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Machine learning prediction of climate multi-stability

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Due to the co-existence of different stable states (multi-stability), various climate components, such as the Amazon forest, the West African monsoon or the Atlantic meridional overturning circulation (AMOC), may undergo catastrophic regime shifts at varying levels of global warming. As a result, our uncertainty in future greenhouse gas emissions renders possible a variety of storylines with drastically different climatic conditions. Assessing the relative likelihood of each storyline by ensemble simulations with realistic climate models is computationally extremely expensive. This could be alleviated with machine learning (ML) models trained on simulation data. But a fundamental challenge is that future regime shifts likely correspond to dynamical regimes that have not been observed in the training data, whether generated from observations or state-of-the-art climate models. Thus, ML predictions of long-term climate change may be unreliable if they only capture the physics of previously observed climate states.

This be overcome by data-efficient and physics-informed ML methods, such as 'Next-Generation Reservoir Computing' (NG-RC), which has has shown promise in the task for simpler dynamical systems. We test this approach on extensive model output previously generated from the global ocean model 'Veros', which features various co-existing dynamical regimes that may be attained under future climate change, including a collapsed ocean circulation. We use system identification methods, such as regularized orthogonal least squares on Veros simulation data, to design functional forms of the nodes in the output layer. Then, we train the customized NG-RC model is on various sub-sets of simulation data and validate on initial conditions that belong to unobserved dynamical regimes. The resulting autonomous system shows great predictive ability, even across several chaotic timescales and shows promise in prediction of unseen stable dynamical states.

Field of study

Computational Physics

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