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Estimating extreme spatial rainfall intensities

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Estimating Extreme Spatial Rainfall Intensities

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Abstract: Determining the impact of catchment flooding requires an estimate of extreme spatial rainfall intensity. Current flood design practice typically converts a point estimate of rainfall intensity into a spatial rainfall intensity using an areal reduction factor, assumed constant across an entire region. Areal reduction factors do not explicitly consider regional variations in extreme rainfall. Here, a new approach for spatial estimates of extreme rainfall is introduced that directly incorporates the spatial area (A) into an intensity-frequency-duration relationship (IFD). This IFDA approach uses spatial rainfall fields to overcome shortcomings of the areal reduction factor by explicitly incorporating spatial variations in the extreme rainfall intensity. The IFDA approach is evaluated for 11 case study regions in Australia, across climates (tropical to Mediterranean), areas (25–7,225 km^2), durations (1–4 days), and average recurrence intervals (ARI 2–100 years). The change in extreme spatial rainfall with respect to area varies markedly within each region suggesting that constant areal reduction factors for a region are inappropriate. Constant areal reduction factors are shown to underestimate extreme spatial rainfall intensities by 5–15%. The IFDA approach avoids these biases and is a promising new technique for use in design flood estimation. **DOI: 10.1061/(ASCE)HE.1943-5584.0001316.**

Introduction

Of all natural disasters, floods have the highest global cost and affect the most people (Kousky and Walls 2014; Miller et al. 2008; Strömberg 2007). A key input for estimating flood risk is the spatial intensity of extreme rainfall events over a catchment. Current techniques for estimating extreme spatial rainfall rely on the use of an areal reduction factor (ARF) to convert intensity estimates of extreme point rainfall to extreme spatial rainfall. It is common practice to ignore the spatial variation in rainfall intensity and assume a fixed ARF applies over large regions. The aim of this paper is to introduce a new approach that explicitly incorporates the area and variation of spatial rainfall, referred to as intensity-frequency-duration area (IFDA).

The IFDA approach uses spatially interpolated rainfall grids to directly provide an estimate of how spatial rainfall intensities vary with duration, frequency, and area for a location. An IFDA adds the extra dimension of area (A) to an IFD curve to account for spatial variation in intensity over a catchment.

Existing design methods rely on interpolated maps of intensity-frequency-duration (IFD) rainfall calculated from point rainfall data. The ARF is then used to determine the areal average rainfall intensity from the point rainfall. The factor is defined as the ratio of extreme rainfall at a point to the extreme rainfall over an area for a given frequency (Asquith and Famiglietti 2000). In brief, the ARF is a spatial correction factor used to fix limitations of a design methodology focused around pointwise rainfall estimates (IFDs).

The validity of assuming a fixed ARF for a region has been previously questioned (Catchlove and Ball 2003; Durrans et al. 2002). However, these evaluations of ARF spatial variation have typically been limited to a single location (Catchlove and Ball 2003) or climatic region (Durrans et al. 2002). In contrast, this study will evaluate these impacts across multiple climate regions.

This paper proposes that estimates of extreme spatial rainfall are better and more efficiently obtained by directly using gridded spatial rainfall in preference to scaling pointwise extreme rainfall. IFDAs, as direct spatial rainfall estimates, overcome the assumption that a single scaling relationship is sufficient for a region.

The key objectives of the paper are:

1. To demonstrate the utility of IFDAs and evaluate their spatial variation for 11 study regions across a range of climates within Australia.
2. To evaluate the differences in spatial rainfall estimates obtained using the ARF-based approach and the "true" spatial rainfall, the IFDA.
3. To evaluate the characteristics of differences between the IFDA and the ARF-based approach with respect to properties of the extreme spatial rainfall such as area, frequency, duration and region.

IFDA Approach

The method of constructing IFD curves has been modified to directly incorporate spatial extent. In this approach, each IFDA relationship corresponds to a grid point of specific longitude and latitude. For each grid cell, a set of IFDAs are produced for a range of areas and durations. The approach is generic and is able to be applied to any gridded spatial rainfall data source such as spatially interpolated point rainfall (Bárdossy and Pegram 2013), radar rainfall, and downscaled rainfall from climate model simulations.

An IFDA curve is constructed by first designating a grid cell within the subject region [Fig. 1(a)]. This grid cell of specific latitude and longitude is the central point around which the spatial variation in rainfall is considered. A fixed area is designated around the center grid cell [Fig. 1(b)]. This designated area is illustrated as

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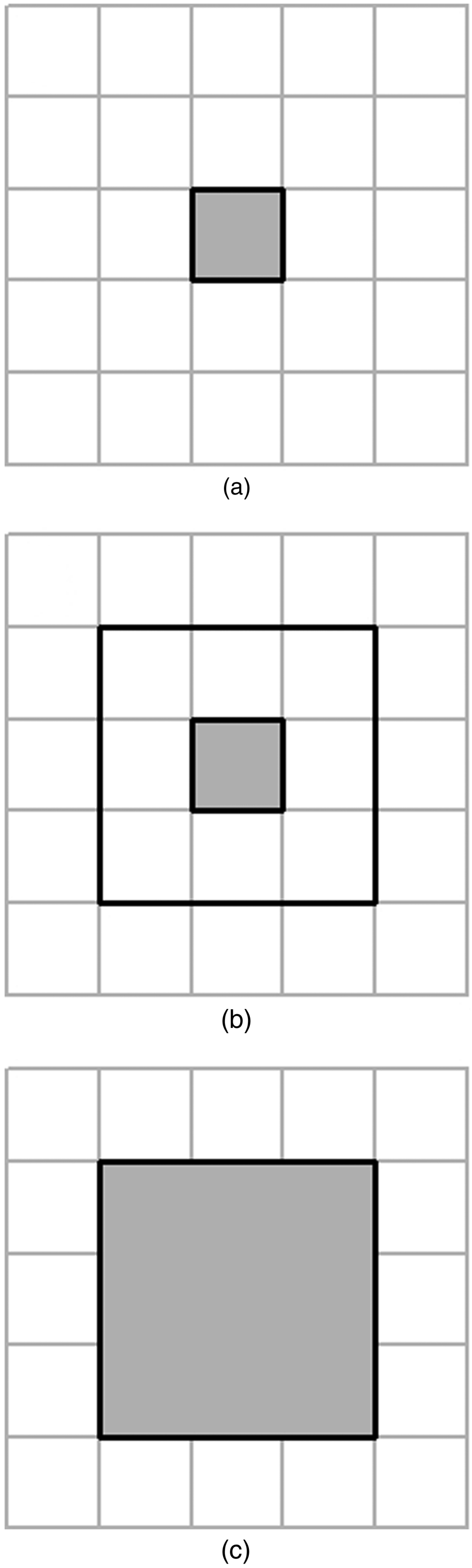

Fig. 1. Schematic of IFDA area designation: (a) centroidal cell identified; (b) area designated around centroidal cell; (c) area consisting of aggregated contributing cells

square in Fig. 1, but the procedure is general and can accommodate areas of any shape.

For each time step the total rainfall in the designated area is summed over the contributing grid cells [Fig. 1(c)]. The increments of spatial rainfall are then summed over the duration and converted to intensity. This results in a time series of spatial rainfall intensities for the designated location, duration, and spatial extent. From this time series the annual maximums are extracted and a generalized extreme value distribution is fitted (Green et al. 2012; Jordan et al. 2011; Siriwardena and Weinmann 1996). The fitted distribution forms the IFDA corresponding to the center grid cell for the designated area and duration.

The IFDA procedure for a single location can be summarized mathematically as follows: Let R_i denote the set of point rainfall intensities for a given duration for all points x in a spatial domain Ω and time increments t in Y_i, the ith year ($i = 1, \ldots, n$), such that $R_i = \{R_i(x,t) | x \in \Omega, t \in Y_i\}$. Let annmax[] be a function that takes the maximum value across all the time increments t in Y_i. For the ith year, the spatial annual maximum rainfall intensity for a catchment domain Ω with area A is defined as

$$C_i(A,t) = \frac{1}{A} \operatorname{annmax}\left[\int_{\Omega} R_i(x,t)dx\right] \tag{1}$$

If the set of extracted events, $C_i = \{C_1, \ldots, C_n\}$ is ordered in terms of magnitude and assigned a frequency, then $C_F(A,t)$ denotes the spatial rainfall intensity for the catchment of area A and frequency F. The rainfall intensities of defined frequency, duration, and area compose the IFDA relationship for that location. The repetition of this process at all locations throughout the domain creates the field of IFDAs and each cell within the region has its own set of IFDA relationships.

Case Study Data

The Australian water availability project (AWAP) gridded rainfall database provides daily rainfall depths on a 5 km square grid across Australia (Raupach et al. 2012). The grids are an interpolated product based on daily point rainfall records and are available from 1900 onwards. This study uses two subsets, 1900–2011 and 1973–2011, where the shorter period provides a check against any changes in gauge density over the period of the longer record.

A conversion factor of 1.15 is applied in this study to account for the restricted time period of the daily observations (e.g., 9 a.m.–9 a.m.). Over restricted periods the maximum is lower than 24 h totals that have been aggregated over an unrestricted time period (Boughton and Jakob 2008; Jakob et al. 2005; van Montfort 1990). For studies that focus on shorter durations (Catchlove and Ball 2003) there is also an implicit need to apply the conversion factor to any daily observations that are used.

The IFDA approach is generic and can be applied to any spatial rainfall data set. For the purposes of this paper the gridded AWAP dataset is regarded as the best estimate of spatial "truth." While spatial interpolation can introduce artifacts (King et al. 2013), the development of better spatial interpolation procedures is a separate (and important) research area. An advantage of the IFDA is that it can easily be updated to take advantage of different or better data products, whereas the current ARF approach cannot (further discussion in "Advantages and Limitations of IFDAs").

Case study regions were selected for detailed analyses based on their gauge density and to ensure coverage of different climates (Tropical: Broome, Cairns, Darwin. Sub-tropical: Brisbane, Sydney. Temperate: Melbourne, Tasmania, Australian Capital Territory (ACT). Mediterranean: Adelaide, Perth. Arid: Alice Springs) (Fig. 2). This paper focuses on the regions of Sydney and Melbourne to illustrate the IFDA relationships. Results from additional regions are included to illustrate that the same general behaviors of

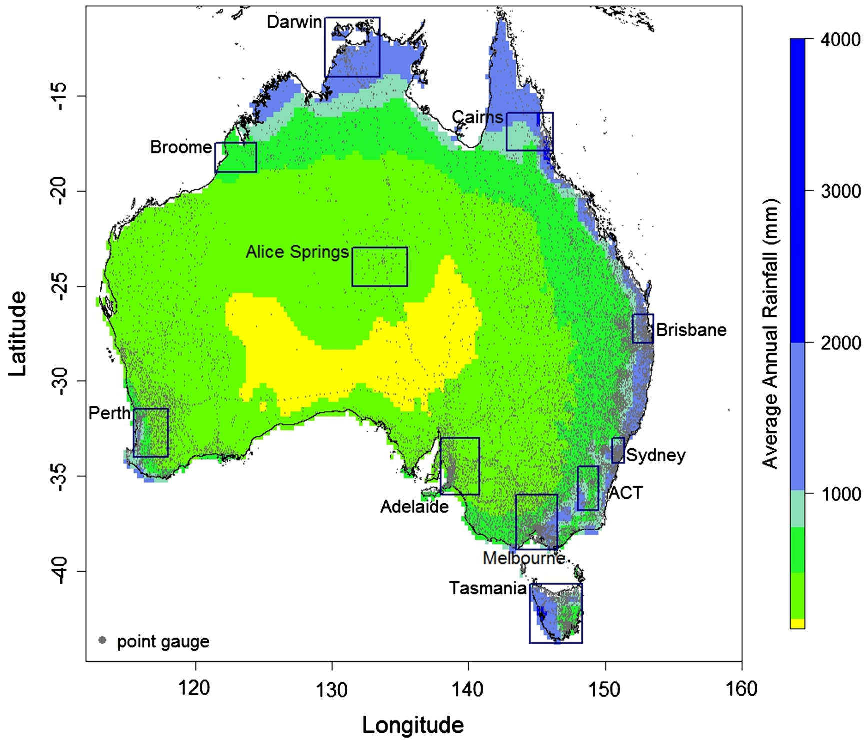

Fig. 2. Location of study regions with annual rainfall isohyets (mm)

the IFDA relationship are exhibited at other locations. The analyses demonstrate the inappropriateness of fixed regional ARFs for estimating extreme spatial rainfall intensities. Melbourne and Sydney have especially dense observation networks, therefore the impact on the results of the AWAP interpolation procedure is minimized.

Methodology

To achieve objective 1, IFDA relationships are derived for all study regions and their behavior is examined to evaluate variations in extreme spatial rainfall. To evaluate the differences between an ARF-based and IFDA approaches (objective 2), the distribution of at-site ARFs calculated using the gridded rainfall are compared with currently recommended fixed regional ARFs (ARF_R). Furthermore, the error induced by using ARF_R is evaluated as a percentage error of the direct estimate of extreme spatial rainfall. The characteristics of the resultant percentage errors are assessed against extreme spatial rainfall properties such as area, frequency, duration, and region (objective 3).

IFDA Calculation

IFDAs were calculated following the method previously mentioned for all study regions and for areas of 25; 225; 625; 1,225; 2,025; 3,025; 5,625; and 7,225 km^2. Durations of 1, 2, 3, and 4 days were investigated and results are presented for average recurrence intervals (ARIs) of 2–100 years. The IFDAs are presented as both location specific relationships and intensity fields. These intensity fields show the rainfall intensity for the specific IFDA area and duration plotted at the center pixel. Therefore, as the area around the center grid increases the boundaries of the region contract to ensure no points outside the original region are sampled in the calculation of intensities for larger areas.

Evaluation of Fixed Area ARFs against the IFDA Approach

Objective 2 is to evaluate the differences in spatial rainfall estimates obtained from the ARF-based approach and the direct estimate of spatial rainfall obtained using the IFDA approach. Therefore, it assesses whether current practice is appropriate for providing robust estimates of extreme spatial rainfall.

Extreme spatial rainfall intensities are traditionally estimated using a representative extreme point rainfall and a regional ARF. The representative point rainfall of a certain frequency is denoted here as R_F, and there are two general approaches for defining it. The first is where the representative extreme point rainfall intensity is taken from a single location, typically the center of the catchment area, $\hat{R}_F^c$. The second is where the spatial average of the extreme point rainfall values within the catchment domain is taken as the representative extreme point rainfall, $\hat{R}_F^{\overline{pt}}$. That is

$$\hat{R}_F^{\overline{pt}}(t) = \frac{1}{A}\int_{\Omega} R_F(x,t)dx \tag{2}$$

This second approach is used in preference to the center extreme point rainfall intensity when there is a strong spatial rainfall trend (e.g., attributable to elevation gradient) within a catchment. In this study, the impact of using both approaches is evaluated.

To evaluate whether the use of fixed regional ARF values, ARF_R, are appropriate for providing robust estimates of extreme spatial rainfall intensities, ARFs were calculated for all locations within each study region. The calculated ARFs are the values required at each sampled location to scale the representative extreme pointwise rainfall to obtain the true extreme spatial rainfall intensity of equivalent ARI. These at-site ARFs were then evaluated against currently recommended ARF_R values.

ARFs are a ratio of spatial rainfall to a representative point rainfall of equal recurrence interval and can be defined as

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$$\mathrm{ARF}_{(A,F,t)} = \frac{C_F(A,t)}{\hat{R}_F(t)} \quad (3)$$

where $C_F(A,t)$ is the spatial rainfall intensity of specified area, A, frequency of F, and duration t. This definition is not a storm-centerd ARF that is based on the point and spatial rainfall of an individual storm (Svensson and Jones 2010). Rather it is a statistical ARF that relates representative extreme point rainfall to extreme spatial rainfall with equal recurrence interval (Allen and DeGaetano 2005; Durrans et al. 2002; Myers and Zehr 1980; Sivapalan and Blöschl 1998). ARFs are constructed by using Eq. (3) with a representative extreme point rainfall intensity for the two different cases outlined above. Where the center extreme point rainfall intensity, $\hat{R}_F^c$, was used in Eq. (3), the resulting at-site ARF has been denoted as ARF_c, where the spatially averaged extreme point rainfall, $\hat{R}_F^{\overline{pt}}$, is used the at-site ARF is denoted as $\mathrm{ARF}_{\overline{pt}}$. For this analysis the single grid cell (25 km^2 area) was nominated as the highest resolution approximation of point rainfall.

The at-site ARF_c and $\mathrm{ARF}_{\overline{pt}}$ values are presented as boxplots to demonstrate the range and distribution of calculated ARF values throughout a region, with a comparison against the fixed regional ARF_R. These fixed regional ARF_R include values published in Pilgrim (1987) (following Myers and Zehr 1980), updated values for New South Wales (Jordan et al. 2011), and updated values for Victoria (Siriwardena and Weinmann 1996). The values used for reference in this study are for the areal rainfall intensity at 25 km^2.

To evaluate the bias present in using the ARF-based approach, the percentage error resulting from using this estimate compared against the spatial rainfall total is calculated. The percentage error is calculated as

$$\%\mathrm{Err} = \frac{\hat{C}_F - C_F}{C_F} \times 100 \quad (4)$$

where C_F is the directly obtained spatial rainfall intensity (i.e., the IFDA value at the required location with corresponding frequency

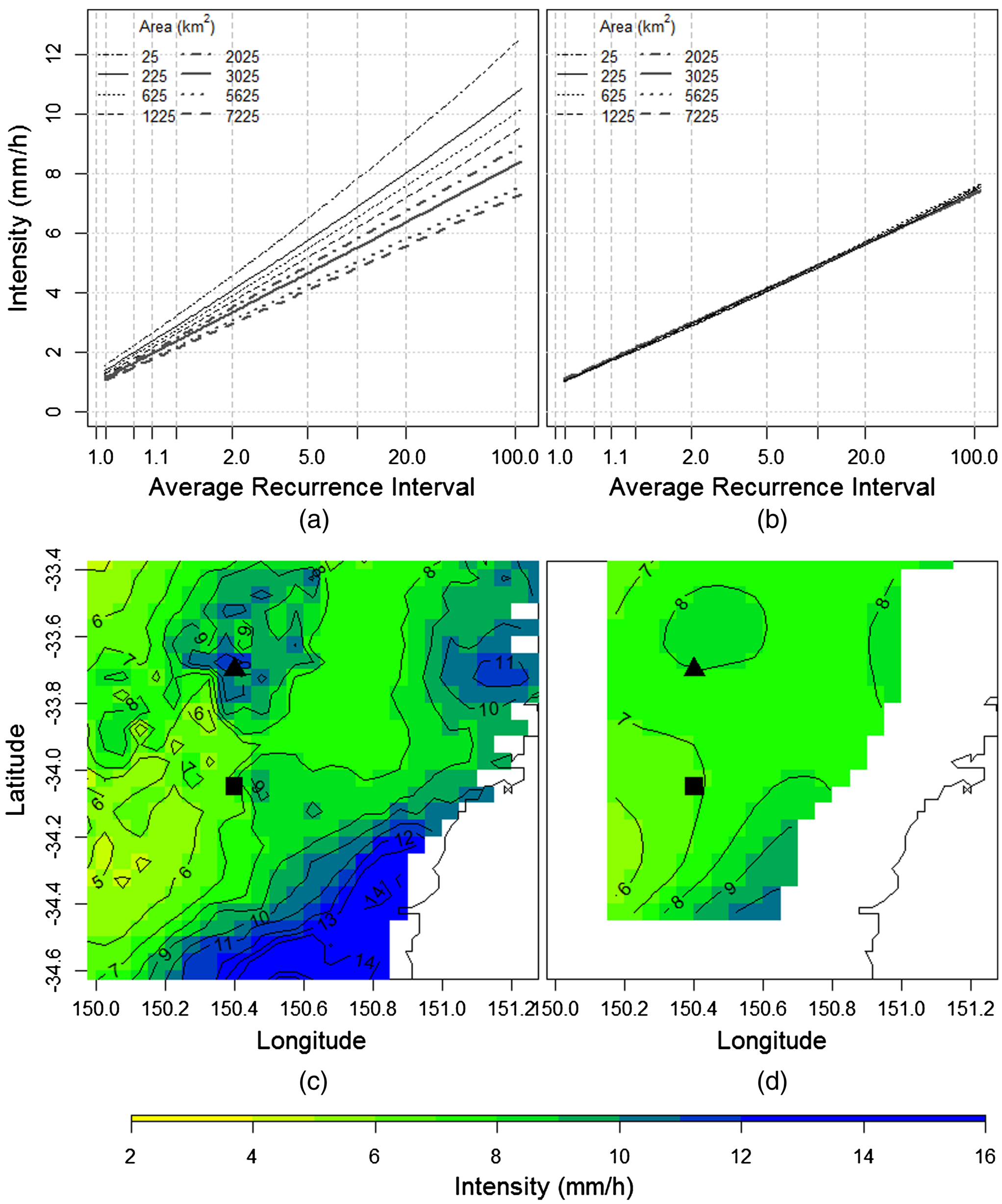

Fig. 3. Sydney region IFDA 1-day: (a) 150.400°E 33.700°S; (b) 150.400°E 34.050°S; (c) IFDA field 25 km^2, 50 year ARI, 1-day; (d) IFDA field 2,025 km^2, 50 year ARI, 1-day

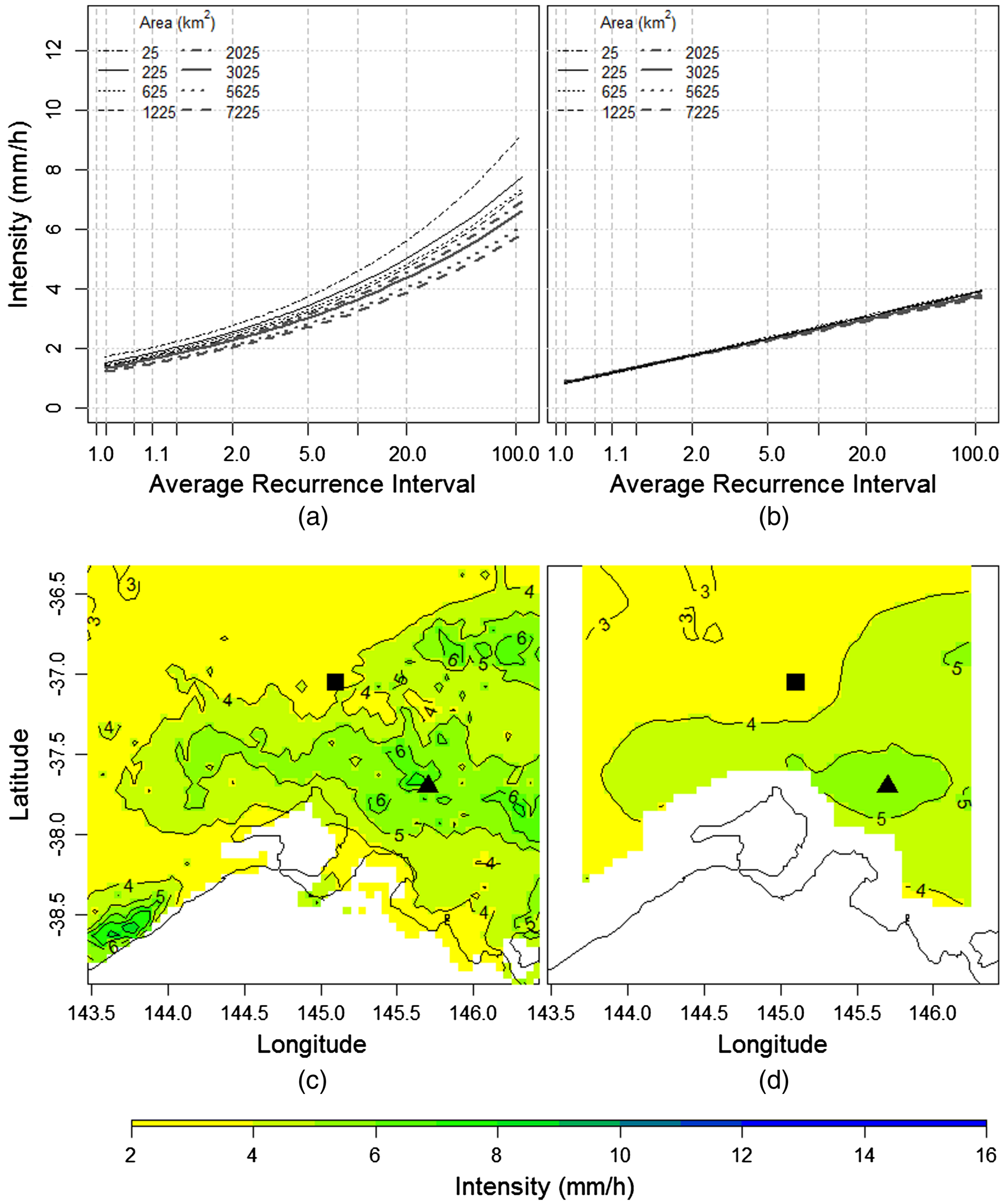

Fig. 4. Perth region IFDA 1-day: (a) 145.700°E 37.700°S; (b) 145.100°E 37.050°S; (c) IFDA field 25 km^2, 50 year ARI, 1-day; (d) IFDA field 3,025 km^2, 50 year ARI, 1-day

F); and $\hat{C}_F$ is the spatial rainfall intensity estimated using a representative extreme point rainfall via Eq. (5)

$$\hat{C}_F = \mathrm{ARF}_F \hat{R}_F(t) \tag{5}$$

For the case $\hat{R}_F^c$, the estimated extreme spatial rainfall and resulting percentage error are denoted as $\hat{C}_F^c$ and $\%\mathrm{Err}_c$, respectively. For the case $\hat{R}_F^{\overline{pt}}$, the estimated extreme spatial rainfall and percentage error are denoted as $\hat{C}_F^{\overline{pt}}$ and $\%\mathrm{Err}_{\overline{pt}}$, respectively.

Identification of Extreme Spatial Rainfall Properties Influencing Errors in the ARF-Based Approach

To evaluate the differences between IFDA and ARF-based approaches four densely gauged regions are considered (Sydney, Brisbane, Melbourne, and Perth). The comparison considers the two cases of $\hat{R}_F^c$ and $\hat{R}_F^{\overline{pt}}$. Specifically the coefficient of variation between the two cases is constructed for ARFs and percentage errors. Changes with respect to properties such as catchment area, frequency, and location are assessed to evaluate which has the largest influence.

Results

IFDA Analysis

At each location within a region the IFDA relationship showed different trends with area. In all regions there were some locations with a large increase in intensity with increasing area, while other locations showed little or no increase in intensity with increasing area. For the Sydney region, with an ARI of 50 years and duration of 1 day, Fig. 3(a) indicates a change of 41% between an area of 25 and 7,225 km^2 whereas Fig. 3(b) illustrates little change in intensity with area. These locations are indicated on Figs. 3(c and d) as triangular and square points. The intensity patterns over the

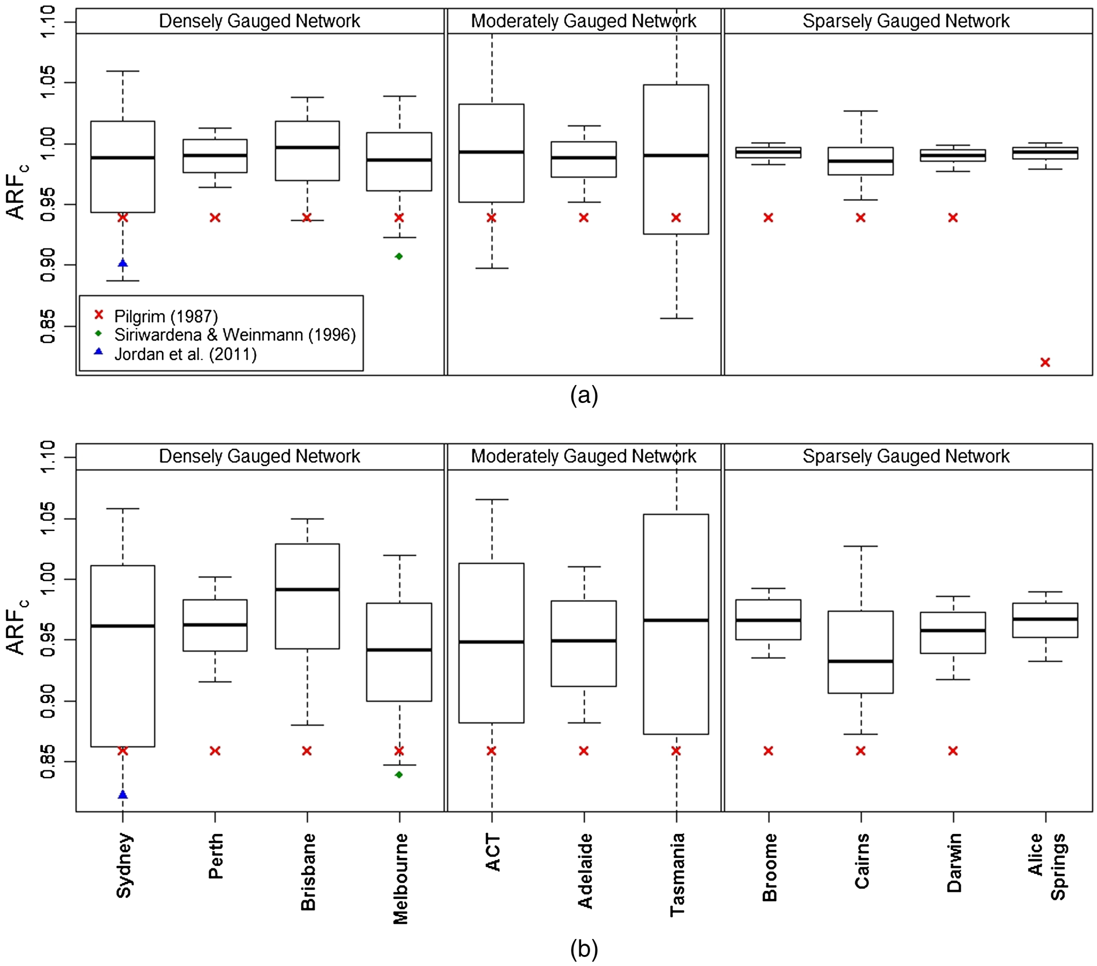

Fig. 5. ARF$_c$ boxplots for 1-day, 50 year ARI rainfall: (a) 625 km^2; (b) 3,025 km^2 (10 and 90% limits shown)

region change as the IFDA area increases. It is this spatial variation in IFDAs that produces the different IFDA curve behaviors exhibited in Figs. 3(a and b).

Fig. 4 similarly shows the change in IFDA with area for the Melbourne region. It similarly illustrates that extreme spatial rainfall intensity patterns change as IFDA areas increase. In Fig. 4 the triangle and square indicate locations at which intensity is highly variable or less variable with area, respectively. Spatial variation in IFDA curves was similarly observed for all other regions (not shown).

The changing spatial patterns of rainfall intensity for different areas can be clearly seen [Figs. 3(c and d), 4(c and d)]. The relationship between intensity and area is spatially heterogeneous and this leads to spatially heterogeneous fields of ARF values.

Evaluation of the Differences between Estimates of Extreme Spatial Rainfall Obtained Using the IFDA and ARF-Based Approaches

Whereas typical flood designs rely on a single ARF value for a given region, there is often considerable variation. To demonstrate this, Fig. 5 summarizes the spatially heterogeneous ARF$_c$ fields as boxplots for all regions, an ARI of 50 years, a 1-day duration, and areas of 625 and 3,025 km^2. The boxplot whiskers extend to the 10 and 90% limits. The derived ARF$_c$ distributions are compared with currently recommended ARF$_R$ values for the Australian regions. The spread of these distributions varies from small to large and is approximately symmetrical. Values greater than 1 occur frequently. An ARF greater than 1 implies that the surrounding spatial rainfall intensity was greater than the individual center point rainfall intensity for that frequency and duration.

Fig. 5 shows that although the regional ARF$_R$ values lie within the range of the derived ARF$_c$ distribution, the fixed values lie below the mean, often significantly so. For example, in Fig. 5(b) the mean ARF$_c$ sits above the ARF$_R$ value of Jordan et al. (2011) by approximately 14% for the Sydney region. The ARF$_c$ distributions exhibit a number of distinctive features. They may be highly variable [Fig. 5(a) Sydney, Tasmania; and Fig. 5(b) Sydney, Melbourne, ACT, Tasmania], indicating that ARF$_R$ may differ significantly from ARF$_c$ values for the majority of locations throughout a region. Alternatively the ARF$_c$ distribution may possess a narrow range of values centering on one [Fig. 5(a) Perth, Broome, Darwin] implying that the ARF$_R$ are biased. Additionally, many ARF$_c$ distributions exhibited values significantly greater than 1 (Fig. 5), indicating that it is common for extreme spatial rainfall surrounding a point to exceed the point rainfall. This behavior was observed for all studied durations.

Fig. 6 presents similar results, using ARF$_{\overline{pt}}$ values. The intention of this alternative is to better account for the spatial variation in point rainfall over the area. However, this modification still leads to significant differences from the recommended ARF$_R$ values. Notably, the ARF$_{\overline{pt}}$ are less variable and have fewer values above 1.

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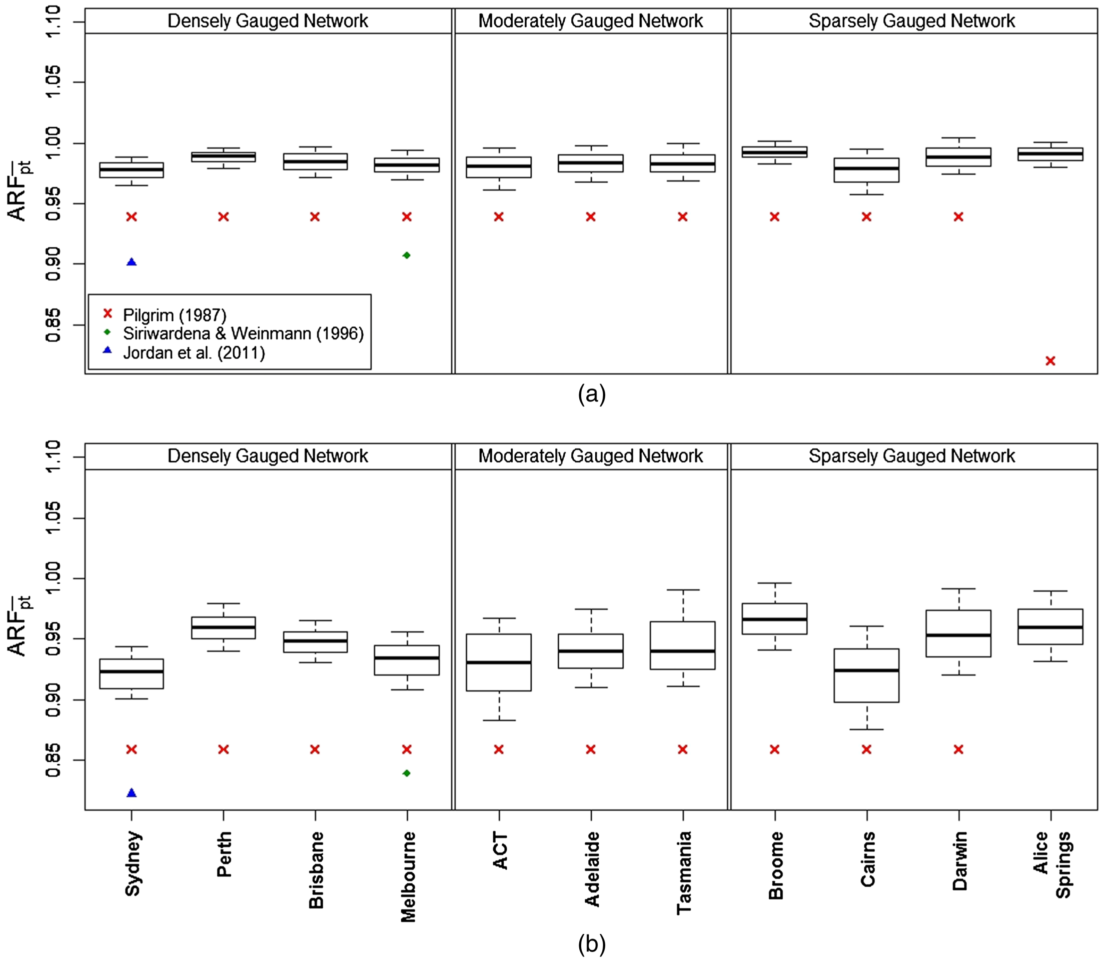

Fig. 6. $ARF_{\bar{pt}}$ boxplots for 1-day, 50 year ARI rainfall: (a) 625 km^2; (b) 3,025 km^2 (10 and 90% limits shown)

Fig. 7 shows percentage errors ($\%Err_c$) resulting from the central point rainfall combined with ARF_R values across areas of 625 and $3,025$ km^2. As a result, the extreme spatial rainfall is consistently underestimated for the majority of locations in all regions. Fig. 8 similarly shows the percentage error for the point-averaged rainfall method ($\%Err_{\overline{pt}}$) and this technique underestimates the extreme spatial rainfall for 95–100% of locations in the region. Therefore, the method of averaging point rainfall does not improve ARF-based techniques.

A further comparison was conducted as check for any influence of changing gauge density over the length of the record. Therefore, the analyses were repeated using a shorter 36 year series of daily grids corresponding to the latter third of the record, which has the highest gauge density. Fig. 9 provides an example summary of calculated ARF and percentage error values for the Sydney region for an ARI of 25 years. The analyses did not find any significant effect of changing gauge density on the results.

Evaluation of Extreme Spatial Rainfall Properties Influencing the Differences between the ARF-Based and IFDA Approaches

Given the variability of the ARF values over the region, it is important to understand situations that are most affected. To assess this, the change in the coefficient of variation of the at-site ARFs against catchment area and ARI was evaluated. Fig. 10 shows typical results for both ARF_c and $ARF_{\overline{pt}}$ for four densely gauged regions (Perth, Melbourne, Brisbane, and Sydney). In all cases the coefficient of variation increases with catchment area and $ARF_{\overline{pt}}$ is less variable than ARF_c. This observation was consistent for all ARIs and durations (not shown). This demonstrates that there is greater variability in estimates of extreme spatial rainfall produced using a fixed regional ARF for larger catchment areas.

Fig. 11 compares the mean percentage error $\%Err_c$ against ARI for areas of 625 and 3,025 km^2. There is a bias towards underestimation for all locations and frequencies. For the 3,025 km^2 area [Fig. 11(b)] the errors are larger and the differences between regions are more pronounced, especially for less frequent events. These observations are consistent over other catchment areas, regions, and for $\%Err_{\overline{pt}}$ (not shown).

Discussion and Practical Implications

This paper has demonstrated that current ARF-based approaches for estimating extreme spatial rainfall are biased, underestimating rainfall for the majority of locations. This motivates the need for more direct approaches that do not rely on fixed regional ARFs. Underestimating extreme spatial rainfall will typically lead to an underestimate of streamflow. There is a nonlinear relationship between the flow and the cost of damage to infrastructure. Therefore, the resulting cost of damage from an underestimate may outweigh the alternative cost of adopting a larger design flood (Botto et al. 2014). By improving design practice the economic impact and cost to society can be significantly reduced.

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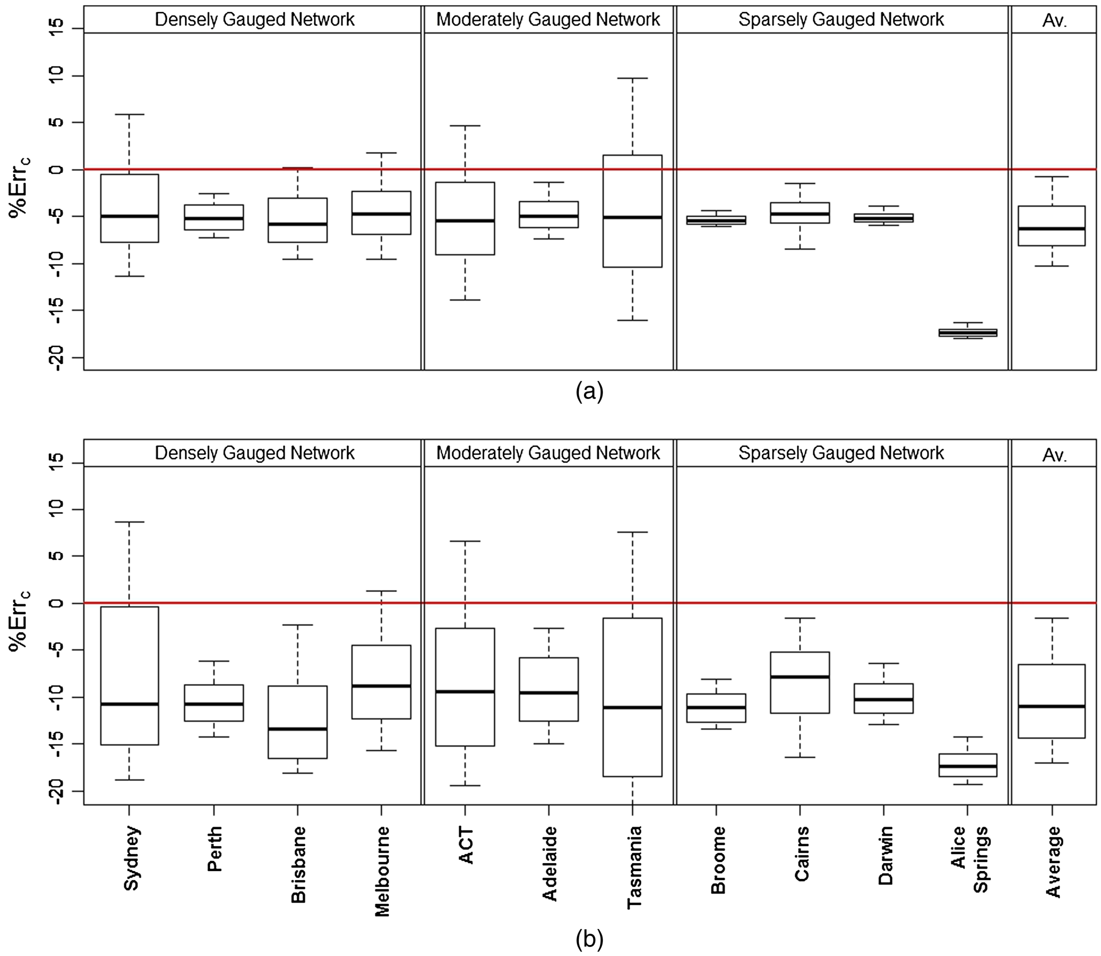

Fig. 7. %Err$_c$ for 1-day, 50y ARI rainfall: (a) 625 km^2; (b) 3,025 km^2 (10 and 90% limits shown)

Sources of Bias

Within a region, the relationship between point and areal rainfall is spatially heterogeneous. For two different locations within a region the scaling of intensity with area can be vastly different. For both ARF approaches, ARF$_c$ and ARF$_{\overline{pt}}$, the derivation of ARFs for each coordinate showed that ARFs varied spatially, leading to a range possible values for a given frequency, duration and spatial extent. The use of a fixed ARF$_R$ contradicts this observed spatial variation. Applying a fixed regional ARF$_R$ introduces bias into estimates of extreme spatial rainfall for the majority of locations (e.g., Fig. 8).

The practice of using a fixed regional ARF$_R$ is attributable to the historical legacy of poor spatial estimates of rainfall. Typically, ARFs have been derived using smaller catchments with higher gauge density and by pooling information from a range of catchments over larger regions (Jordan et al. 2011; Niemczynowicz 1982; Pilgrim 1987; Siriwardena and Weinmann 1996; Yoo et al. 2007). More recently, remotely sensed estimates of rainfall have provided an alternative source to suggest that ARF values are not constant over a region (Durrans et al. 2002). However, the limited length of remotely sensed records prevents definitive conclusions.

This study has relied on spatially interpolated rainfall and was able to show significant spatial variation in ARF values. The challenge with using interpolated data is the inherent spatial smoothing and artifacts introduced by the algorithm used (King et al. 2013). One of the potential impacts of spatial smoothing is that the true at-site ARF values may exhibit more distinct spatial variations than observed in the current study. As a result, the bias in at-site estimates of extreme spatial rainfall are likely to be greater than shown in Figs. 7 and 8.

Few acknowledge that gauge-based estimates of ARFs also rely on an algorithm for constructing the spatial rainfall estimate. Therefore, no matter what method is used there is the potential for influence by an interpolation algorithm. To mitigate this influence the authors focused on densely gauged regions in this study. One of the advantages of the IFDA approach is that it is generic and independent of the interpolation algorithm. Hence it can take advantage of advances in spatial rainfall interpolation techniques.

Both derivation approaches, ARF$_c$ and ARF$_{\overline{pt}}$, exhibited values exceeding 1, indicating the sampled point rainfall was less than the surrounding rainfall. This contrasts with the widely used recommendation that ARF are upper bounded at 1. Only a few previous studies (e.g., Catchlove and Ball 2003) have reported ARF values greater than 1 for three main reasons. Firstly, calculation of an ARF starts with the assumption that extreme point rainfall is more intense than extreme spatial rainfall. This is not always the case, for instance in the presence of a dominant storm path. Secondly, the focus on obtaining a regional ARF value has meant that spatial variations in extreme spatial rainfall are smoothed out. Thirdly, point gauge data is underrepresented in hard to access areas with strong rainfall gradients (Prudhomme and Reed 1999; Svensson and Jones 2010).

Conditions Where Bias Has the Greatest Impact

The paper demonstrated that a significant change in mean percentage error in estimates of extreme spatial rainfall occurs with

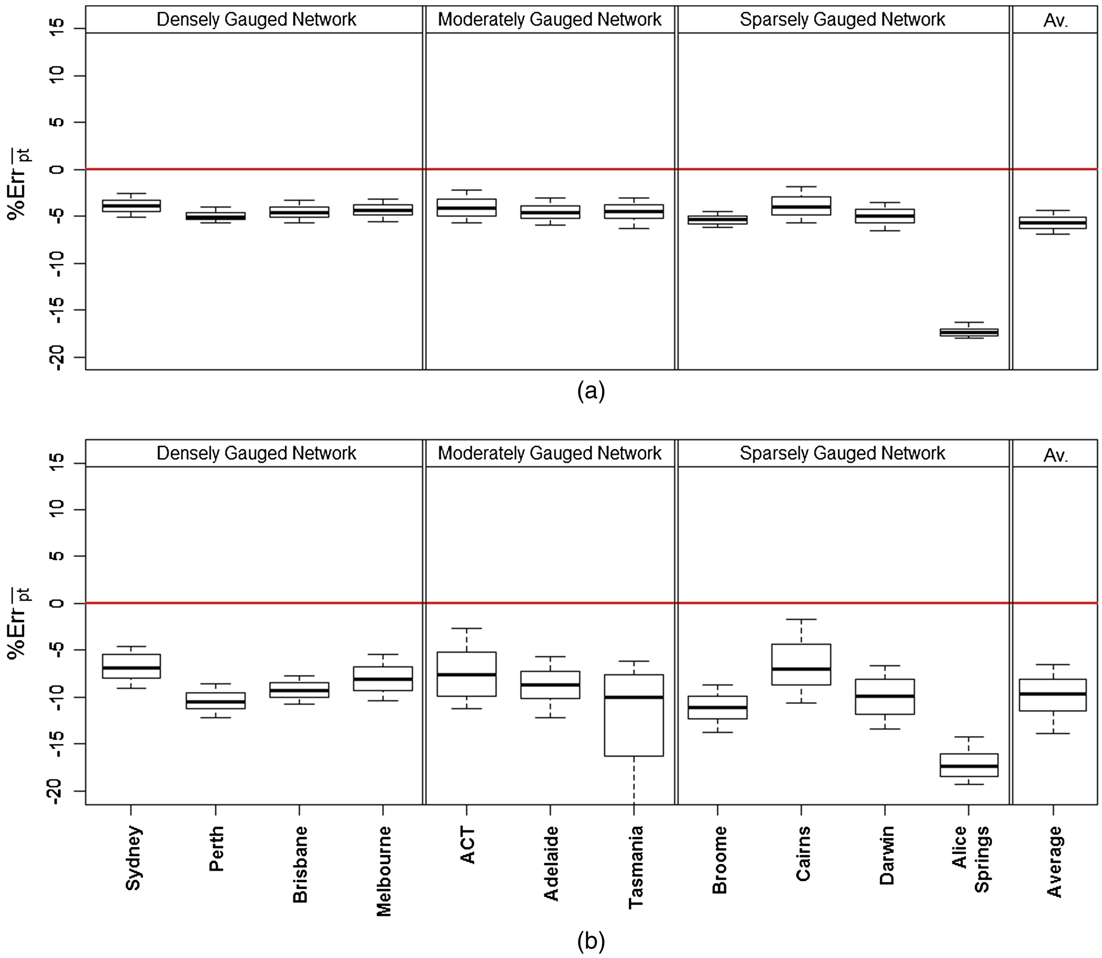

Fig. 8. $\%\mathrm{Err}_{\overline{\mathrm{pt}}}$ for 1-day, 50y ARI rainfall: (a) 625 km^2; (b) 3,025 km^2 (10 and 90% limits shown)

increasing area. The largest mean percentage errors were observed for the largest catchments, suggesting that current practice is least effective for large catchments. The poor performance for large catchments is likely attributable to the typically long distances over which rainfall events are correlated at a daily time step. Because of the spatial correlation structure of large rainfall events, the areal reduction of a sampled point rainfall using an ARF_R is likely to underestimate extreme spatial rainfall intensity.

Significant differences in the percentage errors of the extreme spatial rainfall estimates were observed between each region. The difference between the mean percentage errors at different case study locations is greater than the change in mean percentage error across different frequencies (Fig. 11). Thus the frequency of the event seems to be a less decisive factor than location in producing errors in extreme spatial rainfall estimates. The poor performance of the ARF-based approach across all studied regions implies that further investigation into the governing extreme spatial rainfall properties specific to each region is required. These extreme spatial rainfall properties may include seasonality, topography, and rainfall mechanisms contributing to extreme events.

Advantages and Limitations of IFDAs

To summarize advantages and limitations Table 1 presents a comparison of the IFDA and ARF-based approaches across a range of criteria.

ARF values calculated using point rainfall data are assumed to be spatially homogeneous within a general climatic zone (Jordan et al. 2011; Pilgrim 1987; Siriwardena and Weinmann 1996). As IFDAs are location specific estimates of extreme spatial rainfall, any impact of location or climatic region is directly accounted for in the IFDA.

Current practice relies on an ARF and IFD that have been developed separately. This concern was also raised by Panthou et al. (2014) who, in a different approach, sought statistical consistency between ARF and IFD models rather than adopting direct extreme spatial rainfall estimates. The derivation of IFDAs provides unbiased design rainfall estimates by incorporating the spatial variation in spatial rainfall intensity directly. Furthermore, by estimating extreme spatial rainfall directly the IFDA approach ensures statistical consistency in the extreme spatial rainfall estimate. However, they are not without limitation. For example, the application of the approach to irregular catchment areas and near-miss storms requires further investigation.

An ARF is a ratio of spatial rainfall to a representative point rainfall of equal recurrence interval. Its derivation requires an estimate of spatial extreme rainfall, but the limitations of this interpolation are rarely separated from the limitations of the ARF. While the quality of the spatial interpolation method will influence the derivation of IFDAs as they are direct estimates of rainfall intensity, it is nonetheless preferable to separate out the method of interpolation. Ultimately, the use of IFDAs depends on the availability of

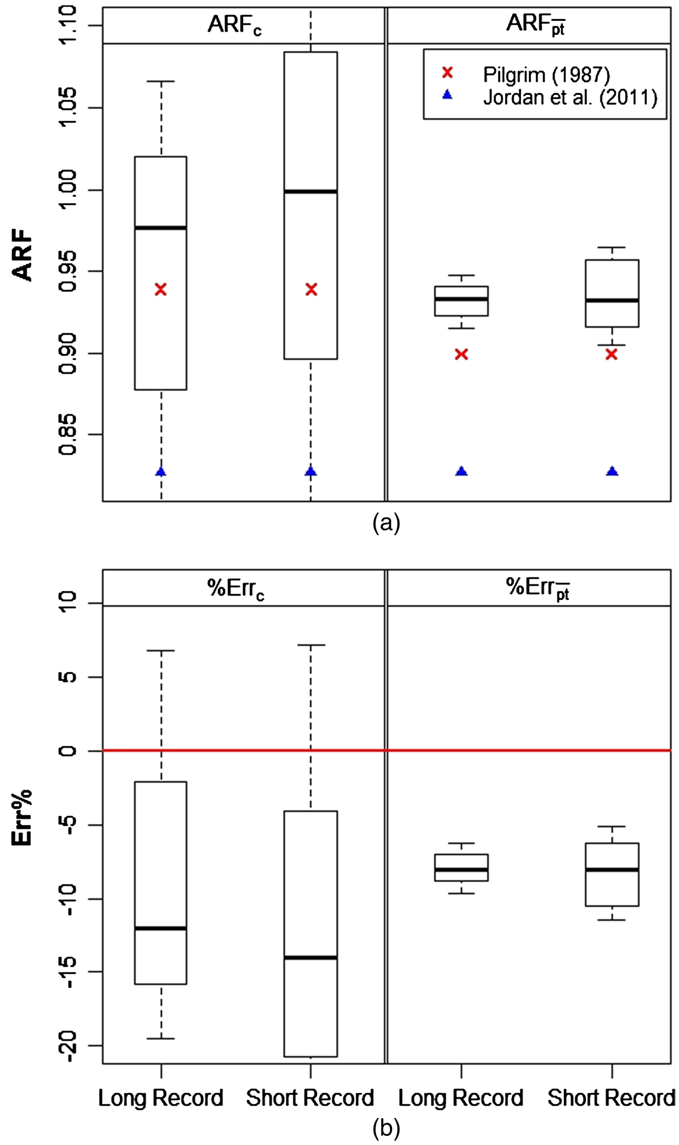

Fig. 9. Sydney ARF and percentage error boxplots for 25y ARI, 1-day rainfall comparing results of the long and short series analysis for an area of 3,025 km^2 (10 and 90% limits shown): (a) ARF$_c$ and ARF$_{\bar{pt}}$; (b) %Err$_c$ and %Err$_{\bar{pt}}$

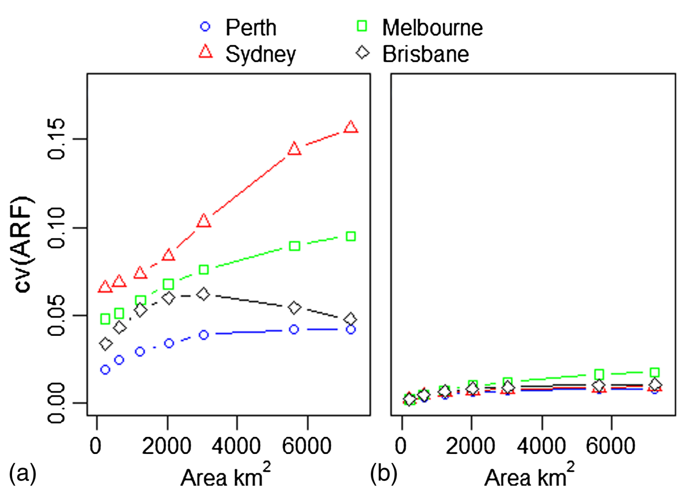

Fig. 10. Comparison of coefficient of variation of at-site ARFs against catchment area for 10y ARI, 1-day rainfall: (a) ARF$_c$; (b) ARF$_{\bar{pt}}$

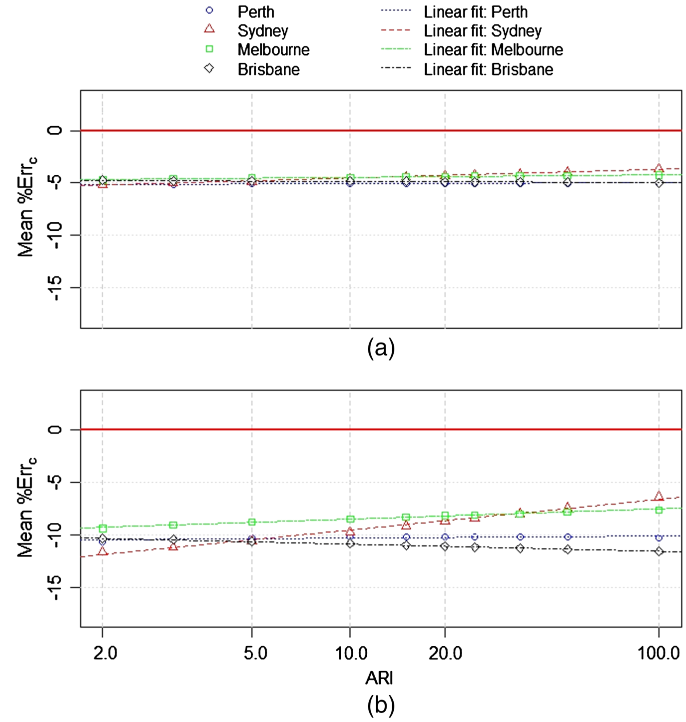

Fig. 11. Mean %Err$_c$ against ARI for 1-day rainfall: (a) 625 km^2; (b) 3,025 km^2

high-quality spatial rainfall data sources. The application of IFDAs to real-world catchments can be improved with further development of continuous spatial rainfall models (Kleiber et al. 2012; Leonard et al. 2008), the continued collection and processing of radar data, and continued development of interpolated spatial rainfall algorithms (Bárdossy and Pegram 2013; Beesley et al. 2009).

Challenges exist in determining the best method to apply IFDAs. This is because as each coordinate within a catchment possesses its own IFDA relationship, for a given ARI/area/duration there will be range of spatial rainfall intensities applicable to the catchment. This characteristic is perhaps a benefit, allowing spatial variability to be incorporated into design estimates.

Conclusions

The key objective of this paper was to introduce and evaluate the IFDA approach for extreme spatial rainfall estimation. An IFDA, which is calculated directly from spatial rainfall fields, adds the extra dimension of area to an IFD curve to account for spatial variation over a catchment. The paper demonstrated that the standard practice of using a fixed regional ARF introduces bias into estimates of extreme spatial rainfall and discussed subsequent implications. The existing approaches for estimating extreme spatial rainfall were typically in error by 5–15% (Figs. 7 and 8). Analysis of the characteristics of these errors showed that they varied with region, catchment area, and frequency.

Gridded daily rainfall from the Australian water availability project (AWAP) for 11 case study regions in Australia (spanning a wide range of climatic zones) was used. The analysis demonstrated that the IFDA relationship varied within regions. This is in contrast with current practice, which assumes that a fixed regional ARF is appropriate. The analysis also demonstrated that ARF values were frequently greater than 1 because of cases where

Table 1. Comparison of ARF-Based and IFDA Approaches

Item	Criteria	ARF-based approach	IFDA approach
1	Spatial scaling relationship	Assumed to be the same for all locations in the region. This causes complications for large catchments or catchments with steep rainfall gradients	Data driven and allowed to vary throughout the region
2	Spatial rainfall estimate	Spatial rainfall estimate has conventionally been coupled to the ARF derivation method	Made directly from spatial gridded estimates. Therefore, the spatial interpolation approach is separate from methodology
3	Conceptual approach	ARF and IFD isolate separate components of an event that are later combined but can potentially be inconsistent	Single metric directly incorporates intensity, frequency, duration, and area of design event
4	Reliance on single representative point rainfall	The ARF scales the extreme rainfall at a key location in the region to yield the spatial estimate	The spatial interpolation is estimated from all gauges in the region without the need to rely on a single location as being representative
5	Type of method for assigning frequency to design event	Indirectly approximates design intensity based on quantile matching of point and areal rainfall not necessarily derived from same event	Directly assigns frequency to design event of certain intensity, area, and duration. This is more consistent with actual events
6	Assumptions of approach	Assumes extreme point rainfall intensity is always greater than the spatial rainfall intensity (i.e., ARF < 1)	Assumes spatial interpolated estimates are appropriate

the extreme spatial rainfall exceeded the intensity of the sampled point rainfall.

The IFDA approach overcomes the shortcomings of existing approaches primarily by avoiding the need to assume a fixed regional ARF value. The IFDA methodology is proposed as a promising technique for obtaining direct and unbiased estimates of extreme spatial rainfall. The application of the method relies on robust methods for interpolating rainfall, and is therefore benefited by improvements to interpolation algorithms.

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