Meta-analysis of nowcasting models on radar data from Ile-de-France

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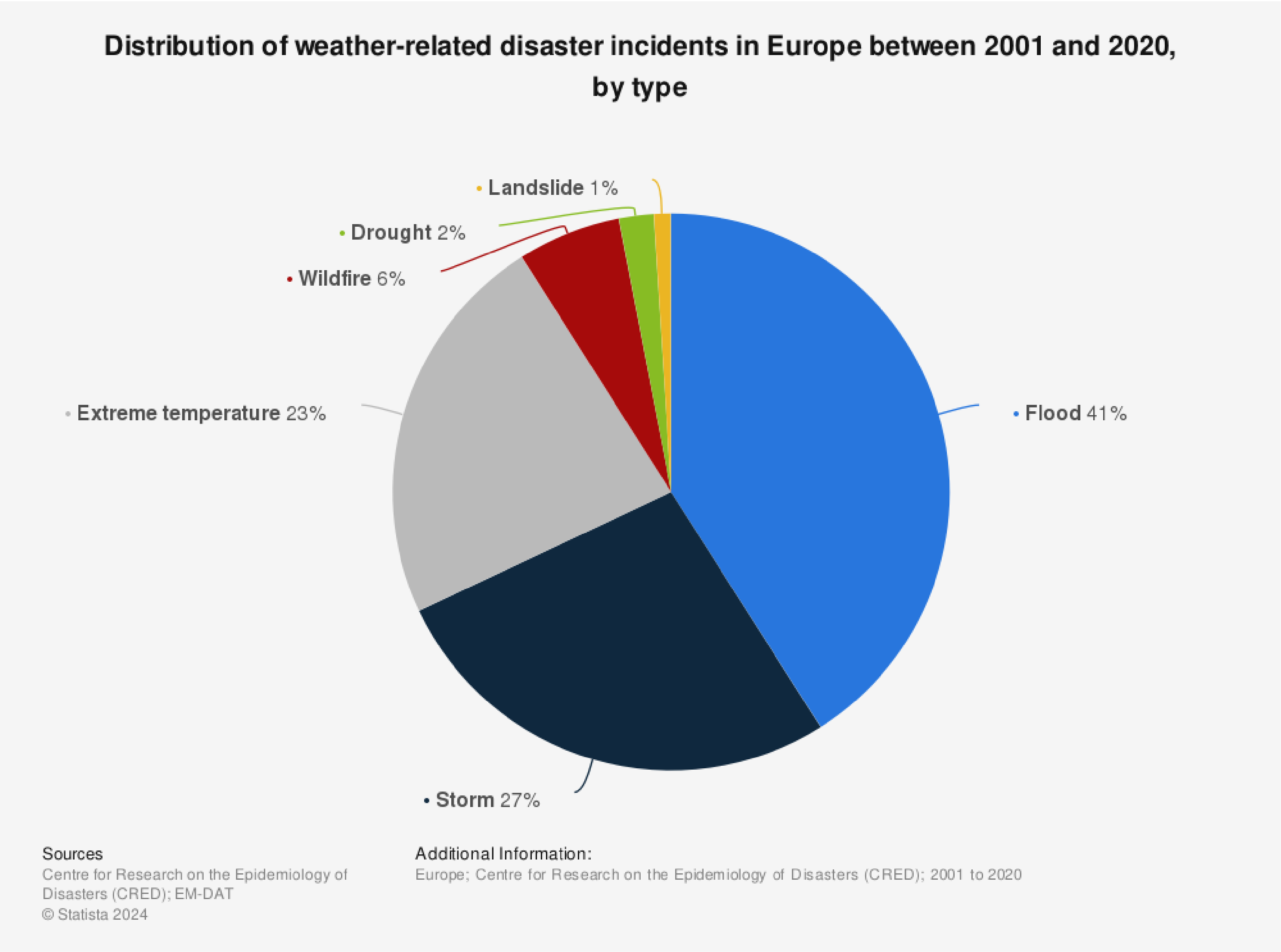
Context

The challenges

Nowcasting rain is a crucial issue for risk forecasting, particularly flash floods.



The challenge in reducing human and material damage is to predict as early as possible with the best possible precision.

Context

Introduction :

Recently, new studies shed light on Deep Learning making it possible to perform nowcasting that rivals classic models.
Many new models : Difficult to compare them.

Goals :

- **Evaluate models on the same dataset on Ile-De-France.**
- **Assess pertinence of scores according to goals.**
- **Pros and cons of the different models and their application domain.**

Database Used

Database used

- Rainfall maps from Météo-France radar mosaic

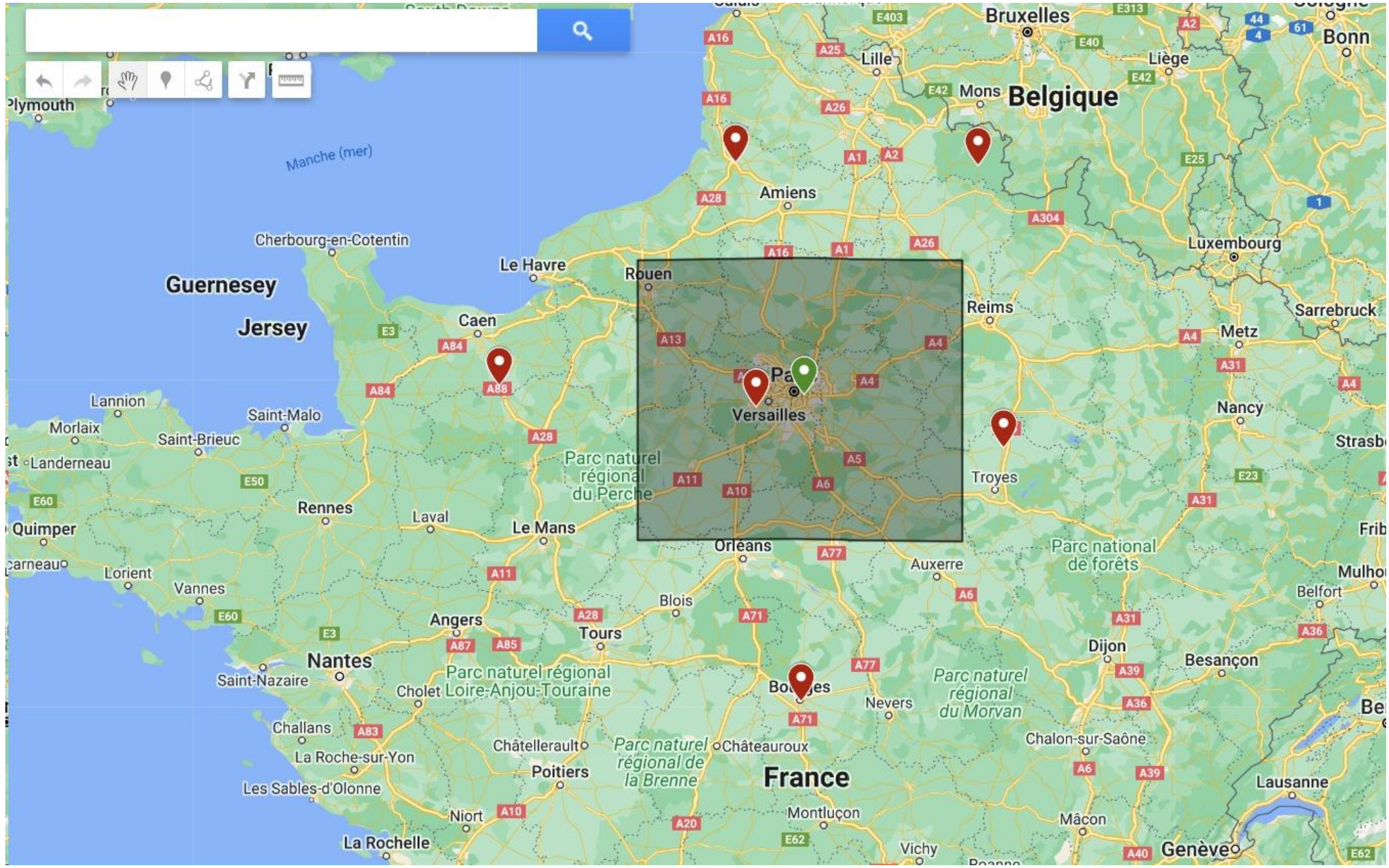
- Spatio-temporal sequence of rain event :

  - Cropped around the Paris region (176*208 km)

  - Therefore, the rains mainly go from west to east and convective rain is rare

  - A total of 11 years of data (1360 rain events/ 25880 maps)

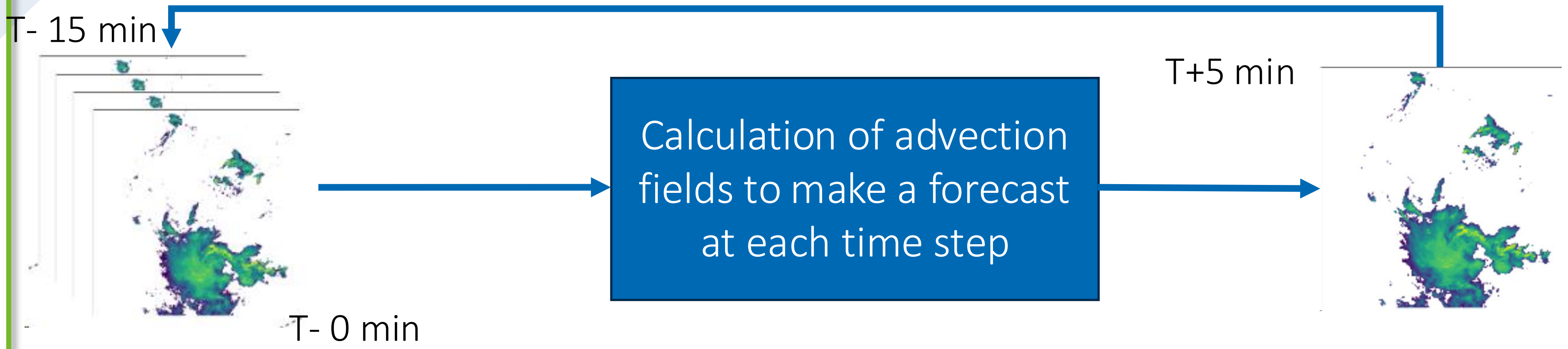
  - 1km/5min of resolution



Principle and dataset

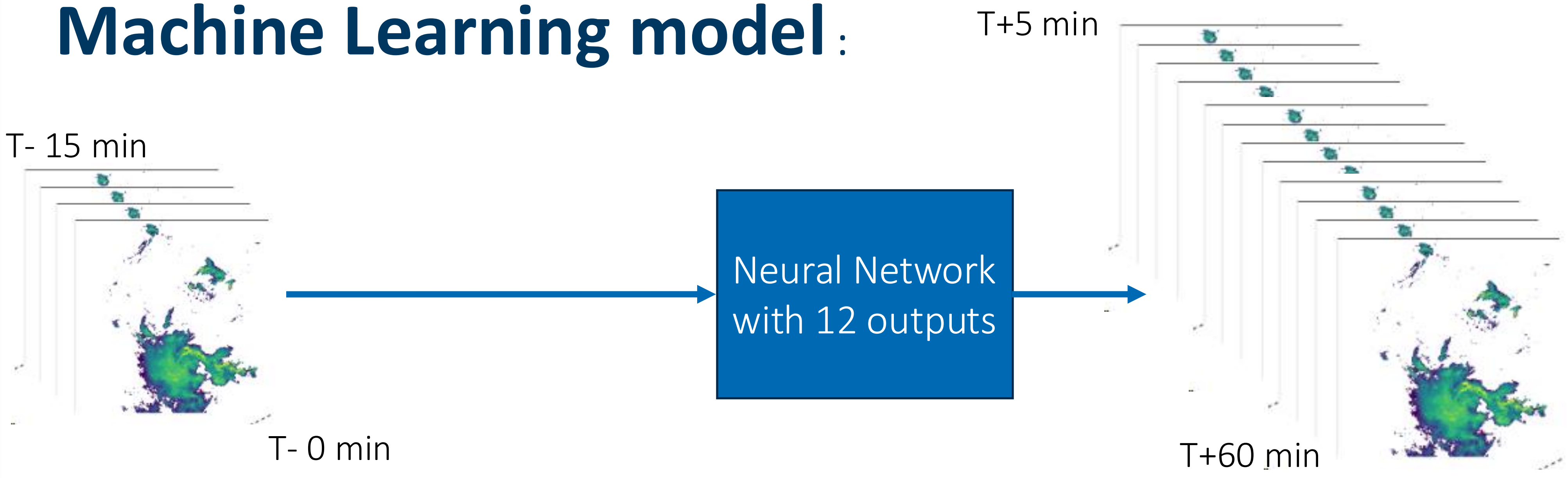
- Most model uses 4 past observation maps (20 minutes) as input :

Optical flow model :



- **Each output is injected into the inputs, to predict next maps**
- **Doesn't need to be trained**

Machine Learning model :



- **Predict directly several maps horizon (5 minutes to 2 hour) from input maps**
- **Needs to be trained**

Data distribution :

2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021

1143 events on Training/Validation Dataset (blue)

217 events on Test Dataset (yellow: 2011, 2019)

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Models Used

Used Models

	▪ Optical flow model			▪ Machine Learning model		
Model	Lagrangian persistance	Sprog	Steps	Smaat Unet	ConvLSTM	DGMR
Specificity	Extrapolation	Decomposition into different scales with an FFT	Ensemble method	Unet architecture with attention mechanism	Recurrent model using 3D convolution (2D spatial and 1D temporal)	Generative model using 2 discriminators (1 spatial and 1 temporal)
Interest	Simple and fast	Adapted to the scaling behavior of the rain	Take into account the uncertain and decreases the bias	Learn to focus on important information at different scale	Allowing a dynamic to be directly learned	Allows to generate the most realistic data possible
Trained	No	No	No	Yes	Yes	Pretrained on UK
Reference	Pulkkinen et al , Pysteps: an open-source python library for probabilistic precipitation nowcasting , 2019			Trebing et al. , 2020	Shi et al. , 2015	Ravuri et al. , 2021

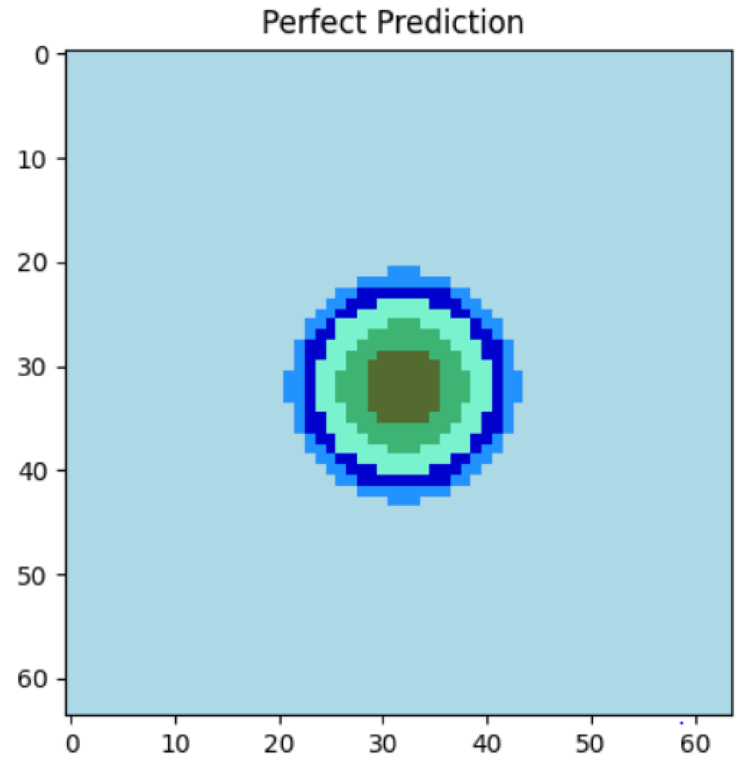
Results and analysis

Used metrics

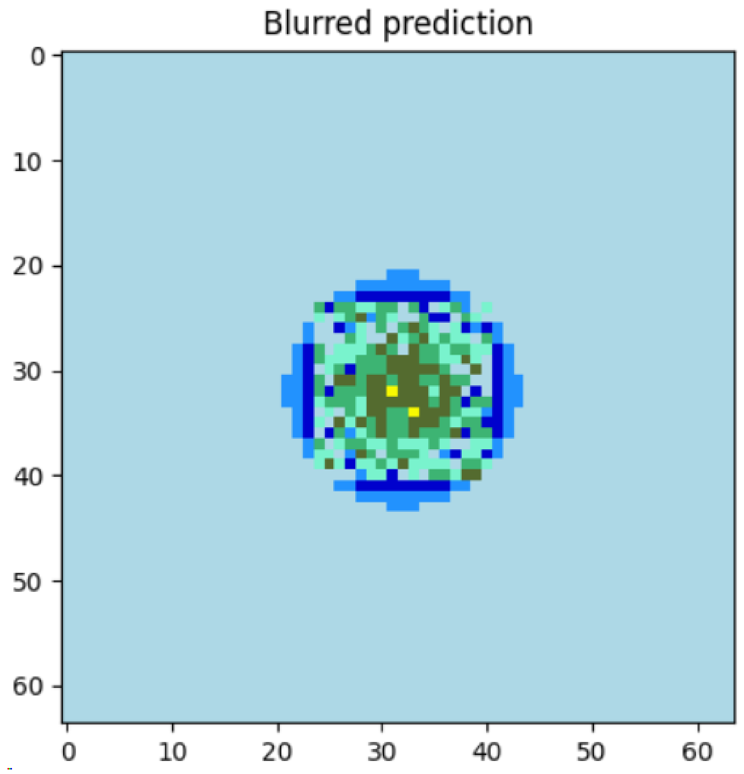
- **3 main criteria:**
  - Spatial consistency between the predicted map and the expected map
  - Pixel localization based on thresholds
  - Rain intensity estimation

- **3 metrics:**
  - Pearson Coefficient
  - Critical Success Index
  - MSE

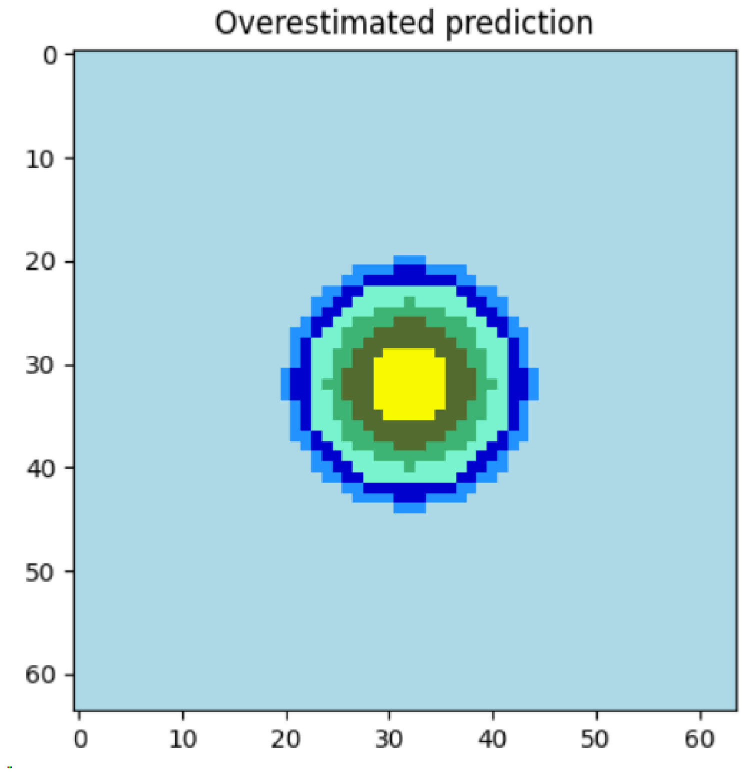
- **Illustration:**



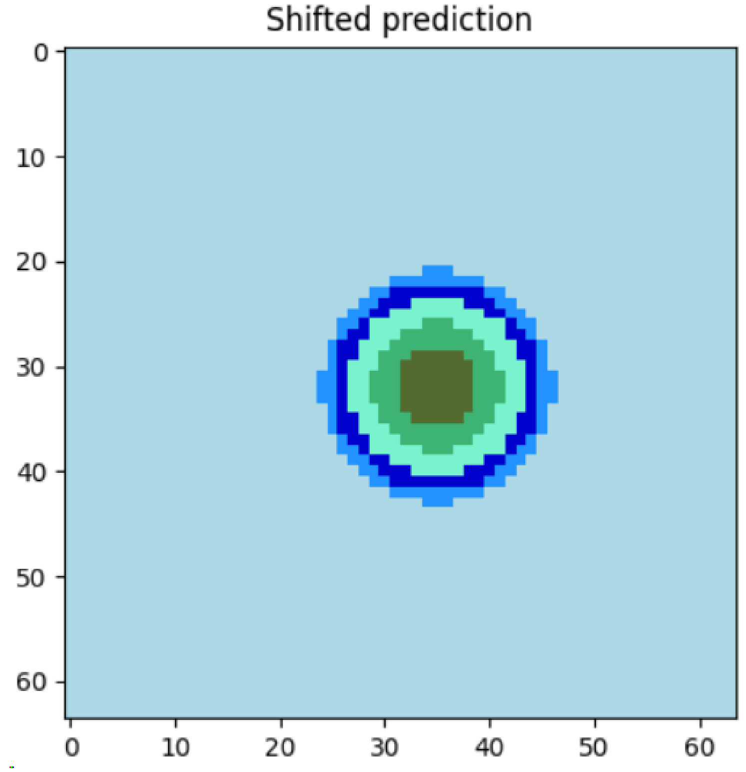
Perfect score :	
Pearson	1
MSE	0
CSI [0,5mm/h]	1



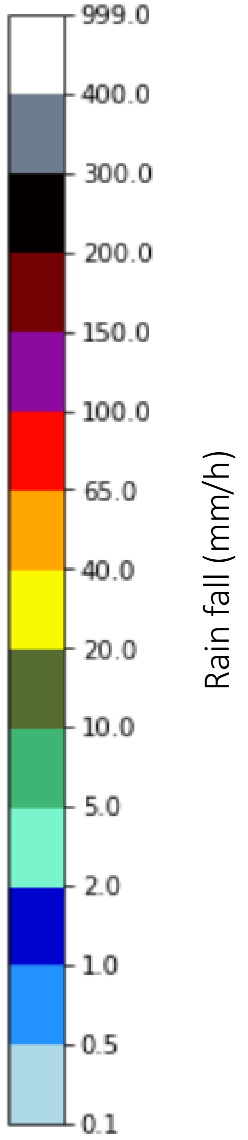
Calculation of metrics compared to the original image	
Pearson	0.83
MSE	1,28
CSI [0,5mm/h]	0,87



Calculation of metrics compared to the original image	
Pearson	1
MSE	3,11
CSI [0,5mm/h]	0,83



Calculation of metrics compared to the original image	
Pearson	0,88
MSE	0,73
CSI [0,5mm/h]	0,69



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Results and analysis : Example of an event

Event of 9 July 2019 at 9:50 pm in the Paris region

T+15min | T+30min | T+45min | T+60min

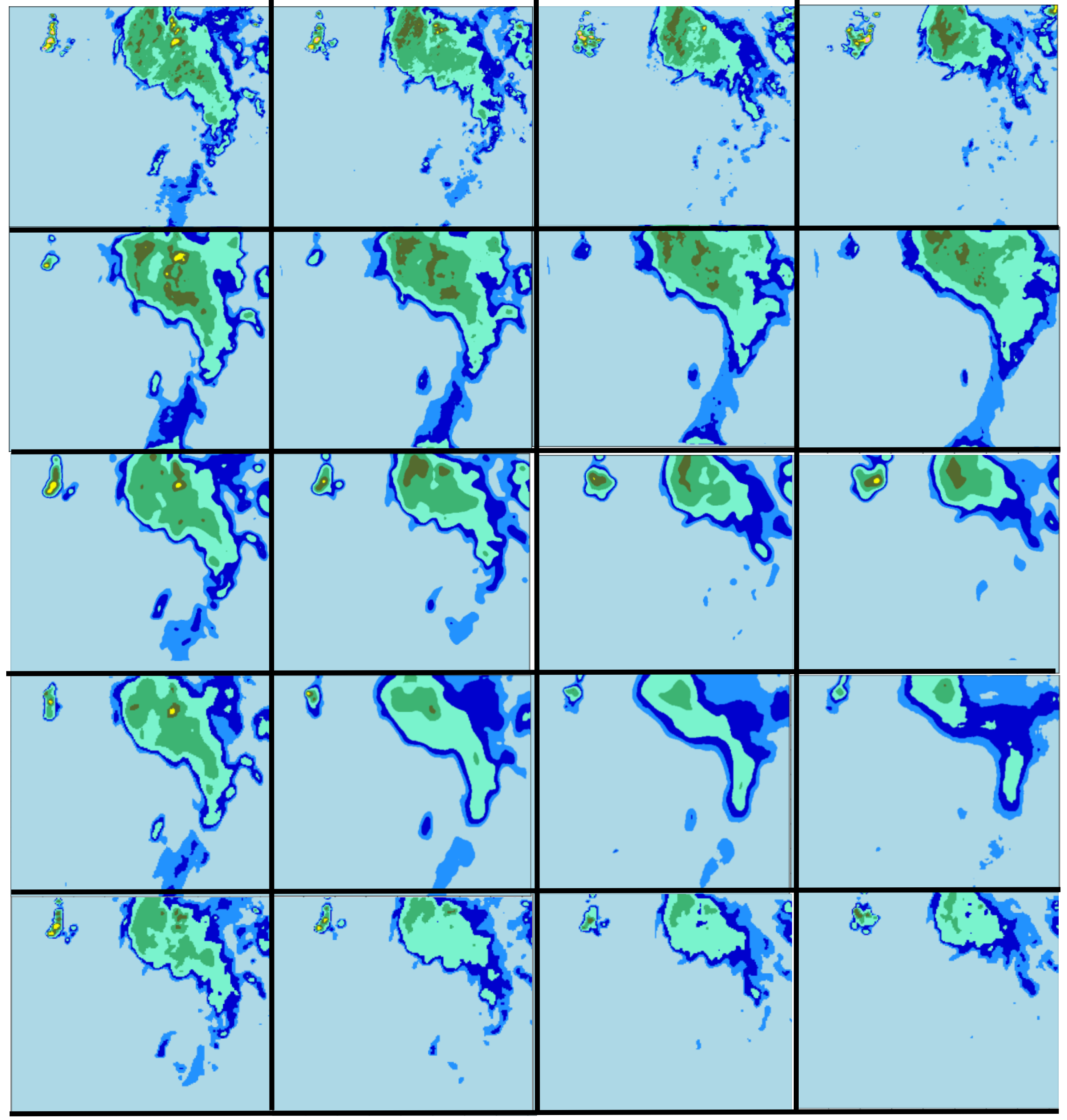
Groundtruth

Pysteps – Steps

SmaAT-Unet

ConvLSTM

DGMR (trained on UK)



Pysteps – Steps:

T+	T+15min	T+30min	T+45min	T+60min
Pearson	0.71	0.74	0.62	0.52
MSE	1.98	1.60	1.83	2.06
CSI [0,5mm/h]	0.83	0.68	0.58	0.53

SmaAT-Unet:

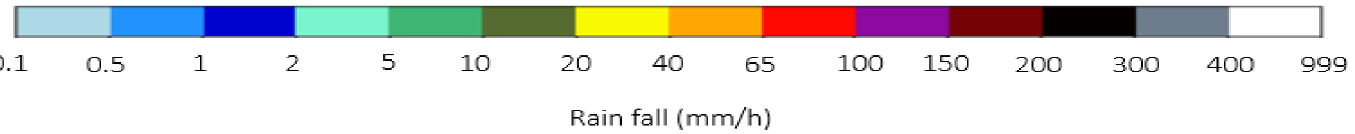
T+	T+15min	T+30min	T+45min	T+60min
Pearson	0.82	0.75	0.57	0.50
MSE	1.53	1.40	1.74	1,94
CSI [0,5mm/h]	0.90	0.74	0.64	0.57

ConvLSTM:

T+	T+15min	T+30min	T+45min	T+60min
Pearson	0.77	0.70	0.57	0.49
MSE	1.72	1.52	1.70	1,90
CSI [0,5mm/h]	0.90	0.76	0.66	0.60

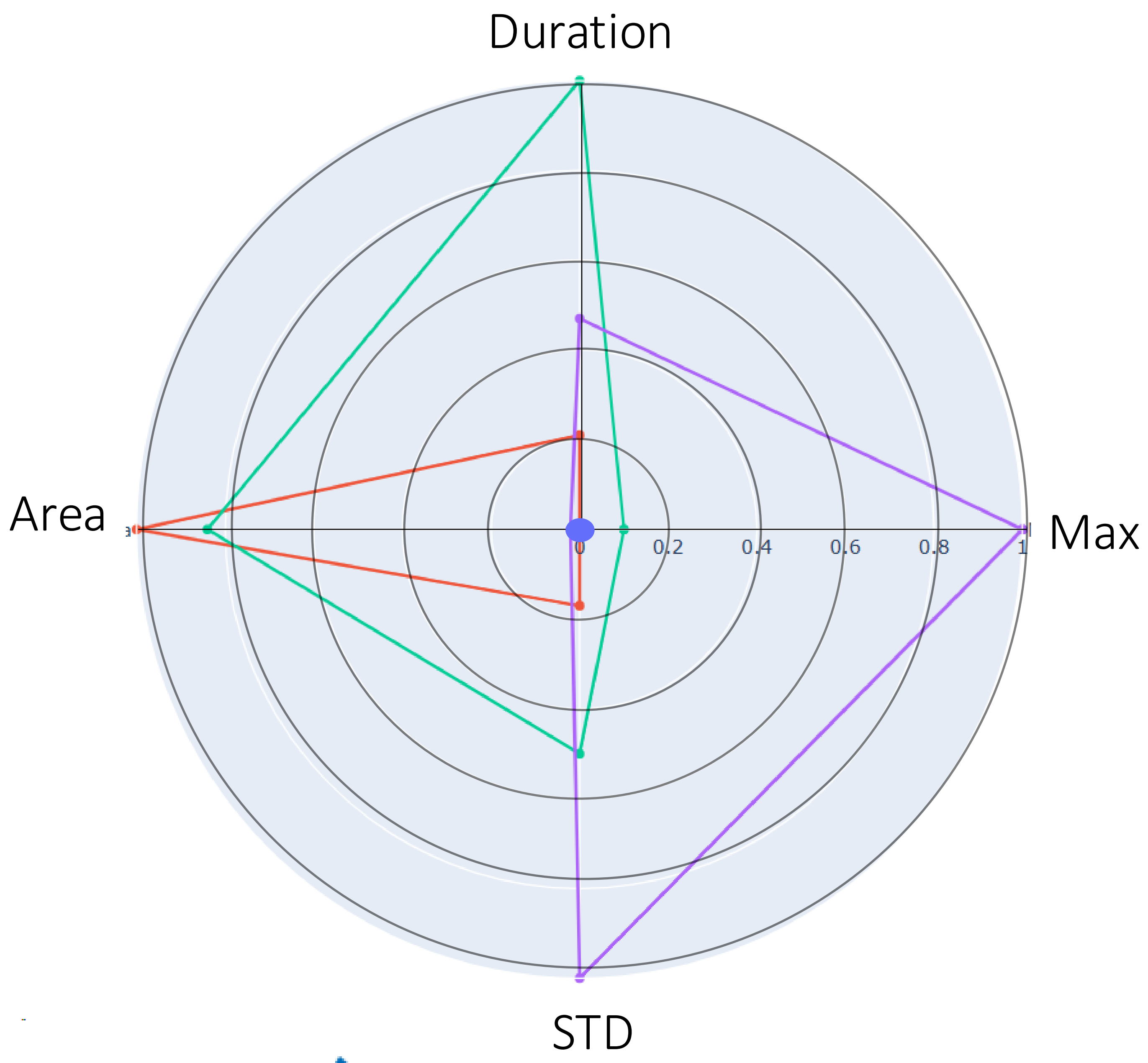
DGMR (trained on UK):

T+	T+15min	T+30min	T+45min	T+60min
Pearson	0.72	0.70	0.66	0.52
MSE	2,06	2,41	2,87	3,8
CSI [0,5mm/h]	0.8	0.71	0.61	0.56



Results and Analysis : results on different rain groups

- Clustering of events to obtain different groups of events for testing



- 4 features were used:
  - **Duration of the event**
  - **Maximal intensity**
  - **Mean size of the event on the maps**
  - **Standard deviation**

- 4 classes were found :

Light local rain (44 events)
Light large rain (61 events)
Medium rain (83 events)
Heavy local rain (29 events)

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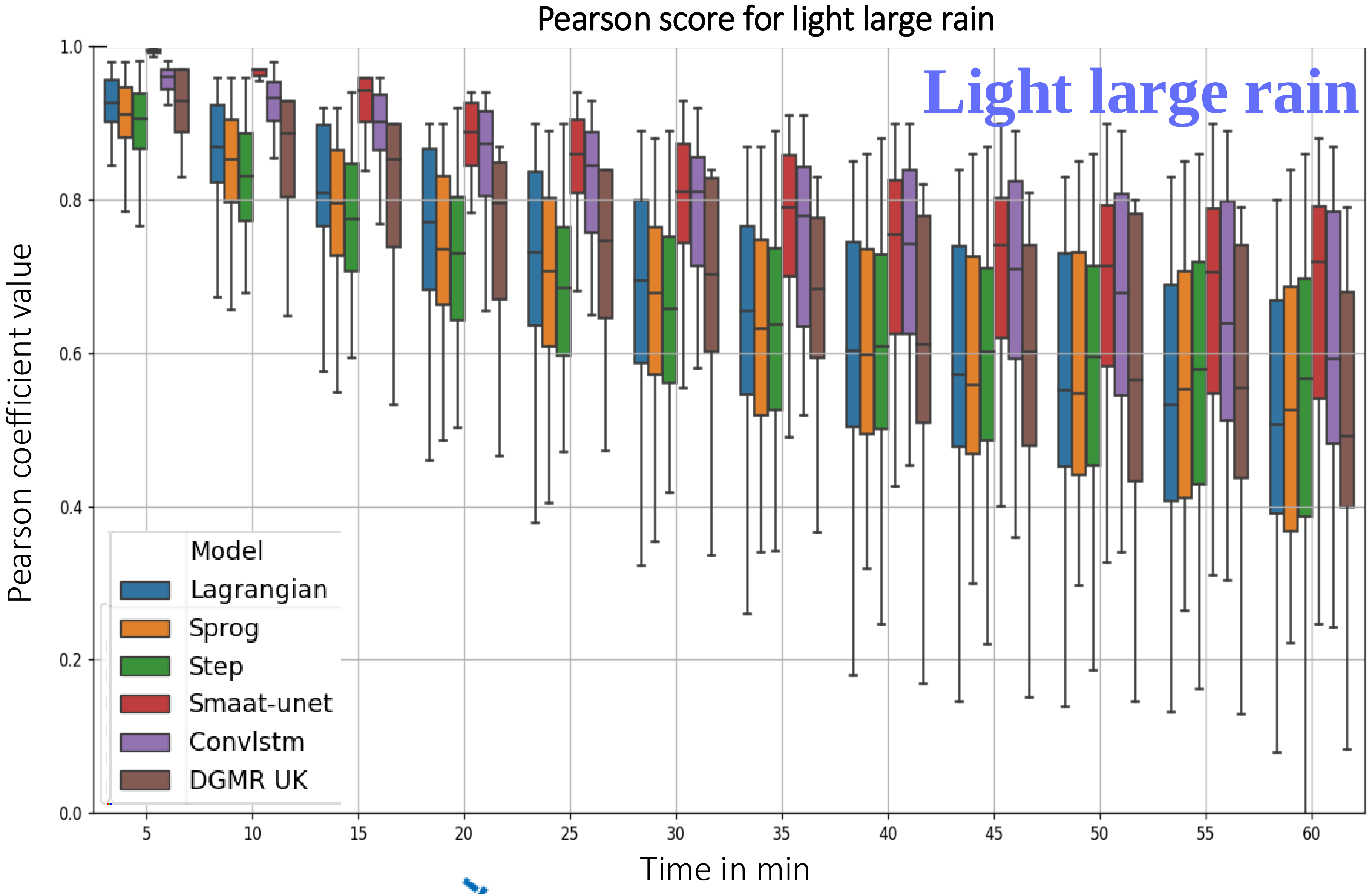
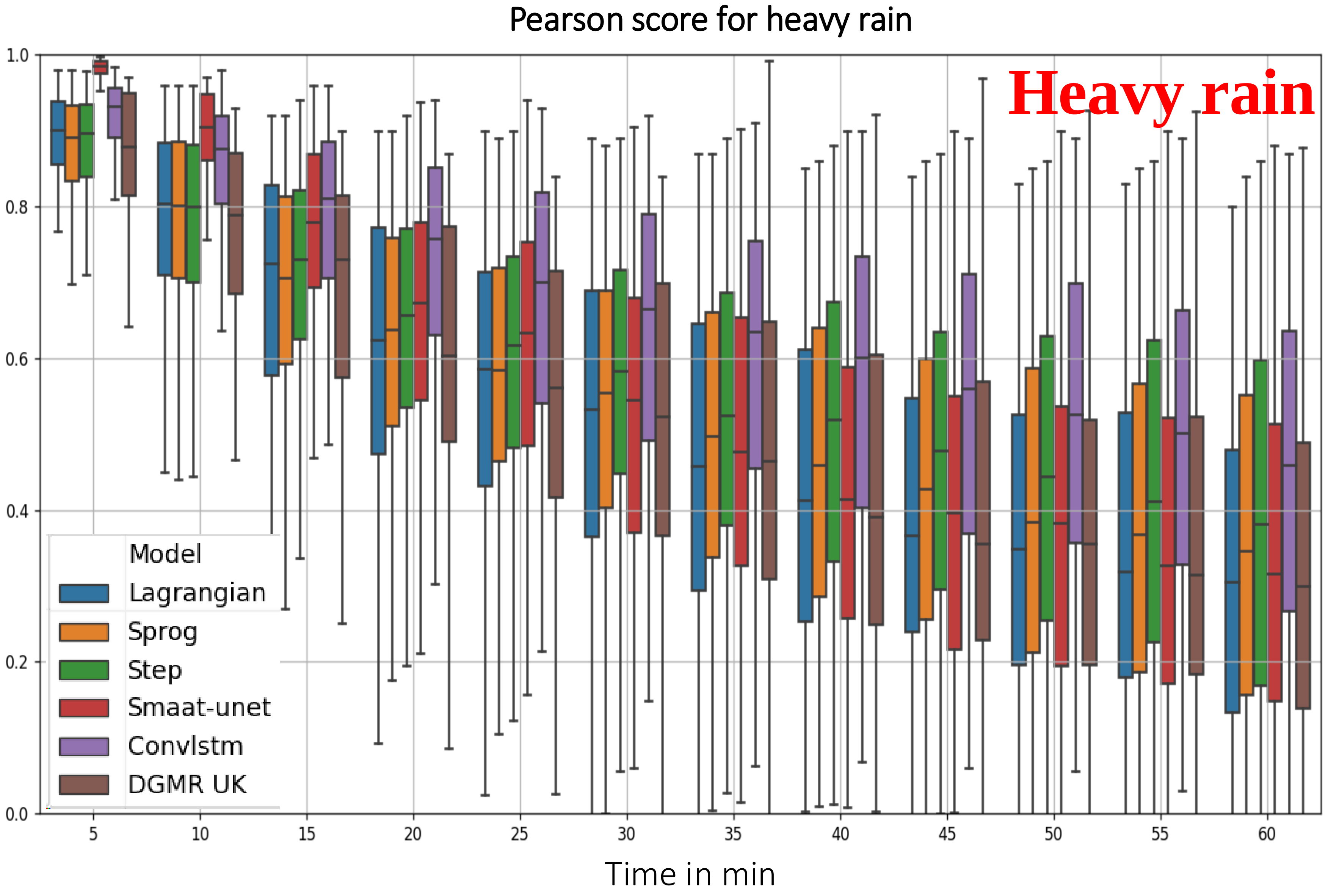
Results and Analysis : results on different rain groups

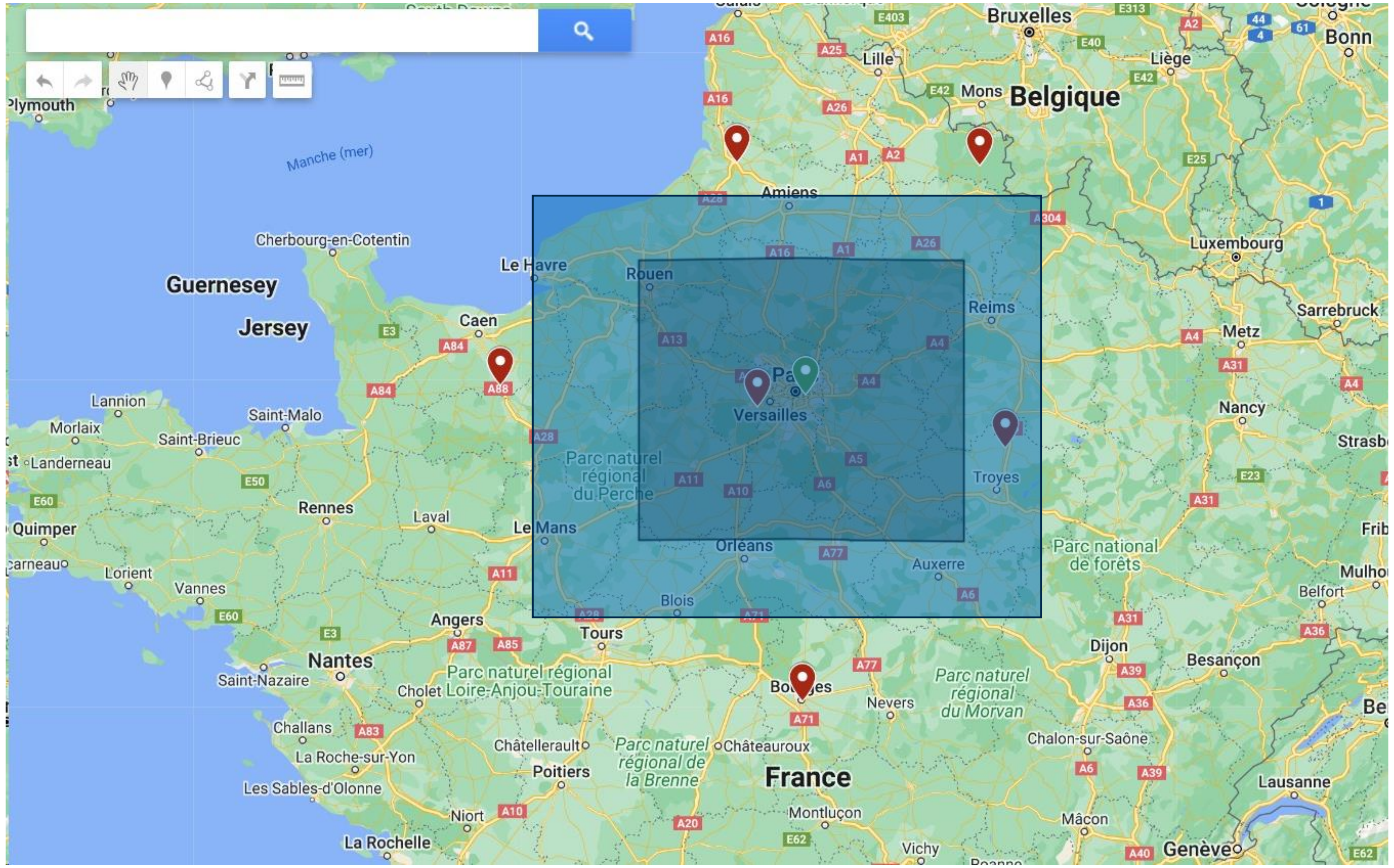
- **Results on 219 events of the test database.**
- **Same trend across different evaluation metrics.**





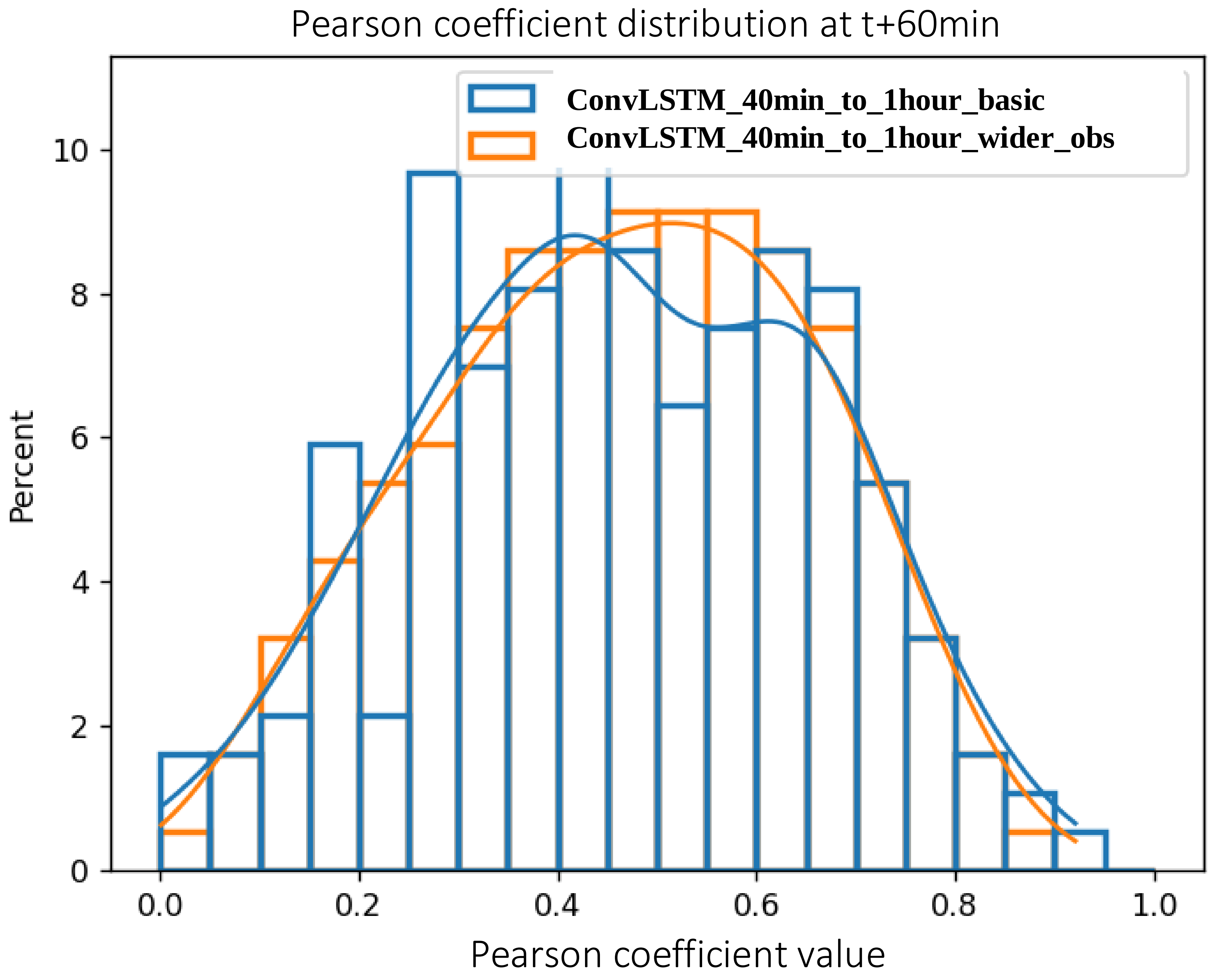
Model improvement

- Repeat the same learning events with a wider observation window:
  - **Backpropagation of the gradients made on the smallest area**
  - **2-hour horizon forecast to improve 1 hour forecast**



Backpropagation of the gradients made on the smallest area

- Pearson score distribution for all events in the test database at 1 hour horizon :
  - *Blue* : Original model with 40 minutes input.
  - *Orange* : Blue model with wider observation and backpropgation on smallest area.



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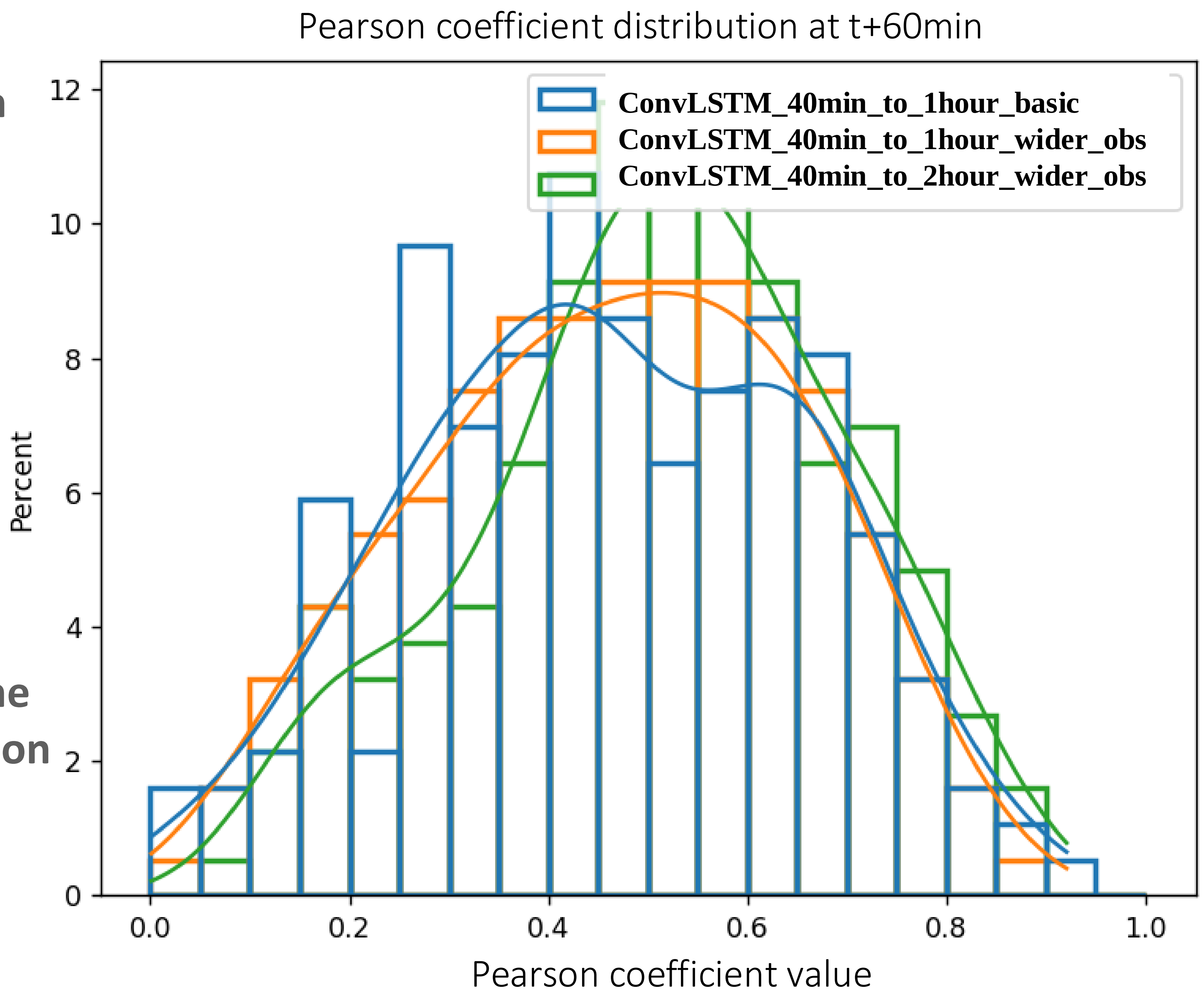
2-hour horizon forecast to improve 1 hour forecast

- Pearson score distribution for all events in the test database at 1-hour horizon :
  - *Blue* : Original model with 40 minutes input.
  - *Orange* : Blue model with wider observation and backpropgation on smallest area.
  - *Green* : Orange model with 2-hour horizon.

- Using 2-hour horizon seems to improve the first hour for recurrent model in Paris region !



Conclusion

Conclusions and perspectives

- Conclusions :
  - **Limited study in the Paris area**
  - **Results of DL methods seem to be better**
  - **Training on a sub-area and enlarging the output window improves model performance.**
- Perspectives :
  - **Model improvement : Addition of additional variables (500hPa wind fields, Cape, Echo-top, VIL, …)**
  - **Model improvement : Quantile regression**
  - **Generalization issues for other geographical areas**