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Physically Based Deep Learning Framework to Model Intense Precipitation Events at Engineering Scales

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The high computational cost of super-resolution (< 250 m) climate simulations is a major barrier for generating climate change information at such high spatial and temporal resolutions required by many sectors for planning local and asset-specific climate change adaptation strategies. This study couples machine learning and physical modelling paradigms to develop a computationally efficient simulator-emulator framework for generating super-resolution climate information. To this end, a regional climate model (RCM) is applied over the city of Montreal, for the summers of 2015 to 2020, at 2.5 km (i.e., low resolution – LR) and 250 m (i.e., high resolution – HR), which is used to train and validate the proposed super-resolution deep learning (DL) model. In the field of video super-resolution, convolutional neural networks combined with motion compensation have been used to merge information from multiple LR frames to generate high-quality HR images. In this study, a recurrent DL approach based on passing the generated HR estimate through time helps the DL model to recreate fine details and produce temporally consistent fields, resembling the data assimilation process commonly used in numerical weather prediction. Time-invariant HR surface fields and storm motion (approximated by RCM-simulated wind) are also considered in the DL model, which helps further improve output realism. Results suggest that the DL model is able to generate HR precipitation estimates with significantly lower errors than other methods used, especially for intense short-duration precipitation events, which often occur during the warm season and are required to evaluate climate resiliency of urban storm drainage systems. The generic and flexible nature of the developed framework makes it even more promising as it can be applied to other climate variables, periods and regions.