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A review of gauge–radar merging methods for quantitative precipitation estimation in hydrology

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In the case of a significant precipitation event, hydrological models play a key role in flood mitigation. To develop a hydrological model that produces results with a high degree of confidence, it is imperative that the model be provided with accurate quantitative precipitation estimates as input. For flood forecasting purposes, quantitative precipitation estimates at high spatial and temporal resolutions are preferable. Rain gauges and weather radar are the most widely used instruments for near real-time collection of precipitation estimates. While rain gauges and radar demonstrate certain strengths, both instruments suffer from a wide variety of well-known errors which inhibit their ability to provide optimal precipitation estimates for hydrological models. Considering this, several methods have been developed to merge the estimates of these two instruments in order to minimize their individual weaknesses and take advantage of their respective strengths. The goal of this paper is to provide a comprehensive review of gauge–radar merging methods and assess the opportunity for near real-time application of gauge–radar merging methods in hydrology. Methods presented include: mean field bias correction, Brandes spatial adjustment, local bias correction with ordinary kriging, range-dependent bias correction, Bayesian data combination, conditional merging, kriging with external drift and statistical objective analysis. While comparison of gauge–radar merging methods is difficult, several factors, including gauge network design, storm type and the temporal resolution of adjustment, have demonstrated a large effect on the overall accuracy of a particular merging method. The majority of research carried out on near real-time application of gauge–radar merging methods has been conducted outside of Canada. Further research is recommended to assess the capability of using gauge–radar merging schemes with Canadian radar products for precipitation estimation in hydrological applications, including operational hydrological modelling for flood forecasting.

Les modèles hydrologiques jouent un rôle clé dans l'atténuation des inondations dans le cas d'un événement de précipitations significatives. Pour élaborer un modèle hydrologique qui produit des résultats avec un degré élevé de confiance, il est impératif que le modèle soit fourni avec des estimations quantitatives de précipitations précises. Des estimations quantitatives de précipitations à résolutions spatiales et temporelles élevées sont nécessaires pour la prévision des inondations. Les pluviomètres et le radar météorologique sont les instruments les plus couramment utilisés pour la compilation en temps quasi réel des estimations de précipitations. Alors que les pluviomètres et le radar montrent certains avantages, ces deux instruments (présentent/connaissent) une grande variétés d'erreurs bien connues qui inhibent leur capacité à fournir des estimations de précipitations précises pour les modèles hydrologiques. Tenant compte de ce fait, plusieurs méthodes ont été développées pour combiner les estimations de ces deux instruments afin de minimiser leurs faiblesses individuelles et de profiter uniquement de leurs avantages. L'objectif de ce manuscrit est de fournir un examen exhaustif des méthodes de combinaison des données des pluviomètres et du radar et d'évaluer la possibilité de leur application en temps quasi réel en hydrologie. Les méthodes incluses dans ce manuscrit sont les plus courantes dans la littérature et les plus souvent utilisées en pratique. En tout, huit méthodes de combinaison des données des pluviomètres et du radar ont été examinées dans ce manuscrit. Bien que la comparaison des méthodes de combinaison des données sur les pluviomètres et le radar soit difficile, plusieurs facteurs, comme la conception des réseaux de pluviomètres, le type d'événement de précipitation et l'ajustement de la correction temporelle, ont démontré un effet important sur la précision globale d'une telle ou telle méthode de combinaison. La majorité des études effectuées sur l'application en temps quasi réel des méthodes de combinaison des données des pluviomètres et du radar ont été menées à l'extérieur du Canada. D'autres études sont recommandées pour évaluer la possibilité d'utiliser de telles méthodes de combinaison avec des produits du radar au Canada pour l'estimations quantitative de précipitations et la prévision des inondations.

Introduction

Throughout Canadian history, flooding events have had a major impact on society, causing billions of dollars in damage and resulting in the loss of life. Flooding events are by far the most common natural disaster experienced in Canada (Sandink et al. 2010). The Institute for Catastrophic Loss Reduction (ICLR) estimates that currently preventable damages due to extreme rainfall exceed CAD $2 billion a year in Canada (Kovacs et al. 2014). In the past few years, costs associated with flooding have

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been rapidly escalating. Flooding events in 2011 in Manitoba and Quebec resulted in damages of CAD $1.1 billion and $78 million, respectively (Thistlethwaite and Feltmate 2013). Damages due to 2013 flooding in Alberta caused by a combination of snowmelt in the headwater regions and extreme rainfall resulted in damages exceeding CAD $6 billion (Environment Canada 2014). Flash flooding in Toronto in July 2013 due to a high-intensity short-duration rainfall event resulted in damages of CAD $1 billion (Environment Canada 2014). The federal, provincial and municipal governments of Canada have largely been responsible for covering the rising costs of these damages, which has resulted in significant impacts to the Canadian economy (Environment Canada 2013a).

Riverine flooding events are a result of increased runoff from the surrounding contributing basin which causes the stream to exceed the level of the banks (Dingman 2002). While this increase in flow can be due to a number of hydrological, meteorological and human-induced factors (Takeuchi 2001), precipitation is the most influential factor controlling the frequency and magnitude of flooding events (Environment Canada 2013b). One of the most important tools for flood mitigation is the use of hydrological models for flow prediction (Takeuchi 2001). A hydrological model, which conceptualizes the complex physical characteristics of a basin (Dingman 2002), is used to analyze stream flow rates and water levels in near real-time as they respond to rainfall events. Output from these models is used to provide early flood warning, allowing for time to evacuate affected areas, shut down vulnerable transportation infrastructure, deploy emergency workers and establish emergency short-term flood protection for important structures (Looper and Vieux 2012).

Despite their many benefits, a lack of confidence in hydrological modelling outputs often leads to underutilization of this tool for flood mitigation (McMillan et al. 2011). The validity of a model depends on the accuracy and reliability of input parameters and initial and boundary conditions (Zhu et al. 2013). Of these parameters and data, rainfall inputs prove the most important (Golding 2009). Additionally, accurate rainfall is needed in hydrological model calibration to produce parameter sets which represent basin characteristics. Widespread use of hydrological models has demonstrated the need for accurate rainfall fields in order to produce runoff and stream flow predictions with a high degree of confidence (Beven and Hornberger 1982; Kalinga and Gan 2006; Cole and Moore 2008; Xu et al. 2013; Berne and Krajewski 2013; etc.). According to McMillan et al. (2011, p. 84): "No model, however well founded in physical theory or empirically justified by past performance, can produce accurate runoff predictions if forced with inaccurate rainfall data." Inaccurate rainfall data directly compromise the integrity of the model and the associated critical decisions made using model output (Golding 2009; McMillan et al. 2011). In particular, for small watersheds, the timing and location of rainfall is critical in reproducing hydrographs. There is thus an urgent need to acquire reliable precipitation estimates at high spatial (e.g. a few km or less) and temporal (e.g. hourly or less) resolutions (Berne and Krajewski 2013). As a result, in recent years significant efforts have been made to develop accurate methods to estimate rainfall accumulations at higher spatial and temporal resolutions during rainfall events.

Rain gauges and weather radar are the most widely used instruments for acquiring rainfall accumulations for use in hydrological models (Berne and Krajewski 2013). While these rainfall measurement techniques have their individual strengths, both techniques result in errors which can limit their ability to produce accurate input for hydrological models. Considering this, numerous techniques have been proposed to merge rain gauge and radar measurement techniques (hereafter referred to as gauge–radar merging methods) at high spatial and temporal resolutions in order to obtain greater accuracy in rainfall accumulations. For hydrologists and engineers developing hydrological models for reliable operational use, the choice of a suitable rainfall estimation technique is a critical decision. The vast number of gauge–radar merging methods present in the literature makes this decision a challenging task.

The goal of this paper is to provide a comprehensive review of the acquisition and merging of rain gauge and radar rainfall data for input into hydrological models. To achieve this goal, the following objectives will be satisfied:

(1) Provide a review and description of the uncertainty associated with the use of rain gauges and radar for the acquisition of rainfall data;
(2) Describe and compare pertinent gauge–radar merging methods to produce greater accuracy in rainfall accumulations; and
(3) Identify and discuss factors which influence the accuracy of gauge–radar merging methods as input into hydrological models to aid in the selection of an appropriate rainfall estimation technique.

The use of radar in hydrological modelling is widely studied academically; however, it is not yet widely implemented operationally. This paper will assist in identifying circumstances in which the addition of data derived from radar output is beneficial in hydrological modelling.

Rainfall estimation: rain gauges

Historically, rain gauges have been the main source for quantitative precipitation estimation (QPE) for use in hydrological models, and remain one of the most popular and widely used rainfall accumulation collection methods today (Environment Canada 2013c). Rain gauges measure the depth of rainfall over a set time for a given location. Therefore, the primary goal of a rain gauge is to obtain representative measurements of rainfall over the area which the measurement represents (World Meteorological Organization [WMO] 2008). Rain gauges typically cover an area of 200 cm^2 (Vuerich et al. 2009). Several types of recording rain gauges are used in practice, including: tipping bucket rain gauges, weighing rain gauges, optical rain gauges and disdrometers. The majority of automatic recording rain gauge networks in Canada consist of a series of automatic weighing gauges and tipping bucket gauges (Environment Canada 2013c). While rain gauges have the ability to provide accurate point measurements, they are subject to numerous sources of error and uncertainty that limit their use in operational flood forecasting models (Sinclair and Pegram 2005). These sources of uncertainty and the effect of this uncertainty on hydrological modelling capabilities will be discussed in the following two subsections.

Uncertainty associated with rain gauge measurements

Wilson and Brandes (1979) identified two critical sources of error which have a significant impact on the ability to use rain gauge measurements for hydrological modelling purposes. These include: (1) the inability of point measurements to accurately characterize the spatial distribution of the rainfall field; and (2) systematic and calibration errors.

The first error relates to the inability of a rain gauge to measure the spatial variability in a rainfall field. Distributed hydrological models require a spatial distribution of rainfall over a basin in order to determine the rainfall–runoff response in the watershed. Rain gauges can provide only fractional coverage of the entire spatial domain and are thus often unable to provide an accurate representation of the variability in a rainfall field. Considering this, a network of gauges (consisting of a series of gauges distributed throughout the basin) is used to produce a spatial distribution and approximate rainfall accumulations at ungauged locations. Spatial distribution of rainfall from point rain gauge values can be determined using well-known distance averaging techniques such as inverse distance weighting, kriging, Thiessen polygons and splines (Dingman 2002). Rainfall fields, however, often exhibit a high degree of spatial variability (Tao et al. 2009), which is often uncaptured through the interpolation of point rain gauge values that generally produce a uniform rainfall field (Sinclair and Pegram 2005). According to previous research investigating the impact of gauge network design on interpolation accuracy (see e.g. Rodriguez-Iturbe and Mejia 1974; Xu et al. 2013), the interpolation accuracy of rainfall data sets is dependent on optimal network density and spacing. However, optimal gauge density and spacing is for the most part never achieved in a river basin (Smith et al. 2007). Economic and practical considerations result in gauge networks that provide poor representation of the rainfall field over the basin (Volkmann et al. 2010). Huff (1970) demonstrated that a rain gauge network density of one gauge per 65 km^2 is required in order to achieve an average sampling error in recorded rainfall accumulations of less than 5% for 6-hour rainfall accumulations. The density required, however, will change depending on operational considerations. According to the US Army Corps of Engineers (1996), the optimal network design should consist of evenly distributed gauges at a spatial density determined by:

$$N = A^{0.33} \tag{1}$$

where N = the number of gauges, and A = the area of the basin in mi^2. The World Meteorological Organization (WMO) recommends rain gauge densities dependent on catchment type (e.g. one gauge per 250 km^2 for a mountainous catchment or one gauge per 900 km^2 for a plains catchment) (WMO 2008). A number of different factors affect the optimal network density of rain gauges, including climatic patterns, topography (Lobligeois et al. 2014) and storm type (Huff 1970). For example, Barge et al. (1979) assessed that during a summer thunderstorm in southern Alberta, a recording rain gauge measured a rainfall depth representative of an extreme rainfall event. If the hydrological model had been based on rainfall recorded by this gauge alone a flood warning would have been issued. However, through subsequent qualitative observations of weather radar and a review of the subsequent stream flow data, it was evident that the rainfall was localized directly above the gauge. A dense rain gauge network is desirable for operational flood forecasting of such localized rainfall events; however, as mentioned above, the installation of such a network is not practical (Zhu et al. 2013). Therefore, rainfall is often mischaracterized during high-intensity, small-spatial-scale events, leading to significant error in predicted stream flows (Golding 2009). Several methodologies have been developed to optimize the location and density of rain gauge networks (see e.g. Pardo-Iguzquiza 1998; Jung et al. 2014).

Secondly, systematic and calibration errors affect the accuracy of gauges through losses due to evaporation, splash-out, wind effects, valley effect, tree cover, building cover or miscalibration (WMO 2008). These errors affect the measured depth and the calculated resulting spatial distribution of rainfall. According to the WMO (2008), two types of wind effects hinder the accuracy of rain gauges:

(1) The effect of the wind translating the droplets of rainfall so that they miss the rain gauge; and
(2) The effect of the gauge changing the trajectory of the wind so that the characteristics of the rainfall are different around the gauge than elsewhere in the watershed.

Larson and Peck (1974) examined the results from several studies on the effect of wind-blown rainfall on the accuracy of final depth measurements; a 12% error exists in wind loading of 5 m/s and a 19% error exists in wind loading of 10 m/s with no wind shield. The data were extrapolated to determine that during the wind loading of an average thunderstorm (10 to 35 m/s) the error would be in the range of 20 to 40% (Larson and Peck 1974). Other environmental effects, such as trees, buildings and valleys, can adversely influence rain gauge measurements with the magnitude of the error dependent on the siting of the gauge. Ideally, gauges should not be situated in valleys or in areas with trees or buildings where measurements can be obstructed (WMO 2008). As seen in basins across Canada, due to economic considerations, gauges tend to be located improperly close to the above obstructions (Volkmann et al. 2010). As an example, operational purposes require the Upper Thames River Conservation Authority (UTRCA), located in Southwestern Ontario, to install their rain gauges to correspond with locations of stream gauges. As a result, many rain gauges in the watershed tend to be located in valleys and in close proximity to trees, where streams are generally present. Lastly, gauge quality control is of critical importance, as rain gauges are prone to malfunctioning (Steiner et al. 1999). Without proper maintenance and calibration, gauges can suffer from errors associated with misreading, an error that is prevalent in many of Canada's automatic recording gauges.

Effect of rain gauge uncertainty on hydrological modelling

Highly variable rainfall fields have a demonstrated effect on runoff modelling (Schilling and Fuchs 1986). The impact of rainfall field variability was investigated by Faures et al. (1995) who studied the effect of varying gauge density and placement on hydrological modelling results for a 4.4-ha semi-arid watershed in southeastern Arizona, USA. By varying the gauges used to generate the rainfall input for the model they found that the peak runoff and the runoff volume varied significantly with a coefficient of variation which ranged from 9 to 76% and 2 to 65%, respectively. This study indicated that in an environment dominated by high-intensity rainfall events with significant spatial variability, rain gauge density and placement can strongly influence predicted stream flows from hydrological modelling, leading to increased uncertainty in model results. The errors within gauge measurements due to systematic and calibration issues also often lead to significant error in subsequent modelling efforts. Habib et al. (2008) examined the effect of tipping bucket uncertainty on the accuracy of hydrological models for a mid-sized watershed in southern Louisiana, USA. These authors determined that wind and dynamic calibration effects can cause variations in hydrograph peak runoff estimations on the order of 5 to 15%.

These uncertainty issues can have a detrimental effect on the ability to use rainfall estimates from rain gauges alone for input into hydrological models for accurate flood forecasting purposes. McClure and Howell (2013) outlined the failure of the Alberta Environment River Forecast Centre to provide warning to the residents of High River, Alberta, during the June 2013 flooding events. By the time a flood warning was issued, the majority of the town was already inundated with flood waters. Hours before flooding occurred, the forecasters updated and ran the hydrological model and found that the flood waters would peak at 650 m^3/s, a flow rate not great enough to fully flood the town. However, hours later the flood flow reached 985 m^3/s which resulted in complete flooding of High River. One of the main reasons attributed to the failure to accurately predict this event is the lack of accurate rainfall estimates and poor or missing gauge readings. The economic consequences of the inaccurate predictions in this example identify the need for re-examination of rainfall inputs used by Canadian flood forecasting centres. The need to improve rainfall estimation has been identified by numerous authors (see e.g. Wilson and Brandes 1979; Kouwen 1988; Borga et al. 2000; Beven 2002; Goudenhoofdt and Delobbe 2009; Looper and Vieux 2012; etc.) leading to the investigation of other methods to increase the accuracy of rainfall estimation.

Rainfall estimation: radar

Weather radar (radio detection and ranging) transmits pulses of microwave signals to detect precipitation in the atmosphere. The microwave pulses travel out from the radar station until they come into contact with particles present in the atmosphere. The reflected energy of the wave is captured by the radar tower, and the quantity of reflected energy (reflectivity in dbz) is related to raindrop size, type and distribution. In the case of rainfall, the raindrop size and distribution is related to the reflectivity using the Marshall–Palmer reflectivity droplet size ratio, Z-R (Marshall and Palmer 1948), following:

$$Z = aR^b \tag{2}$$

where Z is the reflectivity factor measured by the radar station (in dBZ), R is the rainfall intensity (in mm/hr), and a and b are empirical coefficients determined during calibration.

For conventional radar, there exist several different types of radar towers in operational use today, distinguished according to emitted wavelength characteristics as either S-band, C-band or X-band (see Table 1). The typical size of precipitation particles is a determining factor in the size of wavelength used, as there exists an optimal size ratio between the precipitation particle and the radar wavelength (Berne and Krajewski 2013). The optimal size ratio ensures maximum detectability of precipitation while minimizing beam attenuation, as the attenuation by precipitation has a greater effect on smaller wavelengths (Berne and Krajewski 2013). Therefore X-band radar tends to be the most easily attenuated, with S-band radar being the least affected by attenuation of the wavelength. However, the larger S-band wavelength does not detect light rain or snow as well as the smaller wavelengths do (WMO 2008).

The Canadian federal government agency Environment Canada (EC) operates 30 C-band and one S-band radar stations across the country, covering land comprising approximately 90% of the population (Environment Canada 2009). Each radar location has an effective range of 250 km with Doppler capability up to 120 km around the site (Environment Canada 2013a). According to Environment Canada (2009), the purpose of the Canadian Meteorological Radar Network is to provide the country with continuous weather surveillance to enable advanced warning of severe meteorological events. The Canadian C-band radar stations emit 5.6-cm wavelengths, requiring a smaller dish size and less energy to operate, thus making it relatively cost effective. The selection of the optimal radar tower is largely dependent on climate. Accordingly, for the Canadian climate, C-band radar was selected as it is better suited for the detection of solid precipitation (snow) than S-band radar is (Environment Canada 2009). Roughly 80% of the weather radar in use around the world uses C-band radar stations (Environment Canada 2009). The radar networks in Western Europe all rely on C-band radar networks for meteorological surveillance. The United States have adopted S-band radar for their Next Generation Radar (NEXRAD) network, which uses a 10-cm wavelength requiring more energy and a larger dish. S-band radar was selected as the southern states experience numerous high-intensity rainfall events every year and the larger wavelength is not as easily attenuated during these heavy precipitation events (Xie et al. 2006).

Table 1. Weather radar characteristics (modified from WMO 2008, Table I.3.3).

Band	Frequency (GHz)	Wavelength (cm)
S	2–4	5.77–19.3
C	4–8	4.84–7.69
X	8–12	2.75–5.77

Radar for QPE for use in hydrological models began in the early 1960s. Radar was seen to have immense potential in the field of hydrology, as it facilitates the observations of both the location and movement of areas of precipitation within the range of the radar tower, capturing the immense spatial and temporal variability in rainfall fields with a high degree of resolution (Wilson and Brandes 1979). Wilson and Brandes (1979) reported one of the first summaries of weather radar to determine a quantitative measurement of rainfall for use in flood forecasting. For a small catchment in Oklahoma, USA, these authors determined that the spatial distribution of radar had a marked influence on the ability to provide real-time flash flood warning in comparison to rain gauge data. Similarly, Vehvilainen et al. (2004) found that for small catchments in the Baltic Sea region, radar estimates substantially increased the accuracy of flood-forecasting hydrological models during extreme rainfall events. Collier (1986) compared the accuracy of hourly rainfall estimates made using rain gauge and radar data and determined that in order for the rain gauge network to provide a spatial distribution of the rainfall field as accurately as radar, a rain gauge network spacing of one gauge every 20 km^2 was needed. Despite these advantages, in the early stages of its application the lack of knowledge and understanding of the inaccuracies associated with radar imagery limited its widespread use for hydrological modelling (Jayakrishnan et al. 2004; Golding 2009).

Uncertainty associated with radar

The lack of confidence in radar QPE is due to the indirect measurement of the intensity of a rainfall event (Environment Canada 2013d), which introduces uncertainty in measurement accuracy (Goudenhoofdt and Delobbe 2009). Even with substantial improvements in radar signal treatment, significant error still exists in the conversion of raw radar data into QPE (McMillan et al. 2011). Creutin et al. (2000) characterized three major sources of radar error for QPE: (1) electronic instability and miscalibration of the radar system and Z-R relationship; (2) beam geometry; and (3) fluctuation in atmospheric conditions. All three categories of errors can have a significant impact on the ability to use weather radar in hydrological applications. According to Golding (2009), it is the above sources of error that limit the widespread use of radar in hydrological modelling.

The first error outlined by Creutin et al. (2000) relates to the use of the Marshall–Palmer relationship introduced in Equation (2) above. This relationship can be calibrated at each radar location. Once calibrated, the coefficients are held constant (Steiner and Smith 2000). Each droplet, however, does not hold true to the same ratio. Furthermore, the ratio does not hold true for each storm event, and consequently will tend to either underestimate or overestimate the rainfall rate. Vieux and Bedient (1998) and Morin et al. (2006) investigated the effect of manipulating the Marshall–Palmer relationship on simulated hydrographs and found that small manipulations in this relationship can cause substantial changes in the simulated hydrograph.

The second and third categories identified by Creutin et al. (2000) are dependent on the radar environment. These errors include beam broadening, clutter, anomalous propagation, visibility effects, variability in time and space of the vertical profile of reflectivity (VPR), beam power attenuation and issues related to the microphysics of precipitation. These errors affect the measurement of reflectivity from the atmosphere and can result in significant measurement uncertainty. For example, Michelson and Koistinen (2000) demonstrated how beam broadening in a study conducted in the Baltic Sea caused radar accuracy to significantly deteriorate the further the beam traveled. Furthermore, spatio-temporal sampling errors can result from the fact that radar measures rainfall at significant heights above the ground. Between the measurement location and the ground, the rainfall can move substantial lateral distances or even evaporate before reaching the ground. Errors in reflectivity result in significant errors in the subsequent rainfall estimation. A full description of radar environmental errors can be found in Environment Canada (2013d).

Effect of radar uncertainty on hydrological modelling

Numerous studies have attempted to assess the various errors in radar QPE to quantify the corresponding effect on the accuracy of hydrological models. These studies have indicated that uncertainties due to the errors related to calibration and processing can have a detrimental effect on confidence in hydrological modelling results. Borga (2002) studied the impact of errors in radar rainfall estimates on rainfall–runoff modelling in the Brue Catchment in England. Focusing mainly on range-related errors, VPR effects and errors due to miscalibration of the Marshall–Palmer relationship, Borga (2002) observed that the errors significantly affected stream flow simulations resulting in errors of similar magnitude to those in gauge-only simulations. Kouwen and Garland (1989) examined the impact of radar-generated rainfall on a fully distributed hydrological model in the Grand River watershed in southern Ontario, identifying anomalous propagation, clutter and visibility effects as significant sources of error in the estimated rainfall leading to overestimation in predicted peak flows by 10%. Krajewski et al. (2010) attempted to determine if there had been substantial improvements in radar processing technology since the study by Wilson and Brandes (1979) that would lead to improvements in the accuracy of radar QPE. Using upgraded radar and the same gauge network in Oklahoma, USA, as Wilson and Brandes (1979), Krajewski et al. (2010) discovered decreased magnitudes of error in QPE compared to the errors Wilson and Brandes (1979) had found 30 years earlier, concluding that improvements in radar hardware and software have substantially improved radar rainfall estimation. However Jayakrishnan et al. (2004) and Neary et al. (2004), still determined that radar data must undergo correction before they can be used in hydrological modelling.

Uncertainties related to the radar environment also have a profound effect on hydrological modelling confidence. Bell and Moore (1998) investigated the effect of using raw radar data for hydrological modelling and determined that raw radar-derived rainfall estimates significantly increased the accuracy of the hydrological model in small catchments, while it had no significant impact in larger basins. Vehvilainen et al. (2004) summarized similar findings, concluding that in small catchments (less than 500 km^2) where response times are on the order of hours, hydrological models can benefit from the high temporal and spatial resolution of radar data. Borga et al. (2000) explored the impact of mountainous topography on radar QPE, comparing the results of stream flows simulated with raw radar against stream flows simulated with gauge rainfall. Due to significant beam blocking in mountainous regions, radar simulations provided the same accuracy in hydrological modelling as gauge only-driven results (Borga et al. 2000). Therefore, the use of raw radar for rainfall estimation can potentially increase the accuracy of the rainfall input for specific conditions; however, an understanding of location-specific factors is required in order to determine whether radar will aid in rainfall estimation.

A recent Canadian example of the error associated with radar QPE was observed during an extreme rainfall event occurring on 8 July 2013, where heavy rainfall in the Greater Toronto Area caused widespread flash flooding resulting in CAD $1 billion in damage and affecting approximately 300,000 residents (Environment Canada 2014). During this event, the single polarized product from the EC radar tower at King City, Ontario (just north of Toronto) estimated that approximately 27.2 mm of rain fell on the city (Boodoo et al. 2014), while the rain gauge at Pearson International Airport in Mississauga recorded 126 mm over the same period (Government of Canada 2014). This discrepancy is suggested to be a result of attenuation of the C-band wavelength and dome wetting (Boodoo et al. 2014). This example further demonstrates the potential magnitude of radar errors and subsequent consequences caused by using radar QPE operationally for hydrological modelling.

Gauge–radar merging methods

Neither rain gauges nor radar has demonstrated the ability to provide an accurate depiction of the rainfall field. Rain gauges provide accurate point rainfall estimates, but their spatial resolution is limited by the low density of a gauge network and the errors associated with interpolation schemes to fill in missing data. Radar, on the other hand, provides accurate spatial and temporal resolution of the rainfall field at significant heights above the surface of the earth, but numerous measurement errors result in inaccuracies in rainfall depths at the ground. The problems associated with each measurement technique have led to numerous attempts to merge rainfall estimates from the two instruments. This merging allows for the extraction of each instrument's strengths while minimizing individual weaknesses (Erdin 2009). According to Wilson (1970, p. 495): "the combined use of radar and rain gauges to measure rainfall is superior to the use of either separately." It has since been recognized that the combination and adjustment of radar rainfall data with rain gauge accumulations can significantly improve the accuracy of rainfall estimates and subsequent hydrological modelling results (see e.g. Kouwen 1988; Vehvilainen et al. 2004; Kalinga and Gan 2006; Kim et al. 2008; Looper and Vieux 2012; etc.). An extensive review of the literature reveals a number of merging methods that have been developed for operational use to address the limitations of each individual measurement instrument. This paper summarizes the vast majority of gauge–radar merging methods in operational use today. Two merging methods not discussed in this paper are co-kriging (Krajewski 1987) and surface fitting using a multi-quadric surface (Cole and Moore 2008). Co-kriging is not included as its use has decreased due to the approximation methods employed (Todini 2001) and poor suitability for real-time applications (Goudenhoofdt and Delobbe 2009). Surface fitting using a multi-quadric surface is not discussed as its use has been extremely limited. Numerous statistical modifications of the merging methods presented in this paper exist (see e.g. Moore et al. 1989; James et al. 1993); however, the underlying assumptions of the methods are largely identical to the versions presented in this paper.

Gauge–radar merging methods can generally be divided into two categories (Wang et al. 2013): (1) bias reduction techniques and (2) error variance minimization techniques. Each category follows a similar set of assumptions. In the following sub-sections, the merging methods will be discussed according to these two categories.

Bias reduction techniques

Gauge–radar merging methods categorized as bias reduction techniques attempt to correct the bias present in radar accumulations using rain gauge accumulations as the real rainfall value. The radar field represents a background guess which is subsequently adjusted by the known (rain gauge) information. According to Koistinen and Puhakka (1981), the assumptions for bias correction schemes include:

(1) Gauges represent the true rainfall accumulation at the gauge locations;
(2) Radar represents the true spatial and temporal aspects of the rainfall field;
(3) Gauge and radar measurements are valid for the same locations in time and space; and
(4) The relationships developed between rain gauges and radar at gauge locations are valid for other locations in time and space.

It is important to note that these assumptions, although necessary for the adjustment of radar using rain gauges, are false and often lead to erroneous correction factors. Four gauge–radar merging methods categorized as bias reduction techniques will be discussed separately below.

Mean field bias reduction

The mean field bias (MFB) reduction was the first merging method proposed for the correction of measurement bias in radar accumulations (Hitschfeld and Bordan 1954). This method attempts to remove the bias introduced in radar rainfall estimates through the uncertainty in the radar-calibrated Z-R relationship (Borga et al. 2002; Hanchoowong et al. 2012). The correction is, therefore, represented by a single correction factor applied to the entire radar field. Since the rain gauges are assumed to represent the true rainfall accumulation values for bias correction techniques, the mean of the gauge accumulations is assumed to represent the true mean of the rainfall field. Thus, the radar estimates must produce the same mean rainfall accumulation at the gauge locations.

A static, long-term bias correction factor for radar accumulations based on rain gauges was first recommended by Hitschfield and Borden (1954). However, the multiplicative bias in the reflectivity–intensity relationship varies temporally, causing the impact of the static correction factor on the accuracy of the radar rainfall estimates to fluctuate substantially (Smith et al. 2007). A dynamic MFB correction was adopted by Wilson (1970) to continually update the mean correction factor on various temporal scales. The following two steps are taken in order to apply a MFB correction:

(1) The weighted correction factor is calculated using a simple arithmetic mean demonstrated with the following equation according to Wilson and Brandes (1979):

$$C = \frac{\sum_{i=1}^{N} G_i}{\sum_{i=1}^{N} R_i} \tag{3}$$

where C is the correction factor, G_i is the measured rainfall at gauge i, and R_i is the radar measured rainfall at gauge i. The radar measured at the gauge is taken as the spatial integration of rainfall for the radar bin above the rain gauge. The correction factors are obtained at a set time step (e.g. hourly, daily, etc.).

(2) The correction factor is then applied to the entire spatial domain of the radar as it is multiplied with the radar value at each bin location in order to develop the adjusted radar image.

MFB correction has become a widely recognized and applied technique for adjusting radar rainfall grids due to its simplicity and ease in implementation in near-real time. The MFB technique has become a standard merging method for radar images (see e.g. UK Nimrod system; US NEXRAD). Wilson (1970) examined the effect of MFB correction on estimated rainfall accumulations for extreme rainfall events in Oklahoma, USA. For a catchment of 2590 km^2, Wilson (1970) determined that the root mean square error was reduced by 39% after the radar was adjusted using the MFB approach. Wilson and Brandes (1979) discovered large discrepancies (greater than 60% difference) between rain gauge measurements and radar measurements for severe rainfall events in Oklahoma, and determined that by applying a simple MFB correction scheme, this discrepancy decreased by 24%. Borga (2002) used radar corrected with MFB for stream flow predictions in the Brue Catchment, England, and found that corrected rainfall increased model efficiency (i.e. Nash–Sutcliffe) by up to 30% as compared to radar-only rainfall. Many further studies have attempted to combine MFB correction with other merging methods to generate rainfall estimates at a greater degree of accuracy (see e.g. Borga et al. 2002; Jayakrishnan et al. 2004; Kalinga and Gan 2006; Krajewski et al. 2010; Looper and Vieux 2012; etc.).

Brandes spatial adjustment

Brandes spatial adjustment (BSA) is part of a broader category of local bias correction schemes. Local bias correction schemes are similar to MFB correction in that the rain gauges represent the true rainfall accumulation. However, where MFB assumes that the radar biases are evenly distributed across the entire spatial domain, BSA assumes that the biases are spatially dependent. First proposed by Brandes (1975), BSA sought to distribute correction factors across the radar field. Brandes (1975) proposed the use of the Barnes objective analysis scheme (Barnes 1964), a scheme based on the assumption that "the two dimensional distribution of atmospheric variables can be represented by the summation of an infinite number of independent waves" (Barnes 1964, p. 397). BSA uses a distance-weighting scheme with a smoothing factor to determine the influence of a known data point on the interpolated value of a specific radar bin. Proximity controls the influence: the closer the known data point is to the unknown data point, the greater the influence of the known data point. The method determines the value at unknown points as a sum of the determined weights. The technique is a combination of a surface fitting and weighted averaging interpolation methods.

Brandes (1975) suggested two iterations through the objective scheme in order to develop optimal correction factors. The following four steps are taken to determine the correction factors at each radar bin:

(1) The correction factors are calculated at each rain gauge location based on differences between radar estimations and rain gauge accumulations. Similar to the MFB method, the radar measured at the gauge is taken as the spatial integration of rainfall for the radar bin above the rain gauge. The correction factors (C_i) are obtained at a set time step (e.g. hourly, daily, etc.) using:

$$C = \frac{G}{R} \tag{4}$$

(2) The weights (WT) for each radar bin i from each gauge location are determined by:

$$WT_i = \exp\left(\frac{-d^2}{EP}\right) \tag{5}$$

where d is the distance between the gauge and the centroid of bin i, and EP is a smoothing factor based on the rain gauge density.

(3) The correction factors are interpolated across the radar rainfall grid, using two passes (F_1 and F_2) of the multi-pass Barnes interpolation (Barnes 1964), determined by:

$$F_1 = \frac{\sum_{i=1}^{N} (WT_i)(G_i)}{\sum_{i=1}^{N} WT_i} \tag{6}$$

and

$$F_2 = F_1 + \frac{\sum_{i=1}^{N} (WT_i)(D_i)}{\sum_{i=1}^{N} WT_i} \tag{7}$$

where:

$$D_i = C_i - F_{1,i} \tag{8}$$

In the above expressions, WT_i is the weighting of each gauge on radar bin i and D_i is the difference between the gauge and the first-guess estimate.

(4) The spatially interpolated correction factors at each bin are multiplied by the radar rainfall as:

$$R_{new,i} = (R_{old,i})(F_2) \tag{9}$$

where R_{newi}, is the new corrected precipitation value at bin i, and R_{oldi}, is the original rainfall value measured at bin i.

BSA has been demonstrated in numerous studies. Wilson and Brandes (1979) analyzed the effect of MFB and BSA on the accuracy of radar rainfall estimates in Oklahoma, USA. These authors observed that the root mean square error in radar rainfall estimates was reduced from 43–55% without adjustment to 18–35% with a MFB adjustment and 13–27% with BSA, demonstrating that BSA provided significant improvement in the accuracy of radar estimates and improved performance over MFB correction. Using the BSA method to correct radar derived rainfall for use in a distributed hydrological model, Kouwen (1988) observed a significant improvement in the radar-corrected simulated flows against using rain gauge- or radar-only rainfall accumulations. Looper and Vieux (2012) analyzed the impact of using radar rainfall adjusted with BSA versus rain gauge-only rainfall in a fully distributed hydrological model for flood forecasting purposes in San Antonio, Texas, USA, observing that correlation between observed and predicted flows significantly increased with the use of the BSA merging method.

Local bias correction with kriging

Local bias correction with ordinary kriging (LB) applies many of the same concepts identified for the BSA merging method. This method was first proposed as a technique for spatially distributing gauge–radar correction factors over the entire radar domain. The difference between the LB and BSA techniques lies in the distribution of the correction factors. Where Brandes (1975) proposed using the Barnes objective analysis scheme (Barnes 1964) to distribute the correction factors in two dimensions for BSA, LB adopts the geostatistical method of ordinary kriging to distribute the correction factors over the radar spatial domain. Kriging is an optimal interpolation technique which applies a weighted moving average to produce the best local estimate of a regionalized variable (Babish 2000). Kriging is based on a model of the spatial covariance of the data. In this case, the regionalized variable is the correction factor at the gauge location which describes radar bias at discrete locations across the radar field (Seo and Breidenbach 2002). Babish (2000) provided a simple explanation of kriging with the following two parts: (1) the semivariance calculated between each of the regionalized variables is used to generate the shape of the variogram (which displays the semivariance between regionalized variables as a function of distance); and (2) the variogram is then used to determine the weights needed to define the effect of the regionalized variables on the interpolation. A full explanation of ordinary kriging can be found in Wackernagel (2003).

The following steps summarize how the correction factors at each radar bin for the local bias correction technique are determined:

(1) The correction factors (obtained at a set time step) are calculated at each rain gauge location based on differences between radar estimations and rain gauge accumulations (Equation 4). Identical to the MFB and the BSA scheme, the radar measured at the gauge is taken as the spatial integration of rainfall for the radar bin above the rain gauge;
(2) A variogram is developed to explain the spatial correlation as a function of the inter-station distances. From this variogram, kriging weights are then determined for each interpolated location. The weights are then used to develop the unknown correction factors at the interpolated bin locations;
(3) The new grid of correction factors is multiplied by the original radar values to obtain the new corrected rainfall field.

James et al. (1993) analyzed the performance of the LB merging method against BSA and rain gauge-only data in a hydrological model for the Yockanookany watershed in Mississippi, USA. Their analysis examined the effect of the calibrated radar estimates on modeled hydrograph accuracy. The authors found that the LB and BSA merging methods produced significantly superior results in terms of root mean square error as compared to rain gauge-only data. While LB and BSA both produced improved results, neither method proved superior.

Range-dependent bias correction

The range-dependent bias merging method assumes that radar biases are a function of distance from the radar tower (Michelson and Koistinen 2000). As mentioned above, the accuracy of radar estimates deteriorates with distance from the radar tower due to overshooting of the beam, beam broadening, VPR and beam attenuation (Andrieu and Creutin 1995). Michelson et al. (2000) proposed a method which equates the rain gauge to radar ratio as a function of distance, where the relationship is expressed in log-scale and the range is approximated by a second-order polynomial whose coefficients are determined through observation and fitted using least squares fit. The correction factor (C_{RDA}) is determined from:

$$\log[C_{RDA}] = ar^2 + br + c \tag{10}$$

where r is the distance from the radar tower to the radar bin, and a, b and c are coefficients determined through observation and fitted using least squares fit (Michelson and Koistinen 2000).

The range adjustment scheme has been shown to be best applied in combination with other merging methods (see e.g. Michelson and Koistinen 2000; Todini 2001; Goudenhoofdt and Delobbe 2009). For instance, Michelson and Koistinen (2000) examined the effect of combining range-dependent bias correction with BSA in the Baltic Sea Region and found that correlation with an independent gauge network was a significant improvement as compared to unadjusted radar. Goudenhoofdt and Delobbe (2009) used the methodology of Michelson and Koistinen (2000) and came to similar conclusions, observing a significant decrease in the mean absolute error between adjusted radar and unadjusted radar.

Error variance minimization techniques

Error variance minimization techniques attempt to eliminate the bias present in radar accumulations, while minimizing the variance between the two measurements. With minimization of error variance, both radar and rain gauges are assumed to be subject to systematic and random errors that cause the difference between the measurements. Following Wang et al. (2013), error variance minimization techniques are based on the assumption that the error field can be fitted with a mathematical model. Four gauge-radar merging methods categorized as error variance minimization techniques will be discussed separately below.

Bayesian data combination

The Bayesian data combination (BDC) is used not only as a method to eliminate the bias found in radar accumulations by forcing it to the rain gauge data, but also to minimize the variance between the two measurements (Todini 2001). It is also assumed that a rain gauge cannot be directly compared to the integration of radar pixels of over 1 km^2. Todini (2001) proposed the technique to krige the gauge estimates to fit the same grid as the radar grid. According to Todini (2001), the difference between radar and interpolated rain gauge estimates is assumed to be an intrinsic random field, which can be characterized by an experimental variogram. As outlined by Todini (2001), the following steps are performed to apply the BDC merging method:

(1) The rain gauge estimates are block-kriged to fit the radar grid. The difference between the two measurements at each grid location is taken;
(2) The error field is fitted with an experimental variogram to develop a smoothed error field;
(3) A Kalman filter approach is applied to combine the kriged gauge estimates with the modeled error variogram in a Bayesian framework.

Todini (2001) examined the reduction in bias and variance using the BDC merging method in the Reno catchment of Italy, and observed a significant reduction in both bias and variance from the uncorrected radar accumulations. Wang et al. (2013) tested BDC against both uncorrected radar and radar corrected with MFB for an urban catchment in London, England. These authors determined a substantial reduction in the root mean square error for both correction methods against uncorrected radar, and a further improvement in root mean square error for BDC compared to the MFB merging method.

Conditional merging (kriging with radar correction)

Conditional merging (also known as kriging with radar correction) uses kriging to extract the optimal data from each observation set (Pettazzi and Salson 2012). Established by Sinclair and Pegram (2005), conditional merging uses a similar approach to BDC in attempting to remove the bias, while minimizing the variance of error. The process is based on the assumption that the radar observation produces a true field of unknown values, while the rain gauges produce an unknown field of true values (Sinclair and Pegram 2005). The spatial structure of the observed field is based on the radar data and the rain gauge data is fitted into this field using ordinary kriging (described above), thus combining the strengths of each technique (Pegram 2003). The corrected field is determined by the following steps:

(1) The radar values interpolated over each of the gauge locations are found and are kriged in order to create the radar kriged field (R_k);
(2) The difference between the kriged radar field and the original radar field is taken to obtain a correction field with the following equation:

$$\varepsilon_R(s_i) = R(s_i) - R_K(s_i). \quad (11)$$

(3) The correction field is added to the kriged rain gauge surface (G_k) to obtain the corrected rainfall estimates [Corr. Precip(s_i)] at location s_i by the following expression (Sinclair and Pegram 2005):

$$\text{Corr. Precip } (s_i) = G_K(s_i) + \varepsilon_R(s_i). \quad (12)$$

Pettazzi and Salson (2012) compared the accuracy of conditional merging with raw radar on an independent rain gauge network in Italy. Conditional merging was tested for a summer 2011 precipitation event over the city of Galicia, Italy, which resulted in extensive flooding. These authors observed that conditional merging was able to significantly reduce mean absolute error and root mean square error in comparison to raw radar data. Kim et al. (2008) conducted a similar study, examining the effect of conditional merging on the accuracy of generated stream flows from a fully distributed hydrological model in the Anseong-cheon basin in South Korea. Four approaches of rainfall estimation were used: (1) kriged rain gauge only; (2) radar data alone; (3) radar corrected with MFB; and (4) rainfall corrected using conditional merging. Kim et al. (2008) determined that conditional merging provided predicted stream flows that had the lowest mean absolute error, root mean square error, normalized peak error and peak timing error, in comparison to observed stream flows.

Kriging with external drift

Kriging with external drift (KED) belongs to a collection of hybrid non-stationary geostatistical methods that use auxiliary information to improve spatial prediction (Hengl et al. 2003). In this technique, the rain gauge data is used as the primary regionalized variable and radar data is used as the auxiliary information (Erdin 2009). KED is similar to ordinary kriging, except the mean is now a deterministic function of the radar field. The rainfall (P) at location i,j can then be modeled by:

$$P_{i,j} = \alpha + \beta R_{i,j} + z_{i,j} \quad (13)$$

where α and β are the intercept and slope of the linear trend based on the radar data and $z_{i,j}$ is the random process approximated locally by the regionalized rain gauge variable. Therefore, $\alpha + \beta_{i,j} R_{i,j}$ is the deterministic part of the kriging scheme (drift parameter) modeled by the radar data. For more information on KED, refer to Wackernagel (2003).

Erdin (2009) investigated the accuracy of applying KED for extreme rainfall events over Switzerland. In a comparison with LB and radar only rainfall, Erdin (2009) concluded that both KED and LB outperformed raw radar data alone, and KED exhibited the greatest accuracy in determining rainfall accumulations. LB, however, outperformed KED at establishing the spatial structure of the rainfall event. Schuurmans et al. (2007) compared KED to ordinary kriging of rain gauge data over the Netherlands and found that by taking into account radar as secondary information, KED produced more accurate rainfall estimates, particularly over larger areas.

Statistical objective analysis

Statistical objective analysis (SOA), first proposed for the combination of rain gauge and radar data by Pereira et al. (1998), takes advantage of the optimal interpolation equations of Gandin (1965) to generate a corrected field of rainfall estimations. The optimal interpolation equations minimize the expected final error variance. SOA is a computationally intensive merging method (Goudenhoofdt and Delobbe 2009) which computes precipitation estimates at a grid point as a weighted linear function of a background guess corrected by observations. For the case of a rainfall field generated by radar and rain gauges Pereira et al. (1998) proposed the use of radar as the background field, to be subsequently corrected using rain gauges as the observations. The final precipitation field is generated following:

$$P_a(x_i, y_i) = P_r(x_i, y_i) + \sum_{k=1}^{K} w_{ik} \left[P_g(x_k, y_k) - P_r(x_k, y_k) \right], \quad (14)$$

where $P_a(x_i, y_i)$ is the final analyzed precipitation at the grid point i, $P_r(x_i, y_i)$ is the radar rainfall estimate at grid point i, w_{ik} is the posteriori weight at grid point i based on rain gauge location k, $P_g(x_k, y_k)$ is the rain gauge estimate at rain gauge k, $P_r(x_k, y_k)$ is the radar rainfall estimate at rain gauge location k, and x and y are coordinates. The SOA scheme generates weights which minimize the expected error variance of the final precipitation field using the following linear system for the generation of the system of weights:

$$\varepsilon_a^2 = 1 - \sum_{l=1}^{K} \rho_{ki} W_l, \quad (15)$$

where ρ_{ki} is the background cross correlation between grid point i and rain gauge location k, ε_a^2 is the normalized background error and W_l is a posteriori weight. For a full review of the derivation of the SOA equations, see Daley (1991).

Gerstner and Heinemann (2008) investigated the impact of using SOA on an hourly temporal resolution to determine the influence of SOA on accuracy of rainfall estimations in Western Germany. These authors found that in 78% of the comparisons between SOA merged rainfall estimations and raw radar alone, there was a marked improvement in the root mean square error. This improvement resulted in a reduction by 48% in the root mean square error averaged over the 8-month study period. Kalinga and Gan (2006) studied the effect of using SOA to merge rain gauge and radar rainfall estimates on modeled stream flow accuracy from a semi-distributed model in the Blue River Basin of South Central Oklahoma. These authors concluded that the use of SOA as compared to raw radar alone substantially increased model efficiency (Nash–Sutcliffe), particularly during stratiform events.

Selection of appropriate gauge–radar merging methods

The selection of appropriate gauge–radar merging methods is influenced by several location-specific environmental and operational factors. These factors can influence the reliability of radar estimates and gauge–radar merging methods, and include:

(1) The rain gauge network density;
(2) The climate and storm characteristics;
(3) The proximity of the radar station;
(4) The basin response time; and
(5) The time-step of adjustment.

In the selection of an optimal rainfall estimation technique it is important to understand the influence of the above factors on the uncertainty of the rainfall estimate. These factors are inter-related, which makes quantifying the exact numerical uncertainty on the final accuracy a difficult task. Therefore, in the selection of an optimal estimation technique, all factors need to be considered. Furthermore, the diversity of geographic locations in case studies conducted makes comparison of the merging methods difficult and presents an obstacle for establishing best practices. This section discusses these influencing factors separately, summarizing previous attempts to compare various merging methods and identifies opportunities for future research.

Influencing factors

Rain gauge density can play a large role in the assessment and accuracy of gauge–radar rainfall estimates. In general, there are three main conclusions that are determined through a sensitivity analysis of gauge density. First, studies conducted in basins with a high density of rain gauges often conclude that rain gauge estimates alone outperform gauge-adjusted radar. This is due to the ability of the high-density rain gauge network to characterize the spatial variability in the rainfall field. For example, Goudenhoofdt and Delobbe (2009) determined that rain gauges alone had greater accuracy than MFB and range-dependent bias correction at densities greater than one gauge per 330 km^2 and 250 km^2, respectively. The density in the study was decreased to a minimum of one gauge per 175 km^2, where it was found that even at this density spatial adjustment and error variance minimization methods still provided better accuracy than rain gauges alone. Second, changes in density affect individual merging methods differently. Goudenhoofdt and Delobbe (2009) found that the impact of gauge density varied between gauge–radar merging methods, with a decrease in density having the largest effect on spatial adjustment methods and error variance methods, while having a less pronounced influence on MFB reduction and range-dependent bias correction. Finally, the increase in accuracy due to increasing the gauge density is not linear – substantial increases in accuracy occur initially as gauge density increases; however, at a certain gauge density the increase in accuracy asymptotically approaches a finite value. Biggs and Atkinson (2011) observed that while the role of rain gauge density is significant, the greater accuracy provided due to increases in network density yields at a certain point. In a 2065-km^2 basin of the Severn River, England, these authors observed that the use of six gauges for radar correction provided similar accuracy to using 12 gauges. The accuracy decreased with less than six gauges, demonstrating the influence of gauge network density on the accuracy of gauge–radar merging methods. It is important to note, however, that the results from these studies are not transferable between basins as the effective density is influenced by basin topography, climate, gauge distribution, temporal time-step of adjustment and merging method selected. Therefore, it is recommended that a sensitivity analysis be conducted in order to identify the effect of gauge density on rainfall estimations for any particular basin.

Numerous studies (e.g. Stellman et al. 2001; Kalinga and Gan 2006; Erdin 2009; etc.) indicate that storm type has a significant influence on the accuracy of the gauge–radar merging methods. These studies reveal that radar tends to under-estimate rainfall during large magnitude convective events and over-estimate rainfall for stratiform storms. Smith et al. (2007) examined the effect of using radar-corrected rainfall rates for flash flood forecasting in a small urban catchment in Baltimore, Maryland, USA. The rainfall rates were corrected on an event basis using the MFB reduction merging method.

Individual event biases (gauge to radar ratio) were identified ranging from 0.41 (overestimation) to 2.77 (underestimation). According to these authors, the variation in the individual event biases varied as a result of storm type and magnitude, with convective storms producing higher biases and larger magnitudes than stratiform storms. Smith et al. (2007) concluded that correcting based on storm type significantly increased correlation between observed and predicted flood flows. From the analysis of the variation in accuracy due to storm types, it is evident that the addition of radar rainfall estimates is beneficial for the estimation of rainfall from convective cells and provides little to no added benefit in the estimation of rainfall from stratiform or frontal events. This is due to the timing and distribution of the rainfall and its impact on the error of rain gauges alone. Convective cells are characterized by localized high-intensity rainfalls of short duration which are often mischaracterized by rain gauges but picked up by radar, whereas stratiform or frontal events are characterized by widespread low-intensity rainfalls of relatively long duration which rain gauge networks can characterize. In order to adjust radar estimates in stratiform events, local bias adjustment is often unnecessary as MFB correction alone can significantly increase accuracy. Therefore, in basins in which high-intensity localized rainfall events are a concern, the addition of radar for rainfall estimation can substantially increase the accuracy of the estimated rainfall field.

As indicated, proximity to the radar tower influences the accuracy of the radar estimate. The accuracy of radar rainfall estimates deteriorate with distance from the radar tower. This is due to a variety of errors, including beam broadening, beam overshooting, beam attenuation and the area of integration. According to Michelson and Koistinen (2000), at distances greater than 50 km from the radar tower, the addition of range-dependent bias correction increases the accuracy of the rainfall estimates. Therefore, for basins located outside of 50 km, a range-dependent bias correction scheme should be introduced to mitigate the error due to range-related biases.

The need for radar in QPE is dependent on the basin characteristics related to the response time of the basin being modeled. The addition of radar is beneficial in basins with response times on the order of hours (Gjertsen et al. 2004). This is because these basins are heavily affected by high-intensity localized events that require rainfall estimation on small spatial and temporal scales to quantify. This generally includes basins which are smaller in size with surfaces conducive to generating high volumes of excess runoff in short periods of time; i.e. urban, clays, saturated conditions, etc. For larger basins with slower response times the addition of radar has been demonstrated to be less beneficial, as flows are shown to be less affected by short-duration high-intensity rainfall. In instances where larger time-steps (greater than 24 hours) can be used to accurately model basin response, rain gauges alone can often accurately quantify the rainfall field (Gjertsen et al. 2004). While the addition of radar has been demonstrated to be beneficial in modelling small basins, larger basins can also benefit from the addition of radar in remote areas where rain gauge density is extremely limited.

The temporal resolution of rainfall accumulation plays a significant role in the accuracy obtained in radar and rain gauge accumulations. Rainfall accumulations with a high temporal resolution are often required for flash flood modelling. According to Berne and Krajewski (2013, p. 357):

> because precipitation exhibits a strong spatial and temporal variability over a large range of scales, the hydrological research and operational communities need more reliable precipitation estimates and forecasts with increasingly high resolution (i.e. a few kilometers-minutes and below) to adequately capture the dynamics of precipitation events in space and time.

The time-step required for modelling can affect the use of radar in hydrological modelling for two main reasons. First, altering the time-step of adjustment (i.e. the time-step in which rainfall accumulation comparisons are made) is important due to the spatio-temporal sampling errors caused by the assumption that gauge and radar measurements are valid for the same locations in time and space (Kitchen and Blackall 1992). Rain gauges provide point measurements while radar provides a volumetric integration of the atmosphere at a significant height above the rain gauge. The direct comparison between the two data sources at different elevations causes spatio-temporal sampling errors. The magnitude of these errors is affected by the temporal scale at which the accumulation comparison is made, with the comparison naturally becoming stable for longer time-steps as the error fluctuations are averaged out over time. By increasing the time-steps, however, the comparisons may miss out on the short-term variations due to variable meteorological conditions that may, in turn, affect the accuracy of the adjusted radar estimate. It is important to find a balance between the two error sources (Gjertsen et al. 2004). Spatially-dependent bias correction methods are most affected by a change in the time-step. This is due to the fact that at shorter time-steps variations between the gauges and radar are more pronounced, leading to large variations in the correction factors at individual gauge locations. These large variations, however, tend to be averaged out in the MFB method and in error variance methods where more weighting is placed on the gauge observations in situations with large error fluctuation between gauge and radar. Second, gauge estimates and gauge-adjusted radar converge to similar levels of accuracy as the time-step required increases above 24 hours. As the time-step increases above 24 hours, the spatial and temporal advantages offered by radar decrease in importance as the error due to spatial and temporal variations in gauge estimates are averaged out. The vast majority of the studies presented in this paper have identified case studies in which the gauge–radar merging schemes were conducted on daily or event-based temporal resolutions. This resolution is often too coarse for operational purposes in basins with quick response times. Further research into the effect of gauge–radar merging methods on hydrological models at an hourly resolution (or less) is still required.

The inclusion of radar data presents an additional issue in terms of data management and computational requirements. In selecting an appropriate merging method, it is important to examine the computational requirements. Radar data sets are large and efficiency is required in collection and storage. Manipulation of the data sets with the incorporation of rain gauges can be computationally intensive. More complicated merging methods such as the error variance methods requires greater computational effort than simple MFB and local correction methods. The ability to collect, merge and store radar data is important to consider while dealing with large radar data sets.

Comparison of gauge–radar merging methods

No previous study has provided an in-depth comparison of all gauge–radar merging methods discussed in this paper. Case studies are primarily done to assess the viability of implementing one of the merging methods, comparing the corrected rainfall against rain gauge-only data or radar-only data. Several studies have compared various merging methods in particular geographic locations (see e.g. Kim et al. 2008; Goudenhoofdt and Delobbe 2009; Erdin 2009; etc.). The results of these studies tend to be similar to the conclusions of Goudenhoofdt and Delobbe (2009), who compared seven major merging methods in a study conducted in the Netherlands. The mean absolute error and the root mean square error were used as measures of accuracy to compare the daily estimated corrected rainfall values against an independent rain gauge network. Goudenhoofdt and Delobbe (2009) examined: (1) mean field bias correction; (2) range-dependent adjustment; (3) static local bias correction and range dependent adjustment; (4) Brandes spatial adjustment; (5) ordinary kriging of rain gauge data only; (6) conditional merging (kriging with radar based error correction); and (7) kriging with external drift. These authors determined that all correction and merging methods outperformed raw radar alone. In terms of the greatest accuracy, KED was determined to provide the best representation of the rainfall based on spatial distribution and accumulated rainfall volumes. Goudenhoofdt and Delobbe (2009) concluded that error variance minimization methods outperformed bias correction schemes due to the use of optimal interpolation to combine the two data sets, which took into account the covariance structure of the data, reducing bias and minimizing variance. The variability of results from the studies presented in the literature make drawing general conclusions on gauge–radar merging methods difficult. Furthermore, factors that influence accuracy make the selection of an estimation technique for operational purposes challenging. With geographic and operational concerns playing a key role, it is important to test each individual merging method to assess which best suits the environment and constraints of a particular location. Few studies examine the wide range of available gauge–radar merging methods for a variety of different scenarios (i.e. temporal resolution). Therefore, the effect of each of the influencing factors on different merging methods has not been determined. Due to the variability in rainfall fields, watershed geography, rain gauge networks and radar environment, it is challenging to establish standard practice regarding gauge–radar merging methods. The lack of studies conducted in Canada, particularly those conducted at high temporal resolutions (e.g. on an hourly basis), using EC radar makes further assessment necessary. This should determine whether EC radar merged with rain gauge data can be applied on an hourly basis to generate accurate spatially distributed rainfall fields for use in hydrological models.

Opportunities and recommendations

Several radar-related challenges persist that, if answered, could significantly improve the quality of radar estimates in hydrological modelling. First, the development of measures to improve radar estimates in mountainous terrain environments is required, as the interaction between this type of terrain and the atmosphere increases rainfall pattern variability. Second, the incorporation of snow algorithms is required to enable the continual determination of snowpack. This is particularly important for northern regions such as Canada, where spring melt is the dominant source of flooding events. Third, merging methods need improvement at shorter time-steps in heavily urbanized basins where rainfall estimates are required on the order of minutes in order to quantify the predicted flow in the appropriate time frame. Currently, merging methods have been shown to improve accuracy mainly at time-steps of 1 hour and greater. However, at time-steps of less than 1 hour, accuracy approaches that of raw radar alone due to spatio-temporal sampling errors involved in the direct comparison of radar and gauges. Quantifying the spatio-temporal sampling uncertainties at shorter time-steps will aid in developing greater accuracy in rainfall estimation techniques.

Recently, greater focus has been put on the incorporation of radar and rain gauge data into QPE ensemble products with satellite imagery and numerical weather models. The incorporation of radar-based rainfall estimates as input can make substantial improvements in QPE ensemble products. These products rely on empirically based modelling of the uncertainties associated with the individual estimation techniques to develop a product in which the uncertainty is known. A recent example is the development of the Canadian Precipitation Analysis (CaPA) system in Canada. The current operational form of CaPA was released in 2011 and uses the optimal interpolation scheme as outlined in Daley (1991) to adjust rainfall forecasts provided by the Global Environmental Multiscale (GEM) model based on ground observations from rain gauges (Mahfouf et al. 2007). The current operational configuration of the CaPA system does not use radar information as part of the data assimilation process. Initial testing of the CaPA system used radar QPE as observation; however, the inclusion of radar decreased the accuracy of the estimates due to the numerous errors present in radar QPE (Fortin et al. 2014). This led to a significant upgrade to the unified radar processor (URP), the software used to convert reflectivity at Canadian radar stations to rainfall. The current experimental version of CaPA includes radar QPE. The experimental version was compared against the operational system during a test period in the summer of 2013. Using two categorical scores (frequency bias indicator and the equitable threat score), significant increases in the accuracy (in locations within 120–125 km of an EC radar tower) of the generated rainfall grid were observed with the addition of radar observations (Fortin et al. 2014). While rainfall ensemble products such as the CaPA system are able to use the available information to provide accurate rainfall estimates, the spatial and temporal resolution are often coarse. This can make implementation into hydrological models at the basin scale and within "flashy" watersheds challenging. Further research is needed to increase the temporal and spatial resolution of rainfall ensemble products such as CaPA in order to make greater use of such products at the basin scale.

Although the use of radar in hydrological modelling is known to increase the accuracy of rainfall estimates and corresponding confidence in hydrological modelling output in certain circumstances, operational use of radar in hydrological modelling remains limited. This paper provides a comprehensive summary of the use of gauge–radar merging methods which will assist in the implementation of radar products in operational circumstances. While numerous studies have shown that the inclusion of radar in hydrological modelling can improve the accuracy of simulated stream flows, few Canadian studies have been conducted at a basin scale to assess the viability of using gauge–radar rainfall estimates from Environment Canada's radar network. Such research is of the utmost importance in order to advance the use of radar-based ensemble products in operational applications.

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