Combining Satellite Precipitation Products and Deep Learning to Increase Lead Times in Real-Time Riverine Flood Risk Forecasting

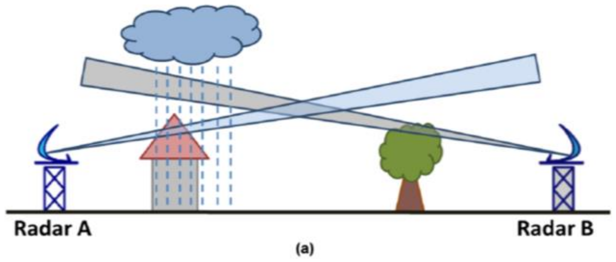
Cristiane Girotto[1,2], Farzad Piadeh[2], Kourosh Behzadian[1,3], Massoud Zolgharni[1]

1. School of Computing and Engineering, University of West London, UK
2. Centre for Engineering research, School of Physics, Engineering and Computer Science University of Hertfordshire, UK
3. Dept of Civil, Environmental and Geomatic Engineering, University College London, UK

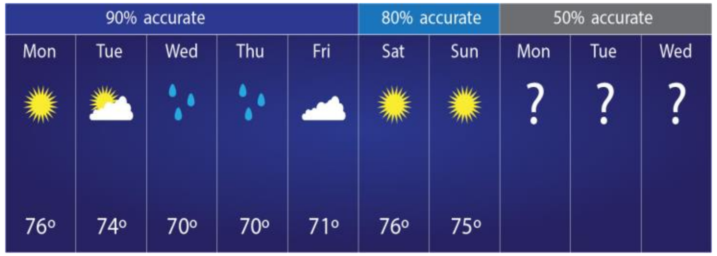
Research objective:

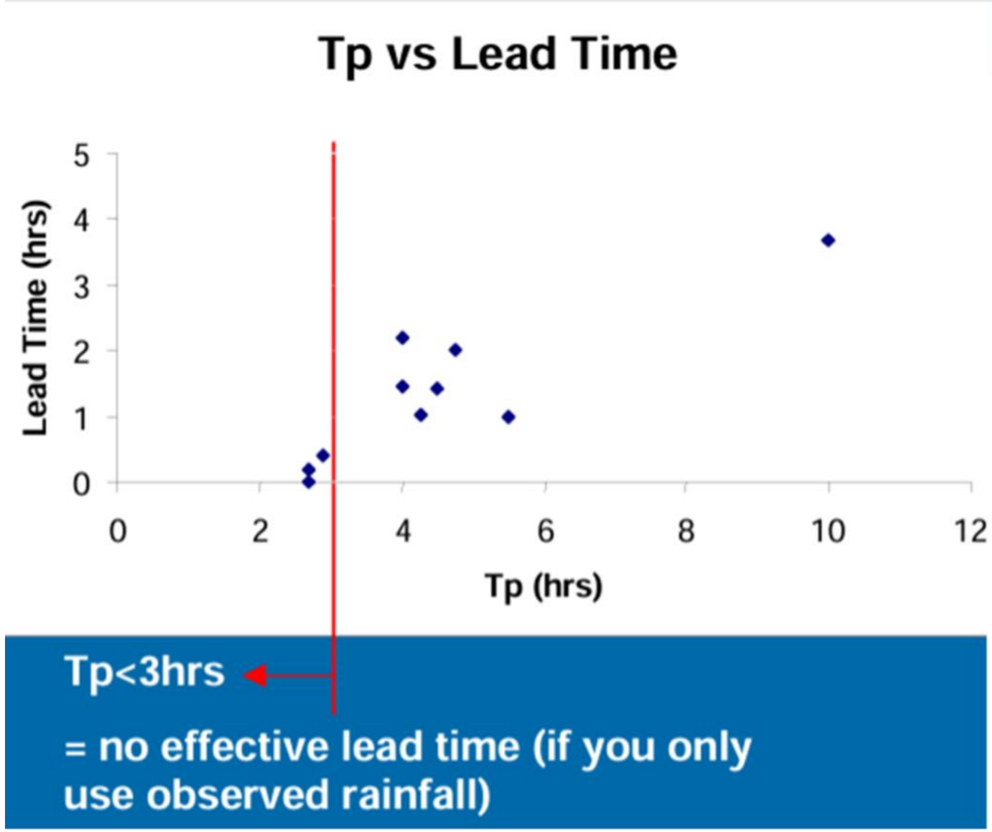
Increase lead times of real-time flooding risk forecasts

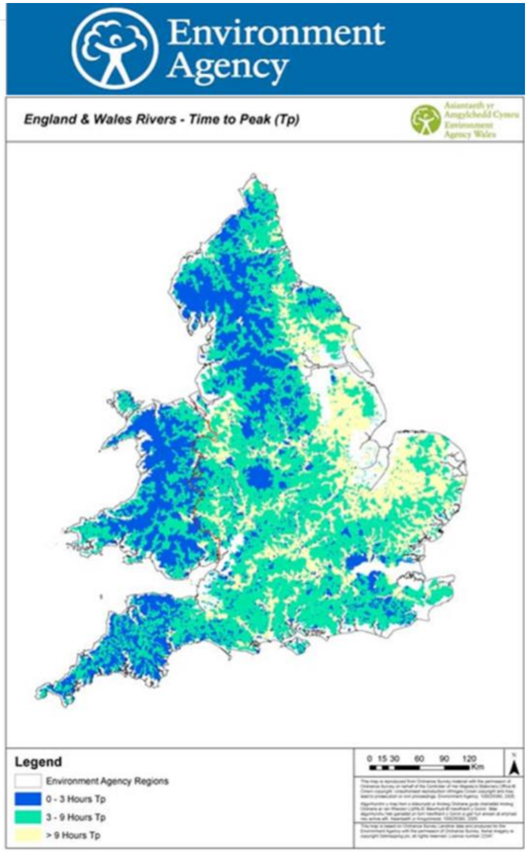
Land-based instruments limitations



Rainfall forecasts low range and accuracy

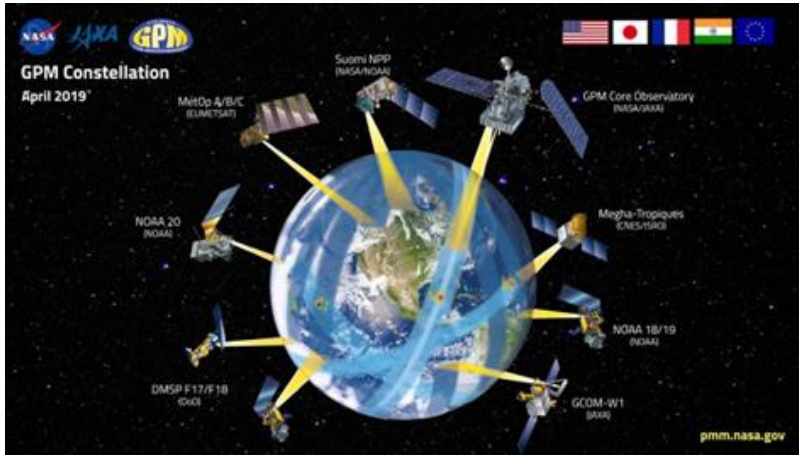






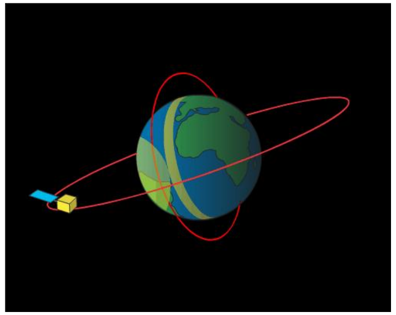
Research opportunity:

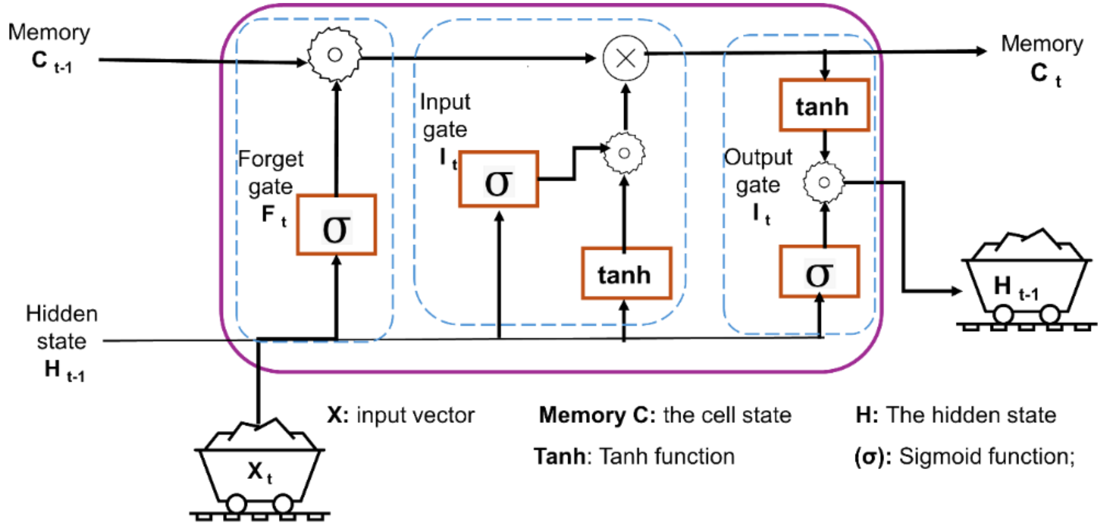
Integration of Satellite Precipitation Products (SPPs) and Deep Learning (DL) for flood risk forecasting



SPPs - IMERG V07 precipitation estimates

- Coverage: Global
- Spatial resolution: 0.1^{o} x 0.1^{o}
- Temporal resolution: 30 min
- *NRT data latency: at least 4hs*





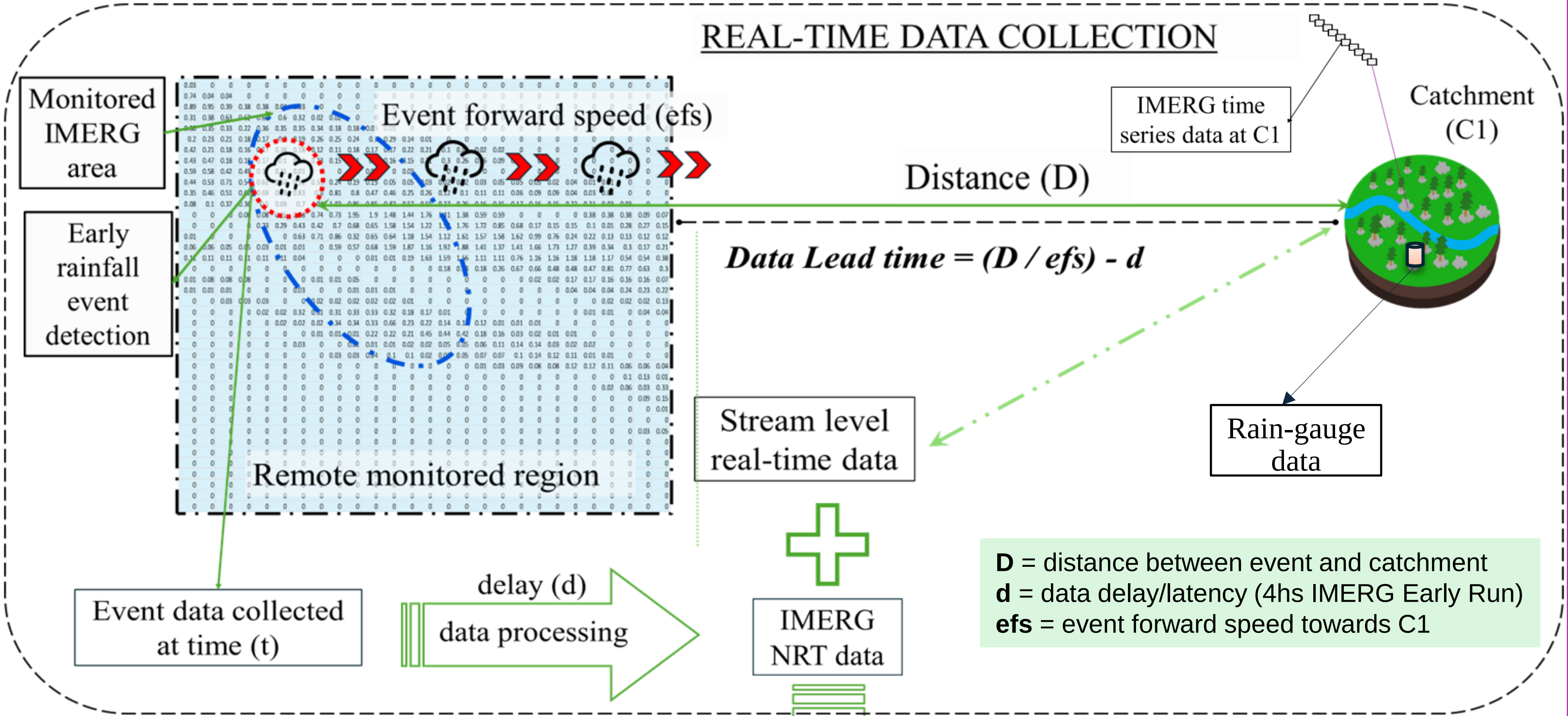
DL - LSTM model

- Flexible, fast processing, easy to adjust and automate.
- Requires fewer input variables
- Extracts spatio-temporal features automatically
- Able to model long-range spatial connections across multiple timescales
- *Demands large volumes of data*

Methodology:

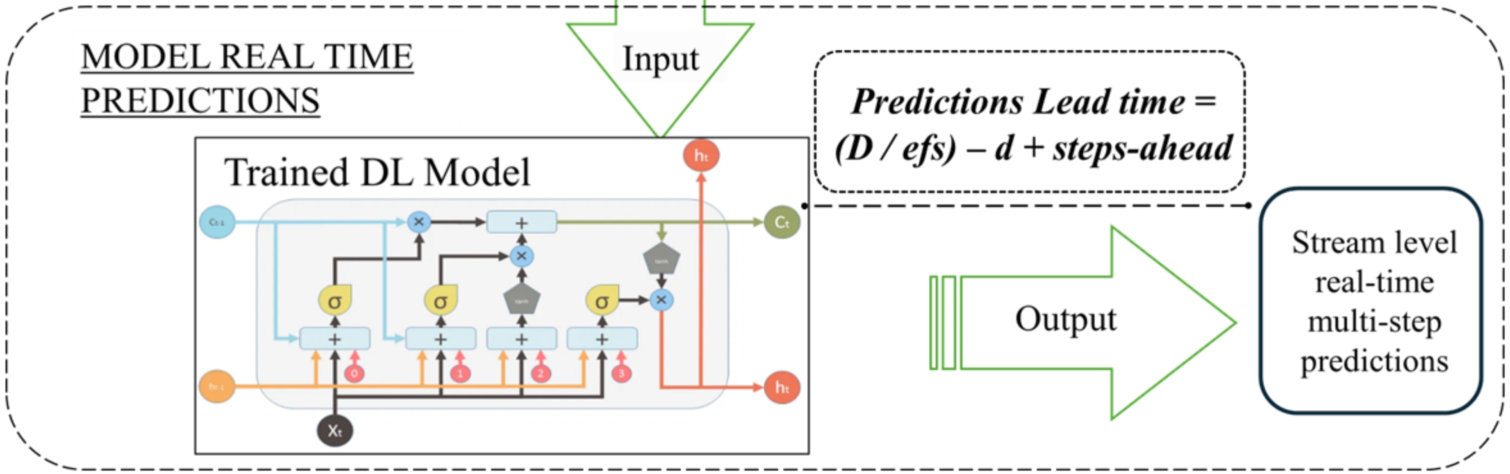
Real-time predictions

- Remote monitoring region determined based on the IMERG data historical correlation with stream level at C1



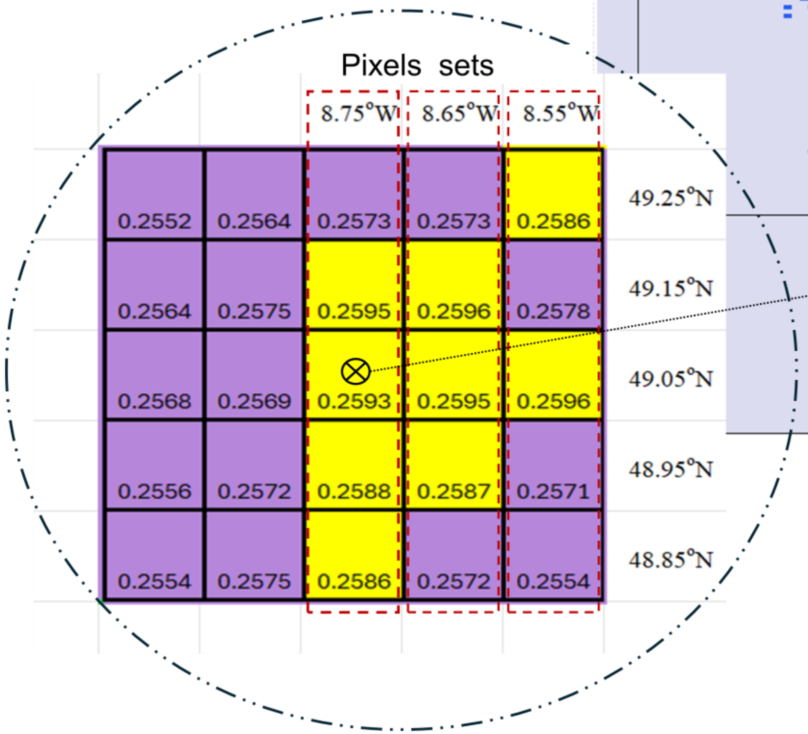
- LSTM model trained with 24 years of historical stream level and rainfall data

- Real-time predictions of rainfall event impact on catchment water levels are generated by the trained model using NRT IMERG and stream level data.

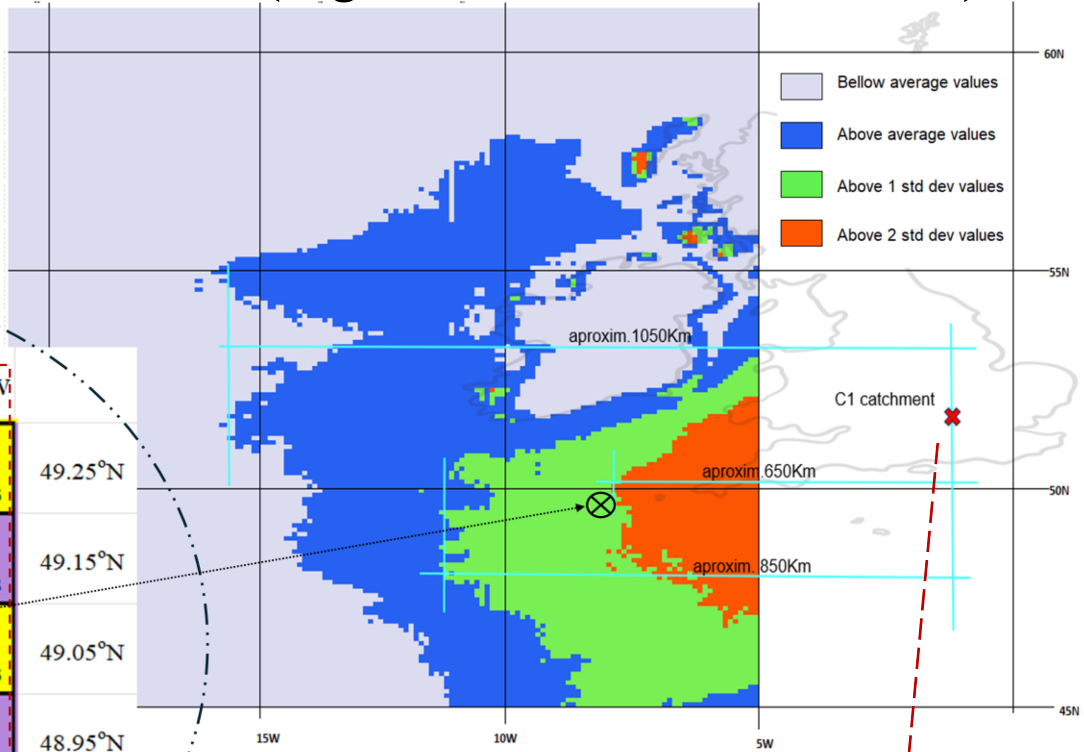


Datasets

IMERG V07
pixels for data
collection



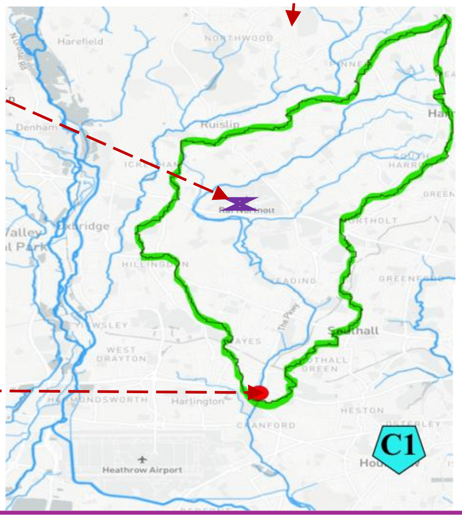
Focus area (high correlation + distance to C1)



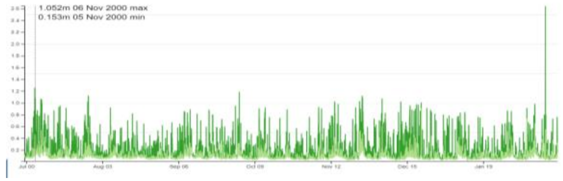
Rainfall events

C1	Oct-22	Oct-23
Initial water level (mm)	157	168
Peak water level (mm)	752	780
Water level rise	479%	464%

Northolt-RAF rain-gauge

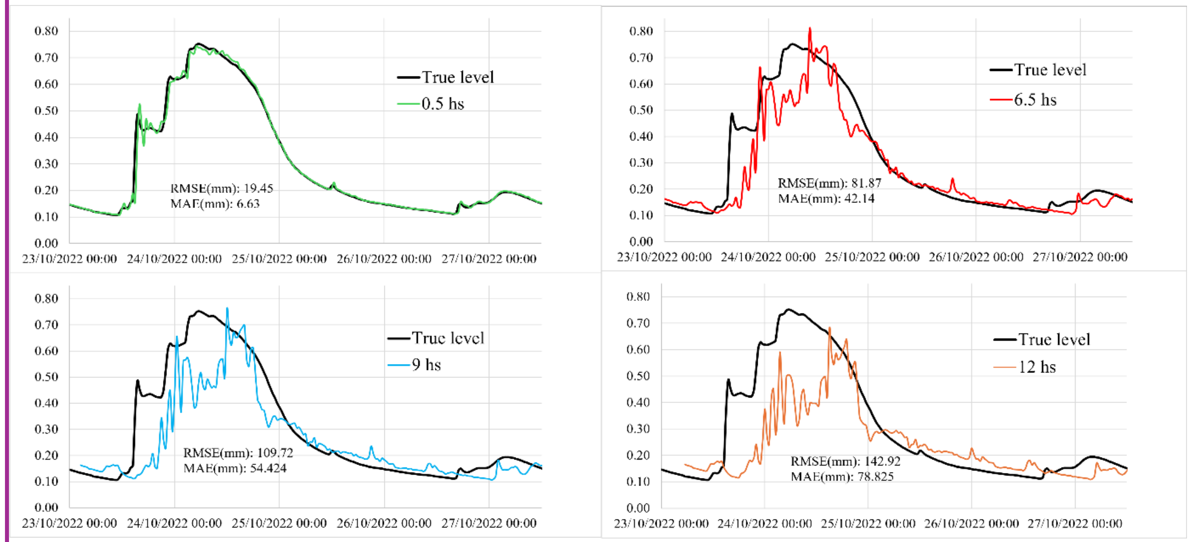


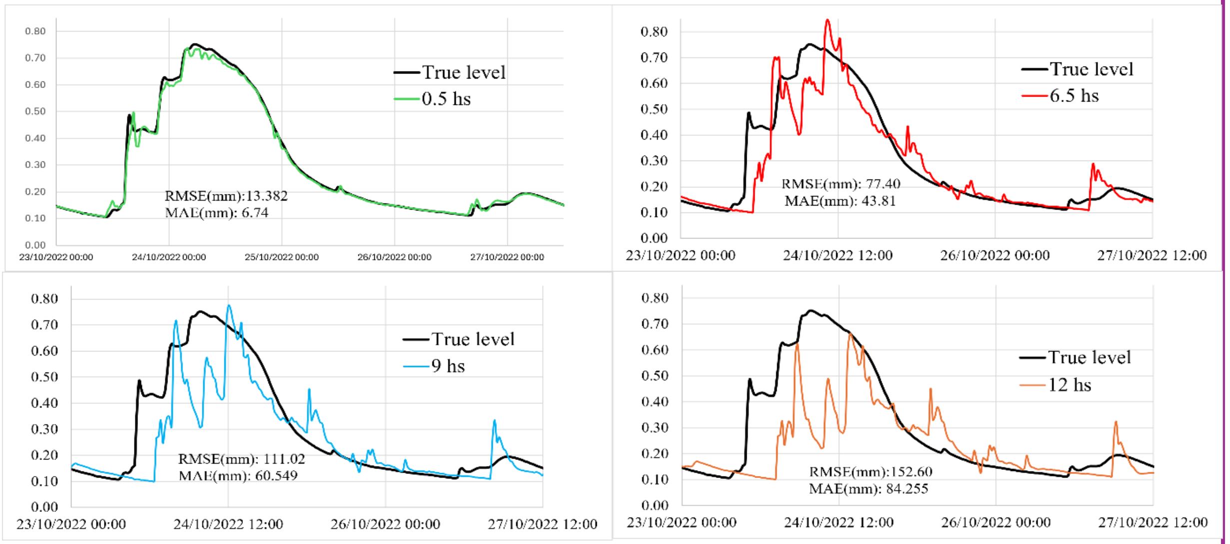
Stream-level timeseries at C1



Validation: LSTM forecasts with historical data (no latency)

Oct 2022

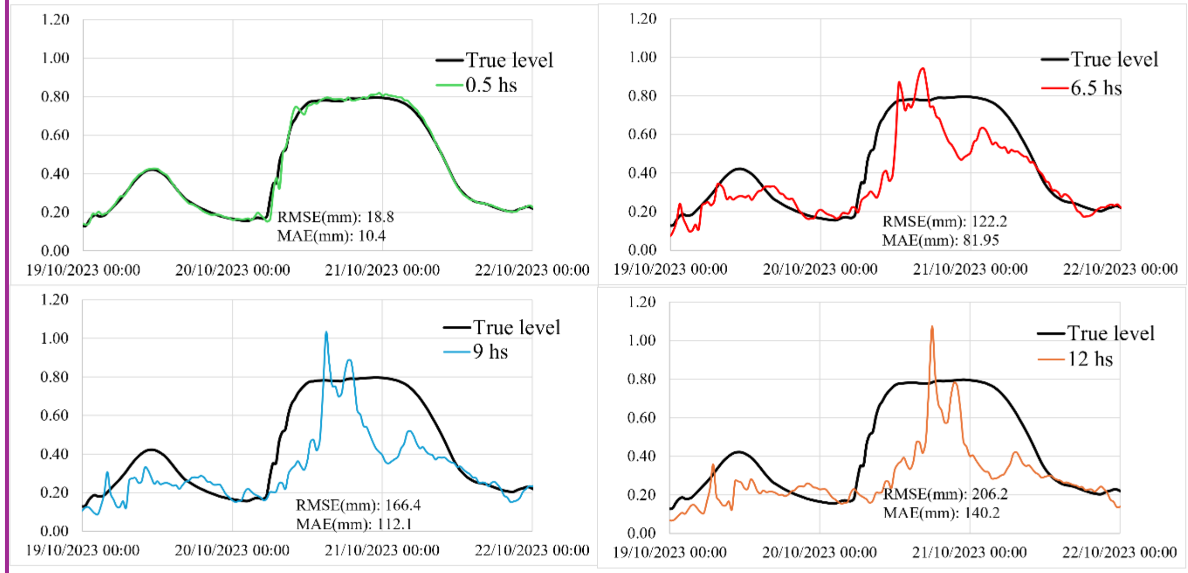


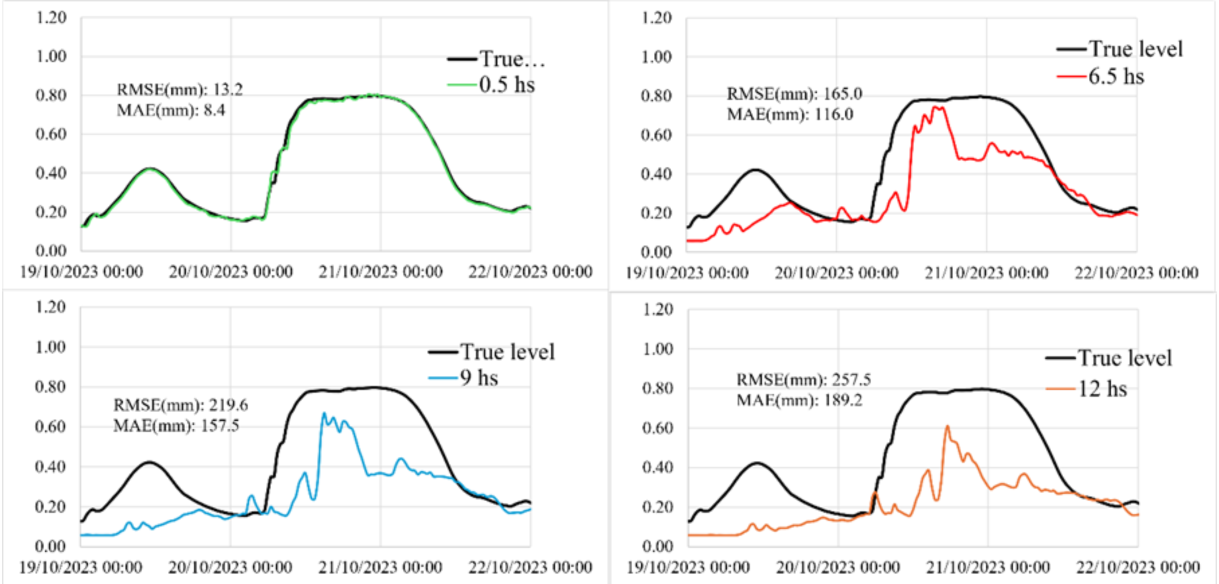


IMERG V07 local pixel at C1

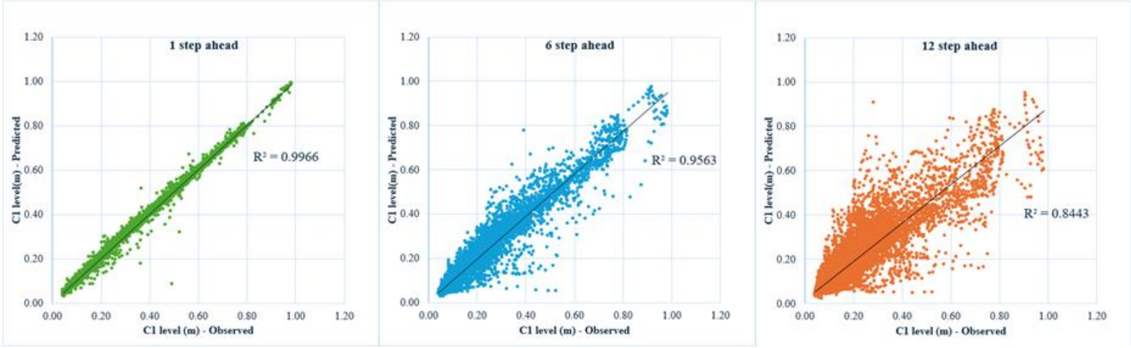
Oct 2023

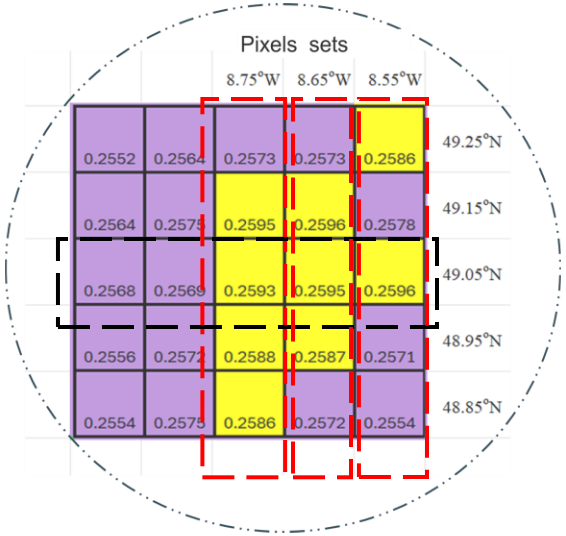
Northolt rain-gauge data

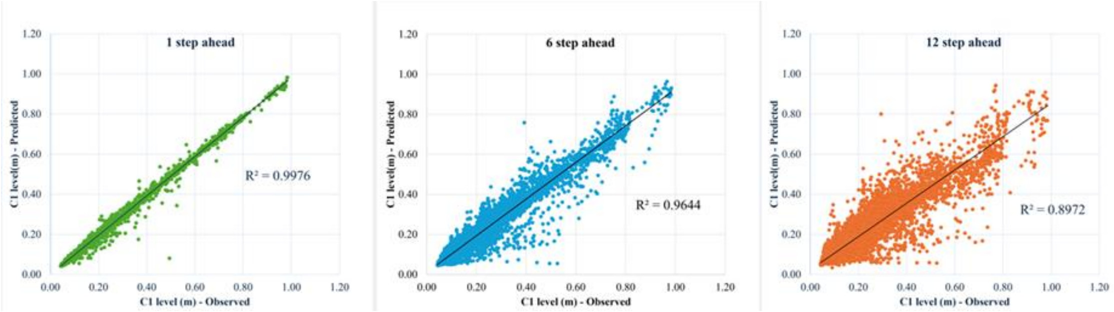


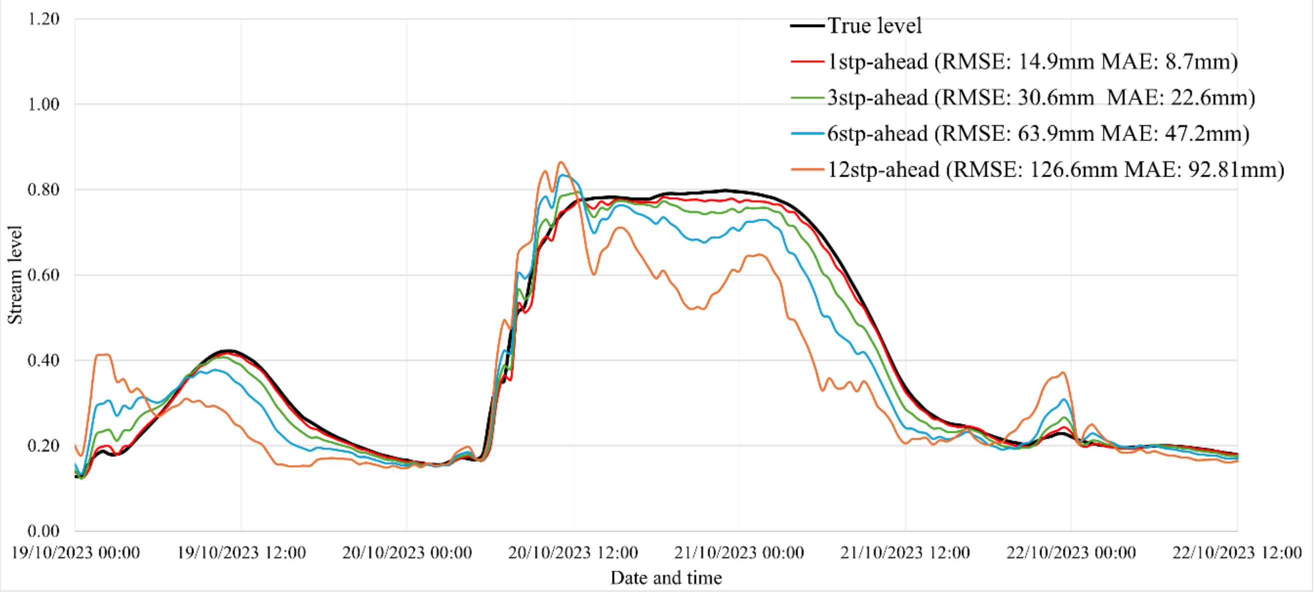


Results: remote IMERG data arrangements

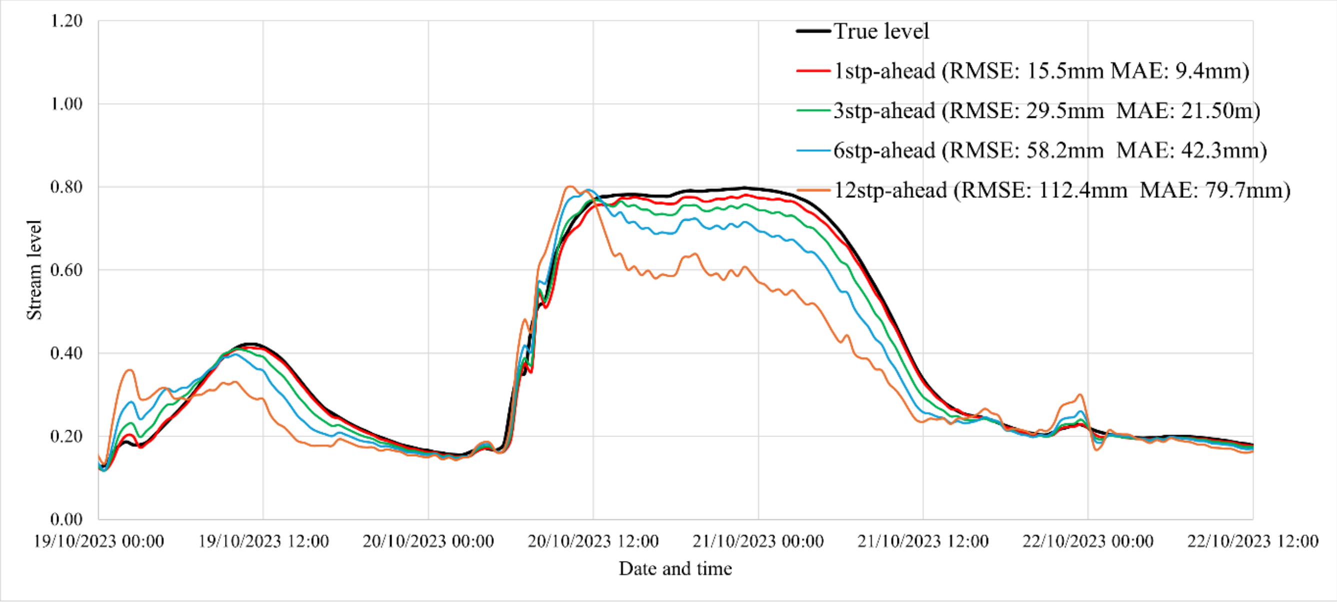








Horizontally spread pixels data predictions

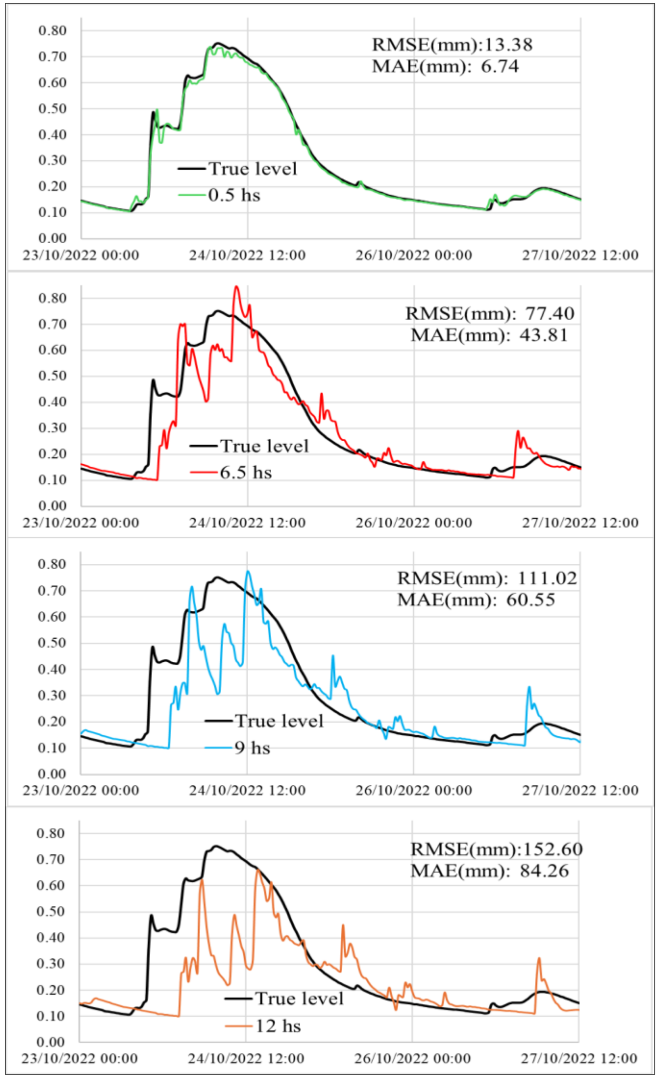


Vertically spread pixels data predictions

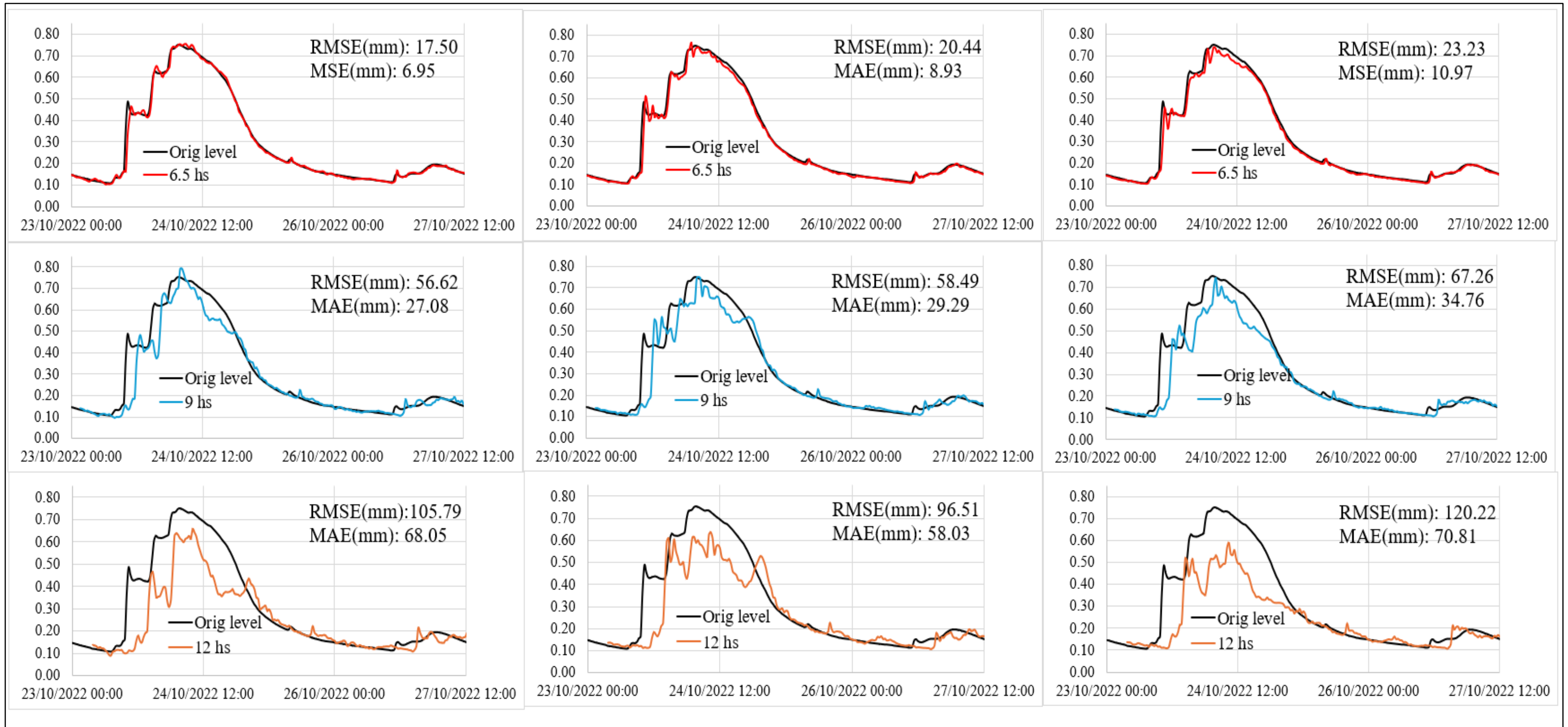
Results: real-time predictions

Oct 2022

Local rain-gauge data



IMERG NRT data at 650 km from catchment



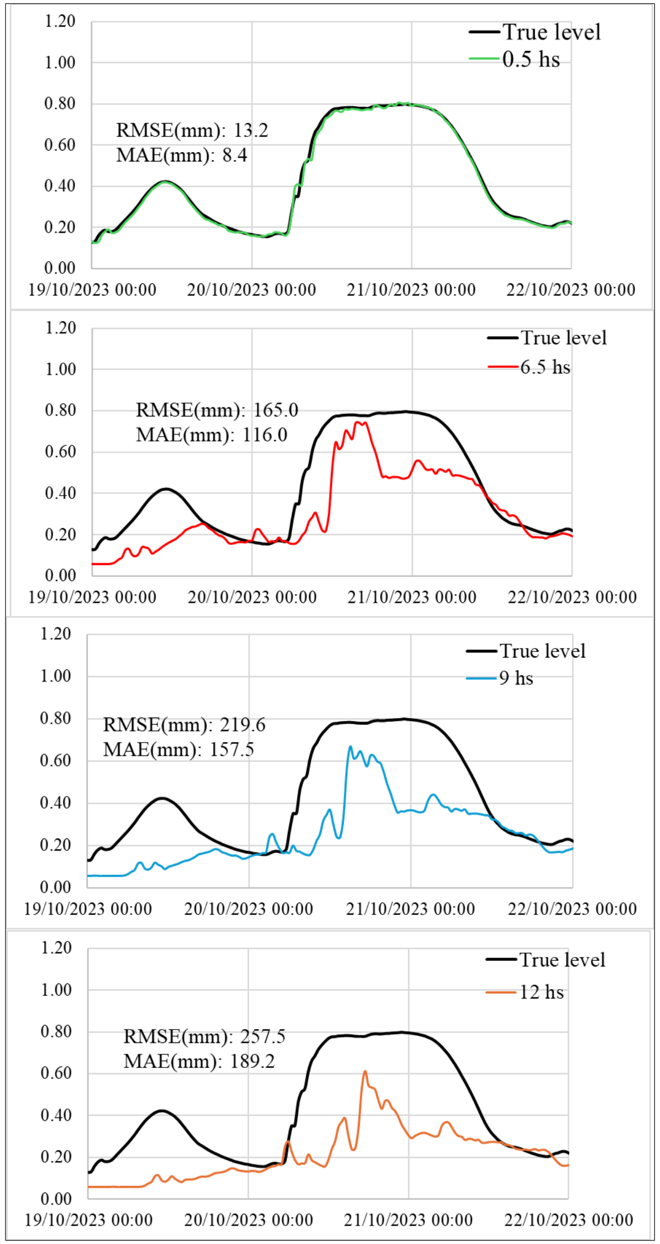
Group 8.75 **Group 8.55** **Group 8.55**

The LSTM model's predictions with NRT IMERG remote data still comparable with the ones with rain-gauge data.

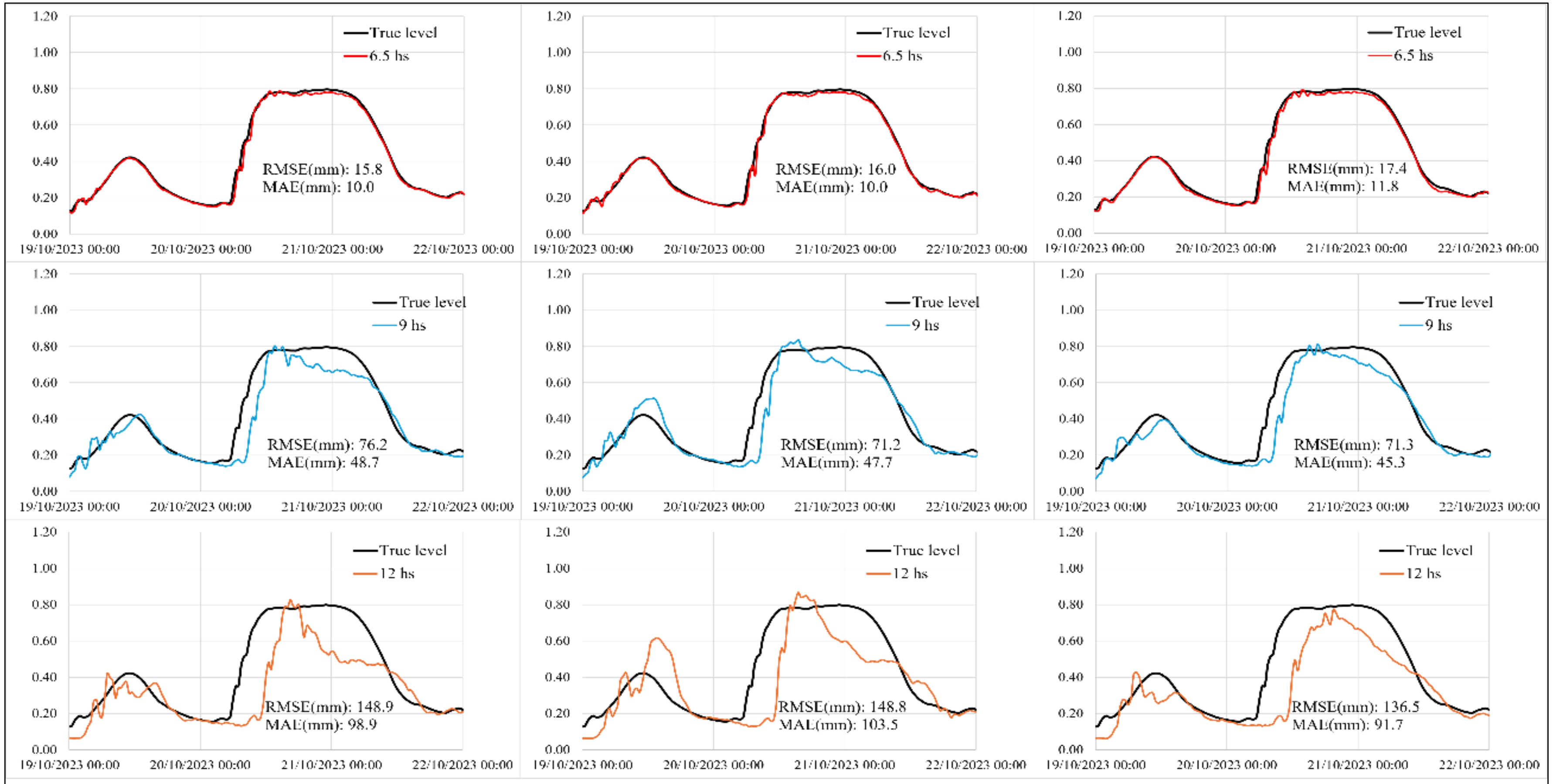
Results: real-time predictions

Oct 2023

Local rain-gauge data



IMERG NRT data at 650 km from catchment



Group 8.75 Group 8.65 Group 8.55

Results:

LSTM event-based performance per lead time

	Event 2022 - RMSE (mm)				Event 2023 - RMSE (mm)			
Lead time	Northolt gauge	NRT Pix 8.75	NRT Pix 8.65	NRT Pix 8.55	Northolt gauge	NRT Pix 8.75	NRT Pix 8.65	NRT Pix 8.55
0.5 hs	13.38				13.18			
1 hs	20.25				21.71			
1.5 hs	29.58				31.09			
2 hs	36.43				42.70			
2.5 hs	41.68				55.38			
3 hs	46.55				67.91			
3.5 hs	50.15				81.09			
4 hs	53.24				95.11			
4.5 hs	56.69				109.68			
5 hs	61.52				123.98			
5.5 hs	67.07				138.23			
6 hs	72.41				152.10			
6.5 hs	77.40	19.66	18.61	27.04	165.02	16.51	15.70	16.44
7 hs	82.42	29.55	29.63	33.84	177.36	27.08	24.61	24.50
7.5 hs	88.16	37.60	38.06	40.94	189.36	38.83	34.41	33.58
8 hs	95.21	44.44	45.42	47.96	200.43	51.71	46.79	45.49
8.5 hs	103.17	50.88	52.74	55.61	210.50	64.42	58.97	58.05
9 hs	111.02	56.66	60.03	62.61	219.55	76.75	71.24	70.00
9.5 hs	118.58	62.43	67.30	69.28	227.83	89.47	83.87	81.87
10 hs	126.06	68.53	75.29	76.38	235.31	101.95	96.53	93.83
10.5 hs	133.21	75.76	83.87	83.69	242.09	114.89	108.70	105.42
11 hs	139.79	83.49	92.28	91.68	247.83	127.43	120.02	117.16
11.5 hs	146.23	91.66	101.62	99.54	252.91	139.17	131.20	128.11
12 hs	152.60	100.07	111.39	107.31	257.48	150.15	141.96	138.29
12.5hs		108.40	121.58	115.39		160.59	152.63	148.12
13.0hs		116.31	131.65	123.96		169.98	162.70	157.52
13.5hs		124.33	141.62	132.75		178.56	171.99	166.58
14.hs		132.93	151.28	141.34		186.88	180.91	175.20
14.5hs		141.30	160.48	149.71		194.63	189.35	183.41
15.0hs		147.69	167.30	158.70		201.60	197.59	191.05
15.5hs		154.81	175.58	166.14		208.32	205.49	198.37

Lead times are of **'at least'** 6.5hs as considers a top efs = 60Km/h

Results: LSTM performance summary

IMERG data validation

Model training / testing

Real-time predictions

Model's training time is approx. 10 sec/epoch.
(GPU NVIDIA GeForce RTX 4090)

Data source		Metrics	Overall	October 2022	October 2023
Local rainfall data	Northolt RAF rain-gauge	RMSE	43.29	80.12	148.2
		MAE	26.55	43.14	105.0
	IMERG-Cranford pixel	RMSE	43.90	81.71	114.8
		MAE	27.71	41.76	77.0
IMERG V07 Final Run product	pixels-group 8.75	RMSE	40.57	105.57	141.9
		MAE	15.92	62.27	96.4
	pixels-group 8.65	RMSE	40.81	102.18	145.8
		MAE	16.50	61.56	104.5
	pixels-group 8.55	RMSE	41.74	121.85	128.4
		MAE	16.87	71.70	92.0
IMERG V07 Early Run product	NRT pixels-group 8.75	RMSE	44.61	100.35	143.03
		MAE	17.89	61.57	96.25
	NRT pixels-group 8.65	RMSE	47.22	116.88	138.7
		MAE	20.20	72.91	95.8
	NRT pixels-group 8.55	RMSE	46.01	112.76	134.2
		MAE	19.77	62.12	87.8

Conclusions

- The LSTM algorithm showed great ability on detecting the spatiotemporal patterns between stream level variations and remote rainfall events represented in the IMERG V07 data.

- Models trained on historical datasets performed similarly when making predictions using NRT data.

- While the dataset optimization allows for faster and effective processing, the main limitation of the IMERG V07 for real-time forecasting is the minimum four-hour latency of the NRT products.

Thank you!

Questions??