NCAR AI4ESS Summer School

June 24, 2020

Machine Learning in Weather Forecasting Systems

Sue Ellen Haupt

National Center for Atmospheric Research

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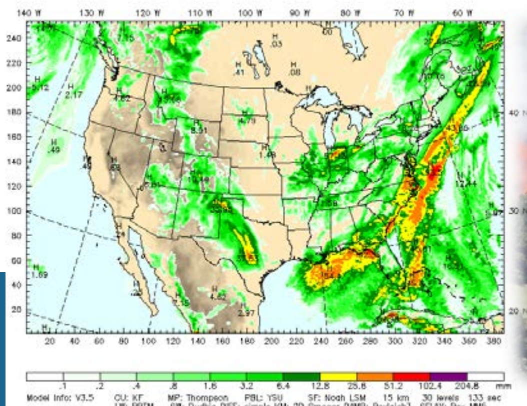
The Plan

Why AI/ML?

- The Nature of Weather
- Traditional Weather Forecasting
- Entrance of AI/ML

Applications

- AI/ML for Postprocessing
- A Systems Approach – Blending Physics with AI/ML
  - Renewable Energy Forecasting
  - Severe Weather
  - Wildland Fire Prediction
- Model Parameterization



Part I:
Weather Forecasting History and Philosophy

Red at Night –

Sailor's Delight

Photo Credit: Bonny Haupt Turayev


He replied, “when evening comes, you say, ‘It will be fair weather for the sky is red,’
and in the morning, ‘Today it will be stormy, for the sky is red and overcast.’”
Matthew 16: 1-2 (NIV)
Red in the Morning –
Sailors Take Warning!

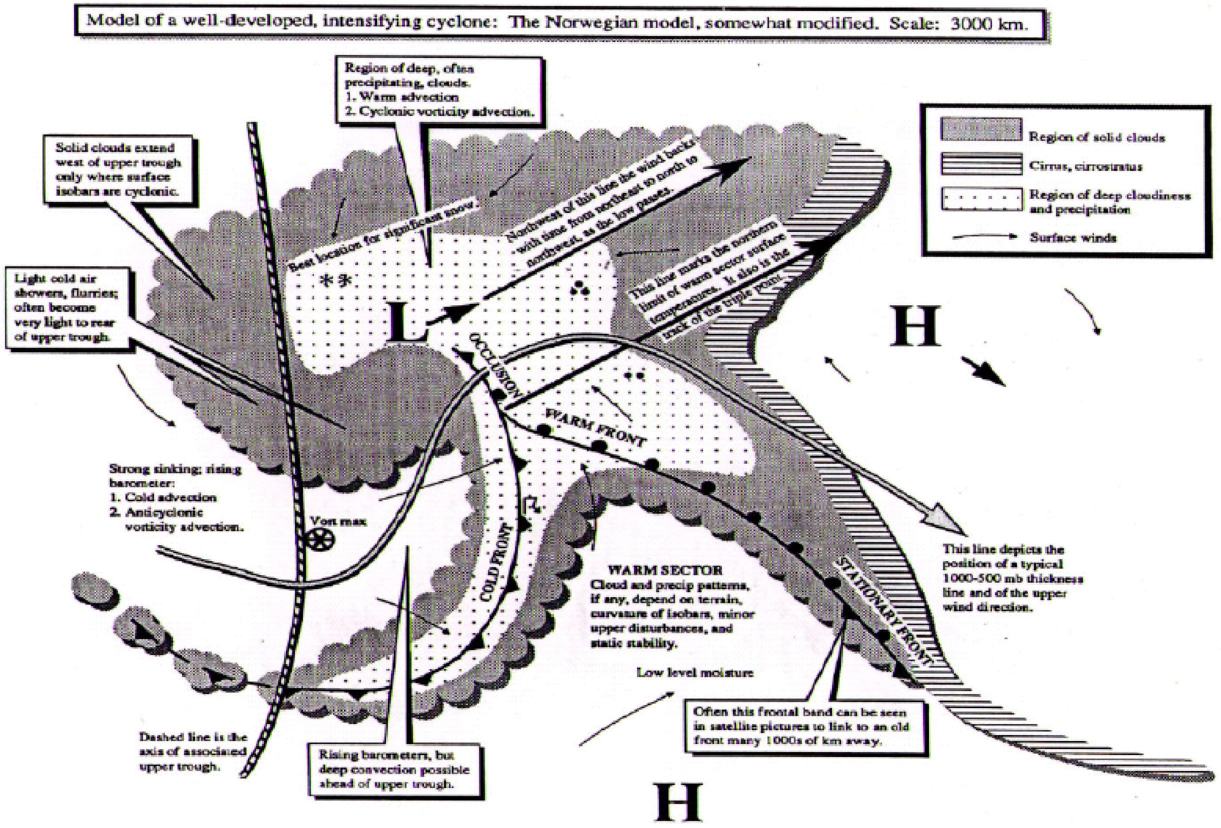
In Broad Sense,
AI was Always Part of Atmospheric Science

Observation and Classification

- Norwegian Cyclone Model

  (V. Bjerknes and J. Bjerknes)

- Explains passage of standard weather systems
- Helped in forecasting based on recent events



Computing Led to Dichotomy

Mathematics – Reductionist approach

If discretize, predict time rate of change

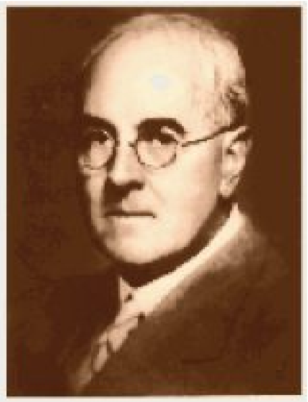
$$\frac{D\vec{V}}{Dt} = -\frac{1}{\rho}\nabla P - 2\Omega \times \vec{V} + \vec{g} + \vec{F}$$

$$\frac{\partial \rho}{\partial t} = -\nabla \bullet \left(\rho \vec{V}\right)$$

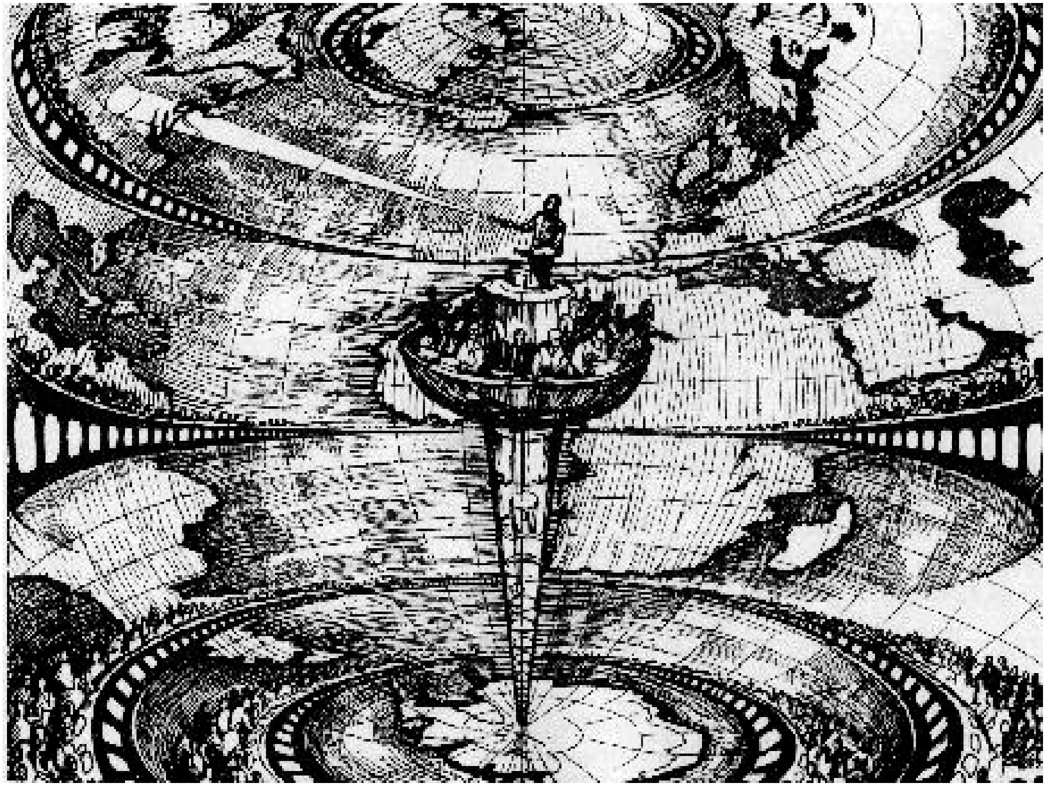
$$P = \rho R T$$

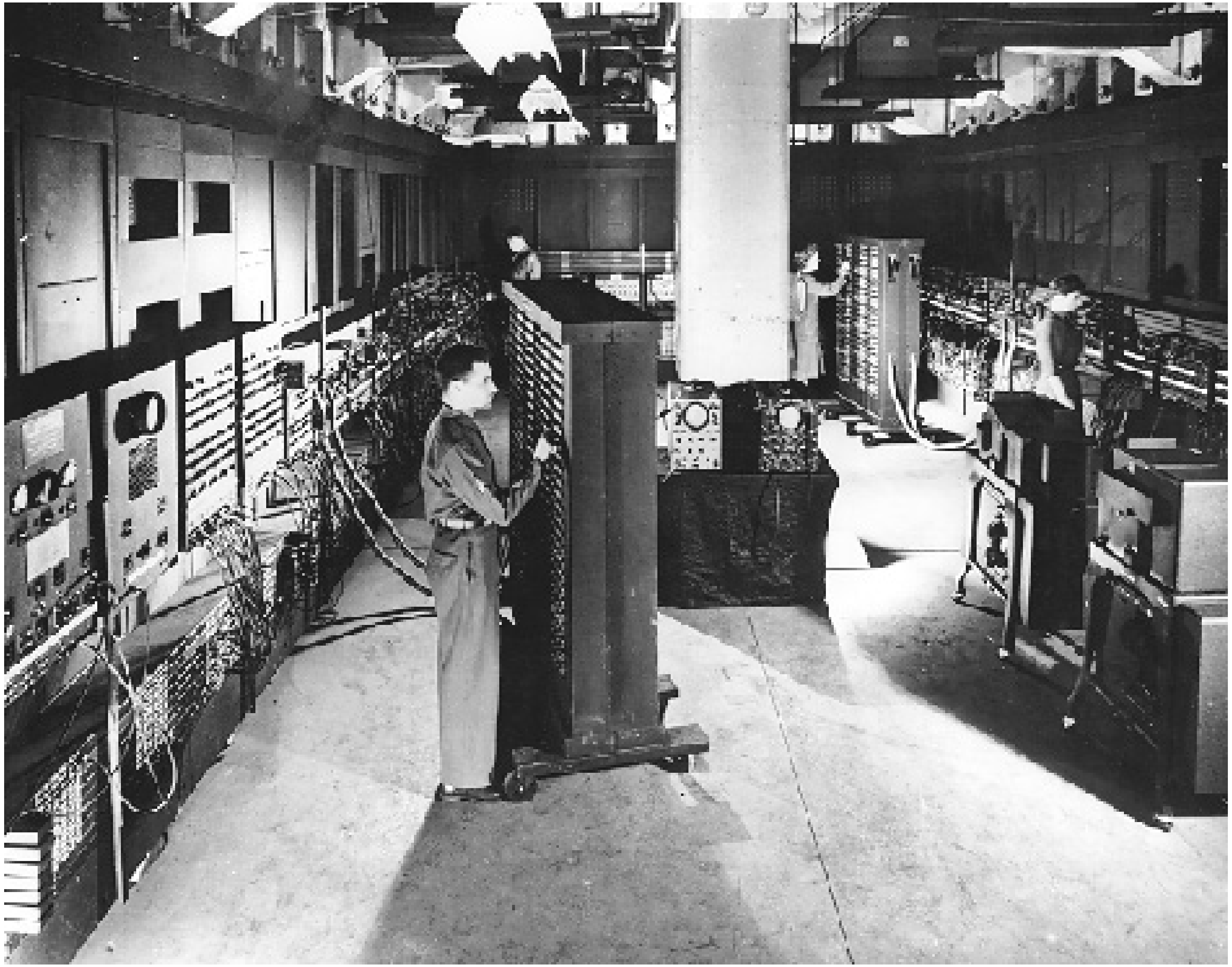
$$Q = c_v \frac{dT}{dt} + P\frac{d\alpha}{dt}$$

-> Numerical Forecasting



Richardson's Dream





http://www.library.upenn.edu/special/gallery/mauchly/jwm0 -1.html

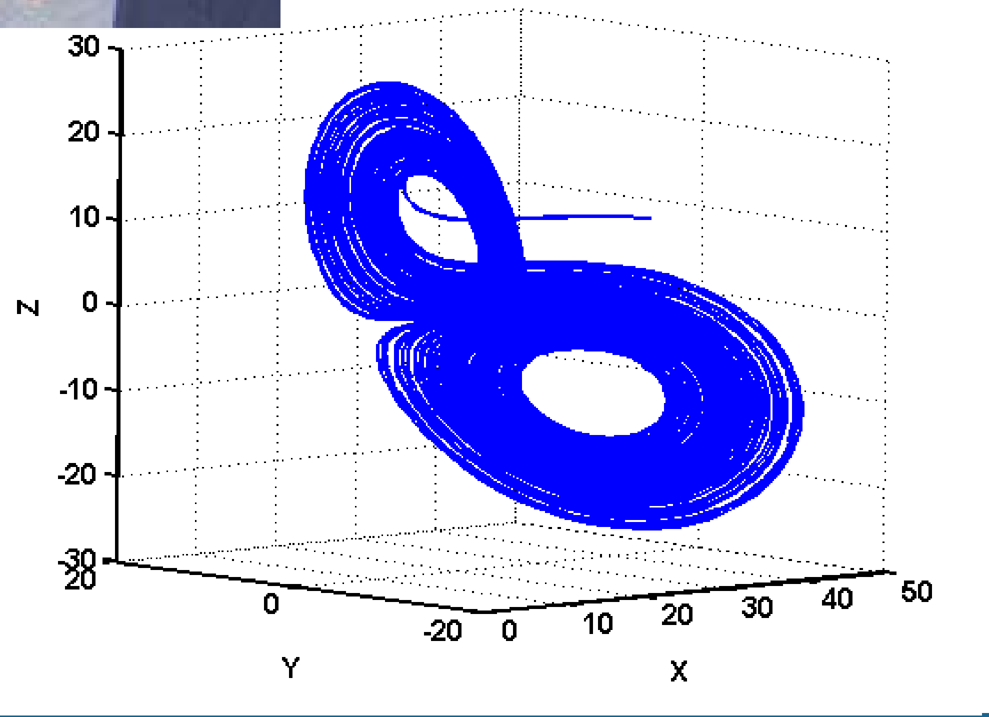
The Rise of Modern Computing

Leads to NWP for Prediction

The ENIAC machine occupied a room thirty by fifty feet.
1946

Charney used filtered equations to produce first numerical forecast

Lorenz and Recognition of Chaos



- Sensitivity to initial conditions
- Chaos – limits to predictability
- Think in terms of attractors & manifolds

Requires

- assimilation
- initialization
- statistical forecasting
- ensemble forecasts
- empirical models
- Value of postprocessing

AI

Two distinct approaches to weather forecasting

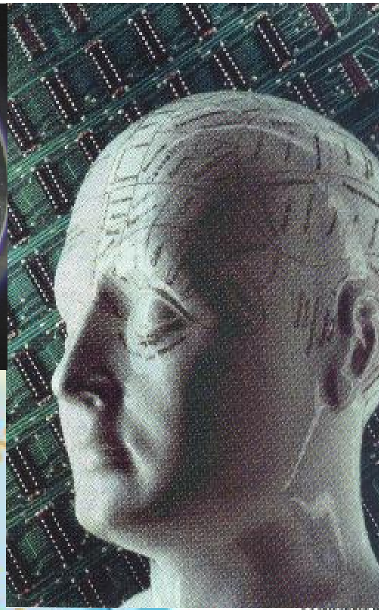
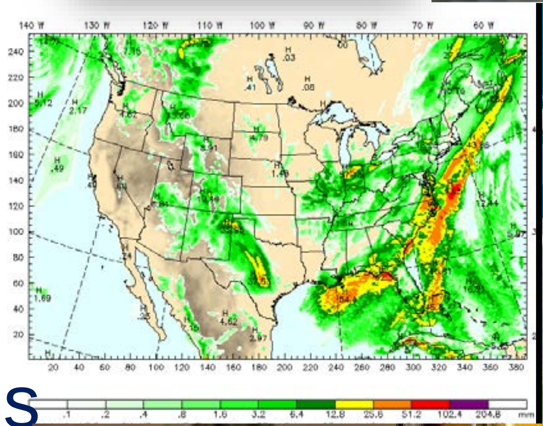
1. Equation based – numerical integration and pre - and post - processing
2. Empirically based – begin with data and find patterns → Artificial Intelligence

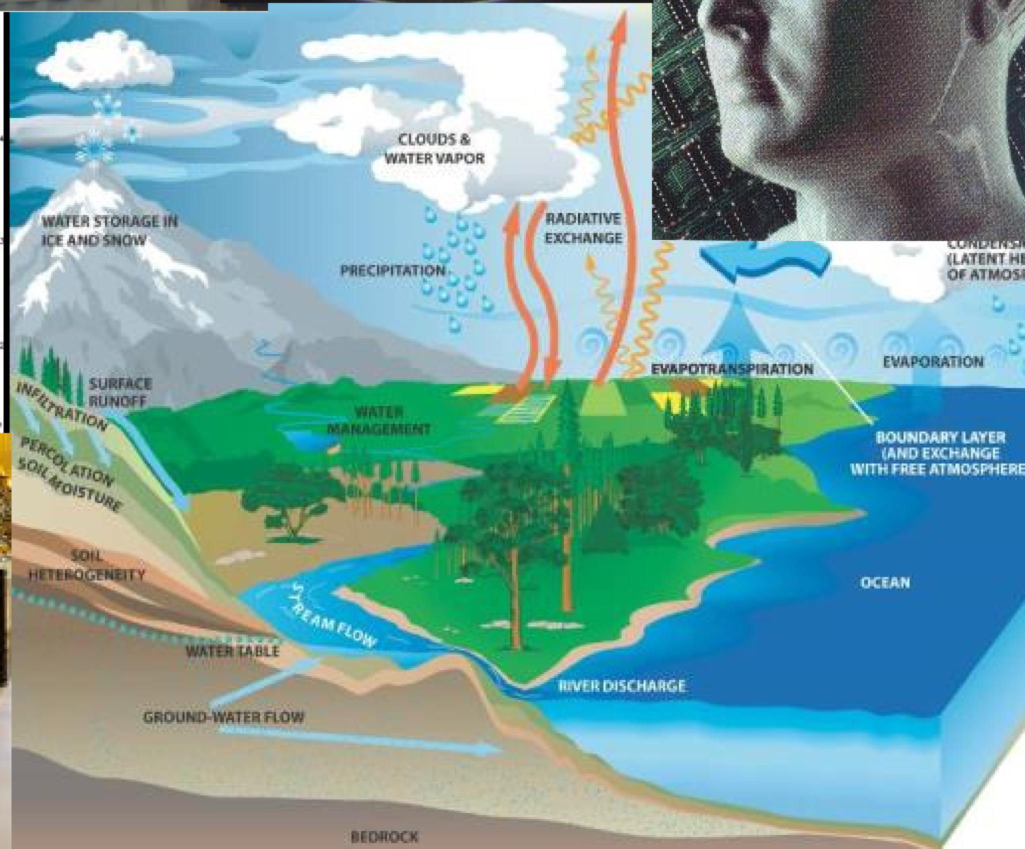
Blend approaches for optimal prediction

Observations, Models, & Artificial Intelligence

- New methods emerged to use observed data to make sense of environmental observations – **IoT**
- Gridded Model Output
- Combine with increases in computer power
- Artificial intelligence / Machine Learning methods both leverage and offer an alternative to traditional methods – **Big Data**





Part II:
AI/ML in Weather Forecasting

NCAR's First Big AI Success: DICast®

***D**ynamic*
***I**ntegrated*
*fore**Cast***
***S**ystem*

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***

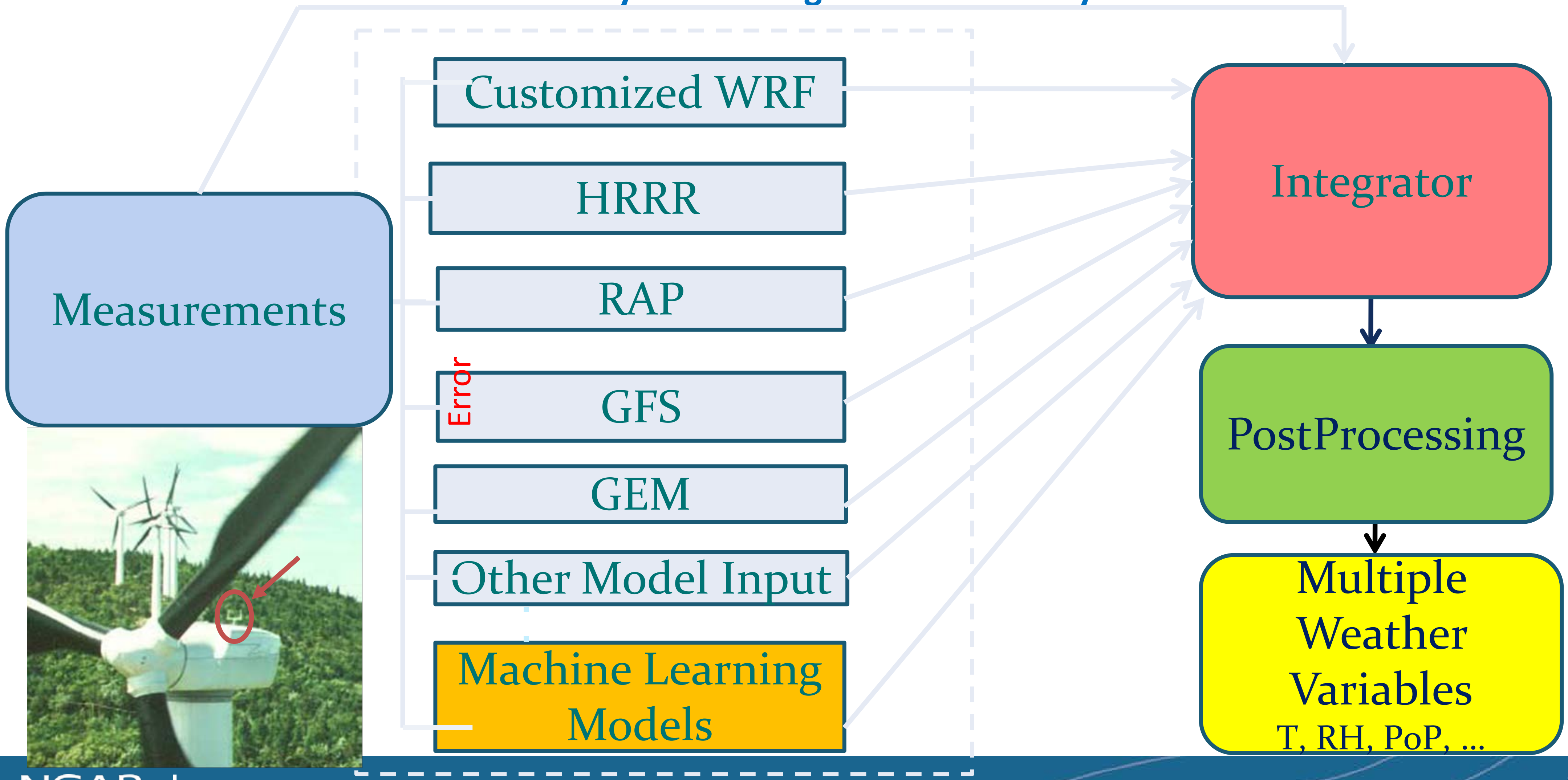
✓ *Real time*
✓ *Historical for training*

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

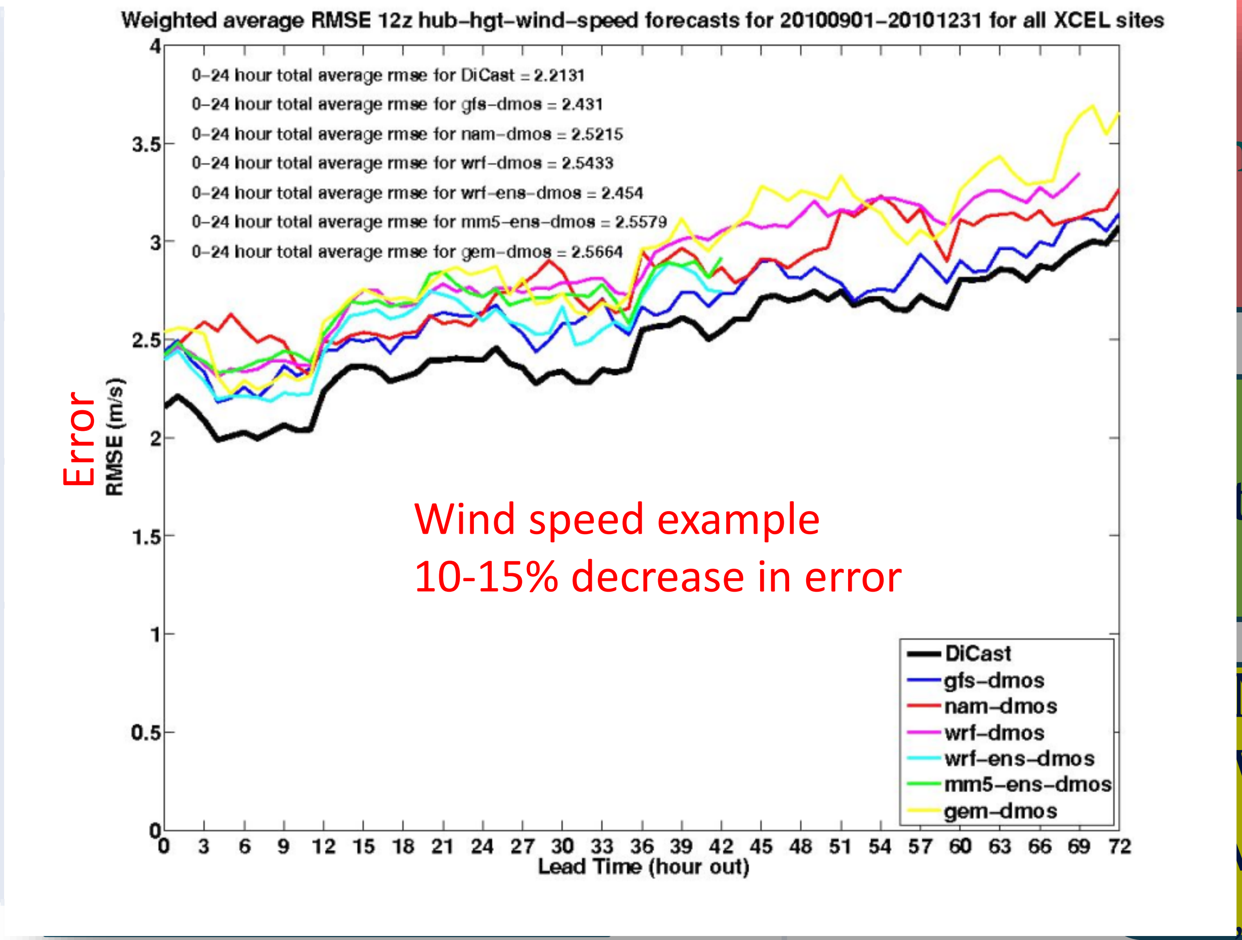


Jim Cowie
Seth Linden
Bill Petzke
Ishita Srivastava

DICast® Application

Dynamic Integrated foreCast System

Measurements



ntegrator

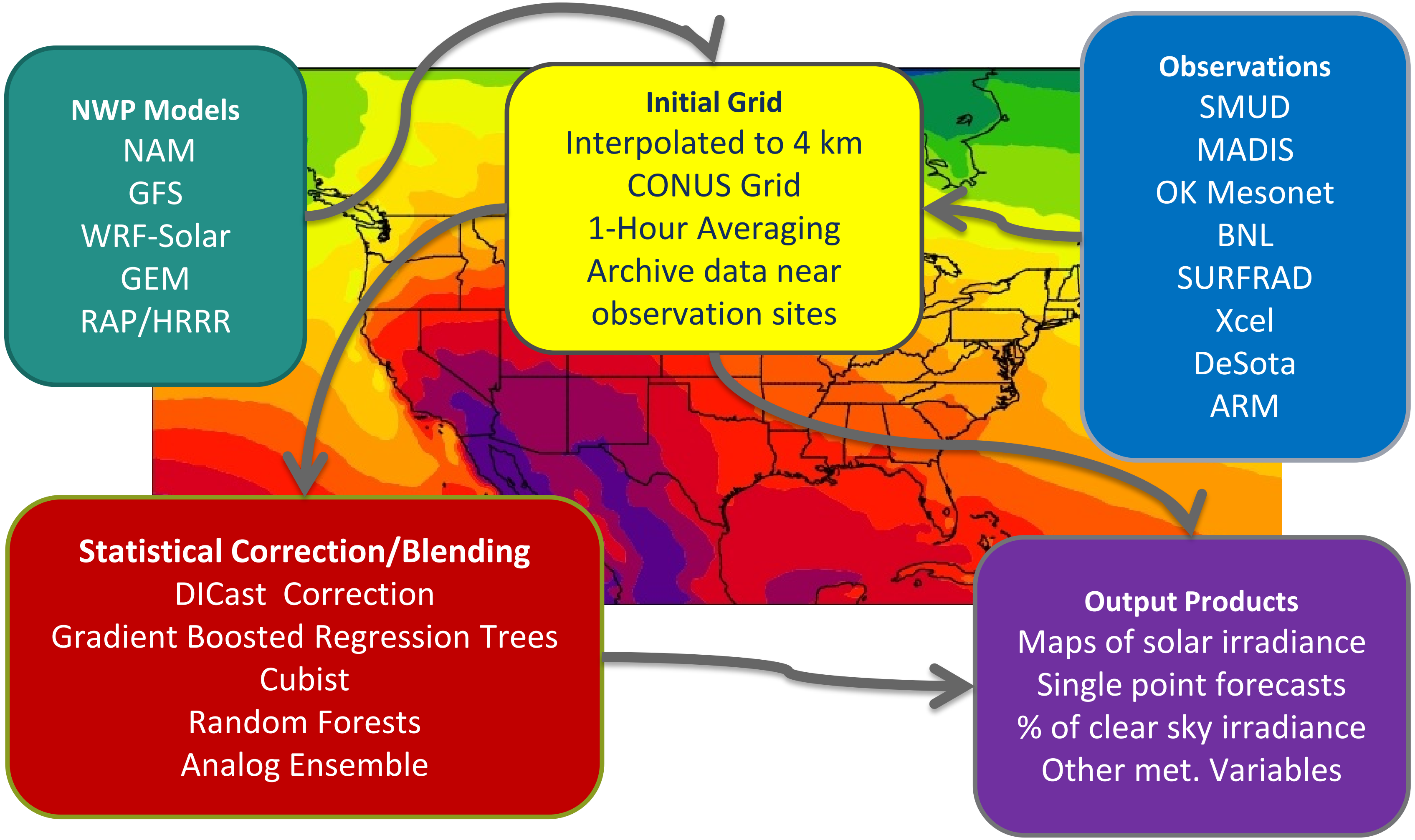
tProcessing

Multiple Weather Variables

, RH, PoP, ...

Jim Cowie
Seth Linden
Bill Petzke
Ishita Srivastava

Gridded Atmospheric Forecasts: GRAFS-Solar



David John Gagne
Jim Cowie
Seth Linden
Bill Petzke

Part III:
AI/ML Postprocessing for Renewable Energy

NCAR Variable Energy Forecasting System

Center Data
NAM, GFS, HRR, RAP, ECMWF, GEM

Wind Farm Data
Nacelle wind speed
Generator power
Node power
Met tower
Availability

WRF RTFDDA System

Ensemble System

Solar Energy Forecast

Supplemental Wind Farm Data
Met towers
Wind profiler
Surface Stations
Windcube Lidar

Dynamic, Integrated Forecast System (DICast®)

VDRAS
(nowcasting)

Expert System
(nowcasting)

Extreme Weather Events

Statistical Verification

Wind to Energy Conversion Subsystem

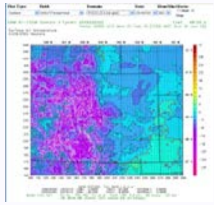
Potential Power Forecasting

Data Mining for Load Estimation

Probabilistic and Analog Forecast

Operator GUI

Meteorologist GUI



WRF Model Output

AI Method

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

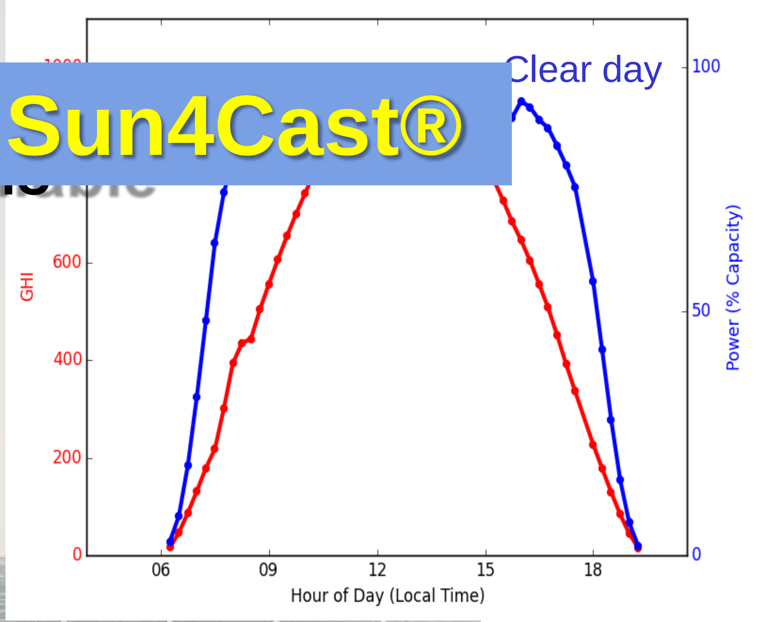
Application of Forecasting: Solar Power

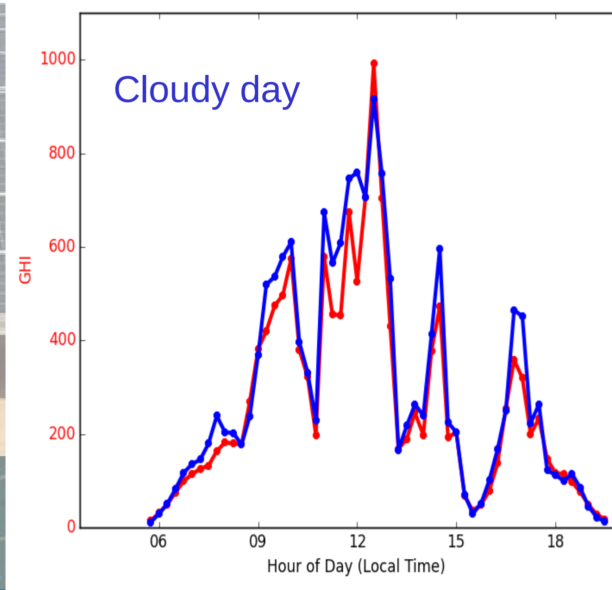
To make the best use of renewable energy,
Utilities need to know when it will be available

- Day Ahead
  → unit allocation
- Hours Ahead
  → grid integration

For Solar Power, this
means forecasting aerosols and clouds

Sun4Cast®





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

Application of Forecasting: Solar Power

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- Day Ahead

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- Hours Ahead

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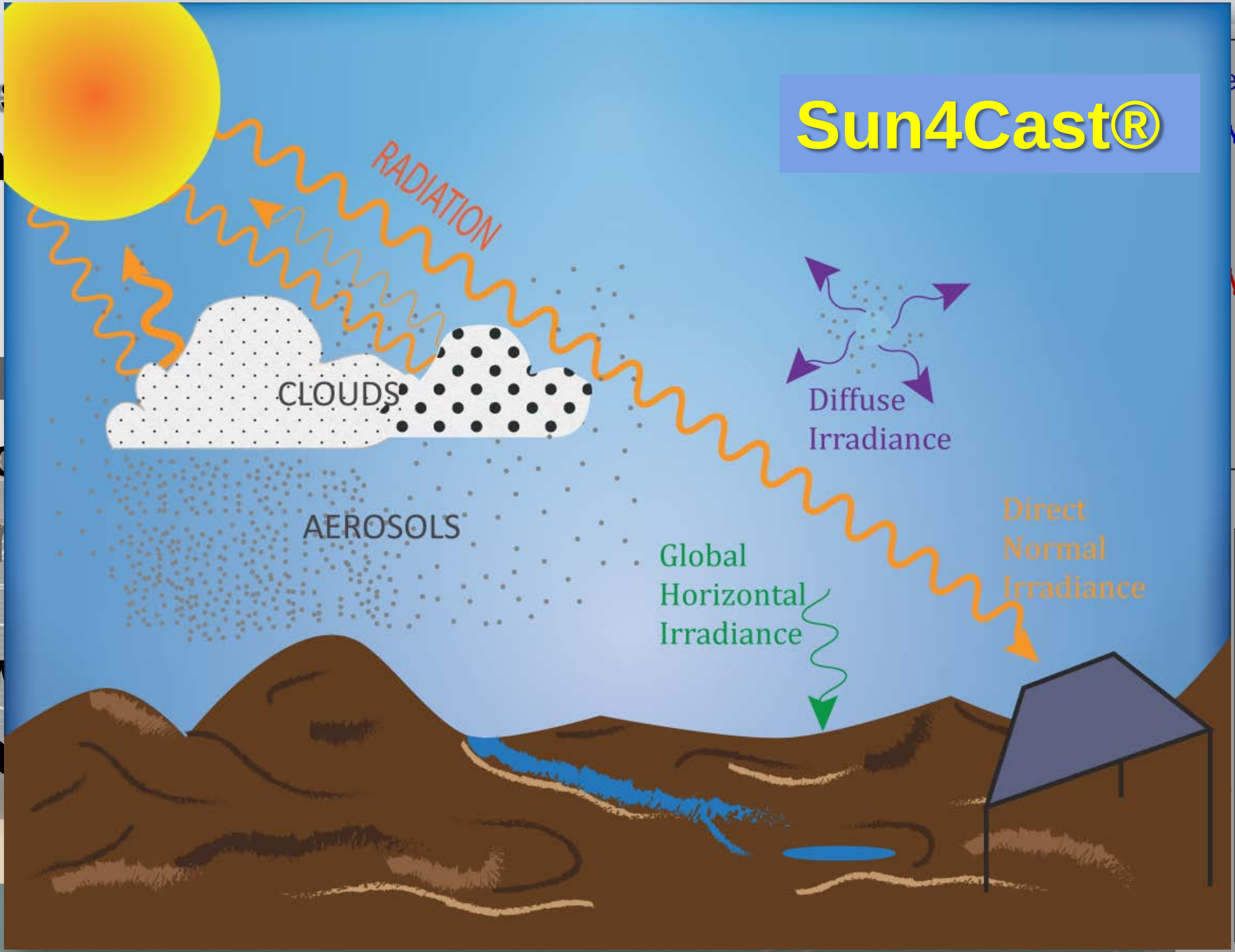

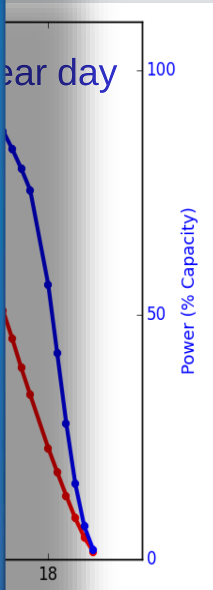

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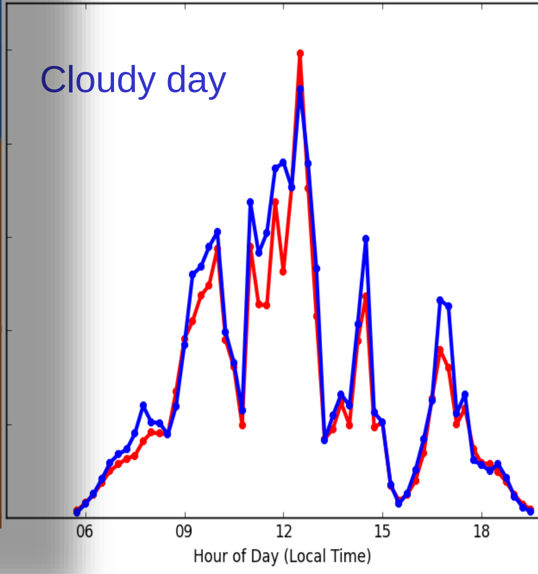

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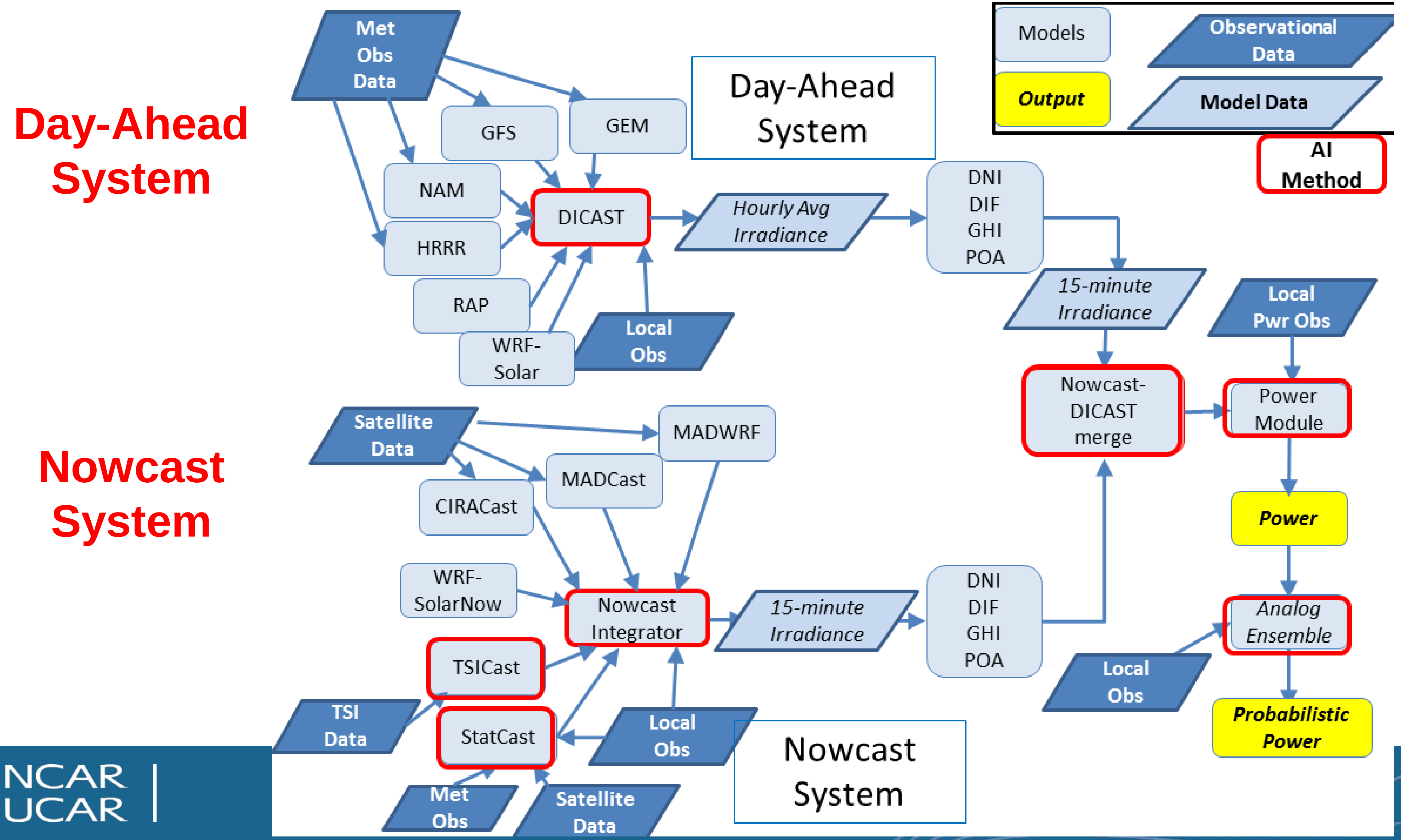
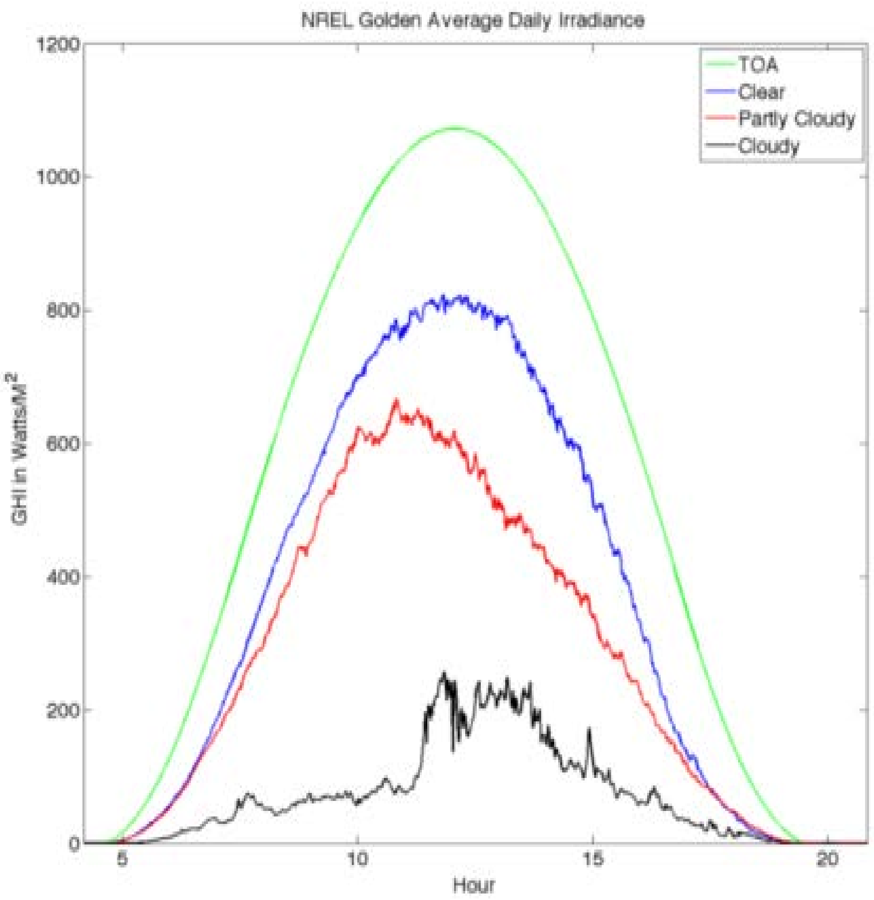
AI as Part of Systems Engineering

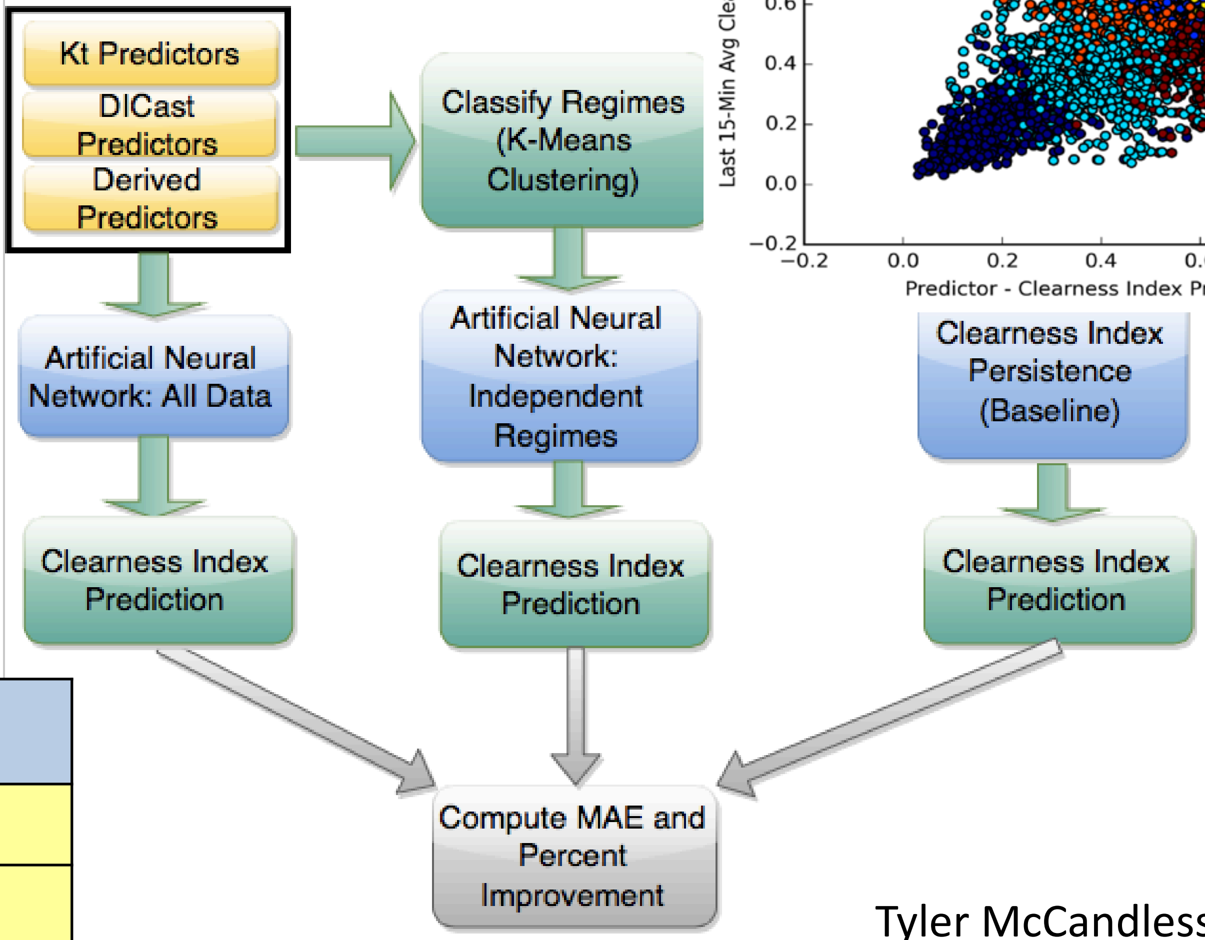
Engineering the Sun4Cast® System

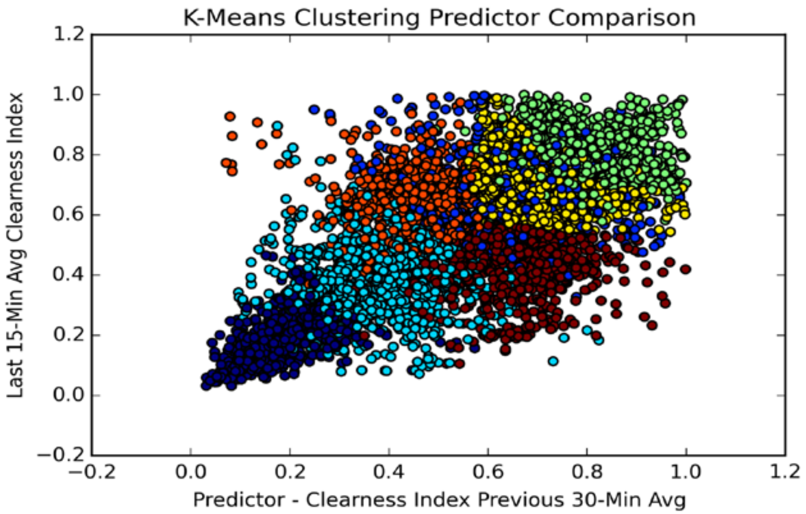


Haupt, S.E. and B. Kosovic, 2017: Variable Generation Power Forecasting as a Big Data Problem, *IEEE Transactions on Sustainable Energy*, **8** (2), pp. 725-732. DOI: 10.1109/TSTE.2016.2604679.

StatCast: Regime Dependent Forecasting







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.

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

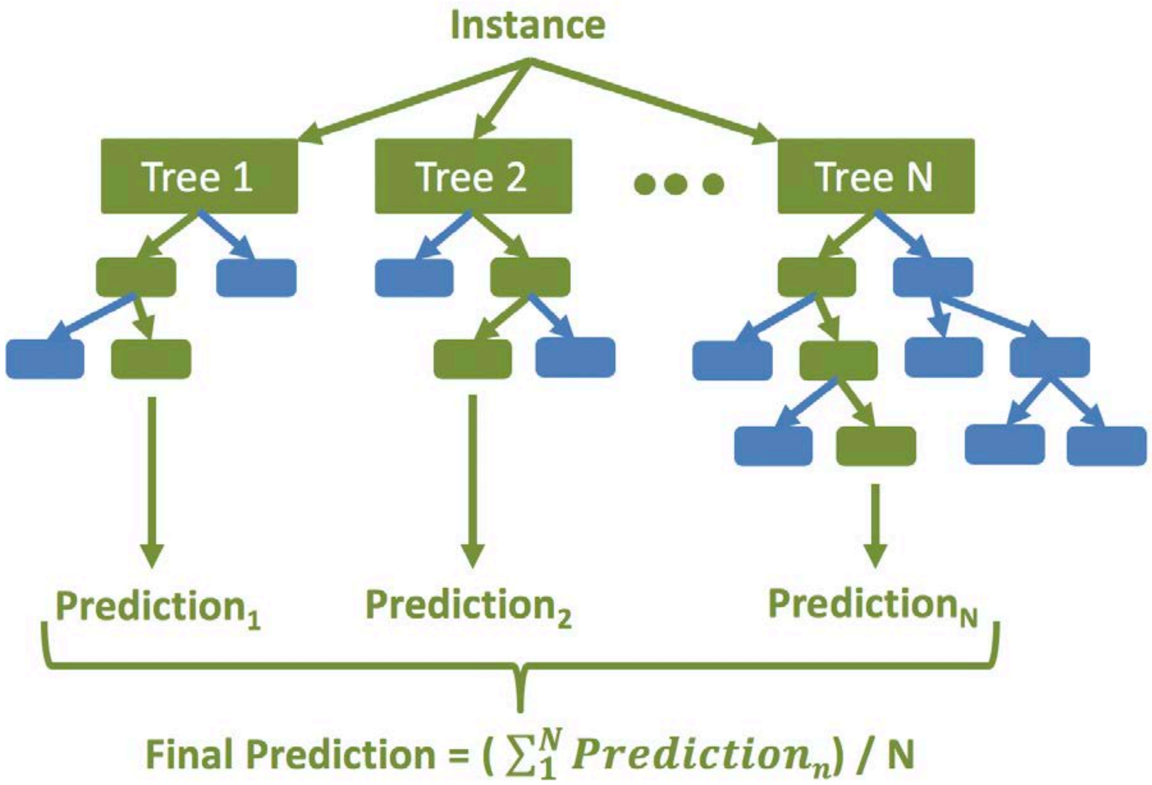
Tyler McCandless

NCAR

StatCast -Solar

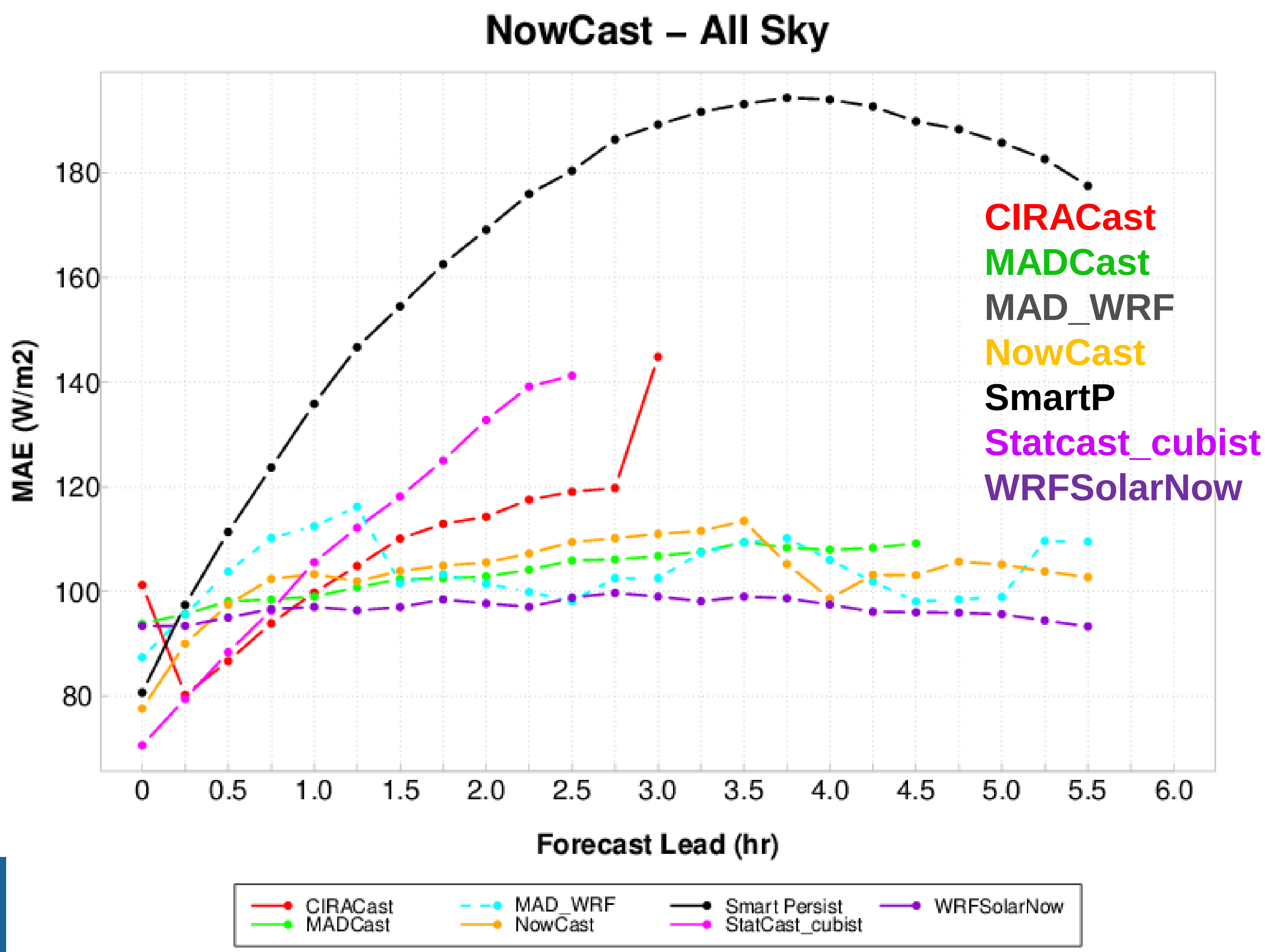
Machine Learning Model

- **Cubist** algorithm used in v1.2
- Cubist produces rule-based linear regression models
  - Prediction is an average of all rules that apply
  - Cubist "Committee" parameter adds ensemble prediction with "boosting" element
- Cubist performed better than Gradient Boosted Regression and Random Forest



Sue Dettling

NowCast Performance – DOE Project – US Sites



Aggregated over All Issue times and All Sky Conditions

Component performance varies by lead time

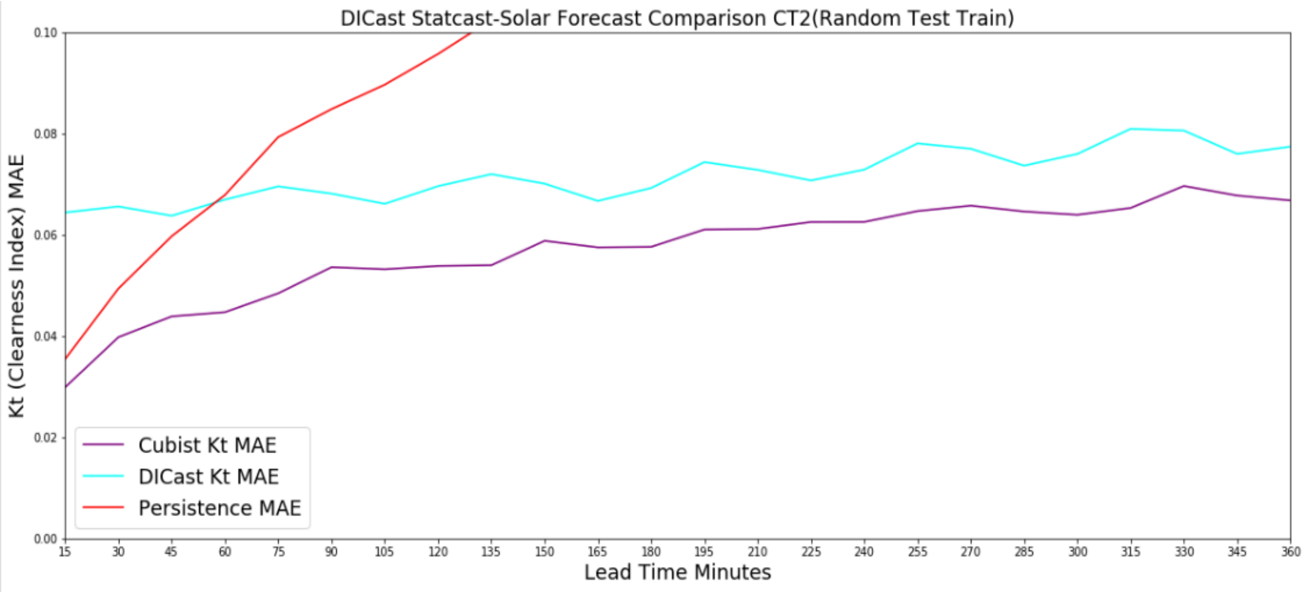
All Compontents have lower MAE (greater skill) after 30 minutes into forecast (lead time)

Tara Jensen

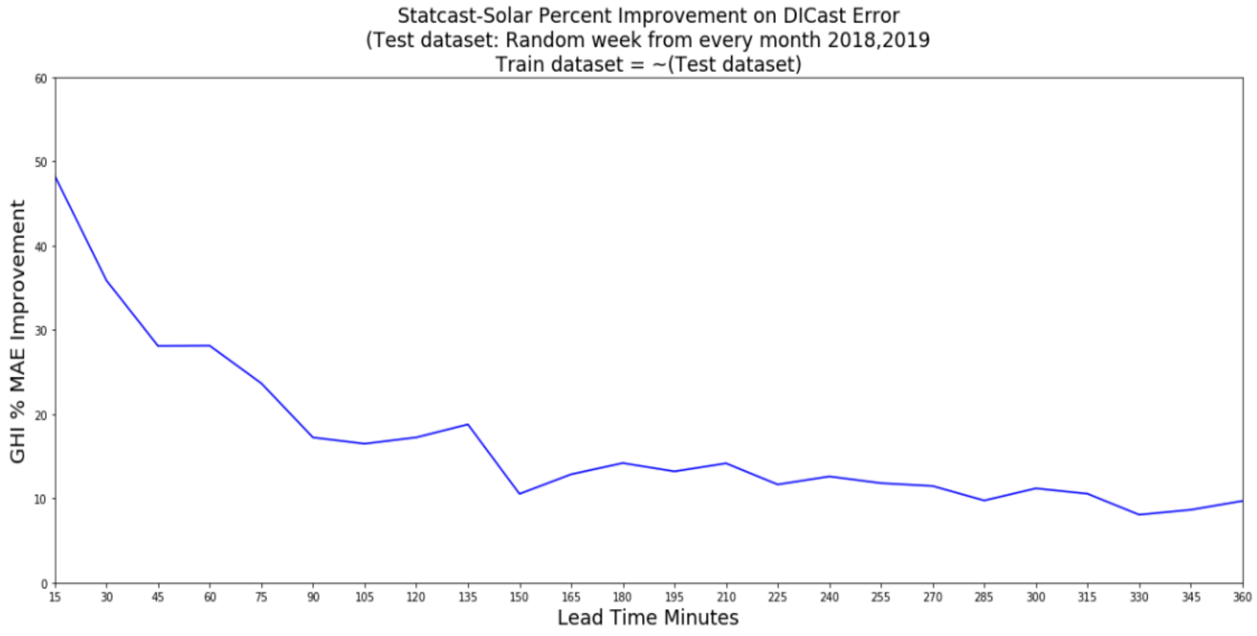
StatCast -Solar — Applied for Kuwait

Initial Results

- Training data from 1 Sep 2018–30 June 2019
- StatCast-Solar can add value to DICast out to 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.

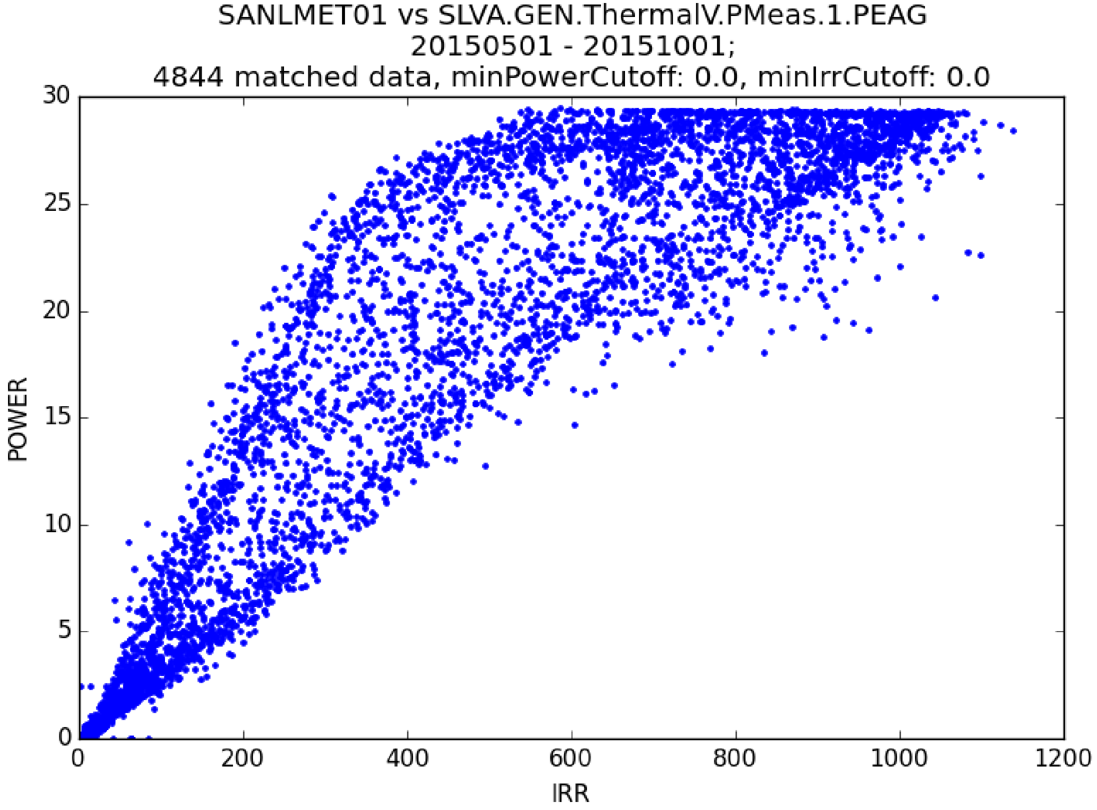
Susan Dettling

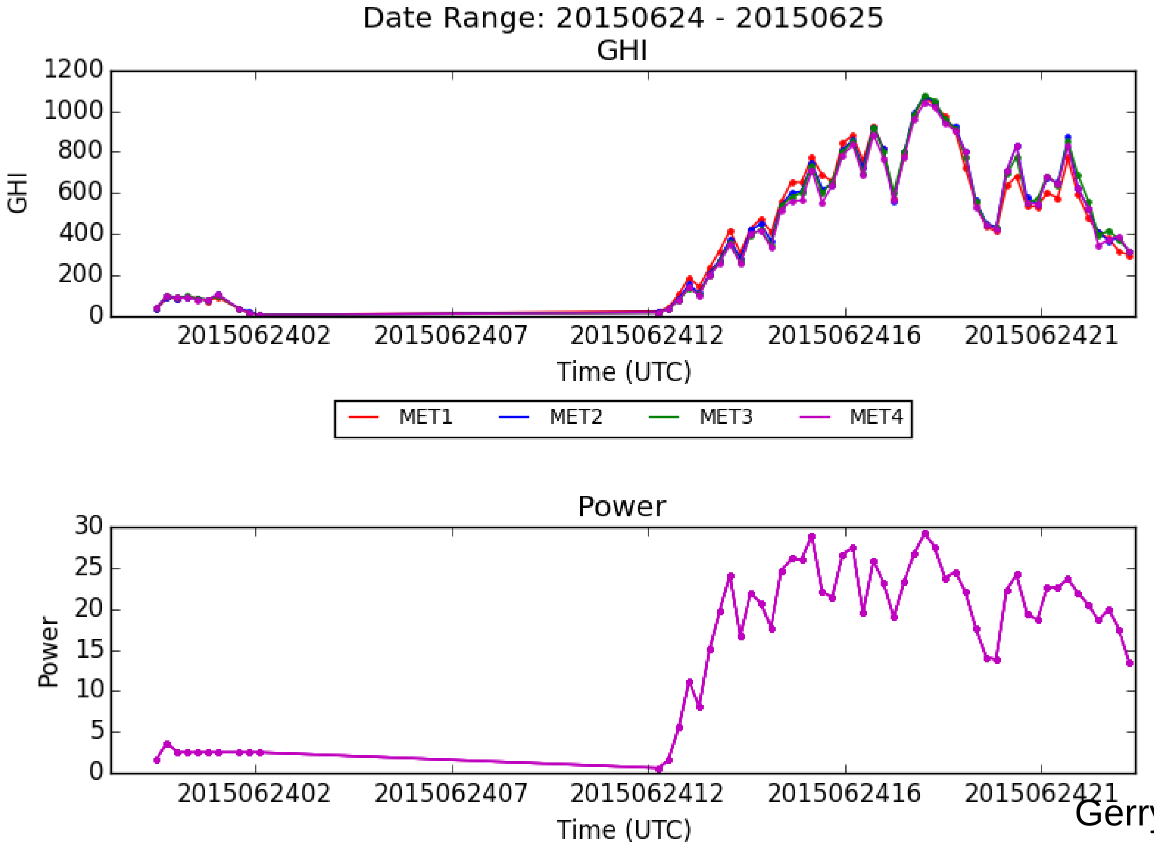
Power Conversion

Empirical Power Conversion: Regression Tree - Cubist

Example for single axis tracking PV plant

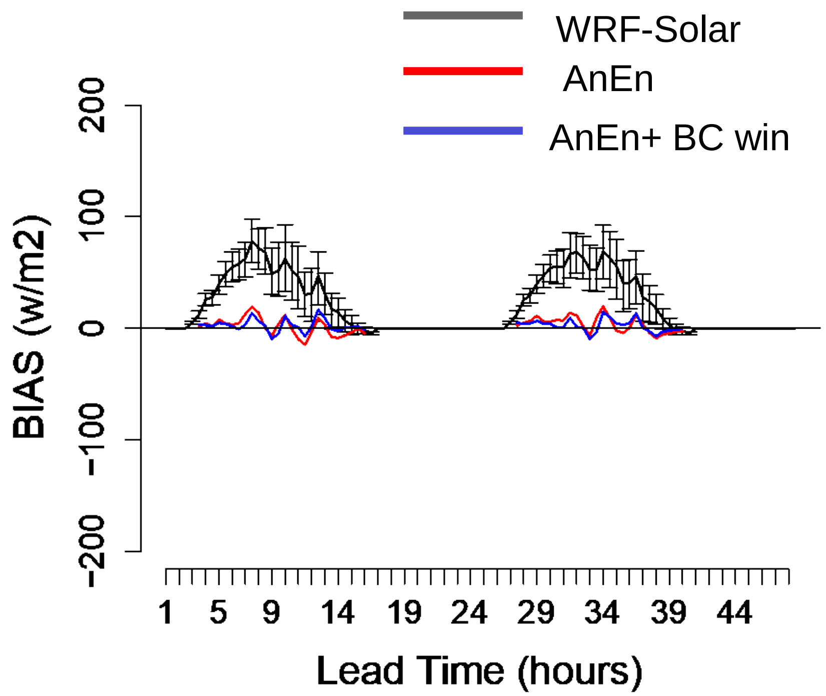
Pattern depends heavily on time of day, AM takes higher route; PM more linear route

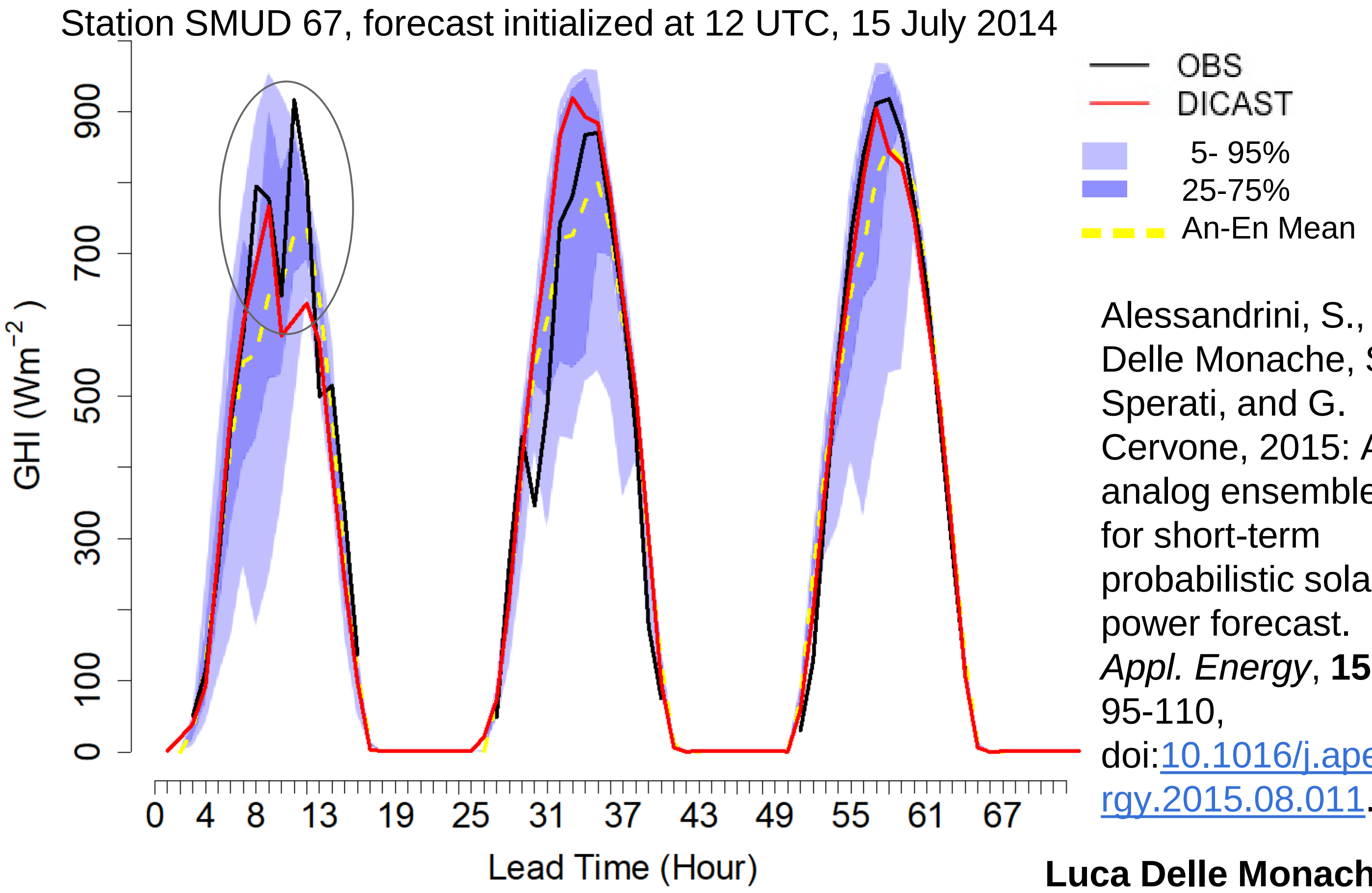




Gerry Wiener

Uncertainty Quantification
Analog Ensemble (AnEn) Approach





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](https://doi.org/10.1016/j.apenergy.2015.08.011).

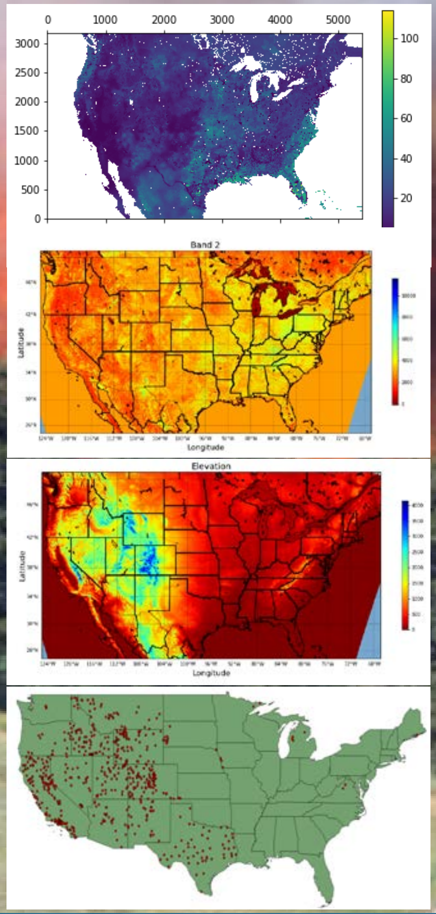
Luca Delle Monache
Stefano Allessandrini

Part IV:
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

Fuel Moisture Content Prediction Errors

- Random Forest (RF)
  - 1000 trees, 25 minimum samples per split, 25 minimum samples per leaf
- Artificial Neural Network (ANN)
- Gradient Boosted Regression (GBR)
- Multiple Linear Regression (MLR)

Dead Fuel Moisture Content

- DFMC Mean = 9.41%
- DFMC Standard Deviation = 4.51%

	Aqua	Terra
Method	Testing	Testing
MLR	2.36%	3.25%
ANN	1.94%	2.65%
GBR	1.73%	2.33%
RF	**1.69%**	**2.28%**

Live Fuel Moisture Content

- LFMC Mean = 94.9%
- LFMC Standard Deviation = 90.4%

	Aqua	Terra
Method	Testing	Testing
MLR	30.37%	30.39%
ANN	28.58%	27.76%
GBR	23.87%	23.56%
RF	**21.92%**	**22.06%**

Tyler McCandless
Branko Kosovic
Bill Petzke

Fuel Moisture Content Prediction System

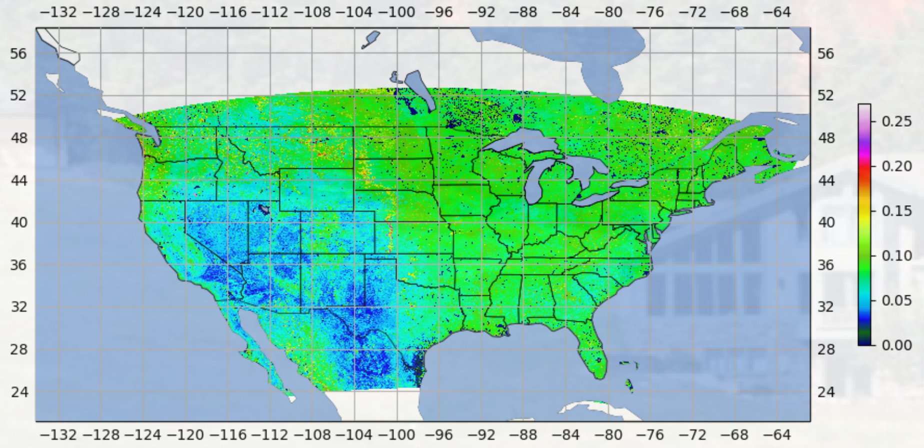
Final Models

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

DFMC Observation Sites

Dead Fuel Moisture Content

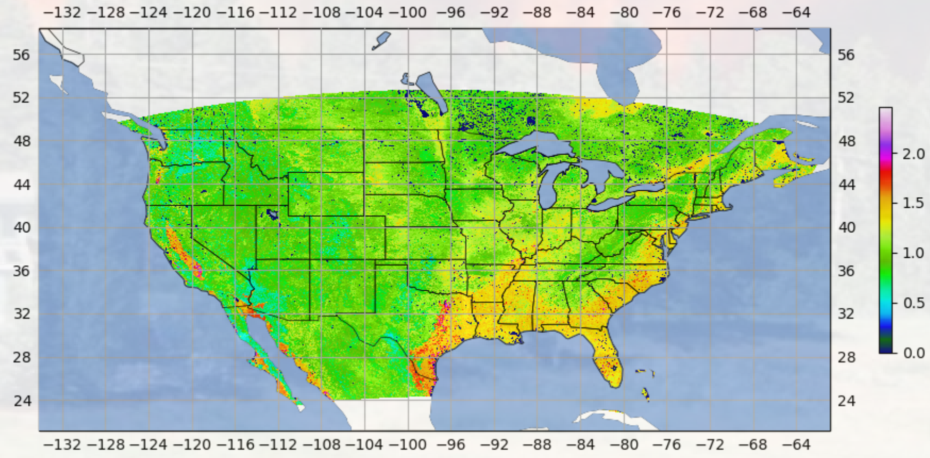
Gridded DFMC Predictions



LFMC Observation Sites

Live Fuel Moisture Content

Gridded LFMC Predictions



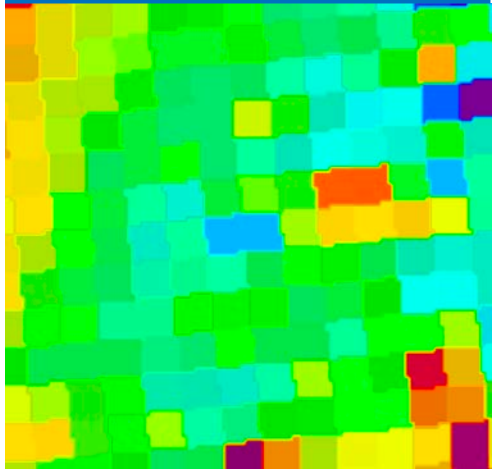
Tyler McCandless
Branko Kosovic
Bill Petzke

Fuel Moisture Content Prediction System

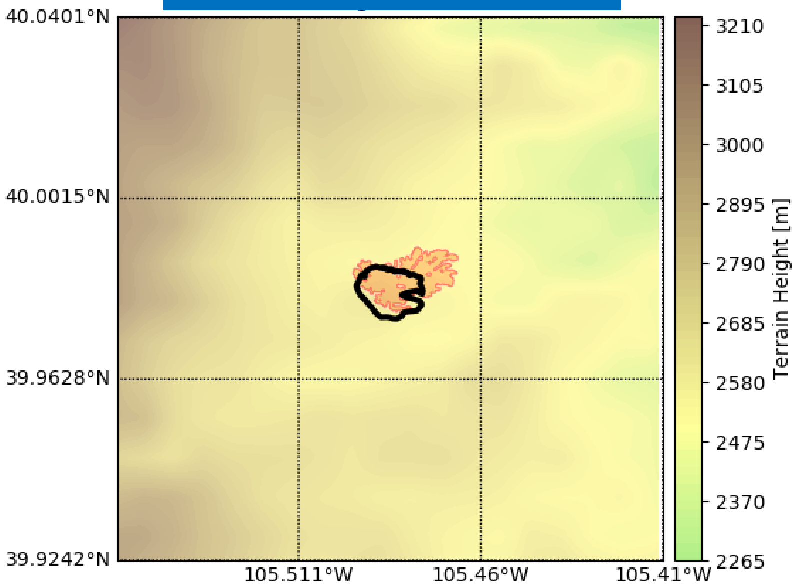
WRF-Fire Evaluation

- 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

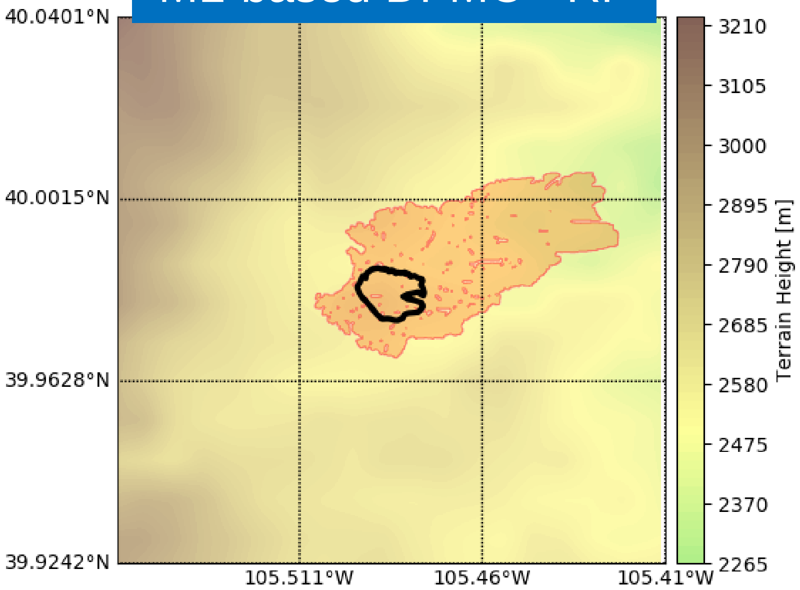
Distribution of the estimated DFMC



Constant DFMC



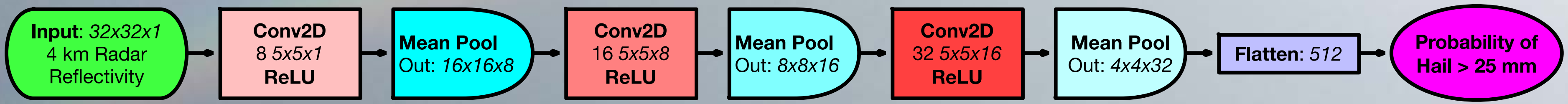
ML-based DFMC - RF



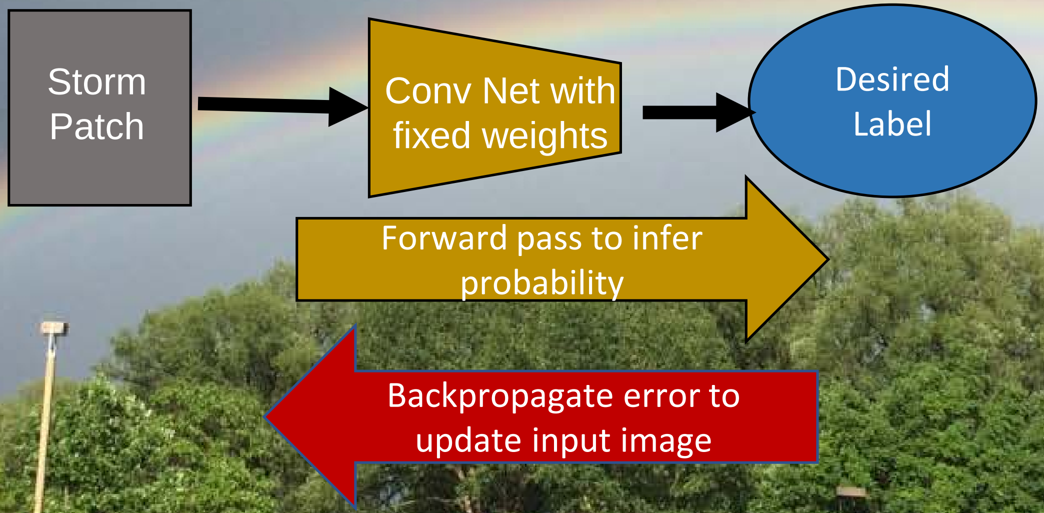
Tyler McCandless
Branko Kosovic
Bill Petzke

Interpretable Deep Learning for Severe Weather Research and Forecasting

Convolutional Neural Networks

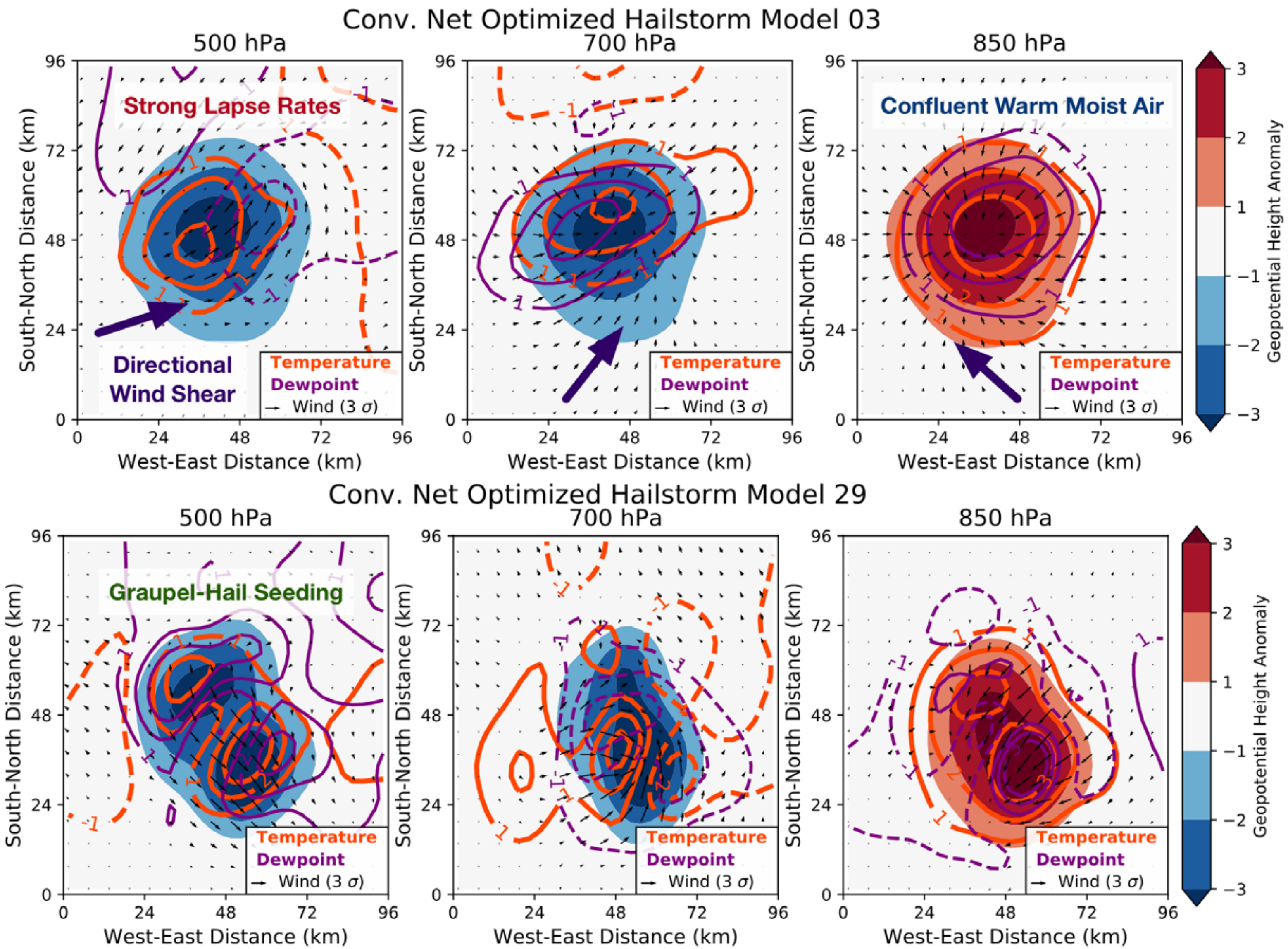


Feature Visualization by Optimization

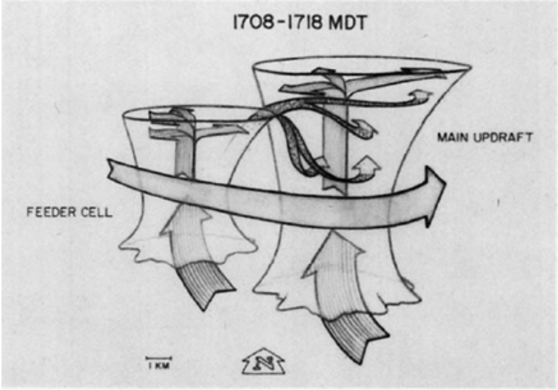


Gagne II, D.J., S.E. Haupt, D.W. Nychka, and G. Thompson, 2019: Interpretable Deep Learning for Spatial Severe Hail Forecasting, *Monthly Weather Review*, **147**, 2827-2845. DOI: 10.1175/MWR-D-18-0316.1

Optimized Conv Net Hailstorm



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

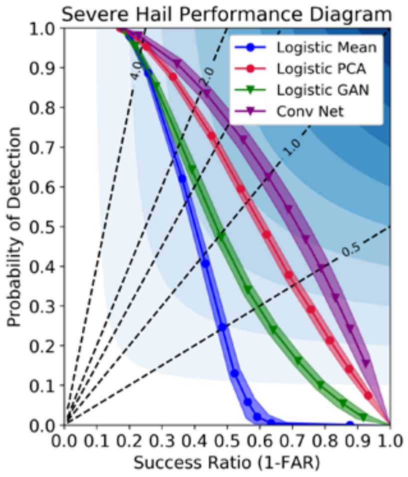


Feeder-Seeder Mechanism
(Heymsfield 1980)

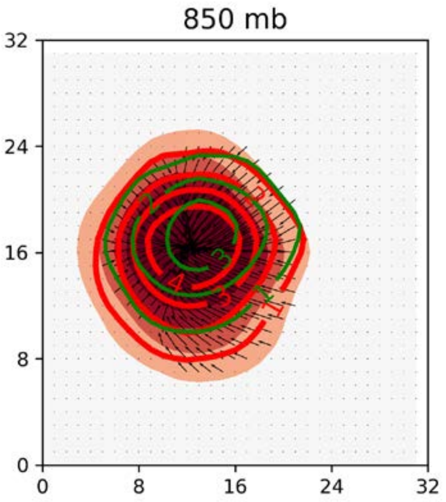
NCAR UCAR

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.

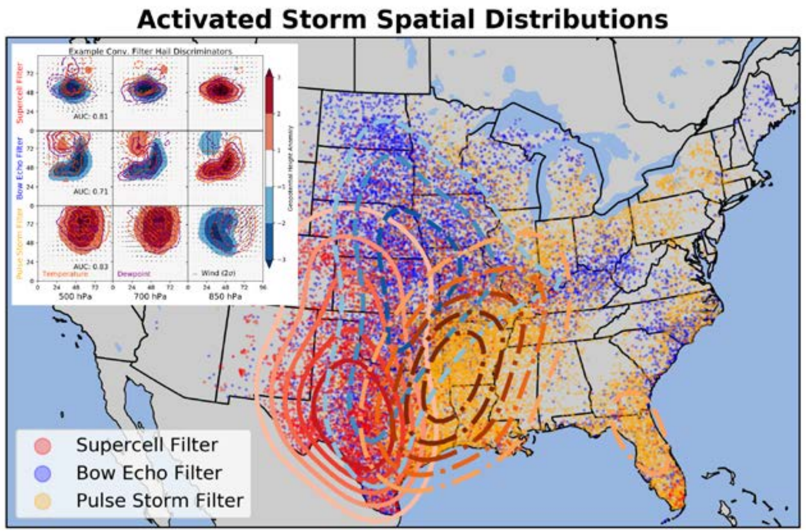
Impact of Using Convolutional Neural Networks



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



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

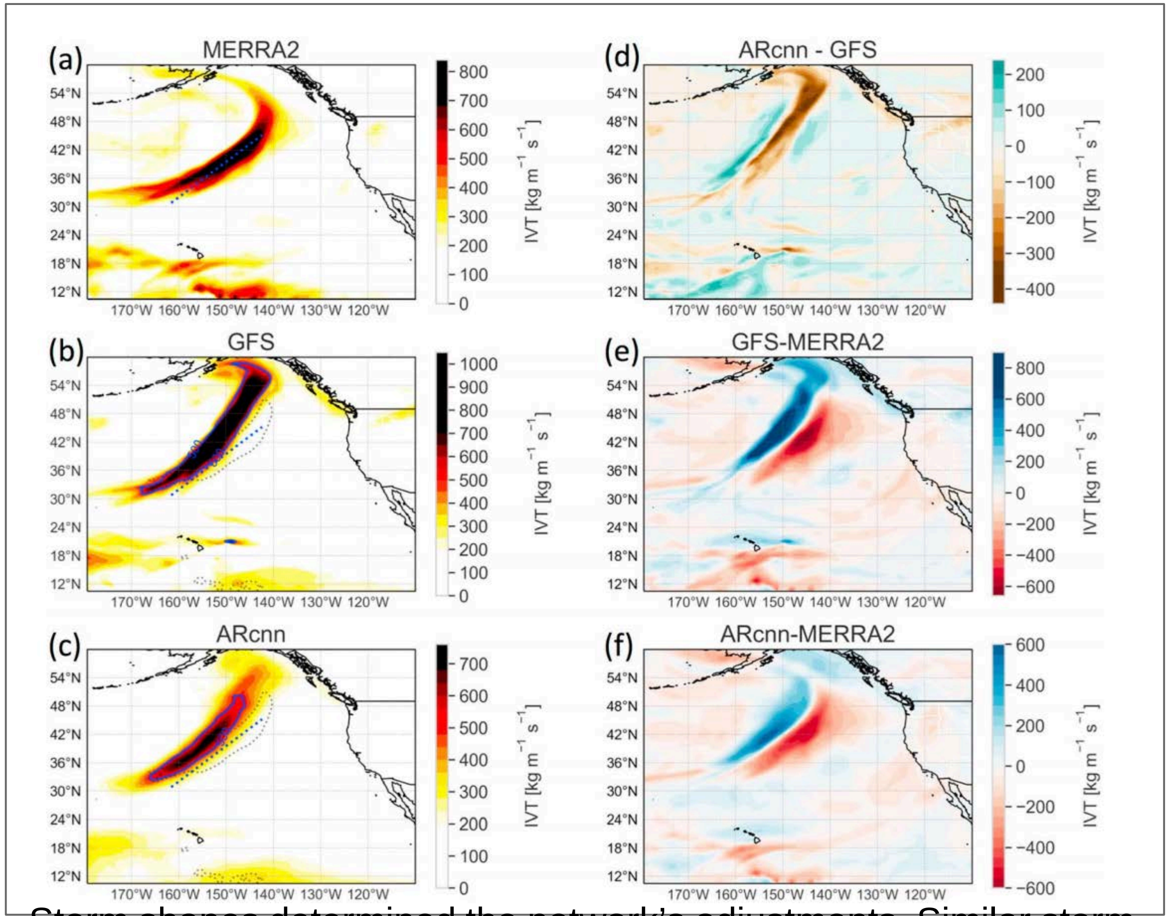


Internal representations of deep learning models could enable more sophisticated analysis of large weather and climate data.

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 Many Problems: Atmospheric Rivers

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



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

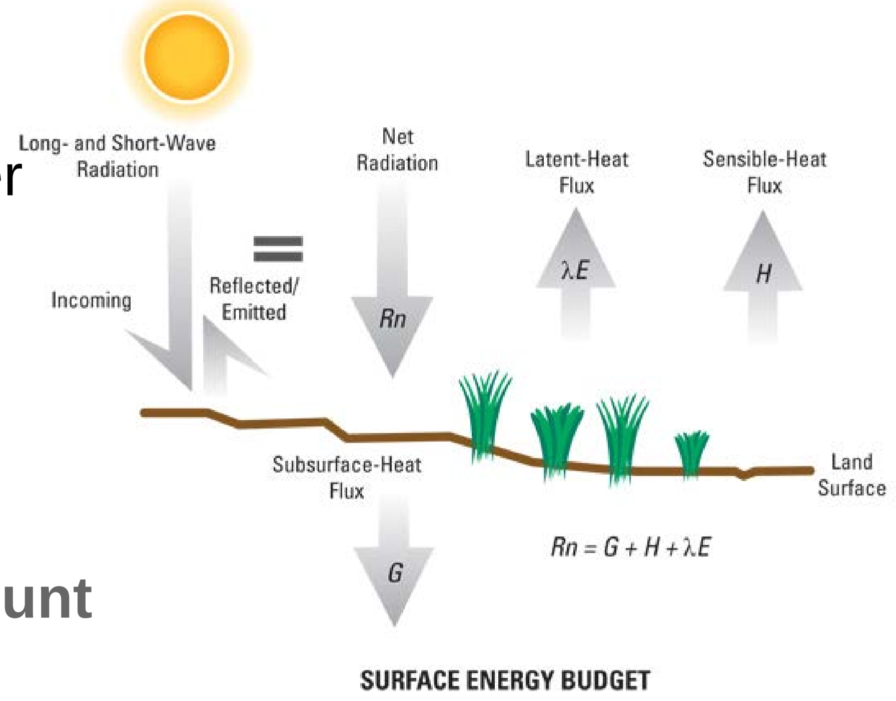
Main Results:

- 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**.

Part V:
AI/ML for Model Parameterization

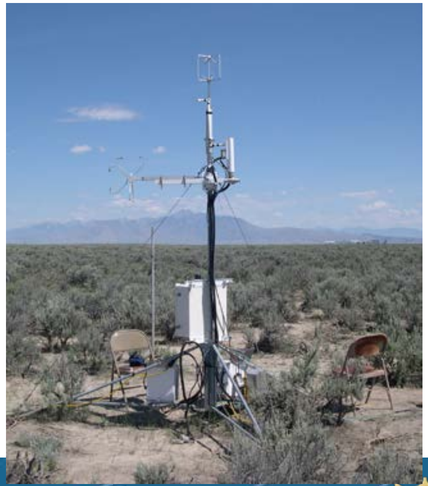
Machine Learning for Surface Layer Parameterization

- 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

Input and Output Variables

Input Variables	Heights (Idaho/Cabauw)
Potential Temperature Gradient (K)	Skin to 10 m, 15 m/20 m
Mixing Ratio Gradient (g kg^{-1})	Skin to 10 m, 20 m
Wind Speed (m s^{-1})	10 m, 15 m/20 m
Bulk Richardson number	10 m- 0 m
Moisture Availability (%)	5 cm/3 cm
Solar Zenith Angle (degrees)	0 m

Output equations

$$\tau = \rho u_*^2$$

$$H = -\rho c_p u_* \theta *$$

$$LH = L_e \rho u_* q_*$$

Predictands

u*=Friction velocity
θ*=Temperature scale
q*=Moisture scale

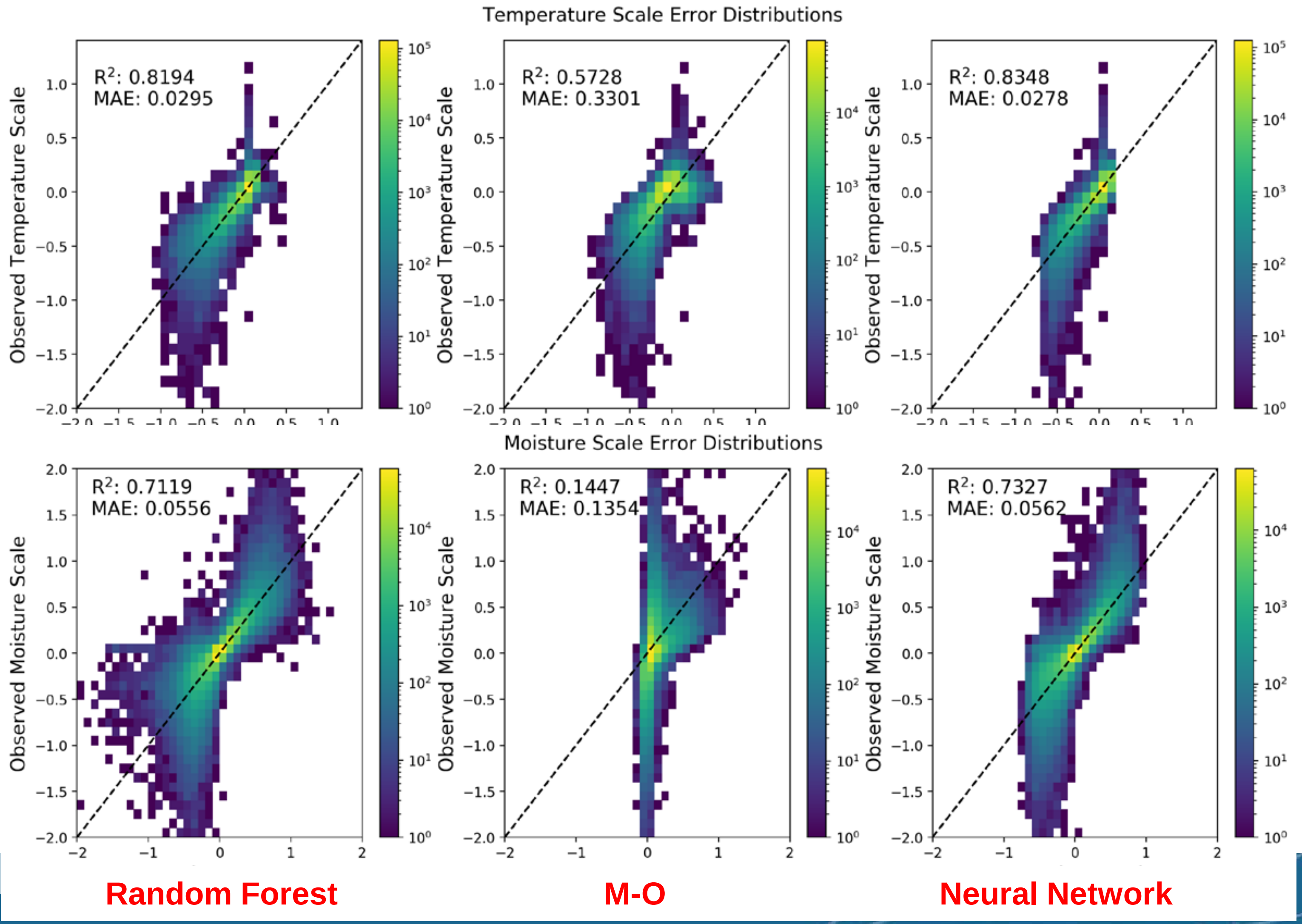
ML Procedure

1. Train ML models on observations
2. Plug in ML models to WRF in surface layer parameterization
3. Surface layer parameterization derives necessary outputs from ML predictions

Random Forest and ANN Prediction of Surface Layer Variables

Temperature Scale

Moisture Scale



Both Random Forest and Neural Networks consistently outpredict Monin-Obukov Similary Theory

- ✓ Higher Correlation
- ✓ Lower MAE

Gagne, McCandless, Kosovic, Haupt

Cross -Testing ML Models

Idaho Test Dataset	R^2 Friction Velocity	R^2 Temperature Scale	R^2 Moisture Scale	MAE Friction Velocity	MAE Temperature Scale	MAE Moisture Scale
MO Similarity	0.85	0.42		0.077	0.203	
RF Trained on Idaho	**0.91**	**0.80**	**0.41**	**0.047**	0.079	**0.023**
RF Trained on Cabauw	0.88	0.76	0.22	0.094	0.139	0.284

Cabauw Test Dataset	R^2 Friction Velocity	R^2 Temperature Scale	R^2 Moisture Scale	MAE Friction Velocity	MAE Temperature Scale	MAE Moisture Scale
MO Similarity	0.90	0.44	0.14	0.115	0.062	0.135
RF Trained on 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

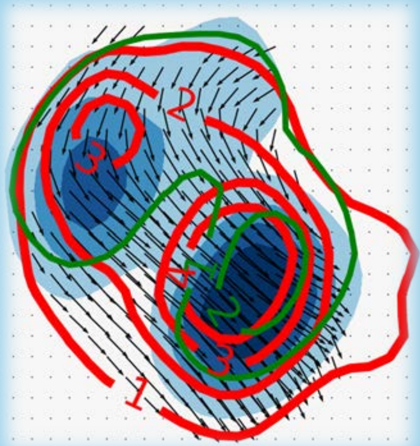
Cross -Testing ML Models

Idaho Test Dataset	Friction Velocity (R^2)	Temperature Scale (R^2)	Moisture Scale (R^2)	Friction Velocity (MAE)	Temperature Scale (MAE)	Moisture Scale (MAE)
MO Similarity	0.85	0.42		0.077	0.203	
RF Trained on Idaho	0.91	0.80	0.41	0.047	0.079	0.023
RF Trai... Cabauw						

- ✓ Random Forest significantly outperforms Monin-Obukov Theory
- ✓ True even when applied to site that is different than the one trained

Summary:

- Machine Learning is advancing applications of weather forecasting
- NCAR has been involved for a couple decades
- A Big Data / IoT application (not new)
- A necessary component of modern weather forecasting systems
- Interpretable Deep Learning may be the future



AI-Physics Blended System

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