Long-term evaluation of gauge-adjusted precipitation estimates from a radar in Norway
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ABSTRACT

The implementation of weather radars in Norway by the Norwegian Meteorological Institute (met.no) has made radar a potential tool to improve hydrological predictions through the use of distributed precipitation input. Met.no supplies gauge-adjusted quantitative hourly radar precipitation estimates. A key concern regarding the use of radar precipitation estimates in hydrology is their accuracy. In this study, the precipitation estimates from the Rissa radar in Norway were evaluated through a comparison with observations from 112 gauges used in the adjustment (dependent) and 15 gauges not included in the adjustment (independent). The comparison with daily measurements from the dependent gauges showed a decline in the radar’s detection probability beyond a range of about 140 km, with a more severe decline in winter. The deviations between radar- and gauge-conditional mean precipitation were significantly higher in summer than in winter. There was an overestimation at most of the gauge locations during summer, while there were more underestimations during winter. A dependence of accuracy on range was identified from the spatial distribution of the Efficiency Index and mean absolute difference. The evaluation against the independent gauges revealed trends mostly similar to the ones obtained from comparison with the dependent gauges. The radar estimates exhibited better agreement with gauge measurements during winter. The main reasons for the errors remaining in the gauge-adjusted precipitation estimates are the absence of correction for the vertical profile of reflectivity, the use of average monthly adjustment factors, derivation of these factors using data from previous years and the use of a single reflectivity–precipitation rate (Z–R) relation.

Key words | evaluation, gauge adjustment, radar precipitation, Rissa radar, vertical profile of reflectivity

INTRODUCTION

The availability of accurate and reliable measurements and estimation of the spatial and temporal distribution of precipitation is of great importance in hydrological applications. With the development of distributed hydrological models running at a finer time step of an hour down to some minutes, the need for spatially distributed precipitation input at a higher time resolution has been steadily increasing. Traditionally, measurements from rain gauges have been used to estimate precipitation input for hydrological modeling. The major problem with rain gauges in estimating areal precipitation is the fact that they represent point measurements. They can provide reliable measurements at a point, but the representativeness of the measurements reduces with distance, particularly in convective events. A lot of procedures have been developed and used over the years which aim at spatially interpolating precipitation between the point measurements gathered from a network of rain gauges. However, the distribution
inferred by these approaches introduces errors because the densities of gauge networks are usually too sparse to capture the spatial variations and patterns of precipitation, especially for regions with complex terrain. Implementing gauge networks which are dense enough would generally be impractical.

Weather radars offer an advantage over rain gauges in that they can provide high-resolution data with a spatial scale on the order of 1 km and a temporal scale of down to 5 min. They cover extended areas, with a spatial extent of up to several hundred kilometers, from one single measurement site. These characteristics make weather radars well suited to hydrological applications. However, quantitative precipitation is not directly measured by weather radars but is derived from measurements of ‘equivalent radar reflectivity factor’ \( Z_e \), which is proportional to the energy backscattered by precipitation particles (Battan 1973; Wilson & Brandes 1979). For spherical drops with diameters small compared to the radar wavelength (i.e. when conditions for Rayleigh backscattering are fulfilled), \( Z_e \) is a good estimate of the ‘radar reflectivity factor’ \( Z \) (Battan 1973). The conversion of the radar reflectivities measured aloft to precipitation rates \( R \) at the ground is a complex task. Both the reflectivity measurements themselves and the process of converting them to precipitation rates are subject to errors and uncertainties. Sources of reflectivity measurement error include hardware calibration problems (Smith et al. 1996; Ulbrich & Lee 1999), attenuation (Uijlenhoet & Berne 2008), ground and sea clutter (Germann & Joss 2004), anomalous propagation (Pamment & Conway 1998; Borga et al. 2002) and beam blockage (Young et al. 1999; Bech et al. 2007). Errors in the conversion process mainly arise due to the vertical change of the radar reflectivity, defined by the vertical profile of reflectivity (VPR), and the limited spatial and temporal representativeness of a fixed radar reflectivity–precipitation rate \( Z–R \) relationship used for conversion. Various studies have documented how \( Z–R \) relationships can vary for different points in a given radar domain, and for every storm-type and storm intensity (Stout & Mueller 1968; Wilson & Brandes 1979; Smith & Krajewski 1993; Ciach & Krajewski 1999a; Ulbrich & Lee 1999; Steiner & Smith 2000). Apart from the storm-to-storm variability, \( Z–R \) relationships can also vary within storms (Uijlenhoet et al. 2003). The VPR becomes a dominant source of error when reflectivity measurements aloft are used to estimate precipitation rates at the ground level without considering profile correction to extrapolate reflectivity measurements from above to ground level (Joss & Waldvogel 1990; Koistinen et al. 2004). And this error normally increases with increasing distance from the radar since the vertical distance between the sample volume of the radar and the ground usually increases as well, making consideration of VPR very important for radar measurements at longer ranges. Performing profile corrections is not an easy task since VPRs are highly variable in time and space.

Because of the above factors, information derived from radar measurements is often combined with rain gauge observations to obtain more accurate precipitation estimates. The two observation systems are generally considered as complementary and assumed as independent estimates of the same unknown quantity. The process of merging them is usually referred to as ‘correction’ or ‘adjustment’. This process had also been termed ‘calibration’ in some studies (Collier 1986; Wood et al. 2000). The general aim of such a process is to improve the quantitative accuracy while retaining the spatial detail obtained from the radar. Several gauge adjustment techniques have been developed over the years: ranging from relatively simple methods which rely on gauge to radar precipitation ratios (Brandes 1975; Collier et al. 1983; Michelson & Koistinen 2000; Gjertsen 2002; Holleman 2007) to sophisticated statistical schemes (Krajewski 1987; Creutin et al. 1988; Seo et al. 1990a,b; Todini 2001). The implicit assumption in these methods is that the rain gauges provide reliable quantitative point measurements of precipitation and that the gauge-adjusted (corrected) radar precipitation estimates are useful at radar pixels away from the gauge locations as well. The limitation of these methods is that it is only the gauge adjustment which is used to account for most of the error sources, including error sources which could be dealt with without introducing raingauge data (VPR effect, beam blockage, etc.). They are, in a way, an attempt to correct many of the error sources mentioned above in one step. A better approach is to correct, as far as possible, for major error sources before making adjustments by using raingauge data (Joss & Waldvogel 1990). Some of the gauge adjustment methods
are not well suited for operational purposes. Gjertsen et al. (2003) have given a review of the gauge-adjustment methods applied operationally or experimentally at 21 European institutes.

A key concern regarding the use of gauge-adjusted radar precipitation estimates in hydrology is their accuracy (Krajewski & Smith 2002). Because they are increasingly being used as inputs for hydrological models, it is essential to assess their accuracy in order to understand the implications the errors have on hydrological predictions. The most common approach to evaluating radar precipitation estimates is to compare them with rain gauge observations. Smith et al. (1996) characterized the systematic biases in the NEXRAD (Next Generation Weather Radar system in the United States) hourly precipitation accumulation estimates from analyses of more than 1 year of hourly radar and rain gauge data from the southern plains of the USA. Xie et al. (2006) evaluated NEXRAD Stage III precipitation data over a semiarid region through a comparison with gauge precipitation for a period of 6 years. Grassotti et al. (2003) carried out a three-way multiple-timescale (monthly, daily and hourly) intercomparison of two radar products and rain gauge observations for a period of more than a year. Jayakrishnan et al. (2004) assessed the accuracy of the NEXRAD Stage III precipitation data for a period of five years using 24-h accumulations from 545 rain gauges. Young et al. (1999) evaluated the NEXRAD precipitation estimates in a complex mountainous terrain using observations from 97 gauges for a 17-month period. Goudenhoofdt & Delobbe (2009) evaluated several radar-gauge merging methods by using observations from a C-band Doppler radar and a dense rain gauge network in Belgium. Borga et al. (2002) performed a long-term assessment of bias adjustment in radar rainfall estimation based on a 3-year database of radar and gauge observations over a hilly terrain in southwest England. Holleman (2007) carried out a long-term verification of the bias-adjusted radar precipitation estimates produced operationally at the Royal Netherlands Meteorological Institute over a six-year period using both dependent and independent gauge data. The results from the above studies and many others (see also Young et al. 2000; Vieux & Vieux 2005; Rogalus & Ogden 2007; Hardegree et al. 2008; Wang et al. 2008) have indicated the importance of rain gauge data in indentifying biases and errors remaining in radar precipitation estimates even after they are gauge-adjusted. It is also crucial to properly check the quality of the rain gauge data used for adjustment as they are subject to error as well (Steiner et al. 1999).

The aim of this study is to evaluate the gauge-adjusted radar precipitation estimates from the Rissa radar in Norway. Current hydrologic modeling efforts in Norway usually involve hourly or daily precipitation data obtained from a network of precipitation gauges. In recent years, however, the implementation of weather radars in Norway by the Norwegian Meteorological Institute (met.no) has made radar a potential tool to improve estimation of precipitation between the gauges. Met.no supplies gauge-adjusted quantitative hourly radar precipitation estimates with a spatial resolution of 1 km × 1 km (Gjertsen & Dahl 2001, 2002; Gjertsen 2002). Here, we have evaluated the estimates from the Rissa radar through a comparison with observations from both dependent and independent rain gauges for the period January 2006–May 2008. While there have been numerous studies evaluating NEXRAD estimates in general, we do not know of (have not come across) any published studies performing a long-term evaluation of the met.no gauge-adjusted radar precipitation products with respect to rain gauge measurements. This study may, therefore, serve as a benchmark for further evaluation and application of radar precipitation data in Norway.

Radar Precipitation Data Processing at MET.NO

The Rissa radar is located at 63.69° latitude and 10.20° longitude at an elevation of 616 m above sea level (Figure 1). It is a Gematronik C-band Doppler radar. It has a beam width of 1° and scans a volume of 12 elevation angles (with a minimum elevation of 0.5°) at a sampling frequency of 15 min. Stationary echoes are removed by using a Doppler filter. The measurements from this radar are not significantly affected by beam blockage (Gjertsen & Dahl 2002). From the scanned 3D data, PseudoCAPPI (Constant Altitude Plan Position Indicator) images are built at an elevation of 500 m above the radar. These Cartesian
products contain reflectivity values \((Z_e)\) and are generated every 15 min at a spatial resolution of \(1 \text{ km} \times 1 \text{ km}\). Since the height of the beam axis changes with range, the lowest elevation angle is used to estimate the CAPPI product at ranges beyond 30 km. At ranges within 30 km, the CAPPI is generated from the beams closest to the surface at 500 m above the radar. The PseudoCAPPI datasets are operationally converted to grids of uncorrected precipitation rate \((R)\) using the \(Z–R\) relationship derived by Marshall & Palmer (1948):

\[
Z = 200R^{1.6} \tag{1}
\]

where \(Z\) is radar reflectivity in \(\text{mm}^6/\text{m}^3\) and \(R\) is precipitation rate in mm/h.

A spatial adjustment method which uses surface gauge measurements is applied to adjust the converted precipitation rates (Gjertsen 2002). This gauge adjustment method is a spatial correction similar to the methods described by Brandes (1975) and Michelson & Koistinen (2000). It is also similar to the P1 (process 1) methodology developed at the Arkansas–Red River Basin River Forecast Center (Young et al. 2000; Grassotti et al. 2003). The steps involved in the adjustment are briefly described below.

All the available stations (synoptic and climate) operated by met.no within the radar coverage (240 km radius) are used. The gauge measurements from these stations are not corrected for typical errors due to wind, evaporation and wetting loss. 24-hour accumulations of gauge measurements \((G)\) and \(R\) are used to compute the gauge-to-radar \((G/R)\) ratio at each gauge location. The radar pixel coinciding with the gauge location is used here without any filtering. There is a mismatch between the 24-h accumulation times for the synoptic and climate stations which is not corrected for. The 24-h accumulations for the synoptic stations run from 06:00–06:00 UTC, while those for the climate stations are from 08:00–08:00 local time all year round, i.e. from 06:00–06:00 UTC in summer and 07:00–07:00 UTC in winter. The accumulations of \(R\) are not continuous since they are derived from data with a sampling interval of 15 min.

The \(G/R\) ratios are then used to compute the mean monthly adjustment factors \((F_m)\) at each gauge location:

\[
F_m = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{G_i}{R_i} \right) \tag{2}
\]

where \(G_i\) and \(R_i\) are 24-h accumulations within a month and \(n\) is the number of 24-h accumulations within a month. Lower thresholds of 0.1 mm and 0.3 mm are applied on \(R_i\) and \(G_i\), respectively. Adjustment factors estimated based on data from one year are used to correct data from the coming year. For example, adjustment factors computed from radar and gauge data of 2006 are used to correct the radar data of 2007.

To obtain adjustment factors for the radar pixels without collocated gauges, a grid (surface) of adjustment factors is constructed using local polynomial regression fitting. A description of this interpolation procedure can be found in Gjertsen (2002). Since there is a higher risk of introducing large errors while adjusting \(R\) using very large
adjustment factors, a factor of 20 is used for cases where the computed or interpolated adjustment factors are higher than 20. $F_m$ grids for January and July generated using data from January 2006 and July 2005, respectively, are given in Figure 2. Then the uncorrected precipitation rates ($R$) are multiplied by the adjustment factors ($F_m$) to obtain a grid of adjusted radar estimates ($R_a$) every 15 min. The grids of $R_a$ are finally accumulated to produce hourly rates. It is these grids of gauge-adjusted quantitative hourly precipitation estimates which are supplied by met.no and used in this study.

**RADAR AND GAUGE DATA**

Radar and gauge data were obtained for this study for the period January 2006–May 2008. Hourly data for the Rissa radar was downloaded from met.no’s server in the form of binary grids. The binary grids are in Hierarchical Data Format (HDF5) (Michelson et al. 2003). Daily precipitation data from 136 stations (Figure 3(a)) within the radar coverage were downloaded from met.no’s climate database along with the times at which the 24 h accumulations are reported. We refer to these stations as ‘dependent’ since data from these stations has been used for adjusting the radar precipitation estimates. Hourly precipitation data for 15 stations within the Sør-Trøndelag County were obtained from two power companies (TrondheimEnergi and TrønderEnergi) (Figure 3(b)). These stations are located within a range of 145 km from the Rissa radar and we refer to them as ‘independent’ since they have not been included in the adjustment of radar data. Fourteen of the independent stations lie within the ranges 60–145 km, while the remaining station is located quite close to the radar at a distance of 5.4 km. The precipitation data from both the dependent and independent stations is not wind-corrected. Hourly temperature and wind speed data for the independent stations was obtained for carrying out wind correction. The rain gauge location coordinates of all the stations were obtained in latitude and longitude.

**DATA PROCESSING**

In order to avoid intercorrelation between evaluation results and the length of gauge data available for a given station, those stations with data missing for more than 20% of the period with available radar data were excluded from the study. 24 of the dependent stations and none of the independent stations were excluded based on this criterion. The hourly gauge data from the independent stations was corrected for catch errors due to wind, following the procedure described in Førland et al. (1996). The hourly precipitation rates which could not be corrected due to either missing wind speed or temperature data were regarded as missing.
Due to the large number of radar grids to handle, a GIS toolset was developed for data processing and analysis (Abdella & Alfredsen 2010). The toolset was developed within the ArcGIS 9.2 environment. The processes within the toolset are developed and automated using a series of Python scripts. The hourly HDF5 radar grids were converted to ESRI Grid files and their original projection, which is polar stereographic projection with a spherical Earth model (radius 6,370,997 m) and an origin at 60°N and 0°E, was defined. Then both the radar grids and the rain gauge coordinates were projected to the UTM system. The rain gauge locations were overlaid on the radar grid and the pixel values at all the gauge locations were extracted for each hour. A text file with a time series of extracted hourly radar precipitation estimates was generated. No spatial interpolation was performed on the radar grid during the extraction process, i.e. only the radar pixel located exactly over the gauge was used.

The extracted estimates corresponding to the dependent gauges were aggregated to daily sums accumulated from 06:00 to 06:00 UTC in summer and 07:00 to 07:00 UTC in winter. A similar daily series was generated for the radar estimates at the independent gauges but with the accumulation time of 06:00 to 06:00 UTC all year round. Daily accumulations were computed only for those days with no missing data for any hour.

So three datasets were generated for carrying out the evaluation in this study: a series of daily radar and gauge data at the dependent stations, a series of daily radar and gauge data at the independent stations and a series of hourly radar and gauge data at the independent stations. In both the daily and hourly datasets, those time steps with missing radar or gauge data were excluded.

**METHODS**

The precipitation estimates from the Rissa radar were evaluated through comparison with measurements from 112 dependent gauges within the entire radar coverage and measurements from 15 independent gauges within the Sør-Trøndelag County. With respect to the gauge adjustment of the radar estimates, the dependent gauge data is only temporally independent, while the independent gauge data is both temporally and spatially independent. Unfortunately three of the independent gauges are located close to gauges from the dependent network. Comparison with data from the dependent gauges evaluates the use of adjustment factors computed from data of a given year and at a given gauge location to adjust radar estimates of another year at the same gauge location. Comparison with data from the independent gauges is used to evaluate the use of adjustment factors computed from data of a given year and interpolated from several gauge locations to adjust radar
estimates of another year at locations different (away) from the same gauges. The comparison with dependent gauge data was carried out on a daily timescale, while daily and hourly timescales were used for the comparison with independent gauge data. The following statistical parameters were computed to quantify the comparison results.

**Estimation bias (EB)**

This is the normalized accumulated difference between the radar estimates and the gauge measurements evaluated over a long period (one year or more) (Jayakrishnan et al. 2004; Wang et al. 2008):

$$\text{EB} = \left(\frac{R_{\text{Total}} - G_{\text{Total}}}{G_{\text{Total}}}\right) \times 100$$  \hspace{1cm} (3)

where $R_{\text{Total}}$ and $G_{\text{Total}}$ are the total precipitation concurrently or individually detected by the radar and gauge, respectively.

**Conditional mean precipitation (CM)**

This is the average of precipitation accumulation over nonzero precipitation hours/days (Smith et al. 1996; Young et al. 1999; Borga et al. 2002; Xie et al. 2006; Wang et al. 2008):

$$\text{CM} = \frac{\text{precipitation accumulation}}{\text{number of time steps with precipitation}}$$  \hspace{1cm} (4)

**Efficiency index (EI)**

This is a widely used statistic for assessing the performance of hydrologic models and was defined by Nash & Sutcliffe (1970). It measures the goodness-of-fit between predicted and measured (observed) time series of variables such as streamflow. Since radar precipitation estimates are not direct measurements, EI can be used to assess their accuracy with respect to gauge observations. The same index was used by Jayakrishnan et al. (2004) to evaluate the NEXRAD Stage III precipitation estimates with respect to rain gauge measurements. The possible values of EI stretch from minus infinity to a maximum of 1.0 for a perfect fit. McCuen et al. (2006) have carried out an evaluation of this index and present some suggestions on how it can be used as a reliable goodness-of-fit statistic:

$$\text{EI} = 1 - \left(\frac{\sum_{i=1}^{n} (R_i - G_i)^2}{\sum_{i=1}^{n} (G_i - G_{\text{avg}})^2}\right)$$  \hspace{1cm} (5)

where $n$ is the number of time steps in the comparison, $R_i$ is the radar precipitation for time step $i$, $G_i$ is the gauge precipitation for the corresponding time step $i$ and $G_{\text{avg}}$ is the mean gauge precipitation over all the time steps.

**Mean absolute difference (MAD)**

This is the average absolute difference between radar and gauge precipitation over the comparison period (Willmott 1982; Wang et al. 2008; Goudenhoofdt & Delobbe 2009):

$$\text{MAD} = \frac{\sum_{i=1}^{n} |R_i - G_i|}{n}$$  \hspace{1cm} (6)

where $n$, $R_i$ and $G_i$ are the same as above.

**Conditional probability of precipitation detection (CPOD)**

This parameter indicates the probability of observing precipitation by one observation system, given that another observation system observed precipitation above a given threshold ($\text{trsh}$). It can be defined for both the radar and gauge.

**Conditional probability of precipitation detection by radar** ($\text{CPOD}_R$) is computed as the probability of observing precipitation by a radar, given that the gauge located in the corresponding radar grid cell has observed precipitation (McCullom et al. 2002; Xie et al. 2006; Wang et al. 2008):

$$\text{CPOD}_R = \frac{\text{count}(R > 0 \text{ and } G > \text{trsh})}{\text{count}(G > \text{trsh})}$$  \hspace{1cm} (7)

where $R$ and $G$ are hourly/daily radar and gauge precipitation, respectively, count $(R > 0 \text{ and } G > \text{trsh})$ is the number of hours/days when precipitation above $\text{trsh}$ recorded by the gauge is also detected by the colocated radar cell and count $(G > \text{trsh})$ is the number of hours/days the gauge detects precipitation above $\text{trsh}$.

**Conditional probability of precipitation detection by gauge** ($\text{CPOD}_G$) is the probability of observing precipitation...
by a gauge, given that precipitation is detected in the radar cell enclosing the gauge (Xie et al. 2006; Wang et al. 2008):

\[
\text{CPOD}_G = \frac{\text{count (} R > \text{trsh and } G > 0 \text{)}}{\text{count (} R > \text{trsh)}}
\]

(8)

where \( R \) and \( G \) are as defined above, count \( ( R > \text{trsh and } G > 0 ) \) is the number of hours/days when precipitation above trsh detected by the radar cell is also detected by the gauge located within the cell and count \( ( R > \text{trsh}) \) is the number of hours/days the radar detects precipitation above trsh.

With regards to CPOD, it is important to recognize that it is inappropriate to compare CPOD\(_R\) with CPOD\(_G\). First, as rain gauges are used as the reference for the true precipitation, one cannot deduce the quality of the rain gauges based on the quality of the radar field. In addition, they are not equivalent quality parameters since CPOD\(_R\) indicates detection within a radar pixel of 1 km\(^2\) while CPOD\(_G\) indicates detection by a rain gauge with an opening of 200 cm\(^2\). The purpose of including CPOD\(_G\) in this study is to consider, in the CPOD analysis, all the time steps (hours/days) when the radar detected precipitation. This is not done by CPOD\(_R\) as it excludes the cases when the radar detects precipitation and the corresponding gauge doesn’t, i.e. cases when \( R > \text{trsh} \) and \( G = 0 \). A higher value of CPOD\(_G\) indicates a lower proportion of such cases and vice versa. Possible causes for such cases to occur are, for example, non-precipitation echoes (ground clutter, insects, etc.) or echoes from precipitation not reaching the ground (overhanging precipitation, evaporation, etc.).

All the above statistical parameters were first computed for the entire study period and then separately for the winter (December, January and February) and the summer months (June, July and August). The objective of this separation was to study the differences between the error characteristics during fully developed winter and summer conditions. In order to quantify the average performance of the radar with respect to only time, the parameters were computed independently for each gauge location (Figures 4–17). And to approximately represent the average performance with respect to both space and time, the median values of the parameters have been given (Table 1). When computing EI and MAD, only those time steps with nonzero precipitation for both the gauge and radar were included. So they are used for evaluating the radar when both the gauge and the corresponding radar cell concurrently detected precipitation. The first reason for using this condition is to separate the radar–gauge differences resulting from over- or under-estimation of detected precipitation from those differences resulting from missed (undetected) precipitation. The latter differences are captured by the computation of CPOD. The second reason is to exclude those time steps for which both the gauge and radar precipitation are zero. The inclusion of such time steps results in a relatively larger sample size and consequently makes EI and MAD artificially in favor of the radar (Grassotti et al. 2003; Jayakrishnan et al. 2004).

Figure 4 | Conditional probability of precipitation detection by radar (CPOD\(_R\)) at the dependent gauge locations.

Figure 5 | Conditional probability of precipitation detection by gauge (CPOD\(_G\)) at the dependent gauge locations.
There is one major difference between CPODR and the rest of the parameters. The gauge adjustment does not affect the CPODR that would have been obtained if the comparison had been made between the unadjusted radar estimates and the gauge measurements. Since the adjustment is carried out by multiplying each radar cell with the corresponding cell from the adjustment grid, only nonzero precipitation values will be changed. CPODR is determined by differentiating zero and nonzero precipitation, without regards to magnitude. Therefore, the performance of the adjustment procedure cannot be assessed by using CPODR and the dependent gauges are independent with respect to CPODR analysis.

Spatial sampling differences between radar and gauge

In carrying out evaluation studies of radar precipitation estimates which are based on comparison with gauge measurements, it is important to recognize that there is a significant difference in spatial sampling of precipitation for the two sensors (Austin 1987; Kitchen & Blackall 1992; Ciach & Krajewski 1999a,b). The rain gauges used in this study sample precipitation over an area of 200 cm², while the radar samples precipitation within a volume and estimates the average accumulation over an area of 1 km x 1 km. Therefore, evaluation and also gauge adjustment procedures which are based on radar–gauge point comparisons are complicated by the problem of sensor sampling differences which, combined with the significant small scale precipitation variability, introduce representativeness errors in the statistical comparisons (Kitchen & Blackall 1992). A significant fraction of the radar–gauge precipitation difference variance at an hourly time step may be explained by the gauge areal representativeness error (Creutin et al. 1997).

Ciach & Krajewski (1999b) derived an error separation method to partition the differences between radar estimates and gauge measurements into the areal radar precipitation estimation error and the error due to the gauge’s non-representativeness of areal precipitation. However, this method requires a high density rain gauge cluster within a radar cell, which is not available in most cases. Another approach proposed by Wang et al. (2008) is to use uniform precipitation events while directly comparing radar

Figure 6 | Scatter plots of conditional mean precipitation (CM) computed at the dependent gauges for the whole study period, for the summer months and the winter months.
estimates with gauge measurements. According to their approach, the gauge recorder precipitation amount better represents the ground truth of areal mean precipitation for uniform precipitation events within a radar cell (4 km × 4 km). They used the coefficient of variation of radar cells in a moving window of 3 × 3 radar cells to identify uniform events.

Up to the present, gauge measurements are the only reference for ground truth precipitation. Despite the sampling differences, valuable information can still be obtained from direct comparisons between radar and gauge data.

RESULTS AND DISCUSSION

Evaluation against dependent gauges

The radar precipitation estimates at the dependent gauge locations were compared with the corresponding gauge data at a daily time scale. CPODR, CPODG, CM, EB, EI and MAD were computed at 112 gauge locations for the entire study period and separately for the summer and winter months. Both CPODR and CPODG were computed for thresholds of zero. The median values of the parameters are given in Table 1. CPODR values for all 112 locations are given in Figure 4 in the form of a plot against distance from the radar. CPODR for the study period ranged from a minimum value of 0.39 to a maximum of 1.0, which indicates complete detection. CPODR for the summer and winter months ranged from 0.69–1.0 and 0.32–1.0, respectively. The summer CPODR is higher than the winter CPODR for 60% of the gauge locations. Detection is generally higher for ranges within about 140 km. Beyond this range, a decline in the level of detection is observed from the plot. The decline beyond this range is steeper during winter, which is sharper during winter, can have a number of reasons. In winter, precipitation mainly

Figure 7  Conditional mean precipitation (CM) computed at the dependent gauges for the whole study period, the summer months and winter months.
falls from low, stratiform clouds. The height of the radar beam axis above the ground increases with range, and at long ranges such precipitation may be completely undetected even by the lowest-elevation scans. The shallowness of winter precipitation is common in cold climates such as the Nordic countries. On the other hand, the precipitating clouds in the summer are often convective clouds with high vertical extension. This reduces the probability of beam-overshooting and leads to a better detection level than in the winter. Similarly, Crochet & Gjertsen (2000) and Gjertsen (2001) had reported a decrease in precipitation detection with range and generally lower detection levels in winter than in spring after assessing the measurements from a radar in Oslo. Attenuation of a low radar signal reflected from light precipitation at long ranges can also result in very low reflectivity, which is transformed into zero precipitation. Another possible reason that the radar may miss precipitation events is that the radar sampling frequency is 15 min, and not continuous as it is for gauges. So fast-moving storms or rapid development/decay of storms could lead to a reduced detection level.

CPOD$_G$ (Figure 5) does not show a distinctive pattern with respect to distance as in the case of CPOD$_R$. This is expected since there isn’t a range-dependent condition which affects the detection by a gauge. The median CPOD$_G$ is 0.72 (Table 1). This indicates that, of the total number of days when the radar detected precipitation, the corresponding rain gauge did not observe precipitation for 28% of the days. Possible causes for a gauge not to observe precipitation when the radar bin above has detected precipitation are horizontal wind drift and evaporation of precipitation.
during the descent from the pseudoCAPPI level to the ground, overhanging precipitation not reaching the ground, localized convective cells and lower threshold of precipitation detection by radar. The lower median CPOD_g than in winter (Table 1) can be attributed to evaporation and localized convective precipitation. And, given that the minimum hourly precipitation rate for the radar is 0.01 mm/h, it is highly likely that the dependent gauges will miss lighter intensities detected by the radar. If this minimum detectable precipitation rate by radar is lower than that of the sensitivity of the gauge then precipitation events with intensities lighter than what the gauge is sensitive to will be undetected by the gauge below. Apart from these, radar measurement errors can also be a cause. A typical example of such a case is when the radar measurements contain some noise due to ground clutter and anomalous propagation during days without precipitation.

It should be noted here that the analysis of detection level using CPOD values computed at a daily timescale has uncertainties due to the 24 h timescale. If any one of several precipitation events detected by a gauge/radar cell is detected in the collocated radar cell/gauge, then the radar/gauge detection requirement is fulfilled. Those undetected precipitation events within the 24 h period do not affect the CPOD computation. This factor leads to CPOD values generally higher than those obtained using data at a finer timescale. However, by using longer periods of analysis and many gauges, as is done in this study, important trends can be revealed even from CPOD computed from daily data.

Scatter plots of radar and gauge CM are given in Figure 6. Radar CM is higher than gauge CM for 77% of the gauge locations when considering the whole study period. The same percentage is 88% for summer and 46% for winter. There is a significantly better agreement between radar and gauge CM in winter than in summer. Also the magnitudes of the differences between radar and gauge CM are significantly higher in summer than in winter. Plots of CM versus range are given in Figure 7. A striking difference is observed between the summer and winter plots. In summer the gauge locations for which the radar CM is higher than the gauge CM lie at ranges beyond 80 km and all gauge locations for which radar CM is lower lie at ranges within 80 km. In addition, most of the gauge locations for which the radar CM is considerably higher than the gauge CM lie at ranges beyond about 120 km. In winter, however, gauge locations for which radar CM is lower are also found at ranges well beyond 80 km, with all gauge locations beyond 210 km having lower radar CM.

The results from EB computation, shown in Figure 8(c), reflect the trends observed in the CM plots. EB computed over the whole study period ranged from −45% (underestimation) to 219% (overestimation), with an
overestimation at 85% of the gauge locations. The gauge precipitation was overestimated at 92% and 53% of the gauge locations in summer and winter, respectively. EB for the summer and winter months ranged from $\pm 31\%$ to $314\%$ and $\pm 80\%$ to $151\%$, respectively. But the highest overestimations of 219% and 314% were computed for a gauge where the corresponding radar cell had an outlier of 284 mm/d. Excluding this outlier, the maximum overestimations for the study period and the summer months are 153% and 244%, respectively. The outliers identified during the comparison occurred as extreme overestimations during summer (Figure 8(a)). One possible reason for these extremes could be the presence of strong ground clutter not removed by Doppler filtering. Such a spurious echo in summer can be caused by anomalous propagation (Koistinen et al. 2004). The occurrence of hail within the sample volume at higher altitudes can be another cause since most of the outliers occur at longer ranges. As observed in Figure 8(c), all underestimations in summer are within a range of 80 km and there are considerable overestimations beyond this range. Underestimation in winter occurs at all ranges, with the highest underestimations at ranges beyond 210 km. The overestimations in winter are much lower than those in summer. For the severe underestimations beyond 210 km, it is important to note that they occur within the ranges where the monthly average adjustment factors can be over 20 but are limited to the maximum value of 20 (Figure 2(a,b)). Even though setting this threshold can, in general, avoid the risk of inducing large errors, it can also result in underestimation for locations where the actual G/R ratio is greater than 20.

Moving to the statistical parameters including only concurrent nonzero precipitation, EI and MAD were computed at each gauge location. Excluding the gauge with the outlier mentioned above, which had an EI of $-43$, EI computed over the whole study period ranged from $-12.9$ to $0.61$. Considering that they have been utilized for the gauge adjustment, these EI values for the dependent gauges are generally low, with 30% of the gauge locations with EI > 0 and only 19% with EI > 0.4. EI for the summer and winter months ranged from $-23.4$ to $0.74$ and $-2.86$ to $0.77$, respectively. A plot of EI versus range is given in Figure 8(a). The radar estimates correspond to the gauge measurements better in winter than in summer with winter-EI higher than summer-EI for 75% of the gauge locations. And there seems to be a dependence of EI on range from the radar. In the case of EI for the whole study period, all gauge locations with EI > 0.4 are within a range of 100 km. This is clearly visible in the spatial distribution of EI within the radar coverage (Figure 9).

The trends in MAD resemble those observed for EI. As observed in the plot of MAD versus range (Figure 8(b)), MAD generally increases with increasing range. MAD computed over the whole study period ranged from $1.8–9.1$ mm/d, and MAD for the summer and winter months ranged from $1.3–13.9$ mm/d and $1.6–11.3$ mm/d,
respectively. The differences in the summer are higher than those in the winter for 68% of the gauge locations. The spatial distribution of MAD computed for the whole period is shown in Figure 10.

**Evaluation against independent gauges**

The evaluation of the radar precipitation estimates against the independent gauges was first carried out at an hourly time scale. CPOD	extsubscript{R}, CPOD	extsubscript{G}, CM, EB, EI and MAD were computed at each gauge location (Figures 11–17) and the medians are given in Table 1. The CPOD	extsubscript{R} values for the independent gauge locations were first computed with a threshold of zero and these ranged from 0.39–0.77 (Figure 11). These detection probabilities are lower than those computed for the dependent gauges within the same range. This difference is expected since CPOD	extsubscript{R} for the independent gauges was derived from hourly data. The decrease in CPOD	extsubscript{R} with decreasing temporal timescale has been documented in previous studies (Xie *et al.* 2006). CPOD	extsubscript{R} for the summer and winter months ranged from 0.65–0.32 and 0.78–0.45, respectively. The winter-CPOD	extsubscript{R} is higher than the summer-CPOD	extsubscript{R} for all the gauge locations except for one where the summer-CPOD	extsubscript{R} is equal to the winter-CPOD	extsubscript{R}. This result is not unexpected since almost all the independent gauges are located within ranges where the detection levels in winter are not predominantly lower than those in summer. The summer-CPOD	extsubscript{G} was lower than the winter-CPOD	extsubscript{G} for 12 of the 15 gauge locations except for one where the summer-CPOD	extsubscript{R} is equal to the winter-CPOD	extsubscript{R}. This result is not unexpected since almost all the independent gauges are located within ranges where the detection levels in winter are not predominantly lower than those in summer. The summer-CPOD	extsubscript{G} was lower than the winter-CPOD	extsubscript{G} for 12 of the 15 gauge locations (Figure 12). Lower summer-CPOD	extsubscript{G} for the majority of the gauge locations is a trend also observed at the dependent gauge locations.

Although CPOD	extsubscript{R} computed from hourly data is expected to be lower than that computed from daily data, the CPOD	extsubscript{R} computed seem to be too low for gauges located within a distance of 145 km from the radar. But analysis of the hours where the radar cell misses precipitation detected by the gauge revealed that cases where the gauge recorded very light intensities (<0.1 mm/h) accounted for a significant proportion of these hours. Some of these cases could be noises in the hourly gauge data. CPOD	extsubscript{R} was recomputed with a threshold of 0.1 mm in order to exclude such cases. The resulting CPOD	extsubscript{R} are significantly better than those with a zero threshold (Figure 13). One important thing to
consider here with regards to the detection of lower precipitation rates by radar and gauge is the temporal sampling difference between the two. The radar precipitation is estimated from instantaneous measurements while the gauge accumulates. After a long-lasting event or a number of intermittent events with an hourly rate less than the radar’s minimum rate (0.01 mm/h), the hourly radar precipitation will be zero. However, the precipitation will accumulate in the gauge and will be recorded when the accumulation reaches the sensitivity level of the gauge. Such situations may occur during winter where there is no evaporation from gauges and longer stratiform events with lighter intensity are more frequent.

Scatter plots of radar and gauge CM are presented in Figure 14. Radar CM is higher than gauge CM for five of the gauge locations when considering the whole study period. In the summer, the radar CM is higher for all the gauge locations within the range 60–145 km, while it is lower for the gauge located close to the radar. Coming to the winter, radar CM is higher at four of the gauge locations. The same trend for the dependent gauges is also evident for the independent gauges in which the magnitudes of the differences between radar and gauge CM are significantly higher in summer than in winter. Plots of CM versus range are given in Figure 15. As observed from the plots, the radar CMs computed for the whole period do not show appreciable variation with range, while the radar CMs in summer are considerably higher for ranges beyond 90 km. Conversely the radar CMs in the winter tend to be lower beyond the 90 km range.

The results from EB computation, shown in Figure 16(c), reflect the trends observed in the CM plots. EB computed over the whole study period ranged from $-50\%$ to $40\%$, with an overestimation at 10 of the gauge locations. EB for the summer and winter months ranged from $-25\%$ to $140\%$ and $-66\%$ to $42\%$, respectively. As with the dependent-gauge locations, the EBs for the independent gauges also reveal that overestimation is predominant in the summer, with a positive EB at 14 of the gauge locations. The gauge precipitation was overestimated at only 5 of the gauge locations in winter. The overestimations in winter are much lower than those in summer.

EI computed over the whole study period were all below zero and ranging from $-0.05$ to $-1.53$. These low
EI values indicate that discrepancies between the radar estimates and the gauge measurements are higher for finer timescales. EI for the summer and winter months ranged from $-11.9$ to $-0.40$ and $-0.94$ to $0.11$, respectively. The lowest summer-EI of $-11.9$ was obtained at a gauge location with an outlier of $38$ mm/h estimated at the collocated radar cell. The next lowest summer-EI is $-5.17$.

A plot of EI versus range is given in Figure 16(a). The agreement between radar estimates and gauge measurements is better in winter than in summer. This is indicated by the higher winter-EI than summer-EI for all the gauge locations. No significant dependence of EI on range from the radar could be identified from the 15 gauge locations based on hourly data.

MAD computed over the whole study period ranged from $0.40–0.71$ mm/h and MAD for the summer and winter months ranged from $0.48–0.96$ mm/h and $0.31–0.77$ mm/h, respectively (Figure 16(b)). The differences in the summer are higher than those in the winter for 13 of the gauge locations.

EI at the independent gauge locations were also computed at a daily timescale. Figure 17 shows both the hourly and the daily-EIs plotted against range. The daily EIs are generally low and range from $-0.55$ to $0.52$. Only one gauge location has an EI $>0.4$, which is a gauge located quite close to one of the dependent gauges. The daily EIs are higher than the hourly EIs at all gauge locations. This is expected because, on an hourly timescale, a significant mismatch between radar and gauge estimates occurs due to the spatial variations in precipitation and the effect of gauge resolution. However, integrating over longer timescales minimizes these factors, revealing systematic differences between the radar estimates and gauge measurements. According to the daily EIs, a slight range dependence is observed where EI reduces with increasing range. Then daily-EIs for the summer and winter months ranged from $-4.49$ to $0.49$ and $-0.25$ to $0.61$, respectively.

**Effects of the vertical profile of reflectivity (VPR)**

The non-uniformity of VPRs is a dominant source of error in using radar measurements to estimate quantitative ground level precipitation (Joss & Waldvogel 1990; Koistinen et al. 2004). Since the precipitation at the ground
must be deduced from a reflectivity measurement sampled aloft, considerable error may result. This error is revealed as a range-dependent bias while comparing measured reflectivity with gauge precipitation since the vertical distance between the sample volume of the radar and the ground usually increases with increasing distance from the radar. This bias is clearly visible in the adjustment factor fields for the Rissa radar shown in Figure 2(a,b). Reflectivity measurements from the full range of the radar (240 km) are used for estimating quantitative precipitation. This utilization of measurements at relatively longer ranges makes VPR a major source of the difference between the radar estimates and gauge measurements. And this importance of considering error due to VPR is greater for Norwegian climate conditions. This is because of the precipitation structure in a cold climate, which is generally characterized by shallowness and large negative reflectivity gradients from the surface level upward (Koistinen et al. 2004). The prevalence of VPRs with such a gradient during winter is reflected in the comparison result (Figure 8(c)), where underestimation in winter occurs over the whole range. Errors caused by ignoring the effects of VPR may be far larger than errors caused by attenuation or variations of the Z–R relationship (Joss & Waldvogel 1990; Joss & Lee 1995).

However, no explicit correction for the effects of VPR has been considered in the generation of precipitation estimates from the Rissa radar. The construction of the CAPPI products can partially compensate the range-dependent bias due to VPR. But this approach will not be able to fully compensate for the range bias. This is because, at ranges beyond 30 km, even the lowest elevation angle of the radar exceeds the representative height at which the CAPPI is built (1.1 km above sea level) and reaches to several kilometers at longer ranges. So the effects of VPR are left to be handled by the gauge adjustment procedure. But the results from the evaluation show that this procedure does not adequately correct the range-dependent bias. It is therefore necessary to use a VPR adjustment procedure. This is appealing because the use of even a simple VPR correction would help to improve the agreement between radar and rain gauge measurements (Joss & Waldvogel 1990; Joss & Lee 1995).

Using a fixed Z–R relationship

The reflectivity measurements (Z_e) from the radar are converted to precipitation rates (R) using a fixed, both temporally and spatially, Z–R relationship which was derived from the drop size distribution measured for stratiform rain (Marshall & Palmer 1948). This results in erroneous estimates of radar precipitation due to variations in the drop size distributions of precipitation that lead to different Z–R parameters (Battan 1973). The gauge-based spatial adjustment procedure attempts to correct (minimize) this error. The use of a single Z–R relation suitable for stratiform precipitation could be one of the reasons for the overestimation during summer, as indicated by the higher radar CM and positive EB for summer at both the dependent and independent gauge locations (Table 1). Analysis of the temporal distribution of precipitation during the summer months shows that fewer high intensity events dominate the summer CM. The use of the Marshall & Palmer (1948) Z–R relation for such convective events may produce overestimation. Therefore, differentiating events based on storm type, as convective and stratiform, and using separate Z–R relationships for the two, may improve the performance of the Z–R conversion (Chumchean et al. 2006).

Another differentiation which is particularly more relevant for Nordic countries, and hence the Rissa radar, is based on the precipitation phase (Koistinen et al. 2004).
Estimating snowfall intensity using a $Z$–$R$ relation developed for rain will result in errors. A number of $Z$–$R$ relations have been derived for snow (Battan 1973). But care should be taken in employing these relations because weather radar systems are customarily calibrated to measure the “water equivalent” $Z_{e}$ (Smith 1984). This is also true for the Rissa radar system. Application of the Marshall & Palmer (1948) relation may lead to underestimation in the case of snow precipitation. This effect, in addition to the strong negative VPR gradient in snowfall, can introduce the underestimations reported for the comparison during winter.

However, the errors caused by not using $Z$–$R$ relations classified by storm type (e.g. stratiform and convective) or precipitation phase are much smaller than the range-dependent bias due to non-uniform VPR (Joss & Waldvogel 1990; Koistinen et al. 2004). This is particularly true in the case of the Rissa radar where the measurement range extends up to 240 km.

### Using interpolated monthly adjustment factors

The spatial gauge adjustment method uses mean monthly adjustment factors derived from daily accumulations for correcting radar estimates at 15 min interval. As discussed above, the bias revealed in the adjustment factor field is mainly due to the effects of vertical sampling differences under non-uniform VPR. Therefore, the average adjustment field represents, to a large extent, the average monthly bias due to the average monthly VPR structure. This means that only errors due to the long-term average VPR structure can be corrected. But, due to the higher temporal variability of VPRs, there will be numerous hours within a given month when the actual adjustment field deviates considerably from the monthly average. Consequently, the errors due to the temporal variance at shorter timescales (hours or days) remain uncorrected. This is evident from the significant daily and hourly radar–gauge differences shown in the comparison. The effects the different characteristics of the VPR structures for convective and stratiform precipitation have on using average monthly correction can be seen from the comparison results for summer and winter. Strong convective events during the summer typically have VPRs with gradients much less than the average monthly VPR. The increase of the actual adjustment factor with range during such events will not be as steep as the increase of the average monthly adjustment factor. This will consequently result in the overestimations during summer, indicated by the higher radar CMs and positive EBs. Another factor which adds to the higher radar–gauge differences during summer is that the spatial and temporal variability of the VPRs associated with convective events are much stronger than that associated with stratiform events.

The adjustment method also uses monthly adjustment factors derived on the basis of data from the previous years. This can result in additional biases because the average
adjustment factors for a month in a given year are not necessarily similar to the factors for the same calendar month in a different year. The average monthly VPR structure is determined by the prevailing weather type and not exactly by the time of the year. Even for a temporally stable monthly VPR structure, this approach requires a stable calibration of the radar from the period used for the generation of the adjustment factors to the period when measurements are to be corrected.

The radar estimates at the independent gauge locations are adjusted by using the interpolated monthly adjustment factors. The use of interpolated factors is questionable because there could be problems when the gauge–radar ratios are representative for a limited spatial extent due to significant spatial variation of precipitation. In the summer season, for example, when convective precipitation is frequent, the gauge–radar ratios could be localized. Interpolation works better in situations in which the precipitation is fairly uniform and the gauge–radar ratios are consistent in space. This is the case during stratiform precipitation, which is frequent during winter. The better agreement with gauge measurements exhibited by the radar estimates during winter, as indicated by the comparison, can be partly attributed to this factor. The above factor also indicates that the gauge adjustment is best suited for areas where the gauge density is high, and may perform poorly in gauge-sparse areas.

**Evaluation at the catchment scale**

Although not included in this study, comparison of radar estimates with gauge measurements can also be performed in terms of catchment-based areal precipitation (Creutin et al. 1997; Johnson et al. 1999; Stellman et al. 2001). Such a comparison is relevant for assessing the use of radar data in hydrological applications where lumped models are used.

The differences between catchment-based areal precipitation from gauge and radar would be less than those obtained from pixel-to-point value comparisons since random errors within the catchment can, to some extent, compensate each other. This has a positive effect on streamflow simulated using a lumped hydrological model, but can still be a problem in the case of a distributed model sensitive to the spatial precipitation distribution.

**SUMMARY AND CONCLUSIONS**

The gauge-adjusted radar precipitation estimates from the Rissa radar were evaluated through comparison with measurements from dependent and independent gauges. The comparison with daily measurements from the dependent gauges showed that a decline in the radar’s detection probability occurs beyond a range of about 140 km. This decline in detection is more severe in winter, which is likely due to radar beam overshooting during low-level stratiform precipitation events. Unlike the radar, the detection by gauges didn’t show a distinct range dependence. The analysis of CM and EB indicated that the radar estimates are generally higher than the corresponding gauge measurements. The deviations between radar- and gauge-CM were significantly higher in summer than in winter. In summer, there was an overestimation at most of the gauge locations, with higher overestimations at ranges beyond 80 km. There were more underestimations during winter, with the highest underestimations at long ranges most probably being caused by low detection probabilities. Despite their inclusion in the gauge adjustment procedure, the EI values computed for the dependent gauges are generally low. The comparison with respect to EI and MAD revealed that there is more agreement between radar and gauge precipitation during winter. Also, the spatial distribution of EI and MAD showed a dependence of accuracy on range existing even after gauge adjustment.

The evaluation against the independent gauges revealed trends mostly similar to the ones above except for CPOD results. The winter-CPOD$_R$ was generally higher than the summer-CPOD$_R$. According to the EB and CM results, overestimation was predominant in the summer, while there was underestimation at 10 of the 15 gauge locations during winter. The EI values computed at these gauges were even lower than those for the dependent gauges, and indicate the increase in the level of mismatch between radar and gauge precipitation at hourly timescales. EI improved when computed from data aggregated to daily amounts. The radar estimates exhibited better agreement with gauge measurements during the winter, both at the hourly and daily timescales.

The evaluation results indicate that significant biases and errors, with respect to gauge measurements, remain in
the gauge-adjusted precipitation estimates. According to the adjustment factor grids (Figure 2), the unadjusted radar precipitation estimates were generally lower than gauge measurements. Also the adjustment factors become higher with increasing range. This range-dependent bias is a direct result of the increase in sampling height and non-uniform VPR. One of the objectives of the spatial adjustment was to remove this range-dependent bias in the radar estimates. However, the comparison results indicate that there is still some degree of dependence of radar–gauge differences on distance from the radar. So it is necessary to use a VPR correction since the gauge adjustment procedure does not adequately remove the range-dependent bias.

The spatial gauge adjustment method uses mean monthly adjustment factors derived from daily accumulations for correcting radar estimates at 15 min interval. This mean adjustment factor represents, to a large extent, the average monthly bias due to the average monthly VPR structure. This means that only errors due to the long-term average VPR structure can be corrected and the error due to the temporal VPR variance at shorter timescales (hours or days) remain uncorrected. This is evident from the significant daily and hourly radar–gauge differences shown in the comparison. Because of the presence of hours when the actual adjustment field deviates considerably from the average, the use of larger factors during summer has led to significant overestimations and the use of large factors during winter has not removed the underestimations.

The equivalent reflectivity factors were converted to precipitation rates \( R \) using a fixed, both temporally and spatially, \( Z–R \) relationship which was derived from the drop size distribution measured for stratiform rain. Though the gauge-based spatial adjustment procedure attempts to correct (minimize) the errors due to the variability of the \( Z–R \) relation, using \( Z–R \) relations classified by storm type (e.g. stratiform and convective) or precipitation phase from the onset can be a better approach.

From the perspective of distributed hydrologic modeling, the differences observed from the comparison limits the usefulness of the radar estimates as quantitative precipitation inputs. This conclusion, however, specifically refers to the gauge-adjusted hourly radar products supplied by met.no because the radar measurements can be used to generate more accurate quantitative precipitation estimates using a different procedure. Based on the finding in this study, such a procedure should also, as far as possible, correct errors originating from non-uniform VPR and use precipitation type and a phase-dependent \( Z–R \) relation before attempting to make adjustment by comparing with gauge data. And, considering the longer measurement ranges used for the Rissa radar and the type of climate it is operating in, performing corrections for VPR is the most important factor for achieving more accurate quantitative precipitation estimates.

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