

Machine learning models for stream level predictions using readings from satellite and ground gauging stations

Cristiane Giroto¹, Farzad Piadeh², Kouros Behzadian^{1,3}, Massoud Zolgharni¹, Luiza C. Campos³, Albert S. Chen

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

4. College of Engineering, Mathematics and Physical Sciences, University of Exeter, UK

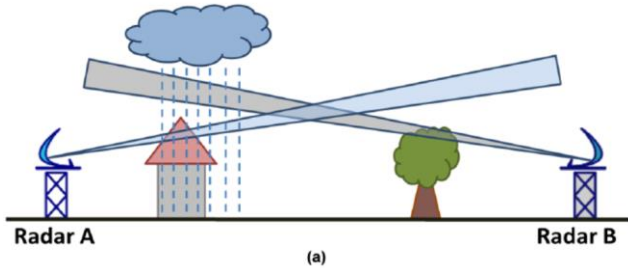
Increasing proactivity of sustainable drainage systems for urban flood reduction

- The biggest challenge for proactive drainage is to increase the lead time of floods forecasting.
- This is particularly difficult due to the rainfall data and modelling intricacies.
- In the UK rainfall often travels from the Atlantic Ocean
- UK's radar network ranges up to 250Km.

Data



Land instruments limitations

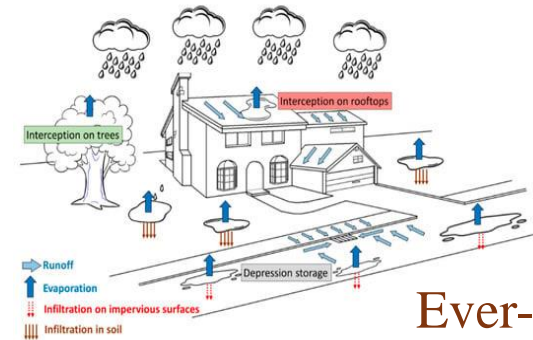


Forecast accuracy

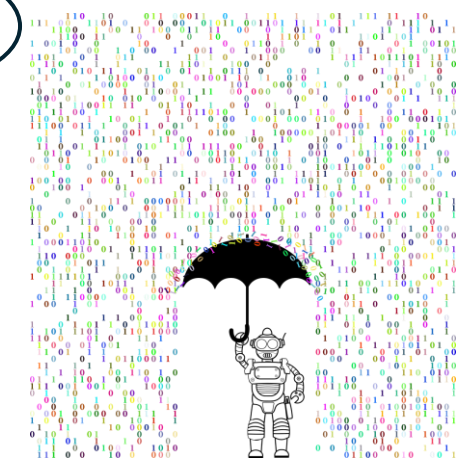
90% accurate			80% accurate				50% accurate		
Mon	Tue	Wed	Thu	Fri	Sat	Sun	Mon	Tue	Wed
							?	?	?
76°	74°	70°	70°	71°	76°	75°			

Model

Complex features

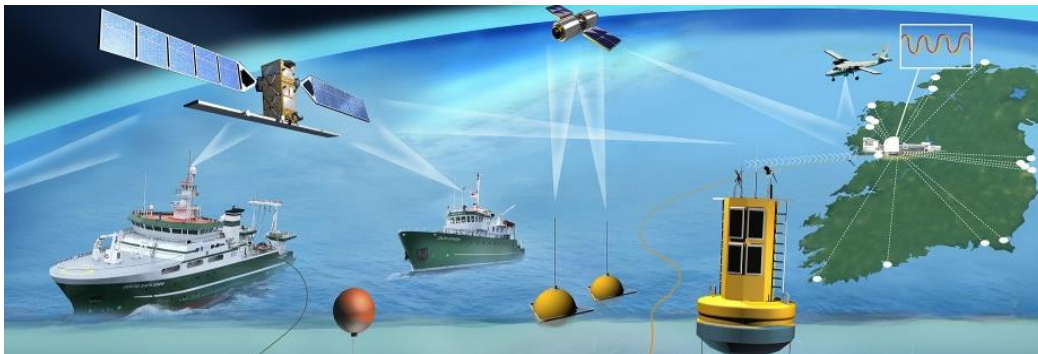


Large datasets



Ever-changing urban environment

Real time monitoring of ungauged regions



Increasing forecast lead time of flood risk events in London

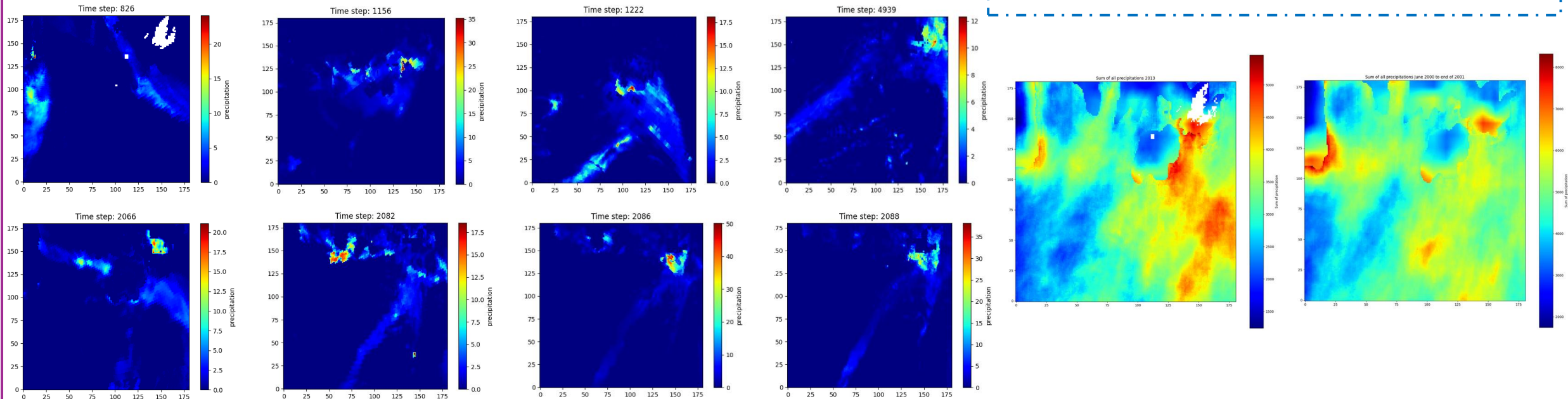
Challenges:

- Monitor an extensive area
- Large data volume
- Long processing time
- Computational expensive
- Discrepancies in datasets



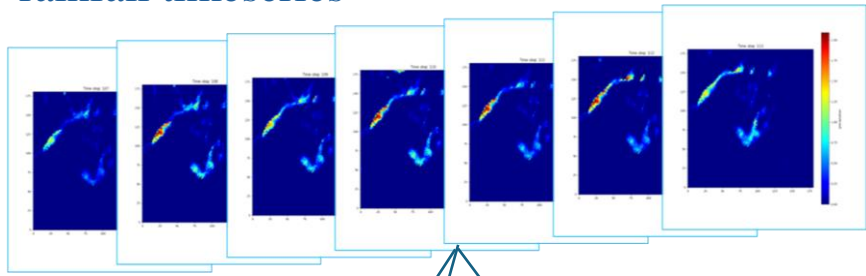
This study's approach to address it:

- GPM IMERG as data source in the Atlantic
- Optimized selection of the rainfall dataset excluding pixels not linked to stream level variations
- Selected pixels' data to train machine learning models for stream level forecast
- Pixels processed individually to avoid distortion from zones of discrepancy

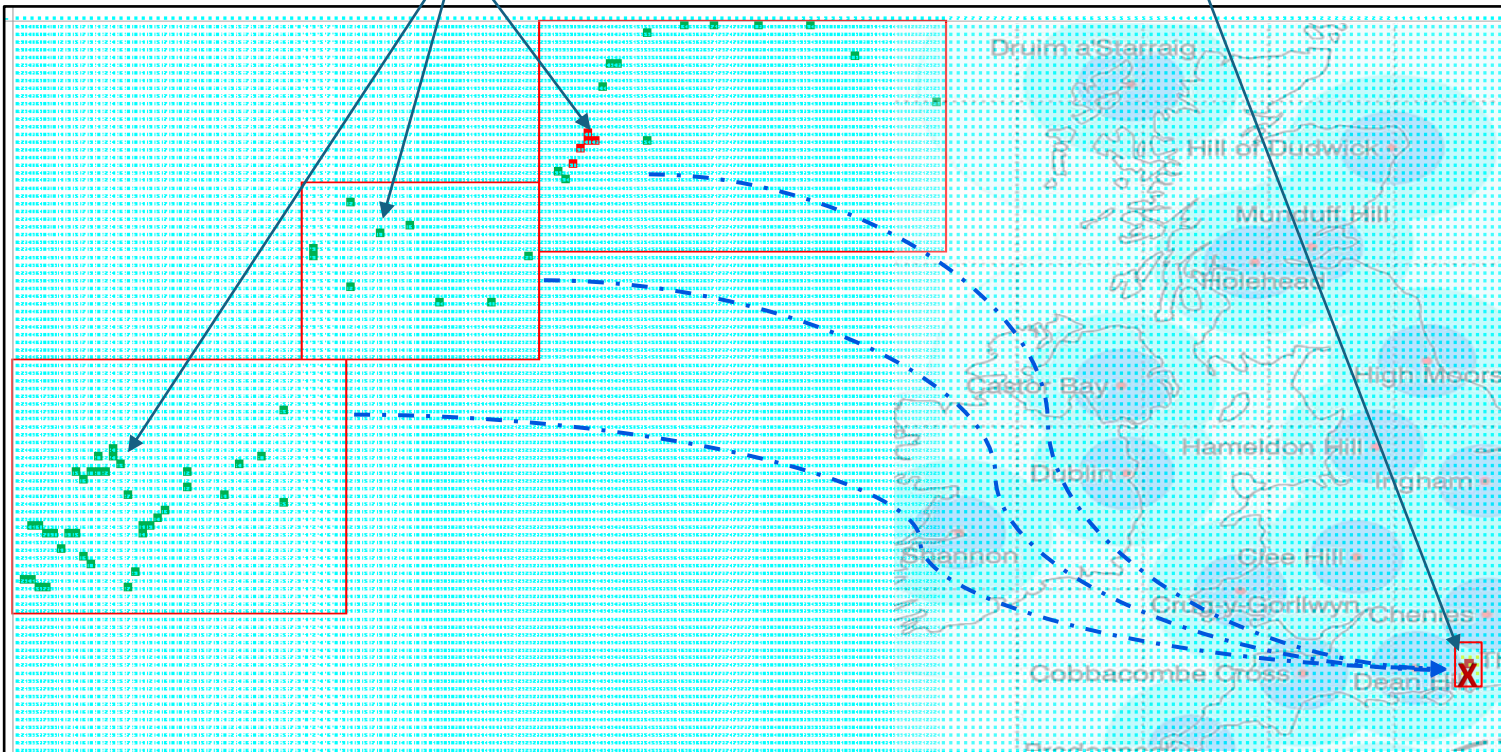
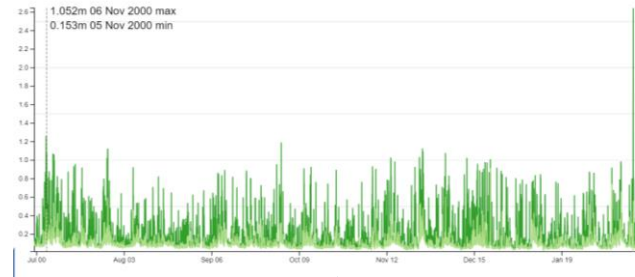


Rainfall data, stream level data and models

IMERG pixel rainfall timeseries



Stream-level timeseries



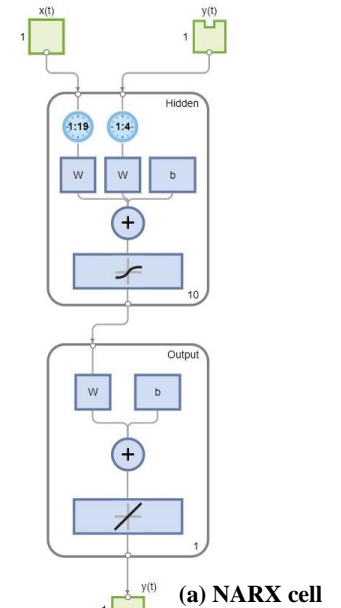
ML models:

IMERG pixels performance was tested by three machine learning models:

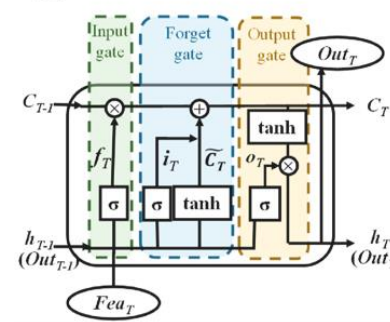
Non-linear regression with exogenous inputs - NARX

Lon short-term memory - LSTM

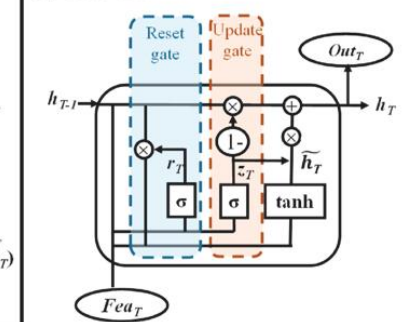
Gated recurrent unit - GRU



(b) LSTM cell

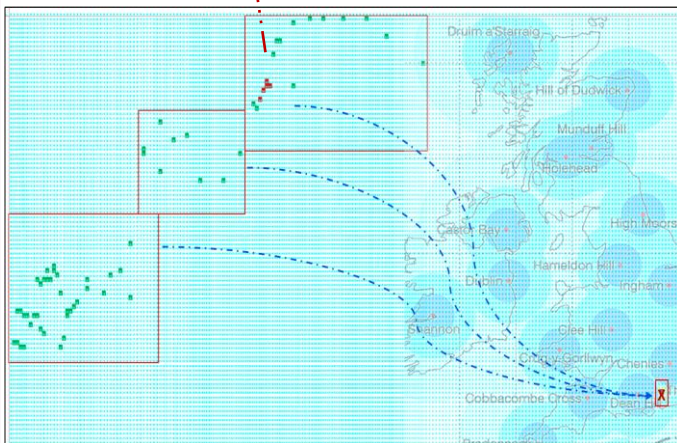
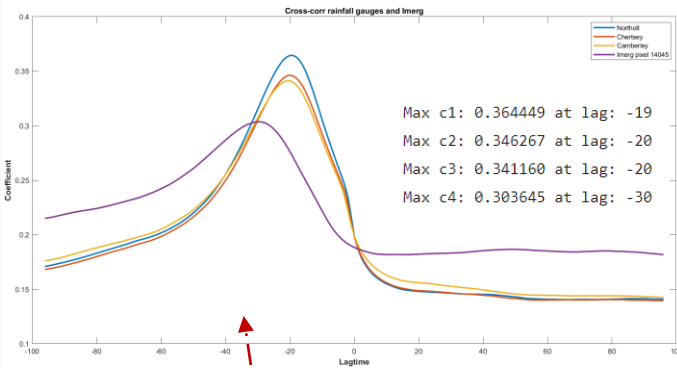


(c) GRU cell



Results

The cross-correlation analyses revealed minimal variance in lags and correlation coefficients between stream level and the IMERG dataset, relative to those between stream level and gauge datasets.

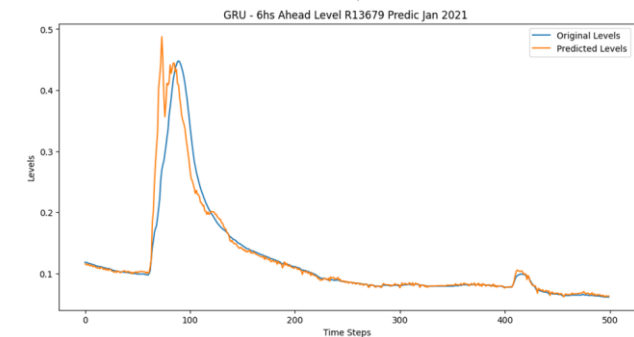
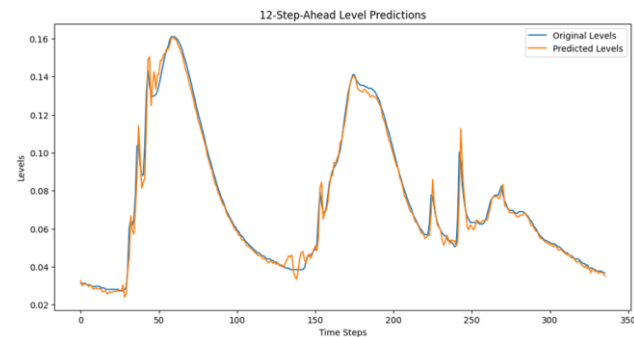
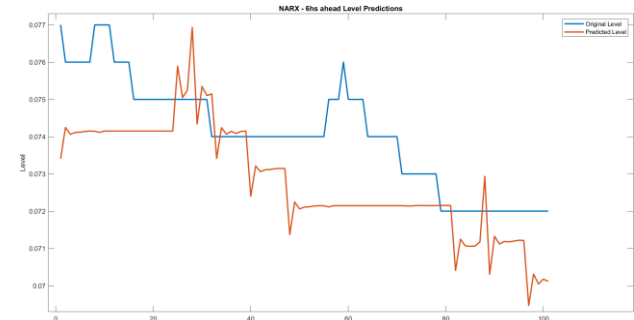


- ✓ NARX model demonstrated high precision in stream level predictions, with MSE values of 1.5×10^{-5} for gauge data and 1.9×10^{-5} for IMERG data.
- ✓ LSTM model also produced good predictions, although with higher MSE values of 1.8×10^{-3} for gauge data and 4.9×10^{-3} for IMERG data.
- ✓ GRU model showed comparable performance, with MSE values of 1.9×10^{-3} for gauge data and 5.6×10^{-3} for IMERG data.

Conclusion

- ✓ The findings demonstrate that all models exhibit satisfactory efficacy, indicating the feasibility of employing machine learning (ML) techniques for stream level prediction solely based on GPM IMERG rainfall and level data.
- ✓ With the integration of satellite rainfall data, we look forward to creating models that can provide predictions with greater lead time to allow for a proactive response with drainage systems.
- ✓ Next, we aim to explore the application of GPM-IMERG Early Run in near real-time (NRT) flood forecasting.

	y_test	y_pred LSTM	y_pred GRU
0	0.031250	0.031459	0.030552
1	0.031250	0.029188	0.027399
2	0.031250	0.031289	0.029401
3	0.031250	0.031253	0.030012
4	0.030449	0.031969	0.030339
...
...
37387	0.069712	0.069604	0.070849
37388	0.068910	0.069157	0.069745
37389	0.068109	0.068251	0.069095
37390	0.067308	0.067444	0.068639
37391	0.067308	0.066689	0.067919



Thank you!

Cristiane Giroto¹Farzad Piadeh², Kourosh Behzadian^{1,3}, Massoud Zolgharni¹, Luiza C. Campos ³, Albert S. Chen ⁴

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

4. College of Engineering, Mathematics and Physical Sciences, University of Exeter, UK