International Conference on Energy and Meteorology

# Data science and new challenges with AI


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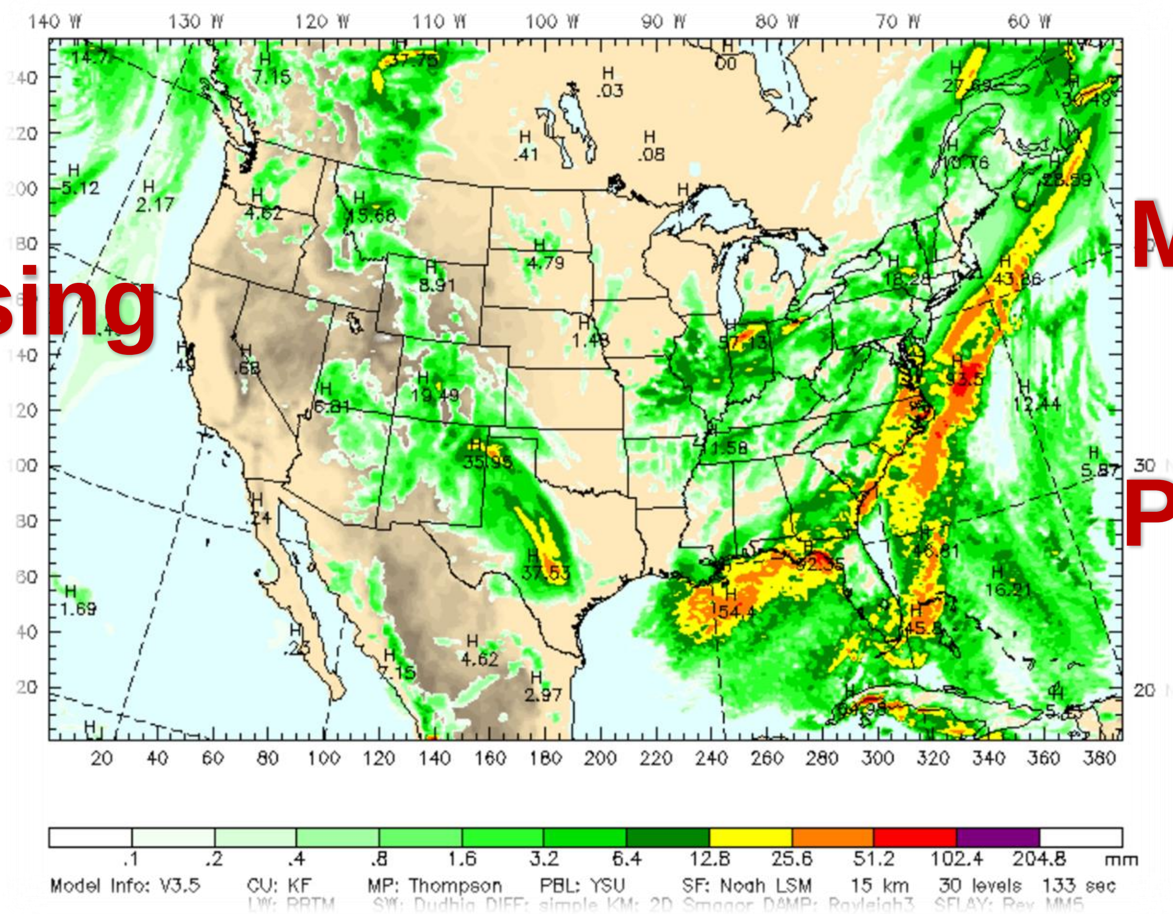
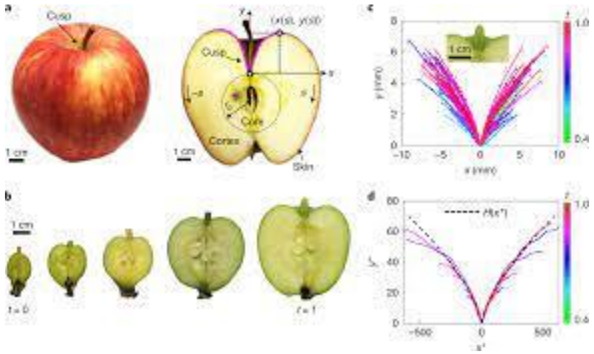
# Approaches to leveraging AI for Weather Forecasting

**Postprocessing**




**ML Dynamic Core**

**ML Parameterizations**



# 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.

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

**WRF RTFDDA System**

**Ensemble System**

**Solar Energy Forecast**

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

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

**Dynamic, Integrated Forecast System (DICast®)**

**VDRAS**
(nowcasting)

**Expert System**
(nowcasting)

**Extreme Weather Events**

**Statistical Verification**

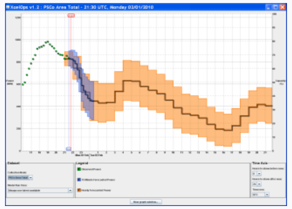
**Wind to Energy Conversion Subsystem**

**Potential Power Forecasting**

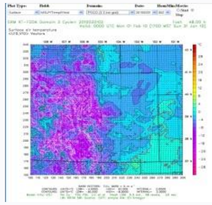
**Data Mining for Load Estimation**

**Probabilistic and Analog Forecast**

**Operator GUI**



**Meteorologist GUI**



WRF Model Output

AI Method

AGU ADVANCING EARTH AND SPACE SCIENCE

JAMES Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2021MS002502

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

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**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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**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).







- 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.



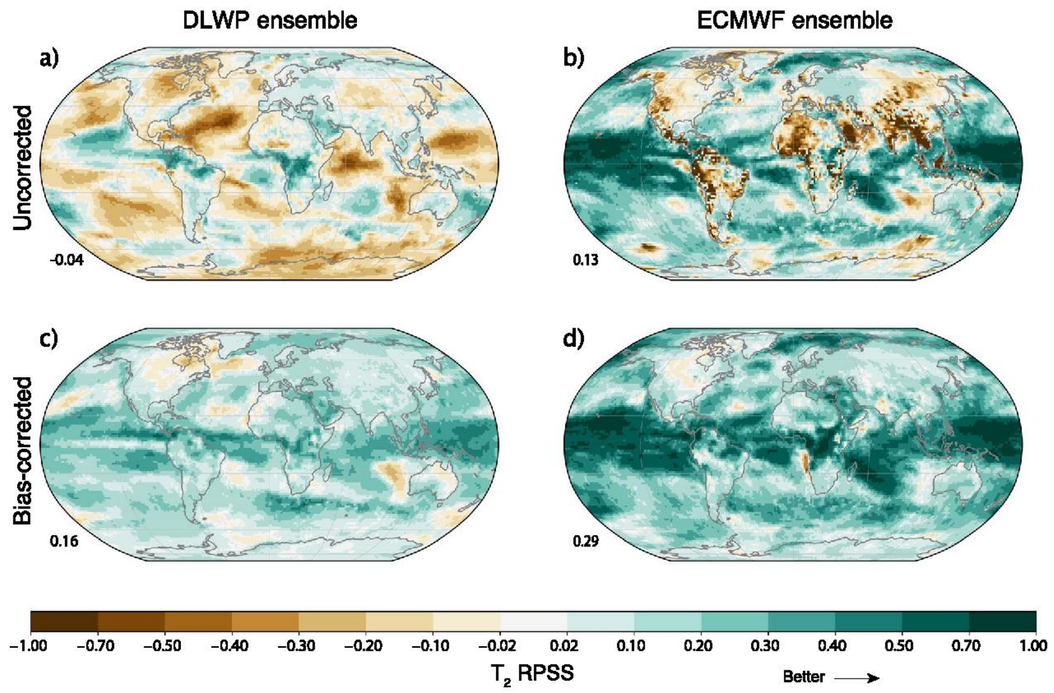
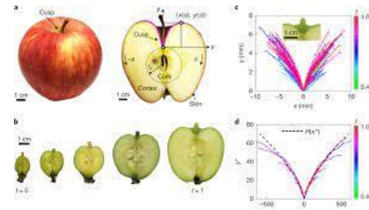
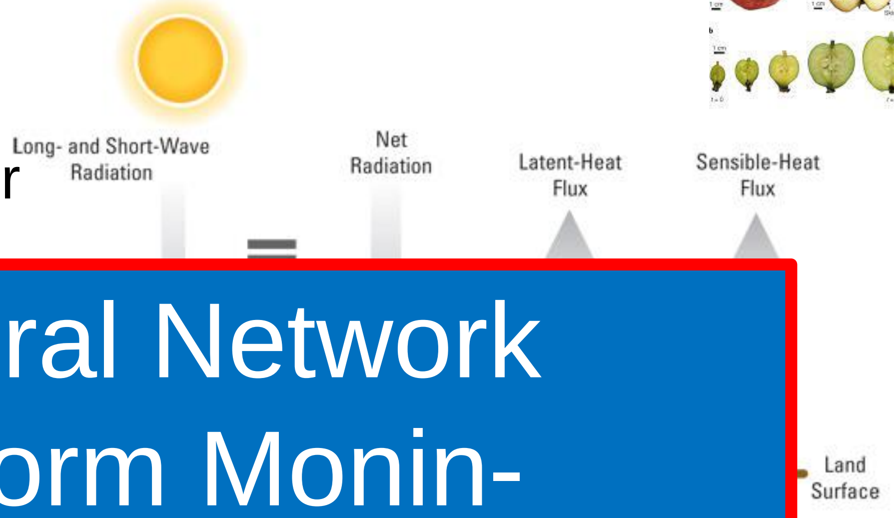



**Figure 13.** Annual average RPSS skill maps for $T_2$ at weeks 5–6. Without bias correction: (a) DLWP ensemble, (b) ECMWF ensemble; with bias correction: (c) DLWP ensemble, (d) ECMWF ensemble. The weighted global mean is noted at the lower left in each panel.

# Machine Learning for Surface Layer Parameterization






- Surface layer parameterizations model energy transfer (flux) from atmosphere to land surface
- Mor
  flux
- Sta
  dete
- **How**
  **of v**
- **Ins**
- We
  reco
  -
  - FDR tower near Scoville, Idaho, 2015 – 2017
- Fit random forest to each site to predict friction velocity, sensible heat flux, and latent heat flux

✓ Random Forest and Neural Network both significantly outperform Monin-Obukov Theory

✓ True even when applied to site that is different than the one trained

red.htm


NCAR UCAR

1. McCandless, D.J. Gagne, T.C., B. Kosovic, S.E. Haupt, B. Yang, C. Becker, and J. Schreck, 2021: Machine Learning for Improving Surface Layer Flux Estimates, *Boundary Layer Meteorology*, https://doi.org/10.1007/s10546-022-00727-4.

https://www.bbc.com/future/article/20230405-why-ai-is-becoming-impossible-for-humans-to-understand

# Session Questions

- How do we see business practices in the energy industry changing in the future as innovative uses of AI proliferate?
- How will it improve energy integration?
- How will improve the energy transition?
- How will humans feel about being replaced by AI?
- And will it be accepted?
- What is the role of interpretable AI and is it essential to full acceptance and utilization?

Generated by AI: https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-