Deep Neural Network (DNN) Perspective On Atmospheric Motion Vectors

Fei He
University of California, Los Angeles
hefeiucla@ucla.edu

Derek J. Posselt, NASA JPL/UCLA

Hai M. Nguyen, NASA JPL

Longtao Wu, NASA JPL

Joaquim P. Teixeira, NASA JPL

Modern technology

In recent decades, artificial intelligence techniques (e.g. machine learning, data mining, deep learning), big data and high performance computing environments power many aspects of modern society and scientific research.

Credit: NVIDIA

UCLA
MICHIGAN ENGINEERING
UNIVERSITY OF MICHIGAN

Application of Machine Learning and Deep Learning in Atmospheric Science

Machine learning refers to a vast set of tools for understanding data.

Deep learning is a sub-topic of machine learning.

Supervised learning

Neural network emulation of longwave and shortwave radiation in a climate model (V. M. Krasnopolsky et al. 2005, 2008, 2010)

Random forests predictions of a multiresolution climate model ensemble (Anderson and Lucas 2018)

Artificial intelligence to improve real-time decision making for high impact weather (storm duration, precipitation classificiation) (A. McGovern et al. 2017)

Deep convolutional neural networks for detecting extreme weather (tropical cyclone, atmospheric river, weather fronts) in climate datasets (Liu et al. 2016)

Unsupervised learning

Self-Organizing Map to cluster the tropical cyclone tracks over the Western North Pacific (Kim and Seo 2016)

Self-Organizing Map to identify the horizontal and vertical structures of the Madden-Julian Oscillation (MJO) through its life cycle. (Chattopadhyay, Vintzileos and Zhang 2013)

Applications are not limited to these examples

UCLA MICHIGAN ENGINEERING UNIVERSITY OF MICHIGAN

Motivation

Explore the potential of deep learning methods in deriving Atmospheric Motion Vectors (AMVs) and charactering its associated errors.

What will be the add value of deep learning methods to existing AMVs community?

Background

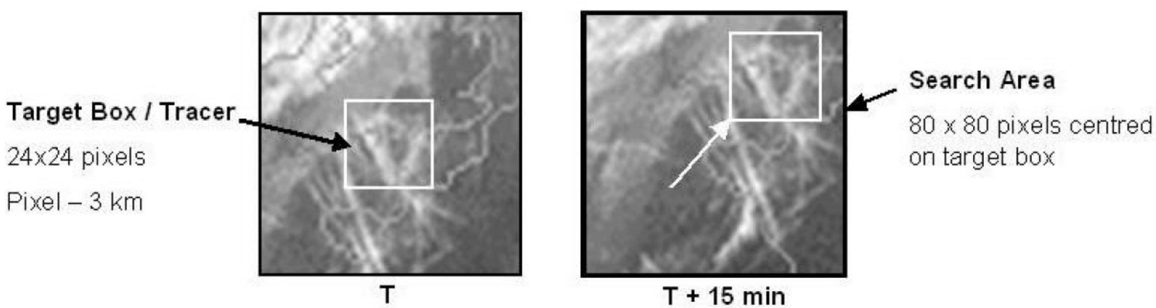
Atmospheric Motion Vectors (AMVs):

Winds derived by tracking clouds or areas of water vapour through consecutive satellite images.

Importance of AMVs:

Provide tropospheric wind information for **numerical weather prediction, data assimilation and observation system simulation experiments (OSSE).** Particularly true over the oceans and at high latitude where conventional wind data (sondes and aircrafts) are scarce.

How to derive AMVs from satellite images?



Winds are calculated based on the movement of water vapor features between two consecutive times, $v = \frac{d}{\Delta t}$.

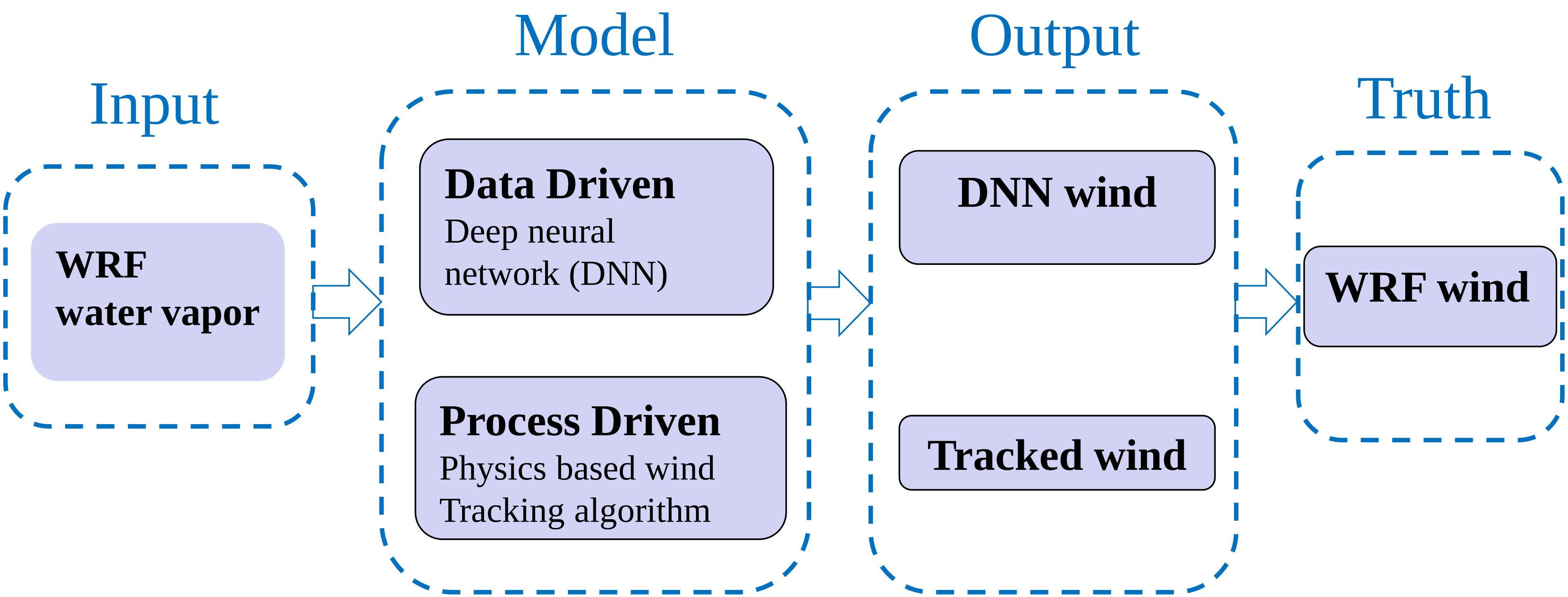
The final AMV is an average of two or three component vectors calculated from a sequence of three or four images.

CREDIT: Mary Forsythe, Met Office, Exeter, UK

UCLA
MICHIGAN ENGINEERING
UNIVERSITY OF MICHIGAN

Experiment Design

Data: qv (water vapor), ua (zonal wind) and va (meridional wind) collected from an extratropical cyclone in a nature run of Weather Research and Forecasting Model (WRF).



Predictors (Features) and Targets (Labels)

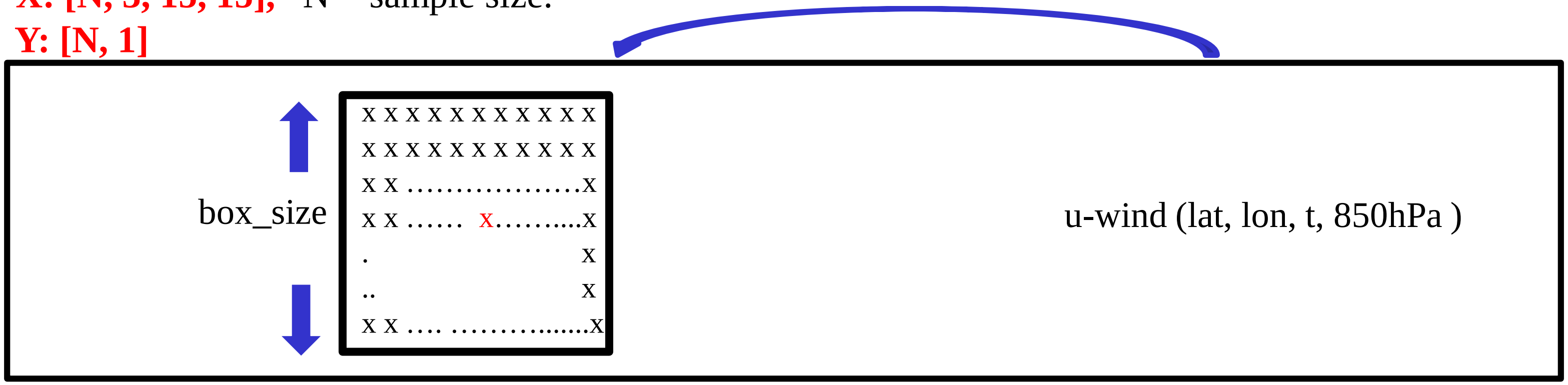
Construct (X, Y):

Y: u-wind (east – west direction) and v-wind (north-south direction) at time (lat, lon, lev, t)

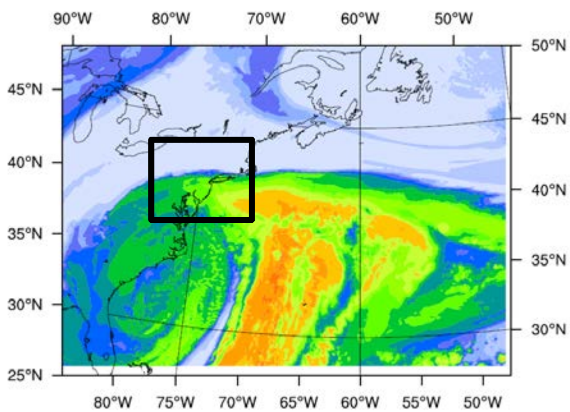
X: has dimensions of 3 × box_size × box_size, 3: water vapor at time (t-1, t, t+1), box_size: a size for the patch, final choice: box_size = 15

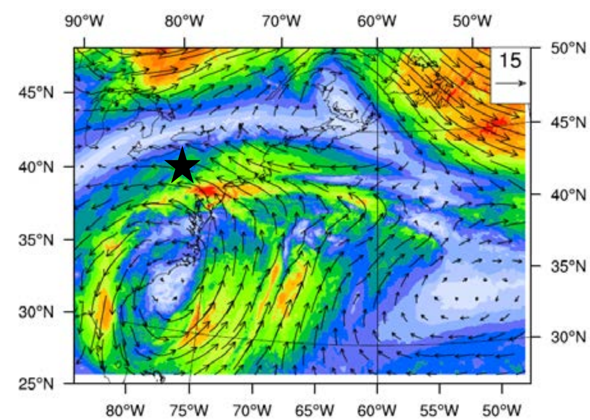
X: [N, 3, 15, 15], N = sample size.

Y: [N, 1]



water vapor



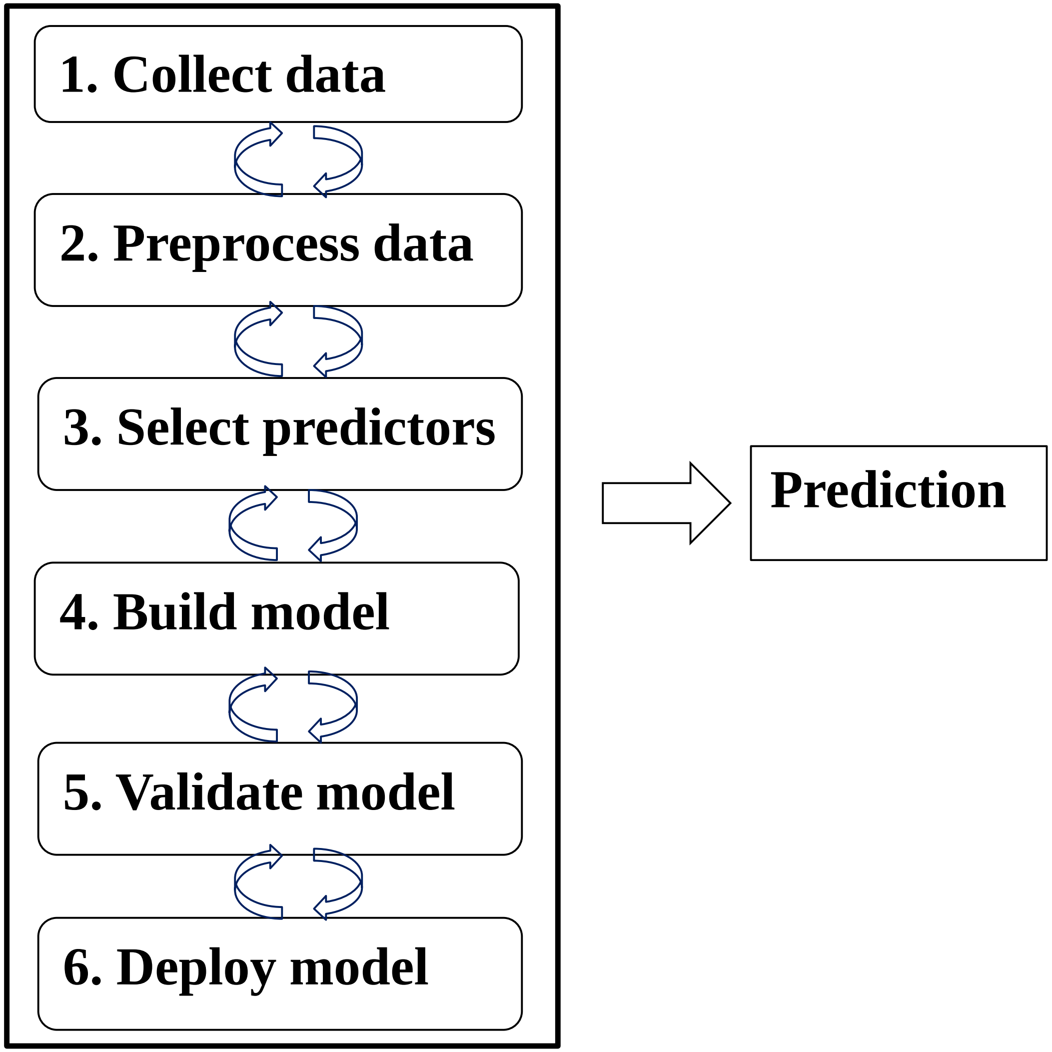


wind

ua, va, qv in a form of nlat = 249, nlon = 337, ntime = 361.
This results in a total of over 30 million sampling points.

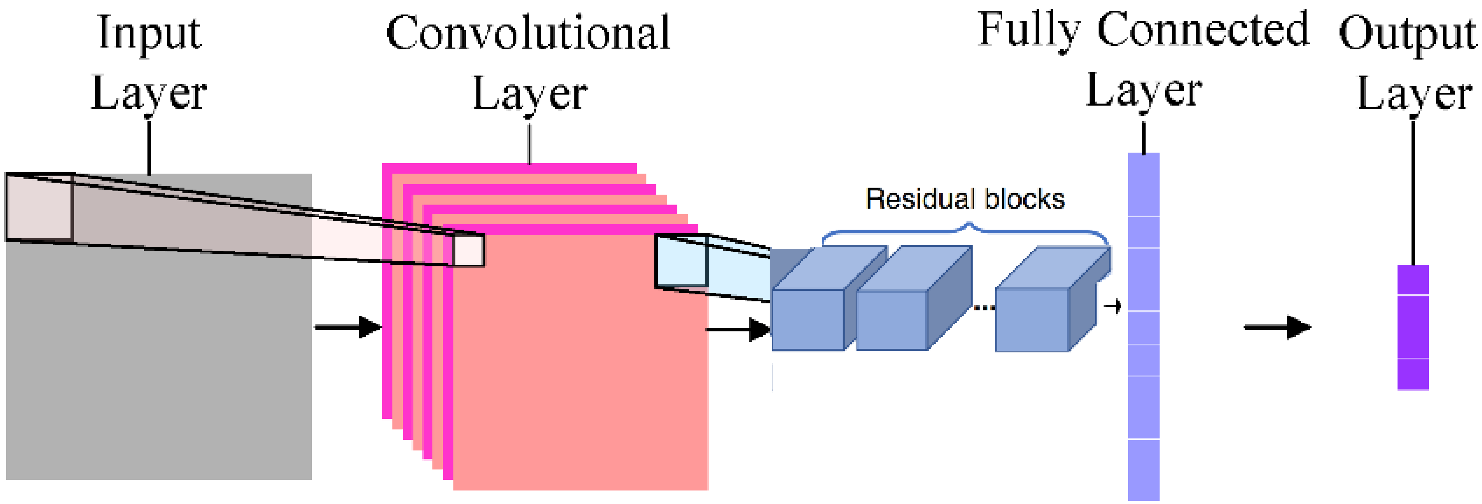
UCLA MICHIGAN ENGINEERING UNIVERSITY OF MICHIGAN

Model Development



Model Component of DNN

- 1 Convolutional layer (nb_filter = 16, filter_size = 3, stride = 1)
- 5 Residual blocks
- 1 global max pooling layer
- 1 Fully connected layer
- 1 Output layer



Note: the image is not the exact description of our model, just helps to visualize the model.

Image Reference: Peng, M.; Wang, C.; Chen, T.; Liu, G. NIRFaceNet: A Convolutional Neural Network for Near-Infrared Face Identification. *Information* **2016**, *7*, 61.

Experiment 1

Training data and prediction data are in the same data pool, which contains about 30 million sample points.
(2006 -11- 22-00-10 to 2006-11-23-05-50, 357 x 337 x 249)
Training data sample size = 500, 000
Randomly selected out of the data pool

Training
N = 500,000

over 30 million
sampling points

Test: 100,000
Prediction

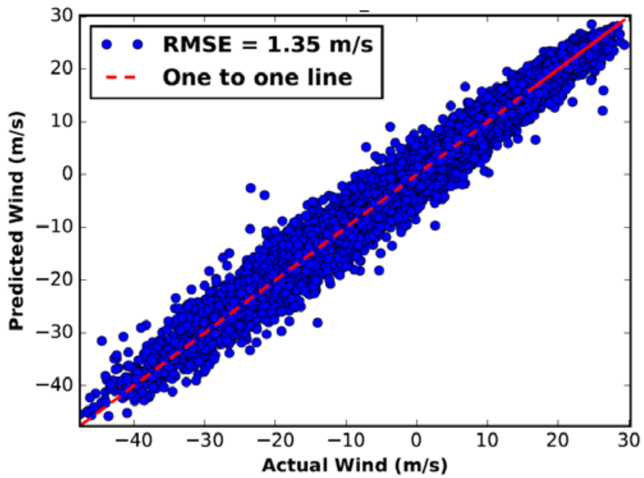
Prediction error = **Reducible error** + **Irreducible error**

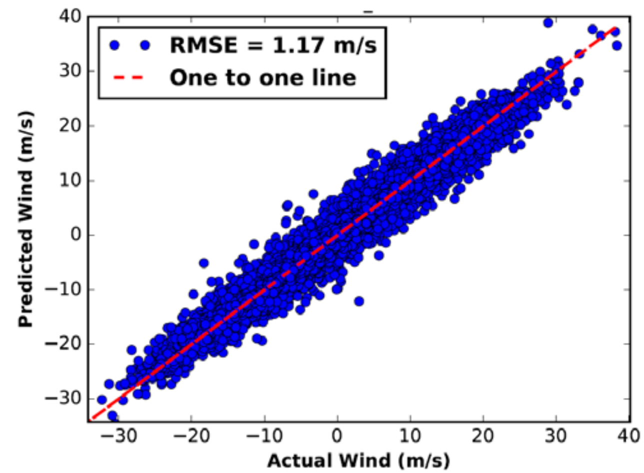
(Feature engineering
Hyperparameter tuning
Random forest/neural networks
Model ensemble, etc…)

(inconsistent data distribution
problem set up, etc…)

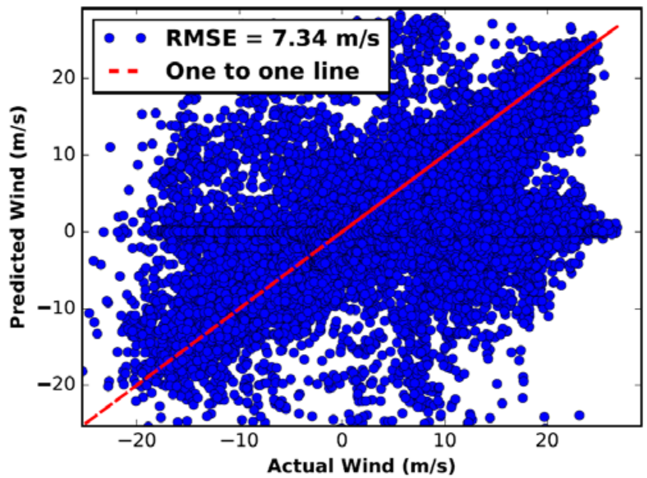
Experiment 1 Results

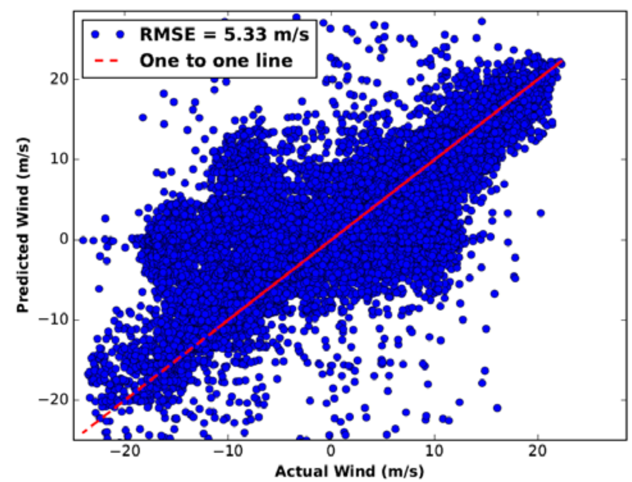
DNN





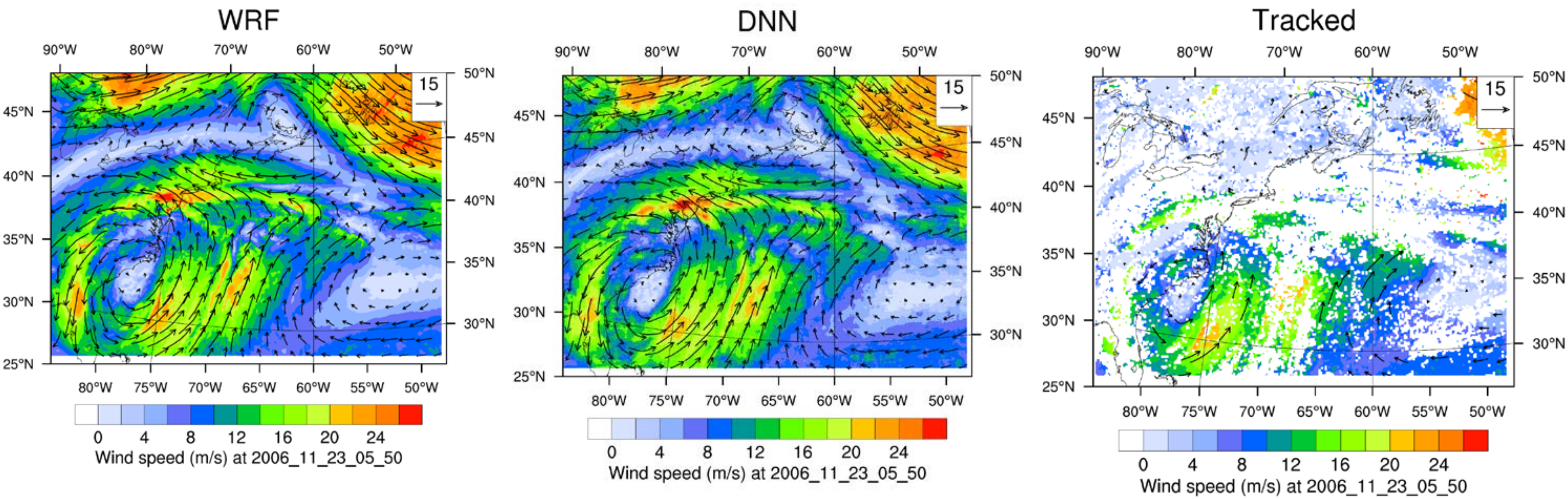
Traditional Method





RMSE: Root mean square error

Truth | DNN method | Traditional method



- DNN method can predict the winds in full coverage, whereas missing data points are present in the traditional method.
- DNN method captures the wind distribution quite well compared to the truth provided that the training data set is fully inclusive and representative.

Experiment 2

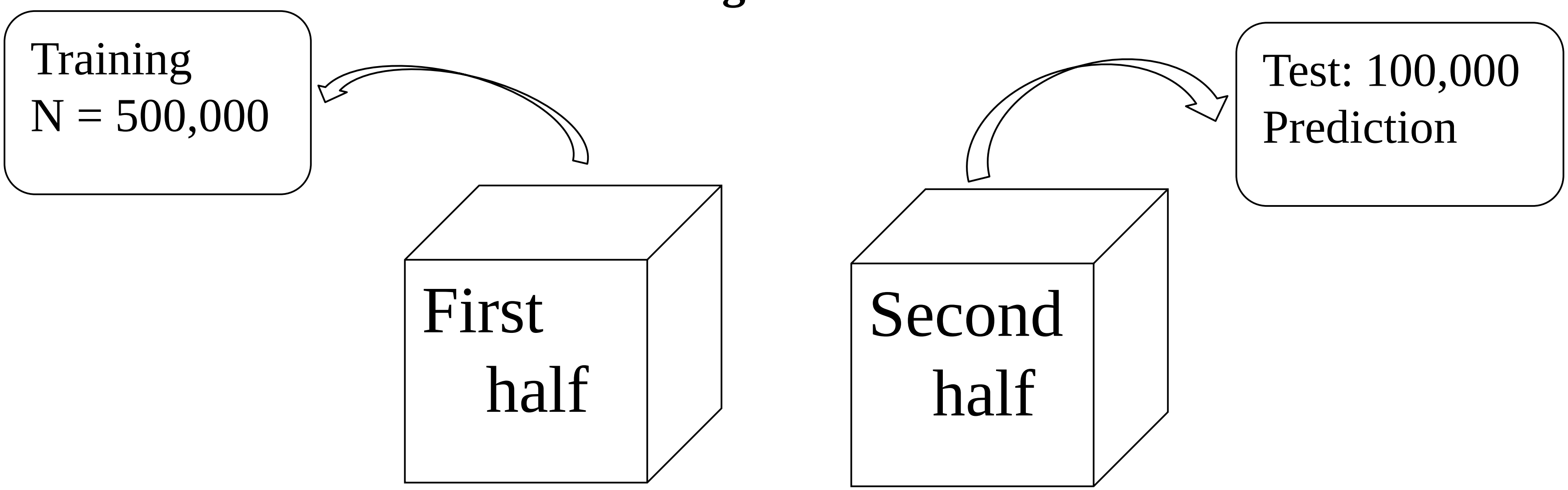
Split the entire data set into two halves

(**First half:** 2006 -11- 22-00-10 to 2006-11-22-14-55

Second half: 2006-11-22-15-00 to 2006-11-23-05-50)

Training on the first half

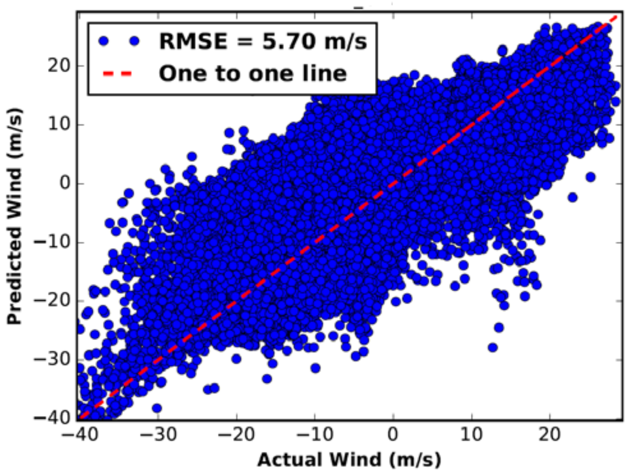
Predicting on the second half

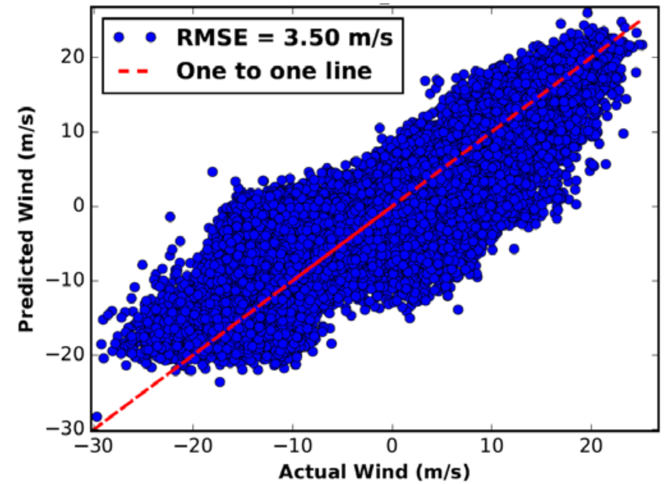


Prediction error = **Reducible error** + **Irreducible error**

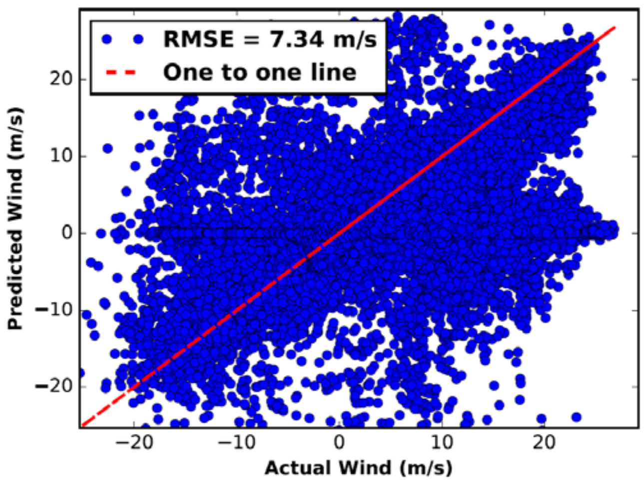
Experiment 2 Results

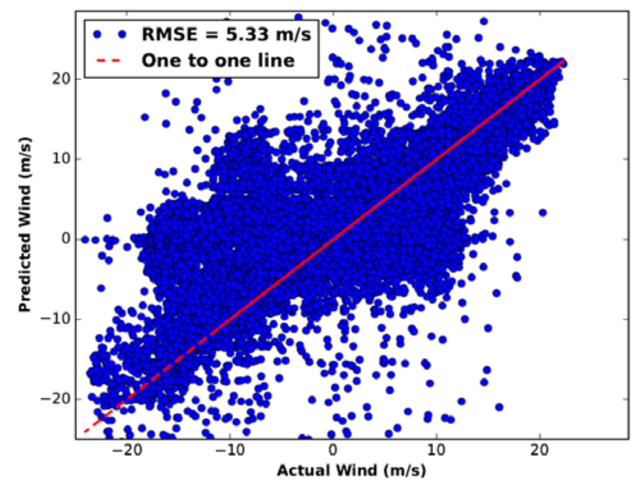
DNN



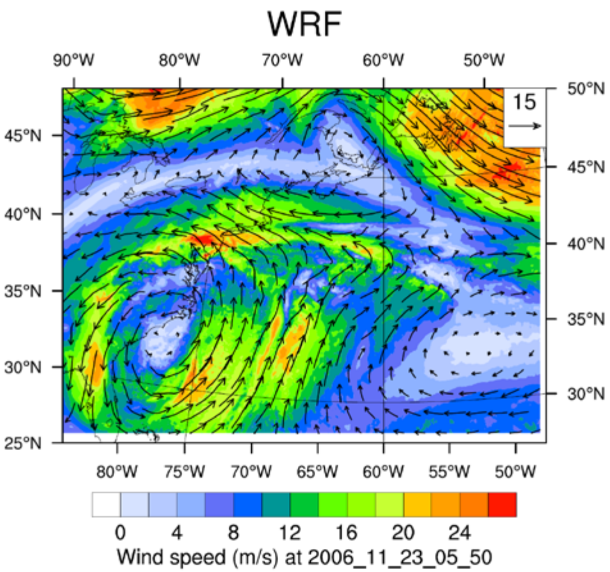
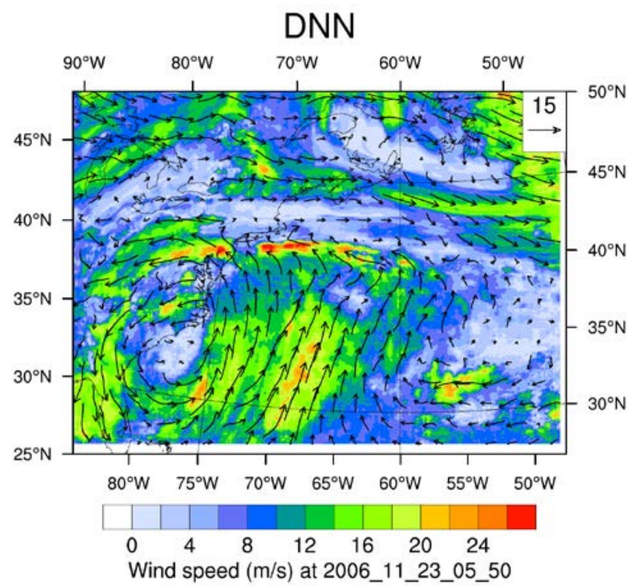
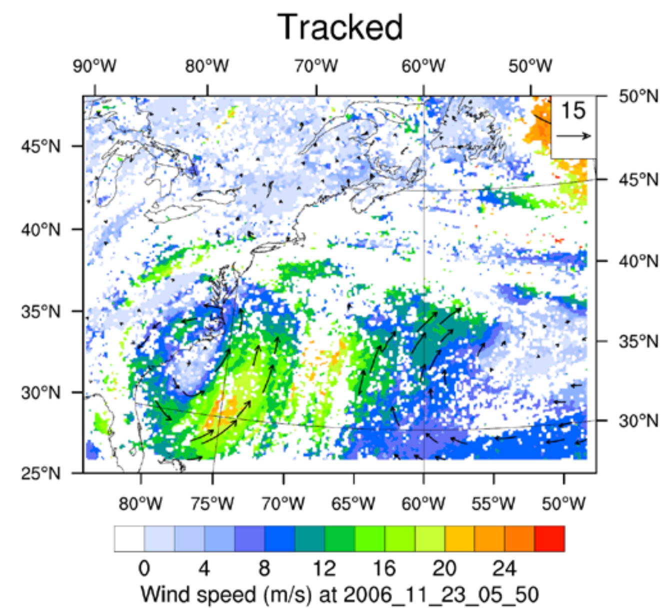


Traditional Method





RMSE: Root mean square error

Truth	DNN method	Traditional method
		

- DNN method can predict the winds in full coverage, whereas missing data points are present in the traditional method.
- DNN method still achieve better performance to traditional method.

Conclusion and Discussion

- DNN is promising in deriving atmospheric motion vectors from water vapor images for better performance and higher data efficiency.
- Collecting data for training samples is key to the success.

Implication for future work:

- Deep neural network to leverage observation winds, tracked winds and numerical simulated winds to deliver another dimension of wind product
- Deep neural network model to predict the AMV error using wind tracking algorithm

Questions?