

Artificial Neural Network models to predict Katabatic Winds over Ross Ice Shelf, Antarctica
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Strong Katabatic winds in Antarctica are responsible for wind-scoured blue ice formations, polynya, overturning ocean circulation, sea ice, and local-scale variations in ice accumulation rates. 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. Notably, ECMWF Pressure is an average 7.9 ± 2.8 hPa higher than AWS pressure, and ECMWF temperature has seasonal bias which varies by station, but in the case of Schwerdtfeger, in the winter months the ECMWF monthly average temperature is 1-2 °C lower than the AWS monthly average temperature with no overlap between the 99.7% confidence intervals surrounding these means. 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 $r = .74$, and to the cleaned and Neural Network filled-in AWS wind speed data with $r = .69$. 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.

****AWS dataset is the cleaned version unless stated otherwise****

**** These are averages from all stations on the Ross Ice Shelf****

****By using NN to predict Wind Speed values we increase the size of the data over which the correlations here are being calculated by an average of 16%, or 4211 data points****

Wind Speed

Avg AWS wind speed vs NN predicted wind speed in Neural Network test set $r = 0.711$

Avg AWS wind speed (null filled with NN) vs ECMWF wind speed $r = 0.689$

Avg AWS wind speed vs ECMWF wind speed $r = 0.742$

Avg Uncleaned AWS wind speed vs ECMWF wind speed $r = 0.607$

U wind speed

Avg AWS U wind speed vs NN predicted U wind speed in Neural Network test set $r = 0.664$

Avg AWS U wind speed (null filled with NN) vs ECMWF U wind speed $r = 0.677$

Avg AWS U wind speed vs ECMWF U wind speed $r = .0699$

Avg Uncleaned AWS U wind speed vs ECMWF U wind speed $r = .623$

V wind speed

Avg AWS V wind speed vs NN predicted V wind speed in Neural Network test set $r = 0.692$

Avg AWS V Wind Speed (null filled with NN) vs ECMWF V wind speed $r = 0.685$

Avg AWS V wind speed vs ECMWF V wind speed $r = 0.707$

Avg Uncleaned AWS V wind speed vs ECMWF V wind speed $r = 0.575$