

# Radars detect most severe weather threats, but see little of their cause, limiting radar-based NWP while making threat nowcasting easy.

## Radar cannot do it alone:

### Fundamental limits of covariance-based DA at storm scales



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### The three-minute story

Fundamentally, **radars constrain** some precipitation features and **one** ( $v_{\text{radial}}$ ) **of seven** ( $u, v, w, P, T, e, q_{\text{cloud}}$ ) dynamical and thermodynamic **properties of relevance** to storms.

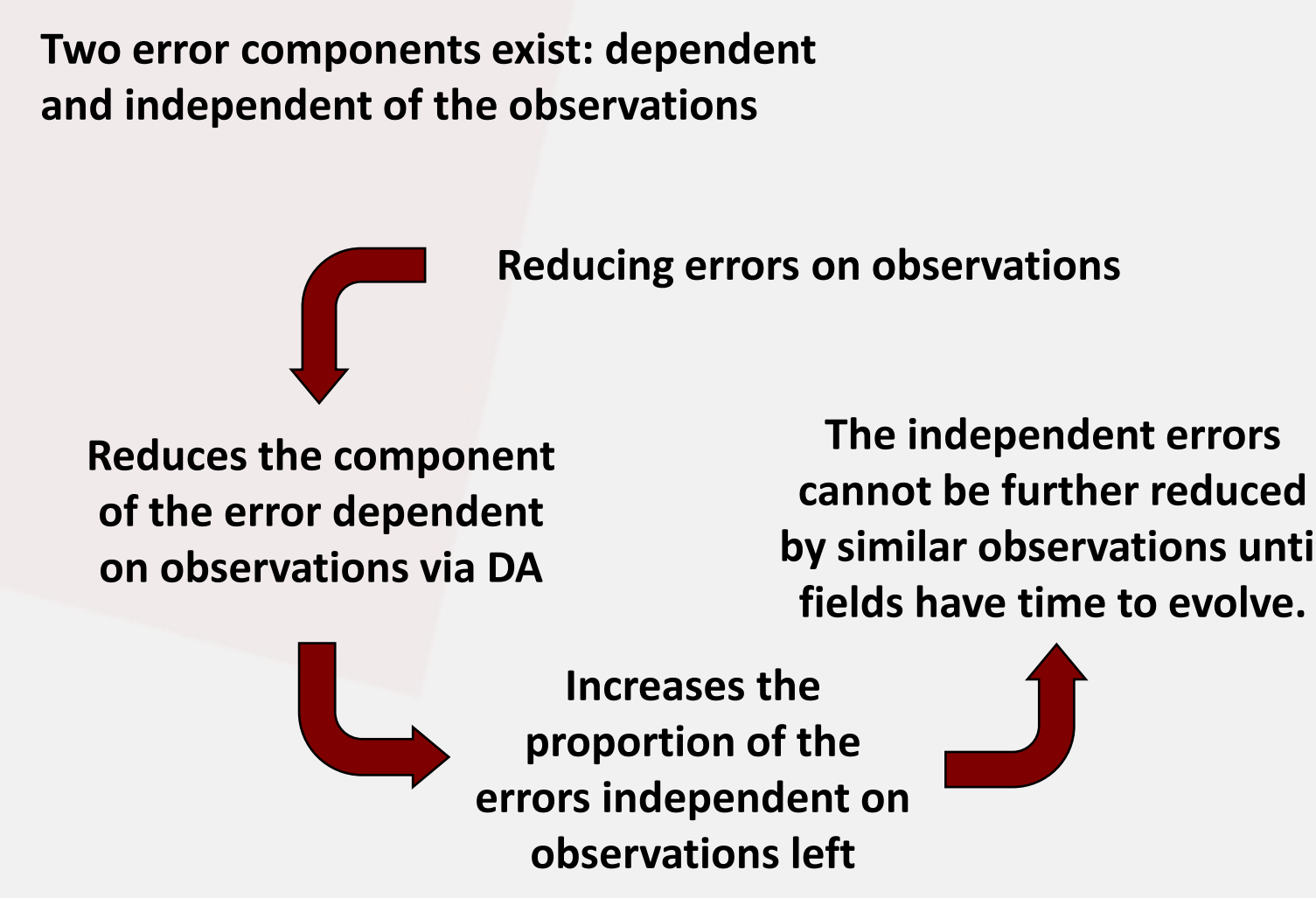
To fill the missing info, most **DA approaches rely on the covariance between errors**. But experience shows that it does not help much at convective scales. **Is it only us having these difficulties?**

We studied the analyses resulting from two state-of-the-art DA systems: the one used for the NSSL Spring Forecast Experiment, and the Japanese cycled assimilation of phased-array radars every 30 s.

**Results:** Ensemble spread of (thermo-)dynamic fields at storm scale exceeds  $\pm 70\%$ , **limiting predictability**

#### Why is this the case?

- Strong relationships between observations and model thermodynamics are needed. But convective **storms evolve too chaotically** for useful linear error relationships to arise;
- **Error correlations are weak**, limiting radars' ability to correct unobserved properties;
- Considerable **uncertainty remains** in key storm fields.
- Plus, every time **error covariances** are used by a DA machine, they are **"consumed"**, reducing their strength and their future usefulness at correcting remaining errors



We have **tried several new approaches** to improve radar data DA in order to fight this limitation, including:

- Multi-scale DA
- Grafting/Bogussing storms
- Assimilating trends / tendencies
- Assimilating future rainfall
- Momentum nudging

However, gains remain marginal as **storm dynamics remains misrepresented**.

Scan QR code for details



#### Sobering conclusions:

- 1) Radar-dominated DA struggles** at constraining supporting fields needed by NWP;
- 2) However, **radars detecting most threats** (heavy rain, hail, strong winds...), rule-based **nowcasting** (imposed or learned) can more easily **take advantage of time continuity** and clear **pattern-based associations** (e.g., weak echo regions, kidney signatures, VIL, ...).

→ This **explains why "simplistic" rule-based nowcasting** generally **outperforms** technically-superior **physically-based NWP** in predicting **storm threats** at short lead times. This may be where the future of threat nowcasting is!

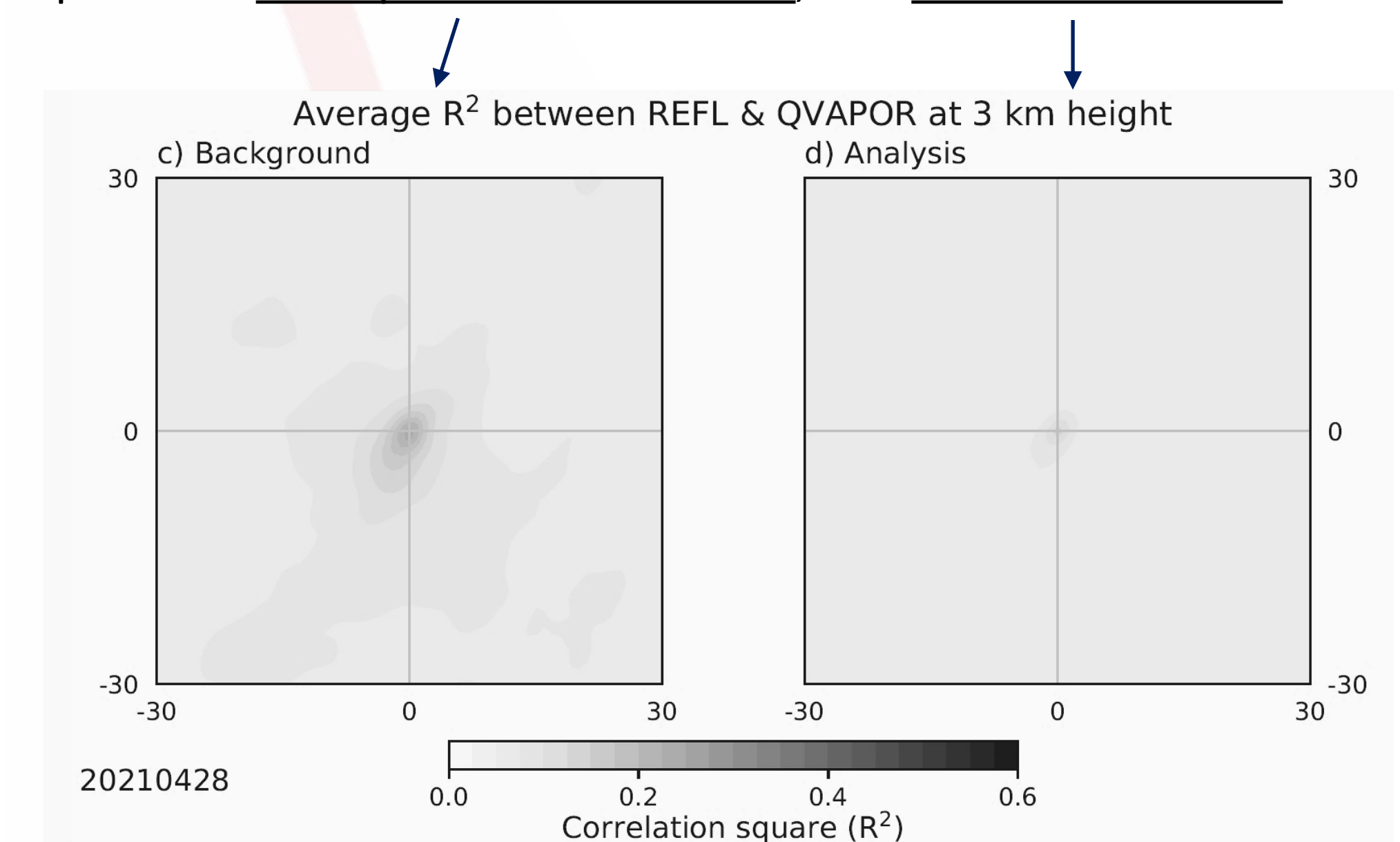
→ Unless we can find a way to constrain many more of  $u, v, w, P, T, e, q_{\text{cloud}}$  at storm scales observationally or otherwise, this will remain so for a long time: **Radar-dominated DA cannot do it alone**.

## Supporting material

### NSSL Spring Forecast Experiment (2020-21):

Large ensemble spreads for 1-hr forecasts below 50-km scale result from large spread at analysis time below 30-km scale.

Reason #1: The correlations  $R$  between reflectivity (or radial velocity) at a grid point and other variables at or near this grid point are weak prior to assimilation, and even weaker after.



Reason #2: Other observations are too sparse to help much.

### 30-s assimilation cycle of phased-array radar data (Ruiz et al. 2021):

Frequent assimilation collapses error correlations  $R$ , reducing their ability to correct unobserved fields.

Context: A perfect observation (ha!) reduces the error on an unobserved quantity by  $1 - \sqrt{1 - R^2}$ :

A correlation of  $\pm 0.5$  leads to a 13% error reduction; a 50% error reduction requires a correlation of  $\pm 0.87$ .

