Post-processing East African precipitation forecasts using a generative machine learning model

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Introduction: Existing weather models are known to have poor skill at predicting precipitation over Africa [4], where there are regular threats of drought and floods that present significant risks to people's lives and livelihoods [2]. Improved precipitation forecasts could help mitigate the negative effects of these extreme weather events, as well as providing significant financial benefits to the region. Recently there have been many successful attempts to use techniques in machine learning to perform tasks like weather prediction, bias correction and downscaling [1, 3]. We build on this work by investigating whether a conditional Generative Adversarial Network (cGAN) can improve precipitation forecasts and realistically represent tropical convective rainfall, which is poorly simulated in conventional forecast

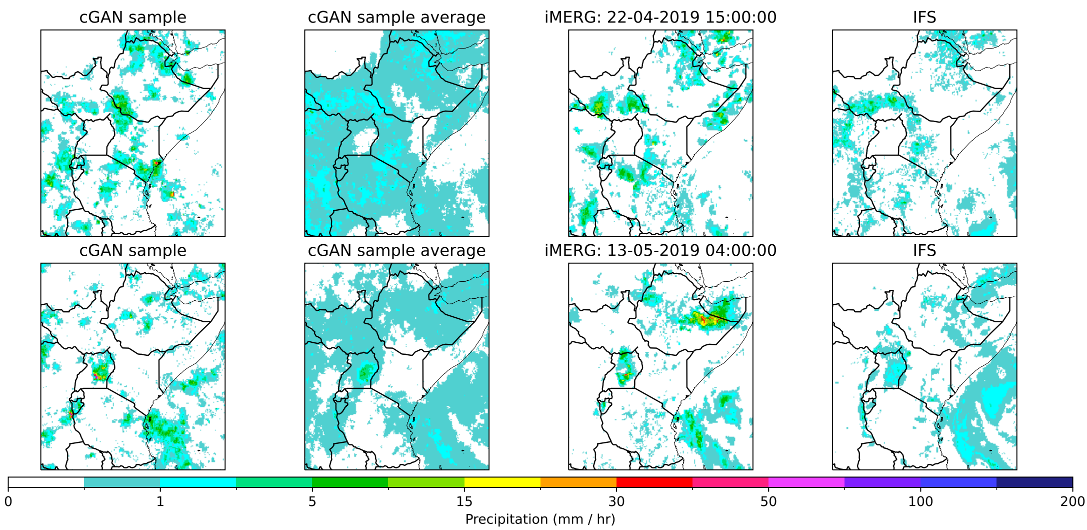
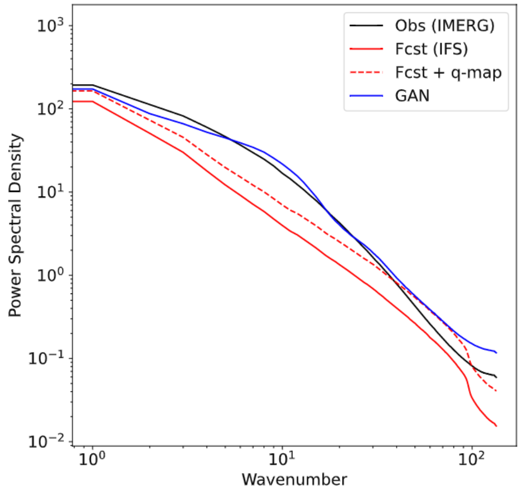
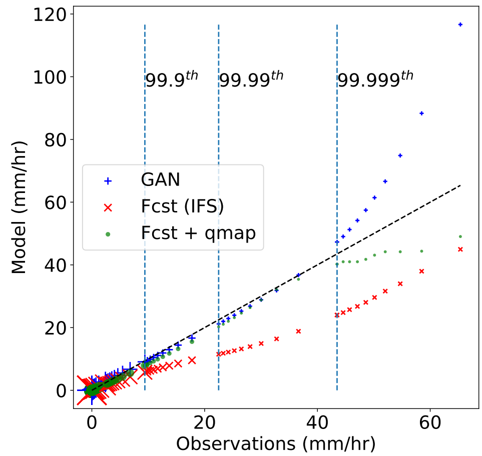


Figure 1. *Example generated results from a cGAN, for two particularly wet hours, with 50 samples produced per hour. From left to right: a random member of the cGAN ensemble, the average of the 50 samples, IMERG observations and the original IFS forecast.*



(a) Radially-averaged power spectral density for the observations and models. IFS qmap represents a quantile-mapped version of the IFS.



(b) Quantile-quantile plot, in steps of 10% up to the 90th percentile, steps of 0.01% up to the 99.99th percentile, steps of 0.001% up to the 99.999th percentile and steps of 0.0001% up to the 99.9999th percentile.

Figure 2. *Metrics evaluated on 1000 hourly samples randomly chosen from June 2018 - May 2019.*

models. This has the potential to enable cost effective improvements to early warning systems in the affected areas.

Methodology: We use the ECMWF IFS forecast as well as a land-sea mask and orography as inputs, with the IMERG satellite dataset as ground truth. The region considered is 12S-16N 25-50E at 0.1 degree resolution, with data taken at hourly intervals, for 6-18h lead times. We take 17 variables from the IFS forecast as input, including precipitation, humidity, wind velocities, temperatures, convective inhibition and convective precipitation. The cGAN architecture follows [1, 3], with deep convolutional neural networks using residual blocks, conditioned on the IFS data and geographic data. The model is trained using hourly data in the period 2016-2017, with assessments performed over 2018-2019.

Results: A visual inspection of samples produced by the cGAN (see Fig. 1) confirms that it produces realistic spatial rainfall patterns, with the radially-averaged spectral density for the cGAN samples closer to the IMERG than the original IFS forecast (Fig. 2(a)). Quantile-quantile plots reveal that the cGAN is able to correct the forecast bias up to the 99.999th percentile, beyond which the network overpredicts the rainfall.

Conclusions: Our results indicate that a cGAN can improve the spatial structure of precipitation forecasts and correct biases in the precipitation intensity up to the 99.999th percentile. Going forward we will improve the training of the cGAN, and investigate how well this model is able to model weather extremes.

References

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