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Can we predict global patterns of long-term climate change from short-term simulations?

Laura Mansfield[1,2], Peer Nowack[4,5], Matt Kasoar[2,3], Richard Everitt[6], William Collins[7], and Apostolos Voulis[2,8]

[1]University of Reading, School of Mathematics and Statistics, United Kingdom (laura.mansfield@pgr.reading.ac.uk)
[2]Department of Physics, Imperial College London, United Kingdom
[3]Grantham Institute, Imperial College London, United Kingdom
[4]Data Science Institute, Imperial College London, United Kingdom
[5]School of Environmental Sciences, University of East Anglia, Norwich, United Kingdom
[6]Department of Statistics, University of Warwick, United Kingdom
[7]Department of Meteorology, University of Reading, United Kingdom
[8]School of Environmental Engineering, Technical University of Crete, Chania, Greece

Furthering our understanding of regional climate change responses to different greenhouse gas and aerosol emission scenarios is pivotal to inform societal adaptation and mitigation measures. However, complex General Circulation Models (GCMs) used for decadal to centennial climate change projections are computationally expensive. Here we have utilised a unique dataset of existing global climate model simulations to show that a novel machine learning approach can learn relationships between short-term and long-term temperature responses to different climate forcings, which in turn can accelerate climate change projections. This approach could reduce the costs of additional scenario computations and uncover consistent early indicators of long-term climate responses.

We have explored several statistical techniques for this supervised learning task and here we present predictions made with Ridge regression and Gaussian process regression. We have compared the results to pattern scaling as a standard simplified approach for estimating regional surface temperature responses under varying climate forcing scenarios. In this research, we highlight key challenges and opportunities for data-driven climate model emulation, especially with regards to the use of even larger model datasets and different climate variables. We demonstrate the potential to apply our method for gaining new insights into how and where ongoing climate change can be best detected and extrapolated; proposing this as a blueprint for future studies and encouraging data collaborations among research institutes in order to build ever more accurate climate response emulators.