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Incorporating human behaviour into Earth system modelling

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Climate change and other challenges to the stability and functioning of natural and managed environmental systems are driven by increasing anthropogenic domination of the Earth. Models to forecast the trajectory of climate change and to identify pathways to sustainability require representation of human behaviour and its feedbacks with the climate system. Social climate models (SCMs) are an emerging class of models that embed human behaviour in climate models. We survey existing SCMs and make recommendations for how to integrate models of human behaviour and climate. We suggest a framework for representing human behaviour that consists of cognition, contagion and a behavioural response. Cognition represents the human processing of information around climate change; contagion represents the spread of information, beliefs and behaviour through social networks; and response is the resultant behaviour or action. This framework allows for biases, habituation and other cognitive processes that shape human perception of climate change as well as the influence of social norms, social learning and other social processes on the spread of information and factors that shape decision-making and behaviour. SCMs move beyond the inclusion of human activities in climate models to the representation of human behaviour that determines the magnitude, sign and character of these activities. The development of SCMs is a challenging but important next step in the evolution of Earth system models.

The Earth is dominated by human activities that increasingly challenge the stability of environmental systems and their capacity to support modern civilization[1–3]. Anthropogenic perturbation of the Earth system risks irreversible change and abrupt shifts away from historical environmental states, with large implications for human welfare[3]. This is best evidenced by anthropogenic climate change but is also manifested in other environmental problems such as ocean acidification, the collapse of fisheries, the loss of biodiversity, the eutrophication of lakes and rivers and the accumulation of plastics in oceans. These environmental challenges involve diverse processes and scientific disciplines, ranging from atmospheric physics to fisheries biology, but they share a common element: human behaviour is a fundamental driver of the stress on natural and managed environmental systems and is essential to solving environmental problems[4,5].

Linking human behaviour with physical and biological systems is necessary to better understand the underlying drivers of environmental problems and to build a sustainable future. The models used to address environmental problems have largely focused on developing the physical and biological components, either incorporating the human system as an external driver outside the disciplinary boundaries that define the problem or not including human behaviour at all[6,7]. An increasing number of researchers have called for human behaviour to be integrated more fully into Earth system models, as humans are an essential and dynamic driver of the Earth system and respond

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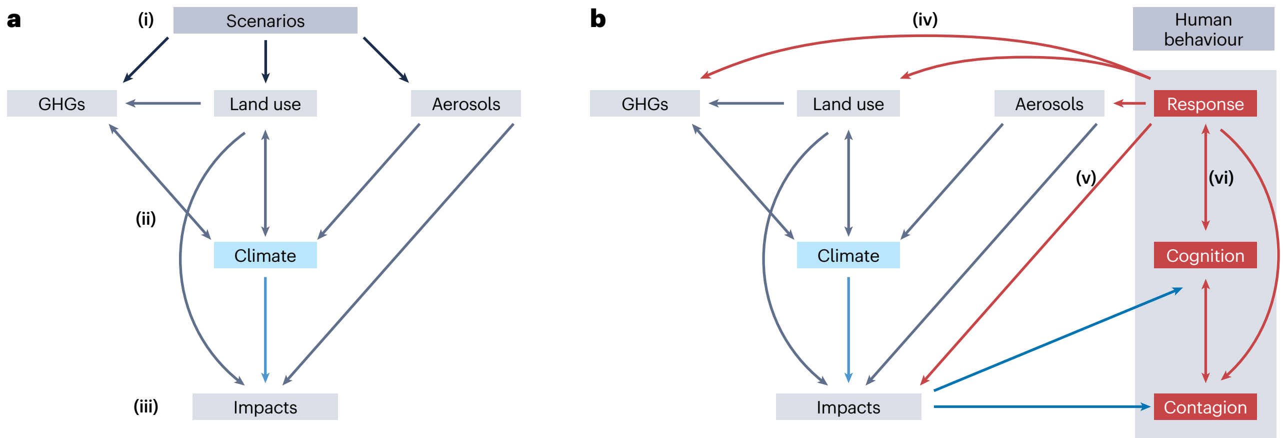

Fig. 1 | Traditional climate models and social climate models. a, Extrinsic scenarios for emissions, land use change and aerosols have traditionally been used to force global climate models. In this approach, a set of possible behavioural pathways are identified (i), and these trajectories determine anthropogenic forcing of climate (ii), mediated by feedbacks internal to the Earth system, to project climate change and impacts (iii). **b**, Coupling climate models with human behaviour allows the models to capture dynamic human responses to climate change that can improve projections of anthropogenic forcing (iv), better represent human adaptation to climate change for improved impact models (v) and characterize behavioural feedbacks that reinforce or balance human responses to climate change to identify points of high leverage for climate change mitigation (vi). Economic, political, and technical dynamics are embedded in the scenarios in **a** and in the behavioural response in **b**.

dynamically to changing environmental conditions in a fully coupled human–natural system[8–14]. In this manuscript, we discuss how to incorporate human behaviour into Earth system models broadly and climate models in particular.

A systems approach

The Earth is a complex system composed of coupled natural and human systems characterized by nonlinear feedbacks that challenge the skill of models and forecasts[10,14,15]. Abstracting the climate system from the human system rather than seeing them as inextricably interconnected leads to a reductionist approach, with model development largely confined to disciplinary boundaries[6]. Model development is then focused on, for example, elaborating the details of climate physics to better parameterize cloud formation in a climate model or the details of hydraulic conductivity to better model the flow of nitrogen in a watershed. Social scientists can be similarly siloed, with economists studying the costs of carbon, political scientists studying climate negotiations and policies, and psychologists studying individual perceptions of climate risks and pro-environmental behaviour adoption. This disciplinary approach improves the representation of individual system components but does not improve our understanding of the interactions and feedback between human and natural systems that underlie and drive unsustainable environmental behaviours. Advancing our understanding of system components has been emphasized over interactions and feedbacks between the climate and human systems[16]. A primary challenge in building the next generation of Earth system models is to fully capture the interactions between and within the human and climate systems, which includes representation of human behaviour.

Uncertainty

A concern around integrating human behaviour into Earth system models is that this could drastically increase the uncertainty of projections. Endogenizing human behaviour in models may increase predictive uncertainty in some cases because it requires the addition of model parameters with additional uncertainty, which is then integrated into model forecasts. But uncertainty may not necessarily increase for several reasons.

First, models that represent human behavioural responses to environmental change as extrinsic forcings will often attempt to bound the range of possibilities using extreme bounds. With respect to climate change, for example, the Intergovernmental Panel on Climate Change has projected climate change using Representative Concentration Pathways (RCPs); the upper RCP (8.5) now appears to be substantially higher than the likely emissions over the twenty-first century[17–19]. Incorporating validated models of human behaviour, grounded in theory, will probably provide tighter constraints on future forcings than choosing a set of extreme bounding cases to bracket all possibilities.

Second, human systems respond to environmental changes such that balancing feedbacks between the human and natural systems may reduce spread in forecasts. For example, as humans perceive increasing risk from climate change, they may work through political institutions or take personal actions to reduce greenhouse gas (GHG) emissions, constraining the magnitude of climate change[20,21]. Alternatively, if the perceived risk from climate change is low, then humans are less likely to incur the costs to transition to less carbon-intensive energy, increasing the magnitude of climate change. The net result is a reduction in uncertainty, as the likely Earth system trajectory is bounded away from the extremes of high or low climate change. Social ecological models have borne this out, suggesting that the likely range of emissions over the twenty-first century is substantially narrower than implied by the range of Shared Socio-economic Pathway and RCP scenarios[21,22], a finding corresponding to other recent studies using a range of approaches[19].

Third, human behavioural uncertainty may decrease with increasing scale of emergent social structure, such as moving from an individual to nations or to markets composed of large numbers of individuals. The potential reduction in human behavioural uncertainty at broader scales is analogous to statistical physics (that is, social physics)[23,24] or coarse graining[25–27].

Human behaviour and climate change

Anthropogenic emissions have emerged as the major forcing of the climate system over the past century, and the largest uncertainty in long-term climate forecasts is the trajectory of global emissions pathways. Projections of future climate change therefore require an understanding of the social, political, economic and technical dynamics that determine emissions pathways and climate change (Fig. 1)[28,29]. Similarly, a changing physical climate will not act on a passive and unresponsive population, but rather people will prepare for and respond to changing risk, subject to the information, resource, legal and other constraints they face[30]. Models of climate impacts depend sensitively on assumptions regarding the effectiveness and availability of adaptive adjustments. Examples include the effectiveness of coastal protection from sea-level rise[31], the role of border policy in enabling or restricting international migration in response to climate risk[32] and the ability of farmers to perceive and respond to changing weather conditions[33]. Forecasting and projecting the impacts of climate change therefore depend on modelling both the evolving climate risk and the adaptive responses of affected individuals and communities. Behavioural models are essential for understanding the responses of individuals, communities and institutions to perceived or anticipated climate change risk and for forecasting the impacts of climate change (Fig. 1).

Climate change models have traditionally been forced by externally prescribed emissions scenarios or storylines (Fig. 1a)[34–40]. Storylines or narrative scenarios, such as the Shared Socio-economic Pathways and RCPs, have been used to represent alternative possibilities for the evolution of human society, including the political and social responses to climate change[28,41]. While the scenario approach is valuable for its clarity in articulating assumptions and harmonizing inputs across climate models, there are drawbacks that limit its utility. First, storylines of future trajectories are not probabilistic in nature so that the uncertainty in climate forecasts is not represented, limiting their efficacy for planning for emerging climate risks[42,43]. Second, the scenario approach lacks dynamic feedback with the climate system. The socio-economic drivers of emissions and climate policy are likely to depend on experienced or perceived climate change and to emerge endogenously from the coupled human–climate system, but the scenario approach does not capture this dependence (Fig. 1a).

Much effort in climate modelling has focused on expanding and improving the representation of physical and biological feedbacks within climate models (Fig. 1a)[6,34–40]. Representing human behaviour in climate models to make emissions and other responses to climate change intrinsic to the models adds important feedback. Humans experience climate change through its biophysical effects (such as flooding or rising temperatures) that impact welfare, broadly defined, and respond through changes in GHG emissions, land use and aerosol production (Fig. 1b) and by implementing adaptation measures (Fig. 1b), which are each mediated by the economic, political and technical systems, that can mitigate their impacts[44,45]. And just as the climate system has internal feedbacks that mediate anthropogenic forcing, the human system has internal feedbacks that mediate both the impacts from and responses to climate change (Fig. 1b)—for example, shifting social norms, endogenous cost reduction and expressive force of law[21,46,47]. Coupling human behaviour with climate models will improve projections of both the anthropogenic drivers of climate change and climate change impacts on human systems.

Representing human behaviour in climate models requires (1) representation of the material and information exchanges between the human and climate systems, (2) determination of which components of human behaviour to include and how to model them, (3) the scale of social structure, and (4) the consideration of heterogeneity in human behaviour. We describe each of these components and discuss how they have been implemented in existing models that link human behaviour with the climate system, which we refer to as social climate models (SCMs), focusing on papers that have included two-way feedbacks between the human and climate systems.

There are other modelling considerations in addition to the four components we list above, such as the modelling framework to use (for example, agent-based, system dynamics or coupled component); model analyses to include calibration, validation and sensitivity; computational issues that arise with model components that operate at different spatial and temporal scales; and computational cost. We do not focus on these here as they have been considered elsewhere or are not specific to integrating human behaviour into climate models[12,48–51]. We also do not focus on the set of human activities that link the human and climate systems (for example, shifts in agriculture, water management and renewable energy adoption) but instead focus on how to represent human behaviour in the context of climate, which then determines the magnitude, sign and nature of interactions between the human and climate systems.

Exchanges between the human and climate systems

Integrating human behaviour into climate models requires an exchange of material and/or information between the human and climate systems. Humans receive information on the state of climate, process the information and respond with a behavioural change that determines the anthropogenic forcing of climate. The climate models used in SCMs have mostly been simplified models with projections of one to a few climate metrics, such as mean global temperature[21,52–54]. These simple climate models usually lack spatial resolution, but some SCMs have leveraged their output with that of full global change models to produce spatially explicit representations of climate change[55] or to represent the stochasticity of weather around climate trends[56]. Other SCMs have used empirical relationships to map the projections from simplified climate models to other climate metrics such as extreme events[20].

The use of simplified climate models is often necessary given the complexity of global change models and the computational costs and technical challenges associated with running them. Nevertheless, the use of single metrics such as global mean temperature is a coarse representation of the impact of climate on the human system. SCMs should strive towards a fuller representation of climate change impacts (for example, precipitation, flooding, droughts, sea-level rise, ocean acidification and windstorms) that shape human perception of climate change. Research could better constrain and guide the choice of climate metrics that most impact the human perception of climate change[57–59]; alternatively, human behavioural models could be integrated with global change models, which produce a spatial representation of a suite of climate metrics, as is the case for some human feedbacks in the integrated Earth system model[60]. The variability of climate impacts in both space and time is likely to interact with heterogeneity in human culture and demographics to mediate human behavioural responses, necessitating that SCMs move beyond spatially and temporally aggregated means.

SCMs have represented anthropogenic forcing of climate primarily through globally aggregated, annual emissions of GHGs, primarily CO_2 or CO_2 equivalent. Human forcing of climate includes emissions of a wide array of GHGs with different residence times and forcing strengths, land use changes that affect GHG fluxes as well as albedo, and emissions of aerosols[61,62]. Aerosols mitigate climate change through increases in albedo but can negatively impact human health through air pollution[63]. Anthropogenic forcing of climate is mediated through feedbacks internal to the climate system, such as temperature, precipitation and CO_2 fertilization effects on the terrestrial carbon sink[38], as well as through human behavioural responses, such as deforestation and other land use change. The ultimate goal of SCMs should be the representation of the set of anthropogenic forcings of climate and a spatially explicit characterization of climate impacts on human risk perception and behaviour.

Representing human behaviour

Human behaviour is complex, boundedly rational and challenging to represent[8]. A broad array of theories and frameworks for describing human behaviour have been proposed, representing diverse taxonomies and drivers of behaviour, with their own implicit assumptions and vocabulary, and few have been translated into quantitative or computational algorithms[12,49,64,65]. For example, 86 theories of human behaviour and response have been identified from diverse social science disciplines such as economics, psychology, political science, sociology, anthropology and law[65]. But much of the theory relevant

Table 1 | Framework for modelling human behaviour

	Human behaviour processes			
Cognition	Risk perception, risk aversion, decision-making, memory, foresight, cognitive biases (for example, biased assimilation and habituation)			
Contagion	Social learning, social norms, persuasion, strategic interactions, price transmission			
Social scale	**Individuals**	**Nations**	**International**	**Markets**
Behavioural response	Attitude change, policy support, behaviour adoption	Mitigation or adaptation policy	Treaty participation	Technology adoption, investment

We include examples of human cognition, contagion and behavioural response with respect to climate change that correspond to four social scales of emergence of human structure.

to modelling the social and human behavioural systems has not been translated into a quantitative modelling framework, and in many cases it has been developed in qualitative disciplines using case studies or comparative case study approaches. Many of the SCMs cited here have started this work, creating model implementations of contagion, cognition and response processes described qualitatively in the social sciences. Others have suggested frameworks for modelling other human behavioural processes[64,66]. However, more work is needed to compare implementations of human behavioural models, since even small changes in formulations of the same theory can often lead to large differences in model outcomes[7,67].

We propose a simple but broad framework for modelling human behaviour that can be used in climate models as well as for other environmental systems and that can incorporate factors from diverse theories of human behaviour while representing how humans receive, process and respond to information. We represent human behaviour through three components: cognition, contagion and response (Table 1). This framework is similar to the individual cognition and social interaction framework suggested for representing social dynamics in social–ecological systems[68].

Cognition refers to how humans process and interpret information to make decisions. Our definition includes perceptions of risks in the world around them, memory of past events, foresight into the future, and how these factors and other biases shape their thinking and decision-making[69]. Contagion represents the spread of information, beliefs or behaviours through social networks or other structures that define interactions between people and institutions. Our definition of contagion includes social learning, social norms and persuasion as well as higher-level processes such as strategic interactions between institutions or price transmission via markets sending information on relative scarcity[70]. Response represents the individual, national, international or market behaviour that results from the internal processing of information (cognition), the social influence or interactions between humans or institutions (contagion), and other external or situational factors that expand or restrict the behaviours. Our definition of response includes attitude change or behaviour and technology adoption, the passage of mitigation or adaptation policies as well as public support for policies, participation in international treaties, and financial investments in mitigation technologies or strategies. Modelling of responses should recognize the constraints faced by actors that limit the set of possible actions and how these constraints might evolve over time. Depending on the scale of modelling, these constraints might be budgetary, technological, legal or political. Different theories of human behaviour can be used to define cognition, contagion or the behavioural response.

Cognition. Some SCMs assume that humans have perfect knowledge of the state of the climate system, ignoring the role of uncertainties and human cognition in processing information on and perceptions of climate change. For example, some SCMs that consider economic responses to climate change assume a single social planner with full knowledge of the current and future climate, including effects on human welfare[71]. Similarly, other SCMs that incorporate contagion processes such as social learning or social norms base the human behavioural response on perfect information on mean global temperature[54]. Most actors in the human system do not experience climate change as average changes in global temperature but rather experience and respond to local weather conditions, which are composed of both anthropogenic forcing and natural variability in climate. Climate variability may be large[43,72], with potentially consequential implications for the experienced signal of anthropogenic climate change[56]. Additionally, cognitive processes can lead to biases in human perception of climate change. People more heavily weigh information that is consistent with their existing beliefs and social networks[73,74]. For example, if a person believes that climate change is an existential threat to humanity, then they are more likely to accept heatwaves as indicative of climate change and discount cold waves as counterfactual evidence. Similarly, humans more heavily weigh recent experiences and discount more distant experiences, leading to a shifting baseline of what is considered the climate normal (that is, habituation), which could lead to the downplaying of the actual extent of perceived climate change[21,75]. Foresight is another cognitive process that increases the urgency to act to mitigate climate change in anticipation (that is, forecasting) of continued climate change and the risk that it poses to human and natural systems[33,76].

Contagion. Many SCMs represent the collective responses of populations, which requires modelling how information, beliefs and behaviours spread—that is, contagion (Table 1). Humans receive information through their social networks, including information on how others are responding to climate change[77]. Even a small tendency of individuals to preferentially associate with like-minded or otherwise similar people (that is, homophily) can lead to sorting, segregation and a disconnected network structure that impedes information flow across populations[78,79]. Network structure can also be used to identify key institutions or corporations that produce and disseminate climate information aimed to persuade others[80]. Changing social norms about the morality of emissions, financial divestment from fossil fuels or governmental subsidies that reduce the price of renewable energy could each lead to positive feedback loops that tip the system towards human mitigation of emissions[81]. Contagion can also operate via pathways other than social networks. For example, policymakers within nations or between nations often interact strategically, making climate policy or treaty decisions at least in part as a reaction to the behaviours of other actors[82,83]. At the subnational level, many participants in 'wicked' policy areas such as climate change governance interact across multiple decision-making forums, resulting in complex networks that can give rise to connections and strategic interactions across issue areas or institutional scales[84,85]. Actors also interact via markets in which trading and supply-chain networks can lead to the transmission of climate shocks as well as information about relative scarcity via price changes[86,87].

Behavioural response. Behavioural responses emerge from complex interactions between cognition, contagion and other external or situational factors across multiple scales of human organization.

Many SCMs model responses as changes in annual GHG emissions or mean per capita emissions[20,54,88]. Some individual-based models focus on specific behavioural responses such as the adoption of low-carbon transportation[89], vegetarian diets[90], land use change[91], migration[92], investing in flood protection[93], or voting and political behaviour[94]. Models of national or international responses instead model changes in policy or treaties[21,70,82,83,95] or examine outcomes such as inequalities that might result from such agreements[55,96]. Models of markets, common in economics, might include responses such as shifting consumption, production and trade patterns, the dynamics of technology adoption or investments in long-lived assets[87,97–100]. The choice of behavioural response depends on the structure and goals of the modelling exercise.

Responses may also include a range of adaptation measures that have been documented[101], including changing cropping patterns and growing areas in agriculture[102,103] and the relocation of coastal communities[104]. The adaptation and coping strategies that individuals and communities deploy in response to a changing climate will be imperfect, costly and inefficient, requiring modelling frameworks that can capture these complexities. For example, heterogeneity in beliefs about climate risk in a coastal housing market with intensifying coastal storms and sea-level rise can lead to overvaluations and rapid market crashes as the effects of climate change become apparent[100]. Adaptation to extreme heat through the adoption of air conditioning is likely to be limited by poverty through the end of the century in densely populated and highly exposed regions such as south Asia and sub-Saharan Africa[105]. These nonlinear processes mean that climate change impacts may lead to tipping points in social systems that force sudden, transformative adaptations leading to a new state: examples include human migration due to sea-level rise and the collapse of winter sports tourism at lower altitudes[106].

Scale of social structure

The human system is composed of individuals that are organized in emergent social structures such as nations, international communities and markets[8,107]. The scale of social structure is the resolution at which human behaviour is represented, whether individuals, loosely defined social groups, nations or markets, and is dependent on the model objectives (Table 1). Humans interact across multiple scales and social settings, influencing each other and exchanging information, goods, values and beliefs. Behaviours are constrained and shaped by the characteristics of the social structures in which they are embedded, which may determine the resources available to act, the set of behavioural options and their perceptions of the costs and benefits of different actions. Moreover, people can and do act collectively, both through formal political institutions and through less formal structures such as social norms and cultures.

The scale of social structure influences how human behaviour is modelled. The modelled response changes with the level of abstraction: nations set policies and negotiate treaties with other nations; markets transmit information over trade networks and supply chains, altering the production, consumption and investment behaviour of market participants; and individuals change their behaviour, such as support for green policies or the adoption of low-carbon technologies. SCMs have usually focused on higher levels of abstraction (that is, the global economy[71,108]), while others have used individuals, though often using a representative individual or human functional type, ignoring heterogeneity and the complex, emergent behaviour that can arise from individual interactions[20,54,109,110]. Other SCMs have explored the potential for climate change to increase conflict or inequality, mediating or disrupting international cooperation on addressing climate change[55,95,111].

Although some modelling approaches such as agent-based modelling focus on individual behaviour to understand how larger-scale dynamics emerge from the interactions of individuals, much social science instead focuses on modelling more aggregate behaviours directly. Examples of aggregate entities considered in social theory and modelling (all of which could be relevant for understanding climate change) include markets and firms, political interest groups, national governments, social movements and cultural groups[107]. Various branches of social science have developed theories and models to explain the behaviour of these different aggregations, which can be a more parsimonious and efficient approach for understanding large-scale or widespread social phenomena than modelling only individual behaviour.

SCMs often focus on a single scale of social structure. A danger is that this ignores feedback processes operating across scales of social structure that can influence or constrain the behaviour of the modelled actors. For example, policy changes or interventions by governments can influence the perception of a problem at the individual scale, which then spreads through social networks with implications for future policy evolution[94,112]. Policies are rarely static, and their implementation has the potential to trigger positive feedback loops through increasing political interest, further mobilizing advocates, funding the innovation and deployment of technologies, and therefore leading to new, more ambitious policies[113]. Major climate policies have wide-ranging effects on a number of outcomes that people may value, such as reduced disruptions to the electricity supply[114] or improved air quality[115]. Some SCMs have addressed this by modelling human behaviour components at the individual, national and/or international levels simultaneously to allow for these interactions[21,56].

Heterogeneity

Heterogeneity enters the coupled human–climate system through climate change impacts, GHG emissions and socio-economic characteristics of the human system[116,117]. Climate change impacts are not uniformly distributed across the Earth: warming occurs disproportionately at higher latitudes, precipitation changes are heterogeneously distributed across land masses and sea-level rise affects coastal regions[117]. GHG emissions are similarly heterogeneous across regions, with industrialized nations disproportionately contributing to and benefiting from emissions. Socio-demographic characteristics of humans also vary widely within and across regions and can partially determine both vulnerability to climate impacts and the capacity to adapt. Discordance between where GHG emissions occur and where people are most vulnerable to climate change impacts can reinforce existing inequalities in the human system. Populations in different regions will thus experience more or less urgency to adapt, mitigate or join global collaborations.

Many SCMs do not represent this heterogeneity but utilize aggregated human costs and benefits[118,119]. Aggregated models do not account for the heterogeneous distribution of the burdens of climate change and the benefits accrued from emissions (for example, economic production) when evaluating potential mitigation and adaptation policies. Some SCMs have incorporated inequalities to assess the effects across different geographical areas[120], countries[121] or income groups[114,122], occasionally incorporating many of these factors into one global model[55]. These studies have demonstrated that inequality and spatial discordance in climate impacts and emissions can disrupt policy formation and cooperation, reducing mitigation and leading to more climate change. By more explicitly including a range of human behaviour and social processes in these models, we have the opportunity to observe not only the differential effects of climate change or policies[119,123] but also the likelihood of equitable policies or commitments emerging from the system.

Modelling goals

Advancing SCMs will improve both our understanding of the feedbacks and interactions that drive the dynamics of the climate system and forecasts of future climate change. Models can help us to understand how human behaviour and climate jointly determine system behaviour and to identify points of high leverage that can inform the design and implementation of mitigation and adaptation strategies, given real-world institutions and political and economic constraints[81,124]. Forecasts can provide foresight to possible future states of the world, anticipating changes in response to internal dynamics or evolving external forcings. The inclusion of human behaviour in climate models will change not only the mean of our climate forecasts but also the uncertainty around that mean.

An additional consideration in reviewing and categorizing SCMs is the distinction between prescriptive and descriptive modelling goals. Some of the earliest and most widely used SCMs are the set of cost–benefit integrated-assessment models such as the DICE model[125]. By positing a particular social welfare function and imagining a single global decision maker acting under perfect information and foresight, this class of models attempts to answer the question 'What should society do about climate change?' Prescriptive models incorporate idealized or optimized representations of policy formation or human behaviour and are neither designed for nor particularly useful for answering descriptive questions.

Descriptive models address the question 'What will society do about climate change?' This class of models represents how humans process and share information and beliefs or form policy; they thus have utility for understanding or forecasting the human response to climate change in terms of both mitigation and adaptation. Although recent work in economics has built on the original DICE framework to incorporate more realistic elements such as uncertainty in the climate system response[126], intergenerational dynamics[127] or strategic interactions between regions[83,128], prescriptive models still deliberately abstract from the messy and imperfect world of real climate policy formation, making them imperfect tools if the modelling goal is to understand what will versus what should happen. Prescriptive models can provide guidance on establishing policy and also provide a reference scenario for comparison with descriptive models of the human response to climate change, to examine questions such as how far actual responses are likely to depart from idealized responses.

Identifying and utilizing data

As quantitative models of the coupled climate–social system continue to develop, collecting and integrating data into the models is a key challenge[129]. SCMs are built from both theory and data and are used to understand likely outcomes as well as possible modes of system behaviour. However, the current landscape of data availability limits our ability to empirically constrain model parameters, limiting the potential of SCMs to forecast likely outcomes and modes of behaviour.

One issue is the lack of global data for many of the model elements. Many SCMs have a global scope because of the global nature of climate change and mixing of GHGs, but human behavioural data that are representative at the global scale are limited. Data about many variables are collected at the national scale by the United Nations or international development agencies, limiting the understanding of subnational heterogeneity. While there are efforts to collate comparable, global data for improved understanding of climate change impacts[130,131], these data tend to be the most complete in richer regions, often with large gaps in areas such as sub-Saharan Africa. Additionally, risk perception, social norms, institutional legitimacy and trust are examples of social constructs often used in SCMs that are abstract and challenging to measure. Even when relevant data exist (for example, from large-scale surveys), these data tend to be representative of national or subnational populations and do not have repeated measures, limiting their utility for constraining the dynamic behaviour of a global model.

However, emerging datasets that can be relevant to understanding social and behavioural dynamics are becoming increasingly accessible and hold promise. Examples include fine-scale administrative data[131]; data from internet use or mobile phones that can shed light on social and informational network structure[79], mood and sentiment[132,133] or mobility patterns[134–136]; bibliographic datasets combined with natural language processing methods[80,137]; and remote-sensing-based data products at increasingly high spatial and temporal resolution[138]. The wide geographic reach of these datasets and their often high temporal resolution are potentially valuable for improving the empirical foundation of SCMs. But it is also important to bear in mind possible pitfalls: detailed data on online behaviour may be easily available but also probably capture only a small part of people's informational and social environment, or data may not be representative of whole populations, possibly providing a biased sample towards particular income or age groups. Using multiple approaches including observational datasets, surveys or even lab experiments to triangulate model calibrations may be the most robust path forward. In the absence of extensive data, models can be constrained using strategies that leverage computational approaches and limited data.

While globally and temporally extensive data that broadly represent human behaviour may be absent, limited samples could be useful in providing initial parameter estimates for use in models. These parameterizations can be improved as more data become available. For instance, Konc et al.[94] calibrated parameters of their agent-based model to the results of a representative survey of Spanish households asking about support for different types of climate policies.

Hindcasting can be used to probabilistically constrain unknown parameters using the computational model and data on state variables represented in the model. This approach takes advantage of existing data streams, which may still be limited in scope, together with the causal relationships embedded in the model structure to impute likely values of unobserved (and often difficult to measure) parameters. This approach has been used, for instance, to calibrate human behaviour with respect to dietary choices in the context of climate change[90] and to constrain behavioural parameters using opinion surveys from a limited set of Western nations[21].

Recognizing the difficulty of direct calibration and parameterization, much work in the literature simply acknowledges this uncertainty and presents extensive uncertainty analyses over parameter distributions (for example, using Monte Carlo sampling or factorial sweeps[20,21]). However, if the goal of modelling is to go beyond characterizing possible system behaviour to instead assess probable outcomes or even to inform policy, then the benefit of better integration between models and data will be substantial. Considering data early in the model development process can help improve this integration—for example, by allowing some model variables to match the available validation data or by allowing time for original data collection via surveys or experiments if necessary.

Conclusion

Models are narratives for understanding how the world works. In the coming decades, the world will delve further into the Anthropocene, with human activities becoming an increasingly dominant driver of physical and biological systems around the world. A modelling framework that systematically excludes human behaviour, treating it as external to the climate systems rather than embedded within it, will be inadequate to meet either the scientific or policy demands of the next century. Our models are making progress in linking components of the human and climate systems, but we must go further than increasing inclusion of economic and biophysical activities to include human behaviours that drive the magnitude, sign and character of the interactions between the human and climate systems. We propose a framework where human behaviour is represented by the processing (cognition) and spread (contagion) of information and beliefs among humans and by the human behavioural response (for example, mitigation and adaptation) to climate change as well as the scale of social structure (for example, individuals, political institutions or markets) and heterogeneity in human behaviour driven by culture, demographics, economics and climate change impacts. A key challenge will be assembling available data for model parameterization and calibration to move beyond models that demonstrate potential modes of system behaviour to prediction.

The development of SCMs will contribute to addressing difficult problems in understanding climate change and achieving a sustainable Earth system through the representation of human behaviour, system-level effects of social processes and the complex dynamics driven by social environmental feedbacks[10]. SCMs can improve insight into the dynamics of the Earth system and may lead to the identification of potential social tipping points, where reinforcing feedbacks within the human system and through interactions with the climate system can lead to large reductions in anthropogenic forcing of climate[81,139,140], analogous to regime shifts in ecological systems[141,142]. In short, humans are the primary driver of current climate change, and so we need to put humans into the equation.

References

1. Gallagher, R. & Carpenter, B. Human-dominated ecosystems. *Science* **277**, 485 (1997).
2. Vitousek, P. M., Mooney, H. A., Lubchenco, J. & Melillo, J. M. Human domination of Earth's ecosystems. *Science* **277**, 494–499 (1997).
3. Steffen, W. et al. Planetary boundaries: guiding human development on a changing planet. *Science* **347**, 1259855 (2015).
4. Geller, E. S. in *Psychology and Social Responsibility: Facing Global Challenges* (eds Staub, S. & Green, P.) 248–268 (New York Univ. Press, 1992).
5. Penn, D. J. The evolutionary roots of our environmental problems: toward a Darwinian ecology. *Q. Rev. Biol.* **78**, 275–301 (2003).
6. Ayllón, D. et al. Cross-disciplinary links in environmental systems science: current state and claimed needs identified in a meta-review of process models. *Sci. Total Environ.* **622–623**, 954–973 (2018).
7. Beckage, B. et al. The Earth has humans, so why don't our climate models? *Clim. Change* https://doi.org/10.1007/s10584-020-02897-x (2020).
8. Palmer, P. I. & Smith, M. J. Earth systems: model human adaptation to climate change. *Nature* **512**, 365–366 (2014).
9. Motesharrei, S. et al. Modeling sustainability: population, inequality, consumption, and bidirectional coupling of the Earth and human systems. *Natl Sci. Rev*. https://doi.org/10.1093/nsr/nww081 (2016).
10. Donges, J. F. et al. Closing the loop: reconnecting human dynamics to Earth system science. *Anthropocene Rev.* **4**, 151–157 (2017).
11. Müller-Hansen, F. et al. Towards representing human behavior and decision making in Earth system models—an overview of techniques and approaches. *Earth Syst. Dyn.* **8**, 977–1007 (2017).
12. Calvin, K. & Bond-Lamberty, B. Integrated human–Earth system modeling—state of the science and future directions. *Environ. Res. Lett.* **13**, 063006 (2018).
13. Steffen, W. et al. The emergence and evolution of Earth system science. *Nat. Rev. Earth Environ.* **1**, 54–63 (2020).
14. Farahbakhsh, I., Bauch, C. T. & Anand, M. Modelling coupled human–environment complexity for the future of the biosphere: strengths, gaps and promising directions. *Phil. Trans. R. Soc. B* **377**, 20210382 (2022).
15. Steffen, W. et al. Trajectories of the Earth system in the Anthropocene. *Proc. Natl Acad. Sci. USA* **115**, 8252–8259 (2018).
16. Shin, Y. A., Lacasse, K., Gross, L. J. & Beckage, B. How coupled is coupled human–natural systems research? *Ecol. Soc.* **27**, art4 (2022).
17. Hausfather, Z. & Peters, G. P. Emissions—the 'business as usual' story is misleading. *Nature* **577**, 618–620 (2020).
18. Burgess, M. G., Ritchie, J., Shapland, J. & Pielke, R. IPCC baseline scenarios have over-projected CO_2 emissions and economic growth. *Environ. Res. Lett.* **16**, 014016 (2021).
19. Hausfather, Z. & Moore, F. C. Net-zero commitments could limit warming to below 2 °C. *Nature* **604**, 247–248 (2022).
20. Beckage, B. et al. Linking models of human behaviour and climate alters projected climate change. *Nat. Clim. Change* **8**, 79–84 (2018).
21. Moore, F. C. et al. Determinants of emissions pathways in the coupled climate–social system. *Nature* **603**, 103–111 (2022).
22. Rennert, K. et al. The social cost of carbon: advances in long-term probabilistic projections of population, GDP, emissions, and discount rates. *Brook. Pap. Econ. Act.* **2021**, 223–305 (2022).
23. Stewart, I. *Do Dice Play God? The Mathematics of Uncertainty* (Hachette, 2019).
24. Jusup, M. et al. Social physics. *Phys. Rep.* **948**, 1–148 (2022).
25. Wolfram, S. *A New Kind of Science* (Mathematica, 2002).
26. Beckage, B., Gross, L. J. & Kauffman, S. The limits to prediction in ecological systems. *Ecosphere* **2**, 1–12 (2011).
27. Flack, J. C. Coarse-graining as a downward causation mechanism. *Phil. Trans. R. Soc. A* **375**, 20160338 (2017).
28. Riahi, K. et al. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob. Environ. Change* **42**, 153–168 (2017).
29. Weyant, J. Some contributions of integrated assessment models of global climate change. *Rev. Environ. Econ. Policy* **11**, 115–137 (2017).
30. Mendelsohn, R. Efficient adaptation to climate change. *Climatic Change* **45**, 583–600 (2000).
31. Diaz, D. B. Estimating global damages from sea level rise with the Coastal Impact and Adaptation Model (CIAM). *Climatic Change* **137**, 143–156 (2016).
32. Benveniste, H., Oppenheimer, M. & Fleurbaey, M. Effect of border policy on exposure and vulnerability to climate change. *Proc. Natl Acad. Sci. USA* **117**, 26692–26702 (2020).
33. Schneider, S. H., Easterling, W. E. & Mearns, L. O. Adaptation: sensitivity to natural variability, agent assumptions and dynamic climate changes. *Clim. Change* **45**, 203–221 (2000).
34. Melillo, J. M., Prentice, I. C., Farquhar, G. D., Schulze, E. D. & Sala, O. E. in *Climate Change 1995: The Science of Climate Change* (eds Houghton, J. T. et al.) 445–481 (IPCC, Cambridge Univ. Press, 1996).
35. Melillo, J. M. et al. Soil warming and carbon-cycle feedbacks to the climate system. *Science* **298**, 2173–2176 (2002).
36. Rial, J. A. et al. Nonlinearities, feedbacks and critical thresholds within the Earth's climate system. *Climatic Change* **65**, 11–38 (2004).
37. Stephens, G. L. Cloud feedbacks in the climate system: a critical review. *J. Clim.* **18**, 237–273 (2005).
38. Bonan, G. B. Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science* **320**, 1444–1449 (2008).
39. Arneth, A. et al. Terrestrial biogeochemical feedbacks in the climate system. *Nat. Geosci.* **3**, 525–532 (2010).
40. Bonan, G. B. & Doney, S. C. Climate, ecosystems, and planetary futures: the challenge to predict life in Earth system models. *Science* **359**, eaam8328 (2018).
41. O'Neill, B. C. et al. The roads ahead: narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob. Environ. Change* **42**, 169–180 (2017).
42. Hawkins, E. & Sutton, R. The potential to narrow uncertainty in regional climate predictions. *Bull. Am. Meteorol. Soc.* **90**, 1095–1108 (2009).
43. Lehner, F. et al. Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. *Earth Syst. Dyn.* **11**, 491–508 (2020).

44. Haer, T., Botzen, W. J. W. & Aerts, J. C. J. H. The effectiveness of flood risk communication strategies and the influence of social networks—insights from an agent-based model. *Environ. Sci. Policy* **60**, 44–52 (2016).
45. Orlov, A. et al. Global economic responses to heat stress impacts on worker productivity in crop production. *Econ. Disasters Clim. Change* **5**, 367–390 (2021).
46. Oppenheimer, M. Climate Change impacts: accounting for the human response. *Clim. Change* **117**, 439–449 (2013).
47. Gawith, D., Hodge, I., Morgan, F. & Daigneault, A. Climate change costs more than we think because people adapt less than we assume. *Ecol. Econ.* **173**, 106636 (2020).
48. Kelly Letcher, R. A. et al. Selecting among five common modelling approaches for integrated environmental assessment and management. *Environ. Model. Softw.* **47**, 159–181 (2013).
49. Verburg, P. H. et al. Methods and approaches to modelling the Anthropocene. *Glob. Environ. Change* **39**, 328–340 (2016).
50. Robinson, D. T. et al. Modelling feedbacks between human and natural processes in the land system. *Earth Syst. Dyn.* **9**, 895–914 (2018).
51. Iwanaga, T. et al. Socio-technical scales in socio-environmental modeling: managing a system-of-systems modeling approach. *Environ. Model. Softw.* **135**, 104885 (2021).
52. Sterman, J. et al. Climate interactive: the C-ROADS climate policy model. *Syst. Dyn. Rev.* **28**, 295–305 (2012).
53. Nordhaus, W. Evolution of modeling of the economics of global warming: changes in the DICE model, 1992-2017. *Clim. Change* **148**, 623–640 (2018).
54. Bury, T. M., Bauch, C. T. & Anand, M. Charting pathways to climate change mitigation in a coupled socio-climate model. *PLoS Comput. Biol.* **15**, e1007000 (2019).
55. Gazzotti, P. et al. Persistent inequality in economically optimal climate policies. *Nat. Commun.* **12**, 3421 (2021).
56. Ricke, K. L. & Caldeira, K. Natural climate variability and future climate policy. *Nat. Clim. Change* **4**, 333–338 (2014).
57. Howe, P. D., Markowitz, E. M., Lee, T. M., Ko, C.-Y. & Leiserowitz, A. Global perceptions of local temperature change. *Nat. Clim. Change* **3**, 352–356 (2013).
58. Howe, P. D., Boudet, H., Leiserowitz, A. & Maibach, E. W. Mapping the shadow of experience of extreme weather events. *Clim. Change* **127**, 381–389 (2014).
59. Sisco, M. R., Bosetti, V. & Weber, E. U. When do extreme weather events generate attention to climate change? *Clim. Change* **143**, 227–241 (2017).
60. Collins, W. D. et al. The integrated Earth system model version 1: formulation and functionality. *Geosci. Model Dev.* **8**, 2203–2219 (2015).
61. Stott, P. A. et al. External control of 20th century temperature by natural and anthropogenic forcings. *Science* **290**, 2133–2137 (2000).
62. Stern, D. I. & Kaufmann, R. K. Anthropogenic and natural causes of climate change. *Clim. Change* **122**, 257–269 (2014).
63. Carmichael, G. R. et al. Asian aerosols: current and year 2030 distributions and implications to human health and regional climate change. *Environ. Sci. Technol.* **43**, 5811–5817 (2009).
64. Schlüter, M. et al. A framework for mapping and comparing behavioural theories in models of social–ecological systems. *Ecol. Econ.* **131**, 21–35 (2017).
65. Eyster, H. N., Satterfield, T. & Chan, K. M. A. Why people do what they do: an interdisciplinary synthesis of human action theories. *Annu. Rev. Environ. Resour.* **47**, 725–751 (2022).
66. Jager, W. Enhancing the Realism of Simulation (EROS): on implementing and developing psychological theory in social simulation. *J. Artif. Soc. Soc. Simul.* **20**, 14 (2017).
67. Muelder, H. & Filatova, T. One theory—many formalizations: testing different code implementations of the theory of planned behaviour in energy agent-based models. *J. Artif. Soc. Soc. Simul.* **4**, 5 (2018).
68. Brown, C. & Rounsevell, M. How can social–ecological system models simulate the emergence of social–ecological crises? *People Nat.* **3**, 88–103 (2021).
69. Bayne, T. et al. What is cognition? *Curr. Biol.* **29**, R608–R615 (2019).
70. Young, H. P. Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning. *Am. Econ. Rev.* **99**, 1899–1924 (2009).
71. Nordhaus, W. Climate change: the ultimate challenge for economics. *Am. Econ. Rev.* **109**, 1991–2014 (2019).
72. Hawkins, E. & Sutton, R. The potential to narrow uncertainty in projections of regional precipitation change. *Clim. Dyn.* **37**, 407–418 (2011).
73. Goldberg, M. H., Linden, S., van der, Leiserowitz, A. & Maibach, E. Perceived social consensus can reduce ideological biases on climate change. *Environ. Behav.* https://doi.org/10.1177/0013916519853302 (2019).
74. Kim, S. C., Pei, D., Kotcher, J. E. & Myers, T. A. Predicting responses to climate change health impact messages from political ideology and health status: cognitive appraisals and emotional reactions as mediators. *Environ. Behav.* **53**, 1095–1117 (2021).
75. Swim, J. et al. *Psychology and Global Climate Change: Addressing a Multi-faceted Phenomenon and Set of Challenges* (American Psychological Association, 2011).
76. Murphy, R. *The Fossil-Fuelled Climate Crisis: Foresight or Discounting Danger?* (Springer International, 2021).
77. Hoffman, A. J. *How Culture Shapes the Climate Change Debate* (Stanford Univ. Press, 2015).
78. Schelling, T. C. *Micromotives and Macrobehavior* (WW Norton, 2006).
79. Williams, H. T. P., McMurray, J. R., Kurz, T. & Hugo Lambert, F. Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Glob. Environ. Change* **32**, 126–138 (2015).
80. Farrell, J. Network structure and influence of the climate change counter-movement. *Nat. Clim. Change* **6**, 370–374 (2016).
81. Otto, I. M. et al. Social tipping dynamics for stabilizing Earth's climate by 2050. *Proc. Natl Acad. Sci. USA* **117**, 2354–2365 (2020).
82. Nordhaus, W. Climate clubs: overcoming free-riding in international climate policy. *Am. Econ. Rev.* **105**, 1339–1370 (2015).
83. Kotchen, M. J. Which social cost of carbon? A theoretical perspective. *J. Assoc. Environ. Resour. Econ.* **5**, 673–694 (2018).
84. Hamilton, M. & Lubell, M. Collaborative governance of climate change adaptation across spatial and institutional scales. *Policy Stud. J.* **46**, 222–247 (2018).
85. Lubell, M. & Morrison, T. H. Institutional navigation for polycentric sustainability governance. *Nat. Sustain.* **4**, 664–671 (2021).
86. Pankratz, N. M. C. & Schiller, C. Climate change and adaptation in global supply-chain networks. *SSRN Electron. J.* https://doi.org/10.2139/ssrn.3475416 (2019).
87. Baldos, U. L. C., Hertel, T. W. & Moore, F. C. Understanding the spatial distribution of welfare impacts of global warming on agriculture and its drivers. *Am. J. Agric. Econ.* **101**, 1455–1472 (2019).
88. Kraan, O., Kramer, G. J., van der Lei, T. & Huppes, G. in *Advances in Social Simulation 2015* (eds Jager, W. et al.) Vol. 528, 207–216 (Springer International, 2017).
89. Mercure, J.-F., Lam, A., Billington, S. & Pollitt, H. Integrated assessment modelling as a positive science: private passenger road transport policies to meet a climate target well below 2 °C. *Clim. Change* **151**, 109–129 (2018).

90. Eker, S., Reese, G. & Obersteiner, M. Modelling the drivers of a widespread shift to sustainable diets. *Nat. Sustain.* **2**, 725–735 (2019).
91. Brown, C., Seo, B. & Rounsevell, M. Societal breakdown as an emergent property of large-scale behavioural models of land use change. *Earth Syst. Dyn.* **10**, 809–845 (2019).
92. Hassani-Mahmooei, B. & Parris, B. W. Climate change and internal migration patterns in Bangladesh: an agent-based model. *Environ. Dev. Econ.* **17**, 763–780 (2012).
93. McNamara, D. E. & Keeler, A. A coupled physical and economic model of the response of coastal real estate to climate risk. *Nat. Clim. Change* **3**, 559–562 (2013).
94. Konc, T., Drews, S., Savin, I. & van den Bergh, J. C. J. M. Co-dynamics of climate policy stringency and public support. *Glob. Environ. Change* **74**, 102528 (2022).
95. Howard, P. & Livermore, M. A. Sociopolitical feedbacks and climate change. *Harv. Environ. Law Rev.* **43**, 119–174 (2019).
96. Tavoni, A., Dannenberg, A., Kallis, G. & Löschel, A. Inequality, communication, and the avoidance of disastrous climate change in a public goods game. *Proc. Natl Acad. Sci. USA* **108**, 11825–11829 (2011).
97. Pettifor, H., Wilson, C., McCollum, D. & Edelenbosch, O. Y. Modelling social influence and cultural variation in global low-carbon vehicle transitions. *Glob. Environ. Change* **47**, 76–87 (2017).
98. Lamperti, F., Dosi, G., Napoletano, M., Roventini, A. & Sapio, A. Climate change and green transitions in an agent-based integrated assessment model. *Technol. Forecast. Soc. Change* **153**, 119806 (2020).
99. Gouel, C. & Laborde, D. The crucial role of domestic and international market-mediated adaptation to climate change. *J. Environ. Econ. Manage.* **106**, 102408 (2021).
100. Bakkensen, L. A. & Barrage, L. Going underwater? Flood risk belief heterogeneity and coastal home price dynamics. *Rev. Financ. Stud.* **35**, 3666–3709 (2022).
101. Berrang-Ford, L. et al. A systematic global stocktake of evidence on human adaptation to climate change. *Nat. Clim. Change* **11**, 989–1000 (2021).
102. Sloat, L. L. et al. Climate adaptation by crop migration. *Nat. Commun.* **11**, 1243 (2020).
103. Menzel, A. et al. Climate change fingerprints in recent European plant phenology. *Glob. Change Biol.* **26**, 2599–2612 (2020).
104. Hino, M., Field, C. B. & Mach, K. J. Managed retreat as a response to natural hazard risk. *Nat. Clim. Change* **7**, 364–370 (2017).
105. Rode, A. et al. Estimating a social cost of carbon for global energy consumption. *Nature* **598**, 308–314 (2021).
106. van Ginkel, K. C. H. et al. Climate change induced socio-economic tipping points: review and stakeholder consultation for policy relevant research. *Environ. Res. Lett.* **15**, 023001 (2020).
107. Chase-Dunn, C. & Lerro, B. *Social Change: Globalization from the Stone Age to the Present* (Routledge, 2016).
108. Matsumoto, K. Climate change impacts on socioeconomic activities through labor productivity changes considering interactions between socioeconomic and climate systems. *J. Clean. Prod.* **216**, 528–541 (2019).
109. Rounsevell, M. D. A., Robinson, D. T. & Murray-Rust, D. From actors to agents in socio-ecological systems models. *Phil. Trans. R. Soc. B* **367**, 259–269 (2012).
110. Edelenbosch, O. Y., McCollum, D. L., Pettifor, H., Wilson, C. & van Vuuren, D. P. Interactions between social learning and technological learning in electric vehicle futures. *Environ. Res. Lett.* **13**, 124004 (2018).
111. Menard, J., Bury, T. M., Bauch, C. T. & Anand, M. When conflicts get heated, so does the planet: coupled social–climate dynamics under inequality. *Proc. R. Soc. B* **288**, 20211357 (2021).
112. Konc, T., Savin, I. & van den Bergh, J. C. J. M. The social multiplier of environmental policy: application to carbon taxation. *J. Environ. Econ. Manage.* **105**, 102396 (2021).
113. Rosenbloom, D., Meadowcroft, J. & Cashore, B. Stability and climate policy? Harnessing insights on path dependence, policy feedback, and transition pathways. *Energy Res. Soc. Sci.* **50**, 168–178 (2019).
114. Rao, N. D. Distributional impacts of climate change mitigation in Indian electricity: the influence of governance. *Energy Policy* **61**, 1344–1356 (2013).
115. Vandyck, T., Keramidas, K., Tchung-Ming, S., Weitzel, M. & Van Dingenen, R. Quantifying air quality co-benefits of climate policy across sectors and regions. *Clim. Change* **163**, 1501–1517 (2020).
116. Fussel, H.-M. How inequitable is the global distribution of responsibility, capability, and vulnerability to climate change: a comprehensive indicator-based assessment. *Glob. Environ. Change* **20**, 597–611 (2010).
117. IPCC *Climate Change 2022: Impacts, Adaptation and Vulnerability* (eds Pörtner, H.-O. et al.) (Cambridge Univ. Press, 2022).
118. Stanton, E. A., Ackerman, F. & Kartha, S. Inside the integrated assessment models: four issues in climate economics. *Clim. Dev.* **1**, 166–184 (2009).
119. Jafino, B. A., Kwakkel, J. H. & Taebi, B. Enabling assessment of distributive justice through models for climate change planning: a review of recent advances and a research agenda. *WIREs Clim. Change* **12**, e721 (2021).
120. Ciullo, A., Kwakkel, J. H., De Bruijn, K. M., Doorn, N. & Klijn, F. Efficient or fair? Operationalizing ethical principles in flood risk management: a case study on the Dutch–German Rhine. *Risk Anal.* **40**, 1844–1862 (2020).
121. Thornton, P. K., Jones, P. G., Alagarswamy, G., Andresen, J. & Herrero, M. Adapting to climate change: agricultural system and household impacts in East Africa. *Agric. Syst.* **103**, 73–82 (2010).
122. Dennig, F., Budolfson, M. B., Fleurbaey, M., Siebert, A. & Socolow, R. H. Inequality, climate impacts on the future poor, and carbon prices. *Proc. Natl Acad. Sci. USA* **112**, 15827–15832 (2015).
123. Sonja, K. & Harald, W. Building equity in: strategies for integrating equity into modelling for a 1.5 °C world. *Phil. Trans. R. Soc. A* **376**, 20160461 (2018).
124. Peng, W. et al. Climate policy models need to get real about people — here's how. *Nature* **594**, 174–176 (2021).
125. Nordhaus, W. D. Revisiting the social cost of carbon. *Proc. Natl Acad. Sci. USA* **114**, 1518–1523 (2017).
126. Cai, Y. & Lontzek, T. S. The social cost of carbon with economic and climate risks. *J. Polit. Econ.* **127**, 2684–2734 (2019).
127. Kotlikoff, L., Kubler, F., Polbin, A., Sachs, J. & Scheidegger, S. Making carbon taxation a generational win win. *Int. Econ. Rev.* **62**, 3–46 (2021).
128. Kotlikoff, L., Kübler, F., Polbin, A. & Scheidegger, S. Economists have needlessly produced a climate war. *VoxEU* (27 October 2021).
129. Elsawah, S. et al. Eight grand challenges in socio-environmental systems modeling. *Socio-environ. Syst. Model.* **2**, 16226 (2020).
130. Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production: evidence from a global panel of regions. *J. Environ. Econ. Manage.* **103**, 102360 (2020).
131. Carleton, T. et al. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *Q. J. Econ*. https://doi.org/10.1093/qje/qjac020 (2022).
132. Baylis, P. et al. Weather impacts expressed sentiment. *PLoS ONE* **13**, e0195750 (2018).
133. Baylis, P. Temperature and temperament: evidence from Twitter. *J. Public Econ.* **184**, 104161 (2020).

134. Lu, X. et al. Detecting climate adaptation with mobile network data in Bangladesh: anomalies in communication, mobility and consumption patterns during cyclone Mahasen. *Clim. Change* **138**, 505–519 (2016).
135. Weill, J. A., Stigler, M., Deschenes, O. & Springborn, M. R. Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proc. Natl Acad. Sci. USA* **117**, 19658–19660 (2020).
136. Burke, M. et al. Exposures and behavioural responses to wildfire smoke. *Nat. Hum. Behav*. https://doi.org/10.1038/s41562-022-01396-6 (2022).
137. Callaghan, M. et al. Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies. *Nat. Clim. Change* **11**, 966–972 (2021).
138. Jean, N. et al. Combining satellite imagery and machine learning to predict poverty. *Science* **353**, 790–794 (2016).
139. Winkelmann, R. et al. Social tipping processes towards climate action: a conceptual framework. *Ecol. Econ*. **192**, 107242 (2022).
140. Eker, S. & Wilson, C. *System Dynamics of Social Tipping Processes* (International Institute for Applied Systems Analysis, 2022).
141. Maslin, M. Ecological versus climatic thresholds. *Science* **306**, 2197–2198 (2004).
142. Rietkerk, M., Dekker, S. C., de Ruiter, P. C. & van de Koppel, J. Self-organized patchiness and catastrophic shifts in ecosystems. *Science* **305**, 1926–1929 (2004).

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Competing interests

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Additional information

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