

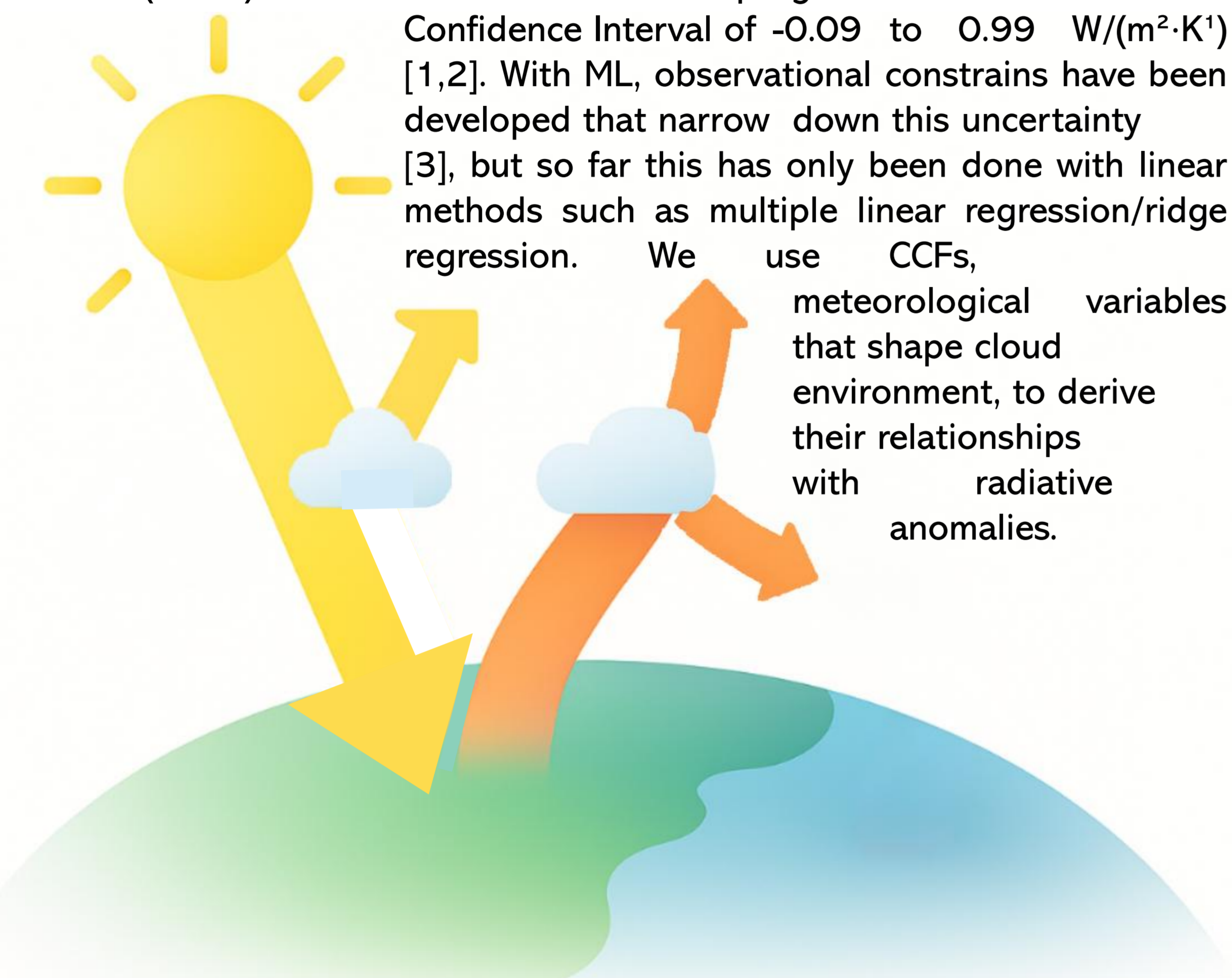
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Motivation

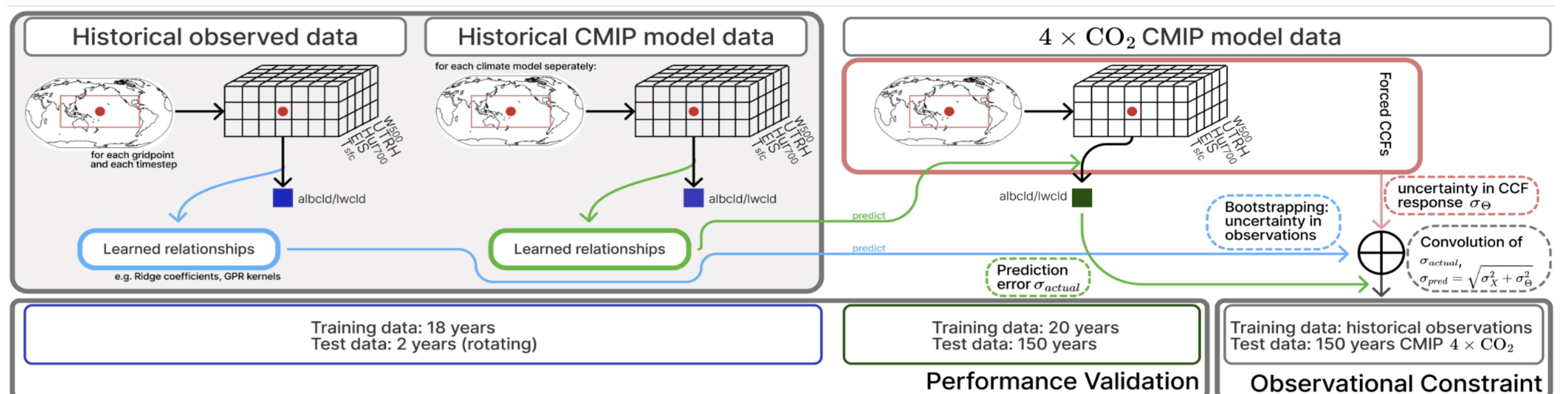
Clouds have a substantial effect on Earth's radiative balance (reflecting incoming solar shortwave (SW) radiation and absorbing outgoing longwave (LW) radiation, creating a net cooling effect) [1]. But the cloud response to global warming is highly uncertain, largely because small-scale physical processes can't be fully represented in Global Climate Models (GCMs). The World Climate Research program estimates a 90%-Confidence Interval of -0.09 to 0.99 $W/(m^2 \cdot K)$ [1,2]. With ML, observational constraints have been developed that narrow down this uncertainty [3], but so far this has only been done with linear methods such as multiple linear regression/ridge regression. We use CCFs,



meteorological variables that shape cloud environment, to derive their relationships with radiative anomalies.

Methods

We implement nonlinear methods such as Gaussian Process Regression (GPR) [4] to observationally constrain cloud feedback for the first time.



Furthermore, we discuss a transfer learning approach [5] with a U-Net [6]. In this approach, a neural network trained on one of the CMIP models (historical + future scenarios) is finetuned on historical data from another model, to evaluate the resulting constraint in a perfect-model-framework. Let i, j be two different CMIP models. We then first pretrain (PT) a U-Net f_{θ}^i on all data of model i , with θ^* minimizing the loss function

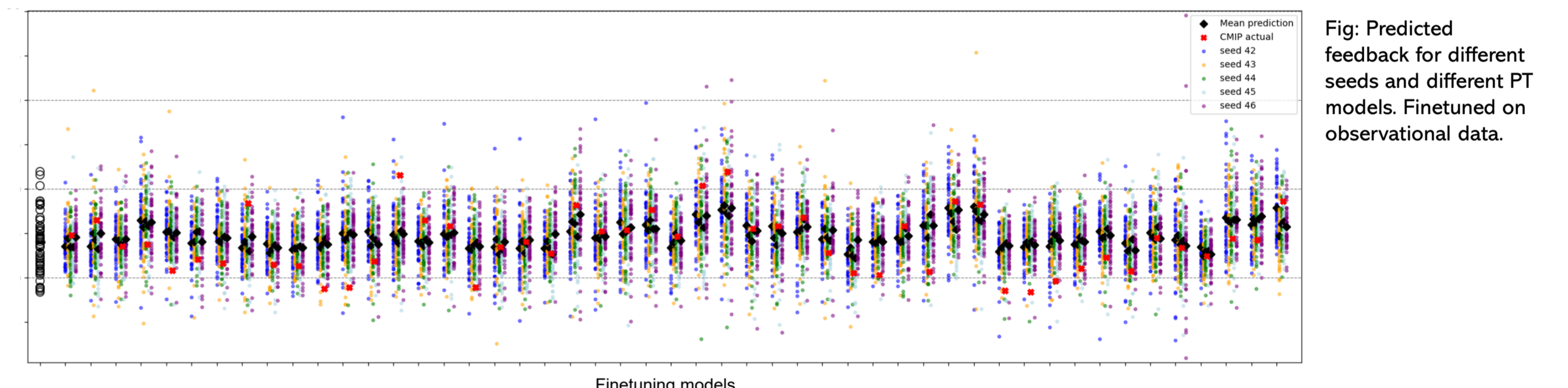
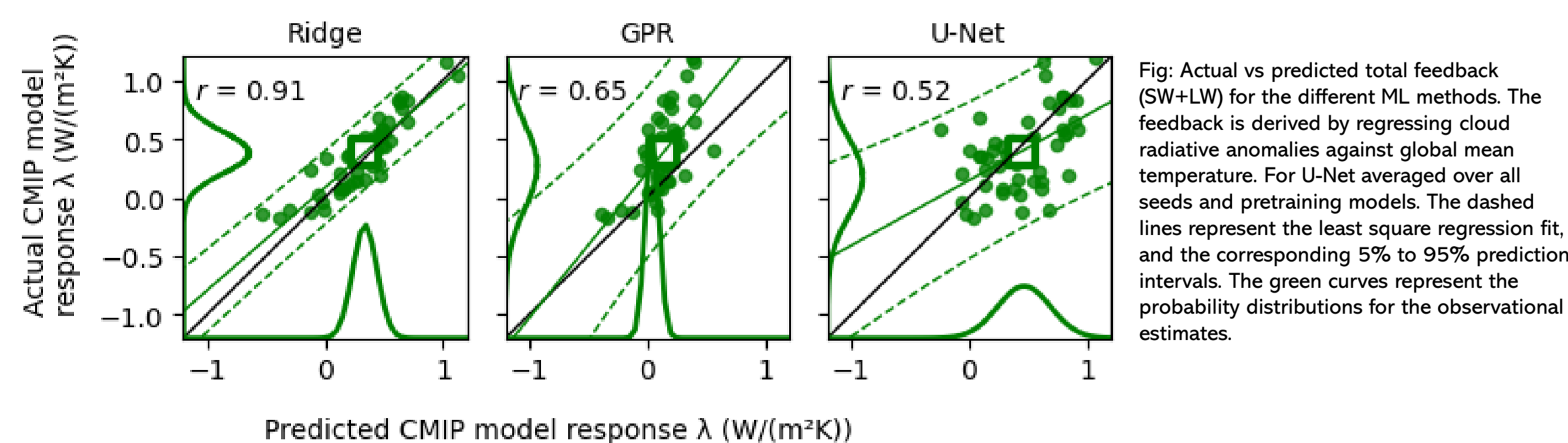
$$\mathcal{L}(f_{\theta}^i(\{X_{hist}^i, X_{4 \times CO_2}^i\}), \{Y_{hist}^i, Y_{4 \times CO_2}^i\}).$$

Then we finetune the U-Net with the historical data of CMIP model j ,

$$f_{\hat{\theta}}^{ij}, \text{ with } \hat{\theta} = \arg \min_{\theta} \mathcal{L}(f_{\theta}^i(X_{hist}^j), Y_{hist}^j).$$

Uncertainty

We distinguish between prediction error σ_{actual} and prediction uncertainty $\sigma_{pred} = \sqrt{(\sigma_{\theta}^2 + \sigma_X^2)}$. The former is given by the fit of the actual cloud feedback λ_{actual} . The latter depends on multiple sources. For ridge regression and GPR it consists of the uncertainties σ_{θ} in the CCF responses and the uncertainties σ_X in the estimates of the observed anomalies estimated through bootstrapping.



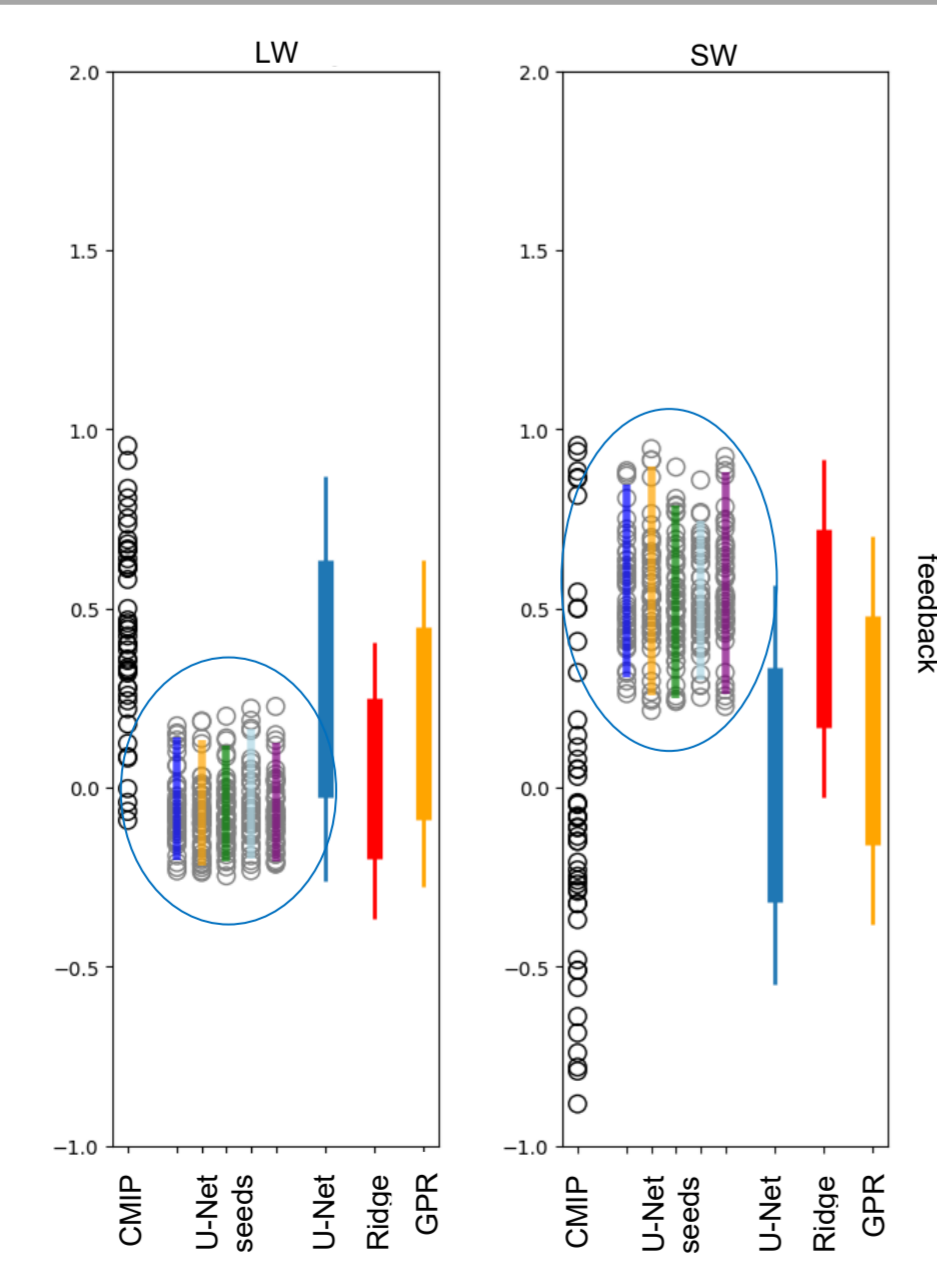
For the U-Nets we add additional sources of uncertainty to the prediction uncertainty σ_{pred} . Firstly, the final prediction depends highly on the initialization, which depends on the chosen random seed. Secondly, because an ensemble of pretrained models is finetuned on historical data of one left out model, there is a spread of different predicted feedbacks. This is the major cause of uncertainty in the prediction uncertainty σ_{pred} . Finally, prediction error σ_{actual} and prediction uncertainty σ_{pred} are convolved to obtain the overall uncertainty:

$$p(\lambda_c) = \int p_{actual}(\lambda_c | \lambda_{pred}) p_{pred}(\lambda_{pred}) d\lambda_{pred}$$

Results

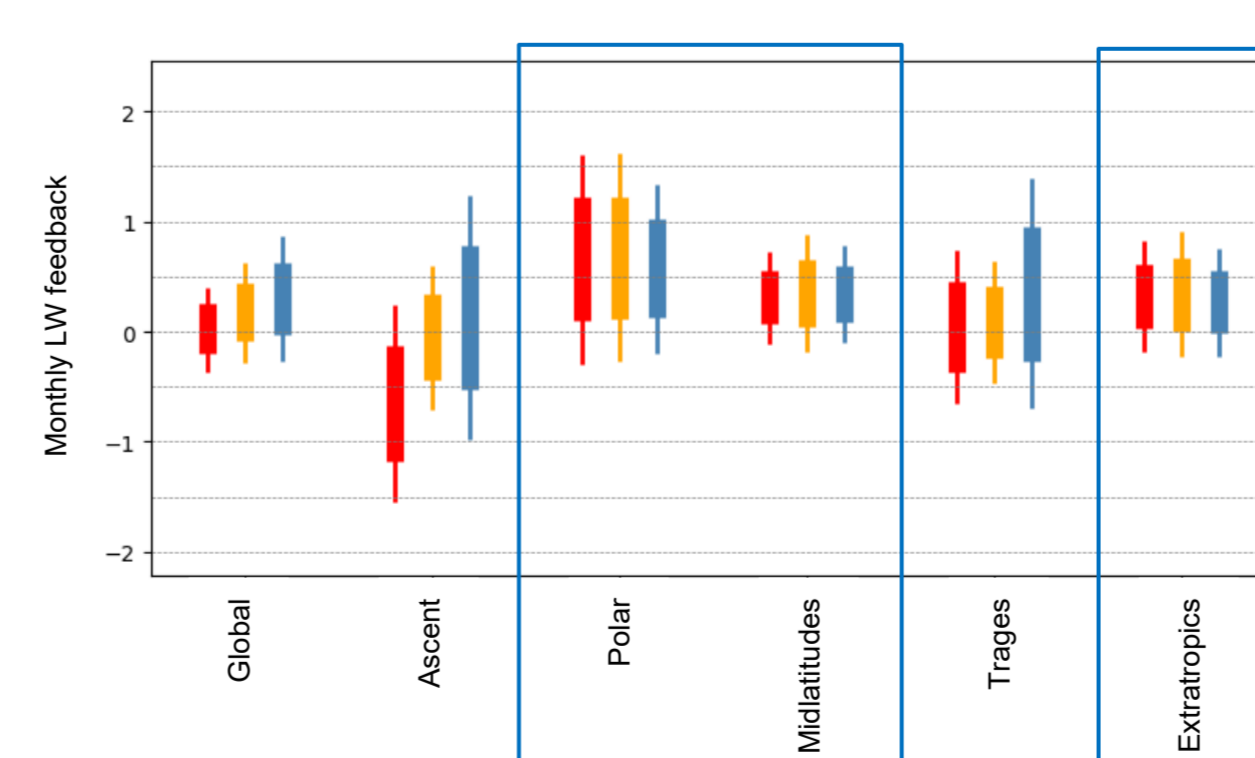
Seed uncertainty

Different seeds result in different results; one can lead to 1.5 times larger CI intervals. This is why the seed uncertainty should be included into the final observational constraint.



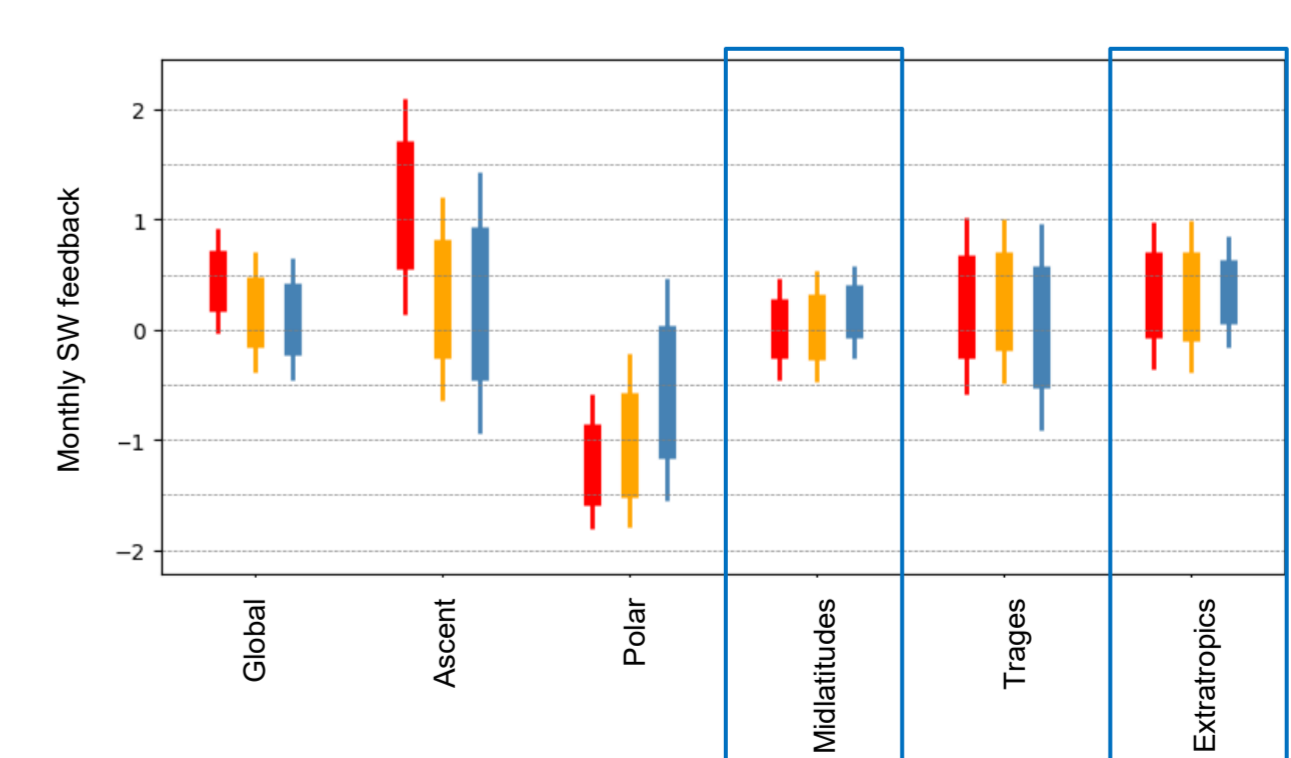
Improvement at higher latitudes for LW

U-Net and GPR lead to improvements in the higher latitudes. In these locations we expect nonlinear behavior due to ice/mixed phase clouds.



Improvement in the extratropics for SW

U-Net improves the results for SW in the extratropical regimes, GPR improves at higher temporal resolution.



References:

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[3] Ceppi and Nowack (2021): Observational evidence that cloud feedback amplifies global warming, <https://doi.org/10.1073/pnas.2026290118>
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[5] Immorano et al. (2023): Transferring climate change physical knowledge, <https://doi.org/10.48550/ARXIV.2309.14780>
[6] Ronneberger et al. (2015): U-Net: Convolutional Networks for Biomedical Image Segmentation, <https://doi.org/10.48550/arXiv.1505.04597>