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Using optimisation method for input data selection in AI-based time-series  
flood forecasting models

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UNIVERSITY OF  
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The Career University



HOT research group

# Using Optimisation Method for Input Data Selection in AI-Based Time-Series Flood Forecasting Models

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July 2022



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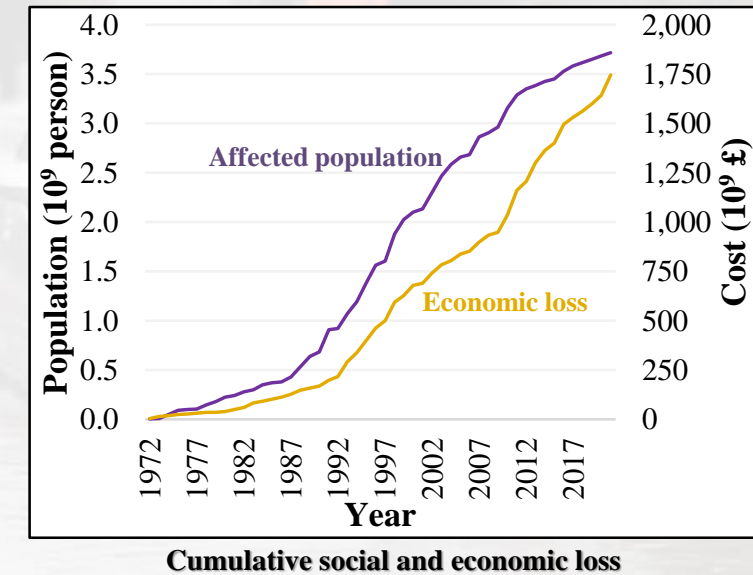
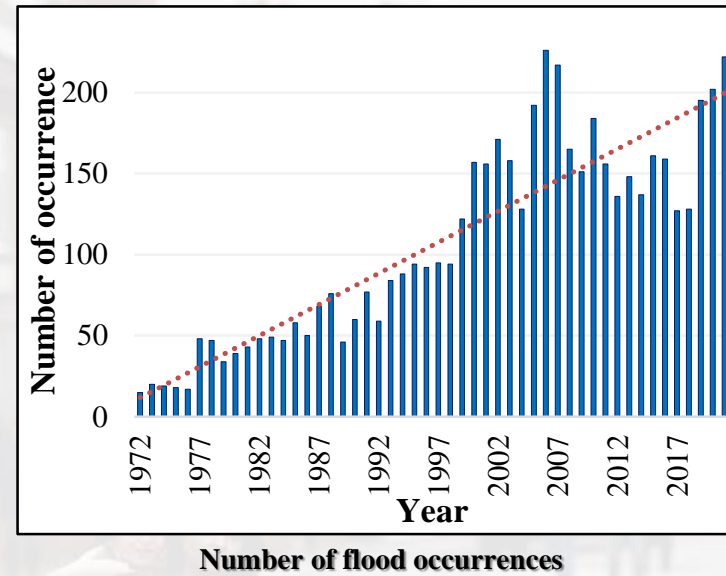


# Introduction

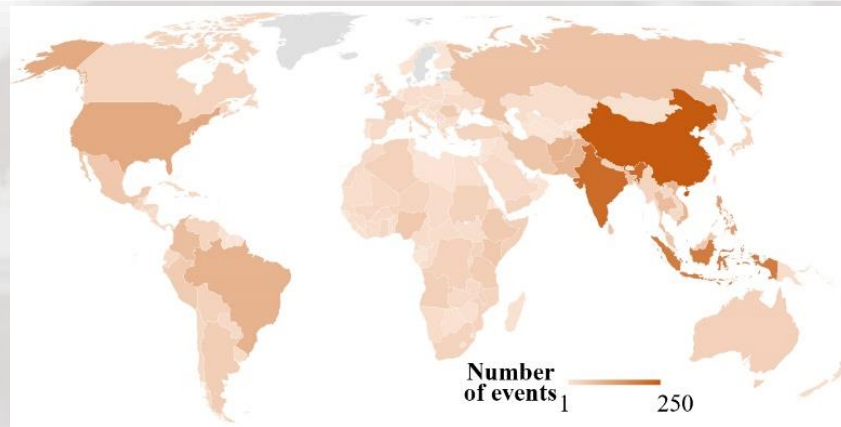


In recent 50 years, floods:

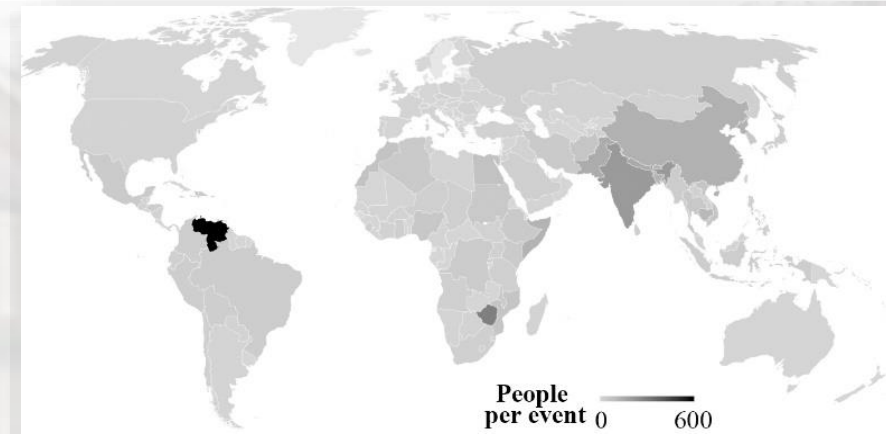
- ❖ **1,750 £ billion** economy damages
- ❖ **3.7 billion people** are affected
- ❖ **235,000 people** are killed



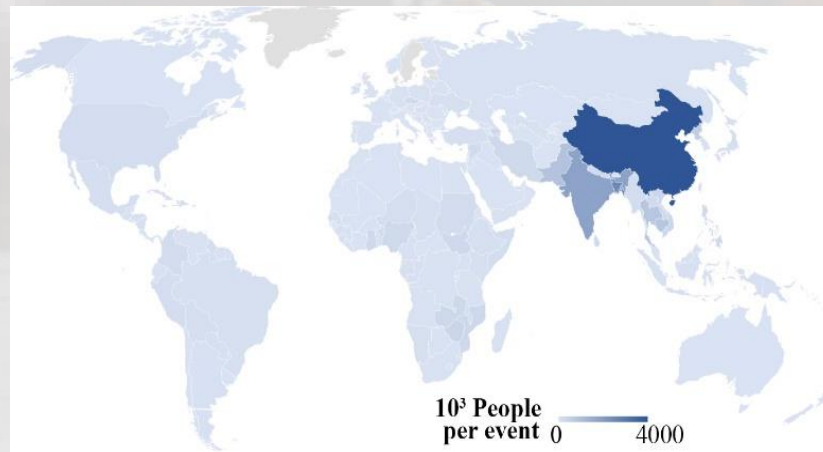




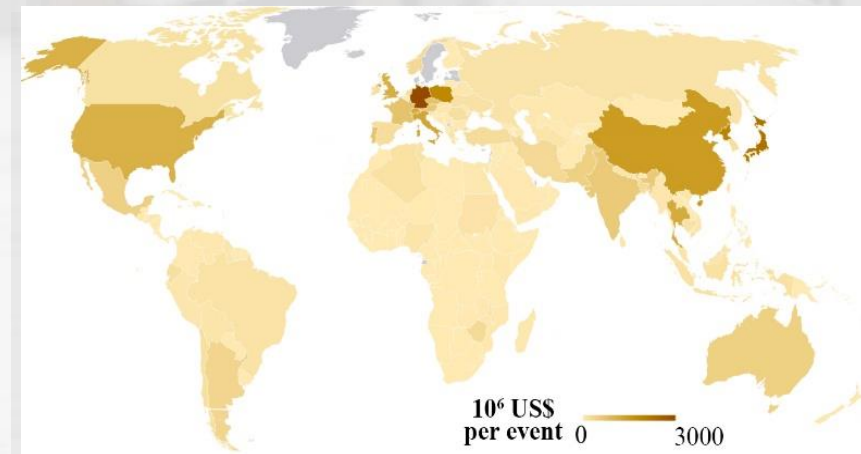
**Number of flood events**



**Average human loss**

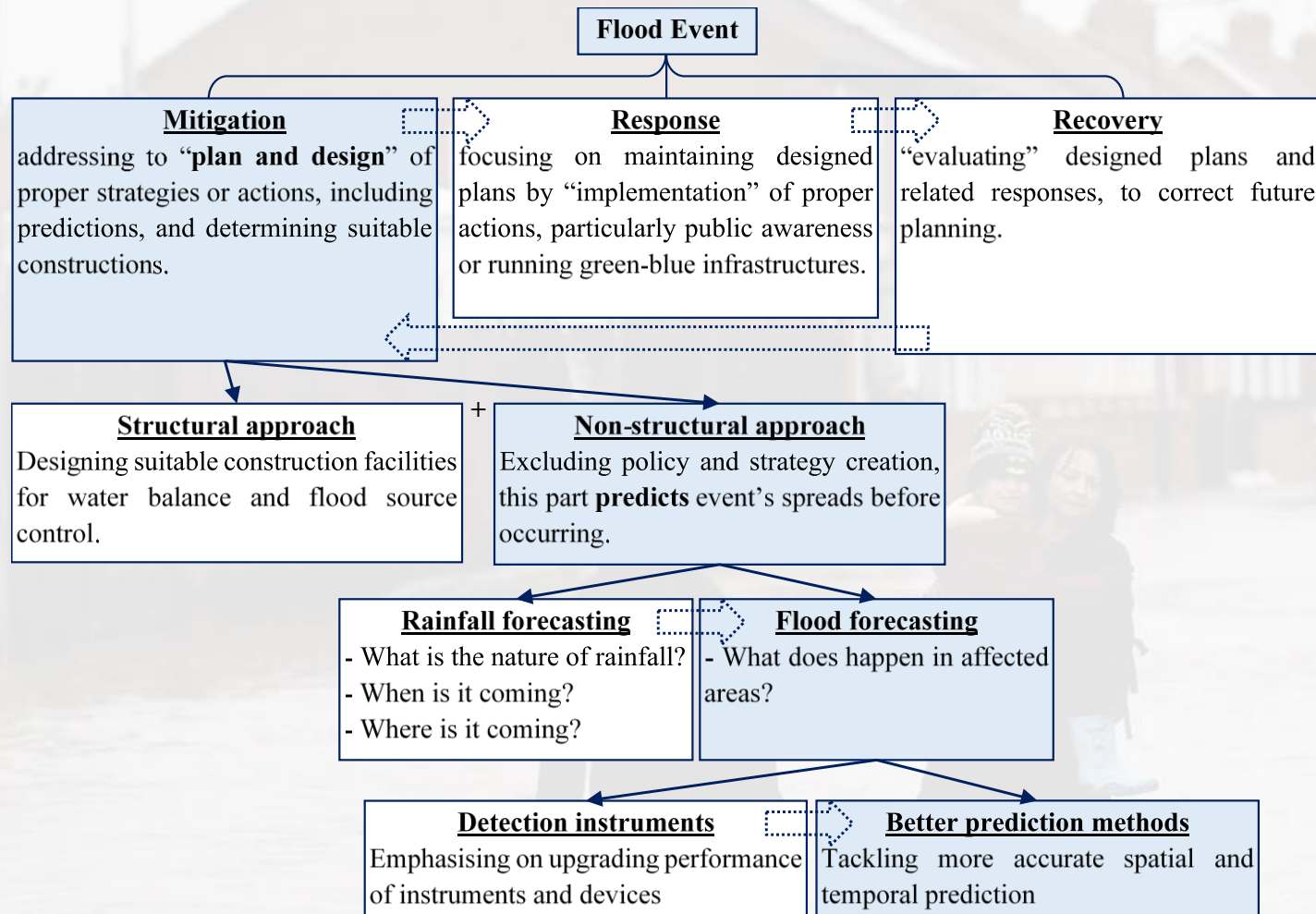


**Average affected people**



**Average economic loss**

Characteristics	Drainage systems	
	Urban areas	Non-urban areas
Flood description	- <b>Overflow</b> of urban drainage infrastructures due to lack of proper drainage in an urban area	- <b>Overflow or rise of water bodies</b> such as rivers, streams, sea level and reservoirs
Flood causalities	- Mainly <b>fast surface runoff</b> generated by rainfall	- Mainly <b>high intensity</b> of rainfall or accumulation of surface runoff
Flood duration	- Between a <b>few minutes to a couple of days</b>	- <b>Part of days to a week</b>
Spatial flood impacts	- <b>Small areas</b> i.e. streets to neighbourhoods, can be extended to all urban areas, but highly distributed	- <b>Large scale</b> such as vulnerable zones, and river riparian zones
Spatial restrictions for flood management	- <b>No flexibility</b> in land surfaces or underground modification as previously occupied. - Fast variation in land use	- <b>High flexibility</b> in non-urban areas
Main types of impacts	- <b>Economic</b> loss and business interruption - <b>Human</b> loss, - <b>Mental</b> and <b>social</b> problems - Urban <b>structure</b> and infrastructure damages	- <b>Soil</b> erosion - Wasting <b>crops</b> and <b>livestock</b> - Natural <b>habitat</b> loss - <b>Water</b> pollution - <b>Reservoir</b> or water infrastructure damages



- **Empirical** models
- **Conceptual** models
- **Physical** models



**Artificial  
intelligence-based  
model**

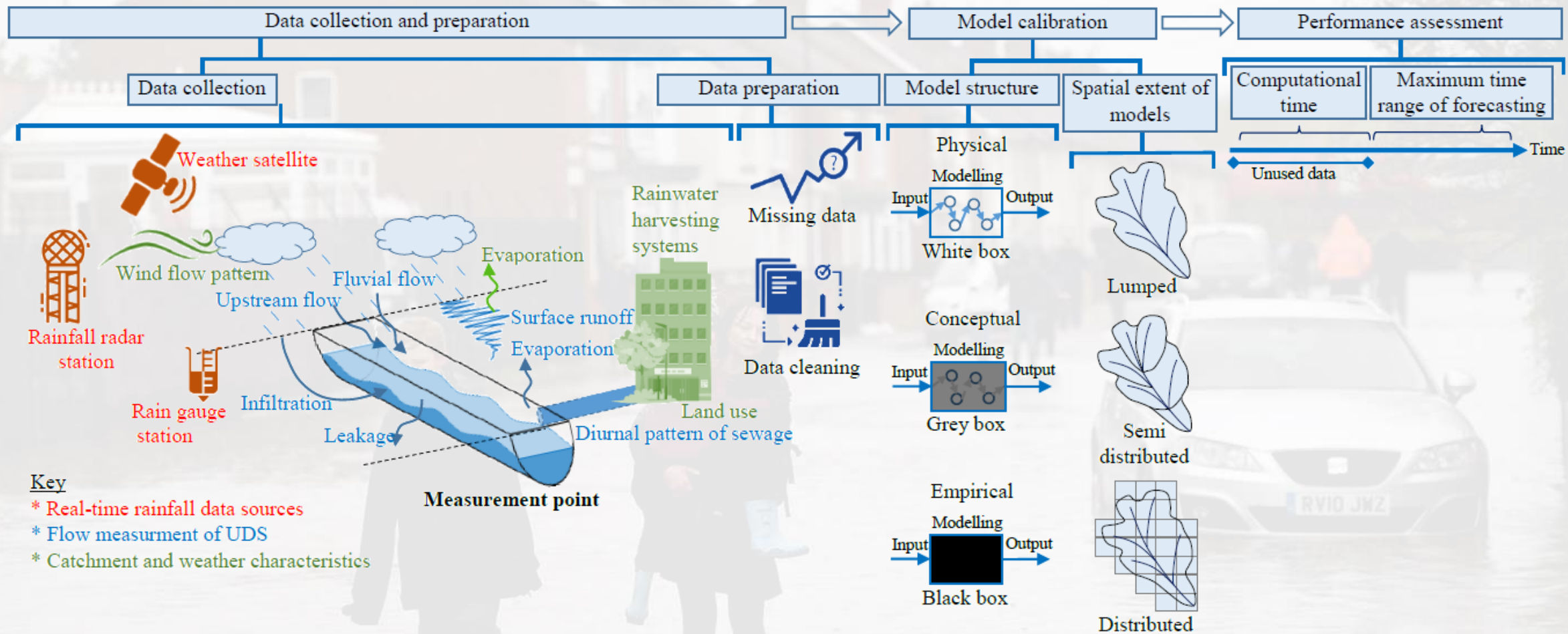


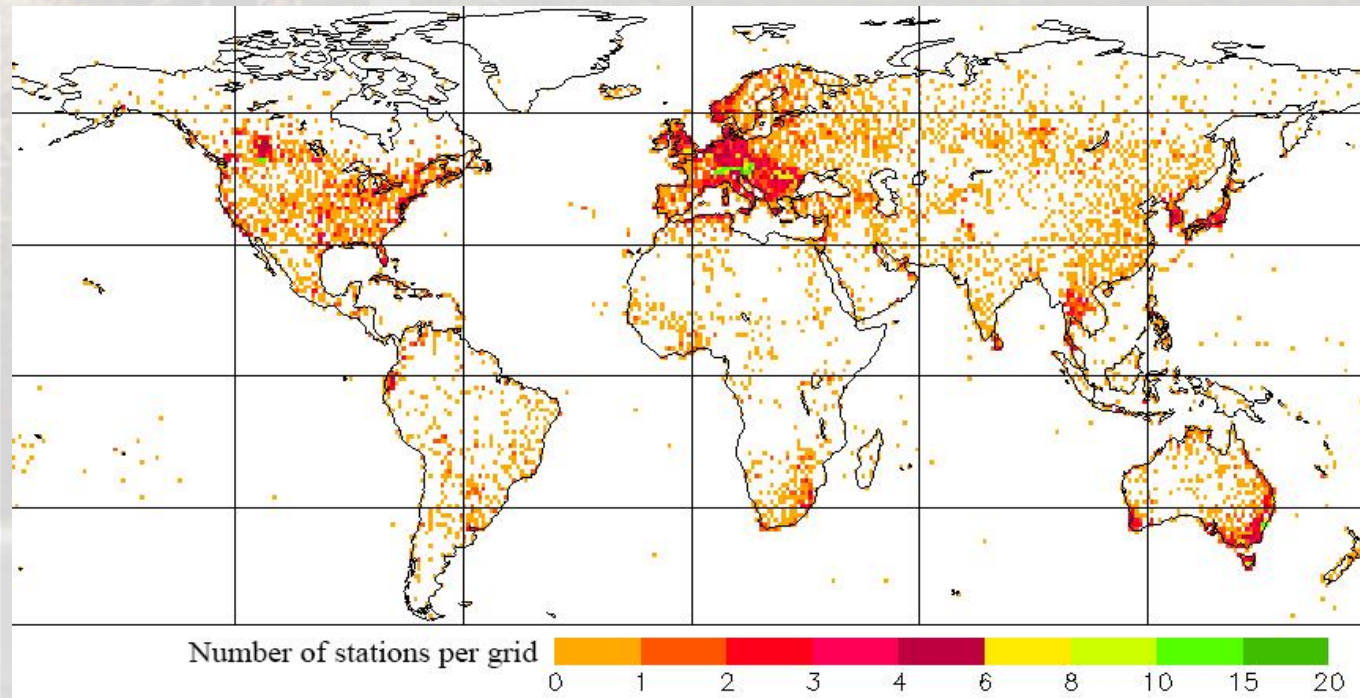
**Artificial  
Neural Network (NN)  
models**



**Time-series real-time NN**







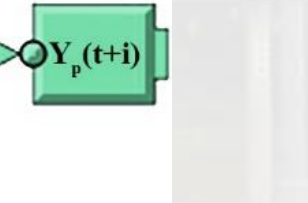
**Global distribution of installed rain gauge stations**

National Centre for Atmospheric Research (NCAR). (2012). *Number of stations used by GPC for May 2012*. [Online]. Available at <https://climatedataguide.ucar.edu>, [Accessed 8 Jan. 2022].

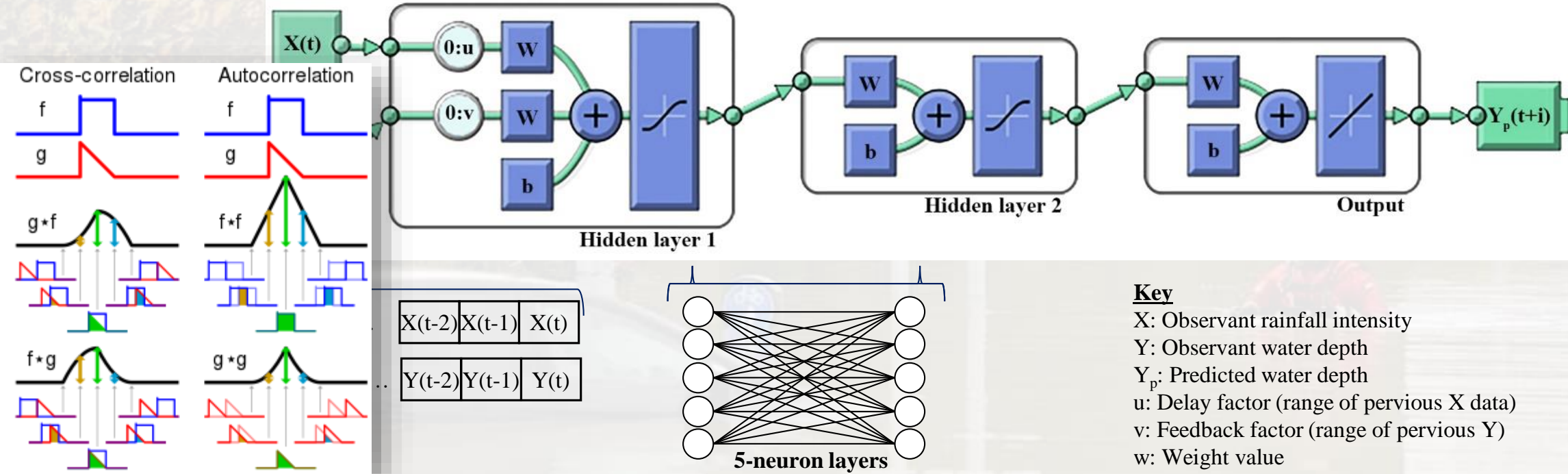
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Email: 21452390@student.uwl.ac.uk



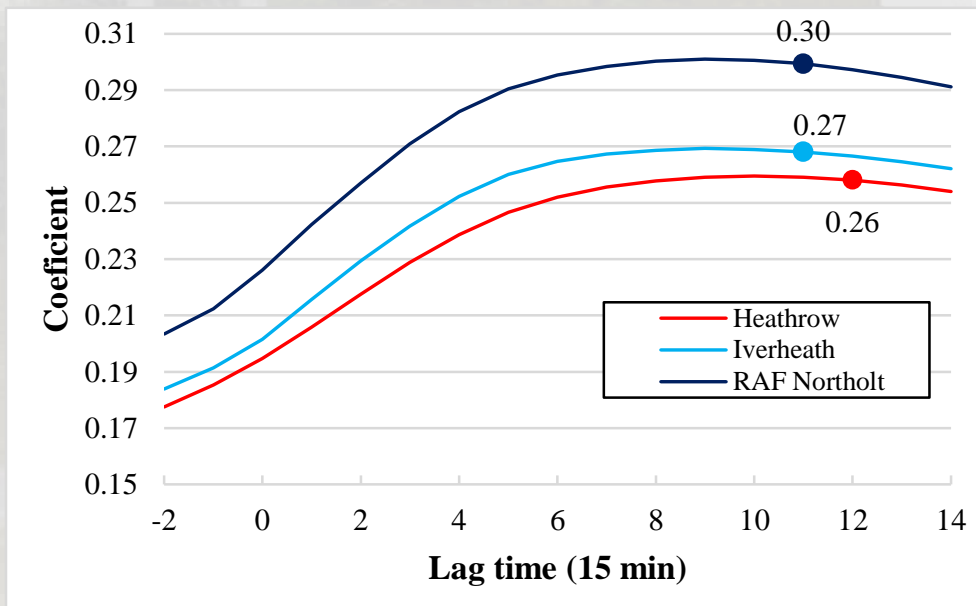
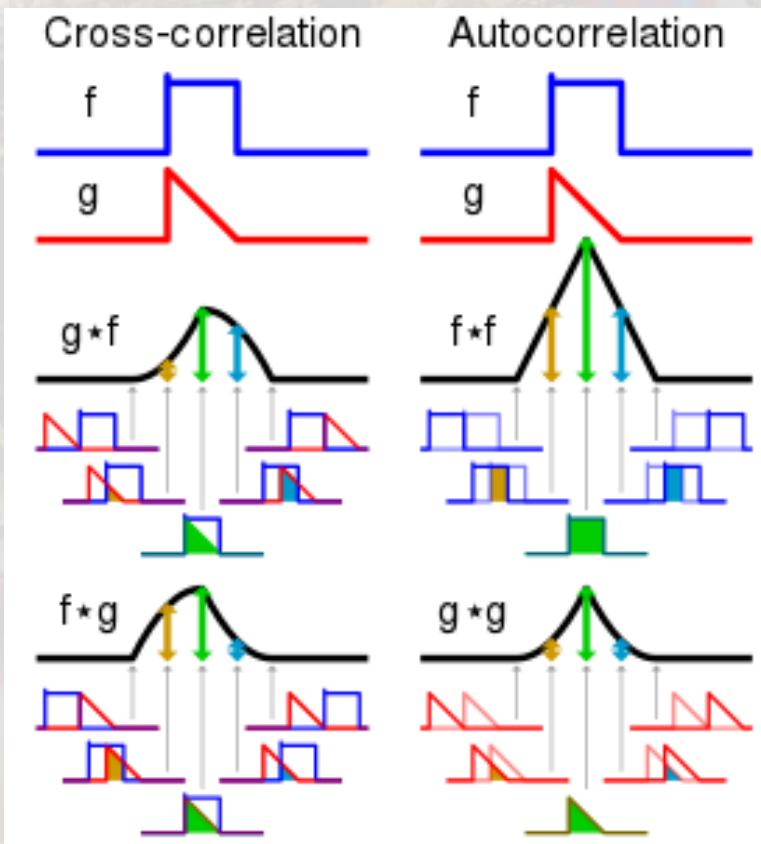


# Recommendation for **range of input data**: Cross correlation and Cross covariance



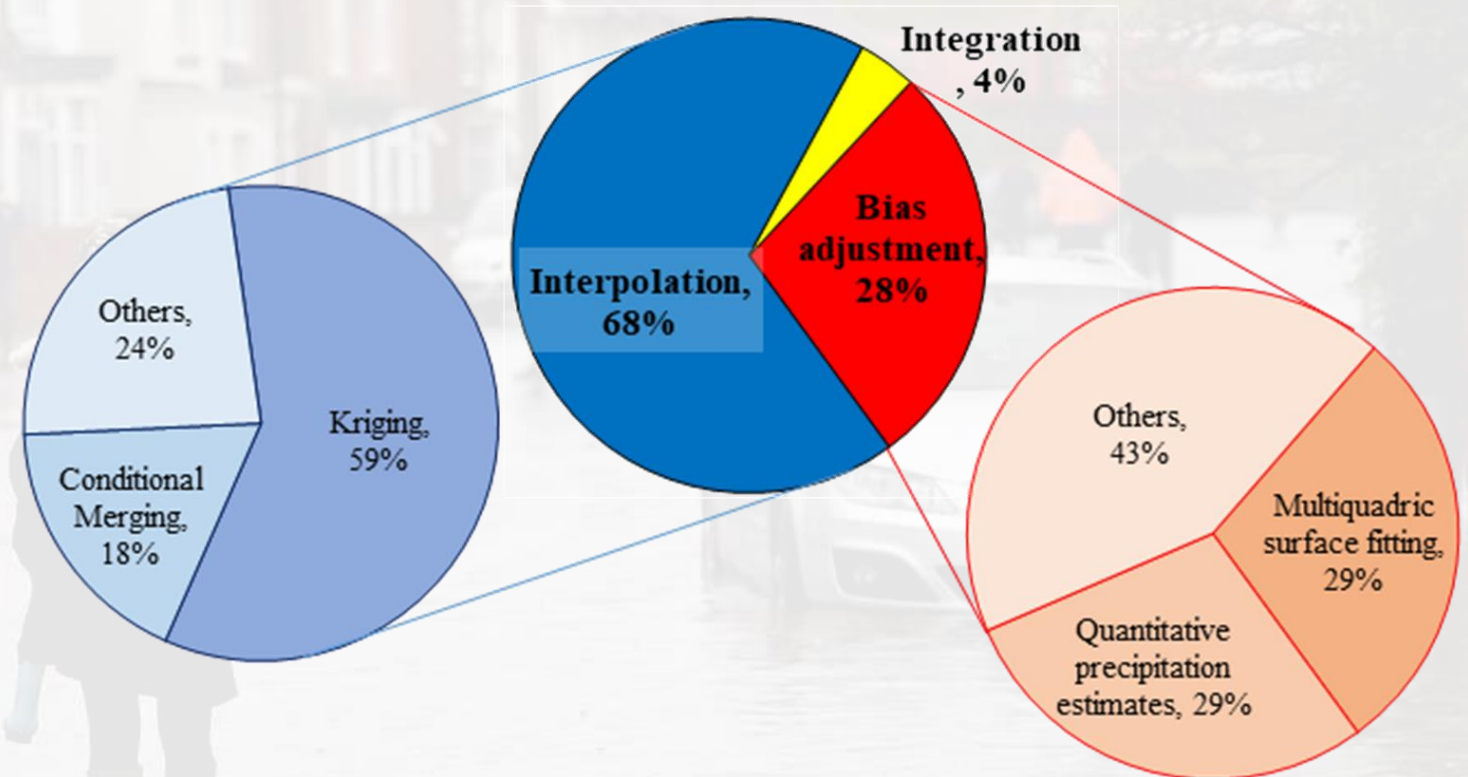
**Key**  
 $X$ : Observant rainfall intensity  
 $Y$ : Observant water depth  
 $Y_p$ : Predicted water depth  
 $u$ : Delay factor (range of pervious  $X$  data)  
 $v$ : Feedback factor (range of pervious  $Y$ )  
 $w$ : Weight value  
 $b$ : Bias value  
 $i$ : Time-step ahead

# Recommendation for **range of input data**: Cross correlation and Cross covariance





- **Integration** techniques have **more capability** to increase the **model accuracy** than other techniques
- Integration **has not much interest** due mainly to requirements for :
  - More model **complexity**
  - More **data** records
  - Higher computational **efforts**



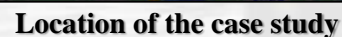
## Research question:

- Which **type** of data **merging** is more **effective**?
- **How many** of **data** should be add to the **time-series model** for each iteration?
- **Recommendations** are **compatible** with **optimisation** of used range of data?



# Method and material





- **Rainfall data**
- **Water level**

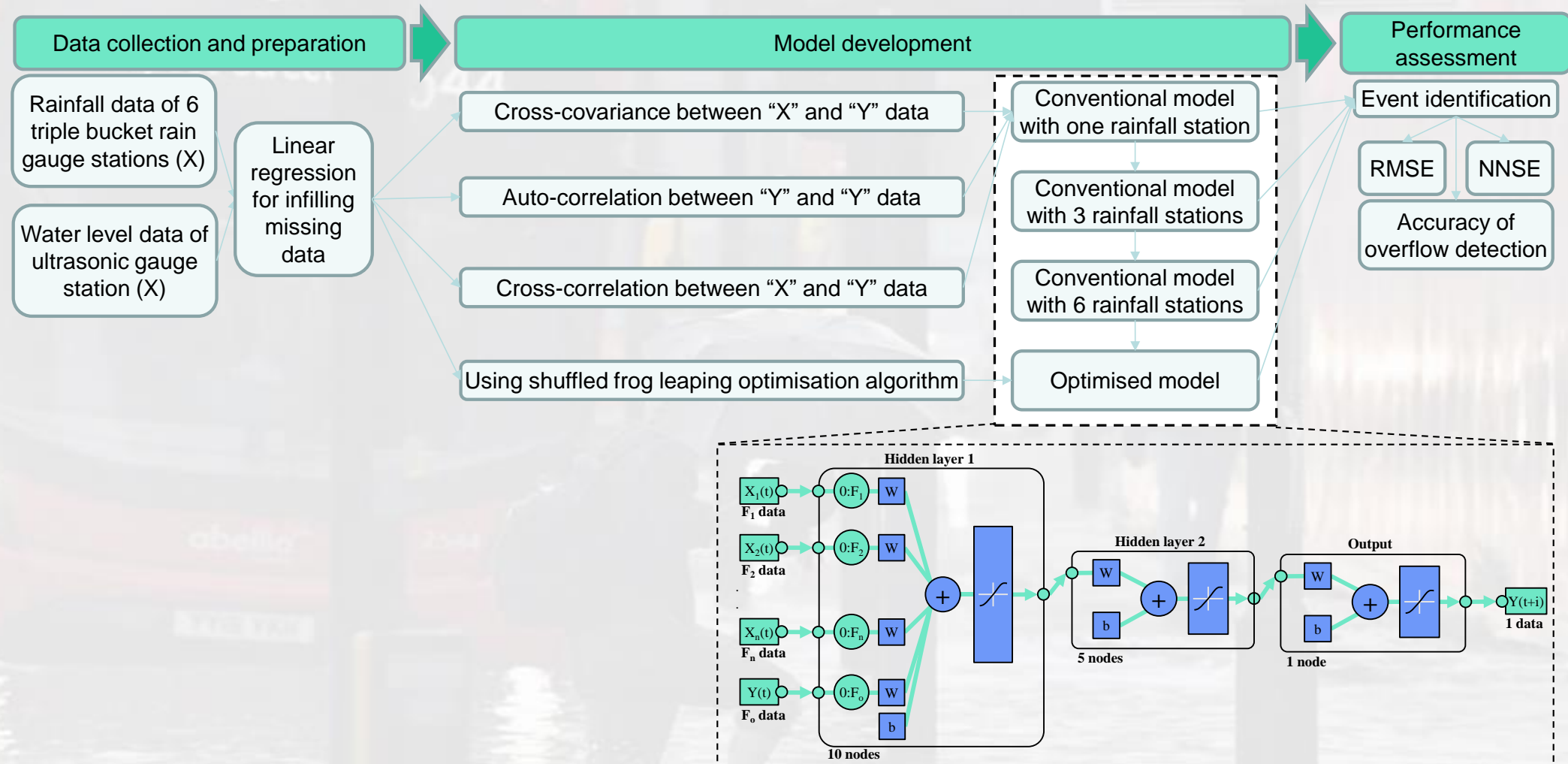
**Selected model: NARX** (The nonlinear autoregressive network with exogenous inputs)

## Pre-phase: Testing the model for 4-step ahead:

- **Best correlated rainfall data and water level**
- **Interpolating all rainfall data** (Kriging with external draft)
- **Bias adjustment of best rainfall data with others** (Multiquadric fitting)
- **Integration of all rainfall data**

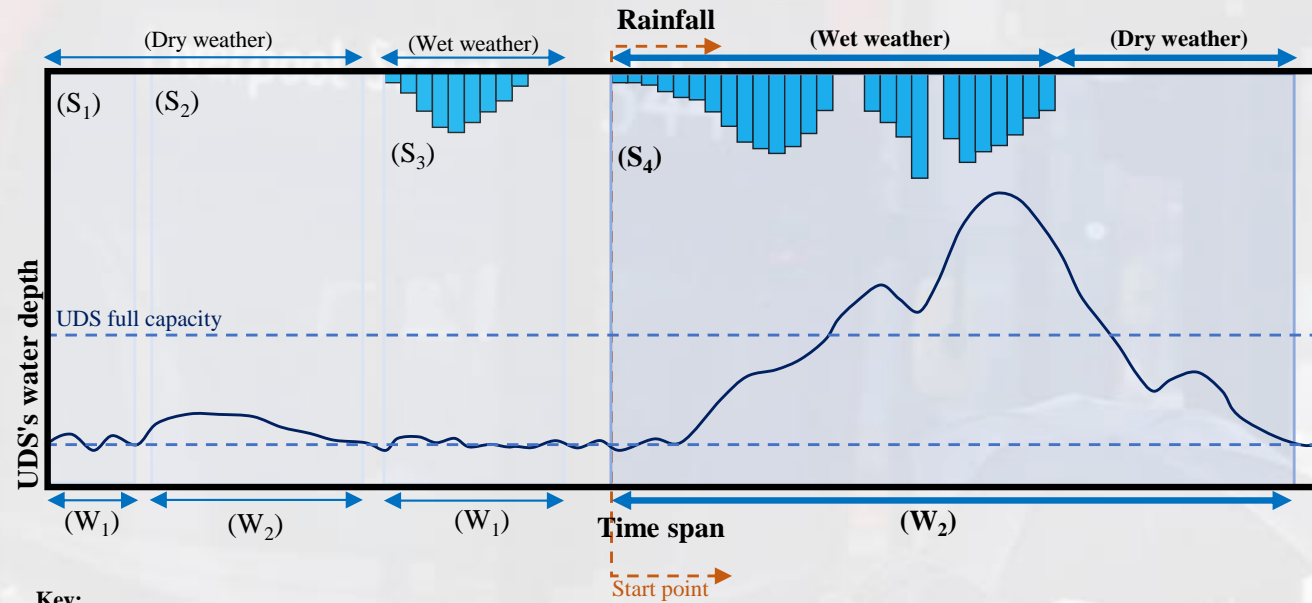


## ❖ Method and concept



All the models were developed on a laptop with Intel i7-6700 HQ CPU @ 2.60GHz and 16 GB RAM Memory

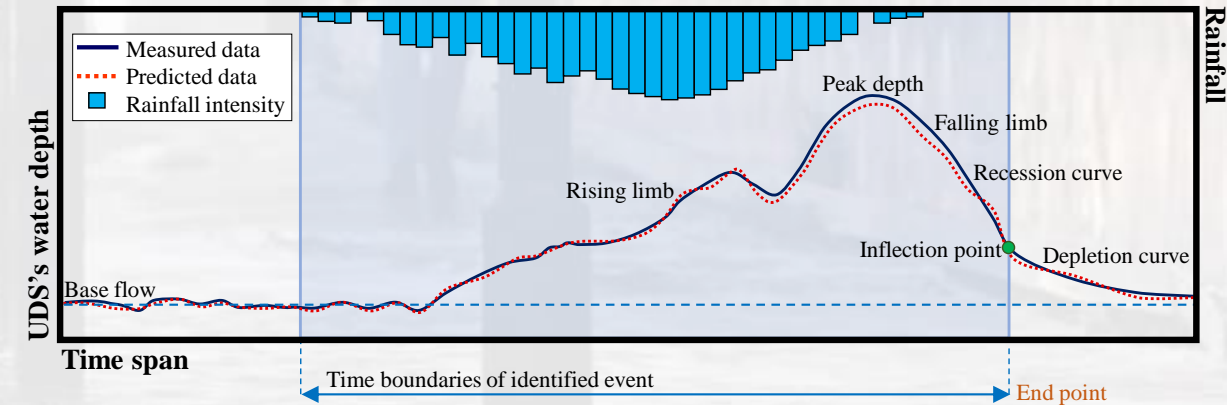
## ❖ Typical flood event with temporal boundaries



### Key:

State	Captured data	
	Rainfall intensity	Water depth
(S1): Dry weather, non-flood event	(R <sub>1</sub> ): -	(W <sub>1</sub> ): -
(S2): Sudden rising flow, non-flood event	(R <sub>1</sub> ): -	(W <sub>2</sub> ): +
(S3): Ineffective precipitation, non-flood event	(R <sub>2</sub> ): +	(W <sub>1</sub> ): -
(S4): Flood event	(R <sub>2</sub> ): +	(W <sub>2</sub> ): +

-: No rainfall, no change for water depth  
+: Rainfall, net change (increase or decrease) for water depth



"A New Event-based Framework for Artificial Intelligence-based Modelling of Real-Time Flood Forecasting", **Piadeh F.**, Behzadian K. Alani A.M., Chen A.S., Campos L.C., *Water research*, Jun. 2022 [Under review]

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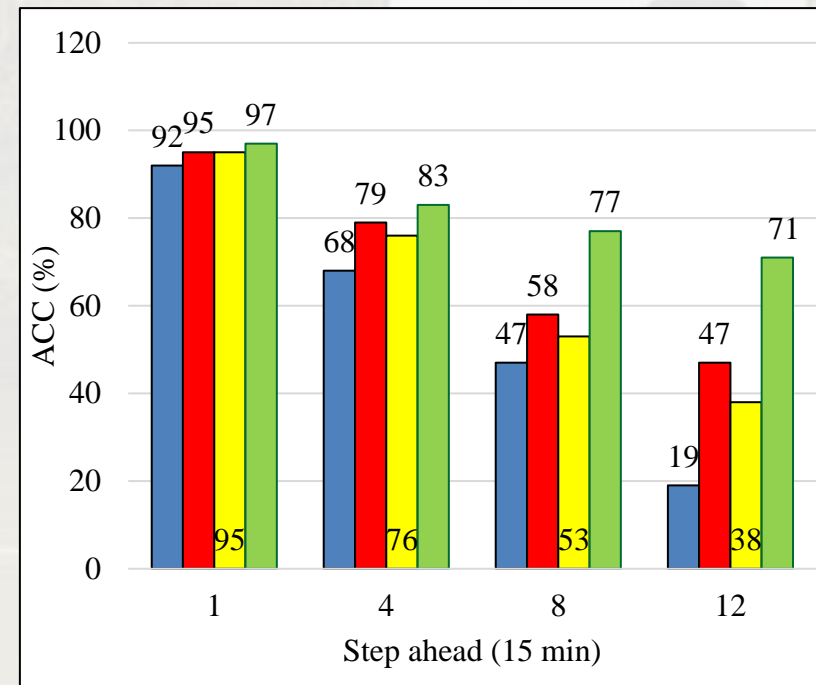
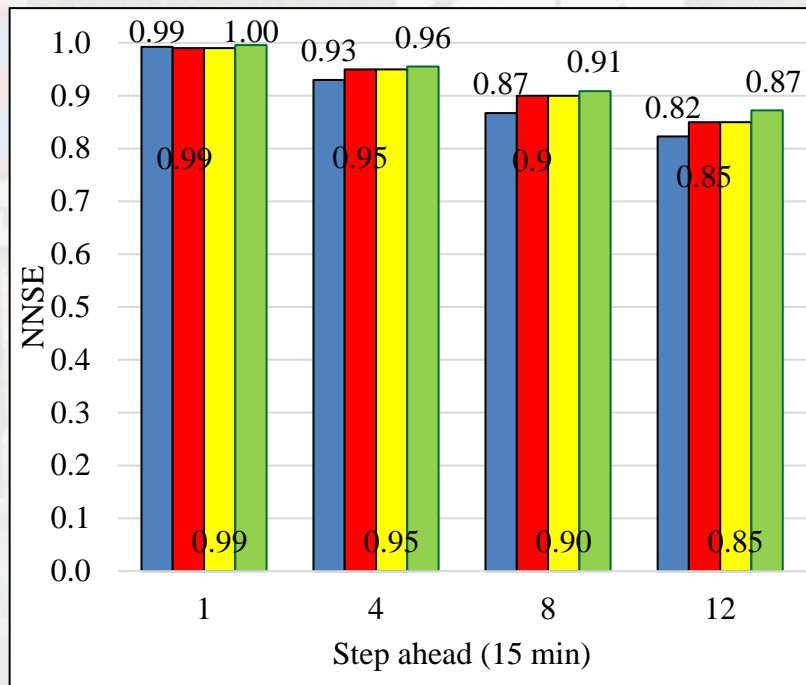
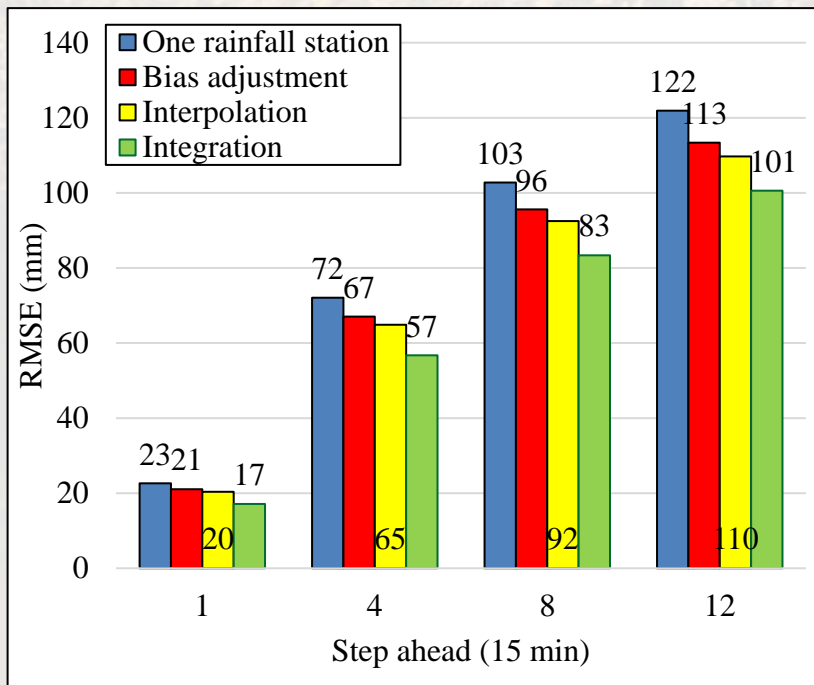


# Results and discussion





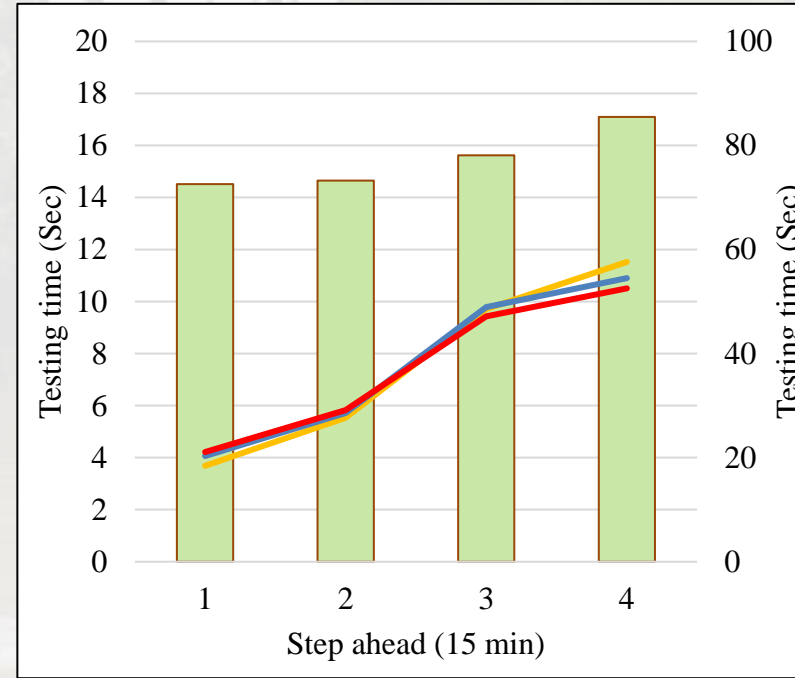
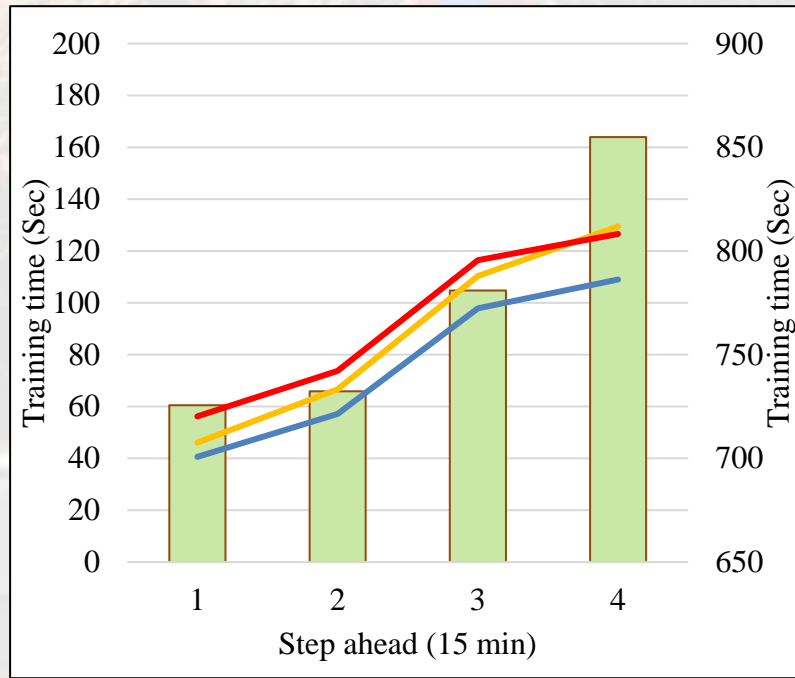
## ❖ Pre-phase analysis



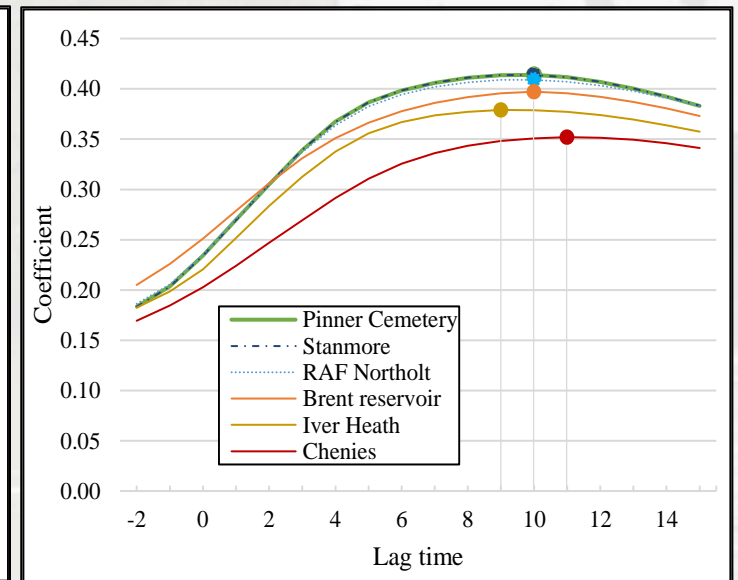
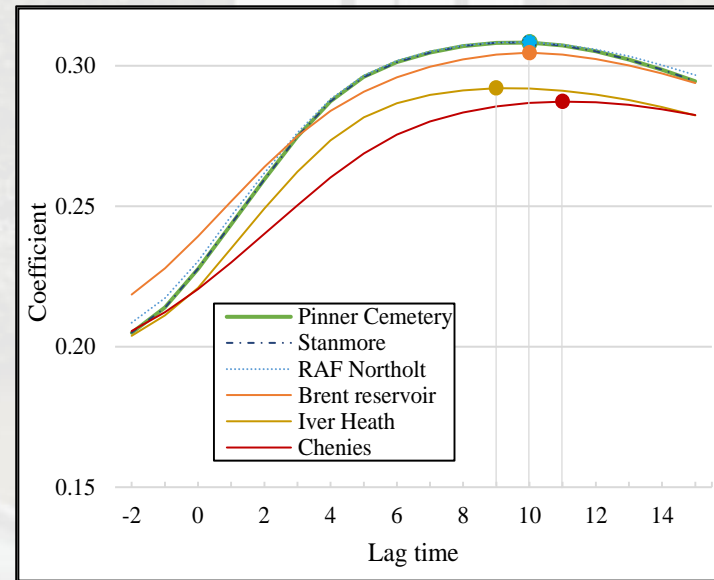
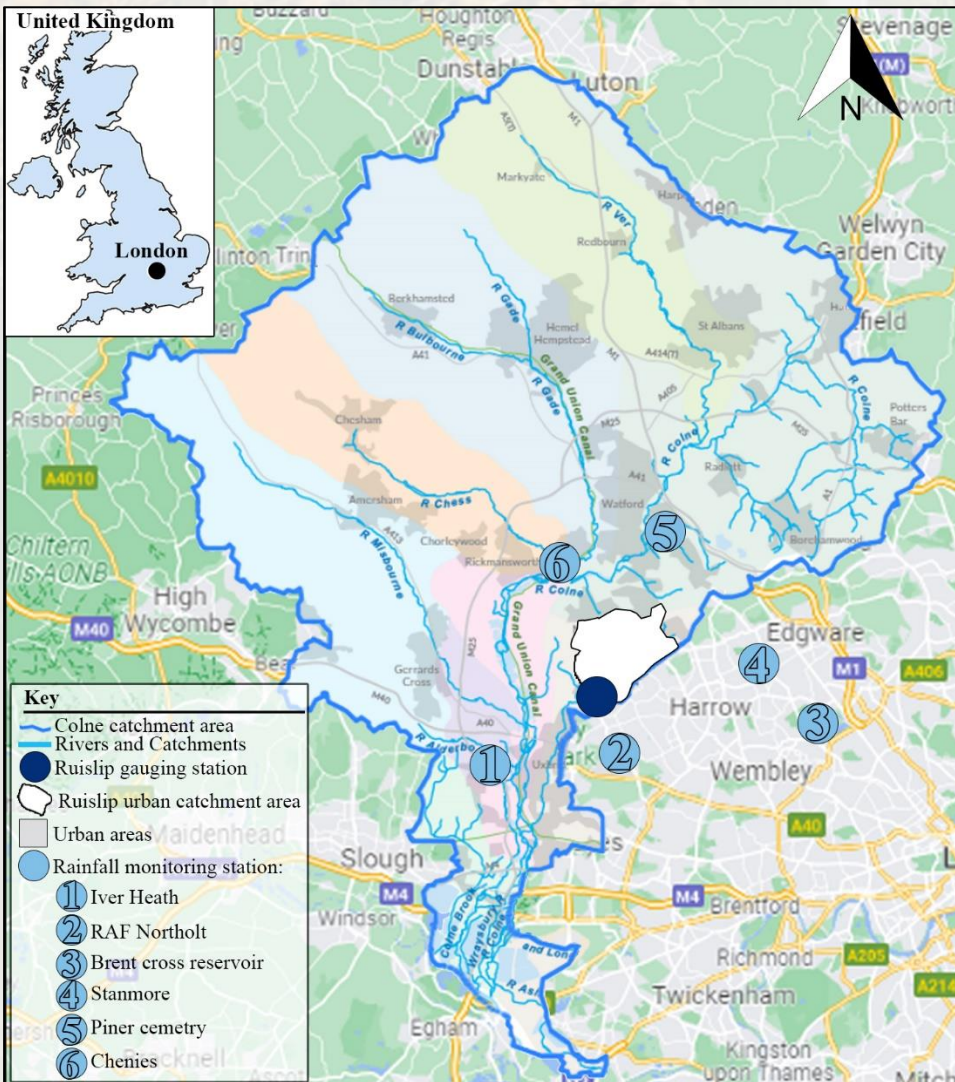


2019/2020  
Academic Year

❖ *Pre-phase analysis*



## ❖ Integration method analysis



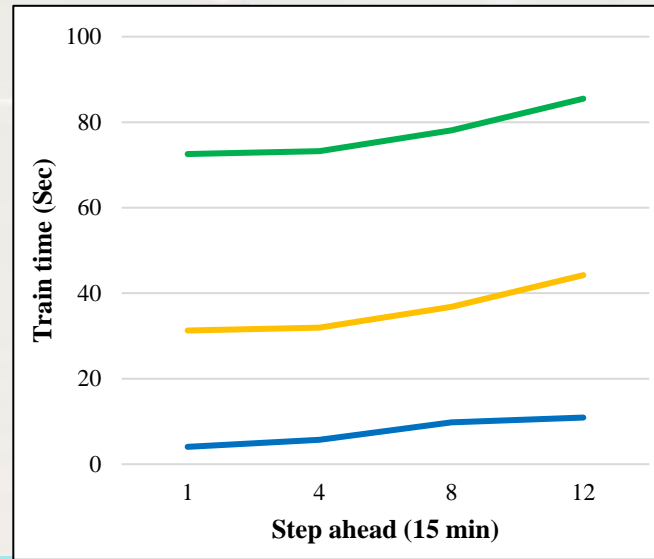
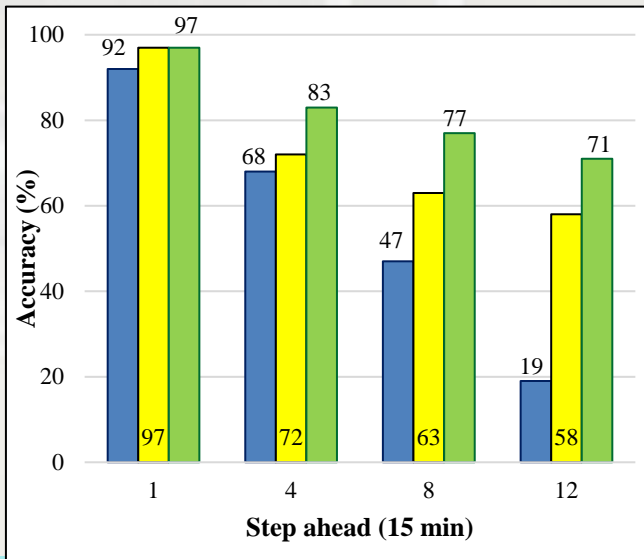
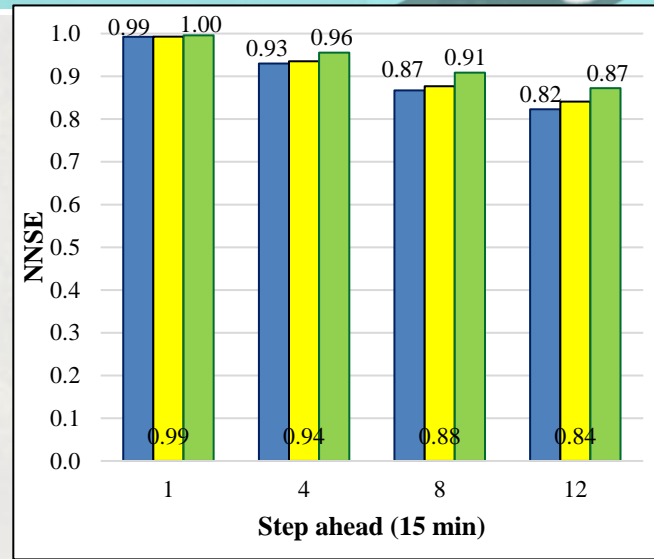
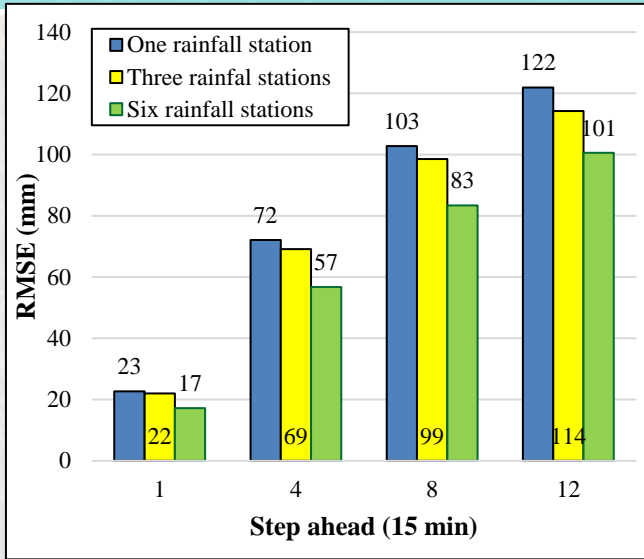
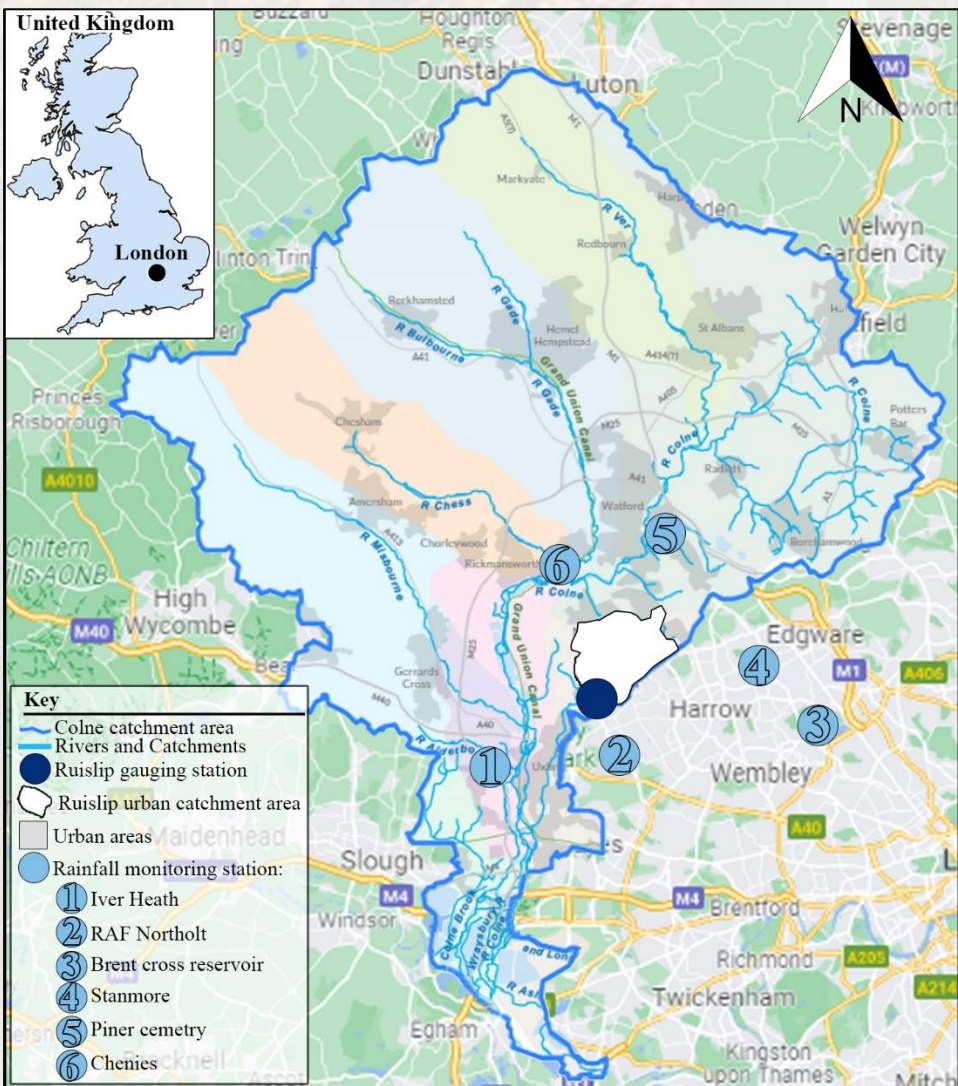
Data relationship between different selected rainfall stations and water level

(Left): Cross-correlation

(Right): Cross-covariance



# ❖ Integration method analysis



## ❖ Optimisation analysis

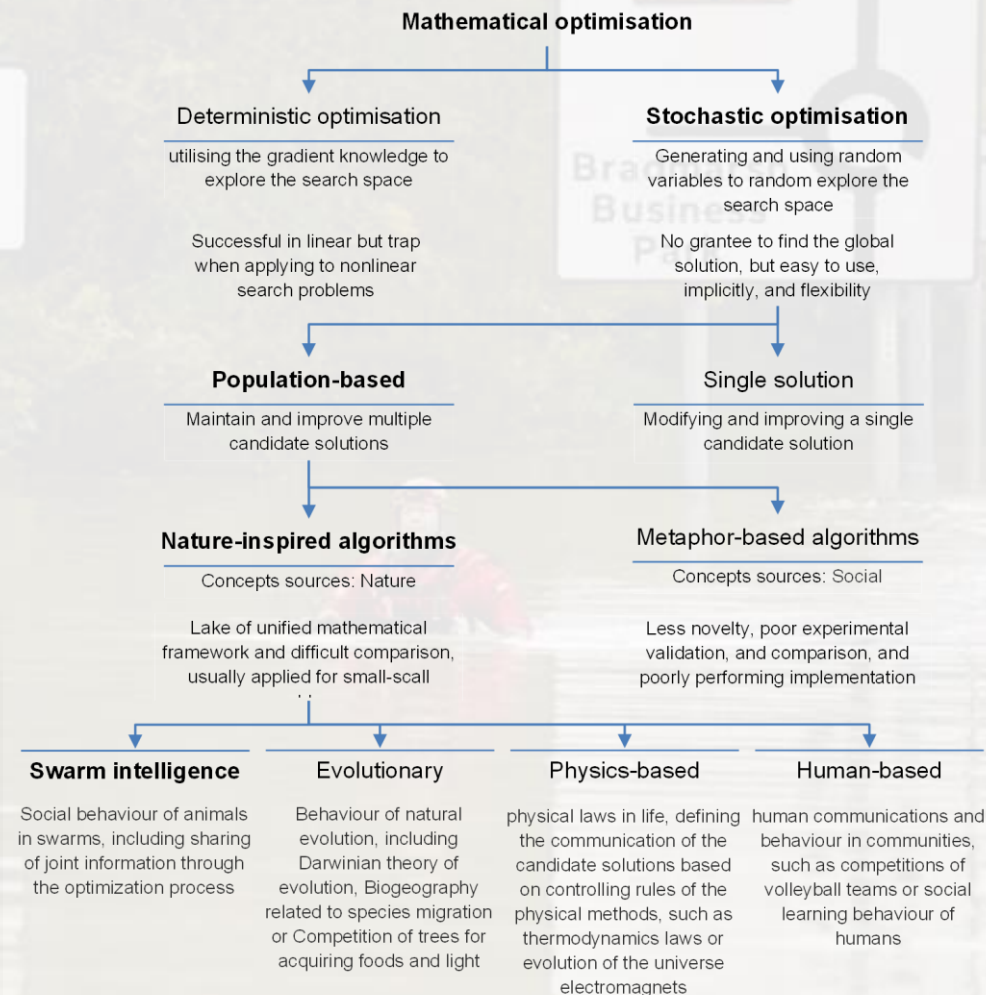
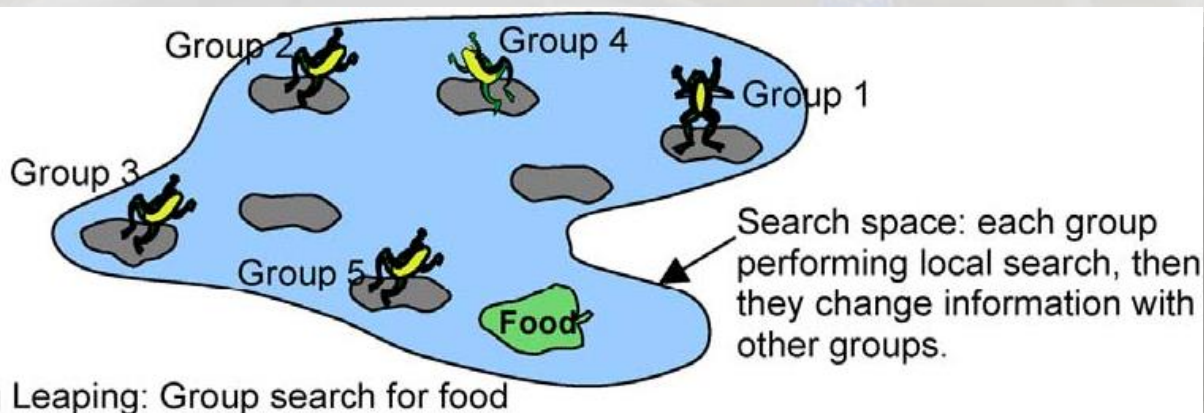
Selected optimisation **algorithm**: Shuffled frog-leaping algorithm (SFLA)

Decision **variables**: Range of time-series **input** data

Each trial: 4 shuffle sample for **exploration** step  
4 shuffle sample for **exploitation** step

**Objectives**: RMSE, NSE, and ACC enhancement

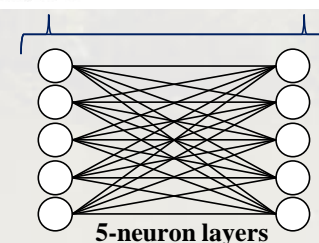
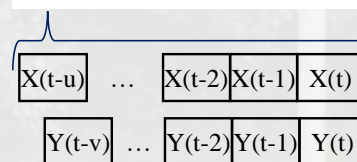
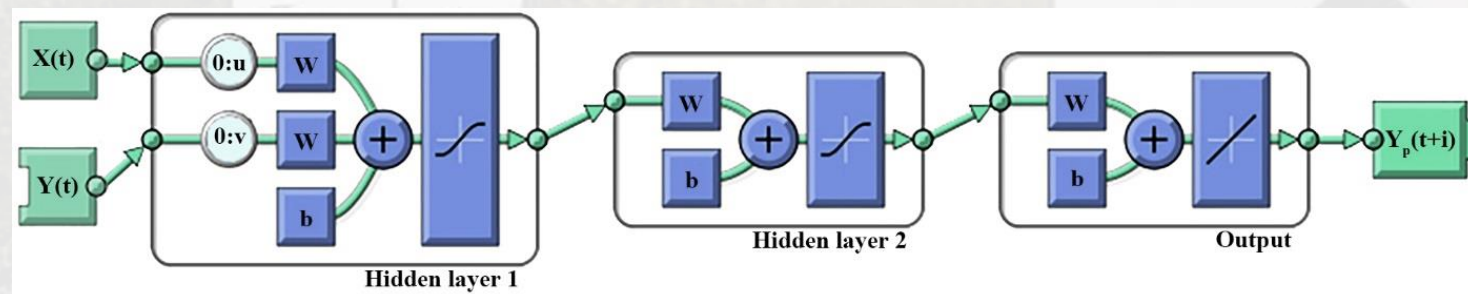
Stopping criteria: Improvement less than **0.01%**





## ❖ Optimisation analysis

Trial	Lag times of dataset						Water level
	R1	R2	R3	R4	R5	R6	
0 (Conventional approach)	9	10	10	10	10	11	1
1	7	7	3	4	8	8	6
2	4	5	9	10	2	11	3
3	4	4	4	9	5	7	2
4	3	3	9	8	5	4	8
5	7	9	6	7	2	5	9
6	2	3	5	3	5	7	2
7	5	5	2	6	8	7	5
8	4	8	8	5	7	7	2
9	3	5	9	6	7	7	5
10	4	5	9	6	7	7	5



### Key

- X: Observant rainfall intensity
- Y: Observant water depth
- $Y_p$ : Predicted water depth
- u: Delay factor (range of pervious X data)
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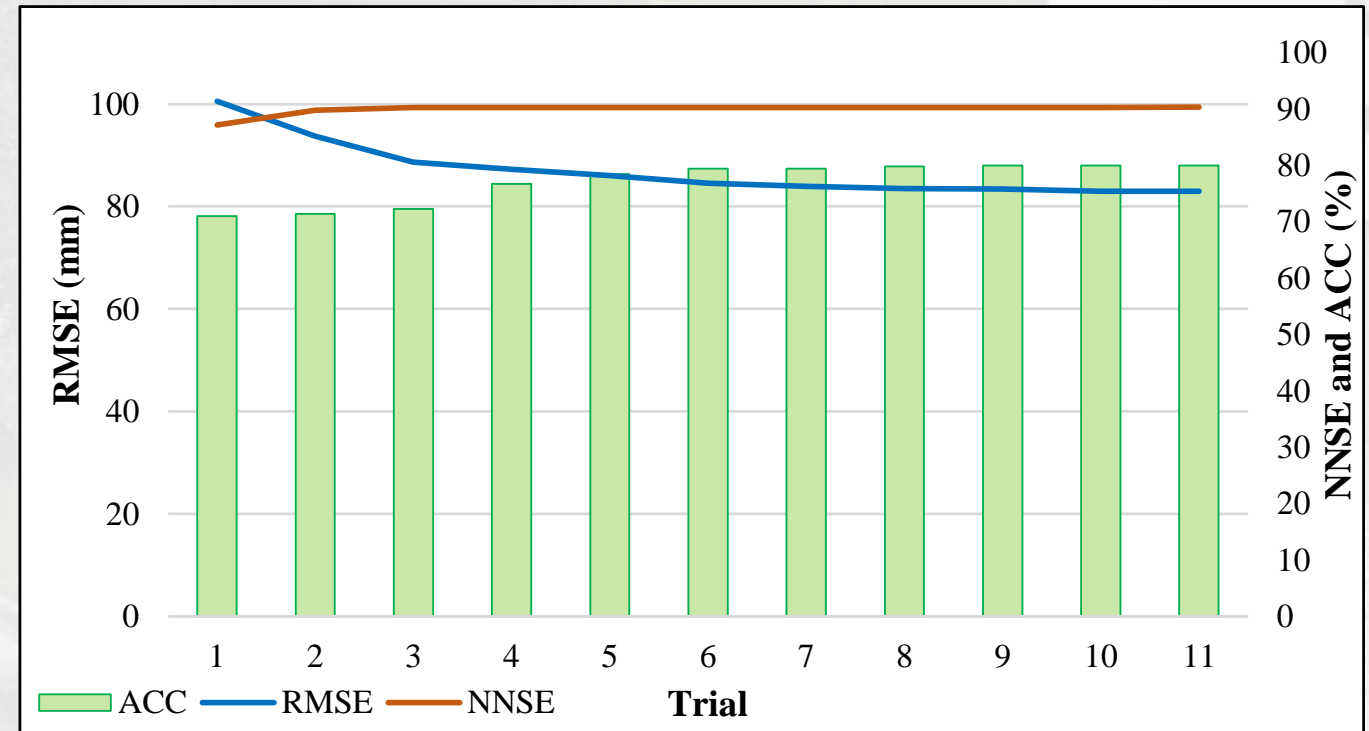
$10 \times 10 \times 10 \times 10 \times 10 \times 10 \times 11 \times 10 \times 15 \text{ (min)} = 314 \text{ Years !!!!!}$

$10 \times 8 \times 15 \text{ (min)} = 20 \text{ Hrs}$

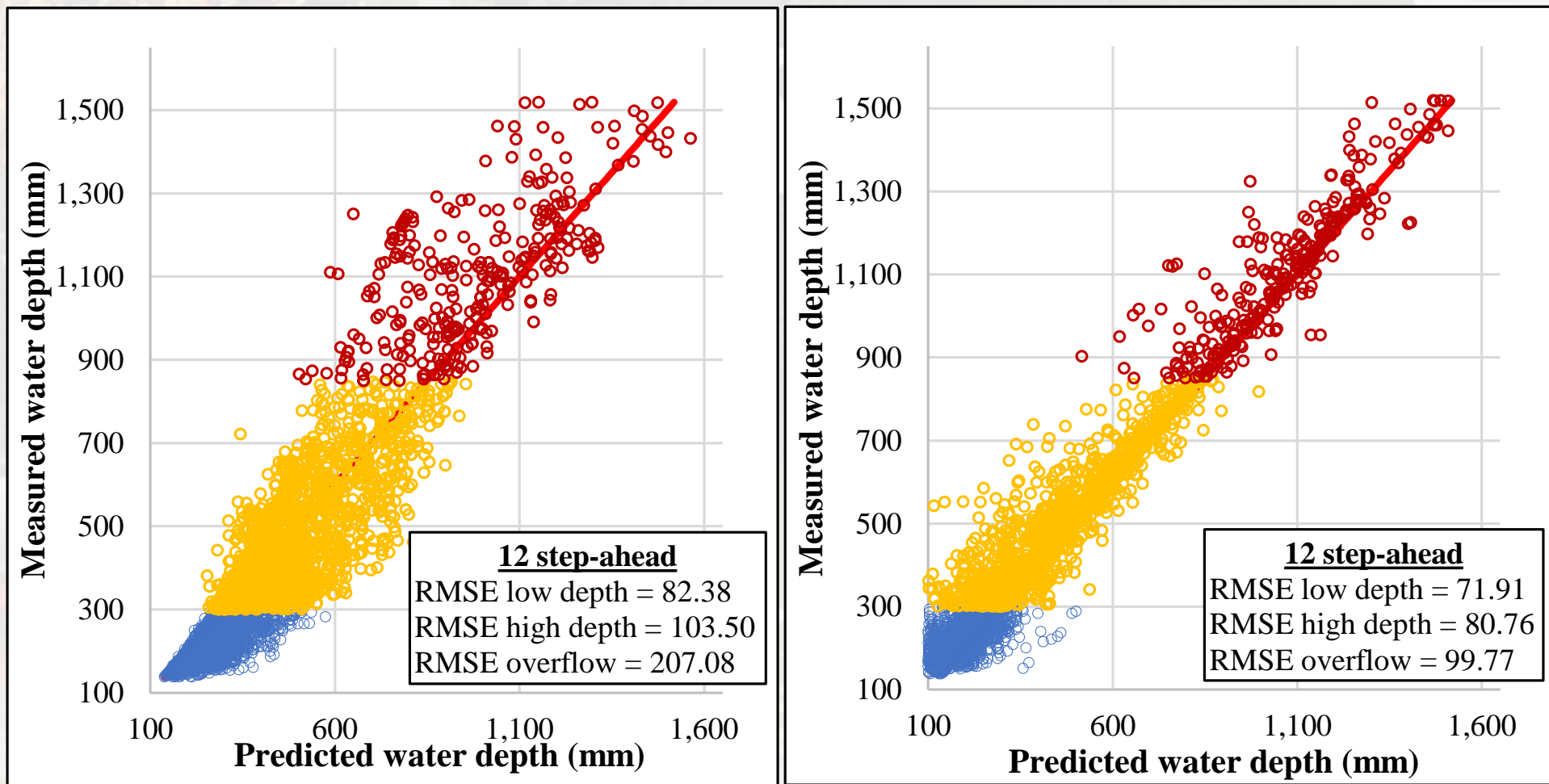


## ❖ Optimisation analysis

Trial	Lag times of dataset						Water level
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1	7	7	3	4	8	8	6
2	4	5	9	10	2	11	3
3	4	4	4	9	5	7	2
4	3	3	9	8	5	4	8
5	7	9	6	7	2	5	9
6	2	3	5	3	5	7	2
7	5	5	2	6	8	7	5
8	4	8	8	5	7	7	2
9	3	5	9	6	7	7	5
10	4	5	9	6	7	7	5



# ❖ Optimisation analysis



Model performance of (Left) Best conventional model, (Right) Optimised model

# Conclusion

## 01 Merging method

Integration is more effective but time consuming

## 02 Integrated method

Regardless of rainfall correlation, increasing input data causes outperformance

## 03 Input selection

Optimisation result is not compatible with conventional approach







Thank You For Your Attention