Forced Climate Response Calibration with Dissipative Neural ODEs

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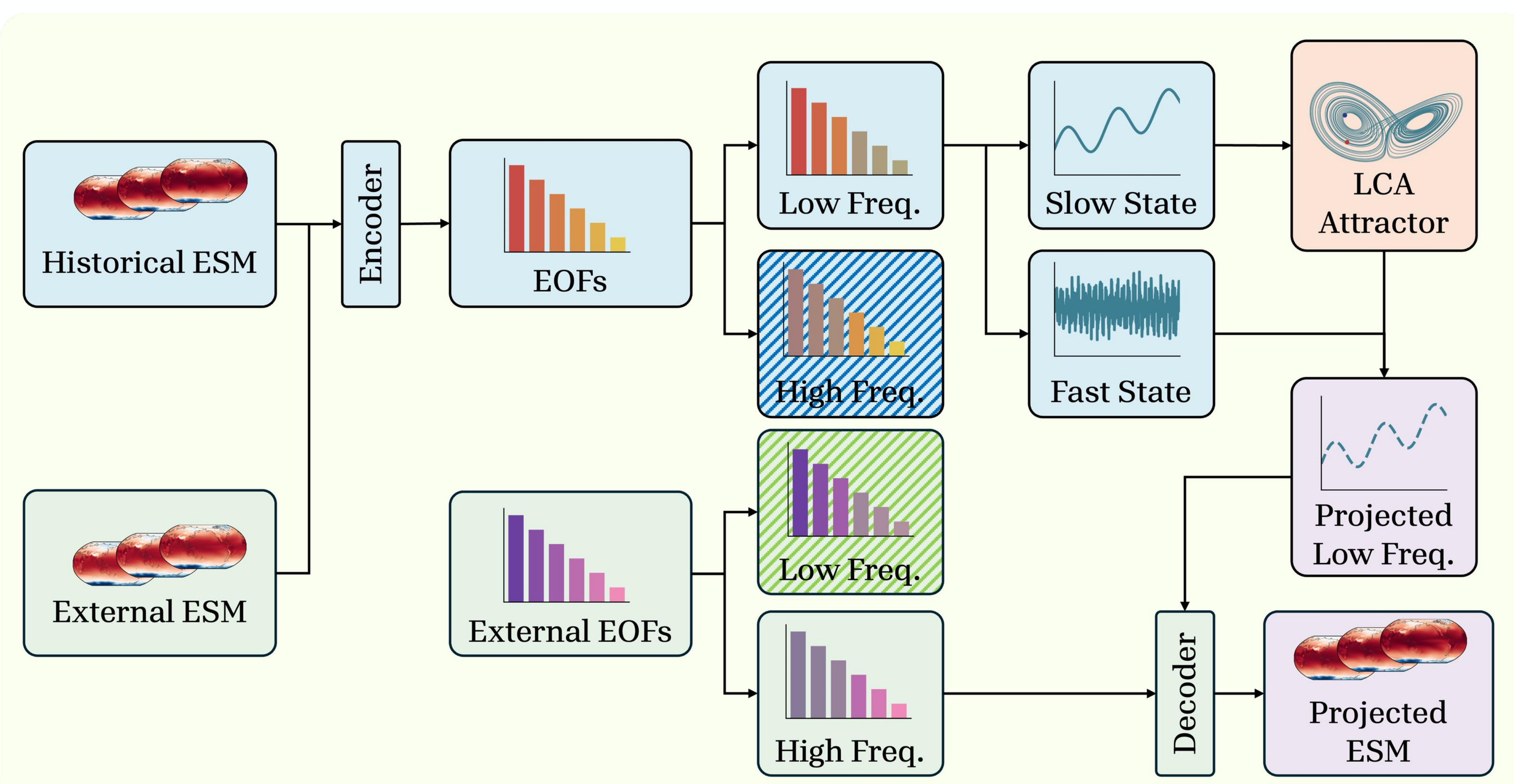
Summary

Question: Can we isolate and learn the forced response from a single climate trajectory?

- It is challenging to identify the externally forced climate response from among the noise of internal variability in the only one realization of the real-world climate.
- Neural ESMs are trained on reanalysis data and often not explicitly constrained to recover the forced response.
- We propose the Latent Climate Attractor (LCA) to calibrate forced response of external ESM model.

Methodology



- The global temperature sequence X was projected into EOF space and trend filter separate **forced response z_s** from **internal variability** in the latent space

$$Y = XV_K^T; \qquad z_s = \underset{z}{\operatorname{argmin}} \frac{1}{2}\left\|Y - z\right\|_2^2 + \lambda\left\|D\,z\right\|_1.$$

- The EOF projection filters out the spatial noise, and the trend filter filters out the temporal noise.
- LCA models the forced response dynamically using a forcing dependent **dissipative neural ODE**

$$\frac{dz}{dt} = -A_\theta(z_s)\cdot\left(z_s - g_\theta(F)\right),$$

  - $A_\theta(z_s)$ is a predicted low rank relaxation matrix,
  - $g_\theta(F)$ is an ICNN that represents forcing-dependent equilibrium state.

Historical-to-Future Extrapolation

Learn LCA from one historical ESM run and roll it forward under future SSP forcings.

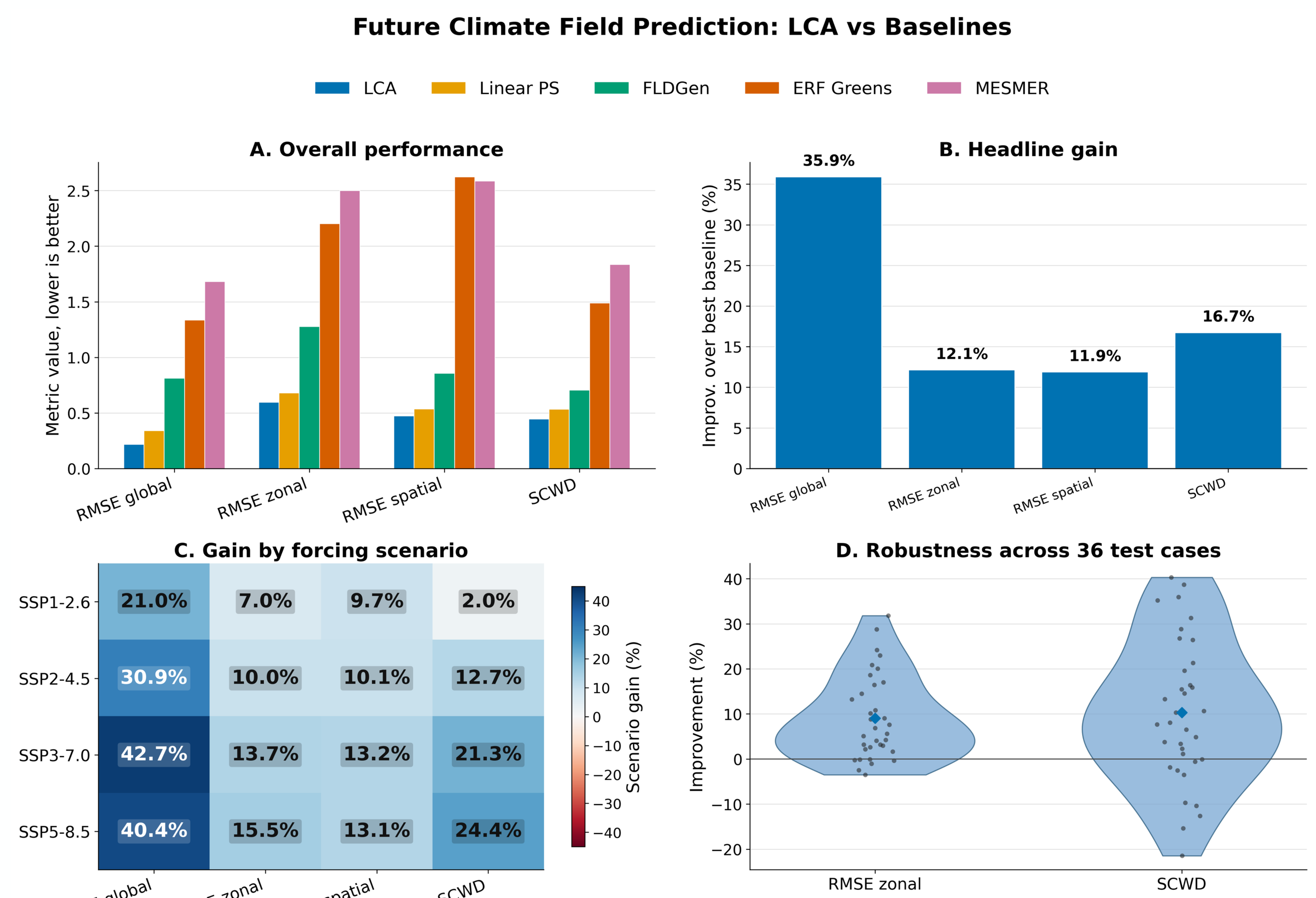


Figure 1. LCA achieves consistently lower prediction error across RMSE and SCWD metrics.

Models	Global RMSE	Zonal RMSE	Spatial RMSE	SCWD
LCA	0.22±0.02	0.60±0.03	0.47±0.03	0.45±0.02
Linear PS	0.34±0.04	0.68±0.05	0.54±0.05	0.54±0.03
FLDGen	0.81±0.05	1.28±0.08	0.86±0.06	0.71±0.04
ERF Greens	1.34±0.12	2.20±0.16	2.62±0.16	1.49±0.09
MESMER	1.68±0.25	2.50±0.35	2.59±0.33	1.84±0.25
Improv. Over best baseline	35.90%	12.10%	11.90%	16.70%

Table 1. LCA significantly improves the forced response over the best baseline across CMIP6 model and scenarios.

- SCWD measures distributional error in fields.
- LCA produces smaller errors across global, zonal, spatial, and distributional metrics predicting future climate fields when only trained with historical data.

Calibrate Forced Response of External ESMs

Learn LCA from one model and use it to calibrate the forced response of another model.

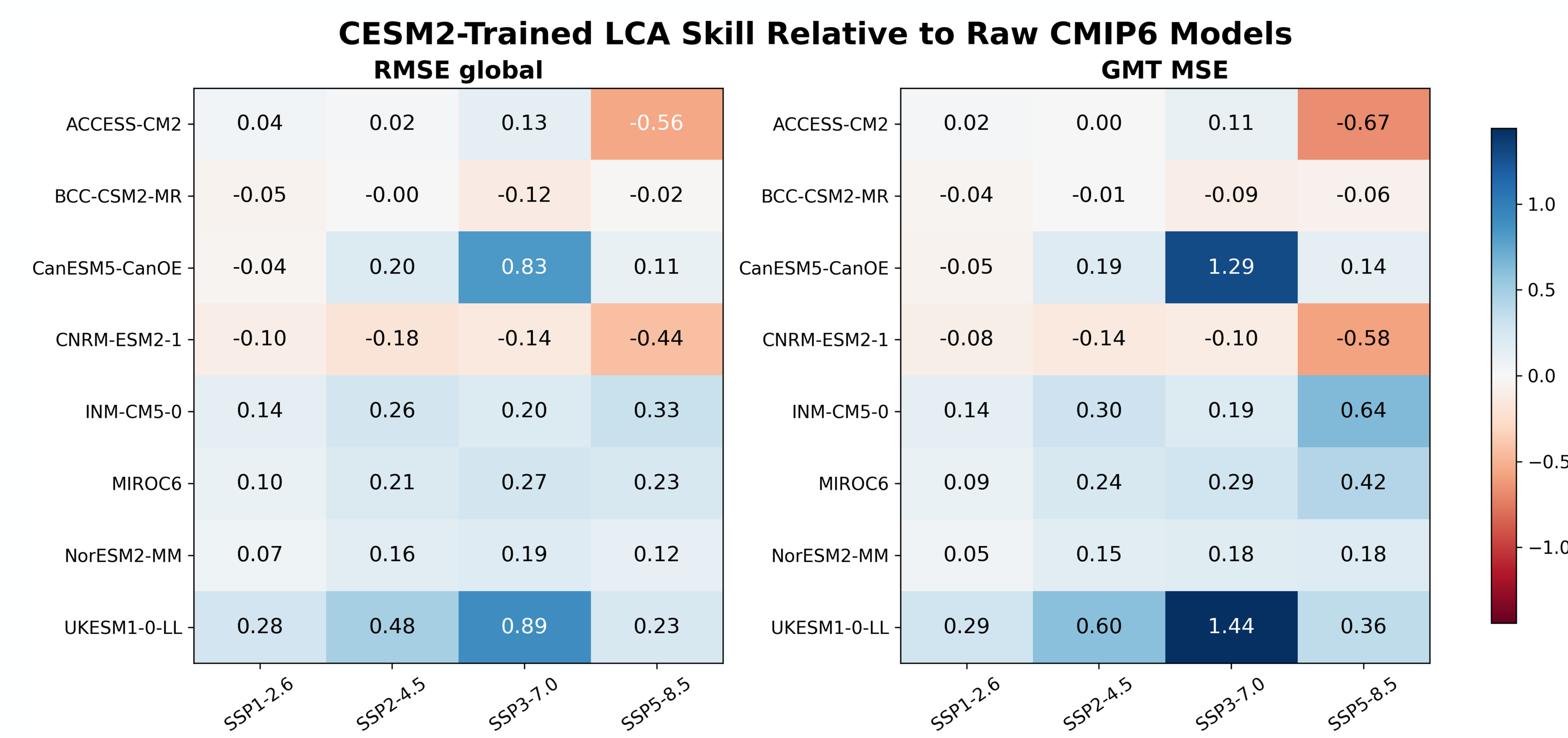


Figure 2 LCA improves future extrapolation across scenarios and CMIP6 models (Blue means LCA is better)

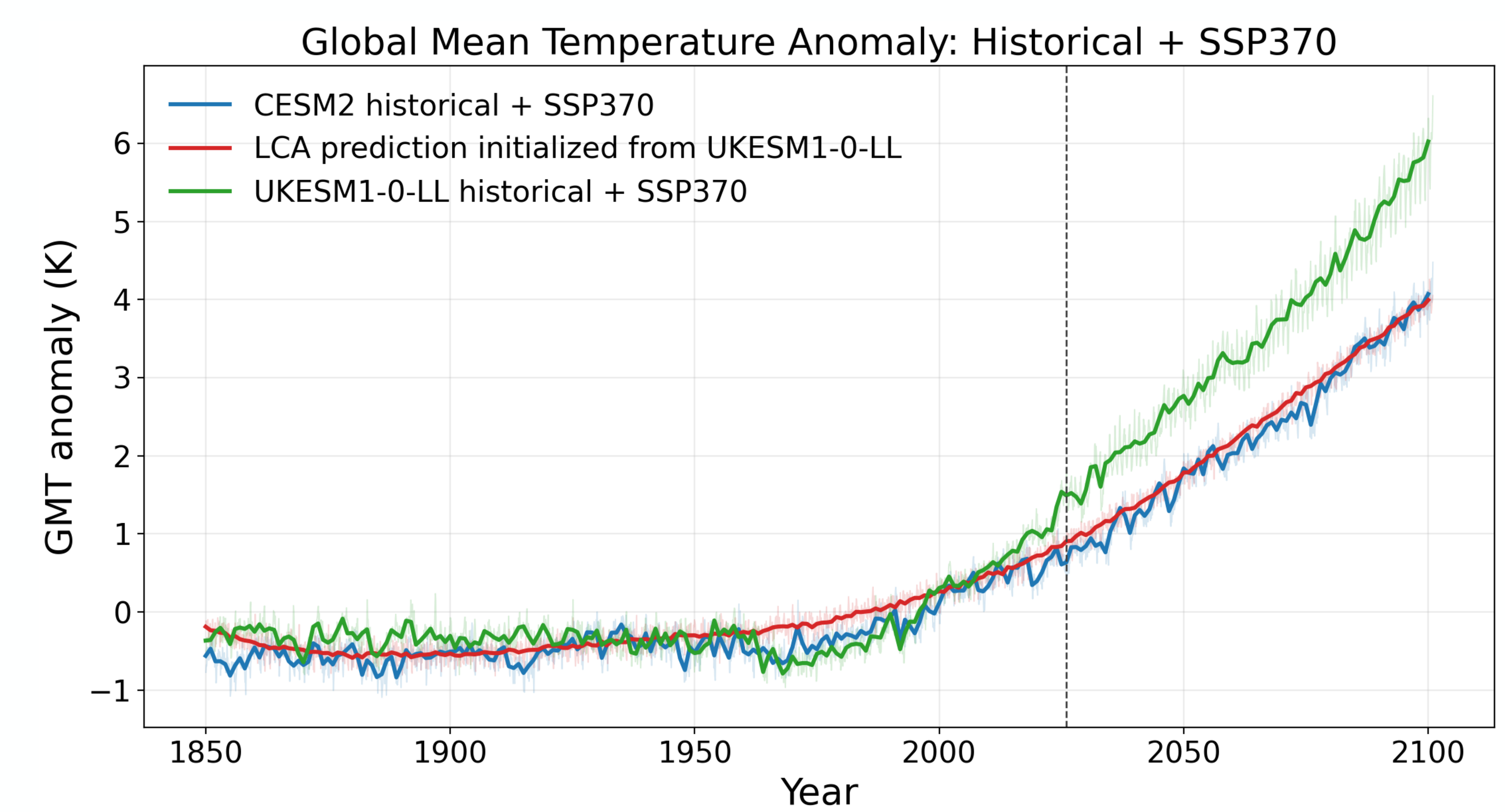


Figure 3. LCA correct the climate trajectory of UKESM1-0-LL to realistic forcing response.

Conclusion

- LCA responds correctly to future SSP forcings when only trained with historical data compared to others.
- LCA calibrate external ESMs to respond correctly to future SSP forcings while retaining internal variability.
- LCA is a lightweight probabilistic climate emulator itself.
- Ongoing work: calibrating Neural ESM on reanalysis data.

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