Towards a Climate Counterfactual Autoencoder

Tackling Climate Change with Machine Learning workshop at NeurIPS 2025

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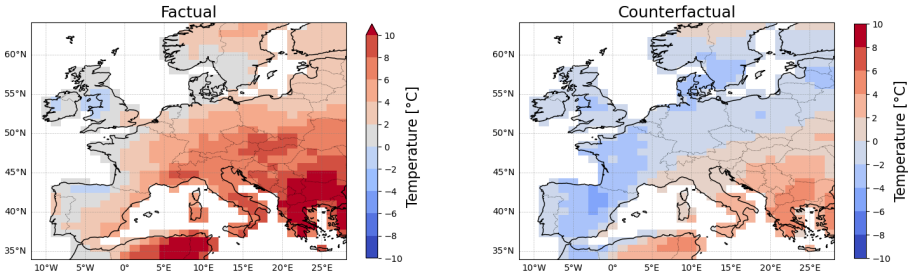
1 Climate Counterfactuals in Climate Attribution

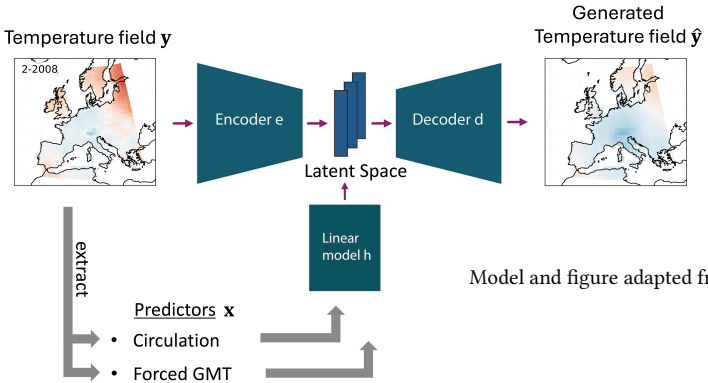
- **Climate Attribution** aims to separate forced climate changes from internal climate variability
- identify forced changes by comparison to a **climate counterfactual**
  - representation of climate hypothetically not undergoing climate change



Can we do this with machine learning?

- we fix atmospheric circulation to study how climate change affects e.g. temperature under this given circulation
- this approach disregards potential changes in atmospheric circulation (following the storyline attribution approach [1])

2 The model: Latent Linear Adjustment Autoencoder (LLAAE)



Model and figure adapted from [2].

Objective function

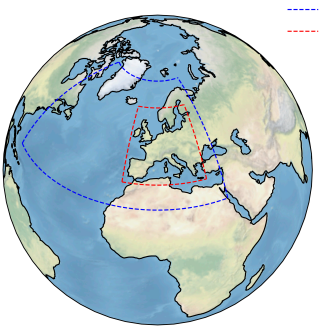
$$L = L_{\text{VAE}} + \lambda L_L$$

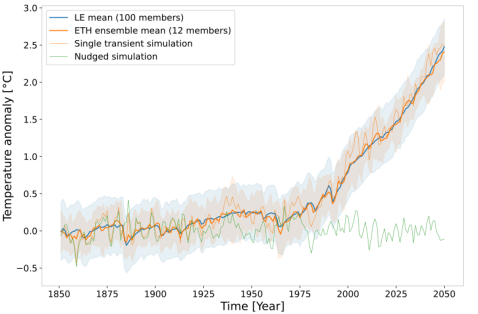
$$L_{\text{VAE}} = E[\| \, y - d(e(y)) \, \|^2 + \beta \cdot \text{KL}(q_e(z|y), p_z(z))]$$

$$L_L = \|y - d(h(x))\|^2$$

- alternating training of Autoencoder and linear model

3 Experimental Setup and Climate Model Data





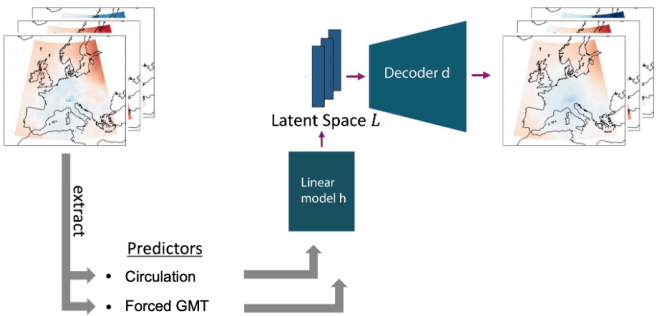
- **monthly data**: December, January, February

- **CESM2 Large Ensemble** (LE)
  - initial condition LE
  - 100 transient members 1850-2100

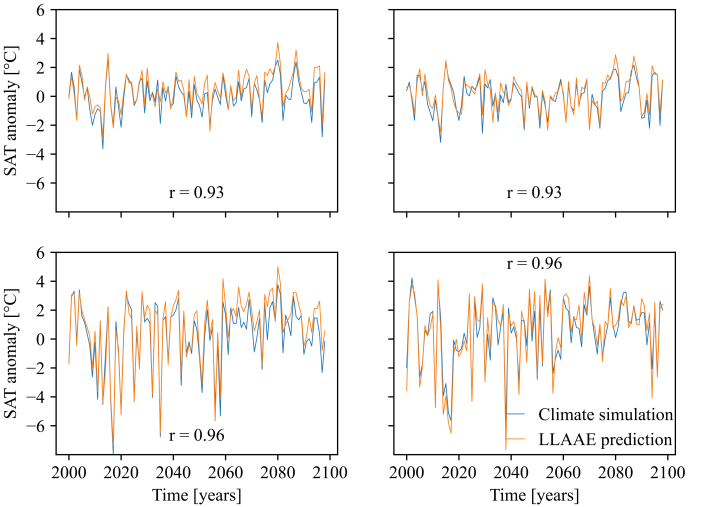
- **CESM2-ETH Ensemble**
  - 12 transient members 1850-2100
  - CESM2-LE forcing
  - 3 **circulation-nudged** members

4 LLAAE Counterfactual Predictions

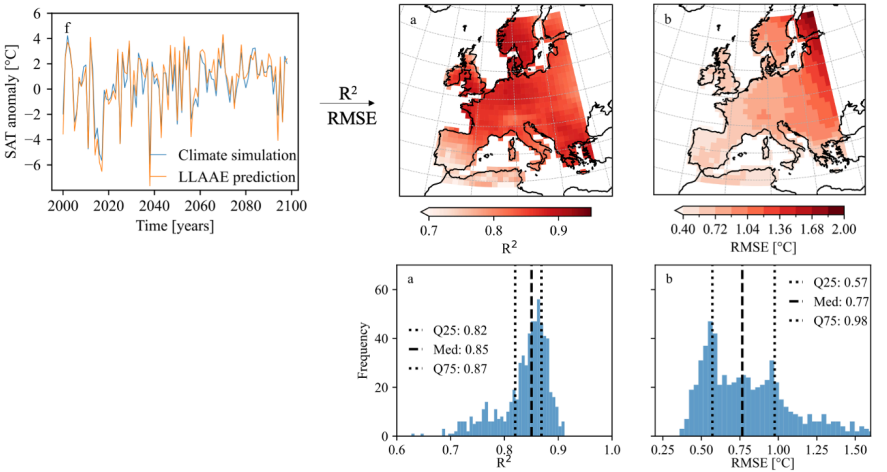
Counterfactual Predictions
$\mathrm{fGMT} = 0°\mathrm{C}$



4 LLAAE Counterfactual Predictions show high skill



4 LLAAE Counterfactual Predictions show high skill



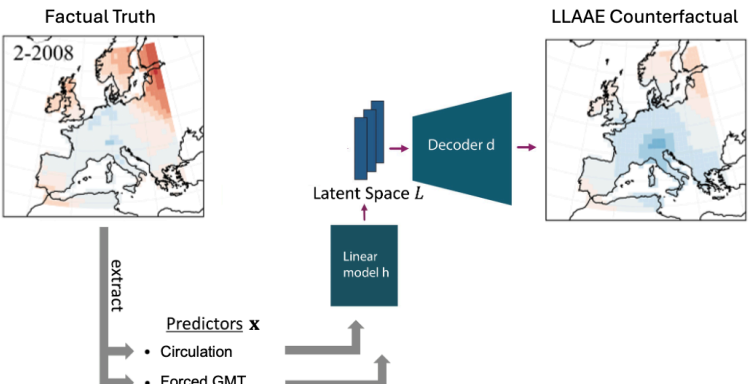
5 Conclusion and Outlook

Summary

- Deep Learning / LLAAE architecture very promising for generating climate counterfactuals.

Outlook

- Application to extreme events and observations



References

[1] Shepherd, Theodore G. A Common Framework for Approaches to Extreme Event Attribution. Current Climate Change Reports 2, Nr. 1 (2016): 28–38. https://doi.org/10.1007/s40641-016-0033-y.

[2] Heinze-Deml, C., Sippel, S., Pendergrass, A. G., Lehner, F., and Meinshausen, N.: Latent Linear Adjustment Autoencoder v1.0: a novel method for estimating and emulating dynamic precipitation at high resolution, Geosci. Model Dev., 14, 4977–4999, https://doi.org/10.5194/gmd-14-4977-2021, 2021.