Towards a Climate Counterfactual Autoencoder

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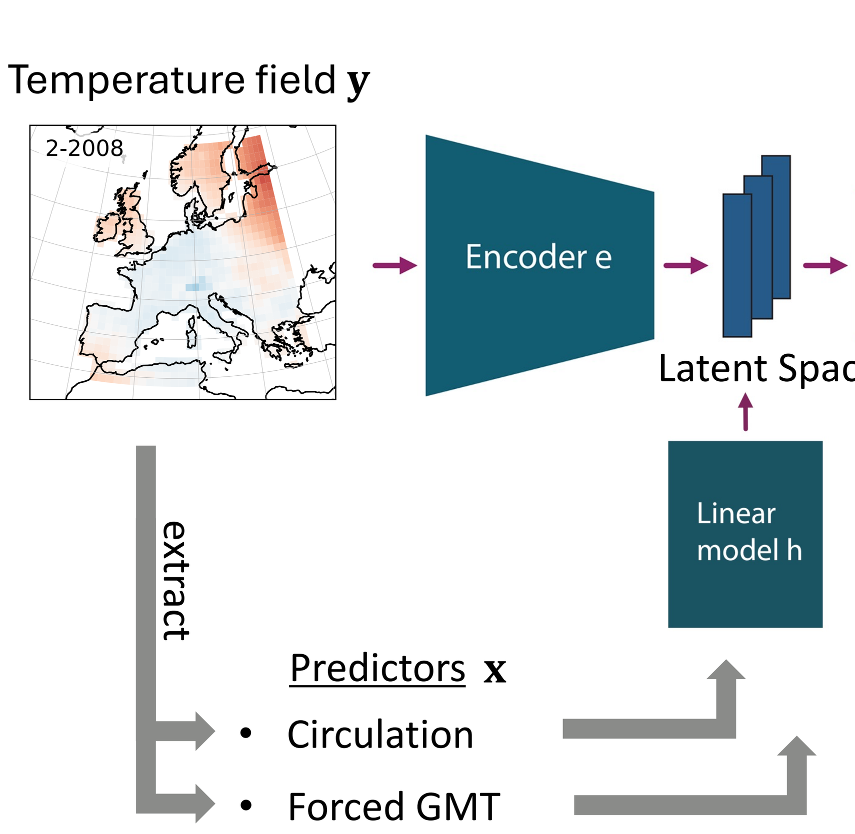
Motivation

- A key goal in **climate attribution** is to distinguish forced climate change from internal variability, especially for extreme events.
- **Climate counterfactuals (CFs)** - hypothetical climates without forced change - help isolate these forced effects.
- Numerical CF simulations:
    - computationally expensive
    - no easy transfer to observations and different climate states
- Here, we investigate the potential of machine learning, specifically the Latent Linear Adjustment Autoencoder (LLAAE) [1], for generating climate counterfactuals.

Method - Latent Linear Adjustment Autoencoder



$$L = L_{VAE} + \lambda L_L \quad [1]$$

$$L_{VAE} = \mathbb{E}\left[\left\|\mathbf{y} - d\big(e(\mathbf{y})\big)\right\|^2 + \beta \cdot \mathrm{KL}\big(q_e(\mathrm{z}|\mathbf{y}), p_z(\mathrm{z})\big)\right]$$

$$L_L = \|\mathbf{y} - d(h(\mathbf{x}))\|_2^2$$

$$L_h = \|e(\mathbf{y}) - h(\mathbf{x})\|_2^2$$

Figure 1: The Latent Linear Adjustment Autoencoder architecture. Encoder and decoder form the variational autoencoder. A linear model estimates the latent space from a proxy of atmospheric circulation and a covariate representing forced global mean temperature (forced-GMT). Only the linear model and decoder are used during inference. Figure and loss functions adapted from [1].

Results – Factual and Counterfactual Predictions

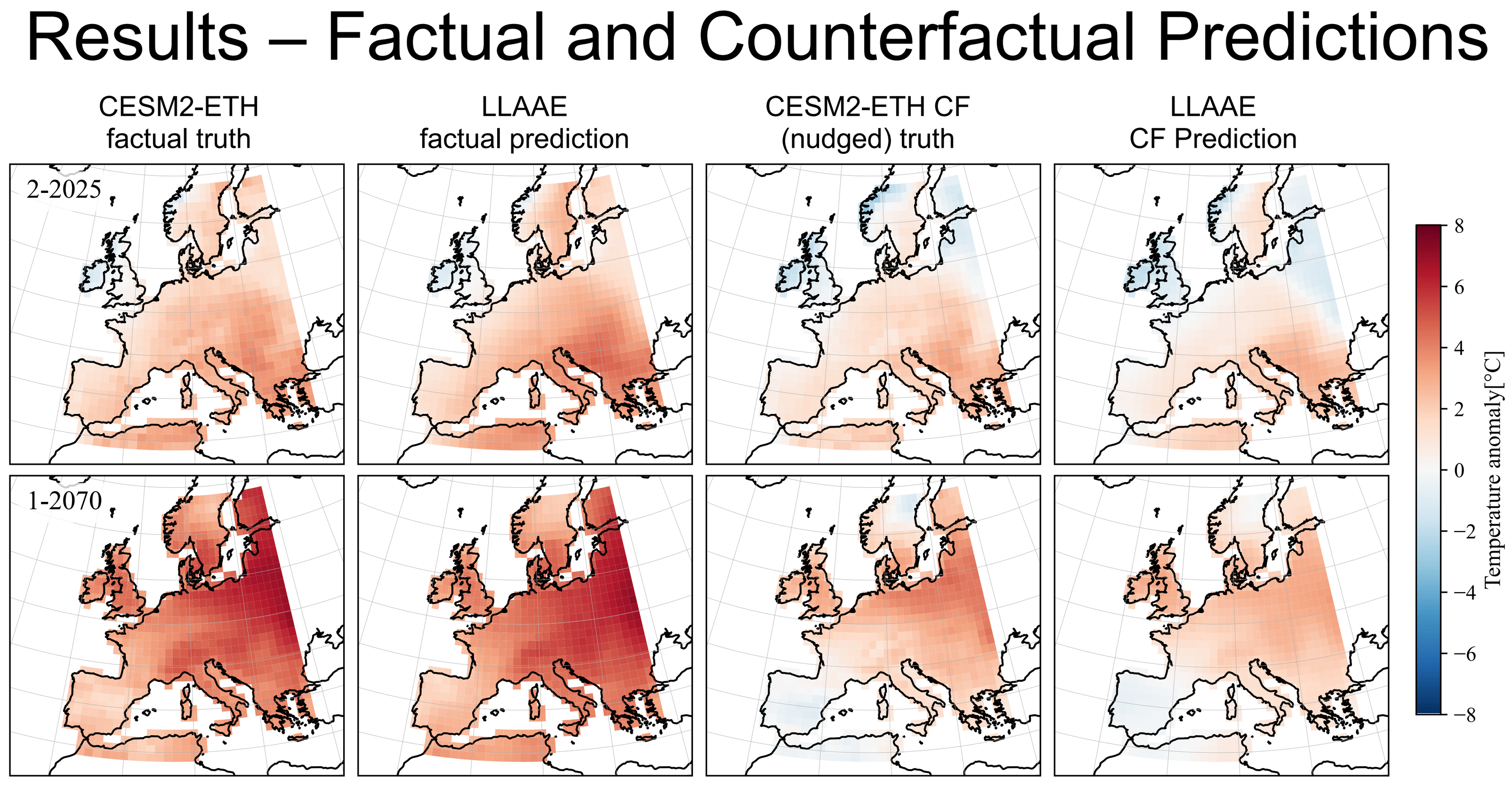
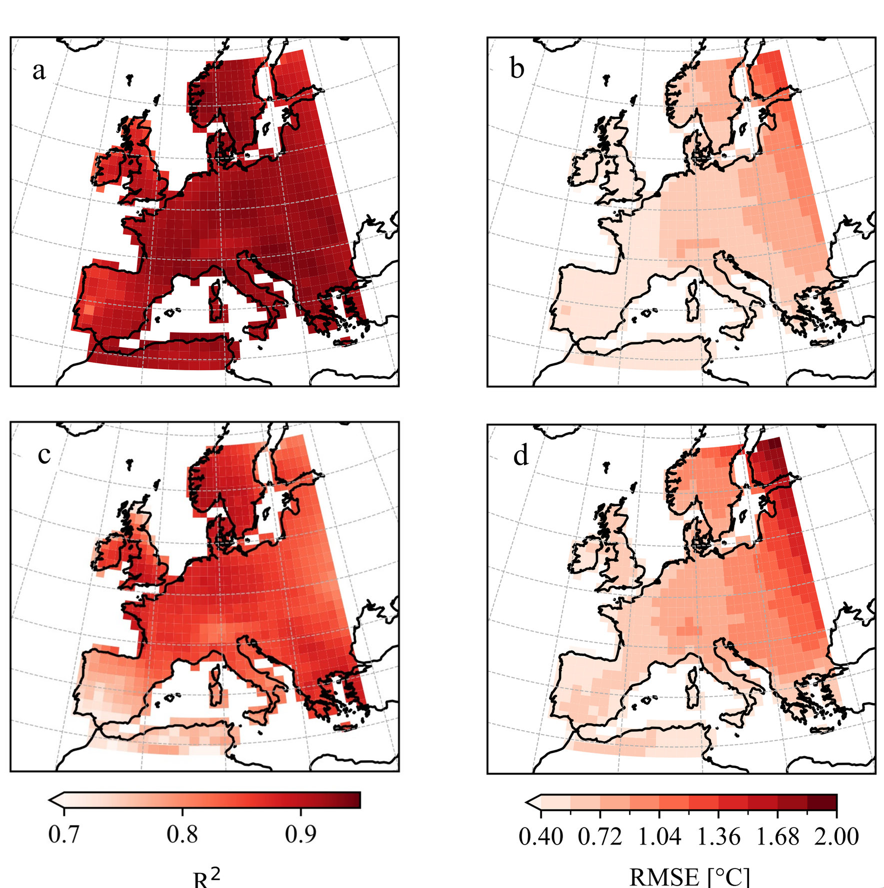


Figure 3: An example of factual and counterfactual LLAAE predictions. Column 1) Sample from transient (factual) climate simulation. Column 2) Corresponding factual LLAAE prediction from circulation proxy and the respective forced-GMT. Column 3) Corresponding circulation-nudged simulation. Column 4) Counterfactual LLAAE prediction from circulation proxy and forced-GMT set to 0°C.

Figure 4: Spatial distribution of R2 and RMSE for factual (a, b) and counterfactual (c, d) predictions. Values are calculated in each grid cell for the temperature time series of factual LLAAE prediction and the corresponding factual climate simulation in the test set. Shown are the mean values per grid cell among the three test members in the period 1950-2100.



Key takeaways and outlook

- Generative deep learning, in particular the LLAAE architecture, demonstrates high potential for generating climate counterfactuals.
- These results motivate further research towards applying this approach to observational data and adaption towards capturing extreme events.
- Outlook: Atmospheric circulation and forced-GMT alone cannot fully explain temperature variability but result in a distribution of possible temperatures. We anticipate to reconstruct this distribution via distributional regression to include extreme events in the distributional tails.

Data

Climate model simulations: CESM2 Large Ensemble (CESM2-LE, 100 members) and individual CESM2 runs (CESM2-ETH, 6 transient/factual runs + 3 circulation-nudged runs). Monthly winter temperatures (December, January, February) under CMIP6 historical and SSP370 future radiative forcing scenarios in 1850-2100. We test the LLAAE predicted counterfactuals against circulation-nudged climate simulations.

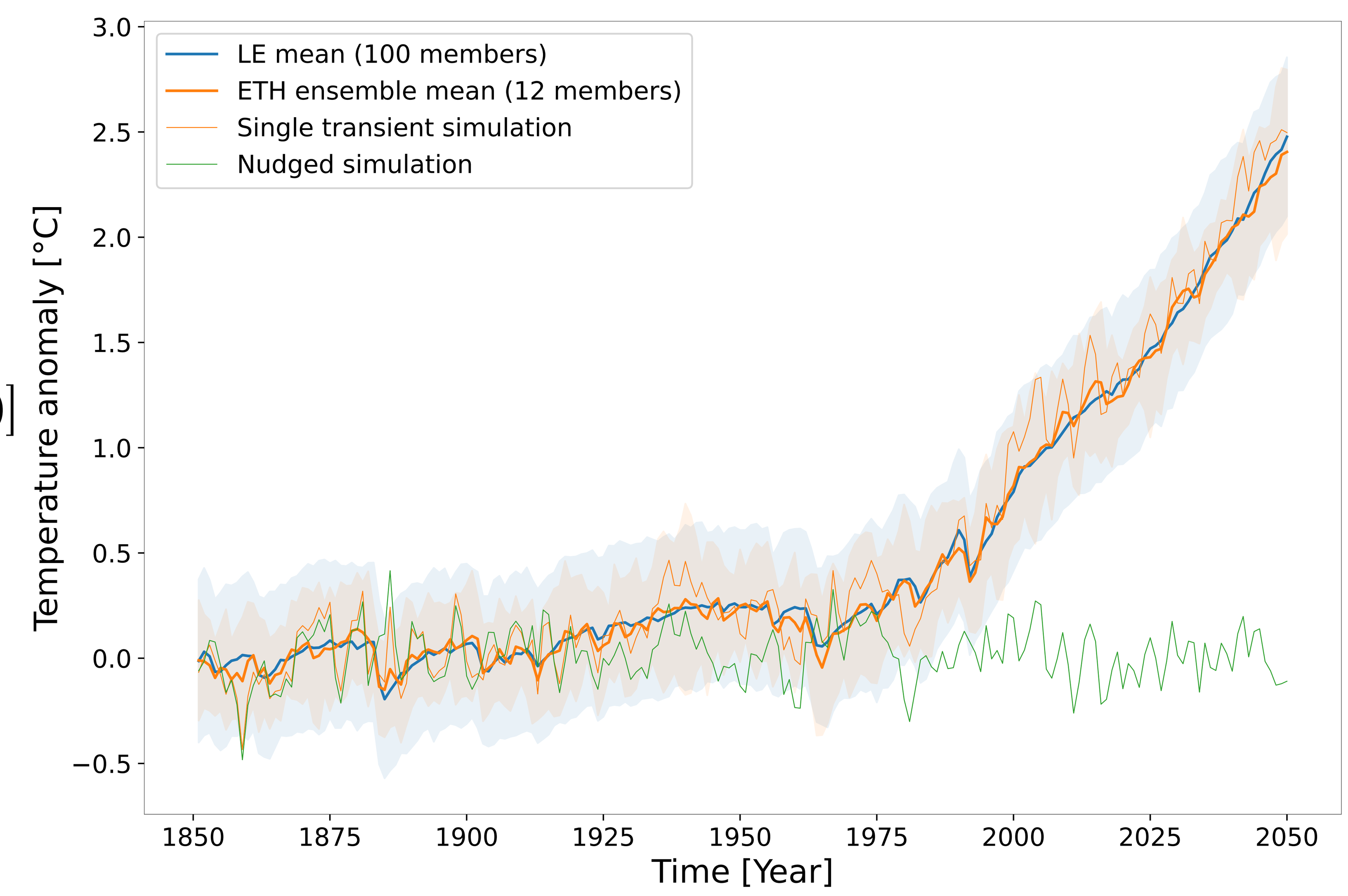


Figure 2: Time series of yearly global mean temperature anomalies against 1850-1900. Ensemble mean values (forced response) are shown as thick lines along with two standard deviations indicated by shading. A single simulation of the ETH ensemble is shown together with the corresponding circulation-nudged run. Due to circulation-nudging, the interannual variability of the two single simulations is very similar.

Train	Validation	Test Factual	Test Counterfactual
100 CESM2-LE members	3 transient CESM2-ETH members	3 transient CESM2-ETH members	3 nudged CESM2-ETH members

Results – Factual and Counterfactual Predictions

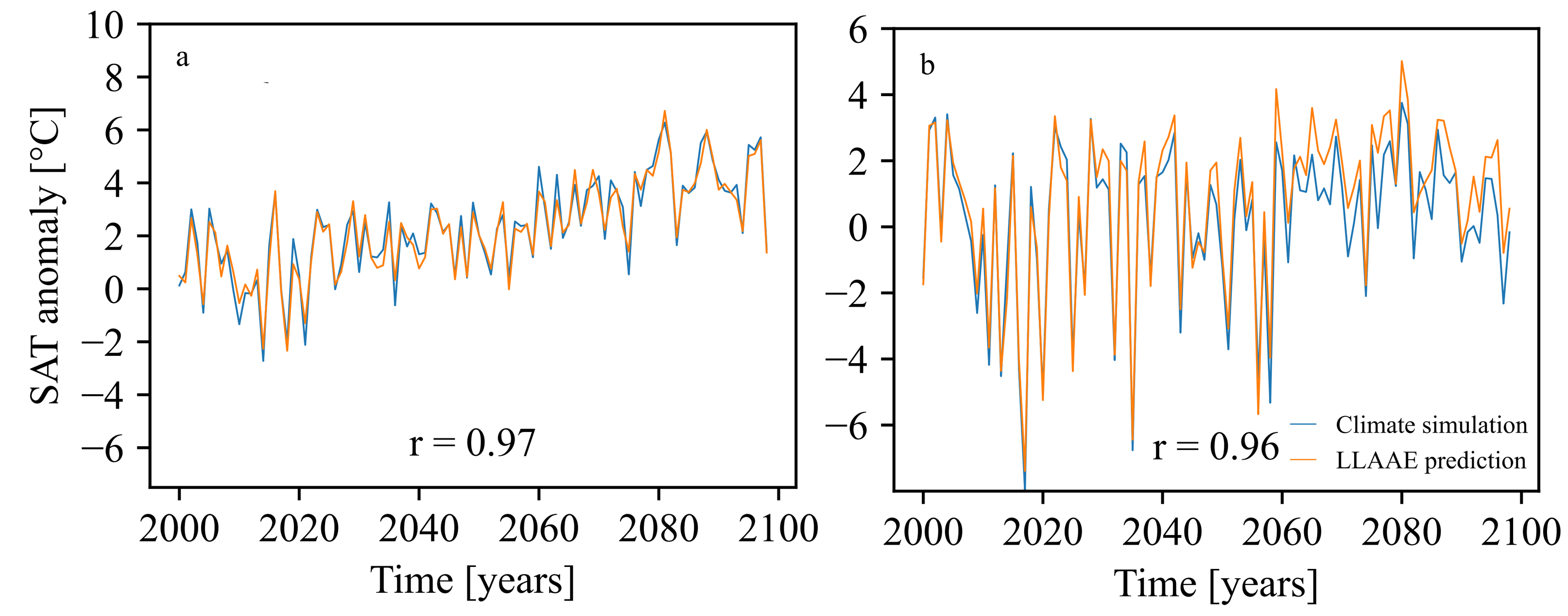


Figure 5: True and LLAAE-predicted time series of factual (a) and counterfactual (b) temperatures from grid cells at the 75th percentile among all grid cells from figure 4 (a) and (c) respectively.

References

[1] 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.
[2] Keith B. Rodgers, Sun-Seon Lee, Nan Rosenbloom, Axel Timmermann, Gokhan Danabasoglu, Clara Deser, Jim Edwards, Ji-Eun Kim, Isla R. Simpson, Karl Stein, Malte F. Stuecker, Ryohei Yamaguchi, Tamás Bódai, Eui-Seok Chung, Lei Huang, Who M. Kim, Jean-François Lamarque, Danica L. Lombardozzi, William R. Wieder, and Stephen G. Yeager. Ubiquity of human-induced changes in climate variability. Earth System Dynamics, 12(4):1393–1411, 2021.

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