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A convolutional neural network for nowcasting rainfall intensities at fine temporal and spatial scales

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The short term forecast of rainfall intensities for fine temporal and spatial resolutions, has always been challenging due to the unpredictable nature of rainfall. Commonly at such scales, radar data are employed to track and extrapolate rainfall storms in the future. For very short lead times, the Lagrange persistence can produce reliable results up to 20 min whilst for longer lead times hybrid models are necessary, in order to account for the birth, death and non-linear transformations of storms that might increase the predictability of rainfall. Recently, data driven techniques, are gaining popularity due to their high learning skills, although their performance is highly dependent on the size of the training dataset and don't include any physical background. Thus the aim of this study is to investigate the use of data driven techniques in increasing the predictability of rainfall forecast at very fine scales.

For this purpose, a deep convolutional artificial neural network (CNN) is employed to predict rainfall intensities at 5min and 1km^2 resolutions for the Hannover radar range area at lead times from 5min to 3 hours. The deep CNN is trained for each lead time based on a past window of 15 minutes. The training dataset consist of 93 events (convective, stratiform and mixed events) from the period 2003-2012 and the validating dataset of 17 convective events from the period 2013-2018. The performance is assessed by computing the correlation and the root mean square error of the forecasted fields from the observed radar field, and is compared against the performance of an existing Lagrange-based nowcast method; the Lucas-Kanade optical flow. Special attention is given to the quality of the radar input by using a merged product between radar and gauge data (100 recording stations are used) instead of the raw radar one.

The results of this study reveal that the deep CNN is able to learn complex relationship and improve the nowcast for short lead times. However there is a limit that a CNN cannot pass; for those lead times a blending of the radar based nowcast with NWP might be more desirable. Moreover, since most urban models are validated on gauge observations, forecasting on merged data yields more reliable results for urban flood forecasting as the forecast agrees better with the gauge observation.