



Merging weather radar data and opportunistic rainfall sensor data to enhance rainfall estimates

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ABSTRACT

Accurate rainfall estimates with high spatiotemporal resolution are vital for urban drainage applications, and if adjusted to ground observations, weather radar data has potential for these applications. The density of meteorological rain gauges for adjustment is, however, often sparse and non-uniformly distributed in space. Opportunistic rainfall sensors provide an increased density of ground observations but often with reduced or unknown accuracy for each individual station. This paper demonstrates the merging of data from weather radar, personal weather stations, and commercial microwave links into an integrated rainfall product. Merging opportunistic rainfall estimates is shown to improve the accuracy of the opportunistic rainfall observations through a quality control algorithm. In this study, we show that the accuracy of rainfall estimates is significantly improved by merging opportunistic rainfall data and weather radar data when compared to the accuracy of each rainfall product without merging. Nash-Sutcliffe efficiency (NSE) values up to 0.88 are obtained for daily accumulated merged rainfall products, while the NSE-values of the individual rainfall products range from −7.44 to 0.65, and similar tendencies are observed for root mean squared error (RMSE) values. For merging weather radar and opportunistic rainfall data, a novel approach, i.e., “moving median bias adjustment” is presented. Applying this approach, a high-performing rainfall product is derived independently from conventional high-quality rain gauges, which in this study are only used for independent validation. In addition, it is demonstrated that accurate rainfall estimates can be obtained by sub-daily merging, underscoring the importance of merging in nowcasting and near real-time applications.

1. Introduction

Obtaining accurate and precise rainfall estimates over larger areas is challenging. Reliable rainfall estimates are crucial for designing, analyzing, and managing urban hydrological systems, and a high spatiotemporal resolution is required for accurate estimates of runoff from urban areas (Berne et al., 2004; Tetzlaff and Uhlenbrook, 2005; Ochoa-Rodriguez et al., 2015). Traditional tipping bucket rain gauges are known to provide rainfall measurements with high temporal resolution and relatively high accuracy. Point observations of rainfall may, however, cause the spatiotemporal variability of convective storms in particular to not be fully captured due to the low density of the rain gauge network (Pollock et al., 2018). Seed and Austin (1990) showed

that for capturing convective storms on a daily scale, a rain gauge network density of one gauge per 150 km² is needed. Weather radars provide rainfall estimates with high spatiotemporal resolution making this technique essential in urban drainage applications. The spatial coverage of weather radar rainfall furthermore facilitates extrapolation of the rainfall field motion and thus short-term precipitation nowcasting.

As a result of weather radars providing indirect measures of rainfall derived from measured radar reflectivity, merging with ground observations of rainfall is a prerequisite for obtaining accurate rainfall estimates with weather radars. Radar-rain gauge merging has been shown vital for the performance of both radar rainfall estimates and radar nowcast, and several techniques for radar-rain gauge merging have been

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developed to improve weather radar rainfall estimates (e.g., Vieux and Bedient, 2004; Goudenhoofd and Delobbe, 2009; Wang et al., 2013; Thorndahl et al., 2014a; McKee and Binns, 2016). A thorough review of radar-rain gauge merging methods is presented in Ochoa-Rodriguez et al. (2019).

The mean field bias is one of the simplest and most efficient merging methods (Smith and Krajewski, 1991). This method provides a single, uniform multiplicative factor for the entire area which is the most significant drawback of the method, as spatial-dependent biases are not adjusted. More complex geostatistical methods have been developed with kriging with external drift (KED) (Haberlandt, 2007) being the most widely applied method within this category (Ochoa-Rodriguez et al., 2019). KED has been shown to perform better than ordinary kriging (OK) (Berndt et al., 2014), which suffers from the drawback of often underestimating the spatial variability of rainfall (Shehu and Haberlandt, 2021). Co-kriging (CoK) (Krajewski, 1987) is a widely used integration method in which the weather radar data and the ground observations are merged based on quantification of the spatial correlation between the measurements, and hence, the weather radar measurements affect the merged rainfall product (Ochoa-Rodriguez et al., 2019; Shehu and Haberlandt, 2021). Reliable nowcasts for forecasting the consequences of severe rainfall in urban drainage systems nonetheless require merging weather radar and ground observations before rainfall reaches urban areas. This leads to a need for a dense ground observation network both within and also around the area of interest. In many areas, the meteorological rain gauge network density is too sparse and potentially results in a lower quality of the weather radar rainfall product; hence, opportunistic rainfall sensors offer the potential to complement meteorological rain gauge measurements and thereby increase the network density.

Crowdsourced rainfall data from personal weather stations (PWS) for urban hydrological purposes has been widely studied (e.g., de Vos et al., 2017; Graf et al., 2021; Overeem et al., 2023). The main advantage of PWS is the quantity of data in comparison to meteorological rain gauge networks, and – since the PWS quantity is highly correlated with the population – the density is particularly high in urban areas. Some manufacturers, e.g., Netatmo (2023), make this data available through an application programming interface (API) if the station owner agrees. For Netatmo, PWS rainfall data is provided in near real-time (available at 10-min intervals) in relatively high temporal resolutions (down to 5 min), making the data highly relevant in urban hydrology and real-time applications. The quality of the PWS data is, nevertheless, not expected to match the quality of meteorological tipping bucket rain gauge data. A potential lower quality of PWS data is caused by hardware quality, software, lack of maintenance, and how the PWS station is set up in the surroundings (de Vos et al., 2017; Bárdossy et al., 2021; Hahn et al., 2022). Quality control (QC) of crowdsourced rainfall products is hence crucial and has led to several methods being developed and tested for crowdsourced rainfall data (de Vos et al., 2019; Bárdossy et al., 2021; Båserud et al., 2020).

Rainfall estimates derived from commercial microwave links (CML) – which have the primary purpose of providing telecommunication systems – have been studied for almost two decades (Messer et al., 2006; Leijnse et al., 2007). Rainfall droplets cause attenuation of the wave radio signal between the telecommunication antennas, and (based on this attenuation) rain rates are derived from CML as path-integrated rainfall information. CML-derived rainfall estimates have been studied extensively and have been shown to complement rain gauges (e.g., Overeem et al., 2016; Andersson et al., 2017; Messer, 2018; Uijlenhoet et al., 2018; Pastorek et al., 2019; van de Beek et al., 2020; Graf et al., 2021; Andersson et al., 2022). Similar to PWS, the density of CML is correlated with population density. The derived rainfall estimates from CML have a high temporal resolution (down to a few seconds), and the length of the links typically ranges from approximately 100 m to a few tens of kilometers.

Weather radar measurements have bin or pixel sizes normally in the

range of 0.01–16 km², whereas rain gauges typically have a collecting area of approximately 200 cm². This difference in measurement scales is known to cause discrepancies in rainfall estimates due to different representativeness (Schilling, 1991; Krajewski and Smith, 2002; Einfalt et al., 2004; Villarini et al., 2008; Peleg et al., 2013; Thorndahl et al., 2017; Schleiss et al., 2020; Thomassen et al., 2022). The more comparable measurement scale of CML and weather radar data potentially leads to fewer discrepancies in representativeness and thus derived rainfall estimates. The high spatiotemporal resolution of CMLs in urban areas favors these opportunistic rainfall products in urban hydrological applications. CML-derived rainfall estimates are, however, subject to uncertainties caused by erratic signal behavior, wet antennas, and temporal blockage of the signal attenuation from non-meteorological obstacles (Upton et al., 2005; van Leth et al., 2018).

The high spatial density of opportunistic rainfall sensors in urban areas proposes a potential to improve spatiotemporal rainfall estimates. Graf et al. (2021) showed that spatially interpolated rainfall maps derived from CML and PWS have significant potential, especially regarding smaller temporal and spatial scales. Overeem et al. (2023) studied the majority of Europe and demonstrated that merging weather radar data with crowdsourced rainfall data from PWS improves precipitation information. The results of the study showed that merging weather radar data and opportunistic data can improve rainfall estimates for urban hydrological applications in areas with few or no meteorological rain gauges.

The objective of the research presented in this article is to investigate if merging data from weather radar and opportunistic rainfall sensors can enhance rainfall estimates relative to the individual rainfall products. We study if merging opportunistic rainfall products, i.e., PWS and CML, through the QC method developed by de Vos et al. (2019) improves rainfall data quality. Merging weather radar and opportunistic rainfall data is carried out by applying three different strategies: mean field bias adjustment, inversed distance weighting interpolated bias adjustment, and moving median bias adjustment. The moving median bias adjustment is a novel approach presented in this paper to investigate if the merged rainfall product is enhanced by applying the spatially distributed bias adjustment with a median filter on a daily and a sub-daily time scale of relevance for near real-time applications and nowcasting. For independent evaluations of the rainfall products, a dense network of meteorological rain gauges is used.

2. Materials and methods

A region in Northeastern Zealand, Denmark with a high density of meteorological rain gauges and opportunistic sensors and a coverage of a C-band weather radar is chosen for this study (Fig. 1). The study region covers an area of 2200 km² and includes both the capital city (Copenhagen) and suburban areas. 70 meteorological rain gauges are located in the area, resulting in an average density of one meteorological rain gauge per 31.5 km².

Rainfall data from September 2019–September 2020 is processed for this study. Approximately 1000 PWSs with rain gauge modules from the manufacturer Netatmo are active during this period. These stations are mainly located in urban areas. Nonetheless, within Greater Copenhagen, where residential areas are primarily dominated by apartment complexes, the density of PWS rain gauges decreases. A total of 186 CMLs – each having two sub-links – are available within the study region for this research. As opposed to PWS rain gauges, the density of CML is highest in Greater Copenhagen where the population density is highest.

2.1. Rainfall data

Opportunistic rainfall data from CML and PWS from September 7, 2019 to September 30, 2020 is available. Due to a malfunction of the weather radar, weather radar data is not available from April 28, 2020, to July 5, 2020. In total, 10.5 months of overlapping rainfall data are

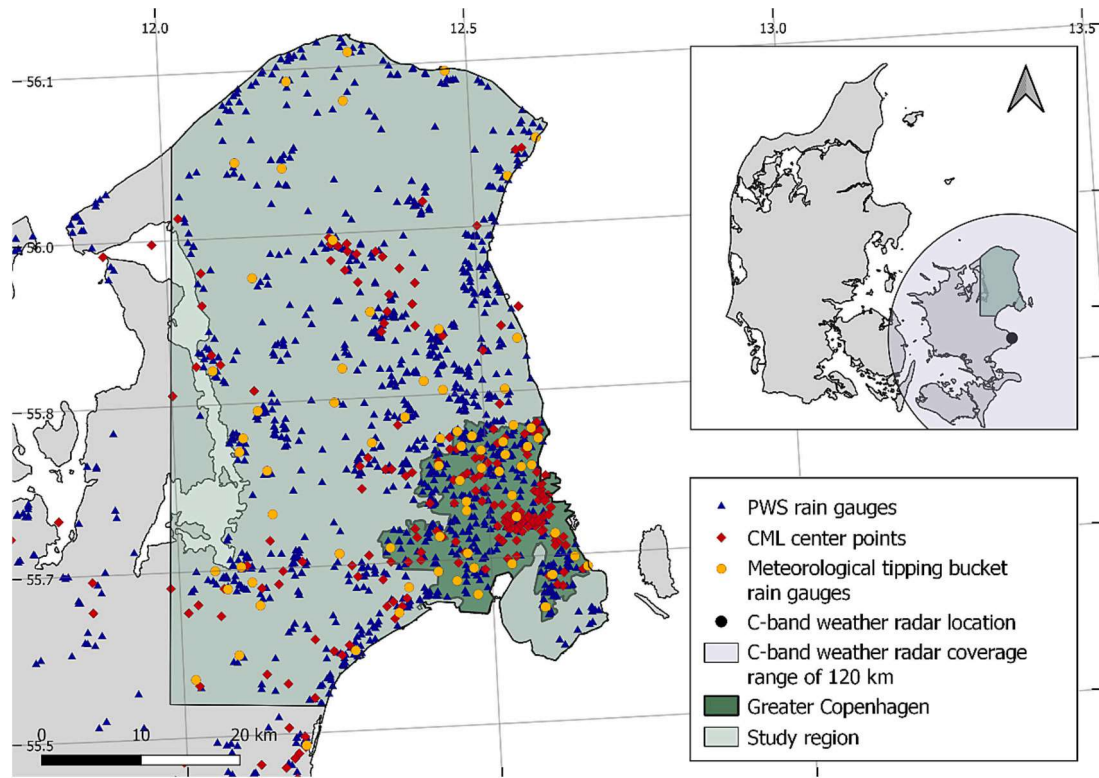


Fig. 1. Study region in Northeastern Zealand, Denmark with the location of the C-band weather radar, PWS rain gauges from Netatmo Weathermap, CML (center points of links) from the network of the mobile operator Hi3G AB, and meteorological tipping bucket rain gauges.

available for this study.

2.1.1. Weather radar data

The C-band weather radar used for this study is a part of the national weather radar network covering Denmark and is owned and operated by the Danish Meteorological Institute (DMI) (Gill et al., 2006). The weather radar is located approximately 50 km south of the study region, and the quantitative precipitation estimation (QPE) range of 120 km covers the region (Fig. 1). The C-band weather radar scans the atmosphere every 10 min at nine elevation angles. The polar scan volume is processed to a cartesian pseudo-CAPPI product of $500 \times 500 \text{ m}^2$ at 1000 m elevation. Corrections are applied to the weather radar data by DMI to account for typical error sources, and the data is thus the best available radar data covering the study region. The corrections are not based on ground observations, and the weather radar data is hence independent from rain gauge measurements. For this study, the weather radar data is interpolated to one-minute temporal resolution by applying the advection-based interpolation method developed by Nielsen et al. (2014), which Thorndahl et al. (2019) and Andersen et al. (2022) have proven to improve short-duration weather radar rainfall estimates. The weather radar-measured reflectivity is converted into rain rates by applying the Z-R relationship by Marshall and Palmer (1948):

$$R = \left(\frac{Z}{A} \right)^b \quad (1)$$

Where R denotes the rain rate [mm/h], Z is the measured weather radar reflectivity [mm^6/m^3], and A and b are power law parameters set to 200 and 1.6, respectively (Marshall et al., 1955). Setting the power law parameters to constant values is known to cause temporal biases, as the Z-R relationship depends on the drop size distribution of the rainfall which may vary between or within rainfall events depending on the atmospheric state and conditions. Merging weather radar data with ground observations is thus typically necessary to obtain valid rainfall estimates from weather radar data (Thorndahl et al., 2014a).

The merging of weather radar and ground observations is typically performed by applying a multiplicative bias correction factor determined as the ratio of ground observation rainfall to weather radar rainfall. In this study, bias factors are derived by hours with observed rainfall in both weather radar and opportunistic sensors. This approach ensures that daily or sub-daily bias adjustments are not affected by temporal outages in either the weather radar or opportunistic sensors.

2.1.2. Commercial microwave link data, CML

The CML data used for this study is collected by Ericsson AB from the network of the mobile operator Hi3G AB and processed by the Swedish Meteorological and Hydrological Institute (SMHI) for deriving rain rates. A selection of 186 links within the study region (Fig. 1) was made. Derived rain rates are extracted for each of these links, and the geographic positions are defined as center point coordinates along the link paths. In general, CML processing has the following four steps: 1) conversion of transmitted (TSL) and received signal (RSL) to attenuation, 2) wet-dry classification, 3) baseline attenuation derivation, and 4) conversion of attenuation to rain rates. A thorough description of the workflow for deriving rain rates from CML is provided by Chwala and Kunstmann (2019). At SMHI, the processing of CML data is performed using the MEMO® software developed by SMHI (2023).

The conversion of TSL and RSL to attenuation is accomplished by calculating the difference between TSL and RSL 10-s values and performing basic checks for erroneous data. The median 10-s values (A_{ml}) are then aggregated into one-minute periods.

The rain-induced net attenuation (k) is derived relative to a baseline attenuation. During dry weather periods, the baseline is determined as the median attenuation (A_{ml}) setting k equal to zero in dry weather. The baseline in wet weather periods is derived as A_{ml} measured over a set dry period before the wet weather. This set period should be long enough to represent the baseline well before a wet event while being short enough to minimize the effect of possible data drifts or jumps in TSL or RSL.

The net attenuation [dB/km] is converted to rain rates (R) [mm/h]

by applying the k-R relation defined in ITU (2005):

$$k = c \cdot R^d \quad (2)$$

In which c and d are parameters depending on frequency and polarization. Hence, these parameters vary between links, and standard values for c and d provided in ITU (2005) are applied. Shorter links are more prone to overestimation and require stronger adjustment; thus, an additional bias adjustment is applied based on link length. This bias adjustment is based on errors observed between rain gauges and CML-derived rain rates in the Gothenburg region, Sweden (Andersson et al., 2017). Due to the similar climates in Gothenburg, Sweden, and North-eastern Zealand, Denmark, the bias adjustment is assumed applicable within the study region.

2.1.3. Personal weather station data, PWS

Personal rain gauges from the manufacturer Netatmo (2023) are, in this study, used for merging with CML and weather radar data. Netatmo rain gauges have a rainfall collecting area of approximately 133 cm² and a plastic tipping bucket with a volume equivalent to 0.1 mm of rainfall. The measurement range is by the manufacturer specified as 0.2–150 mm/h with an accuracy of 1 mm/h (Netatmo, 2023). For a more detailed description of the Netatmo rain gauges, see de Vos et al. (2017). If the user agrees, the Netatmo rainfall data is available online on the Netatmo Weathermap every ~10 min. In addition, the rainfall data is available through an API with a temporal resolution of up to 5 min. For this study, Netatmo rainfall data from approximately 1000 PWSs is obtained through the Netatmo API. The rainfall data is available at different temporal resolutions. For this research, five-minute rainfall data has been collected and temporally accumulated to obtain one-hour rainfall estimates.

The users are encouraged by the manufacturer to calibrate the rain gauge by specifying the tipping bucket volume. Manual calibration by the users might, however, lead to wrong rainfall measurements depending on the calibration technique and accuracy. To avoid data inconsistency caused by erroneous calibrations, any user calibration is removed from the dataset.

2.1.4. Reference rain gauge data

In this study, meteorological tipping bucket rain gauges with a temporal resolution of one minute are used as reference rainfall observations. The meteorological rain gauges are a part of the model series RIMCO and are a part of the national rain gauge network covering Denmark and managed by The Water Pollution Committee of The Society of Danish Engineers. The rainfall is measured by detecting the tipping of an internal bucket occurring every time the bucket fills with water of a volume equivalent to 0.2 mm of rainfall (Madsen et al., 1998; Mikkelsen et al., 1998). A total of 70 meteorological tipping bucket rain gauges are located within the study region (Fig. 1). For this study, it is important to note that the meteorological rain gauges are only used for independent validation and thus not for deriving the merged rainfall product.

2.2. Quality control of opportunistic data

The QC algorithm by de Vos et al. (2019) is applied to the opportunistic rainfall data. The QC algorithm flags suspicious and incorrect rainfall observations based on a comparison with the surrounding observations. Stations are flagged based on three assessments: 1) if they are assessed to report zero values during rainfall events, 2) if high reported values are not assessed to be caused by rainfall, or 3) if the station is evaluated as having a wrong location based on low correlation with the neighboring stations. The QC algorithm is applied to both PWS and CML as an individual QC for each of the two types of opportunistic rainfall data. Also, a merged opportunistic rainfall product is produced by applying the QC method to all opportunistic rainfall data as a whole;

hence, both CML and PWS contribute to filtration and bias correction across the two data types.

The average density of PWS within the study region (1 PWS per 2.1 km²) is approximately four times higher than the average density of PWS used by de Vos et al. (2019). Therefore, we use a search radius of 5 km for finding neighboring PWSs corresponding to one-fourth of the area of the search field used by de Vos et al. (2019). The radius of 5 km is also used for QC of the merged opportunistic rainfall data product. Due to the lower density of CML than PWS, a search radius of 10 km (similar to de Vos et al. (2019)) is used for the individual QC of CML data.

Stations with few (less than five) neighboring stations are flagged in this study and thus not used for merging with weather radar data, as not enough data is available to determine if the station quality is adequate. Moreover, the observations are bias-corrected if the station has a systematic bias compared to the time series of neighboring stations. The method is described in detail in de Vos et al. (2019).

Erroneous high influx values are flagged if the station value is >10 times higher than the median of the surrounding stations, and the station's hourly rainfall measurement is >5 mm higher than the median. Flagging non-high influx values as erroneous observations may be critical if a rainfall product is derived based on a single data product; however, accepting too much erroneous station data is more critical for merging, as more noise might propagate to the merged rainfall product. The applied thresholds differ from the thresholds applied by de Vos et al. (2019) and lead to flagging more observations; even so, only 1.1% of the opportunistic rainfall data is flagged. The applied thresholds are chosen based on evaluating the performance of the opportunistic rainfall estimates and the number of flagged observations with different thresholds. From this, it has been observed that less strict thresholds lead to lower performance for both CML and PWS, while stricter thresholds cause the flagging of more data with no significant performance improvement. Consequently, we find the applied thresholds for flagging high influx measurements advantageous for this study.

If a significant general bias is present for the opportunistic rainfall estimates, merging opportunistic rainfall data and weather radar data will lead to a biased rainfall product. To overcome this challenge, an initial default bias correction factor could be derived from historical meteorological rainfall products as done by de Vos et al. (2019). The scope of this current study is however to produce a merged rainfall product independent of meteorological rain gauges to facilitate independent evaluation of the accuracy and precision. Thus, meteorological rain gauges are not used for initial bias-correcting of opportunistic rainfall estimates.

2.3. Methods for merging weather radar and opportunistic rainfall data

Opportunistic rainfall and weather radar data are merged by applying three different bias-adjustment methods: a mean field bias (MFB) factor, an inversed distance weighting interpolated bias (IDWB) factor, and a moving median bias (MMB) factor. The latter two methods account for possible spatial variations in the bias adjustment, where the MFB is a single bias factor applied for the entire area. For all three merging strategies, a threshold for the maximum bias adjustment factor of 10 is applied. Bias adjustment factors larger than 10 are highly unlikely to be correct but may occur if the QC results in insufficient flagging of erroneous values. The three merging methods are derived on a daily and a sub-daily scale. The temporal resolution of both the daily and the sub-daily merged rainfall products is maintained as the original temporal resolution of one minute. The sub-daily merging time scale of 6 h is chosen in this study as an example of a sub-daily merging in order to demonstrate the relevance of merging opportunistic and weather radar rainfall data in near real-time applications and specifically for nowcasting of weather radar data. A daily merging might be more stable and is therefore often the preferred choice for historical analyses of rainfall.

2.3.1. Mean field weather radar bias adjustment

The mean field bias adjustment is efficient for removing general overall biases of weather radar data for the entire area (Smith and Krajewski, 1991; Thorndahl et al., 2014b). The approach does not however account for spatial variability of biases and is thus often used in smaller regions and for single radars while more advanced approaches with spatially varying bias adjustments are applied for weather radar composites. The MFB is, in this study, determined as the ratio between the opportunistic sensor rainfall estimates and the weather radar rainfall estimate at each radar-sensor pixel pair for all hours with observed rainfall in both weather radar and opportunistic sensor accumulated over the time period (6 and 24 h):

$$MFB = \frac{\sum_{i=1}^N \sum_{j=1}^t R_S[k(i), m(i)]}{\sum_{i=1}^N \sum_{j=1}^t R_R[k(i), m(i)]} \quad (3)$$

In which N denotes the total number of radar-sensor pixel pairs, t is the total hours with observed rainfall [h], R_S is the opportunistic rainfall [mm/h] at the location $[k(i), m(i)]$, and R_R is the radar rainfall in the corresponding radar-sensor pixel [mm/h]. As the MFB is based on the ratio of the measured rainfall in all opportunistic sensors, the merging method will have a noise-filtering effect, meaning that single opportunistic sensors with potential erroneous rainfall estimates will not cause local erroneous bias adjustment.

2.3.2. Inverse distance weighting interpolated weather radar bias adjustment

The inverse distance weighting interpolated bias adjustment is a spatially distributed bias adjustment of the weather radar estimates. Spatial variability in the bias of the radar adjustment can, among other effects, be caused by differences in the drop size distributions forming the rainfall over the study region, obstacles partly blocking the beam in specific directions, or the effective height above the terrain that the weather radar estimate is acquired for in the processed pseudo-CAPPI product. Inverse distance weighting (IDW) is a quick and efficient approach for generating interpolated surfaces (Gentile et al., 2013). The approach has been widely used for spatial interpolation of rainfall data (e.g., Haberlandt, 2007; Nikolopoulos et al., 2015; Tiwari et al., 2019), and Zhou et al. (2022) applied IDW for interpolation of bias factors for bias adjusting satellite precipitation using rain gauges. The high density of opportunistic rainfall sensors in the study region facilitates a spatially distributed bias adjustment of the weather radar data. Nevertheless, depending on the applied smoothness degree, the IDWB merging method might be locally sensitive to noise in opportunistic rainfall estimates as erroneous data points can cause spikes which lead to data noise propagating into the interpolated surface (Gentile et al., 2013; Habibi et al., 2021). The IDWB factor in the radar pixel located in point x_0 is expressed as:

$$IDWB(x_0) = \frac{\sum_{i=1}^N w_i}{\sum_{i=1}^N w_i} \cdot h(x_i) \quad (4)$$

Where N is the total number of opportunistic rainfall sensors, w_i is the weighting coefficients, and $h(x_i)$ is the calculated bias factor in pixel x_i . The weighting coefficients are derived from:

$$w_i = \frac{1}{(d)^p} \quad (5)$$

In which d is the distance [m] between the radar pixel x_0 and x_i and p is the power parameter determining the smoothness degree of $IDWB(x_0)$. For the IDW interpolation of the bias factor, we apply the typical default value of 2 for the power parameter.

The IDWB is calculated by spatial interpolation of bias factors derived from each radar-sensor pixel pair. The bias factor is for each pixel pair determined as the ratio of opportunistic sensor rainfall to weather radar rainfall in all hours with observed rainfall accumulated

over the bias adjustment period (6 and 24 h).

2.3.3. Moving median weather radar bias adjustment

The novel bias adjustment approach, i.e., moving median bias adjustment (MMB), is presented as a spatially distributed adjustment based on the median of bias factors in the nearby area. Applying a median value of several derived bias factors will lead to filtration of noise and erroneous bias factors caused by inadequate QC of opportunistic rainfall data. For each radar pixel, a multiplicative bias factor is derived with the MMB strategy, and a conceptual sketch of the approach is shown in Fig. 2. Each pixel is assigned the median value of the bias factors derived for each radar-sensor pixel pair within the range. The range is variable and depends on the number of active opportunistic sensors. Active opportunistic sensors are defined as opportunistic sensors reporting rainfall information (including 0 mm/h) that have not been flagged by the QC in the bias adjustment period. A minimum range of 10 km and a minimum of 10 active opportunistic sensors is applied. This is to ensure enough contributing opportunistic sensors and hence obtain a smoothed spatially distributed bias adjustment.

2.4. Evaluation metrics

Meteorological rain gauges within the study region are used for independent validation of opportunistic rainfall estimates, weather radar rainfall estimates, and merged rainfall products. Thus, for evaluation, meteorological rain gauge measurements are used as reference rainfall observations despite measurement uncertainties, geographical distances between measurements, and different representativeness and measurement scales.

The performance of opportunistic rainfall estimates is evaluated by comparing the mean of the opportunistic rainfall estimates within a range of 1 km of a meteorological rain gauge with the meteorological rain gauge measurements. Therefore, only opportunistic sensors located near meteorological rain gauges are used for performance evaluation. Due to the high density of meteorological rain gauges and opportunistic sensors in the study region, this performance evaluation is considered representative of the general performance of opportunistic sensors. For the weather radar data and merged rainfall product, the performance is evaluated in each of the 70 radar-rain gauge pixels in the study region.

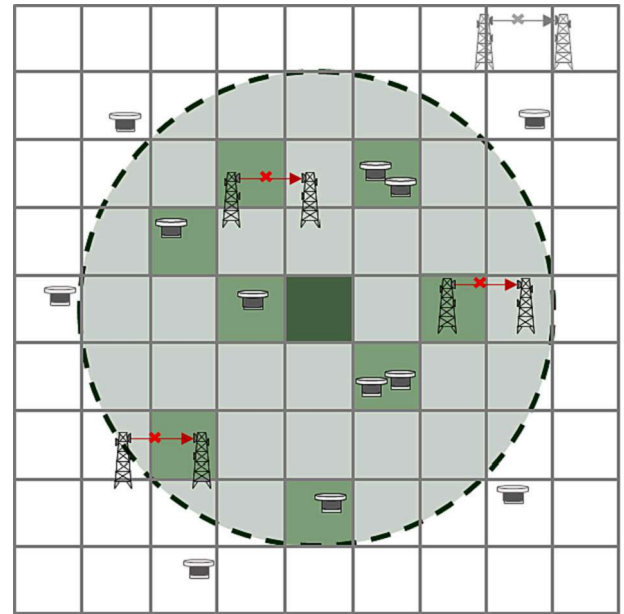


Fig. 2. Conceptual sketch of the moving median bias merging method. The dark pixel is the adjusted pixel based on the median of the bias factors within a range derived in all radar-sensor pixel pairs (marked pixels).

All evaluations are completed on 24-h accumulated rainfall data.

The performance of the rainfall products is evaluated based on three evaluation metrics: The Nash-Sutcliffe model efficiency coefficient (NSE), root mean squared error (RMSE), and percent bias (PBIAS).

The NSE ranges from $-\infty$ to 1 and provides a total measure of the model accuracy relative to the bi-sector (Nash and Sutcliffe, 1970; Moriasi et al., 2007):

$$NSE = 1 - \frac{\sum_{i=1}^N (R_{G_i} - R_{S_i})^2}{\sum_{i=1}^N (R_{G_i} - \overline{R_{G_i}})^2} \quad (6)$$

Where N is the total number of observations, R_G is the meteorological rain gauge rainfall [mm], and R_S is the opportunistic rainfall sensor or weather radar rainfall [mm].

The average model uncertainty is expressed by the RMSE which is a highly used performance measure for model accuracy evaluation (Hyndman and Koehler, 2006):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (R_{S_i} - R_{G_i})^2} \quad (7)$$

The PBIAS expresses the average bias, where a positive value indicates an underestimation of rainfall depths (Gupta et al., 1999) and is in this study primarily used to evaluate if the rainfall estimates over- or underestimate the rainfall depth:

$$PBIAS = \frac{\sum_{i=1}^N (R_{G_i} - R_{S_i})}{\sum_{i=1}^N R_{G_i}} \cdot 100\% \quad (8)$$

These three parameters are selected as they complement each other in the performance assessment. Any evaluation metrics have pros and cons, and thus only applying a single metric does not necessarily provide adequate information regarding total model accuracy, uncertainty, and over- or underestimation.

3. Results

In this section, the accuracy and precision of the rainfall products are assessed by comparison to the reference data provided by the meteorological rain gauges. Firstly, the raw CML, PWS, and weather radar rainfall estimates without QC or bias adjustment are evaluated. Next, we demonstrate the impact of applying the QC algorithm to opportunistic rainfall data both individually and when merged through the QC procedure. The merged rainfall product is evaluated by comparing all 24-h accumulated rainfall data points to the reference data for the entire data period. Finally, the performance of the merged rainfall product with each weather radar merging strategy is exhibited for the day with the

highest measured rainfall depth within the data period.

In Fig. 3, the rainfall estimates derived from CML, PWS, and weather radar without QC or merging are compared to the meteorological rain gauge rainfall. For both PWS and CML rainfall, many falsely high values are reported; and for PWS rainfall, many falsely zero values are reported. In Fig. 3, it is clearly shown that all three rainfall data products contain obviously wrong rainfall estimates in comparison with the meteorological rain gauges. Typical error sources in weather radar data (e.g., attenuation, beam blockage, partial beam blockage) varying in time and space might affect the performance of the weather radar data and hence cause some of the scatter in Fig. 3c if not sufficiently accounted for in the applied radar data processing. It is furthermore evident from the radar data that keeping the power law parameters constant without any gauge adjustment causes significant biases and that the data set is likely to contain significant differences in drop size distributions leading to the two-branched pattern observed in Fig. 3c. Despite similarities in the measurement technique and power law function, the same pattern is not observed in the CML rainfall estimates, as these are much less sensitive to variations in drop size distribution between rain events (Chwala and Kunstmann, 2019).

3.1. QC and merging of opportunistic rainfall data

The QC algorithm is applied to CML and PWS rainfall estimates individually and to all opportunistic rainfall estimates together to obtain merged opportunistic rainfall estimates through data filtration and bias correction across the two types of rainfall data. The total number of active opportunistic rainfall sensors and the number of active sensors after the merged filtration are illustrated in Fig. 4. In the figure, it is shown that the number of rainfall sensors increases over time, which is the general tendency for PWS. Moreover, clear drops in the number of opportunistic rainfall sensors are seen, which are caused by CML rainfall data from some or all links occasionally not being available. In the merged filtration, 19% of PWS are flagged on average, while 8% of CML are flagged. Individual filtration of PWS results in 11% of the stations being flagged on average, while 18% of CMLs are flagged on average with individual filtration. Merging the two data types in the QC results in fewer CMLs being flagged as consequence of too few neighboring links.

The performance of opportunistic rainfall data with QC is shown in Fig. 5 and it is evident that the data performance is increased compared to the data performance without QC (Fig. 3). Merging the opportunistic data through the QC increases the performance of both PWS and CML rainfall estimates. However, the opportunistic sensors overestimate the rainfall depths, and a significant scatter is observed for both types of opportunistic rainfall observations when compared to the measurements of the meteorological gauges.

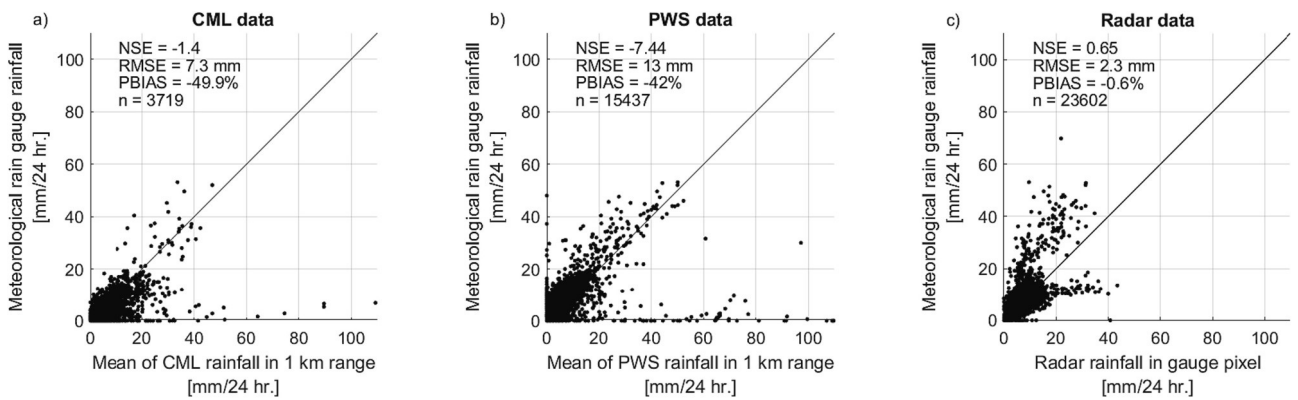


Fig. 3. CML and PWS data illustrated as the mean of daily rainfall within a 1 km range of a meteorological rain gauge compared to daily meteorological rain gauge rainfall (a and b, respectively) and daily weather radar rainfall in radar-rain gauge pixels compared to daily meteorological rain gauge rainfall (c). Rainfall estimates >110 mm/24 h are not shown.

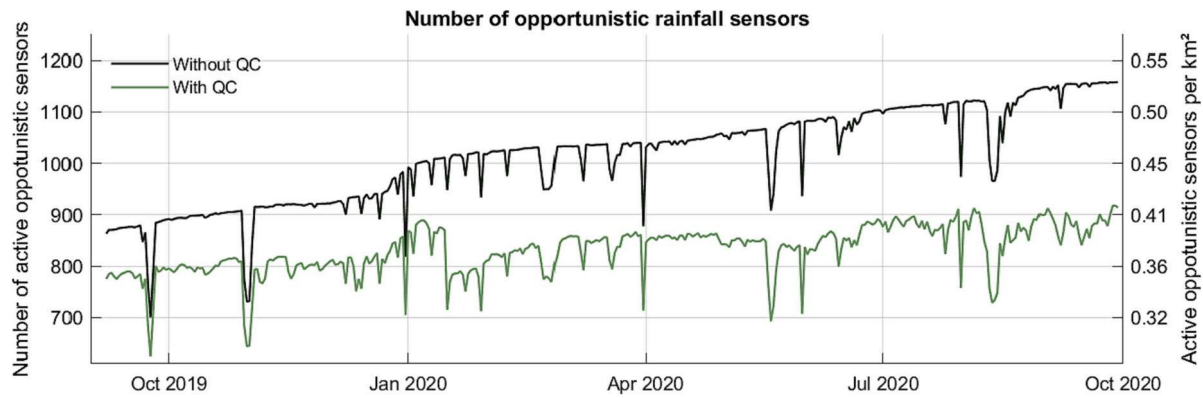


Fig. 4. Number of active opportunistic rainfall sensors with and without quality control. Opportunistic sensors are the sum of PWS and CML, and the quality control is performed on a merged data product.

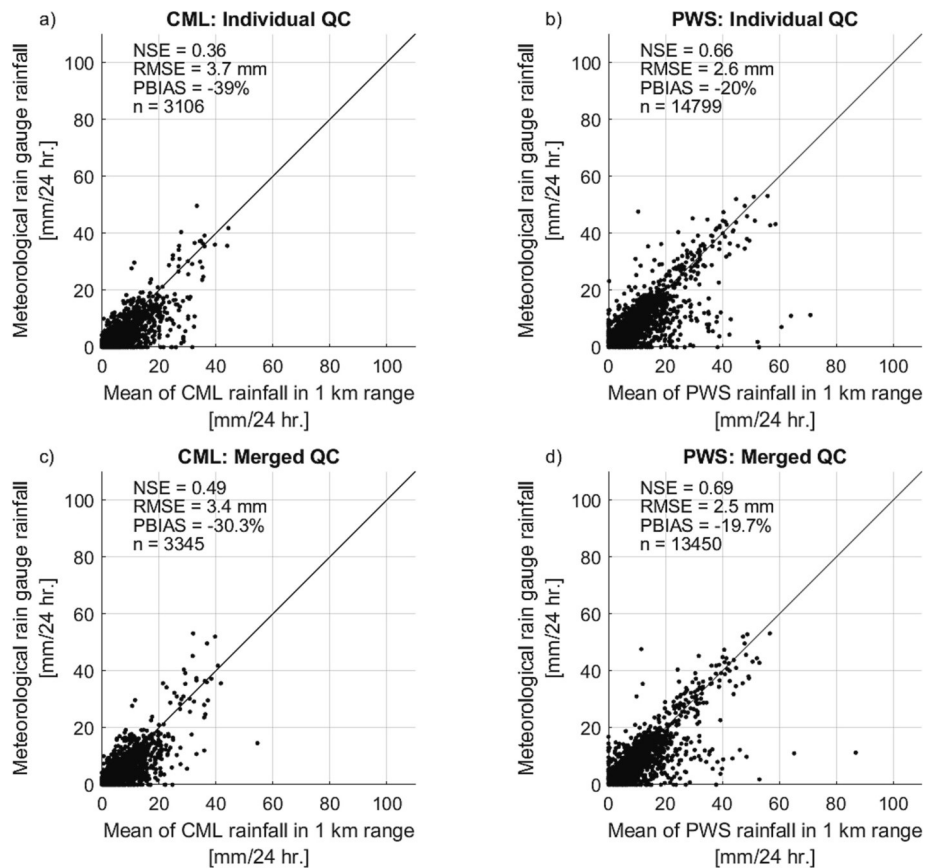


Fig. 5. CML and PWS rainfall estimates when applying QC individually (a and b) and merged (c and d). The CML and PWS rainfall estimates are calculated as a mean value within a range of 1 km from a meteorological rain gauge.

3.2. Merging of weather radar and opportunistic rainfall data

Weather radar data and opportunistic rainfall data are merged by applying both a 6-h and a daily MFB, IDWB, and MMB. The merging is performed with the opportunistic rainfall estimates merged through the QC, as this opportunistic rainfall product has the highest performance (Fig. 5). The daily accumulated merged rainfall product is evaluated by comparing it to meteorological rain gauges as shown in Fig. 6. Generally, high accuracy and precision are obtained for all three merged rainfall products. The NSE-values for the merged products range from 0.67 to 0.88, whereas the NSE-values for the individual rainfall estimates from CML, PWS, and weather radar range from -7.44 to 0.65 (Fig. 3). It is

evident from the evaluation metrics that the MMB adjustment results in the highest performance for both daily and sub-daily (6-h) adjustments.

For MFB and IDWB merged weather radar, the daily bias adjustment performs better than the sub-daily merging as seen by higher NSE-values and smaller RMSE-values. However, the sub-daily merged rainfall product with the MMB approach shows higher performance and less scatter than the daily merging. It is clear from the results shown in Fig. 6 that the additional filtering inherent in the MMB merging strategy eliminates more of the noise from the opportunistic rainfall observations compared to the IDWB merged product. Moreover, the MMB merging approach benefits from the spatially distributed bias adjustment facilitated by the high density of ground observations, which is seen when

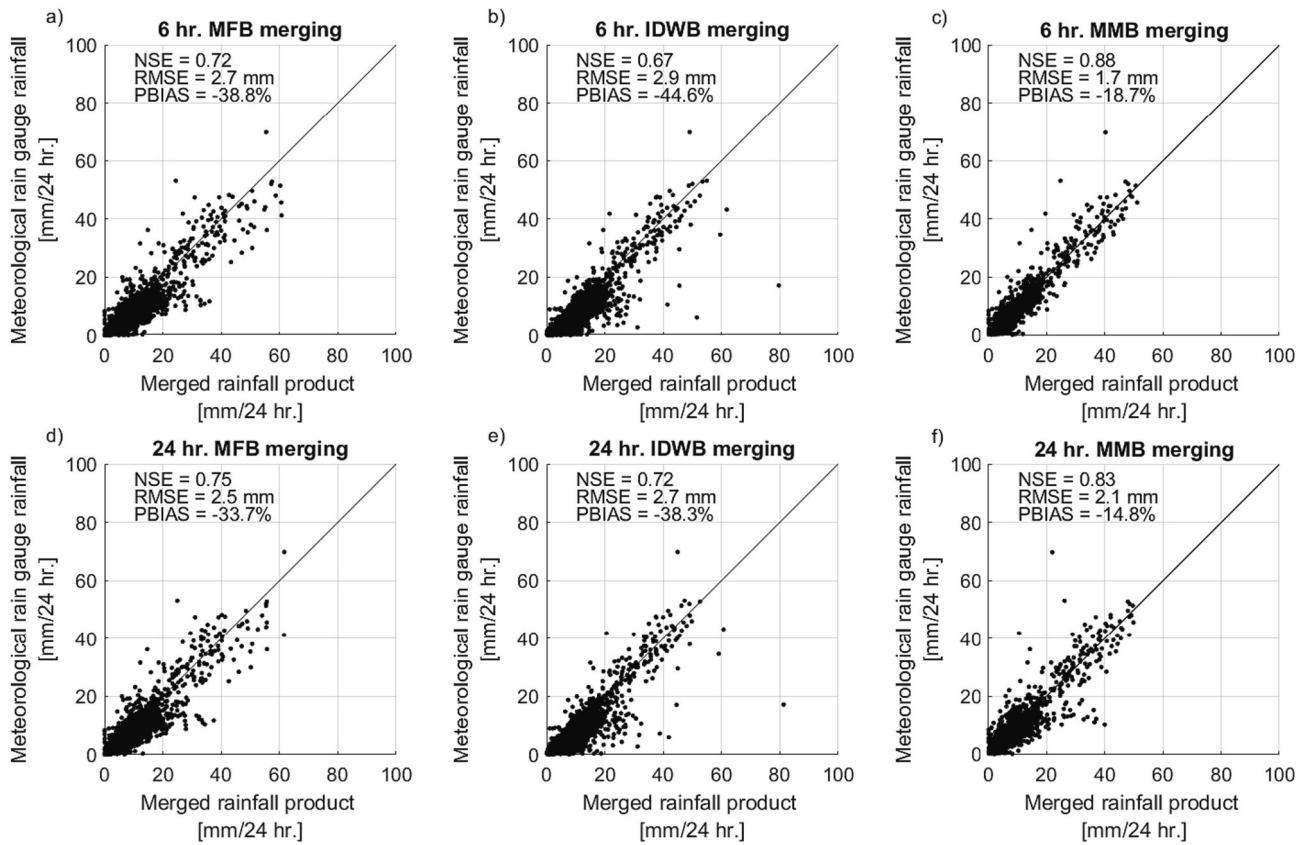


Fig. 6. Merged rainfall products and meteorological rain gauge rainfall based on sub-daily (a, b, and c) and daily (d, e, and f) merging.

compared to the MFB. The results clearly demonstrate the benefits of merging rainfall data estimates and show that the highest accuracy and precision is obtained by applying the MMB merging approach on a sub-daily scale.

3.2.1. Event in September 2021

The rainfall event with the highest rainfall depth measured by meteorological rain gauges is used to illustrate the relevance of data merging on event scale. The largest rainfall depths were recorded on September 25, 2020 and range from 22 to 55 mm between the meteorological rain gauges. The unadjusted weather radar rainfall and the meteorological rain gauge rainfall for this event are shown in Fig. 7 illustrating that the unadjusted weather radar data underestimates the

rainfall event significantly.

The merged rainfall products with the three radar merging strategies with daily adjustment for the September 25, 2020 event are illustrated in Fig. 8. The MFB merged rainfall product reveals the lowest performance as seen from the evaluation metrics ($NSE = -0.29$ and $RMSE = 7.5$ mm for MFB merging compared to $NSE = 0.44$ and $RMSE = 4.9$ mm for MMB merging). Even though MFB is evaluated as the lowest-performing merging strategy from the evaluation metrics, it is seen that noise from opportunistic rainfall products propagate to the IDWB rainfall product, resulting in areas with unrealistic large rainfall gradients which illustrates the disadvantages of IDWB merging using opportunistic rainfall sensors and applying default power parameter.

Fig. 8 shows that the MMB merging strategy entails the highest-

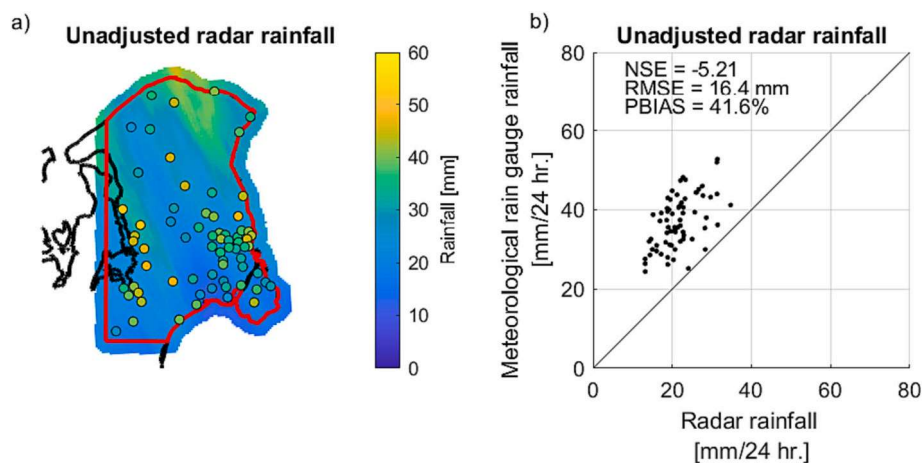


Fig. 7. Unadjusted weather radar rainfall and meteorological rain gauge rainfall on September 25, 2020. The meteorological rain gauges are shown as points in a).

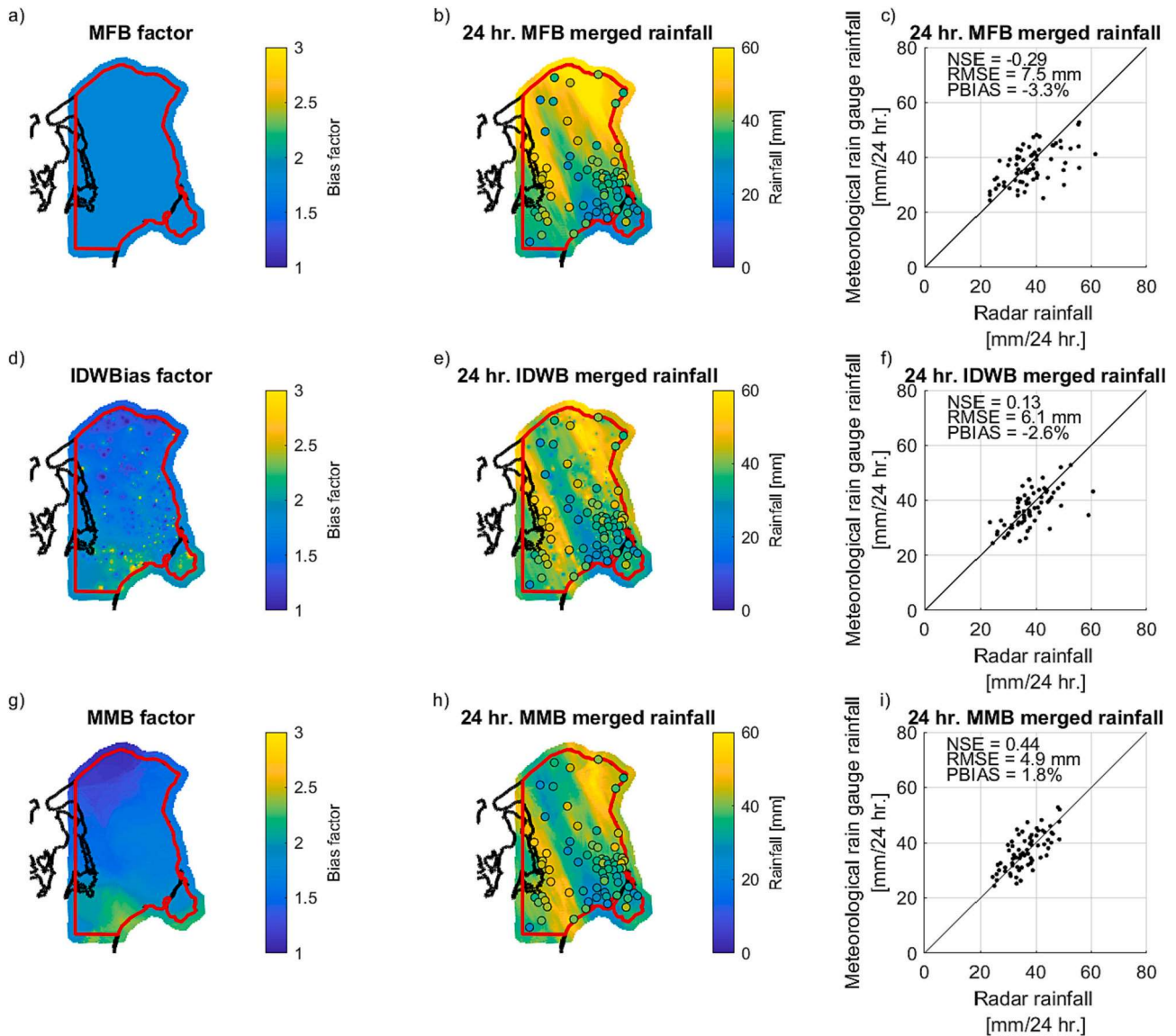


Fig. 8. Merged rainfall products on September 25, 2020. Derived bias factors (a, d, and g) for each merging strategy, merged rainfall product in the study region with meteorological rain gauges illustrated as points (b, e, and h), and daily measured rainfall in both meteorological rain gauges and with the merged rainfall product in radar-rain gauge pixel pairs (c, f, and i).

performing merged rainfall product for this event. Overall, the spatial variability of rainfall measured with meteorological rain gauges is well captured in the MMB merged rainfall product (Fig. 8h). Regardless of the merging strategy, a perfect match to the meteorological rain gauge observations is obviously not obtained for this event. Compared to the unadjusted weather radar rainfall product, both the precision and accuracy are however improved remarkably by applying the MMB merging strategy. Furthermore, from Fig. 6c and f, it is seen that the MMB merging generally provides high accuracy and precision when longer time series are considered.

4. Discussion

The high density of PWS and CML provides unique possibilities for merged rainfall products. The opportunistic rainfall sensors are often clustered in urban areas resulting in less dense opportunistic sensor networks in rural areas and thus reduced advantages of merging weather radar and opportunistic rainfall sensors. However, accurate rainfall estimates and nowcasts with high spatiotemporal resolution are often crucial in urban areas where the density of ground observations is

higher.

The opportunistic rainfall estimates contain obviously incorrect rainfall estimates some of which can be removed through the applied QC algorithm. Not all erroneous rainfall estimates are removed, and using only PWS and CML leads to a lower accuracy than merging weather radar with opportunistic rainfall estimates. Furthermore, the weather radar has the advantage of spatially distributing the rainfall, whereas a spatially distributed rainfall product relying on CML and PWS requires spatial interpolation of the rainfall inevitably introducing uncertainties.

The merged rainfall products perform better than the individual rainfall products, and the improvements are significant for all three merging strategies. It is possible that the performance of the weather radar data could be improved by applying more corrections in the data processing to account for typical error sources leading to temporal and spatial biases and thus reducing the scatter observed in Fig. 3c. This would lead to a less significant improvement in the performance when merging weather radar data and opportunistic rainfall sensor data. Considerable improvements are however expected despite more data correction, as merging weather radar data and opportunistic rainfall sensor data leads to adjustment of the temporal and spatial biases in the

weather radar data, being the reason for the higher performance of the merged rainfall products.

The MFB and MMB merging strategies lead to additional filtering of the opportunistic rainfall estimates since the methods are based on mean and median values, respectively. Hence, applying QC to the opportunistic rainfall estimates before merging with weather radar data is less crucial if the density of opportunistic rainfall sensors is high. QC of opportunistic rainfall estimates is shown to significantly improve the performance of opportunistic rainfall estimates, and despite not all erroneous values being flagged, applying the QC algorithm reduces wrong rainfall estimates being included in the merged rainfall product.

Merging weather radar and opportunistic rainfall estimates with the IDWB approach leads to uncertainties from the opportunistic rainfall estimates propagating into the merged rainfall product. Thus, the rainfall product is affected by wrong rainfall estimates, and the rainfall estimates are not valid locally. It is likely that IDW interpolation of bias factors can be applied with different parameter sets or with additional filters, potentially resulting in a valid rainfall product. This has not however been investigated further in this study.

As previously described, [Overeem et al. \(2023\)](#) performed a study merging PWS and weather radar rainfall estimates for the majority of Europe. Despite similarities in research approaches, the obtained accuracy and precision are difficult to compare due to differences in scale. This current study is performed on a local scale with a high density of opportunistic sensors, a single radar, and the same climate throughout the study region. Hence, higher accuracy and precision are expected compared to studies with differences in climate, composite radar data, and generally larger data sets. Although the evaluation metrics are challenging in terms of direct comparisons, similar performances of daily accumulated merged radar rain rainfall estimates are obtained. [Overeem et al. \(2023\)](#) obtain a coefficient of determination of up to 0.85,

and in the presented study, an NSE-value of up to 0.88 is achieved.

This study region is selected because of its particularly high density of opportunistic rainfall sensors. The region might thus not be representative in general. To study the relevance of merging weather radar data and opportunistic data in less dense regions, the effect of reducing the density of opportunistic sensors to 50% is investigated. The opportunistic rainfall sensor dataset is reduced by 50% by randomized selection to a density of approximately 0.23 sensors per km². The QC algorithm is applied to the reduced dataset of opportunistic rainfall sensors containing CML and PWS rainfall data. The quality-controlled opportunistic dataset is merged with weather radar data by applying the MFB and MMB merging approach on a daily and sub-daily scale. For this analysis, the IDWB merging approach is not applied since [Fig. 8](#) shows that this approach results in propagated noise and consequently unrealistic high gradients in bias factors and rain depths. The performance of the merged rainfall product with a reduced density of opportunistic rainfall sensors is shown in [Fig. 9](#).

Comparing [Figs. 9 and 6](#) shows that the general validity of the sub-daily MMB merged rainfall product is reduced when the available opportunistic rainfall data is reduced to 50%. However, for the daily merging and the sub-daily MFB merging, a slight increase in evaluation metrics is observed. This is likely caused by removal of sensors with high uncertainty in the randomized selection and in the QC and indicates that even though a high density of opportunistic rainfall sensors is a prerequisite for this merging procedure, reducing the density of opportunistic sensors to approximately 0.23 sensors per km² does not lead to remarkably poorer rainfall estimates.

For the event on September 25, 2020, a reduced density of opportunistic rainfall sensors causes a poorer representation of the rainfall on this day ([Fig. 10](#)). It is noteworthy that the merged rainfall product with reduced density of opportunistic rainfall sensors has significantly higher

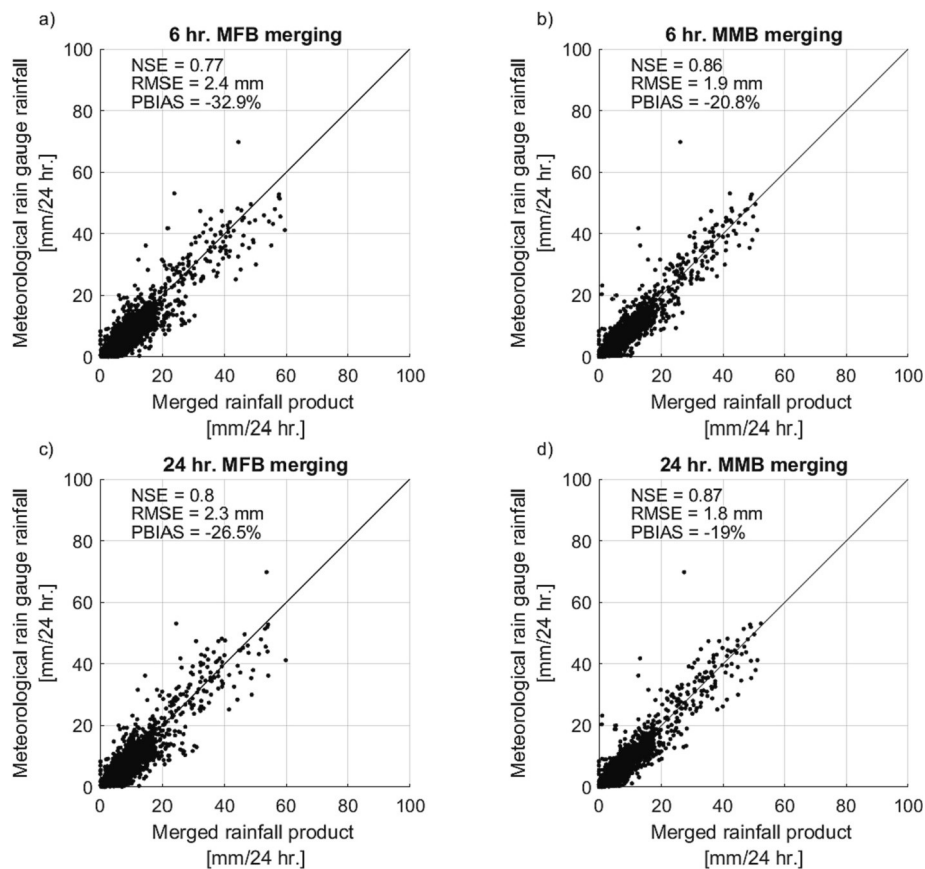


Fig. 9. Merged rainfall products and meteorological rain gauge rainfall based on sub-daily (a and b) and daily (c and d) merging after reducing the density of opportunistic sensors by 50% by randomized selection.

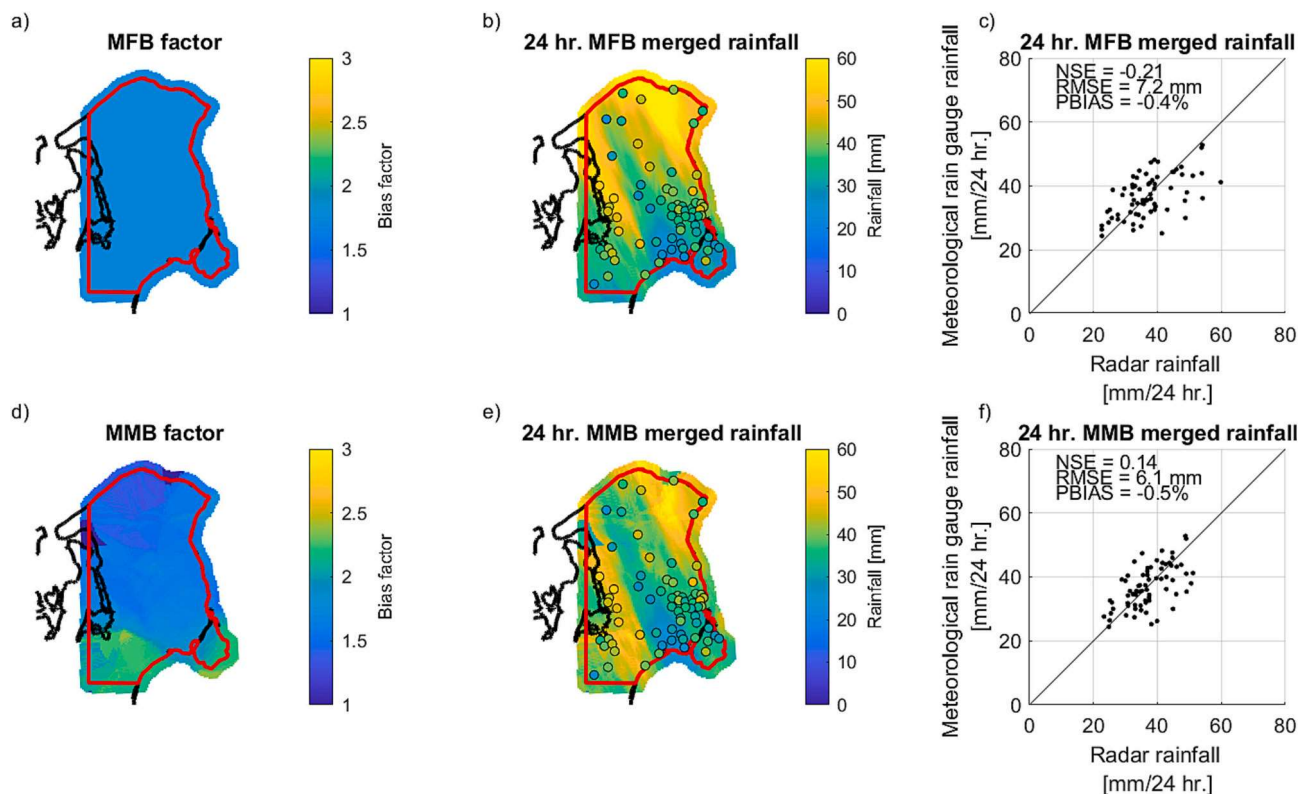


Fig. 10. Merged rainfall products on September 25, 2020 after reducing the density of opportunistic sensors by 50% by randomized selection. Derived bias factors (a and d) for each merging strategy, merged rainfall product in the study region with meteorological rain gauges illustrated as points (b and e), and daily measured rainfall in meteorological rain gauges and with the merged rainfall product in radar-rain gauge pixel pairs (c and f).

accuracy than any of the rainfall products without merging, demonstrating that merging of weather radar data and opportunistic rainfall data has a high relevance even in areas with less dense opportunistic rainfall sensor networks.

5. Conclusion

This study has demonstrated the relevance of merging weather radar and opportunistic rainfall data for improving rainfall estimates, as the merged rainfall products outperform each of the individual rainfall products. The NSE-values of the individual rainfall estimates without merging or QC range from -7.44 to 0.65 , while the NSE-values of the merged rainfall products range from 0.67 to 0.88 . The merged rainfall products exhibit high spatiotemporal resolution, accuracy, and precision, causing high correlation with meteorological high-quality rain gauges and making the merged products valuable for urban hydrological applications.

Comparing the opportunistic rainfall estimates with nearby meteorological high-quality rain gauges on a daily scale without QC leads to NSE-values of -1.4 and -7.44 for CML and PWS, respectively, whereas applying individual QC increases the NSE to 0.36 (CML) and 0.66 (PWS). Moreover, combined QC across the two data types further increases the NSE to 0.49 and 0.69 for CML and PWS, respectively.

A novel approach for merging opportunistic and weather radar rainfall estimates with a spatially distributed bias adjustment has been presented, i.e., the moving median bias adjustment (MMB). The spatially distributed bias adjustment is facilitated by the high density of ground observations and is hence possible when merging with opportunistic rainfall estimates. The MMB approach applies a median filter for spatially smoothed bias adjustment, and the results reveal that the merged rainfall product performance is enhanced by applying this method. Independent validation with meteorological high-quality rain gauges on a daily scale for 10.5 months of data exhibits $\text{NSE} = 0.88$ and

$\text{RMSE} = 1.7$ mm when applying MMB on a sub-daily scale. High accuracy and precision of the merged rainfall product are obtained with both a daily and sub-daily bias adjustment, underlining the relevance of merging in historical, near real-time, and nowcasting applications.

CRediT authorship contribution statement

J.M. Nielsen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **C.Z.R. van de Beek:** Conceptualization, Data curation, Funding acquisition, Methodology, Writing – review & editing. **S. Thorndahl:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **J. Olsson:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing. **C.B. Andersen:** Data curation, Writing – review & editing. **J. C.M. Andersson:** Conceptualization, Data curation, Funding acquisition, Methodology, Writing – review & editing. **M.R. Rasmussen:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **J.E. Nielsen:** Conceptualization, Data curation, Funding acquisition, Methodology, Resources, Software, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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