maura.dewey@misu.su.se

AeroGP: machine learning how aerosols impact regional climate

Maura Dewey[1,3], Hans-Christen Hansson[2,3], Duncan Watson-Parris[4], Bjorn H. Samset[5], Laura J. Wilcox[6], Anna Lewinschal[1,3], Maria Sand[5], Oyvind Seland[7], Srinath Krishnan[5], Annica M.L. Ekman[1,3]

[1]Department of Meteorology (MISU), Stockholm University, Stockholm, Sweden
[2]Department of Environmental Science (ACES), Stockholm University, Stockholm, Sweden
[3]Bolin Centre for Climate Research, Stockholm University, Stockholm, Sweden
[4]Scripps Institution of Oceanography and Halıcıo˘glu Data Science Institute, UC San Diego, San Diego, USA
[5]Center for International Climate Research (CICERO), Oslo, Norway
[6]National Centre for Atmospheric Science, Department of Meteorology, University of Reading, Reading, UK
[7]Norwegian Meteorological Institute, Oslo, Norway

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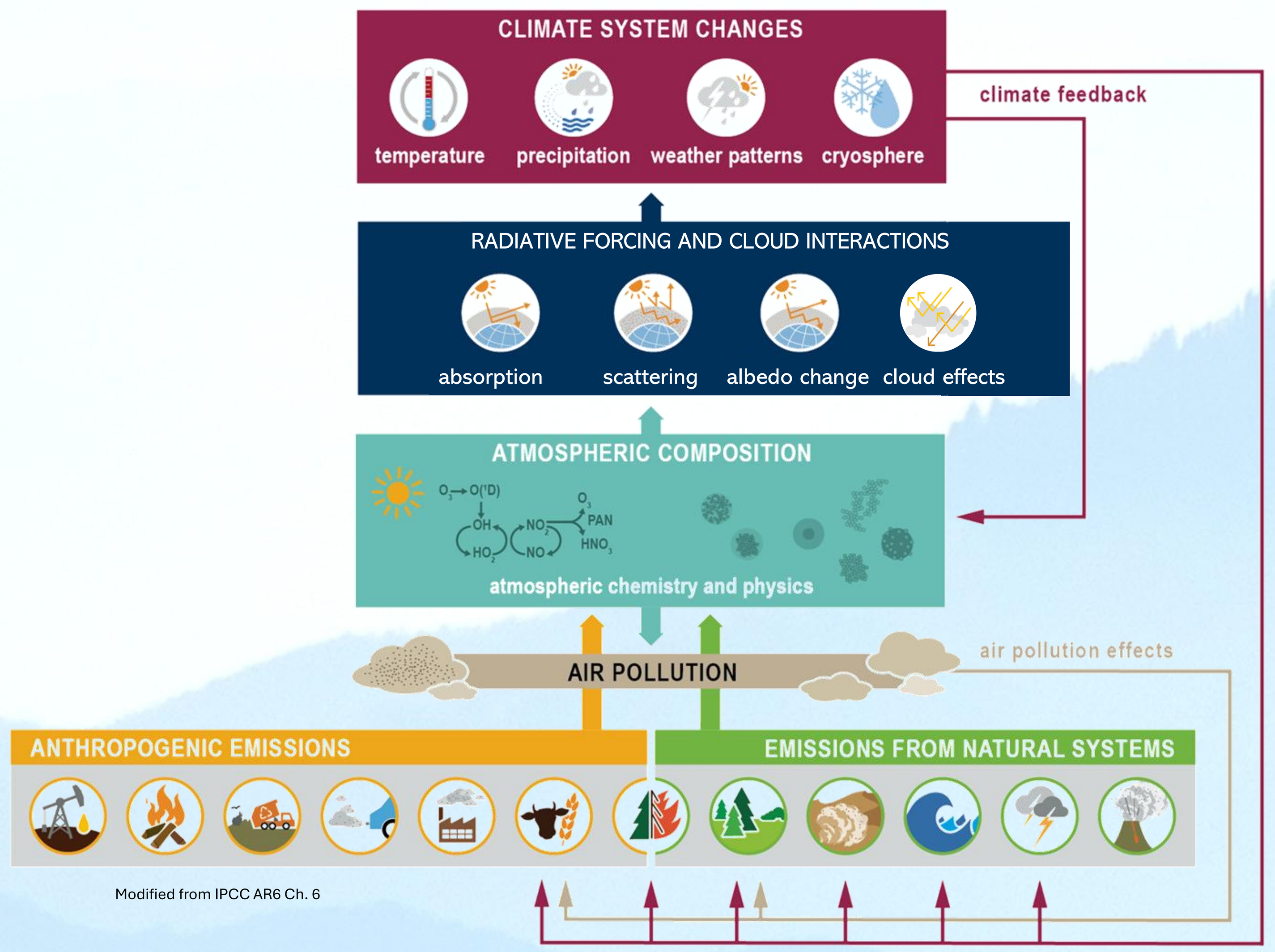
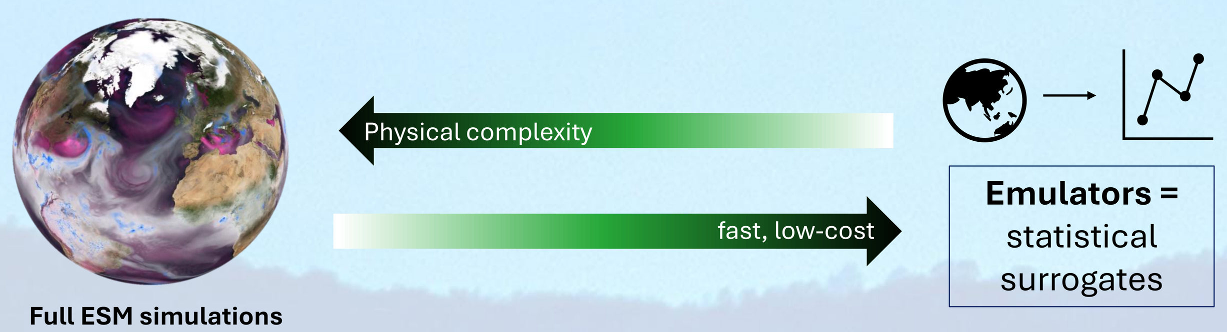
Modelling aerosol-climate interactions

Aerosol-climate interactions are one of the largest sources of uncertainty in future climate projections. The global mean effect of anthropogenic aerosol emissions has been a net cooling over the industrial era, but this mean effect is the result of spatially heterogeneous forcing that depends on both species and emission location. Future reductions and regional redistributions in emissions are likely to reduce this net cooling and produce spatially complex trends in temperature, precipitation, air quality, and extreme events.

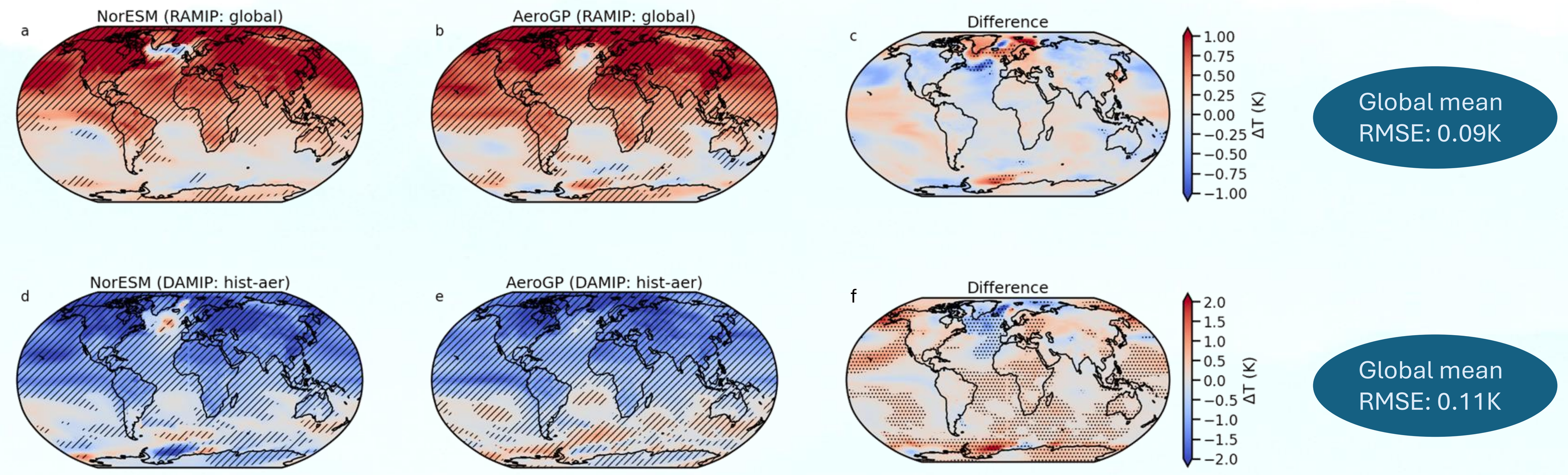
Physics-based Earth System Models (ESMs) can capture these complexities but are computationally expensive and often inaccessible to non-expert stakeholders.



There is a need for **computationally fast aerosol-aware emulators** which can be used for regional climate risk assessments and policy cost-benefit analysis.



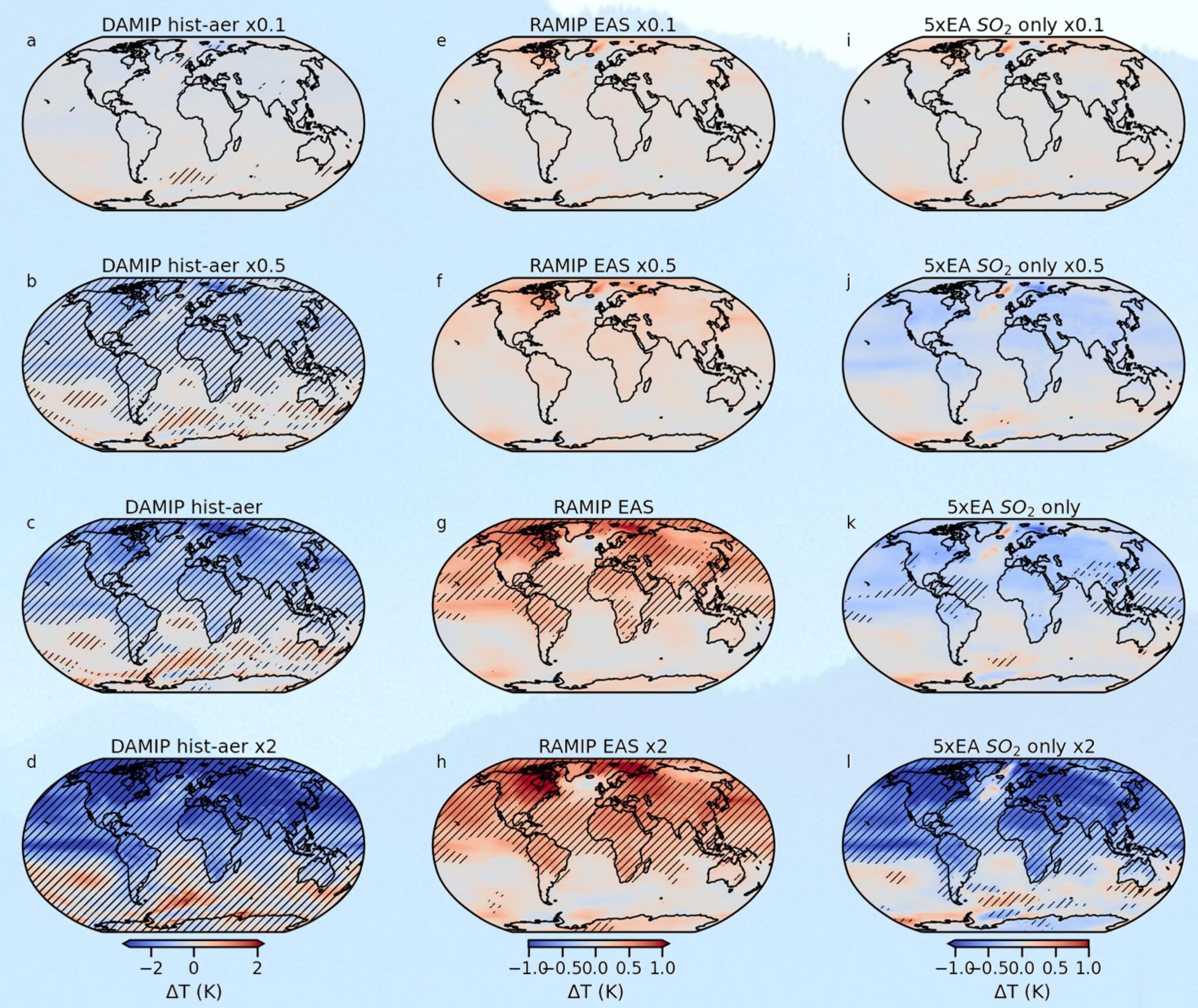
AeroGP performance and testing



Surface air temperature response for RAMIP global ssp370-126aer (2045-2064) and DAMIP hist-aer (1995-2014) aerosol emission perturbations. The left column shows the NorESM target (a,d), the centre shows the AeroGP posterior mean prediction (b,e), and the right column shows the difference between the two (c,f).

We validate AeroGP on two global perturbation scenarios which encompass a range of anthropogenic emissions from historical industrial levels to rapid sustainable reductions. **AeroGP accurately predicts the magnitude and spatial pattern of the temperature response for both scenarios.**

We also test AeroGP on a set of scaled regional perturbations and find a non-linear response depending on the magnitude and location of the emissions.



AeroGP predicted temperature response for scaled emission perturbations.

What's next?

- Increased temporal resolution and smaller emission region definitions could improve AeroGP's internal variability.
- The addition of precipitation and a focus on accurate extremes will increase usefulness for policy and scenario evaluation and for assessing climate risk.

ML method: Gaussian Processes

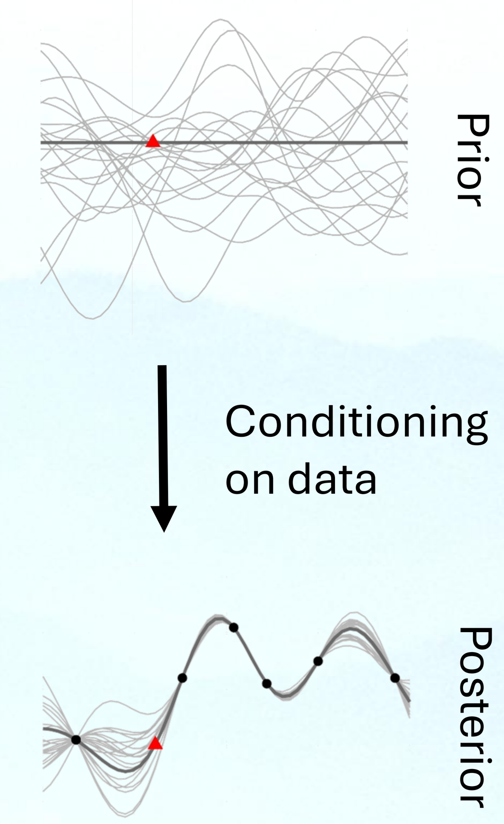
Gaussian Processes (GPs) are a probabilistic supervised learning method in which a model is specified by a mean and a covariance function:

$$f(x) \sim GP(\mu(x), k(x, x'))$$

In AeroGP we use a combination of anisotropic Matérn kernels for the regional response to each aerosol species, a linear kernel for the global response, and a white noise kernel for internal variability.

We account for the spatial correlation of outputs by implementing coregionalization:

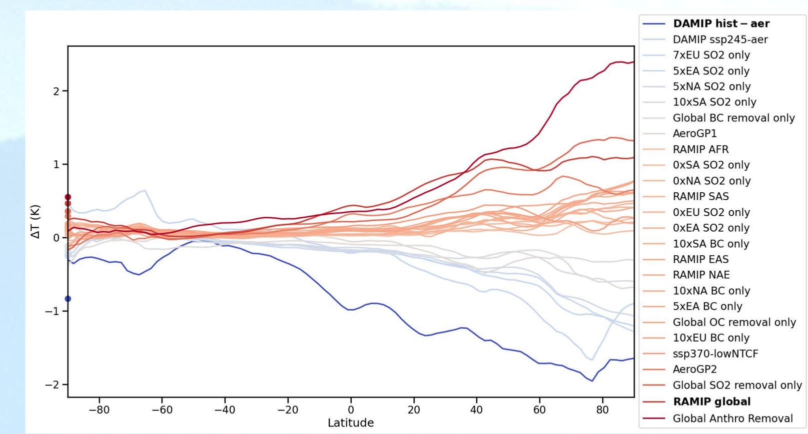
$$k(x, x') = k(x, x') \otimes BB^T$$

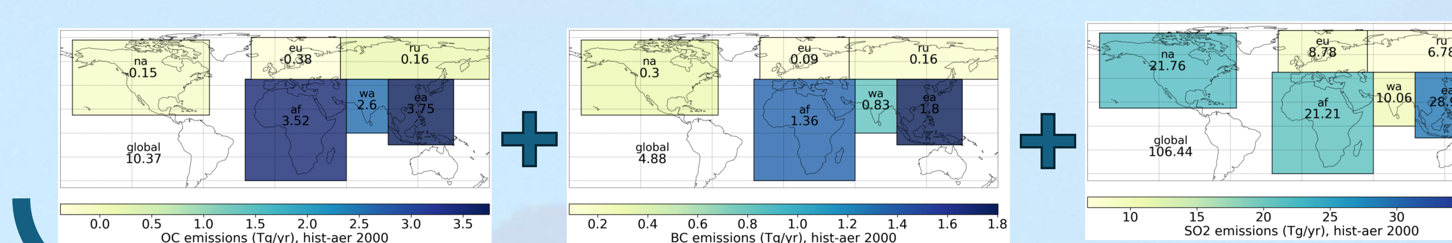


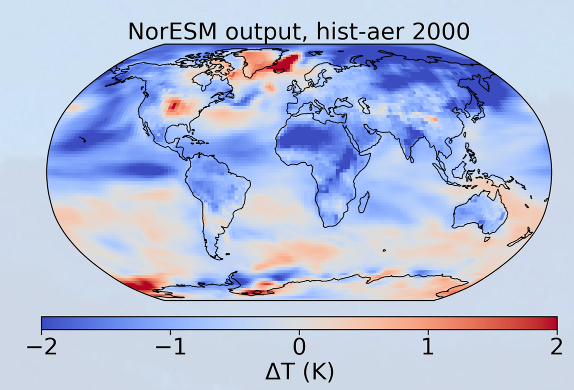
Training Data: NorESM Simulations

26 fully coupled aerosol perturbation experiments.

- sulphur dioxide (SO_2)
- black carbon (BC)
- organic carbon (OC)







Inputs are gridded regional emission perturbations and the target for emulation is the resulting annual mean surface temperature change at native NorESM spatial resolution (~2˚).

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