



How can social–ecological system models simulate the emergence of social–ecological crises?

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Abstract

1. The idea that human impacts on natural systems might trigger large-scale, social–ecological ‘crises’ or ‘breakdowns’ is attracting increasing scientific, societal and political attention, but the risks of such crises remain hard to assess or ameliorate.
2. Social–ecological systems have complex dynamics, with bifurcations, nonlinearities and tipping points all emerging from the interaction of multiple human and natural processes. Computational modelling is a key tool in understanding these processes and their effects on system resilience. However, models that operate over large geographical extents often rely on assumptions such as economic equilibrium and optimisation in social–economic systems, and mean-field or trend-based behaviour in ecological systems, which limit the simulation of crisis dynamics.
3. Alternative forms of modelling focus on simulating local-scale processes that underpin the dynamics of social–ecological systems. Recent improvements in data resources and computational tools mean that such modelling is now technically feasible across large geographical extents.
4. We consider the contributions that the different types of model can make to simulating social–ecological crises. While no models are able to predict exact outcomes in complex social–ecological systems, we suggest that one new approach with substantial promise is hybrid modelling that uses existing model architectures to isolate and understand key processes, revealing risks and associated uncertainties of crises emerging. We outline convergent and efficient functional descriptions of social and ecological systems that can be used to develop such models, data resources that can support them, and possible ‘high-level’ processes that they can represent.

KEYWORDS

agent-based modelling, functional roles, high-level process, human–environment interactions, hybrid modelling, process-based, socio-ecological

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1 | INTRODUCTION

While global attention has been focused on the COVID-19 pandemic, rapid climatic change and biodiversity loss threaten further ‘crises’ or ‘breakdowns’ in which social–ecological dynamics undermine established human and natural systems (IPBES, 2019; Masson-Delmotte et al., 2018). Such events are increasingly referenced in scientific and popular media, and actions to reduce their likelihood are the subject of intense debate (Hagedorn et al., 2019). Computational models provide valuable information to these debates because they can synthesise, quantify and extrapolate from large bodies of evidence, making them core elements of science–policy interface programmes such as those of the IPCC and IPBES (Nicholson et al., 2019; Rogelj et al., 2018). Models that deal with the social–ecological interactions that can cause or potentially avert crises are especially pertinent, but most have been developed to reproduce relatively stable historical dynamics (Filatova et al., 2016; Ripple et al., 2020).

In principle, models can fulfil a wide range of roles, from developing and testing theory to analysing data and exploring system dynamics including breakdown or, conversely, recovery (Epstein, 2008). What they cannot do, in the context of complex social–ecological systems, is predict when, where and how specific future events will occur (Brown et al., 2016; de Matos Fernandes & Keijzer, 2020). This limit is significant, and essential to recognise, but within it exist a range of useful contributions that models can make. In this article, we consider whether and how models can be used to fulfil more of their realisable potential for simulating social–ecological crises or breakdowns as tools for informing societal and political responses. In doing so, we use the terms *crisis* and *breakdown* to refer to broad types of event in which social–ecological dynamics have a destructive effect on (some of) the social or ecological properties of the system in question (see Box 1).

There are three main reasons to take stock of social–ecological modelling at this point in time. First, there is an ongoing increase in attention given to potential (and current) crises such as the ‘climate crisis’ (United Nations, 2019), ‘biodiversity crisis’ (Driscoll et al., 2018) and more specific ‘crises’ relating, for instance, to the management of water resources for ecological and societal sustainability (Srinivasan et al., 2012) or the decline of pollinating insects (Levy, 2011). There is also an increasing use of computational models to identify ways to avoid such crises (Rogelj et al., 2018). Second, despite this attention and modelling, efforts to prevent expected crises in climatic and ecological systems have been largely unsuccessful, with progress towards major international agreements such as the Paris climate targets and Sustainable Development Goals being inadequate at best (Brown, Alexander, et al., 2019; Xu et al., 2020). Third, there has been a proliferation in the number, scope and type of available modelling tools and supporting data, suggesting that necessary new approaches may now be feasible. It is this third reason that we focus on here.

In the remainder of this article, we briefly outline aspects of current social–ecological systems modelling that make the simulation of crisis dynamics particularly challenging. We then go on to consider

BOX 1 Terminology

Social–ecological systems modelling involves concepts and terms from different scientific fields, applied to problems that are widely discussed across society as a whole. Terminology is often unclear as a result, with many overlapping terms being defined differently by different groups (Colding & Barthel, 2019; Filatova et al., 2016; Herrero-Jáuregui et al., 2018). We do not attempt to select or develop definitions here, but provide this brief glossary to explain our own use of terms.

We use ‘**social–ecological**’ to refer to interacting social and ecological processes or systems, where those interactions determine outcomes to a substantial extent. We use ‘social–ecological’ rather than ‘socio–ecological’ to formally give equal weight to both sides (Colding & Barthel, 2019).

We use **crisis** and **breakdown** as two words commonly used in popular discourse to refer to climatic, environmental and associated societal problems at large scales, with breakdown relating specifically to altered dynamics in the system in question. We also use related (but not synonymous) terms that are more widespread in the scientific literature (e.g. ‘tipping points’, ‘thresholds’ and ‘regime shifts’; see e.g. Filatova et al., 2016), but as occurrences from which crises or breakdowns can emerge, or which can occur in their absence (see e.g. Figure 1). We also note that both ‘crisis’ and ‘breakdown’ imply a value judgement, and that many relevant changes in social–ecological systems can have both positive and negative impacts, depending on perspective. While our usage of the terms reflects their broad and subjective meanings, it is also consistent with more formal (if disputed) definitions such as that of Craig (2017), in which crisis is the state in which societies’ ecological ‘conditions of possibility’ are no longer secure. The term ‘collapse’, as used and reviewed by Cumming and Peterson (2017), is largely equivalent, and literature that uses converse concepts such as ‘resilience’ is also highly relevant (associated terminology is outlined by Egli et al., 2019).

the nature of required improvements, before suggesting promising new approaches, resources and precedents. We finally identify potential contributions that new models can make and some main constraints that they will face.

1.1 | ‘Crisis-blind’ modelling

Social–ecological systems models have developed rapidly in number and scope, covering more and larger systems in increasing detail (Hamilton et al., 2015; Harrison et al., 2016). While they have numerous valid uses (including the simulation of social–ecological

'recovery'), their development to date does not necessarily make them suitable for simulating social–ecological breakdown, especially where those breakdowns are large-scale in nature. In fact, many of the models that operate over the large geographical extents relevant for climatic, environmental or other social–ecological crises contain basic assumptions that preclude breakdowns from emerging.

In ecology, models dealing with species, community or ecosystem dynamics across large geographical extents have often been correlational, statistical or pattern based. For instance, the great majority of studies of species extinction risks rely on Species Distribution Models (Urban, 2015, 2019). The correlations that underpin these models are usually robust in observed conditions, but will not necessarily hold as those conditions change in the future. Indeed, rapid and substantial changes in climate and human activity are likely to fundamentally alter the basic processes behind those correlations, and are already affecting most core ecological processes in terrestrial and marine systems (Scheffers et al., 2016).

The correlational approach also makes it difficult to account for links to social system dynamics. Studies that seek to identify impacts of human land use on ecological communities (including around half of meta-analyses) do so using simple metrics such as total species richness and abundance that carry little information about ecosystem composition, function or stability (Blüthgen et al., 2016; Hekkala & Roberge, 2018). In omitting many of the characteristics that actually determine ecological responses (positive and negative) to land-use change, these studies can provide little guidance about potential future changes (Urban, 2019), and established models can become unreliable as a result (e.g. Williams et al., 2015).

Similarly, most models of large-scale human systems (e.g. economic or land-use systems) have adopted simplifying assumptions that allow general trends to be extrapolated into the future without accounting for underlying processes. Land-use models covering large areas tend to rely on assumptions that land management is optimised to meet demand for food or economic returns, and not the result of the social, cultural and behavioural processes that shape land managers' decisions (Huber et al., 2018; Rosa et al., 2014; Stehfest et al., 2019). Land uses such as forestry, which do not contribute to food production, are often left as 'residual' land covers on areas not assigned to agriculture (Brown et al., 2017; Rosa et al., 2014). As with ecology, the relevance of these equilibrium-based approaches to novel and variable future conditions is doubtful, and makes the simulation of crises particularly challenging.

Another consequence of such approaches is a disconnect between models and the stakeholders who use them. Stakeholders can find it hard to relate to models' primarily biophysical parameters, correlational structures and abstract output indicators, instead preferring models that represent recognisable processes and decision-relevant outcomes (e.g. Borsuk et al., 2001; Hunka et al., 2013; Jönsson et al., 2015; Scown et al., 2019). Quite apart from the basic need to improve model accuracy, this preference justifies improved representation of breakdown dynamics as a topic of great current interest to stakeholders and society at large (Holtz et al., 2015; Millington & Wainwright, 2017).

1.2 | New challenges: Seeing the wood for the trees

Closing the blind spots identified above is a major challenge for social–ecological modelling. It requires the development of models that can simulate the emergence of unprecedented dynamics and impacts, including the feedbacks, regime shifts and thresholds involved in pushing system behaviour away from that observed in the past (Filatova et al., 2016; Synes et al., 2019; Wisz et al., 2013). Inevitably, this forces modellers to grapple with highly complex relationships.

For example, the ongoing loss of tropical forests—a frequent subject of modelling studies—involves numerous social and ecological processes. Approximately 50% of tropical forests have already been partially or completely cleared (Asner et al., 2009; FAO, 2016) and the remainder fragmented into more than 130 million patches (Taubert et al., 2018). Forty percent of the world's population currently lives in the tropics (FAO, 2016; Harding et al., 2014), and land-use change is expected to have greater effects there than in any other biome this century (Sala, 2000). Deforestation is increasingly driven by international markets, trade flows and corporations (Austin et al., 2017; Newbold, 2019), the pressures of which interact with a range of local factors such as land tenure, social capital, value systems and institutional capacities (Feurer et al., 2019; Nepstad et al., 2014). Pervasive human disturbances such as selective logging, hunting and burning have dramatic impacts on the dynamics even of apparently pristine forest areas (Asner et al., 2009), but indigenous peoples practising sustainable forms of forest management currently protect more tropical forest than do designated protected areas (Schwartzman et al., 2000). Both positive and negative effects may be self-reinforcing, with negative impacts of forest clearance on local climate (e.g. rainfall and temperature) being particularly likely to undermine ecosystem dynamics and agricultural production (Lovejoy & Nobre, 2018; Oliveira et al., 2013). Interactions can therefore ripple out through space and time, producing successive waves of fragmentation, degradation and ultimate deforestation that may soon exceed a critical threshold beyond which runaway collapses in stocks of carbon and biodiversity occur as ecosystem functions break down (Laurance et al., 2011; Taubert et al., 2018).

The complexity of such systems represents a real problem for models intended to generate meaningful outcomes without themselves being excessively complex. Potential solutions might exist among the diversity of models used to simulate social–ecological dynamics across small geographical extents, but these models are usually impossible to apply over large extents because their data or resource requirements become impracticable (Elsawah et al., 2020). Where upscaling is possible, difficult choices must be made about which simplifications are achievable without undermining model utility or the coherence of the overall system representation. These choices are complicated by recent evidence, of the kind outlined above, that even very small-scale processes can have system-level impacts under some circumstances. Without novel ways

of handling complexity at large scales, any insight gained through social–ecological modelling may therefore be limited.

1.3 | Ways out of ‘the mess’

Simulating complex, unpredictable systems to understand and avoid damaging outcomes is not a problem faced by social–ecological modelling alone, and much can be learned from other disciplines (Schulze et al., 2017). Lawton (1999) pithily summarised community ecology as ‘a mess’ when identifying a need for similarly novel approaches. Urban (2019) argued that biological modelling should follow the example of climate modelling and ‘improve in accuracy by incorporating mechanistic understanding, employing multi-model ensemble approaches, coordinating efforts worldwide, and validating projections against records from a well-designed network of [observational] stations’. Achieving this vision might require considerably larger resources than are currently available to biological modelling, but certain methods may facilitate the incorporation of mechanistic understanding without incurring excessive costs or model complexity. We suggest that one approach in particular has promise in this regard: the simulation of ‘high-level’ social–ecological processes that play key roles in system dynamics.

Focusing on a few key fundamental processes that span scales and contexts, and omitting other less general or important dynamics, is an approach that has had significant success in community ecology. This approach emphasises understanding the nature and effects of these fundamental processes, in isolation if necessary, as sufficient for capturing the effects of numerous sub-processes without accounting for them directly (Rapacciuolo & Blois, 2019). In community ecology, Vellend (2010) argued that myriad processes belong to one of four fundamental ‘high-level’ processes—drift, speciation, dispersal and selection—that together produce observed patterns in the composition and diversity of species across timescales. Identifying such processes of course requires a strong conceptual basis and evidence of the importance and generality of the processes included (Steel, 2007). Although the resultant processes are broad, this approach has been successful in prompting discussion, modelling and new results in community ecology, obviating the need for complex models and precise parameterisation to some extent.

We suggest that it is possible in principle to identify a similar group of processes from literature on social and ecological systems as being key in contributing to or averting breakdown dynamics. We do not perform a systematic search for such processes here, but offer tentative suggestions based on our interpretation of earlier reviews and categorisations (Brown et al., 2017; Urban et al., 2016) and a non-systematic review undertaken for this article (Table 1). We do so with the aim of prompting discussion, in the hope that debate, testing and refinement of these suggestions will benefit future modelling efforts.

For this purpose, we propose that high-level processes in social–ecological systems could include adaptation, interaction, dispersal or movement, demographic change, and intervention by institutional and governance actors (Table 1). Each of these processes has

been identified as important in the literature (Table 1), although cases could certainly be made (and, we hope, will be) for additional or alternative processes. Notably, despite being broad in nature, these processes are currently not widely included in social–ecological systems models (e.g. Brown et al., 2017; Urban et al., 2016). As a result, the appropriate inclusion of these or similar processes has the potential to increase the scope and utility of large-scale modelling.

These processes are analogous to classifications such as the mechanisms of collapse identified by Cumming and Peterson (2017), the ‘action-situation’ processes identified by Schlüter, Haider, et al. (2019) or the more empirical or theory-oriented classifications of review papers (Brown et al., 2017; Groeneveld et al., 2017; Huber et al., 2018; Meyfroidt et al., 2018; van Vliet et al., 2015). They differ in being specifically intended to contribute to modelling rather than theory, and in particular the modelling of dynamics that are outside the range observed in the recent past. They are intended to do so by focusing on general processes from which changes emerge (Figure 1), rather than providing a description of variation at a certain time, or specific effects or situations that lead to breakdowns. Research that highlights observed similarities among social–ecological contexts such as land system archetypes (Václavík et al., 2013) or decision-making types (Malek et al., 2019), can also aid identification of shared major processes (Rocha et al., 2019) or drivers of change (Harrison et al., 2018).

Another existing approach with notable relevance is the use of functional typologies to describe and model social or ecological dynamics (Grêt-Regamey et al., 2019; Rocha et al., 2019). Indeed, this functional approach has already been transferred from ecological modelling to social–ecological modelling as an efficient method of capturing major forms of human activity (Arneith et al., 2014; Brown, Seo, et al., 2019; Grêt-Regamey et al., 2019). In this case, functional typologies have been developed to represent not only the environmental requirements and contributions of different land managers but also their decision-making characteristics (e.g. innovative, conservative, risk averse, profit-oriented, etc.; Blanco et al., 2015; Díaz et al., 2011). Such convergent descriptions lend themselves to interdisciplinary modelling, both in terms of similarity in model architecture and in ability to capture key processes operating across large-scale systems.

A separate benefit of adopting a ‘high-level’ process approach is that the resulting models are likely to be widely understandable because the processes accord with those experienced by actors and stakeholders in any given system. This extra interpretability can be a benefit in itself, partially independent of ultimate model quality, because it allows models to enable informed dialogue by illuminating differing perspectives (Holtz et al., 2015; Millington & Wainwright, 2017; Parrott, 2017). Evidence suggests that models incorporating key, recognisable processes would be welcomed by many stakeholders who are uneasy about more ‘black box’ statistical models (Borsuk et al., 2001; Hunka et al., 2013). The shared understandings that can be developed in this way may additionally help to overcome social science’s ‘incoherency problem’ by revealing—or

TABLE 1 Potential 'high-level' processes relevant to breakdown dynamics in social–ecological systems. References are provided to give examples of the importance of these processes in social and/or ecological systems, but are not exhaustive

Processes	Explanation/role	References
Adaptation	Genetic, physiological or behavioural changes in response to (or in social systems, in anticipation of) alterations in environmental or other conditions. Includes learning and socio-cultural change in social systems	Social: (Adger et al., 2003; Crane et al., 2011; Holman et al., 2018; Vulturius et al., 2018; Wolf, 2011) Ecological: (Holt & Gaines, 1992; Merilä & Hendry, 2014; Pardini et al., 2010; Romero-Mujalli et al., 2019) Social–ecological: (Janssen et al., 2007; Preston et al., 2013)
Interaction	Competition, cooperation, facilitation, (in social systems) knowledge and information diffusion, social learning and changes to norms or values	Social: (Baird et al., 2014; Brown, Alexander, et al., 2018; Gupta et al., 2010; Huet et al., 2018; Meyfroidt, 2012; Müller-Hansen et al., 2017; Wolf, 2011) Ecological: (Butterfield et al., 2010; Götzenberger et al., 2012; Levine et al., 2017; Schweiger et al., 2008; Urban et al., 2012) Social–ecological: (Krausmann et al., 2008; Stern et al., 1995)
Dispersal/movement	The extent to which organisms, people or other entities can utilise space to generate, capitalise on or escape changes in conditions, for example, in species moving between habitat patches or people abandoning land uses and migrating. Can include many forms of human-mediated dispersal (e.g. species eradications or introductions) in social–ecological systems	Social: (Bardsley & Hugo, 2010; Fig ueiredo & Pereira, 2011; Hermans-Neumann et al., 2017; McLeman & Smit, 2006; Pinho et al., 2015) Ecological: (Aben et al., 2016; Carrasco et al., 2012; Ibáñez et al., 2013; Travis et al., 2013; Urban et al., 2016; Vellend, 2010) Social–ecological: (Aide & Grau, 2004; Chazdon, 2003; Kannan et al., 2014; Warren, 2011)
Demographic change	Changes in population structures, requirements and performance, as a cause of and response to wider systemic changes	Social: (Butzer, 2012; Downey et al., 2016; Goldstone, 2002) Ecological: (Crozier & Dwyer, 2006; Jenouvrier et al., 2009; Pearson et al., 2014; de Silva & Leimgruber, 2019) Social–ecological: (Ferrara et al., 2016; Kelly et al., 2015; Tadesse et al., 2014)
Institutional & governance interventions	Interventions associated with informal and formal groupings and entities. Includes institutional learning, architecture and adaptability, among others. Inherently related to social systems, even when operating on ecological systems	Brooks et al., 2005; Butzer, 2012; Cote & Nightingale, 2012; Dryzek & Stevenson, 2011; Grove, 2014; Jedd & Bixler, 2015; Juhola, 2016; Preston et al., 2013; Spies et al., 2010; Young, 2010

generating—links between apparently contradictory perspectives on the basis of fundamental processes common to all (Grimm & Berger, 2016; Watts, 2017). If so, models can play a highly beneficial role in capitalising on a diversity of perspectives to generate improved understandings and responses to social–ecological problems (Page, 2014).

Of course, high-level processes modelling represents just one possible approach in a field of great theoretical and practical diversity. One notable alternative could be to represent only the most fundamental of processes, and allow all others to emerge from these. For example, it has been suggested that social system dynamics are ultimately reducible to individual cognition and social interaction, from which pressures of cultural selection and characteristics of diversity emerge, determining the extent and impacts of negative disturbances in social–ecological systems (Figure 1; Baggio et al., 2019; Barnes et al., 2020; Freeman et al., 2020;

Richerson & Boyd, 2020). In this case, all other outcomes, including the processes we identify above (with the exception of interaction itself), can be seen as emergent phenomena. This argument is well grounded in theory and offers an elegant basis for limiting model complexity, although may not in itself ensure model versatility, for instance if only specific, limited forms of cognition and interaction are represented (Page, 2014). The high-level, action-situation or functional processes identified above, among others, may therefore remain useful in informing model design even under this more fundamental approach.

1.4 | Suitable models and data

Whatever the theoretical advantages of high-level and other forms of 'key' process modelling, their practicability cannot be taken for

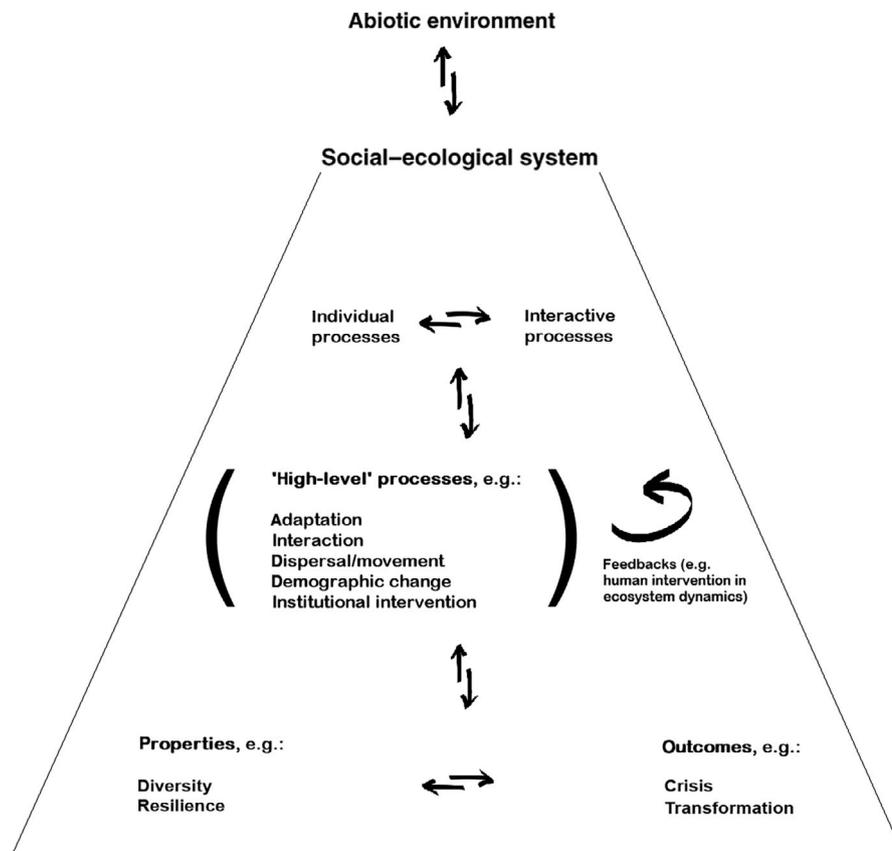


FIGURE 1 A stylised representation of social-ecological system dynamics relating 'high-level' processes to more fundamental processes, system properties and outcomes. Examples are illustrative, while the representation as a whole is presented as one possible conceptualisation that may support social-ecological modelling. The fundamental processes shown generalise the role of individual cognition and interaction in social systems described in the text. High-level processes can be seen as intermediate emergent phenomena, or as an alternative framework from which to construct models. Similarly, system properties and outcomes may emerge from either set of processes, but the high-level processes listed may be especially pertinent to the simulation of breakdowns and crises

granted. Currently, relatively few models incorporate the processes suggested above (Figure 2; Brown et al., 2017; Egli et al., 2019; Holman et al., 2018; Urban et al., 2016), and advancing beyond this limited capability is likely to be challenging. Here too, cross-disciplinary precedent can be a useful guide. The incorporation

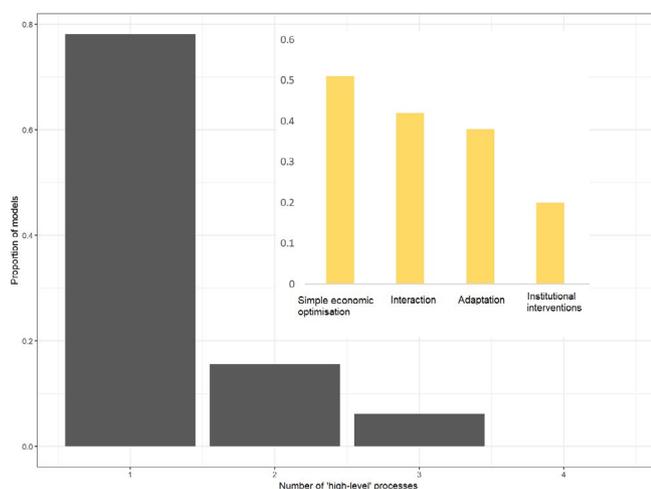


FIGURE 2 Number (main plot) and identity (coloured insert) of three high-level processes and a converse economic optimisation in behavioural models of climate change adaptation and mitigation in land-based sectors (based on Brown et al., 2017). (An equivalent summary of ecological models can be found in Urban, 2019, and of social-ecological ABMs from the perspective of resilience in Egli et al., 2019)

of high-level processes, functional typologies or similar categorisations in large-scale social-ecological models could be achieved via a number of existing modelling approaches in both ecology and social science.

Correlational statistical and pattern-based models can include greater process accuracy to some extent, as demonstrated, for example, by 'joint attribute' models that represent entire ecological communities and their internal interactions (Clark et al., 2017). System dynamics modelling can also incorporate some social-ecological process accuracy (Elsawah et al., 2017), as can Earth System and marine 'whole ecosystem' models (Donges et al., 2020; Fulton et al., 2011; Pongratz et al., 2018). Network modelling has recently been used to explore the ways in which individual and social characteristics affect responses to climate change (Barnes et al., 2020). A structured typology of social-ecological model types and the roles they can play in exploring system dynamics is provided by Schlüter, Müller, et al. (2019), and can be related to more general existing frameworks for social-ecological systems modelling (Robinson et al., 2018) and analysis (e.g. Binder & Hinkel, 2013).

In general, these analyses conclude that process-based approaches such as agent-based modelling (ABM) have particular promise for simulating key processes because they have an established history of representing social and ecological dynamics as emergent from such processes, and attempting to realistically represent real-world problems on this basis (Gras et al., 2009; Schlüter, Müller, et al., 2019). ABM is already used to represent the human decision-making that mediates social and environmental interactions (Egli et al., 2019;

Groeneveld et al., 2017; Lippe et al., 2019; Schulze et al., 2017) including in the contexts of breakdowns in large-scale food systems (Brown, Seo, et al., 2019) and marine fisheries management (Gao & Hailu, 2012). It has also been used to some extent to identify high-level or cross-context processes (Parker et al., 2008) and their relative impacts on social–ecological change (Brown, Holzhauer, et al., 2018). Such models have also been developed using functional accounts that are compatible across social and ecological sub-systems, and can similarly incorporate biologically and socially meaningful metrics related to system structure (Arneth et al., 2014; Blüthgen et al., 2016; Grêt-Regamey et al., 2019; Hekkala & Roberge, 2018). Nevertheless, a number of technical types of model overlap in their ability to provide process-based representations (Schlüter, Müller, et al., 2019), as illustrated by the further examples of model applications relating to suggested high-level processes in Table 2.

The advantages of different modelling approaches can be combined through various forms of integrated modelling (Lippe et al., 2019). Of particular relevance may be hybrid modelling, which allows model complexity to be tailored to the level of detail necessary for each process or component (Parrott, 2011). This has been used, for example, in land and marine management models that include distinct descriptions of different system components (e.g. relatively simple Bayesian Belief Networks to simulate human decision-making within broader modelling frameworks; Romagnoni et al., 2015; Stelzenmüller et al., 2010; Sun & Müller, 2013). Hybrid modelling has also been proposed for ‘World-Earth’ models that embed process-based social simulation within an Earth system model framework (Donges et al., 2020). Even more feasible from a technical perspective is the combination of a series of single human and natural process models to explore the dynamics that emerge from their interaction (e.g. Ullah, 2013) or, to avoid unwieldy combinations of different models, a targeted approach that focuses on specific social–ecological interactions (e.g. Sarjoughian et al., 2015).

Encouragingly, models that have adopted some of these methods to simulate fundamental social–ecological processes have repeatedly generated emergent dynamics that differ substantially from those produced by correlative or single-sector models, including dynamics that produce potential crises related to climatic, environmental and social change (Brown, Seo, et al., 2019; Bury et al., 2019; Lade et al., 2013; Synes et al., 2019; Ullah, 2013). Upscaling these approaches to make them operate over the large geographical extents relevant to major crises currently remains an acknowledged challenge, but one for which progress is being made (Elsawah et al., 2020; Robinson et al., 2018). Given that, the above precedents suggest that modelling high-level processes is both possible and profitable, with scope for rapid knowledge gains to be made.

While models may well be capable of modelling the roles of high-level processes in social–ecological crises, they will undeniably require substantial data inputs. In fact, data requirements have often proved an insurmountable barrier to process-based models of social–ecological systems even at relatively small spatial scales (Verburg et al., 2019). Focusing on a few key, transferrable processes

limits data requirements to some extent, particularly where it is used in hybrid modelling that seeks to remove unnecessary detail. Furthermore, considerable advances have recently been made in data resolution and availability, with a number of datasets and repositories capable of supporting modelling of this kind (see e.g. Elsawah et al., 2020; Magliocca et al., 2018; Willcock et al., 2018). An illustrative selection of these datasets is provided in Table 2, as examples of valuable building blocks for a new programme of high-level process modelling across large geographical extents.

1.5 | The potential of new models

1.5.1 | Possible contributions

A number of avenues for social–ecological systems modelling are now open, and steps are already being taken along each of them. While it is not yet possible to be certain where these avenues will lead, positive progress is likely for our ability to simulate and understand social–ecological crises. The correlational modelling approaches that are currently best-placed to simulate large-scale changes are notably constrained in their ability to simulate the emergence of unprecedented dynamics, and the *potential* for models to produce novel, unexpected results is the clearest advance that new forms of modelling can make.

Many of the major challenges that human societies now face are a product of local processes operating in a global context. Thanks to increasing computational and data resources, modelling these processes and context is now technically feasible. The exploration of social–ecological process interactions across scales that this permits is another clear and achievable objective for new models (Elsawah et al., 2020; Lippe et al., 2019; Robinson et al., 2018).

Nevertheless, the construction of more detailed process-based models is of limited utility in itself. Such models can quickly become excessively complex, and are in any case unlikely to have greater predictive accuracy than far simpler models (Grimm & Berger, 2016; Salganik et al., 2020). To maximise their contribution, models must be designed to focus in on the processes that are most relevant to the issues being studied, and most representative of social–ecological systems at large scales. The identification of such processes is a substantial challenge that requires engagement from a range of perspectives. Our suggested ‘high-level’ processes (Table 1) are examples only, inspired by similar and successful categories used in community ecology (Vellend, 2010), and presented here with the sole aim of prompting discussion, testing and refinement. To the extent that modelling can contribute to these aims, it may meaningfully contribute to social–ecological research as a whole simply by supporting conceptual discussions. In linking research models to the concepts through which people experience social–ecological change, high-level processes may also be able to support greater social engagement and knowledge exchange (Holtz et al., 2015; Millington & Wainwright, 2017).

While developments in other disciplines suggest that high-level and analogous approaches are useful, recently developed

TABLE 2 Examples of models and data that cover key social–ecological processes. Single examples are chosen to represent feasibility of incorporating processes in models, and do not provide a summary of existing approaches (relevant reviews include Brown et al., 2017; Egli et al., 2019; Fisher et al., 2018; Groeneveld et al., 2017; Huber et al., 2018; Leroux et al., 2013; Maguire et al., 2015; Robinson et al., 2018; Urban, 2019)

Processes	Models	Data
Adaptation	Social: Agent-based modelling of water usage decisions under environmental variability (Arnold et al., 2015)	Social: Mobile phone usage and social media data for assessing vulnerability and adaptation (Ford et al., 2016)
	Ecological: Loci-based modelling of genomic adaptation of poplar tree species to environmental gradient at community-level (Fitzpatrick & Keller, 2015)	Ecological: Long-term tropical forest censuses from permanent plots around the world, incorporating environmental change and human disturbance (Anderson-Teixeira et al., 2015; Sist et al., 2015)
	Social–ecological: Modelling of adaptive forest management informed by socio-economic and ecological conditions under climate change (Yousefpour et al., 2017)	Social–ecological: FAO global fisheries data and participatory methods for vulnerability/adaptation assessments (FAO, 2015, 2019)
Interaction	Social: Agent-based modelling of technology uptake based on social interactions and individual attitudes (Rai & Robinson, 2015)	Social: Collections of large-scale social network data (e.g. Stanford Large Network Dataset Collection, (Leskovec & Krevl, 2014)
	Ecological: Large-scale mechanistic modelling of trophic interactions in ecosystems (Bartlett et al., 2016)	Ecological: Open-access data collections on species interaction networks and food webs (e.g. GlobalWeb, 2019; IWDB, 2016)
	Social–ecological: Agent-/individual-based modelling of interactive species dynamics and responsive, interactive land management decisions (Synes et al., 2019)	Social–ecological: Global data on land use and land cover based on social–ecological modelling of observational data (Li et al., 2017)
Dispersal/movement	Social: System dynamics modelling of human migration under climate change, incorporating a range of socio-economic and environmental drivers (Naugle et al., 2018)	Social: Official government-sponsored collections of global migration data (Global Migration Data Portal, 2019)
	Ecological: Mechanistic modelling of honeybee populations based on individual-, colony- and population-level processes (Becher et al., 2018)	Ecological: Databases of species traits such as the ‘TRY’ Plant Trait Database including dispersal traits (Kattge et al., 2011)
	Social–ecological: Agent-based modelling of hunter-gatherer strategies and environmental resources/prey species in spatially explicit environment (Janssen & Hill, 2014, 2016)	Social–ecological: Use of invasive species monitoring data to disentangle human-mediated and natural dispersal processes (Horvitz et al., 2017)
Demographic change	Social: Parallelised agent-based modelling of human population dynamics based on key processes (Montañola-Sales et al., 2016)	Social: Global demographic databases (United Nations Statistics Division, 2019)
	Ecological: Stochastic population modelling of emperor penguin responses to climate change (Jenouvrier et al., 2009)	Ecological: Bayesian modelling to extend species demography data coverage to under-studied species (Kindsvater et al., 2018)
	Social–ecological: Agent-based modelling of demographic change in indigenous hunting communities and their prey species (Iwamura et al., 2014)	Social–ecological: Long-term data records covering changes in social and ecological communities as, e.g., road network develops in Amazon (Klarenberg et al., 2019)
Institutional & governance interventions	Social: Agent-based modelling of individual and institutional activities in land system (Holzhauer et al., 2019)	Global/regional databases of policies and impacts relating to, for example, environment or climate (New Climate Institute, 2019; OECD, 2019)
	Ecological: Multi-model framework to identify pathways and policies to reverse biodiversity loss trends (Leclère et al., 2020)	
	Social–ecological: Economic-environmental modelling to explore effects of different policies on land use and biodiversity (Bryan et al., 2016), and network modelling of the effects of social institutions on ecological conditions, for example, of coral reefs (Barnes et al., 2019)	

social–ecological models and datasets suggest that they are feasible (Table 2). If this approach is successfully developed and applied, it could have a number of other benefits. Most obviously, it could extend the ability of process-based models to simulate the emergence of breakdowns and crises (e.g. Brown, Seo, et al., 2019; Ullah, 2013) to other contexts and scales. Such simulation is strictly distinct from prediction (see below), but it can reveal situations and dynamics from which crises can emerge that might otherwise not be recognised, opening up potential opportunities for designing new interventions. Less tangible, but possibly more fundamental, is the scope for such models to allow exploration of the ways in which social–ecological systems diverge from anticipated behaviour; the nonlinearities, thresholds and regime shifts that characterise complex system dynamics (Filatova et al., 2016; Synes et al., 2019). In particular, the roles of social processes in prompting such events remain poorly understood, but amenable to modelling of this kind (Barceló & Del Castillo, 2016; Lade et al., 2013; Ullah, 2013). Where these social processes go beyond historical precedents or available data, process-based modelling has the important final advantage of allowing fuller exploration of uncertainties (Gostoli & Silverman, 2020; Salganik et al., 2020).

1.5.2 | Impassable constraints

Whatever the reach of new forms of data and analysis, social–ecological models cannot be parameterised to exactly represent reality. They can only ever be an approximate guide to system dynamics, and cannot be used to predict how systems will develop in the future because the systems in question—and especially crises in those systems—are inherently unpredictable (de Matos Fernandes & Keijzer, 2020; Oreskes et al., 1994). This limit not only highlights the importance of rigorous and transparent uncertainty analysis as a way of exploring the scope for unexpected developments (Gregg & Chan, 2015) but also highlights the need for a range of models and modelling approaches to be developed.

In fact, many theoretical and computational approaches may be equally valid or useful for simulating social–ecological crises. Ecological and, especially, social theories remain diverse, difficult to precisely encode algorithmically, and legitimately open to differing representations (Watts, 2017). Making assumptions explicit and investigating associated uncertainties is essential in this context (Gregg & Chan, 2015). Modelling nevertheless remains, to a small but crucial extent, an imaginative, interpretative exercise that is hindered by methodological convergence (Feyerabend, 1993; Yusoff & Gabrys, 2011). Rigorous model evaluation, including formal sensitivity and uncertainty analyses, benchmarking, reproducibility checks and open, transparent model dissemination are all important contributions to model utility (Batty & Torrens, 2005; Gregg & Chan, 2015; Oreskes et al., 1994), but perhaps their greatest value is to underscore the difficult questions that models raise and undermine the easy answers they sometimes appear to provide.

2 | CONCLUSIONS

The need for models that can simulate the emergence of crises related to climate and environmental change, biodiversity loss and associated human processes is growing. This need coincides with rapid advances in computational and data resources that allow for new forms of modelling to be developed. We argue that the simulation of social–ecological dynamics as emergent from ‘high-level’ processes or similar conceptual frameworks has particular promise. These processes should have broad thematic and geographical relevance, and the potential to be simulated in existing process-based models using efficient functional descriptions of social and ecological systems. The further development of this approach across large (continental-global) geographical extents appears to be both technically feasible and scientifically worthwhile on the basis of recent precedents. While this would not represent a step towards illusory predictive accuracy, it would have a number of potential benefits. These include the generation of ‘out-of-sample’ results, of which crises are one important kind, and exploration of how they can arise from the actions and interactions of basic processes. The ability to explore a wide range of system dynamics is valuable from a research perspective and, in principle, for policy support, to the extent that it allows various conditions associated with crises to be identified. Such models can also act as a focus for theoretical and empirical development, prompting debate and suggesting new research questions including via direct societal engagement. Perhaps most fundamentally, new models are required to illuminate the inherent complexity of social–ecological systems, marking out uncertainties in our knowledge and weaknesses in our strategies before they emerge as real-world impacts.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHORS' CONTRIBUTIONS

C.B. conceptualisation, investigation, writing—original draft; M.R. conceptualisation, writing—review and editing.

DATA AVAILABILITY STATEMENT

No data are used or made available in this article.

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REFERENCES

Aben, J., Bocedi, G., Palmer, S. C. F., Pellikka, P., Strubbe, D., Hallmann, C., Travis, J. M. J., Lens, L., & Matthysen, E. (2016). The importance of realistic dispersal models in conservation planning: Application of

- a novel modelling platform to evaluate management scenarios in an Afrotropical biodiversity hotspot. *Journal of Applied Ecology*, 53(4), 1055–1065. <https://doi.org/10.1111/1365-2664.12643>
- Adger, W. N., Huq, S., Brown, K., Conway, D., & Hulme, M. (2003). Adaptation to climate change in the developing world. *Progress in Development Studies*, 33, 179–195. <https://doi.org/10.1191/1464993403ps0600a>
- Aide, T. M., & Grau, H. R. (2004). Ecology. Globalization, migration, and Latin American ecosystems. *Science (New York, NY)*, 305(5692), 1915–1916. <https://doi.org/10.1126/science.1103179>
- Anderson-Teixeira, K. J., Davies, S. J., Bennett, A. C., Gonzalez-Akre, E. B., Muller-Landau, H. C., Joseph Wright, S., Abu Salim, K., Almeyda Zambrano, A. M., Alonso, A., Baltzer, J. L., Basset, Y., Bourg, N. A., Broadbent, E. N., Brockelman, W. Y., Bunyavejchewin, S., Burslem, D. F. R. P., Butt, N., Cao, M., Cardenas, D., ... Zimmerman, J. (2015). CTFS-ForestGEO: A worldwide network monitoring forests in an era of global change. *Global Change Biology*, 21(2), 528–549. <https://doi.org/10.1111/gcb.12712>
- Arneth, A., Brown, C., & Rounsevell, M. D. A. (2014). Global models of human decision-making for land-based mitigation and adaptation assessment. *Nature Climate Change*, 4(7), 550–557. <https://doi.org/10.1038/nclimate2250>
- Arnold, R. T., Troost, C., & Berger, T. (2015). Quantifying the economic importance of irrigation water reuse in a Chilean watershed using an integrated agent-based model. *Water Resources Research*, 51(1), 648–668. <https://doi.org/10.1002/2014WR015382>
- Asner, G. P., Rudel, T. K., Aide, T. M., Defries, R., & Emerson, R. (2009). A contemporary assessment of change in humid tropical forests. *Conservation Biology*, 23(6), 1386–1395. <https://doi.org/10.1111/j.1523-1739.2009.01333.x>
- Austin, K. G., González-Roglich, M., Schaffer-Smith, D., Schwantes, A. M., & Swenson, J. J. (2017). Trends in size of tropical deforestation events signal increasing dominance of industrial-scale drivers. *Environmental Research Letters*, 12(5), 054009. <https://doi.org/10.1088/1748-9326/aa6a88>
- Baggio, J. A., Freeman, J., Coyle, T. R., Nguyen, T. T., Hancock, D., Elpers, K. E., Nabity, S., Dengah II, H. J. F., & Pillow, D. (2019). The importance of cognitive diversity for sustaining the commons. *Nature Communications*, 10(1), 1–11. <https://doi.org/10.1038/s41467-019-08549-8>
- Baird, J., Plummer, R., Haug, C., & Huitema, D. (2014). Learning effects of interactive decision-making processes for climate change adaptation. *Global Environmental Change*, 27, 51–63. <https://doi.org/10.1016/j.gloenvcha.2014.04.019>
- Barceló, J. A., & Del Castillo, F. (2016). Simulating the past for understanding the present. A critical review. In J. A. Barceló & F. Del Castillo (Eds.), *Simulating prehistoric and ancient worlds. Computational social sciences* (pp. 1–140). Springer. https://doi.org/10.1007/978-3-319-31481-5_1
- Bardsley, D. K., & Hugo, G. J. (2010). Migration and climate change: Examining thresholds of change to guide effective adaptation decision-making. *Population and Environment*, 32(2–3), 238–262. <https://doi.org/10.1007/s11111-010-0126-9>
- Barnes, M. L., Bodin, Ö., McClanahan, T. R., Kittinger, J. N., Hoey, A. S., Gaoue, O. G., & Graham, N. A. J. (2019). Social-ecological alignment and ecological conditions in coral reefs. *Nature Communications*, 10(1), 2039. <https://doi.org/10.1038/s41467-019-09994-1>
- Barnes, M. L., Wang, P., Cinner, J. E., Graham, N. A. J., Guerrero, A. M., Jasny, L., Lau, J., Sutcliffe, S. R., & Zamborain-Mason, J. (2020). Social determinants of adaptive and transformative responses to climate change. *Nature Climate Change*, 10(9), 823–828. <https://doi.org/10.1038/s41558-020-0871-4>
- Bartlett, L. J., Newbold, T., Purves, D. W., Tittensor, D. P., & Harfoot, M. B. J. (2016). Synergistic impacts of habitat loss and fragmentation on model ecosystems. *Proceedings of the Royal Society B: Biological Sciences*, 283(1839), 20161027. <https://doi.org/10.1098/rspb.2016.1027>
- Batty, M., & Torrens, P. M. (2005). Modelling and prediction in a complex world. *Futures*, 37(7), 745–766. <https://doi.org/10.1016/j.futures.2004.11.003>
- Becher, M. A., Twiston-Davies, G., Penny, T. D., Goulson, D., Rotheray, E. L., & Osborne, J. L. (2018). Bumble-BEEHAVE: A systems model for exploring multifactorial causes of bumblebee decline at individual, colony, population and community level. *Journal of Applied Ecology*, 55(6), 2790–2801. <https://doi.org/10.1111/1365-2664.13165>
- Binder, C., & Hinkel, J. (2013). Comparison of frameworks for analyzing social-ecological systems. *Ecology and Society*. Retrieved from <http://dlc.dlib.indiana.edu/dlc/handle/10535/9198>
- Blanco, V., Brown, C., & Rounsevell, M. (2015). Characterising forest owners through their objectives, attributes and management strategies. *European Journal of Forest Research*, 134(6). <https://doi.org/10.1007/s10342-015-0907-x>
- Blüthgen, N., Simons, N. K., Jung, K., Prati, D., Renner, S. C., Boch, S., Fischer, M., Hölzel, N., Klaus, V. H., Kleinebecker, T., Tschapka, M., Weisser, W. W., & Gossner, M. M. (2016). Land use imperils plant and animal community stability through changes in asynchrony rather than diversity. *Nature Communications*, 7(1), 10697. <https://doi.org/10.1038/ncomms10697>
- Borsuk, M., Clemen, R., Maguire, L., & Reckhow, K. (2001). Stakeholder values and scientific modeling in the neuse river watershed. *Group Decision and Negotiation*, 10(4), 355–373. <https://doi.org/10.1023/A:1011231801266>
- Brooks, N., Neil Adger, W., & Mick Kelly, P. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change*, 15(2), 151–163. <https://doi.org/10.1016/j.gloenvcha.2004.12.006>
- Brown, C., Alexander, P., Arneth, A., Holman, I., & Rounsevell, M. (2019). Achievement of Paris climate goals unlikely due to time lags in the land system. *Nature Climate Change*, 9(3), 203–208. <https://doi.org/10.1038/s41558-019-0400-5>
- Brown, C., Alexander, P., Holzhauser, S., & Rounsevell, M. D. A. (2017). Behavioral models of climate change adaptation and mitigation in land-based sectors. *Wiley Interdisciplinary Reviews: Climate Change*, 8, e448. <https://doi.org/10.1002/wcc.448>
- Brown, C., Alexander, P., & Rounsevell, M. (2018). Empirical evidence for the diffusion of knowledge in land use change. *Journal of Land Use Science*, 13(3), 269–283. <https://doi.org/10.1080/1747423X.2018.1515995>
- Brown, C., Brown, K., & Rounsevell, M. (2016). A philosophical case for process-based modelling of land use change. *Modeling Earth Systems and Environment*, 2(2), 50. <https://doi.org/10.1007/s40808-016-0102-1>
- Brown, C., Holzhauser, S., Metzger, M. J., Paterson, J. S., & Rounsevell, M. (2018). Land managers' behaviours modulate pathways to visions of future land systems. *Regional Environmental Change*, 18(3), 831–845. <https://doi.org/10.1007/s10113-016-0999-y>
- Brown, C., Seo, B., & Rounsevell, M. (2019). Societal breakdown as an emergent property of large-scale behavioural models of land use change. *Earth System Dynamics*, 10(4), 809–845. <https://doi.org/10.5194/esd-10-809-2019>
- Bryan, B. A., Runting, R. K., Capon, T., Perring, M. P., Cunningham, S. C., Kragt, M. E., Nolan, M., Law, E. A., Renwick, A. R., Eber, S., Christian, R., & Wilson, K. A. (2016). Designer policy for carbon and biodiversity co-benefits under global change. *Nature Climate Change*, 6(3), 301–305. <https://doi.org/10.1038/nclimate2874>
- Bury, T. M., Bauch, C. T., & Anand, M. (2019). Charting pathways to climate change mitigation in a coupled socio-climate model. *PLoS Computational Biology*, 15(6), e1007000. <https://doi.org/10.1371/journal.pcbi.1007000>

- Butterfield, B. J., Betancourt, J. L., Turner, R. M., & Briggs, J. M. (2010). Facilitation drives 65 years of vegetation change in the Sonoran Desert. *Ecology*, 91(4), 1132–1139. <https://doi.org/10.1890/09-0145.1>
- Butzer, K. W. (2012). Collapse, environment, and society. *Proceedings of the National Academy of Sciences of the United States of America*, 109(10), 3632–3639. <https://doi.org/10.1073/pnas.1114845109>
- Carrasco, L. R., Cook, D., Baker, R., MacLeod, A., Knight, J. D., & Mumford, J. D. (2012). Towards the integration of spread and economic impacts of biological invasions in a landscape of learning and imitating agents. *Ecological Economics*, 76, 95–103. <https://doi.org/10.1016/j.ecolecon.2012.02.009>
- Chazdon, R. L. (2003). Tropical forest recovery: Legacies of human impact and natural disturbances. *Perspectives in Plant Ecology, Evolution and Systematics*, 6(1–2), 51–71. <https://doi.org/10.1078/1433-8319-00042>
- Clark, J. S., Nemergut, D., Seyednasrollah, B., Turner, P. J., & Zhang, S. (2017). Generalized joint attribute modeling for biodiversity analysis: Median-zero, multivariate, multifarious data. *Ecological Monographs*, 87(1), 34–56. <https://doi.org/10.1002/ecm.1241>
- Colding, J., & Barthel, S. (2019). Exploring the social-ecological systems discourse 20 years later. *Ecology and Society*, 24(1). <https://doi.org/10.5751/ES-10598-240102>
- Cote, M., & Nightingale, A. J. (2012). Resilience thinking meets social theory. *Progress in Human Geography*, 36(4), 475–489. <https://doi.org/10.1177/0309132511425708>
- Craig, M. P. A. (2017). Two Conceptualisations of Socio-ecological Crisis. *Ecological political economy and the socio-ecological crisis* (pp. 11–18). Springer International Publishing. https://doi.org/10.1007/978-3-319-40090-7_2
- Crane, T. A., Roncoli, C., & Hoogenboom, G. (2011). Adaptation to climate change and climate variability: The importance of understanding agriculture as performance. *NJAS - Wageningen Journal of Life Sciences*, 57(3–4), 179–185. <https://doi.org/10.1016/j.njas.2010.11.002>
- Crozier, L., & Dwyer, G. (2006). Combining population-dynamic and ecophysiological models to predict climate-induced insect range shifts. *The American Naturalist*, 167(6), 853–866. <https://doi.org/10.1086/504848>
- Cumming, G. S., & Peterson, G. D. (2017). Unifying research on social-ecological resilience and collapse. *Trends in Ecology & Evolution*, 32(9), 695–713. <https://doi.org/10.1016/j.TREE.2017.06.014>
- de Matos Fernandes, C. A., & Keijzer, M. A. (2020). No one can predict the future: More than a semantic dispute. In *Review of artificial societies and social simulation*. Retrieved from <https://rofasss.org/2020/04/15/no-one-can-predict-the-future/>
- de Silva, S., & Leimgruber, P. (2019). Demographic tipping points as early indicators of vulnerability for slow-breeding megafaunal populations. *Frontiers in Ecology and Evolution*, 7, 171. <https://doi.org/10.3389/fevo.2019.00171>
- Diaz, S., Quetier, F., Caceres, D. M., Trainor, S. F., Perez-Harguindeguy, N., Bret-Harte, M. S., Finegan, B., Pena-Claros, M., & Poorter, L. (2011). Linking functional diversity and social actor strategies in a framework for interdisciplinary analysis of nature's benefits to society. *Proceedings of the National Academy of Sciences of the United States of America*, 108(3), 895–902. <https://doi.org/10.1073/pnas.1017993108>
- Donges, J. F., Heitzig, J., Barfuss, W., Wiedermann, M., Kassel, J. A., Kittel, T., Kolb, J. J., Kolster, T., Müller-Hansen, F., Otto, I. M., Zimmerer, K. B., & Lucht, W. (2020). Earth system modeling with endogenous and dynamic human societies: The copan: CORE open World-Earth modeling framework. *Earth System Dynamics*, 11(2), 395–413. <https://doi.org/10.5194/esd-11-395-2020>
- Downey, S. S., Haas, W. R., & Shennan, S. J. (2016). European Neolithic societies showed early warning signals of population collapse. *Proceedings of the National Academy of Sciences of the United States of America*, 113(35), 9751–9756. <https://doi.org/10.1073/PNAS.1602504113>
- Driscoll, D. A., Bland, L. M., Bryan, B. A., Newsome, T. M., Nicholson, E., Ritchie, E. G., & Doherty, T. S. (2018, May 1). A biodiversity-crisis hierarchy to evaluate and refine conservation indicators. *Nature Ecology and Evolution*, 2(5), 775–781. <https://doi.org/10.1038/s41559-018-0504-8>
- Dryzek, J. S., & Stevenson, H. (2011). Global democracy and earth system governance. *Ecological Economics*, 70(11), 1865–1874. <https://doi.org/10.1016/J.ECOLECON.2011.01.021>
- Egli, L., Weise, H., Radchuk, V., Seppelt, R., & Grimm, V. (2019). Exploring resilience with agent-based models: State of the art, knowledge gaps and recommendations for coping with multidimensionality. *Ecological Complexity*, 40, 100718. <https://doi.org/10.1016/j.ecocom.2018.06.008>
- 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 modeling. *Socio-Environmental Systems Modelling*, 2, 16226. <https://doi.org/10.18174/sesmo.2020a16226>
- Elsawah, S., Pierce, S. A., Hamilton, S. H., van Delden, H., Haase, D., Elmahdi, A., & Jakeman, A. J. (2017). An overview of the system dynamics process for integrated modelling of socio-ecological systems: Lessons on good modelling practice from five case studies. *Environmental Modelling & Software*, 93, 127–145. <https://doi.org/10.1016/J.ENVSOFT.2017.03.001>
- Epstein, J. M. (2008). Why Model? *Journal of Artificial Societies and Social Simulation*, 11(412).
- FAO. (2015). Community-level socio-ecological vulnerability assessments in the Benguela current large marine ecosystem. In *FAO Fisheries and Aquaculture Circular* (Vol. 1110). Retrieved from <http://agris.fao.org/agris-search/search.do?recordID=XF2017000920>
- FAO. (2016). *State of the world's forests 2016*. <https://doi.org/10.1146/annurev-environ-020411-130608>
- FAO. (2019). *FAO Fisheries & Aquaculture - Statistics - Introduction*. Retrieved from <http://www.fao.org/fishery/statistics/en>
- Ferrara, A., Kelly, C., Wilson, G. A., Nolè, A., Mancino, G., Bajocco, S., & Salvati, L. (2016). Shaping the role of 'fast' and 'slow' drivers of change in forest-shrubland socio-ecological systems. *Journal of Environmental Management*, 169, 155–166. <https://doi.org/10.1016/J.JENVMAN.2015.12.027>
- Feurer, M., Heinimann, A., Schneider, F., Jurt, C., Myint, W., & Zaehring, J. G. (2019). Local perspectives on ecosystem service trade-offs in a forest frontier landscape in myanmar. *Land*, 8(3), 45. <https://doi.org/10.3390/land8030045>
- Feyerabend, P. (1993). *Against method*. Verso. <https://books.google.com/books?hl=en&lr=&id=8y-FVtrKeSYC&oi=fnd&pg=PR7&dq=against+method&ots=vEZlcYLA5F&sig=ujLg8NByD0tbGkWERagl80o151l>
- Figueiredo, J., & Pereira, H. M. (2011). Regime shifts in a socio-ecological model of farmland abandonment. *Landscape Ecology*, 26(5), 737–749. <https://doi.org/10.1007/s10980-011-9605-3>
- Filatova, T., Polhill, J. G., & van Ewijk, S. (2016). Regime shifts in coupled socio-environmental systems: Review of modelling challenges and approaches. *Environmental Modelling and Software*, 75, 333–347. <https://doi.org/10.1016/j.envsoft.2015.04.003>
- 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., ... Moorcroft, P. R. (2018, January 1). 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>

- Fitzpatrick, M. C., & Keller, S. R. (2015). Ecological genomics meets community-level modelling of biodiversity: Mapping the genomic landscape of current and future environmental adaptation. *Ecology Letters*, 18(1), 1–16. <https://doi.org/10.1111/ele.12376>
- Ford, J. D., Tilleard, S. E., Berrang-Ford, L., Araos, M., Biesbroek, R., Lesnikowski, A. C., MacDonald, G. K., Hsu, A., Chen, C., & Bizikova, L. (2016). Opinion: Big data has big potential for applications to climate change adaptation. *Proceedings of the National Academy of Sciences of the United States of America*, 113(39), 10729–10732. <https://doi.org/10.1073/pnas.1614023113>
- Freeman, J., Baggio, J. A., & Coyle, T. R. (2020). Social and general intelligence improves collective action in a common pool resource system. *Proceedings of the National Academy of Sciences of the United States of America*, 117(14), 7712–7718. <https://doi.org/10.1073/pnas.1915824117>
- Fulton, E. A., Link, J. S., Kaplan, I. C., Savina-Rolland, M., Johnson, P., Ainsworth, C., Horne, P., Gorton, R., Gamble, R. J., Smith, A. D. M., & Smith, D. C. (2011). Lessons in modelling and management of marine ecosystems: The Atlantis experience. *Fish and Fisheries*, 12(2), 171–188. <https://doi.org/10.1111/j.1467-2979.2011.00412.x>
- Gao, L., & Hailu, A. (2012). Ranking management strategies with complex outcomes: An AHP-fuzzy evaluation of recreational fishing using an integrated agent-based model of a coral reef ecosystem. *Environmental Modelling and Software*, 31, 3–18. <https://doi.org/10.1016/j.envsoft.2011.12.002>
- Global Migration Data Portal (2019). *Migration data portal*. Retrieved from https://migrationdataportal.org/?i=stock_abs_&t=2019
- GlobalWeb. (2019). *Food Web Database - University of CANBERRA*. Retrieved from <https://www.globalwebdb.com/>
- Goldstone, J. A. (2002). Population and security: How demographic change can lead to violent conflict. *Journal of International Affairs*, 56(1), 3–21. <https://doi.org/10.2307/24357881>
- Gostoli, U., & Silverman, E. (2020). Sound behavioural theories, not data, is what makes computational models useful. In *Review of artificial societies and social simulation*. Retrieved from <https://rofass.org/2020/04/22/sound-behavioural-theories/>
- Götzenberger, L., de Bello, F., Bräthen, K. A., Davison, J., Dubuis, A., Guisan, A., Lepš, J., Lindborg, R., Moora, M., Pärtel, M., Pellissier, L., Pottier, J., Vittoz, P., Zobel, K., & Zobel, M. (2012). Ecological assembly rules in plant communities—approaches, patterns and prospects. *Biological Reviews*, 87(1), 111–127. <https://doi.org/10.1111/j.1469-185X.2011.00187.x>
- Gras, R., Devaurs, D., Wozniak, A., & Aspinall, A. (2009). An individual-based evolving predator-prey ecosystem simulation using a fuzzy cognitive map as the behavior model. *Artificial Life*, 15(4), 423–463. <https://doi.org/10.1162/artl.2009.Gras.012>
- Greg, E. J., & Chan, K. M. A. (2015). Leaps of faith: How implicit assumptions compromise the utility of ecosystem models for decision-making. *BioScience*, 65(1), 43–54. <https://doi.org/10.1093/biosci/biu185>
- Grêt-Regamey, A., Huber, S. H., & Huber, R. (2019). Actors' diversity and the resilience of social-ecological systems to global change. *Nature Sustainability*, 2(4), 290. <https://doi.org/10.1038/s41893-019-0236-z>
- Grimm, V., & Berger, U. (2016). Structural realism, emergence, and predictions in next-generation ecological modelling: Synthesis from a special issue. *Ecological Modelling*, 326, 177–187. <https://doi.org/10.1016/j.ecolmodel.2016.01.001>
- Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., & Schwarz, N. (2017). Theoretical foundations of human decision-making in agent-based land use models – A review. *Environmental Modelling & Software*, 87, 39–48. <https://doi.org/10.1016/J.ENVSOFT.2016.10.008>
- Grove, K. (2014). Biopolitics and adaptation: Governing socio-ecological contingency through climate change and disaster studies. *Geography Compass*, 8(3), 198–210. <https://doi.org/10.1111/gec3.12118>
- Gupta, J., Termeer, C., Klostermann, J., Meijerink, S., van den Brink, M., Jong, P., Nootboom, S., & Bergsma, E. (2010). The Adaptive Capacity Wheel: A method to assess the inherent characteristics of institutions to enable the adaptive capacity of society. *Environmental Science & Policy*, 13(6), 459–471. <https://doi.org/10.1016/j.envsci.2010.05.006>
- Hagedorn, G., Kalmus, P., Mann, M., Vicca, S., Van den Berge, J., van Ypersele, J.-P., Bourg, D., Rotmans, J., Kaaronen, R., Rahmstorf, S., Kromp-Kolb, H., Kirchengast, G., Knutti, R., Seneviratne, S. I., Thalman, P., Cretney, R., Green, A., Anderson, K., Hedberg, M., ... Hayhoe, K. (2019). Concerns of young protesters are justified. *Science (New York, NY)*, 364(6436), 139–140. <https://doi.org/10.1126/science.aax3807>
- Hamilton, S. H., ElSawah, S., Guillaume, J. H. A., Jakeman, A. J., & Pierce, S. A. (2015). Integrated assessment and modelling: Overview and synthesis of salient dimensions. *Environmental Modelling & Software*, 64, 215–229. <https://doi.org/10.1016/j.envsoft.2014.12.005>
- Harding, S., McComiskie, R., Wolff, M., Trewin, D., & Hunter, S. (2014). *State of the tropics 2014*. James Cook University. Retrieved from <https://www.jcu.edu.au/state-of-the-tropics/publications/2014/2014-report/State-of-the-Tropics-2014-Full-Report.pdf>
- Harrison, P. A., Dunford, R. W., Holman, I. P., & Rounsevell, M. D. A. (2016). Climate change impact modelling needs to include cross-sectoral interactions. *Nature Climate Change*, 6(9), 885–890. <https://doi.org/10.1038/nclimate3039>
- Harrison, P. A., Hauck, J., Austrheim, G., Brotons, L., Cantele, M., Claudet, J., & Turok, J. (2018). Chapter 5: Current and future interactions between nature and society. In M. Rounsevell, M. Fischer, A. Torre-Marín Rando, & A. Mader (Eds.), *The IPBES regional assessment report on biodiversity and ecosystem services for Europe and Central Asia* (pp. 571–658). IPBES Secretariat.
- Hekkala, A.-M., & Roberge, J.-M. (2018). The use of response measures in meta-analyses of land-use impacts on ecological communities: A review and the way forward. *Biodiversity and Conservation*, 27(11), 2989–3005. <https://doi.org/10.1007/s10531-018-1583-1>
- Hermans-Neumann, K., Priess, J., & Herold, M. (2017). Human migration, climate variability, and land degradation: Hotspots of socio-ecological pressure in Ethiopia. *Regional Environmental Change*, 17(5), 1479–1492. <https://doi.org/10.1007/s10113-017-1108-6>
- Herrero-Jáuregui, C., Arnaiz-Schmitz, C., Reyes, M., Telesnicki, M., Agramonte, I., Easdale, M., Schmitz, M., Aguiar, M., Gómez-Sal, A., & Montes, C. (2018). What do we talk about when we talk about social-ecological systems? A literature review. *Sustainability*, 10(8), 2950. <https://doi.org/10.3390/su10082950>
- Holman, I. P., Brown, C., Carter, T. R., Harrison, P. A., & Rounsevell, M. (2018). Improving the representation of adaptation in climate change impact models. *Regional Environmental Change*, 19(3), 711–721. <https://doi.org/10.1007/s10113-018-1328-4>
- Holt, R. D., & Gaines, M. S. (1992). Analysis of adaptation in heterogeneous landscapes: Implications for the evolution of fundamental niches. *Evolutionary Ecology*, 6(5), 433–447. <https://doi.org/10.1007/BF02270702>
- Holtz, G., Alkemade, F., de Haan, F., Köhler, J., Trutnevyte, E., Luthe, T., Halbe, J., Papachristos, G., Chappin, E., Kwakkel, J., & Ruutu, S. (2015). Prospects of modelling societal transitions: Position paper of an emerging community. *Environmental Innovation and Societal Transitions*, 17, 41–58. <https://doi.org/10.1016/J.EIST.2015.05.006>
- Holzhauser, S., Brown, C., & Rounsevell, M. (2019). Modelling dynamic effects of multi-scale institutions on land use change. *Regional Environmental Change*, 19(3), 733–746. <https://doi.org/10.1007/s10113-018-1424-5>
- Horvitz, N., Wang, R., Wan, F.-H., & Nathan, R. (2017). Pervasive human-mediated large-scale invasion: Analysis of spread patterns and their underlying mechanisms in 17 of China's worst invasive plants. *Journal of Ecology*, 105(1), 85–94. <https://doi.org/10.1111/1365-2745.12692>

- Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q. B., Mack, G., Meyfroidt, P., Millington, J., Müller, B., Polhill, J. G., Sun, Z., Seidl, R., Troost, C., & Finger, R. (2018). Representation of decision-making in European agricultural agent-based models. *Agricultural Systems*, 167, 143–160. <https://doi.org/10.1016/J.AGSY.2018.09.007>
- Huet, S., Rigolot, C., Xu, Q., De Cacqueray-Valmenier, Y., & Boisdon, I. (2018). Toward modelling of transformational change processes in farm decision-making. *Agricultural Sciences*, 09(03), 340–350. <https://doi.org/10.4236/as.2018.93024>
- Hunka, A. D., Meli, M., Thit, A., Palmqvist, A., Thorbek, P., & Forbes, V. E. (2013). Stakeholders' perspective on ecological modeling in environmental risk assessment of pesticides: Challenges and opportunities. *Risk Analysis*, 33(1), 68–79. <https://doi.org/10.1111/j.1539-6924.2012.01835.x>
- Ibáñez, I., Diez, J. M., Miller, L. P., Olden, J. D., Sorte, C. J. B., Blumenthal, D. M., Bradley, B. A., D'Antonio, C. M., Dukes, J. S., Early, R. I., Grosholz, E. D., & Lawler, J. J. (2013). Integrated Assessment of Biological Invasions. *Ecological Applications*, 24(1), 25–37. <https://doi.org/10.1890/13-0776.1>
- IPBES. (2019). *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services* (E. S. Brondizio, J. Settele, S. Díaz, & H. T. Ngo [Eds.]). IPBES Secretariat. https://doi.org/10.1007/978-3-319-99244-0_2
- Iwamura, T., Lambin, E. F., Silvius, K. M., Luzar, J. B., & Fragoso, J. M. V. (2014). Agent-based modeling of hunting and subsistence agriculture on indigenous lands: Understanding interactions between social and ecological systems. *Environmental Modelling & Software*, 58, 109–127. <https://doi.org/10.1016/J.ENVSOF.2014.03.008>
- IWDB. (2016). *Interaction Web DataBase*. Retrieved from <https://www.nceas.ucsb.edu/interactionweb/>
- Janssen, M. A., Anderies, J. M., & Ostrom, E. (2007). Robustness of social-ecological systems to spatial and temporal variability. *Society & Natural Resources*, 20(4), 307–322. <https://doi.org/10.1080/08941920601161320>
- Janssen, M. A., & Hill, K. (2014). Benefits of grouping and cooperative hunting among ache hunter-gatherers: insights from an agent-based foraging model. *Human Ecology*, 42(6), 823–835. <https://doi.org/10.1007/s10745-014-9693-1>
- Janssen, M. A., & Hill, K. (2016). An agent-based model of resource distribution on hunter-gatherer foraging strategies: Clumped habitats favour lower mobility, but result in higher foraging returns. In J. Barceló & F. Del Castillo (Eds.), *Simulating Prehistoric and Ancient Worlds*, Computational Social Sciences. Springer. https://doi.org/10.1007/978-3-319-31481-5_3
- Jedd, T., & Bixler, R. P. (2015). Accountability in networked governance: Learning from a case of landscape-scale forest conservation. *Environmental Policy and Governance*, 25(3), 172–187. <https://doi.org/10.1002/eet.1670>
- Jenouvrier, S., Caswell, H., Barbraud, C., Holland, M., Stroeve, J., & Weimerskirch, H. (2009). Demographic models and IPCC climate projections predict the decline of an emperor penguin population. *Proceedings of the National Academy of Sciences of the United States of America*, 106(6), 1844–1847. <https://doi.org/10.1073/pnas.0806638106>
- Jönsson, A. M., Anderbrant, O., Holmér, J., Johansson, J., Schurgers, G., Svensson, G. P., & Smith, H. G. (2015). Enhanced science-stakeholder communication to improve ecosystem model performances for climate change impact assessments. *Ambio*, 44(3), 249–255. <https://doi.org/10.1007/s13280-014-0553-4>
- Juhola, S. (2016). Barriers to the implementation of climate change adaptation in land use planning. *International Journal of Climate Change Strategies and Management*, 8(3), 338–355. <https://doi.org/10.1108/IJCCSM-03-2014-0030>
- Kannan, R., Shackleton, C. M., & Shaanker, R. U. (2014). Invasive alien species as drivers in socio-ecological systems: Local adaptations towards use of Lantana in Southern India. *Environment, Development and Sustainability*, 16(3), 649–669. <https://doi.org/10.1007/s10668-013-9500-y>
- Kattge, J., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Bönsch, G., Garnier, E., Westoby, M., Reich, P. B., Wright, I. J., Cornelissen, J. H. C., Violle, C., Harrison, S. P., Van BODEGOM, P. M., Reichstein, M., Enquist, B. J., Soudzilovskaia, N. A., Ackerly, D. D., Anand, M., ... Wirth, C. (2011). TRY - A global database of plant traits. *Global Change Biology*, 17(9), 2905–2935. <https://doi.org/10.1111/j.1365-2486.2011.02451.x>
- Kelly, C., Ferrara, A., Wilson, G. A., Ripullone, F., Nolè, A., Harmer, N., & Salvati, L. (2015). Community resilience and land degradation in forest and shrubland socio-ecological systems: Evidence from Gorgoglione, Basilicata, Italy. *Land Use Policy*, 46, 11–20. <https://doi.org/10.1016/J.LANDUSEPOL.2015.01.026>
- Kindsvater, H. K., Dulvy, N. K., Horswill, C., Juan-Jordá, M.-J., Mangel, M., & Matthiopoulos, J. (2018). Overcoming the data crisis in biodiversity conservation. *Trends in Ecology & Evolution*, 33(9), 676–688. <https://doi.org/10.1016/J.TREE.2018.06.004>
- Klarenberg, G., Muñoz-Carpena, R., Perz, S., Baraloto, C., Marsik, M., Southworth, J., & Zhu, L. (2019). A spatiotemporal natural-human database to evaluate road development impacts in an Amazon tri-national frontier. *Scientific Data*, 6(1), 93. <https://doi.org/10.1038/s41597-019-0093-7>
- Krausmann, F., Schandl, H., & Siefert, R. P. (2008). Socio-ecological regime transitions in Austria and the United Kingdom. *Ecological Economics*, 65(1), 187–201. <https://doi.org/10.1016/J.ECOLECON.2007.06.009>
- Lade, S. J., Tavoni, A., Levin, S. A., & Schlüter, M. (2013). Regime shifts in a social-ecological system. *Theoretical Ecology*, 6(3), 359–372. <https://doi.org/10.1007/s12080-013-0187-3>
- Laurance, W. F., Camargo, J. L. C., Luizão, R. C. C., Laurance, S. G., Pimm, S. L., Bruna, E. M., Stouffer, P. C., Bruce Williamson, G., Benítez-Malvido, J., Vasconcelos, H. L., Van Houtan, K. S., Zartman, C. E., Boyle, S. A., Didham, R. K., Andrade, A., & Lovejoy, T. E. (2011, January 1). The fate of Amazonian forest fragments: A 32-year investigation. *Biological Conservation*, 144(1), 56–67. <https://doi.org/10.1016/j.biocon.2010.09.021>
- Lawton, J. H. (1999). Are there general laws in ecology? *Oikos*, 84(2), 177–192.
- Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, F., Jennings, N., Krisztin, T., ... Young, L. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. *Nature*, 585(7826), 551–556. <http://dx.doi.org/10.1038/s41586-020-2705-y>
- Leroux, S. J., Larrivé, M., Boucher-Lalonde, V., Hurford, A., Zuloaga, J., Kerr, J. T., & Lutscher, F. (2013). Mechanistic models for the spatial spread of species under climate change. *Ecological Applications*, 23(4), 815–828. <https://doi.org/10.1890/12-1407.1>
- Leskovec, J., & Krevl, A. (2014). *SNAP datasets (Stanford Large Network Dataset Collection)*. Retrieved from <http://snap.stanford.edu/data>
- Levine, J. M., Bascompte, J., Adler, P. B., & Allesina, S. (2017). Beyond pairwise mechanisms of species coexistence in complex communities. *Nature*, 546(7656), 56–64. <https://doi.org/10.1038/nature22898>
- Levy, S. (2011, November 10). The pollinator crisis: What's best for bees. *Nature*, 479, 164–165. <https://doi.org/10.1038/479164a>
- Li, X., Chen, G., Liu, X., Liang, X., Wang, S., Chen, Y., Pei, F., & Xu, X. (2017). A new global land-use and land-cover change product at a 1-km resolution for 2010 to 2100 based on human-environment interactions. *Annals of the American Association of Geographers*, 107(5), 1040–1059. <https://doi.org/10.1080/24694452.2017.1303357>

- Lippe, M., Bithell, M., Gotts, N., Natalini, D., Barbrook-Johnson, P., Giupponi, C., Hallier, M., Hofstede, G. J., Le Page, C., Matthews, R. B., Schlüter, M., Smith, P., Teglio, A., & 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>
- Lovejoy, T. E., & Nobre, C. (2018). Amazon tipping point. *Science Advances*, 4(2), eaat2340. <https://doi.org/10.1126/sciadv.aat2340>
- Magliocca, N. R., Ellis, E. C., Allington, G. R. H., de Bremond, A., Dell'Angelo, J., Mertz, O., Messerli, P., Meyfroidt, P., Seppelt, R., & Verburg, P. H. (2018). Closing global knowledge gaps: Producing generalized knowledge from case studies of social-ecological systems. *Global Environmental Change*, 50, 1–14. <https://doi.org/10.1016/j.gloenvcha.2018.03.003>
- Maguire, K. C., Nieto-Lugilde, D., Fitzpatrick, M. C., Williams, J. W., & Blois, J. L. (2015). Modeling species and community responses to past, present, and future episodes of climatic and ecological change. *Annual Review of Ecology, Evolution, and Systematics*, 46(1), 343–368. <https://doi.org/10.1146/annurev-ecolsys-112414-054441>
- Malek, Ž., Douw, B., Van Vliet, J., Van Der Zanden, E. H., & Verburg, P. H. (2019). Local land-use decision-making in a global context. *Environmental Research Letters*, 14(8), 083006. <https://doi.org/10.1088/1748-9326/ab309e>
- Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S., Matthews, J. B. R., Chen, Y., Zhou, X., Gomis, M. I., Lonnoy, E., Maycock, T., Tignor, M., & Waterfield, T. (2018). *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*. Retrieved from <https://www.ipcc.ch/sr15/>
- McLeman, R., & Smit, B. (2006). Migration as an adaptation to climate change. *Climatic Change*, 76(1–2), 31–53. <https://doi.org/10.1007/s10584-005-9000-7>
- Merilä, J., & Hendry, A. P. (2014). Climate change, adaptation, and phenotypic plasticity: The problem and the evidence. *Evolutionary Applications*, 7(1), 1–14. <https://doi.org/10.1111/eva.12137>
- Meyfroidt, P. (2012). Environmental cognitions, land change, and social-ecological feedbacks: An overview. *Journal of Land Use Science*, 8(3), 341–367. <https://doi.org/10.1080/1747423X.2012.667452>
- Meyfroidt, P., Roy Chowdhury, R., de Bremond, A., Ellis, E. C., Erb, K.-H., Filatova, T., Garrett, R. D., Grove, J. M., Heinimann, A., Kuemmerle, T., Kull, C. A., Lambin, E. F., Landon, Y., le Polain de Waroux, Y., Messerli, P., Müller, D., Nielsen, J. Ø., Peterson, G. D., Rodríguez García, V., ... Verburg, P. H. (2018). Middle-range theories of land system change. *Global Environmental Change*, 53, 52–67. <https://doi.org/10.1016/J.GLOENVCHA.2018.08.006>
- Millington, J. D. A., & Wainwright, J. (2017). Mixed qualitative-simulation methods: Understanding geography through thick and thin. *Progress in Human Geography*, 41(1), 68–88. <https://doi.org/10.1177/0309132515627021>
- Montañola-Sales, C., Onggo, B. S. S., Casanovas-Garcia, J., Cela-Espín, J. M., & Kaplan-Marcusán, A. (2016). Approaching parallel computing to simulating population dynamics in demography. *Parallel Computing*, 59, 151–170. <https://doi.org/10.1016/J.PARCO.2016.07.001>
- Müller-Hansen, F., Schlüter, M., Mäs, M., Donges, J. F., Kolb, J. J., Thonicke, K., & Heitzig, J. (2017). Towards representing human behavior and decision making in Earth system models – An overview of techniques and approaches. *Earth System Dynamics*, 8(4), 977–1007. <https://doi.org/10.5194/esd-8-977-2017>
- Naugle, A. B., Backus, G. A., Tidwell, V. C., Kistin-Keller, E., & Villa, D. L. (2018). A regional model of climate change and human migration. *International Journal of System Dynamics Applications*, 8(1), 1–22. <https://doi.org/10.4018/ijds.a.2019010101>
- Nepstad, D., Mcgrath, D. G., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., Seroa, R., da Motta, E., Armijo, L. C., Brando, P., Hansen, M. C., McGrath-Horn, M., Carvalho, O., & Hess, L. (2014). Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. *Science*, 344(118), 1118–1123.
- New Climate Institute. (2019). *Climate policy database – NewClimate Institute*. Retrieved from <https://newclimate.org/portfolio/climate-policy-database/>
- Newbold, T. (2019). The trouble with trade. *Nature Ecology & Evolution*, 3(4), 522–523. <https://doi.org/10.1038/s41559-019-0816-3>
- Nicholson, E., Fulton, E. A., Brooks, T. M., Blanchard, R., Leadley, P., Metzger, J. P., Mokany, K., Stevenson, S., Wintle, B. A., Woolley, S. N. C., Barnes, M., Watson, J. E. M., & Ferrier, S. (2019). Scenarios and models to support global conservation targets. *Trends in Ecology & Evolution*, 34(1), 57–68. <https://doi.org/10.1016/J.TREE.2018.10.006>
- OECD. (2019). *Environmental policy tools and evaluation – OECD*. Retrieved from <http://www.oecd.org/environment/tools-evaluation/>
- Oliveira, L. J. C., Costa, M. H., Soares-Filho, B. S., & Coe, M. T. (2013). Large-scale expansion of agriculture in Amazonia may be a no-win scenario. *Environmental Research Letters*, 8(2), 024021. <https://doi.org/10.1088/1748-9326/8/2/024021>
- Oreskes, N., Shrader-Frechette, K., & Belitz, K. (1994). Verification, validation, and confirmation of numerical models in the Earth sciences. *Science (New York, NY)*, 263(5147), 641–646. <https://doi.org/10.1126/science.263.5147.641>
- Page, S. E. (2014). Where diversity comes from and why it matters? *European Journal of Social Psychology*, 44(4), 267–279. <https://doi.org/10.1002/ejsp.2016>
- Parker, D. C., Entwisle, B., Rindfuss, R. R., Vanwey, L. K., Manson, S. M., Moran, E., An, L. I., Deadman, P., Evans, T. P., Linderman, M., Mussavi Rizi, S. M., & Malanson, G. (2008). Case studies, cross-site comparisons, and the challenge of generalization: Comparing agent-based models of land-use change in frontier regions. *Journal of Land Use Science*, 3(1), 41–72. <https://doi.org/10.1080/17474230802048151>
- Parrott, L. (2011). Hybrid modelling of complex ecological systems for decision support: Recent successes and future perspectives. *Ecological Informatics*, 6(1), 44–49. <https://doi.org/10.1016/J.ECOINF.2010.07.001>
- Parrott, L. (2017). The modelling spiral for solving ‘wicked’ environmental problems: Guidance for stakeholder involvement and collaborative model development. *Methods in Ecology and Evolution*, 8(8), 1005–1011. <https://doi.org/10.1111/2041-210X.12757>
- Pearson, R. G., Stanton, J. C., Shoemaker, K. T., Aiello-Lammens, M. E., Ersts, P. J., Horning, N., Fordham, D. A., Raxworthy, C. J., Ryu, H. Y., McNeese, J., & Akçakaya, H. R. (2014). Life history and spatial traits predict extinction risk due to climate change. *Nature Climate Change*, 4(3), 217–221. <https://doi.org/10.1038/nclimate2113>
- Pelini, S. L., Keppel, J. A., Kelley, A. E., & Hellmann, J. J. (2010). Adaptation to host plants may prevent rapid insect responses to climate change. *Global Change Biology*, 16(11), 2923–2929. <https://doi.org/10.1111/j.1365-2486.2010.02177.x>
- Pinho, P. F., Marengo, J. A., & Smith, M. S. (2015). Complex socio-ecological dynamics driven by extreme events in the Amazon. *Regional Environmental Change*, 15(4), 643–655. <https://doi.org/10.1007/s10113-014-0659-z>
- Pongratz, J., Dolman, H., Don, A., Erb, K.-H., Fuchs, R., Herold, M., Jones, C., Kuemmerle, T., Luyssaert, S., Meyfroidt, P., & Naudts, K. (2018). Models meet data: Challenges and opportunities in implementing land management in Earth system models. *Global Change Biology*, 24(4), 1470–1487. <https://doi.org/10.1111/gcb.13988>
- Preston, B., Dow, K., & Berkhout, F. (2013). The climate adaptation frontier. *Sustainability*, 5(3), 1011–1035. <https://doi.org/10.3390/su5031011>
- Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral,

- economic, and environmental factors. *Environmental Modelling & Software*, 70, 163–177. <https://doi.org/10.1016/j.envsoft.2015.04.014>
- Rapacciuolo, G., & Blois, J. L. (2019). Understanding ecological change across large spatial, temporal and taxonomic scales: Integrating data and methods in light of theory. *Ecography*, ecog.04616. <https://doi.org/10.1111/ecog.04616>
- Richerson, P. J., & Boyd, R. (2020). The human life history is adapted to exploit the adaptive advantages of culture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 375(1803), 20190498. <https://doi.org/10.1098/rstb.2019.0498>
- Ripple, W. J., Wolf, C., Newsome, T. M., Barnard, P., & Moomaw, W. R. (2020). World scientists' warning of a climate emergency. *BioScience*, 70(1), 8–12. <https://doi.org/10.1093/biosci/biz152>
- Robinson, D. T., Di Vittorio, A., Alexander, P., Arneth, A., Barton, C. M., Brown, D. G., Kettner, A., Lemmen, C., O'Neill, B. C., Janssen, M., Pugh, T. A. M., Rabin, S. S., Rounsevell, M., Syvitski, J. P., Ullah, I., & Verburg, P. H. (2018). Modelling feedbacks between human and natural processes in the land system. *Earth System Dynamics*, 9(2), 895–914. <https://doi.org/10.5194/esd-9-895-2018>
- Rocha, J. C., Baraibar, M. M., Deutsch, L., de Bremond, A., Oestreicher, J. S., Rositano, F., & Gelabert, C. C. (2019). Toward understanding the dynamics of land change in Latin America: Potential utility of a resilience approach for building archetypes of land-systems change. *Ecology and Society*, 24(1), art17. <https://doi.org/10.5751/ES-10349-240117>
- Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Séférian, R., & Vilariño, M. V. (2018). Mitigation pathways compatible with 1.5°C in the context of sustainable development. In V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, P. R. Skea, J. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, & T. Waterfield (Eds.), *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change* (p. 82). IPCC Secretariat.
- Romagnoni, G., Mackinson, S., Hong, J., & Eikeset, A. M. (2015). The Ecospace model applied to the North Sea: Evaluating spatial predictions with fish biomass and fishing effort data. *Ecological Modelling*, 300, 50–60. <https://doi.org/10.1016/j.ecolmodel.2014.12.016>
- Romero-Mujalli, D., Jeltsch, F., & Tiedemann, R. (2019). Individual-based modeling of eco-evolutionary dynamics: State of the art and future directions. *Regional Environmental Change*, 19(1), 1–12. <https://doi.org/10.1007/s10113-018-1406-7>
- Rosa, I. M. D., Ahmed, S. E., & Ewers, R. M. (2014). The transparency, reliability and utility of tropical rainforest land-use and land-cover change models. *Global Change Biology*, 20(6), 1707–1722. <https://doi.org/10.1111/gcb.12523>
- Sala, O. E. (2000). Global biodiversity scenarios for the year 2100. *Science*, 287(5459), 1770–1774. <https://doi.org/10.1126/science.287.5459.1770>
- Salganik, M. J., Lundberg, I., Kindel, A. T., Ahearn, C. E., Al-Ghoneim, K., Almaatouq, A., Altschul, D. M., Brand, J. E., Carnegie, N. B., Compton, R. J., Datta, D., Davidson, T., Filippova, A., Gilroy, C., Goode, B. J., Jahani, E., Kashyap, R., Kirchner, A., McKay, S., ... McLanahan, S. (2020). Measuring the predictability of life outcomes with a scientific mass collaboration. *Proceedings of the National Academy of Sciences of the United States of America*, 117(15), 201915006. <https://doi.org/10.1073/pnas.1915006117>
- Sarjoughian, H. S., Mayer, G. R., Ullah, I. I., & Barton, C. M. (2015). Managing hybrid model composition complexity: Human-environment simulation models. In L. Yilmaz (Ed.), *Concepts and Methodologies for Modeling and Simulation*, Simulation Foundations, Methods and Applications. Springer. https://doi.org/10.1007/978-3-319-15096-3_6
- Scheffers, B. R., De Meester, L., Bridge, T. C. L., Hoffmann, A. A., Pandolfi, J. M., Corlett, R. T., Butchart, S. H. M., Pearce-Kelly, P., Kovacs, K. M., Dudgeon, D., Pacifici, M., Rondinini, C., Foden, W. B., Martin, T. G., Mora, C., Bickford, D., & Watson, J. E. M. (2016). The broad footprint of climate change from genes to biomes to people. *Science*, 354(6313), aaf7671. <https://doi.org/10.1126/science.aaf7671>
- Schlüter, M., Haider, L. J., Lade, S. J., Lindkvist, E., Martin, R., Orach, K., Wijermans, N., & Folke, C. (2019). Capturing emergent phenomena in social-ecological systems: An analytical framework. *Ecology and Society*, 24(3), art11. <https://doi.org/10.5751/ES-11012-240311>
- Schlüter, M., Müller, B., & Frank, K. (2019). The potential of models and modeling for social-ecological systems research: The reference frame ModSES. *Ecology and Society*, 24(1). <https://doi.org/10.5751/ES-10716-240131>
- 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), 8. <https://doi.org/10.18564/jasss.3423>
- Schwartzman, S., Moreira, A., & Nepstad, D. (2000, October 18). Rethinking tropical forest conservation: Perils in parks. *Conservation Biology*, 14(5), 1351–1357. <https://doi.org/10.1046/j.1523-1739.2000.99329.x>
- Schweiger, O., Settele, J., Kudrna, O., Klotz, S., & Kühn, I. (2008). Climate change can cause spatial mismatch of trophically interacting species. *Ecology*, 89(12), 3472–3479. <https://doi.org/10.1890/07-1748.1>
- Scown, M. W., Winkler, K. J., & Nicholas, K. A. (2019). Aligning research with policy and practice for sustainable agricultural land systems in Europe. *Proceedings of the National Academy of Sciences of the United States of America*, 116(11), 4911–4916. <https://doi.org/10.1073/pnas.1812100116>
- Sist, P., Rutishauser, E., Peña-Claros, M., Shenkin, A., Hérault, B., Blanc, L., Baraloto, C., Baya, F., Benedet, F., da Silva, K. E., Descroix, L., Ferreira, J. N., Gourlet-Fleury, S., Guedes, M. C., Bin Harun, I., Jalonen, R., Kanashiro, M., Krisnawati, H., Kshatriya, M., ... Yamada, T. (2015). The tropical managed forests observatory: A research network addressing the future of tropical logged forests. *Applied Vegetation Science*, 18(1), 171–174. <https://doi.org/10.1111/avsc.12125>
- Spies, T. A., Giesen, T. W., Swanson, F. J., Franklin, J. F., Lach, D., & Johnson, K. N. (2010). Climate change adaptation strategies for federal forests of the Pacific Northwest, USA: Ecological, policy, and socio-economic perspectives. *Landscape Ecology*, 25(8), 1185–1199. <https://doi.org/10.1007/s10980-010-9483-0>
- Srinivasan, V., Lambin, E. F., Gorelick, S. M., Thompson, B. H., & Rozelle, S. (2012). The nature and causes of the global water crisis: Syndromes from a meta-analysis of coupled human-water studies. *Water Resources Research*, 48(10). <https://doi.org/10.1029/2011WR011087>
- Steel, D. (2007). *Across the boundaries: Extrapolation in biology and social science*. Oxford University Press. https://books.google.de/books?hl=en&lr=&id=oldZhf7DuggC&oi=fnd&pg=PR9&dq=pattern+based+extrapolation+social+systems&ots=94-iYes-PI&sig=Nm_l8i6dQuzvfEoysHKWGO9ty8
- Stehfest, E., van Zeist, W.-J., Valin, H., Havlik, P., Popp, A., Kyle, P., Tabeau, A., Mason-D'Croz, D., Hasegawa, T., Bodirsky, B. L., Calvin, K., Doelman, J. C., Fujimori, S., Humpenöder, F., Lotze-Campen, H., van Meijl, H., & Wiebe, K. (2019). Key determinants of global land-use projections. *Nature Communications*, 10(1), 2166. <https://doi.org/10.1038/s41467-019-09945-w>
- Stelzenmüller, V., Lee, J., Garnacho, E., & Rogers, S. I. (2010). Assessment of a Bayesian Belief Network-GIS framework as a practical tool to support marine planning. *Marine Pollution Bulletin*, 60(10), 1743–1754. <https://doi.org/10.1016/j.marpolbul.2010.06.024>
- Stern, P. C., Kalof, L., Dietz, T., & Guagnano, G. A. (1995). Values, beliefs, and proenvironmental action: Attitude formation toward emergent

- attitude objects. *Journal of Applied Social Psychology*, 25(18), 1611–1636. <https://doi.org/10.1111/j.1559-1816.1995.tb02636.x>
- Sun, Z., & Müller, D. (2013). A framework for modeling payments for ecosystem services with agent-based models, Bayesian belief networks and opinion dynamics models. *Environmental Modelling & Software*, 45, 15–28. <https://doi.org/10.1016/J.ENVSOFT.2012.06.007>
- Synes, N. W., Brown, C., Palmer, S. C. F., Bocedi, G., Osborne, P. E., Watts, K., Franklin, J., & Travis, J. M. J. (2019). Coupled land use and ecological models reveal emergence and feedbacks in socio-ecological systems. *Ecography*, 42(4), 814–825. <https://doi.org/10.1111/ecog.04039>
- Tadesse, G., Zavaleta, E., Shennan, C., & FitzSimmons, M. (2014). Policy and demographic factors shape deforestation patterns and socio-ecological processes in southwest Ethiopian coffee agroecosystems. *Applied Geography*, 54, 149–159. <https://doi.org/10.1016/J.APGEOG.2014.08.001>
- Taubert, F., Fischer, R., Groeneveld, J., Lehmann, S., Müller, M. S., Rödig, E., Wiegand, T., & Huth, A. (2018). Global patterns of tropical forest fragmentation. *Nature*, 554(7693), 519–522. <https://doi.org/10.1038/nature25508>
- Travis, J. M. J., Delgado, M., Bocedi, G., Baguette, M., Bartoň, K., Bonte, D., Boulangeat, I., Hodgson, J. A., Kubisch, A., Penteriani, V., Saastamoinen, M., Stevens, V. M., & Bullock, J. M. (2013). Dispersal and species' responses to climate change. *Oikos*, 122(11), 1532–1540. <https://doi.org/10.1111/j.1600-0706.2013.00399.x>
- Ullah, I. (2013). *The consequences of human landuse strategies during the PPNB-LN transition: A simulation modeling approach*. Arizona State University.
- United Nations. (2019). *The climate crisis – A race we can win*. Retrieved from <https://www.un.org/en/un75/climate-crisis-race-we-can-win>
- United Nations Statistics Division. (2019). *UNSD – Demographic and social statistics*. Retrieved from <https://unstats.un.org/unsd/demographic-social/products/>
- Urban, M. C. (2015). Climate change. Accelerating extinction risk from climate change. *Science (New York, NY)*, 348(6234), 571–573. <https://doi.org/10.1126/science.aaa4984>
- Urban, M. C. (2019). Projecting biological impacts from climate change like a climate scientist. *Wiley Interdisciplinary Reviews: Climate Change*, e585. <https://doi.org/10.1002/wcc.585>
- Urban, M. C., Bocedi, G., Hendry, A. P., Mihoub, J.-B., Peer, G., Singer, A., Bridle, J. R., Crozier, L. G., De Meester, L., Godsoe, W., Gonzalez, A., Hellmann, J. J., Holt, R. D., Huth, A., Johst, K., Krug, C. B., Leadley, P. W., Palmer, S. C. F., Pantel, J. H., ... Travis, J. M. J. (2016). Improving the forecast for biodiversity under climate change. *Science*, 353(6304), aad8466. <https://doi.org/10.1126/SCIENCE.AAD8466>
- Urban, M. C., Tewksbury, J. J., & Sheldon, K. S. (2012). On a collision course: Competition and dispersal differences create no-analogue communities and cause extinctions during climate change. *Proceedings of the Royal Society B: Biological Sciences*, 279(1735), 2072–2080. <https://doi.org/10.1098/rspb.2011.2367>
- Václavík, T., Lautenbach, S., Kuemmerle, T., & Seppelt, R. (2013). Mapping global land system archetypes. *Global Environmental Change*, 23(6), 1637–1647. <https://doi.org/10.1016/J.GLOENVCHA.2013.09.004>
- van Vliet, J., de Groot, H. L. F., Rietveld, P., & Verburg, P. H. (2015). Manifestations and underlying drivers of agricultural land use change in Europe. *Landscape and Urban Planning*, 133, 24–36. <https://doi.org/10.1016/J.LANDURBPLAN.2014.09.001>
- Vellend, M. (2010). Conceptual synthesis in community ecology. *The Quarterly Review of Biology*, 85(2), 183–206. <https://doi.org/10.1086/652373>
- Verburg, P. H., Alexander, P., Evans, T., Magliocca, N. R., Malek, Z., Rounsevell, M. D. A., & van Vliet, J. (2019, June 1). Beyond land cover change: Towards a new generation of land use models. *Current Opinion in Environmental Sustainability*, 38, 77–85. <https://doi.org/10.1016/j.cosust.2019.05.002>
- Vulturius, G., André, K., Swartling, Å. G., Brown, C., Rounsevell, M. D. A., & Blanco, V. (2018). The relative importance of subjective and structural factors for individual adaptation to climate change by forest owners in Sweden. *Regional Environmental Change*, 18(2). <https://doi.org/10.1007/s10113-017-1218-1>
- Warren, R. (2011). The role of interactions in a world implementing adaptation and mitigation solutions to climate change. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 369(1934), 217–241. <https://doi.org/10.1098/rsta.2010.0271>
- Watts, D. J. (2017). Should social science be more solution-oriented? *Nature Human Behaviour*, 1(1), 0015. <https://doi.org/10.1038/s41562-016-0015>
- Willcock, S., Martínez-López, J., Hooftman, D. A. P., Bagstad, K. J., Balbi, S., Marzo, A., Prato, C., Sciandrello, S., Signorello, G., Voigt, B., Villa, F., Bullock, J. M., & Athanasiadis, I. N. (2018). Machine learning for ecosystem services. *Ecosystem Services*, 33, 165–174. <https://doi.org/10.1016/j.ecoser.2018.04.004>
- Williams, G. J., Gove, J. M., Eynaud, Y., Zgliczynski, B. J., & Sandin, S. A. (2015). Local human impacts decouple natural biophysical relationships on Pacific coral reefs. *Ecography*, 38(8), 751–761. <https://doi.org/10.1111/ecog.01353>
- Wis, M. S., Pottier, J., Kissling, W. D., Pellissier, L., Lenoir, J., Damgaard, C. F., Dormann, C. F., Forchhammer, M. C., Grytnes, J.-A., Guisan, A., Heikkinen, R. K., Høye, T. T., Kühn, I., Luoto, M., Maiorano, L., Nilsson, M.-C., Normand, S., Öckinger, E., Schmidt, N. M., ... Svenning, J.-C. (2013). The role of biotic interactions in shaping distributions and realised assemblages of species: Implications for species distribution modelling. *Biological Reviews*, 88(1), 15–30. <https://doi.org/10.1111/j.1469-185X.2012.00235.x>
- Wolf, J. (2011). Climate change adaptation as a social process. In *Climate change adaptation in developed nations*. Springer. https://doi.org/10.1007/978-94-007-0567-8_2
- Xu, Z., Chau, S. N., Chen, X., Zhang, J., Li, Y., Dietz, T., Wang, J., Winkler, J. A., Fan, F., Huang, B., Li, S., Wu, S., Herzberger, A., Tang, Y., Hong, D., Li, Y., & Liu, J. (2020). Assessing progress towards sustainable development over space and time. *Nature*, 577(7788), 74–78. <https://doi.org/10.1038/s41586-019-1846-3>
- Young, O. R. (2010). Institutional dynamics: Resilience, vulnerability and adaptation in environmental and resource regimes. *Global Environmental Change*, 20(3), 378–385. <https://doi.org/10.1016/J.GLOENVCHA.2009.10.001>
- Yousefpour, R., Temperli, C., Jacobsen, J. B., Thorsen, B. J., Meilby, H., Lexer, M. J., Lindner, M., Bugmann, H., Borges, J. G., Palma, J. H. N., Ray, D., Zimmermann, N. E., Delzon, S., Kremer, A., Kramer, K., Reyer, C. P. O., Lasch-Born, P., Garcia-Gonzalo, J., & Hanewinkel, M. (2017). A framework for modeling adaptive forest management and decision making under climate change. *Ecology and Society*, 22(4), art40. <https://doi.org/10.5751/ES-09614-220440>
- Yusoff, K., & Gabrys, J. (2011). Climate change and the imagination. *Wiley Interdisciplinary Reviews: Climate Change*, 2(4), 516–534. <https://doi.org/10.1002/wcc.117>

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