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Improving the spatial accuracy of extreme tropical cyclone rainfall in ERA5 using deep learning

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Tropical cyclones (TCs) are one of the costliest and deadliest natural disasters due to the combination of their strong winds and induced storm surges and heavy precipitation, which can cause devastating floods. Unfortunately, due to its high spatio-temporal variability, complex underlying physical process, and lack of high-quality observations, precipitation is still one of the most challenging aspects of a TC to model. However, as precipitation is a key forcing variable for hydrological processes acting across multiple space-time scales, accurate precipitation input is crucial for reliable hydrological simulations and forecasts.

A popular source of precipitation data is the ERA5 reanalysis dataset, frequently used as input to hydrological models when studying floods. However, ERA5 systematically underestimates TC-induced precipitation compared to MSWEP, a multi-source observational dataset fusing gauge, satellite, and reanalysis-based data, currently one of the most accurate precipitation datasets. Moreover, the spatial distribution of TC-rainfall in ERA5 has large room for improvement.

Here, we present a precipitation correction scheme based on U-Net, a popular deep-learning architecture. Rather than only adjusting the per-pixel precipitation values at each timestep of a given TC, we explicitly design our model to also adjust the spatial distribution of the precipitation; to the best of our knowledge, we are the first to do so. The key novelty of our model is a custom-made loss function, based on the combination of the fractions skill score (FSS) and mean absolute error (MAE) metrics. We train and validate the model on 100k time steps (with an 80:20 train:test split) from global TC precipitation events. We show how a U-Net trained with our loss function can reduce the per-pixel MAE of ERA5 precipitation by nearly as much as other state-of-the-art methods, while surpassing them significantly in terms of improved spatial patterns of precipitation. Finally, we discuss how the outputs of our model can be used for future research.