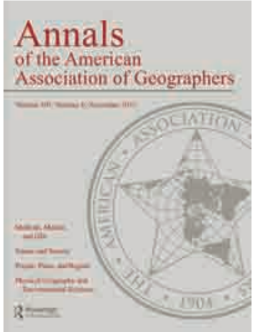

Annals of the American Association of Geographers

ISSN: 2469-4452 (Print) 2469-4460 (Online) Journal homepage: www.tandfonline.com/journals/raag21

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Estimates of Extreme Precipitation Frequency Derived from Spatially Dense Rain Gauge Observations: A Case Study of Two Urban Areas in the Colorado Front Range Region

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Precipitation design values, which describe precipitation extremes expected within a specified time period, provide critical guidance for public policy and the design of hydrologic infrastructure. Unfortunately, conventional design value calculations are limited by a major assumption: They treat precipitation as a point-based phenomenon, measured at spatially isolated gauges. We argue that because precipitation occurs over areas, design value calculations should be based on an areal conception of precipitation. Using spatially dense Community Collaborative Rain, Hail and Snow (CoCoRaHS) Network data in two Colorado cities (Fort Collins and Boulder), we develop a "hyperlocal" design value calculation in which nearby observations within a representative precipitation region (RPR) "compete" to capture a single twenty-four-hour maximum. We find that design values for shorter return periods (one to fifty years) derived from just ten years of hyperlocal data, which we express as probabilistic distributions rather than single values, typically exceed those calculated using single-point records of 100 years or more. Hyperlocal design values for longer return periods (more than fifty years) are generally smaller than those calculated from the single-point data due to the temporally limited CoCoRaHS record. We also find that the dependence of design values on RPR size contrasts between Fort Collins and Boulder, as design values grow markedly larger as the RPR size increases in Fort Collins but not in Boulder. We attribute this behavior to the Boulder Global Historical Climatology Network station's location in a topographically favored area for precipitation and propose that future studies evaluate the hyperlocal design value method in a variety of geographic settings. *Key Words: city planning, extreme value statistics, flooding, precipitation design values, precipitation return periods*.

降水设计值描绘在特定期间的预期极端降水, 提供了公共政策及水文基础建设设计的关键指引。但不幸的是, 传统的设计值计算, 受限于以下主要预设: 降水被当作以点为基础的现象, 并在空间隔离的范围上进行测量。我们主张, 由于降水发生在全部范围中, 因此设计值的估算应该根据降水的面积概念。运用科罗拉多两座城市 (科林斯堡与波德) 在空间上密集的社区合作式雨、冰雹及雪 (CoCoRaHS) 的网络数据, 我们建立 "在地水文" 设计值估算, 其中再现降水区域 (RPR) 中的各个邻近观察相互 "竞争", 以捕捉二十四小时的最大值。我们发现, 一般而言, 从仅为十年的在地水文数据衍生出的较短重现期 (一至五十年)——我们将之表达为可能的分佈而非单一值——超过运用一百年或更久期间的单点记录所估计的值, 因为 CoCoRaHS 之纪录在时间上有所限制。我们同时发现, 科林斯堡与波德在 RPR 规模与设计值的相依上相互矛盾, 在科林斯堡, 设计值随着 RPR 规模的增加而明显变大, 但在波德则非如此。我们将此一现象归因于波德的全球历史气象水文网络站, 在地理上设置于偏向降水的地区, 并提出未来的研究应在多样化的地理情境中评估在地水文的设计值。 *关键词: 关键词: 城市规划, 极端值统计, 洪泛, 降水设计值, 降水重现期。*

Los valores de la precipitación prevista, que describen los extremos de precipitación esperados dentro de un período de tiempo específico, proporcionan una guía crítica para las políticas públicas y para el diseño de infraestructura hidrológica. Infortunadamente, los cálculos convencionales del valor previsto están limitados por una importante suposición: Aquellos consideran la precipitación como un fenómeno de base puntual, medido en calibradores espacialmente aislados. Nosotros argumentamos que en razón de que la precipitación ocurre sobre áreas, los cálculos del valor previsto deben basarse también en una concepción areal de la precipitación. Mediante el uso de datos espacialmente densos de la Red Colaborativa Comunitaria sobre Lluvia, Granizo y Nieve (CoCoRaHS, por el acrónimo en inglés) para dos ciudades de Colorado (Fort Collins y Boulder), desarrollamos un cálculo "hiperlocal" del valor previsto en el que observaciones cercanas dentro de una región de

Annals of the American Association of Geographers, 107(6) 2017, pp. 1499–1518 © 2017 by American Association of Geographers
Initial submission, February 2016; revised submission, October 2016; final acceptance, January 2017
Published by Taylor & Francis, LLC.

precipitación representativa (RPR) "compiten" en captar un máximo sencillo de veinticuatro horas. Encontramos que los valores previstos para períodos de información más cortos (entre uno y cincuenta años) derivados de apenas diez años de datos hiperlocales, que nosotros expresamos más como distribuciones probabilísticas que valores individuales, típicamente exceden a aquellos que se calculan usando registros para puntos individuales de cien años o más. Los valores previstos hiperlocales para períodos de información más largos (más de cincuenta años) son generalmente más pequeños que los que se calculan a partir de datos de puntos individuales debido al registro CoCoRaHS temporalmente limitado. Encontramos también que la dependencia de los valores previstos en el tamaño de la RPR contrasta entre Fort Collins y Boulder por cuanto los valores previstos crecen de manera ostensiblemente mayor a medida que el tamaño de la RPR se incrementa en Fort Collins, pero no en Boulder. Atribuimos este comportamiento a la localización de la estación de la Red de Climatología Histórica Global de Boulder en un área topográficamente favorable a la precipitación, y proponemos que estudios futuros evalúen el método del valor previsto hiperlocal en una variedad de escenarios geográficos. *Palabras clave: planificación urbana, estadísticas de valores extremos, inundación, valores previstos de precipitación, períodos de información de la precipitación.*

Cities throughout the United States have experienced an alarming number of deadly and costly floods in recent years. Atlanta in September 2009; Nashville in May 2010; Boulder in September 2013; and Oklahoma City, Austin, and Houston in May 2015 are just a few examples of major urban flooding events that have occurred during the past decade. These numerous high-profile floods, along with countless other "minor" or more localized instances of flooding, have contributed to a well-documented, decades-long increasing trend in the financial costs of flooding (Pielke and Downton 2000; Ashley and Ashley 2008; Changnon 2008; Kundzewicz et al. 2014). Flooding is the costliest type of natural disaster in terms of human casualties and property damage (Gourley et al. 2012; Brody 2014).

Most government policies, infrastructure design requirements, and other measures taken to mitigate flooding hazards are based on the "return period" concept—the period of time that can be expected to elapse between precipitation or flooding events of a given magnitude at a certain location (Salas et al. 2012). Reliable return period estimates of precipitation extremes are thus foundational to a broad range of societal interests. Unfortunately, there remain significant and unavoidable uncertainties in the calculation of expected return periods that are a consequence of the incomplete spatial and temporal coverage of the rain gauge networks used to observe precipitation amounts (Klemeš 2000a, 2000b). These gaps in precipitation sampling have led to the use of statistical techniques to interpolate and extrapolate precipitation estimates (or design values) to lengths of time greater than those covered by historical observations (e.g., 500, 1,000, and 10,000 years; Katz, Parlange, and Naveau 2002; Koutsoyiannis 2004). Recent design value estimates incorporate the latest advances in extreme value statistics, including a "regionalization" approach that combines precipitation observations across regions with relatively homogenous hydroclimatic regimes (Hosking and Wallis 2005; Perica et al. 2013). Despite their relative statistical sophistication compared to earlier calculations, however, the recent updates to official precipitation design values are conceptually equivalent to earlier estimates in that they treat precipitation as a point-based phenomenon.

A growing body of evidence suggests that the point-based conceptualization of extreme precipitation underlying official precipitation design values might result in systematic underestimation of the magnitude and frequency of hydrological extremes (Blumenfeld and Skaggs 2011). This evidence includes numerous recent precipitation events with amounts exceeding 100- to 1,000-year return period thresholds over large areas (see National Weather Service Hydrometeorological Design Studies Center [2017] exceedance probability analyses). As day-to-day experience suggests and numerous studies confirm (Changnon and Vogel 1981; Winkler 1988; Huff 1994; Villarini, Smith, and Vecchi 2013; Dzotsi et al. 2014; Zolina et al. 2014; Yang et al. 2016), accumulated precipitation amounts often vary dramatically across fine spatial scales (on the order of tens of kilometers or less), especially during warm-season convective precipitation events. Because the most intense portion of a storm occurring over a given area (e.g., a municipal government's jurisdiction or a watershed contributing runoff to a reservoir) will likely not be sampled by a single rain gauge, the resulting point-based design value estimates will be unrealistically small for the area as a whole. Even assuming a perfect

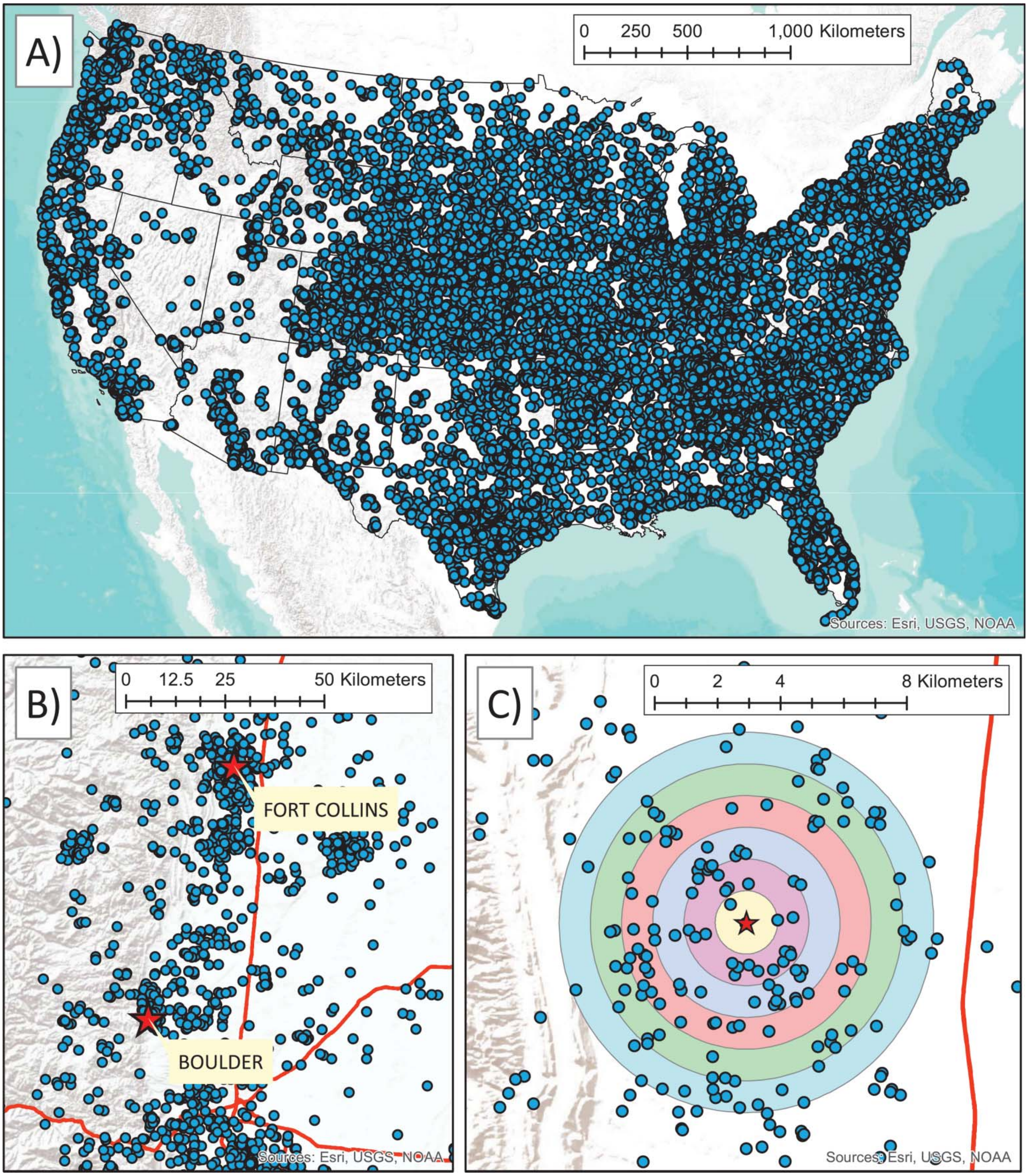

Figure 1. The locations of CoCoRaHS stations across (A) the continental United States, (B) the Colorado Front Range region, and (C) the immediate Fort Collins, Colorado, area. In (B), the two cities for which extreme rainfalls were examined in this study are marked with a red star. In (C), the 1–6-km radii are depicted by concentric circles centered on the Fort Collins GHCN station (red star). CoCoRaHS = Community Collaborative Rain, Hail and Snow Network; GHCN = Global Historical Climatology Network. (Color figure available online.)

statistical model, the (for example) 100-year return period event as calculated using traditional point-based methods will occur somewhere in a localized area (e.g., a city or a watershed) more than once, and likely a number of times, during a given 100-year period.

Therefore, in this article we follow Blumenfeld and Skaggs (2011) in arguing that because extreme precipitation and its impacts occur across areas, rather than at discrete points, it is advantageous to conceptualize and sample extreme precipitation events as spatially

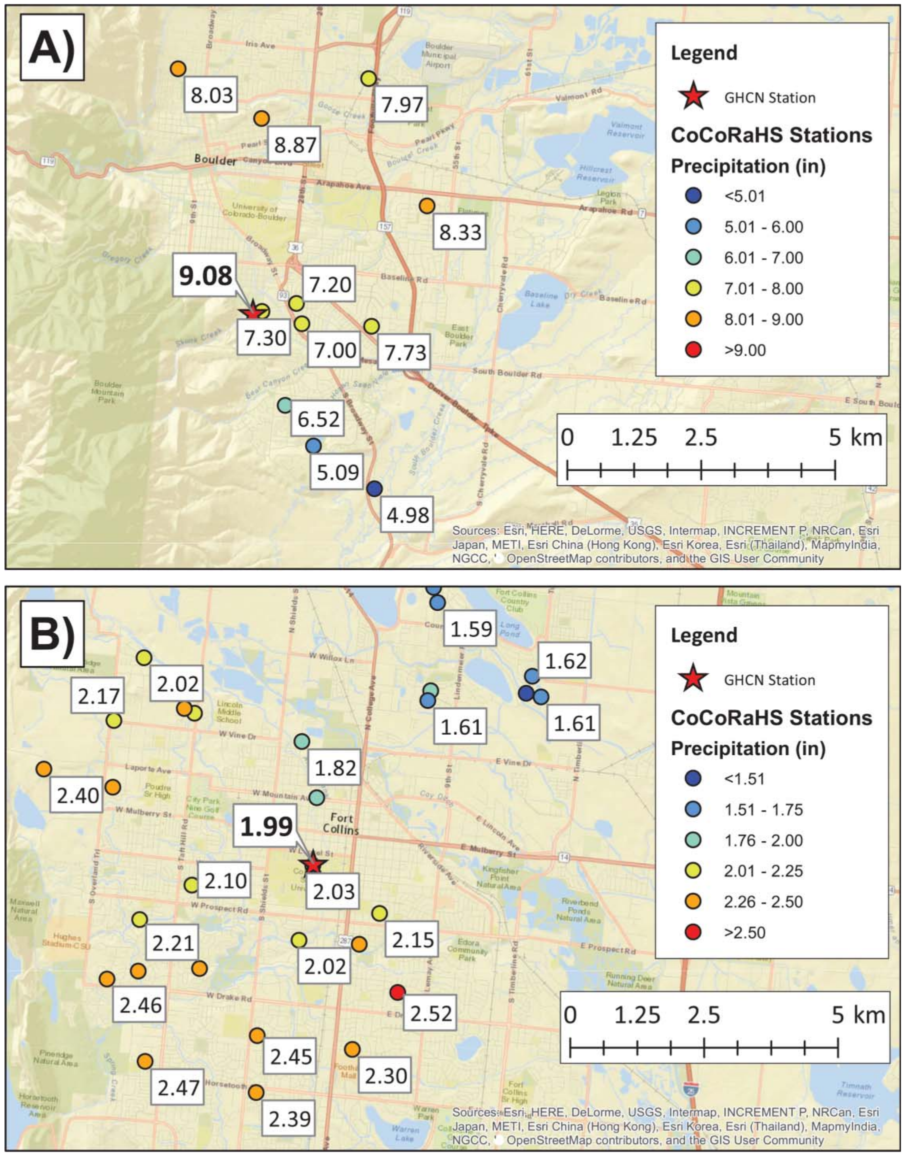

Figure 2. An example of local rainfall variations detected by the CoCoRaHS network in (A) Boulder and (B) Fort Collins, Colorado. In some cases, the twenty-four-hour precipitation total detected by the GHCN station is the greatest measured within a 6-km radius (A), but it is common for the greatest precipitation totals to be spatially displaced from the GHCN site (B). The twenty-four-hour totals shown here were measured on 12 September 2013, although not all stations recorded the same twenty-four-hour period. More details regarding the observation period offset can be found in the Methods section. CoCoRaHS = Community Collaborative Rain, Hail and Snow Network; GHCN = Global Historical Climatology Network. (Color figure available online.)

extensive phenomena when calculating their associated return periods. Moreover, we contend that an area-based assessment of vulnerability to extreme precipitation—rather than a single point-based design value—is more useful to stakeholders (e.g., water managers, stormwater infrastructure designers, city maintenance departments) whose objects of responsibility (e.g., reservoirs, sewer systems, and urban street networks) are spatially extensive. An area-based conception of precipitation extremes is also more in tune with the lived experience of most people, who experience precipitation and flooding while moving around in space and are affected by weather events that occur outside their immediate vicinity.

The discontinuity of spatial orders (i.e., one-dimensional observations of a two-dimensional phenomenon) poses a special challenge for geographers. In this study, we prioritize the spatial density of observations over the temporal length of the recording period. It is hypothesized that spatially dense distributions of rainfall observed during a relatively short recording period (e.g., ten years or less) can provide greater insight into

Table 1. Summary of Global Historical Climatology Network station observation periods

Station name	Station ID	Period of record
Boulder	GHCND:USC00050848	1 October 1893–present
Fort Collins	GHCND:USC00053005	1 January 1893–present

precipitation extremes than sparse point-based observations recorded over a much greater period of time (e.g., several decades or longer). Previous studies support this hypothesis (Willmott, Robeson, and Janis 1996; Blumenfeld and Skaggs 2011), having found that precipitation extremes are more accurately captured by increasing the spatial density of rain gauges than by increasing the record length of a single station. We demonstrate this approach by employing spatially dense precipitation observations from the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS; Figure 1A; Cifelli et al. 2005) to calculate design values for two urban areas in the Colorado Front Range region: Boulder and Fort Collins (Figure 1B).

Study Area

The Colorado Front Range was selected as the testbed for this new approach given the area's large number of CoCoRaHS stations, as well as the immediate proximity of these stations to several Global Historical Climatology Network (GHCN) sites with record lengths of at least several decades (Figure 1B, 1C). In fact, this area possesses the highest concentration of CoCoRaHS stations in the United States, with most other high-density locations situated in university towns or large cities. The spatial pattern of CoCoRaHS stations in Boulder reflects the influence of the rugged, mountainous topography west of the GHCN site with nearly all nearby CoCoRaHS sites located to the east in flatter terrain (Figure 2A). In contrast, the CoCoRaHS sites in Fort Collins relatively evenly surround the GHCN site on all sides (Figures 1C, 2B). Heterogeneities in CoCoRaHS distribution in this and other regions are likely unavoidable due to differences in topography, residential housing density, and socioeconomic factors. Although the Colorado Front Range was selected for this proof-of-concept study, our method should not be viewed as limited to this geographic setting. Other locations with high CoCoRaHS station densities include Las Cruces, New Mexico; Albuquerque, New Mexico; Cheyenne, Wyoming; Huntsville, Alabama; Hays, Kansas; Eugene, Oregon; Tucson, Arizona; and Norman, Oklahoma. As the CoCoRaHS network continues to expand, the list of such examples will only grow larger.

Data

Two daily precipitation observation data sets were obtained from the National Centers for Environmental Information (NCEI) Climate Data Online (CDO)

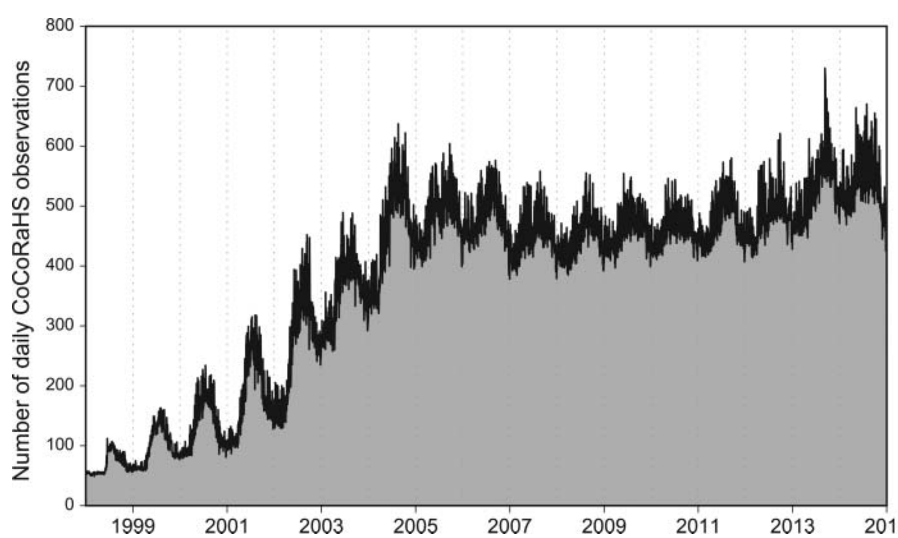

Figure 3. Frequency of observations from CoCoRaHS stations in the Colorado Front Range region. The number of measurements increases rapidly between 2001 and 2005 and stabilizes between 2005 and 2015. CoCoRaHS = Community Collaborative Rain, Hail and Snow Network.

portal. The first, from stations belonging to the GHCN (Menne, Durre, Korzeniewski, et al. 2012), were accessed for their entire period of record (Table 1). GHCN stations receive intensive quality control (Menne, Durre, Vose, et al. 2012) and are frequently used in climatological studies. The GHCN is a publicly accessible archive.

In contrast, most high-density rain gauge networks used to study precipitation variability are not publicly accessible (e.g., X. Wang et al. 2008; Habib, Larson, and Graschel 2009; Dzotsi et al. 2014; Rafieeinasab et al. 2015). Fortunately, CoCoRaHS is a recently developed, open-access archive that, in certain areas with a large concentration of volunteer observers, offers the rain gauge density necessary for calculating area-based precipitation design values. Established in 1998 following a highly localized flash flood in Fort Collins, Colorado, which was not adequately observed by traditional gauge networks, CoCoRaHS is now the largest daily precipitation reporting network in the United States (Muller et al. 2015; Figure 1A). The CoCoRaHS network consists of volunteer observers who report precipitation totals once daily. The temporal record of the CoCoRaHS network is relatively short (ten to fifteen years for most areas) compared to the thirty-year-or-greater station records common to the GHCN. CoCoRaHS observations were accessed between 2005 and 2014 based on the temporal trend in observation frequency of all stations in the Colorado Front Range region, with 2005 marking the beginning of a roughly stable observation frequency period (Figure 3).

The greater CoCoRaHS station density compared to the GHCN network offers a unique opportunity to capture the mesoscale variations in precipitation intensity and better characterize precipitation maximums over a given area. Although CoCoRaHS represents a relatively new observational data set, its potential benefit to climatological research is already being realized (e.g., Keighton et al. 2009; Kelly et al. 2012). Simultaneously, other researchers have demonstrated the consistency of CoCoRaHS observations with professional observers and automated rain gauges (Cifelli et al. 2005; Moon et al. 2009). To ensure that CoCoRaHS observations captured a representative seasonal distribution of daily precipitation totals, each station was required to have reported values on at least 80 percent of days in a given year for that year's observations to be included in the analysis. Additionally, for a station's monthly maximum to be included, the station must have recorded measurements for at least 80 percent of the days in that month. An 80-percent data coverage threshold is consistent with other climatological studies of precipitation extremes (e.g., Dulière, Zhang, and Salathé 2013).

Methods

It is important to clarify that our areal approach to design value estimation is not equivalent to the "regionalization" techniques used by the National Oceanic and Atmospheric Administration's National Weather Service (NWS), nor are our subsequent results meant to be a direct comparison to NWS return period estimates. Regionalization is based on interpolation of isolated point-based estimates and tends to "dampen out" the most significant precipitation extremes observed at any one station within a region to maintain spatial homogeneity in return period estimates. In our method, as in Blumenfeld and Skaggs (2011), all stations within a given area "compete" to determine a single monthly maximum precipitation value that represents the amount that could potentially occur somewhere within the area. In this case, we define the area of interest as a circle, up to 6 km in radius (Figure 1C), which we refer to as the representative precipitation region (RPR). The area encompassed by the minimum bounding circle of the RPR roughly corresponds to the region of responsibility of a local government, but other practically relevant spatial domains such as watersheds could also be employed for other applications. We term our technique, modeled after Blumenfeld and Skaggs (2011), a hyperlocal approach to design value rainfall estimation. The hyperlocal method is summarized in the step-by-step process described next.

1. Define a Series of RPRs with Radii $r = 1, \ldots, 6$ km Centered at the GHCN Station

Only the 6-km RPR will be used for design value inference, whereas the 1-, . . ., 5-km RPRs will be used to illustrate the benefit of areal-based design value estimation. The 6-km RPR represents the nearest integer radius yielding a search area (113 km^2) comparable to the 10 × 10-km (100 km^2) grid cells used by Blumenfeld and Skaggs (2011). This value is also comparable to the results of rainfall autocorrelation distance studies (Dzotsi et al. 2014; Kriebel 2016; Kidd et al. 2017).

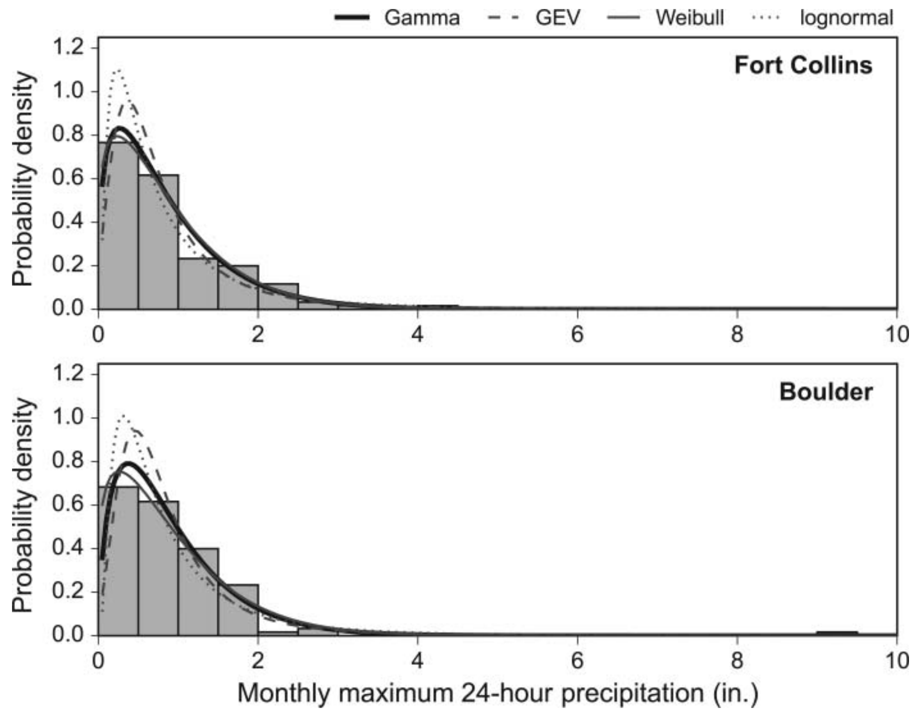

Figure 4. Comparison of distribution fits for both Fort Collins and Boulder overlaid on a histogram of the data sets. Both gamma and Weibull distributions appear to give good fits. The statistics in Table 2 make the better fit more clear. GEV = generalized extreme value.

2. For Each Month in the Ten-Year Window (2005–2014), Find the Maximum Twenty-Four-Hour Precipitation within the Combined Daily Rainfall Data Set of GHCN and All Qualifying CoCoRaHS Stations within the RPR

Taking the maximum over the region for each month eliminates the need to consider spatial correlation, as only one monthly maximum is observed for the entire RPR. Observations of twenty-four-hour rainfall are certainly serially (temporally) correlated; however, block maximums over large enough blocks (in our case, a block size of about thirty) are approximately independent (Coles 2001). Thus, there is no compelling evidence for temporal correlation in these maximums. Similarly, there is also no evidence of seasonality in them.

It is worth noting that the recording windows of the CoCoRaHS and GHCN twenty-four-hour precipitation observations are not directly aligned. CoCoRaHS network operators request that volunteer observers report their twenty-four-hour precipitation totals at 7 a.m. local time, but twenty-four-hour totals reported

Table 2. Goodness-of-fit statistics comparing the fit of the gamma and Weibull distributions to the Fort Collins and Boulder data

	Fort Collins		Boulder	
fit	Gamma	Weibull	Gamma	Weibull
K–S	0.9007	0.7549	0.8568	0.5079
A–D	0.9696	0.9176	0.6319	0.2182
NLLH	99.8730	100.4410	100.6277	104.1538

Note: The statistics given for the K–S and A–D tests are p values. In the case of the negative log-likelihood for the fit, smaller values indicate better fits. K–S = Kolmogorov–Smirnov; A–D = Anderson–Darling; NLLH = negative log-likelihood.

Table 3. K–S and A–D goodness-of-fit p values for the distributions of monthly maximum twenty-four-hour precipitation

Data set	Test	Boulder	Fort Collins
GHCN for entire	K–S	0.0601	0.0222
period of record	A–D	0.0987	0.0775
Hyperlocal since	K–S	0.8568	0.9007
2005 with 6-km RPR	A–D	0.6319	0.9696

Note: In each case, the null hypothesis is that the proposed distribution (here, a gamma distribution) fits the data. Small p values indicate that the null hypothesis (that the gamma distribution fits the data) should be rejected. The gamma distribution yields a much better description of spatially rich hyperlocal distributions than the temporally rich GHCN distributions. K–S = Kolmogorov–Smirnov; A–D = Anderson–Darling; GHCN = Global Historical Climatology Network; RPR = representative precipitation region.

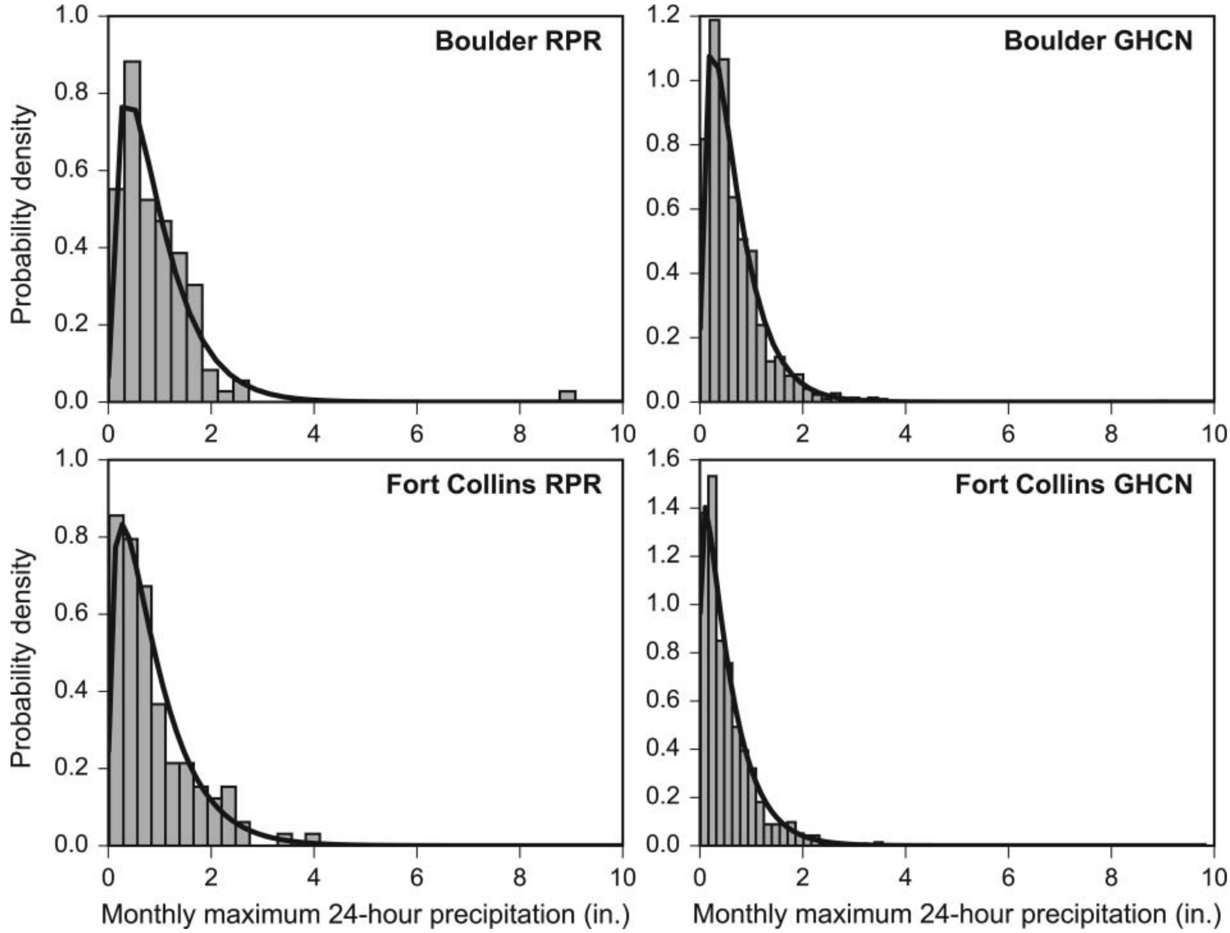

Figure 5. Histograms and fitted gamma distributions for 6-km RPR monthly maxima between 2005 and 2014 (left) and GHCN period-of-record monthly maxima only (right) for Boulder (top) and Fort Collins (bottom). RPR = representative precipitation region; GHCN = Global Historical Climatology Network.

at any hour of the day are accepted for inclusion in the data set. The Fort Collins GCHN station reported twenty-four-hour precipitation totals at 7 p.m. local time during our study period. Meanwhile, the time of observation for the Boulder GHCN station is unreported prior to May 1985 and twenty-four-hour totals are reported at 5 p.m. local time for most of the record length thereafter. Depending on the timing and duration of precipitation, these discrepancies in the recording window might cause the maximum twenty-four-hour precipitation amount to be preferentially recorded by either the GCHN or CoCoRaHS station(s) during individual events. We have no reason, however, to believe that twenty-four-hour precipitation maximums within the RPR are systematically biased toward one network by the offset in recording windows, and the amount of observations in our data set should be sufficient to neutralize the effects of recording period bias during any individual precipitation event.

3. Fit a Gamma Distribution to the RPR Maxima and Assess the Fit Both Visually and with Goodness-of-Fit Statistics

The gamma distribution (also called Pearson Type III; Thom 1958) was chosen to model the monthly maximum twenty-four-hour precipitation. Several distributions were chosen to fit the data based on its shape and scale. All fits were estimated via maximum likelihood (Fisher 1922). Exploratory fits to both the Fort Collins and Boulder data sets, calculated using functions available in the MatLab software package, indicated that the gamma, Weibull, generalized extreme value, and log-normal distributions provided the best fits. Figure 4 shows each of these fits against histograms of the monthly twenty-four-hour precipitation maximums, and Table 2 shows the goodness-of-fit statistics for gamma and Weibull. Although the Weibull distribution might appear to more closely match the observed data in Figure 4, the statistics in Table 2

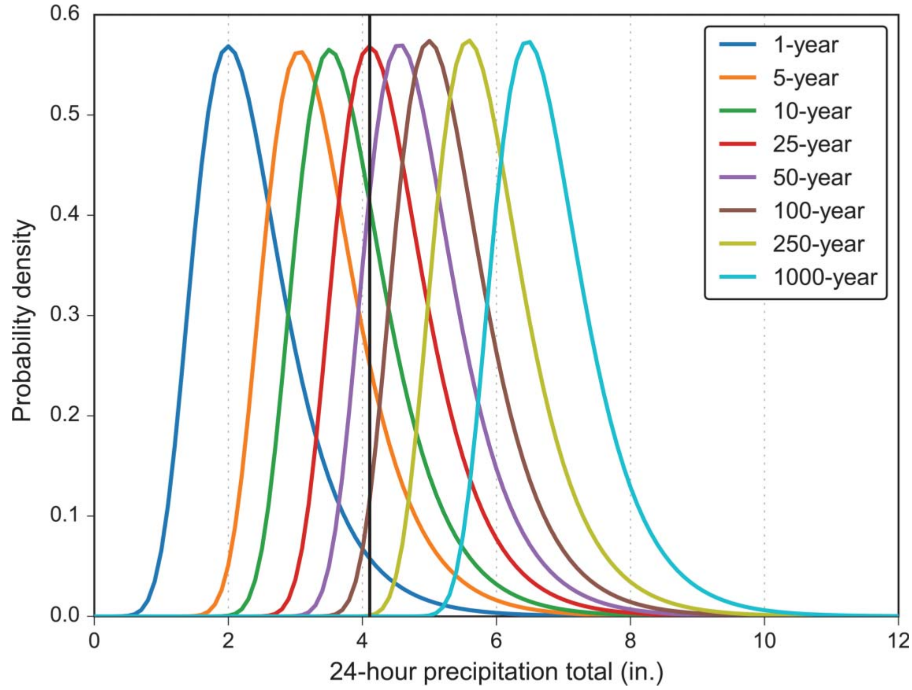

Figure 6. Probability density functions of the *n*-year hyperlocal return periods for Fort Collins. The 4.11-in. (104.4-mm) annual maximum from 2007 is marked by a vertical line. The percentiles in Table 4 are calculated by determining the fraction of the total area for each curve lying to the left of the vertical line. (Color figure available online.)

clearly indicate that the gamma distribution is a better fit for both Fort Collins and Boulder.

The primary goodness-of-fit tests used in this study, the Kolmogorov–Smirnov (K–S; Hogg and Tanis 2006) and Anderson–Darling (A–D; Anderson and Darling 1952) tests, both share the same null hypothesis: The data come from a proposed distribution—the gamma distribution, in this case. The *p* values for these tests (Table 3) are computed using Monte Carlo methods that simulate data from the hypothesized distribution. The gamma distribution provides a much better description of the ten-year 6-km RPR monthly maximum series than the century-long GHCN monthly maximum series (Table 3, Figure 5). Although the gamma distribution appears to capture many characteristics of the GHCN-only monthly maximums over the period of record (Figure 5), goodness-of-fit statistics reject the null hypothesis that the data came from the fitted gamma distribution. One reason that fitting any distribution to the entire GHCN series is more challenging is that the distribution can change over time: Precipitation from the beginning of the series can behave differently from precipitation today (see Discussion). These gradual changes are less influential during the ten-year CoCoRaHS series, however, than they are for the much longer GHCN series. Temporal changes within the GHCN series are currently under investigation.

4. For a Given Return Period, Simulate Data from the Fitted Gamma Distribution

For instance, to calculate a single *n*-year daily maximum rainfall event, $12 \times n$ values would be simulated from the fitted gamma distribution, and the largest value would be retained to represent the *n*-year maximum daily rainfall event. This process is repeated to form a new maximum precipitation distribution data set composed entirely of simulated *n*-year maximum daily rainfalls. The *n*-year return period distributions simulated from the fitted gamma distribution are the annual, 5-year, 10-year, 25-year, 50-year (1 million values each), 100-year, 250-year (100,000 values each), and 1,000-year (10,000 values). The number of simulated values decreased as return period length increased due to computational limitations.

5. Fit Generalized Extreme Value Distributions to These Simulated Data and Plot the Density Curves for Each Return Period Distribution

Figure 6 shows the density curves for the Fort Collins 6-km RPR. Given the number of values sampled for each of these distributions, the generalized extreme value (GEV) fits are near perfect.

Repeated sampling from these distributions using many values will yield tiny variations in the parameters of each of the fits.

6. Generate Descriptive Statistics for the *n*-Year GEV Distributions to Describe the Rainfall Events Associated with Each Return Period

Traditional practices assign a mean maximum precipitation total to a particular return period and provide a corresponding confidence interval about the mean maximum (e.g., Perica et al. 2013). Our approach avoids most discussion of the mean maximum precipitation event (except to compare our results to previous work) and instead chooses to emphasize the distribution of all possible maximum twenty-four-hour precipitation totals for a given return period. The metric that will be used to describe the distributions is the range of values spanning from the fifth to the ninety-fifth percentiles of the simulated maximum twenty-four-hour precipitation observations for each return period. These bounds, capturing the middle 90 percent of the distributions, will be referred to as the 90 percent interquantile range (IQnR). The 90 percent IQnR was selected to remain consistent with the 90 percent confidence intervals provided by the NWS. However, the 90 percent IQnR is not statistically comparable to the 90 percent confidence interval about the mean provided with the NWS twenty-four-hour precipitation estimates.

As mentioned earlier, the hyperlocal technique possesses four key differences from the method used to derive the return periods in the NWS Precipitation Frequency Atlas:

1. This study uses monthly maximums rather than annual maximums. Because CoCoRaHS stations have only been reporting consistently since 2005 (Figure 3), considering annual maximums would reduce the data set to only ten values at each site, whereas monthly block maximums increase the data set by a factor of twelve (see Step 2 earlier). Inferences resulting from 120 observations are much stronger than those formed from only ten.
2. Maximum likelihood estimation was used instead of *L*-moments to fit the distributions.

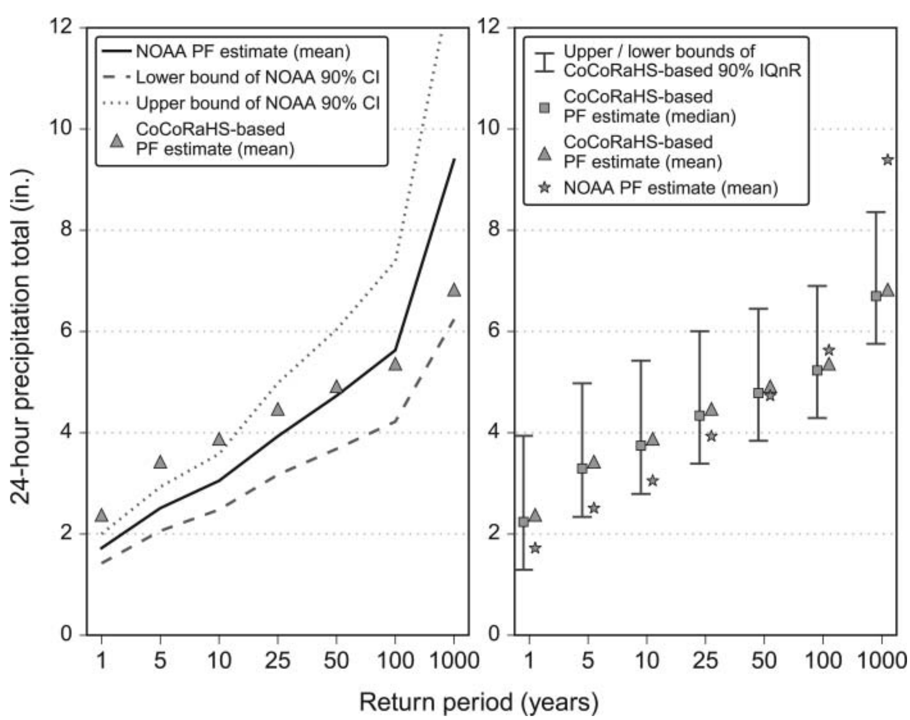

Figure 7. Comparison of NWS design value estimates to the hyperlocal estimates for Fort Collins. The left pane compares the mean *n*-year maximum daily rainfall found in this study to the NWS mean *n*-year event and 90 percent CIs. The right pane depicts the NWS *n*-year mean in terms of the 90 percent IQnRs for the same return periods. The left and right panes have been separated to emphasize that the 90 percent CIs and 90 percent IQnRs are not equivalent statistical measures. NOAA = National Oceanic and Atmospheric Administration; PF = precipitation frequency; CI = confidence interval; CoCoRaHS = Community Collaborative Rain, Hail and Snow Network; IQnR = interquantile range; NWS = National Weather Service.

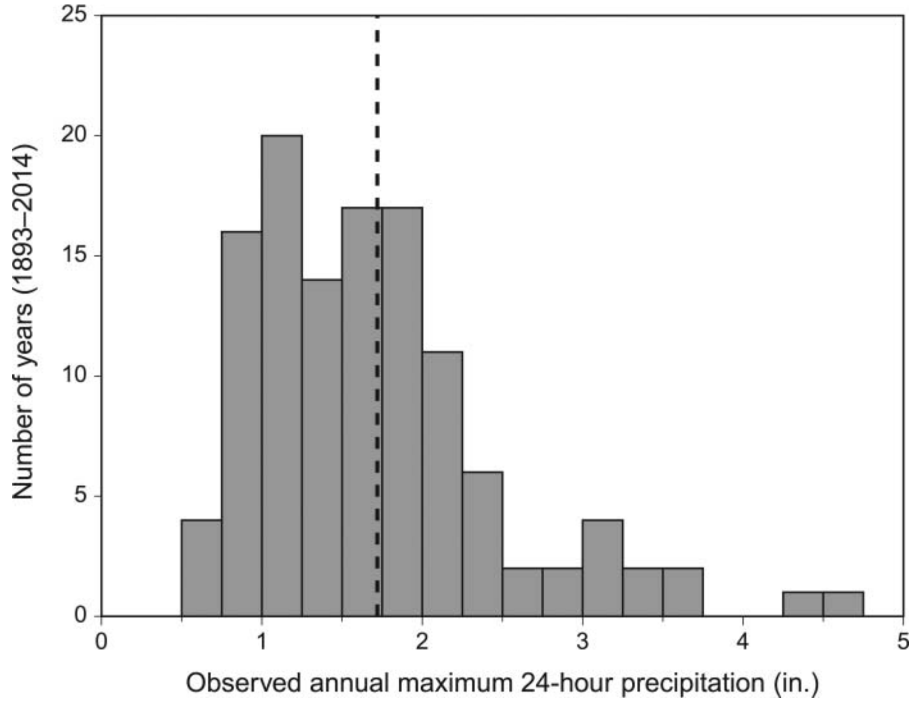

Figure 8. Histogram of one-year maximum daily rainfalls observed by the Fort Collins Global Historical Climatology Network between 1893 and 2014. Essentially, this represents the distribution of all observed one-year rainfall events. The National Weather Service–estimated one-year mean maximum is shown by the dashed vertical line.

When enough data are available to use maximum likelihood estimation techniques (as in this case with 120 observations), maximum likelihood is always the preferred option, because its properties are well established in the statistical literature as better in most cases than those of any moment-based techniques. See Wackerly, Mendenhall, and Scheaffer (2008), Casella and Berger (2002), or any similar text addressing mathematical statistical inference.

3. This study also uses regions to stabilize the statistical inferences, but the analysis applies to the entire region from which data were gathered. The data gathering also reached beyond official measuring stations to take advantage of the information contained in CoCoRaHS stations in this case. Any extreme reading was not only supported by the GHCN station reading but was also a newsworthy event that was well documented to have occurred.
4. Finally, and most notably, probability density functions are used to describe extreme events. All probabilities of interest can be derived from these densities, but they also completely characterize the variability of events occurring within a return period of interest and how such events might fall within the grander picture of what is normal. Indeed, every 1,000-year maximum must be an annual maximum.

Results

Before presenting the results, we reiterate that our findings should not be viewed as directly comparable to NWS estimates. Our area-based method calculates the probability of precipitation amounts occurring somewhere within the Fort Collins or Boulder area (as defined by a 6-km radius around each city's GHCN station) for the given return interval, whereas the point-based NWS values represent the expected precipitation amount for the given return interval at any given point in the area. The NWS values are only presented to contextualize the hyperlocal estimates calculated in this study. Further, as mentioned in the Methods section, the 90 percent IQnRs used here and the NWS 90 percent confidence intervals are not statistically equivalent. The 90 percent IQnR was selected to maintain some aesthetic continuity between the two different estimation methods.

The high CoCoRaHS station density in the Fort Collins area contributes a much larger volume of data (greater than twice the station-months) than any other location. Thus, the advantages of the hyperlocal approach can be best illustrated by studying the results from this site. In contrast, the analysis for Boulder represents a potentially unique situation where the advantages of hyperlocal rainfall frequency estimation are more limited. This section is roughly broken into two corresponding sections. The first section focuses largely on the analysis for Fort Collins, and the second section contrasts these findings with the Boulder case and explains its limiting factors.

Maximum Twenty-Four-Hour Precipitation Distributions by Return Period

Figure 7 depicts the results of the hyperlocal precipitation frequency analysis for both Fort Collins and Boulder. To more clearly relate the results of this work to existing NWS estimates, the left panes plot the mean design value of each return period distribution alongside the NWS calculated means. Keeping in mind that our area-based design value estimates do not conceptually represent the same quantity as the point-based NWS values, Figure 7A does effectively communicate one of the general findings of this study—a hyperlocal approach produces larger design values than point-based methodologies for more frequent return periods. For Fort Collins, the one-year (2.38 in.; 60.5 mm), five-year (3.43 in.; 87.1 mm), and ten-year (3.88 in.; 98.6 mm) hyperlocal maximums are 38, 36, and 27 percent greater than the NWS mean estimates (1.72 in. [43.7 mm], 2.52 in. [64.0 mm], and 3.06 in. [77.7 mm], respectively). At the fifty-year return period, the hyperlocal (4.92 in.; 125.0 mm) and NWS (4.75 in.; 120.7 mm) means are nearly equal, and for the most infrequent return periods (100- and 1,000-year), the mean hyperlocal design value is less than the NWS estimated mean.

Figure 7B mimics Figure 7A except that the NWS means are matched to the 90 percent IQnR for each return period—the more desired method of comparison. It is again readily apparent in Figure 7B that for the shorter return periods (i.e., one, five, and 10 years), much of the 90 percent IQnR lies above the NWS estimated means. This suggests that for return periods shorter than twenty-five years, twenty-four-hour precipitation totals previously characterized as ten-, twenty-five-, or fifty-year events would more accurately be associated with a more frequent return period. In contrast, for the 1,000-year return period, the 90 percent IQnR lies entirely below the NWS estimated mean. Thus, our hyperlocal results would seem to indicate that a 1,000-year daily precipitation can be achieved with an accumulation several inches less than expected by the NWS estimates, although it must be noted that this is likely due to the relatively short record length of the CoCoRaHS observations (see Discussion).

Another point of emphasis is the width of the 90 percent IQnRs associated with each return period. To reiterate the error bars in Figure 7B are not confidence intervals but are the range of values capturing the middle 90 percent of the n-year maximum precipitation distributions. As Figure 7B shows, these 90 percent IQnRs are relatively constant in width regardless of

Table 4. Return period percentiles for the annual maximum twenty-four-hour rainfalls recorded in Fort Collins from 2005 to 2014

Year	24-hour maximum rainfall in inches (mm)	1-year	5-year	10-year	25-year	50-year	100-year	250-year	1,000-year
2005	1.57 (39.9)	14.35	0.01	0.00	0.00	0.00	0.00	0.00	0.00
2006	2.39 (60.7)	57.84	6.31	0.40	0.00	0.00	0.00	0.00	0.00
2007	4.11 (104.4)	96.13	82.13	67.37	37.32	13.89	1.89	0.01	0.00
2008	2.29 (58.2)	52.88	4.04	0.16	0.00	0.00	0.00	0.00	0.00
2009	3.36 (85.3)	88.34	53.37	28.45	4.35	0.19	0.00	0.00	0.00
2010	1.94 (49.3)	33.47	0.42	0.00	0.00	0.00	0.00	0.00	0.00
2011	2.24 (56.9)	50.19	3.11	0.10	0.00	0.00	0.00	0.00	0.00
2012	2.66 (67.6)	69.73	16.10	2.60	0.01	0.00	0.00	0.00	0.00
2013	2.52 (64.0)	63.87	10.37	1.08	0.00	0.00	0.00	0.00	0.00
2014	1.97 (50.0)	35.04	0.53	0.00	0.00	0.00	0.00	0.00	0.00

Note: Nonzero percentiles are highlighted as a tool to visually gauge how a year's annual maximum falls into the family of return period distributions. Notice how the observed annual maxima are distributed in each of the return-period distributions, serving as a check that our method is performing well.

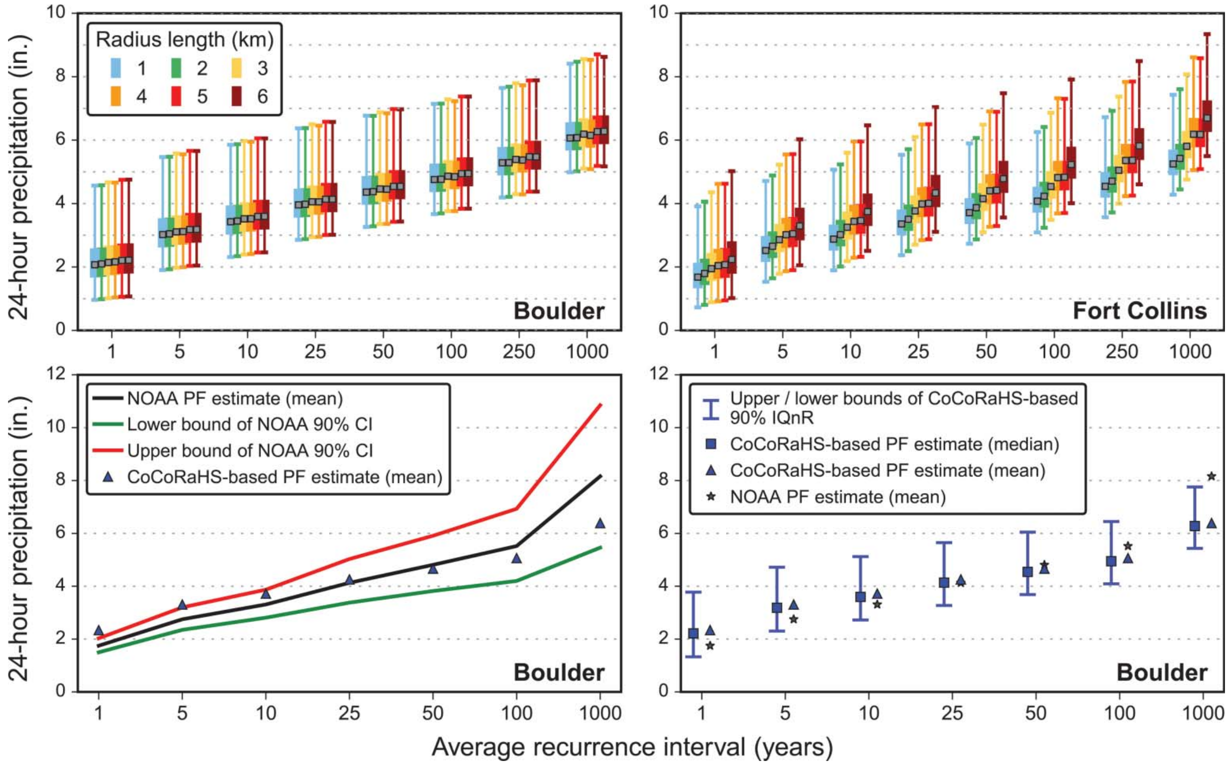

Figure 9. Top: Boxplots of the 90 percent IQnRs for Boulder (left) and Fort Collins (right) as a function of the representative precipitation region. Bottom: Same as Figure 7 except with results from Boulder, Colorado. NOAA = National Oceanic and Atmospheric Administration; PF = precipitation frequency; CI = confidence interval; CoCoRaHS = Community Collaborative Rain, Hail and Snow Network; IQnR = interquantile range. (Color figure available online.)

the length of the return period. Although this might seem undesirable for shorter return periods, it is much more representative of how *n*-year maximums actually behave. For instance, consider all of the one-year maximum daily precipitations measured by the Fort Collins GHCN station during its entire period of record (i.e., the observed one-year precipitation events; Figure 8). To describe the one-year maximum daily precipitation as a single value can be misleading because all of the values in Figure 8 are legitimate one-year precipitation events.

To further illustrate this point, consider a maximum fifty-year event. This value is also the maximum during the twenty-five-year period in which it occurred, the ten-year period in which it occurred, the five-year period in which it occurred, the year in which it occurred, and the month in which it occurred—otherwise, it could not be a fifty-year maximum. Because all 5-, 10-, 25-, 50-, 100-, and 1,000-year rainfalls would also represent the maximum for all lesser return periods whenever they occur, it is intuitive that these distributions should somewhat overlap between return periods. Figure 6 shows all of the *n*-year return period distributions for Fort Collins plotted simultaneously. Clearly, there is considerable coincidence between the *n*-year distributions, a trait not often recognized by the traditional return period paradigm.

Characterizing return periods using the 90 percent IQnR is also much more advantageous for longer intervals. As Figure 7 shows, for the fifty-year return period and greater, the 90 percent IQnRs are roughly as wide as

Table 5. Comparison of the maximum daily rainfall for each GHCN station during its entire period of record to the maximum daily rainfall detected by surrounding 6-km RPR CoCoRaHS stations since 2005

GHCN station	Daily maximum during entire period of record in inches (mm)	GHCN months	Daily maximum since 2005 for 6-km RPR in inches (mm)	CoCoRaHS station-months
Boulder	9.08 (230.6)	1,238	8.87 (225.3)	1,289
Fort Collins	4.63 (117.6)	1,417	4.11 (104.4)	3,161

Note: GHCN = Global Historical Climatology Network; RPR = representative precipitation region; CoCoRaHS = Community Collaborative Rain, Hail and Snow Network.

the 90 percent confidence intervals for the NWS mean n-year maximum for the same interval. The 90 percent IQnRs, however, can describe a broad spectrum of possible outcomes, whereas a confidence interval only addresses the uncertainty associated with a single descriptive statistic of that distribution. For the 1,000-year return period, the width of the 90 percent IQnR is roughly half that of the NWS 90 percent confidence interval.

In some situations, it might be desirable to assign a precipitation event to a single return period. Although we discourage this practice, a more cautious categorization can be achieved by assigning the precipitation event a percentile for each return period being considered (Table 4, Figure 9). In this case, the percentile would represent the fraction of n-year maximums composing the n-year return period distribution that is less than or equal to the design value being considered. The precipitation total might most reasonably be assigned to the return period whose distribution captures it nearest the fiftieth percentile. This technique emphasizes that the same daily precipitation total belongs to multiple return period distributions, and assigning it to a single return period is a probabilistic, not a deterministic, process.

For example, the Fort Collins maximum daily rainfall for 2007 illustrates how one maximum has a probabilistic membership in multiple return interval distributions. According to Table 4, this 4.11-in. (104.4 mm) twenty-four-hour precipitation total would represent a very large one-year maximum: It is greater than 96.13 percent of all annual maximum daily precipitation. Similarly, the 4.11-in. total moves closer to the centers of the five-year (82.13 percent) and ten-year (67.37 percent) return period distributions. For the 50-year (32.40 percentile) and 100-year (10.46 percentile) return periods, the 2007 event becomes decreasingly likely to be a commonly observed value in these distributions. A 4.11-in. daily total could still very well constitute a 100-year maximum, but it is expected to be larger than only 10.46 percent of all possible 100-year maximums. For the least frequent return periods (250- and 1,000-year), nearly all of the n-year maximums would exceed the 4.11-in. total from 2007. Thus, a 4.11-in. daily rainfall total would most likely represent something between a ten- and twenty-year event.

Design Value Estimates as a Function of Space

As the RPR expands beyond each GHCN site, more data are included from nearby CoCoRaHS stations. Intuitively, as more observations are included, the larger station sampling should lead to greater monthly maximums being selected to represent the locality as a whole. Indeed, this is the case—Table 5 illustrates that, for both Fort Collins and Boulder, using a 6-km RPR allows the maximum daily rainfall from the 10-year CoCoRaHS data set to approach the 119-year maximum of the GHCN station. This suggests that a spatially dense CoCoRaHS record of length equivalent to that of the GHCN station would capture extreme precipitation values substantially higher than those observed in the GHCN record (see Discussion). The hyperlocal maximums provide a superior estimate of the precipitation that is climatically possible but has not been measured due to small spatial displacements between the GHCN station and precipitation maximums.

Although precipitation design values increase with increasing RPR for both Fort Collins and Boulder, a closer look at the relationship between RPR expansion and design value increases reveals markedly different outcomes between the two cities (Figure 9). In the case of Fort Collins, the large number of CoCoRaHS stations surrounding the Fort Collins GHCN station (Figure 1C) results in a substantial increase in the sample of station-months with increasing RPR. As larger hyperlocal maximums are included in the sample, the 90 percent IQnR shifts steadily toward greater precipitation totals. It is clear from Figure 9 that mesoscale variations in rainfall accumulations captured by the CoCoRaHS network in Fort Collins dramatically influence the range of values that we would consider common or uncommon, depending on the size of the RPR. By considering all values within the RPR as representative of the precipitation totals that are possible somewhere within the Fort Collins area, expectations for the monthly maximums substantially increase. Even during the short, ten-year period studied here, the incorporation of spatial variations in precipitation provides more insight toward monthly precipitation extremes in Fort Collins than 119 years of single point observations.

The case of Boulder offers a potentially unique exception to the relationship between increasing RPR and increasing design values described for Fort Collins earlier. As illustrated in Figure 2, the greatest twenty-four-hour rainfall total associated with the 12 September 2013 precipitation event was actually measured at the Boulder GHCN station. Not only was this the greatest precipitation total on that day, but it was the greatest twenty-four-hour precipitation total ever measured by the Boulder GHCN or any of its surrounding CoCoRaHS stations. The rare case when such an extreme precipitation total is detected by the GHCN station limits the additional insight that can be obtained through a hyperlocal approach. The 9.08-in. (230.6 mm) maximum observed by the Boulder GHCN so strongly dictates the shape of each return period distribution that the dozens of additional CoCoRaHS maximums contribute only to shaping the body of the distribution, rather than the upper tail. Consequently, Figure 9 shows that as the RPR increases around the Boulder GHCN, the *n*-year maximum distributions increase only slightly for each return period.

The limited benefit of the hyperlocal approach in the case of Boulder can also be observed by comparing the results of our hyperlocal approach to the NWS estimates. The hyperlocal results for Boulder bear more resemblance to the NWS calculations than for Fort Collins. Theoretically, the two estimation techniques would most resemble each other when either (1) the GHCN monthly maximum was consistently the greatest monthly maximum within the RPR or (2) if when a CoCoRaHS station did observe the greatest monthly maximum, it did not differ substantially from the GHCN monthly maximum. Indeed, both of these circumstances occur more frequently in the Boulder data set than for Fort Collins. Roughly 25 percent of Boulder monthly maximums were contributed by the GHCN station as opposed to roughly 10 percent in Fort Collins. Additionally, whenever a CoCoRaHS station observed the monthly maximum, the difference between the CoCoRaHS maximum and the GHCN maximum was smaller for Boulder (0.20 in. [5.08 mm] mean difference) than Fort Collins (0.34 in. [8.64 mm] mean difference).

Ultimately, the Boulder GHCN station's systematic advantage for detecting heavy precipitation events serves to dampen the increase in precipitation design values with increasing RPR in Boulder. The greater resemblance of the hyperlocal maximums to the GHCN-only maximums results in similar design value estimations between the two techniques. This Boulder example, however, represents another potential problem of point-based design value estimates—the microclimate of the site used to calculate a return period might not be representative of the larger area to which the return period is applied. As the Boulder case illustrates, the GHCN station's location at the base of the Rocky Mountain Front Range is a favored area for orographically enhanced rainfall (e.g., Lin et al. 2001). Thus, the Boulder GHCN station is likely predisposed to capture larger precipitation totals than locations where such influences are weaker (i.e., Fort Collins). In this case, the siting bias of the GHCN station might lead to design value estimates that are not representative of the whole area to which they are applied. With a greater spatial density of stations from CoCoRaHS or some other high-density network, the spatial distribution of precipitation maxima can be studied in greater detail. Locations of consistently larger precipitation maxima can be more confidently attributed to topographic, atmospheric, or land use features in areas with high gauge density, and design values in these locations might be appropriately adjusted.

Discussion

The estimated intensity of precipitation events is critical to hydrological infrastructure design, as a wide variety of regulations exist to ensure that infrastructure is constructed to withstand runoff generated by the interaction between precipitation extremes and land surface characteristics. "Minor" stormwater infrastructure elements (storm drains, small ditches, retention ponds, etc.) are typically designed to prevent or minimize flooding from a "design storm" with a return period ranging from two to twenty-five years. "Major" hydrologic infrastructure projects, the failure of which could result in catastrophe, are engineered to withstand hydrological extremes that are much less common. For example, the transportation departments of most U.S. states assume a fifty-year storm event in the design of highway bridges across freshwater rivers (Meyer and Weigel 2010), and most large flood control structures such as dams and levees are engineered to contain extremely rare floods with return periods of 500 to 10,000 or more years (Jansen 1988; Williams 1997).

The results presented in the previous section show that conventional methods likely underestimate precipitation design values in both Fort Collins and Boulder for the relatively short return periods considered for "minor" infrastructure projects. Our hyperlocal method actually yields smaller design values than the point-based NWS method for the longer return periods associated with "major" infrastructure projects (100 and 1,000 years), but these lower values can almost certainly be attributed to the short record length (ten years) of the CoCoRaHS data relative to the multidecadal GHCN records. If the spatially dense CoCoRaHS record length were equal to that of the stations utilized for the NWS point-based estimates, our hyperlocal method would predict design values at least equal to, and very likely greater than, the NWS estimates for higher return periods as well. The higher CoCoRaHS station density, if available over the entire GHCN record length would enable a greater probability of detecting localized precipitation extremes in convective regimes characterized by a high degree of small-scale spatial variability and would also be more likely to capture the peak precipitation totals in an area during widespread extreme precipitation events with strong synoptic forcing. Although we have no way of knowing exactly how much design values would increase with a long record of spatially dense observations in the Colorado Front Range region, a long-term study utilizing a dense rain gauge network in Germany found that precipitation extremes observed by the dense gauge network were typically 10 to 25 percent larger than those observed by a more conventional sparse network (Zolina et al. 2014).

With many urban and rural areas in the United States slated for hydrologic infrastructure replacement or upgrades in the next decade, it is critical to develop sound methods for accurately determining design values. In many cities, the "gray" stormwater infrastructure designed to drain precipitation runoff from developed areas to nearby waterways—including elements such as storm sewers, pipes, and treatment facilities—was built in the early- to mid-twentieth century and is in need of repair or replacement (Environmental Protection Agency 2008; Kessler 2011; Grigg 2012; R. Wang, Eckelman, and Zimmerman 2013). Further, the introduction of impervious surfaces such as roads and buildings in flood-prone areas exposes more human lives and property to risk (Brissette et al. 2003; Brody et al. 2008; Booth and Bledsoe 2009). When selecting a design value for these systems, the distribution of all possible maximums is often overlooked in favor of estimates for the descriptive statistics of those distributions (i.e., the mean twenty-five-year rainfall). A more cautious option is to pick a design value from an upper percentile of the return period's distribution rather than its mean. Designing infrastructure based on the mean rainfall total for a return period excludes a large number of legitimate outcomes possible during that time span. Additionally, the 90 percent confidence intervals about the mean are so large for the longest return intervals (Figures 7 and 9) that most of the practical value is eliminated.

The increased flooding risks caused by the combination of land surface change and aging stormwater infrastructure are also exacerbated by ongoing and projected increasing trends in the intensity of heavy precipitation due to climate change (e.g., Groisman, Knight, and Karl 2012; Higgins and Kousky 2013; Kunkel et al. 2013). Modeling studies suggest that this intensification of hydrologic extremes will grow more pronounced through the remainder of the twenty-first century (Mailhot and Duchesne 2010; Kendon et al. 2014; Ban, Schmidli, and Schär 2015; Trenberth, Fasullo, and Shepherd 2015). Herein lies an additional advantage of the hyperlocal approach—the large increase in useful data volume that can be achieved on very short timescales. Although other data sets (e.g., remotely sensed precipitation estimates from radar or satellite platforms) can offer this benefit, they are still subject to significant errors (Habib, Ciach, and Krajewski 2004; Villarini and Krajewski 2010; Seo et al. 2014). Specifically, radar-based precipitation products such as the NWS's multisensor precipitation estimate (MPE) tend to underestimate precipitation totals for intense precipitation events (Westcott, Knapp, and Hilberg 2008; Habib, Larson, and Graschel 2009; Wootten and Boyles 2014). Rain gauge observations are still subject to error (Moreau, Testud, and Le Bouar 2009) but nonetheless remain the standard by which remotely sensed precipitation estimates are judged (e.g., Rafieeinasab et al. 2015).

In light of the projected increase in extreme rainfalls, built infrastructure and flood management plans will need to be designed to withstand the new normal. Current point-based approaches to precipitation frequency estimation, however, cause the difficult decisions by stakeholders such as civil engineers, city planners, and emergency managers to be made using potentially misleading guidance. Because traditional single-station calculations require decades of observations to produce their estimates, climate normals might very well have changed by the time enough data are available, as we found to be the case in both Fort Collins and Boulder (see Step 3 in Methods section). With current practices, practitioners will be perpetually ill equipped to plan for realistic amounts of precipitation and runoff. Hyperlocal precipitation frequency estimations provide a solution by generating more accurate calculations on much shorter time scales. The high-density spatial network used here provided more realistic twenty-four-hour precipitation estimates, using only ten years of observations, than a point-based estimate produced with greater than 100 years of data. If the predictions of climate modeling studies prove true, the rainfall measurements accumulated over the past hundreds of years might be of little value in characterizing rainfall extremes within changing climate regimes. As Table 3 shows, even internal modes of climate variability can significantly hinder the robustness of precipitation frequency estimates from long historical records. Thus, the ability of dense gauge networks to provide short-term design value estimates under prevailing climate conditions permits a greater understanding of, and ability to plan for, precipitation extremes in a changing climate.

Conclusions

This article presents a new technique, inspired by Blumenfeld and Skaggs (2011), for calculating twenty-four-hour precipitation design values using the spatially dense CoCoRaHS rain gauge network. Our hyperlocal approach employs data collected from this network over a relatively brief record length (ten years) to determine the distribution of rainfall accumulations associated with several return periods. This technique is in contrast to conventional methods that rely on single point observations over a long period of time (more than fifty years) to generate their estimates. Not only are such suitable stations few in number but, in addition, considering precipitation observations from a single point ignores the areal dimension of precipitation events. By treating all observations collected within a 6-km-radius domain as relevant to the entire area (rather than just for the point at which they were collected), more robust design value estimations can be generated. For practitioners such as city planners, engineers, and water managers tasked with designing infrastructure capable of withstanding the most intense events possible within a given urban or rural area, a hyperlocal approach is much more appropriate.

This preliminary study illustrates the advantage of hyperlocal design value estimates by analyzing CoCoRaHS twenty-four-hour rainfall totals from the Colorado Front Range region. By considering the daily precipitation totals recorded by area CoCoRaHS stations in addition to GHCN daily precipitation measurements, the estimates for the high-frequency return periods increased relative to estimates based purely on the GHCN observations. In contrast, for the most infrequent return periods, hyperlocal estimates were smaller than traditionally expected, although this effect can likely be attributed to the relatively short record length of the CoCoRaHS data. These areal-based estimates are much more relevant to stakeholders than the single point estimates that dominate contemporary return period calculations. The benefits of a hyperlocal approach can be constrained, though, by the microclimates experienced by CoCoRaHS stations compared to the GHCN site—a situation well illustrated by the results for Boulder, Colorado.

Additionally, the results presented here depart from conventional return period discussions by emphasizing the distribution of all rainfall totals associated with each interval. Traditional characterizations rely on a single descriptive statistic used to describe the rainfall amount associated with a return period. We choose to express the results of the hyperlocal approach probabilistically, however, by presenting the entire distribution of possible outcomes. By emphasizing the range of outcomes, rather than a single statistic, it is possible to better communicate the variability of maximum twenty-four-hour precipitation totals indicative of a given return period. Presenting the results in this manner will allow stakeholders to identify more appropriate precipitation thresholds around which to plan for future precipitation and flooding events.

Given the promise of the hyperlocal approach demonstrated by this article, future research should consider expanding hyperlocal design value estimates to new locations. Although Fort Collins and Boulder possessed the greatest CoCoRaHS station density in the United States, other previously mentioned cities with relatively high station densities include Las Cruces, New Mexico; Albuquerque, New Mexico; Cheyenne, Wyoming; Huntsville, Alabama; Hays, Kansas; Eugene, Oregon; Tucson, Arizona; and Norman, Oklahoma, with the number of viable locations continuing to grow in proportion to the spread of the CoCoRaHS Network. Although future study locations based on CoCoRaHS data will probably be limited to densely populated regions due to the concentration of volunteers in these areas, design values calculated in these urbanized areas can likely be used to correct point-based design values in adjacent rural areas with similar hydroclimatic characteristics, particularly in areas with relatively uniform topography. Future work should also investigate the suitability of the 6-km RPR and the influence of decreased station density (compared to the very high density of Boulder and Fort Collins) on the resulting return interval estimates. Applying and refining our hyperlocal method in many different geographic settings will allow a wide variety of stakeholders to better plan for the precipitation extremes they will face.

Acknowledgments

The authors thank the three anonymous reviewers whose comments greatly improved the quality of this article.

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