

# Guided by Artificial Intelligence: New Zealand's first sub-seasonal drought forecast

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## Introduction

Sub-seasonal-to-seasonal (S2S) weather prediction models are typically run at resolutions of  $\sim 50$  km. This coarse resolution does not provide the detail required for local-level decision making. Our approach uses artificial intelligence (AI) to enhance the resolution or downscale S2S forecasts from a 50km resolution to 5km (Figure 1). Here, we create a 5km resolution forecast of the New Zealand Drought Index (NZDI) which is dependent on four drought indicators: the standardised precipitation index (SPI), soil moisture deficit (SMD), soil moisture deficit anomaly (SMDA), and the potential evapotranspiration deficit (PED).

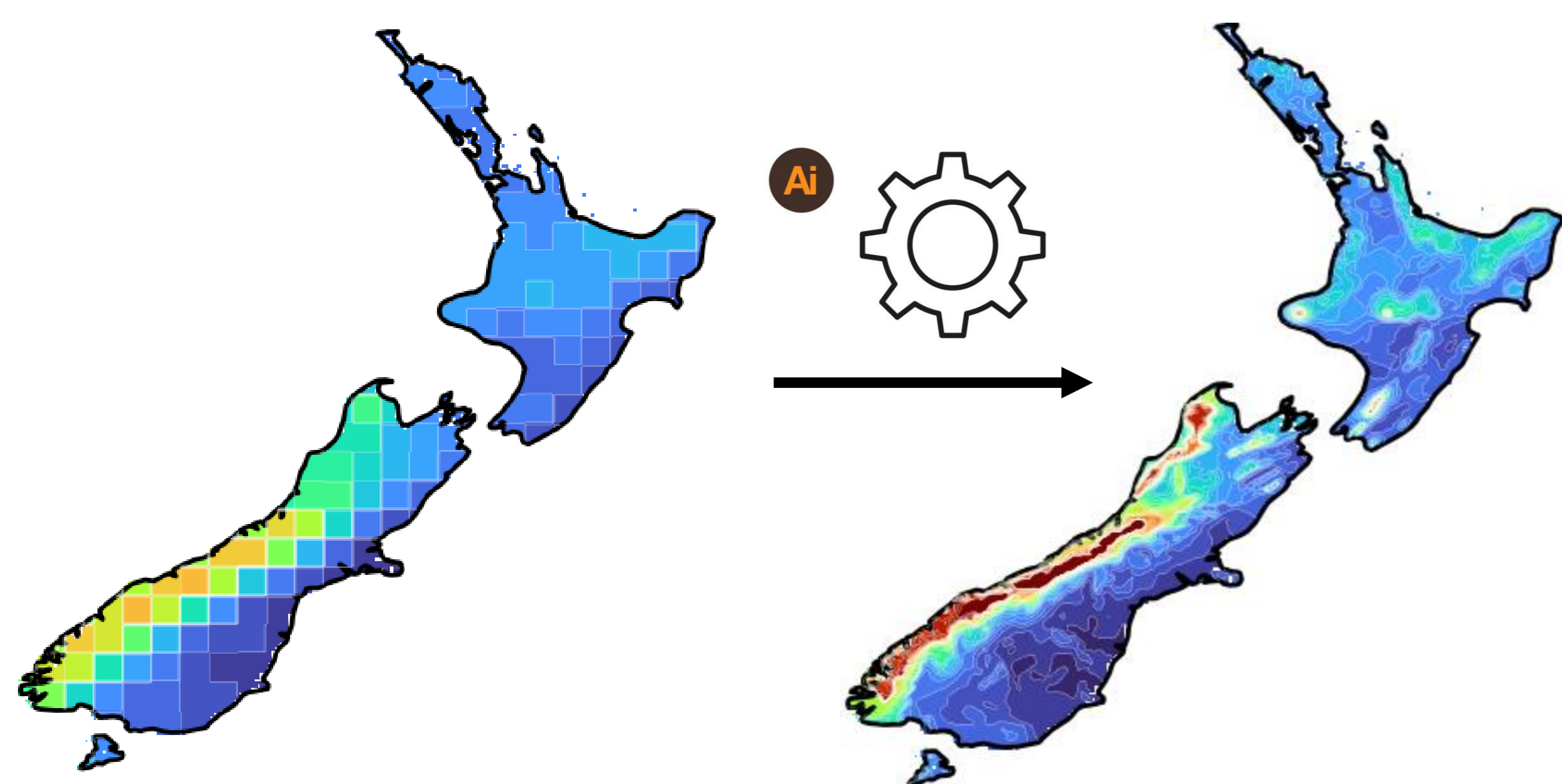


Figure 1: AI enhances the resolution of the original rainfall forecast (left) and provides a high-resolution weather forecast (right).

## AI Workflow for Post-processing S2S forecasts

To create a 5km resolution S2S forecast of the NZDI, we first need to **downscale** the S2S ensemble forecasts from National Center for Environmental Prediction (NCEP) from its native resolution of 50km to a 5km resolution for each of the drought indicators.

### AI-based Downscaling

Training an AI-based model is analogous to any regression problem, where the AI-based model is trained to learn a mapping from  $X$  to  $y$ . Here, we trained a spatio-temporal Convolutional Neural Network (CNN) using prognostic variables from 6-hourly ERA5 re-gridded to a resolution of 50km as predictors ( $X$ ) to predict gridded potential evapotranspiration (PET) and daily rainfall ( $y$ ) on the NZ Virtual Climate Station Network (VCSN) grid, which has a resolution of 5 km. The CNN learns to associate large-scale reanalysis ( $u, v, w, q, t$ ) at 1000 hPa, 850 hPa and 200 hPa to rainfall and PET [2]. The CNN is trained on over 45 years of observations.

### Applying the AI model to S2S Forecasts

The operational workflow of applying our AI model to forecast meteorological drought is summarized in Figure 2, and is outlined below.

- The trained AI model is applied to the outputs of the 31-member ensemble forecast provided by NCEP, which has a lead-time of 35-days and is run daily.
- The downscaled rainfall and PET forecasts are embedded in a water-balance model, which also takes into account the antecedent observations of soil moisture. The downscaled rainfall is also used to create a 60 day SPI ensemble forecast by combining the forecast with the most recent rainfall observations from the VCSN.

- In addition to SPI, the water balance model provides us with the remaining three drought indicators: SMD, SMDA and PED. These indicators are normalised and combined together to create a probabilistic forecast for the NZDI [1].

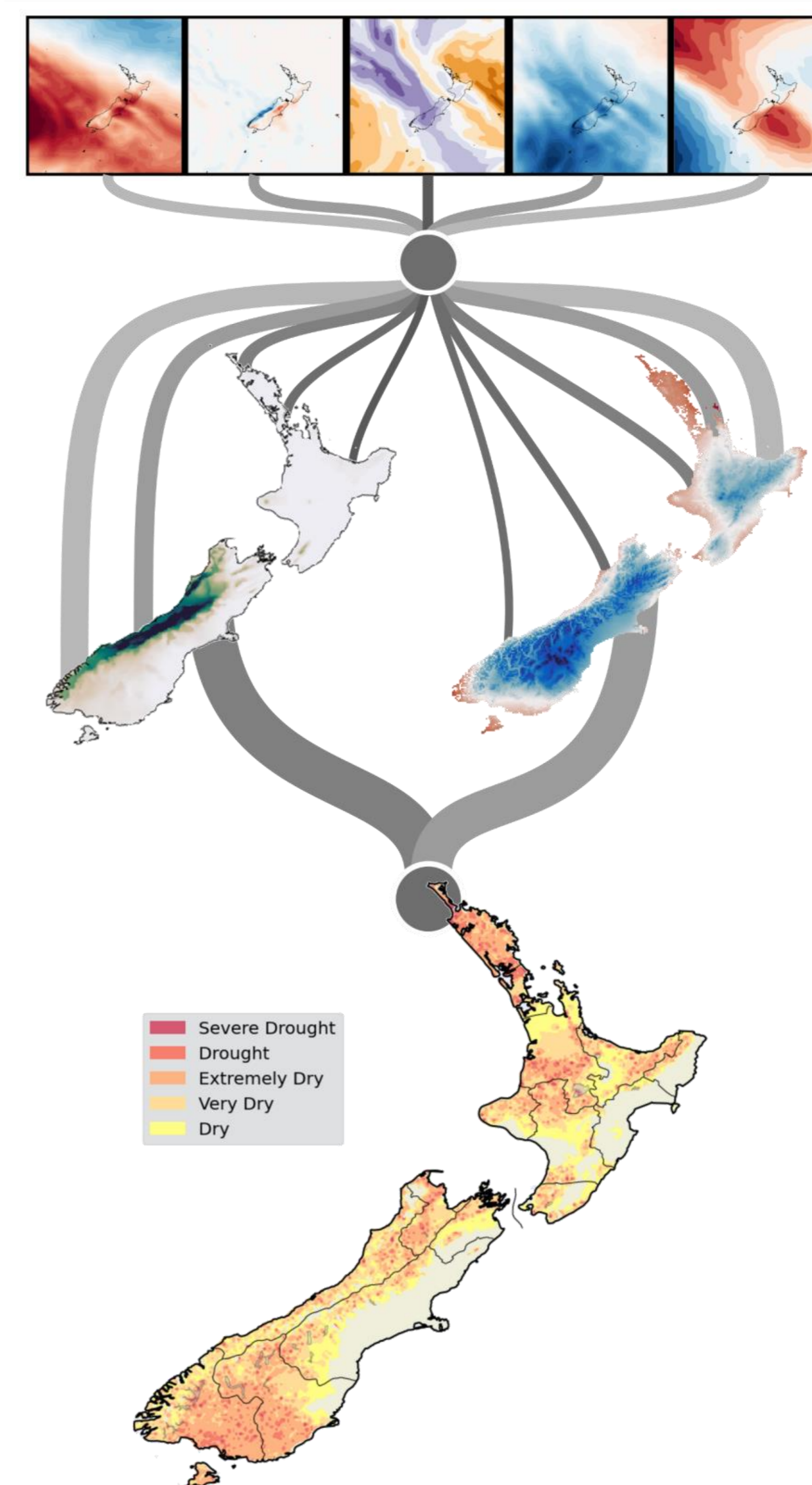


Figure 2: The S2S drought forecasting pipeline which is run operationally at NIWA

## Conclusions

We have created a high-resolution probabilistic drought forecast using AI, which enables us to better communicate drought-related risks to stakeholders.

- AI-based downscaling has reduced computational costs by three orders of magnitude when compared to dynamical downscaling.
- Preliminary results suggest that AI-based downscaling reduces biases in precipitation when compared to the NCEP GEFS over a 20-year model hindcast.
- The probabilistic NZDI forecast has skill over climatology in providing forecasts for some significant historic drought events.

Further work will include comprehensive evaluation of the model's skill and its added value over dynamical downscaling.

## References

[1] Mol, A., Tait, A., & Macara, G. (2017). An automated drought monitoring system for New Zealand. *Weather and Climate*, 37(1), 23-36.

[2] Rampal, N., Gibson, P. B., Sood, A., Stuart, S., Fauchereau, N. C., Brandolino, C., ... & Meyers, T. (2022). High-resolution downscaling with interpretable deep learning: Rainfall extremes over New Zealand. *Weather and Climate Extremes*, 100525.