# A deep-learning strategy to reliably downscale to future climates

**Neelesh Rampal,** Peter Gibson, Steve Sherwood, Gab Abramowitz & Sanaa Hobeichi

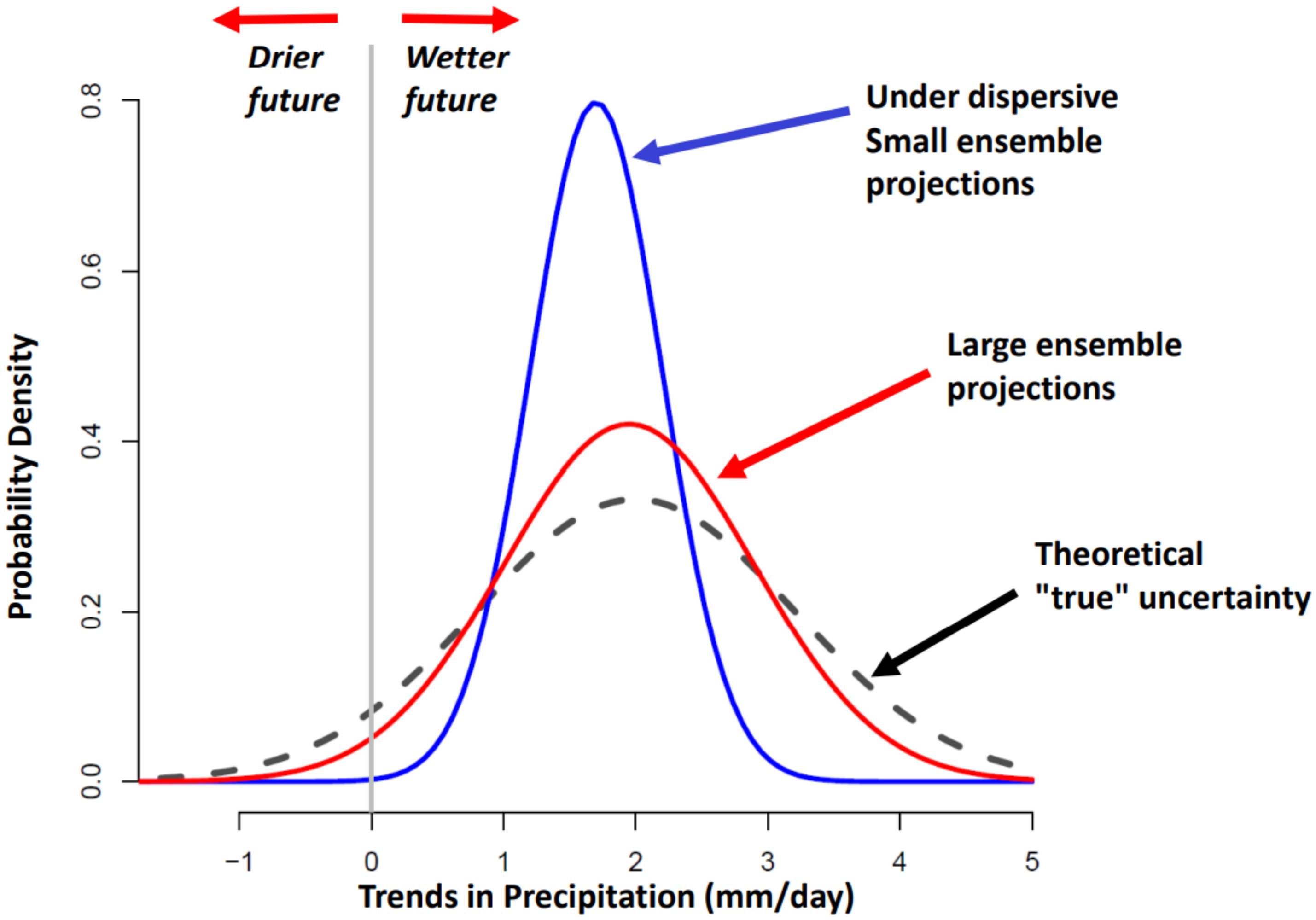
# What's the Problem?

- **Dynamical** are very expensive

- Due it's expense, only several GCMs are often selected for dynamical downscaling

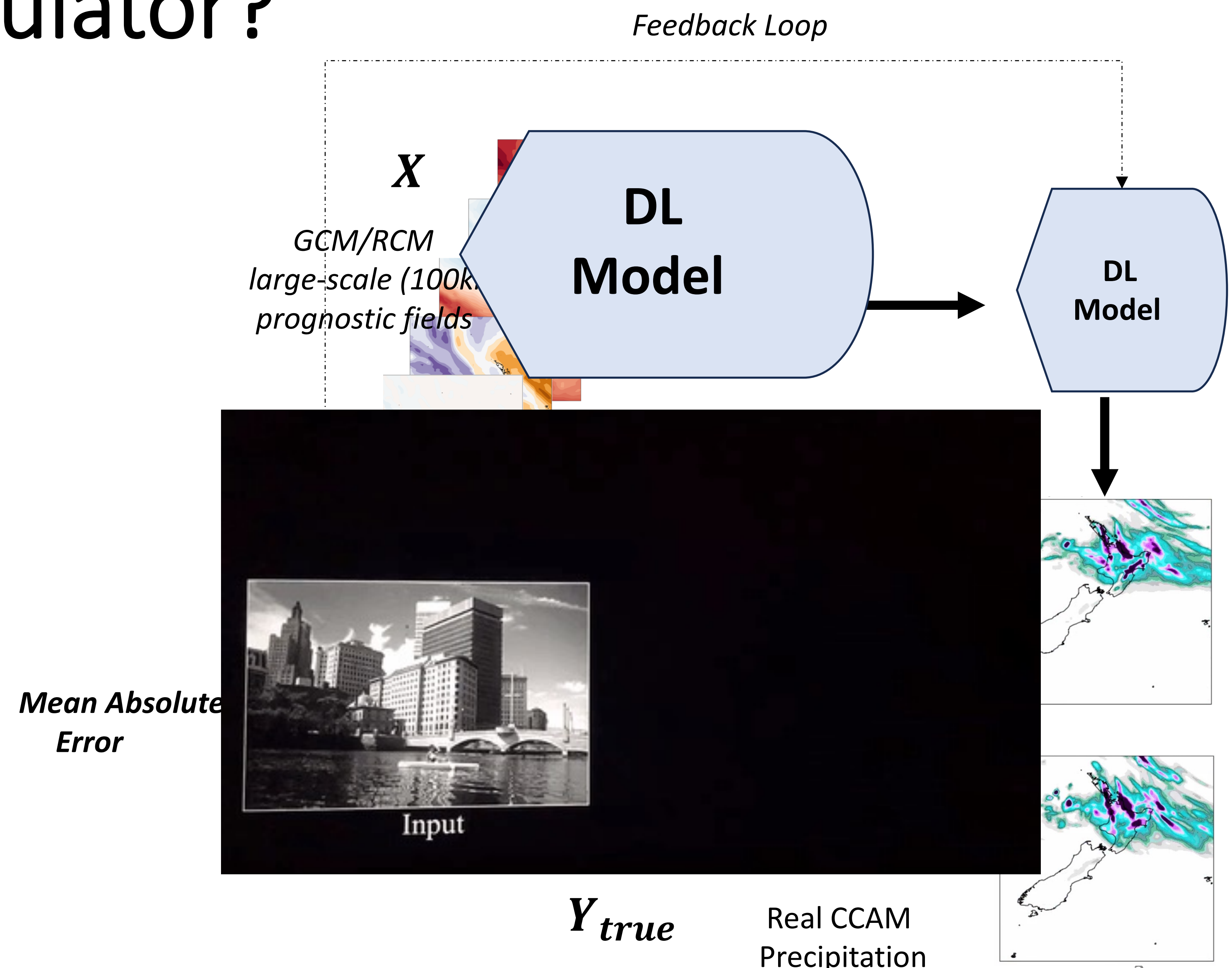
- We risk under sampling the distribution of possible climate outcomes

- **We develop an AI-surrogate RCM emulator**



# What is an Emulator?

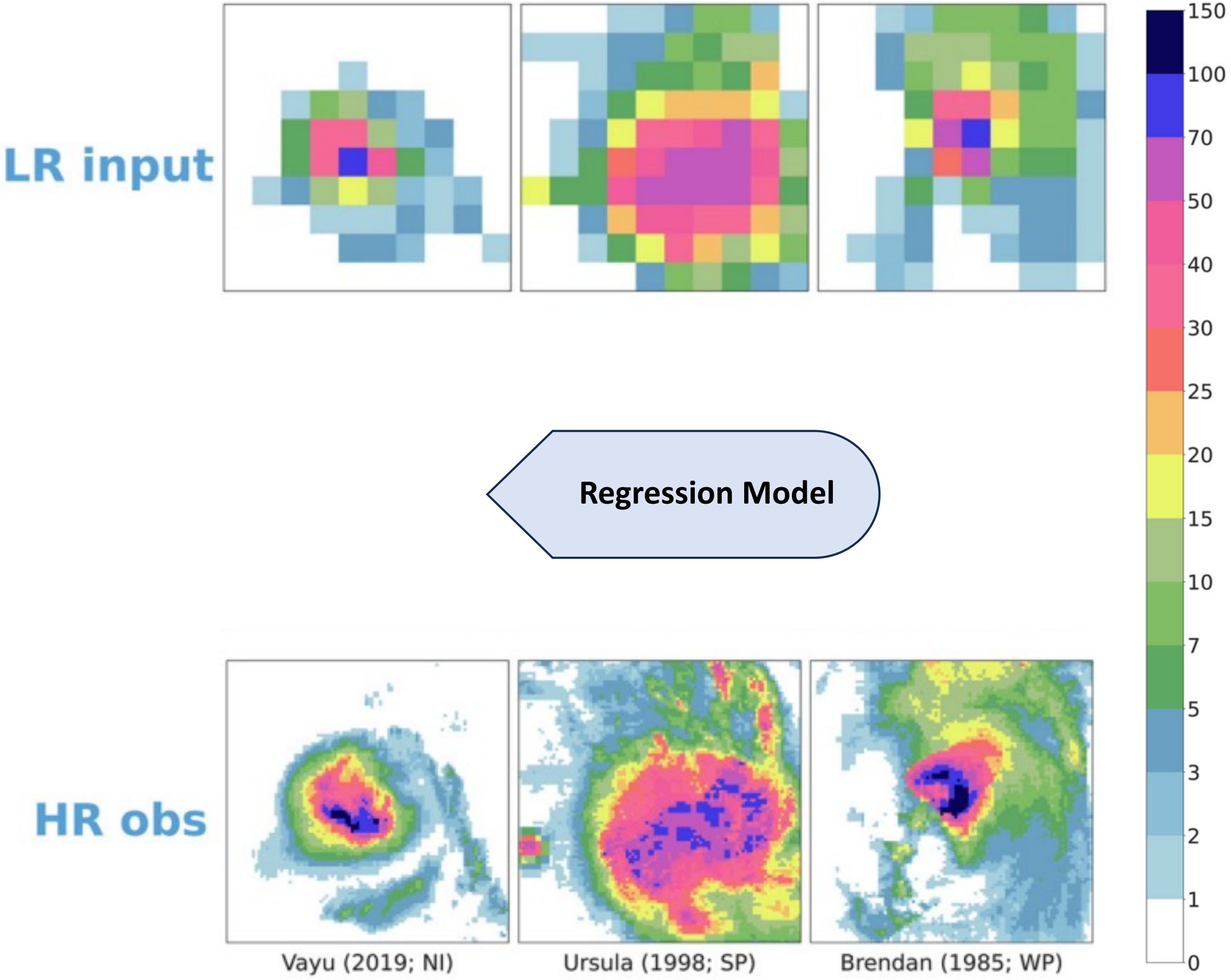
- They are trained in a feedback loop to optimize an objective function (**Content loss**).
- An Emulator Training a surrogate model that “emulates” the function of RCM at fraction of the computational cost.
- Other benefits (e.g., Sparse observations, large amounts of training).



# Challenges of Regression Approaches *e.g. Vosper et al., (2023)*

- Many RCM emulator / SR studies train a DL model to map from LR inputs **(X)** -> HR obs **(y)**

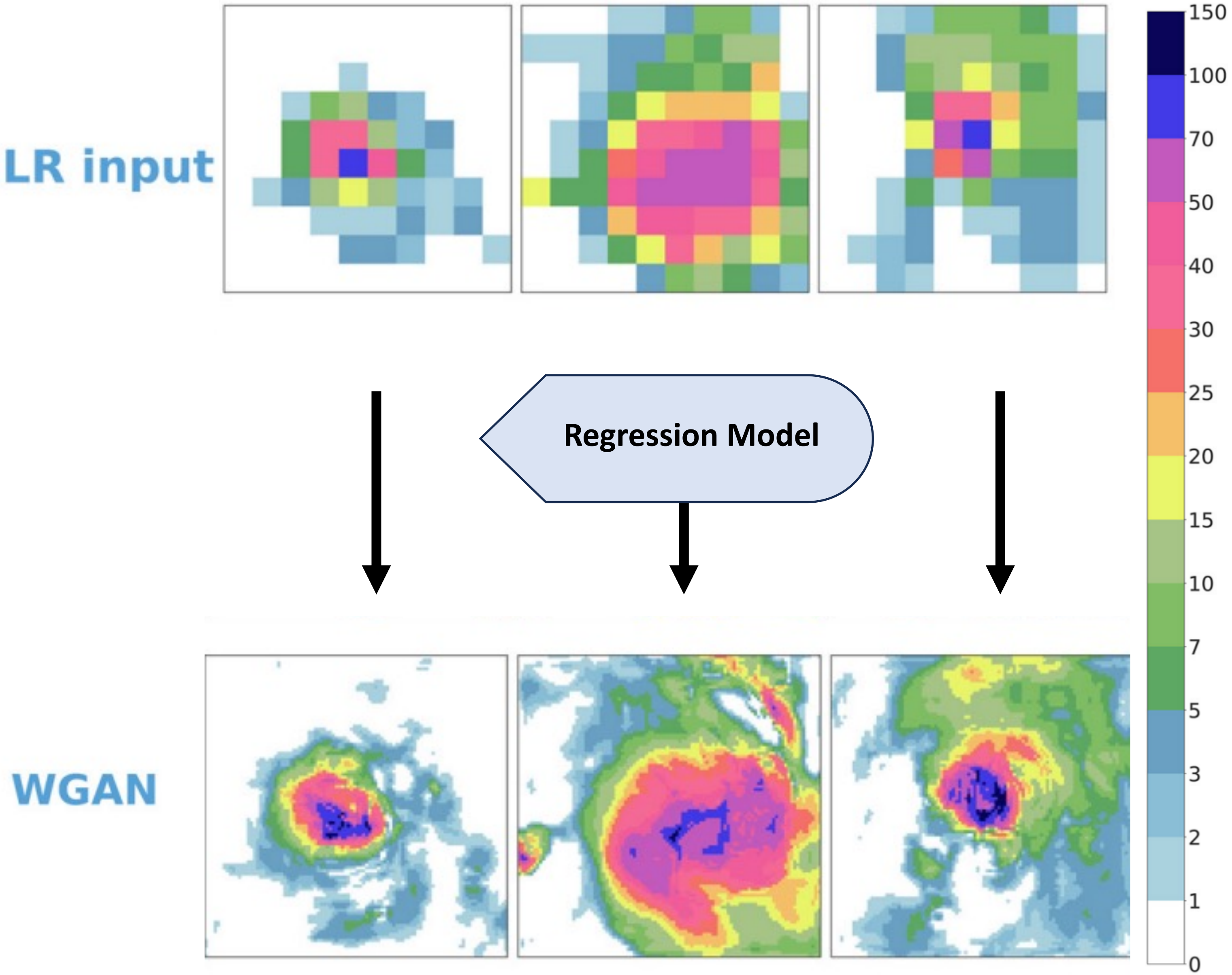
- Low resolution (LR) input is coarsened HR obs



# Deep Learning Challenges

*Vosper et al., (2023)*

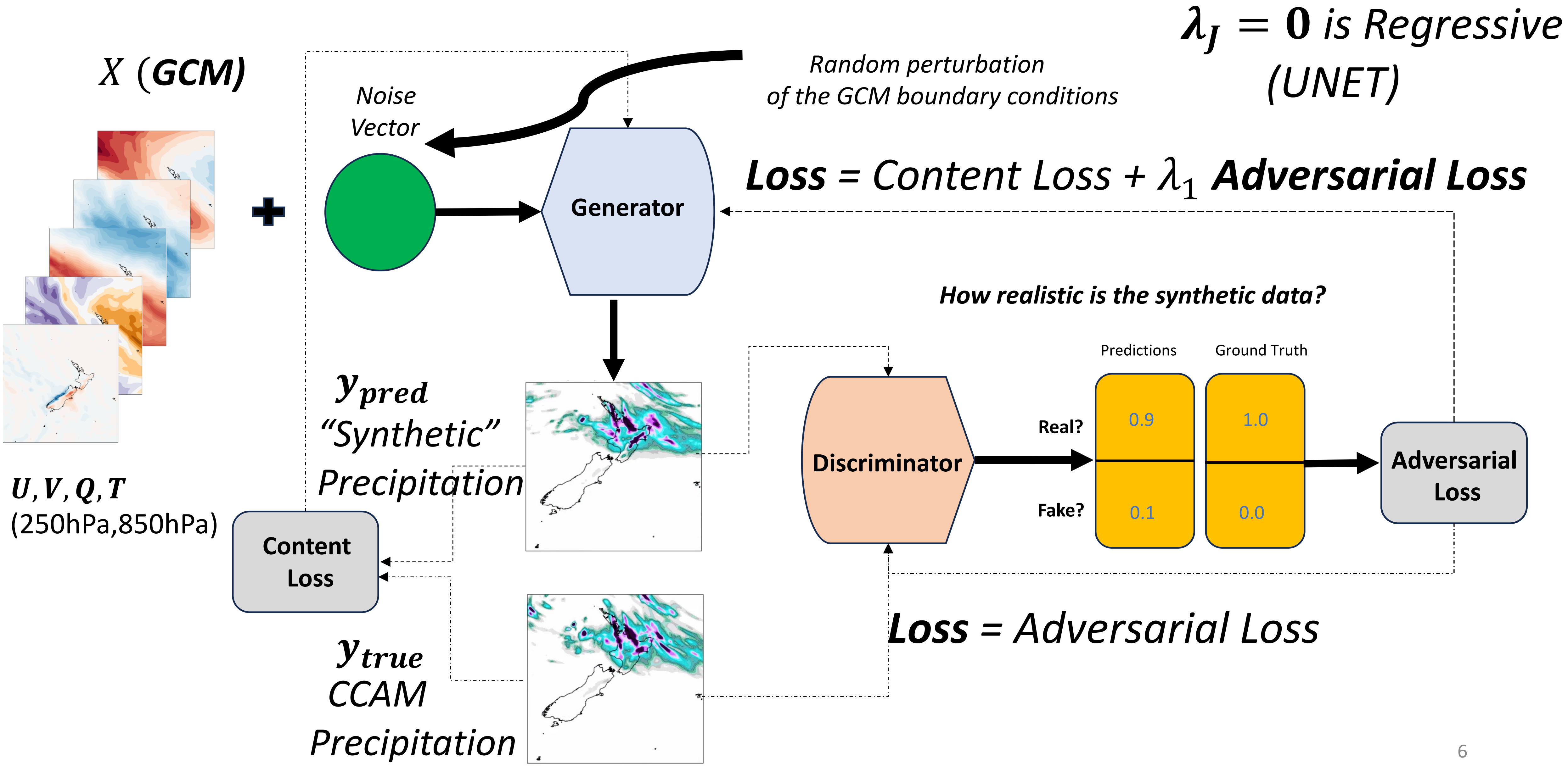
- DL regression-based approaches "smooth" the extremes and high-frequency detail.

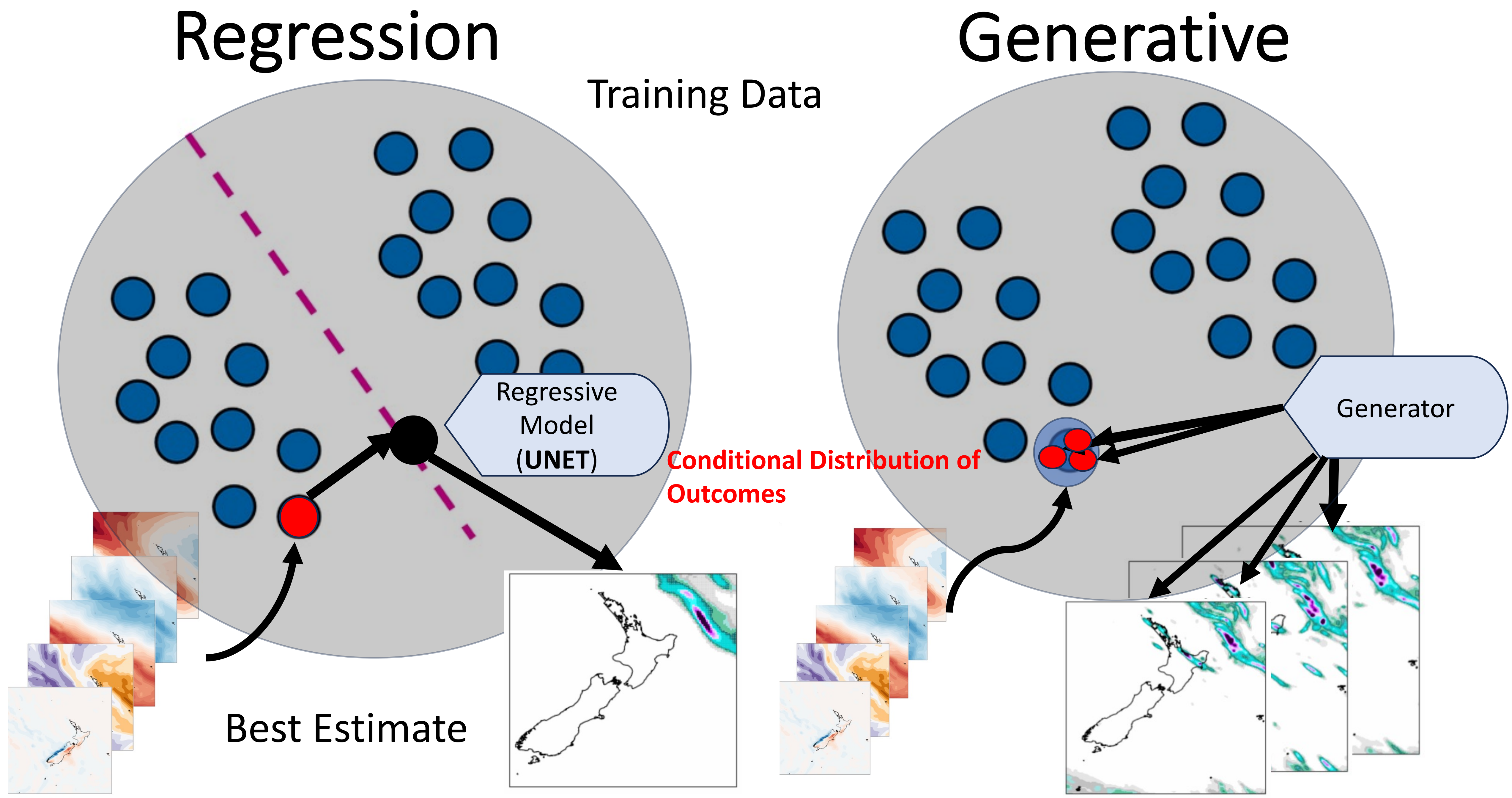



Best Estimate by Regression model

**Generative Model**

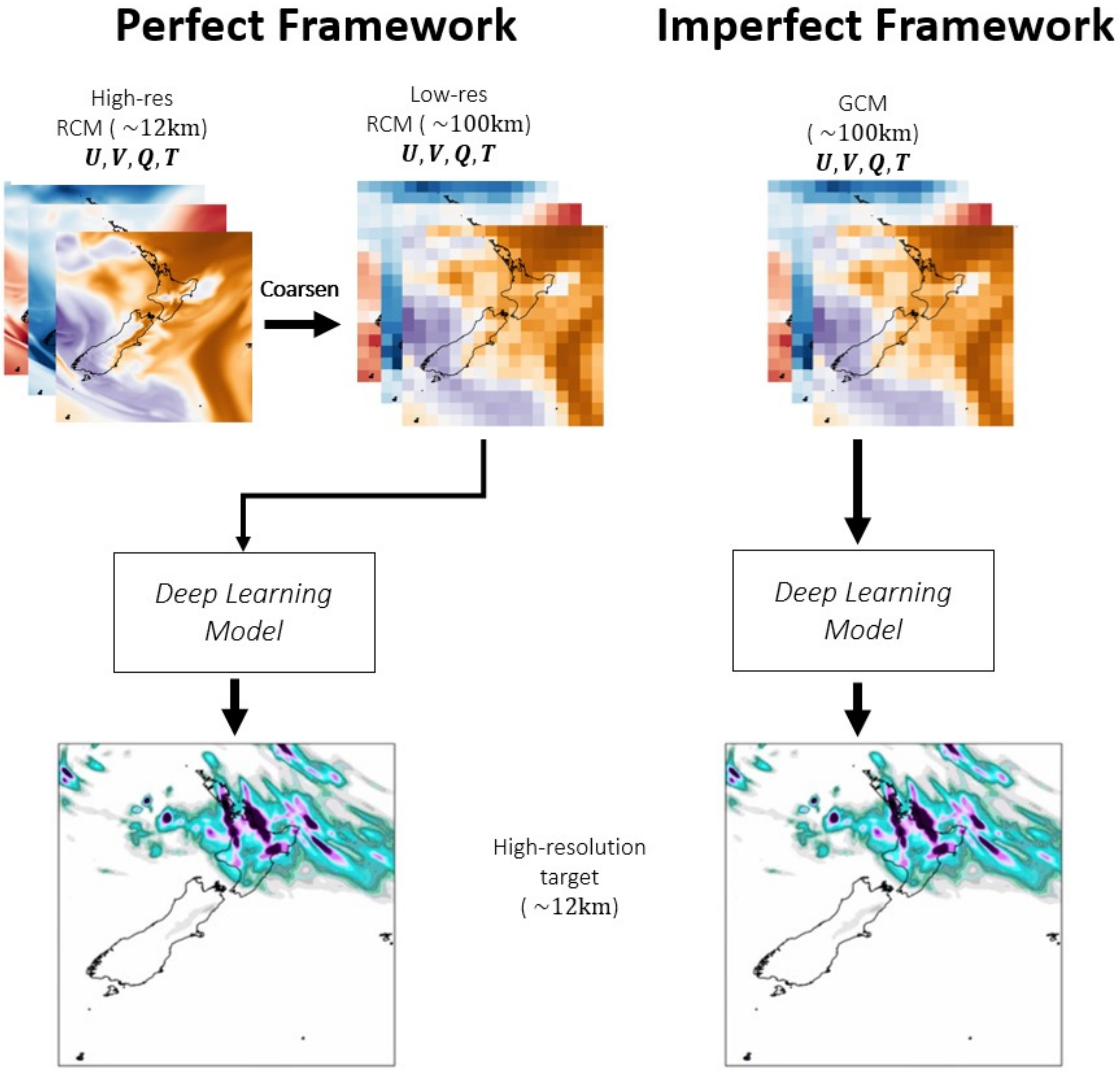
# Generative Adversarial Networks




Regression
Generative
Training Data
Regressive Model (UNET)
Generator
Conditional Distribution of Outcomes
Best Estimate

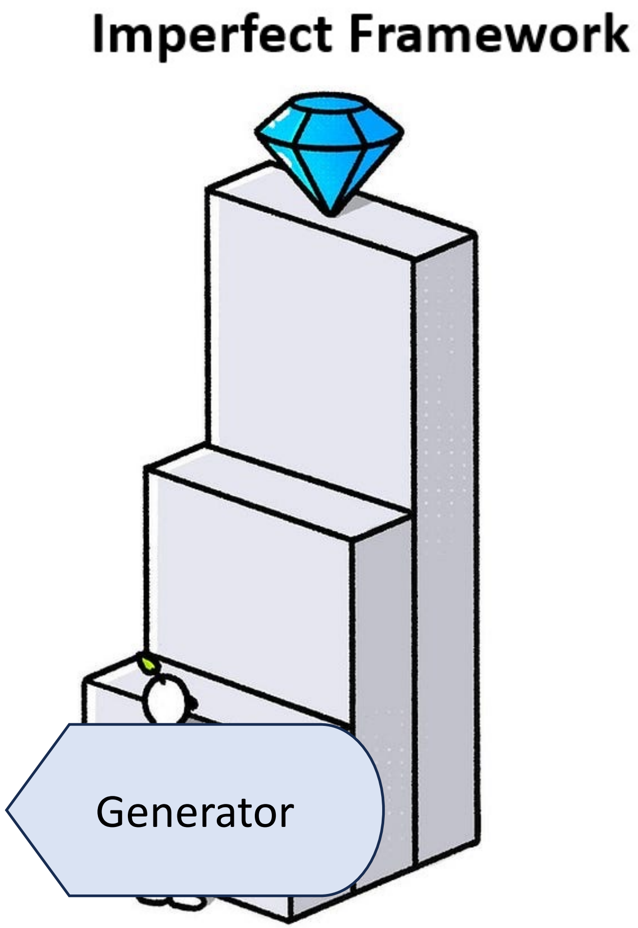
# Model Training

- **Perfect:** Training a DL model from coarse resolution RCM to RCM fields
- **Imperfect:** GCM directly to RCM fields
- The Imperfect framework represents the true function of an RCM.
- We train our GAN on 85 years of ACCESS-CM2 SSP370 (2015-2100) daily fields.



# A New Training Framework

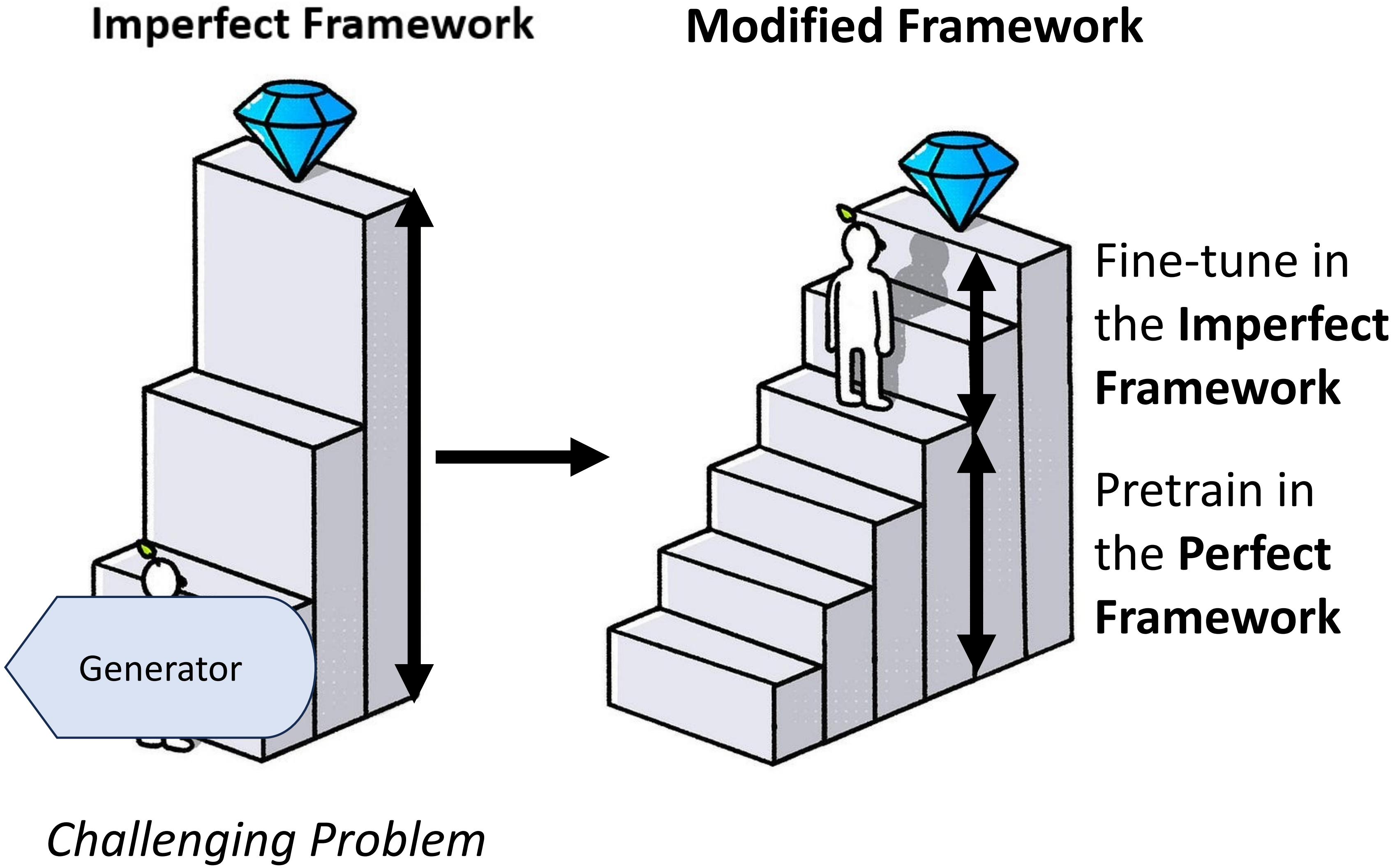
- Perfect framework is easier to train
- Inconsistencies between the GCM and RCM outputs make it challenging to train a model.
- This can affect the relationships learnt by the model




*Challenging Problem*

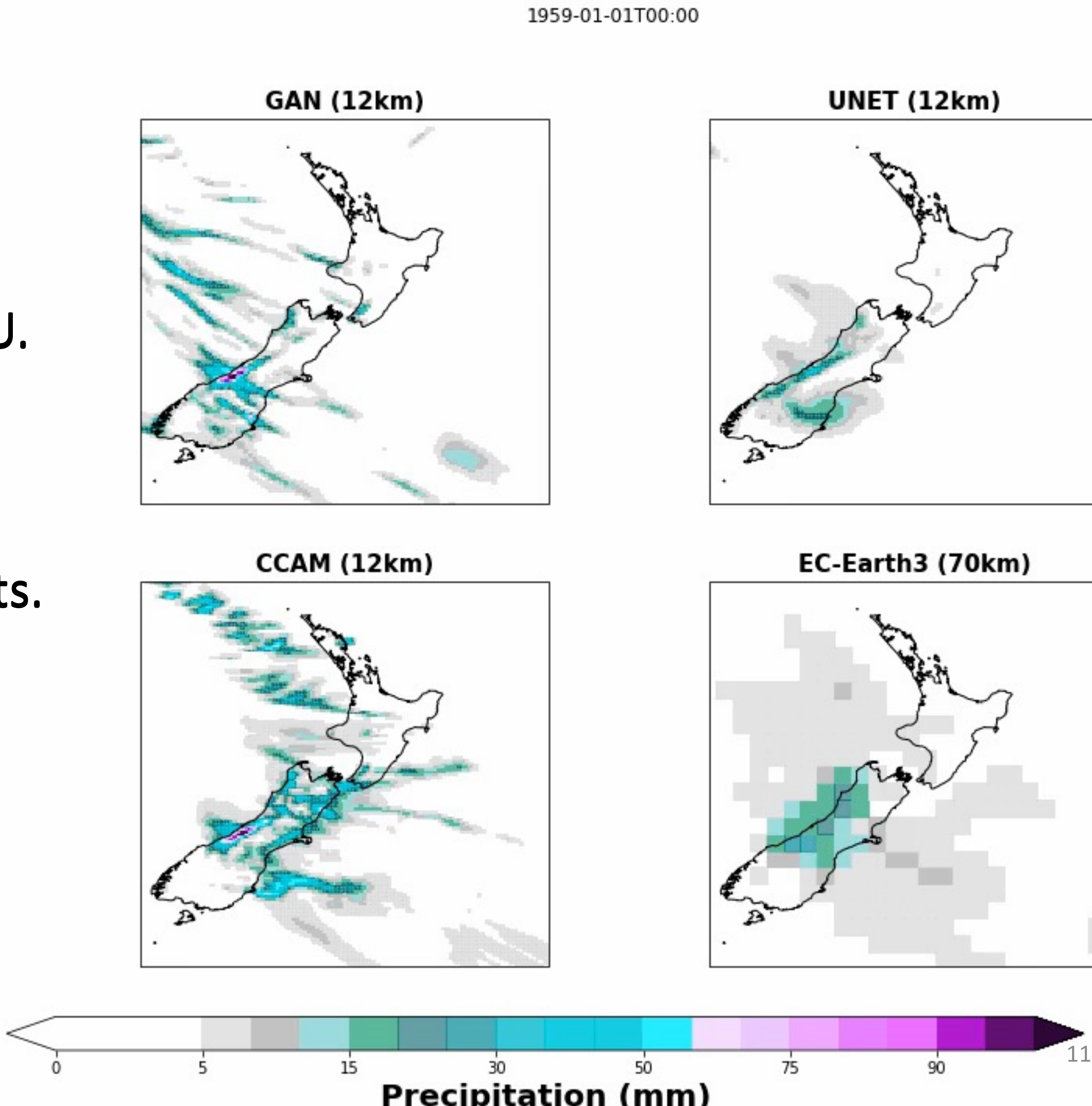
# A New Training Framework

- In our **Modified Framework** we achieve a 25% lower error than the **Imperfect**
- Model trained in the imperfect would learn spurious features and poorly generalized.
- We train both a GAN and a **UNET** as a benchmark.

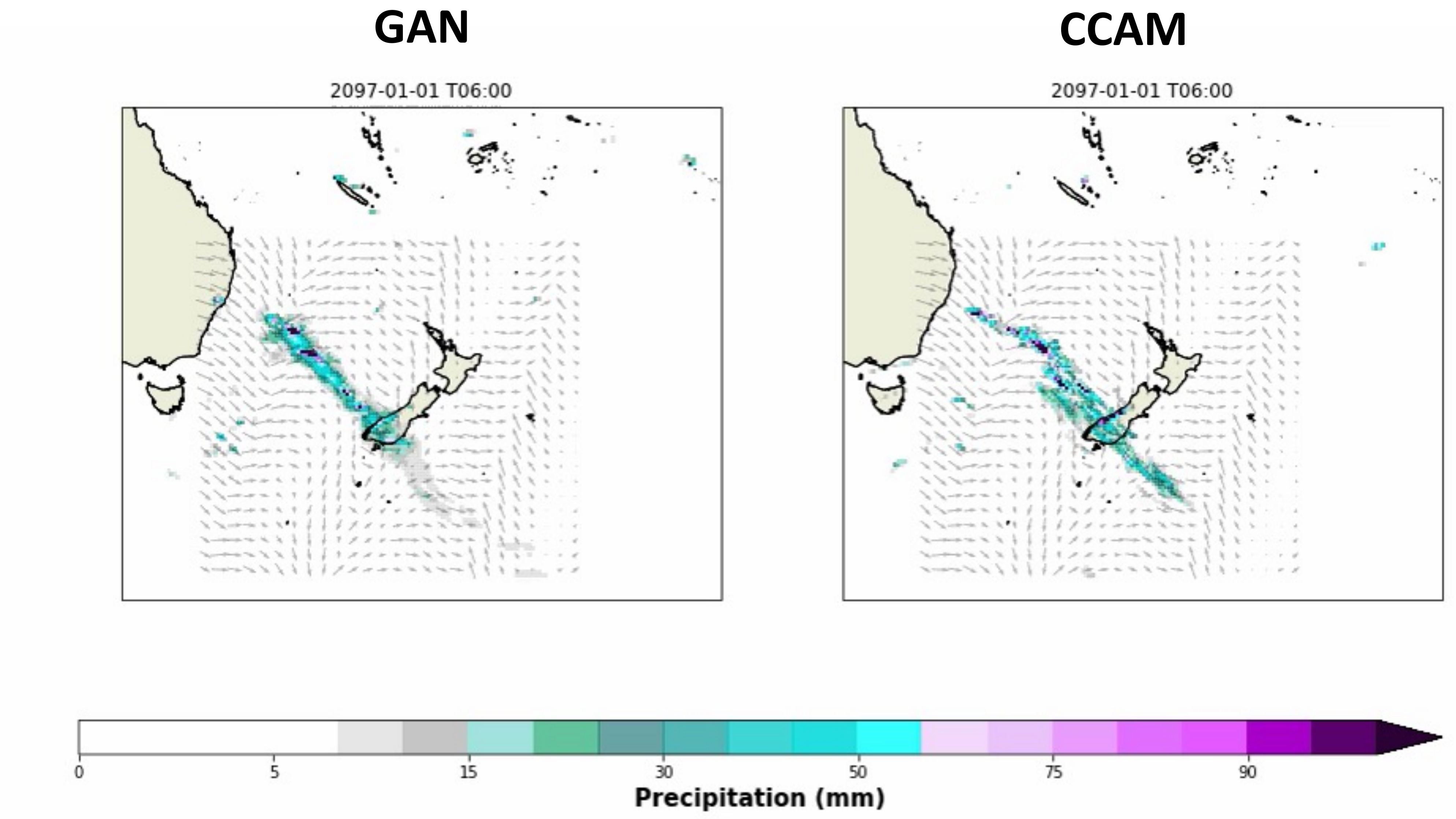


# Evaluation

- **GANs** can downscale a scenario from a GCM in less than 5 minutes on a A100GPU.
- **UNETs** tend to “smear” out precipitation and often underestimate extreme events.
- **GANs** can generate realistic spatial structures of daily precipitation, with consistent statistics.



# Sub-daily Precipitation Generation

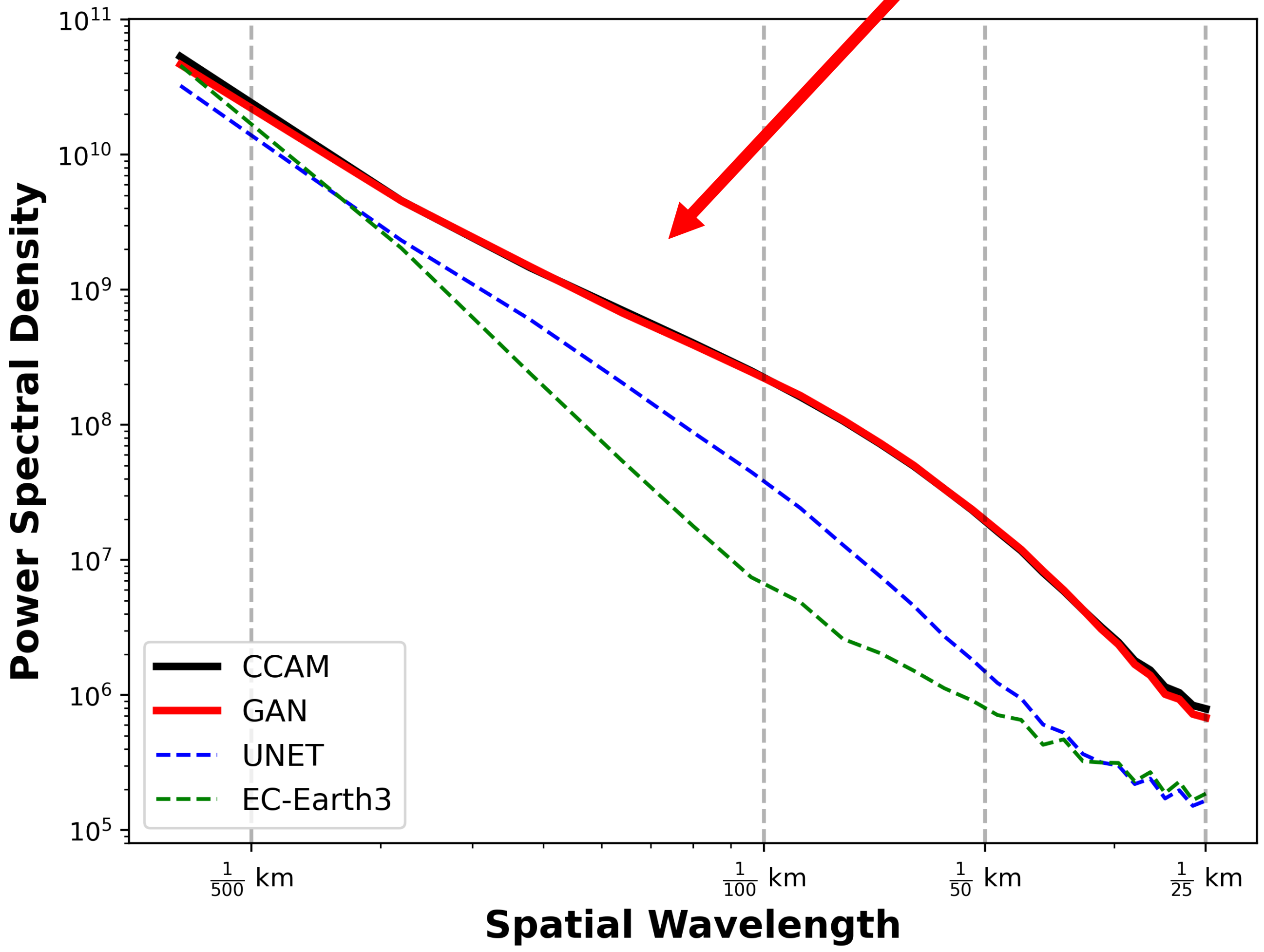


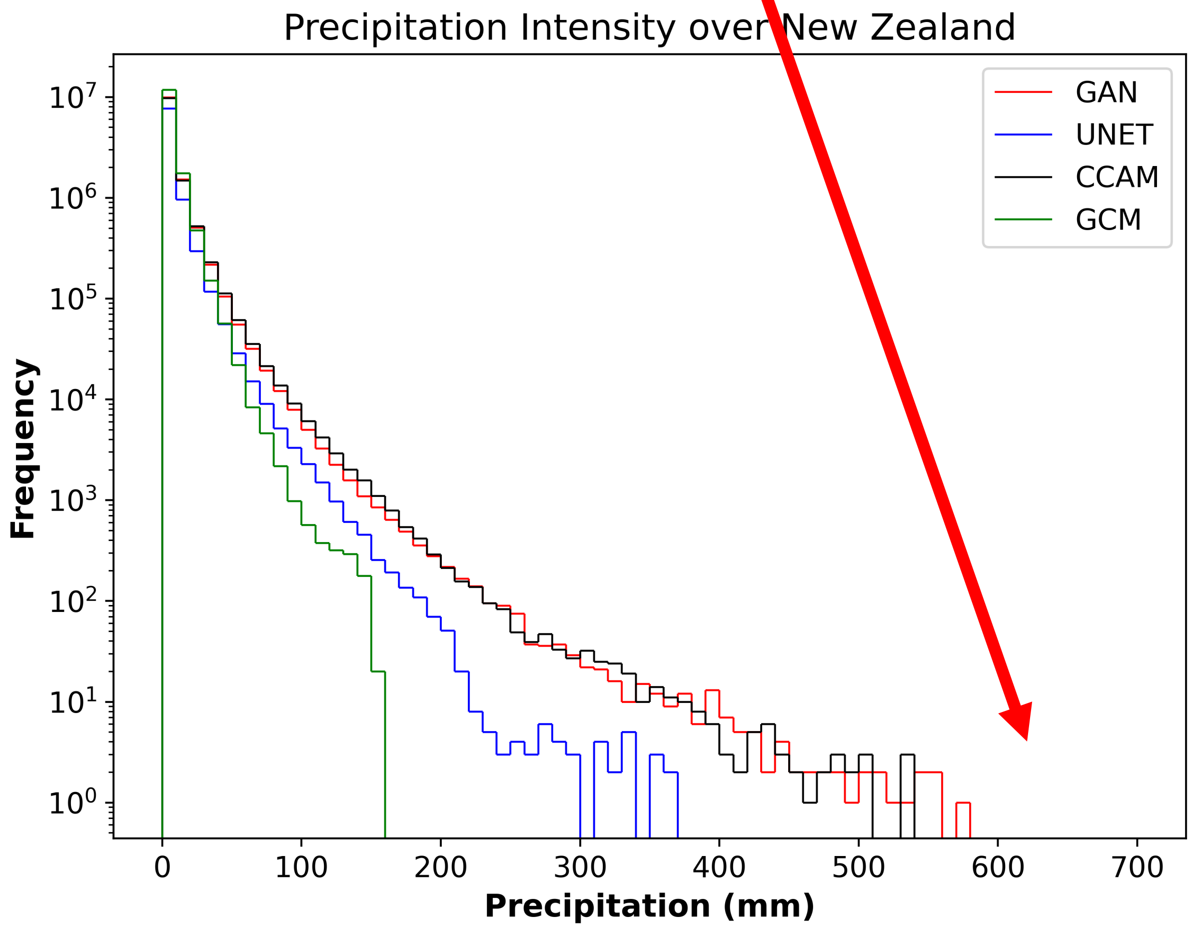
# Evaluation: Test Performance

- **10 years** (2090-2100) of ACCESS-CM2 was reserved for validation

**GANs can better capture the spatial patterns and distribution of precipitation**

**GANs better capture the distribution of precipitation extremes**



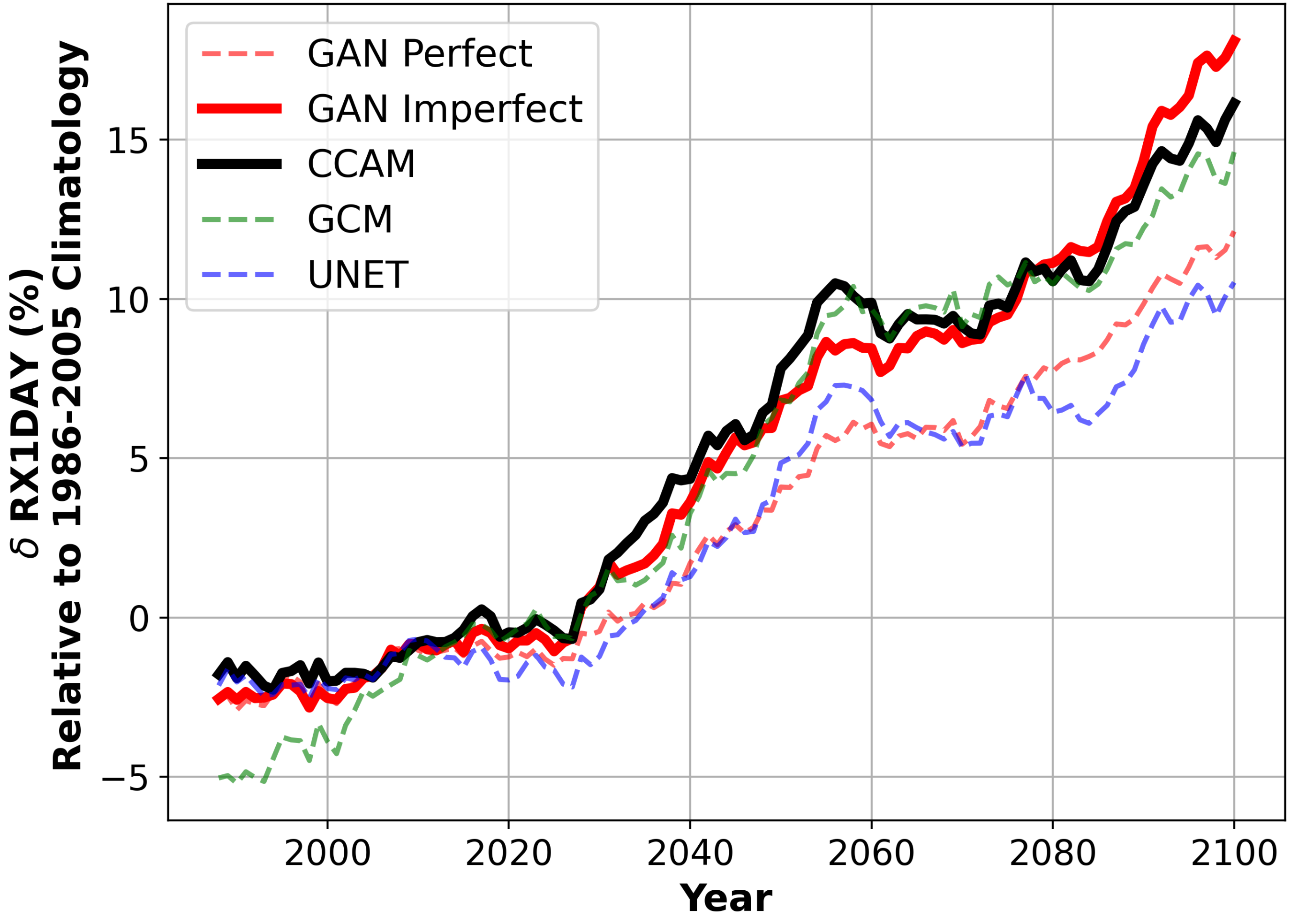



# End-of-Century RX1Day trends (EC-Earth3)

- All UNETs and “Perfect” framework models **<u>underestimate out-of-sample</u>** future RX1Day changes.

- The imperfect training framework can better capture extremes in comparison to other methods

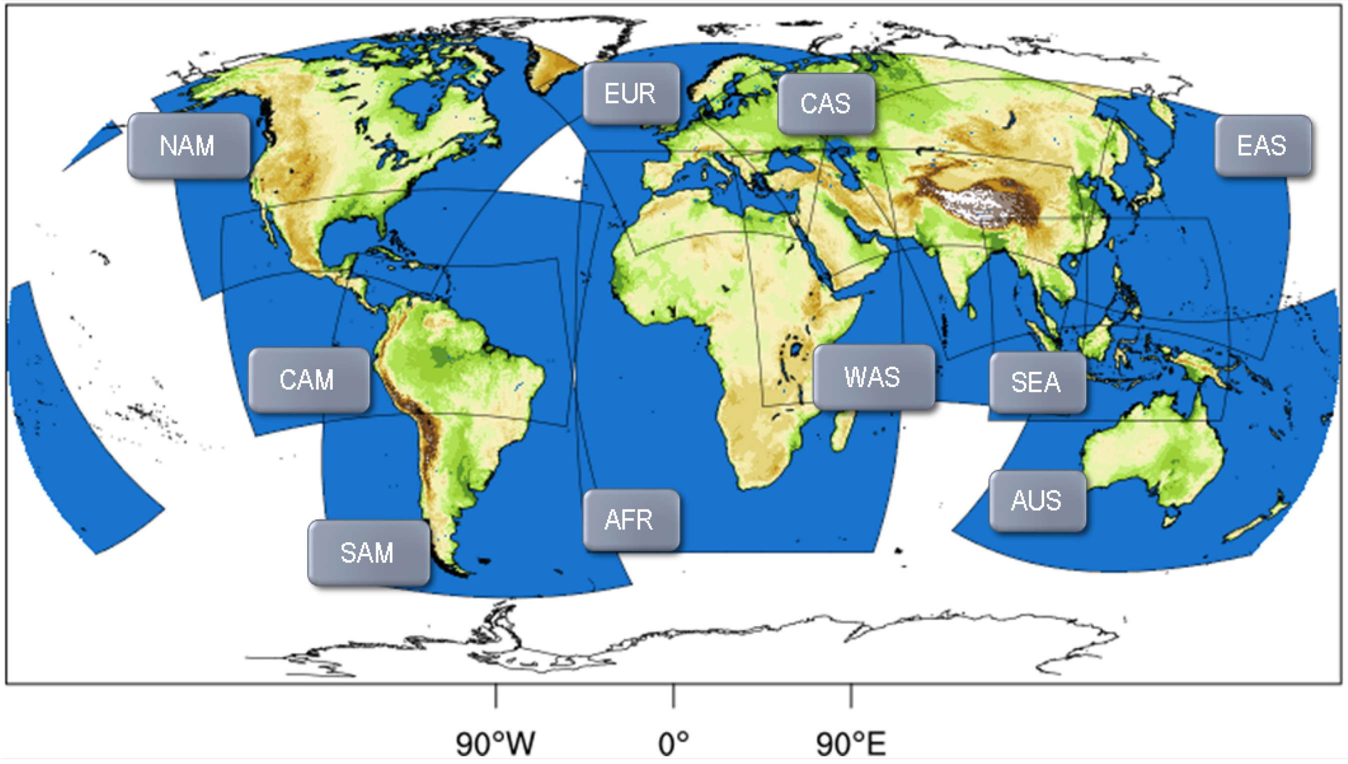
- Other metrics such as the climate change signal are well preserved all Emulators



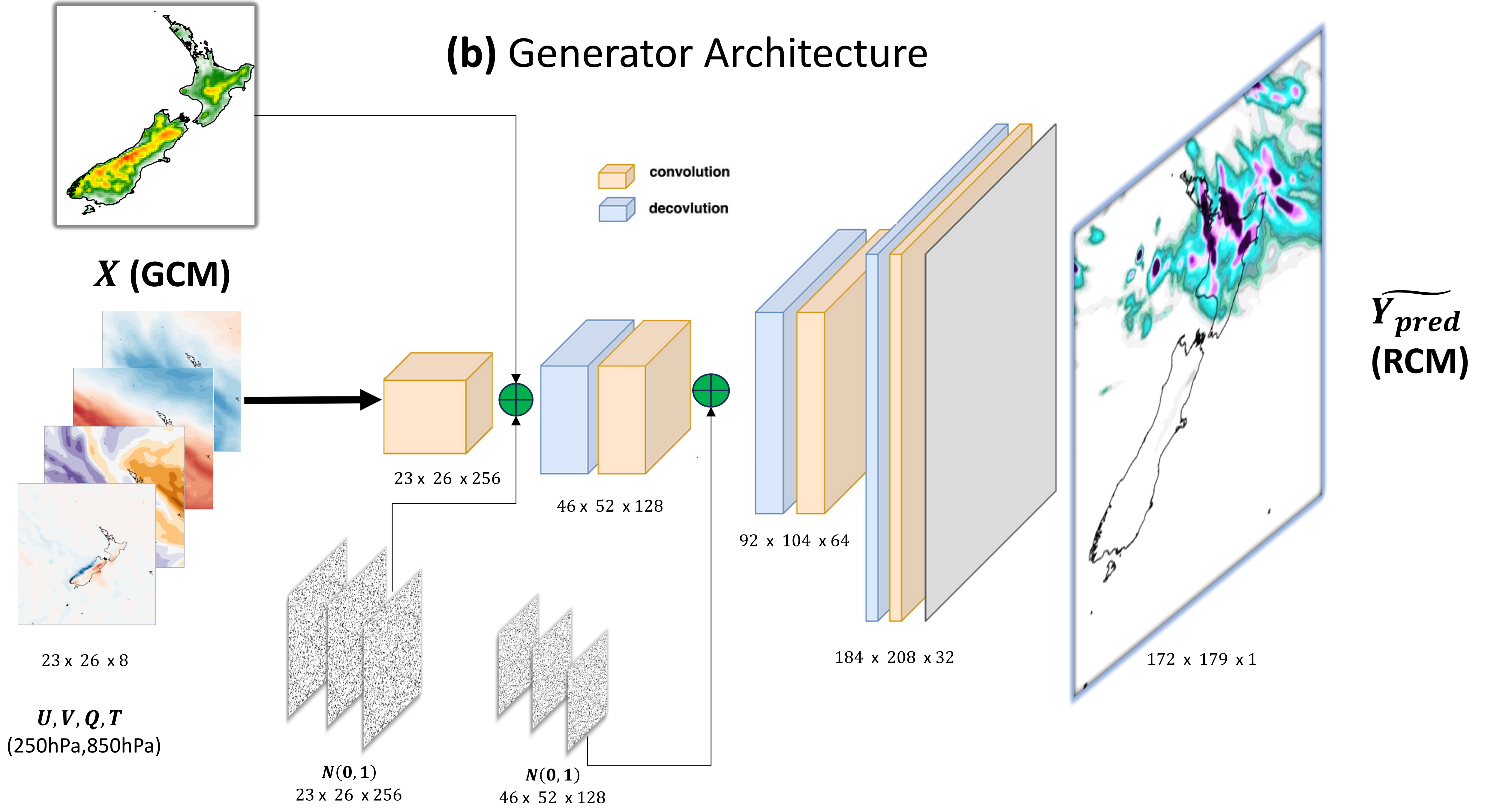
# Conclusions

- GANs better capture the spatio-temporal variability of rainfall in comparison to regressive approaches.
- GANs can better resolve the extremes of precipitation (RX1Day)
- Training in two-stages results in better out-of-sample performance for **capturing extremes**.
- We can apply our model to many GCMs

**We want to apply our methods to other domains!**

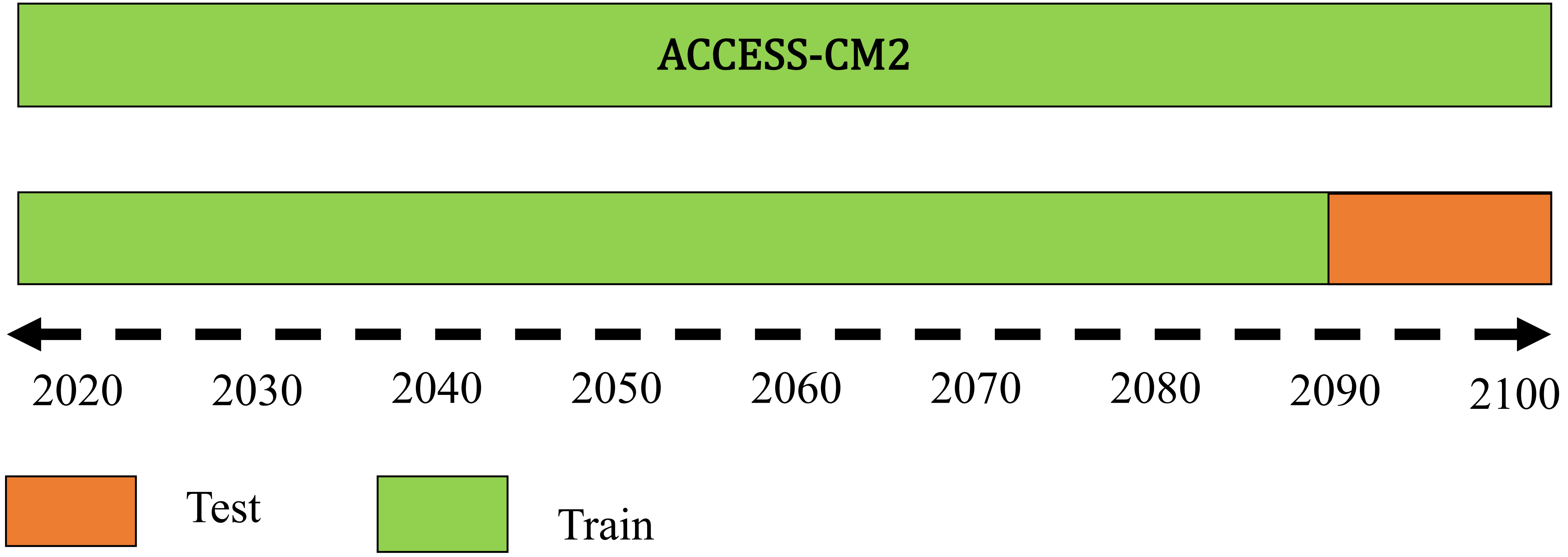



Contact: **Neelesh.rampal@niwa.co.nz**



(b) Generator Architecture
convolution
decovlution
X (GCM)
23 x 26 x 8
U, V, Q, T
(250hPa,850hPa)
23 x 26 x 256
46 x 52 x 128
92 x 104 x 64
184 x 208 x 32
172 x 179 x 1
N(0, 1)
23 x 26 x 256
N(0, 1)
46 x 52 x 128
Y_pred
(RCM)

# Training Data

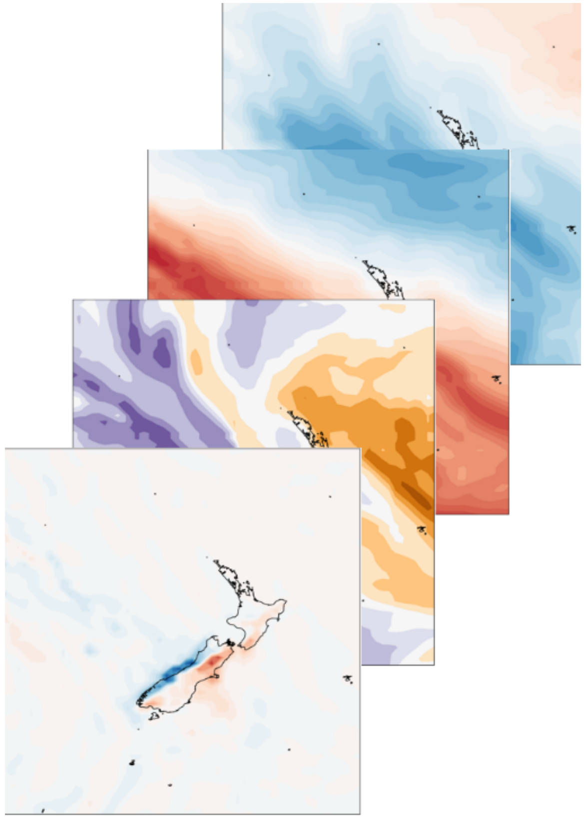


# Training Data

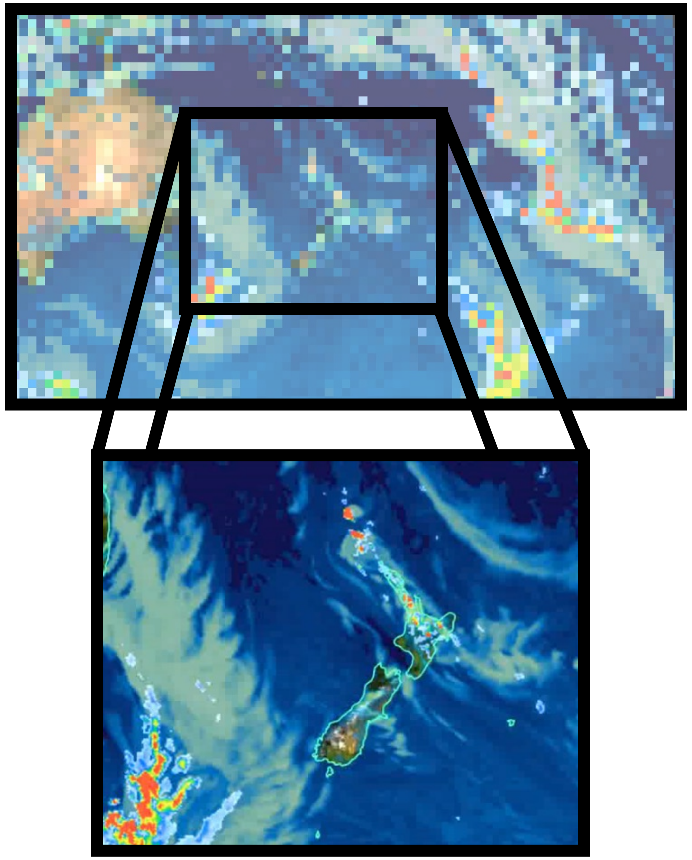
- We train on daily averaged prognostic fields from **ACCESS-CM2 (31000 days).**

- **ACCESS-CM2** is re-gridded to a resolution of $1.5°$.

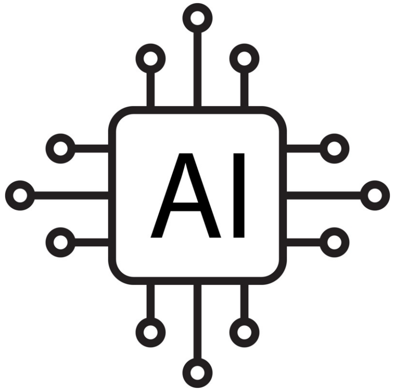
- We use $U, V, Q, T$ as predictor variables at two pressure levels.



**ML RCM Emulator**



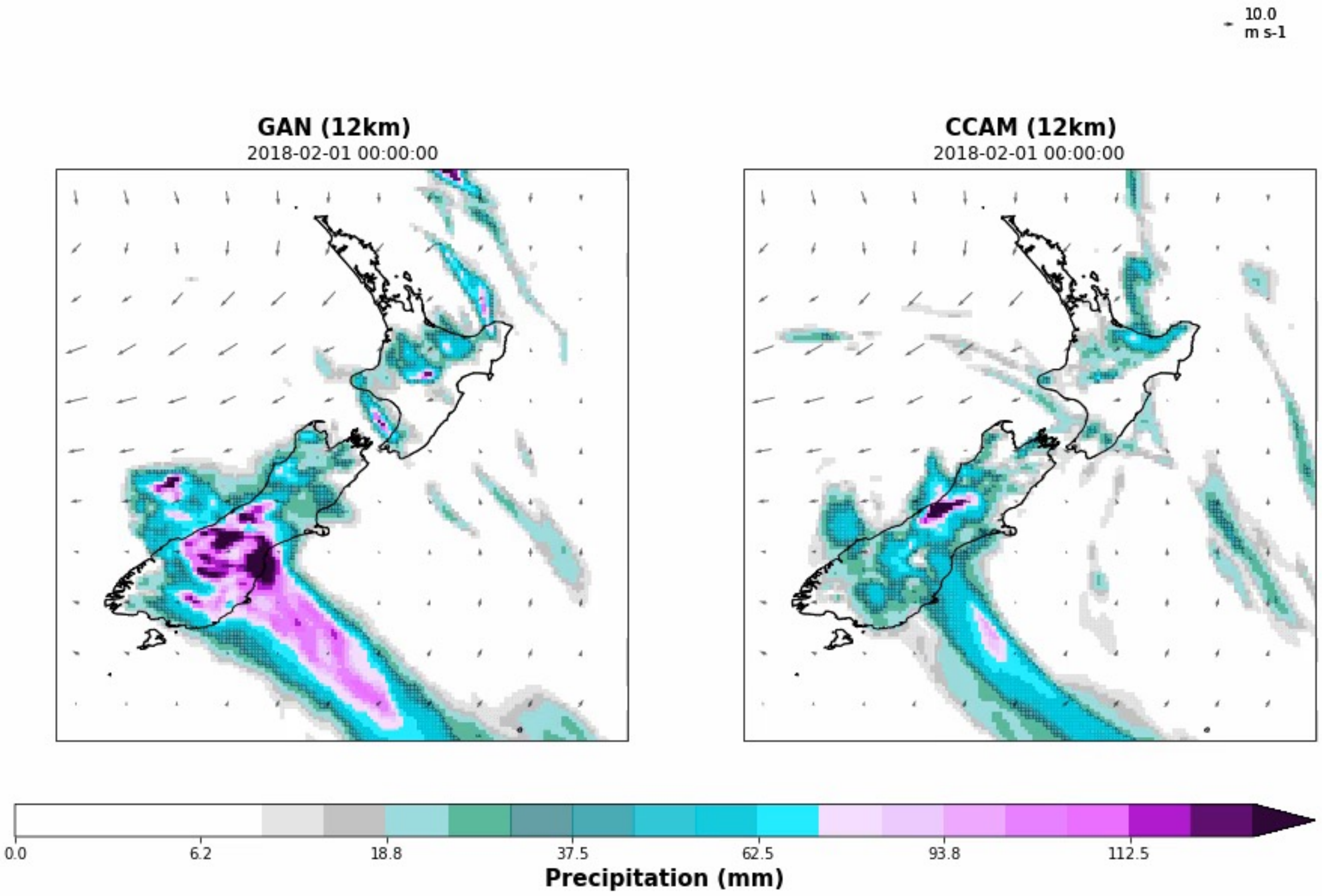
30 **GCMs** (~100km) from the CMIP6 archive are selected




**Trained Emulator is applied to the GCM outputs**

GCMs are “dynamically downscaled” with an **RCM** to 12km

# Extreme Events in ERA5 (Training time)



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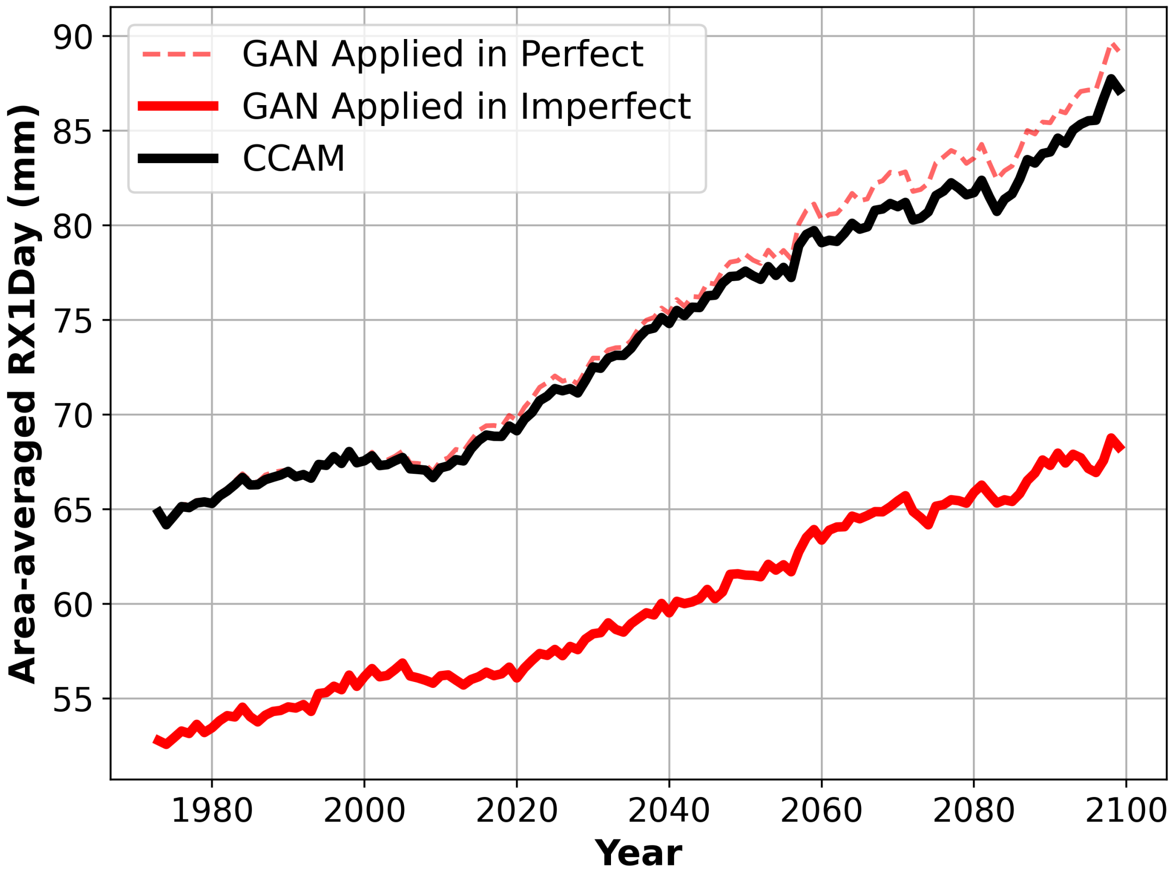


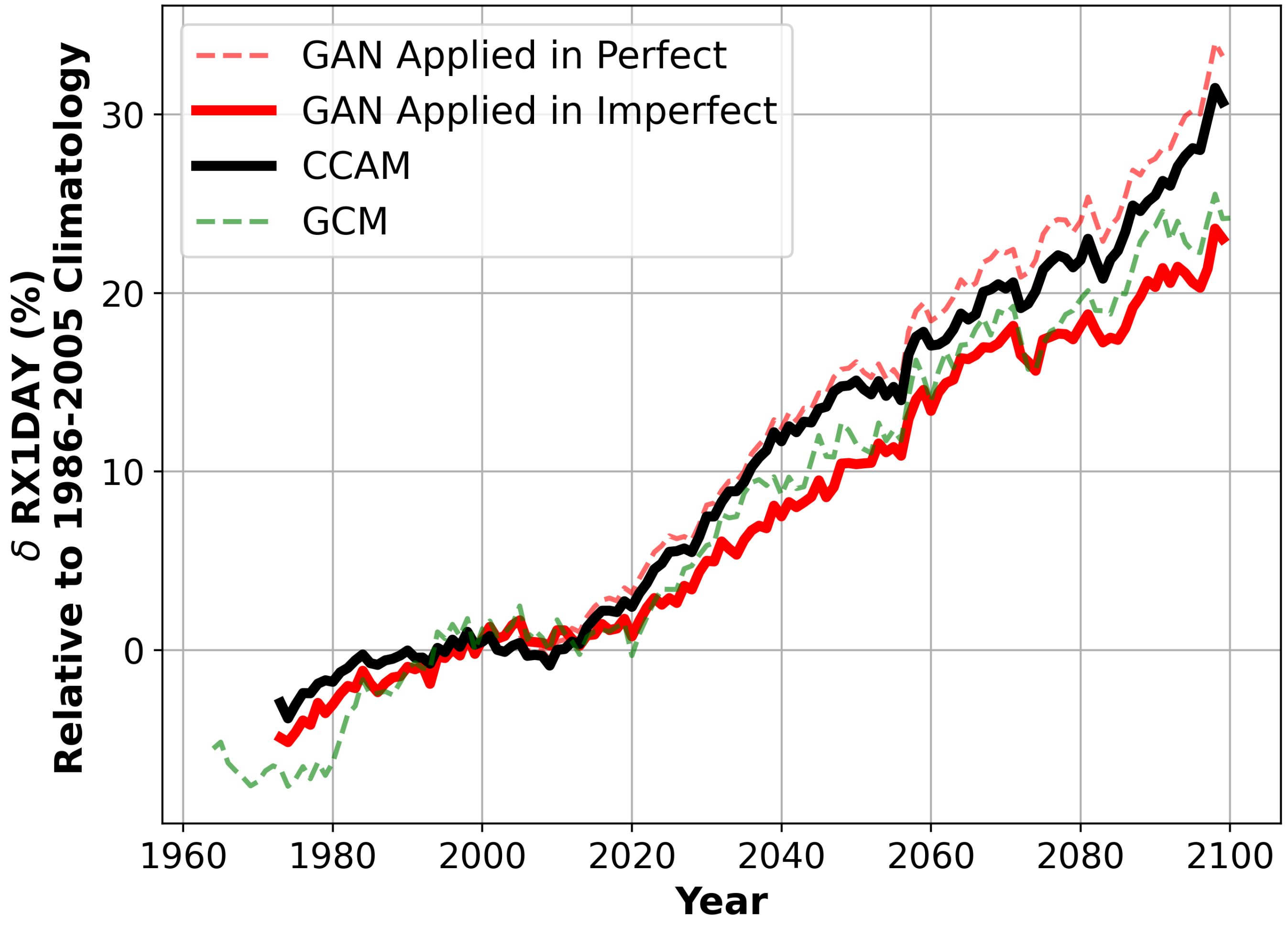

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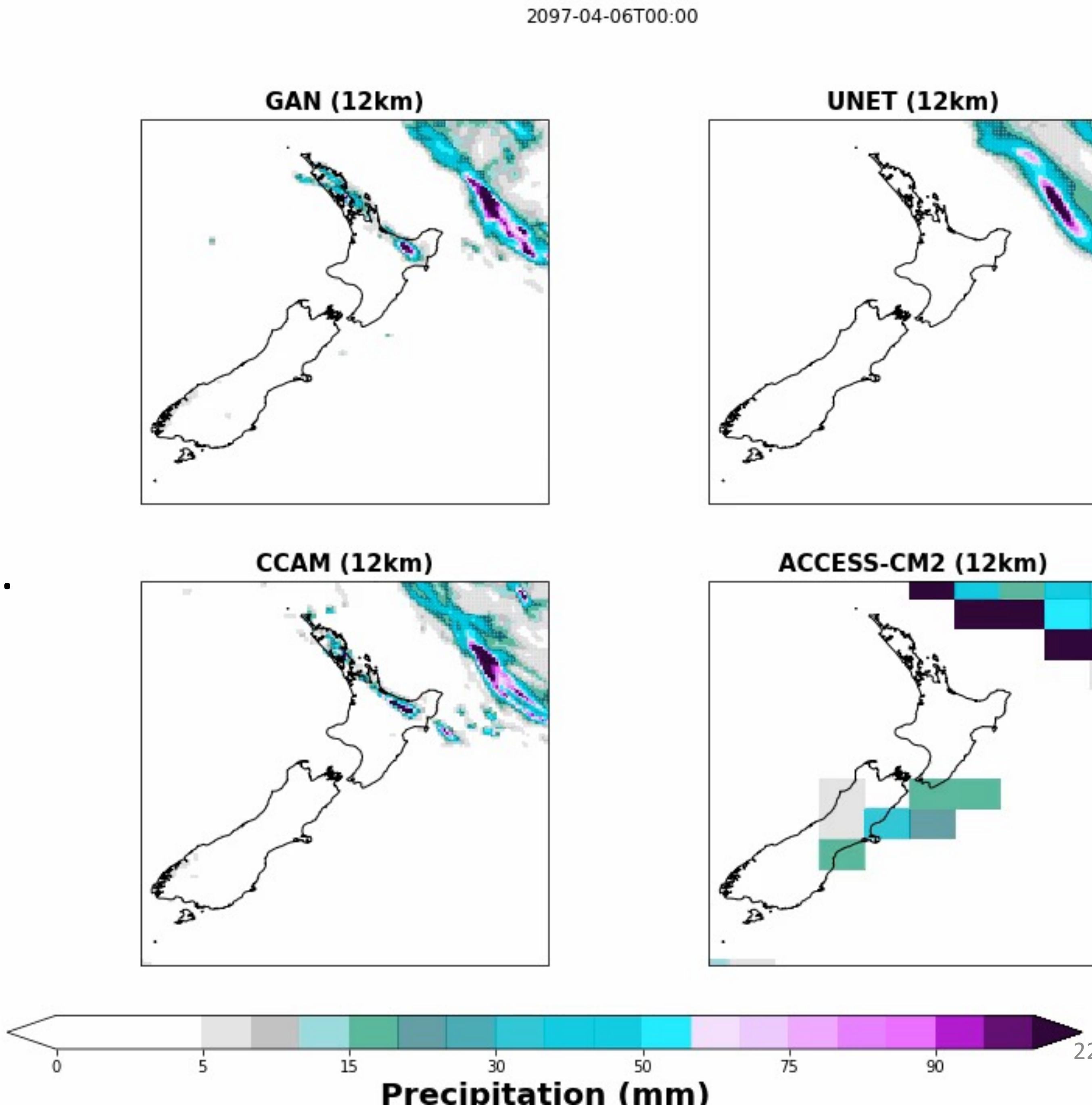
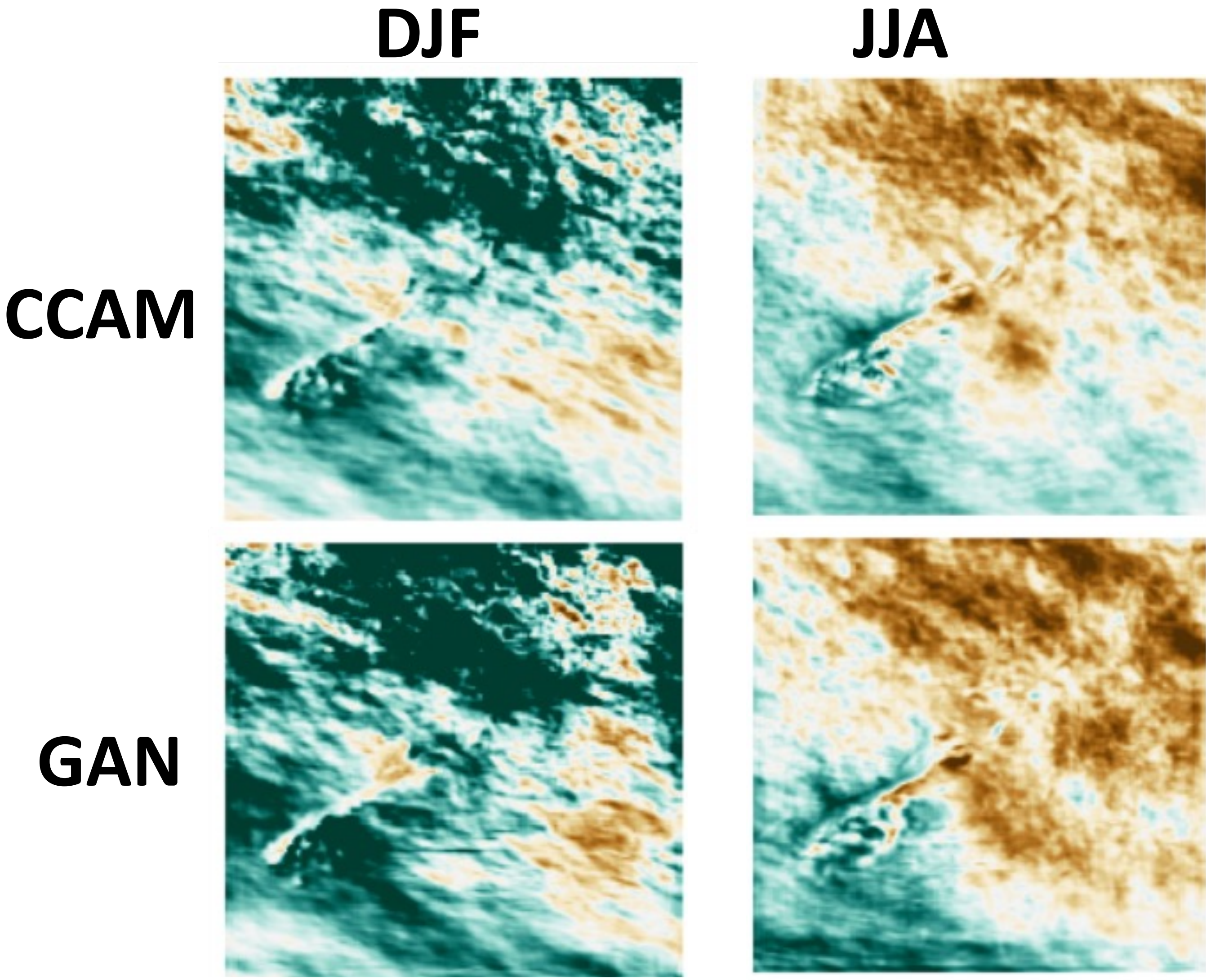


# CC Signal: ACCESS-CM2 (In sample)

- Climate Change Signal is the % change in End-of-century precipitation (2080-2099) relative to the historical period (1986-2005)

- The imperfect framework GAN nearly perfectly conserves the CC signal.



# Out of Sample (EC-Earth)

- All methods reproduce CCAMs CC signal accept during MAM.
- UNETs CC signal is too “smooth”.
- During MAM there is poor agreement between EC-Earth3 and CCAMs CC signal