

SWGEM 2025 - Conference on Stochastic Weather Generators

Generative Machine Learning for Downscaling Earth System Model Simulations

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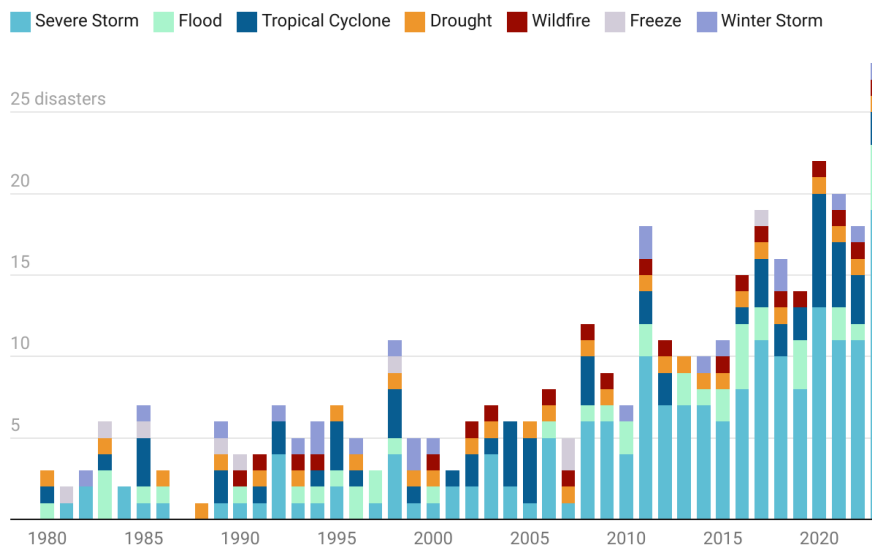
Assessing the impacts of climate change



Credits: NASA Earth Observatory, Wikipedia

US billion-dollar disasters by year

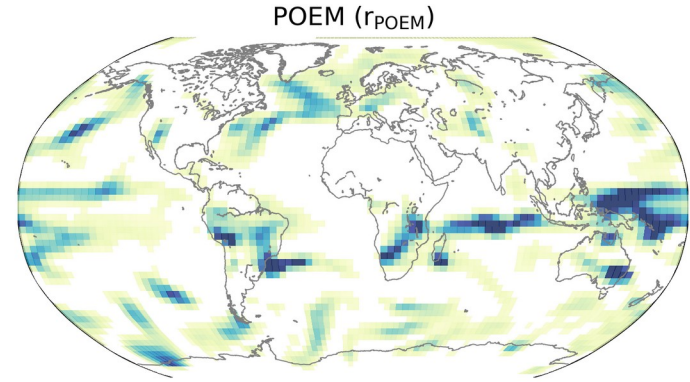
The number of weather and climate disasters exceeding \$1 billion in damage each has grown in recent decades, with costs adjusted for inflation.



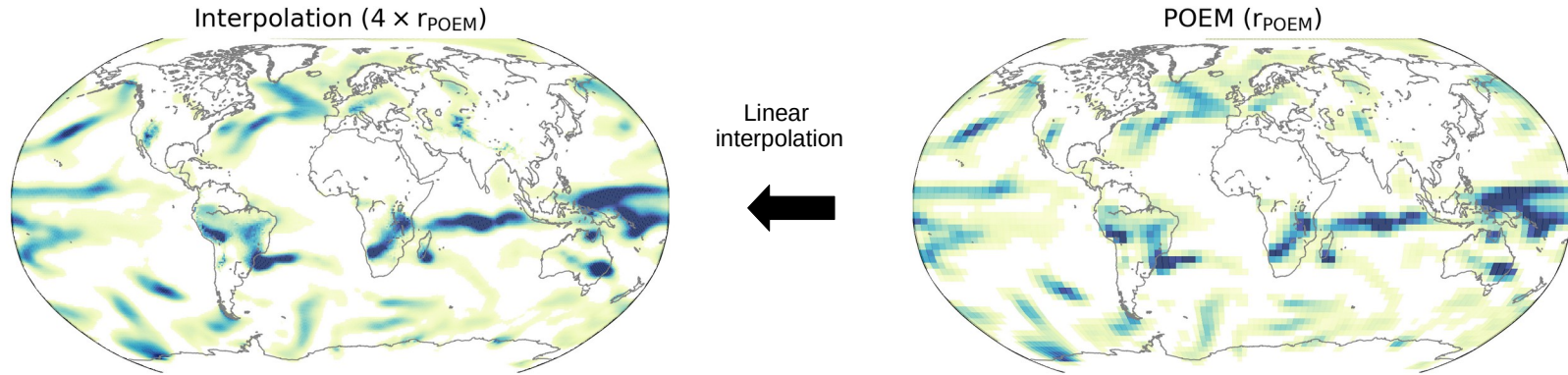
Data as of Jan 9, 2024. Wildfires are generally grouped together as a single event

Chart: The Conversation/CC-BY-ND • Source: NCEI/NOAA • Created with Datawrapper

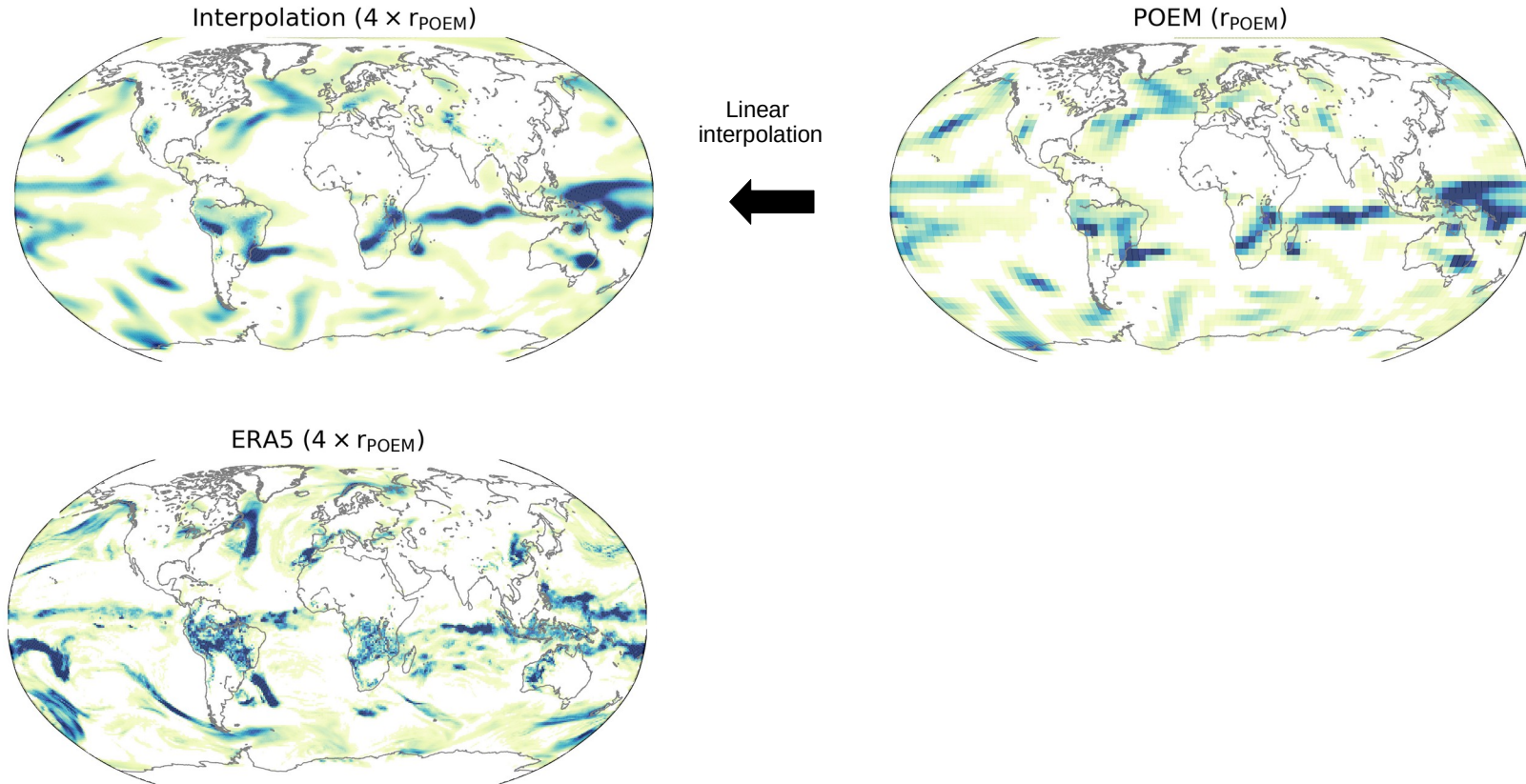
Downscaling Earth system model simulations



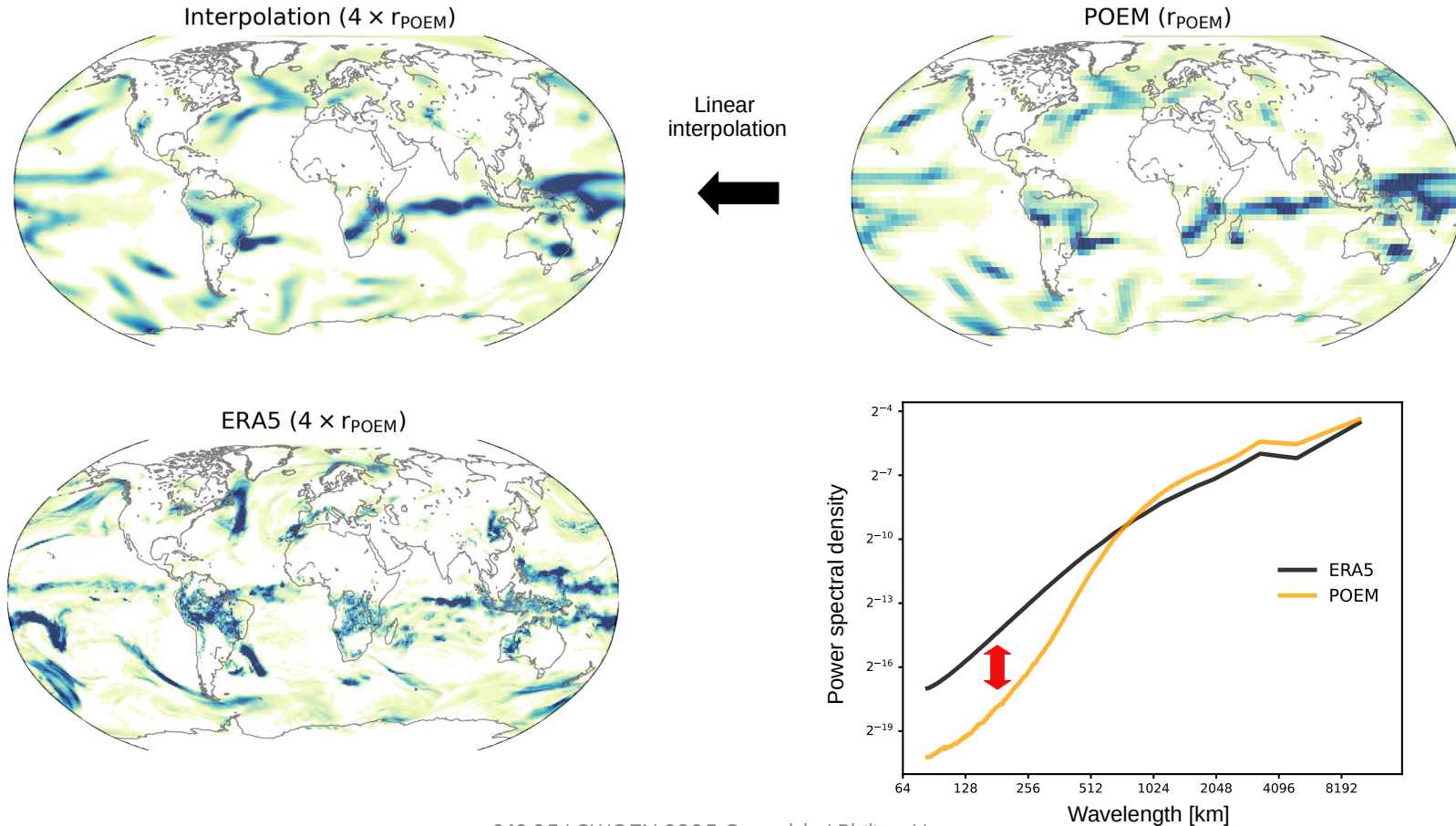
Downscaling Earth system model simulations



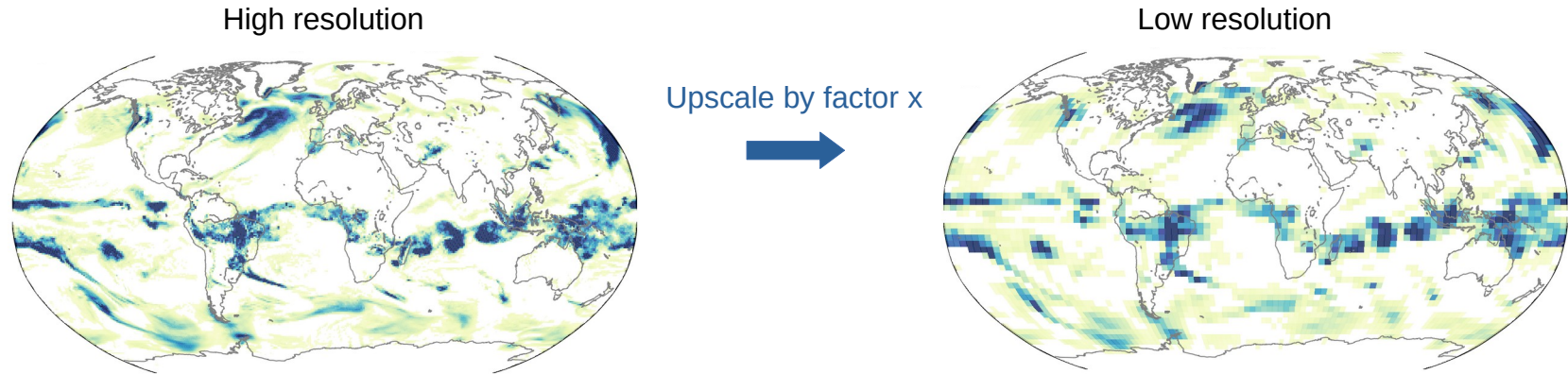
Downscaling Earth system model simulations



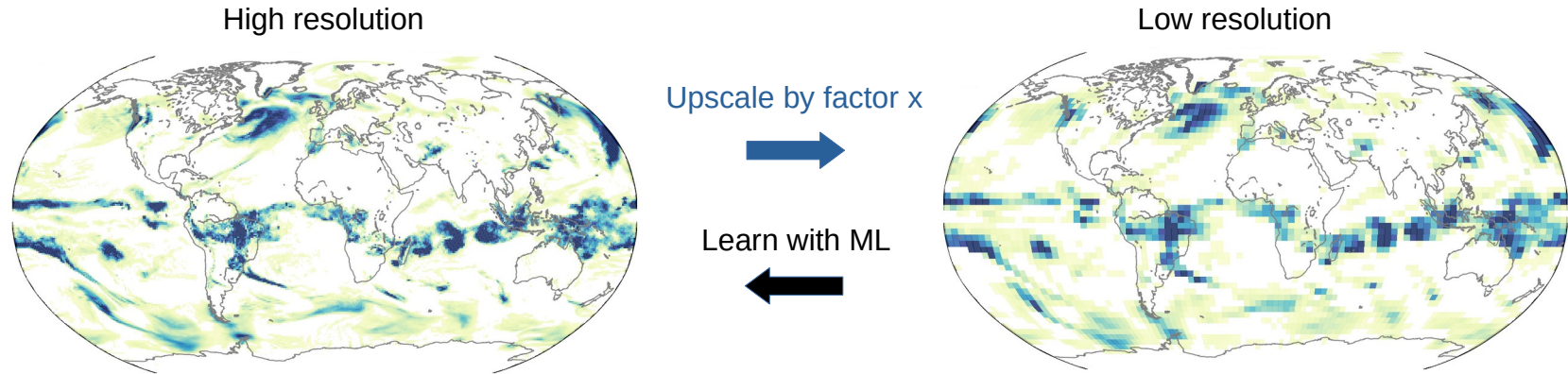
Downscaling Earth system model simulations



Downscaling as a super-resolution task

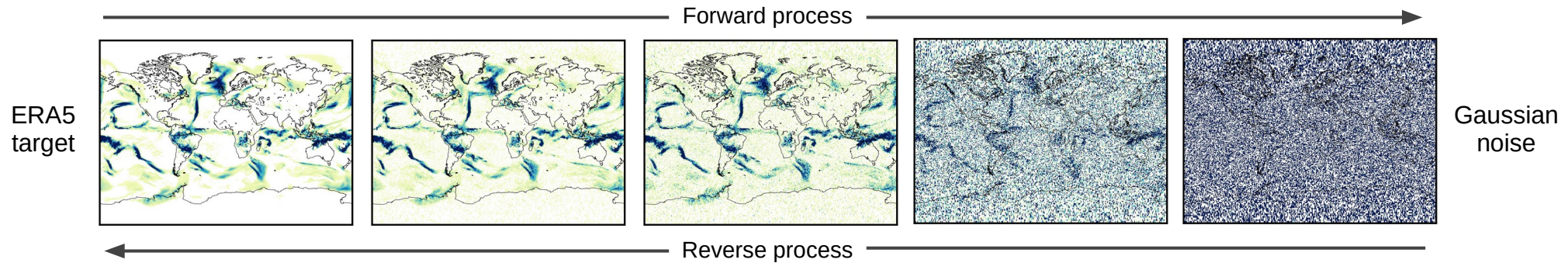


Downscaling as a super-resolution task

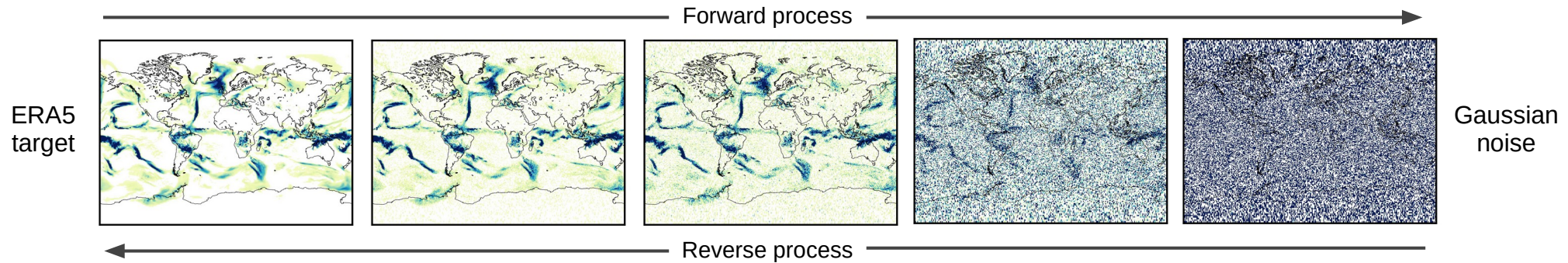


This approach requires retraining when changing the Earth system model.

Unsupervised training with denoising generative models

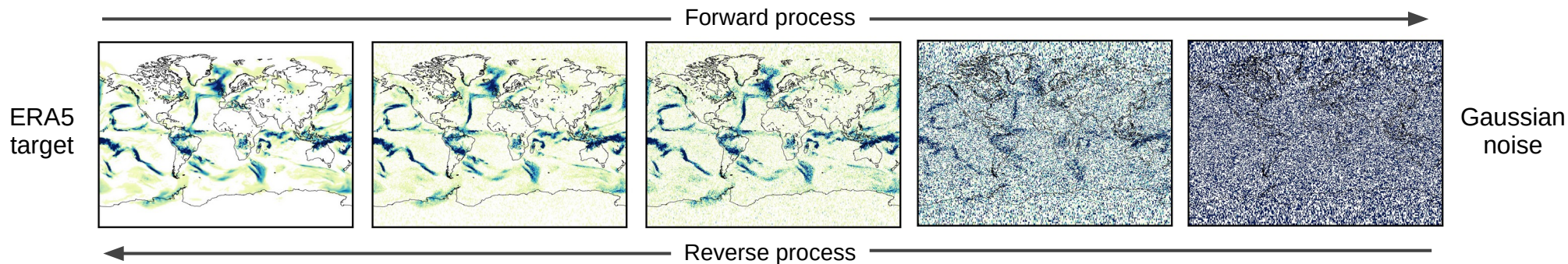


Unsupervised training with denoising generative models



Reverse diffusion SDE:
$$d\mathbf{x} = [\mu(\mathbf{x}, t) - g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})] d\bar{t} + g(t) d\bar{\mathbf{w}}$$

Unsupervised training with denoising generative models

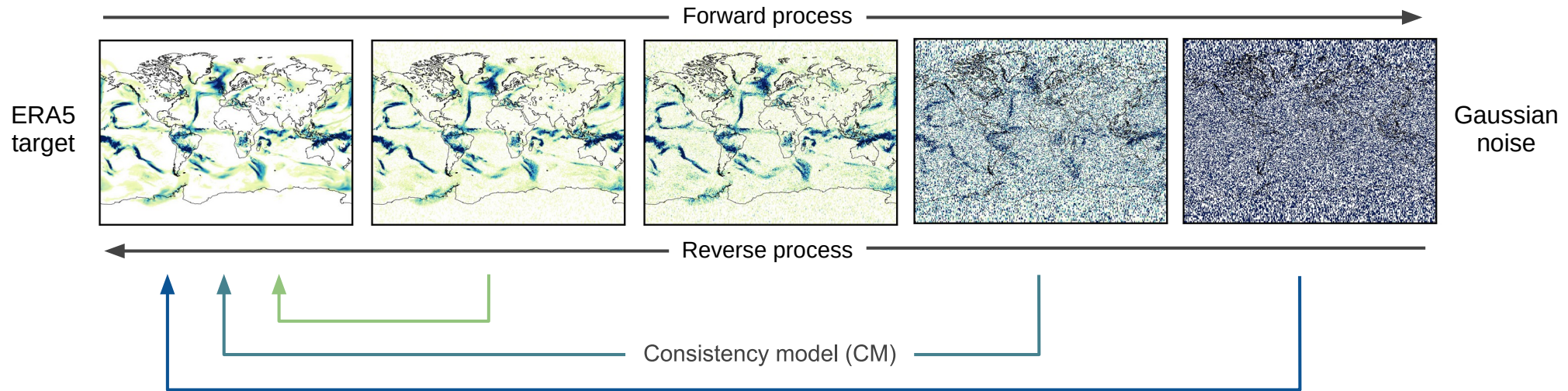


Reverse diffusion SDE:
$$d\mathbf{x} = [\mu(\mathbf{x}, t) - g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})] d\bar{t} + g(t) d\bar{\mathbf{w}}$$



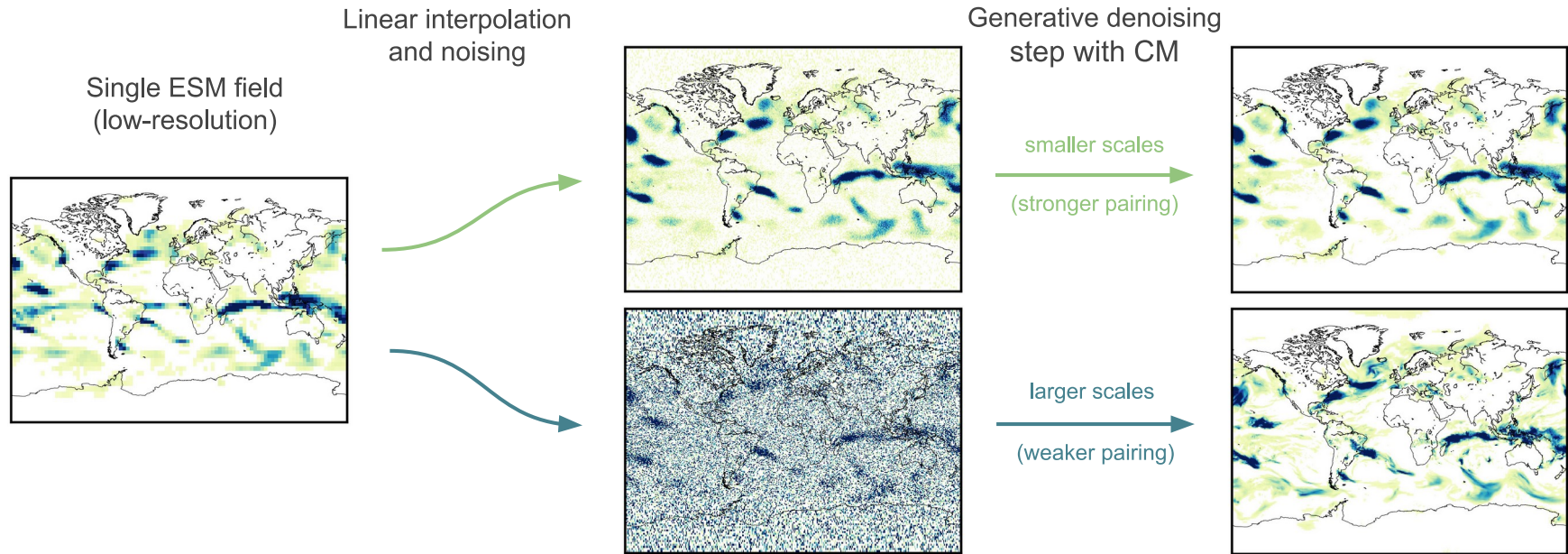
Learn with denoising score matching:
$$s_{\phi}(\mathbf{x}, t) \approx \nabla_{\mathbf{x}} \log p_t(\mathbf{x})$$

Efficient denoising with consistency models



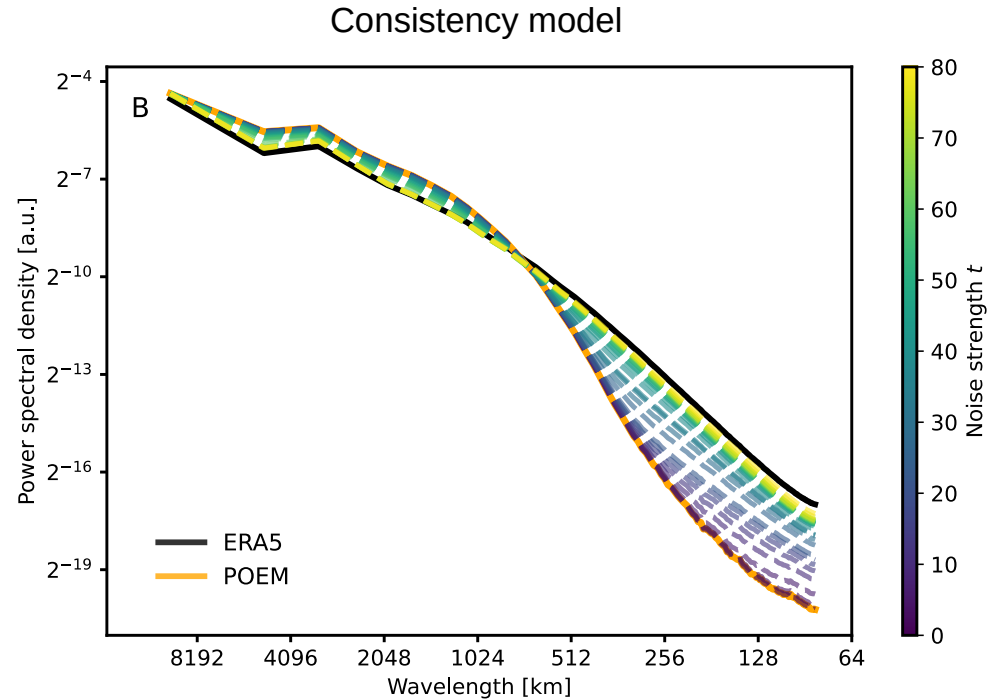
Consistency models: $\mathbf{x}_0 = f_\theta(\mathbf{x}_t, t), \quad f_\theta(\mathbf{x}_t, t) = f_\theta(\mathbf{x}_{t'}, t') \quad \forall t, t' \in [t_\epsilon, T]$

Scale-adaptive downscaling after training

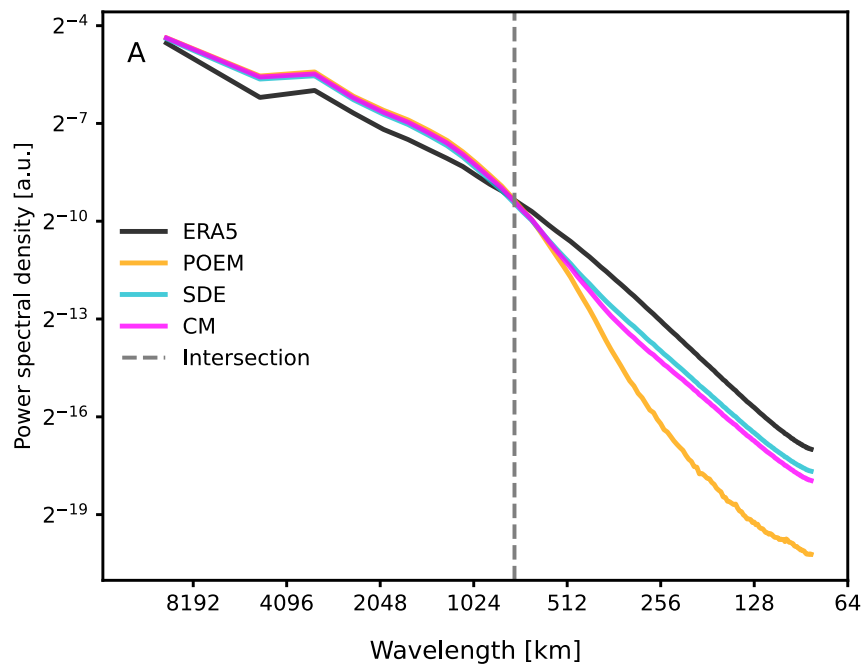


➡ The noise variance determines the spatial scale that is preserved in the Earth system model.

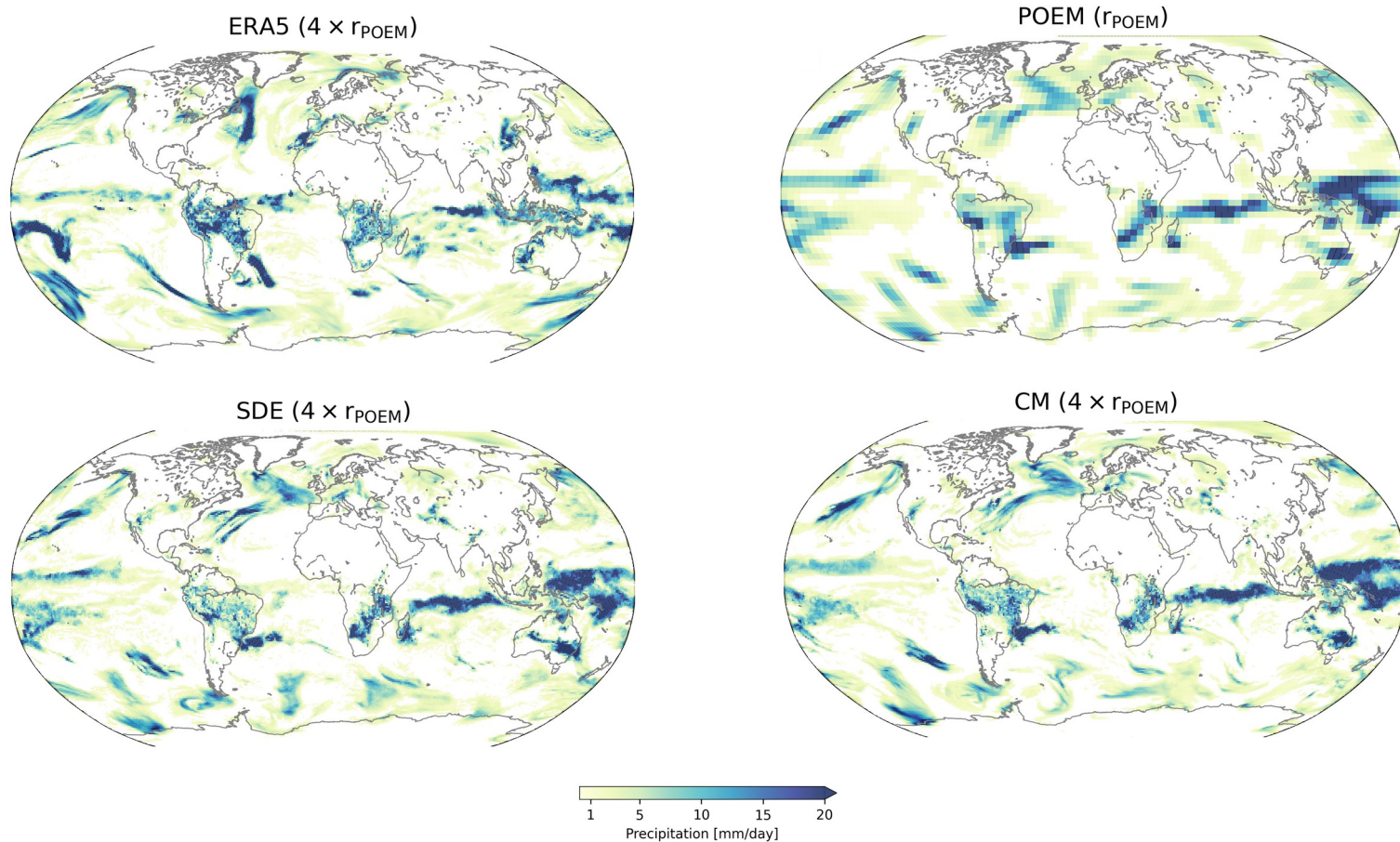
Scale-adaptive downscaling after training



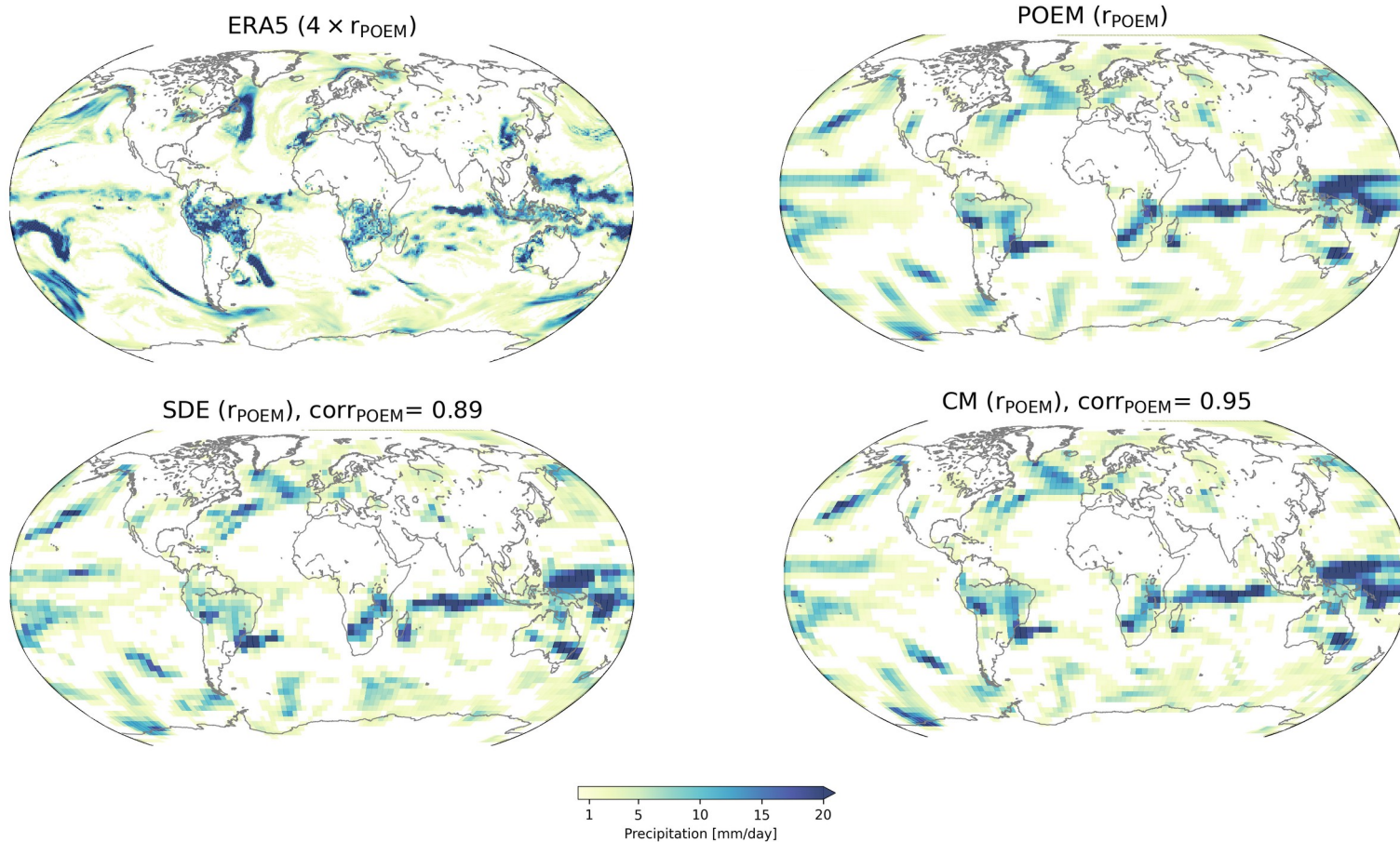
Choosing a suitable noise scale



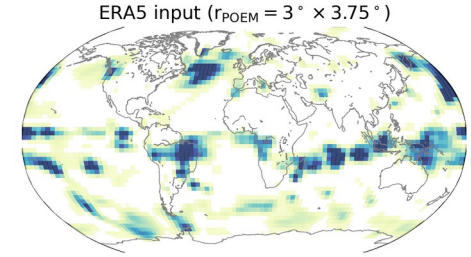
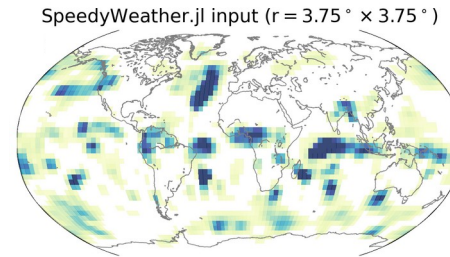
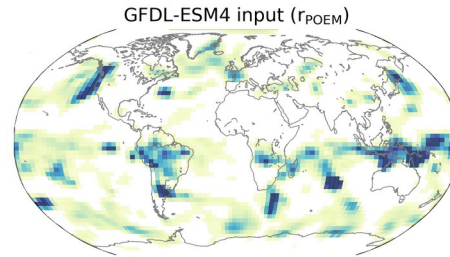
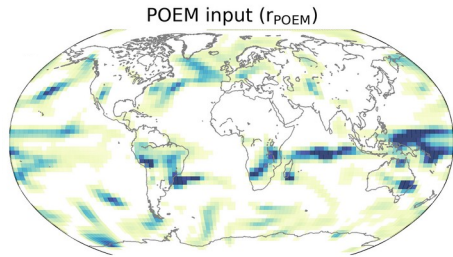
Qualitative comparison of high-resolution fields



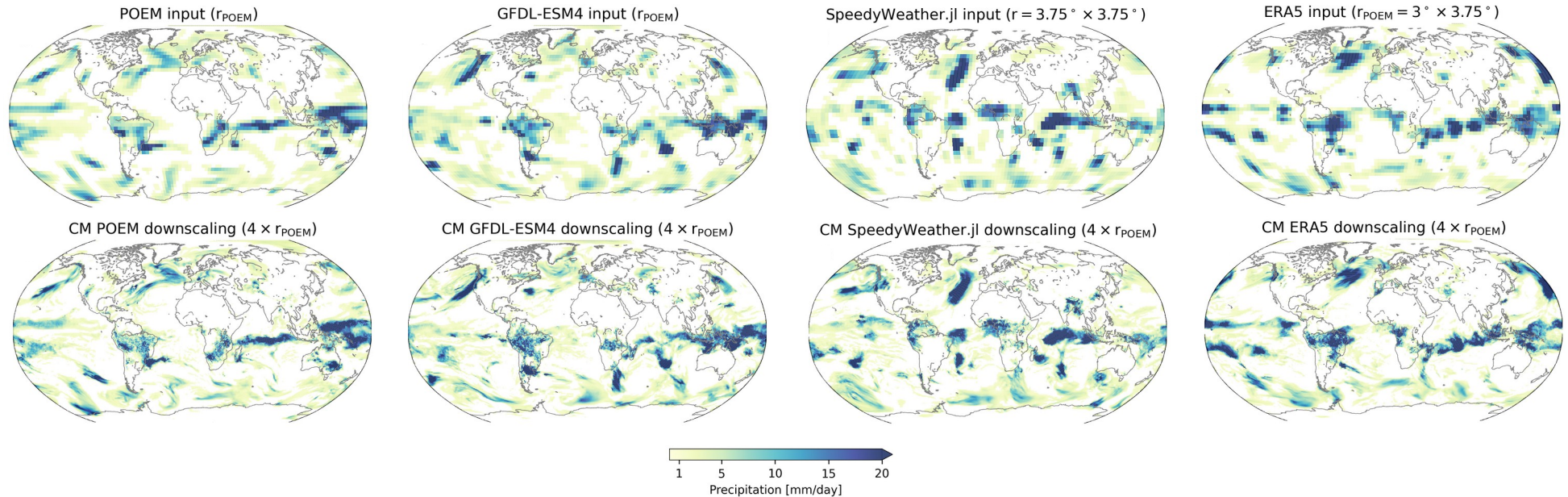
Preserving large-scale patterns on the coarse grid



Downscaling any atmosphere model without retraining



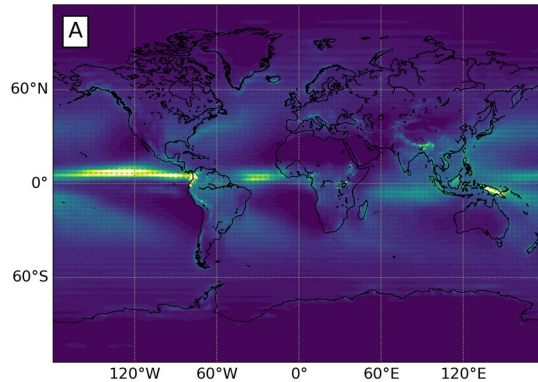
Downscaling any atmosphere model without retraining



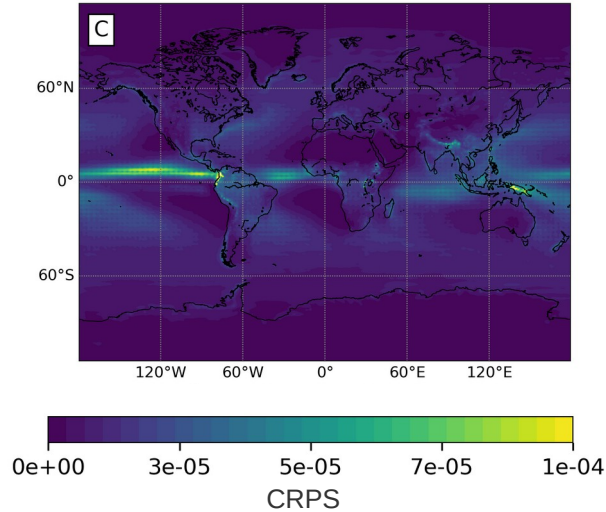
Uncertainty-aware downscaling

smaller spread / higher skill

CM ($t = t_{\min}$): mean CRPS = $1.35\text{e-}05$

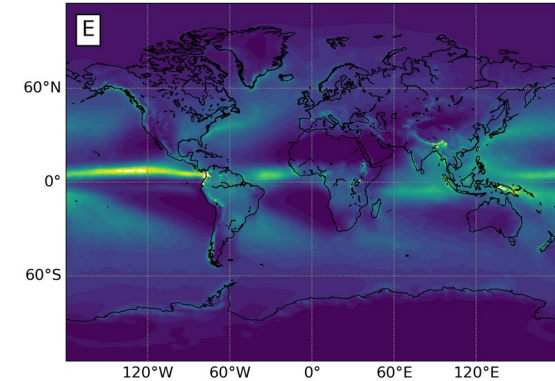


CM ($t = t^*$): mean CRPS = $1.04\text{e-}05$



larger spread / lower skill

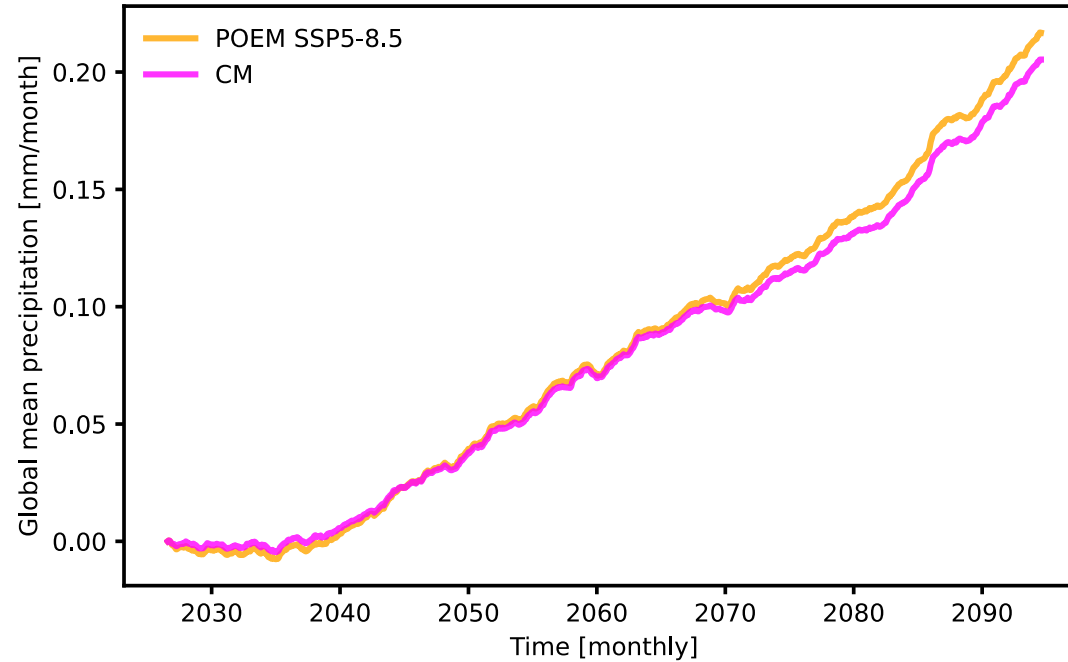
CM ($t = t_{\max}$): mean CRPS = $1.91\text{e-}05$



Noise scale

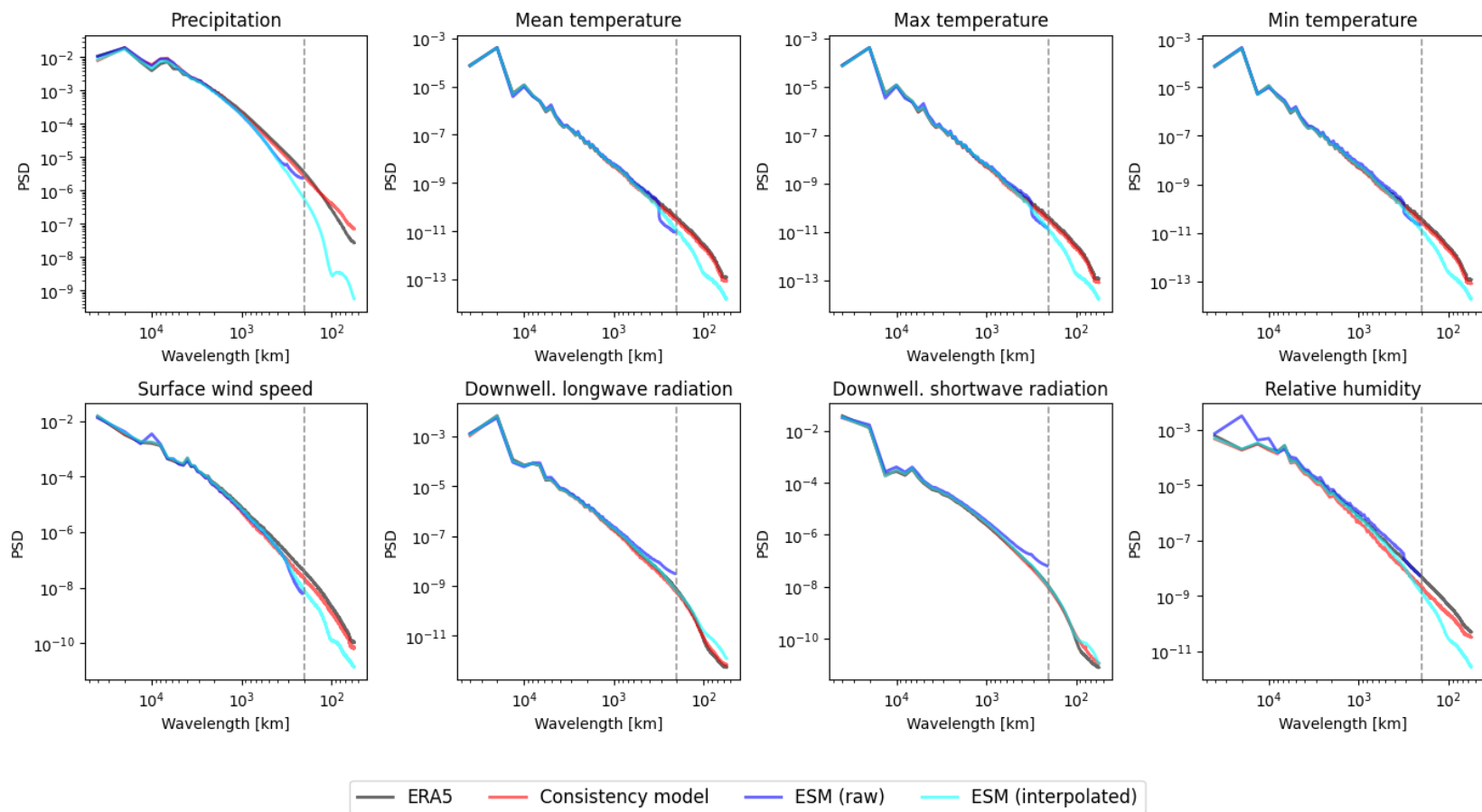


Preserving trends in non-stationary climates

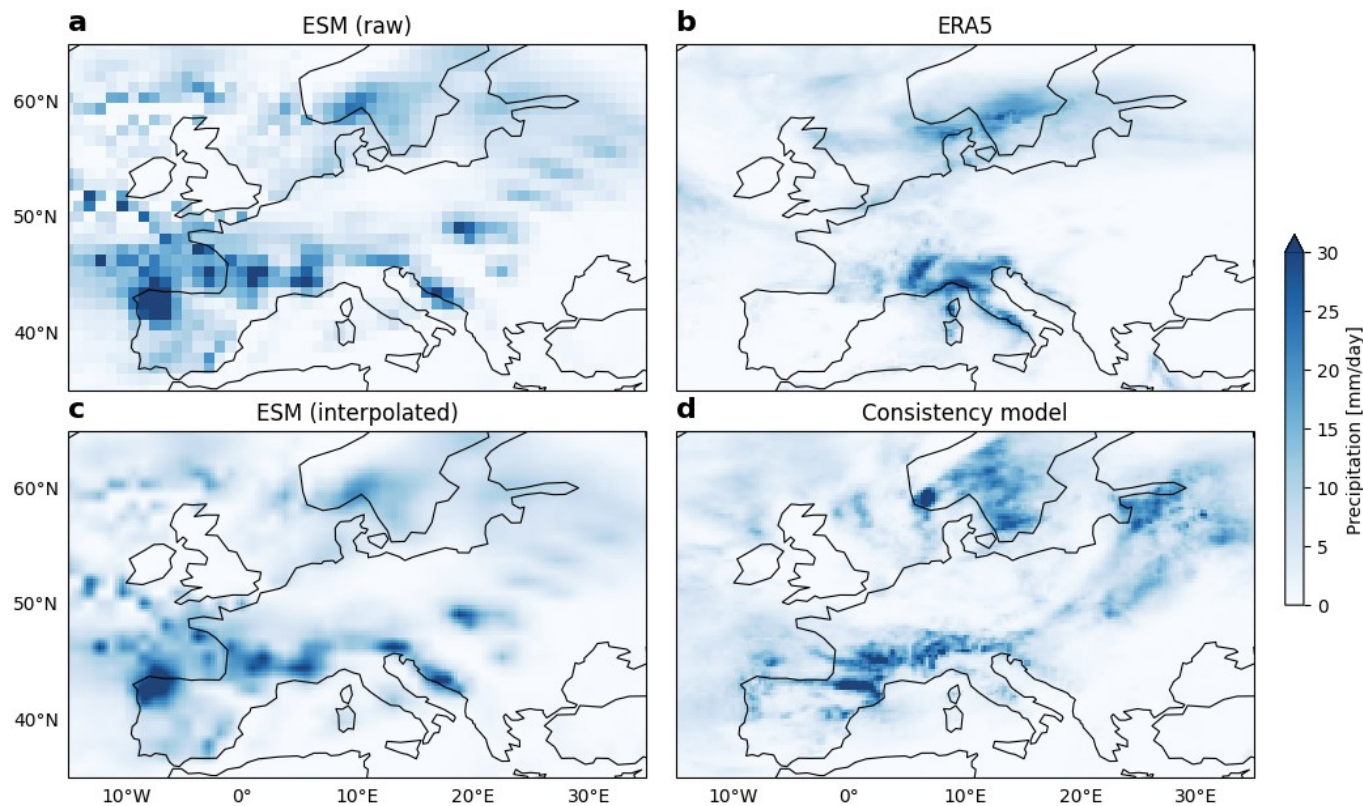


Multivariate downscaling of global Earth system model simulations

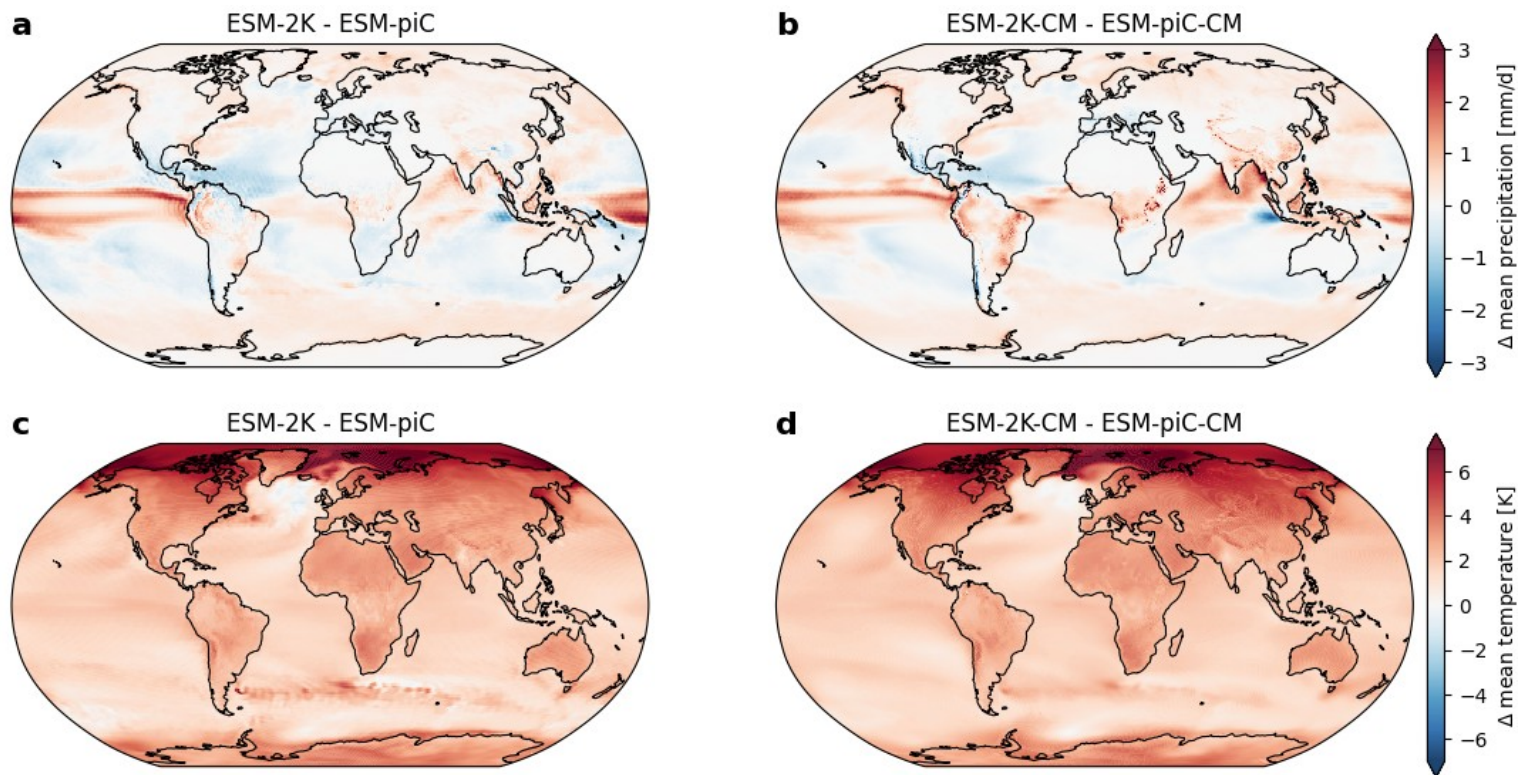
Multivariate downscaling results



Qualitative comparison on regional scales

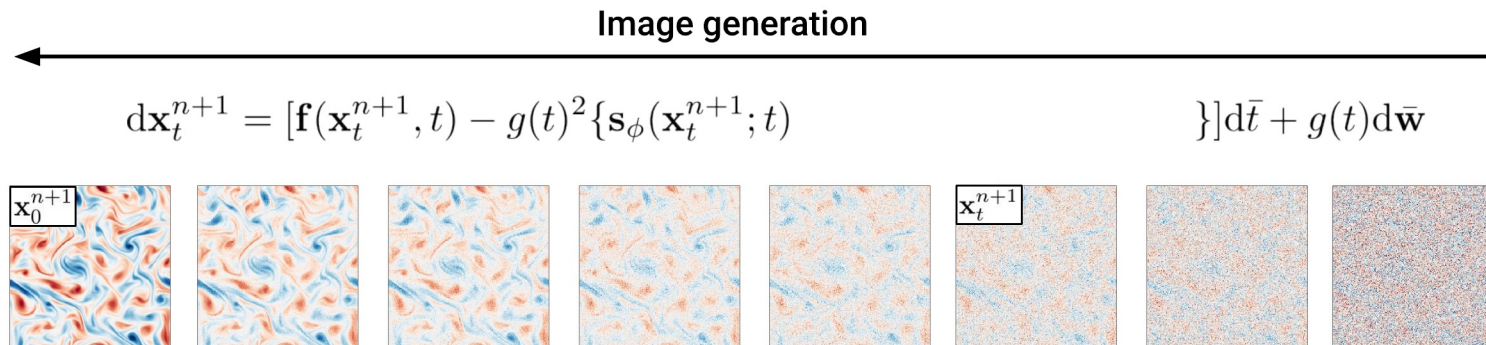


Preserving global warming trends

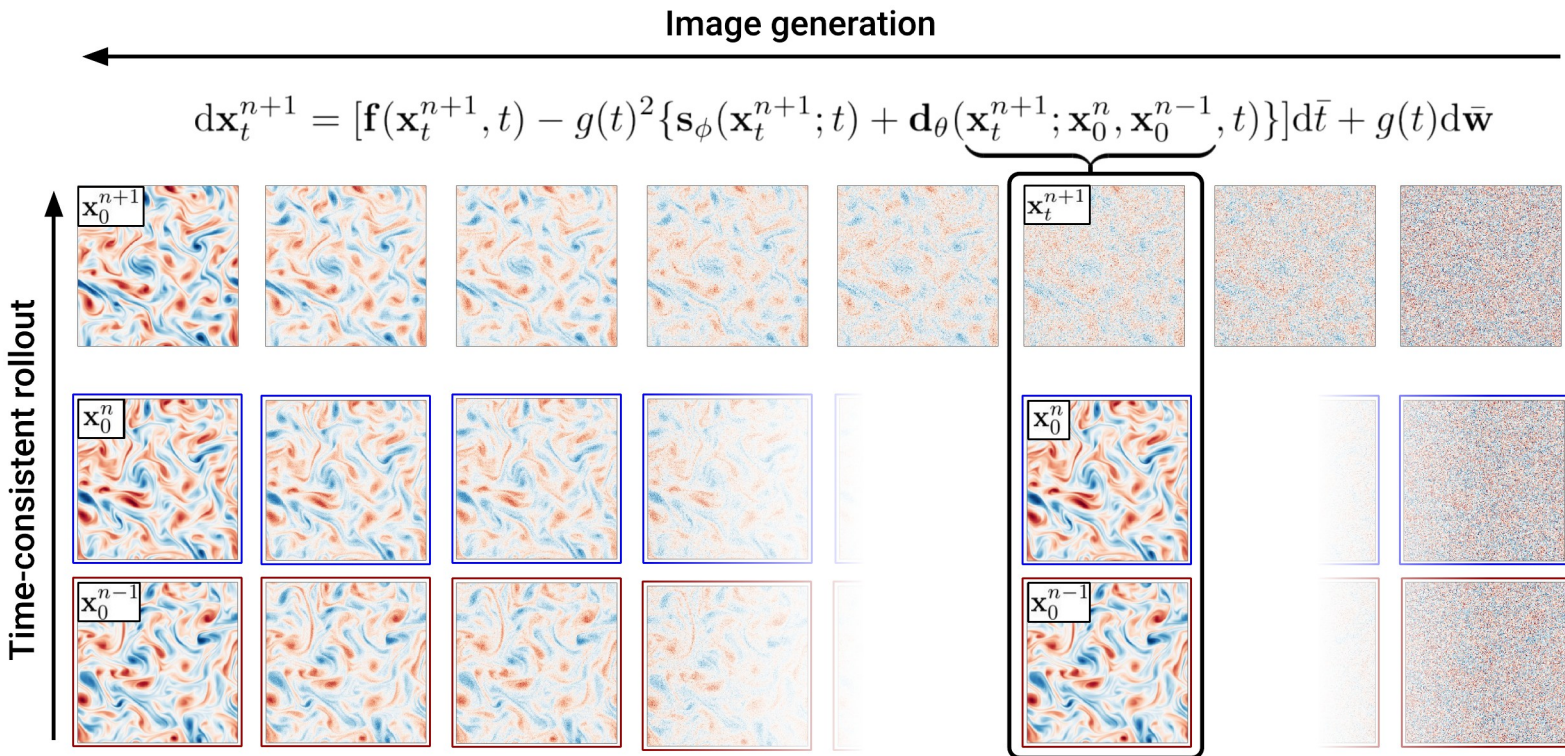


Generating time-consistent dynamics with discriminator-guided image diffusion models

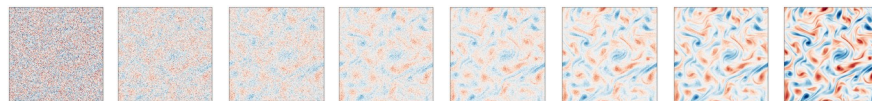
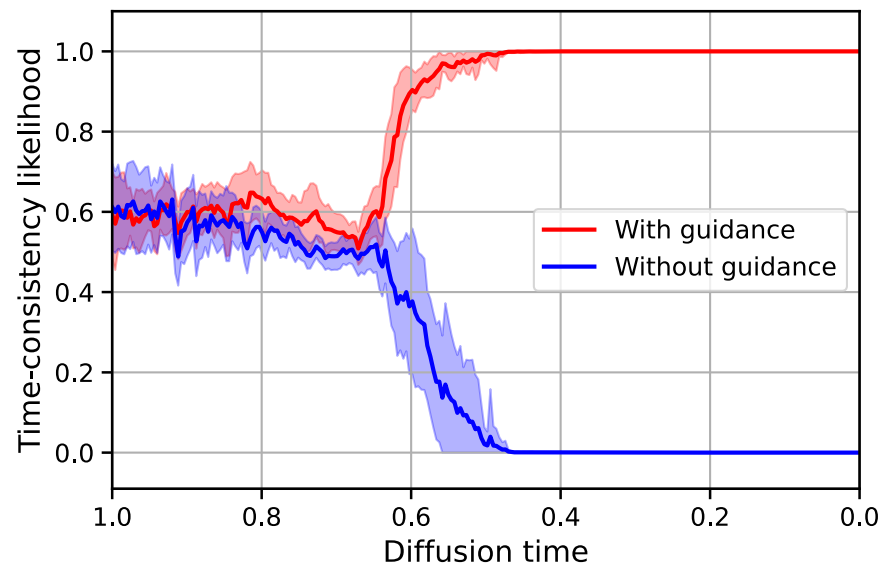
Discriminator-guidance for plug-in time consistency



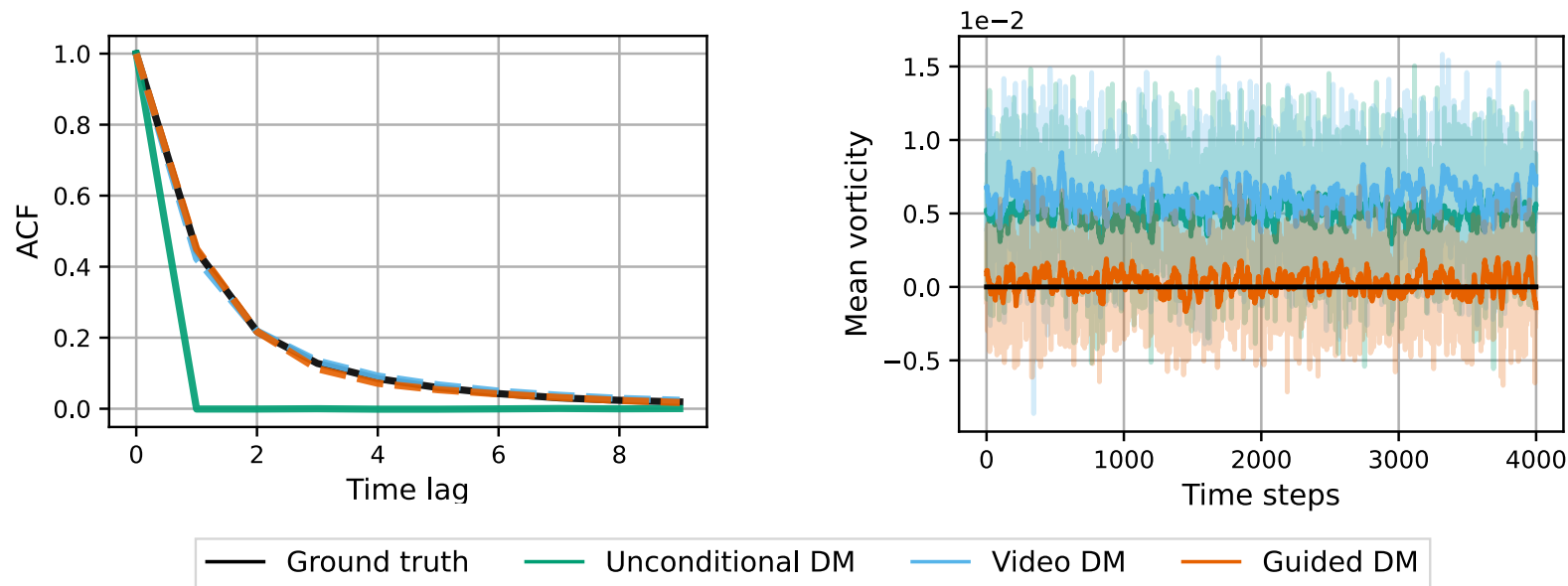
Discriminator-guidance for plug-in time consistency



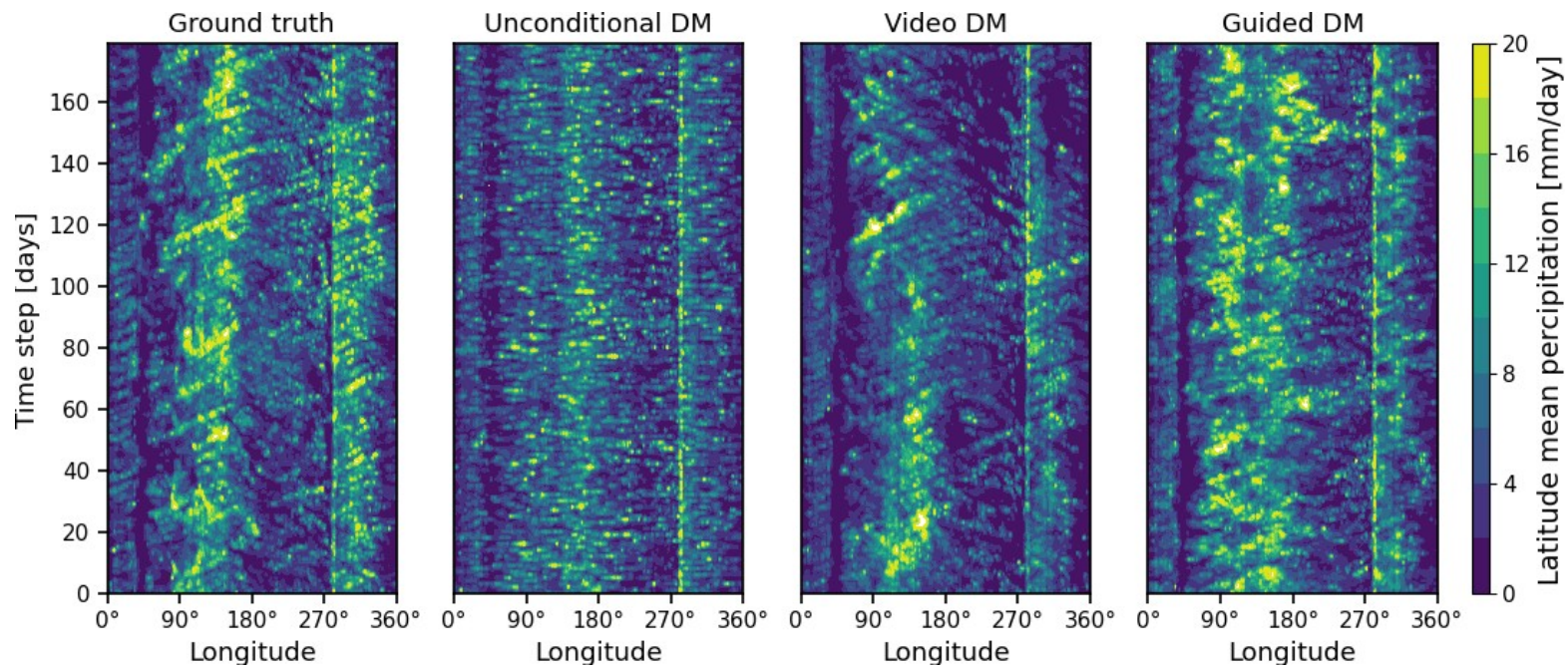
Discriminator-guidance for plug-in time consistency



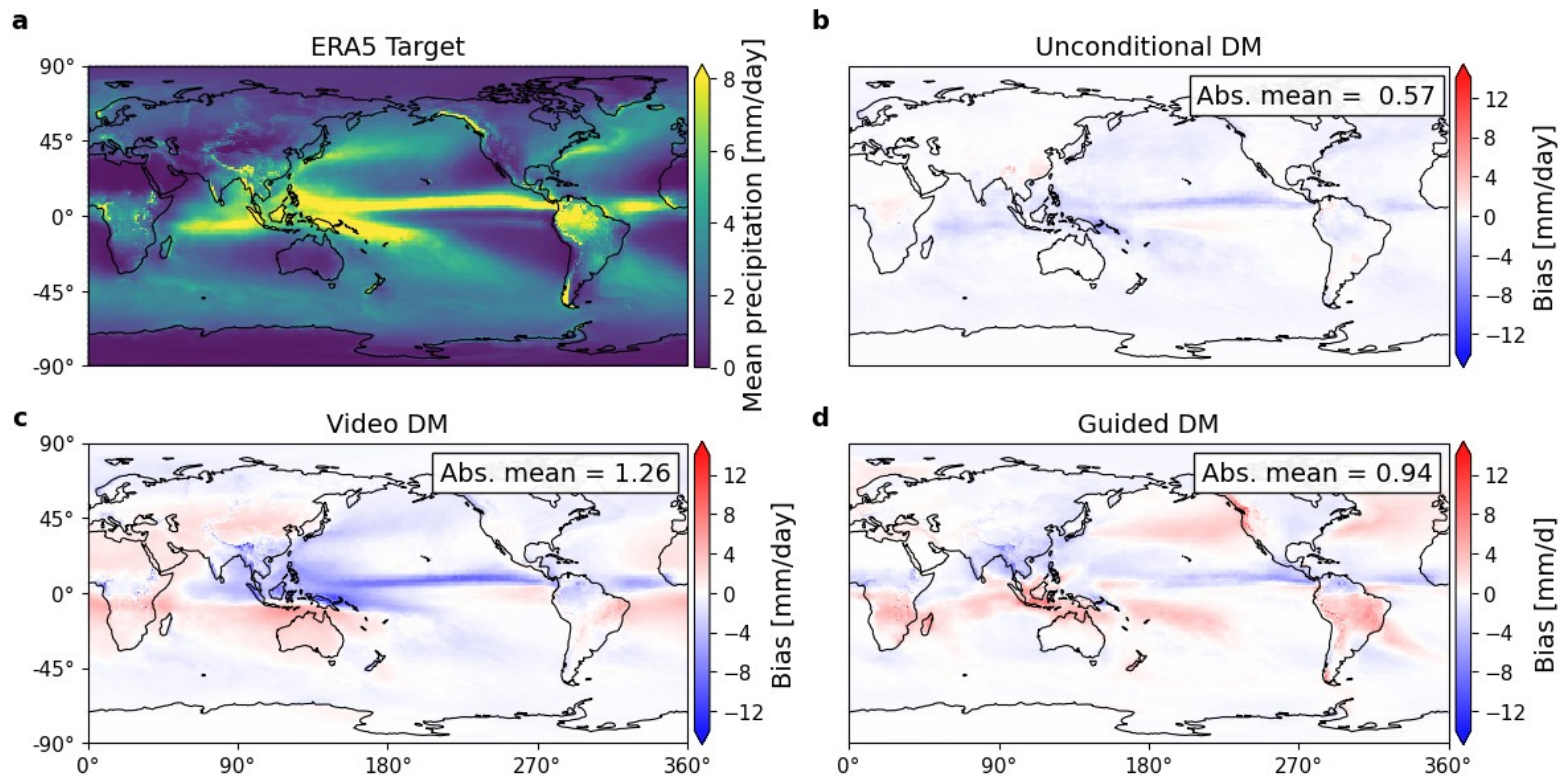
2D Navier-Stokes vorticity results



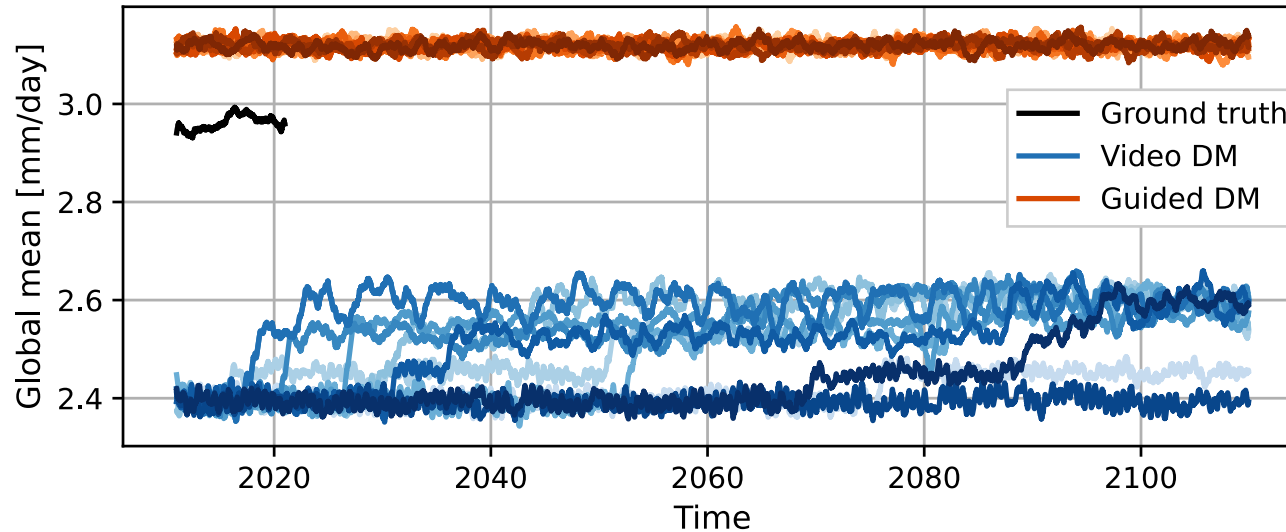
Global precipitation dynamics



Reduced precipitation biases



Improved stability in long-term simulations



Summary

- **Generative downscaling:**
 - Can be adapted to any model resolution.
 - Consistency models are skillful and particularly efficient.
 - Stochastic approach is uncertainty-aware.
- **Time consistency guidance.**
 - Can be “plugged” into any image diffusion model.
 - Only requires cheap training of a binary classifier.
 - Reduces biases and improves long-term stability.

Feel free to contact me: hess@pik-potsdam.de

Downscaling
paper:



Guidance
paper:



Thanks!