DeepWeather

Two-Way Coupling of an Observation-Enhanced AI Model with an NWP Model to Improve Weather Forecasting in Aotearoa New Zealand

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Imagine being able to assimilate probabilistic, future 'pseudo-observations' into a numerical weather prediction model.

In the DeepWeather project, we aim to produce **high-resolution, probabilistic weather forecasts.** These weather forecasts are generated by an AI model, using numerical weather prediction (NWP) forecasts as input. We then **nudge the NWP forecast towards the high-resolution AI forecast**, as if this output were a gridded map of **observations**, encouraging the NWP model to remain in line with the AI model outputs.

What data is available when starting a regional forecast at time t_0?

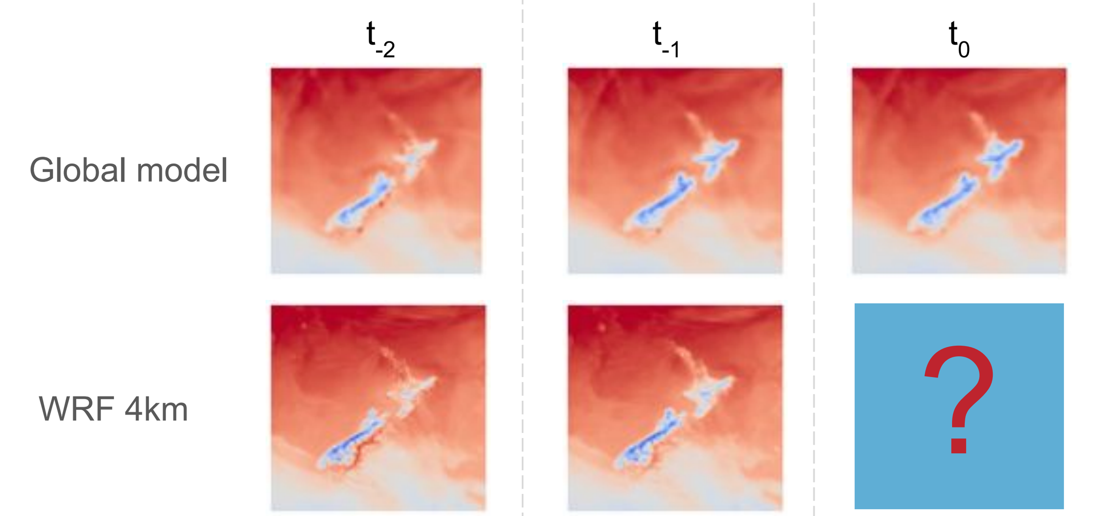

Fig 1. Available model data when initialising a regional NWP model at time t_0: global model data into the past and future, and NWP model data into the past.

When starting the Weather Research and Forecasting (WRF) model at 00:00UTC to forecast NZ's weather, we have available:

- **Global model data**, e.g., ECMWF's IFS, NCAR's GFS or the UKMO model. This data will be available from the most recent model run, so will include time before 00:00UTC and into the future.
- **Previous WRF data**, assuming we are performing a warm-start.
- Recent **station observations** for a variety of atmospheric variables.
- **Static data**, such as topography.

The DeepWeather model

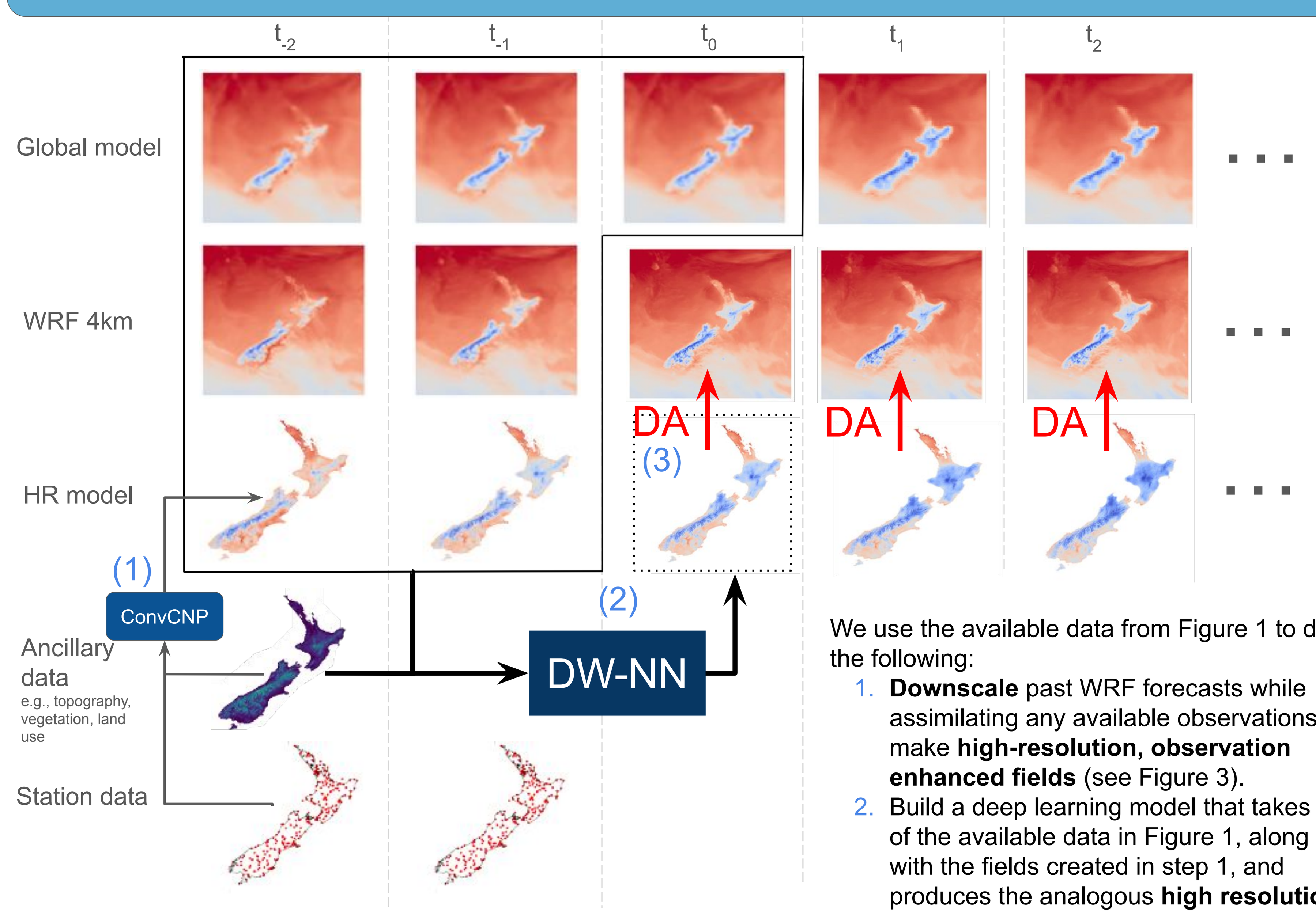

Fig 2. A schematic of the DeepWeather architecture. The black box surrounding 7 fields represents the input into the DeepWeather Neural Network (DW-NN), and the high-resolution output is shown in the dotted box. This output is available before the next hour of WRF forecast, so we use data assimilation (DA) to nudge the WRF forecast using this high-resolution forecast. The ConvCNP model used to create the initial HR outputs at t_{-2} and t_{-1} is described in the next section.

We use the available data from Figure 1 to do the following:

1. **Downscale** past WRF forecasts while assimilating any available observations to make **high-resolution, observation enhanced fields** (see Figure 3).
2. Build a deep learning model that takes all of the available data in Figure 1, along with the fields created in step 1, and produces the analogous **high resolution field at time t_0**, as illustrated in Figure 2.
3. Use this new high-resolution field to **nudge the dynamical WRF forecast at t_0**, as shown by the red arrow.

Creating a high-resolution, observation-enhanced, regional hindcast

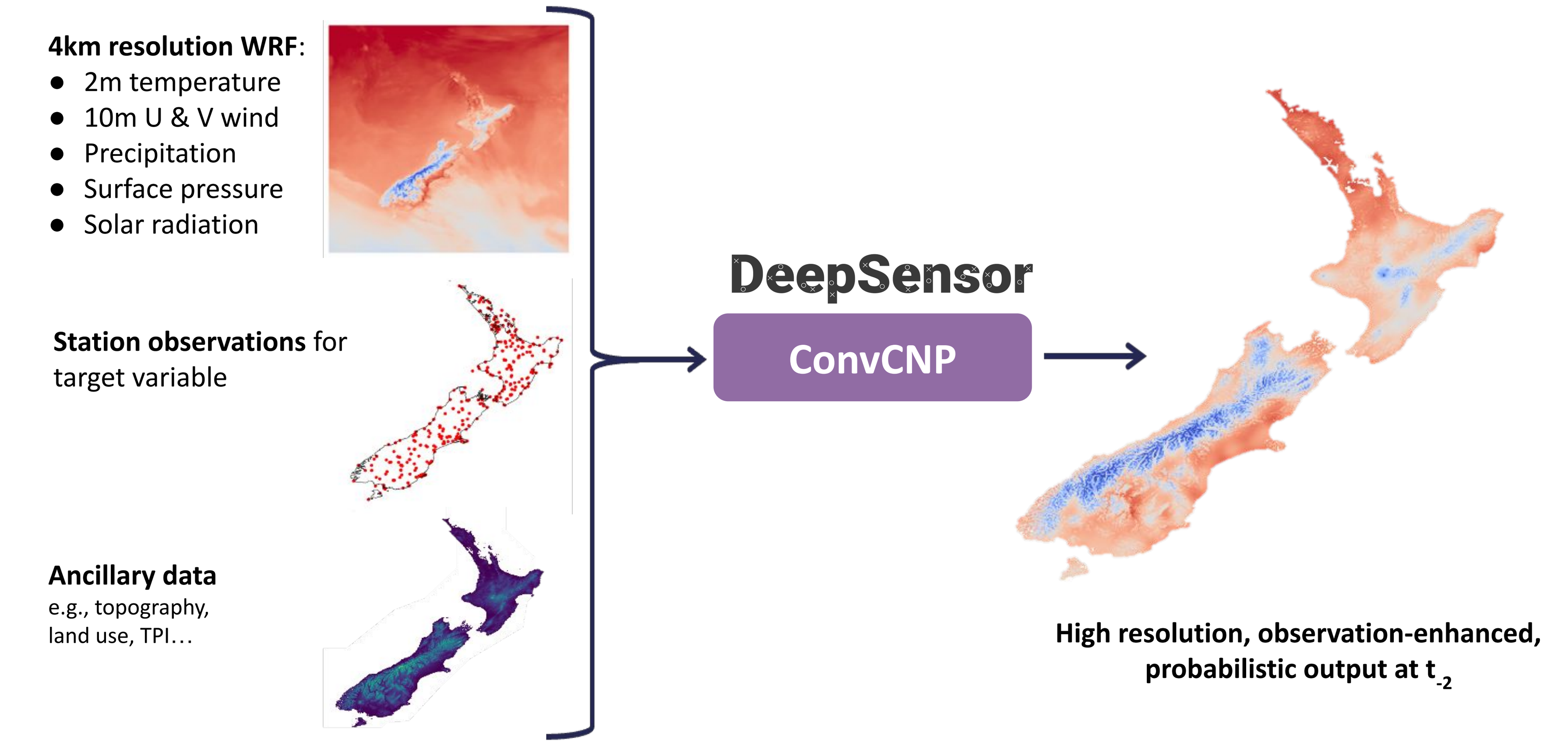

Fig 3. An overview of our approach in applying ConvCNP models to predict high resolution weather fields in Aotearoa New Zealand from WRF foreasts and station observations. We use the Python package DeepSensor [2], and station data from the New Zealand National Climate Database [4]. Ancillary data includes topography, land use, 3 levels of topographical positional index, and sinusoidal embeddings of the day of the year.

Using the available previous WRF forecasts, and station observations at the corresponding times, we employ **convolutional conditional neural processes** (onvCNP) to create **high resolution, observation-enhanced** fields of the previous forecasts. Convolutional conditional neural process (ConvCNP) models have been shown to be an effective method to downscale and bias-correct a variety of environmental variables [1]. We make use of the DeepSensor Python package [2] to implement ConvCNPs.

ConvCNPs are meta-learning models that **learn the parameters of a stochastic process** from the input to the target data [5, 6]. By predicting a stochastic process, the model also provides **uncertainty quantification** and can be used to produce an **ensemble of predictions.** ConvCNPs leverage **convolutional neural networks** (CNNs) to process data and model complex relationships between input and target variables, and the use of CNNs introduces **translation equivariance** into the model.

ConvCNP outputs

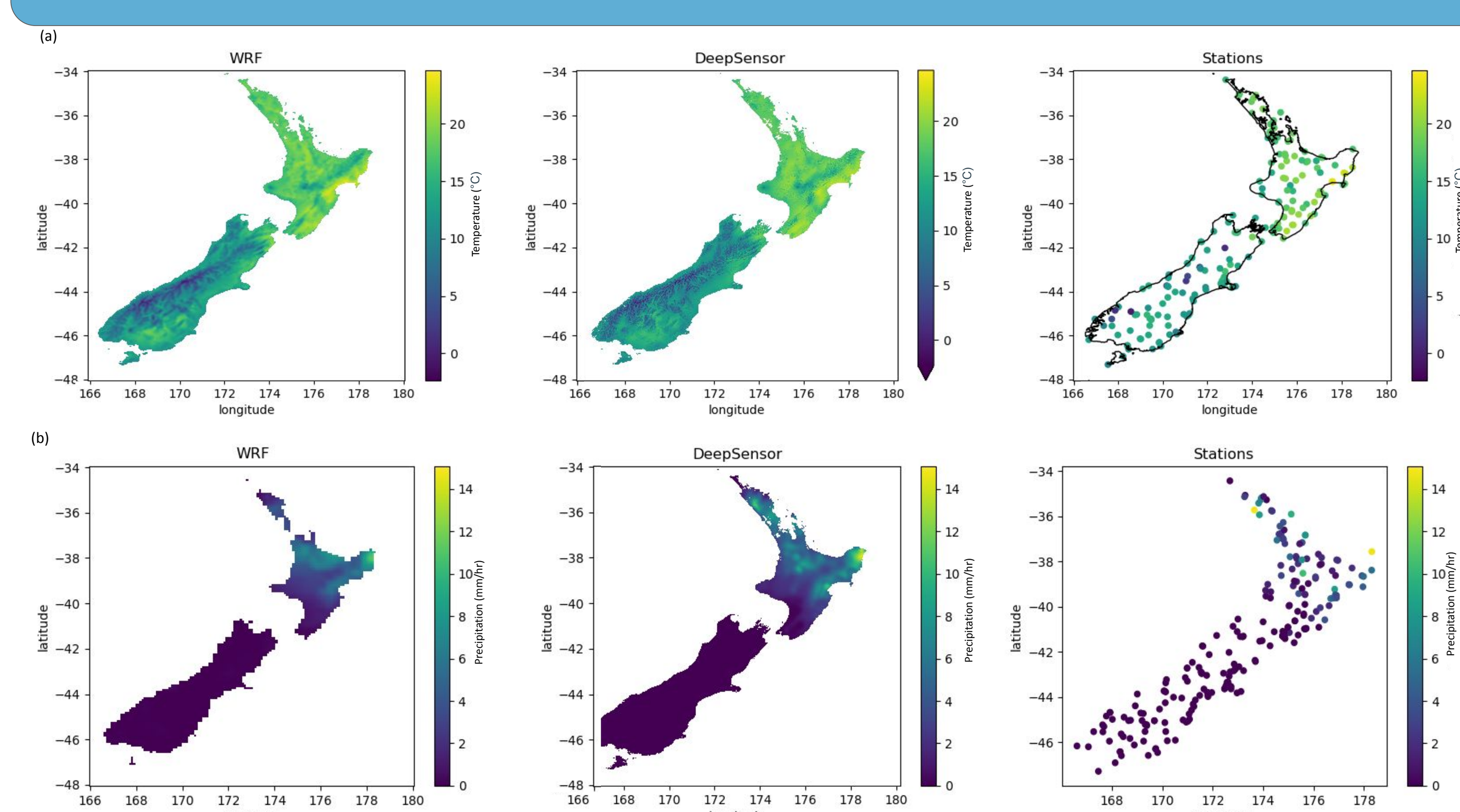

Fig 4: WRF forecasts downscaled and corrected to station observations, for (a) temperature, and (b) precipitation. The left column shows the original forecast, the middle column is the ConvCNP mean output, and the right column shows the station observations.

Figure 4 shows WRF temperature and precipitation forecasts on 14th February 2023, when Cyclone Gabrielle hit the north east of New Zealand.

Temperatures are downscaled to better align with station observations, and precipitation is increased by over a factor of 3 to better represent the rainfall that impacted Te Ika-a-Māui (the north island).

ConvCNP training and outputs (continued)

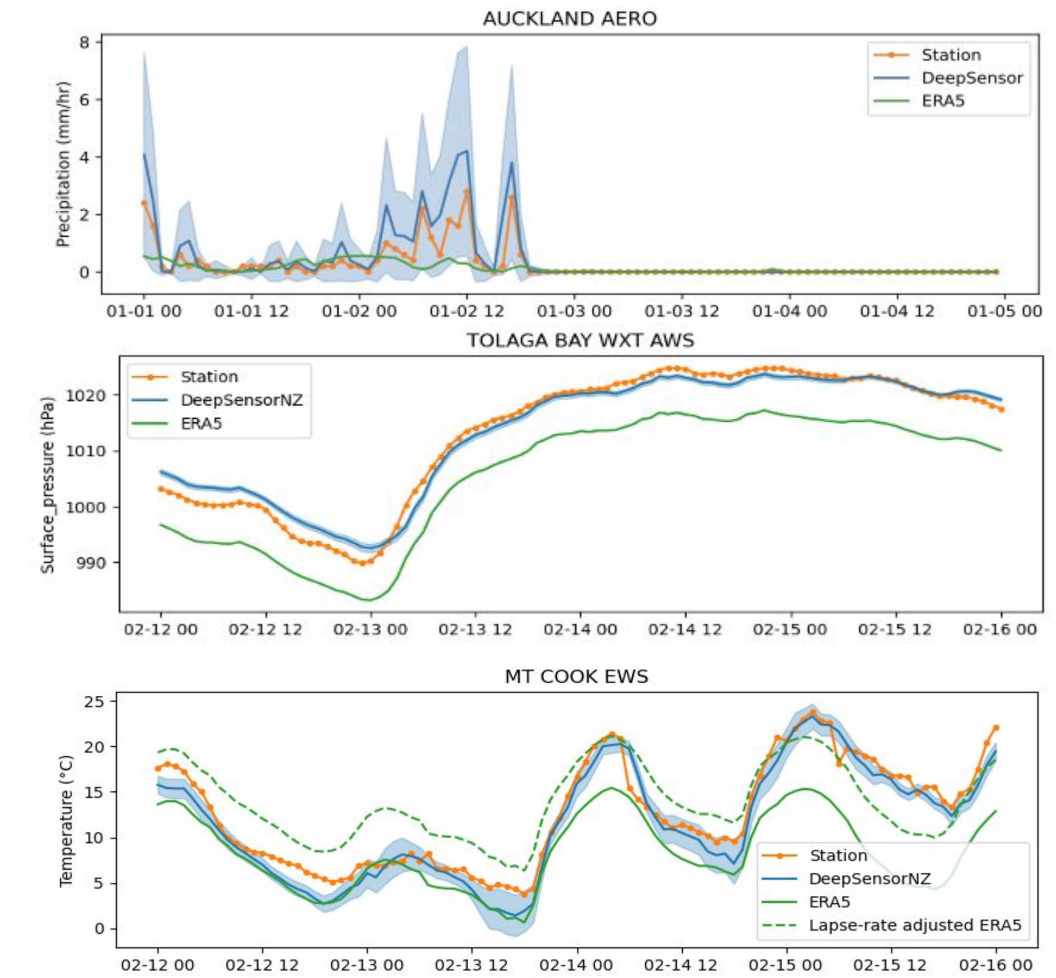

Fig 5. Timeseries of the ConvCNP mean model predictions (blue) with standard deviations for (a) temperature at Mt Cook, (b) Precipitation at Auckland Airport, and (c) pressure at Tolaga Bay, compared to stations (orange) and ERA5-Land (green). These stations are not given to the model in training or 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.

Due to the high cost of archiving WRF forecasts, we only have access to one year's worth of training data. We therefore **train our models using ERA5 and ERA5-Land**, before **fine-tuning the models with the available WRF data**.

Figure 3 shows the trends of the DeepSensor models using ERA5-Land 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, this difference is not as pronounced for WRF. 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.

Each variable of interest follows a different distribution. Below is a list of the **distributions** being predicted for each surface variable:

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

The DeepWeather neural network

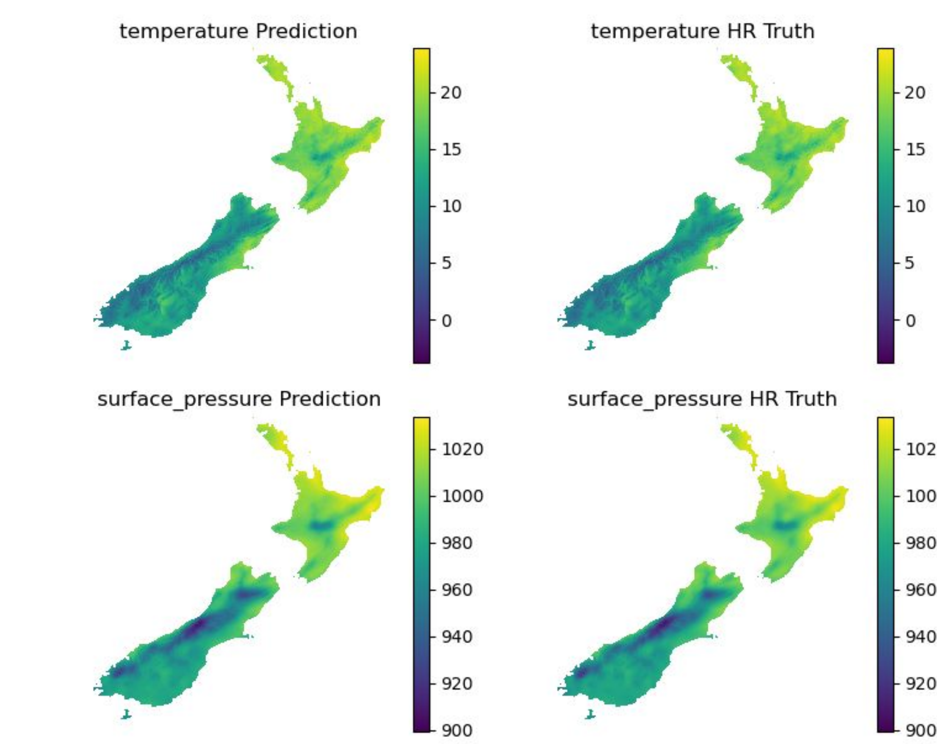

Fig 4. Examples of validation outputs when training an Attentive UNet. The 'truth' data on the right is output from the ConvCNP model.

The DeepWeather neural network is in development, with the following architectures currently being tested:

- **Generative Adversarial Networks**
- **Attentive UNets**
- **Diffusion models**
- **ConvNeXTv2** convolutional models [3]

Our current approach is to **predict the difference** between t_i and t_{i-1} as these difference fields are likely to be more normally distributed for many variables than the target t_i fields themselves. We are also exploring adding hard and/or soft **physics constraints** into the model, by ensuring physically realistic gradients.

Get in touch!
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