Towards a science of climate diversity

The examples above offer a glimpse of the complex and often hidden social forces that impact STEM participation. However, addressing the unique challenge of minority underrepresentation in climate STEM fields and the climate movement at large will require a more comprehensive and coordinated response between behavioural scientists and climate researchers. Psychologists need to engage climate scientists and advocacy groups to identify organizational norms and practices that may impede broader engagement with the movement. The climate community, in turn, needs to engage psychologists and other diversity researchers to develop research-informed solutions for addressing the problem. These collaborations should also consider how other forms of diversity beyond race, such as socioeconomic, geographic and religious diversity, impact public interest in climate initiatives and receptiveness to advocacy efforts.

We outline five steps that the climate community can take to foster these collaborations and develop new evidence-based remedies (Fig. 2). These include enhancing funding and support for basic research on climate STEM diversity; establishing the scientific study of climate diversity as a sub-specialization within the climate sciences; expanding opportunities for disseminating diversity research at scientific conferences, as well as between academics and non-academics; and using diversity research to guide climate advocacy and reform efforts. Current funding mechanisms, such as the US National Science Foundation's Sustainability Research Networks competition, and existing organizational partnerships[1] can help lay the groundwork for these collaborations, but addressing the diversity crisis will require new infrastructure and new commitments on the part of scientists and non-scientists alike.

Climate science is a fundamentally collaborative and interdisciplinary enterprise, tasked with understanding complex biophysical and social forces contributing to climate challenges. A science of climate diversity can help us better understand what brings diverse stakeholders to the table. Leveraging these insights will allow the climate community to more effectively engage policymakers and the public, and help build a more informed and influential movement for the twenty-first century. ❐

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References

1. Taylor, D. E. *The State of Diversity in Environmental Organizations: Mainstream NGOs, Foundations and Government Agencies* (Green 2.0, 2014); www.diversegreen.org/report
2. United Nations Development Programme *Human Development Report 2009. Overcoming Barriers: Human Mobility and Development* (Palgrave Macmillan, 2009).
3. Mohai, P. *Res. Soc. Prob. Public Policy* **15,** 21–49 (2008).
4. Brulle, R. J., Carmichael, J. & Jenkins, C. *Climatic Change* **114,** 169–188 (2012).
5. Anderegg, W. R. L. & Goldsmith, G. R. *Environ. Res. Lett.* **9,** 1–8 (2014).
6. Taylor, D. E. *Res. Soc. Prob. Public Policy* **18,** 385–407 (2010).
7. Landivar, L. C. *Disparities in STEM Employment by Sex, Race, and Hispanic Origin* (US Census Bureau, 2013).
8. Leiserowitz, A. & Akerlof, K. *Race, Ethnicity and Public Responses to Climate Change* (Yale Project on Climate Change, 2010).
9. Murphy, M. C., Steele, C. M. & Gross, J. J. *Psychol. Sci.* **18,** 879–885 (2007).
10. Purdie-Vaughns, V. *et al. J. Pers. Soc. Psychol.* **94,** 615–630 (2008).
11. Stout, J. G., Dasgupta, N., Hunsinger, M. & McManus, M. A. *J. Pers. Soc. Psychol.* **100,** 255–270 (2011).
12. Unzueta, M. M. & Binning, K. R. *Pers. Soc. Psychol. B* **38,** 26–38 (2012).
13. Steinke, J. *et al. Sci. Commun.* **29,** 35–64 (2007).
14. Pearson, A. R. & West, J. in *Proc. Soc. Pers. Soc. Psychol.* (eds Finkel, E. & Kaiser, C.) 107–108 (Society for Personality and Social Psychology, 2014).
15. Kraft, M. & Kamieniecki, S. *Handbook of US Environmental Policy* (Oxford Univ. Press, 2012).
16. Cheryan, S., Plaut. V. C., Handron, C. & Hudson, L. *Sex Roles* **69,** 58–71 (2013).
17. Schuldt, J. P., Konrath, S. H. & Schwarz, N. *Public Opin. Quart.* **75,** 115–124 (2011).
18. Apfelbaum, E. P., Norton, M. I. & Sommers, S. R. *Curr. Dir. Psychol. Sci.* **21,** 205–209 (2012).
19. Dobbin, F. & Kalev, A. *Oxford Handbook of Diversity and Work* (Oxford Univ. Press, 2013).

COMMENTARY:

Going back to basics

Christian Jakob

Climate models have increased in complexity over time as more processes have been included. Now we need to return to the underpinning basics in the models and ensure they are the best they can be.

All predictions and projections of weather and climate from days to centuries ahead fundamentally rely on models of the atmosphere, ocean and land, increasingly including representations of biological and chemical processes. Much of our scientific enquiry in climate science makes use of the same set of tools, which are collectively referred to as climate models. Lives and property are saved every day by the application of weather models, and climate model results underpin major planning decisions for our future.

The use of models is very common well beyond the field of climate science. However, unbeknownst to many, climate models differ fundamentally from those used to predict the behaviour of many other systems, such as population or economic models. While the latter are often based on statistical relationships derived from the observed behaviour of the system, at the core of climate models are well-known fundamental laws that describe the circulation of the atmosphere and ocean complemented by complex sub-models of less well-understood and unresolved processes.

Building climate models involves four fundamental steps:

(1) Expressing the fundamental laws in mathematical terms[1].
(2) Applying numerical approximations to the resulting set of equations[2].
(3) Building and implementing sub-models — often referred to as parameterizations — for those processes that are excluded from the

model equations, but are important. This includes processes that act on scales smaller than those represented by the numerical model grid and processes for which there are no straightforward equations or for which our understanding is incomplete, such as biological processes[3].
(4) Assembling all components and adjusting model parameters to fulfil observed global constraints, often referred to as tuning[4].

Over recent decades climate models have become increasingly complex by including an ever larger number of processes deemed potentially important to the climate system (Fig. 1). The community using climate models for its own scientific enquiry and for decision-making has grown dramatically, culminating in the establishment of climate services alongside the weather services in many countries[5]. Given this, it should be self-evident that building and improving such models should be one of the highest priorities in climate science. Is it?

There is good evidence that in a broad sense climate models are improving[6,7]. However, there is equally strong evidence that some long-standing model errors elude improvement. Many of those are associated with the representation of clouds and precipitation in atmospheric models[8]. This has some major consequences for climate prediction. It is well known that uncertainties in our estimates of climate sensitivity — the change in global mean temperature for a doubling of CO_2 concentrations in the atmosphere — largely result from differences in the simulation of cloud responses in climate models[9]. This explains the range of projected changes in global mean temperature, which has stubbornly remained the same since the dawn of climate modelling in the 1970s. Assessing potential precipitation changes in particular regions of our planet is among the most important tasks of climate projection, and yet, precipitation is one of the most poorly simulated quantities in climate models[10]. Why is this so hard? First, because of their dependence on small-scale processes, clouds and precipitation need to be represented by parameterization. Worse still, they strongly interact with the circulation. As a result, even small errors in their representation in a particular location spread and amplify quickly as they are communicated through circulation changes.

The slow progress in the representation of clouds and precipitation and their coupling to atmospheric circulation features currently revolves around two main issues: our inability to link the long-standing model errors to a small set of processes and phenomena that require most rapid improvement, and our lack of investment in developing actual improvements to key cloud and precipitation processes[11]. Both are intrinsically intertwined activities as model improvement naturally requires us to know what to improve (Box 1).

Model evaluation constitutes the meeting of model results and observations in the context of a model's purpose. It is a major scientific activity in itself, in particular if it is to support model development. Contrary to popular belief it is not to establish model perfection, but whether or not a model is fit for the purpose it is applied to. While simple in principle, this proves a deeply difficult question for climate change modelling. There is little doubt that modern climate models are fit to predict the overall increase in global mean temperature in response to CO_2 increases. However, for more regional changes — especially in important quantities such as precipitation — the question remains largely unresolved. Here, large errors in the basic model state imprint themselves strongly on the model response[12]. Hence, while we can use current global climate models to conclude that mitigation of climate change is important, they do not produce sufficiently accurate results to inform local adaptation decisions in many parts of the world.

Why have we not been able to improve models more quickly? Attempting to answer this question exposes a combination of complex issues from the mechanisms to prioritize the science, to the institutional support of model development to the evaluation of scientific output.

As the use of climate models expanded from purely scientific interrogation to decision support for policymakers, priorities for their development needed to be reassessed. Consciously or subconsciously the priority became to expand the scope of the applications of climate models by adding more processes, such as cloud–aerosol interactions or bio–geochemical processes. In principle, this allows a broader range of questions about the climate system to be answered;

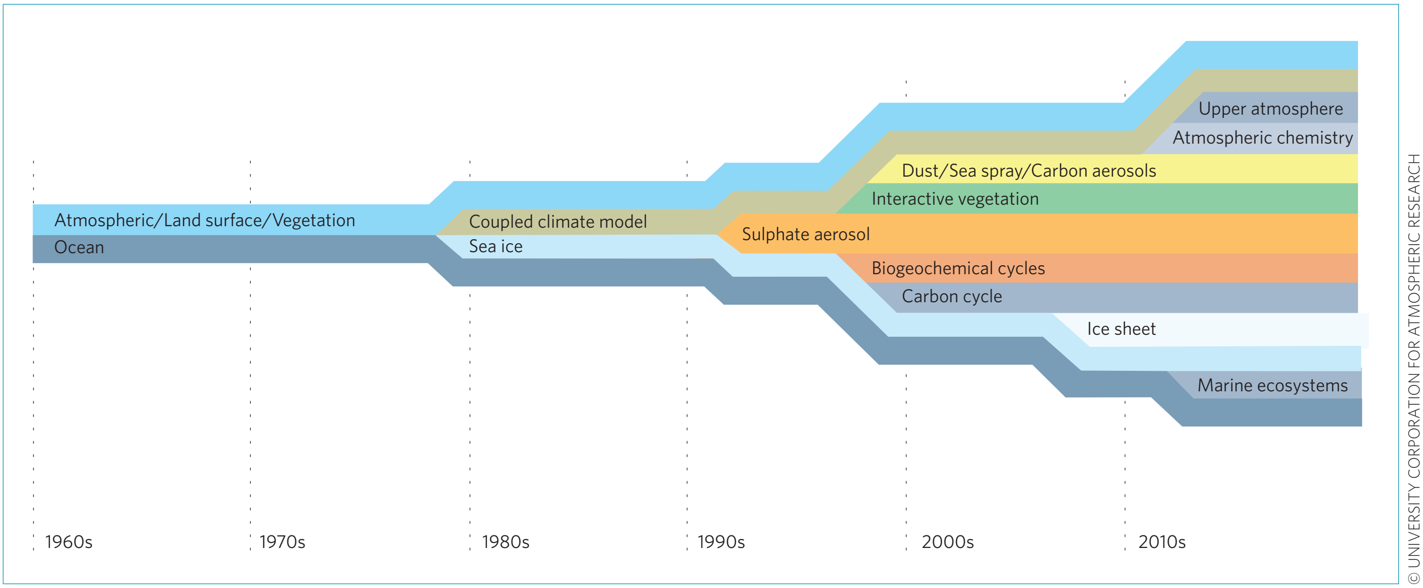
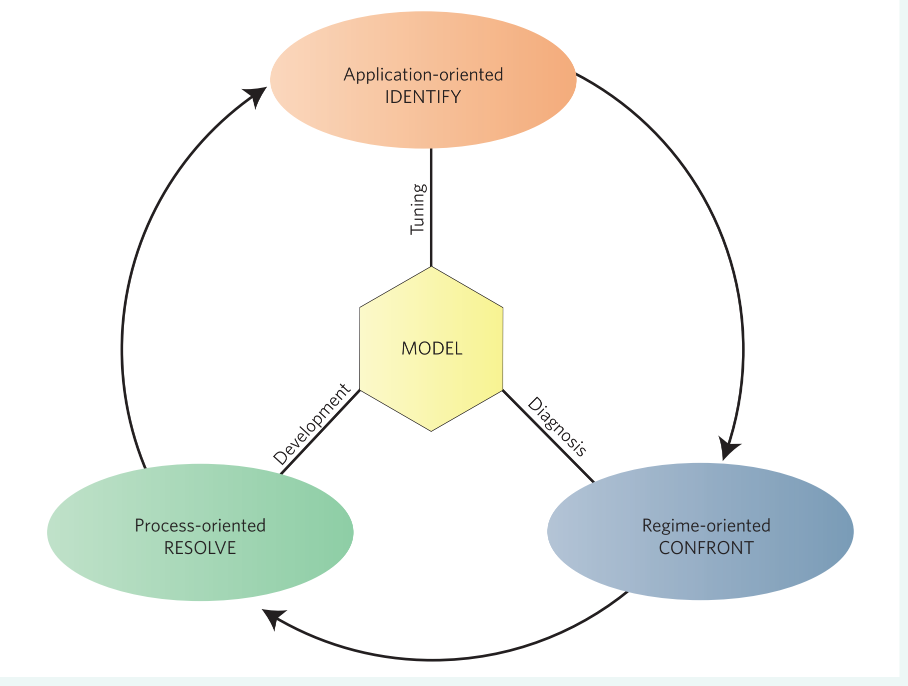


Figure 1 | The history of climate model complexity.

Box 1 | The model development process.

Model development is influenced by a number of often interacting drivers. The most obvious amongst those are the performance of a model in its application — the model purpose — and the credibility of the model ingredients at the process level, the model formulation. Investment in model improvement is commonly driven by both. Paradoxically, if unconnected, the two approaches to model development can become counterproductive and ultimately hinder progress. Model errors are first identified in the application of the model. However, too much focus on model performance in this context alone without attention to the processes will lead to heavily tuned models, which then become difficult to improve through the common incremental approach. Model shortcomings can ultimately only be resolved at the process level, but concentrating on improving model processes without a link to the overall model performance will result in increased model complexity without addressing key model shortcomings. Both approaches are in use today and the disconnect between them has contributed to the slow progress in the improvement of the representation of clouds and precipitation in climate models. Accelerating progress will require building a stronger connection between the application-driven and process-driven approaches to model development. This can be achieved through the development of more insightful model diagnosis and evaluation techniques, which confront the model errors by identifying the key regimes or phenomena contributing to them. Those regimes and phenomena can then be used to provide focus to the process studies that drive model improvement. This increases the probability that improvements in a model's process representation will actually improve its performance when it is applied for its purpose.



for instance, the role of carbon feedbacks. However, the expansion of the models came at the price. Several 'old' problems, such as the more realistic treatment of precipitation were left behind. It has now become clear that to realize the potential of the new 'Earth system' components of climate models will require us to pay more attention to these old difficulties.

Another important set of issues ranks around the community's appreciation of those who develop models. Model development is a challenging task that often takes a long time to bear fruit. Unfortunately, this goes against the grain of many of the trends in modern science, in which success is measured using simple metrics, often based on the quantity of output, rather than its quality. This and the poor communication of the opportunities for creative young minds to make a real difference to society by applying their skills to build better climate models is increasingly turning people away from building what fundamentally supports much of climate science — better climate models.

For us to deliver on the promise to society to provide the best information possible on climate change at regional scales relevant to decision-makers requires a course correction.

The opportunities for making progress in core physical model development, in particular in the key areas of clouds and precipitation, have never been better than today. Over the past decade our ability to observe the climate system at process level both from the ground and from space has taken an enormous leap. Likewise, thanks to large increases in our computational capabilities it is increasingly possible to probe the behaviour of many processes that are unresolved in global models as well as their interactions with circulations across many scales through the application of process-resolving models. New ideas for the representation of key physical processes, for instance through the use of more stochastic approaches, have emerged.

What then is required to turn these opportunities into progress in model development? It is unlikely that a single action will solve what is a complex problem, but some guidance emerges from the discussion above.

Perhaps first and foremost, we must instil a new sense of urgency and excitement into solving long-standing problems in climate models. This will require breaking through the paradigm that progress is synonymous with complexity. Most importantly, it will require prioritization. It has become abundantly clear that by trying to solve every problem we failed to solve some of the bigger ones. The World Climate Research Programme has recently embarked on a major process of prioritizing climate research by defining a small number of Grand Science Challenges (http://www.wcrp-climate.org/index.php/grand-challenges). One of them is to address the problem at the heart of the issues discussed above by focusing on clouds and precipitation, their coupling to the circulation and their role in climate sensitivity (http://www.wcrp-climate.org/index.php/gc-clouds).

The quasi-operational use of climate models in regular rounds of climate projections has strongly affected community behaviour regarding model development. Modern climate models are equivalent to well-tuned car engines. Over time, their parts have been built to neatly fit and operate well together. As a result the risk of initially degrading model performance by making substantial changes to key components is high, the time to implement ideas is long and the reward often not guaranteed. We must overcome the natural conservatism in making decisions around developing and applying new model components that has emerged through 'operational' climate models.

Ultimately though, solving what are clearly challenging but also very exciting scientific problems will require us to attract many new creative minds to work on them. This has proved difficult and people working on the fundamental issues in model development have become somewhat akin to an endangered species. It is timely then to think about dedicated activities that both improve their habitat and 'breed' the next generation. Improving the recognition of solving old model problems as a vital activity throughout the community and increasing the engagement of model developers in the broader climate science agenda are crucial. How many of the papers published in this journal alone would exist without the efforts of the modelling community? This increased recognition must go hand-in-hand with educational programmes ranging from short courses to the deeper engagement of academia in the model development enterprise, conceivably driven by an increased number of appointments of model developers in academic institutions so that the skills and excitement of being a model developer can be transferred to the next generation.

Both the climate science community and society rely on high-quality model representations of the climate system. Making climate models the best they can be at any given time should go without saying. The time to make it so is now. ❐

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References

1. Holton, J. R. & Hakim, G. J. *An Introduction to Dynamic Meteorology* (Elsevier, 2012).
2. Haltiner, G. J. & Williams, R. T. *Numerical Prediction and Dynamic Meteorology* (Wiley, 1980).
3. Stensrud, D. J. *Parameterization Schemes — Keys to Understanding Numerical Weather Prediction Models* (Cambridge Univ. Press, 2007).
4. Mauritsen, T. *et al. J. Adv. Model. Earth Syst.* **4,** M00A01 (2012).
5. *Implementation Plan of the Global Framework for Climate Services* (World Meteorological Organization, 2014).
6. Flato, G. M. *et al.* in *Climate Change 2013: The Physical Science Basis* (eds Stocker, T. F. *et al.*) 741–866 (IPCC, Cambridge Univ. Press, 2013).
7. Reichler, T. & Kim, J. *Bull. Am. Meteorol. Soc.* **89,** 303–311 (2008).
8. Stevens, B. & Bony, S. *Science* **340,** 1053–1054 (2013).
9. Dufresne, J-L. & Bony, S. *J. Clim.* **21,** 5135–5144 (2008).
10. Stephens, G. L. *et al. J. Geophys. Res.* **115,** D24211 (2010).
11. Jakob, C. *Bull. Am. Meteorol. Soc.* **91,** 869–875 (2010).
12. Medeiros, B., Stevens, B. & Bony, S. *Clim. Dynam.* http://dx.doi.org/10.1007/s00382-014-2138-0 (2014).

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COMMENTARY:

Uncertainty in projecting GHG emissions from bioenergy

Thomas Buchholz, Stephen Prisley, Gregg Marland, Charles Canham and Neil Sampson

The definition of baselines is a major step in determining the greenhouse-gas emissions of bioenergy systems. Accounting frameworks with a planning objective might require different baseline attributes and designs than those with a monitoring objective.

To evaluate the impact of any proposed greenhouse-gas (GHG) mitigation we have to be able to compare GHG emissions expected under the mitigation activity with some alternative future — typically a counterfactual baseline that reflects emissions under a 'business-as-usual' (BAU) scenario[1,2]. Defining an alternative future has been at the heart of recent controversy over the assessment of net GHG emissions associated with development and expansion of forest-based bioenergy[3–5]. Major uncertainties in the quantification of the net GHG emissions associated with forest biomass energy lie in the prediction of the baseline. The challenges inherent in predicting net GHG emissions under BAU conditions can be illustrated using the periodic assessments of the United States' forest carbon stocks from the Forest and Rangeland Renewable Resources Planning Act (RPA) assessments.

Gillenwater[6] defined a baseline as "a prediction of the quantified amount of an input to or output from an activity resulting from the expected future behaviour of the actors proposing, and affected by, a proposed activity in the absence of one or more policy interventions, holding all other factors constant (*ceteris paribus*)". Accounting strictures consider both what information would be useful to decision-makers (relevance) and the ability of experts to make meaningful measurements (reliability)[7]. To make useful decisions we must be able to compare the path travelled with an alternate path not travelled (the baseline). If wood is not harvested for energy it will be left in the forest or harvested for some other purpose.