Nowcasting hail and convective initiation using deep learning



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Outline

- Using deep learning to nowcast convective phenomena
 - Hail
 - Convective initiation
 - Updraft strength

Gridded Severe Hail Nowcasting Using 3D U-Nets, Lightning Observations, and the Warn-on-Forecast System

Tobias G. Schmidt, Amy McGovern, John T. Allen, Corey K. Potvin, Randy J. Chase, Chad M. Wiley, William R McGovern-Fagg, Montgomery L. Flora, Cameron R. Homeyer, John K. Williams

Accepted with major revisions to Weather and Forecasting















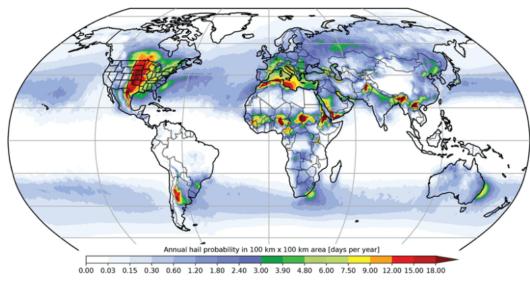


Motivation

- Hail causes billions of dollars of damage annually
- Hail is too small to be resolved in current NWP models
- Research questions:
 - Can we use AI to improve hail nowcasting in the 0-60 min window?
 - Can we develop an approach that could scale globally?
 - Can we combine NWP predictions with observations to improve real-time predictions?



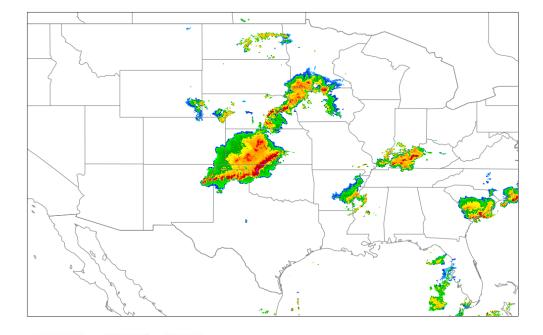
Photo credit: Amy McGovern

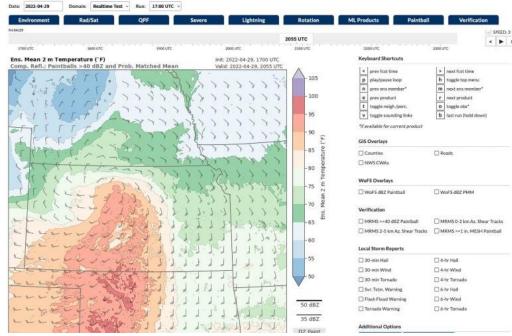


https://doi.org/10.1016/j.wace.2018.10.004

Approach

- Train a deep learning method to combine NWP output with observations to predict hail in CONUS
 - Input data:
 - NSSL's Warn on Forecast system
 - Vaisala's global lightning observations
 - Ground truth: GridRad MESH
- Deep learning method: 3D U-net

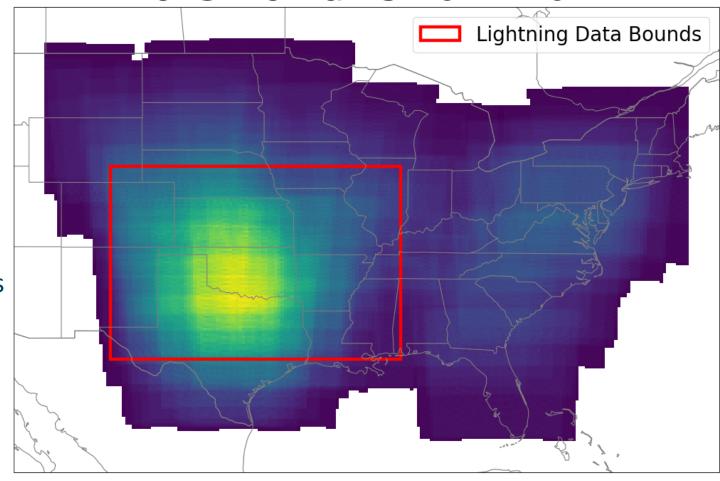




Study domain

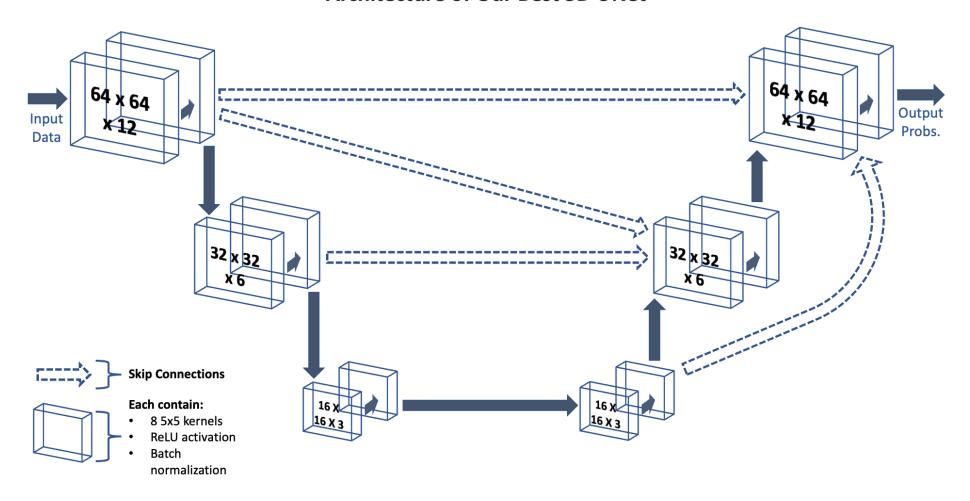
- WoFS runs during the US spring spring season
 - High resolution (3x3 km gridcells, 5-minute time intervals)
 - Rapidly incorporates assimilated real-time observations
 - Domain moves each day to focus on area of highest severe weather probabilities
- Lightning data limited
 - Training and testing restricted to inside this area

WoFS Domains 2017-2021

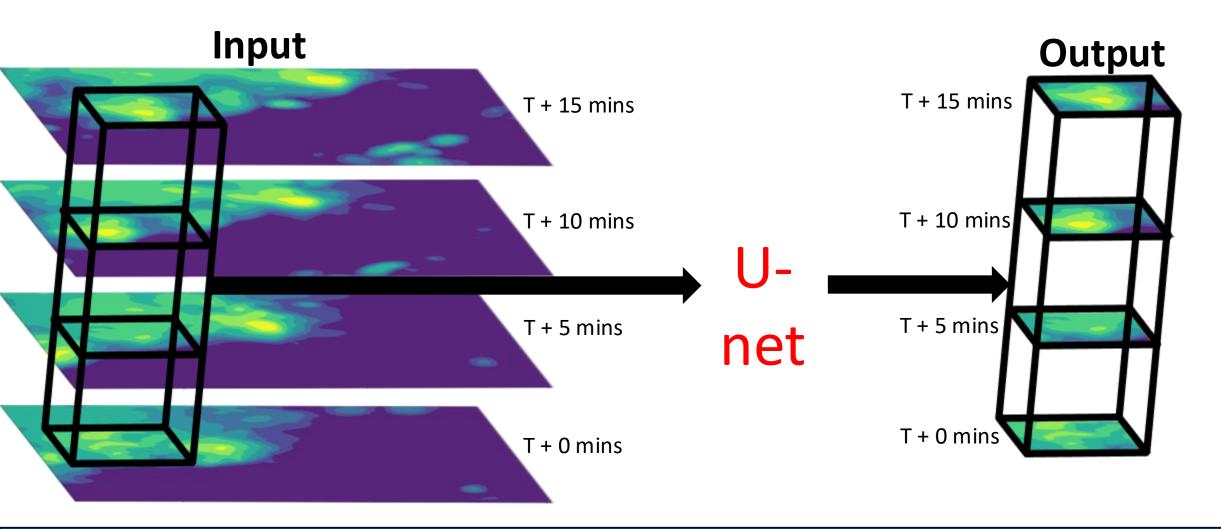


U-net architecture

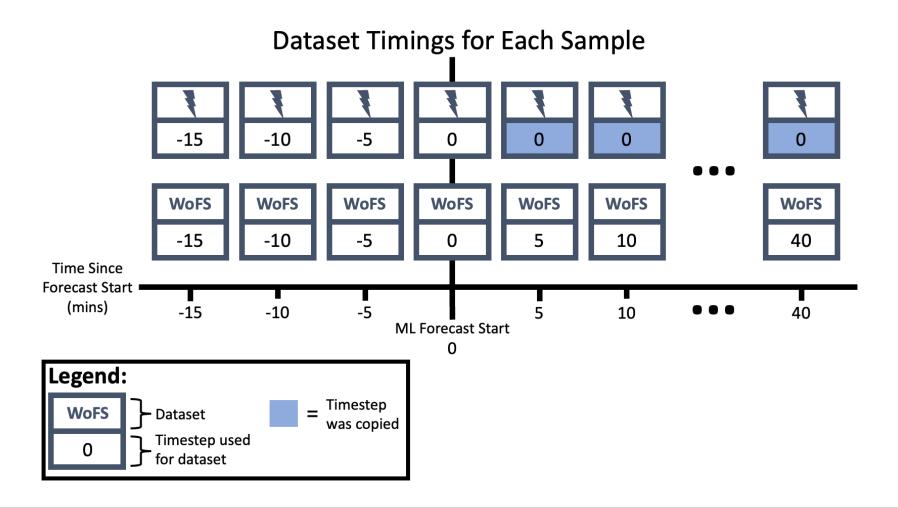
Architecture of Our Best 3D UNet



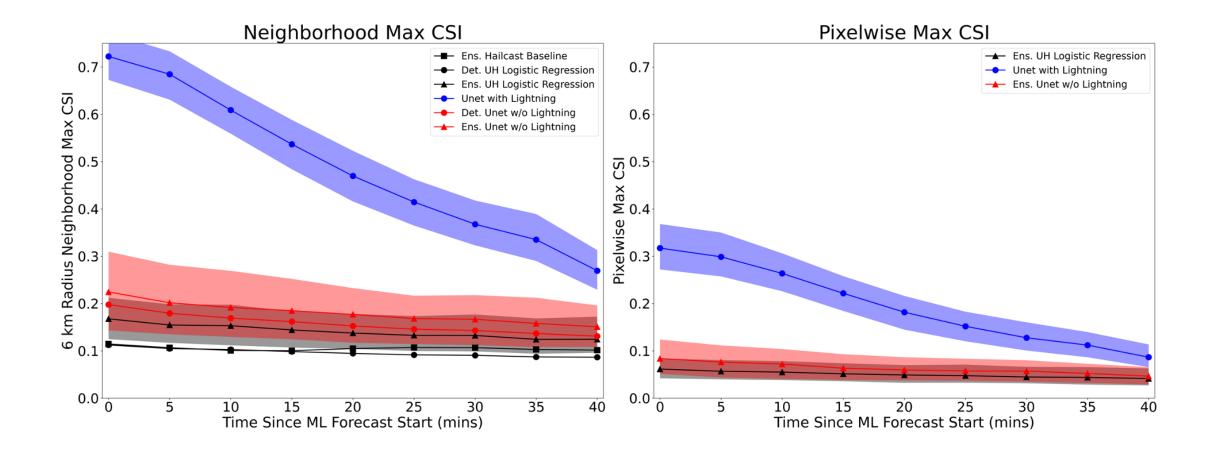
U-net architecture: handling time



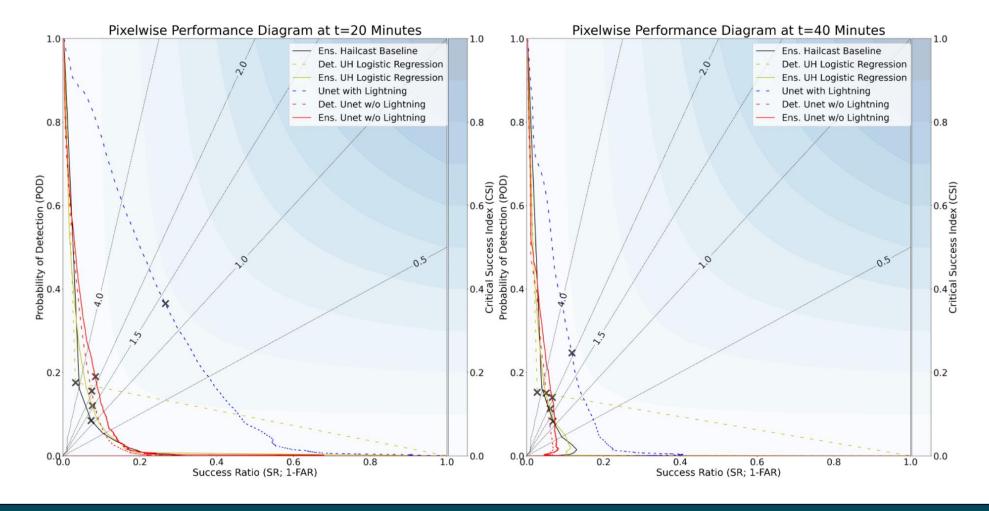
U-net architecture: handling time



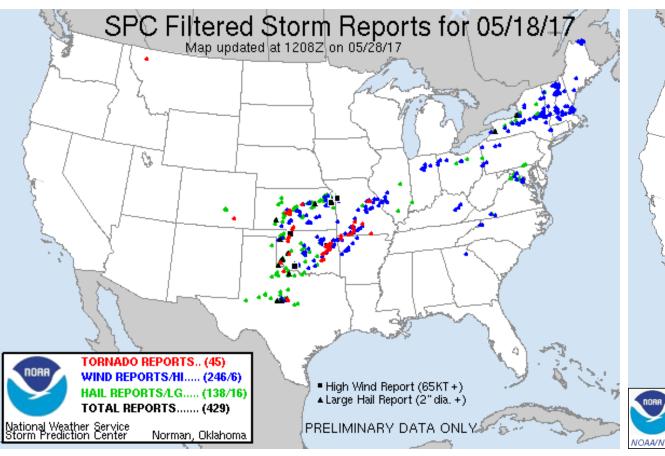
Objective verification

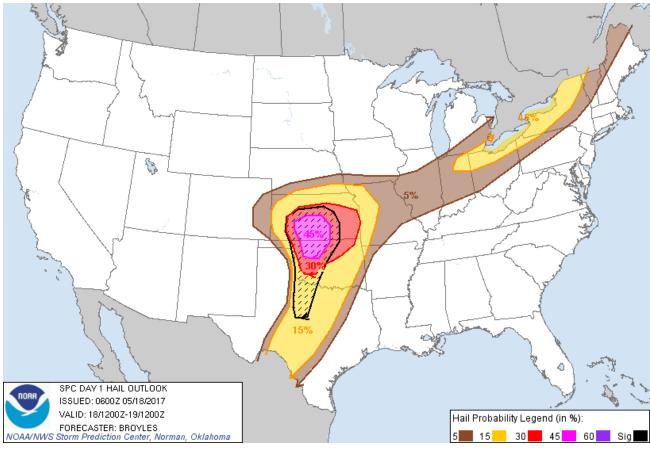


Objective verification

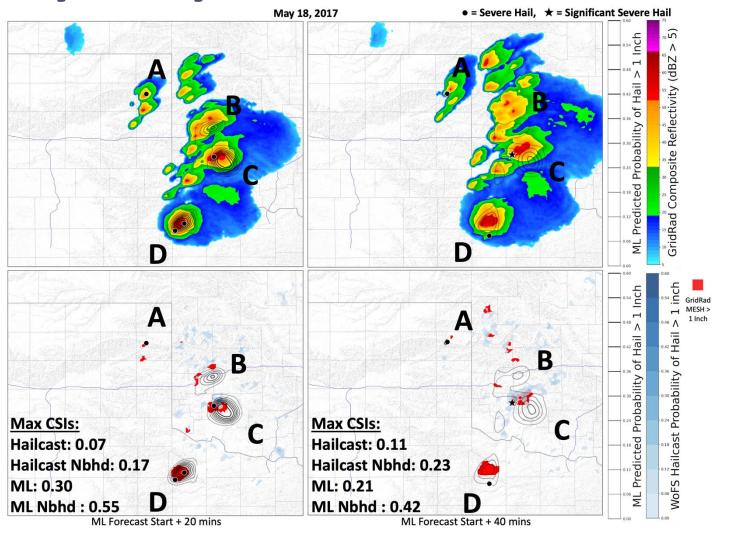


Case study: May 18, 2017





Case study: May 18, 2017



Current and future work on hail nowcasting

- Results are very promising
- Student leading this work graduated with his MS and went to private industry
- Paper accepted with major revisions and under review again now
- Our long-term goal is to extend this (or a similar) approach globally

Using Deep Learning to Improve the Warn-On-Forecast System Prediction of Thunderstorm Location

Chad Wiley, Montgomery Flora, Corey Potvin, Randy Chase, Tobias Schmidt, Brian Matilla, and Amy McGovern







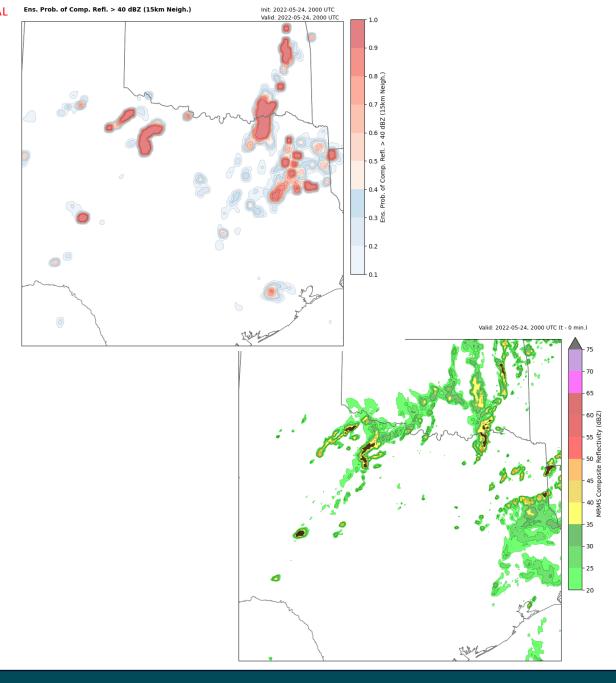






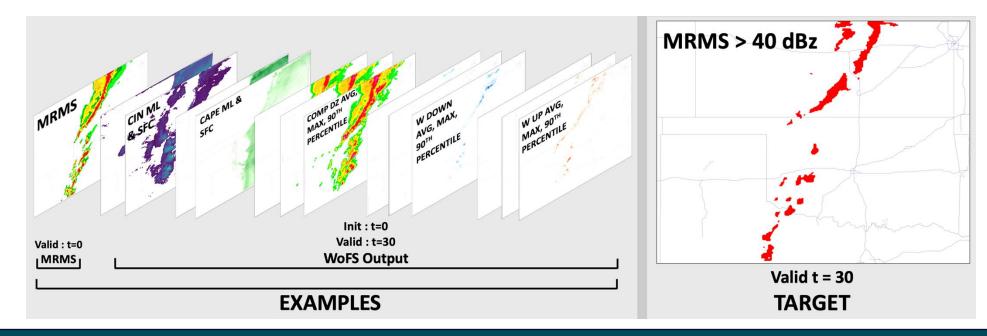
Motivation

- Accurate convective initiation forecasts are important for a wide variety of impacts
 - Convective-Induced Turbulence (CIT) is responsible for about 60% of turbulence related aircraft accidents (Corman and Carmichael, 1993)
 - Public outdoor safety
- WoFS has a strong overforecasting bias for CI

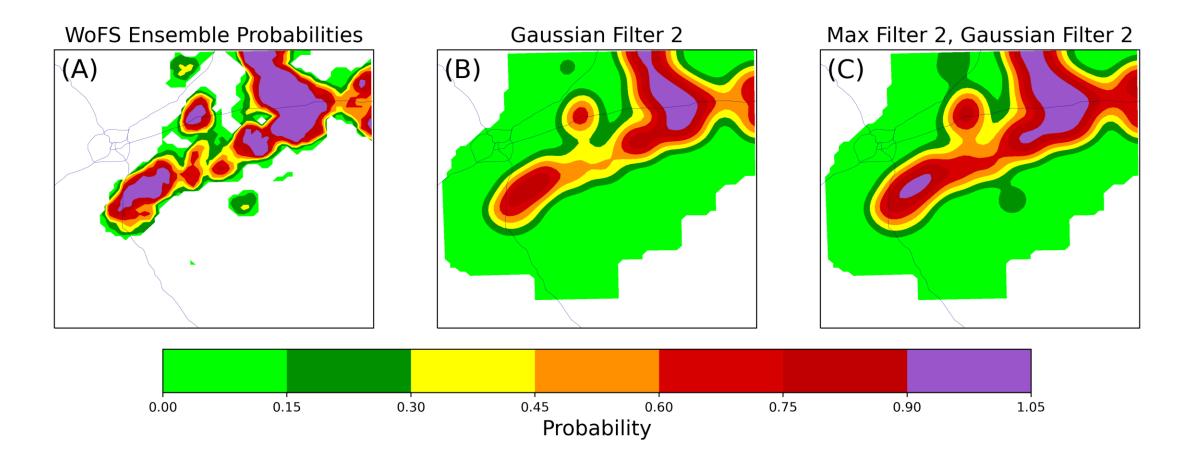


Approach

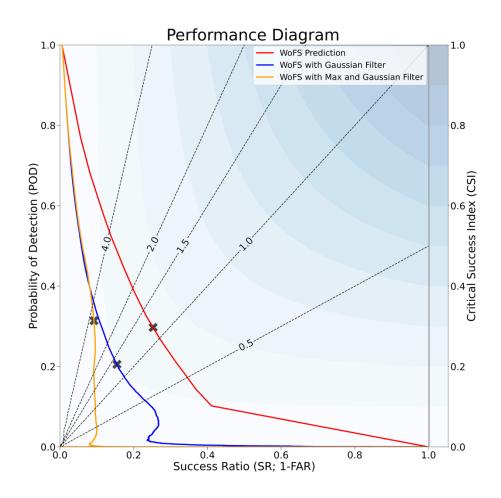
- MRMS and WoFS input to a U-net
- Training data is MRMS > 40 dBz 30 min in future
- Output probability of convection

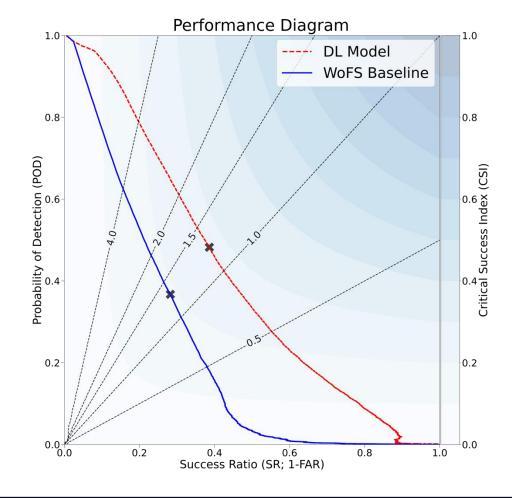


Comparison method



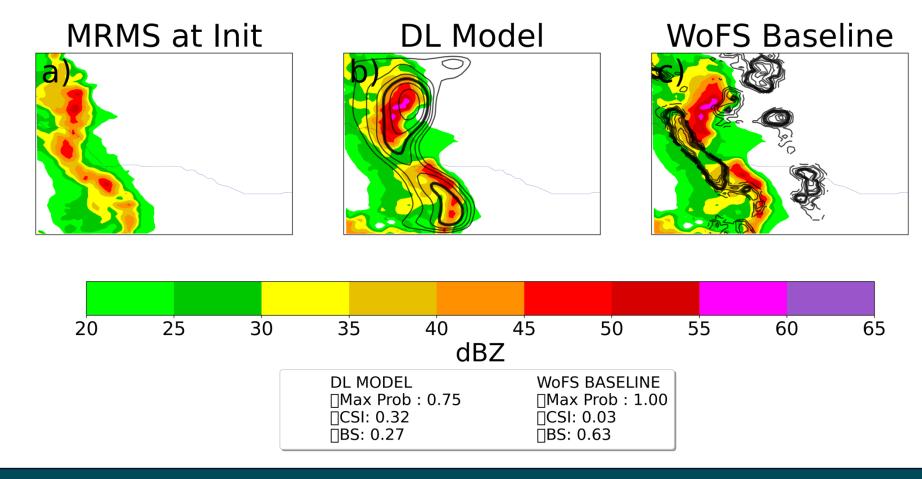
Objective performance



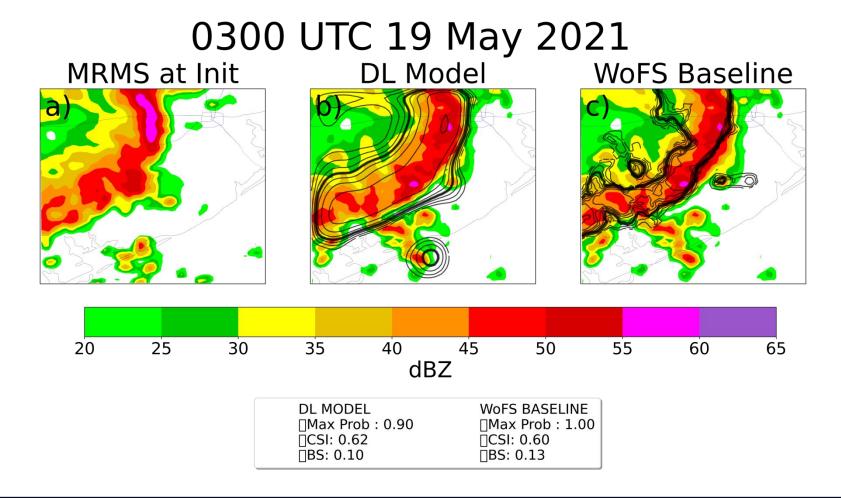


Case study: South Dakota storm

0230 UTC 21 May 2021

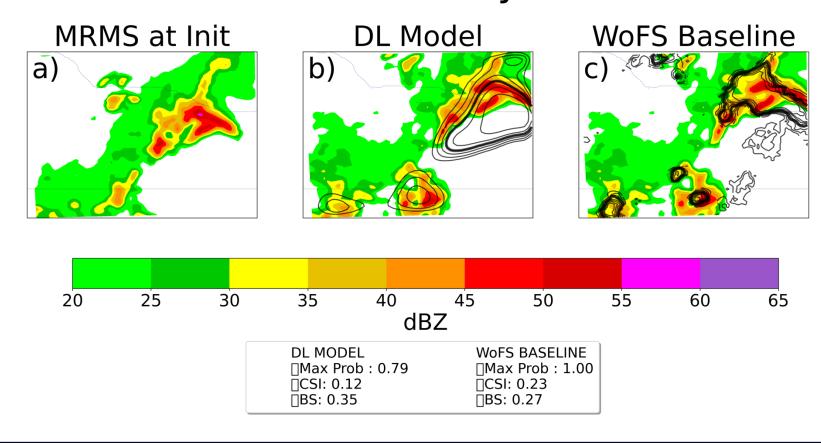


Case study: Southeastern Texas



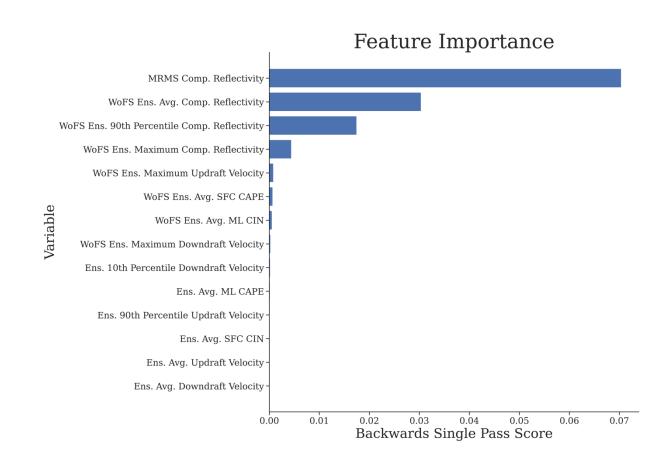
Case study: Nebraska-South Dakota

0230 UTC 22 May 2021



Looking inside the model

- MRMS Composite Reflectivity at initialization was the most important variable
- WoFS composite reflectivity products were also important
- Environmental variables were not important



Current and future work on CI

- Deep learning U-Nets were able to substantially increase skill and discrimination of a 30-minute forecast of reflectivity values >= 40 dBZ
 - MaxCSI on testing dataset was raised from 0.17 to 0.27
- MRMS Composite Reflectivity greatly impacted the performance and helped in cases of poorly initialized storms
- Student leading this work also graduated and went to private industry

Machine learning estimation of storm updrafts

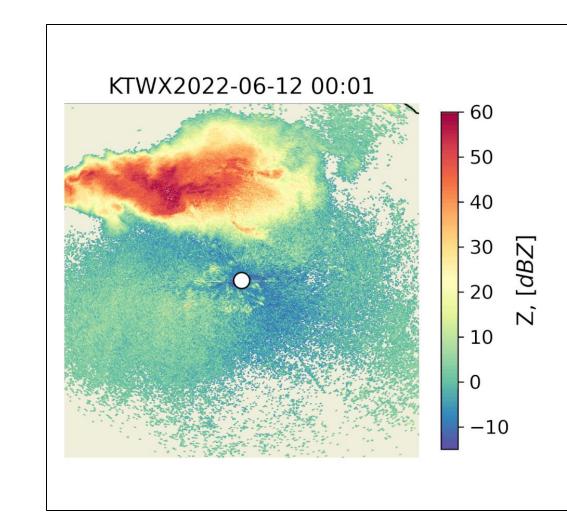


Randy J. Chase, Kayla Hoffman, Dan Stechman, Cameron Homeyer, Corey Potvin and Amy McGovern

Chase, R. J., A. McGovern, C. R. Homeyer, P. J. Marinescu, and C. K. Potvin, 2024: Machine Learning Estimation of Maximum Vertical Velocity from Radar. *Artif. Intell. Earth Syst.*, **3**, 230095, https://doi.org/10.1175/AIES-D-23-0095.1.

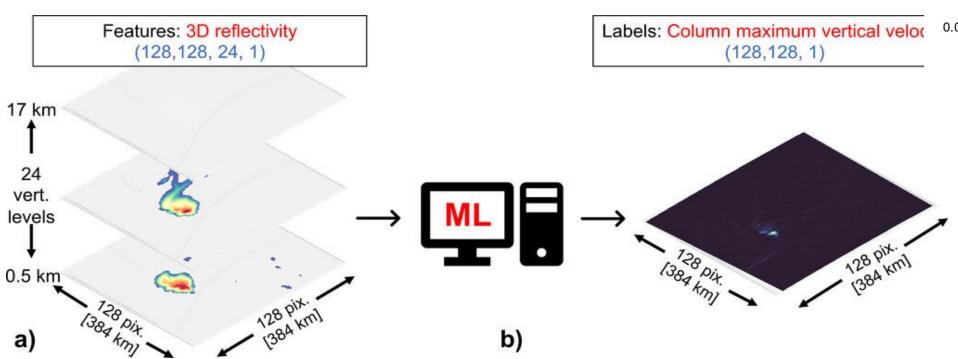
Estimating Vertical Velocity from Radar

- The NEXRAD system is underutilized (e.g., most only use low level scans)
- Physics retrievals of updrafts (i.e., multi-dop) are costly, baselines are not good and low level data is often missing
- CAMs can provide updraft info but are also unavailable in real-time
- Can we use AI/ML to estimate updrafts in real-time?

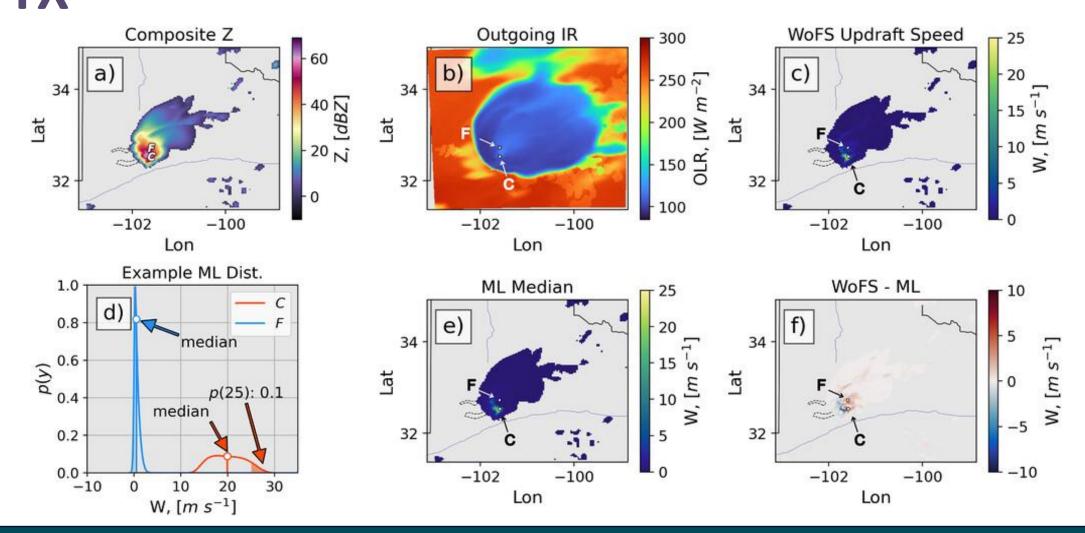


Approach

• U-net trained on WoFS to predict distribution of values

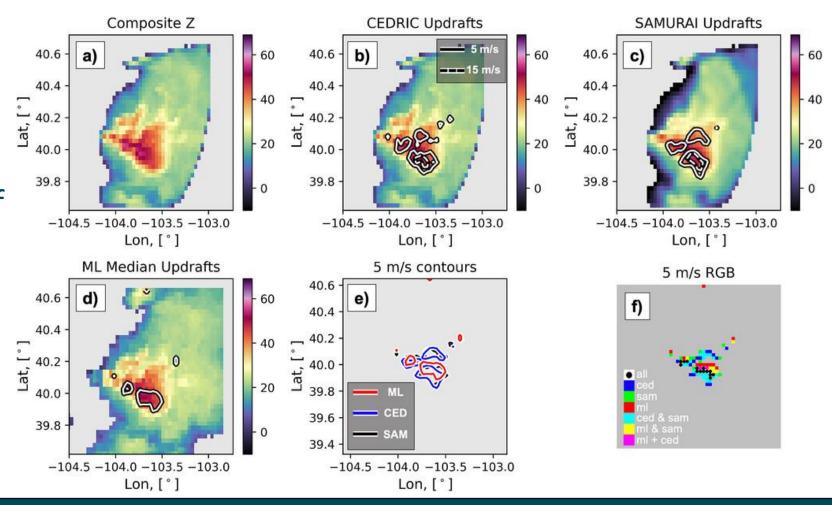


Case study: WoFS evaluation April 30 2019 TX



Case study: Eastern Colorado 26 May 2017

- Estimates from ML are close to the observed retrieved data
- Strong promise of ML to do this in real-time
- Now let's use this data to improve understanding of storm evolution



NSF Al Institute for Research on Trustworthy Al in Weather, Climate, and Coastal Oceanography (AI2ES)

AI2ES is developing *novel*, *physically based* AI techniques that are demonstrated to be *trustworthy*, and will directly improve *prediction*, *understanding*, *and communication* of high-impact weather and climate hazards, directly improving climate resiliency.



















































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