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Climate, Freshwater & Ocean Science

Regional Downscaling of Climate Data using Deep Learning and Applications for Drought / Rainfall Forecasting

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What are General Circulation Models (GCMs)?

- GCMs are computer models that <u>**try**</u> <u>to</u> physically simulate the climate and all its of processes at 100 – 200 km resolution.
- Even with today's fastest computers, an ideal model that can **resolve processes such as clouds** is computationally impossible.

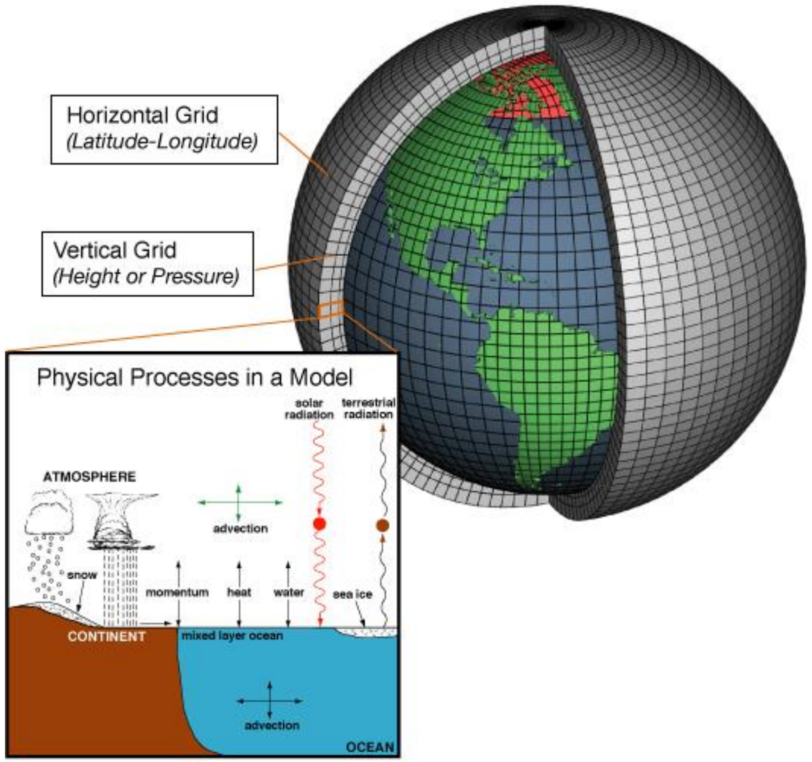


Figure 1: An illustration of the grid for which the computer model is run on (from NOAA).

What are General Circulation Models (GCMs)?

- Small scale processes are represented by parameterizations or relationships (often statistical).
- **GCMs aren't perfect;** they are flawed mostly due to poor representation of resolution dependent processes (e.g., clouds, convection).

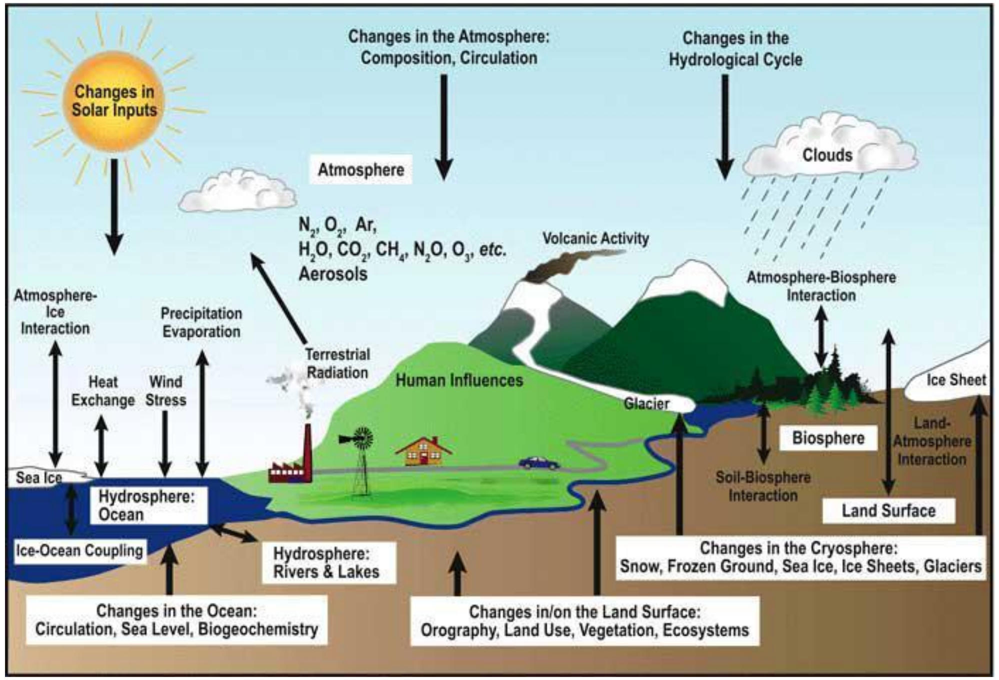


Figure 2: An illustration of the variety of different processes parameterized in a GCM (From Le Treut et al., 2007).

Why are GCMs useful?

- GCM can **simulate changes in climate** as a result of "slow" changes in external forcing's (e.g., Greenhouse gases)
- Projections of climate have important implications on policy making (e.g., setting emission reduction targets), insurance, businesses etc.
- GCMs are **dynamically downscaled** through a Regional Climate Model (RCM) to provide localized climate projections.

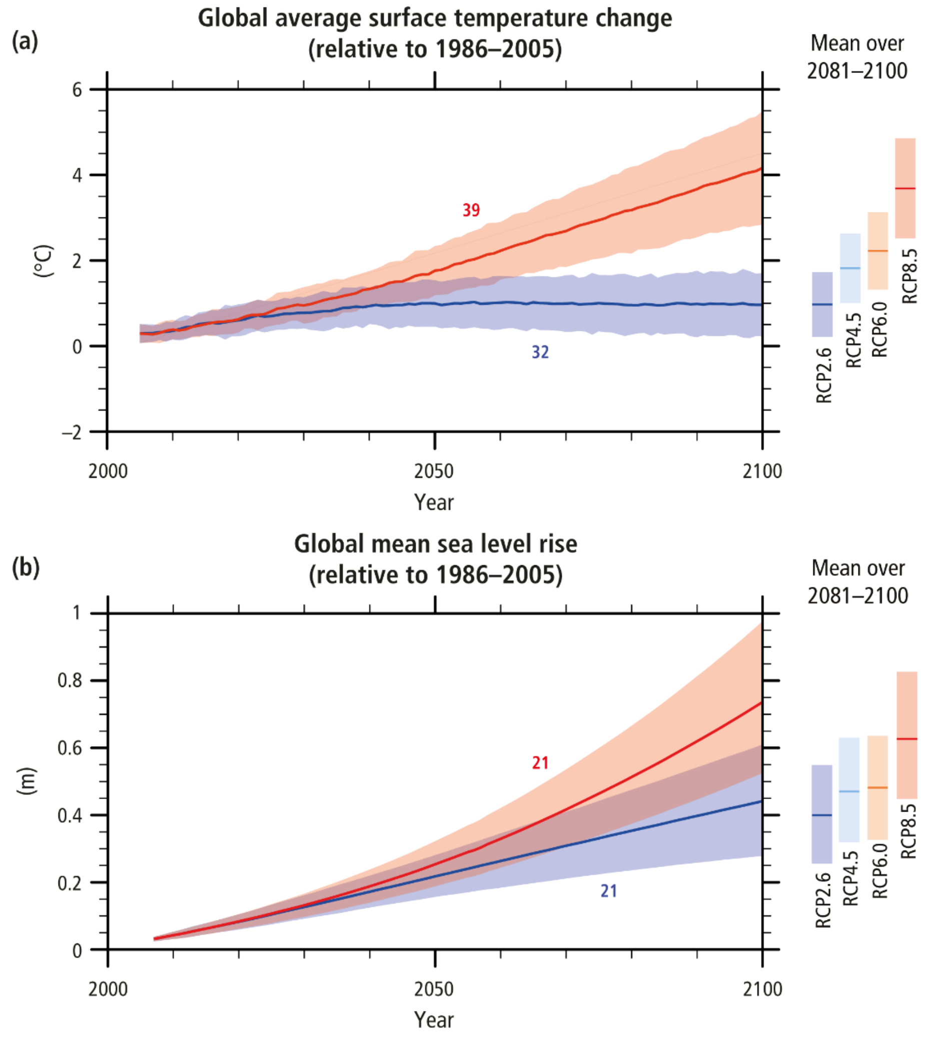


Figure 3: Projected temperature and sea-level change for a variety of RCP scenarios (from IPCC).

What is Dynamical Downscaling?

- “Downscaling” techniques follow two complementary approaches – statistical and dynamical.
- Statistical techniques use relationships between resolved GCM large-scale climate patterns and observed local climate responses.
- Dynamical techniques use high resolution regional simulations to dynamically extrapolate the effects of large-scale climate processes.

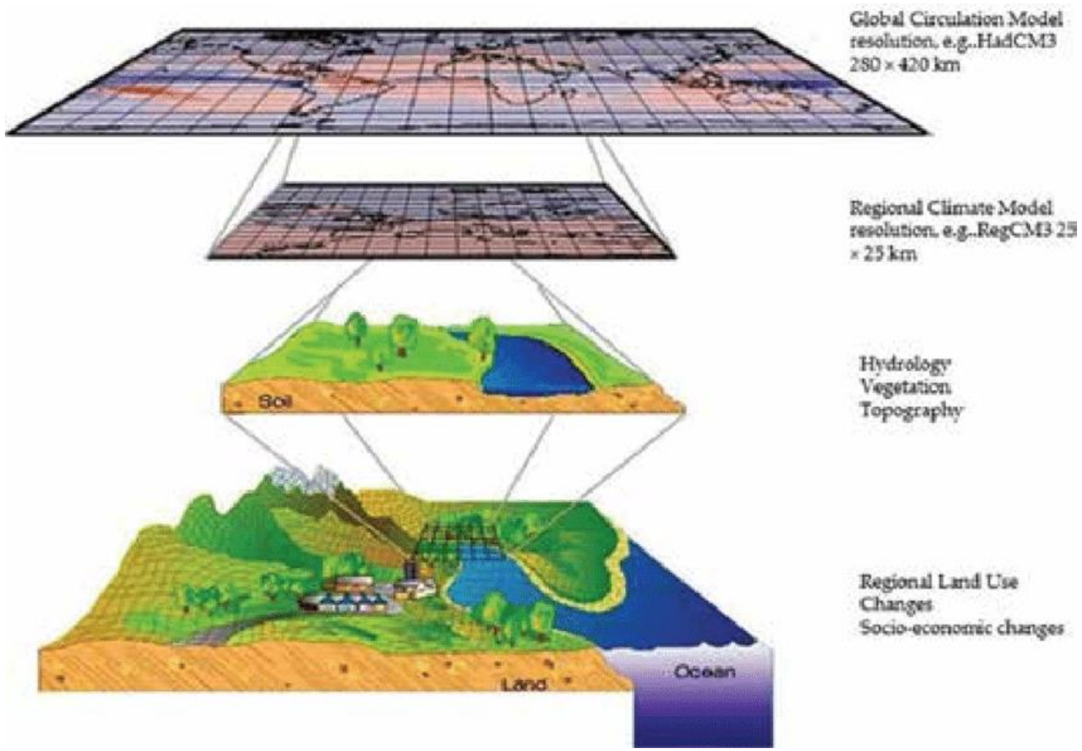


Figure 4: An illustration of the steps required to downscale climate change projections (NOAA).

Limitations of Dynamical Downscaling?

- Biases from GCMs can propagate through the RCM.
- Computationally very expensive.
- Locally processes are still not resolved (winds over complex terrain) and lead to new biases.

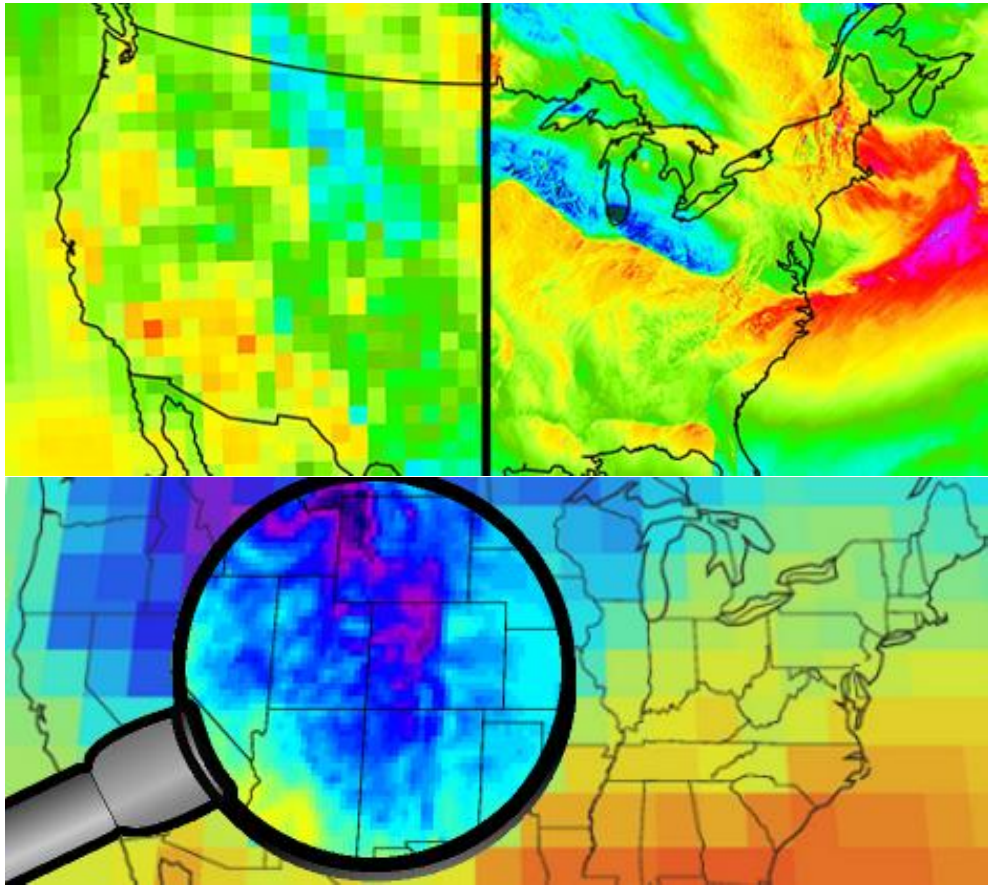


Figure 5: Super-resolution climate model downscaling using Machine Learning (NOAA).

A Vision for Numerical Weather Prediction and GCM

The grand challenge is to produce reliable high-resolution data for studying climate change impacts

- Using a blend physics-based model and data-based model to downscaled high resolution RCM and GCM outputs.
- Data-based models will learn to account for GCM biases and provide physically consistent, accurate and high-resolution projections.

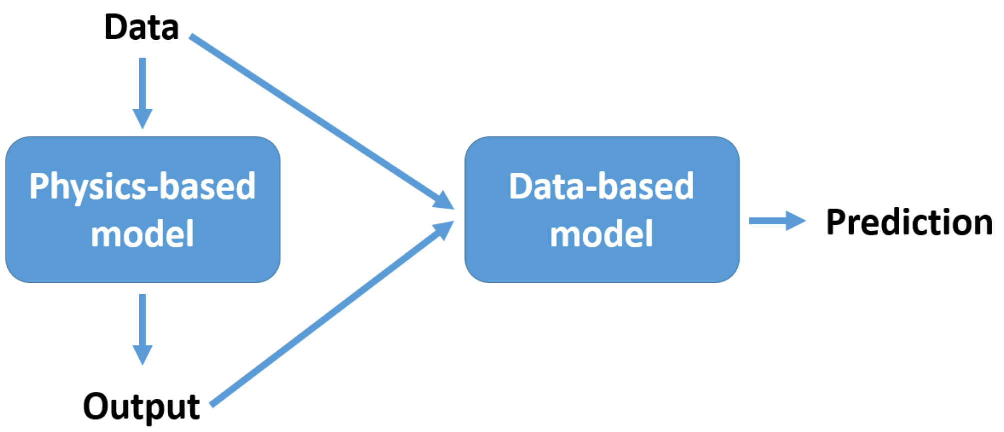


Figure 6: A flow diagram of a hybrid machine learning and data-driven pipeline (from Karpatne et al., 2018).

A Vision for Numerical Weather Prediction and GCM

- Removing the “black box” of machine learning by incorporating physics-based constraints (increasing interpretability).

$$\arg\min_{f} \underbrace{Loss(\hat{Y},Y) + \lambda\, R(f)}_{\text{Typical loss function}} + \underbrace{\lambda_{PHY}\; Loss.PHY(\hat{Y})}_{\text{Physical Inconsistency}}$$

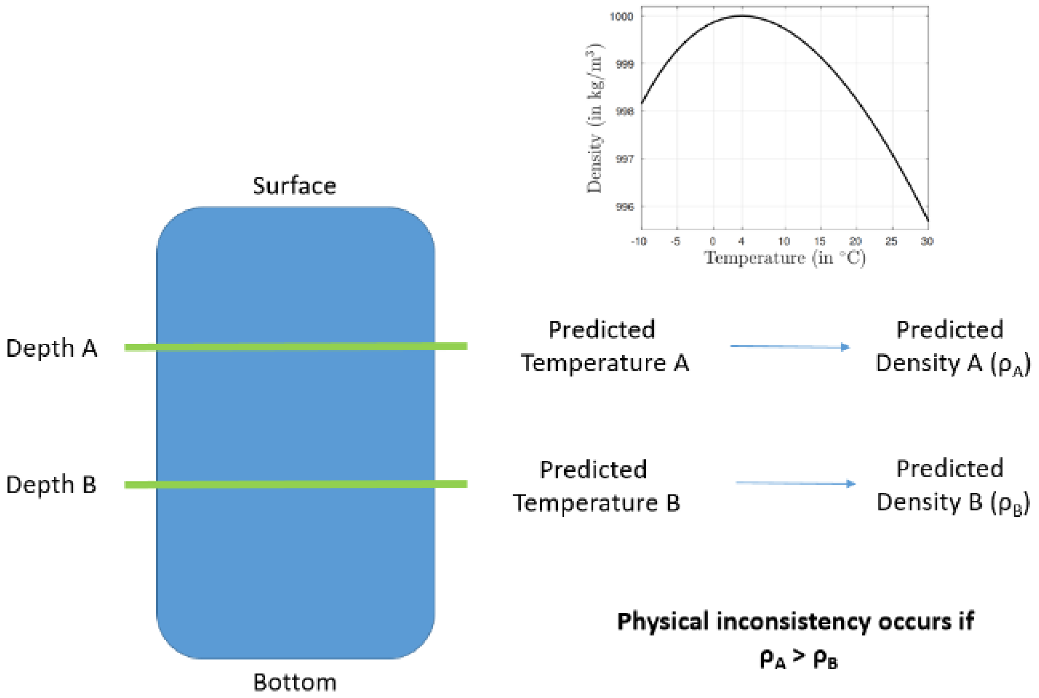


Figure 7: An illustration of how to incorporate a physics-based loss function into a model (left), and an illustration of how to assess physical inconsistency (right). Figure from (from Karpatne et al., 2018)

Example Case Studies

- Super-resolution satellite imagery
- Lightning Forecasts from NWP outputs.
- Location-based rainfall downscaling.

Producing High Resolution Cloud fields

- Training a Pre-trained UNET model (using transfer-learning) to reconstruct a blurred satellite image.
- Using physics-based metrics to assess physical consistency of the reproduced fields (e.g., sub-pixel heterogeneity, 2D Fourier Transform).
- **Training**: 2000 MODIS satellite images - 200 pixels (km) by 200 pixels (km).
- Methodology adapted from Hu et al., 2019

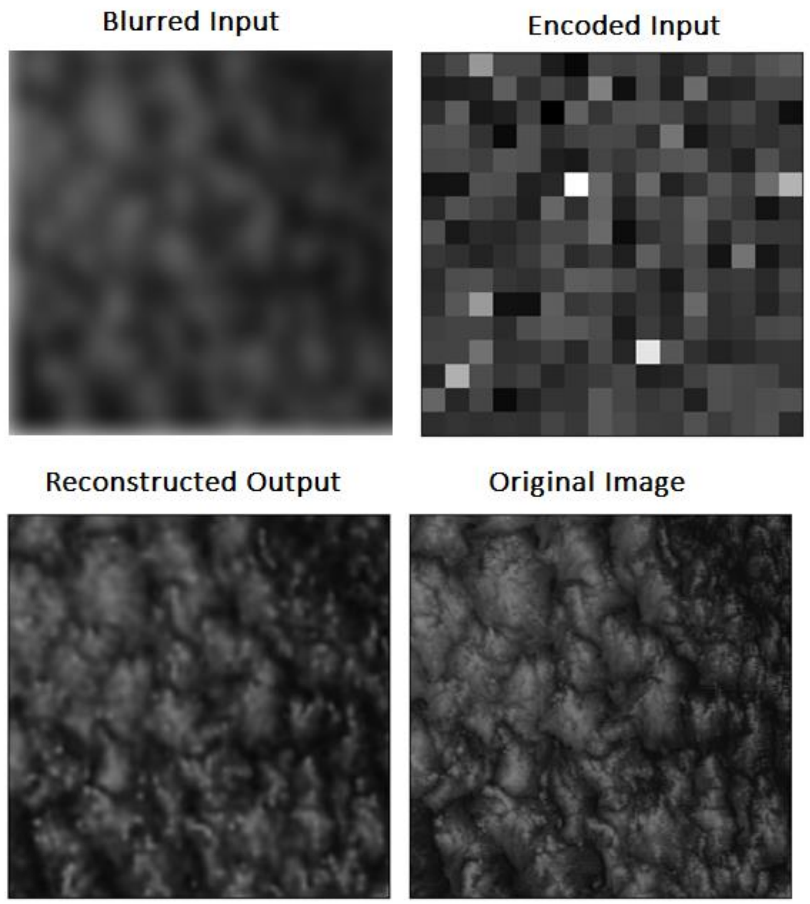


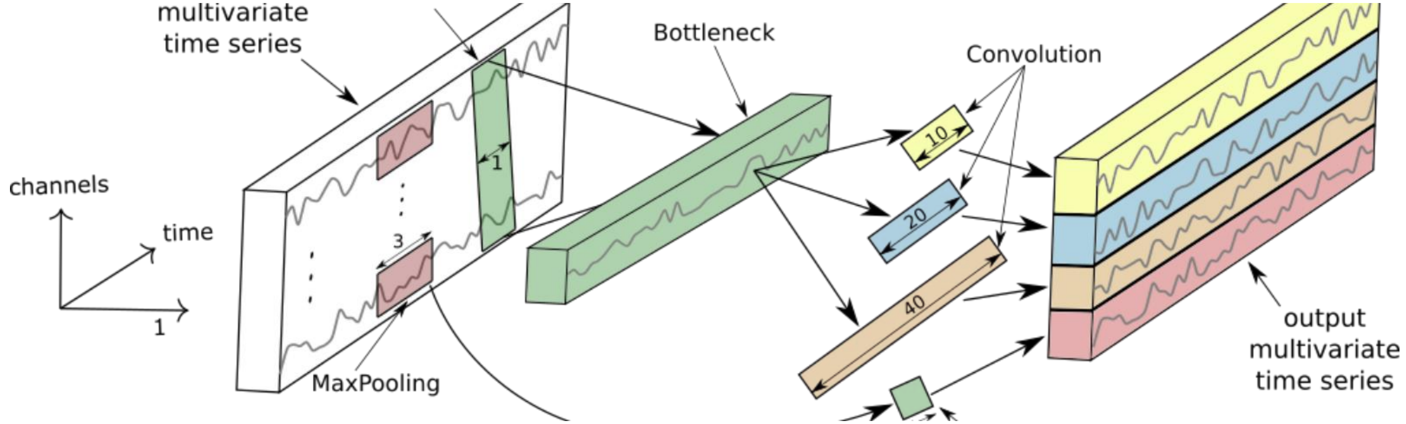
Figure 8: Super-resolution image reconstruction using UNET
(data from Rampal, N. and Davies, R., 2020)

Producing accurate Lightning Forecasts

- Inputs: Forecasts of a variety of variables (e.g., humidity, divergence, temperature).
- Outputs: Lightning Risk for a given time window.

Training:

- 3 years of forecast data and observations (once daily) – 48 hours lead time.
- **4 times the accuracy over modelled lightning!**



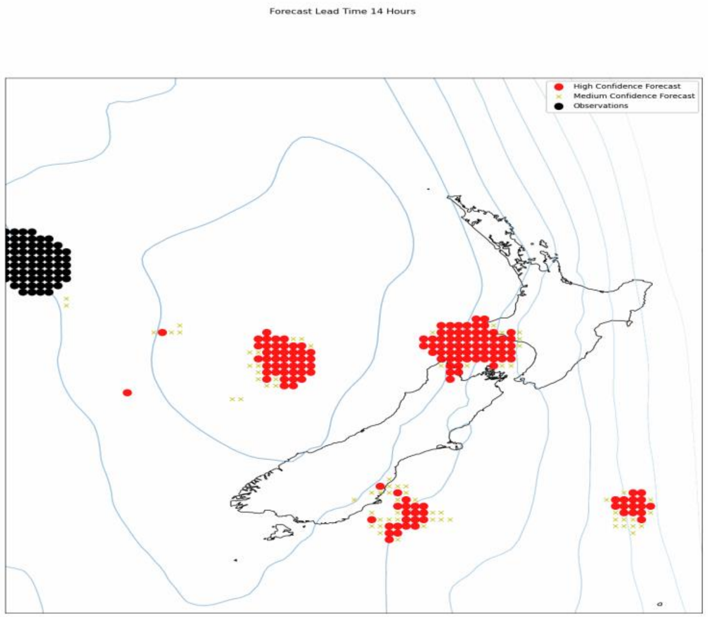


Figure 9: Bottle neck architecture used for AI lightning forecast (top), an illustration of a lightning forecast (bottom).

An Experimental Pipeline for Rainfall Downscaling (NeSI consultancy)

- Using a wide variety of climate predictors / indices (lagged 96 months) to predict the monthly rainfall anomaly at a single site.
- A wide variety of models (e.g., CNNs, MLPs, Linear Regression) were trained simultaneously using a ***Snakemake*** pipeline developed by NeSI.
- The pipeline enabled us to become more efficient with our workflows and experiments.

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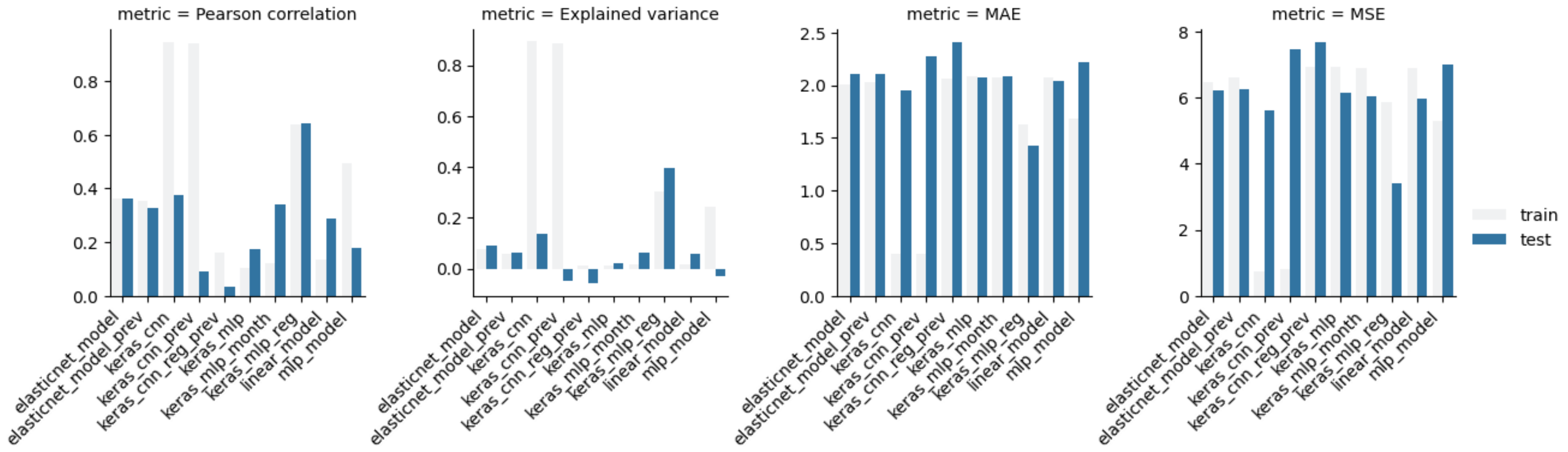

Figure 10: Model scores/metrics from the ***Snakemake*** pipeline.

An Experimental Pipeline for Rainfall Downscaling (NeSI consultancy)

- Regularized MLP models significantly outperformed all other models.
- The regularized MLP model explained over 50% of the variance in rainfall.
- Other models only explained between 10 -15 % of the variance in rainfall.

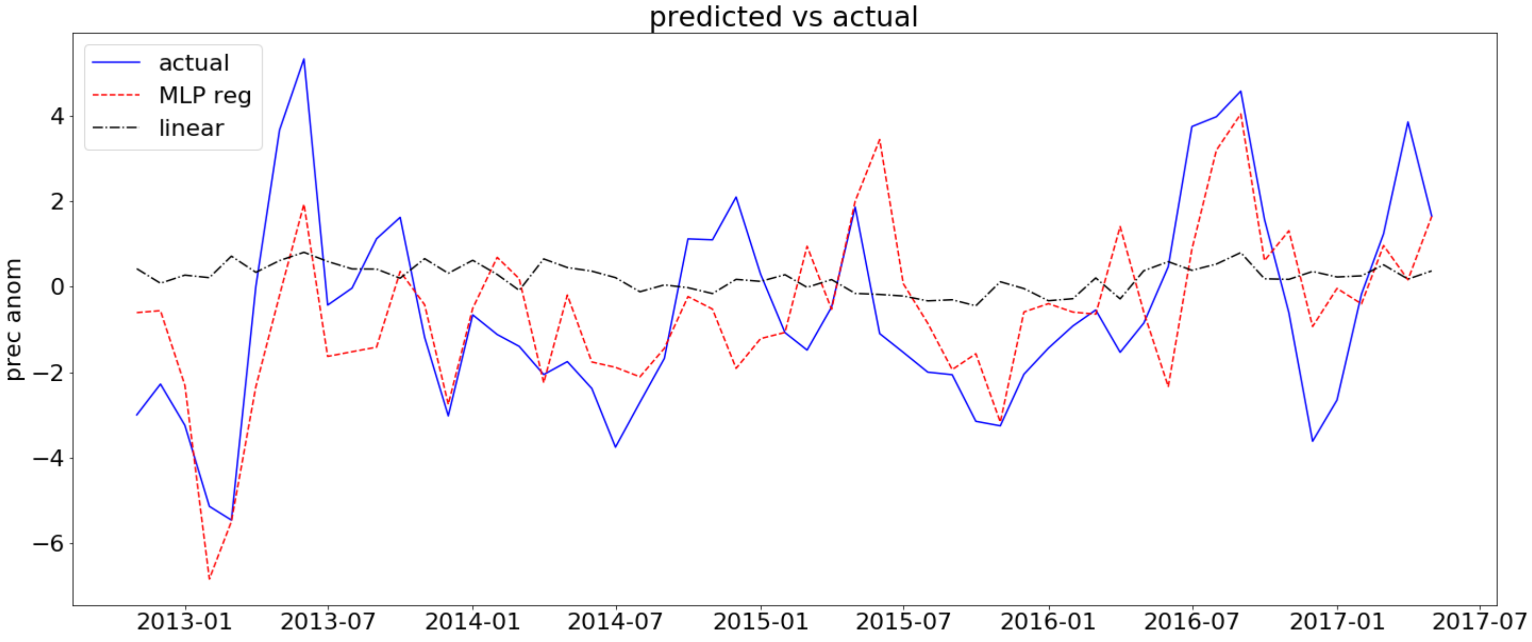

Figure 11: An example rainfall hindcast using a regularized MLP model, results are compared to a linear baseline.

Where to Next?

- Two-Dimensional downscaling of climate data using GANs.
- Exploring Convolutional LSTM to capture spatio-temporal relationships.

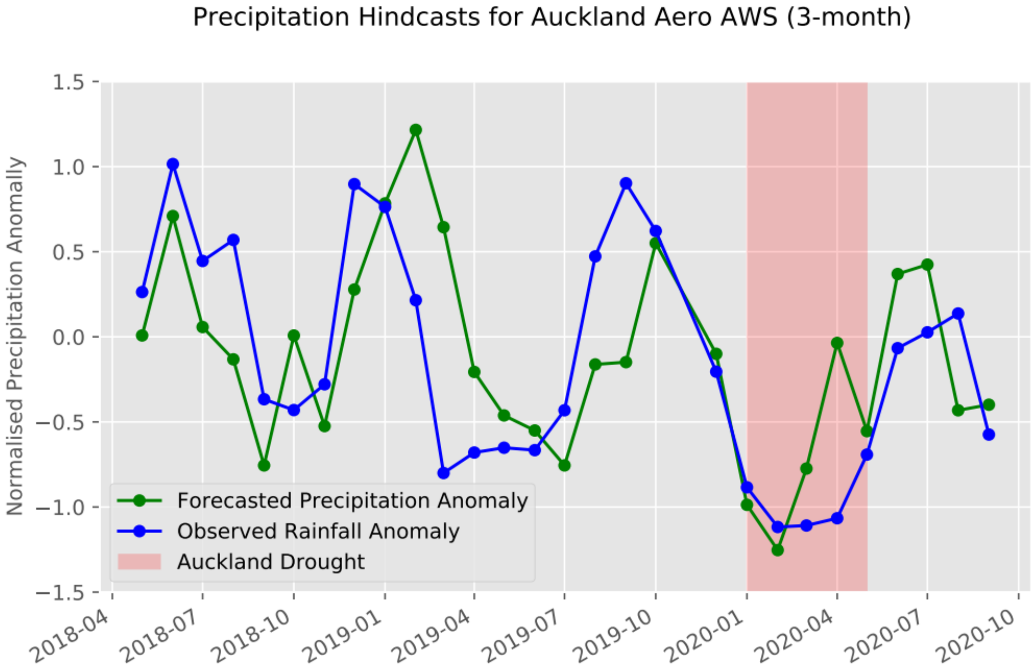

Figure 12: A 2020 drought hindcast for Auckland.

Thank You!

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