Improved Precipitation Information for Hydrological Problem Solving

Focus on Open Data and Simulation

Tero Niemi
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A doctoral dissertation completed for the degree of Doctor of Science (Technology) to be defended, with the permission of the Aalto University School of Engineering, at a public examination held at the lecture hall TU1 of the school on 1 September 2017 at 12.

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Abstract

Precipitation acts as the starting point and the driving force in nearly every field of hydrology. Rainfall-runoff models in particular require accurate rainfall input data in order to provide accurate runoff results. The data requirements are emphasized in urban environments due to small sizes and rapid runoff responses of urban catchments. In recent years, the amount of open precipitation data has increased due to changes in governmental policies and legislations. However, since measuring everything is ultimately impossible, there remains a need for precipitation simulation models no matter how much data is (openly) available. This thesis studied the benefits of improved precipitation information in hydrological assessments by addressing the following questions: 1) How can open precipitation data be utilized more extensively in hydrological research? 2) How can simulation models be improved via more realistic spatial description of precipitation fields? The feasibility of open weather radar and rain gauge data for urban hydrological assessments was studied by conducting high-resolution rainfall-runoff simulations at small Finnish catchments utilizing open precipitation data and rainfall-runoff data collected at the catchments. The open gauge data performs well, given that the gauge is located at the studied catchment or close to it. When the distance to the gauge increases, gauge corrected radar data can give superior results even when the studied catchment is much smaller than the radar data spatial resolution.

A new method was developed to quantify the anisotropic shape of precipitation fields and the evolution of the shape during storm events utilizing the linear Generalized Scale Invariance formalism. The shape description was implemented into a state-of-the-art stochastic precipitation generator to provide a parsimonious way for a more realistic description of precipitation features. Impact of the field shape on the catchment response was studied by conducting rainfall-runoff simulations replicating an extreme storm event. While the description of anisotropy allows for creating stochastic precipitation events that produce the desired rainfall accumulations without sacrificing other event characteristics such as storm advection or storm evolution, its effect was attenuated when exploring the catchment response.

This thesis lays groundwork for future advances in understanding the precipitation process from coarse radar scales to detailed urban scales by utilizing the open precipitation data more comprehensively. Amongst other things, the open data enables studying precipitation features across scales. The presented anisotropy quantification method allows for building better stochastic precipitation simulation models capable of reproducing more realistic precipitation fields for situations where measurement data, open or not, is unavailable.

Keywords design storm, GSI, open data, precipitation, precipitation simulation, rainfall, rain gauge, urban hydrology, weather radar

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Tiivistelmä


Avoimen sääntutka- ja sadenkiintaradan soveltuvuutta kaupunkihydrologiseen tutkimukseen selvitetään korkean resolutoon sadanta-valuntasimulaation kohdalla suomalaissilla valuma-alueilla hyödyntäen sekä avointa sadetiedon että valuma-alueilla kerättävän sade- ja virtaamataadan.

Sadenkiintaradan antaa hyviä tuloksia, kun mittari on sijoitettu valuma-alueelle tai sen välittömään läheisyyteen. Etäisyyden kasvaessa sadenkiintaratalalla korjattu tutkidata voi olla sadenkiintaria parempien vaihtoehtojen tulemon, joissa tutkittava alue on paljon tutkidakseen paikkaahdekuutiota pienempi.


Työn tulokset tarjoavat perustan sadeprosessien ymmärrykselle karkeasta tutkamittakaavasta yksityiskohtaiseneen kaavavaa avoimien datan entistä kokonaisvaltaisemman hyödyntämisen kautta. Esimerkiksi sateen ominaisuuksien tutkiminen eri mittakaavaövissä helpottuu. Menetelmä sadenkiintien muodon määrittämiseen auttaa aiempaa parempien stokastisten sadenmällien kehityksessä entistä realistisempien sadenkiintien luomiseksi tilanteisiin, joista ei ole saatavilla mitattua dataa.

Avainsanat: avoin data, GSI, kaupunkihydrologia, sadanta, sadenkiintari, sateen simulointi, suunnittelusade, sääntutka
Acknowledgements

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I had the pleasure to spend a six month research exchange at the Bureau of Meteorology, Melbourne, Australia during 2013-2014. This period and the invaluable guidance from Dr. Alan Seed before, during, and after my research exchange has been the single most important factor in advancing my understanding of precipitation processes and especially stochastic precipitation modelling. Thank you, Alan.

Conducting research is a collaborative work. The research and especially the publications appended to this thesis would not have been possible without the contribution of the numerous co-authors I had. Thank you Teemu, Alan, Joseph, Tam, Lassi, Majja, Gerald, Kersti, Harri, Brandon, Seppo, and Dmitri. I would also like to thank Prof. Heikki Setälä and the other URCA project members for taking me into the team and for the opportunity to publish the urban hydrology related papers in the project. Jarmo Koistinen has showed interest towards this thesis and given his guidance from the very beginning – thank you.

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Lopuksi, isot kiitokset perheelle ja ystäville tuesta ja tsemppauksesta vuosien mittaan.

Helsinki, June 2017

Tero Niemi
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List of publications

This doctoral dissertation consists of a summary and of the following publications which are referred to in the text by their numerals:


Publications I–IV are reprinted with permission and copyrighted as follows:

Publication I: © 2017 Informa UK Limited, trading as Taylor & Francis Group. (http://dx.doi.org/10.1080/1573062X.2017.1325496)
Publication IV is an open access article available under the CC BY-NC-ND license. (https://dx.doi.org/10.1002/2015WR017521)
Author’s contribution

I. The author was fully responsible for analysing the rainfall data, and participated in preparing and analysing the runoff data, analysing the simulation results, and designing the research. Dr. Warsta was fully responsible for developing the automated subcatchment generator and conducting the rainfall-runoff simulations, as well as mainly responsible for designing the research, analysing the simulation results, and writing the article. Dr. Kokkonen participated in designing the research. Dr. Taka was responsible for collecting the runoff data. All authors participated in writing the article.

II. The author was mainly responsible for designing the research, preparing and analysing the rainfall-runoff data, analysing the simulation results, and writing the article. Dr. Warsta was fully responsible for conducting the rainfall-runoff simulations and participated in designing the research and analysing the simulation results. Dr. Kokkonen participated in designing the research. Dr. Taka was responsible for collecting the on-site rainfall-runoff data. MSc. Hickman and Prof. Moisseev were responsible for collecting and processing the Kerava weather radar data. Dr. Pulkkinen was responsible for collecting and adjusting the FMI radar data. All authors participated in writing the article.

III. The author was mainly responsible for designing the research, analysing the results and writing the article, as well as fully responsible for developing the anisotropy quantification method. Dr. Kokkonen and Dr. Seed participated in designing the research, analysing the results, and writing the article.

IV. The author was mainly responsible for designing the research, analysing the results, and writing the article, as well as fully responsible for implementing the anisotropy description in the STEPS model, calibrating STEPS, and running the rainfall simulations. Dr. Guillaume and Dr. Kokkonen participated in designing the research and analysing the results. Dr. Hoang was responsible for conducting the rainfall-runoff simulations. Dr. Seed was responsible for initiating the research. All authors participated in writing the article.
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<th>Definition</th>
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<td>2 × 2</td>
<td>automatically constructed SWMM model description with 2 × 2 m² grid cell size</td>
</tr>
<tr>
<td>4 × 4</td>
<td>automatically constructed SWMM model description with 4 × 4 m² grid cell size</td>
</tr>
<tr>
<td>8 × 8</td>
<td>automatically constructed SWMM model description with 8 × 8 m² grid cell size</td>
</tr>
<tr>
<td>2D</td>
<td>two-dimensional</td>
</tr>
<tr>
<td>AR(p)</td>
<td>autoregressive process of order p</td>
</tr>
<tr>
<td>a.s.l.</td>
<td>above sea level</td>
</tr>
<tr>
<td>DEM</td>
<td>digital elevation model</td>
</tr>
<tr>
<td>DSD</td>
<td>drop-size distribution</td>
</tr>
<tr>
<td>E1–E5</td>
<td>rainfall-runoff events studied in Publication II</td>
</tr>
<tr>
<td>FMI</td>
<td>Finnish Meteorological Institute</td>
</tr>
<tr>
<td>GO</td>
<td>open rain gauge data from the FMI Kumpula weather station</td>
</tr>
<tr>
<td>GR1</td>
<td>rain gauge data from on-site gauge in Pihlajamäki</td>
</tr>
<tr>
<td>GR2</td>
<td>rain gauge data from on-site gauge in Veräjämäki</td>
</tr>
<tr>
<td>GSI</td>
<td>generalised scale invariance</td>
</tr>
<tr>
<td>INSPIRE</td>
<td>Infrastructure for Spatial Information in the European Community</td>
</tr>
<tr>
<td>K-S</td>
<td>Kolmogorov-Smirnov</td>
</tr>
<tr>
<td>Man</td>
<td>manually constructed SWMM model description</td>
</tr>
<tr>
<td>MFB</td>
<td>mean field bias</td>
</tr>
<tr>
<td>NLS</td>
<td>National Land Survey of Finland</td>
</tr>
<tr>
<td>OGC</td>
<td>Open Geospatial Consortium</td>
</tr>
<tr>
<td>RDA</td>
<td>Research Data Alliance</td>
</tr>
<tr>
<td>RO1</td>
<td>open radar data from the FMI weather radar network</td>
</tr>
<tr>
<td>RO2</td>
<td>open radar data from the FMI weather radar network with advection interpolation</td>
</tr>
<tr>
<td>RO3</td>
<td>open radar data from the FMI weather radar network with the MFB gauge adjustment</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>---------</td>
<td>-------------</td>
</tr>
<tr>
<td>RO4</td>
<td>open radar data from the FMI weather radar network with advection interpolation and the MFB gauge adjustment</td>
</tr>
<tr>
<td>RR</td>
<td>research radar data from Vaisala Oyj Kerava weather radar</td>
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<tr>
<td>STEPS</td>
<td>Short Term Ensemble Prediction System</td>
</tr>
<tr>
<td>STREAP</td>
<td>Space-Time Realizations of Areal Precipitation</td>
</tr>
<tr>
<td>SWMM</td>
<td>Storm Water Management Model</td>
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<tr>
<td>URBS</td>
<td>Unified River Basin Simulator</td>
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<tr>
<td>Z-R</td>
<td>radar reflectivity - rainfall intensity</td>
</tr>
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</table>
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<th>Symbol</th>
<th>Units</th>
<th>Description</th>
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<tr>
<td>bias</td>
<td>[-]</td>
<td>mean bias</td>
</tr>
<tr>
<td>B</td>
<td>[-]</td>
<td>GSI ball</td>
</tr>
<tr>
<td>$B_1$</td>
<td>[-]</td>
<td>GSI unit ball</td>
</tr>
<tr>
<td>$B_\lambda$</td>
<td>[-]</td>
<td>GSI non-unit ball</td>
</tr>
<tr>
<td>$c, d, e, f$</td>
<td>[-]</td>
<td>parameters of the GSI generator $G$ in 2D</td>
</tr>
<tr>
<td>$E^2$</td>
<td>[-]</td>
<td>error function</td>
</tr>
<tr>
<td>$G$</td>
<td>[-]</td>
<td>GSI generator</td>
</tr>
<tr>
<td>$H$</td>
<td>[-]</td>
<td>power law filter</td>
</tr>
<tr>
<td>$I$</td>
<td>[-]</td>
<td>identity matrix</td>
</tr>
<tr>
<td>$L$</td>
<td>[L]</td>
<td>field side length</td>
</tr>
<tr>
<td>$l_s$</td>
<td>[L]</td>
<td>spherio-scale</td>
</tr>
<tr>
<td>$M$</td>
<td>[-]</td>
<td>number of individual power spectra</td>
</tr>
<tr>
<td>$MAE$</td>
<td>[-]</td>
<td>mean absolute error</td>
</tr>
<tr>
<td>$N$</td>
<td>[-]</td>
<td>number of time steps</td>
</tr>
<tr>
<td>$NSE$</td>
<td>[-]</td>
<td>Nash-Sutcliffe efficiency</td>
</tr>
<tr>
<td>$P$</td>
<td>[-]</td>
<td>power spectrum (spectral density function)</td>
</tr>
<tr>
<td>$P_{avg}$</td>
<td>[-]</td>
<td>ensemble average power spectrum</td>
</tr>
<tr>
<td>$P_{cand}$</td>
<td>[-]</td>
<td>power spectrum candidate</td>
</tr>
<tr>
<td>$PFD$</td>
<td>[%]</td>
<td>peak flow difference</td>
</tr>
<tr>
<td>$PTD$</td>
<td>[T]</td>
<td>peak time difference</td>
</tr>
<tr>
<td>$Q_p$</td>
<td>[L^3T^{-1}]</td>
<td>peak flow</td>
</tr>
<tr>
<td>$Q_{p,s}$</td>
<td>[L^3T^{-1}]</td>
<td>simulated peak flow</td>
</tr>
<tr>
<td>$Q_{p,GR1}$</td>
<td>[L^3T^{-1}]</td>
<td>simulated peak flow with GR1 input rainfall data</td>
</tr>
<tr>
<td>$R$</td>
<td>[LT^{-1}]</td>
<td>precipitation field</td>
</tr>
<tr>
<td>$r$</td>
<td>[-]</td>
<td>extent of stretching in precipitation features</td>
</tr>
<tr>
<td>$R_{wet}$</td>
<td>[LT^{-1}]</td>
<td>average wet time step rain rate</td>
</tr>
</tbody>
</table>
\[ T_\lambda \quad [-] \quad \text{scale changing operator} \]
\[ \mathcal{T}_\lambda \quad [-] \quad \text{Fourier space scale changing operator} \]
\[ t \quad [T] \quad \text{time} \]
\[ t_p \quad [T] \quad \text{time to peak} \]
\[ t_{p,s} \quad [T] \quad \text{simulated peak time} \]
\[ t_{p,GR1} \quad [T] \quad \text{simulated peak time with GR1 input rainfall data} \]
\[ V \quad [L^3] \quad \text{flow volume} \]
\[ V_o \quad [L^3] \quad \text{observed flow volume} \]
\[ V_s \quad [L^3] \quad \text{simulated flow volume} \]
\[ VE \quad [%] \quad \text{volume error} \]
\[ WAR \quad [-] \quad \text{wetted area ratio} \]
\[ WSD_{max} \quad [T] \quad \text{maximum wet spell duration} \]
\[ WTS \quad [-] \quad \text{fraction of wet time steps} \]
\[ x \quad [-] \quad \text{spatial domain} \]
\[ x \quad [L] \quad \text{spatial index} \]
\[ y \quad [L] \quad \text{spatial index} \]
\[ \bar{x}_o \quad [L] \quad \text{observed mean rainfall/runoff} \]
\[ x_{t,o} \quad [L] \quad \text{observed rainfall/runoff at time } t \]
\[ x_{t,s} \quad [L] \quad \text{simulated rainfall/runoff at time } t \]
\[ y_t \quad [-] \quad \text{symbol for any GSI input parameter at time } t \]
\[ \hat{y}_t \quad [-] \quad \text{estimator of } y_t \]
\[ \beta \quad [-] \quad \text{scaling exponent} \]
\[ \sigma \quad [\text{dB}] \quad \text{field standard deviation} \]
\[ \lambda \quad [-] \quad \text{scale ratio} \]
\[ \mu \quad [\text{dBZ}] \quad \text{field mean} \]
\[ \rho \quad [-] \quad \text{correlation coefficient} \]
\[ \theta \quad [^\circ] \quad \text{orientation of stretched precipitation features} \]
\[ \omega \quad [-] \quad \text{frequency domain} \]
\[ \omega_1 \quad [-] \quad \text{frequencies on unit scale} \]
\[ \omega_\lambda \quad [-] \quad \text{frequencies on non-unit scales} \]
\[ \omega \quad [L^{-1}] \quad \text{spatial frequency} \]
\[ \omega_x \quad [L^{-1}] \quad \text{frequency index} \]
\[ \omega_y \quad [L^{-1}] \quad \text{frequency index} \]
\[ \omega_\lambda \quad [L^{-1}] \quad \text{norm of } \omega_\lambda \]
1 Introduction

1.1 Background

1.1.1 Precipitation in hydrology

People have been interested in precipitation measurements for a long time. The earliest recorded measurements date back to at least 400 BC when a network of rain gauges was established in India, whereas the invention of the modern non-recording gauge is attributed to the Chinese and the Koreans in the 1400s AD (Biswas, 1970). The first recording (tipping-bucket) rain gauge was invented some 200 years later in England by Sir Christopher Wren (Shaw, 1998). Year 1850 and the paper published the following year by Mulvany (1851) could be considered as the starting point in the modern hydrology. Mulvany presented the rational method for estimating peak flow based on observed average rainfall intensity, and his study is often considered to be the first rainfall-runoff modelling paper (Loague, 2010).

The interest towards precipitation is not surprising, considering the special role precipitation has in hydrology; the source of all fresh water over land is ultimately precipitation. Therefore, understanding the amount, the intensity and the duration of precipitation acts as the starting point and the driving force in nearly every field of hydrology. One of the principal hydrological applications is evaluation of runoff response to large rainfall events. Here rainfall-runoff models come to use, first by determining the ratio of runoff from rainfall (runoff generation), and secondly by taking account of distributing that runoff in time to create a shape for the storm hydrograph (runoff routing). The success of any hydrological model is ultimately decided by the data used to set up and drive the model (Beven, 2012).

Due to the global climate change, understanding precipitation is more topical than ever. The climate projections indicate that precipitation patterns are changing globally, and climate related extremes such as droughts and heavy precipitation are increasing in frequency and intensity in many regions (European Environment Agency, 2017; IPCC, 2014). Urban areas are particularly vulnerable to potential damage to people and infrastructure from precipitation induced problems, as world-wide over 54% of people now live in urban areas and the share exceeds 80% in high-income countries (United Nations, Department of Economic and Social Affairs, Population Division, 2015). Due to the high fraction of impervious surfaces and altered hydrological cycle, urban areas are characterized by fast
surface runoff generation processes and rapid storm flow response to rainfall events (Shuster et al., 2005; Sillanpää and Koivusalo, 2015).

1.1.2 Precipitation physics

Precipitation results from cooling of moist air, usually caused by vertical uplift. While the moist air ascends, it cools adiabatically and the water vapour condenses to form cloud droplets or ice crystals. Under favourable conditions, the droplets and the crystals grow into raindrops, snowflakes, or hailstones and precipitation occurs. Based on the relative dominance of precipitation mechanism, precipitation can be classified into two broad classes: stratiform and convective.

Stratiform precipitation occurs when weather fronts are forced to move on top of each other (Houze, 1993; Karttunen et al., 2008). In a warm front, when the lighter warm air is forced on top of the cold air, vertical air motions are weak, and the precipitation is areally wide-ranging and relatively uniform. In a cold front, the denser cold air is forced under the warm air, and the resulting precipitation is more intense, areally more concentrated, and shorter in duration than precipitation associated with a warm front.

Convective precipitation results from the warm air near the earth’s surface rising and adiabatically cooling until it condensates and precipitates (Dingman, 2002). Ascension rates are high, the precipitation is relatively intense, and individual convective cells are areally small and short-lived (Aaltonen et al., 2008). Several different-aged or consecutive convective cells often form groups where precipitation intensity varies greatly inside the group.

Orographic precipitation occurs when air masses are forced to move over mountains or hills. It can be of both stratiform and convective origin. While orographic precipitation near mountain ranges can produce extreme local rainfall amounts (Houze, 2012), even in a relatively flat country such as Finland orography can have an effect on the areal distribution of precipitation (Solantie and Pirinen, 2006).

1.1.3 Measuring precipitation

While rain gauges date back millennia as a source of precipitation information, even today they remain as the main basis of information regarding surface rainfall amounts (Kidd et al., 2017). Moreover, the basic operation principles of rain gauges have not changed much over the years. The non-recording storage gauges are still used to provide manual measurements of cumulative rainfall. In operational use they are usually read once a day. Automatically recording gauges note the amount of rain collected as a function of time usually in much higher temporal resolution (often < 10 min). Automatic gauges come in many types, the most common ones being float gauges, weighing gauges, and by far the most common type, tipping bucket gauges (Habib et al., 2010). Despite the seemingly simple method of operation: collecting the precipitation falling on a container open to the air with known dimensions, rain gauges suffer from numerous sources of errors. The errors include systematic errors due to e.g. wind effects, flaws in gauge calibration, and wetting-evaporation losses (Humphrey et al., 1997; Sevruk, 1974a, 1974b;
Sevruk and Hamon, 1984), as well as random errors due to instrumental and observational effects (Ciach, 2003; Habib et al., 2001), and errors due to e.g. malfunction and inappropriate device placement. The combined error may result in underestimation of true rainfall by up to 30% or more (World Meteorological Organization, 2014). However, rain gauges still offer the most accurate measurements of true surface rainfall accumulations and intensities at a single point.

The main problem with rain gauge measurements is related to their areal representativeness (Aaltonen et al., 2008). For hydrological purposes, the interest is usually in estimating areal precipitation for a catchment or another area of interest rather than in point measurements. The total area of all currently available operational rain gauge orifices worldwide is equivalent to only about half a soccer field, and even assuming each gauge being representative of a 5 km distance from the gauge, they still only represent about 1% of the Earth's surface (Kidd et al., 2017). Moreover, precipitation is known to have extremely large variation in space and time especially in convective rain events (e.g. Fiener and Auerswald, 2009; Jensen and Pedersen, 2005; Pedersen et al., 2010; Peleg et al., 2013). Therefore, point observations based on rain gauges can provide only a very limited picture of the spatiotemporal variation in a precipitation field (Seo et al., 2010). While the areal precipitation may be estimated from a network of gauge observations using e.g. very simple direct weighted averages such as arithmetic averaging or Thiessen Polygons (Thiessen, 1911), or using more sophisticated geostatistical methods such as Kriging (e.g. Creutin and Obled, 1982), the areal estimates are ultimately dependent on the gauge network density.

In addition to rain gauges, also more recent methods for precipitation monitoring exist. The most important instrument is weather radar, which has been actively developed since after the Second World War (Rinehart, 2010). Nevertheless, it has been in operational hydrological use only about since 1980s and 1990s (Krajewski and Smith, 2002).

The main reason for using weather radar lies in its capability to provide spatially continuous estimates of rainfall at a relatively high spatial resolution (typically in the order of 1 × 1 km²) to a distance of hundreds of kilometres from the radar at small (< 5 min) temporal sampling intervals (Berne and Krajewski, 2013; Cifelli and Chandrasekar, 2010; Seo et al., 2010). Therefore, weather radar is an essential tool in observing the spatiotemporal structure, movement, and evolution of precipitation systems over a large range of scales. The radar has potential particularly in situations where there is a need for high-resolution rainfall input, such as when preparing for flash floods (e.g. Smith et al., 1996a, 2001) or in the field of urban hydrology (e.g. Einfalt et al., 2004; Thorndahl et al., 2017).

However, since weather radar observes precipitation indirectly via measuring the power of the signal backscattered by hydrometeors in a given volume above the ground, there are inherent errors and uncertainties in radar measurements of precipitation. The main error sources are related to a) radar hardware; e.g. radar calibration errors (Smith et al., 1996b) or attenuation due to wet radome (Kurri and Huuskonen, 2008), b) beam propagation; e.g. ground clutter and false echoes from insects, birds, windborne particles and other non-precipitating targets (Steiner and Smith, 2002), beam blockage by terrain obstacles (Krajewski et al., 2006),
Introduction

attenuation in heavy rainfall (Delrieu et al., 2000), or anomalous propagation due to atmospheric conditions (Patterson, 2008), and c) rain rate retrieval; i.e., inappropriate reflectivity-rainfall (Z-R) transformation of the backscattered signal into rain rate due to e.g. uncertainties in the drop-size distribution (DSD) (Lee and Zawadzki, 2005) or in the vertical profile of reflectivity (Kirstetter et al., 2013). For an extensive review of errors in radar-based estimates of rainfall see Villarini and Krajewski (2010).

Using dual-polarization radar rainfall estimates offers several advantages over traditional single-polarization radars, including additional information regarding the size, the shape, and the orientation of the hydrometeors (Cifelli and Chandrasekar, 2010). This information can be used e.g. to describe the DSD more accurately (e.g. Brandes et al., 2004; Gorgucci et al., 2002), identify the types of hydrometeors (e.g. Chandrasekar et al., 2013; Lim et al., 2005; Zrnić et al., 2001), and correct for attenuation in heavy rainfall (e.g. Bringi et al., 2001; Vulpiani et al., 2008). The research on dual-polarization radars has matured enough so that the existing radar networks in many countries are being upgraded by replacing the old single-polarization radars with new dual-polarization radars. For example, in Finland all ten radars in the national weather radar network have dual-polarization capabilities as of June 2017, even though the dual polarization properties of the radars are not yet extensively used in the operational radar product (Gregow et al., 2017).

To achieve a more accurate precipitation estimate than only using rain gauges or weather radars individually, radar estimates with large spatiotemporal coverage can be adjusted using the more accurate point measurements from rain gauges (e.g. Seo et al., 2010). In addition to rain gauges and weather radars, other precipitation observations e.g. from satellites (e.g. Kidd et al., 2010), microlinks (e.g. Overeem et al., 2016), or complementing measurements of e.g. lightnings (e.g. Gregow et al., 2017), can be used to improve the precipitation estimate. Still, despite the advances in multisensory precipitation estimation, bias remains a large problem hindering the use of weather radar estimates in hydrological applications (Seo et al., 2015). In the end, it also remains important to bear in mind that the different instruments measure different properties of rain. Where weather radar takes snapshots of the drop-size distribution in some large volume above the ground, rain gauges attempt to quantify the DSD flux using direct measurements in a small volume on the ground (Michaelides et al., 2009). Therefore, direct comparison of precipitation estimates from different sensors is challenging and not always even sensible.

Measuring precipitation in its solid form, i.e., snow, is even more challenging than measuring rainfall (Michaelides et al., 2009; Saltikoff et al., 2015). In gauge measurements of snowfall especially the undercatch due to wind effects is emphasized, with e.g. accumulation of snow on the rim of the gauge, or snow sticking to the gauge or the bucket of a tipping bucket gauge causing additional problems (Goodison et al., 1998). For radar measurements alike the snow poses problems. The snow size distributions vary even more than the drop size distributions, often snowstorms are rather shallow so that they may suffer from beam overshooting, and in case observations are made far from the radar they are at such high altitude
that the snow may drift significant distances before reaching ground (Saltikoff et al., 2015). Again, utilizing dual-polarization capabilities of weather radars can help in providing more accurate snow measurements by improved hydrometeor classification and more accurate snow size distributions (Cifelli and Chandrasekar, 2010). However, even then problems persist, such as detecting snow with a radar that will melt while drifting further down to be collected as rain by a gauge.

1.1.4 Precipitation input in rainfall-runoff models

Since precipitation acts as the input to rainfall-runoff models, a large part of the modelling errors can be explained by the uncertainties in the rainfall estimates (e.g. Arnaud et al., 2011; Borga, 2002; Moulin et al., 2009; Willems, 2001). Moreover, the requirements for satisfactory precipitation information are largely dependent on the application. In e.g. climate or drought studies even spatially and temporally relatively low resolution measurements may suffice, as long as they are accurate and temporally extensive. For catchment hydrology and rainfall-runoff studies, the requirements are more stringent with the catchment and the storm properties largely dictating the necessary precipitation information resolution. For example, the catchment size (Adams et al., 2012; Cunha et al., 2012; Fu et al., 2011; Nicótina et al., 2008), land use (Pechlivanidis et al., 2016; Segond et al., 2007), and the initial soil moisture conditions (Paschalis et al., 2014; Pechlivanidis et al., 2016; Shah et al., 1996) have all been noticed to affect the rainfall-runoff model sensitivity to input rainfall information. On the other hand, the storm spatiotemporal variability (Chaubey et al., 1999; Lobligeois et al., 2014; Paschalis et al., 2014) due to e.g. storm type (stratiform vs. convective) (Bell and Moore, 2000; Faurès et al., 1995; Peleg et al., 2013), storm shape (Doswell et al., 1996; Guan et al., 2016), and storm movement (de Lima and Singh, 2002; Seo et al., 2012; Seo and Schmidt, 2012; Singh, 1997) have also been noticed to matter when considering an adequate rainfall input to a model. Finally, the choice of the model and especially the spatial description, i.e., lumped vs. semi-distributed vs. distributed, may also affect the requirements for suitable rainfall information (Krajewski et al., 1991; Reed et al., 2004; Smith et al., 2004).

Especially in urban hydrological assessments it becomes critical to select a suitable model (Pina et al., 2016; Salvadore et al., 2015) and to have high-quality high-resolution input data for the model (Salvadore et al., 2015). In the urban environment the requirements for the rainfall input data are more stringent than in rural areas, with a general conception that the smaller and more urbanized a catchment, the higher resolution and more localized the precipitation information is required (Berne et al., 2004; Bruni et al., 2015; Cristiano et al., 2016; Krebs et al., 2014; Ochoa-Rodriguez et al., 2015; Segond et al., 2007). Due to the high spatiotemporal resolution requirements, weather radar data have potential to provide an invaluable source of precipitation information for urban hydrological applications (Einfalt et al., 2004; Emmanuel et al., 2012; Thorndahl et al., 2017; Wright et al., 2014), where the spatial and temporal scales of traditional rain gauge networks are usually not sufficient (Berne and Krajewski, 2013; Cristiano et al., 2016). However, since precipitation exhibits extreme variability in space and time (Lovejoy and Schertzer, 2006), the resolution of the current operational radar
products is often not sufficient for urban hydrological assessments (Bruni et al., 2015; Gires et al., 2013, 2012; Krajewski and Smith, 2002; Thorndahl et al., 2016). In addition, the numerous uncertainties in radar precipitation estimates (see Section 1.1.3) hamper their use.

### 1.1.5 Open data

New possibilities for environmental research and monitoring are emerging due to the shift towards open access, fuelled by the widespread access to internet since the 1990s and the formulation of the open access concept in the early 2000s (Budapest Open Access Initiative in 2002\(^1\), the Bethesda Statement on Open Access Publishing in 2003\(^2\), and the Berlin Declaration on Open Access to Knowledge in the Sciences and Humanities in 2003\(^3\)). While the term open access is often connected with open access publishing, i.e., providing the results of research output free of restrictions controlling their access or further use, it also extends to open sharing of data (open data) and tools to collect, access, and utilize the data and the research outputs (open source software).

In particular, the emergence of internet has allowed large data sets to be easily accessible in a machine-readable form via web-services (Kokkonen et al., 2003). The accessibility is enabled by adopting standardized means to communicate and exchange information between different systems with differing operational software. For geospatial information, such standards are provided by the Open Geospatial Consortium (OGC)\(^4\) via a suite of generic specifications to search and discover geospatial resources (Lehmann et al., 2014). In addition, OGC provides standards for more detailed information models tailored specifically for particular needs, such as for exchanging hydrological observations data (WaterML 2.0; Taylor et al., 2014), or for oceanography and atmospheric sciences (NetCDF; Domencio and Nativi, 2014).

In addition to increased opportunities for distributing data via internet, the changes in legislation and governmental policies at national and international levels are encouraging open sharing of data produced with public funding. For example, the Research Data Alliance (RDA)\(^5\) works to facilitate research data sharing and exchange at a global level (Treloar, 2014). The INSPIRE directive (European Parliament, 2007), on the other hand, requires authorities in European Union to collect and maintain spatial data sets and publish them online for end-users to browse and utilize. At national level, the open data portals such as data.gov.uk in the United Kingdom or avoindata.fi in Finland present umbrella domains for collecting and publishing national open data sets.

As a result of the open data movement, increasing amounts of environmental data with spatial information are now openly and easily available for end users. For example in Finland, the Finnish Meteorological Institute (FMI) has openly

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1 budapestopenaccessinitiative.org/read
2 legacy.earlham.edu/~peters/fos/bethesda.htm
3 openaccess.mpg.de/Berlin-Declaration
4 opengeospatial.org
5 rd-alliance.org
published continuous real-time meteorological observations, historical time series, and model forecast data for public use implementing the INSPIRE directive and the OGC standards (Honkola et al., 2013). Even before that, the Helsinki Testbed provided open data for research from the joint experimental observation network in Helsinki operated by several stakeholders including the FMI (Koskinen et al., 2011).

1.1.6 Rainfall modelling

Even though the availability of open data increases possibilities to observe and understand the physical processes in the environment, there remains a need to approach problems via simulation. Firstly, measuring everything is ultimately impossible, and secondly, often the interest is in studying e.g. future events or scenarios where there are no reliable measurements available. Since precipitation acts as an input to rainfall-runoff models, the need to simulate precipitation in such cases emerges. Ensemble simulations, on the other hand, provide means to study the errors and uncertainties in precipitation estimates and to quantify their impact on runoff results (Emmanuel et al., 2015; Germann et al., 2009; Man-dapaka and Germann, 2010).

An important distinction between rainfall simulation models concerns the type of model. In this thesis, the focus is solely on stochastic simulation models based on the statistical properties of rainfall, whereas dynamic models of rainfall based on a set of partial differential equations describing the conservation of mass, momentum, and energy are not discussed. While the stochastic models are capable of reproducing important characteristics of observed rainfall, such as moments and correlations, they fail to capture the exact details of rainfall event, such as the position of peak rainfall (Cortis et al., 2010). However, the mathematical description of stochastic models is generally much more straightforward than that of the dynamic models and the requirements for computation power are substantially lower (Foufoula-Georgiou and Vuruptur, 2001).

The early stochastic rainfall models were point process models, which dominated the research until the mid-1980s (Georgakakos and Kavvas, 1987). The models often suffered from the inability to describe the rainfall spatial structures across scales and from being difficult to parameterize (Foufoula-Georgiou and Krajewski, 1995). Since the early days, some of the point process models have evolved and become widely used tools for precipitation simulation (e.g. Burton et al., 2010, 2008, Cowpertwait, 2010, 1995). However, the problems with the spatial structure representation and overparameterization persist (Paschalis et al., 2013).

Since the late 1980s, stochastic rainfall models based on scaling random fields have gained popularity (Foufoula-Georgiou and Krajewski, 1995). Of particular interest are those models that are capable of creating ensemble simulations of stochastic precipitation events with realistic spatiotemporal characteristics. Notable models for design storm generation are the model of Seed et al. (1999) and the derived nowcasting system STEPS (Bowler et al., 2006; Seed et al., 2013), the String-of-Beads model (Clothier and Pegram, 2002; Pegram and Clothier, 2001), and the recent STREAP model (Paschalis, 2013; Paschalis et al., 2013).
Scaling models are attractive, as they are able to generate rain fields that reproduce the precipitation statistics over a wide range of spatial and temporal scales with concise parameterization (Foufoula-Georgiou and Krajewski, 1995; Seed, 2004). Furthermore, a large volume of earlier research has shown rainfall to comply with the concept of scaling (e.g. Harris et al., 1996; Mandapaka et al., 2009; Nykanen and Harris, 2003; Seed et al., 2013; Veneziano et al., 1996). Scaling, or scale invariance, indicates that a system observed at a given scale is statistically similar to the system observed at a different scale and that the properties of small and large scales are related by a scale changing operation involving only the scale ratio, i.e., there is no characteristic scale (Lovejoy and Schertzer, 1995).

In relation to precipitation, a precipitation field is scale invariant if its spatial spectral density function, or power spectrum, follows a power law function of frequency:

$$P(\omega) \sim \omega^{-\beta}$$  \hspace{1cm} (1)

where $\omega$ is the spatial frequency (km$^{-1}$) and $\beta$ is the scaling exponent, i.e., the slope of the power spectrum.

Usually scaling is assumed isotropic, i.e., statistically the field at a large scale is assumed simply a zoomed version of the field at a smaller scale. Accordingly, when two-dimensional (2D) fields are analysed for scaling behaviour, the 2D power spectrum $P(\omega) = P(\omega_x, \omega_y)$ is commonly radially averaged over all angles about $\omega_x = \omega_y = 0$. In this way a power spectrum $P(\omega)$ according to Eq. (1) is obtained, where $\omega = |\omega| = (\omega_x^2 + \omega_y^2)^{1/2}$. This is often referred to as the isotropic power spectrum, as the anisotropy present in the 2D power spectrum is averaged out to simplify the analysis of the scaling properties of the field (Nykanen and Harris, 2003). In simulations, stochastic rainfall fields having a power spectrum as presented in Eq. (1) are easily generated by applying a power law filter to a field of white noise. When the filter is symmetric about $\omega_x = \omega_y = 0$, the simulated fields are isotropic, as is the case in most models relying on the scale invariance, including the STEPS and the String-of-Beads models (e.g. Berenguer et al., 2011; Pegram and Clothier, 2001; Rebora et al., 2006; Seed et al., 2013).

Assuming isotropic scaling, an inherent assumption of isotropic rain features is made. In reality, however, rain fields are often anisotropic in space and rainfall is organized into bands with visible elongation. Depending on the shape and the movement of a storm, the anisotropy may have a large impact on the accumulated rainfall (Doswell et al., 1996). In relation to precipitation type (see Section 1.1.2), weather fronts with stratiform precipitation often form rain bands that can extend hundreds or even thousands of kilometres along a front (Rauber and Ramamurthy, 2003). On the other hand, individual convective cells may form destructive squall lines where several individual cells are joined in a line-like structure that may extend in length to several hundred kilometres but be only tens of kilometres wide (Karttunen et al., 2008). See the cover image for an example of large scale frontal rain band extending over Finland and for a smaller scale line of rain showers from Helsinki towards Lahti on 15 May 2016 at 07:15 UTC.
1.1.7 Generalized scale invariance

To take account of anisotropic scaling, i.e., to be able to consider also banded or otherwise anisotropic precipitation structures, the magnification or reduction between scales has to be supplemented with stretching and rotation. Generalized scale invariance (GSI; Schertzer and Lovejoy, 1985) is a formalism developed to deal with scaling anisotropy, allowing both rotation and stretching to vary from place to place in either deterministic or even random manners (Lovejoy and Schertzer, 1995). It states the most general conditions under which a system can be considered as scale invariant.

A scale changing operator, $T_\lambda$, is used in the GSI to relate the statistical properties between scales, so that these properties are a function of only the ratio $\lambda$ between the scales:

$$ T_\lambda = \lambda^{-G} \quad (2) $$

where $G$ is the generator defining the transformation between the scales. In the linear GSI, an approximation of a more comprehensive non-linear GSI, the anisotropy is assumed to be statistically homogenous, i.e., independent of a location in a field. Accordingly, $T_\lambda$ is a linear transformation and the generator $G$ is a matrix. For example, the simple isotropic scaling between the original (large) scale feature set, $B_1$, and a small scale set, $B_2$, is obtained from the operation $B_2 = T_\lambda B_1 = \lambda^{-G} B_1 = \lambda^{-d} B_1 = \lambda^{-1} B_1$, where $G$ in this case is simply an identity matrix $I$ and $T_\lambda$ is a simple reduction by a factor $\lambda$. In a general (anisotropic) case in 2D, $G$ is a $2 \times 2$ matrix with four parameters controlling the anisotropy through rotation ($e$), stretching ($c$ and $f$), and overall contraction ($d$) of scales (Lovejoy and Schertzer, 1985):

$$ G = \begin{bmatrix} d + c & f - e \\ f + e & d - c \end{bmatrix} \quad (3) $$

In 2D linear GSI the overall contraction parameter $d$ can always be taken as $d = 1$ (Lovejoy and Schertzer, 2013). Therefore, it remains to find values for the generator parameters $c$, $e$, and $f$, as well as an expression for the unit scale $B_1$ to fully define the anisotropic scaling of a rain field, and hence to (statistically) parameterize the shape of the rain features in a field.

Previously, three methods have been developed to estimate the GSI parameters of geophysical fields; the “Monte Carlo differential rotation” method (Pflug, 1991; Pflug et al., 1993), the “scale-invariant generator” technique (Lewis, 1993; Lewis et al., 1999), and the “differential anisotropy scaling” technique (Beaulieu et al., 2007). In addition, Pecknold et al. (1993) have used the GSI to generate anisotropic structures on static fields, without considering temporal development of the fields. Later, Marsan et al. (1996) suggested a method to generate full space-time rainfall simulations utilizing anisotropic multifractal fields, but applications of the proposed method have been scarce and the tools are not currently available in commonly used precipitation generators.
1.2 Research gap

Precipitation forms the basis for hydrological research in the land phase of the hydrological cycle. Its role is pronounced in fields such as urban hydrology, where accurate precipitation information is needed to prevent damages to population and infrastructure due to rapid storm response (see Section 1.1.1). While methods to measure precipitation both at a single point (e.g. rain gauges) and over an area (e.g. weather radars) are available, the measurements are prone to errors (see Section 1.1.3). Rainfall-runoff models are the prevailing tool to assess hydrological problems computationally, and the models are dependent on the input precipitation data in order to give meaningful results especially in sensitive urban areas (see Section 1.1.4).

In recent years, vast amounts of environmental data have become openly available for end-users, including meteorological observations provided by e.g. national meteorological offices (see Section 1.1.5). The increased availability of open data and open tools, such as open source models, enable conducting research relying almost entirely on openly available material and methods. However, the quality and suitability of data and tools may be unknown and need to be assessed in order to gain confidence in the research outcomes. Especially the impact of open precipitation data and modern precipitation products, such as weather radar estimates, as a substitute for local measurements as an input data to rainfall-runoff models is an interesting problem that deserves further research. While open precipitation measurements are widely available, the measurements may be relatively far from the area of interest or of insufficient spatiotemporal resolution especially for urban hydrological problems.

Despite the increasing access to (open) data, precipitation simulations are still necessary. The focus is usually on events that are either difficult to measure, due to e.g. rare occurrence or ungauged location, or are impossible to gain data from, e.g. future scenarios. Stochastic precipitation generators are capable of creating credible design events with parsimonious parameterization and realistic spatio-temporal statistics, which can be used as an input to rainfall-runoff models. However, the current generation of precipitation generators usually assume that the precipitation features are isotropic in space, which is often an unrealistic assumption (see Section 1.1.6). Methods to take into account the anisotropic shape of precipitation fields exist, such as the GSI formalism. Nevertheless, it is not implemented into current precipitation generators (see Section 1.1.7).

1.3 Objectives and scope of the thesis

Based on the research needs stated in Section 1.2, the main objective of the thesis is to study the new possibilities that improved precipitation information can provide to hydrological research. The focus is on precipitation simulation models and increased use of open precipitation data. In a larger scope, the thesis aims to increase the appreciation for precipitation complexity in hydrological problem solving. In the author’s opinion we, hydrologists, often neglect the role of precipitation in approaching a hydrological problem even though as a driving force of the hydrological cycle, errors in the precipitation estimates can propagate through the
assessments all the way to the end results. In a way, the goal is therefore to bridge the gap between meteorologists (meteorological sciences) and hydrologists (hydrological sciences).

Two key questions concerning the research problem of improving the precipitation information used for hydrological problem solving are addressed in this thesis:

A) How can open precipitation data be utilized more extensively in hydrological research? (Publications I and II)

B) How can rainfall simulations be improved via a more realistic spatial description of precipitation fields? (Publications III and IV)

More specifically, the objectives of this thesis are to:

(i) evaluate the suitability of openly available (precipitation) data as input for high-resolution urban hydrological simulations (Publications I, II)

(ii) compare the performance of open precipitation data sources with on-site measurements in urban hydrological simulations and provide suggestions for the users of the open data (Publication II)

(iii) improve the description of precipitation fields in stochastic simulation models by introducing a new method to better parameterize the shape of the precipitation fields (Publication III)

(iv) study the impact of improved spatial description of precipitation fields in precipitation simulation models with regard to computed precipitation fields and computed runoff (Publication IV).

Figure 1 illustrates an outline of the thesis and presents the steps conducted to meet the thesis objectives by showing a broad overview of the appended publications (Publications I – IV) and the whole formed by the thesis.

As pointed out in Section 1.1.3, observing snowfall reliably is even more challenging than observing rainfall. Therefore, focus in this thesis is on rainfall. While weather radars measure precipitation in both liquid and solid forms, the cases studied in this thesis are selected so that the precipitation at ground occurred as rain. Furthermore, the simulated precipitation fields are assumed to represent rainfall at the ground level, free of errors, and in liquid form.
Figure 1. Graphical outline of the thesis. Publications I and II focus on evaluating the suitability of open precipitation data from rain gauges and weather radars as an input to urban hydrological models. Publications III and IV focus on improving the precipitation field spatial shape description in stochastic design storm generators and studying the impact of precipitation field shape on rainfall-runoff simulation results. More details of the adopted materials and methods are provided in the appended publications and in the following Sections of this thesis.
2 Study sites and data

2.1 Study sites

2.1.1 Pihlajamäki and Veräjämäki catchments

Stormwater runoff at two small urban catchments of Pihlajamäki and Veräjämäki were studied in Publications I (both) and II (Pihlajamäki). The catchments are located approximately 2 km from each other in Helsinki, Finland (Figure 2a). The city has a humid continental climate with warm summers (Peel et al., 2007). The average annual air temperature is 5.9 °C and the average annual precipitation is 655 mm (Pirinen et al., 2012). Rain events responsible for excessive surface runoff in urban areas of Helsinki are typically intensive convective summer showers with a short duration (Aaltonen et al., 2008).

The 33.5 ha Pihlajamäki catchment (Figure 2b) is a residential area with a total imperviousness of 47% and it is characterized by tall concrete buildings surrounded by yards, small forested patches, and rock outcrops. The 13.9 ha Veräjämäki catchment (Figure 2c) is less intensively built (imperviousness 29%) residential area consisting of mostly single-family houses and large forested areas. Both catchments are located on top of a hill, with the average elevation and the median slope being 32.2 m a.s.l. and 5.1%, respectively, for Pihlajamäki and 29.5 m a.s.l. and 4.3% for Veräjämäki. The granite bedrock at the catchments is very close to the surface overlain only by a thin layer of topsoil. Separate stormwater networks comprising mainly concrete pipes with diameters ranging between 0.3 m and 1.0 m drain the catchments. There are no open streams at the catchments conveying the water, but there is a small pond in Pihlajamäki catchment. Table 1 presents the land cover fractions for the catchments.

For the most part, open data were used to build the catchment descriptions for rainfall-runoff modelling. The catchment delineations were based on a 2×2 m² digital elevation model (DEM) from the National Land Survey of Finland (NLS). The land cover descriptions were based on maps acquired from the City of Helsinki, aerial photographs from NLS, and Google Maps and Google Street View. These are all freely available. In addition, several site visits were conducted to complement and verify the mapped data.
Table 1. Land cover fractions (%) in Pihlajamäki and Veräjämäki catchments. (Modified from Publication I)

<table>
<thead>
<tr>
<th>Land cover</th>
<th>Pihlajamäki</th>
<th>Veräjämäki</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>47.43</td>
<td>65.37</td>
</tr>
<tr>
<td>Asphalt</td>
<td>26.37</td>
<td>14.55</td>
</tr>
<tr>
<td>rooftops</td>
<td>12.90</td>
<td>12.36</td>
</tr>
<tr>
<td>Rock outcrops</td>
<td>7.54</td>
<td>0.29</td>
</tr>
<tr>
<td>Sand or gravel</td>
<td>5.19</td>
<td>4.10</td>
</tr>
<tr>
<td>Stone paver</td>
<td>0.32</td>
<td>1.64</td>
</tr>
<tr>
<td>Water</td>
<td>0.25</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Figure 2. a) Locations of Pihlajamäki and Veräjämäki catchments in Helsinki, Finland. Land use and pipe networks in b) Pihlajamäki and c) Veräjämäki. Locations of rain gauges at catchments (GR1, GR2) and in Kumpula (GO) are indicated by red circles and the location of the Vantaa radar (RO) by a green circle. The arrow in a) points to the location of the Kerava radar (RR) north-east from the catchments. Catchment outfalls are indicated by green triangles. (Modified from Publications I and II)
2.1.2 Bunyip River catchment

The 1,094 km² Bunyip River catchment is located in Victoria, Australia (Figure 3). The catchment has a temperate oceanic climate with a mean annual rainfall of 1,021 mm. The annual rainfall is strongly correlated with topography, the elevation in the catchment ranging from 883 m a.s.l. in the north to close to sea level in the south. The catchment is characterized by forested natural areas in the upstream parts and rural areas with small townships in the lower parts of the catchment, with imperviousness of approximately 3%. The 114 km long Bunyip River originates from the Bunyip State Park in the northern parts of the catchment. The headwaters of the Tarago River, its major tributary, are in the Tarago State Forest wherefrom the river flows into the Tarago reservoir before converging with the Bunyip River. In the lower parts, many creeks are modified into agricultural drains, and the Bunyip River is straightened and converted into the Bunyip Main Drain discharging to Western Port bay. Runoff generation in Bunyip River catchment was studied in Publication IV.

Figure 3. The Bunyip River catchment in Victoria, Australia. Red circles refer to water level gauges in the river. The red star depicts the catchment outlet. (Modified from Publication IV)

2.2 Rainfall data

2.2.1 Finland

Rain gauge data from Kumpula weather station (GO in Figure 2a) were utilized in Publications I and II. In Publication II, data from on-site gauges in Pihlajamäki (GR1 in Figure 2) and Veräjämäki (GR2 in Figure 2) catchments were used as well. In addition to the rain gauge data, weather radar data from dual-polarization C-band Doppler radars in Vantaa (RO in Figure 2a) and Kerava (RR in Figure 2a) were utilized in Publication II.
Study sites and data

GO data are from the FMI operated Kumpula weather station, which has a weighing type rain gauge (OTT Pluvio², OTT Hydromet, USA) with a Tretyakov wind shield providing data at 10 min temporal resolution. The data are freely available through the FMI Open data interface. The weather station is located approximately 3 km away from the Veräjämäki catchment and 5 km away from the Pihlajamäki catchment. In addition to the open gauge data, two tipping-bucket rain gauges (Decagon ECRN-100 High Resolution Rain Gauge, Decagon Devices, Inc., USA) were installed for the snow-free periods of 2014 and 2015 in Pihlajamäki (GR1) and Veräjämäki (GR2) catchments. The gauges reported the rainfall intensity as a number of 0.2 mm tips per one minute (2014) or two minutes (2015). To minimize interference due to vandalism and obstruction from the urban environment, the gauges were installed on top of low-rise kindergarten buildings. The gauge measurements were based on the manufacturer-provided calibration of the devices and were not adjusted e.g. for wind effects.

RO data from the FMI operated weather radar in Vantaa correspond to the open data released for public through the FMI Open data interface, with a temporal resolution of 5 min and processed to a Cartesian grid with a resolution of 1 × 1 km². The dual-polarization capabilities of the radar are only used for removing false echoes due to non-meteorological targets and for filling the resulting gaps, with the rainfall estimate (mm/h) based on conversion from radar reflectivity (dBZ) using a Z-R relation $Z = 223 R^{1.53}$ (Leinonen et al., 2012). Four products were created from the RO data. In RO1 a rainfall accumulation time series from the radar cell directly above the on-site gauge GR1 with the original 5 min temporal resolution of the data was produced by assuming that the radar fields stay stationary within the sampling interval. In RO2 the temporal resolution of the time series was increased to 1 min by using advection interpolation to create new fields between the scanned fields. In RO3 the radar data were adjusted using a time varying mean field bias (MFB) correction (Goudenhoofdt and Delobbe, 2009) with the data from the eight nearest FMI gauges to the Vantaa radar. Finally, in RO4 both the advection interpolation and the MFB correction were utilized. The RR data from the Vaisala Oyj operated research radar in Kerava were provided as rain intensity maps (mm/h) with a nominal spatial resolution of 250 × 250 m² and an average temporal resolution of 2 min 29 s, with the actual resolution varying between scans in time and space. A blended rainfall estimate was used, where an estimate based on dual-polarization parameters was utilized for rain intensities exceeding 4 mm/h and in cases where hail was detected, while an estimate based on radar reflectivity was reserved for light precipitation. A rainfall accumulation time series with 1 min temporal resolution was created by linearly interpolating the rainfall intensities from the radar cell directly above the on-site gauge GR1. The details of the data sets are provided in Publication II.

The 11 rainfall-runoff events studied in Publications I and II are listed in Table 2. Except for the events of 15-20 Jun 2016 for Publication I and 6 Aug 2015 for Publication II, the rainfall-runoff events were selected such that there was rainfall and runoff information available from all the studied data sources with minimal missing data breaks or data deemed as unreliable. The two events were studied separately from the others due to missing runoff measurements. The 6 Aug 2015
Study sites and data

The most intense storm event recorded at the Pihlajamäki catchment during summer 2015 was the 15-20 Jun 2016 event, while the 15-20 Jun 2016 event represented an intense event.

<table>
<thead>
<tr>
<th>Catchment</th>
<th>Publication</th>
<th>Event code in Publication II</th>
<th>Date</th>
<th>Duration (h)</th>
<th>Rainfall depth (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I, II</td>
<td>E1</td>
<td>20-21 Aug 2014</td>
<td>14</td>
<td>GO 28.5 GR1 34.4 GR2 33.2 RO1 32.0 RO2 27.0 RO3 41.7 RO4 31.1 RR 23.9</td>
</tr>
<tr>
<td>Pihlajamäki</td>
<td>II</td>
<td>E2</td>
<td>22-23 Sep 2014</td>
<td>15</td>
<td>18.6 14.8 17.6 12.7 12.7 12.3 12.4 9.6</td>
</tr>
<tr>
<td></td>
<td>I, II</td>
<td>E3</td>
<td>18-19 Jun 2015</td>
<td>32</td>
<td>21.0 24.0 28.0 19.8 20.0 22.5 22.4 18.3</td>
</tr>
<tr>
<td></td>
<td>II</td>
<td>E4</td>
<td>30-31 Jul 2015</td>
<td>12</td>
<td>23.8 18.8 24.2 9.7 10.5 12.5 12.9 15.2</td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>-</td>
<td>6 Aug 2015</td>
<td>4</td>
<td>19.3 26.0 32.6 13.4 12.4 29.6 26.6 26.3</td>
</tr>
<tr>
<td></td>
<td>I, II</td>
<td>E5</td>
<td>6 Dec 2015</td>
<td>8</td>
<td>6.8 8.6 8.0 6.0 6.0 6.2 6.3 5.7</td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>-</td>
<td>15-20 Jun 2016</td>
<td>120</td>
<td>100.9 - - - - - -</td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>-</td>
<td>9 Nov 2015</td>
<td>6</td>
<td>6.5 - - - - - -</td>
</tr>
<tr>
<td>Veräjämäki</td>
<td>I</td>
<td>-</td>
<td>15 Nov 2015</td>
<td>4.5</td>
<td>6.9 - - - - - -</td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>-</td>
<td>4 Dec 2015</td>
<td>12</td>
<td>10.7 - - - - - -</td>
</tr>
<tr>
<td></td>
<td>I</td>
<td>-</td>
<td>15-20 Jun 2016</td>
<td>120</td>
<td>100.9 - - - - - -</td>
</tr>
</tbody>
</table>

Table 2. Studied rainfall-runoff events in Publications I and II. Data codes for rainfall input data sources are given in text and in Figure 2. (Modified from Publications I and II)
2.2.2 Australia

Two major rainfall events recorded by the Australian Bureau of Meteorology S-band Doppler weather radars were studied in Publications III and IV. In Publication III, a 20 h rain event of 11 Dec 2010 captured by Mt. Stapylton radar near Brisbane in Queensland, Australia was analysed, whereas in Publication IV a 43 hour rain event from 3-5 Feb 2011 recorded by Melbourne radar in Victoria, Australia was studied. The latter event resulted in widespread flooding in many Victorian rivers, including the Bunyip River. For both events pre-processed radar reflectivity (dBZ) fields from the radars were available with a temporal resolution of 6 min and a spatial resolution of $1 \times 1 \text{ km}^2$ covering a $256 \times 256 \text{ km}^2$ square centred at the radar. For the conducted analyses, it was sufficient to assume the reflectivity fields free of errors and representing the rain features at the ground level. Both events represent very anisotropic storms with their elongated shape almost parallel to the general advection direction of the storms.

2.3 Runoff data

Stormwater discharge data recorded at the Pihlajamäki and Veräjämäki catchments were utilized in Publications I (Pihlajamäki and Veräjämäki) and II (Pihlajamäki). Recording devices were installed at the catchment outfalls inside a 1.0 m diameter concrete stormwater sewer pipes. In Pihlajamäki, the discharge was recorded using a Nivus OCM Pro ultrasound probe (Nivus GmbH, Germany) at 1 min resolution. In Veräjämäki the stormwater discharge was computed at 5 min resolution based on water level measurements (ToughSonic14 ultrasonic sensor; Senix Co., USA) and flow velocity measurements (Starflow Ultrasonic Doppler Instrument Model 6526H; Unidata Pty Ltd, Australia) assuming uniform flow velocity across the flow cross section.

Runoff measurements in Pihlajamäki suffered from sporadic device malfunctions, which caused short periods of missing data and sudden jumps in the observed discharge time series especially during high flows. This was taken into account in Publications I and II by selecting events with mostly unbroken discharge time series. In addition, when evaluating the peak flow performance of different rainfall data sources in Publication II, the simulated discharges with on-site rain gauge recordings (GR1) as input data were used as a reference instead of the unreliable observed flows. An additional problem was encountered with the discharge observations being lagged in time, supposedly due to the logger clock being too fast. As this was only noticed near the end of the measurement campaign, there was no time to replace the unreliable logger but the measurements were used as such in Publication I. For Publication II the discharge observations were shifted in time following the proposal of Moussa (2010) using the simulated discharges with on-site gauge recordings (GR1) as the basis for shifting.

In Veräjämäki, the catchment outfall was located downhill of a relatively steep hill, i.e., the discharge measurements were conducted in a suboptimal location. This was assumed to have caused underestimation to the observed discharge values due to the rapidly flowing water.
3 Methods

3.1 Parameterization of precipitation field anisotropy

A new method to parameterize the anisotropic scaling of precipitation fields, and hence the spatial shape of precipitating features, was developed in Publication III. The method relies on the linear GSI formalism in two dimensions, i.e., it is applicable to precipitation fields and assumes that the scaling of precipitation is homogenous across the field. Furthermore, it is assumed that there exists a scale where the structures are approximately isotropic, i.e., roundish in their shape, and this spherio-scale \( l_s \) is used as the unit scale. This is argued to be a reasonable assumption, as often despite the radar observed large scale structures being anisotropic the small scale structures are still approximately isotropic (Kumar and Foufoula-Georgiou, 1993; Zawadzki, 1973).

To visualize the method, it can be thought of as a generalization of the radially averaged power spectrum used to study scaling of fields in isotropic terms. Consider a precipitation field \( R(x) = R(x, y) \) and its corresponding 2D Fourier power spectrum \( P(\omega) = P(\omega_x, \omega_y) \), where \( (\omega_x, \omega_y) \) is the location in the frequency domain corresponding to location \( (x, y) \) in the spatial domain. Now, instead of radially averaging \( P(\omega) = P(\omega_x, \omega_y) \) about \( \omega_x = \omega_y = 0 \), the averaging is performed according to scales. The scales in \( P(\omega) \) present themselves as isolines of constant power, and in the perfectly isotropic situation the isolines are circles with a radius of \( \omega = |\omega| = (\omega_x^2 + \omega_y^2)^{1/2} \). In an anisotropic situation, however, the isolines can be of any shape as long as they do not cross each other. Assuming that there exists a sphero-scale, the isoline for this scale is a circle in \( P(\omega) \) and can be described using only one parameter, \( l_s \), the radius of the circle. In the prevailing GSI literature the scales (isolines) are traditionally referred to as “balls”, \( B \), even though in 2D they are in fact two-dimensional objects. Using the sphero-scale as the unit ball, \( B_1 \), all the other non-unit balls, \( B_\lambda \), can be constructed using:

\[
B_\lambda = \tilde{T}_\lambda B_1
\]

where \( \tilde{T}_\lambda = \lambda^{-\alpha_T} \) is the Fourier space scaling operator corresponding to \( T_\lambda \) (Pflug et al., 1993).

In practice an ensemble average power spectrum \( P_{avg}(\omega) \), which is constructed using a centered moving average of \( M \) consecutive spectra over some time period, is used instead of the spectrum of an individual field, \( P(\omega) \). Precipitation fields can be considered as realizations of a stochastic process and hence the scaling is not expected to hold exactly for any individual field but only over an ensemble
average of fields produced using the same GSI parameters. Furthermore, the fields evolve constantly which causes $G$ and $l_s$ to vary between consecutive fields. However, as the anisotropy of the fields is typically caused by mesoscale structures, the evolvement of these structures is assumed sufficiently slow so that $P_{avg}(\omega)$ can be used to capture the anisotropy of the system.

The developed method proceeds as follows (Figure 4):

1. $P_{avg}(\omega)$ is computed centered in time around the studied field.
2. Assuming some values for $l_s$ and parameters $G = G(c, e, f)$ a field of balls $B_i$ is constructed. In practice, every pixel in the field is forced to belong to one and only one scale (i.e., ball).
3. Assuming that parameters for $G$ and $l_s$ are correct, the balls $B_i$ should correspond to isolines of constant power in $P_{avg}(\omega)$. A candidate spectrum $P_{cand}(\omega)$ is constructed by overlaying $P_{avg}(\omega)$ with $B_i$ and adopting for each ball the corresponding average value from the underlying $P_{avg}(\omega)$ field.
4. An error function $E^2$ between $P_{avg}(\omega)$ and $P_{cand}(\omega)$ is computed (Eq. 5).
5. The values of $G$ and $l_s$ are altered in step 2 until $E^2$ is minimized.

The following error function $E^2 = E^2(c, e, f, l_s)$ is used to minimize the difference between $P_{avg}(\omega)$ and $P_{cand}(\omega)$, where the summation is over all the pixels in the field and $\omega^{-1}$ refers to inverse distance weighting:

$$E^2 = \sum \frac{1}{\omega} \left[ 10 \log_{10} P_{avg}(\omega) - 10 \log_{10} P_{cand}(\omega) \right]^2$$  \hspace{1cm} (5)$$

The minimum of $E^2$ can be searched using any derivative free optimization method, such as the downhill simplex method (Nelder and Mead, 1965) as in Publication III. For a time series of precipitation fields, the initial parameter values for each field are set to the parameters giving the minimum of the previous field, as the parameters for consecutive fields are likely to be relatively close to each other. In the beginning of the search and after a dry period, the search has to be restarted from random values drawn from uniform distribution for each parameter. Parameters $c$ and $f$ are constrained to the interval of $[-1, 1]$ by condition $1 \geq c^2 + f^2$ (Schertzer and Lovejoy, 1985). There are no such constraints for $e$, but for practical reasons the limits suggested by Lewis (1993) are used, i.e., $e$ is restricted to $[-1.5, 1.5]$. The Fourier transform used to generate the power spectrum restricts $l_s$ (in real-space units) between twice the pixel size and the side length of the field.

**Figure 4.** Quantifying the anisotropy of an individual field. (Modified from Publication III)
3.2 Rainfall simulation models

3.2.1 Simple anisotropic field generator

The performance of the developed anisotropy parameterization method was studied in Publication III using simulated stochastic fields as well as an observed precipitation event. The stochastic fields were generated by power law filtering Gaussian noise (Bell, 1987; Pegram and Clothier, 2001; Schertzer and Lovejoy, 1987) with modifications to account for the spatial anisotropy.

To obtain a field with isotropic spatial structure from a field of white noise, the white noise field can be filtered using a power law filter $H$ with the following form:

$$ H(\omega) = \omega^{-\beta} $$

where $\beta$ is the desired spatial scaling exponent. For anisotropic spatial structure, each frequency $\omega = |\omega|$ used to construct the filter needs to be replaced with $\omega_\lambda$ resolved from:

$$ \omega_\lambda = \hat{\eta}_\lambda \omega_1 $$

where $\omega_1$ refer to the frequencies corresponding to unit scale (defining the unit ball $B_1$) and $\omega_\lambda$ refer to the remaining frequencies defining the non-unit scales (and non-unit balls $B_\lambda$) (Figure 5). Pecknold et al. (1993) present a detailed procedure for calculating $\omega_\lambda$ using given GSI generator parameters $c, e, f$ and sphero-scale $l_s$.

Four parameters are required to create stochastic fields resembling observed precipitation fields (Pegram and Clothier, 2001): $\mu$ and $\sigma$, the mean and standard deviation of the generated fields; $WAR$, the wetted area ratio describing the proportion of rainy cells to the total number of cells; and $\beta$, the scaling exponent.

The following procedure was used to generate stochastic fields with given spatial statistics, with further details provided in Publication III:

1. Generate a field of Gaussian white noise.
2. Transform the field into Fourier space.
3. Filter the field using a power law filter with the desired value for $\beta$.
4. Inverse transform the field back to real space.
5. Set values smaller than a given threshold value to zero in order to obtain the desired $WAR$.
6. Scale and shift the field to the desired $\mu$ and $\sigma$.
Methods

3.2.2 Short Term Ensemble Prediction System (STEPS)

The Short Term Ensemble Prediction System (STEPS) utilized in Publication IV, is an operational probabilistic nowcasting system developed at the Australian Bureau of Meteorology and the UK MetOffice (Bowler et al., 2006; Seed et al., 2013). While the model is primarily used for precipitation nowcasting, it can also be used in a purely parametric mode to create ensembles of stochastic design storms with realistic spatiotemporal properties. The model exploits the spatial scaling behaviour of rainfall (e.g. Nykanen and Harris, 2003; Veneziano et al., 1996) as well as the dynamic scaling (e.g. Foresti and Seed, 2014; Mandapaka et al., 2009; Vennegopal et al., 1999) which relates the lifetime of a precipitation structure to its size with a power law equation.

When STEPS is used in parametric mode to simulate design events, time series for $\mu$ and for advection velocities to eastern and southern directions over the study area are generated using the broken line model of Seed et al. (2000). The spatial structure for the fields is generated by filtering Gaussian white noise using two power-law filters; one for small-scale and another for large-scale features. The spatially correlated noise fields are decomposed into cascade levels using a set of Gaussian band-pass filters, where each level represents features of the original field at a given spatial scale. The Lagrangian temporal evolution of the fields is
accomplished by modelling the lifetimes of the cascade levels as second order autoregressive AR(2) processes (Seed, 2003). This relates the temporal autocorrelations to spatial scale according to dynamic scaling.

In publication IV, modifications to the parametric version of STEPS were implemented. The power law and band pass filters were improved by replacing the spatial frequencies $\omega$ in the filters with $\omega_A$ obtained from Eq. (7) to account for the spatial anisotropy in precipitation fields. To ensure a smooth advection handling and spatially continuous features for the fields having a final size of $L \times L$ pixels, the advection scheme of Pegram and Clothier (2001) was implemented. Utilizing the 'wrap-around' property of the Fourier transform, noise fields having a size of $2L \times 2L$ were generated where the rain features seemingly continue from one side of the field to another. Advection was simulated by moving a slice of the field from one side of the field to another side before trimming the fields to the final size by only using the central part of the field. Finally, explicit relationships between time series of $\rho$ and $\mu$ as well as between $\sigma$ and $\mu$ were constructed using quadratic functions, as $WAR$ and $\sigma$ were discovered to be strongly correlated with $\mu$ ($\rho > 0.95$). This allowed adjusting $\mu$ and the related $\sigma$ and $WAR$ by using a thresholding procedure followed by scaling and shifting in a similar manner as with the simple anisotropic field generator in Section 3.2.1.

When simulating the anisotropic structures, the two GSI parameters controlling stretching of the structures ($c$ and $f$) were replaced with parameters describing the extent of stretching ($r$) and the direction of stretching ($\theta$) following Lovejoy and Schertzer (2013):

\begin{align}
    r &= \sqrt{c^2 + f^2} \\
    c &= r \sin(2\theta) \\
    f &= r \cos(2\theta)
\end{align}

where $r$ is the stretching parameter varying between $r = 0$ for isotropic structures and 1 and $\theta$ is the directional parameter between $[0^\circ, 180^\circ]$ such that $0^\circ$ refers to structures being stretched in North-South direction and $90^\circ$ to structures being stretched in West-East direction. This simplifies the simulation process since the extent ($r$) and orientation ($\theta$) of anisotropy can be controlled individually instead of controlling both via $c$ and $f$ simulatenously.

3.3 Rainfall-runoff models

3.3.1 Stormwater Management Model (SWMM)

The US EPA Stormwater Management Model (SWMM) is a free and open source dynamic rainfall-runoff simulation model used for simulation of runoff quantity and quality in urban areas (Rossman, 2015). The studied area can be divided into irregularly shaped subcatchments to account for the spatial variability of land use. The model consists of components describing the main hydrological processes.
controlling runoff generation. Runoff is then routed through a stormwater network composed of closed conduits and open channels. The surface runoff at each subcatchment is simulated as a non-linear reservoir receiving inflows from precipitation and adjacent subcatchments, and generating outflow while accounting for losses due to evaporation, infiltration and interception. SWMM model was utilized in Publications I and II.

3.3.2 Unified River Basin Simulator (URBS)

The Unified River Basin Simulator (URBS) is a semi-distributed rainfall-runoff model focused primarily on flood forecasting and design flood assessments (Carroll, 2012). The studied catchment is divided into sub-areas and the total rainfall over each sub-area is determined. From the total rainfall over a sub-area, losses are abstracted to yield the excess rainfall, which is then converted to runoff. Runoff routing is separated into sub-area and channel components to obtain stream flow hydrographs at given locations. URBS is in operational flood forecasting use across Australia (Pagano et al., 2016), including the Bunyip River catchment where it was applied in Publication IV.

3.4 Simulation setups

An automated subcatchment generator, GisToSWMM5, was developed in Publication I. It divides the studied area into a matrix of subcatchments with a regular Cartesian grid, connects the subcatchments with each other and to the underlying stormwater network, and finally produces a SWMM input file. The subcatchment generator was used in Publications I and II to create SWMM models with progressively denser grids (cell area 8×8, 4×4 and 2×2 m²) for the Pihlajamäki and Veräjämäki catchments. In addition, traditional, manually constructed SWMM models were created for both catchments in high resolution. The developed models were not explicitly calibrated for the studied catchments but instead a SWMM parameter set Krebs et al. (2014) calibrated for a similar small urban catchment (6.63 ha) in Lahti, Finland, was adopted. The models were run using different input rainfall data as specified in Table 2 (p. 17) to produce runoff simulations with 1 min resolution. The simulated discharges were compared to observed values at the catchment outfall visually as well as numerically using several performance measures. In Publication I, Nash-Sutcliffe efficiency NSE (Eq. 11) (Nash and Sutcliffe, 1970) was used. In Publication II, NSE and volume error VE (i.e., bias) (Eq. 12) were used to compare the different rainfall data sources directly as well as to compare the simulated discharges to observed discharge. In addition, the peak flow difference PFD (Eq. 13) and peak time difference PTD (Eq. 14) were used in Publication II by comparing simulation results produced with other input rainfall data sources to simulations produced with on-site gauge measurements.

\[
NSE = 1 - \frac{\sum_{t=1}^{N}(x_{t,o} - x_{t,s})^2}{\sum_{t=1}^{N}(x_{t,o} - \bar{x}_o)^2}
\]  

(11)
\[ VE = \frac{V_s - V_o}{V_o} \times 100 \quad (12) \]

\[ PFD = \frac{Q_{p,s} - Q_{p,GR1}}{Q_{p,GR1}} \times 100 \quad (13) \]

\[ PTD = t_{p,s} - t_{p,GR1} \quad (14) \]

where \( x_{t,s} \) and \( x_{t,o} \) are the simulated and observed rainfall/runoff values, respectively, \( V_s \) and \( V_o \) are the simulated and observed rainfall/runoff volumes, respectively, at time \( t, \bar{x}_o \) is the observed mean rainfall/runoff, \( N \) is the number of time steps, \( Q_{p,s} \) and \( Q_{p,GR1} \) are the simulated peak flows, \( t_{p,s} \) and \( t_{p,GR1} \) are the simulated peak times, and the subscript \( GR1 \) refers to the on-site gauge as the rainfall data source while \( s \) refers to the remaining data sources used alternatively as input.

The performance of the developed anisotropy estimation method (Section 3.1) was evaluated in Publication III using both simulations with known anisotropic structures as well as an observed precipitation event with an unknown anisotropy. The simulations started with non-zero random fields, where features continued from one side of the field to the other, i.e., considering periodic fields. These represent the ideal conditions for the proposed parameterization method as no information on the spatial structure of the fields is lost. Next, the non-zero fields were windowed using a rectangular window, which is necessary to prevent distortions to the spectrum in case a field is non-periodic. Finally, fields resembling observed radar reflectivity fields were generated where the features were not allowed to fold over the edges, i.e., non-periodic fields, and where increasing amounts of intermittency was gradually introduced to the fields. These fields were also windowed using the rectangular window. All fields were generated using the simple anisotropic field generator (Section 3.2.1) and the anisotropy was gradually introduced to the fields by starting from isotropic situation and then changing the anisotropy parameters first one at a time and later on simultaneously.

The observed event of 11 December 2010 from Brisbane, Australia, was used as a verification event with an unknown spatial anisotropy. The performance of the anisotropy parameterization method was assessed by repeating the parameterization 15 times and studying both the time series of individual parameter estimates from each round as well as the time series of average parameter estimates with 95% confidence intervals. For the generated fields with known anisotropy, the average of a given input parameter \( y_t \) for field \( t \) was used as the estimator \( \hat{y}_t \) when computing the mean absolute error \( MAE \) (Eq. 15) and mean bias (Eq. 16) of the parameter estimates.

\[ MAE = \frac{1}{N} \sum_{t=1}^{N} |\hat{y}_t - y_t| \quad (15) \]

\[ bias = \frac{1}{N} \sum_{t=1}^{N} \hat{y}_t - y_t \quad (16) \]
where \( N \) is the number of time steps.

In publication IV, the modified STEPS model (Section 3.2.2) was used to generate two 1 000 member ensembles of realistic design storms statistically resembling the observed event of 3-5 Feb 2011 in Melbourne, Australia. The design storms were created with identical parametrizations except for their spatial storm shape description; one ensemble was generated with and another without accounting for the spatial anisotropy of the observed event. The STEPS parameters were estimated directly from the observed successive radar reflectivity fields following the methods described in Seed et al. (2000) and Seed et al. (2014). The anisotropy parameters were estimated using the developed anisotropy estimation method from Section 3.1. Since the anisotropy of the observed event was predominantly caused by mesoscale rainbands, to simplify the parameter estimation and simulations it was assumed that the sphero-scale was constant at \( l_s = 2 \) km and that there was no rotation between the scales \( (\rho = 0) \). Furthermore, the anisotropic features were assumed to have a constant orientation of \( \theta = 112.5^\circ \) while the magnitude of anisotropy \( (\tau) \) was simulated using the broken line model of Seed et al. (2000). The success of anisotropy reproduction was analysed at the radar scale covering an area of \( 256 \times 256 \) km\(^2\) by estimating the anisotropy parameters of 100 random members from both ensembles and comparing the obtained estimates against each other and against the estimated anisotropy parameters of the observed event. At the scale of the Bunyip River catchment (~ 1 100 km\(^2\)) the impact of anisotropy to rainfall accumulations was studied. The Bunyip River catchment was placed in 25 locations over the \( 256 \times 256 \) km\(^2\) radar field in a regular \( 5 \times 5 \) grid formation (see Figure 16, p. 36) and the catchment rainfall accumulations were computed at each location for every ensemble member, thus totalling for 25 000 catchment rainfall accumulations per ensemble. The differences in the distributions of catchment rainfall accumulations were studied at each location using the two-sample \( t \)-test, the Kolmogorov-Smirnov (K-S) test, and the quantile test (Johnson et al., 1987). A subset of members from both catchment rainfall accumulation ensembles were selected such that the accumulations were restricted to be similar to the accumulation in the observed event. The significance of difference in the ensemble distributions of the fraction of wet time steps \( (WTS) \), the average wet time step rain rate \( (R_{wet}) \), and the maximum wet spell duration \( (WSD_{max}) \) were studied using the K-S test. Both ensembles were used to drive URBS model of the Bunyip River catchment constructed by Carroll (2013) and operated by Melbourne Water. In the model the catchment is divided into 56 sub-areas with an average size of 19.5 km\(^2\), and the key parameters are set uniform for the entire catchment and optimized using the PEST (Doherty, 2010) software. The streamflow response between the ensembles was compared by studying the differences in distributions of peak flow \( (Q_p) \), time to peak \( (t_p) \), and flow volume \( (V) \) using the K-S test.
4 Results

4.1 Open data in high-resolution urban hydrological simulations

Data mostly available in open access format were used to build SWMM models for Pihlajamäki and Veräjämäki catchments (Publication I). The automated sub-catchment generator GisToSWMM5 developed in Publication I allowed creating models with varying computational grid resolutions easily. Simulations were performed utilizing the open precipitation data (GO) from Kumpula weather station to compare the runoff simulation results from automatically generated SWMM model descriptions to manually constructed descriptions (Section 3.4).

The observed discharge time series at Pihlajamäki and Veräjämäki catchments as well as the simulated time series for the manually constructed (\( \text{Man} \)) and automatically generated models with the highest 2 × 2 m² computational grid resolution (2 × 2) are presented in Figure 6 (Publication I). The simulation results between \( \text{Man} \) and 2 × 2 are very similar regardless of the event or the catchment, which justifies the use of GisToSWMM5 in facilitating the model building process. Both models showed promise for the use of open data as model input since the simulated time series follow the dynamics of the observed time series, although the peak flows are generally underestimated in Pihlajamäki (Figure 6a–c) and overestimated in Veräjämäki (Figure 6d–f).

While some differences in peak heights and timings between simulations and observations were to be expected since the open precipitation data was measured off-site, 3 – 5 km away from the catchments, the simulation results seemed to improve when the grid resolution was lowered from the highest resolution of 2 × 2 m² to 4 × 4 m² and to 8 × 8 m² (Figure 7) (Publication I). With coarsening grid resolution the simulated discharges were decreased, due to more water being routed to pervious surfaces where it infiltrates. This led to seemingly overestimated simulated discharges for the highest resolution models when compared to observations, and was seen also in the lowering NSE values from coarse to high resolution models. Nevertheless, the models with the most detailed computational grids (2 × 2 m²) were considered the best. Not only did the 2 × 2 models produce simulated discharges very close to the manually constructed high-resolution models (Figure 6), but they also had the land cover described most accurately, and had the peak flows closest to observed ones in Pihlajamäki. In addition, the problems in the discharge measurement devices (see Section 2.3) were assumed to affect the observations favouring the low resolution models. The drift in
the Pihlajamäki data logger clock caused a 4–20 min time shift between the simulated and observed discharges which penalized especially the $2 \times 2$ model due to a comparison against observations at the rising limb of the hydrograph. In Veräjämäki, the suboptimal location of the flow measurement station led to underestimated observations especially in high flow situations thus favouring the lower resolution models.

**Figure 6.** Observed (1 min in Pihlajamäki, 5 min in Veräjämäki) and simulated ($M_{\text{Man}}$ and $2 \times 2$, 1 min) discharges for a) 20–21 Aug 2014, b) 18–19 Jun 2015 and c) 27–28 Aug 2015 events in Pihlajamäki and for d) 9 Nov 2015, e) 15 Nov 2015 and f) 4 Dec 2015 events in Veräjämäki. Nash-Sutcliffe efficiencies ($NSE$) for each simulation are also displayed. (Modified from Publication I)
4.2 Open precipitation data for urban rainfall-runoff simulations

The encouraging results of using the open precipitation data (GO) from Kumpula weather station as an input to the SWMM model (Publication I) urged to study in more detail the effect of varying precipitation input data sources on SWMM model performance in urban rainfall-runoff simulations (Publication II). The SWMM model performance was assessed for six rainfall-runoff events from 2014–2015 (Table 2, p. 17). The simulation results achieved with using open gauge (GO) and open radar (RO1, RO2, RO3, RO4) data as model input were compared to results obtained using the on-site gauge data (GR1), a nearby gauge data (GR2), as well as research radar (RR) data as rainfall data sources (Section 3.4). The 2 × 2 model for Pihlajamäki from Publication I was used in the simulations.

Figure 8 presents the volume errors (VE) and the Nash-Sutcliffe efficiencies (NSE) for the studied five events (Publication II). A table of the performance statistics is given in Appendix B of Publication II.

The on-site gauge GR1 performed best for the studied events as indicated by constantly small VE and high NSE. The performance degraded when gauge data
further away from the catchment were used, as shown by decreasing NSE and increasing VE from GR1 to GR2 to GO. The widening intervals of the performance measures for GR2 and GO as compared to GR1 suggest that the further away the precipitation is measured from the catchment the more the performance is dependent on the individual event. The radar data sources tended to underestimate flow volumes with RR having the most consistent behaviour whereas the performance of the open radar data sources varied more depending on the studied event. The rising trend in the NSE values of the open radar data sources from RO1 to RO4 for individual events in Figure 8b is an indication of the benefits gained with using advection interpolation and especially the MFB adjustment to improve the open radar data.

Figure 9 presents the peak flow difference (PFD) and the peak time difference (PTD) between the GR1 simulations and the simulations using the other data sources as input (Publication II). The GR1 simulation results instead of the observed flow were used in the peak flow performance analysis due to the occasionally missing flow observations. This was justified with an assumption that high-resolution on-site gauge data should give the most reliable peak flow results. A table of the peak flow performance statistics is given in Appendix B of Publication II.

![Figure 9. Peak flow performance statistics for the studied rainfall input data sources. a) Peak flow difference (PFD) and b) peak time difference (PTD) computed using GR1 simulation results as a reference. Values of PFD > 60% and PTD < -20 min or PTD > 10 min are shown at the lower and upper edges of the plots. (Modified from Publication II)](image)

The peak flows were constantly underestimated with some exceptions (Figure 9a). Since also the GR1 simulation results used as the reference for computing the peak flow statistics tended to underestimate the peak levels, the underestimation for other data sources was even more severe than indicated by the values in Figure 9a. As noticed with VE and NSE earlier, also the PFD values became poorer as the distance between the catchment and the gauge increased. Also, a greater dependence on the studied event was noticed for gauges located at a greater distance. The radar data sources constantly underestimated the peak flows, except for RO3 in E1 where the peak flow was drastically overestimated. This shows as a very poor NSE value in Figure 8b. Except for RO3 in E1, the open radar data sources benefited from the advection interpolation and the MFB adjustment in terms of the peak flow estimation. The peak timings were mostly close to the GR1 simulation results (within roughly 10 minutes) with some exceptions. In some cases rainfall
occurred outside but not within the catchment, such as in event E4 (Figure 10),
where small convective cells hit Veräjämäki (GR2) and Kumpula (GO) but did not
generate much precipitation in Pihlajamäki (GR1). This shows as a large overes-
timation of peak flows and wrong peak timing for GR2 and GO (Figure 10b, c; Figure 9) and overestimated flow volumes and low NSE values (Figure 8). For the
same event, the open (RO) (Figure 10d, e, g, h) and research (RR) (Figure 10f)
radar data sets were able to only properly capture the first peak of the event while
the latter peaks were largely missed thus leading to underestimated flow volumes (Figure 8a). In event E5 as well, the FMI radar (RO) was unable to detect the in-
tense rainfall producing the main peak, and the peak flow in RO1 – RO4 corre-
sponds to the secondary peak of the event 2 h 42 min prior to the GR1 simulated
maximum flow (Figure 9). Advection interpolation resulted in minor improve-
ments to peak timing for RO data sources.

![Figure 10. Simulated discharges for event E4 using rainfall input data sources a) GR1, b) GR2, c) GO, d) RO1, e) RO2, f) RR, g) RO3, and h) RO4. Discarded runoff observations (18:54 – 18:57) are in grey. (Modified from Publication II)](image)

The simulation results for the event of 6 Aug 2015 representing the most intense
studied rainfall event are presented in Figure 11. The blended single- and dual-
polarization product (RR) from the research radar produced the rainfall volume
Results

(Table 2, p. 17) as well as the simulated hydrograph (Figure 11f) and the peak flow with closest resemblance to those produced using the on-site gauge (GR1) data (Figure 11a). The off-site gauge GR2 simulation results (Figure 11b) overestimated the peak flow and rainfall volume whereas the open gauge GO results (Figure 11c) underestimated them. The MFB adjustment brought the open data simulation results (Figure 11g) closer to GR1 simulation results, but the advection interpolation for this event increased PFD (Figure 11e, h).

Figure 11. Simulation discharges for 6 Aug 2015 using rainfall input data sources a) GR1, b) GR2, c) GO, d) RO1, e) RO2, f) RR, g) RO3, and h) RO4. Discarded runoff observations (02:12 – 02:55 and 03:03 – 03:14) are in grey. (Modified from Publication II)

4.3 Describing precipitation field spatial shape

The developed GSI parameter estimation method (Section 3.1) was tested by estimating anisotropy parameters for both simulated and observed radar reflectivity fields in Publication III.

The developed method was able to find accurate anisotropy parameter estimates for the non-zero fields. The parameter estimates were slightly less accurate when the rectangular window was introduced, as indicated by increased MAE and bias.
Results

The estimates were further deteriorated when intermittency was introduced, i.e., when considering simulated reflectivity fields. This is a consequence of the reduced information content in more realistic fields caused by windowing and intermittency (Figure 12).

Table 3. Mean bias (bias) and mean absolute error (MAE) of the GSI parameter estimates (c, e, f, l) for simulated fields. Ideal refers to nonzero random fields, and ideal rect to nonzero random fields with rectangular window applied.

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</table>

Table 3. Mean bias (bias) and mean absolute error (MAE) of the GSI parameter estimates (c, e, f, l) for simulated fields. Ideal refers to nonzero random fields, and ideal rect to nonzero random fields with rectangular window applied.
Results

Figure 12. Examples of a) non-zero random field and c) simulated radar reflectivity field with corresponding spatial power spectrum $P_{\text{avg}}$ in b) and d), respectively. The fields are generated with anisotropy parameters $G = G(-0.2, -0.2, 0.2)$ and $l_x = 12$ km. The white ellipses in b) and d) correspond to selected $B_4$ produced with estimated anisotropy parameters $G = G(-0.203, -0.200, 0.204)$ and $l_x = 12.07$ km (red circle) in b) and $G = G(-0.171, -0.203, 0.166)$ and $l_x = 12.07$ km (red circle) in d). (Modified from Publication III)

The anisotropy parameter estimates for the observed event of 11 Dec 2010 in Brisbane, Australia with unknown anisotropy are presented in Figure 13. The individual parameterization rounds produced parameter estimates very similar with each other, as indicated by the 95% confidence limits closely surrounding the average values of the 15 parameterization rounds. The method had most difficulties in finding reliable parameter estimates near the beginning of the event as indicated by the largest confidence intervals between 00:00 and 04:00.
Individual fields generated using the simple anisotropic field generator of Publication III (Section 3.2.1) are presented in Figure 14. The fields have otherwise identical properties, but one was generated with and the other one without accounting for the anisotropy estimated for the observed field of 11 Dec 2010 at 07:00 UTC in Brisbane, Australia. It is evident that the field with anisotropy (Figure 14c) resembles more the observed field (Figure 14a) than the otherwise identical, but isotropic field (Figure 14b).

In Publication IV, the STEPS model was extended to produce entire precipitation events respecting the field spatial anisotropy (Section 3.2.2). The distribution for the magnitude of anisotropy (r) was very close to the distribution in the observed event of 4 Feb 2011 in Melbourne, Australia for the ensemble of design events where the anisotropy was taken into account (Figure 15a). In addition, the average orientation of the precipitation features (θ) was close to the average orientation in the observed event, due to the decision to keep the orientation constant for the duration of the event (Figure 15b). As the features produced using isotropic power-law filter are only isotropic on average, also the design events
with isotropic spatial description had some minor anisotropy in the fields with random orientations of anisotropy.

Figure 15. Ensemble average distributions of the GSI parameters a) \( r \) and b) \( \theta \) for 100 randomly selected members from the ensembles with anisotropic (blue) and isotropic (red) spatial field shape description. Confidence bands for 5th and 95th percentile around the mean values are depicted with dashed lines. (Modified from Publication IV)

### 4.4 Impact of precipitation field shape

The impact of improved rain field shape description on rainfall characteristics and rainfall-runoff model response was studied in Publication IV. Two 1 000 member ensembles of design storms were created with isotropic spatial storm shape description in one ensemble and anisotropic in the other one. Rainfall accumulations were computed by placing the Bunyip River catchment in 25 locations over the field to form a total of 25 000 catchment rainfall accumulations per ensemble.

Both ensembles were expected to have the same mean accumulated rainfall at every catchment location due to the disaggregation nature of the STEPS model. While there were location dependent differences in the catchment rainfall accumulations, for most catchment locations both ensembles had similar mean accumulation (Figure 16a). As expected, the anisotropic model generated high (as well as low) catchment rainfall accumulations more frequently than the isotropic model (Figure 16b).

Figure 16. p-values at each catchment location for a) the two-sample t-test for equal mean catchment rainfall accumulations under the null hypothesis that the means are the same, and b) the quantile test for the difference in the 95th percentile of the catchment rainfall accumulation distributions under the null hypothesis that there are no differences. (Modified from Publication IV)
When selecting a subset of members from both catchment rainfall accumulation ensembles such that the accumulations had to be similar to the accumulation in the observed event, the anisotropic model generated 100 such accumulations whereas the isotropic model generated only 40. This offered further indication of the capabilities of the anisotropic model to generate high rainfall accumulations more easily than the isotropic model. Among the subsampled catchment accumulations, the anisotropic storms had higher $WTS$ and $WSD_{max}$ than the isotropic storms. The isotropic storms had higher $R_{wet}$ than the anisotropic storms to compensate for the longer duration of the anisotropic storms (Figure 17).

![Figure 17. Distributions of a) $WTS$, b) $R_{wet}$, and c) $WSD_{max}$. $p$-values depict the K-S test result for the null hypothesis that the studied descriptors in a) – c) follow the same probability distribution. (Modified from Publication IV)](image)

Runoff simulation results with URBS model did not reveal statistically significant differences in the Bunyip River catchment response to rainfall input generated using STEPS model with anisotropic and isotropic spatial shape description, as long as the catchment rainfall accumulation was (approximately) the same (Figure 18). While the anisotropic precipitation fields resulted in marginally higher peak flow and flow volume, the differences were too small to be statistically significant. However, as expected, a strong connection between rainfall accumulation and peak flow, as well as between rainfall accumulation and flow volume was noticed when not controlling for the rainfall accumulation.

![Figure 18. Distributions of a) $Q_p$, b) $t_p$, and c) $V$. $p$-values depict the K-S test result for the null hypothesis that the studied descriptors in a) – c) follow the same probability distribution. (Modified from Publication IV)](image)
5 Discussion

5.1 Prospects of open precipitation data

Even though the amount of easily available meteorological data is constantly increasing due to the shift towards open data sharing, the suitability of such data for hydrological assessments is often unknown. Especially in urban environments data requirements are high due to the rapid response to rainfall events characteristic for often relatively small and largely impervious urban catchments (Salvadore et al., 2015). In this thesis, a quantitative analysis of the openly available rain gauge and weather radar precipitation data offered by the FMI was conducted in a much smaller setting than usually studied. The open data were used as an input to SWMM rainfall-runoff model in small (in the order of tens of hectares) urban catchments in Helsinki, Finland, and the results were compared to simulation results obtained using traditional, locally measured, rain gauge data.

Freely and openly available data sets, such as land cover data, DEM, and especially meteorological data obtained from the FMI, were able to yield acceptable runoff simulation results even in urban environments where high-resolution simulations are necessary (e.g. Berne et al., 2004; Cristiano et al., 2016; Krebs et al., 2014) (Publications I and II). As noted by Krebs (2016) the downside of high-resolution approach is the required time for acquiring, complementing and preparing the necessary data for model development. Relying on open data for model construction as well as utilizing the regionalization concepts of Krebs et al. (2016, 2014) in model parameterization, as in Publications I and II, relieves the effort of acquiring the data via burdensome measurements and also demonstrates the potential of open data in providing stormwater flow predictions for ungauged urban areas.

The suitability of open gauge data for urban rainfall-runoff modelling was confirmed to be largely determined by the distance between the catchment and the rain gauge, supporting the earlier findings of e.g. Krebs et al. (2014). The open gauge data with 10 min resolution from Kumpula, 3–5 km from the studied catchments, performed adequately as an input to SWMM model in Publication I where the goal was to compare the automatically and manually generated models. However, the more detailed analysis in Publication II revealed the significance of the gauge distance for high-resolution event based urban rainfall-runoff simulations. Increasing distance between the catchment and the rainfall measurement point decreases the consistency between the recorded rainfall and the actual rainfall at
the catchment. This leads to error propagation from imperfect rainfall measurements to simulated runoff, which is in agreement with many previous studies (e.g. Gabellani et al., 2007; Notaro et al., 2013; Rico-Ramirez et al., 2015). The problem with gauge observations is related to the sampling error of rain gauges (Villarini et al., 2008). The highly spatiotemporally varying rainfall (e.g. Fiener and Auerswald, 2009; Jensen and Pedersen, 2005; Pedersen et al., 2010; Peleg et al., 2013) may change considerably between the observation point and the point of interest, so that the measurements obtained far from the point of interest may not be representative. As the operative gauge networks are generally sparse (Kidd et al., 2017) and have a trend rather to decline than to expand (Lorenz and Kunstmann, 2012), the gauge data, whether open or not, are mainly useful in urban settings only if the gauge is located at or very near the studied catchment.

The open radar data studied in Publication II were prone to underestimation of the rainfall amounts especially during intense rainfall. This affected the simulated flow volumes and peak flows. As the open radar products were based on conversion from radar reflectivities this was expected, and in line with previous studies utilizing single-polarization radar products (e.g. Bringi et al., 2011; Villarini and Krajewski, 2010; Zhu et al., 2014). The blended single- and dual-polarization product yielded very good runoff simulation results for the most intense rainfall-runoff event that was studied, and the results were mostly on par with the open radar input data for other events as well. These results are in line with previous studies of e.g. Bringi et al. (2011), Hickman et al. (2017), and Zhu and Cluckie (2012) encouraging a more widespread use of dual-polarization radar products in hydrology. However, more research is needed to increase the reliability of the blended single- and dual-polarization estimates. In future, improvements to the FMI open radar product are to be expected when the dual-polarization rainfall estimates are incorporated into the operational radar products.

The runoff simulation results improved when the open radar product was adjusted using the MFB gauge corrections and when the temporal resolution of the data was increased using advection interpolation. The improvements gained from advection interpolation confirm the importance of the temporal sampling resolution in radar rainfall estimates (Fabry et al., 1994; Piccolo and Chirico, 2005; Shucksmith et al., 2011). Best results were obtained when advection interpolation was combined with the MFB gauge correction, which is in line with the results of Thorndahl et al. (2014) and Wang et al. (2015). A gauge correction is therefore recommended for the users of the FMI open radar data. While even a simple hourly MFB-correction did improve the quality of the data, more sophisticated methods for gauge correction are also available, such as the recent method by Pulkkinen et al. (2016). Advection interpolation is more demanding computationally, but still a useful method to increase the temporal sampling interval of the radar product. End users would benefit if a gauge adjusted radar product was offered directly by the data provider, even though performing a simple gauge correction is straightforward. Having an improved radar product readily available would likely lower the threshold of utilizing such data in hydrological research.

The somewhat poor performance of off-site gauge and radar data as input data sources was emphasised for some events studied in Publication II. This could be
explained by the nature of warm-season rainfall. In Finland, summertime convective precipitation is almost a daily phenomenon, with even heavy convective precipitation occurring more frequently than every second day somewhere in the country (Punkka and Bister, 2015, 2005). In event E4 (Figure 10, p. 31) especially, rainfall originating from convective rainfall cells with limited areal extent was observed with the off-site gauges but not at the studied catchment. This caused a considerable peak flow overestimation and a wrong timing of the peaks when using the off-site gauges as input data. These results highlight the problems of observing small areal extent convective rainfall events using a sparse rain gauge network, especially since the three gauges used in this study were located rather close to each other within a 3 km radius. For the same event, the radars on the other hand were not able to capture all secondary rainfall peaks leading to underestimation of flow volume. The radar underestimation of intense rainfall could be partly explained by the large size of the radar cells (1 km²) in open radar products compared to the study catchment area (33.5 ha). As rainfall is known to vary considerably even inside areas of 500 m x 500 m (Jensen and Pedersen, 2005; Pedersen et al., 2010), using the open radar data with 1 km² spatial resolution leads to areal averaging of high and low intensity rain features inside the radar cell. While the areal averaging is always a problem with radar data, these effects are pronounced when the rain features are smaller than the radar spatial resolution (Shucksmith, 2013; Shucksmith et al., 2011). Higher resolution radar data, e.g. from local X-band radars, could help to alleviate the problem by allowing measurement of the precipitation variability at smaller scales (e.g. Bruni et al., 2015; Gires et al., 2013, 2012; Ochoa-Rodriguez et al., 2015).

The applicability of the FMI radar products to hydrological assessments in such small catchments as in this thesis (~35 ha) have not been studied previously. Aaltonen et al. (2008) studied heavy rains and floods in urban areas utilizing the FMI radar data, but the minimum area considered was 1 km². The new results from this thesis showed that when the distance to the nearest gauge exceeded a few kilometres, even the rather coarse resolution (1 km²) open radar data can be a viable option for urban rainfall-runoff simulations despite the catchment being much smaller than the radar data resolution. While the off-site gauges suffered from inconsistencies in the rainfall time series due to the distance between the gauge and the catchment, the open radar data mostly suffered from underestimation of intense rainfall. With these rather predictable shortcomings of radar data, the user facing a choice between far away gauge and radar data probably should rather use radar data with its known problems than gauge data with unknown representativeness of the rainfall at the catchment.

5.2 Precipitation field shape description

While precipitation often forms banded features with visible elongation, most scaling based precipitation simulation models choose to neglect this spatial anisotropy and settle for describing isotropic features. In this thesis, a new method for quantifying the spatial shape of precipitation features was developed based on
the linear GSI formalism. Later on, it was incorporated into a stochastic precipitation generator to enable simulations with anisotropic precipitation features.

The new anisotropy parameterization method (Publication III) provides a pragmatic approach for quantifying the spatial shape of features in precipitation fields as well as the evolution of the shapes during an entire storm event. Previously, Pflug et al. (1993), Lewis et al. (1999), and Beaulieu et al. (2007) have proposed GSI-based methods for quantifying the anisotropic scaling in geophysical fields, but only for individual fields one at a time. While the methods of Pflug et al. (1993) and Lewis et al. (1999) aimed to quantify the exact anisotropic scaling in geophysical fields, the developed method settles for finding the necessary parameters to describe a short-period ensemble average 2D power spectrum of observed precipitation fields via trial and error. By directly utilizing the observed 2D power spectra of consecutive precipitation fields the evolution of anisotropy during an entire storm event can be quantified, which is necessary when reproducing storms with changing anisotropy using scaling based stochastic precipitation generators.

Since the developed anisotropy parameterization method is based on observing changes in the 2D power spectrum of precipitation fields, it performs well as long as the spectrum is descriptive of the precipitation features in the field. Therefore, a slight degradation in the performance of the method was noticed when moving from ideal conditions with non-zero random fields first to more realistic simulated fields with intermittency and then to observed precipitation fields (Table 3 & Figure 12, p. 33-34). The diminishing information content in a field when rainy areas are replaced with dry areas creates perturbations to the power spectrum of the field, which are then reflected in the estimated parameter values as small deviations from the values used in generating the field. Similar degradation in performance has been observed with the methods of Pflug et al. (1993) and Lewis et al. (1999) when moving from theoretical simulations to observed fields with noisier power spectra.

The method performed well in estimating the temporal changes in the spatial anisotropy for entire precipitation events (Publications III and IV). There were some problems related to the beginning of the 11 Dec 2010 event (Figure 13, p. 35) as well as to isotropic situations, but the problems are explained by the properties of the 2D power spectrum. The beginning of the 11 Dec 2010 event is relatively dry, thus having high intermittency and therefore less descriptive power spectrum. Moreover, in Publication III the search of parameter estimates for the beginning of the event started from randomly selected parameter estimates. For the rest of the fields, the parameters estimated for the previous field were used as the initial guess. Therefore, in the beginning of the event it took some time for the downhill simplex method to find the global minimum. In Publication IV, the search was improved by using a warm-up period consisting of future fields to guide the downhill simplex towards the global minimum even before the event started. In isotropic situations, on the other hand, the parameters controlling for the stretching of the event, $c$ and $f$, become zero. Consequently, when there is no stretching in the system the remaining parameters, $e$ describing the rotation of the system and $l_o$ the location of the sphero-scale, become meaningless. Therefore, in a perfectly isotropic situation, any values of $e$ and $l_o$ should result in the
same error function value and consequently in nearly isotropic situations a large spread in the estimates for $e$ and $l_e$ is observed.

The method is particularly useful for observing the shapes of the large scale anisotropic structures in precipitation fields. These can be caused by rain bands of either weather fronts (e.g. Rauber and Ramamurthy, 2003) or convective thunderstorm squall lines (e.g. Karttunen et al., 2008). Depending on the orientation of anisotropy in relation to the movement of the storm, the large scale anisotropy can have a substantial impact on the accumulated rainfall (Doswell et al., 1996). While identifying the large scale anisotropy of the precipitation fields in Publication III and IV, the parameters controlling the stretching of the field, $c$ and $f$, were noticed to be the most significant. The role of the differential rotation parameter, $e$, controlling for the rotation of the features at different scales, was rather small. Also, the precipitation features are often approximately isotropic near the smallest scales (Kumar and Foufoula-Georgiou, 1993; Zawadzki, 1973), as was noticed in Publications III (Figure 13, p. 35) and IV as well. Therefore, the parameter estimation and simulation processes can be simplified by neglecting the differential rotation parameter $e$ and assuming the sphero-scale $l_e$ to be at the smallest scale (Publication IV). This provides a parsimonious way to describe the most significant features of anisotropy in precipitation simulations.

The advantage of using a GSI-based method lies in its capability of describing the anisotropy using a single parameter set of generator $G$ and sphero-scale $l_e$ for the entire range of scales from smallest to largest structures. This allows describing simple situations such as large scale feature elongation using only two parameters as in Publication IV, while more complex situations can be described by giving values also for the remaining two parameters. For example, a storm event described in detail by Ebtehaj and Foufoula-Georgiou (2010), with small-scale precipitation features perpendicular to large scale features and with isotropic intermediate scale features, could be easily described using a single parameter set. Alternative methods based e.g. on geostatistics (e.g. Ali et al., 2003; Berne et al., 2009; Kirstetter et al., 2010) or using different scaling parameters in different directions (e.g. De Michele and Bernardara, 2005; Ebtehaj and Foufoula-Georgiou, 2011) could result in a cumbersome or insufficient description of the precipitation field shape, since the orientation and magnitude of elongation in precipitation features change between scales.

One of the main advantages of utilizing the GSI is that it allows a straightforward extension to scaling based precipitation generators. This enables generation of more diverse and more realistic precipitation features than what relying only on isotropic spatial scaling offers. In this thesis one such generator, STEPS, was extended with the linear GSI formalism (Publication IV). This new enhanced model is the first attempt to supply an existing and widely used precipitation generator with the ability to generate fields that have more realistic shape than what can be achieved with the traditional isotropic description. Other existing precipitation generators such as String of Beads (Clothier and Pegram, 2002; Pegram and Clothier, 2001) and STREAP (Paschalis et al., 2013) currently settle for simulating isotropic precipitation structures. However, as these models essentially generate the precipitation structures the same way as STEPS, i.e., filtering a white noise
field using a power law filter in the Fourier domain, they could be extended to produce anisotropic structures as well by following the methods described in this thesis. Recently, Nerini et al. (2017) presented a concept for a further improvement to future precipitation generators by introducing an approach for generating precipitation fields with locally varying anisotropy utilizing the method applied in Publication III (Section 3.2.1) for anisotropy generation.

Adding the anisotropic description of precipitation fields to simulations had clear benefits over the traditional isotropic description in reproducing the shape of precipitation fields. The simulated fields acknowledging anisotropy resembled more the observed precipitation fields than the fields produced using isotropic models, irrespective whether the anisotropy was generated utilizing the full four parameter anisotropy description in Publication III (Figure 14, p. 35) or the simplified two parameter description in Publication IV (Figure 15, p. 36).

The linear approximation of the GSI and the way it was implemented in this thesis lead to some limitations influencing the estimation and simulation of realistic precipitation field shapes. The main limitations are related to 1) the ellipse approximation in describing the scales in power spectrum, 2) the homogeneity assumption, and 3) the data requirements.

Firstly, the method assumes the scales in the power spectrum of a precipitation field to be approximated as a set of ellipses. While this seems to be a reasonable assumption allowing a plausible characterization of precipitation features, it restricts the method from being suited for situations that require a more complicated scale geometry description. E.g. Pecknold et al. (1997), Lewis et al. (1999), and Lovejoy and Schertzer (2013) have presented more general cases where the scales are described using higher order polynomials. However, this complicates computations and such enhancements were not considered necessary in the cases studied in this thesis.

Secondly, precipitation fields are assumed to be homogenous in the linear approximation of the GSI (Lovejoy and Schertzer, 2013), as well as in STEPS and other similar scaling based stochastic precipitation generators (Seed, 2004). While the homogeneity assumption is often not valid for real precipitation fields, precipitation generators capable of directly simulating heterogeneous scaling fields are scarce. Jothityangkoon et al. (2000), Pathirana and Herath (2002), Badas et al. (2006), and the recent implementation of STEPS (Seed et al., 2013) apply deterministic weighting factors to account for the heterogeneous structures, but this can rather be considered as a gimmick than a proper solution as it tends to destroy the scaling of the fields. A promising approach was recently presented by Nerini et al. (2017) where heterogeneous fields with locally varying (an)isotropic scaling are generated utilizing Short-Space Fourier transform (Hinman et al., 1984) and the method applied in Publication III. Alternatively, utilizing the full non-linear GSI is also an option, but models depending on the non-linear GSI would be much more complex than models resorting to the linear approximation (Lovejoy and Schertzer, 2013).

Finally, the anisotropy parameterization method presented here, and any precipitation generator relying on the scale invariance, require high-resolution data from large domains. In practice, fine spatiotemporal resolution weather radar
data are necessary e.g. for reliable estimation of large-scale anisotropic scaling in space and for estimating the temporal scaling and evolution of fields in time. So far, in Publications III and IV, the anisotropy parameterization method has been applied only to data from individual radars. This is convenient, because data from a single radar can be windowed to a circle using a symmetrical window function to minimize the distortion caused by the domain boundaries. Still, especially the phases when a rain feature is entering or exiting the domain are problematic, as the shape of the feature becomes distorted while it is not fully visible to the radar. On larger, multi-radar domains, estimating especially the large scale anisotropy and the evolution of precipitation features becomes easier since more of the precipitation system is visible for longer periods of time than in case of individual radars. However, the problem with the validity of the homogeneity assumption is emphasized, as the likelihood of encountering intermittency and heterogeneity increases. This increase can result e.g. form precipitation covering only a part of the domain or from precipitation features emerging from several individual birth processes. Also, if the domains are non-symmetrical, the distortion problems are increased and simple windowing may lead to a large amount of lost information. Luckily, in countries such as Finland the openly available data from the extensive radar network offers a good ground for studying precipitation processes across scales. As individual radars have enough overlap in their coverage, distortion caused by non-symmetrical domain boundaries can be avoided even if data from multiple radars is utilized.

5.3 Hydrological impact of precipitation field description

The shape of the precipitation field together with the movement of the field can have a large impact on the associated rainfall amounts, and has previously been discussed e.g. by Doswell et al. (1996), Morin et al. (2007), and Rigo and Llasat (2005) in relation to lessons learned from observed precipitation events. This thesis presents a novel study where the impact of precipitation field on the rainfall accumulations was studied by separating the effect of precipitation field shape from the other factors affecting the rainfall accumulations. This was made possible by the more realistic description of the precipitation field shape incorporated into the STEPS model, which allowed creating two ensembles of stochastic design storms having otherwise identical properties differentiated only by their storm field spatial description (Publication IV).

The extension for anisotropic field shape description in STEPS was shown to be valuable, as accounting for the anisotropy increased the probability of achieving high catchment rainfall accumulations compared to the traditional field description with isotropic shapes (Figure 16, p. 36). This is important especially when reproducing extreme events such as the one studied in Publication IV, where the isotropic model struggled to produce catchment rainfall accumulations as high as observed during the event. The larger number of high catchment rainfall accumulations produced by the anisotropic model is attributable to the longer time it took for an elongated precipitation feature to move over the catchment than for an otherwise identical but isotropic feature. Therefore, producing high accumulations
using isotropic models easily leads to sacrificing also other properties of the precipitation event by altering the parameterization of the model e.g. by increasing the mean areal event accumulation or by decreasing the advection velocity.

Despite the differences in rainfall time series, runoff response at the Bunyip River catchment according to the URBS model was insensitive to the spatial structure of the precipitation fields at catchment scale when the model was run using anisotropic and isotropic ensemble members producing (approximately) equal catchment accumulations (Figure 18, p. 37). This suggests that the spatial anisotropy may not be as important as other factors affecting streamflow generation especially in a largely rural catchment like the one studied here. These results support the understanding that an accurate estimation of the volume of water input, rather than its spatial distribution per se, is the dominating factor affecting the streamflow response at rural catchments due to the catchment’s dampening effect. This has been previously suggested e.g. by Beven and Hornberger (1982), Obled et al. (1994), and Nicótina et al. (2008).

However, it remains unclear how much of the insensitivity in the runoff response between the ensembles is due to the catchment properties and how much is caused by the rainfall-runoff model. Because of the relatively small size of the Bunyip River catchment in respect to the size of the precipitation structures, the anisotropic and isotropic precipitation features appear spatially similar from the catchment perspective regardless of their large-scale shape. Moreover, the URBS model requires the precipitation fields having a spatial resolution of 1 km² to be resampled into spatially uniform sub-areal time series having a coarser resolution. This has been criticized by Yu et al. (2005) as it diminishes the advantage of having rainfall input with a high spatial resolution. Nevertheless, since the sub-areas were mainly relatively small (average area 19.5 km²) with a spatial scale (~5 km) rather close to the sphero-scale of the anisotropic fields (2 km), the anisotropic structures at the scale of a sub-area were nearly isotropic even at the original resolution of the precipitation fields. Therefore, the differences in runoff response were expected to result from the large-scale anisotropy of the fields, while the distortion due to sub-areal averaging was assumed to have only a small effect on the runoff simulation results. In any case, the sensitivity of the URBS model to any structure in rainfall fields even at the catchment scale was questioned, since when repeating the simulations using spatially uniform rainfall input over the entire catchment no major differences in runoff response were noticed to using spatially varying input.

Finally, a need for improvements to the precipitation generator and to the parameterization process of the generator emerged from the difficulties encountered in reproducing the small-scale temporal behaviour of an extreme event such as the one studied in Publication IV. Even though the anisotropic model was capable of producing rain events with longer duration of continuous rainfall than the isotropic model, the rainfall time series over the catchment for both the isotropic and the anisotropic ensemble members had too few intermediate and too many high intensity values compared to the observed event. Consequently, high rainfall accumulations in both cases typically resulted from a few very high-intensity rain cells hitting the catchment for a short period of time. In the observed
event, the high catchment accumulation resulted from long durations of continuous but less intense rainfall.

5.4 Future perspectives

Since the early days of radar meteorology in 1940s, the use of weather radar data in hydrological assessments has been advocated time after time (e.g. Austin and Austin, 1974; Barge et al., 1979; Berne and Krajewski, 2013; Delrieu et al., 2009; Krajewski and Smith, 2002; Seo et al., 2015). Especially in fields such as urban hydrology where precipitation data with high temporal and spatial resolutions are required, the role of radar data has been emphasized (e.g. Einfalt et al., 2004; Thorndahl et al., 2017; Tilford et al., 2002). Still, the use of radar data in day-to-day hydrological research seems more like an exception rather than a norm at least in Finland. This is regrettable, since Finland hosts an extensive 10 C-band dual-polarization Doppler weather radar network (Gregow et al., 2017; Saltikoff et al., 2010). Moreover, since the FMI provides the radar data together with the data from ca. 200 rain gauges openly for end-users, a prime environment for conducting hydrological research utilizing high-quality precipitation information is being offered. This thesis has already shown how weather radar data can provide useful precipitation information that can aid in hydrological assessments in both small (Publications I and II) and large (Publications III and IV) scales.

The open data from the extensive Finnish radar network allows for studying the scaling properties of rainfall, and especially the shape of the precipitation features, more extensively than in this thesis where only data from individual radars were utilized. In Publication IV, the anisotropy (stretching of structures) was described using parameters for the magnitude (\(r\)) and orientation (\(\theta\)) of stretching instead of the two stretching parameters (\(c\) and \(f\)). While this facilitates interpreting the anisotropy, more studies quantifying the anisotropy in different meteorological situations would be useful to give a better understanding of the absolute values of \(r\) encountered in different precipitation situations. Now the only limitations for \(r\) are the upper and lower boundaries [0,1] set by the properties of the linear GSI in 2D (Lovejoy and Schertzer, 2013), but already with a \(r\) value of 0.2–0.3 quite extreme anisotropy is achieved. In the long term, utilizing the available data should allow for building an entire “shape directory” together with a comprehensive parameter library for typical precipitation situations at different scales. Such a directory could be used for example as a basis for generating generic design storms without a specific observed event as an input data.

The direct impact of precipitation field shape in runoff generation was studied only on a relatively large (~1 000 km²) rural catchment, where the runoff response was found out to be insensitive to the field shape (Section 4.4, Publication IV). However, the results from the small urban catchments (~35 ha) (Section 4.2, Publication II) as well as from previous research (e.g. Guan et al., 2015; Shuster et al., 2005; Sillanpää and Koivusalo, 2015) have shown, how the hydrological response in urban areas is much more sensitive to precipitation than in rural areas. Moreover, Guan et al. (2016) have shown how the flow regime in urban areas is sensi-
tive to the shape of the rainfall hyetograph, with the same rainfall volume producing a noticeably different runoff response depending on the hyetograph pattern. In their study, the rainfall patterns were generated artificially by simply changing the shape of a given rainfall intensity time series between three predefined patterns. Therefore, repeating the experiment from Publication IV in an urban area, e.g. in Pihlajamäki catchment utilizing the FMI open data, would provide new insights on the impact of precipitation field shape on the runoff response in a more responsive environment. It would also provide opportunities to study the sensitivity of runoff response in urban areas to the hyetograph pattern using more realistic appearing rainfall events than in Guan et al. (2016).

The results regarding the role of accurate precipitation information required for urban hydrological assessments and the benefits of describing the shape of precipitation fields more realistically have provided a glance at the complexity of the precipitation process and have given tools for more comprehensive understanding of the role of precipitation in hydrology. Precipitation fields should not be assumed isotropic and a single rain gauge far from the point of interest cannot be expected to provide a sufficient picture of the precipitating system even at the small urban scale. Now that increasing amounts of radar observations are becoming openly available, the use of weather radar data should increase in hydrological assessments, and especially in fields such as urban hydrology where high spatio-temporal resolution precipitation information is required. This thesis has already demonstrated the applicability of open data for hydrological assessments in the demanding urban environment, hopefully encouraging further use of the easily available data. More widespread utilization of openly available data would lower the threshold of initiating research as the need for costly measurement campaigns is reduced. When adequate observations are not available, simulated precipitation data provides a useful alternative. Even though precipitation is a complex phenomenon, relatively simple models based on the scale invariance can be used to describe the process. Straightforward extensions, such as the anisotropy description incorporated into the STEPS model in this thesis, can make the existing models even better.
6 Conclusions

In this thesis the role of precipitation in hydrological assessments was studied in order to improve the use of precipitation information in hydrological research. The problem was approached from two angles. First, the suitability of openly available precipitation products to rainfall-runoff simulations in the field of urban hydrology was studied, to encourage their use as an alternative to locally measured precipitation information. Secondly, the description of precipitation feature shape in simulation models was improved to enable a more realistic depiction of precipitation fields in stochastic design events used for hydrological assessments.

The following major conclusions are drawn from this thesis:

1. The easily accessible open precipitation data was found to provide a useful alternative input data source to on-site rain gauge data for hydrological assessments even in small-scale high resolution urban settings studied in this thesis.

2. As urban rainfall-runoff assessments require data with high spatiotemporal resolutions, the distance to the closest rain gauge dictates the appropriate alternative data source in small urban catchments. Rain gauges are preferable for small distances, but when the distance to the closest gauge exceeds a few kilometres, gauge adjusted radar data may be preferred despite the rather coarse radar data resolution (1 km²) in comparison to the size of small urban catchments (~tens of hectares).

3. The open radar data as such tended to underestimate the rainfall amounts at a single point, but the quality of the radar data could be improved using gauge correction and advection interpolation. These measures are recommended for the future users of the open radar data. In future, more extensive use of the dual-polarization parameters should also improve the quality of the data especially in heavy rainfall events.

4. A new method based on the linear GSI formalism was developed to parameterize the spatial shape of precipitation features and the evolution of the shape during entire precipitation events.

5. The description of precipitation features in stochastic precipitation generators was improved by incorporating the linear GSI formalism into STEPS model. This new tool can be used to produce design storms with more realistic spatial shapes in a straightforward manner. The same approach is applicable also to other scaling based stochastic precipitation generators.
6. Even a simple two parameter setup was found sufficient in generating credible (large-scale) shapes for precipitation fields.

7. The available open data from the extensive weather radar network in Finland should be taken into better use in hydrological research. It offers great opportunities for conducting research and for developing a deeper understanding of precipitation processes and of the role of precipitation in hydrological problems.
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