

Integrated modelling of social-ecological systems for climate change adaptation

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Abstract

Analysis of climate change risks in support of policymakers to set effective adaptation policies requires an innovative yet rigorous approach towards integrated modelling (IM) of social-ecological systems (SES). Despite continuous advances, IM still faces various challenges that span through both unresolved methodological issues as well as data requirements. On the methodological side, significant improvements have been made for better understanding the dynamics of complex social and ecological systems, but still, the literature and proposed solutions are fragmented. This paper explores available modelling approaches suitable for long-term analysis of SES for supporting climate change adaptation (CCA). It proposes their classification into seven groups, identifies their main strengths and limitations, and lists current data sources of greatest interest. Upon that synthesis, the paper identifies directions for orienting the development of innovative IM, for improved analysis and management of socio-economic systems, thus providing better foundations for effective CCA.

Keywords

integrated modelling; social-ecological system; climate change adaptation; integrated assessment model; agent-based model

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1. Introduction

We live in the Anthropocene (Crutzen, 2002), the epoch in which human influence on the environment has extended to the global scale, as in the case of anthropogenic radiative forcing of climate (Steffen et al., 2011; Stocker et al., 2013). In the complex Earth System, a comprehensive description of the driving forces of the Anthropocene requires a holistic approach to study the coupled natural and human systems. This includes integrated approaches and accurate monitoring and reporting to decision/policy makers and the general public (Claussen et al., 2002). The traditional disciplinary dichotomy between natural sciences and social and economic ones has to come to an end, in particular for what concerns monitoring, analysis, and modelling of the complex systems emerging from the interaction of natural and human elements.

The complex interconnected processes of the Earth System, such as self-organisation, emergence, and feedback responses, challenge our modelling capabilities, often leading to biased or incomplete results (Folke, 2006; Ratter, 2012). The notion of Social-Ecological Systems (SESs; Adger, 2000; Berkes and Folke, 1998; Dearing et al., 2015; Eakin and Luers, 2006; Gain et al., 2020; Holling and Gunderson, 2002; Liu et al., 2015; Walker et al. 2006) provides a logical context for a holistic, integrative approach to this challenge. The SES can be defined as a complex dynamic system that includes people and nature, and continuously changes in response to internal or external pressures (Schlüter et al., 2014). Internal pressures may emerge from the behaviour of their socio-economic (e.g. demographic changes) and ecological components (e.g. natural climate fluctuations), or the combination of both (e.g. human-induced climate change), while the interactions between different SES and macro scale drivers enact external pressures.

Global changes expose SESs to stresses which are accelerating over time (Steffen et al., 2015), thus imposing the need to guide adaptation to evolving conditions of both human and ecological components of the ecosystem. International guidance frameworks, such as the Sustainable Development Goals (SDGs) of the UN Agenda 2030, or the Sendai Framework for Disaster Risk Reduction endorse long-term monitoring and policy efforts to enable climate change mitigation and adaptation measures, and the management of risks from natural disasters. The implementation of climate change adaptation (CCA), with its varying combinations of planned and autonomous actions, is one of the greatest challenges for SESs in the coming decades and also a challenge for integrated modelling aimed at simulating SES behaviour (Adams, 2021; Sansilvestri et al., 2020; Walker et al., 2002).

Models are indispensable tools to support CCA and the policy-making process (Harris, 2002; Gain et al., 2020), because they enable the investigation of complex system behaviour not only in past and current conditions, but also in the future, through scenario analysis (de Vries 2001; 2007). To be useful for CCA, models must be capable of dealing with SES complexity, characterised by human-nature and human-society interrelationships, non-linearity, and feedback loops (Gain et al., 2021). More and more CCA studies adopt a conceptual framework deriving from the literature on disaster risk reduction (DRR), which focuses on climate risks resulting from the interactions among climatic hazards, exposed receptors (e.g. people, buildings, infrastructures, etc.), and the socio-economic and environmental vulnerabilities of the SES (Giupponi and Biscaro, 2015).

SES integrated modelling (IM) for CCA is not substantially different from IM for other purposes, in terms of tools and data needs, but it requires specific capabilities for (i) simulation of a variety of interacting multi-scale elements and endogenous phenomena (ecosystem dynamics and human activities); (ii) consideration of multiple exogenous drivers (in particular climate and macro-economic trends and scenarios); and (iii) reliable simulations over long periods (e.g. 30-50 years or more). Lack of such capabilities may limit the potential for exploration of possible adaptation pathways and lead to short-sighted or wrong decisions (Essenfelder et al., 2018; Pande and Sivapalan, 2017; Di Baldassarre et al., 2013), eventually leading to maladaptation, i.e. increasing vulnerability to climate-related risks, at present or in the future (Noble et al., 2014). For example, some farmers from Zimbabwe offset climate uncertainty by increasing pesticide use, which destroys beneficial insects, and consequently makes the condition worse (UNEP, 2019).

Indeed, the uncertainty arising from the complexity of SES and the interactions between hazards, exposed receptors and SES vulnerability is one of the main challenges for planning CCA strategies and measures (Fedele et al., 2019; de Jong & Kok, 2021). Even more challenging is the need to consider not only planned adaptation (i.e., the one typically defined with public or private ad hoc plans), but also autonomous adaptation actions implemented by individual agents, such as farmers revising cultivation practices (e.g., switching irrigation systems or cropping patterns) within their farms (Pérez-Blanco et al., 2021). From a modelling perspective,

capturing autonomous CCA requires methodologies that can consider the behaviour of agents at adequate granularity. It also needs to address their self-organisation and the consequences from fine-grained behaviours on system-wide phenomena (i.e., following the previous example, the emergence of system-wide phenomena, such as variations in the supply of agricultural commodities and thus their prices, as a consequence of autonomous individual adaptations such as the substitution of water demanding crops with drought-resistant ones).

Modelling of CCA to explore SES behaviour under the effects of exogenous drivers (including climate policies) requires consideration of both the planned and the autonomous components and thus the integration of various modelling components (Brown and Rounsevell, 2021). It also requires a long-term perspective to include the consideration of the effects of drivers of climate change and social inertia (Bourne et al., 2016). In this context, Integrated Models (Giupponi et al., 2013) are tools allowing us to analyse and prove interrelations between human and natural systems. IM techniques can be applied to various aspects of climate change, for instance, biophysical relationships for understanding the causal mechanisms controlling the relationships between ecosystem productivity and species richness (Grace et al., 2016), or water-energy-food nexus relationships (Miralles-Wilhelm, 2016).

Models for each discipline and/or system employ different "metaphors" for the system's structure (e.g. process-based vs. empirical, probabilistic vs. deterministic, spatial vs. non-spatial, continuous vs. discrete time etc.) (Hollowed et al., 2020). In this sense, models can be seen as brittle monoliths, relatively easy to disassemble into their parts, but hard to reassemble into an integrated, methodologically sound and easily actionable approach. This difficulty stems from multiple factors, including the need for an easily communicable overarching conceptualisation, which is hampered by the diversity of the paradigms adopted, and the difficult engineering of model coupling at different scales and representations. As a result, it remains difficult to combine models incarnating different paradigms across the lifecycle of a study. Integrating architectures and modelling standards, such as OpenMI, (Moore and Tindall, 2005) have been proposed, but with limited adoption and impact in the long term.

Recently, Elsworth et al. (2020) explored socio-ecosystem modelling and identified eight grand challenges researchers face today that need to be overcome to accelerate the development of SES modelling, ranging from epistemological issues to uncertainty, scales and data types and sources. This paper develops upon the cited paper of Elsworth and others, and in particular on the two challenges related to representing the human dimension in SESs and furthering the adoption of SES modeling on policy, with a focus on CCA. There are three main objectives of this paper: (i) survey and analyse currently available modelling solutions and available data sources that could be useful for the long-term analysis of SES for CCA; (ii) identify the main knowledge gaps and modelling challenges; and (iii) envision a way forward for enhanced IM, improved analysis and management of natural resources and socio-economic systems, and better foundations for the sustainable management of SESs and effective CCA. Developing upon the current state of the art, this paper intends to offer a baseline of orientation for fellow researchers from the fields related to SES modelling who are interested in connecting their methods with current CCA research and for CCA experts interested in opportunities and research gaps in integrated modelling.

An overview is provided of integrated modelling and its capabilities and constraints, which emerged from the discussions conducted remotely within the group of co-authors, consolidated through two rounds of literature review. In the first we searched the Scopus Database for the presence of specific terms of interest in titles, abstracts and keywords of articles and review papers of any time. The paucity of the results confirmed the interest and novelty of the topic. The query targeted papers dealing with integrated modelling and climate change adaptation and socio-ecosystems, and resulted in 9 papers only¹. Among them, interesting studies are those conducted in New Zealand by Kalaugher et al. (2013) who integrated bottom-up qualitative research with top-down quantitative research by using a mixed-method approach for an adaptation study in the dairy sector. By drawing on theories from ecosystem services, climate change adaptation and sustainability science, Brink et al. (2016) developed an analytical framework for the urban ecosystem-based adaptation (EbA). Wabnitz et al. (2018) applied a quantitative social-ecological model to explore policy scenarios involving tourism, marine

¹ The query in Scopus Advanced Search was: TITLE-ABS-KEY (integrated AND model* AND ("climate change adaptation" OR CCA) AND (socioecosystem OR (soci* AND ecolog* AND system)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re"))). Last access on 9 September 2021.

conservation and local food security for Palau. Koenigstein et al. (2016) integrated stakeholder perceptions of ecological changes with the current state of scientific knowledge, to investigate the marine-human system under climate change and identify societal adaptation options for the Barents Sea and Northern Norwegian Sea region. Overall, the results of literature search corroborated the idea of this paper, showing that that a part from a few examples of SES integrated modelling, the research in the field of integrated modelling of SESs for CCA is not adequate.

The paper is organised following the three main objective. In the following section we analyse the constituent elements of SES modelling in the context of CCA, we survey available modelling solutions, we provide a proposal for a classification of modelling approaches in seven classes with different coverage of SES constituent elements, and we present an overview of possible sources of input data. In section 3 we analyse the main modelling challenges in this field, confronting data availability and modelling capacity, presenting open issues in the integration of socioeconomic and environmental data at different scales together with those related to uncertainty management and validation, with reference to CCA studies. Section 4 explores the way forward for enhanced IM, in particular for what concerns the simulation of human interactions, which are crucial in CCA, the potentials offered by unconventional data sources and new technologies. Section 5 concludes the paper and identifies ways forward of greater interest.

2 Constituent elements for integrated modelling of social-ecological systems

2.1 Models to support the adaptation of social-ecological systems

The long-term analysis of SESs for effective adaptation to climate change (CCA) is a truly interdisciplinary problem that requires the integration of data and methods from environmental, social and computer sciences at multiple scales. Currently, a variety of models can be used to model SESs for supporting adaptation, many of which, however, were not developed for this objective. We have categorised the models into seven different classes. Table 1 summarises the strengths and limitations of models in each class.

The table includes models that are mainly focused on the natural systems – Biophysical Process-Based Models (BPBMs), Earth System Model (ESMs), Dynamic Global Vegetation Models (DGVMs), and Global Circulation Models (GCMs) – as well as those that target more directly the social system – Computable General Equilibrium models (CGEs) and Agent-Based Models (ABMs). In addition, Integrated Assessment Models (IAMs), have the ambition to describe and simulate both the human and the natural systems. In Figure 1 we present a graphical description of the SES with areas covered by the various model classes and their intersections.

Global Circulation Models (GCMs) have been developed when weather forecasting was a major research focus, leading to the research of a deeper understanding of the general circulation of the atmosphere (Phillips, 1956). As the understanding of the climate system has increased along with computational power, GCMs developed both in terms of process details and of spatial-temporal resolutions. The current generation of GCMs, grounded in well-established physical laws, both theoretically and empirically, is capable of reproducing many of the natural processes that are part of the climate system, such as large-scale temperature and precipitation patterns, and seasonal and periodical weather oscillations (Reichler and Kim, 2008).

The climate, however, is not an isolated system and a product of physical and chemical processes only. Accordingly, future projections made under these forcings alone might prove to be both myopic and misleading when evaluating CCA actions; instead, the biosphere (considering the interaction of biotic and abiotic factors) should also be taken into account when projecting future climatic pathways (IPCC, 2001a).

Biophysical Process-Based Models (BPBMs; Martin et al., 2013) and Dynamic Global Vegetation Models (DGVMs; Krinner et al., 2005) are focused on primary production and use mathematical formulations to represent dynamic processes of vegetation, in natural (DGVMs), or anthropic (BPBMs) ecosystems, under the effects of climate variables of and biogeochemical cycles and – in the case of BPBMs – of human management. Earth System Models (ESMs) seek to close the gap between geophysical and biological processes when simulating the climate system by incorporating processes simulated within DGVMs and BPBMs at the level of the whole biosphere, thus modelling the state of regional and global climate under a wide variety of conditions. ESMs (Scheiter et al., 2013) are more integrative models than GCMs since they integrate interactions between the biosphere and the climate (Figure 1). However, ESMs are generally designed in such a way that human influence

on the natural system is considered as an external driving force, leading Claussen et al. (2002) to suggest that a better definition for this class of models would be "Natural Earth System Models".

Table 1: Classes of integrated models and their strengths and limitations for being used in support to CCA.

Model Class	Model Class Name	Description	Strengths	Limitations	Main References and Reviews
BPBM	Biophysical Process-Based Model	BPBMs are defined as biophysical models (e.g. Landscape, Agro-Ecosystem and Eco-Hydrological models) relying on the usage of mathematical formulations to represent key dynamic processes affecting particular physical or biophysical processes.	Landscape/regional scale is appropriate for most decision-makers. Linking between BPBM becomes possible (e.g. hydrologic and crop models) to assess climate change scenarios and adaptation options.	Lack of intrinsic human system representation (e.g. farmers decision on land as dynamic feedbacks).	(Martin et al., 2013; Turner et al., 2016; Rosenzweig et al., 2014; Gupta et al. 2019; van Oijen et al. 2018)
DGVM	Dynamic Global Vegetation Model	Models capable of simulating the dynamics of potential vegetation and its associated biogeochemical and hydrological cycles as a response to shifts in climate (Scheiter et al., 2013).	Strong capabilities to simulate the behaviour of vegetation under the effects of biogeochemical and hydrological cycles and climate.	Lack the human decision-maker and not very sophisticated on the agricultural side to model the breadth of management decisions in adaptation.	(Fisher et al., 2017; Krienner et al., 2005)
ESM	Earth System Model	Models that integrate the interactions of atmosphere, ocean, land, ice, and biosphere to estimate the state of regional and global climate under a wide variety of conditions (Stocker et al., 2013).	High level of integration to better represent the biochemical processes and feedbacks between climate and land systems.	Limited representation of agricultural systems: e.g. need for better inclusion of irrigation, carbon and GHG fluxes, management practices (sowing dates, rotations etc.).	(McDermid et al., 2017; Weigel et al., 2021)
GCM	General Circulation Model	Physical law-based models rely on the mathematical formulation to compute the general circulation in the atmosphere, ocean, cryosphere and/or land surface systems (IPCC, 2013).	Can be used to make projections about future climate and the knowledge gained can contribute to policy decisions regarding climate change	The global scale is not appropriate for considering human/social adaptation that occurs at a local scale	(Cess et al., 1990; Khan et al. 2018; Warszawski et al., 2014)
CGE	Computable General Equilibrium model	Class of economic models that focus on economics and market trends as a result of modelling behaviour of representative economic agents upon microeconomic principles. Commonly used to assess the impact of economic, policy or climate shocks on the economic system (IPCC, 2001b).	Allows to look at social decisions based on economic profitability and investigate climate policies.	Focus only on the economic system. No feedback human-natural system. The spatial scale (i.e. regional/national level) may not be compatible with the scale of natural phenomena happening at a local scale.	(Calzadilla et al., 2016; Duan et al., 2019; Fouré et al., 2020)

(Table continued on next page)

Table 1 (continued)

Model Class	Model Class Name	Description	Strengths	Limitations	Main References and Reviews
ABM	Agent-Based Model	Class of models that allows the simulation of heterogeneous agents, with their behavioural complexity, the interdependencies among them, and their organisational capabilities. In the field of CCA they are mainly used to simulate human societies exposed to climate change impacts.	Can simulate adaptive behaviour at the individual, or community level, considering also individual and mutual learning, thus providing a realistic representation of the system and allowing for exploration of emergent properties.	Validation - if possible - is very challenging. Complicated calculation processes, applied to the multitude of agents at play, with limits in transparency and communication. Very much case-specific, with limited transferability and replicability.	(Arneth et al., 2014; Balbi and Giupponi, 2010)
IAM	Integrated Assessment Model	Models that include an economic growth, a damage, and a climate module (IPCC 2001b). They are used to assess the costs of climate protection by integrating both the economic and biophysical systems, and by considering the interactions between them.	A holistic view of the world, with several interacting modelling components and efforts, is designed to improve interactions between human/natural systems. Allows scenario exploration for adaptation options.	Uncertainty propagation. The ease of use is decreasing as it becomes more expert-driven. Coarser resolution in time and space creates challenges around multi-scale processes. Heavy assumptions for the economic model. Over-simplification of biophysical processes and land use patterns.	(Ewert et al., 2015; Kling et al., 2017; Metcalf & Stock, 2017; Metcalf & Stock, 2015; Shiraki & Sugiyama, 2020)

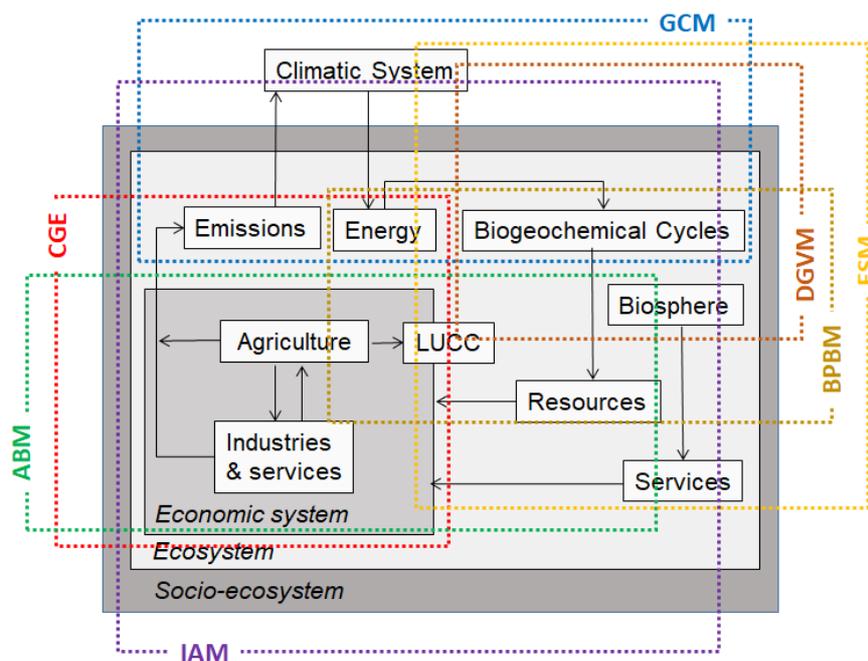


Figure 1: The economic and ecological systems nested in the socio-ecosystem in connection with the climatic system, with their main elements and relationships and the identification of the areas covered by the seven IM classes of Table 1.

The inter-relationships between people and nature are dynamic and continuously change in response to internal or external pressures (Schlüter et al., 2014). Major feedbacks between human and nature systems need to be considered in the modelling of SESs (Palmer and Smith, 2014). Population growth and urbanisation (Satterthwaite, 2009), migration (Black et al., 2013) and conflict (Hsiang et al., 2013) will all compound reactions to global climate change. Intrinsically, agricultural systems represented in ESM also assume that there is no local adaptation from farmers. ESMs assume that pressures coming from human systems are only external forcing to natural systems is therefore a strong limitation of this class of models (Ellis and Ramankutty, 2008).

CGE models have been widely used for the analysis of international climate policy questions at a macro-economic level due to their capability of integrating the interactions among several economic sectors (Bernstein et al., 1999; Hertel et al., 2009; Matsumoto and Masui, 2011; Rutherford, 1999). Duan et al. (2019) and Babatunde et al. (2017) have provided a comprehensive survey of a wide range of CGE models that were developed for climate change studies across different geographical regions and economic sectors. CGE models have been used to study a variety of topics ranging from energy (renewable and efficiency), emissions (trading and reduction) to carbon (tax, storage, and capture). Initial CGE models in the 1990s were mainly static and incapable of capturing climate change dynamics. Recursive dynamic and full dynamic CGEs were later applied to climate mitigation (Kompas et al., 2018), but criticism has been raised for their myopic view about the future (Babatunde et al., 2017). Generally, CGE models are structurally complex, consisting of a detailed set of equations defining several economic sectors of the human components of an SES system. They are assuming representative and aggregated production functions and consumers' utility functions (Arigoni Ortiz and Markandya, 2009), full rationality of those two groups of agents, complete markets, perfect information, and optimality of decisions. Therefore, they contain a large number of input variables and parameters to be quantified across the globe to provide outputs that are usually at a national to regional scale. In that, they are often defined as top-down models. Both their assumptions and their needs in terms of inputs have led to criticisms and questioning within the economics and policy analysis communities, in particular when they are used for exploring long-term scenarios driven by global changes. Moreover, due to their lack of representation of the natural system, CGE models, in the context of CCA modelling, may not be able to estimate the costs of adaptation strategies by failing to capture the social costs of externalities and feedbacks occurring in the natural system.

ABMs have emerged as a way to improve modelling of complex systems' behaviour from the bottom-up (Balbi and Giupponi, 2010), and have been used to help explore CCA strategies. A growing body of literature seems to agree that agent-based modelling is a flexible but computationally intensive methodology that has the power to encapsulate (1) the heterogeneity of the modelled components, (2) their behavioural complexity, (3) the multilevel interdependencies among them, and (4) their organisational capabilities (O'Sullivan, 2008; Arneth et al., 2014). The main advantages of ABMs for the analysis of climate change are the abilities to take into account adaptive behaviour at the individual or system level and to introduce a higher degree of heterogeneity resulting in a more realistic representation of the system, compared to equilibrium-based models (Balbi and Giupponi, 2010). However, ABMs have also several limitations some of which are particularly relevant for integration purposes. Individually developed and stand-alone ABMs are very often complicated artefacts (Bradhurst et al., 2016; Filatova et al., 2013) that ingest a wide set of different datasets combining them into calculation processes, applied to the multitude of agents at play. While modelling frameworks in other fields, such as land use and land cover change (LULCC), may be shared widely by researchers (consider for example the CLUE or FEARLUS models; Verburg et al., 2002; Izquierdo et al., 2003), ABMs appear more difficult to coalesce under a common approach, due to the particular and case-specific assumptions made by each author (Bell et al., 2015). Notwithstanding the significant progress in development and communication protocols (e.g. Müller et al., 2014), still, too often ABMs appear as black boxes. In addition, it is difficult to reuse them due to the lack of developing common codes that nest multiple models (Topping et al., 2010; Innocenti et al., 2020). Additionally, and even more importantly, those ABMs that aim to have some empirical value are difficult to validate statistically (both individual-level rules and system-level outcomes should be tested). Researchers tend to focus on sensitivity analysis (Bell, 2017) and qualitative comparisons with observed social phenomena, often because of a lack of available data, opening the door for uncertainty and misuse.

When it comes to the integration of separately developed ABMs with ecological models, challenges increase. One main difficulty is scaling mediation: agents constrained to exist within a bounded spatial and temporal context and granularity might need to interact with other agents bound to other spatial-temporal constraints.

For example, human agents are often modelled using daily time steps while ecological agents and processes might require finer or coarser time scales. Thus, from a technological point of view, integrating models with agents represented at different scales requires uncommon features in existing modelling platforms, and only experienced model developers with competencies in all the domains at play can manually integrate different modelling components (Voinov and Shugart, 2013). However, even when these technical difficulties are solved, aggregation and propagation of errors due to scale mismatch remain difficult to quantify, as in any other modelling approach, and have the potential of significantly affecting the uncertainty in the results.

Integrated Assessment Models (IAM) are commonly used for assessing strategies to address climate change-related issues, and in particular to analyse interrelations of climate with its societal impacts, e.g. identifying alternative adaptation actions. IAM consider the integrative nature of the earth and human systems, providing techniques that economists use to analyse expected costs and benefits of climate policies (Ackerman et al. 2009), for instance by cost-effectiveness, cost-impact, or cost-benefit framing (Dowlatabadi, 1995). Their strength resides mainly in the integration of potential feedback loops between the human and the natural system (Figure 1). IAM are typically not designed to create new insights on climate science issues; their value is in understanding and projecting the interaction between the climate and the economic systems for policy development and evaluation (van Vuuren et al., 2011). They are very useful tools for raising awareness and testing future scenarios at the regional and national scale (Jäger et al., 2015), enabling the creation of a space for discussion with different groups of stakeholders (Harrison et al., 2016). However, since the interrelationships between the human and natural systems are extremely complex, simplifications are usually necessary, and some of which may shadow either natural or human phenomena. As in any modelling exercise, simplifications should be avoided in the representation of core adaptation phenomena. For example, McDermid et al. (2017) pointed out that incorporating irrigation as an adaptation measure is a key model development required for an accurate simulation of agroecosystems, with consideration of feedback loops on both water and human systems, but the full amplitude of adaptation measures that are available at a local scale may not be reflected (Patt et al., 2010).

As another challenge, information on damages due to climate is always incomplete (Ewert et al. 2015). Besides, IAMs are still limited to looking at other socio-economic elements such as impacts on demographics, job loss/opportunities or socio-cultural factors that may be either influential or affected. Some global models such as the latest IMAGE release (Stehfest et al., 2014) are starting to consider long-term impacts on human development (food consumption, water supply and sanitation). However, model representation is less developed for the human system, compared to the physical system. Technical adaptation measures such as carbon tax adoption can therefore be evaluated as policy options, but not others such as R&D or governance systems. This highlights the limitation of current IAMs on the understanding of societal factors.

With the scenario settings from IPCC AR5 (O'Neill et al., 2014), shared socioeconomic pathways (SSP) are providing a framework to explore future alternative and plausible scenarios for the future evolution of our society and economy. These have been categorised by the IPCC along with challenges to both mitigation and adaptation and they represent fundamental references for adaptation modelling, to provide comparability of results obtained in different locations. Representative concentration pathways (RCPs) are typically giving space to models relating to climate change risks. SSPs are referring to the exposure, sensitivity and adaptive capacity of socio-economic systems under the effects of climate change and the related policies. As we move towards more integration between human and natural systems, interdisciplinarity between domains such as economic modelling, biophysical modelling, and social science must become prevalent. Moreover, SSPs have been developed on a global scale, and to provide country-relevant detail to understand climate change risks at the national and local scales. Methodologies to downscale storylines from global to national scale should be developed to ensure credibility, saliency and legitimacy of scenarios across multiple scales (Ausseil et al., 2019; Frame et al., 2018; Kebede et al., 2018; Mitter et al., 2020).

2.2 Data sources for SES modelling

To model and analyse SES, multiple data sources at various scales are needed, from global to local scale. In addition to global socio-economic and demographic datasets, global natural systems datasets are required for soils, groundwater and various kinds of natural disasters. In Table 2, we list some candidate datasets for global information to support attempts to implement the various modelling approaches described in Table 1.

Table 2: Some candidate sources of global socio-environmental data.

Platform	Product description and Link	SES component
Aalto University	Gridded global dataset for GDP and Human Development Index 1990-2015 (https://datadryad.org/stash/dataset/doi:10.5061/dryad.dk1j0)	GCM, ABM, IAM
AQUASTAT	FAO Global water information system (http://www.fao.org/nr/water/aquastat/main/index.stm)	ESM
CEIP Emission Database	Analysis and visualisation of the officially reported emissions data submitted under the LRTAP Convention by the European Environment Agency (https://www.ceip.at/data-viewer)	ESM
Blue Earth Data Platform	Free, web-based application to support the study and sharing of integrated water and subsoil-related data (https://blueearthdata.org/).	DGVM, BPBM
Climate Research Unit	Weather and Climate Monthly climatic indicators (1901-2013) at 0.5 deg. resolution by East Anglia University (http://www.cru.uea.ac.uk/)	GCM
Climate Data Store	The Climate Data Store (CDS) provides easy access to a wide range of climate datasets, including information about the past, present and future climate (https://cds.climate.copernicus.eu/).	GCM, ESM, DGVM, BPBM
Climate Watch	Latest historical greenhouse gas emissions data, track net-zero targets and explore nationally determined contributions (NDCs) and long-term strategies to reduce GHG emissions by the World Resources Institute (https://www.wri.org/initiatives/climate-watch)	ESM
Cordex	Downscaled climate projections (http://www.cordex.org/)	GCM
DataBank	Analysis and visualisation tool that contains collections of time series data on a variety of topics by the World Bank (https://databank.worldbank.org/home.aspx)	CGE, ESM,
DesInventar	The occurrence of daily disasters of small and medium impact. (http://www.desinventar.org/)	CGE
Digital Observatory for Protected Areas (EU-JRC)	Data, maps and tools on global protected areas (https://dopa.jrc.ec.europa.eu/dopa/)	DGVM, BPBM
Disasters, natural hazards	International disasters database EM-DAT (http://www.emdat.be/)	CGE
Earth2Observe	Freshwater resources worldwide (https://wci.earth2observe.eu/)	DGVM, BPBM
EarthMap	Historical environmental and climate analysis data (https://earthmap.org/)	ESM
Emissions Database for Global Atmospheric Research (EDGAR)	Emissions as national totals and gridmaps at 0.1 x 0. degree resolution at global level, with yearly, monthly and up to hourly data by the Joint Research Centre/European Commission (https://edgar.jrc.ec.europa.eu/)	ESM
Environmental Data Compendium	Data linking pollution and natural resources with activity in such economic sectors as energy, transport, industry and agriculture by OECD (https://www.oecd.org/env/indicators-modelling-outlooks/oecdenvironmentaldatacompendium.htm)	ESM
Environmental Data Explorer (EDE)	National, sub-regional, regional and global statistics and maps, covering themes like Freshwater, Population, Forests, Emissions, Climate, Disasters, Health and GDP by UNEP and its partners in the Global Environment Outlook (GEO) (http://geodata.grid.unep.ch/)	CGE, ESM
GEOSS Portal	Earth observation data and resources (https://www.geoportal.org/)	ESM
Global air pollution map	High-resolution global atmospheric map of nitrogen dioxide pollution by the European Space Agency (http://www.esa.int/Applications/Observing_the_Earth/Envisat/Global_air_pollution_map_produced_by_Envisat_s_SCIAMACHY)	ESM
Global Forest Watch	Data and tools for monitoring forests (https://www.globalforestwatch.org/)	DGVM, BPBM

(Table continued on next page)

Table 2 (continued)

Platform	Product description and Link	SES component
Global Risk Data Platform (PREVIEW)	Spatial data information on global risk from natural hazards, human and economical exposure and risk (tropical cyclones and related storm surges, drought, earthquakes, biomass fires, floods, landslides, tsunamis and volcanic eruptions by UNEP and UNISDR (http://preview.grid.unep.ch/index.php?preview=home&lang=eng))	DGVM, BPBM
Global Surface Water Occurrences (EU-JRC)	Maps with location and temporal distribution of water surfaces at the global scale over the past 3.7 decades (https://global-surface-water.appspot.com)	DGVM, BPBM
GloFAS	Part of the Copernicus Management Service (CEMS), Global Flood Awareness System (GloFAS) is designed to support preparatory measures for flood events worldwide (https://www.globalfloods.eu/).	BPBM
Google Earth Engine	Historical remote sensing imagery and scientific datasets (https://earthengine.google.com/)	DGVM, BPBM
GRID core datasets	Global socioeconomic and natural resources data (https://datacore.unepgrid.ch/geonetwork/srv/eng/catalog.search#/search?any=GRID%20core%20datasets)	CGE, IAM
IIASA	Harmonised world soil database (http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/)	DGVM, BPBM
ISRIC	Soil data layers from around the world (http://www.isric.org/explore/isric-soil-data-hub)	DGVM, BPBM
Global Human Settlement Layers (EU-JRC)	Data on built-up areas, urban settlements, population distribution (https://ghsl.jrc.ec.europa.eu/index.php)	GCM, ABM, IAM
Living Atlas of the World	Collection of geographic information from around the globe (https://livingatlas.arcgis.com/en/home/)	CGE, IAM
Measurement of Air Pollution from Satellites (MAPS)	Near-global database of atmospheric carbon monoxide levels by NASA (https://www.nasa.gov/centers/langley/news/factsheets/MAPS.html)	ESM
NOAA	Climate summaries from land surface stations across the globe. (https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn)	ESM, GCM
Resource Watch	Global data related to different topics (from climate change to poverty, water risk to state instability, air pollution to human migration, etc.) (https://resourcewatch.org/data/explore)	CGE, IAM
Shared Socioeconomic Pathways	The SSP Database (Shared Socioeconomic Pathways) - Version 2.0 (https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10)	CGE, ABM, IAM
Socioeconomic Data and Applications Center (SEDAC)	Socioeconomic and earth science data (https://sedac.ciesin.columbia.edu/data/sets/browse)	CGE, IAM
The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)	Projection of climate change impacts across affected sectors and spatial scales (https://www.isimip.org/)	DGVM, BPBM
University of Groningen Growth and Development Centre	Comprehensive databases on indicators of growth and development in four main research areas: Productivity, Value Chains, Historical Development and Structural Change (https://www.rug.nl/ggdc/)	GCM, IAM
World Bank	Socio-economic, demographic and governance data, World Development Index, etc. at country level (https://data.worldbank.org/)	CGE, IAM
World Resources Institute (WRI)	Global flood and water scarcity data (https://www.wri.org/aqueduct/data)	DGVM, BPBM
WorldClim	Monthly temperatures and precipitation (1950-2000) at 1 km resolution (http://www.worldclim.org/)	ESM, GCM

For CCA, and for identifying local adaptation measures, for instance, fine-scale datasets can be used for detailed analysis at the local case study level. The scale of the individual household is likely the most appropriate to simulate adaptation in detail (Neumann and Hilderink, 2015). To this end, longitudinal household-level information covering livelihoods and wellbeing is provided by a large number of countries. For example, the Ethiopian Rural Household Survey by IFPRI, the Bangladesh Integrated Household Survey also by IFPRI, or the Indonesian Family Life Survey by RAND. Similar data are available at a country level for most countries in the world and through the World Bank (see Table 2). Methods to define agent typologies for an entire region have been proposed for multi-agent spatial modelling of households in the Netherlands (Valbuena et al., 2008). Of course, it is a challenge to find or access data, and even in industrialised countries, open data findability, availability and reusability are quite heterogeneous.

Nightlight satellite data have been used in many instances to map urban areas at a global scale (e.g. Zhou et al., 2015), but also to derive socioeconomic layers, for the allocation of economic activities and spatialisation of indicators, such as the gross domestic product (Chen and Nordhaus, 2011). Additionally, novel mobile data sources and big data approaches make it possible to observe how populations respond to environmental changes in near real-time (Bell et al., 2016; Lu et al., 2016) or to look into the digital footprints left behind in the transaction logs of mobile phones to measure economic development, wealth and poverty (Eagle et al., 2010), unemployment (Choi and Varian, 2012) or electoral outcomes (Wang et al., 2014). For example, Llorente et al. (2015) extracted data on social media metrics of technology adoption, mobility, diurnal activity and communication style, which allowed to explain unemployment in different regions of Spain. Blumenstock et al. (2015) used mobile phone metadata to reconstruct the distribution of wealth throughout Rwanda and show that the predictions matched well with those from detailed boots-on-the-ground surveys of the population. During the COVID-19 pandemic, mobile data have been used to monitor the impact of social distancing on mobility (Zhang et al., 2020) and on mobility concerning income (Ruiz-Euler et al., 2020). Such information can significantly improve our capabilities to map adaptation capacities and the resilience potential of communities.

Finally, data can be crowdsourced from citizens and citizen scientists, participating voluntarily to open research projects (e.g., OpenStreetMap), which can be contributed to without professional training. Social media could also be used to identify spatio-temporal patterns, values and activities in the frame of SES monitoring and biodiversity conservation, to characterise threats and opportunities (Di Minin et al., 2015). For instance, they can be employed in forest monitoring (Daume et al., 2014), for understanding tourists' preferences for nature-based experiences in protected areas (Dolan et al., 2021; Hausmann et al., 2018), for understanding travel behaviour (Rashidi et al., 2017) and the complexity of socio-ecological interaction in leisure and tourism activities (Lenormand et al., 2018; Roberts et al., 2017), or to improve outcomes in natural resource management (Groce et al., 2018).

3 Modelling challenges for climate change adaptation

The state of the art of modelling approaches and data sources presented in the previous section demonstrates that several approaches are available and combinations are possible. Integrated modelling of the environmental dimensions of climate change and adaptation appears more consolidated, while mainstream climate change economic modelling is often criticised and by evidence it does not allow to consider important dimensions, such as the role played by the diversity of individual preferences and their interactions at various scales. Expectations are growing for the contributions that may come from ABMs, but we are far from solutions and the literature is poor. Therefore, several challenges are open for the development of IM in this field.

We identify some of them in this section. The intent is not that of providing a systematic review of all the open issues in the field, but that of driving the attention of the reader to a set of challenges which currently constrain scientific developments more than others, and which may potentially benefit in particular for wider integration of multi-agent approaches.

Firstly, we focus on confronting data availability and modelling capacity, which is an issue common to all modelling fields and which has some interesting specific features for adaptation and potential for ABMs. We move then to the consideration of challenges related to the needs to combine multiple scales and implement long term simulations, in the joint analysis of both the social and the environmental dimensions of the SES. The last part of this section is dedicated to the issues of uncertainty management and validation, which are often unresolved issues in particular in the field of multi-agent modelling.

3.1 Global vs. local data availability and modelling capacity

Top-down models require macro data that in climate change sciences typically cover the whole planet. For instance, Computable General Equilibrium (CGE) models require global country-level data such as population, land area and use, GDP, productivity, infrastructure, damages and losses, to feed simulation routines and provide us with a prediction about future prices, trade and economic development. These data are almost always homogenised among data-gathering agencies at national and international levels. For instance, international organisations such as FAO (Food and Agriculture Organization of the United Nations), UNSD (United Nations Statistics Division) and the World Bank as well as national statistics offices around the world collect similar types of data for all countries, using similar methodologies, compatible vocabularies, and uniform open-access protocols (such as SDMX). This facilitates building and running top-down models. However, information on the level of uncertainty associated with these datasets is usually missing, requiring caution about the reliability, and contemporaneity and thus trustworthiness of the input data. For instance, the Forest Resource Assessment is reported by FAO every five years, and there are known issues around data that may be withheld by some countries. In parallel, the level of aggregation of some data sources referred to as administrative units makes it hard to bridge what amounts to a chasm between the statistical and the biophysical modelling worlds: both the temporal and spatial scale mismatch between statistical information and the data needed to parameterise SES models are such that often these sources can only be used to provide boundary conditions in the context of an integrated modelling approach, rather than inputs with the required granularity.

Bottom-up models, in comparison, allow for heterogeneity among agents and therefore they should be calibrated to local and regional characteristics of agents such as preferences, attributes, endowments, etc. Since in many cases these models are spatially explicit, this means that bottom-up models require fine resolution GIS layers (landscape category, population density, natural resource availability, risk, vulnerability and resilience categories etc.) to account for the geographical location of agents and the spatial interlinkages between agents and landscapes. This often puts a constraint on the scale and modelling capacity of ABM as relevant data are either missing in some areas (such as developing countries), or are not homogenous across political/geographical boundaries. In addition, many ABM researchers use field surveys, the collection of which can be enormously time-consuming and expensive, particularly in global-scale studies. In bridging these two approaches, Verburg et al. (2016) suggest an upscaling method based on observed response patterns at an aggregated level (i.e., instead of individuals, the behaviour of the entire community is represented).

Despite an increasing amount of data becoming available from sources such as satellite remote sensing, mobile phones, or social networks, ABM are still limited by the amount of data they can homogeneously collect from social, economic or ecological systems to enable integrated modelling. On top of data availability, ethical issues concerning the collection of information about individual behaviour and uncertainty regarding data quality are other challenges for ABM modellers to overcome to be able to provide an accurate simulation of coupled systems. Because of these data constraints, mainly local or regional ABM have been developed.

Schulze et al. (2017) reviewed ABM for SES analysis using the TRACE framework (Grimm et al., 2014) to analyse ABM literature in terms of model development, testing and analysis and they found that gaps are substantial in particular for what concerns the communication of the realism of the models and the transparency of model formulation concerning observations, recommending a mix of strategies based upon participatory approaches, standard protocols, code sharing and improved tools for model design and analysis.

Given the strong interest for the potential of ABM that emerged from the above, a second systematic review was carried out to explore the applications of ABM for integrated modelling of SES adaptation phenomena². Only 10 papers were retained after having cleared the selection for papers not pertinent to the topic and those included because of multiple meanings of the CCA acronym. The selection of papers demonstrates the recent interest in such applications (all the articles were published in the last 9 years). Rural contexts are those more frequently analysed, thus appearing as a preferable environment for the development of innovative approaches. Case studies were in New Zealand (Gawith et al., 2020), China (Liu et al., 2013), Mongolia (Wang et al., 2013), Ethiopia (Hailegiorgis et al., 2018), and Burkina Faso (Kniveton et al., 2012).

² The query in Scopus Advanced Search was: TITLE-ABS-KEY (("climate change adaptation" OR "CCA") AND ("ABM" OR "agent based model*")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) . Last access on 9 September 2021.

3.2 Cross-scale integration and flow of information between top-down and bottom-up models as a challenge for CCA

As stated above, bottom-up models such as ABM usually focus on the local or regional scale and cannot deal with the global scale, therefore neglecting the big picture, such as global market, population and economy. This is a big caveat of this approach in the context of climate change adaptation that involves global interdependencies of systems and markets. On the contrary, top-down models such as CGE focus on a global scale and are heavily based on assumptions that simplify the integrated system to reduce data requirements. Therefore, they can produce a global picture of the global system, but with substantial constraining assumptions, averaging and aggregation effects, and without making sure that physical laws and constraints are satisfied. One example is neglecting the availability of local natural resources such as water in agricultural production since the top-down models are focused on labour and capital. Concerning assumptions in top-down models, a common one is the representative agent assumption (Nikas et al., 2019), that all agents share the same characteristics. While this can be sufficient for many problems (all people share similar basic needs, for instance), many others – and this is the case of CCA – are driven strongly by individual interactions (e.g., changing farming practices due to interaction with other farmers). Relying on this assumption is one of the reasons that top-down models cannot consider emergent properties and crises and thus fail to jointly predict idiosyncratic and systemic risks. To compensate for this drawback, researchers sometimes couple the two approaches but the challenge of integrating them remains and the flow of information is only asynchronous. For example, Giupponi and Mojtahed (2018) coupled an ABM simulating water and land allocations at the scale of 100 km grid cells, with information recursively derived from a CGE model providing macroeconomic trends (e.g. the prices of agricultural commodities) driven by climate change scenarios. Similarly, Pérez-Blanco et al. (2020) coupled an economic model based on a positive multi-attribute utility programming tool with a hydrologic model that simulates the behaviour of farmers for assessing the economic and water reallocation potential of a return flow-neutral inter-basin water market, using a sequential modular approach.

From the above, it appears that the prerequisite for coupling the two modelling approaches and benefiting from the strength of each approach is to integrate the two on the same scale so that information can flow between them and corrects for over/underestimations or negligence of local or global drivers of change. Solutions are available for loose coupling of different models at nested scales that allow for some improvements to the state of the art based upon the alternative between top-down and bottom-up approaches (Giupponi and Mojtahed, 2018). Once more, ABM seem to have promising potentials to cross the gap between micro-scale actors and larger-scale environmental, infrastructural and political systems to support policy analysis in the current and future situations characterised by multiscale crises. Lippe and others (2019) propose conceptual avenues for such endeavours, using combinations of big data, including social networks and remote sensing and acknowledging scale as a dynamic issue.

3.3 Global modelling for adaptation purposes and long-term analysis

The feasibility of a long-term analysis of climate change adaptation is a three-folded issue. The first part is to address the challenge of to what degree we can use the advances in our modelling knowledge to capture the dynamics of integrated social, economic, and ecological systems. For instance, social scientists are still not satisfied with the parametrisation and modelling of agents' decision-making and behavioural responses with or without uncertainty. The second challenge is the scale of the analysis. As mentioned before, parametrising ABM at the global scale is either costly or difficult due to data constraints. New data sources, particularly from earth observations, are coming online with great speed and can contribute to the advancement of ABMs. However, our ability to ingest these data sources moves at a much slower speed (Martínez-López et al., 2019), and much research in remote sensing, image recognition, and artificial intelligence is needed before these advances can readily and reliably turn into an increase in the prediction power of ABMs. Finally, the last issue is related to the long-term analysis of adaptation. Naturally, increasing the time scale of the analysis adds to the uncertainty of the model's outputs.

3.4 Results validation and uncertainties

Recently, An et al. (2020) identified several impending tasks to improve the science and application of ABM including validation, and transparency and reusability. Dealing with uncertainty is one of the crucial issues of IM in the field of CCA, due to the presence of multiple sources of uncertainties in this type of assessment (Van Asselt

and Rotmans, 2002). Uncertainties that are introduced to the sub-systems by using probabilistic methods can be propagated through the model and affect the final results. Epistemic uncertainties are also introduced when models are poorly integrated and certain processes are under-represented or not presented at all. The sources of uncertainties can increase exponentially as we develop more and more complex models with thousands of variables and parameters. Therefore, improved frameworks are required for managing the uncertainties and assessing the robustness of the results. In this frame, advances in Machine Learning (ML) models can help to discover patterns of risks in the millions of simulated outcomes and track them back to their sources. For instance, Essenfelder and Giupponi (2020) explored the utilisation of a coupled hydrologic-machine learning modelling framework to account for the complex decision-making in managing inter-basin water transfer under data-scarce conditions, concluding that ML can be a useful instrument to support complex system analysis under such conditions. Linear based models are not adequate tools for discovering potential non-linearities between sources of uncertainties and results. But, with the help of non-parametric ML models such as random forests, or neural networks, we can identify tipping points and better describe complex-system processes that may prove to be more critical in CCA (van der Hoog, 2017; Rolnick et al., 2019; O’Gorman et al., 2018).

A global sensitivity analysis is always needed to understand how the prediction accuracy of the model changes if the future drivers of change follow different trajectories from the inputs that were given to the model, but, despite advances in sensitivity analysis and uncertainty management, a fundamental question remains: how can we validate the results? Unfortunately, there is no way for validating future predictions and establishing ground truth, before an event or evolving process appear and thus assumptions have to be made that validations over the past can hold also for projections into the future. However, since the main interest is about future-proofing policies and decisions, researchers have developed various methodologies that are embedded into IM for evaluating the robustness of decisions. Info-Gap (Ben-Haim, 2006) and Robust Decision Making Under Deep Uncertainties (Lempert and Collins, 2007) are two examples of how researchers turned around the question to support long term adaptation decisions. The search of optimal choices is replaced by another paradigm such as the identification of solutions that are robust under numerous possible future conditions, or of the conditions that may determine the switch to alternative solutions through time and change them when results are taking undesirable trajectories (Groves and Lempert, 2007; Hall et al., 2012).

4 Opportunities for enhanced integrated modelling of climate change adaptation

Approaching the challenges described above, requires innovative solutions. In this section we explore in greater details the opportunities to go beyond state of the art by taking advantage of ABMs for modelling human interactions and adaptation dynamics. Moreover, we explore how unconventional data sources, such as social media and mobile networks, and emerging technologies, such as artificial intelligence, could contribute to improved IM for CCA.

4.1 Modelling human interactions

Notwithstanding their limitations, ABMs present evident opportunities for modelling CCA and contributing to solving some of the main weaknesses of the various categories of models described above, in particular for what concerns the simulation of autonomous adaptation. The added value of ABMs is in their ability to provide a descriptive representation of the simulated system – i.e., the human component of the SES interacting with the surrounding environment – according to four main key dimensions briefly described below.

The first is heterogeneity. Typically, ABMs consist of computationally intense, detailed dynamic simulations where many heterogeneous human and natural agents interact at multiple temporal and spatial scales. For instance, autonomous adaptation is typically implemented at the household level by individuals even day by day, while planned adaptation, which lasts for years, is defined and implemented at a national or regional scale. Indeed, one of the main advantages of ABM is that it can avoid a coarse, average and thus unrealistic representation of the system's components. Human agents can vary by demographic characteristics, location, endowments, individual abilities, perception of the world, attitudes and behaviour. Natural agents can also vary both in terms of spatial and temporal attributes.

The second is internal complexity. Compared to natural agents, human agents are more complex to simulate, because they execute subjective deliberative processes (i.e., they take individual autonomous decisions for adaptation). Behavioural complexity derives from the agents' internal world, their mental models (Lynam et al., 2012) or architectures, which include their cognition ability and learning capacity. There exists an abundance of theories in social sciences beyond the rational agent (Simon, 1978) about how human agents behave in various contexts, which can capture how people make decisions, also taking into account emotions, motivations and perceptions (Schlüter et al., 2017). ABM has the potential of allowing exploring this whole set of decision-making theories including the agents' capacity of learning from past experiences (An, 2012), which is extremely important for long term simulations required by CCA analyses.

Interactions and in particular social ones are the third dimension. Not only are most human agents deliberative, but they are also social: they communicate with other agents, and their behaviour derives from multi-level interactions with other human and non-human agents and the environment. This aspect is fundamental to capture dynamics like clustering (or kinship), imitation, learning and diffusion processes. ABM lends itself to graph and network analysis allowing to represent the topology of the network of information between social agents, and the relative importance of such agents within the network. This is a crucial modelling feature for modelling adaptation in that agent's interactions, and in particular informal relationships and opinion dynamics (e.g., word of mouth), can shape behavioural patterns.

Organisation and structure are the fourth dimension, strictly related to the previous. Interactions are greatly related to the emergence of an organisational structure. This is because most complex systems can be described as networks of interacting elements and these interactions may lead to the emergence of global behaviours that are not observable at the level of the single elements (Baggio, 2008). As mentioned above, human agents are deliberative and social, but they are also organisational: they can form into social and organisational structures. Cooperation and coordination or competition can be a consequence of the original system structure (e.g., Lansing and Kremer, 1993). At the same time, norms and institutions can direct individuals to act to the benefit or detriment of the collective, which can be crucial for reducing vulnerability to climate change impacts.

The potential of ABM appears evident, even if methodological challenges are still there. As previously mentioned, in the short term, the integration of top-down (i.e., general and partial equilibrium models) and bottom-up models should be considered. The top-down model could consider global drivers such as population growth, productivity increase, etc. and produce global prices and trade patterns, which should then be used by ABM in a bottom-up model to simulate e.g., local production of agricultural products, which can, in turn, be used by the top-down model to correct for its estimations (Giupponi and Mojtahed, 2018).

To be functional to CCA, integration in policy/decision-making frameworks should also be considered, such as the adaptive pathways (Bosomworth & Gaillard, 2019), to explore the long-term dimension of climate change and adaptation solutions, to identify preferable solutions over time. Modelling should thus be integrated into participatory approaches with stakeholders, to approach the challenges of temporal changes, as pathways reflect the changes faced by the actors. A consolidated stream of literature and experiments is available in this regard. Notable are the studies conducted by the French researchers at CIRAD in the agricultural sector (see e.g. Naivinit et al., 2010). In New Zealand, biophysical models were used to illustrate potential impacts from climate change and were interpreted to identify dynamic adaptation pathways and plausible scenarios (Cradock-Henry et al., 2018; Frame et al., 2018; Steger et al., 2021).

4.2 Unconventional sources of data: social media and mobile phones

New sources of data such as data from social media and mobile phones have opened new frontiers for socio-ecological studies. In the poorest countries, sources of big data are normally scarce. In fact, in case of the limited internet infrastructure, such as in remote or developing regions, few people may have access to social media and therefore approaches based on these sources of data may be less useful. Mobile phones are an exception. They are used extensively also in poor countries and they can provide very useful behavioural data (Blumenstock et al., 2015), like volume, frequency and timing of communication events (Candia et al. 2008), the structure of an individual's social network (Onnela et al., 2007; Palla et al., 2007), history of consumption and expenditure (González & Hidalgo, 2008), or patterns of mobility, migration, travel and location choice (Deville et al., 2014). They make it possible to observe how populations respond to environmental changes in near real-time (Bell et al., 2016; Lu et al., 2016).

Nowadays the global smartphones penetration is rapidly increasing, a phenomenon mainly driven by the growth in emerging economies. The growth of social networks, mobile apps and games, etc. boosted the availability of different sensors present on smartphones such as GPS, accelerometers, compasses, gyroscopes, barometers, cameras, and light/proximity sensors. Smartphones are no longer devices just to make calls and send messages, now they are powerful sensing devices, which allow us to trace individual profiles. This enables a different way of measuring and classifying human behaviour and people density in the real world.

Continuous monitoring of human behaviour has plenty of potentials provided that adequate ethical rules are adopted and accepted by all and that the resulting big data could be used by all, and in particular by those using them for research and non-profit purposes. Promising applications of these techniques are on traffic monitoring, by controlling and optimising the routes that are recommended to the users to reduce fuel consumption, carbon emission on traffic jams (Higuchi et al., 2015). The integration of these data with satellite remote sensing data can be used for estimating regional vulnerability in nearly real-time since they are updated with high frequency (Blumenstock et al., 2016). Potential applications of those data sources for climate-related risks and adaptation are numerous and range from increasing coping capacities during extreme events and natural hazards, to support the understanding of autonomous adaptation strategies for improved CCA policies and measures.

4.3 Opportunities in new technologies: cloud computing, Internet of Things, and artificial intelligence

CCA is a cross-cutting theme and IM aims at combining different natural, biological, physical, and societal dimensions. Challenges within one dimension in terms of data, method, scale, focus etc. as indicated in the previous sub-sections, thereby also affecting the overall picture. It is therefore important to observe opportunities and challenges from other cross-cutting trends to address such complex matters. We have selected three examples from the range of current digitalisation trends to exemplify this. Cloud computing can offer more decentralised access and storage of information thereby enabling researchers worldwide to exchange data and models more easily. Previous concerns regarding security risks, data privacy have been accounted for by adhering to new security protocols and legislations on encryption methods (Pearson, 2020). Similarly, the Internet of Things (IoT) offers promises of the more and better interconnection of mobile and stationary data collection devices to enable smarter energy usage, communication and logistics. Sensors (including micro-sensors) can measure air pollution levels, soil moisture, soil nutrients, improve agricultural production as well as household logistics. Just as cloud computing, this may also involve energy savings as well as more energy demands at the same time. Higher interconnectivity between sectors also means more interdependencies that could trigger cascading effects when one main sector such as the energy grid, or the internet, fail, for example through wildfires, floods or technical failure. But of course, many of the challenges addressed in previous sections such as the difficulty of bottom-up approaches with wider regional coverage can be addressed by utilising the better availability of very personal or high-resolution spatial and temporal data continuously flowing from IoT devices or mobile phones to cloud data. Big data has made progress in exploiting such data sources by marrying various data sets and enriching our data through various dimensions. Artificial intelligence probably is a renewed trend only due to the recent upcoming of the new accessibility to mass data.

It seems as if many constraints currently assigned to top-down or bottom-up approaches alike that are due to a lack of human resources in data mining can be improved by mass data and related algorithms. However, caveats to expectations must be expressed, too. So far, artificial intelligence and machine learning manage to derive better insights by analysing big amounts of data and finding non-linearity patterns. Most of the data in use had been tediously collected and pre-arranged. However, such data must be made accessible, and also, the choice of data entry categories must still be done by humans.

5 Conclusions

The analysis of the literature and the discussions within the group of co-authors brought us to the conclusion that integrated modelling of CCA is feasible if the major challenges of tension between bottom-up and top-down modelling approaches and lack of our understanding of the complex relationships between humans and nature can be addressed. The literature on disaster risk reduction (DRR) can provide inspiration and useful examples

for framing CCA analysis within a risk assessment framework in support of the identification of preferable adaptation measures and pathways.

We have identified a crucial role that could be played by ABM, because of their potential to deal with specific needs of CCA modelling, such as the simulation of emergent SES properties deriving from the combination of policy measures and adaptation actions autonomously implemented by individual agents or groups. ABM can be considered as bottom-up modules to be dynamically integrated with top-down CGE models, or they may even substitute the latter. However, this second option appears to be less realistic at the moment, while the first has the potential to exploit the extensive work carried out on CGE in climate studies over several decades.

This offers a baseline of orientation for fellow researchers from the fields outside of SES, but who are interested in better connecting their research gaps or methods with current CCA research. Examples of such fields are mathematics, insurance and actuarial research, fuelled by trends and developments such as Big Data, IoT, artificial intelligence as well as general digital developments and sector-specific developments, like new insurance products such as catastrophe bonds, and resilience- or risk-based financing.

Integrated modelling for CCA with the required capabilities for long-term multi-scale analysis under the effect of exogenous global change drivers is feasible, but then the models – and ABM in particular – should go through a rigorous verification and validation phase for the results to be useful for informing policymakers. Because of future uncertainties, we can only rely on retrospective validation of results, which is currently almost neglected in the literature.

We believe that many of the challenges concerning computational restrictions, knowledge sharing, data availability and integration can ultimately be overcome in the coming years. Earth observations and data-sharing initiatives have helped us to tune the integrated models. Advances in artificial intelligence and machine learning have helped us to become better at deriving insights from data and using them in modelling. Cloud computing has helped us with lifting heavy computations. However, we still face challenges to validating results and establishing ground truth.

Another main challenge is our knowledge limitations in modelling human behaviour, for which once more ABM offer potential solutions. But it requires substantial improvement in our capability to effectively acquire empirical information and use them to set the models for realistic simulations. A key modelling issue is the interaction of human/social and ecological systems within the SES. We are still facing uncertainties in how societies will make decisions concerning climate change. Recent events such as new diseases (i.e. Covid-19), have shown us that emerging risks can substantially change our knowledge of responses of societies and socio-economic dynamics. More research efforts are needed to fully comprehend the behaviour of societies and handle adaptation decisions under deep uncertainty.

Envisioning a way forward for enhanced integrated modelling of adaptation requires methodological developments focused in particular on the challenge emerging from two contrasting needs:

- a. the need to simulate the socio-ecosystem at a level of detail that allows to represent the interactions between ecological and anthropic elements without excessive averaging and aggregation effects; and
- b. the need to build a global picture of the integration between adaptation and mitigation strategies and actions implemented to support effective policies to combat climate change.

These two needs are in evident contrast in terms of spatial and temporal scales as discussed above. The current IM solutions are compromising these needs by either excessive aggregation and averaging, thus losing the possibility of analysing the dynamics and the emergence of the phenomena of interest (an example being current CGE models), or by proposing models posing insurmountable problems in data needs and validation at large or even global scales (e.g. current ABMs).

To overcome the current limitations of IM we propose here to invest in two research directions:

- i. To set aside the ambition to have an accurate full coverage (e.g., pixel by pixel) of global phenomena, opting instead for the development of a network of representative study areas where research efforts may converge and thus allow for the highest granularity and detail in functional representations of the phenomena required to develop further our understanding of SES complexity.
- ii. To invest in the development of shared virtual experiments in which researchers could converge to

conduct experiments aimed at exploring SES dynamics in typified synthetic worlds in which the uncertainty pervading SES analyses could be controlled, so that what is learnt there could be used to improve the capabilities to simulate and manage real-world systems.

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References

- Ackerman, F., De Canio, S.J., Howarth, R.B. Richard, & Sheeran, K. (2009). Limitations of integrated assessment models of climate change. *Climatic Change*, 95, 297–315. <https://doi.org/10.1007/s10584-009-9570-x>
- Adams, S. (2021) The pragmatic holism of social–ecological systems theory: Explaining adaptive capacity in a changing climate. *Progress in Human Geography*, 03091325211016072.
- Adger, W.N. (2000). Social and Ecological Resilience: Are They Related? *Progress in Human Geography*, 24 (3), 347–64. <https://doi.org/10.1191/030913200701540465>.
- An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*, 229, 25 – 36, <https://doi.org/10.1016/j.ecolmodel.2011.07.010>.
- An, L., Grimm, V., & Turner II, B.L. (2020). Editorial: Meeting Grand Challenges in Agent Based Models. *Journal of Artificial Societies and Social Simulation (JASSS)*, 23(1), 13. doi:10.18564/jasss.4012.
- Arigoni Ortiz, R. & Markandya, A. (2009). Literature Review of Integrated Impact Assessment Models of Climate Change with Emphasis on Damage Functions. BC3 Working Paper Series. 2009-06. <http://hdl.handle.net/10810/14255>
- Arneth, A., Brown, C. & Rounsevell, M. (2014). Global models of human decision-making for land-based mitigation and adaptation assessment. *Nature Climate Change*, 4, 550–557. <https://doi.org/10.1038/nclimate2250>
- Ausseil A.-G.E., Daigneault A., Frame B., & Teixeira E. (2019). Towards an integrated assessment of climate and socio-economic change impacts and implications in New Zealand. *Environmental Modelling and Software*, 119, 1-20.
- Babatunde, K.A., Begum, R.A., & Said, F.F. (2017). Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renewable and Sustainable Energy Reviews*, 78, 61-71.
- Baggio, R. (2008). Symptoms of complexity in a tourism system. *Tourism Analysis*, 13, 1–20.
- Balbi, S., & Giupponi, C. (2010). Agent-based modelling of socio-ecosystems: a methodology for the analysis of adaptation to climate change. *International Journal of Agent Technologies and Systems (IJATS)*, 2(4), 17-38.
- Bell, A.R., Robinson, D.T., Malik, A. & Dewal, S. (2015). Modular ABM Development for Improved Dissemination and Training. *Environmental Modelling and Software*, 73, 189–200. <https://doi.org/10.1016/j.envsoft.2015.07.016>.
- Bell, A.R., Ward, P.S., Killilea, M.E., & Tamal, M.E.H. (2016). Real-time social data collection in rural Bangladesh via a 'Microtasks for Micropayments' platform on Android smartphones. *PloS one*, 11(11), p.e0165924.
- Bell, A.R. (2017). Informing Decisions in Agent-Based Models: A Mobile Update. *Environmental Modelling and Software*, 93, 310–21. <https://doi.org/10.1016/j.envsoft.2017.03.028>.
- Ben-Haim, Y. (2006). Info-gap decision theory: decisions under severe uncertainty. 384 p. Academic Press. <https://doi.org/10.1016/B978-0-12-373552-2.X5000-0>.
- Berkes, F. & Folke, C. (2000). Linking Social and Ecological Systems: Management Practices and Social Mechanisms for Building Resilience. Cambridge U.P, Cambridge, UK, 476 p.
- Bernstein, P.M., Montgomery, W.D., & Rutherford, T.F. (1999). Global impacts of the Kyoto agreement: results from the MS-MRT model. *Resource and Energy Economics*, 21(3-4), 375-413. [https://doi.org/10.1016/S0928-7655\(99\)00009-3](https://doi.org/10.1016/S0928-7655(99)00009-3).
- Black, R., Arnell, N.W., Adger, W.N., Thomas, D., & Geddes, A. (2013). Migration, immobility and displacement outcomes following extreme events. *Environmental Science and Policy*, 27, S32-S43. <https://doi.org/10.1016/j.envsci.2012.09.001>.
- Blumenstock, J.G. Cadamuro, & On, R. (2015). Predicting Poverty and Wealth from Mobile Phone Metadata. *Science* 350

(6264), 1073–76. <https://doi.org/10.1126/science.aac4420>.

- Bosomworth, K., & Gaillard, E. (2019). Engaging with uncertainty and ambiguity through participatory ‘Adaptive Pathways’ approaches: Scoping the literature. *Environmental Research Letters*, 14(9), 093007.
- Bourne, A., Holness, S., Holden, P., Scorgie, S., Donatti, C.I., & Midgley, G. (2016) A Socio-Ecological Approach for Identifying and Contextualising Spatial Ecosystem-Based Adaptation Priorities at the Sub-National Level. *Plos One*, 11, e0155235.
- Bradhurst, R.A., Roche, S.E., East, I.J., Kwan, P., & Garner, M.G. (2016). Improving the computational efficiency of an agent-based spatiotemporal model of livestock disease spread and control. *Environmental Modelling and Software*, 77, 1–12. <https://doi.org/10.1016/j.envsoft.2015.11.015>
- Brown, C., & Rounsevell, M. (2021) How can social–ecological system models simulate the emergence of social–ecological crises? *People and Nature*, 3, 88–103.
- Calzadilla, A., Rehdanz, K., Roson, R., Sartori, M., & Tol, R.S.J. (2016). Review of CGE Models of Water Issues. In: Calzadilla, A., Rehdanz, K., Roson, R., Sartori, M., Tol, R.S.J. (Eds.), *The WSPC Reference on Natural Resources and Environmental Policy in the Era of Global Change*. World Scientific, pp. 101–123. https://doi.org/doi:10.1142/9789813208179_0004.
- Candia, J., González, Wang, P., Schoenharl, T., Madey, G., & Barabási, A.L. (2008). Uncovering Individual and Collective Human Dynamics from Mobile Phone Records. *Journal of Physics A: Mathematical and Theoretical*, 41, 224015. <https://doi.org/10.1088/1751-8113/41/22/224015>.
- Cess, R.D., Potter, G.L., Blanchet, J.P., Boer, G.J., Del Genio, A.D., Déqué, M., Dymnikov, V., Galin, V., Gates, W.L., Ghan, S.J., Kiehl, J.T., Lacis, A.A., Le Treut, H., Li, Z.-X., Liang, X.-Z., McAvaney, B. J., Meleshko, V.P., Mitchell, J.F.B., Morcrette, J.-J., Randall, D.A., Rikus, L., Roeckner, E., Royer, J.F., Schlese, U., Sheinin, D.A., Slingo, A., Sokolov, A.P., Taylor, K.E. Washington, W.M., Wetherald, R.T., Yagai, I., Zha, M.-H., (1990). Intercomparison and Interpretation of Climate Feedback Processes in 19 Atmospheric General Circulation Models. *Journal of Geophysical Research: Atmospheres*, 95 (D10), 16601–16615. <https://doi.org/10.1029/JD095iD10p16601>.
- Chen, X. and Nordhaus, W.D. (2011). Using luminosity data as a proxy for economic statistics, *Proceedings of the National Academy of Sciences* 108, 8589–8594. [10.1073/pnas.1017031108](https://doi.org/10.1073/pnas.1017031108).
- Choi, H., & Varian, H. (2012). Predicting the Present with Google Trends. *Economic Record*, 88 (SUPPL.1), 2–9. <https://doi.org/10.1111/j.1475-4932.2012.00809.x>.
- Claussen, M., Mysak, L., Weaver, A., Crucifix, M., Fichetef, T., Loutre, M.F., Weber, S., Alcamo, J., Alexeev, V., Berger, A., Calov, R., Ganopolski, A., Goosse, H., Lohmann, G., Lunkeit, F., Mokhov, I., Petoukhov, V., Stone, P. and Wang, Z., (2002). Earth System Models of Intermediate Complexity: Closing the Gap in the Spectrum of Climate System Models. *Climate Dynamics*, 18 (7), 579–586. <https://doi.org/10.1007/s00382-001-0200-1>.
- Cradock-Henry, N.A., Frame, B., Preston, B.L., Reisinger, A., & Rothman D.S. (2018). Dynamic adaptive pathways in downscaled climate change scenarios. *Climatic Change*, 150, 333–341. <https://doi.org/10.1007/s10584-018-2270-7>.
- Crutzen, P.J. (2002). Geology of Mankind. *Nature*, 415, 23. <https://doi.org/10.1038/415023a>.
- Daume, S., Albert, M. & von Gadow, K. (2014). Forest Monitoring and Social Media - Complementary Data Sources for Ecosystem Surveillance? *Forest Ecology and Management*, 316, 9–20. <https://doi.org/10.1016/j.foreco.2013.09.004>.
- Dearing, J.A., Acma, B., Bub, S., Chambers, F.M., Chen, X., Cooper, J., Crook, D., Dong, X.H., Dotterweich, M., Edwards, M.E., Foster, T.H., Gaillard, M.-J., Galop, D., Gell, P., Gil, A., Jeffers, E., Jones, R.T., Anupama, K., Langdon, P.G., Marchant, R., Mazier, F., McLean, C.E., Nunes, L.H., Sukumar, R., Suryaprakash, I., Umer, M., Yang, X.D., Wang, R., & Zhang, K. (2015). Social-Ecological Systems in the Anthropocene: The Need for Integrating Social and Biophysical Records at Regional Scales. *The Anthropocene Review* 2 (3), 220–246. <https://doi.org/10.1177/2053019615579128>.
- Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F.R., Gaughan, A.E., Blondel, V.D., & Tatem, A.J. (2014). Dynamic Population Mapping Using Mobile Phone Data. *Proceedings of the National Academy of Sciences*, 111 (45), 15888–15893. <https://doi.org/10.1073/pnas.1408439111>.
- de Jong, C.E., & Kok, K. (2021) Ambiguity in social ecological system understanding: Advancing modelling of stakeholder perceptions of climate change adaptation in Kenya. *Environmental Modelling and Software*, 141, 105054.
- Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Blöschl, G. (2013). Socio-hydrology: conceptualizing human-flood interactions. *Hydrology and Earth System Sciences*, 17, 3295–3303. <https://doi.org/10.5194/hess-17-3295-2013>
- Di Minin, E., Tenkanen, H. & Toivonen, T. (2015). Prospects and challenges for social media data in conservation science. *Frontiers in Environmental Science*, 3:63. <https://doi.org/10.3389/fenvs.2015.00063>.
- Dolan, R., Bullock, J.M., Jones, J.P.G., Athanasiadis, I.N., Martínez-López, J., & Willcock, S. (2021). The flows of nature to people, and of people to nature: Applying movement concepts to ecosystem services. *Land*, 10(6), 576. <https://doi.org/10.3390/land10060576>

- Dowlatabadi, H., (1995). Integrated assessment models of climate change: An incomplete overview. *Energy Policy*, 23(4-5), 289-296. [https://doi.org/10.1016/0301-4215\(95\)90155-Z](https://doi.org/10.1016/0301-4215(95)90155-Z)
- Duan, H., Zhang, G., Wang, S., & Fan, Y. (2019). Robust climate change research: a review on multi-model analysis. *Environmental Research Letters*, 14(3), 033001.
- de Vries, B.J.M. (2001). Perceptions and Risks in the Search for a Sustainable World: A Model-Based Approach. *International Journal of Sustainable Development*, 4 (4), 434–53. <https://doi.org/10.1504/IJSD.2001.001560>.
- de Vries, B.J.M. (2007). Scenarios: Guidance for an Uncertain and Complex World. In: Costanza, R., Graumlich, L.J., Steffen W. (eds.) *Sustainability or collapse?*, MIT Press, Cambridge, USA, , 378–398.
- Eagle, N., Macy, M., & Claxton, R. (2010). Network Diversity and Economic Development. *Science* 328:1029–31. <https://doi.org/10.1126/science.1186605>.
- Eakin, H., & Luers, A.L. (2006). Assessing the Vulnerability of Social-Environmental Systems. *Annual Review of Environment and Resources*, 31 (1),365–394. <https://doi.org/10.1146/annurev.energy.30.050504.144352>.
- Ellis, E.C. & Ramankutty, N. (2008). Putting people in the map: anthropogenic biomes of the world. *Frontiers in Ecology and the Environment*, 6(8), 439-447. <https://doi.org/10.1890/070062>
- Elsawah, S., Filatova, T., Jakeman, A.J., Kettner, A.J., Zellner, M.L., Athanasiadis, I.N., Hamilton, S.H., Axtell, R.L., Brown, D.G., Gilligan, J.M., Janssen, M.A., Robinson, D.T., Rozenberg, J., Ullah, I.I.T., & Lade, S.J. (2020) Eight grand challenges in socio-environmental systems modelling *Socio-Environmental Systems Modelling*, 2, 16226. doi:10.18174/sesmo.
- Essenfelder, A.H., & Giupponi, C. (2020). A coupled hydrologic-machine learning modelling framework to support hydrologic modelling in river basins under Interbasin Water Transfer regimes. *Environmental Modelling and Software*, 131, 104779. <https://doi.org/10.1016/j.envsoft.2020.104779>.
- Essenfelder, A.H., Pérez-Blanco, C.D., & Mayer, A.S. (2018). Rationalizing systems analysis for the evaluation of adaptation strategies in complex human-water systems. *Earth's Future*, 6, 1181– 1206. <https://doi.org/10.1029/2018EF000826>
- Ewert, F., Rotter, R.P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K.C., Olesen, J.E. Ewert, F., Rötter, R.P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K.C., Olesen, J.E., van Ittersum, M.K., Janssen, S., Rivington, M., Semenov, M.A., Wallach, D., Porter, J.R., Stewart, D., Verhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P.P., Bartošová, L., & Asseng, S. (2015). Crop Modelling for Integrated Assessment of Risk to Food Production from Climate Change. *Environmental Modelling and Software*, 72, 287-303. <https://doi.org/10.1016/j.envsoft.2014.12.003>.
- Fedele, G., Donatti, C.I., Harvey, C.A., Hannah, L., & Hole, D.G. (2019) Transformative adaptation to climate change for sustainable social-ecological systems. *Environmental Science and Policy*, 101, 116-125.
- Filatova, T., Verburg, P.H., Parker, D.C., & Stannard, C.A. (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental Modelling and Software*, 45, 1-7. doi: 10.1016/j.envsoft.2013.03.017
- Fisher, R.A., Koven, C.D., Anderegg, W.R.L., Christoffersen, B.O., Dietze, M.C., Farrior, C., Holm, J.A., Fisher, R.A., Koven, C.D., Anderegg, W.R. L., Christoffersen, B.O., Dietze, M. C., Farrior, C.E., Holm, J.A., Hurtt, G.C., Knox, R.G., Lawrence, P.J., Lichstein, J.W., Longo, M., Matheny, A.M., Medvigy, D., Muller-Landau, H.C., Powell, T.L., Serbin, S.P., Sato, H., Shuman, J.K., Smith, B., Trugman, A.T., Viskari, T., Verbeeck, H., Weng, E., Xu, C., Xu, X., Zhang, T., & Moorcroft, P.R., (2018). Vegetation Demographics in Earth System Models: A Review of Progress and Priorities. *Global Change Biology*. 24(1), 35-54. <https://doi.org/10.1111/gcb.13910>.
- Folke, C. (2006). Resilience: The Emergence of a Perspective for Social-Ecological Systems Analyses. *Global Environmental Change*, 16 (3), 253–267. <https://doi.org/10.1016/j.gloenvcha.2006.04.002>.
- Foure, J., Aguiar, A., Bibas, R., Chateau, J., Fujimori, S., Lefevre, J., Leimbach, M., Rey-Los-Santos, L., & Valin, H. (2020). Macroeconomic drivers of baseline scenarios in dynamic CGE models: review and guidelines proposal. *Journal of Global Economic Analysis*, 5 (1), 28-62. <https://doi.org/10.21642/JGEA.050102AF>.
- Frame, B., Lawrence, J., Ausseil, A.G., Reisinger, A., & Daigneault, A. (2018). Climate Risk Management Adapting Global Shared Socio-Economic Pathways for National and Local Scenarios. *Climate Risk Management*, 21, 39-51, 1–13. <https://doi.org/10.1016/j.crm.2018.05.001>.
- Gain, A.K., Giupponi, C., Renaud, F.G., & Vafeidis, A.T. (2020). Sustainability of complex social-ecological systems: methods, tools, and approaches. *Regional Environmental Change*, 20(3), 102. doi: 10.1007/s10113-020-01692-9
- Gain, A.K., Hossain, S., Benson, D., Di Baldassarre, G., Giupponi, C., & Huq, N. (2021) Social-ecological system approaches for water resources management. *International Journal of Sustainable Development and World Ecology*, 28, 109-124.
- Gawith, D., Hodge, I., Morgan, F., & Daigneault, A. (2020). Climate change costs more than we think because people adapt less than we assume, *Ecological Economics*, 173.
- Giupponi, C., & Biscaro, C. (2015). Vulnerabilities—bibliometric analysis and literature review of evolving concepts.

- Environmental Research Letters, 10(12), 123002.
- Giupponi, C., Borsuk, M.E., de Vries, B.J.M., & Hasselmann, K. (2013). Innovative Approaches to Integrated Global Change Modelling. *Environmental Modelling and Software*, 44, 1–9. <https://doi.org/10.1016/j.envsoft.2013.01.013>.
- Giupponi, C., & Mojtahed, V. (2018). Spatial and temporal dynamics of adaptation in agricultural socio-ecosystems: an agent based approach applied to three Mediterranean cases. Paper presented at the XXXIV Giornata dell'Ambiente - Accademia Nazionale dei Lincei - Strategie di adattamento al cambiamento climatico, Rome, Italy.
- González, M.C., & Hidalgo, C.A. (2008). Understanding Individual Human Mobility Patterns. *Nature*, 453, 1–12. <https://doi.org/10.1038/nature06958>.
- Grace, J., Anderson, T., Seabloom, E.W., Borer, E.T., Adler, P.B., Harpole, W.S., Hautier, Y., Hillebrand, H., Lind, E.M., Pärtel, M., Bakker, J.D., Buckley, Y.M., Crawley, M.J., Damschen, E.I., Davies, K.F., Fay, P. A., Firn, J., Gruner, D.S., Hector, A., Knops, J.M.H., MacDougall, A.S., Melbourne, B.A., Morgan, J.W., Orrock, J.L., Prober, S.M., & Smith, M.D. (2016). Integrative modelling reveals mechanisms linking productivity and plant species richness. *Nature*, 529, 390–393. <https://doi.org/10.1038/nature16524>.
- Grimm, V., Augustiak, J., Focks, A., Frank, B.M., Gabsi, F., Johnston, A.S.A., Liu, C., Martin, B.T., Meli, M., Radchuk, V., Thorbek, P. & Railsback, S.F. (2014). Towards better modelling and decision support: Documenting model development, testing, and analysis using TRACE. *Ecological Modelling*, 280, 129–139. <https://doi.org/10.1016/j.ecolmodel.2014.01.018>.
- Groce, J.E., Farrelly, M.A., Jorgensen, B.S., & Cook, C.N. (2018). Using Social-Network Research to Improve Outcomes in Natural Resource Management. *Conservation Biology*. 33, 53–65 <https://doi.org/10.1111/cobi.13127>.
- Groves, D.G. & Lempert, R.J. (2007). A new analytic method for finding policy-relevant scenarios. *Global Environmental Change*, 17(1), 73–85. <https://doi.org/10.1016/j.gloenvcha.2006.11.006>.
- Gupta, R., Sharma, L.K., 2019. The process-based forest growth model 3-PG for use in forest management: A review. *Ecological Modelling*, 397, 55–73. <https://doi.org/10.1016/j.ecolmodel.2019.01.007>.
- Hailegiorgis, A., Crooks, A. & Cioffi-Revilla, C. (2018). An agent-based model of rural households' adaptation to climate change, *Journal of Artificial Societies and Social Simulation* 21 (4) 4. <https://doi.org/10.18564/jasss.3812>.
- Hall, J.W., Lempert, R.J., Keller, K., Hackbarth, A., Mijere, C. & McInerney, D.J. (2012). Robust climate policies under uncertainty: A comparison of robust decision making and info-gap methods. *Risk Analysis: An International Journal*, 32(10), 1657–1672. <https://doi.org/10.1111/j.1539-6924.2012.01802.x>
- Harris, G. (2002). Integrated Assessment and Modelling: An Essential Way of Doing Science. *Environmental Modelling and Software*, 17, 201–207. [https://doi.org/10.1016/S1364-8152\(01\)00058-5](https://doi.org/10.1016/S1364-8152(01)00058-5).
- Harrison, P.A., Dunford, R.W., Holman, I.P., & Rounsevell, M.D. (2016). Climate change impact modelling needs to include cross-sectoral interactions. *Nature Climate Change*, 6(9), 885–890. <https://doi.org/10.1038/nclimate3039>
- Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V., & Di Minin, E. (2018). Social Media Data Can Be Used to Understand Tourists' Preferences for Nature-Based Experiences in Protected Areas. *Conservation Letters*. 11(1), 1–10 <https://doi.org/10.1111/conl.12343>.
- Higuchi, T., Yamaguchi, H. & Higashino, T. (2015). Mobile devices as an infrastructure: A survey of opportunistic sensing technology. *Journal of information processing*, 23(2), pp.94–104. <https://doi.org/10.2197/ipsjip.23.94>
- Hertel, T.W., Rose, S., & Tol, R.S. (2009). Land use in computable general equilibrium models: An Overview. In: *Economic Analysis of Land Use in Global Climate Change Policy*. Hertel, T. W., Rose, S., & Tol, R.S.J. (eds.), Routledge, London, 3–30, <https://doi.org/10.4324/9780203882962>.
- Holling, C.S., & L.H. Gunderson (2002). Resilience and adaptive cycles. In: Gunderson L.H., & Holling, C.S. (eds.) *Panarchy: understanding transformations in human and natural systems*. Island Press, Washington, D.C., USA. 25–62..
- Hollowed, A.B., Holsman, K.K., Haynie, A.C., Hermann, A.J., Punt, A.E., Aydin, K., Ianelli, J.N., Kasperski, S., Cheng, W., Faig, A., Kearney, K.A., Reum, J.C.P., Spencer, P., Spies, I., Stockhausen, W., Szuwalski, C.S., Whitehouse, G.A., & Wilderbuer, T.K. (2020) Integrated Modeling to Evaluate Climate Change Impacts on Coupled Social-Ecological Systems in Alaska. *Frontiers in Marine Science* 6, 775.
- Hsiang, S.M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151) 1–17. <https://doi.org/10.1126/science.1235367>
- Innocenti, E., Detotto, C., Idda, C., Parker, D.C., & Prunetti, D. (2020). An iterative process to construct an interdisciplinary ABM using MR POTATOHEAD: An application to Housing Market Models in touristic areas. *Ecological Complexity* 44, 100882. doi: 10.1016/j.ecocom.2020.100882.
- IPCC (2001a). *Climate Change 2001: Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Third*

- Assessment Report of the Intergovernmental Panel on Climate Change. Climate Change 2001: Impacts, Adaptation, and Vulnerability.
- IPCC (2001b). Climate Change 2001: Mitigation, Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Edited by B. Metz, O. Davidson, R. Swart, and J. Pan. Cambridge, United Kingdom and New York, NY, USA.: Cambridge University Press.
- IPCC (2013). What Is a GCM? IPCC Guidance on the Use of Data. 2013.
- Izquierdo, L.R., Gotts, N.M., & Polhill, J.G. (2003). FEARLUS-W: an agent-based model of river basin land use and water management. Framing Land Use Dynamics: integrating knowledge on spatial dynamics in socio-economic and environmental systems for spatial planning in western urbanized countries, University, The Netherlands.
- Jäger, J., Rounsevell, M.D.A., Omann, I., Harrison, P., Wesely, J., Pataki, G., Dunford, R., Kammerlander, M., & Pataki, G., (2015). Assessing policy robustness of climate change adaptation measures across sectors and scenarios, *Climatic Change*, 128, 395-407. 10.1007/s10584-014-1240-y.
- Kalaugher, E., Bornman, J.F., Clark, A., & Beukes, P. (2013). An integrated biophysical and socio-economic framework for analysis of climate change adaptation strategies: The case of a New Zealand dairy farming system. *Environmental Modelling and Software*, 39, 176-187.
- Kebede, A.S., Nicholls, R.J., Allan, A., Arto, I., Cazcarro, I., Fernandes, J.A., Hill, C.T., Hutton, C.W., Kay, S., Lázár, A.N., Macadam, I., Palmer, M., Suckall, N., Tompkins, E.L., Vincent, K., & Whitehead, P.W. (2018). Applying the Global RCP–SSP–SPA Scenario Framework at Sub-National Scale: A Multi-Scale and Participatory Scenario Approach. *Science of The Total Environment*, 635, 659–672. <https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.03.368>.
- Khan, N., Shahid, S., Ahmed, K., Ismail, T., Nawaz, N., & Son, M. (2018). Performance Assessment of General Circulation Model in Simulating Daily Precipitation and Temperature Using Multiple Gridded Datasets. *Water*, 10(12), 1793. <https://doi.org/10.3390/w10121793>.
- Kling, C.L., Arriitt, R.W., Calhoun, G., & Keiser, D.A. (2017). Integrated Assessment Models of the Food, Energy, and Water Nexus: A Review and an Outline of Research Needs. *Annual Review of Resource Economics*, 9, 143–163. <https://doi.org/10.1146/annurev-resource-100516-033533>.
- Kniveton, D.R., Smith, C.D., & Black, R. (2012). Emerging migration flows in a changing climate in dryland Africa, *Nature Climate Change*, 2, 444-447.
- Koenigstein, S., Ruth, M., & Gößling-Reisemann, S. (2016). Stakeholder-informed ecosystem modeling of ocean warming and acidification impacts in the barents sea region. *Frontiers in Marine Science* 3, 93, 13 p. doi: 10.3389/fmars.2016.00093
- Kompas, T., Pham, V.H., & Che, T.N. (2018). The effects of climate change on GDP by country and the global economic gains from complying with the Paris Climate Accord. *Earth's Future*, 6, 1153–1173. <https://doi.org/10.1029/2018EF000922>
- Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch, S., Prentice, I.C. (2005). A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system. *Global Biogeochemical Cycles* 19(1) 1-33. <https://doi.org/10.1029/2003GB002199>.
- Lempert, R.J. & Collins, M.T. (2007). Managing the risk of uncertain threshold responses: comparison of robust, optimum, and precautionary approaches. *Risk Analysis: An International Journal*, 27(4), 1009-1026. <https://doi.org/10.1111/j.1539-6924.2007.00940.x>
- Lenormand, M., Luque, S., Langemeyer, J., Tenerelli, P., Aalders, I., Chivulescu, S., Clemente, P., Dick, J., Dijk, J.V., van Eupen, M., Giuca, R.C., Kopperoinen, L., Lellei-Kovács, E., Leone, ;M., Lieskovský, J., Schirpke, U., Smith, A.C., Tappeiner, U., & Woods, E. (2018). Multiscale Socio-Ecological Networks in the Age of Information. *PLoS ONE* 13(11): e0206672., 1–16.
- Lansing, J.s., & Kremer, J.F., (1993). Emergent properties of Balinese Water Temple Networks: coadaptation on a rugged fitness landscape. *American Anthropologist* 95(1):97-114.
- Lippe, M., M. Bithell, N. Gotts, D. Natalini, P. Barbrook-Johnson, C. Giupponi, M. Hallier, G.J. Hofstede, C. Le Page, R.B. Matthews, M. Schlüter, P. Smith, A. Teglio, & Thellmann, K. (2019). Using agent-based modelling to simulate social-ecological systems across scales. *Geoinformatica*, 23(2), 269–298. <https://doi.org/10.1007/s10707-018-00337-8>.
- Liu, J., Mooney, H., Hull, V., Davis, S.J., Gaskell, J., Hertel, T., Lubchenco, J., Seto, K.C., Gleick, P., Kremen, C., & Li, S. (2015) Systems integration for global sustainability. *Science*, 347, 1258832.
- Liu, Y., Zhang, T., Geng, X., He, L., & Pang, Z. (2013). Herdsmen's adaptation to climate changes and subsequent impacts in the ecologically fragile zone, China, *Advances in Meteorology* 748715, 8. <http://dx.doi.org/10.1155/2013/748715..>
- Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social Media Fingerprints of Unemployment. *PLoS ONE*, 10 (5), 1–13. <https://doi.org/10.1371/journal.pone.0128692>.

- Lu, X., Wrathall, D.J., Sundsøy, P.R., Nadiruzzaman, M., Wetter, E., Iqbal, A., Qureshi, T., Tatem, A., Canright, G., Engø-Monsen, K., & Bengtsson, L. (2016). Unveiling hidden migration and mobility patterns in climate stressed regions: A longitudinal study of six million anonymous mobile phone users in Bangladesh. *Global Environmental Change*, 38, 1-7.
- Lynam, T., Mathevet, R., Etienne, M., Stone-Jovicich, S., Leitch, A., Jones, N., Ross, H., Du Toit, D., Pollard, S., Biggs, H., & Perez, P. (2012). Waypoints on a journey of discovery: mental models in human-environment interactions. *Ecology and Society*, 17 (3), 23.
- Martin, G., Martin-Clouaire, R. and Duru, M. (2013). Farming system design to feed the changing world. A review, *Agronomy for Sustainable Development* 33, pp 131-149. 10.1007/s13593-011-0075-4.
- Martínez-López, J., Bergillos, R.J., Bonet, F.J. & de Vente, J. (2019). Connecting research infrastructures, scientific and sectorial networks to support integrated management of Mediterranean coastal and rural areas. *Environmental Research Letters*, 14(11), 115001. <https://doi.org/10.1088/1748-9326/ab4b22>.
- Matsumoto, K.I. & Masui, T. (2011). Analyzing long-term impacts of carbon tax based on the imputed price, applying the AIM/CGE model. *Management of Environmental Quality: An International Journal*, 22(1), 33-47. <https://doi.org/10.1108/14777831111098462>
- McDermid, S.S., Mearns, L.O. & Ruane, A.C. (2017). Representing Agriculture in Earth System Models: Approaches and Priorities for Development. *Journal of Advances in Modeling Earth Systems*, 9, 2230–2265.. <https://doi.org/10.1002/2016MS000749>.
- Metcalfe, G.E., & Stock, J.H. (2017). Integrated Assessment Models and the Social Cost of Carbon: A Review and Assessment of U.S. Experience. *Review of Environmental Economics and Policy* 11 (1), 80–99. <https://doi.org/10.1093/reep/rew014>.
- Metcalfe, G., & Stock, J. (2015). The Role of Integrated Assessment Models in Climate Policy: A User's Guide and Assessment, Discussion Paper 15-68, 29 pp. https://www.belfercenter.org/sites/default/files/legacy/files/dp68_metcalfe-stock.pdf
- Miralles-Wilhelm, F. (2016). Development and application of integrative modeling tools in support of food-energy-water nexus planning—a research agenda. *Journal of Environmental Studies and Sciences*, 6, 3–10. <https://doi.org/10.1007/s13412-016-0361-1>
- Mitter, H., Techen, A.-K., Sinabell, F., Helming, K., Schmid, E., Bodirsky, B.L., Holman, I., Kok, K., Lehtonen, H., Leip, A., Le Mouél, C., Mathijs, E., Mehdi, B., Mittenzwei, K., Mora, O., Øistad, K., Øygarden, L., Priess, J.A., Reidsma, P., Schaldach, R., & Schönhart, M. (2020). Shared Socio-economic Pathways for European agriculture and food systems: The Eur-Agri-SSPs. *Global Environmental Change*, 65, 102159 <https://doi.org/10.1016/j.gloenvcha.2020.102159>.
- Moore, R.V., & Tindall, C.I. (2005). An overview of the open modelling interface and environment (the OpenMI). *Environmental Science & Policy*, 8(3), 279-286. <https://doi.org/10.1016/j.envsci.2005.03.009>.
- Müller, B., Balbi, S., Buchmann, C. M., De Sousa, L., Dressler, G., Groeneveld, J, Klassert, C.J., Le, Q.B., Millington, J.D.A., Nolzen, H., Parker, DC., Polhill J.G., Schlüter, M., Schulze, J., Schwarz, N., Sun, Z., Taillandier, P., & Weise, H. (2014). Standardised and transparent model descriptions for agent-based models: Current status and prospects. *Environmental Modelling and Software*, 55, 156-163
- Naivinit, W., C. Le Page, G. Trébuil, & Gajaseni, N. (2010). Participatory agent-based modeling and simulation of rice production and labor migrations in Northeast Thailand. *Environmental Modelling and Software*, 25(11), 1345-1358. <https://doi.org/10.1016/j.envsoft.2010.01.012>.
- Neumann, K., & Hilderink, H. (2015). Opportunities and challenges for investigating the environment-migration nexus. *Human Ecology*, 43(2), 309-322.
- Nikas A., Doukas H., Papandreou A. (2019) A Detailed Overview and Consistent Classification of Climate-Economy Models. In: Doukas H., Flamos A., Lieu J. (eds) *Understanding Risks and Uncertainties in Energy and Climate Policy*. Springer, Cham.1-54. https://doi.org/10.1007/978-3-030-03152-7_1.
- Noble, I.R., Huq, S., Anokhin, Y.A., Carmin, J., Goudou, D., Lansigan, F.P., Osman-Elasha, B. & Villamizar, A. (2014). Adaptation needs and options. In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 833-868.
- O’Gorman, P.A. & Dwyer, J.G. (2018). Using machine learning to parameterize moist convection: Potential for modeling of climate, climate change, and extreme events. *Journal of Advances in Modeling Earth Systems*, 10(10), 2548-2563.

- Onnela, J.P., Saramäki, J., Hyvönen, J., Szabó, G., Lazer, D., Kaski, K., Kertész, J., & Barabási, A.L. (2007). Structure and Tie Strengths in Mobile Communication Networks. *Proceedings of the National Academy of Sciences of the United States of America*, 104 (18), 7332–7336. <https://doi.org/10.1073/pnas.0610245104>.
- O’Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., & van Vuuren, D.P. (2014). A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic change*, 122(3), 387-400. <https://doi.org/10.1007/s10584-013-0905-2>
- O’Sullivan, D. (2008). Geographical information science: agent-based models. *Progress in Human Geography* 32(4), 541-550.
- Palla, G., Barabási, A.L. & Vicsek, T. (2007). Quantifying Social Group Evolution. *Nature*, 446 (7136), 664–67. <https://doi.org/10.1038/nature05670>.
- Palmer, P., Smith, M. (2014). Earth systems: Model human adaptation to climate change. *Nature* 512, 365–366. <https://doi.org/10.1038/512365a>
- Pande, S., & Sivapalan, M. (2017). Progress in socio-hydrology: A meta-analysis of challenges and opportunities. *WIREs Water*, 4, 1–18. <https://doi.org/10.1002/wat2.1193>.
- Patt, A.G., van Vuuren, D.P., Berkhout, F., Aaheim, A., Hof, A.F., Isaac, M., & Mechler, R. (2010). Adaptation in integrated assessment modeling: where do we stand? *Climatic Change*, 99(3-4), 383-402. <https://doi.org/10.1007/s10584-009-9687-y>
- Pearson, S.D. (2020) Encryption Methods in Protecting Cloud Data when Adopting Cloud Solutions: A Delphi Study. PhD Thesis, Capella University, MN., USA.
- Pérez-Blanco, C.D., Essenfelder, A.H., & Gutiérrez-Martín, C. (2020). A tale of two rivers: Integrated hydro-economic modeling for the evaluation of trading opportunities and return flow externalities in inter-basin agricultural water markets. *Journal of Hydrology*, 584, 124676. <https://doi.org/10.1016/j.jhydrol.2020.124676>.
- Pérez-Blanco, C.D., H. González-López, & Hrast-Essenfelder, A. (2021). Beyond piecewise methods: Modular integrated hydroeconomic modeling to assess the impacts of adaptation policies in irrigated agriculture. *Environmental Modelling and Software*, 136, 104943. <https://doi.org/10.1016/j.envsoft.2020.104943>
- Phillips, N.A. (1956). The General Circulation of the Atmosphere: A Numerical Experiment. *Quarterly Journal of the Royal Meteorological Society*, 82 (352), 123–164. <https://doi.org/10.1002/qj.49708235202>.
- Rashidi, T.H., Abbasi, A., Maghrebi, M., Hasan, S., & Waller, T.S. (2017). Exploring the Capacity of Social Media Data for Modelling Travel Behaviour: Opportunities and Challenges. *Transportation Research Part C: Emerging Technologies*, 75, 197–211. <https://doi.org/10.1016/j.trc.2016.12.008>.
- Ratter, B.M.W. (2012). Complexity and Emergence Key Concepts in Non-Linear Dynamic Systems. In: *Human-Nature Interactions in the Anthropocene: Potentials of Social-Ecological Systems Analysis*, Glaser, M., Krause, G., Ratter, B.M.W., Welp, M. (eds.) pp. 90–104. <https://doi.org/10.4324/9780203123195>.
- Reichler, T., & Kim, J., (2008). How Well Do Coupled Models Simulate Today’s Climate? *Bulletin of the American Meteorological Society*, 89 (3), 303–311. <https://doi.org/10.1175/BAMS-89-3-303>.
- Roberts, H., Sadler, J., & Chapman, L. (2017). Using Twitter to Investigate Seasonal Variation in Physical Activity in Urban Green Space. *Geo: Geography and Environment*, 4 (2). e00041. <https://doi.org/10.1002/geo2.41>.
- Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A. and Luccioni, A. (2019). Tackling climate change with machine learning. *arXiv preprint arXiv:1906.05433*.
- Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C. Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., & Jones, J.W. (2014). Assessing Agricultural Risks of Climate Change in the 21st Century in a Global Gridded Crop Model Intercomparison. *Proceedings of the National Academy of Sciences of the United States of America*, 111 (9), 3268–3273. <https://doi.org/10.1073/pnas.1222463110>.
- Ruiz-Euler, A., Privitera, F., Giuffrida, D., Lake, B., & Zara, I. (2020). Mobility Patterns and Income Distribution in Times of Crisis: US Urban Centers During the COVID-19 Pandemic. Available at SSRN 3572324. <https://dx.doi.org/10.2139/ssrn.3572324>
- Rutherford, T.F. (1999). Applied general equilibrium modeling with MPSGE as a GAMS subsystem: An overview of the modeling framework and syntax. *Computational Economics*, 14(1-2), 1-46. <https://doi.org/10.1023/A:1008655831209>
- Sansilvestri, R., Cuccarollo, M., Frascaria-Lacoste, N., Benito-Garzon, M., & Fernandez-Manjarrés, J. (2020) Evaluating climate change adaptation pathways through capital assessment: five case studies of forest social-ecological systems in

- France. *Sustainability Science*, 15, 539-553.
- Satterthwaite, D. (2009). The implications of population growth and urbanization for climate change. *Environment and Urbanization*, 21(2), 545-567. <https://doi.org/10.1177/0956247809344361>
- Scheiter, S., Langan, L., & Higgins, S.T. (2013). Next-Generation Dynamic Global Vegetation Models: Learning from Community Ecology. *The New Phytologist*, 198 (3), 957–969. <https://doi.org/10.1111/nph.12210>.
- Shiraki, H., & Sugiyama, M. (2020). Back to the basic: toward improvement of technoeconomic representation in integrated assessment models. *Climatic Change*, 162, 13–24. <https://doi.org/10.1007/s10584-020-02731-4>.
- Schlüter, M., Hinkel, J., Bots, P.W.G., & Arlinghaus, R. (2014). Application of the SES Framework for Model-Based Analysis of the Dynamics of Social-Ecological Systems. *Ecology and Society*, 19 (1) 36. <https://doi.org/10.5751/ES-05782-190136>.
- Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M.A., McAllister, R.R., Müller, B., Orach, K., Schwarz, N., & Wijermans, N. (2017). A framework for mapping and comparing behavioral theories in models of social-ecological systems. *Ecological Economics*, 131, 21–35.
- Schulze, J., Müller, B., Groeneveld, J., & Grimm, V. (2017). Agent-based modelling of social-ecological systems: achievements, challenges, and a way forward. *Journal of Artificial Societies and Social Simulation*, 20 (2), art. 8. <https://doi.org/10.18564/jasss.3423>.
- Simon, H.A. (1978). Rationality as process and as product of thought. *The American Economic Review*, 68(2), 1–16.
- Steffen, W., Broadgate, W., Deutsch, L., Gaffney, O., & Ludwig, C. (2015). The trajectory of the Anthropocene: The Great Acceleration. *The Anthropocene Review*, 2(1), 81-98. doi:10.1177/2053019614564785
- Steffen, W., Grinevald, J., Crutzen, P., & McNeill, J. (2011). The Anthropocene: Conceptual and Historical Perspectives. *Philosophical Transactions of the Royal Society. Series A, Mathematical, Physical, and Engineering Sciences*, 369 (1938), 842–867. <https://doi.org/10.1098/rsta.2010.0327>.
- Steger, C., S. Hirsch, C. Cosgrove, S. Inman, E. Nost, X. Shinbrot, J.P.R. Thorn, D.G. Brown, A. Grêt-Regamey, B. Müller, R.S. Reid, C. Tucker, B. Weibel, & Klein, J.A. (2021). Linking model design and application for transdisciplinary approaches in social-ecological systems. *Global Environmental Change*, 66, 102201.
- Stehfest, E., van Vuuren, D., Kram, T., & Bouwman, L. (2014). *Integrated Assessment of Global Environmental Change with IMAGE 3.0: Model Description and Policy Applications*. PBL Netherlands Environmental Assessment Agency, The Hague, NL, 366 p.
- Stocker, T.F., Dahe, Q., Plattner, G.J., Alexander, L.V., Allen, S.K., Bindoff, N.L., Bréon, F.M., Church, J.A., Cubasch, U., Emori, S., Forster, P., Friedlingstein, P., Gillett, N., Gregory, J.M., Hartmann, D.L., Jansen, E., Kirtman, B., Knutti, R., Krishna Kumar, K., Lemke, P., Marotzke, J., Masson-Delmotte, V., Meehl, G.A., Mokhov, I.I., Piao, S., Ramaswamy, V., Randall, D., Rhein, M., Rojas, M., Sabine, C., Shindell, D., Talley, L.D., Vaughan, D.G., & Xie, S.-P. (2013). Technical Summary. In *Climate Change 2013: The Physical Science Basis*. In Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Bex, V., Xia, Y., & Midgley, P.M. (eds) *Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA.: Cambridge University Press.
- Topping, C.J., Høye, T.T., & Olesen, C.R. (2010). Opening the black box—Development, testing and documentation of a mechanistically rich agent-based model. *Ecological Modelling*, 221(2), 245-255. <https://doi.org/10.1016/j.ecolmodel.2009.09.014>.
- Turner, K.G., Anderson, S., Gonzales-Chang, M., Costanza, R., Courville, S., Dalgaard, T., Dominati, E., Kubiszewski, I., Ogilvy, S., Porfirio, L., Ratna, N. Sandhu, H., Sutton, P.C., Svenning, J.-C., Turner, G.M., Varennes, Y.-D., Voinov, A., Wratten, S. (2016). A Review of Methods, Data, and Models to Assess Changes in the Value of Ecosystem Services from Land Degradation and Restoration. *Ecological Modelling* 319, 190–207. <https://doi.org/10.1016/j.ecolmodel.2015.07.017>.
- UNEP (2019) *Frontiers 2018/19 Emerging Issues of Environmental Concern*. United Nations Environment Programme, Nairobi. ISBN: 9789280737370 <https://www.unep.org/resources/frontiers-201819-emerging-issues-environmental-concern>.
- Valbuena, D., Verburg, P.H., & Bregt, A.K. (2008). A method to define a typology for agent-based analysis in regional land-use research, *Agriculture, Ecosystems & Environment* 128, 27-36. <https://doi.org/10.1016/j.agee.2008.04.015>.
- Van Asselt, M.B. and Rotmans, J. (2002). Uncertainty in integrated assessment modelling. *Climatic change*, 54(1-2), 75-105. <https://doi.org/10.1023/A:1015783803445>.
- van der Hoog, S. (2017). Deep learning in (and of) agent-based models: A prospectus. arXiv preprint arXiv:1706.06302.
- van Oijen, M., Bellocchi, G., Höglind, M. (2018). Effects of Climate Change on Grassland Biodiversity and Productivity: The Need for a Diversity of Models. *Agronomy*, 8(2), 14.

- van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011. The representative concentration pathways: an overview. *Climatic Change* 109(1) 6-31. <https://doi.org/10.1007/s10584-011-0148-z>.
- Verburg, P.H., Dearing, J.A., Dyke, J.G., Leeuw, S.V.D., Seitzinger, S., Steffen, W., & Syvitski, J. (2016) Methods and approaches to modelling the Anthropocene. *Global Environmental Change*, 39, 328-340. <https://doi.org/10.1016/j.gloenvcha.2015.08.007>.
- Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S.S. (2002). Modeling the spatial dynamics of regional land use: the CLUE-S model. *Environmental Management*, 30(3), 391-405. <https://doi.org/10.1007/s00267-002-2630-x>.
- Voinov, A., & Shugart, H. H. (2013). 'Integronsters', integral and integrated modeling. *Environmental Modelling & Software*, 39, 149-158. <https://doi.org/10.1016/j.envsoft.2012.05.014>.
- Wabnitz, C.C.C., Cisneros-Montemayor, A.M., Hanich, Q., & Ota, Y. (2018). Ecotourism, climate change and reef fish consumption in Palau: Benefits, trade-offs and adaptation strategies, *Marine Policy*, 88, 323-332. <https://doi.org/10.1016/j.marpol.2017.07.022>.
- Walker, B., Carpenter, S.R., Anderies, J., Abel, N., Cumming, G., Janssen, M., Lebel, L., Norberg, J., Peterson, G.D., & Pritchard, R. (2002). Resilience Management in Social-Ecological Systems: A Working Hypothesis for a Participatory Approach. *Conservation Ecology*, 6 (1), 14.
- Walker, B., Gunderson, L., Kinzig, A., Folke, C., Carpenter, S., & Schultz, L. (2006). A Handful of Heuristics and Some Propositions for Understanding Resilience in Social-Ecological Systems. *Ecology and Society*, 11, 1, Art.13. <https://doi.org/10.5751/ES-01530-110113>.
- Wang, J., Brown, D.G., Riolo, R.L., Page, S.E., & Agrawal, A. (2013). Exploratory analyses of local institutions for climate change adaptation in the Mongolian grasslands: An agent-based modeling approach. *Global Environmental Change*, 23, 1266-1276.
- Wang, W., Rothschild, D., Goel, S., & Gelman, A. (2014). Forecasting Elections with Non-Representative Polls. *International Journal of Forecasting*, 31 (3), 980–991. <https://doi.org/10.1016/j.ijforecast.2014.06.001>.
- Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., & Schewe, J. (2014). The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP): Project Framework. *Proceedings of the National Academy of Sciences*, 111 (9), 3228–3232. <https://doi.org/10.1073/pnas.1312330110>.
- Weigel, K., Bock, L., Gier, B.K., Lauer, A., Righi, M., Schlund, M., Adeniyi, K., Andela, B., Arnone, E., Berg, P., Caron, L.-P., Cionni, I., Corti, S., Drost, N., Hunter, A., Lledó, L., Mohr, C.W., Paçal, A., Pérez-Zanón, N., Predoi, V., Sandstad, M., Sillmann, J., Sterl, A., Vegas-Regidor, J., von Hardenberg, J., & Eyring, V. (2021) Earth System Model Evaluation Tool (ESMValTool) v2.0 – diagnostics for extreme events, regional and impact evaluation, and analysis of Earth system models in CMIP. *Geoscientific Model Development*, 14, 3159–3184. <https://doi.org/10.5194/gmd-14-3159-2021>.
- Zhang, L., Ghader, S., Pack, M.L., Xiong, C., Darzi, A., Yang, M., Sun, Q., Kabiri, A., & Hu, S. (2020). An interactive COVID-19 mobility impact and social distancing analysis platform. *medRxiv*. <https://doi.org/10.1101/2020.04.29.20085472>.
- Zhou, Y., Smith, S.J., Zhao, K., Imhoff, M., Thomson, A., Bond-Lamberty, B., Asrar, G.R., Zhang, X., He, C., & Elvidge, C.D. (2015). A global map of urban extent from nightlights. *Environmental Research Letters*, 10(5), 054011. <https://doi.org/10.1088/1748-9326/10/5/054011>.