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The Earth has humans, so why don't our climate models?

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Abstract
While climate models have rapidly advanced in sophistication over recent decades, they lack dynamic representation of human behavior and social systems despite strong feedbacks between social processes and climate. The impacts of climate change alter perceptions of risk and emissions behavior that, in turn, influence the rate and magnitude of climate change. Addressing this deficiency in climate models requires a substantial interdisciplinary effort to couple models of climate and human behavior. We suggest a multi-model approach that considers a range of theories and implementations of human behavior and social systems, similar to the multi-model approach that has been used to explore the physical climate system. We describe the importance of linking social factors with climate processes and identify four priorities essential to advancing the development of coupled social-climate models.

Keywords Coupled social-climate models · Natural-human systems · Climate change · Behavioral theory

The analysis and projection of climate began with the conceptualization of numerical weather forecasting (Richardson 1922; Lynch 2006) and efforts to model global atmospheric flow (Phillips 1956). These early global climate models evolved through refined representations of physical processes (Walsh et al. 2013; Prodhomme et al. 2016) and inclusion of other Earth system components, notably the coupling of the ocean with the atmosphere (Manabe and Bryan 1969) and linkages with terrestrial vegetation (Sellers et al. 1986; Dickinson et al. 1993). This progression has led to modern, well-developed climate models that can simulate global temperature, precipitation, and a broad range of climate variables, along with societal impacts such as crop yields and water availability (Bonan and Doney 2018). While climate models have incorporated feedbacks between climate and natural systems, for example, the

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absorption of CO_2 by the oceans (Plattner et al. 2001) and carbon sequestration in terrestrial ecosystems (Field et al. 2007), they continue to rely on static, external projections of anthropogenic greenhouse gas (GHG) emissions, despite the likelihood of strong feedbacks between the state of the climate system and human emissions (Palmer and Smith 2014; Thornton et al. 2017). Externalizing anthropogenic GHG emissions sidesteps much of the complexity and interplay between the climate and human system that in turn limits the realism of projections of climate change.

Integrated assessment models (IAMs) have incorporated primarily economic feedbacks between climate and the human system. The DICE model (Dynamic Integrated Climate-Economy) and its variations incorporate linkages between climate, economic growth, climate damage to the economy, and mitigation costs to maximize per capita utility and project associated climate change (Nordhaus 2018, 2019). IAMs have also considered climate feedbacks with specific economic sectors such as agriculture and building energy expenditures, finding, for instance, that higher plant productivity from climate change will lead to increased production of biofuels and reductions in fossil fuel emissions (Thornton et al. 2017) and that warmer temperatures due to climate change will lead to increased GHG emissions to cool buildings (Clarke et al. 2018).

The next step in the evolution of global climate models, Earth system models, and integrated assessment models (henceforth referred to collectively as “climate models”) is to endogenize anthropogenic GHG emissions beyond economics to broadly consider human social and behavioral systems. The dynamic coupling of climate models with models of human social and behavioral systems (henceforth referred to as “social models”) to incorporate human behavior, decision-making, and other social processes is needed to provide robust projections of climate change (Palmer and Smith 2014). Humans respond dynamically to climate change in a boundedly rational manner, updating beliefs and behavior in response to experiences of climate change, the influence of social networks, and other social, cultural, and political factors (Hoffman 2010; Demski et al. 2017). Climate change solutions, therefore, need to account for human preferences and behavior (“demand-side” solutions) that drive the adoption of mitigation policies, technologies, and infrastructure (“supply-side” solutions) by government and industry (Creutzig et al. 2016). The linking of social models with climate models would, for example, allow harmful changes in climate to lead to more aggressive improvements in energy efficiency and more rapid deployment of renewable energy, thereby reducing subsequent emissions (perhaps significantly) and projected change in climate (Beckage et al. 2018). Social factors may also predict lags in mitigation to visible and damaging climate events due to the difficulty of altering entrenched beliefs and industries (Penna and Geels 2015), or mismatches between nations most responsible for creating emissions and nations most vulnerable to climate change impacts (Füssel 2010). Human behavioral responses to climate change might also lead to drastic actions such as geoengineering, which, though controversial (Kiehl 2006), could directly reduce atmospheric CO_2 or manage solar radiation (Wigley 2006; Vaughan and Lenton 2011) while also decreasing the perceived urgency for curtailing greenhouse gas emissions.

The social components of climate change are among the largest sources of uncertainty in the timeline and extent of GHG emissions and projected climate change (Beckage et al. 2018). Behavioral responses impact mitigation through perceptions of risk from climate change, access to resources to reduce emissions or adapt to climate change, social norms, and existing worldviews and social practices (Gifford 2011; Palmer and Smith 2014; Niamir et al. 2020). Attitudes towards mitigation behaviors are representative of social, political, and religious ideologies and group membership (Weber 2010; Hoffman 2010; McCright et al. 2013) and interact with perception of risk from climate change. For example, climate change can produce increased weather extremes which may enhance the perceived urgency of response (Demski et al. 2017) but also weather extremes inconsistent with the overall direction of climate change (Vavrus et al. 2006). These extremes are perceived differently depending on prior beliefs (Weber 2010). Linking social and climate models will thus enable a more complete and dynamic representation of the climate system that will lead to (1) improved quantification of future climate change uncertainty and (2) greater understanding of climate sensitivity to social and behavioral components that can be leveraged to reduce the magnitude of future climate change.

Early efforts to couple social and climate models, henceforth, social-climate models or SoCMs, have demonstrated that social uncertainty in projections of climate change is potentially as large as the uncertainty in the physical climate system (Beckage et al. 2018; Calvin and Bond-Lamberty 2018). SoCMs have also demonstrated the large influence of social learning, social norms, and perceived behavioral control on mitigation behavior and future climate change (Beckage et al. 2018; Bury et al. 2019). Perceived behavioral control and perceived social norms, for instance, exhibit a strong interaction in some SoCMs such that high values of both are required to produce emissions reductions, indicating leverage points in this representation of the social climate system (Beckage et al. 2018). But this result is from a single instantiation of one behavioral theory, the Theory of Planned Behavior (Ajzen 1991), coupled with a simplified, zero-dimensional climate model. Furthermore, the entire population of Earth was modeled as a homogenous group, neglecting different cultures, emissions, and experience of impacts. A wide set of behavioral theories could be used to construct social models of human behavioral responses to climate change at the individual or group level (Hargreaves 2011; Schlüter et al. 2017), just as there is a large set of climate models of varying complexity that could be linked with a social model (Taylor et al. 2012). We expect relatively more variation across social models compared to climate models.

The first attempts to couple a social model with a climate model have demonstrated the importance of doing so, but further exploration and development of SoCMs is necessary for more realistic and actionable projections. A next step in developing SoCMs is a multi-model approach to examine the robustness of climate projections to choice of behavioral theory and model implementation (Fig. 1). The assumptions of different behavioral theories and their parameterizations to represent diverse cultural groups and social systems will influence emissions through behavioral responses. Emissions behavior may result from regional policies or individual decisions that increase or decrease GHG emissions in response to climate impacts and perceived risks. These emissions influence the atmospheric concentrations of GHGs that then feed back into the climate system.

We suggest the following priorities for developing SoCMs:

1. Evaluate an array of behavioral theories: Similar to the design and assessment of multiple climate models, a robust analysis is needed to examine a diverse set of human behavioral theories and implementations in social models. This includes characterizing the uncertainty of climate projections for each behavioral theory and its implementation, as well as for integrated models that consider human behavior at individual and group levels.
2. Differentiate climate impacts on humans across physical regions of the world: The regional distribution of GHG emissions does not align with the regional distribution of global climate change impacts. Regions with low emissions that experience high impacts

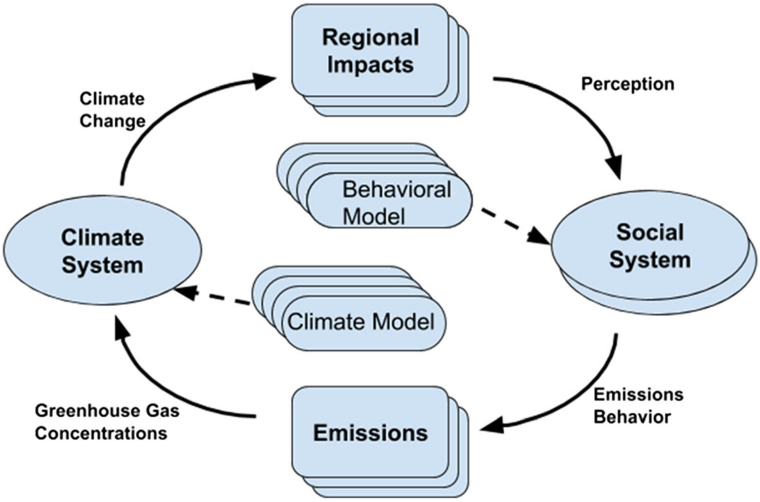

Fig. 1 Schematic diagram of the coupling of climate and social models. The climate system is forced by atmospheric concentrations of greenhouse gasses (GHGs), leading to climate change that differently impacts physical regions of the globe through mean and extreme climate change. Regional impacts influence perception of risk from climate change, which is processed by the social system that overlaps a physical region and its associated cultural context. The interactions of social systems from multiple regions with alternative behavioral models influence emissions behaviors, through regional policies and individual human behaviors. GHG emissions then drive atmospheric concentrations of GHGs that feed back into the climate system. The choice of climate and behavioral model, parameterized for different cultural or political social systems, leads to a multi-model set of simulations with differing emissions and regional impacts

may have little ability to reduce global emissions, whereas some regions with high emissions may not experience sufficient impacts to alter perceptions of climate change and emissions behavior. Regional discordance in impacts of climate change and sources of anthropogenic GHG emissions will likely lead to regionally unique human responses that interact through social contagion and adoption of policy.

3. Incorporate the influence of diverse social systems: Social models should consider the political structures, wealth distribution, cultural worldviews, and belief systems of diverse populations that vary globally and will likely interact with the behavioral theory chosen and the spatial patterns of climate change impacts to alter human behavior. The social models can be informed by global or regional surveys, such as public opinion regarding support for geoengineering (Visschers et al. 2017) and behavioral data, such as mobile phone data (Lu et al. 2016).
4. Improve the representation of how perceptions and behavior shape GHG emissions: Further analysis is needed on how individuals and groups respond to physical climate and social factors and to implementation of emissions-related policies that potentially alter investments in renewable energy, subsidies for emissions-intensive livestock, and infrastructure to support electric vehicles. Different regional policy responses contribute to increases or decreases in emissions.

This proposed set of model development goals will lead to SoCMs evolving from stylized conceptual models to fully parameterized, operational models that provide robust projections of climate change. SoCMs will more fully characterize the uncertainty in climate change projections by integrating uncertainties in both the social and physical systems. Although

SoCMs may initially lead to increased uncertainty in climate projections, they will more realistically capture the range of likely climate futures and allow the scientific community to directly address critical model deficiencies that may eventually reduce climate uncertainties (Carslaw et al. 2018). Data collection that addresses these deficiencies could then be prioritized so as to quickly reduce the overall uncertainty of SoCMs. The coupling of physical and social processes may also identify complex feedbacks that potentially reduce overall uncertainty in projected climate change. For example, extreme climate change may motivate strong human behavioral responses to reduce GHG emissions, while more moderate climate change may lead to decreased mitigation efforts. The overall result might then be to constrain the likely range of projected climate change away from extreme high or low ranges. Importantly, an analysis of SoCMs would guide mitigation efforts by identifying points of high leverage, e.g., those components of the model where small changes in parameters lead to comparatively large changes in projected climate change. The emergence of SoCMs will allow for a more complete examination of climate change uncertainty and also enable the partitioning of climate change uncertainty into irreducible components intrinsic to the climate and social systems and components that can be reduced with continued model development and incorporation of human behavioral data (Lorenz 2006; Beckage et al. 2011).

The complexity of the human response to climate change suggests the development of a Social Sciences Model Intercomparison Project (SMIP) that focuses on human social and behavioral systems. SMIP would be similar to the Coupled Model Intercomparison Project that has developed a common experimental protocol and set of forcing scenarios to project future climate change, providing the basis for the work of the Intergovernmental Panel on Climate Change (Taylor et al. 2012). The successes of climate models stem, in large part, from the process by which the models were created: parallel teams tackling the same set of problems from an array of perspectives and with a diverse set of approaches, then comparing and contrasting the relative strengths and weaknesses of each modeling choice. This competitive collaboration led to the emergence of the modern set of climate models. The creation of SoCMs would benefit from a similar framework that captures diverse perspectives and theories in modeling human systems in relation to climate change. We encourage the parallel development of diverse candidate models that can then be considered by the community and refined based on their relative strengths. Whether this process leads to convergence to a small set of models or a larger set of similarly appropriate but divergent models that could be employed in concert to examine the role of human behavior in climate projections, the process itself would enrich our understanding of the social dimensions of climate change and lead to better-informed policies.

Incorporating human social models into climate models is an important next step in projecting future climate change and its impacts. Critical questions concerning global climate change involve humans and cannot be addressed in the absence of models that couple physical and social systems: How will regional differences in GHG emissions and climate change impacts modify future climate? What components of human social systems provide the most leverage to curb GHG emissions? How might global climate change impacts on food insecurity, migration, and international conflicts alter human perception of risk and influence GHG emissions policies? We have learned about the rate, magnitude, and impacts of climate change from physical models. The next step towards achieving a deeper understanding of climate change is the integration of models of human behavior and social systems. This integration of social and climate models will enhance our ability to understand, adapt to, and mitigate climate change.

Though daunting, similar efforts have been made to incorporate feedbacks between human behavior and the environment. Models of social-ecological systems, for example, often include human behavior and decision-making coupled with ecological processes on landscape or watershed scales (Schlüter et al. 2012, 2017; Müller-Hansen et al. 2017). Similarly, the dynamics of human behavior in an economic context have been modeled with respect to environmental hazards and regional energy demand (Filatova 2015; Niamir et al. 2020). These efforts can provide insights into modeling complex social systems, including human behavior at various levels of granularity, that will help organize and streamline this process for SoCMs. Given past advancements in climate modeling, the benefits of linking social models with climate models may be greater than the marginal improvements that come from a continued focus solely on the refinement of models of the physical climate system. The coupling of social and climate models builds on the work of Meadows et al. (1972, 2004) and continues pioneering efforts to integrate humans into Earth system models to assess our global impacts.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Code availability N/A

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