Session ID 18: Progress in modelling solar radiation modification through GeoMIP
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Comparing Machine Learning and Traditional Downscaling Methods for Climate Projections Under Stratospheric Aerosol Intervention

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Machine learning (ML) is well-suited for downscaling and bias correction, as it can integrate diverse datasets, learn complex spatial-temporal patterns, and produce high-resolution outputs. This is critical for capturing climate extremes and enabling timely analysis. However, like traditional methods, ML struggles with non-stationarity and lacks interpretability. Conventional approaches use either statistical models or resource-intensive regional climate models, each with trade-offs. In stratospheric aerosol intervention (SAI)—a novel climate state—these limitations raise concerns about ML's reliability. Yet, because SAI aims to maintain the climate within historical bounds, ML may offer a practical, scalable alternative for generating usable data for this emerging field. This study compares dynamical, statistical, and ML-based downscaling methods under SAI conditions.

We apply a recent ML algorithm to bias-correct and downscale multivariate CESM2 outputs. We use ERA5 reanalysis (1979–2014, 0.25° horizontal resolution) as the reference and CESM2 simulations at 1° horizontal resolution for historical, SSP2-4.5, and SAI scenarios. The ML models are trained on ERA5 and historical CESM2, and then applied to downscale future projections. Results are compared with dynamically downscaled outputs and the ISIMIP statistical method. Years after the 1991 Pinatubo eruption are used as an evaluation analog for SAI. We then evaluate how downscaling method-driven differences compare to the scale of scenario-driven ones under future climate scenarios. This project represents a first step toward applying ML in SAI contexts. If effective, outputs will be made openly available to support global, equitable climate impact research.