Towards Improved Hail Detection and Size Estimation Using Convolutional Neural Networks

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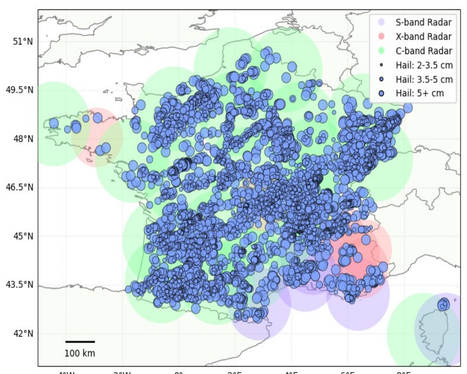
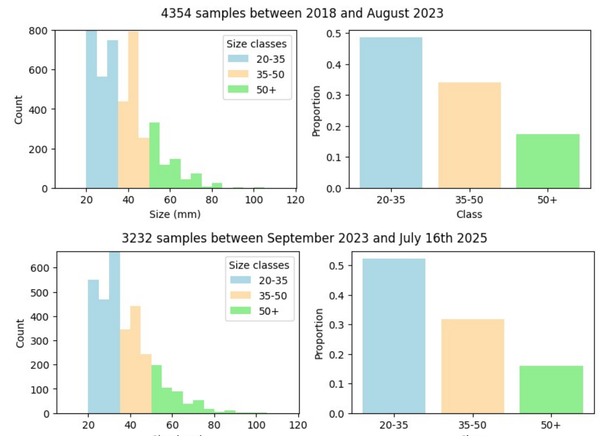
Motivation

- **Hail hazard in France:** Causes major damage to agriculture, vehicles, infrastructure, and solar installations; e.g., €300M insured losses from Paris hailstorm (3 May 2025).
- **Limitations of current methods:** Traditional radar-based hail detection struggles to predict severe hail (>2 cm) and accurately estimate size, ignoring storm morphology.
- **CNN-based approach:**
  - Severe hail detection : ***Forcadell et al., AMT, 2024*** used 19 radar-derived features (polarimetric variables, storm severity diagnostics) to detect severe hail over 30×30 km² areas. Outperforms existing hail proxies,
  - Hail size estimation: Treated as multi-class classification (medium 20–35 mm, large 35–50 mm, giant ≥50 mm) using sequences of radar images over six timesteps (~25 min) to capture storm evolution : PhD V. Forcadell (***PhD thesis Forcadell 2024***)
- **Ongoing work:** Expanding datasets for 2024–2025 events to improve model generalization and validate CNN-based hail size predictions.

Hail reports dataset

Radar network over France and hail reports (2018-2025)

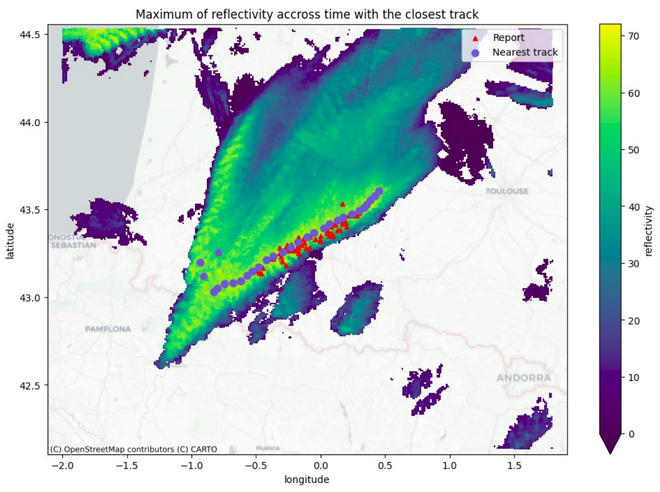




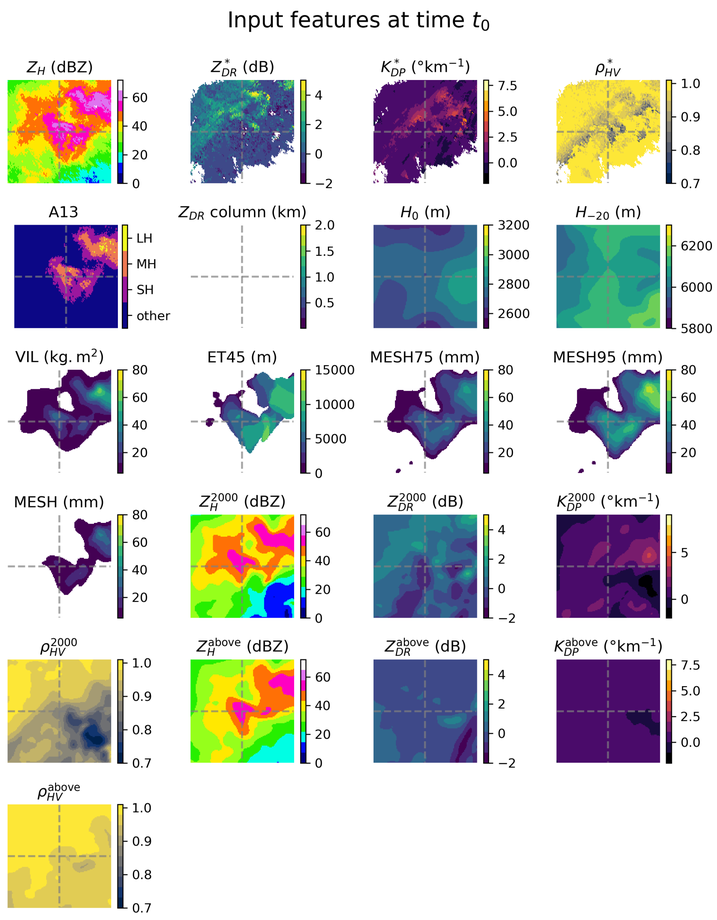
Methodology

1. Storm cells are tracked and matched to the severe hail reports

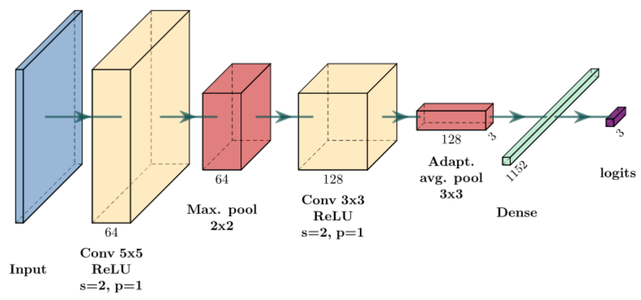
- using tobac (Heikenfeld, 2019) python library applied on radar Zh composite
- only cells of 25 minutes (6 timesteps) are kept
- **Cells are labelled** with the **average size of all reports** within the cell enveloppe at t0



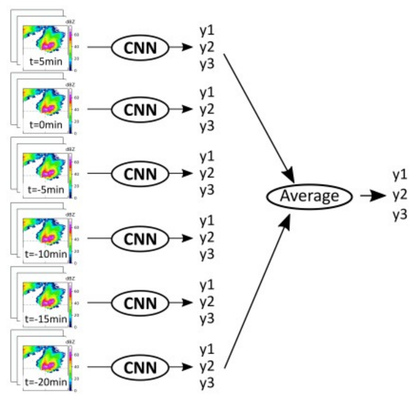
2. Radar diagnostics within 30x30 km2 areas are computed from 3D radar grids for each cell centroïd = **predictors**



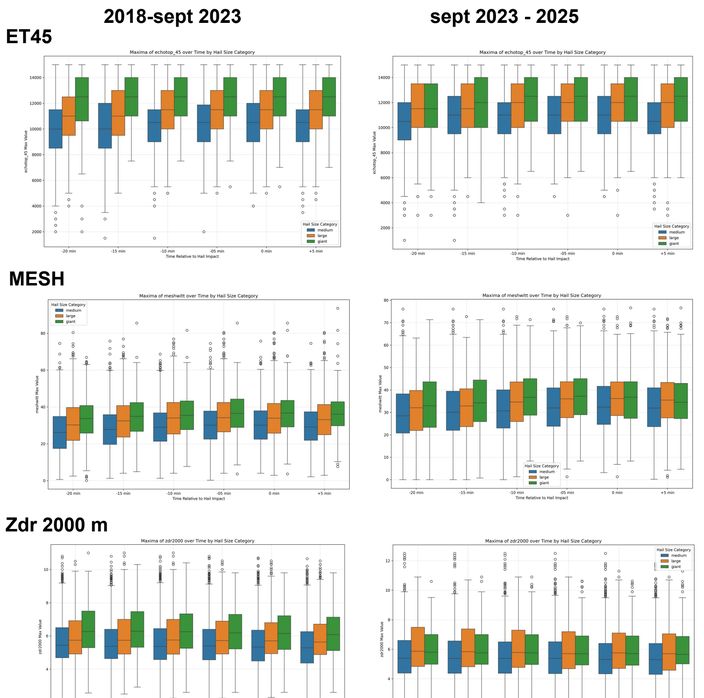
3. Predictors (30x30 km2 images) are fed as input to CNN (Medium ConvNet, see Forcadel 2024), trained to predict the associated hail size class



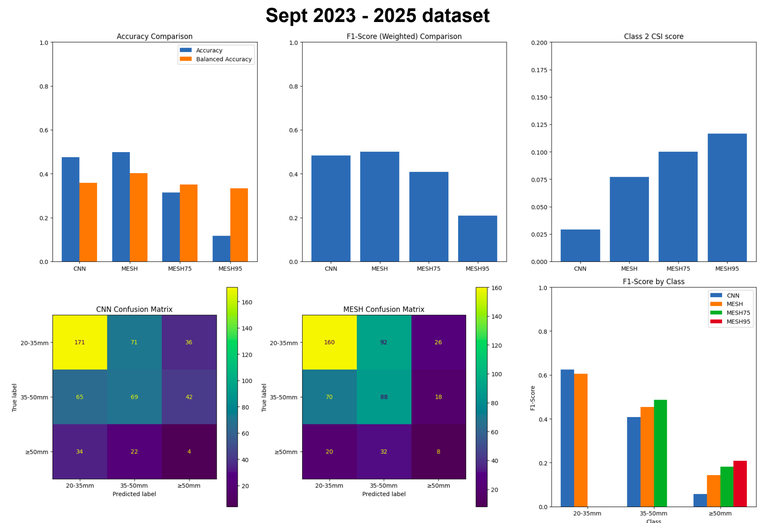
4. Temporal aggregation : the probabilities of each hail size class are averaged within the 25 minutes period



Study of the predictors

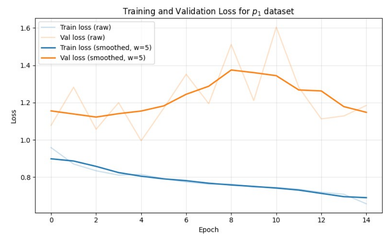


Performance of the CNN and comparison to MESH



- Scores are similar for all periods subsets
- Not improved with the addition of new reports (2023-2025)
- CNN often outperforms MESH but performance varies with hail class size and remains limited…

⇒ During training and validation, the CNN model struggles to reach a minimum



Conclusions and future work

- **Extension of previous work:** The Forcadell et al. (2024) study was expanded in V. Forcadell's PhD thesis to focus on hail size discrimination.
- **Application to new data:** The method was applied to a new radar-feature dataset covering hail events from 2024 and 2025.
- **Feature analysis insights:** Certain predictors show strong potential for discriminating hail size, with consistent behavior across both datasets.
- **Performance comparison:** The CNN consistently outperforms MESH, although overall skill remains limited.
- **Ongoing work:** Additional tests are underway, supported by the scientific visit of Hernan Bechis (Argentina), who is also adapting the algorithm for use in Argentina.

References

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- Heikenfeld, M., Marinescu, P. J., Christensen, M., Watson-Parris, D., Senf, F., van den Heever, S. C., & Stier, P. (2019). tobac 1.2: towards a flexible framework for tracking and analysis of clouds in diverse datasets. Geoscientific Model Development, 12(11), 4551–4570. https://doi.org/10.5194/gmd-12-4551-2019