Evaluating Machine Learning Updraft Retrieval Skill: Convective Case Studies

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1. Motivation

- Severe thunderstorms are life threatening and cause billions of dollars in damage yearly in the United States(1).
- Thunderstorm updrafts can cause many types of severe weather(2); thus, understanding storm updraft behavior is crucial to the protection of life and property.
- Updraft proxies show promise(3,4,5) but only provide direct information about select regions of the storm updraft (e.g., overshooting tops: storm top).
- Forecasters have few tools to assess the strength of convective updrafts in real time(6).
- Machine learning (ML) could provide timely and comprehensive quantifications of updraft characteristics.
- Chase et al. 2024 showed promising ML updraft retrievals for one real world case.

Goal:

Test machine learning updraft retrieval techniques from Chase et al. 2024 in an alternate supercell case study and assess implications for forecasting severe hazards.

2. Case Study: 20 May 2019

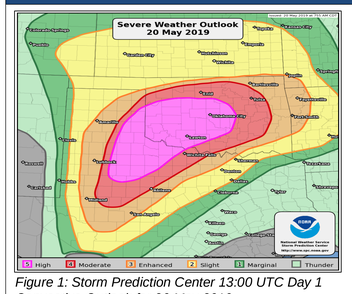


Figure 1: Storm Prediction Center 13:00 UTC Day 1 Convective Outlook for 20 May 2019.

- Severe weather outbreak unfolded across Kansas (KS), Oklahoma (OK), Texas (TX), and surrounding regions.
- Severe reports: Tornado (38), wind (92), and hail (90).
- A supercell developed in North TX and tracked into Southwest OK, impacting Mangum, OK at ~ 22:00 UTC.
- The TORUS (7) field campaign allowed for high-quality radar data collection on the supercell.

3. Methods: Multi-Doppler (MD)

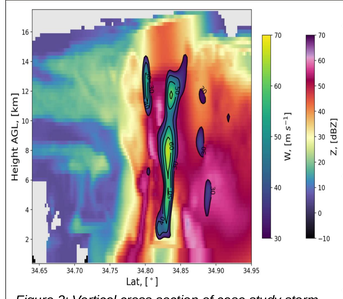


Figure 2: Vertical cross section of case study storm updraft region. Reflectivity (Z) (fill), upward vertical velocity (w) (contour, fill).

- Supercell radar data was analyzed with National Severe Storms Laboratory (NSSL) Multi-Doppler Analysis System(8) to compute vertical velocity values (w).
  - w computed using mass continuity equation on base velocity data(9,10).
- 250 m horizontal resolution, 19 timesteps (20:24 UTC - 23:24 UTC, 10-min average temporal resolution).
  - MD data later resampled to 3 km resolution to equal that of the ML output.
- MD vertical velocity data were compared to ML updraft predictions to evaluate retrieval skill.

4. Methods: Machine Learning (ML)

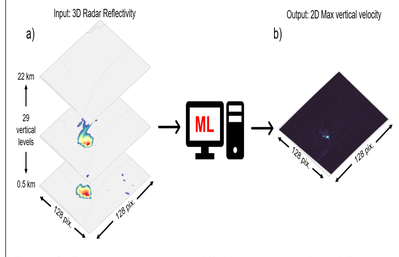


Figure 3: Graphic depicting the ML idea and data flow. ML input: 29 vertical GridRad levels. ML output: max vertical velocity in column.

- Models used: 2D Convolutional U-Net3+ (2d24f) and full 3D convolutional U-Net (3d)(6).
  - Model input: 3D radar reflectivity
  - Model output: 2D max vertical velocity
- 3 km horizontal output resolution, 5-min temporal resolution.
- Parametric regression technique ran with ML models. *Allowed for a distribution of max updraft velocities.* 50th , 80th, and 95th percentiles used in this study (ML_{50}, ML_{80}, ML_{95}).
- ML models trained on NSSL Warn-On-Forecast System WRF model reflectivity and vertical velocity data(11).
- Trained models applied to GridRad Severe radar dataset for the 20 May 2019 case (12).

5. ML Data Preparation

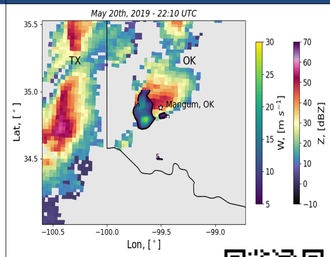


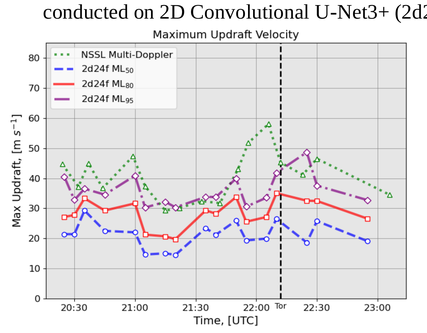
Figure 4: GridRad Severe radar reflectivity, overlaid with median (ML_{50}) 2D ML maximum vertical velocity. Example from 22:10 UTC ML timestep.

Scan for Fig. 4 loop

- Needed to isolate ML output domain to the supercell updraft.
- Supercell MD dataset consisted of a variable called n_radars, which returned number of radars scanning each pixel.
- The ML data were isolated by the multi-Doppler latitude-longitude pair where $n_{radars} \geq 2$.
- ML and MD temporal resolutions differed. The 19 ML timesteps closest to the MD timesteps were used in comparative analysis.
- Analyzed two updraft characteristics: 5 $m\ s^{-1}$ updraft area, maximum vertical velocity (w_{max}).

6. Results: ML-MD Time Series Comparisons

*Full 3D convolutional U-Net (3d) performed poorly, and thus all analysis that follows was conducted on 2D Convolutional U-Net3+ (2d24f).



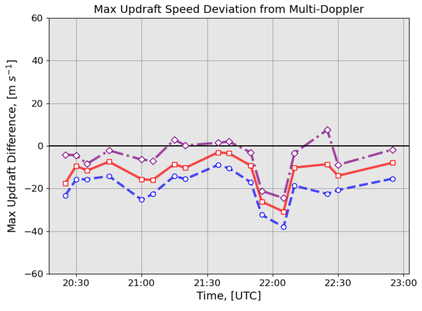
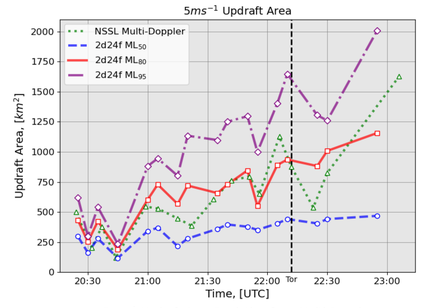
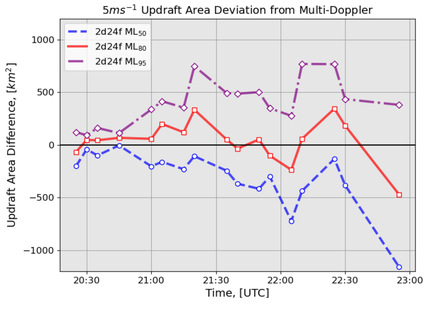


Figure 5: (top) Time series of maximum updraft velocity for all datasets (w_{max}). Time of tornadogenesis plotted with black dashed line. (bottom) Time series showing maximum updraft velocity (w_{max}) deviation from multi-Doppler w_{max} output.

- ML_{95} best predicted the time series of w_{max}.
  - In part due to the strong vertical velocities within supercells.
- All machine learning percentiles (ML_{50}, ML_{80}, ML_{95}) captured temporal variability in NSSL multi-Doppler w_{max}.
- Missed on a significant increase in NSSL multi-Doppler w_{max} prior to tornadogenesis (22:12 UTC).





- 5 $m\ s^{-1}$ updraft area increased over time in all datasets, with a local maximum around tornadogenesis.
- ML_{80} best predicted values of 5 $m\ s^{-1}$ updraft area.
  - ML_{95} overpredicts; ML_{50} underpredicts.
- All ML percentiles captured temporal variability in 5 $m\ s^{-1}$ updraft area present in multi-Doppler data.

Figure 6: (top) Time series of 5 $m\ s^{-1}$ updraft area for all datasets. Time of tornadogenesis plotted with black dashed line. (bottom) Time series showing 5 $m\ s^{-1}$ updraft area deviation from multi-Doppler 5 $m\ s^{-1}$ updraft area output.

7. Results: Correlations

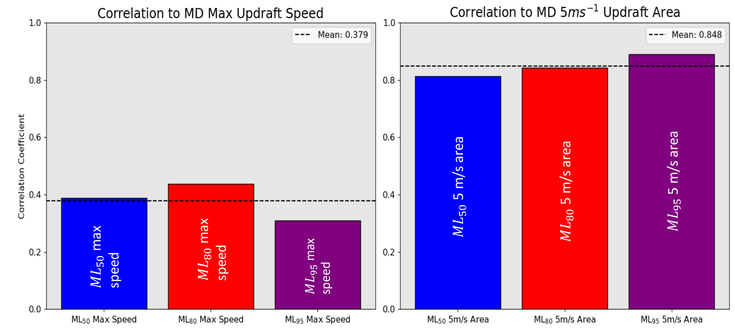


Figure 7: (left) ML w_{max} correlation to MD w_{max}. (right) ML 5 $m\ s^{-1}$ updraft area correlation to MD 5 $m\ s^{-1}$ updraft area.

- Weak correlation (0.3-0.5) between ML percentile w_{max} and multi-Doppler w_{max} over the timeseries.
- Strong correlation (0.8-0.9) between ML percentile and multi-Doppler 5 $m\ s^{-1}$ updraft areas over the time series.
- ML products using reflectivity data may be better suited for estimating updraft area, as opposed to updraft magnitude.
- Modest correlation (0.5-0.6) between the MD and ML 5 $m\ s^{-1}$ updraft area with area of severe hail, which was derived from radar product maximum expected hail size (MESH) (13).
- Correlation of area with severe hail are similar between machine learning and multi-Doppler.

Figure 8: ML, MD 5 $m\ s^{-1}$ updraft area correlation to area with severe hail (hail diameter ≥ 1 inch).

8. Conclusions

- Reflectivity-based, machine learning updraft models can skillfully quantify supercell updraft properties.
  - Most skillful for 5 $m\ s^{-1}$ updraft area and less skillful for updraft speed.
- Modest relationship between 5 $m\ s^{-1}$ updraft area and area with severe hail for both multi-Doppler and machine learning.
- Increase in updraft area near tornadogenesis in both ML and MD datasets.
- The 3D model performed poorly (not shown) and should be reevaluated. The 2D model performed better, but different percentiles may be needed for different updraft characteristics (e.g., ML_{50} underpredicted updraft strength and area).
- Next steps: conduct similar analysis on non-supercell case studies. A QLCS case study will be presented on 14 January in the Symposium on Radar Research to Operations.

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AI tools ChatGPT: https://chatgpt.com/ , Blackbox AI: https://www.blackbox.ai/.

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