Sensitivity of Streamflow Simulations to Temporal Variability and Estimation of *Z–R* Relationships

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Abstract: This study focuses on the sensitivity of streamflow simulations to temporal variations in radar reflectivity–rainfall (i.e., $Z-R$) relationships. The physically based continuous-mode distributed hydrologic model—gridded surface subsurface hydrologic analysis—is used to predict runoff during three major rainfall-runoff periods observed in a 35 km^2 experimental watershed in southern Louisiana. $Z-R$ relationships are derived at a series of temporal scales ranging from a climatological scale, where interstorm $Z-R$ variations are ignored, down to a subevent scale, where variations in rainfall type (convective versus stratiform) are taken into account. The analysis is first performed using Z and R data pairs derived directly from disdrometer drop size distribution measurements, and then repeated using WSR-88D radar reflectivity data. The degree of sensitivity in runoff simulations to temporal variations in $Z-R$ relationships depends largely on the method used to derive the parameters of these relationships. Using event-specific $Z-R$ relationships results in accurate hydrographs when the parameters are derived based on bias removal and minimization of random errors of rainfall estimates. Methods based on least-squares fitting require refining the derivation of $Z-R$ parameters down to a subevent scale, which is not practically feasible. A simple and practical method based on selection of a climatologically representative exponent of the $Z-R$ relationships and adjusting the multiplier coefficient through bias removal still results in reasonably accurate runoff simulations, but only when event-specific $Z-R$ relationships are used.

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Introduction

Recent advances in the field of weather radars present unprecedented opportunities for improving hydrologic predictions and forecasting. However, a fundamental step in radar-rainfall estimation is the transformation of radar-measured reflectivities (Z) into estimates of surface rainfall rates (R). It has been a common practice to use a simple power-law relationship between Z and R ($Z=AR^b$), where A and b are usually referred to as the multiplier and the exponent parameters. Battan (1973) listed a total of 69 such power-law relationships that reflect climatological variability of different rainfall types and geographic locations. However, it has been recognized that the estimation of proper $Z-R$ relationships is subject to several sources of uncertainties (e.g., Joss and Waldvogel 1990; Steiner and Smith 2000; Campos and Zawadzki 2000; Tokay et al. 2001; Steiner and Smith 2004; among others). A main factor is the natural variability in rainfall drop size distributions (DSD) from one climatological region to another, from one storm to another, and within the same storm (e.g., Smith and Krajewski 1993; Atlas et al. 1999; Steiner and Smith 2000; Uijlenhoet et al. 2003; Lee and Zawadzki 2005). Several of these studies have demonstrated that accounting for temporal variability in DSD and the corresponding $Z-R$ relationships (or lack of thereof) plays a major role in determining the overall accuracy of rainfall estimates. Based on an extensive analysis of disdrometer DSD measurements, Steiner and Smith (2000) showed that storm-to-storm variability in $Z-R$ parameters, especially the multiplier A, can be significant, which makes use of a single fixed $Z-R$ relationship problematic. In addition to interstorm variations, intrastorm variability (i.e., within the same storm) has also been proven significant. Uijelenhoet et al. (2003) analyzed different phases of a squall line rainstorm (initial convection, transitional, and stratiform) and showed that intrastorm variability of $Z-R$ relationships is a major source of uncertainty in radar-rainfall estimation. Lee and Zawadzki (2005) performed an extensive analysis of 5 years of disdrometer measurements to study the scale dependence of DSD variability and its effect on rainfall estimation from radar reflectivity. They examined different scales (climatological, day to day, within a day, and within and between rainfall physical processes) and showed that most of DSD variability has its origin within a storm or between storms within a day.

Numerous studies have focused on effects of radar-rainfall estimation errors on runoff simulations (e.g., Sharif et al. 2002; Sun et al. 2000; Neary et al. 2004; Borga 2002; Bedient et al. 2000; among several others). Recognizing the role that DSD and $Z-R$ variability play in determining accuracy of radar-rainfall esti-

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mates, attention has been dedicated to analyze runoff uncertainties caused by $Z-R$ temporal variability. Pessoa et al. (1993) showed that different $Z-R$ relationships can result in significantly different simulated runoff hydrographs. Based on analysis of radar-driven streamflow forecasts, they concluded that the use of a proper $Z-R$ relationship is the most crucial factor in obtaining accurate flood hydrographs. Vieux and Bedient (1998) found better agreement between measured and simulated runoff response during an extreme event in south Texas when a relationship appropriate for tropical events, $Z=250R^{1.2}$, was used instead of the National Weather Service (NWS) default relationship, $Z=300R^{1.4}$ (Fulton et al. 1998). Winchell et al. (1998) investigated effects of $Z-R$ variability between storms on runoff simulations, but their analysis focused only on integrated properties of the runoff response such as storm total runoff volumes. In the context of real-time flood forecasting in urban areas, Vieux and Bedient (2004) illustrated that gauge adjustment of the selected $Z-R$ relationships can significantly improve the accuracy of simulated hydrographs in terms of runoff volumes and discharge peaks. Morin et al. (2005) analyzed radar and gauge data from 13 storms in Arizona and derived a single $Z-R$ relationship with a fixed exponent and a bias-adjusted multiplier parameter. The resulting relationship was more adequate for predicting runoff response than the default NWS relationship. However, as their focus was on summer monsoon storms in Arizona, Morin et al. (2005) based their analysis on climatologically similar and dominantly convective rainfall events and did not analyze effects related to intrastorm $Z-R$ variability.

The current study is motivated by ample evidence on variability in $Z-R$ relationships and its effect on radar-rainfall estimates. To gain insight into the implications of such variability for hydrologic prediction purposes, this study examines the sensitivity of runoff simulations to the use of $Z-R$ relationships that are allowed to vary during the course of hydrologic events. Following Lee and Zawadzki (2005), the $Z-R$ relationships are established at a series of scales: a climatological scale, a storm scale that includes multiple rainfall events, a single rainfall event scale, and finally a subevent scale that accounts for variations in rainfall type (convective versus stratiform) within a single event. For each considered time scale, we also test the use of three different methods (Steiner and Smith 2000) that can be used to derive the A and b parameters of the $Z-R$ relationship. The first method is based on least-squares regression, the second method is a simple bias adjustment scheme, and the third method combines bias removal with minimization of random errors in rainfall estimates. Variability in $Z-R$ relationships is first analyzed based on rainfall rates and reflectivities derived directly from disdrometer DSD measurements collected in the proximity of the study watershed. Then we use Weather Surveillance Radar-88 Doppler (WSR-88D) radar reflectivity data to establish radar-based $Z-R$ relationships at different scales and with different parameter estimation methods and assess their effect on runoff simulations. The analysis is performed on three major rainfall-runoff periods observed in a midsize subtropical watershed in southern Louisiana. A physically based continuous-mode distributed hydrologic model [gridded surface subsurface hydrologic analysis (GSSHA)] is used to simulate runoff response in the watershed. Disdrometer DSD data and the calibrated GSSHA model are used to establish a "reference" state of rainfall input and runoff response against which runoff hydrographs simulated using different $Z-R$ relations can be assessed. The sensitivity of runoff predictions in terms of total runoff volumes, hydrograph patterns and magnitudes, and runoff peaks is tested. The paper closes with summary and conclusions on some practical aspects of the results.

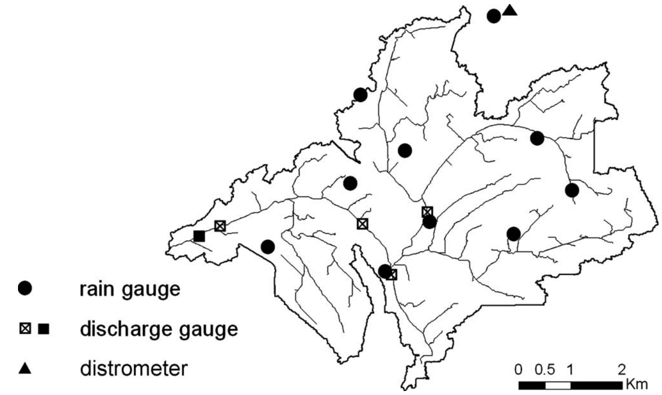

Fig. 1. Layout of the Issac Verot (IV) study watershed showing the locations of rainfall (rain gauges and disdrometer) and streamflow monitoring sites. The gauge at the watershed outlet is marked in a closed box.

Study Site, Data, and Hydrologic Model

Study Site

The site of this study is the 35 km^2 Isaac Verot (IV) watershed located in the city of Lafayette in southern Louisiana (Fig. 1). The watershed is a subdrainage area of the Vermilion River basin which drains into the Gulf of Mexico. This is a low-gradient watershed where open channel flow plays a vital role in runoff production (Habib and Meselhe 2006). The watershed is frequently subject to frontal systems, air-mass thunderstorms, as well as tropical cyclones with annual rainfall of about 140 to 155 cm and monthly accumulations as high as 17 cm. The main soil type in the watershed is texturally classified as silt loam with low to medium drainage capacity. Land use in the watershed is composed of urban areas, cropland, pasture, and some forested areas.

Rainfall and Runoff Data

The Department of Civil Engineering at the University of Louisiana at Lafayette has deployed a dense experimental network of rainfall and runoff monitoring sites over the watershed (Fig. 1). A total of 13 tipping-bucket rain gauge sites are distributed over the watershed and every site has a dual-gauge setup for improved data continuity and quality (Krajewski et al. 2003). The gauges have an orifice size of 30.5 cm (12 in.) and are equipped with a digital data logger that records the time of occurrence of successive 0.254 mm (0.01 in.) tips, which can be used to construct time series of rainfall intensities at any desired time scale (e.g., a few minutes or hourly). Streamflow measurements are collected at the outlet of the watershed, as well as at four interior locations using bidirectional acoustic velocity meters, from which discharge estimates can be obtained.

Rainfall DSD data are collected at one of the experimental sites located close to the boundary of the IV watershed (Fig. 1) using a Joss-Waldvogel disdrometer. The data are recorded as the number of raindrops (n_i) falling on the disdrometer sensing area ($A=0.005$ m^2) classified into 20 intervals ($i=1:20$) of drop diam-

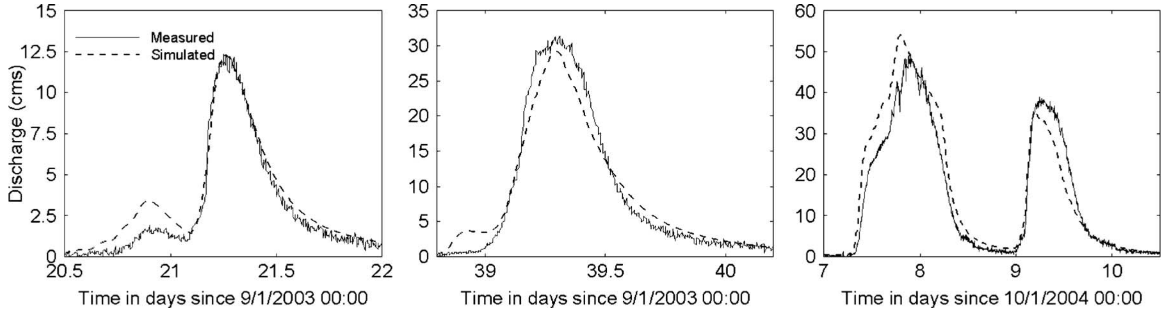

Fig. 2. Examples of calibration (first and second panels) and validation (third panel) results of hydrologic model GSSHA

eters (D_i) ranging from 0.35 to 5.25 mm. DSD measurements are recorded with a sampling resolution of 1 min. The disdrometer-based reflectivity factor Z_D ($\mathrm{mm}^6\,\mathrm{m}^{-3}$) and rainfall rate R_D ($\mathrm{mm\,h}^{-1}$) can be computed as follows (e.g., Steiner and Smith 2000):

$$Z_D = 10^6 \sum_{i=1}^{20} D_i^6 N(D_i) \Delta D_i \tag{1}$$

$$R_D = 0.6\pi \sum_{i=1}^{20} v(D_i) D_i^3 N(D_i) \Delta D_i \tag{2}$$

where $N(D_i)$ ($\mathrm{m}^{-3}\,\mathrm{mm}^{-1}$)=drop size distribution calculated from number of drops (n_i) in each class interval:

$$N(D_i) = \frac{n_i}{v(D_i) A \Delta t \Delta D_i} \tag{3}$$

where $v(D_i)$ ($\mathrm{m\,s}^{-1}$)=fall velocity of a drop of diameter D_i (cm) estimated following Beard (1976); Δt=sampling interval (60 s); and ΔD_i (cm)=width of the ith diameter interval. As the disdrometer data are affected by uncertainties due to drop sorting and small sampling volume, 1 min DSD with rainfall intensity less than 0.1 mm/h and total number of drops less than 10 are discarded to avoid undersampling effects (Tokay et al. 2001).

The radar data used in this study are the Level II reflectivity data collected at the Lake Charles National Weather Service (NWS) WSR-88D (Crum and Alberty 1993) operational radar site (KLCH site). Radar data are available in polar coordinates at a resolution of $1° \times 1$ km for different elevation angles starting at 0.5° and with a time sampling interval of 5 to 6 min. As the interest is in surface rainfall information, data from the lowest elevation angle of the radar beam are used, which is about 1.7 km above the disdrometer site and is free of any ground clutter. The watershed is located about 116 km east of the radar site where at such a distance, the average size of radar polar pixels over the watershed is 1 km$\times$1.9 km. It is known that problems related to hardware calibration can introduce systematic errors into radar-rainfall estimates. In a comparative analysis versus space-borne radar observations, Anagnostou et al. (2001) found that the KLCH radar site does not suffer from any significant calibration problems.

Hydrologic Model

In this study, the GSSHA system is used to develop a rainfall-runoff model for the IV watershed. GSSHA is a fully distributed-parameter, process-based hydrologic model (Downer and Ogden 2004). It uses finite difference and finite volume methods to simulate different hydrologic processes such as rainfall distribution and interception, overland water retention, infiltration, evapotranspiration, two-dimensional overland flow, one-dimensional channel routing, and different methods (e.g., Green and Ampt method, and Richards' equation) for modeling the soil moisture profile in the unsaturated zone. The model setup adopted in this study included the following options: two-dimensional diffusive wave approximation of the de Saint Venant equations for overland flow, one-dimensional explicit diffusive wave method for channel flow, Penman–Monteith equation for evapotranspiration calculations, and the Green and Ampt infiltration with redistribution (GAR) method for flow simulation in the unsaturated zone. The GAR method simulates the soil moisture redistribution during a runoff event, as well as the change in soil moisture due to evapotranspiration between rainfall events. This soil moisture accounting scheme allows for continuous-mode simulations that include both rainy and dry periods. The watershed topographic and hydrologic properties are represented using a $100 \times 100\ \mathrm{m}^2$ Cartesian grid. Overland hydraulic properties (e.g., roughness parameters), soil hydraulic parameters (e.g., saturated hydraulic conductivity, soil suction head, effective porosity), and evapotranspiration parameters (e.g., vegetation transmission coefficients and root depths) were initially assigned based on spatial variations in the combined classifications of soil type and land use maps. The parameters were further adjusted through model calibration.

Prior to being used in further analysis, the GSSHA IV model was subject to a rigorous calibration and validation procedure based on observations from the dense network of rainfall and streamflow gauges distributed in the watershed. The model was calibrated on a continuous rainfall-runoff period that included a series of rainfall events (September 9–October 11, 2003) and validated on two other periods (April 22–May 2, 2004 and October 7–10, 2004). Examples of calibration and validation results are shown in Fig. 2. Model calibration was designed to minimize differences in runoff volumes and peaks and to provide an overall match between observed and simulated runoff hydrographs. Model parameters were adjusted during calibration where the simulated runoff peaks and volumes were found to be most sensitive to changes in the soil saturated hydraulic conductivity. Adjustment to channel and overland roughness coefficients were also found to have an impact on the timing and slope of rising and recession parts of the simulated hydrographs. Analysis of differences between model-predicted and measured runoff volumes and discharge peaks showed errors less than 10% for most of the simulated events. Further model assessment indicated similar satisfactory results when the model was validated against interior runoff stations and soil moisture sensors that were not included in the model calibration. Based on these tests, we proceed with the consideration that the model is likely capable of providing a physically reasonable representation of the rainfall-runoff transformation processes in the watershed.

Selected Rainfall-Runoff Periods

Three main rainfall-runoff periods (referred to as storms) were selected for more in-depth analyses on $Z-R$ variability and its effect on runoff simulations. Each storm included several rainfall events and resulted in a continuous runoff response at the watershed outlet. The first storm (June 22–27, 2004) included a sequence of squall line thunderstorms crossing the watershed and generating significant rainfall accumulations especially on June 24th (125 mm) and June 25th (60 mm). This storm contained heavy rainfall episodes with 1 min rainfall intensities exceeding 100 mm/h. Runoff response was in the form of a double-peak hydrograph with a maximum discharge value of 54 m^3/s ($\sim$1.5 $m^3/s/km$) at the watershed outlet. The second storm is Tropical Storm Matthew on October 7–10, 2004 with rainfall accumulations at the disdrometer site exceeding 250 mm. The storm resulted in widespread flooding where the streamflow gauge at the watershed outlet recorded a flood peak of about 50 m^3/s followed by a smaller one of 30 m^3/s. The third storm period (November 17–27, 2004) is an extensively wet period with a combination of five scattered and heavy rainfall events, generating total rainfall accumulation of about 150 mm. The runoff observed at the watershed outlet did not lead to high discharge values (mostly less than 15 m^3/s), but had a consistent response to rainfall that was almost continuous over the entire period. It is also noted that no observations of hail were reported for the three selected storm periods.

Methods

Rainfall-Runoff Reference State

To investigate sensitivity of runoff simulations to estimation and variability of $Z-R$ relationships, the writers will rely on an estimate of "reference" rainfall and assume that it represents true rainfall during the analyzed periods. This reference rainfall is based on calculating 1 min rainfall intensities from the DSD disdrometer measurements according to Eq. (2). Despite the recognized uncertainties associated with disdrometer observations, they advantageously provide a direct linkage between rainfall rates and DSD measurements. The use of Eq. (2) with high temporal-resolution (1 min) DSD measurements provides rainfall rates that are free from errors caused by $Z-R$ transformation or by the selection of a certain $Z-R$ estimation method or time scale. Reference rainfall rates are then used to drive the GSSHA model and simulate runoff response at the watershed outlet during the three selected rainfall-runoff periods. Runoff predictions resulting from these simulations are considered as reference hydrographs. The reference rainfall and runoff information, along with the well calibrated and validated hydrologic model, represent a reference state of rainfall-runoff transformation in the watershed. This reference state is used as a basis to assess the sensitivity of runoff simulations to variations and uncertainties in estimation of $Z-R$ relationships. The writers focus on two main effects: the temporal scale at which $Z-R$ relationship is estimated, and the method used to estimate the multiplier (A) and the exponent (b) parameters. For a certain estimation time scale and estimation method, the procedure of our analysis can be summarized as follows: (1) use 1 min Z and R pairs to estimate A and b in the $Z=AR^b$ relationship, (2) use the derived $Z-R$ relationship to produce estimates of rainfall rates, (3) run GSSHA using these estimates and produce runoff predictions, and (4) assess runoff predictions against reference hydrographs. The main interest here is on radar-based simulations; however, to focus on factors related mainly to $Z-R$ variability and estimation, the analysis will first be based on using Z and R data solely from disdrometer (Z_D, R_D). In this disdrometer-only analysis, variations in $Z-R$ relationships and their sensitivity to the utilized estimation scale and procedure will be distinguished without being possibly affected by other sources of the radar error (e.g., changes in reflectivity from radar beam elevation to the surface). The analysis is then repeated using Z from the Level II radar data and surface R from disdrometer (Z_R, R_D) to fit $Z-R$ relationships. These relationships can then be used to estimate rainfall rates from radar reflectivity measurements. As the reference rainfall is based on disdrometer "point" rainfall measurements, we use Z_R data from one radar pixel only (over the disdrometer site). This is consistent with the overall objective of the analysis presented here, which does not focus on factors related to rainfall spatial variability.

Z–R Methods

Steiner and Smith (2000) indicated that the method used to determine A and b in the power-law relationship ($Z=AR^b$) can have a significant effect on the estimated optimal values of these parameters and on the resulting rainfall estimates. In this study, three distinctly different methods for estimating A and b are considered. The first method is a commonly used procedure based on a least-square-fit regression technique (termed herein as LSF). In this method, A and b are estimated as the linear regression coefficients determined on the logarithmically transformed Z and R pairs. As R is the dependent variable, and following Steiner and Smith (2000) and Ciach and Krajewski (1999), the writers will regress $\log(R)$ on $\log(Z)$ to estimate A and b. The second estimation method (FIX) is based on removing the overall bias of rainfall volumes. This is done by fixing the exponent b and determining A in such a way that the total rainfall accumulations estimated by the $Z-R$ relationship (i.e., summation of $(Z_i/A)^{1/b}$; i=time step) is set equal to the accumulation of reference rainfall ($R_{\text{ref},i}$) as observed by the disdrometer. The selection of a certain b value for the FIX method is usually based on some prior knowledge about the present rainfall regime. We use the default value of $b=1.4$ (default NWS operational $Z-R$ relationship) for June and November rainfall periods, and $b=1.2$ (recommended by NWS for tropical storms) for October period. It is noted that a method similar to FIX has been used by Vieux and Bedient (2004) in their gauge-based adjustment of $Z-R$ relations. The third estimation method (BIAS_RMSE) is based on bias removal and minimizing root-mean-square errors. The parameter A is determined in a similar way to the FIX method, whereas b is sought by minimizing the summation of squared residuals between measured reference rainfall rates, $R_{\text{ref},i}$ and the corresponding estimates of the $Z-R$ relationship, $(Z_i/A)^{1/b}$.

Z–R Scales

To investigate effects related to variability in $Z-R$ relationships, runoff simulations will be driven by rainfall estimates based on $Z-R$ relationships that are determined at different time scales. Here, "time scale" refers to the period over which instantaneous Z and R pairs are grouped together into a single sample and used to

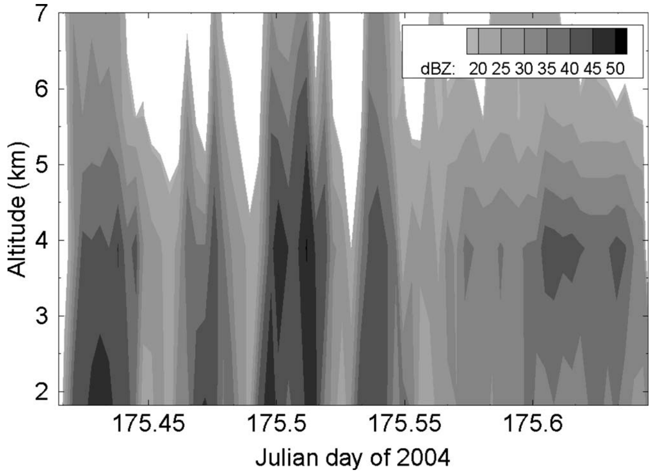

Fig. 3. Time series of vertical profile of WSR-88D radar instantaneous reflectivity data for the first event of the June 2004 storm as observed over the disdrometer site

estimate the optimal parameters of the relationship. The following range of time scales is considered in our analysis:

1. *Climatological scale*: The study site is characterized with various rainfall types such as convective thunderstorms, scattered stratifrom rain during frontal systems, and tropical storms. A climatological-representative Z–R relationship can be estimated using Z–R data pairs for the entire data set of the year 2004, which included about 60 storms with different rainfall types. This estimation scale ignores any Z–R variability between or within different rainfall storms.
2. *Storm scale:* From a runoff perspective, we consider each of the selected three rainfall-runoff periods as a *storm*. Each storm may have included several rainfall *events*, but has resulted in a runoff response that is almost continuous over the storm duration (i.e., individual hydrographs separated by no longer than 1 day). Reflectivity and rainfall rate pairs from each storm are used to derive a storm-specific Z–R relationship. By doing so, all variability that exists within each storm (i.e., between events) is not accounted for.
3. *Event scale:* Within a single storm, rainfall periods with clear separation of 6 h or longer of nonraining periods are considered as separate events. According to this convention, each of the above-identified storms contained several events, which spanned several hours with some events lasting more than 1 day. Pairs of Z and R in each event are used to estimate A and b that correspond to individual rain events. By estimating an event-specific Z–R relationship, the writers are accounting for variability present between events within the storm, but ignoring variability that may exist within a single event.
4. *Subevent scale:* To investigate effects of Z–R variations within a single rainfall event on runoff simulations, we separated each event into three classes: stratiform, convective, and transitional. The classification was achieved by visual examination of time series of vertical profiles of instantaneous reflectivity extracted from volume scan data of the Lake-Charles WSR-88D radar over the disdrometer site (see an example in Fig. 3 for the first event in June storm). Phases of stratiform rainfall are distinguished visually based on the presence of bright-band signatures (Fabry and Zawadzki 1995) where large reflectivity values exist at the melting level, but decrease sharply toward the ground surface (see period between days 175.6 and 175.7 in Fig. 3). Convective rainfall is distinguished as localized cells of high-intensity rainfall with large reflectivity values that may extend from deeper elevations in the atmospheric column down to the surface (see three cells between days 175.45 and 175.6 in Fig. 3). In some cases, transitional phases between convective and stratiform were also identified. Reflectivity and rainfall rate pairs from each rainfall type are grouped together so that three sets of Z and R pairs (convective, stratiform, and transitional) are identified within each event. Some rain events were composed of only convective and stratiform rainfall. Z–R relationships are estimated separately for each rainfall type within an event to reflect variability in relationship parameters on a subevent scale.

Results

Analysis of Z–R Relationships and Rainfall Estimates

Results based solely on disdrometer data (i.e., R_D–Z_D pairs) are first described. Fig. 4(a) shows 1 min R_D–Z_D pairs plotted for the three analyzed storm periods and their respective fitted Z–R relationships. The figure also shows the climatological Z–R relationship. It is clear that a climatological relationship does not provide a reasonable fit for all of the three analyzed rainfall-runoff periods. Climatological parameters are quite different from those estimated at the storm scale, especially for the multiplicative factor. Now consider estimation of Z–R parameters at a storm scale; an example is shown in Fig. 4(b) for the October storm period. Significant variability is evident in the plotted Z–R pairs within the same rainfall-runoff storm, which is caused by variability in DSD during the storm. Such variability was reflected in the wide range of A and b parameters estimated for different events in each storm period. For example, a storm-scale value of $A=133$ was obtained for November period with the BIAS_RMSE method, whereas event-scale A values were found to be in the range of 43–452. Similar variations are also reported for the exponent b parameter (1.65 for storm scale and 1.23–1.97 for event scale). By further examining the plotted Z–R pairs in Fig. 4(b), it is noticed that an event-scale Z–R relationship may not be able to explain all variability within a certain event. The convective-stratiform classification procedure was applied to each event in the three periods to establish subevent Z–R relationships. Subevent A and b parameters showed significant variations within each analyzed event (see an example from the first event in June storm; Fig. 5). In addition to their scale dependency, A and b parameters also showed clear sensitivity to which method (LSF, FIX, or BIAS_RMSE) was followed to estimate their optimal values. This agrees with several findings established in pervious studies (e.g., Krajewski and Smith 1991; Ciach and Krajewski 1999; Steiner and Smith 2000; Tokay et al. 2001).

The above-presented analysis was repeated using R_D–Z_R data; however, estimation of a climatological radar-based Z–R relationship was not considered as it would require downloading and processing radar volume scan data for a full year, which is beyond the scope of this analysis. Similar to the disdrometer-based results, A and b parameters estimated based on R_D–Z_R data show significant variations between different storms, between events within the same storm, and within a single event.

Next, we use the above-derived Z-R relationships derived above to estimate rainfall rates in each period and use them to examine effects of accounting for variability in Z-R parameters on

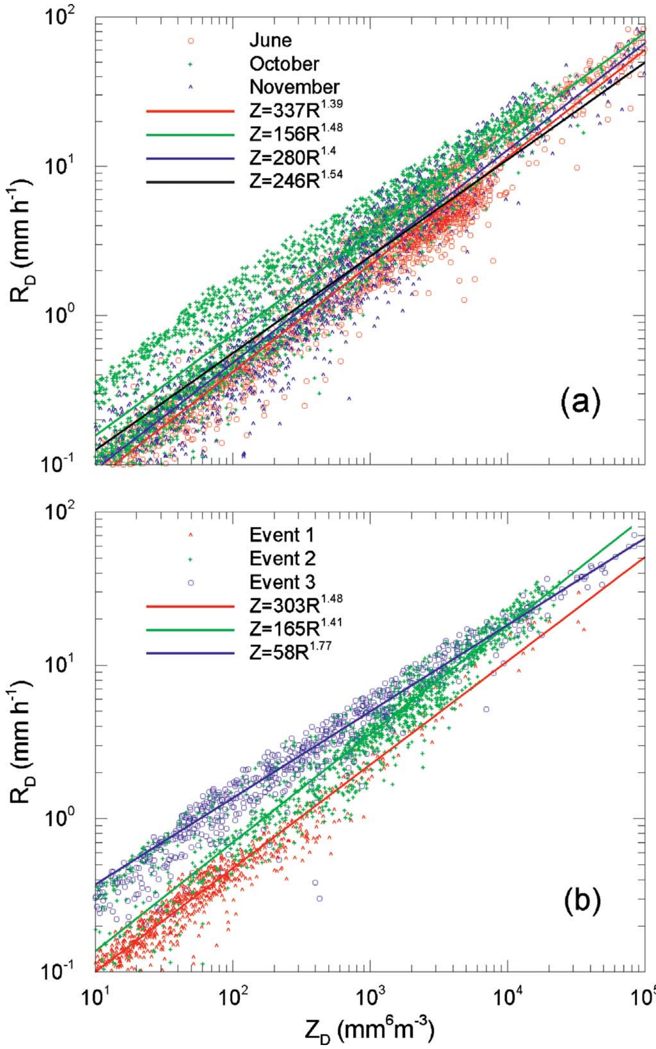

Fig. 4. Reflectivity Z_D versus rainfall rate R_D derived from 1 min DSD of JW disdrometer. (a) Storm-scale fitted $Z-R$ relationships for the three analyzed storms. The last line shows the climatological-scale relationship ($Z=246R^{1.54}$). (b) Different events within the October 2004 storm and their fitted $Z-R$ relationships.

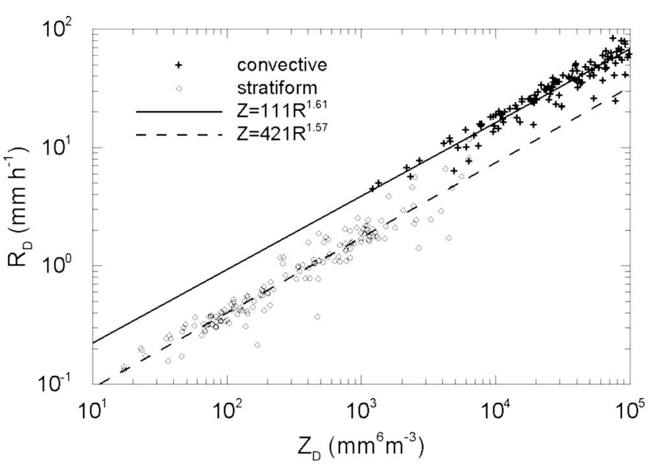

Fig. 5. Reflectivity Z_D versus rainfall rate R_D derived from 1 min DSD of JW disdrometer for the first event of the June period 2004

the accuracy of runoff simulations. Again, this analysis was performed for two cases of data sets: disdrometer-only data, Z_D-R_D, and radar reflectivity data, Z_R-R_D. Results from both cases indicated similar behavior in terms of the sensitivity of runoff simulations to $Z-R$ temporal variability and the dependence on A and b estimation method. Therefore, and as we are more interested in radar-based runoff simulations, results are presented only from the second case (Z_R-R_D).

To track how rainfall errors caused by $Z-R$ effects transform into runoff errors, the writers examine rainfall rates (R_{est}) estimated using different scale- and method-specific $Z-R$ relationships versus the corresponding reference rainfall rates (R_{ref}) represented by R_D in Eq. (2). Three statistical measures are used to assess differences between R_{ref} and R_{est}: bias, computed as the average difference between R_{est} and R_{ref} normalized by the mean of R_{ref}; RMSE, computed as root of mean of squares of differences between R_{est} and R_{ref}; and coefficient of efficiency, E. For each estimation scale, the bias, RMSE, and E values were calculated over the entire duration of each rainfall-runoff storm period (Table 1). For example, event-scale $Z-R$ relationships were applied to the corresponding events within a storm to estimate rainfall rates from radar reflectivity measurements. R_{est} and R_{ref} data from all events within a storm were combined together and used to compute the storm statistics.

As expected, BIAS_RMSE and FIX methods, which are designed to remove overall bias, resulted in bias-free rainfall estimates regardless of the $Z-R$ scale. The LSF fitting approach caused significant rainfall biases especially when the $Z-R$ relationship was derived at an aggregated scale. With LSF storm-scale $Z-R$ relationships, high negative biases were reported for the three periods. When a $Z-R$ event scale is used (i.e., substorm scale), LSF rainfall bias ratios were still relatively high. As seen in Table 1, the bias maintained nonnegligible levels even when $Z-R$ parameters were derived at a subevent scale. Such persistent bias in rainfall estimates is caused by the lack of bias adjustment in the LSF procedure. Estimates of rainfall rates using LSF method were also associated with random errors larger than those obtained with BIAS_RMSE. This is explained by the fact that the BIAS_RMSE method is designed to explicitly minimize random errors between R_{est} and R_{ref}, and therefore, attained the lowest (highest) RMSE (E) values.

Comparison of RMSE and E values across different $Z-R$ scales indicates that the accuracy of rainfall estimates improves gradually as we account for inter- and intrastorm variability in deriving $Z-R$ parameters. Going from a storm scale to an event substorm scale, both RMSE and E showed systematic improvement for all $Z-R$ estimation methods. At a subevent $Z-R$ scale, such an improvement is still observed for all three storm periods when using BIAS_RMSE and LSF methods, but not always for the case of FIX method.

Evaluation of Streamflow Simulations

Rainfall estimates based on $Z-R$ relationships established at different scales and with different parameter derivation methods were used to drive GSSHA runoff simulations in the IV watershed. Simulated runoff hydrographs were compared against the reference hydrographs. The comparison between reference (Q_{ref}) and estimated (Q_{est}) runoff is done visually, by examining plots of runoff hydrographs, and quantitatively, in terms of the same statistical measures, bias, RMSE, and E that were used earlier to assess rainfall estimates. In addition, errors in simulating runoff peaks were quantified as the difference between reference and

Table 1. Statistical Assessment of Rainfall Estimates from Z–R Relationships Derived Using Different Methods and Time Scales

Time scale	Estimation method	Bias (%)			RMSE (mm/h)			Efficiency		
Storm	LSF	−30	−37	−40	9.0	4.6	8.2	0.44	0.39	0.48
	BIAS_RMSE	0	0	0	8.2	3.9	6.6	0.57	0.64	0.68
	FIX	0	0	0	8.2	5.2	9.4	0.57	0.39	0.41
Event	LSF	−27	−23	−32	8.5	4.1	7.6	0.51	0.57	0.56
	BIAS_RMSE	0	0	0	7.9	3.6	6.1	0.60	0.68	0.73
	FIX	0	0	0	8.0	6.1	7.0	0.60	0.20	0.66
Subevent	LSF	−19	−15	−8	7.8	3.4	5.4	0.59	0.70	0.78
	BIAS_RMSE	0	0	0	7.1	3.3	5.2	0.69	0.74	0.81
	FIX	0	0	0	8.5	5.3	7.8	0.54	0.37	0.60

Note: The three columns under each statistic correspond to the three simulated periods (June, October, and November; from left to right).

estimated peaks normalized by the reference peak value. The results are summarized in Tables 2 and 3, with some examples of the simulated hydrographs plotted in Fig. 6. Apparently, there is a gradual improvement in the accuracy of estimated hydrographs in comparison to the reference case as we move from an aggregate Z–R scale (storm) down to a more refined scale (event and subevent). However, the accuracy associated with a certain scale, and the rate of improvement in runoff simulation accuracy depends largely on the method by which the Z–R relationship parameters were estimated. As expected, the BIAS_RMSE method, which was associated with the most favorable rainfall estimates, resulted in runoff simulations with minimal bias values at all Z–R scales. However, despite the overall reasonable agreement with reference hydrographs, runoff simulations based on storm-scale Z–R relationships with BIAS_RMSE still show some pronounced levels of errors. These errors diminish significantly as we move from storm-scale to event-scale Z–R relationships where the simulated runoff hydrographs traced very closely the corresponding reference hydrographs.

Going from a storm to an event scale, improvements in runoff simulations were evident in E, RMSE, and the peak error for most of the simulated hydrographs. Further improvements are still noticeable when going from an event to a subevent Z–R scale especially for the June period where simulated runoff hydrographs became almost identical to the reference case. However, such improvements are less in magnitude and importance compared to those obtained when going from a storm to an event scale.

It is noted that although BIAS_RMSE rainfall estimates were bias-free, their runoff simulations were subject to some biases at storm and event scales. Because of the nonlinearity of rainfall-runoff transformation processes, bias-free rainfall estimates, espe-

Table 2. Statistical Assessment of Runoff Simulations Based on Using Z–R Relationships Derived with Different Methods and Time Scales

Time scale	Estimation method	Bias (%)			RMSE (m^3/s)			Efficiency		
Storm	LSF	−47	−57	−69	8.6	8.9	2.4	0.52	0.41	0.05
	BIAS_RMSE	−5	−5	−11	5.6	5.0	1.4	0.83	0.87	0.74
	FIX	−5	0	6	5.8	3.8	2.5	0.82	0.92	0.26
Event	LSF	−42	−35	−54	7.0	6.0	1.6	0.66	0.74	0.55
	BIAS_RMSE	−7	0	−10	3.0	3.4	0.6	0.95	0.93	0.95
	FIX	−5	4	−2	2.6	3.5	0.2	0.96	0.93	0.99
Subevent	LSF	−26	−22	−16	4.4	3.9	0.7	0.87	0.89	0.93
	BIAS_RMSE	0	−1	0	0.8	2.4	0.2	0.99	0.96	0.99
	FIX	0	2	1	0.9	3.3	0.2	0.99	0.94	0.99

Note: The three columns under each statistic correspond to the three simulated periods (June, October, and November; from left to right).

Table 3. Statistical Assessment of Runoff Peaks Based on Using Z–R Relationships Derived with Different Methods and Time Scales

Time scale	Estimation method	Peak errors (June period) (%)	Peak errors (October period) (%)	Peak errors (November period) (%)
Storm	LSF	−53.2, −12.0	−52.9, −75.4	−88.4, −81.6, −58.2
	BIAS_RMSE	−17.7, 47.1	−9.5, −35.4	−57.9, −43.4, 20.2
	FIX	−18.7, 47.6	−3.6, −5.8	−72.6, −29.5, 96.1
Event	LSF	−36.2, −22.6	−28.8, −45.9	−46.3, −53.4
	BIAS_RMSE	−12.1, 4.1	−8.9, −1.2	−44.9, −8.0, −3.2
	FIX	−9.2, 4.2	−4.7, 33.2	−7.0, −2.0, −0.6
Subevent	LSF	−16.1, −15.0	−12.8, −32.9	−42.5, −18.5, 3.0
	BIAS_RMSE	−2.5, −1.2	−6.4, −0.8	−4.4, −0.8, −1.7
	IX	−2.0, −3.0	−5.3, 17.2	1.7, −0.2, 1.8

Note: June and October periods had two peaks each, and the November period had three peaks.

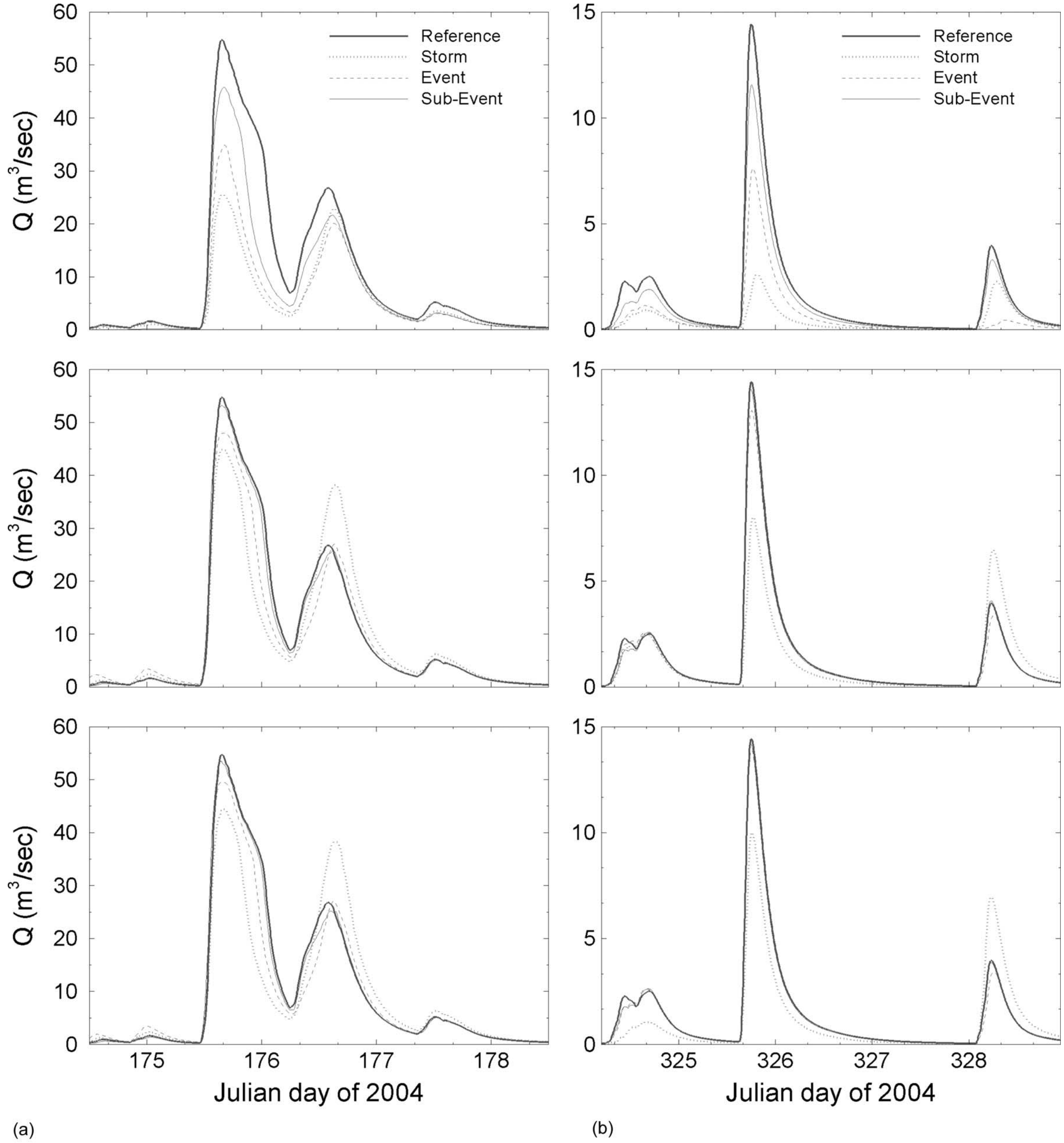

Fig. 6. Runoff hydrographs of the June period (a) and November period (b) simulated using rainfall estimates based on $Z-R$ relations established at different time scales and using different estimation methods (LSF, BIAS_RMSE, and FIX, from top to bottom)

cially when associated with nonnegligible random errors, do not necessarily guarantee complete elimination of runoff biases.

It is clear that with LSF method, runoff simulations are far less accurate at all $Z-R$ scales in comparison to BIAS_RMSE method (Tables 2 and 3). As expected, biased LSF rainfall estimates (Table 1) led to biased runoff simulations. LSF hydrographs are also characterized with large random errors as reflected in the RMSE and E statistics of runoff estimates. Significant improvements are obtained when using rainfall estimates that were based on event-scale $Z-R$ relations. However, at this scale runoff simulations are still considerably different from the reference hydrographs with relatively low efficiency E values for the three storms. Even at subevent scales, runoff simulations still suffer from considerable errors. Biases remain significant, RMSE values are two and three times larger than those of BIAS_RMSE, and relative peak errors are significantly large. It is interesting to note that even when event or subevent scale $Z-R$ relations were used, LSF-based hydrographs are still less accurate than BIAS_RMSE results obtained using more aggregate $Z-R$ scales (storm or event). This is probably due to the lack of rainfall bias removal in regression methods, which makes it difficult for the temporally refined optimization of $Z-R$ parameters to improve the quality of runoff simulations.

The importance of rainfall bias removal in deriving $Z-R$ relationships is further confirmed by examining results from the FIX method. For most cases, the FIX method results are overall similar and comparable in accuracy to those obtained with the BIAS_RMSE method. For the June period, FIX and BIAS_RMSE hydrographs have equivalent accuracy in terms of RMSE, E, and peak errors. However, during the November period, FIX results are less accurate when using a storm $Z-R$ scale, but become equivalent to BIAS_RMSE at the subevent scale. Despite the overall more favorable accuracy in BIAS_RMSE rainfall estimates (Table 1), it is interesting to notice that FIX-based rainfall estimates resulted in runoff simulations that are sometimes slightly more accurate than those based on BIAS_RMSE estimates (e.g., the October period with storm scale, and the November period with event scale). This is possibly attributed to the rather homogeneous rainfall regime observed during the October period (tropical) and November period (mostly stratiform) than during the June period.

Summary and Conclusions

This study analyzed the sensitivity of runoff simulations to the temporal scale and the estimation method used to derive radar reflectivity-rainfall rate (Z–R) relationships. Temporal scales were investigated ranging from a fine scale that accounts for stratiform/convective rainfall types within a rainfall event, to integrated storm and climatological scales. At each scale, three approaches to estimate the multiplier and exponent parameters of Z–R relationships were explored. The first approach is based on least-squares regression, the second approach is based on removal of overall bias in rainfall volume while fixing the exponent parameter, and the third method combines bias removal with minimization of random differences in instantaneous rainfall rates. Runoff analysis was performed during three major rainfall-runoff periods for a 35 km^2 subtropical watershed in southern Louisiana using a distributed and physically based hydrologic model. The analysis was first performed using Z and R data from a rain disdrometer located close to the watershed boundary, and then repeated using instantaneous reflectivity data extracted from WSR-88D radar volume scans. Runoff hydrographs were compared to reference runoff simulations that were based on rainfall rates computed directly from disdrometer measurements on rainfall drop size distributions. The main conclusions of this study can be summarized as follows:

1. In agreement with previous studies, Z–R relationships showed significant variations between storms and within the same storm. The estimated multiplier and exponent parameters show strong dependence on the time scale selected to establish the Z–R relationship, and on the method used to derive the optimal values of these parameters.
2. Z–R methods based on a combination of bias removal and minimization of random errors showed superior accuracy even when Z–R relations were derived at an aggregate scale (e.g., storm or event). This high accuracy is particularly evident when the Z–R relation was derived and applied at an event-specific scale.
3. Use of least-squares fitting to estimate the Z–R parameters resulted in relatively less accurate rainfall estimates and rather poor runoff predictions. This was most evident when aggregate time scales were used to determine the Z–R relationships. A regression-based method gives improved results only when the Z–R relationship is established on a subevent scale (i.e., by accounting for Z–R dependence on startiform and convective rainfall variations within the same event). Even at such scales, the least-squares fitting method still results in nonnegligible runoff biases, random errors, and peak errors. It is recommended that such methods should not be used in rainfall-runoff modeling applications that deal with radar-rainfall data.
4. A simple estimation method based only on bias removal and selection of a climatologically representative Z–R exponent has resulted in reasonably accurate runoff simulations. Despite the relatively larger rainfall random errors associated with this method, runoff predictions were equivalent in accuracy to those obtained using a more elaborate Z–R estimation procedure, especially if the adjustment of parameter A was done on an event basis. The importance of overall bias removal for hydrologic prediction purposes confirms earlier results by Vieux and Bedient (2004) which illustrated that once radar estimates are bias adjusted, remaining random errors tend to diminish as being digested by a real-time streamflow forecasting model.
5. Z–R estimation temporal scales that account for variations in the underlying rainfall processes (i.e., stratiform versus convective variations within an event) did not necessarily lead to significant improvements in the accuracy of simulated runoff hydrographs. This conclusion appears to be in contradiction to studies on recent operational-oriented algorithms that propose convective-stratiform Z–R segregation [e.g., the Quantitative Precipitation Estimation and Segregation Using Multiple Sensors, QPESUMS, of the National Severe Storms Laboratory (Gourley et al. 2001; Gourley and Vieux 2005)]. However, such contradiction can be explained by some of the following considerations: (1) our event-based estimation scale might be already accounting for Z–R differences between events that are either mostly stratiform or mostly convective, and (2) radar-reflectivity values are sampled at an elevation of 1.7 km above the ground surface, which is well below the bright band level, and therefore do not require adjustment for any possible reflectivity overestimation during stratiform events.

Finally, the writers point to some considerations that should be taken into account when interpreting the results of this study. The well-calibrated and validated hydrologic model (which was possible due to the availability of dense and high-quality monitoring of both rainfall and streamflow) and the relatively small size of the watershed allowed the writers to focus on uncertainties related to temporal uncertainties in estimation of Z-to-R transformation relationships. In different data and modeling setups, other sources of uncertainties (e.g., modeling errors, data limitations, accounting for spatial variation in Z–R relations, correct representation of rainfall spatial distribution in larger watersheds, etc.) might mask the gains in runoff prediction accuracy gained through the use of temporally refined Z–R relationships. Despite these factors, the writers believe that the results of this study are practically relevant for hydrologic modeling applications. Although it is recognized that variability-induced errors in Z–R relationships are not the only source of uncertainty in radar-rainfall estimates, our analysis indicates that the effects of such errors on runoff simulations can be significant. This was evident in the relatively large runoff simulations errors (both systematic and random) caused by the lack of accounting for temporal variations in Z–R relationships. The current study indicated that, from a hydrologic point of view, this problem can be addressed through the use of simple bias-adjustment based Z–R relationships, but only if the adjustment is performed on a rainfall event-specific scale. It is also pointed out that the analysis was performed for three rainfall-runoff storms only. Although it is expected that the reported findings will be applicable for other events, issues such as model calibration and seasonal adjustment of model parameters need to be resolved before the analysis can be expanded to longer temporal domains (e.g., annual). Similarly, issues such as watershed size and characteristics need to be investigated to understand how the combined spatial and temporal variability in Z–R relationships can affect the accuracy of radar-based rainfall estimates and subsequent runoff simulations.

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