



Estimating Radar Precipitation in Cold Climates: The role of Air Temperature within a Nonparametric Framework

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Abstract. In cold climates, the form of precipitation (snow or rain or a mixture of snow and rain) results in uncertainty in radar precipitation estimation. Estimation often proceeds without distinguishing the state of precipitation which is known to impact the radar reflectivity – precipitation relationship. In the present study, we investigate the use of air temperature within a nonparametric predictive framework to improve radar precipitation estimation for cold climates. Compared to radar reflectivity - gauge relationships, this approach uses gauge precipitation and air temperature observations to estimate radar precipitation. A nonparametric predictive model is constructed with radar precipitation rate and air temperature as predictor variables, and gauge precipitation as an observed response using a k-nearest neighbour (k-nn) regression estimator. The relative importance of the two predictors is ascertained using an information theory-based rationale. Four years (2011-2015) of hourly radar precipitation rate from the Norwegian national radar network over the Oslo region, hourly gauged precipitation from 68 gauges, and gridded observational air temperature were used to formulate the predictive model and hence make our investigation possible. Gauged precipitation data were corrected for wind induced catch error before using them as true observed response. The predictive model with air temperature as an added covariate reduces root mean squared error (RMSE) by up to 15 % compared to the model that uses radar precipitation rate as the sole predictor. More than 80 % of gauge locations in the study area showed improvement with the new method. Further, the associated impact of air temperature became insignificant at more than 85 % of gauge locations when the temperature was above 10° C, which indicates that the partial dependence of precipitation on air temperature is most important for colder climates alone.

1 Introduction

Hydrological applications require accurate precipitation estimates at the catchment scale. Use of point precipitation gauges often proves inadequate in representing the spatio-temporal variability in the precipitation field (Beven, 2012; Kirchner, 2009). Weather radars provide quantitative precipitation estimates over a large area with high spatial and temporal resolution. However, weather radars measure the precipitation rate indirectly, using the energy scattered back by hydrometeors in the volume illuminated by a transmitted electromagnetic beam (Villarini and Krajewski, 2010b). The backscattered energy is measured as reflectivity which is used to estimate precipitation. This measured reflectivity depends on many factors such as size, shape,



orientation (if non-spherical), state and concentration of particles in the radar illuminated volume in the atmosphere along with their dielectric properties (Hong and Gourley, 2015; Joss et al., 1990).

The nature of radar precipitation measurements is subject to many sources of error. These errors occur during the sampling or measurement of reflectivity as well as in the process of converting the reflectivity (Z) to precipitation rates (R) (Chumchean et al., 2006). Some of the known errors in the reflectivity measurement are ground clutter, beam blocking, anomalous propagation, bright band, hail, and attenuation (Berne and Krajewski, 2013; Chumchean et al., 2003). During the conversion, the use of inappropriate Z - R relationship leads to Z - R conversion error. Due to the presence of such significant errors (both random and systematic), radar data are still not used in hydrological applications as broadly and efficiently as they could be (Berne and Krajewski, 2013; Chumchean et al., 2003). Many studies (e.g., Abdella, 2016; Villarini et al., 2008; Ciach et al., 2007; Chumchean et al., 2006) have focused on estimating these errors in order to improve quantitative radar precipitation estimates; however, some of the underlying physical processes are still not understood well enough to allow significant advances (Villarini and Krajewski, 2010a).

Conventionally, radar measurements of reflectivity (Z) are converted into precipitation rate (R) using the parametric Z - R relationship derived by Marshall and Palmer (1948) in the form of a power law, $Z = aR^b$. The variability of the power law parameters is related to a number of factors including the drop size distribution (DSD) of hydrometeors. Drop size distribution varies in time and space as well as for the type and the phase of precipitation (Chumchean et al., 2008; Joss et al., 1990; Uijlenhoet, 2001). The Z - R relationship is not unique and hence, we depend on empirical relationships instead (Wilson and Brandes, 1979). Most radar systems in cold climate countries (Canada and Finland etc.) use two sets of Z - R relations, one for rain and one for snow, often calibrated in situ to measure a water equivalent radar reflectivity factor (the dielectric constant for water is used) (Koistinen et al., 2004). However, the Norwegian radars and European radar project OPERA have used a single Z - R relationship (Marshall and Palmer (1948) relation for rain) throughout the year. The use of the single reflectivity-precipitation relationship can result in phase dependent bias in radar precipitation estimation.

In cold climates, quantitative radar precipitation estimates are often formulated for warmer summer months and / or specific storm events (Berne and Krajewski, 2013; Saltikoff et al., 2015). Norway and adjacent countries in northern Europe experience cold temperatures below +10 degrees Celsius for nearly three quarter of the year. Continuous runoff simulation is required for water resources management applications such as hydropower production planning, design and operation of water infrastructure, flood forecasting and ecological assessments (Hailegeorgis et al., 2016). Today, precipitation runoff models mostly use gauge precipitation measurements for continuous simulation. A continuous timeseries of radar-based precipitation estimates and the reduced reliance on traditional precipitation gauges are of great interest to hydrologists given the spatio-temporal detail that is offered. Further, a single radar can measure precipitation over many small catchments with its extended spatial coverage, which otherwise remain ungauged without any ground precipitation measurement (Berne and Krajewski, 2013). An example of the usefulness of radar precipitation data for continuous simulation was presented by Fassnacht et al. (1999). If a radar based continuous precipitation time series is to be generated with the objective of use in hydrological modelling in boreal regions, the effect of varying precipitation phase on radar precipitation estimates must be considered.



Starting from its origin and throughout its entire journey, the rain drop or snow crystal is shaped by temperature. During the formation and growth of cloud droplets, different temperatures cause different shapes of crystals to form, and then the crystals start to fall. The falling crystals are then characterised by the temperature of the air through which they fall. As a result, the air temperature determines the final properties and the phase of the hydrometeor that reaches the ground surface (Fassnacht et al., 2001). Further, studies showed that there are multiple snow types and they vary in time, based partially on temperature (Saltikoff et al., 2015). Many studies (Auer Jr, 1974; Kienzle, 2008; Killingtveit, 1976; Rohrer, 1989) examined the relationship between the precipitation phases (snow, rain and mixture of snow and rain) and temperature. The probability of occurrence of snowfall versus temperature shows an approximately 'S' shaped structure in these studies. Additionally, as mentioned earlier, measured reflectivity depends on dielectric properties of hydrometeors. The dielectric property of solid particles (ice) is very different from liquid particles (water) and moreover, it varies with temperature (Joss et al., 1990). These imply that temperature is intrinsic to both the phase of precipitation and the ensuing conversion of reflectivity into the incident ground precipitation.

Hasan et al. (2016b) presented a nonparametric approach to estimate ground rainfall using radar reflectivity as a univariate predictor variable in a tropical setting. Historical radar reflectivity and rain were used in formulating the nonparametric model. In the present work, we tested their method in the context of Norwegian radar precipitation estimation and found it to be sub-optimal especially for the colder precipitation events. Norway is a cold climate country located in the northern high latitudes, experiencing different phases of precipitation. Norwegian radars use a single $Z - R$ relationship throughout the year and the phase of the precipitation is not considered. If phase dependent $Z - R$ relationships were used, they will still require an added algorithm to establish the dominant phase for the event. Based on the discussion in the previous paragraph, the intuition is that air temperature observations can be used together with observed gauge precipitation to adjust radar precipitation in cold climates. Moreover, the nonparametric approach of Hasan et al. (2016b) can be extended to allow use of a bivariate predictor vector with temperature as an additional predictor variable. This forms the basis for the investigation reported here.

This study set out to investigate the use of air temperature as an additional predictor in the radar precipitation estimation with the objective of improving quantitative radar precipitation estimation for cold climates. Compared to traditional radar-gauge adjustment, the proposed method is based on nonparametric approach using gauge precipitation and air temperature observations to adjust the radar precipitation. The rest of the paper is structured as follows. The following section reviews radar precipitation estimation in cold climates as well as nonparametric methods and their use in radar precipitation estimation. The methods and tools used to formulate the nonparametric model are presented in Section 3. Section 4 describes the study area and data used to test the method. The results from the study are discussed in Section 5. Finally, summary and conclusions are presented in Section 6.

2 Background

2.1 Radar precipitation estimation in cold climates

In cold climates, precipitation occurs in the form of snow or rain or a mixture of snow and rain. As mentioned earlier, radar operations in cold climates often use two sets of parameters to convert radar reflectivity Z , into precipitation intensity (rain(R))



or snow(S), mm h^{-1}). Several studies (Battan, 1973; Marshall and Gunn, 1952; Sekhon and Srivastava, 1970) have investigated and then proposed different parameter sets (coefficients “a” and “b” in the power law equation relating reflectivity to precipitation) for rain and snow. The parameter set proposed by Sekhon and Srivastava (1970) has been used as a standard for snow, just as the work by Marshall and Palmer (1948) has been used widely for rain (Fassnacht et al., 2001; Saltikoff et al., 5 2015).

The Finish Meteorological Institute operationally uses their own equations for rain ($Z = 316R^{1.5}$) and snow ($Z_e = 100S^2$) (Saltikoff et al., 2015). Here Z_e represents the equivalent radar reflectivity factor of snow and it is different from Z because the radar signal processing uses the dielectric constant of liquid (water) instead of dielectric constant of solid (ice) for snow. Zhang et al. (2016) used the equation $Z_e = 75S^2$ for the NEXt Generation Radar network (NEXRAD) in the United States which 10 offers similarities to the equation by the Finish meteorological institute for snow. However, Saltikoff et al. (2000) reported that real time phase dependent adjustment of two different parameter sets does not improve the snowfall estimate significantly. To account for varying precipitation phase (multiple snow types and mixture of snow and rain), many parameter sets could be required. Moreover, the precipitation phase changes rapidly even within the single winter storm and hence, operationally, switching between different parameter sets can be a challenging task (Koistinen et al., 2004; Saltikoff et al., 2015).

15 For the use of phase dependent reflectivity-precipitation (Z - R) relationship, the precipitation phase of the radar pixel must be estimated. Earlier, weather radar operations in cold climates switched between summer and winter Z - R relationships according to calendar date. However, this is obviously uncertain. As mentioned in the introduction, air temperature can be used to determine the phase (whether snow or rain) of the precipitation. The Finnish Meteorological Institute uses temperature and humidity observations from synoptic stations to estimate the precipitation phase and uses that information to apply a different 20 parameter set for rain or snow (Koistinen et al., 2004; Saltikoff et al., 2015). Fassnacht et al. (2001) demonstrate the use of surface air temperature to estimate the fraction of snow content in mixed precipitation and use it to adjust the radar estimate for mixed precipitation. It is reported that these adjustments improve the accumulated snow estimates in Ontario, Canada. Observations from dual polarised weather radars can also be used to classify precipitation phases (Ryzhkov and Zrnica, 1998). However, many radars use a single polarity and moreover, even from dual polarised radars, data on phase information are not 25 readily available to end users to help refine their estimation algorithms. Operational use of dual polarised radars in hydrometeor classification has progressed significantly; however, the classification for high latitude winter storms is still challenging (Chandrasekar et al., 2013).

2.2 Nonparametric Radar rainfall estimates

Parametric (or regression type) and nonparametric approaches have been used to build predictive models for a range of ap- 30 plications. When sufficient data are available, nonparametric approaches are efficient alternatives for specifying an underlying model as compared to parametric approaches. Nearest neighbour and kernel density estimation are amongst the most commonly used nonparametric methods. The simplicity of nonparametric approaches have made them attractive for use in hydrology and other sciences (Mehrotra and Sharma, 2006). A key advantage of nonparametric approaches is that less rigid assumptions about the distribution of the observed data are needed (Silverman, 1986) and hence no major assumptions about the process being



modelled are required to construct the complete predictive system (Sharma and Mehrotra, 2014). Due to the availability of sufficient radar precipitation rate observations, nonparametric methods provide an attractive basis for assessing the hypotheses posed here.

5 Ciach et al. (2007) used nonparametric kernel regression to model radar rainfall uncertainty. They described the relation between true rainfall and radar-rainfall as the product of a systematic distortion function along with a random component and presented procedures to identify the two components. The distortion function could account for systematic biases which can be mathematically defined as a conditional expectation function, while the random component accounts for random errors in radar rainfall estimation. Villarini et al. (2008) estimated the conditional expectation function (distortion function) using both nonparametric (similar to Villarini et al. (2008)) and copula-based methods and compared the difference in performance 10 between the two approaches using different quality metrics. It was found that performance of the nonparametric method was comparable with the copula-regression estimate and even outperformed when Nash Sutcliffe Efficiency (NSE) was used as a quality metric. The strength of nonparametric approaches is the ability to adapt to the data locally and the weakness is that the method is sensitive to outliers and to large variability of data at the smallest (sub hourly) time scales. Hasan et al. (2016b) used a kernel based nonparametric method for radar rainfall estimation. In their approach, expected ground rainfall was estimated for 15 a given reflectivity using a kernel-based conditional probability distribution. However, none of the methods above considered an additional covariate as air temperature as proposed in this study.

3 Methodology

This section describes the methods used to formulate a nonparametric predictive model with incident air temperature and radar precipitation rate as the two predictors for radar precipitation in cold climates. A description of how the incident air temperature 20 is incorporated as a covariate in the nonparametric radar precipitation estimation approach is presented next.

3.1 Radar precipitation estimation

The proposed radar precipitation estimation algorithm consists of two steps. The first step quantifies the partial dependence of precipitation on radar precipitation rate and incident air temperature. The second step then uses the identified predictors in a non-parametric setting to estimate the precipitation response. Gauge precipitation is used as a ground reference or true 25 precipitation in this study.

The conditional estimation of precipitation using the two covariates can be described as follows:

$$R_{est}(t) | [R(t), T(t)] \quad (1)$$

Here, ($R_{est}(t)$) is the estimated ground precipitation from a given pair of radar rain rate ($R(t)$) and incident air temperature ($T(t)$) values at a given geographical location in the two-dimensional space (x, y) and time, t .

30 The conditional estimation in Eq. (1) uses two covariates, in contrast to Hasan et al. (2016a, b) where a nonparametric kernel regression estimator using a single covariate ($R(t)$) was adopted. Readers are referred to (Mehrotra and Sharma, 2006; Sharma



and Mehrotra, 2014; Sharma et al., 2016) for further details on the nonparametric modelling framework used in this work. This study uses the k-nearest neighbour (k-nn) regression estimator as the nonparametric predictive model. This model can be expressed as:

$$E\left(R_{est}(t)|[R(t),T(t)]\right) = \sum_{k=1}^K \frac{g_k}{\sum_{j=1}^K \frac{1}{j}} \quad (2)$$

- 5 Where k denotes the number of observed pairs of radar precipitation rate and temperature considered “similar” to the current conditioning vector $[R, T]$. Similarity here is defined on the basis of a weighted Euclidean distance that is further explained below. $E(\cdot)$ denotes the expectation operator, in the absence of which the uncertainty about the expected value can be computed. The term g_k represents the observed gauge precipitation corresponding to k^{th} neighbour of the conditioning vector. K is a maximum number of neighbours permissible and it is an important parameter in the k-nearest neighbour method. In the
- 10 present study, K is taken as equal to the square root of the sample size as suggested by Lall and Sharma (1996). The order of each neighbour is ascertained based on a weighted Euclidean distance metric, written as:

$$\xi_i^2 = \left(\frac{\beta_R(R - r_i)}{s_R}\right)^2 + \left(\frac{\beta_T(T - t_i)}{s_T}\right)^2 \quad (3)$$

- Here, ξ_i is the distance of the conditioning vector $[R, T]$ to the i^{th} data point (r_i, t_i) in a two-dimensional space. s_R and s_T are sample standard deviations of the radar precipitation rate and temperature, and β_R and β_T are partial weights denoting the rela-
- 15 tive importance each conditioning variable has on the ensuing response respectively (Sharma and Mehrotra, 2014). The sample standard deviations are used to standardise the predictor variables to make them independent of their measurement scale, while the partial weights allow elimination of a predictor variable if not relevant to the prediction being made. Readers are referred to Sharma and Mehrotra (2014) for the informational theory rationale that allows for the estimation of these partial weights, and the NPRED, R package ((Sharma et al., 2016), downloadable from <http://www.hydrology.unsw.edu.au/download/software/npred>)
- 20 that enables their estimation for any sample data set.

3.2 Model evaluation criteria

- A number of metrics have been used in literature to evaluate and compare the performance of models (Hasan et al., 2016b; Villarini et al., 2008). The root mean square error (RMSE) is commonly used as a performance measure and it provides the overall skill measure of a predictive model (Hasan et al., 2016b). We used primarily RMSE as a quality metric to evaluate the
- 25 performance of the proposed model. Mean absolute error (MAE) and mean error (ME) were used as additional quality metrics. Definition of RMSE, MAE and ME can be found in the literature (e.g., Hasan et al., 2016b; Villarini et al., 2008).



3.3 Determination of phase

In order to assess the usefulness of the proposed approach, it was compared against an alternate approach where the precipitation phase for first ascertained, followed by the application of different Z-R relationships for snow and rain. For the classification of precipitation phase at gauge level, we adopted the method from Finnish Meteorological Institute which is used operationally in Finland for phase classification (Koistinen et al., 2004; Saltikoff et al., 2015):

$$P_{lp} = \frac{1}{1 + e^{22 - 2.7T - 0.2H}} \quad (4)$$

Here, P_{lp} represents the probability of liquid precipitation, T ($^{\circ}C$) the air temperature, and H (%) the relative humidity at a height of 2 m. If $P_{lp} < 0.2$, precipitation is considered as solid and if $P_{lp} > 0.8$, precipitation is considered as liquid. For the case of $0.2 \leq P_{lp} \leq 0.8$, precipitation is considered as mixed (Koistinen et al., 2004; Saltikoff et al., 2015).

10 4 Study area and data

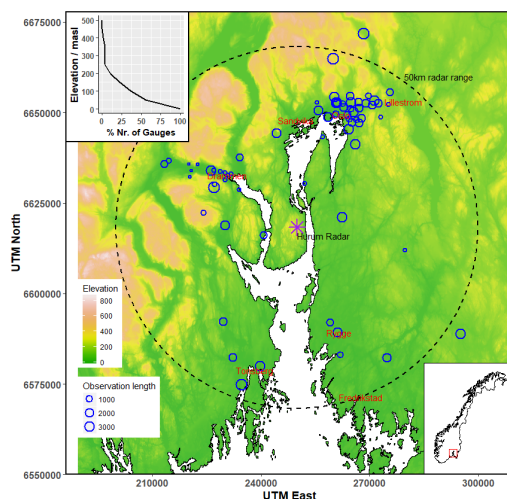


Figure 1. Precipitation gauge locations (blue circles) and length of the observations at each precipitation gauge location (size of the circles) and radar station (purple star mark) overlaid on topography of the study area, Oslo region of Norway. Hypsometric (elevation) distribution of the gauges is on the top left corner

The proposed nonparametric predictive model using radar precipitation rate and temperature as covariates was tested on radar data over the Oslo region in Norway. The radar data used in the current research is the accumulated hourly radar precipitation rate product generated from the national weather radar network of Norway. The present study area is limited to the 50 km radius of radar range from Hurum radar station as shown in Fig. 1 where a relatively dense network of precipitation gauges are available. The Hurum radar is located at 59.63° N latitude and 10.56° E longitude and it is about 30 km from Oslo, the capital city of Norway and it is in operation since November 2010.



The Norwegian Meteorological Institute (met.no) operates nine C-band Doppler weather radar installations which covers the entire land surface of Norway. The sensitive C-band installations with smaller wavelengths (4 - 8 cm) are placed in the Nordic to detect snowfall and clear air echoes (Koistinen et al., 2004). The wave length of the Hurum radar is 5.319 cm. The Norwegian radar network scans the atmosphere with a 7.5 minute temporal resolution. The met.no processes the raw radar volume scan from the radar stations. The data goes through extensive quality control and data transformations before the radar products are distributed to end users (Elo, 2012). The met.no performs a routine that removes clutter and other noise (non-meteorological echo) from the radar scan first. Then it reconstructs the gap in the data caused by clutter. The processing algorithm segments the volumetric radar reflectivity data as convective or stratiform precipitation type and it computes the Vertical Profile of Reflectivity (VPR) depending on precipitation types. VPRs of convective and stratiform precipitation types are distinctly different (Abdella, 2016; Chumchean et al., 2008). Bright band effect and non-uniform vertical profile of reflectivity are major sources of uncertainties in radar precipitation estimation in high latitude regions (Abdella, 2016; Joss et al., 1990; Koistinen et al., 2004; Koistinen and Pohjola, 2014). The radar data are corrected for bright band effects that appear in the VPR.

After the processing, the met.no generates and distributes various radar products. One of the radar precipitation rate products available for the public to use in hydrological applications is the Surface Rainfall Intensity (SRI). The SRI product uses the lowest Plan Position Indicator (PPI) and projects the aloft reflectivity data down to a reference height (1 km) near to the ground. The projection method is known as VPR correction that takes the vertical variability of reflectivity and bright band effect into account (Elo, 2012). The VPR corrected reflectivity is transformed from polar to Cartesian coordinate system with 1 km \times 1 km spatial resolution and the mosaic of nine weather radar imageries is merged to single SRI product covering the entire Norway. Finally, the reflectivity is converted to precipitation rate by using parametric Z - R relationship ($Z = 200R^{1.6}$) derived by Marshall and Palmer (1948) and the precipitation rate is accumulated to the temporal resolution desired (hourly in this case). It can be noted that the Norwegian meteorological institute uses the single Z - R relationship (Marshall-Palmer for rain) for all seasons throughout the year.

Data for the period from January 2011 to May 2015 were used for this study. A spatial subset of accumulated hourly radar precipitation rate with 1 km \times 1 km spatial resolution for the study area was downloaded from the met.no's "thredds" server (<http://thredds.met.no/>). The data are in netCDF file format and the gridded array is in Universal Transverse Mercator (UTM) projected coordinate system. The hourly precipitation measurements from precipitation gauges are downloaded from the met.no's web portal for accessing meteorological data for Norway, "eKlima" (<http://eklima.met.no>). Within the study area, 88 precipitation gauges are in operation with hourly observation, however only 68 gauges are available during the period from 2011 to 2015. The precipitation gauges' locations (68 gauges) used in the study are shown in Fig. 1 overlaid on the topography of the study area. As shown in Fig. 1, precipitation gauges are not evenly distributed. The urban areas (Oslo, Drammen, Lillestrom and Tonsberg) are densely gauged (Nearly 0.25 gauges/km² near Oslo and approximately 0.1 gauges/km² near other major cities) and rest of the area is sparsely gauged with hourly observation. Further, the precipitation data from precipitation gauges come with varying length because some gauges are in operation since 2013 or later and some gauges have a number of missing values during their operation. However, we used data from all available precipitation gauges for this study.



Some of the gauging stations are equipped with hourly temperature and other meteorological measurements (including wind speed and relative humidity). For this study, we used gridded hourly temperature and wind speed dataset with $1 \text{ km} \times 1 \text{ km}$ grid resolution. The data are available from the Norwegian meteorological institute. The gridded wind speed data is available until May 2015. Even though, radar precipitation rates and air temperature data are available from January 2011 to date, due to the unavailability of wind speed data for catch correction of gauge precipitation, the study period is limited to four years (January 2011 - May 2015). More details on the procedure adopted for catch correction are provided in the next sub-section.

The gridded temperature dataset for Norway is spatially interpolated based on the historical air temperature observations from Norwegian meteorological stations. The interpolation is based on Optimal Interpolation in a Bayesian setting (Lussana et al., 2016). In this three-dimensional spatial interpolation, the elevation of each grid point is obtained from a high-resolution digital elevation model and the real elevation of stations stored as metadata used. The resulted interpolated air temperature is on the regular grid which is 2 m above the ground terrain elevation. For further details of the interpolation method, readers are referred to the Norwegian meteorological institute's report by Lussana et al. (2016). This gridded temperature data with an hourly temporal resolution was used to derive temperature time series for the precipitation gauge locations.

The gridded hourly wind speed datasets are derived from a statistical downscaling of a 10 km numerical model dataset onto a 1 km grid (same grid as the hourly gridded air temperature). Gridded wind speed data was used to correct wind induced under-catch of precipitation gauges. Hourly measured relative humidity data is available at 25 gauge locations within the study area. Relative humidity data together with air temperature were used to compute the phase of the precipitation at gauge level in this study. Spatial variation of relative humidity is relatively small within 50 - 100 km distances and hence simple interpolation techniques can be used (Beek, 1991). It can be noted that nearest gauge with relative humidity measurement is less than 50 km for most gauges in this study. In this study, for gauge locations with missing relative humidity data, relative humidity data available from nearest gauge were used.

As precipitation gauge locations and radar precipitation rate grids are in the same UTM33 coordinate system, they were simply overlaid and the radar pixel of 1 km^2 overlapping each precipitation gauge was located. One location near Oslo has three precipitation gauges within a $1 \text{ km} \times 1 \text{ km}$ pixel. Except for that, all pixels consist of a single gauge. The pixel value (precipitation rate) for each hour was extracted and continuous hourly time series of radar precipitation rates for all gauges were generated. The precipitation intensities in the study area (high latitudes) is relatively low. An analysis of statistical properties of precipitation rates in mid Norway showed that intensities less than 1.76 mm h^{-1} contributes to 50 % of the total precipitation volume while less than 6 mm h^{-1} contributes to 88 % (Engeland et al., 2014). Further, the same study found that precipitation intensities below 0.1 mm h^{-1} contributes little to the total precipitation and might be treated as zero precipitation. Timesteps with gauge precipitation or radar precipitation rate less than 0.1 mm h^{-1} were therefore removed in this study. Finally, an observed dataset of hourly gauge precipitation and corresponding radar precipitation rate and air temperature for those hourly timesteps were prepared for all precipitation gauge locations. The length of the dataset at each gauge location used in this study is shown with the size of the circles in Fig. 1.



4.1 Catch correction for precipitation gauges

Accuracy of precipitation gauge measurement is essential to achieve better results from water balance calculations, hydrological modelling and calibration of remote sensing algorithms. Solid precipitation exhibits significant under-catch in windy conditions. Consideration of catch errors is more important in high latitude Nordic and mountainous regions due to large catch errors for snow. Field study in Norway showed that precipitation gauges, even with wind shield, catch 80 % of true precipitation at wind speeds of 2 m s^{-1} , 40 % at 5 m s^{-1} , and only 20 % at 7 m s^{-1} for solid precipitation at temperatures equal or below -2° C (Wolff et al., 2015). As this study uses gauge observation as a ground observed truth, corrected gauge observation is required for a reliable outcome from the investigation.

We corrected gauge precipitation for wind induced under catch by using the Nordic precipitation correction model (Førland et al., 1996). The Nordic model classifies the precipitation phase using air temperature and uses different equations for solid and liquid precipitation and average value of the two equations was used for mixed precipitation. The correction equations use wind speed and air temperature at each gauge location. As mentioned above, gridded hourly wind speed data was used for aerodynamic correction. It was found that correlation between the corrected precipitation by using measured wind speed data (15-gauge locations) and gridded data are over 0.97 for all those 15 gauge locations. Based on the catch error computations in this study, the mean correction factor of hourly precipitation (corrected precipitation/observed precipitation) is 1.61 for solid and 1.14 for liquid precipitation while median are 1.53 and 1.11 for solid and liquid precipitation respectively. Corrected gauge precipitation was used as true observed precipitation in this study.

5 Results and Discussion

The performance of nonparametric radar precipitation estimation using air temperature as an additional covariate is presented in this section. The bivariate model is compared with the bench mark of the univariate nonparametric model where radar precipitation is used as the sole predictor. We tested the proposed method for a number of criteria and the results are presented below.

5.1 Partial weight of predictors

For each precipitation gauge location, we estimated the partial weights associated with radar precipitation rate and incident air temperature using the observed hourly radar precipitation rate and air temperature and the corresponding gauge precipitation data.

Figure 2 shows the histogram of partial weight of radar precipitation rate (β_R) computed for 68 precipitation gauge locations in the study area of 50 km radius from the Radar station as shown in Fig. 1. It is noted that the summation of partial weights of radar precipitation rate (β_R) and air temperature (β_T) is scaled to 1. Hence, the partial weight associated with air temperature (β_T) is equal to $1 - \beta_R$. Looking at Fig. 2, almost 87 % of the gauge locations resulted in non-zero partial weight for air temperature ($\beta_T > 0$). In these locations, radar precipitation estimation partially depends on air temperature. It can be seen

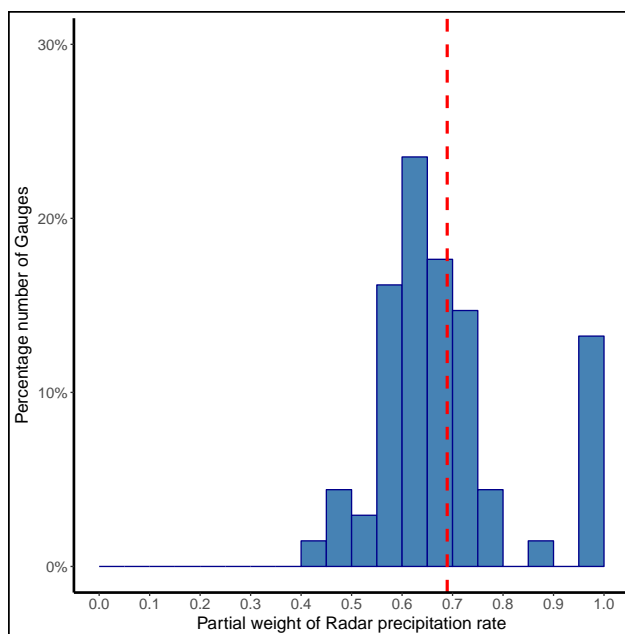


Figure 2. Percentage of precipitation gauge locations against estimated partial weight of radar precipitation rate (β_R) at those gauge locations and the mean partial weight (red dash line) for gauge locations (68 gauges) in the study area. Partial weights provide a measure of relative importance of predictor variables on the response (refer Eq. (3)) and the summation of partial weights ($\beta_R + \beta_T$) is equal to 1.

Table 1. Summary statistics of computed partial weights for radar precipitation rate and air temperature in the study area.

Partial Weight	Mean	1st Quartile	3rd Quartile	15th Percentile	85th Percentile
Radar precipitation rate (β_R)	0.68	0.60	0.73	0.57	0.79
Air temperature (β_T)	0.32	0.40	0.27	0.43	0.21

that partial weight of radar precipitation rate (β_R) is equal to 1 for nearly 13 % of the gauge locations and the partial weight associated with temperature (β_T) is therefore zero. There, the bivariate problem collapsed into a univariate problem with radar precipitation rate as a single predictor.

Table 1 shows the summary statistics of computed partial weights among the precipitation gauge locations in the study area. It can be seen that the partial weight associated with air temperature is in the range of mean ± 0.1 for more than 70 % of gauge locations. The gauge locations which resulted in associated partial weight for air temperature ($\beta_T > 0$) are spread throughout the study area. However, we have not found a clear pattern of spatial variation in the estimated partial weights at gauge locations within the study area.



5.2 Performance of k-nn prediction model

The k-nearest neighbour regression based estimator was used to predict precipitation at each gauge location. The observed dataset and the computed partial weights of predictors were used with the NPRED k-nn regression tool to specify the model. For comparison, a reference model using the k-nn regression estimator but a single predictor variable (hourly radar precipitation rate) was also developed.

We calculated the k-nn regression estimate of expected response by using the leave-one-out cross-validation (LOOCV) procedure, whereby leaving out one observed response value (gauge precipitation) from the regression and estimating the expected response value for that observed response. This ensures the modelled outcomes represent the results that will be obtained using a new or independent data set. The improvement in radar precipitation estimation with the use of air temperature as an additional covariate is measured as a percentage reduction in RMSE compared to the reference model.

All the gauge locations with an associated partial weight of air temperature ($\beta_T > 0$) show an improvement in radar precipitation estimation. The mean improvement in RMSE is 9 % while the median is 7.5 % and it is more than 5 % for 80 % of the gauge locations where air temperature was identified as an additional covariate. It can be noted that partial weight for each gauge location was calculated independently using the data from that specific location and then the RMSE was estimated by LOOCV estimated using the entire data at that gauge location. However, a split sample test was done to verify the results, where two-thirds of the data were used to estimate partial weight and one-third of the data were used to estimate RMSE for each gauge location. The split sample test gave similar results as before.

We also examined the spatial cross-validation of computed partial weights. First, a single average partial weight was calculated by taking the arithmetic mean of partial weights of all gauge locations which were computed independently at each gauge location and presented in Fig. 2 and Table 1. This single average value of partial weight (0.68, 0.32) was used with the predictive models to estimate radar precipitation and the improvement in RMSE estimated. Then, for each gauge location, an average partial weight was calculated by leaving that gauge out and adopting the mean partial weight from five nearest gauges. The k-nn prediction model was again re-specified for each gauge location using the computed average partial weight of 5 nearest gauges. The results of percentage improvement in RMSE showed a strong resemblance to the results with a single mean value of partial weight for the study area. It is possible, therefore, that a regional or nearest neighbour average value of partial weight can be used for ungauged locations. As with the partial weight, improvement in RMSE at gauge locations does not clearly show any systematic pattern of spatial variation.

Based on above examinations, spatial variation of station specific partial weight can be discarded and a single average value adopted. Hence, in the results that follow, we use a single average partial weight computed for the study area. As shown in Table 1, the mean value of partial weight for radar precipitation rate is 0.68 and air temperature is 0.32. The k-nn regression prediction model with radar rain rate and air temperature as two predictors at each gauge location was specified with this single average partial weight.

Figure 3 shows the percentage improvement in RMSE for the proposed model with radar precipitation and air temperature as two predictors with the single average partial weight of (0.68, 0.32) compared to the reference model with radar precipitation

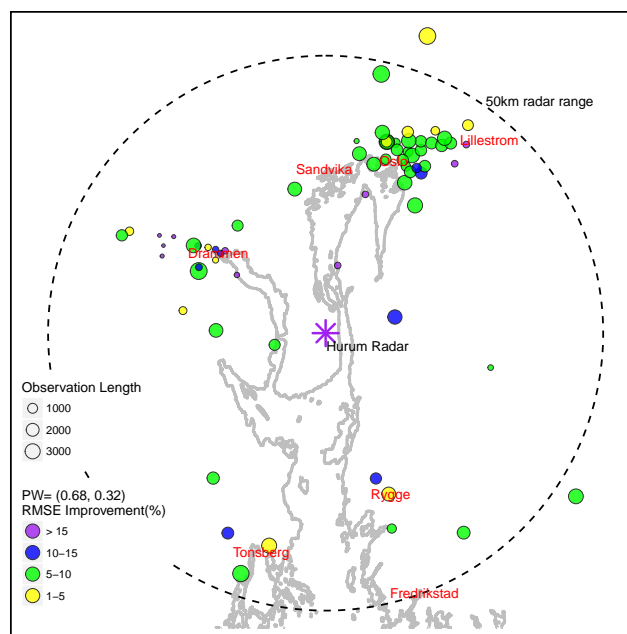


Figure 3. Percentage of improvement in RMSE at each gauge locations (colour scale) for predictive model with radar precipitation rate and air temperature as two predictors with the single average partial weight ($\beta_R = 0.68$ and $\beta_T = 0.32$) compared to radar precipitation rate as a single predictor and length of the data (circle size), which are used in the predictive model, overlaid on the coastline of the study area.

rate as a single predictor. The precipitation gauges' locations are shown by circles and their sizes are proportional to the length of the data used in the nonparametric predictive models at each gauge location. A filled discrete colour scale is used to show percentage improvement in RMSE. All the gauge locations show improvement in RMSE with the use of temperature as an additional covariate comparing with the reference model of radar precipitation as a single predictor. Looking at Fig. 3, majority of gauge locations have a green colour and the improvement is 5 - 10 % on those locations. Mean value of improvement is 8.5 % while the median is 7 %. Over 80 % of the gauge locations in the study area show more than 5 % improvement in RMSE while nearly 15 % show more than 15.0 % improvement. As discussed earlier and as seen in Fig. 3, this study did not find any pattern of spatial variation in the results. However, this spatial plot clearly shows that the improvement in RMSE with the use of temperature as an additional predictor is spread throughout the study area.

In addition to RMSE, we computed MAE and ME for the proposed model and the reference model with radar precipitation as a single predictor at gauge locations. The above quality metrics were also computed for the original data of radar precipitation rates for comparison.

Figure 4 shows the computed quality metrics for the two predictive models (knn-R and knn-RT) and the original data of radar precipitation rates. Looking at Fig. 4, the mean error of the original data (denoted as MP) was negative for almost all gauge locations. This shows the under estimation of radar precipitation compared to precipitation measured by gauges. Both nonparametric predictive models reduce the mean error considerably and bring it to near zero while they reduce the RMSE and

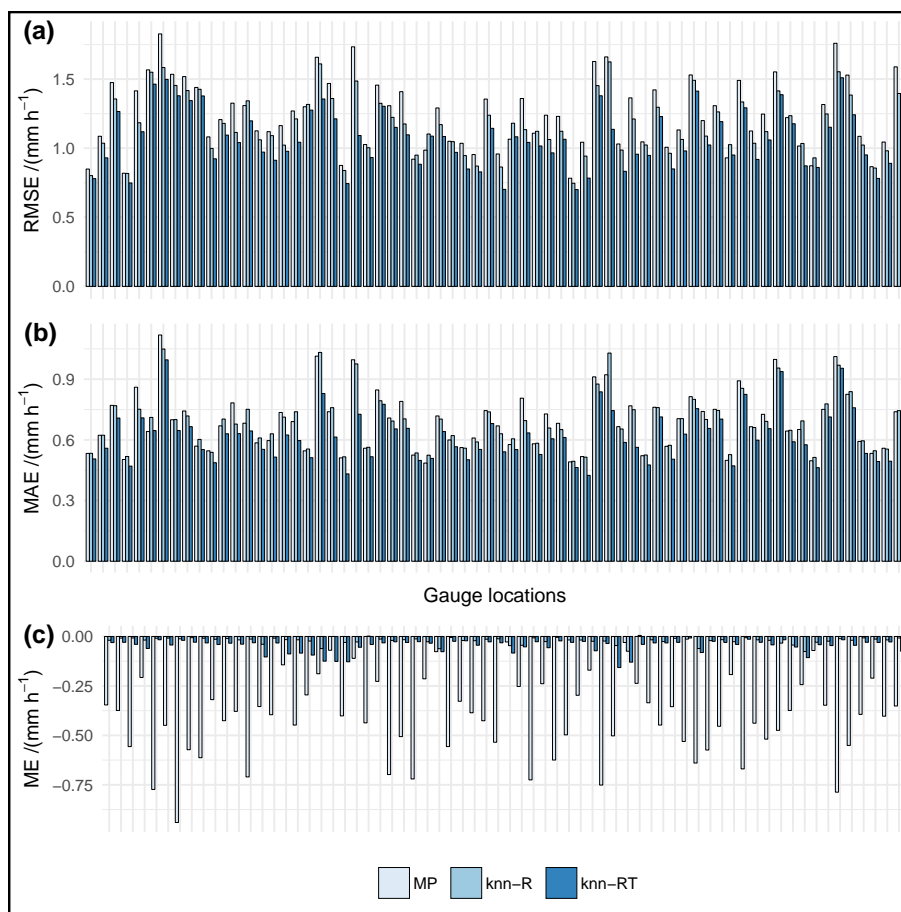


Figure 4. Bar plot representing three quality metrics (RMSE, MAE and ME) at gauge locations for the original data (MP) and for the two nonparametric models (knn-R and knn-RT). Here, knn-R denotes the nonparametric model with radar precipitation rate as a single predictor, while knn-RT denotes the nonparametric model with radar precipitation rate and air temperature as two predictors with fixed partial weight of (0.68, 0.32).

MAE significantly for almost all gauge locations. It can be seen from the Fig. 4 (a) and (b) that the predictive model with radar precipitation as a single predictor reduces the RMSE and MAE. The proposed predictive model with radar precipitation and air temperature as two predictors further reduces both RMSE and MAE and improves the radar precipitation estimation for most of the gauge locations.

- 5 Although the main focus of this paper is to investigate the benefit of using temperature as an additional covariate in radar precipitation estimation, the results of the nonparametric radar precipitation estimation in this study are comparable with the results of Hasan et al. (2016b), although in a different setting. They tested their nonparametric method of radar rainfall estimation (radar reflectivity as a single predictor) in Sydney, Australia and they have reported 10 % improvement in RMSE compared to the traditional parametric Z - R relationship. In our study, k-nearest neighbour nonparametric method with radar



precipitation rate as a single predictor resulted in a mean 6 % reduction in RMSE. The bivariate model with air temperature as an additional predictor resulted in a mean 14 % reduction in RMSE compared to the original radar precipitation rate data derived using a parametric equation ($Z = 200R^{1.6}$).

The above results demonstrate the usefulness of air temperature as an additional predictor variable in deriving radar precipitation in cold climates. Some further investigations of when this improvement can be expected to be most are presented next.

5.3 Performance for different threshold intensities

This study used the precipitation intensities of radar precipitation and gauge precipitation equal or above 0.1 mm h^{-1} . As described in Sect. 4, precipitation intensities are relatively low in this region, consistent with intensities in cold climates. A data analysis showed that intensities are lower than 0.5 mm h^{-1} for around 60 % of the observations and only 5 % of the data have either gauge or radar precipitation rates above 2.0 mm h^{-1} .

To investigate whether very low intensities dominate the results presented earlier, we tested our proposed model for a range of intensities for both gauge and radar precipitation. Figure 5 shows the box plot of RMSE values estimated at gauge locations for threshold intensities 0.1 mm h^{-1} , 0.5 mm h^{-1} and 2.0 mm h^{-1} . Looking at Fig. 5, the improvement with the use of air temperature as an additional covariate is still significant for more severe intensities as well.

5.4 Variation with Temperature Classes

For each gauge location, we also estimated partial weights for different temperature classes. Partial informational correlation and hence the partial weight was found to vary with temperature class. For temperature above 10° C , more than 85 % of the gauge locations were estimated as having zero partial weight for air temperature. It is therefore likely that radar precipitation estimation depends on air temperature for colder climates dominantly. The presence of hail may be the reason for a few precipitation gauge locations still exhibiting non-zero partial weight for air temperature above 10° C . Further, we estimated RMSE for the dataset above 10° C for each gauge location using the average partial weight (0.68, 0.32) and estimated the improvement compared to the reference model with radar precipitation rate as a single predictor. Nearly 70 % of gauge locations still showed improvement in RMSE; however, the improvement is insignificant when the air temperature is above 10° C .

5.5 Separate parametric equations for rain and snow as a benchmark

As we discussed in Sect. 2, the switch between a snow and rain $Z - R$ relation is fast becoming a standard for weather radar operations in cold climates. We compared the proposed nonparametric radar precipitation estimation models with radar precipitation estimation by using two different parametric $Z - R$ relationships, one for snow and other for rain. In this study, we used the radar snow equation of Finish Meteorological Institute ($Z_e = 100S^2$) while keeping the Marshall and Palmer equation ($Z = 200R^{1.6}$) for rain.

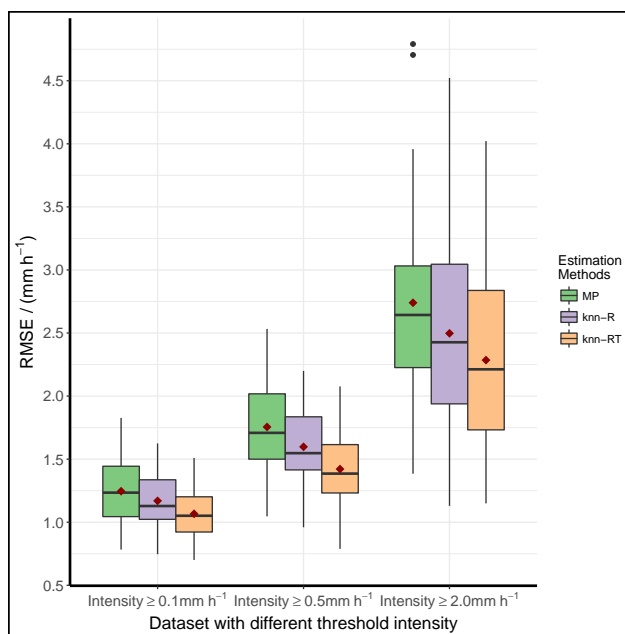


Figure 5. Box plot of $RMSE$ (mm h^{-1}) values estimated at gauge locations for the original data (MP) and the two nonparametric models (knn-R and knn-RT) using data with intensities of radar precipitation rate and gauge precipitation greater than or equal 0.1 mm h^{-1} , 0.5 mm h^{-1} and 2.0 mm h^{-1} . Mean value of $RMSE$ for each model by red diamond point. Here, knn-R - nonparametric model with radar precipitation rate as single predictor and knn-RT - nonparametric model with radar precipitation rate and air temperature as two predictors with the partial weight of (0.68, 0.32)

For this investigation, we converted the original radar precipitation rates back to reflectivity using inversion of the Marshall and Palmer equation ($R = (Z/200)^{1/1.6}$). We estimated also the probability of liquid precipitation (P_{lp}) using Eq. (4) in order to classify and hence apply different Z - R relationships according to the precipitation phase. Hourly air temperature and relative humidity at each gauge location were used in this study for the estimation of probability of liquid precipitation (P_{lp}). Data were classified as solid or liquid or mixed precipitation using the computed value of probability of liquid precipitation (P_{lp}). The back calculated reflectivity was converted to precipitation rates using snow equation ($Z_e = 100S^2$) for solid phase and rain equation ($Z = 200R^{1.6}$) for liquid phase. A weighted combination of solid and liquid was used for mixed precipitation by using the value of P_{lp} as recommended by Koistinen et al. (2004); Saltikoff et al. (2015). Precipitation rates estimated by the two equations as described above is denoted by FMIMP.

For each gauge location, $RMSE$ was calculated for the estimated radar precipitation rates by two equations (FMIMP). Here wind corrected gauge precipitation was used as a true observed value. $RMSE$ of FMIMP is compared with the $RMSE$ of original radar precipitation rates (MP) and the two nonparametric predictive models (knn-R and knnRT). Figure 6 shows the box plot comparison of $RMSE$ values in mm h^{-1} estimated at gauge locations for entire data and phase classes separately.

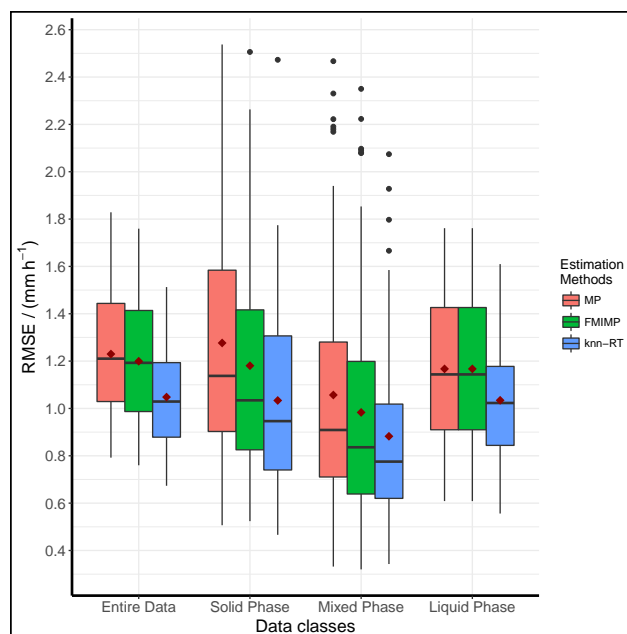


Figure 6. Box plot of comparison of $RMSE$ ($mm\ h^{-1}$) estimated at gauge locations for the original precipitation rates by Marshall and Palmer equation (MP) and precipitation rates estimated by different equation for snow and rain (FMIMP) and for the nonparametric model (knn-RT). $RMSE$ values shown for entire data and separately for solid, mixed and liquid phase classes. Mean value of $RMSE$ for each model by red diamond point. Here knn-RT - nonparametric model with radar precipitation rate and air temperature as two predictors with the partial weight of (0.68, 0.32).

Looking at Fig. 6, the use of two equation (FMIMP) with the snow equation for solid and partially for mixed phase reduces the $RMSE$ for solid and mixed precipitation phase classes and hence the $RMSE$ of entire dataset compared to the original precipitation rates estimated by Marshall and Palmer (MP). The application of a different equation for snow reduces the phase dependent bias in the Norwegian radar precipitation estimation. The average reduction in $RMSE$ at gauge locations is 6 % of $RMSE$ value of the original precipitation rates. However, it can be seen in Fig. 6 that the use of different equations for snow and rain does not reduces the $RMSE$ to the level of the nonparametric approach (knn-RT). Comparing FMIMP and knn-RT, there is a further reduction of nearly 10 % in $RMSE$.

It should be noted that the phase classification used in this study is a model-based classification even though it is used operationally. The estimated phase can differ from actual observed phase at gauge level. Observations from disdrometers can provide a more accurate phase information at gauge level. However, disdrometers are not available everywhere. Even if a few disdrometers were located within the study region, their representativeness in space and time would be limited (Saltikoff et al., 2015). Further, our phase classification is at gauge level, and represents near surface conditions. The phase of the precipitation can be different at the elevation where the radar measures the reflectivity. The measurement of phase information with the use of dual polarized radars can be a useful data source for further investigation.



5.6 Uncorrected gauge precipitation as an observed response

We tested the proposed method with measured gauge precipitation without wind induced catch correction. The uncorrected gauge precipitation was used there as an observed response in the model. For this investigation, we used six years of data from 88 precipitation gauges in the study area. Even though the wind induced catch error is making the observations less reliable, the use of temperature as an additional predictor variable is having consistent impact as with the results presented earlier using corrected gauge precipitation.

6 Summary and conclusions

The purpose of the current study was to improve the quantitative radar precipitation estimates for hydrological applications. For this objective, this study assessed the relevance of temperature as an additional factor in the computation of radar precipitation for cold regions and climates. While parametric phase dependent Z-R relationships adjusted with gauged precipitation have been discussed extensively in the literature, this is the first investigation to our knowledge that evaluates the use of temperature as a covariate in the radar precipitation adjustment and presents a procedure whereby precipitation can be estimated in cold climates. The proposed nonparametric bivariate model was evaluated using different quality metrics and tested for a number of criteria.

The key findings from this study are the following:

1. The use of air temperature as an additional predictor variable in a nonparametric model improved the estimation of radar precipitation significantly. While this appears mostly due to the different phase of precipitation in colder temperatures (including the presence of hail), the proper use of temperature as a covariate can assist in better quantification of precipitation when knowledge of precipitation phase is not available.
2. Care must be taken to use appropriate techniques to estimate precipitation when including temperature as a covariate. In the present study, use was made of a nonparametric technique which allowed for databased relationships to be formed. When equivalent data (ground precipitation especially) is not available, parametric equivalents will be needed instead. More work is needed to determine the best parametric relationship that could be adopted in such a situation.
3. An improvement of 15 % in the root mean squared error was noted using the simple nonparametric approach adopted when including air temperature as an additional covariate. More than 80 % of the locations data was available for exhibited clear improvements in estimates.

While this study uses data for one weather radar in arriving at its conclusions, preliminary analysis suggests the problems noted here to be generic. Given the importance of weather radars as a means of precipitation measurement, and their ability to observe in remote regions in a continuous setting, the above finding has considerable implications for ongoing operations in cold climates.



Code and data availability. Radar rain rate data used in the study are available in the Norwegian Meteorological Institute's (met.no) thredds server (<http://thredds.met.no/thredds/catalog/remotesensingradaraccr/catalog.html>). Precipitation observations from precipitation gauges, other meteorological measurements (wind speed and relative humidity) and gauges' meta information can be obtained from met.no's web portal "eKlima" (<http://eklima.met.no>). Access to the web portal is available upon request. Gridded observational hourly air temperature data and

5 gridded wind speed data are available in the met.no's thredds server (<http://thredds.met.no/thredds/catalog.html>). NPRED programming tool, which is used for computation in the study, is available as R package and it can be downloadable from the following link as follows: <http://www.hydrology.unsw.edu.au/download/software/npred>

Competing interests. The authors declare that there are no competing interests.

Acknowledgements. The authors gratefully acknowledge Norwegian meteorological institute (met.no) for providing radar rain rate, gauge

10 precipitation and air temperature data for this study. The authors would particularly like to thank Christoffer Artturi Elo at met.no for assisting to get the radar precipitation rate data. A great appreciation goes to Water Research Centre, University of New South Wales (UNSW), Sydney, Australia for hosting the first author for research practicum. The authors acknowledge the Norwegian Research Council and Norconsult for funding this research work under the Industrial Ph.D. scheme (Project No.: 255852/O30).



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