S1 Optical flow models' parameters

S1.1 Local optical flow models (the Sparse group)

Shi–Tomasi corner detector parameters:

- Maximum number of corners to return (default: 200; ranges: [50, 300])
- Minimal accepted quality of image corners (default: 0.2; ranges: [0.1, 0.7])
- Minimum possible Euclidean distance between the returned corners (default: 0.2; ranges: [0.1, 0.7])
- Size of an average block for computing a derivative covariation matrix over each pixel neighborhood (default: 21; ranges: [10, 50])

Lucas–Kanade tracking algorithm:

- Size of the search window at each pyramid level (default: 20; ranges: [10, 30])
- Zero-based maximal pyramid level number (default: 2; ranges: [0, 4])

Interpolation algorithm:

- Regression model for tracking features extrapolation (default: linear regression)
- Features are used for building a regression model (default: ordinal, options: [polynomial])
- Warping scheme (default: affine, options: [euclidean, similarity, projective])

Parameters values were set up based on trial-and-error experimentation and the following online sources:

- http://docs.opencv.org/2.4/modules/imgproc/doc/feature_detection.html?highlight=goodfeaturestotrack#goodfeaturestotrack
- http://docs.opencv.org/2.4/modules/video/doc/motion_analysis_and_object_tracking.html

Experimentation with model parameters showed that the parameter of a minimal accepted quality of image corners is the most sensitive (affects results the most).

S1.2 Global optical flow models (the Dense group)

Farnebäck global optical flow algorithm parameters:

- Image scale to build pyramids (default: 0.5; ranges: [0.1, 0.9])
- Number of pyramid layers (default: 3; ranges: [1, 7])
- Averaging window size (default: 15; ranges: [5, 30])
- Number of iterations at each pyramid level (default: 3; ranges: [2, 10])
- Size of the pixel neighborhood (default: 5; ranges: [3, 10])
- Standard deviation of the Gaussian for smoothing derivatives (default: 1.1; ranges: [0.9, 2])

Parameters values were set up based on trial-and-error experimentation and the following online source:

- http://docs.opencv.org/2.4/modules/video/doc/motion_analysis_and_object_tracking.html#calcopticalflowfarneback

Experimentation with model parameters showed that the parameter of an averaging window size is the most sensitive (affects results the most).

S2 Implementation of a warping for an advection of a precipitation field

Figure S1 shows the simplified example of warping implementation to the problem of precipitation field advection. We suppose that we have precipitation field with uniform intensity and sharp boundaries. This assumption allows us to perfectly identify source corners (or "features"). The second assumption is that each "feature" has the same displacement (vector field is collinear). This assumption allows us to avoid uncertainty related to corners tracking (we assume the perfect tracking), and we can precisely identify target corners. Based on these assumptions, we calculate the affine transformation matrix and then implement it to our precipitation field to get advected (warped, nowcasted) precipitation field.

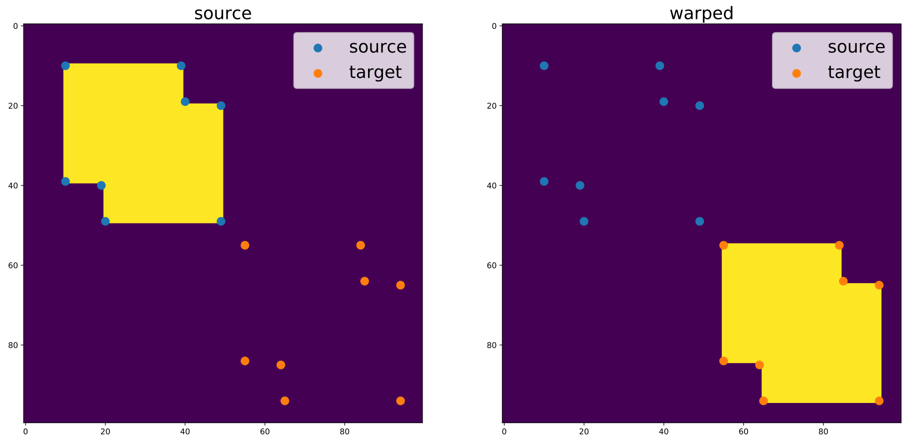

Figure S1. Result of well-defined warping operation

S3 Video clips of the selected events

You can find a Youtube playlist of the animated events by the following link:
https://www.youtube.com/playlist?list=PLeSStAZ1xRYDkzpJp7YLo8Eo12VLNEIJw

S4 Results in different categorical scores

We use the following categorical scores, where *hits*, *false alarms*, *misses*, and *correct negatives* are defined by the contingency table (Table S1) and the corresponding threshold value:

1. the false alarm ratio (FAR) – the fraction of falsely forecasted rain pixels to all forecasted rain pixels. FAR varies from 0 (best) to 1 (worst);
$$FAR = \frac{false\ alarms}{hits + false\ alarms}$$
2. the probability of detection (POD) – the fraction of correctly forecasted rain pixels to all rain pixels. POD varies from 0 (worst) to 1 (best);
$$POD = \frac{hits}{hits + misses}$$

3. the critical success index (CSI) – the fraction of correctly forecasted rain pixels to the sum of all rain pixels and false alarms. CSI varies from 0 (worst) to 1 (best);

$$CSI = \frac{hits}{hits + false\ alarms + misses}$$

4. the equitable threat score (ETS) – the adjusted and unbiased version of CSI, adjusted for the hits obtained by random chance. ETS varies from 1/3 (worst) and 1 (best) with 0 being the value of the random forecast.

$$ETS = \frac{hits - Dr}{hits + false\ alarms + misses - Dr}$$

$$Dr = \frac{(hits + false\ alarms)(hits + misses)}{hits + false\ alarms + misses + correct\ negatives}$$

Table S1. Contingency table for the categorial scores

Nowcast	Observation	
	Yes	No
Yes	hit	false alarm
No	miss	correct negative

Below you can find figures with FAR, POD, CSI, and ETS metrics for the selected events and different precipitation intensity threshold as follows:

– threshold = 0.125 mm h^{-1} : Figure S2

– threshold = 0.25 mm h^{-1} : Figure S3

– threshold = 0.5 mm h^{-1} : Figure S4

– threshold = 1 mm h^{-1} : Figure S5

– threshold = 5 mm h^{-1} : Figure S6

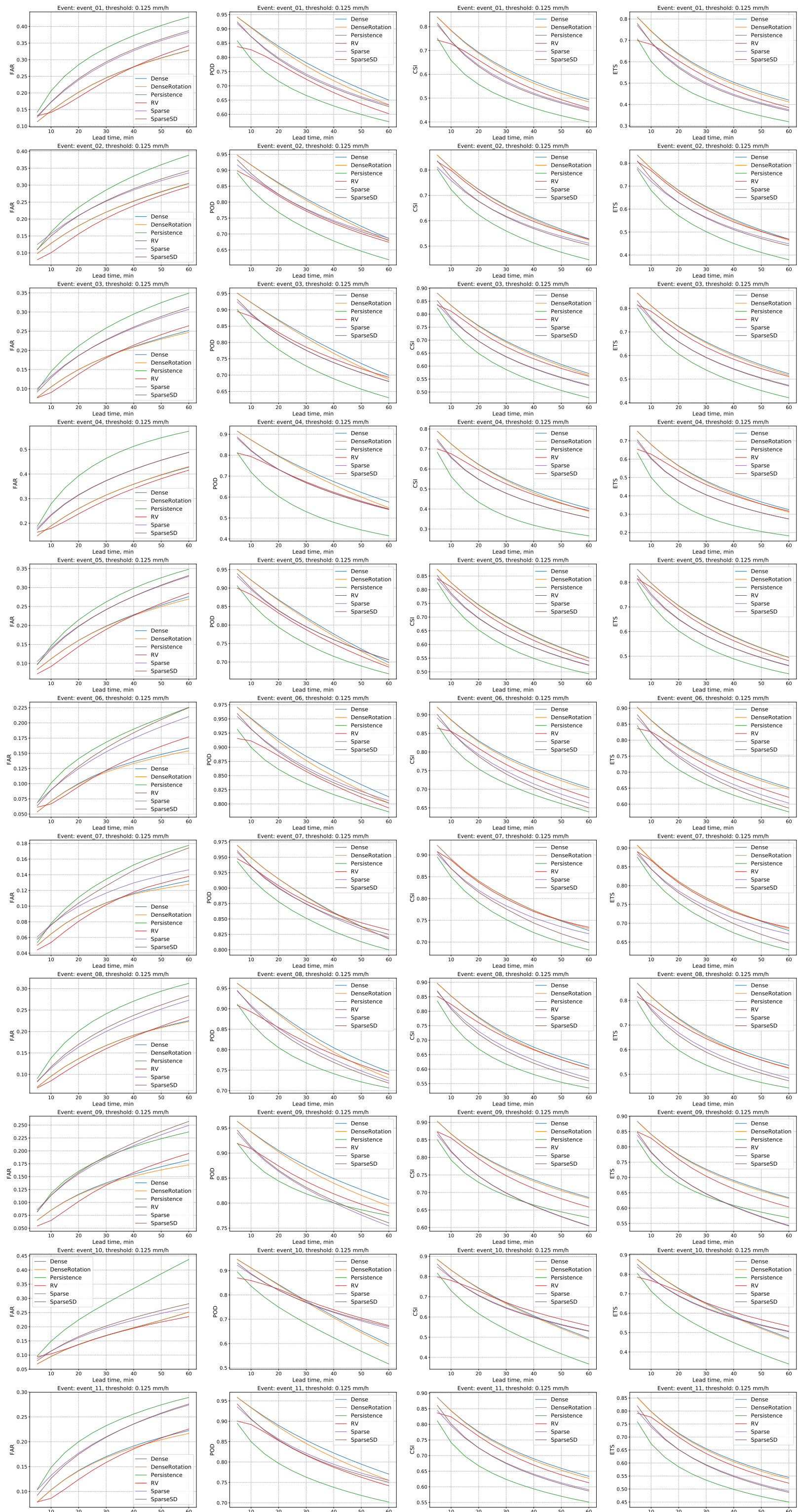

Figure S2. FAR, POD, CSI, and ETS for a rainfall threshold of 0.125 mm h^{-1}

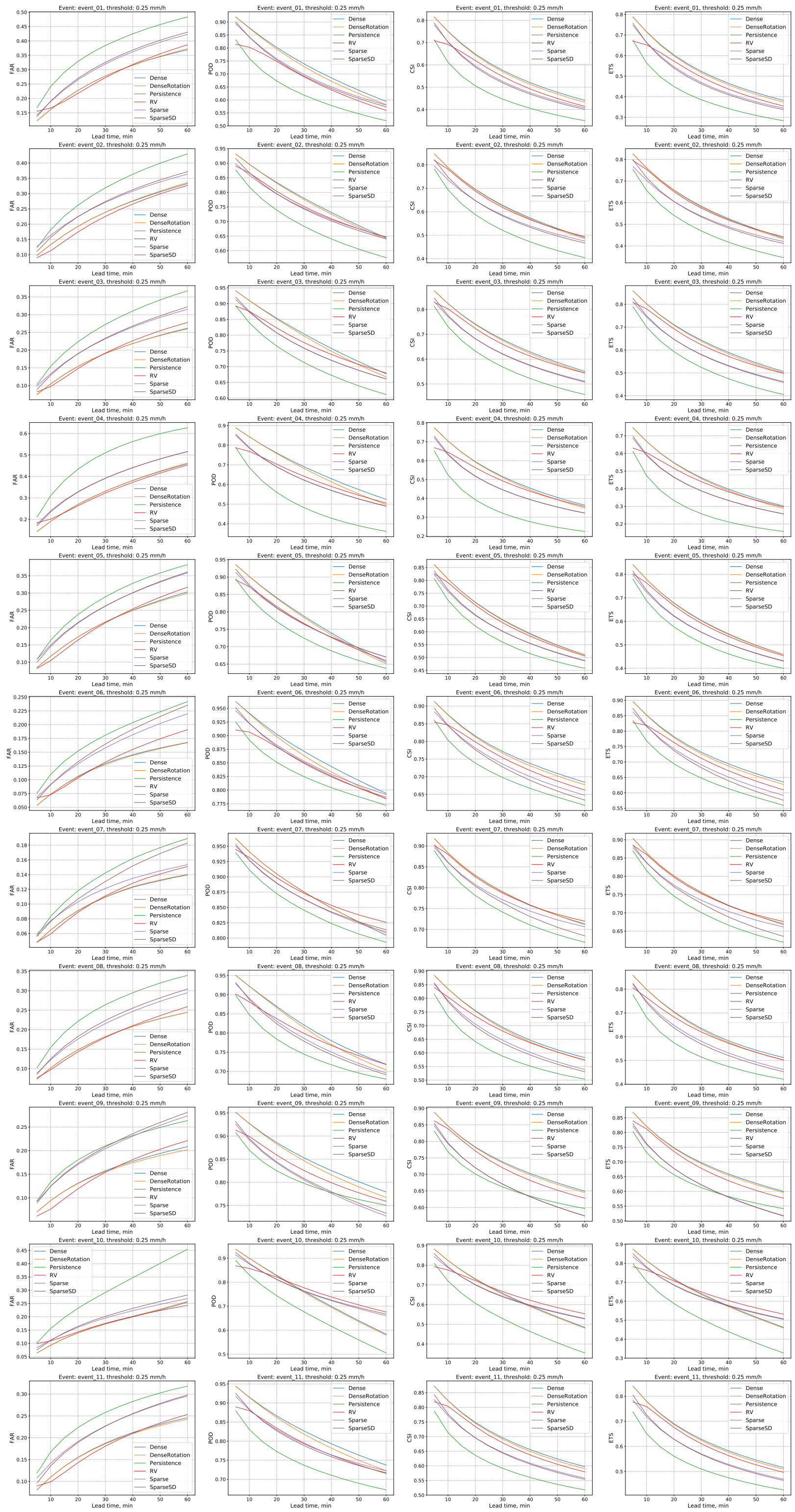

Figure S3. FAR, POD, CSI, and ETS for a rainfall threshold of 0.25 mm h^{-1}

Figure S4. FAR, POD, CSI, and ETS for a rainfall threshold of 0.5 mm h^{-1}

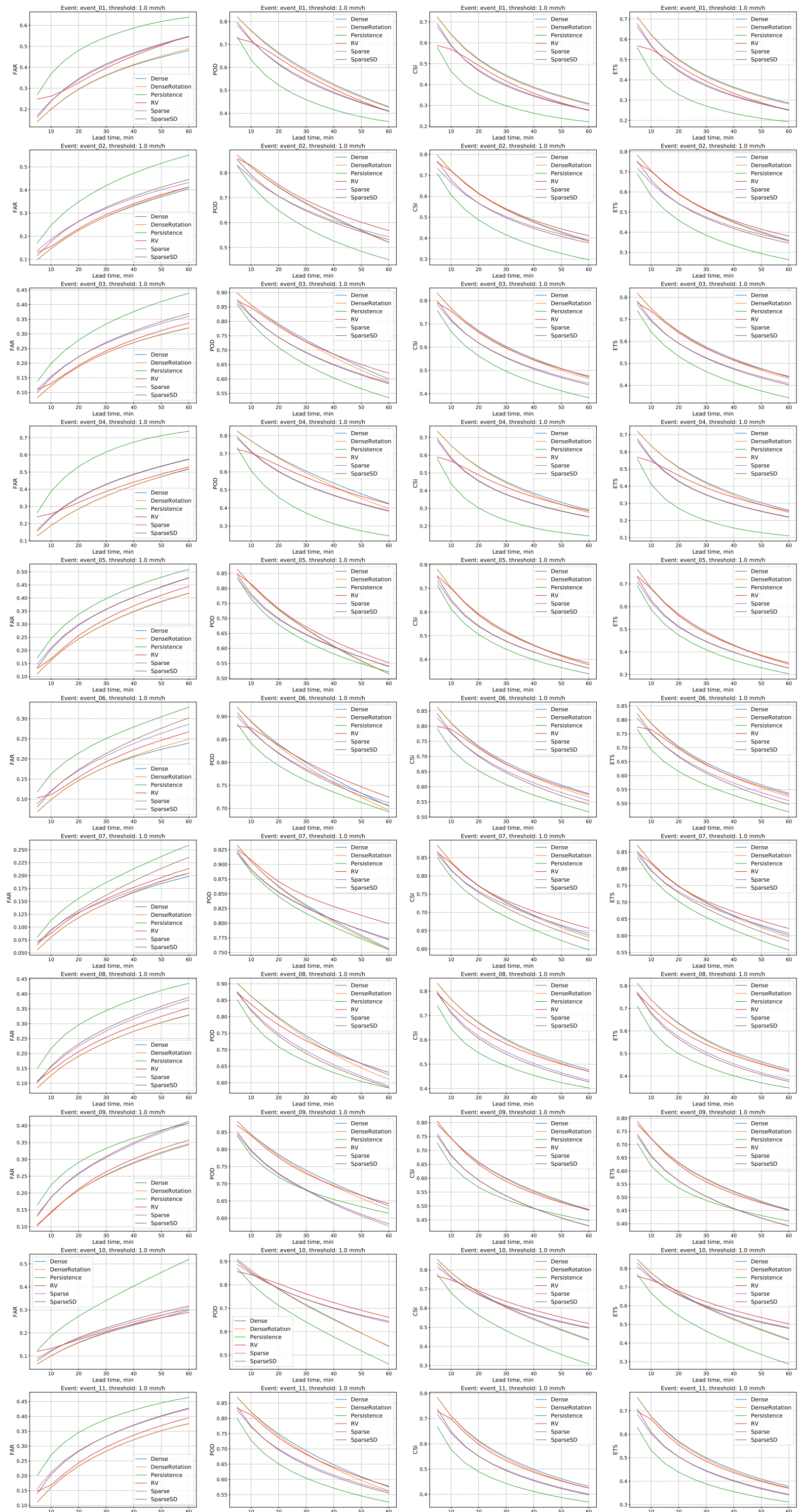

Figure S5. FAR, POD, CSI, and ETS for a rainfall threshold of 1 mm h^{-1}

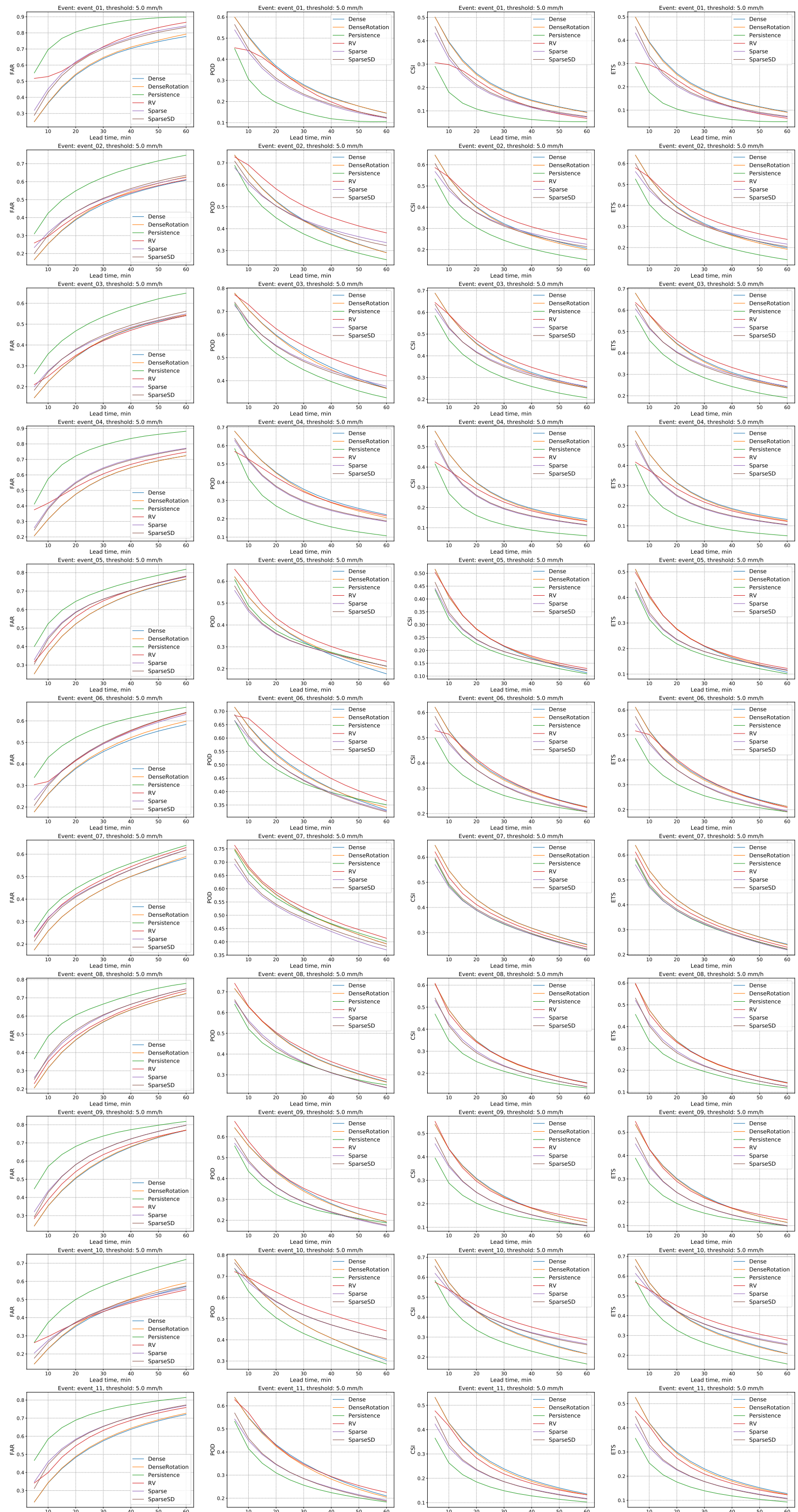

Figure S6. FAR, POD, CSI, and ETS for a rainfall threshold of 5 mm h^{-1}