

# **Double-moment normalization of hail size distributions and** retrieval of its moments from polarimetric radar measurements

# **1. Introduction**

Using measurements collected by the Swiss network of automatic hailsensors, we aim to estimate the hail size distributions (HSD) from polarimetric radar data. First, we describe the double-moment normalization of the HSD measured by the hailsensors, which allows us to estimate the HSD from two of its moments. The results are evaluated on an independent dataset, collected through drone-based photogrammetry.

Then, we extract radar volumes within a cone above each hailsensors. We select a series of descriptors (features) from these data and investigate their relationship with the moments of the hailsensors HSD. Using a smaller dataset, we use a regression for estimating the value of the HSD moments from a subset of the features, allowing us to reconstruct the full HSD.

# 2. Data

#### Swiss hailsensor network

80 hailsensors, partnership between La Mobilière and MeteoSwiss. Installed between 2018 and 2020 (Kopp et al., 2023).

Used in this study: 118 events with more than 20 hailstone impacts.

### Swiss radar network

5 C-band polarimetric Doppler radars. PPI scans at 20 elevations (-0.2° to 40°). Radial resolution: 500m Temporal resolution: 5 minutes.



#### Drone measurements

Single event (20 June 2021), 18209 hailstones. Source: Lainer et al. (2023).

4. Testing the normalization on drone data

Using the h(x) fitted over the hailsensor data, and the empirical moment of the HSD distribution

measured by the drone, we can test the double-moment normalization on the drone HSD. The original HSD and the estimates from the doublemoment normalization (only combinations using moments between 2 and 6) are shown on the right.

While the reconstruction has some difficulties with D < 10 mm, the largest hailstones are relatively well represented, especially for the reconstruction based on the median h(x).



# Alfonso Ferrone<sup>1,2</sup>, Marco Gabella<sup>2</sup>, Urs Germann<sup>2</sup>, Alexis Berne<sup>1</sup>

<sup>1</sup>Environmental Remote Sensing Laboratory, École Polytechnique Fédéral de Lausanne EPFL, Lausanne, Switzerland | <sup>2</sup>Radar, Satellite and Nowcasting Department, Federal Office of Meteorology and Climatology MeteoSwiss, Locarno-Monti, Switzerland



# **3. Double-moment normalization**

#### **1. Measured hail size distributions**

Dataset split into training set (70% of all data) and test set (30%). The HSDs are shown on the right.

#### 2. Normalization

We follow Lee et al. (2004) and define the normalized diameter *x* as:

(1)  $x = D M_i^{1/(j-i)} M_i^{-1/(j-i)}$ 

where  $M_{i,i}$  are the moments of order *i,j* of the HSD, and D is the equivalent-volume spherical diameter. Using x and the two moments, the HSD can be rewritten as: (2)  $N(D) = M_i^{(j+1)/(j-i)} M_i^{(i+1)/(i-j)} h(x)$ 

Were h(x) is the **normalized distribution**.

We compute the discrete h(x), and its median and average value over all events in the training set.

These values are fitted using a generalized gamma function.

The fit can be performed with or

without weights (number of occurrences at each discrete x).

An example fit is shown on the right.

## **3.** Estimating the HSD using its moments and the fitted h(x)

In the test set, we use the empirical moments and the fitted h(x) to estimate the HSD.

On the right, an example event using moments 2,4.



### 4. Validation

To evaluate the quality of the estimate, we follow Raupach et al. (2019) and compute:

- root mean square error (RMSE), - bias,
- relative bias,

- Pearson correlation coefficient. The median and IQR of two metrics over the test set are show on the right.

Moment couples in the range (2,3) to (4,6) have the best performances.

Fit that use the median h(x)have higher correlation, lower RMSE, but higher biases than the ones based on the average h(x).









#### **Radar data processing**

For each PPI we extract the data within a cone **(1)**. The variables selected are: horizontal (Z<sub>H</sub>) and vertical (Z<sub>v</sub>) reflectivity factors, differential reflectivity (Z<sub>DR</sub>), copolar correlation coefficient ( $\rho_{hv}$ ), specific differential phase (K<sub>DP</sub>), and the hydrometeor type (Besic et al., 2016).

Data from all elevations (2) and all radars (3) are merged and interpolated onto a regular grid.

#### Feature extraction

We define a series of regions in the cone using thresholds (**4**). We extract geometrical descriptors of the region, and quantiles of the distribution of all variables. The spatial continuity of the region is also taken into account. The number of features extracted is 2460.

### **HSD** estimation

A regression provides a relationship between a subset of these features and the moments. We test the relationship via leave-one-out cross-validation, using a limited set of 21 events: the values of the moments are used in conjunction with the h(x) estimate previously derived to reconstruct the HSD. An example of this estimate for one hail event, alongside its hailsensorderived counterpart, is shown in the figure on the right (5). Overall, differences between the HSD reconstructed from the

# **6. References**

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hailsensor momements and the drone ones are small, especially for the moment couple 2, 4. The results are still preliminary, and more data will be used to obtain more robust conclusions.

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Raupach, T. H., Thurai, M., Bringi, V. N., & Berne, A. (2019). Reconstructing the drizzle mode of the raindrop size distribution using doublemoment normalization. Journal of Applied Meteorology and Climatology, 58(1), 145-164.