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Machine learning parameterizations for ozone in climate sensitivity simulations

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Ozone is an important feedback factor in climate simulations [1-5]. However, interactive atmospheric chemistry schemes needed for calculating changes in ozone are computationally expensive. Climate modelers therefore often use climatological ozone fields, which are neither consistent with the actual climate state simulated by each model nor with the specific climate change scenario. We suggest a novel method using a machine learning regression algorithm to model ozone in pre-industrial and abrupt 4xCO_2 climate sensitivity simulations [6]. Using the atmospheric temperature field as the only input, the regression reliably predicts three-dimensional ozone distributions. In particular, the representation of stratospheric ozone variability is much improved compared with a fixed climatology. Our method requires training data covering only a fraction of the usual length of simulations and, as we show here, is transferable between generations of the UK Met Office's climate model. Our method thus promises to be an important stepping stone towards a range of new computationally efficient methods to consider ozone changes in long climate simulations.

Short German summary:

Interaktive Ozonchemie ist eine wichtige, aber rechenzeittechnisch teure, Komponente in der Klimamodellierung. Wir zeigen hier das Algorithmen des Machinellen Lernens für viele Klimasimulationen eine effektive und schnellere Alternative zu interaktiven Atmosphärenchemieschemen darstellen können.

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