

Urban pluvial flood modelling with real time rainfall information – UK case studies

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ABSTRACT

In order to effectively prevent, mitigate and manage urban pluvial flooding, it is necessary to accurately model and predict the spatial and temporal distribution of both rainfall and surface flooding. A number of different modelling and prediction techniques have been applied to three UK case studies. The case studies illustrated potential improvements in the duration of model simulations as well as localised rainfall estimation (downscaling). A method of describing uncertainty in flow forecasts has been illustrated. The provision of urban pluvial flood forecasts, however, remains a challenging issue and it is anticipated that a combination of several techniques may be necessary, depending on catchment size and required forecast accuracy and lead time.

KEYWORDS:

Urban pluvial flooding, flood modelling, radar, rainfall forecasting, rainfall downscaling

INTRODUCTION

In recent years, urban pluvial flooding has been occurring with increasing frequency in the UK as well as many other countries. After extensive floods in the UK in the summer of 2007, the government requested a comprehensive review of the lessons learned from these events. According to the review carried out by Pitt (2008): “Perhaps the most significant feature of last summer’s events was the high proportion of surface water flooding compared with flooding from rivers. ... There are no warnings for this type of flooding, which can occur very rapidly, and people, including the response organizations, were not well prepared.” Following the recommendations of the Pitt review, the UK Met Office and the Environment Agency set up the Flood Forecasting Centre (<http://www.ffc-environment-agency.metoffice.gov.uk/>), which provides ‘river, tidal and coastal flooding warnings as well as warnings of extreme rainfall which may lead to surface water flooding’. There are as yet no official surface water flood warnings and/or urban pluvial flood warnings supplied. The Flood Risk Management Research Consortium Phase 2 (FRMRC2) is a multidisciplinary UK research consortium, focusing on recently identified strategic research investigating the prediction and management of flood risk with a particular focus on coastal and urban flooding

(<http://www.floodrisk.org.uk/>). As part of the urban flooding work package, a number of case studies have been identified in order to illustrate the potential of urban pluvial flood predictions using existing as well as newly developed modelling techniques.

Schilling (1991) described a ‘wish-list’ of the ideal type of rainfall data necessary for urban hydrology as: “... recording period 20 years (or more), temporal resolution 1 min, spatial resolution 1 km², time synchronization errors 1 min (or less), volumetric accuracy < 3%, and without gaps in the records”. Twenty years later we are getting closer to this wish-list, but there are still questions remaining on how we could make optimum use of this data to forecast floods at urban scales. Different approaches can be used for urban rainfall forecasting and flood modelling. The application of radar-based rainfall forecasts to model run-off on a sub-catchment of the urban drainage system of Vienna was discussed by Krämer et al. (2006). A few examples of the use of radar nowcasting techniques for real time control of urban drainage systems can be found in literature e.g. Yuan et al. (1999) for Bolton or Roualt et al. (2007) for Berlin. The results of these studies are mixed, and mainly deal with predictive real time control of sewer systems and not necessarily with urban pluvial flooding. Vieux et al. (2005) and Faure et al. (2005) are one of the few studies that describe flood warning systems specifically developed for urban areas; these studies employed radar data but no rainfall forecasting techniques. The aim of this paper is to illustrate the use of a selection of existing rainfall forecasting and urban drainage modelling tools for the purpose of urban pluvial flood forecasting, to identify shortcomings and describe potential improvements and new tools for the prediction of floods in urban areas.

METHODS – RAINFALL PREDICTION AND FLOOD MODELLING

The UK Met Office (UKMO) operates a network of 15 C-band radars. The data are quality-controlled by the UKMO, resulting in the NIMROD composite radar rainfall product (Harrison et al., 2009). The UKMO developed a new stochastic precipitation forecasting system known as STEPS (Short-Term Ensemble Prediction System) which can merge precipitation forecasts from a nowcasting system with downscaled NWP (Numerical Weather Prediction) forecasts (Bowler et al., 2006). The blending incorporates stochastic components to account for the inherent uncertainties in the forecasts. The original version of STEPS uses the NWP forecasts from the UKMO Unified Model. However, for the purposes of this study, and in order to produce high-resolution NWP forecasts, the NWP Mesoscale Model 5 (MM5) developed by PSU/NCAR (Dudhia, 1993, Dudhia et al., 2005, Grell et al., 1994) was used. The initial and lateral boundary conditions to the MM5 mesoscale model were provided by the global model developed at the European Centre for Medium Range Weather Forecast (ECMWF). The first case study explored the use of STEPS as input to the commercial hydrodynamic sewer network model (Infoworks CS, v 10.0, by MWHSoft) to predict rainfall run off from the urban area as well as flows through the sewer network conduits. The hydrodynamic sewer model was obtained from the sewer operators and had been calibrated following current industrial standards (WaPUG, 2002).

In the second case study, two types of physically based surface flooding models are employed: a 1D-1D model and a 1D-2D one. Improved statistically-based space-time downscaling techniques are being developed in order to generate a statistically-feasible street-scale rainfall product which can be further fed to the associated flooding models. Based upon the characteristics of scale-invariance that have been widely observed in the process of rainfall, the 1km 5-min NIMROD radar data is further downscaled into smaller scales (approximately 100 – 500 m). This downscaling process is expected to introduce higher spatial variability of urban-scale rainfields to the corresponding hydraulic modelling. Both types of models

(1D-1D and 1D-2D) take into account the dual drainage concept and are set up and run in Infoworks CS. In the 1D-2D approach, the surface network is modelled as a 2D mesh of triangular elements generated based on the DTM (Digital Terrain Model). The 2D model of the surface network is coupled with the 1D model of the sewer network, thus obtaining a 1D-2D model. Although the 2D models of the surface network are detailed and accurate, modelling 2D surface flows is computationally intensive and the simulations take a long time, making it unsuitable for real time applications. In the 1D-1D model approach, the Automatic Overland Flow Delineation (AOFD) tool (Maksimović et al., 2009) is used to create the 1D model of the overland network, which is coupled with the 1D model of the sewer network. The AOFD tool uses a high-resolution DTM, obtained from 1 m resolution LiDAR data, for creation of a network of ponds (modelled as storage nodes) connected by preferential pathways (modelled as conduits with associated geometry derived from the DTM). The output of the AOFD tool is a 1D model of the overland network which can be imported into Infoworks CS and is coupled with the sewer network model (the connection between these two systems takes place at the manholes). The 1D-1D dual drainage models can reproduce the behaviour of the system, while keeping computational time reasonably short, enabling the use of these models for real-time forecasting of pluvial flooding. Moreover, in order to further decrease simulation time, techniques for simplifying the 1D-1D physically based models have been implemented (Simões et al, 2010) and hybrid models that combine 1D-1D and 1D-2D are currently under development.

In the third case study the application of AI techniques for flood modelling is explored. The Radar Pluvial flooding Identification for Drainage System (RAPIDS) is an Artificial Neural Networks (ANNs) technique. RAPIDS1 is a 2-layer, feed-forward MLP (Multi-Layer Perceptron), which provides a fast surrogate DDM (Data Driven Model) for a conventional hydro-dynamic simulator (such as InfoWorks). It rapidly relates incoming rainstorm data to the extent of flooding present at each manhole in the sewer network. A moving time-window approach is implemented: rainfall data (intensity, cumulative total, elapsed time) spanning recent history (of 10 time steps, i.e. 30-minutes) provides inputs to the ANN. Output target signals for training and evaluation of ANN performance are provided by the corresponding flood-level hydrographs generated by a hydrodynamic simulator for each manhole (Duncan et al., 2011). By time-advancing the target data used for training, the ANN can provide prediction of flooding for up to 60-minutes ahead. The framework of the ANN is such that it can be trained using the flow information from either hydraulic modelling results, or field measurements whenever the observations are available. The flooding assessment of RAPIDS1 relies on rainfall input, for which currently UKMO NIMROD 1 km composite radar data is used. Development on RAPIDS2, a novel ANN approach to rainfall nowcasting that can be linked to RAPIDS1, is currently ongoing.

DESCRIPTION OF CASE STUDIES AND RESULTS

First case study: a town in the Pennine hills

The first case study is a town in the Pennine hills in the North of England. The majority of the sewer network is combined and the contributing area is covered by 25 different 1km² radar pixels and 4 rain gauges. Three rainfall events were studied in detail (25th June 2007, 1st July 2008 and 7th July 2008), the events and rainfall forecasts are more extensively described in Schellart et al. (2009b) and Rico-Ramirez et al. (2009). For these events, the overall performance of the rainfall forecasting system (STEPS) decreased with increasing rainfall intensities, and stratiform precipitation was forecasted better than convective precipitation.

MM5 proved necessary to enable to anticipate convective rainfall, but was not always accurate enough spatially to forecast the location of rainfall occurrence within the catchment. Comparing the images in Fig. 1, for example, indicates that for an 8-hour lead time the overall rainfall pattern as measured by the radar network over the UK (left) is captured by the MM5 NWP forecasts. However, the differences between actual and forecasted rainfall can be large when comparing a small area of a few square kilometres. Research was therefore carried out using different versions of the STEPS model (as a deterministic nowcast, ensemble nowcast or blended with ensemble MM5 NWP forecasts). The sewer system was modelled using 432 ‘nodes’, 444 ‘links’, 13 pumps and 134 sub catchments. The total contributing area of is 11 km², of which 0.71 km² is impermeable and 10.35 km² is pervious, reflecting a relatively large amount of park and garden areas within the town (3.15 km²) as well as surrounding steep moorland (7.2 km²). Actual radar and rain gauge data as well as rainfall predictions from the different versions of STEPS have been imported to Infoworks CS to generate quantitative sewer flow simulations as well as predictions. Fig. 2 shows an example of how ensemble forecasts may be utilised to provide cumulative probability density functions of flow peaks exceeding a certain threshold (in this case a combined sewer overflow weir). For the third hour after the forecast was supplied, Fig. 2 (right) shows that the ensemble STEPS forecast indicated 20% probability of spill exceeding 1000 m³ and a 60% probability of no spill, whereas the model using radar data simulated 298 m³ spill, the model using rain gauge data 646 m³ spill and deterministic STEPS 0 m³ spill. So there is also a considerable difference between radar and rain gauge input, when looking at local rainfall peaks, as is described in more detail in Schellart et al. (2009a).

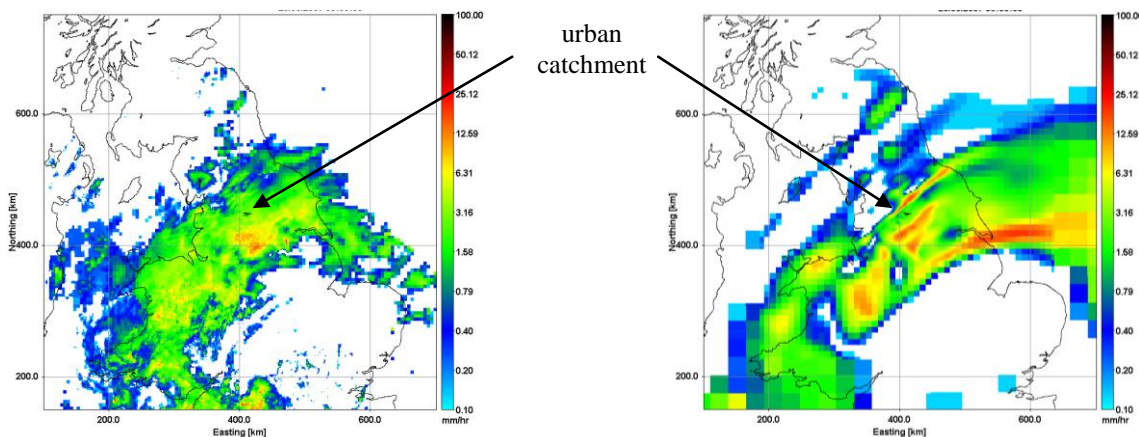


Figure 1. Radar scan 25th Jun. 2007, 08:00 (left), corresponding NWP forecast (right).

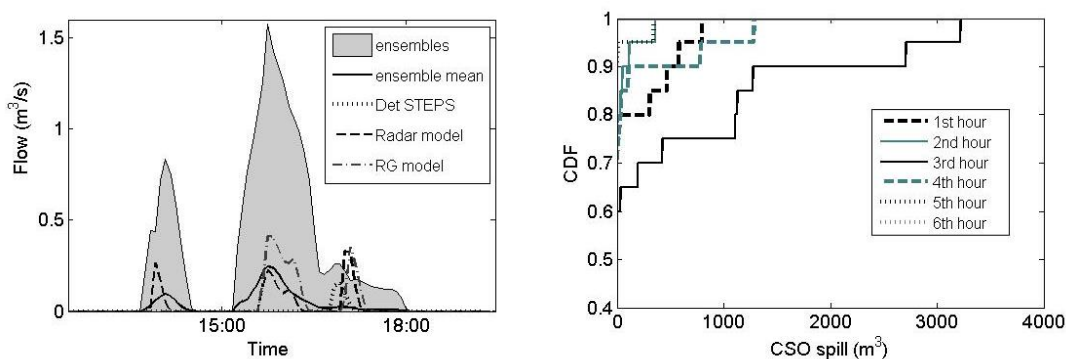


Figure 2. Simulated CSO spill using ensemble and deterministic forecasts of STEPS blended with MM5, created for 13:15, 7th Jul. 2008, actual radar data and actual rain gauge data (left). Cumulative probability density of CSO spill based on ensemble forecasts (right).

Second case study: The Cranbrook catchment

The second case study is the Cranbrook catchment, in the London Borough of Redbridge, an area with a history of local flooding. The drainage area is approximately 910 hectares; the main water course is about 5.75 km long, of which 5.69 km are piped or culverted. A rainfall and flow monitoring campaign is being carried out and all gauges have wireless communication devices. Physically based 1D-1D and 1D-2D models of this area were set up in Infoworks CS and were calibrated with the data obtained from the monitoring system. Two rain events were selected to demonstrate the proposed method. The event on 22nd-23rd Aug. 2010 was associated with a warm front and the rainfall falling within the Cranbrook catchment was approximately 30 mm in around 18 h, with more than 20 mm falling in a period of 5 h. The event on 17th-18th Jan. 2011 was associated with an occluded front passing over Southeast England, producing heavy rain in the Cranbrook catchment with total accumulations of around 30 mm in 24 h. The 1D-1D model yields good results and is much faster than the 1D-2D (10 to 50 times – depending on the mesh properties and duration of the rainfall events) which makes it more suitable for real time flood forecast. Regarding rainfall estimates, enhanced statistically-based downscaling techniques were developed based upon the cascade theory, which has been proven to have the potential to generate high-resolution rainfall products (Wang et al., 2010). The 1 km Nimrod data are used herein as references to highlight the differences when downscaled higher-resolution estimates (respectively in 250 and 500 m) are used as inputs for hydraulic modelling in this case study. Due to space limitations, only preliminary results of the August event are presented in this paper (Fig. 3).

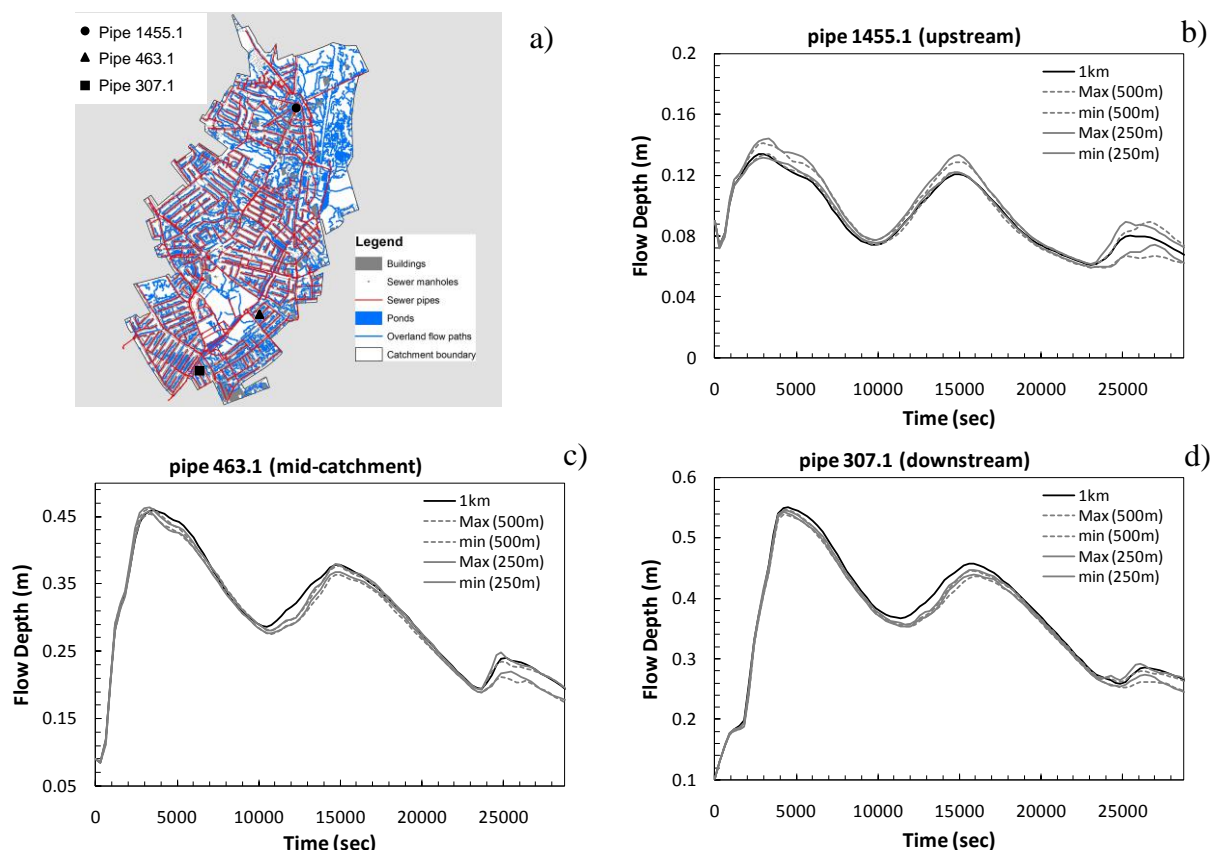


Figure 3. a) the 1D-1D overland and sewer network for Cranbrook catchment, b – d) simulated flow depth profiles for pipes 1455.1, 463.1 and 307.1 using 1 km (dark solid line), 500 m (grey dashed lines) and 250 m (grey solid lines) rainfall estimates as inputs.

In order to analyse the impact of the spatial resolution of the rainfall input, three pipes were selected respectively from the upstream, middle and downstream areas of the Cranbrook catchment (Figure 3a). For each scale of interest (500 and 250 m), ten rainfall realisations were stochastically generated from the Nimrod data via the downscaling process and used as inputs to estimate the associated uncertainties in flow simulation. The associated maximal and minimal flow depths, which envelop all flow-depth realizations, are plotted in Figure 3b – 3d. Some changes in flow-depth profiles can be observed when higher-resolution rainfall estimates are used. In the upstream pipe (1455.1), generally higher flow depths are obtained, which is different from the middle and downstream pipes (463.1 and 307.1). The uncertainty ranges (i.e. the averaged relative differences between maximal and minimal flow depths) are investigated and showed that a larger uncertainty range is obtained in pipe 1455.1 (0.188 and 0.169, respectively, for the 500 and 250 m rainfall resolutions) compared to the other two pipes (pipe 463.1: 0.085 and 0.088; pipe 307.1: 0.047 and 0.051). These results show that the upstream pipe, which has smaller sub-catchment area, is more sensitive to the use of higher-resolution precipitation as input. The effect of high-resolution rainfall input is however smoothed when the drainage area of the pipe increases. This indicates the importance of using higher-resolution rainfall inputs, particularly for smaller areas.

Third case study: the Stockbridge catchment

In the third case study, the Stockbridge area of Keighley, West Yorkshire, the RAPIDS system is used to simulate the underlying drainage system. The catchment area is 9 km². Daily rainfall data from 1 tipping-bucket rain gauge are used to calibrate the system ‘ground truth’ (Schellart et al. (2009a) discussed sources and levels of error present in this data). Due to lack of historical flood level information, a conventional hydraulic simulator, SIPSON (Djordjević et al., 2005), was adapted to produce target data for training the ANN. A flood severity classification scheme with 4 classes [no flood | slight | moderate | severe] corresponding to flood depths from the hydraulic model is then implemented. RAPIDS1 produced flood severity classification results for 16 rainfall events with typical weighted misclassification errors of 2.65% (see Fig. 4) averaged over all 123-manholes, when compared with the target classes derived from the hydro-dynamic model. Classification Percentage Error metric assigns values 0 to 3 to the 4 classes of flood severity, then uses:

$$CPE(y) = \frac{\left(\sum_{t=1}^N \frac{|C(T_t) - C(Y_t)|}{w_{C(T_t)}} \right)}{N} * 100 \quad \text{Eqn. 1}$$

Where: CPE(y) is classification percentage error for single output (manhole);

t = timestep number; N = total number of timesteps in data set;

C(T_t) = Classification function operating on Target data sample at time t;

C(Y_t) = Classification function operating on MLP output data sample at time t;

w_{C(T_t)} = Weight associated with instantaneous value of: $C(T_t) \begin{cases} \{0,3\} \Rightarrow w = 3 \\ \{1,2\} \Rightarrow w = 2 \end{cases}$

Fig. 5 indicates similar ANN classification performance for 0, 30 and 60 minutes prediction advance for a selection of 5 manholes in each of upstream, midstream and downstream network zones. However, for the case study network, using prediction advance of >30-minutes means that the hydrograph peak flood levels are missed, rendering the model ineffective. For the Keighley system, a 30 minute advance was optimum. Timing trials for the 123-manhole UDN in the RAPIDS1 Keighley case study gave a typical SIPSON simulator runtime of 195s for a 6-hour trial, with a 3-minute sampling period. The trained ANN took less than 0.12s; a factor of 1700-times faster. This opens the possibility of efficient modelling of very large networks in real-time on desktop machines.

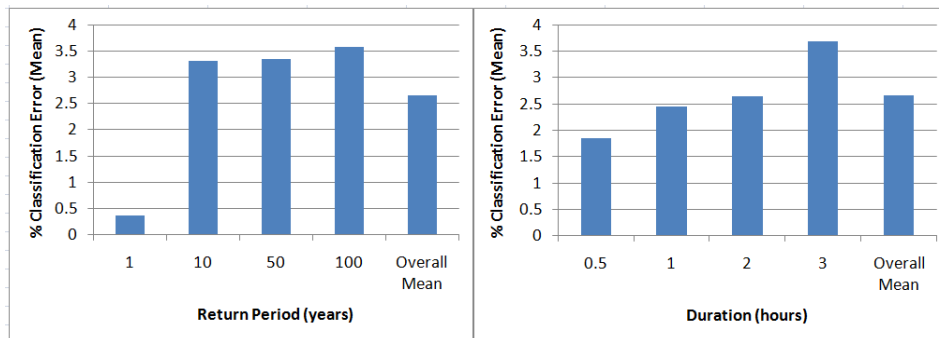


Figure 4. Test Classification Errors vs Storm Return Period and Duration

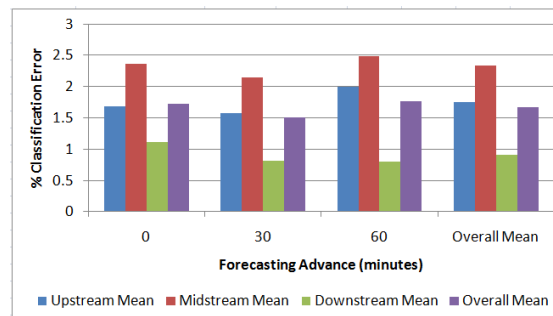


Figure 5. Test Classification Errors vs Prediction Timesteps Ahead and Network Zone

DISCUSSION AND CONCLUSIONS

The first case study illustrated the difficulty of accurately forecasting precipitation in a relatively small area with a lead time of several hours. NWP models can see potential new heavy convective rainfall cells developing several hours ahead, but MM5 is currently not accurate enough on small spatial scales, i.e. it can ‘miss’ a relatively small urban area by several 10s of kilometres. The use of ensemble forecasts is promising as it can give early warning in terms of probability of heavy rainfall occurring over a certain area. A remaining challenge, however, is how to practically deal with probabilistic forecasts in an urban pluvial flood warning system. In the second case study, several physically based hydraulic models were tested and the 1D-1D approach (and its simplifications) proved to be more suitable for real time flood forecast. In addition, the importance of employing downscaling techniques to generate higher-resolution rainfall estimates (or nowcasts in the future) in the urban areas is particularly addressed through evaluating the associated uncertainties of hydraulic modelling results. However, a further investigation must be carried out to identify the relation of sub-catchment areas and the resolution of rainfall estimates used as inputs. Moreover, a comparison with real observations of flow depths is also necessary and will be conducted in the near future. The third case study illustrated the advantage of using an ANN approach to provide limited prediction capability and significantly reduce hydraulic sewer network simulation duration, as well as the use of a flood classification scheme. Operationally useful urban pluvial flood forecasting remains a challenge, and it is likely that several modelling approaches may be necessary to achieve forecasts with the desired accuracy and lead time.

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