Deep Learning for downscaling tropical cyclone rainfall

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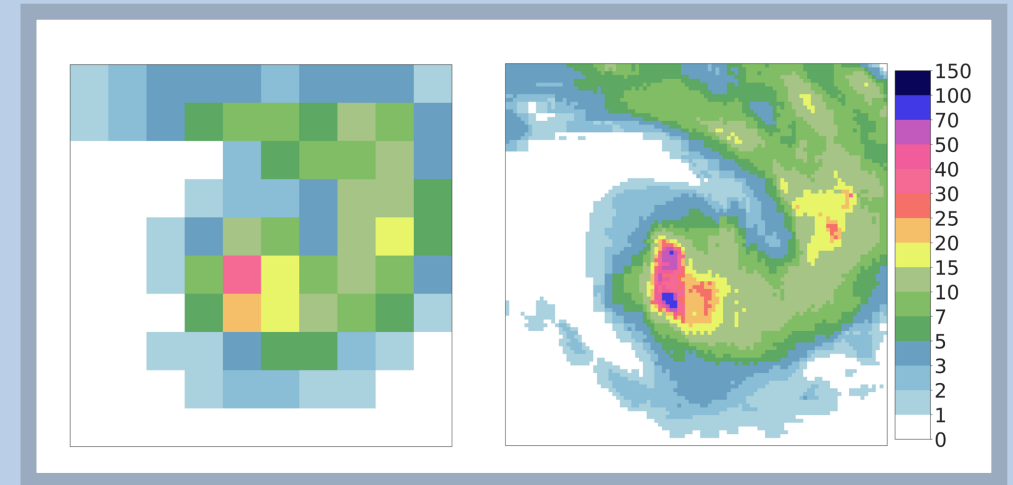Department of Physics, University of Oxford[3]

Photo credit: NASA

Flooding is often the biggest hazard from tropical cyclones

Hurricane Fiona 2022: Canada

Hurricane Fiona 2022: Dominican Republic

What is downscaling and why do we need it?

- Modelling TCs with global climate models is computationally expensive, especially when you run them at high resolution (<50 km)

- TC downscaling models only focus on regions or TC-relevant output so are faster to run

- Generative models have the potential to be computationally cheaper than alternative methods

Figure 1. Using only precipitation data at 100 km resolution (left), the models predict the corresponding high-resolution rainfall field (right), which increases resolution by a factor of 10.
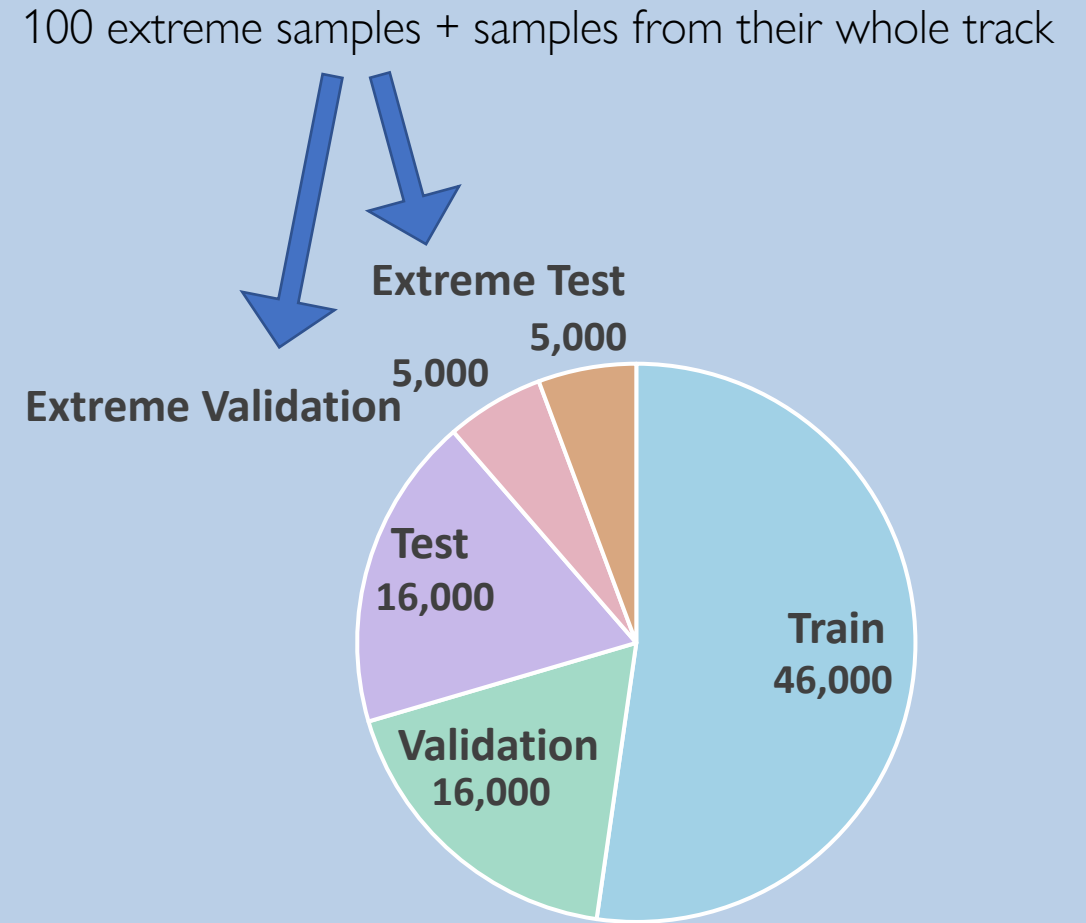
Methods

- Bilinear interpolation baseline

- Convolutional Neural Network (U-Net) baseline   Ronneberger, et al., (2015).

- Variational Autoencoder Generative Adversarial Network (VAEGAN)

- Wasserstein Generative Adversarial Network (WGAN)

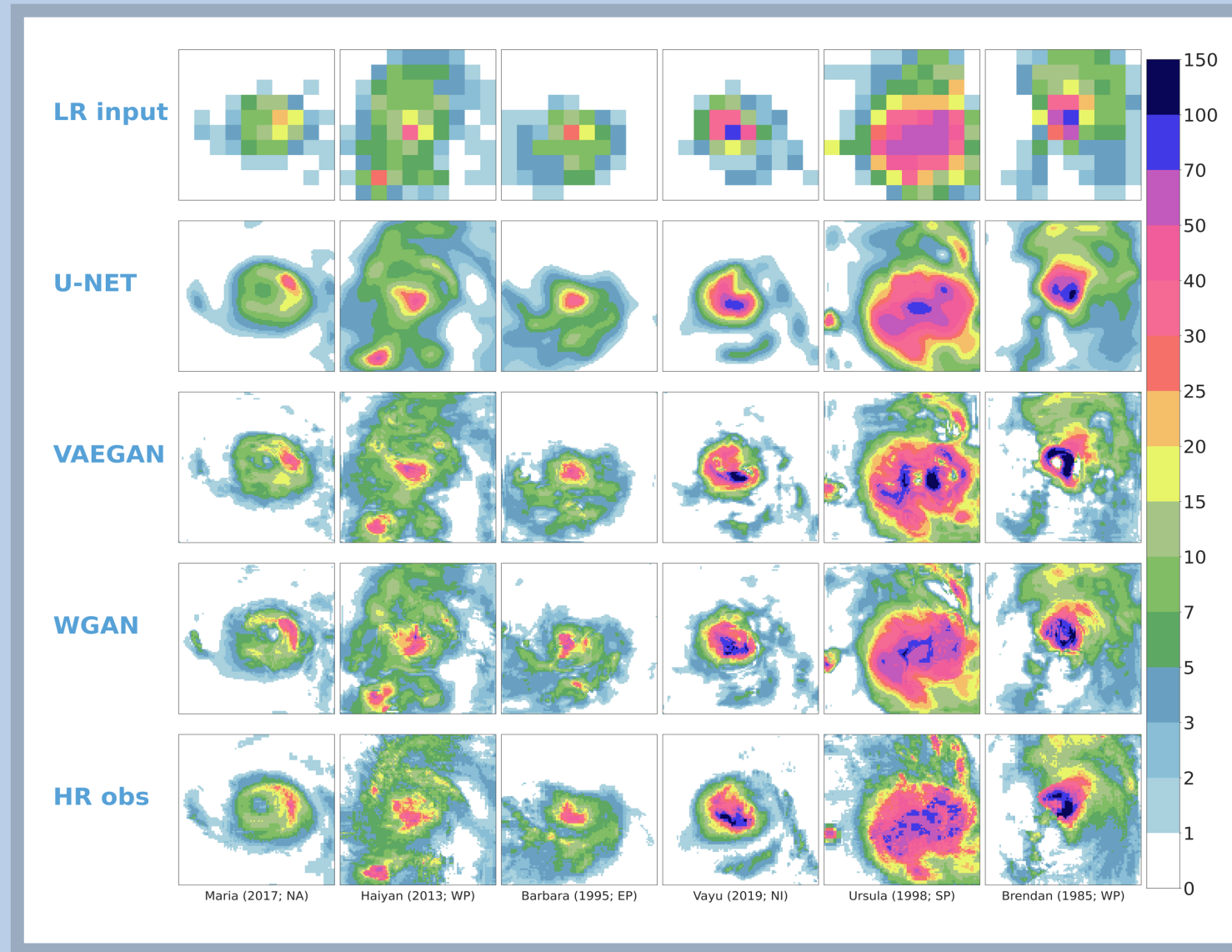Leinonen, et al., (2021).
Harris, et al. (2022).

Data processing

1. Gathering 3-hourly tracking information from IBTrACS, a global TC track dataset

2. Locating track points within MSWEP global rainfall dataset at 10 km resolution and crop to cover a 1000 km square image.

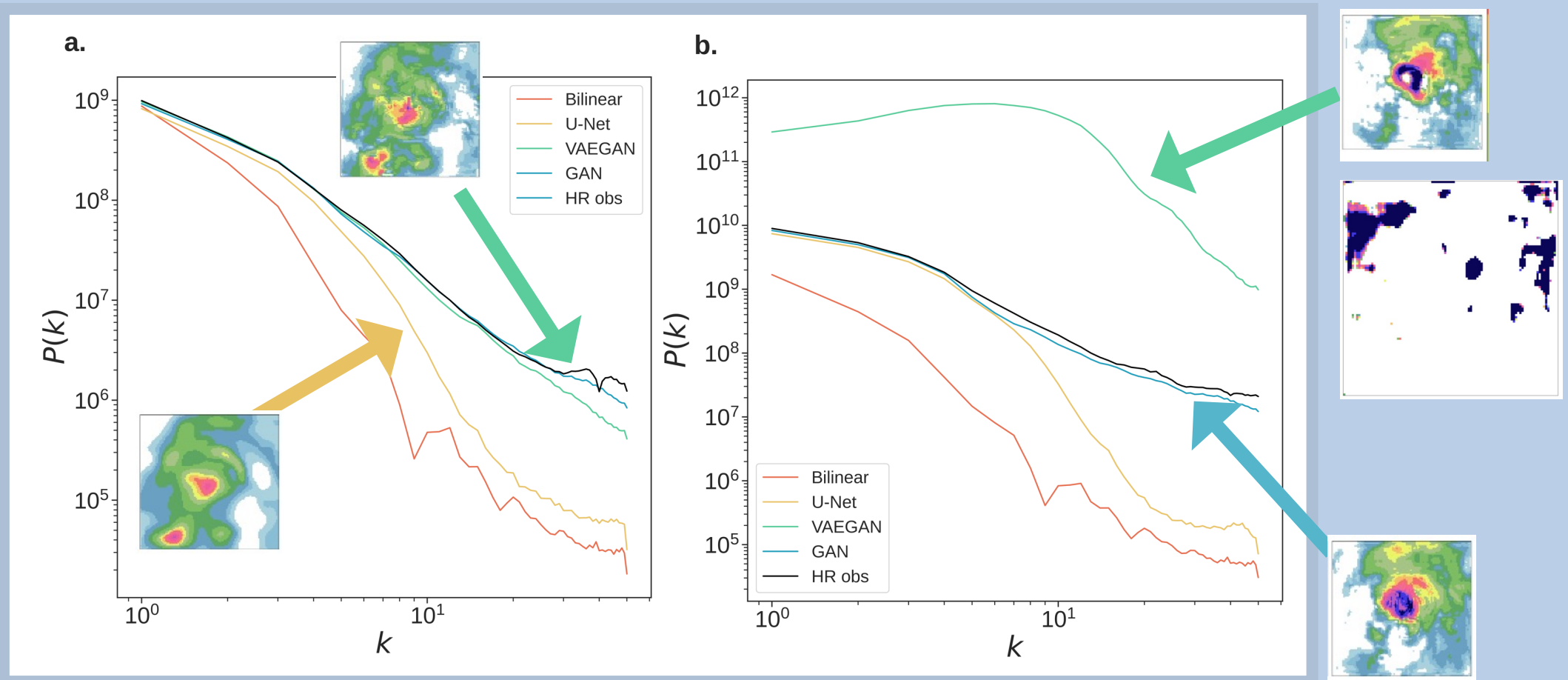3. Generating the low-resolution images using conservative interpolation

We generated rainfall data from around 2,000 TCs which resulted in over 90,000 samples.

100 extreme samples + samples from their whole track

Extreme Test
5,000

Extreme Validation
5,000

Test
16,000

Validation
16,000

Train
46,000

Figure 2. Train test split

Figure 3. Model predictions of rainfall from six notable tropical cyclones chosen for their distinct visual patterns: Hurricane Maria (2017; North Atlantic), Typhoon Haiyan (2013; West Pacific), Hurricane Barbara (1995; East Pacific), Cyclone Vayu (2019; South Indian), Cyclone Ursula (1998; South Pacific) and Typhoon Brendan (1985; West Pacific Ocean). The first and second three are from the regular and extreme test sets respectively, those from the extreme test set are taken at the point where maximum rainfall occurs at coarse resolution.

Figure 4. Spectral Power against Wavenumber of the predictions from bilinear interpolation and machine learning models on the regular test set (panel a.) and the 100 extreme test set samples (panel b.).

Conclusions

- Evaluating models at the 'unseen' extremes is important. There were some very large errors present in VAEGAN at the upper end of the extreme test set.

- The WGAN can reproduce realistic tropical cyclones using input data that lies outside of the original training distribution.

- Full paper submitted to JGR: Atmospheres Nov 9th 2022