Observations-based machine learning model constrains uncertainty in future regional warming projections

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Abstract

Knowledge about future global and regional warming is essential for effective adaptation planning and our current temperature projections are based on the output of global climate models (GCMs). GCMs can provide projections of temperature under a range of future emissions scenarios but despite agreeing on the direction of this signal there are still discrepancies in the magnitude of the projected response[1].

Here we develop a novel method[2,3] for constraining uncertainty in future regional temperature projections based on the predictions of an observationally trained machine learning algorithm, Ridge-ERA5. Ridge-ERA5 - a Ridge regression model[4] - learns coefficients to represent observed relationships between daily temperature anomalies and a selection of thermodynamic and dynamical variables in the ECMWF Re-Analysis (ERA) 5 dataset[5]. Climate-invariance of the Ridge relationships is demonstrated in a perfect model framework: we train a set of 23 Ridge-CMIP model on historical data of the Coupled Model Intercomparison Project (CMIP) phase 6[6] in order to emulate these models and then evaluate the predictions of these emulators using future scenario data from the most extreme future emissions pathway, SSP 5-8.5, which represents the most extreme extrapolation challenge for the Ridge models.

Combining the historically constrained Ridge-ERA5 coefficients with normalised inputs from CMIP6 future climate change simulations forms the basis of a new methodology to derive observational constraints on regional climate change. For daily, regional (2.5°x2.5°), summer (JJA) temperatures across the Northern Hemisphere, the Ridge-ERA5 observations-based constraint implies, for example, that a group of higher sensitivity CMIP6 models is inconsistent with observational evidence (including in Eastern, West & Central, and Northern Europe), see Figure 1, potentially suggesting that the sensitivity of these models is indeed too high[7,8]. A key advantage of our new method is the ability to constrain regional projections at very high – daily – temporal resolution which includes extreme events such as heatwaves.

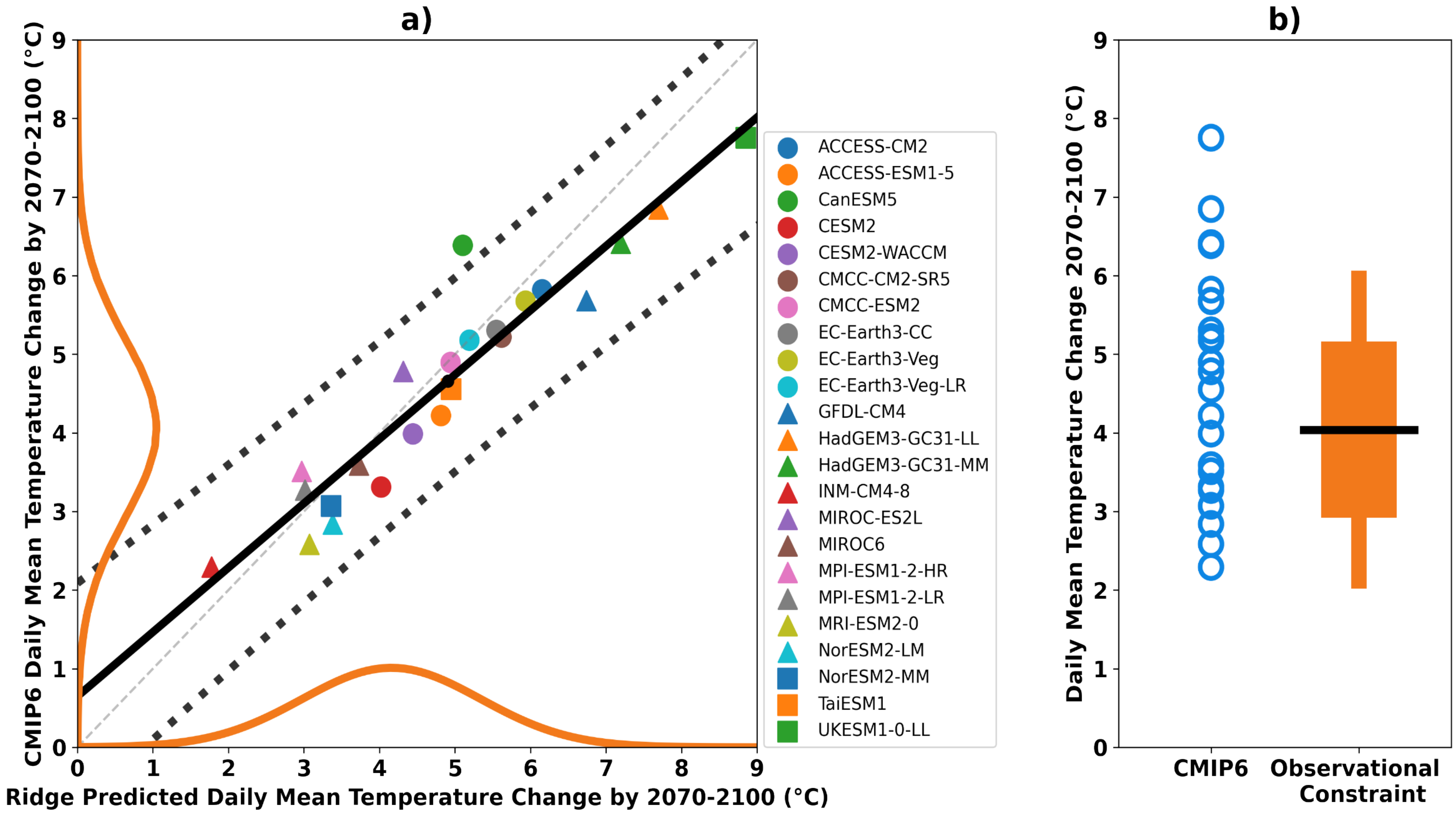

Figure 1: For Northern Europe (NEU AR6 Region[9]) **a)** Points show projected mean daily temperature change (by 2070-2100) under SSP5-8.5 from CMIP6 models (y-axis) plotted against predicted change by corresponding Ridge-CMIP emulators (x-axis) with least squares fit to points (black line) & prediction interval[10] (black dashed line). Probability distributions (orange lines) for Ridge-ERA5 future predictions given SSP5-8.5 inputs (x-axis) convolved with Ridge prediction error (substituted into linear fit to points) for final constraint (y-axis). **b)** Mean daily temperature change projected by each CMIP6 model (blue circles) alongside observationally constrained mean (black line), 60% (thick orange bar) and 90% (thin orange bar) intervals.

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