Machine Learning Estimation of Storm Updrafts

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Motivation

Storm updrafts have been linked to tornado damage (i.e., larger updraft, more damaging tornado; Trapp et al. 2017, Marion et al. 2019, French and Kingman 2021) and hail formation (i.e., wider updraft, larger hail; Kumjian et al. 2021). Thus, there is potential in using updraft characteristics in real time to diagnose storm hazard potential.

Physics methods of determining updraft (i.e., multi-doppler analysis) take too much time and quality-control. Furthermore, baselines (distances between radars) are often not conducive for high quality estimates of updrafts. Thus, physics-based methods are not available in real time for forecasting applications.

Goal:
Train a machine learning algorithm (i.e., U-Net) to estimate storm updrafts from measured radar reflectivity.

Data

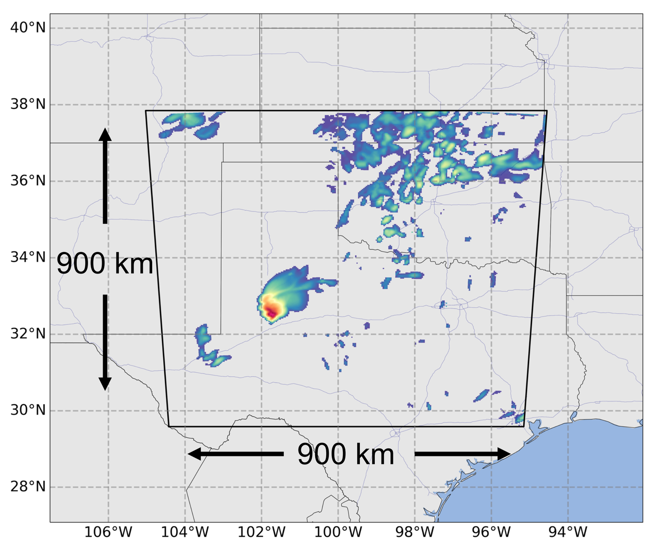


Fig. 1: Example WoFS domain from 2019-04-30

NSSL Warn-on-Forecast System (WoFS)

- 5-min temporal resolution
- 3 km horizontal grid spacing
- 18-member forecast ensembles (different PBL and radiation schemes)
- Domain follows expected severe weather

Training data: 2018; 19,000 training samples

Validation data: 2019; 9,000 validation samples

Machine Learning: Data and Loss

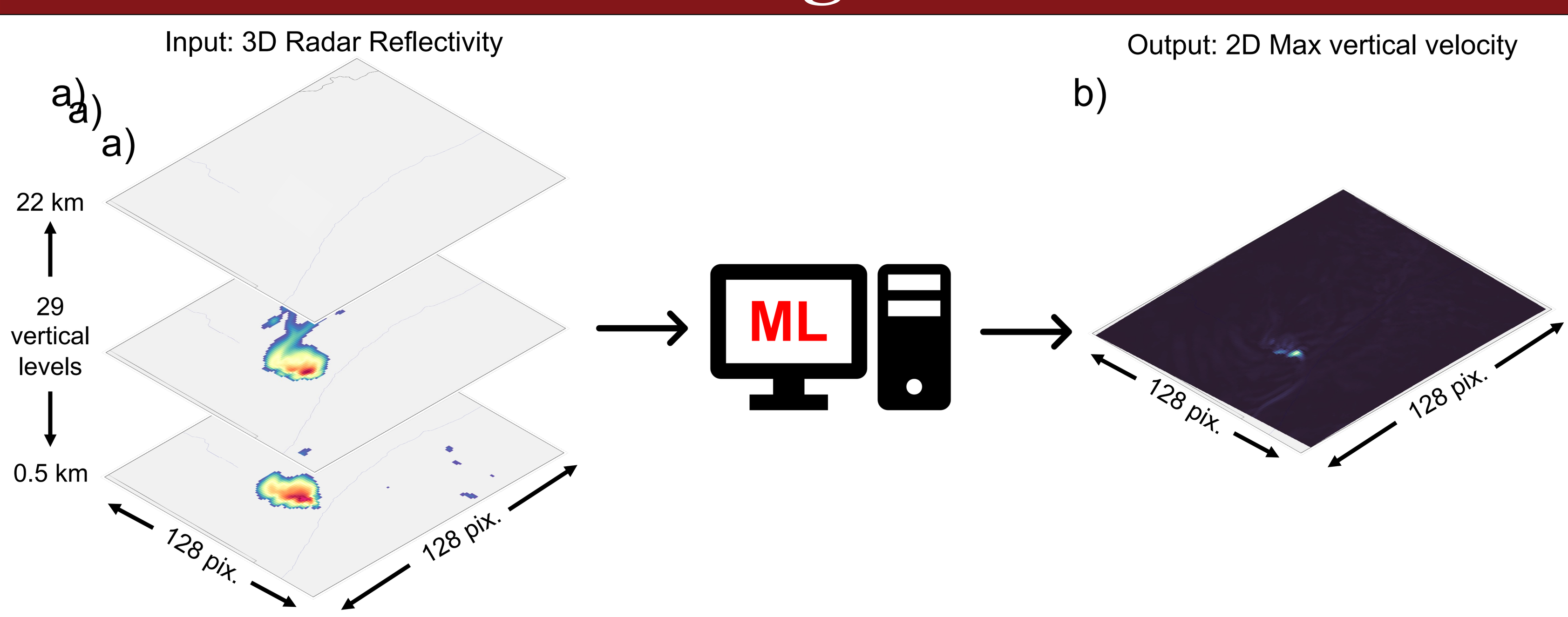


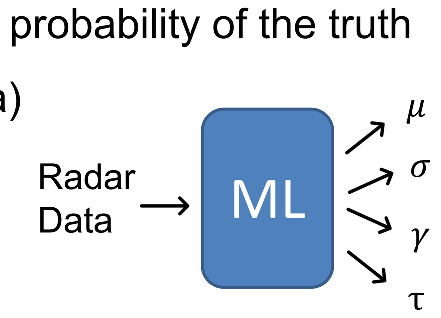
Fig. 2: Graphic depicting the ML idea and data flow. (a) is 3 of the total of 29 vertical levels (0.5 km – 22 km) of radar reflectivity, units are dBZ and the colorbar is shown in Fig. 4. (b) the output label of the ML is the maximum vertical velocity in the column. The units are m/s and the colorbar is found in Fig. 4.

Data Generation:

1. One map (size 128x128) of 3d radar reflectivity and maximum vertical velocity are sliced from every model initialization time, every forecast time and every model ensemble member.
2. Only maps with at least 1 pixel > 10 m/s in the vertical velocity are kept for the training and validation dataset

Loss Function:

1. ML model outputs 4 parameters of *Sinh-Arcsinh* distribution (SHASH; Barnes et al. 2022)
2. Loss is *neg-log likelihood* , which optimizes the probability of the truth updraft



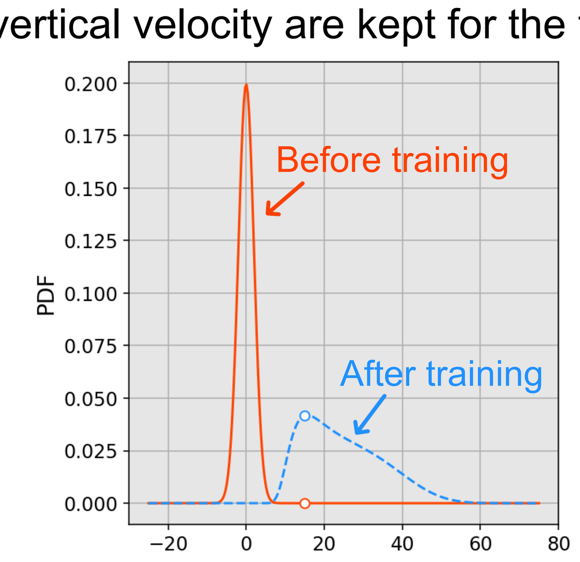


Fig. 3: (a) Schematic depicting how the ML predicts a distribution rather than a deterministic output. Inspired by Barnes et al. (2022). (b) example distributions before and after training

Training Domain Example

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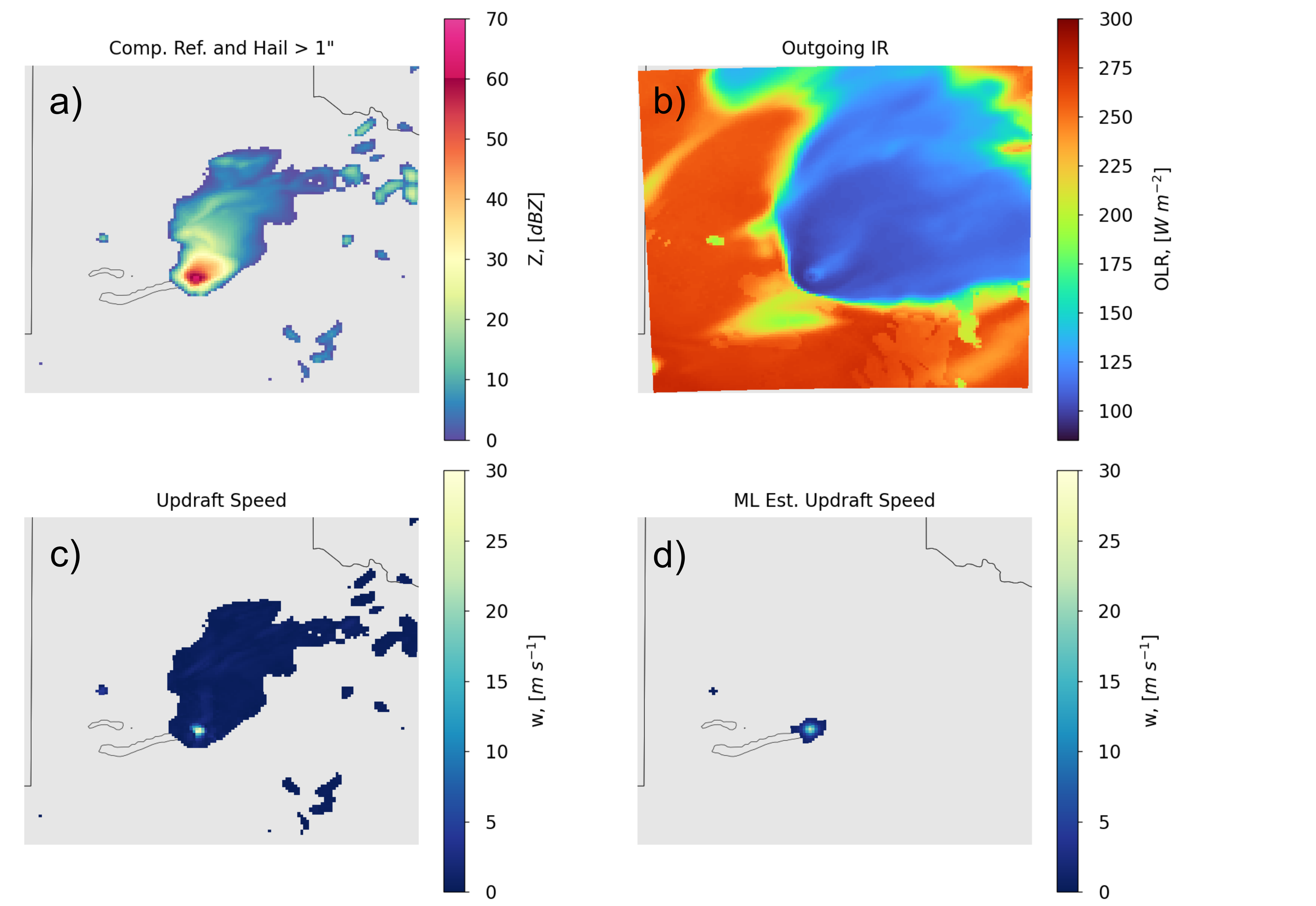


Fig. 4: An example WoFS case from the validation dataset, 2019-04-30 in Texas. (a) Composite reflectivity (color shading) and HAILCAST 1" hail contour. (b) Outgoing longwave infrared radiation (c) WoFS maximum vertical velocity (color shading) and the 1" hail contour (d) Machine learning estimated maximum updraft speed (color shading) [this is the median of the predicted distribution] and 1" hail contour. The video of this event can be watched using the QR code to the left.

- A long-lived discrete supercell near Amarillo, Texas on 2019-04-30 persisted for more than 4 hours
- Simulated IR shows hints of overshooting top and Above Anvil Cirrus Plume
- HAILCAST (Adams-Selin and Zeigler 2016) suggests hail larger than 1" possible
- WoFS updrafts exceed 30 m/s
- ML output (median calculated from the distribution) suggests good correspondence with WoFS (*truth*)

Training Domain Validation

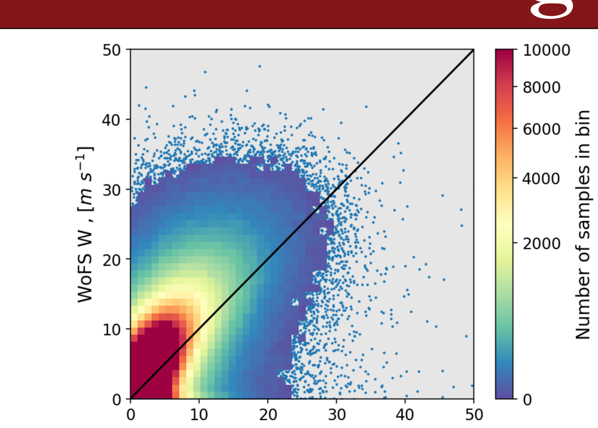


Fig. 5: Pixel based evaluation of ML prediction (median of distribution) on validation set (2019).

- Comparing each pixel to each other, qualitatively the ML has good correspondence with the label
- R^2 values exceed 0.6

- The ML prediction slightly underestimates for predicted updrafts between 5-10 m/s
- Overestimates predicted updrafts greater 25 m/s

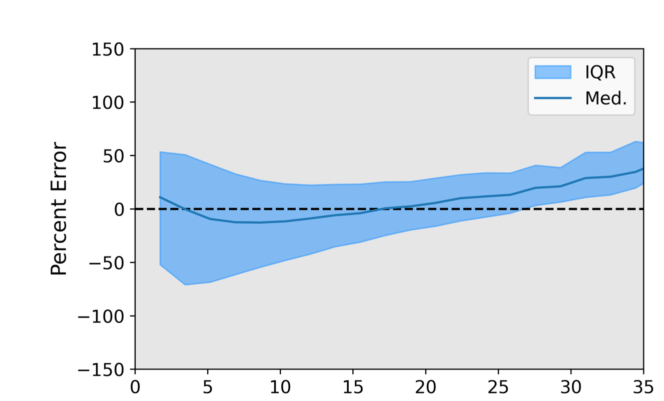
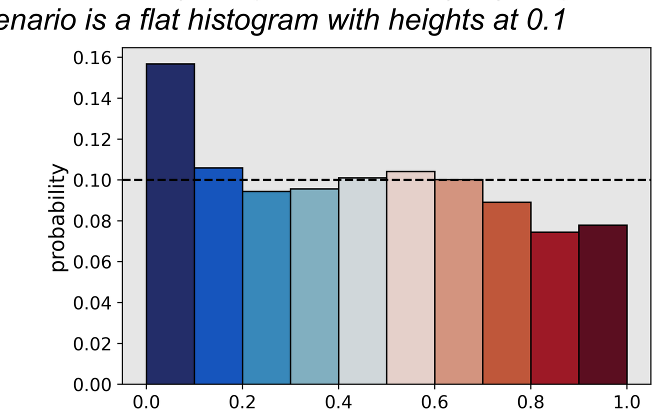


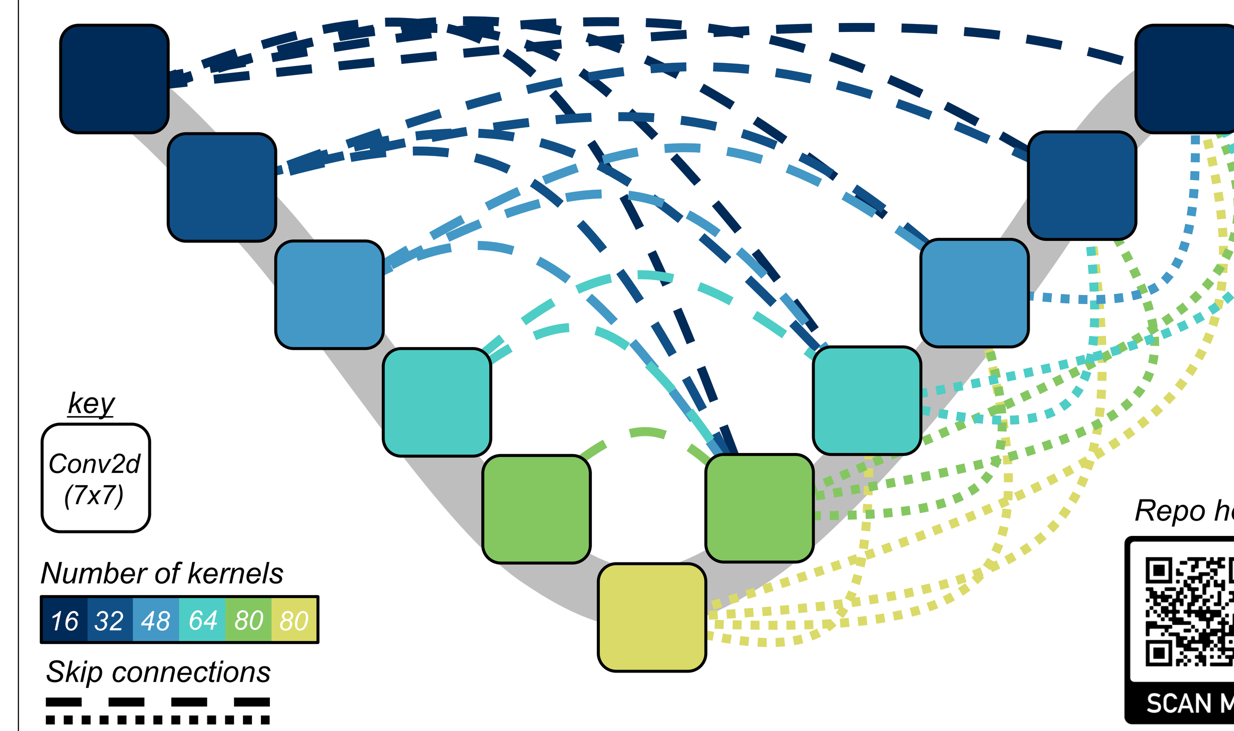
Fig. 6: Median Pixel based error (ML – Truth; solid line) as function of ML prediction (median of distribution) on validation set (2019). Shading is the 25th to 75th percentile of the error

Fig. 7: Probability integral transform (PIT) diagram. Ideal scenario is a flat histogram with heights at 0.1



- The interquartile range probabilities are well calibrated (IQR fraction = 0.494)
- Weak probabilities are overestimated
- Large probabilities are underestimated

Machine Learning: Model



- The ML method used is a U-Net3+ (Huang et al. 2020), which has full-scale skip-connections
- A hyperparameter search of more than 100 models is done where many parameters are varied (e.g., depth, kernel size etc.)

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Fig. 8: U-Net3+ schematic (inspired by Huang et al. 2020) used for translating 3d radar data into maximum vertical velocity

Transfer Domain Example

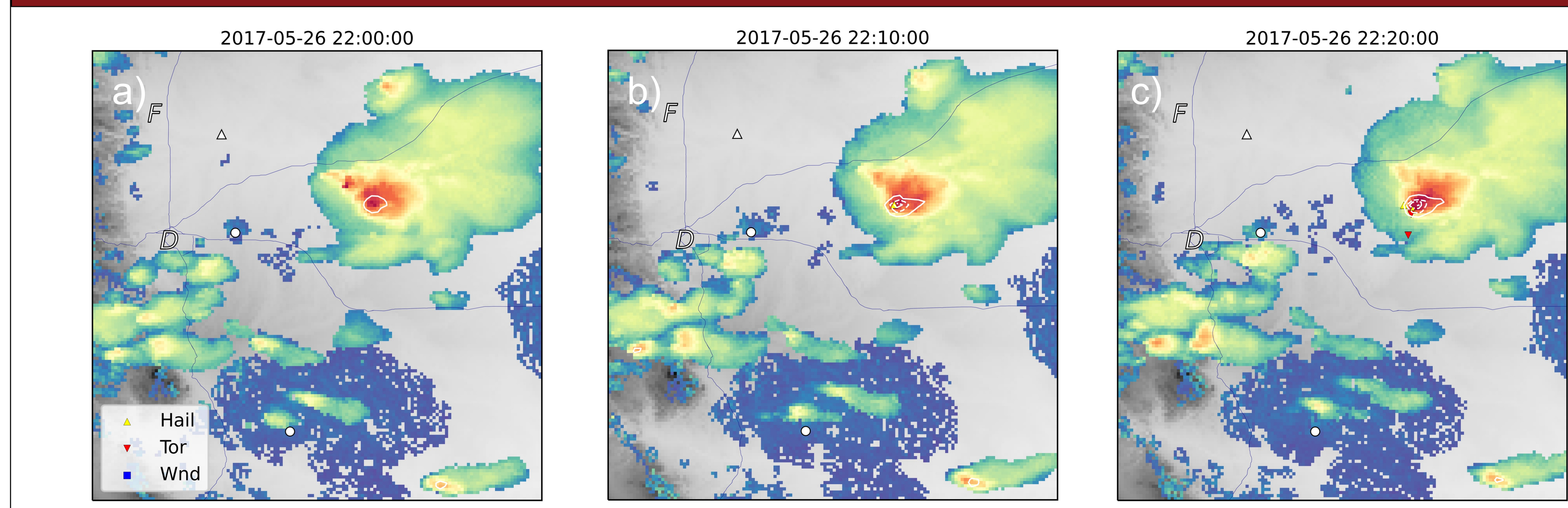

Fig. 9: Case study from 2017-05-26 where the U-net is applied to observed 3d gridded radar data (GridRad Severe). Plotted is the composite reflectivity with the same colorscale as Fig. 4. Contours are the updraft speeds determined by the U-net with speeds of 5, 10, 15 and 20 m/s. (a) is at 20:00 UTC (b) is at 20:10 UTC and (c) is at 22:20

- The U-net updraft speeds look plausible, showing up near high reflectivity
- Updraft intensity increases (5 m/s) at the same time as the first severe hail report
- Maximum Updraft intensity increases from 5 m/s at 20:00 to 20 m/s at 20:15 (prior to tornado reports)

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Conclusions

1. A machine learning model (U-net) was trained to translate radar reflectivity to maximum vertical velocity using NWP data
2. The U-net produces skillful estimates of updraft speed (median errors < $\pm$ 50%)
3. The uncertainty information is well behaved (PIT diagram, pred in IQR ~ 50% of the time)
4. A case study on real radar data showed the U-net could be transferred from NWP to observations and look plausible

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Acknowledgments

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