Experiment driven and user eXPerience oriented

Analytics for eXtremely Precise outcomes and decisions

## Big Data Analytics for Natural Disaster Management

# Improve flash flood modeling in urban areas using high resolution hydrodynamic and machine learning models

*12h30 – 13h30 EET*


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a Sopra Steria company

ExtremeXP


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# Agenda

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   - Floods and context
   - Main flood types and characteristics
2. **Challenges and objectives of the study**
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   - Objective: flash flood modeling using AI approach
3. **Use Case : the city of ExtremeXP**
4. **Methodology**
   - General methodology
   - Data complexity
5. **Scenarios of use**
   - Hydrodynamic model setup
   - Scenario 1 – Use AI to facilitate input data definition
   - Scenario 2 – Surrogate model
6. **Conclusion**


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# 1. Floods and context

**Flash floods**: floods created by **heavy rainfalls** on a **short interval of time** (one hour to a day).

**Augmentation of events** due to climate changes everywhere in Europe.

Risks increase for different reasons: urbanization, land artificialization, river development.

Damages are dramatic as human and economic cost.

Therefore, there is a strong need for modeling the event and elaborate reliable forecast

- ✓ To anticipate (resiliency approach, feedback, long term infrastructures planning).
- ✓ To trigger actions at the right time (population alert, restricted zones …).
- ✓ To decrease/avoid the consequences.

*Recently, on September 2024, storm Boris cost the life about twenty people*



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# 1. Main flood types and characteristics

## Rough classification: plain versus flash flood

| Characteristics | Plain | Flash |
|---|---|---|
| **Event cinematic** | Slow (days to week) | Minutes (water rising up) - days (for duration) |
| **Occurrence** | Very progressive | Brutal |
| **Morphological environment** | Plain, smooth topography | Relief (in mountains), streets, buildings (in urban) |
| **Extension** | Large (province) | Small (few $km^2$) |
| **Required data precision** | Low precision | High level of details |

# 2. Challenges for flash flood modeling

Considering the flash flood characteristics, **their modeling must cope with specific performances**.

**Constraints on model**

- Traditional hydrological modeling tend to be based on all physical parameters influencing the event.
- Data are numerous, heterogenic, sometimes difficult to acquire or totally missing
  ➞ very few places/organizations can acquire these data in the real life/conditions.
- The model tuning is difficult and fastidious since all parameters are interacting.
- The model execution is usually time and CPU consuming.

**Operational needs to use the models in crisis conditions**

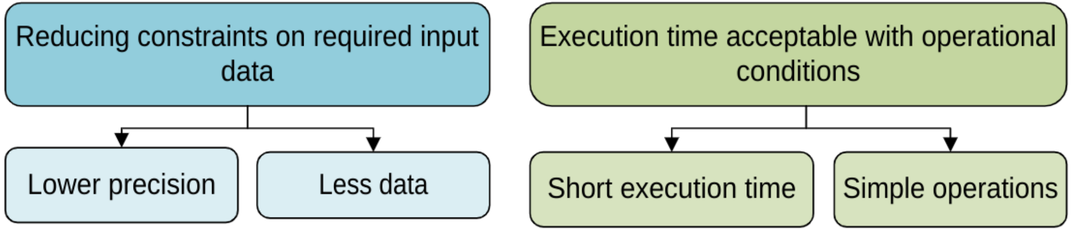
| Event occurences = rapid + versatile | Re-execute model fast (most recent data) | Short execution time | Low CPU consumption |
|---|---|---|---|

# 2. Objective: flash flood modeling using AI approach

**Project global objective**: Use of AI models along with and/or as a replacement of hydrodynamical models

- to reduce the difficulties/complexity of flash flood modeling in urban areas to make it more accessible in operation.
- to be able to model flash floods and predict their evolution as fast as possible
- Potentially, to simulate more easily unknown event/conditions

**2 main axis to make it more accessible:**




**Using IA modeling requires:**

- Representative data for the training phase (amount, various conditions, space, time, ...).
- Result verification : thanks to existing records, other way to model.

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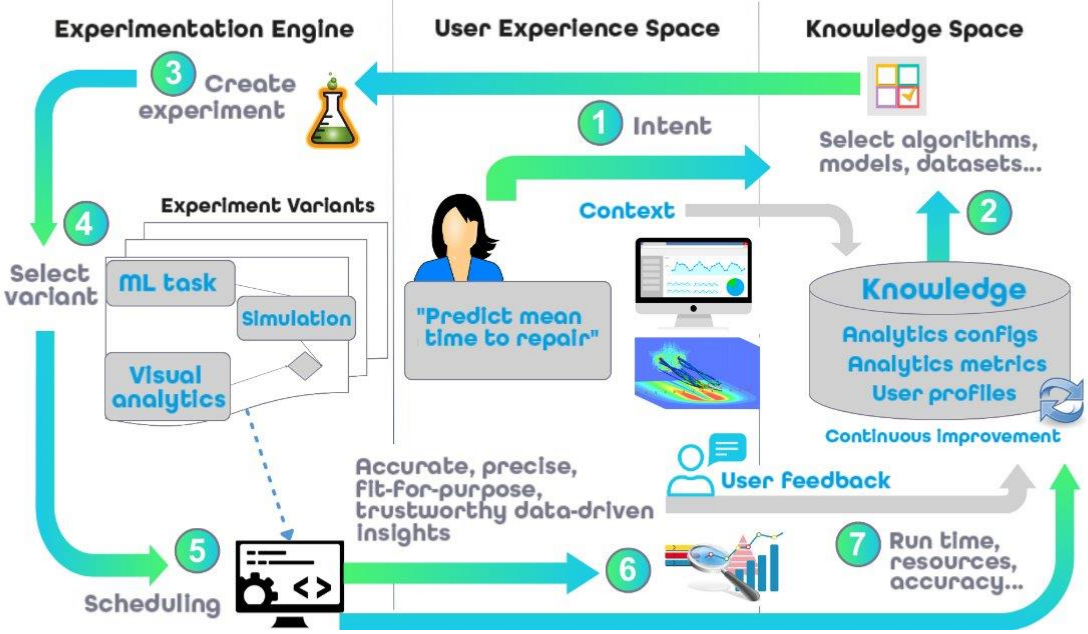
# 3. Use case of Extreme XP

**Objective:** Create a decision support system integrating data integration, machine learning, explainable AI, decentralized trust, and visual analytics into a unified framework.

**A continuously evolving, self-improving system that adapts to user needs and dynamic environments.**




## Use Case 1: Improvement of flash flood forecasting via AI



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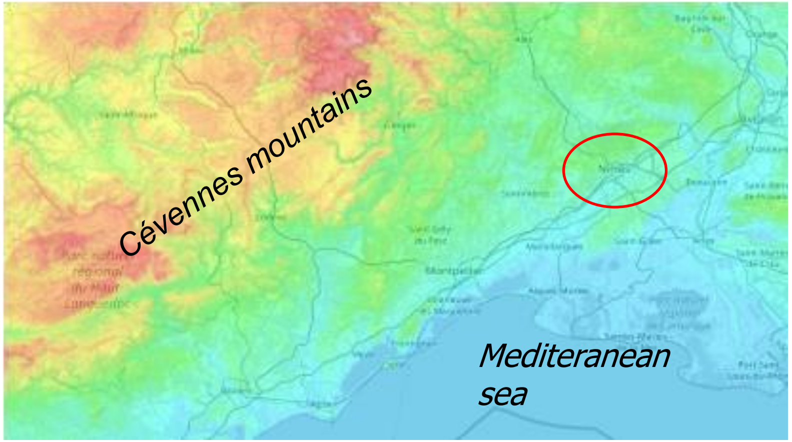
# 3. Use Case : city of Nîmes




**Geographic localization:**

- close to Mediterranean sea and backed by mountains (Cévennes).
- Meteorological event: in fall large amount of warm water available from the sea are blocked by relief.

**City characteristics:**

- Old city with narrow streets in downtown district
- 150 000 residents
- Stress of urbanization, ground imperviousness, runoff increase
- Natural drainage channels partly obstructed

**Has experienced severe flashfloods events (1988, 2002, 2005, 2014) caused by heavy rainfall.**

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# 3. Use Case : city of Nîmes

**Existing modeling system**

- Operational modelisation and forecasting, sensors
- Studies, archived data of all major events since 1988
- Difficulties: evolution of hydro infrastructures to reduce flooding impact (reservoir, surge tank…)
- Hydraulic conditions changed

**Data, documentation available**

**Acceptable conditions of experimentation**

- To train deep learning models
- To validate it versus validated existing data

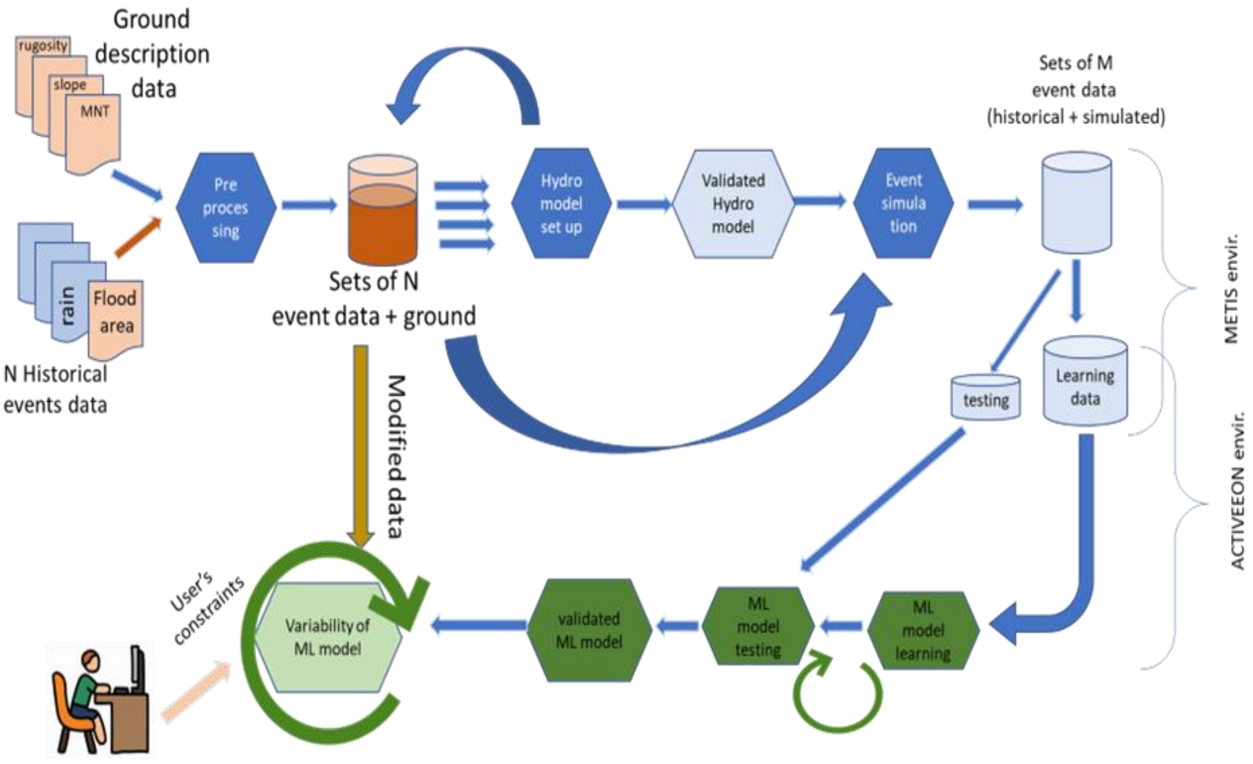
# 4. General methodology

## 1. Set up a hydrodynamic model (as a reference)

- Based on physical parameters, that we can fully control/parameter/exploit
- To produce many reference outputs in various run conditions to validate the future AI model (simulated events)

## 2. Set up the AI model

- To train it with existing field and simulated data
- to validate AI results against a set of hydrodynamic model outputs



# 4. Data complexity

## Complexity due to use of data variability

Various types and formats

Spatial resolution

Registration

Temporal registration

Need to be "cleaned"

## Some are massive (long time series) , grid data (rain radar, HR lidar)

## Data processing for HD model

- Splitting the area of interest in small triangles.
- All data must have a value for each triangle as for all output calculation

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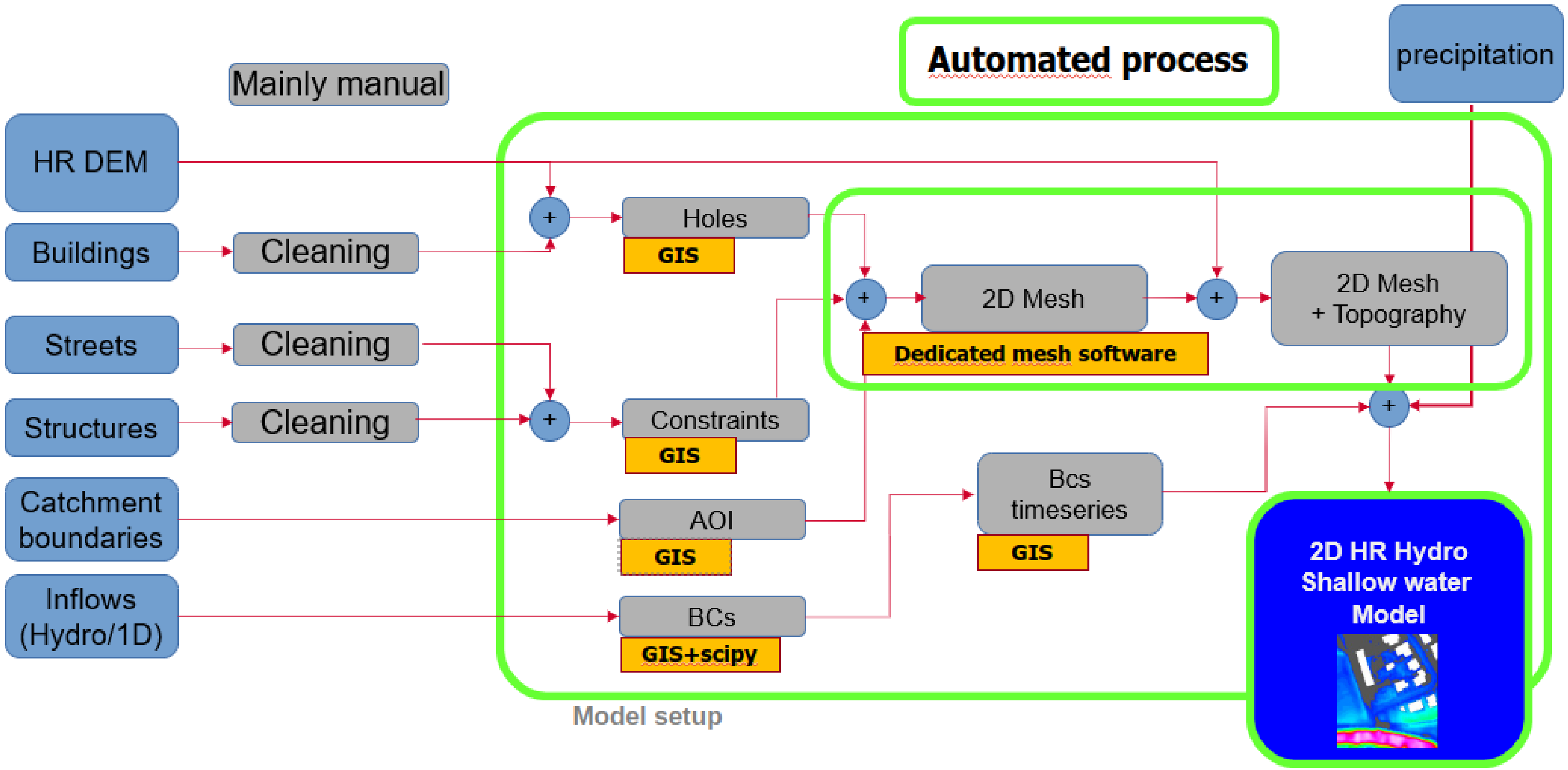
# 5. Hydrodynamic model set up

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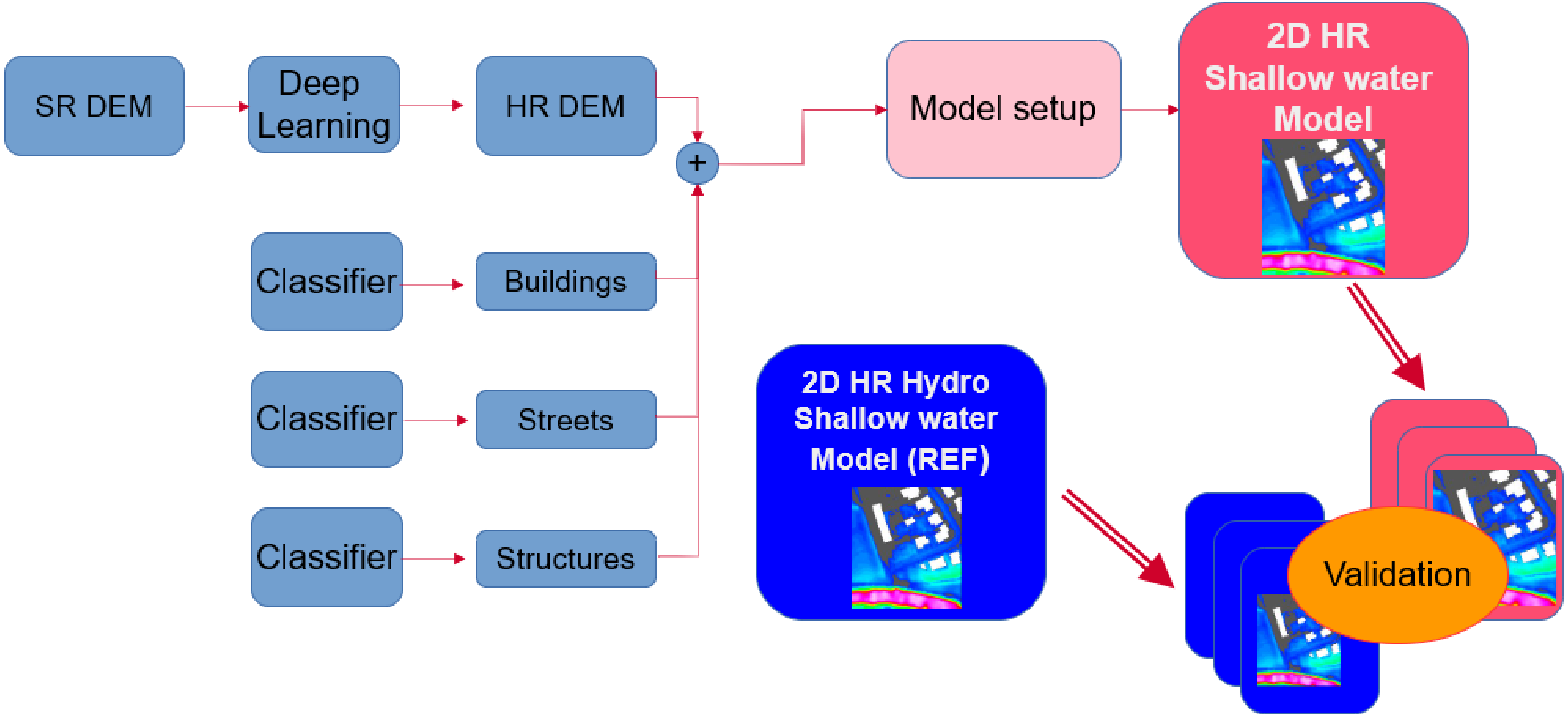
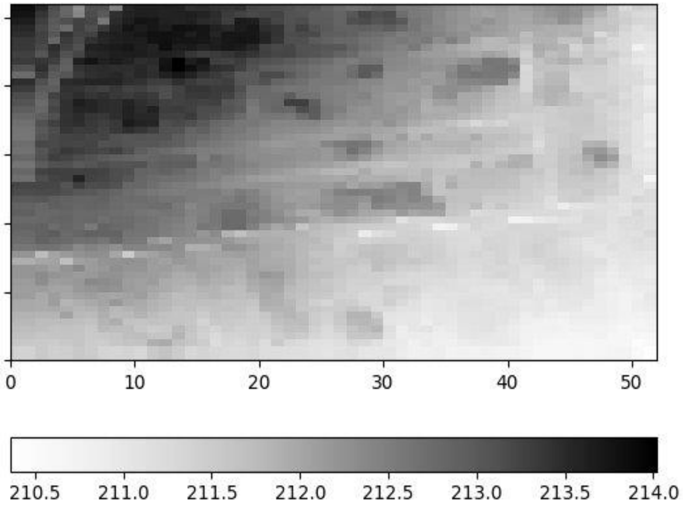
# 5. Scenario 1 – Using AI to facilitate definition of input data

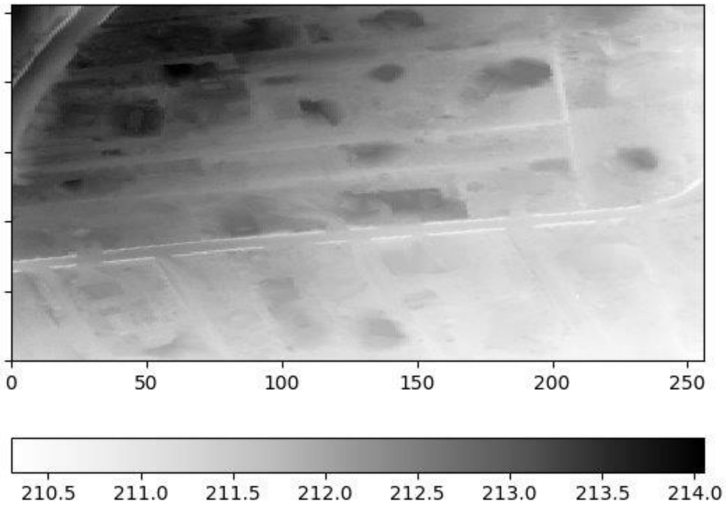


# 5. Experiment: Super resolution of DEM

**Low resolution DEM 5m**




**High resolution DEM 1m**




- ❑ Data: IGN DEM, LiDAR,
- ❑ Models: Generative Adversarial Network, CNN, Vision Transformer
- ❑ Tested against the bicubic interpolation

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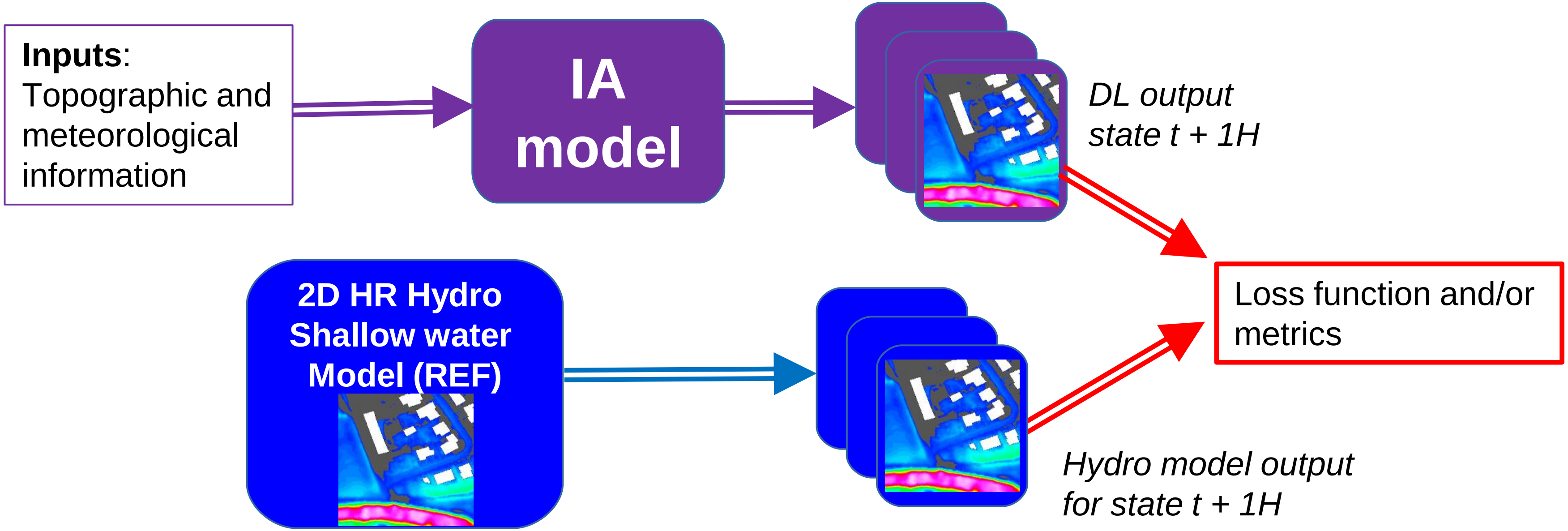
# 5. Scenario 2 – Surrogate model



# 5. Metrics

**Recall**: Sensitivity or true positive rate. Ability to detect all the flooded area (threshold defined by user).

$$Recall = \frac{TP}{TP + FN}$$

**Precision**: The efficiency to a model to predict correctly a flooded area(threshold defined by user).

$$Precision = \frac{TP}{TP + FP}$$

**CSI**: Categorical index for evaluating location accuracy, considered both misses and false alarms(threshold defined by user).

$$CSI = \frac{TP}{TP + FN + FP}$$

**Accuracy**: Percentage of well predicted pixels. Error tolerance defined by user.

$$Accuracy = \frac{Nb(|y_{pred} - y| < tol)}{Nb_{total}}$$

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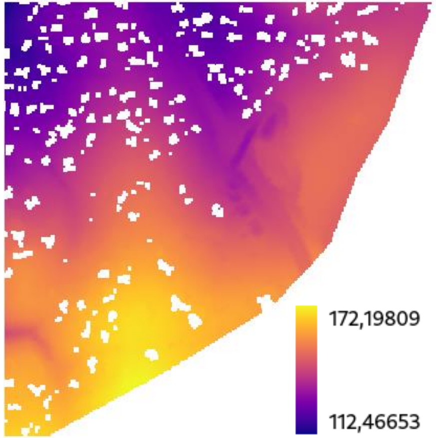
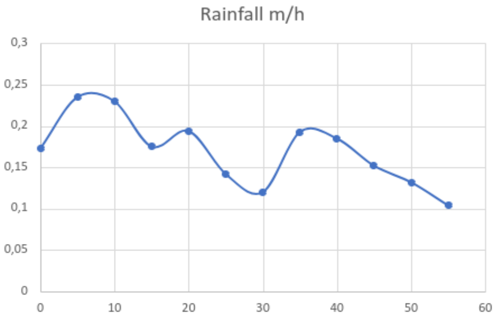
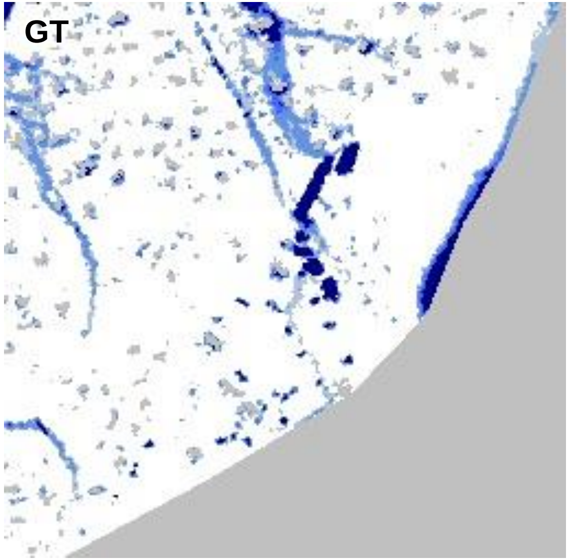
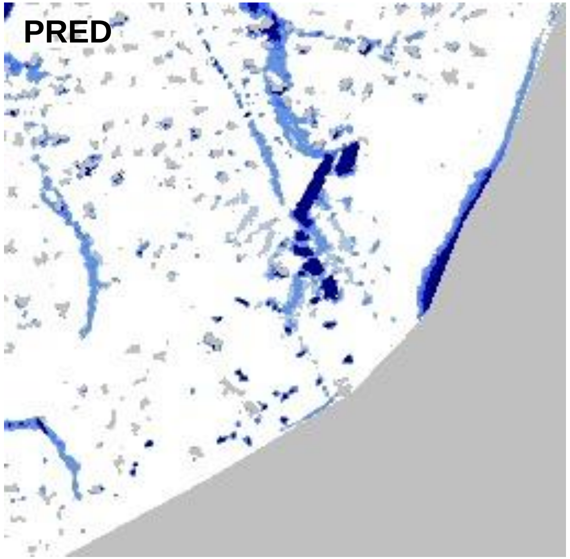
# 5. Inferences and results

- **Nimes dataset: 5m resolution** (resolution limited by the generation of data with the HD model)




| | |
|---|---|
| | [0.05 m - 0.1 m[ |
| | [0.1 m - 0.3 m[ |
| | [0.3 m - 0.5 m[ |
| | [0.5 m – inf [ |
| | Not flooded |
| | NO_DATA |

**Accuracy at 5 cm : 92%**

**Inference time: 0.1 s/tile on GPU***

**NVIDIA RTX A6000*

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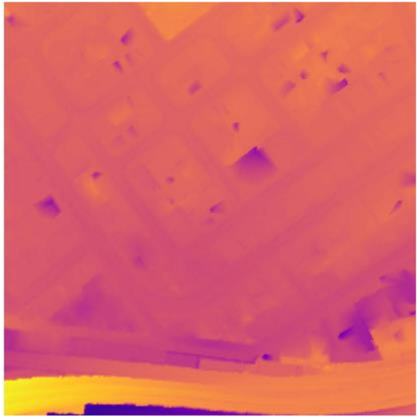
# 5. Experiment on Zurich

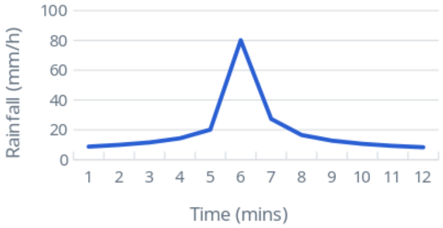
- **Zurich dataset: 1m resolution**

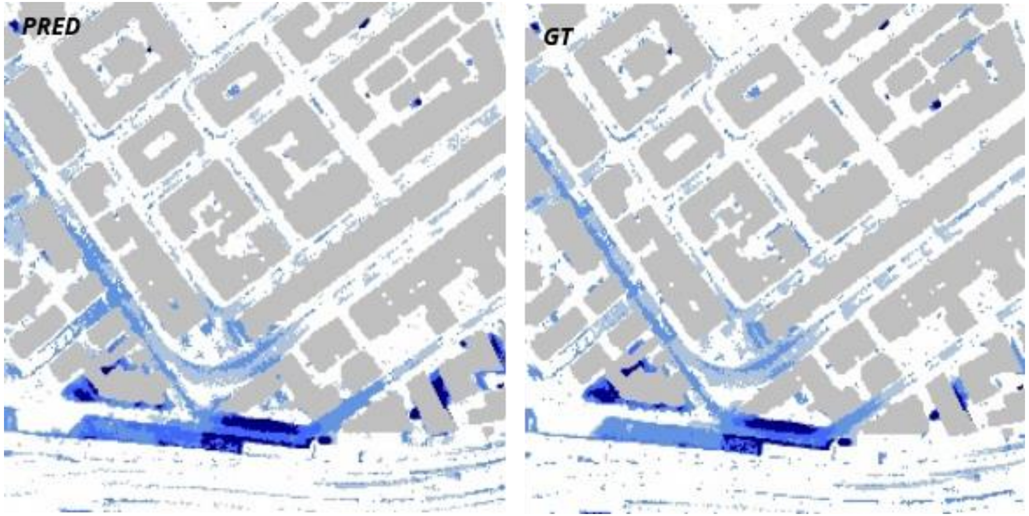
# 5. Inferences and results

- **Zurich dataset: 1m resolution**



Rainfall input




| | |
|---|---|
| | [0.05 m - 0.1 m[ |
| | [0.1 m - 0.3 m[ |
| | [0.3 m - 0.5 m[ |
| | [0.5 m – inf [ |
| | Not flooded |
| | NO_DATA |

**Accuracy at 5 cm : 96%**

# 6. Conclusion

- A very challenging objectives due to data complexity and variability
- Generalization of AI model, to be able to use in different geographical areas.
- Work in progress:
  - Data processing (new event in Nîmes 2014)
  - Coordinates encoding to link one tile to the ones that surrounds it.
- When successful, it will ease the flash flood modeling
  - Example : To evaluate potential impact of changes in the city (ex : new roads, buildings, infrastructures, etc …) even if data are partially missing.
  - Potential use in country with few/no sensors/data to model the flood.

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6. **DassFlow2D**; https://www.math.univ-toulouse.fr/DassFlow/

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# Thank you !

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