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Enhancement of radar rainfall estimates for urban hydrology through optical flow temporal interpolation and Bayesian gauge-based adjustment

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Abstract

Rainfall estimates of the highest possible accuracy and resolution are required for urban hydrological applications, given the small size and fast response which characterise urban catchments. While radar rainfall estimates have the advantage of well capturing the spatial structure of rainfall fields and its variation in time, the commonly available radar rainfall products (typically at ~1 km / 5-10 min resolution) may still fail to satisfy the accuracy and resolution –in particular temporal resolution– requirements of urban hydrology. A methodology is proposed in this paper, to produce higher temporal resolution, more accurate radar rainfall estimates, suitable for urban hydrological applications. The proposed methodology entails two main steps: (1) Temporal interpolation of radar images from the originally-available temporal resolutions (i.e. 5 – 10 min) to finer resolutions at which local rain gauge data are commonly available (i.e. 1 – 2 min). This is done using a novel interpolation technique, based upon the multi-scale variational optical flow technique, and which can well capture the small-scale rainfall structures relevant at urban scales. (2) Local and dynamic gauge-based adjustment of the higher temporal resolution radar rainfall estimates is performed afterwards, by means of the Bayesian data merging method. The proposed methodology is tested using as case study a total of 8 storm events observed in the Cranbrook (UK)

and Herent (BE) urban catchments, for which radar rainfall estimates, local rain gauge and depth / flow records, as well as recently calibrated urban drainage models were available. The results suggest that the proposed methodology can provide significantly improved radar rainfall estimates and thereby generate more accurate runoff simulations at urban scales, over and above the benefits derived from the mere application of Bayesian merging at the original temporal resolution at which radar estimates are available. The benefits of the proposed temporal interpolation + merging methodology are particularly evident in storm events with strong and fast-changing (convective-like) rain cells.

Key words: weather radar; temporal interpolation; advection; urban hydrology; optical flow; Bayesian merging

1 INTRODUCTION

Rainfall estimates of the highest possible accuracy and resolution are required for urban hydrological applications, given the small size and fast response which characterise urban catchments (Berne et al., 2004; Collier, 2009; Fabry et al., 1994; Liguori et al., 2012; Ochoa-Rodríguez et al., 2015). Due to their ability to well capture the spatial characteristics of rainfall fields and their evolution in time, radar rainfall estimates are playing an increasingly important role in urban hydrological applications (Krajewski and Smith, 2002; Krämer et al., 2007; Schellart et al., 2012; Villarini et al., 2010; Wang et al., 2011). However, the operational radar rainfall products provided by national weather services (typically at ~ 1 km / 5-10 min resolution) may still fail to meet the demanding requirements of urban hydrology, both in terms of accuracy and resolution.

As regards accuracy, since radar quantitative precipitation estimates (QPEs) are an indirect measurement of rainfall, they are subject to multiple sources of error. Firstly, radar reflectivity measurements, from which QPEs are subsequently derived, may be affected by factors such as radar beam blockage, attenuation, ground clutter and anomalous propagation of the signal (Collier, 1996; Einfalt et al., 2004; Harrison et al., 2000). A number of corrections are usually applied in order to reduce errors arising from these sources; however, it is virtually impossible to have error-free reflectivity measurements. Additional errors arise in the conversion of reflectivity measurements (Z) to rainfall rates (R), which is usually done using

the Z-R relationship, $Z = aR^b$ (Marshall and Palmer, 1948). The variables a and b can be theoretically linked to rain drop size distribution and are generally deduced by physical approximation or empirical calibration based upon long-term comparisons (Collier, 1986; Krajewski and Smith, 2002). However, the highly dynamic nature of rain drop size distribution, even within a single storm event (Smith et al., 2009; Ulbrich, 1983), renders the use of a static Z-R relationship - as used for single-polarisation radars - imperfect, especially when extreme rainfall rates are observed (Einfalt et al., 2005; Goudenhoofd and Delobbe, 2013). In the case of dual-polarisation radars (dual-pol radars hereafter), dual-polarisation parameters provide useful information which enables significant reduction of some of the sources of error mentioned above (especially detection of non-weather echoes and improved attenuation correction), as well as a dynamic adjustment of the Z-R relationship according to drop-size distribution; this results in much more accurate rainfall rate estimates (Bringi and Chandrasekar, 2001). Dual-pol radars are being deployed in a number of countries around the world (e.g. Sugier and Tabary, 2006; Chandrasekar et al., 2009; Bringi et al., 2011; Wang et al., 2011; Kim et al., 2012; Vasiloff, 2012; Berkowitz et al., 2013), and it is likely that in the near future most existing single-pol radars will be upgraded to dual-pol. However, despite the advantages of this new technology and the better QPEs that can be achieved with it, dual polarisation will not change the limitations inherent to radar, such as the fact that rainfall is measured indirectly, often well above the ground and often far away from the radar, which results in beam broadening and range degradation.

The uncertainties in QPEs propagate through hydrological and hydraulic models and their effect is particularly evident at the small scales of urban catchments (Collier, 2009; Schellart et al., 2012; Vieux and Bedient, 2004). Gauge-based adjustment of radar QPEs has proven effective to reduce these errors and improve the accuracy of the estimates, thus improving their applicability for hydrological applications (Harrison et al., 2009). However, most gauge-based adjustment methods have been tested and applied at large spatial and temporal scales (Anagnostou and Krajewski, 1999; Cole and Moore, 2008; Fulton et al., 1998;

Germann et al., 2009; Gerstner and Heinemann, 2008; Goudenhoofdt and Delobbe, 2009; Harrison et al., 2009; Seo and Smith, 1991; Todini, 2001). Relatively few tests have been conducted at urban/small scales and all of them have concluded that at these scales more dynamic and localised adjustments are required (Borup et al., 2015; Sinclair and Pegram, 2005; L.-P. Wang et al., 2013). In fact, at urban scales, commonly used coarse-scale methods such as Mean Field Bias (MFB) correction have proven to be insufficient, while other more dynamic and higher (statistical-) order methods (e.g. geostatistical methods) have exhibited a better ability to reproduce fine-scale rainfall structures and dynamics (Wang et al., 2015).

With regards to the resolution of radar QPEs, recent studies suggest that the currently commonly available resolutions (i.e. ~ 1 km / 5-10 min) may be insufficient for urban-scale applications. In fact, the effect of insufficient spatial-temporal information of rainfall inputs on urban hydrological simulations may be as significant as that caused by insufficient accuracy. This is especially the case when the drainage area of interest is small (Gires et al., 2014, 2012; Schellart et al., 2012; Wang et al., 2012). Therefore, the impact of rainfall data resolution should not be ignored in urban hydrology. Although the spatial and temporal resolution of rainfall inputs are strongly related, a number of studies have suggested that the latter generally constitutes a more critical factor than the former (Ochoa-Rodríguez et al., 2015; Singh, 1997; Thorndahl et al., 2014) and that temporal resolutions of ~ 1 -2 min (i.e. below those currently available) are required for urban hydrological applications, while spatial resolutions of ~ 1 km (i.e. close to those currently available) appear to be sufficient. The predominant effect of temporal resolution, as well as the above mentioned resolution requirements for urban hydrological applications are illustrated in Figure 1 (adapted from Ochoa-Rodríguez et al., 2015). Moreover, it is often the case that local rain gauge (RG) records are available at temporal resolutions finer than those of radar QPEs. However, in order to perform local gauge-based adjustments, the RG records are usually aggregated to the temporal resolution of radar QPEs, thus losing valuable information. In fact, for small-

scale applications, recent studies suggest that performing gauge-based adjustment of radar QPEs at shorter time intervals leads to better results than doing so at longer intervals (Borup et al., 2015; Thorndahl et al., 2014). Traditional strategies for obtaining higher temporal resolution radar QPEs include changes in radar scanning and sampling strategies (Delobbe et al., 2008; Gill et al., 2006; Sadjadi, 2000; Tabary, 2007; Zhang et al., 2005) and stochastic downscaling (Deidda, 2000; Gires et al., 2012; Gupta and Waymire, 1993; Koutsoyiannis and Onof, 2001; Marsan et al., 1996; Pegram and Clothier, 2001; Segond et al., 2006; Tessier et al., 1993; Wang et al., 2010). The former is not always possible, due to hardware and operational limitations. With regards to the stochastic temporal downscaling, albeit applications exist that meet the high temporal resolution requirements mentioned above (~1-2 min; e.g. Gires et al., 2014), they result in large ensembles, which are difficult to use operationally, given the runtimes associated to urban hydrodynamic models (Leandro et al., 2014). More recently, an advection based temporal interpolation method, combined with MFB correction, has been proposed by (Nielsen et al., 2014; Thorndahl et al., 2014). Although this method has shown to improve the performance of hourly and daily radar QPEs (assessed through comparison against ground rain gauge measurements), its performance at sub hourly scales was inconsistent. The unsatisfactory performance at smaller scales may be explained by the way in which storm movement is estimated in advection-based techniques, as well as by the MFB-based adjustment techniques that were employed, which may be insufficient to well capture and preserve the small rainfall structures relevant at urban scales (Gao et al., 1999; Germann and Zawadzki, 2002; Horne, 2003; Laroche and Zawadzki, 1995; Rinehart and Garvey, 1978; G. Wang et al., 2013; Weickert and Schnörr, 2001; Wilson et al., 2004).

[Figure 1 about here]

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138 In this paper a methodology is proposed for producing accurate radar rainfall estimates with
139 high temporal resolution, suitable for urban hydrological applications. Similar to the method
140 proposed by Nielsen et al. (2014), the procedure proposed herein entails two main steps: (1)
141 temporal interpolation of radar images, followed by (2) gauge-based adjustment of radar
142 QPEs at short time intervals (1-2 min). Nonetheless, different from Nielsen's method, the
143 techniques employed in this study to carry out the aforementioned steps are particularly well
144 suited to capture and reproduce small-scale rainfall structures, thus making the proposed
145 method more appropriate for urban hydrological applications. For the first step, a novel
146 temporal interpolation technique, based upon the multi-scale variational optical flow
147 technique, is proposed to generate high temporal resolution (i.e. 1-2 min) radar rainfall
148 estimates. The optical flow technique was initially developed to characterise detailed image
149 motion and has also been employed for short-term rainfall forecasting. In both realms it has
150 shown to outperform many other techniques. Considering the nature of this technique, it is
151 expected to be suitable for carrying out temporal interpolation of radar images, especially
152 when small-scale rainfall structures are critical. For the second step, the Bayesian data
153 merging technique is used (Todini, 2001); this has shown to outperform many other merging
154 techniques, both at large and small (urban) scales (Mazzetti and Todini, 2004; L.-P. Wang et
155 al., 2013), is applied locally and dynamically.

156 The proposed methodology is tested using as case study a total of eight storm events
157 observed between 2012 and 2014 in the Cranbrook (London, UK) and Herent (Leuven,
158 Belgium) urban catchments. For these pilot locations radar estimates, local rain gauge
159 measurements, flow records, as well as recently calibrated urban drainage models were
160 available.

161 The paper is organised as follows. In Section 2 a detailed explanation is provided of the
162 temporal interpolation + gauge-based adjustment methodology. In Section 3 we present the

case study, including a description of the two study catchments and available dataset, the strategy and performance criteria used to evaluate the proposed methodology, and the results of the testing. Lastly, in Section 4 the main conclusions are presented and future work is discussed.

2 METHODOLOGY

2.1 OVERVIEW

A schematic of the proposed methodology for producing accurate radar rainfall estimates with high temporal resolution is shown in Figure 2. Let RD_t and RG_t , respectively, be radar and rain gauge rainfall records at a specific time step t , but each with different temporal resolutions: ΔT for radar images and Δt for point rain gauge records, where $\Delta T = n \cdot \Delta t$ and $n \geq 1$, as is often the case in urban catchments (i.e. the temporal resolution of local rain gauge records is finer than that at which radar rainfall estimates are available). The first step of the proposed method is to derive a field of movement vectors $\mathbf{W}$ between two successive radar images (i.e. RD_t and $RD_{t+\Delta T}$) based upon the *optical flow technique*. Assuming that this movement field remains constant within each time interval (ΔT), intermediate radar images (RD') with temporal resolution Δt are derived through *temporal interpolation with occlusion reasoning*. Afterwards, the original RD and the intermediate (interpolated) RD' images are *dynamically merged* with the coincidental RG records at time steps Δt , using the *Bayesian data merging* method. This yields high temporal-resolution radar rainfall estimates with better accuracy (RD'' with temporal resolution Δt). Note that for the first two steps (i.e. movement field estimation and temporal interpolation), radar images over a large domain ($>100 \text{ km} \times 100 \text{ km}$) are used, while for the last step (i.e. dynamic data merging) only a sub-domain of the radar images is used (which coincides with the urban area of interest and with the coverage of the local rain gauge network).

The key techniques that are employed in the proposed methodology are: 1) optical flow estimation, 2) temporal interpolation with occlusion reasoning, and 3) Bayesian data merging. Each of these techniques is described in the following sub-sections.

[Figure 2 about here]

2.2 OPTICAL FLOW ESTIMATION

Optical flow estimation is a technique used to characterise image motion, which has been widely applied in the field of computer vision, e.g. object detection and video compression (Ehrhardt et al., 2007; Herbst et al., 2009; Larsen et al., 1997; Sadek et al., 2012). Due to the nature of the technique, it is in particular suitable for handling consecutive images with short time intervals (e.g. video frames). Consequently, it has also been applied to meteorological data processing and proven to be successful in short-term rainfall forecasting (Bowler et al., 2004; Cheung and Yeung, 2012; Krajewski and Smith, 2002).

The optical flow constraint (OFC, also known as the grey value constancy assumption) constitutes the core of the optical flow estimation (Bab-hadiashar and Suter, 1998; Baker et al., 2011; Brox et al., 2004; Bruhn et al., 2005; Horn and Schunck, 1981; Papenberg et al., 2006; Sun et al., 2010):

$$I(x, y, t) = I(x + u, y + v, t + \Delta T), \quad \text{Equation 1}$$

where $I(x, y, t)$ is the grey value (i.e. radar rainfall rate, in our case) of a pixel located at $\mathbf{x} = (x, y)$ of a given image $\mathbf{I}_t$ at time step t , and $\mathbf{w} = (u, v)$ is the movement vector to be estimated between images $\mathbf{I}_t$ and $\mathbf{I}_{t+\Delta T}$. This constraint indicates that image pixels only translate within ΔT , but their grey values remain invariant. However, this is usually not the case, particularly for natural scenes. For instance, in the case of high-resolution radar rainfall images, the decay or growth of rainfall cell intensities can be observed even during a short duration (Foresti and Seed, 2014; Radhakrishna et al., 2012). In order to obtain better

results, some smoothing treatment (e.g. median filter) is usually applied to the images before optical flow estimation is conducted (Bowler et al., 2004; Cheung and Yeung, 2012). This smoothing process is indeed helpful for solving OFC and has proven to be useful in large-scale applications (e.g. country-wide rainfall nowcasting and short-term flood forecasting; Bowler et al., 2006). However, for urban-scale applications, the smoothing process is usually not desirable because it may lead to significant underestimation of extreme rainfall magnitudes and associated runoff estimates (Wang et al., 2015).

In this work an alternative approach to handling the variations in pixel values between consecutive images is used. In this approach, an additional constraint, called gradient constancy assumption, is incorporated into the optical flow estimation (Brox et al., 2004; Papenberg et al., 2006; Sun et al., 2010). It is expressed as:

$$\nabla I(x, y, t) = \nabla I(x + u, y + v, t + \Delta T), \text{ Equation 2}$$

where $\nabla = (\partial_x, \partial_y)$ denotes the spatial gradient. This expression allows slight changes in pixel values, which somewhat relaxes the grey value constancy constraint. However, this constraint, as well as the OFC, focuses exclusively on the movement of individual pixels; their interactions with neighbouring pixels are not taken into account. This may cause the so-called aperture problem, which means that there may be spatial discontinuities (or holes) in the resulting movement fields. This is unrealistic and undesirable for applications. To prevent this, it is necessary to introduce a third constraint which ensures the smoothness of the movement field. This can be achieved by minimising the Laplacian of the movement fields (i.e. $\Delta \mathbf{w}$ or $\nabla^2 \mathbf{w}$), or equivalently by minimising the two components of the expansion of $\nabla^2 \mathbf{w}$,

$$\text{i.e., } \nabla^2 u = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \text{ and } \nabla^2 v = \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \text{ (Bowler et al., 2004; Brox et al., 2004; Horn and}$$

Schunck, 1981).

To completely incorporate the three constraints described above into the optical flow estimation, a variational approach is used in this work, which was proposed by Brox et al. (2004) and is termed:

$$E(u, v) = E_{Data} + \alpha \cdot E_{Smooth}, \quad \text{Equation 3}$$

where

$$E_{Data}(u, v) = \int_{\Omega} \Psi(|I(\mathbf{x} + \mathbf{w}) - I(\mathbf{x})|^2) d\mathbf{x} + \gamma \cdot \int_{\Omega} \Psi(|\nabla I(\mathbf{x} + \mathbf{w}) - \nabla I(\mathbf{x})|^2) d\mathbf{x}, \quad \text{Equation 4}$$

and

$$E_{Smooth}(u, v) = \int_{\Omega} \Psi(\nabla^2 u + \nabla^2 v) d\mathbf{x}. \quad \text{Equation 5}$$

where Ψ is a penalty function and Ω is the radar domain. These two constraints define an energy functional that ‘penalises’ the deviation of image pixel values (i.e. E_{Data}) and the variation of movement fields (i.e. E_{Smooth}). The aim is therefore to determine a movement field that minimises the overall (penalty) energy $E(u, v)$, which is a linear combination of each constraint with a given weight. In our research, weight values of $\alpha = 0.5$ and $\gamma = 50.0$ were assigned, based upon literature review (Sun et al., 2010) and a number of parametric analyses that confirmed the robustness of this selection. In addition, following the suggestion given in Brox et al. (2004) and Sun et al. (2010), the Charbonnier penalty function $\Psi(s^2) = \sqrt{s^2 + \epsilon^2}$ (where $\epsilon = 0.001$) is employed to better retain the convexity of each energy term during the minimisation process.

This overall (penalty) energy functional can be minimised by solving the associated Euler-Lagrange equations. Because it is a classic approach to optimisation problems, the numerical formulation of this problem will not be repeated in this paper; for details readers are referred to Brox et al. (2004). Nonetheless, it is worth mentioning that another advantage of Brox’s approach is the use of the multi-scale numerical strategy. This is done by firstly aggregating (in space) the original images into a number of images with coarser spatial

resolutions. The estimation then starts by solving the coarsest version of the problem (i.e. energy functional on the images with the coarsest spatial resolution). The associated solution is then used as the initial guess for solving a finer version of the problem. This iteration then continues until the original problem (i.e. at the original resolution) is solved. Numerically, this strategy can effectively prevent the estimation from being trapped in a local minimum and has proven to be able to largely improve optical flow estimation (Brox et al., 2004; Sun et al., 2010). Physically, this strategy explicitly takes into account the characteristic differences of images (in particular natural scenes) at various spatial and temporal scales, which has proven to be critical for rainfall field modelling (Deidda et al., 1999; Foresti and Seed, 2014; Germann and Zawadzki, 2004; Goudenhoofd and Delobbe, 2013; Lovejoy and Schertzer, 1990).

2.3 TEMPORAL INTERPOLATION WITH OCCLUSION REASONING

The temporal interpolation method used in this study is a bi-directional (i.e. forward-backward) advection-based one, which is similar to the one used in Nielsen et al. (2014). However, Nielsen et al. (2014) did not take into account the occlusion effect that is usually found in the temporal interpolation of consecutive images. Neglecting this effect may cause problems, such as the difficulty in interpolating pixel values along the image boundary and the generation of an over-smooth (in space) intermediate image, which may be problematic in the case of radar images over urban areas.

In order to include the occlusion effect, an additional technique, called occlusion reasoning, is employed in this paper before the intermediate images are interpolated (Herbst et al., 2009; Sadek et al., 2012). The algorithm used to conduct the temporal interpolation with occlusion reasoning is summarised as follows:

- (0) Estimation of forward and backward movement fields ($\mathbf{w}^f = (u^f, v^f)$ and $\mathbf{w}^b = (u^b, v^b)$) using optical flow technique described in Section 2.2.

(1) Let $I(\mathbf{x}_{t+i\Delta t})$ be the grey value (or intensity) of a given pixel at location $\mathbf{x}_{t+i\Delta t} = (x, y)$ of an intermediate image $\mathbf{I}_{t+i\Delta t}$ (where $i = 1, 2, \dots, n-1$).

(2) By forward projection (i.e. using only the forward movement field $\mathbf{w}^f = (u^f, v^f)$), the corresponding pixels (i.e., $\mathbf{x}_t^f$ and $\mathbf{x}_{t+\Delta T}^f$) respectively in images $\mathbf{I}_t$ and $\mathbf{I}_{t+\Delta T}$ can be inversely identified. They can be termed:

$$\mathbf{x}_t^f = (x, y) - \delta(u^f, v^f) \quad \text{Equation 6}$$

and

$$\mathbf{x}_{t+\Delta T}^f = (x, y) + (1 - \delta)(u^f, v^f), \quad \text{Equation 7}$$

where $\delta = i/n$.

(2-1) If the (absolute) difference between $I(\mathbf{x}_t^f)$ and $I(\mathbf{x}_{t+\Delta T}^f)$ is smaller than a given threshold τ (that means, within time interval ΔT , $I(\mathbf{x}_t^f)$ is not in a significant decay or growth stage, so presumably occlusion does not occur), forward interpolation is conducted; i.e., $I(\mathbf{x}_{t+i\Delta t}) = (1 - \delta) \cdot I(\mathbf{x}_t^f) + \delta \cdot I(\mathbf{x}_{t+\Delta T}^f)$.

(2-2) If the difference is larger than the threshold, no forward interpolation is conducted (the targeting pixel value will temporarily be a hole).

(3) (Backward projection) Based upon the backward movement field, the same algorithm as the forward projection is applied to fill the holes.

(4) If there are still holes left, they will be filled by the linear combination of $I(\mathbf{x}_t^f)$ and $I(\mathbf{x}_{t+\Delta T}^b)$; i.e., $I(\mathbf{x}_{t+i\Delta t}) = (1 - \delta) \cdot I(\mathbf{x}_t^f) + \delta \cdot I(\mathbf{x}_{t+\Delta T}^b)$.

2.4 BAYESIAN DATA MERGING

The Bayesian data merging method (BAY) is a dynamic adjustment method (applied independently at each time step) intended for real-time applications (Todini, 2001). In

previous studies this method has shown to outperform other commonly-used adjustment methods (Mazzetti and Todini, 2004; L.-P. Wang et al., 2013). This is why it was adopted to conduct the gauge-based adjustment of radar estimates in the present study.

The underlying idea of the BAY method is to analyse and quantify the uncertainty of rainfall estimates (in terms of the co-variance of estimation errors) from multiple data sources – in this case, radar and rain gauge sensors – and then combine these estimates in such a way that the overall (estimation) uncertainty is minimised.

The implementation of the BAY merging method includes the techniques of block-kriging interpolation and Kalman filter (Kalman, 1960). The former is used to generate a field of rain gauge estimates (which represent the ‘measurements’ in the Kalman filter) and the latter is used to combine radar (defining the ‘a priori’ estimate) and block-kriged rain gauge rainfall estimates, to produce the merged rainfall output (i.e. the ‘a posteriori’ estimate). For a detailed description of the BAY technique the reader may refer to Todini (2001), L.-P. Wang et al. (2013) and Wang et al. (2015).

3 CASE STUDY

The proposed temporal interpolation method, in combination with the Bayesian merging, is tested using as case study a total of eight (8) storm events observed between 2012 and 2014 in the Cranbrook (London, UK) and Herent (Leuven, Belgium) urban catchments. For these events radar estimates, rain gauge and flow records are available. Moreover, recently-calibrated urban drainage models are available for each of the two pilot catchments.

3.1 PILOT CATCHMENTS AND DATASETS

3.1.1 Cranbrook catchment

The Cranbrook catchment (Figure 3) is located within the London Borough of Redbridge (north-east part of Greater London). It is predominantly urban, of residential and commercial character, and stretches over an area of 8.5 km². Approximately 52 % of the catchment

corresponds to impervious surfaces. The main water course (the Cran Brook) is about 5.75 km long, of which 5.69 km are culverted and have become part of the storm water drainage system, which is mainly separate. The storm water drainage system of this catchment discharges into the Roding River and, in turn, the Roding River discharges into the river Thames.

[Figure 3 about here]

Hydraulic model: A high-resolution semi-distributed model of the storm-water drainage system of the Cranbrook catchment, including its sewer system, was setup in the integrated catchment modelling software InfoWorks ICM 5.5. In this model the whole catchment surface is split into sub-catchment units to which rainfall is applied (within each sub-catchment rainfall is assumed to be uniform). Each sub-catchment comprises a mix of pervious and impervious surfaces whose runoff drains to a common outlet point, which corresponds to an inlet node of the sewer system (i.e. a gully or a manhole). The sub-catchments are characterised by a number of parameters, including total area, length, slope, proportion of each land use type, amongst others. Based upon these parameters, the runoff volume at each sub-catchment is estimated using a fixed runoff coefficient, which varies according to the type of surface. The estimated runoff is then routed to the sub-catchment outlet using the Wallingford (double linear reservoir) model (HR Wallingford, 1983). Sewers are modelled as one-dimensional conduits and flows within them are simulated based on the full de Saint-Venant equations.

The Cranbrook model contains a total of 4,409 sub-catchments, with areas ranging between 0.01 and 40.02 ha and a mean area of 0.19 ha. Sub-catchment slopes range from 0.02 to 0.41 m/m, with a mean slope of 0.05 m/m. The model of the sewer system comprises 6,953 nodes and 6,994 conduits. The total length of modelled sewers is 147 km. The sewer system ranges in height from 63.15 m above ordnance datum (mAOD) at the upstream end of the catchment to 6.05 mAOD at the downstream end. The modelled pipes have gradients

ranging from 0 to 4.44 m/m, with mean and median gradients of 0.20 and 0.09, respectively.

The flow in the sewer system is mainly driven by gravity.

Following UK standards (WaPUG, 2002), the model of the Cranbrook catchment was calibrated in early 2014 using data from the monitoring system described below.

Local monitoring data available for this catchment: A real time accessible monitoring system has been maintained in the Cranbrook catchment since April 2010. It includes three tipping bucket rain gauges (with 1-min resolution), two pressure sensors for monitoring water levels at the Roding River (downstream boundary condition of the catchment; with 2-min resolution), one sensor for water depth measurement in sewers (with 2-min resolution), one sensor for flow (i.e. simultaneous water depth and velocity) measurement in sewers (with 2-min resolution), and one sensor for water depth measurement in open channels (with 1-min resolution) (see Figure 3).

Radar rainfall data: The Cranbrook catchment and surroundings are within the coverage of C-band radars operated by the UK Met Office (UKMO). Radar rainfall estimates for the storm events selected for this study – for an 800 km x 800 km domain, centred at the Cranbrook catchment – were obtained through the British Atmospheric Data Centre (BADC). These estimates were available at spatial and temporal resolutions of 1 km and 5 min respectively, and correspond to a quality controlled multi-radar composite product generated with the UK Met Office Nimrod system (Golding, 1998), which includes corrections for the different errors inherent to radar rainfall measurements, as well as an hourly-based nation-wide mean field bias correction (Harrison et al., 2009, 2000).

Storm events selected for this study: Four storm events observed between May and September 2014 were selected to test the temporal interpolation + radar adjustment method proposed in this study. These events are different from those used for the calibration of the model. The dates and main characteristics of these events are summarised in Table 1.

[Table 1 about here]

3.1.2 Herent area

The catchment of Herent (called after the municipality of the same name) is located immediately northeast of the town of Leuven, the capital town of the Belgian province of Flemish Brabant. It includes several villages, with a predominantly urban residential character, which are separated by more rural areas. Important railway lines and a motorway are cutting through the catchment and contribute partly to the urban drainage system. The drainage area analysed in this study stretches over an area of approximately 25 km², of which about 14 % corresponds to impervious surfaces. The sewer system in this area is mostly combined and includes several combined sewer overflows (CSOs) along the main flow path. The drainage system does not follow the natural topographical runoff direction of the catchment (the main brook is situated more along the northern edge), as a result of which there are also several pumping stations on the main drainage flowpath.

[Figure 4 about here]

Hydraulic model: A semi-distributed model of the drainage system of Herent was setup in the software package InfoWorks CS 15.0 by the water company Aquafin. Same as in the Cranbrook model, runoff volumes are estimated using a fixed runoff coefficient, runoff is routed to the sub-catchment outlets using the Wallingford (double linear reservoir) model (HR Wallingford, 1983), and sewer flow is simulated based upon the full de Saint-Venant equations.

Herent's model contains a total of 2,495 sub-catchments, with areas ranging between 0.001 and 16.30 ha and a mean area of 0.40 ha. Sub-catchment slopes range from 0.00 to 0.34 m/m, with a mean slope of 0.01 m/m. The model of the sewer system comprises 3,030 nodes and 2,987 conduits. The total length of modelled sewers is 222 km. The sewer system ranges in height from 90.22 mAOD at the upstream end of the catchment to 13.12 mAOD at

the downstream end. The modelled pipes have gradients ranging from 0 to 0.68 m/m, with mean and median gradients of 0.01 and 0.003, respectively. While the catchment is relatively flat, the flow in the sewer system is mainly driven by gravity.

The original model (built in the late '90s) was validated using the Flemish standard procedures described in Aquafin's Hydronaut procedure (Aquafin nv, 2014). In the years following, further validation was performed on a regular basis using data from the monitoring system described below, as well as from occasional short term flow surveys.

Local monitoring data available for this catchment: A monitoring system has been maintained in Herent and surroundings since 2006. It includes eight tipping bucket rain gauges (initially with 2 min resolution and since 2013 with 1 min resolution) and three flow (i.e. depth and velocity) gauges in sewers (with 2 min resolution) (see Figure 4).

Radar rainfall data: C-band radar rainfall estimates for the whole of Belgium, including Herent, were derived from the radar reflectivity product provided by the Royal Meteorological Institute of Belgium (RMI) (Delobbe and Holleman, 2006). The reflectivity measurements, originally in dBZ units and at temporal and spatial resolutions of 529 m and 5 minutes respectively, were converted into rainfall rates (mm/h) using the so-called Marshall-Palmer Z-R relationship: $Z = 200R^{1.6}$ (Marshall and Palmer, 1948). Although a new radar product is currently under development in RMI (Goudenhoofdt and Delobbe, 2013, 2009), for this study the estimates for Belgium do not include any gauge-based adjustment.

Storm events selected for this study: Four storm events observed in Herent between September 2012 and July 2013 were selected to test the temporal interpolation + radar adjustment method proposed in this study. The dates and main characteristics of these events are summarised in Table 2.

[Table 2 about here]

3.2 EXPERIMENTAL DESIGN AND EVALUATION METHODOLOGY

With the purpose of covering a range of operational conditions, the proposed temporal interpolation and the Bayesian data merging method were applied to radar (RD) rainfall estimates at two commonly-available temporal resolutions: 5 min and 10 min. Although for the pilot locations under consideration (i.e. Cranbrook and Herent) radar estimates were available at 5-min resolution, radar estimates at 10-min resolution are still commonly provided by national weather services (Chen et al., 2007; Gill et al., 2006; Vieux et al., 2003) and were for that reason included in the test. In order to realistically simulate operational radar scanning strategies, in this study the 10-min radar images were obtained through sampling (instead of aggregation). Following the methodology described in Section 2, the original RD estimates (at 5- and 10-min resolutions, respectively) were temporally interpolated to the finer temporal resolution at which rain gauge (RG) estimates were available. Afterwards, the Bayesian data merging was applied.

The performance of the resulting temporally-interpolated + Bayesian-adjusted estimates was assessed by inter-comparison against original RD and RG estimates, as well as against temporally-interpolated-only RD estimates (i.e. without merging) and Bayesian-adjusted-only estimates (i.e. at the original temporal resolution of RD estimates, without temporal interpolation). A summary of the rainfall estimates considered in the analysis, including the notation used to refer to them, is provided in Table 3. Two strategies were employed in the evaluation of the proposed method:

- (1) Direct analysis and inter-comparison of the different rainfall estimates, both at areal level as well as at point RG locations;
- (2) Analysis of the hydraulic outputs obtained by feeding the different rainfall estimates as input to the hydraulic model of the pilot locations and comparison of these against

available water depth records. Note that the RG estimates were applied to the models using Thiessen polygons.

The performance measures employed in the evaluation are described below. Both evaluation strategies, however, have limitations. Firstly, the fact that all rainfall estimates (including RG ones) contain errors and the differences in the spatial resolution of RG and gridded rainfall estimates render any direct comparison of rainfall estimates imperfect (Brandes et al., 2001). While the hydraulic evaluation strategy allows some of these drawbacks to be overcome, it has other deficiencies: hydraulic (depth and flow) records contain errors, and hydraulic modelling results encompass uncertainties from multiple sources in addition to rainfall input uncertainty (Deletic et al., 2012). Despite these limitations, both strategies provide useful and complementary insights into the performance of the proposed temporal interpolation + Bayesian data merging method.

[Table 3 about here]

Performance measures

Four performance measures were used to evaluate the proposed temporal interpolation + Bayesian data merging method. The first performance measure (i.e. event sample bias) was only employed in the rainfall evaluation strategy. The other three performance measures were used in both the rainfall and hydraulic evaluation strategies. In the case of the rainfall evaluation strategy, RG records at the highest-available temporal resolution were used as reference or ‘observed’ values, while the radar and radar-processed (gridded) rainfall estimates being assessed are referred to as ‘modelled’ estimates. Moreover, in the rainfall evaluation performance measures were estimated both at areal level (see areas shown in Figure 3 and Figure 4), as well as at RG point locations. In the case of the hydraulic evaluation strategy, water depth records at given locations within the pilot catchments were used as reference or ‘observations’, and the hydraulic simulation results associated to the different rainfall inputs constitute the ‘modelled’ estimates. The locations whose water depth

records were used in the hydraulic evaluation are circled in black in Figure 3 and Figure 4; these locations were selected such that consistent records were available for all the storm events under consideration in this study.

(1) Event sample bias ratio (B): estimated as $B = \sum R_{gridded} / \sum RG$, where $R_{gridded}$ corresponds to the gridded (i.e. radar-processed) rainfall product being assessed. B is used to quantify the cumulative event bias between gridded rainfall estimates and RG estimates (i.e. unconditional bias). $B = 1$ means no cumulative bias; $B > 1$ means that the accumulations of the gridded estimates are greater than those recorded by RG, and $B < 1$ the opposite.

(2) Coefficient of determination (R^2): R^2 corresponds to the coefficient of determination of a simple linear regression analysis applied to each pair of observed and modelled time series. The R^2 measure ranges from 0 to 1 and describes how much of the observed variability is explained by the modelled one. In practical terms, R^2 provides a measurement of the similarity between the patterns of the observed and modelled time series. This measure, however, cannot detect systematic bias (under- or over-estimation) of the modelled estimates (Krause et al., 2005).

(3) Regression coefficient (β): β corresponds to the slope or gradient of the linear regression analysis conducted between each pair of observed and modelled time series. This measure provides information about conditional bias of the modelled estimates. $\beta \approx 1$ represents good agreement in the magnitude of observed and modelled estimates; $\beta > 1$ means that the modelled estimates are higher in the mean (by a factor of β) than the observations; and $\beta < 1$ means the opposite.

(4) Root mean square error (RMSE): the RMSE represents the standard deviation of the differences between observed (O) and modelled (M) values. The RMSE is estimated as

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (O_t - M_t)^2}{n}}. \text{ A perfect fit between observed and modelled values corresponds}$$

to RMSE = 0. This measure provides information about overall performance of the modelled estimates.

3.3 RESULTS AND DISCUSSION

The results of the rainfall and hydraulic evaluation strategies, including selected images of the rainfall events and associated runoff estimates, as well as tables with summary performance measures, are presented in Figures 5 – 11 and Tables 4 – 7. In what follows the results are analysed per rainfall product, starting with a brief discussion of the original radar estimates, continuing with an analysis of the independent effect of temporal interpolation and Bayesian merging, respectively, and concluding with the analysis of the temporally-interpolated + Bayesian merged estimates. Given that the results of the rainfall evaluation strategy are closely linked to those of the hydraulic evaluation, these are analysed simultaneously.

3.3.1 Analysis of raw radar rainfall estimates and associated runoff estimates

As can be seen from Tables 1 and 4 and Figure 6 (see sample bias ratio), in the Cranbrook catchment the accumulations of RD estimates, both at areal level and at point RG location, are generally similar to those of RG records. This is however not the case for the Herent area (see Tables 2 and 5 and Figure 7). Except for the HER-S02 event (which was a rather weak event), a large bias between RD and RG accumulations is observed in Herent. This difference in the performance in cumulative rainfall between UKMO and Belgian RMI RD products may be attributed to the different correction routines that are applied, in particular the gauge-based adjustment that is applied to the UKMO RD product on an hourly basis, but not to the RMI product.

In terms of areal-average peak intensities, as compared with the rainfall accumulation performance, a larger bias between RD and RG estimates can generally be seen in both study areas (see Table 1, Table 2 and Figure 5). Except for the HER-S01 event, RD rain

rates appear to consistently underestimate the areal-average peak intensities recorded by RG. For the Cranbrook catchment, the relative difference between RG and RD areal-average (5-min) peak intensities ranges between 12-36%, while for the Herent area the relative difference may be up to 80% (see HER-S03 event). Even when the cumulative rainfall bias is small, the underestimation of peak rain rates by RD estimates has a large effect on the subsequent urban runoff estimates (notice how in Figure 10 and Figure 11 water depth estimates associated to RD 5 and RD 10 inputs underestimate the recorded water depth peaks). This corroborates the view that the correction processes that have been applied to both UKMO and RMI RD products are insufficient to satisfactorily capture the fine-scale dynamics of rainfall fields, which are critical at urban scales. This confirms the need for local and dynamic adjustment of original RD estimates. Another detail worth noticing is the better performance of RD 5 associated hydraulic outputs, as compared to those associated to RD 10 estimates; this already suggests that there is an added benefit in using higher temporal resolution radar rainfall estimates.

3.3.2 Analysis of temporally-interpolated-only radar rainfall estimates and associated runoff estimates

From a visual point of view (see snapshot images in Figure 8 and Figure 9), the temporally-interpolated RD images show a smooth and realistic transition of the rainfall clusters, including small-scale rainfall structures, between the available RD observations. By comparing the interpolated RD image over the Cranbrook catchment at time 02:05 (interpolated from 10 – 1 min) vs. the observed RD at the same time (Figure 8), high consistency can be observed in the location of the storm cell cluster between the two images, although some differences are observed in terms of intensities. Based upon visual inspection, it can be concluded that the proposed temporal-interpolation method is suitable for the small scales characteristic of urban areas. The fact that the location and shape of storm clusters is well reproduced suggests that the assumption of a constant field of motion vectors holds well within short time intervals. However, the differences observed in rainfall

rates between the interpolated and observed RD images suggests that assuming a linear change in rainfall rates within the time intervals under consideration may be inappropriate and that additional and complementary sources of information (e.g. RG records at higher temporal resolution) are required to compensate for this deficiency.

Quantitatively, at the areal level, it can be seen that the temporal interpolation has a negligible effect in rainfall accumulations: in all cases coefficients B and β of the interpolated RD estimates stay very close to those of the original RD estimates (see Table 4 and Table 5). In terms of pattern, the intensities of the interpolated RD estimates show higher and generally better dynamics. This is reflected in the generally higher R^2 values associated with RD 5-1 and especially RD 10-1 estimates, particularly in the case of storms with strong peaks (see Table 4 and Table 5). However, magnitude-wise the intensities of the interpolated RD estimates stay very close to the original RD intensities (see rain rate values in Figure 5 and β values in Table 4 and Table 5). This is due to the assumption of linear change in rainfall intensities mentioned above. Similar trends can be observed at RG point locations (see Figure 6 and Figure 7). However, when looking at the distribution of statistics at point locations, a larger spread is observed in the results associated to the interpolated RD estimates as compared to those of the original RD observations. This could be partially due to the uncertainty in the interpolation itself, as well as to the uncertainty in the high-resolution RG estimates.

In terms of hydraulic outputs (Table 6, Table 7, Figure 10 and Figure 11), the temporally-interpolated RD estimates do not lead to significant improvements, as compared to the original RD rainfall inputs. The difference between the temporally-interpolated-only and the original RD estimates is usually small (i.e. RD 5-1 vs. RD 5 and RD 10-1 vs. RD 10) and mainly lies in the shifting (generally improving) of the timing to peak flow depth. Nonetheless, the improvements observed in the R^2 values of the interpolated RD estimates are generally smoothed-out throughout the hydrological and hydraulic modelling. Moreover, it is often found that the RD 5-1 and RD 10-1 estimates result in lower peak flow depths than

the original RD estimates, which may be attributed to the inevitable smoothing nature of the interpolation process.

From the analysis of the individual effect of interpolation it can be concluded that while the interpolation helps re-gain the dynamics of rainfall inputs, it is not sufficient to fully correct rainfall estimates. This implies that other sources of error are still present and that a gauge-based adjustment is still necessary.

3.3.3 Analysis of Bayesian-adjusted-only radar rainfall estimates and associated runoff estimates

In contrast to the temporal interpolation, the gauge-based adjustment alone generally has a large impact on rainfall estimates and subsequent runoff simulations.

With regards to rainfall estimates, the Bayesian merging alone largely improved the magnitude of peak rainfall rates as well as the event rainfall accumulations, both at areal level and at point RG locations (see magnitudes of peak intensities in Figure 5 and B values in Table 4, Table 5, Figure 6 and Figure 7). However, the application of the merging at the original temporal resolutions, particularly at 10 min, often caused a deterioration in the timing of peak intensities and in the pattern of rain rate time series in general, as compared to the original RD estimates. This is reflected in a decrease in R^2 and β values, often accompanied by a deterioration in RMSE values (see Table 4, Table 5, Figure 6 and Figure 7). The deterioration of the pattern implies a loss of dynamics which can be attributed to the joint effect of using RD estimates at coarse resolution in combination with RG estimates aggregated to a coarser resolution.

The effects of the Bayesian merging alone propagate through the hydraulic simulations, but are somehow smoothed in the process. On the one hand, the improvement in peak rainfall rates and accumulations clearly translated into improved reproduction of runoff peaks (see Figure 10 and Figure 11). The loss of dynamics of rainfall time series, on the other hand, did result in shifts (worsening) in the time to runoff peaks, particularly for the BAY 10 rainfall

inputs. Nonetheless, the degree of dynamic loss (or alteration in time series pattern) observed in the runoff simulations is not as significant as that initially observed in the BAY 5 and BAY 10 rainfall estimates.

3.3.4 Analysis of temporally-interpolated and Bayesian-adjusted radar rainfall estimates and associated runoff estimates

As compared to the temporally-interpolated-only RD images, the temporally-interpolated and Bayesian-adjusted images show a similar shape and displacement of rain cells. Nonetheless, the latter display stronger and less linear changes in rainfall intensities, as a result of incorporating of high resolution RG information (see Figure 8 and Figure 9). This incorporation allows a more realistic representation of the growth and decay of storm cells, which is particularly evident in the CBK-S03 event (Figure 8).

An interesting visual feature worth highlighting is the difference in the 07:55 images of BAY 5-1 (observed+merged) and BAY 10-1 (interpolated+merged) estimates in Figure 9. It can clearly be seen that the pattern of the BAY 10-1 estimates is much smoother and less similar to the associated radar image than that of the BAY 5-1 one. This is because the interpolated radar estimate of the BAY 10-1 is found to be less reliable than the observed radar estimate at time 07:55 employed in the generation of BAY 5-1. As a result, given the theoretical formulation of the Bayesian merging method, the proportion of the RG information that is preserved throughout the adjustment is larger in the case of the BAY 10-1. This finding highlights the advantages of using the Bayesian merging method - as opposed to other adjustment methods, which do not account for the uncertainty of the different data sources being merged - in combination with the temporal interpolation.

Quantitatively, the combined application of temporal interpolation and Bayesian merging led to the best performing rainfall estimates (BAY 5-1 and BAY 10-1), both in terms of magnitude and pattern, at areal level as well as at point RG locations (see Figure 5, Table 4, Table 5, Figure 6 and Figure 7). Remarkably, the BAY 10-1 estimates performed better than

BAY 5 estimates in almost all events, thus bringing out the advantages of the proposed methodology. The improvements observed in the rainfall estimates are clearly seen in the associated runoff estimates, with BAY 5-1 and BAY 10-1 associated hydraulic outputs generally performing better than others, often even better than the outputs resulting from the original high resolution RG estimates. As compared to the runoff estimates associated to the Bayesian-adjusted-only rainfall inputs, the BAY 5-1 and BAY 10-1 estimates display a better agreement with observations, particularly in terms of the time to runoff peak. This highlights the benefits of applying gauge-based adjustments at higher temporal resolutions.

[Figure 5 about here]

[Table 4 about here]

[Table 5 about here]

[Figure 6 about here]

[Figure 7 about here]

[Figure 8 about here]

[Figure 9 about here]

[Figure 10 about here]

[Figure 11 about here]

[Table 6 about here]

[Table 7 about here]

4 CONCLUSIONS AND FUTURE WORK

In this paper a methodology is proposed to produce higher temporal-resolution (1-2 min), more accurate radar rainfall estimates, aiming at meeting the stringent requirements of

urban hydrological applications. The proposed methodology involves two main steps: firstly, radar images are temporally interpolated from the original operational temporal resolutions (5-10 min) to a higher resolution at which local RG records are available (1-2 min). This is done using a novel interpolation technique introduced in the present paper, based upon the multi-scale variational optical flow technique, and which can well capture the small-scale rainfall structures relevant at urban scales. Afterwards, the higher temporal resolution radar rainfall estimates are dynamically merged with local rain gauge records by means of the Bayesian data merging method, which in previous studies had shown to outperform other merging methods, both at large and at small (urban scales).

Using as case study a total of eight storm events observed in the Cranbrook catchment (~9 km²) (London, UK) and in the Herent area (~25 km²) (Leuven, Belgium), the performance of the proposed method, in terms of the resulting rainfall estimates and the subsequent runoff estimates, was evaluated and compared against that of the original radar estimates and of the merged-only (i.e. without temporal interpolation) and interpolated-only (i.e. without merging) rainfall estimates. This analysis clearly brought out the benefits of the proposed combination of temporal interpolation and local and dynamic gauge-based adjustment of radar rainfall estimates. The main conclusions and implications of the testing are the following:

- The novel temporal interpolation technique introduced in this study proved able to handle small-scale rainfall features, resulting in realistic intermediate (interpolated) radar images, which served as basis for the subsequent local gauge-based adjustment. While the temporal interpolation alone does not show consistent quantitative results, its benefits are always evident in the case of storm events with fast-changing features.
- The proposed temporal interpolation + merging methodology can significantly improve radar rainfall estimates and associated runoff simulations at urban scales, much more so than the mere application of Bayesian merging at the original temporal

resolution at which radar estimates are available. In other words, the results indicate that it is more effective to adjust or merge radar estimates at higher temporal resolutions, as opposed to doing so at coarser ones. In fact, at the coarsest temporal resolution analysed in this study (10 min), the Bayesian merging generally led to smaller improvements, and sometimes even caused deterioration, in both radar QPEs and associated runoff at the small urban scales considered in this study. This finding implies that the nation-wide gauge-based adjusted radar rainfall products which are generated through adjustments often performed at rather coarse temporal resolutions (≥ 10 min) – e.g. the UKMO-Environment Agency product (Jewell and Gaussiat, 2015) and the Belgian RMI product being developed (Goudenhoofd and Delobbe, 2009) – may not provide tangible benefits at urban scales.

However, in order to draw more robust conclusions about the applicability of the proposed method, further testing is required based on more storm events and pilot locations. Other aspects on which future work is recommended are the following:

- Testing of the proposed methodology using radar rainfall estimates at higher spatial resolutions. Given the strong relationship between the temporal and spatial resolution of rainfall inputs (Ochoa-Rodríguez et al., 2015), it is likely that the benefits of the proposed methodology will become more evident when using radar estimates of higher spatial resolution, which is in agreement with the high temporal resolutions obtained through the methodology demonstrated in this study.
- Application of the temporal interpolation technique proposed herein in combination with the singularity-sensitive Bayesian merging method (Wang et al., 2015), which has proven to better preserve small-scale singularity structures throughout the merging process, thus being more suitable for urban applications. However, the fact that the singularity analysis would be applied on temporally-interpolated radar images, as opposed to actual radar observations, poses particular challenges which need to be carefully examined.

- Development of a stochastic temporal interpolation method, which accounts for the uncertainties associated with the advection model. This stochastic model could serve as basis for a rainfall error model for urban scales.
- Exploration of the use of the improved rainfall estimates obtained with the proposed methodology in a wider range of urban hydrological applications, including calibration of urban drainage models, reconstruction of historical storm events leading to known pluvial flooding, real-time simulation of urban runoff, amongst others.

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Figure 1: Errors in urban runoff estimates in relation to drainage area, as a result of the coarsening of the spatial and temporal resolution of rainfall inputs. Logarithmic functions were fitted to the hydrodynamic simulation results obtained for 7 urban catchments in North-West Europe, forced with data from 9 storm events recorded at high resolution (100 m / 1 min) by a polarimetric X-band radar. Coarser resolution rainfall estimates were generated by averaging in space, whereas coarser resolution temporal estimates were generated by sampling radar images at the desired temporal resolution, thus replicating radar scanning strategies. Performance statistics were estimated using as reference the runoff estimates associated to the highest available resolution rainfall estimates (adapted from Ochoa-Rodriguez et al., 2015).

Figure 2: Schematic of the proposed methodology for generating accurate radar rainfall images with high temporal resolution. RD and RG (with solid outlines) respectively represent radar and rain gauge observations; RD' (with dashed outlines) corresponds to temporally-interpolated radar rainfall estimates; and RD'' (with dotted outlines) corresponds to interpolated plus gauge-adjusted (through Bayesian (BAY) merging) radar rainfall estimates.

Figure 3: Cranbrook catchment boundary, sewer layout, sensor location and radar grid over the catchment.

Figure 4: Herent drainage area boundary, sewer layout, sensor location and radar grid over the catchment.

Figure 5: Areal-average rainfall rate profiles of the different estimates under consideration for the CBK-S01 event. Top: RG vs. temporally-interpolated and/or adjusted rainfall estimates derived from 5-min RD estimates; Bottom: RG vs. temporally-interpolated and/or adjusted rainfall estimates derived from 10-min RD estimates.

Figure 6: Plots of performance measures at RG point locations for the different gridded rainfall estimates, for the selected storm events over the Cranbrook catchment.

Figure 7: Plots of performance measures at RG point locations for the different gridded rainfall estimates, for the selected storm events over the Herent area. The red circles correspond to the median of the performance measures estimated at all 7 or 8 point RG locations for each rainfall product.

Figure 8: Snapshot images of the original RD measurements in 5- and 10-min time intervals (images with red outlines), interpolated 1-min RD (i.e. RD 5-1 and RD 10-1, respectively interpolated from 5- and 10-min RD measurements) and the Bayesian-adjusted rainfall estimates (i.e. BAY 5, 5-1, 10 and 10-1) during the period of areal average peak intensity for the CBK-S03 event.

Figure 9: Snapshot images of the original RD measurements in 5- and 10-min time intervals (images with red outlines), interpolated 1-min RD estimates (i.e. RD 5-1 and RD 10-1, respectively interpolated from 5- and 10min RD measurements) and Bayesian adjusted rainfall estimates (i.e. BAY 5, 5-1, 10 and 10-1) during the period of areal-average peak intensity for the HER-S03 event.

Figure 10: Observed and simulated flow depths for the selected events at the Valentine Open Channel (the circled blue round marker in Figure 3) in the Cranbrook catchment.

Figure 11: Observed and simulated flow depths for the selected events at the M5 gauging site (the circled red round marker in Figure 4) in the Herent area.

Fig. 1

ΔT : temporal resolution of radar (RD) images
 Δt : Temporal resolution of rain gauge (RG) data (note that $\Delta T = n \cdot \Delta t$)

Fig. 2

Legend

Catchment boundary	Depth monitor in open channel
Roding River	Depth monitor in river
Sewer Network	Rain gauges
Flow monitor in sewer	Radar grid
Depth monitor in sewer	

Fig. 3

Fig. 4

Fig. 5

Fig. 6

Fig. 7

Fig. 8

Fig. 9

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Table 1: Selected rainfall events over the Cranbrook catchment

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ID	Date	Duration (h)	RG#	RG Total (mm)	RG Peak (mm/h) 1/5/10min	RD Total (mm)	RD Peak (mm/h) 5/10min
CBK-S01	01-02 May 2014	23	3	25.8	36.00/28.80/26.80	19.94/20.35	18.22/17.70
CBK-S02	25-26 Aug 2014	20	3	28.73	16.00/8.00/6.80	28.84	7.01/5.56
CBK-S03	19 Sep 2014	3.5	3	11.47	40.00/34.40/32.00	12.47	25.73/25.73
CBK-S04	19 Sep 2014	3	3	7.07	32.00/25.60/18.40	10.06	20.10/20.02

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Table 2: Selected rainfall events over Herent area

ID	Date	Duration (h)	RG#	RG Total (mm)	RG Peak (mm/h) 1-2*/5/10min	RD Total (mm)	RD Peak (mm/h) 5/10min
HER-S01	23 Sep 2012	1.8	8	9.99	25.94*/20.40/19.16	20.00	41.89/24.91
HER-S02	08 May 2013	4	7	9.22	32.48/28.97/20.80	7.97	18.16/18.16
HER-S03	27 Jul 2013	5	8	21.39	86.11/78.94/62.70	10.06	16.20/16.20
HER-S04	27 Jul 2013	3	8	21.73	88.85/78.11/67.25	10.75	22.23/21.67

* For event HER-S01 rain gauge records were available at 2 min resolution. For all other events, rain gauge records were available at 1 min resolution.

Table 3: Summary of rainfall estimates under consideration in this study

Notation	Description	Temporal Interpolation	Bayesian Adjustment
RG	Local rain gauge rainfall records at highest available temporal resolution (i.e. 2-min for HER-S01 event and 1-min for all other events)	No	No
RD 5	Original radar rainfall estimates sampled at 5-min time intervals	No	No
RD 5-1 (or RD 5-2)	Temporally-interpolated radar rainfall estimates, obtained from RD 5	Yes	No
RD 10	Original radar rainfall estimates sampled at 10-min time intervals	No	No
RD 10-1 (or RD 10-2)	Temporally-interpolated radar rainfall estimates, obtained from RD 10	Yes	No
BAY 5	Bayesian-adjusted rainfall estimates, obtained from RD 5 and 5-min RG rainfall estimates (aggregated from 1- or 2-min RG records)	No	Yes
BAY 5-1 (or BAY 5-2)	Temporally-interpolated + Bayesian-adjusted rainfall estimates, obtained from RD 5-1 (or RD 5-2) and RG rainfall estimates	Yes	Yes
BAY 10	Bayesian-adjusted rainfall estimates, obtained from RD 10 and 10-min RG rainfall estimates (aggregated from 1- or 2-min RG records)	No	Yes
BAY 10-1 (or BAY 10-2)	Temporally-interpolated + Bayesian-adjusted rainfall estimates, obtained from RD 10-1 (or RD 10-2) and RG rainfall estimates	Yes	Yes

Table 4: Summary of performance measures for the areal average gridded rainfall estimates for the selected storm events over the Cranbrook catchment (note that performance measures were estimated using areal-average RG records as reference)

ID	RD 5-1	RD 5	RD 10-1	RD 10	BAY 5-1	BAY 5	BAY 10-1	BAY 10
Sample bias ratio - B								
CBK-S01	0.772	0.773	0.788	0.789	0.994	0.962	0.993	0.954
CBK-S02	1.005	1.004	1.009	1.005	1.034	1.002	1.033	0.999
CBK-S03	1.081	1.088	1.136	1.129	1.135	1.144	1.142	1.171
CBK-S04	1.430	1.424	1.417	1.414	1.114	1.126	1.084	1.125
Coefficient of determination - R^2								
CBK-S01	0.697	0.714	0.683	0.691	0.985	0.737	0.985	0.619
CBK-S02	0.315	0.310	0.304	0.277	0.962	0.302	0.962	0.284
CBK-S03	0.854	0.843	0.893	0.780	0.989	0.825	0.988	0.478
CBK-S04	0.596	0.634	0.628	0.624	0.956	0.578	0.968	0.348
Regression coefficient - β								
CBK-S01	0.501	0.513	0.505	0.520	0.924	0.723	0.926	0.644
CBK-S02	0.360	0.359	0.350	0.340	0.973	0.352	0.974	0.326
CBK-S03	0.830	0.832	0.895	0.824	1.093	0.971	1.092	0.712
CBK-S04	0.874	0.909	0.896	0.929	0.975	0.697	0.974	0.519
Root mean square error – RMSE (in mm)								
CBK-S01	0.038	0.037	0.038	0.037	0.009	0.032	0.009	0.039
CBK-S02	0.037	0.037	0.037	0.038	0.009	0.037	0.009	0.037
CBK-S03	0.054	0.056	0.046	0.066	0.022	0.063	0.022	0.112
CBK-S04	0.072	0.068	0.068	0.071	0.021	0.064	0.017	0.082

Table 5: Summary of performance measures for the areal average gridded rainfall estimates for the selected storm events over the Herent area (note that performance measures were estimated using areal-average RG records as reference)

ID	RD 5-1 /RD 5-2	RD 5	RD 10-1 /RD 10-2	RD 10	BAY 5-1 /BAY 5-2	BAY 5	BAY 10-1 /BAY 10-2	BAY 10
Sample bias ratio - B								
HER-S01	1.629	2.002	1.418	1.833	1.170	1.287	1.158	1.241
HER-S02	0.846	0.864	0.824	0.854	1.061	1.040	1.055	1.043
HER-S03	0.464	0.470	0.428	0.484	1.033	1.044	1.036	1.054
HER-S04	0.489	0.495	0.429	0.491	1.027	1.022	1.022	1.020
Coefficient of determination - R^2								
HER-S01	0.684	0.718	0.575	0.405	0.968	0.652	0.964	0.245
HER-S02	0.859	0.740	0.843	0.444	0.993	0.646	0.993	0.336
HER-S03	0.754	0.631	0.563	0.381	0.998	0.617	0.998	0.200
HER-S04	0.883	0.862	0.898	0.700	0.999	0.723	0.999	0.292
Regression coefficient - β								
HER-S01	1.093	1.300	0.803	0.787	0.970	0.734	0.958	0.420
HER-S02	0.592	0.556	0.579	0.444	0.984	0.750	0.985	0.492
HER-S03	0.216	0.196	0.152	0.156	1.032	0.777	1.033	0.411
HER-S04	0.309	0.311	0.277	0.281	1.024	0.849	1.023	0.516
Root mean square error – RMSE (in mm)								
HER-S01	0.213	0.277	0.189	0.280	0.053	0.154	0.054	0.231
HER-S02	0.047	0.054	0.049	0.073	0.009	0.060	0.008	0.084
HER-S03	0.181	0.186	0.196	0.197	0.013	0.145	0.013	0.226
HER-S04	0.218	0.218	0.228	0.230	0.013	0.163	0.013	0.280

Table 6: Summary statistics of the simulated flow depths at the Valentine open channel (the circled blue round marker in Figure 3) of the Cranbrook catchment.

Event ID	RG	RD 5-1	RD 5	RD 10-1	RD 10	BAY 5-1	BAY 5	BAY 10-1	BAY 10
Coefficient of determination - R^2									
CBK-S01	0.827	0.796	0.838	0.789	0.874	0.886	0.858	0.881	0.775
CBK-S02	0.815	0.515	0.527	0.500	0.488	0.843	0.857	0.848	0.849
CBK-S03	0.976	0.970	0.972	0.971	0.888	0.980	0.955	0.972	0.814
CBK-S04	0.835	0.907	0.963	0.891	0.963	0.939	0.953	0.924	0.903
Regression coefficient - β									
CBK-S01	0.770	0.786	0.803	0.776	0.806	0.989	0.956	0.973	0.895
CBK-S02	1.012	0.780	0.782	0.772	0.762	0.973	0.951	0.981	0.938
CBK-S03	0.942	0.935	0.929	0.949	0.909	0.947	0.929	0.950	0.882
CBK-S04	1.460	1.423	1.457	1.474	1.534	1.343	1.371	1.384	1.420
Root mean square error – RMSE (in metre)									
CBK-S01	0.100	0.106	0.100	0.106	0.094	0.079	0.084	0.080	0.098
CBK-S02	0.076	0.110	0.108	0.111	0.112	0.070	0.068	0.070	0.070
CBK-S03	0.057	0.080	0.076	0.074	0.117	0.065	0.079	0.071	0.142
CBK-S04	0.153	0.117	0.102	0.135	0.124	0.095	0.093	0.105	0.122

Table 7: Summary statistics of the comparison of observed and simulated flow depth at the M5 (the circled red round marker in Figure 4) of the Herent area.

ID	RG	RD 5-1 /RD 5-2	RD 5	RD 10-1 /RD 10-2	RD 10	BAY 5-1 /BAY 5-2	BAY 5	BAY 10-1 /BAY 10-2	BAY 10
Coefficient of determination - R^2									
HER-S01	0.965	0.930	0.936	0.889	0.879	0.957	0.953	0.962	0.978
HER-S02	0.962	0.903	0.892	0.903	0.892	0.943	0.919	0.941	0.905
HER-S03	0.890	0.724	0.693	0.708	0.636	0.985	0.970	0.984	0.934
HER-S04	0.929	0.888	0.869	0.870	0.856	0.994	0.979	0.994	0.937
Regression coefficient - β									
HER-S01	1.022	1.045	1.044	1.030	1.036	0.979	0.998	1.075	1.111
HER-S02	0.734	0.520	0.524	0.474	0.571	0.731	0.712	0.692	0.781
HER-S03	0.911	0.655	0.693	0.663	0.617	0.974	0.972	0.972	0.955
HER-S04	0.846	0.786	0.775	0.766	0.775	0.904	0.897	0.903	0.877
Root mean square error – RMSE (in metre)									
HER-S01	0.144	0.170	0.162	0.199	0.236	0.197	0.162	0.118	0.111
HER-S02	0.304	0.583	0.566	0.643	0.576	0.298	0.332	0.346	0.313
HER-S03	0.230	0.432	0.409	0.418	0.474	0.152	0.171	0.152	0.210
HER-S04	0.184	0.299	0.309	0.330	0.299	0.148	0.165	0.148	0.210

1150 **HIGHLIGHTS**

- 1151 - A methodology to produce high temporal resolution accurate radar rainfall estimates is
1152 proposed
- 1153 - The method was tested in two urban catchments in Belgium and UK
- 1154 - 1 min, accurate rainfall estimates suitable for urban hydrological applications were generated
- 1155 - The improved rainfall estimates showed to improve urban runoff estimation

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