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Observational constraints on uncertainties in stratospheric water vapour projections: how to open the black-box with explainable machine learning

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Stratospheric water vapor (SWV) plays an important role in Earth's climate. For example, variations in SWV levels can feedback onto global temperatures and climate patterns. However, projections of future changes in SWV still pose a difficult challenge for global climate models, mainly due to their dependence on a variety of highly uncertain factors ranging from chemical reactions to changes in the tropospheric and stratospheric circulation (Charlesworth et al. 2023).

Diverse factors lead to significant variations in SWV projections among CMIP6 climate models (Keeble et al., 2021). To tackle this issue, we aim to narrow down and comprehend model uncertainty in SWV projections by employing advanced, explainable machine learning (XML) frameworks. We build on recent work by Nowack et al. (2023) who used a linear XML approach to infer historical relationships between atmospheric temperature patterns and tropical lower SWV. Across CMIP models, they demonstrated that these relationships also hold under strong greenhouse gas forcing scenarios, opening up a direct link between present-day observations and future projections.

However, Nowack et al.'s work highlighted the challenge of interpreting the patterns learned by the statistical model. In this presentation, our goal is to decode these patterns, relating them to key physical mechanisms. Additionally, we aim to validate the reliability of prominent features from observations by testing equivalent patterns in selected climate models over longer timescales. To achieve this, we'll utilize advanced non-linear XML techniques like SHAP values combined with regression-tree methods to estimate feature importance.

The outcomes stress the importance of local temperature patterns near the targeted level in estimating SWV. Additionally, the impact of a two-month lag stands out comparing to one- and zero-month lags. Although CMIP dataset training period aligned with observations seems consistent, it varies across models. A longer training period results in a more stable and robust training pattern.

References:

Charlesworth, E., Plöger, F., Birner, T. *et al.* Stratospheric water vapor affecting atmospheric circulation. *Nat Commun* **14**, 3925 (2023). https://doi.org/10.1038/s41467-023-39559-2

Keeble, J., Hassler, B., *et al*. Evaluating stratospheric ozone and water vapour changes in CMIP6 models from 1850 to 2100. *Atmospheric Chemistry and Physics*, **21(6)**, 5015-5061 (2021). https://doi.org/10.5194/acp-21-5015-2021

Nowack, P., Ceppi, P., Davis, S.M. *et al.* Response of stratospheric water vapour to warming constrained by satellite observations. *Nat. Geosci.* **16**, 577–583 (2023). https://doi.org/10.1038/s41561-023-01183-6