

Convection Classification in a Future Climate: What did Deep Learning Really Learn?



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Convolutional neural networks (CNNs; LeCun et al. 1998) have proven skillful for multiple tasks in the atmospheric and climate sciences, given their ability to detect nonlinear relationships and spatial invariances in input features. Here we show that a CNN can classify storms of a future climate with skill when trained with a historical climate. With machine learning interpretability methods, we also gain insight into what the model learned (Molina et al.; under review).

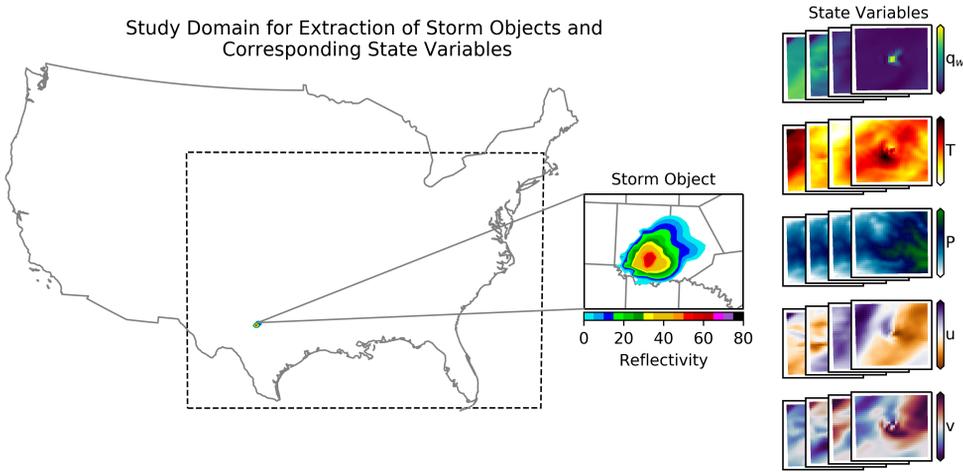


Fig. 1 (left): The dashed-line polygon contains the study domain. State variables were chosen as input channels and include moisture (q_w), temperature (T), pressure (P), and meridional (v) and zonal (u) winds interpolated onto 1, 3, 5, and 7-km above ground level height.

- The watershed transform algorithm (Lakshmanan et al., 2009) was used to identify high-intensity updrafts associated with thunderstorms (Fig. 1; above) from a climate dataset spanning 26 years at 4-km grid spacing.
- A CNN was trained to classify thunderstorms that were strongly or not strongly rotating in a current climate (Fig. 2; below).
- Rotation was determined using updraft helicity between 2-5-km, which is computed using vertical wind speed and vorticity.

Deep Learning Model Architecture

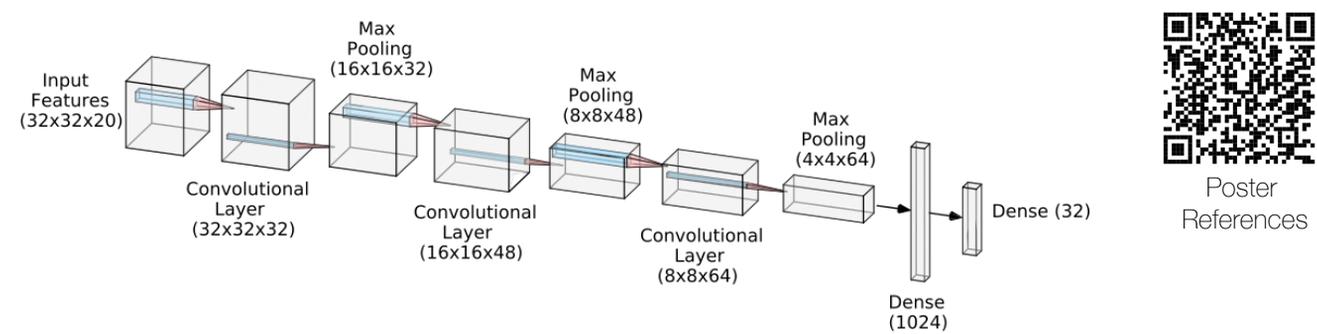


Fig. 2: The CNN used in this study consists of three convolutional layers, max pooling, batch normalization, and 2D spatial dropout (30%). A sigmoid function was used in the final dense layer, with a higher magnitude output probability representing a greater likelihood that the storm is strongly rotating and more likely to produce severe weather (model visualization: LeNail, 2019).

- Evaluation of the classification of future storms reveals a high probability of detection (POD) and critical success index (CSI), which shows that a model trained using a current climate can still perform well in a warmer and more moist climate (RCP8.5).
- Future outlier storms (99th percentile of low-level moisture in the future) also reveal excellent performance (Fig. 3; right).

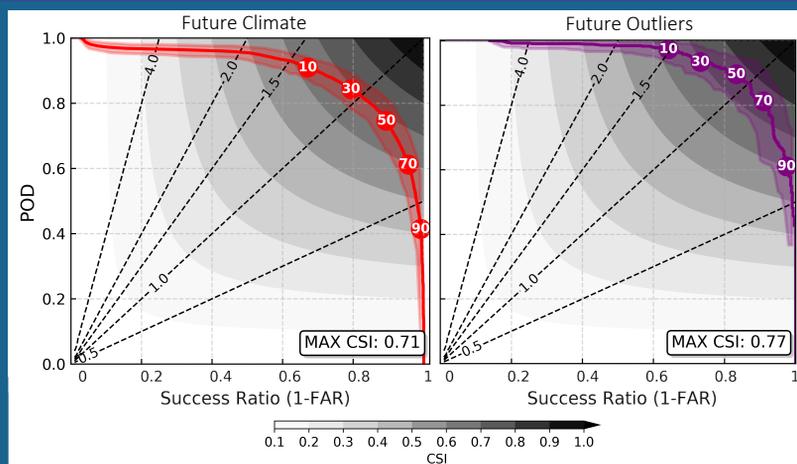


Fig. 3: Evaluation of CNN. Gray contours represent CSI, dashed lines represent bias, and probability thresholds shown in circles.

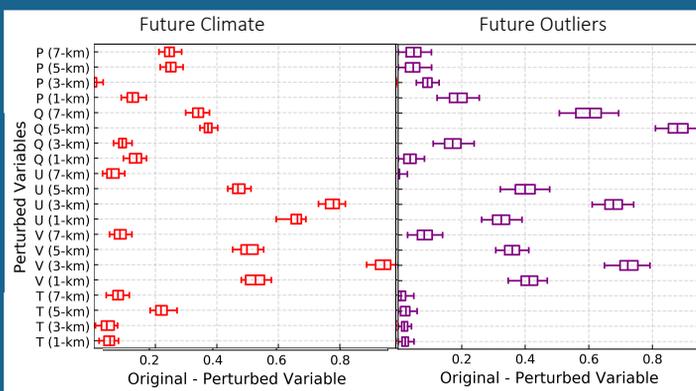


Fig. 4: Permutation feature importance analysis of future climate and outlier events.

- A simple explainability method is permutation feature importance, which ranks input features based on how much randomizing individual features increases error (Fig. 4; left).
- The future climate and outlier cases show that u and v winds at 3-km have high importance (based on CSI). Future outliers also show that moisture at higher vertical heights is important.

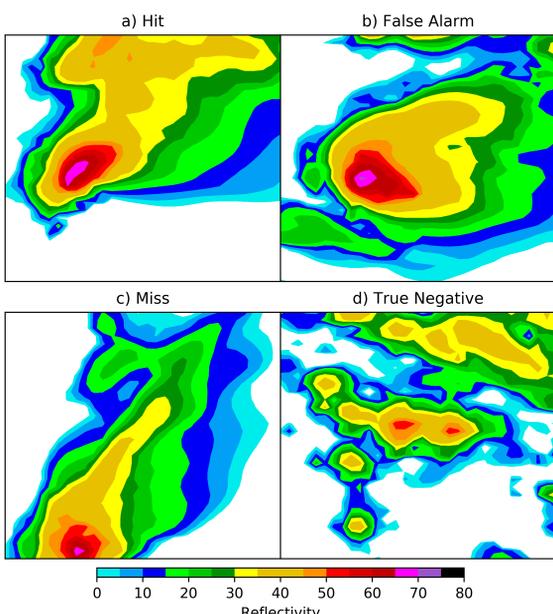


Fig. 5: Simulated reflectivity of various model predictions.

- Saliency maps reveal that the deep CNN focuses on the mesocyclone region of organized convection for kinematic and thermodynamic variables (Fig. 6; right).
- Saliency maps (Simonyan et al., 2013) for non-strongly rotating convection contain farther dispersed gradients.

- Storms classified as strongly-rotating resemble supercellular convection, while non-strongly rotating storms are less organized.
- False alarms contain storms with high updraft helicity and misses contain storms that are near the edge of the object (Fig. 5; left).

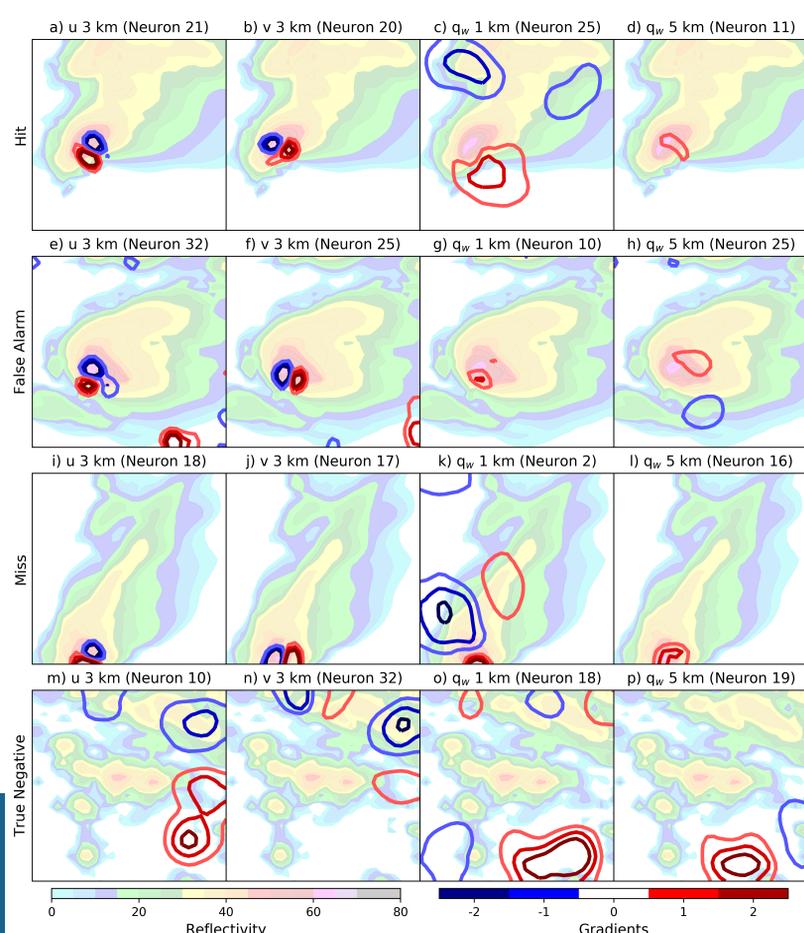


Fig. 6: Saliency maps for a hit, false alarm, miss, and true negative case.

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