# A Generative Adversarial Network-based Stochastic Weather Generator

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## PROJECT OVERVIEW

Stochastic weather generators are used to generate synthetic weather time series which follow the statistical characteristics of observed weather time series for a location of interest. Stochastic weather generators are generally used to understand the likelihood of weather events under the current climate, especially considering the limited historical record of observations. Here we present the development of a deep learning-based stochastic weather generator, which is trained on observations from the last 50 years. Given a sequence of weather fields such as surface temperature and precipitation, the trained generator will provide an ensemble of potential weather time series for one year for only West Coast Canterbury region of New Zealand.

## GENERATOR ARCHITECTURE

- A partial Nested U-Net (see Figure 2) reduces the semantic gap between encoder and decoder feature maps.
- We concatenated a normally distributed vector to the down sampling layer to add stochasticity.

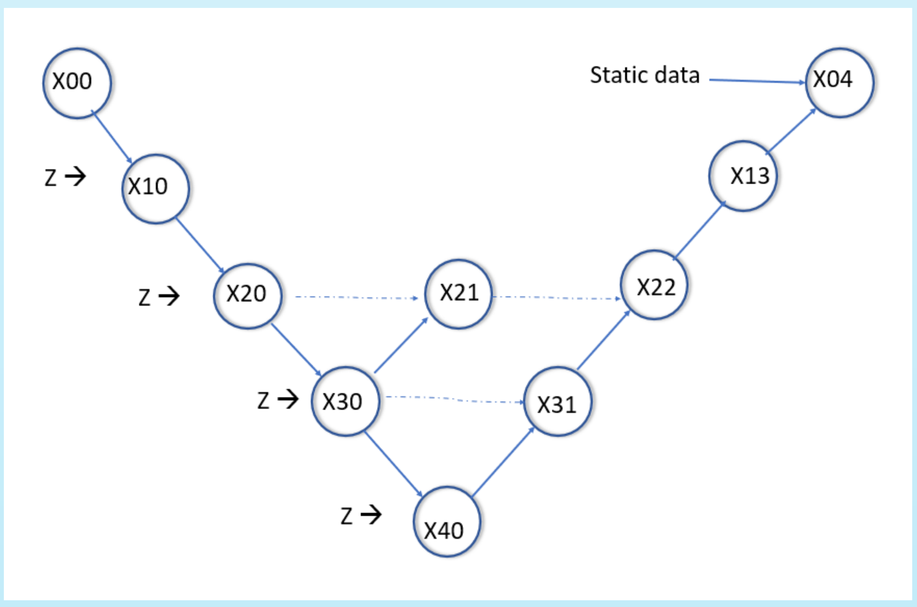


**Figure 2**: The general architecture of a partial Nested U-Net, adapted from UNet++: A Nested U-Net Architecture for Medical Image Segmentation.

- We used the trained model to generate a 365 days time series given an input day.
- The model generated realistic weather fields for one year as shown in Figure 4.

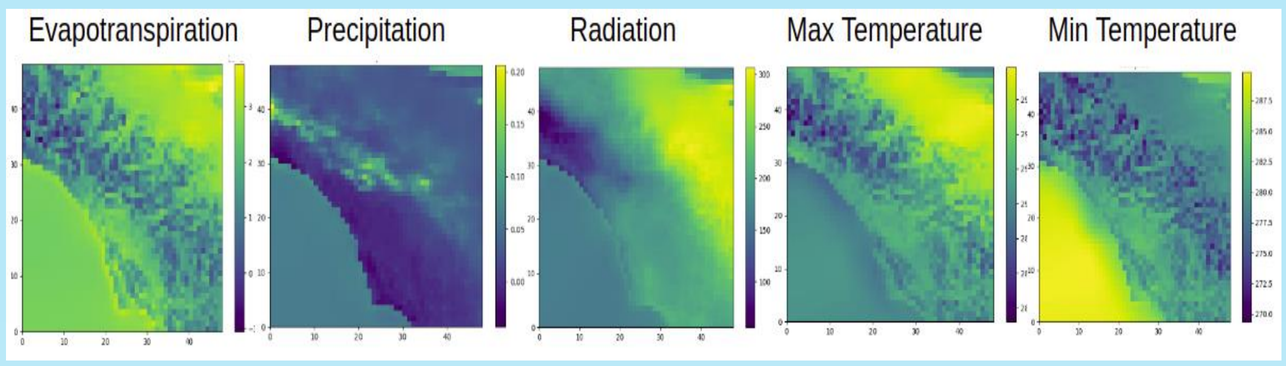


**Figure 4**: Figure shows the predicted weather fields for the 100th day, Potential Evapotranspiration (kg m-2), Precipitation (kg m-2), Surface Downwelling Shortwave Radiation (W m-2), Daily Maximum Near-Surface Air Temperature (K), and Daily Minimum Near-Surface Air Temperature (K),

## GENERATIVE ADVERSARIAL NETWORK (GAN)

The GAN architecture consists of two neural networks; the generator and the discriminator. The stochastic weather generator creates synthetic time series for a given input and the discriminator classifies it as fake or real (Figure 1).

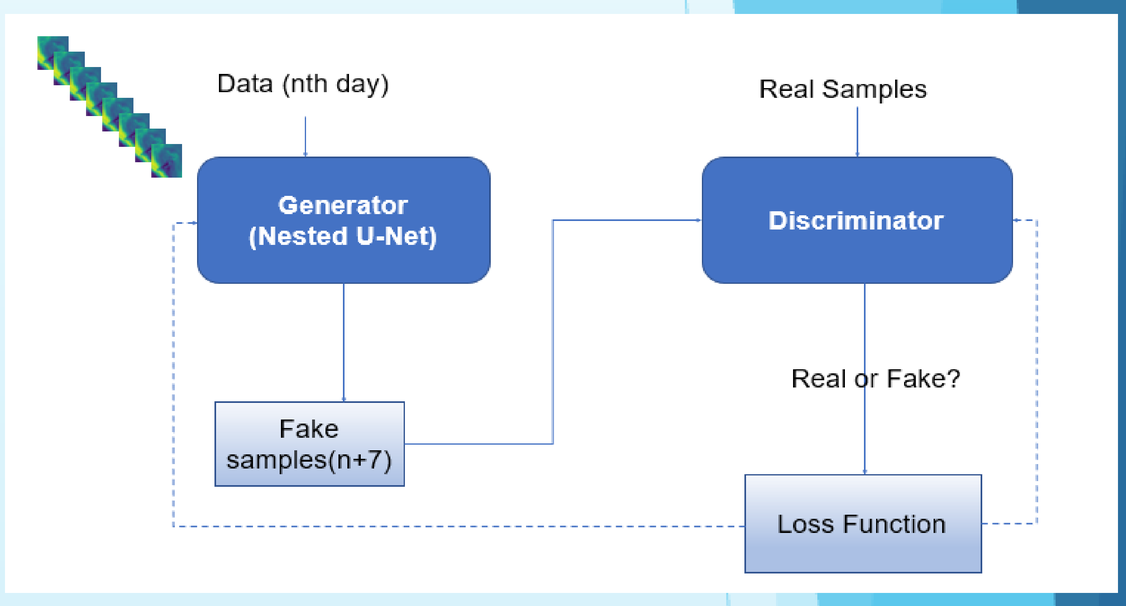


**Figure 1**: The general architecture of GAN.

## METHODOLOGY

- Trained the GAN using gridded observations for the West Coast Canterbury region
- The generator is trained to create realistic and diverse samples of the next 7 day weather fields given an input of one day time step.
- The loss function is the Mean Absolute Error between the predicted and actual observations, hinge loss, and diversity loss to encourage diversity.

## RESULTS

- The model produced realistic images of weather fields with a batch size of N(4) and 130 epochs using 4 GPU. Figure 3 shows the validation output for maximum temperature.

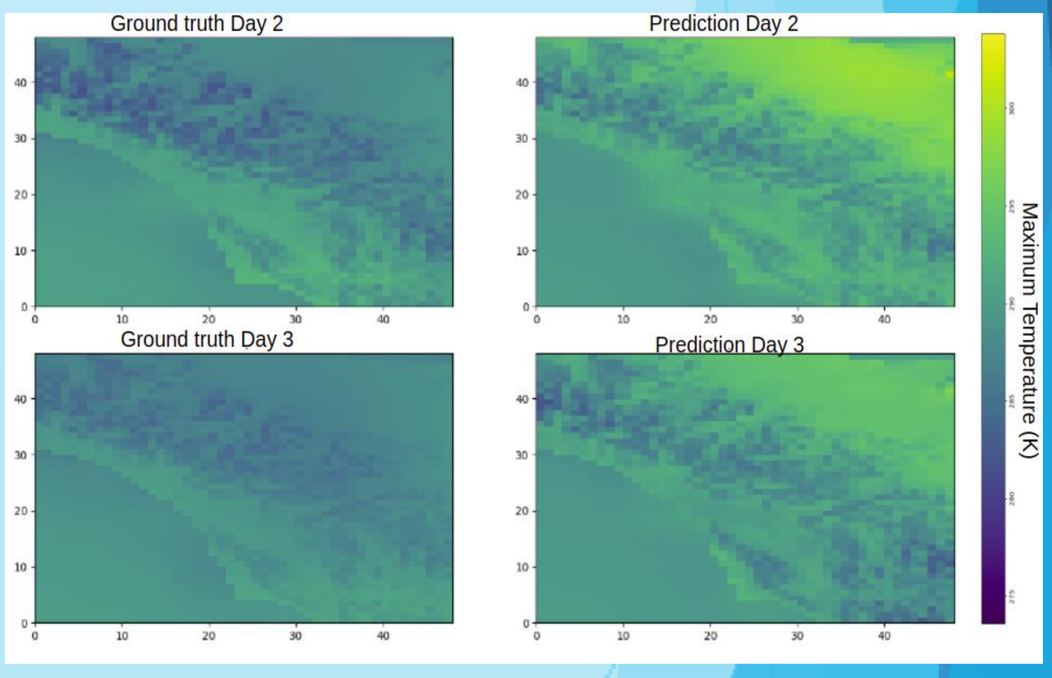


**Figure 3:** Ground truth and predicted sample for the variable maximum temperature for next two days.

## FUTURE WORK

The GAN proved to produce realistic and diverse one year time series. We need to validate the results as well as generate time series for entire New Zealand.

## ACKNOWLEDGEMENTS

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