

Rule-based BPNN model for real-time IDF prediction of rainfall: Valuable Input for Early Warning Systems

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Outline

➤ Introduction

- Concepts, necessity and gap finding

➤ Methodology

- Defining proposed approaches

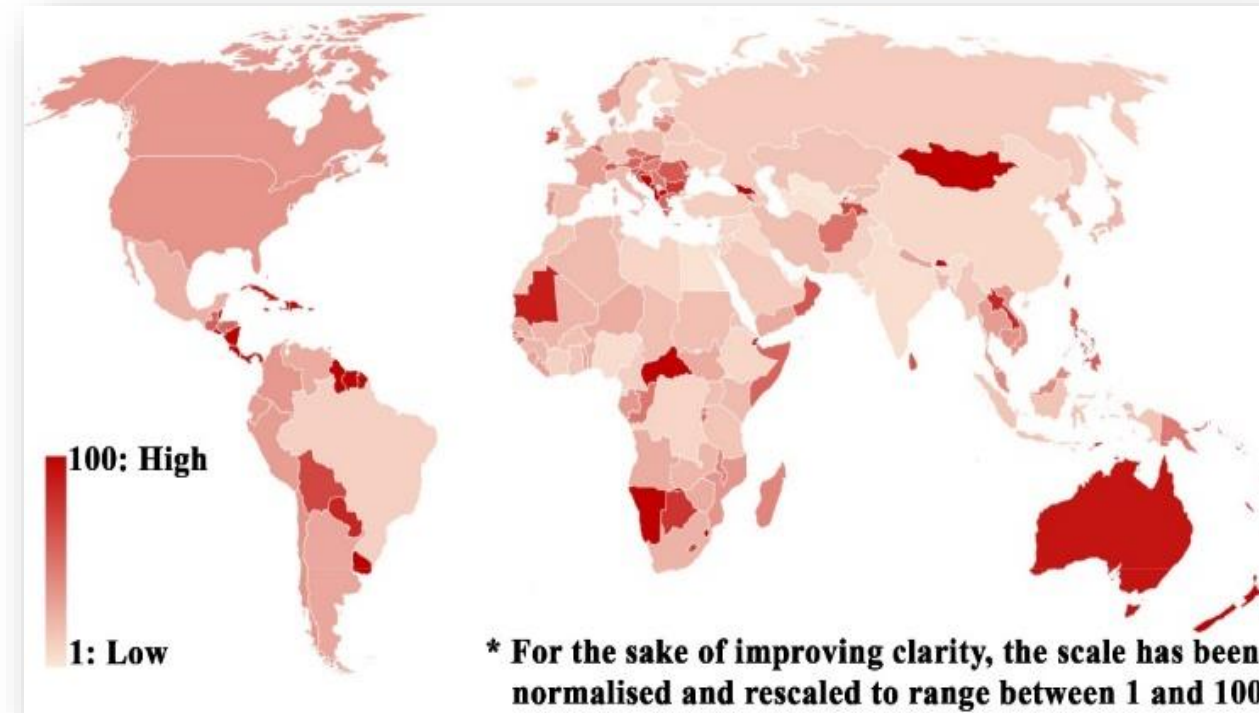
➤ Case study/Results

- Verifying proposed approach by real case study

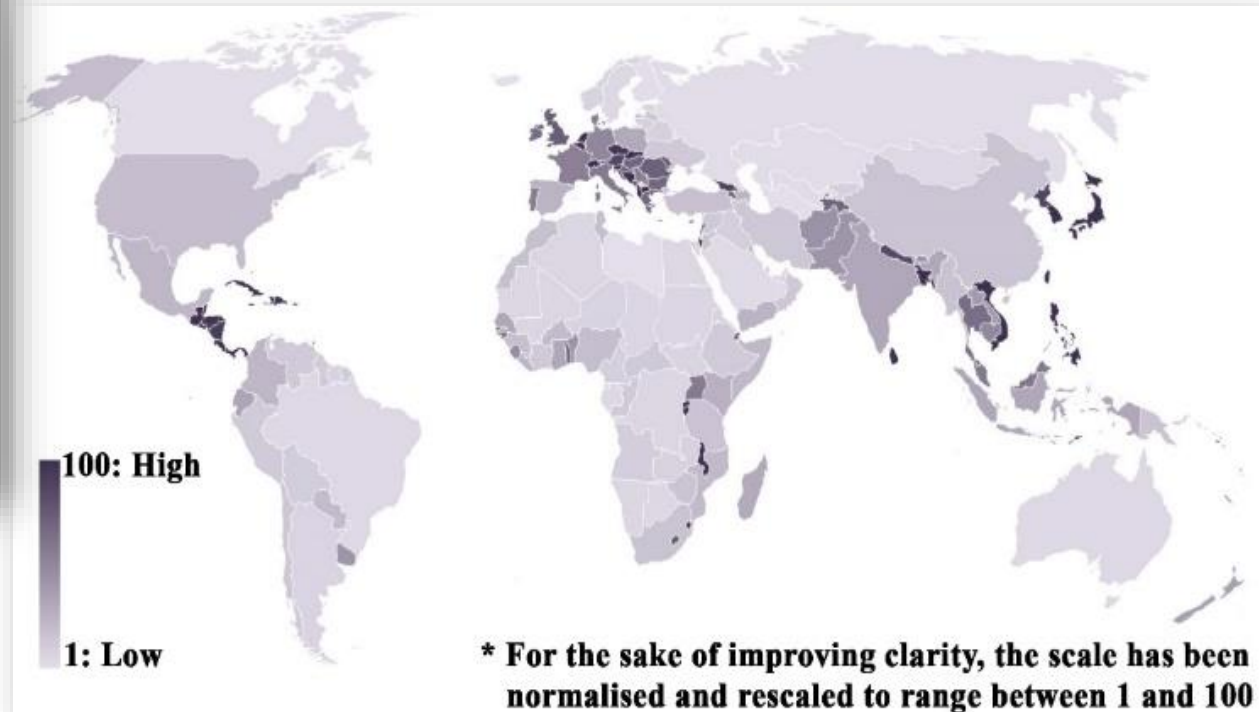
➤ Conclusions

- Key findings and future works

Urban flood Occurrence



Population-based



Area-based

Gaps & Aims

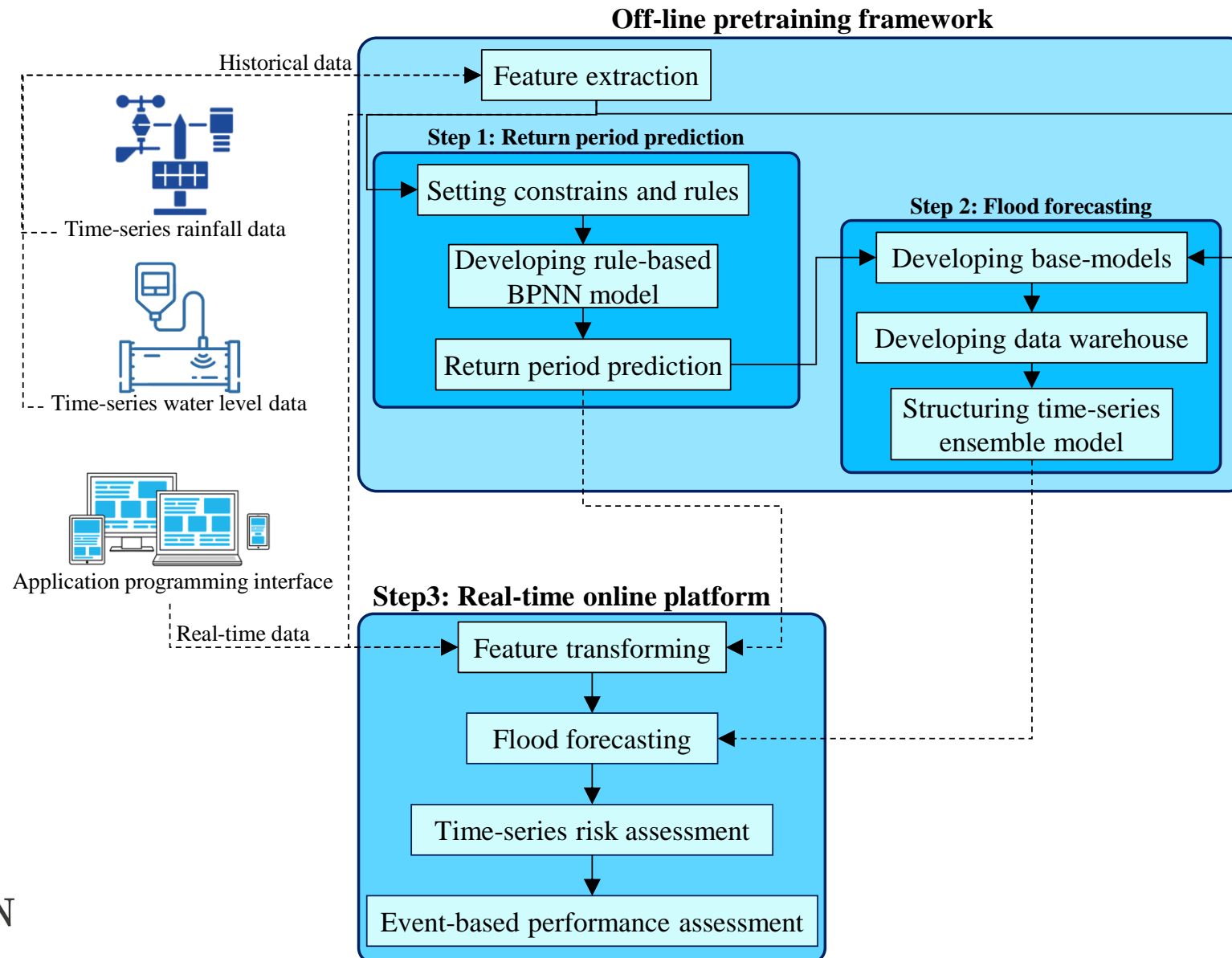
Research gaps

- ❖ **Rainfall** is the foundation of training/validation and testing **EWS**.
- ❖ Usually used by **duration**, **intensity** and **peak time**
- ❖ More **details** can significantly assist real-time **flood forecasting** systems

Research aim

One of the rainfall characteristics that can bring valuable insight into the EWS are **return period (RP)** or **position of rainfall into the intensity-duration-frequency (IDF) curves**

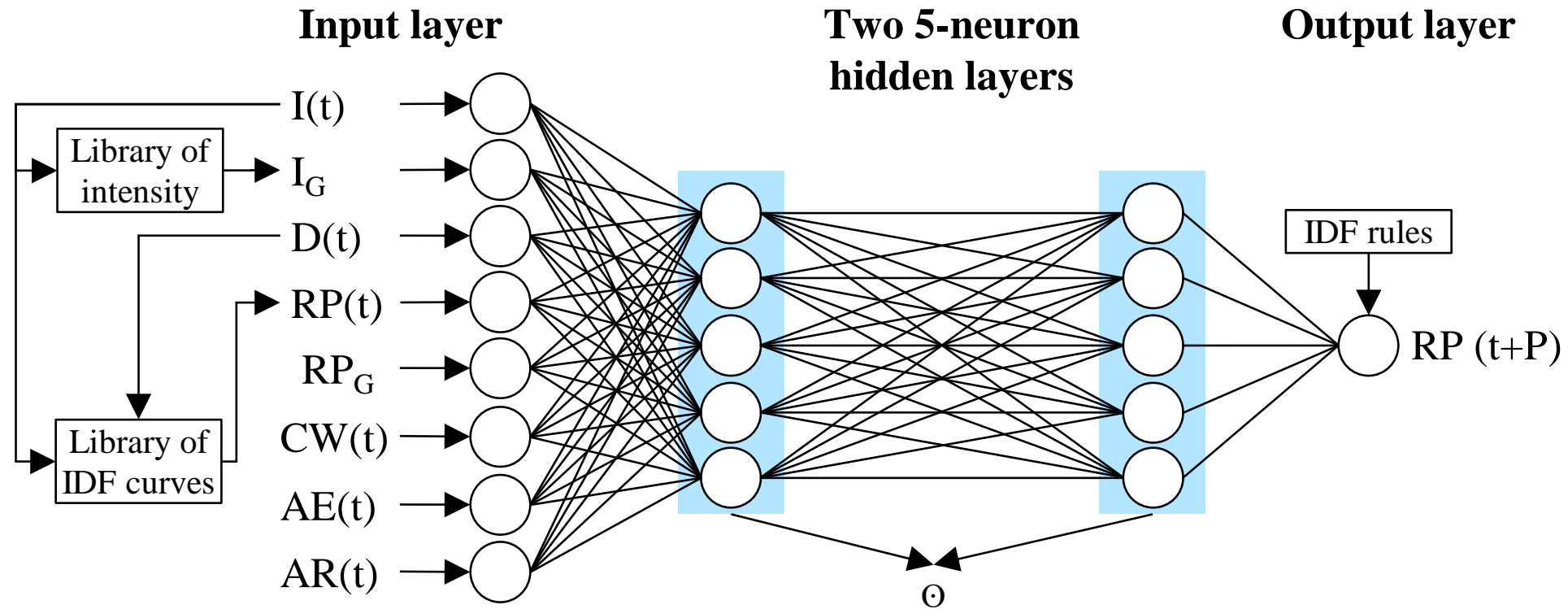
Methodology



Rainfall feature extracted

Extracted rainfall feature	Description	Transformation key	Unit/class
Intensity (I)	The ratio of total depth to the duration	Numerical	mm/hr
Intensity gradient	I_t / I_1	Numerical	mm/mm
Duration	Time period of between the onset and end of the precipitation	Numerical	min
Current RP	Class of RP for timestep t	Class	1-7
RP gradient	RP_t / RP_1	Numerical	-
continuous wavelet transform	$\frac{\sum_{i=2}^t (R_i - R_{i-1})^2}{\bar{R}}$		mm
Absolute energy	$\frac{\sum_i R_i^2}{R}$	Numerical	mm
Anthropic	$\sum_i P(R_i) \times \log_2 R_i$	Numerical	-
RP predicted	RP of the rainfall for timestep of t	Class	No

Structure of the model



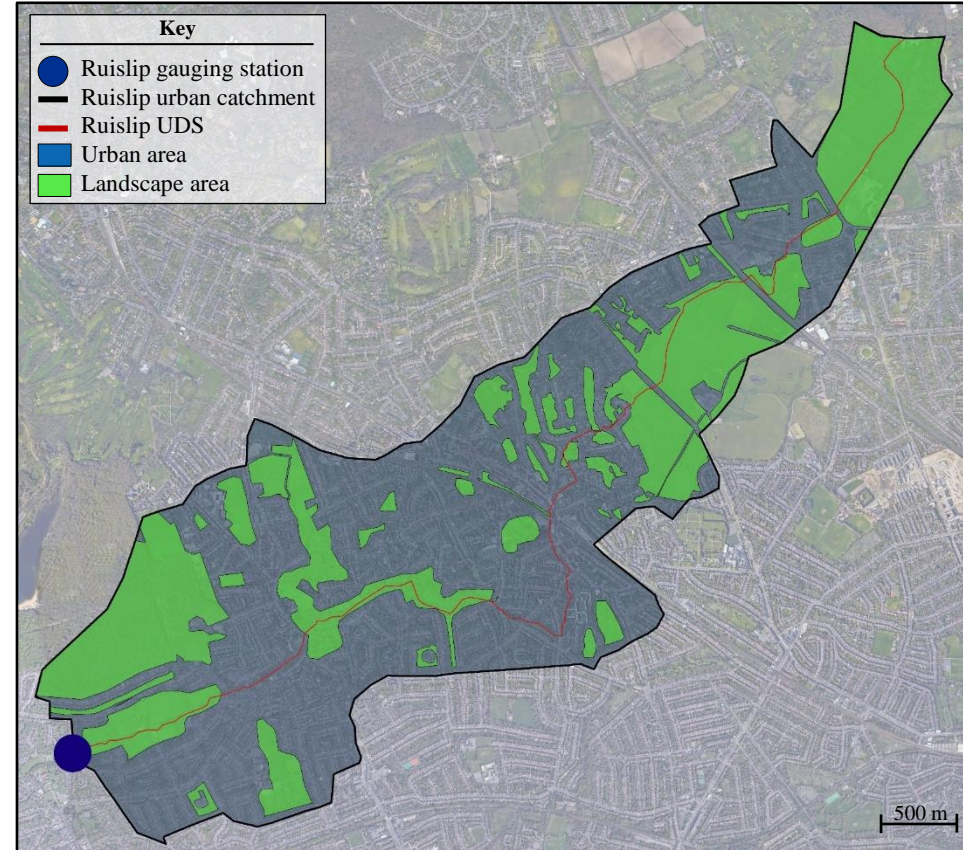
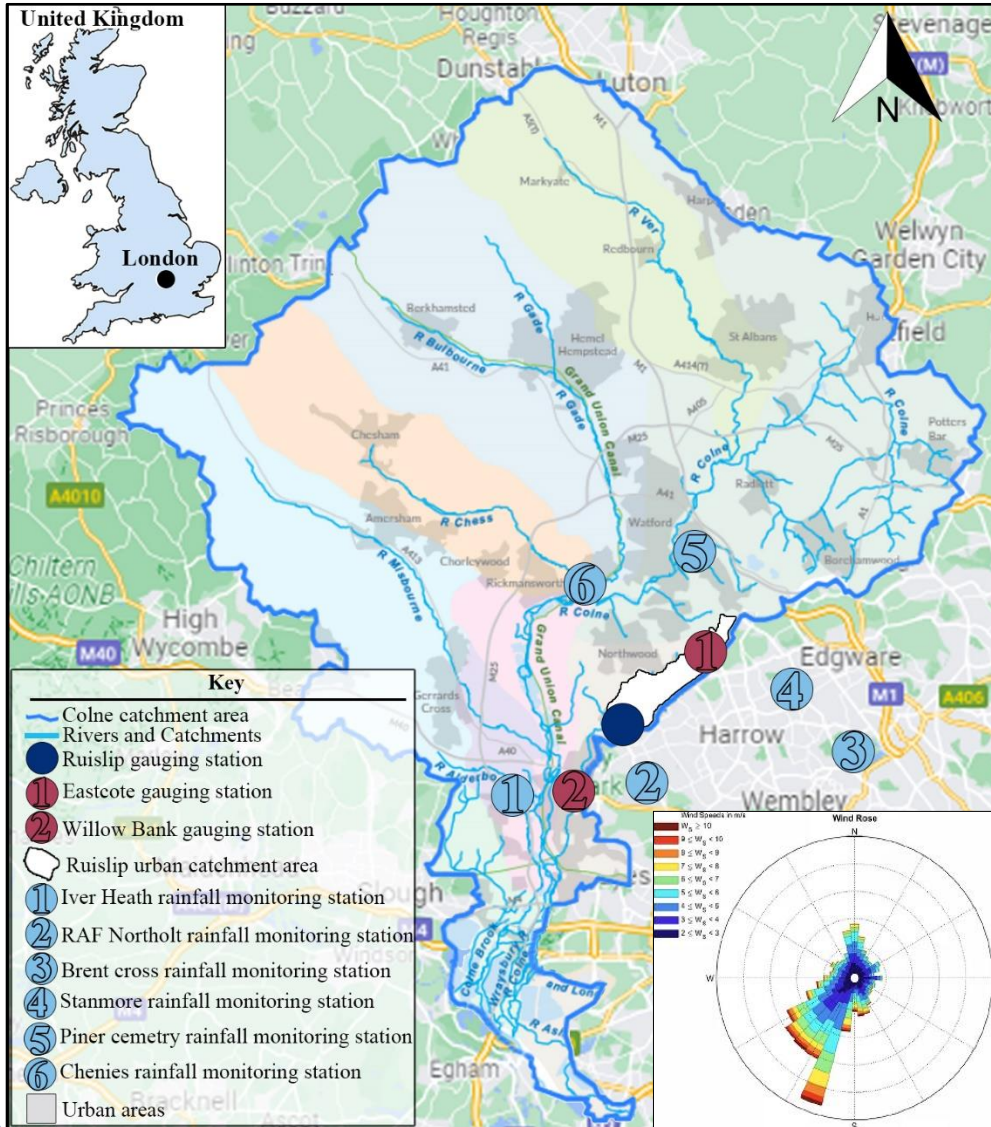
Rainfall inputs:

- (1) Current Intensity $I(t)$
- (2) Intensity gradient determined from an intensity library I_G
- (3) Current duration $D(t)$
- (4) Current RP determined using rules from the IDF curve library $RP(t)$
- (5) RP gradient RP_G
- (6) Continuous wavelet transform $CW(t)$
- (7) Absolute energy $AE(t)$
- (8) Anthropropic $AR(t)$

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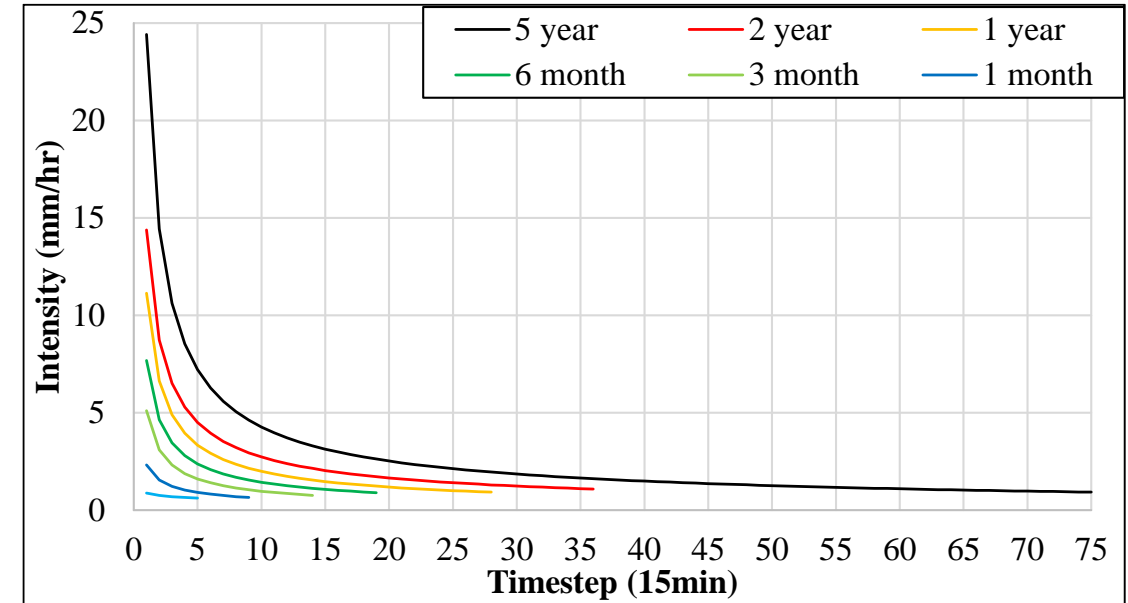
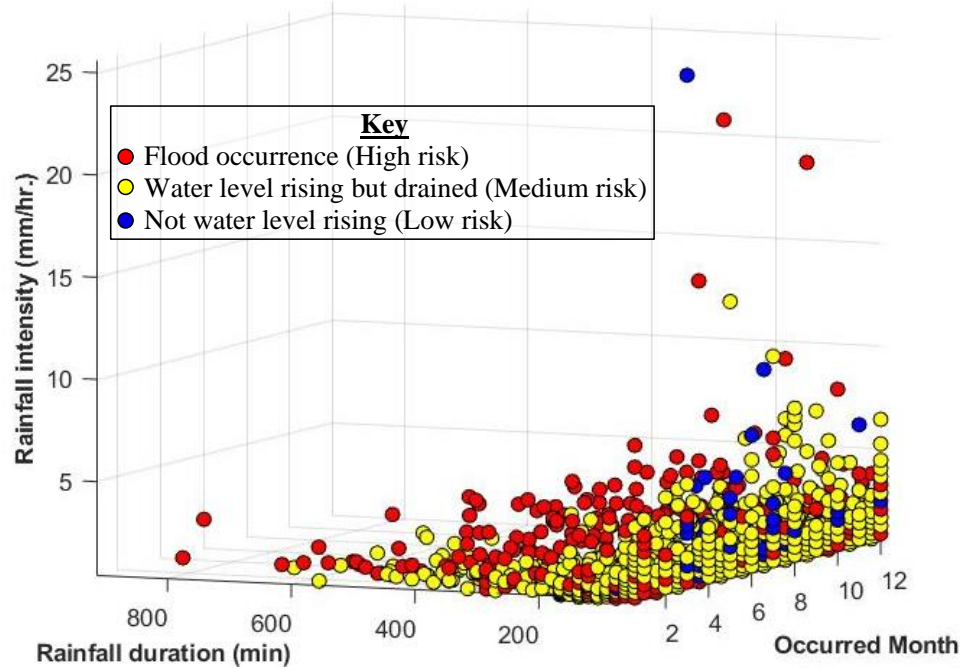
- I_G
- $RP(t)$
- $CW(t)$
- $AR(t)$

Case study description



Geographical location of the pilot study: (left) location of case study catchment and monitoring stations, and (right) layout of Ruislip UDS and catchment

Initial assessment



Initial analysis on database of case study: (left) Flood event assessment between Ruislip water level rising and RAF Northolt rainfall events, and (right) IDF curve of RAF Northolt rainfall station

Performance of the model

Confusion matrix

7	90	3	1	1	3	1	1	1
6	3	91	1	2	0	2	0	1
5	0	1	94	0	0	1	1	1
4	3	1	0	91	1	3	1	0
3	2	1	1	0	89	1	0	1
2	1	0	1	3	3	90	3	1
1	1	1	1	0	1	1	92	1
0	0	2	1	2	1	1	2	94
	7	6	5	4	3	2	1	0

(a) 15min

7	80	2	4	3	2	4	2	4
6	2	82	3	3	2	3	4	0
5	2	2	83	3	2	4	2	2
4	1	3	0	87	3	1	2	4
3	4	3	0	4	83	4	1	2
2	3	2	3	4	3	84	0	1
1	3	2	2	2	0	4	84	2
0	0	2	2	0	1	3	2	90
	7	6	5	4	3	2	1	0

(b) 1hr

7	77	4	4	2	5	1	2	5
6	2	82	3	3	1	5	2	3
5	1	5	87	0	3	3	1	0
4	1	2	4	79	3	5	2	4
3	5	0	1	2	79	5	4	4
2	4	3	4	3	3	78	3	2
1	4	3	2	1	5	3	80	2
0	0	0	3	3	1	4	2	86
	7	6	5	4	3	2	1	0

(c) 2hrs

7	66	2	2	5	6	7	5	6
6	6	72	4	4	1	6	1	5
5	4	3	75	4	6	1	6	2
4	3	4	7	67	6	2	5	6
3	3	2	6	6	79	4	0	0
2	4	6	5	5	2	71	1	5
1	3	5	4	2	4	5	77	1
0	2	3	0	6	1	2	2	84
	7	6	5	4	3	2	1	0

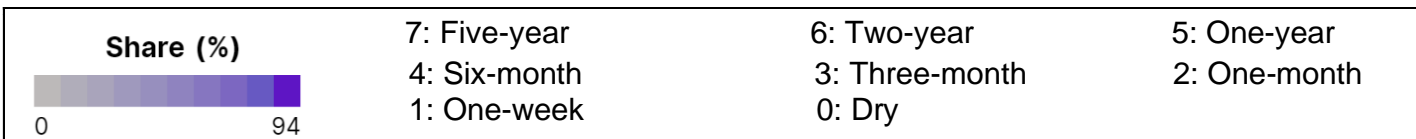
(d) 3hrs

7	52	3	3	7	6	10	3	5
6	9	54	0	9	6	8	2	1
5	8	8	68	9	1	9	2	1
4	4	4	10	50	6	5	7	1
3	9	9	5	5	64	4	6	8
2	3	4	8	8	5	58	4	4
1	7	10	4	2	6	5	67	0
0	8	8	2	9	6	1	9	78
	7	6	5	4	3	2	1	0

(e) 4hrs

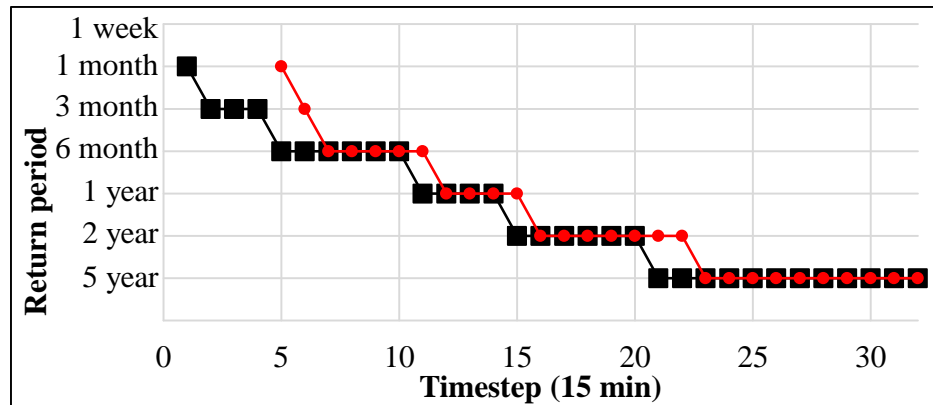
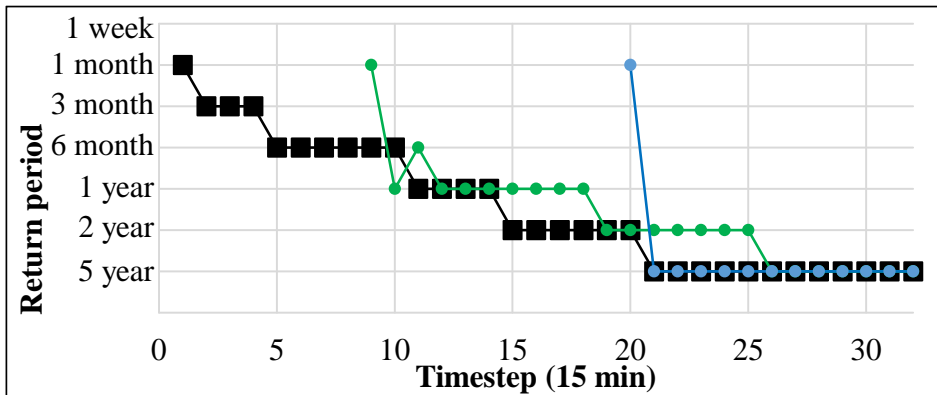
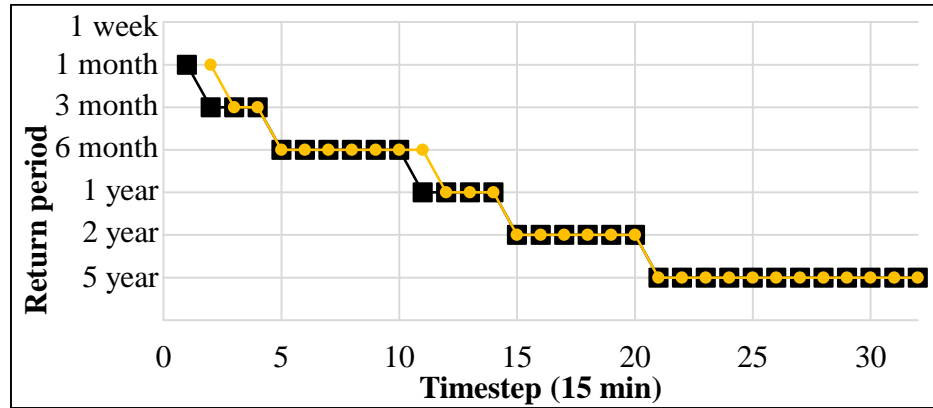
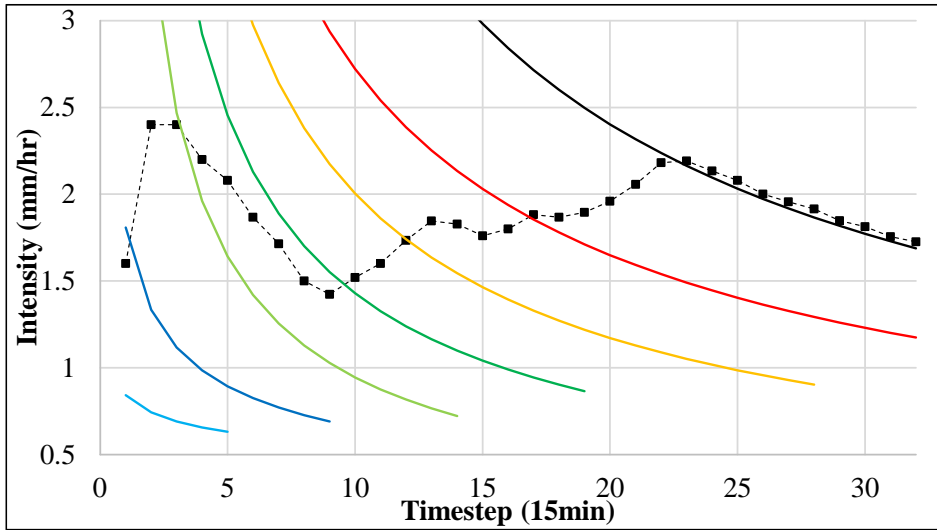
7	22	13	18	13	4	16	6	7
6	3	27	8	14	15	15	4	13
5	16	4	21	18	3	13	7	17
4	13	8	18	35	3	12	2	10
3	11	6	10	15	32	16	9	2
2	12	17	15	4	9	32	2	9
1	16	16	12	18	7	15	13	4
0	7	7	6	7	1	6	6	60
	7	6	5	4	3	2	1	0

(f) 5hrs



Performance of the model

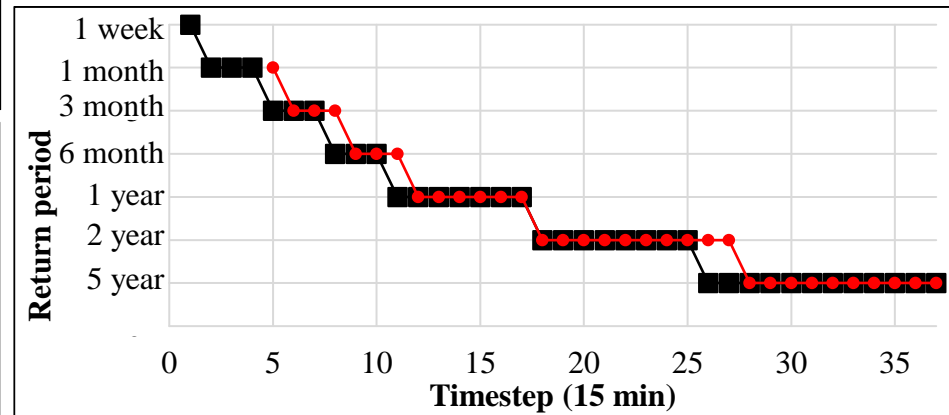
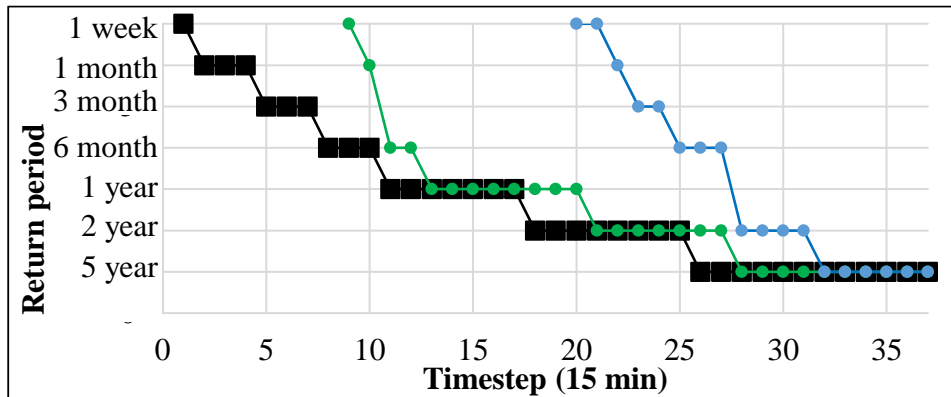
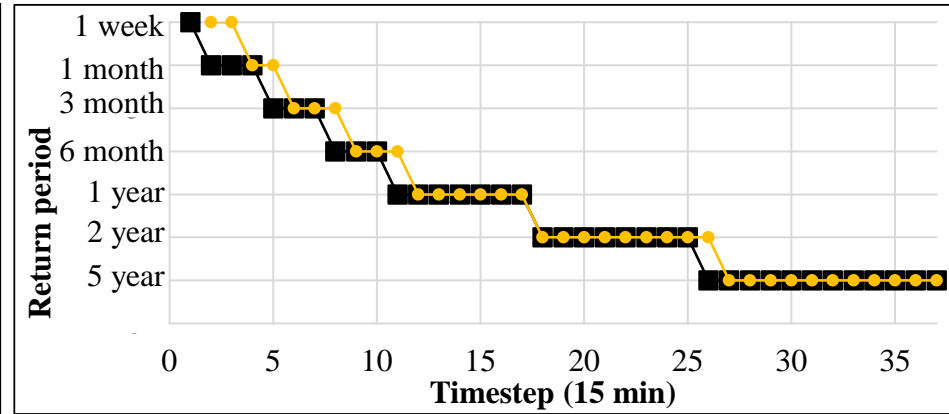
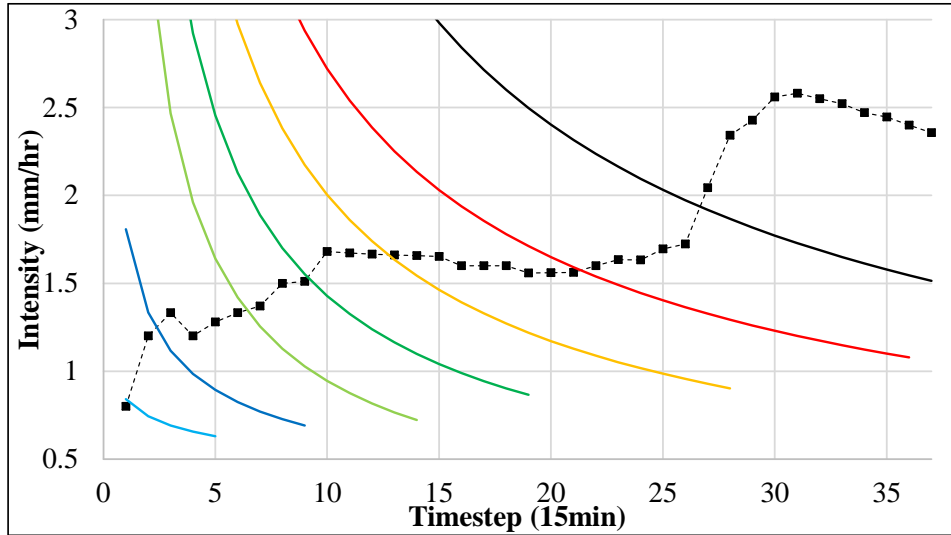
Rainfall tracking



- 5 year — 2 year — 1 year — 6 month — 3 month — 1 month — 1 week
- ■ - Measured intensity of rainfall
- 1-timestep ahead of Rainfall RP prediction ● 4-timestep ahead of Rainfall RP prediction
- 8-timestep ahead of Rainfall RP prediction ● 20-timestep ahead of Rainfall RP prediction
- Measured event class

Performance of the model

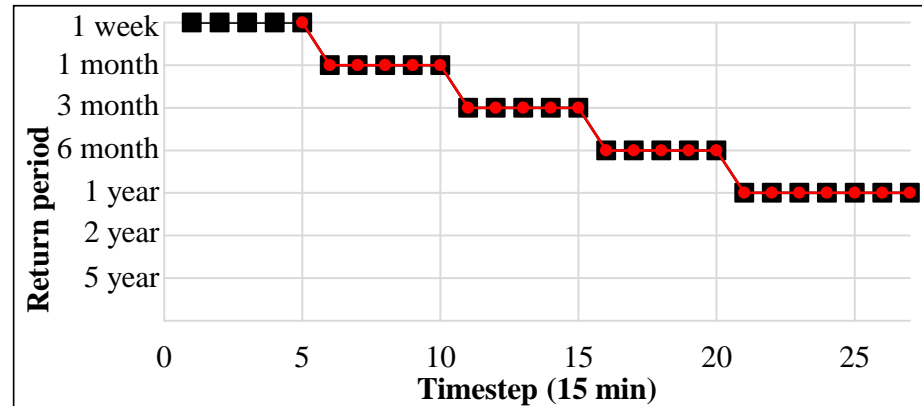
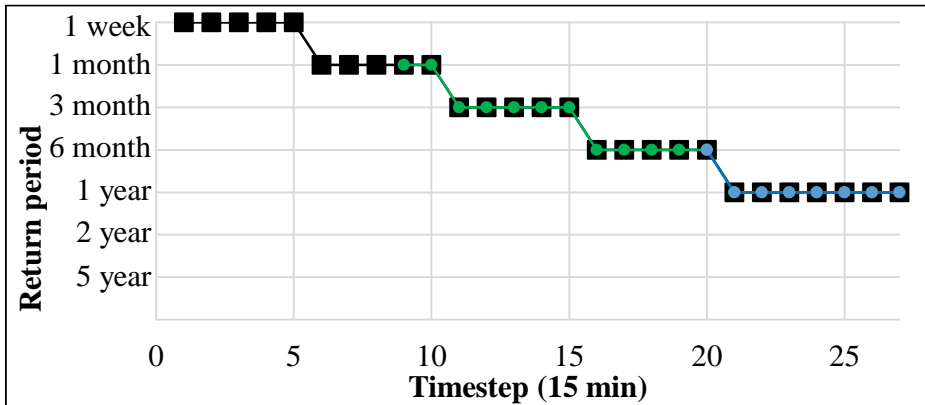
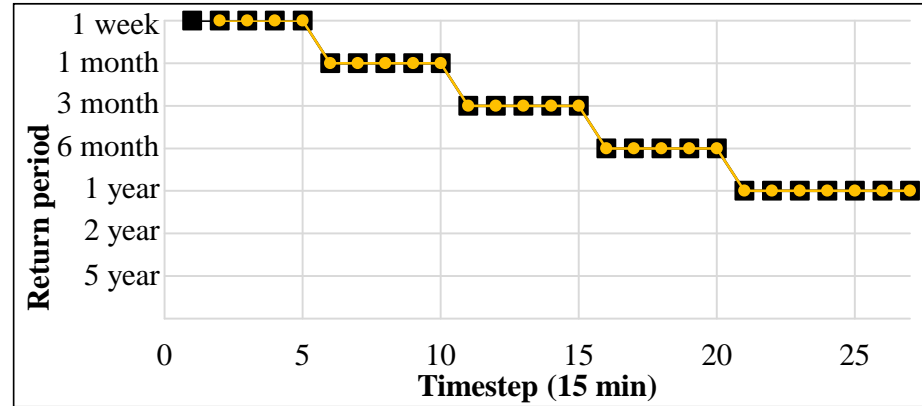
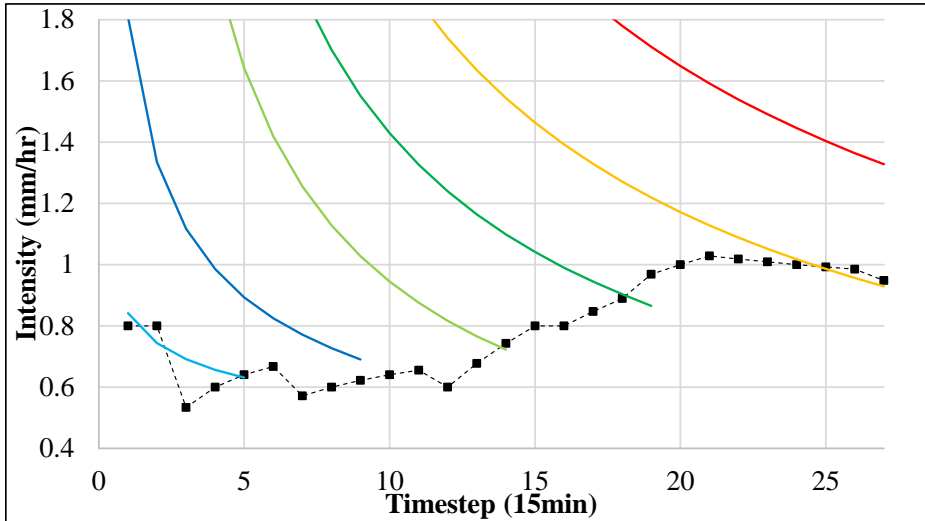
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Conclusions

01 Performance

Perfect performance (>90) up to 2hr lead time

Acceptable performance (>70%) up to 4hr lead time

02 Suitability

Perfect for normal and heavy rainfalls

Lacks on flash flood for the longer lead time

03 Future works

Integrating proposed model with physics-informed model

Thanks for your attention!

Q&A?