FAST DOMAIN-AWARE NEURAL NETWORK EMULATION OF A PLANETARY BOUNDARY LAYER PARAMETERIZATION IN A NUMERICAL WEATHER FORECAST MODEL

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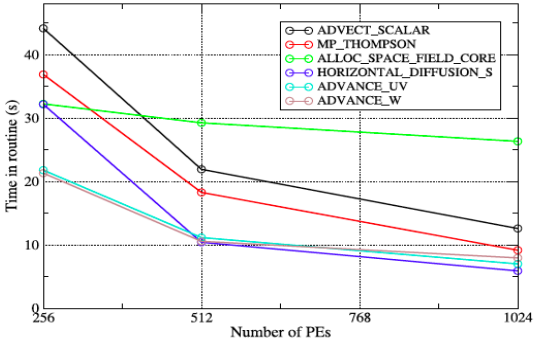
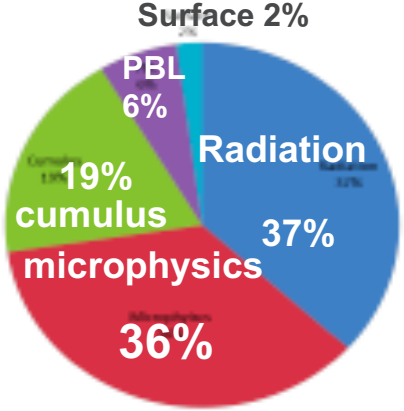
NEED FOR FASTER PHYSICS MODULES

Physics parameterizations take significant amount of the computational research

- We will talk about regional weather/climate models for th rest of the talk. Similar concepts apply to earth system models
  - In a forecast mode, the model computing times are dominated by initial conditions/setup (1-3 day run)
    - Cray (WOMPS- WRF code optimization for Meso-Scale Process Studies) found that all physical process take up uniform amount of time (4% each)
  - In a downscaled climate model mode (10 to 30 yr simulation)
    - Various DOE systems (NERSC, ALCF) we find that parameterizations take significant time with radiative transfer taking about 37% of the total



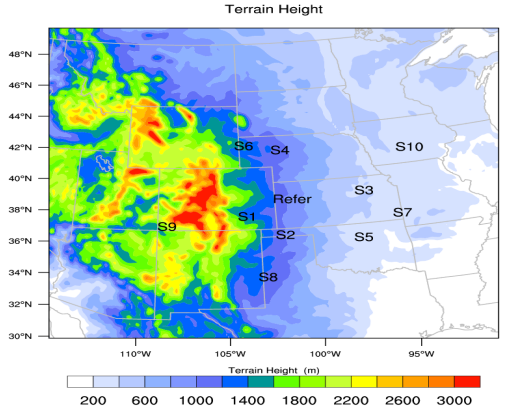
Porter et al.. 2013

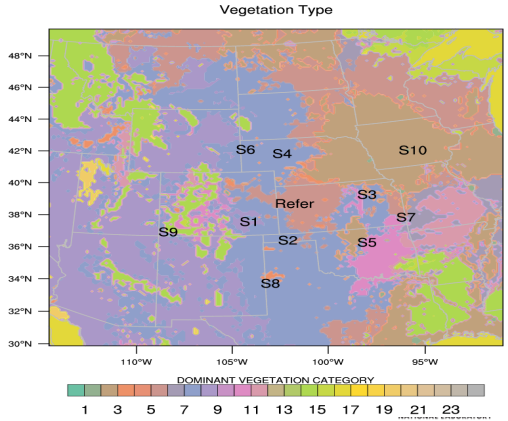


CAN DEEP LEARNING HELP IN DEVELOPING FASTER PHYSICS EMULATORS?

DNN schemes can potentially run in the GPUs or accelerators in the next generation of compute platforms

- We develop a DNN emulator of planetary boundary layer physics parameterization
- Demonstrate that domain expertise considerably influences the amount of data needed for learning
- DNN model learned from a single point is transferable over a large domain
- The type of DNN models used directly influences the model accuracy and errors





LEARNING AND TESTING DATA SET

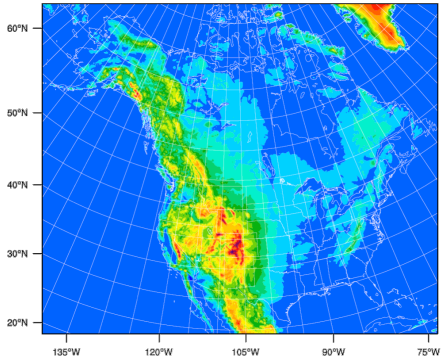
Model output used for learning

- Thirty years of WRF model output simulations at 12 km spatial resolution and saved every three hours covering all of North America is available
- Input to the subroutine that calculates the PBL physics, known as the YSU scheme is used to train the DNN model.
- 22 years of data available for training and tested with data for the year 2005

Input variables
2-meter water vapor mixing ratio (Q2),
2-meter air temperature (T2),
10-meter zonal and meridional wind (U10, V10)
ground heat flux (GRDFLX)
Downward short wave flux (SWDOWN)
Downward long wave flux (GLW)
latent heat flux (LH)
Upward heat flux (HFX)
Planetary Boundary Layer height (PBLH)
surface friction velocity (UST)
ground temp (TSK)
soil temperature at 2m below ground (TSLB)
Soil moisture for 0-0.3cm below ground (SMOIS)
geostrophic wind component at 700hPa (Ug, Vg)

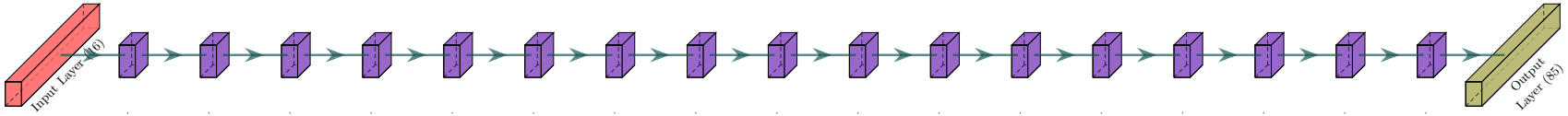
Output variables
zonal wind (U)
meridional wind (V)
Temperature (tk)
Water vapor mixing ratio (QVAPOR)

Data Domain

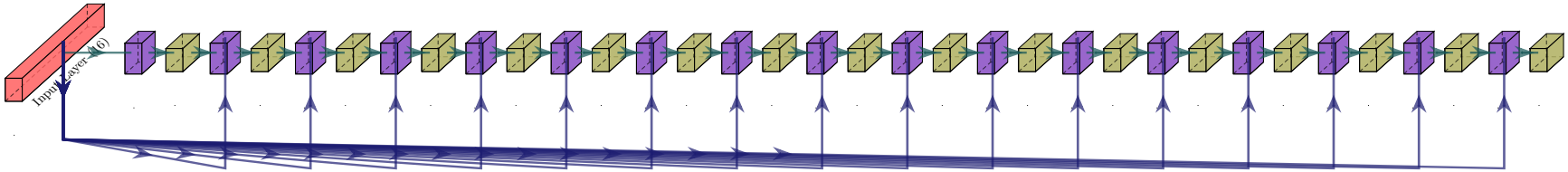


DNN ALGORITHMS TESTED

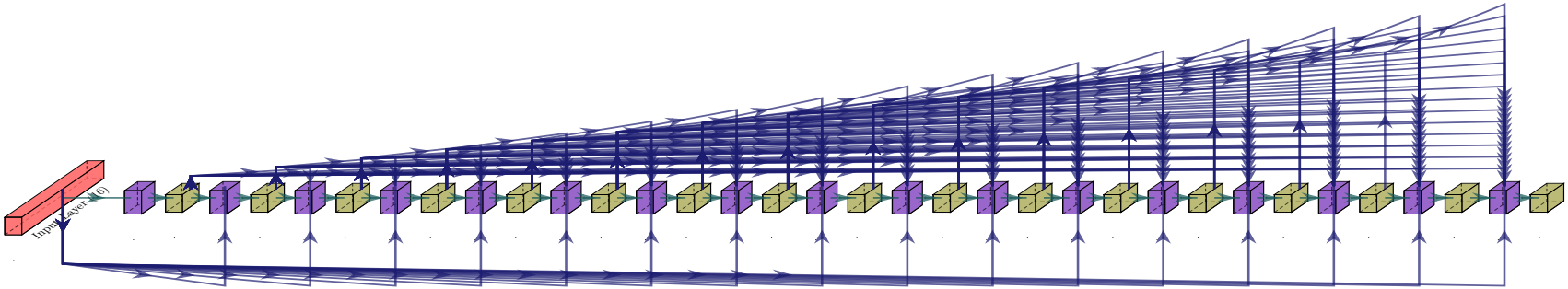
From no domain knowledge to increasing levels of domain knowledge



fully connected feed forward neural network (FFN)



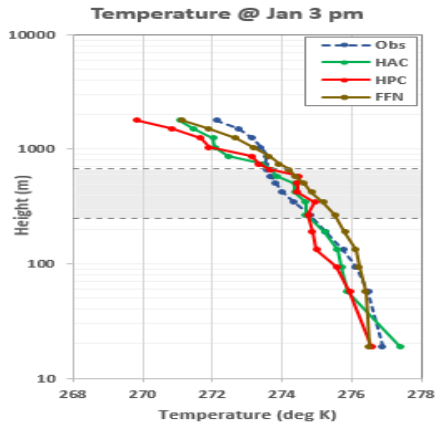
hierarchically connected network with previous layer only connection (HPC)

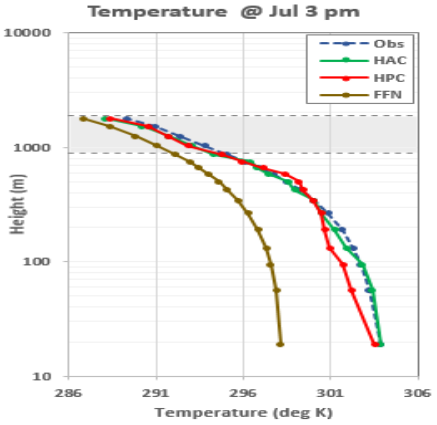


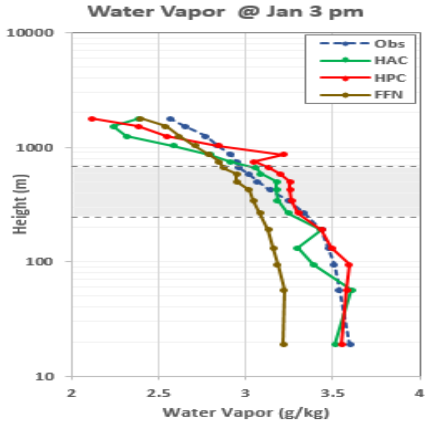
hierarchically connected network with all previous layers connection (HAC)

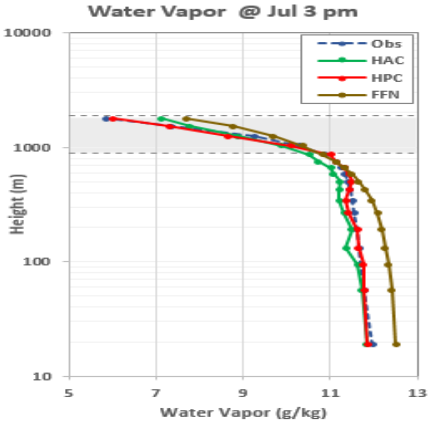
RESULTS OF THE TRAINING

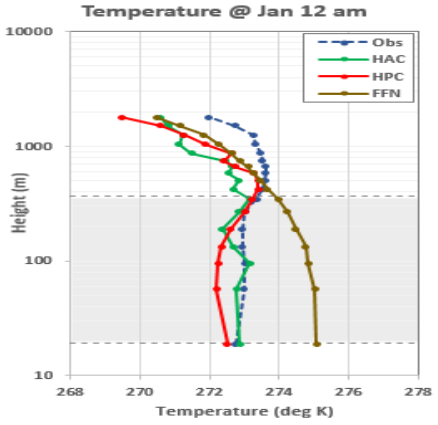
The DNN emulator reproduce the profiles with high accuracy

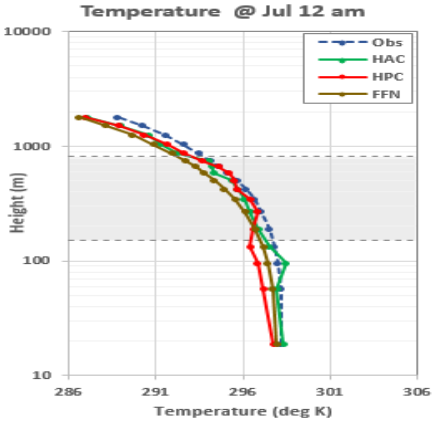


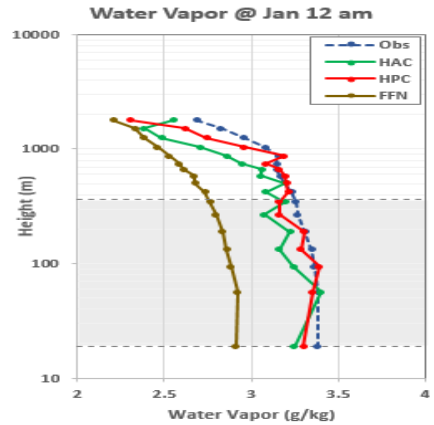


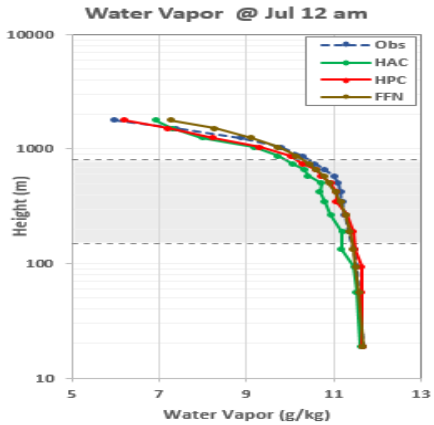












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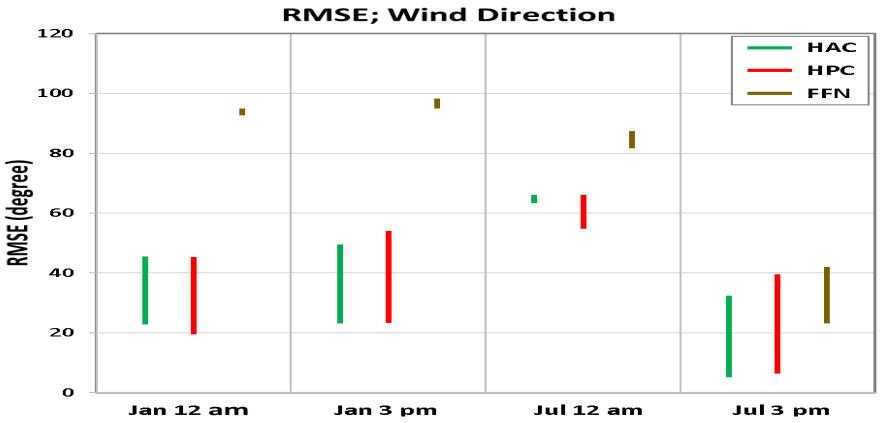

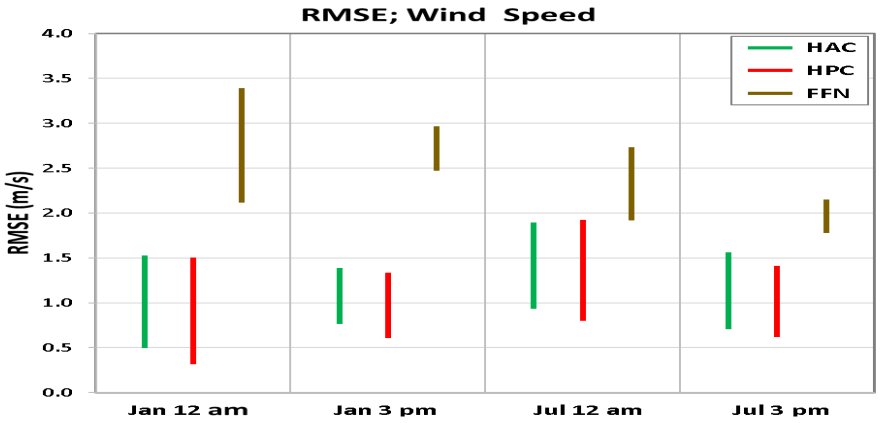

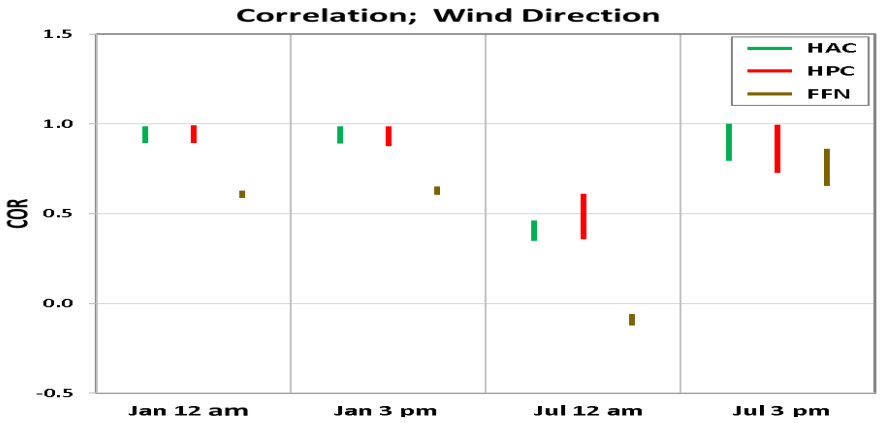

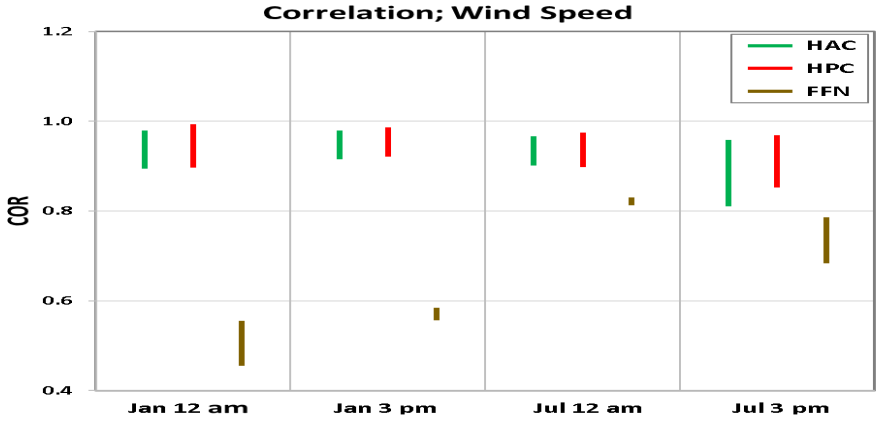

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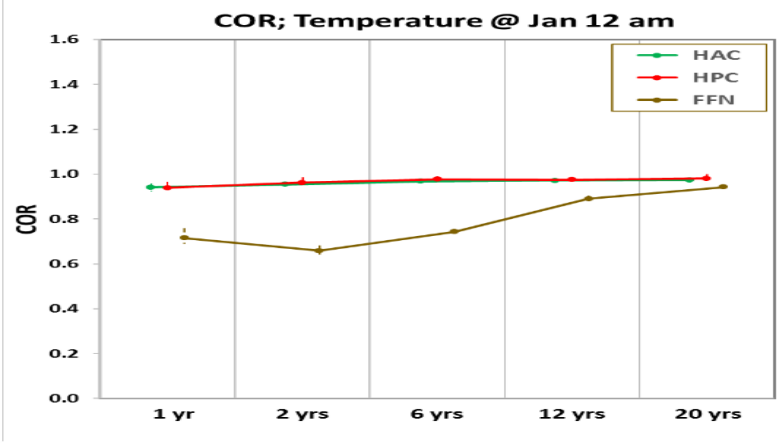
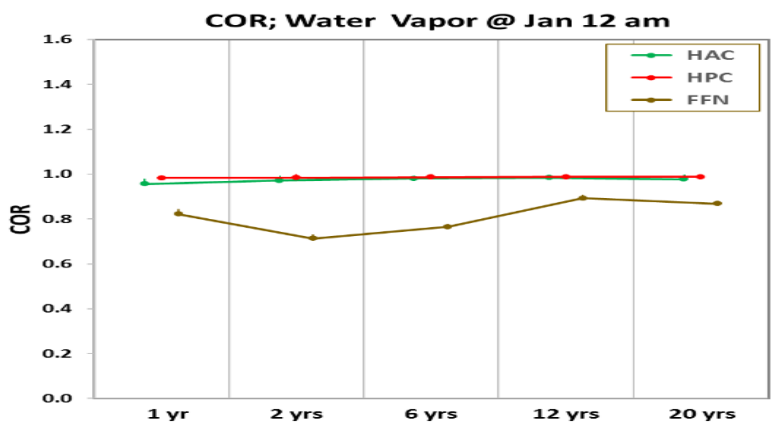
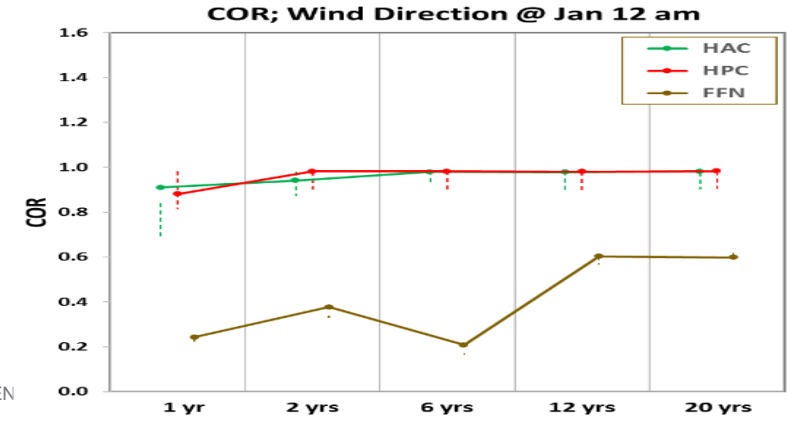
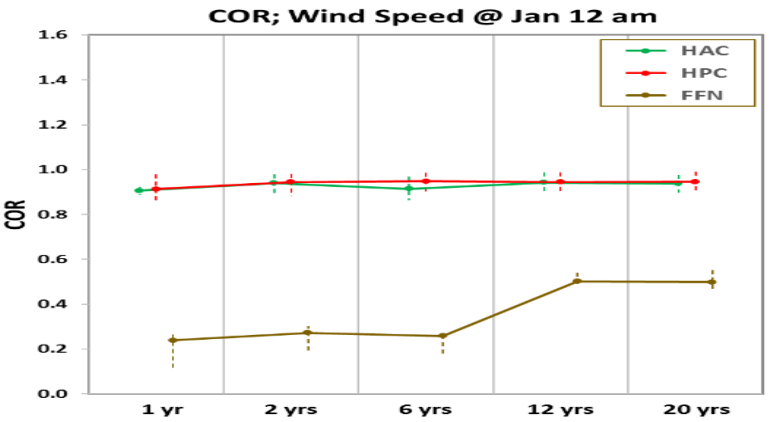








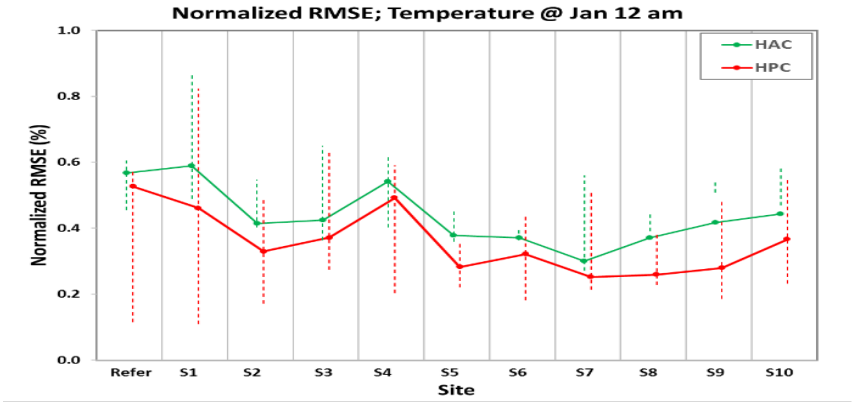
DATA REQUIRED FOR TRAINING AND COMPLEXITY OF THE DNN

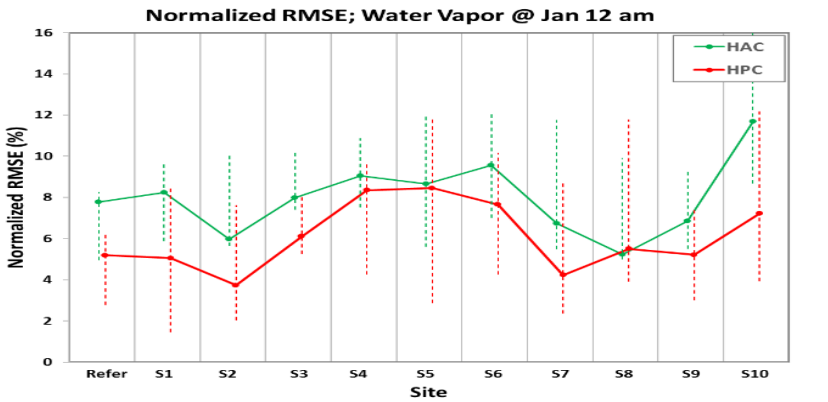
Domain informed DNN needs lot less data to produce reasonable results

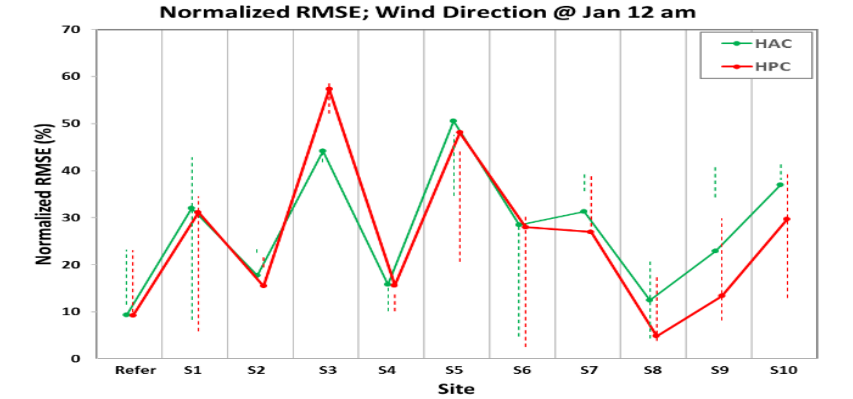
- For the HAC and HPC networks we need six years of data to get high accuracy of predictions
- Increasing the training data by another six years doesn't improve the model performance
- The FFN network needs twelve years of data to obtain the same level of accuracy as the HAC and HPC trained with six years of data
- The performance of FFN has not reached a plateau even after using twenty years of data
- FFN performance suggests that even this scheme can be used to 'learn' if enough data is available

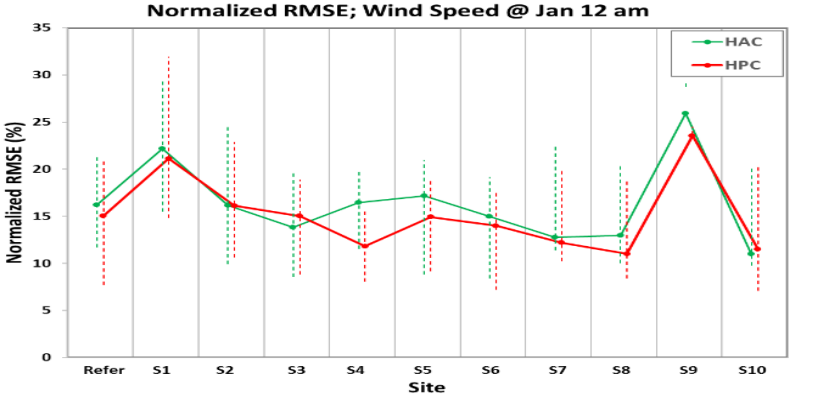
TRANSFERENCE

Model trained with a single point works over large domains









CONCLUSIONS

- DNN based process model emulator was developed
- The emulator is about a factor ~2-3 faster
- The DNN model built with domain expertise requires less training data
- The FFN takes double the training data and is still on a path of improving accuracy of prediction
- Given large enough data the FNN could produce equally accurate results as the DNN informed by domain expertise

ACKNOWLEDGEMENTS

ASR (Rao) & ARGONNE LDRD (Wang)