Multicriteria design of rain gauge networks for flash flood prediction in semiarid catchments with complex terrain

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Despite the availability of weather radar data at high spatial (1 km2) and temporal (5–15 min) resolution, ground-based rain gauges continue to be necessary for accurate estimation of storm rainfall input to catchments during flash flood events, especially in mountainous catchments. Given economical considerations, a long-standing problem in catchment hydrology is to establish optimal placement of a small number of rain gauges to acquire data on both rainfall depth and spatiotemporal variability of intensity during extreme storm events. Using weather radar observations and a dense network of 40 tipping bucket rain gauges, this study examines whether it is possible to determine a reliable “best” set of rain gauge locations for the Sabino Canyon catchment near Tucson, Arizona, USA, given its complex topography and dominant storm track pattern. High-quality rainfall data are used to evaluate all possible configurations of a “practical” network having from one to four rain gauges. A multicriteria design strategy is used to guide rain gauge placement, by simultaneously minimizing the residual percent bias and maximizing the coefficient of correlation between the estimated and true mean areal rainfall and minimizing the normalized spatial mean squared error between the estimated and true spatiotemporal rainfall distribution. The performance of the optimized rain gauge network was then compared against randomly designed network ensembles by evaluating the quality of streamflows predicted using the Kinematic Runoff and Erosion (KINEROS2) event-based rainfall-runoff model. Our results indicate that the multicriteria strategy provided a robust design by which a sparse but accurate network of rain gauges could be implemented for semiarid basins such as the one studied.


1. Introduction

Accurate and reliable spatiotemporal estimates of precipitation are crucial to the successful prediction of catchment response, and are particularly important in the case of (flash) flooding. In real-time flood forecasting and warning situations, rainfall errors can dominate the uncertainty in the modeled runoff response [e.g., Goodrich et al., 1994; Faurès et al., 1995]. The task of monitoring precipitation for flood prediction is particularly challenging in arid and semiarid regions, which span approximately one third of the global land surface [Goodrich et al., 2000]. In such regions, a major characteristic of rainfall is the occurrence of intense convective thunderstorms that develop very rapidly and preferentially over high terrain, and cause severe flash flooding. The resulting precipitation events are highly localized, heterogeneous (in space and time), and strongly influenced by topography [Roeske et al., 1989; Michaud, 1992; Michaud and Soroooshian, 1994b; Gupta et al., 2002; Yatheendradas et al., 2008]. The corresponding complex spatiotemporal interplay of distributed watershed and rainfall properties strongly influences the shape and volume of the flood hydrograph in semiarid catchments where streamflow originates predominantly from partial area infiltration excess runoff generation and is subject to significant transmission losses [Osborn, 1964; Michaud, 1992], potentially magnifying the effects of rainfall estimation errors with respect to runoff (and flood) prediction [Goodrich, 1990; Goodrich et al., 1997].

A common approach to monitor extreme variability in rainfall is through ground-based radar remote sensing. Use of radar for rainfall estimation can improve flood prediction by providing data at high spatial (as small as 1 km2) and temporal (5–15 min) resolution over extended areas [e.g., Krajewski and Smith, 2002; Maddox et al., 2002; Morin et al., 2006; Yatheendradas et al., 2008]. However, uncertainties and biases in radar-based estimates arise due to the combined effects of limitations in our representations of the underlying processes, poor parameter estimation, and inaccuracy in measuring devices [Smith et al., 1996; Young et al., 1999, 2000; Krajewski and Smith, 2002; Villarini et al., 2008]. This
is especially true in mountainous semiarid catchments, where the estimation of storm depth and intensity from radar data is more challenging than in flat terrain, due to the poor functioning of the standard Z–R (reflectivity–rainfall) relationship for convective storms [Morin et al., 2003, 2005], and complications by ground returns and considerable signal loss associated with beam blockage through mountains [Young et al., 1999; Krajewski and Smith, 2002]. Consequently, it is not clear to what degree radar-based estimates of rainfall can satisfy the requirements of accurate flash flood predictions. Yatheendradas et al. [2008] recently concluded that the current generation of weather radar alone, i.e., without any real-time bias removal or data augmentation, does not allow for acceptable skill and precision of flash flood forecasts.

[4] Despite the availability of weather radar data at high spatiotemporal resolution, ground-based rain gauge networks are still necessary to enable accurate estimation of storm rainfall input to catchments during flash flood events. Unlike radar systems which (indirectly) measure continuously in space, a network of rain gauges represents a discrete finite sampling of the two-dimensional pattern of land surface precipitation depths [Robinson, 2005]. Even though rain gauges provide relatively accurate (direct) rainfall measurements [Villarini et al., 2008] they are only representative of a limited spatial extent and must therefore be interpolated to obtain estimates of the areal pattern of precipitation or mean areal precipitation (MAP) across a catchment [e.g., Villarini et al., 2008; Garcia et al., 2008]. The accuracy of gauge-based areal estimates of rainfall depends on both the number of gauges in the network, and on their spatial location and distribution. Specification of these characteristics of a rain gauge network is necessarily related to the natural variability of the precipitation across an area [Rodríguez-Iturbe and Mejia, 1974], which arises from physiographic and hydrometeorological factors [Eagleson, 1967; Rodríguez-Iturbe and Mejia, 1974; Robinson, 2005] including topography and climate [Harris et al., 1996; Pandey et al., 1999]. It is typically assumed that in semiarid mountainous areas, having significant variability and intermittency [Barancourt et al., 1992] larger numbers of rain gauges are needed to characterize and monitor precipitation fields than in flat terrain and/or regions where rainfall results from frontal storm systems [Robinson, 2005].

[5] While numerous technical “guidelines” exist for the deployment of gauge networks to measure areal rainfall [World Meteorological Organization (WMO), 1994], the vast majority of existing observational networks around the globe (and particularly in semiarid mountainous regions) do not adequately capture the variability of the precipitation in space and time, as they tend to be sparse and to sample only locations that are relatively accessible and at low altitudes [Osborn et al., 1972; Michaud and Sorooshian, 1994b; Villarini et al., 2008]. As a result, rapidly changing patterns of precipitation over mountains are poorly monitored, and there are gaps in the information important to the modeling of runoff generation. This makes it difficult to obtain sufficient lead time and accuracy on hydrological forecasts [Michaud and Sorooshian, 1994a, 1994b; Gupta et al., 2002; Yatheendradas et al., 2008]. As such, the design of hydrological measurement networks has received considerable attention in research settings; see Bras and Rodríguez-Iturbe [1985] or the recent review by Mishra and Coulibaly [2009].

Taken together, these issues constitute a long-standing problem in rainfall–runoff modeling and flood prediction, namely, given economical limitations on the number of rain gauges that can be installed and maintained, where should they be placed to best measure both the depth and spatio-temporal variability of rainfall intensity during extreme storm events?

2. Scope and Motivation

[6] The scope of this study is to develop and evaluate a robust multicriteria strategy for identifying the best locations for installation of rain gauges based on empirical data (i.e., given a basin’s topography and dominant storm tracks), with a particular focus on semiarid mountainous regions. This should allow for a design of high-quality networks that enable an optimal accomplishment of the challenging task [e.g., Michaud and Sorooshian, 1994b] of providing accurate rainfall data for the prediction of flash floods in semiarid catchments with complex terrain while being of operationally practical density. The method is evaluated using a series of extreme rainfall–runoff events in the Catalina Mountains located near Tucson, Arizona, USA, allowing an exploration of network design considerations under realistic conditions. Specifically, we test the degree of improvement and level of accuracy actually achievable in flash flood prediction by use of realistically dense but optimally configured networks in combination with a semiarid rainfall–runoff model.

[7] Of course, such a data-based inverse network design approach is accompanied with increased effort and requirements on the data collection side compared to an a priori network design strategy. Although tempting, no attempt was made in this study to derive quantitatively general guidelines that could be used for such an a priori network design (i.e., where appropriate data to design networks is not available and cannot be collected). Several studies have used theoretical models of the rainfall process to provide results that can be considered as more general guidelines to the design of rain gauge networks or the estimation of related sampling errors and uncertainties. The statistical approaches involved modeling of the spatial covariance function of the rainfields [e.g., Rodríguez-Iturbe and Mejia, 1974; Morrissey et al., 1995; Berne et al., 2004] or simulations from conceptual stochastic space–time models of rainfall [e.g., Peters-Lidard and Wood, 1994]. These models typically assume that the statistical characteristics of precipitation do not vary in space (i.e., a stationary or weakly stationary random field) [Bradley et al., 2002]. This allows estimation of the accuracy of each possible network before any experiments or observations are actually made. Such estimate depends only on the geometric configuration of the gauge locations (sample points) and on the domain to be estimated, and is independent of actual observations except for the spatial variability of precipitation [Delhomme, 1978]. It is this condition that permits a priori network design. In addition to providing information on the required number or spacing of gauges for a given area, the most common general a priori design guideline on the spatial arrangement of gauges is to cover the domain under consideration as uniformly as possible; that is, centered uniform networks result in the lowest errors in precipitation estimates.

[8] However, the assumption of (weak) stationarity limits the applicability of such design guidelines to areas where
mountain range (required sampling density), will be unique for a given information and pattern, and thus sampling positions (and also the many areas in which the effects of Earth results cannot be transposed with confidence to or between temporal and spatial scales. Patterns in manifold and complex ways and on various semiarid mountainous catchments, where orography is mountainous terrain, such as the flash flood generating hydrologically homogeneous regions). In areas of complex rainfall can be considered essentially random in space (i.e., hydrologically homogeneous regions). In areas of complex mountainous terrain, such as the flash flood generating semiarid mountainous catchments, where orography is known to affect precipitation formation and accumulation patterns in manifold and complex ways and on various temporal and spatial scales [Barros and Lettenmaier, 1994; Roe, 2005], spatial biases (i.e., nonstationarity) in the rainfall distribution on both short and long time scales are usually evident and climatic differences in precipitation can occur even over short distances [e.g., Michaud et al., 1995; Bradley et al., 2002]. As such the orientation of the entire sampling network relative to the resulting dominant storm tracks and rainfall gradients will exert major controls on the accuracy of the network and the combined properties of the multiple gauges with respect to parameters such as elevation, slope, aspect, location of barriers, and wind speed and direction will be important [Spreen, 1947; Burns, 1953; Schermerhorn, 1967; Houghton, 1979; Daly et al., 1994].

The combined effects of such factors on rainfall formation and pattern, and thus sampling positions (and also required sampling density), will be unique for a given mountain range [Barros and Lettenmaier, 1994], such that results cannot be transposed with confidence to or between the many areas in which the effects of Earth-atmosphere interactions on the depth and distribution of precipitation cannot be neglected. This is especially true when it is required to capture the (short) time distribution of rainfall which is important for runoff simulations [Woolhiser and Goodrich, 1988] and often (such as in the case studied here) differs significantly in its spatial distribution from the long-term mean during extreme rainfall [Obled, 1990]. Thus, despite of the undoubted worth of approaches aiming for an ultimately sublime goal of enabling (or guiding) an a priori design of networks, the complexity and diversity of the problem makes it impracticable to derive a universally satisfactory procedure for the design of rain gauge networks. However, these problems can be circumvented by use of high-resolution rainfall data in rain gauge network design in an attempt to mimic the “true” space–time patterns of precipitation [Huff, 1970] and implicitly integrating all the complex influences and interactions.

[10] From the above, it should be clear that the a priori network design and network optimization based on empirical data should be considered complementary rather than concurrent strategies. This is because they provide a trade-off between design effort on the one hand and, depending on the considered area and associated precipitation characteristics, varying degrees of resulting network optimality and reliability (and thereby arguably of expectable cost efficiency in operation concerning both maintenance and prevented loss) on the other. The most suitable design approach depends on this trade-off in deliberation of the anticipated objective(s) of the network, implying a certain accuracy requirement, difficulty and criticality of accomplishment. Regardless, there is clearly a need for an optimization method (like the one presented in this study) in regions where general a priori guidelines cannot be applied with confidence, particularly when high-quality network observations are required for a critical task.

3. Site Description and Data Sets

3.1. Site Description

Rainfall and streamflow were monitored in the 91 km² Sabino Canyon catchment for the summer 2006 monsoon season (Figure 1). This catchment has an elevation ranging from 820 m to 2790 m and is positioned on the south face of the Santa Catalina Mountains, located northeast of downtown Tucson, Arizona, USA. The annual total precipitation varies greatly with elevation, leading to a semiarid climate near the base of the mountain (average rainfall 300 mm/yr) and a more humid climate near the top (average rainfall 800 mm/yr) [Guardiola-Claramonte, 2005]. The precipitation falls predominantly during two distinct seasons: a summer monsoon season (usually July through September) and a winter season (with the majority of precipitation occurring between December and March), separated by dry periods [Desilets et al., 2008]. Approximately 45% of the annual precipitation falls in the summer, during the North American Monsoon, when incursions of moist, tropical air from the south promote localized convective storms of high rainfall intensity and short duration. Winter season precipitation (approximately 34% of annual precipitation; partially as snow) is characterized by more widespread frontal storms from the Pacific Ocean of longer duration and lower rainfall intensity [Green and Sellers, 1964]. The region is particularly rugged and steep with v-shaped valleys, conditioned by the geology of the area, and is predominantly

![Figure 1. Site map and instrumentation of the Sabino Creek catchment located in the Santa Catalina Mountains northeast of Tucson, Arizona, USA. The grid shows a reposition of the KEMX weather radar (42 km to the southwest) coverage over the area and has a resolution of 1 × 1 km. The stream gauge is located at 32°25′20″ latitude and 110°45′05″ longitude.](image)
granitic with the Catalina schist being the most characteristic facies present [Guardiola-Claramonte, 2005]. The relatively thin soil and steep slopes promote rapid surface runoff and interflow of summer rains.

3.2. Event Description and Data Collection

[12] The Sabino Canyon catchment is extensively instrumented at several scales as part of ongoing research [Lyon et al., 2008]. Here, we consider streamflow, tipping bucket rain gauge and radar data for this catchment over a period of extreme rainfall events occurring in the summer of 2006. During the last week of July 2006, an upper level disturbance stalled over northwestern New Mexico, steering moisture-laden air into central and southern Arizona from the north. Combined with a surge of humid, tropical air from the south, the low pressure generated widespread, early morning thunderstorms over southeastern Arizona during a 7 day period [Magirl et al., 2007]. Destabilization of the atmosphere’s vertical structure over the mountain range and forced ascent and convergence of warm, moist air impinging on the southwest trending canyons on the fore range led to orographically enhanced precipitation and triggering of deep and localized convection over the study site. More complete descriptions of the events are provided by Magirl et al. [2007], Lyon et al. [2008], and Griffiths et al. [2009]. Streamflow was monitored by the United States Geological Survey at the outlet of the Sabino Canyon catchment (USGS site 09484000). A total of 40 tipping bucket rain gauges (RainWise Inc.) sampling at 1 min intervals were installed to monitor spatial-temporal variability of monsoon storms in mountainous areas (Figure 1). Locations for rain gauge installation were limited by accessibility to remote sites within the catchment. As such, most gauges were installed at upper elevations (which coincides with nested hillslope and catchment studies in the Upper Sabino and Marshall Gulch research catchments). Rain gauges were installed in clusters of two to five gauges, and at maximum separation distances ranging from 500 m to 2,000 m, based on recommendations from studies of rainfall variability [Krajewski et al., 2003; Ciach, 2003]. Radar data over the same region and period was available from the Tucson WSR-88D (Weather Surveillance Radar-1988 Doppler) weather radar KEMX, which is a part of the National Weather Service (NWS) NEXt generation RADar (NEXRAD) weather radar network. The KEMX station is located approximately 50 km south of the outlet of the Sabino Canyon catchment, and has an unimpeded view of the atmosphere above the mountains. The Digital Hybrid Reflectivity Scan (DHR) product from the WSR-88D provides reflectivity on a polarimetric grid of 1 x 1 km, at every volume scan (~5 min) [Morin et al., 2005]. A total of 94 radar pixels completely cover the study area (Figure 1).

3.3. Data Preparation

3.3.1. Rain Gauge Data

[13] Following the monsoon season of 2006, data were downloaded in the field from each rain gauge. Initial quality control was performed to identify data from gauges that experienced large data logger time shifts or were subject to mechanical failure. 15% of the gauges were removed from the data set due to mechanical failure, and 25% were removed due to extremely large time drift during the study period (>10 min over 2 months). To further reduce the influence of rainfall variability and produces severe, quick, and sharply peaked flash flooding at the study site [Desilets et al., 2008], such that its monitoring represents the most difficult and important challenge for a rain gauge network designed for flood prediction. We consider both the entire period of data (referred to as all events) and each individual rainfall event separately (referred to as single events) in rain gauge network optimization. This section is organized into two parts: section 4.1 presents the strategy for rain gauge network optimization and section 4.2 describes our strategy for.
evaluating the optimized networks (in terms of flash flood response predictions).

4.1. Rain Gauge Network Optimization

[17] The problem can be formulated as that of finding locations for a limited number of rain gauges that provide optimal estimates of both the spatial precipitation distribution and the mean areal precipitation (MAP). Based on the observed rainfall, MAP is defined for this study as the arithmetic mean over the set of 94 grid cells covering the catchment area.

[18] The center of each of the 94 grid cells (i.e., spatially discrete units) was used to define potential positions for rain gauges. We can then consider all possible network configurations consisting of one to four gauges as separate network designs. This gives 49, 4371, 134,044 and 3,049,501 possible one-gauge, two-gauge, three-gauge, and four-gauge configurations, respectively. We only consider up to four-gauge network configurations, since these correspond to a density of one per 23 km², which is denser than typically utilized for real-time flash flood forecasting and warning in semiarid regions of the United States (one gauge per 25 km² [see Michaud and Sorooshian, 1994a, 1994b]). Each possible network configuration was used to sample the true rain field. The resulting “observations” were interpolated over the catchment area using an inverse distance squared weighting method (considering the three available nearest neighbors to an unsampled location [National Weather Service, 1999]), which was selected for its simplicity, objectivity (not requiring user interaction or interference), and demonstrated efficiency and reliability even in regions of strong orographic effects [Dirks et al., 1998; García et al., 2008]. This resulted in a catchment-wide map of rainfall at each 15 min time step for each possible network configuration prepared in a manner consistent with NWS recommendations. The MAP of each rainfall map was computed for each time step.

[19] To identify the “best” network configuration for a given number of gauges, we used a multicriteria approach based on values computed for three objective functions (OFs). OFs were selected that effectively measure the characteristics of rainfall behavior important for flash flood forecasting (i.e., enable accurate prediction of flood volumes and hydrograph shape and timing). The first OF was therefore selected to measure errors in global rainfall volume input to the catchment, computed as the residual percent bias (PBIAS):

\[
PBIAS = \frac{\sum_{i=1}^{n} (X_i - P_i)}{\sum_{i=1}^{n} P_i} \times 100\%
\]  
(1)

where \(P_i\) is the true mean areal precipitation (MAP) at time interval \(i\), \(X_i\) is the sampled MAP from a given network configuration at that time interval, and \(n\) is the number of 15 min time intervals analyzed (Table 1).

[20] Given the temporal dynamics of the runoff generation process in semiarid environments (the flashiness of flash floods), accurate estimates of rainfall volumes alone will not necessarily provide the ability to predict either the flood hydrograph shape and peak flows or the volume. The second OF was therefore selected to measure errors in the temporal variation of rainfall over the entire catchment area, computed as the coefficient of correlation (CORR):

\[
CORR = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}}
\]  
(2)

where the over score operator (as in \(\bar{P}\)) indicates the average of the measure (here \(P_i\)) over all \(n\) time intervals considered.

[21] Finally, the spatial localization of runoff generation consequent to the highly variable rainfall forcing over the catchment can exert a strong influence on the various aspects of the flood hydrograph. The third OF was therefore selected to measure errors in the spatial distribution of rainfall across the catchment, computed as the normalized spatial mean squared error (NSMSE):

\[
NSMSE = \frac{1}{k} \sum_{i=1}^{n} \left[ \frac{\sum_{i=1}^{n} (X_{i,i} - P_{i,i})^2}{\sum_{i=1}^{n} (P_{i,i} - \bar{P})^2} \right]
\]  
(3)

where \(i\) is the grid cell index and \(k\) is the number of grid cells covering the catchment area.

[22] These three OFs provide noncommensurable measures of information whose simultaneous optimization can help in the selection of rain gauge networks that are optimal with respect to the purpose of flood prediction, by extracting relevant information from a single signal [Gupta et al., 1998]. Note also that the simultaneous use of these multiple OFs, as opposed to a single OF of the common Simple Least Squares type, reduces the need for assumptions regarding the error distribution [e.g., Gupta et al., 2005] and avoids an overly strong sensitivity of the optimization results to potentially large errors for few very high rainfall intensity values (and thus also to specific rainfall events). Of course, while any number of relevant OFs could be considered, they should, as is the case for equations (1)–(3), be selected to be relatively unrelated in the information they add to the network design process in the sense that they measure different important

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### Table 1. Summary of the Seven Rainfall Events Occurring at the End of July 2006 in the Sabino Canyon Catchment

<table>
<thead>
<tr>
<th>Event</th>
<th>Start Date</th>
<th>Total Storm Depth</th>
<th>15 Min Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time (LT)</td>
<td>Areal Mean (mm/h)</td>
<td>Areal Max. (mm/h)</td>
</tr>
<tr>
<td>1</td>
<td>25 Jul 2130</td>
<td>150 6.9 22.2 2.6</td>
<td>0.588 2.8 10.7 67.1</td>
</tr>
<tr>
<td>2</td>
<td>27 Jul 0000</td>
<td>660 16.2 26.0 10.8</td>
<td>0.256 1.5 12.8 31.4</td>
</tr>
<tr>
<td>3</td>
<td>27 Jul 2300</td>
<td>720 36.6 68.9 11.2</td>
<td>0.316 3.0 48.4 163.8</td>
</tr>
<tr>
<td>4</td>
<td>28 Jul 2230</td>
<td>855 85.1 164.3 43.3</td>
<td>0.283 6.0 33.4 235.8</td>
</tr>
<tr>
<td>5</td>
<td>30 Jul 0315</td>
<td>180 32.5 93.1 18.5</td>
<td>0.378 10.8 37.8 207.3</td>
</tr>
<tr>
<td>6</td>
<td>31 Jul 0000</td>
<td>540 73.5 205.3 27.7</td>
<td>0.480 8.2 32.9 197.0</td>
</tr>
<tr>
<td>7</td>
<td>31 Jul 2330</td>
<td>555 60.7 183.0 5.2</td>
<td>0.691 6.6 54.6 328.0</td>
</tr>
</tbody>
</table>

*CV is the coefficient of variation.
aspects of the differences between the estimated and the true rainfall.

[23] To select networks that optimize all OFs simultaneously, we adopt a multicriteria concept analogous to Gupta et al. [1998] and formulate the multicriteria network design problem as:

$$\min_{\Theta \subseteq \Theta} F(\theta) = [F_1(\theta), F_2(\theta), \ldots, F_m(\theta)]$$  \hspace{1cm} (4)$$

where $\theta$ represents the possible gauge combinations within the feasible set $\Theta$ and $m$ represents the number of criteria used (in this case, $m = 3$). This multicriteria optimization problem does not, in general, have a unique solution that simultaneously optimizes each criterion. Instead, it is generally necessary to adopt a Pareto set of solutions which have the property that moving from one solution to another will result in the improvement of at least one criterion while causing deterioration in at least one other. This Pareto set (often referred to as the trade-off set, noninferior set, nondominated set, or the efficient set) defines the minimum uncertainty in network selection that can be achieved without stating a subjective relative preference for minimizing one specific component of $F(\theta)$ at the expense of another.

[24] However, any practical rain gauge network design demands a single solution. And, while it is impossible to distinguish any of the Pareto solutions as being objectively better than any of the other Pareto solutions, the identification of a restricted set of Pareto solutions allows for the subjective selection of an appropriate single network in a well-informed manner. There usually are Pareto solutions which correspond (basically) to optimization on only one of the competing OFs (e.g., very low PBIAS but high NSMSE and low CORR), and Pareto solutions which correspond to a more balanced trade-off between the OFs and thus to optimization on all OFs simultaneously (i.e., low PBIAS and NSMSE and high CORR). It is this latter type of solutions, referred to as “compromise solutions,” that fulfills the multiple-criteria requirements for an appropriate final “best” network. Specifically, we select as the final “best” network the Pareto solution which corresponds to the most favorable compromise between the three OFs, that is the solution for which each objective has been optimized to the extent that if we try to optimize it any further, only minor improvements are traded off for a stronger deterioration of at least one other objective, such that each single criterion takes on a reasonable, though usually not optimal value (in a single-criterion sense). Identification of this network was done manually based on inspection of plots of all possible network solutions in the three-dimensional objective function space.

[25] In such plots, it is also possible to identify the solutions forming the boundary of the solution space toward the theoretical optimum at $\text{CORR} = 1$, $\text{PBIAS} = 0$, and $\text{NSMSE} = 0$ (i.e., a Pareto front). So, while a best network can be selected, all solutions lying along (or close to) the Pareto front in proximity to this best solution may be of interest as they represent “good” networks that are similar with respect to their compromise between the OFs. To account for the subjectivity in the above method for selecting a best network solution and to evaluate the robustness of the proposed network design strategy, we identify, in addition to a single best compromise solution, a compromise set of solutions. To form the compromise set, we first select networks from the highly compromised part of the Pareto set excluding solutions at the ends of the Pareto front. These ends are avoided as they correspond (basically) to single-criteria optimizations. Second, we add solutions in proximity to the best network solution (but not along the Pareto front). Here, proximity was defined as solutions in a tetrahedral region of the three-criteria space with vertices located at (1) $\text{CORR} = 1$, $\text{PBIAS} = 0$, and $\text{NSMSE} = 0$; (2) the $x$th percentile of $\text{CORR}$, $\text{PBIAS} = 0$, and $\text{NSMSE} = 0$; (3) $\text{CORR} = 1$, the $x$th percentile of $\text{PBIAS}$, and $\text{NSMSE} = 0$; and (4) $\text{CORR} = 1$, $\text{PBIAS} = 0$, and the $x$th percentile of $\text{NSMSE}$. The value $x$ was selected by iteratively increasing from the 95th percentile until the resulting tetrahedral region contained 10 (or less) solutions. Other approaches to define proximity to the best network were considered, but did not provide significant differences to the resulting compromise sets of network configurations.

[26] The best network configuration (the compromise solution) and set of good networks (the compromise set of solutions) were identified using the entire rainfall data set (all events). In addition, the best network and the set of good networks were identified using each of the single rainfall events individually (single event) to investigate the influence of length of record on network optimization and to evaluate the temporal persistency of network performance (i.e., the performance outside of the optimization period in the sense of a split-sample test). This provided eight best network configurations and eight sets of good configurations for each network density considered (one through four gauge networks).

4.2. Evaluation of Optimized Networks in Flood Simulation Performance

[27] To evaluate the appropriateness of rain gauge networks for accurate flash flood forecasting, we used the rainfall time series observed by a network as input to the Kinematic Runoff and Erosion (KINEROS2) model developed by USDA-ARS scientists for watersheds in semiarid environments [Woolhiser et al., 1990; Smith et al., 1995; Goodrich et al., 2006]. This event-oriented, distributed, physically based model was developed to simulate runoff responses in basins dominated by overland flow, and is currently being used by the Tucson NWS to provide quantitative operational flash flood forecast guidance [Gupta et al., 2006]. The model represents the watershed as a cascade of overland flow planes and channels, thereby allowing rainfall, infiltration, runoff and erosion parameters to vary spatially. Gauge sampled rainfall depth is interpolated to the model subunits (plane elements) by inverse distance squared weighting using a maximum of three nearest neighbor gauges (i.e., same as for network rainfall estimation using a different spatial discretization).

[28] To generate an “observed” hydrograph, KINEROS2 was run using all available rainfall data (94 raster cells) at each 15 min time step for the rainfall event on July 31, 2006 (event 6 in Table 1). Model parameters and initial soil moisture states were estimated using geospatial data (delineation of 226 planes with an average area of 0.404 km$^2$ and 91 channel elements) and were refined by calibrating model response to modest runoff events from 2004 and 2005 and to the extreme event on July 31, 2006 [Gupta et al., 2006; Magir et al., 2007]. The model configuration was kept constant for all simulations.
The model was then run using rainfall sampled by each of the best network configurations and using each of the sets of good network configurations identified from both the entire record of observation (all events) and using each individual event (single events). For baseline comparison, ensembles of 1000 different gauge network realizations were randomly selected for networks of each density (one through four gauges), to simulate the effect of observations obtained by randomly assigning the locations of gauges in the network. The model simulations obtained by each of these network configurations can then be compared to the model-generated “observed” hydrograph. This strategy allows us to separate, to some degree, the influence of errors in network sampling from other error sources related to the model structure, parameter estimates and data error. Of course, rain errors and other errors may not be, in general, independent [Gupta et al., 2005] so that the considered errors are still a function of both the rainfall sampling error and the model, which transforms rainfall errors into runoff errors.

Model performance evaluations were based on several overall statistical measures considered to be relevant in the context of flood prediction, including the Nash–Sutcliffe efficiency index (NSE), the percent volume error (PVE; equivalent to PBIAS), and the percent peak error (PPE) defined as follows:

\[
NSE = 1 - \frac{\sum_{t=1}^{n} (Y_t - Q_t)^2}{\sum_{t=1}^{n} (Q_t - \bar{Q})^2}
\]  

(5)

\[
PVE = \frac{\sum_{t=1}^{n} (Y_t - Q_t)}{\sum_{t=1}^{n} Q_t} \times 100\%
\]  

(6)

\[
PPE = \frac{\max_{1 \leq t \leq n} (Y_t) - \max_{1 \leq t \leq n} (Q_t)}{\max_{1 \leq t \leq n} (Q_t)} \times 100\%
\]  

(7)

where \(Y_t\) is simulated runoff at time step \(t\) using rainfall sampled from a given network configuration, \(Q_t\) is the model-generated “observed” runoff at time step \(t\) computed using the entire rainfall field, and \(n\) is the total number of 15 min time intervals comprising the runoff event being simulated.
modeled. For the model runs based on the 1000 random rain gauge networks, the statistics from equations (4)–(6) for each ensemble member were aggregated into mean values and used to estimate percentile ranges.

5. Results

5.1. Optimal Rain Gauge Networks

The multicriteria network optimization methodology was first applied to the entire record of rainfall (Figure 2). As we increase the number of gauges in the network (moving from Figures 2a to 2d), the network solutions, including both the all events best network (AE-BN) and all events compromise set of networks (AE-CSN; dominated solutions included in the AE-CSN are not shown in Figure 2), move closer in performance to a theoretically perfect network (i.e., CORR = 1, PBIAS = 0, NSMSE = 0; see auxiliary material). The overall performance of the different possible gauge network configurations (all possible permutations of locations of a selected number of gauges) shows considerable scatter and only minor reductions in the error limits (i.e., CORR ≈ 0.6, PBIAS ≈ 80%, NSMSE ≈ 6 for all networks from one to four gauges; most likely due to spatial clustering of gauges and associated redundancy of information). The Pareto front, however, becomes increasingly more right-angled in shape (with respect to each combination of two OFs) as the number of gauges is increased. This result facilitates an increasingly unambiguous (informed) identification of the best network. Note there is a lack of any obvious relationship between the performance of the networks with respect to the two individual criteria CORR and PBIAS measuring the network accuracy with regard to the MAP. This indicates the complementary nature of the information provided by the two criteria with respect to constraining the networks to the data. The NSMSE further constrains the networks with respect to errors in the spatial rainfall representation, which are seen to be not entirely unrelated to the errors in the MAP (in terms of the PBIAS and CORR OFs in combination).

The actual physical locations of the AE-BN and the corresponding AE-CSN solutions can be mapped back into the catchment (Figure 3). The relative frequency of occurrence of a potential gauge location in the selected compromise set of networks of a given number of gauges is indicated by shading the enclosing grid cell (here 100% represents a gauge location selected by all networks of the compromise set). The maps clearly indicate significant spatial clustering of high selection frequencies in proximity to the locations of AE-BN gauges; that is, the compromise set networks exhibit very similar spatial gauge configurations.

Optimal rain gauge networks were also identified using single rainfall events individually. Using the method-

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Figure 3. All events best networks (AE-BNs) of (a) one, (b) two, (c) three, and (d) four gauges (white circles) mapped into the Sabino Canyon catchment. The shading of the grid cells indicates the frequency of inclusion to the all events compromise sets of networks (AE-CSNs).

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1Auxiliary materials are available in the HTML. doi:10.1029/2010WR009145.
ology discussed above, we can define single event best network (SE-BN) solutions and corresponding single event compromise set of networks (SE-CSN). This results in seven different best networks and compromise sets for each configuration from one to four gauges (Figure 4). While shading indicating selection frequency is not shown in Figure 4, the SE-CSNs tend to cluster about the SE-BNs in a manner similar to that using all-event data. Note that, while the optimized networks are different for each event, some relatively consistent patterns are apparent (particularly with network configurations of three or more gauges).

5.2. Network Accuracy Evaluation Across Events

[34] The accuracy of areal and spatially distributed rainfall estimation for the identified best networks and the corresponding compromise sets can be compared with the aggregated results obtained for all possible network realizations by comparing summary statistics of performance across all events. While the accuracy for each individual event is explicitly quantified by each of the OFs (PBIAS, CORR, and NSMSE), it can also be expressed as a normalized mean squared error (NMSE):

\[
NMSE = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{X_i - P_i}{C_0} \right)^2
\]

We include the NMSE as it is a measure commonly used in network design studies [e.g., Rodriguez-Iiturbe and Mejia, 1974; Bras and Rodriguez-Iiturbe, 1976; Seed and Austin, 1990], which provides a somewhat different check on the accuracy of the optimized networks.

Figure 4. Maps of best networks of one to four rain gauges (first through fourth columns; solid dots) optimized based on single events (events 1–7 in Table 1 correspond to the first through the seventh rows, respectively) and all events (eighth row) for the Sabino Canyon catchment.
As should be expected for convective storm environments, there is significant variability in the accuracy measures owing to significant differences in spatial variability, localization and intermittency between various storm events (Figure 5). However, a clear trend of improvement in PBIAS, CORR, NSMSE, and NMSE is evident for increasing number of rain gauges in the network. Compared to all possible configurations of gauges, the network configurations optimized based on all events or single events are superior with respect to all four performance statistics (see auxiliary material for an evaluation of MAP estimates from AE-BNs at the 15 min time step). The compromise sets of networks (e.g., AE-CSNs) show only small variation in performance and result in very similar overall accuracy to that obtained by the selected best networks (e.g., AE-BNs). Note that the increase in overall performance is lower for network designs based on single events compared to those based on all events, yet it is considerable for this system. So, while the use of a longer rainfall record is favorable, it may not be necessary and a short record of observation already provides remarkable improvements over a random design strategy. Also, these results indicate that the superiority of optimized networks persists beyond the time period used for optimization (e.g., a single event).

Figure 5. Evaluation of rainfall sampling accuracy of optimized networks. For sets of multiple networks, statistics were computed for each network and subsequently averaged. Solid lines show the mean statistic across the seven events, and error bars show maximum and minimum values for the selected best networks for (a–d) all events and (e–h) single events and (i–l) all possible networks. In Figures 5a–5h for the respective compromise sets of networks and Figures 5i–5l for all possible networks, dashed gray lines show the mean statistic across the seven events, with lighter gray shading showing the range of the maximum and minimum. The 5th to 95th percentile ranges of the mean statistic for these sets of networks are indicated as darker gray shading.

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5.3. Evaluation of Rainfall Estimates for Flash Flood Simulation

[36] Hydrographs were generated using the calibrated KINEROS2 model for the July 31, 2006 flood event occurring in the Sabino Canyon catchment (Figure 6; results for single event optimized networks not shown). The improvement in simulation performance achieved using optimized rain gauge network design versus a random network design was assessed (Figure 7; results for SE-CSNs not shown). Note that the “observed” hydrograph is generated using the same KINEROS2 model configuration based on the “true” rainfall field and agrees well (NSE ~ 0.88; PPE ~ 6%; PVE ~ 7%) with the real observed hydrograph [e.g., Magirl et al., 2007].

[37] The results for rainfall observation errors (Figure 5) are reflected in the runoff simulation accuracy (Figures 6 and 7). The range of runoff trajectories and statistical measures for the random network design ensemble indicates a high a priori level of uncertainty associated with the network selection. Further, the mean from the ensembles indicates poor simulation accuracy for random network designs for all network densities (although there is a decrease in error with increasing number of gauges).

[38] By optimizing the network design, however, it is possible to capture the major modes of the spatiotemporal rainfall distribution relevant for distributed flood simulations using a rain gauge network of only three or four gauges. Similar to the rainfall estimates, the uncertainty in runoff simulations is strongly reduced by limiting feasible network alternatives to the compromise sets. This is indicated by runoff simulation trajectories and statistics of compromise networks forming a relatively narrow band around the best network design results. Both precision (refers to width of the simulation percentile ranges) and, more strongly, accuracy (refers to unbiased tracking of or closeness to the target) improve with increasing network density; however, the improvement appears to start leveling off for more than three gauges. Overall, rainfall inputs from the compromise networks enable significantly improved flood simulation performance compared to the average results for random networks. Thus, even if we cannot identify the best locations for rain gauge installation exactly, adequate results are achieved by selecting locations that are

Figure 6. Simulated hydrographs for the 31 July 2006 flood event using the complete rainfall data (solid black) and various network designs of (a) one, (b) two, (c) three, and (d) four rain gauges: all events best networks (solid gray), all events compromise set networks (darker shading), and an ensemble of 1000 random network designs (lighter shading). Shading indicates 95% central percentile ranges associated with the respective set of networks. The dashed black line corresponds to the real observed hydrograph for reference.
close to the best (i.e., close is good enough). Also, again, even consideration of a very short time period of data can result in network designs (SE-BNs) capable of providing improved rainfall inputs for and consequently improved performance of a flood simulation model (Figure 7) during events beyond the optimization time period.

It should be noted here that the relative importance of capturing the spatial variability of rainfall can depend significantly on the degree of catchment saturation and associated prevailing runoff generation mechanisms [Ogden and Julien, 1994; Koren et al., 1999]. Spatial variability of rainfall seems to be of particular importance for infiltration excess dominated catchments [Michaud and Sorooshian, 1994b; Winchell et al., 1998] and in cases where the catchment is initially dry [Shah et al., 1996]. Although the studied catchment is generally infiltration excess dominated across much of its area, it had reached a high degree of soil saturation previous to the simulated rainfall-runoff event [Lyon et al., 2008]. This may have decreased the sensitivity to the spatial rainfall distribution representation particularly at higher elevations where soils in this catchment tend to be deeper (but where no high-intensity rain fell). Regardless, the considered rainfall event led to record flooding at the study site, thus representing a very relevant evaluation case.

6. Discussion
6.1. On the Optimality of Rain Gauge Networks

Several aspects of the results in this study indicate that the networks identified by our approach are robust and optimal. First, the optimizations based on the entire record of rainfall (AE-BNs) consistently provided a high degree of accuracy for sampling the areal mean and spatial distribution of rainfall (Figure 5). This held across several extreme events with varying spatiotemporal rainfall distribution properties. Second, some relatively constant patterns of optimal gauge configurations emerged based on the comparison of results from single events (SE-BNs), particularly for a larger number of gauges (Figure 4). These networks provided (on average) improved rainfall estimation accuracy as compared to randomly assigned networks. Third, the compromise sets of optimized networks (AE-CSNs and SE-CSNs) tended to cluster in space with these configurations being similar to the best networks, showing very little performance variation. From these results, we can infer that a relatively stable pattern of extreme event rainfall exists for this catchment over this series of events. This pattern defines regions in the catchment where gauges can be confidently installed to achieve a consistent high degree of network accuracy. This pattern is better identified using a longer rainfall record, but is seen to be somewhat independent of the record length likely due to interactions between catchment topography and hydrometeorological conditions influencing the spatiotemporal rainfall patterns.

The optimal networks identified with multiple gauges exhibit a certain uniformity of gauge distribution. In general, uniformly distributed networks provide better spatial coverage and representation of storm events. They also tend to reduce the probability of missing an entire storm core (or being entirely covered by a small-scale core) during convective events [e.g., Garcia et al., 2008]. Clearly, however, a variety of complex interactions must enter into the deter-
mination of a truly optimal network configuration and a priori determinable attributes such as “centered” and “uniform” do not provide a sufficient way of discriminating between networks. This will be particularly true in semiarid mountainous catchments with marked orographic effects, where as a consequence, more general concepts that can provide valuable a priori guidance on the number and locations of rain gauges where rainfall can be assumed essentially random in space [e.g., Rodríguez-Iiturbe and Mejía, 1974; Morrissey et al., 1995; Berne et al., 2004] are lacking. In such regions, there is clearly a need for a data-based optimization strategy like the one presented in this study, which is robust and generally applicable to likely arrive at reliable optimal network designs independent of the catchment under consideration and of assumptions of rainfall stationarity.

[3] Both the spatial precipitation distribution and the MAP were used in this study to evaluate and optimize networks (in terms of the three OFs), thereby accounting for the needs associated with the network objective of providing accurate rainfall estimates for flash flood forecasting. Estimation of the MAP is a basic requirement in many hydrological applications, and flash flood warnings in the southwestern United States (provided by the Weather Forecast Offices of the NWS) are typically based (either directly or through lumped rainfall–runoff models) on estimates of spatially averaged rainfall [Tatheendrasad et al., 2008]. Moreover, it has been reported by Beven and Hornberger [1982] and Obled et al. [1994] that a correct assessment of the global volume of rainfall input in a variable pattern is more important than the rainfall pattern (by itself) for simulating streamflow hydrographs. However, in semiarid regions with high spatial variability and localization of rainfall forcing and consequent runoff processes, the uncertainty in the modeled runoff response will be influenced by rainfall estimation errors arising from both biases in observations of the spatial rainfall representation and in the average rainfall volumes [Goodrich et al., 1994; Faurès et al., 1995]. Accurate spatial rainfall estimates are particularly required by distributed rainfall–runoff models now becoming operational in some semiarid regions [Gupta et al., 2006] to provide improved flood forecasting by accounting for this spatial complexity.

6.2. Realistic Rainfall Fields and Assumptions

[3] An advantage of adopting observed data as “true” in rain gauge network design is that climatic variations in precipitation (as observed by radar and gauges) are represented empirically. Particularly in semiarid mountainous regions, where the space–time patterns of nonstationary storm precipitation guiding the network optimization are very difficult to represent with theoretical (stochastic) rainfall models [Bradley et al., 2002; Gupta et al., 2002], observed data is beneficial and needed to arrive at truly optimal network designs. In this study, KED was used to merge the merits of information contained in the data from a dense rain gauge network and weather radar to arrive at a spatial-temporal rainfall data set that is considered to be of very high quality and superior compared to each individual source taken alone. However, using observed data sets involves uncertainties due to measurement errors (gauges and radars) [Groisman and Legates, 1994; WMO, 1994; Young et al., 1999; Krajewski and Smith, 2002] as well as the interpolation technique [Tsintikidis et al., 2002]. An assumption made in this study is that a point measurement within a grid cell will actually measure the same rainfall as represented by the grid cell. This may be a poor assumption if the subgrid variability of precipitation is substantial, implying the lack of good representativeness of the grid–scale rainfall by the rain gauges that measure the process at a point [Zawadzki, 1975; Kitchen and Blackall, 1992; Ciach and Krajewski, 1999]. For the 1 km² grid scale and 15 min accumulation times, however, the resulting mismatch can be assumed to be reasonably small [Journel and Huijbregts, 1978; Villarini et al., 2008].

[4] The 15 min rainfall accumulation time used throughout the analysis is expected to be appropriate for the objective of flash flood forecasting (i.e., to correctly reproduce runoff dynamics) considering, besides rainfall data quality, the size of the catchment and the approximate temporal scale of its hydrologic response in light of general [Schaake et al., 1967; Morin et al., 2001; Berne et al., 2004] and site specific [e.g., Desilets et al., 2008; Lyon et al., 2008] information. It should be noted, however, that the temporal resolution of rainfall data can significantly affect simulations of runoff dynamics and response [Krajewski et al., 1991] as well as the required density [Rodríguez-Iiturbe and Mejía, 1974] and possibly the optimal distribution of rain gauge networks.

[5] To generate rainfall maps and estimate MAP from gauge–sampled measurements, we used an inverse distance squared method. This method was selected because it is simple, objective, and has demonstrated efficient and reliable use even in regions of strong orographic influence on precipitation patterns, making it a common choice in operational settings [Garcia et al., 2008]. Of course, many other approaches could be used for the interpolation of point measurements of rainfall [Singh and Chowdhury, 1986; Singh, 1989], including more sophisticated and often favorable methods such as kriging [e.g., Delhomme, 1978; Creutin and Obled, 1982; Goovaerts, 2000]. Compared to gauge density and related sampling errors, however, the differences in objective function values resulting from different interpolation methods are likely of secondary importance.

[6] Given these assumptions, optimized networks of a few gauges (e.g., three or four) were consistently superior to any randomly designed networks. The impact of design strategy exceeds that of the combined effect of other sources of error inherent in a flood simulation model application (Figure 6). There is thus a high degree of a priori uncertainty associated with the network design and selection process. Even worse, if inappropriately designed, rain gauge networks are unable to provide reliable rainfall estimation. Proper network optimization thus becomes an important issue. These results are in line with previous studies highlighting that network design should not just consider the density of observations and the spatial structure of the measured field, but should include the geometrical configuration of gauges in the network [e.g., Bras and Rodríguez–Iturbe, 1976; Morrissey et al., 1995; Garcia et al., 2008]. By limiting the feasible network space to the most compromise multicriteria space region, it was possible to strongly reduce the initial uncertainty to a narrow range of location and performance variations around the best networks results. So, while the a priori network selection uncertainty is large, the uncertainty associated with the optimal locations is small (Figures 3 and 4).
6.3. Flood Modeling and Remarks on Operational Warning Systems

Previous studies conducted in the semiarid environment (southern Arizona) have indicated that very dense (nonoptimized) operational networks (at least one gauge per 4 km²) are needed to accurately estimate spatial rain fields required to simulate the spatially heterogeneous runoff results of this study, however, indicate that a realistically sparse network of a density between one gauge per 23 km² (the optimized four gauge network) or 31 km² (the optimized three gauge network) may, for catchments such as the Sabino Canyon, be able to provide sufficiently accurate estimates of rainfall fields to enable a skilled simulation of the observed flash flood (if and only if the network is properly designed). While many factors besides input data affect the accuracy of runoff simulations that may not be independent from each other [Gupta et al., 2005], including the runoff model structure and calibration as well as the characteristics and size of the watershed [Michaud and Sorooshian, 1994a], we find that three to four measurements can extract the major modes of information relevant for flash flood prediction from spatio-temporal rainfall maps of 94 pixels with a 1 km² pixel size at a relevant time step of 15 min (Figures 5–7). Note that the required network density is directly proportional to the relevant temporal resolution associated with a specific network objective and spatial scale; that is, sparser (denser) networks may be appropriate for longer (shorter) accumulation times [Berne et al., 2004; Villarini et al., 2008].

Investing in the optimization and appropriate design of operational on-site networks may be worthwhile, as a relatively minor effort can lead to a real increase in ability to monitor rainfall and to provide real time runoff predictions. An inverse network design strategy like the one presented in this study requires high-resolution rainfall information of sufficient amount and quality to optimize rain gauge network configurations. Of course, such a data-based approach is restricted to locations where high-resolution data are available. It may, as demonstrated in this study, be worth the effort to conduct an initial, high spatial resolution sampling campaign before considering the installation of a permanent rain gauge network for flood forecasting or to redesign an inappropriate, existing network. This could include the short-term deployment of many inexpensive tipping bucket rain gauges or the use of mobile radar units similar to Anagnostou et al. [2004] or Loescher et al. [2007]. Moreover, high-resolution radar data alone, which is now being collected across the United States [Klazura and Imy, 1993], could be used as the basis for network design as indicated by Bradley et al. [2002]. Such efforts can provide the necessary information to enable the design of a cost-efficient, sparse, but optimally employed network.

7. Conclusion

While the formulation of simple guidelines for defining optimal rain gauge network configurations for (semiarid) mountainous catchments based on a priori knowledge remains elusive, it is possible to develop strategies to optimize network design based on empirical data. The multicriteria method developed in this study can provide a robust strategy for this purpose, resulting in network configurations (Figures 3 and 4) that provide good performance accuracy for estimating the spatiotemporal rainfall distribution and MAP and associated flash flood streamflow hydrographs (Figures 5–7). For our study basin, the strategy gave results that were relatively insensitive to the subjectivity involved in selection of the single best network and to the record length. The PBIAS, CORR, and NSMSE objective functions selected for this study appear to be suitable for guiding network selection in support of flash flood prediction. Of course, additional OFs may be included to further constrain the networks and alternative OFs should be tested for appropriateness under different circumstances. For example, cost criteria as well as inaccessibility constraints could also be easily included when seeking to explore the trade-off between accuracy and networks that are easier or less expensive to install and maintain. It should, nevertheless, be noted that any single (scalar) objective function, no matter how carefully chosen, will likely be inadequate to ensure that the multiple relevant characteristics of the observed data are incorporated into the network design.

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References


Bruns, J. I. (1953), Small-scale topographic effects on precipitation distribution in San Dimas Experimental Forest, Trans. AGU, 34, 761–768.


