Combination of radar and daily precipitation data to estimate meaningful sub-daily precipitation extremes

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Abstract

Short duration extremes are important for design. The purpose of this paper is not to improve the day by day estimation of precipitation, but to obtain reasonable statistics for the subdaily extremes at gauge locations. The use of radar measurements for the space time estimation of precipitation has for many decades been a central topic in hydro-meteorology. Herein we are interested specifically in daily and sub-daily extreme values of precipitation at gauge locations. We do not employ the common procedure of using time series of control station to determine the missing data values in a target. We are interested in individual rare events, not sequences. The idea is to use radar to disaggregate daily totals to sub-daily amounts. In South Africa, an S-band radar operated relatively continuously at Bethlehem from 1998 to 2003, whose scan at 1.5 km above ground [CAPPI] overlapped a dense (10 km spacing) set of 45 pluviometers recording in the same 6-year period. Using this valuable set of data, we are only interested in rare extremes, therefore small to medium values of rainfall depth were neglected, leaving 12 days of ranked daily maxima in each set per year, whose sum typically comprised about 50.
1. Introduction

Short duration rainfall extremes are important for hydrological and hydraulic design of drainage in urban areas and airport runways, where the model spatial scales are a kilometer or less. For these applications the design storm duration is typically from 1 hour down to 15 minutes, usually caused by convective rainfall events. In these designs, it is sensible to reproduce meaningful spatio-temporal storms exploiting the information from ground-based gauge records combined with radar-rainfall fields. These are preferred to the established procedure of estimating the rainfall of a given duration and probability over the subcatchments using Area Reduction Factors (ARFs) and Intensity (or Depth) Duration Frequencies (IDFs or DDFs). The use of radar measurements for the space time estimation of precipitation has for decades been a central topic in hydro-meteorology. For example, an early report by Stewart (1989) described the use of radar to design ARFs for durations from 1 to 8 days in the United Kingdom using radar and gauges, so there is an early precedent for this study, but our methodology goes beyond that idea and treats subdaily intervals down to 15 minutes comparing and evaluating six different disaggregation methods.

We found that radar scans in our data-base typically offer much larger extremes than gauges, so they need to be carefully sourced for information and, although they have value as spatial interpolators, their maxima obtained through quantile transforms need to be adjusted to offer meaningful extreme values. This radar/gauge combination was shown to be appropriate by ?)
who developed a combination procedure using ground and radar observations and noted that the radar extremes are typically biased when compared to gauge estimates. They and others who used radar combined with gauges used radar for high temporal and spatial resolutions in hydrological modelling as well as determining rainfall frequencies of a range of intervals. For example, supporting the standard rainfall intensity design methodology, radar has often been used for areal reduction factor estimation.

The idea behind this paper is to provide and compare different methodologies to enable reasonable estimation of subdaily extremes using radar and daily precipitation observations. The purpose is not to improve the day by day estimation of precipitation, but to obtain reasonable statistics for the relatively few subdaily extremes at gauge locations. We do not employ the common procedure of using control station time series to determine the missing data values in a target. We are interested in individual rare events, not sequences. The data we choose to use is from pluviometers and radar. The pluviometers we have are not used for infilling. They are aggregated to daily amounts which are only used for two operations (i) spatial interpolation at a target location where we have left the data out, and then (ii) for cross-validation of the disaggregated values determined from the radar. We use Ordinary Kriging solely for interpolating the daily rainfall at the target. The correlation structure for this activity is determined from the daily network data.

The methods of disaggregating daily to sub-daily values is done in two groups of methods. In the first group of 5 connected methods, we start by
selecting the 12 wettest days of gauge data (daily pluviometer accumulations) in each of the six years of record and then the radar rainfall in each of these selected days, in which data were not missing. Thus 60 very wet days were selected for analysis. To be specific, we selected between eight and twelve gauges surrounding each of the 37 target locations, at which site only radar data are available, its pluviometer data having been hidden. In the sixth method in the other group, matching the days is abandoned and the 12 wettest control gauges per year are selected in one subset, while the 12 wettest radar days over the target area in each year are selected in the second subset. We thus examine the effectiveness of 6 different methods of disaggregation of daily rainfall in intervals from 12 hours down to half an hour. The 6 subsections describing the algorithms in section 3 are briefly summarised as follows.

In subsection 3.1 describing the first of the 5 methods in group 1, we ignored the gauge data and on each of the 60 preselected wettest days, Kriged the values from the control stations to the target; no gauge was involved. We then selected the 12 largest of the 60 interpolated values, in each subinterval, for ranking and analysis. This procedure of selection of the top 12 wettest estimated from the 60 amounts, in each of the subdaily intervals, is applied to all the methods. In subsection 3.2 we first interpolate the 60 heaviest daily precipitation events, at the target location using daily values of gauges in its vicinity. We subsequently disaggregate the daily values to subdaily interval amounts using the ratio of the subdaily radar to the daily radar values at the same location. This approach attempts to remove the bias inherited from the radar. In Subsection 3.3, we exploit the mild difference between the
measured radar at the target location used in 3.2 and the interpolated radar value at the target, which was Kriged from the corresponding values at the controls. This is an attempt to counter the bias introduced by the Kriging. In Subsection 3.4 we note that on days with short intense precipitation at the target location it is likely that a convective event occurred, and thus an underestimation of the daily amounts is likely. Instead of using the storm duration, the entropy of the subdaily precipitation distribution is used to scale the output from the rescaling done in Subsection 3.2. In Subsection 3.5 we modify the method described in Subsection 3.4, by scaling the entropy by the ratio of Kriged to recorded radar rainfall at the target, which was introduced in Subsection 3.3. Finally, in Subsection 3.6, we break the temporal link of gauge and radar rainfall matching on each day, which was the feature of the above 5 methods. We assume that statistics (ranks and matching amounts of heavy rainfall) observed from daily values can be estimated for target locations via interpolation, while the statistical properties of subdaily behavior can be derived from the radar. These two components are then merged to obtain possible extremes. The temporal correspondence between daily values and subdaily behavior is not synchronized anymore in this method. Section 4 presents the results of the analyses in Tables and Figures; the paper is concluded and summarised in section 5.

2. Study area and data

The region under study is near Bethlehem in the Free State, South Africa. The climate for the region is characterised as semiarid with average annual rainfall of about 650 mm, most major storm events happening in the summer
months from October to April. Much of the rainfall approaches from the West and North West with both convective through to stratiform rainfall types occurring. Orography has little effect on the rainfall in the region, as it is gently undulating or flat with the exception of the mountains in the south-east. The annual mean temperature is around 24°C. The anisotropy of daily rainfall accumulations is largely a function of the space/time properties of the advection field. If the advection is constant over the day, then there will be significant anisotropy in the accumulations, whereas days with rapidly changing advection will tend to present more isotropic accumulations even for days of isolated convection. These features are evident from the radar scans, but not obvious from point data at gauge sites.

Figure 1 shows the mask (of 64 km radius) of the MRL5 S-band radar sited near Bethlehem, corresponding to a height of 600 m above the radar at the outer radius. This limited range was used in an earlier study (Pegram and Clothier, 2001) to ensure the data were collected where the base scan was below the bright band (freezing layer) to maximise spatial homogeneity in measurement. This radar, which completes one volume scan every 5 mins, has been operational since 1994, and data from 1995 to 2003 were sourced from the South African Weather Service for the earlier study. These scans have been masked by a 14 km diameter hole at the centre of the radar images to remove local ground-clutter; the other dead zones were blanked out to exclude the interference of topography. Also shown in the figure are the locations of 45 pluviometers of which 37 are within the white mask, whose data set is contemporaneous with the radar scans. These pluviometer data were used.
1. to provide daily point rainfall totals and
2. to perform the validation of our methodologies,

but they were not used in the interpolation of subdaily values. The radar data at the pluviometer sites were aggregated from 5 to 15 minutes and then accumulated to intervals of $\frac{1}{2}$, 1, 3, 6, 12 and 24 hours.

3. Methodology and application

In this section six different methods used to obtain subdaily extreme are described. The methods are all evaluated using a cross validation approach. This means that each individual station is removed one by one, and the local extremes are estimated using daily precipitation amounts measured at other stations combined with the sub-daily radar based precipitation estimates. Finally the estimated and observed extremes of different durations are compared in the cross validation exercise.

3.1. Radar only

The simplest procedure is to use observed radar precipitation for extreme value analysis. Unfortunately radar based extremes are in most cases significantly higher than those measured on the ground (refs!). This effect occurs despite the fact that radars measure averages over blocks much larger than the area of a single raingage (ref).

3.2. Radar based disaggregation of interpolated daily precipitation

The second procedure is first to interpolate daily precipitation at the target location using daily values of gauges in its vicinity and subsequently
disaggregating the daily values to subdaily using the radar values at the same location. Formally let $Z(x, t, k)$ be the daily precipitation amount on day $t$ in year $k$ of $K$ years at location $x$. Let $r(x, t, \tau, k)$ be the subdaily radar precipitation amount corresponding to resolution $\Delta t$ hours and the number of daily intervals $M = \frac{24}{\Delta t}$. The daily radar based precipitation amounts in this case are:

$$R(x, t, k) = \sum_{m=1}^{M} r(x, t, \tau_m, k)$$ (1)

The simplest idea is to use the radar data for the disaggregation of daily precipitation. The relative values $\frac{r(x, t, \tau_m, k)}{R(x, t, k)}$ are used as multiplier of the daily observations to obtain high temporal resolution data. If there is no observed daily precipitation at the target location, then daily precipitation is first interpolated using Kriging and the interpolated values are disaggregated.

$$z^*(x, t, \tau_m, k) = r(x, t, \tau_m, k) \frac{Z^*(x, t, k)}{R(x, t, k)}$$ (2)

Subdaily extremes are subsequently assessed using these disaggregated values.

This procedure is very simple but unfortunately leads to a serious underestimation of the extremes. The reason for this is that the highest daily precipitation amounts at the target location are often seriously underestimated by interpolation. On a day where the spatial maximum occurred at the target location the interpolated daily value is necessarily below the observed. This is the case for station 16 on February 10, 2000 where the observed daily precipitation was 80.4 mm. All other stations recorded high precipitation amounts, but the second biggest observation was 64 mm. The interpolated
rainfall for that day was 41.4 mm. Disaggregating this value to subdaily
using the radar leads to significantly lower extremes than observed. Under-
estimation can also occur on days where the maximum was not at the target
station, for example for the same station on January 15, 2000 the observed
precipitation of 51 mm was underestimated as 41.9 mm via interpolation,
despite the fact that the maximum over the other stations was 69 mm. A
systematic evaluation of this underestimation problem is summarised as fol-

low. Figure ?? shows the frequencies of observed intense daily precipitations
measured at the 37 observation stations over the 7 years. The histogram of
the daily precipitations obtained by interpolation without consideration of
the target station (cross validation) is also shown. It is clearly visible that
the interpolated daily precipitations are likely to be smaller than the ob-
served. This underestimation is then inherited at the sub-daily resolution.
This is the reason for the serious underestimation of local extremes in global
datasets.

3.3. Radar based spatial correction of the interpolated daily values

The next procedure is based on a correction of the interpolated daily pre-
cipitation prior to the disaggregation. It is assumed that radar and observed
precipitations follow a similar spatial pattern on the day in question. We have
already estimated $Z^*(x, t, k)$ by Kriging and used it in (??), which equation
we adjust using the following procedure. Using radar estimates $R(x, t, k)$ of
daily rainfall at the same control locations $x$, we Krige them (possibly us-
ing the same coefficients as for the gauges if the same variogram is used) to
estimate $R^*(x, t, k)$ at the target. We then postmultiply equation ((??)) by
the ratio $\frac{R(x, t, k)}{R^*(x, t, k)}$, to obtain the following equation (3). It is assumed that if
the radar based local precipitation differs from the radar based interpolation, then the same type of error will occur for the measured daily precipitation. Formally this leads to correction of the daily interpolated precipitation proportional to the ratio of the radar based observation and interpolation:

$$z^*(x, t, \tau_m, k) = r(x, t, \tau_m, k) \frac{Z^*(x, t, k)}{R(x, t, k)} \cdot \frac{R(x, t, k)}{R^*(x, t, k)}$$  \hspace{1cm} (3)

The multiplicative correction factors $\frac{R(x,t,k)}{R^*(x,t,k)}$ are in most cases $> 1$ for very wet days. Thus this procedure improves the extremes.

### 3.4. Radar entropy based correction of the interpolated daily values

The above correction (3) uses the radar based local daily precipitation amount for the correction. However the subdaily temporal behavior of precipitation has also an important influence on the quality of the precipitation interpolation. On days with short intense precipitation at the target location it is likely that a convective event occurred, and thus an underestimation of the daily amounts is likely. Radar measurements provide useful information on the subdaily temporal behavior. Instead of using the duration, the entropy of the subdaily precipitation distribution is used. Let:

$$p_m(x, t, k) = \frac{r(x, t, \tau_m, k)}{R(x, t, k)}$$  \hspace{1cm} (4)

be the $m$-th observed relative radar precipitation amounts at the target location. As $p_m(x, t, k) \geq 0$ and:

$$\sum_{m=1}^{M} p_m(x, t, k) = 1$$
these values can be interpreted as probabilities. Their entropy

\[ H(x, t, k) = - \sum_{m=1}^{M} p_m(x, t, k) \log p_m(x, t, k) \]  

provides information on the degree to which the precipitation is uniform on day \( t \) or not. If all precipitation falls within one single subdaily time period \( m_0 \) then \( H(x, t, k) = 0 \). If precipitation falls with uniform intensity then \( H(x, t, k) = \log M \). In general

\[ 0 \leq H(x, t, k) \leq \log M \]  

The smaller the entropy the more uneven is the temporal distribution of precipitation. Uneven distributions with some time steps with high intensity and many with low intensity usually correspond to convective events, where the estimation of extremes via interpolation is biased. On the other hand for temporally relatively evenly distributed precipitation the corresponding spatial distribution is also relatively uniform and the spatial estimation is much less biased. Therefore a linear correction of the form:

\[ z^*(x, t, \tau_m, k) = r(x, t, \tau_m, k) \frac{Z^*(x, t, k)}{R(x, t, k)} (a + bH(x, t)) \]  

can be considered. Here coefficients \( a \) and \( b \) are calculated via linear regression.

Note that this correction as in (3) is designed to improve the estimation of extremes. Opposed to the previous corrections this procedure if applied for the assessment of precipitation on medium and low intensity days is likely to introduce a serious bias.
3.5. Combined correction of the interpolated daily values

The previous two correction methods (3) and (7) used different features of the radar measurements. The spatial correction (3) was based on the spatial distribution of the daily sums, while the second one (7) used the subdaily relative distribution. Therefore a combination of the two corrections seems reasonable. As both corrections are multiplicative it is straightforward to use the geometric mean of the two coefficients as new correction factor:

$$z^*(x, t, \tau_m, k) = r(x, t, \tau_m, k) \frac{Z^*(x, t, k)}{R(x, t, k)} \sqrt{\frac{R(x, t, k)}{R^*(x, t, k)}} (a + bH(x, t))$$  \hspace{1cm} (8)

This procedure requires the same data as the previous ones.

3.6. Multi day aggregation based methodology

A completely different philosophy is used in the following procedure. It is assumed that statistics observed daily values can be estimated for target locations from via interpolation, while the statistical properties of subdaily behavior can be derived from the radar. These two components are then merged to obtain possible extremes. The temporal correspondence between daily values and subdaily behavior are is not synchronized anymore, as the dates corresponding to the extremes are not maintained anymore. The two components are assessed separately.

Annual maxima of daily precipitation can be assessed from the daily observations for each control location. Interpolation of these data provides an estimator for the maximum daily precipitation at any target location. Note that the occurrence day of this maximum is not known. The daily maxima are disaggregated using the relative values corresponding to the maximum
daily precipitation obtained from radar measurements for the target location. This procedure does not necessarily provide a reasonable estimator for the subdaily extremes as for example the 30 minutes maximum of a year does not always occur on the day with the maximal daily precipitation. On the other hand subdaily extremes always occur on days with relatively high daily sums. Therefore the $L$ highest daily precipitation amounts are interpolated and disaggregated to obtain estimators for subdaily extremes.

As we are interested in extremes these data are ordered for each location $x$ in year $k$:

$$Z(x, t_1, Z, k) \geq Z(x, t_2, Z, k) \geq \ldots \geq Z(x, t_{365}, Z, k)$$

Instead of interpolating the biggest, second biggest etc. precipitations separately a single interpolation of the sum of the $L$ biggest days is carried out. The sum of the biggest $L$ days in a given year is:

$$Z(x, s_L, k) = \sum_{i=1}^{L} Z(x, t_i, Z, k)$$ (9)

The values of $Z$ are available at the observation locations $Z(x_j, t_i, Z, k)$ $i = 1, \ldots, 365$ and $Z(x_j, s_L, Z, k)$ $L = 1, \ldots, 365$.

The biggest $L$ days are important as they include the subdaily extremes and represent a large portion of the total precipitation at a given location, for our case we choose the $L = 12$ days with the heaviest precipitation which typically produced 40% to 70% of the total annual sum. Considering the heaviest $L = 1$ only is not sufficient as the most intense subscale precipitation does not always correspond to the heaviest single day.
\[ Z^*(x, s_L, k) = \sum_{j=1}^{n} \lambda_j Z(x_j, s_L, k) \]  

The interpolated \( L \) day sums show a moderate spatial variability, the bigger \( L \) the smoother is the surface of the \( L \) intense day sums. The interpolation of these values reduces the underestimation of extremes which required corrections for the previous procedures. In order to obtain subdaily extremes these \( L \) day sums have to be disaggregated to single days. To prevent a smoothing this is done by using a nearest neighbour concept.

For each location \( x \) without an observation let \( c(x) \) indicate the index of the closest of the \( n \) chosen observation locations \( x_j \):

\[ d(x, c(x)) \leq d(x, x_j) \quad \text{for all } j = 1, \ldots, n \]

where \( d \) is the geographical distance between points.

The interpolated \( L \) day sums of the maxima \( Z^*(x, s_L, k) \) are first disaggregated at the target location using the nearest neighbour approach:

\[ Z^*(x, t_i, k) = Z^*(x, s_L, k) \frac{Z(x_{c(x)}, t_i, k)}{Z(x_{c(x)}, s_L, k)} \]  

Now the \( i \)-th estimated daily precipitation estimates in year \( k \), \( Z^*(x, t_i, k) \) have to be disaggregated to sub daily durations using the radar data. Let \( R(x, t, k) \) be the daily precipitation amount on day \( t \) in year \( k \) at location \( x \) obtained by the radar. Each is ordered analogously to the measured daily precipitation, at location \( x \), for each year \( k \):

\[ R(x, t_{1,R}, k) \geq R(x, t_{2,R}, k) \geq \ldots \geq R(x, t_{365,R}, k) \]
The subscale values disaggregated from the rescaled, spatially interpolated, daily gauge estimates are:

\[ z^*(x, t_i, \tau_m, k) = Z^*(x, t_i, k) \frac{r(x, t_{i, R}, \tau_m, k)}{R(x, t_{i, R}, k)} \]  

For a given aggregation the highest values obtained in (12) are used for extreme value statistics.

As for this method radar precipitation is only used for disaggregation this method could also be used for the estimation of extremes based on past daily observations where radar was not available. This could be tested using long high resolution series

4. Results

The above methods were used for the selected time series with a 15 min temporal resolution. Highest values corresponding to the durations 15, 30 minutes and 1, 2, 3, 6 and 12 hours were evaluated.

In order to compare the methods the distribution of the precipitation amounts with a return period of 0.5 years or longer (2 biggest events per year) were used. The observed distributions at the 37 target locations were compared to the distributions obtained using the above procedures. Figures 2 and 3 shows the distributions of the highest 14 precipitation values observed and estimated for four durations using the different methods. The strong overestimation by the radar based precipitation and the underestimation obtained via disaggregated interpolation are visible. The other procedures provide better fits.
Table 1 shows the results of the two sample Kolmogorov-Smirnov tests. The distribution of the observed precipitation extremes was taken as reference and the estimated extremes were compared for each method. The table shows that the straightforward methods using radar only or radar based disaggregation of the interpolated daily values do not perform well. For short durations the Multidays method seems to perform best, while for longer durations the combined corrections provide the best estimators. The biggest differences between the observed and simulated distributions leading to rejection occur on the boundary Figure 2 shows such an extrapolation case. Tables 2 and 3 show the mean squared error of the estimated 1 year return period precipitation amounts for the different estimators and the different durations. These tables support the conclusions obtained from the Kolmogorov-Smirnov tests namely that for short durations the Multidays method works best while for long durations the corrections are better. The combined correction seems to be the best compromise.

5. Discussion and conclusions

In this paper different methods to estimate precipitation extremes of sub-daily resolution were presented. It was shown that a reasonable estimation can be achieved if the daily values are corrected leading to a better distribution.

Interpolation is seriously underestimating - this leads to the underestimation of the extremes. Conditional simulation could improve the situation. This means that instead of interpolation one would conditionally simulate precipitation at the target location. This however would require a very good
precipitation simulation model and would complicate the procedure considerably.

A correction of the interpolation is done in a distributional sense - we correct the high daily precipitations before disaggregation. This correction is not though to improve precipitation estimation, but to improve the statistics of the extremes.

The above procedures were concentrating on the specific case namely only daily observations and radar are available. If there are also some pluviometer available than the procedure has to be extended.

The multidays methodology requires modifications in areas where daily extremes are not only caused by convection.

The idea was to provide a range of different methodologies to enable reasonable estimation of subdaily extremes using radar and daily precipitation observations. The purpose is not to improve the day by day estimation of precipitation, but to obtain reasonable statistics for the subdaily extremes at gauge locations. We intend to use these ideas in spatial estimation, an important extension, but this will not be done here.

An alternative would be to use a rainfall model and simulation, however this would require a model which is good both in mean and variability.

References
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Table 1: Number of not rejected distributions (95% level) for the cross validation results
Table 2: Mean bias (mm) of the 1 year return period precipitation estimation for the different methods based on 37 stations.

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<td>121.93</td>
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<tr>
<td>Mean</td>
<td>53.29</td>
<td>8.66</td>
<td>10.42</td>
<td>7.80</td>
<td>7.81</td>
<td>6.63</td>
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Table 3: Root mean squared error (mm) of the 1 year return period precipitation estimation for the different methods based on 37 stations

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<th>Aggregation hours</th>
<th>Combination dense</th>
<th>Combination sparse</th>
<th>12 d Aggregation dense</th>
<th>12 d Aggregation sparse</th>
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</thead>
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<td>12</td>
<td>8</td>
<td>33</td>
<td>32</td>
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<tr>
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<td>19</td>
<td>14</td>
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</table>

Table 4: Number of not rejected distributions (95% level) for the cross validation results using different station densities
Figure 1: Scatterplot of observed and radar hourly precipitations at location L001.
Figure 2: Scatterplot of observed and radar daily precipitations at location L001.
Figure 3: Frequencies of observed daily precipitations exceeding 30 mm - red observed blue interpolated from using other stations.
Figure 4: Results for station L003.
Figure 5: Results for station L024.