Applications of Radar Based Rainfall Estimates for Urban Flood Studies

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Spatial and temporal variability in extreme rainfall (Morin et al., 2006), and its interactions with heterogeneous land cover (Mejia and Moglen, 2010; Wright et al., 2012) and drainage network structure (Meierdiercks et al., 2010), are central controls of flood response. In urban settings, where flow path lengths are short, runoff velocities are high, and the spatial distribution of land use and hydrologic infrastructure is highly heterogeneous, understanding and representing the dynamic interactions of rainfall with the land surface and drainage network is critical. Rainfall frequency analysis, therefore, should ideally be tied directly to the characteristics of storm systems that produce extreme rainfall and flooding in the watershed of interest.

In engineering practice we make simplifying assumptions about the spatial and temporal structure of extreme rainfall to facilitate rainfall frequency analyses for design and risk assessment. These assumptions ignore the complexity and variety of meteorological processes that contribute to the extreme rainfall and flood climatology of a region or watershed. When these assumptions were developed, measurements of rainfall at high spatial and temporal resolution were not possible. The impacts of these simplifying assumptions on subsequent design or risk assessment have received little attention. With the NEXRAD (next generation radar) network, rainfall estimates with high space-time resolution have become routine across most of the United States (Crum and Alberty, 1993; Smith et al., 1996; Crum et al., 1998; Fulton et al., 1998).

Radar rainfall estimates, when subject to proper quality control, offer ways to examine conventional methods and to develop more robust techniques for estimating extreme rainfall frequency (Overeem et al., 2009b). This chapter briefly examines several of the key assumptions made in conventional rainfall frequency analysis and then presents an alternative framework that takes full advantage of the spatial and temporal characteristics of radar rainfall estimates and of modern computational resources.

Conventional flood frequency analysis makes assumptions about the movement of water through the watershed once it has reached the land surface. These assumptions vary depending on the exact techniques being used but involve disregarding spatial and temporal variability in runoff processes and how they are affected by variability in rainfall, land cover, and drainage network properties. Thus, flood frequency analyses are potentially subject to errors arising from the multiple assumptions made. Again, the impact of these assumptions on design and risk assessment is poorly understood.

The rainfall frequency analysis framework presented in this paper is known as stochastic storm transposition (SST). SST based rainfall frequency analysis can be thought of as a recreation of the extreme rainfall climatology of a user defined area. This is done by *substituting space for time*, in which inferences at a particular location are made by using not only rainfall observations from that location but also from surrounding locations. Difficulties in the estimation of long return intervals arising from short observation records are at least partially mitigated through the inclusion of additional observations of nearby storms. The transposition element of the procedure has been standard practice in probable maximum precipitation estimation for 75 y (Hansen, 1987).

A thorough description of the probabilistic framework and associated challenges is provided in Fofoula-Georgiou (1989), assessed in Wilson and Fofoula-Georgiou (1990), and extended to flood frequency analysis in Franchini et al. (1996). The SST procedure described in this study is similar to previous efforts but attempts to address some of the limitations of previous studies, principally the lack of high quality spatially and temporally continuous rainfall data. This paper presents intensity–duration–frequency (henceforth referred to as IDF; known as IFD in some countries) curves calculated using an SST based approach and using radar rainfall estimates that have been corrected for systematic errors. SST–IDF curves are compared to curves computed using conventional (i.e. rain gauge based) methods.

The paper consists of the following sections: some common assumptions in extreme rainfall frequency analysis are discussed in section 6.1; the study area, data, and the SST based procedure for IDF estimation are discussed in

section 6.2; IDF results of the SST based methods are presented and compared with conventional estimates in section 6.3; discussion of some limitations and ongoing efforts in SST based rainfall frequency analysis and some comments on SST based flood frequency analysis are made in section 6.4. Concluding remarks are given in section 6.5.

6.1 Conventional Assumptions

6.1.1 Design Storms

Estimates of extreme rainfall for hydrologic design and risk assessment usually make use of IDF curves. Regional IDF curves are generated by pooling and interpolating rainfall observations from nearby rain gauges and estimating the rainfall intensity associated with different return periods over a range of temporal scales by selecting and fitting statistical distributions to the observations. Extreme rainfall rates corresponding to long return intervals are then estimated via extrapolation. Observational records used in the estimation process are often short compared to the return intervals of interest. As more gauges have become available and observation records become longer, there has been a tendency for IDF estimates to be revised upward (e.g. Guo, 2006; Madsen et al., 2009; Adamowski et al., 2010). Upward revisions may be climate induced changes in rainfall extremes, but can more likely be attributed to improved statistical inference with increased sample size. Additional errors can arise due to excessive spatial interpolation that tends to mask local variations in rainfall due to topography and other local features. Many rain gauges record only daily accumulations, making short duration IDF estimation a significant challenge. Sparse gauge networks have difficulty detecting and characterizing small scale rainfall systems, while dense networks are rare due to high costs.

Alternate methods employing a variety of statistical methods (e.g. Treffry et al., 2005; Singh and Zhang, 2007) or weather radar (e.g. Overeem et al., 2009a) produce varied IDF estimates. In principle, uncertainties in IDF estimates could be incorporated into flood risk assessment and design. In practice, however, uncertainties in IDF estimates are rarely considered (Overeem et al., 2008), potentially leading to poor characterization of risk.

Different storm types are responsible for extreme rainfall and flooding at a range of spatial and temporal scales due to differences in characteristic size, motion, and structure. In the southeastern United States for example, summer thunderstorm systems produce high rain rates and flash flooding at short time and length scales, while tropical cyclones produce high rain rates

and regional flooding at larger scales. Differentiation of IDF estimates based on season or storm type can be relevant for the design of infrastructure or for developing adaptation strategies in light of anticipated changes in the frequency of certain types of storms (tropical cyclones or extratropical cyclones, for example). Willems (2000) derives IDF curves for different storm types and different seasons at a particular location in Belgium, but in general these distinctions are not made. Considering that the rain gauge records used to generate IDF curves are already limited, it is likely that in many regions there are insufficient data to produce robust estimates of long return intervals using data stratified by season or event type.

In engineering practice, IDF estimates are assumed to be uniform in space and often in time, while in reality, the structure of extreme rainfall is much more complex. In some cases, the IDF estimate is temporally disaggregated using a dimensionless rainfall distribution based on geographic region, such as the 24 h storm distributions found in National Resources Conservation Service (1986). The dimensionless rainfall distributions are intended to represent the temporal structure of extreme rainfall of that region, but make no distinction of storm type (e.g. tropical cyclones, extratropical cyclones, summertime thunderstorms), or storm organization (e.g. single cell or multi-cell thunderstorms, mesoscale convective systems, cyclonic rain bands). Spatial disaggregation is not commonly done, despite the fact that spatial variation of extreme rainfall is important even in small urban catchments (e.g. Zhang et al., 2001; Smith et al., 2001; 2002; Zhang and Smith, 2003).

6.1.2 Area Reduction Factors

Conventional IDF estimates are based on observations from rain gauges, which measure rainfall over an area of approximately 0.1 m^2 . These estimates are then converted to areal estimates using area reduction factors (ARFs; also known as depth–area adjustment factors). The United States Weather Bureau Technical Paper 29 (TP-29, U.S. Weather Bureau, 1958) is the most commonly used source of ARFs for watersheds up to about $1\,000 \text{ km}^2$ in the United States and elsewhere (Omolayo, 1993). There are also numerous techniques in the academic literature for determining ARFs using rain gauge networks and, recently, weather radar (see Svensson and Jones, 2010, for a review of techniques). The various techniques differ in their assumptions, formulations, data requirements, and, most importantly, the resulting ARF estimates (see Figure 6.1 for a comparison of ARFs from TP-29 and those calculated using the methodology of Asquith and Famiglietti, 2000, for the Charlotte, North Carolina area). One common feature of all methods, however, is that they involve an averaging process whereby the considerable variability of rainfall

input data is reduced to a single ARF curve. A great deal of information regarding the spatial and temporal variability of extreme rainfall is lost through this averaging process. In light of significant variability in input data, it is both feasible and advisable to develop measures of estimation uncertainty that would be useful for practitioners. We are not familiar with any technique, however, that considers the uncertainties associated with the ARF estimates.

Figure 6.1 Comparison of area reduction factors from U.S. Weather Bureau TP-29 (gray lines) and computed from the CRN rain gauge data using the procedure from Asquith and Famiglietti (2000) for the 1995–2010 period (black lines).

Several studies have suggested that ARFs should be dependent on rainfall return interval (e.g. Sivapalan and Bloschl, 1998; Durrans et al., 2002), which is not considered in TP-29. One additional weakness of ARFs is that they are intended to be general enough to be applied to all watersheds of a

given area without consideration of local or regional extreme rainfall climatology or the interplay of unique basin geometry with storm motion. There is evidence suggesting that regionally or locally estimated ARFs can deviate significantly from each other and from nationwide estimates (e.g. Asquith and Famiglietti, 2000; Durrans et al., 2002).

Poor agreement in ARF estimates between different methodologies, combined with the information loss associated with the averaging processes used in ARF estimation, suggest that rainfall and flood frequency analysis techniques that do not require the use of ARFs may be preferable. The SST based procedure for IDF estimation (section 6.2.4) and results (section 6.3.2) presented in this study do not require any assumptions regarding ARFs or point-to-area rainfall transformation.

6.2 Data and Methods

6.2.1 Study Area

The study region is centered on the Charlotte, North Carolina metropolitan area. The Blue Ridge Mountains to the west affect storm initiation and evolution across the region. Local topography is minimal (Figure 6.2, left panel). Charlotte is an ideal setting for flood hydrology research due to the quantity of data resources and instrumentation and the variety of flood producing hydrometeorological processes. The Charlotte raingauge network (CRN) consists of 71 5 min resolution raingauges (Figure 6.2, right panel) operated jointly by the U.S. Geological Survey (USGS) and Charlotte–Mecklenburg Storm Water Services. Most of these gauges have been operational since at least 1995. The equipment and data are subject to a high degree of quality control. Two Weather Surveillance Radar 1988 Doppler (WSR-88D) radars operated by the National Weather Service (NWS) cover the Charlotte area. The Greer (KGSP) radar has been selected for use in this study due to minimal beam blockage and the favorable range from the Charlotte area (Figure 6.2, left panel; for a discussion of the importance of range effects, see sections 6.2.2, 6.3.2, and 6.4).

The study watershed in the work is the Little Sugar Creek at Archdale (Figure 6.2, right panel). It has an area of 110 km², an average slope of 5.8%, and an impervious landcover of 32%. The predominant land use is mixed intensity development. There is extensive stormwater management infrastructure including storm drains and detention basins, resulting in a drainage network that has been significantly altered from its pre-development state (Smith et al., 2002).

Figure 6.2 Study region. Left panel: 200 km radius KGSP radar umbrella with state boundaries, regional topography and the Charlotte metropolitan boundary. Right panel: Charlotte metropolitan area with the location of CRN rain gauges and the Little Sugar Creek watershed. The background map shows percent imperviousness ranging from 0 to 100%; darker colors indicate a higher percentage of impervious land cover.

6.2.2 Radar Rainfall Estimation

In this study we develop a 10 y (2001–2010), 15 min, 1 km² bias corrected radar estimated rainfall dataset using the Hydro-NEXRAD system (Krajewski et al., 2010; Smith et al., 2012). The Hydro-NEXRAD processing system converts three-dimensional polar coordinate volume scan reflectivity fields into two-dimensional cartesian surface rainfall fields. The standard convective rainfall–reflectivity (Z – R) relationship ($R = aZ^b$, where $a = 0.017$, $b = 0.714$, R is rain rate in mm/h, and Z is the radar reflectivity factor in km/m³), and several standard quality control algorithms were used (Seo et al., 2011). In addition to the 10 y bias corrected radar rainfall dataset, extreme rainfall from 23–24 July 1997 was included in the radar dataset.

The bias correction procedure used in this study has two components: a mean field bias correction done at the daily scale, and a conditional bias correction which is a function of rain rate and the accumulation period being considered. Each component is discussed in more detail below. Prior to bias correction, daily rain gauge accumulations for each gauge are examined for consistency. Spurious gauges and gauging periods are excluded from the bias correction procedure.

The daily mean field bias correction removes systematic bias due to variability in $Z-R$ relationships and radar calibration errors (see Smith and Krajewski, 1991; Villarini and Krajewski, 2010). We compute a daily mean field multiplicative bias correction based on daily (12 to 12 UTC) rain gauge accumulations computed from the network of 71 CRN rain gauges. The daily mean field bias computation takes the form:

$$B_i = \frac{\sum_{S_i} G_{ij}}{S_i} \quad (6.1)$$

where:

- G_{ij} = the daily rainfall accumulation for gauge j on day i ,
- R_{ij} = the daily rainfall accumulation for the radar pixel containing gauge j on day i , and
- S_i = the index of the rain gauge stations from which both rain gauge and radar have positive rainfall accumulations for day i .

Each 15 min radar rainfall field from day i is then multiplied by the bias correction factor B_i . A bias value different from unity is applied only if there are at least five radar gauge pairs with positive precipitation accumulations for day i . The mean field bias correction procedure is the same as that used in Smith et al. (2012) and Wright et al. (2012).

An additional source of error in radar rainfall estimates is bias associated with magnitude dependent radar rainfall estimation $R_R(t)$, referred to as conditional bias (see Baeck and Smith, 1998; Ciach et al., 2007; Villarini and Krajewski, 2009). A conditional bias model was developed using the methodology presented in Villarini and Krajewski (2009) using a power law function of the form:

$$R_T(t) = a(t) R_R(t)^{b(t)} \quad (6.2)$$

where:

- t = the aggregation period,
- $a(t)$, $b(t)$ = empirical parameters,
- $R_R(t)$ = the radar rainfall estimate, and
- $R_T(t)$ = the estimate of true rainfall.

In this study, the empirical parameters $a(t)$ and $b(t)$ are themselves described by power law functions of the form:

$$\begin{aligned} a(t) &= ct^d \\ b(t) &= et^f \end{aligned} \tag{6.3}$$

where:

c, d, e, f = empirical parameters.

It should be noted that range dependent bias was not explicitly addressed for most of the following analyses. Analyses of rainfall fields over the Charlotte metropolitan area show that range dependent bias is small (not shown). Applications of radar rainfall estimates over larger areas or areas close to or far from the radar should consider the effects of range dependent bias.

6.2.3 Additional Hydrometeorological Data

Observations of cloud-to-ground lightning from the National Lightning Detection Network (NLDN) are used in section 6.3.2 as a surrogate for convective activity (e.g. Tapia et al., 1998; Ntelekos et al., 2007). Tropical storms were identified using the Hurricane Database (HURDAT; Jarvinen et al., 1984; Neumann et al., 1993) in order to examine IDF dependency on storm type (tropical vs nontropical) in section 6.3.2.

6.2.4 Stochastic Storm Transposition

The steps for watershed specific IDF estimation using SST and bias corrected radar rainfall data are as follows:

1. Identify a geographic domain over which the extreme rainfall climatology is homogeneous. Homogeneity can be assessed using a number of metrics, including storm counts, mean storm depths or intensities, measures of convective activity such as cloud-to-ground lightning observations, or analyses of spatial and temporal rainfall structure;
2. Identify the largest m storms within the domain at the t h time scale. This set of m storms is henceforth referred to as a *storm catalogue*. Since the ultimate goal is the estimation of extreme flood exceedance probabilities within a specific watershed, the m largest storms are selected with respect to shape and orientation of the watershed. For example, Little Sugar Creek at Archdale is orientated north–south with an area of 110 km², the top m storms that constitute the storm catalogue are those associated with high t h rainfall intensities over an area of 110 km² with the same shape and orientation as Little Sugar Creek. The

m storms are selected from an n y record, such that an average of $\lambda = m/n$ storms per year are included in the storm catalogue. We assume that annual storm counts have a Poisson distribution with parameter λ (storms per year). Wilson and Fofoula-Georgiou (1990) also assume a Poisson distribution for annual extreme storm counts;

3. Select a subset of k storms at random from the storm catalogue where k is the number of occurrences of the event and is Poisson distributed with rate parameter λ . Due to the assumption of homogeneous extreme rainfall climatology over the domain, these k storms could have occurred with equal likelihood anywhere within the domain. Therefore, it is valid to transpose the storms to randomly selected locations within the domain. This transposition can be thought of as shifting the initiation location of the storm. The transposed storm then progresses across the domain for t h, while the motion and structure of the original storm is preserved. Since the radar data has a 15 min temporal resolution, a 3 h storm, for example, consists of 12 periods. Each period within the storm is transposed by the same distance north–south and the same distance east–west, such that the motion and shape of the storm at all periods is unaltered during the transposition and only the location is changed;
4. For each of the k transposed storms, compute the t h basin-averaged rainfall rate that occurs over the watershed of interest. Once t h rain rates have been computed for each the k storms, the maximum is retained. This procedure of selecting storms is designed to mimic the annual pattern of extreme rainfall, so this maximum value can be considered to be the annual peak t h rainfall rate for one year for the watershed; and
5. Repeat steps 3 and 4 many times. This procedure of repeatedly selecting subsets of data to make inferences is referred to as *resampling*. In this study, steps 3 and 4 were repeated 1 000 times to generate 1 000 y synthetic annual maximum rainfall rate estimates. The ordered annual maxima are then used to generate return period estimates of up to 1 000 years of annual peak t h rainfall rates; 5 000 realizations of 1 000 year series were generated and the results were averaged at each return interval to reduce errors associated with the resampling procedure.

The procedure described above takes advantage of the structure of rainfall captured by radar measurements to estimate the frequency of extreme

rainfall without any assumption of spatial and temporal uniformity or of point-to-area transformation using ARFs. The effects of storm motion and orientation are preserved. If the procedure is adapted to flood frequency analysis using a distributed hydrologic model, the effects of storm motion and structure are explicitly accounted for, and no assumption regarding runoff travel time such as time of concentration or lag-to-peak time is necessary.

SST based IDF estimates are compared to conventional rain gauge based estimates from the NOAA Atlas 14 (Bonnin et al., 2004). These IDF estimates are updated based on recent rain gauge observations and in North Carolina are based on observations from a state wide network of ~200 rain gauges reporting at the daily scale and ~50 gauges reporting at hourly and subhourly scales. Nearby stations in South Carolina are also used.

6.3 Results

6.3.1 Radar Rainfall

In this study, daily mean field bias correction improves the coefficient of determination (R^2) from 0.50 to 0.88, and decreases the daily root mean square error (RMSE) from 11.6 mm to 5.3 mm, the daily mean absolute error (MAE) from 5.8 mm to 3.0 mm, and eliminates the systematic measurement errors at the daily scale (Figure 6.3).

Figure 6.3 Comparison of co-located rain gauge and radar estimated daily rainfall accumulations prior to (left panel) and after mean field bias correction (right panel) over 2001–2010 period. Conditional bias has not been corrected. Dark gray lines are the results of LOESS smoothing and are used to illustrate conditional bias.

Conditional bias at the daily scale is minimal. The bias corrected radar rainfall estimates capture the important features of extreme rainfall associated with tropical storm Fay, a major rainfall event in the Charlotte area on 27–28 August, 2008 (Figure 6.4). See Villarini et al. (2010) for similar analyses for the 23–24 July 1997 event.

Figure 6.4 Radar and rain gauge intercomparisons for tropical storm Fay, 26–27 August 2008. Mean field bias was 1.73 for August 26 and 1.93 for August 27. Left panel: comparison of 15 min rainfall accumulations for all functioning gauges and co-located radar pixels before and after mean field bias correction. The dark gray line is the result of LOESS smoothing and is to used illustrate conditional bias. Conditional bias has not been corrected. Right panel: comparison of 15 min rain rates for rain gauge CRN-20 and the co-located radar pixel before and after mean field bias correction. Results are comparable for other CRN gauge locations (not shown). Conditional bias has not been corrected.

Conditional bias was examined for time scales ranging from 15 min to 24 h. Both the effects of conditional bias and of measurement error are more pronounced at short time scales (Figure 6.4) than at longer time scales (Figure 6.3, right panel). Consistent with Villarini and Krajewski (2009), the radar tends to underestimate heavy rainfall relative to rain gauges. Table 6.1 contains the estimated parameters for the conditional bias power law model for the cold (October–March) and warm (April–September) seasons. Corrections for both daily mean field bias and t h conditional bias are used for the SST based IDF results presented in section 6.3.2.

Table 6.1 Power law parameters for conditional bias correction procedure. The cold season is October–March, the warm season is April–September.

Season	c	d	e	f
Cold season	1.0521	-0.0229	1.0745	-0.0141
Warm season	1.0041	-0.0142	1.0407	-0.0232

Examination of the spatial and temporal structure of rainfall at the 15 min scale as measured by rain gauges and co-located bias corrected radar shows good agreement between the two instruments (Figure 6.5), especially considering the scale mismatch affecting rainfall estimates at short scales.

Figure 6.5 Left panel: comparison of the spatial correlation structure of rain gauge and radar estimated rainfall at the 15 min time scale for warm season (April–September). Right panel: comparison of the temporal correlation structure of rain gauge and radar estimated rainfall at the 15 min time scale for warm season.

6.3.2 Stochastic Storm Transposition

Several measures were used to examine the assumption of homogeneity in heavy rainfall over the region. Mean annual rainfall and the number of days with rainfall accumulations >25 mm were computed based on the bias corrected radar rainfall data for the 2001–2010 period (Figure 6.6, top panels). These two analyses use a simple long term range dependent bias correction achieved by dividing the radar domain into concentric range dependent 1 km rings, computing the mean quantity for each ring and then multiplying each pixel in the radar domain by the ratio of its range ring mean quantity to the

radar domain mean quantity. The effect of missing records on seasonal averages was addressed by computing a seasonal mean pixel-by-pixel from available records and then multiplying it by the ratio of the total number of 15 min periods in the season to the number of available 15 min records.

Figure 6.6 Assessment of rainfall homogeneity over study region. Mean annual rainfall in mm over 2001–2010 period (top left). Mean annual number of days over 2001–2010 period with rainfall accumulations >25 mm (top right). Mean number of cloud-to-ground lightning strikes per year/km² over the 1994–2010 period (bottom left). Mean rainfall in mm of the fifty highest 12 h rainfall rates at the 110 km² scale based on the selection procedure described in sections 6.2.4 and 6.3.2.

The mean number of cloud-to-ground lightning strikes per km² per year was computed from the NLDN (Figure 6.6, bottom left panel). All three

measures show maxima in rainfall and convective activity over the Charlotte metropolitan area, though the maxima are less pronounced than in some other urban areas in the eastern United States such as Atlanta, Georgia (Wright et al., 2012) or Baltimore, Maryland (Ntelekos et al., 2007; Smith et al., 2012). We conclude that extreme rainfall is relatively homogeneous over a square 3 600 km² area centered on the Little Sugar Creek watershed. The procedure was repeated for 1 600 km² and 6 400 km² square domains to assess the sensitivity of the IDF results to domain size. The impacts of domain size were minimal (results not shown).

In this study, the SST procedure was conducted both at the point/radar pixel scale (Figure 6.7, overleaf) and for the 110 km² Little Sugar Creek watershed (Figure 6.8, overleaf) at 1 h, 3 h, 6 h and 12 h scales. For both scales, the domain that was used for event selection was a square with an area of 3 600 km² centered on the radar pixel of the centroid of the watershed. From the bias corrected radar rainfall dataset, a storm catalogue of 50 events was created for each temporal and spatial scale, with a resulting rate parameter λ equal to 5.0 events/y. We imposed a minimum time span of 24 h for separate events to be included in the catalogue; in the event that two or more distinct periods of heavy rainfall occurred within 24 h, only the highest rate was included in the catalogue.

Since the extreme rain rates at different spatial and temporal scales depend on a variety of factors, the storms that compose each catalogue can vary. For example, the 50 storms that compose the 1 h catalogue for Little Sugar Creek are not necessarily the same storms that compose the 12 h catalogue for Little Sugar Creek, or that compose the 1 h catalogue at the point/radar pixel scale. A high degree of overlap across catalogues, however, is both expected and observed.

The mean storm depth for the 50 storms selected shows a predominant southwest–northeast pattern consistent with the patterns observable in longer term rainfall averages (shown for the 12 h scale in the bottom right panel of Figure 6.6; results are similar for other time scales). This reflects the predominant direction of storm motion toward the northeast along the eastern side of the Blue Ridge Mountains.

SST based IDF estimation was also repeated using only non-tropical storms to examine the sensitivity of extreme rainfall estimates to storm type (Figures 6.7 and 6.8, bottom panels). Rainfall associated with tropical storms was identified as time periods in which rain fell concurrently with the passage of a tropical storm within 500 km of Charlotte. Rainfall occurring during these time periods was excluded from subsequent analyses. The rate parameter of the Poisson process was reduced in proportional to the number of tropical storms that were excluded.

Figure 6.7 Comparison of point/pixel scale IDF relationships for the Charlotte area estimated from the NOAA Atlas 14 and the SST method. Top panel: SST-IDF estimates based on all storm types. Bottom panel: SST-IDF estimates based on nontropical storms. Solid lines are the 90% confidence intervals from the NOAA Atlas 14.

There is relatively good agreement between IDF estimates from the NOAA Atlas 14 gauge based point estimates and from pixel scale SST based estimates (Figure 6.7). At the 1 h time scale for long return intervals (500 y to 1000 y), the SST based estimates are greater than the NOAA estimates. This reflects the limitations of sparse rain gauge networks used to generate NOAA IDF estimates. Infrequent and extreme rain rates at short time scales are

typically associated with summertime thunderstorms that are small in spatial extent and duration (often on the order of several km² and <1 h for single cell thunderstorms), meaning there is a high likelihood that a sparse rain gauge network will fail to sample the location of maximum rain rate. Weather radar, on the other hand, provides estimates everywhere within the radar umbrella, making it better suited to capture these small intense storm cells.

Figure 6.8 Comparison of IDF relationships for Little Sugar Creek (110 km²) estimated from the NOAA Atlas 14 with TP-29 ARFs and the SST method. Top panel: SST-IDF estimates based on all storms types. Bottom panel: SST-IDF estimates based on nontropical storms. Solid lines are the 90% confidence intervals from the NOAA Atlas 14 with TP-29 ARFs.

Sparse rain gauge networks are better suited to measure extreme rain rates for storms with larger spatial extents and durations than they are at measuring extreme rain rates for smaller, short duration storms. This is reflected in the 110 km² watershed scale estimates (Figure 6.8). At the 110 km² watershed scale, the SST based IDF estimates are within the NOAA Atlas 14 confidence bounds for return periods $>\sim 6$ (at the 12 h time scale) to ~ 25 y (at the 1 h time scale). Low IDF estimates for short return intervals using the SST technique, are discussed in Section 6.4.

The minimal differences at the 1 h scale between SST based IDF estimates based on all storm types and based only on nontropical storms can be explained by predominance of small, short duration thunderstorms in the 1 h storm catalogues. This is true for both the pixel and watershed scale SST based IDF estimates. It should be noted that NOAA Atlas 14 and other common sources of IDF estimates do not discriminate between different storm types. Extreme rain rates for longer time scales are typically associated with tropical storms, due to their large spatial extents. This is reflected in the differences between the differences between the SST based IDF estimates generated using all event types and using only nontropical storms at time scales >1 h. These differences are evident both at the point/radar pixel scale and at the watershed scale, and increase with increasing time scale.

6.4 Discussion

The SST procedure presented in this study addresses some of the shortcomings of previous attempts at SST based rainfall frequency analysis, but several challenges remain. These challenges and potential solutions are discussed in this section. This section closes with some comments on extending the technique to SST based flood frequency analysis.

Past SST studies have acknowledged the assumption of rainfall homogeneity over the storm selection domain. This study addresses this challenge by examining the regional climatology of rainfall and convective activity. Assessments of spatial heterogeneity of rainfall and convective activity in Figure 6.6 show coherent structure in rainfall patterns across the domain. Results showed little sensitivity of the procedure to different selection domain sizes. It may be that more rigorous methods for determining homogeneity are preferable. Statistical approaches including examination of the intensity and of the spatial and temporal structure of extreme rainfall over the domain hold some promise in establishing homogeneity in a more objective framework.

A potential solution to the homogeneity challenge is to relax the assumption. Currently, the selected storms are assumed to have an equal probability

of occurring anywhere within the domain, and thus are transposed from their true starting positions uniformly north–south and east–west. If, however, storms preferentially initiate within the domain due to topographic or other features but their intensity is not substantially impacted, it should be fairly straightforward to alter the way in which they are transposed to reflect this nonuniformity in initiation. This approach was adopted in Wilson and Fofoula-Georgiou (1990), where transposition locations were drawn from a transformed bivariate normal distribution independent in the north–south and east–west directions.

Nonhomogeneity in storm intensity, on the other hand, due to factors such as topography, urban impacts, or variability in surface roughness, would nonuniformly impact different storm types and would be more difficult to characterize and account for.

In this study, the SST technique was used to estimate IDF relationships for one watershed (Little Sugar Creek at Archdale; 110 km²) and for a radar pixel in the Charlotte area. The technique, however, can in principle be used to estimate unique IDF relationships for watersheds of any size, shape, and orientation, if the spatial extent of the rainfall data is sufficiently large. The importance of size, shape and orientation on IDF estimates depend on the regional climatology of storm motion and shape and on watershed geomorphology. The SST approach allows direct examination of the importance of storm motion and shape combined with watershed shape size, shape, and orientation in a way that IDF estimation using sparse rain gauge networks cannot.

In this study, IDFs were estimated using SST based on all storm types (tropical and nontropical) and using only nontropical storms. The method can also be used to examine the seasonality of IDF relationships by tracking the month or season of occurrence of storm events throughout the resampling process.

One challenge in applying the SST method to larger watersheds is the limited range of weather radar. In this study, the 3 600 km² domain was completely enclosed by the KGSP radar domain and range effects on radar rainfall estimation were found to be minimal. In cases where the storm selection domain must be large with respect to the radar domain, range effects can become a major challenge. In addition, the finite area of the radar umbrella imposes a limit on the size and position of the domain, irrespective of range effects. As with other radar rainfall applications, blocked radials due to mountainous terrain or poor radar siting would represent major challenges. Some radar products such as NCEP Stage IV and the upcoming NMQ Q2 use data from multiple radars and other sensors to cope with blocked radials, but this merging process is a major challenge.

The SST based IDF results in this study tend underestimate rainfall for short return periods relative to NOAA Atlas 14 IDF estimates. This tendency can be seen in Foufoula-Georgiou (1989), Wilson and Foufoula-Georgiou (1990), and Franchini et al. (1996). The poor agreement is the result of the relatively high likelihood that all k storms are transposed in such a way that little or no rainfall occurs over the watershed for that simulated year. This underestimation can be compensated for by increasing both the size of the storm catalogue and the rate parameter λ . Additional less intense storms would be included in the resampling, contributing little to the estimation of extreme rain rates with long return periods, but improving estimates for short return periods. This can be intuitively understood as moving from using SST to reconstruct the hydroclimatology of only extreme rainfall towards reconstructing the complete rainfall climatology. In practice, however, there is little advantage to doing this since short return period estimates are fairly well constrained by rain gauge records, at least in areas with good observation networks, and because it is long return interval events that are of interest for design and risk assessment.

The full advantages of SST based techniques can be realized when the concept is extended to flood frequency analysis. Transposed radar rainfall can be coupled with a distributed hydrologic model and perhaps with a hydraulic model to develop unique and independent flood frequency estimates at any point along a drainage network. Peak discharge at a range of return intervals can be estimated everywhere in the watershed independently of rainfall return interval (see, for instance, Natale and Savi, 2007). This stands in contrast to conventional flood frequency methods, which presume a 1:1 relationship between return intervals of rainfall and of discharge, often presume that a T y peak discharge at one point along the drainage network corresponds to a T y peak discharge elsewhere in the network, and require the selection of a storm duration (usually the time of concentration) based on basin size and structure. Estimation of time of concentration can be troublesome, however, especially in urban areas where the timing of flood response can be highly variable due to complex interactions of storm motion with heterogeneous land cover and drainage network properties (see, for example, Wright et al., 2012).

Using the SST procedure, each watershed will have a unique storm catalogue for any event duration, comprised of spatially and temporally realistic observed storms, eliminating the need for time of concentration estimates if coupled with a fully distributed hydrologic model. The complexity of interactions between spatially and temporally variable rainfall, distributed land use, and complex drainage networks, especially in urban areas, suggests that conventional practices and their inherent assumptions may not adequately determine flood risk. SST based methods could represent a useful alternative.

6.5 Summary and Conclusions

Spatial and temporal variability of extreme rainfall, and its interactions with spatially distributed surface, subsurface and channel processes, is a key determinant of flood response. These interactions are unique to every watershed and every storm event. Therefore an approach to rainfall and flood frequency analysis that explicitly considers these unique relationships is desirable. Conventional approaches, however, are designed to be easily applicable to a wide range of watersheds across broad geographic areas. To be so, a number of simplifying assumptions are made, but the impacts of these assumptions on flood risk estimation and design are poorly understood.

Spatially and temporally uniform design storms commonly used in practice neglect important features of rainfall structure. Design storms also do not discriminate by storm type or by season. There are often data limitations associated with the IDF curves that are used to develop design storms. These limitations cast doubt on the usefulness of IDF estimates for long return intervals, but uncertainties in IDF curves are rarely considered in practice.

Conventional IDF curves are derived from point (rain gauge) observations, but engineers are interested in rainfall over areas. Point rainfall estimates are converted to areal estimates using area reduction factors. A number of different techniques for computing ARFs can be found in practice and in the literature. These techniques can produce widely varied ARF estimates. They tend to ignore local rainfall climatology and geomorphology. Most methods also neglect other important factors such as rainfall return interval and storm type. While the methodologies employed by different ARF estimation techniques vary, they all use an averaging process to reduce considerable rainfall variability to a single ARF estimate that is usually only a function of area. Information regarding inter- and intra-event spatial and temporal rainfall variability is lost through this averaging process. To our knowledge, no ARF-estimation technique in the literature considers estimation uncertainties.

A 10 y high resolution (15 min, 1 km²) radar rainfall dataset encompassing the Charlotte metropolitan area and the surrounding region has been developed using the Hydro-NEXRAD processing system. Daily mean field and timescale dependent conditional bias corrections were developed using a dense network of rain gauges. Bias corrected radar rainfall estimates capture the important features of extreme rainfall, while the spatially continuous radar estimates provide advantages over rain gauge measurements, especially with respect to the detection of isolated cells of extreme rainfall.

A method for rainfall frequency analysis is presented which combines SST with high resolution radar rainfall estimation. The technique recreates the extreme rainfall climatology for a specific watershed by using rainfall

observations from the surrounding region. Major storms from the region are chosen and placed at random within the region and the resulting basin-averaged rainfall is computed. Short observation records can thus be extended by this space-for-time substitution. This resampling procedure is repeated many times to develop IDF estimates at a range of return intervals.

The SST based approach to rainfall frequency analysis using the bias corrected radar rainfall dataset was used to generate IDF estimates for return intervals of up to 1 000 years at a range of spatial and temporal scales. SST based IDF estimates computed using only nontropical storms are compared to estimates computed using all storm types. The results are also compared to conventional rain gauge based IDF estimates and highlight the importance of storm type and spatial and temporal scales in rainfall frequency analysis.

Conventional IDF estimates and SST based estimates agree at long return intervals, supporting the validity of the SST technique. No assumption regarding spatial or temporal rainfall structure and no point-to-area transformation using ARFs is necessary using the SST technique. SST based techniques based on a 10 y bias corrected radar rainfall dataset can reproduce conventional IDF estimates that are generated using significantly longer rain gauge records, highlighting the usefulness of the spatial and temporal information embedded in radar rainfall estimates and its potential for improving hydrologic practice.

We close by reiterating a very important aspect of extreme event analysis, made in Wilson and Foufoula-Georgiou (1990). Critics wrongly question the validity of extrapolating extreme rainfall estimates out to 1 000 y or more based on short rainfall records, due to nonstationarity in the climate system or to incomplete representation of climatic variability. Rainfall and flood frequency analyses, SST-based or otherwise, do not claim to represent the range of events that could occur over a 1 000 y or longer period, but rather to provide, given the observed climate during the period of record, an estimate of the rainfall or flood magnitude associated with the annual probability of exceedence of $\geq 10^{-3}$. The efficacy of any new frequency analysis presented here should be judged in relation to other methods. The results of the SST-based method using weather radar presented here agree well with conventional methods and the method has several previously discussed advantages when extended to flood frequency analysis.

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