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The pattern effect: How radiative feedbacks depend on surface warming patterns and influence near-term projections

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Recent research has highlighted that radiative feedbacks — and thus climate sensitivity — are not constant in time but depend sensitively on sea surface temperature patterns. I will discuss three implications of this realization.

First, I will show how coupled climate models fail to reproduce observed surface warming patterns and global mean top of the atmosphere (TOA) radiation trends. I use large initial condition ensembles to compare observations to account for internal variability and model mean-state biases. For certain periods, not a single ensemble member can reproduce observed values of surface temperature trends and TOA radiation trends. Models which more greatly underestimate the observed local sensitivity of surface and TOA, and models with a weak variability in the Equatorial Pacific surface temperatures tend to have a higher equilibrium climate sensitivity. Despite these astonishing observation-model discrepancies their global-mean temperatures are simulated well which points to a common model problem in surface heat fluxes and ocean heat uptake.

Second, I will discuss the relevance of the pattern effect for climate change projections. Given that problems coupled models have in reproducing observed warming patterns, we should doubt their pattern evolution in projections. I will introduce “surface warming pattern storylines” starting from the observations and bridging to simulated future patterns in standard scenarios. I show that (CMIP) coupled climate models used ubiquitously for climate change projections underestimate the uncertainty of possible global-mean temperature evolutions due to their surface warming patterns throughout the 21st century.

Third, I will introduce how a feed-forward convolutional neural network (CNN) can be trained to learn the pattern effect and predict global-mean TOA radiation from surface warming patterns. I use explainable artificial intelligence methods to visualize and quantify that the CNN draws its predictive skill for physically meaningful reasons. Remarkably and different from traditional approaches, I can predict radiation under strong climate change from training the CNN on internal variability alone. This out-of-sample application works only when feedbacks are allowed to be non-linear or equivalent, changing in time, which is another, independent manifestation of the relevance of the pattern effect.