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# Model-to-model Machine Learning downscaler for urban scales

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We are developing a model-to-model temperature downscaler for urban climate applications, the goal is extracting information in cities at hectometric scales. For this purpose, we use the Met Office global ensemble model MOGREPS-G (20 km resolution) with an intermediate grid length nest of 2.2 km over France, as the low-resolution model. This model has been dynamically downscaled to 300 m over the Paris area. A dynamical downscaler is excessive computational expensive for 300 m climate downscaling, for this reason we decided to develop a ML model using available weather data. The dataset was created for the Paris 2024 Olympics Research Demonstration Project (RDP).

The machine learning (ML) model developed in this project, will try to emulate the 300m dynamical downscaler by using low-resolution (2.2km) data as predictors and the 300m high-resolution downscaled data as target. We started with a limited set of hourly data, covering the period from 17$^{th}$ July 2024 to 10$^{th}$ September 2024. We are using all the data (80% of data was used for training and 20% for testing). We explored two different approaches: sequential (training from 17$^{th}$ July to 30$^{th}$ of August, the rest of the days for testing) and random which uses a random splitting. We are evaluating different models on the same dataset, using various predictors. The predictors include model variables from the low-resolution model reconfigured at 300m as well as fixed values used in the model, which influence temperature (such has surface altitude and urban fraction). Early results indicate that increasing the number of predictors does not significantly improve the ML model's performance. Additionally, using random days for training and testing the model is necessary to provide a more statistically robust basis for the method.

The best 'Paris trained ML model' (optimum configuration in regard to ML approach and predictors), is being tested over the UK, using UKCP18-local climate predictions, to evaluate spatial transferability to cities not included in the training. We will present results on the ability of the approach to spatially transfer to cities not included in the training data set.