FloodCitiSense

Project Overview

with a focus on data-driven flood forecasting models

December 2020

Project Objective

To improve cities' resilience to floods, FloodCitiSense aims at developing a pluvial flood early warning service for, but also by citizens and city authorities.

Website: http://www.floodcitisense.eu/main

Infographic: http://www.floodcitisense.eu/

April 2017 – July 2020 (…)

Project Funding

EU ERA-NET Smart Urban Futures Call

New dynamics of public services

- **Innovative approaches** to **increase the capacity** of urban areas to answer **local challenges**
- **Interdisciplinary** research and collaboration
- Encouraging **involvement of civil society**, thus bridging gaps between research disciplines, citizens and decision makers, cities and consumers

Partnership & Pilot Cities

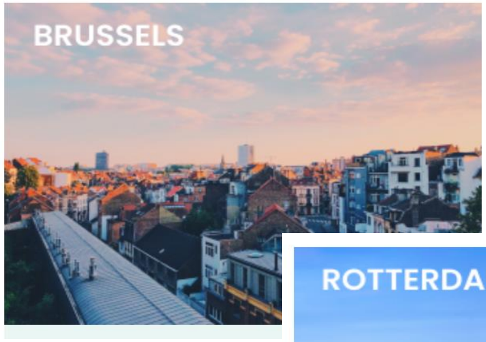
- Free University of Brussels
- Etat Géréraux de l'Eau à Bruxelles
- *Brussels City*

- TU Delft
- Disdrometrics
- *Rotterdam City*

- International Institute for Applied Systems Analysis

- National Taipei University of Technology

Imperial College London
Local Government Flood Forum
RAIN++
rps
Birmingham City Council
SEVERN TRENT



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Working Steps

1. Stakeholder analysis and engagement – understanding needs & tool co-creation

Birmingham City Council

Selly Park South Flood Action Group & Interested citizens

SEVERN TRENT

Environment Agency

Led by

- SMIT institute of Imec (Studies in Media, Innovation and Technology) (BE)
- Local Government Information Unit (UK)

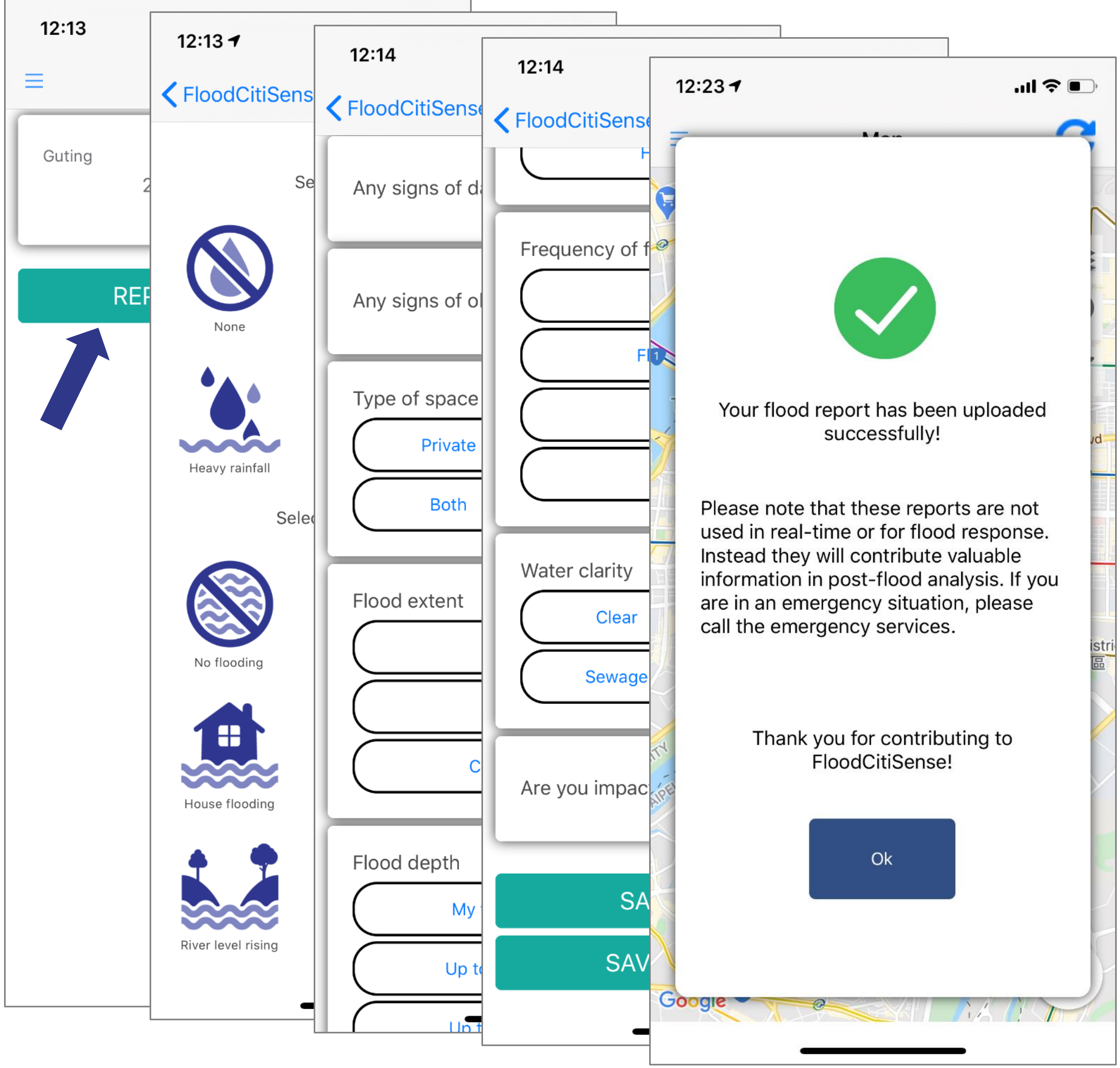
Following protocols for UX design and methods widely used in social sciences to assess tech uptake / acceptance in urban living labs

Engagement workshops held throughout all working steps

Working Steps

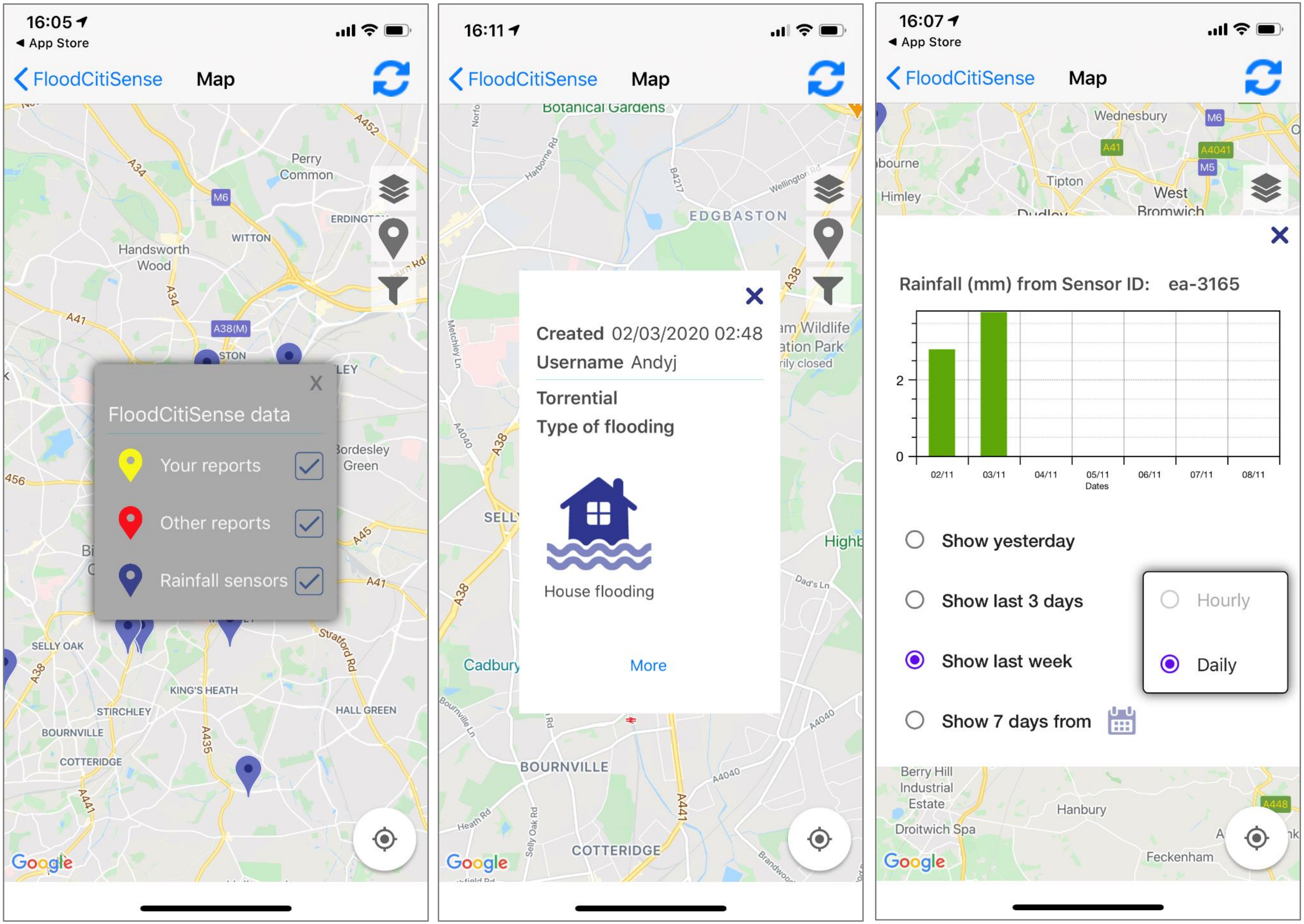
1. Stakeholder analysis and engagement

2. Urban Living Labs (ULL) – Data collection through app & low-cost rainfall sensors



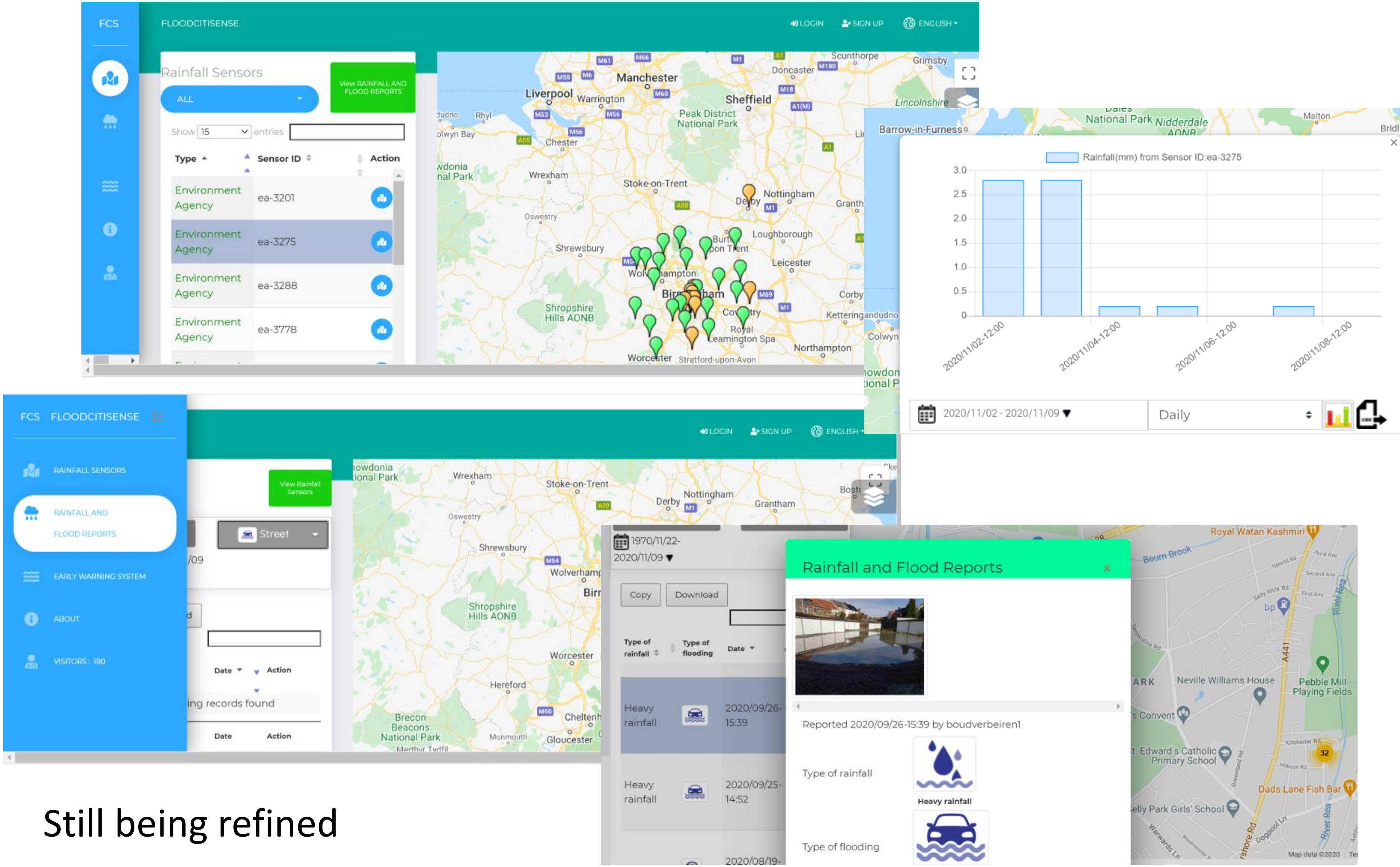
Mobile App

- Dev by IIASA
- Available on App Store & Google Play
- 1yr post-project support



Rainfall data & report visualisation in app

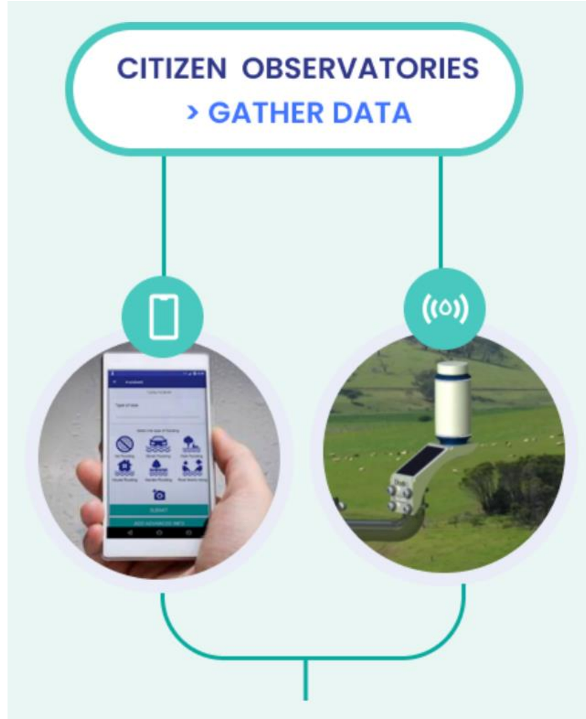
Web platform for flood report & rain data visualisation



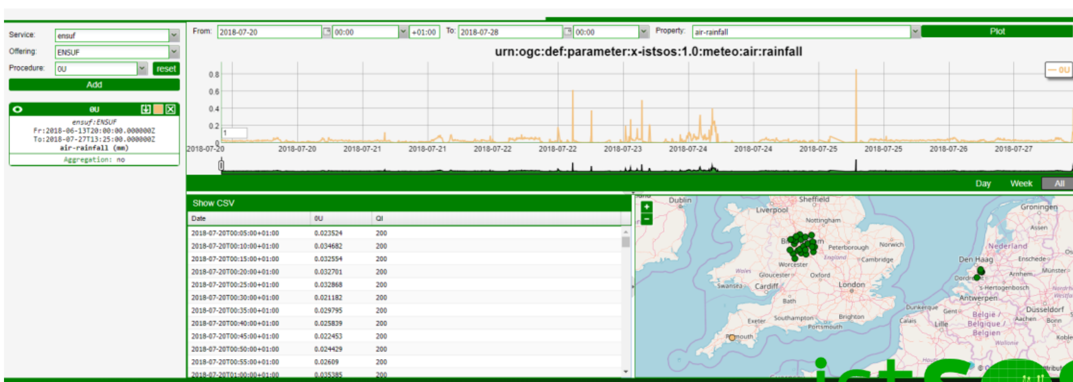
Still being refined

Piezoelectric low-cost sensors

- Supplied by Disdrometrics (NL)
- Assembled by citizens
- Solar battery powered
- LoRa transmission



Back-end



- OGC Sensor Observation Service server implementation
- Written in Python, PostgreSQL DB
- User friendly interface
- Rich feature collection to easily manage time series data (APIs, aggregation fxns, etc)

Stakeholders shaped the ULL

- Stakeholder engagement from the start was key and local stakeholders (inc. citizens) helped co-create the solution (all functionalities were discussed), evaluate the solution and collect data.
- Some concerns raised by stakeholders which shaped the ULL implementation include:
  - ✓ **Safety first:** ‘missions or journeys’ (proactively asking app users to report on flooding) not implemented over safety concerns
  - ✓ **Data protection:** besides personal data handling, concerns expressed over photos uploaded as part of flood reports, exact location of rainfall sensor not shown
  - ✓ **Managing expectations is key:** what happens after report is uploaded (concern from users and BCC side)
  - ✓ **What if the system (app) is sabotaged?** – potential implementation of ‘expert users’ who can validate reports
  - ✓ **Access to smart phones limited in some age groups** – hence need for website

Urban Living Lab Evaluation

Assessments were carried out throughout the ULL implementation – some key results following sensor-building workshop include:

- Workshops attended by a cross section of ages
- 40% of group had experienced flooding
- 90% of participants agreed and strongly agreed that they had learned new things
- 80% agreed that they felt empowered to use sensor and mobile app
- Everyone agreed that the FCS project will allow citizens to help researchers in sharing information about floods
- Willingness to use tools: 90% agreed to use the mobile app for reporting urban floods
- 70% agreed that they had a better understanding of flooding in their area

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Working Steps

1. Stakeholder analysis and engagement

2. Urban Living Labs – Data collection through app & low-cost rainfall sensors

3. Data-driven flood forecasting model

Focus of this presentation

Working Steps

1. Stakeholder analysis and engagement

2. Urban Living Labs – Data collection through app & low-cost rainfall sensors

3. Data-driven flood forecasting model

4. Operational implementation & testing of flood early warning system (EWS)

@ Birmingham:

- Only proof of concept – including visualisation of predicted flooding on website
- BCC not ready to use EWS, but may use flood reporting data in hindcast (S19)
- Performance needs to be better understood before system is deployed operationally
- Integration of FCS solutions with existing systems also key to enable effective use

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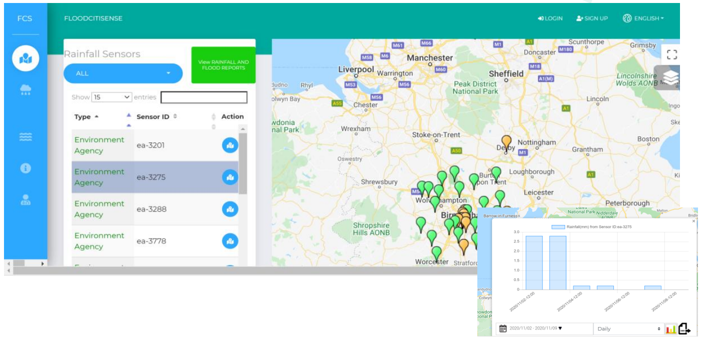
Summary - Main Deliverables

1. Mobile app for flood reporting by citizens
2. Network of rainfall sensors across urban living labs
3. Platform for rainfall data and flood report visualisation
4. Data-driven urban (pluvial) flood forecasting model – <u>proof of concept (not operational)</u>



Data driven flood prediction at Birmingham Pilot

Why a data-driven model?

- Three main types of flood forecasting systems (FFS):
  A. Empirical warning thresholds (e.g. rainfall thresholds supplemented by antecedent rain)
  B. Pre-simulated scenario (data-driven)
  C. RT hydraulic simulation

Model Type	Implementation Cost	Operational Cost	Other Features
A	Low	Low	• Based on catchment knowledge • Spatial variability of thresholds not accounted for
B	High	Low	• Model re-training needed following catchment changes
C	High	High	• Hydraulic model must comply with RT requirements (short runtimes, etc)

- Intermediate complexity & cost
- Low operational cost make it suitable for LLFAs

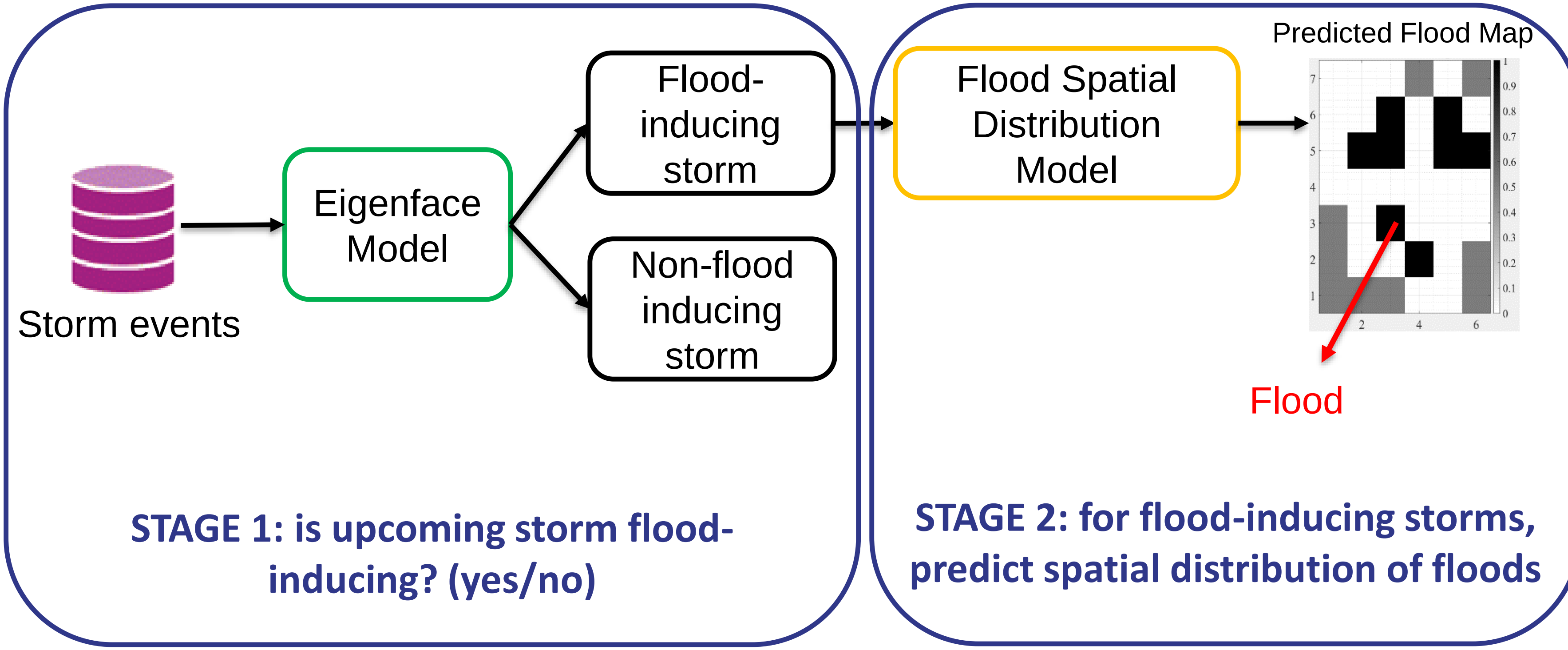
Two approaches were tested

- Machine learning-based, assuming rainfall forecast available and reliable
- Analogue system, including analogue weather and flood forecasting

Machine Learning Model

(assuming rainfall forecasting available)

2-Stage Prediction Model



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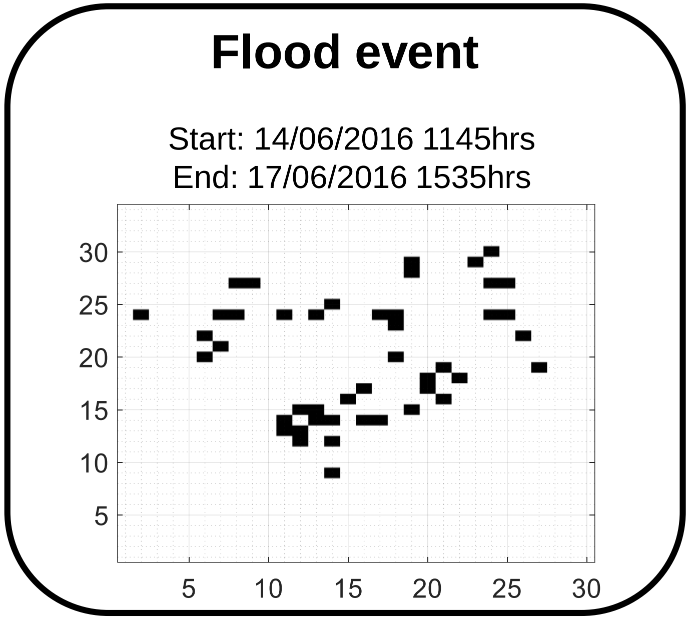
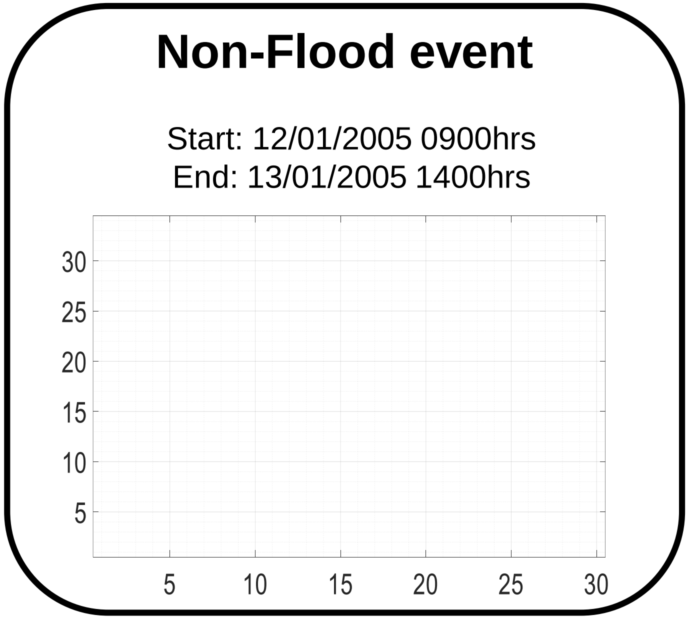
Dataset

Flood Records

- ST & BCC flood records (compiled into a single dataset)





- (Flood records were later supplemented with simulated max depth flood maps)

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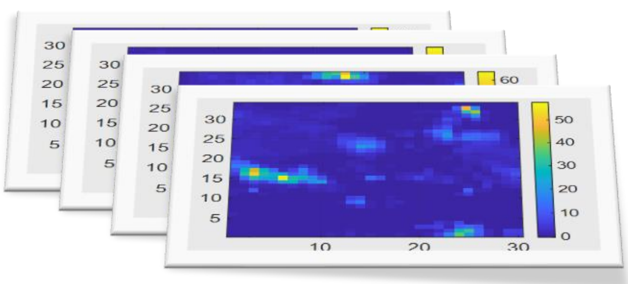
Storm Event Features

- Storm event separation & identification of runoff-generating events between 2005-2017 based on WaPUG criteria @ Minworth RGs
- Each flood/non-flood event has a set of feature maps (in a 34 by 30 grid) derived from radar data

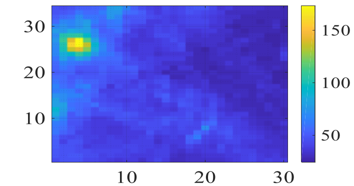
Rainfall radar maps from event start to end time
- Temporal resolution: 5 minutes
- Spatial resolution: 1km



Feature extraction

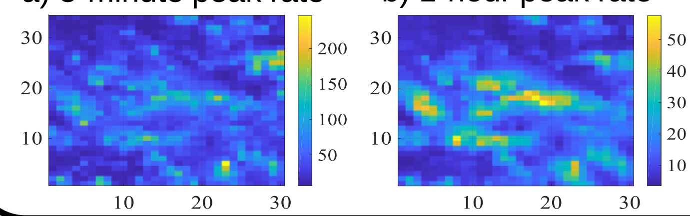
4 main feature maps

Rainfall accumulation [mm]

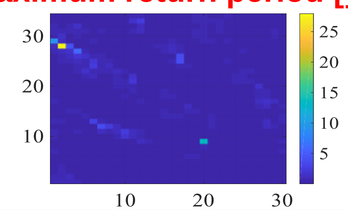


Rainfall peak rate [mm/h]

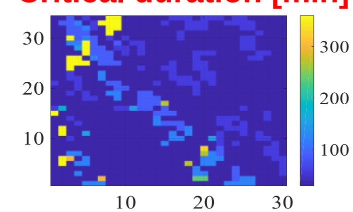
a) 5-minute peak rate b) 1-hour peak rate



Maximum return period [yr]



Critical duration [min]

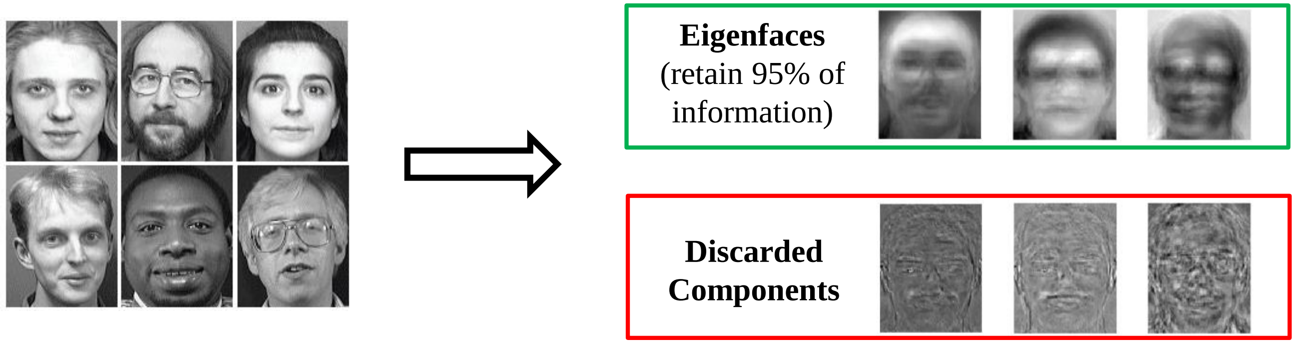


- A DB of flood (128) and non-flood (1511) rainfall events & associated features was created

Model Implementation

Stage 1: Eigenface (flood/non-flood)

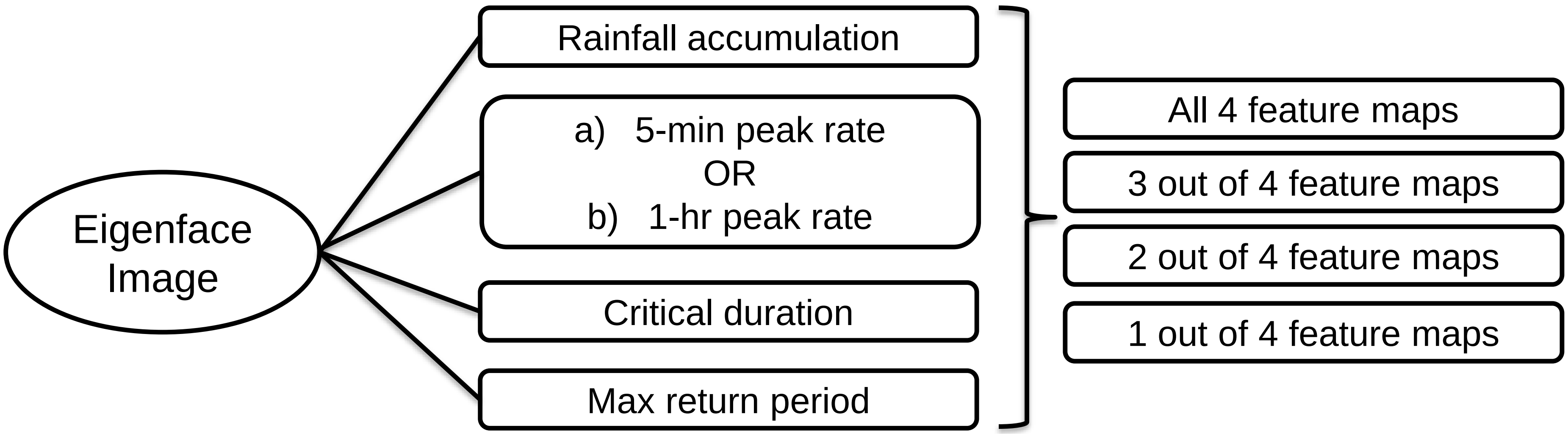
- Common algorithm used in Facial Recognition Systems
- Concept:
  - ✓ Create a database of images (Eigenfaces) which have undergone dimensionality reduction (PCA), while keeping main features



  - ✓ Compare the test image with database images.
  - ✓ Find the most similar database image based on the minimum Euclidean score.
  - ✓ If the most similar database image is associated to a flood event, then the test event is a flood event.

Stage 1: Eigenface (flood/non-flood)

- 23 different Eigenface models were created, each considering a different combination of the rainfall feature maps to form the "facial image".



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Stage 1: Eigenface - Results

- Best Eigenface models have an accuracy of approximately 70%.
- Best performing model: accumulation + 1h peak rate -> 72% accuracy
- The critical duration is a poor predictor.

Best Eigenface Models

Model 3
- Accumulation
- 5-min peak rate
- Max return period

Accuracy: 71.05%

Model 6
- Accumulation
- 5-min peak rate

Accuracy: 70.87%

Model 15
- Max return period

Accuracy: 71.22%

Model 20
- Accumulation
- 1-hr peak rate

Accuracy: 71.99%

Model 22
- 1-hr peak rate
- Max return period

Accuracy: 70.90%

Model 23
- 1-hr peak rate

Accuracy: 71.15%

Poor Eigenface Models

Model 10
- Max return period
- Critical Duration

Accuracy: 65.05%

Model 14
- Critical Duration

Accuracy: 43.10%

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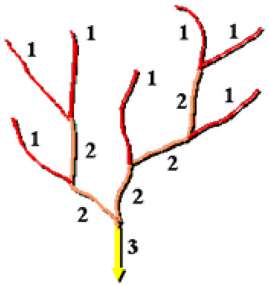
Stage 2: Spatial Flood Distribution

Aim: predict flood occurrence at each 1kmx1km grid

Features (predictors) under consideration:

Rain Features	x_1: Rainfall accumulation [mm]
	x_2: 5-minute peak rainfall rate [mm/h]
	x_3: 1-hour peak rainfall rate [mm/h]
	x_4: Critical duration [min]
	x_5: Maximum return period [yr]
Topo Features	x_6: Elevation [m]
	x_7: Maximum Strahler order [-]
	x_8: Average Strahler order [-]
Sewer Features	x_9: Sewer density [m^3]
	x_{10}: Sewer return period analysis median [yr]
	x_{11}: Sewer return period analysis minimum [yr]
	x_{12}: Sewer return period analysis 10th percentile [yr]
Land Use	x_{13}: Impermeable area [m^2]

Hierarchy of streams



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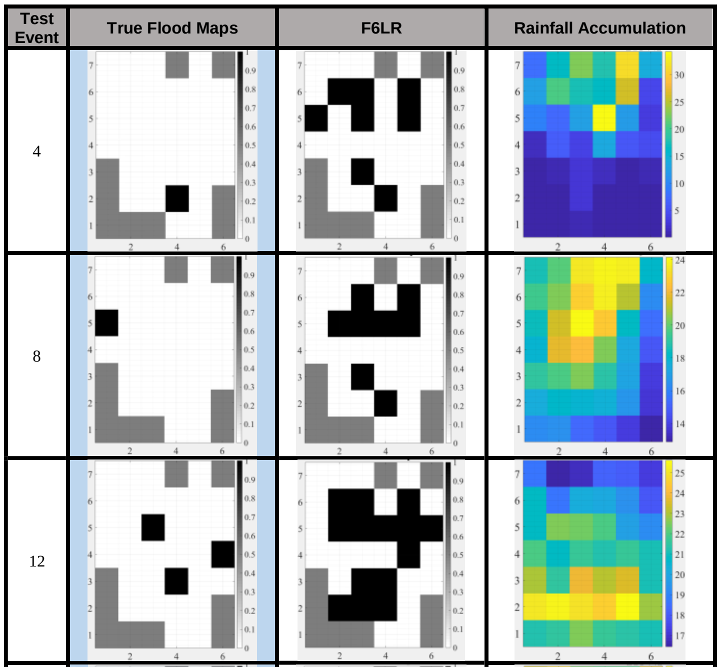
Stage 2: Spatial Flood Distribution

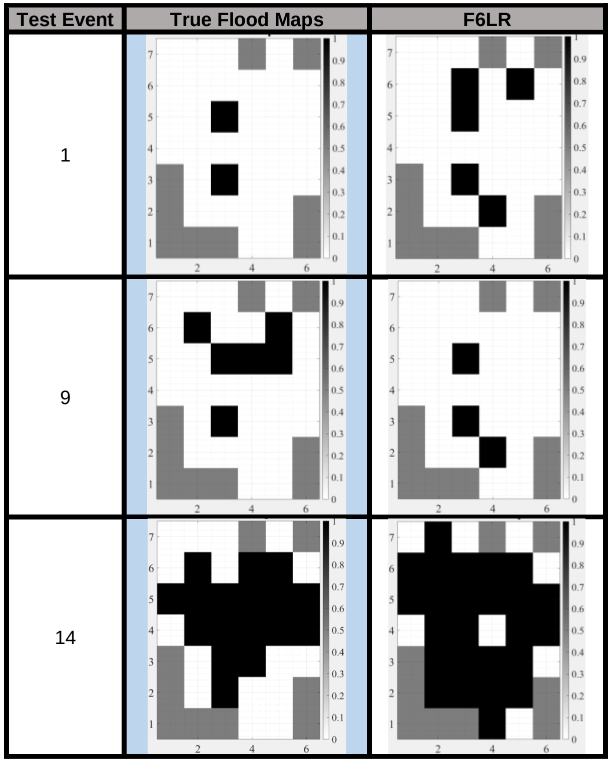
ML models under consideration:

- Logistic Regression (weighted combination of features)
- Artificial Neural Networks
- 6 types of Support Vector Machine (SVM) models
  - ✓ Linear
  - ✓ Quadratic (QSVM)
  - ✓ Cubic (CSVM)
  - ✓ Fine Gaussian (FGSVM)
  - ✓ Medium Gaussian (MGSVM)
  - ✓ Coarse Gaussian (CGSVM)

Stage 2 - Results

- Best performing model is Logistic Regression (F6LR)
- Good predictive ability for pluvial flood events with larger flood extent.

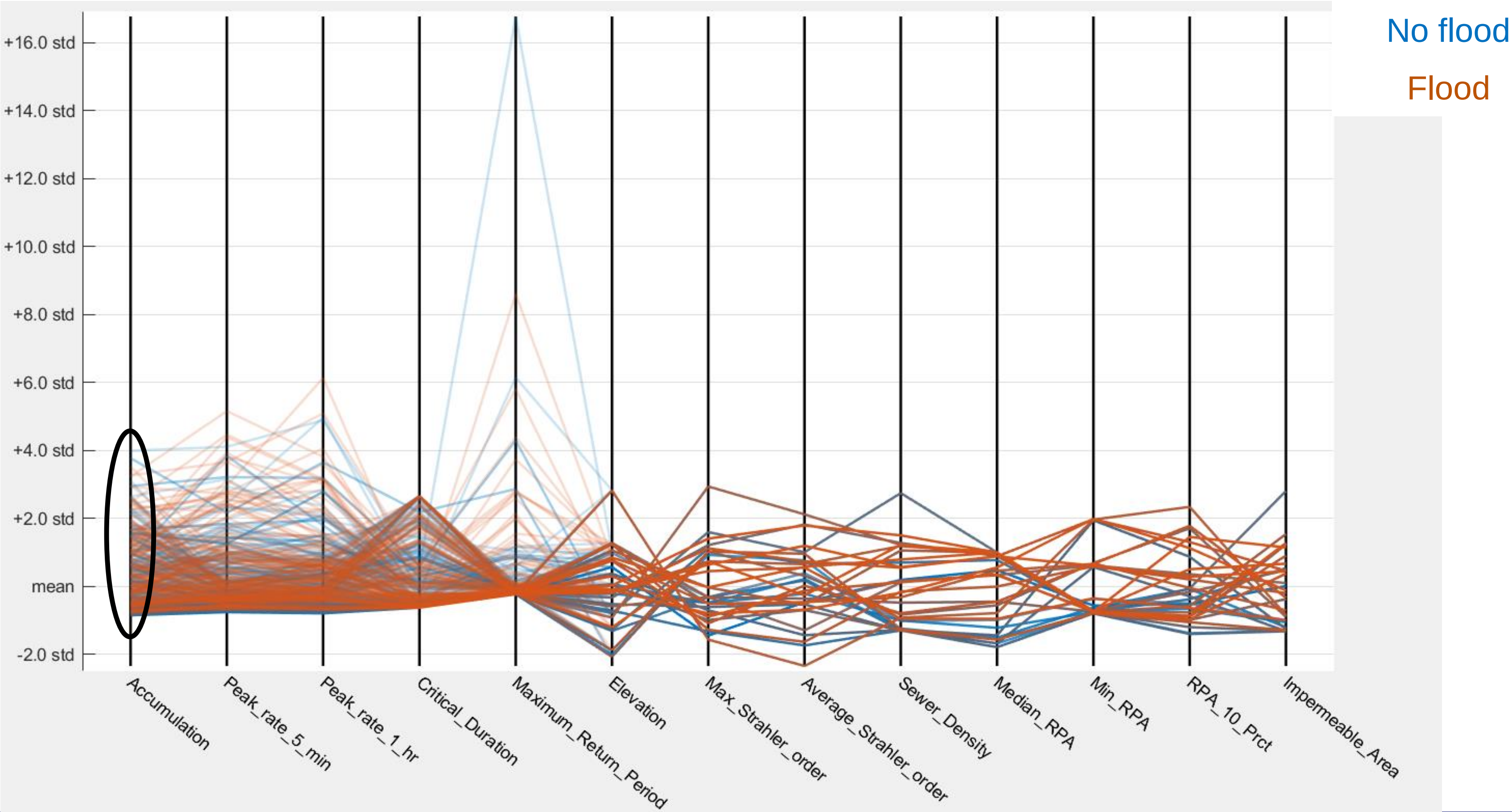




- Lower predictive ability for localised flooding events (potentially erroneously reported as hydraulic flooding?).

Stage 2 – insights & challenges

No distinct set of features that separate flood from non-flood pixels.



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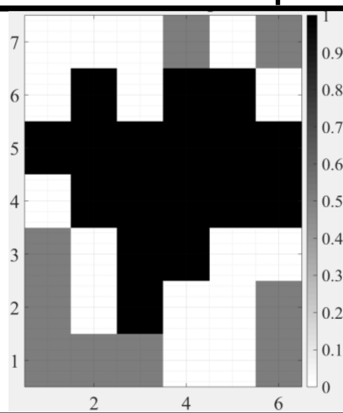
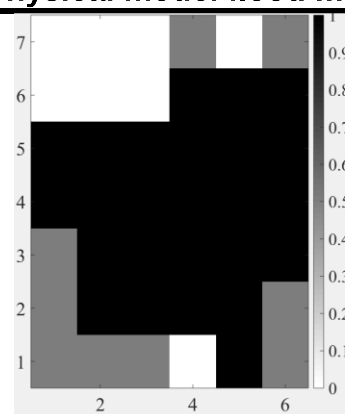
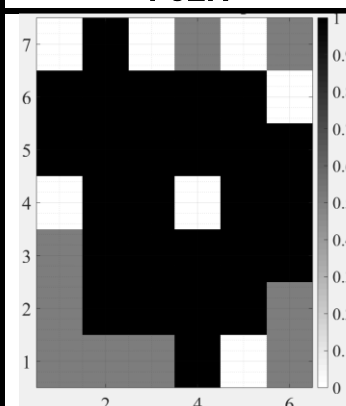
Limitations

- Flood records may underrepresent flooding extent
- Some isolated flooding incidents may have been erroneously reported as hydraulic flooding
- **Potential solution:** use simulated flood extent instead of flood records to train data-driven model -> initial results show significant better performance of data-driven model

Event	True flood map	Physical model flood map	F6LR
14			

Other potential improvements

Use Deep Learning (Convolutional Neural Networks)

- CNN may better capture system performance and result in better predictive ability – CNNs are particularly well suited for image processing
- Initial testing undertaken, but results inconclusive
- Yet to figure out optimal way of applying CNN

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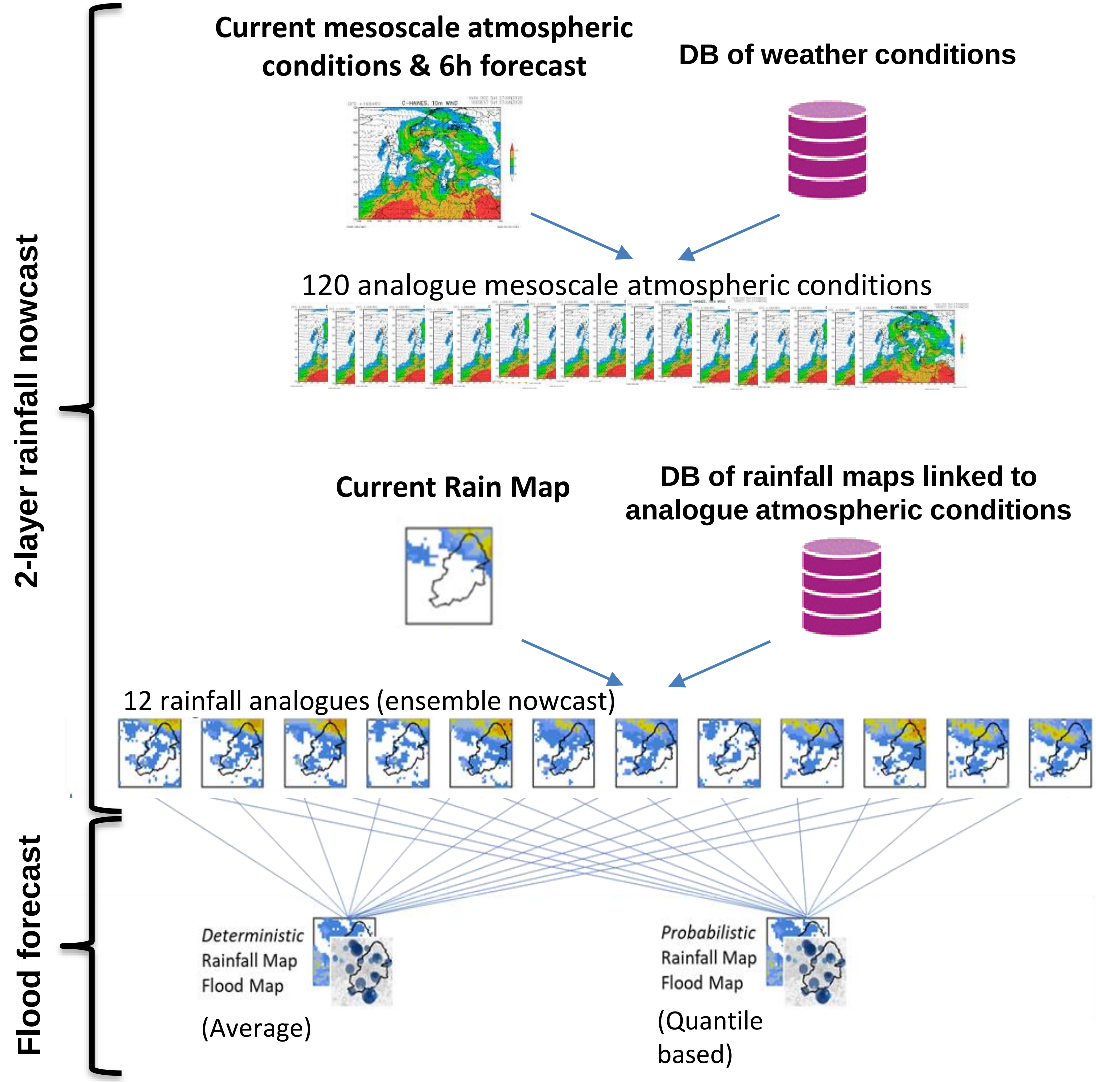
Analogue flood prediction model

(Current weather forecast is matched to climatic conditions from historical catalogue. Then, the associated flood map is extracted – a fancy LOOKUP!)

Forecasting Model Structure

- **Stage 1 - Rainfall nowcasting (0-6h):** NORA analogue-based forecasting tool, consisting of two layers:
  - ✓ Layer 1: Identification of analogue mesoscale atmospheric conditions (120)
  - ✓ Layer 2: from radar images linked to atmospheric analogues, select 12 most similar to those currently observed (images initially vectorised)
  - ✓ Effectively, an ensemble rainfall forecast is obtained

- **Stage 2 - Selection of flooding map(s) associated to historical rainfall from catalogue**
  - ✓ A deterministic flood prediction is obtained by using the averaged response from twelve flood maps, where for each gridded area (1×1 Km), the median value is adopted used (assuming 12 flood maps are equiprobabilistic).
  - ✓ A probabilistic flood prediction is obtained by generating a quantile-based flood map.



Key techniques: PCA-based dimensionality reduction, K nearest neighbour

Offline training database (historical)

- **Historical climate data:**
  - ✓ ERA5 reanalysis data from ECMWF (free) @ 1h /0.25deg resolution (~17x28km)
  - ✓ This constitutes the 'forcing' in the rainfall forecasting model (i.e. climatic conditions which result in a given rainfall map)
- **Historical rainfall data:**
  - ✓ KED merged radar-rain gauge records from 2005-2017 @ 5min/1km resolution
- **(Simulated) historical flooding response:**
  - ✓ Simulated max depth flood maps (IW + PondsimPro) for each of 157 flood-inducing storm events

Real-time (RT) data

- **Climate forecast:**
  - ✓ US Global Forecasting System (GFS) available every 6h (@ 00, 06, 12 and 18h UTC) @ 0.5° x 0.5° (~50 km)
  - ✓ This avoids the need for Met Office rainfall forecast (£££)
- **RT Met Office radar data assumed to be available**
- **RT rain gauge data at 15min resolution assumed to be available:**
  - ✓ Operationally, EA data is only available with some hours of delay, but it is assumed that RT RG data can become available either from citizen or ST sensors

Evaluation

- Cross-assessment for each of 157 flooding events, by leaving one event out from training in each iteration and using it for evaluation
- Focus on spatial replication of flood/non-flood pattern – flood maps therefore converted to binary (flood/non-flood) maps
- Quantitative assessment undertaken following **contingency table** below

	Flooding in Hydraulic(”true”) output	**Non-flooding in Hydraulic (“true”) output**	
Flooding in Data-driven output	True positives (TP)	False positives (FP)	Positive predictive rate (PPR) = TP/(TP+FP)
Non-flooding in Data-driven output	False negatives (FN)	True negatives (TN)	Negative predictive rate (NPR) = TN/(TN+FN)
	True positive rate (TPR) = TP/(TP+FN)	True negative rate (TNR) = TN/(FP+TN)	Accuracy (ACC) = (TN+TP)/(TP+TN+FN+FP)

Proportion of correct predictions, out of all test events

Evaluation

- Results

	True conditions		
Predicted conditions	***True Positive:*** ***28.6%*** *(14.3%~42.9%)* Areas are correctly predicted as flooding	***False Positives:*** ***14.3%*** *(0%~21.43%)* Areas are incorrectly predicted as flooding area	***Positive Predictive Rate:*** ***63.6%*** *(50%~75%)* (63.6% of predicted flooding areas are truly flooding areas)
	False Negatives: ***0%*** *(0%~7.1%)* Flooding areas are incorrectly predicted as non-flooding area	***True Negatives:*** ***28.6%*** *(28.6%~35.7%)* Areas are correctly predicted as non-flood	***Negative Predictive Rate:*** ***99.9%*** *(79.9%~99.9%)* (99.99% of predicted non-flooding areas are truly non-flooding areas)
	True Positive Rate: ***85.7%*** *(50.0%~99.9%)* (85.7% truly flooding areas can be correctly predicted as flooding)	***True Negative Rate:*** ***75.0%*** *(63.6%~99.9%)* (75.0% truly non-flooding areas can be correctly predicted)	***Accuracy Rate:*** ***71.4%*** *(57.1% ~ 78.6%)* (The overall accuracy is 71.4%)

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Future work

- Refine model using time-varying flood extent maps rather than final (max depth) maps only
- The proposed framework allows incorporation of data from low-cost rainfall sensors and citizen reports:
    - ✓ Rainfall data could be incorporated as extra drift in the KED merging process
    - ✓ Flooding reports could be used to add weights to analogue flood maps, rather than treating them as equiprobabilistic.
- Formal comparison of ML vs. analogue model not yet undertaken

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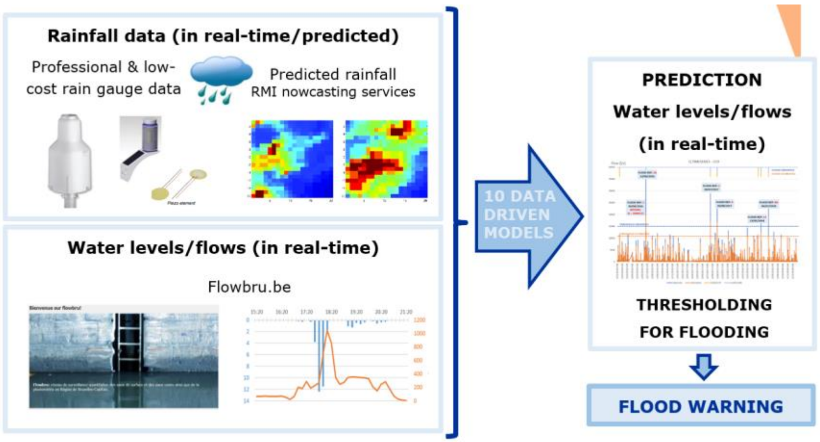
Flood Prediction at Other FCS Pilots

Brussels

- No hydraulic model available
- But:
  - ✓ Rainfall nowcasting readily available
  - ✓ Flow monitoring at key locations available
  - ✓ 20yrs of flow and rainfall records available for model training
- Focus: forecasting of peak flow in response to rainfall (i.e. rainfall-runoff)



- Data-driven models under consideration:
  - ✓ Linear regression model
  - ✓ Neural network
  - ✓ Multi-layer Perceptron
  - ✓ K Nearest Neighbours
  - ✓ Support Vector Machines
  - ✓ Random

It will be operational!

- Random Forest – best performing on accuracy and time needed to train the model.
- Random Forest models implemented for 9 critical sub-catchments

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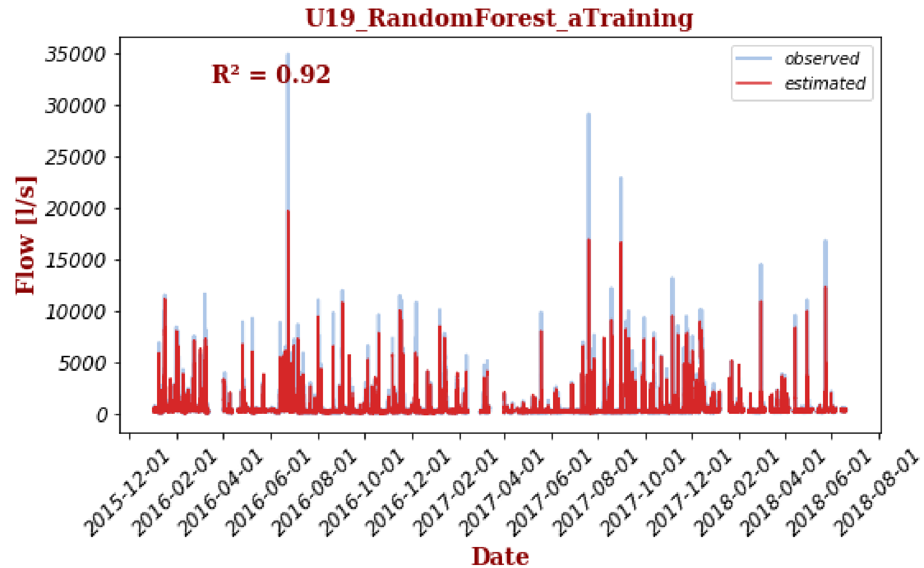
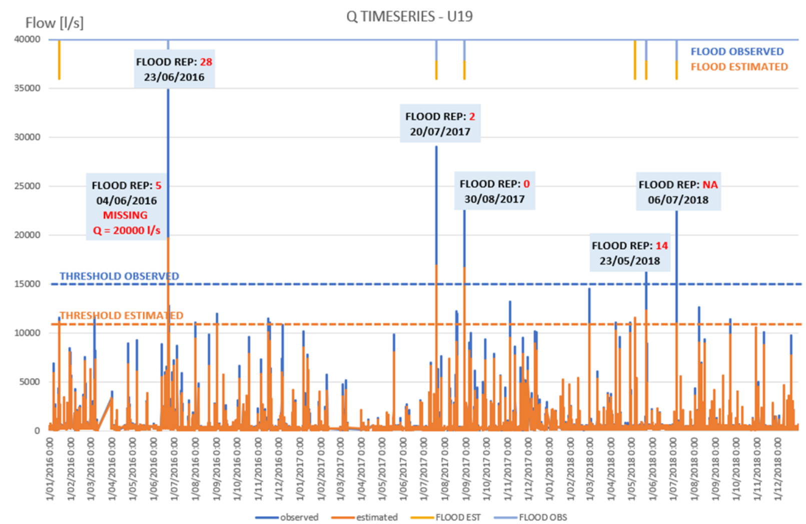
Brussels – Results & Future Work

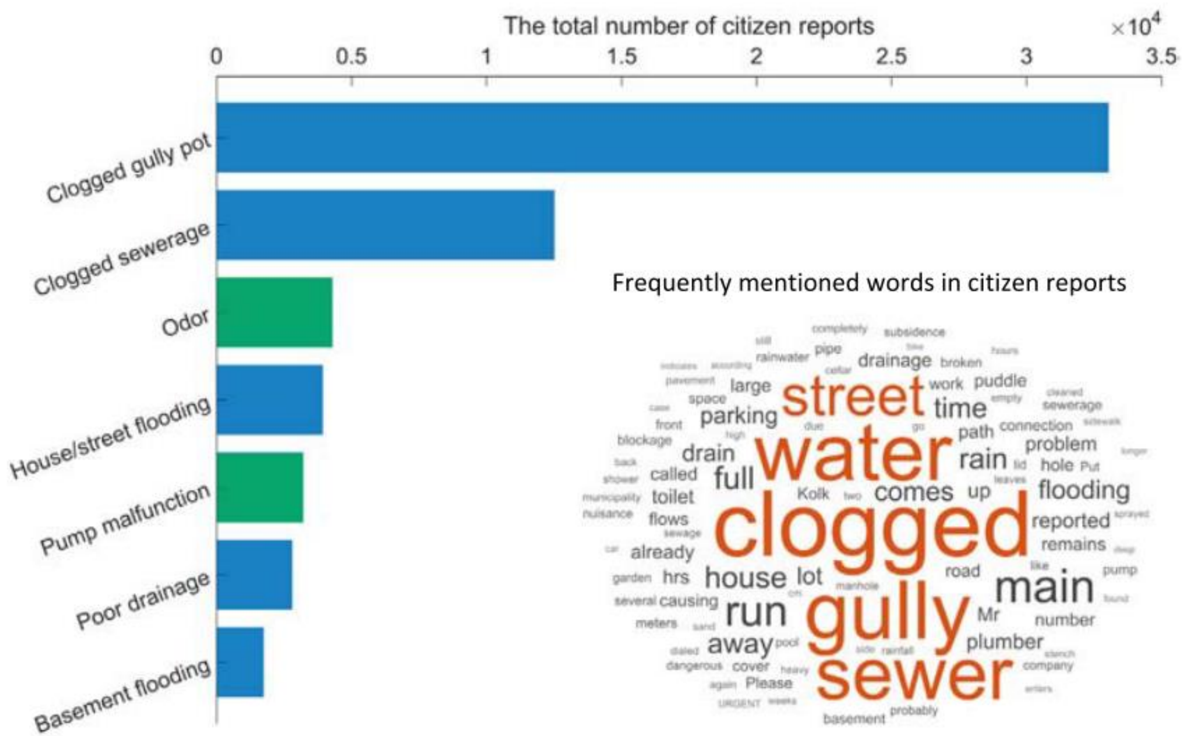
- 2h forecast horizon
- High correlation, but systematic underestimation of peak flows – potentially due to use of RG data (at coarse spatial resolution) for model training
- Flood prediction accuracy (using flood threshold): 70%
- Future work:
  - ✓ Re-train models with radar data





Rotterdam

- Review of ~38,000 citizen reports about water nuisance (2008-2017)
- Limited spatial data
- 20 reports on typical dry day
- Rainfall forecasts not available, so never intended for operational use



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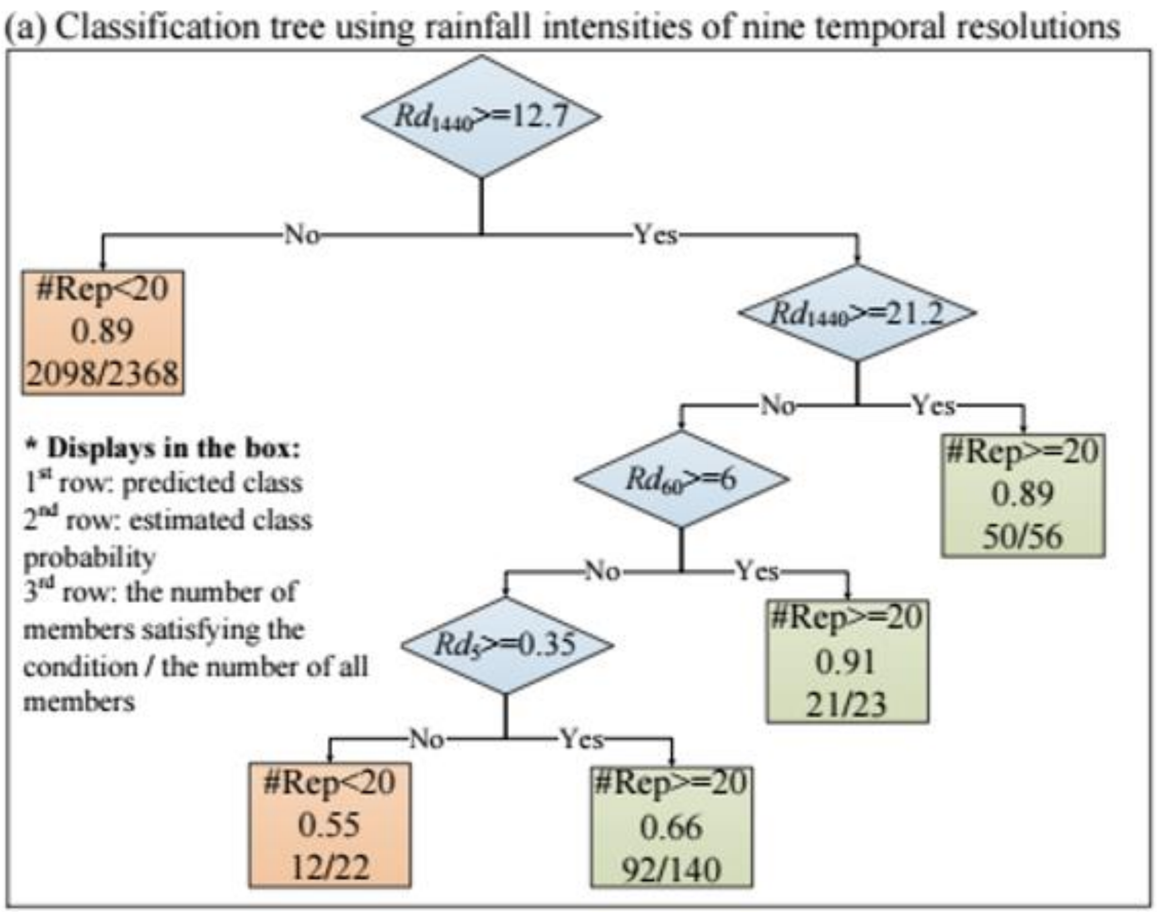
Rotterdam



Decision trees used to evaluate rainfall features likely to result in flooding

>20 reports = flood

Three different decision trees – e.g. daily rainfall, hourly maxima and 5-min peak rainfall used in model shown left (these max rainfall accumulations are computed at daily scale – so 1h max observed in given day)

Positive prediction rates 66-74%, depending on decision tree

Concluding Remarks

Concluding remarks

- Example exercise (survey results) to identify FFS uses and requirements – Ochoa-Rodriguez et al. (2018)

Potential response of LLFAs to localized surface water flood warning of different probability of occurrence and lead time

	Potential actions										
Lead time – probability	A1 (%)	A2 (%)	A3 (%)	A4 (%)	A5 (%)	A6 (%)	A7 (%)	A8 (%)	A9 (%)	A10 (%)	A11 (%)
12 h – 20% prob.	69	21	7	10	0	0	0	7	0	0	0
12 h – 40% prob.	21	47	24	26	0	12	18	32	0	0	0
6 h – 20% prob.	55	31	10	14	0	7	0	17	0	0	0
6 h – 40% prob.	9	52	24	33	3	15	24	42	0	3	0
2 h – 40% prob.	13	53	23	33	7	13	23	50	3	3	0
2 h – 60% prob.	**3**	**48**	**36**	**45**	**12**	**30**	**36**	**64**	**6**	**9**	**0**
1 h – 40% prob.	9	44	28	31	6	16	28	53	3	3	0
1 h – 60% prob.	3	41	32	47	18	32	32	62	6	6	0
1 h – 80% prob.	**3**	**45**	**36**	**48**	**24**	**33**	**42**	**70**	**15**	**18**	**9**
0.5 h – 60% prob.	3	41	28	44	19	34	31	56	6	13	3
0.5 h – 80% prob.	**3**	**45**	**33**	**48**	**24**	**33**	**42**	**64**	**15**	**24**	**15**

A1: do nothing; A2: monitoring of watercourses, gullies, trash screens and the like; A3: cleansing of gullies and screens in high risk areas; A4: notification of contractors and partners; A5: activation of control elements (e.g. pumps, storage); A6: notification of flood wardens; A7: notification of the general public; A8: placement of staff and resources on standby; A9: deployment of temporary flood defences; A10: road closures; A11: closure of public locations susceptible to pluvial flooding (e.g. underground passages).

The values in bold correspond to the combinations of lead time and probability at which the greatest response would be possible.

Concluding remarks

- For operational deployment:
  - ✓ FFS objectives and requirements (considering resources and needs) need to be clearly identified
  - ✓ All stakeholders (internal and external) should be included from onset – ideally in a co-creation framework. This will not only improve design, but also acceptability.
  - ✓ Effective integration with other existing systems would help maximise benefit

Concluding remarks

- Proof of concept: this work shows that current data, models and technology do enable implementation of data-driven flood forecasting models
- However, further testing is required to confirm system performance and fitness for purpose (e.g. are accuracy, uncertainty, lead time and spatial resolution enough to drive relevant actions? What actions could be implemented at different lead times and levels of uncertainty?)

FloodCitiSense

Questions?

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