Editorial: Climate Science: An Invitation for Physicists

Climate science is rooted in physics and in many of the methods used by physicists. Although it's a cliché to say that the practice of science changed dramatically with the advent of the digital age, computers have had an enormous impact on the growth and evolution of climate science. Before computing, progress in explaining observations or making predictions in the physical sciences, including climate science [1], was made using pencil and paper calculations. Computers changed this completely.

There are currently two main approaches to climate theory: numerical simulations, which use large-scale general circulation models of the atmosphere and/or oceans, and idealized models—a physicist's bread and butter—which are generally geared towards understanding the behavior of a key physical phenomenon within the larger climate system [2]. Simulations of the climate operate like enormous coarse-grained weather forecasts; the global climate is represented by the output from a computational approximation of all of the known physics. In contrast, idealized models focus on individual subsystems of the climate, such as El Niño [3] or Arctic sea ice [4]. Breaking down the problem in this way facilitates mathematical analysis of the processes involved and their observational manifestations. There is a vast gulf, both conceptually and in terms of space and time scales, between simulations and idealized models. Attempts to reconcile them will have to focus on the problem of scales, a task well suited to physicists: The challenge of scale separation in both condensed matter and particle physics led to the development of the renormalization group, unifying concepts in previously disparate fields [5]. Renormalization group concepts and methods have been successfully applied to fluid dynamics problems [6,7], which are central to climate dynamics.

Climate science gave birth to one of the most far-reaching branches of mathematics: chaos theory. Meteorologist Edward Lorenz uncovered chaos theory when developing an idealized model of thermal convection, similar to that which occurs when water is heated on a stove [8]. Some 50 years later, almost every physicist has heard of chaos, and ideas and concepts based on the theory have lengthy tendrils that extend throughout many branches of science [9]. In this sense, climate science is indeed basic science. By considering idealized models motivated by specific climate problems, could other discoveries akin to chaos be made? We know that approaches from statistical mechanics normally used to describe microscopic systems can be applied to large-scale geophysical systems, such as planetary flows, rain, and sea ice thickness [10–12]. What other concepts could shed light on idealized models and inform our thinking about geophysical flows? Lorenz advocated that examining the statistics of a flow could provide more insight into the phenomena than calculating only the flow field itself [13]. His idealizations continue to push our thinking in many new directions [14–16].

Data analysis is another important area where mainstream physics and climate science can connect. Experimental high-energy physicists, for example, are experts in locating small signals in large quantities of data so that they can correctly interpret particle collision events [17]. Could climate scientists examining data from sediment or ice cores learn from the theoretical and data analysis methodologies particle physicists use? In turn, could physicists in general learn from the methodologies employed in climate research [18–22]?

Physicists have successfully addressed a wide swath of science and engineering problems using myriad methods. Many of these applications have motivated the invention of entirely new approaches. Climate science offers many exciting opportunities for physicists with broad interests. The field is as interdisciplinary as, for example, soft matter [23], with practitioners spanning nearly all science and engineering departments. The problems are rich and vast; they range from figuring out how to approach challenges like turbulence and multiscale phenomena [24–26] to embracing the analysis of wide ranging climate proxy data [27–29]. New ideas will emerge from perspectives that come from the range of approaches used across all areas of physics. Not only will this help scientists better understand the climate, but what they learn will, as shown by the legacy of chaos theory, impact fields far beyond climate science.

0031-9007/16/116(15)/150002(2)

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Published 14 April 2016
DOI: 10.1103/PhysRevLett.116.150002

[1] Geophysical fluid dynamics summer program: Woods Hole Oceanographic Institution, http://www.whoi.edu/gfd/ (c.f., Program History) (2016).
[2] I. M. Held, The gap between simulation and understanding in climate modeling, Bull. Am. Meteorol. Soc. **86**, 1609 (2005).
[3] E. Tziperman, H. Scher, S. E. Zebiak, and M. A. Cane, Controlling Spatiotemporal Chaos in a Realistic El Nino Prediction Model, Phys. Rev. Lett. **79**, 1034 (1997).
[4] W. Moon and J. S. Wettlaufer, A stochastic perturbation theory for non-autonomous systems, J. Math. Phys. (N.Y.) **54**, 123303 (2013).
[5] L. P. Kadanoff, Innovations in statistical physics, Annu. Rev. Condens. Matter Phys. **6**, 1 (2015).
[6] N. Goldenfeld, *Lectures on Phase Transitions and the Renormalization Group* (Addison-Wesley, Reading, MA, 1992).
[7] G. I. Barenblatt, *Scaling, Self-Similarity, and Intermediate Asymptotics: Dimensional Analysis and Intermediate Asymptotics* (Cambridge University Press, Cambridge, England, 1996).
[8] E. N. Lorenz, Deterministic nonperiodic flow, J. Atmos. Sci. **20**, 130 (1963).
[9] J. Gleick, *Chaos: Making a New Science* (Viking, New York, NY, 1987).
[10] A. Venaille and F. Bouchet, Statistical Ensemble Inequivalence and Bicritical Points for Two-Dimensional Flows and Geophysical Flows, Phys. Rev. Lett. **102**, 104501 (2009).
[11] M. Wilkinson, Large Deviation Analysis of Rapid Onset of Rain Showers, Phys. Rev. Lett. **116**, 018501 (2016).
[12] S. Toppaladoddi and J. S. Wettlaufer, Theory of the Sea Ice Thickness Distribution, Phys. Rev. Lett. **115**, 148501 (2015).
[13] J. B. Marston, Looking for new problems to solve? Consider the climate, Physics **4**, 20 (2011).
[14] H. M. Arnold, I. M. Moroz, and T. N. Palmer, Stochastic parametrizations and model uncertainty in the Lorenz 96 system, Phil. Trans. R. Soc. A **371**, 20110479 (2013).
[15] A. N. Souza and C. R. Doering, Maximal transport in the Lorenz equations, Phys. Lett. A **379**, 518 (2015).
[16] S. Agarwal and J. S. Wettlaufer, Maximal stochastic transport in the Lorenz equations, Phys. Lett. A **380**, 142 (2016).
[17] G. J. Feldman and R. D. Cousins, Unified approach to the classical statistical analysis of small signals, Phys. Rev. D **57**, 3873 (1998).
[18] J. Pedlosky, *Geophysical Fluid Dynamics* (Springer, New York, NY, 1992).
[19] A. J. Majda and X. Wang, *Nonlinear Dynamics and Statistical Theories for Basic Geophysical Flows* (Cambridge University Press, Cambridge, England, 2006).
[20] R. T. Pierrhumbert, *Principles of Planetary Climate* (Cambridge University Press, Cambridge, England, 2010).
[21] H. Dijkstra, *Nonlinear Climate Dynamics* (Cambridge University Press, Cambridge, England, 2013).
[22] C. Wunsch, *Modern Observational Physical Oceanography: Understanding the Global Ocean* (Princeton University Press, Princeton, NJ, 2015).
[23] S. C. Glotzer, Editorial: Soft Matters, Phys. Rev. Lett. **114**, 050001 (2015).
[24] E. N. Lorenz, The predictability of a flow which possesses many scales of motion, Tellus **21**, 289 (1969).
[25] T. N. Palmer, More reliable forecasts with less precise computations: A fast-track route to cloud-resolved weather and climate simulators?, Phil. Trans. R. Soc. A **372**, 20130391 (2014).
[26] F. Bouchet, T. Grafke, T. Tangarife, and E. Vanden-Eijnden, Large deviations in fast-slow systems, J. Stat. Phys. **162**, 793 (2016).
[27] B. Saltzman, *Dynamical Paleoclimatology: Generalized Theory of Global Climate Change*, International Geophysics Series (Academic, San Diego, CA, 2002), Vol. 80.
[28] A. Bunde, J. F. Eichner, J. W. Kantelhardt, and S. Havlin, Long-Term Memory: A Natural Mechanism for the Clustering of Extreme Events and Anomalous Residual Times in Climate Records, Phys. Rev. Lett. **94**, 048701 (2005).
[29] D. H. Rothman, Earth's carbon cycle: A mathematical perspective, Bull. Am. Math. Soc. **52**, 47 (2015).