Machine learning emulation of a local-scale UK climate model

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Understanding rainfall at a local scale is important for better adapting to its future changes. Using physical simulations, however, to produce such high resolution projections is expensive. For the first time we use diffusion models[1] (a state-of-the-art machine learning (ML) method for generative modelling) to emulate a high-resolution, convection-permitting model (CPM) by downscaling general circulation model (GCM) outputs. We apply this method to model high-resolution UK rainfall where climate change is predicted to cause intensification of heavy rainfall extremes [2]. The ML model can complement existing expensive CPM output with cheaper samples and also enable generating high-resolution samples from other climate model datasets. The samples have realistic spatial structure, which previous statistical approaches struggle to achieve.

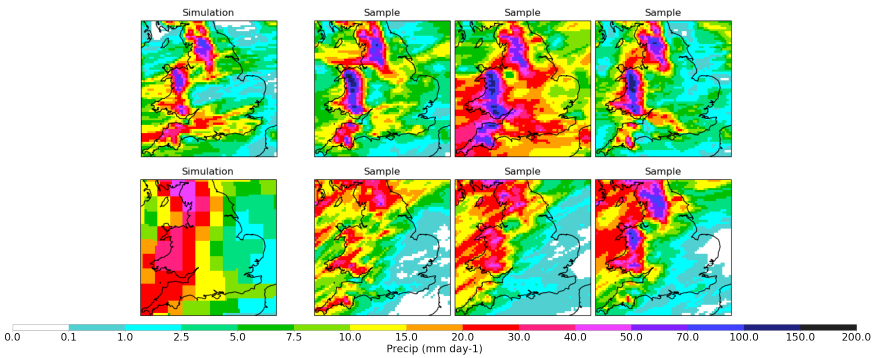
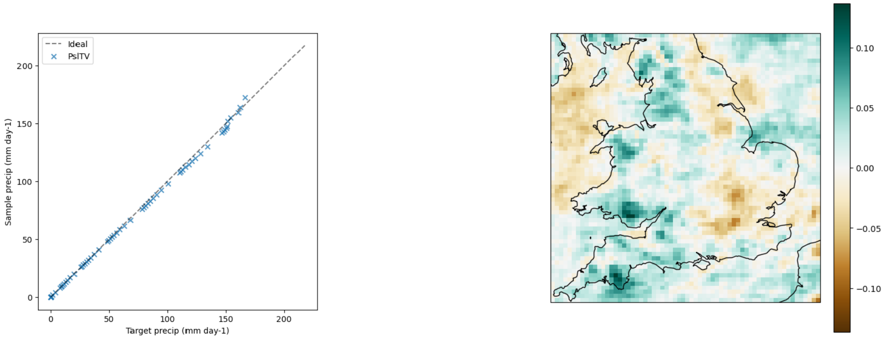


Figure 1. *Example samples conditioned on data from CPM (top) and GCM (bottom). The left column is rainfall from the simulation of the conditioning input, the others are samples from the ML model. Note the samples should represent the full range of plausible rainfall for the given low resolution conditions.*

Deep generative ML models have been successfully applied to problems in weather and climate such as short-term forecasting of sequences of rainfall radar fields [3] and downscaling [4]. Commonly these use Generative Adversial Networks (GANs) but these can be difficult to train and their limitations imply they might underestimate the probability of extreme events. Diffusion models instead model the full data distribution and should not suffer these same problems. To our knowledge this work is the first application of diffusion models in the domain of climate downscaling.

The ML-based emulator is a score-based generative model based on NCSN++[1], adapted to allow conditional generation. It is trained on output from the Met Office CPM[5] because there is a direct connection between the coarsened conditioning variables and the target CPM rainfall. We can then use



(a) QQ plot of per-grid-box ML samples vs CPM output from 10th to 99.99999th centiles.

(b) Normalized bias ($\frac{\mu_{samples} - \mu_{CPM}}{\mu_{CPM}}$) of coarsened-CPM-driven samples

Figure 2. *Summary of ML samples based on by coarsened-CPM inputs.*

either coarsened CPM output or low-resolution output from the Met Office HadGEM3 GCM[6] to make predictions about 8.8km daily rainfall. 8.8km was chosen over the full 2.2km resolution of the CPM at this early stage to cover a large area (England and Wales) while still providing a big improvement in resolution for the available computational resources. We use relative vorticity and temperature at multiple altitudes and mean sea-level pressure as our conditioning variables, all physical process-based predictors of rainfall. To further improve the ML model we added location-specific parameters which tie grid boxes to the underlying physical location. This allows the model to learn relevant features for each location which effect rainfall that may not be available from the climate variable inputs alone.

Figure 1 shows example high resolution samples. The samples look realistic and cover a range that plausibly includes the rainfall from the simulation. For each of the 4,320 days in the validation set, 3 samples were generated to capture the range of rainfall that is possible given coarsened CPM conditions. The QQ plot in Figure 2a shows how well matched the marginal grid-box distributions of rainfall are between the ML samples and target CPM output, out to at least as far as the 99.999999th centile. Figure 2b shows normalized bias of the ML model is no more than 10% in our domain. We have found that different random initializations of the ML model can lead to variations of around 10% in the quantiles on the validation set. The version selected is the first run version of the model before this variability had been sampled.

We will discuss the challenges of selecting and applying the model trained on coarsened CPM variables to GCM variables and present results about the method's ability to reproduce the spatial and temporal behaviour of rainfall and extreme events that are better represented in the CPM than the GCM due to the CPM's ability to model atmospheric convection.

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