Probabilistic prediction of tipping points in Earth system with deep learning

Wenjie Zhang [1,2] Yu Huang [2,3] Sebastian Bathiany [2,3] Yechul Shin [4] Suiping Zhou [1] Niklas Boers [2,3,5]

[1]Xidian University, China [2]Technical University of Munich, Germany [3]Potsdam Institute for Climate Impact Research, Germany
[4]Seoul National University, Republic of Korea [5]University of Exeter, UK

Motivation

- Abrupt transitions in key Earth-system components, such as the **Atlantic Meridional Overturning Circulation (AMOC)**, may occur when external forcing exceeds **critical thresholds** or changes faster than the system can adapt.
- However, AMOC tipping is not necessarily controlled by a single **deterministic threshold**. Internal variability can interact with changing freshwater forcing, so that **identical forcing scenarios** may lead to different outcomes across ensemble realizations.
- This stochasticity raises two central challenges: how to characterize the **safe operating boundary** under combined bifurcation-, rate-, and noise-induced tipping mechanisms, and how to anticipate tipping from an **individual noisy trajectory** before the transition occurs.
- Traditional early-warning indicators based on **critical slowing down** are mainly designed for bifurcation-induced tipping and may be unreliable when rate and noise effects contribute to the transition. This motivates a **real-time, trajectory-level prediction** framework that can learn warning signals directly from ensemble simulations.

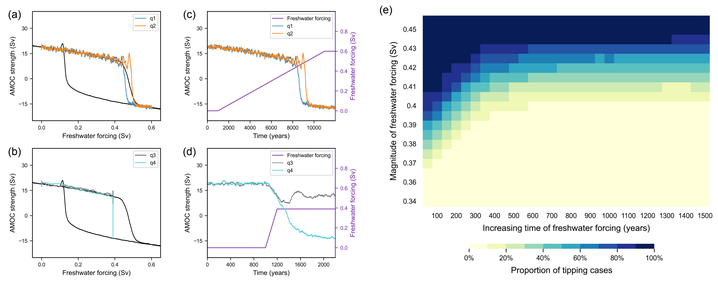


Figure 1. Large ensembles from a calibrated five-box AMOC model [1,2] reveal a probabilistic safe operating boundary under varying freshwater forcing magnitudes and rates.

Highlights

- Tipping components in the Earth system can exhibit **a probabilistic safe operating boundary** under the combined effects of bifurcation-, rate-, and noise-induced tipping mechanisms.
- In this stochastic regime, the deep learning-based **early warning indicator** enhances the realized predictability of impending abrupt transitions, outperforming traditional critical slowing down indicators.
- The pretrained deep learning model demonstrates **robust prediction skill** and transferability across diverse forcing magnitudes and rates in a complex system.

Aim

Estimate **real-time AMOC tipping probabilities** from individual noisy trajectories under combined bifurcation-, rate-, and noise-induced tipping.

Classical early-warning indicators are unreliable

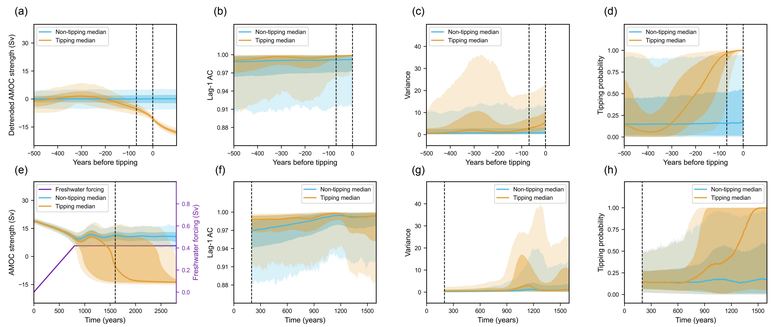


Figure 2. Classical indicators remain ambiguous, whereas the DL-based tipping probability separates tipping from non-tipping AMOC trajectories in real time.

- Identical freshwater forcing can produce both **tipping** and **non-tipping** AMOC trajectories, with a wide spread in tipping times.
- Classical CSD indicators show **large overlap** between the two trajectory classes and provide little skill at long forecast lead times.
- The DL-based probability separates the ensembles earlier and provides **real-time probabilistic warning** without requiring a fixed forecast lead time.

LRP reveals hidden predictive signals learned by CNNs

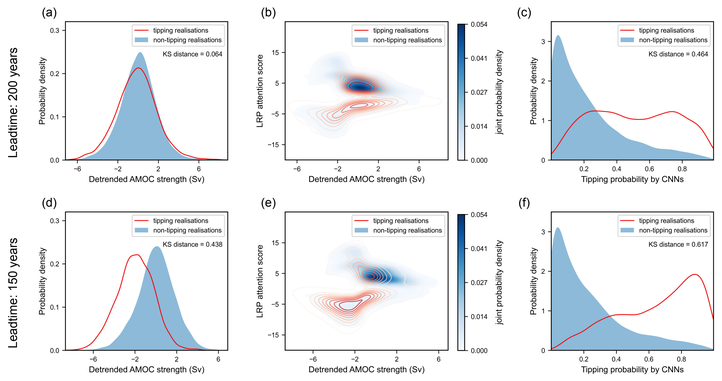


Figure 3. LRP attention scores reveal higher-dimensional features that separate tipping from non-tipping AMOC trajectories before collapse.

Generalization across forcing scenarios

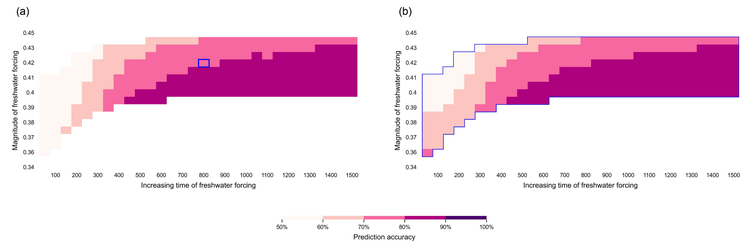


Figure 4. Prediction accuracy of the DL model for AMOC tipping across freshwater forcing scenarios.

- A CNN trained on **a single representative forcing scenario** generalizes skillfully across a broad region of stochastic tipping regimes.
- Training on samples from multiple forcing scenarios improves robustness, especially under **rapid forcing** and near the boundaries of the stochastic tipping regime.

Capturing time-series signatures across varying lead times

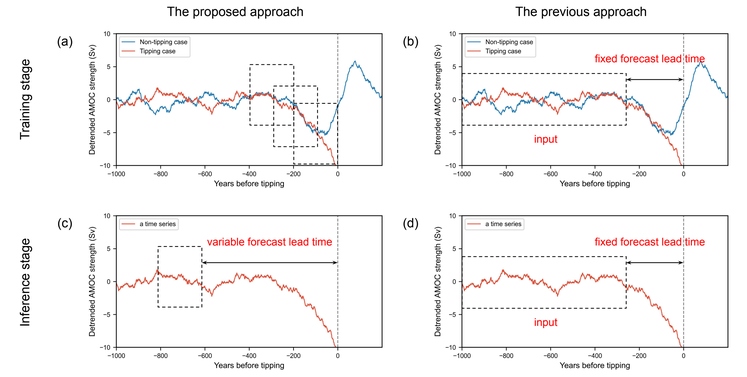


Figure 5. Sliding-window training enables real-time tipping prediction across varying forecast lead times, overcoming the fixed forecast lead time limitation of previous approaches [3].

References

[1] Wood et al. (2019), *Climate Dynamics*; [2] Chapman et al. (2024), *Environmental Research Communications*;

[3] Huang et al. (2024), *Nature Machine Intelligence*; [4] Zhang et al. (2026), *Chaos, Solitons & Fractals*;

[5] Zhang et al. (2026), *in preparation*;