The effect of spatially uniform and non-uniform precipitation bias correction methods on improving NEXRAD rainfall accuracy for distributed hydrologic modeling
Kwangmin Kang and Venkatesh Merwade

**ABSTRACT**

In order to improve the accuracy of rainfall estimates from next generation radar (NEXRAD) uncertainties, data assimilation technique is performed by considering NEXRAD and available rain gauges which can be used to assimilate spatially uniform Multisensor Precipitation Estimator (MPE) scheme and non-uniform (based on rainfall interpolation and bias interpolation) NEXRAD bias estimations during a storm event by Kalman filtering. Even though NEXRAD provides a better spatial representation of rainfall variability than rain gauge information, it suffers from uncertainties and biases due to Z–R (reflectivity–rainfall) conversion method and limitation of available rain gauge information for NEXRAD bias correction in a particular river basin. Analysis of correcting NEXRAD bias rainfall with three different bias correction schemes is described in this study. The prediction accuracy of the STORE DHM (Storage Released based Distributed Hydrologic Model) simulations is also evaluated by using three different NEXRAD bias corrected rainfall inputs. The Upper Wabash River (17,907 km²) and the Upper Cumberland River (38,160 km²) basins are selected as the study areas to evaluate rainfall input sensitivity on different spatial characteristics. Use of spatially non-uniform NEXRAD bias correction schemes results have better rainfall and prediction accuracy compared to that of spatially uniform NEXRAD bias correction rainfall.

**Key words** | bias correction, Kalman filter, NEXRAD, STORE DHM, Upper Cumberland River, Upper Wabash River

**INTRODUCTION**

Representation of spatio-temporal rainfall variability is critical for making accurate hydrologic predictions (Abedini et al. 2013; Feiccabrino et al. 2013; Jeong et al. 2013). Numerous studies in the past decades have investigated the sensitivity of runoff hydrographs to rainfall data obtained from point gauges. In addition to the accuracy of gauged rainfall input, the predictability and sensitivity of hydrologic models is dependent on the spatio-temporal representation of rainfall (Nicótina et al. 2008; Viglione et al. 2010; Zoccatelli et al. 2010, 2011; Li et al. 2013), which can be obtained from radar rainfall data (Smith et al. 2004). The next generation radar (NEXRAD) products available since 1992 provide high resolution rainfall information in space and time for the United States. Currently, the NEXRAD precipitation products are categorized into four levels based on the extent of preprocessing, calibration, and quality control performed. The StageI product is an hourly digital precipitation (HDP) directly derived from reflectivity measurements using a Z–R (reflectivity–rainfall) relationship after the application of several quality control algorithms (e.g., Fulton et al. 1998). StageII is the single radar site HDP product, which is merged with surface rain gauge observations in order to correct mean field bias (MFB) using Kalman filtering (Smith & Krajewski 1991; Anagnostou et al. 1999). In StageIII, the
Stage II rainfall data from multiple weather radars covering a River Forecast Center (RFC) region are combined (Fulton et al. 1998; Reed & Maidment 1999). Finally, Stage IV is the mosaicked Stage II rainfall product covering the entire Continental United States (CONUS).

The most commonly used NEXRAD product in hydrometeorological applications is the NEXRAD Stage III data (e.g., Young et al. 2000) because the radar rainfall rates are corrected using multiple surface rain gauges and it undergoes a significant degree of meteorological quality control by trained personnel at individual RFCs (Fulton et al. 1998). Since around 2002, Multisensor Precipitation Estimator (MPE), which is developed by the National Weather Service (NWS) Office of Hydrology, is available for each RFC. The MPE product is obtained by merging radar, gauge, and satellite estimates of rainfall and is adjusted for MFBs. In spite of better spatial representation of rainfall variability by radar, there are limitations of radar estimates due to data contamination and uncertainty issues (Smith et al. 1996; Legates 2000; Xie et al. 2006). In particular, uncertainty in radar rainfall is caused by Z-R conversion method, limitation of available rain gauge information for MFB adjustment, and spatially uniform bias correction for entire RFCs.

Schmid & Wuest (2005) suggest that new decade research in hydrometeorology is minimizing radar precipitation errors. Smith & Krajewski (1991) found that combining radar and gauge information produces improved precipitation estimates, in terms of both quality and spatial resolution, in comparison with either radar or gauge estimates alone. Dinku et al. (2002) investigated different radar rainfall error correction schemes in mountainous areas. These schemes included correction for terrain blocking, adjustment for rain attenuation, interpolation of reflectivity data, and Kalman filtering-based mean field radar bias correction scheme similar to that of Anagnostou et al. (1999). Dinku et al. (2002) found that adjustment of radar bias with the filtering approach produced high accuracy radar rainfall. Despite several techniques available for merging radar data with rainfall gauges, uncertainty persists in radar precipitation products because large portions of radar coverage areas do not have rain gauge data to adjust biases in radar rainfall (Winchell et al. 1998; Habib et al. 2009).

In NEXRAD Stage III (MPE), analysis bias in radar rainfall is corrected using available rain gauges. The correction procedures assume that the biases are spatially uniform over the entire RFC region. These spatially uniform biases are referred to as MFB (Smith & Krajewski 1991). However, recent studies have shown that the assumption of spatially uniform bias is not valid over particular regions (Li & Shao 2010). The NEXRAD rainfall bias over a small watershed in an RFC region could be very different from the mean bias over the entire RFC region. Looper et al. (2012) concluded that even though MPE accounts for radar bias, the resulting precipitation may not be accurate for a particular river basin, because adjustment is performed on the entire RFC region. Consequently, hydrologic model simulations for a particular watershed with MPE analysis data could be unrealistic. In addition, the effect of these spatially non-uniform local biases on hydrologic simulations is not well understood (Li & Shao 2010). Furthermore, a few methods that are available in order to correct spatially non-uniform local biases (Seo & Breidenbach 2002) have limitations such as insufficient rain gauge and uneven rain gauge networks, and their sensitivity to hydrologic model simulations has not been tested.

Use of radar rainfall in hydrology is a challenge and further work remains to be done on how to refine radar rainfall for hydrology (Berne & Krajewski 2012). Dense and high quality rain gauge networks are one of the key factors in solving the problem of radar-rainfall uncertainties (Krajewski et al. 2010; Villarini & Krajewski 2010). Applying constant bias factor for correcting radar rainfall to the entire radar-rainfall field was suggested by Anagnostou et al. (1999), Smith & Krajewski (1991), and Seo et al. (1999). After that, Seo & Breidenbach (2002) investigated spatially varying radar rainfall biases which can be adjusted by using against rain gauge data. Consequently, studying radar-rainfall error correction shifted to find out spatially varying radar rainfall biases.

Most research focus has already tried to find the best way of correcting spatial radar rainfall biases (Young et al. 2000; Jayakrishnan et al. 2004; Xie et al. 2006; Wang et al. 2008; Habib et al. 2009). Seo & Breidenbach (2002), Haberlandt (2007), and Li et al. (2008) suggest that rain gauge data interpolation into radar rainfall, especially NEXRAD precipitation, is the most common method to reduce spatially varying radar rainfall biases. A more advanced attempt has been tried by Li et al. (2008), using a linear regression based Kriging method to improve daily NEXRAD precipitation using rain gauge data applied in Texas to estimate daily

Stage II rainfall data from multiple weather radars covering a River Forecast Center (RFC) region are combined (Fulton et al. 1998; Reed & Maidment 1999). Finally, Stage IV is the mosaicked Stage II rainfall product covering the entire Continental United States (CONUS).

The most commonly used NEXRAD product in hydrometeorological applications is the NEXRAD Stage III data (e.g., Young et al. 2000) because the radar rainfall rates are corrected using multiple surface rain gauges and it undergoes a significant degree of meteorological quality control by trained personnel at individual RFCs (Fulton et al. 1998). Since around 2002, Multisensor Precipitation Estimator (MPE), which is developed by the National Weather Service (NWS) Office of Hydrology, is available for each RFC. The MPE product is obtained by merging radar, gauge, and satellite estimates of rainfall and is adjusted for MFBs. In spite of better spatial representation of rainfall variability by radar, there are limitations of radar estimates due to data contamination and uncertainty issues (Smith et al. 1996; Legates 2000; Xie et al. 2006). In particular, uncertainty in radar rainfall is caused by Z-R conversion method, limitation of available rain gauge information for MFB adjustment, and spatially uniform bias correction for entire RFCs.

Schmid & Wuest (2005) suggest that new decade research in hydrometeorology is minimizing radar precipitation errors. Smith & Krajewski (1991) found that combining radar and gauge information produces improved precipitation estimates, in terms of both quality and spatial resolution, in comparison with either radar or gauge estimates alone. Dinku et al. (2002) investigated different radar rainfall error correction schemes in mountainous areas. These schemes included correction for terrain blocking, adjustment for rain attenuation, interpolation of reflectivity data, and Kalman filtering-based mean field radar bias correction scheme similar to that of Anagnostou et al. (1999). Dinku et al. (2002) found that adjustment of radar bias with the filtering approach produced high accuracy radar rainfall. Despite several techniques available for merging radar data with rainfall gauges, uncertainty persists in radar precipitation products because large portions of radar coverage areas do not have rain gauge data to adjust biases in radar rainfall (Winchell et al. 1998; Habib et al. 2009).

In NEXRAD Stage III (MPE), analysis bias in radar rainfall is corrected using available rain gauges. The correction procedures assume that the biases are spatially uniform over the entire RFC region. These spatially uniform biases are referred to as MFB (Smith & Krajewski 1991). However, recent studies have shown that the assumption of spatially uniform bias is not valid over particular regions (Li & Shao 2010). The NEXRAD rainfall bias over a small watershed in an RFC region could be very different from the mean bias over the entire RFC region. Looper et al. (2012) concluded that even though MPE accounts for radar bias, the resulting precipitation may not be accurate for a particular river basin, because adjustment is performed on the entire RFC region. Consequently, hydrologic model simulations for a particular watershed with MPE analysis data could be unrealistic. In addition, the effect of these spatially non-uniform local biases on hydrologic simulations is not well understood (Li & Shao 2010). Furthermore, a few methods that are available in order to correct spatially non-uniform local biases (Seo & Breidenbach 2002) have limitations such as insufficient rain gauge and uneven rain gauge networks, and their sensitivity to hydrologic model simulations has not been tested.

Use of radar rainfall in hydrology is a challenge and further work remains to be done on how to refine radar rainfall for hydrology (Berne & Krajewski 2012). Dense and high quality rain gauge networks are one of the key factors in solving the problem of radar-rainfall uncertainties (Krajewski et al. 2010; Villarini & Krajewski 2010). Applying constant bias factor for correcting radar rainfall to the entire radar-rainfall field was suggested by Anagnostou et al. (1999), Smith & Krajewski (1991), and Seo et al. (1999). After that, Seo & Breidenbach (2002) investigated spatially varying radar rainfall biases which can be adjusted by using against rain gauge data. Consequently, studying radar-rainfall error correction shifted to find out spatially varying radar rainfall biases.

Most research focus has already tried to find the best way of correcting spatial radar rainfall biases (Young et al. 2000; Jayakrishnan et al. 2004; Xie et al. 2006; Wang et al. 2008; Habib et al. 2009). Seo & Breidenbach (2002), Haberlandt (2007), and Li et al. (2008) suggest that rain gauge data interpolation into radar rainfall, especially NEXRAD precipitation, is the most common method to reduce spatially varying radar rainfall biases. A more advanced attempt has been tried by Li et al. (2008), using a linear regression based Kriging method to improve daily NEXRAD precipitation using rain gauge data applied in Texas to estimate daily...
spatial precipitation in 2003. Even though several research results in which radar error correction was done by rain gauge data promise spatially better radar rainfall distributions, minimal research has been devoted to evaluate the accuracy in localized precipitation that is critical for accurate hydrologic simulations (Xie et al. 2011; Parkes et al. 2013).

The aim of this research is to provide better methods for correcting radar precipitation error by using available rain gauges through a spatial grid based Kalman filtering approach instead of a MFB scheme. Those correcting radar precipitation data should improve the correct simulation prediction in hydrologic models. The literature shows that the availability of high-resolution precipitation data from different weather radar platforms has led to improved understanding of rainfall uncertainty in hydrologic models, but few efforts have been directed towards understanding the influence of NEXRAD precipitation and its bias correction on rainfall-runoff simulations (Xie et al. 2011). Thus, results from this study will provide insight into the performance of three different NEXRAD rainfall bias correction schemes and their influence on the sensitivity of a grid based distributed hydrologic model simulation with two study areas (flat and mountainous).

**STUDY AREAS AND DATA**

The Upper Wabash River (UWR) and the Upper Cumberland River (UCR) (Figure 1) basins were selected as the test beds for this study. In addition to providing two distinct geographic locations, both study areas include a reasonable rain gauge network to compare bias correction schemes using NEXRAD data. The UWR basin (17,907 km²) is located in north central Indiana and drains into the Wabash River. The elevation in UWR ranges from 149 to 529 m. Normal annual precipitation of the UWR ranges between 920 and 1,120 mm as computed by using data from 17 rain gauges in the region. The UCR basin (38,160 km²) is located in southeastern Kentucky bordering with Virginia and Tennessee. The UCR is primarily mountainous and forested, and it lies in the Eastern Coal Field.
physiographic region. The elevation in the UCR ranges from 146 to 1,428 m. Normal annual precipitation of the UCR ranges from 950 to 1,300 mm as computed from 19 rain gauges in the region.

The NEXRAD domain of the Ohio River Forecast Center (OHRFC) encompasses both study areas. Hourly NEXRAD StageIII precipitation (4 km × 4 km resolution) estimates are obtained from the National Oceanic Atmospheric Administration’s (NOAA) Hydrologic Data System group website (http://dipper.nws.noaa.gov/hds/data/nexrad/ohrfcmpe), and hourly gauge precipitation estimates are obtained from the National Climatic Data Center (NCDC) website (http://gis.ncdc.noaa.gov/maps/). The NEXRAD rainfall dataset for the study area is available with the HRAP (Hydrologic Rainfall Analysis Project) geographic projection. The HRAP or secant polar stereographic projection is an earth-centered datum coordinate system. Reed & Maidment (1999) describe the HRAP projection and its transformations to other geodetic coordinate systems. The NEXRAD StageIII data are pre-processed by using the algorithm of Xie & Zhou (2005): (1) convert the XMRG (binary) file format to ASCII; and (2) create a desired coordinate system by projecting the HRAP data which format is converted to GIS grid from ASCII. The streamflow data for the study sites were obtained from the United States Geological Survey’s (USGS) Instantaneous Data Archive (IDA) website (http://ida.water.usgs.gov/ida/). The straight line base flow separation method was used for retrieving surface runoff hydrographs from streamflow. The study was conducted by selecting five storms for each study region. The details of these storm events are provided in Table 1.

### NEXRAD Bias Correction Methods

A statistical method should be used to remove the bias between NEXRAD estimates at the rain gauge locations, and corresponding gauge rainfall measurements because

<table>
<thead>
<tr>
<th>Summary of storm events and calibrated Manning’s n values for each study site</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Upper Wabash River</td>
</tr>
<tr>
<td>Upper Wabash River basin</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Event</th>
<th>Start date and time (mm)</th>
<th>Total precipitation (mm)</th>
<th>Total streamflow (mm)</th>
<th>Peak flow: PF (m³/s)</th>
<th>PF/Mean annual PF</th>
<th>Time to peak (hr)</th>
<th>Land use calibration (Agricultural, Forest, Developed, Water)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>06-02-17, 01:00</td>
<td>3.864</td>
<td>0.558</td>
<td>37.37</td>
<td>1.41</td>
<td>41</td>
<td>0.023 0.013 0.011 0.006</td>
</tr>
<tr>
<td>2</td>
<td>06-04-16, 19:00</td>
<td>5.057</td>
<td>1.635</td>
<td>142.15</td>
<td>5.38</td>
<td>23</td>
<td>0.02 0.019 0.015 0.005</td>
</tr>
<tr>
<td>3</td>
<td>06-07-12, 03:00</td>
<td>4.884</td>
<td>1.515</td>
<td>197.14</td>
<td>7.46</td>
<td>39</td>
<td>0.019 0.014 0.011 0.006</td>
</tr>
<tr>
<td>4</td>
<td>06-10-27, 19:00</td>
<td>4.519</td>
<td>1.184</td>
<td>86.98</td>
<td>3.29</td>
<td>32</td>
<td>0.025 0.02 0.018 0.006</td>
</tr>
<tr>
<td>5</td>
<td>06-11-16, 08:00</td>
<td>4.995</td>
<td>1.865</td>
<td>147.41</td>
<td>5.58</td>
<td>27</td>
<td>0.018 0.015 0.013 0.005</td>
</tr>
</tbody>
</table>

(b) Upper Cumberland River

| Upper Cumberland River basin |

<table>
<thead>
<tr>
<th>Event</th>
<th>Start date and time (mm)</th>
<th>Total precipitation (mm)</th>
<th>Total streamflow (mm)</th>
<th>Peak flow: PF (m³/s)</th>
<th>PF/Mean annual PF</th>
<th>Time to peak (hr)</th>
<th>Land use calibration (Agricultural, Forest, Developed, Water)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>05-01-11, 12:00</td>
<td>9.108</td>
<td>1.076</td>
<td>160.55</td>
<td>4.73</td>
<td>39</td>
<td>0.051 0.035 0.033 0.016</td>
</tr>
<tr>
<td>2</td>
<td>05-02-13, 10:00</td>
<td>12.944</td>
<td>2.462</td>
<td>354.81</td>
<td>10.46</td>
<td>33</td>
<td>0.081 0.055 0.043 0.026</td>
</tr>
<tr>
<td>3</td>
<td>05-03-27, 23:00</td>
<td>10.548</td>
<td>1.531</td>
<td>252.3</td>
<td>7.44</td>
<td>47</td>
<td>0.061 0.036 0.023 0.02</td>
</tr>
<tr>
<td>4</td>
<td>05-04-01, 18:00</td>
<td>12.577</td>
<td>2.379</td>
<td>305.25</td>
<td>9.00</td>
<td>60</td>
<td>0.062 0.043 0.037 0.012</td>
</tr>
<tr>
<td>5</td>
<td>05-07-13, 08:00</td>
<td>6.579</td>
<td>0.486</td>
<td>76.54</td>
<td>2.26</td>
<td>22</td>
<td>0.054 0.037 0.035 0.015</td>
</tr>
</tbody>
</table>
NEXRAD rainfall estimates have errors from reflectivity measurement and the Z–R conversion. In order to test the sensitivity of NEXRAD bias correction on rainfall–runoff simulation, three methods based on Kalman filtering are used in this study which can be considered a time updated mechanism. The first method is based on the application of spatially uniform bias correction as used in the MPE data. The second and third methods are based on the application of spatially non-uniform bias correction. A brief description of the Kalman filtering and its application for spatially and non-spatially uniform bias correction is presented below.

**Kalman filter**

The Kalman filtering equations have two steps in the form of time update and measurement update, in order to estimate the best possible bias. Projection of the current state to a forward time step is performed via time update, and the correction of a priori estimate at the current time step is performed via measurement update (Welch & Bishop 2001).

**Discrete Kalman filter time update**

According to Smith & Krajewski (1991), NEXRAD bias (β) is assumed as an autoregressive order one (AR1) process whose parameters are updated using a Kalman filter as given by Equation (1):

\[ \beta(t) = \rho_\beta \times \beta(t-1) + W(t); \ W(t) \sim N(0, \nu) \]  

where \( \beta(t) \) is the NEXRAD bias for hour \( t \), \( \rho_\beta \) is lag-one correlation coefficient of the logarithmic bias, and \( W(t) \) is a sequence of independent normally distributed random variables with zero mean and variance \( \nu \). The stationary process variance \( \nu \) and the stationary variance of the log bias process \( \sigma_\beta^2 \) are given by Equations (2) and (3):

\[ \nu = (1 - \rho^2_\beta) \times \sigma^2_\beta \]  

\[ \sigma^2_\beta = \text{Var}[\beta(t)]; t = 0, \ldots, T \]  

where \( T \) is storm duration.

The a priori estimate of \( \beta \) can be estimated using Equation (4):

\[ \beta^a(t) = \rho_\beta \times \beta^a(t-1) \]  

where \( \beta^a \) takes into account the new measurement that is observed and corrects for any errors that may be present in the newly measured value.

The process variance \( P^a(t) \) is estimated using Equation (5):

\[ P^a(t) = \rho^2_\beta \times P(t-1) + (1 - \rho^2_\beta) \times \sigma^2_\beta \]  

where \( P(t-1) \) is the a posteriori estimate of error variance at time \( t - 1 \). The initial value of \( \beta_0 \) and \( P_0 \) are zero and \( \sigma^2_\beta \), respectively.

**Discrete Kalman filter measurement update**

In each time and measurement update, the process is repeated with the previous a posteriori estimates in order to project or predict the new a priori estimates. This recursive nature is one of the important features of the Kalman filter. Updating the a priori estimates of the logarithmic NEXRAD bias \( \beta^a(t) \) and its variance \( P^a(t) \) based on the actual bias for the current time step \( t \) are performed in measurement update. The errors associated with the observed rain field lead to a deviation between the observed and true values for \( \beta_0 \). Observed logarithmic NEXRAD bias \( Y(t) \) is represented by using Equation (6):

\[ Y(t) = \beta(t) + M(t); \ M(t) \sim N(0, \sigma[\eta(t)]^2) \]  

where \( \sigma(\eta) \) is a non-negative function representing the observation error given that the number of gauges with measurable rainfall is \( \eta \), and \( M(t) \) is a sequence of independent normally distributed random variable with zero mean and variance of \( \sigma(\eta)^2 \), which is given by Equation (7) from Smith & Krajewski (1991):

\[ \sigma(\eta)^2 = n^{-2} \]  

where \( n \) is the number of the rain gauge.
The measurement update of the Kalman filter allows estimation of $\beta^x(t)$ and $P(t)$ by Kalman gain $K(t)$ and it is presented in Equations (8), (9), and (10).

$$K(t) = P^-(t) \left( P^-(t) + \sigma^2 \right)^{-1}$$  \hspace{1cm} (8)

After this stage for time step $t$, the estimated logarithmic bias $\beta^x(t)$ and its variance $P(t)$ are calculated by Equations (9) and (10).

$$\beta^x(t) = \beta^x(t) + K(t) \cdot (Y(t) - \beta^x(t))$$  \hspace{1cm} (9)

$$P(t) = (1 - K(t)) \times P^-(t)$$  \hspace{1cm} (10)

Due to the bias model defined in terms of the log bias process, Smith & Krajewski (1999) suggest Equation (11) for the state expectation of the bias correction factor at the time $t$ as shown below:

$$B(t) = 10^{\beta^x(t) + 0.5P(t)}$$  \hspace{1cm} (11)

### Spatially uniform NEXRAD precipitation bias correction using Kalman filter

According to Seo et al. (1999) and Dinku et al. (2002), the MFB corrections and vertical profile of reflectivity adjustments are needed for correcting spatially uniform biases in NEXRAD data. The variance of the observed MFB should affect the magnitude of the Kalman filter observation error model. The time-dependent variance of the observed MFB is estimated by using the variance of logarithmic bias proposed by Smith & Krajewski (1999). The correction procedures assume that the biases are spatially uniform over the entire study area. The logarithmic MFB between NEXRAD estimates at the rain gauge locations and the corresponding gauge rainfall amounts is computed by Equation (12):

$$\beta(t) = \frac{1}{n} \sum_{i=1}^{n} \frac{\log_{10}(G(t)_i)}{\log_{10}(R(t)_i)}$$  \hspace{1cm} (12)

where $G(t)_i$ is hourly rain gauge rainfall at NEXRAD-gauge paired cell $i$ for hour $t$, $R(t)_i$ is hourly NEXRAD rainfall at NEXRAD-gauge paired cell $i$ for hour $t$, and $n$ is the number of pairs of radar-gauge data. Spatially uniform bias corrected NEXRAD rainfall is then computed by using Equation (13):

$$R^*(t)_j = B(t) \cdot R(t)_j$$  \hspace{1cm} (13)

where $R^*(t)_j$ is bias corrected NEXRAD rainfall at cell $j$ at time $t$, and $R(t)_j$ is hourly NEXRAD rainfall at gauge cell $j$ for hour $t$ within and around the study area.

### Spatially non-uniform NEXRAD precipitation bias correction using Kalman filter

In the spatially uniform bias correction method, the radar rainfall bias (Equation (12)) over the cells with observed rain gauge data is assumed to be uniform for all NEXRAD cells. The assumption of uniform bias may or may not be true depending on the rainfall dynamics and the size of the watershed. For example, the bias may be higher for NEXRAD cells that do not overlap with rain gauge locations. In order to minimize such ungauged NEXRAD cell bias, this study suggests application of spatially non-uniform bias correction using the Kalman filter. Unlike the MFB (Equation (12)), the spatially non-uniform biases vary from pixel to pixel across the NEXRAD domain. Corrected NEXRAD rainfall at an ungauged NEXRAD pixel $j$ for hour $t$, $R^*(t)_j$, is computed by multiplying spatially non-uniform bias correction factor ($B(t)_j$) at each ungauged NEXRAD grid location $j$ using Equation (14):

$$R^*(t)_j = B(t)_j \cdot R(t)_j$$  \hspace{1cm} (14)

There are two approaches for computing the spatially non-uniform bias. In the first approach, the rain gauge data are interpolated using squared inverse distance weighting (Equation (15)) to yield rainfall estimates for ungauged NEXRAD pixels:

$$G^*(t)_j = \frac{\sum_{i=1}^{n} w_i G(t)_i}{\sum_{i=1}^{n} w_i}$$  \hspace{1cm} (15)
where $G^*(t)_i$ is interpolated gauge information at an ungauged NEXRAD pixel $j$ for hour $t$, and $w_i$ (Equation (16)) is the weight corresponding to each gauged point:

$$w_i = \frac{1}{\sum_{j=0}^{n} 1/d^b_j}$$

where $d_i$ is the distance between a radar pixel and the $i$th rain gauge with $b = 2$ for squared inverse distance weighting, and $n$ is the number of rain gauges. The spatially non-uniform local NEXRAD biases can then be estimated and corrected by using the interpolated rainfall (Equation (17)):

$$\beta(t)_i = \frac{\log_{10}(G^*(t)_i)}{\log_{10}(R(t)_i)}$$

where $\beta(t)_i$ is logarithmic local bias at an ungauged NEXRAD pixel $j$ for hour $t$ within the study area.

In the second approach for applying non-uniform bias, the error of radar rainfall at each gauged location is computed using Equation (18):

$$e(t)_i = \frac{\log_{10}(G(t)_i)}{\log_{10}(R(t)_i)}$$

The errors of radar rainfall at each $i$th gauge are then interpolated in order to get errors at all ungauged NEXRAD pixels using squared inverse distance weighing. Ware (2009) found that the interpolation errors associated with this IDW are comparable to those obtained using the multi-quadric interpolation (Nuss & Titley 1994) and ordinary kriging. An ungauged NEXRAD bias for spatially non-uniform bias correction is computed based on the surrounding ratios of precipitation errors and the distance of each gauge from the selected grid cell (Equation (19)):

$$\beta(t)_i = \frac{\sum_{i=1}^{n} w_i e(t)_i}{\sum_{i=1}^{n} w_i}$$

where $\beta(t)_i$ is logarithmic local precipitation bias at ungauged NEXRAD pixel $j$ for hour $t$ within the study area.

**HYDROLOGIC MODEL**

The sensitivity of bias correction methods for runoff prediction was tested by using the bias corrected rainfall data to run a storage release based distributed hydrologic model (STORE DHM) developed by Kang & Merwade (2009, 2011). The STORE DHM is a grid based conceptual model that involves computing excess rainfall, volumetric flow rate, and travel time to the basin outlet by combining steady-state uniform flow approximation with Manning’s equation. After computing excess rainfall by using the SCS curve number method, the direct runoff is routed by using a simple storage release approach. In this approach (Figure 2), water within a watershed or stream can be assumed to flow through a series of buckets. At any given time step, each bucket stores the accumulated water of all upstream buckets that drain into it, and then releases the stored water to its next downstream bucket at the next time step, as shown in Figure 2. Following the conceptual model from Figure 2, storage at any given time in any given bucket (a raster cell in the model) is given by Equation (20):

$$S_{i,t} = Q_{i,t}\Delta t + S_{i,t-1} - R_{i,t}\Delta t + \sum R_{u,i}\Delta t$$

where $R_{i,t}$ (given by Equation (21)) represents the release term from a cell $i$ in the $t$th time step, and the difference between $S$ and $R$ represents the storage in the cell. The subscript $u$ in Equation (20) represents the surrounding upstream cells that are draining to cell $i$. In Figure 2, each bucket or cell releases its stored water to a downstream cell depending on the residence or travel time of the water within each cell. The connectivity of all raster cells is established from the flow direction grid derived by using the eight points pour model. Each release term in Equation (20) is computed by using Equation (21):

$$R_{i,t} = \begin{cases} S_{i,t-1} \frac{\Delta t}{T_{i,t-1}} & \text{if } T_{i,t-1} < \Delta t \\ S_{i,t-1} \frac{\Delta t}{T_{i,t-1}} \left( \frac{\Delta t}{T_{i,t-1}} - 1 \right) & \text{if } T_{i,t-1} > \Delta t \end{cases}$$

where $T_{i,t}$ is the travel time within each cell, and is estimated depending on the flow conditions (overland flow or channel...
flow). In Equation (21), all the water stored within a cell is released downstream if the travel time ($T_i$) is smaller than the model time step ($\Delta t$), or a fraction ($\Delta t/T_i$) of the water is released if the travel time is greater than the model time step. More details on computation of travel time for overland flow and channel flow, and selection of appropriate time step can be found in Kang & Merwade (2014). The data requirements for STORE DHM include DEM of the study area, rainfall data (gauged points or NEXRAD grid), and land use. STORE DHM is selected in this study because of its simplicity involving only one calibration parameter (Manning’s $n$).

RESULTS

Results are presented in two sections. In the first section, the quality of NEXRAD data is assessed through cross-validation with observed rainfall. The NEXRAD data used in cross-validation are prepared by using the spatially uniform bias correction method (MPE), spatially non-uniform bias correction method by interpolating rainfall data (SNU-R), and spatially non-uniform bias correction method by interpolating errors (SNU-E). In the second section, the sensitivity of STORE DHM hydrograph outputs to rainfall created by using spatially uniform and non-uniform bias correction is presented.

Assessment of NEXRAD rainfall inputs

The cross-validation of NEXRAD rainfall inputs created by using MPE, SNU-R, and SNU-E is conducted by using a total of 17 rain gauges in UWR and 19 rain gauges in UCR basins for five different events (Table 1). From the complete set of gauging stations, three stations are excluded for cross-validation. The scatter plot of NEXRAD bias corrected rainfall and cross-validated observed gauge rainfall for the UWR and the UCR are shown in Figure 3. The results presented in Figures 3(a) and 3(b) show that the NEXRAD rainfall created using the MPE scheme has considerable scatter in comparison with data created by applying spatially non-uniform bias correction schemes. The performance of bias corrected NEXRAD is assessed by computing the root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination ($R^2$) as shown in Tables 2 and 3.

The spatially non-uniform NEXRAD bias correction improves rainfall accuracy for the UWR events by reducing error from 1.17 mm RMSE for MPE to 0.80 mm RMSE for SNU-R and 0.94 mm RMSE for SNU-E. For the UCR
events, the RMSE is reduced from 13.76 mm for MPE to 6.16 mm for SNU-R and 6.75 mm for SNU-R. The reduction in RMSE from the MPE scheme to the non-uniform bias correction method is more than 53% for the UCR, and more than 25% for the UWR. Average values for MAPE also show similar results where the MAPE is reduced by more than 65% for UWR with the SNU-R scheme, and is reduced by 80% for UCR with the SNU-R scheme. The average $R^2$ in the UWR (Table 2) is 0.67 for the MPE scheme, 0.82 for SNU-R, and 0.57 for SNU-E. For the UCR dataset, the
average $R^2$ is 0.30 for the MPE scheme, 0.58 for the SNU-R scheme, and 0.64 in the SNU-E scheme (Table 3). Overall, the most reduction in errors is achieved by SNU-R compared to SNU-E for both watersheds. In addition, the reduction in error is greater for UCR compared to UWR. The UCR basin has greater rainfall variability compared to the UWR basin (Figure 4). Thus, it can be hypothesized that the reduction in error is greater in larger areas with more variable rainfall compared to smaller areas with a less variable rainfall pattern.

Sensitivity of model hydrographs with different NEXRAD bias correction schemes

To study the sensitivity of the model hydrograph to rainfall inputs obtained by using three different NEXRAD bias correction approaches, the STORE DHM model was calibrated with original NEXRAD for each event for both watersheds. The model was manually calibrated by using the Nash–Sutcliffe efficient coefficient ($E_{NS}$; Equation (22)) for discharge and RMSE (Equation (23)) for the total runoff volume.

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n} (Q_{sim}^i - Q_{obs}^i)^2}{\sum_{i=1}^{n} (Q_{sim}^i - \bar{Q})^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Q_{sim}^i - Q_{obs}^i)^2}{n}}$$

where $Q_{sim}$ is the simulated hourly streamflow, $Q_{obs}$ is the observed hourly streamflow, and $\bar{Q}$ is the mean hourly observed streamflow. Calibration parameters used to adjust the model and the corresponding parameter values are presented in Table 1. The results from calibration are presented in Table 4 and Figure 5.

![Figure 4](https://iwaponline.com/hr/article-pdf/45/1/23/370634/23.pdf)
Figure 5 | Calibrated model results for every event using NEXRAD rainfall input (e.g. UWR1 represents event 1 for UWR basin). X-axis represents time in hours and Y-axis represents flow in cubic meters per second. (a) UWR basin. (b) UCR basin.
Figure 6 | Storm event 1 model hydrographs for both (a) the UWR basin and (b) the UCR basin. X-axis represents time in hours and Y-axis represents flow in cubic meters per second.
Figure 7 | Storm event 2 model hydrographs for both (a) the UWR basin and (b) the UCR basin. X-axis represents time in hours and Y-axis represents flow in cubic meters per second.
Figure 8  Storm event 3 model hydrographs for both (a) the UWR basin and (b) the UCR basin. X-axis represents time in hours and Y-axis represents flow in cubic meters per second.
Figure 9  Storm event 4 model hydrographs for both (a) the UWR basin and (b) the UCR basin. X-axis represents time in hours and Y-axis represents flow in cubic meters per second.
Figure 10 | Storm event 5 model hydrographs for both (a) the UWR basin and (b) the UCR basin. X-axis represents time in hours and Y-axis represents flow in cubic meters per second.
After calibration, each event is simulated with the STORE DHM using three variations of NEXRAD rainfall created by applying uniform and non-uniform spatial bias correction. The hydrographs from these simulations are presented in Figures 6–10, and the results are summarized in Tables 5 and 6. For the UWR basin (Figures 6(a)–10(a) and Table 5), the calibrated $R^2$ of 0.96 decreased to 0.92 for MPE, and 0.95 for both SNU-R and SNU-E. The calibrated $E_{NS}$ of 0.95 decreased to 0.82 for MPE, but remained unchanged for SNU-R and SNU-E. The calibrated RMSE of 8.47 m$^3$/s changed to 16.49 m$^3$/s for MPE, 9.86 m$^3$/s for SNU-R, and 11.20 m$^3$/s for SNU-E. Similarly, the calibrated MAPE of 26.62% changed to 33.75% for MPE, 27.98% for SNU-R, and 30.80% for SNU-E. Overall, SNU-R improved the RMSE by 67%, and MAPE by 21% in the output hydrographs compared to hydrographs from MPE rainfall input. SNU-E improved the RMSE by 47% and MAPE by 10% in the output hydrographs compared to hydrographs from MPE rainfall input.

For the UCR basin (Figures 6(b)–10(b) and Table 6), the calibrated $R^2$ of 0.96 decreased to 0.80 for MPE, and 0.94 for both SNU-R and SNU-E. The calibrated $E_{NS}$ of 0.95 decreased to 0.72 for MPE, but decreased to 0.65 for MPE, 0.88 for SNU-R, and 0.94 for SNU-E. The calibrated RMSE of 20.52 m$^3$/s changed to 47.36 m$^3$/s for MPE, 27.08 m$^3$/s for SNU-R and 24.73 m$^3$/s for SNU-E. Similarly, the calibrated MAPE of 21.72% changed to 54.75% for MPE, 26.99% for SNU-R, and 26.56% for SNU-E. Overall, SNU-R improved the RMSE by 75% and MAPE by 103% in the output hydrographs compared to hydrographs from MPE rainfall input. SNU-E improved the RMSE by 92% and MAPE by 106% in the output hydrographs compared to hydrographs from MPE rainfall input.

The rainfall input derived by applying a spatially uniform bias correction to NEXRAD data decreased calibrated model prediction accuracy as evident from $R^2$, $E_{NS}$, RMSE, and MAPE values in comparison to input derived by applying a spatially non-uniform bias correction scheme. The improvement in model results from the

### Table 5 | Details of simulation results with different NEXRAD bias corrected rainfall for the UWR basin

<table>
<thead>
<tr>
<th>Event</th>
<th>Simulation with MPE scheme</th>
<th>Simulation with SNU-R scheme</th>
<th>Simulation with SNU-E scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>$E_{NS}$</td>
<td>RMSE (m$^3$/s)</td>
</tr>
<tr>
<td>1</td>
<td>0.96</td>
<td>0.92</td>
<td>3.51</td>
</tr>
<tr>
<td>2</td>
<td>0.90</td>
<td>0.72</td>
<td>25.83</td>
</tr>
<tr>
<td>3</td>
<td>0.86</td>
<td>0.84</td>
<td>20.43</td>
</tr>
<tr>
<td>4</td>
<td>0.96</td>
<td>0.85</td>
<td>10.63</td>
</tr>
<tr>
<td>5</td>
<td>0.94</td>
<td>0.79</td>
<td>22.08</td>
</tr>
<tr>
<td>Ave.</td>
<td>0.92</td>
<td>0.82</td>
<td>16.49</td>
</tr>
</tbody>
</table>

### Table 6 | Details of simulation results with different NEXRAD bias corrected rainfall for the UCR basin

<table>
<thead>
<tr>
<th>Event</th>
<th>Simulation with MPE scheme</th>
<th>Simulation with SNU-R scheme</th>
<th>Simulation with SNU-E scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>$E_{NS}$</td>
<td>RMSE (m$^3$/s)</td>
</tr>
<tr>
<td>1</td>
<td>0.88</td>
<td>0.81</td>
<td>23.24</td>
</tr>
<tr>
<td>2</td>
<td>0.92</td>
<td>0.60</td>
<td>74.64</td>
</tr>
<tr>
<td>3</td>
<td>0.36</td>
<td>0.19</td>
<td>92.02</td>
</tr>
<tr>
<td>4</td>
<td>0.89</td>
<td>0.89</td>
<td>34.51</td>
</tr>
<tr>
<td>5</td>
<td>0.95</td>
<td>0.73</td>
<td>12.40</td>
</tr>
<tr>
<td>Ave.</td>
<td>0.80</td>
<td>0.65</td>
<td>47.36</td>
</tr>
</tbody>
</table>
spatially non-uniform bias corrected input are better in the UCR basin compared to the UWR basin because the NEXRAD values are more variable in time over the UCR basin compared to the UWR basin, as shown in Figure 4. Although the spatially non-uniform bias correction scheme takes care of both spatial and temporal NEXRAD bias, the results from this study show that the bias correction is more effective for the UCR basin, which has more spatial-temporal variability in rainfall compared to the UWR basin.

Even though the NEXRAD input is adjusted by using gauged rainfall, some under-prediction or over-prediction of runoff volume and peak flow is found for both study areas, as shown in Figures 6–10. Simulations with SNU-E inputs performed the best with regard to the estimation of peak flow as shown in scatter plots in Figure 11. Similarly, the input from both methods using spatially non-uniform bias correction produced an overall better output compared to input from spatially uniform bias correction method in terms of total runoff volume. Within the UCR basin, the prediction accuracy with SNU inputs is considerably better than the flat elevation region such as the UWR basin.

CONCLUSIONS

Three different NEXRAD bias correction schemes are applied to two study basins (UWR and UCR) in order to evaluate the effects of each NEXRAD bias correction scheme on the representation of the rainfall, and its effect on hydrologic simulations. The following conclusions can be drawn from this study:

1. For the two basins used in this study, the cross-validation of rainfall estimates obtained by applying spatially non-uniform bias correction methods have better accuracy in terms of RMSE compared to spatially uniform bias correction method.

2. Between the two spatially non-uniform bias correction methods used in this study, the method that involves interpolation of rainfall before applying the bias correction (SNU-R) performed better in the hydrologic model simulation than the method that involves interpolation of error (SNU-E).

3. Hydrologic simulations performed using a grid based distributed hydrologic model show that the input rainfall obtained by using spatially non-uniform bias correction method produced output hydrographs that are more comparable with the calibrated model output compared to the output from the model using spatially uniform bias corrected rainfall input. Of the two spatially non-uniform bias correction methods, the SNU-R method produced better runoff hydrographs compared to the SNU-E method.

4. The improvement in rainfall estimates and hydrologic simulations from using spatially non-uniform bias correction methods is consistent for both watersheds used in this study. The overall improvement is greater in the UCR basin compared to the UWR basin. This shows that the application of spatially non-uniform bias correction for
radar rainfall is more effective in larger areas with more variable rainfall (i.e., UCR) compared to smaller areas with less variable rainfall (i.e., UWR) basin. However, this conclusion is based on only the two watersheds used in this study, and in order to make it generally applicable it must be investigated further by including more watersheds.

5. Although SNU methods show better performance than MPE rainfall, there are still several issues that need investigating for correcting radar-rainfall error: limitation of rain gauge density (instead of making an interpolated rain gauge in a non-gauge grid), large scale of radar rainfall grid (4 km × 4 km is large to get spatially distributed rainfall dynamic), and many assumptions about the physical radar function (Z–R law).

6. Calibration in each event is needed to investigate simulation validity depending on the individual NEXRAD bias correction scheme. However, the aim of this research was to investigate three different NEXRAD bias correction schemes on hydrologic modeling performance. Thus, this research has focused more on sensitivity checks for rainfall inputs.

7. For further research, new interpolation methods to gain a robust rainfall input in hydrologic modeling are encouraging, such as Parameter-elevation Regression on Independent Slope Model (PRISM) which can be considered by temperature, elevation, distance from true rainfall grid (4 km × 4 km is large to get spatially distributed rainfall dynamic), and many assumptions about the physical radar function (Z–R law).

REFERENCES


First received 21 November 2012; accepted in revised form 14 May 2013. Available online 18 June 2013.