



## Machine learning-based emulation of a km-scale UK climate model

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High resolution projections are useful for planning climate change adaptation [1] but are expensive to produce using physical simulations. We make use of a state-of-the-art generative machine learning (ML) method, a diffusion model [2], to predict variables from a km-scale model over England and Wales. This is trained to emulate daily mean output from the Met Office 2.2km UK convection-permitting model (CPM) [3], averaged to 8.8km scale for initial testing, given coarse-scale (60km) weather states from the Met Office HadGEM3 general circulation model. This achieves downscaling at much lower computational cost than is required to run the CPM and when trained to predict precipitation the emulator produces samples with realistic spatial structure [4, 5]. We show the emulator learns to represent climate change over the 21<sup>st</sup> century. We present some diagnostics indicating that there is skill for extreme events with ~100 year return periods, as is necessary to inform decision-making. This is made possible by training the model on ~500 years of CPM data (48 years from each of 12 ensemble members). We also show the method can be useful in scenarios with limited high-resolution data. The method is stochastic and we find that it produces a well-calibrated spread of high resolution precipitation samples for given large-scale conditions, which is highly important for correctly representing extreme events.

Furthermore, we are extending this method to generate coherent multivariate samples including other impact-relevant variables (e.g. 2m temperature, 2m humidity and 10m wind). We will show the model's performance at producing samples with coherent structure across all the different variables and its ability to represent extremes in multivariate climate impact indices.

### References

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