

Using convolutional neural processes to generate high-resolution weather datasets over New Zealand

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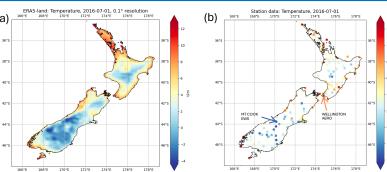
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Detailed and accurate reanalysis datasets are imperative to improving weather forecasting and its validation. ERA5 is known to have a mostly cold bias over NZ and to under-predict heavy rainfall¹. Furthermore, the resolution of available reanalysis datasets limits the representation of convective and other small-scale features. We present the use of convolutional neural processes (ConvNPs) to produce higher resolution temperature datasets over New Zealand that are informed by observations from weather stations.

Convolutional Neural Processes

NPs use meta-learning to model a stochastic process based on a set of predictors and targets. ConvNPs use convolutional neural networks to learn this stochastic process. Given the model output is a stochastic process, we can obtain uncertainty estimations and produce ensembles of predictions. We make use of the Python package DeepSensor² to implement ConvNPs.



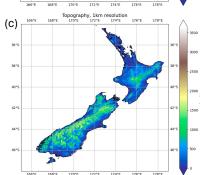
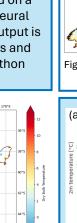


Figure 1: Examples of model input data on 1st July 2016.



Model Inputs

Context set:

- ERA5-land temperature (0.1° resolution) (a)
- Topography (5km resolution)
- · Land-sea mask
- Circular time variable

Target set:

 National Climate Database temperature observations (b)

Auxiliary at targets:

- Topography (1km resolution) (c)
- Topographical position index

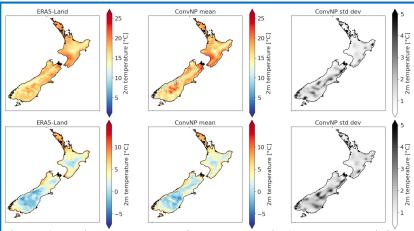


Figure 2: Comparisons of ERA5-Land daily temperatures with ConvNP mean predictions and standard deviations on 1st January 2016 (top) and 1st July 2016 (bottom)

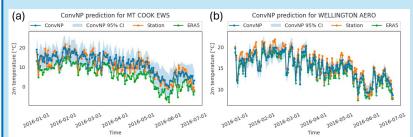


Figure 3: Comparisons of ConvNP output with ERA5-Land and station data at unseen locations ((a) Mount Cook and (b) Wellington) and unseen dates (first half of 2016).

Figure 3 gives two examples of ConvNP predicting temperature data at unseen locations effectively, particularly in Figure 3(a) where ERA5-Land does not align well with station data. Figure 4 indicates that ERA5-Land tends to perform worse in areas of higher altitude, but that this problem is much less prominent in the ConvNP predictions.

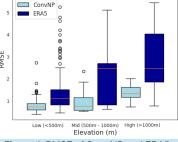


Figure 4: RMSE of ConvNP and ERA5-Land to station data during test years, split by low, mid and high elevation.

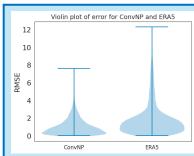


Figure 5: Violin plot of unseen location errors for the ConvNP mean prediction and ERA5-land.

10 stations were held out in training, and the RMSE is measured for both the ConvNP prediction and ERA5-Land at these locations during the unseen test years (2016-2017). These locations include mountainous, coastal and urban areas. Figure 5 and Table 1 show the mean output from the ConvNP model produces smaller RMSE at these 10 stations than ERA5-land.

	ConvNP	ERA5-Land (interpolated)
Held out locations	1.0904	1.8877
All stations	0.8286	1.5019

Table 1: RMSE between station readings and a) ConvNP mean predictions, b) ERA5-land reanalysis locations, at unseen and all station locations in 2016-2017 inclusive. Note that ERA5-Land was interpolated to 1km resolution.

Model details

The results shown here are from a ConvNP model trained for 100 epochs on daily data, with an internal grid of 250. The model is trained using data from 2000 – 2011, validated on 2012 – 2015 and tested on 2016 – 2017 (all dates inclusive).

Future work

To further improve this model, we will be adding more variables to the context set. We will train over longer periods of time, and at hourly intervals. The final datasets produced will be available online.

This work is to be extended to other weather variables over New Zealand,

This work is to be extended to other weather variables over New Zealand including precipitation, wind speed, surface pressure and humidity.

References:

- 1. Pirooz, A. A. S., et al. "Evaluation of global and regional reanalyses performance over New Zealand." *Weather and Climate* 41.1 (2021): 52-71.
- Andersson, T. R. (2024). DeepSensor: A Python package for modelling environmental data with convolutional neural processes (Version 0.3.6) [Computer software]. https://github.com/alan-turing-institute/deepsensor