An Operational Weather Radar–Based Quantitative Precipitation Estimation and its Application in Catchment Water Resources Modeling

The Danish Meteorological Institute operates a radar network consisting of five C-band Doppler radars. Quantitative precipitation estimation (QPE) using radar data is performed on a daily basis. Radar QPE is considered to have the potential to significantly improve the spatial representation of precipitation compared with rain-gauge-based methods, thus providing the basis for better water resources assessments. The radar QPE algorithm called ARNE is a distance-dependent areal estimation method that merges radar data with ground surface observations. The method was applied to the Skjern River catchment in western Denmark where alternative precipitation estimates were also used as input to an integrated hydrologic model. The hydrologic responses from the model were analyzed by comparing radar- and ground-based precipitation input scenarios. Results showed that radar QPE products are able to generate reliable simulations of stream flow and water balance. The potential of using radar-based precipitation was found to be especially high at a smaller scale, where the impact of spatial resolution was evident from the stream discharge results. Also, groundwater recharge was shown to be sensitive to the rainfall product selected. Radar QPE appears to have unprecedented potential in optimizing precipitation input to distributed hydrologic models and thus model predictions.

Weather radar is a sophisticated remote sensing instrument that measures the reflectivity of objects in a given volume of the atmosphere. Research in the use of weather radar based quantitative precipitation estimation (radar QPE) in hydrologic applications has increased in recent years mainly due to the increasing demand for more refined spatial and temporal resolution of rainfall products for modeling purposes. Many meteorological institutes around the world, including the Danish Meteorological Institute (DMI), have considered using radar QPE as an important supplement to the conventional rain gauge rainfall products (Klazura and Imy, 1993; Fulton et al., 1998; Golding, 2000; Harrison et al., 2000; Tabary, 2007; Tabary et al., 2007). Operational radar QPE is a complex system that involves several elements including hardware design, signal processing, image analysis, data quality control, uncertainty analysis, and database organization. Due to the fact that each radar operation has its unique climatologic conditions, geographical terrain, and economic capacity, however, agreement on a standard procedure in the development of radar QPE products can hardly be reached.

Despite the lack of standard procedures in implementation, the basic principles of radar precipitation estimation are well known and have been discussed in many textbooks (Batton, 1973; Collier, 1989; Rinehart, 1997). Radar emits and measures electromagnetic waves backscattered by raindrops; these electromagnetic waves are directly related to reflectivity. The relation between radar reflectivity (Z) and precipitation rate (R) is physically based because both Z and R are integrations of the raindrop size distribution (DSD); however, the Z–R relationship can be described by many different approaches. One of the common approaches is to deploy distrometers to observe the DSD at ground level. The Z–R relationship can thereby be computed by statistical analysis of the DSD observations and selected according to different rainfall regimes (Steiner and Smith, 2000; Ulbrich and Miller, 2001; Bringi et al., 2004; Lee and Zawadzki, 2006). Another approach is to establish the Z–R relationship between radar reflectivity and surface rainfall measurement.
(typically from rain gauges) using nonlinear weighted regression or probability matching methods, which can also be seen as empirical optimizations (Krajewski and Smith, 1991; Rosenfeld et al., 1994; Ciach and Krajewski, 1999; Gabella and Amitai, 2000; Morin and Gabella, 2007). Although the principle for estimating precipitation from radar data is simple, observations of radar reflectivity are prone to measurement errors that impose a potential risk to the quality of radar QPE products (Austin, 1987; Joss and Lee, 1995; Smith et al., 1996; Anagnostou et al., 1999; Borga et al., 2006).

The main reason that radar QPE may not represent surface rainfall properly is that most radar beams are far above the ground. Differences between ground rainfall estimates derived from radar and rain gauges can be categorized from different perspectives. If the error characteristics are of interest, they are commonly classified as (i) systematic bias that is a result of using a uniform \( Z-R \) relationship to represent a varying \( Z-R \) relationship, attenuation by a wet radome, or radar calibration problems; (ii) range-dependent error that is mainly due to the vertical variation in the reflectivity profile with distance, attenuation of the radar pulse by rain, or radar beam occultation; and (iii) random errors from radar signal noise such as radar clutter effects. If the classification is performed from an operational point of view, errors in the measurement of reflectivity or in the process of retrieving the rainfall estimation using the \( Z-R \) relationship may appear (Collier et al., 1983; Kitchen and Jackson, 1993; Klazura et al., 1999; Germann et al., 2006; Ciach et al., 2007).

Due to the lack of agreement between ground rainfall estimates based on elevated radar reflectivity and those based on rain gauges, algorithms must be developed to convert radar signals to rainfall intensity at ground level. Rain gauges provide point measurements with a precision that is still considered to be the most accurate at ground level. Therefore, the common solution to obtain an optimal rainfall product is to combine radar and rain gauge information such that the strengths from both products are utilized. Methods for merging radar and rain gauge data have many degrees of complexity, starting with a simple bulk adjustment in mean field bias (Smith and Krajewski, 1991). More complex methods have been proposed such as co-kriging (Krajewski, 1987; Sun et al., 2000), kriging with external drift (Sinclair and Pegram, 2005; Haberlandt, 2007), or Kalman filtering (Seo and Breidenbach, 2002; Chumchean et al., 2006). To implement those complex methods operationally is very time consuming and computationally demanding; therefore, the choice of a radar–rain gauge merging technique is subjective and largely depends on the radar operator’s experience and practical conditions (Goudenhoofdt and Delobbe, 2009; Velasco-Forero et al., 2009). The current radar QPE system in use in Denmark was used in this study and suggestions were developed to improve the quality of the radar QPE products; however, a thorough description of the error correction strategies is beyond the scope of this work.

It is commonly acknowledged that precipitation plays an important role in the simulation of the water balance and hydrologic behavior at the catchment scale (Beven, 2001, 2002). The sensitivity of hydrologic models to precipitation resolution in space and time has been studied in many experiments (Watts and Calver, 1991; Finnerty et al., 1997; Singh, 1997; Winchell et al., 1998; Koren et al., 1999; Bell and Moore, 2000; Carpenter and Georgakakos, 2006; Morin et al., 2006). All these studies have generally concluded that the spatial and temporal resolution of rainfall input to a model can significantly influence the timing and peak of the simulated catchment response. Although rain gauge rainfall products are still considered to be a reliable data source, increasing attention has been given in recent years to the use of radar precipitation in forward hydrologic modeling, where comparisons are made based on model performance using radar and rain gauge data (Bell and Moore, 1998a,b; Sun et al., 2000; Wood et al., 2000; Carpenter et al., 2001; Carpenter and Georgakakos, 2004; Guo et al., 2004; Cole and Moore, 2008, 2009). Inverse hydrologic modeling involving radar QPE has also been attempted in several studies (Corral et al., 2000; Borga, 2002; Morin et al., 2009). Most studies on the hydrologic applications of radar QPE have been concerned with flood forecasting and surface water management; however, impacts on other hydrologic processes and the overall water balance have not been fully investigated. Moreover, the application of radar data is normally constrained to a short time scale, of hours or days. The pros and cons regarding long-term radar QPE in water balance modeling, especially the difference between accumulated radar precipitation and traditional methods of rainfall measurement, have not been intensively studied.

The main objectives of this study were (i) to document and investigate the Danish radar QPE algorithm from both meteorological and hydrologic perspectives, and (ii) to analyze the impact of different precipitation input scenarios on the simulation of water fluxes and the water balance of the Skjern catchment using a distributed integrated hydrologic model.

**Materials and Methods**

**The Danish Radar Quantitative Precipitation Estimation Algorithm**

The first radar deployed in Denmark for weather surveillance purposes was installed in 1986 to serve the Copenhagen airport. Since then the radar network has been constantly updated. By 2009, the DMI has been responsible for operating five C-band Doppler radars that offer a countrywide coverage. The geographic locations of the radars are shown in Fig. 1. All of the radars were purchased from Electronic Enterprise Corporation within the past few years. The most recent installations at Bornholm (in 2007) and Viring (in 2008) are capable of making dual-polarization scans. The operational radar parameter settings are summarized in Table 1. Volume scans are undertaken every 10 min with a maximum detection range of 240 km. With the software provided by the
radar manufacturer, the Constant Altitude Plan Position Indicator (CAPPI) products are visualized at heights from 1 to 12 km at 1-km vertical intervals. It is a common technique for radar operators to produce an artificial CAPPI image at a certain height by using higher elevation angles to fill the near ranges and the lower elevation angle to fill the far ranges so there will be no blank areas on the integrated CAPPI image (so-called pseudo-CAPPI). The DMI uses software developed in-house to generate pseudo-CAPPIs at 2 km above ground level with the same time frequency and a horizontal resolution of 2 km.

Table 1. Operational parameter settings for the Danish national radar network.

<table>
<thead>
<tr>
<th>Radar parameters</th>
<th>Settings</th>
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<tbody>
<tr>
<td>Wavelength</td>
<td>5 cm (C-band)</td>
</tr>
<tr>
<td>Range</td>
<td>240 km</td>
</tr>
<tr>
<td>Pulse length</td>
<td>2 μs</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>250 Hz</td>
</tr>
<tr>
<td>Peak power</td>
<td>250 kW</td>
</tr>
<tr>
<td>Rotation rate</td>
<td>20 °/s</td>
</tr>
<tr>
<td>Antenna gain</td>
<td>45 dB</td>
</tr>
<tr>
<td>Vertical beam width</td>
<td>±0.5°</td>
</tr>
<tr>
<td>Horizontal beam width</td>
<td>1.0°</td>
</tr>
<tr>
<td>Volume scan angles</td>
<td>0.5, 0.7, 1.0, 1.5, 2.4, 4.5, 8.5, 13.0, 15.0</td>
</tr>
<tr>
<td>Scans</td>
<td>plan position indicator</td>
</tr>
</tbody>
</table>

The Danish radar QPE algorithm (called ARNE) is based on the method developed by the Baltic Sea Experiment (BALTEX), which is a European regional project focusing on the hydrologic cycle and the exchange of energy between the atmosphere and the Earth’s surface (Michelson, 2000; Michelson and Koistinen, 2000). A flow chart illustrating the overall processing chain of ARNE is shown in Fig. 2.

Taking the main concept from the BALTEX method, ARNE has been modified to accommodate the Danish climatological and instrumental conditions from a number of aspects. First, retrieval of pixels from the raw radar images has several resampling options, which include averaging among nine pixels in the vicinity and bilinear resampling. Second, considering the relatively flat terrain in Denmark, the composite strategy of radar images is either to choose the nearest radar antenna or the maximum output values in the overlapping area. Other countries in the BALTEX region are characterized by mountainous terrain and the composite scenario was therefore originally developed to obtain values from the lowest radar beam. Third, a 7-d moving window is used to obtain radar (\( R \)) and rain gauge (\( G \)) observation pairs, which means ARNE is performed by considering \( G–R \) samples outside the current day. It is specified that the minimum number of \( G–R \) pairs has to be \( >200 \) in the moving window. This empirical number is set to avoid the risk that the number of samples during the past 7 d with precipitation may not be sufficient to perform the distance corrections based on the climatological situation in Denmark. Last but not least, the accumulation period is 24 h instead of the 3 and 12 h used in the BALTEX method, so that errors caused by the vertical profile of reflectivity will be largely smoothed out.

According to the description above, ARNE is regarded as a range-dependent accumulated precipitation estimation algorithm. Its main scripts have three primary components: (i) calculation of the accumulated precipitation from the radar, (ii) establishment of relationships between radar measurement bias (obtained from comparing with rain gauge observations) and distance (from the radar site to the rain gauge sites), and (iii) generation of spatial adjustment factor fields. These components are explained in detail below. To generalize the estimation of radar QPE, assumptions are made that the rain gauge measurements are ground truth, that the radar measurements account for the true spatial and temporal variability of the areal precipitation field, and that the radar and rain gauge measurements are both valid at the same location in time and space.
According to Michelson (2000), the accumulated precipitation is first estimated based on the 10-min pseudo-CAPPI images kept in the DMI’s radar archive as radar reflectivity (in dBZ). These images are piped into ARNE and converted to rainfall intensity (mm/h) using the classic Marshall–Palmer equation (Marshall et al., 1947; Marshall and Palmer, 1948):

$$Z = AR^b \rightarrow R = \left( \frac{Z}{A} \right)^{1/b}$$  \[1\]

with standard parameter values $A = 220$ and $b = 1.6$ ($A$ and $b$ are both dimensionless). Estimated 10-min rainfall intensities are accumulated as 24-h sums. Daily rain gauge point observations are then matched with pixels on the radar rainfall sums that have the same geographic coordinates.

Second, the relationship between the distance from the radar and the bias is established. The bias of radar measurements is represented by the logarithmic gauge/radar ratio $F_g = \log(G/R)$ for each collocated radar–gauge pair. Based on the available $G–R$ pairs, the distance dependency of the bias can be formulated for every pixel on the radar composite. Based on the assumption that a second-order polynomial will enable a nonlinear relationship to reflect the systematic variation of reflectivity with distance, the fundamental methodology is to use a second-order polynomial to express the relation between bias and distance:

$$F_{r(i,j)} = a + br + cr^2$$  \[2\]

where $F_{r(i,j)}$ is the distance-dependent adjustment factor field and $r$ is the distance to the radar, while coefficients $a$, $b$, and $c$ (dimensionless) can be determined using least square fits between all $F_g$ values and their corresponding distances to the radars. The $F_{r(i,j)}–r$ relationship provides the estimate of the bias ($\bar{F}_g$) at each rain gauge location. A quality control is then conducted to evaluate the difference between the observed and estimated bias, $F_g$ and $\bar{F}_g$, respectively, to determine whether the observed bias is captured by the model:

$$Z_g = \frac{F_g - \bar{F}_g}{\sigma}$$  \[3\]

where $Z_g$ is the normalized residual and $\sigma$ is the standard deviation of $F_g$. A quality flag, $Q_g$, is assigned to each value of $Z_g$ using the following criteria:

$$Q_g = \begin{cases} 1 & |Z_g| \leq \sigma \\ 1 - \left| \frac{Z_g}{\sigma} \right| & \sigma < |Z_g| \leq 2\sigma \\ 0 & |Z_g| > 2\sigma \end{cases}$$  \[4\]

Observations with $Q_g = 0$ are rejected and a new $F_{r(i,j)}–r$ relationship can be established using the quality-ensured $G–R$ pairs. The
reason for this quality control is to remove outliers from the data set so that they will not affect the bias correction. The significance of the new relationship is then evaluated by a t-test between the two sets of bias values with a 95% confidence interval: bias estimated by distance relation \(F_g\) and bias calculated by quality-controlled \(G-R\) pairs \(F_g^\prime\). If the test is failed, it means that the influence of distance to bias for the sample in the 7-d moving window is not large enough. Therefore the original radar precipitation sum is adjusted by considering only the average bias of the \(G-R\) pairs.

The third step and the overall objective of the rain gauge adjustment is to obtain a final adjustment factor field (explained below), \(\bar{F}_{(i,j)}\), which will be multiplied, pixel by pixel, by the original radar precipitation sum. This field is defined by

\[
\bar{F}_{(i,j)} = F_{r(i,j)} + w_{s(i,j)} \left( F_{s(i,j)} - F_{r(i,j)} \right) \tag{5}
\]

where \(F_{r(i,j)}\) is the distance-dependent adjustment factor field, \(F_{s(i,j)}\) is the spatially analyzed adjustment factor field, \(w_{s(i,j)}\) is the spatial weighting factor, and \((i,j)\) denotes the location of the pixel. The calculation of \(F_{s(i,j)}\) is explained above. The spatially analyzed adjustment factor field, \(F_s\), is the result of a combination of two factors:

\[
F_s(i,j) = \bar{F}_{(i,j)} + F_r(i,j) \tag{6}
\]

where \(F_r(i,j)\) is the first-guess adjustment field and \(\bar{F}_{(i,j)}\) is the interpolation of the first-guess adjustment field. The first-guess adjustment factor for each pixel is a weighted mean of all \(F_g\) observations in a day:

\[
F_{r(i,j)} = \frac{\sum_{g=1}^{N} w_{g(i,j)} F_g}{\sum_{g=1}^{N} w_{g(i,j)}} \tag{7}
\]

where \(w_{g(i,j)}\) is the rain gauge weighting factor determined by

\[
w_{g(i,j)} = \exp\left( -\frac{r_{g(i,j)}^2}{4k(i,j)} \right) \tag{8}
\]

where \(r_{g(i,j)}\) is the distance between each pixel and the location of the individual rain gauges in the field and \(4k\) is a filtering parameter that controls the degree of smoothing (Koistinen and Puhakka, 1981). Having the first-guess adjustment factor field prepared, the interpolation procedure is then formulated as

\[
\bar{F}_g = F_g - \frac{4}{\sum_{n=1}^{4} \frac{1}{r_n}} \sum_{n=1}^{4} \left( \frac{1}{1/r_n} \right) \tag{9}
\]

The interpolated first-guess adjustment field is calculated using Eq. [7] with \(F_g\) substituted by \(\bar{F}_g\), \(n\) indicates the four observation points that are closest to the center rain gauge, and \(r_n\) is the distance from the surrounding rain gauges to the center rain gauge. The spatial weighting factor of Eq. [5], \(w_s\), is determined by

\[
w_s(i,j) = \exp\left( -\frac{D_{p(i,j)}}{D_0} \right) \tag{10}
\]

where \(D_0\) is the decorrelation distance, which is based on an analysis of the spatial correlation structure of the \(F_g\) data set. The value of \(D_0\) characterizes the distance between gauges where the correlation between errors is insignificant. It is assumed that the decorrelation distance for each day is constant across the entire rainfall field because all qualified rain gauges in the country are taken into account. The value of \(D_0\) is obtained by using \(F_g\) values for each gauge as well as their distance from each other. For each 10-km interval, the semi-variance \(\gamma^2\) between observations is calculated. The value of \(D_0\) is estimated as twice the distance where \(\gamma^2 = 1/e\), assuming a linear interpolation between two quantized distance intervals. The variable \(D_{p(i,j)}\) is the local observation density, defined by the square root of the area covered by five local \(F_g\) observations. The observation density is not constant so that the weighting factor has to vary accordingly to account for the local variations (Koistinen and Puhakka, 1981).

With all these steps finished, the adjustment of the original radar composite sum, \(R_{(i,j)}\), becomes

\[
R_{(i,j)} = R_{r(i,j)} 10^\bar{F}_{(i,j)} \tag{11}
\]

where \(R_{r(i,j)}\) is the final adjusted daily rainfall field.

As an alternative to this radar–rain gauge merging technique, a simple mean field bias (MFB) correction method was used in this study for comparison purposes. The MFB is defined as

\[
MFB = \frac{\sum_{i=1}^{n} G_i}{\sum_{i=1}^{n} R_{0i}} \tag{12}
\]

and

\[
R_{(i,j)} = R_{0(i,j)} MFB \tag{13}
\]

where \(G_i\) is the ith rain gauge observation and \(R_{0i}\) is the radar-estimated value at the pixels that contain \(G_i\). With \(R_{0(i,j)}\) being the original radar precipitation field, the adjusted precipitation field \(\{R_{(i,j)}\}\) suggests that the entire precipitation field will be multiplied by a single correction factor regardless of the distance relations. Therefore the original radar rainfall spatial structure will be preserved, whereas ARNE reshapes the rainfall field based on rain gauge locations. It should be mentioned that unlike the method in ARNE that uses a 7-d moving window, MFB takes into account only the radar and rain gauge data from the current day.
Grid Precipitation Products from the Danish National Rain Gauge Network

The present Danish national rain gauge network consists of three types of rain gauges: the manual Hellmann gauge, the Geonor automatic gauge, which measures precipitation based on the vibrating string principle (Bakkehoi et al., 1985), and the Rimco 7499 tipping bucket gauge. The Hellmann gauges have been deployed nearly 100 yr and were the most widely used rain gauges in Denmark in 2006. The first automatic rain gauge was introduced to Denmark in 1979. With the update of rain gauge networks over the years, automatic gauges are concentrated around the large cities, leaving the countryside dominated by manual gauges. The temporal resolution of rainfall measurement for Hellmann, Geonor, and Rimco gauges are 24 h, 10 min, and 1 min, respectively. The Danish national rain gauge network in 2007 is presented in Fig. 3a.

It is known that wind-induced errors in rain gauge precipitation measurement will result in systematic deficits, especially at high wind speed. The magnitude of the deficit can be as high as half of the true precipitation. To account for this error, a systematic error correction method was developed, where a multiplicative factor is applied to each observed rain gauge recording (Allerup et al., 1997). Because the correction factors consider the architectural and vegetation surroundings close to the gauge, rain gauge catch correction is performed by using wind shelter categories (A, B, and C) that are assigned to each rain gauge with seasonal variations. The correction factors are provided on a monthly basis and are shown in Table 2. All rain gauges are corrected based on this table before the measurements are subjected to any type of application. Uncertainty in the calculation of correction factors has been found to be approximately 4% in terms of standard deviations. The factors are based on data from the period 1961 to 1990. The average precipitation amount in the recent period has, however, been significantly higher than in the calculation period. Therefore the correction factors listed here are prone to a larger degree of uncertainty if applied to recent situations.

The grid precipitation products based on rain gauge information were represented using two techniques in this study. One is DMI’s 10- by 10-km grid product (DMI10 in short), which uses an inverse distance technique (Scharling et al., 2006). The other technique uses ordinary kriging, which is one of the most widely used interpolation methods in geoscience to estimate point values at locations without observation by weighting of neighboring points (Davis, 1986).

Rain gauge precipitation products are included in this study for various reasons. The results and application of the radar QPE should be compared and validated against the most reliable data sources. The DMI10 is recognized as one of the official Danish rainfall products, which has been used for developing and

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**Table 2.** Monthly rain gauge catch correction factors for Denmark recommended by the Danish Meteorological Institute (Allerup et al. 1997).

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<tbody>
<tr>
<td>Freely exposed (C)</td>
<td>1.53</td>
<td>1.53</td>
<td>1.45</td>
<td>1.29</td>
<td>1.16</td>
<td>1.13</td>
<td>1.12</td>
<td>1.13</td>
<td>1.17</td>
<td>1.29</td>
<td>1.48</td>
<td>1.27</td>
<td></td>
</tr>
<tr>
<td>Moderate wind (B)</td>
<td>1.41</td>
<td>1.42</td>
<td>1.35</td>
<td>1.24</td>
<td>1.13</td>
<td>1.11</td>
<td>1.10</td>
<td>1.11</td>
<td>1.14</td>
<td>1.23</td>
<td>1.37</td>
<td>1.21</td>
<td></td>
</tr>
<tr>
<td>Ideal wind (A)</td>
<td>1.29</td>
<td>1.30</td>
<td>1.26</td>
<td>1.19</td>
<td>1.11</td>
<td>1.09</td>
<td>1.08</td>
<td>1.09</td>
<td>1.10</td>
<td>1.17</td>
<td>1.26</td>
<td>1.16</td>
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Fig. 3. The Danish national rain gauge network, including three types of rain gauges: (a) operational rain gauges up to present time, used for radar-gauge adjustment, and (b) rain gauges that had observations until 2006 and were closed down in 2007. This group was subjected to validation.
calibrating distributed hydrologic models in Denmark in the past. The DMII10, however, is based on all available rain gauge records. The intention of the present study was that part of the rain gauges should be reserved for validation purposes. Additionally, the grid size of the DMII10 is not consistent with the radar QPE products. Therefore, kriging was introduced not only to provide an alternative rain gauge rainfall product but also because it is easy to control the number of rain gauges used in spatial interpolation and grid size on the rainfall domain. The kriging domain had a spatial resolution of 2 by 2 km and it was thus consistent with that of the radar rainfall domain and the calculations were performed by using only data from the rain gauges shown in Fig. 3a.

Hydrologic Model for the Skjern Catchment

The Skjern catchment is located on the west coast of the Jutland peninsula. The catchment covers an area around 3500 km² excluding the fjord area, with land use consisting of 56% agriculture, 29% grass, 5% heath, 7% forest, and 2% urban areas. The shallow geology in western Jutland is dominated by Quaternary outwash plains of sand and gravel. Isolated islands of Saalian sandy till are found between the outwash plains. The thickness of the Quaternary deposits varies between 50 and 250 m. Miocene sediments formed by alternating layers of clayey and sandy marine deposits are found below. These sediments have a thickness of 200 to 300 m. The Quaternary and Miocene sand formations form large interconnected aquifers (van Roosmalen et al., 2007). Precipitation is measured by more than 20 rain gauges located across the catchment (Fig. 4). Records show that the annual average precipitation is 1057 mm, with a 50% variation during the years 1990 to 2004 (van Roosmalen et al., 2007). Stream discharge gauging stations are also shown in Fig. 4.

A water resources model was developed for the Skjern catchment with the intention to explore the entire water cycle and the water balance at the catchment scale. The MIKE-SHE code originally derived from the SHE model (Abbott et al., 1986) was used as the modeling framework. The MIKE-SHE code is a deterministic, distributed, physically based hydrologic modeling system that integrates the entire land phase of the hydrologic cycle, including surface and groundwater. The model for the Skjern catchment was built on a 500- by 500-m grid and was based on the current version of the Danish National Water Resources Model, the DK-Model (Henriksen et al., 2003). New field data collected as part of the HOBE project will be integrated into the model and it is an ideal tool for investigating water balance issues while experimenting with new modeling strategies (Jensen and Illangasekare, 2011; Stisen et al., 2011).

We investigated the impact of different precipitation input scenarios on water balance modeling with particular emphasis on the radar QPE products. The baseline Skjern River model was calibrated by the PEST optimization tool (Doherty, 2004) using observed stream discharge and hydraulic head data. Rain gauge data were used to define the precipitation input, and Thiessen polygons were used to estimate the spatial rainfall distribution. In the calibration process, the number of free parameters was limited to nine, which is relatively few considering the substantial number of parameters in the model setup. More details on the objective functions as well as their weights can be found in Stisen et al. (2011). For the hydrologic simulations using various kinds of precipitation inputs, the model was run for 2002 to 2006. Only the precipitation for the last year was replaced each time by different data sources. Hence 2002 to 2005 can be regarded as the warming up period to ensure that the different precipitation scenarios were tested for the same initial condition in the beginning of 2006.

Results and Discussion

Precipitation Estimation Based on Radar and Gauge Data

A case study was undertaken based on the precipitation estimation schemes described above. Both radar and rain gauge data are presented in daily values. The date of 27 June 2006 was chosen as an example because it represented a typical rainfall event in Denmark based on the structure and intensity of the rainfall. The meteorological condition of this case was frequent showers and occasional heavy convective cells. A total of 60% of the rain gauge stations reported <15 mm of rainfall, whereas a few stations had high amounts up to 55 mm.

The effects of rain gauge adjustment of radar images for each step of the ARNE algorithm are shown on Fig. 5. The main land area

Fig. 4. Map of the Skjern catchment. The Skjern River network as well as observation points for precipitation and stream discharge stations are shown. Discharge stations no. 20020, 20082, and 20078 are marked for further discussion.
of Denmark including Zealand, Fuen, and Jutland were considered, whereas the sea areas and the island of Bornholm were left out of the figures. The radars used in this example were Roemoe, Sindal, and Stevns (see Fig. 1 for locations), and the composite scenario for merging radar images was the maximum pixel values. As a primary quality control, 359 valid $G$–$R$ pairs were used for adjustment and 13 pairs were rejected for representativeness reasons. The calculated decorrelation distance was found to be $D_0 = 56$ km.

The distance-dependent adjustment factor field ($F_i$) is shown in Fig. 5a. It is evident that the signals returned from the Roemoe radar were the strongest in that a large numbers of pixels close to the Sindal and Stevns radar sites were taken over by the signals from the Roemoe radar. Figure 5a also reveals stronger distance dependency in the areas close to the radar sites. The first-guess adjustment factor field ($\hat{F}_{i,j}$) shown in Fig. 5b gives much higher values in the northwestern part of Jutland, which indicates higher mean bias values between radar-estimated and rain-gauge-measured rainfall in that area. The interpolated adjustment factor field ($\hat{F}_{i,j}$), Fig. 5c, clearly reflects the local density of the rain gauges, and a lighter color denotes larger spatial variations (Eq. [9]). On the final adjustment factor field ($R_{i,j}$), Fig. 5d, the highest value reached 0.726, indicating that some pixels on the original radar image underestimated the rainfall by a factor of 5.3. This value is considered rather high and speculations have arisen that the radar hardware may have had a malfunction at some point. Ultimately,
\( R_{(i,j)} \) was applied in Eq. [11], which completed the adjustment of the raw radar image.

Following the steps above, radar precipitation estimates before and after the ARNE adjustment are shown in Fig. 6a and 6b, along with the rain-gauge-generated precipitation products in Fig. 6c and 6d. The raw radar composite image suffers from a severe underestimation of rainfall. The system bias has been largely removed in the ARNE-adjusted image and more details on the precipitation field are revealed. The DMI10 is the most widely used data source in Denmark even though it has the coarsest spatial resolution. Its spatial distribution coincides with what can be obtained from ARNE and kriging of rainfall data from the rain gauge stations.

By visual inspection, the kriging method performed just as good as the inverse distance method although based on fewer observation points.

**Performance of Radar Precipitation Estimation against Ground Measurement**

A quantitative evaluation for the case study was performed. To do that, the total number of rain gauges was divided into two groups. The rain gauges that were still in operation after 2006 were used for radar image adjustment in ARNE, the removal of the mean field bias, and the spatial interpolation using kriging. The rain gauges that were closed in 2007 were regarded as reference gauges subjected to independent validation. The locations of these two groups

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Fig. 6. Estimation of precipitation using different approaches for Denmark on 27 June 2006: (a) original radar image, (b) ARNE-adjusted radar quantitative precipitation estimation product, (c) Danish Meteorological Institute 10-km grid product, and (d) kriging of rain gauge rainfall data.
of rain gauges are shown in Fig. 3a and 3b. The objective functions used for the performance evaluation were bias (both absolute and logarithmic), RMSE, and the correlation coefficient (r).

The absolute bias between different rainfall measures and co-located validation gauges for the case study (Fig. 6) on 27 June 2006 are shown in Fig. 7a. Among them, ARNE mostly stayed bias neutral but shows overestimation under small rainfall intensity and underestimation in the range of higher rainfall intensity. This indicates that the systematic bias in radar QPE caused by raindrop size variations was not completely removed. The raw radar data show severe underestimation, which confirms the observation in Fig. 6a. The kriging result shows overestimation in the lower rainfall intensity range, which is a result of the kriging algorithm neglecting the observation points with zero precipitation. The MFB-corrected radar data largely removed the bias but was still inferior to ARNE. In summary, merging of radar and rain gauge estimation showed significant improvements in bias reduction compared with the case where information from either radar or rain gauge was used alone.

Figure 7b explicitly illustrates the relation between logarithmic bias and distance from the validation points to the radars. Without any means of adjustment, the raw radar data show a minimum bias at 50 km, which then increases with distance. This curve offers a good example of the errors residing in the process of radar QPE. At short distance, the radar suffers from partial beam blockage, whereas at longer distance, underestimation occurs when the radar detects a hydrometeor with a smaller size at higher altitude and the radar beams overshoot the main precipitating clouds. In the current case study, the meteorological condition was summer convective rain so that there was no presence of melting ice. During the wintertime, however, melting ice crystals coated with water layers will have extremely high reflectivity, which would result in a bright area on the radar display (the so-called “bright band”). Therefore, this curve may have a different shape during the wintertime with the same precipitation type when a bright band is present. The MFB corrects the radar image such that it increases or decreases the overall precipitation field as a whole. Hence, no impact on the distance relation was found except that the curve of the raw radar data was shifted downward. The ARNE successfully removed the distance-induced bias. It was also able to keep the bias considerably small and almost constant with an increase of distance.

The case study for 27 June 2006 was selected as a demonstration of daily precipitation; however, the general precipitation conditions throughout the whole year are also essential. In Table 3, the results of a performance evaluation for 2006, using all wetted validation gauges, are listed. The ARNE method was superior to the other precipitation products in every aspect. The ARNE is also the only product that had positive bias. The raw radar data provided the least promising rainfall product. These data led to the most severe underestimation of −0.79 mm/d, which accounts for >20% of the daily average precipitation for that year. Possible explanations

<table>
<thead>
<tr>
<th>Product</th>
<th>Bias (mm/d)</th>
<th>RMSE (mm)</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw data</td>
<td>−0.790</td>
<td>2.137</td>
<td>0.638</td>
</tr>
<tr>
<td>ARNE algorithm adjusted</td>
<td>0.173</td>
<td>1.683</td>
<td>0.651</td>
</tr>
<tr>
<td>Mean field bias corrected</td>
<td>−0.351</td>
<td>2.220</td>
<td>0.638</td>
</tr>
<tr>
<td>Kriging</td>
<td>−0.766</td>
<td>4.060</td>
<td>0.587</td>
</tr>
</tbody>
</table>

can be inappropriate use of the Z–R relationship, an underdeveloped clutter and noise cancellation program, problematic radar hardware calibration, or a combination of these factors. It again
emphasizes the importance of a sophisticated clutter filter and the use of rain gauge adjustment procedures applied to raw radar images given the current condition of raw data quality. The MFB was the second most favorable rainfall product after ARNE, especially in the removal of bias and the RMSE. Kriging had the worst performance in all categories and therefore was not considered for the hydrologic analysis.

Overall, radar-based rainfall estimation had a higher accuracy than rainfall values projected by rain gauge interpolation at the same locations, which clearly suggests that the combination of radar and rain gauge captures more spatial variability of precipitation than traditional rain gauge measurements. Therefore it was expected that radar QPE would influence the results of hydrologic modeling when switching from rain-gauge-based rainfall input. The ARNE and the MFB methods were the tools used to study the impact of precipitation on the hydrologic responses.

**Impact of Radar Quantitative Precipitation Estimation on Water Balance Modeling**

One of the primary objectives of this study was to assess the utility of radar QPE from a hydrologic modeling perspective. To achieve that, daily radar precipitation products were prepared using the ARNE and MFB methods for the Skjern catchment. Along with the rain-gauge-derived precipitation products, Fig. 8 illustrates four precipitation estimates that were imported to the hydrologic model in the form of the accumulated precipitation amount in 2006. It should be mentioned that accumulation of the radar-estimated precipitation inevitably resulted in magnified static ground clutter and artifacts. It was decided in this study to identify the pixels in the top 2% of the histogram and replace the erroneous data by averaging the values from adjacent pixels. This is a common methodology in the interpretation of remote sensing data and reduces the impact of data contamination on the water balance modeling.

Mean areal precipitation estimated from rain gauge observations and Thiessen polygons had the coarsest spatial resolution (Fig. 8a). It was also the rainfall product used for the calibration of the hydrologic model (Stisen et al., 2011). The combination of radar and rain gauge observations showed comprehensible advantages in that ARNE not only provided much more detail than DMI10 but also extended the area with high rainfall in the northern part of the catchment to the northeast corner. This area is interesting from a modeling perspective and is discussed below. The accumulated

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**Fig. 8. Precipitation estimates for 2006 for the hydrologic model of the Skjern catchment: (a) rain gauge station measurement with Tiessen polygon, (b) Danish Meteorological Institute 10-km grid product, (c) ARNE algorithm adjusted radar quantitative precipitation estimation product, and (d) mean field bias (MFB) corrected raw radar image.**
precipitation was not expected to exhibit drastic spatial variation at the local scale, which makes the smoother transition of the rainfall field in ARNE more plausible compared with the DMI10. The MFB-removed product also showed a smoother spatial distribution than the rain gauge products. We noted that MFB indicated an entirely different rainfall distribution than the other data sets. The high-rainfall area tended to shift to the west side, which is close to the fjord. This reveals that the original radar images actually captured a considerable amount of precipitation at places where few rain gauge sampling points were located. This was not a significant issue in this study because the fjord was not accounted for in the calculation of the total water balance, but in catchments with large open water bodies surrounded by land, radar data may have more viability than a rain gauge network.

Statistics on the precipitation in the Skjern catchment during 2006 are shown in Fig. 9. To plot the frequency distribution in Fig. 9a, a bin width of 5 mm/d was chosen and equal spacing was applied except for the first band, which was 0.5 mm/d. Consistent agreement for the different precipitation products was observed in every band thanks to the bias adjustment. More than 40% of the days were either dry or had precipitation <0.5 mm/d. It was also recognized that precipitation events in the 10 to 15 mm/d interval had a more frequent occurrence than precipitation in preceding and succeeding intervals. In Fig. 9b, the temporal distribution of precipitation on a monthly basis is shown, revealing that the agreement between the radar products and the gauge product was acceptable in most cases. It also shows that the last 3 mo of the year accounted for more than half of the annual precipitation, which makes it the time of interest to observe hydrologic responses caused by precipitation forcing.

In Fig. 10, the simulated hydrographs at the three discharge stations indicated in Fig. 4 are shown. The response of runoff to precipitation was the most instant process compared with other hydrologic responses such as groundwater level variations. As radar data were available for just 1 yr, stream discharge was an ideal indicator to explain the impact of radar precipitation on the hydrologic model response. At the smaller scale represented by the upstream station (Fig. 10a), the choice of precipitation product had a significant impact on the simulated discharge. The ARNE method generated higher precipitation in the catchment draining to this discharge station (see Fig. 8c), which resulted in higher stream discharge. Especially during the event that occurred in mid-December, the ARNE input resulted in much higher peak flow than the other input scenarios. The consequences of model calibration become obvious at the smaller scale because only the baseline model (precipitation estimated by station data with Thiessen polygons) coincides with the observation during the event in December; however, the dynamics of the three hydrographs are comparable. On the other hand, all analytical rainfall products lacked the ability to reproduce many of the small peaks found in the observations. This is presumably due to the uncertainties in the hydrologic model structures rather than insufficient information on the spatial and temporal distribution of the precipitation.

In contrast to the relatively large discrepancies found between the three simulations at the upstream station, much closer agreement was observed at the two downstream stations (Fig. 10b and 10c). Simulated discharges from the radar products were able to reproduce the volume and timing of the major peak flows. It can be seen that the peak flows are closely related to the mean quantity of precipitation, which indicates that the simulated stream discharge is more sensitive to the integrated volume of rainfall entering the system rather than the spatial variation of rainfall as the catchment size increases. Therefore, radar QPE is expected to have a higher potential for improving the performance of hydrologic modeling at the small scale. The peak flow from mid-May to early June was not captured by any of the precipitation input scenarios or the baseline model. This indicates that the current hydrologic model needs more advanced model descriptions or calibration. The precipitation of the MFB method was much higher

Fig. 9. Statistics of the precipitation estimates used in the hydrologic model: (a) frequency distribution of averaged daily precipitation, and (b) seasonal variation of precipitation in 2006 estimated as the Danish Meteorological Institute 10-km grid product, ARNE algorithm adjusted radar quantitative precipitation estimation product, and mean field bias (MFB) corrected raw radar image.
in the southern part of the catchment, which caused the higher discharges at Station 20078 (Fig. 10c). As mentioned above, MFB preserves the original distribution of the radar rainfall field, while ARNE reshapes the precipitation field based on the rain gauge properties. Therefore, we believe that the differences observed in Fig. 10 can be resolved by using wind correction factors for individual rain gauges on a daily basis instead of the universal monthly correction factors implemented currently. It is inconclusive, however, which rainfall distribution is more dependable at this stage.

As a primary discovery found from the simulated stream discharge, the sensitivity of the model predictions highly depended on the scale of the catchment size. This theory was further investigated by delineating the Skjern catchment into 15 subcatchments (Fig. 11), each with an actual discharge station at the outlet. The water collection areas ranged from 41 to 1553 km². The mean areal runoff was calculated by dividing the accumulated discharge volume at each outlet by the size of the subcatchments individually. Figures 12a and 12b show high dynamics at smaller subcatchment scales for the simulated discharge volume determined by all three precipitation products. The fluctuations tended to decrease with an increase in the subcatchment size. Comparing the modeled results from the radar products (ARNE and MFB) and the rain gauge product (DMI10), large differences occurred when the subcatchment size was less than around 400 km². This confirms our previous finding in a quantitative manner that the radar precipitation can effectively influence the simulated stream discharge when the catchment size is smaller than roughly 400 km² for the current Skjern River model. Nash–Sutcliffe coefficients were also calculated for the simulated daily discharge driven by radar precipitation to capture the dynamic differences between the simulations. In this process, the simulated discharge from DMI10 was assumed to represent the observed values. Figure 12c depicts that the simulations driven by radar-based precipitation deviated significantly from the DMI10 at a small scale. This is especially clear for Station 250091, where a Nash–Sutcliffe coefficient for the MFB of nearly zero was found, which is also consistent with the spatial distribution of precipitation observed from Fig. 8.

The simulated recharge to the groundwater is shown in Fig. 13. The importance of the rainfall products selected is underscored because the simulated groundwater recharge reflects exactly the same spatial pattern as the precipitation input (Fig. 8). The radar-based simulations provided a smoother and hence more realistic distribution of recharge.
compared with the two station-based simulations, where the boundaries between the precipitation zones are easily recognized. In addition, large differences in the spatial distribution of groundwater recharge were found. This is expected to result in long-term effects on groundwater levels that are not captured by the present simulations with a duration of only 1 yr.

Total water balances for the three models are summarized in Table 4 and a diagram depicting each element in the table is shown in Fig. 14. For annual precipitation, the baseline model returned the lowest value while the value estimated by the ARNE method was around 50 mm or 5% higher. The ARNE algorithm, being the candidate for a future radar QPE product in Denmark, proved to have sufficient accuracy in serving as input to distributed modeling of the seasonal behavior of hydrologic processes. The outcomes of the ARNE method were very close to that from the baseline model, which is considered promising.

**Conclusions**

A methodology for the generation of a daily radar QPE product by using the DMI ARNE algorithm was introduced. The ARNE intermediate products as well as the final product were evaluated, indicating that the radars in the network are calibrated inadequately, with an underestimation of precipitation of around 20%. The bias correction procedures in ARNE, however, successfully removed both the systematic mean bias and the distance-induced bias. The performance evaluation in 2006 for different precipitation estimators suggested that merging radar and rain gauge measurements could improve the overall data quality over using a single data source. The resulting product revealed more spatial details of the precipitation field that might not be captured by interpolation of rain gauge data. The effect of improved spatial distribution and resolution was demonstrated by simulated stream flows of the hydrologic model.
Fig. 13. Simulated groundwater recharge from the MIKE-SHE model: (a) result using precipitation input with station data and Thiessen polygons, (b) result using precipitation input with the Danish Meteorological Institute 10-km grid product (DMI10), (c) result using precipitation input with ARNE-adjusted radar quantitative precipitation estimation, and (d) result by using precipitation input with the mean field bias (MFB) corrected raw radar image.

Table 4. Simulated total water balance for the Skjern River catchment using scenarios of baseline precipitation, the Danish Meteorological Institute 10-km grid product (DMI10), the ARNE algorithm adjusted radar quantitative precipitation estimation product and mean field bias (MFB) corrected raw radar data as precipitation inputs.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Baseline</th>
<th>DMI10</th>
<th>ARNE</th>
<th>MFB</th>
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<tr>
<td>mm/yr</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Precipitation</td>
<td>1054</td>
<td>1066</td>
<td>1117</td>
<td>1103</td>
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<tr>
<td>Evapotranspiration</td>
<td>588</td>
<td>592</td>
<td>599</td>
<td>587</td>
</tr>
<tr>
<td>Subsurface storage change</td>
<td>117</td>
<td>117</td>
<td>136</td>
<td>133</td>
</tr>
<tr>
<td>Overland storage change</td>
<td>7</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>Overland flow to river</td>
<td>21</td>
<td>22</td>
<td>23</td>
<td>24</td>
</tr>
<tr>
<td>Base flow to river</td>
<td>186</td>
<td>187</td>
<td>195</td>
<td>191</td>
</tr>
<tr>
<td>Groundwater drain to river</td>
<td>80</td>
<td>84</td>
<td>89</td>
<td>90</td>
</tr>
<tr>
<td>Irrigation</td>
<td>12</td>
<td>11</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Pumping</td>
<td>17</td>
<td>17</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td>Error</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Fig. 14. Hydrologic fluxes simulated by the hydrologic model.
The main contribution of this study is the application of radar QPE for long-term water resources modeling. After having demonstrated that radar gives promising results in estimating precipitation from a meteorological perspective, radar-based daily precipitation products were brought into a distributed water resources model to analyze the hydrologic responses. Simulated stream discharge with the radar QPE as model input gave reliable results with reference to what was obtained from the baseline model. The hydrologic model also showed high sensitivity to the spatial distribution in relatively small subcatchments with sizes of <400 km², while for larger areas, it was more dependent on the total precipitation volume. The importance of using the radar QPE in hydrologic modeling is also illustrated by the close match between the simulated annual groundwater recharge and the precipitation products used as model input. The differences of the precipitation components between the three water balance model scenarios were found to be <5%. In addition, the study revealed some model development issues such as model parameter calibration.

The most urgent task for the future is to improve data quality in radar measurement. This will include a refined hardware calibration strategy and a clutter removal program. Longer time series of radar data are also needed for more thorough testing and to facilitate calibration of the hydrologic model using radar data as input. We also plan to operate radar QPE on a subdaily basis, not only to meet the requirement for more precise hydrologic modeling but also to accommodate automation of the rain gauge network.


References


