

Using Deep Learning to Develop a High Resolution Planetary Boundary Layer Model for Infrasound Propagation

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Abstract

Previous research has shown the utility of deep learning in predicting atmospheric structure for regional infrasound propagation. A Long-Short Term Memory network can be used to predict temperature, wind speed, and wind direction up to altitudes of ~40 km with performance equal to or better than state-of-the-art reanalysis models. However, these regional models do not resolve the planetary boundary layer (PBL), the lowermost part of the atmosphere, well. An accurate model of the PBL is important at local distances for acoustic waveform modeling. This is often accomplished by using a suite of robust and expensive meteorological sensors. A method to predict atmospheric structure at this resolution would be very beneficial for low yield monitoring scenarios where the ability to field sensors is limited or the timing of the event is not known beforehand. Here we show progress towards a high resolution PBL model developed via deep learning techniques using an ambient urban infrasound data set coupled with weather measurements in Las Vegas, Nevada, USA. We anticipate results will show the ability to use a data-driven method to predict, interpolate, and extrapolate an atmospheric model that can be used in acoustic waveform modeling.

Motivation

- Previous work used deep learning to predict atmospheric structure for regional infrasound propagation.
- Performance was equal to or better than state-of-the-art models.

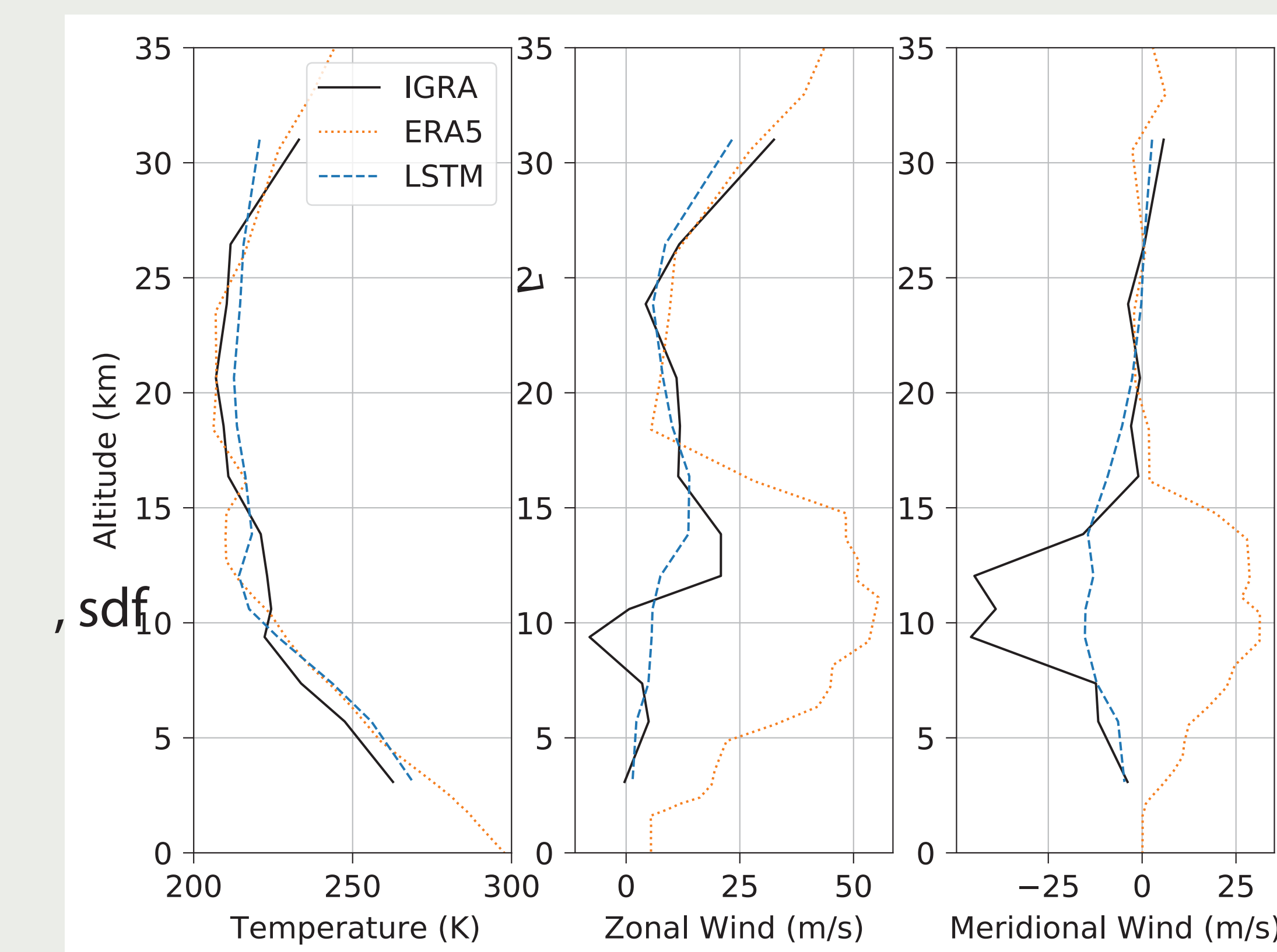


Figure 1. Previous work. Atmospheric profiles for Albuquerque, NM, USA on January 22, 2019 at 00:00 UTC from:
1. Ground truth (IGRA, black)
2. Deep learning (LSTM, orange)
3. State-of-the-art (ERA5, blue)
models. In this instance, the deep learning model outperforms the state-of-the-art model, though overall it performs similarly as well. The fact that the deep learning model performs equally as well is particularly important because it is faster and provides a forecast, unlike the ERA5 model.

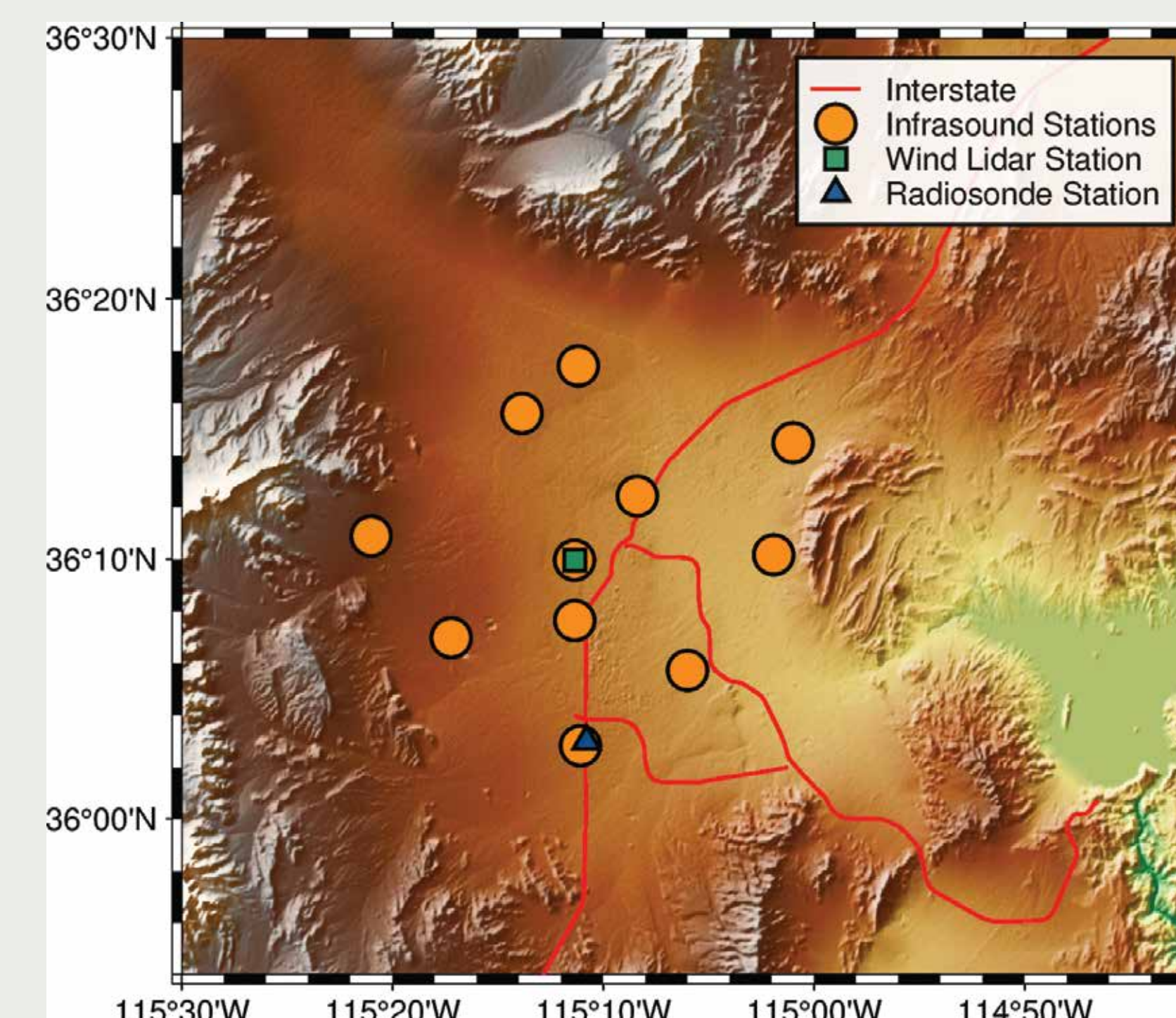
- Accurate atmospheric model is important for acoustic waveform modeling at local distances.
- Often accomplished by using a suite of robust and expensive meteorological sensors.
- Predicting atmospheric structure at the same resolution would be very beneficial for scenarios where the ability to field sensors is limited or the timing of an event is not known beforehand.

Data Collection

Infrasound and Meteorological Data

- 11 single sensor infrasound stations
- Radiosonde observations 2x/day
- Wind Lidar observations ~10 minute intervals
- High density observations up to 1 km

Figure 2. Infrasound, radiosonde, and wind lidar station locations.



Current Work: Data Curation

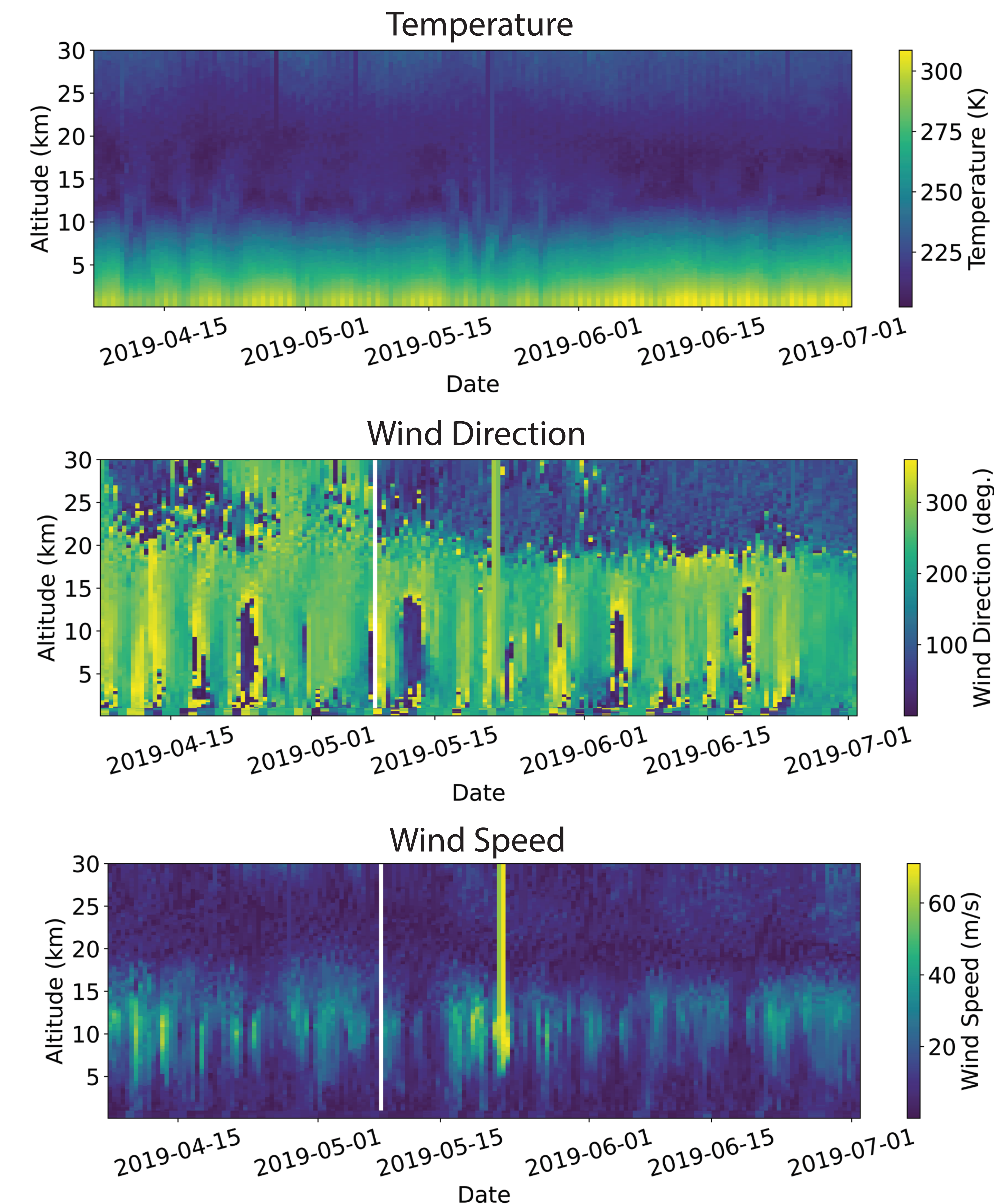


Figure 3. Data curation to merge datasets prior to input into the deep learning algorithm.

Key Highlights

- Expected diurnal variations in temperature
- High resolution data below 1 km shows large variations in wind direction
- Tropospheric jet present ~10 km altitude
- Smaller dataset might not capture seasonal changes

Deep Learning Algorithm

- Vanilla RNNs struggle with learning in the presence of increments greater than 5-10 time steps so they are not well suited for weather forecasting.
- Long-Short Term Memory (LSTM) networks are a type of RNN that are capable of learning order dependence in sequence prediction problems (Hochreiter & Schmidhuber, 1997).
- LSTMs do not suffer from the same vanishing and exploding gradient issues, make use of gates to help control the gradient flow, and the number of repeating layers are increased for learning long-term dependencies in time series data.
- Shown to work well at forecasting ground weather data (Zaytar & Amrani, 2016) and atmospheric profiles (manuscript in review).

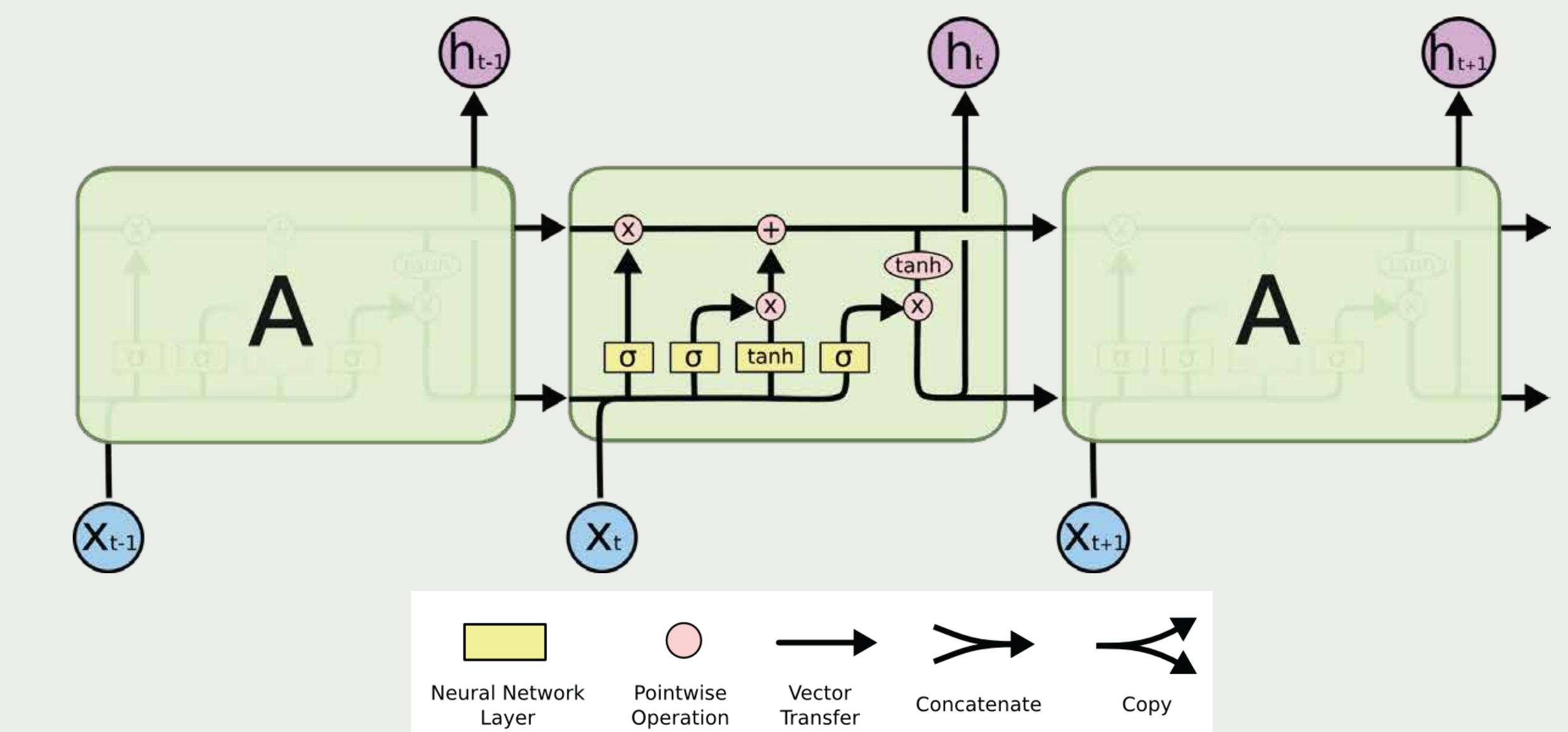


Figure 4. Example LSTM network structure from Olah (2015). The network consists of a “forget gate layer”, an “input gate layer”, updating the cell state, and providing an output.

Future Work

- Apply LSTM to merged dataset.
- Determine how high resolution up to 1 km affects infrasound waveform and/or propagation models.
- Apply LSTM model to a nearby location for waveform modeling.

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