NOAA UFS Virtual Seminar

Enhancing Forecast Value with Artificial Intelligence

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October 13, 2022

NCAR | RESEARCH APPLICATIONS LABORATORY

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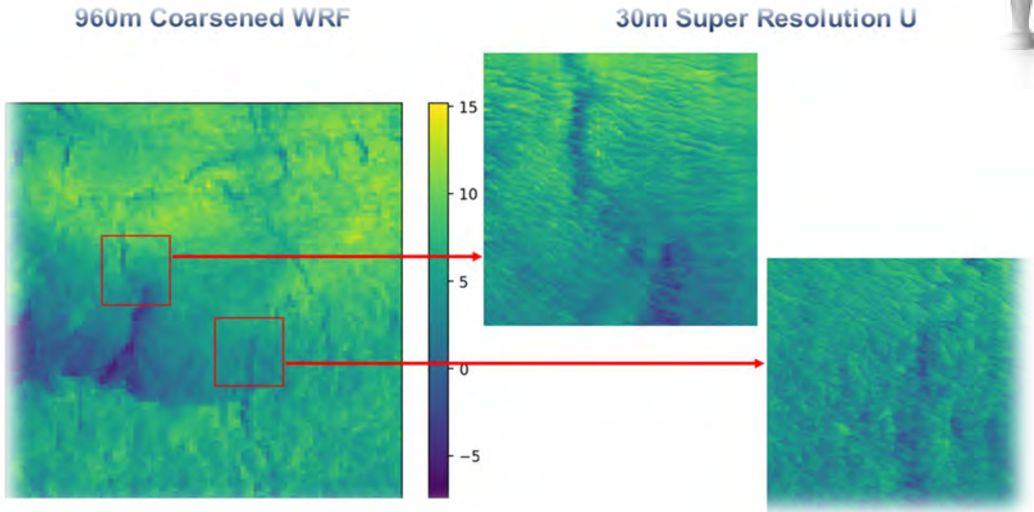
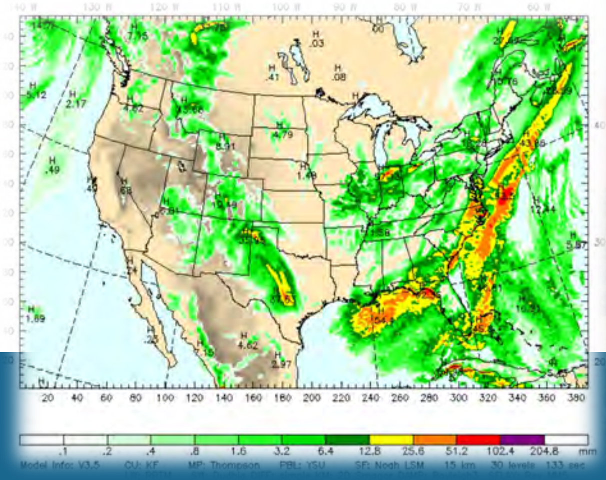
The Plan

- AI/ML for Weather Forecasting
- A Systems Approach – Blending NWP with AI/ML for Renewable Energy
- AI/ML for
  - Severe weather forecasting
  - Model Parameterization
  - Dynamics
  - Downscaling
- Where are we Going?





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My First AI Presentation

2/5/96

Climate and Global Dynamics

DIVISION BRIEFINGS &
RESEARCH REPORTS
Main Seminar Room
Mondays, 3:30 p.m.

11 March 1996 —

D. Pollard, R. Madden, R. Milliff

18 March 1996 —

D. Baumhefner, J. Kiehl, J. Hurrell

25 March 1996 —

M. Taylor, E. Brady, J. Lee

1 April 1996 —

S. Thompson, P. Ditlevsen, T. Hoar

8 April 1996 —

L. Mearns and A. Seth

29 April 1996 —

D. Schimel, S. Haupt, T. Wigley

April 29 is the final Research Reports session for 1996.

Eigenvalue Matching,

a Traveling Salesman, and

a Genetic Algorithm

Sue Ellen Haupt

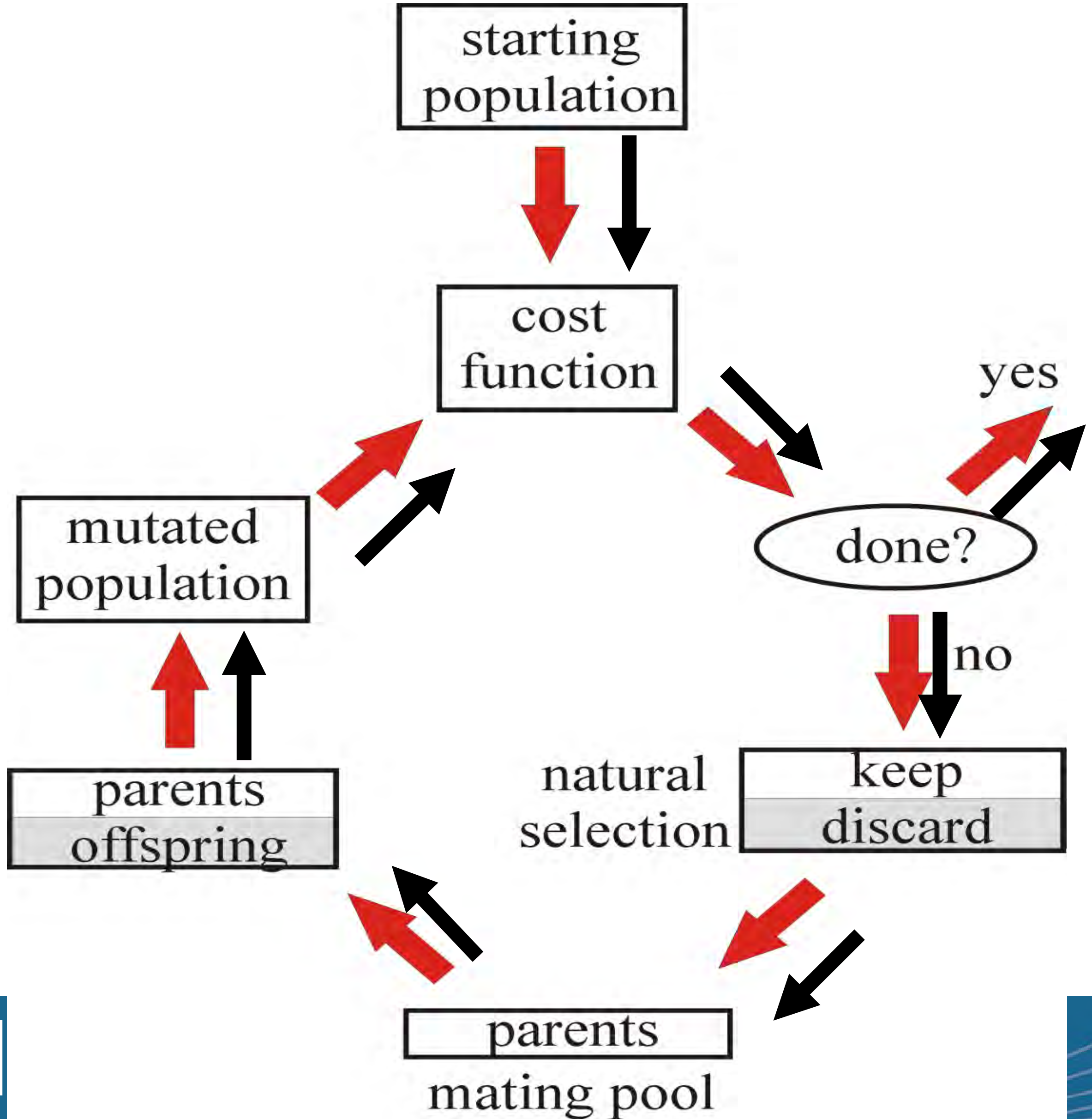
Collaborators:

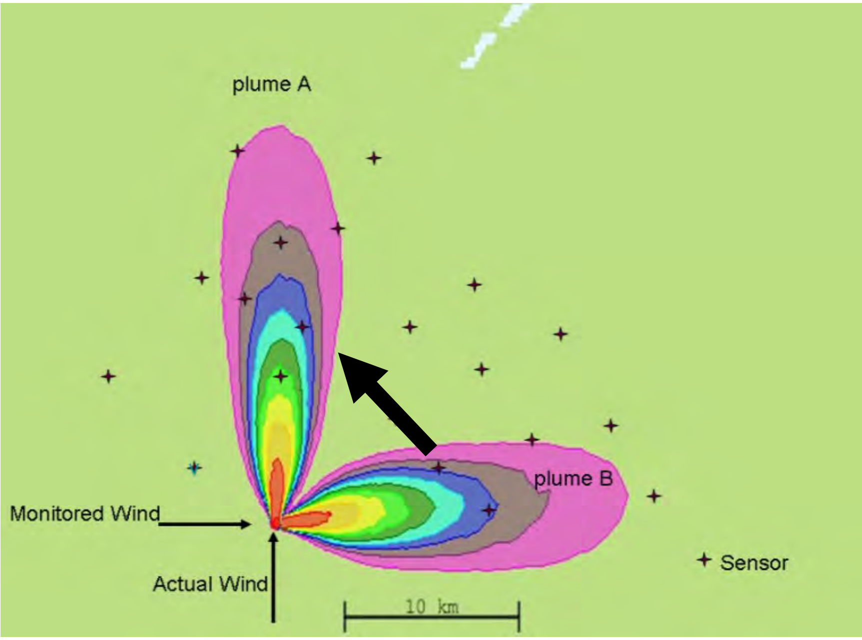
Grant Branstator

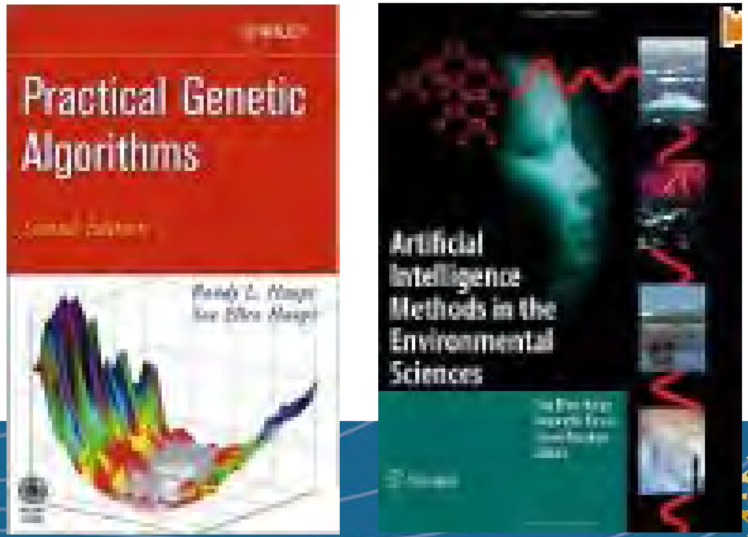
Randy Haupt

Evolution of my Work

GA-Variational Data Assimilation and Source Term Estimation

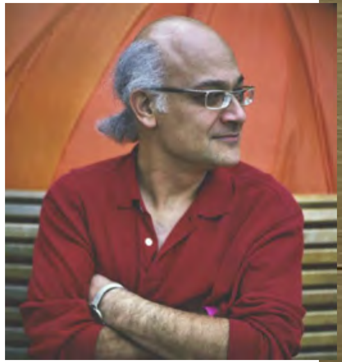






Lots of great folks helping to advance use of AI / ML in the Environmental Sciences

Current and Past Chairs of AMS AI Committee
American Meteorological Society



The History and Practice of AI in the Environmental Sciences
Sue Ellen Haupt, Philippe Tissot, Vladimir Krasnopolsky, Caren Marzban, Amy McGovern, David John Gagne, Valliappa Lakshmanan, John Williams, William Monager, *Bulletin American Meteor. Soc.*, E1351–E1370, https://doi.org/10.1175/BAMS-D-20-0234.1.

BAMS
Article

The History and Practice of AI in the Environmental Sciences

Sue Ellen Haupt, David John Gagne, William W. Hsieh, Vladimir Krasnopolsky, Amy McGovern, Caren Marzban, William Moninger, Valliappa Lakshmanan, Philippe Tissot, and John K. Williams

Focus on AMS Community

ABSTRACT: Artificial intelligence (AI) and machine learning (ML) have become important tools for environmental scientists and engineers, both in research and in applications. Although these methods have become quite popular in recent years, they are not new. The use of AI methods began in the 1950s and environmental scientists were adopting them by the 1980s. Although an "AI winter" temporarily slowed the growth, a more recent resurgence has brought it back with gusto. This paper tells the story of the evolution of AI in the field through the lens of the AMS Committee on Artificial Intelligence Applications to Environmental Science. The environmental sciences possess a host of problems amenable to advancement by intelligent techniques. We review a few of the early applications along with the ML methods of the time and how their progression has impacted these sciences. While AI methods have changed from expert systems in the 1980s to neural networks and other data-driven methods, and more recently deep learning, the environmental problems tackled have remained similar. We discuss the types of applications that have shown some of the biggest advances due to AI usage and how they have evolved over the past decades, including topics in weather forecasting, probabilistic prediction, climate estimation, optimization problems, image processing, and improving forecasting models. We finish with a look at where AI as employed in environmental science appears to be headed and some thoughts on how it might be best blended with physical/dynamical modeling approaches to further advance our science.

Keywords: Artificial intelligence; Data science; Decision trees; Deep learning; Expert systems; Machine learning

https://doi.org/10.1175/BAMS-D-20-0234.1

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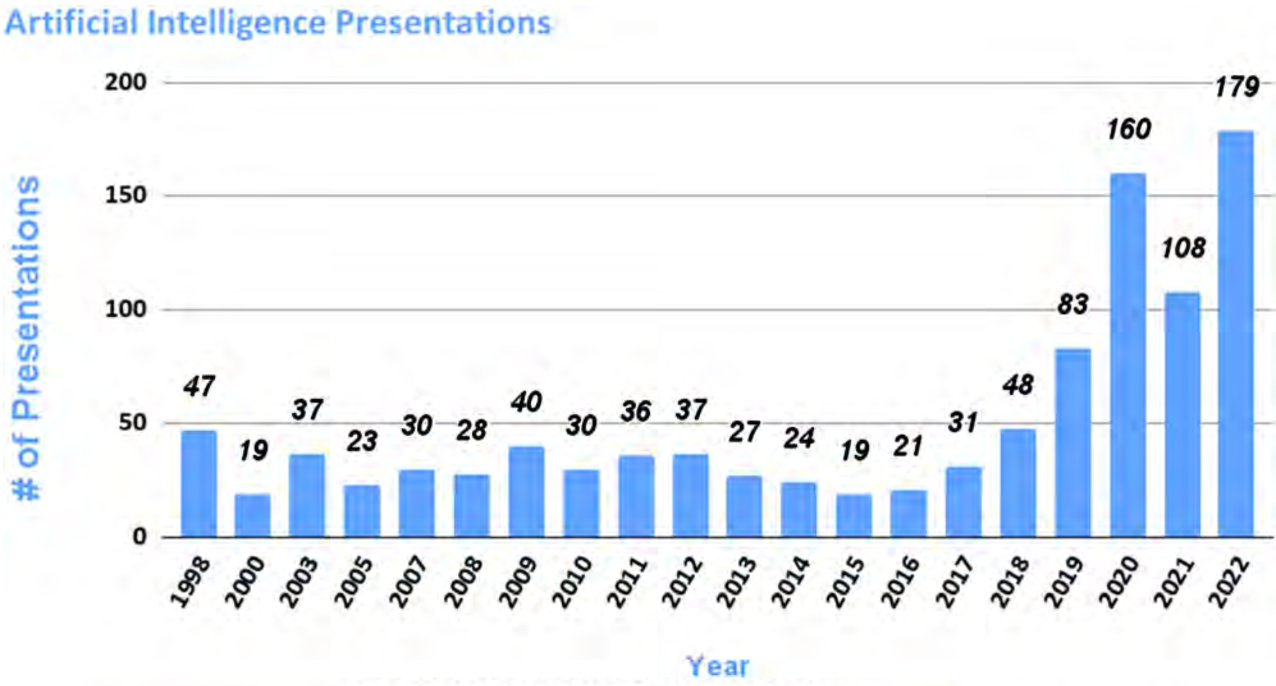
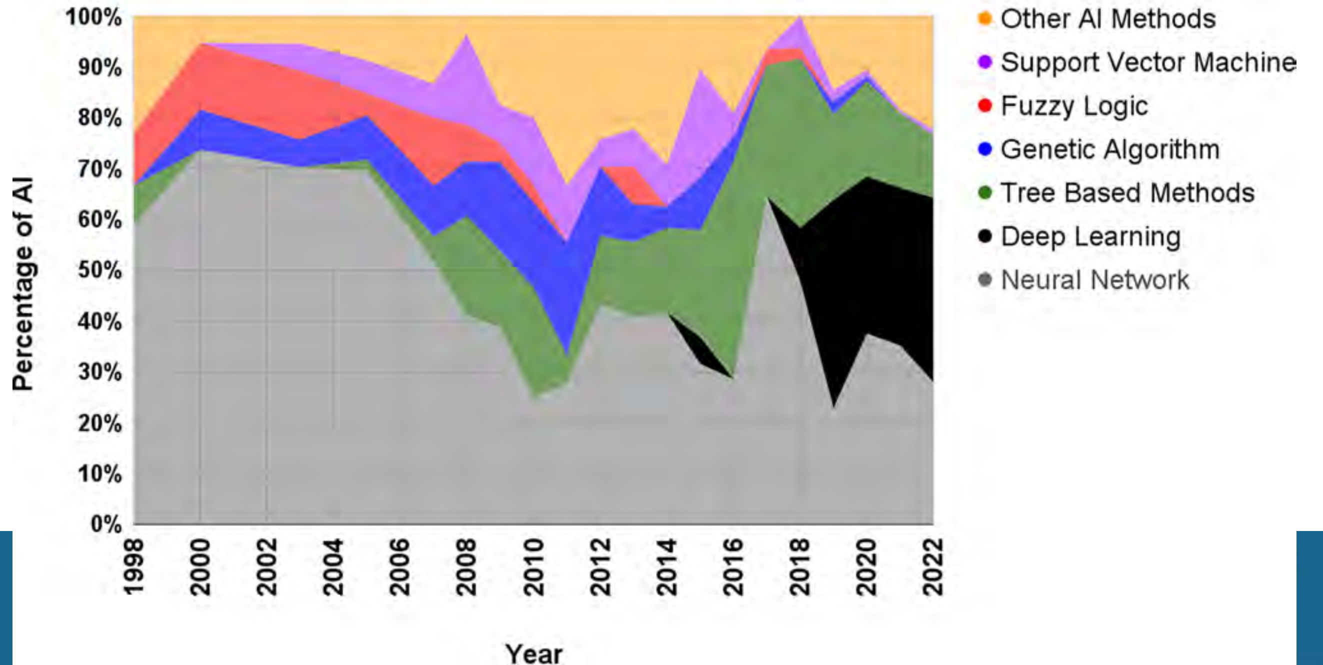
In final form 5 December 2021





AI/ML in Weather Forecasting

Two distinct approaches to weather forecasting

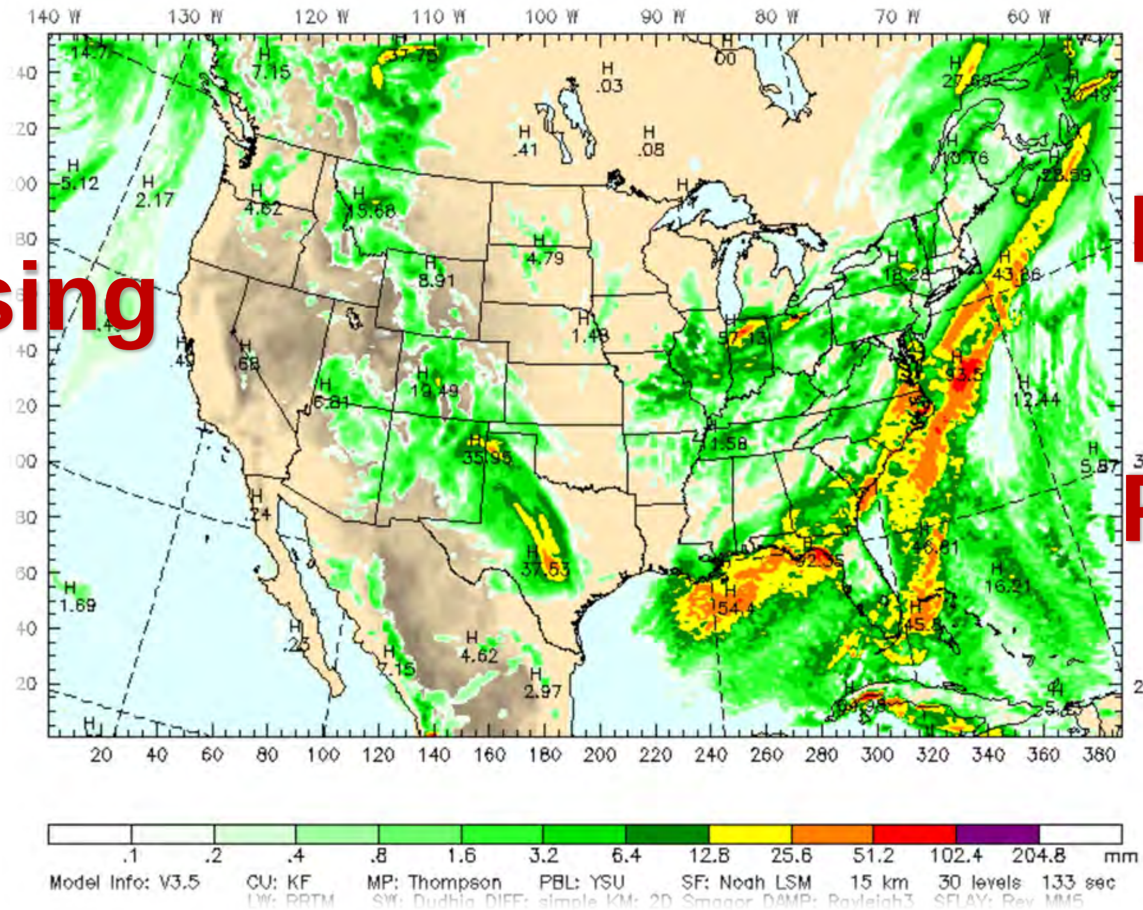
1. Equation based – numerical integration and pre - and post - processing
2. Empirically based – begin with data and find patterns →

Artificial Intelligence

Blend approaches for optimal prediction

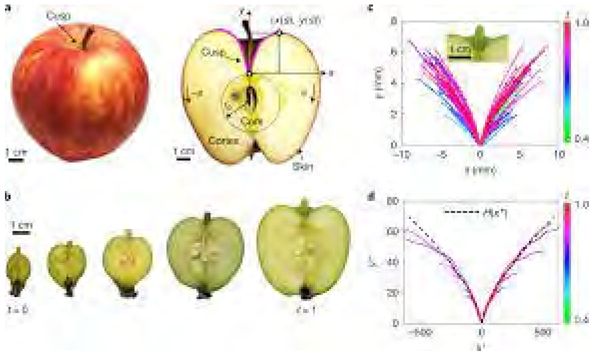
Approaches to leveraging AI for Weather Forecasting

Postprocessing



ML Dynamic Core

ML Parameterizations



NCAR's First Big AI Success: DICast®

Dynamic
Integrated
fore**Cast**
System

DICast® In a Nutshell

- *Machine-Learning Post-processer of model data*
  - *Create predictive relationships between model output, observations and desired forecast variables*
- *Optimal Forecast Combiner*
  - *Create best combination of inputs*

- ***Enables Decision Support***
- ***Uses Real-Time Data – IoT***
- ***Uses Large amounts of Model Data***

✓ *Real time*
✓ *Historical for training*

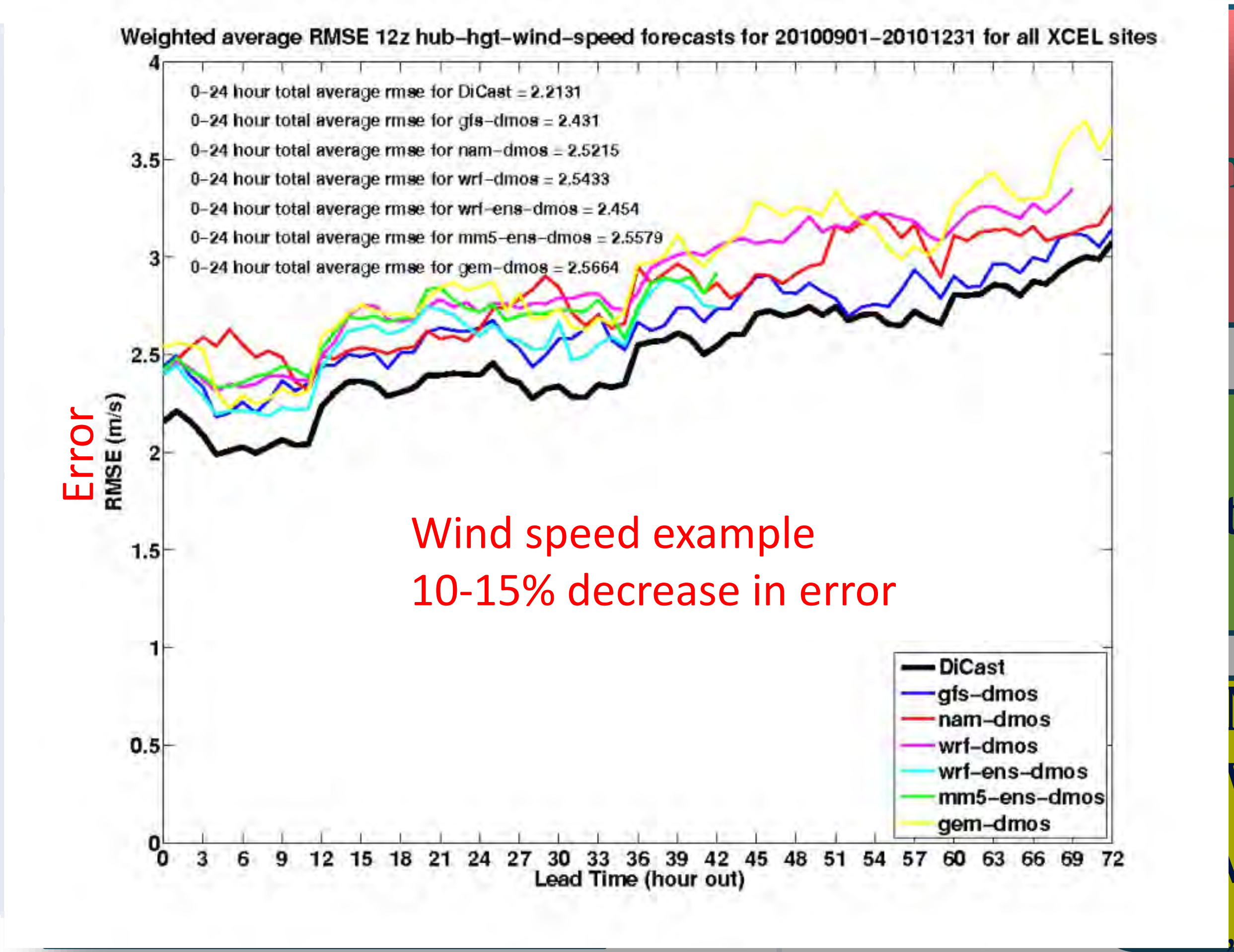
History of DICast®

- Originally developed for The Weather Channel (now The Weather Company - part of IBM) to produce public-oriented forecasts
- Development started in 1999 in Research Applications Program
- Used in many other projects as the 'weather engine'
  - Transportation (MDSS, Pikalert®, DIA, MSP)
  - Solar Energy (DOE, Kuwait)
  - Wind Energy (Xcel Energy, Kuwait)
  - Agriculture (NASA)
  - Commercial forecasting companies
    - DTN/Schneider/Telvent/Meteorlogix/Kavouras
    - Panasonic Weather Systems
    - Global Weather Corp
    - Skymet Weather Services of India

DICast® Application

Dynamic Integrated foreCast System

Measurements



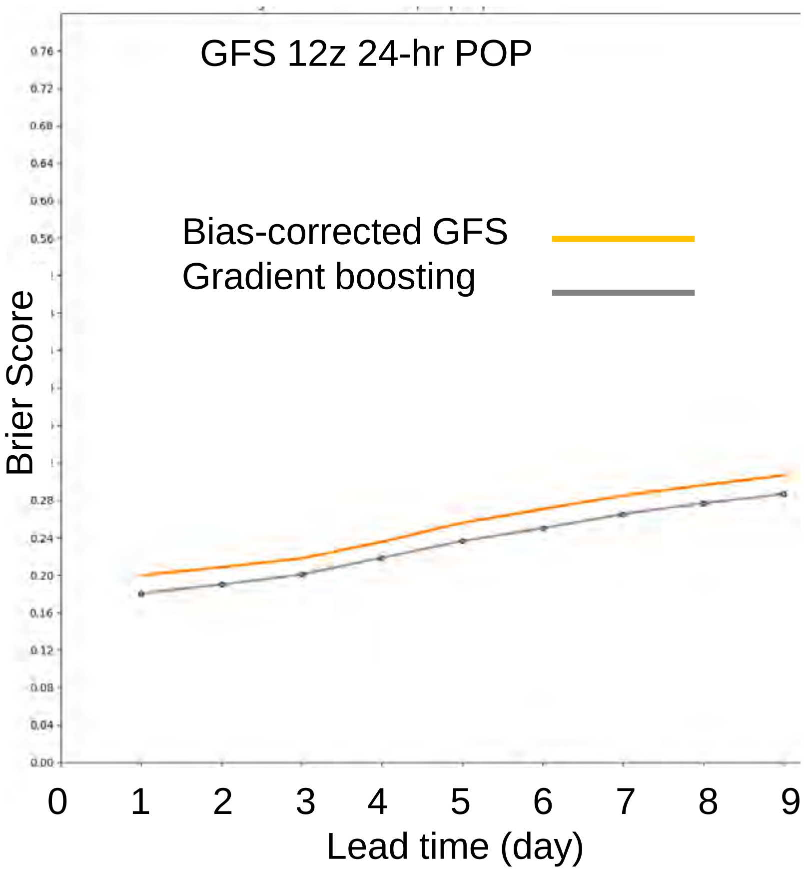
ntegrator

tProcessing

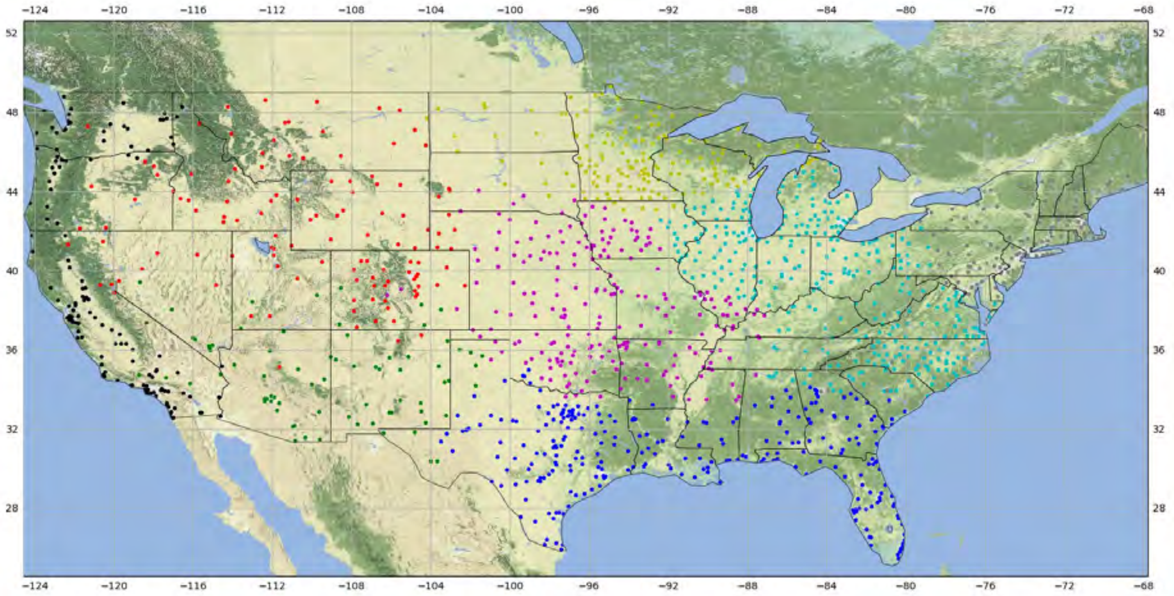
Multiple
Weather
Variables
, RH, PoP, ...

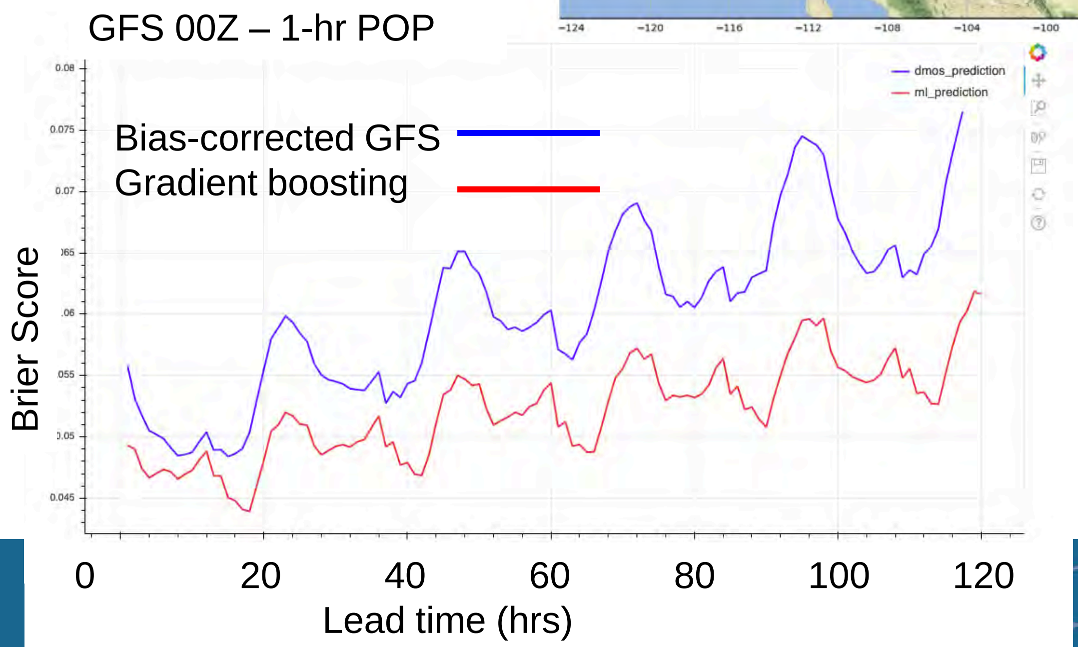
Jim Cowie
Seth Linden
Bill Petzke
Ishita
Srivastava

DICast® Advances



Improve prediction of Probability of Precipitation with Machine Learning



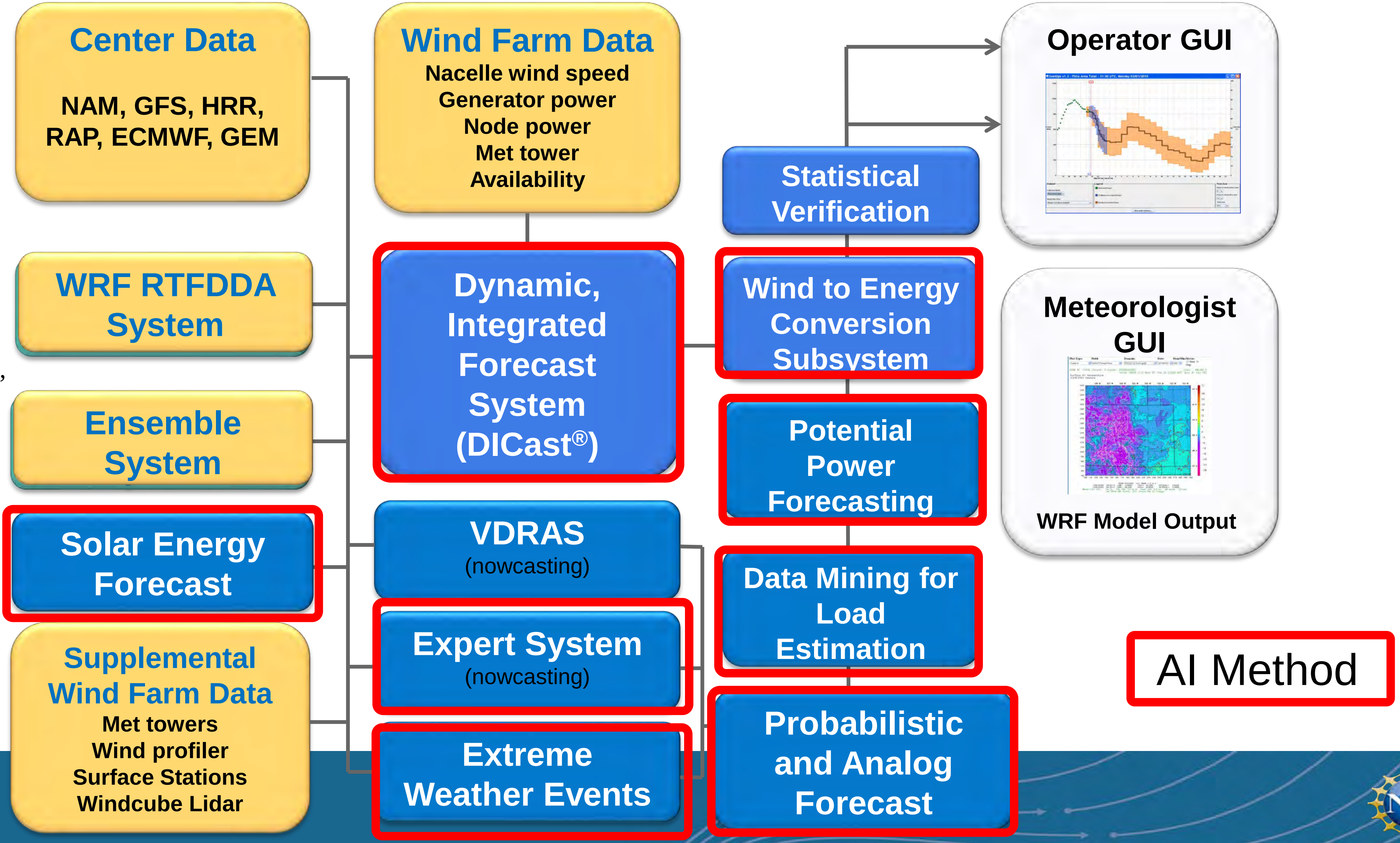


Clusters of climatologically similar METAR sites.
8 clusters based on GFS

Bill Petzke
Jim Cowie
Ishita Srivastava

Integrating AI with NWP for Renewable Energy

NCAR Variable Energy Forecasting System



Mahoney, W.P., K. Parks, G. Wiener, Y. Liu, B. Myers, J. Sun, L. Delle Monache, D. Johnson, T. Hopson, and S.E. Haupt, 2012: A Wind Power Forecasting System to Optimize Grid Integration, special issue of *IEEE Transactions on Sustainable Energy* on Applications of Wind Energy to Power Systems, **3** (4), 670-682.

Real Cost Savings by Using AI

Wind Power Forecasts Resulted in Savings for Ratepayers

Forecasted MAE 2009	2014*	Percentage Improvement	Savings
16.83%	10.10%	40%	$60,000,000

Also: saved > 267,343 tons CO_2 (2014)

Real Emissions Savings by Using AI/ML

Drake Bartlett, Xcel

Application of Forecasting: Solar Power

To make the be

Utilities n

- Day Ahead

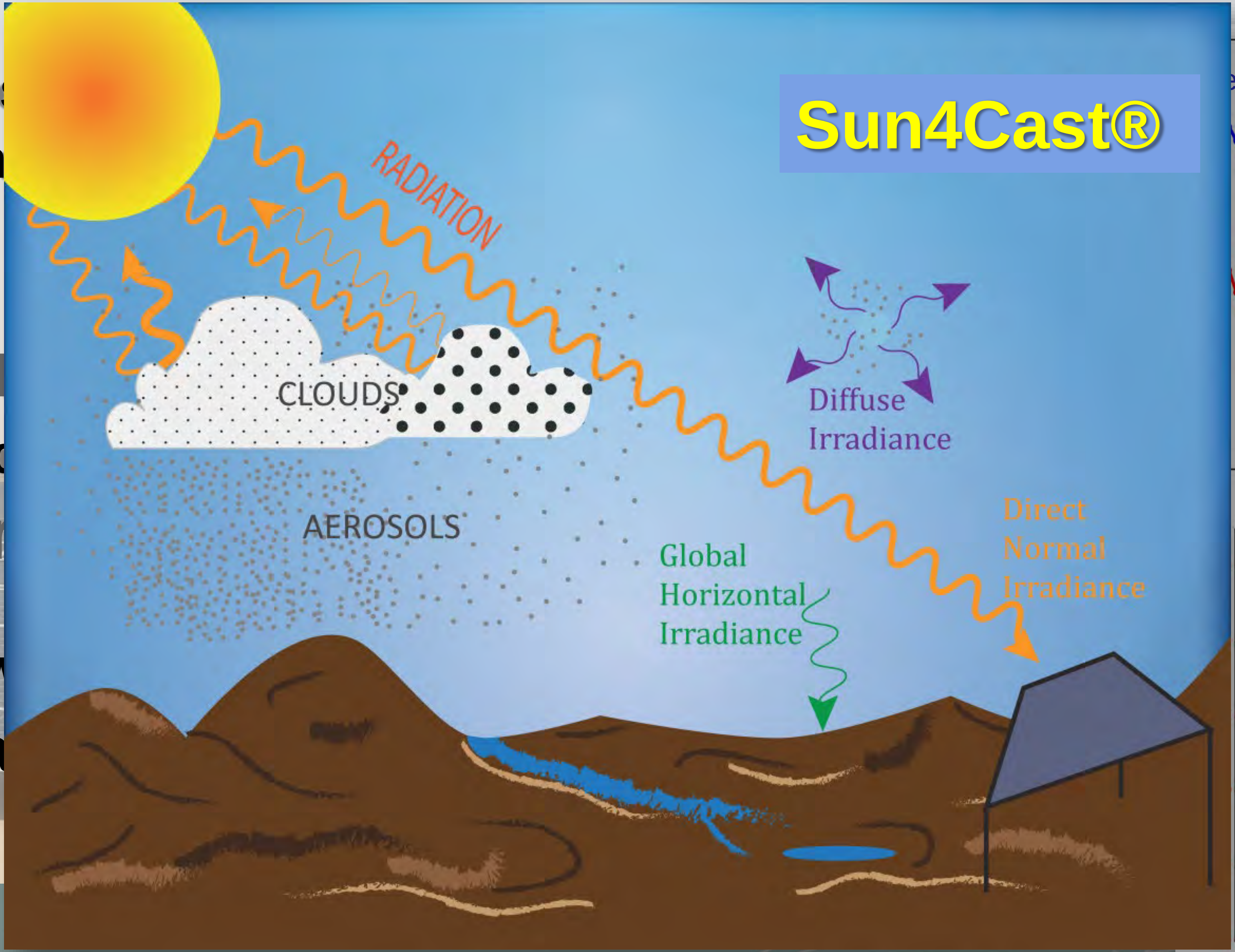
  → u

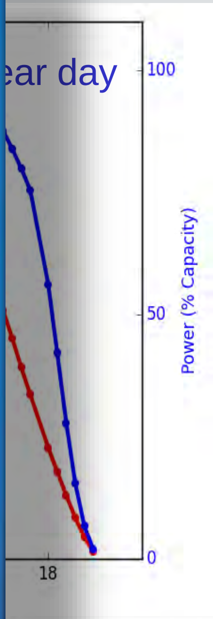
- Hours Ahea

  → g

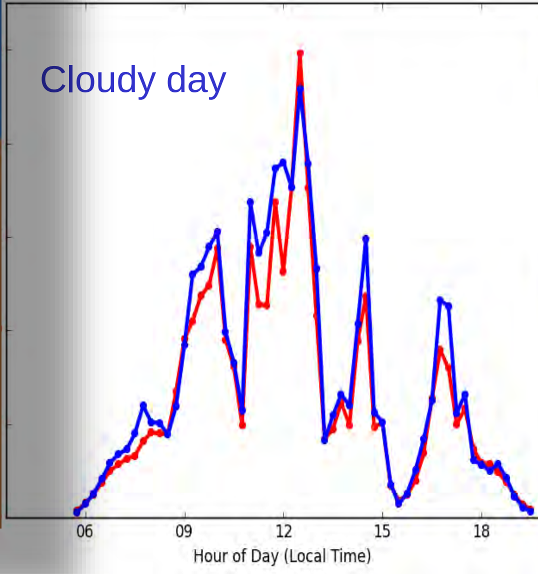
For Solar Pow

means foreca



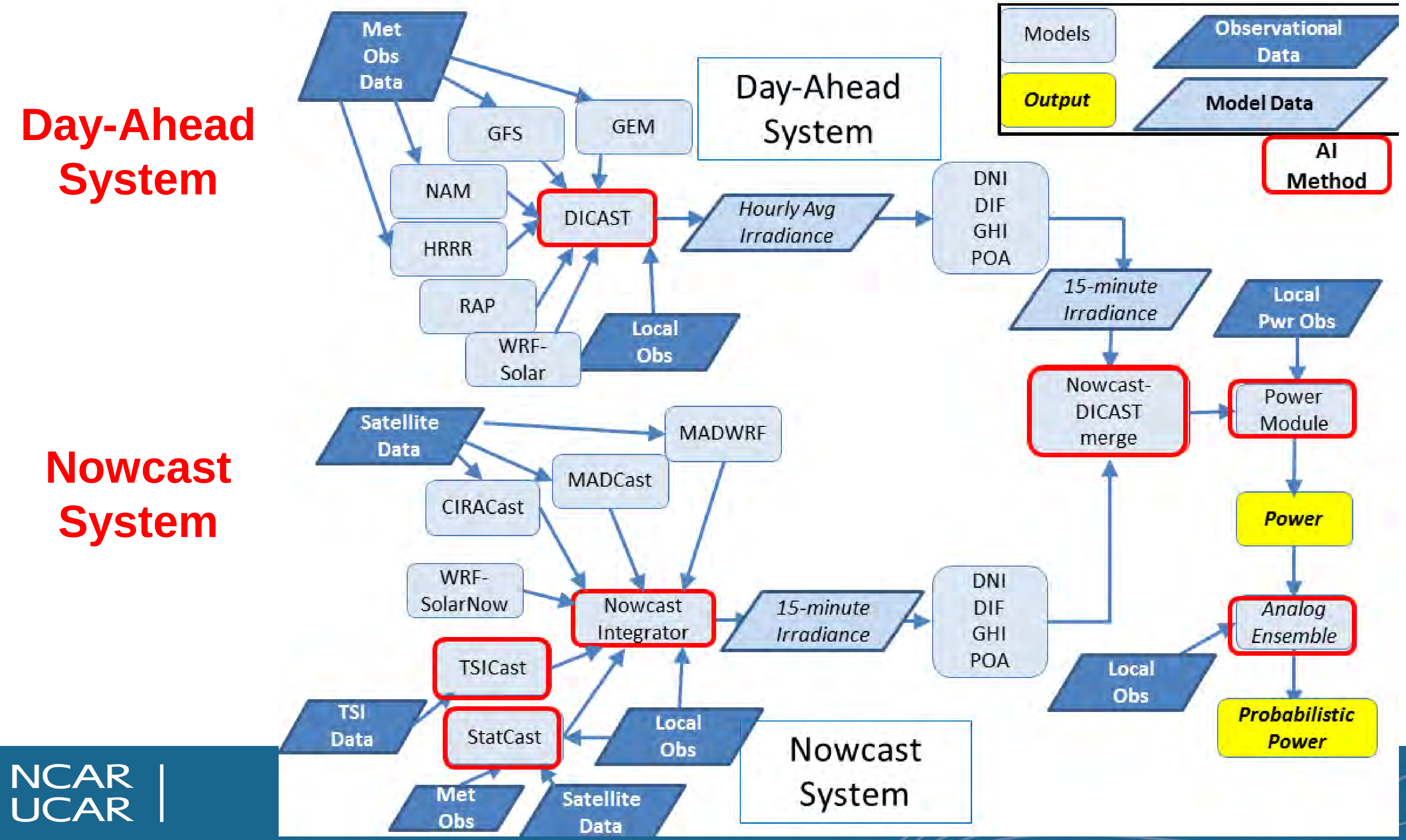


Haupt, S.E et al., 2018: Building the Sun4Cast System: Improvements in Solar Power Forecasting, *Bulleti of the American Meteorological Society*, Jan. 2018, 121-135. doi: 10.1175/BAMS-D-16-0221.1



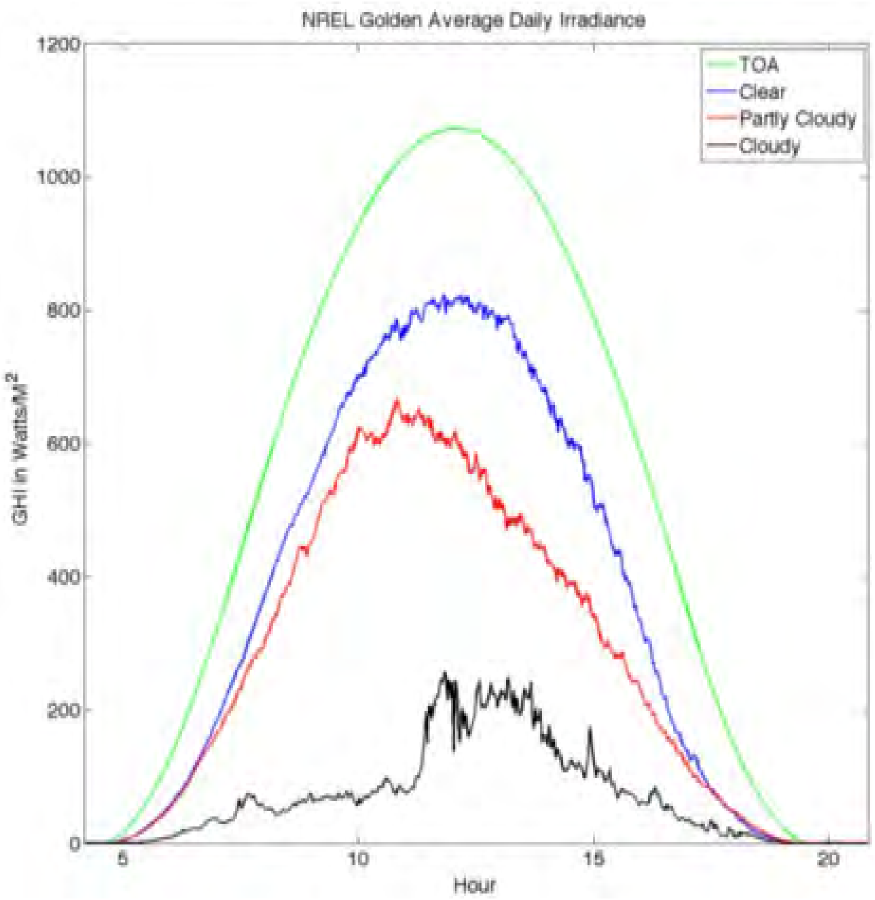
AI as Part of Systems Engineering

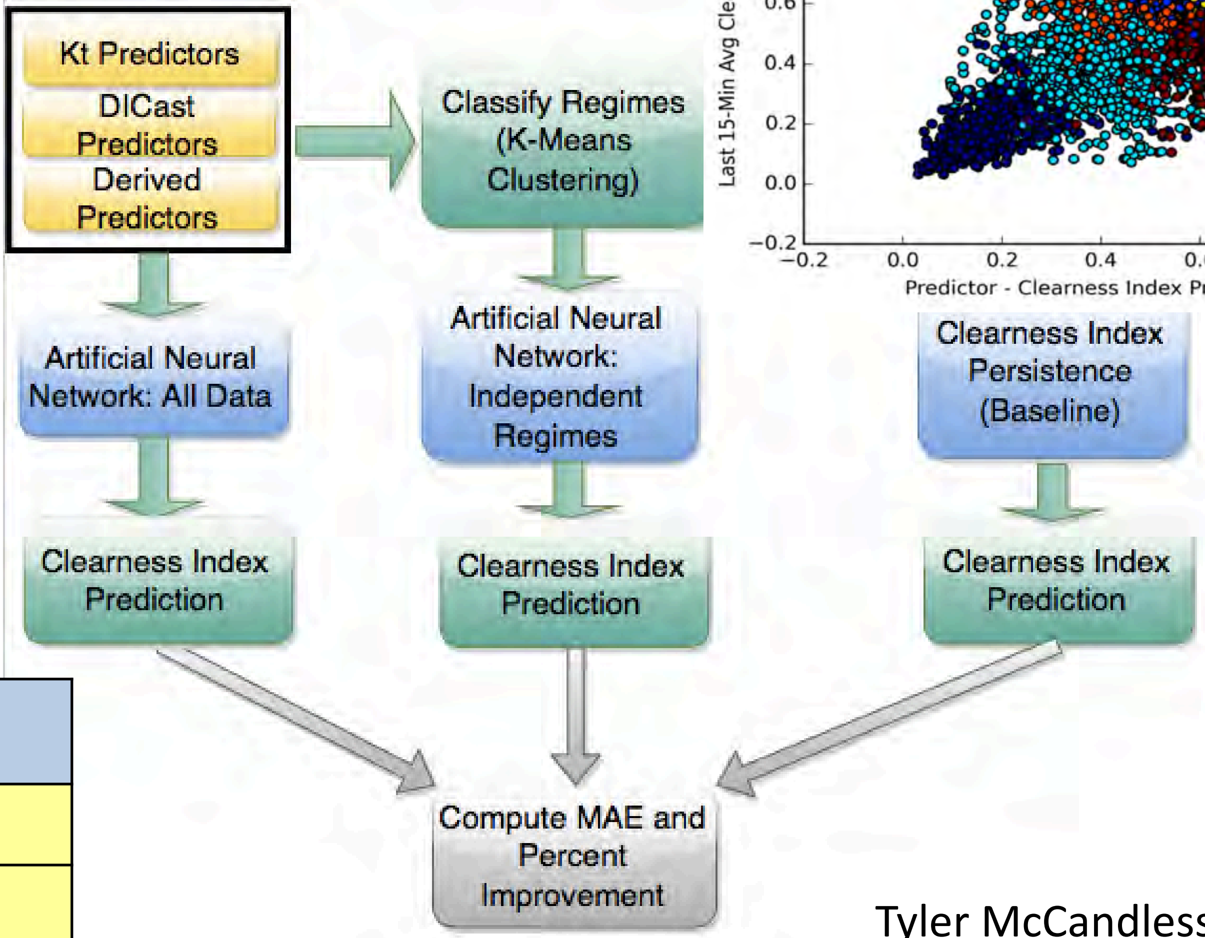
Engineering the Sun4Cast® System

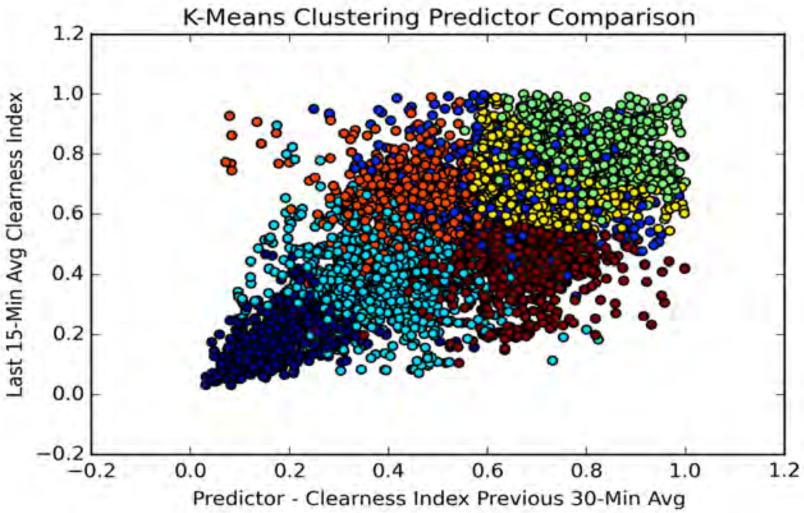


Haupt, S.E. and B. Kosovic, 2017: Variable Generation Power Forecasting as a Big Data Problem, *IEEE Transactions on Sustainable Energy*, **8** (2), pp. 725-732. DOI: 10.1109/TSTE.2016.2604679.

StatCast: Regime Dependent Forecasting





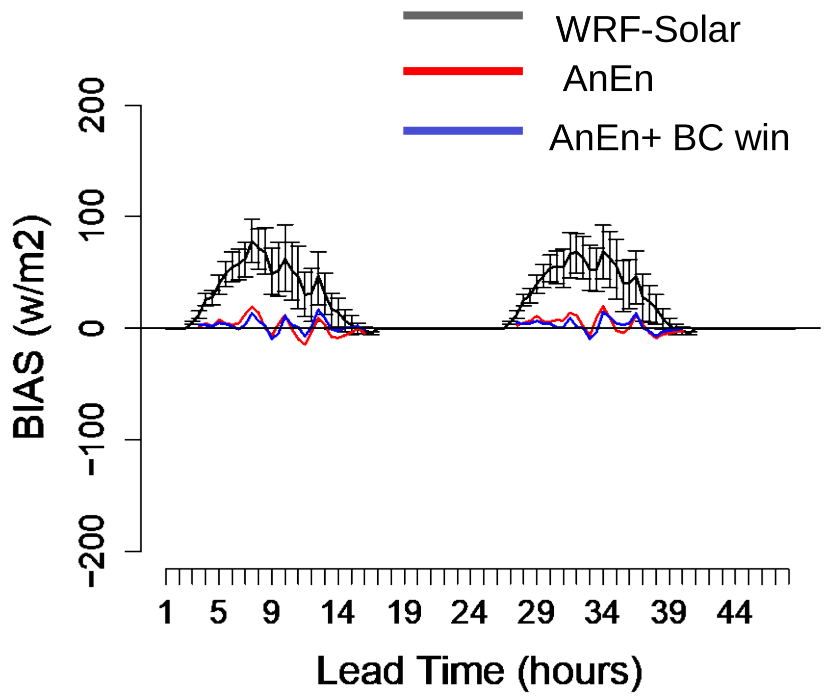


Improvement over Clearness Index Persistence	
ANN	**RD-ANN**
13.7%	**18.6%**

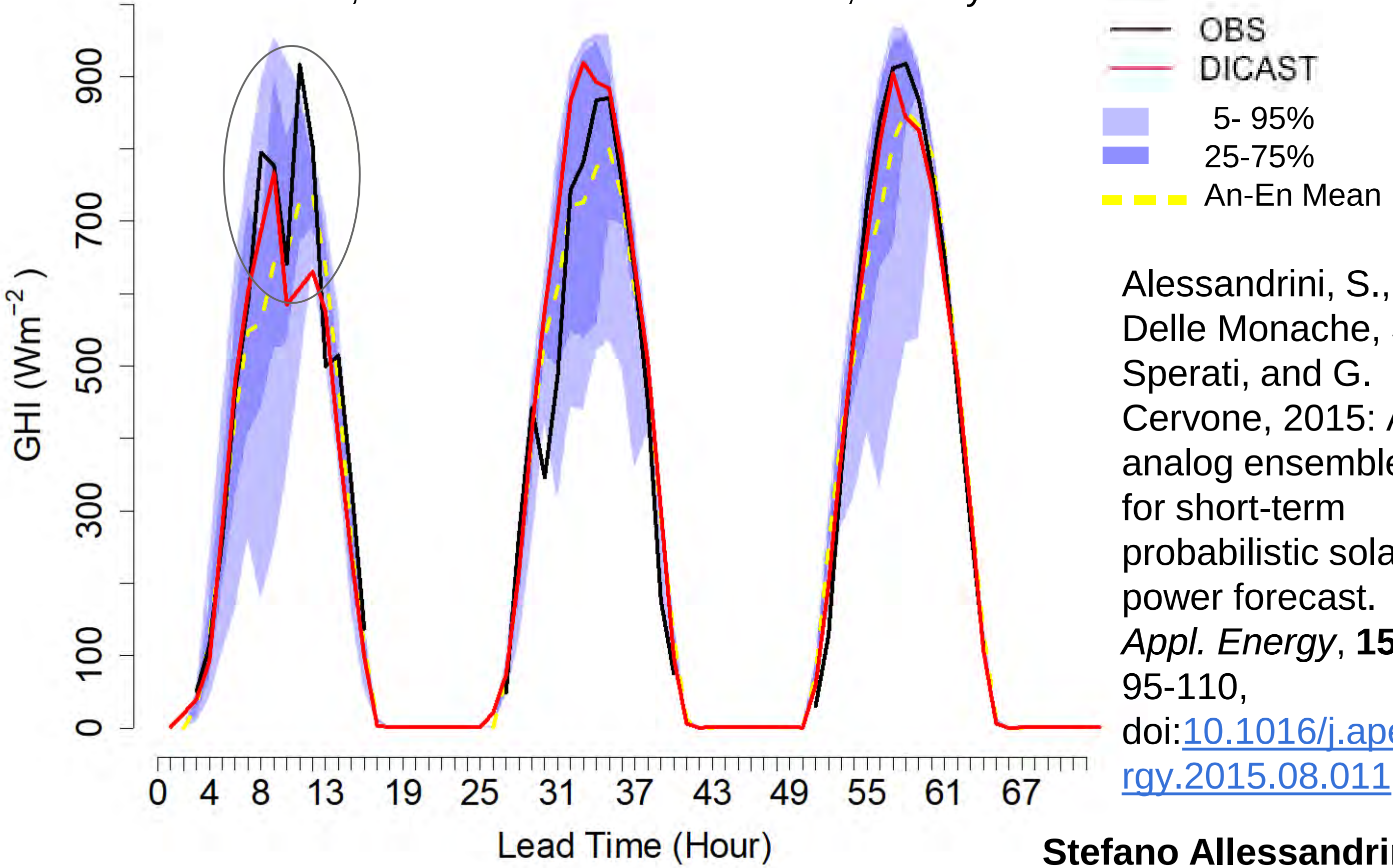
McCandless, T.C., S.E. Haupt, and G.S. Young, 2016: A Regime-Dependent Artificial Neural Network Technique for Short-Range Solar Irradiance Forecasting, *Applied Energy,* **89**, 351-359.

Tyler McCandless

Uncertainty Quantification
Analog Ensemble (AnEn) Approach



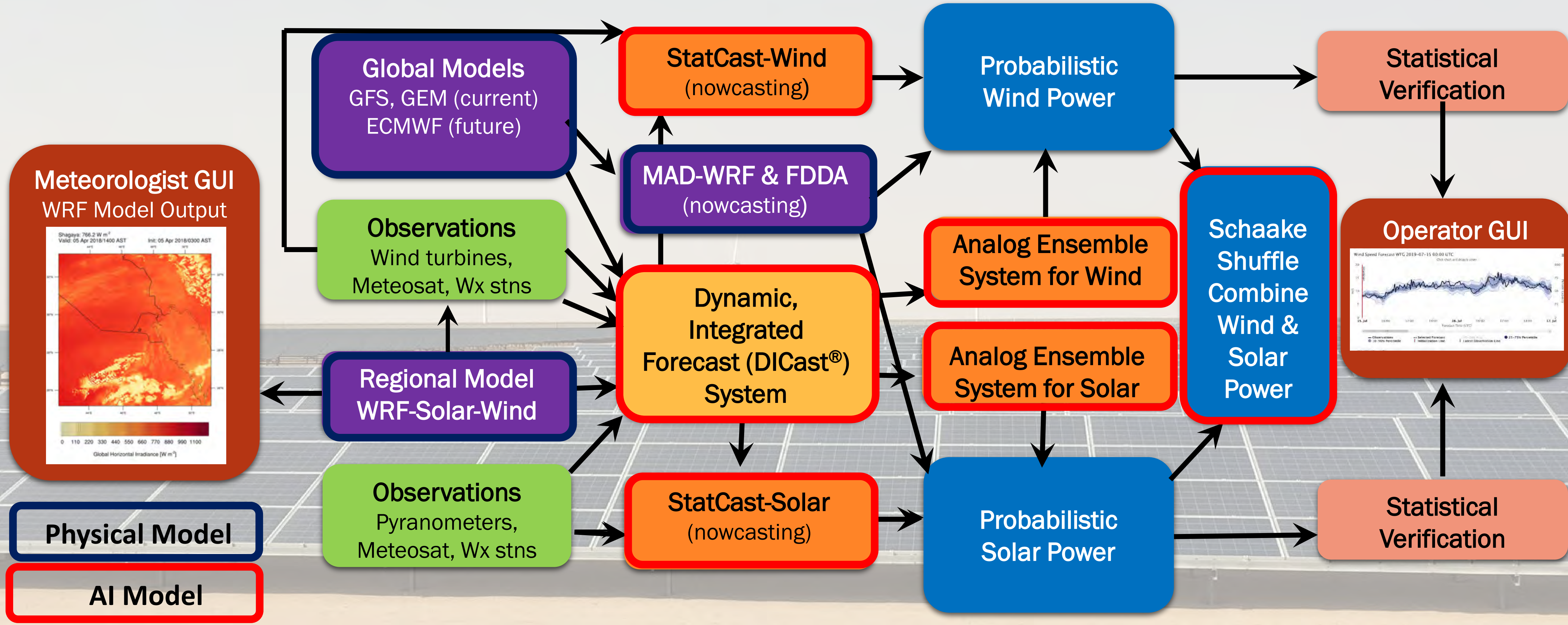
Station SMUD 67, forecast initialized at 12 UTC, 15 July 2014



Alessandrini, S., L. Delle Monache, S. Sperati, and G. Cervone, 2015: An analog ensemble for short-term probabilistic solar power forecast. *Appl. Energy*, **157**, 95-110, doi:10.1016/j.apenergy.2015.08.011.

Stefano Alessandrini
Luca Delle Monache

Kuwait Renewable Energy Prediction System (KREPS)



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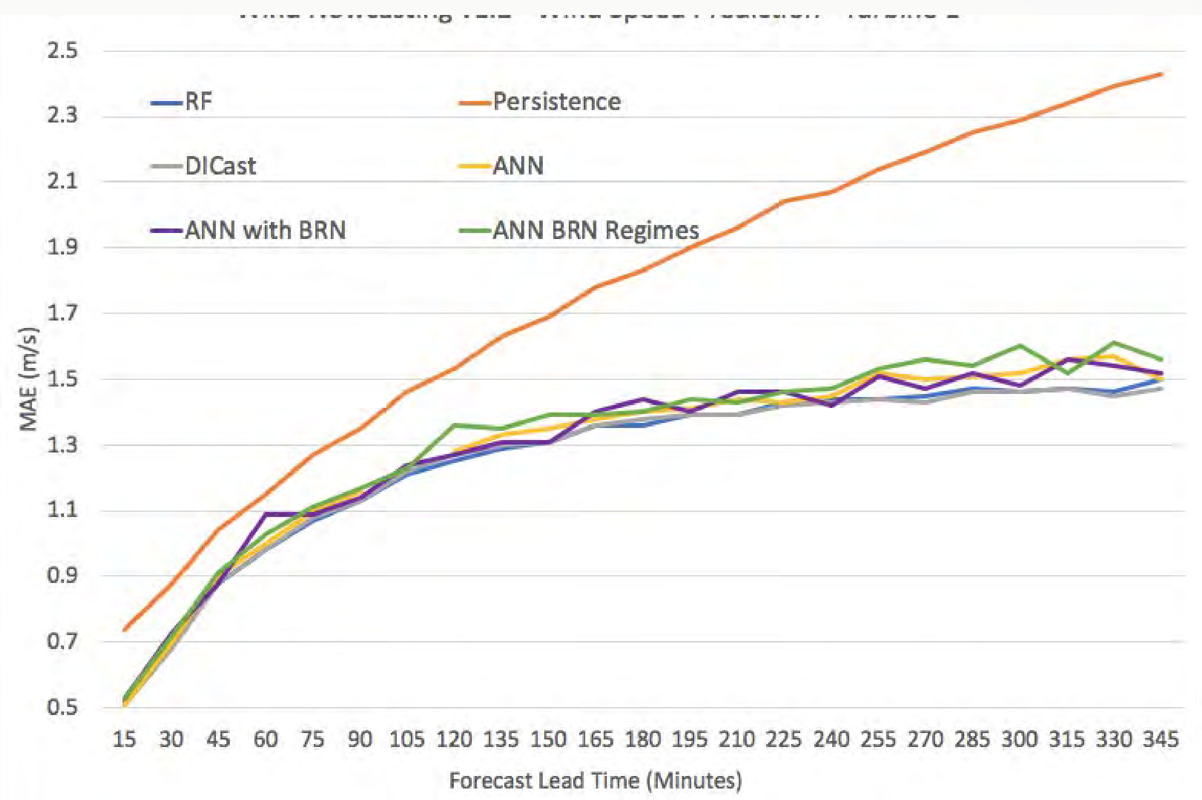
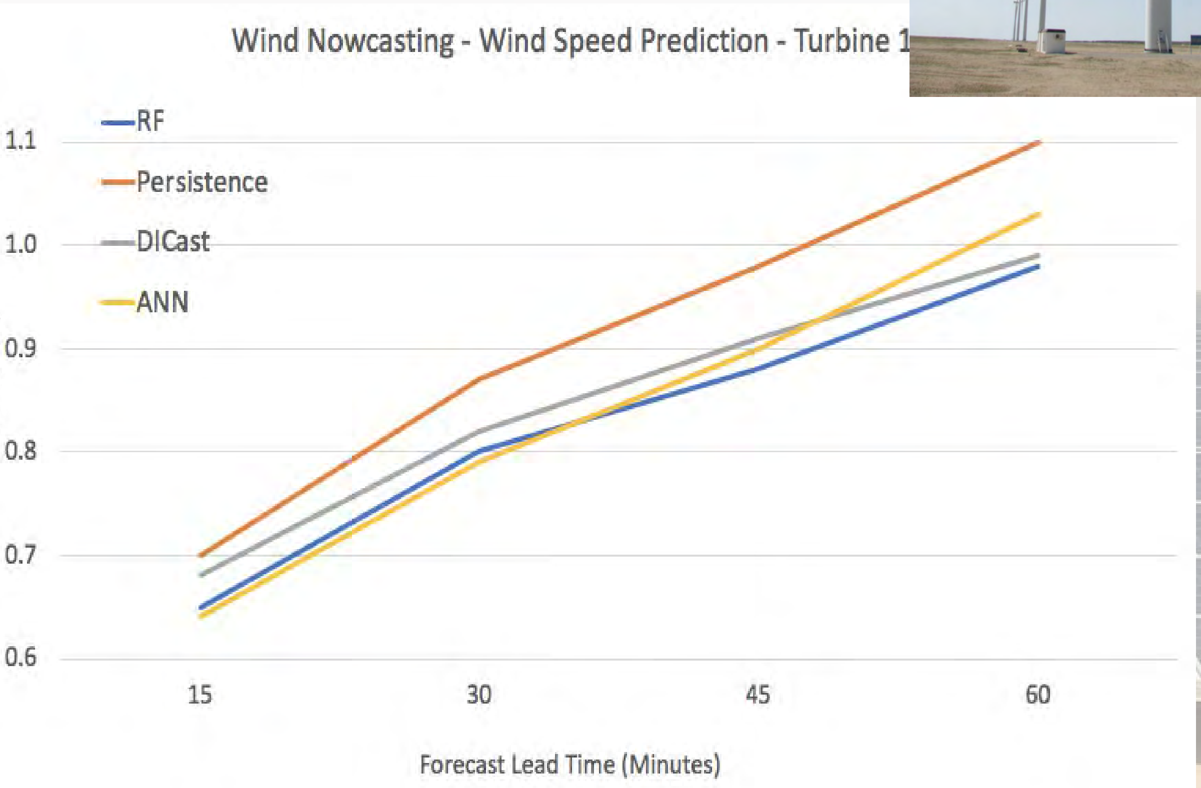
Haupt, S.E., T. McCandless, S. Dettling, S. Alessandrini, G. Wiener, J. Lee, S. Linden, W. Petzke, T. Brummet, N. Nguyen, B. Kosovic, T. Hussain, and M. Al-Rasheedi, 2020: Combining Artificial Intelligence with Physics-Based Methods for Probabilistic Renewable Energy Forecasting, *Energies*, **13**, 1979; doi:10.3390/en13081979.

StatCast-Wind

- StatCast Wind: Improvements over persistence for wind speed and power after 15-min (similar for all turbines), using either random forests (RF) or ANNs





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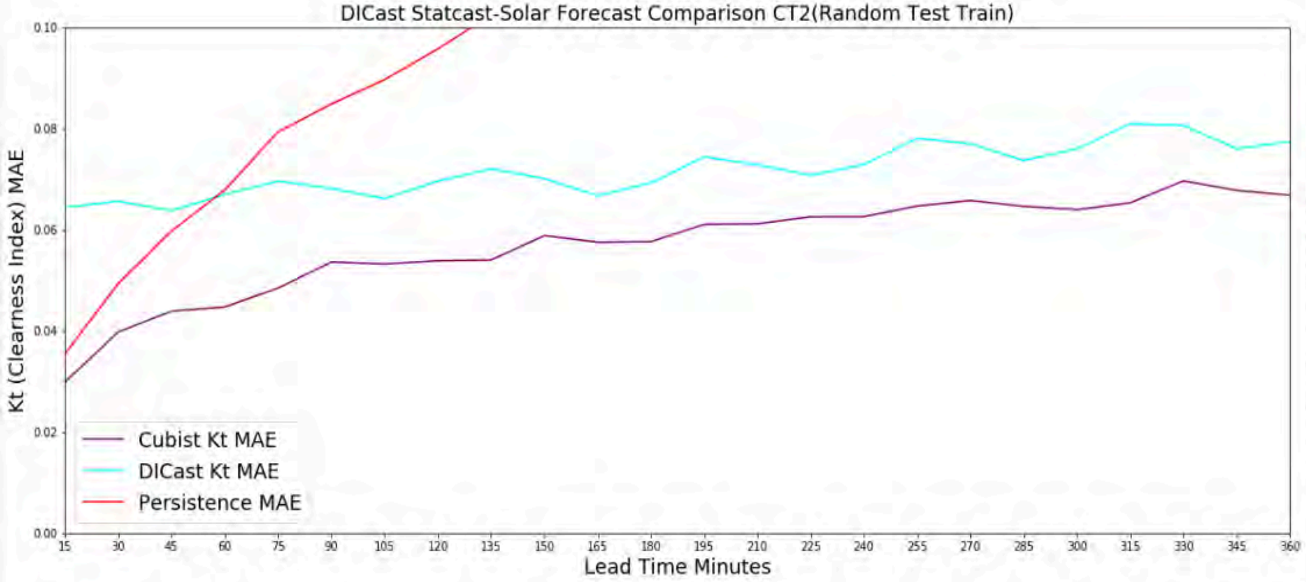
Tyler McCandless
Ishita Srivastava

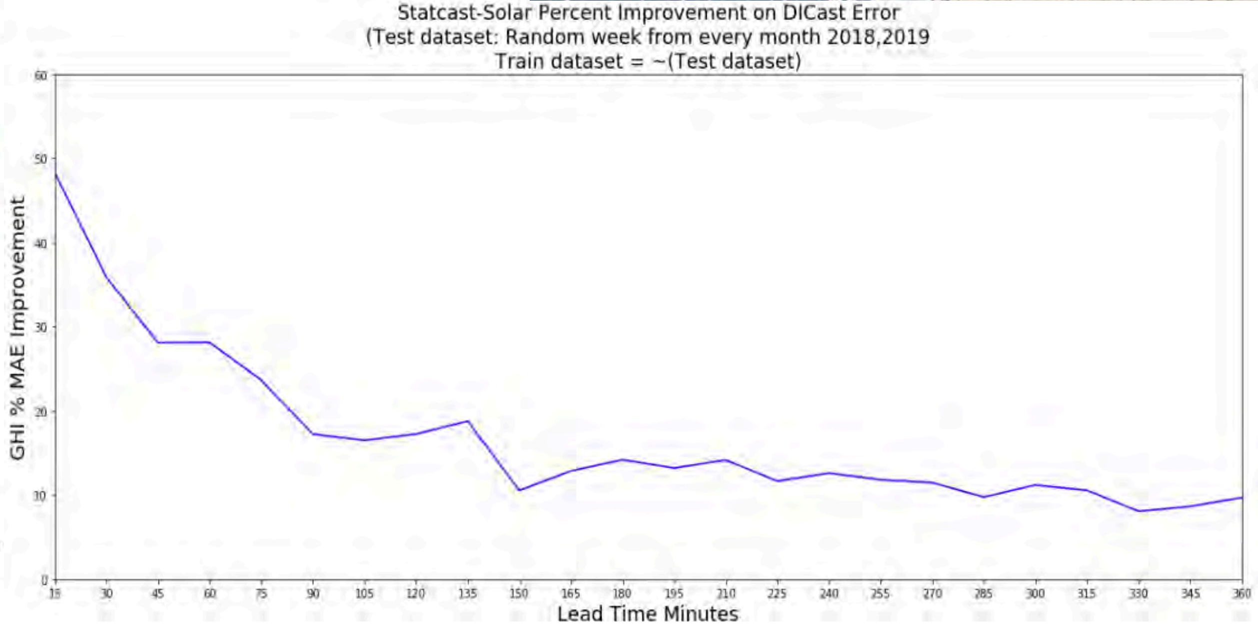
StatCast-Solar

Initial Results

- Training data from 1 Sep 2018–30 June 2019
- Cubist – Model Regression Tree
- StatCast-Solar can add value to DICast for at least 6 hours



Comparison of the Cubist model to the DICast forecasts of Kt and smart persistence. The Cubist-based method performs best for all time periods from 15 min to 360 min compared to either DICast or smart persistence.



Percentage improvement of StatCast-Solar over DICast for all lead times from 15 min to 360 min.

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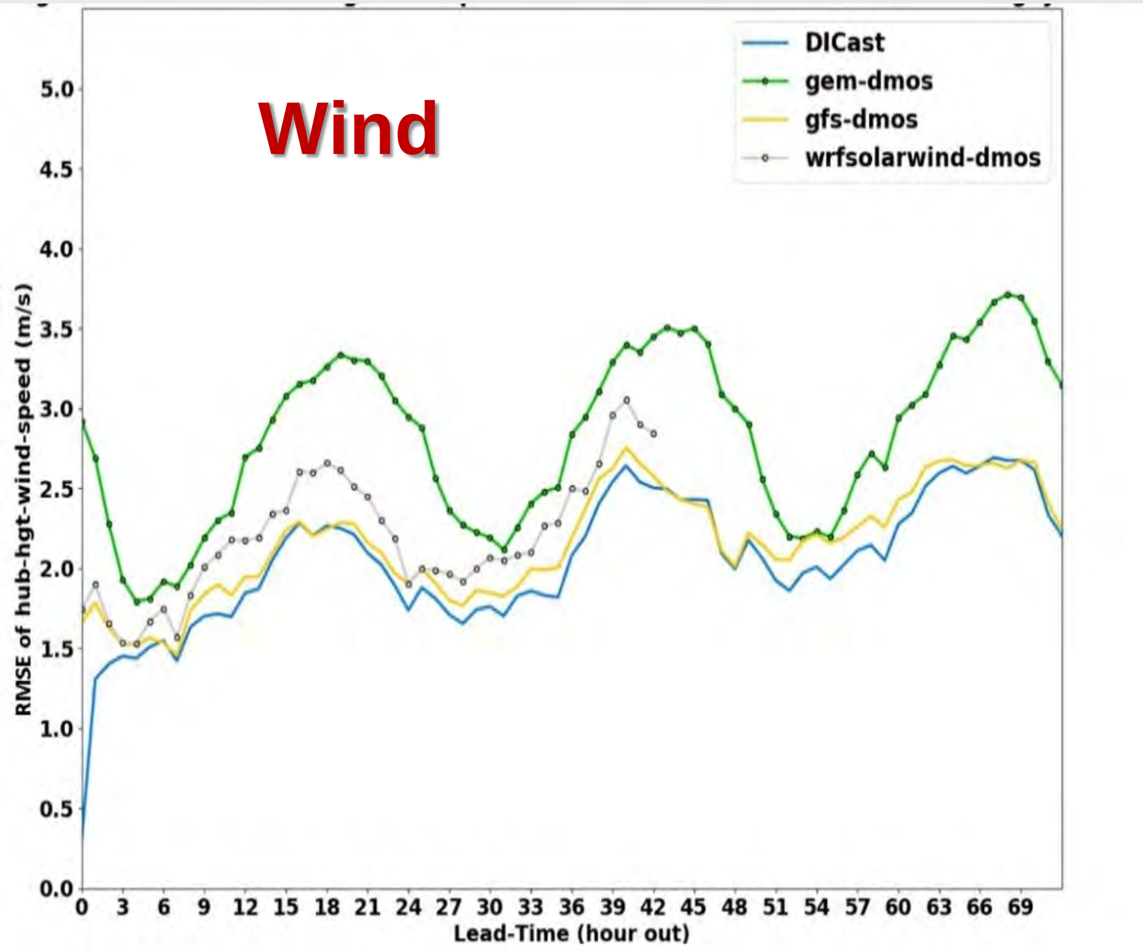
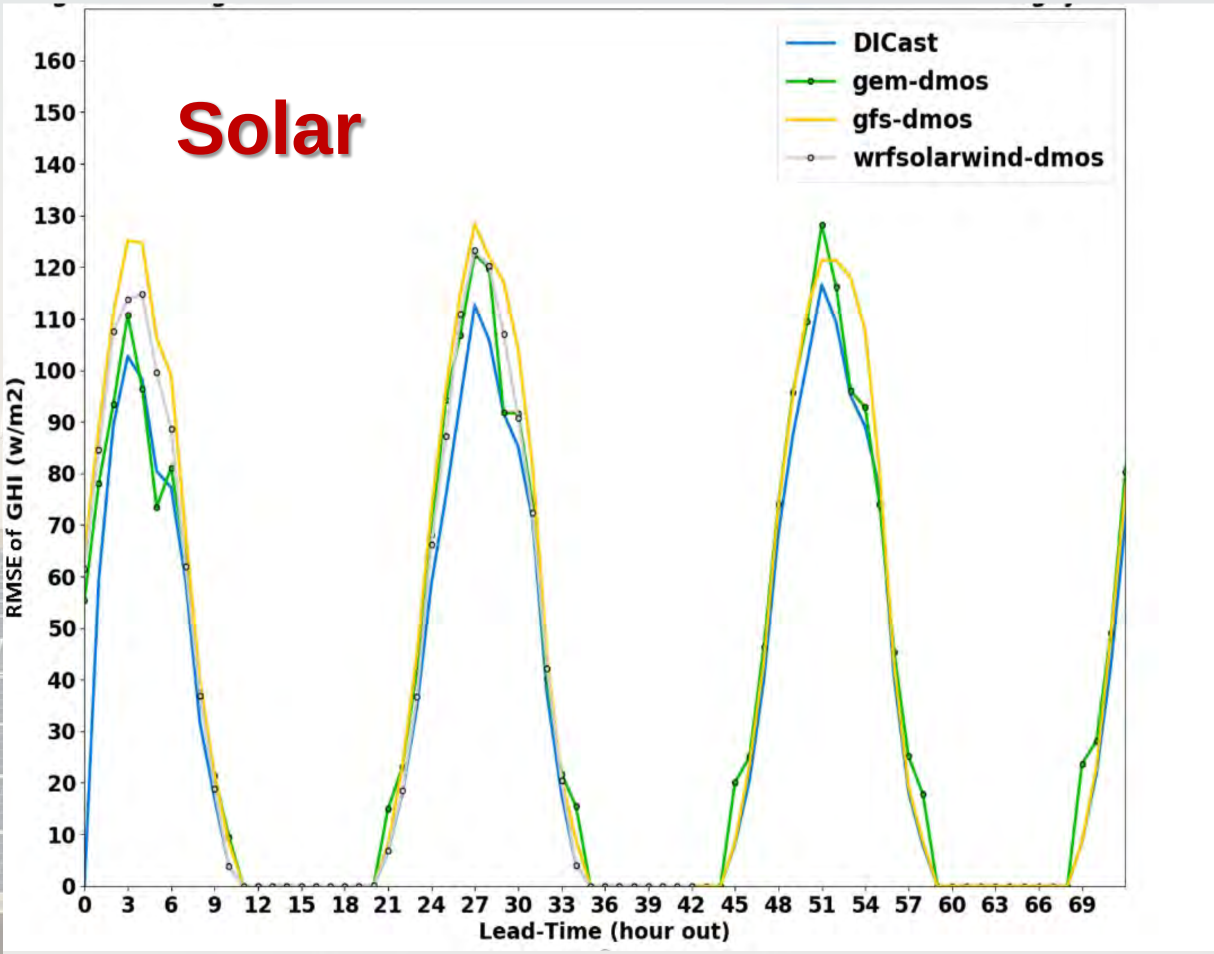
McCandless, T., S. Dettling, and S.E. Haupt, 2020: Comparison of Implicit vs Explicit Regime Identification in Machine Learning Methods for Solar Irradiance Prediction, *Energies*, **13** (682), 14 pp. doi:10.3390/en13030689.

Sue Dettling
Tyler McCandless
Tom Brummet

DICast® Preliminary Verification



Average RMSE of hub ht wind speed
1 Dec 2018–30 Nov 2019



Average RMSE of global horizontal irradiance
1 Dec 2018–30 Nov 2019; valid 06 UTC

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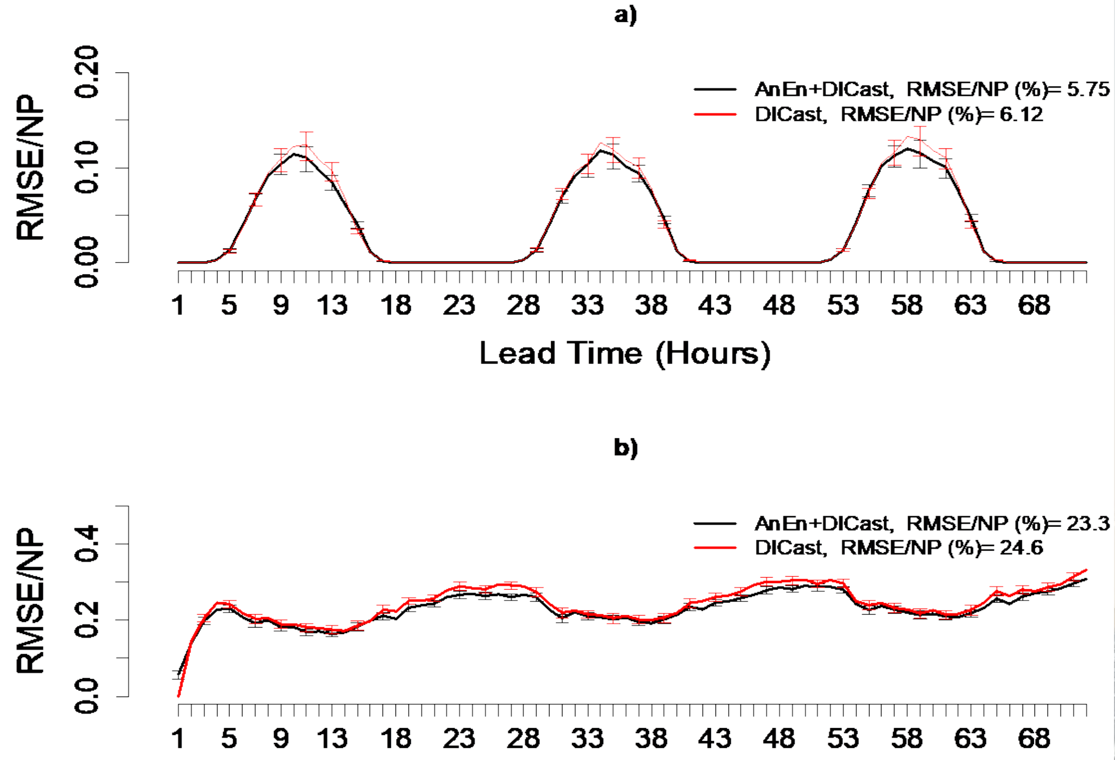
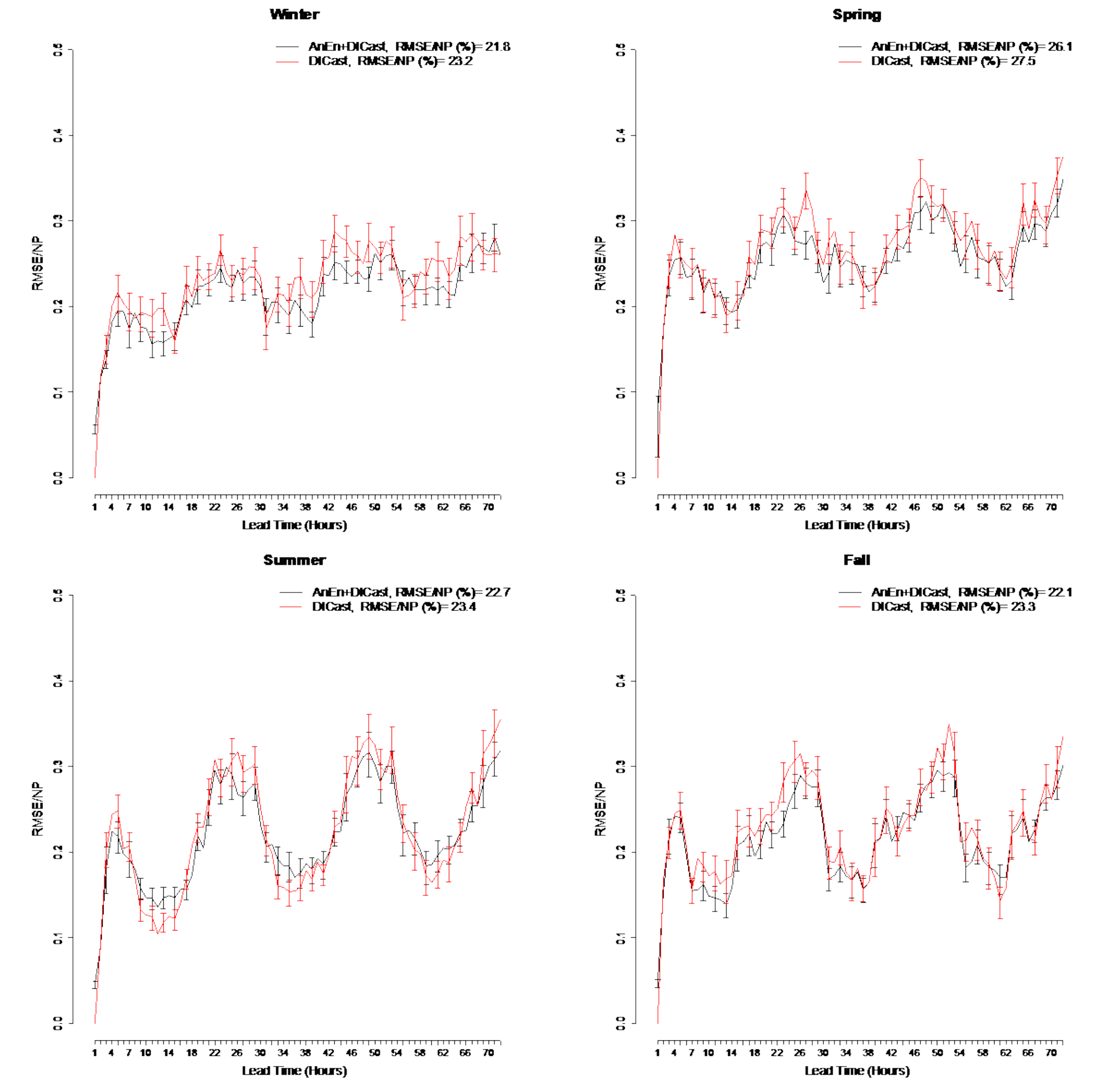
Seth Linden
Tom Brummet

Stefano Alessandrini
Tyler McCandless

Analog Ensemble (AnEn)



AnEn + DICast (black) and DICast (red) for solar power (**a**) and wind power (**b**). The vertical bars represent the 5%–95% bootstrap intervals that are plotted every other lead time to reduce clutter. RMSE values are normalized by the nominal power of a single turbine (2 MW) or of a single PV plant (5 MW) and they are obtained by pooling data from all wind turbines or solar plants together.

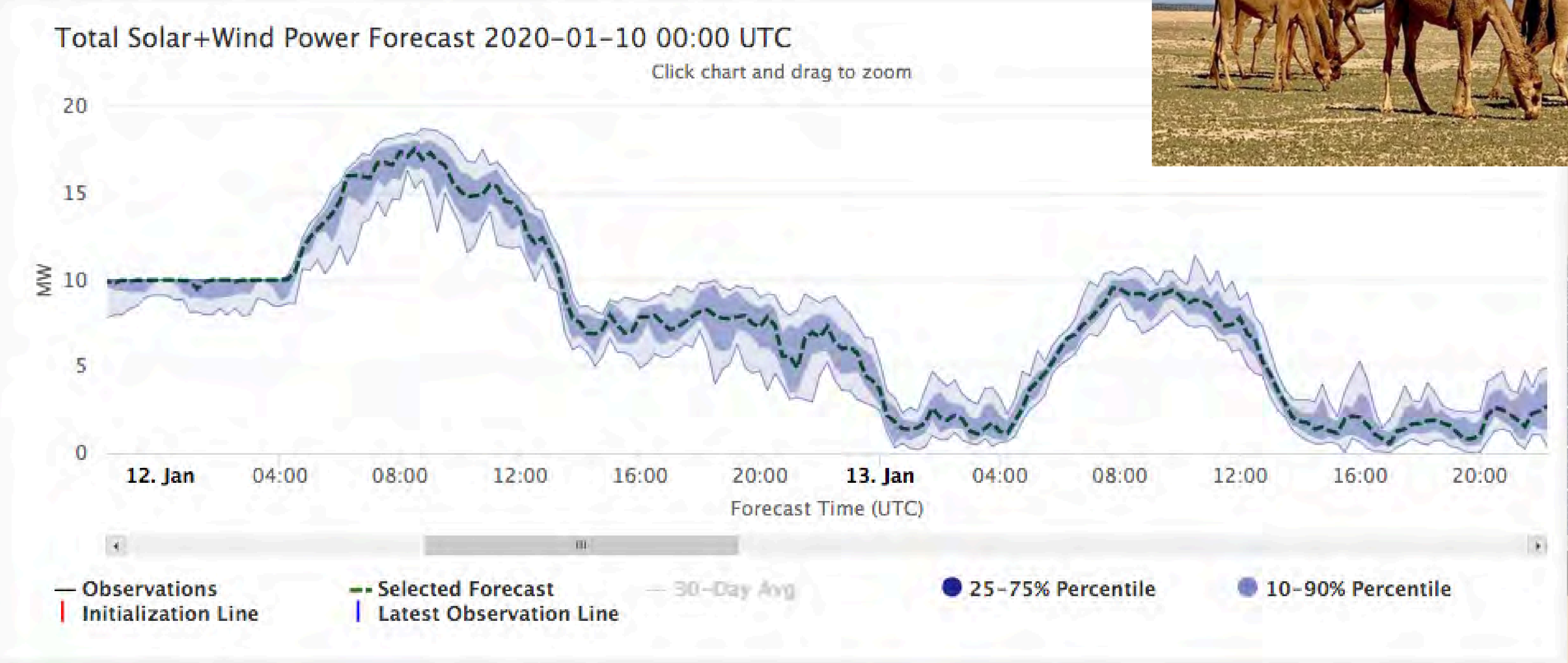


NCAR

Alessandrini, S. and T. McCandless, 2020: The Schaake Shuffle Technique to Combine Solar and Wind Power Probabilistic Forecasting, Energies, 13, 2503; doi:10.3390/en13102503

Display Probabilistic Power Output

Outputs from DICast+AnEn as displayed by the web display



NCAR Alessandrini, S. and T. McCandless, 2020: The Schaake Shuffle Technique to Combine Solar and Wind Power Probabilistic Forecasting, Energies, 13, 2503; doi:10.3390/en13102503

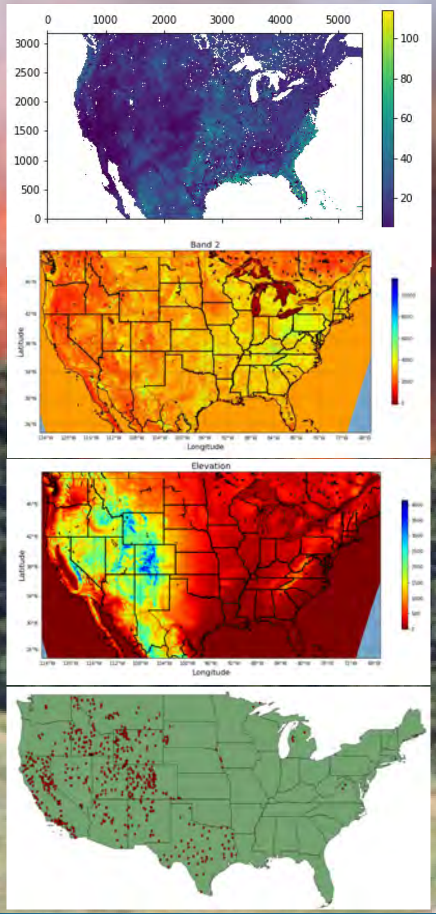
Bill Petzke
Nhi Nguyen

AI/ML for Severe Weather Forecasting

Fuel Moisture Content Prediction System

Satellite Derived Gridded Product

+ **Goal:** Create Gridded Product by using Artificial Intelligence to Learn Representative Relationships Between Satellite Data and Surface Observations



WRF-Hydro Model
Accumulated Evapotranspiration, Land Use Category, Soil Moisture, Temperature

MODIS Satellite Data
Reflectance Bands 1-7

Surface Characteristics
Elevation, East/West Slope, North/South Slope, Regions

Fuel Moisture Content
Live and Dead FMC (Target Predictand)

Machine Learning
Trained to Learn Relationships Between Predictors and FMC at Nearest Neighbor Grid Cells

Tyler McCandless
Branko Kosovic
Bill Petzke

Fuel Moisture Content Prediction System

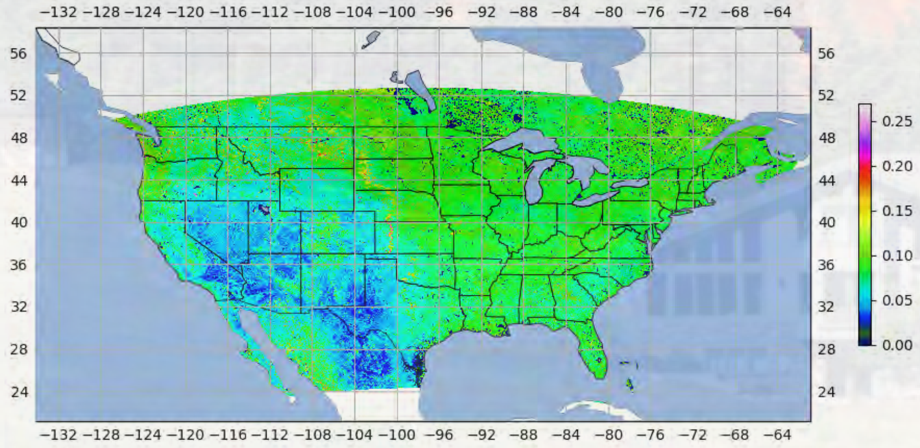
Final Models

+ Final Gridded Product Provides More Realistic Representation of Fuel Moisture Content Across CONUS

DFMC Observation Sites

Dead Fuel Moisture Content

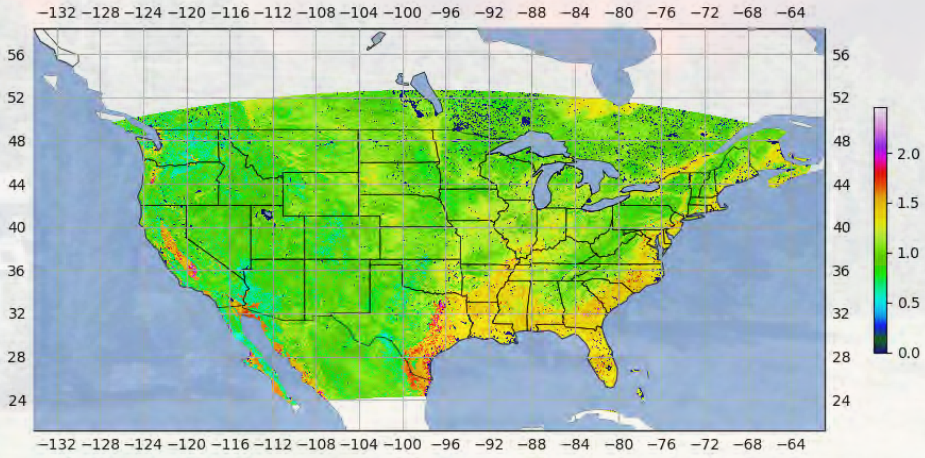
Gridded DFMC Predictions



LFMC Observation Sites

Live Fuel Moisture Content

Gridded LFMC Predictions



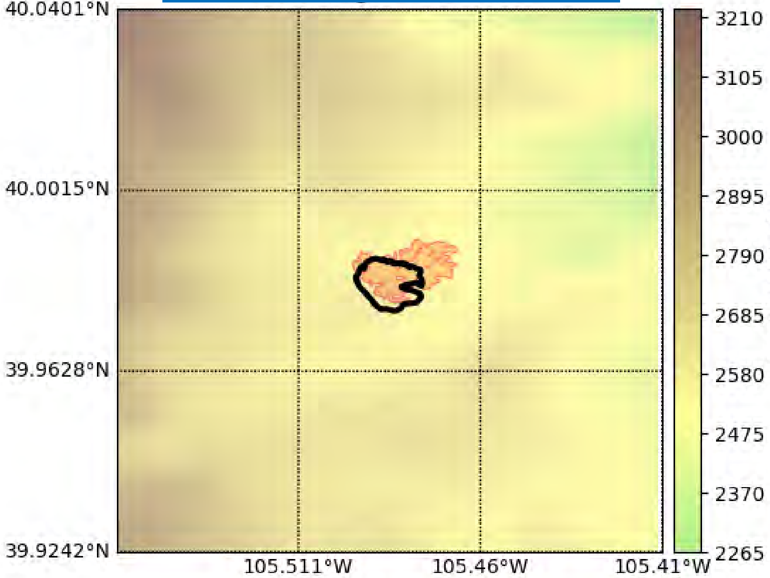
Tyler McCandless
Branko Kosovic
Bill Petzke

Fuel Moisture Content Prediction System

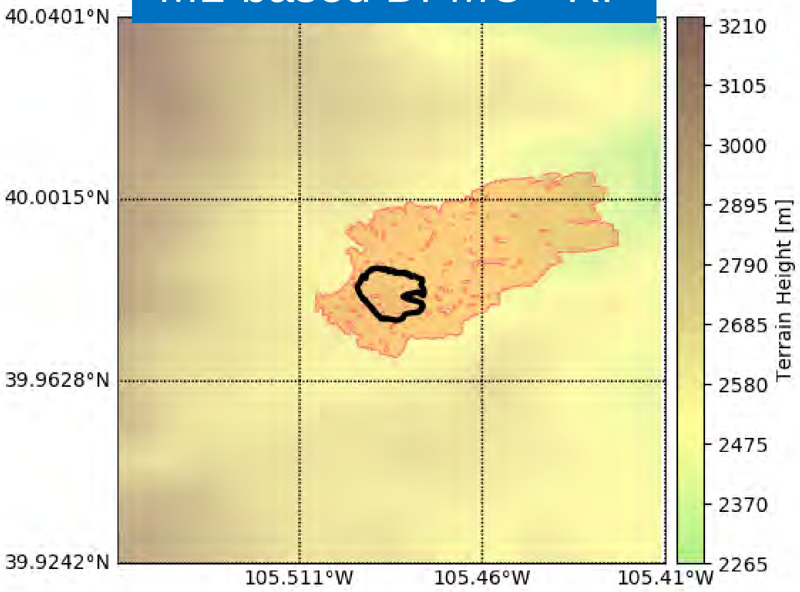
WRF-Fire Evaluation

+ Cold Springs fire simulated using constant Dead Fuel Moisture Content of 8% and machine learning predicted DFMC
+ Our NWP-based wildland fire prediction model tends to overestimate the rate of spread of fire due to lack of including fire suppression
+ Thus, it is positive to see burn area increase

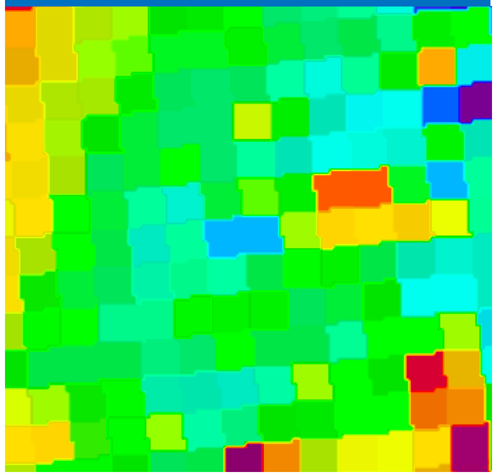
Constant DFMC



ML-based DFMC - RF



Distribution of the estimated DFMC



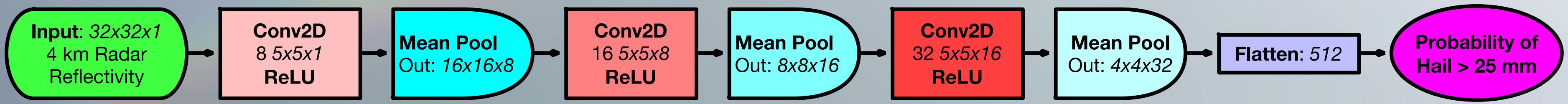
Tyler McCandless
Branko Kosovic
Bill Petzke

NCAR UCAR

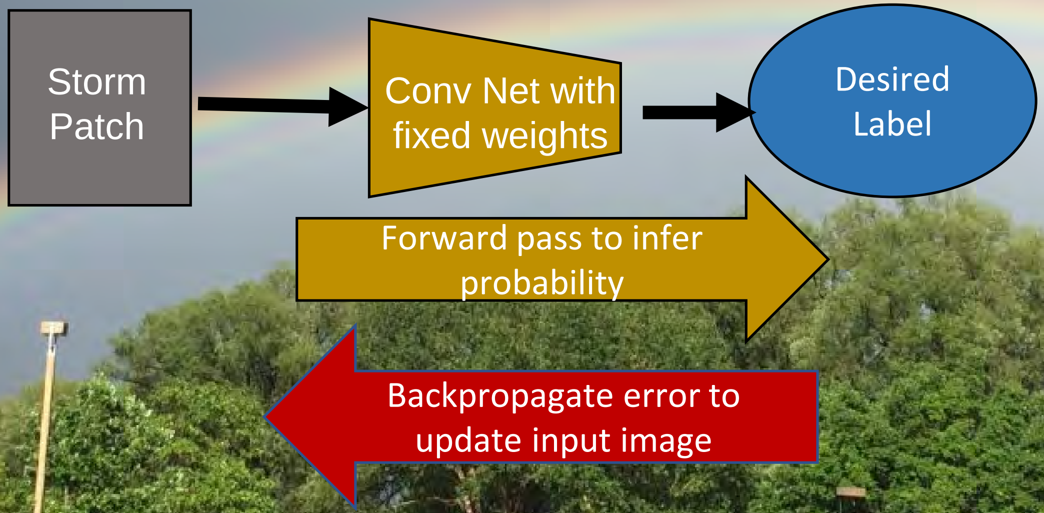
NSF

Interpretable Deep Learning for Severe Weather Research and Forecasting

Convolutional Neural Networks

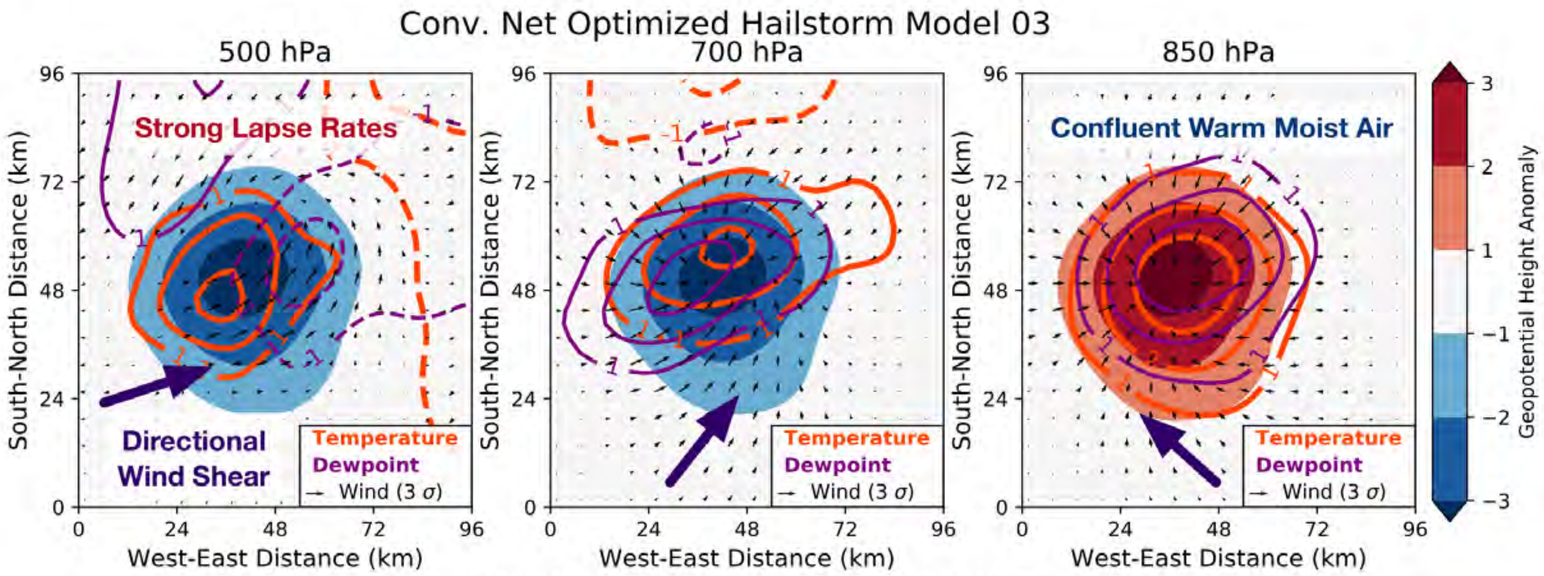


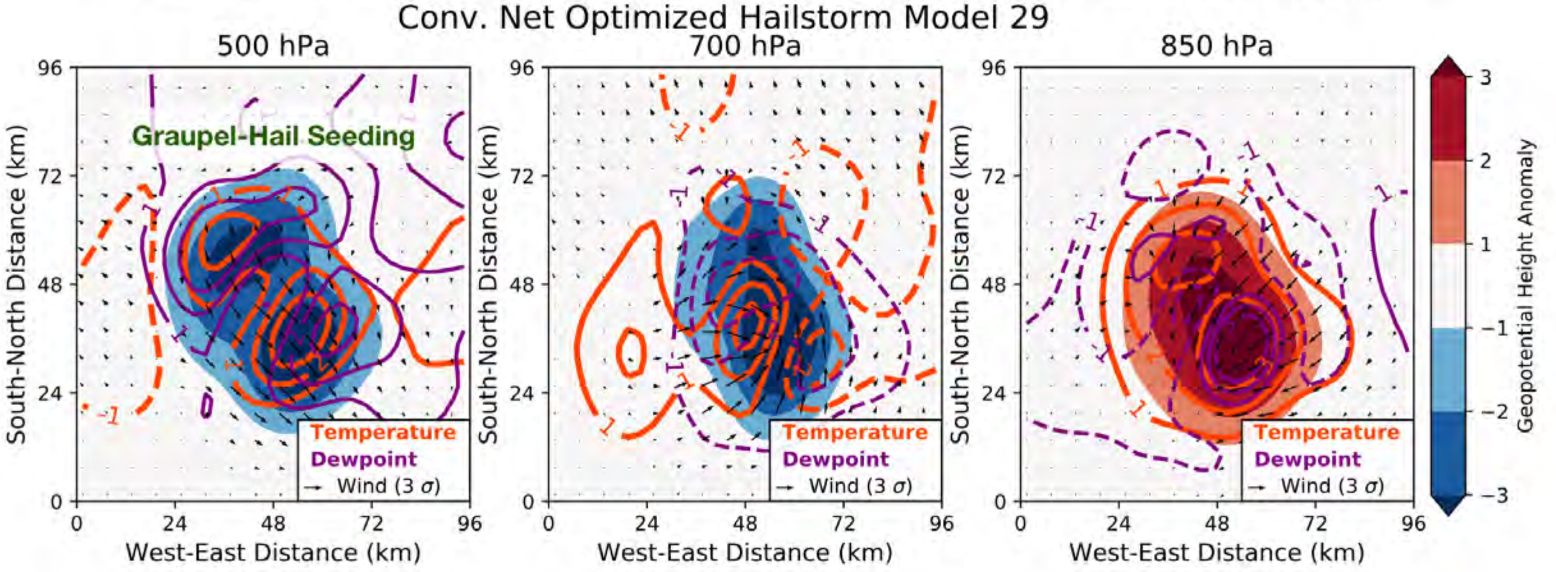
Feature Visualization by Optimization



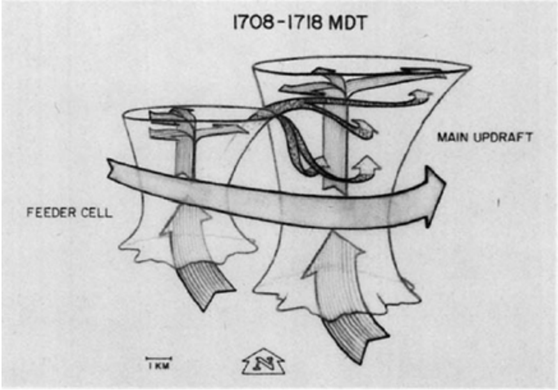
Gagne II, D.J., S.E. Haupt, D.W. Nychka, and G. Thompson, 2019: Interpretable Deep Learning for Spatial Severe Hail Forecasting, *Monthly Weather Review*, **147**, 2827-2845. DOI: 10.1175/MWR-D-18-0316.1

Optimized Conv Net Hailstorm





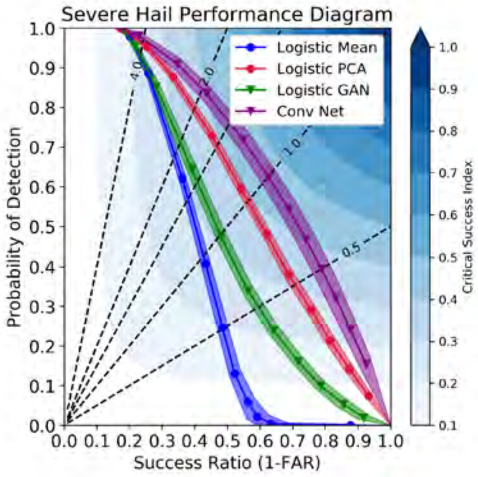
Reconstruct storms with vertical structures that make sense dynamically and physically.



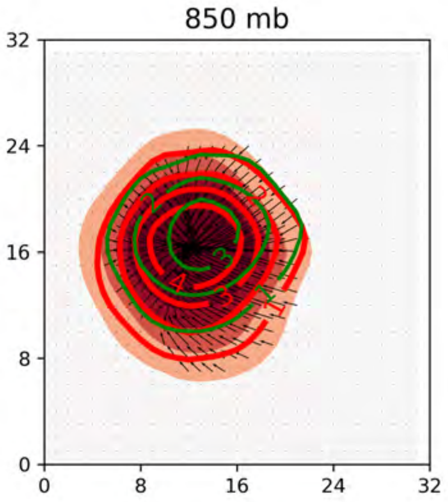
Feeder-Seeder Mechanism (Heymsfield 1980)

Gagne II, D.J., S.E. Haupt, D.W. Nychka, G. Thompson, 2019: Interpretable Deep Learning for Spatial Severe Hail Forecasting, *Monthly Weather Review*, **147**, 2827-2845. DOI: 10.1175/MWR-D-18-0316.1.

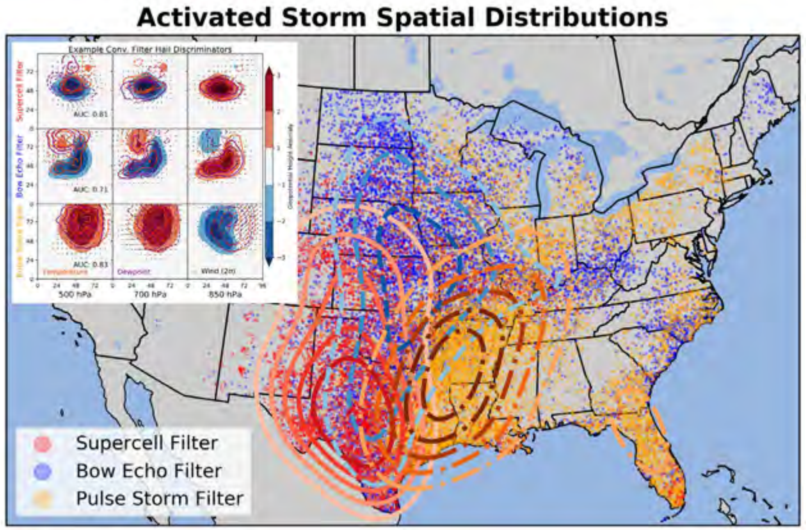
Impact of Using Convolutional Neural Networks



Convolutional neural networks produce more skilled hail predictions than other models.



Convolutional neural networks encode realistic storm features and hail growth processes.



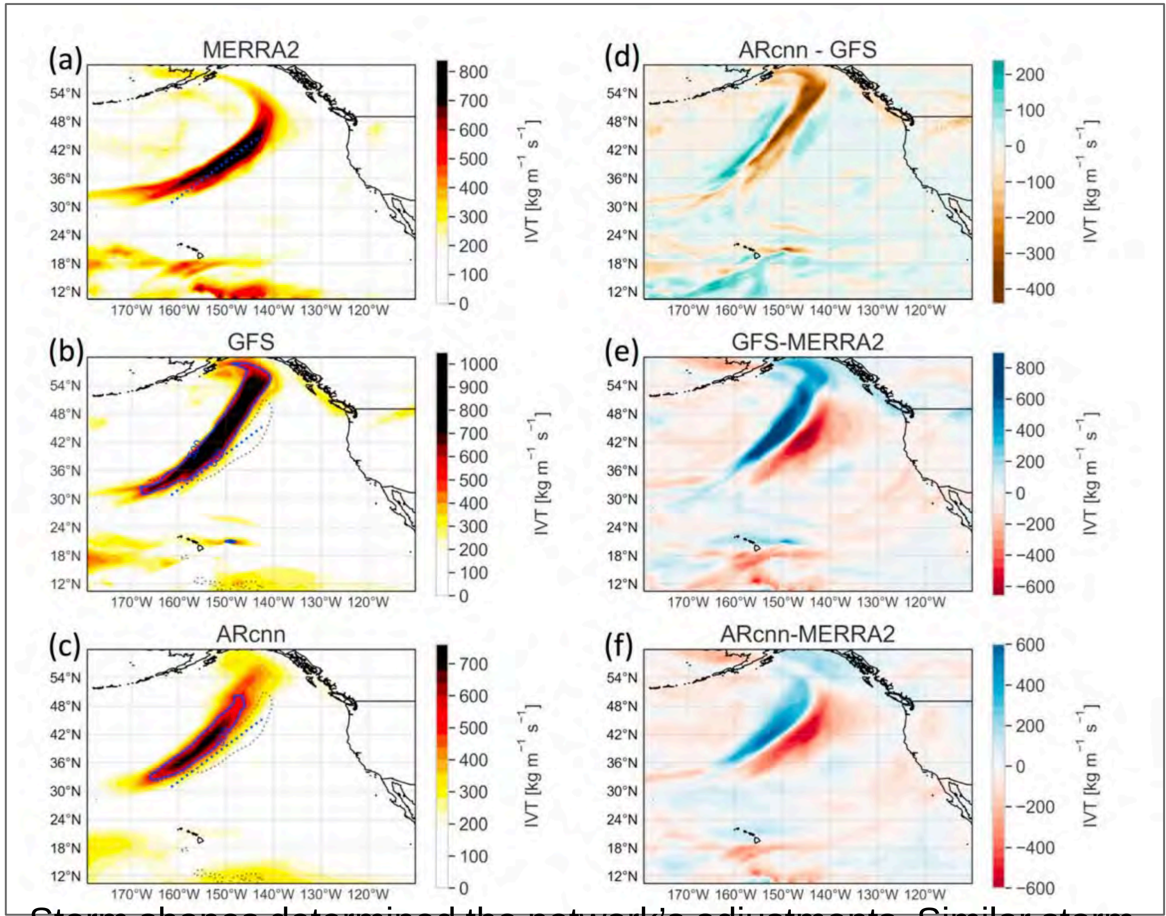
Internal representations of deep learning models could enable more sophisticated analysis of large weather and climate data.

NCAR | UCAR
Gagne II, D.J., S.E. Haupt, D.W. Nychka, G. Thompson, 2019: Interpretable Deep Learning for Spatial Severe Hail Forecasting, *Monthly Weather Review*, **147**, 2827-2845. DOI: 10.1175/MWR-D-18-0316.1.

Applying Deep Learning to Atmospheric Rivers

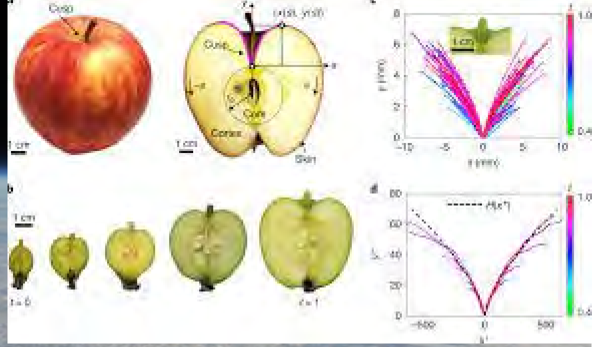
Main Results:

- The GFS forecast field of **integrated vapor transport** is used for a convolutional neural network-based forecast post-processing method.
- The machine learning algorithm reduces the full-field RMSE and improves the correlation with ground truth.
- An error deconstruction shows that the dominant improvements come from the reduction of random error and **conditional biases**.



Storm shapes determined the network's adjustments. Similar storm (i.e. zonal, meridional, stunted etc.) types were corrected in very similar ways.

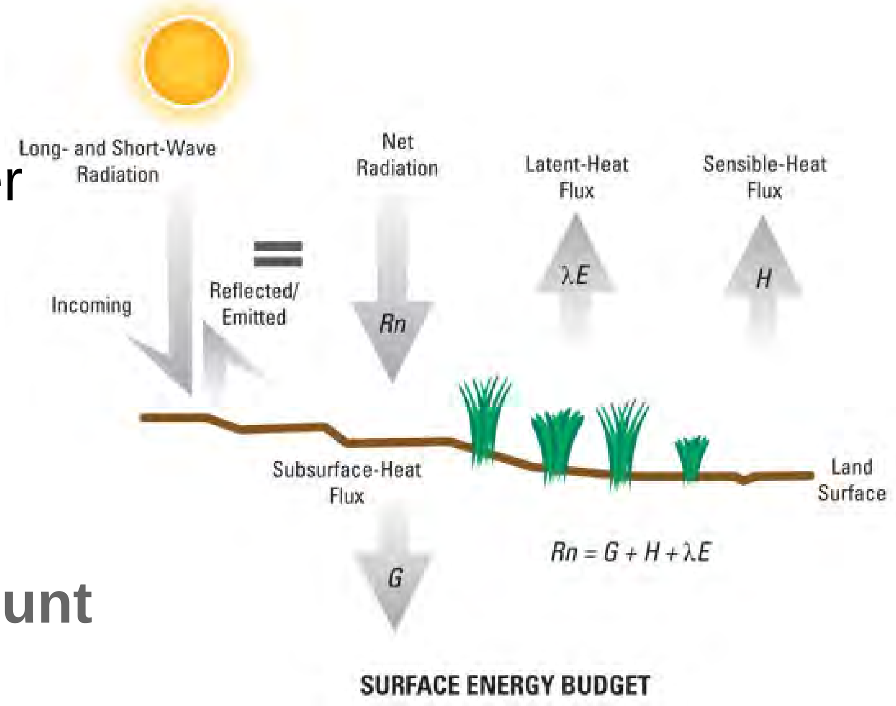
Chapman, W. E., Subramanian, A. C., Delle Monache, L., Xie, S. P., & Ralph, F. M. (2019). Improving atmospheric river forecasts with machine learning. *Geophysical Research Letters*, 46, 10627–10635. https://doi.org/10.1029/2019GL083662



AI/ML for Model Parameterization

Machine Learning for Surface Layer Parameterization

- Surface layer parameterizations model energy transfer (flux) from atmosphere to land surface
- Monin-Obukhov similarity theory determines surface fluxes and stresses in atmospheric models.
- Stability functions Φ_M (momentum) and Φ_H (heat) are determined empirically from field experiments.
- **However, the stability functions show a large amount of variation.**
- **Instead, we will use machine learning flux estimates.**
- We have therefore selected two data sets that provide multiyear records:
  - KNMI-mast at Cabauw (Netherlands), 213 m tower, 2003 - 2017
  - FDR tower near Scoville, Idaho, 2015 – 2017
- Fit random forest to each site to predict friction velocity, sensible heat flux, and latent heat flux



https://nevada.usgs.gov/et/measured.htm

Cabauw

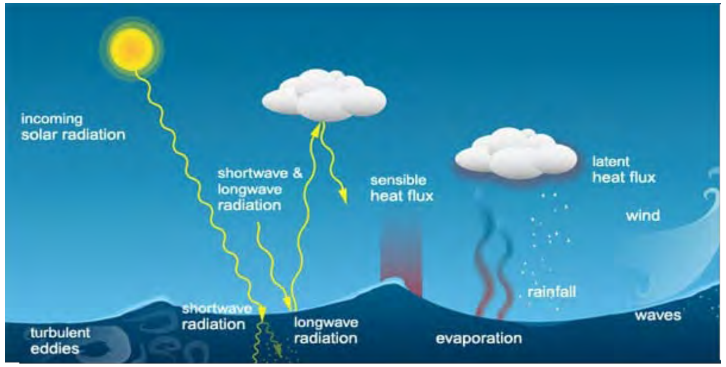
Idaho

Cross-Testing ML Models

- ✓ Random Forest and Neural Network both significantly outperform Monin-Obukov Theory
- ✓ True even when applied to site that is different than the one trained

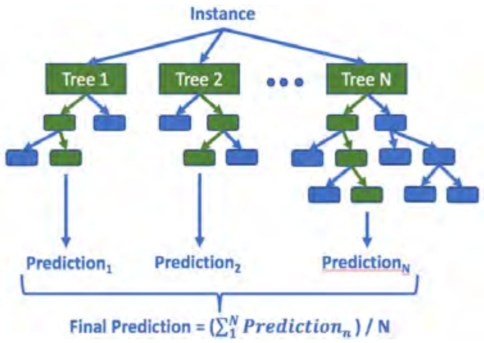
	R^2			MAE		
RF T[illegible] Cabauw	0.93	0.82	0.73	0.031	0.030	0.055
RF Trained on Idaho	0.90	0.77	0.49	0.074	0.049	0.112

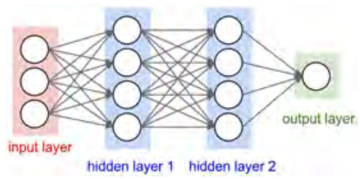
Machine -Learning Surface Layer Parameterization for Offshore



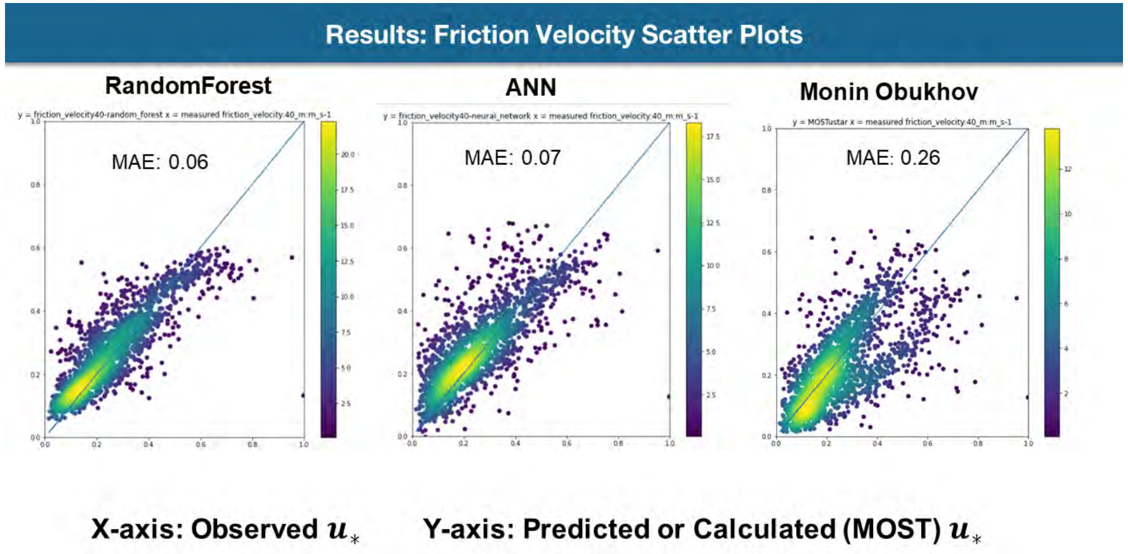
Can we use ML to parameterize the marine surface layer?

Tested Random Forests and Artificial Neural Networks





Used weather data and flux measurements from the FINO1 tower and buoys to train machine learning models to **estimate friction velocity u_*** and **temperature scale θ_* directly**

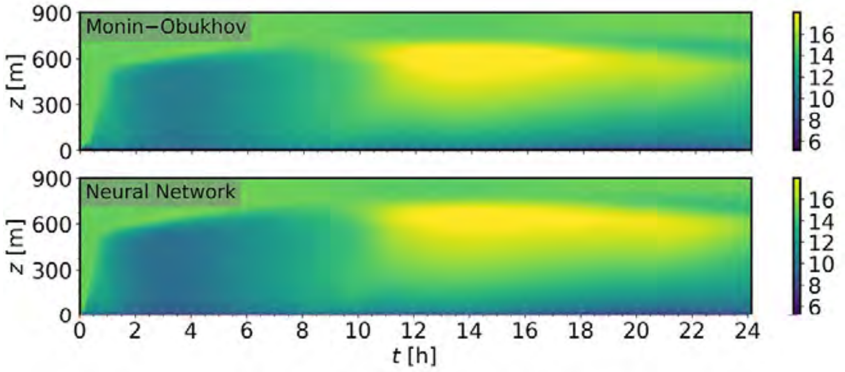


Both ML methods outperformed traditional Monin-Obukhov Similarity Theory!

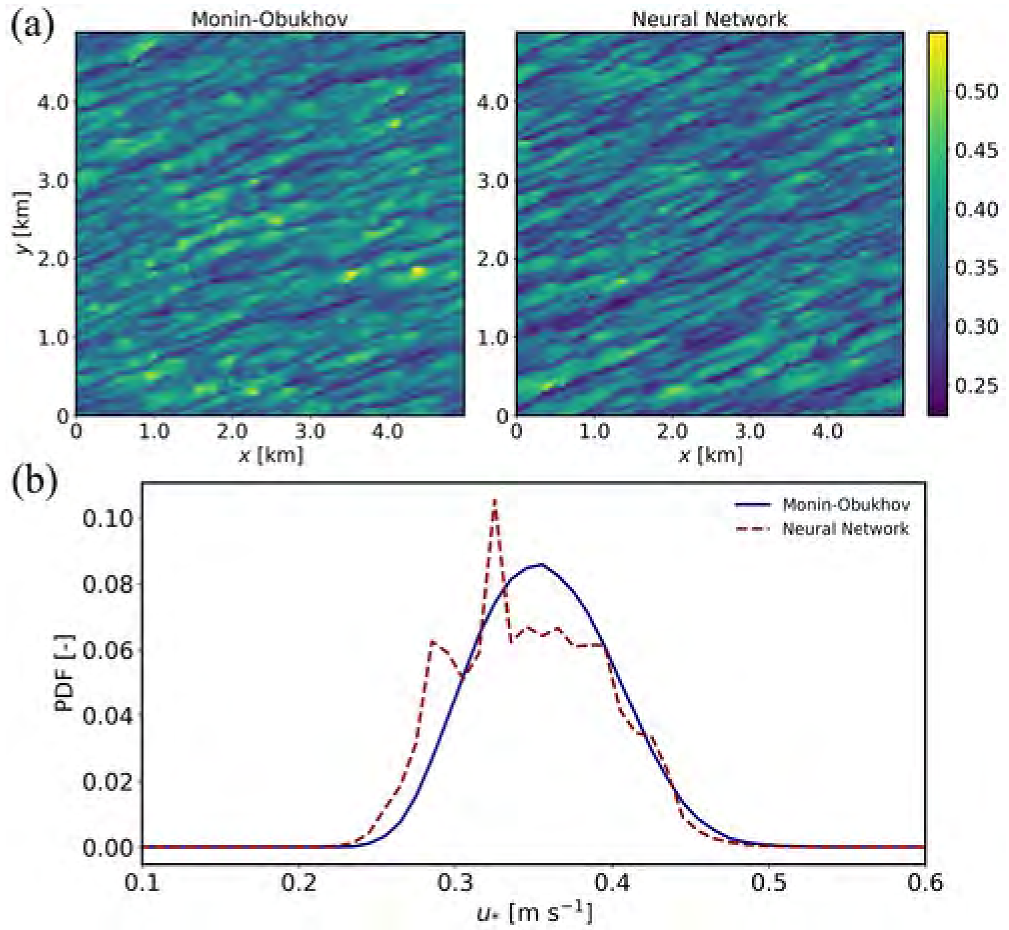
Sue Dettling
Tom Brummet
David John Gagne
Branko Kosovic
Sue Haupt

Application of ML Surface Layer in Large Eddy Simulation Models

- Tested in NCAR's GPU-enabled FastEddy® Large Eddy Simulation Model
- Testing in community Weather Research and Forecasting Model
- Much faster – speed real-time modeling
- Can train for specific surface conditions



U-wind speed from Neural Network Surface Scheme implemented in FastEddy for Diurnal Cycle.



Munoz-Esparza, D., C.Becker, J.A. Sauer, D.J. Gagne II, J. Schreck, B. Kosovic, 2022: On the Application of an Observations-based Machine Learning Parameterization of Surface Layer Fluxes within an Atmospheric Large-Eddy Simulation Model, *JGR Atmospheres*, https://doi.org/10.1029/2021JD036214.

AI/ML for Dynamics

Geosci. Model Dev., 11, 3999–4009, 2018
https://doi.org/10.5194/gmd-11-3999-2018

Geoscientific Model Development EGU

Challenges and design choices for global weather and climate models based on machine learning

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Received: 16 June 2018 – Discussion started: 28 June 2018
Revised: 30 August 2018 – Accepted: 12 September 2018 – Published: 1 October 2018

Abstract. Can models that are based on deep learning and trained on atmospheric data compete with weather and climate models that are based on physical principles and the basic equations of motion? This question has been asked often recently due to the boom in deep-learning techniques. The question is valid given the huge amount of data that are available, the computational efficiency of deep-learning techniques and the limitations of today's weather and climate models in particular with respect to resolution and complexity.

In this paper, the question will be discussed in the context of global weather forecasts. A toy model for global weather predictions will be presented and used to identify challenges and fundamental design choices for a forecast system based on neural networks.

1 Introduction

In recent years, artificial intelligence and machine learning have become very important for hardware development in high-performance computing (HPC) and have attracted a large amount of public interest. Neural networks (NNs) are tools from machine learning that are used successfully within many applications such as computer vision, speech recognition and data filtering. If a sufficient amount of data are available, NNs can be trained to describe the evolution of non-linear processes. Due to the fundamentally application-unaware character, no complete understanding of the underlying process is necessary. Very complex NNs can be trained that use more than a billion trainable parameters and millions of datasets for training on HPC architecture; see, for example, Le (2013).

On the other hand, numerical weather forecasts are computationally expensive and forecast quality reduces significantly already after a couple of days even in the best models available. Most processes in the Earth system are described by non-linear differential equations with non-linear interactions between Earth system components. Due to the complexity and size of the Earth system and the limited capacity of today's supercomputers, it is necessary to make approximations when weather prediction models are formulated and resolution is truncated in space and time. The use of limited resolution makes it necessary to parameterise processes that are not resolved explicitly within model simulations. To optimise parameterisation schemes a large number of parameters has to be tuned towards optimal model performance, and the traceability of physical laws of the underlying process as well as the physical interpretation for each parameter is often lost during this exercise. Furthermore, to perform weather predictions, a huge amount of data need to be processed and assimilated to create initial conditions. This is a process that will again cause significant errors and uncertainties. Only a rather small fraction of all observations can be assimilated into state-of-the-art weather prediction models due to the large computational cost and simplified assumptions required such as vanishing error correlation.

NNs have been used to post-process data from weather forecast models to optimise predictions; see, for example, Krasnopolsky and Lin (2012) or Rasp and Lerch (2018). NNs have also been used for radiation parameterisation in operational forecasts at ECMWF in the past (Chevallier et al., 1998, 2000; Krasnopolsky et al., 2005) as well as for the parameterisation of ocean physics (Krasnopolsky et al., 2002; Tolman et al., 2005) and convection (Krasnopolsky et al., 2013). Recently, the representation of atmospheric sub-grid

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It is possible to make global weather forecasts with a toy NN model that are better than persistence and competitive with T21 Atmospheric models of similar complexity for short lead times

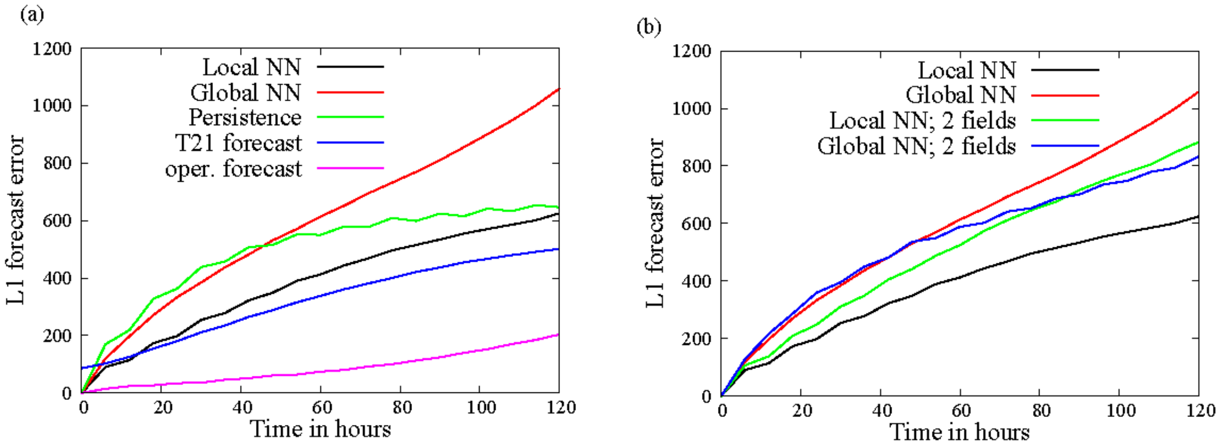


Figure 3. **(a)** Globally integrated absolute forecast error for the best local network (9×9 stencil), the global network, a persistence forecast, an IFS forecast at TL21 resolution and the operational weather forecast of ECMWF. The persistence forecast shows a 12-hourly fluctuation since Z500 has a weak 12-hourly cycle in the tropics due to atmospheric tides. **(b)** The same globally integrated absolute forecast error for the best local and global network as in **(a)** plus the best results for local and global networks that use 2mT as additional prognostic field.

Using a Genetic Algorithm to capture behavior of a Lorenz System

A Quadratic Empirical Model

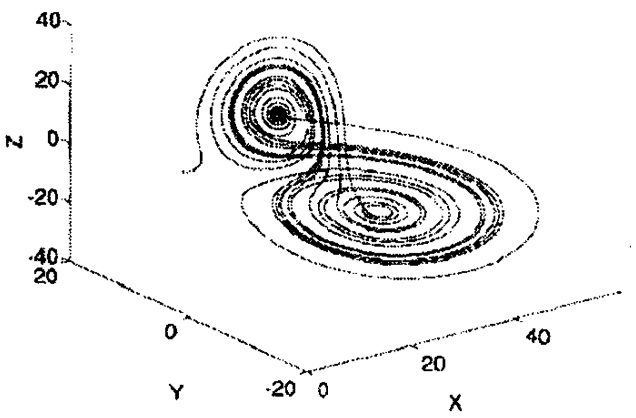


Figure 8. A Lorenz attractor computed by integrating equations (15) in time 2000 steps.

Solution with a Genetic Algorithm

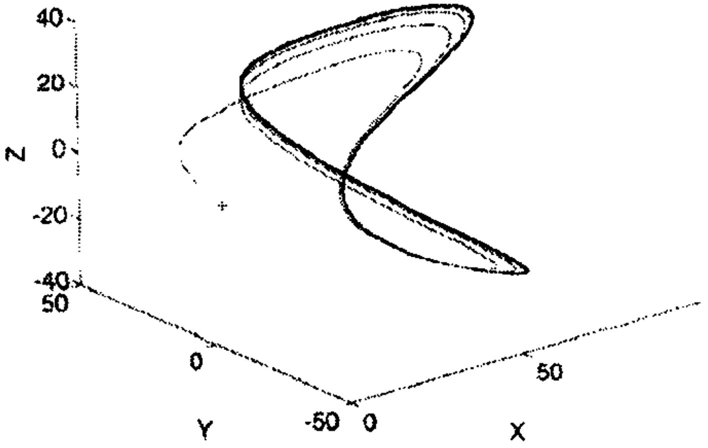
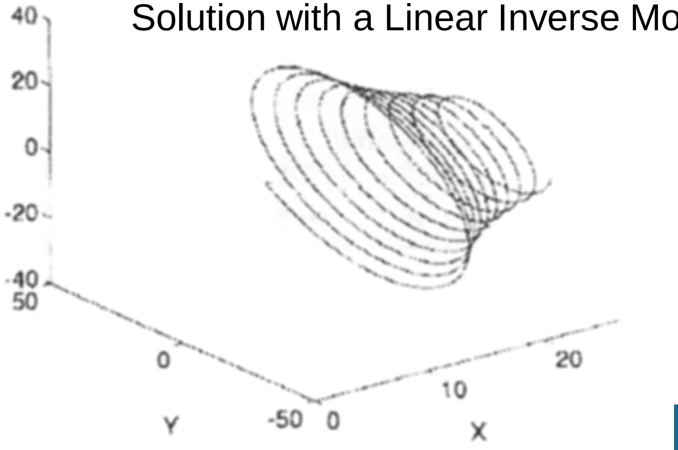


Figure 9. Nonlinear model of Lorenz attractor (equation (12)) as computed with a GA.

Solution with a Linear Inverse Model



Haupt, S.E., 2006: A quadratic empirical model formulation for dynamical systems using a Genetic Algorithm,, *Computers and Mathematics with Applications,* **51**, 431-440.

- Built deep-learning-based convolutional neural network ensemble system for S2S forecasting.
- Requires 3 min to produce a 320-member 6-wk ensemble forecast
- Similar scores (CRPS and RPSS) for 4-wk fx/ and 5-6-wk fx/ as ECMWF S2S ensembles.

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RESEARCH ARTICLE
10.1029/2021MS002502

Key Points:

- An ensemble forecast system is developed using convolution neural networks (CNNs) to generate data-driven global forecasts
- Only 3 s are required to compute a large 320-member ensemble of skillful 6-week sub-seasonal predictions
- Shorter lead time forecasts also show skill, including a single deterministic 4-day forecast for Hurricane Irma

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Citation:
Weyn, J. A., Durran, D. R., Caruana, R., & Cresswell-Clay, N. (2021). Sub-seasonal forecasting with a large ensemble of deep-learning weather prediction models. *Journal of Advances in Modeling Earth Systems, 13*, e2021MS002502. https://doi.org/10.1029/2021MS002502

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Sub-Seasonal Forecasting With a Large Ensemble of Deep-Learning Weather Prediction Models

Jonathan A. Weyn[1,3], Dale R. Durran[1], Rich Caruana[2], and Nathaniel Cresswell-Clay[1]

[1]Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA, [2]Microsoft Research, Redmond, WA, USA, [3]Microsoft, Redmond, WA, USA

Abstract We present an ensemble prediction system using a Deep Learning Weather Prediction (DLWP) model that recursively predicts six key atmospheric variables with six-hour time resolution. This computationally efficient model uses convolutional neural networks (CNNs) on a cubed sphere grid to produce global forecasts. The trained model requires just three minutes on a single GPU to produce a 320-member set of six-week forecasts at 1.4° resolution. Ensemble spread is primarily produced by randomizing the CNN training process to create a set of 32 DLWP models with slightly different learned weights. Although our DLWP model does not forecast precipitation, it does forecast total column water vapor and gives a reasonable 4.5-day deterministic forecast of Hurricane Irma. In addition to simulating mid-latitude weather systems, it spontaneously generates tropical cyclones in a one-year free-running simulation. Averaged globally and over a two-year test set, the ensemble mean RMSE retains skill relative to climatology beyond two-weeks, with anomaly correlation coefficients remaining above 0.6 through six days. Our primary application is to subseasonal-to-seasonal (S2S) forecasting at lead times from two to six weeks. Current forecast systems have low skill in predicting one- or 2-week-average weather patterns at S2S time scales. The continuous ranked probability score (CRPS) and the ranked probability skill score (RPSS) show that the DLWP ensemble is only modestly inferior in performance to the European Center for Medium Range Weather Forecasts (ECMWF) S2S ensemble over land at lead times of 4 and 5–6 weeks. At shorter lead times, the ECMWF ensemble performs better than DLWP.

Plain Language Summary The world's leading weather forecasting institutions currently rely on computationally expensive weather models running on massive supercomputers. In order to have predictive skill for forecasts two to six weeks in the future, large ensembles of many nearly identical runs of these models are required, but the computational resources needed for these ensembles scales with the number of forecasts run. Since the resources needed rapidly approaches modern-day computing limits, we explore the possibility of using computationally cheap weather models based on machine learning algorithms which learn to reproduce the evolution of weather. Our machine-learning model is capable of running 320 forecasts in three minutes on a single workstation, while the state-of-the-art model from the European Center for Medium-Range Weather Forecasts (ECMWF) utilizes supercomputers to run 50 forecasts. Our ensemble weather model produces realistic forecasts of weather events such as Hurricane Irma in 2017 and is even capable of nearly matching the performance of the ECMWF ensemble for forecasts of temperature four to six weeks in the future.

1. Introduction

Weather forecasting relies heavily on data assimilation to estimate the current state of the atmosphere and on numerical weather prediction (NWP) to approximate its subsequent evolution. The skill of such deterministic weather forecasts is typically limited to about two weeks by the chaotic growth of small initial errors and inaccuracies in our approximate models of the atmosphere. On much longer, multi-month time scales, the coupling of the atmosphere with slowly evolving ocean-land forcing allows skillful seasonal forecasts of monthly or seasonally averaged conditions. Between these two extremes, the production of skillful one- or two-week averaged forecasts at lead times ranging roughly between two weeks and two months (the subseasonal-to-seasonal or S2S time frame) has proven particularly challenging; yet there are many societal sectors that would greatly benefit from improved S2S forecasts (White et al., 2017). Several major operational centers have developed NWP-based ensemble systems focused on improving S2S forecasting (Vitart et al., 2017).

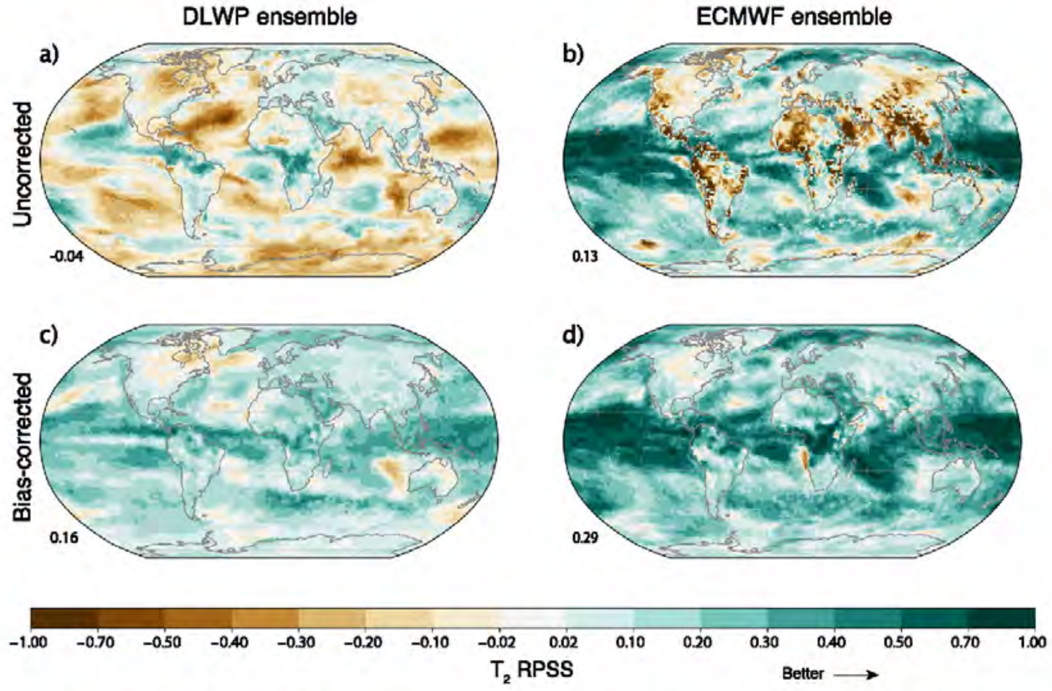
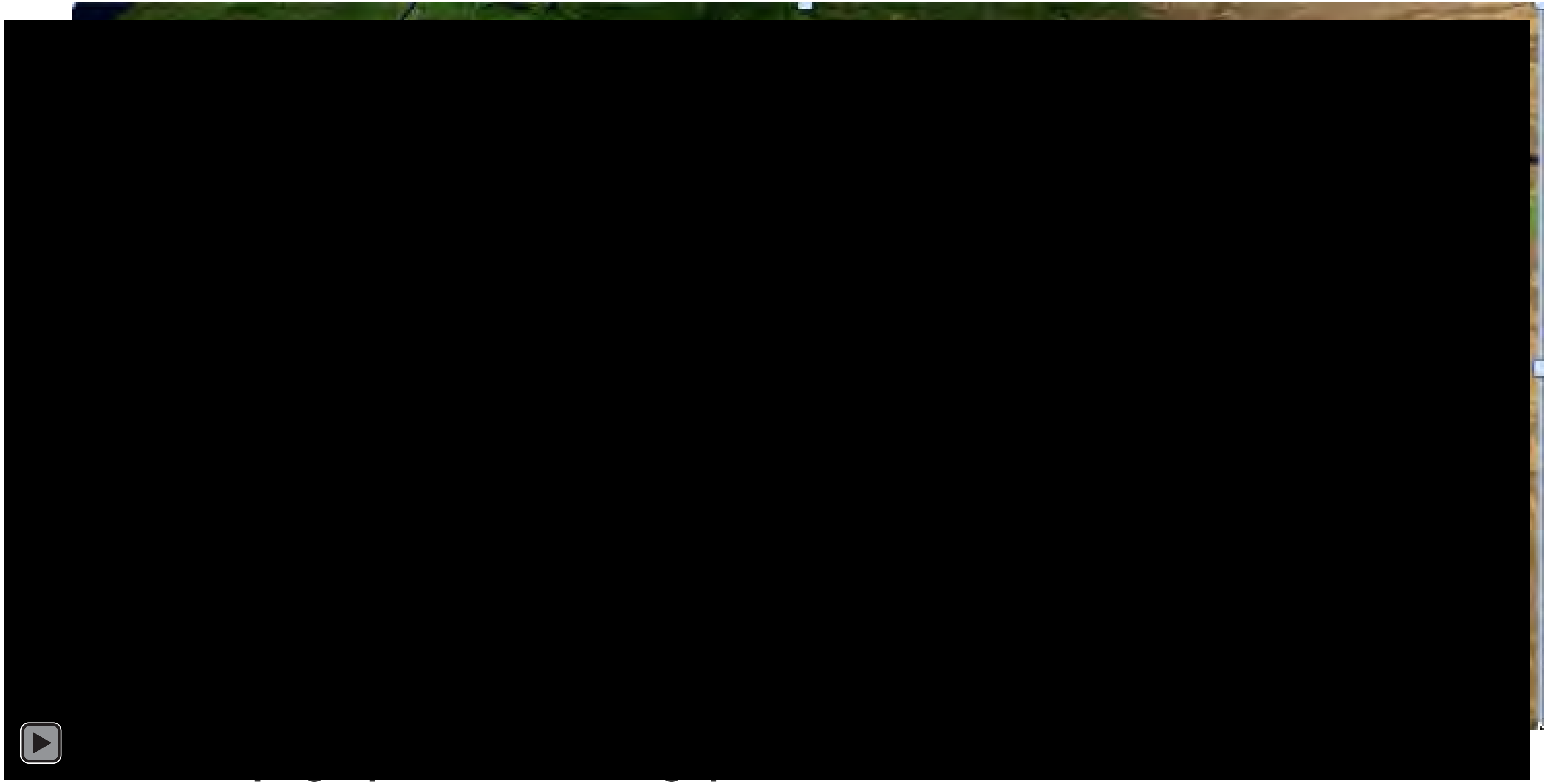


Figure 13. Annual average RPSS skill maps for T_2 at weeks 5–6. Without bias correction: (a) DLWP ensemble, (b) ECMWF ensemble; with bias correction: (c) DLWP ensemble, (d) ECMWF ensemble. The weighted global mean is noted at the lower left in each panel.

AI/ML for Downscaling

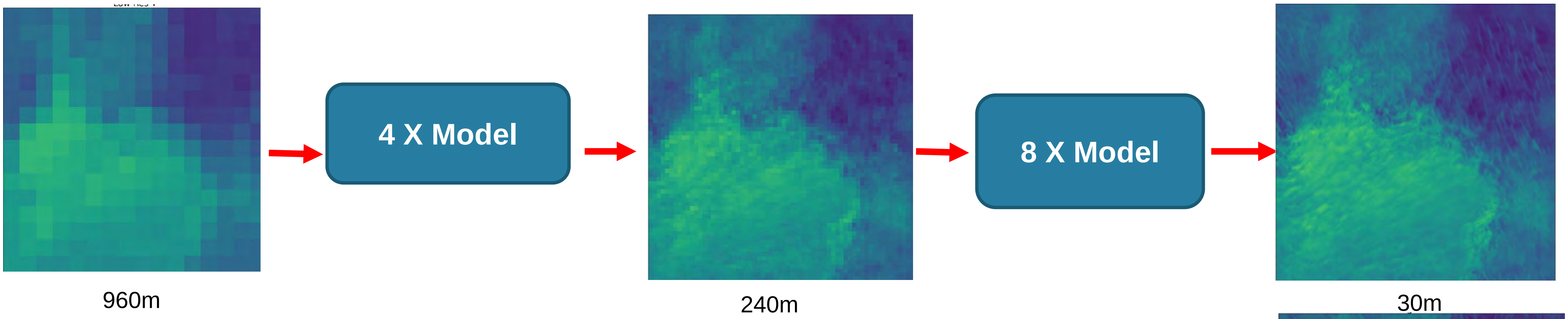
High-Resolution Modeling with 3D PBL Scheme



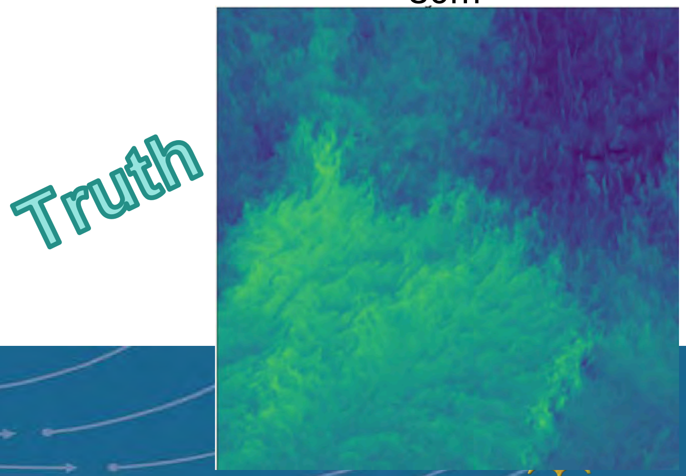
Branko **Kosović,Pedro Jimenez, Tim** Juliano, **NCAR**

Downscale Model Architecture

- Train two GANS **independently** (4x and 8x downscale networks)
  - use 960m coarsened LES to train 4x model
  - use 240m coarsened LES to train 8x model
- Apply sequentially

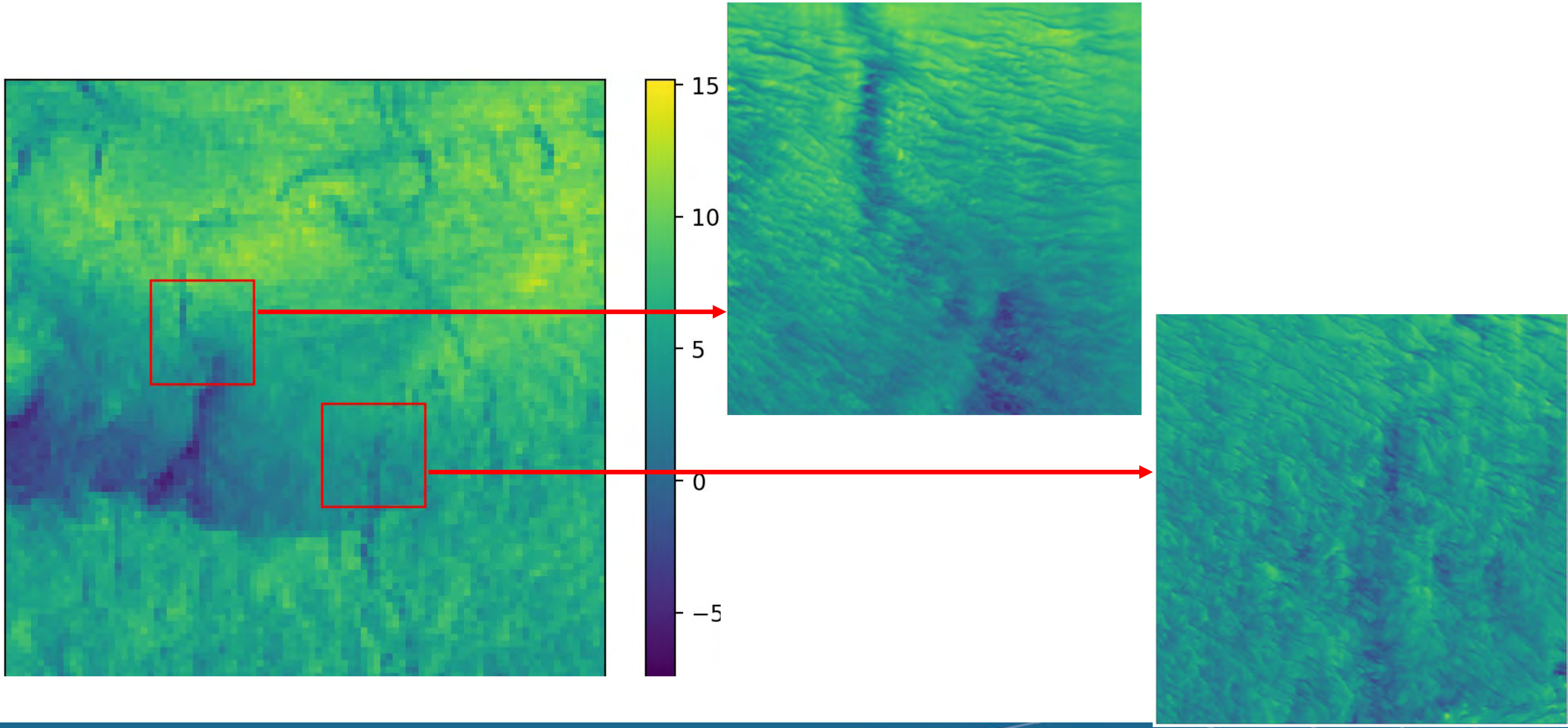


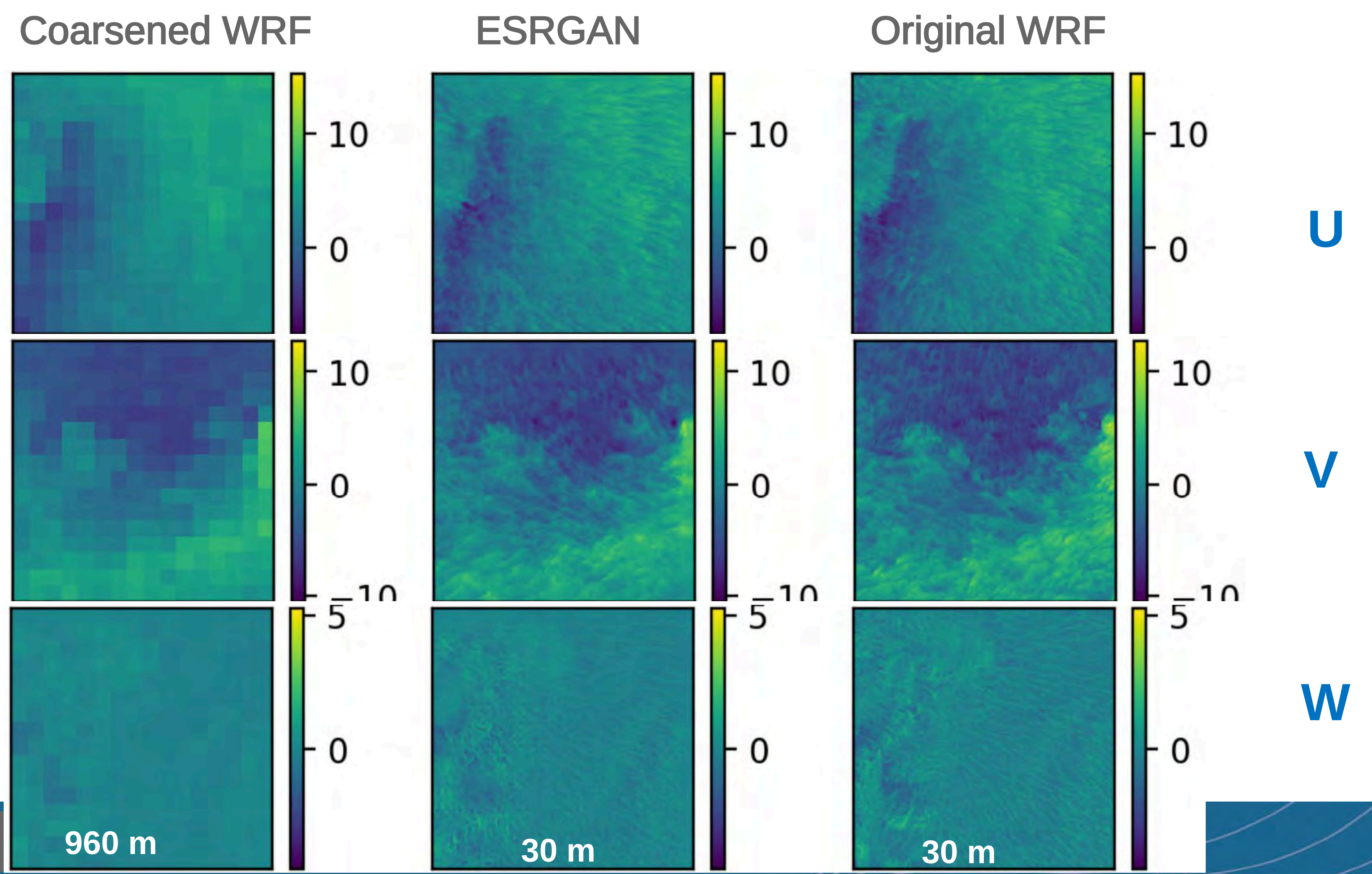
Generative Adversarial Network



960m Coarsened WRF

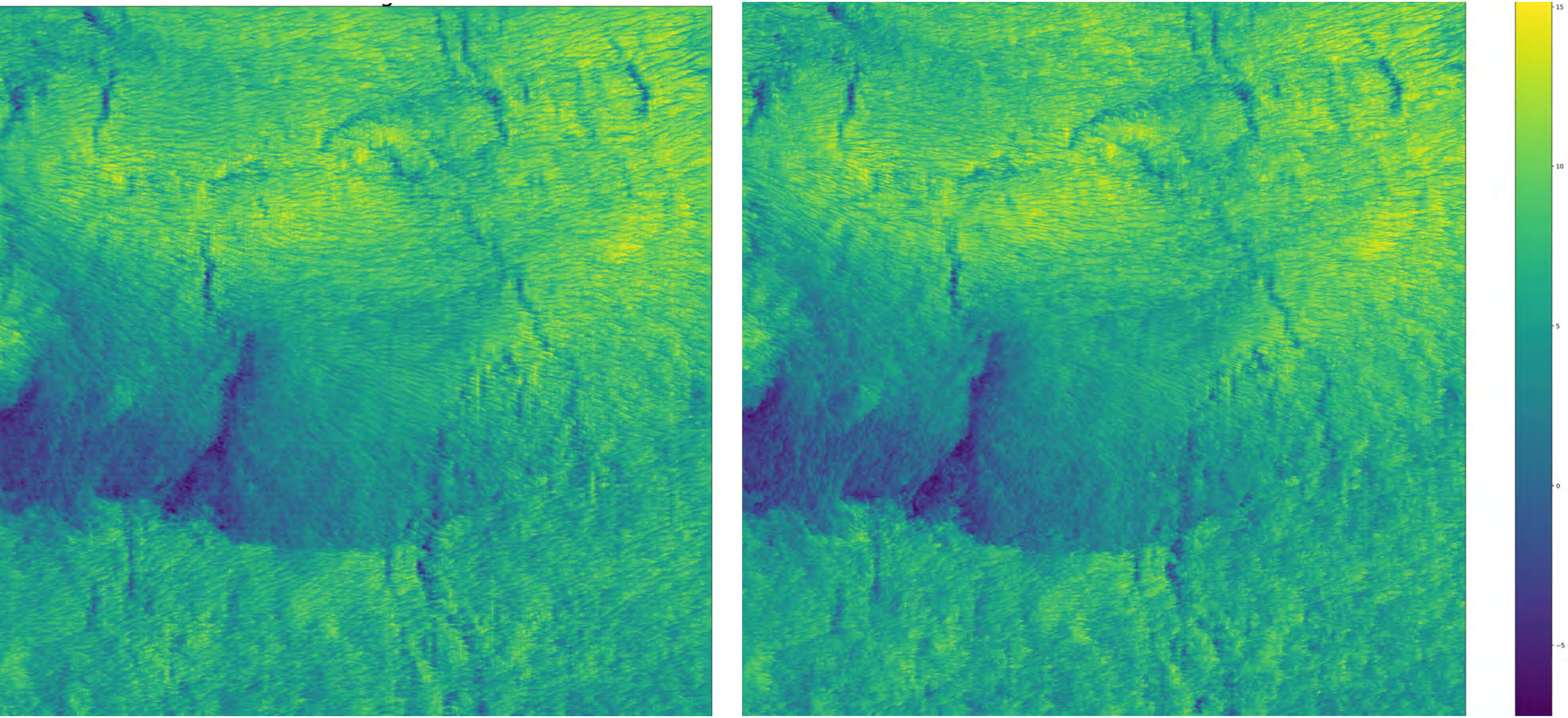
30m Super Resolution U





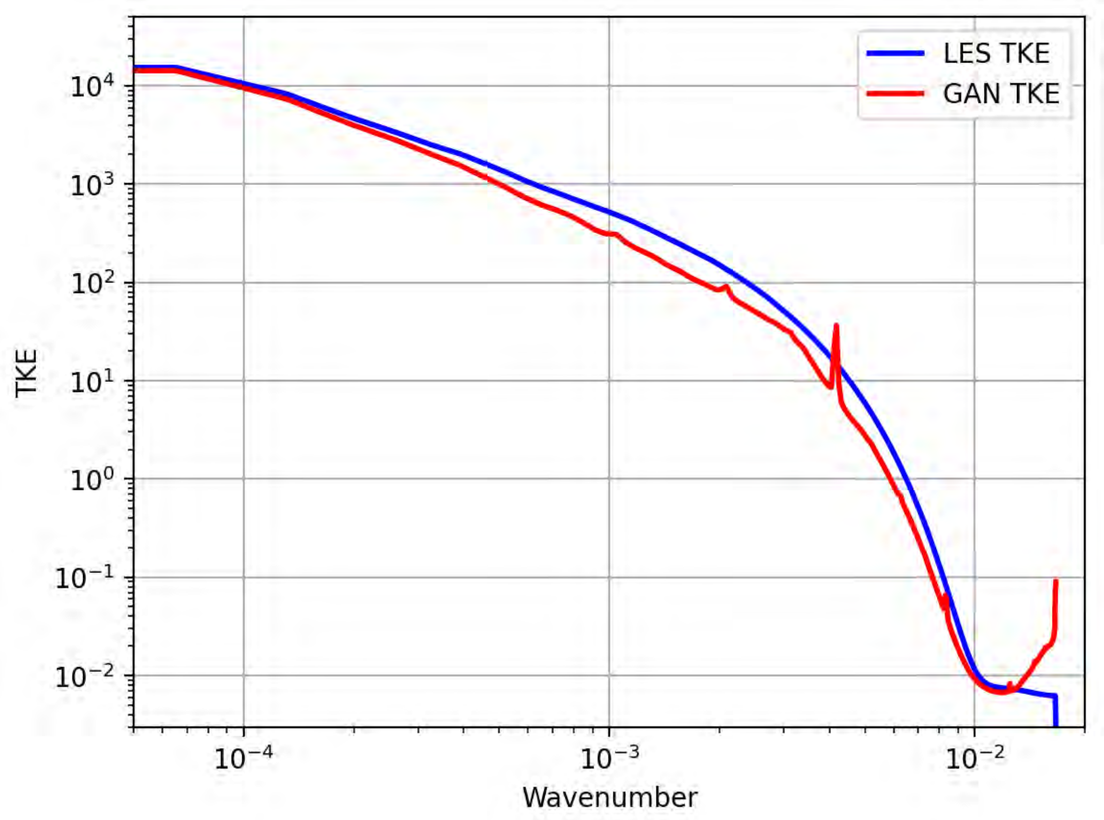
Coarsened WRF
ESRGAN
Original WRF
10
0
−10
5
U
V
W
960 m
30 m
30 m

Full Domain Generated U vs WRF 30m U

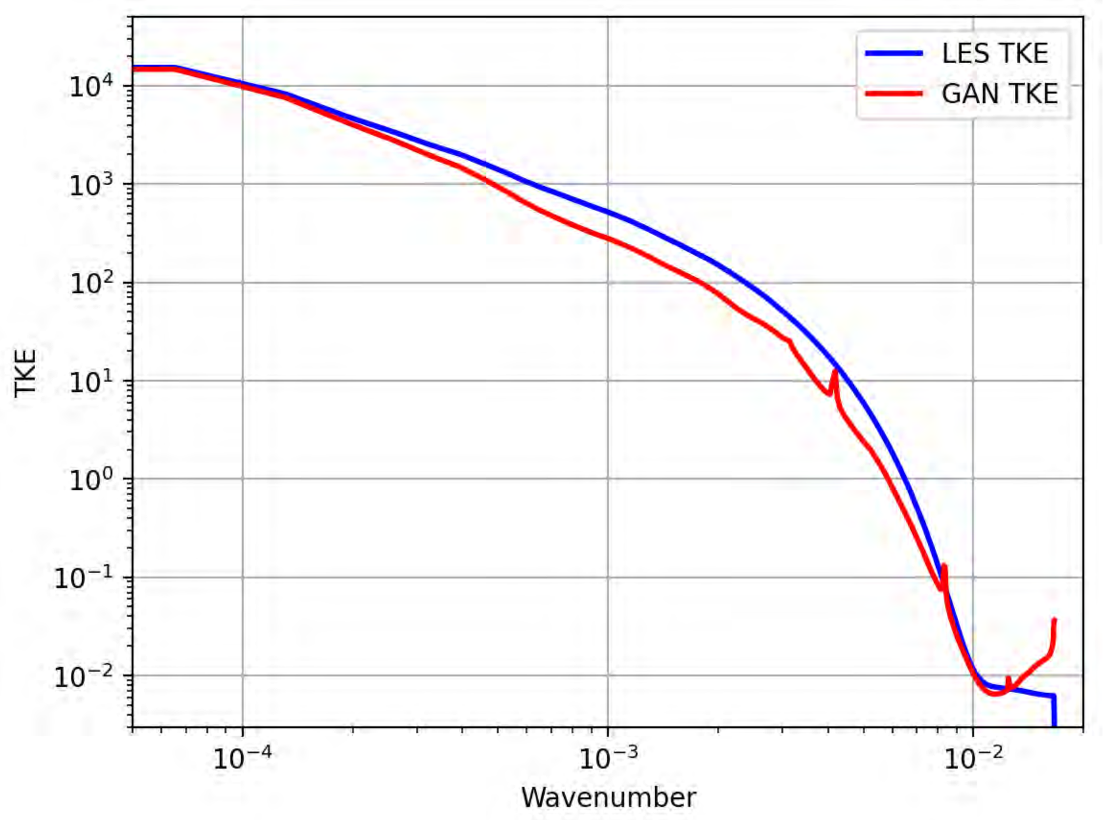


Spectra Plots Testing Region

TKE AS A FUNCTION OF WAVENUMBER



8X model trained independent of 4X model



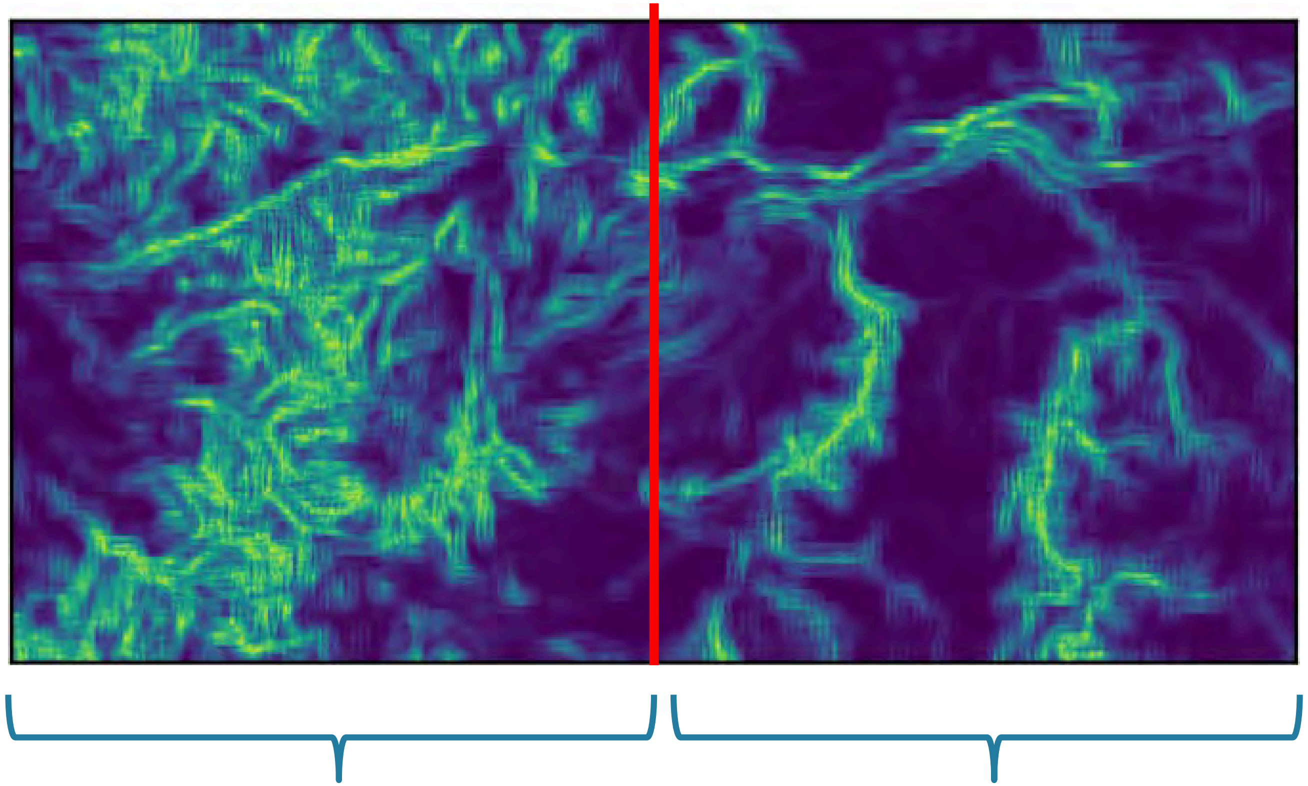
8X model trained on output of 4X model

Smoothed Output = 3x3 convolutional filter applied to LES and applied to GAN output , low pass filter

Demonstrate Transfer Learning

Test model on unique domain

Transfer Learning Region

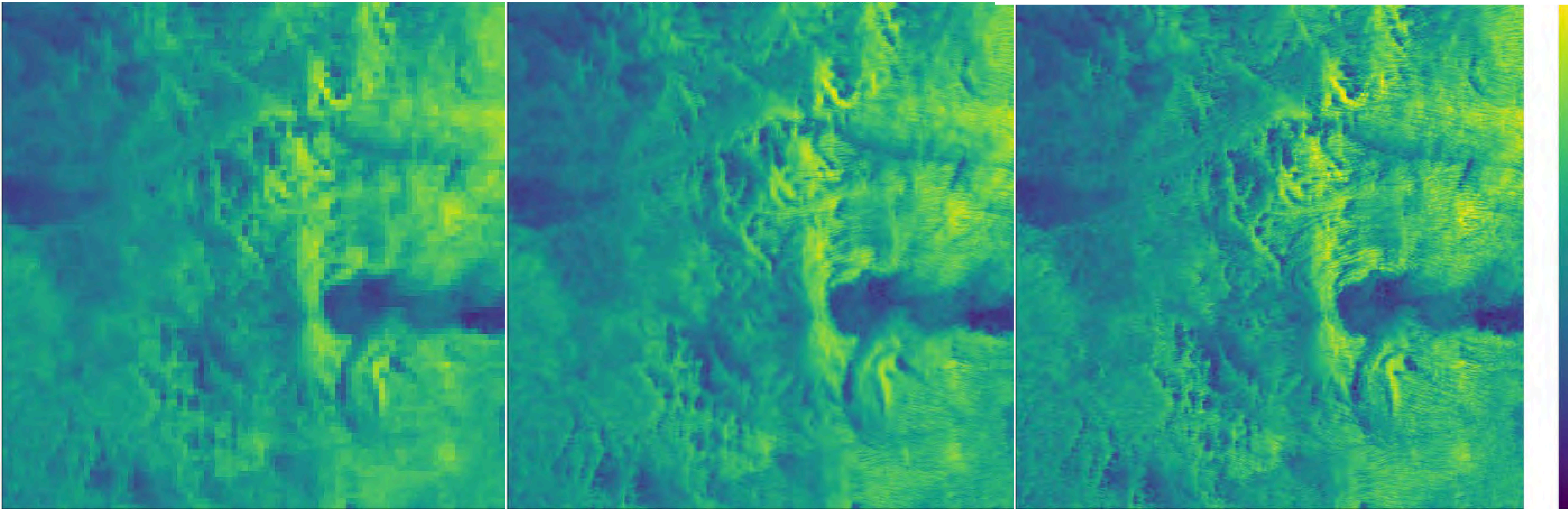


Train / Test Region

Transfer Learning Examples

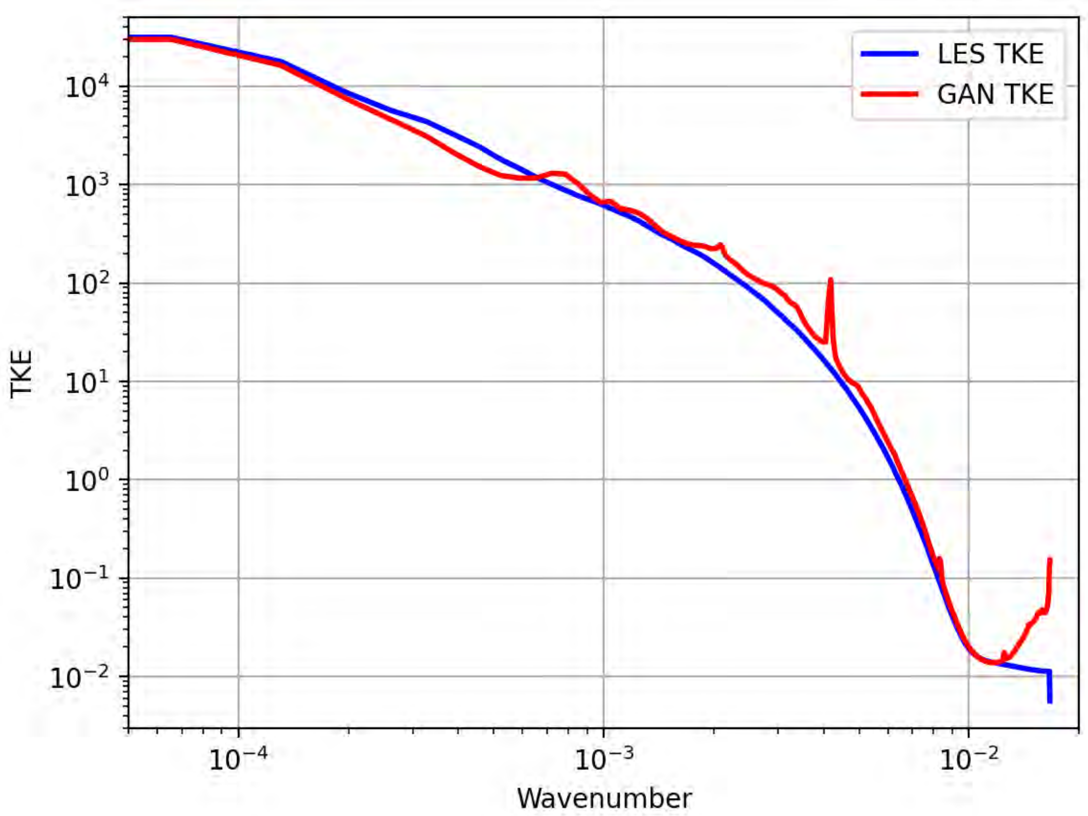
U Wind

Coarsened 960m U | **Smoothed 30 m ESRGAN U** | **Smoothed 30 m LES U**

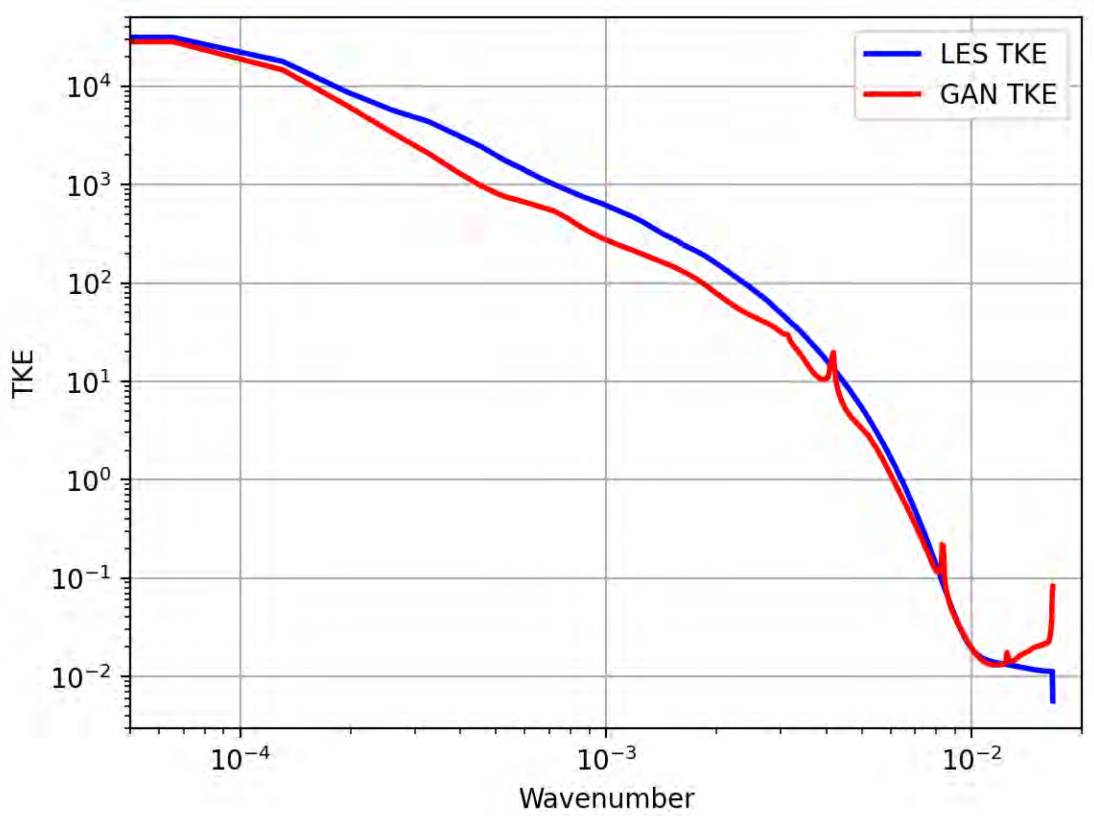


Spectra Plots Transfer Region

TKE AS A FUNCTION OF WAVENUMBER



8X model trained independent of 4X model



8X model trained on output of 4X model

Smoothed Output = 3x3 convolutional filter applied to LES and applied to GAN output , low pass filter

Where are We Going?

What is needed to move Forward?

1) Trustworthiness

2) Interpretability

3) Data Usability

4) Technique

PHILOSOPHICAL TRANSACTIONS A

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Discussion

Check for updates

Cite this article: Haupt SE, Chapman W, Adams SV, Kirkwood C, Hosking JS, Robinson NH, Lerch S, Subramanian AC. 2021 Towards implementing artificial intelligence post-processing in weather and climate: proposed actions from the Oxford 2019 workshop. *Phil. Trans. R. Soc. A* **379**: 20200091. https://doi.org/10.1098/rsta.2020.0091

Accepted: 24 August 2020

One contribution of 13 to a theme issue 'Machine learning for weather and climate modelling'.

Subject Areas:
meteorology

Keywords:
artificial intelligence, machine learning, weather, climate, post-processing

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Towards implementing artificial intelligence post-processing in weather and climate: proposed actions from the Oxford 2019 workshop

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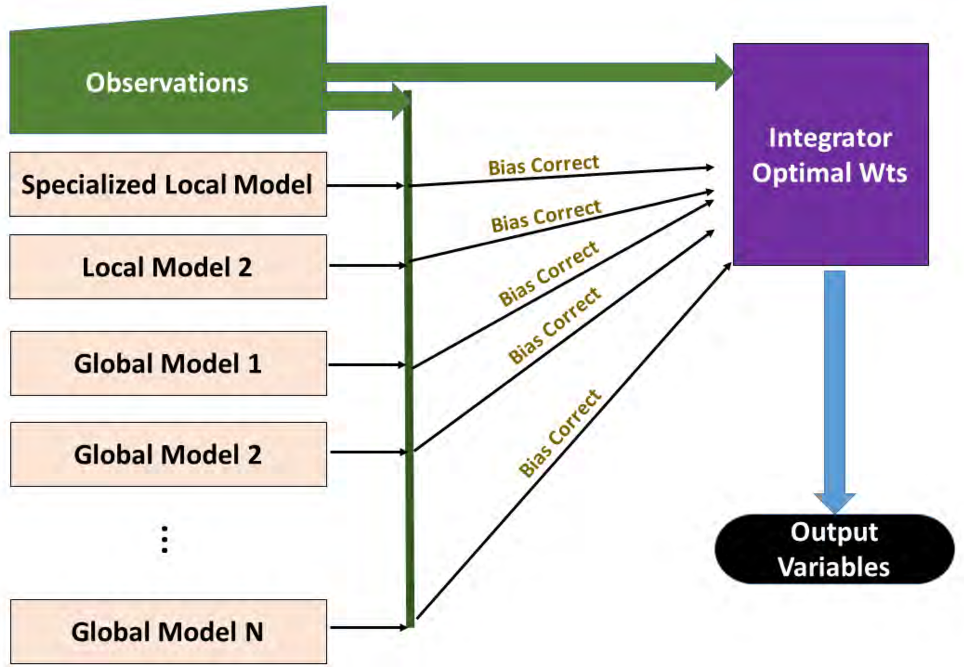
The most mature aspect of applying artificial intelligence (AI)/machine learning (ML) to problems in the atmospheric sciences is likely post-processing of model output. This article provides some history and current state of the science of post-processing with AI for weather and climate models. Deriving from the discussion at the 2019 Oxford workshop on Machine Learning for Weather and Climate, this paper also presents thoughts on medium-term goals to advance such use of AI, which include assuring that algorithms are trustworthy and interpretable, adherence to FAIR data practices to promote usability, and development of techniques that leverage our physical knowledge

THE ROYAL SOCIETY PUBLISHING

What will Constitute Success?

When major centers include AI post-processing as a step in how they make their forecasts.

- When systems are changes, consider the post-processed result rather than the output of the NWP model alone.
- Prioritize computation space and time for the AI method
- Potential regime dependent corrections
- Downscaling using AI to save computational power

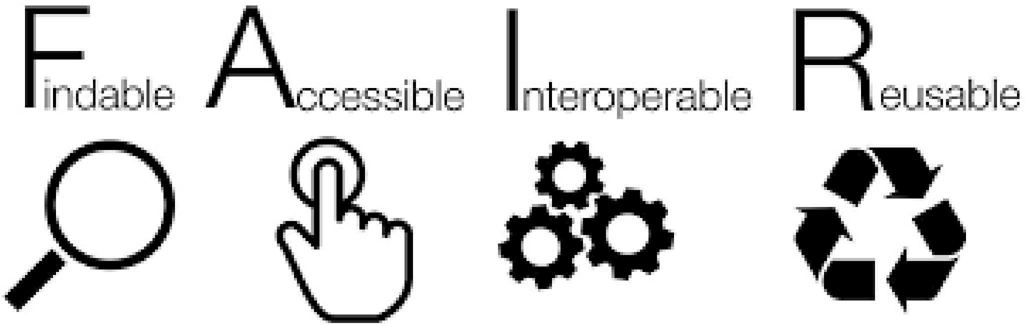


Haupt, S.E., W. Chapman, S.V. Adams, C. Kirkwood, J.S. Hosking, N.H. Robinson, S. Lerch, and A.C. Subramanian, 2020: Towards Implementing AI Post-processing in Weather and Climate: Proposed Actions from the Oxford 2019 Workshop. *Philosophical Transactions of the Royal Meteorological Society A.* **379**: 20200091. https://doi.org/10.1098/rsta.2020.0091.

Actionable Items

Roadmap formation via:

1) Development of a data repository for fast development of post -processing techniques
2) Data standardization methods (FAIR)
3) Calls for studies on interpretability methods
4) Metadata and model documentation for labelled training data
5) Database of recorded AI failures to limit duplication of effort across the research community



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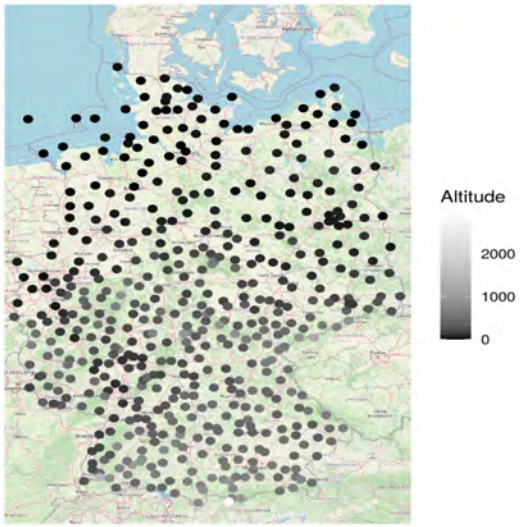
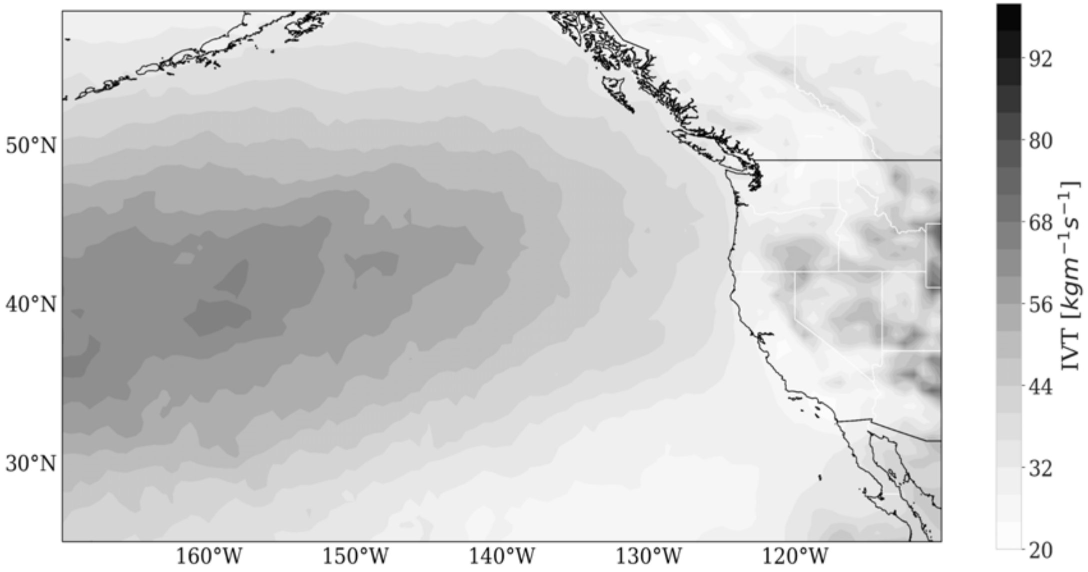
Post-processing Discussion Group from the 2019 Oxford on Machine Learning in Weather and Climate Modeling



Datasets and test python code for processing available at:
https://github.com/NCAR/PostProcessForecasts

Example Problems:

- MJO Ensemble Forecasts
- PNA Ensemble Forecasts
- GFS Integrated Vapor Transport
- ECMWF 2-m Temperature Ensemble over Germany
- UK Surface Road Conditions



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Summary:

- Machine Learning is becoming a necessary component of modern weather forecasting systems
- Levels of applications
  - Dynamic core
  - Model parameterizations
  - Post-processing: Model improvements based on observations

AI-Physics Blended System

- **Planned outcome:** to advance applications of weather forecasting through a systems approach, NWP, observations, and machine learning