Areal Reduction Factors for Two Eastern United States Regions with High Rain-Gauge Density

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Abstract: National Oceanic and Atmospheric Administration Technical Paper-29, published in the late 1950s, remains the most commonly used reference for estimating extreme areal precipitation from station data in the United States. Although a number of alternative methods have been proposed over the intervening years, a rigorous evaluation of the assumptions used in the compilation of TP-29 has not been presented. Overall, TP-29 areal reduction factors provide a conservative means of relating station precipitation extremes to basin average values. For watershed areas less than 1000 km^2, reevaluated areal reduction factors, are in close agreement with the TP-29 values. For larger watersheds, which TP-29 does not address, the areal reduction factors continue to decay exponentially. The areal reduction factors were found to be particularly sensitive to return period and season, with less extreme areal precipitation relative to the corresponding station precipitation at longer return periods and during the warm season. The reevaluated factors exhibit modest differences between study areas in North Carolina and New Jersey. The influence of station density, interpolation method, and topographical rainfall biases appears insignificant.

DOI: 10.1061/(ASCE)1084-0699(2005)10:4(327)

CE Database subject headings: Rainfall intensity; Climatic data; Spatial analysis; Storm runoff; Interpolation; United States.

Introduction

Many hydrological and meteorological applications require knowledge about the spatial and temporal variability of rainfall over an area. The intensity of point precipitation is only applicable for relatively small areas (<4 km^2) (Srikanthan 1995). For larger areas, design storms need to be converted to average areal depths. Areal reduction factors (ARFs) have been commonly used to obtain this correction (e.g., U.S. Weather Bureau 1957). ARFs transform point rainfall depths to an equivalent rainfall depth over an area. It is often assumed that the areal rainfall has the same probability of exceedence as that of the point rainfall. Generically, ARF is defined as the ratio between the average areal depth of precipitation and the average point depth. ARF ranges from $0 < \text{ARF} \leq 1$ and is a function of storm characteristics, such as intensity and duration, as well as basin characteristics, such as size, shape, and geographic location (Asquith and Famiglietti 2000).

Perhaps the most common source of ARF for the United States is Technical Paper 29 (TP-29) (e.g., U.S. Weather Bureau 1957). TP-29 defines an ARF as

$$\text{ARF}_{\text{TP-29}} = \frac{\dfrac{1}{n}\sum_{j=1}^{n}\hat{R}_j}{\dfrac{1}{k}\sum_{i=1}^{k}\left(\dfrac{1}{n}\sum_{j=1}^{n}R_{ij}\right)}, \tag{1}$$

where $\hat{R}_j$ is the annual maximum areal rainfall for year j, R_{ij} is the annual maximum point rainfall for year j at station i, k is the number of stations in the area, and n is the number of years. It is not a requirement that $\hat{R}_j$ and R_{ij}, or that the individual R_{ij}s, occur on the same date. Areal rainfall, of duration t, is simply an unweighted average the t-duration point rainfall at each station.

Due to the relatively short record lengths of precipitation data available at the time of TP-29's compilation (between 5 and 16 years), frequency considerations could not be accurately determined. Given the use of averages, the ARF curves in TP-29 correspond to events with return frequencies of approximately two years. It is generally assumed that these relationships are representative of events with longer return intervals. Likewise, the area-depth relationship is assumed independent of geographic location. Thus, Leclerc and Schaake (1972) express this relationship using a single equation of the form

$$\text{ARF} = 1 - \exp(at^b) + \exp(at^b - cA), \tag{2}$$

where t is event duration (hr) and A is area (km^2). The coefficients a and c as well as the exponent b are empirically fit with $a=-1.1$, $c=2.59\times 10^{-2}$, and $b=0.25$. TP-29 specifies ARF for areas up to 1,100 km^2 and storm durations of 1, 3, 6, and 24 h.

Several similar methodologies for computing ARF have been suggested. In the United Kingdom, ARF is defined as the average (over n years) ratio of the sum of the individual station rainfall totals that comprise the maximum areal rainfall in year j to the sum the annual maxima at each site for year j (Natural Environment Research Council (NERC) 1975). The annual maxima most often occur on different dates than that which corresponds to the

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Note. Discussion open until December 1, 2005. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on April 1, 2004; approved on November 9, 2004. This paper is part of the ***Journal of Hydrologic Engineering***, Vol. 10, No. 4, July 1, 2005. ©ASCE, ISSN 1084-0699/2005/4-327–335/$25.00.

maximum areal rainfall. Although similar to TP-29, the NERC method generally produces smaller ARF, with the largest differences for small areas and short durations (Srikanthan 1995). Bell (1976) developed another popular empirical approach that is similar to the NERC method, but accounts for return period. Stewart (1989) found that ARF values based on the Bell (1976) method were considerably lower than those given by the NERC and TP-29 methods; ARF also decreased with increasing return period.

Other methods for ARF calculation use mathematical models to characterize the variation of rainfall over space and time. The Rodriguez-Iturbe and Mejia (1974) method is based on the spatial correlation of point rainfall and consistently leads to lower estimates of ARF than the other methods (Omolayo 1993; Asquith and Famiglietti 2000). Omolayo (1993) shows ARF to be inversely related to the number of stations used in its computation, as well as return period. Asquith and Famiglietti (2000) also show that return period has a significant influence on ARF, with lower reduction factors for longer return periods. In comparison to TP-29, their approach results in lower ARF. Their ARF curves also exhibit considerable between-city (and seasonal) variation.

Despite a large selection of ARF methodologies, TP-29 remains the the most common source of ARF in the United States (Asquith 1999). In addition to being dated, several assumptions used in TP-29 might be oversimplifications, based on several more recent investigations. With over 40 years of additional precipitation data now available and a substantial increase in the number of high quality precipitation observing stations, TP-29 ARF is reevaluated in this paper. These additional data also allow the assumptions of independence with regard to geographic location and return period to be assessed. The dependence of ARF on spatial averaging method is also investigated, as more computationally intensive methods are now feasible. Finally, we speculate on the future role of ARF in estimating extreme areal precipitation return frequencies, given that the direct computation of extreme areal precipitation return periods is possible for individual basins.

Data

Daily precipitation data from the National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer Network form the basis of this study. The sparse data network for shorter (e.g., hourly) duration accumulation precludes an analysis on a finer temporal scale. The distribution of stations across the country is not uniform, with two notable areas of high station density located in northern New Jersey and southwest North Carolina (DelGreco, personal communication). Both regions possess at least one station per 32.2×32.2 km grid, with many of the grids having three or four stations. These two locations also exhibit climatological and topographic differences allowing an assessment of these geographic differences on ARF.

The New Jersey (NJ) study area was divided into two rectangular basins. The first has a relatively small area of 3,500 km^2, with a relatively high station density of five stations per 1,000 km^2 [Fig. 1(a)]. The second is a larger area (18,000 km^2) with a lower station density of 1 station per 1,000 km^2 [Fig. 1(a)] that corresponds to the North Carolina (NC) basin in size and station density [Fig. 1(b)]. In each case, the basins do not reflect actual watersheds, but rather define areas with maximum rain gauge density. The NJ study area is characterized by relatively flat, homogeneous topography in close proximity to the Atlantic Ocean. The NC area is located in the central Blue Ridge Mountains and accordingly has variable topography.

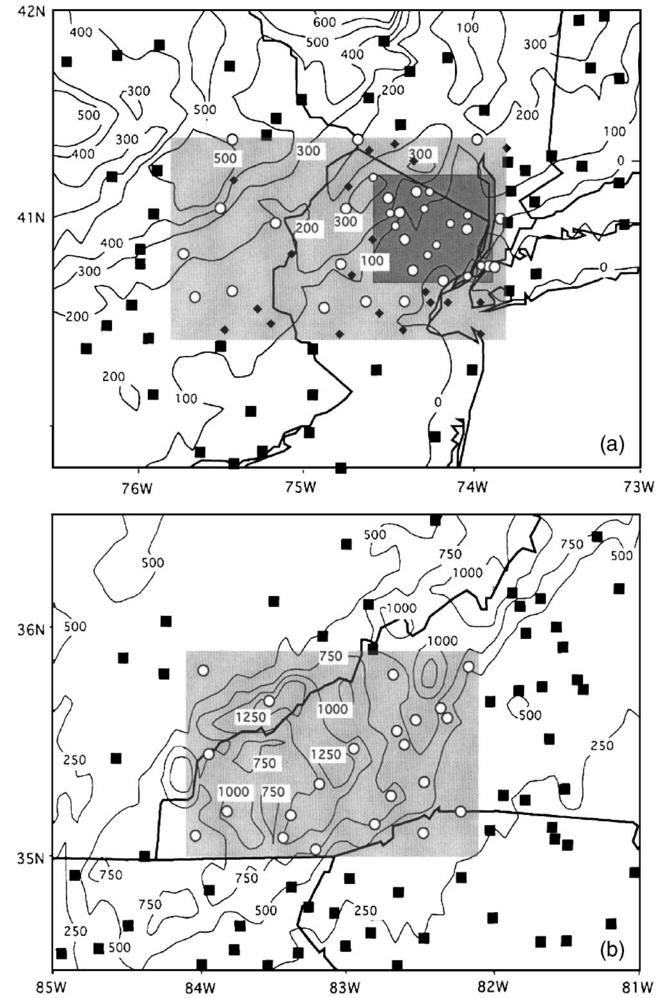

Fig. 1. Map of the (a) New Jersey and (b) North Carolina study areas. Open circles represent stations within each shaded study basin. A small and large basin were used in New Jersey and are shown by differential shading. The smaller circles are stations that were used in the small basin only. Black squares show the locations of stations outside of the basin available for spatial interpolation of precipitation within the basin. The small black diamonds are stations that were available for interpolation of precipitation in the small New Jersey basin. Elevation contours (*m*) and state borders (heavier lines) are also included.

Missing Data

Trace daily precipitation amounts were set to zero. Accumulated precipitation totals (i.e., daily precipitation observations flagged as an accumulation over a >24 h period) were assumed missing, as were data values flagged as invalid in the archived data. Stations included in the analysis were required to have records that at least spanned the period 1949–1995, with no year completely missing during this interval.

Individual missing daily observations have important implications in the analysis of ARF. Such occurrences do not preclude the computation of ARF, provided there is a high degree of confidence that the missing values do not occur on the day of true annual maximum precipitation. The apparent annual maximum (i.e., the maximum in a year with at least one missing daily observation) for each station-year was tested for validity by comparing the dates of the missing values with those of the three largest precipitation events at the closest station. If any of these dates were coincident, the missing-value year was omitted from subsequent analyses. Presumably, nearby stations experience relatively extreme precipitation on coincident days of the year, particularly in the eastern United States. To be included in the analysis, stations were required to have at least 90% of their annual maxima pass the above test.

Testing indicated that using the three largest events provided an appropriate trade-off between correctly flagging an apparent annual maximum, given that the true maximum was missing, and limiting the chance of incorrectly flagging the true maximum. Years with complete data records were identified and the ten largest events in each year were assumed missing. When only the annual maxima at neighboring sites were considered, 36% of apparent annual maxima were correctly identified, using this data set. For three events, this percentage jumped to 76%, with a slight increase to 83% using the five highest events. However, when only the largest event was used, the true maximum was incorrectly flagged 6% of the time, compared to corresponding percentages of 21% and 39% for the three and five highest events, respectively.

Areal Precipitation Calculation

In TP-29, the area of an ersatz watershed containing n gauges is equal to that of n circles, each with a diameter equal to the average station spacing. Since this approach produces reasonable areas only when stations are uniformly spaced, an alternative method based on the rectangular basins shown in Fig. 1 was adopted. These artificial basins were defined to include as many valid stations as possible. Smaller subbasins were then defined in a regular fashion by dividing the large basin into halves, thirds, quarters, etc., until the basin resolution became too small (<2 stations per basin) for the density of the network.

In addition to unweighted averaging of point rainfall depths to calculate mean areal precipitation, Thiessen polygons, and inverse distance weights were also used. Cells with dimensions of approximately 4.8×4.8 km were used for the Thiessen and inverse distance interpolations (Reed and Maidment 1995). Using the inverse distance method, north–south and east–west lines divide the area surrounding each grid point into four quadrants. Within each quadrant, the closest station to the grid point is found and its precipitation total is weighted by the reciprocal of the square of the distance. The estimated precipitation at the grid point was then calculated as the sum of the four inverse distance weighted amounts, normalized by the sum of the weights. Fewer stations (quadrants) were used if the distance to the closest station in a quadrant exceeded 80 km. Regardless of interpolation method, it should be noted that the “true” areal average rainfall will differ from the estimate. This error, which is difficult to quantify, implicitly determines the error bars for the estimated ARF values presented in this paper.

Adjustment for Observation Time

Daily precipitation totals at Cooperative Observer Network sites typically represent accumulation over a 24-hr period ending either during the morning (07:00–08:00), evening (16:00–19:00) or midnight (24:00) (DeGaetano 2000). The variation in observation time introduces inconsistencies when comparing daily precipitation totals and calculating areal precipitation. To address this problem, precipitation totals at each station were redistributed so that the daily totals were consistent with a standard 08:00 local time observation schedule. More than 50% of the station-years corresponded to a 07:00 or 08:00 observation schedule.

Redistribution of daily precipitation totals based on a different observation time required the use of hourly precipitation data from nearby reporting stations. Precipitation events, defined as the total precipitation occurring between consecutive at-least-two-day dry periods were identified. This assured that the second and second-to-last days of the run were rain free, regardless of the observation hour at the daily reporting station. A corresponding event total was calculated for the closest hourly station, as were simulated daily precipitation totals based on an 08:00 observation time (i.e., the 24 hourly values were summed to obtain a daily total). Multiplying the event total for the daily station by the ratio of the daily, simulated total to the event total at the hourly station yields the redistributed precipitation amount at the daily station.

The accuracy of the observation time adjustment procedure was quantified in terms of its ability to redistribute extreme precipitation so that the dates of the adjusted annual maxima are coincident with the dates of the actual annual maxima. In an evaluation of this procedure based on actual observation schedules, 74% of the adjusted annual maxima were identified as having occurred on the correct day at NJ sites; 63% of these values were correctly dated at NC stations. If the redistribution procedure was not used, two-thirds of the annual maxima occurred on a different day, when comparing the occurrences from morning and afternoon observation schedules simulated with hourly data from Newark, NJ and Asheville, NC. When comparing morning and midnight observations more than 80% of the annual maxima occurred on different dates. The redistribution procedure results in a substantial increase in the number of correctly dated annual maxima.

Related to the correct identification of the dates of the annual maxima is the accuracy and bias of the adjusted extreme precipitation series amounts. In all cases, the redistributed rainfall amounts are unbiased with median differences (redistributed$-$actual based on a known observation schedule) equal to zero. In NJ median absolute differences are low ranging from 0.05 cm when all nonzero precipitation totals are considered to 0.58 cm when only those events exceeding the 99.9th percentile are used. This absolute error is only 4% of the extreme totals. In NC, the median absolute errors are somewhat higher, ranging from 0.18 cm for all events to 1.41 cm (12% of the extreme amounts) in events $>$99.9th percentile. It appears that larger distances between daily and hourly stations in NC as well as the more varied topography contribute to this decrease in precipitation redistribution accuracy.

Return Period Computation

In order to explore the functional dependence of ARF on return period, several theoretical probability distributions were empirically evaluated to determine which most accurately estimated extreme areal precipitation. Each of the distributions was fit to the annual extreme series, as well as the partial duration series. For point precipitation, Wilks (1993) shows that the beta-P distribution outperforms eight other probability distributions in representing both observed and extrapolated extreme precipitation, in particular when applied to the partial duration series. Since it was unclear whether the beta-P exhibits similar performance when applied to a series of areal precipitation extremes, this distribution was compared to the Gumbel and log-Pearson type III distributions using the methods of Wilks (1993).

Overall, none of the three candidate distributions provided unbiased extrapolations with high accuracy and low variance, a result similar to that of Wilks (1993). For partial duration series, each distribution fit the less extreme events well. However, all distributions underestimated the most extreme accumulations with the beta-*P* and log-Pearson III exhibiting the least bias. Estimates of the 50-year return period areal rainfall from 1000 bootstrap samples of size 25 years were also biased toward underestimation using all three distributions, with the beta-*P* distribution exhibiting the least bias and sampling variance. Since the beta-*P* fit to the partial duration series displayed relatively low bias, high accuracy, modest variance, and consistent performance for point and areal precipitation, it was adopted for the subsequent analyses.

The general definition of TP-29 ARF, the ratio of areal precipitation to average point precipitation, was retained by substituting the beta-*P* estimated *T*-year return interval areal precipitation amount for the average in the numerator of Eq. (1). Similarly in the denominator, the station-averaged value was replaced with the average of the *k* beta-*P* *T*-year return period point precipitation amounts.

Topographic Adjustment

The Thiessen polygons and inverse distance weighting methods used to compute areal precipitation do not directly account for topography. This can be a problem at high elevations because the network of rain gauges tends to be less dense at higher elevations (Prudhomme and Reed 1999). Since it is likely that simple interpolation procedures do not accurately represent areal precipitation in mountainous areas, a topographical bias adjustment factor was developed as a means of modifying the areal precipitation values given by the interpolation procedures.

To compute this adjustment, precipitation depths were interpolated to the grid point closest to each station, withholding that station's rainfall total. Both inverse distance weighting and Thiessen polygons were used. Adjustments for each point were expressed as the ratio of the observed precipitation at the withheld station to the interpolated amount. This process was repeated for each of the 47 annual maximum areal rainfall events. Median adjustments at each of the *k* stations were then calculated and related to several topographical variables, representing three general topographic features, elevation, slope and distance to the coast. Each potential regression variable was derived from the National Geophysical Data Center 5-min latitude/longitude digital elevation model (ETOPO5). Through an iterative least-squares regression fitting procedure, the relationship that explained the highest percentage of the variability in these median adjustments was identified for each study area. This regression relationship provided a means of incorporating elevation into the Thiessen and inverse distance interpolations used to compute ARF.

In the NC study area (Fig. 1), slopes to the east, southeast, and south account for the greatest percentage of the variability in the interpolation adjustment. For inverse distance weighting, 46% of the variation in the interpolation bias is explained by the degree of slope to the east and south. In each case, the adjustment increases (underestimation increases) with increasing slope, a result physically supported by Konrad (1996). In NJ, slope to the north and west explained 30% of the variability in the adjustments. Interpolated extreme precipitation is overestimated in areas where the north and west slope is positive.

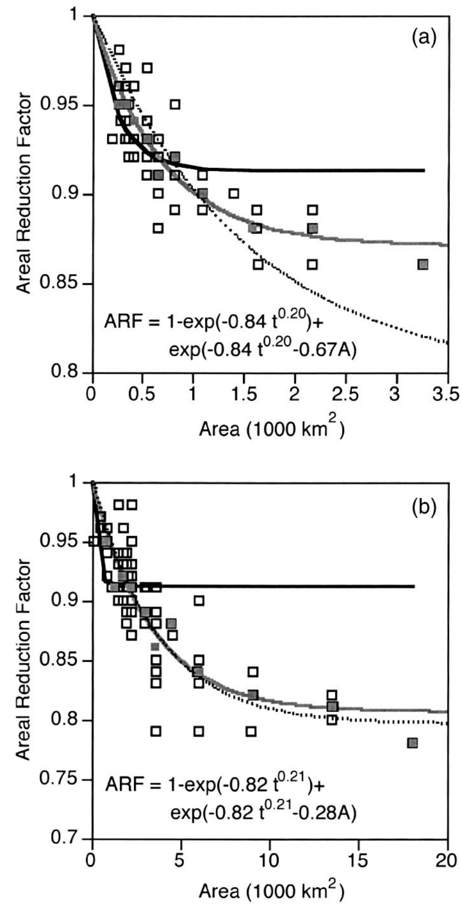

Fig. 2. Two-year return period areal reduction factor-area curves based on TP-29 using Eq. (2) (black solid) and the reevaluated values for (a) New Jersey and (b) North Carolina. The reevaluated curves are fit to a model of the form of Eq. (2) using nonbinned (gray dashed, open boxes) and binned (gray solid, closed boxes) areas. The equation for binned area is included, where $t=24$ h and A has units of 1,000 km^2.

Results

Comparison to TP-29

The reevaluated ARF-area curves presented in subsequent figures are based on "binned" area—the 65 NJ and 80 NC subbasins have been divided into class intervals (or bins) based on area. Since the sub-basins were constructed by systematically partitioning the largest basin, a priori grouping of basins of similar sizes existed. Most bins have a width <100 km^2, but some interval widths used for the larger NC basin are as large as 400 km^2. This procedure is analogous to TP-29 rounding basins to the nearest 300 km^2.

For each bin, average values of ARF were used to plot reevaluated depth-area curves. Binning reduces the relatively large variability in ARF for a given basin area. In NJ, the range of ARF for most basin bins is 0.04, with basin areas of between 500 and 800 km^2 exhibiting the greatest variability [Fig. 2(a)]. ARF for the NC study area is more variable, with ARF ranges of 0.08 to

0.09 in most bins [Fig. 2(b)]. For a given basin bin, the variability of ARF does not appear to be related to bin width. For example, ARF ranges from 0.79 to 0.91 in 10 basins with areas that differ by no more than 33 km^2.

Figure 2 compares the TP-29 ARF-area curves based on Eq. (2) with reevaluated 2-year ARF-area values [Eq. (1)] for the two study areas. The reevaluated ARF-area curves are shown for both unbinned and binned basins and are fit using an exponential, least-squares model in the form of Eq. (2). This allows a direct comparison with the results of Leclerc and Schaake (1972). Based on the binned data, the ARF-area regression exhibits an R^2 of 95% in NJ, whereas 93% of the ARF-area variability is explained in NC. For unbinned data the R^2 values decrease to near 70% in both regions. Because more small basins were evaluated for both study areas, the nonbinned regressions tend to emphasize the smaller basins and thus the relation tends to underestimate ARF for the largest basins (Fig. 2). Binning gives equal weight to each basin size interval, resulting in a regression line that better fits the entire range of basin areas investigated.

For both locations, TP-29 ARF decreases at a slightly faster rate than the reevaluated ARF for basins less than 1,000 km^2 (Fig. 2). However this deviation is modest at best, particularly considering that almost 40 years of additional data have been incorporated. The reevaluation shows that ARF continues to exponentially decay beyond the 1,000 km^2 TP-29 limit, assuming its lowest value for the largest basin in each study area. For NJ, this translates into a reduction factor of 0.81 at 3,500 km^2. ARF is 0.80 at 20,000 km^2 in NC. TP-29 ARF provides a conservative ARF for areas larger than 1,000 km^2.

ARF based on inverse distance and Thiessen weights are similar for both study areas (not shown). For the NC study area, the unweighted average interpolation used in TP-29, however, gives a larger ARF for a given area greater than about 4,000 km^2. This bias amounts to a 0.05 difference in ARF at 20,000 km^2. For the large NJ study area, the difference is less than 0.01 at 20,000 km^2.

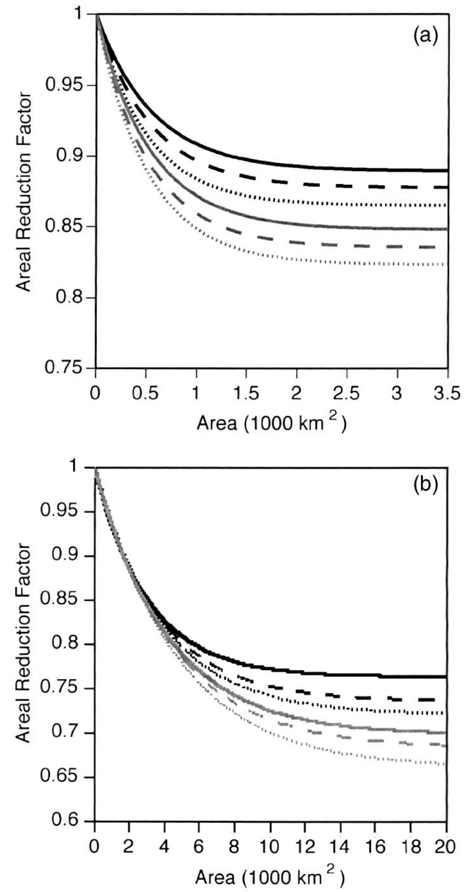

Fig. 3. Reevaluated areal reduction factor-area curves for the 2-year (black solid); 5-year (black dashed); 10-year (black dotted); 25-year (gray solid); 50-year (gray dashed), and 100-year (gray dotted) return period for the (a) New Jersey and (b) North Carolina study area. Areal interpolation of precipitation is based on Thiessen weights.

Return Period comparison

Figure 3 shows NJ and NC reevaluated ARF-area curves based on Thiessen weights for 2-, 5-, 10-, 25-, 50-, and 100-year return periods. The other two spatial interpolation methods yield analogous results. Each curve has an R^2 of at least 91%. The coefficients and exponents necessary to express these curves in the form of Eq. (2) are given in Table 1. There is a clear separation of the ARF-area curves, with longer return periods associated with lower ARFs. For NJ, this dependence of ARF on return period is small for basin area less than approximately 250 km^2, but becomes larger for more expansive basins. At 3,500 km^2, the average 100-year point precipitation needs to be reduced by 7% more than the average 2-year point precipitation (ARF=0.82 versus 0.89). In NC, the dependence of ARF on return period is not as large. For basins smaller than 2,000 km^2, there is little difference in ARF with return period. For an area of 3,500 km^2, the difference between the 2- and 100-year ARF is less than 2%, compared to the 7% difference in NJ. For the maximum basin area (20,000 km^2), the difference across the range of return periods is nearly 10%.

To assess the statistical significance of return period on the ARF-area relationship, a permutation test was used (Wilks, 1995). A test statistic was defined as the difference between ARF for two different return periods (T_1 and T_2 with $T_1 < T_2$) for a specific basin bin. The null hypothesis (H_o) that ARF does not depend on return period implies that this difference is zero. Since other ARF studies (Omolaya 1993; Asquith and Famiglietti 2000; Bell 1976) have found an inverse relationship between ARF and return period (for a constant area and storm duration), a one-tailed test [H_A: ARF (T_1) > ARF (T_2)] is used. The null hypothesis was tested on a bin-by-bin basis by pooling ARF (T_1) and ARF (T_2) (i.e., creating a combined sample of the T_1- and T_2-year ARFs). The largest bin was excluded from the procedure since it consists of a single basin. ARF values were then randomly selected without replacement from this combined sample, such that the number

Table 1. Coefficients and Exponents Necessary to Express the Areal Reduction Factor Curves in Fig. 3 in the Form of Eq. (2). Each Value is Based on an Event Duration $t=24$ hr and Reflects a Basin Area A, with Units of 1,000 km^2.

	New Jersey			North Carolina		
Return interval	*a*	*b*	*c*	*a*	*b*	*c*
2-year	−0.99	0.25	1.75	−0.79	0.19	0.33
5-year	−0.97	0.24	1.85	−0.75	0.18	0.28
10-year	−0.94	0.24	1.96	−0.73	0.18	0.26
25-year	−0.91	0.23	1.85	−0.69	0.17	0.24
50-year	−0.89	0.22	1.92	−0.67	0.17	0.23
100-year	−0.87	0.22	1.94	−0.64	0.17	0.22

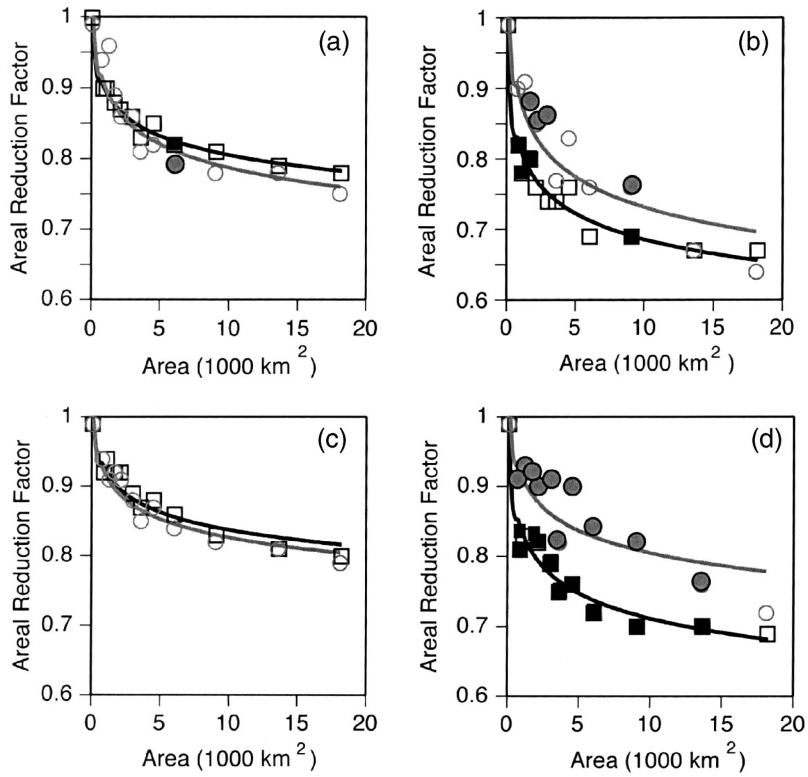

Fig. 4. Reevaluated areal reduction factor area curves comparing the large New Jersey study area (black, squares) with North Carolina (gray, circles) based on areal precipitation calculated using Theissen weights for the (a) 2-year and (b) 100-year return periods and unweighted averages for the (c) 2-year and (d) 100-year return periods. Basin bins that are significant at the 10% level are indicated by solid symbols.

of basins comprising the histogram bins was preserved. For example, 14 NJ basins comprise the 326–365 km^2 bin. Therefore, the set of pooled ARF values for this bin contained 28 elements, 14 for T_1 and another 14 for T_2. These 28 values were then randomly assigned to two 14-value groups. This procedure was then repeated 1,000 times, yielding a null distribution of 1,000 artificial test statistics.

Since subbasins were defined by partitioning the largest basin, each smaller basin is contained within a larger basin and therefore the hierarchy of basins is not independent. As the same stations represent the subbasins, there may be an underestimation of the variability of ARF between the different basin area bins. The resampling test does not account for this dependence, which potentially increases the collective (across all area bins) chance of a Type I error. Thus, the results of the resampling procedure should be viewed with this caveat in mind.

For the NJ study area, 70% of the bin-specific 2-year return period ARFs are significantly ($\alpha=0.05$) different when compared to those for 100-, 50-, and 25-year return periods. As the difference in return period decreases, few pairs show significant ARF differences. For example, there is no significant difference between the 50- and 100-year ARF values. This resampling test was also run on the NC study area. Only eight differences were found to be statistically significant, which is consistent with the narrower spread of the ARF-area curves in Fig. 3. These were confined to the 13,577–13,615 km^2 bin and tended to be associated with the 2-year return period.

Dependence on Geographic Location

The differences in return period and interpolation method sensitivity between the two regions suggest that the original TP-29 assumption of geographically invariant ARF relations may be in error. The geographical variation of ARFs was tested for statistical significance using a procedure analogous to that used to test the dependence of ARF on return period. Instead of pooling a bin-specific ARF for two different return periods from a single study area, ARFs for the same return period for corresponding bins in NJ and NC were pooled. However, because no prior knowledge exists to suggest ARF for one study area was larger (or smaller) than that for the other study area, a two-tailed test was used. Although NC has six more subbasins than the large NJ study area, the bin widths used to describe the basins are identical. The resampling procedure accounted for this difference in basin number.

Figure 4 shows ARF-area curves comparing the large NJ basin with the NC basin for the 2- and 100-year return periods using Thiessen weights and unweighted averages. Based on Thiessen weights, ARF for the NC basins generally exceeds that for NJ [Fig. 4(b)]. Four of these differences are significant ($\alpha=0.05$) based on the 100-year return period. The maximum difference between the two study areas is associated with small basins for the 100-year return period, where ARF=0.88 in NC and ARF=0.80 in NJ for an area of 1,700 km^2. This relationship reverses (NJ ARF>NC ARF) for larger basins, when the 2-year and other less extreme return periods are considered [Fig. 4(a)]. However, none of these bin-specific ARF differences is statistically significant.

Based on unweighted averages [Figs. 4(c and d)], NC ARF also exceeds that for NJ for all return periods [except the 2-year values shown in Fig. 4(c)] and basin sizes. The two locations differ the most at longer return periods, where ARF in NC is up to

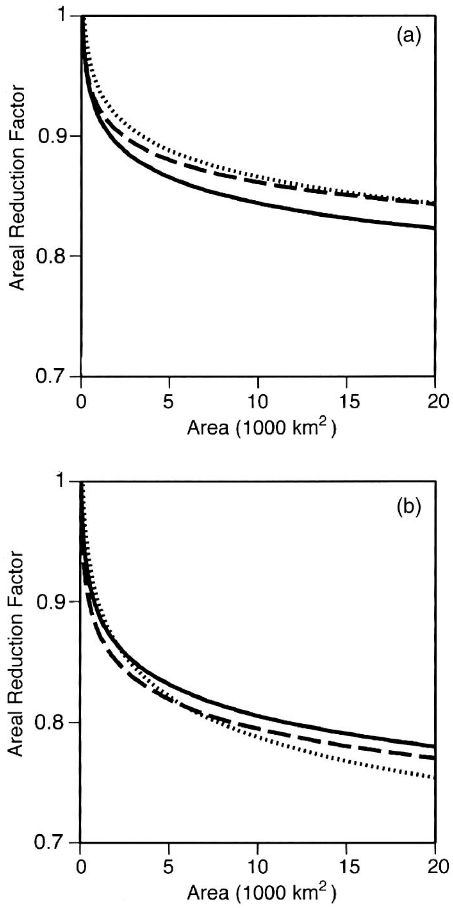

Fig. 5. Two-year return period reevaluated areal reduction factor-area curves based on unweighted averages for low (dotted), medium (solid) and high (dashed) rain gauge densities for basins in (a) New Jersey and (b) North Carolina.

10% larger for all areas. More than 80% of the bin-specific ARF differences are statistically significant for the 100-year return period.

It should be noted at this point that the regression-based topographic adjustments had little effect on the ARF curves in either region. The maximum difference between adjusted and unadjusted reduction factors in both NJ and NC was approximately 1%. Although substantial topographic adjustments were indicated for individual grids within the basins, over all grids, the net adjustment was approximately zero.

Influence of Station Density

To allow a comparison of ARF based on differences in station density, precipitation data for a recent 5-year period (1996–2000) were used to compute short-return-period ARF curves. Using this abbreviated period of record permitted a higher station density to be examined, than was previously used. Stations were selected as in the original data set. In the NJ basin, a high density network of 43 stations was used, 38 from the Cooperative Observer Network and 5 part of the New Jersey Home Network (NJHN). NJHN data were acquired via the Internet at http://climate.rutgers.edu/stateclim/. The moderate and low density NJ networks consisted of 22 and 11 stations, respectively, which subjectively maintained adequate spatial coverage of the largest basin. For NC, the high-, moderate-, and low-density networks consisted of 33, 20, and 10 Cooperative Network stations, respectively.

The ARF-area relationships for these three gauge density networks is shown in Fig. 5. Areal precipitation was computed based on unweighted averages given that this interpolation method maximized the geographical differences. In both regions the difference between ARF is small. In NJ, ARF was also computed omitting rainfall associated with Hurricane Floyd (September 16, 1999). Floyd produced widespread extreme rainfall, and it was assumed that this might have influenced the comparison of ARF based on different station densities. Although the omission of Floyd lowered ARF, the reduction in ARF was similar between the three network densities. It appears that density of observations (within the evaluated range) does not have a substantial effect of the ARF-area relationship.

Seasonal Variation of Areal Reduction Factor

The seasonal variations in ARF in both eastern U.S. regions were substantial, with warm season ARF decaying at a quicker rate than the cold season ARF (Fig. 6). Here, the warm season is defined from April to September, and the cold season from October to March. These definitions generally segregate the primary precipitation formation mechanisms in each region. In NC, warm season precipitation occurs primarily on the mesoscale and is characterized by convective instability, with orographic influences playing a limited role in heavy rainfall (Konrad 1996, 1997). Conversely, cold season precipitation tends to be dominated by frontal overrunning, synoptic-scale systems and orographic uplift (Konrad 1996). The seasonal pattern of rainfall is similar in NJ (Landin and Bosart 1985; Scott and Shulman 1979).

An exception to this categorization is tropical systems, as the conventional Atlantic hurricane season spans these two groups of months. Moreover, most hurricanes are classified as warm season events, despite their propensity to produce widespread areas of heavy rainfall. Nonetheless, the small number of tropical events precludes the formation of a third ARF season. Including tropical storms with other warm season events will presumably moderate any differences in ARF between the seasons.

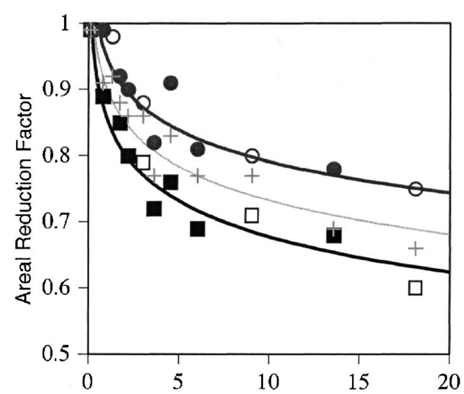

Fig. 6. Areal reduction factor curves comparing warm season areal reduction factor (ARF) (black, squares) with cold season ARF (dark gray, circles) for the 50-year return period using Thiessen weights in North Carolina. Bin-specific seasonal differences that are significant at the 10% level are indicated with solid symbols. The annual ARF curve is also included (light gray, crosses).

To quantify the statistical significance of seasonal differences in ARF, a resampling procedure was again invoked. A one-tailed test is used given the seasonal influences described by Asquith and Famiglietti (2000). For NC, at least 50% of the bin intervals show significant seasonal differences in ARF for each of the six return periods. As expected cold season ARF tends to be higher and decays with area at a slower rate than that for the warm season ARF. Stronger results are observed in NJ, where at least 70% of the bin-specific seasonal differences are significant. Interpolation method has little influence on the seasonal differences.

These seasonal differences raise two important issues. First, in areas outside the eastern United States, these seasonal differences can translate to geographic ARF differences. The contrast between mesoscale summer and synoptic scale winter precipitation mechanisms in the East may be analogous to predominant (without regard to season) synoptic-scale precipitation mechanisms in regions like the Pacific Northwest and convective precipitation mechanisms in the southern Plains or Florida.

Second, although virtually all uses of design storm data rely on an annual probability (Asquith 1999), there are some applications in which the seasonal dependence of ARF could be exploited. For example, if winter and early spring reservoir management is primarily concerned with flood control, the use of cold season ARF in operation protocols may be prudent. Conversely, during the summer and early fall maximizing the available water supply might warrant the use a lower warm season ARF value.

Summary and Conclusions

Despite a considerable increase in the amount of data available (both in terms of number of years and spatial station density), reevaluated ARF values were in general agreement with those published in TP-29 for watershed areas less than 1,000 km^2. For larger watersheds, 2-year return period ARF continues to decay exponentially, reaching values of 0.80 at 20,000 km^2 in the North Carolina study area and 0.88 at 3,500 km^2 in the northern NJ basin.

Despite this similarity, subsequent analyses revealed several important conclusions:

(1) There is a statistically significant variation in ARF with return period, with higher return periods associated with lower ARF values. This agrees with the results of several other studies (Bell 1976; Omolaya 1993; Asquith and Famiglietti 2000) that evaluated ARFs computed using methods different from TP-29.

(2) Warm season (April–September) ARF decays at a faster rate than cold season (October–March) ARF. This is attributed to the season-dependent precipitation generating mechanisms and the associated spatial variability of rainfall.

(3) Only modest differences in ARF are noted between study areas in North Carolina and NJ. This qualitatively agrees with TP-29 (U.S. Weather Bureau 1957) and Omolayo (1993), who concludes that the U.S. one-day ARF can be satisfactorily transposed to Australian capital cities for areas between 200 and 500 km^2. Differences in the variability of ARF for a given region (with respect to the interpolation method used and return period) are noted. Based on the seasonal analysis, there are indications that larger geographic differences in ARF may exist between regions with different primary precipitation mechanisms. A more rigorous evaluation of regional differences could detect specific regional ARF values.

Table 2. Comparison of the 1996–2000 Areal Extreme Precipitation (cm) Calculated Based on the Reevaluated Areal Reduction Factor Curves in Fig. 3 and the Direct Fit of a Beta-*P* Distribution to the Annual Maximum Areally Interpolated Gauge Data. Results are Shown for an 18,000 km^2 Basin in Each Study Area.

	Return period					
	2-year		5-year		10-year	
Area	Fig. 5	Direct beta-*P*	Fig. 5	Direct beta-*P*	Fig. 5	Direct beta-*P*
New Jersey	7.2	7.1	9.5	10.8	11.8	14.8
North Carolina	6.0	6.1	6.8	6.9	7.5	7.7

(4) Spatial interpolations based on Thiessen weights or inverse distance weighted averages intuitively appear to be better alternatives to the simple unweighted averages used in TP-29, given better agreement between these methods. Nonetheless, this similarity does not assure the accuracy of the interpolated areal estimates.

(5) The spatial density of observing sites seems to have little effect on ARF within the range of station densities tested (one to four stations per 1,800 km^2).

Although the concept of ARFs provides a simple and convenient way of estimating *T*-year areal precipitation extremes based on station data, it could be argued that today's fast and affordable computer power facilitates the direct calculation of the *T*-year areal precipitation extremes for specific basins. In fact, the computation of these extremes was required to calculate the ARF values presented in this study. Whereas this direct approach may be warranted for specific basins, nationally the lack of data sets with the necessary spatial and temporal resolution precludes the widespread direct computation *T*-year areal precipitation extremes for arbitrary basins. ARFs continue to provide guidance for catchments with insufficient spatial rain gauge density or inadequate historical precipitation data, allow for spatial smoothing of sampling variations, and facilitate the development of national or regional engineering design guidelines. Furthermore, the computation of areal precipitation extremes for individual basins requires the arduous task of identifying and adjusting for inhomogeneities in the precipitation record. Provided these discontinuities are addressed in the computation of ARF, subsequent application of the factors is generally resilient to these nonclimatic factors.

Using data for the period 1996–2000, Table 2 compares areal precipitation extremes computed directly with those based on the reevaluated ARF curves presented in this study. As the ARF curves are based on data from an earlier period (1949–1995), using this limited data record provides an independent data sample for comparing the two methodologies at a similar set of stations.

In both regions, the precipitation extremes are similar, with larger differences associated with longer return periods (Table 2). For the 2-year return period the ARF-based extreme is 0.1 cm less than that based on the direct estimate in both NC and NJ. This difference increases to 0.2 cm for the 10-year return period in NC, with a larger 3.0 cm difference noted for NJ. This is primarily because the limited 5-year data record is influenced by Hurricane Floyd. Nonetheless, this short subset of years suggests that the ARF methodology provides a simple means of estimating areal precipitation extremes.

Acknowledgments

This work was supported by NOAA Grant No. NA17RJ1222. It represents a portion of the principal author's M.S. thesis, and thus thanks are extended to Dr. Dan Wilks and Dr. Bill Philpot for their guidance, time, and suggestions as graduate committee members.

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