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eRISE

On the application of generative modelling for seasonal climate predictions

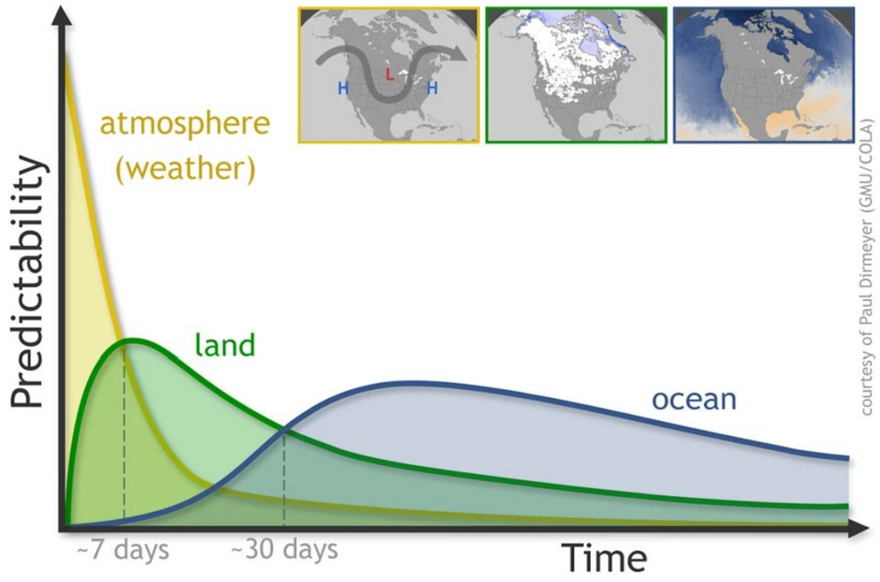
Lluís Palma, Alejandro Peraza, Amanda Duarte, Stefano Materia, Núria Pérez-Zanón, Ángel Muñoz, Albert Soret and Markus Donat

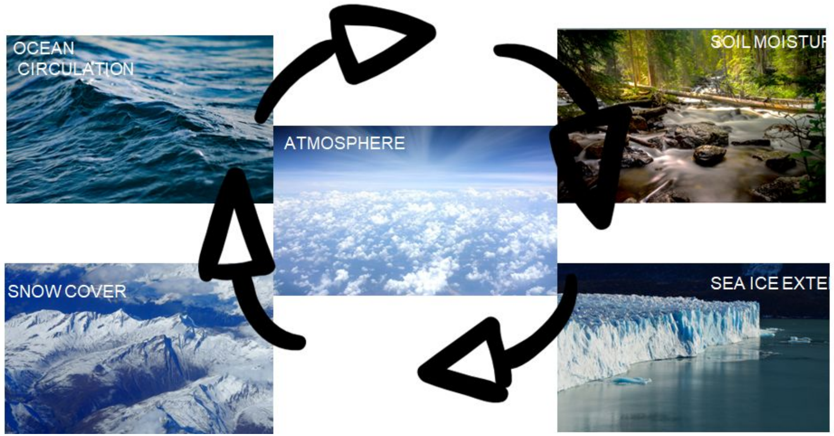
lluis.palma@bsc.es

ICTP | 13th May, 2025 | Trieste

Background

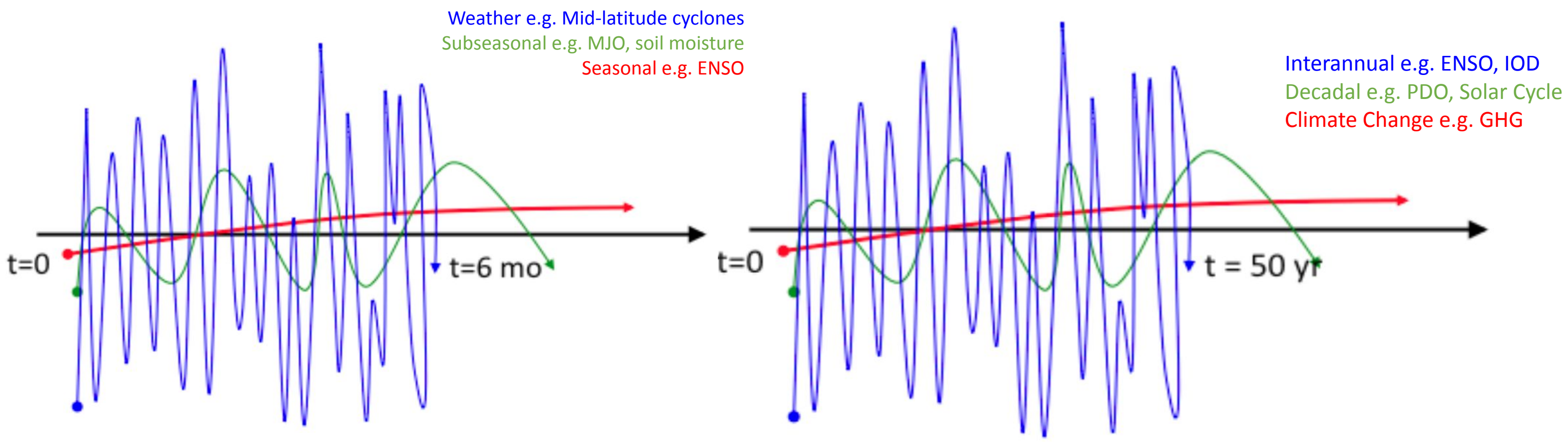
Based on Fig. 2 (Box 11.1) in AR5-WG1.





How can we predict climate for the coming season if we cannot predict the atmosphere beyond the next two weeks?

- **Slow components (land, ocean, etc.) force the atmosphere.**

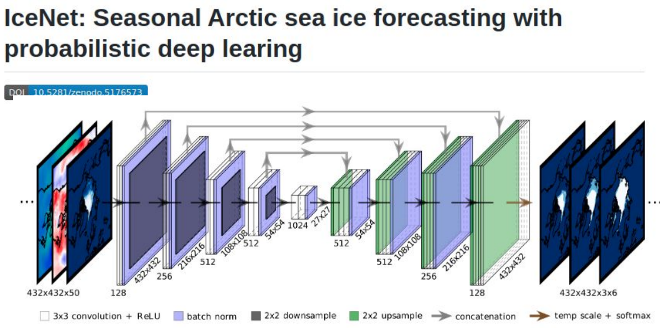


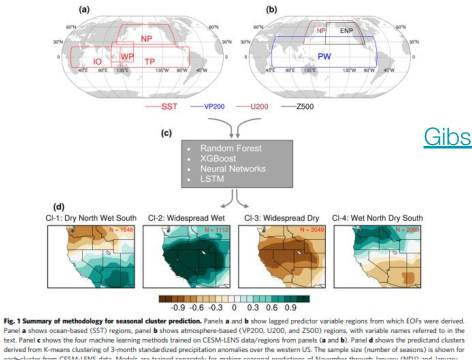
- At the seasonal timescale, interannual processes dominate, resulting in as few as one independent sample per year.

- Consequently, seasonal forecasting applications have up to two orders of magnitude less samples compared to weather applications over the same period.

Adapted from Next Generation Earth System Prediction: Strategies for Subseasonal to Seasonal Forecasts Fig. 4.1

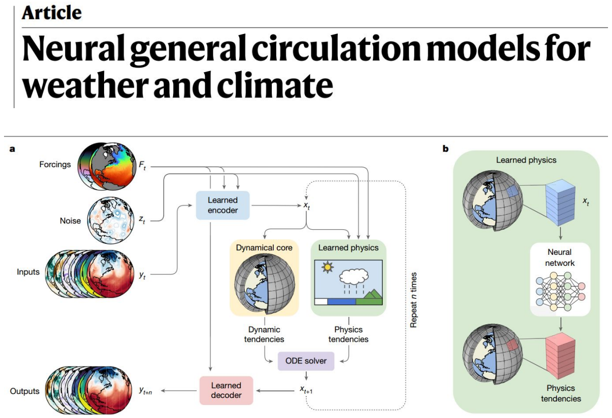
Train on climate model output like CMIP or large ensembles

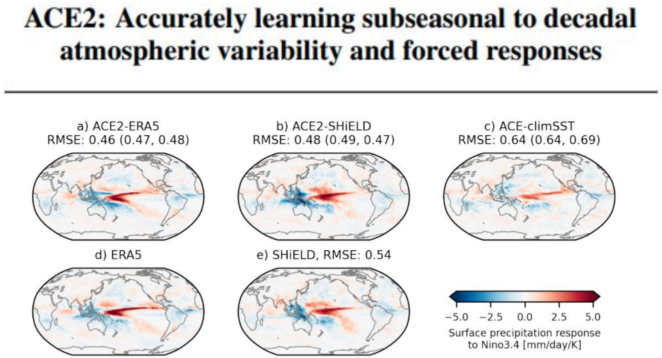




Gibson et al. 2021

Stabilize weather emulators with hybrid approaches or hard physical constraints





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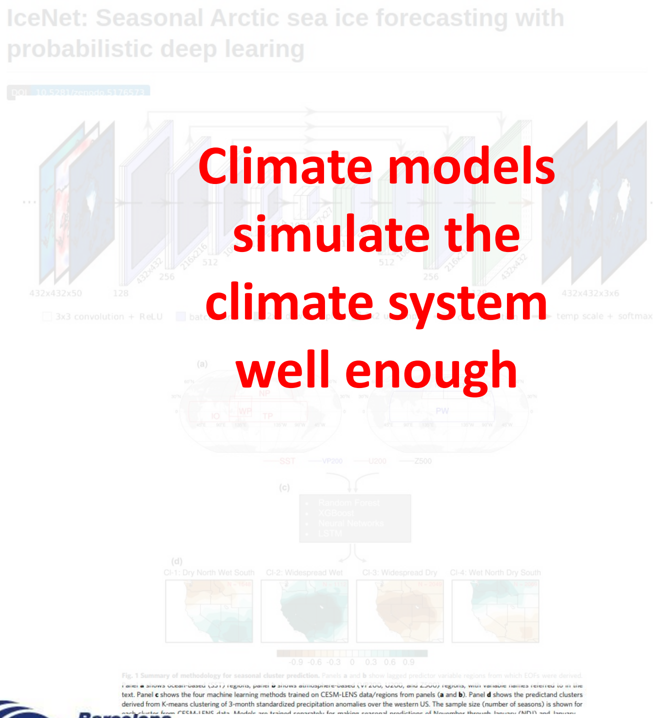
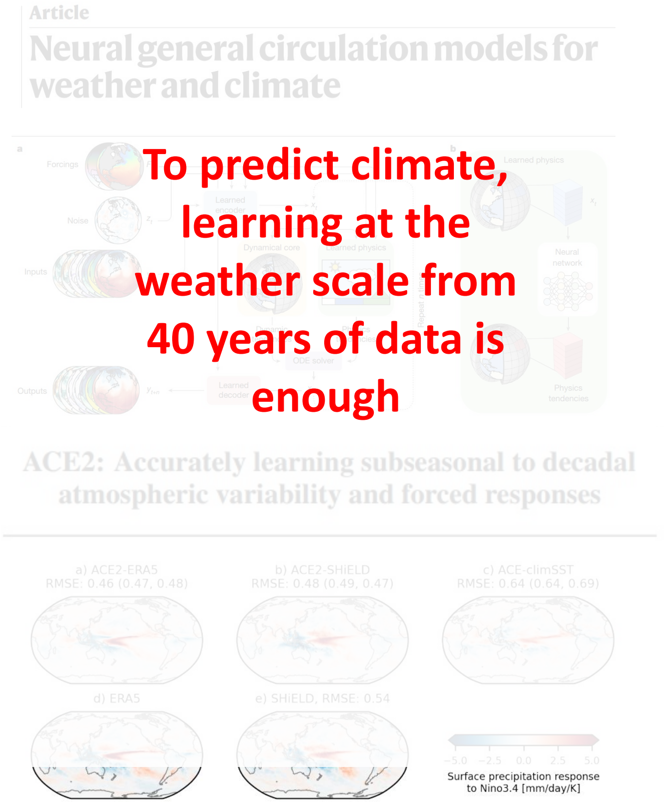
Train on climate model output like CMIP or large ensembles



Climate models simulate the climate system well enough

Stabilize weather emulators with hybrid approaches or hard physical constraints



To predict climate, learning at the weather scale from 40 years of data is enough

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Train on climate model output like CMIP or large ensembles

Climate models simulate the climate system well enough

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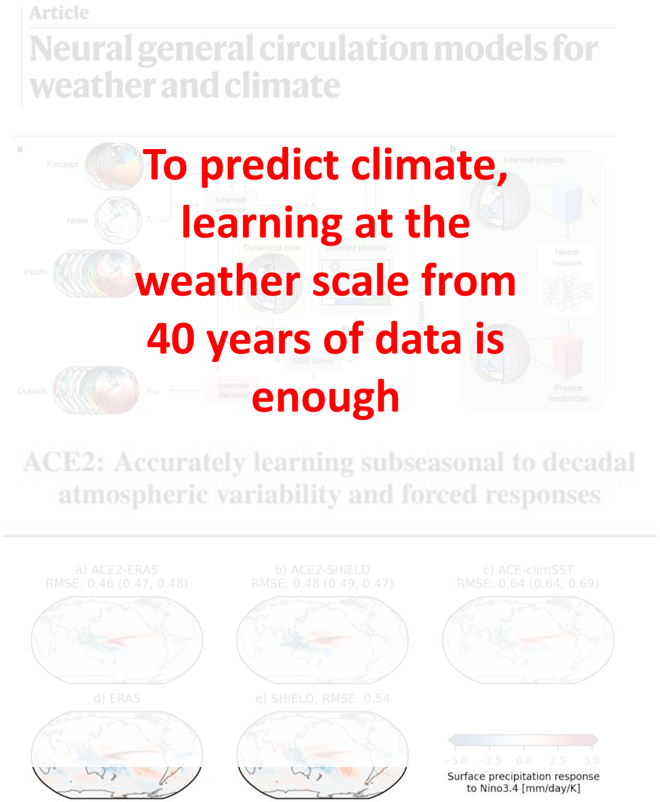

To predict climate, learning at the weather scale from 40 years of data is enough

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Main objectives

1. **Build a generative seasonal prediction model**
   - Probabilistic (ill-posed problem)
   - Predict Global/Regional gridded ECVs
   - Lead times 1 to 3 (i.e 1st Nov -> DJF)

2. **Use climate model output to train it**

3. **Assess its performance**: can we get any skill at all?
   - vs the climatological forecast and SEAS5
   - In a context of climate change

4. **Understand its sources of skill**

X

Monthly means from the preceding 6 months: 2t, pr, sst, g500, g300

Y

3-month (lead 1-3) seasonal averages: 2t, pr, sst, g500, g300

Split	Source	Time Period	Models
Training	CMIP6 (Hist. + SSP245)	1880 - 2080	CanESM5_r(6:25)i1p1f1, CanESM5_r(6:25)i1p2f1, MIROC-ES2L_r(6:25)i1p1f2, MIROC6_r(6:25)i1p1f1 & MPI-ESM1-2-LR_r(6:25)i1p1f1
Validation	CMIP6 (Hist. + SSP245)	1880 - 2080	CanESM5_r(1:5)i1p1f1, CanESM5_r(1:5)i1p2f1, MIROC-ES2L_r(1:5)i1p1f2, MIROC6_r(1:5)i1p1f1 & MPI-ESM1-2-LR_r(1:5)i1p1f1
Test	ERA5	1950 - 2021	

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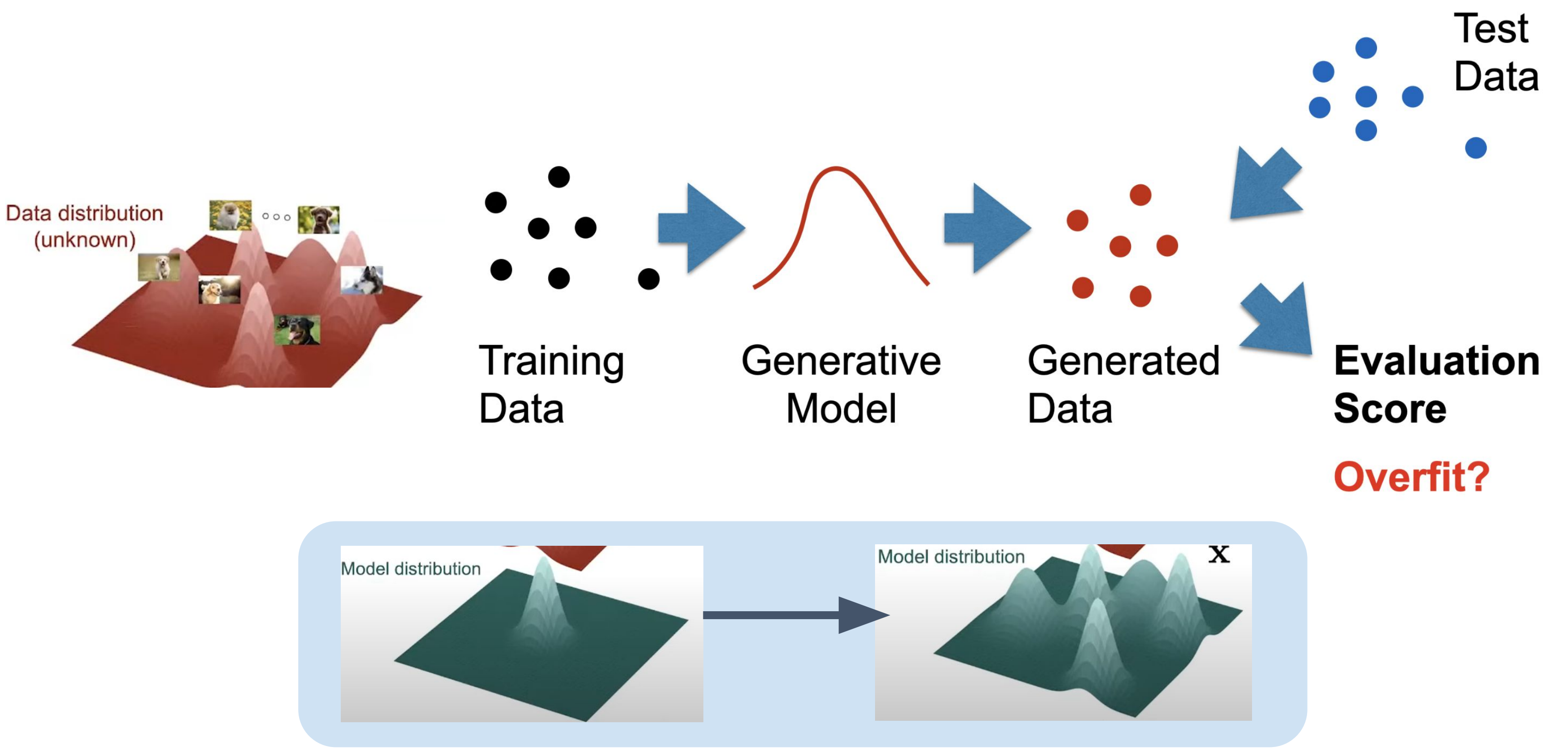
Generative models 101



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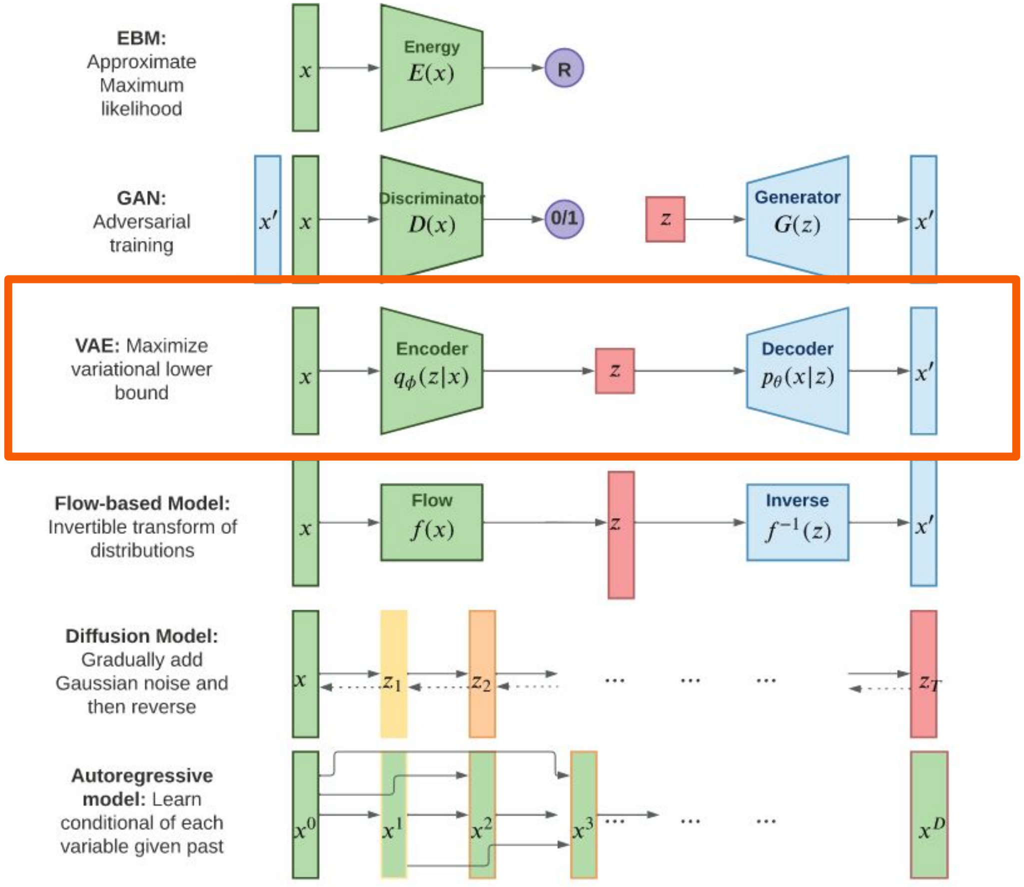
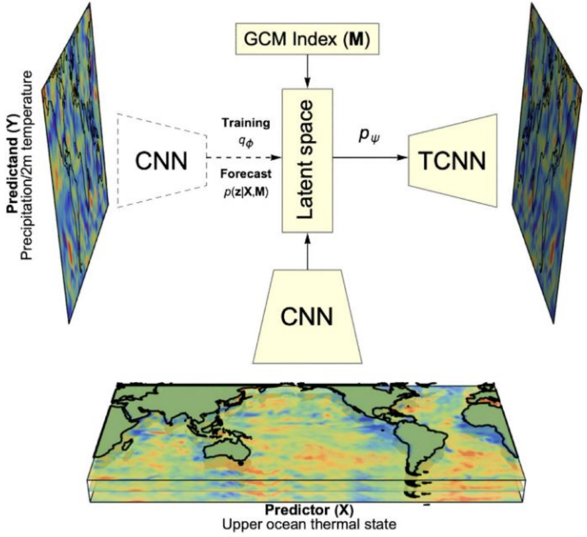


source: Murphy 2023



Pan et al., 2022

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Learning distributions

Learning p(Y|X):

We need to minimize the difference between our distribution and the real distribution [1]:

- Neither our model or the data distributions have an analytical form: KL -> Empirical NLL [2]

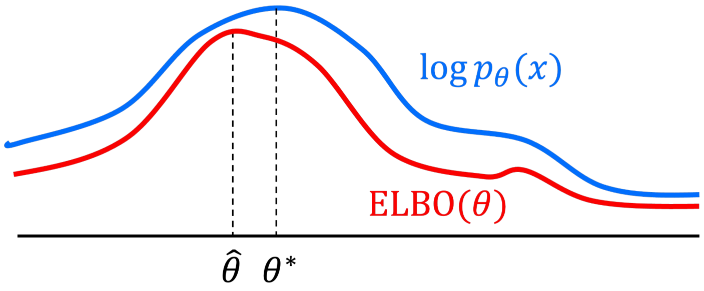
- Yet, computing the log-likelihood is **intractable** as it requires integration over z for each data point [3]

- VAEs (Kingma and Welling 2022) offer an alternative by narrowing the integration space of z to values that are likely to generate y [4]

$$D_{KL}(p\|q) = -\mathbb{H}(p) + \mathbb{H}_{ce}(p,q) \quad (1)$$

$$\mathrm{NLL}(\theta) = -\sum_{i=1}^{N} \log p_\theta(y_i|x_i) \quad (2)$$

$$\boxed{p_\theta(y|x) = \int_z p_\theta(y|z,x)\, p_\theta(z|x)\, dz} \quad (3)$$



$$\mathcal{L}(\theta,\phi) = -\mathbb{E}_{q_\phi(z|x,y)}[\log p_\theta(y|z,x)] + D_{KL}(q_\phi(z|y,x)\|p_\theta(z|x)) \quad (4)$$

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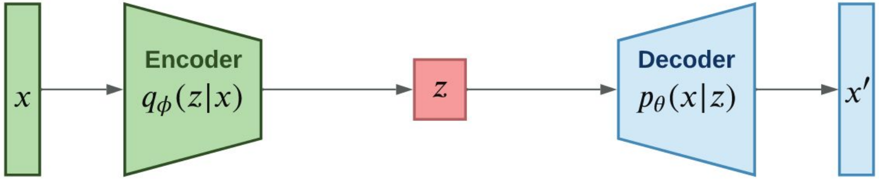
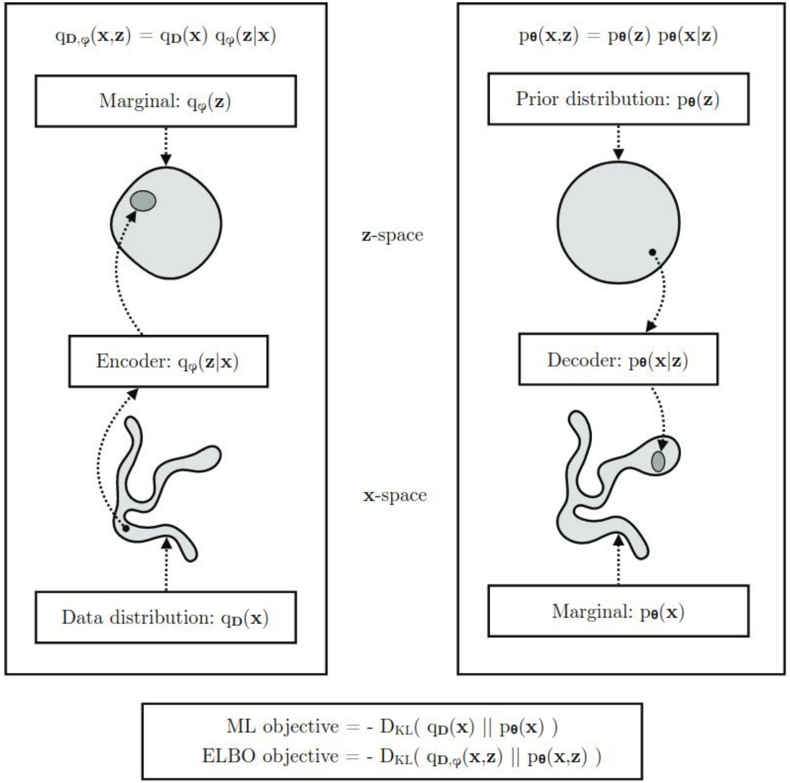
Learning distributions





source: Murphy 2023

Architecture

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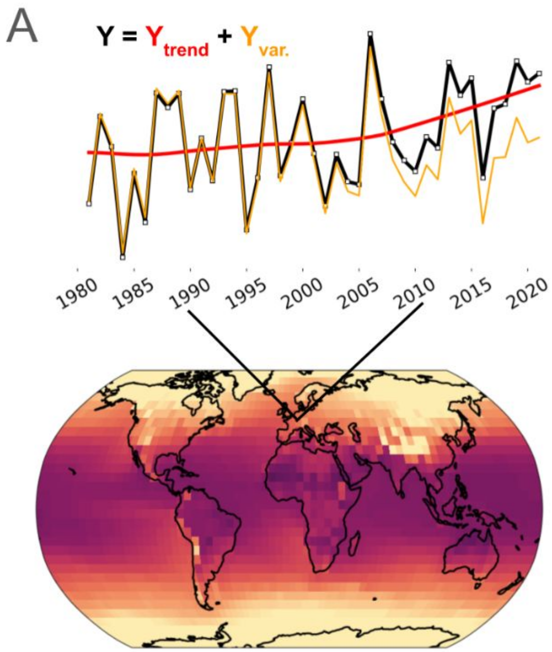
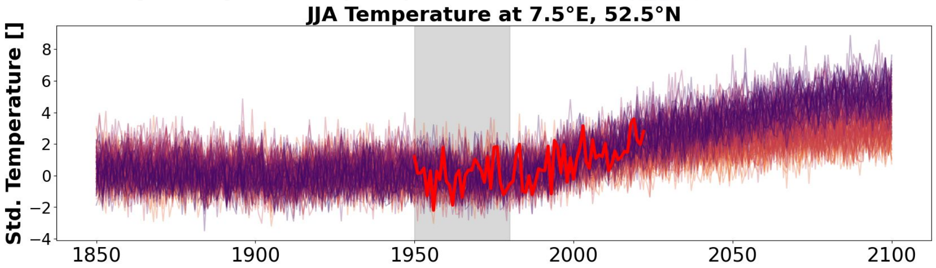
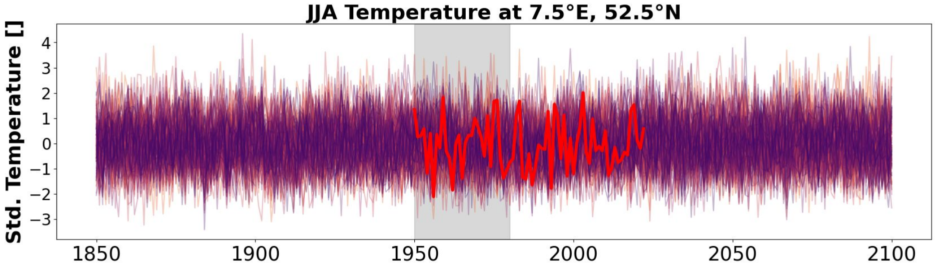
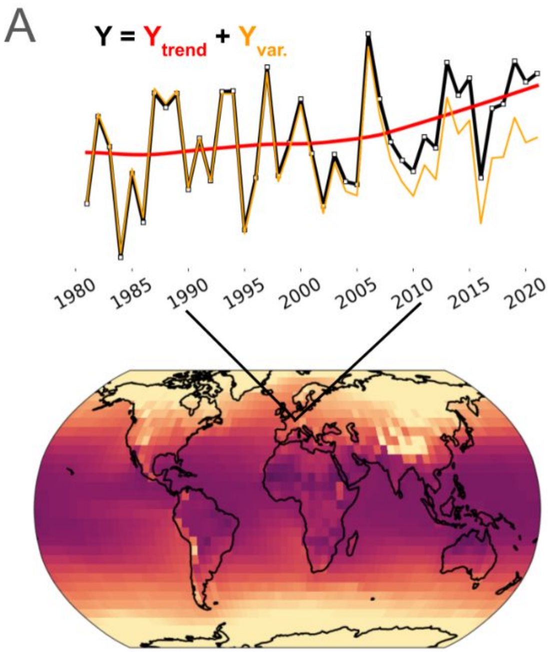
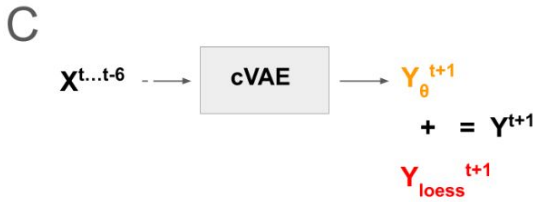


- We perform signal decomposition on the target variable to divide the trend induced by climate change from the interannual variability.









- Our generative model predicts the interannual variability while a non-linear regression model predicts the contribution from the trend.

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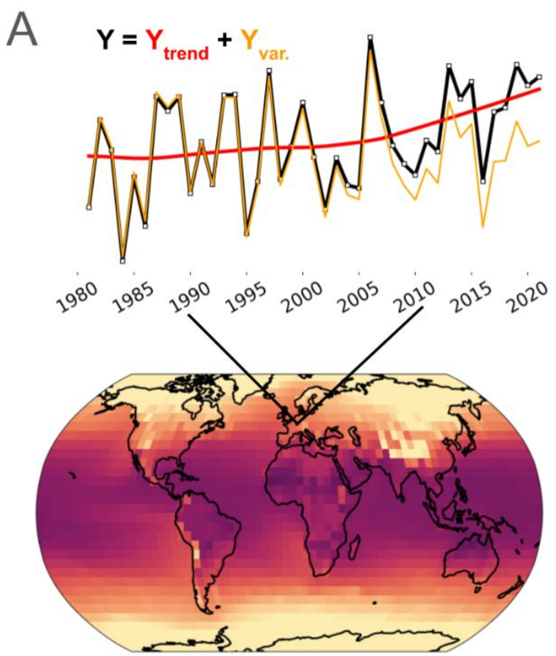
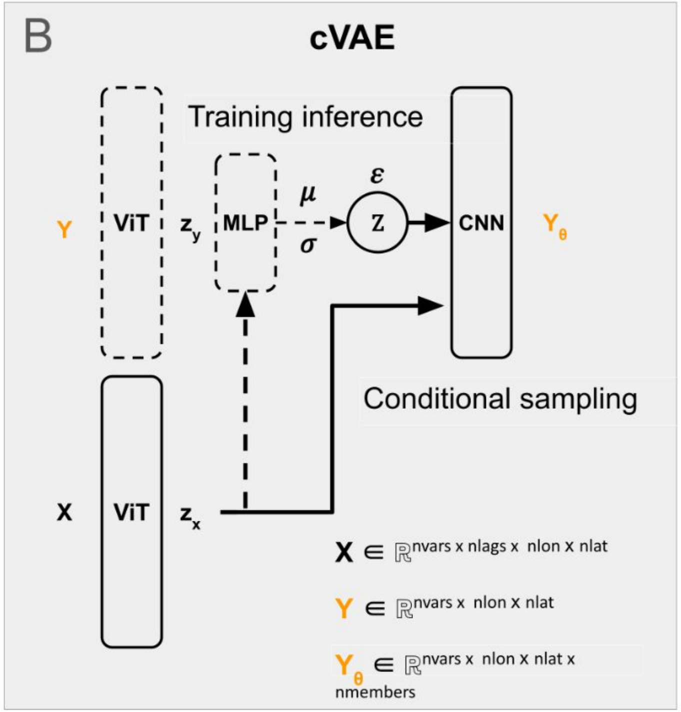
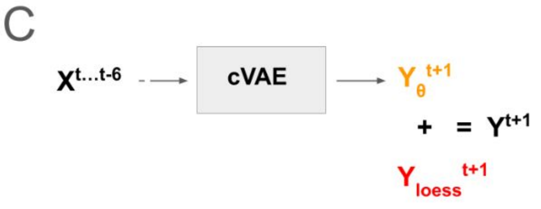
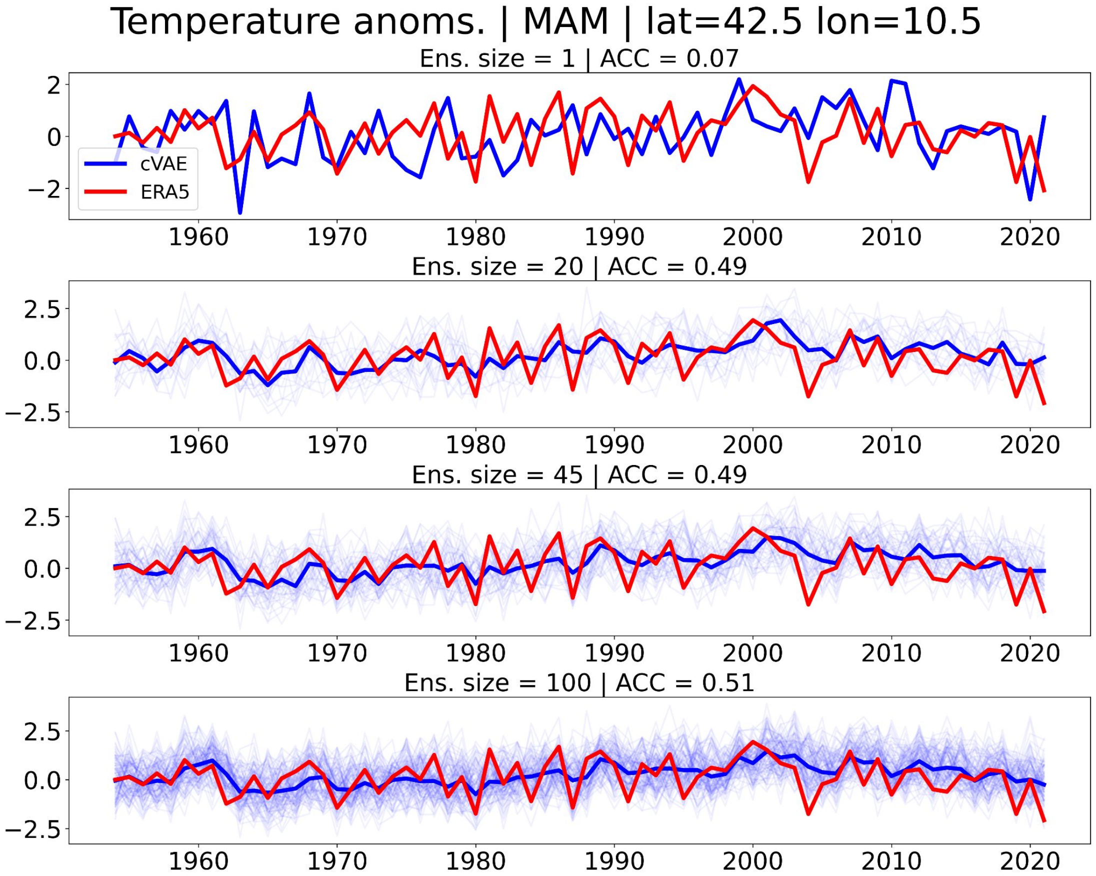






- The Y encoder is only used during training.
- During inference multiple values from z are sampled and combined with the initial state X, obtaining an ensemble of predictions



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Results

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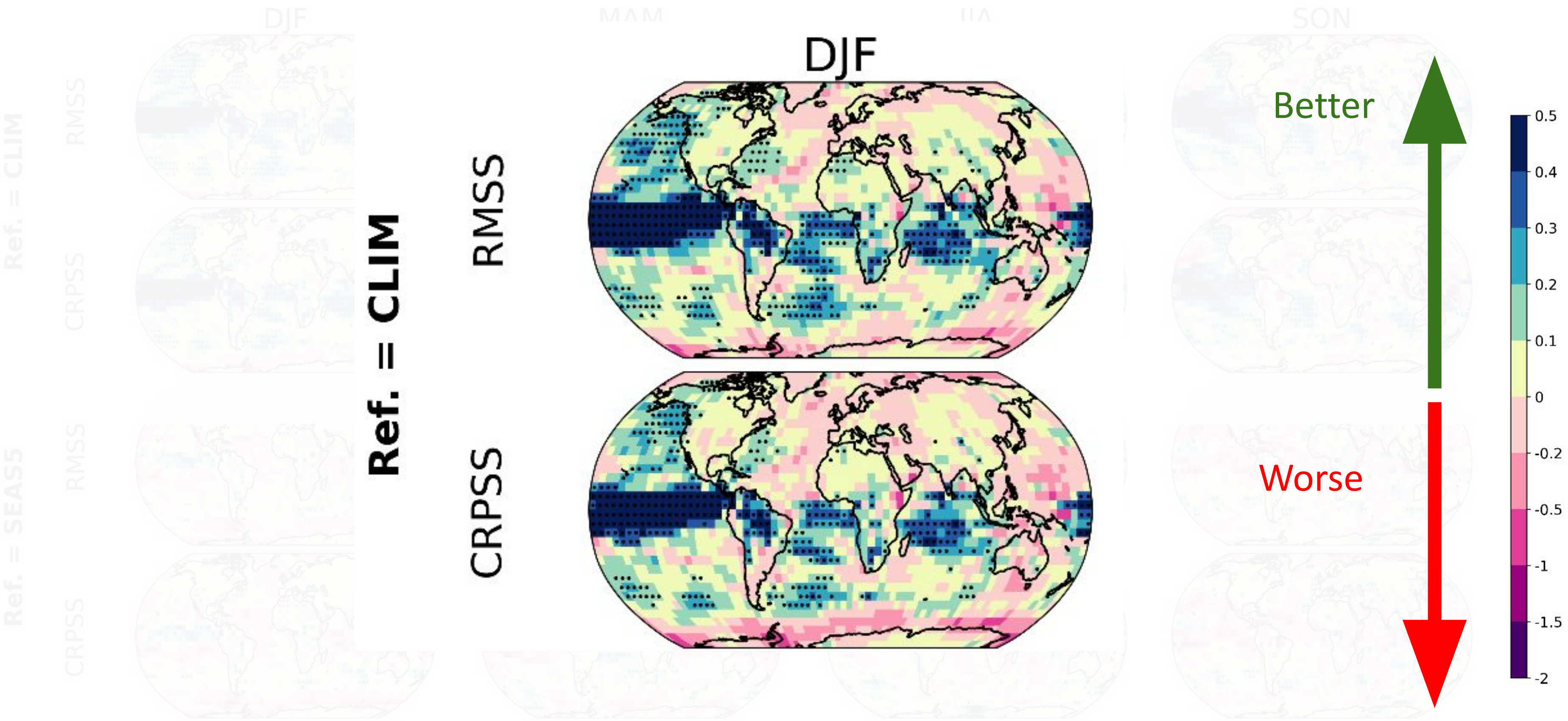
tas | skill scores 2001-2021 [ref. 1981-2000] | De-trended



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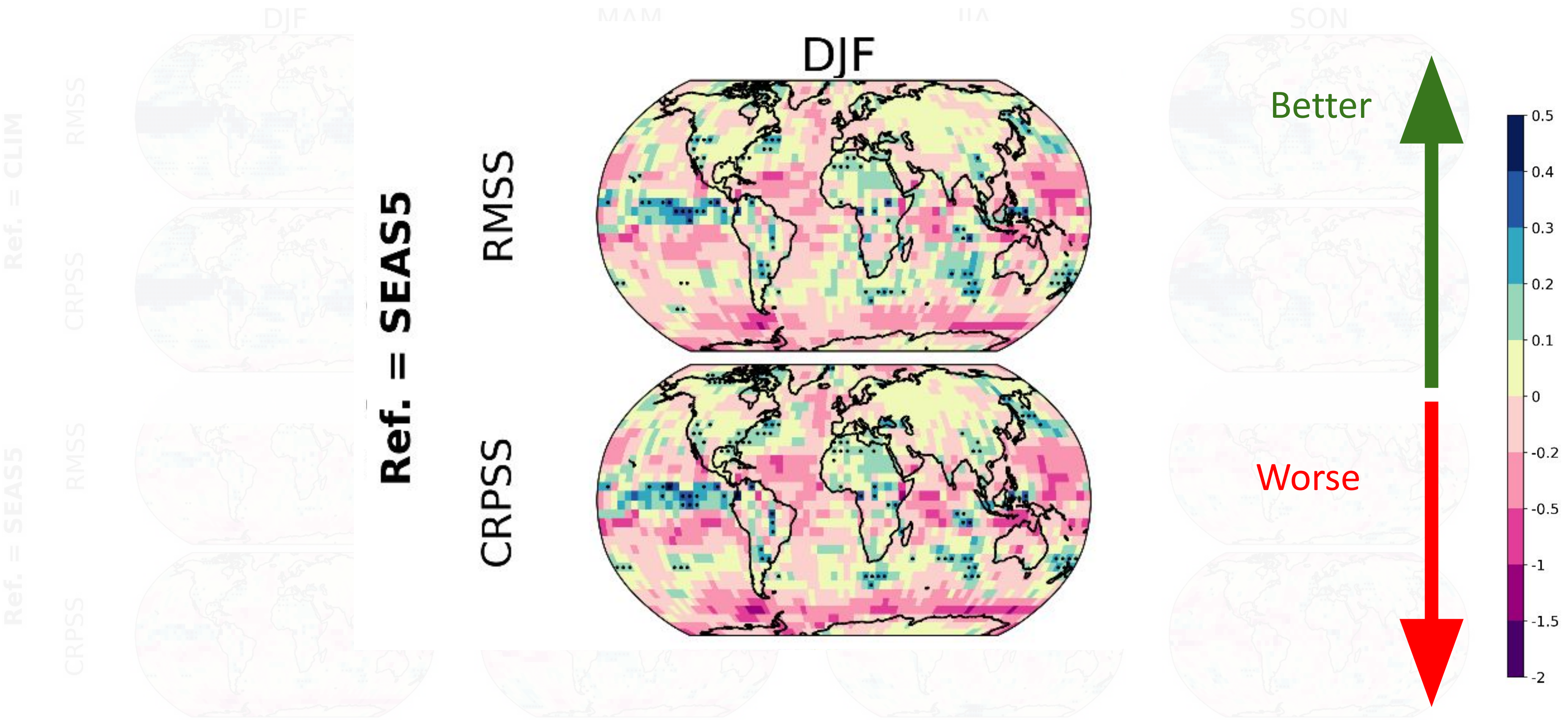
tas | skill scores 2001-2021 [ref. 1981-2000] | De-trended



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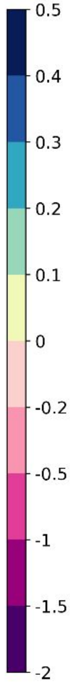
tas | skill scores 2001-2021 [ref. 1981-2000] | De-trended

- Skill over the climatological forecast is obtained in most regions

- Skill over SEAS5 is found in most inland areas



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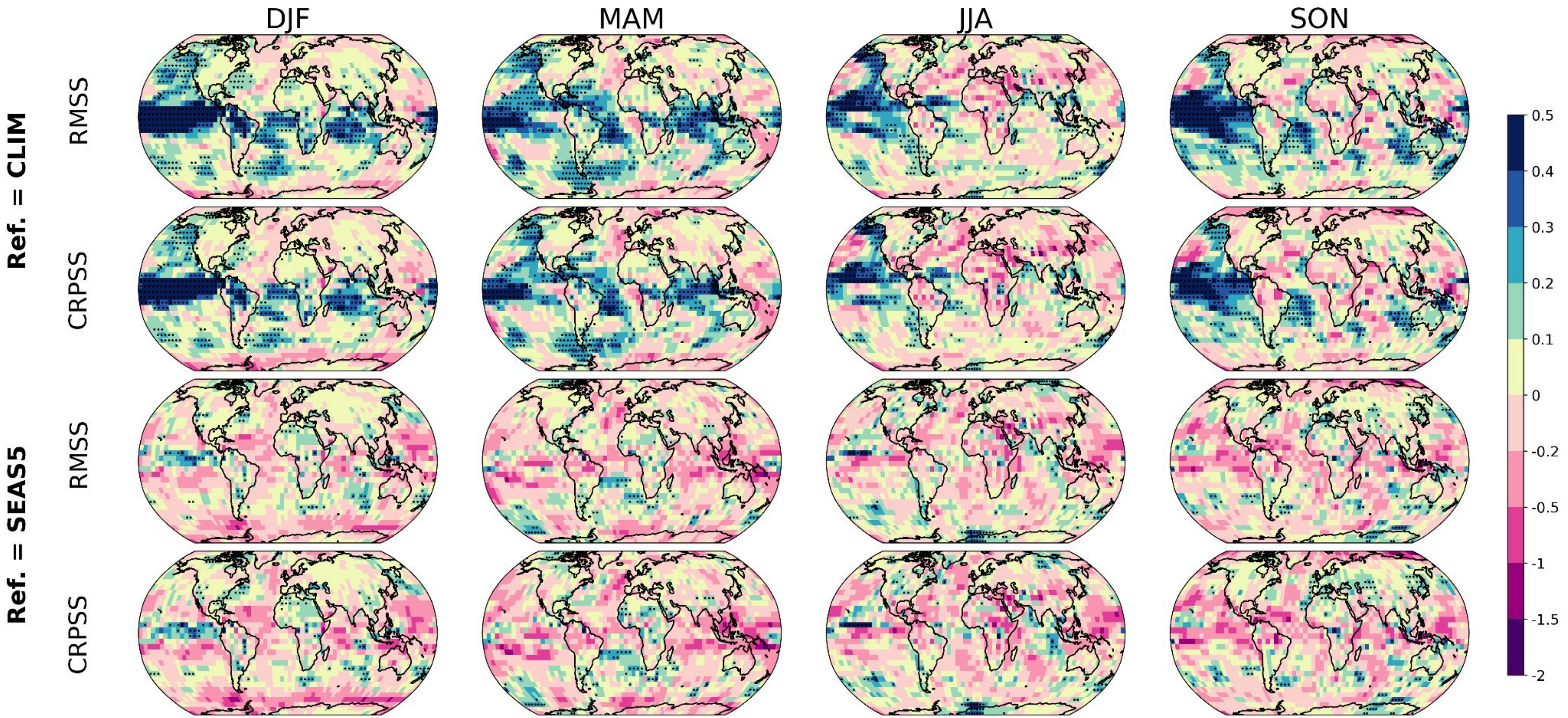
tas | skill scores 2001-2021 [ref. 1981-2000] | De-trended



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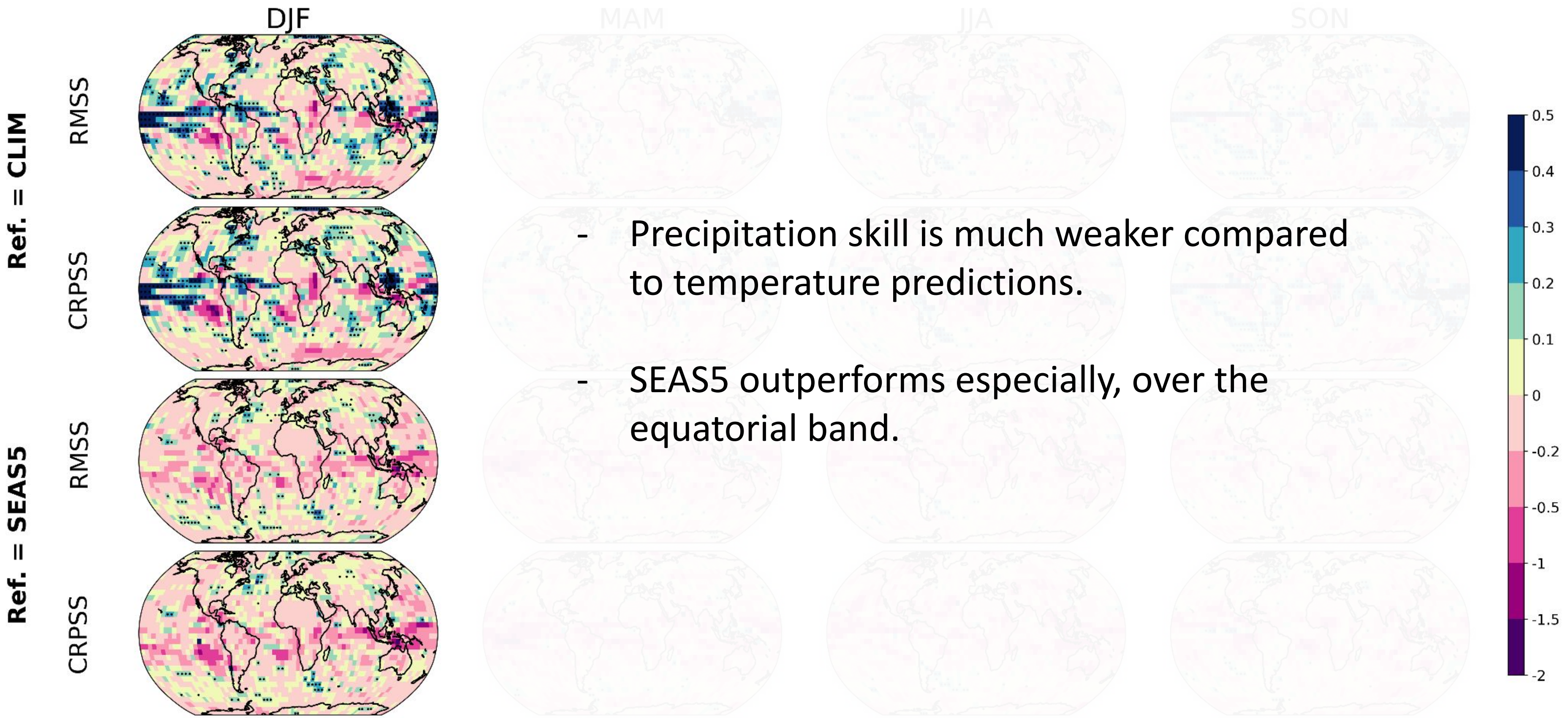
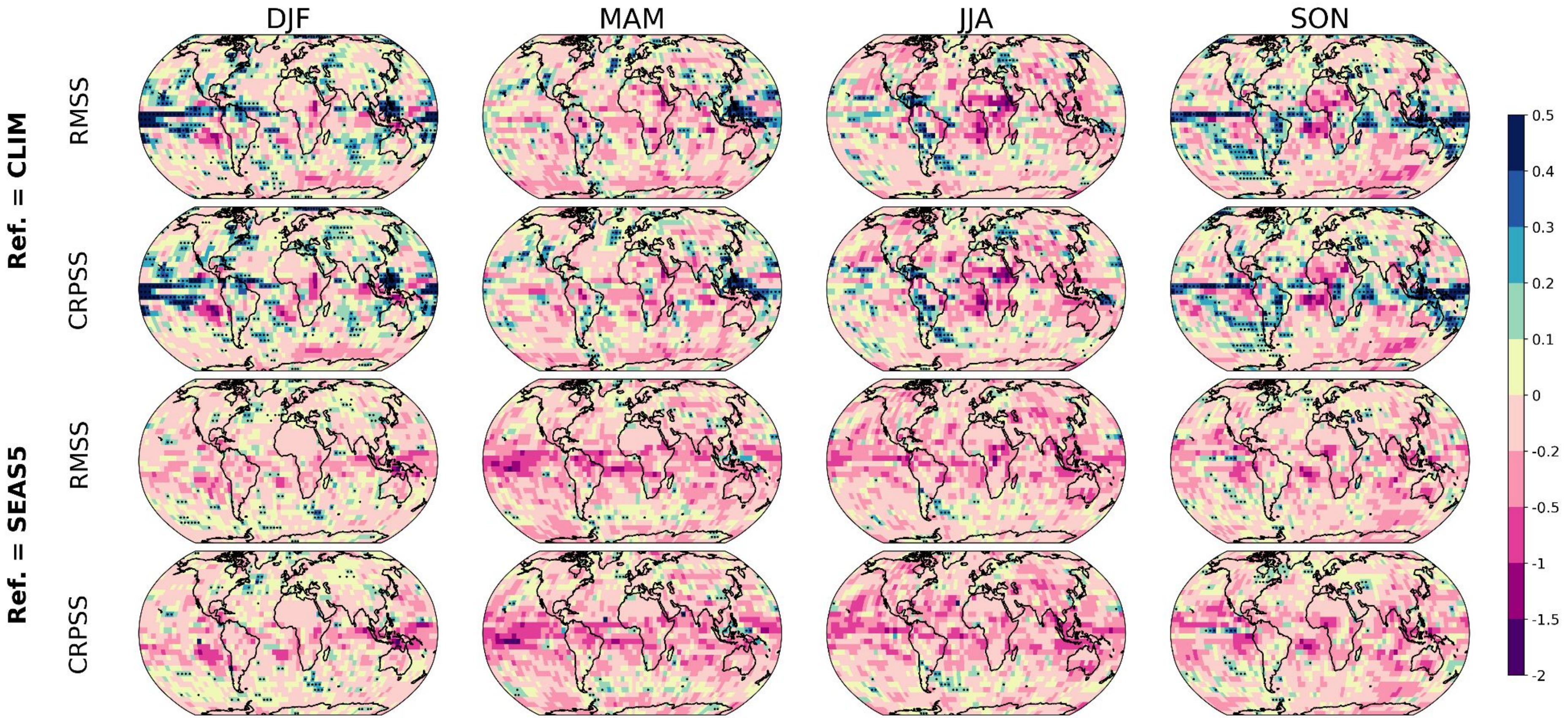
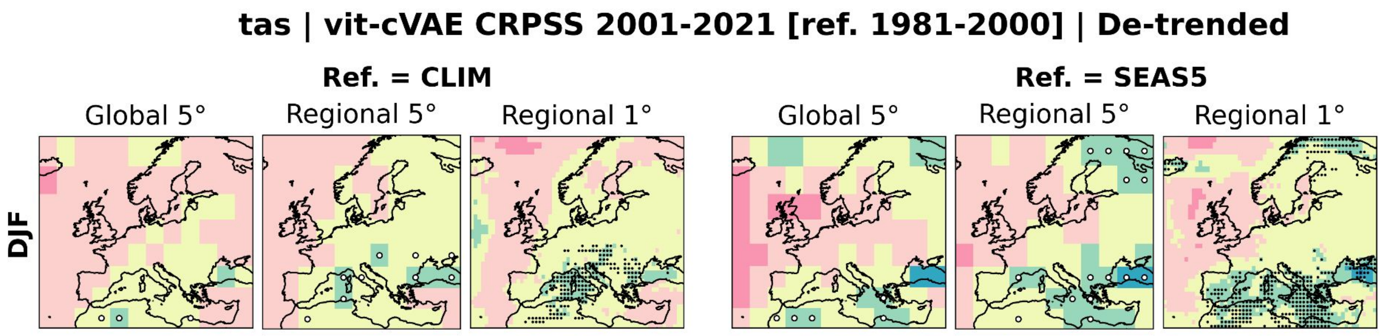
pr | skill scores 2001-2021 [ref. 1981-2000]

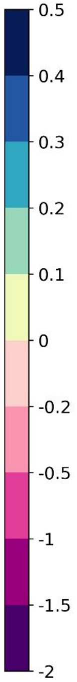


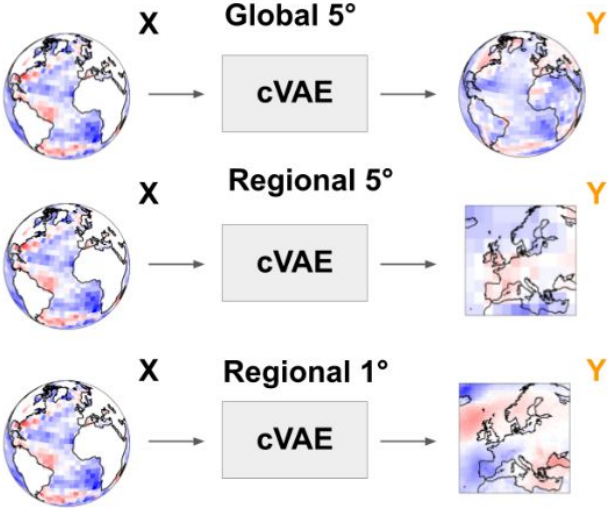
- Precipitation skill is much weaker compared to temperature predictions.
- SEAS5 outperforms especially, over the equatorial band.

pr | skill scores 2001-2021 [ref. 1981-2000]



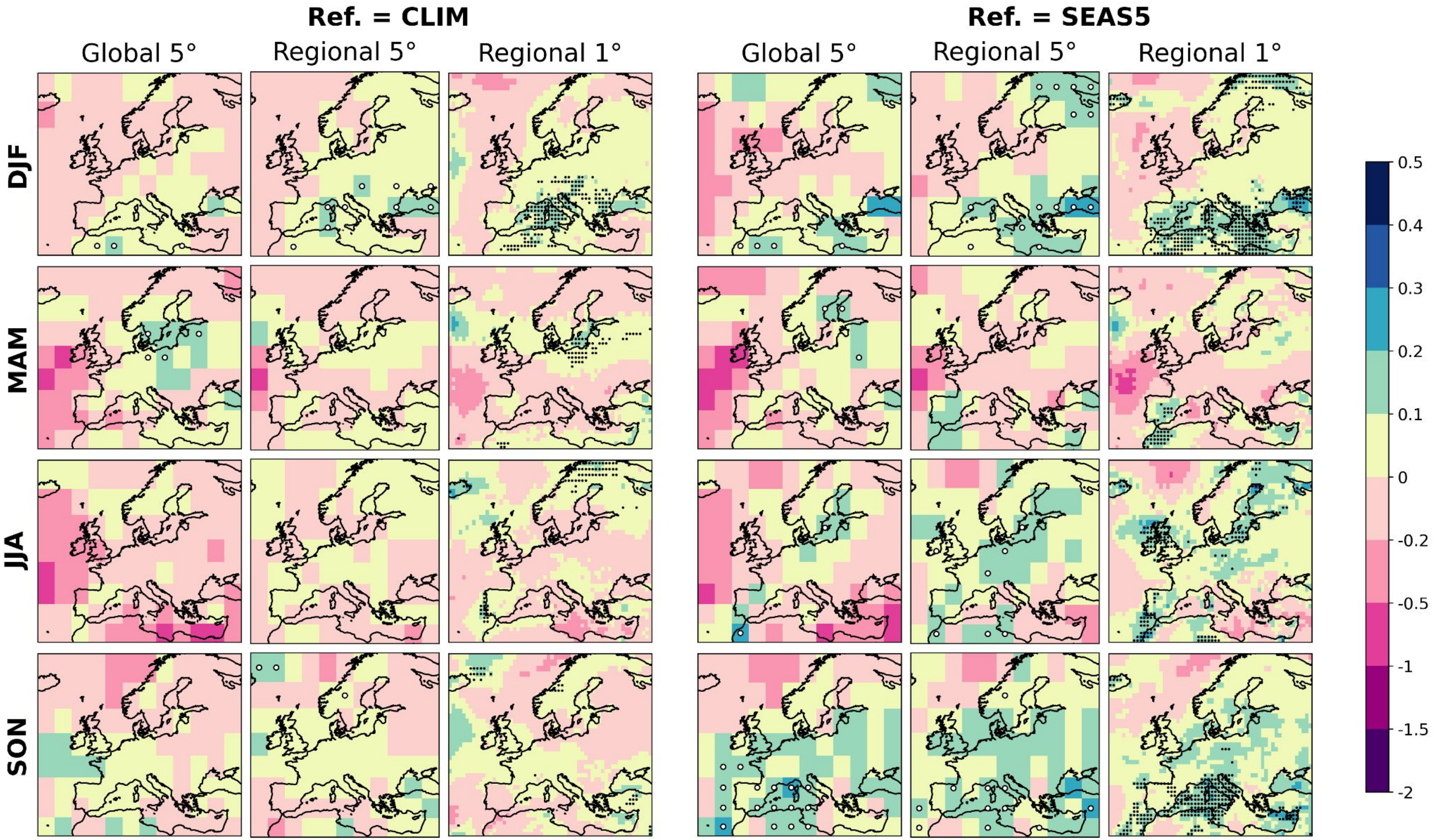






Three target setups are compared, in which both the domain and spatial resolution are changed but the input domain and spatial resolution are preserved.

tas | vit-cVAE CRPSS 2001-2021 [ref. 1981-2000] | De-trended



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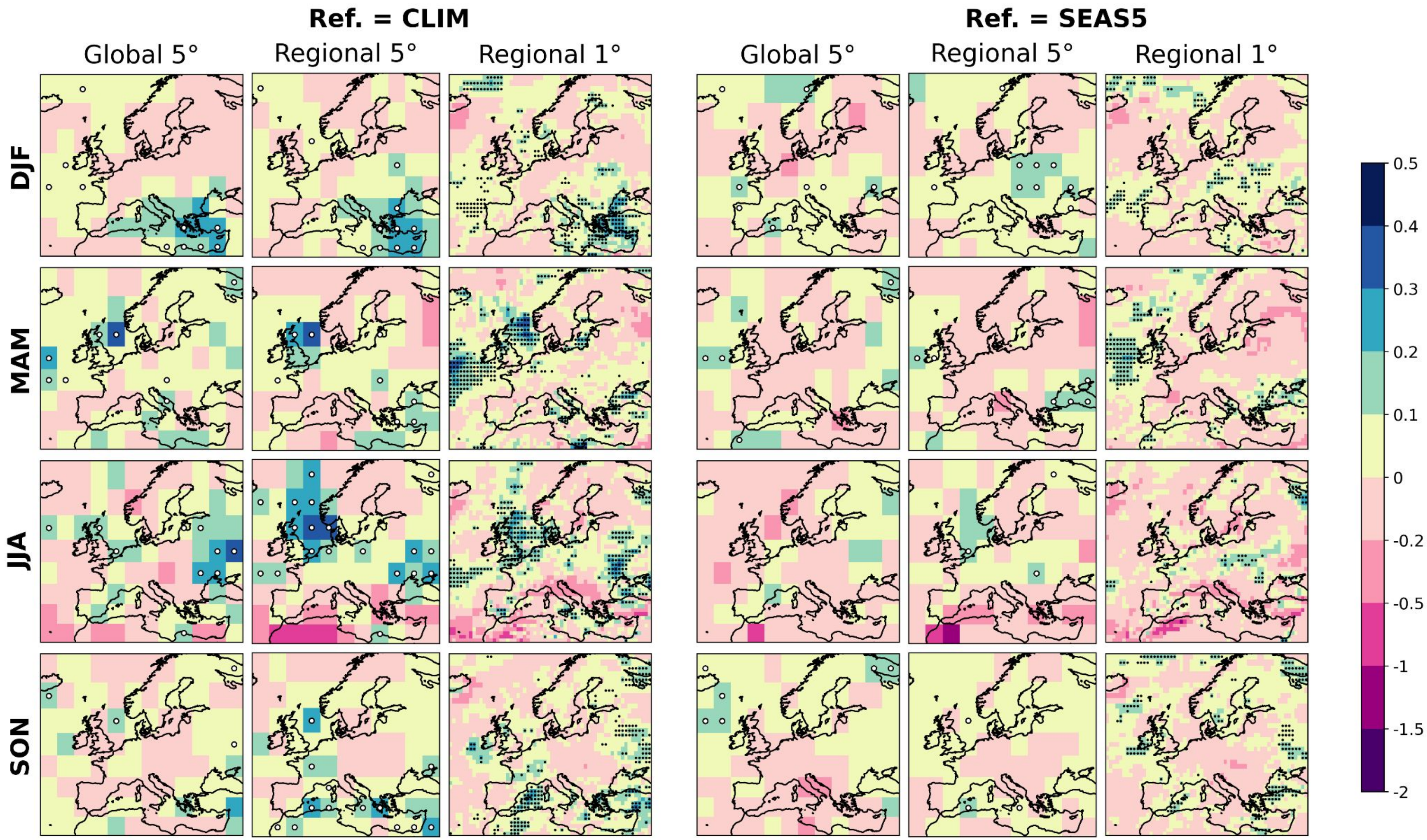
pr | vit-cVAE CRPSS 2001-2021 [ref. 1981-2000]



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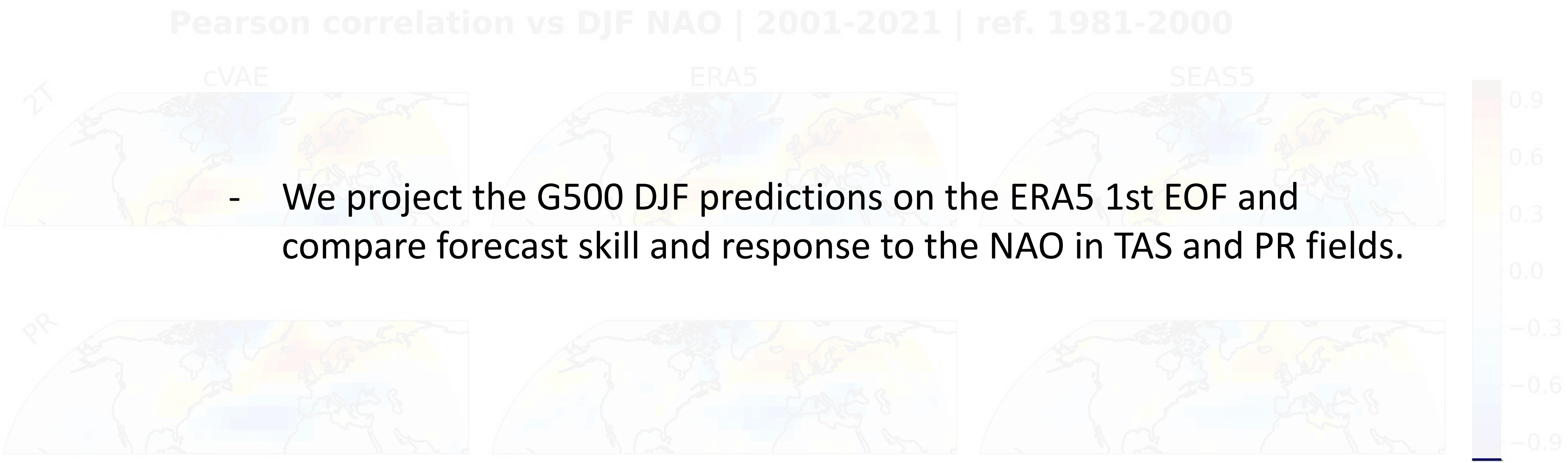
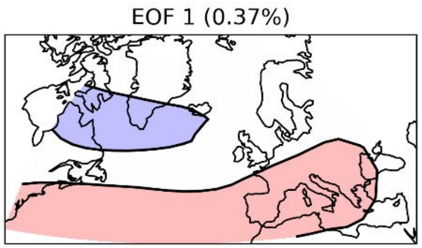
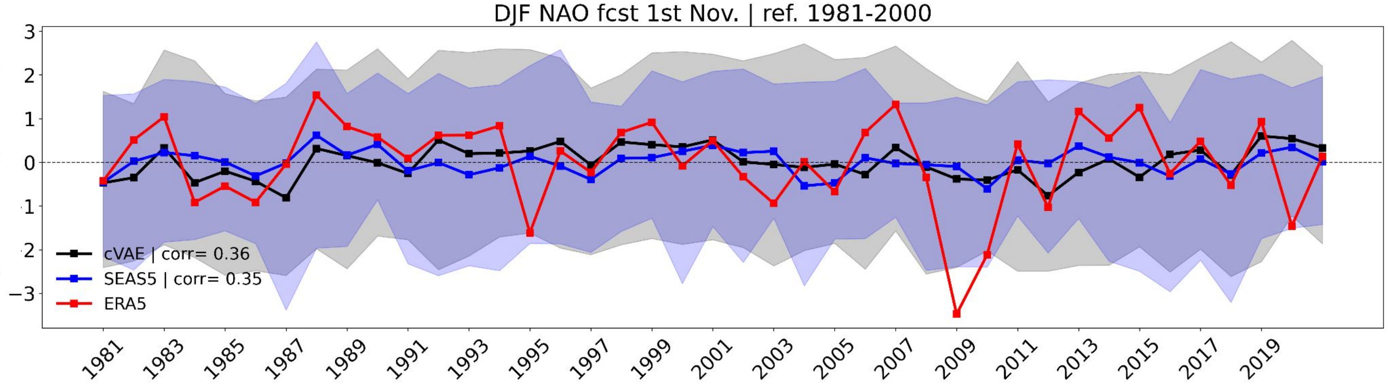
Teleconnections



- We project the G500 DJF predictions on the ERA5 1st EOF and compare forecast skill and response to the NAO in TAS and PR fields.

ERA5 DJF ZG500 EOFs





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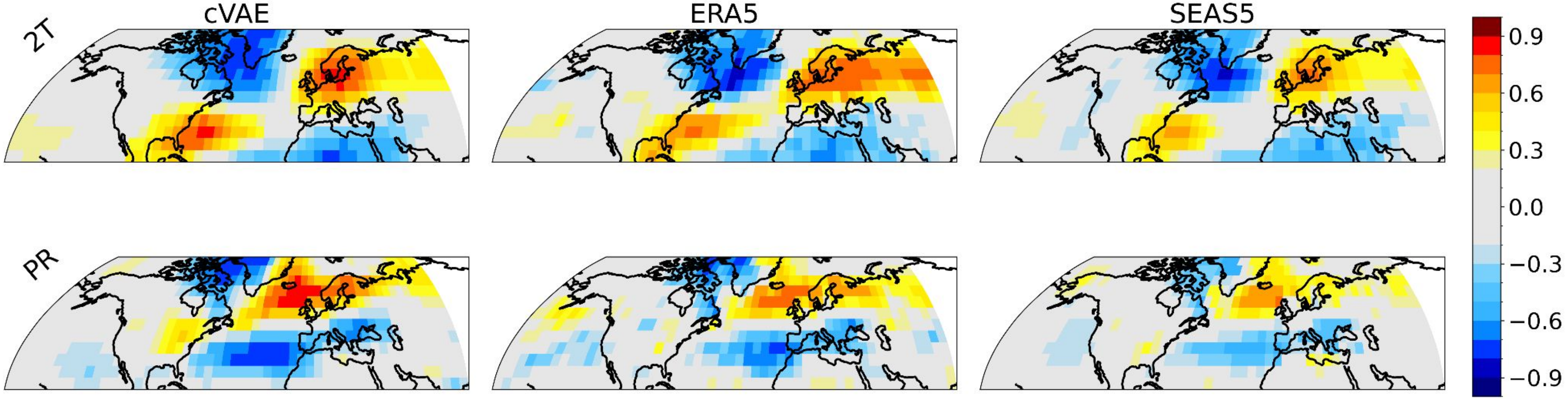
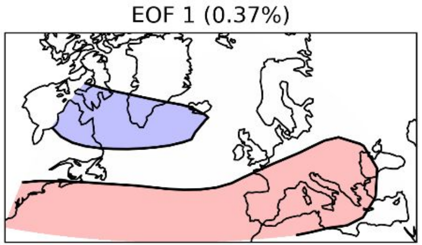
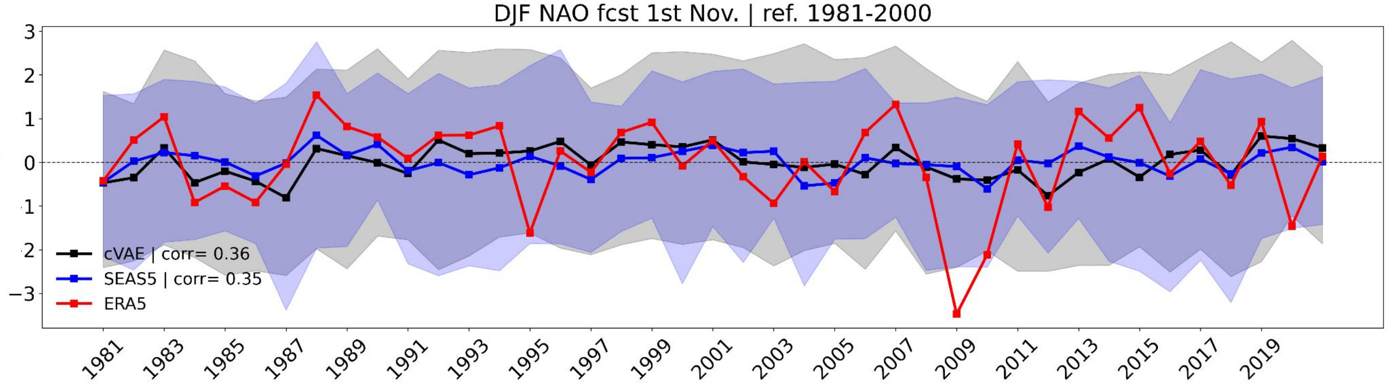
Pearson correlation vs DJF NAO | 2001-2021 | ref. 1981-2000

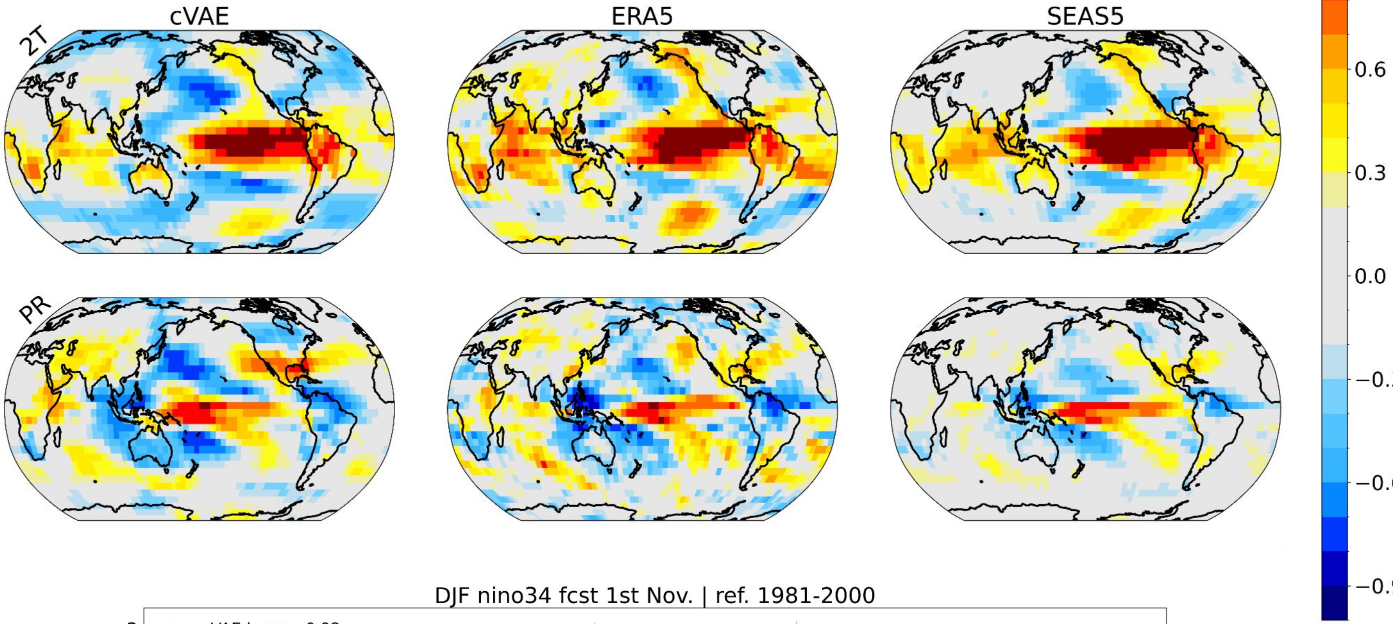


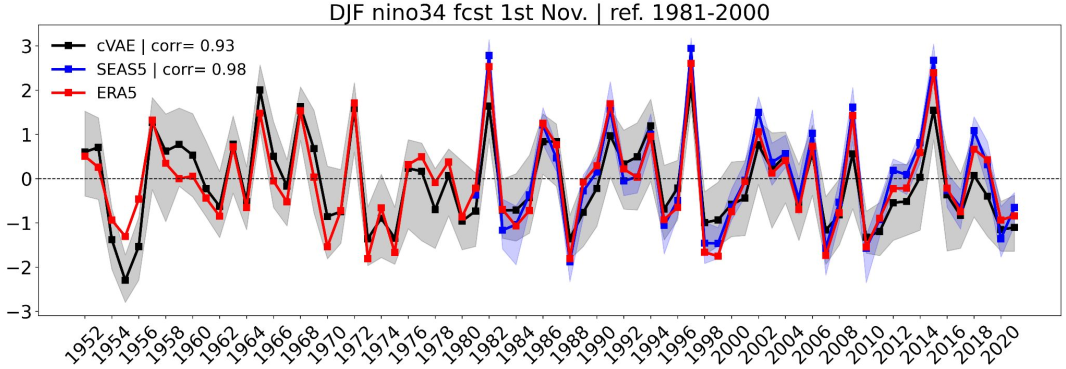
ERA5 DJF ZG500 EOFs





Pearson correlation vs DJF Nino3.4 | 2001-2021 | ref. 1981-2000





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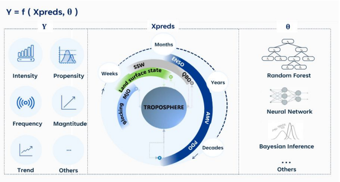
1. Using climate model output, we stably trained a generative seasonal prediction model that reached valuable skill levels.

2. Temperature predictions demonstrate skill beyond that induced by the climate-change trend, outperforming SEAS5 in numerous inland areas. Precipitation forecasts show very limited skill, with fewer regions outperforming climatology and fewer surpassing SEAS5.

3. Latent-based generative models are valuable tools due to their ensemble generation capabilities and consistency across target configurations.

4. A simple teleconnection analysis shows the model's capabilities in learning "realistic" teleconnection patterns.



Received: 24 September 2023 | Revised: 17 July 2024 | Accepted: 24 July 2024
DOI: 10.1002/wcc.914

SYSTEMATIC REVIEW

WIREs CLIMATE CHANGE WILEY

Artificial intelligence for climate prediction of extremes: State of the art, challenges, and future perspectives

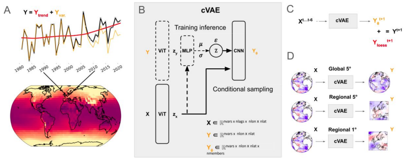
*Materia, S., **Palma, Ll.**, van Straaten, C., Sungmin, Mamalakis, A., Cavicchia, L., Coumou, D., de Luca, P., Kretschmer, M., & Donat, M. (2024). Artificial intelligence for climate prediction of extremes: State of the art, challenges, and future perspectives. Wiley Interdisciplinary Reviews. Climate Change. https://doi.org/10.1002/wcc.914*

arXiv > physics > arXiv:2503.20466

Physics > Atmospheric and Oceanic Physics

[Submitted on 26 Mar 2025 (v1), last revised 28 Mar 2025 (this version, v2)]

Data-driven Seasonal Climate Predictions via Variational Inference and Transformers



__Palma, Ll.__, Peraza, A., Civantos, D., Duarte, A., Materia, S., Muñoz, Á. G., Peña-Izquierdo, J., Romero, L., Soret, A., & Donat, M. G. (2025). Data-driven seasonal climate predictions via variational inference and transformers. In arXiv [physics.ao-ph]. http://arxiv.org/abs/2503.20466

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Thanks!

lluis.palma@bsc.es