Artificial Neural Networks (ANNs) for Urban Flood Modelling

WP 3.6

A. Duncan, E. Keedwell, A. S. Chen,

S. Djordjević, D. Savić

University of Exeter
Centre for Water Systems

www.floodrisk.org.uk

EPSRC Grant: EP/FP202511/1

Overview

- Introduction
- Objectives
- Methodology
- Results
- Conclusions
- Future work

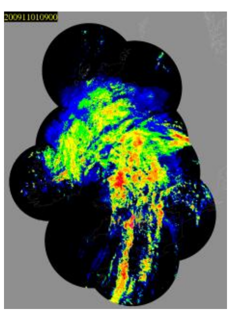
SPECIFIC INTERACTION BETWEEN DATA AND MODELS

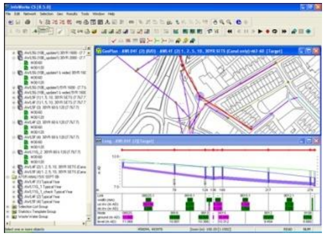
DATA	RAIN FORECAST MODELS: MODEL	RAIN FORECAST MODELS: RUNNING TIME	URBAN FLOODING MODELS
RADAR 1 km / 5 min (for the UK) and 5 km/15 min (for the UK)	STEPS (NWP+ Nowcast)	Approx 5hr + < 5 min	**INFOWORKS**
RAW POLAR DATA 250 m / 1°/ 5 min (Can be converted to Cartesian, so it can be used as input to run the Nowcast, STEPS and HyRaTrac models)	STEPS* (only Nowcast)	< 5 min (only Nowcast)	**IMPERIAL COLLEGE'S MODEL** (AOFD for runoff modelling + Infoworks / SWMM)
ECMWF (ERA 40 & forecast data) used as lateral boundary conditions for LAM – mm5 and WRF	HyRaTrac	< 1 min	**AI** Exeter's Artificial Intelligence Model
UM global model dump files lateral boundary conditions for UM LAM	MM5/WRF	Approx. 5 h	
FLOW DATA Historic and RT data	UM	Approx 1h	

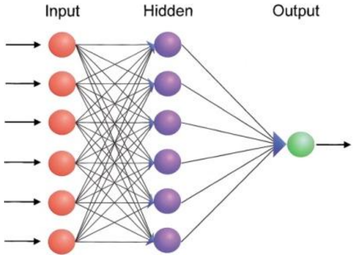
-----------→ Historical data

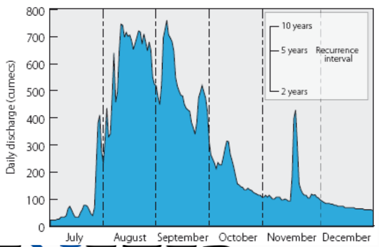
AI: Pattern Recognition

- Learning patterns from historical input/output data
- Urban Flood Modelling
  - Input: RT Radar data
  - Output 1: Model results
  - Output 2: Measurements









Literature Review – Hydrology & ANNs

- Auckland Sewer Overflow Model – Single CSO
  - (Fernando, Zhang, Kinley, 2005)
- Data-Driven Modelling – Fluvial flow and flooding
  - (Solomatine, 2007)
- Data-Driven Modelling - Optimisation using Genetic Algorithms
  - (Solomatine, 2008)
- ANN - Flood Forecasting in River Arno, Florence, Italy
  - (Campolo, 2003)

RAPIDS: RAdar Pluvial flooding Identification for Drainage System

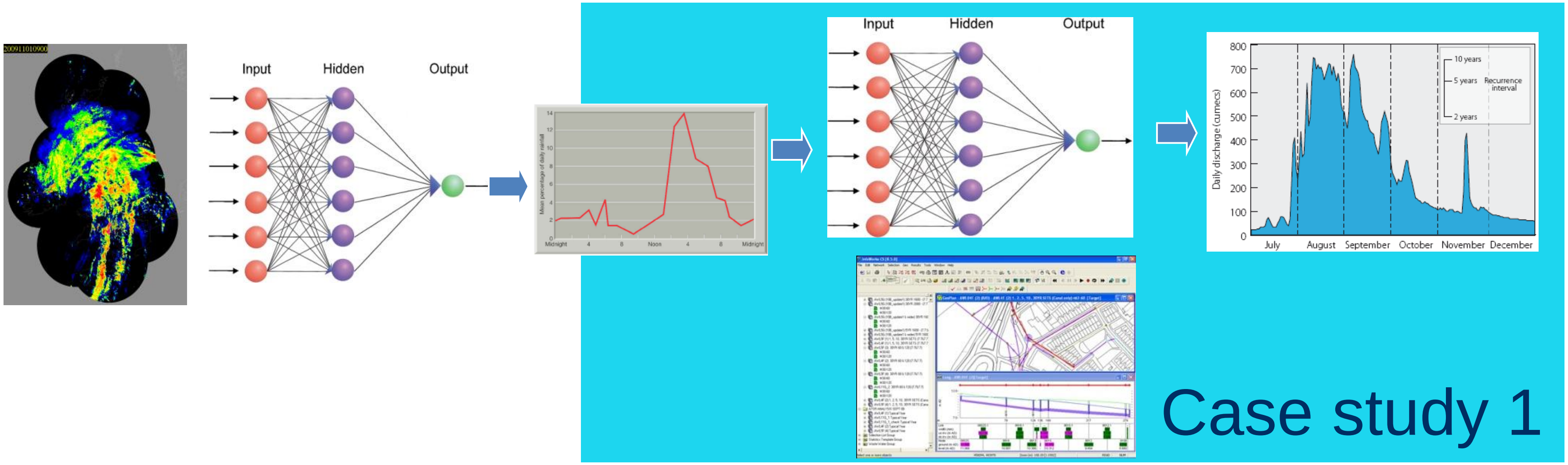
- Two ANNs:

– Input 1: RT Radar data

– Output 1: Rainfall prediction

– Input 2: Rainfall prediction

– Output 2: Flood severity prediction

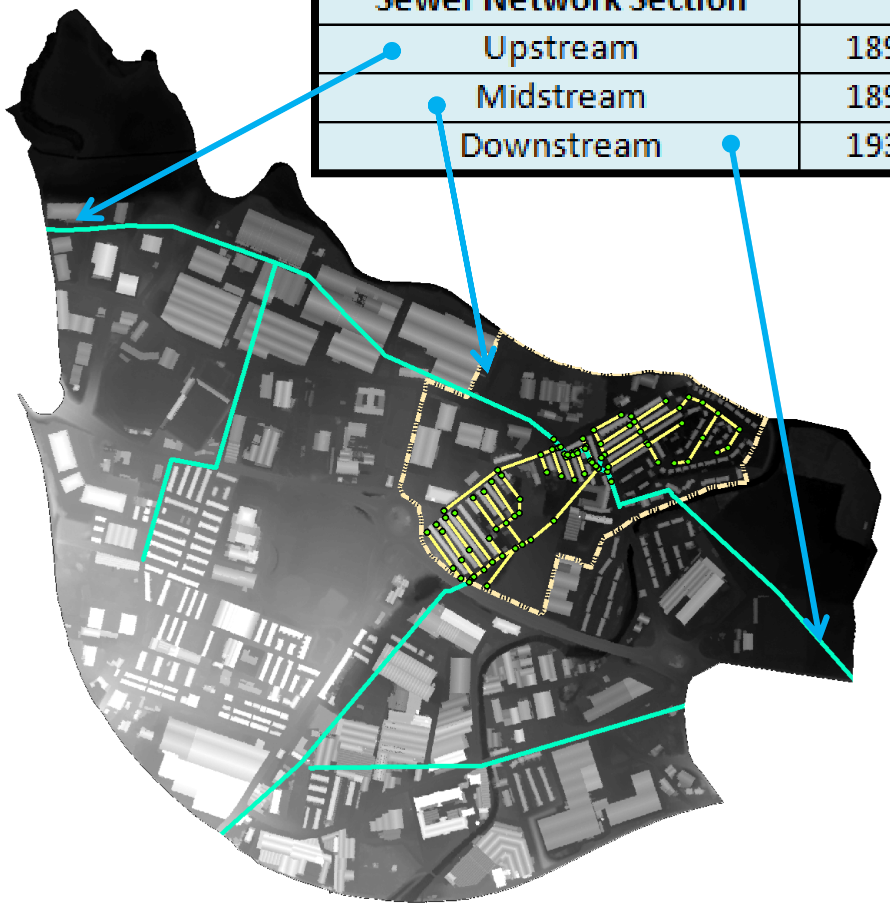


RAPIDS: Case Study 1

Keighley : Combined sewer network model

123-manhole sub-section

Sewer Network Section	Manhole Identifiers
Upstream	1895, 1913, 2169, 3060, 3068
Midstream	1898, 1908, 1918, 1938, 2160
Downstream	1931, 1939, 1940, 1941, 8398



Objectives

- To replace SIPSON with a faster, AI-based DDM
- To provide classification of flood status/severity at each manhole in a given network
  - Optionally - full flood-level regression (metres)
- Speed is traded off with accuracy
- Ability to predict potential flooding severity

Methodology

- Designed rainfall (durations & return periods)
- SIPSON simulator
  – simulated flood levels for 123 street manholes
- ANN used = Multi-Layer Perceptron (MLP)
  – Input:
    - rainfall intensity, cumulative rainfall, elapsed time
  – Output: flooding level at each manhole
  – Different storms used for cross-validation and testing

Methodology (continued)

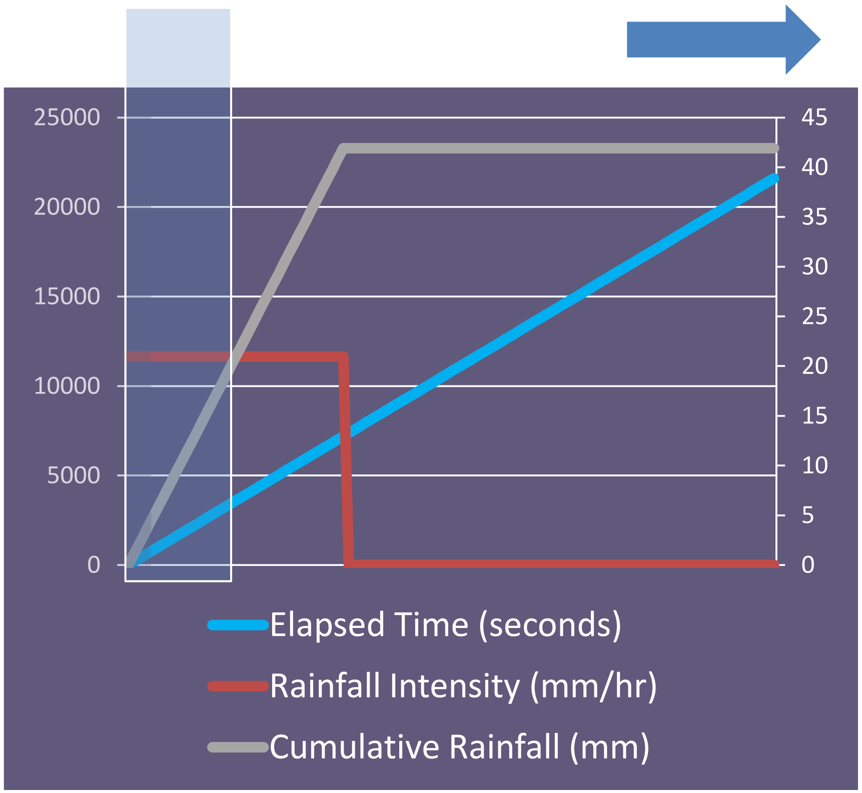
- Classification Scheme:

Flood Class	Description	Min Flood Depth (metres)	Max Flood Depth (metres)
3	Severe	5.00	1.00E+100
2	Moderate	1.00	5.00
1	Slight	0.00	1.00
0	None	-1.00E+100	0.00

- Vary ANN setup parameters
  - Input (number of 3-minute time steps)
  - Output – prediction up to 90 minutes

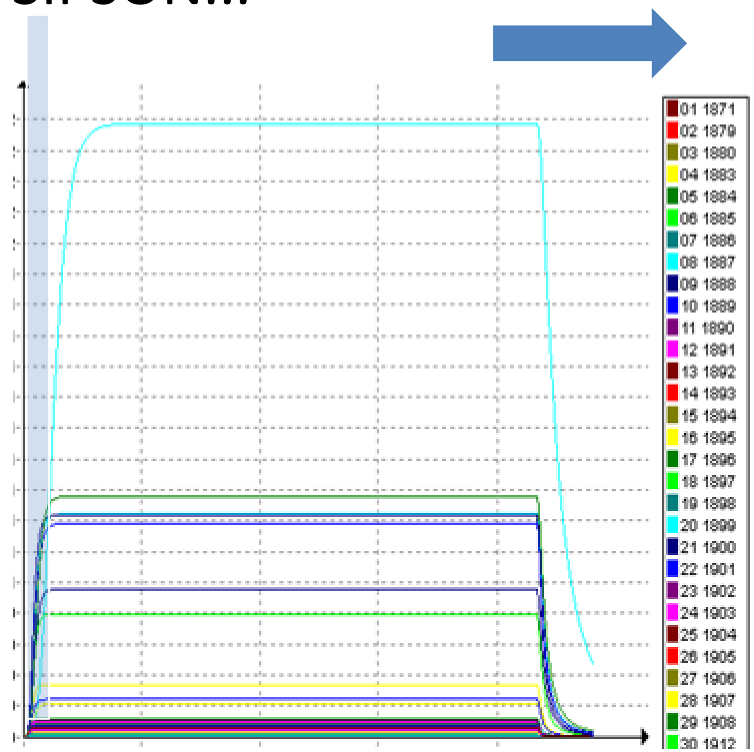
Methodology: Input and Output

- ANN Inputs

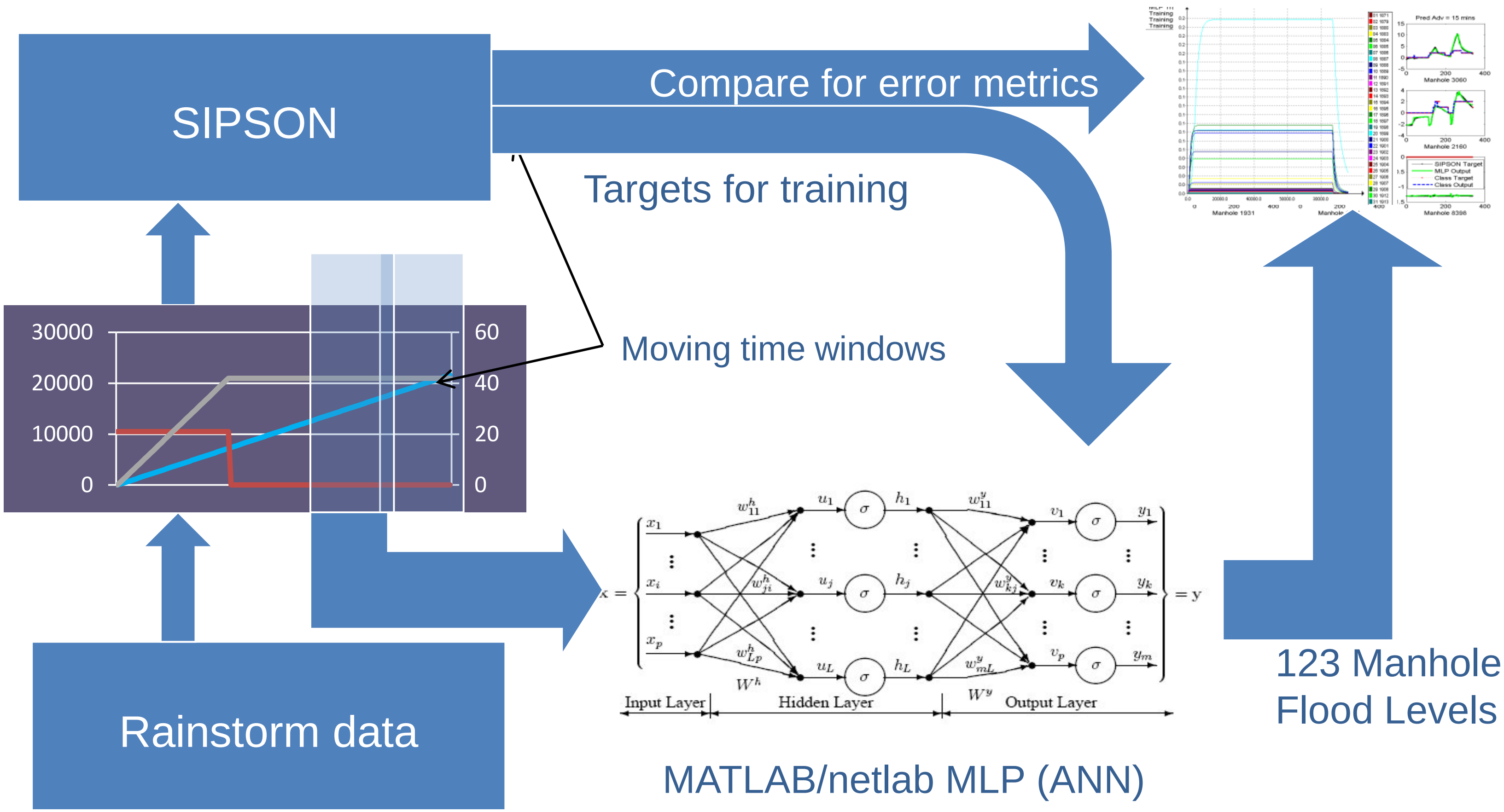


Time

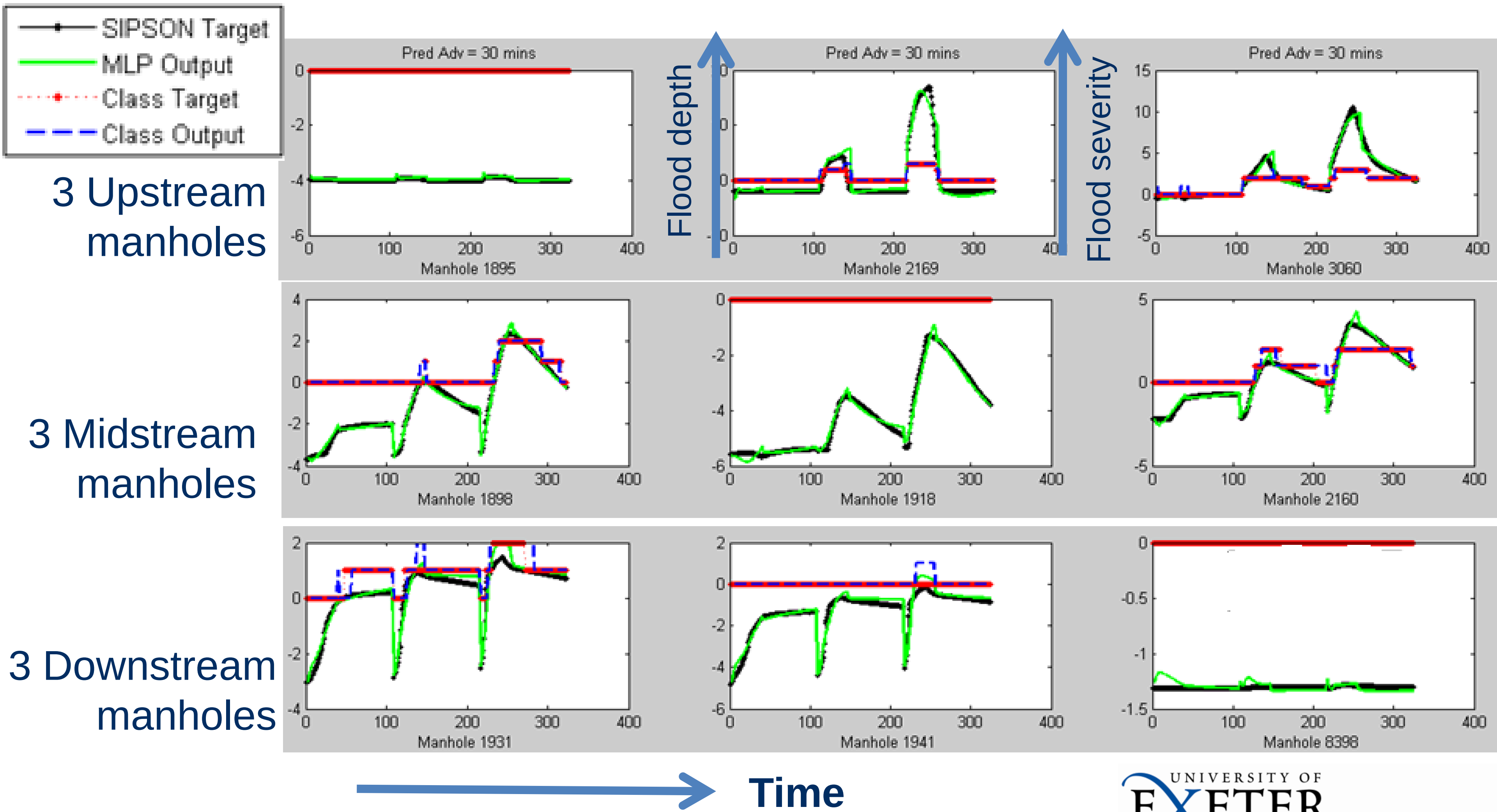
- ANN Output Targets from SIPSON...



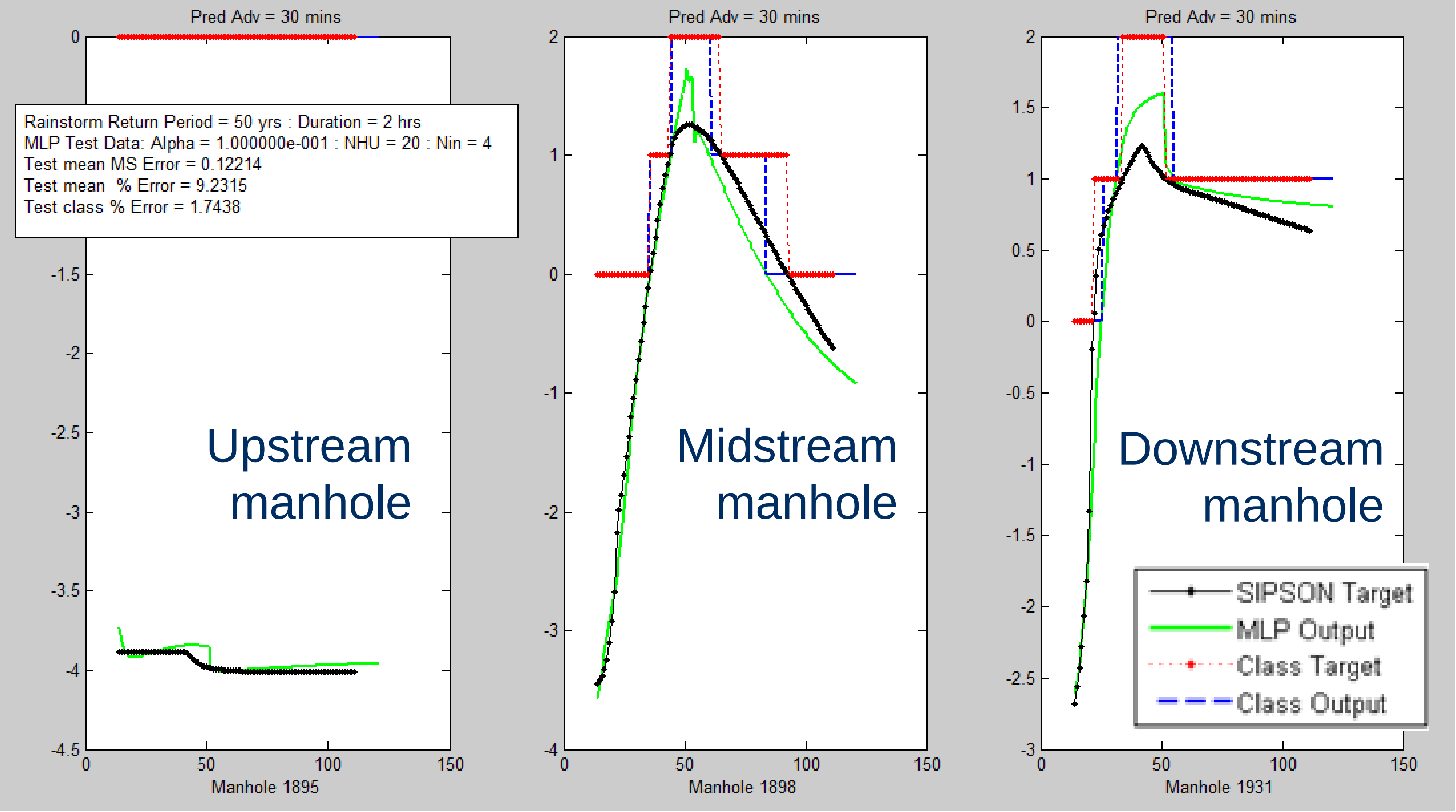
RAPIDS - ANN Model Training



Results → Training: Regression & Classification

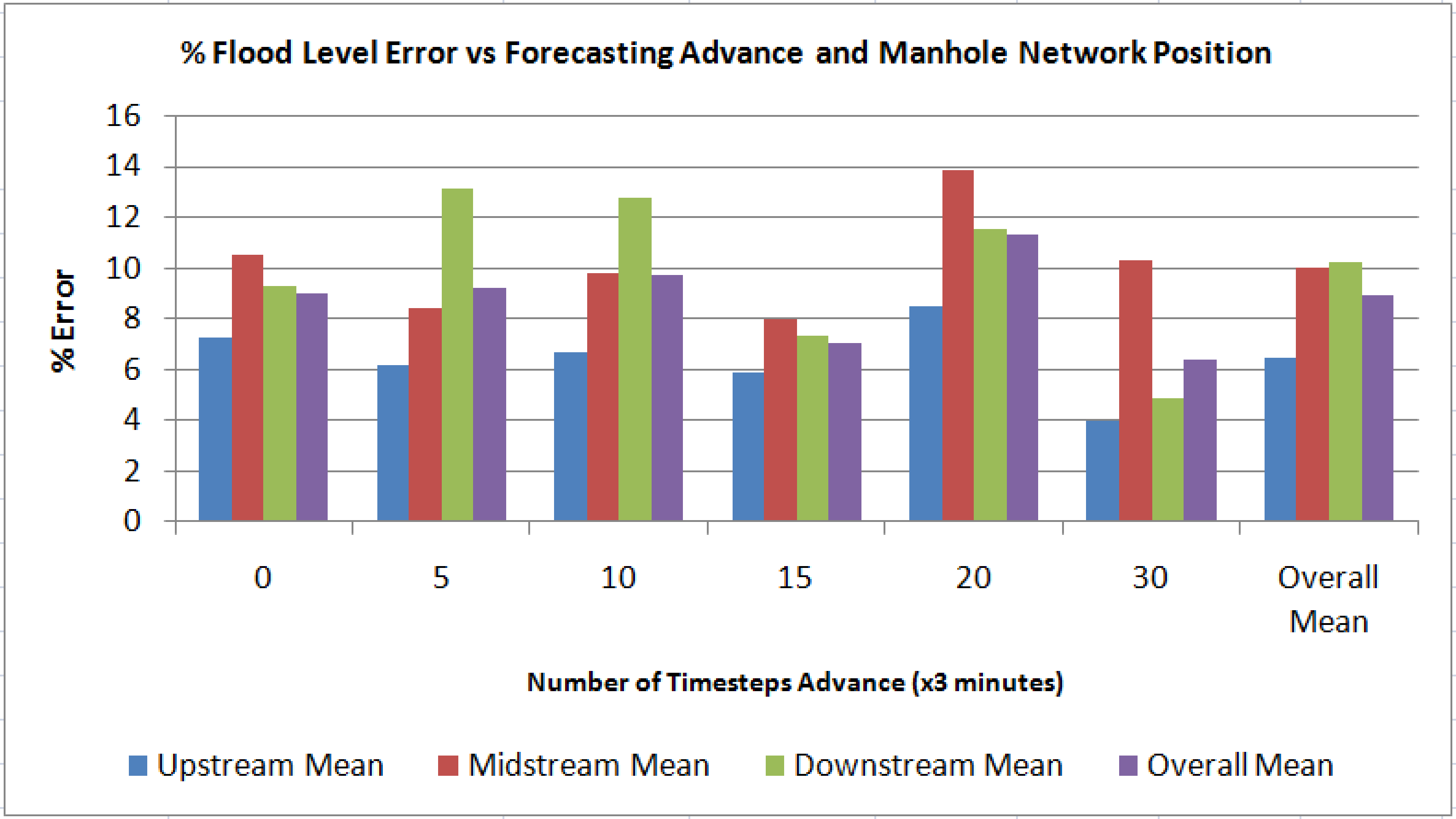


Results → Test: Regression & Classification



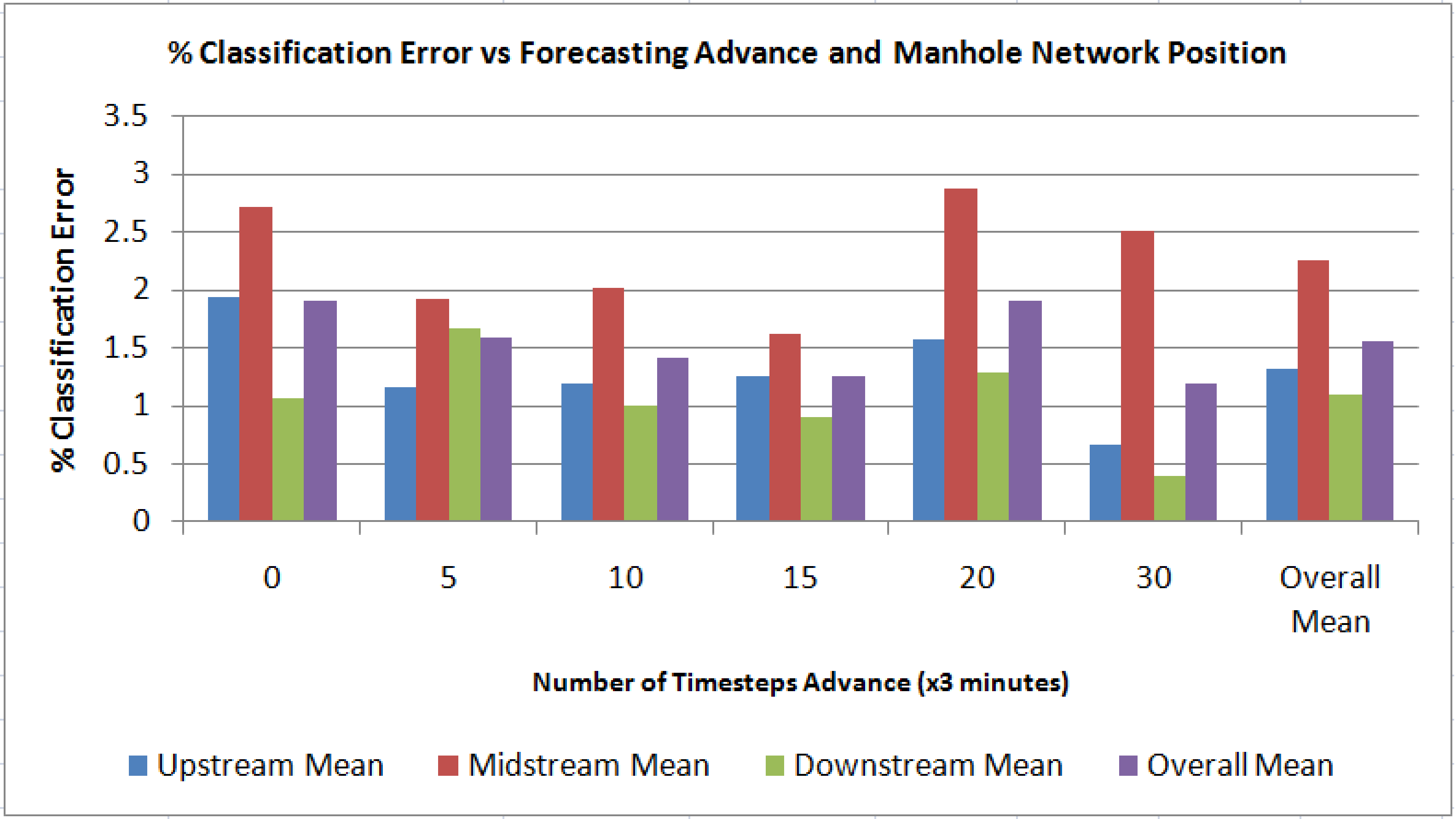
Time

Results → Test: Flood Level %Error



UNIVERSITY OF EXETER
Centre for Water Systems

Results → Test: Classification %Error



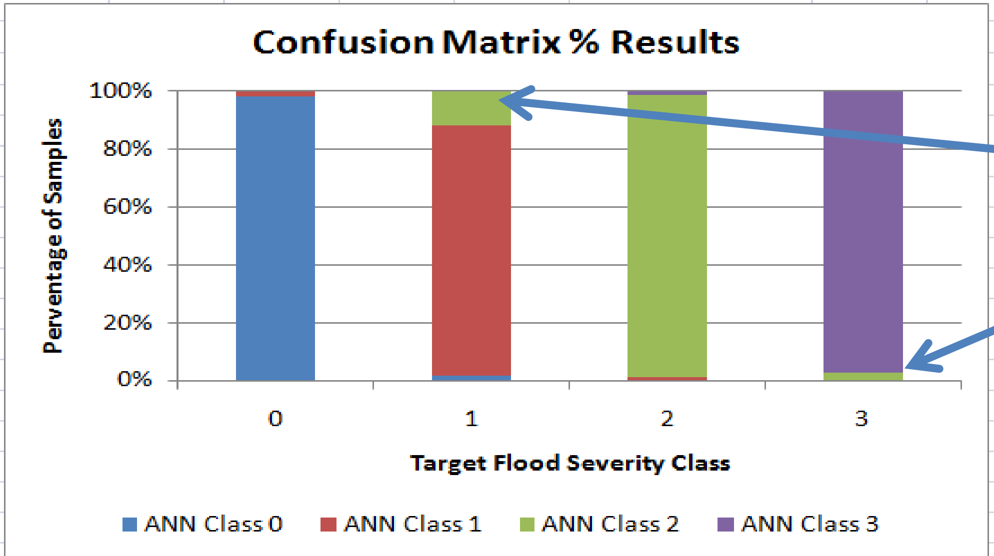
Results → Typical Confusion Matrix

- 30-minute prediction; 12-minute input window

Target (SIPSON) Flood Severity Class

ANN classified as	labels	0	1	2	3	Sum
	0	9470	28	0	0	9498
	1	168	1685	45	0	1898
	2	2	230	3856	6	4094
	3	1	4	37	212	254
	Sum	9641	1947	3938	218	15744

Classification Rate %	96.69
Error Rate %	3.31
Weighted Error Rate %	3.36



Key

	False alarm
	Correct
	Missed alarm

Conclusions

- Novel features of RAPIDS Case Study 1
  - Multiple locations modelled simultaneously
    - For urban rather than fluvial flooding
  - 3 minute sampling rate faster than other reported studies
- Regression with wrapper → Classification method successful
- Limit of prediction ≈ concentration time of network
- ANNs can model this 123 manhole network with in excess of 12-times improvement in computational time

Possible future research

- Test with 5-minute / 1-hour BADC rainfall data
- Use of rain radar to improve prediction
- Provide extra sewer flow data signals – more accurate?
- Experiment → modify ANNs
- Try modelling each manhole with a separate ANN

Possible Benefits to Water Industry

- Faster modelling than conventional simulators
  - Real time
- Forecasting prediction capability possible
- Flexible classification of flood severity
- Could potentially generate automated alerts
- Automated classification of flooding ‘hotspots’
  - based on frequency of surcharge events at manholes

References

- Bishop, C. (2008). *Neural Networks for Pattern Recognition.* Oxford, UK: OUP.
- Campolo, M. S. (2003). Artificial neural network approach to flood forecasting in the River Arno. *Hydrological Sciences, 48(3)* , 381-398.
- Fernando, A. Z. (2005). Combined Sewer Overflow forecasting with Feed-forward Back-propagation Artificial Neural Network. *International Journal of Applied Science, Engineering and Technology 1;4* , 211-217.
- McCulloch, W. a. (1943). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics Vol 5* , 115-133.
- Nabney, I. (2002). *NETLAB Algorithms for Pattern Recognition.* London: Springer.
- Nabney, I. T. (2010). *Netlab download page*. Retrieved Sep 07, 2010, from The MathWorks: http://www.mathworks.com/matlabcentral/fileexchange/2654-netlab
- Rosenblatt, F. (1958). THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN. *Psychological Review Vol. 65, No. 6* , 386-408.
- Rumelhart, D. a. (1986). *Parallel Distributed Processing - Explorations in the Microstructure of Cognition.* Cambridge MA: MIT Press.
- Solomatine, D. (2007). Baseflow Separation Techniques for modular ANN modelling in flow forecasting. *Hydrological Sciences 52(3)* , 491-507.
- Solomatine, D. C. (2007). Knowledge-based modularization and global optimization of artificial neural network models in hydrological forecasting. *Neural Networks, Special issue* , 1-9.
- Solomatine, D. O. (2008). Data-driven modelling: some past experiences and new approaches. *Journal of Hydroinformatics 10.1* , 3-22.
- The MathWorks Inc. (2010). *MATLAB Products Page*. Retrieved Sep 07, 2010, from The MathWorks: http://www.mathworks.com/products/product_listing/index.html
- University of Belgrade. (2010). *3DNet Users' Manual.* Belgrade, Serbia: University of Belgrade, Faculty of Civil Engineering, Institute for Hydraulic and Environmental Engineering.
- Wikimedia Inc. (2010, Sep 02). *Artificial Neural Networks (diagram).* Retrieved Sep 08, 2010, from Wikipedia: http://en.wikipedia.org/wiki/File:Artificial_neural_network.svg

Centre for Water Systems

Thank You

Questions?

Acknowledgement

The research reported in this presentation was conducted as part of the Flood Risk Management Research Consortium with support from the:

- **Engineering and Physical Sciences Research Council**
- **Department of Environment, Food and Rural Affairs/Environment Agency Joint Research Programme**
- **United Kingdom Water Industry Research**
- **Office of Public Works Dublin**
- **Northern Ireland Rivers Agency**

Data were provided by the EA and the Ordnance Survey.

EPSRC Grant: EP/FP202511/1