Estimation of Areal Reduction Factors in South Africa, Part 2: Application and validation at catchment level

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TECHNICAL PAPER

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Various empirical methods have evolved over the years in South Africa to estimate either design floods, design rainfall, catchment response time, and/or Areal Reduction Factors (ARFs). The verification of any empirical method requires the use of observed data not used during the calibration process, while observed data is also required for validation purposes. In the case of ARFs, which are used to convert average design point rainfall depths to an areal (catchment) design rainfall depth, all the calibration/verification data sets remain only estimated sample values of design rainfall. Subsequently, this paper presents an independent application and validation of the regional geographically-centred ARF method (Pietersen 2023) against the currently recommended geographically-centred ARF method (Alexander 2001) by incorporating the different ARF estimates into the Rational Method (RM) to highlight the impact thereof on the resulting flood estimates. In applying a ranking-based goodness-of-fit selection procedure, the RM in combination with the newly derived regional geographically-centred ARF method (Pietersen 2023) resulted in the best deterministic flood estimates when compared to the at-site statistical flood peaks. Apart from the ARFs, catchment response time, design rainfall, and weighted runoff coefficients are all regarded as key input parameters for design flood estimation in ungauged catchments.

Keywords: Areal Reduction Factors, catchment response time, design flood estimation, design rainfall, Rational Method

INTRODUCTION

In South Africa three event-based approaches to at-site Design Flood Estimation (DFE) are available: (i) statistical, (ii) deterministic, and (iii) empirical methods (Smithers 2012; Van der Spuy & Rademeyer 2021). In gauged catchments, with long and reliable streamflow records, statistical methods provide the best estimate of the design floods at a particular site. In ungauged catchments, deterministic and empirical DFE methods are generally applied in practice. Deterministic DFE methods generally lump all heterogeneous catchment processes into a single process to enable the estimation of the T-year (return period) flood event assumed to result from the T-year rainfall event. Empirical DFE methods are algorithms derived from the unique relationships between a criterion variable (e.g. peak discharge) and a set of predictor variables (e.g. catchment area and/or other physiographical/climatological indices) (SANRAL 2013).

Apart from the above-mentioned DFE methods, various other empirical methods have evolved over the years in South Africa to estimate either design rainfall (Gericke & Du Plessis 2011), catchment response time (Gericke & Smithers 2014), and/or Areal Reduction Factors (ARFs) (Van Wyk 1965; Wiederhold 1969; Alexander 2001; Pietersen 2023). In developing any empirical method, the assumption is that the derived relationship is only applicable to the homogeneous region in which it was calibrated and subsequently independently verified, while being subjected to certain conditional criteria and parameter ranges. However, most empirical methods are generally applied outside their bounds in South Africa without using any correction factors, both in terms of their original regions of development and parameter ranges. In addition, the verification of any empirical equation requires the use of observed data not being used during the calibration process, while observed data is also required for validation purposes. In

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the case of ARFs, which are used to convert average design point rainfall depths to an areal (catchment) design rainfall depth, all the data sets used for calibration and/or verification remain only estimated sample values, given that these ratios are typically based on estimates of areal design and average design point rainfall (Pietersen *et al* 2023).

The empirical ARF methodologies in South Africa are limited to the storm-centred approaches of Van Wyk (1965) and Wiederhold (1969), and the geographically-centred approaches of Alexander (1980; 2001) and Pietersen (2023). Apart from the recent methodology developed by Pietersen (2023), Gericke and Pietersen (2020) also highlighted that the other local ARF methodologies: (i) are only applicable to specific temporal and spatial scales due to their calibration and verification being limited to pilot case studies and therefore do not account for any regional differences across South Africa, (ii) provide constant ARF values which are independent of return period, and (iii) are based on limited/no local rainfall data. In contrast, Pietersen (2023) developed a regionalised approach to estimate long duration (≥ 24-hour), geographically-centred ARFs which vary with return period and are based on daily rainfall data from 1 779 daily rainfall stations distributed throughout South Africa in five distinctive ARF regions. The latter methodology is not only new to the South African flood hydrology research community and practice, but was subjected to extensive calibration and verification processes to result in the stand-alone ARF software interface as reported and further evaluated by Pietersen *et al* (2024) in a range of default catchment areas, storm durations, and return periods.

It is evident from the paragraph above that the development of ARFs is an ongoing process in South Africa. Subsequently, as an alternative to the traditional ARF approaches, Van der Spuy and Rademeyer (2021) proposed the Daily Catchment Rainfall (DCR) approach. In principal, the DCR approach considers daily rainfall statistics which have been patched and weighted on a daily basis. Hence, given that the DCR approach constitutes the analysis of catchment rainfall on a daily basis, Van der Spuy and Rademeyer (2021) further argued that there is no need to apply an ARF; however, this still needs to be proved at a catchment level in South Africa. In addition, given that very few practitioners apply detailed at-site rainfall frequency analyses using patched rainfall data, and/or having the luxury of access to the relevant rainfall data sets, the use of the DCR approach will only evolve over time once the claim that no ARFs are required has been confirmed at a catchment level.

Given the importance of the required validation of any empirical method in the absence of observed benchmark data as highlighted above, the aim of this paper is to independently validate the regional ARF methodology and associated ARF software (Pietersen 2023; Pietersen *et al* 2023; 2024) at a catchment level throughout South Africa in actual catchments by incorporating the ARF estimates in an appropriate deterministic event-based DFE method to highlight the impact thereof on the design flood estimates. The specific objectives are to: (i) conduct and/or critically evaluate the at-site statistical flood frequency analysis results as obtained from Gericke (2021) and applicable to the selection of gauged catchments in the study area, (ii) compare and evaluate the use of the currently recommended geographically-centred ARF method (Alexander 2001) to the regional geographically-centred ARF method (Pietersen 2023; Pietersen *et al* 2023), (iii) apply the ARF estimates to translate the average design point rainfall estimates into areal (catchment) design rainfall estimates to assess changes in the design peak discharges as estimated using an appropriate deterministic event-based DFE method, (iv) verify and test the consistency, robustness and accuracy of the deterministic design estimates (Q_{Ti}) by comparing these estimates with the at-site statistical flood frequency analyses (Q_{Pi}), and (v) identify the influence of possible factor(s) that might contribute to the differences in the ARFs and the resulting flood estimates, given that many other factors contribute to the uncertainty involved when rainfall is converted into runoff using an appropriate DFE method.

The Rational Method (RM) (SANRAL 2013) was selected as the most suitable deterministic event-based DFE method to estimate the design peak discharges, given that it was identified by Gericke (2021) as the most appropriate DFE method in 48 gauged catchments located in four distinctive climatological regions of South Africa. In this paper, only 32 of the 48 gauged catchments are considered, given their uniform distribution across the five ARF regions (Pietersen 2023), as well as having representative catchment response times ranging between 10 and 80 hours. As this paper primarily focuses on the impact of different ARF estimation methods on the areal (catchment) design rainfall and resulting estimates of the peak discharge, the specific DFE method being used becomes irrelevant since the same conversion process from average design point to areal design rainfall depths basically applies to all the deterministic event-based DFE methods. Thus, by applying different ARF estimation methods to the same average design point rainfall input, and by using the same DFE method to estimate the peak discharge, the impact of any other factors and/or subjective (erroneous) selections inherently associated with the chosen DFE method becomes irrelevant and is overruled. Furthermore, given that it is generally assumed in all the event-based deterministic DFE methods (except for the Synthetic Unit Hydrograph (SUH) method), that the peak discharge will occur after/at the time of concentration (T_C), the T_C-based catchment response times are regarded as equal to the critical storm durations (D, hours) used in all the relevant ARF equations.

A summary of the study area is contained in the next section, followed by a description of the methodologies adopted and the results obtained. This is followed by the discussion and conclusions.

STUDY AREA

South Africa is located on the southernmost tip of Africa and is demarcated into 22 primary drainage regions (A to X), which are further delineated into 148 secondary drainage regions, i.e. A1, A2, to X4 (Midgley *et al* 1994). As shown in Figure 1, the five ARF regions (Pietersen 2023; Pietersen *et al* 2023) encompass all the latter secondary drainage regions. The 32 gauged catchments are distributed throughout the five ARF regions with catchment areas ranging between 338 km² and 31 283 km². The Department of Water and Sanitation (DWS) flow-gauging stations are located at the outlet of each catchment; hence, the reference to 'gauged' catchments. Table 1 contains a summary of the ARF region numbers and main catchment characteristics as applicable to the RM, e.g. mean annual precipitation (MAP), catchment area (A), hydraulic length (L_H), main river slope (S_{CH}), and the critical storm duration (D).

METHODOLOGY AND RESULTS

This section contains the methodology adopted to achieve all the specific objectives and the associated results in each of the 32 gauged catchments.

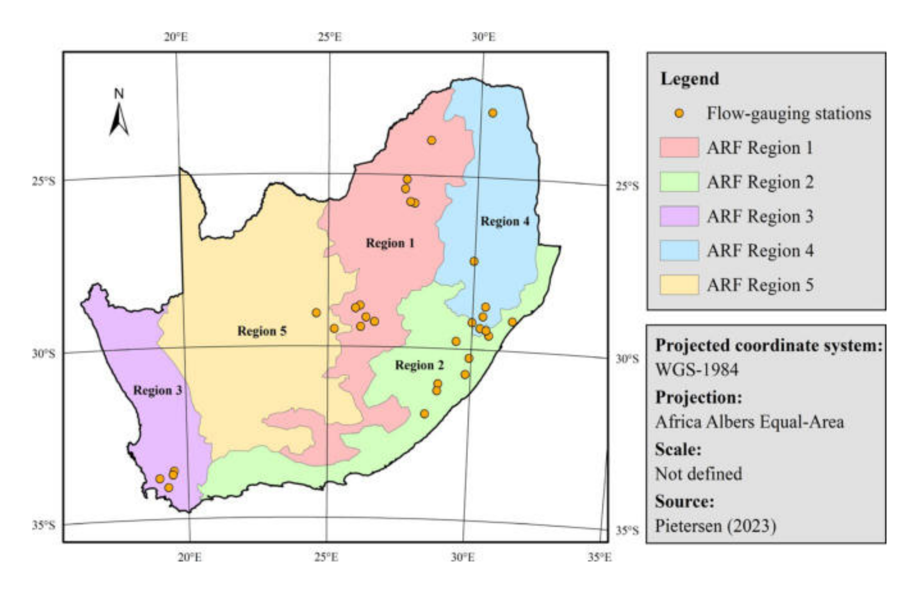


Figure 1 Location of the 32 gauged catchments in the five ARF regions (after Gericke 2021; Pietersen *et al* 2023)

Table 1 Catchment characteristics of the 32 gauged catchments (after Gericke 2021)

ARF region	Catchment	Catchment characteristics				
		MAP (mm)	A (km^2)	L_H (km)	S_{CH} (%)	D (h)
1	A2H012	690	2 555	57.4	0.69	10.2
	A2H013	672	1 161	64.2	0.52	12.4
	A2H019	670	6 120	132.2	0.36	24.9
	A2H021	611	7 483	215.5	0.19	46.6
	A5H004	623	636	68.4	0.71	11.6
	C5H007	495	346	40.8	0.34	10.3
	C5H015	519	5 939	160.5	0.14	41.1
	C5H039	516	6 331	187.1	0.13	48.5
	C5R001	488	922	86.4	0.23	21.4
	C5R003	549	937	53.8	0.27	13.8
	C5R004	518	6 331	186.7	0.13	47.9
2	T1H004	897	4 923	204.5	0.50	30.6
	T3H005	877	2 565	160.2	0.45	26.5
	T3H006	853	4 282	197.0	0.34	34.5
	T4H001	881	723	68.0	0.95	10.3
	T5H001	960	3 639	199.6	0.61	27.9
	T5H004	1 060	537	67.4	0.77	11.1
	U2H005	979	2 523	175.0	0.68	24.2
	U2H012	953	431	57.3	0.68	10.2
	V2H002	993	945	104.8	0.41	19.8
	V5H002	841	28 893	505.0	0.27	78.3
3	G1H007	899	724	55.5	0.46	11.6
	H2H003	267	743	62.0	1.54	7.9
	H4H006	450	2 878	109.9	0.47	19.6
	H6H003	859	500	38.6	0.97	6.6
4	A9H001	830	914	82.1	0.50	15.1
	U2H006	1 130	338	49.0	0.67	9.1
	V2H001	901	1951	188.5	0.40	31.5
	V3H005	895	677	86.2	0.25	20.8
	V6H002	839	12 854	312.3	0.24	56.7
5	C5H014	433	31 283	326.2	0.10	81.3
	C5R002	420	10 260	201.7	0.13	50.5

At-site statistical flood frequency analyses

All the streamflow record lengths (N) in each of the 32 gauged catchments exceed 25 years, i.e. $25 \leq N \leq 95$, and are characterised by a high degree of variability and skewness. The standard DWS discharge rating tables at each flow-gauging station were either within the maximum rated flood level (H) or, as recommended by Gericke (2021), the individual stage extrapolations (H_E) were limited to 30%, i.e. $H_E \leq 1.3\ H$. Subsequently, only 1.8% (34 events) of the 1 862 annual maximum series (AMS) events analysed were subjected to the latter H_E extrapolations. The Design Flood Estimation Tool (DFET) (Gericke & Du Plessis 2013; Gericke 2021) was used to conduct the at-site statistical flood frequency analyses by considering the probability distributions recommended for general use in South Africa, e.g. Log-Normal (LN), Log-Pearson Type 3 (LP3), and General Extreme Value (GEV) (Van der Spuy & Rademeyer 2021), and fitted using the Method of Moments (MM). The General Logistic (GLO) distribution fitted using Linear Moments (LM) was also considered due to being less sensitive to outliers. As recommended by Van der Spuy and Rademeyer (2021), the statistical properties of each AMS and the visual inspection of the plotted values were used to select the most suitable theoretical probability distribution in each catchment.

Given the asymmetrical nature of the data sets, the LN distribution was not considered. The GEV/MM and LP3/MM probability distributions were respectively found as the most suitable distributions in 50% and 31% of all the catchments under consideration. In addition, when using log-transformed data sets having a positive skewness, it was evident that the LP3/MM is not only sensitive to high outliers, but it can also be affected by low outliers. Although the GEV/MM proved to be the preferred distribution, especially at higher return periods, the relative performance thereof decreased when visually compared to the other probability distributions for $T > 2$-year. The GLO/LM probability distribution proved to be the most appropriate distribution in the remainder of the catchments.

In Figure 2, typical examples of the Cunnane-based statistical plots at a catchment level for five catchments representative of each ARF region are shown.

Estimation of design rainfall and ARFs

The average design point rainfall values associated with the critical storm duration (D)

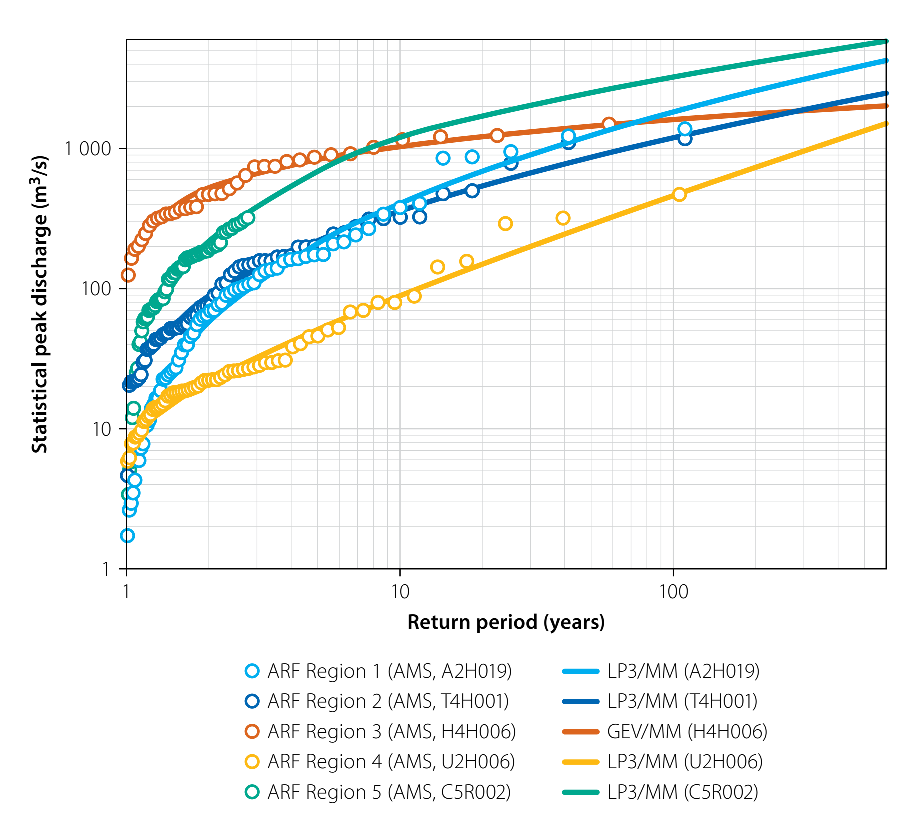


Figure 2 Example of at-site statistical plots (1< T ≤ 200-year) in five gauged catchments representative of each ARF region (after Gericke 2021)

Table 2 ARF estimation results

ARF region	Catchment	ARF_1 (Eq 1 %)	ARF_2 (Eq 2 %) for T-year						
			2	5	10	20	50	100	200
1	A2H012	77.4	48.7	55.5	59.7	63.3	67.0	69.2	70.9
	A2H013	84.0	59.4	65.5	69.2	72.4	75.7	77.6	79.0
	A2H019	75.9	64.6	70.2	73.7	76.6	79.7	81.4	82.8
	A2H021	78.1	73.0	78.0	81.0	83.5	86.1	87.6	88.7
	A5H004	87.5	61.1	67.0	70.7	73.8	77.0	78.8	80.2
	C5H007	90.7	61.2	67.1	70.8	73.8	77.0	78.9	80.3
	C5H015	79.0	72.8	77.8	80.8	83.3	85.9	87.4	88.6
	C5H039	79.5	74.5	79.3	82.3	84.7	87.2	88.6	89.7
	C5R001	88.2	72.6	77.7	80.7	83.2	85.8	87.3	88.5
	C5R003	86.0	63.5	69.3	72.8	75.8	78.8	80.6	82.0
	C5R004	79.4	74.3	79.2	82.1	84.6	87.1	88.5	89.6
2	T1H004	78.8	73.7	78.2	80.9	83.2	85.5	86.9	87.9
	T3H005	82.6	74.8	79.2	81.8	84.0	86.3	87.6	88.6
	T3H006	80.4	76.1	80.3	82.9	85.1	87.3	88.5	89.5
	T4H001	86.2	61.5	66.9	70.2	73.0	75.9	77.7	79.0
	T5H001	80.4	73.9	78.3	81.0	83.3	85.6	87.0	88.0
	T5H004	88.4	64.8	70.0	73.2	75.8	78.6	80.2	81.4
	U2H005	82.2	73.4	77.9	80.6	82.9	85.3	86.6	87.6
	U2H012	89.4	63.8	69.0	72.3	75.0	77.8	79.4	80.7
	V2H002	87.6	74.5	78.9	81.6	83.8	86.1	87.4	88.4
	V5H002	70.4	74.3	78.7	81.4	83.6	85.9	87.3	88.3
3	G1H007	86.7	68.2	72.7	75.7	78.4	81.5	83.6	85.5
	H2H003	84.7	57.5	62.6	66.1	69.3	73.0	75.5	77.8
	H4H006	80.2	74.2	78.2	80.9	83.3	86.1	88.0	89.6
	H6H003	86.3	52.9	58.3	62.0	65.3	69.3	71.9	74.3
4	A9H001	86.6	63.0	68.4	71.9	74.9	78.4	80.7	82.6
	U2H006	90.3	52.9	58.9	62.8	66.3	70.2	72.8	75.0
	V2H001	85.3	74.6	79.2	82.1	84.7	87.5	89.4	90.9
	V3H005	89.9	71.7	76.4	79.5	82.2	85.3	87.2	88.8
	V6H002	75.1	73.6	78.2	81.2	83.8	86.7	88.6	90.2
5	C5H014	70.0	72.4	76.4	79.0	81.2	83.6	85.1	86.3
	C5R002	76.1	74.5	78.4	80.8	83.0	85.3	86.7	87.8

values (*cf* Tables 1 and 2) in each catchment were adopted from Gericke (2021). Typically, the design point rainfall values are estimated using the widely-used Regional Linear Moment and Scale Invariance (RLMA&SI) approach developed by Smithers and Schulze (2004). The RLMA&SI approach is automated and included in the software program *Design Rainfall Estimation in South Africa*, which facilitates the estimation of design point rainfall depths at a spatial resolution of 1-arc minute, for any location in South Africa, for durations 5 minutes ≤ D ≤ 168-hour, and 2-year ≤ T ≤ 200-year. Given that the RLMA&SI gridded design rainfall values are point values, these gridded point values associated with the different storm durations and T-years were converted to average design point rainfall values (*cf* Table A1 in Appendix A) using the arithmetic mean and linear interpolation between the standard storm durations, respectively.

The average design point rainfall values listed in Table A1 in Appendix A were then converted to areal (catchment) design rainfall values using both the currently recommended geographically-centred ARF method (Equation 1 after Alexander 2001; SANRAL 2013) and the regional geographically-centred ARF method (Equation 2 after Pietersen 2023) to highlight any differences which will ultimately impact on the RM-based design floods as discussed in the next section.

$$ARF_1 = [90000 - 12800Ln(A) + 9830Ln(60D)]^{0.4} \quad (1)$$

$$ARF_2 = aX^2 + bX - c \quad (2)$$

$$X = x_1 log\left(\frac{D}{24}\right)^2 + x_2 log\left(\frac{D}{24}\right) - x_3 \log(T)^2 + x_4 log(T) - x_5 log(A)^2 - x_6 log(A) + x_7 \quad (3)$$

Where:

ARF_1 (after Alexander 2001; SANRAL 2013) and ARF_2 (Pietersen 2023) are the estimated Areal Reduction Factors (%) subjected to $0 < ARF_1 \leq 100\%$

A is the catchment area (km²) with Equation 3 subjected to $A \leq 30\ 000$ km²

D is the critical storm duration (hours), with Equation 3 subjected to 24-hour ≤ D ≤ 168-hour

T is the return period (years) subjected to T ≤ 200-year

X is the major expression variable

a to c are the major expression constants

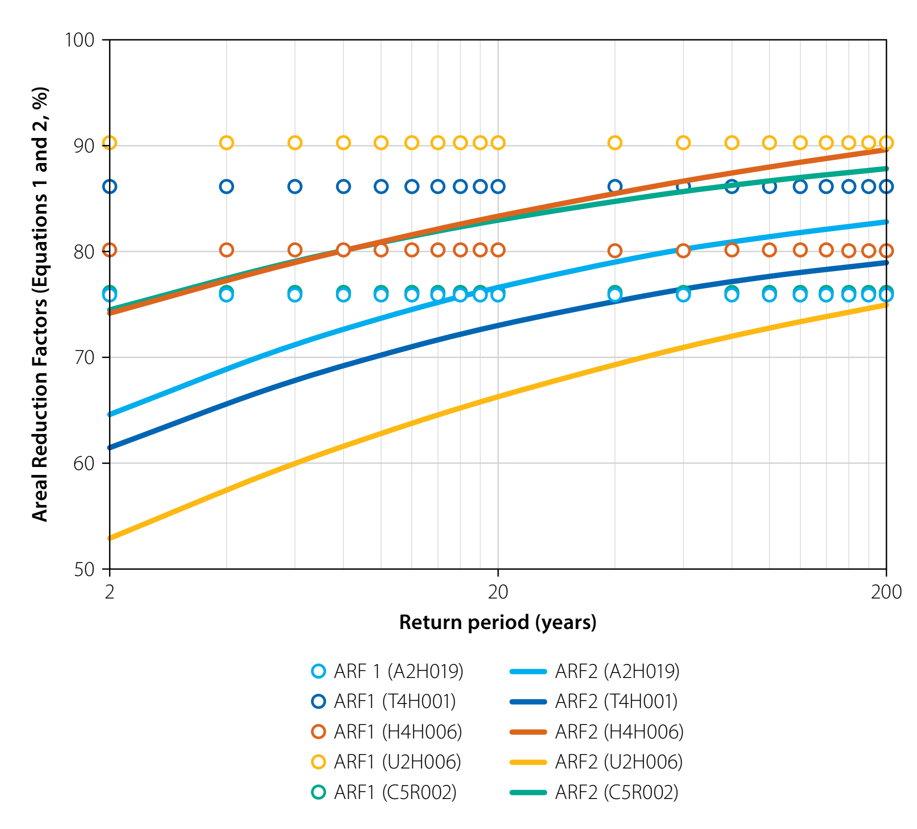


Figure 3 **Comparison of ARF estimation results (Eq 1 vs Eq 2) for 2 ≤ T ≤ 200-year in five catchments representative of each ARF region**

x_1 to x_7 are the regional calibration coefficients (Pietersen *et al* 2024) for the regions shown in Figure 1.

The ARF estimation results are listed in Table 2, while Figure 3 provides a graphical comparison between Equations 1 and 2 for five catchments representative of each region. As expected, all the ARF estimates in Table 2 decrease with an increasing catchment area.

In both Table 2 and Figure 3, the ARF estimates based on Equation 1 (ARF_1) remained constant for all return periods; although, the higher ARFs are associated with increasing storm durations. In contrast, Equation 2 (ARF_2) increased with both an increasing return period and storm duration in all the ARF regions.

Apart from these general trends witnessed in Table 2 and Figure 3, the ARF_2 values are generally less than the ARF_1 values in the following return period (T) ranges and regions (R):

i. **2-year ≤ T ≤ 200-year:** R1 (A2H012, A2H013, A5H004, C5H007 & C5R003), R2 (T4H001, T5H004 & U2H012), R3 (G1H007, H2H003 & H6H003) and R4 (A9H001, U2H006 & V3H005)
ii. **2-year ≤ T ≤ 100-year:** R1 (C5R001) and R2 (V2H002)
iii. **2-year ≤ T ≤ 20-year:** R4 (V2H001)
iv. **2-year ≤ T ≤ 10-year:** R1 (A2H019) and R2 (T3H005 & U2H005)
v. **2-year ≤ T ≤ 5-year:** R1 (A2H021, C5H015, C5H039 & C5R004), R2 (T1H004, T3H006 & T5H001) and R3 (H4H006)
vi. **T ≤ 2-year:** R4 (V6H002) and R5 (C5R002).

In contrast, the ARF_1 values are less than the ARF_2 values associated with all the return period ranges only in R2 (T4H001) and R4 (U2H006), respectively.

Estimation and assessment of deterministic design floods

As highlighted in the Introduction, the RM was used to estimate the deterministic design floods in each catchment. The catchment parameter (*cf* Table 1) and design rainfall information (*cf* Table A1 in Appendix A) were processed using the DFET (Gericke & Du Plessis 2013; Gericke 2021). All the standard DFE procedures associated with the RM are fully automated in the DFET, and the peak discharges associated with each T-year were estimated using Equation 4.

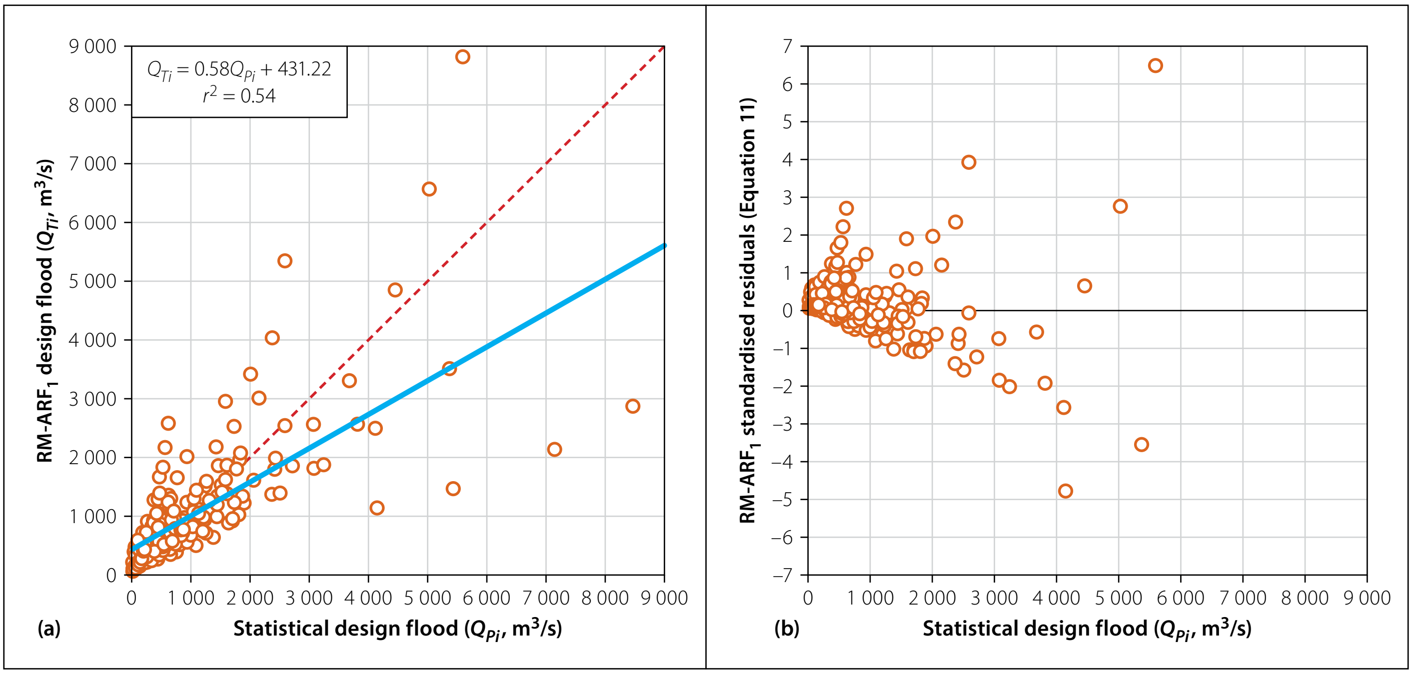
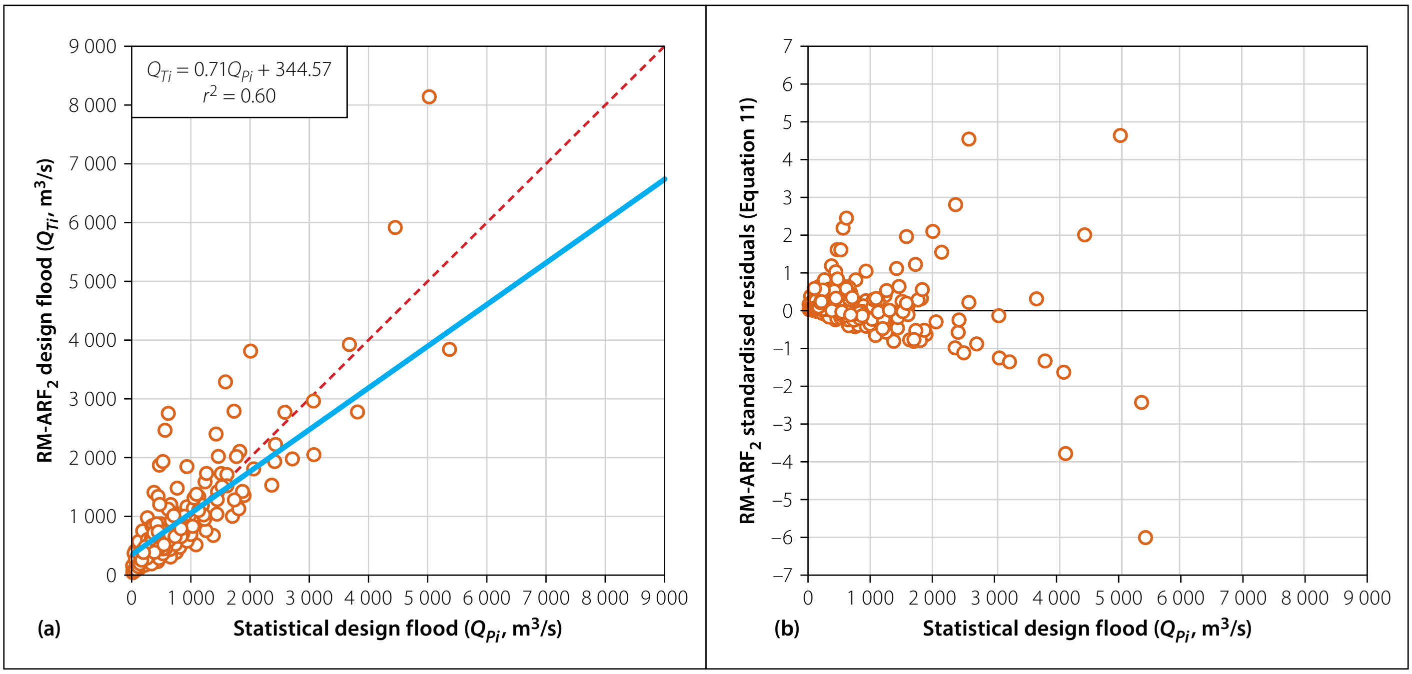


Figure 4 **Design floods and residuals plots associated with the RM-ARF$_1$ method: (a) RM-ARF$_1$ design floods, (b) RM-ARF$_1$ residual plots**



Figures 5 Design floods and residuals plots associated with the RM-ARF$_2$ method: (a) RM-ARF$_2$ design floods, (b) RM-ARF$_2$ residual plots

$$Q_{Ti} = 0.278C_{Ti}I_{TAi}A_i \quad (4)$$

Where:

Q_{Ti} is the peak discharge (m^3/s) for the T-year

A_i is the catchment area (km²)

C_{Ti} is the weighted runoff coefficient for the T-year (*cf* Table A2 in Appendix A)

I_{TAi} is the areal design rainfall intensity (mm/h) based on the product of the average RLMA&SI design point rainfall and the respective ARF values (Equations 1 and 2) divided by the storm duration

i is from 1 to N, depending on the number of catchment areas and return periods (2–200-year) considered.

Figures 4(a) and 5(a) are illustrative of the linear regression plots between the statistical Q_{Pi} and deterministic Q_{Ti} values, while the standardised residual distribution of each method is shown in Figures 4(b) and 5(b), respectively.

The moderate to low r^2 values ($0.54 \leq r^2 \leq 0.60$) in Figures 4(a) and 5(a) confirm the low to reasonable degree of association between the deterministic Q_{Ti} and statistical Q_{Pi} values. On average, both methods' positive y-intercept values (431 and 345) and slope values (0.58 and 0.71) are less than unity, and highlight that these two methods have an overall tendency to overestimate the statistical Q_{Pi} values < ±1 000 m^3/s more frequently, while the larger Q_{Pi} values are underestimated in some catchments.

In considering the standardised residuals in Figures 4(b) and 5(b), it is evident that ± 94% of the total samples associated with either the RM-ARF$_1$ and RM-ARF$_2$ methods have standardised residuals less than ± 2. According to Chatterjee and Simonoff (2013), when ± 95% of all standardised residuals are $-2 \leq SR \leq 2$, estimations could be regarded as reliable, while any larger values should be investigated as potential outliers impacting on the estimates. The visual inspection of the residual plots highlighted that generally unbiased and reasonable trends are present, with the variance (c_v) ranging between 4.9 and 7.9. The standardised residuals also follow an asymmetrical distribution, i.e. negative skewness (g) within the range $-6.2 \leq g \leq -7.6$.

A ranking-based selection procedure was developed to assess and select the best performing version of the RM, i.e. RM-ARF$_1$ (Equation 4 with ARFs based on Equation 1) and RM-ARF$_2$ (Equation 4 with ARFs based on Equation 2) in each of the five ARF regions. In other words, the RM-ARF$_1$ and RM-ARF$_2$ deterministic DFE results (Q_{Ti}) were compared to the at-site statistical flood frequency analyses (Q_{Pi}) in each catchment (i) by considering a set of quantitative goodness-of-fit (GOF) criteria in order to assess the accuracy and bias of each method. The standard error of the estimate (SE, Equation 5), mean relative error (MRE, Equation 6), root mean square error ($RMSE$, Equation 7), coefficient of determination (r^2, Equation 8), and Nash-Sutcliffe coefficient (NSE, Equation 9) were selected as assessment criteria (Zhong & Dutta 2015). The RM-ARF$_1$ and RM-ARF$_2$ methods were ranked against the different assessment criteria and summed to provide the overall performance ranking. Finally, the overall rankings were used to establish the hierarchical order of the two methods.

$$SE = \left[\frac{1}{(N-2)}\left\{\sum_{i=1}^{N}(Q_{Ti} - \overline{Q_T})^2 - \frac{\left(\sum_{i=1}^{N}(Q_{Pi} - \overline{Q_P})(Q_{Ti} - \overline{Q_T})\right)^2}{\left(\sum_{i=1}^{N}(Q_{Pi} - \overline{Q_P})^2\right.}\right\}\right]^{0.5} \quad (5)$$

$$MRE = 100\left[\frac{1}{N}\sum_{i=1}^{N}\frac{(Q_{Ti} - Q_{Pi})}{Q_{Pi}}\right] \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_{Pi} - Q_{Ti})^2}{N}} \quad (7)$$

$$r^2 = \left[\frac{\sum_{i=1}^{N}(Q_{Pi} - \overline{Q_P})(Q_{Ti} - \overline{Q_T})}{\sqrt{\sum_{i=1}^{N}(Q_{Pi} - \overline{Q_P})^2\sum_{i=1}^{N}(Q_{Ti} - \overline{Q_T})^2}}\right]^2 \quad (8)$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{N}(Q_{Pi} - Q_{Ti})^2}{\sum_{i=1}^{N}(Q_{Pi} - \overline{Q_P})^2}\right] \quad (9)$$

Where:

SE is the standard error of the estimate (m^3/s)

MRE is the mean relative error (% with underestimations denoted by (–) negative values)

$RMSE$ is the root mean square error

r^2 is the coefficient of determination

NSE is the Nash-Sutcliffe coefficient

i is from 1 to N depending on the number of catchment areas and return periods (2–200-year) considered

N is the sample size

Q_{Pi} is the at-site statistical design flood peaks (m^3/s)

Table 3 GOF statistics and ranking of RM-ARF$_1$ and RM-ARF$_2$ methods in ARF Regions 1 to 4 (10-hour ≤ D < 24-hour)

ARF regions	1		2		3		4	
GOF statistics	RM-ARF$_1$	RM-ARF$_2$	RM-ARF$_1$	RM-ARF$_2$	RM-ARF$_1$	RM-ARF$_2$	RM-ARF$_1$	RM-ARF$_2$
SE (Eq 5, m^3/s)	326	279	151	148	253	229	117	128
SE ranking	2	1	2	1	2	1	1	2
MRE (Eq 6, +%)	118.5	84.9	76.9	60.4	114.2	72.1	207.7	156.3
MRE ranking (+)	2	1	2	1	2	1	2	1
MRE (Eq 6, –%)	–23.8	–26.4	–	–3.5	–17.1	–20.9	–	–5.6
MRE ranking (–)	1	2	–	–	1	2	–	–
RMSE (Eq 7)	344	278	259	205	325	250	236	179
RMSE ranking	2	1	2	1	2	1	2	1
r^2 (Eq 8)	0.530	0.589	0.890	0.884	0.579	0.735	0.916	0.896
r^2 ranking	2	1	1	2	2	1	1	2
NSE (Eq 9)	–0.217	0.207	0.515	0.696	0.459	0.681	0.446	0.683
NSE ranking	2	1	2	1	2	1	2	1
Sum of rankings	11	7	9	6	11	7	8	7
Overall ranking	2	1	2	1	2	1	2	1

$\overline{Q_P}$ is the mean of the Q_{Pi} values (m^3/s)
Q_{Ti} is the deterministic design flood peaks (m^3/s) using either the RM-ARF$_1$ and/or RM-ARF$_2$ methods
$\overline{Q_T}$ is the mean of the Q_{Ti} values (m^3/s).

Tables 3 and 4 contain the quantitative GOF statistics and ranking applicable to the two methods as applied at a catchment level in each ARF region for 10-hour ≤ D < 24-hour and D ≥ 24-hour, respectively. The overall rankings based on the quantitative GOF statistics in all the catchments, and for all storm durations and return periods, are summarised and shown in Figure 6.

It is evident from Table 3 that the deterministic flood peaks (Q_{Ti}) based on both the RM-ARF$_1$ and RM-ARF$_2$ methods generally tend to overestimate the at-site statistical flood peaks (Q_{Pi}) in the ARF regions under consideration. In considering the 15 catchments within the storm duration range 10-hour ≤ D < 24-hour, most of the Q_{Pi} values were overestimated by both methods. Typically, the positive *MRE* values associated with these overestimations ranged between 60% and 119% in ARF Regions 1 to 3, while the *MRE* values in ARF Region 4 are notably higher, i.e. 208% (RM-ARF$_1$) and 156% (RM-ARF$_2$), respectively. The negative *MRE* values associated with the underestimations ranged between 4% and 26%. The RM-ARF$_2$ method demonstrated the best individual rankings, except in ARF Regions 2 and 4 where the r^2 rankings of the RM-ARF$_1$ method were better. In considering the GOF ranking-based selection procedure, the RM-ARF$_2$ method demonstrated the best overall ranking for 10-hour ≤ D < 24-hour.

Table 4 GOF statistics and ranking of RM-ARF$_1$ and RM-ARF$_2$ methods in ARF Regions 1, 2, 4 and 5 (D ≥ 24-hour)

ARF regions	1		2		4		5	
GOF statistics	RM-ARF$_1$	RM-ARF$_2$	RM-ARF$_1$	RM-ARF$_2$	RM-ARF$_1$	RM-ARF$_2$	RM-ARF$_1$	RM-ARF$_2$
SE (Eq 5, m^3/s)	434	490	887	1 136	541	696	409	491
SE ranking	1	2	1	2	1	2	1	2
MRE (Eq 6, +%)	189.9	186.4	81.0	89.6	67.8	61.7	283.3	290.8
MRE ranking (+)	2	1	1	2	2	1	1	2
MRE (Eq 6, –%)	–33.6	–31.8	–21.1	–18.3	–6.9	–5.5	–51.0	–45.2
MRE ranking (–)	2	1	2	1	2	1	2	1
RMSE (Eq 7)	557	570	884	1 228	743	1 041	2 982	2 660
RMSE ranking	1	2	1	2	1	2	2	1
r^2 (Eq 8)	0.479	0.488	0.739	0.725	0.854	0.834	0.845	0.859
r^2 ranking	2	1	1	2	1	2	2	1
NSE (Eq 9)	0.473	0.450	0.627	0.278	0.158	–0.654	0.008	0.211
NSE ranking	1	2	1	2	1	2	2	1
Sum of rankings	9	9	7	11	8	10	10	8
Overall ranking	1	1	1	2	1	2	2	1

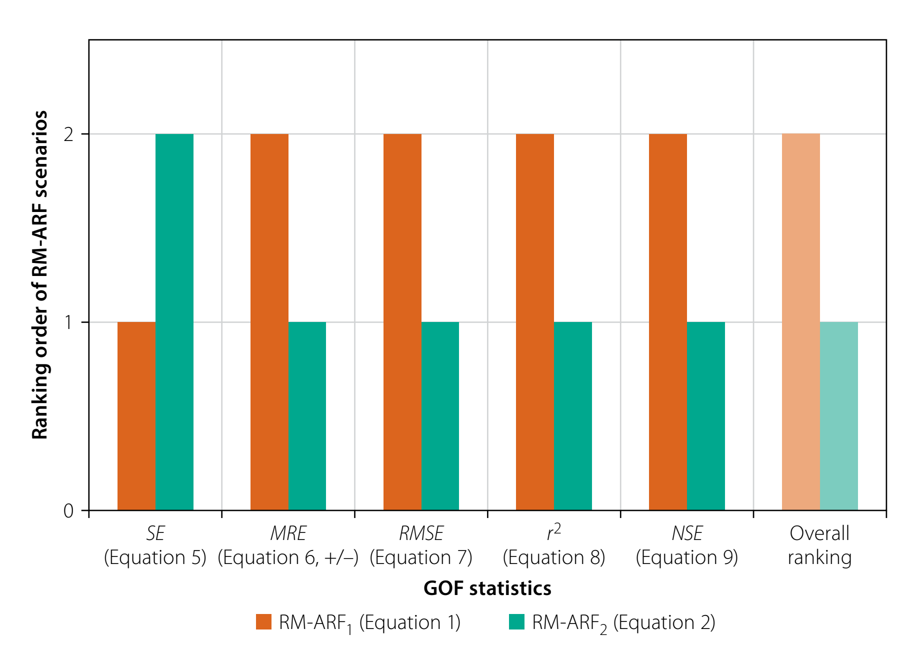


Figure 6 GOF-based ranking of the RM-ARF$_1$ and RM-ARF$_2$ methods as applied in the 32 gauged catchments. Ranking = 1 (best) and ranking = 2 (poorest)

It is evident from Table 4 that the Q_{Ti} flood peaks based on both the RM-ARF$_1$ and RM-ARF$_2$ methods generally tend to overestimate the Q_{Pi} flood peaks more frequently in the ARF regions under consideration. In considering the 17 catchments within the storm duration range $D \geq$ 24-hour, most of the Q_{Pi} values were overestimated by both methods. Typically, the positive *MRE* values associated with these overestimations ranged between 62% and 190% in ARF Regions 1, 2 and 4, while the *MRE* values in ARF Region 5 are notably higher, i.e. 283% (RM-ARF$_1$) and 291% (RM-ARF$_2$), respectively. The negative *MRE* values associated with the underestimations ranged between 6% and 51%. For $D \geq$ 24-hour, the two methods demonstrated comparable rankings for the individual GOF criteria under consideration. Subsequently, the methods are equally ranked in ARF Region 1, the RM-ARF$_1$ method demonstrated the best overall ranking in ARF Regions 2 and 4, while the RM-ARF$_2$ method is the best performing method in ARF Region 5.

In considering the overall ranking based on the quantitative GOF statistics in all the catchments, and for all storm durations and return periods collectively as shown in Figure 6, it is evident that the RM-ARF$_2$ method demonstrated the best individual rankings, except for *SE*, and as a result it is also regarded as the preferred method to contribute towards reasonable deterministic Q_{Ti} estimates of the at-site statistical Q_{Pi} values in each ARF region. However, this would only apply to a perfect rainfall-runoff model, given that apart from ARFs, other factors also have an impact on the Q_{Ti} estimates and contribute to the uncertainty involved.

DISCUSSION

Despite the improvement in the deterministic flood peaks (Q_{Ti}) achieved by using the RM-ARF$_2$ estimation method, the high over- and/or underestimations of the statistical Q_{Pi} values are still regarded as unacceptable and indicative that ARFs could not be regarded as the only fundamental input to deterministic event-based DFE in these catchments. In essence, the flood peak estimates are influenced by: (i) the specific deterministic event-based DFE method used to convert rainfall into runoff, (ii) the design rainfall estimation, (iii) the catchment response time estimation, and (iv) the basic assumption of 'average catchment conditions' as reflected by the use of weighted runoff coefficients in the RM.

Given that the preferred use of the RM was highlighted in the Introduction and confirmed by Gericke (2021) as the most suitable deterministic event-based DFE method to be used in the 32 gauged catchments under consideration, point (i) can somehow be ignored, while taking cognisance of the basic assumptions and limitations associated with the RM. Furthermore, as this paper primarily focused on the impact of different geographically-centred ARF estimation methods on the areal (catchment) design rainfall and resulting peak discharge estimates, the specific DFE method being used becomes irrelevant, given that the same conversion process from average design point to areal design rainfall depths basically applies to all the deterministic DFE methods.

In terms of point (ii) above, the RLMA&SI design point rainfall estimates adopted in this study are also recommended and widely used in practice; hence, the design point rainfall used as input is regarded as being the most representative design point rainfall information currently available. The averaging of the RLMA&SI design point rainfall is also regarded as acceptable, given that the arithmetic mean of the gridded design point rainfall depths and/or interpolation between the different storm durations were used to estimate the average design point rainfall values. Typically, these gridded design point rainfall values are uniformly distributed at a spatial resolution of 1-arc minute within each catchment.

In converting the latter average design point rainfall into areal (catchment) design rainfall using the two different ARF methods, it was evident, with the aid of a ranking-based GOF selection procedure, that in all the catchments and for all the storm durations and return periods under consideration, the RM-ARF$_2$ method (Equation 4 with ARFs based on Equation 2) resulted in improved deterministic Q_{Ti} estimates of the at-site statistical Q_{Pi} values in each ARF region. Furthermore, Equation 2 is also return-period dependent, i.e. ARFs increase with both an increasing return period and storm duration, while in contrast Equation 1 (after Alexander 2001; SANRAL 2013) resulted in constant ARFs for all return periods. Given that Equation 2 was calibrated and verified for storm durations ranging from 24-hour to 168-hour, it was interesting to note that the RM-ARF$_2$ method (Equation 4 with ARFs based on Equation 2) demonstrated the best overall ranking for 10-hour $\leq D <$ 24-hour. For $D \geq$ 24-hour, the two methods demonstrated comparable rankings for the individual GOF criteria under consideration, while the RM-ARF$_1$ method (Equation 4 with ARFs based on Equation 1) only demonstrated the best overall ranking in ARF Regions 2 and 4. Although the interim downscaling of the 24-hour ARFs based on Equation 2 using the RLMA&SI scaling factors was recommended by Pietersen *et al* (2023; 2024), the results achieved in the 10-hour ≤ D < 24-hour range confirm the opposite, i.e. Equation 2 can be successfully applied for 10-hour ≤ D < 24-hour. Although, this would only apply to a perfect rainfall-runoff model, given that apart from ARFs, the other factors as listed above (points (i) – (iv)) also have an impact on the Q_{Ti} estimates and contribute to the uncertainty involved. As a result, further investigations are required and/or short duration ARFs for South Africa should be developed by either using an updated sub-daily (continuous) rainfall database or an improved approach to disaggregate daily rainfall data into sub-daily rainfall values. As highlighted in the Introduction, the DCR approach as proposed by Van der Spuy and Rademeyer (2021) should also be further investigated as an alternative to the traditional ARF approaches.

The catchment response time (T_C) in point (iii) should be regarded as enigmatic, since although it is assumed to be an independent time parameter, it is actually dependent on the design rainfall, which in turn is also dependent on T_C to estimate the design rainfall intensity which will result in the peak discharge. Gericke and Smithers (2014) highlighted that the underestimation of T_C by 80% or more could result in the overestimation of peak discharges of up to 200%, when it is assumed that T_C equals the most critical storm duration (D), and that the peak discharge will occur after/at the T_C duration. Similarly, the opposite is also true, i.e. the overestimation of T_C values will result in underestimated peak discharges. Hence, the critical storm duration could be regarded as one of the key input parameters contributing to either the over- or under-estimation of peak discharges. This is also the reason why the National Flood Studies Programme (NFSP) (Smithers *et al* 2014) identified it as a high-priority research topic, and subsequently various research initiatives related to catchment response time, e.g. Gericke and Smithers (2014; 2016; 2017) followed thereafter with an envisaged deployment of a new methodology at a national scale in South Africa in the near future.

In terms of point (iv), the 'average catchment conditions' assumed when deterministic DFE methods are used to estimate the T-year flood event from the T-year rainfall event implies that the weighted runoff coefficients are constant. However, the runoff coefficients actually depend on both the antecedent soil moisture conditions and on the rainfall intensity. To overcome this shortcoming, larger runoff coefficients are normally assigned to higher return periods in the RM, i.e. runoff coefficients increase with increasing return periods. Although the latter approach is general practice, such a recommendation is not based on any systematic investigations, and favours arbitrary choices. Hence, despite the simplicity of estimating runoff coefficients, it definitely plays a role in the overall predictive ability of any deterministic event-based DFE method. As a result, several modifications were suggested in South Africa, e.g. modified runoff coefficients (Pegram 2003) and probabilistic approaches (Alexander 2002; Calitz & Smithers 2016).

CONCLUSIONS

The aim of this paper was to independently validate and compare the regional ARF methodology and associated ARF software developed by Pietersen *et al* (2023; 2024) with the currently recommended geographically-centred ARF method (Alexander 2001) in 32 gauged catchments distributed throughout South Africa. In converting the average design point rainfall into areal (catchment) design rainfall using the two different ARF estimation methods, it was evident with the aid of a ranking-based GOF selection procedure that in all the catchments, and for all storm durations and return periods, the RM based on ARFs estimated using Equation 2 (Pietersen 2023; Pietersen *et al* 2023; 2024) resulted in the best deterministic Q_{Ti} estimates of the at-site statistical Q_{Pi} values in each ARF region. Apart from the ARFs, it was also evident that catchment response time, design rainfall, and weighted runoff coefficients are all key input parameters for DFE in ungauged catchments.

Typically, higher ARFs and weighted runoff coefficients, underestimated storm durations and associated lower average design point rainfall depths, although of much higher intensities multiplied with the higher ARF values, will result in the overestimation of peak discharges. In contrast, lower ARFs and weighted runoff coefficients, higher storm durations and associated higher average design point rainfall depths, although of much lower intensities multiplied with the lower ARF values, will result in the underestimation of peak discharges. Subsequently, this may result in either the over- or under-design of hydraulic infrastructure, with associated socio-economic implications.

Given that Equation 1 (after Alexander 2001; SANRAL 2013) is independent of the return period and has not been validated using local and up-to-date rainfall data applicable throughout South Africa, it is recommended that Equation 2, as incorporated in the ARF software interface developed by Pietersen *et al* (2024), should be incorporated as the standard estimation procedure for long duration (≥ 24-hour) geographically-centred ARFs in SA. In addition, the proposed methodology and ARF software should also be further validated against the DCR approach to either confirm or reject the need to further refine ARF methodologies in South Africa.

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APPENDIX A

Table A1 Average RLMA&SI design point rainfall values (after Gericke 2021)

ARF region	Catchment	*D* (h)	Average RLMA&SI design point rainfall (mm) for *T*-year						
			2	5	10	20	50	100	200
1	A2H012	10.2	51	71	85	100	122	140	159
	A2H013	12.4	58	79	94	109	130	147	166
	A2H019	24.9	56	77	92	108	130	148	167
	A2H021	46.6	67	91	109	128	154	176	199
	A5H004	11.6	58	79	94	109	131	148	167
	C5H007	10.3	44	60	71	82	96	108	120
	C5H015	41.1	56	75	89	103	122	136	152
	C5H039	48.5	59	80	94	109	129	144	160
	C5R001	21.4	52	71	84	97	115	129	144
	C5R003	13.8	49	66	79	91	108	122	137
	C5R004	47.9	59	79	94	108	128	144	160
2	T1H004	30.6	57	78	94	111	135	156	178
	T3H005	26.5	56	75	90	105	127	144	163
	T3H006	34.5	62	84	100	118	143	163	186
	T4H001	10.3	60	85	105	127	161	191	225
	T5H001	27.9	59	81	97	114	139	160	182
	T5H004	11.1	57	76	91	106	127	144	163
	U2H005	24.2	58	81	100	121	152	180	212
	U2H012	10.2	60	85	107	131	168	202	242
	V2H002	19.8	64	86	102	119	143	162	183
	V5H002	78.3	88	119	141	163	194	219	246

ARF region	Catchment	*D* (h)	Average RLMA&SI design point rainfall (mm) for *T*-year						
			2	5	10	20	50	100	200
3	G1H007	11.6	62	81	95	108	127	142	157
	H2H003	7.9	48	63	73	83	97	107	118
	H4H006	19.6	72	94	109	124	143	158	172
	H6H003	6.6	61	81	95	109	129	144	160
4	A9H001	15.1	86	121	146	170	204	230	257
	U2H006	9.1	55	76	92	109	135	157	181
	V2H001	31.5	58	78	93	107	128	145	163
	V3H005	20.8	71	94	110	126	148	166	184
	V6H002	56.7	72	107	126	145	170	190	210
5	C5H014	81.3	63	87	103	119	140	157	175
	C5R002	50.5	55	66	78	90	107	120	133

Table A2 Weighted runoff coefficients applicable to the RM (after Gericke 2021)

ARF region	Catchment	Weighted runoff coefficients (C_T) for *T*-year						
		2	5	10	20	50	100	200
1	A2H012	0.182	0.186	0.190	0.195	0.207	0.220	0.235
	A2H013	0.144	0.158	0.172	0.192	0.237	0.284	0.341
	A2H019	0.164	0.173	0.182	0.195	0.225	0.256	0.293
	A2H021	0.170	0.180	0.190	0.205	0.237	0.272	0.313
	A5H004	0.132	0.146	0.159	0.178	0.220	0.265	0.318
	C5H007	0.164	0.180	0.195	0.216	0.265	0.317	0.379
	C5H015	0.152	0.165	0.178	0.196	0.238	0.282	0.334
	C5H039	0.150	0.163	0.176	0.194	0.235	0.280	0.331
	C5R001	0.183	0.201	0.219	0.245	0.304	0.366	0.439
	C5R003	0.178	0.196	0.213	0.238	0.295	0.355	0.425
	C5R004	0.173	0.188	0.204	0.225	0.275	0.327	0.389
2	T1H004	0.254	0.275	0.295	0.324	0.390	0.460	0.543
	T3H005	0.225	0.245	0.264	0.291	0.353	0.419	0.496
	T3H006	0.252	0.275	0.298	0.330	0.403	0.482	0.574
	T4H001	0.207	0.228	0.248	0.276	0.342	0.411	0.492
	T5H001	0.277	0.305	0.332	0.370	0.458	0.552	0.661
	T5H004	0.281	0.309	0.337	0.376	0.465	0.560	0.672
	U2H005	0.217	0.238	0.259	0.288	0.355	0.426	0.510
	U2H012	0.206	0.226	0.247	0.276	0.341	0.411	0.492
	V2H002	0.256	0.282	0.307	0.343	0.424	0.511	0.613
	V5H002	0.211	0.231	0.252	0.280	0.345	0.414	0.496
3	G1H007	0.262	0.277	0.293	0.308	0.323	0.338	0.398
	H2H003	0.224	0.238	0.253	0.268	0.282	0.297	0.356
	H4H006	0.203	0.216	0.229	0.242	0.255	0.268	0.319
	H6H003	0.300	0.320	0.339	0.359	0.379	0.399	0.478
4	A9H001	0.175	0.190	0.205	0.226	0.275	0.326	0.386
	U2H006	0.196	0.215	0.235	0.262	0.325	0.391	0.470
	V2H001	0.247	0.271	0.296	0.330	0.409	0.492	0.590
	V3H005	0.204	0.224	0.244	0.272	0.337	0.405	0.485
	V6H002	0.228	0.250	0.272	0.303	0.374	0.449	0.537
5	C5H014	0.125	0.137	0.149	0.165	0.203	0.244	0.292
	C5R002	0.185	0.203	0.221	0.246	0.304	0.365	0.438