Using Artificial Neural Networks to Understand Climate Variability on the Ross Ice Shelf

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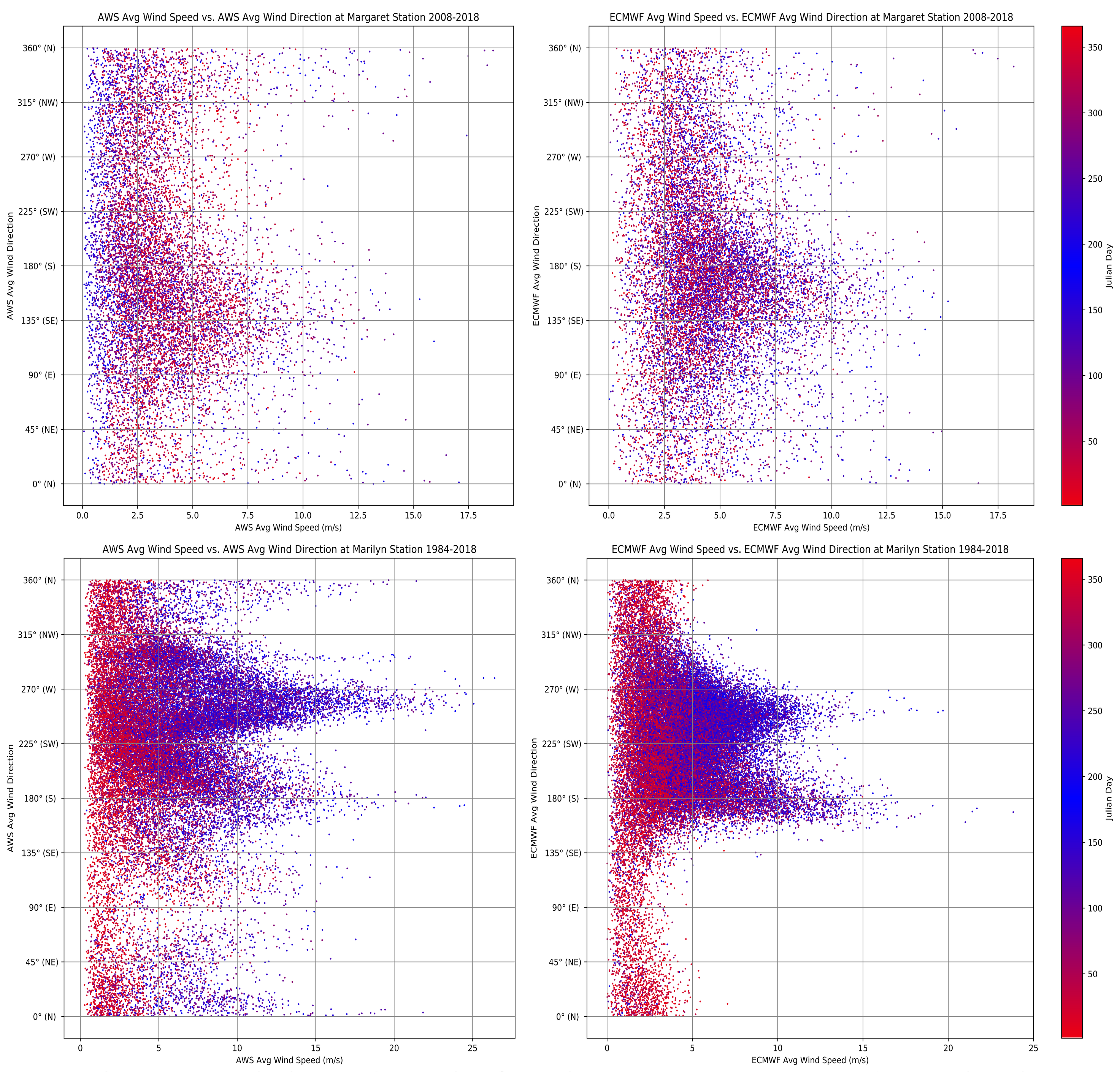
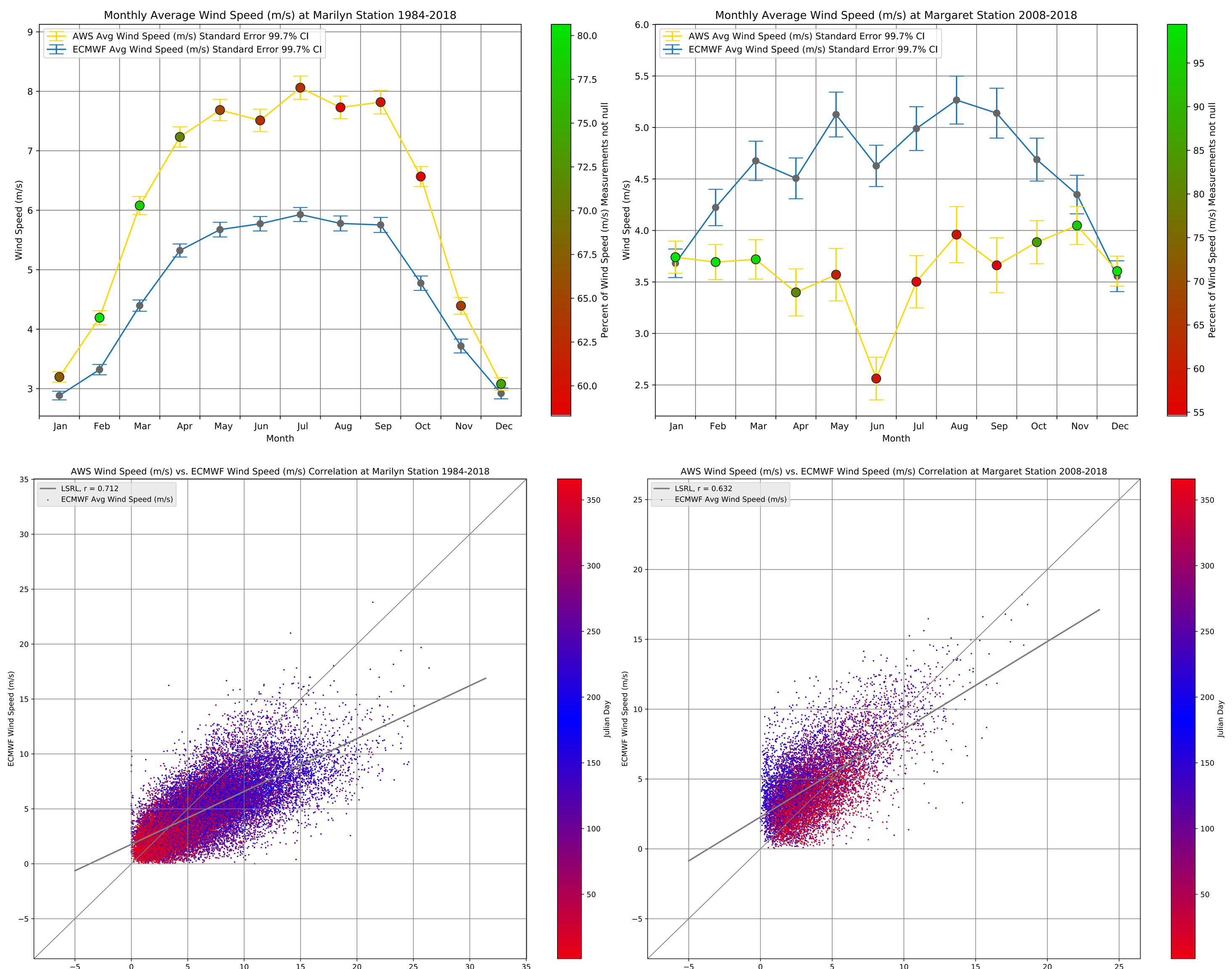
Cumulative Wind Speed and Direction Trends



At Marilyn station, which is under 100km from the Transantarctic range and, as such, subject to violent katabatic winds, the ECMWF predicts the overall shape of the prevalent winds inadequately: missing numerous peaks (i.e. directions with a high frequency of high wind speeds) and predicting peaks 10-15° different to their actual location. At Margaret station, subject to far fewer violent winds, the ECMWF predicts the rough direction of the prevalent winds well, but, as with Marilyn, predicts peaks 10-15° different to their actual direction.

Seasonal Wind Speed and Direction Trends



Wind speed is over-estimated each month at Marilyn station and under-estimated each month at Margaret station by over 1 m/s. At both stations, the ECMWF is least accurate during the winter months: the 99.7% CI are disjunct by over 1.5 m/s during winter months and overlap, or are slightly disjunct, during summer months.

Graphing Methodology

All Graphs of AWS data shown here were calculated using 6 hour averages with null values excluded and at least 10 of the 36 potential values present.

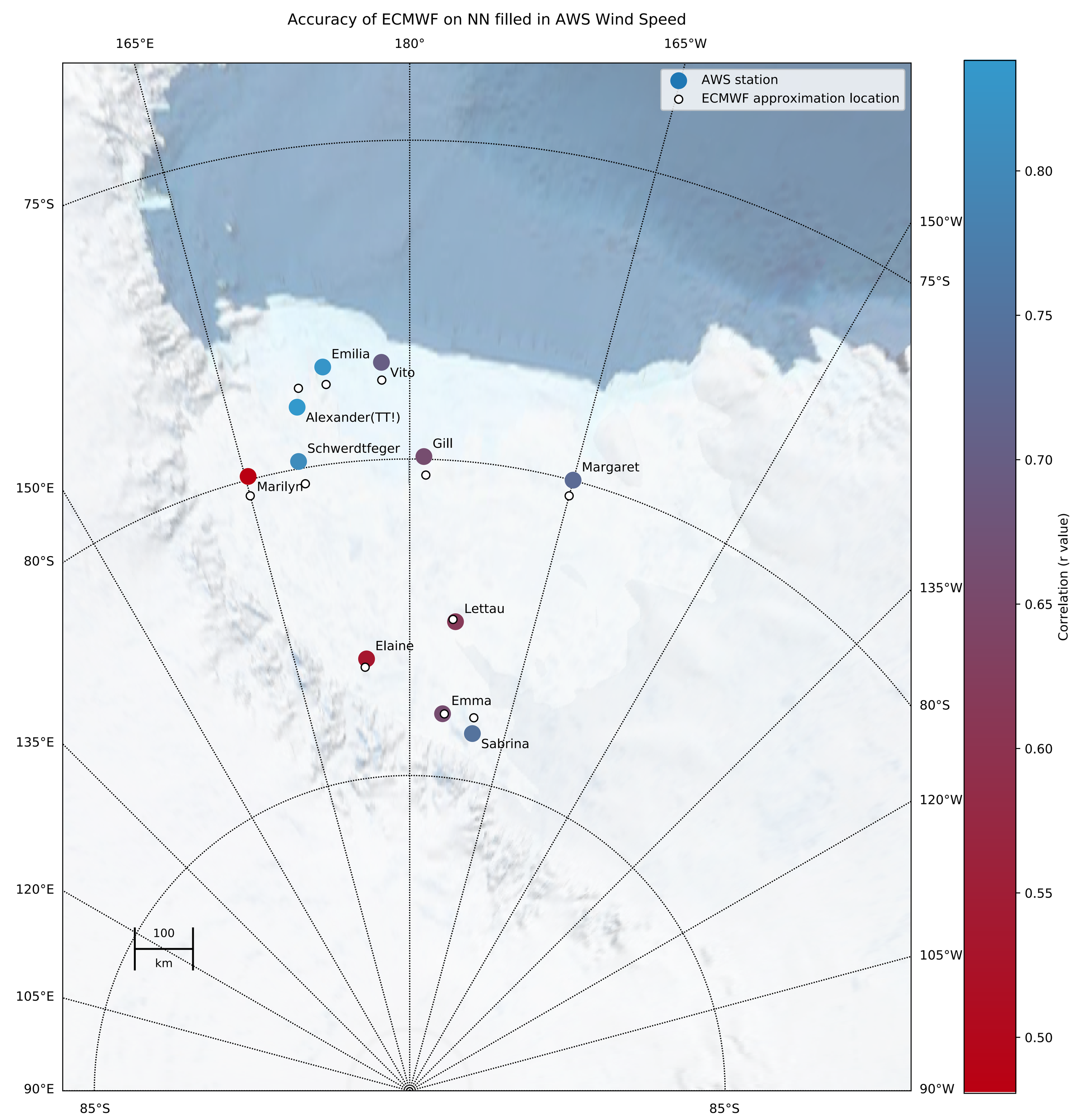
Null values were identified based on the following characteristics:

- Sticky values – if the same measurement is recorded for many subsequent 10 minute intervals, this is a null value. These were removed if there were more than six of the same value in a row. Sticky values are present in windspeed/direction and temperature.
- Artificial maximums – if there are more than 100 measurements of a wind speed measurement which is 15 m/s greater than the average windspeed at a location, this is a null value. This is an artificial cap in the data, since the chance that a high and rare wind speed measurement would consistently occur at a precision of .1 m/s is null.
- AWS listing – values were listed as defect by the Antarctic Meteorological Research Center

Abstract

Katabatic wind patterns are controlled by temperature and pressure gradients and have high diurnal and seasonal variability. In this project, data from 11 Automatic Weather Stations (AWS) and optimally structured neural networks are used to explore the accuracy of near-surface wind data from the European Centre for Medium-Range Weather Forecasts (ECMWF), a dataset with many biases. Using the controlling mechanisms of the Katabatic winds as inputs, optimally structured neural networks were trained and used to fill in the sizable data gaps in the AWS wind speed measurements. Our results show from 1985 to present the ECMWF wind speed correlates to the uncleaned AWS wind speed data with r = 0.61, to the cleaned AWS wind speed data with r = 0.74, and to the cleaned and Neural Network filled-in AWS wind speed data with r = 0.69. These preliminary results demonstrate that artificial neural networks can be used to predict missing values and reduce biases in large datasets which has implications for regional climate models that use ECMWF as boundary conditions.

Map of Results



This map captures the accuracy of the ECMWF in the across Ross Ice Shelf region, and, as such, is a central finding to this project. In regions near the Transantarctic Mountain Range, the accuracy of wind speed prediction is lowest, with the ECMWF predicting actual windspeed at correlation coefficients nearing 0.5. This accuracy improves going to the middle of the region. Towards the coast and McMurdo station, the accuracy of wind speed prediction is highest, with the ECMWF predicting actual windspeed at correlation coefficients nearing 0.8.

Conclusion

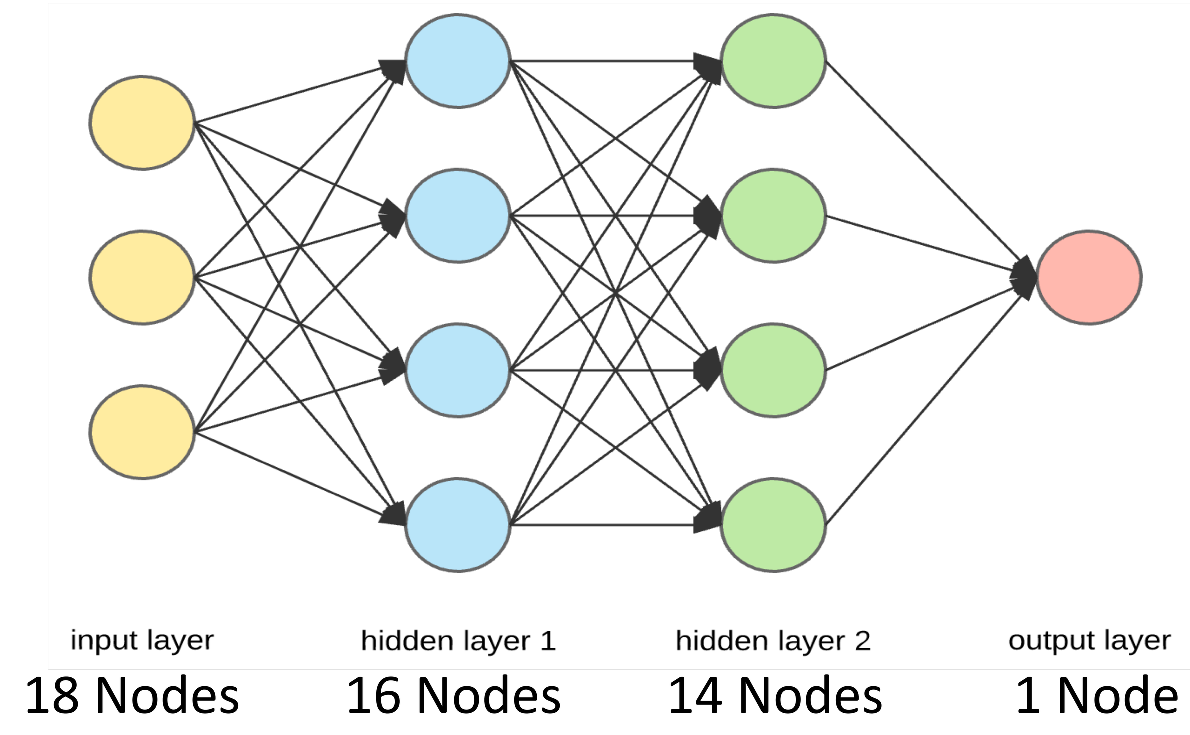
Using an Artificial Neural Network with optimized parameters - in particular, using 49 total nodes - to fill in the gaps in the AWS wind speed data sets proved to be a twofold success. Its first success was simply filling in the gaps in AWS wind speed data. The efficacy of this approach towards this goal is demonstrated by the two graphs on the right: all gaps in the wind data at Margaret Station between 2008-2011 were filled by use of the neural network. The approach was also a success in regard to achieving a better understanding of the biases of ECMWF wind speed measurements, the primary challenge of this being the missing AWS data with which to compare. This is particularly relevant to winter measurements since, during winter, there are the most violent and erratic winds and, consequently, the biggest gaps AWS data. Using our neural network we were able to increase the number of winter wind speed measurements in the AWS data set by 60%. This has drastically improved the validity of our results regarding the biases of the ECMWF during winter, given a far more comprehensive picture of actual wind patterns in the region.

Neural Network Methodology

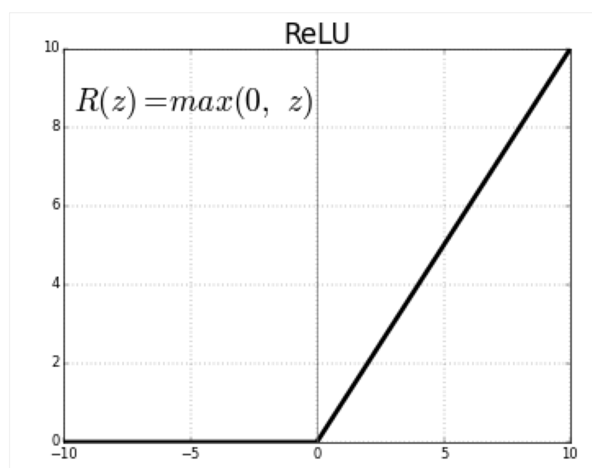
We used the Neural Network tools available in the Python 3 library scikit-learn. We picked our input variables based on the major factors affecting windspeed. This included mainly regional temperature and pressure gradients. These variables serve as the nodes of the input layer of our neural network. In order to optimize parameters of our neural network like its architecture, activation function, learning rate, gradient descent function, we conducted a random search on all the available options for each parameter in the scikit-learn library. This identified the optimal Neural Network structure to be trained to best predict the wind speeds in the region.

In order to test the accuracy of this search, we trained the resulting Neural Network with our input variables and measured its accuracy for predicting non-null, existing wind speed data. It was predict wind speed values at all locations with a correlation of no less than r = 0.7.

Neural Network Architecture



Neural Network Parameters



Activation Function – RELU

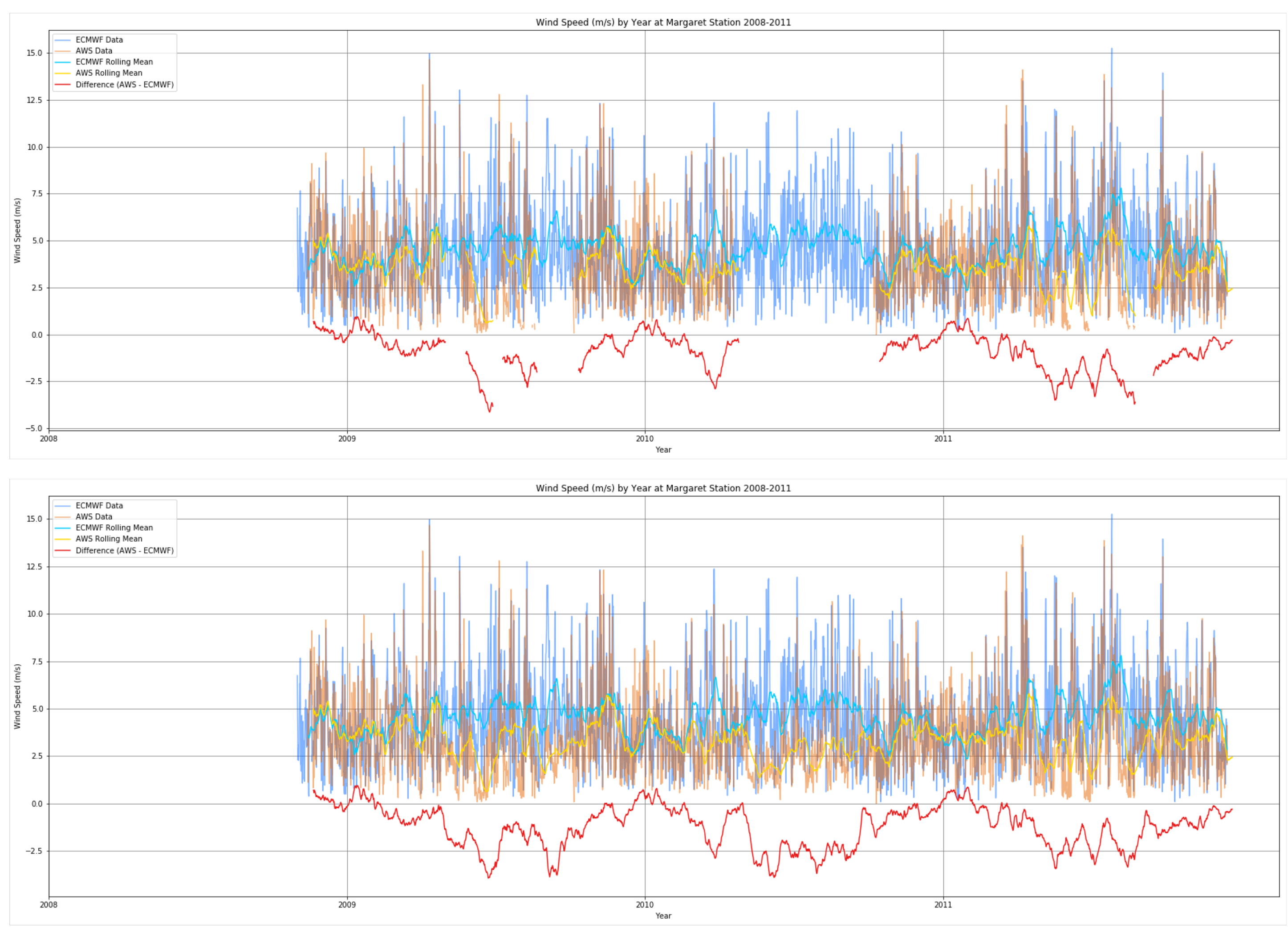
Learning Rate – 0.001

Gradient Descent Function – Limited-memory BFGS

Neural Network Essential Results

- Uncleaned AWS wind speed vs ECMWF wind speed (r = 0.607)
- Filled AWS wind speed vs ECMWF wind speed (r = 0.689)
- Avg AWS wind speed vs NN predicted wind speed (r = 0.711)

Neural Network Graph of Results



These graphs capture the effectiveness of our artificial neural network approach. Above is the graph of windspeed values at Margaret between 2008-2011, as they are in the cleaned data. Below that is the graph of windspeed values at Margaret between 2008-2011, after the data gaps have been filled in using our artificial network. Clearly, in the bottom plot we filled in the numerous gaps in our data and, as a result, have a much better picture of the actual wind speed patterns in the region than in the top plot.