UNIVERSITY OF EXETER
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COLLEGE OF ENGINEERING, MATHEMATICS AND PHYSICAL SCIENCES

Probabilistic Real-Time Urban Flood Forecasting Based on Data of Varying Degree of Quality and Quantity

Submitted by Jeanne-Rose Christelle René to the University of Exeter

as a thesis for the degree of

Doctor of Philosophy in Engineering

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature: Jeanne-Rose René

Dedicated to my family:

Veronica René (mom)

Winnie – Della René

Lovell René

Paul René

Melanie Meidor

Also specially dedicated to the especially vulnerable people of Saint Lucia because of their poor start in life!

Abstract

This thesis provides a basic framework for probabilistic real-time urban flood forecasting based on data of varying degree of quality and quantity. The framework was developed based on precipitation data from two case study areas:Aarhus Denmark and Castries St. Lucia. Many practitioners have acknowledged that a combination of structural and non-structural measures are required to reduce the effects of flooding on urban environments, but the general dearth of the desired data and models makes the development of a flood forecasting system seem unattainable. Needless to say, high resolution data and models are not always achievable and it may be necessary to override accuracy in order to reduce flood risk in urban areas and focus on estimating and communicating the uncertainty in the available resource. Thus, in order to develop a pertinent framework, both primary and secondary data sources were used to discover the current practices and to identify relevant data sources. Results from an online survey revealed that we currently have the resources to make a flood forecast and also pointed to potential open source quantitative precipitation forecast (QPF) which is the single most important component in order to make a flood forecast. The design of a flood forecasting system entails the consideration of several factors, thus the framework provides an overview of the considerations and provides a description of the proposed methods that apply specifically to each component. In particular, this thesis focuses extensively on the verification of QPF and QPE from NWP weather radar and highlights a method for estimating the uncertainty in the QPF from NWP models based on a retrospective comparison of observed and forecasted rainfall in the form of probability distributions. The results from the application of the uncertainty model suggest that the rainfall forecasts has a large contribution to the uncertainty in the flood forecast and applying a method which bias corrects and estimates confidence levels in the forecast looks promising for real-time flood forecasting. This work also describes a method used to generate rainfall ensembles based on a catalogue of observed rain events at suitable temporal scales. Results from model calibration and validation highlights the invaluable potential in using images extracted from social network sites for model calibration and validation. This framework provides innovative possibilities for real-time urban flood forecasting.

Acknowledgements

A number of persons have contributed to the successful completion of this thesis and they have done so in diverse ways and in diverse places. I am indebted to them all.

My supervisors: Slobodan Djordjevic, David Butler, Ole Mark and Henrik Madsen; for putting me on course and providing feedback which allowed me to develop as a scientific researcher. You have been a tremendous mentor to me in each your own way.

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During this research I was faced with several technical challenges and I would like to thank Jesper Grooss, Ronni Tjener and Anders Sloth for without them it sometimes felt impossible to carry on.

In my daily work, I have been blessed to share office space with some friendly and cheerful people. Thank you to Claus Jørgensen, Albert Chen and Andrew Duncan.

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For those who prepared me for being here: Veronica Rene´, Norbert Cox and Keith Richards!

Last but not least, special thanks to my family and to Ronni Tjener and his family. Words cannot express how grateful I am for all the sacrifices you’ve made on my behalf.

Anyone else who believed in me!

Declaration of Co-Authorship

Acknowledgement of Published and Unpublished Papers Included in this Thesis

This thesis incorporates the outcome of a joint research undertaken in collaboration with University of Exeter and DHI under the supervision of Professors Slobodan Djordjevic, David Butler, Ole Mark and Henrik Madsen.

Included in the thesis are papers, presented in the form of chapters with the following titles which are co-authored with my supervisors.

I. Assessing the potential for real-time urban flood forecasting based on a worldwide survey on data availability
II. A methodology for probabilistic real-time forecasting – an urban case study
III. An operational real-time pluvial flood forecasting and warning system for Castries St. Lucia
IV. Getting started with urban flood modelling for real-time pluvial flood forecasting: A case study with sparse data
V. Probabilistic forecasting for urban water management: a case study
VI. Evaluating an X-band Radar area-based nowcasting algorithm for urban drainage model forecasting

In all cases, the key ideas, primary contributions, investigative designs, data analysis and interpretation, were performed by the author, and the contribution of co-authors was primarily through the provision of feedback.

Appropriate acknowledgements of those who contributed to the research but did not qualify as authors are included in each paper.

(Signed) Jeanne-Rose René (Date): 29-09-2014
Name of Student: Jeanne-Rose René

Part 1 – Extended Introduction

Part 2 - Published Papers

Abbreviations

1D	One-Dimensional
2D	Two-Dimensional
CDF	Cumulative Distribution Function
CSI	Critical Success index
DEM	Digital Elevation Model
DQ	Direct Quantile
DTM	Digital Terrain Model
DWF	Dry Weather Flow
EPS	Ensemble Prediction System
FAR	False Alarm Ratio
FSS	Fractional Skill Score
GFS	Global Forecast System
LAWR	Local Area Weather Radar
LHS	Latin Hypercube Sampling
MAE	Mean Absolute Error
NRMSE	Normalized Root Mean Square Error
NWP	Numerical Weather Prediction
POD	Probability of Detection
PQPF	Probabilistic Quantitative Precipitation Forecast
QPE	Quantitative Precipitation Estimates
QPF	Quantitative Precipitation Forecasts
SR	Success Rate
SS	Skill Score
TOF	Time of Forecast
WD	Water Depth
WWW	World Wide Web

Notations

a_i	Scaling factor
C_D	Critical depth
e_i	Rainfall ensemble
N	Number of observations
P	Probability
$\hat{S}$	Single value quantitative precipitation forecast
S	Rainfall observation
S_T	Transformed observed rainfall
$\sigma_{S_T}{}^2$	Variance of transformed observed rainfall
$\sigma_{\hat{S}_T}{}^2$	Variance of transformed forecasted rainfall
μ_{S_T}	Mean of transformed observed rainfall
$\mu_{\hat{S}_T}$	Mean of transformed forecasted rainfall
T_D	Trigger depth
T_{obs}	Observed rainfall threshold
T_{sim}	Rainfall threshold estimated from rainfall simulations
$TS_{\Delta t}$	Time Series of selected timestep
x^*	Non-zero rainfall forecast
$\hat{X}_{CL}$	Bias corrected rainfall forecast with selected confidence level
Y_{MW}	Observed moving sum over a selected moving window

1 Introduction

In general, flooding in urban areas occurs when the carrying capacity of the natural or the artificial storm-water collection system is exceeded. Urban areas can be flooded by one or a combination of rain falling on urban surfaces (pluvial flooding), rivers (fluvial flooding), the sea (due to storm surges – high tides), groundwater and artificial failures (such as dam breach) (Jha et al., 2012).

An increase in the frequency and severity of weather patterns because of climate change will inevitably increase the risk of flooding from rivers, the sea and from unmodified urban drainage systems. As a result, urban flood risk management is becoming increasingly challenging for responsible authorities to address and is even more testing in some regions of the world because of difficulties which will be hardly able to overcome.

In fact, when we speak of urban flood risk management too often the focus is on high quality data, and hydraulic modelling which often proves unrealistic in most cases. Thus, we should endeavour to develop innovative and robust approaches for flood risk management since flooding can have a huge socio-economic impact on a country's development.

Flooding generally retards economic growth because restoration of a flood stricken area can usually take time. Despite such prevalence and significant impact on economic progress, urban water professionals are to this date still struggling to adequately address flooding and flood risks in general mainly because of the unavailability of the desired data at suitable temporal and spatial resolutions.

Flood forecasting and warning is an essential part of flood risk management; in fact it complements structural measures given that there is a probability that they will fail, or their capacity exceeded. Globally, there is a well-recognised need for approaches to real-time urban flood forecasting based on data of varying degree of quality and quantity. However, it is perhaps not at all surprising that relevant practitioners have great difficulty establishing reliable real-time urban flood forecasting approaches because there are very few operational and published example cases. After all, people tend to be motived when they have practical examples of cases to associate to, which are found in scientific publications. The lack of examples is compounded by the general dearth of data of high spatial and temporal resolution, which in most cases can be prohibitive to acquire.

The preceding issues that challenge urban hydrology on the global scale become inordinately more vexed and paralyzing in developing countries. The threats and consequences of floods are enormously multiplied in developing areas. It is therefore the thesis of this researcher, to make a concerted effort to demonstrate that we have resources at our disposal which can potentially be used to address pluvial flood risk.

1.1 Aim and Objectives

This thesis continues research in the field of urban water management in real-time flood forecasting. Within this field, there is evidence of constant innovation regarding computational efficiency of urban drainage models for the provision of real-time flood forecasts in order to mitigate damages caused by flooding in the light of climate change and rapid urbanization. It is the intention of this PhD research to underpin an approach for real-time flood forecasting with an estimate of the uncertainty that can be implemented operationally in the real world. This study focuses on flooding resulting from rainfall on the urban catchment (pluvial flooding). The three principal objectives are:

1. To assess the skill of quantitative precipitation forecast (QPF) from weather radar and numerical weather predictions (NWP) for use in urban flood forecasting. This component of the study involves a comparison of QPF from the two sources and observed rainfall obtained by rain gauges as well as radar quantitative precipitation estimates (QPE). This was assessed for two case studies (Aarhus, Denmark and Castries, St. Lucia) each with varying degree of data quality and quantity.
2. To develop a framework for real-time urban flood forecasting with uncertainty estimation based on QPF from NWP models. The developed framework should be applicable to data rich and data poor areas. The applicability of the method was demonstrated using the St. Lucia case study.
3. To test and evaluate the approach by comparing the simulated results to the observed events.

1.2 Case study data and method overview

The underlying reason for undertaking this project is related to the issue of data quality and quantity which is closely entrenched with one's ability to create an urban flood model yet alone a probabilistic real-time urban flood forecasting system. As a result, it was only fitting to design the research approach along the lines of finding out the current practices and what kind of data is actually available in order to develop a pertinent framework.

A case study approach is used to develop the framework. Two case studies were selected; one case is in Aarhus, Denmark and the other in Castries, Saint Lucia. The selection of these cases was based on two main reasons. The first is a matter of access to the required data and the second reason is related to the quantity and quality of the available data. Data access was not a problem for the Aarhus case mainly because of organizational relations between the municipality and DHI. In addition, this case had data at finer temporal and spatial resolution which makes it an ideal bench mark case. For the St. Lucia case, all the required data was limited both in spatial and temporal scales making it a suitable example for the development of the framework.

To provide a relative perspective of the data quality and quantity the characteristics of the different types of data used are highlighted in Table 1-1 and Table 1-2 .

Table 1-1: Datasets used and an overview of their corresponding characteristics

Aarhus, Denmark	Castries, Saint Lucia
NWP QPF	
Originated from a regional WRF model, run routinely by StormGeo for DHI (StormGeo, 2011). Model uses ECMWF product as its boundary and has a resolution for the Aarhus model domain of $0.1\ x\ 0.1$ degree and a time resolution of 1 hour for the prognosis period of 0 - 12 hours. Data covered the period 2009-2010.	Originated from the Global Weather Forecast (GFS) model produced by the National Centre for Environmental Prediction (NCEP) (NOAA, 2013). The horizontal resolution is $0.5\ x\ 0.5$ degree and having a time resolution of 3 hours for the prognosis period of 12 hours. Data covered the period Jan-Dec 2013.
Radar based QPF and QPE	
Originated from an X-band radar area based nowcasting algorithm which produces nowcasts at 5 minute intervals up to 70 minutes. Main characteristic of the calibrated radar based QPE of the X-band radar are	None

presented in Table 1-2. Data covered the period Nov 2012-Nov 2013.	
Observed rain gauge rainfall	
Originated from 3 tipping bucket rain gauges with a minimum tip of 0.2mm, with 1 minute time steps. Data covered the period 2001- Nov 2013.	Originated from a tipping bucket rain gauge with resolution of 0.1mm which was installed at the start of the study (July 2011) and collects information in real-time with 1 minute time step.
Physical data/models	
Calibrated 1D urban drainage model for the city. Other data included 1.6m horizontal resolution digital terrain model. Sewer model is coupled to a 2D overland model with grid cell size of 10x10m.	Sporadically spaced spot heights, 2 orographic images, a shape file of buildings in area, images reporting floods extracted from Facebook and other online sources

Table 1-2: Main Characteristics of the X-band radar data used in this study

Peak Power [kW]	25
Wave length [cm]	3.2
Pulse length [μs]	1.2
Frequency [MHz]	9.41 GHz ±30
Antenna diameter [m]	2.5 m slotted waveguide array
Receiver	Logarithmic receiver
Vertical opening angle	± 10°
Horizontal opening angle	0.95°
Samples per rotation	360
Range (forecast/QPE) [km]	60
Spatial resolution [m]	500x500
Temporal resolution [minutes]	5
Scanning strategy	Single layer and continuous scanning
Rotation speed [RPM]	24

The methodology utilized in this thesis can be considered as comprising of four parts:

1. *Data collection* – which involves the collection of general data for flood modelling as well as the discovery of state-of-the-art in flood forecasting and modelling approaches and the identification of potential data sources.
2. *Verification analysis* – which examines the agreement between different data sources for two case study locations and need for potential improvements using different statistical methods. This involved both precipitation verification and verification of variables derived from the urban drainage model.

3. *Uncertainty estimation* - which is supported by a case study and involves the integration of the collected data, solutions based on the verification statistics along with probability distribution functions to represent the error in the forecast.
4. *Development of a probabilistic real-time urban flood forecasting system* – which is supported by forecasted and observed data and involves the integration of the solutions based on the uncertainty estimation along with numerical tools for flood modelling.

The core issues investigated include:

- State-of-the-art approaches in urban flood forecasting and it's applicability in real-time
- The available data, its quality and sources, specifically from open sources
- Assessment of the value of QPF from different sources including open sources
- The value of the QPF in forecasting water depths in urban drainage systems

1.3 Publications arising from this thesis

This thesis also includes six original papers, some which has been previously published and some which are submitted for publication in peer reviewed journals, and some presented at conferences as follows:

Chapter	Title/full citation	Status
6	Jeanne-Rose René , Slobodan Djordjević , David Butler , Henrik Madsen & Ole Mark (2013): Assessing the potential for real-time urban flood forecasting based on a worldwide survey on data availability, *Urban Water Journal*, DOI:10.1080/1573062X.2013.795237	*published*
7	Jeanne-Rose René , Henrik Madsen & Ole Mark (2013): A methodology for probabilistic real-time forecasting – an urban case study, *Journal of Hydroinformatics* Vol 15 No 3 pp 751–762 © IWA Publishing 2013 doi:10.2166/hydro.2012.031	*published*
8	Jeanne-Rose René , Slobodan Djordjević , David Butler , Henrik Madsen & Ole Mark (2013): Getting started with urban flood modeling for real-time pluvial flood forecasting: A case study with sparse data, Paper presented at the International Conference on Flood Resilience: Experiences in Asia and Europe, Exeter, United Kingdom 2013	*conference proceedings*
9	Jeanne-Rose René, Slobodan Djordjević, David Butler, Ole Mark & Henrik Madsen (under review): A real-time pluvial flood forecasting system for Castries, St. Lucia, *Journal of Flood Risk Management*	*Submitted revision 1 Jan 2015*
10	Jeanne-Rose René , Henrik Madsen & Ole Mark (2012): Probabilistic forecasting for urban water management: a case study, Paper presented at the 9th International Conference on Urban Drainage Modelling, Belgrade, Serbia 2012	*conference proceedings*
11	Jeanne-Rose René, Slobodan Djordjević, David Butler, Ole Mark & Henrik Madsen (under review) Evaluating an X-band Radar area-based nowcasting algorithm for urban drainage model forecasting, *Journal of Hydrology*	*Submitted for review Sept 2014*

1.4 Contribution and Originality

A probabilistic real-time flood forecasting system constitutes a number of components and is usually tailored to the location for which the warnings are to be provided. The necessity to address flooding in urban areas as a result of climate change and increased imperviousness has stimulated the interest in urban real-time flood forecasting. References in the scientific literature to flood forecasting of both deterministic and probabilistic formats extend as far back as the middle of the last century. However, studies that bear relevance to this topic are scarce (Liguori et al., 2012, Thorndahl and Willems, 2008). Nevertheless, the approaches of the few published cases go well beyond deterministic forecast and borrow ideas from approaches used on the river basin scale. The main elements of probabilistic real-time flood forecasting framework, which are usually embedded in a decision support system, include: (i) precipitation forecasts (e.g. NWP QPF, or weather radar QPF), (ii) Telemetric data (e.g. Rain gauge rainfall, pipe flow data) and (iii) Simulation tools (e.g. urban drainage models) (WMO, 2011, WMO and GWP, 2013, Jha et al., 2012). However, this study would like to replace simulation tools with the term "estimation methods" mainly because in the framework of sparse data, it is not always possible to have models. Each of the listed components will be discussed in the coming chapters since they form the basis for the real flood-forecasting framework. The main contributions made by this thesis in the area of probabilistic real-time flood forecasting are highlighted in Figure 1-1.

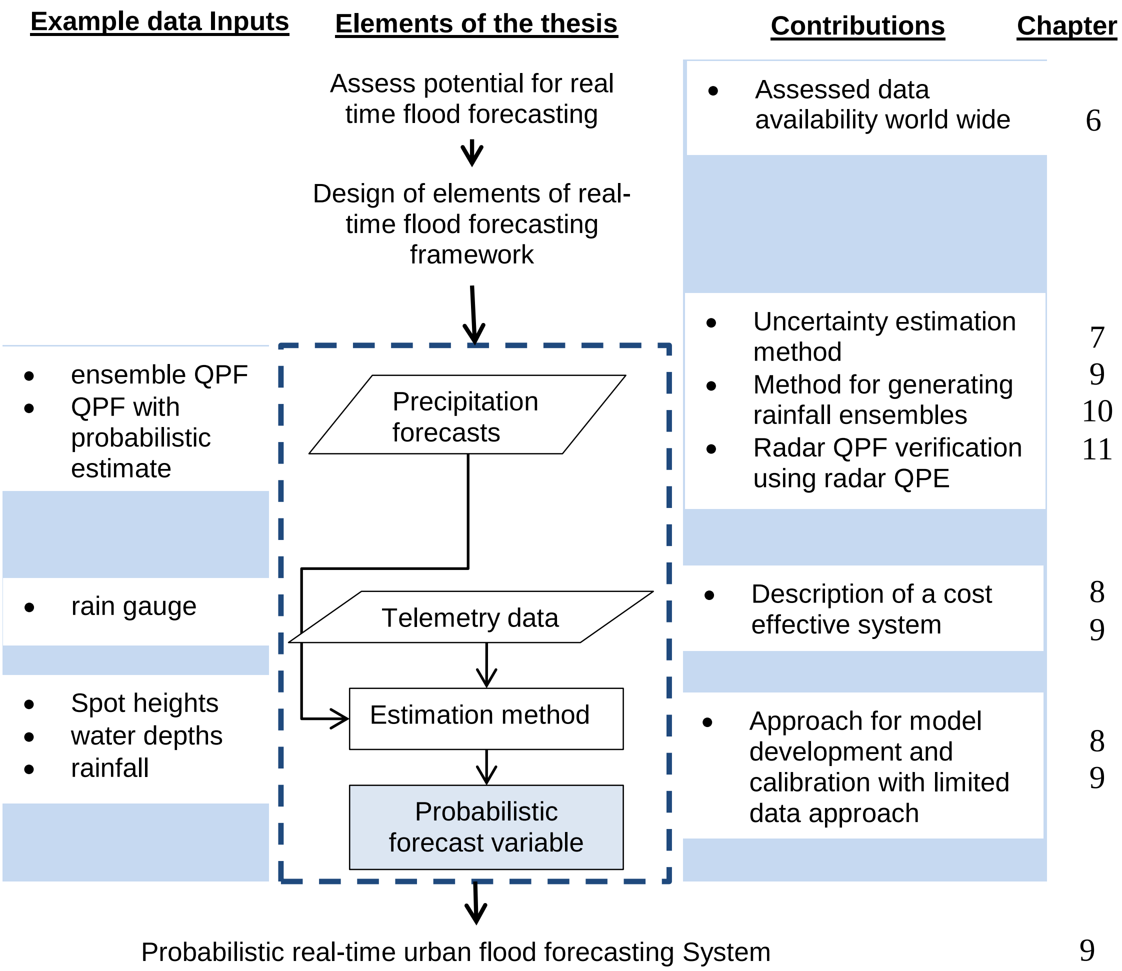

Figure 1-1: Thesis framework highlighting the elements of the probabilistic real-time urban flood forecasting framework in the box with dash lines. Example inputs and contributions for the different elements are highlighted to the left and right of the main framework respectively. The figure also highlights the linkages between the manuscripts by showing which paper relates to which element of the work.

The figure outlines the thesis framework in relation to the probabilistic real-time flood forecasting framework, which is outlined in the blue box in broken lines. It shows example data inputs and emphasizes the main contributions made in relation to the thesis objectives and the chapters in which they are covered. It also shows the linkages between the papers in order of the elements of the thesis framework. For example, the research entails first assessing the potential for real-time flood forecasting and the main contribution is described in paper presented in Chapter 6. This is then followed by a design of the main components of a real-time flood forecasting system, using the data from the two case studies. In that, the design first entailed the verification of the QPF and the development of the uncertainty estimation method which are described in the papers outlined on the right. The column on the left highlights the example data inputs into each element of the framework.

The thesis uses guidance from manuals prepared by World Meteorological Organization, Global Water Partnership and the World Bank (WMO, 2011, WMO and GWP, 2013, Jha et al., 2012). The concepts applied are not new in themselves, but the novelty lies in some of the approaches used to gel the different elements together. Since this thesis is founded on the premise that a lack of examples for motivation is the reason for so few published cases, much of the work presented provides assistance on how to systematically design a probabilistic real-time urban flood forecasting system in the context of current practice.

1.4.1 Overview of links between manuscripts

Satisfactory performance of real-time urban flood forecasting systems depends mainly on the quality of the meteorological inputs and the methods used for estimating the forecast variable. Consequently one of the most important issues regarding the appropriate use of meteorological inputs and estimation methods (simulation tools) is the proper assessment and estimation of its accuracy using various uncertainty estimation and calibration techniques, respectively. These methods all play a vital role in the development of real-time flood forecasting systems. However, while the theoretical applicability of the methods is sound, in some case its practical applicability is a far cry from reality, mainly because of data constraints.

In order to describe a relevant framework, it is therefore logical to turn to current literature as well as urban flood practitioners themselves for insights into the use of the available data for flood management, the perceived challenges in data acquisition as well as their data sources and the principle constraints in urban flood modelling. ***Chapter 6*** clarifies and confirms the potential for real-time urban flood forecasting based on the responses from the online survey particularly highlighting that we currently have the resources to make a flood forecast in any urban area prone to flooding. ***Chapter 9*** actually demonstrates that it can be done even with limited data.

Estimation methods play a significant role in accurately predicting the forecast variable (e.g. water depths and flow rates) and as such inadequate model calibration and validation (where models are being used) would lead to a poor forecast model. ***Chapter 8*** highlights the development and calibration of a 2D overland model with limited data for use in real-time flood forecasting and stresses on the potential in the use of images extracted from social networks for model calibration and validation.

The component which influences the outcome of the flood forecasting system the most is the precipitation inputs. As such a major part of the design involves precipitation forecast verification. The main focus of ***Chapter 11*** is to evaluate the accuracy of the forecast from weather radar, using both statistical techniques as well as an urban drainage model for verification. This paper focuses on statistics which will reflects hit rates which are close enough rather than an exact match, mainly because it is more challenging to predict the exact location and intensity of rain clouds at such fine scales. ***Chapter 7*** also reports results from precipitation verification from NWP forecast and rain gauges, but in addition describes in detail a probabilistic approach and sampling method for modelling uncertainty from the single value QPF from NWP models. The applicability of the uncertainty estimation method is presented in ***Chapter 10*** for a date rich case and ***Chapter 9*** for a data poor case.

The outcomes from the previous papers were combined to develop a probabilistic real-time urban flood forecasting system for one of the case study locations and presented in ***Chapter 9***. The developed approach shows how limited data and resources can be used to successfully implement a flood forecasting system.

1.5 Thesis outline

This thesis is composed of five chapters which summarizes the results of the research work in the context of state-of-the art and a compilation of papers at the end (Chapters 6 - 11). The second chapter presents an overview of the elements of a probabilistic real-time urban flood forecasting system as well as summary results and descriptions for some elements of the framework. Chapter three and four presents a summary of the main findings based on the objectives of precipitation verification and uncertainty estimation. The five chapter draws upon the entire thesis, tying up the various components in a coherent whole. Finally, areas for further research are identified and Chapters 6 - 11 presents the papers arising from the thesis.

2 Elements of a probabilistic real-time urban flood forecasting system

Probabilistic real-time flood forecasting for urban areas is increasingly getting more attention in light of rapid urbanisation, climate change and other anthropogenic stresses on urban areas. In recent years there has been an increasing interest in QPF at temporal and spatial resolutions corresponding to the requirements of urban drainage system modelling (Tilford et al., 2002, Liguori et al., 2012) and to extend the effective forecasting lead-time for warning and mitigation.

In a probabilistic real-time flood forecasting system, the first priority is to have real-time access to probabilistic quantitative precipitation forecasts (PQPFs) which can be combined with urban drainage models if available. These precipitation forecasts can be from two sources, weather radar and NWP models, thus enabling longer lead times. This is usually complemented by data from telemetric stations to underpin the conditions on the ground.

This chapter presents an overview of the main components of the probabilistic real-time urban flood forecasting system. It is divided into four sections. The first three sections provide an overview of the elements of the framework, with example results and implementation descriptions in some cases. The last section highlights the potential for real-time urban flood forecasting based on results from the survey (***Chapter 6***).

2.1 Probabilistic quantitative precipitation forecasts (PQPFs)

Precipitation is one of the most important components in flood forecasting because it serves as the forcing from which management decisions are based upon. The most widely used source of short term (0 – 6 hours) QPFs, which may find useful application in urban flood forecasting originates from NWP models. However, its usefulness is still limited for urban applications since high spatial and temporal resolutions are required.

It has been shown repeatedly that the skill of radar based QPFs decreases rapidly with increasing lead time and that NWP models produce superior QPFs beyond a few hours (Lin et al., 2005). However tremendous effort has been devoted to the improvement of the quality of NWP QPFs beyond the first hour and as such there has been attempts to integrate radar echoes with NWP QPFs to generate a seamless product in both deterministic and probabilistic formats (Liguori et al., 2012, He et al., 2012).

Radar estimates are subject to a number of errors and uncertainties, but it is not addressed in this work since it has been extensively covered in literature (Seo et al., 2013, Schröter et al., 2011, Jensen, 2012). Despite the inherent uncertainties in the radar based QPE, only recently have approaches for estimating radar based PQPFs been published in scientific literature (Dai et al., 2014). As a result, today, radar based QPFs are predominately in deterministic formats.

Outputs from NWP models can generally be of both deterministic (single value QPFs) and probabilistic formats (ensembles) as outlined in Figure 2-1. With some post processing, as will be demonstrated in Chapter 4, the deterministic single value QPFs can be used to generate precipitation ensembles or precipitation with an estimate of uncertainty in the form of confidence level (See Chapter 4).

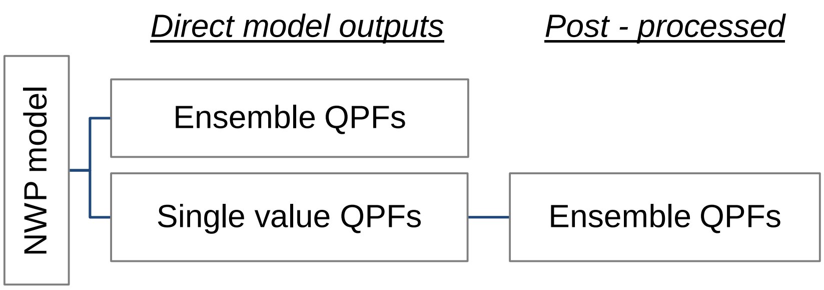

Figure 2-1: Formats of NWP model outputs

Based on responses from the survey, the two most widely used open data sources of NWP QPFs () include:

1. The global forecast system (GFS) - www.ncep.noaa.gov
2. Norway Meteorological Institute – www.yr.no

These are global scale models (covering the entire earth) and their products can be downloaded from the website for the different prognosis periods. Because of the computational time required to solve the equations, global scale models are solved on coarse grids and regional models (covering certain parts of the earth) on finer grids. Using finer grids makes it possible to explicitly represent small scale meteorological phenomena (Kaufmann et al., 1999) which are significant for urban flood forecasting, despite the general complexity in representing microphysical processes (Reyniers, 2008). Nonetheless, getting access to precipitation data of fine temporal and spatial resolution can be prohibitive. Global forecast data on the other hand is easily accessible on the World Wide Web (open source) but its spatial and temporal scales severely limit its application in urban environments. But it is one of the objective of this thesis to demonstrate that there is some value in open sourced QPFs for urban flood forecasting.

2.2 Telemetry data

As a prefatory for the overall design of the real-time flood forecasting system, observed data which may consist of rain gauge rainfall, water depths, flow rates etc. must be collected in real time. Jha et al., (2012), suggest that the development of a real-time flood forecasting system is hindered by the lack of surface measurement stations for rainfall and other land surface parameters in real-time. Today, the ubiquity of the internet along with its inherent reliability and speed, makes automated real-time data collection easily attainable, thus making the use of telemetric data in real-time flood forecasting more possible.

A real-time data collection system for flood forecasting can consist of my many different process flows and thus many components. However, this study presents the components of a simple system which can be used in conjunction with urban drainage models for making flood forecast with uncertainty estimation. The process flows of the real-time data collection system used in this study for urban flood management is presented in Figure 2-2.

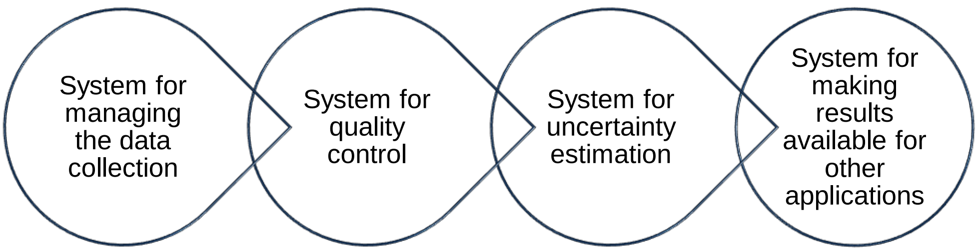

Figure 2-2: Process flow of a real-time probabilistic flood forecasting system utilized in this study

The system for managing the data collection (i.e. scripts or protocols for extracting the data) is also responsible for communicating simultaneously with open source online data portals and with measurement hardware (e.g. radar and rain gauge) and storing the collected data for use either in real-time or for historical studies. This can be seen as the biggest challenge for automated data collection, but fortunately most free online data sources have prepared readily available scripts to extract the data from their portals. The use of data collection devices also makes automated data collection easier because manufacture's usually provide guidelines on how to communicate to the hardware.

Once the data has been collected and transferred electronically to the storage location a system for quality control is also important to validate the data. Data validation is import to detect errors and to adjust the data to ensure the quality of the forecast. This may include very simple techniques such as data infilling, flagging of very large values amongst many others.

There are several types of real-time rainfall data collection devices but it is beyond the scope of this study to investigate such devices. However, part of this work involved the installation of a rain gauge for real-time data acquisition in one of the case study locations, Castries St. Lucia (See Figure 2-3), with a total estimated cost of approximately €660. The location selection was based primarily on a safe place with consistent internet connection within the catchment, with personnel who can easily maintain or check the equipment.

Figure 2-3: Physical installation of the tipping bucket rain gauge

Another part of the installation involved the set-up of the real-time rain gauge data collection system (Figure 2-4). The system is built on the components highlighted in Figure 2-2. Data is loaded frequently to a MSSQL database server at regular intervals, where it is then available for operational use.

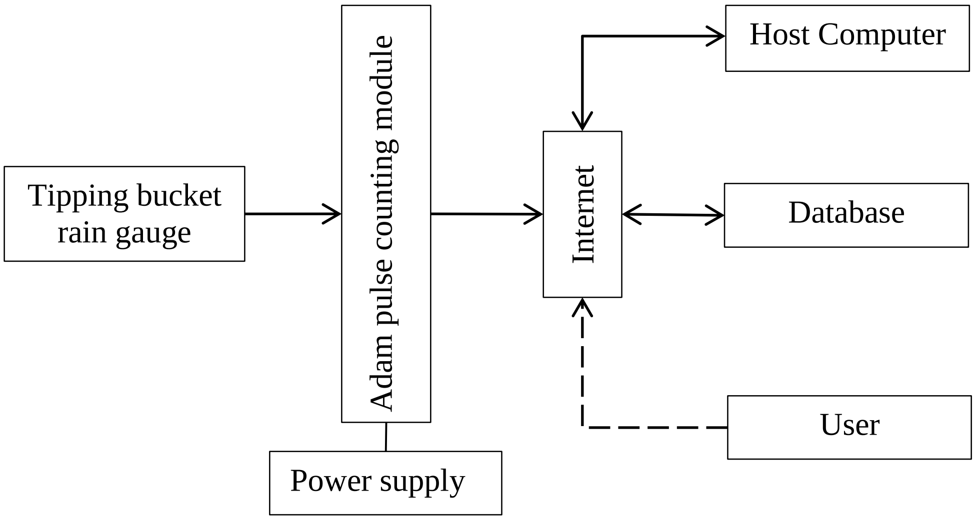

Figure 2-4: Components of the real-time rain gauge rainfall collection system

In this setup a special command and response protocol is used for this purpose, which is initiated by the host computer. This is scheduled and executed at 1 minute intervals. Since flood forecasting and warning systems are expected to operate in real-time or near real-time, the remotely measured data based on current observations are transmitted to the operating flood forecasting system in almost real-time. It is inevitable to have delays but they should be kept at a minimum. In this case, the transmission delay to the server in Denmark is only a few seconds.

The usefulness of the flood forecasting system depends greatly on the completeness of the available time series data. However, in practice there are several reasons why there may be discontinuities in the data collected based on the real-time data collection setup in Figure 9-2. These include: (i) power outages (rain pulses will not be counted and data will be lost), (ii) host computer might be switched off (timing information on rain pulses will be lost, but total amount of rain is still counted), and (iii) failure in the internet connection from the module to the host computer (timing information on rain pulses will be lost, but total amount of rain is still counted) or from the host computer to the MSSQL database server (data might be buffered on host-PC until connection is established again, but if host PC is restarted the buffer will be lost).

2.3 Estimation methods for the urban drainage forecast variable

A study relevant to this framework classifies real-time flood forecasting systems into three categories, namely (i) empirical scenario, (ii) pre-simulated scenario and (iii) real-time simulations (Henonin et al., 2013). According to Henonin et al., (2013) in the empirical scenario, hydraulic models are not involved and are based on historical accounts, in the pre-simulated scenario, the hydraulic simulations are done previously and is based on a scenario catalogue, in the real-time simulation approach the hydraulic simulations are done in real-time. As a result, “simulation tools” are replaced with the term “estimation methods” mainly because it is not always possible to have models. This thesis has developed a flood forecasting approach based on a combination of two estimation methods are empirical approach and a real-time simulation approach. However, the real-time simulation approach can always be replaced with the pre-simulation approach if computational time becomes an issue.

The most rudimentary way to tackle real-time flood forecasting is based merely on rainfall forecast and historical account of past flood events (empirical approach). Rainfall thresholds are established beyond which a flood forecast is made. However, this study found that it is not so straight forward to establish such thresholds and the lack of scientific literature on the subject substantiates the findings. Ideally, according to Hurford et al., (2012) in order to facilitate a better understanding of the relationship between rainfall intensity and flood magnitude, improvements in data recording of flood magnitudes and durations is required.

Thus, in order to make a forecast based on the empirical approach in St. Lucia (as described in ***Chapter 9***), a rainfall threshold is defined by studying a small number of rainfall events (three) that have resulted in flooding. The threshold was obtained using a moving sum window and by visually selecting a critical rainfall accumulated depth, using the observed peak values for the specific dates of known flood events as a guide over the moving sum window. Several thresholds were possible depending on the size of the moving window, but the analysis showed that the predictive power (minimize false alarms) is best for larger windows (Figure 2-5). As a result a moving sum rainfall threshold of 35 mm in 12 hours was selected as the suitable threshold that will induce flooding.

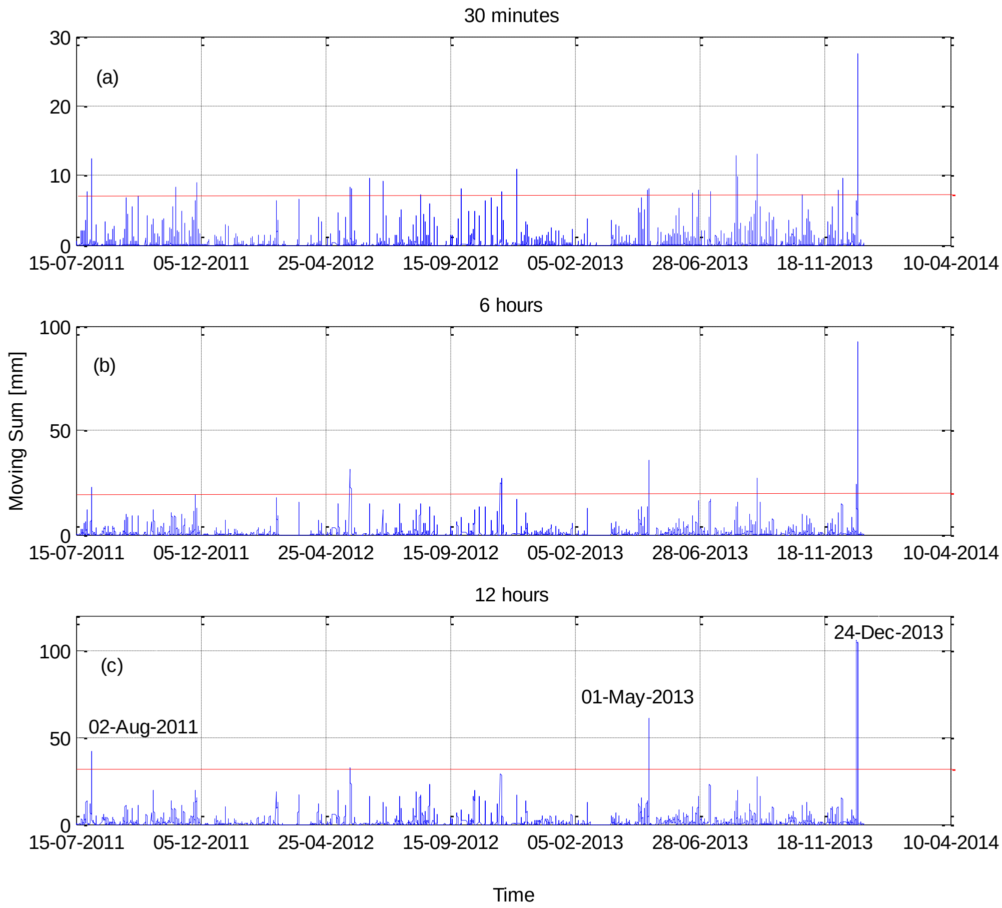

Figure 2-5: Time series of the moving sum with a 30 minute, 6 hour and 12 hour moving window. Distinct peaks are observed for the 3 known flood events when using the 12 hour moving window for plot (c). Red horizontal line highlights potential threshold limits for all moving windows, but plot (a) and (b) highlights the possibility of false alarms since there are a few peaks other than the flood events above the red line. The threshold limit of approximately 35mm of rainfall is selected for the 12 hour window plot (c)

Since the Caribbean region and St. Lucia in particular is dominated by short duration, high intensity events the use of such a large moving window actually increases the predictive ability. A Larger window results in thresholds that are more distinct because it tends to dampen the effect of small rain events. As in any forecast system, there will be adjustments to be made to the estimated threshold values amongst other things to incorporate the lessons learnt. It is also expected that the evaluation of more flood events will provide more in-depth knowledge for the selection of a suitable rainfall threshold which initiates floods.

With respect to the real-time simulation approach, urban drainage models are used in real-time to estimate the forecast variable such as water levels, and as such the models should be calibrated and validated in order to be considered fit for purpose.

Urban flood models need to be able to simulate flow in pipe systems as well as the urban surface and as such urban flood model can be modelled either with 1D models (Mark et al., 2004), 2D overland models or as a coupled system of 1D/1D, 1D/2D or 1D/1D/2D (Leandro et al., 2011, Simões et al., 2011a, Mark and Djordjevic, 2006). When using models to estimate the flood forecast variable, part of the development includes model calibration and validation (verification) with the ultimate goal of producing accurate results. 1D model calibration is very much straightforward since there are usually flow and water level gauges installed in the drainage (sewer) systems. The issue arises when calibrating 2D overland models when they are not coupled to a 1D model. Images, particularly areal images obtained via remote sensing (LIDAR) have played a vital role in the calibration and validation process of 2D overland models (Horritt and Bates, 2002, Mason et al., 2009) but the methods used to acquire them can be prohibitive therefore limiting its availability. This thesis has highlighted the invaluable benefit of the use of images extracted from social networking sites for calibrating and validation 2D surface models.

The method involves estimating water depths relative to objects identified in the images (e.g. pole of a lamp or sign post, car, curb etc.) extracted from the secondary data sources (e.g. Facebook) and comparing to the water depths estimated from the 2D overland model. Knowledge of the area is required to be able to use this approach since the images are not geo-referenced. Other challenges include the absence of time stamps on the images since it is not known at what time the image was taken so the user has to assume that the maximum depth extracted from the model should never be less than the depth extracted from the image. Otherwise the model is underestimating the water depth. Figure 2-6 demonstrates how images were used to calibrate and validate the 2D overland model for St. Lucia (Chapter 8 and 9). The estimated water depth in the image is 0.5m and the simulated water depth is also around 0.5m at the corresponding location. The results indicate significant potential in using water depths extracted from images for selecting an appropriate 2D overland model for flood forecasting and for flood modelling in general.

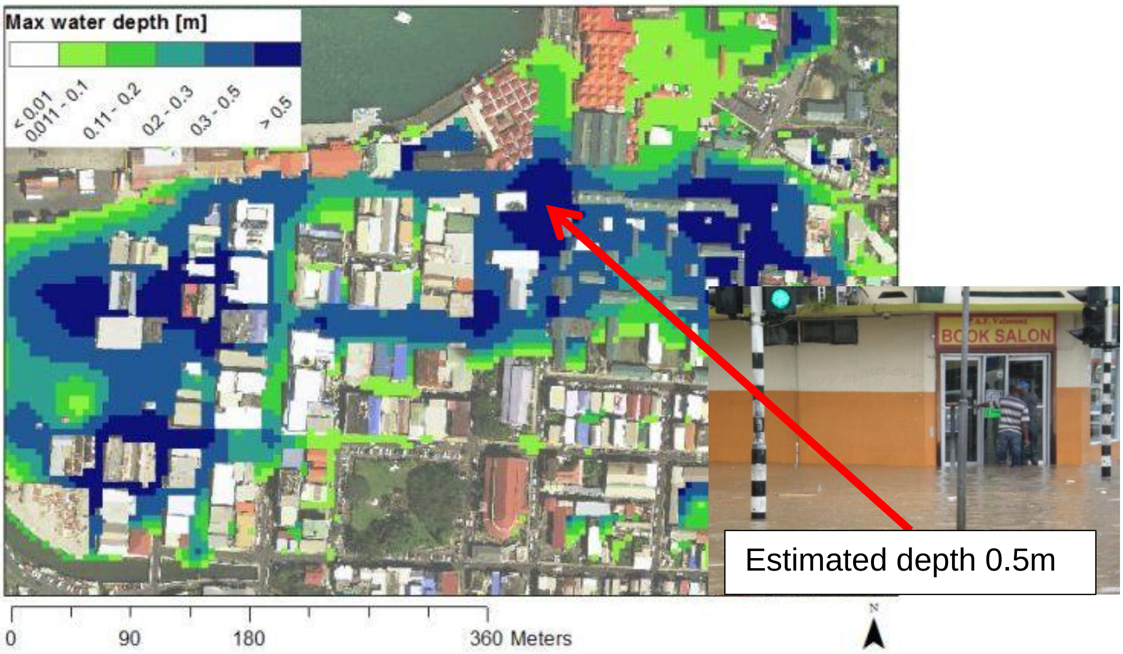

Figure 2-6: Maximum flood map simulated from observed rainfall for a flood event in Castries Saint Lucia, with a picture reporting flood. In the image a man is standing on stair and the water depth is just above knew height. Therefore the approximated depth is 0.5m

2.4 Challenges and constraints

The online survey (as presented in **Chapter 6**) was aimed at investigating data availability. The principal constraints in urban flood modelling and forecasting suggest that we currently have the resources to make a flood forecast (i.e. 61.4% of the 176 respondents have access to rainfall in real-time and 68.8% are using simulation tools). A possible explanation why there are so few cases of real-time urban flood forecasting systems is that urban flood practitioners *may* not be aware that they have the means to make a pluvial flood forecast, albeit not as detailed. This may be attributed to the misconception, although not fully substantiated, that sophisticated models for estimating the forecast variable and high resolution data are required. While this is always desired, it is not always possible because of challenges which will be hardly overcome in some regions in the world, thus flood risk reduction should still be addressed.

Findings from the survey suggest that model calibration and validation is considered as one of the principal constraints in urban flood modelling. This is consistent with what has been considered to be one of the most limiting factors in urban flood modelling (Beven, 2009, Refsgaard et al., 2005) and the importance of tying this to real-time urban flood forecasting continues to challenge many urban flood practitioners. However, although it is essential to improve model credibility through model calibration and validation, it should not limit one’s ability to address flood problems because models can always be improved as lessons are learnt. In fact, one can almost always make a forecast based on the empirical approach.

Despite all the challenges and constraints outlined by the respondents, this thesis believes that there are other more important barriers which will affect the ability to make a real-time flood forecast, yet alone a probabilistic flood forecast. These are summarized in Table 2-1.

Table 2-1: Challenges that may hinder the use of a forecasting approach

Approach	Challenge
Empirical	• Lack of information on past flood events (no observations) • Urbanization which may affect flood locations • Uncertainty in rainfall input
Pre-simulated	• The rules for scenario selection are not adequate • Catalogue does not contain a wide range for scenario selection • Model calibration and validation • Uncertainty in rainfall input • Real-time data access
Real-time simulation	• Model calibration and validation • Uncertainty in rainfall input • Lack of data, technology and human resources • Real-time data access

All in all, the results from the survey provide important insight, on the challenges relating to data for real-time urban flood forecasting and modelling in general. The discernment of the available resource globally gives each practitioner a better indication about what can potentially be done in their areas relative to their available resource. As a result of this realization there *may* be a rise in the number of operational real-time cases.

3 Quantitative precipitation forecast verification

In general, data plays an important role in simulating reality. In fact measured (where possible) or simulated data is the only evidence of the reality. However, there are several factors affecting the quality or accuracy of the forecasted data. It is therefore necessary to perform verification checks to ensure that the data meets the requirements for a successful forecast system. This process is critical because poor quality data may lead to an unreliable system.

According to Rossa et al., (2008) the strategy for any forecast verification application includes the following steps:

1. Choosing the matching set of forecast and observation pairs
2. Defining a technique to compare them
3. Aggregating or stratifying the forecast and observation pairs in an appropriate data sample
4. Applying relevant verification statistics
5. Interpreting the scores

This study adopts the steps suggested by Rossa et al.,(2008) and has been applied to the following data combinations:

- Gridded QPF from global scale NWP versus rain gauge rainfall
- Gridded QPF from regional NWP model versus rain gauge rainfall
- Radar QPF versus radar QPE

This chapter presents the main findings based on the QPF verification for the data combinations outlined above.

3.1 Verification of NWP based QPFs against rain gauge

Verification of QPF made by NWP is often been performed against precipitation analyses produced by NWP models (Golding, 1998) and/or observations either from rain gauges or weather radar (Roberts and Lean, 2008, Mittermaier et al., 2013). Precipitation analyses can consist of combinations from different precipitation sources and include rain gauges, radars and satellites (Golding, 1998, NOAA, 2014). According to Casati, (2004) precipitation analyses from NWP (QPE) is the most appealing for QPF verification since it is considered the most reliable, complete and coherent product.

Verification of NWP QPF is also often been performed against rain gauge measurements (Rossa et al., 2008). Most studies advocate the use of merged data (e.g. radar-rain gauge) for QPF verification from NWP models, but in reality the method of verification is always, in part, limited to the available data.

In addressing the issue of using gridded global precipitation forecast for urban flood forecasting, one of the key questions is at what temporal scale (which is potentially a coarser temporal resolution) is there sufficient skill for this application. As a first step, the 12 hour 3 hourly forecasts for Castries, Saint Lucia was verified, followed by verification of 6 hourly and 12 hourly accumulations at different lead times against one rain gauge. A number of verification scores were considered and are discussed throughout ***Chapter 9***.

Nonetheless, the key highlight from this analysis is that there is more skill in the forecast at the 12 hourly accumulations which is consistent with expected results. The results (Figure 3-1) show that the normalized root mean square error (NRMSE) is smallest for the 12 hour accumulated data.

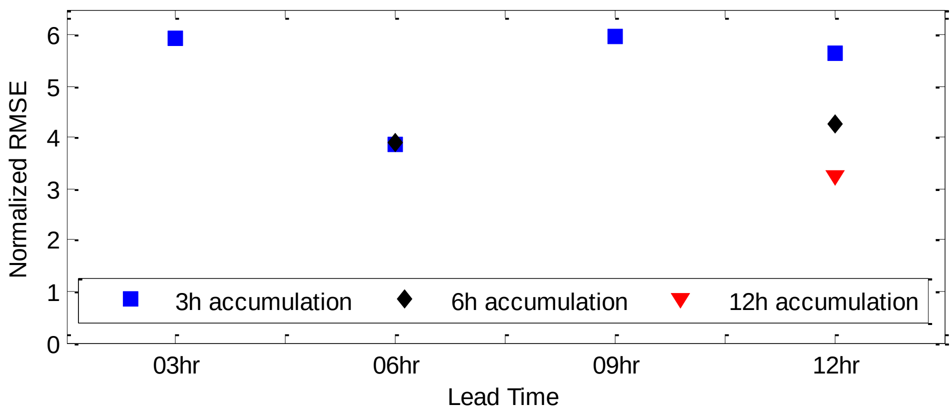

Figure 3-1: Normalized root mean square error (NRMSE) for the different data resolutions when compared to the stationed rain gauge and the forecast grid above the rain gauge during the period July 2011- December 2013 for case study in St. Lucia. The 12 hour accumulated data has the smallest deviation from the mean.

Another interesting finding is that the total forecasted accumulated rainfall during the study period deviated only by +1.2% from the total accumulated observed rainfall. This observed finding mirrors that of the previous studies which have suggested that global forecast data is better for long term forecasting due to a number of scientific issues which are beyond the scope of this study (Fan and van den Dool, 2011), which is not limited to the complexity of modelling the atmosphere.

A major limitation of these findings is that the temporal resolution of accumulated 12 hourly forecasts does not correspond to the requirements of urban drainage system modelling (Tilford et al., 2002, Liguori et al., 2012). In addition, the changes experienced as a result of increased imperviousness, makes the urban environment more sensitive to the spatial distribution of rainfall (Segond et al., 2007), making the GFS data unattractive in all respects. To handle this, this thesis proposes an approach on how to use this 12 hourly 12 hour forecast which is presented in Chapter 4.

Conditional bias scores for the verification of higher resolution NWP forecast (obtained from a regional scale model) against a network of 3 rain gauges over a period also showed inconsistency between observed and forecasted rainfall (See ***Chapter 10 -*** Figure 10-1).

The findings from the comparison of global scale forecast to a single rain gauge and regional scale forecast to 3 rain gauges, suggest that there is a persistent disagreement between observed and forecasted rainfall. This mismatch is more pronounced when comparing global forecast data of increasing (finer) temporal resolution to rain gauge data. The results suggested that in general the deviation in observed and forecasted rainfall pairs decreases as the temporal resolution decreases (i.e. gets coarser).

3.2 Verification of radar based QPFs against radar based QPEs

The past decade has seen the rapid development of precipitation verification techniques which go beyond point-to-point pair verification. This emanated from the necessity to appropriately evaluate goodness of fit of data of fine temporal and spatial resolutions since the traditional approaches were likely to penalize small differences in location and intensities, by trying to find an exact match based on point-to-point verification (Rossa et al., 2008).

In the context of radar nowcasting (short term forecasting 1-6 hours), it is very likely that the area-based nowcasting technique used to generate the forecast will produce a forecast with seemingly realistic precipitation patterns but with intensities and locations somewhat misplaced (Mesin, 2011), and so it is unreasonable to expect a perfect match. These small errors in magnitude and displacements can potentially have significant impact on hydrological applications in urban catchments, depending on the size of the catchments.

Accordingly, the verification approach should give an indication of the forecast skill at different spatial scales.

Publications relating to the verification of radar based QPFs against QPEs are rare. Instead more studies have focused on the comparison of radar based QPE against rain gauge data mainly to provide information in order to improve their estimates, such as for calibration (Seo et al., 2013, Russell et al., 2010, Chumchean et al., 2006, Brown et al., 2001, Borga, 2002).

Comparing radar based QPFs against radar based QPEs gives an indication of how well the nowcasting technique performs, making the understanding of uncertainty sources a little less complex. To illustrate the verification of radar based QPFs data with radar based QPEs ,a method which is more commonly used for verifying NWP QPF against radar QPE is applied (Mittermaier et al., 2013, Zacharov and Rezacova, 2010, Roberts and Lean, 2008). In the fractions skill score (FSS) method, developed by Roberts and Lean (2008), the condition of exact match is relaxed to provide an estimate of goodness of fit at different scales for different rainfall thresholds.

The gridded observational and forecasted data sets considered covered 5 stratiform and 5 convective events during the period Nov 2012- Nov 2013, for the X-band radar. The method involves splitting the verification area into a number of neighbourhood windows of a certain spatial scale s, and computing the proportions of both the observed and forecasted fractions for a particular rainfall threshold. In order to determine at which scale the neighbourhood is useful, the size of the neighbourhood is increased. The verification score, in this case, the Fractions Skill Score (FSS), is computed using:

$$FSS = 1 - \frac{1/N \sum_N \left[P_{F_s} - P_{O_s}\right]^2}{1/N\left[\sum_N {P_{F_s}}^2 + \sum_N {P_{O_s}}^2\right]} \tag{1}$$

where N is the number of neighbourhood windows in the verification area; $P_{F_s}$and P_{O_s} are the neighbourhood proportions at the i^{th} grid box in the model forecast and observed fraction fields s. This is discussed in more detail in ***Chapter 11.***

The FSS values for a convective and stratiform event as a function of lead time for a rainfall threshold exceeding 0.3mm/hr are presented in Figure 3-2. As expected there is an increase in FSS as the spatial scale increases for both events. However, more encouraging results were shown for the stratiform event, plot (b) even at radar pixel scale (0.5km). The big difference in FSS scores for stratiform and convective regimes is related to their characteristic features. Stratiform events are a lot easier to forecast because of their fairly large homogenous extents. The evidence from this study suggest that the forecast are generally better for stratiform regimes, a more extensive study is required to generalize the results since the value of the FSS depends on the number of events evaluated.

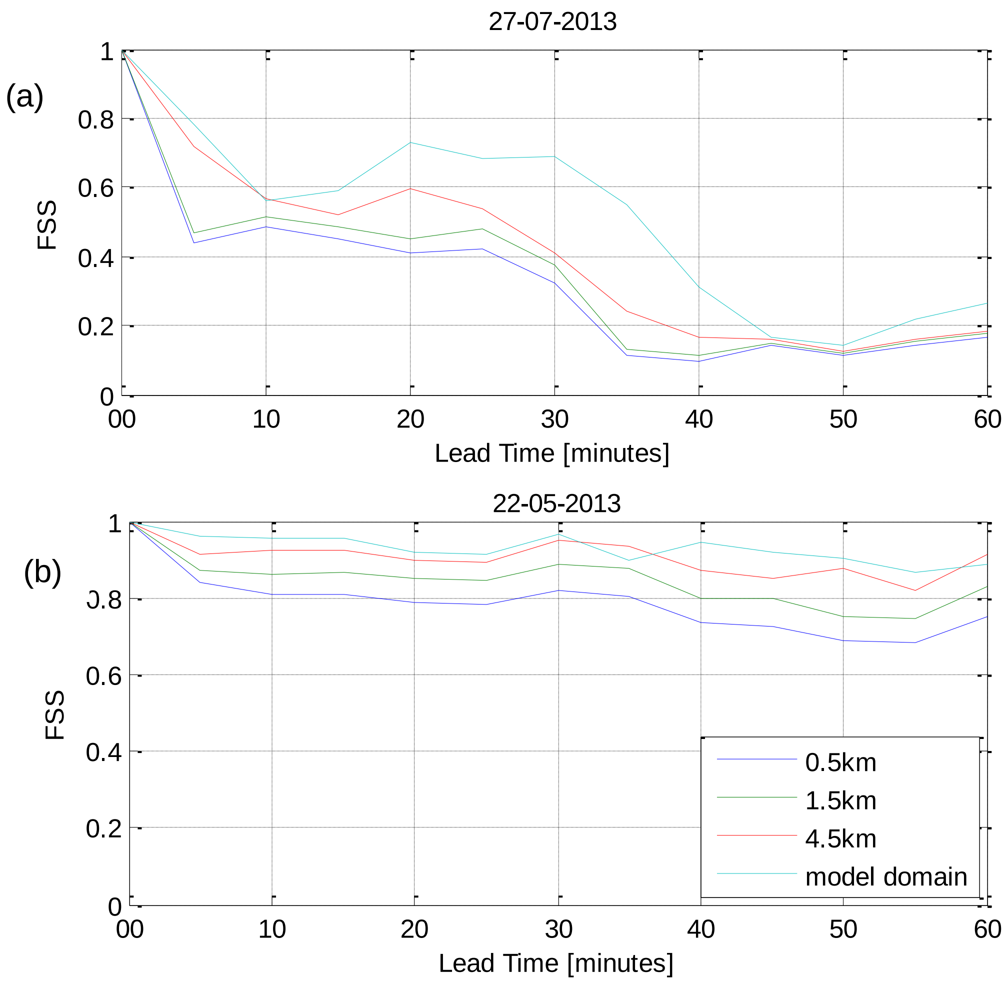

Figure 3-2: Fractions skill scores for the 5 minute forecasted precipitation intensities at different spatial scales as a function of forecast lead time with the threshold of 0.3mm/hr for a convective (a) and stratiform (b) event. The model domain is 4.5x13.5km.

4 Uncertainty estimation in QPF

Precipitation is the most dominant input in flood forecasting. This is of greatest interest as precipitation is the single most uncertain variable in hydrological modelling. According to Butts et al. (2002) operational experience suggests that in many cases the forecasted and observed precipitation inputs are the most significant source of forecast uncertainty and therefore it is desirable and recommended that estimates of forecast uncertainties are made as part of the forecast.

To date, there are many methods for uncertainty estimation in NWP QPFs but less so for radar based QPFs (Dai et al., 2014, Liguori et al., 2012), despite the inherent uncertainties in the radar based QPEs. Radar based QPFs are a derivative of radar based QPEs, and as such there is an uncertainty cascade which is not limited to the uncertainty in the QPEs but also with the nowcasting technique. Nonetheless, this chapter only presents and demonstrates the applicability of a method for uncertainty estimation in NWP QPFs and relates it to current approaches. The method is developed on a case with high resolution data and a modified version is presented on a case with poor quality data. The uncertainty estimation method could also be applied to QPFs from weather radar with some modification to distribute the error spatially.

4.1 Uncertainty estimation in single value NWP QPFs

There are many methods for uncertainty estimation based on single value deterministic QPFs (Anagnostopoulou et al., 2008, Schaake et al., 2007, Anagnostou et al., 1999, Sloughter et al., 2007) for probabilistic forecasting of flood forecast variables as well as methods for improving the precipitation forecast which is not limited to bias correction (Fang and Kuo, 2013).

For the sake of practicability and simplicity this study has developed an approach which is easily adaptable which does both bias correction and uncertainty estimation at once, therefore making it attractive for real-time applications. The method is first developed and applied to a case study with high temporal and spatial resolution data (***Chapter 7 and 10***), followed by a demonstration of the method modification for its applicability on a case study with coarser resolution data (***Chapter 9***).

The method involves a retrospective comparison of single value QPFs from NWP models (denoted $\hat{S}$) with actual observed rainfall (denoted S) measured using a rain gauge to develop a probability relationship in the form of stochastic models for each forecast lead time. The sampled rainfall forecast for each leadtime is used as a forcing for the hydrodynamic model. As a consequence, the stochastic model must be developed on the same data source which will be used for the flood forecasting system.

The stochastic model is developed by adapting the procedure used by Schaake et al., (2007). The probability relationship at different lead times is estimated by first decomposing the data into lead times. In order to reflect the intermittent nature of the rainfall for each lead time two stochastic models are defined. The first is given by the probability conditioned on a zero rainfall forecast:

$$P\left(S \le x \middle| \hat{S} = 0\right) = P\left(S \le x \middle| S > 0, \hat{S} = 0\right) P\left(S > 0 \middle| \hat{S} = 0\right) + P\left(S = 0 \middle| \hat{S} = 0\right) \tag{2}$$

where $P\left(S \le x \middle| S > 0, \hat{S} = 0\right)$ is obtained by fitting the data to a parametric or non-parametric distribution and the conditional probabilities $P\left(S > 0 \middle| \hat{S} = 0\right)$ and $P\left(S = 0 \middle| \hat{S} = 0\right)$ are obtained from the data.

The other stochastic model comprises of probability distributions for each lead time for a rainfall forecast more than zero, denoted $x*$. In this case the data is transformed from its original domain to the normal domain (e.g. Box-Cox transformation). The probability conditioned on a non-zero rainfall forecast is given by:

$$P\left(S \le x \middle| \hat{S} = x^*\right) = P\left(S \le x \middle| S > 0, \hat{S} = x^*\right) P\left(S > 0 \middle| \hat{S} = x^*\right) + P\left(S = 0 \middle| \hat{S} = x^*\right) \tag{3}$$

where $P\left(S \le x \middle| S > 0, \hat{S} = x^*\right)$ is obtained by fitting the transformed data to a bivariate normal distribution. The conditional probability $P\left(S > 0 \middle| \hat{S} = x^*\right)$ is obtained using logistic regression or other functional relationship and $P\left(S = 0 \middle| \hat{S} = x^*\right) = 1 - P\left(S > 0 \middle| \hat{S} = x^*\right)$.

The following provides a step-by-step summary of the method as described in ***Chapter 7***.

Method summary

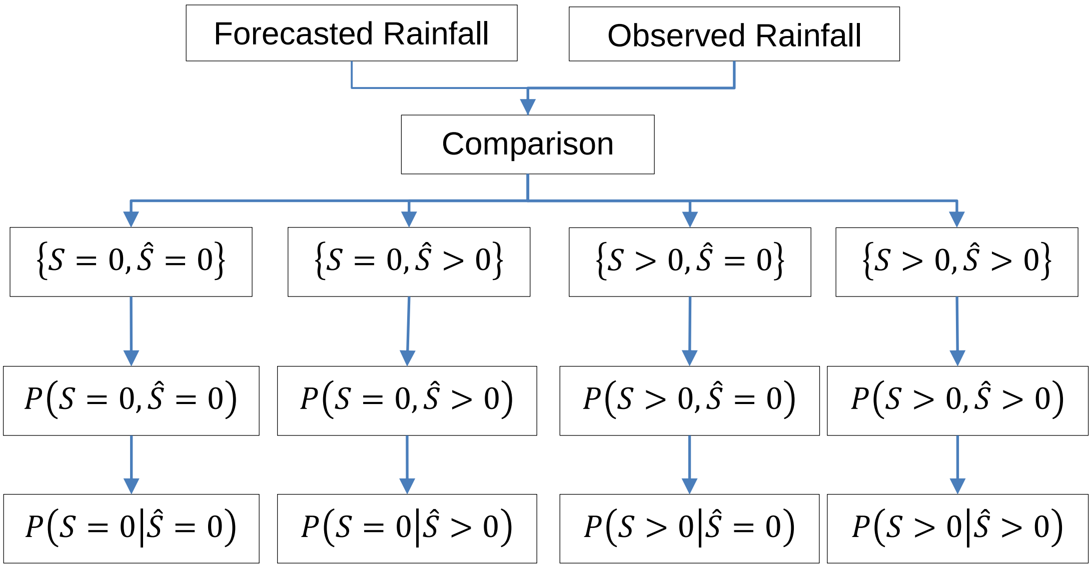

Figure 4-1: Uncertainty estimation method summary for estimating the parameters of the probability distribution functions

Split data according to lead-time and perform the following for each lead time as outlined in Figure 4-1:

1 Compute number of observations N

2 Compute the joint probabilities:

a. $P(S = 0, \hat{S} = 0) = \#\, of\ events\ \{S = 0, \hat{S} = 0\}/N$

b. $P(S > 0, \hat{S} = 0) = \#\, of\ events\ \{S > 0, \hat{S} = 0\}/N$

c. $P(S = 0, \hat{S} > 0) = \#\, of\ events\ \{S = 0, \hat{S} > 0\}/N$

d. $P(S > 0, \hat{S} > 0) = \#\, of\ events\ \{S > 0, \hat{S} > 0\}/N$

2. Compute the conditional probabilities:

a. $P(S = 0|\hat{S} = 0) = P(S = 0, \hat{S} = 0)/P(S = 0, \hat{S} = 0) + P(S > 0, \hat{S} = 0)$

b. $P(S > 0|\hat{S} = 0) = P(S > 0, \hat{S} = 0)/P(S = 0, \hat{S} = 0) + P(S > 0, \hat{S} = 0)$

c. $P(S = 0|\hat{S} > 0) = P(S = 0, \hat{S} > 0)/P(S = 0, \hat{S} > 0) + P(S > 0, \hat{S} > 0)$

d. $P(S > 0|\hat{S} > 0) = P(S > 0, \hat{S} > 0)/P(S = 0, \hat{S} > 0) + P(S > 0, \hat{S} > 0)$

3. Model 1: when $\hat{S} = 0$

The probability conditioned on a zero rainfall forecast:

$$P(S \leq x|\hat{S} = 0) = P(S \leq x|S > 0, \hat{S} = 0)P(S > 0|\hat{S} = 0) + P(S = 0|\hat{S} = 0)$$

Extract data $= \{S > 0|\hat{S} = 0\}$ and estimate marginal probability distribution $P(S \leq x|S > 0, \hat{S} = 0)$

Outputs are parameter estimates of marginal distribution

4. Model 2: when $\hat{S} > 0$

   The probability conditioned on a forecast $\hat{S} = x^*$

   $P(S \le x | \hat{S} = x^*) = P(S \le x | S > 0, \hat{S} = x^*) P(S > 0 | \hat{S} = x^*) + P(S = 0 | \hat{S} = x^*)$

   Consider $P(S = 0 | \hat{S} = x^*)$

   Split data $\{S = 0 | \hat{S} = x^*\}$ into equal intervals and estimate the probability of observing zero, then using the mid-point of the interval and the probability estimate, fit to logistic regression function (as in this study) or any other functional relationship.

   Outputs are parameter estimates of logistic regression

   Then the $P(S > 0 | \hat{S} = x^*) = 1 - P(S = 0 | \hat{S} = x^*)$

   For describing $P(S \le x | S > 0, \hat{S} = x^*)$, extract data $\{S > 0 | \hat{S} = x^*\}$ and transform from original domain to normal domain using Box Cox transformation (as done in this study) or other method.

   Outputs are parameters of transformation

   Then estimate bivariate distribution of transformed data.

   Outputs are parameter estimates of bivariate distribution

Within the frame of error representation using probability distributions, a variety of sampling methods can be employed to produce probabilistic precipitation forecasts for hydraulic simulations. For real-time flood forecasting applications, the factor most commonly influencing the choice of the sampling method relates to the number of simulations required. Therefore the method selected should be sufficiently fast for real-time applications. Thus to generate the probabilistic forecast derived from the establish probability distribution, this study used two sampling methods; the Latin Hypercube (LHS) and the Direct Quantile (DQ) approach. In the LHS approach, the probability distribution is divided into a number of intervals of equal probability and a possible precipitation outcome from each interval is generated given a forecast value. In the DQ approach on the other hand, the precipitation outcome is determined for a given quantile of the probability distribution. The one thing which makes it possible to compare these methods is the assumption of complete temporal dependence between lead times. This means that you pair data from the corresponding interval across each lead time when sampling from the probability distribution functions using the LHS approach. In order for this to be valid, the rainfall and the considered forecast variables must have a monotonic relationship. This means that the quantile of the forecast variable can be computed based on the quantile of forecasted rainfall. For this to be true the urban drainage model should be free from interventions which will control run-off as the intensity increases. In that case there is no need for multiple LHS simulations to estimate the uncertainty.

4.1.1 Application results based on a data rich case: Aarhus

The application of the stochastic model for uncertainty estimation was demonstrated using 1 hour rainfall forecast from a regional scale model in combination with both and 1D and a 1D/2D urban drainage model (***Chapter 10 and 7***) respectively.

The uncertainty model is first estimated using two years of continuous hourly forecast and observed rainfall which originated from a network of 3 rain gauges which had an original temporal resolution of 1 minute. A prerequisite for the development of the model is that the scales of the data pair samples must match. The Thiessen polygon method was used to estimate the catchment rainfall for comparison with the 12 hour hourly NWP product which covered two 6.2x11.1km grids. Then the error conditioned on a rainfall forecast in the form of probability distributions were estimated as a function of lead time using equations (1) and (2).

The results using an ensemble size of 50 suggests that there is not a significant difference between the two approaches in terms of accuracy, but a significant difference in terms of computational time, making the selection obvious for real-time applications. The LHS approach requires a number of simulations (i.e. 1 for each ensemble) while the DQ only requires a simulation for each percentile (Refer to ***Chapter 7*** and ***10***).

4.1.2 Application results based on a data poor case: Saint Lucia

One of the main challenges when using open sourced data is that the temporal and spatial scales are often not sufficient for urban flood application and as such this case involves the generation of high resolution rainfall ensembles based on observed rainfall given the coarse rainfall forecast. In this approach, the forecast is accumulated over a suitable period (12 hours) (see Figure 3-1) because it is expected that there is more skill when considering larger temporal scales.

The stochastic models are developed in the same manner as described before except that there is only 1 lead time because the forecasted value is the accumulation of the 3 hourly 12 hour forecast because it showed more skill based on the verification results.

The method requires that observed rainfall is at timescales of 1-15 minutes or any suitable resolution for the study area. It involves first creating a catalogue of observed rainfall events with same duration as the forecast period, whose accumulated value of each event is above a critical threshold of rainfall depth (i.e. events which can generate floods). For a given accumulated forecast value, which has been bias corrected with uncertainty estimates, rainfall ensembles with time-steps suitable for urban flood modelling derived from the observed data are generated simply by multiplying each event in the catalogue by a suitable factor which is estimated based on the accumulated depth of each event in the catalogue and the accumulated forecast depth for a specific confidence level. This is done to get different patterns of rainfall forecasts each with the same accumulated rainfall depth for the forecast period. The number of ensembles is always limited to the number of events in the catalogue.

Table 4-1 is quite revealing in several ways. First it shows the actual forecasted 12 hour precipitation and the actual observed precipitation for 12 forecasted events and highlights a tendency to over forecast small events and under forecast large events. Secondly it highlights the performance of the stochastic model in estimating the forecasted precipitation with uncertainty estimates. What is revealing in the estimates is that the bias correction becomes quite severe for large events. Consider the 1st event with a rainfall forecast of 71.2mm. It can be seen that the corrected rainfall forecast value with a 95% confidence level is 18.0 mm, and the actual observed is 10.5 mm. But if we consider the 10th event with a rainfall forecast of 103.1mm, the corrected rainfall forecast value with a 95% confidence level is 26.7mm and the actual observed is 96.1mm. The results highlight that in this case, based on the data used to develop the model, the stochastic model always tries to compensate for the overall overestimation and reduce the rainfall for the large forecasts.

Table 4-1: GFS forecasted 12 hour rainfall, estimated forecast with a 95% confidence level and actual observed rainfall all in [mm] for a few selected rain events

	Forecasted [mm]	Estimated 95% confidence	Observed rainfall [mm]
1	71.2	*18.0*	10.5
2	25.6	16.4	12.9
3	52.0	17.6	33.2
4	2.4	9.2	3.3
5	0.8	4.0	8.7
6	44.8	22.5	8.9
7	46.3	17.4	52.3
8	4.2	10.6	0
9	3.8	8.9	3.3
10	103.1	26.7	96.1
11	23.0	19.4	33.2
12	83.1	25.6	0

Figure 4-2 presents the rainfall ensembles generated for the accumulated 12 hour forecast for the 24-Dec-2013 event based on the corrected rainfall forecast, item 10 in Table 4-1. In this case the 2D overland model is run with each rainfall ensemble. The maximum flood map is then extracted for each rainfall ensemble, after which the 95th percentile of the maximum maps are computed and presented (Figure 4-3).

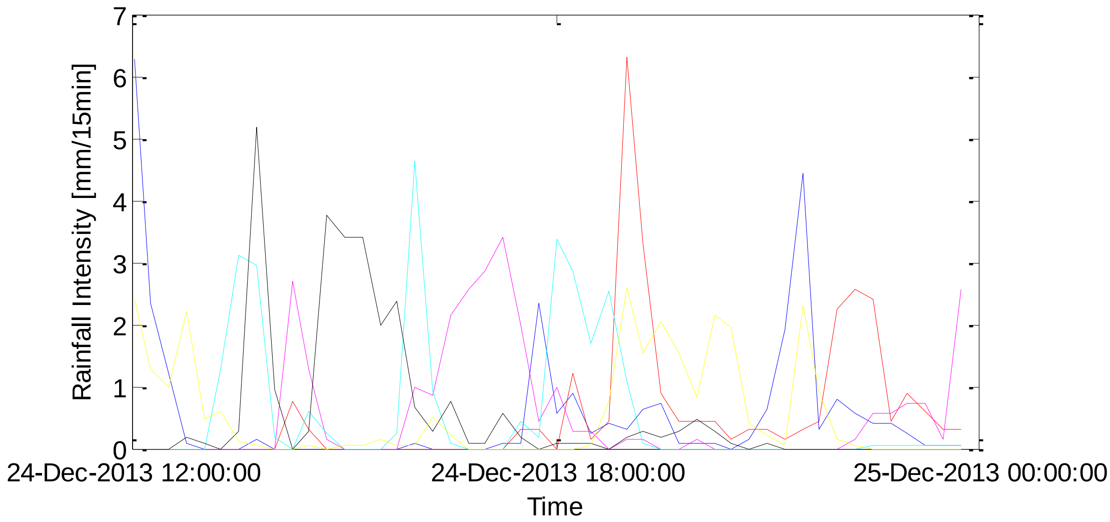

Figure 4-2: 10 Ensembles for the generated for a forecast value from the 95th quantile of the probability distribution

This map was validated by comparing to the maximum depth computed based on the observed rain gauge rainfall. The comparison suggests that in general the maximum flood extents are the same although the maximum flood depths observed are different. When using such coarse forecast and coarse model data, the general idea is to be able to pin point flood locations and extents and not exact flood depths. As such, running the model just gives an indication of flood locations but the flood forecasting approach proposed which relies on rain gauge information provides secondary support if the computational times are too long.

Strong evidence based on the analysis of global forecast data against a single rain gauge suggests that with some work, there is some usefulness in the forecast for urban flood applications. The application of the method for generating the ensembles of rainfall patterns shows great potential, but would require that there is sufficient data to create the catalogue.

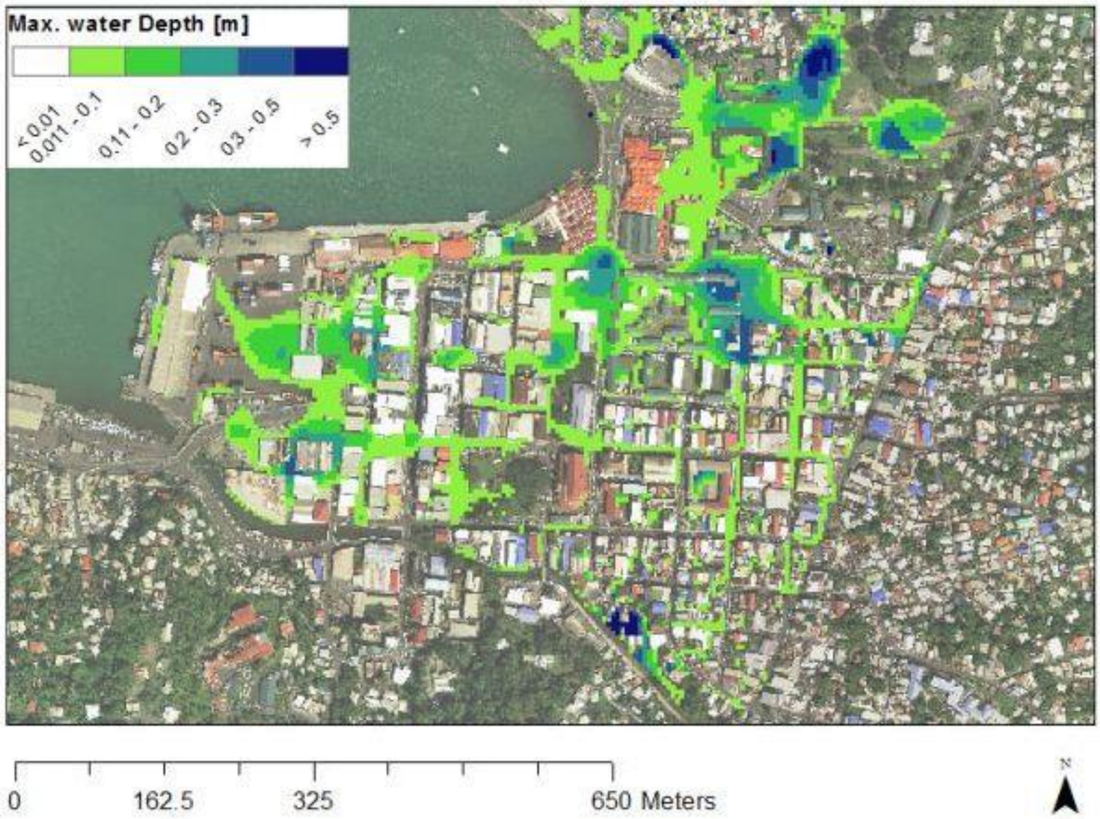

Figure 4-3: Resulting maximum flood map for the test event with a 5% chance that a larger event is observed

5 Conclusions

This thesis has assessed the skill of QPF and QPE from global and regional scale NWP models and weather radar respectively by comparing to rain gauge measurements. This has been done for QPF from a regional scale model and QPE from weather radar for Aarhus Denmark, and for QPF from a global scale model for Castries St. Lucia.

An approach for uncertainty estimation in QPF from NWP has also been introduced in this thesis. This approach has been specifically designed to bias correct and quantify uncertainty in QPF. Moreover, this approach has been integrated within the general flood-forecasting framework to provide probabilistic flood forecasts. The framework has been illustrated using the St. Lucia case study.

In particular, this work has illustrated the applicability of a methodology for estimating the uncertainty in precipitation forecasts from NWP QPF in both a data rich and data sparse case. Moreover, the approach aims to estimate the uncertainty in the precipitation forecast as a function of lead-time in the form of probability distributions estimated from rain gauges as ground reference. It has so far been designed to work for gridded QPF and point observed rainfall, but does not limit its applicability for point-to-point comparisons. The approach has been designed to generate QPF ensembles (LHS approach) or QPF with a probabilistic estimate (DQ approach) assuming complete temporal dependence across lead times. The resulting PQPFs are then used as a forcing in urban drainage models.

In addition, this work has also demonstrated how the approach can be modified to generate the rainfall ensembles in data poor cases such as in St. Lucia. The results from the application show significant potential but the number of ensemble members is limited to the number of events in the catalogue. This is a major limitation, yet recognizing this limitation under some circumstances; a probabilistic rainfall forecast still provides useful information.

With regard to the assessment of the quality of the QPF from weather radar, this work has applied a scale dependent technique which is more commonly used for verifying NWP QPF against radar QPE, to verify radar based QPF against radar based QPE. It is based on giving an indication of something which is close enough instead of an exact match. The FSS gives an indication of the forecast skill based on the forecasted and observed proportions over an area. The results of this comparison showed that there was more skill in forecasting stratiform regimes than convective regimes in the study location.

However, in reality the choice of the verification approach is limited to the available data. Therefore this study also presented verification of grid-to-point data pairs. The QPF data in this case was obtained from a global scale model and resulting observed data from a rain gauge which was installed during this study. The verification of this data was limited to traditional verification scores such as NRME. The results showed that there is more skill when considering rainfall accumulations over coarser temporal scales. These findings are consistent with expected performance of global scale data which has to do with scientific limitations of NWP forecasting on the global scale.

Another finding relating to verification of forecasted and observed precipitation is that it is important to select a suitable method to assess the relationship. The selection of the approach is determined by the objective of the verification. For example in the case of verification of high resolution radar forecast, a method which will not penalize because of small errors in displacements is paramount.

Another key contribution of this study is the demonstration of the application of images extracted from social media sites for model calibration and validation. A major limitation is that the extracted images and limited meta-data are generally in a format which is not efficient for use and an arguable weakness is the inaccessibility in real-time.

The assessment of data availability on a worldwide scale has extended our knowledge of the current state on urban flood management. This in turn provides some inspiration to apply similar approaches in our areas. Despite its exploratory nature this study provides some important insights of how to methodically design the different elements of a probabilistic real-time urban flood forecasting system.

5.1 Future directions and implications

This research has not only pioneered an operational real-time urban flood forecasting system based on QPF from global scale NWP model but also provided the uncertainty bounds using the forecasted rainfall as the source of uncertainty. The results are important to demonstrate and to encourage other urban flood practitioners, especially in developing countries where data is limited, to use flood forecasting as a non-structural approach to flood risk management.

This work has initiated the establishment of a data collection and recording of forecasted rainfall as well as observed rainfall in real-time in Castries Saint Lucia. This in turn facilitates the established framework for uncertainty estimation in the rainfall forecast. The uncertainty model applied in this work does not account for the temporal correlation structure in forecast lead times. More research is required to determine the efficacy of applying such temporal correlation structures in conjunction with the developed stochastic model.

The scientific literature on flood forecasting over the last decade and a half or so is replete with references that point to the inevitably deterministic nature of the prevailing forecast and admits to its intrinsic limitations. Clearly, probabilistic approaches are much more desirable. If, as it appears the principle constraints to the development and use have been a challenging complexity of the statistical computations and availability of QPF, perhaps now is the time to seize the moment.

A concrete extension of this work is to apply the stochastic model to the precipitation from weather radar, since the intention is to make probabilistic flood forecasts. However, this is not a straightforward process mainly because of the uncertainty cascade in the radar QPE to radar QPF, which is not limited to the limitations in the forecast method and errors in radar estimates. As a first step, it is essential to decide at which point in the radar precipitation nowcasting sequence the uncertainty estimation should be applied and propagated.

Moreover, the system established in Castries Saint Lucia may well be transferrable to other parts of Saint Lucia, to other Islands in the Caribbean, Asia and to other developing nations. Although the development of a real-time flood forecasting system may require specific skills, this study has proposed a viable option which may very well become the most important outcome of this research. Because most developing countries face similar economic and technical constraints, conceivably, Saint Lucia could become a pilot case study area as it now is, for the benefit of other countries.

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6 Assessing the potential for real-time urban flood forecasting based on a worldwide survey on data availability

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This paper explores the potential for real-time urban flood forecasting based on literature and the results from an online worldwide survey with 176 participants. The survey investigated the use of data in urban flood management as well as the perceived challenges in data acquisition and its principal constraints in urban flood modelling. It was originally assumed that the lack of real-time urban flood forecasting systems is related to the lack of relevant data. Contrary to this assumption, the study found that a significant number of the participants have used some kind of data and that a possible explanation for so few cases is that urban flood managers or modellers (practitioners) *may* not be aware they have the means to make a pluvial flood forecast. This paper highlights that urban flood practitioners can make a flood forecast with the resources currently available.

Keywords: Data availability, modelling, pluvial flooding, real-time urban flood forecasting, urban flood modelling

6.1 Introduction

One of the most significant current discussions in urban flood management is the need for and use of real-time flood forecasting. Researchers have continued to show an increased interest in the performance of urban drainage systems because flood problems will undoubtedly worsen in some parts of the world due to climate change (Willems et al., 2012, E E A, 2012). This is of particular importance because unmodified urban drainage systems will not be able to maintain the same level of flood protection, therefore emphasising the need for effective flood forecasting.

During the last few years, developments in surface flow modelling, and the means of data transfer in real-time in a stable and consistent way, have facilitated realistic research on real-time flood forecasting as a means of mitigating flood impacts. However, a major problem in real-time urban flood forecasting is the lack of practical experience in building such systems. Currently there are very few operational cases and published material on real time urban flood forecasting systems (Henonin et al., 2013, Mark et al., 2002, Raymond et al., 2006, Montero et al., 2010) and so potential flood modellers may be unaware of recent progress and the potential of such systems.

One major issue that has dominated the field for many years concerns the computational time required for hydraulic simulations. Despite advances in computing software and hardware, high-resolution modelling still remains a challenge and most people resort to simplified approaches which affect the accuracy of the results. This has been challenged before in the hybrid modelling approach that couples a 1D surface model in areas which are less flood-prone and a 2D surface model in more flood prone areas to the 1D buried drainage network (Simões et al., 2011b); and more recently by Chen et al. (2012b) in a study demonstrating a multi-layered approach to 2D modelling that can improve the accuracy of a coarse grid model while also shortening the computational time.

Flood forecasting is an important component of flood warning. Flood forecasting involves predictions of water levels and flows at particular locations at a particular time, while flood warning is the task of making use of the flood forecasts to make decisions on whether flood warnings should be issued to the general public. Typically it is the role of the flood modeller or manager to pass on information to the appropriate authorities, which then has the responsible to warn the general public or properties of the impending flood risk (Werner et al., 2005).

So far there has been little research about the potential for real-time urban flood forecasting based on current available resources. This paper describes the work undertaken in order to assess the potential for real-time urban flood forecasting and will attempt to show that flood practitioners can make the simplest of urban flood forecasts based on even the sparsest of data. The main questions addressed in this paper are: a) how widespread is the use of specific data amongst urban water professionals, b) what are some of their perceived challenges, and c) how do they perceive data availability?

The section 6.2 of the paper will give a brief review of real-time urban flood forecasting and modelling. Section 6.3 will present how the study was carried out and this is followed by the results in section 6.4. The following section (section 6.5) presents a discussion of the results and this is followed by concluding remarks in section 6.6.

Throughout the paper, the following terms will be used to refer to:

1) Quantitative Precipitation Forecasts (QPF) – expected amount of precipitation over a specified period of time and specified area. The forecasts can be made through weather radar and weather forecast models or a combination of both.

2) Numerical Weather Prediction (NWP) forecasts – quantitative precipitation estimates over a specified period of time and specified area provided by numerical weather prediction models (weather forecast models).

3) Operational data – data that supports the control of flow in the drainage network. This includes but is not limited to pump discharge and location, gate locations etc.

6.2 Real-time urban flood forecasting and modelling

The first and perhaps most important thing in forecasting in general is that there must be a need for it. Despite the fact that real-time flood forecasting systems are relatively widespread based on the features involved, they can be classified into three general categories. That is the empirical, pre-simulated and real-time simulation approach. On the former hydrodynamic models are not used, instead it is based on historical account on past events. However the other two approaches makes use of hydrodynamic simulations which are characterised by dimensionality. This section will elaborate on the modelling approaches that can be possibly applied, its selection and application as it relates to data availability as well as the flood forecasting systems categories. This section will also emphasise on uncertainty in flood forecasting.

6.2.1 Modelling approaches for simulating floods in urban areas

In urban flood modelling, hydrological processes are commonly separated conceptually from the hydraulics of the drainage system. Two types of models are therefore required: (i) a hydrological model which simulates surface runoff, and (ii) a hydrodynamic model which simulates the flows in pipes, streets and storage of water on the surface. Runoff generated from rain generally starts as overland flow before entering the underground pipe system through manholes or catch-pits/gullies. Runoff computations can be carried out by a standard surface runoff model, e.g. time-area, kinematic wave, linear reservoir and rational method

(Price and Vojinović, 2011). Surface runoff is typically computed for each sub-catchment and the resulting hydrograph is used as the input into the hydrodynamic model (Mark et al., 2004).

The hydrodynamic representation of flow is usually characterised by dimensionality: (i) a one-dimensional (1D) model such as a sewer (drainage) and/or surface channel model, or (ii) a two-dimensional (2D) model such as a surface flow model. Alternatively, a combination of approaches may be used known as coupled modelling (Djordjević et al., 1999, Simões et al., 2011b).

Typically, the choice of modelling approach depends on the overall purpose of the model and ultimately the desired accuracy. However, in practice the choice depends most importantly on the available data, as data is the limiting factor in the ability to apply accurate models. 1D modelling relies heavily on geometrical data whereas 2D modelling relies heavily on terrain/Lidar data. Coupled approaches will inevitability rely on both data types.

6.2.2 Real-time flood forecasting approaches

According to Henonin et al, (2013) real-time flood forecasting can be classified into three main categories: (i) empirical scenarios, (ii) pre-simulated scenarios, and (iii) real-time simulations.

The *empirical scenario approach* relies on experience and observations of the past. This approach uses knowledge of previous flood events (e.g. accumulated rainfall in one hour, water levels) and establishes threshold levels based on historical accounts. Once these thresholds are exceeded a warning is issued. In the *pre-simulated scenario approach* a scenario catalogue is created covering a range of flood events. As the name suggests, this approach requires some form of hydrological and hydrodynamic simulation. The modelling approach is based on data availability and a library of scenarios is created and stored. In general, this approach uses information about the given rainfall forecast along with a set of rules for selecting the probable scenario. This can be done manually or by an automated system, and based on the results of the selected scenario, a warning is issued. In the *real-time simulation approach,* hydrodynamic simulations are performed in real-time and their results are disseminated to responsible authorities and/or to the public through web services or as a SMS-message on mobile phones. The calibrated hydrological and hydrodynamic simulation model is fed with rainfall information in real-time and the simulations are performed and flood locations are identified. Areas or facilities with greater risk are usually identified in pre-studies and once the water level exceeds a certain threshold (e.g. stair/curb level at train station) at that facility a warning is issued.

Timeliness is paramount for flood forecasting and for that reason flood forecasting systems should be computationally fast. Real-time urban flood forecasting has been progressing in a direction aimed at utilizing physical information about the urban catchment, which strongly affects the computational time required for running simulations. However, the use of physical information is not only important for hydrologic and hydrodynamic computations but from the end user perspective is ideal for visualising the actual flood location.

The absence of a physically-based hydrodynamic model for the empirical scenario approach means that although computational time is not an issue, visualising the actual flood location is not possible. In addition, care should be taken when using this approach when there are significant physical changes in the urban environment (e.g. urbanization). Nevertheless, this approach is suitable for identifying problem areas and in a situation when data and models are limited, it provides an opportunity to make the simplest of “what if” flood forecasts.

Although the pre-simulated approach considers the physical characterises of the urban environment and the computational time may not be an issue because computations have already been performed, and just like the empirical approach, changes in the urban environment pose a continual challenge to urban flood modellers. This approach therefore requires continuous maintenance and updating of the catalogue involving hydrodynamic simulations with recent information about the urban topography which covers a wide range of events.

There are several things to consider for the real-time simulation approach and these include: computational time which depends on the modelling approach, size of the computational grid, and the size of the model area; response time of the catchment; rainfall forecast data source and its lead-time, and real-time model updating for improving the accuracy of the forecast (data assimilation).

However, the benefit of the real-time simulation approach is the advantage to provide a more accurate forecast, regardless of the modelling approach, since the model and the data represent the current state of the system. Rainfall, water levels, and flow rates are key inputs for running the hydrodynamic models. During the rain event, information about these variables is the key point for the success of the flood warning (Beven, 2009).

Each approach has it strength and weaknesses, but it is important to update the catalogue for the success of the approaches.

6.2.3 The choice of a particular approach

The most accurate way to forecast the future is by using a lot of information. Very often, much focus is on making the most accurate forecast; while in some instances (e.g. where data is sparse) it makes sense to consider making a forecast and accepting that there is an inherent uncertainty associated with the forecast. In many respects, the issue we need to address in flood forecasting is recognising and accepting that it is always uncertain, but provides valuable information to end users such as decision makers, planners, public etc.

Typically the choice of a particular flood forecasting approach is based on the desired accuracy, forecast horizon, degree of complexity required, cost of producing the forecast, technological capacity and finally the available data. Each approach for flood forecasting has its advantages and disadvantages, but data constraints, technological capacity and the desired level of accuracy will ultimately determine the approach that can be implemented. While more effort in flood forecasting may cause increased cost due to data collection and analysis, less forecasting activity may result in increased damages and possibly loss of revenue depending on the severity of the flood event. Therefore, a balanced should be maintained in the flood forecasting effort and the desired forecast accuracy, or in other words, the tolerable level of uncertainty.

The roles that each data type plays based on the classification scheme presented in Henonin et al, (2013) as well as what role that different modelling approaches play in each scheme are summarized in Table 6-1.

Table 6-1: Role of different data type in each real-time flood-forecasting scheme

	Compone	Empirical scenario	Pre-simulated	Real-time
Historical Data	Rain gauge	Used to set threshold level	Input for development of the scenario catalogue	Used for model building (e.g. model calibration)
	Network	-	Flow conveyance in sewer and storm water systems	Flow conveyance in sewer and storm water systems
	Water levels and flow rates	Used to set threshold level	Used for model calibration and validation	Used for model calibration and validation (offline)
	Terrain	-	Flow conveyance for 2D overland model	Flow conveyance for 2D overland model
	Land Use	-	Used in model development	Used in model development
	Operational Data	-	Used in model development	Used in model development
	Radar	Used to set threshold level	input for development of the scenario catalogue	Used for model building
Real-time Data	QPF (NWP and radar)	Used for scenario selection when threshold level is exceed	Used for scenario selection	Used as input for online hydraulic simulations
	Rain gauge	Used for scenario selection when threshold level is exceed	Used for scenario selection	Input
	Flow rates	Used for scenario selection when threshold level is exceed	Used for scenario selection	May be used in data assimilation for model updating
	Water levels	Used for scenario selection when threshold level is exceed	Used for scenario selection	May be used in data assimilation for model updating
Models	1D, 2D, 1D/1D, 1D/2D, 1D/1D-2D	-	Used for hydraulic simulations for creating scenario catalogue	Used for performing computations online (in real-time)

6.3 Methodology

6.3.1 Survey Development

A literature review was carried out to ascertain the current state of real-time pluvial flood forecasting for urban areas. The study revealed that presently there are very few published cases and that in order to accurately forecast floods in urban areas, data of high spatial and temporal resolution is required (Schilling, 1991, Mark et al., 2004, Berne et al., 2004). It was assumed that there are very few cases because of the lack of relevant data for urban flood management; herein referred to as data of suitable resolution and length for fulfilling the objective. For a better understanding of the issues that dominate the field of urban flood management, a survey was designed to determine the existence of data for urban flood management and the perceived challenges and constraints in data acquisition, to evaluate the prospects for real-time flood forecasting.

The questions from the survey were focused on evaluating the resolutions, sources and applications of the relevant data for urban flood management. The accessibility of data in real-time was also addressed. Some questions were related to the limitations of the available data as well as how practitioners perceived data availability. Background characteristics, such as nationality, profession, years of experience as well as type of organisation were collected.

The research design of this study was descriptive and inferential as it aimed to explore relationships for assessing the potential for urban flood modelling and management based on the quality, quantity and accessibility of data. The survey contained 20 closed ended questions each with sub-questions and 1 open ended question. Most of the closed ended questions were multiple response questions. The data was captured using the Bristol Online Survey system (René).

6.3.2 Participants

A frequent impediment for conducting large scale internet based surveys is the lack of a registry for specific populations. However, globally urban flood practitioners exist in very small numbers and fortunately for this study a few mailing lists (e-mail address) are available which makes it possible to permit generalization. To achieve this, convenience samples were obtained from two representative target groups which were invited to participate.

- *Scientific community:* Urban drainage mailing list (IWA, 2012) as well as participants who submitted an abstract to the 9th Urban Drainage Modelling Conference (UDM) held in Belgrade in 2012 (University of Begrade, 2012).
- *Consulting community:* DHI's MikeUrban client mailing list. Although it only covers one product it is representative for this community

A pre-survey was sent to a representative sample of 30 urban flood practitioners to see if they understood and responded well to the format of the questions. The test sample included participants from both the scientific and consulting community. The improved survey was then sent to approximately 250 urban flood professionals. Participants were also asked to share the survey with whom they may have found it relevant. The survey was also publicized on various social media sites (e.g. LinkedIn) and was open to anyone with an interest in the area.

6.3.3 Data analysis

Data analysis was performed using a statistical analysis package known as PASW (Premier Analytical Software) Statistics (IBM, 2010). Since most of the questions were multiple responses, a multiple response frequency procedure was adopted. This is demonstrated in **Error! Reference source not found.** with the total percentage under organisations being more than 100, due to overlapping between the categories of organizations that were selected.

6.4 Results

There was a huge spread in the demographics of the data collected. There were 176 completed responses and the characteristics of the participants are presented in Table 6-2. The response rate for the survey was 70.4%.

Table 6-2: Background characteristics of participants

Profession	%	Organisation	%	Experience	%
Hydraulic Engineer	28.4	Governmental	17.0	< 1 year	4.0
Hydrologist	12.5	Private	31.8	1-4 years	29.0
Civil Engineer	35.2	University	44.3	5-10 years	25.6
Environmental	2.8	Research	22.7	> 10 years	40.9
Researcher	1.7	Other	2.3		
GIS/Remote	2.8				
Hydroinformatician	6.8				
Other	9.7				
Total	100%		118.2%		100%

6.4.1 What are their experiences with data?

Of the 176 participants who completed the questionnaire, the majority (90.9%) indicated they have used rainfall data from rain gauges with a minority (39.8%) having used radar data (Figure 6-1). More than 1/3 of the participants have used terrain, land use, water and flow rates, drainage network and rain gauge data. Fewer persons have used operational data (50.0%) and QPF (49.4%).

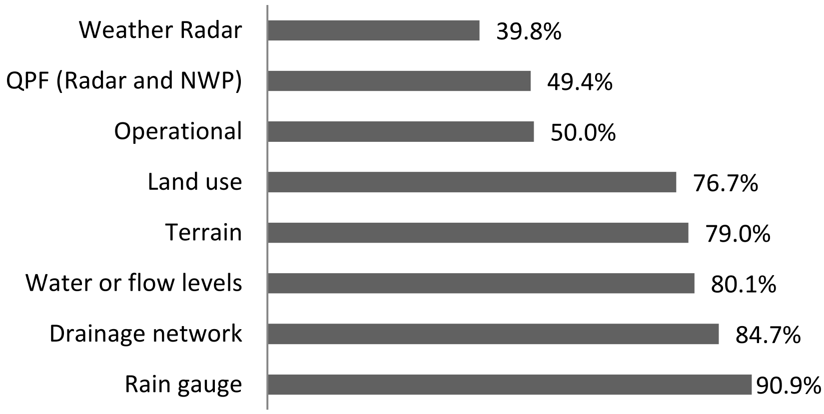


Figure 6-1: Percentage of participants who have used the relevant data

6.4.2 Real-time data access

Concerning real-time data access, less than half of the participants have access to data in real-time except for rainfall data with 61.4% (Figure 6-2).

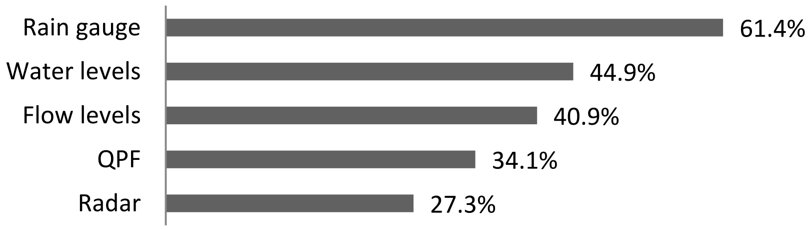
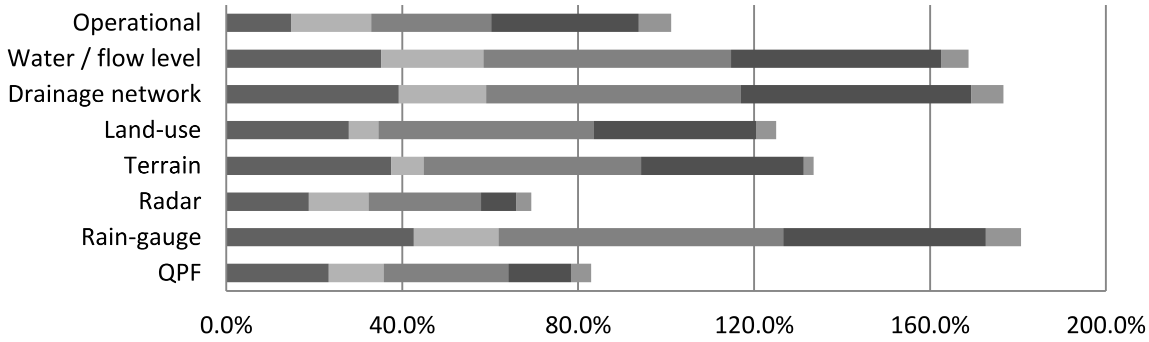


Figure 6-2: Percentage of participants with real-time data access

6.4.3 What are people actually doing with the data?

The majority of the participants used the data for research (Figure 6-3). Most are using rain gauge data in general when compared to the other data types. However, considering flood forecasting, more participants are using rain gauge data (42.6%) as well as drainage network data (39.2%), flow or water levels data (35.2%) and terrain data (37.5%).



	QPF	Rain-gauge	Radar	Terrain	Land-use	Drainage network	Water / flow level	Operational
Flood forecasting	23.3%	42.6%	18.8%	37.5%	27.8%	39.2%	35.2%	14.8%
Real-time control	12.5%	19.3%	13.6%	7.4%	6.8%	19.9%	23.3%	18.2%
Research	28.4%	64.8%	25.6%	49.4%	48.9%	58.0%	56.3%	27.3%
Design	14.2%	46.0%	8.0%	36.9%	36.9%	52.3%	47.7%	33.5%
Other	4.5%	8.0%	3.4%	2.3%	4.5%	7.4%	6.3%	7.4%

Figure 6-3: Data applications

An even smaller percentage of the participants are using the data for real-time control. Real-time control was presented as an option because it gives an indication of the percentage of participants who have the infrastructure for real-time data access (e.g. SCADA).

When asked about software, 68.8% of the participants are using some kind of modelling software with the majority of those participants using commercial packages (72.7%). Fewer of those 121 participants (30.6%, 31.4% and 32.2%) are using university owned, open source or in house packages respectively.

6.4.4 What are their perceptions on data availability?

A little more than half of the participants (59.1%) felt they had difficulty getting data while the remaining 40.9% did not have any difficulty acquiring data. Their reasons for each case are highlighted in Table 6-3 and Table 6-4:

Table 6-3: Percentage of participants with different perceptions on why they had no difficulty in obtaining data

Reasons for not having difficulty in obtaining data	%
Client provided or paid for data collection	23.3
Data was available at the office	21.6
I had access to technology that enabled easy transfer	15.3
I knew someone who could have obtained the data for me	10.8
I knew someone at the office where the data was available	7.4

Table 6-4: Percentage of participants with different perceptions on why they had difficulty in obtaining data

Reasons for having difficulty in obtaining data	%
Not been measured in the first place	43.8
Measured but considered not to be reliable enough for exchange	22.7
Measured but collecting organization policy is to keep data confidential	21.0
Measured but there are legal restrictions including intellectual property rights	21.0
Measured but not in a format that enables exchange	14.2
Measured but is prohibitively expensive	14.2
Measured but too expensive to download	13.6
Measured but perceived not to be important to others	11.9
Measured and are suitable for exchange and the technology exists but lack of capacity to implement it	5.1
Measured and are suitable for exchange and the technology exists but is not reliable	5.1
Measured and are suitable for exchange but the technology for transfer does not exist	3.4

6.4.5 Perceived challenges in urban flood modelling

The perceived challenges in urban flood modelling were obtained by categorizing the participants responses based on the themes that emerged from the survey. The key themes were summarized and the top 10 challenges collated and presented in decreasing order.

(1) Cost of data acquisition

(2) Limited ability to calibrate and validate models

(3) Copyright bureaucracy

(4) Data Resolution

(5) Limited information on assets (e.g. location and geometry of pipes and drains, weirs, pumps sizes etc.)

(6) Dealing with uncertainty in historical data

(7) Inability to implement statistical models due to short time series

(8) Unavailability of data in real-time

(9) Urban topography is constantly changing

(10) Lack of urban flood forecasting cases published in the literature

6.5 Discussion

Contrary to expectations, this study found that over half of the participants *had* used all the different data types except for weather radar which only 39.8% had used (Figure 6-1), and more than 2/3 (68.8%) are using some kind of modelling software. The observed difference in the use of weather radar compared to rain gauge data is not surprising because the application of weather radar in urban hydrology may still not be so common for reasons stated in Einfalt et al, (2004).

Another important finding was that less than half of the participants have real time data access except for rain gauge data with a frequency of 61.4% (Figure 6-2). One anticipated finding in terms of real time data access was that there would not be many participants with access to weather radar data and numerical weather prediction forecast in real-time merely because very few are currently using it and it is only recently used in urban flood modelling (Liguori et al., 2012). Comparing the frequency of real-time access of water levels and flow rates data to that of rain gauge data (Figure 6-2), the results suggests that it seems a lot easier to get real-time access to rain gauge data than flow rates and water level data.

The most interesting finding was that most participants are using the data for research followed by flood forecasting (Figure 6-3) although it is less than half in both cases. This result *may* be explained by the fact that most of the respondents were from universities (Table 6-2). Other possible reasons why the respondents are not using the data for flood forecasting *may* include:

- Lack of interest in issuing a real-time urban flood forecast – However, the increase in the frequency of flooding in some areas (E E A, 2012) and the added urgency to address urban flooding (CORFU, 2012)) does not confirm a lack of interest as an explanation.
- Lack of awareness that a real-time urban flood forecast can actually be issued – Real-time urban flood forecasting is not trivial; if more work is published in scientific journals which can be used as reference and motivation, perhaps there would be more cases.
- Ongoing doubts about the quality and quantity of the data for urban flood modelling – Strong evidence is provided in the results under section 6.4.4 as one of the main challenges in urban flood management. Findings on data resolution suggest that only a small percentage of the participants who have used the different types of data have used data of fine resolution, for example: 25% of the participants used terrain data of resolution less

than 2.0m, 13.1% used rainfall data from rain gauge of 1 minute resolution: 3.4% of the participants used radar data with grid cell coverage of 100m etc. The percentage with fine resolution data is much less than the percentage doing flood forecasting, therefore suggesting that fine resolution data is not necessary in all cases, it depends ultimately on the desired level of accuracy.

Let us first explore how many of the participants can actually make a flood forecast based on the empirical approach. It is not straightforward to say that, since 61.4% indicated they have used real-time access to rainfall information from a rain gauge (Figure 6-2), then 61.4% should potentially be able to make an urban flood forecast based on the empirical scenario. Similarly it cannot be said that the percent having access to radar data (27.3%) (Figure 6-2) in real-time should potentially be able to make a forecast based on any of the approaches. In fact there are several factors which would influence the type of forecast that can be issued.

The main difficulty in using rain-gauge information is that it provides information about the past. The location of the rain gauge relative to the catchment as well as the size of the catchment will determine if it is possible to issue a real-time flood forecast based on rain gauge information. In general, if the response time from the time the information is received (lead-time) is less than the time of concentration of the catchment (runoff time), then the reliance on rain gauge information would be obsolete. Therefore, in order to say how many can issue a forecast based on the empirical approach, topological information which would give an indication of time of concentration as well as the size of the catchment is required. Other information such as location of rain gauge, as well as a historical records of past flood events in the form of reports, witness accounts of the events etc. would be required.

It would be much too optimistic to think that the use of QPF either from radar or NWP model would increase the number of cases who do flood forecasting using QPF; considering that the mere purpose would be to extend the lead-time. The high level of uncertainty which is usually associated with QPF is the reason why its use is not so widespread (René et al., 2013c, Anagnostou et al., 1999).

The choice between weather radar and NWP forecasts depends on the desired level of accuracy and the desired forecast horizon. Weather radar provides high quality precipitation forecasts (nowcasts) for a lead time of a couple of hours, but if a longer lead-time is desired, other sources of information are required, such as NWP forecasts (Lin et al., 2004). NWP models will also provide data for short lead-times but the quality is not the same as radar nowcasts. The data needs to be evaluated to see if it is fit for purpose.

Aside from radar, the World Wide Web is a substantial source of information. Everyone who has access to the internet can potentially get access to QPF for instance from NWP (www.yr.no) . Although NWP forecasts has its limitations (Best, 2005), it is still a valuable source. Based on this assumption, urban flood practitioners can make a flood forecast based on the empirical scenario regardless of the catchment size, location of rain gauge etc. However there is always a tradeoff between the accepted accuracy and damage reduction cost, but this source provides the best possible information about the future when other more reliable rainfall sources are not available. Generally, most online sources of any kind of information are a rough approximation. More refined data usually costs a lot of money to produce and compile.

Having access to more information introduces some sophistication in urban flood forecasting. Rather than a simple forecast based on rainfall forecast and information of historical events (empirical scenario) another potential means of urban flood forecasting would involve running simple or extremely detailed computationally intensive simulations which is currently within the grasp of the urban flood practitioners. The simplest of models would be a 1D or 2D model. 1D modelling has been the conventional approach to urban flood modelling particularly because pipe systems were designed for the collection and disposal of storm and waste water in urban environments. More recently, because of urban growth and climate change and thus the increased frequency of floods in some places, the urban surface is now considered to have a dual purpose, one of which is to channel water out of the urban area. For that reason, using a 2D terrain model in an urban environment is appropriate for urban flood modeling (Gourbesville, 2009).

Recent advances in the ability to obtain low cost terrain data can account for why 79.0% of the participants have access to terrain data. Despite this access, only 47.1% (which is 37.5% of the participants) are using it for flood forecasting (Figure 6-3). The most probable explanations as to why so few are using terrain data for flood forecasting *may* be because they are probably not interested in making a flood forecasts or they *are* not sure how to handle the storage or the carrying capacity of the pipe system. In the latter case, if the design capacity of the urban drainage system is known in equivalent rainfall, the closest approximation would be to subtract it from the rainfall input for the event being modelled. In effect, the pipe system is seen as storage and its rainfall equivalent to its storage capacity that is removed prior to running the simulation of the event. In that way, the carrying capacity of the drainage system is almost accounted for. This approach is an approximation but is useful when additional information about the pipe system is not known.

6.5.1 Perceptions

Some other issues emerging from this finding relating specifically to data quality and quantity are based on an understanding of the experiences and perceptions of those who took part in the survey. One unanticipated finding was that a significant percentage (40.9%) of the participants did not have difficulty getting data with the majority (Table 6-3) saying it was because a client paid or provided the data or the data was available at the office. It is not surprising that the majority who did not have problems got the data from their office or were provided or paid by the client. It is interesting to note that in real life implementations, data are considered to be a necessity and the cost for data acquisition is usually small compared to the consultancy and construction costs.

There are also several possible reasons why 59.1% had difficulty finding data (Table 6-4). As can be seen from the table, the most common (43.8%) reason is that the data has not been measured in the first place. Adding to the problem is the increasing evidence (Table 6-4) that in some instances the data is measured but is not easily available. This is not limited to the cost of purchasing the data, technological incapacity, organizational policies, reliability etc. These are common problems which demands more focus to mitigate risks in urban environments.

The principal constraints for urban flood modelling and management as perceived by the participants are the cost for data acquisition, limited ability to calibrate and validate models, copyright bureaucracy and so on (Refer to Section 6.4.4). All hydrological and hydrodynamic applications require data, and acquiring (measuring) data in some instances can be prohibitive. For research, the cost of data is generally perceived to be high, but as previously mentioned cost for data acquisition is usually not an issue in real life implementations. As a result, data procurement should not be assessed in isolation but rather relative to the damage reduction costs.

Model calibration and validation has been the most important modelling issue for some time (Beven, 2009, Refsgaard et al., 2005) and the importance of tying this to real-time urban flood forecasting continues to challenge many urban flood practitioners. The credibility of the predictive skill of the model ultimately depends on rigorous model calibration and validation when datasets are available. Otherwise, a sensitivity analysis on the impact of flood from impervious area and roughness is required. This is essential to reduce uncertainty and to increase the user confidence in the predictive ability of the model, which makes the application of the model more effective.

It has been argued by Refsgaard et al, (2005) that although limitations in data may affect the reliability of the model, it is not the main reason for poor modelling results. They argued that the inadequate use of guidelines and quality assurance procedures and improper interaction between the client and the modeller is the dominant reason for poor results, therefore suggesting that there is potential in the resources at our disposal.

Data resolution has an effect on the predictability of the model. Generally, finer resolution data better represents the reality and is usually considered much better. However, it is not necessarily the case as it all depends on how precise the results from the computational procedures should be. Fine resolution data have their own constraints and may not necessarily be ideal for all applications. Coarser resolution data can be used in some instances and may be considered fit for the purpose. On the other hand, most research applications (such as climate change impact studies) would require finer resolution data since it is important to determine the impact, particularly because it may have huge implications.

Another challenge which has been an issue for some time is the subject of uncertainty (Beven, 2009, Pappenberger and Beven, 2006). Uncertainty in data has been the main limitation to the development of accurate flood modelling, in particular, land use data, sewer system data and DEM (Djordjević et al., 2013) and accuracy in historical rainfall records, especially when modelling floods for long return periods. As emphasised by one of the respondents, "*Statistically you need over 100 years of flow data to derive 100 year flows with high confidence*". It is of course correct the more data the smaller the uncertainty of estimation of extreme events. However, use of statistical models allows quantification of the uncertainty related to the available sample (sampling uncertainty), which is important for the decision making. It is also important to consider not only the uncertainties in the input datasets but also the uncertainties in flood forecasting per se (outputs).

In order to get access to data in real-time, the data must be available through high speed devices. However, it is not so difficult to get access to data in real-time because of ease of access of internet connections in areas of interest for data collection. While this may have been a problem on the river basin scale, in an urban setting internet connection should not be an issue, even in the most remote settings. Nevertheless, at the river basin scale progress has been made in the collection of real-time data from remote hydrological monitoring stations (Keoduangsine and Goodwin, 2012).Existence of real-time information systems is more of a problem than internet access which is paramount for real-time data access.

The only phenomenon that presents a challenge to urban flood managers is that of urbanization. Urbanization results in demographic changes which bring about unprecedented changes in land use which constantly needs updating. The constant change means that models should be constantly updated which results in significant cost.

Despite all the challenges and constraints outlined by the participants in the survey that are discussed above, the authors have identified what they believe are the main barriers that affect the ability to issue an urban flood forecast and these are summarised in Table 6-5.

Table 6-5: Challenges that may hinder the use of forecasting systems

Approach	Challenge
Empirical scenario	• Lack of information on past flood events (no observations) • Urbanization which may affect flood locations • Uncertainty in rainfall input
Pre-simulated scenario	• The rules for scenario selection are not adequate • Catalogue does not contain a wide range for scenario selection • Model calibration and validation • Uncertainty in rainfall input • Real-time data access
Real-time simulation scenario	• Model calibration and validation • Uncertainty in rainfall input • Lack of data, technology and human resources • Real-time data access

6.6 Conclusions

This paper has given an account of the possible reasons why real-time urban flood forecasting systems are not so widespread, based on a world-wide survey. In this investigation, the aim was to assess the potential for real-time urban flood forecasting based on specific data for urban flood management currently at our disposal.

The study has shown that data for urban flood management is more widespread than is generally perceived. Only 59.1% of the 176 participants have actually had difficulty acquiring data. It was also shown that most participants were actually using the data for research followed by flood forecasting. Although it was only a small percentage, the most interesting comment from some participants is that they see the lack of published cases as a challenge in urban flood forecasting. These finding suggests that, although not confirmed, urban flood practitioners may not know that they can make a very simple forecast, though with increased uncertainty based only on rainfall forecast and information of past flood events when software and models and finer resolution data are not available. The conclusion is drawn from the fact that generally people tend to get motivated when practical examples of cases to associate to are available, which usually appear in publications.

The evidence from the study suggests that there *may* be more cases as urban flood practitioners become more aware of what *can* be done. In conclusion, the present study provides a state-of-the –art view of current real time flood forecasting, highlights the perceived challenges, and most importantly indicates what the authors believe to be the real challenges that hinder the progress of real-time urban flood forecasting.

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7 A methodology for probabilistic real-time forecasting: an urban case study

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The phenomenon of urban flooding due to rainfall exceeding the design capacity of drainage systems is a global problem and can have significant economic and social consequences. The complex nature of quantitative precipitation forecasts (QPFs) from numerical weather prediction (NWP) models has facilitated a need to model and manage uncertainty. This paper presents a probabilistic approach for modelling uncertainty from single-valued QPFs at different forecast lead times. The uncertainty models in the form of probability distributions of rainfall forecasts combined with a sewer model is an important advancement in real-time forecasting at the urban scale. The methodological approach utilized in this Chapter 6nvolves a retrospective comparison between historical forecasted rainfall from a NWP model and observed rainfall from rain gauges from which conditional probability distributions of rainfall forecasts are derived. Two different sampling methods, respectively, a direct rainfall quantile approach and the Latin hypercube sampling based method were used to determine the uncertainty in forecasted variables (water level, volume) for a test urban area, the city of Aarhus. The results show the potential for applying probabilistic rainfall forecasts and their subsequent use in urban drainage forecasting for estimation of prediction uncertainty.

Keywords: forecasted rainfall, numerical weather prediction model, observed rainfall, real-time forecast, sewer model, uncertainty in rainfall forecast

7.1 Introduction

Real-time flood forecasting systems at the basin scale are operational in many parts of the world (Parker & Fordham 1996; Todini *et al*. 2005, and references therein) and most of them rely on hydrometeorological models to develop the flood forecast. These systems are established to issue warnings to flood plain residents and other authorities before a critical threshold is exceeded, thus allowing time to mitigate the consequences.

Globally there is a well-recognized need for improved techniques and approaches to flood forecasting (Krzysztofowicz 2001; Pappenberger & Beven 2006; Demeritt *et al*. 2007). Accurate predictions of flood levels resulting from precipitation and subsequent run-off have long been the goal of hydraulic engineers and hydrological modellers. More accurate predictions of water levels would not only influence demographic decision-making and urban planning in flood-prone areas but would also lead to improvements in flood warning systems.

State-of-the-art systems incorporate quantitative precipitation forecasts (QPFs) either from rainfall radar, numerical weather prediction (NWP) models, or a combination of the two, with the objective of increasing the forecast lead time (De Roo *et al*. 2003). Provision of longer lead times implies more time for mitigation action.

The shift towards QPFs from NWP models for operational forecasting systems has highlighted the need to address uncertainty in the rainfall forecast (Demeritt *et al*. 2007). Deterministic and probabilistic approaches both play an integral part of flood forecasting. In fact, they complement each other to provide additional insights into the flood risk. Making decisions under uncertainty is one of the most difficult management decisions but is the most important one. Addressing uncertainty as a reality in real-time flood forecasting shifts the question from 'should a flood warning be issued' to 'with what confidence might it succeed'?

Over the last few decades operational flood forecasting systems have increasingly moved towards use of meteorological ensemble prediction systems (EPS) rather than deterministic forecasts to drive flood forecasting systems (Cloke & Pappenberger 2009). Refer to Seo *et al*. (2000) and Gouweleeuw *et al*. (2005) for examples of such systems at the river basin scale. However, using rainfall ensembles to make hydrological predictions is not as straightforward and has proven to be very challenging (Wu *et al*. 2011). According to Schaake *et al*. (2007) much remains to be done to make them reliable enough for operational hydrological predictions.

The use of single-valued QPFs for hydrological and hydrodynamic modelling at the urban scale is challenging as rainfall forecast of high temporal and spatial resolution is required. A few studies have assessed the feasibility of using QPFs as well as probabilistic forecasting schemes in combination with a sewer model in urban flood forecasting (Rico-Ramirez *et al*. 2009; Schellart *et al*. 2009; Liguori *et al*. 2012).

The approach presented here has some similarities to the method described first by Schaake *et al*. (2007), which was then further improved by Wu *et al*. (2011), in the sense that it portions the historical observed and corresponding forecasted data into four sub-regions to estimate the uncertainty of the rainfall forecast and provide a probabilistic hydrological forecast. The conditional distribution of rainfall for a given single-valued QPF is used to represent the corresponding probability distribution for the given forecast. Although the approach presented here shares similarities in the estimation methods with the method presented in Wu *et al*. (2011), the application is different as well as some of the assumptions and hence their implications are different.

The novelty in this work lies within the forecast method which is focused on pluvial flooding in urban drainage systems. Urban drainage systems differ from river systems in the way that the concentration time is much smaller (in the order of 1–3 hours) and hence the computations needs to be much faster for real-time applications. So far, operational implementations on flood forecasting for urban drainage systems have all been based on deterministic QPFs (Henonin *et al*. submitted for review). The current research develops and analyses a probabilistic pluvial urban flood forecasting method.

This article outlines a method to estimate the probability distributions of single-valued QPFs based on a retrospective comparison of archived forecasted and observed rainfall. Single-valued QPFs are used instead of meterological ensembles because single-valued QPFs are more easily available, thus making the method more attractive. The method presented here is simple and thus easy to implement in real time. It can be attached to a forecasting system to produce a probabilistic quantitative precipitation forecast (PQPF) that can be used as input to a sewer model. The approach is implemented in conjunction with a Latin hypercube sampling (LHS) approach and a direct quantile approach that produces 12-hour hourly time series of rainfall forecasts. The results are consequently ingested into a sewer model using both approaches for comparison, and the results of the forecasted water levels and volumes are compared to the resulting water levels and volumes obtained from simulation using the observed rainfall.

The Chapter 6s organized as follows. The first section describes the methodology for estimation of probabilistic rainfall forecasts from single-valued QPFs. The second section describes the case study and presents the implementation of the method for the case study as well as demonstrate the overall performance and validity of the probabilistic rainfall model. The subsequent section presents the results of application of the probabilistic rainfall forecasts for providing probabilistic forecasts of the sewer system. Finally, a discussion of the significance of the proposed approach and the conclusions are given.

7.2 Methodology

7.2.1 Estimation of probabilistic rainfall forecasts

The stochastic approach used in this study estimates the uncertainty in rainfall forecast based on a retrospective comparison between historical forecasted rainfall and observed rainfall (herein denoted by $\hat{S}$ and *S,* respectively). The uncertainty model in the form of probability distributions will be estimated at different lead times by conditioning the forecast error on the rainfall forecast itself. Once the distributions are known, they can be imposed on the forecasted values to determine the probability distribution of the rainfall conditioned on the rainfall forecast, i.e.,

$$\mathrm{P}(\mathrm{rainfall} \mid \mathrm{rainfall\ forecast})$$

We estimate this probability relationship at different lead times because it is expected that the forecast error increases with lead time.

We propose to use two stochastic models, which reflect the intermittent nature of rainfall itself, i.e., non-zero ('rain') and zero ('no rain') forecasts. This study assumes that the observed rainfall is the 'true rainfall', i.e., no additional uncertainty is added to account for the representation error of the rain gauge measurements.

We consider conditional probability distributions corresponding to the rainfall forecast being zero or non-zero. In the case of a zero rainfall forecast $(\hat{S} = 0)$, the probability distribution consists of two parts: 1) the probability of zero rainfall, and

2) the probability of non-zero rainfall. The two parts can be combined to form the probability distribution conditioned on a zero rainfall forecast:

$$P(S \leq x \mid \hat{S} = 0) = P(S \leq x \mid S > 0, \hat{S} = 0) P(S > 0 \mid \hat{S} = 0) + P(S = 0 \mid \hat{S} = 0) \tag{7-1}$$

where the conditional probabilities are estimated from the data:

$$\hat{P}(S > 0 \mid \hat{S} = 0) = \frac{(No\ of\ events \{S > 0 \mid \hat{S} = 0\})}{(Total\ No\ of\ events \{\hat{S} = 0\})} \tag{7-2}$$

$$\hat{P}(S = 0 \mid \hat{S} = 0) = 1 - \hat{P}(S > 0 \mid \hat{S} = 0) \tag{7-3}$$

The marginal distribution for $P(S \leq x \mid S > 0, \hat{S} = 0)$ may be estimated using parametric or non-parametric techniques, such as lognormal or kernel density estimates, respectively. This is done using the data points $\{S > 0 \mid \hat{S} = 0\}$. In the case study presented below, a parameteric distribution approach has been applied.

For the other case of a rainfall forecast larger than zero $(\hat{S} > 0)$, we consider the probability distribution of S conditioned on $\hat{S} = x^*$. Again this has two components:

I. The probability of zero rainfall
$P(S = 0 \mid \hat{S} = x^*)$

II. The probability of a non-zero rainfall
$P(S \leq x \mid S > 0, \hat{S} = x^*)$

Considering the first component $P(S = 0 \mid \hat{S} = x^*)$, it is expected that the conditional probability of a zero rainfall will decrease with increasing rainfall forecast. To model this relationship, different approaches can be used, such as a logistic regression or any other functional relationship that would ensure a value between [0,1] for a given forecast (x^*).

For describing the second component $P(S \leq x \mid S > 0, \hat{S} = x^*)$ a bivariate distribution is applied to $P(S < x, \hat{S} \leq x^* \mid S > 0, \hat{S} > 0)$. This can be done by first transforming the non-zero rainfall forecast and observations to new variables that are approximately normally distributed. There are several methods for applying such transformations, including the Box Cox transformation (Box & Cox 1964) and the normal quantile transformation (NQT) (Krzysztofowicz 1997), among others. Alternatively, the bivariate distribution can be estimated using a copula approach (Nelsen 1999).

We consider here the former approach. In this case the probability distribution of the transformed rainfall s_T given a forecast $\hat{s}_T = x_T^*$ can be determined from the bivariate normal distribution. This is a normal distribution with mean and variance given by:

$$\mu_{s_T|\hat{s}_T=x_T^*} = \mu_{s_T} + \rho\,\sigma_{s_T}\frac{(x_T^* - \mu_{\hat{s}_T})}{\sigma_{\hat{s}_T}} \tag{7-4}$$

$$\sigma_{s_T|\hat{s}_T=x_T^*}^{\;2} = \sigma_{s_T}^{\;2}(1-\rho^2) \tag{7-5}$$

where μ_{s_T} and $\sigma_{s_T}^{\;2}$ are the mean and variance of s_T, $\mu_{\hat{s}_T}$ and $\sigma_{\hat{s}_T}^{\;2}$ are the mean and variance of $\hat{s}_T$, and ρ is the linear correlation between s_T and $\hat{s}_T$ (Ersbøll & Conradsen 2007). Realizations of s_T can be obtained from the inverse transformations.

Finally, the probability conditioned on a forecasted non-zero rainfall $\hat{s} = x*$ is obtained by combining the two components:

$$P(S \le x \,|\, \hat{S} = x*) = P(S \le x \,|\, S > 0, \hat{S} = x*)\; P(S > 0 \,|\, \hat{S} = x*) + P(S = 0 \,|\, \hat{S} = x*) \tag{7-6}$$

where

$$P(S > 0 \,|\, \hat{S} = x*) = 1 - P(S = 0 \,|\, \hat{S} = x*) \tag{7-7}$$

Once these relationships and probability distributions are estimated for each lead-time, the probability distribution of rainfall conditioned on the rainfall forecast can be found.

7.2.2 Probabilistic forecasts of the sewer system

The probabilistic rainfall forecasts are used as input to a sewer model to produce probabilistic forecasts of the sewer system. This is done using an ensemble approach based on sampling of the estimated rainfall probability distribution. The ensemble is here generated using the LHS approach. For simplicity, this study is based on the assumption that there is complete temporal dependence between lead times. This means that for a given 12-hour hourly forecast, the ensemble members are generated by pairing each outcome from an interval to the same interval across lead times in the LHS, thereby creating an ensemble of 12-hour hourly time series of possible rainfall outcomes.

As a result of this pairing, the LHS approach is compared to a direct quantile (DQ) approach. In order for this approach to be valid, rainfall (S) and considered quantities in the sewer system such as water level *(h)* or flow *(Q)* must have a monotonic relationship. This means that from the rainfall quantile (q_S) we can calculate the quantile of *Q* as $M(q_S))$, where $M(S))$ is a model that predicts *Q* in the urban drainage system given rainfall S as input. In that way, there is no need for multiple LHS simulations to get the distribution (or estimated uncertainty) of the variables considered in the sewer system. Mathematically, for *Q*, this means that the following must be true:

$$P(S < q_S) = P(Q < M(q_S)) \tag{7-8}$$

$$\int_0^{q_s} p_S(s)ds = \int_0^{M(q_S)} p_Q(q)dq \tag{7-9}$$

where p_S and p_Q are probability density functions of rainfall and flow, respectively. The quantile of *Q* can be derived from Equation (9) using the change of variable p_Q to p_S:

$$\int_0^{q_s} p_S(s)ds = \int_0^{M(q_S)} p_S(M^{-1}(s))\left|\frac{d}{ds}M^{-1}(s)\right|ds \tag{7-10}$$

In essence, Equation (7-10) suggests that if $M(S)$ is monotonic in S then it means that the model predicts more run-off if the rain increases, which is what is expected. However, there are situations where this may not be fulfilled, e.g., in an urban drainage system which has some intervention to control run-off as rainfall intensity increases.

The implications of using this approach means that we are only able to give an upper bound (i.e., the worst case scenario). However, recognizing this limitation under some circumstances, the probabilistic forecast information is still valuable, especially when used for risk assessment and when any other additional information is unknown. The benefit of using the direct quantile approach means that with just one hydraulic simulation we can quantify the uncertainty in the sewer system making it very attractive for real-time applications.

The assumption applied for the temporal dependence on the rainfall probability distributions between lead times also implies an upper bound on the estimated quantile (worst case scenario). This applies both for the LHS and the direct quantile approach. However, a large temporal correlation is generally expected.

7.3 Case study

The case study used in this study considers urban drainage in Aarhus (Figure 7-1), the second largest city in Denmark, located on the eastern coast of the Jutland peninsula. The city has a population of 250,000. This city was chosen because of the existing high quality data for the sewer system. The sewer network consists of 1,926 manholes, 65 outlets, 1,657 pipes, 196 weirs, 83 basins and 26 pumps. The sewer model has been calibrated by the municipality and is considered to be fit for purpose for this research by being able to reproduce observed flows and water levels.

Figure 7-1: Setup of sewer model for Aarhus.

The PQPF is prepared for a 12-hour period with 1-hour time steps. The 12-hour hourly product provided from the NWP model (StormGeo 2011) has a resolution of (6.2 × 11.1) km. The archived forecasted data covered the period February 2009–December 2010. Single-valued QPFs over the urban catchment were composed of two forecast grids with a total area of 138 km^2 (Figure 7-2). Historical observed rainfall from three tipping bucket rain gauges covering the period 2001–2011 was provided. The observed data were at a higher temporal resolution (1 minute) and volumetric resolution of 0.2 mm. The Thiessen polygon method was used for estimating areal precipitation from the rain gauge data, and the data were subsequently converted to hourly rainfall.

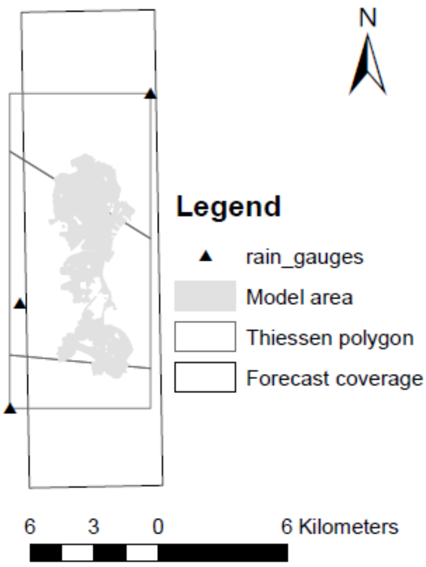

Figure 7-2: Model area, total forecast coverage, Thiessen polygon and rain gauge locations

The areal historical meteorological forecasts were compared with areal rainfall observations for the period 2009–2010. First analyses of the data showed a number of inconsistencies. The most important issue is the frequent occurrence of a non-zero forecast and zero observed rainfall. As a result, a precipitation threshold of 0.2 mm was imposed on the rainfall forecast to define zero rainfall. See Figure 7-3 for comparison of observed and forecasted rainfall data. The estimated conditional probabilities of the rainfall are shown in Table 7-1.

Table 7-1: Conditional probabilities of rainfall given rainfall forecasts for entire data set

	Forecast = 0	Forecast > 0
Rainfall = 0	93.2	45.0
Rainfall > 0	6.8	55.0

Figure 7-3 also shows that there is a tendency of underestimation of the rainfall forecast for larger rain events and an overestimation for smaller rain events. This is supported in Table 7-2 by the negative values of conditional bias as the forecast gets larger and positive values of the conditional bias for smaller values of the rainfall forecast. Since there are very few data points for the larger events there are large uncertainties in the bias estimates.

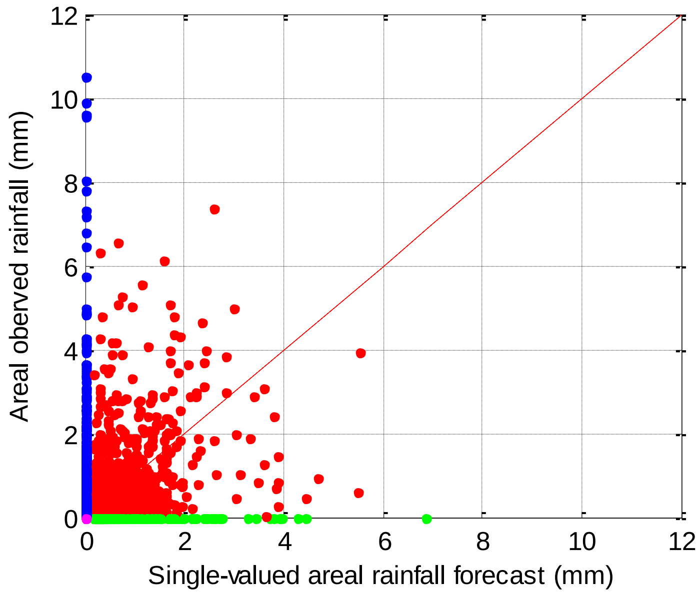

Figure 7-3: Observed and forecasted rainfall for the period 2009–2010. Data points on the y-axis represent rainfall given a zero rainfall forecast, data points on the x-axis represent zero rainfall given a rainfall forecast more than zero, and the data points inside the plot represent non-zero rainfall given a non-zero rainfall forecast

Table 7-2: Conditional bias and standard deviation of the rainfall forecasts for the data set used

Interval	Number of points in interval	Bias (mm)	Standard deviation (mm)
0	11954	0.026	0.259
0.01–1.0	4361	0.031	0.616
1.01–2.0	255	−0.519	1.086
2.01–3.0	35	−0.777	1.895
3.01–4.0	20	−2.636	1.020
4.01–7.0	7	−4.271	1.411

From this preliminary analysis, it can be concluded that there are large uncertainties in the meteorological forecasts. In the following is presented the estimation of a probabilistic forecast model for Aarhus using the approach described in the previous section.

7.3.1 Estimation of conditional distributions

Using the two years of observed and forecasted areal rainfall, probabilistic rainfall models are estimated for each forecast lead-time, 1–12 hours.

For $\hat{S}=0$, for each lead time the conditional probability distribution $P(S \le x \mid S > 0, \hat{S}=0)$ has been estimated by fitting a probability distribution to the data $\{S > 0 \mid \hat{S}=0\}$. The lognormal distribution provided the better fit for most lead times and was therefore selected for all lead times for consistency (fit of a lognormal distribution is shown in Figure 7-4 for a 1-hour lead time). The probabilities $\hat{P}(S > 0 \mid \hat{S}=0)$ and $\hat{P}(S = 0 \mid \hat{S}=0)$ were estimated from the data and $P(S \le x \mid \hat{S}=0)$ is then obtained from Equation (7-1).

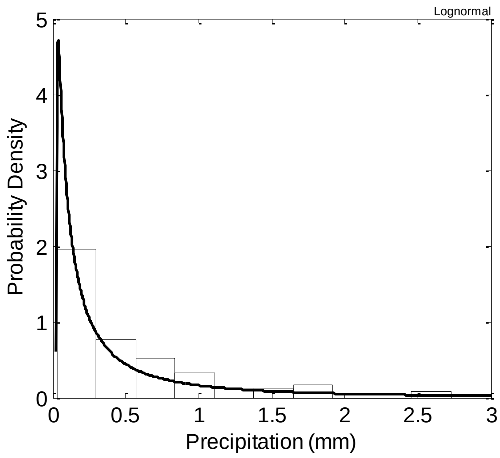

Figure 7-4: Estimated log-normal distribution for a lead time of 1 hour

For the data $\{S > 0 \mid \hat{S} > 0\}$ for each lead-time, the normality of the data was first checked by the use of simple Q-Q plots. This clearly showed that the rainfall data could not be approximated by normal distributions, and thus were transformed using the Box–Cox transformation method (Box & Cox 1964). The Box–Cox transformation is defined by

$$x_T = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & (\lambda \neq 0) \\ \log x & (\lambda = 0) \end{cases} \qquad (7\text{-}11)$$

and is applied to both the observed and forecasted rainfall. There are several statistical tools available for computing an optimal λ-parameter and MATLAB was used in this case. The transformation does not necessarily guarantee normality and the transformed data were further checked for normality using probability plots. For each lead time the transformed data were found to be well described by normal distributions. Figure 7-5 demonstrates the estimated bivariate normal distribution of the transformed data for a lead time of 1 hour.

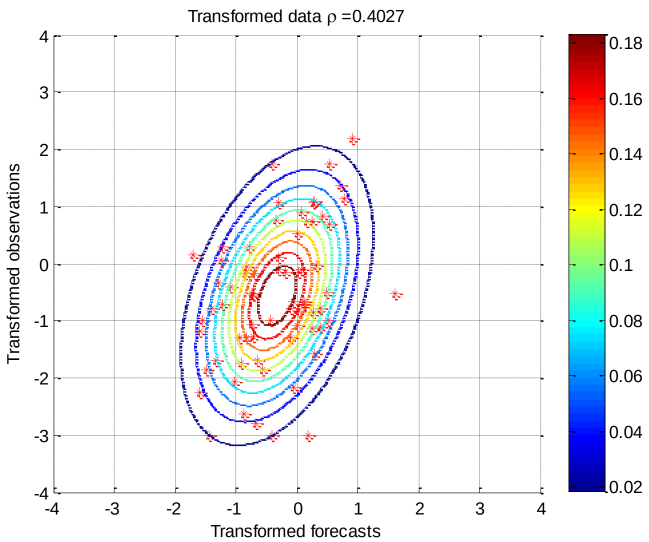

Figure 7-5: Contours of the joint distribution of transformed observed and forecasted data for a lead time of 1 hour

The probability $P(S = 0 \mid \hat{S} = x^{*})$ was derived using regression analysis on the entire data set as opposed to each lead time to provide a more robust estimation. In this case we found that a logistic regression based on the logistic maximum likelihood method better fitted the observed probabilities. The probability using the logistic regression is given by:

$$P(S=0\,|\,\hat{S}=x^{*}) = \frac{exp^{B_0+B_1x^{*}}}{1+exp^{B_0+B_1x^{*}}} \tag{7-12}$$

where B_0 and B_1 are the regression coefficients. They are estimated by fitting a logit link function to the data. The data, in this case the probabilities, are approximated by splitting the data into forecast intervals and computing the probability of observing zero for this interval. The mean of the rainfall in each interval is an estimation of $P(S=0\,|\,\hat{S}=x^{*})$. See Figure 7-6 for results of the logistic regression. The results depict what is expected, as the values of rainfall forecast increases the probability of observing zero rainfall decreases. Finally, the estimated conditional probability distribution for a non-zero rainfall forecast is obtained from Equation (7-6).

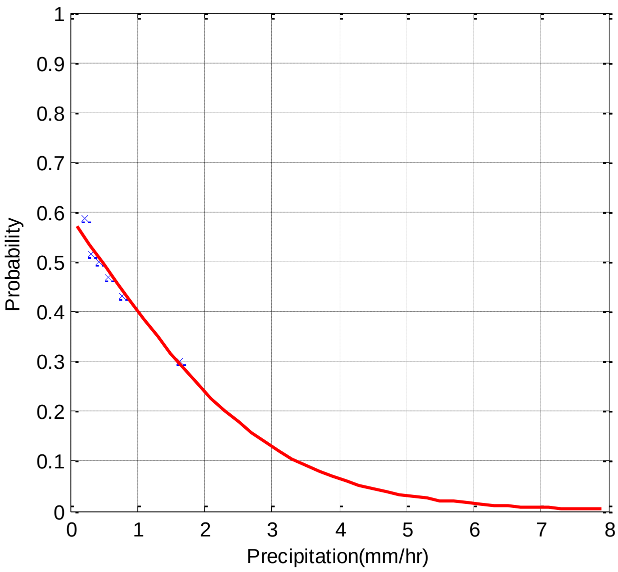

Figure 7-6: Estimated logistic regression to represent the $P(S=0|\hat{S}=x^{*})$

The estimated probability distributions are combined to create a stochastic model to generate 12-hour hourly time series of rainfall given a 12-hour hourly forecast. When the forecast is zero, the model samples from the estimated lognormal distribution. When the forecast is non-zero, the model first estimates the probability of observing zero rainfall given the non-zero forecast using the logistic regression function. Then, the rainfall value is transformed from its original domain to the normal domain using Equation 7-11 and its corresponding estimated λ-parameter for the considered lead-time. The conditional mean and variance is computed using the parameters of the data in the normal domain

(Equations (7-4) and (7-5), respectively) to determine the marginal distribution which is then used to generate the rainfall ensemble and rainfall quantiles. The corresponding observations for the non-zero forecast value are then back-transformed to the original domain using Equation (7-11) to create the 12-hour hourly time series.

7.3.2 Validity of the distribution functions – goodness of fit

The performance of the model is checked by comparing the empirical CDFs of the observed rainfall sampled for a range of rainfall forecasts to the theoretical CDFs (predicted) obtained from the estimated models. Because of very few observed larger rainfall events, CDFs are only presented up to 2.0 mm of rainfall. The theoretical CDF can be obtained but there are not enough data to construct the empirical CDF. These results for a lead time of 1 hour are presented in Figure 7-7.

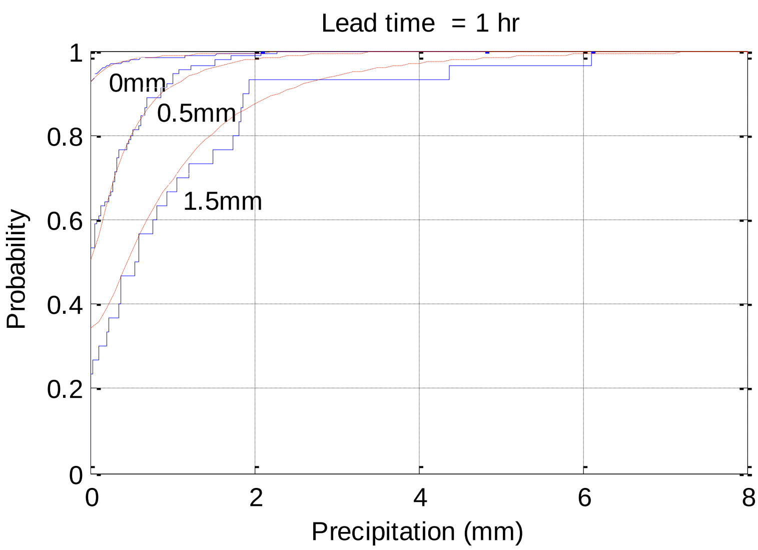

Figure 7-7: Estimated versus empirical CDFs for different values of rainfall forecast – lead time 1 hour. The smooth curves represent the prediction from the developed models and the step-like curves represent the observations from the data

The theoretical model gives a good description of the data by closely following the empirical CDFs thereby confirming the formulation of the stochastic model. The statistical model follows the empirical CDFs more closely for smaller rainfall forecasts (0–1 mm) than for larger rainfall forecast across lead times; however, these also have larger uncertainties due to the small number of larger rainfall events.

7.3.3 Implementation

For illustration of the use of the probabilistic rainfall forecasts for providing probabilistic forecasts of the sewer system two rainfall events are considered:

I. Event A where the accumulated observed rainfall is larger than the corresponding rainfall forecast (Figure 7-8).
II. Event B where the accumulated rainfall forecast is larger than the observed rainfall (Figure 7-9).

The two methods presented above (LHS sampling and the direct quantile approach) are applied for sampling the probability distributions to be used as input to the sewer model.

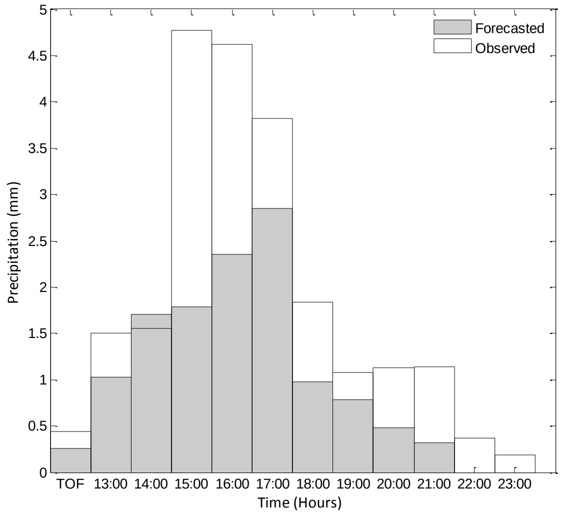

Figure 7-8: Forecasted and observed rainfall (Event A)

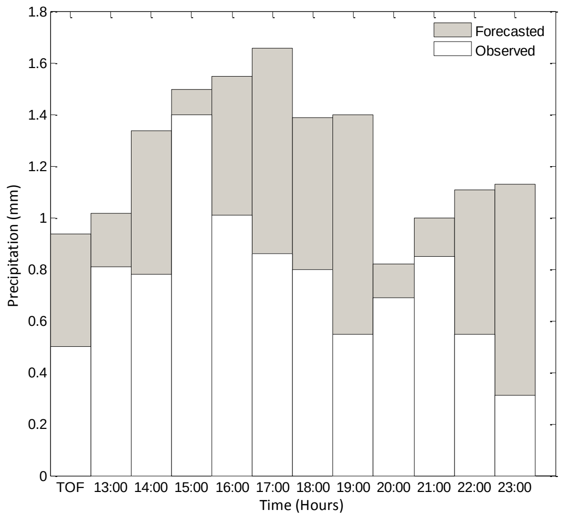

Figure 7-9: Forecasted and observed rainfall (Event B)

Latin hypercube sampling approach

For a given 12-hour rainfall forecast (Figure 7-8 and Figure 7-9), the LHS approach was used to generate 50 ensemble members of 12-hour hourly rainfall forecasts for the two selected rain events (see Figure 7-10). Each hourly rainfall forecast in the 12-hour period has a corresponding probability distribution. The approach samples 50 times from each rainfall forecast of equal probability. The 50 precipitation forecasts are then used as input to the sewer model. This results in 50 simulated outputs from which the probability distribution of model outputs can be estimated.

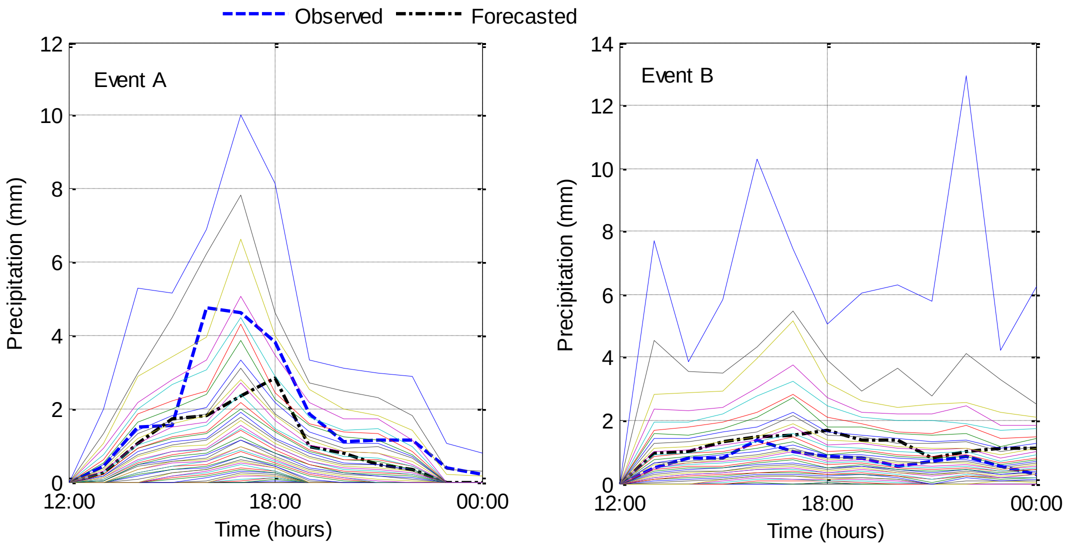

Figure 7-10: Ensemble members for Events A and B, respectively. The broken lines represent the observed and forecasted rainfall, respectively, and the solid lines represent possible outcomes of rainfall from the stochastic model for the given rainfall forecast

Direct quantile approach

For the same two events (see Figure 7-8 and Figure 7-9) a few percentiles of rainfall (see Figure 7-11) were extracted from the probability distributions and used as input to the sewer model. It is then assumed that the probability of the considered output corresponds to the probability of the precipitation input.

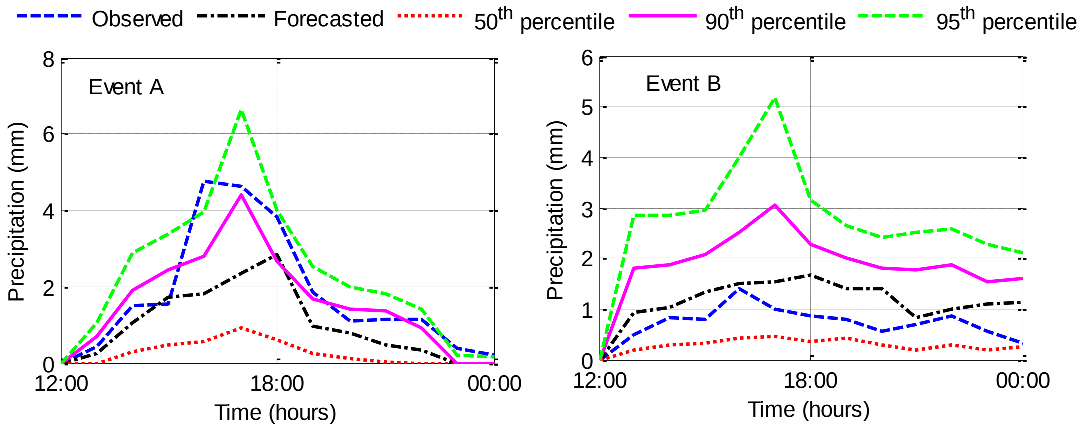

Figure 7-11: Quantiles for Events A and B, respectively. The broken lines represent the observed and forecasted rainfall, respectively. The other three lines represent three selected quantiles extracted directly from the probability distributions developed for each

7.3.4 Sewer model results

For the two selected events, the resulting rainfall ensemble members from the LHS approach and the rainfall percentiles from the direct quantile approach were simulated through the sewer model. At different locations throughout the model, time series of water levels and volumes were extracted for comparison to the simulation results based on the observed rainfall. This method is used because actual observed data were not available. This, however, does not affect the assessment of the performance of the proposed approach, because the method only considers the uncertainty in the precipitation input and everything else stays the same in the model.

The plots presented in Figure 7-12 and Figure 7-13 show the system response to the rainfall ensembles as well as rainfall percentiles. Both approaches show an overall similarity in water levels and volumes at the selected locations.

A comparison of the water levels obtained from the LHS approach and the direct quantile approach in Figure 7-12(a) and Figure 7-12(b) for Event A show slightly larger peak values for the LHS approach. Overall, the resulting percentiles of the ensemble are almost the same compared to the system response to the direct quantile approach. Figure 7-12(c) and Figure 7-12(d) also show similarities for both approaches except that the LHS approach again results in slightly larger forecast volume percentiles. The same is observed for the forecasted water levels and volumes presented in Figure 7-13 for Event B. Overall, results of the forecasted variables using both approaches show similarities, particularly for the larger percentiles. Notwithstanding the differences in peak values for the two methods, they occur at the same time for both approaches, therefore suggesting that both approaches are comparable and the difference is merely caused by the response of the sewer system controlled by pumps.

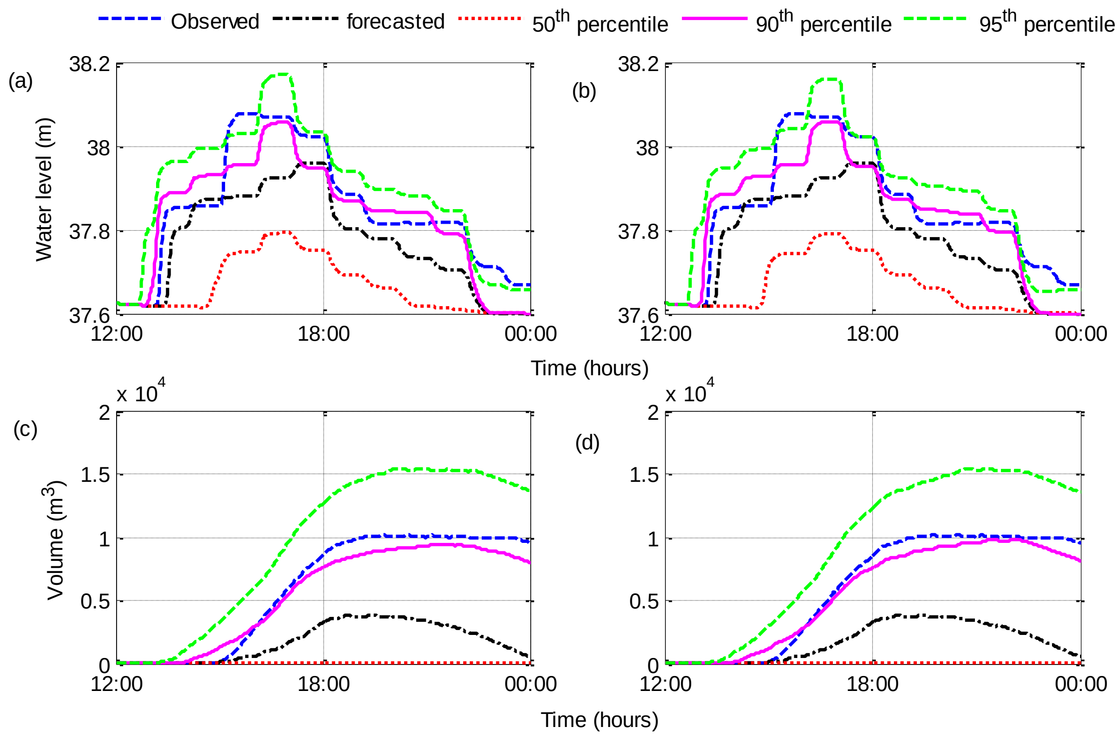

Figure 7-12: Comparison of three percentiles of water level and volume at selected locations in the model of the LHS and direct quantile approach for event A. Plots (a) and (c) represent the results obtained for the LHS approach and plots (b) and (d) demonstrate the results obtained from the direct quantile approach

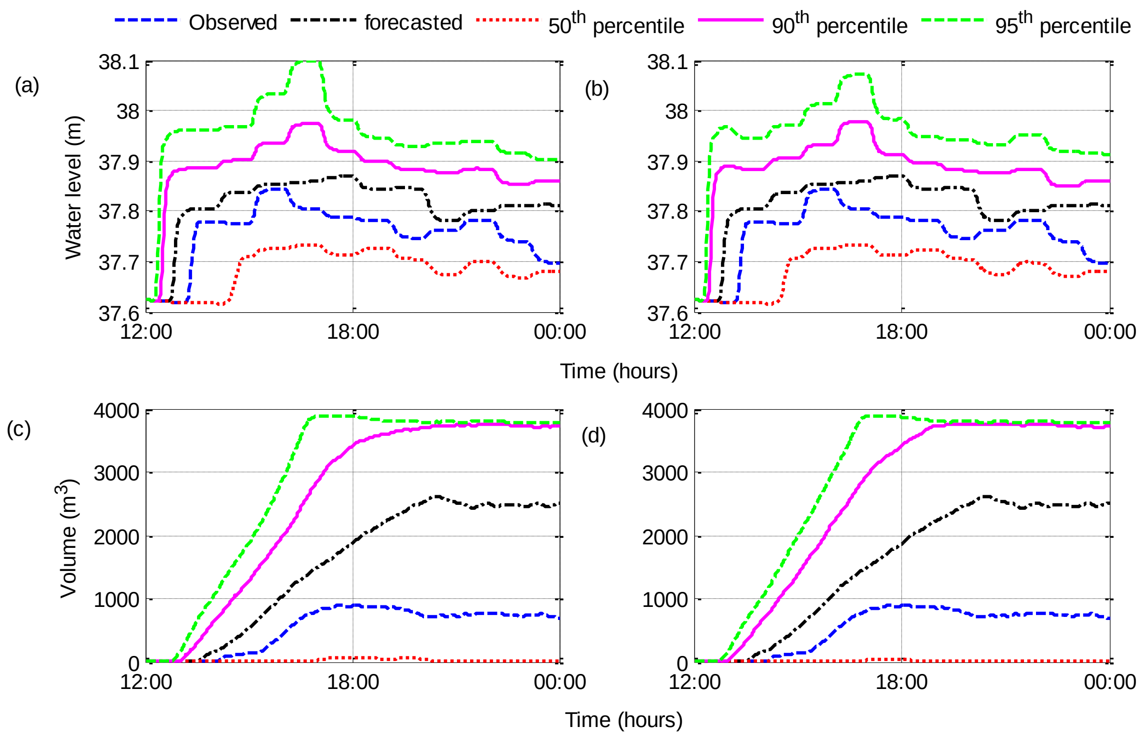

Figure 7-13: Comparison of three percentiles of water level and volume at selected locations in the model of the LHS and direct quantile approach for Event B. Plots (a) and (c) represent the results obtained for the LHS approach and plots (b) and (d) demonstrate the results obtained from the direct quantile approach

7.4 Discussion

The proposed approach using probability distributions to represent the forecast uncertainty has demonstrated the feasibility of using QPF for forecasting of different variants at the urban scale. Two approaches for implementation of the probabilistic rainfall forecasts have been presented.

The main reason for the differences between the two approaches is that the results obtained from the LHS approach are a combination of the system response to each individual rainfall ensemble member simulated through the non-linear model, from which percentiles are estimated, while the direct quantile approach assumes the same probability in the outputs as in the rainfall input. The sewer model is a complex network controlled by pumps, hence making it highly non-linear. The model responds differently to each rainfall pattern. Generally, patterns with larger intensities will provide similar results because the system is running full; therefore assuming that it has a linear response. In contrast, it is easier to notice small changes in water level for smaller rainfall patterns and hence the difference in the simulated 50th percentiles.

Generally, the stochastic model displays a usable amount of skill for forecasting rainfall. The propagation of this forecast through the hydraulic model also displays a usable amount of skill in forecasting node water level as well as inflow volume to basins, making it possible to use in real-time application.

Notwithstanding, the overall performance depends on the quality of the data sets used. Long historical records of observed and forecasted rain data are needed for applying the developed approach. In this case, only two years of forecast data were available.

The results presented are derived from relatively small intensity rainfall events. Further investigation for large intensity rainfall is required in order to draw more concrete conclusions for such complex urban drainage systems.

The main operational difference between the two forecast methods is the computational time. Using the more comprehensive LHS approach would require a simulation for each ensemble member, while the direct quantile approach requires simulations for only a selected number of percentiles. Although the LHS approach is more theoretically sound, simply simulating a certain rainfall percentile gives a quantitative estimate of the uncertainty in the forecasted variant without costly simulations. This makes the use of the direct quantile approach for probabilistic forecasting a more attractive method for real-time forecasting at the urban scale.

In practice, the results from the proposed method are useful for decision support for urban water management and flood warning and emergency management. The method can be extended to include other sources of uncertainty in order to provide a more robust approach to decision support. Flood warnings are typically issued when a threshold is expected to be exceeded. Therefore, for selected locations in the sewer systems, certain thresholds are established, and the probabilistic forecasts give an estimate of the probability of exceeding these thresholds.

7.5 Conclusions

A method to quantify the uncertainty in rainfall forecasts from NWP models is presented. The developed method provides the opportunity to make probabilistic forecasts of different variants (water levels, volumes, discharges) in urban areas in real time by means of LHS or direct quantile simulations. The developed method does not consider other sources of uncertainty, but merely an estimate of input uncertainty (precipitation).

The method was tested by using 12-hour hourly rainfall forecasts and was applied to a 1D sewer hydraulic model. From the results it can be concluded that the direct use of rainfall quantiles to provide uncertainty estimates of water level and volume forecasts instead of LHS is promising. Moreover, the developed method is simple to apply once the data are available, and most importantly, it is computationally efficient.

However, there are some limitations to the method presented here. The direct quantile approach assumes that rainfall and sewer system reponse have a monotonic relationship, which may be violated (although not indicated in the presented case study). Both the direct quantile and the LHS approach assume complete temporal dependence across lead times. It is possible to take the temporal error structure into account using the LHS technique, although this was not considered in the study.

In order for the developed approach to be successful, it requires diligent collection of both observed and forecasted rainfall data. This is not necessarily conducted at meteorological offices, especially in developing countries. This requires a paradigm shift in the modus operandi of meteorological offices around the world, which may be the greatest limitation to the success of the proposed approach.

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8 Getting started with urban flood modelling for real-time pluvial flood forecasting: A case study with sparse data

Conference Proceedings: International Conference on Flood Resilience: Experiences in Asia and Europe, Exeter, United Kingdom 2013

It is becoming increasingly difficult to ignore the threats fronted by island nations from tropical storms or hurricanes in some regions and typhoons in others. The recent increase in urban flooding in these regions due to rainfall has attracted the attention of relevant authorities to address flooding in a more proactive manner. However, this has been a challenge in many regions where the data required for flood management in general is sparse. This study will demonstrate how to utilize the available resources to understand the magnitude of flooding in the urban area and how this information can be used for real-time pluvial flood forecasting. The extent of modelling that can be done depends greatly on the kind of data which is available. This study utilizes spot heights, orographic images, buildings shapes derived from the images and knowledge of the area to build a 2D overland model which will be used for real-time pluvial flood forecasting for the study.

Keywords: Data, DEM, Flood Management, Flood modelling, urban flooding

8.1 Introduction

Flooding is perhaps the most frequently occurring natural disaster affecting developing island nations in Asia (Jha et al., 2012, Tingsanchali, 2012) and the Caribbean (Vojinovic and Van Teeffelen, 2007). It is most prevalent during tropical storms and hurricanes in some regions or typhoons or monsoons in others, depending on the region in the world. These bring along heavy rains, strong winds and storm surges that can cause destructive flooding in both coastal and inland areas (Vojinovic and Van Teeffelen, 2007). Some areas are more severely affected than others which is dependent on a number of factors which are not limited to topography or development as it relates to infrastructure.

Over the last decade there has been a dramatic increase in the incidents of floods in these regions which has had a serious effect on their socio-economic developments (Jha et al., 2012). The inadequacy of data for urban flood modelling in some of these regions has made it particularly challenging in addressing flood problems. More recently, literature has emerged that shows that one can make the simplest of urban flood forecast only based on rainfall forecast and a historical account of past flood events (Henonin et al., 2013). One ardent observer has already drawn attention to the fact that urban flood practitioners can issue a flood forecast no matter where they are in the world (René et al., 2013b).

In order to prepare for changes in rainfall related to climate variability and change, this paper outlines (i) how a simple flood model can be built with limited data for a small coastal city; (ii) how to select a suitable model that can issue a real-time pluvial flood forecast based on rainfall forecast from a numerical weather prediction (NWP) model and (iii) how this model can be used to understand the causes and magnitude of flooding in the city. This would likely reduce economic devastation from floods for island nations.

8.1.1 Case study

The idea in this study is to utilize minimal physical data but with some knowledge of the area to demonstrate causes of flooding and to use the acquired information to build a flood model of which to make a meaningful pluvial flood forecast. The case study in this research is the administrative capital of a small island in the Caribbean region with an area of approximately 0.45km^2. Although loss of life due to flooding in the area is rare, it does however result in property damage and loss in productivity which has a huge impact on the economic development. Minor floods usually occur after short duration high intensity rainfalls, with more severe flooding occurring as a result of storm events which include storm surges.

8.1.2 Drainage features in study area

The study area is located on the right side (flood plains) of the estuary of the main river which has been directed through a concrete channel in some areas (river training). There are a number of small ravines which also drain into the city. The city contains a system of storm drains which are pumped to two outfalls in the harbour. Coastal wave action can limit the effectiveness of the drains as well as the river from discharging flow into the harbour. This may lead to standing water in the drains that run within the city as well as the main river and in more severe cases may lead to backwater effects which may cause surcharging at manholes and may cause the river to overflow its banks thus resulting in overland flooding. Because of its location and the features that surround it, the area is prone to: (i) fluvial flooding because of the river that runs adjacent it; (ii) Coastal flooding due to storm surges and (iii) pluvial flooding. In an effort to control flooding back a detention basin (dry/holding pond) was constructed a few years. This basin is connected to the harbour via one of the two outfalls (Figure 8-1).

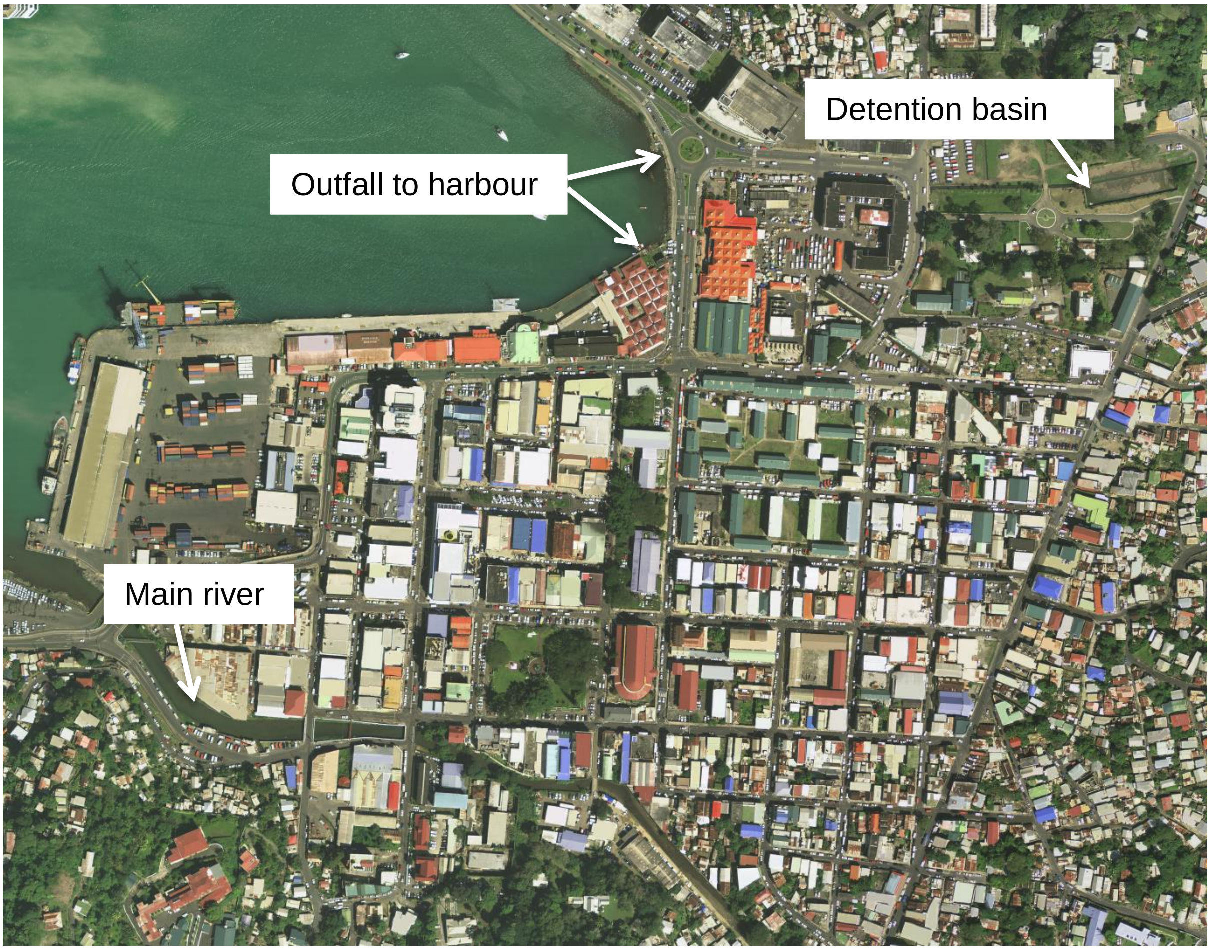

Figure 8-1: Drainage features in the study area

8.2 Data sets used

The data utilized in this study includes: (i) sporadically-spaced spot heights; (ii) buildings shape file; (iii) 24 hour rainfall for an event (533.3mm – hurricane Tomas October 2010); (iv) orographic images of the area (v) images reporting the extent of damage from Facebook which were captured after the event.

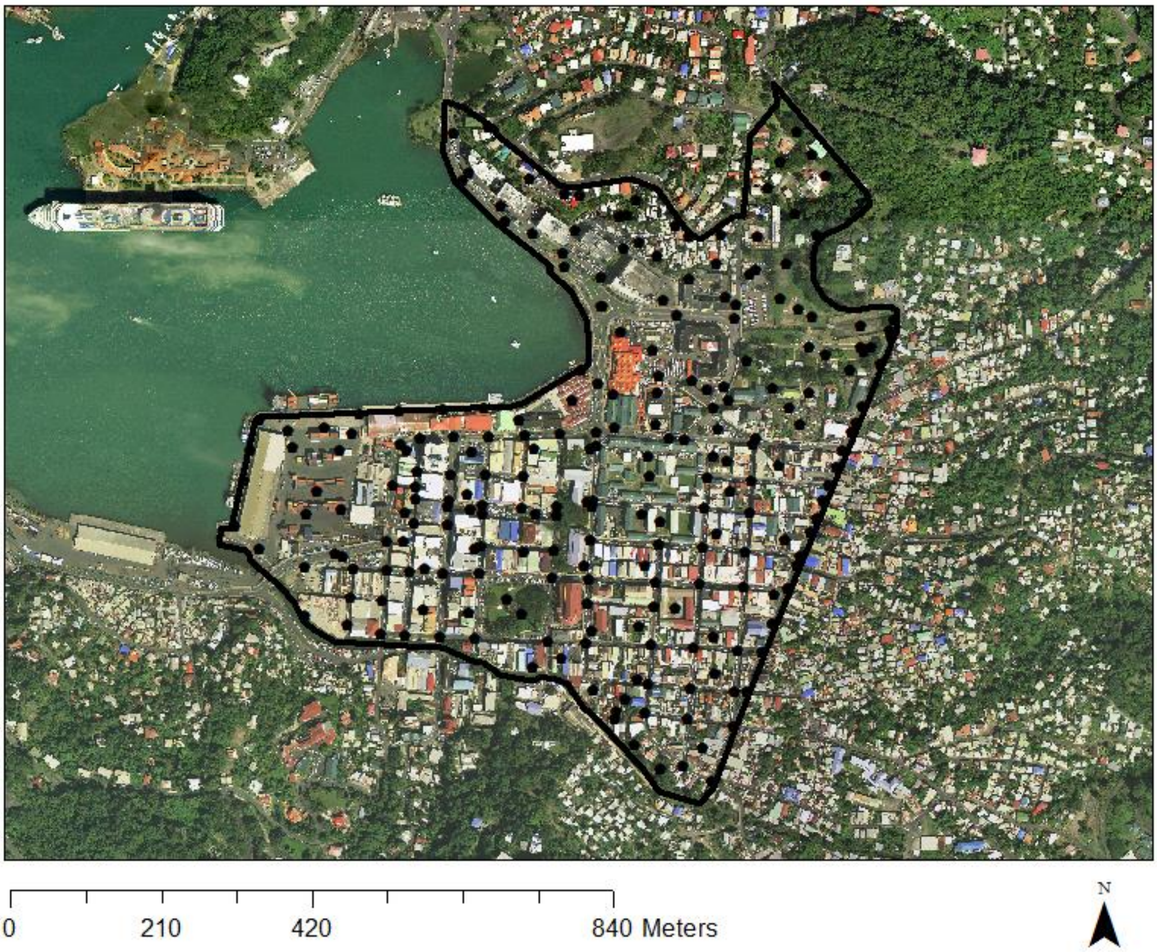

Figure 8-2: Spot heights in study area

8.3 Methodology

For the purpose of the study, four different resolutions (10m, 5m, 2.5m and 1m) of digital terrain models (DTM) was derived from the spot heights (Figure 8-2) in order to evaluate which DEM resolution best represents the study area assuming the kriging method for interpolation. The buildings were also added to the DTM to create digital elevation models (DEM) which was then used to construct four simple overland flood models. All buildings were raised to a height of 25m which represents the highest elevation which cannot be wet or flooded during the hydrodynamic simulation (calculation). The harbour was also represented in the model by lowering the area derived from a shape file to minus 3.0m.

The absence of times series of water levels at the mouth of the river or flow from upstream into the study area would mean that fluvial flooding cannot be considered intrinsically in the model. And likewise, the absence of time series of tidal variations means that coastal flooding cannot be explicitly considered in the model. In order to reflect these conditions i.e. to narrow down the analysis to pluvial flooding only the edges of the terrain model, except the area open to the harbour were raised to an elevation of 25m to represent a closed boundary. The area open to the harbour represents an open boundary which means that water will flow away from the boundaries and drain into the harbour.

Each model is subject to uniformly distributed rainfall of 533.3mm in 24 hours, since then the exact hyetograph (rainfall intensity versus time) is unknown.

Water depths were derived from images from Facebook, posted by individuals who experienced the event, which was then used to help select a meaningful model based on the areas affected. The selected model was then used to understand the extent of pluvial flooding in the city based on the event.

In order to quantify the extent of pluvial flooding in the study area a shape file of the river was created and the river inscribed into the selected resolution of the terrain model. The river was then lowered the same depth as the harbour and was allowed to connect to the harbour. The boundary of the study area on the river side of the model was placed on the outer edge (from study area) of the river banks because exact terrain data representing the outer banks is not known. In this case the river is represented by a depression in the model and water will flow accordingly and eventually drain into the harbour.

8.4 Results and discussion

Based on the available data, a 2D overland hydrodynamic model was selected to model pluvial flooding in the study area (MIKE21). The typical approaches in urban flood modelling in terms of dimensionality would be 1D modelling of drainage systems (e.g. MOUSE) or the 1D-2D coupled approach (e.g. MIKEURBAN). However, in both cases, information about the drainage network is required which is modelled by the 1D component of the modelling software. This is the conventional approach because urban drainage systems (1D) are designed to direct surface flow out of the urban area. More recently because of climate change and other anthropogenic stresses on urban environments, existing infrastructure in most urban centres is unable to cope with surface runoff, thus resulting in overland flooding and hence the combination of the 1D-2D modelling approach is required.

In reality, there will always be data constraints for reasons beyond control. In cases where terrain data is available and drainage systems data is not; an approximate approach to urban flood modelling is the 2D surface flow modelling. This approach is an approximation because it does not intrinsically consider the capacity of the drainage system but if known can be accounted for by subtracting its design capacity in equivalent rainfall from the rainfall input, although the sensitivity of this approach has not been documented.

Based on the available data, there were two possibilities when creating the overland model from the spot heights; (i) elevation model which is the bare ground (no buildings included) and (ii) a terrain model which includes the buildings. Inclusion of the buildings will give a more realistic representation of the flooded locations and depths, because not only do buildings somehow control or direct the flow paths by creating an obstruction, but they occupy land area in the model and will therefore result in larger water depths. In this study, in order to get realistic flood locations because the area is reasonably flat the buildings were included.

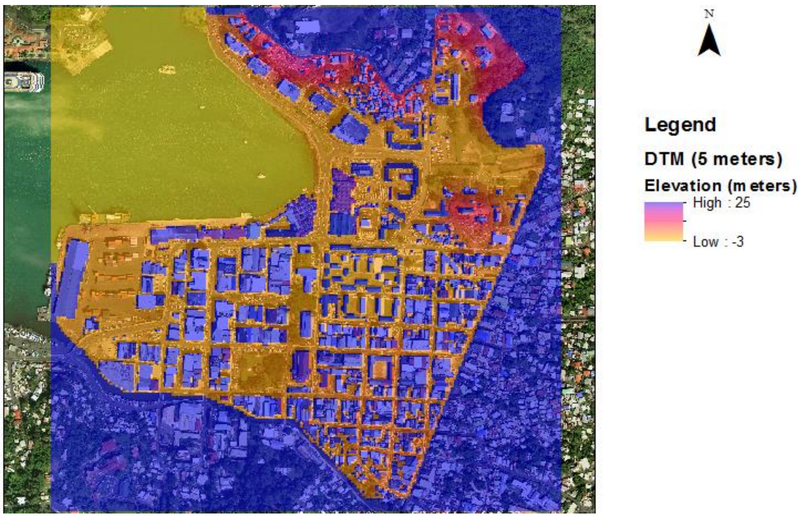

Figure 8-3: Example of terrain model with buildings included (Resolution 5 meters)

8.4.1 Model selection and verification

Selecting an appropriate model is usually based on how accurately the modelling results represent the reality. It is suggested in Mark et al. (2004) that the interval for spot height elevations for urban flood analysis should be in the range of 10-40cm to achieve a DEM resolution which is sufficiently accurate. However, in this case, model selection is not based on accuracy but rather on subjective reasoning that would provide meaningful results.

Because the images used to determine water depths did not contain time stamps and geographic location, it is unclear at what time the pictures were taken. This information could be useful in reconstructing the approximate distribution of the rainfall event. However, knowledge of the area in this case has helped identify some approximate locations of the images but not time taken; hence the rainfall was uniformly distributed over the 24 hours. In this case the maximum water depths as well as flood extents were extracted and compared to the images assuming that the water levels may have receded a bit since the images are assumed to be taken after the rainfall had subsided.

Figure 8-4: Example of the images used to extract water depths and extents for comparing to model results. In first image for example the depth is approximately 0.4m and the second image was used to extract extent since the water depth is not the same throughout the area

In this study any water depth less than 0.02m (20mm) is not considered to be significant enough to cause any damages, and is thus not represented on the flood maps.

Figure 8-5 demonstrate the results for different model resolutions for the simulated event. A number of authors have pointed that different terrain resolutions give significantly different results (Vojinovic et al., 2011, Chen et al., 2012a), and this study corroborates these earlier findings. Although there are similarities in flood extents for the resolutions used here; the coarse (10m) DTM gives shallower water depths compared to the finer resolutions. Since the exact water depths are unknown it is difficult to justify selection of an appropriate model. However, one thing which stands out in terms of selecting an appropriate model for real-time simulations is the computational time.

The objective of building the model is to be used in conjunction with quantitative precipitation forecasts (QPF) for real-time flood forecasting in the area. The input time series of rainfall has a 12 hour, 3 hourly format; i.e. a time step of 3 hours. This means, that the simulation time of the selected model should be less than three hours in order to be able to issue a forecast in time in case of an event during the nowcast. In this case it is possible to use either of the terrain models because they all take less than 3 hours to run a 12 hour simulation. However, selecting one with a shorter run time would mean that there is a possibility to make a flood forecast soon after the nowcast therefore providing more time for warning and response.

When also selecting a suitable resolution in this case, a few assumptions were made regarding the interpolation of the spot heights. It was assumed that for so few irregularly spaced points, finer resolutions would not necessarily lead to a more realistic DEM. Therefore for the reasons mentioned above, the 5 and 10 meter resolution models were selected.

Figure 8-5: Max flood depths of the simulated event for model resolutions of 1.0, 2.5, 5.0 and 10.0 meters

These two models also corroborate well with reports about the worst affected areas, however the main difference lies in the water depths. Then again, most streets in the area are not more than 5 meters wide. Although the streets are not included in the model per se, they can be approximately represented by the densely spaced buildings and so making the selection in accordance with recommendations on DEM resolutions for urban flood modelling made by Mark et al. (2004). Consequently the 5m resolution model was selected as an appropriate model – efficient yet sufficiently accurate – to make a meaningful real-time flood forecast for the area in the near future.

8.4.2 Understanding the causes of flooding in the area

Using the selected 5m resolution model, a river same depth as the harbour was burnt into the DTM (with a slope relative to the edge of the DTM) and the simulation re-run. It is obvious, that the river water levels will affect pluvial flood alleviation in some areas, once the level at the outlet is low enough (no back water effects) and water can flow out into the harbour without spilling over its banks. What's not obvious is by how much and where will the reduction be observed.

The results show that there is a reduction in water depths in some of the worst affected areas because of the inclusion of the river although the extent of flooding is still the same. It was also pointed out that there is a detention basin in the study area. This was not modelled in this case not only because the depth dimension is not known (length and width can be extracted from the image) but it is located in a relatively open area where the consequences due to flooding are quiet low. Although there is flooding in that area as shown in Figure 8-6, carving the detention basin would act like a pond in the DTM therefore channelling some of the surface runoff into its storage and possibly reducing the flood depths in some of the worst affected areas. However, since the exact depth of the pond is not known, this analysis is not included because the results can be misleading if a depth larger than the actual depth is used.

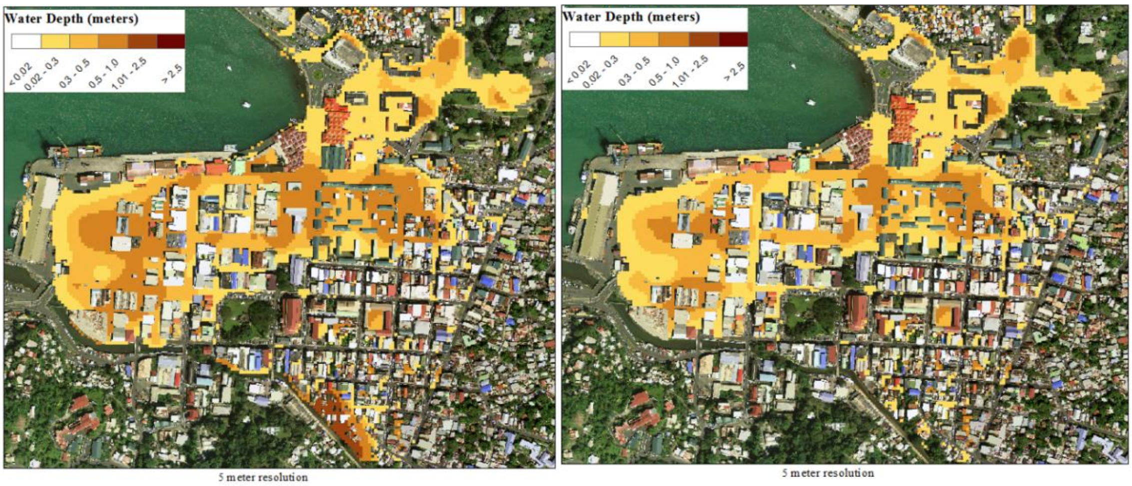

Figure 8-6: Influence of the river on pluvial flooding in the area. The first image (left) shows the maximum flood depths when the river is not included in the model and the second image (right) shows the results after the river was included

8.5 Future Work

The work presented represents the initial phase in setting up a real time model for the case study. The selected 5m resolution model is currently running in real time using a 12 hour 3 hourly forecasts from a numerical weather prediction model (GFS – NCEP/NOAA) as the main hydrological forcing and observed rainfall data received in real-time with a 1 minute resolution to initiate the model. The setup is currently being tested against real rainfall events and will later be used to make flood forecasts which will be used by the relevant authorities to issue warnings. As time progresses and more information is acquired, the model will perhaps be modified to improve the quality of the forecast.

8.6 Conclusion

This paper has given an account of the work done in building an urban flood model with limited data which is then used for real-time urban pluvial flood forecasting. In this study, the aim was to construct a 2D overland model, select an appropriate model resolution and access the major causes of flooding in the area. The findings suggest that in general, it is possible with the sparsest of data and modelling tools, to understand and to some degree quantify the extent of damage that can be expected from a rain event. An implication of this is the possibility to avert island nation from being economically devastated from flood events. The current findings add substantially to our understanding of not only flooding in this case study, but also on how to use the limited resources at our disposal to assist in urban flood management. The study provides additional evidence that suggest that urban flood modellers can make the simplest of flood forecast anywhere in the world with the possibility of improving the accuracy of the flood forecast as more data is acquired.

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9 A real-time pluvial flood forecasting system for Castries, St. Lucia

Under review, *Journal of Flood Risk Management*

In the last decade, real-time flood forecasting has become a more feasible approach to reducing the impacts of flooding in urban areas. Two key tools in this context are high resolution hydrodynamic modelling in combination with s accurate hydrological forcing. In some cases, when it is not possible to produce such accurate flood forecasts based on high-resolution models and data, it may nevertheless be possible to use the resources currently available, accepting that there is a greater degree of uncertainty involved. This paper demonstrates the feasibility of a remotely controlled, real-time, pluvial flood forecasting system for Castries, St. Lucia that utilizes the limited data available locally. The results from the study suggest that although Global Forecast System (GFS) rainfall data may be considered coarse for urban applications, there is still a significant amount of skill and usability after it is post–processed and used in combination with observed rainfall data. Evidence from the study also suggests that the use of images from different sources is invaluable for 2D overland model calibration and validation in urban areas. Conclusions from the study are potentially transferable to other sites in similar data-scare and resource-limited locations.

Keywords: flood forecasting, hot spot, operational, rainfall forecasts, real-time, urban flood, trigger values

9.1 Introduction

With the rise in flood frequency in some areas, flood managers currently face an increased mandate to mitigate the effects of floods using forecasting to complement the already existing structural measures. Globally, there is a well-recognized need for real-time flood forecasting systems in urban areas (Jha et al., 2012), but this need has not yet been fulfilled in all major cites let alone smaller urban areas. Flood risk management as opined by Jha et al.,(2012) can be difficult to achieve where municipal managements suffer from a lack of technical capacity, funding and resources.

The preceding issues that challenge municipal managers on the global scale are magnified in developing countries such as the Caribbean and St. Lucia in particular. There are geographical issues relating to meteorological phenomenon such as hurricanes (Taylor et al., 2011, Giannini et al., 2001) and physical issues such as the difficulty of short lead times for the small urban catchments (Kirton, 2013). There are also financial issues impacting the quality of infrastructure as well as a general dearth of data. However, the ubiquity of the internet and its inherent speed and the ability to access information and data in real-time in a consistent way, today negates to some extent these functional challenges. It is therefore the objective of this paper to demonstrate that real-time flood forecasting can be achieved remotely even in areas with limited data.

There is no set design for a flood forecasting and warning system, but Werner et al., (2005) have outlined the general steps which are adaptable to the circumstances. They include detection, forecasting, warning and response. Presently there are no known real-time urban flood forecasting systems on the island states of the Caribbean community, but the Caribbean Institute for Meteorology and Hydrology (CIMH) has been commissioned to issue real-time flood forecasts in response to the recurring flooding affecting the member states primarily at the watershed level (CIMH, 2014).

Urban areas are characterised by highly impermeable surfaces, and typically very high spatial and temporal resolution data and models are required to effectively manage floods in urban areas (Zevenbergen et al., 2010) with sufficient lead-time for mitigation action. Quantitative precipitation forecasts (QPF) are an essential part of the flood forecast system, but some of their characteristic features still limit applicability in urban flood forecasting. However, the steady increase in the development of the technology that provides access to data in real-time has presented a possibility to improve the QPF by blending with other rainfall products (Sokol, 2006, Wang et al., 2013). Nonetheless, when dealing with QPF for extending forecast lead times, flood forecasts should include a quantification of uncertainty (Robertson et al., 2013, Liguori et al., 2012, René et al., 2013c, Dai et al., 2014).

This paper elaborates on the suggestions in René et al., (2013b) , and attempts to show how limited but available data and resources from the World Wide Web

(WWW) can be used to establish a real-time pluvial flood forecasting system for Castries, St. Lucia. The paper begins by presenting the St. Lucia case study and the data used. It then goes on to outline the real-time flood forecasting approach developed, followed by a demonstration of its implementation on the case study. The third section presents the results and discusses the synergies between the different components. Finally, the last section outlines the summary and conclusions.

9.2 Case study

The feasibility of the operational real-time flood forecasting approach is demonstrated using the administrative capital (Castries) of a small island (St. Lucia) in the Caribbean region with an area of approximately 0.45km^2 shown in Figure 9-1. Although loss of life due to flooding in Castries is rare, it does however result in property damage and loss of productivity. Minor floods usually occur after short duration high intensity rainfalls, with more severe flooding occurring as a result of storm events. The city contains a system of storm drains which discharges via two outfalls into the harbour during favourable conditions and otherwise pumped when free drainage conditions are less favourable (e.g. during storm surges). The area is prone to pluvial flooding as well as fluvial flooding from the river that flow adjacent to it and the small ravines which drain into the city. Coastal flooding in the study area is rare although it may occur during storm events. In an earlier effort to control fluvial flooding originating from the ravines, a detention basin was constructed in 2004. This basin is connected to the harbour via one of the two outfalls.

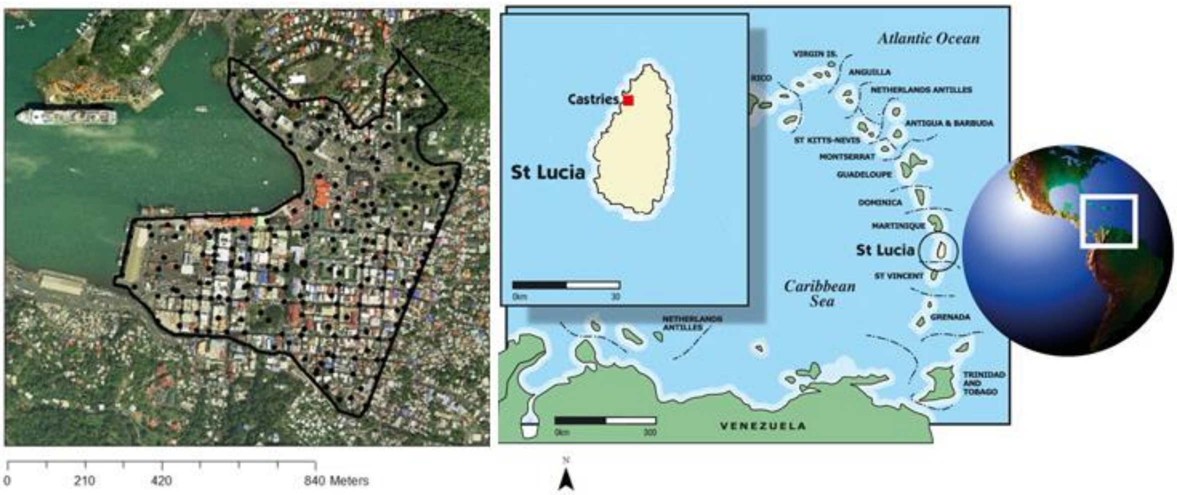

Figure 9-1: Study area location. The solid black line indicates the boundary of the applied 2D model (study area) and the black dots the spot heights used to generate the terrain model

9.2.1 2D overland flow model

A 2D flood model was set up for the study area (Figure 1). The model is based on a 5m resolution digital elevation model (DEM) which was derived from available spot heights using a kriging interpolation method, building shape file and orographic images of the area. A detailed explanation of the model development and calibration for this study is presented by René et al., (2013a). The calibration was performed using the only available storm event (hurricane Tomas on 31st October 2010 with a measured rainfall of 533 mm) which had a limited number of images reporting flooding. The Director of Meteorological Services, who completed an assessment of the damage after the event, further verified the model calibration (Auguste, 2013).

9.2.2 Forecast data

The rainfall forecast data originates from the Global Weather Forecast (GFS) model produced by the National Centre for Environmental Prediction (NCEP) (NOAA, 2013). The model runs four times a day at 00, 06, 12 and 18 UTC and produces operational weather forecasts 180 hours into the future. However, for this study, GFS QPF forecasts were downloaded twice daily only for the 00 and 12 UTC model run times, every time updating the data. This means that only the first 12 hours of the forecasts were available in this study. The horizontal resolution is 0.5^0 x 0.5^0, with forecast hours of 3 hours resolution and archived in a database server. The forecasts were extracted at 04 and 16 UTC after it had been made available by NCEP. The start date of the rainfall forecast archive is July 2011.

9.2.3 Observed data

Figure 9-2 illustrates the process flow for the real-time rainfall data collection in St. Lucia as of 15th July 2011, which was installed primarily to support tactical decisions involved in the workflow of the real-time pluvial flood forecasting approach. This demonstrates how to get started with flood forecasting with limited resource. Several things were considered when designing such a system including organizational polices on external access to a local network, firewall settings, etc.

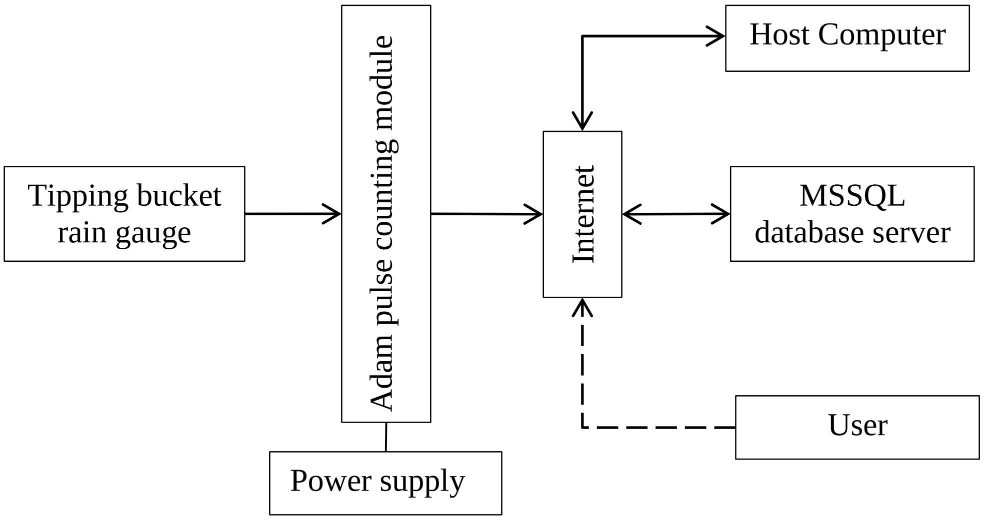

Figure 9-2: Components of the real-time rainfall data collection system used in the case study

Data is loaded frequently to a MSSQL database server using a special command and response protocol, where the host computer sends a query to the counting device and receives a response (counted rain pulse) back from the device. This is scheduled and executed regularly at 1-minute intervals, with a transmission delay to the server in Denmark of only a few seconds.

9.3 Methods

This section highlights the methods used to develop the different components of the real-time flood forecasting system (see Figure 9-3). The following sections will go step-by-step through Figure 9-3 (from the primary to secondary system) starting with an overview of the general flood forecasting approach followed by a demonstration of its implementation on the St. Lucia case study.

9.3.1 Overview of real-time approach

The approach is designed to provide a flood forecast based on both forecasted and observed rainfall, herein considered the primary system and the secondary system, respectively. Figure 9-3 visualizes the method. Two systems are considered to account for errors in the rainfall forecast. Flood forecasts are made once the rainfall thresholds are triggered. Two rainfall thresholds are considered here; one relates to the observed rainfall (T_{obs}) which reflects conditions on the ground and is continuously computed and the other is based on an accumulated rainfall depth within the forecast lead time (T_{sim}) which can generate flooding of a specific depth (trigger depth). This is derived from simulating historical events using the overland flow model. The primary system works as follows given a rainfall forecast:

1. Sum the rainfall forecast over the forecast lead time (X)

2. Apply the uncertainty estimation model to X to get bias corrected rainfall $\hat{X}_{CL}$ with a selected level of confidence

3. If $\hat{X}_{CL} < T_{sim}$ then there is no flood forecast. Otherwise, a flood forecast is made.

4. Once $\hat{X}_{CL} \geq T_{sim}$ is triggered, an ensemble of rainfall events is generated by scaling the events from an event catalogue, all of same duration as the rainfall forecast with the bias corrected forecast ($\hat{X}_{CL}$). Scaling factors are determined for each record and are given by:

$$a_i = \frac{\hat{X}_{CL}}{Y_i} \tag{9-1}$$

where a_i denotes the scaling factor for the i^{th} record, Y_i denotes the accumulated rain for the i^{th} record. The rainfall ensemble is given by:

$$e_i = a_i(TS_{\Delta t})_i \tag{9-2}$$

where $TS_{\Delta t}$ denotes the time series for the i^{th} record in the catalogue with time step Δt, which is considered suitable to reflect variability in the study area.

5. Each member of the rainfall ensemble (e_i) is used as hydrological forcing for the overland flow model. The results from the simulations are communicated by presenting a maximum flood map of a selected percentile (e.g. 95th) computed from the maximum of each ensemble member over the entire 2D model domain.

The secondary system works as follows:

Continuously compute the observed moving sum (Y_{MW}) of the observed rainfall over a suitable moving window. If $Y_{MW} \geq T_{obs}$, then make a flood forecast, otherwise there is no flood forecast. T_{obs} is the observed rainfall threshold estimated from rainfall of historical flood events.

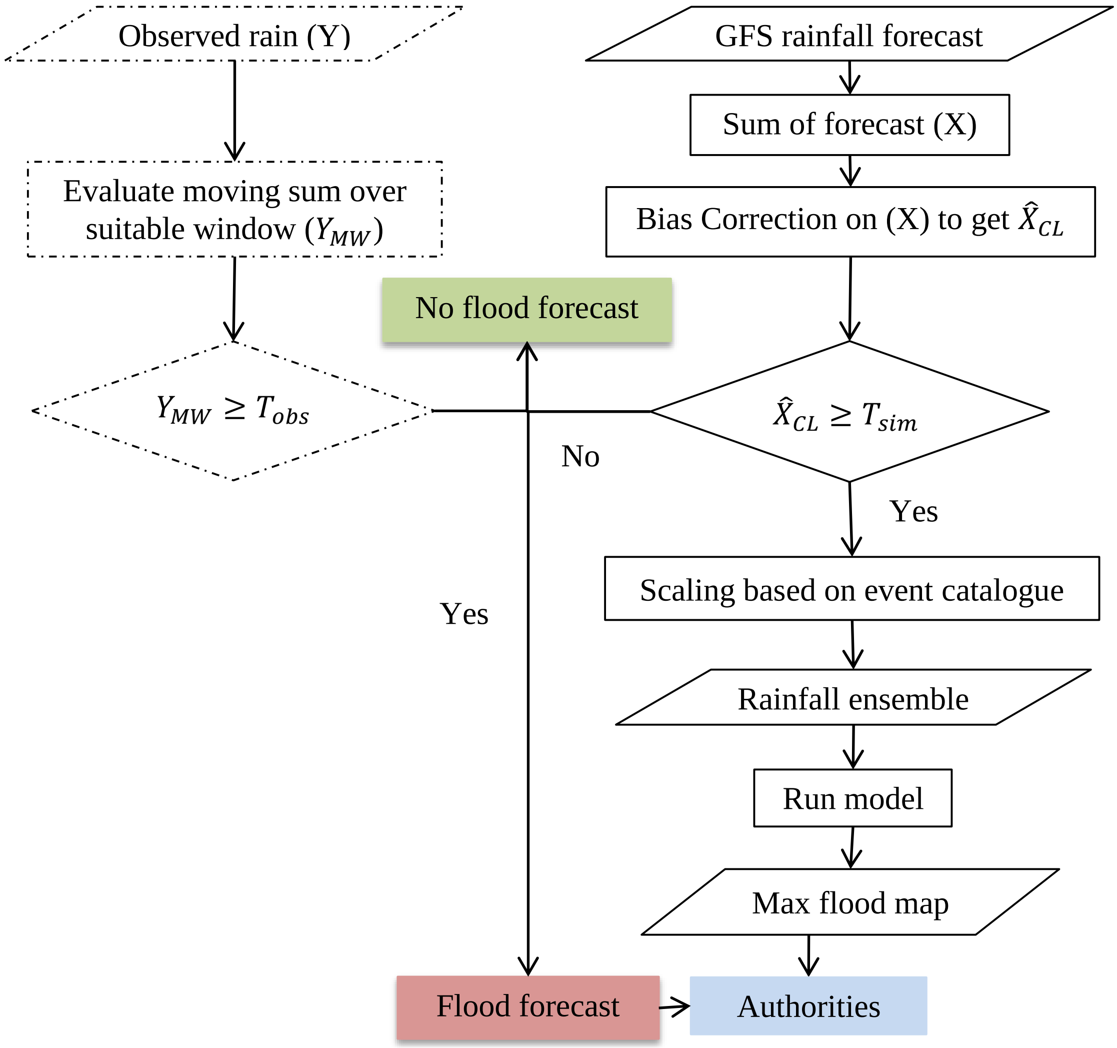

Figure 9-3: Automated flood forecasting sequence (systems flowchart). The primary system is represented using the solid shaped outline and the secondary system the dashed shape outline. The common aspects are shaded. $\hat{X}_{CL}$ represents the bias corrected forecast for a specific confidence level. Y_{MW} represents the observed moving sum value of a selected time window . T_{obs} represents the rainfall threshold derived based on observed rainfall and T_{sim} the rainfall threshold derived on the simulated rainfall which can generate flooding based on a specified trigger depth

9.3.2 Evaluation of forecast skills

To evaluate the benefits of the GFS QPF product and understand its limitations and utility in the context of flood forecasting different temporal resolutions are considered: (i) 3-hourly (original format), (ii) 6-hour accumulation, and (iii) 12-hour accumulation. In addition, a drizzle threshold of 0.1mm was applied to the observed and forecasted 3-hourly data.

Forecast verification was used to evaluate the accuracy of the 3, 6 and 12 hourly QPF. The accuracy was evaluated at different lead times because it is expected that the forecast error increases with lead time.

The forecast was verified by comparing the stationed rain gauge observations to the gridded QPF value of the grid cell in which the rain gauge station exists. The normalized root-mean-square error (NRMSE) is presented as a measure of accuracy and gives the average magnitude of error relative to the mean of the observations and is given by:

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2}}{\overline{Y_{obs}}}$$

(9-3)

where X_i , Y_i represents the forecast and observation, respectively, and $\overline{Y_{obs}}$ represents the mean of the observations. The NRMSE can range between zero and infinity; but values closer to zero are better.

Another verification approach utilized involves contingency tables, which describe the frequency of forecast and observation pairs within different categories defined by the 80th and 95th percentile of the observed data. Observed percentiles were selected to make it possible to compare the datasets of different intensities. Based on the entries in the table, the following scores were computed: (i) Probability of Detection (POD); (ii) False Alarm Ratio (FAR); (iii) Critical Success Index (CSI); (iv) Frequency Bias and (v) over and under-forecasting rate.

The POD = hits/(hits+misses) represents the portion of the data correctly forecasted in the category and ranges from a worst case of 0 to a perfect score of 1, whereas the FAR = false alarms/(hits+false alarms) represents the portion of the data forecasted in a category that were not observed. The worst score is one and a perfect score is zero. The CSI = hits/(hits+misses+false alarms) measures how well the forecasted rain events correspond to the observed rain events by comparing the hits to the number of cases forecasted and observed for the category. Again, values range from zero to 1 in the direction of no skill to perfect score. The frequency bias = (hits+false alarms)/ (hits+misses) on the other hand represents how well the forecast rain frequency compares to the observed rain frequency. This score has the range $0 - \infty$ with 1 as the perfect score. The under and over-forecasting rate represents the portion of the data which is under or over-forecasted in the category. A score closer to zero is desirable.

The scores were computed to evaluate the overall forecast performance of the different data resolutions. Based on guidelines provided by WMO (2011) for the forecast to be useful, the POD should be more than 33% regardless of the other scores. This means that the forecast detects at least one in every three observed events.

9.3.3 Uncertainty estimation

For this case the method by René et al., (2013c) was applied to correct the GFS QPF for bias and to quantify forecast uncertainty in real-time. Because of the distinct dry and wet season on the Island the available data period (July 2011 – Dec 2013) is divided into a dry (Dec - Apr) and wet (May - Nov) season.

The method considers two stochastic models to reflect the intermittent nature of rainfall itself ("rain", "no rain") for each season. In reality a rainfall forecast can be either zero or a non-zero value. Conditional probability distributions are derived from the data, conditioned on a zero and non-zero rainfall forecast, respectively, using:

$$P(Y \leq y|X=0) = P(Y \leq y|Y>0, X=0)P(Y>0|X=0) + P(Y=0|X=0) \tag{9-4}$$

$$P(Y \leq y|X=x^*) = P(Y \leq y|Y>0, X=x^*)\,P(Y>0|X=x^*) + P(Y=0|X=x^*) \tag{9-5}$$

where X and Y again represent the forecast and observation, respectively. Imposing these conditional distributions on a given rainfall forecast will bias correct the rainfall forecast as well as provide an estimation of forecast uncertainty. From the distribution a quantile is selected that reflects the level of confidence in the bias corrected forecast. In this study the 95th percentile ($\hat{X}_{95}$) was selected because there is a higher chance of a hit at higher percentiles.

9.3.4 2D Model Validation

The credibility of the model to replicate flood depths and extents was established using two rainfall events (18th November 2010 – daily time step and 1st May 2013

– 1 minute time step) for which images were available for extracting depths, locations, extents etc. This involved a comparison of observed depths extracted from images to that obtained from the hydrodynamic simulations of the observed rainfall from rain gauges.

9.3.5 Estimation of observed rainfall trigger value

Here we present the method used to identify the rainfall threshold which was used to issue a flood forecast based on the secondary flood forecast system (see Figure 9-3). We started by identifying known flood events during the study period (Jul 2011 – Dec 2013). We then adopted the moving sum technique of the rainfall depth time series for specific moving windows, and compared the moving sum with the timing of flood events. In the determination of a suitable rainfall trigger value, the predictive power was not only measured by successful prediction of floods given the rainfall, but also by the prediction of no floods given the rainfall. As such, the rainfall threshold was identified when distinct peaks are observed for the known flood events for a specific moving window.

9.3.6 Creation of events catalogue and estimation of trigger value

In order to get representative rainfall patterns at time scales which are relevant for urban flood modelling we used an approach which creates 12 hour time series with 15 minutes time resolution and ensures that the volume for each ensemble member equals the forecast volume of the bias corrected rainfall forecast with 95% confidence level ($\hat{X}_{95}$). This was achieved by first identifying 12-hour historical events which generated floods of 0.1m or more at an identified hot spot location. These events were used to create a catalogue of events which were then used to generate an ensemble of shape patterns of the “most probable” rain events based on the scaling procedure in Eqs. (9-1) and (9-2).

The location of the hot spot was established based on the simulation of historical observed rainfall and knowledge of the study area. We first identified a “trigger depth” (T_D), hereby defined as the depth at which relevant authorities should be informed of a looming threat, and a “critical depth” (C_D) defined as the water depth after which there will be damage to property as well as disruption in the movement of people and traffic; where $T_D < C_D$. However, this is not a straightforward exercise when there are few flood events (3 known flood events) in the data record (Jul 2011-Dec-2013). Since the model area is relatively small and is developed on coarse data, only one hot spot was considered, to reduce the possibility of false alarms. The “hot spot” was identified as a location which is at a high risk to flooding

9.3.7 Validation of flood forecasting approach

To demonstrate the performance of the stochastic model in correcting rainfall forecast the same events used to estimate the water depth trigger values were analysed. Both forecast values for a given day (00:00 and 12:00) were evaluated to verify possible timing issues in the rainfall forecast. The 50th, 90th and 95th quantiles of the conditional distributions of rainfall observations were calculated to give an idea of the deviation between percentiles and to demonstrate why a higher quantile was selected as the rainfall forecast quantile. The selected quantile gives an indication of the confidence level.

For cases where flooding was actually observed and $\hat{X}_{95} \geq T_{sim}$, rainfall ensemble was generated based on the scaling approach. The resulting ensemble was used as hydrological forcing into the 2D overland model. The 10th, 50th and 95th percentile were computed from the probability distribution of maximum water depths derived from each ensemble simulation at the hot spot, to get an idea of the distribution of maximum water depth.

9.4 Results and Discussion

9.4.1 Verification of rainfall forecast

For the analysis period, the total observed rainfall was $2324.1\ mm$ and the total forecasted precipitation of the grid above the rain gauge $2352.5mm,$ a difference of only 1.2%. The accuracy of the forecast using the NRMSE for the different datasets ($mm/3hr\ , mm/6hr\ \ and\ \ mm/12hr$) is shown in Figure 9-4. Contrary to expectations, **Error! Reference source not found.** does not highlight that the accuracy of the forecast decreases with increasing lead-time. However, it does highlight that the accumulated forecast datasets are more accurate. Although it is not desired to use such coarse temporal resolution for urban flood applications, it provides a higher confidence in its application. As a result, the accumulated 12-hour forecast was chosen as the tentative resolution for the operational system and to be confirmed based on the results from the contingency scores.

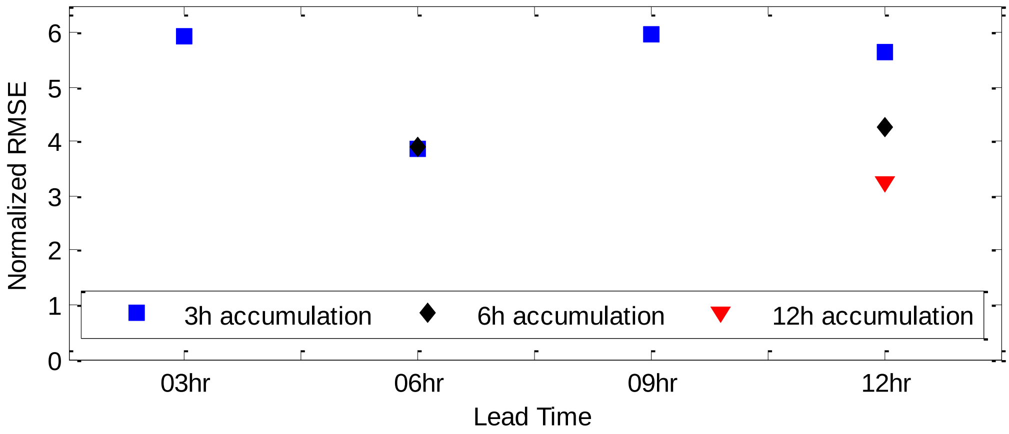

Figure 9-4: Normalized root mean square error (NRMSE) for the different data resolutions for the stationed rain gauge and the forecast grid above the rain gauge for the period July 2011- December 2013

Turning now to the categorical forecast verification based on the percentile threshold criteria that defined the categories. Table 9-1 is an example of the 3x3 contingency table for the 12 hourly-accumulated forecasts showing the frequency distribution for the three categories. From the data in Table 9-1, there is a general tendency for the forecast to underestimate large events and a slight tendency to overestimate smaller events. This is also reflected in the bias scores presented in Table 9-2 for the 12 hourly dataset for the below and above category respectively.

Table 9-1: 3X3 contingency table for the 12 hourly accumulated forecast for threshold of 1.6 and 6.4 mm which corresponds to the 80th and 95th observed percentiles respectively

12 hourly		Observation			
		Below	Within	Above	Total
Forecast	Below	1208	181	56	1445
	Within	197	69	17	283
	Above	35	21	17	73
	Total	1440	271	90	1801

Based on the defined categories some verification scores were computed to evaluate the forecast performance, although it is not usual to compare forecast to a single rain gauge. It is apparent from Table 9-2 that the GFS rainfall data for this study location has a higher skill at forecasting small rain events (i.e. the below category) based on the POD values for all datasets.

Table 9-2: Quality scores derived from contingency table for the different lead times (LT) for the 3, 6 and 12-hourly forecasts for the different categories. Ideal situation is a value of 1, 0, 1 and 1 for the POD, FAR, CSI and Frequency bias, respectively

LT	POD			FAR			CSI			Frequency bias		
	B	W	A	B	W	A	B	W	A	B	W	A

00	0.608	0.460	0.148	0.155	0.813	0.862	0.547	0.153	0.077	0.720	2.463	1.068
03	0.788	0.232	0.056	0.190	0.830	0.844	0.665	0.109	0.043	0.972	1.360	0.356
06	0.667	0.262	0.202	0.189	0.855	0.857	0.577	0.103	0.091	0.822	1.812	1.416
09	0.721	0.347	0.133	0.181	0.793	0.818	0.622	0.149	0.083	0.880	1.677	0.733
00	0.841	0.233	0.144	0.170	0.775	0.794	0.717	0.129	0.093	1.013	1.033	0.700
06	0.756	0.247	0.124	0.178	0.824	0.876	0.650	0.114	0.066	0.920	1.409	1.000
00	0.839	0.255	0.189	0.164	0.756	0.767	0.720	0.142	0.116	1.003	1.044	0.811

*B, W and A represents the below, within and above category

However, it is more important that the model is able to correctly predict the large events (above) and it does not show much skill in that respect based on the very small POD. Considering the ‘above’ category the 12 hourly-accumulated forecast has, in general, better skill compared to the other datasets and their lead times based on the POD. On the contrary the 12 hourly data also has a very high FAR and ultimately a low success ratio (SR = 1-FAR) which is also not desirable for real time flood forecasting applications. A low SR implies that the forecast does not have a good warning skill. A high FAR implies a small CSI which indicates that there are few forecasted rain events which were correctly forecasted.

The skill of the forecast can potentially be improved using the bias correction approach. Nonetheless, overall the raw 12 hourly forecasts perform slightly better than the other datasets. The shortcomings in the forecast can mean a lot for the development of the operational flood forecasting system, but the findings are useful for identifying the usefulness of the data for this application.

9.4.2 Bias correction

This section highlights the skill of the stochastic model in predicting rainfall where more emphasis is placed on the ‘above’ category since it is the most important for the application discussed in this paper. This is done in a similar manner, based on contingency scores as shown for selecting the dataset of suitable temporal resolution. The verification results are presented for the raw and 95th percentile bias corrected 12 hourly forecast dataset (Table 9-3).

In the raw dataset there is a general tendency to underestimate for the 'within' and 'above' category. However, after bias correction, this tendency has decreased (e.g. under-forecasting rate was improved from 81.1% to 33.3%) as well as an increase in the POD. However, the FAR has increased. The high FAR means that the overall SR is low. The low CSI for all categories suggest that on average there is a 9% chance of an observed event given a forecast. This score is sensitive to false alarms and misses; therefore a high FAR would imply a very low CSI. The over-forecasting rate has increased for the 'below' and 'within' category, therefore resulting in low POD for these categories. The low POD for the 'below' and 'within' category is not an issue which warrants inquiry because these categories are not significant for flood forecasting. These findings have important implications for developing the flood forecasting approach. The high FAR (low SR) suggests that the flood forecasting system will be riddled with false alarms. Nonetheless, the POD of 67% suggests that the stochastic model has some skill in predicting large events (hits two out of 3 events) but tries to compensate for the overall underestimation by overestimating the events in the 'below' and 'within' category. Another interesting observation is that frequency bias has increased. This is because the numbers of false alarms have increased and the number of misses decreased.

Table 9-3: Quality scores for the raw and bias corrected 12 hourly dataset

Score	Raw Data			Bias Corrected		
	Below	Within	Above	Below	Within	Above
POD	0.839	0.255	0.189	0.077	0.442	0.667
FAR	0.164	0.756	0.767	0.035	0.876	0.917
SR	0.836	0.244	0.233	0.965	0.124	0.083
CSI	0.720	0.142	0.116	0.077	0.107	0.080
Frequency bias	1.003	1.044	0.811	0.080	3.572	7.989
Over-forecasting rate	0.161	0.077		0.923	0.546	
Under-forecasting rate		0.668	0.811		0.011	0.333

9.4.3 Observed rainfall trigger value

The trigger value analysis revealed that no unique set of measurements exists to characterise the rainfall conditions that are likely (or not likely) to trigger flooding. In this analysis different thresholds are possible depending on the size of the moving window, but the predictive power is best for larger moving windows (i.e. fewer false alarms). Although it is also not common practice to estimate rainfall trigger values on so few events, for the case study considered, a peak rainfall threshold of 35mm in a 12-hour moving sum window was selected as the rainfall trigger value (Figure 9-5). As more information is acquired, there will be more lessons learnt and the system will be modified in a similar manner in which it was designed to incorporate these experiences.

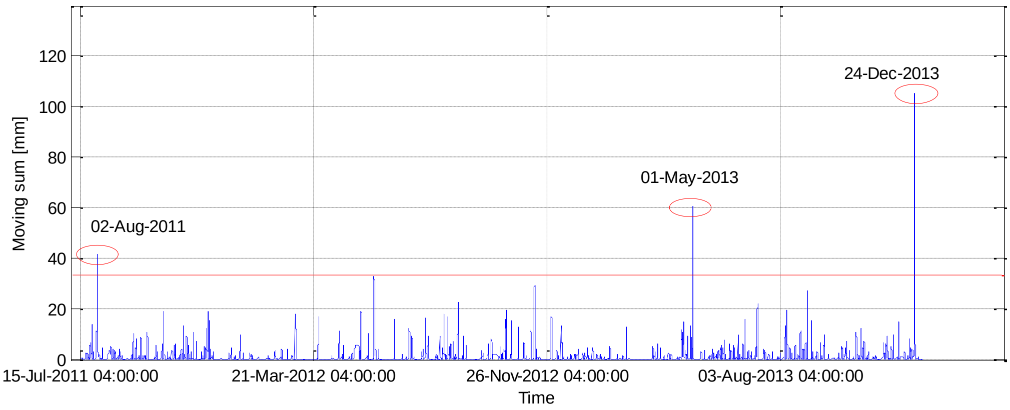

Figure 9-5: Time series of the moving sum with a 12-hour moving window. Distinct peaks are observed for the three known flood events. Red horizontal line highlights the threshold limit of approximately 35mm of rainfall

9.4.4 2D model validation

There is currently no rigorous operational procedure to outline how urban flood models should be calibrated and validated (Vojinovic and Abbot, 2012). However, conventional strategies typically involve the comparison of simulated model variables to observed data at specific points on the model grid. This remains the only attainable option in many practical cases. In practice observed data, which may be in many different formats (e.g. images, video), can still be invaluable for model calibration and validation even if it is not necessarily efficient for use (Zevenbergen et al., 2010).

In this case study, water depths were derived from images from the WWW, posted by individuals who experienced the events as well as news reports. For the flood observed on 18th November 2010 only daily rainfall data was available since the real-time rainfall data collection system had not yet been installed. This event was selected because there were many images posted online during the rain event. The other event selected is 1st May 2013. In this case rainfall data with a temporal resolution of 1 minute was available

The flood depths are estimated from the images using objects such as a vehicle, a person, a pole, curb walls, building entrances or doors etc. as a reference. Images from the two events are shown in Figure 9-6 and Figure 9-8. The simulated maximum flood maps with indicated locations and direction where the photos are taken are shown in Figure 9-7 and Figure 9-9. Simulated maximum depths and estimated observed depths from the images are compared in Table 9-4.

Figure 9-6: Images captured during or after the November 18th, 2010 flood event; locations indicated by numbers 1-8 are shown on the map in Figure 9-7

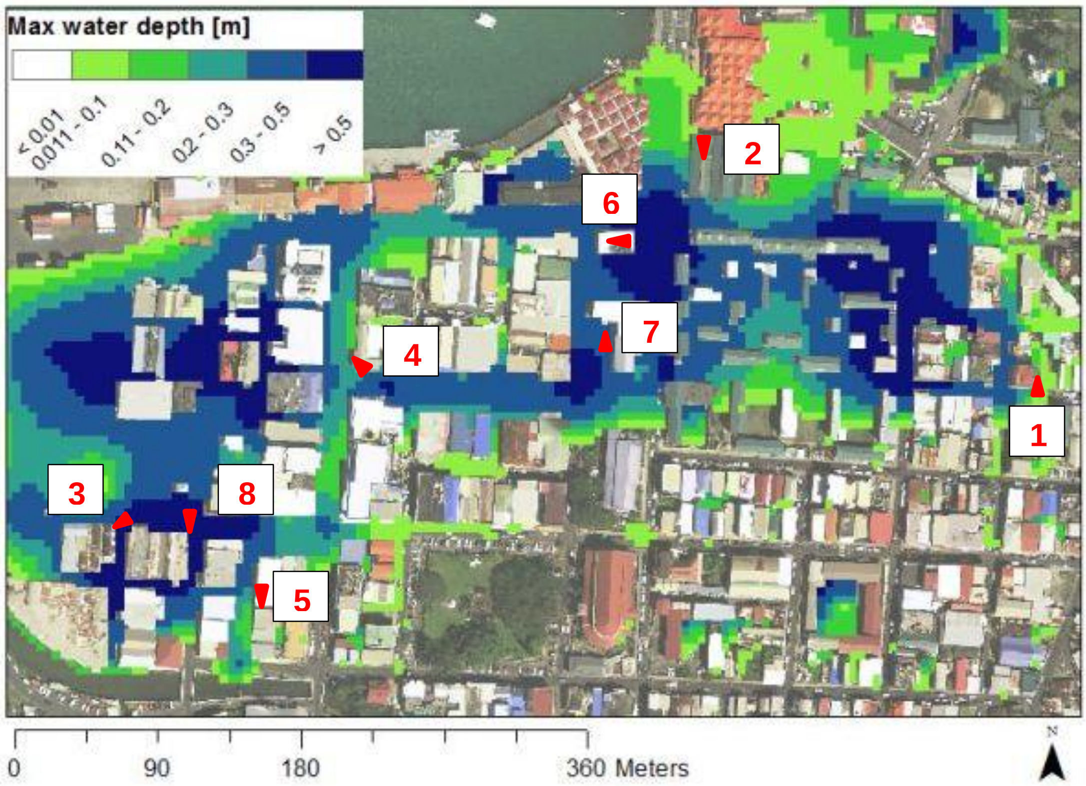

Figure 9-7: Locations where available images shown in Figure 9-6 are depicting flood for the 18th November 2010 rain event. The direction of the arrows show the direction in which the pictures were taken

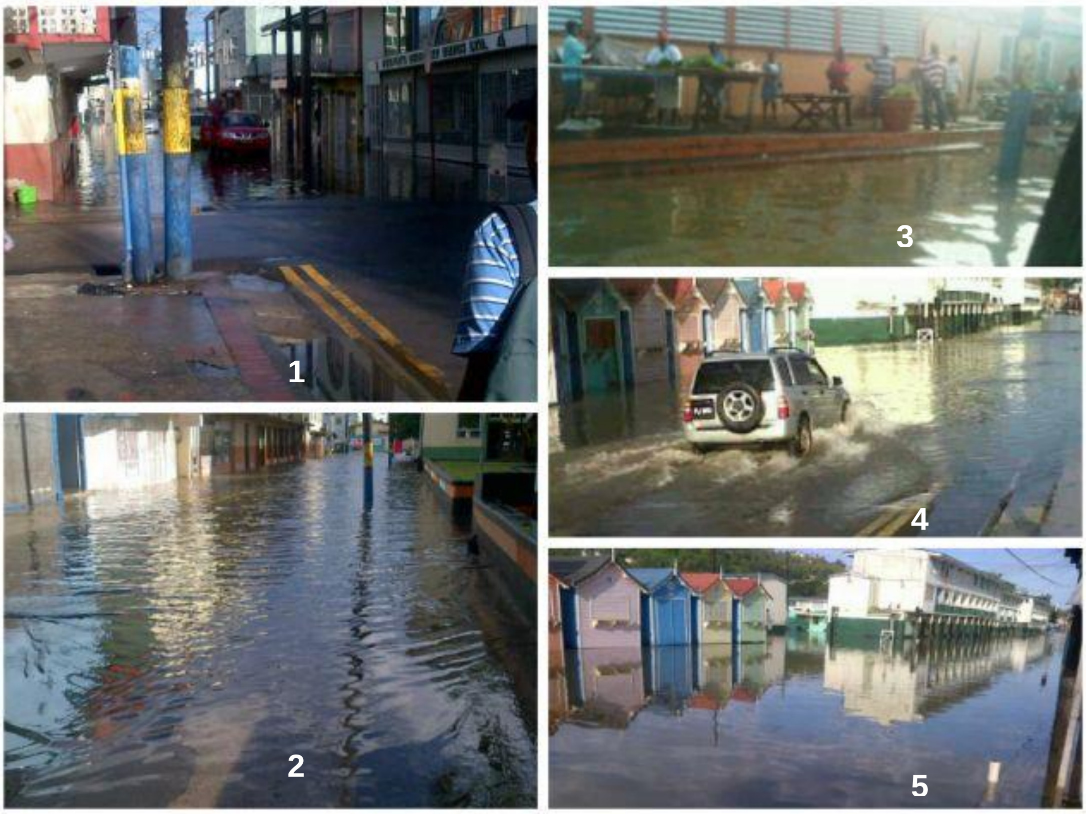

Figure 9-8: Pictures posted on the WWW on the morning on 1st May, 2013; locations indicated by numbers 1-5 are shown in Figure 9-9

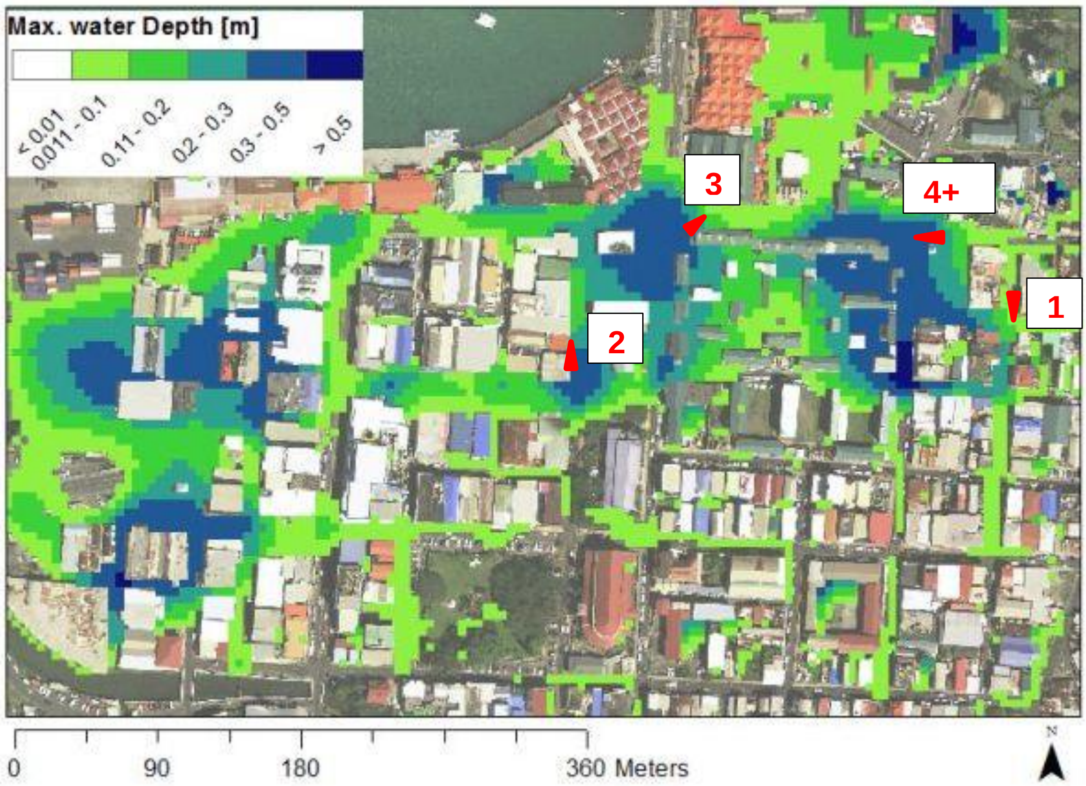

Figure 9-9: Locations where the available images shown in Figure 9-8 are depicting flood for the Morning of 1st May 2013. The direction of the arrows show the direction in which the pictures were taken

Based on a comparison of the observed and simulated depths and their reasonably good agreement (Table 9-4), it can be said that the model is suitable for use for real-time flood forecasting. The computed forecast may not necessarily yield the exact flood depths but it gives an indication of the magnitude of the observed water depths and flood extents.

Table 9-4: Estimated observed depths and simulated depths for selected locations in the model

Event	November 2010								May 2013				
Image number	1	2	3	4	5	6	7	8	1	2	3	4	5
Observed estimated depth [m]	0.3	0.1	0.2	0.4	0.2	0.4	0.4	0.2	0.1	0.2	0.1	0.1	0.2
Simulated max depth [m]	0.4	0.2	0.3	0.3	0.2	0.4	0.4	0.5	0.2	0.2	0.1	0.3	0.3

Although the results above demonstrate a large potential in using images for model calibration and validation, the validity of the concept rests upon the spatial and temporal distribution of the available images. The lack of images over the entire model domain can potentially introduce a bias in the overall flood picture, but this bias can be minimized bearing in mind the following.

It is argued that if there are images reporting flooding in an area, there is a high probability there was in fact flooding. However, if there are no images available, can one conclude there is a high probability that there was no flooding? There is no straightforward answer to this, but possible explanations depend on different factors such as time of flood (day or night) and location (residential, commercial, or industrial).

9.4.5 Hot spot location

An interesting insight into flood susceptibility was revealed during model calibration and validation, and the knowledge acquired was used to identify potential hot spots. The hot spot is defined at a junction of one of the major carriageways in and out of the city. A depth of 0.1 and 0.2m was selected as the T_D and C_D respectively. T_D was selected as 0.1m because based on simulations with observed rainfall for the flood events, on average it takes 45 minutes to reach the C_D at the hotspot after T_D is reached, therefore providing adequate time for response. C_D was selected as 0.2m because it represents a height at which pedestrians can no longer use the sidewalks, when business should start taking the necessary action to protect their property and when road traffic becomes difficult. Potential mitigation measures include traffic diversion, and placement of sand bags at business entrances.

9.4.6 Rainfall threshold based on events catalogue

Based on the investigation of historical records (each of 12 hour duration) which generates a flood of more than 0.1m at the hot spot, we found ten historical records which were used to create the events catalogue. The minimum 12 hourly-accumulated rainfall depth in the catalogue is 17.8mm. As a result a T_{sim} of 17.0mm was selected as the minimum threshold which is used to trigger the hydrodynamic simulations in Figure 9-3, and thus make a flood forecast.

9.4.7 Validation of flood forecasting approach

Table 9-5 presents the bias corrected rainfall forecast for the selected forecast events as well as an indication of whether it would have been a hit, miss, false alarm or correct negative, using the uncertainty model. The table highlights (in red) the forecast time within which floods were observed to give an indication of the reliability of the overall system. The results suggest that there is significant skill in the flood forecasting approach. Interestingly, despite all the shortcomings of the data based on verification scores (Table 9-3), in all cases studied, except 01-Aug-2011 00:00, the 12 hourly forecasts are able to correctly detect a flood within the 12 hours. Despite only observing 8.9mm of rainfall for the 12 hour forecast on 30-Apr-2013 12:00 flooding was observed. There are several possible explanations, which are not limited to antecedent rainfall conditions and rainfall intensity.

Table 9-5: Bias corrected forecast for dates of events used for identifying trigger depths in the 2D overland model . X represents the raw 12 hour accumulated forecast value, Y represents the actual observed rainfall and $\hat{X}_{50},\ \hat{X}_{90}\ and\ \hat{X}_{95}$ represents the bias corrected forecast for confidence levels of 50, 90 and 95 percent. The table also outlines whether it was a hit, miss, false alarm or a correct negative based on the $\hat{X}_{95}$ forecast.

Season	Event	[mm]					Status
		X	$\hat{X}_{50}$	$\hat{X}_{90}$	$\hat{X}_{95}$	Y	
Wet	01-Aug-2011 00:00 12:00	71.2 25.6	2.3 2.0	11.6 10.5	*18.0* 16.4	10.5 12.9	False Alarm Correct negative
Wet	02-Aug-2011 00:00 12:00	52.0 2.4	2.3 0.4	11.3 5.5	17.6 9.2	33.2 3.3	Hit Correct negative
Dry	30-Apr-2013 00:00 12:00	0.8 44.8	0 1.5	2.1 11.2	4.0 22.5	8.7 8.9	Correct negative Hit
Wet	01-May-2013 00:00 12:00	46.3 4.2	2.2 0.7	11.2 6.4	17.4 10.6	52.3 0	Hit Correct negative
Dry	24-Dec-2013 00:00 12:00	3.8 103.1	0.4 1.7	4.6 13.1	8.9 26.7	3.3 96.1	Correct negative Hit
Dry	25-Dec-2013 00:00 12:00	23.0 83.1	1.4 1.6	9.8 12.6	19.4 25.6	33.2 0	Hit Hit

Another observation is that for small forecast event, although there is some over-forecasting it does not trigger $\hat{X}_{95} \geq 17.0$. Therefore, the likelihood for false alarms is small. However, for large events, in some cases $\hat{X}_{95}$ is just at the limits of $\hat{X} \sim 17.0$ (under-forecasting rate of 33% - Table 9-3) therefore suggesting that there is a 33% chance that large events can go almost undetected (i.e. one in three events).

Table 9-5 illustrates that the bias correction becomes quite severe for large events. For example for a forecast of 71.2 mm, the correct rainfall forecast with 95% confidence level is 18.0 mm and the actual observation is 10.5 mm. But if we consider the rainfall forecast of 103.1 mm, the corrected value with 95% confidence level is 26.7 mm and the actual observation is 96.1 mm. This suggests that the uncertainty model always tries to compensate for the overall overestimation and reduces the rainfall for large rainfall forecasts.

Table 9-6 presents the water depths at the hot spot location with different levels of confidence derived from the probability distribution of the maximum water depths from the 10-member rainfall ensemble for the event. The results highlight a small difference between the presented quantiles which reflects the 2D model's response to different rainfall patterns.

Table 9-6: Evaluation of the skill of the event catalogue for difference confidence levels for known flood events. WD_{10}, WD_{50} and WD_{95} represent the computed water depths at the hot spots for the 0.1, 0.5 and 0.95 quantiles of the maximum flood maps derived from the rainfall ensemble for the event.

Event forecast times	$\hat{X}_{95}$ [mm]	Maximum water depth (WD) at hot spot [m]		
		WD_{10}	WD_{50}	WD_{95}
02-Aug-2011 00:00	17.6	0.238	0.246	0.252
25-Dec-2013 00:00	19.4	0.250	0.257	0.265
24-Dec-2013 12:00	26.7	0.297	0.340	0.342
25-Dec-2013 12:00	25.6	0.291	0.301	0.321
30-Apr-2013 12:00	22.5	0.271	0.278	0.287

A 95th percentile maximum flood map based on the corrected forecast ($\hat{X}_{95}$) is presented for the event of 24-Dec-2013 (Figure 9-10) as well as the maximum flood map derived from observed rainfall for the same period (Figure 9-11). Comparison of the flood maps suggests that, in general, the flood extents are very similar, although the maximum depths are not the same throughout. There is an approximate difference of 10cm in the worst affected places. Considering all the uncertainties in the overall approach the results does affirm confidence in the forecast system.

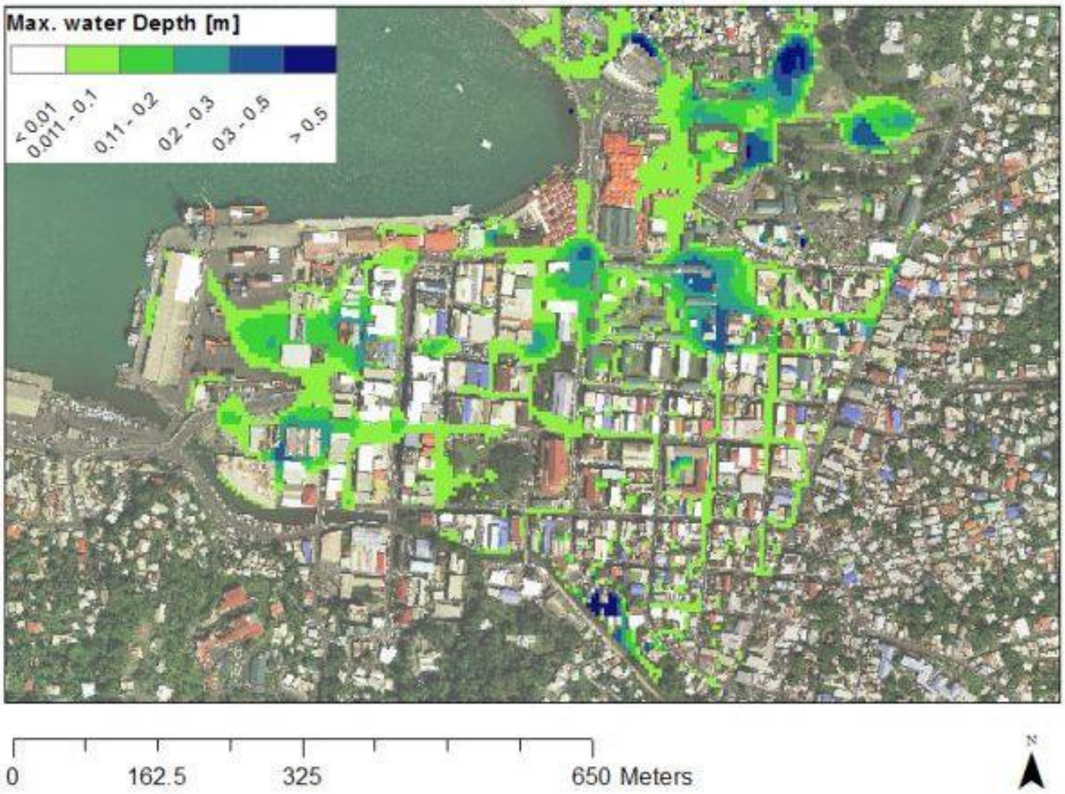

Figure 9-10: Maximum flood map for the event on 24-Dec-2013 between 12:00 - 00:00 UTC based on the 95th percentile of the maximum of the simulated ensemble

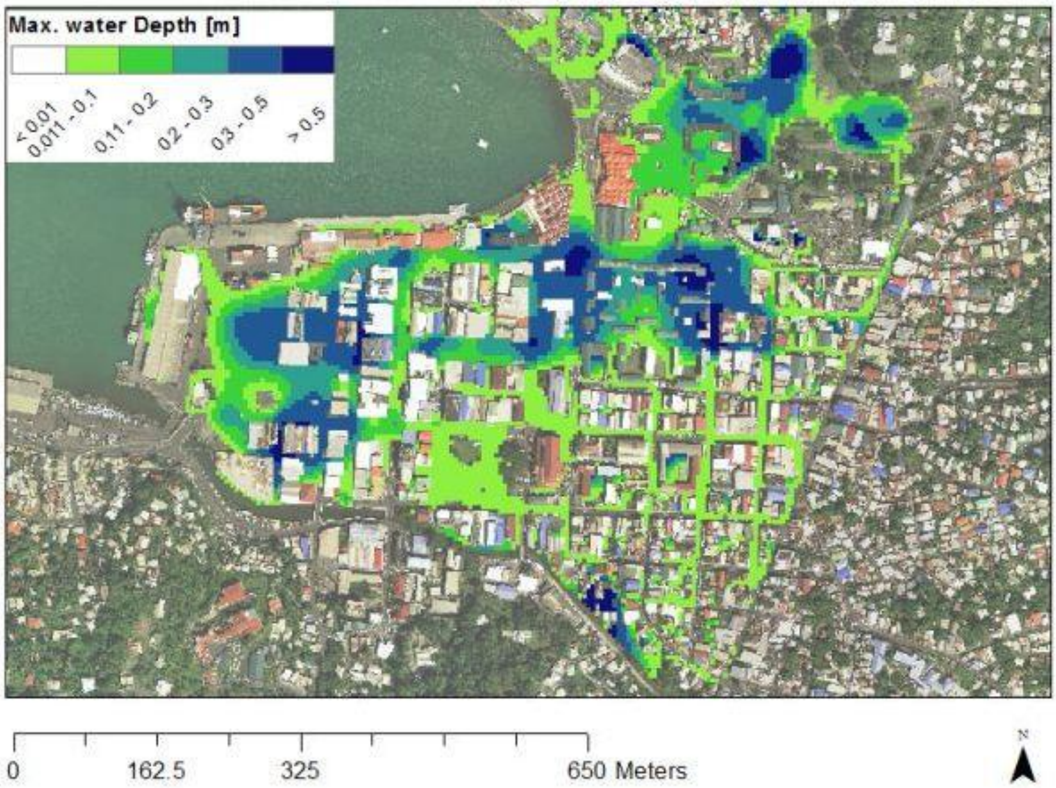

Figure 9-11: Maximum flood map obtained from simulating the observed rainfall for the event on 24-Dec-2013 between 12:00 - 00:00 UTC

9.5 Conclusions

This paper has demonstrated the feasibility of how to remotely bridge the gap between real-time urban flood forecasting and the lack of technical capacity and other resources, while effectively using free data from WWW. This project was undertaken to provide some inspiration on how to get started with real-time flood forecasting in a data sparse area (Castries, St. Lucia) and to highlight that urban flood managers can relatively easily make accurate yet cost-effective forecasts.

This study has shown that the current level of forecast skill for the GFS rainfall forecast is still not good enough and bias correction or post processing is needed before the rainfall forecast can be used for flood forecasting. A method which bias corrects and quantifies uncertainty is used in this study. To improve the forecast skill (e.g. POD), the 3-hourly 12 hour raw rainfall forecasts was accumulated to a 12 hour forecast. To assess the forecast skill for large events the data was divided into three categories based on percentile thresholds (below, within and above). The raw 12-hour accumulated rainfall forecast for the above category has some skill but hardly better than the other data sets used. The bias corrected 12-hour rainfall forecast indicates some improvements over the raw 12 hour forecast particularly for the above category (POD 67%) which is useful for this flood forecasting application. However, the overall level of skill of the bias corrected rainfall for the ‘above’ category in terms of frequency bias and FAR is still modest. The evidence suggests that although GFS rainfall data may be considered coarse for urban flood applications, there is still a significant amount of skill and usability after it is post-processed.

Combining a system based on the rainfall forecast and observed rainfall provides an opportunity to increase lead-time. Developing the system based on the rainfall forecasts provides the possibility to prepare to take action. In an urban system like this, mitigation action does not necessarily mean drastic measures, but simple action such as mobility of traffic control personnel and placement of sand bags in front of businesses can reduce flood impacts.

The results also show that the use of images from different online sources is invaluable for 2D overland model calibration and validation in urban areas. The relevance of the 2D model for identifying flood prone areas is clearly supported by the images. Results of their comparison suggest that the 2D model is sufficient to represent flooding in the area albeit as a simplification.

The feasibility of the approach to other case studies of different sizes, nature, severity and extent of flooding, physical characteristic. in other regions of the world needs further investigation. However, we consider the results of this study to be potentially generalizable.

A future study investigating the contribution of the use of weather radar in the system would be very interesting. The impact of including drainage network data, and considering fluvial flooding as well as coastal flooding would also be interesting for comparing accuracy against model complexity.

Acknowledgements

This work was carried out as part of the CORFU (Collaborative research on flood resilience in urban areas) project and was funded by the European Commission through Framework Programme 7, Grant Number 244047. The authors would like to thank the Director of the Meteorological Services in St. Lucia, Mr Thomas Auguste as well as Mr Govinda Augustin for their continued support throughout this project.

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10 Probabilistic forecasting for urban water management: a case study

Conference Proceedings: The 9th International Conference on Urban Drainage Modelling, Belgrade, Serbia 2012

This Chapter 6llustrates the application of a probabilistic approach for the estimation of the uncertainty in rainfall forecast from a numerical weather prediction model in combination with a 1D/2D hydrodynamic model for producing probabilistic flood forecasts. The approach quantifies the uncertainty conditioned on the rainfall forecast in the form of probability distribution functions. The method utilized in this Chapter 6nvolves a retrospective comparison at different lead times between archived forecasted rainfall and its corresponding observed rainfall for the second largest city in Denmark, Aarhus. Since there were no large events on record to generate flooding, a synthetic forecast event is used for illustration of the method. The Latin hypercube sampling technique was used to generate ensembles of rainfall for the synthetic rainfall forecast which has been used in conjunction with the 1D/2D hydrodynamic model. For comparison, a direct quantile approach was used to generate rainfall quantiles which were also ingested into the 1D/2D model to enable the selection of a robust approach that can be used in real time.

Keywords: Flood forecasting, numerical weather prediction model, probabilistic rainfall forecasting, real-time modelling, urban flooding

10.1 Introduction

It has generally been acknowledged by most literature sources in the field of water management that flood forecasts should be made with a quantifiable estimate of the uncertainty in the forecast (Krzysztofowicz, 2001, Pappenberger and Beven, 2006). For this reason, many studies are moving away from the conventional deterministic approach and towards probabilistic approaches. However, most of the approaches are applicable at the river basin scale and less so at the urban scale. One of the reasons for this is that hydrological and hydrodynamic modelling at the urban scale requires rainfall forecast of high temporal and spatial resolution. A few studies have attempted to assess the feasibility of using quantitative rainfall forecasts as well as probabilistic forecasting schemes in combination with a 1D sewer model in urban flood modelling (Rico-Ramirez et al., 2009, Schellart et al., 2009, Liguori et al., 2012).

More recently, with the increased frequency of floods due to climate change and rapid urbanization, more studies are trying to increase lead-time by investigating the feasibility of using different rainfall forecast products and different approaches for downscaling the rainfall forecast for forecasting flows and water levels in urban drainage system (Schellart et al., 2011, Simões et al., 2011a, Simões et al., 2011b). However, in order to achieve the desired level of accuracy in an operational context of the presented approaches, further investigation must be carried out using a combination of approaches and techniques.

This paper proposes a new approach for probabilistic flood forecasting in urban areas. The approach comprises of three components: (1) estimation of a probabilistic rainfall forecast model which is based on a retrospective comparison of archived historical forecasted rainfall and its corresponding observed rainfall; (2) prediction of rainfall quantiles or rainfall ensembles based on the stochastic model of the rainfall forecast; and (3) prediction of probabilistic flood maps using the probabilistic rainfall forecasts as input for the physically-based 1D/2D hydrodynamic model. The proposed approach is tested using a synthetic extreme rainfall event for a case study in Aarhus, Denmark. Two methods for the generation of probabilistic rainfall forecasts; Latin Hypercube Sampling (LHS) approach and direct quantile approach are compared.

10.2 Methodology

10.2.1 Rainfall data

In this research, two years of continuous hourly data (2009 – 2010) for observed and forecasted rainfall was used for the city of Aarhus, Denmark. The observed data originated from a network of 3 tipping bucket rain gauges (Figure 10-1) installed in the catchment. The data had an original temporal resolution of 1 minute. The Thiessen polygons method was used for estimating catchment rainfall based on the rain gauge data (Figure 10-1). The forecasted rainfall data originated from a numerical weather prediction model (StormGeo, 2011) and was used as the source of historical rainfall forecast. A 72 hour, hourly product of (6.2 x 11.1) km resolution updated every 12 hours was used. The data provided covered two rainfall forecasts grids, which fell directly over the study area (Figure

10-1). Observed and forecasted rainfall data used for estimation of the stochastic rainfall model are shown in Figure 10-1.

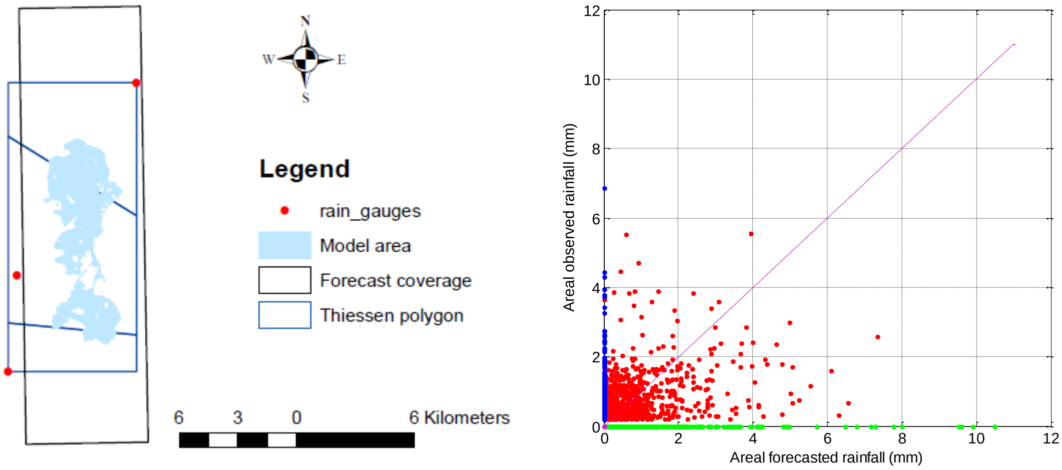

Figure 10-1: Left: Model area, total forecast area used, Thiessen polygons and rain gauge locations. Right: observed and forecasted hourly areal rainfall for a forecast lead time of 12 hours.

10.2.2 Stochastic model

This study utilizes the probability distributions obtained from the retrospective comparison of observed rainfall and its corresponding forecasts as described in (René et al., 2012), denoted S and Ŝ, respectively. The method involves decomposing the observed and corresponding forecast data into lead times and approximating the error conditioned on the rainfall forecast in the form of probability distribution functions. These functions are then imposed on the forecasted rainfall value for the corresponding lead time to determine the probability of rainfall given a rainfall forecast, i.e.:

$$\mathrm{P}(\text{rainfall} \mid \text{rainfall forecast})$$

Two stochastic models are defined to reflect the intermittent nature of rainfall. One model comprises of lognormal probability distributions for each lead time when the rainfall forecast is zero. The probability conditioned on a zero rainfall forecast is given by:

$$\mathrm{P}(\mathrm{S} \leq x \mid \hat{\mathrm{S}} = 0) = \mathrm{P}(\mathrm{S} \leq x \mid \mathrm{S} > 0, \hat{\mathrm{S}} = 0)\mathrm{P}(\mathrm{S} > 0 \mid \hat{\mathrm{S}} = 0) + \mathrm{P}(\mathrm{S} = 0 \mid \hat{\mathrm{S}} = 0) \tag{10-1}$$

where $P(S \leq x \mid S > 0, \hat{S} = 0)$ is obtained by fitting the data to a lognormal distribution, and the conditional probabilities $P(S > 0 \mid \hat{S} = 0)$ and $P(S = 0 \mid \hat{S} = 0)$ are obtained from the data.

The other stochastic model comprises of probability distributions for each lead time for a rainfall forecast more than zero, denoted $x*$, but in this case for data transformed from its original domain to the normal domain using the Box-Cox transformation method. The probability conditioned on a non-zero rainfall forecast is given by:

$$P(S \leq x \mid \hat{S} = x*) = P(S \leq x \mid S > 0, \hat{S} = x*)\ P(S > 0 \mid \hat{S} = x*) + P(S = 0 \mid \hat{S} = x*) \tag{10-2}$$

where $P(S \leq x \mid S > 0, \hat{S} = x*)$ is obtained by fitting the transformed data to a bivariate normal distribution, the conditional probability $\hat{P}(S = 0 \mid \hat{S} = x^*)$ is estimated from data by fitting a functional relationship of the form:

$$\hat{P}(S = 0 \mid \hat{S} = x^*) = a \exp(bx*) + c \tag{10-3}$$

and:

$$P(S > 0 \mid \hat{S} = x*) = 1 - P(S = 0 \mid \hat{S} = x*) \tag{10-4}$$

Using these relationships, the probability distribution of a rainfall conditioned on a rainfall forecast can be found.

10.2.3 Urban hydrodynamic 1D/2D model

A 1D/2D hydrodynamic MIKE URBAN (DHI, 2011) model is used in this study. The runoff computations are performed using a simple time-area model. The runoff hydrographs are generated and subsequently used as hydraulic loads in the pipe network which overflows onto the 2D surface model once the pipe system becomes surcharged.

The sewer system is a combined system carrying storm water run-off as well as industrial and domestic waste water. The system has been modeled using 1985 manholes, 1722 circular pipes, 184 weirs, 83 basins and 26 pumps. The sewer model has been calibrated by the municipality and is considered to be fit for the purpose for this research by being able to produce realistic flood maps.

The sewer model was coupled with a 2D surface model of 1.6m resolution digital terrain model (DTM) – no buildings included. A calculation grid cell size of 10 x 10 m was selected.

10.2.4 Experimental setup

The probabilistic forecast model was tested using a synthetic rainfall forecast event. The event was generated by multiplying a 12-hour rainfall forecast on record by a factor of 10 to generate a 12-hour event with the accumulated rainfall of the 95th percentile of the rainfall equivalent to a 100-year event. This approach was selected in order to generate flooding.

10.2.5 Generation of probabilistic rainfall forecast

Using the established stochastic model, the rainfall forecast for input into the hydrodynamic model was generated using the LHS approach and the direct quantile approach. This is done by imposing the 12 hour-hourly deterministic rainfall forecast from the NWP model on the stochastic model and then the two approaches are used to generate rainfall ensembles and percentiles of rainfall forecasts respectively.

LHS Approach - For the synthetic 12-hour rainfall forecast, the LHS approach was used to generate an ensemble of 12-hour hourly rainfall forecasts. In this case an ensemble size of 50 was used. Each hour in the 12 hour forecast has a corresponding rainfall probability distribution. The approach samples 50 times from each distribution resulting in rainfall forecasts of equal probability. The ensemble forecasts were computed based on the assumption of complete temporal dependence. This implies that the ensemble is generated by pairing values from the same sampling interval across lead-times to generate the 12 hour-hourly time series of rainfall forecasts.

Direct Quantile Approach - This approach uses percentiles of rainfall extracted from the rainfall probability distributions as input to the 1D/2D hydrodynamic model. For a given 12 hour - hourly rainfall forecast, each lead-time has a corresponding probability distribution. The exact value corresponding to a selected quantile can be extracted from each probability distribution (lead-time) to generate a 12 hour - hourly time series. This time series is approximately equal to the corresponding percentile from the rainfall ensembles obtained using the LHS approach.

10.2.6 2D Result processing

In order to present flood maps with an estimation of the uncertainty for the LHS approach, the results from each computational grid cell from the 2D computational domain for each rainfall ensemble member are used to compute different percentiles. In this paper the 50th and 95th percentile is considered.

Consider a 2D overland model with horizontal and vertical extents $J\Delta x$ and $K\Delta y$ respectively. The computational grid is divided into individual cells each of dimension Δx x Δy for the 2D computation (Figure 10-2). For each rainfall ensemble, the maximum water levels in each cell are obtained. The results from the rainfall ensembles corresponding to each cell are then used to compute the selected percentiles for that cell.

In the direct quantile approach the 50th and 95th percentile flood maps are obtained directly from the simulations of the 50th and 95th rainfall forecast percentiles.

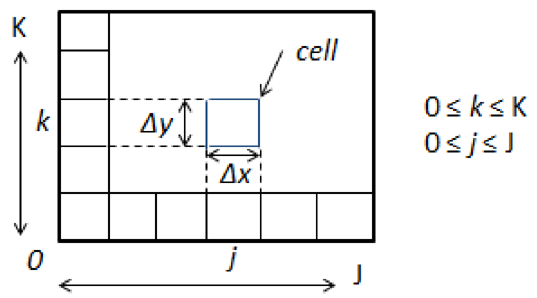

Figure 10-2: Schematic representation of 2D computational domain for the 2D overland model

10.3 Results and Discussion

Rainfall ensembles from the stochastic model

Initial analysis of the data presented in Figure 10-1 shows that there is a tendency that the forecast overestimates for large events and underestimates for smaller events. Thus, when using the stochastic rainfall model on a large rainfall forecast the model will compensate for this overestimation and reduce the rainfall. The bias correction becomes quite severe for the extreme synthetic rainfall event used in this study (see

Figure 10-3). It should be noted, however, that the synthetic rainfall event is more than 3 times larger than the largest event used for estimation of the stochastic model, and hence the model has not been validated for such events.

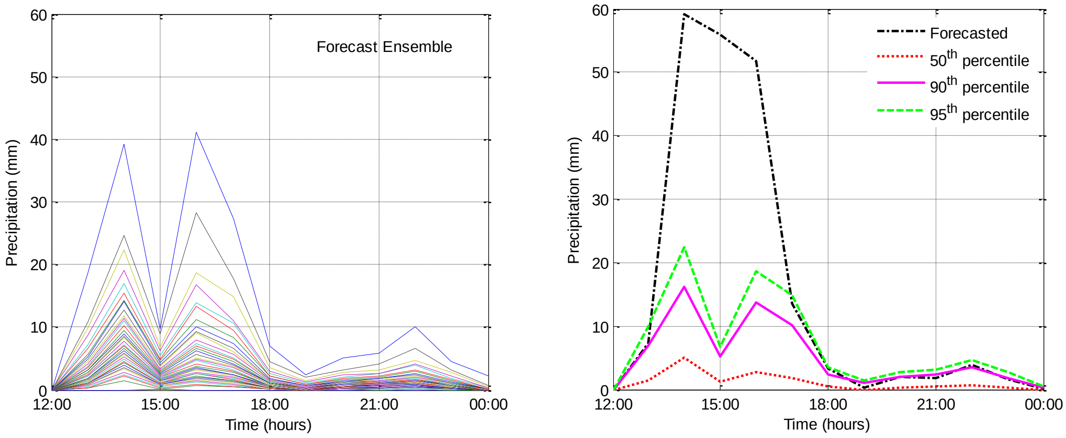

Figure 10-3: Forecast ensemble from probabilistic rainfall model, forecasted 12-hour rainfall and forecast percentiles estimated from the forecast ensemble

1D/2D hydrodynamic model simulation results

For a selected area in the model domain, flood maps for the 50th and 95th percentile are presented in Figure 10-4-Figure 10-7.

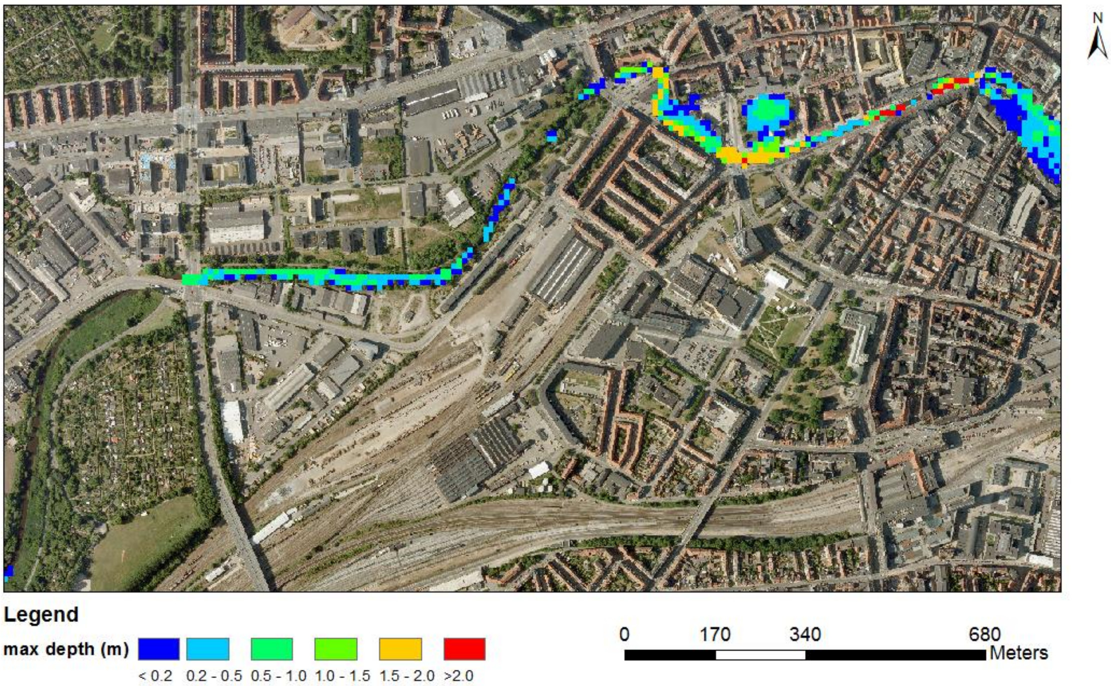

Figure 10-4: 50th Percentile of the maximum flood depths obtained from the rainfall ensembles (LHS approach)

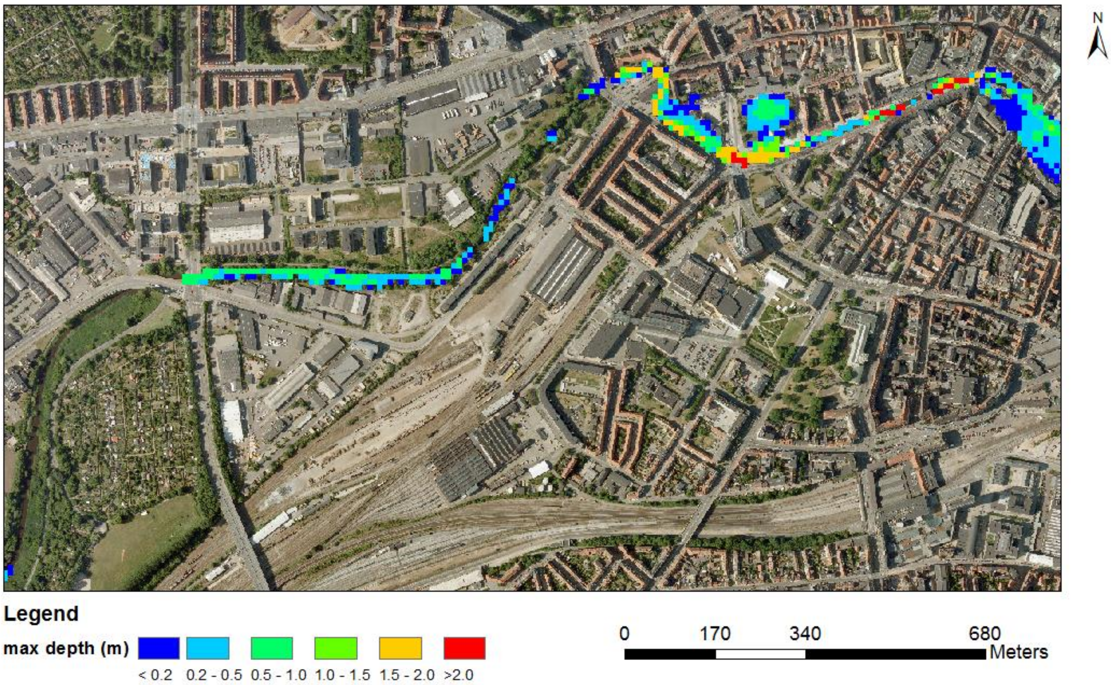

Figure 10-5: Maximum depth obtained when using the 50th percentile of the rainfall probability distribution (direct quantile approach)

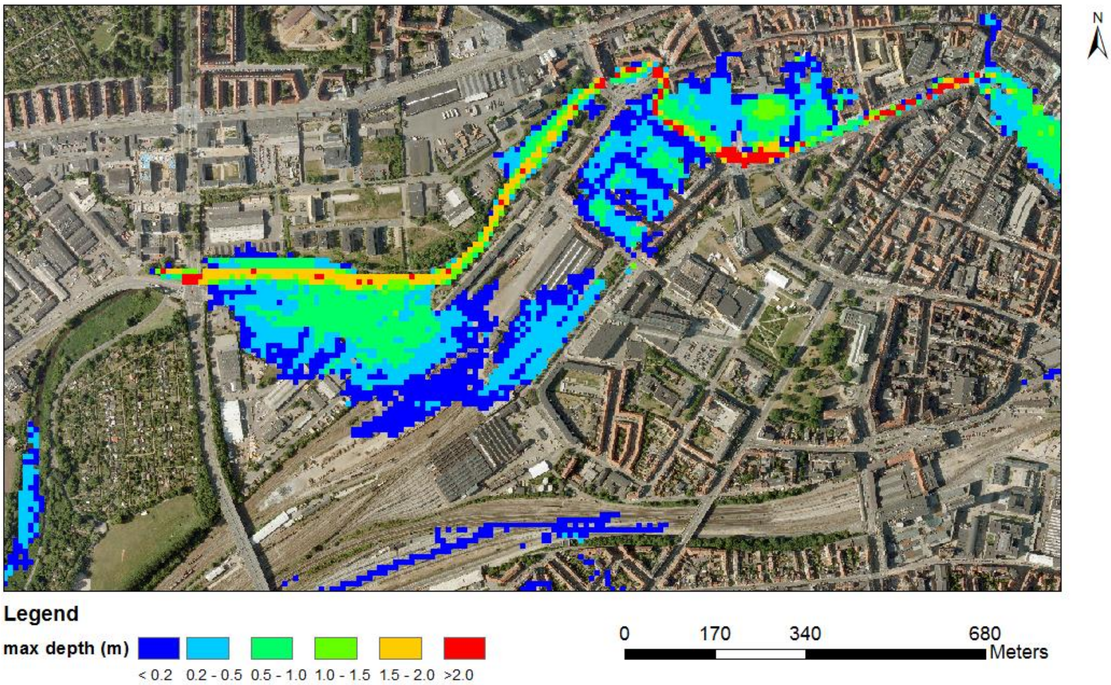

Figure 10-6: 95th Percentile of the maximum flood depths obtained from the rainfall ensembles (LHS approach)

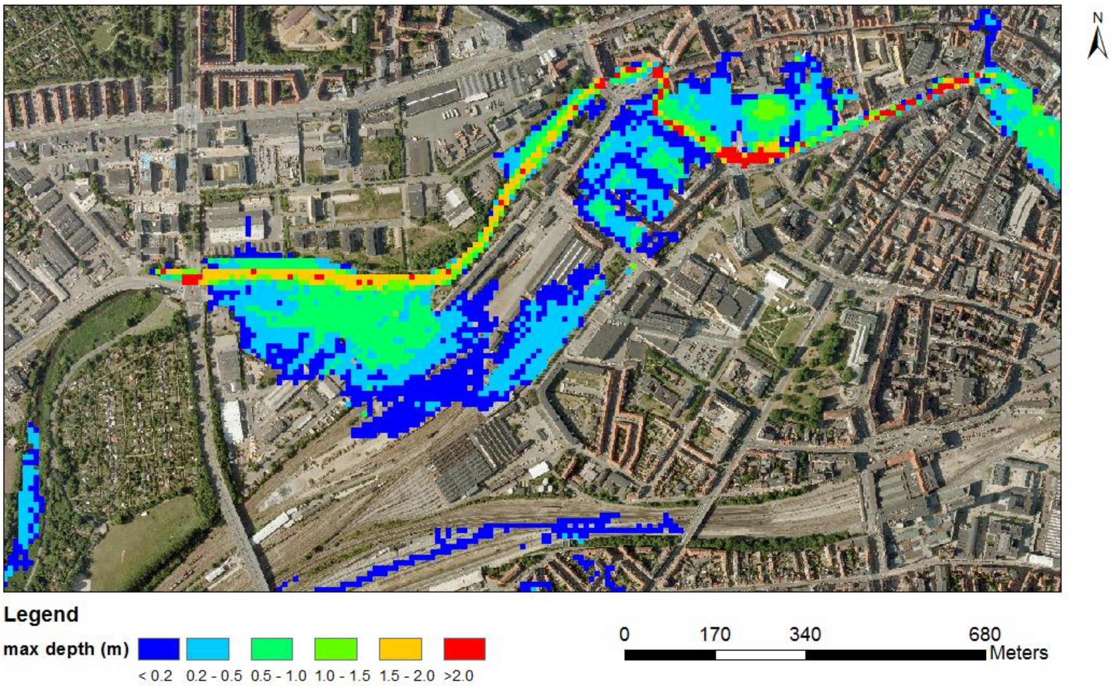

Figure 10-7: Maximum depth obtained when using the 95th percentile of the rainfall probability distribution (direct quantile approach)

Comparison of 50th and 95th percentiles of maximum flood depths over each computational grid cell over the entire model domain for the LHS approach and the direct quantile approach shows that the methods give approximately the same results as shown in the histogram plot in Figure 10-8.

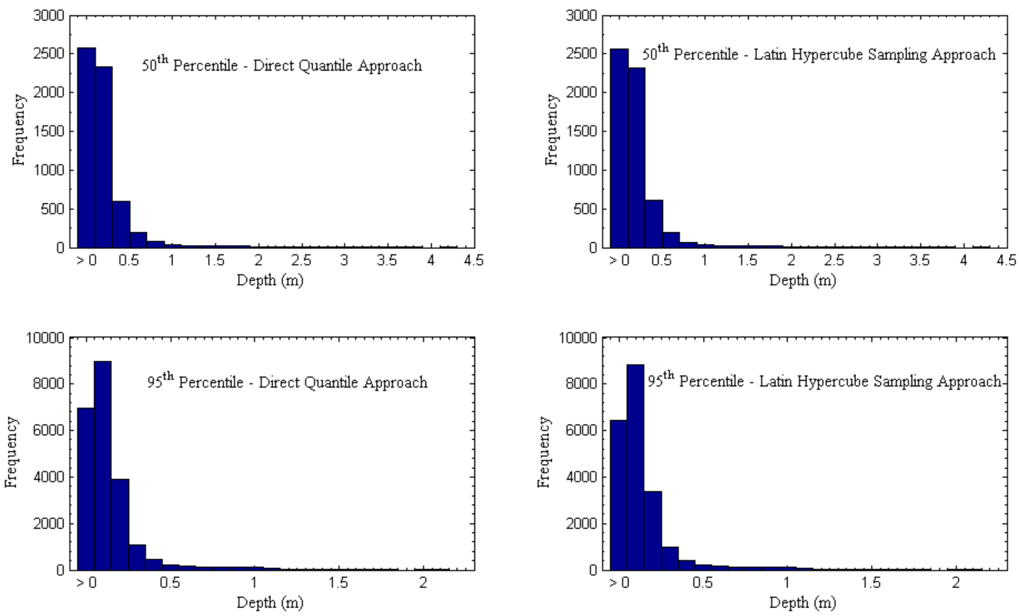

Figure 10-8: Comparison of the 50th and 95th percentile of the maximum flood depth obtained using the direct quantile approach and the Latin hypercube sampling approach. The data represents the maximum flood depth obtained for each grid cell over the model domain

From the figure, it can be observed that both methods generally show similarity in producing maximum flood depth distribution. Although the total number of wet cells is not the same as shown in Table 10-1, the difference is very small.

Table 10-1: Number of wet cells obtained for each percentile using LHS and direct quantile approach

	Number of wet cells	
Percentile	Direct Quantile Approach	Latin Hypercube Sampling
50^{th}	5928	5905
95^{th}	22323	20971

The difference in maximum water levels between the methods can be visualised using a scatter plot as presented in Figure 10-9.

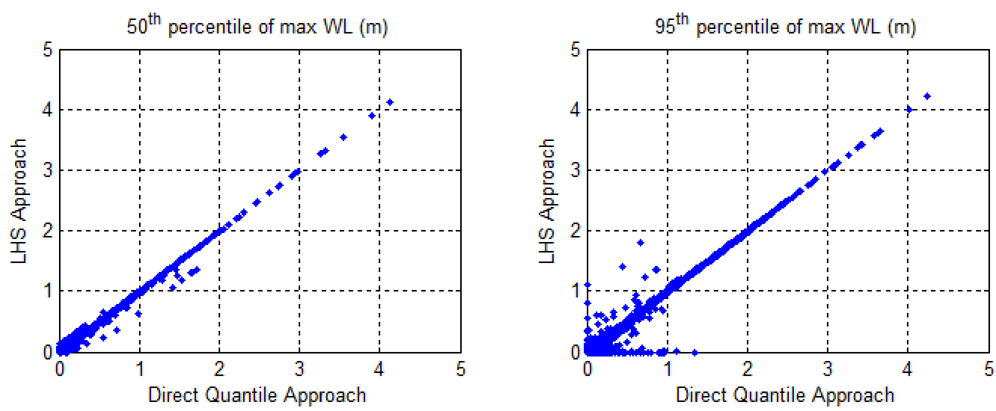

Figure 10-9: Maximum flood depth obtained for each grid cell over the model domain

It is observed that in some instances the direct quantile approach computes water on the surface whereas the LHS doesn't and vice versa, but more so for the direct quantile approach. This is observed for only a small quantity of grid cells.

The methods are also compared by viewing time series plots for a selected grid cell i.e. a specific location in the model (see Figure 10-10). These results also confirm similarity in the methods for simulation of the temporal development of the flooding.

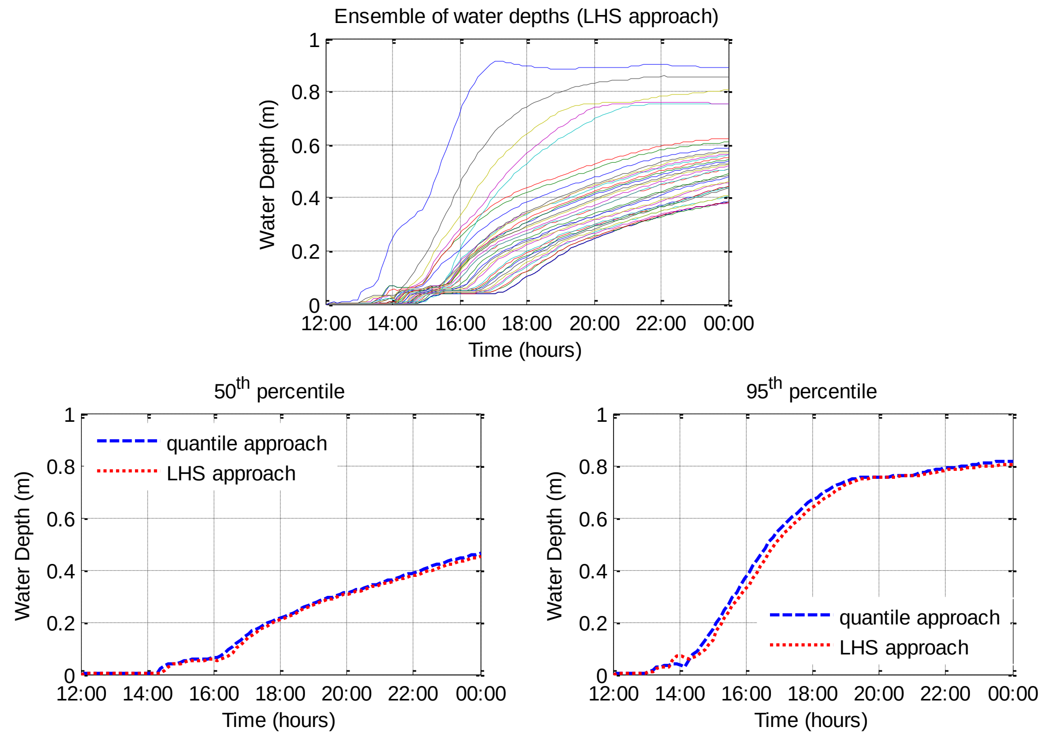

Figure 10-10: Comparison of time series of water level at a selected location in the urban flood model

The results show that the direct quantile approach provides an accurate estimate of the probabilistic flood maps. The direct quantile approach only requires a few model simulations compared to a series of simulations when using the LHS approach. The efficiency in computational time makes the direct quantile approach feasible for real-time application.

The large difference between flood extents maps between the two percentiles in Figure 10-4- Figure 10-7 highlight the relevance of making probabilistic forecasts. Because the actual observed event is not known, then conclusions concerning accuracy of flood depths and extents cannot be made. However, the results reiterate the relevance of probabilistic flood forecasting and the potential in using the direct quantile approach.

10.4 Conclusion

The applicability of an approach for probabilistic urban water management has been presented in this paper. Two methods for generating probabilistic rainfall forecasts from probability distribution functions are compared for the selection of an efficient approach which can be applied in real-time. The results from the LHS approach and the direct quantile approach show similarities in many ways and as a result the direct quantile approach proved to be the most attractive for real-time application.

The results obtained from the case study looks very promising for use operationally for 1D/2D models in conjunction with deterministic quantitative rainfall forecasts. The approach provides the opportunity for decision makers to make better-informed decisions by providing them with confidence levels in the flood forecast. This has been found to be an important feature for risk assessment, warning and evacuation. It is clear that the rainfall forecast has a large contribution to the uncertainty in the flood forecast. Moreover, in order for this approach to be successful, it requires diligent collection of both observed and forecasted rainfall data.

Acknowledgement

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11 Evaluating an X-band Radar area-based nowcasting algorithm for urban drainage model forecasting

Under review, *Journal of Hydrology*

This study evaluates the performance of an area-based X-band radar nowcasting algorithm in managing an urban drainage system subject to stratiform and convective rainfall regimes. The paper examines the accuracy of the precipitation forecast for both rainfall regimes using the fraction skill score technique over an urban drainage model area. The model predictive skill is evaluated based on water depths and discharges derived from the simulated radar estimated and forecasted precipitation at specific model locations as a function of sub-catchment area. Area-related precipitation frequency verification results indicate more forecast skill for stratiform regimes than for convective regimes over the urban drainage model area, albeit a bias in the forecasted precipitation. This skill is further confirmed by the skill scores derived as a result of the forecasted precipitation fields. The findings suggest that the performance of the nowcasting algorithm depends on the rainfall regime. The inability to forecast changes in structure and intensity of rain cells can limit its applicability for decision making in urban flood management, especially in cases where changes in rain cell structure and intensity are severe.

Keywords: Radar, Nowcasting, X-band, fraction skill score, hydrodynamic modelling

11.1 Introduction

Quantitative Precipitation Estimates (QPE) from weather radar are an important data source in urban hydrology because they provide precipitation estimates at the scales relevant to describe the hydrological behaviour of urbanized catchments (Berne et al., 2004). A derivative of radar-based QPE is radar-based Quantitative Precipitation Forecasts (QPF) also known as nowcasting, which can play a key role in the real-time management of urban drainage systems (Thorndahl et al., 2013, Liguori et al., 2012). Central to radar nowcasting is the well-known fact that the accuracy rapidly decreases with increasing lead times (Moreno et al., 2013), as most operational radar nowcasting algorithms do not have mechanisms which model the changes in structure or intensity of precipitation (Sokol, 2006). However, drainage systems which have a time of concentration longer than the nowcasting period can obtain higher accuracy QPF at longer lead times by the combined use of data from numerical weather prediction (NWP) models and local area weather radar (Thorndahl et al., 2013, Liguori et al., 2012, He et al., 2012).

Precipitation forecasting at very short lead times is one of the most challenging in urban radar hydrology. This difficulty is not due to the lack of effort as there are various radar nowcasting algorithms (Bellon et al., 2010, Liguori et al., 2012), but it relates to the difficulty in predicting the exact position and intensity of precipitation at such small time scales. Ruzanski et al., (2011) provide an overview of the four categories of approaches used for radar nowcasting. These are area-based, object-based, statistical and probabilistic approaches, each having their own benefits and drawbacks. For this reason, research has focused on improving the quality of radar-based nowcasting algorithms by including components which account for the formation, growth and depletion of clouds (Mesin, 2011, Grecu and Krajewski, 2000).

A large and growing body of literature has evaluated the accuracy of radar estimates using rain gauge data since it is considered more representative of the rainfall reaching the ground (Gires et al., 2014, Burcea et al., 2012, Einfalt et al., 2005). However, to better understand the performance of the radar nowcast, a more appropriate comparison would be to compare the observed radar fields to the forecasted radar fields. Verification statistics based on pixel-pixel comparisons do not quantitatively assess the impact of small errors in displacements of rain clouds on the urban drainage system. Therefore, a more relevant statistic should reflect a 'hit rate' which indicates something which is 'close enough' rather than a perfect match. For this reason this study has adopted the Fraction Skill Score (FSS) verification technique (Roberts and Lean, 2008, Ebert, 2008), for verifying precipitation over the urban drainage area. So far this technique is more widely used for verifying QPF from NWP with radar-based QPE (Zacharov and Rezacova, 2010, Mittermaier et al., 2013). Other studies have validated their nowcasting techniques by evaluating its potential for forecasting flows and other hydrological variables in their study locations, based on different kinds of local area weather radars (Berenguer et al., 2005).

The focus of this work is to provide some insight into the radar nowcasting procedure and to investigate/evaluate the implications and relevance of its shortcoming on urban drainage modelling. This is done by first comparing the radar QPF against the radar QPE at different spatial scales over the urban drainage model area and secondly by comparing simulated water depths and flows with the forecasted and estimated rainfall fields using an urban drainage model.

This Chapter is divided into four parts. Section 11.2 begins by laying out the case study and the datasets used. The third section is concerned with the methodology used for this study. The fourth section presents the findings and analysis of the study focusing on the themes highlighted in the previous chapter. Finally the conclusion gives a brief summary and critique of the findings.

11.2 Case study

The study uses QPE and QPF data from an X-band radar system located near the city of Aarhus, Denmark. A calibrated 1D hydrodynamic sewer model for the urban centre for the city of Aarhus forms the basis for this study and covers a drainage area of 25.24km^2. The area is relatively flat and is dominated by convective and frontal regimes in the summer and winter periods respectively. This area has been selected mainly because of the availability of the data.

11.2.1 Local Area Weather Radar Estimates (QPE)

The Local Area Weather Radar (LAWR) data used in this study is from a small scale, marine X-band radar situated near the city of Aarhus, Denmark. The system works in the X-band (3.2cm wavelength) with peak powers of 25kW and short antenna diameter of 2.5m. The maximum range of the radar is 60km but only the inner 20 km range is for quantitative precipitation estimation (Jensen, 2010, Pedersen et al., 2010). The LAWR scans continuously with a rotation speed of 24RPM at 0.95° elevation angle resulting in 360 scans in each rotation. During this period, each scan line contains 24 data points. The output is the integrated signal over a 5 minute sampling period.

The LAWR has two output parameters; reflectivity and variance as well as two image formats; polar (10-bit) and Cartesian (8-bit). This study uses the reflectivity in Cartesian format. The stored Cartesian images has a spatial resolution of 500x500m and a pixel resolution of 240 pixels wide by 240 pixels high and contains a total of 57600 pixels (57KB). The byte values (values range from 0-255 for 256 positions in all) in the radar image file are converted to reflectivity data in units of radar reflectivity $Z(dBZ)$ to a suitable range $[0, 63.75]$ using the following equation.

$$Z(dBZ) = (Z(byte\ value) - offset) * slope$$

(11-1)

The slope and offset conversions are 0.25 and 0 respectively. There is a fixed range-independent relation between the reflectivity value Z and the rainfall intensity $[mm/h]$. The following semi-empirical Marshall and Palmer $Z - R$ relation is used:

$$Z = AR^B$$

(11-2)

where the rainfall intensity is given by:

$$R\ [mm/h] = \left[10^{dBZ/10}/A\right]^{1/B}$$

(11-3)

where the parameters A and B are 200 and 1.6, respectively.

In order to improve the accuracy of radar QPE, it is common practice in radar hydrology to adjust the backscattered signals to remove artefacts measured during scanning and to compensate for some features of the operating characteristic of the X-Band radar. For this radar system, beam filling and attenuation effects are given particular attention as well as clutter removal. A volume and attenuation correction algorithm has been developed to adjust rainfall estimates in addition to the mechanical clutter fence installed.

11.2.2 Local Area Weather Radar Nowcasts (QPF)

Radar nowcasts at 5 minute intervals up to 70 minutes from the time of forecast are generated operationally using correlation analysis between the two last consecutive images. It is based on the establishment of a rain-cloud movement (velocity) field and then using this velocity information to transport the rain (Pedersen, 2009).

The forecast principle is explained using the image at time t and $t-5$. Firstly, the image at t and $t-5$ is divided into a number of sub-images (9 in this study). The velocity vector for each sub-image V_x and V_y are estimated by calculating the correlation between sub-images at $t-5$ and t. This is done several times for each sub-image since there is a small displacement of 1-5 pixels in both directions. An intensity threshold above which should be expected on both sub-images is also applied when estimating the correlation. The displacement giving the highest correlation is selected and the movement vector for each pixel is found by interpolation. This movement vector can now be translated to a velocity vector since the time between the two consecutive images is known. The major shortcoming in this method is that the procedure cannot account for the formation, growth or depletion of clouds.

11.2.3 Urban drainage model description

A 1D MIKE URBAN (Andersen et al., 2004) physically-based operational sewer model forms the basis for the urban drainage analysis. The focus area of the radar analysis is within the sewer model area, herein considered the verification area. The combined sewer model consists of 1988 manholes, 90 basins, 69 outlets, 199 weirs or orifices, 1737 circular pipes, 6 rectangular pipes and 32 pipes with non-circular cross-sections. There are a total of 36 pumps which controls flow in the system. The modelled area is divided into a total of 1267 sub-catchments. Two models are required: a model which simulates the surface runoff (hydrological model) and a model which describes the flows in the sewer network. The rainfall information serves as input for the hydrological model and the resulting runoff output serves as the forcing for the drainage network.

11.3 Methodology

This study focuses on the 5 minute time step 70 minute radar nowcast (QPF) computed from the correlation analysis of successive images during the period November 2012 – November 2013, herein referred to as the verification period. Ten rain events were selected for evaluating the value of the nowcast algorithm and two of the selected events; a convective and stratiform were used for evaluating the aggregated effect of the errors in the QPF in the urban drainage model. Different performance measures were used to evaluate the accuracy of the QPF as well as the deviations in water depths in the urban drainage model.

The area of analysis on the radar Cartesian grid covering the region of the urban drainage model area has a total of 198 pixels with an area of $49.5 km^2$.

11.3.1 Meteorological Analysis of QPE

Rain events within the verification area were determined by computing a time series of area average rainfall with a 5 minute time step for the verification period. The top 10 rain events were extracted and classified based on their characteristic features. As a first assumption, all events which were recorded in the summer months (May-Sept) were considered to have a convective regime and those in the winter months (Nov-Apr) as stratiform. The classification of the events were further verified and confirmed by examining the radar images for the selected events, although in some cases it is not always clear-cut. Clouds which are convective in nature usually have the following characteristics: cores of high intensities, short duration, fast moving, limited horizontal extent (isolated) and move in clustered cells. On the other hand, stratiform clouds have large horizontal extents, move across the area (front), longer durations, fairly homogeneous in the horizontal and usually there is a build-up of precipitation. The distinction between convective and stratiform precipitation is useful for this analysis because the nowcasting algorithm cannot account for the formation, growth or depletion of clouds.

11.3.2 Radar-based QPF verification using radar-based QPE

In this study we quantify the accuracy of the nowcasting algorithm in predicting the frequency and magnitude of rainfall intensity estimates of the QPF by applying the Fractions Skill Score (FSS) and computing the bias, respectively. The FSS is a type of "fuzzy" verification which gives an indication of the approximate agreement of the forecast to observations in time, space and intensity (Roberts and Lean, 2008, Ebert, 2008, Mittermaier et al., 2013). This involves splitting the verification area into a number of neighbourhood fractions of a certain spatial scale (herein referred to the number of pixels along a dimension) and computing the proportion of both the observed and forecasted fractions for a particular rainfall threshold. The proportion is given by the number of pixels in terms of rain cells above a threshold in the fraction divided by the total number of pixels in that fraction. In the context of the considered spatial scale, if the same proportion of the observations is achieved, then the model is considered to be correct. The FSS is defined by:

$$FSS = 1 - \frac{1/N \sum_N \left[P_{F_s} - P_{O_s}\right]^2}{1/N\left[\sum_N {P_{F_s}}^2 + \sum_N {P_{O_s}}^2\right]}$$

(11-4)

where N is the number of neighbourhood windows in the verification domain; $P_{F_s}$and P_{O_s} are the neighbourhood proportions at the i^{th} fraction with precipitation above the defined threshold in the model forecast and observed fraction fields s, respectively. The comparison of radar-based QPE and radar-based QPF were made for a threshold of rainfall exceeding 0.3mm/hr , and spatial scales s of 1, 3, 9 pixels (0.5km, 1.5km, 4.5km) and the entire verification domain (4.5x11km) for each forecast lead time. The main goal has been to see if the proportion of forecasted rain cells is the same as the observed proportion at different spatial scales for each lead time. The FSS values were computed for each lead-time for each time of forecast for each of the selected events. However, we present the mean FSS against the lead time for each spatial scale for convective and stratiform events, as well as the overall mean FSS (combination of convective and stratiform FSS) for the verification area. The FSS ranges from 0 to 1. A score of 1 is attained for a perfect forecast and a score of 0 indicates no skill. A target score of 1 over the verification area suggests an unbiased forecast.

To estimate the bias in magnitude the following equation was used:

$$Bias_{rainfall} = \frac{QPF_{mean}}{QPE_{mean}}$$

(11-5)

where QPF_{mean} and QPE_{mean} are the mean rainfall intensities in the verification area for the forecasted and observed images respectively. The bias ranges from$-\infty$ to ∞. A value of 1 indicates an unbiased forecast, a value less than 1 suggests that there is an underestimation in the forecast and values more than 1 suggest an overestimation in the forecast. This analysis was performed for each lead time.

11.3.3 Hydrological modelling

Runoff simulations were performed for each urban sub-catchment covering a total area of 25.24km^2 using a lumped conceptual model based on the time-area curve. This model makes use of the time of concentration as well as the shape of the sub-catchment which defines the conceptual description and controls the flow routing. The resulting time area curve is an extension of the mathematical expression of the rational formula.

The most widely used approach for applying rainfall as input in urban flood modelling ignores the variability in spatial rainfall structure and applies rainfall information from rain gauges to all sub-catchments based on the contributing area estimated using the Thiessen polygon method and similar approaches. However, in this study, because of the distributed rainfall fields, the rainfall intensity per sub-catchment is determined based on an ‘area weighting’ estimated based on the percentage of the intersection area of the catchment and pixels in the radar Cartesian grid. The ‘weighting’ expresses the coverage ratio that each pixel has over each sub-catchment. Calculation of the area weighted precipitation intensity is computed based on the following equation:

$$TS_{SCTotal} = \sum_i \sum_j \alpha_{i,j}.TS_{i,j} \,, \qquad (i,j) \in A \tag{11-6}$$

where $TS_{SCTotal}$ is the resulting area weighted precipitation time series for the sub-catchment, $TS_{i,j}$ is the precipitation time series for the pixel (i,j), and $\alpha_{i,j}$ is the relative area of pixel (i,j) compared to the total catchment area and A is the total sub-catchment set.

11.3.4 Simulation set up

Two events were selected for evaluating the potential of the nowcasting algorithm for forecasting discharge and water depths in the drainage system. As a first step, the QPE was simulated for the event period, which is used for comparison with the forecasts. The model is initialized by simulating 48 hours of dry weather flow (DWF) up until the start of the event, see Figure 11-1. In order to produce the forecasted simulated water depths and flow at time t_i to mimic operational real-time conditions, the forecasting approach is built on a sequence of 1 hour forecasts made every 30 minutes after the previous time of forecast (TOF) for the entire event duration. The model is always assumed to be running with DWF up until the start of the rain event. Therefore for the first 1 hour forecast the model is initialized with the DWF but for the forecasts following this, the model is initialized with the QPE up until that point.

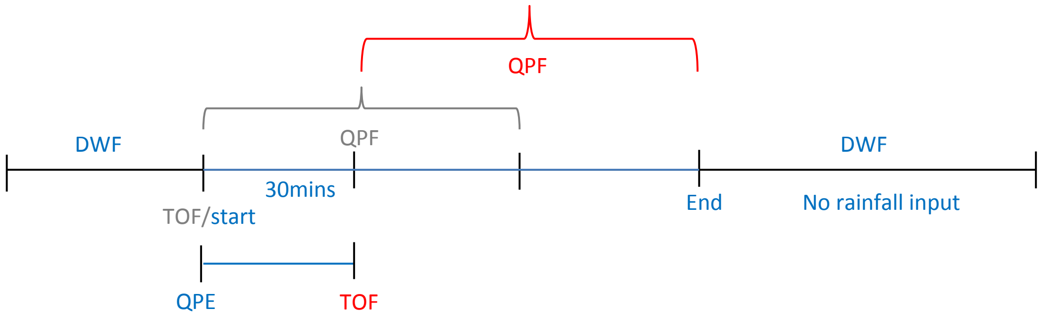

Figure 11-1: Example of a 90 minute event depicting the hydrodynamic initializing forecasting approach

11.3.5 Verification of hydrodynamic variables

Hydrodynamic verification consists of comparing results simulated from the radar-based QPF against that of the radar-based QPE at different manhole locations in the model area, representing different drainage areas. This evaluation consisted of computing the difference between the simulated water depths and simulated discharges. Water depth was selected as the main analysis variable since it is the parameter controlling most urban drainage systems such as pumps, overflows and flood conditions. Results are presented in terms of:

(i) Bias

$$Bias = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)$$

(11-7)

where x_i and y_i are the water depth values derived from the QPE and QPF at $i-th$ time, respectively, and N is the number of data points.

(ii) Relative Error (RE)

$$RE_i = {|x_i - y_i|}/{x_i}$$

(11-8)

(iii) Mean Absolute Error (MAE)

$$MAE = 1/N\left(\sum_{i=1}^{N}|x_i - y_i|\right)$$

(11-9)

(iv) Skill Score (SS)

$$SS = 1 - \frac{\sum_{i=2}^{N}(x_i - y_i)^2}{\sum_{i=2}^{N}\left(x_i - x_{ref}\right)^2}$$

(11-10)

where x_{ref} is the naïve forecast derived from the QPE at the time of forecast. SS can range from $-\infty\ to\ 1$. A skill score of 1 corresponds to a perfect match. Values of 0 or less suggest that x_{ref} is a better predictor than y_i .

11.4 Results and discussion

11.4.1 Precipitation event analysis

Classification of rain events into rainfall regimes proved to be challenging because it can sometimes be difficult to differentiate, since some events can show mixed characteristic features. However, Table 11-1 highlights the 10 events used for evaluating the accuracy of the QPF using the FSS as well as a classification of the rainfall regime based on expert judgement.

Table 11-1: Top 10 events, mean rainfall intensity, its duration and best estimate of its rainfall regime

Event	Date	Duration [minutes]	Mean rainfall intensity [mm/h]	Rainfall Regime
1	27/07/2013 03:00	360	3.08	Convective
2	30/07/2013 12:45	120	2.58	Convective
3	08/11/2012 05:35	135	1.37	Stratiform
4	01/09/2013 14:00	330	0.93	Convective
5	22/05/2013 00:00	1050	0.91	Stratiform
6	25/11/2012 07:35	445	0.83	Stratiform
7	09/09/2013 08:05	835	0.43	Stratiform
8	28/10/2013 07:00	515	0.38	Stratiform
9	10/08/2013 08:30	90	0.31	Convective
10	25/10/2013 18:30	120	0.18	Convective

11.4.2 Evaluation of the forecasted rainfall fields

Figure 11-2 presents the overall mean FSS as well as the mean FSS computed based on the 5 convective and 5 stratiform events as a function of forecast lead time for rainfall exceeding a threshold of 0.3mm/hr. As expected there is a general increase in FSS with increasing spatial scale s. The results show that for the convective events, the FSS value deceases much more rapidly than for the stratiform events as the lead time increases.

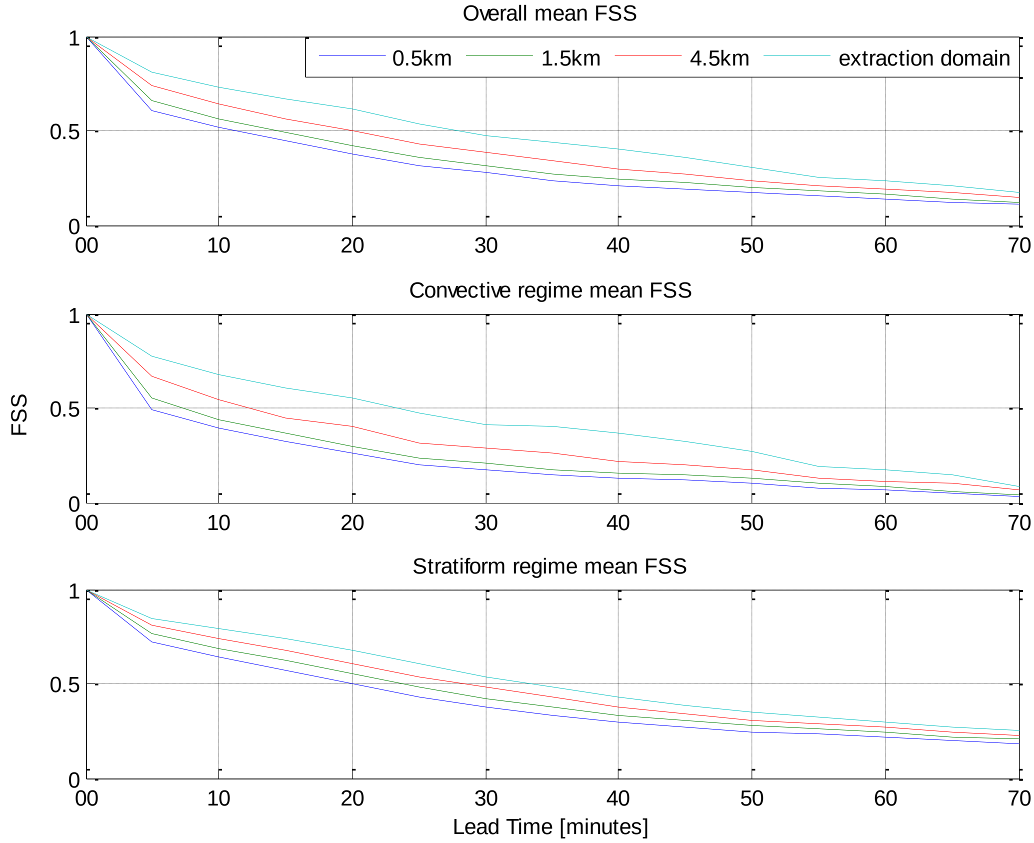

Figure 11-2: Mean FSS against lead time for fractions of 0.5km, 1.5km, 4.5km and the entire verification domain (4.5x11km) for a threshold of 0.3mm/hr computed based on 5 convective events and 5 stratiform events

Interestingly, the FSS over the entire verification area is never equal to 1 (i.e. the forecast frequency of rain cells is not the same as the observed frequency of rain cells), not even after the first few lead times. In fact this bias in frequency increases with lead time (Figure 11-2). While this score gives an indication of the forecast skill in the extraction area, it does not necessarily represent an overall skill score for the radar QPF because the statistics were calculated in a relatively small area over the entire Cartesian grid. The results of FSS at grid scale 0.5km, suggest that there is an overall disagreement in the proportions of forecasted and observed rain cells which can reflect both and over and underestimation in the forecasted variable in the urban drainage model.

The bias in mean rainfall intensity over the verification area is also investigated for the two events selected for simulation in the urban drainage model and is presented in Figure 11-3. The two events are a convective event that occurred on 27-07-2013 03:00-09:00 and a stratiform event that occurred on 22-05-2013 00:00 – 17:30 (see Table 11-1).

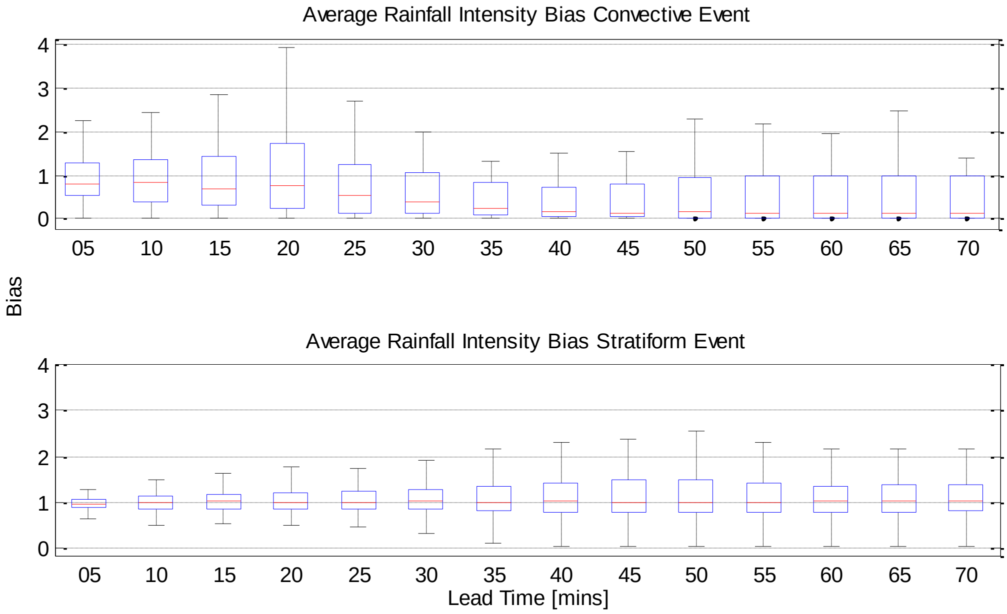

Figure 11-3: The distribution of the bias as function of lead time of the mean rainfall intensity in the verification area for the convective and stratiform event. The red line represents the median of the bias scores. The blue box indicates the range in which the middle 50% of the bias scores falls. The lines extending vertically from the boxes indicate variability in the bias outside the lower 25th and upper 75th quantiles. Outliers are not represented on this plot because of too large ranges

The results highlight that the boxplot is comparatively smaller for the stratiform event compared to the convective event for all lead times. This suggests that the difference between the mean QPE and mean QPF is smaller for the stratiform event compared to the convective event. For the stratiform event, the median is close to 1 for all lead times, and the bias range increases for increasing lead time up to 0 – 2.5. The results suggest that the QPF is generally unbiased for the stratiform event. For the convective event, the medians are very different for each lead time decreasing from a value which is very close to 1 towards zero. This implies that there is a general tendency to underestimate the QPF. Overall there is no structure in the variability of bias across lead times, which may be explained by the build-up and depletion of clouds in time, which is not accounted for in the QPF. Overall, because of the bias in both magnitude and frequency in the precipitation field in the verification area, the effect of small displacements in rain cells as examined by the FSS would be difficult to quantify in the hydrodynamic model results.

11.4.3 Evaluation of maximum water depths

Water depths in 6 manholes representing drainage areas between 0.06 and 7.05 km^2 was analysed. An investigation of the maximum simulated and forecasted water depths was performed first since it is of paramount interest for the management of sewer systems. This was done as a function of the forecast lead time where the first half hour as well as the entire forecast hour was considered. Scatter plots of maximum water depths, with its associated bias and MAE are displayed in Figure 11-4 - Figure 11-7.

There is a slight forecast bias (underestimation) of maximum values for the stratiform event for 1 hour lead times. This bias is evident when considering the scatter plots in Figure 11-4 where there are a few points that fall slightly below the diagonal. The forecasts have a negative bias of approximately $0.1\,m$ at all locations except location A12531K which has a notable underestimation of $0.5\,m$. On average, for the stratiform event a MAE of approximately $0.1\,m$ is observed in the forecasts at all locations except for location A12531K which has a MAE of $0.8\,m$. At this location although there is a general tendency to underestimate the forecast, there are few overestimated forecasts.

For the convective event (Figure 11-5), for 1 hour lead times, there is also a tendency of underestimation in the forecasted maximum water depths, in the range $0.04 - 0.55\,m$. The MAE ranges between $0.14 - 0.58\,m$. The convective event has, in general, a larger bias and MAE than the stratiform event.

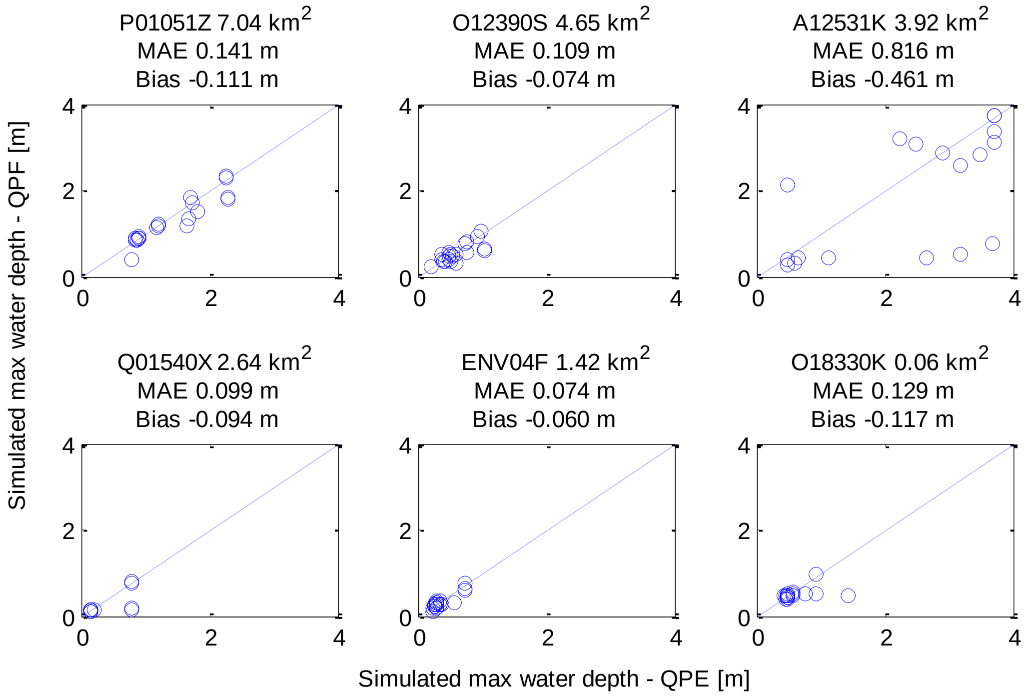

Figure 11-4: Simulated Observed and Forecasted maximum water depths for 1 hour lead times at different locations in the model as a function of total sub-catchment drainage area for the stratiform rain event.

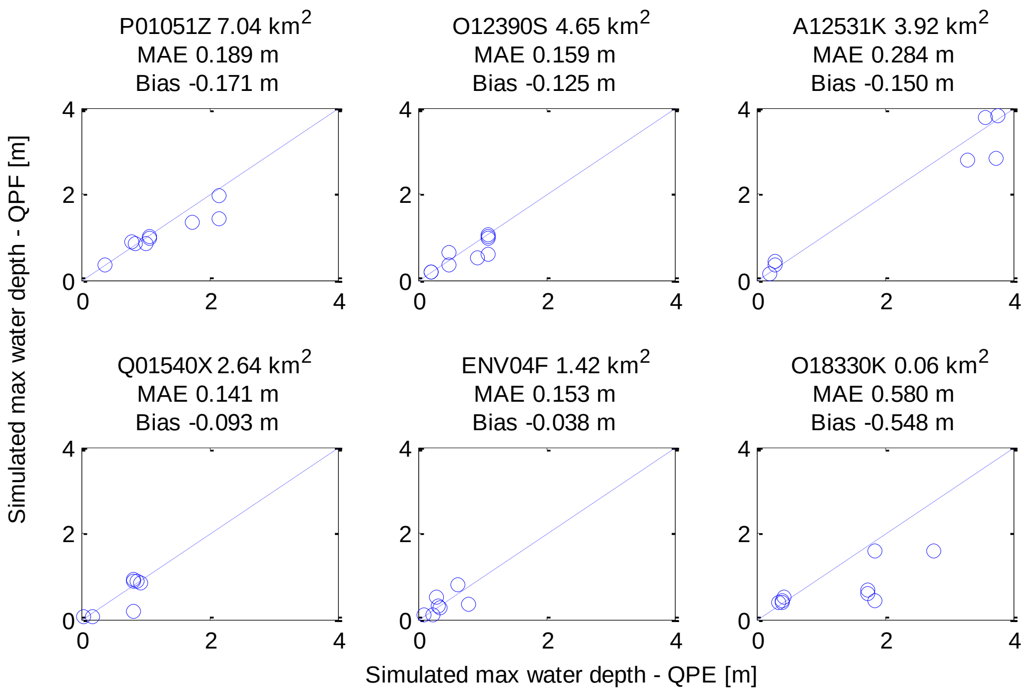

Figure 11-5: Simulated Observed and forecasted maximum water depths for 1 hour lead times at different locations in the model as a function of total sub-catchment drainage area for the convective rain event.

Turning now to the 30 minute lead time maximum water depth analysis for the stratiform event (Figure 11-6), there are no really significant biases in this case, the highest being $0.07m$ and the lowest $0.054m$. In fact there is an overall reduction in the bias and MAE when compared to the 1 hour lead times. This implies that a significant part of the error in the forecast is in the last half hour of the forecast.

Similarly for the convective event, for 30 minute lead times (Figure 11-7), the bias became less negative and in some cases positive, which signifies a slight overestimation in the forecast when compared to the results obtained for the 1 hour lead times. While there have been an improvement in the bias, on average, the MAE at the different locations in some cases increased (e.g. location A12531K and Q01540X). The increase in MAE was due to overestimation of the forecasts.

In general, there is an overall notable improvement in the MAE when considering the 30 minute lead time as opposed to the 1 hour lead time for both events, which would have significant implications on the overall management of the urban drainage system.

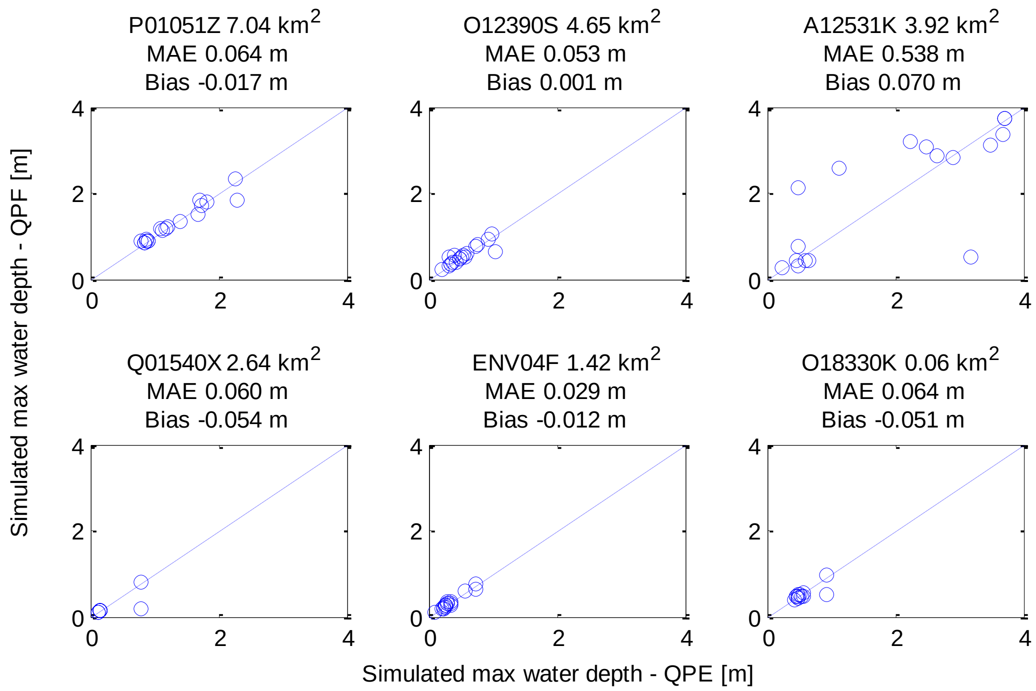

Figure 11-6: Simulated Observed and Forecasted maximum water depths for 30 minute lead times at different locations in the model as a function of total sub-catchment drainage area for the stratifom rain event. The bias is computed using $1/n(\sum_{i=1}^{n} QPF_i - QPE_i)$

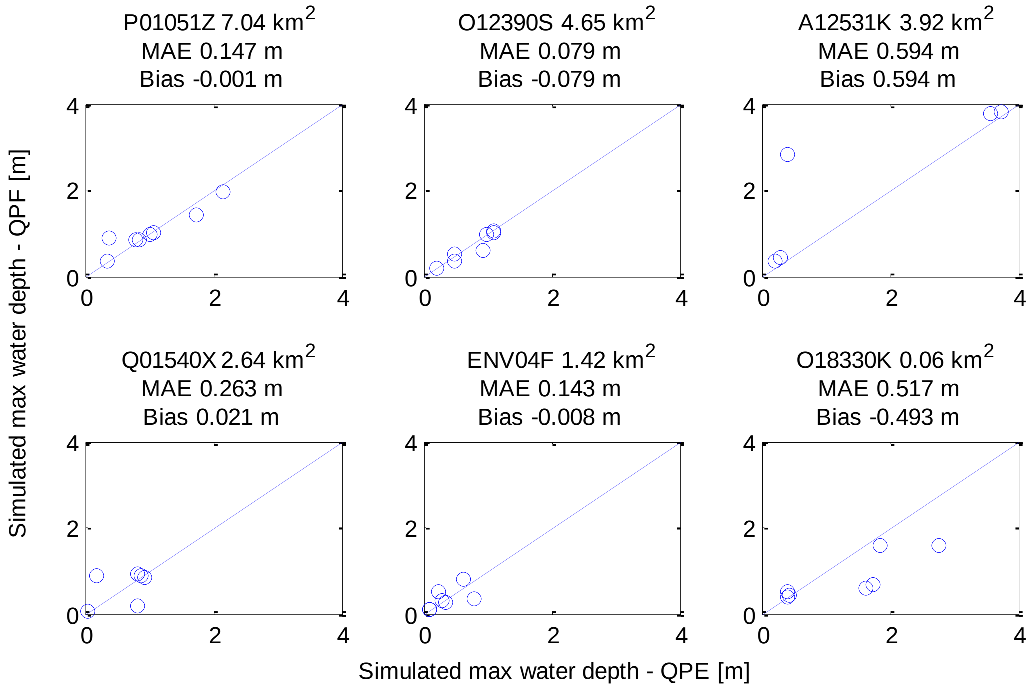

Figure 11-7: Simulated Observed and forecasted maximum water depths for 30 minute lead times at different locations in the model as a function of total sub-catchment drainage area for the convective rain event. The bias is computed using $1/n(\sum_{i=1}^{n} QPF_i - QPE_i)$

11.4.4 Evaluation of forecasted water depths

In this section a similar analysis as the one applied to the maximum water depths was applied to the entire time series of water depths. Figure 11-8 and Figure 11-9 show scatter plots for the water depth forecasts for the stratiform and convective rain events at different model locations as a function of lead time. A quick glance at the plots immediately reveals some characteristics: the forecast is more reliable (points tend to cluster on the 45 degree line) at some locations than others for either lead times. However in the cases where the points do not cluster along the 45 degree line, there is no obvious structure as a function of lead time. There is a slight tendency to underestimate the forecast (negative bias values). The overall discrepancies between the forecasted and observed water depths at some locations are due to changes in rainfall intensity and spatial extents over the event period, which is not accounted for in the nowcasting algorithm.

For example, in the case of the stratiform event, the forecast is bad at three of the locations (A12531K, Q01540X and O18330K). The disparity at the location with the smallest drainage areas (O18330K) as shown in Figure 11-8 is expected; since errors in displacement will have a larger impact. However, the disagreement between the forecasted and observed water depths for both events can be explained by a change in the rain cell motion in some cases as well as a change in intensity.

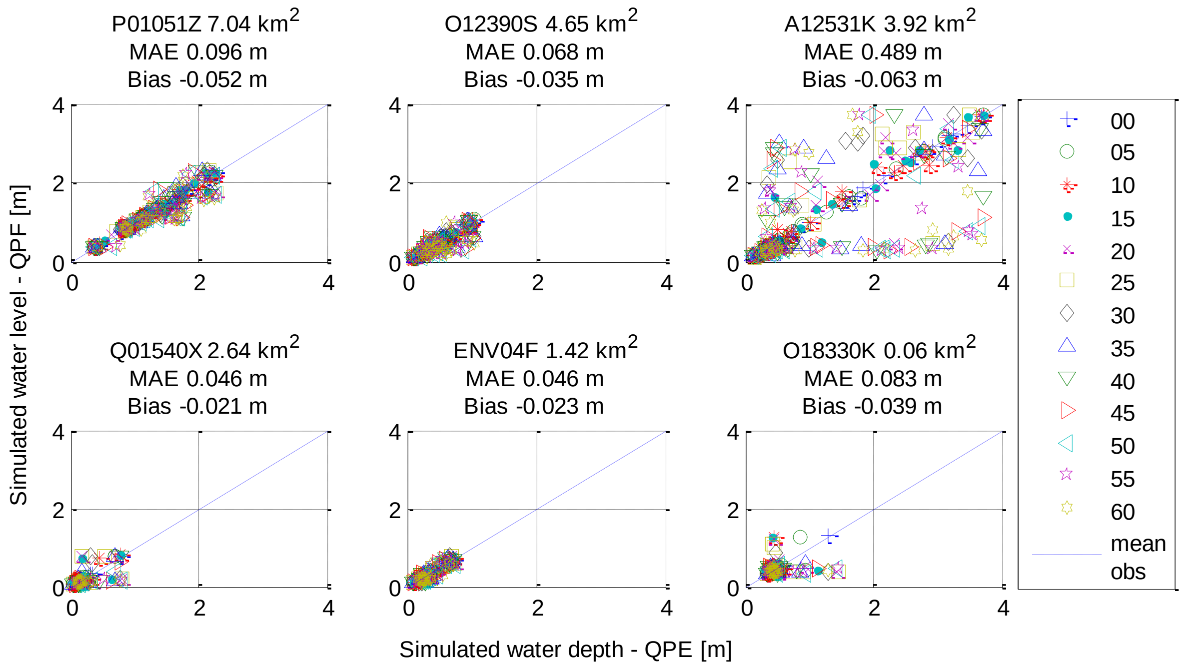

Figure 11-8: Scatter plot for the forecasted water depths produced as a result of the simulated forecasted precipitation based on the area-based nowcasting technique. The verification data is obtained by simulating the QPE in the hydrodynamic model for the 22-05-2013 stratiform event. The markers represent the forecast value for each lead time.

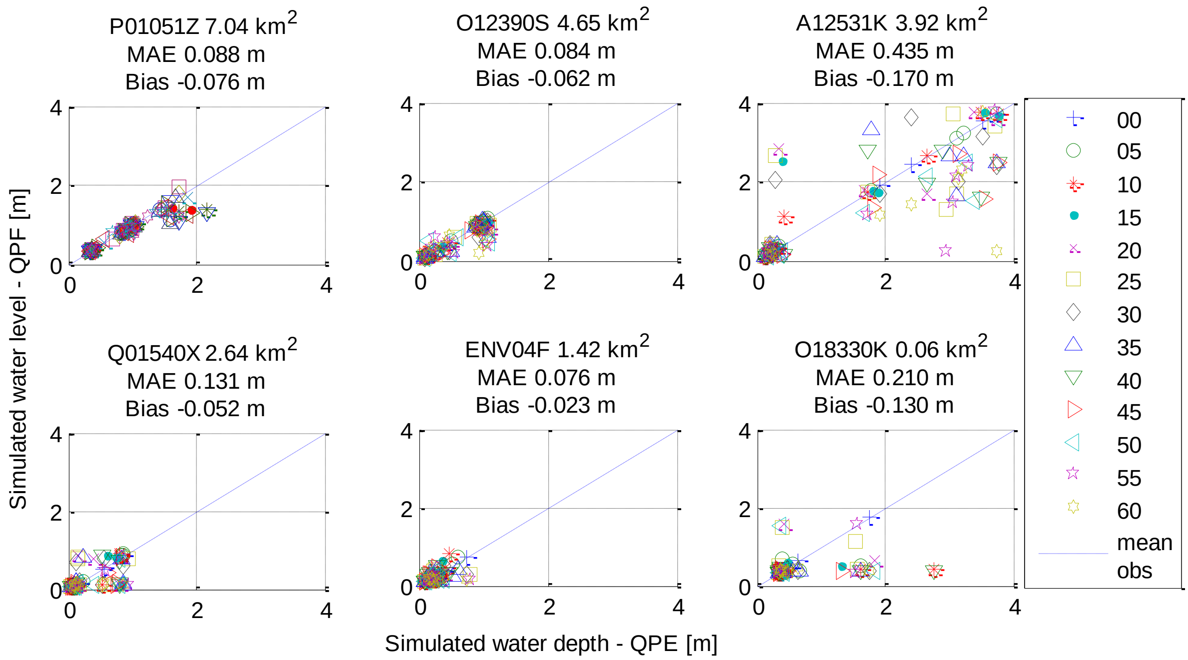

Figure 11-9: Scatter plot for the forecasted water depths produced as a result of the simulated forecasted precipitation based on the area-based nowcasting technique. The verification data is obtained by simulated the observed rainfall fields in the hydrodynamic model for the 27-07-2013 convective event

A first glance of the radar images, at the time of forecast the stratiform precipitation event seemed fairly homogenous in the horizontal and was moving constantly towards the south west. However during the event, there was an apparent stop in motion, as well as some growth and decay of rain clouds which mainly influenced the southern part of the model area, where the drainage areas for locations A12531K, Q01540X are. An apparent stop in motion means that clouds which were forecasted to be out of the model area were hanging over the model area, therefore resulting in an underestimation in the forecast. Another example where changes in the rain cloud structure (growth and decay) is observed is presented in Figure 11-10 for the stratiform event. It is expected that the errors resulting from the convective event will have greater influence on the forecasted water depth. This is what is actually observed in Figure 11-9, for example based on the MAE and bias scores.

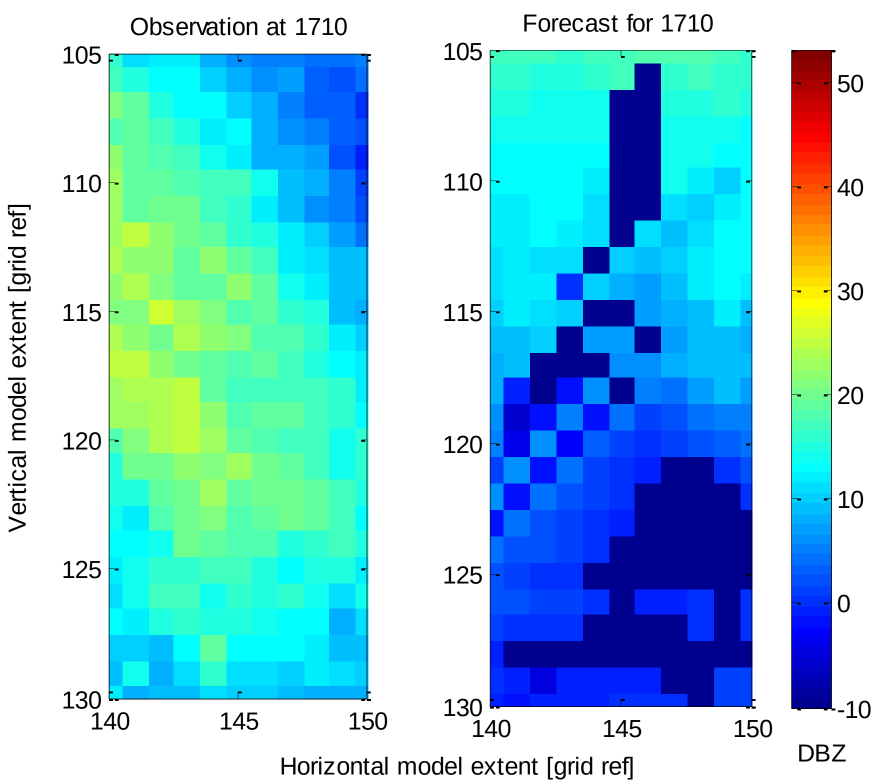

Figure 11-10: Illustration of the observed and forecasted radar image in DBZ over the urban drainage model extent. In some areas on the forecasted image there is an underestimation (southern part) and in others an overestimation (northwest) in the precipitation. Features such as this can explain the disparity in the observed and forecasted water depths

Figure 11-11 shows the MAE that resulted from comparing the water depths obtained from simulated observed and forecasted precipitation fields over the verification area as a function of forecast lead time. In general, the MAE increases with lead time which is as expected and falls within $0.01 - 0.25m$ for most model locations for both events, except for location A12531K which ranges from $0 - 1\,m$. The increase in MAE is more uniform across lead times for the stratiform event compared to the convective event. This may well be attributed to the fact that stratiform events have a large horizontal extent, therefore making it more predictable compared to the convective events that have more isolated clusters. Taken together the difference in the range of approximately $0.01 - 1.0\,m$ can have significant implications on the management decisions of the sewer network.

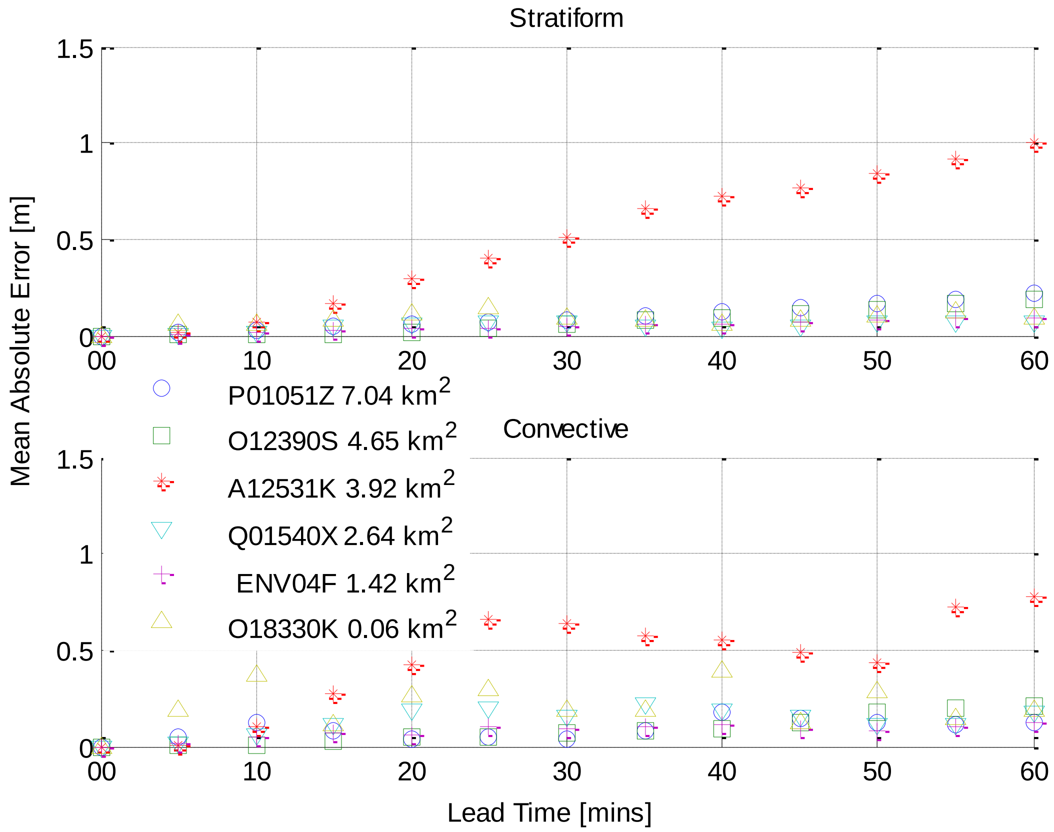

Figure 11-11: Mean absolute error between the simulated water depths for the QPE and QPF for both stratiform and convective event from 5 minute data as a function of sub-catchment drainage area

An evaluation of the SS (Figure 11-12) for forecasting water depths for both events suggest that, in general, the forecasts of the stratiform event (range 1 to -0.8) have better skills than for the convective event (range 1 to -2.5). At individual locations the skill score at some lead times for the convective event is slightly better than the stratiform event. It is expected that the skill score for larger drainage area will be better than for the smaller areas as they dampen the effect of displaced rain fields. There is a slight tendency to observe this for both events but it is not as clear-cut as there is no defined structure as the lead time increases.

But, for both events, at the smallest drainage location O18330K the skill scores fall below zero at some lead times. This poor performance can partly be explained by the fact that the sub-catchment drainage area is much less than the dimension of the radar forecast grid ($0.25km^2$) and therefore cannot compensate for errors in displacement.

It is also expected that the SS will decrease with increasing lead time. This is more pronounced for the stratiform event than the convective event. At all model locations for both events, the skill score is above 0 for most lead times, which implies that the forecast is an improvement over the naïve forecast.

The present findings seem to be consistent with the findings from the rainfall verification, in that there is more overall skill in the rainfall forecast for the stratiform event based on the FSS and bias scores. The finding from the SS further supports that the accuracy of the nowcasting algorithm depends on the nature of the rainfall regime and on the precipitation distribution over the sub-catchments (Berenguer et al., 2005).

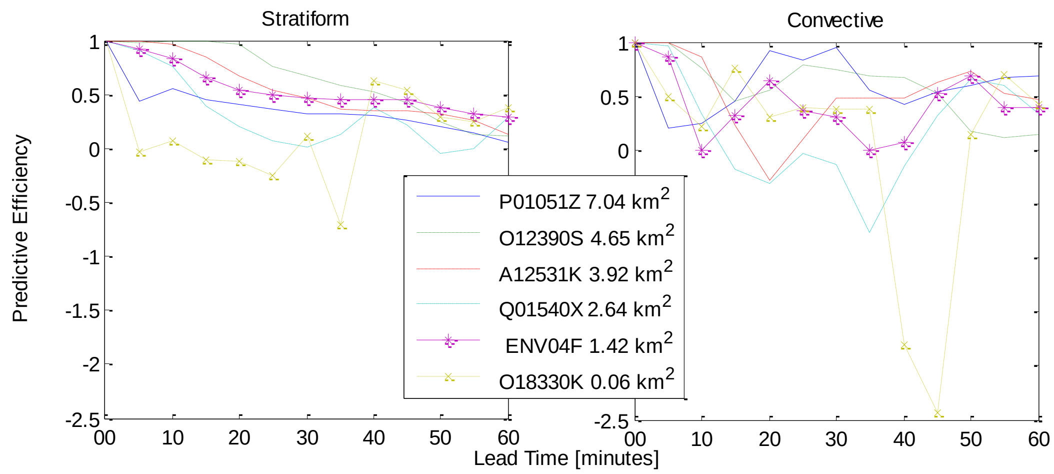

Figure 11-12: Skill Score as a function of forecast lead time for the stratiform and convective event

11.4.5 Evaluation of forecast volumes

The ability to forecast volumes, which are important for forecasting combined sewer overflows, were investigated by comparing integrated flows over the first 30 minutes of each 1 hour forecast as well as the flows over the entire 1 hour forecast period. This was investigated at five out of the six locations, since for the smallest drainage area, flow was not significant because it was a diverging node.

The resulting simulated observed mean volumes as well as the mean RE is presented in Table 11-2 for both lead times investigated. It is apparent from the table that there is a general tendency for the mean RE to increase with decreasing drainage area for both events. These results are consistent with what is expected since smaller drainage areas are more sensitive to errors arising as a result of displaced rain cells.

The table also shows that there is significant value in forecasting the accumulated volume in a 30 minute period for the convective and stratiform events at the two largest locations, based on the RE values. The magnitude seems well within an acceptable range of 10-20%. The results are not so promising for the 1 hour lead times and as expected, there is more value in the 30 minute forecast than the 1 hour forecasts for forecasting volume at all locations.

Table 11-2: Mean observed volume and mean relative error for forecasting volume in a 30 minute period as well as the hour forecasts at 5 model locations

		STRATIFORM				CONVECTIVE			
		30 minute		1 hour		30 minute		1 hour	
Location	Area (km^2)	V (m^3)	RE (%)	V (m^3)	RE (%)	V (m^3)	RE (%)	V (m^3)	RE (%)
P01051Z	7.04	1100.8	6.2	2094.1	14.4	840.3	6.8	1642.5	12.2
O12390S	4.65	493.3	10.9	915.2	32.9	509.6	6.9	1015.5	27.2
A12531K	3.92	344.3	29.9	642.7	39.3	300.6	27.3	609.9	31.1
Q01540X	2.64	428.5	24.6	805.5	36.0	521.3	23.4	987.2	36.7
ENV04F	1.42	146.3	27.3	275.8	39.7	175.1	32.3	326.5	43.2

11.5 Conclusions

This study was undertaken to evaluate the performance of an area-based radar nowcasting algorithm for X-band radar in managing urban drainage systems for both stratiform and convective regimes. The nowcasting technique involves computing the velocity field based on the correlation of the last two successive images. The resulting precipitation forecast was fed into an urban drainage model and an evaluation of the simulated observed and forecasted water depths and discharges performed. Urban drainage modelling coupled with radar-based precipitation provides the possibility to examine the effect of displaced rainfall clouds and incorporate it into management decisions of urban drainage systems.

This study has shown that the performance of the nowcasting algorithm depends on the rainfall regime. FSS results based on 5 stratiform and 5 convective events indicate that the performance is better for the stratiform regime. This was further confirmed by computing the bias of the mean rainfall intensity for two events selected for simulation in the urban drainage model over the model verification area. The results are better for the stratiform regime mainly because the large horizontal homogeneous extent of stratiform precipitation is generally much easier to predict than movement of convective cells.

The performance of the nowcasting algorithm was further verified by simulating both the observed and forecasted rainfall fields for the convective and stratiform events into the urban drainage model and the resulting water depths evaluated. MAE and bias values indicate that the forecast performs better for the stratiform event except for one of the locations. The exception emphasized the importance of accounting for changes in structure and intensity of radar nowcast, which is a major shortcoming in the nowcasting algorithm applied. For effective forecasting of maximum water depths at some locations, based on the MAE and bias results, the first 30 minutes of the forecast had more skill than the 1 hour forecasts. In general MAE indicates a deviation between $0.05 - 0.5m$ in the forecasted water depths for all lead times. The results also showed that smaller drainage areas are more influenced by errors in displaced rainfall cells. These findings have important implications in the overall management of urban drainage systems in real-time.

For the quantitative validation of the simulation results, which in turn validates the nowcasting approach, the SS was presented. The investigation of SS as a function of forecast lead time for the two events suggests that there is more skill in forecasting stratiform events than convective events. The results of the SS are consistent with the results based on the FSS and the mean bias in magnitude of the verification area.

It was also shown that there is a considerable amount of skill in forecasting volumes over a 30 minute period at two of the largest drainage areas. This suggests that the forecast can potentially be used for forecasting overflow volumes over a period. However, most operations rely on accurate predictions of water depths, making this variable more important.

Together, these results provide important insights into the usefulness of the precipitation forecast for the X-band radar using an area-based nowcasting approach and highlight the relevance of good spatial description of precipitation fields in urban catchments. Nevertheless, the differences observed here between the scores used for evaluation are event dependent and a more extensive study with more events is required in order to generalise. However, there is a definite need for improved approaches for radar nowcasting, which can account for changes in extents and intensity in the rain field.

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