the Chair for International Economic Policy at the University of Göttingen. She uses field experiments and microeconometrics to study decision making under uncertainty in the context of education and household finance. Here she is particularly interested in the role of social networks and norms.

Daniel Osgood leads the Financial Instruments Sector Team at the International Research Institute for Climate and Society at Columbia University. He links climate information to financial tools to improve livelihoods in developing countries. His research topics include uncertainty in decision-making, environmental valuation, remote sensing proxies, information, forecast based preparedness triggers and index insurance in economic development.

Masresha Taye is a doctoral researcher for the PASTRES project at the Institute of Development Studies (University of Sussex, UK). His research focuses on the financialisation of risk (livestock insurance) and risk and uncertainty in the drylands.

Birgit Müller is head of the working group POLISES at the Department of Ecological Modelling of the Helmholtz Centre for Environmental Research. She uses process-based models for an enhanced understanding and governance of social-ecological systems under global change with a focus on exploring dynamics of socio-environmental resource systems under uncertainty, the effects of policy instruments for global food security and for coping with climate and advancing methods related to incorporate cross-scale effects in land use models.

ORCID

Meike Will http://orcid.org/0000-0001-9638-5862
Marco Campenni http://orcid.org/0000-0001-7649-4869
Lee Cronk http://orcid.org/0000-0002-7583-7417
Gunnar Dressler http://orcid.org/0000-0002-1769-3064
Christoph Gornott http://orcid.org/0000-0003-3933-3358
Jürgen Groeneveld http://orcid.org/0000-0003-2338-4636
Kati Kraehnert http://orcid.org/0000-0001-7319-9581
Friederike Lenel http://orcid.org/0000-0002-2833-6222
Daniel Osgood http://orcid.org/0000-0002-7380-6043
Masresha Taye http://orcid.org/0000-0002-5008-4543
Birgit Müller http://orcid.org/0000-0001-8780-4420

References

Aktipis, A., Cronk, L., & de Aguiar, R. (2011). Risk-Pooling and herd survival: An Agent-Based Model of a Maasai gift-giving system. *Human Ecology*, *39*(2), 131–140. https://doi.org/10.1007/s10745-010-9364-9

Aktipis, A., de Aguiar, R., Flaherty, A., Iyer, P., Sonkoi, D., & Cronk, L. (2016). Cooperation in an uncertain world: For the Maasai of east Africa, Need-Based Transfers outperform account-keeping in volatile environments. *Human Ecology*, *44*(3), 353–364. https://doi.org/10.1007/s10745-016-9823-z

Anderberg, D., & Morsink, K. (2020). The introduction of formal insurance and its effect on redistribution. *Journal of Economic Behavior & Organization*, *179*, 22–45. https://doi.org/10.1016/j.jebo.2020.08.005

Arumugam, P., Chemura, A., Schauberger, B., & Gornott, C. (2020). Near real-time biophysical rice (oryza sativa L.) yield estimation to support crop insurance implementation in India. *Agronomy*, *10*(11), 1674. https://doi.org/10.3390/agronomy10111674

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P. J., Rötter, R. P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P. K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A. J., Doltra, J., … Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change. *Nature Climate Change*, *3*(9), 827–832. https://doi.org/10.1038/nclimate1916

Benami, E., Jin, Z., Carter, M. R., Ghosh, A., Hijmans, R. J., Hobbs, A., Kenduiywo, B., & Lobell, D. B. (2021). Uniting remote sensing, crop modelling and economics for agricultural risk management. *Nature Reviews Earth & Environment*, *2*, 140–159. https://doi.org/10.1038/s43017-020-00122-y

Bertram-Huemmer, V., & Kraehnert, K. (2018). Does index insurance help households recover from disaster? Evidence from IBLI Mongolia. *American Journal of Agricultural Economics*, *100*(1), 145–171. https://doi.org/10.1093/ajae/aax069

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(Supplement 3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Boote, K. J., Jones, J. W., White, J. W., Asseng, S., & Lizaso, J. I. (2013). Putting mechanisms into crop production models. *Plant, Cell & Environment*, *36*(9), 1658–1672. https://doi.org/10.1111/pce.12119

Brown, C., Alexander, P., Holzhauer, S., & Rounsevell, M. D. A. (2017). Behavioral models of climate change adaptation and mitigation in land-based sectors. *Wiley Interdisciplinary Reviews: Climate Change*, *8*(2), e448. https://doi.org/10.1002/wcc.448

Brown, M. E., Osgood, D. E., & Carriquiry, M. A. (2011). Science-based insurance. *Nature Geoscience*, *4*(4), 213–214. https://doi.org/10.1038/ngeo1117

Cai, J. (2016). The impact of insurance provision on household production and Financial decisions. *American Economic Journal: Economic Policy*, *8*(2), 44–88. https://doi.org/10.1257/pol.20130371

Campennì, M., Cronk, L., & Aktipis, A. (2021). Need-Based Transfers enhance resilience to shocks: An Agent-Based Model of a Maasai Risk-Pooling system. *Human Ecology*. https://doi.org/10.1007/s10745-021-00273-6

Cecchi, F., Duchoslav, J., & Bulte, E. (2016). Formal insurance and the Dynamics of social capital: Experimental Evidence from Uganda. *Journal of African Economies*, *25*(3), 418–438. https://doi.org/10.1093/jae/ejw002

Challinor, A. J., Müller, C., Asseng, S., Deva, C., Nicklin, K. J., Wallach, D., Vanuytrecht, E., Whitfield, S., Ramirez-Villegas, J., & Koehler, A.-K. (2018). Improving the use of crop models for risk assessment and climate change adaptation. *Agricultural Systems*, *159*, 296–306. https://doi.org/10.1016/j.agsy.2017.07.010

Chávez-Juárez, F. (2017). On the role of agent-based modeling in the theory of Development economics. *Review of Development Economics*, *21*(3), 713–730. https://doi.org/10.1111/rode.12264

Cheong, S.-M., Brown, D. G., Kok, K., & Lopez-Carr, D. (2012). Mixed methods in land change research: Towards integration. *Transactions of the Institute of British Geographers*, *37*(1), 8–12. https://doi.org/10.1111/j.1475-5661.2011.00482.x

Claessens, S., Ayers, J. D., Cronk, L., & Aktipis, A. (2021). Need-based transfer systems are more vulnerable to cheating when resources are hidden. *Evolution and Human Behavior*, *42*(2), 104–112. https://doi.org/10.1016/j.evolhumbehav.2020.08.004

Clement, K. Y., Botzen, W. J. W., Brouwer, R., & Aerts, J. C. J. H. (2018). A global review of the impact of basis risk on the functioning of and demand for index insurance. *International Journal of Disaster Risk Reduction*, *28*, 845–853. https://doi.org/10.1016/j.ijdrr.2018.01.001

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to household risk management: Evidence from India. *American Economic Journal: Applied Economics*, *5*(1), 104–135. https://doi.org/10.1257/app.5.1.104

Cole, S., Giné, X., & Vickery, J. (2017). How does Risk Management influence production decisions? Evidence from a field experiment. *The Review of Financial Studies*, *30*(6), 1935–1970. https://doi.org/10.1093/rfs/hhw080

Collier, B., Skees, J., & Barnett, B. (2009). Weather Index Insurance and climate change: Opportunities and challenges in lower income countries. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *34*(3), 401–424. https://doi.org/10.1057/gpp.2009.11

Conradt, S., Finger, R., & Spörri, M. (2015). Flexible weather index-based insurance design. *Climate Risk Management*, *10*, 106–117. https://doi.org/10.1016/j.crm.2015.06.003

Cronk, L. (2007). The influence of cultural framing on play in the trust game: A Maasai example. *Evolution and Human Behavior*, *28*(5), 352–358. https://doi.org/10.1016/j.evolhumbehav.2007.05.006

Cronk, L., Aktipis, A., Gazzillo, S., White, D., Wutich, A., & Sopher, B. (2019). Common knowledge promotes risk pooling in an experimental economic game. *PLOS ONE*, *14*(8), e0220682. https://doi.org/10.1371/journal.pone.0220682

Dalhaus, T., & Finger, R. (2016). Can gridded precipitation data and phenological observations reduce basis risk of weather index–based insurance? Weather. *Climate, and Society*, *8*(4), 409–419. https://doi.org/10.1175/WCAS-D-16-0020.1

DellaVigna, S., & Pope, D. G. (2019). Stability of Experimental Results: Forecasts and Evidence.

Dercon, S., Hill, R. V., Clarke, D., Outes-Leon, I., & Seyoum Taffesse, A. (2014). Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia. *Journal of Development Economics*, *106*, 132–143. https://doi.org/10.1016/j.jdeveco.2013.09.006

Enenkel, M., Osgood, D., Anderson, M., Powell, B., McCarty, J., Neigh, C., Carroll, M., Wooten, M., Husak, G., Hain, C., & Brown, M. (2019). Exploiting the convergence of Evidence in satellite data for advanced Weather Index Insurance design. Weather. *Climate, and Society*, *11*(1), 65–93. https://doi.org/10.1175/WCAS-D-17-0111.1

Folberth, C., Elliott, J., Müller, C., Balkovic, J., Chryssanthacopoulos, J., Izaurralde, R. C., Jones, C. D., Khabarov, N., Liu, W., Reddy, A., Schmid, E., Skalský, R., Yang, H., Arneth, A., Ciais, P., Deryng, D., Lawrence, P. J., Olin, S., Pugh, T. A. M., … Wang, X. (2019). Parameterization-induced uncertainties and impacts of crop management harmonization in a global gridded crop model ensemble. *PLOS ONE*, *14*(9), e0221862. https://doi.org/10.1371/journal.pone.0221862

Gebrekidan, T., Guo, Y., Bi, S., Wang, J., Zhang, C., Wang, J., & Lyu, K. (2019). Effect of index-based livestock insurance on herd offtake: Evidence from the borena zone of southern Ethiopia. *Climate Risk Management*, *23*, 67–77. https://doi.org/10.1016/j.crm.2018.10.003

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H.-H., Weiner, J., Wiegand, T., & DeAngelis, D. L. (2005). Pattern-Oriented modeling of agent-based complex systems: Lessons from ecology. *Science*, *310*(5750), 987–991. https://doi.org/10.1126/science.1116681

Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., & Schwarz, N. (2017). Theoretical foundations of human decision-making in agent-based land use models – A review. *Environmental Modelling & Software*, *87*, 39–48. https://doi.org/10.1016/j.envsoft.2016.10.008

Grosh, M. E., & Glewwe, P. (2000). *Designing household survey questionnaires for developing countries: Lessons from 15 years of the living standards measurement study*. The World Bank.

Hallegatte, S., & Rozenberg, J. (2017). Climate change through a poverty lens. *Nature Climate Change*, *7*(4), 250–256. https://doi.org/10.1038/nclimate3253

Hao, Y., Armbruster, D., Cronk, L., & Aktipis, C. A. (2015). Need-based transfers on a network: A model of risk-pooling in ecologically volatile environments. *Evolution and Human Behavior*, *36*(4), 265–273. https://doi.org/10.1016/j.evolhumbehav.2014.12.003

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., & Gintis, H. (2004). *Foundations of Human sociality*. Oxford University Press.

Hernandez-Aguilera, J. N., Mauerman, M., Herrera, A., Vasilaky, K., Baethgen, W., Loboguerrero, A. M., Diro, R., Tesfamariam Tekeste, Y., & Osgood, D. (2020). Games and fieldwork in agriculture: A systematic Review of the twenty-first century in Economics and social science. *Games*, *11*(4), 47. https://doi.org/10.3390/g11040047

Hernandez-Aguilera, J. N., Mauerman, M., & Osgood, D. (2020b, June). Playing to Adapt: Crowdsourcing Historical Climate Data with Gamification to Improve Farmer's Risk Management Instruments.

Hill, R. V., Kumar, N., Magnan, N., Makhija, S., de Nicola, F., Spielman, D. J., & Ward, P. S. (2019). Ex ante and ex post effects of hybrid index insurance in Bangladesh. *Journal of Development Economics*, *136*, 1–17. https://doi.org/10.1016/j.jdeveco.2018.09.003

Hill, R. V., & Viceisza, A. (2012). A field experiment on the impact of weather shocks and insurance on risky investment. *Experimental Economics*, *15*(2), 341–371. https://doi.org/10.1007/s10683-011-9303-7

IPCC. (2012). Summary for policymakers. In C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G.-K. Plattner, S. K. Allen, M. Tignor, & P. M. Midgley (Eds.), *Managing the risks of extreme events and disasters to advance climate change adaptation. A Special Report of working groups I and II of the intergovernmental panel on climate change* (pp. 1–19). Cambridge University Press.

IPCC. (2018). Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. (V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R.Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M.Tignor, and T. Waterfield, Eds.).

Janzen, S. A., & Carter, M. R. (2019). After the drought: The impact of microinsurance on consumption smoothing and asset protection. *American Journal of Agricultural Economics*, *101*(3), 651–671. https://doi.org/10.1093/ajae/aay061

Jensen, N. D., Barrett, C. B., & Mude, A. G. (2017). Cash transfers and index insurance: A comparative impact analysis from northern Kenya. *Journal of Development Economics*, *129*, 14–28. https://doi.org/10.1016/j.jdeveco.2017.08.002

John, F., Toth, R., Frank, K., Groeneveld, J., & Müller, B. (2019). Ecological vulnerability through insurance? Potential unintended consequences of livestock drought insurance. *Ecological Economics*, *157*, 357–368. https://doi.org/10.1016/j.ecolecon.2018.11.021

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., & Wheeler, T. R. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural Systems*, *155*, 269–288. https://doi.org/10.1016/j.agsy.2016.09.021

Jones, P. G., & Thornton, P. K. (2013). Generating downscaled weather data from a suite of climate models for agricultural modelling applications. *Agricultural Systems*, *114*, 1–5. https://doi.org/10.1016/j.agsy.2012.08.002

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, *129*(2), 597–652. https://doi.org/10.1093/qje/qju002

Kelly, R., Mackay, M., Nash, K. L., Cvitanovic, C., Allison, E. H., Armitage, D., Bonn, A., Cooke, S. J., Frusher, S., Fulton, E. A., Halpern, B. S., Lopes, P. F. M., Milner-Gulland, E. J., Peck, M. A., Pecl, G. T., Stephenson, R. L., & Werner, F. (2019). Ten tips for developing interdisciplinary socio-ecological researchers. *Socio-Ecological Practice Research*, *1*(2), 149–161. https://doi.org/10.1007/s42532-019-00018-2

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, *20*(2), 183–230. https://doi.org/10.1007/s10100-011-0210-y

Kline, J. D., White, E. M., Fischer, A. P., Steen-Adams, M. M., Charnley, S., Olsen, C. S., Spies, T. A., & Bailey, J. D. (2017). Integrating social science into empirical models of coupled human and natural systems. *Ecology and Society*, *22*(3), 25. https://doi.org/10.5751/ES-09329-220325

Kraehnert, K., Osberghaus, D., Hott, C., Habtemariam, L. T., Wätzold, F., Hecker, L. P., & Fluhrer, S. (2021). Insurance against extreme weather events: An overview. *Review of Economics*, *72*(2), 71–95. https://doi.org/10.1515/roe-2021-0024

Landmann, A., Vollan, B., & Frölich, M. (2012). Insurance Versus Savings for the Poor: Why One Should Offer Either Both or None.

Landy, J. F., Jia, M., Ding, I. L., Viganola, D., Tierney, W., Dreber, A., Johannesson, M., Pfeiffer, T., Ebersole, C. R., Gronau, Q. F., Ly, A., van den Bergh, D., Marsman, M., Derks, K., Wagenmakers, E.-J., Proctor, A., Bartels, D. M., Bauman, C. W., Brady, W. J., … Uhlmann, E. L. (2020). Crowdsourcing hypothesis tests: Making transparent how design choices shape research results. *Psychological Bulletin*, *146*(5), 451–479. https://doi.org/10.1037/bul0000220

Lenel, F., & Steiner, S. (2020). Formal insurance and solidarity. *Experimental Evidence from Cambodia. Journal of Economic Behavior and Organization*, *174*, 212–234. https://doi.org/10.1016/j.jebo.2020.02.002

Li, H., Porth, L., Tan, K. S., & Zhu, W. (2021). Improved index insurance design and yield estimation using a dynamic factor forecasting approach. *Insurance: Mathematics and Economics*, *96*, 208–221. https://doi.org/10.1016/j.insmatheco.2020.11.003

Lin, W., Liu, Y., & Meng, J. (2014). The crowding-out effect of formal insurance on informal risk sharing: An experimental study. *Games and Economic Behavior*, *86*, 184–211. https://doi.org/10.1016/j.geb.2014.03.004

Lobell, D. B., & Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, *12*(1), 015001. https://doi.org/10.1088/1748-9326/aa518a

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: A review of applications. *Landscape Ecology*, *22*(10), 1447–1459. https://doi.org/10.1007/s10980-007-9135-1

Millington, J. D. A., & Wainwright, J. (2017). Mixed qualitative-simulation methods: Understanding geography through thick and thin. *Progress in Human Geography*, *41*(1), 68–88. https://doi.org/10.1177/0309132515627021

Mobarak, A. M., & Rosenzweig, M. R. (2012). Selling Formal Insurance to the Informally Insured.

Mobarak, A. M., & Rosenzweig, M. R. (2013). Informal risk sharing, index insurance, and risk taking in developing countries. *American Economic Review*, *103*(3), 375–380. https://doi.org/10.1257/aer.103.3.375

Müller, B., Johnson, L., & Kreuer, D. (2017). Maladaptive outcomes of climate insurance in agriculture. *Global Environmental Change*, *46*, 23–33. https://doi.org/10.1016/j.gloenvcha.2017.06.010
Müller, B., Quaas, M. F., Frank, K., & Baumgärtner, S. (2011). Pitfalls and potential of institutional change: Rain-index insurance and the sustainability of rangeland management. *Ecological Economics*, *70*(11), 2137–2144. https://doi.org/10.1016/j.ecolecon.2011.06.011
Norton, M., Osgood, D., Madajewicz, M., Holthaus, E., Peterson, N., Diro, R., Mullally, C., Teh, T.-L., & Gebremichael, M. (2014). Evidence of demand for index insurance: Experimental games and commercial Transactions in Ethiopia. *Journal of Development Studies*, *50*(5), 630–648. https://doi.org/10.1080/00220388.2014.887685
Paluck, E. L. (2010). The promising integration of qualitative methods and field experiments. *The ANNALS of the American Academy of Political and Social Science*, *628*(1), 59–71. https://doi.org/10.1177/0002716209351510
Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., & Deadman, P. (2003). Multi-Agent systems for the simulation of land-Use and land-cover change: A review. *Annals of The Association of American Geographers*, *93*(2), 314–337. https://doi.org/10.1111/1467-8306.9302004
Quidt, J. d., Haushofer, J., & Roth, C. (2018). Measuring and bounding Experimenter demand. *American Economic Review*, *108*(11), 3266–3302. https://doi.org/10.1257/aer.20171330
Railsback, S. F., & Grimm, V. (2012). *Agent-Based and individual-based modeling: A Practical introduction*. Princeton University Press.
Robinson, D. T., Brown, D. G., Parker, D. C., Schreinemachers, P., Janssen, M. A., Huigen, M., Wittmer, H., Gotts, N., Promburom, P., Irwin, E., Berger, T., Gatzweiler, F., & Barnaud, C. (2007). Comparison of empirical methods for building agent-based models in land use science. *Journal of Land Use Science*, *2*(1), 31–55. https://doi.org/10.1080/17474230701201349
Rounsevell, M. D. A., Arneth, A., Alexander, P., Brown, D. G., de Noblet-Ducoudré, N., Ellis, E., Finnigan, J., Galvin, K., Grigg, N., Harman, I., Lennox, J., Magliocca, N., Parker, D., O'Neill, B. C., Verburg, P. H., & Young, O. (2014). Towards decision-based global land use models for improved understanding of the Earth system. *Earth System Dynamics*, *5*(1), 117–137. https://doi.org/10.5194/esd-5-117-2014
Rötter, R. P., Hoffmann, M. P., Koch, M., & Müller, C. (2018). Progress in modelling agricultural impacts of and adaptations to climate change. *Current Opinion in Plant Biology*, *45*, 255–261. https://doi.org/10.1016/j.pbi.2018.05.009
Santos, F. P., Pacheco, J. M., Santos, F. C., & Levin, S. A. (2021). Dynamics of informal risk sharing in collective index insurance. *Nature Sustainability*, *4*(5), 426–432. https://doi.org/10.1038/s41893-020-00667-2
Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M. A., McAllister, R. R. J., Müller, B., Orach, K., Schwarz, N., & Wijermans, N. (2017). A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecological Economics*, *131*, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008
Seaborn, K., & Fels, D. I. (2015). Gamification in theory and action: A survey. *International Journal of Human-Computer Studies*, *74*, 14–31. https://doi.org/10.1016/j.ijhcs.2014.09.006
Shirsath, P., Vyas, S., Aggarwal, P., & Rao, K. N. (2019). Designing weather index insurance of crops for the increased satisfaction of farmers, industry and the government. *Climate Risk Management*, *25*, 100189. https://doi.org/10.1016/j.crm.2019.100189
Siebert, A. (2016). Analysis of the future potential of index insurance in the west African Sahel using CMIP5 GCM results. *Climatic Change*, *134*(1-2), 15–28. https://doi.org/10.1007/s10584-015-1508-x
Smajgl, A., Brown, D. G., Valbuena, D., & Huigen, M. G. A. (2011). Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling & Software*, *26*(7), 837–844. https://doi.org/10.1016/j.envsoft.2011.02.011
Smith, E. B., & Rand, W. (2018). Simulating macro-level effects from micro-level observations. *Management Science*, *64*(11), 5405–5421. https://doi.org/10.1287/mnsc.2017.2877
Surminski, S., Bouwer, L. M., & Linnerooth-Bayer, J. (2016). How insurance can support climate resilience. *Nature Climate Change*, *6*(4), 333–334. https://doi.org/10.1038/nclimate2979
Trærup, S. L. M. (2012). Informal networks and resilience to climate change impacts: A collective approach to index insurance. *Global Environmental Change*, *22*(1), 255–267. https://doi.org/10.1016/j.gloenvcha.2011.09.017
Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences*, *100*(14), 8074–8079. https://doi.org/10.1073/pnas.1231335100
UNFCCC. (2013). Approaches to address loss and damage associated with climate change impacts in developing countries that are particularly vulnerable to the adverse effects of climate change.
Wallach, D., Mearns, L. O., Ruane, A. C., Rötter, R. P., & Asseng, S. (2016). Lessons from climate modeling on the design and use of ensembles for crop modeling. *Climatic Change*, *139*(3-4), 551–564. https://doi.org/10.1007/s10584-016-1803-1
Wang, E., Brown, H. E., Rebetzke, G. J., Zhao, Z., Zheng, B., & Chapman, S. C. (2019). Improving process-based crop models to better capture genotype × environment × management interactions. *Journal of Experimental Botany*, *70*(9), 2389–2401. https://doi.org/10.1093/jxb/erz092
Webber, H., Lischeid, G., Sommer, M., Finger, R., Nendel, C., Gaiser, T., & Ewert, F. (2020). No perfect storm for crop yield failure in Germany. *Environmental Research Letters*, *15*(10), 104012. https://doi.org/10.1088/1748-9326/aba2a4
White, H. (2014). The case of mixed methods for impact evaluation in microinsurance. In R. Radermacher, & K. Roth (Eds.), *A Practical guide to impact assessments in microinsurance. Microinsurance network and micro insurance academy* (pp. 173–183). Microinsurance Network and Micro Insurance Academy.
White, J. W., Hoogenboom, G., Kimball, B. A., & Wall, G. W. (2011). Methodologies for simulating impacts of climate change on crop production. *Field Crops Research*, *124*(3), 357–368. https://doi.org/10.1016/j.fcr.2011.07.001
Will, M., Groeneveld, J., Frank, K., & Müller, B. (2021). Informal risk-sharing between smallholders may be threatened by formal insurance: Lessons from a stylized agent-based model. *PLOS ONE*, *16*(3), e0248757. https://doi.org/10.1371/journal.pone.0248757
Wooldridge, J. M. (2012). Introductory Econometrics: A Modern Approach. Cengage Learning.
World Bank. (2009). World Development Report 2010: Development and Climate Change.
Wossen, T., Di Falco, S., Berger, T., & McClain, W. (2016). You are not alone: Social capital and risk exposure in rural Ethiopia. *Food Security*, *8*(4), 799–813. https://doi.org/10.1007/s12571-016-0587-5
Zizzo, D. J. (2010). Experimenter demand effects in economic experiments. *Experimental Economics*, *13*(1), 75–98. doi:10.1007/s10683-009-9230-z