Using Convolutional Neural Processes to Produce High Resolution Weather Datasets for Aotearoa New Zealand

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NEURAL INFORMATION PROCESSING SYSTEMS

Problem: Data driven forecast models are only as good as the data they are trained on.

AI-based global weather forecast models are equalling and surpassing the skill of physics-based models [1], and are typically trained on ECMWF's 0.25° resolution ERA5 reanalysis. For regional data-driven weather forecasting, **higher resolution weather datasets are required to capture extreme weather phenomena**, such as convection and topography-driven events. The ability to represent, and therefore forecast, these high-impact events is vital as the effects of climate change continue to worsen.

Method: Use convolutional neural processes to probabilistically downscale and bias-correct gridded datasets to station observations.

Regular supervised learning aims to take an input *x* and learn a mapping

$$x \rightarrow f(x),$$

where the objective is to minimize the difference between *f(x)* and a target *y*.

Convolutional conditional neural processes (ConvCNPs) are **meta-learning models** [2, 3]. They are instead trained on a context set $C = \{x^{(c)}, y^{(c)}\}_{c=1,\ldots,N}$, and aim to **learn a parameterized distribution** conditioned on C:

$$C \rightarrow f(x; C).$$

These mappings are validated on a target dataset $T = \{x^{(t)}, y^{(t)}\}_{t=1,\ldots,N}$. By learning a parameterization of a distribution, ConvCNP models provide **uncertainty quantification** for their predictions.

ConvCNPs leverage **convolutional neural networks** (CNNs) to process data and model complex relationships in the context set. The use of CNNs also introduces **translation equivariance** into the model. ConvCNPs have shown success in environmental data science [4], including weather and climate applications [5], thanks to these properties.

Implementation for Aotearoa New Zealand

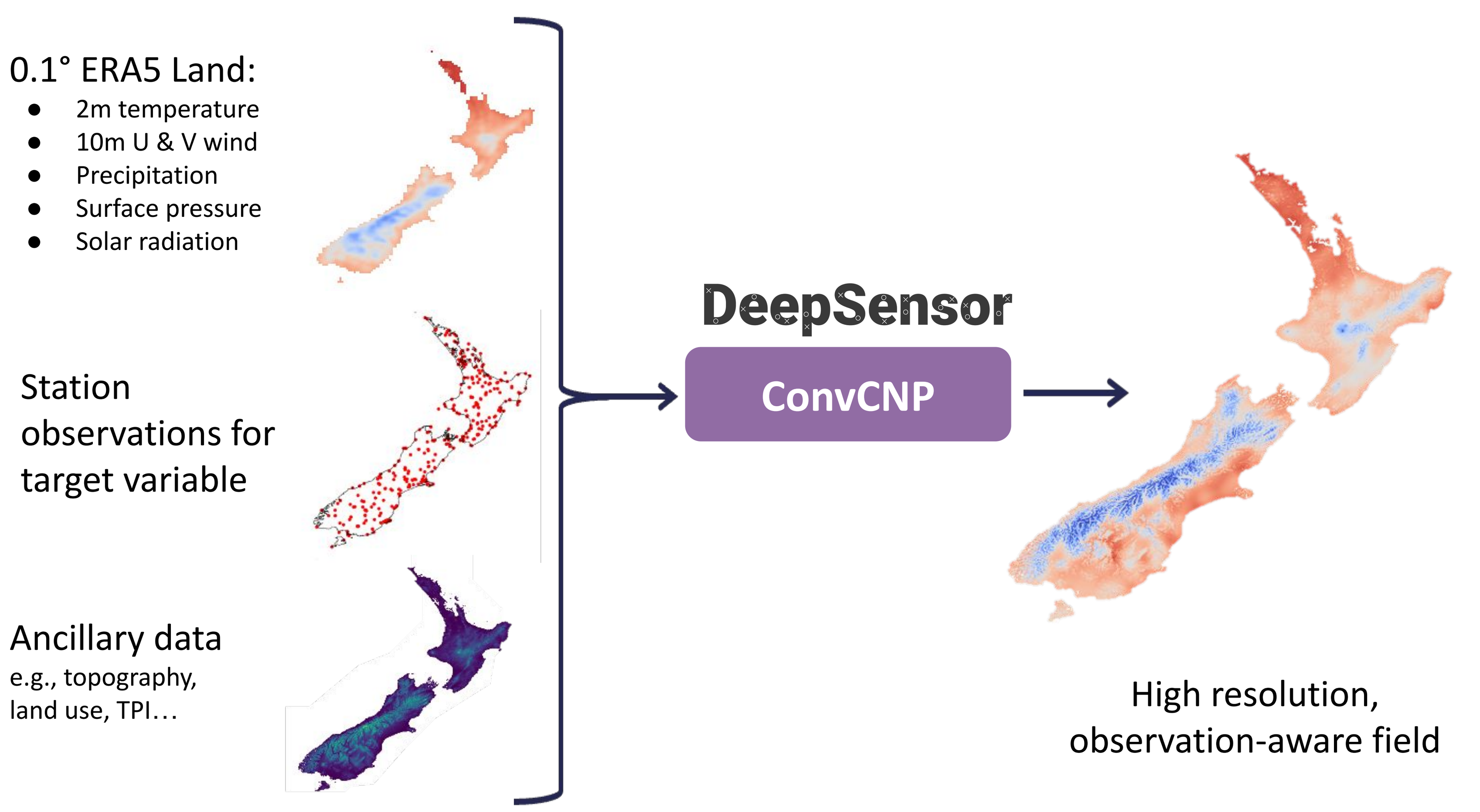

Fig 1. An overview of our approach in applying ConvCNP models to predict high resolution weather fields in Aotearoa New Zealand. We use the Python package DeepSensor [6], and station data from the New Zealand National Climate Database [7]. Ancillary data includes topography, land use, 3 levels of topographical positional index, and sinusoidal embeddings of the day of the year.

Distribution choices for different surface variables

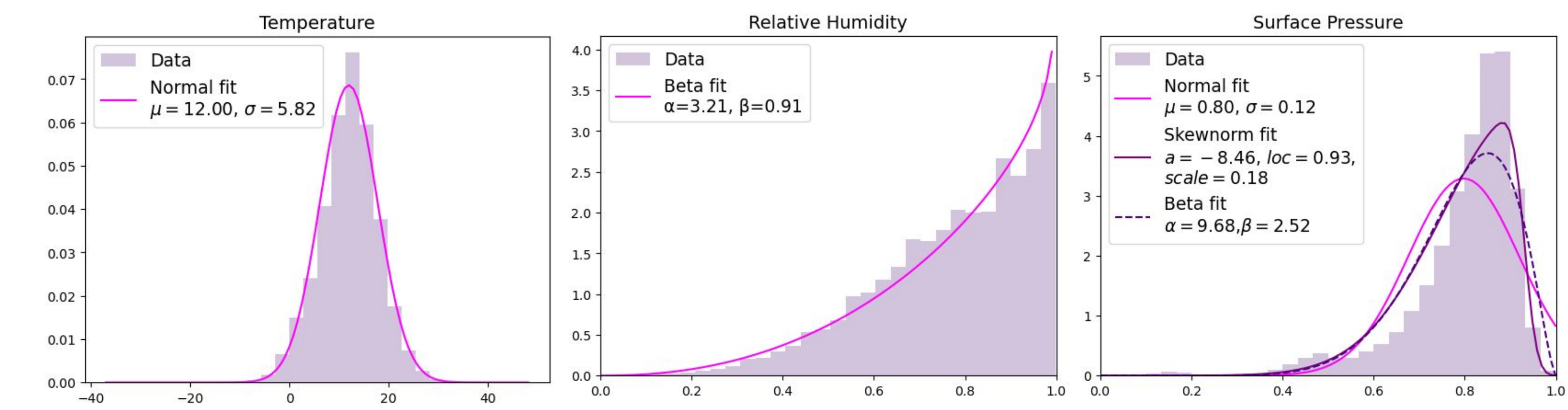

Fig 2. Histograms of hourly New Zealand station data from 2020 with statistical distributions fitted to the data. Surface pressure normalised to [0,1].

The distributions we have used to model the following surface variables are:

- Temperature: Gaussian
- Precipitation: Bernoulli-Gamma
- U and V wind: Gaussian
- Relative Humidity: Beta
- Pressure: Beta or Skewnorm

Timeseries comparison to ERA5

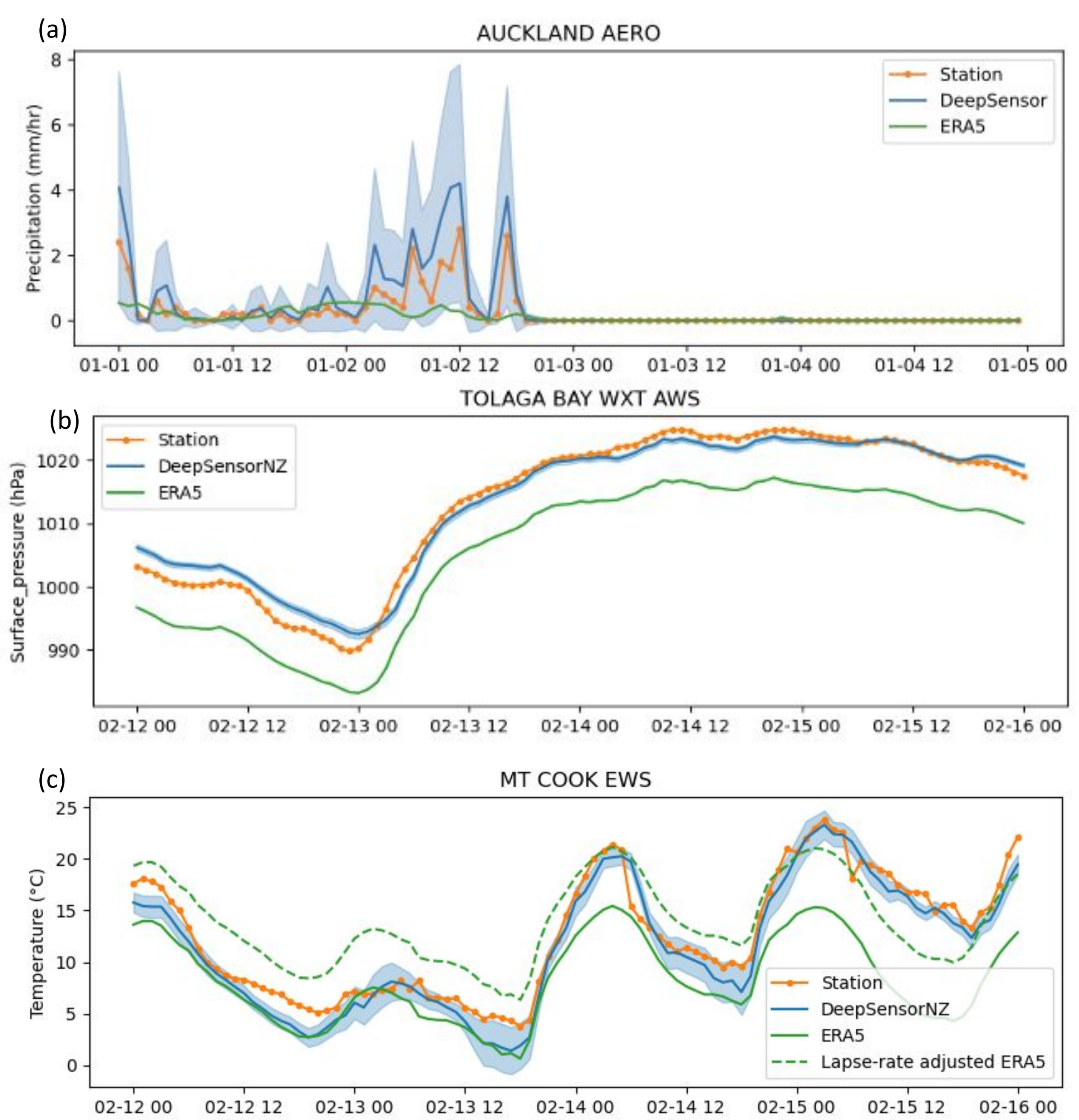

Fig 3. Timeseries of the ConvCNP mean model predictions (blue) with standard deviations for (a) temperature at Mt Cook, (b) Precipitation at Auckland Airport, and (c) pressure at Tolaga Bay, compared to stations (orange) and ERA5-Land (green). These stations are not given to the model in training or at inference. In (c), a lapse-rate adjustment of 6K/1000m is applied to the temperature value for ERA5-Land, shown by the green dashed line, given the station is located in a valley in the Southern Alps.

Figure 3 shows the trends of the DeepSensor model compared to unseen station locations at unseen times.

In Figure 3(a), the model improves precipitation representation in Auckland/Tāmaki Makaurau, with wide but reasonable confidence intervals.

In Figure 3(b), the model adjusts surface pressure in line with stations at coastal Tolaga Bay/Uawa. We found ERA5-Land typically underpredicts surface pressure in NZ.

In Figure 3(c), the model fits the temperature at the Mt Cook/Aoraki station well, compared to ERA5-Land and the 6K/1000m lapse-rate adjusted ERA5-Land.

Uncertainty quantification

Figure 4 illustrates the uncertainty maps for two DeepSensor outputs. In Figure 4(a), the lighter spots represent areas of least uncertainty, which are located at stations fed into the model. In Figure 4(b), the model's source of uncertainty falls where rainfall is predicted, rather than at station locations.

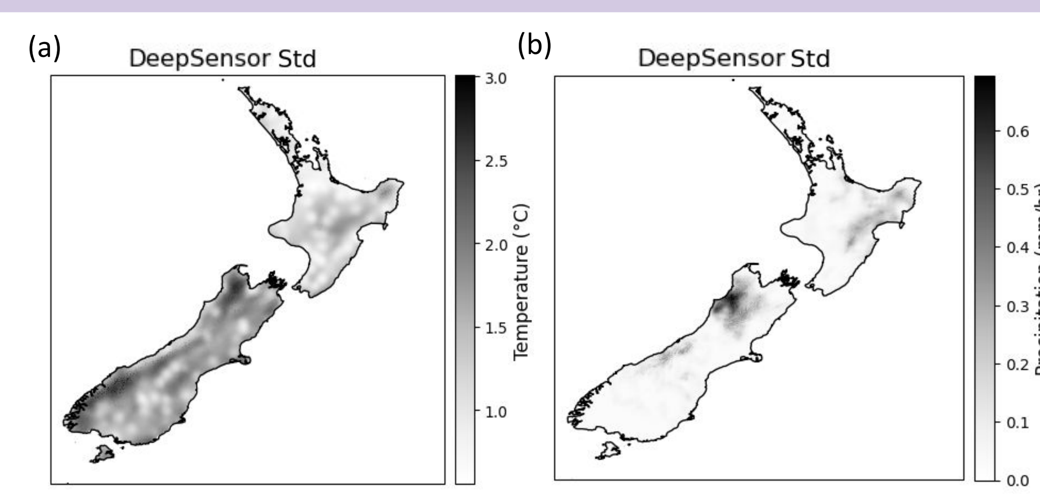

Fig 4. Maps of the standard deviations for two DeepSensor model predictions, for (a) temperature and (b) precipitation.

Fine-tuning for forecast models

We are in the process of fine-tuning our ConvCNP models to be used with numerical weather prediction (NWP) model data, allowing us to either:

- Downscale and correct previous weather forecasts, allowing us to use these as more **accurate targets in training AI-based weather forecast models** (see https://www.deepweather.org.nz/);
- **Downscale operational weather forecasts to higher-resolutions.** The flexibility of ConvCNP models allows us to run in inference mode with no observations present, still achieving effective downscaling and bias correction.

Figure 5 shows some of the results of this, downscaling from a 4km WRF run to 1km using ConvCNP models. The images in Figure 5 are taken from a WRF forecast during Cyclone Gabrielle in February 2023, and the DeepSensor precipitation output shows more realistic, high-valued rainfall in the north and east of Te Ika-a-Māui (NZ's North Island).

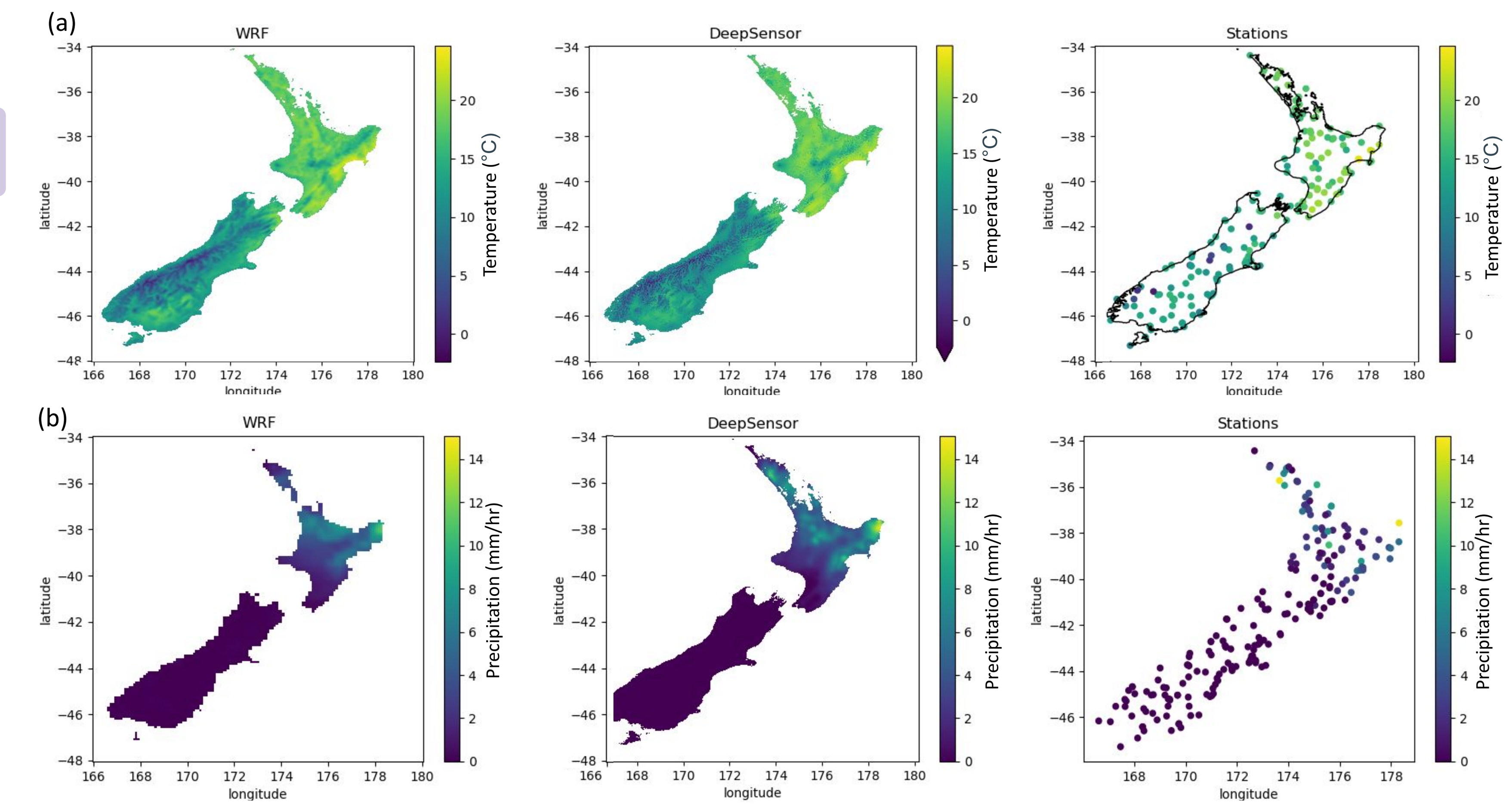

Fig 5: WRF forecasts downscaled and corrected to station observations, for (a) temperature, and (b) precipitation. The left column shows the original forecast, the middle column is the DeepSensor mean output, and the right column shows the station observations.

Take a look at the **DeepSensorNZ github** repo by scanning the QR code, or get in touch at emily@bodekerscientific.com

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1 Bodeker Scientific 2 British Antarctic Survey 3 The Alan Turing Institute 4 NeSI New Zealand eScience Infrastructure