A DATA-DRIVEN APPROACH TO IDENTIFYING KEY REGIONS OF CLIMATE CHANGE IN GFDL SPEAR

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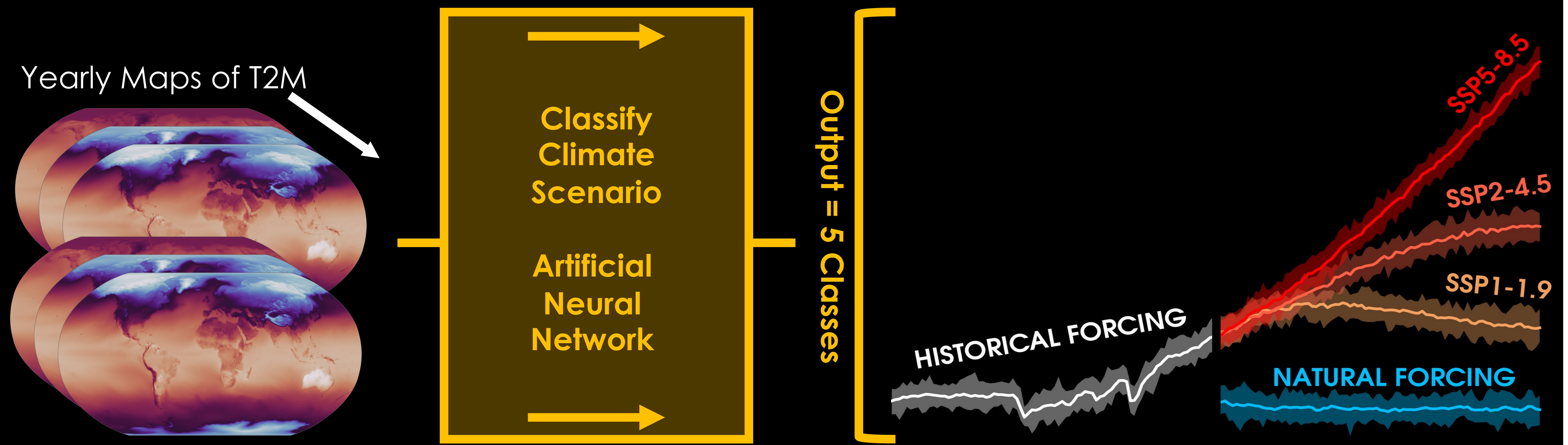
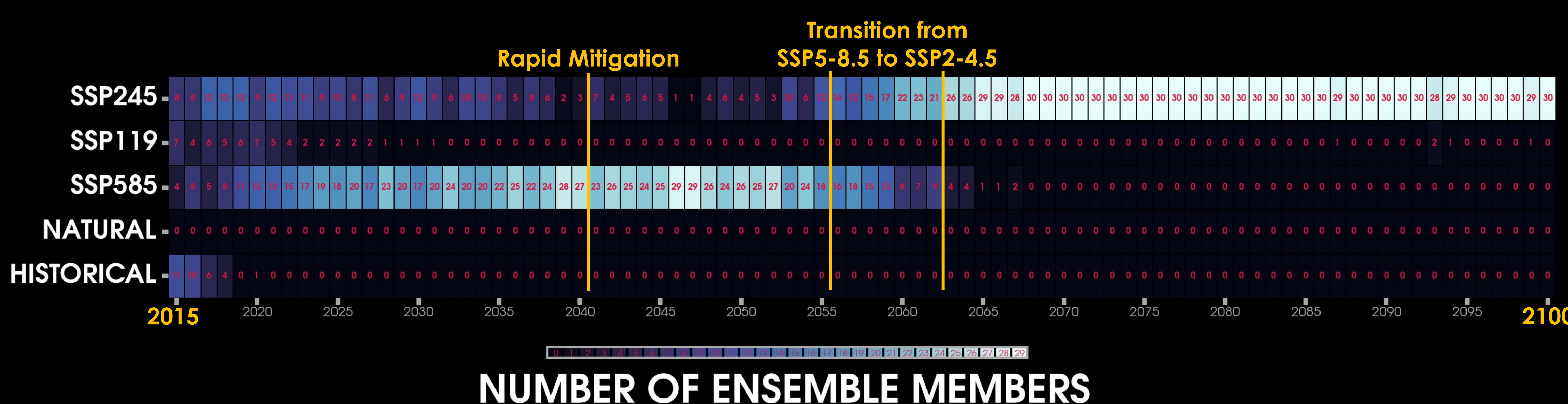
EXPLAINABLE AI METHODS REVEAL AREAS OF CHANGE UNIQUE TO A RANGE OF CLIMATE PATHWAYS



An artificial neural network takes inputs of annual mean maps of global temperature (or another gridded field) and then classifies it with a climate scenario (natural forcing, historical forcing, SSP1-1.9, SSP2-4.5, or SSP5-8.5).

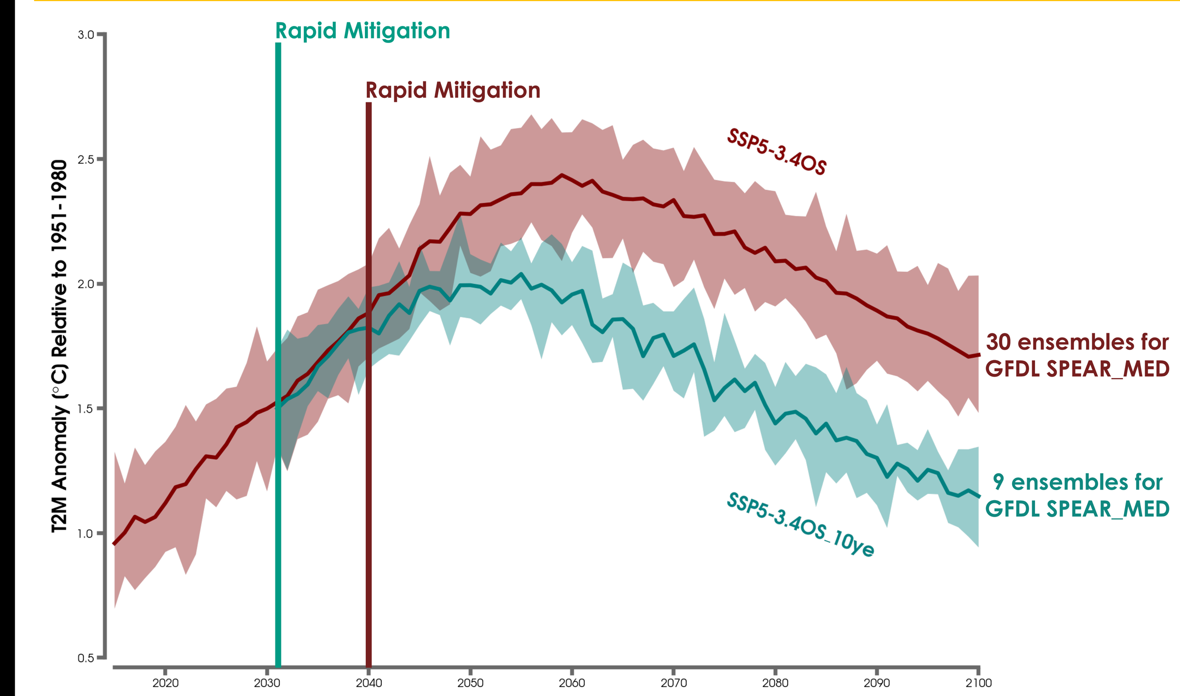


Classifications by year across 30 ensemble members for SSP5-3.4OS

The opportunity

The popularity of deep learning for climate science applications continues to rapidly grow. The interest in these tools also coincides with a growing demand for high-performance computing capabilities and greater efficiency in solving a range of prediction tasks.

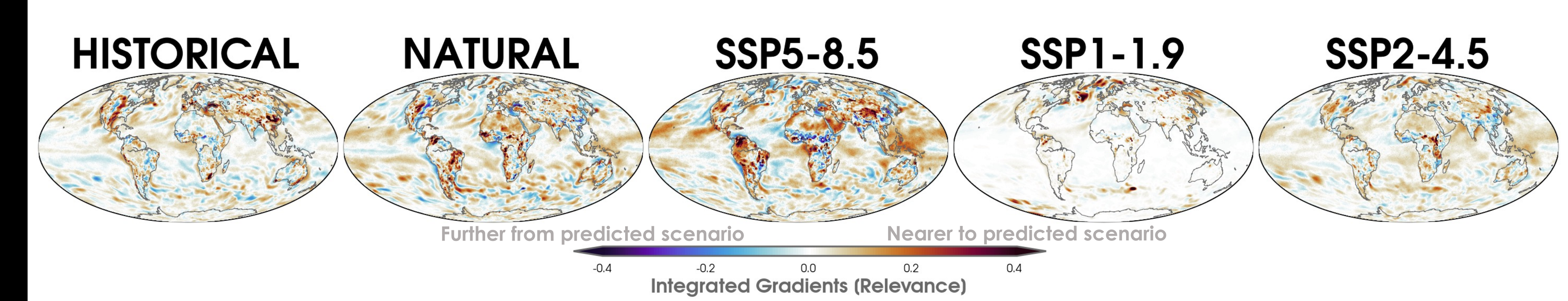
Recent work has shown that neural networks are powerful tools for disentangling climate change and variability in model simulations and observations by spatially leveraging time-evolving regional patterns.



After training on data from the 5 climate scenarios, we can input out-of-sample temperature maps from rapid mitigation scenarios, such as simulated overshoot pathways (e.g., SSP5-3.4OS).

Feature attribution methods in explainable artificial intelligence (XAI), such as integrated gradients, can reveal important regions of change unique to each climate projection scenario across SPEAR_MED large ensembles.

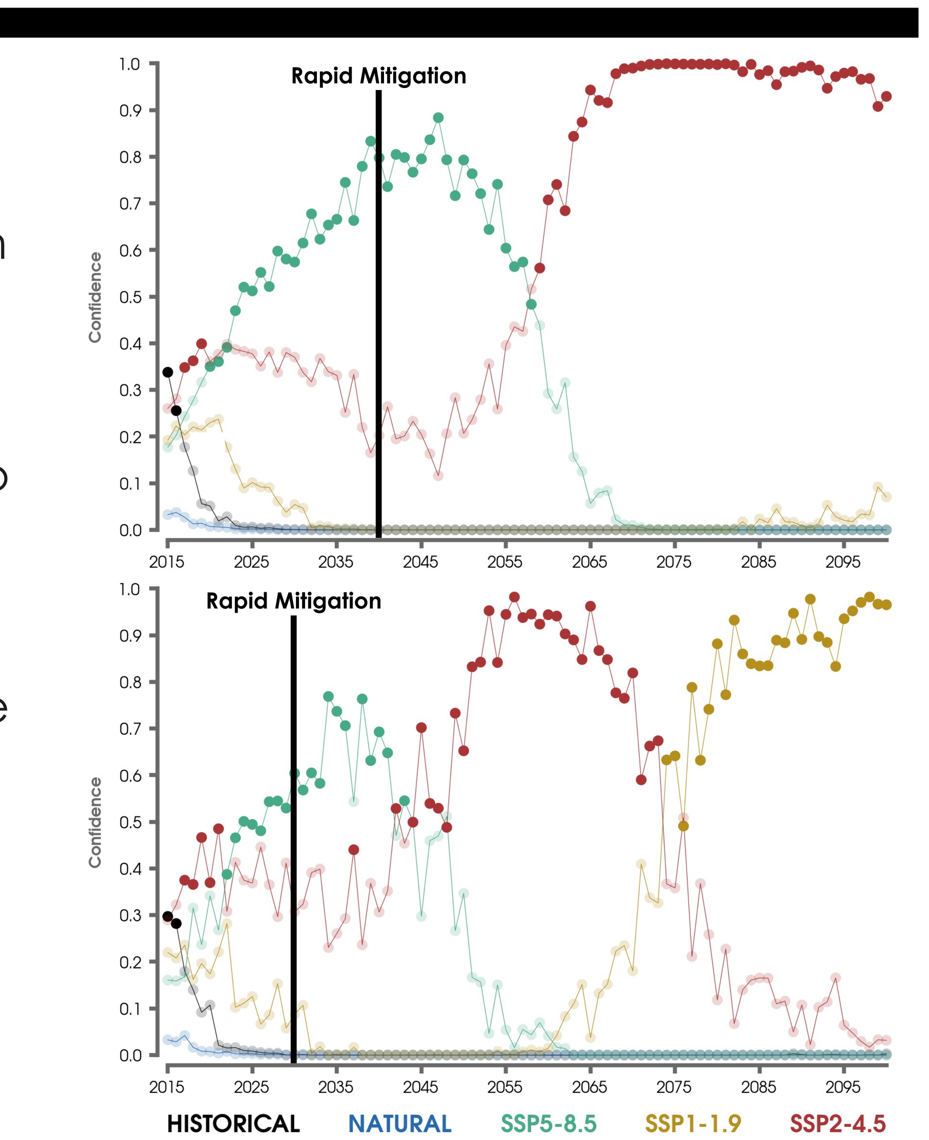
The relevance maps are composited across all years, where positive values are temperature signals that pushed the neural network to its predicted class.



A softmax activation function is applied to the final layer of the neural network in order to transform the class probabilities so that they sum to one. This is referred to as the neural network model confidence.

In other words, the climate scenario (class) that is ultimately selected receives the highest confidence in the neural network output.

The confidence plots here show the classifications for each year using a large ensemble following the SSP5-3.4OS pathway (mitigation starts in 2040; top) compared to an exploratory large ensemble simulation called SSP5-3.4OS_10ye (mitigation starts in 2031; bottom).



The conclusions

In addition to monitoring observations by comparing with GFDL SPEAR_MED, this new data-driven framework can identify and quantify the regional benefits for addressing climate impacts that are associated with different timings of rapidly reducing greenhouse gas emissions.

Data

SPEAR_MED (0.5°) Large Ensembles

Delworth, T. L., et al. (2020). SPEAR: The Next Generation GFDL Modeling System for Seasonal to Multidecadal Prediction and Projection. Journal of Advances in Modeling Earth Systems, 12(3), e2019MS001895. DOI: 10.1029/2019MS001895

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