

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36

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

Brian Beckage<sup>1,2\*</sup>, Katherine Lacasse<sup>3</sup>, Jonathan M. Winter<sup>4</sup>, Louis J. Gross<sup>5,6</sup>, Nina Fefferman<sup>5,6</sup>, Forrest M. Hoffman<sup>7</sup>, Sara S. Metcalf<sup>8</sup>, Travis Franck<sup>9</sup>, Eric Carr<sup>6</sup>, Asim Zia<sup>2,10</sup>, and Ann Kinzig<sup>11</sup>

<sup>1</sup>Departments of Plant Biology, University of Vermont, Burlington, Vermont, USA.  
<https://orcid.org/0000-0002-5908-6924>

<sup>2</sup>Department of Computer Science, University of Vermont, Burlington, Vermont, USA..

<sup>3</sup>Department of Psychology, Rhode Island College, Providence, RI, USA.

<sup>4</sup>Department of Geography, Dartmouth College, Hanover, NH, USA.

<sup>5</sup>Departments of Ecology and Evolutionary Biology and Mathematics, University of Tennessee, Knoxville, TN, USA.

<sup>6</sup>National Institute for Mathematical and Biological Synthesis, University of Tennessee, Knoxville, TN, USA.

<sup>7</sup>Oak Ridge National Laboratory, Oak Ridge, TN, USA.

<sup>8</sup>Department of Geography, The State University of New York at Buffalo, Buffalo, NY, USA.

<sup>9</sup>Climate Interactive, Belmont, MA, USA.

<sup>10</sup>Community Development and Applied Economics, University of Vermont, Burlington, Vermont, USA.

<sup>11</sup>School of Life Sciences, Arizona State University, Tempe, Arizona, USA.

\* To whom correspondence should be addressed. E-mail: [Brian.Beckage@uvm.edu](mailto:Brian.Beckage@uvm.edu)

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

47 **Keywords:** Coupled social-climate models, natural-human systems, climate change, behavioral  
48 theory  
49

## 50 **Main Text:**

51 The analysis and projection of climate began with the conceptualization of numerical  
52 weather forecasting (Richardson 1922; Lynch 2006) and efforts to model global atmospheric  
53 flow (Phillips 1956). These early global climate models evolved through refined representations  
54 of physical processes (Walsh et al. 2013; Prodhomme et al. 2016) and inclusion of other Earth  
55 system components, notably the coupling of the ocean with the atmosphere (Manabe and Bryan  
56 1969) and linkages with terrestrial vegetation (Sellers et al. 1986; Dickinson et al. 1993). This  
57 progression has led to modern, well-developed climate models that can simulate global  
58 temperature, precipitation, and a broad range of climate variables, along with societal impacts  
59 such as crop yields and water availability (Bonan and Doney 2018). While climate models have

60 incorporated feedbacks between climate and natural systems, for example, the absorption of CO<sub>2</sub>  
61 by the oceans (Plattner et al. 2001) and carbon sequestration in terrestrial ecosystems (Field et al.  
62 2007), they continue to rely on static, external projections of anthropogenic greenhouse gas  
63 (GHG) emissions, despite the likelihood of strong feedbacks between the state of the climate  
64 system and human emissions (Palmer and Smith 2014; Thornton et al. 2017). Externalizing  
65 anthropogenic GHG emissions sidesteps much of the complexity and interplay between the  
66 climate and human system that in turn limits the realism of projections of climate change.

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

77         The next step in the evolution of global climate models, Earth system models, and  
78 integrated assessment models (henceforth referred to collectively as “climate models”) is to  
79 endogenize anthropogenic GHG emissions beyond economics to broadly consider human social  
80 and behavioral systems. The dynamic coupling of climate models with models of human social  
81 and behavioral systems (henceforth referred to as “social models”) to incorporate human  
82 behavior, decision-making, and other social processes is needed to provide robust projections of

83 climate change (Palmer and Smith 2014). Humans respond dynamically to climate change in a  
84 boundedly rational manner, updating beliefs and behavior in response to experiences of climate  
85 change, the influence of social networks, and other social, cultural, and political factors  
86 (Hoffman 2010; Demski et al. 2017). Climate change solutions, therefore, need to account for  
87 human preferences and behavior ('demand-side' solutions) that drive the adoption of mitigation  
88 policies, technologies, and infrastructure ('supply-side' solutions) by government and industry  
89 (Creutzig et al. 2016). The linking of social models with climate models would, for example,  
90 allow harmful changes in climate to lead to more aggressive improvements in energy efficiency  
91 and more rapid deployment of renewable energy, thereby reducing subsequent emissions  
92 (perhaps significantly) and projected change in climate (Beckage et al. 2018). Social factors may  
93 also predict lags in mitigation to even visible and damaging climate events due to the difficulty  
94 of altering entrenched beliefs and industries (Penna and Geels 2015), or mismatches between  
95 nations most responsible for creating emissions and nations most vulnerable to climate change  
96 impacts (Füssel 2010). Human behavioral responses to climate change might also lead to drastic  
97 actions such as geoengineering, which, though controversial (Kiehl 2006), could directly reduce  
98 atmospheric CO<sub>2</sub> or manage solar radiation (Wigley 2006; Vaughan and Lenton 2011) while also  
99 decreasing the perceived urgency for curtailing greenhouse gas emissions.

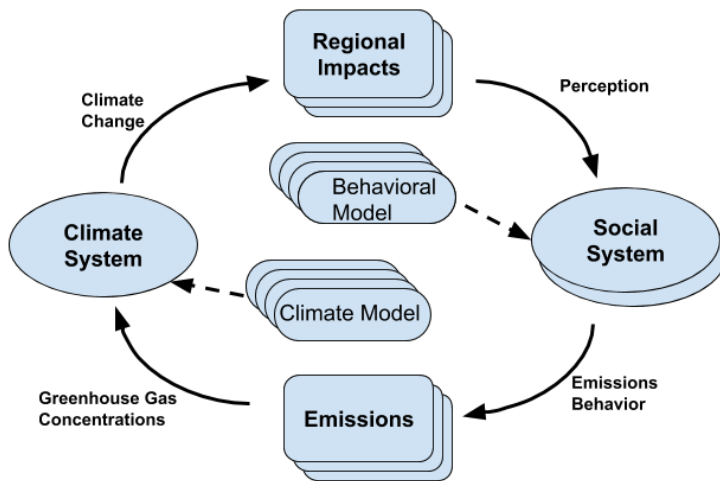
100         The social components of climate change are among the largest sources of uncertainty in  
101 the timeline and extent of GHG emissions and projected climate change (Beckage et al. 2018).  
102 Behavioral responses impact mitigation through perceptions of risk from climate change, access  
103 to resources to reduce emissions or adapt to climate change, social norms, and existing  
104 worldviews and social practices (Gifford 2011; Palmer and Smith 2014; Niamir et al. 2020).  
105 Attitudes towards mitigation behaviors are representative of social, political, and religious

106 ideologies and group membership (Weber 2010; Hoffman 2010; McCright et al. 2013) and  
107 interact with perception of risk from climate change. For example, climate change can produce  
108 increased weather extremes which may enhance the perceived urgency of response (Demski et  
109 al. 2017), but also weather extremes inconsistent with the overall direction of climate change  
110 (Vavrus et al. 2006). These extremes are perceived differently depending on prior beliefs  
111 (Weber 2010). Linking social and climate models will thus enable a more complete and dynamic  
112 representation of the climate system that will lead to (1) improved quantification of future  
113 climate change uncertainty and (2) greater understanding of climate sensitivity to social and  
114 behavioral components that can be leveraged to reduce the magnitude of future climate change.

115         Early efforts to couple social and climate models, henceforth social-climate models or  
116 SoCMs, have demonstrated that social uncertainty in projections of climate change is potentially  
117 as large as the uncertainty in the physical climate system (Beckage et al. 2018; Calvin and Bond-  
118 Lamberty 2018). SoCMs have also demonstrated the large influence of social learning, social  
119 norms, perceived efficacy, and perceived behavioral control on mitigation behavior and future  
120 climate change (Beckage et al. 2018; Bury et al. 2019). Perceived behavioral control and  
121 perceived social norms, for instance, exhibit a strong interaction in some SoCMs such that high  
122 values of both are required to produce emissions reductions, indicating leverage points in this  
123 representation of the social climate system (Beckage et al. 2018). But this result is from a single  
124 instantiation of one behavioral theory, the Theory of Planned Behavior (Ajzen 1991), coupled  
125 with a simplified, zero dimensional climate model. Furthermore, the entire population of Earth  
126 was modeled as a homogenous group, neglecting different cultures, emissions and experience of  
127 impacts. A wide set of behavioral theories could be used to construct social models of human  
128 behavioral responses to climate change at the individual or group level (Hargreaves 2011;

129 Schlüter et al. 2017), just as there is a large set of climate models of varying complexity that  
130 could be linked with a social model (Taylor et al. 2012). We expect relatively more variation  
131 across social models compared to climate models.

132



133

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

144

145 The first attempts to couple a social model with a climate model have demonstrated the

146 importance of doing so, but further exploration and development of SoCMs is necessary for

147 more realistic and actionable projections. A next step in developing SoCMs is a multi-model

148 approach to examine the robustness of climate projections to choice of behavioral theory and

149 model implementation (Fig. 1). The assumptions of different behavioral theories and their

150 parameterizations to represent diverse cultural groups and social systems will influence

151 emissions through behavioral responses. Emissions behavior may result from regional policies or  
152 individual decisions that increase or decrease GHG emissions in response to climate impacts and  
153 perceived risks. These emissions influence the atmospheric concentrations of GHGs that then  
154 feed back into the climate system.

155 We suggest the following priorities for developing SoCMs:

156 1. Evaluate an array of behavioral theories: Similar to the design and assessment of  
157 multiple climate models, a robust analysis is needed to examine a diverse set of human  
158 behavioral theories and implementations in social models. This includes characterizing the  
159 uncertainty of climate projections for each behavioral theory and its implementation, as well as  
160 for integrated models that consider human behavior at individual and group levels.

161 2. Differentiate climate impacts on humans across physical regions of the world: The  
162 regional distribution of GHG emissions does not align with the regional distribution of global  
163 climate change impacts. Regions with low emissions that experience high impacts may have  
164 little ability to reduce global emissions, whereas some regions with high emissions may not  
165 experience sufficient impacts to alter perceptions of climate change and emissions behavior.  
166 Regional discordance in impacts of climate change and sources of anthropogenic GHG emissions  
167 will likely lead to regionally unique human responses that interact through social contagion and  
168 adoption of policy.

169 3. Incorporate the influence of diverse social systems: Social models should consider the  
170 political structures, wealth distribution, cultural worldviews, and belief systems of diverse  
171 populations that vary globally and will likely interact with the behavioral theory chosen and the  
172 spatial patterns of climate change impacts to alter human behavior. The social models can be

173 informed by global or regional surveys, such as public opinion regarding support for  
174 geoengineering (Vissschers et al. 2017) and behavioral data, such as mobile phone data (Lu et al.  
175 2016).

176 4. Improve the representation of how perceptions and behavior shape GHG emissions  
177 behaviors: Further analysis is needed on how individuals and groups respond to physical climate  
178 and social factors and to implementation of emissions-related policies that potentially alter  
179 investments in renewable energy, subsidies for emissions-intensive livestock, and infrastructure  
180 to support electric vehicles. Different regional policy responses contribute to increases or  
181 decreases in emissions.

182 This proposed set of model development goals will lead to SoCMs evolving from stylized  
183 conceptual models to fully parameterized, operational models that provide robust projections of  
184 climate change. SoCMs will more fully characterize the uncertainty in climate change  
185 projections by integrating uncertainties in both the social and physical systems. Although SoCMs  
186 may initially lead to increased uncertainty in climate projections, they will more realistically  
187 capture the range of likely climate futures and allow the scientific community to directly address  
188 critical model deficiencies that may eventually reduce climate uncertainties (Carshaw et al.  
189 2018). Data collection that addresses these deficiencies could then be prioritized so as to quickly  
190 reduce the overall uncertainty of SoCMs. The coupling of physical and social processes may also  
191 identify complex feedbacks that potentially reduce overall uncertainty in projected climate  
192 change. For example, extreme climate change may motivate strong human behavioral responses  
193 to reduce GHG emissions while more moderate climate change may lead to decreased mitigation  
194 efforts. The overall result might then be to constrain the likely range of projected climate change  
195 away from extreme high or low ranges. Importantly, an analysis of SoCMs would guide



196 mitigation efforts by identifying points of high leverage, e.g. those components of the model  
197 where small changes in parameters lead to comparatively large changes in projected climate  
198 change. The emergence of SoCMs will allow for a more complete examination of climate change  
199 uncertainty, and also enable the partitioning of climate change uncertainty into irreducible  
200 components intrinsic to the climate and social systems, and components that can be reduced with  
201 continued model development and incorporation of human behavioral data (Lorenz 2006;  
202 Beckage et al. 2011).

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

218 human behavior in climate projections, the process itself would enrich our understanding of the  
219 social dimensions of climate change and lead to better informed policies.

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

231           Though daunting, similar efforts have been made to incorporate feedbacks between  
232 human behavior and the environment. Models of social-ecological systems, for example, often  
233 include human behavior and decision-making coupled with ecological processes on landscape or  
234 watershed scales (Schlüter et al. 2012, 2017; Müller-Hansen et al. 2017). Similarly, the dynamics  
235 of human behavior in an economic context have been modeled with respect to environmental  
236 hazards (Filatova 2015; Niamir et al. 2018). These efforts can provide insights into modeling  
237 complex social systems, including human behavior at various levels of granularity, that will help  
238 organize and streamline this process for SoCMs. Given past advancements in climate modeling,  
239 the benefits of linking social models with climate models may be greater than the marginal  
240 improvements that come from a continued focus solely on refinement of models of the physical

241 climate system. We believe that the coupling of social and climate models builds on the  
242 influential work of Meadows et al. (1972, 2004) and continues their pioneering efforts to  
243 integrate humans into Earth system models to assess our global impacts (Meadows et al. 1972,  
244 2004).

245

## 246 **Declarations**

247 **Funding:** This work resulted from a working group jointly supported by both the National  
248 Institute for Mathematical Biological Synthesis, a synthesis center supported by the National  
249 Science Foundation through NSF Award DBI-1300426 with additional support from The  
250 University of Tennessee, Knoxville, and the National Socio-Environmental Synthesis Center  
251 (SESYNC) under funding received from the National Science Foundation DBI-1052875. BB,  
252 JW, and AZ additionally acknowledge support from NSF through VT EPSCoR Grant Nos. EPS-  
253 1101317 and OIA-1556770.

254 **Conflicts of interest/Competing interests (include appropriate disclosures):** The authors  
255 declare that they have no conflict of interest.

256 **Availability of data and material:** N/A

257 **Code availability:** N/A

258 **Authors' contributions:** Manuscript was conceptualized at working group meetings including  
259 all authors. BB, KL, JW, LG, NF, & FH were all involved in writing the initial manuscript, BB,  
260 KL, JW, and LG revised the final manuscript. All authors commented on previous versions of  
261 the manuscript and approved of final manuscript.

262

263 **References**

- 264 Ajzen I (1991) The theory of planned behavior. *Organizational Behavior and Human Decision*  
265 *Processes* 50:179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- 266 Beckage B, Gross LJ, Kauffman S (2011) The limits to prediction in ecological systems.  
267 *Ecosphere* 2:1–12
- 268 Beckage B, Gross LJ, Lacasse K, et al (2018) Linking models of human behaviour and climate  
269 alters projected climate change. *Nature Climate Change* 8:79–84.  
270 <https://doi.org/10.1038/s41558-017-0031-7>
- 271 Bonan GB, Doney SC (2018) Climate, ecosystems, and planetary futures: The challenge to  
272 predict life in Earth system models. *Science* 359:eaam8328.  
273 <https://doi.org/10.1126/science.aam8328>
- 274 Bury TM, Bauch CT, Anand M (2019) Charting pathways to climate change mitigation in a  
275 coupled socio-climate model. *PLoS computational biology* 15:
- 276 Calvin K, Bond-Lamberty B (2018) Integrated human-earth system modeling—state of the  
277 science and future directions. *Environmental Research Letters* 13:063006.  
278 <https://doi.org/10.1088/1748-9326/aac642>
- 279 Carlsaw KS, Lee LA, Regayre LA, Johnson JS (2018) Climate models are uncertain, but we can  
280 do something about it. *Eos*
- 281 Clarke L, Eom J, Marten EH, et al (2018) Effects of long-term climate change on global building  
282 energy expenditures. *Energy Economics* 72:667–677.  
283 <https://doi.org/10.1016/j.eneco.2018.01.003>
- 284 Creutzig F, Fernandez B, Haberl H, et al (2016) Beyond Technology: Demand-Side Solutions  
285 for Climate Change Mitigation. *Annual Review of Environment and Resources* 41:173–  
286 198. <https://doi.org/10.1146/annurev-environ-110615-085428>
- 287 Demski C, Capstick S, Pidgeon N, et al (2017) Experience of extreme weather affects climate  
288 change mitigation and adaptation responses. *Climatic Change* 140:149–164.  
289 <https://doi.org/10.1007/s10584-016-1837-4>
- 290 Dickinson E, Henderson-Sellers A, Kennedy J (1993) Biosphere-atmosphere transfer scheme  
291 (BATS) version 1e as coupled to the NCAR community climate model
- 292 Field CB, Lobell DB, Peters HA, Chiariello NR (2007) Feedbacks of Terrestrial Ecosystems to  
293 Climate Change. *Annu Rev Environ Resour* 32:1–29.  
294 <https://doi.org/10.1146/annurev.energy.32.053006.141119>
- 295 Filatova T (2015) Empirical agent-based land market: Integrating adaptive economic behavior in  
296 urban land-use models. *Computers, Environment and Urban Systems* 54:397–413.  
297 <https://doi.org/10.1016/j.compenvurbsys.2014.06.007>

- 298 Füssel H-M (2010) How inequitable is the global distribution of responsibility, capability, and  
 299 vulnerability to climate change: A comprehensive indicator-based assessment. *Global*  
 300 *Environmental Change* 20:597–611. <https://doi.org/10.1016/j.gloenvcha.2010.07.009>
- 301 Gifford R (2011) The dragons of inaction: psychological barriers that limit climate change  
 302 mitigation and adaptation. *American Psychologist* 66:290
- 303 Hargreaves T (2011) Practice-ing behaviour change: Applying social practice theory to pro-  
 304 environmental behaviour change. *Journal of consumer culture* 11:79–99
- 305 Hoffman AJ (2010) Climate change as a cultural and behavioral issue: Addressing barriers and  
 306 implementing solutions. Social Science Research Network, Rochester, NY
- 307 Kiehl J (2006) Geoengineering climate Change: Treating the symptom over the cause? *Climatic*  
 308 *Change* 77:227
- 309 Lorenz EN (2006) Predictability-a problem partly solved. In: Palmer T, Hagedorn R (eds)  
 310 Predictability of weather and climate. Cambridge University Press, pp 40–58
- 311 Lu X, Wrathall DJ, Sundsøy PR, et al (2016) Detecting climate adaptation with mobile network  
 312 data in Bangladesh: anomalies in communication, mobility and consumption patterns  
 313 during cyclone Mahasen. *Climatic Change* 138:505–519. [https://doi.org/10.1007/s10584-](https://doi.org/10.1007/s10584-016-1753-7)  
 314 [016-1753-7](https://doi.org/10.1007/s10584-016-1753-7)
- 315 Lynch P (2006) The ENIAC integrations. *The Emergence of Numerical Weather Prediction* 206–  
 316 208
- 317 Manabe S, Bryan K (1969) Climate calculations with a combined ocean-atmosphere model.  
 318 *Journal of the Atmospheric Sciences* 26:786–789
- 319 McCright AM, Dunlap RE, Xiao C (2013) Increasing influence of party identification on perceived  
 320 scientific agreement and support for government action on climate change in the United  
 321 States, 2006–12. *Wea Climate Soc* 6:194–201. [https://doi.org/10.1175/WCAS-D-13-](https://doi.org/10.1175/WCAS-D-13-00058.1)  
 322 [00058.1](https://doi.org/10.1175/WCAS-D-13-00058.1)
- 323 Meadows D, Randers J, Meadows D (2004) *Limits to growth: The 30-year update*. Chelsea  
 324 Green Publishing
- 325 Meadows DH, Meadows DL, Randers J, Behrens WW (1972) *The limits to growth*. New York  
 326 102:27
- 327 Müller-Hansen F, Schlüter M, Mäs M, et al (2017) Towards representing human behavior and  
 328 decision making in Earth system models – an overview of techniques and approaches.  
 329 *Earth System Dynamics* 8:977–1007. <https://doi.org/10.5194/esd-8-977-2017>
- 330 Niamir L, Filatova T, Voinov A, Bressers H (2018) Transition to low-carbon economy: Assessing  
 331 cumulative impacts of individual behavioral changes. *Energy Policy* 118:325–345.  
 332 <https://doi.org/10.1016/j.enpol.2018.03.045>

- 333 Niamir L, Kieseewetter G, Wagner F, et al (2020) Assessing the macroeconomic impacts of  
334 individual behavioral changes on carbon emissions. *Climatic Change* 158:141–160.  
335 <https://doi.org/10.1007/s10584-019-02566-8>
- 336 Nordhaus W (2018) Evolution of modeling of the economics of global warming: Changes in the  
337 DICE model, 1992-2017. 22
- 338 Nordhaus W (2019) Climate Change: The Ultimate Challenge for Economics. *American*  
339 *Economic Review* 109:1991–2014. <https://doi.org/10.1257/aer.109.6.1991>
- 340 Palmer PI, Smith MJ (2014) Earth systems: Model human adaptation to climate change. *Nature*  
341 *News* 512:365. <https://doi.org/10.1038/512365a>
- 342 Penna CCR, Geels FW (2015) Climate change and the slow reorientation of the American car  
343 industry (1979–2012): An application and extension of the Dialectic Issue LifeCycle  
344 (DILC) model. *Research Policy* 44:1029–1048.  
345 <https://doi.org/10.1016/j.respol.2014.11.010>
- 346 Phillips NA (1956) The general circulation of the atmosphere: A numerical experiment. *Quarterly*  
347 *Journal of the Royal Meteorological Society* 82:123–164.  
348 <https://doi.org/10.1002/qj.49708235202>
- 349 Plattner G-K, Joos F, Stocker TF, Marchal O (2001) Feedback mechanisms and sensitivities of  
350 ocean carbon uptake under global warming. *Tellus B: Chemical and Physical*  
351 *Meteorology* 53:564–592. <https://doi.org/10.3402/tellusb.v53i5.16637>
- 352 Prodhomme C, Batté L, Massonnet F, et al (2016) Benefits of Increasing the Model Resolution  
353 for the Seasonal Forecast Quality in EC-Earth. *J Climate* 29:9141–9162.  
354 <https://doi.org/10.1175/JCLI-D-16-0117.1>
- 355 Richardson LF (1922) *Weather prediction by numerical methods*. Cambridge University Press,  
356 London
- 357 Schlüter M, Baeza A, Dressler G, et al (2017) A framework for mapping and comparing  
358 behavioural theories in models of social-ecological systems. *Ecological Economics*  
359 131:21–35. <https://doi.org/10.1016/j.ecolecon.2016.08.008>
- 360 Schlüter M, Mcallister RRJ, Arlinghaus R, et al (2012) New Horizons for Managing the  
361 Environment: A Review of Coupled Social-Ecological Systems Modeling. *Natural*  
362 *Resource Modeling* 25:219–272. <https://doi.org/10.1111/j.1939-7445.2011.00108.x>
- 363 Sellers PJ, Mintz Y, Sud Y e al, Dalcher A (1986) A simple biosphere model (SiB) for use within  
364 general circulation models. *Journal of the Atmospheric Sciences* 43:505–531
- 365 Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design.  
366 *Bulletin of the American Meteorological Society* 93:485–498
- 367 Thornton PE, Calvin K, Jones AD, et al (2017) Biospheric feedback effects in a synchronously  
368 coupled model of human and Earth systems. *Nature Climate Change* 7:496–500.  
369 <https://doi.org/10.1038/nclimate3310>

- 370 Vaughan NE, Lenton TM (2011) A review of climate geoengineering proposals. *Climatic Change*  
371 109:745–790. <https://doi.org/10.1007/s10584-011-0027-7>
- 372 Vavrus S, Walsh JE, Chapman WL, Portis D (2006) The behavior of extreme cold air outbreaks  
373 under greenhouse warming. *International Journal of Climatology* 26:1133–1147.  
374 <https://doi.org/10.1002/joc.1301>
- 375 Visschers VHM, Shi J, Siegrist M, Arvai J (2017) Beliefs and values explain international  
376 differences in perception of solar radiation management: insights from a cross-country  
377 survey. *Climatic Change* 142:531–544. <https://doi.org/10.1007/s10584-017-1970-8>
- 378 Walsh K, Lavender S, Scoccimarro E, Murakami H (2013) Resolution dependence of tropical  
379 cyclone formation in CMIP3 and finer resolution models. *Clim Dyn* 40:585–599.  
380 <https://doi.org/10.1007/s00382-012-1298-z>
- 381 Weber EU (2010) What shapes perceptions of climate change? *WIREs Clim Change* 1:332–  
382 342. <https://doi.org/10.1002/wcc.41>
- 383 Wigley TML (2006) A Combined Mitigation/Geoengineering Approach to Climate Stabilization.  
384 *Science* 314:452–454. <https://doi.org/10.1126/science.1131728>
- 385