Using AI/ML to Understand Rapid Updraft Strengthening

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BACKGROUND

All theories of tornadogenesis require a strong updraft at low-levels to stretch vorticity into a tornado, regardless of the "source" of this vorticity. Prior to tornadogenesis, many supercells undergo a period of rapid updraft strengthening. This "dynamical response" occurs as vorticity and associated nonlinear dynamic pressure perturbations strengthen above cloud base, but less is known about what precedes this response.

Can we train a machine learning model on idealized numerical simulations to predict rapid updraft strengthening and use explainable AI to interpret the results?

By understanding precursors to updraft strengthening at low-levels, we can understand precursors to tornadogenesis.

SIMULATION SETUP

- CM1 v21.0 (Bryan and Fritsch 2002) compiled in OMP
- 100 x 100 x 18.5 km storm-following domain
- dx = dy = 1000 m, dz = 500 m
- CI: +5 K warm bubble (as in Muehr et al. 2024)
- 1800 total simulations from 900 unique input soundings, using ihail = 0 and 1 with Morrison et al. (2009) microphysics
- 706 simulations selected for training dataset

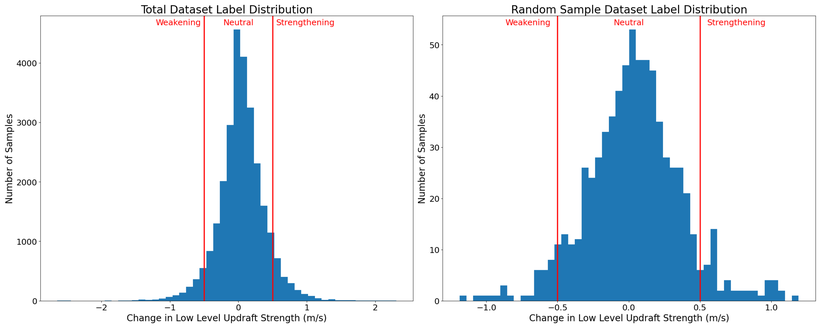


Figure 1. Distribution of change in low-level updraft strength for total dataset (left) and random sample (right)

MODEL ARCHITECTURE

- Tensorflow & Keras
- Convolutional and Long-Short Term Memory layers to analyze 3D and temporal features
- Classification to Updraft Strengthening, Weakening, and No Change

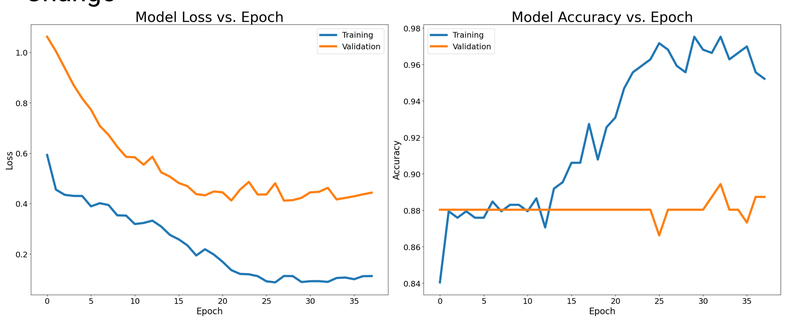


Figure 2. Model loss (left) and accuracy (right) for training and validation datasets during training

RESULTS

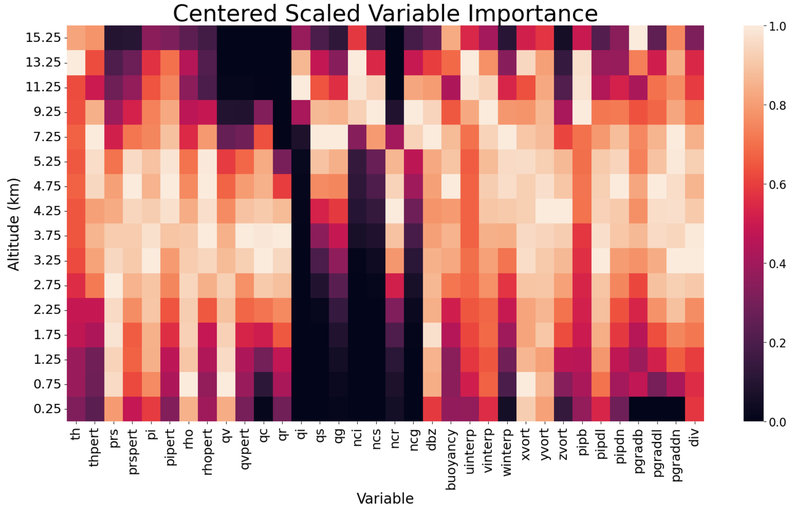


Figure 3. Vertical distribution of variable importance (mean absolute integrated gradients) showing the levels that each variable is most important. Each variable is scaled between 0 and 1.

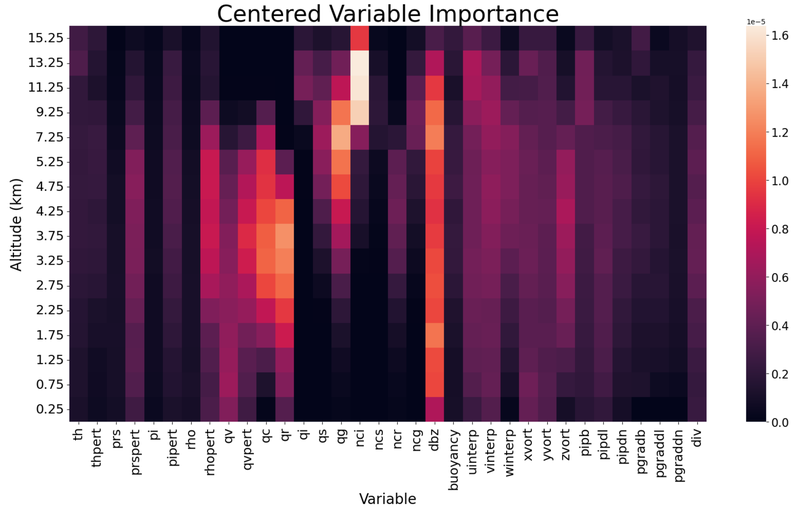


Figure 4. Vertical distribution of variable importance (mean absolute integrated gradients) showing the relative importance of each variable.

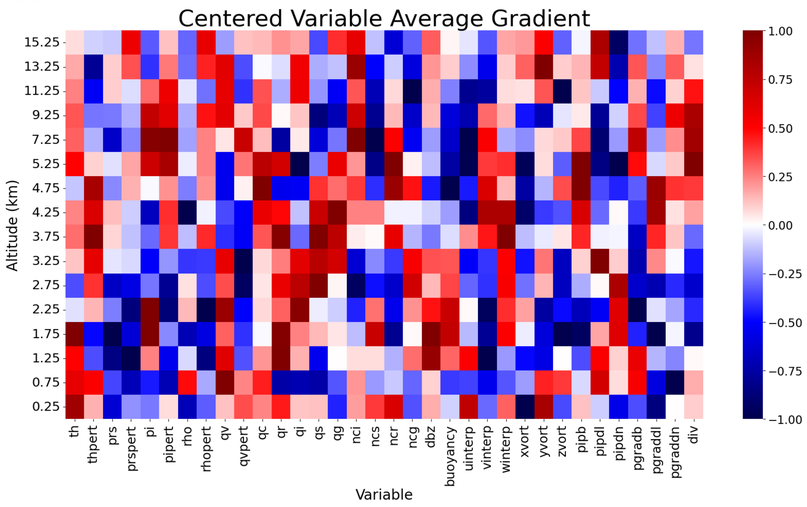


Figure 5. Vertical distribution of variable gradient (mean gradients) showing the impact of each variable on the probability of strengthening. Each variable is scaled between -1 and 1.

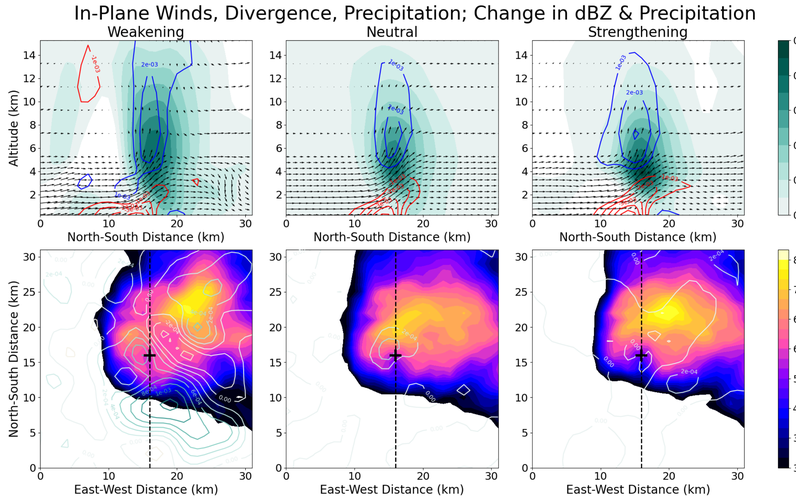


Figure 6. Vertical cross section (top) of precipitating hydrometeors (fill, kg/kg), convergence (red contours, s^{-1}), divergence (blue contours, s^{-1}), and in-plane winds (vectors) from 10 minutes prior to prediction time. Plan view (bottom) of change in dBZ at 2.25 km (fill) and precipitation mixing ratio at 4.25 km (contours, kg/kg) from 10 min to 2 min before prediction with transect of cross section shown by dashed black line.

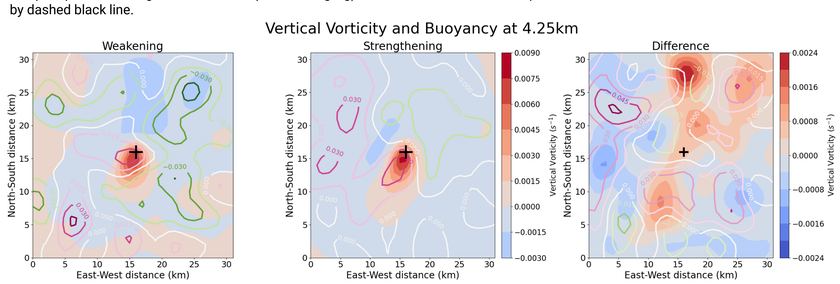


Figure 7. Vertical vorticity (fill, s^{-1}) and buoyancy (contours, m s^{-2}) for weakening updrafts (left), strengthening updrafts (middle), and the difference (right) between the two at 4.25 km.

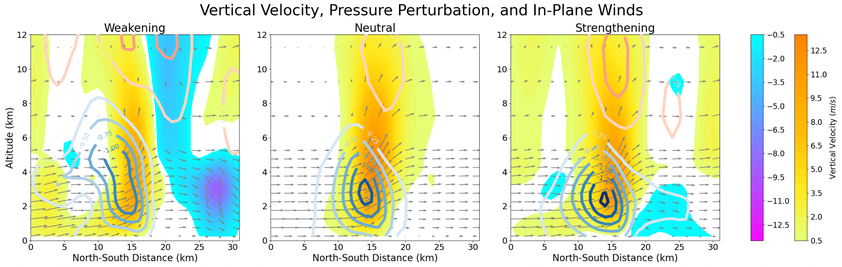


Figure 8. South (left) to north (right) vertical cross sections through the updraft center 10 minutes before prediction time showing vertical velocity (fill, m s^{-1}), pressure perturbation (contours, hPa), and in-plane winds (vectors).

CONCLUSIONS

According to the explainable AI techniques applied to the machine learning model:

- Water vapor, cloud, and precipitation mixing ratios play an important role in updraft strengthening
- In non-weakening supercells, dBZ takes on a more hook-like appearance over time
- Buoyancy and vertical vorticity have surprisingly little importance
- Pressure perturbations are stronger in strengthening updraft supercells and are less vertically tilted
- Weakening supercells have strong downdrafts north of updraft

Acknowledgements

All simulations and artificial intelligence work were performed on NCAR's Derecho supercomputer