Skillful Subseasonal Forecasts of Weekly Tornado and Hail Activity using the Madden-Julian Oscillation*

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1. Motivation

Annually, in the United States:

- Tornadoes kill ~80 people and injure ~1,500 more.
- Hail storms cause ~one billion dollars in damage to property and crops.
- Accurate subseasonal forecasts of tornado and hail activity with lead times of 2.5 weeks would increase public awareness and benefit stakeholders, emergency managers, and insurers.

Can we skillfully forecast convective severe weather activity at subseasonal timescales with knowledge of the current state of the Madden-Julian Oscillation (MJO)?

2. Data & Methods

- Tornado and hail reports from NCEP/FNL’s storm reports database
  - Only F1+ tornado reports considered
  - Only hail reports of greater than 1” diameter considered
- Tornado and hail events defined as at least one tornado or hail report occurring in a given 1.5° x 1.5° grid box in a given day
- Two principal 7.5° x 7.5° regions studied: The Plains and The Southeast
- Environmental convective severe weather parameters of surface-based convective available potential energy (CAPE), storm relative helicity (SRH), and CAPE × SRH (CSRH2) derived from ERA-Interim (1979-2015)
- Composite, overlapping, weekly composites and forecasts made in a function of MJO phase (DIM) and lead time:
  - Days 8 to 14
  - Days 10 to 16
- Empirical prediction model based on Mundhenk et al. (2018)
  - Use the current state of the MJO as a predictor
  - Predict above or below normal activity by comparing the median of the conditional, MJO-phase versus lead time-based distribution of the March-June climatological distribution
- Cross-validate using typical, leave-one-year-out methodology
- Verify with the Heidke Skill Score

3. Climatology of Tornado and Hail Events

- Tornadoes are common in the Plains and Southeast, while hail is more common in the Plains.
- CSRH2 serves as a better proxy for tornado and hail events than either CAPE or SRH alone.

4. Seasonal Cycles of Tornado Events, Hail Events, CAPE, SRH, and CSRH2

- The season of interest: March-June, is shaded in light brown. The seasonal cycle for each variable has been normalized by its respective annual maximum.
- Regions in the Plains exhibit higher average skill scores for forecasts of tornado and hail events than elsewhere.

5. MJO Phase versus Lead Time Composites of Severe Weather Variables

- CAPE, SRH, and CSRH2 have signals that propagate through MJO phases deep into subseasonal lead times.
- Tornado and hail events also distinctly propagate, especially in the Plains.

6. Heidke Skill Scores of the Empirical Prediction Model

- “Forecasts of opportunity” with significant skill for CAPE, SRH, and CSRH2 extend deep into subseasonal lead times.
- Tornado and hail forecasts also have significant skill at subseasonal lead times in the Plains.

7. Average Heidke Skill Scores for Overlapping 7.5° x 7.5° Regions

- Regions in the Plains exhibit higher average skill scores for forecasts of tornado and hail events than elsewhere.

8. Conclusion & Discussion

- Using only the current state of the MJO as a predictor, skillful weekly “forecasts of opportunity” exist for convective severe weather parameters and actual tornado and hail events themselves out to subseasonal lead times of 5 weeks.
- Possible ways to improve the empirical model include using additional predictors, expanding to three-classes, and hybridizing with dynamical model predictions of the MJO.

9. References and Acknowledgements

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