



Supplement of

Warm-sector heavy rainfall over the eastern China plains: identification, characteristics, and precursor dynamic signals

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S1. Objective frontal detection based on the Thermal Front Parameter

Following the framework of Renard and Clarke (1965), Hewson (1998) and Jenkner et al. (2010), and adapted to the warm-season North China configuration of Fu et al. (2020), an automated front-detection algorithm was developed and applied to ERA5 hourly reanalysis on the 850-hPa isobaric surface over the domain 97° – 132° E, 22° – 57° N (14640 hourly time steps spanning the analysis period). The algorithm comprises three modules that

(i) compute diagnostic fields from the 850-hPa pseudo-equivalent potential temperature (θ_e),

(ii) apply masking and threshold rules to retain candidate fronts, and

(iii) invert the retained fronts for type, length, and position.

A flow chart of the procedure is given in Fig. S1, and a worked example for 1700 BJT, August 18, 2023 is shown in Fig. S2.

S1.1. Input data and pre-processing

For each hourly time step T_i , the specific humidity q , relative humidity RH , air temperature T , and the horizontal wind components u and v at 850 hPa were extracted from ERA5 ($0.25^{\circ} \times 0.25^{\circ}$). The pseudo-equivalent potential temperature θ_e was computed from T , q and pressure following Bolton (1980). To suppress the high-frequency noise to which the second- and third-order spatial derivatives of θ_e are extremely sensitive, the θ_e field was smoothed eight times with a Gaussian filter, consistent with Jenkner et al. (2010) and Fu et al. (2020).

S1.2. Diagnostic fields (Module i)

Four diagnostic fields are then derived on the smoothed θ_e field. The Thermal Front Parameter (TFP; Renard and Clarke, 1965; Hewson, 1998) is defined as the projection of the gradient of the gradient magnitude of θ_e onto the unit vector pointing down-gradient:

$$\text{TFP} = -\nabla |\nabla \theta_e| \cdot \frac{\nabla \theta_e}{|\nabla \theta_e|} \quad (\text{S1})$$

In addition, the gradient magnitude of θ_e (used as a measure of frontal strength), the masking parameter MP, and the front-normal wind component V_f are computed as:

$$\text{GEPT} = |\nabla\theta_e| \quad (S2)$$

$$\text{MP} = -\frac{\nabla\theta_e \cdot \nabla|\nabla\theta_e|}{|\nabla\theta_e|} \quad (S3)$$

$$V_f = \mathbf{V}_{850} \cdot \frac{\nabla\theta_e}{|\nabla\theta_e|} \quad (S4)$$

where $\mathbf{V}_{850} = (u, v)$ is the 850-hPa horizontal wind, and $\frac{\nabla\theta_e}{|\nabla\theta_e|}$ is the unit vector along $\nabla\theta_e$, which by construction points from the cold air toward the warm air. Hence positive (negative) V_f indicates motion of the front toward (away from) the warm air, i.e., cold-frontal (warm-frontal) propagation. All horizontal derivatives were evaluated by centered differences on the spherical grid, and TFP and MP were converted to units of $\text{K} (100 \text{ km})^{-2}$ for visualization.

The locus $\text{TFP} = 0$ identifies the line along which $|\nabla\theta_e|$ is maximized in the down-gradient direction, i.e., the center of the frontal zone (Hewson, 1998).

51.3. Masking and threshold rules (Module ii)

Three successive rules are applied to convert raw $\text{TFP} = 0$ contours into synoptic-scale fronts.

Rule A — Strength and warm-side masking. Only grid points satisfying both

$$\text{GEPT} \geq K_1 = 4 \text{ K} (100 \text{ km})^{-1} \text{ \& } \text{MP} \leq 0 \quad (S5)$$

are retained. The first criterion isolates strongly baroclinic zones, while $\text{MP} \leq 0$ restricts the candidate to the warm side of the frontal zone, which in the Hewson (1998) framework corresponds to the operationally drawn front line. The threshold $K_1 = 4 \text{ K} (100 \text{ km})^{-1}$ was selected for warm-season North China and is consistent with the value adopted by Fu et al. (2020) and Song et al. (2023).

Rule B — Extraction of $\text{TFP} = 0$ contour segments. Within the binary mask defined by Eq. (S5), zero-contours of TFP are extracted using the marching-squares algorithm. Each connected polyline constitutes a candidate front.

Rule C — Synoptic length filter. The arc length of each candidate front is measured along its polyline. Candidates shorter than 10° of arc are discarded as sub-synoptic noise, and the remainder are promoted to synoptic fronts.

S1.4. Front-type, length and position inversion (Module iii)

For each retained synoptic front, three attributes are diagnosed.

Position. The geometric position of the front is given by the sequence of vertices $\{(\lambda_k, \varphi_k)\}$, $k = 1, 2, \dots, N$, that define the $\text{TFP} = 0$ polyline, where λ_k and φ_k are the longitude and latitude of the k -th vertex along the polyline. As shown by Hewson (1998), this locus coincides with the center of the baroclinic zone.

Length. The arc length is reported in both degrees and kilometers.

Type. The polyline is resampled into M equispaced points and the front-normal wind $V_{f,m}$ is interpolated from the 850-hPa u and v fields at each sampling point using bilinear interpolation. The along-front mean

$$\bar{V}_f = \frac{1}{M} \sum_{m=1}^M V_{f,m} \quad (S6)$$

is converted to m s^{-1} and used to classify the front following Berry et al. (2011) and the rules in Fu et al. (2020):

$$\text{Front type} = \begin{cases} \text{Quasi-stationary front,} & |\bar{V}_f| \leq 1.5 \text{ m s}^{-1}, \\ \text{Cold front,} & \bar{V}_f > +1.5 \text{ m s}^{-1}, \\ \text{Warm front,} & \bar{V}_f < -1.5 \text{ m s}^{-1}. \end{cases} \quad (S7)$$

The classified fronts at T_i are written to the synoptic frontal field $\text{SFF}[T_i]$, together with their geometric coordinates, length, $\bar{V}_f$, and type label.

S1.5. Worked example: 1700 BJT, August 18, 2023

Figure S2 illustrates the algorithm at 1700 BJT, August 18, 2023. Panel (a) shows the smoothed 850-hPa θ_e field overlaid with the 850-hPa wind. The navy polygon outlines the warm, moist air mass (340–344 K) over the North China Plain. A sharp θ_e gradient marks its northern and northwestern edge (35–40°N), where northerly flow

advection cooler air. Panel (b) shows the TFP field with the contours $TFP = 0$ (green), $GEPT = 4K (100 km)^{-1}$ (black) and $\nabla^2 |GEPT| = 0$ (yellow). Segments satisfying Rules A–C (blue) are the candidate fronts. The principal segment crosses the analysis box (104.5–129.5°E, 24.5–46.5°N), exceeds 10° in arc length, and is classified as a cold front.

S2. Identification of Low-level jet

An LLJ is identified from each 6-min RWP profile as a low-level wind-speed maximum (a jet nose) overlain by substantial shear. Its strength is the wind-speed maximum at the nose, V_{max} . The shear parameter is $\Delta V = V_{max} - V_{min}$, where V_{min} is the first wind-speed minimum above the core; when no minimum is found below 3 km, the speed at 3 km (V_{3km}) is used, so that $\Delta V = V_{max} - V_{3km}$. Following Whiteman et al. (1997), a profile is taken to contain an LLJ when $V_{max} > 10 m s^{-1}$ within the lowest 3 km AGL and $\Delta V \geq 5 m s^{-1}$. The height and direction of the LLJ are those of V_{max} . A worked example, showing the jet core, the wind-speed minimum above it, and the resulting ΔV , is given in Fig. S3.

When a profile shows more than one jet nose, as in the double-nosed or double low-level jet structures in which a boundary-layer jet underlies a synoptic-system-related jet (Du and Chen, 2018, 2019), only the strongest nose (the largest V_{max}) is retained, and the two jets are not identified or treated separately. This single-maximum treatment follows the classical jet-core criterion of Bonner (1968) and Whiteman et al. (1997).

S3. Sample dependence and uncertainty assessment

S3.1. Episode grouping and composite weighting

Rainfall events were defined at individual stations, so multiple station-based events could be associated with the same weather episode. The distributions of event counts per station are shown in Fig. S4a, b. Under the selected spatial and onset-time difference thresholds of 500 km and 24 h, the full WSHR sample contains 148 episode

clusters. The 62 RWP-observed WSHR events belong to 47 of these clusters, comprising 37 clusters with one RWP event, six with two, three with three, and one with four events (Fig. S4d). These clusters are operational groupings of potentially related events; their statistical independence is not established.

The main composites give equal weight to station-based events. To assess sensitivity to episodes contributing multiple events, equal-episode composites were also examined (Fig. S5). Event diagnostics were first averaged within each cluster and then averaged across clusters with equal weight. Each station event retained its own local rainfall-onset reference time.

S3.2. Bootstrap confidence intervals for LLJ occurrence frequency

At each lead time, LLJ occurrence frequency was calculated as the percentage of events with an identified LLJ among events with valid LLJ classifications. The pointwise confidence intervals in Fig. 11d were obtained separately for WSHR and WS non-HR using 1000 event-bootstrap replicates and a random seed of 42. Each replicate resampled complete event sequences with replacement, thereby preserving temporal dependence within individual events. The 2.5th and 97.5th percentiles of the bootstrap frequencies define the pointwise 95% confidence intervals.

To assess sensitivity to dependence among station events, event and episode-cluster bootstrap intervals are compared in Fig. S10 using 5000 replicates. In the episode-cluster bootstrap, clusters are sampled with replacement and all member event sequences of each selected cluster are retained together. Frequencies are then recalculated from the sampled events. These intervals quantify uncertainty at individual lead times and are not simultaneous confidence bands for the entire time series.

S3.3. Paired changes in LLJ occurrence

For each WSHR event, the LLJ occurrence proportion was calculated over an early window from -180 to -120 min and a late window from -60 to 0 min, including both endpoints. Each window contains 11 observations at 6-min intervals. The paired change

was defined as the late-window proportion minus the early-window proportion, expressed in percentage points. All 62 events had complete LLJ classifications for these windows.

The mean paired change is 7.04 percentage points. Resampling the 47 episode clusters with replacement 5000 times, with all member events retained and a random seed of 42, gives a percentile-based 95% confidence interval of -0.25 to 14.18 percentage points. A sensitivity calculation uses the windows from -180 to -126 min and from -60 to -6 min, excluding rainfall onset. Each window contains 10 observations. The mean change is 6.94 percentage points, with a 95% confidence interval of -0.52 to 14.22 percentage points. Both estimates indicate an increase in the sample mean, but neither interval excludes zero.

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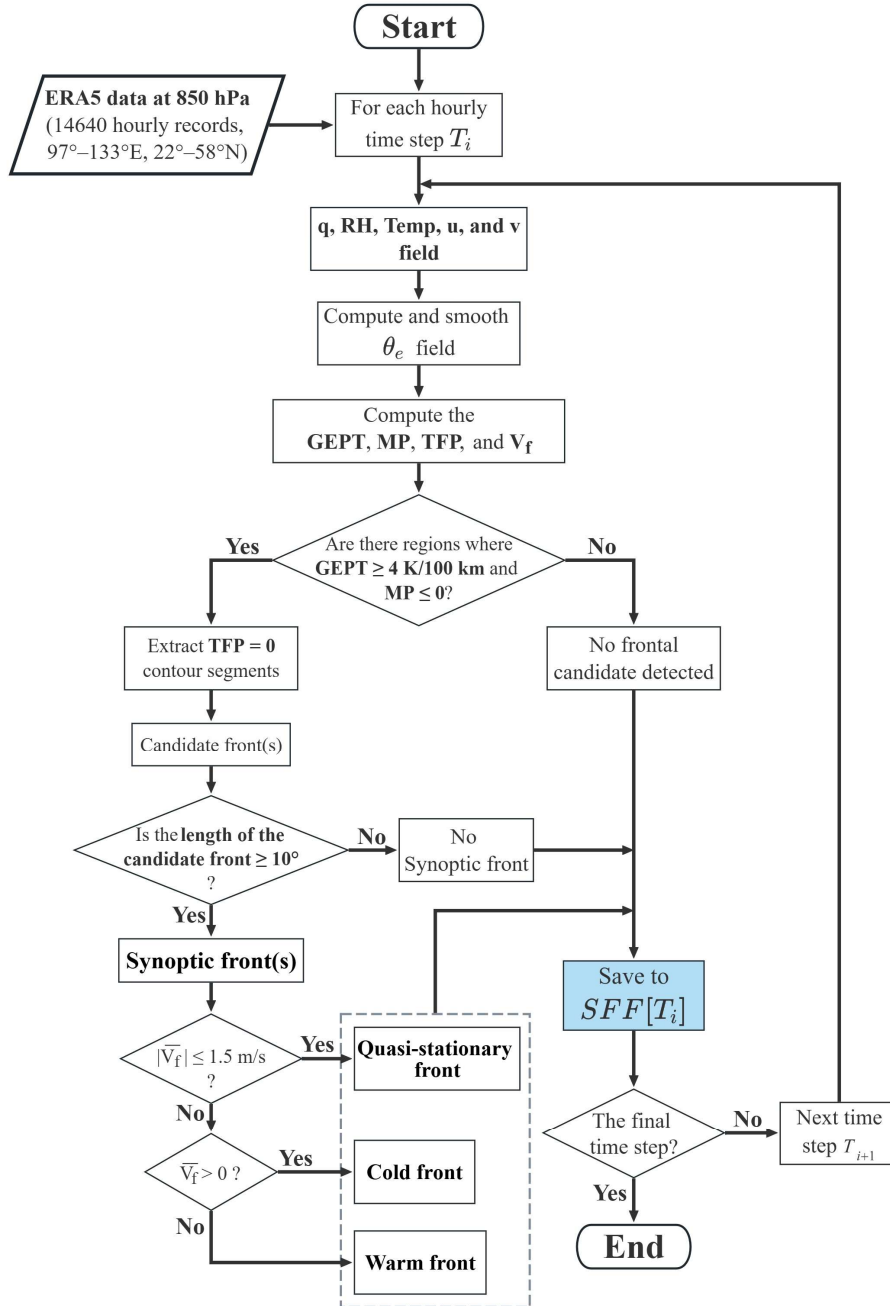
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209

210 **Figure S1.** Flow chart of the objective front-detection algorithm (Sect. S1) applied to
 211 the hourly 850-hPa ERA5 fields. GEPT denotes the magnitude of the θ_e gradient, MP
 212 the masking parameter, TFP the thermal front parameter, and V_f the along-front mean
 213 front-normal wind. Fronts retained at each time step T_i are written to the synoptic
 214 frontal field $SFF[T_i]$.

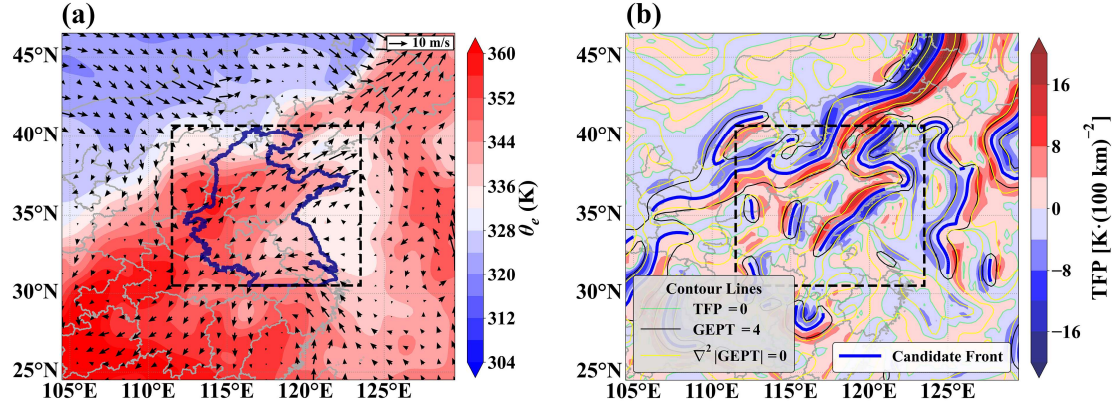
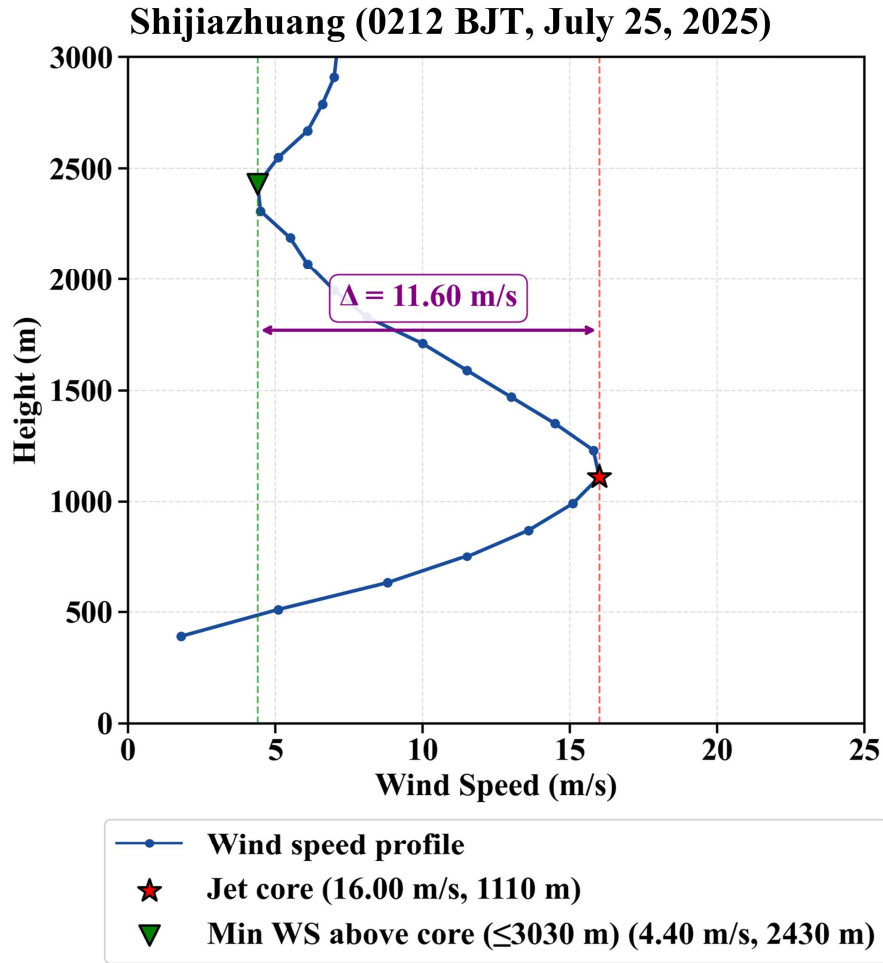


Figure S2. Worked example of the front-detection algorithm at 1700 BJT, August 18, 2023 (Sect. S1.5). (a) Smoothed 850-hPa θ_e (shading; K) and 850-hPa wind (vectors); the navy polygon outlines the warm, moist air mass (340–344 K). (b) TFP [shading; K (100 km)^{−2}] with the TFP = 0 (green), GEPT = 4 K (100 km)^{−1} (black), and $\nabla^2|\text{GEPT}| = 0$ (yellow) contours; candidate fronts satisfying Rules A–C are drawn in blue.



221

222 **Figure S3.** Worked example of the low-level jet (LLJ) identification (Sect. S2) for
 223 Shijiazhuang station at 0212 BJT, July 25, 2025. The wind-speed profile (blue) has its
 224 jet core (red star) at $V_{max} = 16.0 \text{ m s}^{-1}$ and 1110 m AGL; the wind-speed minimum
 225 above the core (green triangle) is 4.4 m s^{-1} at 2430 m, giving $\Delta V = 11.6 \text{ m s}^{-1}$. Both
 226 criteria ($V_{max} > 10 \text{ m s}^{-1}$ and $\Delta V \geq 5 \text{ m s}^{-1}$) are satisfied.

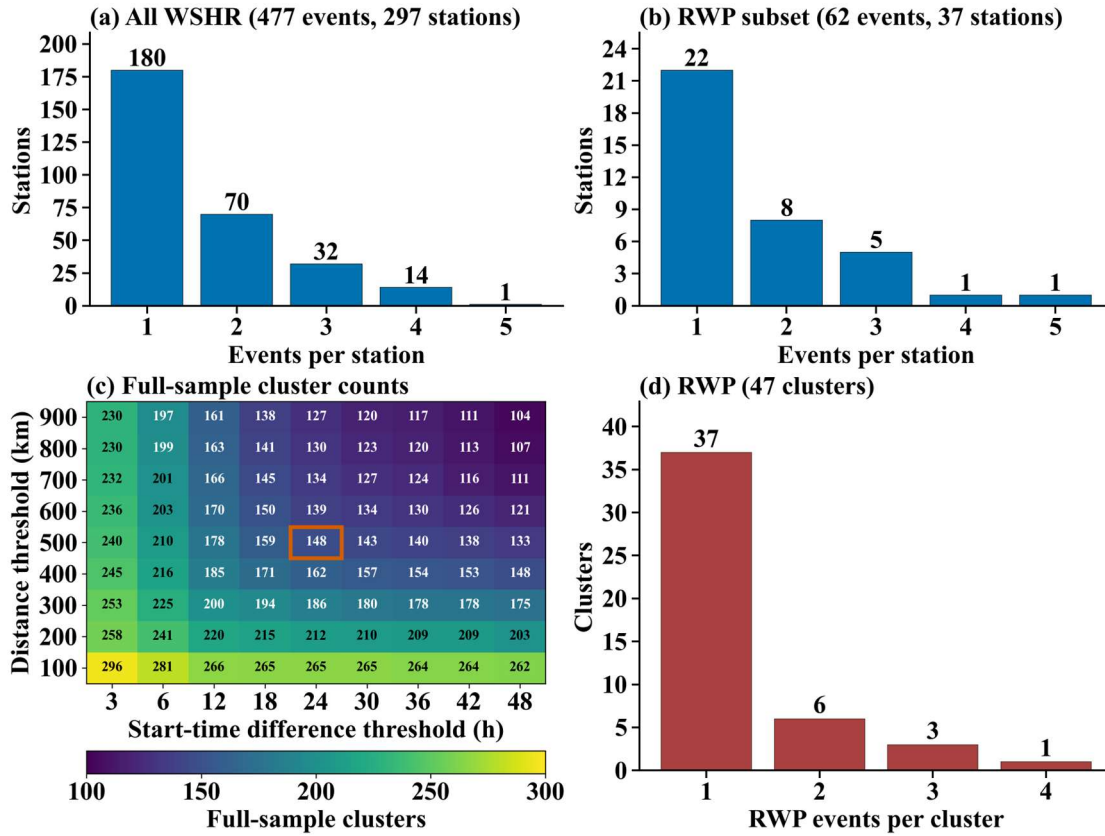


Figure S4. Distribution and clustering of warm-sector heavy rainfall (WSHR) events. (a, b) Numbers of stations with different event counts in the full sample (477 events) and the radar wind profiler (RWP) subset (62 events), respectively. (c) Episode-cluster counts for different spatial and temporal thresholds; the orange box marks the selected thresholds of 500 km and 24 h. (d) Distribution of RWP-observed events per episode cluster, using the 500 km and 24 h thresholds highlighted in (c). Panel (a) includes only the 297 stations with at least one WSHR event; the 196 stations without WSHR are excluded.

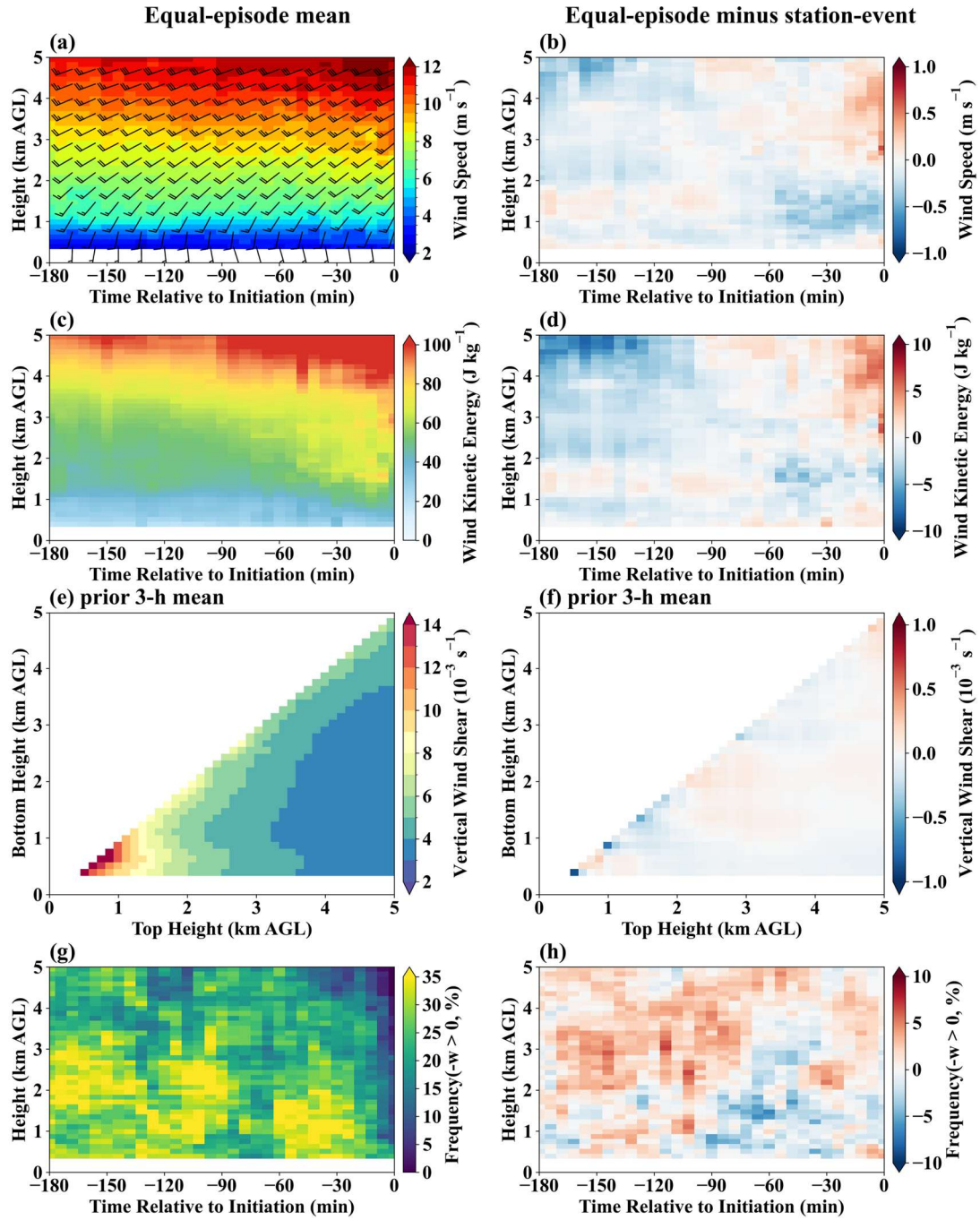


Figure S5. Equal-episode composites of WSHR events (left) and differences relative to station-event composites (right). (a, b) horizontal wind speed, (c, d) wind kinetic energy, (e, f) vertical wind shear averaged over the preceding 3 h, and (g, h) ascending motion frequency. The right-hand panels show the equal-episode composite minus the station-event composite. Differences in ascending-motion frequency are expressed in percentage points.

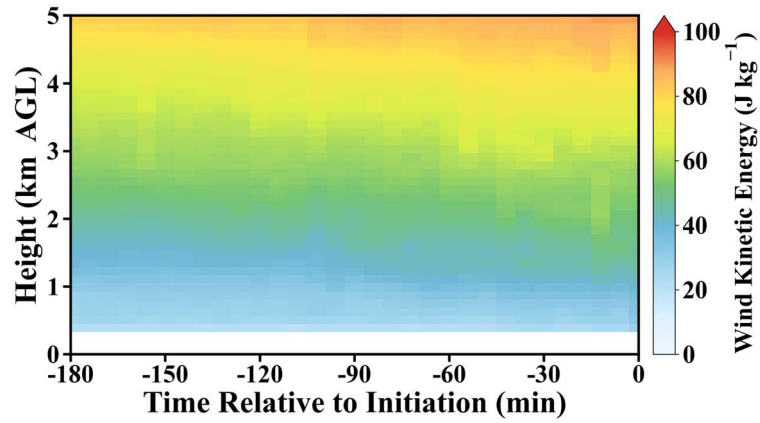


Figure S6. Composite time–height evolution of wind kinetic energy (shading, J kg^{-1}) during the 180 min preceding local rainfall onset for 271 warm-sector non-heavy rainfall (WS non-HR) events from the same 37 co-located stations as the WSHR sample. Time zero denotes local rainfall onset at the rain gauge, and height is above ground level. The color scale is the same as in Fig. 9c to facilitate comparison with the WSHR composite.

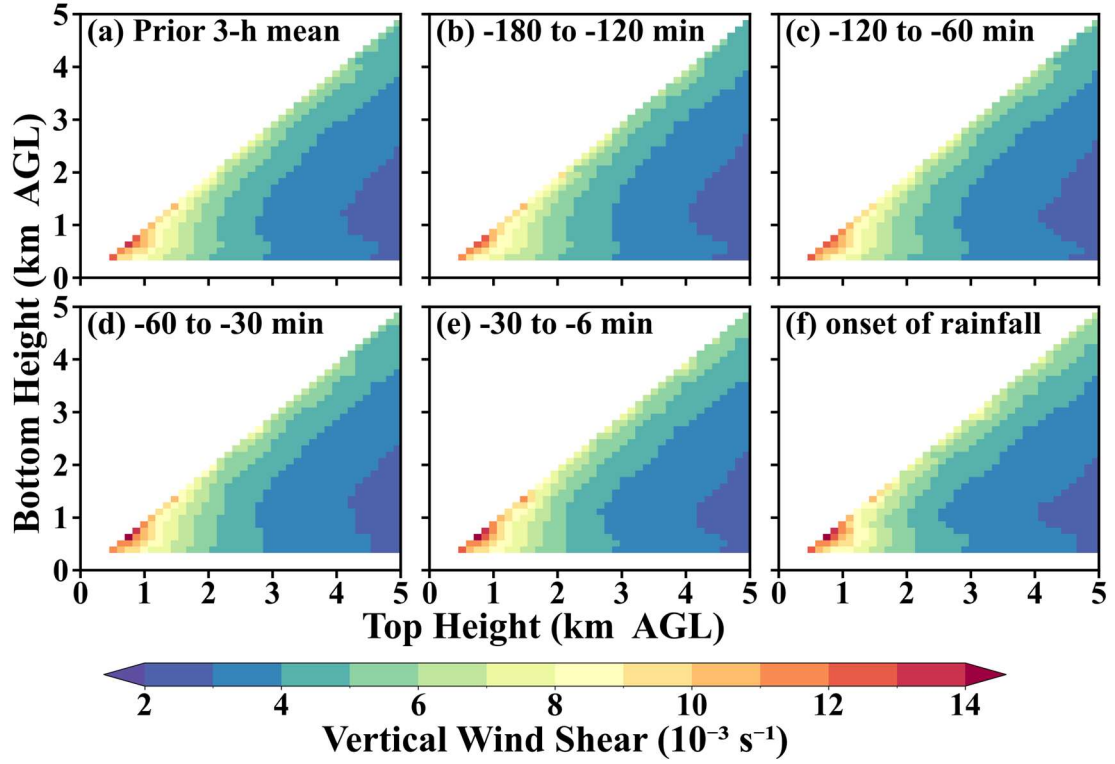


Figure S7. Composite vertical wind shear (shading, 10^{-3} s^{-1}) preceding the onset of WS non-HR events. (a) prior 3-h mean, (b) -180 to -120 min, (c) -120 to -60 min, (d) -60 to -30 min, (e) -30 to -6 min, and (f) the onset of rainfall. The abscissa and ordinate denote the top and bottom heights (km AGL), respectively, of the layer over which the bulk shear is computed.

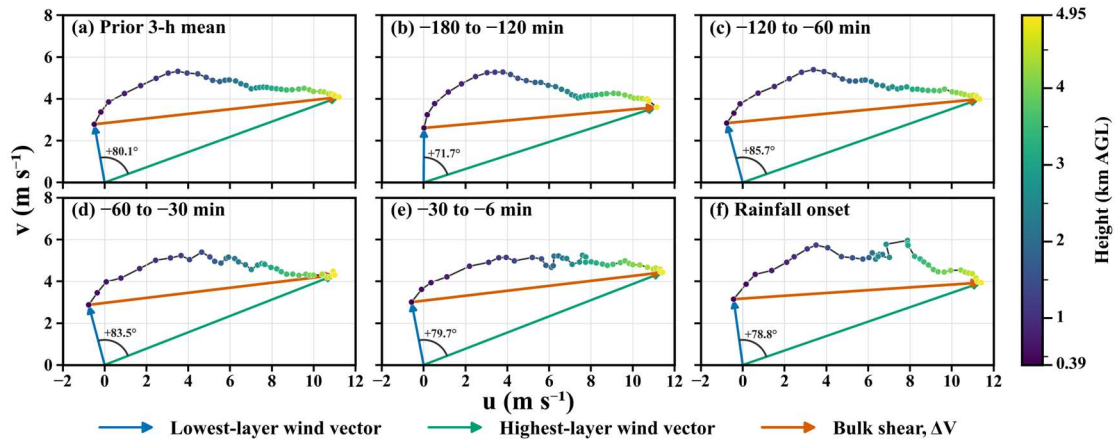


Figure S8. Composite hodographs for WSHR events: (a) the 3 h preceding rainfall onset, (b–e) the indicated pre-onset intervals, and (f) rainfall onset. Colors indicate height above ground level. Blue and green arrows denote the lowest- and highest-layer wind vectors, respectively; orange arrows indicate the top-minus-bottom wind-vector difference (ΔV , m s^{-1}). Annotated angles show the angular separation between the two wind vectors.

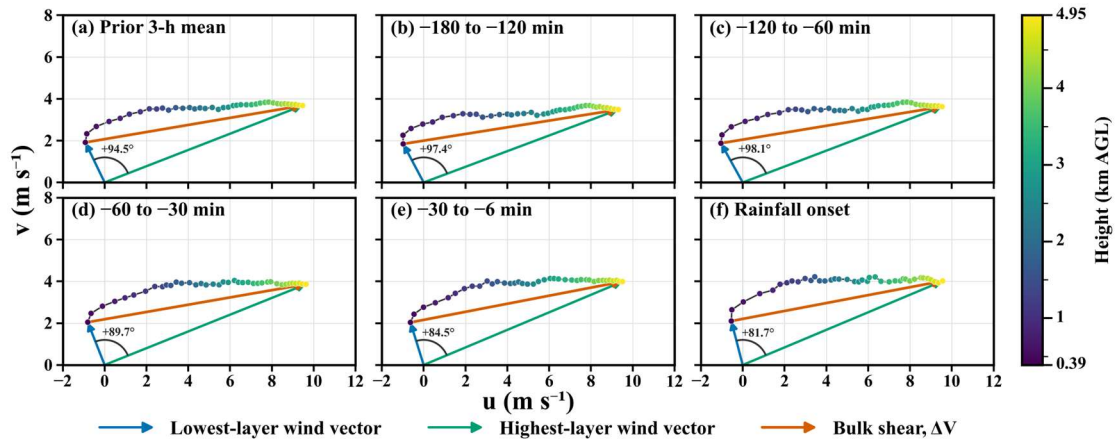


Figure S9. Same as Fig. S8, but for WS non-HR events.

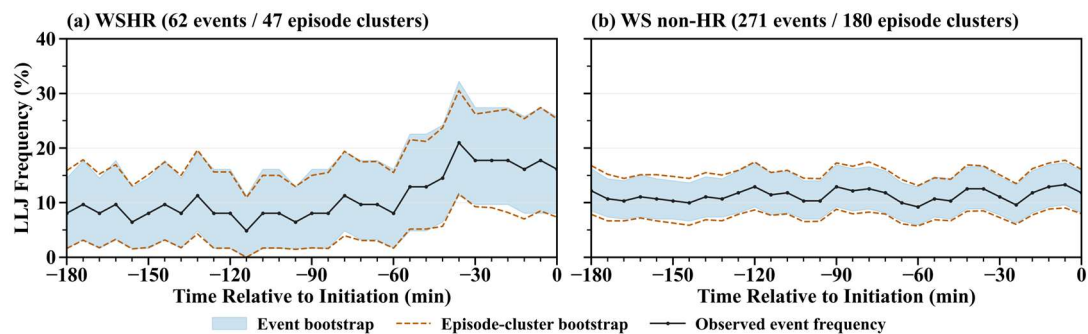


Figure S10. Event and episode-cluster bootstrap comparisons of LLJ frequency for (a) WSHR and (b) WS non-HR. Black curves show observed frequencies at 6-min intervals relative to local rainfall onset. Blue shading and orange dashed boundaries denote pointwise 95% confidence intervals from 5000 event and episode-cluster bootstrap replicates, respectively. Episode clusters use 500-km and 24-h thresholds.