DEVELOPMENT AND ASSESSMENT OF AN ENSEMBLE JOINT PROBABILITY EVENT BASED APPROACH FOR DESIGN FLOOD ESTIMATION IN SOUTH AFRICA

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ABSTRACT

It has been reported that global climate change has impacted on the frequency as well as severity of flood events. Reliable flood estimates are required for managing and designing hydraulic structures, which is essential under extreme weather regimes in the future. Design flood estimation methods in South Africa are based on statistical analysis of past streamflow data, and rainfall based methods. Rainfall-based methods often have preference over streamflow-based methods for design flood estimation due to longer records of rainfall data that also have a greater spatial and temporal coverage than streamflow records. A key assumption in rainfall based methods for design flood estimation is the assumption regarding the exceedance probability of the estimated flood. It is generally assumed that the return period of the estimated flood will be the same return period as the input rainfall. This equality of rainfall and flood return periods is generally not true given the use of model parameters representing average conditions and the impact of antecedent moisture conditions on hydrological response. Hence, a Joint Probability Approach (JPA) where the key input model parameters, and not only the input design rainfall, are treated probabilistically will overcome the limitations associated with rainfall based design flood estimation. The underlying approach to the JPA is that instead of the use of a single combination of input variables to determine the flood characteristics, the method uses multiple combinations of flood producing parameters to determine the flood characteristics. In this study, a JPA was applied using the SCS-SA model, and the modelling framework used to determine the derived flood frequency curve is based on three principal elements. These include: (i) defining the key model inputs with their respective probability distributions and correlations, (ii) a stochastic model to synthesise sequences of the selected variables, and (iii) selecting an appropriate deterministic hydrological model to simulate the flood generation process, and use of the simulated outputs to derive the flood distribution. To evaluate the performance of the model, the results were compared to observed streamflow data. A statistical analysis was conducted in conjunction with graphs to verify the performance of the model. The Nash-Sutcliff Efficiency (NSE), absolute relative difference and Mean Absolute Relative Error (MARE) were used to evaluate the performance of the model. The results produced from applying the Ensemble SCS-SA model with rainfall that was fitted to the probability distribution of the 1 day design rainfall and sampling from the 90 % prediction intervals for each return period indicates that the model was performing relatively poorly in terms of estimating both the observed design runoff volume and design peak discharge for all the selected test catchments. The incorporation of the correlation between the

rainfall depth and rainfall duration using a conditional probability distribution and in conjunction with the probability distributions of the other key input variables in the Ensemble SCS-SA model, resulted in significantly improved estimated runoff volume and peak discharges for all the catchments used. The Ensemble SCS-SA model has also shown potential and flexibility to deal with uncertainty by accounting for the distributed nature of the input variables and taking on values across the full range of their distribution in the modelling process, thus avoiding the potential of bias that can occur when adopting a single set of pre-determined input values. This study has shown the potential and flexibility of the Ensemble SCS-SA model to deal with uncertainty, providing opportunity for the expanded application of the model.

PREFACE

I, Nkosinathi Sethabile Dlamini declare that

1.   The research reported in this dissertation, except where otherwise indicated is my original work.

2.   This dissertation has not been submitted for any degree or examination at any other university.

3.   This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

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      a.   Their words have been re-written but the general information attributed to them has been referenced.

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Signed: ………………………………….

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Supervisor: …………………………….....

Professor JC Smithers

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1. INTRODUCTION

Global climate change has resulted in an increase in the frequency as well as severity of flood events (Charalambous *et al.*, 2013). According to Zaman *et al.* (2012), reliable flood estimates can provide means for managing the impacts of floods, which is essential under future extreme weather regimes. Numerous water resources infrastructure designs require design flood estimation, and these include the design of hydraulic structures such as culverts, bridges, spillways and detention basins (Reis and Stedinger, 2005).

According to Smithers and Schulze (2001), design flood estimation methods in South Africa are either based on statistical analysis of past streamflow data or rainfall based methods. Analysis of streamflow data includes the transposition and ordering of past flood experiences (HRU, 1972), and rainfall based-methods use a deterministic approach to translate rainfall into a runoff. Rauf and Rahman (2004) noted that rainfall-based methods often have preference over streamflow-based methods for design flood estimation due to longer records of rainfall data that also have a greater spatial and temporal coverage then streamflow records. In South Africa, analysis of streamflow data as well as rainfall-based methods are recommended by SANRAL (2013), but these methods require modernisation and updating (Smithers, 2012).

According to Caballero and Rahman (2014), rainfall-based methods for design flood estimation consider the probability distribution of rainfall when modelling, but ignore the distributions of other inputs such as rainfall temporal patterns, as well as storm losses, which also have probability distributions (Hill *et al.*, 1996). It has also been identified by Weinmann *et al.* (2002) that when selecting the representative input variables that are likely to simulate a significant flood, there are no guidelines that guide the selection. Thus, the choice of a single set of flood producing model variables, which each have a probability distribution, can lead to inconsistencies as well as significant bias in design flood estimates for a given return period, and has been widely criticised (Kuczera *et al.*, 2006; Gioia *et al.*, 2008; Kjeldsen *et al.*, 2010).

According to Charalambous *et al.* (2013), the thorough treatment of the probabilistic aspects of the key input variables can be used to significantly improve the limitations associated with rainfall-based methods. This includes the application of a Joint Probability Approach (JPA), which involves sampling from marginal distributions of key input variables, and then the use of a deterministic model to obtain the probability-distributed flood hydrograph (Rahman *et al.*, 2001). Further studies have indicated the significance of using a JPA in design flood estimation

(Caballero *et al.*, 2011; Loveridge *et al.*, 2013). The National Committee in Water Engineering of Engineers Australia is also promoting the adoption of a JPA in preference to their Design Event Approach (Nathan, 2013).

The aim of this study is to apply and assess the performance an Ensemble Joint Probability Approach to an event based rainfall-runoff model used for design flood estimation in South Africa. Specific objectives include undertaking a comprehensive review of event-based design flood estimation models and the use of joint probability approaches to design flood estimation , model selection, development of probability distributions for key input variables using readily available data, and the development, application and assessment of an ensemble model configuration.

Chapter 2 contains a review of the current event based rainfall-runoff methods for design flood estimation used in South Africa. Chapter 3 contains a review and synthesis of the literature on Ensemble JPA and the general methodology is discussed in Chapter 4. The results from the use of the ensemble and single event models using one-day duration design rainfall input are presented in Chapter 5 and Chapter 6 summarises an investigation into improving the simulations obtained in Chapter 5. Chapter 7 contains the results from the use of the ensemble and single event models using design rainfall duration equal to catchment response time. Discussion, conclusions and recommendations from the study are presented in Chapter 8.

2. REVIEW OF RAINFALL BASED METHODS FOR DESIGN FLOOD ESTIMATION IN SOUTH AFRICA

According to Schulze (1989) and Rahman *et al.* (1998), rainfall based methods have an advantage of generally having longer rainfall records at more sites, with better quality, and are more available for analysis compared to streamflow records. Smithers (2012) also pointed out that design engineers and hydrologists are most frequently faced with situations where there is no, or inadequate, streamflow data at the site of interest. Rainfall based methods used for design flood estimation in South Africa, including their limitations, have been extensively reviewed by Smithers (2012). The following sections include a brief overview of different rainfall based methods commonly used in South Africa, and provides some limitations associated with applying the methods.

2.1   SCS-SA Method

The SCS-SA method adapted for design flood estimation in South Africa by Schmidt *et al.* (1987), utilises adaptations that were computerised by Schulze *et al.* (1992) which stems from the developments and verifications from multiple studies (Schulze, 1979; Schulze, 1982; Schmidt and Schulze, 1984; Dunsmore *et al.*, 1986). Alexander (2002) recommends the SCS-SA method to be applicable to agricultural catchments with areas less than 10 km^2. According to Smithers (2012), the SCS-SA method is now extensively applied to estimate design floods for small urban and rural catchments less than 30 km^2 in South Africa. One advantage of using the method is that instead of estimating peak discharges only, it can also generate full hydrographs (SANRAL, 2013). The equations that govern how the stormflow and peak discharge are estimated are shown in Equations 2.1 and 2.2 (Schulze *et al.*, 2004):

$$Q = \frac{(P - I_a)^2}{P + I_a + S} \tag{2.1}$$

where: Q   =   stormflow depth (mm),

P   =   daily rainfall depth (mm),

I_a =   initial losses (mm), and

S   =   potential maximum soil water retention (mm).

$$\Delta Q_p \quad = \quad \frac{0.2083 \times A \times \Delta Q}{\frac{\Delta D}{2} + L} \tag{2.2}$$

where: ΔQ_p =   peak discharge of incremental unit hydrograph ($m^3.s^{-1}$),

A   =   catchment area (km^2),

ΔQ =   incremental stormflow depth (mm),

ΔD =   unit duration of time (h), and

L   =   catchment lag (h).

A number of options to estimate catchment lag are available in the SCS-SA model and the widely used Schmidt-Schulze equation (Schmidt and Schulze, 1984) is shown in Equation 2.3:

$$L \quad = \quad \frac{A^{0.35} \times MAP^{1.1}}{41.67 \times y^{0.3} \times I_{30}^{0.87}} \tag{2.3}$$

where: L   =   catchment lag (h),

A   =   catchment area (km^2),

MAP   =   mean annual precipitation (mm),

y   =   average catchment slope (%), and

I_{30} =   2-year return period 30-minute rainfall intensity (mm/h).

2.2   Unit Hydrograph Method

The use of the Unit Hydrograph (UH) to estimate design floods began during the 1960s and is well documented in Chow *et al.* (1988). Maidment *et al.* (1996) describes a UH as means of representing a linear system response at the catchment outlet after a rainfall event has occurred in the catchment. The UH does not account for spatial variation within a catchment, resulting in lumping of the whole catchment (Maidment *et al.*, 1996). Chow *et al.* (1988) points out that the unit hydrograph is based on multiple assumptions, the first assumption is based on the

catchment response, which is assumed to be linear, indicating a direct proportion between the effective rainfall and surface runoff.

Design flood estimation using a UH approach has been developed for South Africa, and is suitable for application in catchments between the sizes of $15 - 5000$ km^2 (HRU, 1972), but it can also be extended to catchments larger than 5 000 km^2 (SANRAL, 2013). According to HRU (1972), the study catchments used in the development of the Synthetic Unit Hydrograph method in South Africa were regionally grouped according to surface features such as relief, soils, rainfall, and vegetation cover. These regional groupings resulted in nine veld type zones, each of which have an associated representative physiographic index such as the runoff lag coefficient (C_t) and the generalised catchment coefficient (K_u), and for each zone the appropriate dimensionless one-hour unit hydrographs were generalized (HRU, 1972). Equations 2.4 and 2.5 are used to dimensionalize the dimensionless UHs (HRU, 1972):

$$Q_p = K_u \left(\frac{A}{T_l} \right) \tag{2.4}$$

where: Q_p = unit hydrograph peak discharge (m^3. s^{-1}),

K_u = generalised catchment coefficient (dimensionless),

A = catchment area (km^2), and

T_l = lag time (hours).

$$T_l = C_t \left(\frac{LL_c}{\sqrt{S}} \right) \tag{2.5}$$

where: L = hydraulic length of catchment (m),

L_c = distance between outlet and centroid of catchment (m),

S = average slope of stream as for Rational Method (m/m), and

C_t = generalized lag coefficient (dimensionless).

2.3   Rational Method

The Rational Method is the most extensively applied method to estimate design flood peak discharges in small rural and urban catchments in South Africa (Alexander, 2002). The method is extensively applied worldwide, as it is easy and simple to use and understand (Parak and Pegram, 2006). The HRU (1972) outlines the Rational Method in South Africa as applicable to catchments with areas less than 15 km^2. The peak discharge can be obtained by the use of the Rational formula, as shown in Equation 2.6 (HRU, 1972):

$$Q \quad = \quad \frac{C \times I \times A}{3.6} \tag{2.6}$$

where: Q   =   peak discharge (m^3.s^{-1}),

C   =   dimensionless runoff coefficient,

I   =   point rainfall intensity (mm.h^{-1}),

A   =   catchment area (km^2),

3.6   =   conversion factor

According to SANRAL (2013), the Rational Method produces good results when compared to other rainfall-based methods. Parak and Pegram (2006) pointed out that the probabilistic approach to applying the Rational Method is essential to overcome the limitations associated with the deterministic application of the method.

2.4   Standard Design Flood (SDF) Method

The SDF method is a probabilistic-based approach to the application of the Rational Method developed for application in South Africa (Alexander, 2002). The runoff coefficient (C factor) in the Rational Method was calibrated to convert design rainfall into design peak discharge, and the calibrated runoff coefficients were also subjectively adjusted to produce a more conservative estimate (Parak and Pegram, 2006)

Görgens (2002) pointed out that over-design of some hydraulic structures may result from the adoption of the SDF method, thus having economic implications. Van Bladeren (2005) recommended that the SDF method requires further investigation and refinement, due to the

method performing inconsistently. Some of the recommendations by Van Bladeren (2005) include improving the regionalisation and re-estimating the catchment characteristics. (Gericke and Du Plessis, 2012) evaluated the performance of the SDF methods in 19 of the 29 SDF basins and developed adjustment factors for the SDF method which improved the design flood estimates compared to the original probabilistic-based SDF approach.

2.5   Limitations of the Current Rainfall Event Based Methods

According to Weinmann *et al.* (2002), floods of a given magnitude are possibly the result of different rainfall events that are combined with a range of other flood producing variables. Event based rainfall based methods consider the probability distribution of rainfall depth, but ignore the probability distribution of other model inputs such as rainfall temporal patterns and storm losses (Dunsmore *et al.*, 1986). Charalambous *et al.* (2013) states that there are no definite guidelines on selecting representative values for the input variables, and it is difficult to estimate the a priori representative value for the input variable. Another key assumption involving event based rainfall based methods is the assumption regarding the exceedance probability of the computed output flood, and it is generally assumed that a design rainfall depth for a given return period will produce a design flood of the same given return period (Chow *et al.*, 1988; Rahman *et al.*, 2002b; SANRAL, 2007). Weinmann *et al.* (2002) also pointed out that the arbitrary selection of the critical storm duration as the basis for estimating the design flood is the same as assuming that the marginal distribution of flood magnitude is equivalent to the conditional distribution of flooding for the critical rainfall duration. This results in a systematic bias in flood frequency estimates and a tendency to over-estimate the magnitude of design floods (Weinmann *et al.*, 2002). According to Suresh Babu and Mishra (2012) the effect of rainfall intensity and rainfall duration, which have great impact on the quantity of runoff, is not taken into account in the method such as SCS-CN.

The random choice of these probabilistic aspects of various flood-producing variables in event based rainfall-runoff methods, could lead to inconsistency as well as bias in the estimated design floods (Chow *et al.*, 1988; Rahman *et al.*, 2002b; SANRAL, 2007) and has been widely criticised (Kuczera *et al.*, 2006; Gioia *et al.*, 2008; Kjeldsen *et al.*, 2010; Svensson *et al.*, 2011). This arbitrary treatment could lead to either the over- or under-design of flood structures, which has economic, environmental and social implications (Rauf and Rahman, 2004). According to Charalambous *et al.* (2013), the probabilistic aspects of key input variables that can produce

significant floods needs to be adopted in order to improve the limitations associated with event rainfall based methods, and this can be achieved through applying a JPA.

3. JOINT PROBABILITY APPROACH TO DESIGN FLOOD ESTIMATION

Joint probability has been described by Hawkes (2008) as the chance of two or more conditions occurring simultaneously. There are two methods that can be used under a JPA, namely an ensemble event simulation and continuous simulation (Svensson *et al.*, 2013).

The continuous simulation approach explicitly simulates the correlations between the significant flood generation variables over different time scales, is the most comprehensive tool to account for joint probabilities in flood frequency estimation (Kjeldsen *et al.*, 2014). However, the approach often requires a significant modelling effort and data collation for input to the model, as well as long periods of observed or stochastic rainfall and climate data (Ling *et al*., 2015). The continuous simulation approach is not widely used in practice due to the cost of using the approach, and the difficulty in simultaneously calibrating a model to simulated flood volumes, peaks and hydrograph shape (Ling *et al.*, 2015).

The ensemble event simulation approach is simpler than the continuous simulation approach, as it evaluates all joint probability interactions during a storm event only (Svensson *et al.*, 2013). It uses deterministic event-based rainfall-runoff models in a Monte Carlo framework, together with stochastically generated design rainfall events for varying durations, to simulate runoff with sensitive model parameters randomly sampled from a defined distribution (Svensson *et al.*, 2013). Conditional probabilities are also used to account for the correlation between input variables where necessary (Charalambous *et al.*, 2013). For the purpose of this study, only the ensemble event approach is reviewed further in detail.

3.1   Description and Application of the Joint Probability Approach

The underlying approach to the JPA is that instead of the use of a single combination of input variables to determine the flood characteristics, the method rather uses multiple combinations of flood producing variables to determine the flood characteristics (Nathan, 2013). According to Rahman *et al.* (2001) the JPA accounts for the probability distributed nature and behaviour of the main flood producing variables, each of which has an associated degree of uncertainty that affects the shape and magnitude of the estimated design flood hydrograph (Loveridge *et al.*, 2013). Rahman *et al.* (2001) considers four inputs (rainfall duration, rainfall intensity, temporal pattern and storm loss) as random variables while other model parameters are fixed.

Kjeldsen *et al.* (2010) showed that the foundation of this method was provided by Eagleson (1972) who estimated the flood frequency analysis without streamflow records by deriving it from density functions for climatic catchment variables. Svensson *et al.* (2013) points out that numerous researchers have since advanced the performance of the approach (Russell *et al.*, 1979; Sivapalan *et al.*, 1990; Rahman *et al.*, 2001). Rahman *et al.* (1998) found from the previous summarised studies on the JPA, that the most previous applications were limited to theoretical studies and not practical applications due to limited flexibility, resulting in mathematical complexity and difficulty in parameter estimation, thus preventing how the method was applied.

Svensson *et al.* (2013) pointed out that with the advent of improved computing power, the generating samples of the input variables within a Monte Carlo simulation framework has become a useful tool. The Monte Carlo-type methods generally involve the stochastic simulation (multiple realizations) of input variables (such as rainfall, antecedent soil moisture, initial flow), followed by the use of these as inputs into a rainfall–runoff model that may be fully deterministic or have stochastic components (Russell *et al.*, 1979; Sivapalan *et al.*, 1990; Rahman *et al.*, 2002b; Aronica and Candela, 2007). Since then, the Ensemble JPA has been explored in numerous studies (Rahman *et al.*, 2001; Rahman *et al.*, 2002b; Weinmann *et al.*, 2002; Aronica and Candela, 2007).

According to Rahman *et al.* (2001), the modelling framework used to apply the Ensemble JPA and determine the desired design flood hydrograph includes three steps (Rahman *et al.*, 1998; Weinmann *et al.*, 1998) and these include:

i)   Selecting an appropriate deterministic hydrological model to simulate the flood hydrograph.
ii) Defining the key inputs and their respective probability distributions as well as correlations.
iii) A stochastic model to synthesise the distributions of key input variables.

Rahman *et al.* (2001) stated that there are two stochastic modelling frameworks that can be used, and this includes a deterministic approach and a Monte Carlo simulation (MCS) approach. According to Rahman *et al.* (2001) the deterministic approach uses a discrete representation of continuous probability distributions, whereas the MCS approach selects specific sets of input and model parameter by sampling values from their respective

distributions, and allowing any correlation between the variables by using conditional probability distributions (Rahman *et al.*, 1998; Weinmann *et al.*, 1998).

Goodness-of-fit tests such as the Chi-Squared (C-S), Kolmogorov-Smimov (K-S), and Anderson-Darling (A-D) tests were used to check if the hypothesis of the distributions is accepted and fits the data well (Rahman *et al.*, 2001; Caballero and Rahman, 2014). Figure 3.1 illustrates how the JPA is applied within a Monte Carlo framework, which is widely reported in the literature.
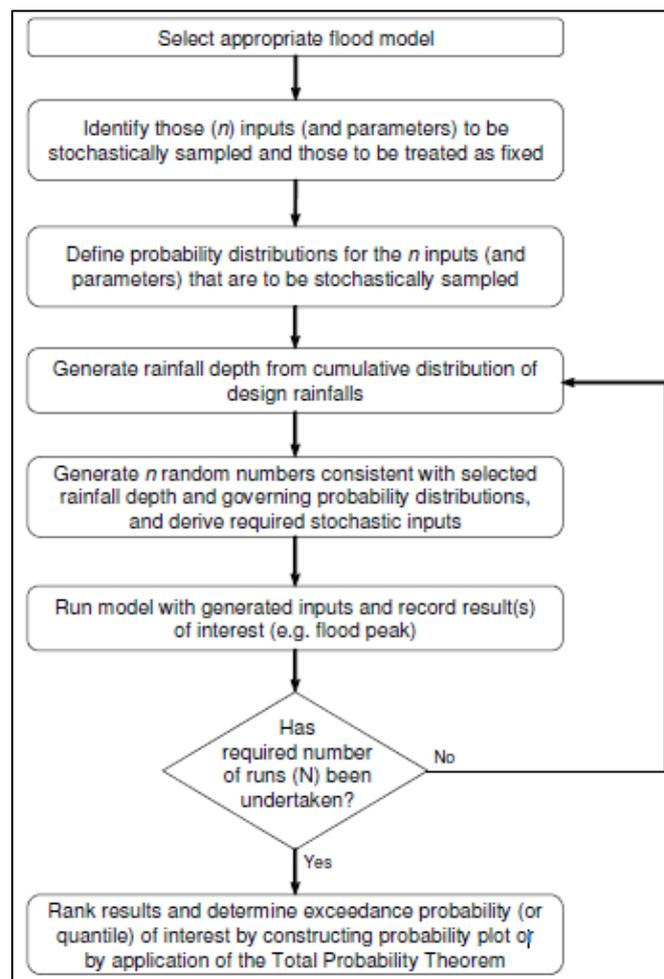
Figure 3.1   Schematic diagram of the Monte Carlo simulation process (Nathan and Ball, 2016)

3.2   Distribution of Key Input Variables

According to Rahman *et al.* (2006), sources of uncertainty in rainfall-based methods include the storm losses, temporal pattern, rainfall duration, and rainfall intensity. Rahman *et al.* (2001) pointed out that rainfall events need to be defined, from which the associated rainfall intensity, duration, temporal distribution and soil moisture deficit (SMD) can be subsequently extracted.

Kjeldsen *et al.* (2010) recommends that, in order to determine the probability distribution of key input variables, observed events need to be selected based on rainfall data, and a trial and error approach applied.

According to Hoang *et al.* (1999) a "complete storm" and "storm-core" are defined in order to select all the events having the potential to produce a flood and include parts that also have the potential to affect the flood response. A complete storm is defined by Hoang (2001) as the storm starting and ending with a non-dry hour, followed by a minimum of six dry hours (Rahman *et al.*, 1998). A storm-core on the other hand is defined as an intense rainfall burst occurring within a complete storm (Rahman *et al.*, 1998).

Once observed events are available and have been checked for inconsistencies and errors, the events likely to produce floods are selected using the average rainfall intensity during the complete storm duration, or storm-core duration, and selected events are further analysed to determine the respective distributions of the key input variables. The average rainfall intensity must satisfy conditions where the average rainfall intensity exceeds a certain threshold, as illustrated by Equation 3.1 (Hoang *et al.*, 1999):

$$I_D \quad \geq \quad f_1 \times I_{2,D} \tag{3.1}$$

where: I_D = rainfall intensity (units) for complete storm duration = D hours,

f_1 = reduction factor, and

$I_{2,D}$ = 2-year, D hour design rainfall intensity (mm/hour).

3.2.1 Storm losses

According to Hill *et al.* (1996), initial losses can be defined as the rainfall that occurs before the commencement of surface runoff. Rahman *et al.* (2002a) pointed out that initial losses show temporal and spatial variability. According to Hill *et al.* (1996) it is essential to consider the interaction of design losses with temporal patterns, as initial losses have a larger effect on an early peak temporal pattern than for a temporal pattern which has a peak in the middle portion.

According to Rahman *et al.* (Rahman *et al.*) the average catchment rainfall is used to compute initial losses given there are multiple rain gauges available in the catchment for analysis. Rahman *et al.* (2002a) also points out that the important statistics of the initial loss distributions

are the mean, median, standard deviation and coefficient of skewness. In South Africa, the Curve Number (CN) is used as in index to express the catchments stormflow response in the SCS-SA method, and is characterised by hydrological soil properties, land cover properties and catchment antecedent soil moisture conditions (Schulze *et al.*, 2004).

Figure 3.2 illustrates an example of the distribution exhibited by storm-core initial losses, where Rahman *et al.* (2002a) found that the four-parameter Beta distribution is appropriate to approximate the storm-core initial losses distribution.
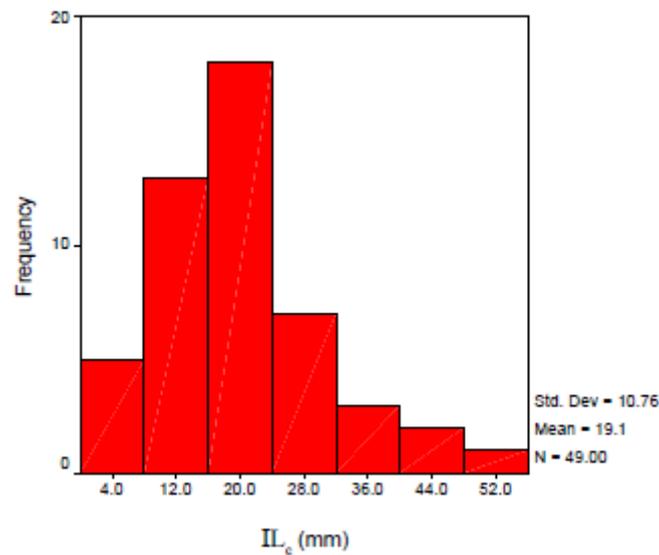
Figure 3.2   An example of initial loss distribution for the storm-core duration (IL_c) with the relative statistics (Rahman *et al*., 2001)

3.2.2   Temporal distribution

Rainfall temporal distribution is a dimensional representation of the variation of rainfall intensity over the duration of the rainfall event (Rahman *et al.*, 2001). According to Knoesen (2005) the distribution of the rainfall intensity during a storm affects the timing as well as the magnitude of the peak discharge of a catchment. The temporal distribution is also characterised by a dimensionless mass curve, which includes the cumulative rainfall depth versus the dimensionless storm duration divided into 10 equal time increments (Hoang, 2001). The design temporal distribution can be obtained using two methods, where the first method includes the development of distributions with the use of Intensity-Duration-Frequency (IDF) curves, and the second method includes hyetographs derived from observed rainfall data, which include a triangular rainfall distribution, Huff curves, the average variability method, and sampling of historical records (Knoesen, 2005).

In South Africa, the SCS-SA method initially adopted four temporal distribution types (Smithers and Schulze, 2003), and was later revised by Knoesen (2005) to 480 synthetic distributions which represented different storm types for South Africa. Figure 3.3 illustrates an example of the typical variability in the observed dimensionless temporal distribution using historical records.
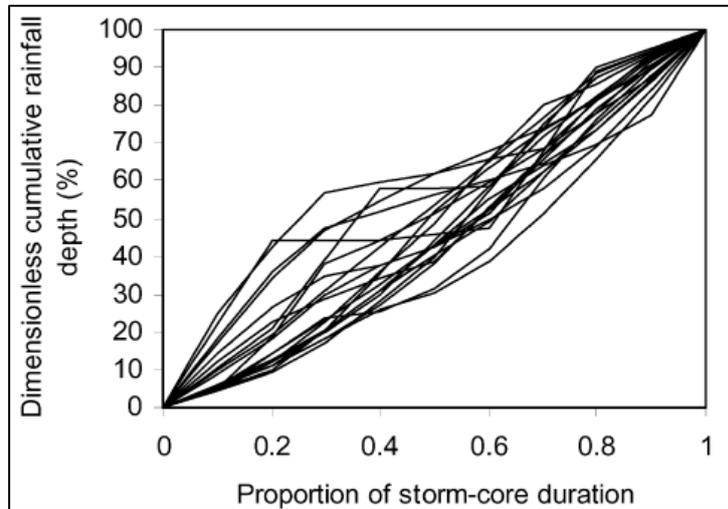
Figure 3.3   Typical temporal distributions using storm-core durations (Rahman *et al.*, 2002)

3.2.3   Rainfall duration

The distribution of the storm duration is obtained from hourly rainfall data (Rahman *et al.*, 2002b). To determine the storm duration distribution, the duration is split into a number of class intervals up to 100 hours and then the frequency of the storm durations occurring within each of the class intervals is determined (Rahman *et al.*, 2002b). The results are then plotted and the considered statistics include the mean, standard deviation and skewness.

Many studies have found the exponential distribution to fit the storm duration data relatively well (Rahman *et al.*, 2001; Rahman *et al.*, 2002b; Charalambous *et al.*, 2013; Caballero and Rahman, 2014). Figure 3.4 illustrates an example of a histogram showing the probability of different storm-core durations (D_c). Figure 3.4 also shows that the probability distribution of the storm-core duration is approximately exponentially distributed.

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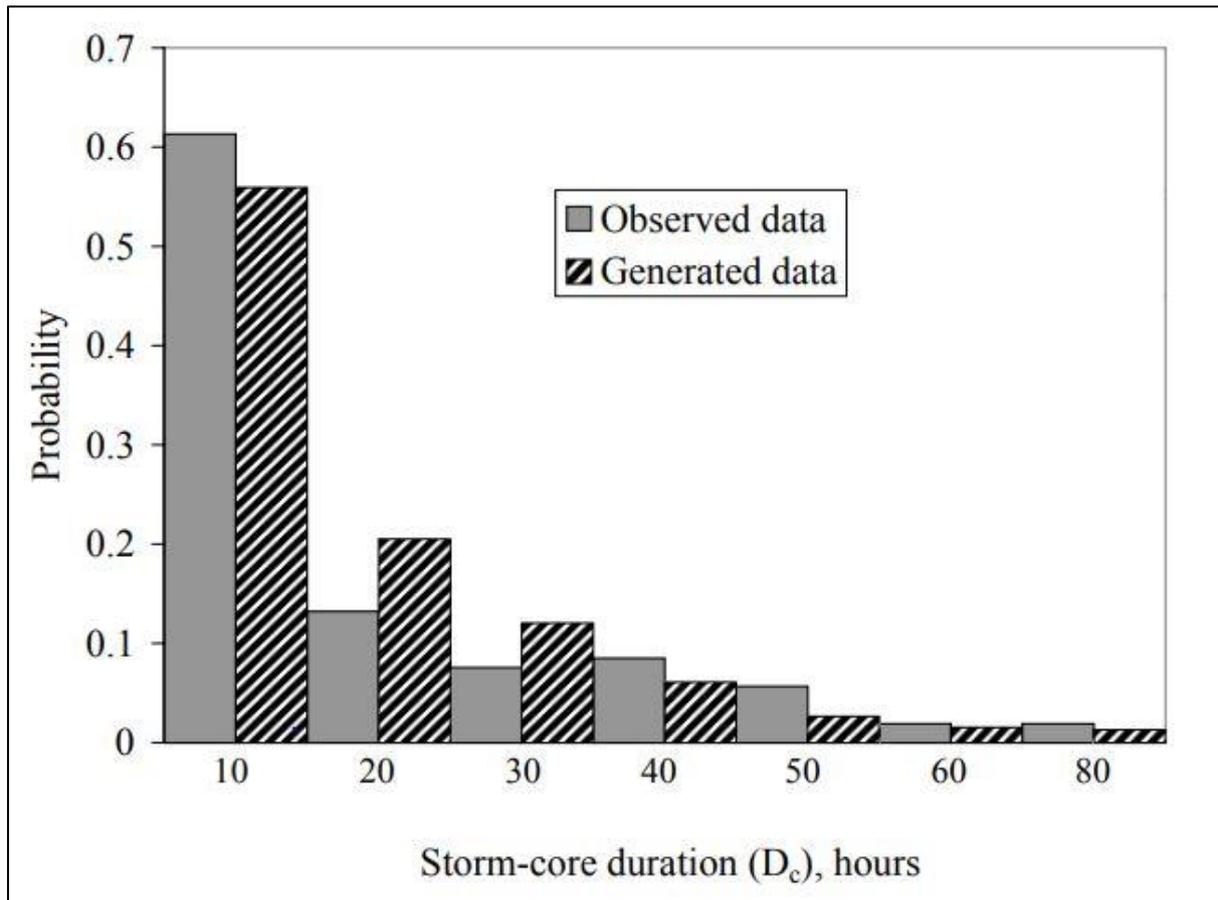
Figure 3.4   Example of rainfall duration distribution (Rahman *et al*., 2001)

3.2.4   Rainfall intensity

Several studies have indicated that there is a strong relationship between the storm duration and the storm intensity (Sivapalan *et al.*, 1996; Bloschl and Sivapalan, 1997; Rahman *et al.*, 2001). Thus, the storm intensity needs to be conditioned to the storm duration in the form of Intensity-Frequency-Duration (IFD) curves, where the rainfall intensity is plotted as a function of rainfall duration and frequency (Rahman *et al.*, 2001). According to Rahman *et al.* (2002b), developing IFD curves require the following steps:

(i)   The first step is to divide the range of storm durations into a number of intervals with a representative midpoint for each class. This is illustrated in Table 3.1.

(ii) A linear regression line is then fitted between the log (rainfall duration) and log (rainfall intensity) for the data in each class interval, except the one-hour class. The slope of the fitted regression line is then applied to adjusting the intensities for all durations within the interval to the representative midpoint duration. A partial series is formed in each class interval of the adjusted intensity values.

(iii) The following step would be to fit an exponential distribution to the partial duration series and the design intensity values are computed for the different return periods. For a selected return period, the computed intensity values for each duration range were used to fit a second-degree polynomial between the log transformed rainfall duration and the log transformed rainfall intensity, the R^2 values are used to indicate the confidence that can be represented by the fitted polynomials. These polynomials are then used for each selected return period to obtain the rainfall intensity value for any given rainfall duration value.

Table 3.1   An example of representative points for the duration class intervals (after Rahman *et al*., 2001)

Class interval (h)	Representative point (h)
1	1
2 - 3	2
4 - 12	6
13 - 36	24
37 - 96	48

The adopted MCS begins by generating a duration value from the probability distribution, then the return period is randomly generated, and the rainfall intensity value is selected from the conditional distribution of the rainfall intensity which is expressed in the form of IFD curves, as illustrated in Figure 3.5. The preparation of an IFD table is used in conjunction with an interpolation procedure to generate rainfall intensity estimates, for any given combination of duration and return period values. Table 3.2 illustrates the output of this procedure.

Table 3.2   An example of an IFD table used to generate intensity values in mm.h^{-1} (after Rahman *et al*., 2001)

D (h)	Annual Recurrence Interval (years)									
	0.1	1	1.11	1.25	2	5	10	20	50	100
1	10.1	13.6	14.4	15.3	19.0	26.1	31.5	36.5	44.0	49.4
2	6.7	8.5	9.0	9.4	11.3	14.9	17.6	20.3	23.9	26.7
6	3.4	4.2	4.4	4.6	5.4	7.0	8.2	9.4	11.0	12.2
24	1.3	1.8	1.9	2.0	2.5	3.4	4.1	4.8	5.7	6.4
48	0.8	1.2	1.3	1.4	1.8	2.6	3.3	3.9	4.7	5.4
72	0.6	0.9	1.0	1.1	1.5	2.3	3.0	3.6	4.4	5.0
100	0.5	0.8	0.9	1.0	1.3	2.1	2.8	3.4	4.3	4.9

Figure 3.5 illustrates IFD curves that were obtained using the above outlined method for the different return periods.
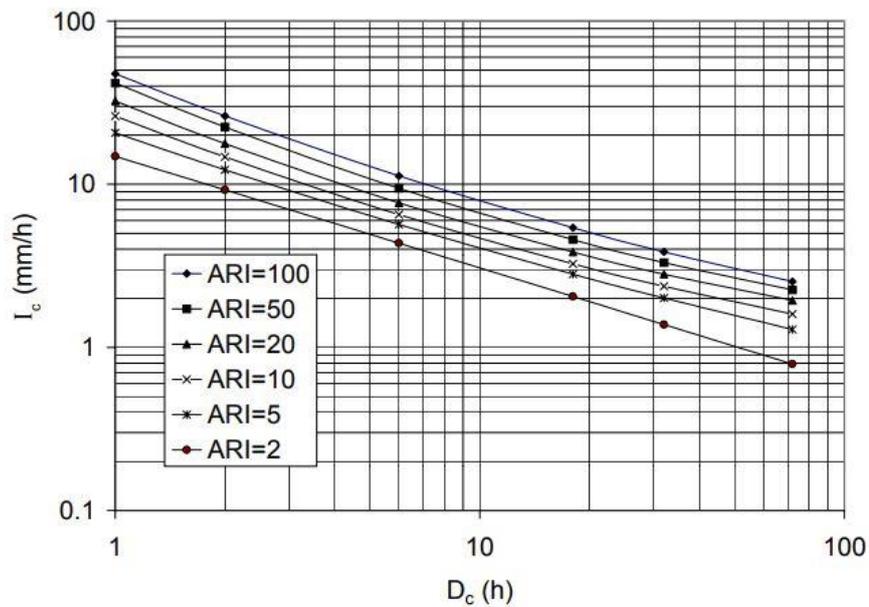
Figure 3.5   IFD curves (Rahman *et al*., 2001)

3.3 Recent Research on the JPA

This sub-section provides a review of current studies with a particular focus on how the JPA method was practically applied, including the data requirements and challenges, the results of the studies in terms of the impact it has on the estimation of design floods, and the recommendations on improving the efficiency of the method.

Rahman *et al.* (2002a) examined the application of probability-distributed initial losses using the JPA in the Victorian catchments of Australia. To determine the distribution of the initial losses, hourly rainfall, streamflow and potential evaporation data was used to determine initial loss for each event. Statistics such as the mean, median, standard deviation, skewness, lower and upper limits were determined from a set of extracted events. The distribution that was found to fit the derived initial losses data was the four-parameter Beta distribution, and the four parameters included statistics such as the mean, lower and upper limits, and standard deviation. The stochastic losses were applied in a MCS to determine the desired design flood hydrograph. It was found that initial storm losses values for observed floods showed wide variability, thus indicating that the catchment moisture conditions vary at the start of storms. The application of the JPA produced design flood estimates that closely matched observed floods estimates. It was also found that applying a mean value instead of a probability distributed initial loss significantly reduces the magnitudes of floods.

Aronica and Candela (2007) applied the JPA using a MCS approach to derive design flood estimates in poorly gauged Mediterranean catchments in Sicily, Italy. The catchment response i.e. initial losses or excess rainfall was modelled using the Soil Conservation Service-Curve Number (SCS-CN), and the method was implemented in a probabilistic form with respect to prior-to-storm conditions (curve number). Many authors (Sivapalan *et al.*, 1990; De Michele and Salvadori, 2002; Muzik, 2002) highlighted that antecedent moisture conditions (AMC) which is used to estimate the curve number (CN) is the most important factor influencing design flood estimates, thus AMC should be treated as a random variable.

According to Aronica and Candela (2007) the AMC probability distributions was derived by calculating the antecedent precipitation index (API) which is an index of the sum of precipitation over the preceding five days before the event, the number of flood events for each of the three classes (representing dry, average and wet catchment conditions prior to an event), and the probability of occurrence in each class as a ratio of the number of events in the single

class relative to the total number of events. It was found that the JPA can reproduce observed design flood estimates with reasonable accuracy over a range of return periods. Sufficient data, and reliable data was found to be also lacking in the study area.

Kjeldsen *et al.* (2010) applied the JPA in the UK where the revitalised FSR/FEH rainfall-runoff method is used as the UK standard for event-based flood modelling. The key inputs that were used based on their probability distribution, was the rainfall duration and intensity, Soil Moisture Deficit (SMD), initial flow at the gauging station and the inter-event arrival time. The marginal distributions of observed data for rainfall intensity and duration, were modelled using an exponential distribution and a gamma distribution, respectively. The Probability Distribution Model (PDM) model developed by Moore (2007) was used to generate appropriate SMD values at the start of the event. The initial flow was modelled as a function of the SMD at the onset of the event. It was found that the JPA simulated the flood frequency curve reasonably well when compared to the observed flood frequency curve and tended to be less biased.

Loveridge *et al.* (2013) applied probabilistic flood hydrographs in New South Wales, Australia, using the MCS framework to determine the potential impacts flood inundation could have on the flood frequency curve. This was also accounted for by considering how hydraulic analysis can be affected by uncertainties in design losses. The relative distributions of the initial losses, as well as the continuing losses which are the losses that continue to occur after surface runoff has commenced, were approximated by a 2-parameter Gamma distribution and 3-paramter Weibull distribution, respectively. The MCS framework was applied to determine the uncertainties in the design losses, a string of simulations were run to determine the confidence limits for the peak flow, flood volume and time to peak flow characteristics. It was found that the uncertainties in design losses when using the RORB rainfall-runoff model, can result in differences of up to approximately 55 % for peak flows, 105 % for flood volumes and 9 % for time to peak flows.

Svensson *et al.* (2013) applied the JPA to incorporate the input variables that are seasonally varying to two catchments in the UK. Hourly river flow data, average hourly rainfall and catchment average potential evaporation was used to extract the input marginal distributions. The key input variables included the inter-event arrival time, rainfall duration, rainfall intensity and the rainfall temporal distribution. The marginal distributions of the rainfall intensity and rainfall duration were modelled using a one-parameter exponential distribution and a two-

parameter gamma distribution, respectively. The temporal distribution was modelled using a double triangle profile to reflect two bursts of rainfall. A continuous hourly series of SMD was derived for each catchment through continuous simulation using the PDM rainfall-runoff model, and the initial flow was modelled as function of the SMD at the start of the event. It was found from the study that the flood frequency curves derived using the JPA do not fit the upper bound of the General Extreme Value (GEV) distribution fitted to the observed annual maximum series. Furthermore, it was also found that some of the input variables are more sensitive to sampling variability than others.

3.4   Uncertainty in Flood Estimates from the JPA Approach

According to Svensson *et al.* (2013) the uncertainty in design flood estimates produced by the JPA can be described by the 95% confidence intervals which are estimated using a bootstrapping method. Uncertainty analysis using the described method can be applied to both predicted flood peak magnitudes, as well as the predicted flood volumes (Svensson *et al.*, 2013).

Kjeldsen *et al.* (2014) showed that the major cause of uncertainty is a result of estimating flood frequency from observed flow records which have limited record lengths, sampling errors which are often associated with flow measurements and the selection of correct distributions (Muzik, 2002). Another uncertainty includes the purely deterministic processes that are adopted by traditional streamflow models, which do not account for the non-stationary time series (Muzik, 2002). According to Muzik (2002) implementing these deterministic models within a stochastic framework and using stochastic model parameters to generate ensembles of simulated streamflow series, are proposed as useful to assessing risk and uncertainty in design flood estimation and accommodate non-stationary hydrological processes, and time series (Muzik, 2002). However, Loveridge and Rahman (2018) has also highlighted that the method is prone to errors for infrequent events due to the rarity of such events occurring in the observed records.

3.5   Discussion and Conclusions

It is evident from the literature reviewed that rainfall based methods for design flood estimation tend to produce significantly uncertain design estimates and leads to inconsistencies in the design flood estimates. This is a result of the assumptions involved in the methods, as well as the arbitrary treatment of the probabilistic nature of model inputs such as the rainfall temporal

patterns, rainfall intensity and storm losses. The JPA is becoming a very comprehensive tool to account for joint probabilities in flood frequency estimation, as the method evaluates all the joint probability interactions during a storm, and also accounts for correlation between input variables where necessary. The only disadvantages found with using the JPA is due to the method requiring long periods of observed or stochastic rainfall and climate data when adopting the continuous simulation approach, which also calls for a data and modelling effort. There are also uncertainties that can arise from sampling methods and the record length available.

When applying the JPA method, it is essential to adopt a modelling framework which is based on three principle elements: (i) estimation of the respective probability distributions from their marginal distributions, (ii) generation of design values by sampling from the respective input distributions using a Monte Carlo simulation approach, and (iii) selecting an appropriate deterministic model to simulate ensemble flood events, and derive a flood frequency curve or design flood for a specific recurrence interval from the ensemble flood events.

It is also evident from literature that, when considering the distribution of the initial loss, the four-parameter Beta distribution is appropriate to approximate the storm initial losses. Studies also show that the probability distribution of the rainfall duration is best approximated by an exponential distribution, however, there are cases where the distribution has been approximated by a two-parameter gamma distribution in UK catchments (Kjeldsen *et al.*, 2014). It has also been found from literature that the probability distribution that best approximates the distribution of the rainfall intensity is an exponential distribution, and the rainfall intensity is correlated to the rainfall duration as studies have shown there is a strong relationship between the rainfall intensity and duration. Studies have also shown that the temporal distribution is commonly represented by a dimensionless mass curve, through the sampling of historical records, and adopting a triangular distribution. Numerous studies have shown that the JPA has performed consistently better compared to using a single set of input variables which frequently results in poor estimation, whereas the JPA approach tend to be more accurate.

In conclusion, the JPA approach to design flood estimation has been shown to reduce bias for a given return period, as well as reduce inconsistencies associated with using one set of input variables, and this improvement in design flood estimation has positive economic implications. The JPA method also shows potential to be applied in South Africa using an event-based model.

4. METHODOLOGY

This section includes a brief description of the catchments used in the study as well as their locations. This is followed by model selection, the framework developed to apply the Ensemble SCS-SA model, data collation and processing, the fitting of distributions to the processed data, goodness-of-fit tests used, model set up and assessment criteria used to determine the performance of the model.

4.1 Study Area

Sixteen catchments were selected for use in the study and are located in different climatic regions of the country. Given the need to estimate the distribution of catchment response times using readily available data, as detailed in Section 4.4, most of the stations were selected in regions used by Gericke (2016) and these include the winter coastal region, summer coastal region and the northern interior (Gericke, 2016). This catchment selection was done to determine how well the model performs in these different climatic regions. Nine of the sixteen catchments were selected from the study done by Gericke (2016), and the rest of the catchments were obtained from the study undertaken by Rowe (2019). The locations of these catchments are illustrated in Figure 4.1.
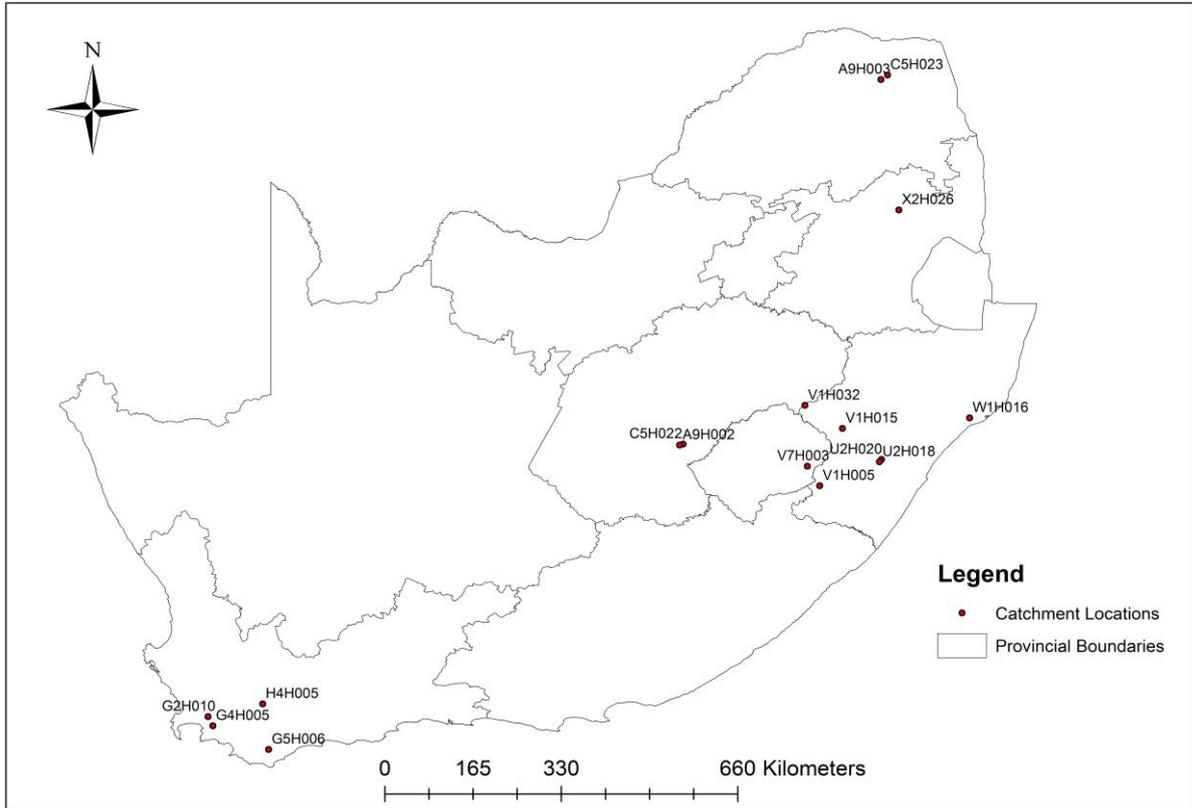
Figure 4.1   Location of catchments used in the study

4.2   Hydrological model Selection

The criteria used for selecting a suitable model was based on the number of key input variables, the models' accessibility and operational support, as well as the ability of the model to estimate peak discharges. Table 4.1 provides a summary of the criteria used to select the model.

Table 4.1   Summary of hydrological model selection

Model	Key Input Variables	Accessibility
SCS-SA	Rainfall (P)	Free from Prof Smithers and Prof Schulze
	Time to Peak (lag time)	
	Temporal Distribution (Dimensionless)	
	Antecedent Moisture Conditions (S)	
Unit Hydrograph	Regionalised catchment coefficient (K_u)	Utilities Programs for Drainage or manual application
	Lag time	
	Regionalised lag coefficient (Ct)	
Rational Method	Rainfall (P)	
	Intensity (I)	

Model	Key Input Variables	Accessibility
	Dimensionless runoff coefficient (c)	Utilities Programs for Drainage or manual application
Standard Design Flood	Basin number Calibrated runoff coefficients (C_2-C_{100})	Utilities Programs for Drainage or manual application

From the above, the SCS-SA model was selected for use in this study as the model is readily available, there is readily available data for the key input variables and there is sufficient operational support available.

4.3 Development of an Ensemble Framework for the SCS-SA Model

The modelling framework used to apply the Ensemble SCS-SA and determine the derived flood frequency curve is based on three principal elements (after Rahman et al., 1998; Weinmann et al., 1998) and these include:

(i) Defining the key model inputs with their respective probability distributions and correlation.

(ii) A stochastic model to synthesise sequences of selected variables.

(iii) Selecting an appropriate deterministic hydrological model to simulate the flood formation process, and use the outputs to derive the flood distribution.

The Ensemble SCS-SA uses the SCS-SA stormflow and peak discharge equations to estimate the runoff volume and peak discharge, as presented in Equations 2.1 and 2.2. The sampling procedure adopted includes generating 100 samples from the respective probability distributions for each key input variable and using each randomly selected sample as input to the Ensemble SCS-SA model in order to generate 100 sets of results for analysis.

4.4 Data Collation and Distribution Fitting

This sub-section contains a summary of the data collation and derivation of information used in the study.

4.4.1 Catchment information

The catchment information required to run SCS-SA for the catchments used in the study include the catchment area, the Mean Annual Precipitation (MAP), the mean catchment slope, mean catchment elevation, the land cover and treatment class, the soil group, and the geographical coordinates of the centroid of the catchment. The mean catchment slope and altitude of the catchments were derived using the ArcGIS software, and the 90 m resolution raster Digital Elevation Model (DEM) for South Africa (Van der Spuy and Raddemeyer, 2014).

The national land cover database for South Africa which was published in 2005 by the ARC and CSIR (2005) was used to determine the SCS-SA land cover class of the catchments. Soils information for catchments obtained from Gericke (2016) was obtained using ARCMAP, and for the research catchments from literature (Smithers and Schulze, 1994a; Smithers and Schulze, 1994b; Scott *et al.*, 2000; Gush *et al.*, 2002; Royappen, 2002; Royappen *et al.*, 2002; Lorentz and van Zyl, 2003). The MAP for the centroid for each catchment was obtained from the design rainfall estimation software developed by Smithers and Schulze (2003), which used information published by Lynch (2004).

The SCS-SA soil group was obtained by using the soil group map published by Schulze *et al.* (2004) and clipping it to the relative catchment. Other catchment soils information required by the model such as the soil depth and soil texture were obtained from the South African Atlas of Climatology and Agrohydrology published by Schulze (2007), converted to a raster format using ArcGIS, then clipped to the relative catchments, and the mean soil depth and soil texture were estimated for each of the catchments. The Schmidt-Schulze lag equation was estimated using Equation 2.3, and the observed mean lag was estimated from the observed time to peak data, as detailed in Section 4.4.2. Table 4.2 contains a summary of the catchment information and variables which were used as input into the SCS-SA model for the each of the catchments.

Table 4.2   Catchment information and parameters for the catchments used in the study

Catchment	Area (km²)	MAP (mm)	Mean Altitude (m)	Mean Slope (%)	SCS-SA Land Cover Class	Treatment/Class Type	SCS-SA Soil Group	Schmidt-Schulze Lag (hours)	Observed Mean Lag (hours)
U2H020 (Cedara)	0.26	873	1106	11	Veld (range) and Pasture	In fair condition	A/B	0.38	0.43
V7H003 (Ntabamhlophe)	0.52	1103	1497	14.6	Veld (range) and Pasture	In fair condition	B/C	0.5	0.67
G2H010 (Jonkershoek-Lambrechtsbos B)	0.73	1677	517	36.9	Forests and Plantations	Humus Depth > 100 mm	A/B	0.62	5.6
V1H005 (Cathedral Peak IV)	0.98	1262	2011	32.7	Veld (range) and Pasture	In Good Condition	A/B	0.54	1.4
V1H015 (Ntabamhlophe)	1.04	871	1512	17	Veld (range) and Pasture	In Good Condition	B	0.84	0.56
U2H018 (Cedara)	1.31	957	1269	23.3	Forests and Plantations	Humus Depth > 100 mm	B	0.75	1.25
G5H006	3	1285	350	2.3	Veld (range) and Pasture	In Poor Condition	B	9.7	3.9
W1H016 (Zululand)	3.3	1238	260	13.2	Veld (range) and Pasture	In Good Condition	B	1.35	7.23
X2H026	13.82	999	1450	30.8	Forests and Plantations (24%)	Humus Depth 50-100 mm	A/B	0.98	2.3
					Veld (range) and Pasture (76%)	In Good Condition			

Catchment	Area (km²)	MAP (mm)	Mean Altitude (m)	Mean Slope (%)	SCS-SA Land Cover Class	Treatment/Class Type	SCS-SA Soil Group	Schmidt-Schulze Lag (hours)	Observed Mean Lag (hours)
A9H006	16	1404	1055	32.3	Forests and Plantations	Humus Depth > 100 mm	B/C	1.5	2.4
H4H005	29	502	680	5.2	Veld (range) and Pasture	In fair condition	C	3.4	10.9
C5H022	39	610	1638	1.2	Veld (range) and Pasture	In Poor Condition	B/C	10.5	4.8
V1H032	67.8	1321	1571	26.5	Veld (range) and Pasture	In Poor Condition	C	2.2	1.3
A9H002	103	1157	850	2.1	Forests and Plantations	Humus Depth > 100 mm	B/C	23.1	7.6
G4H005	146	1156	380	25.9	Veld (range) and Pasture	In Good Condition	B/C	5.9	5.1
C5H023	185	586	1540	2.45	Veld (range) and Pasture	In Good Condition	C	35.8	29

The catchments range in size from 0.26 km^2 to 185 km^2. Although the SCS-SA model is applicable to catchments with an area less than 30 km^2, catchments with an area greater than the maximum prescribed area which is 30 km^2 were selected due to insufficient smaller catchments with reasonable observed data record lengths.

4.4.2 Catchment data and information

Historical streamflow data was obtained from various sources, including from the Department of Water and Sanitation (DWS), from archives housed by the Centre for Water Resources Research (CWRR) at UKZN, and the Council for Scientific and Industrial Research (CSIR). The observed record lengths ranged from 11 to 70 years. A distribution fitting tool using L-moments developed by Smithers and Schulze (2000) was then used to fit the GEV distribution to the annual maximum series of observed streamflow data for each streamflow gauging station. Table 4.3 contains a summary of the streamflow gauging stations, record lengths and the source of the data.

Table 4.3   Source of streamflow data and record length

Catchment	Record Length (years)	Period of Record	Data Source
U2H020 (Cedara)	17	1978 - 1994	CWRR
V7H003 (Ntabamhlophe)	23	1970 - 1992	CWRR
G2H010 B (Jonkershoek-Lambrechtsbos)	52	1947 - 2006	CSIR
V1H005 (Cathedral Peak IV)	31	1950 - 1981	CSIR
V1H015 (Ntabamhlophe)	15	1965 - 1994	CWRR
U2H018 (Cedara)	19	1976 - 1994	CWRR
G5H006	31	1956 - 1994	DWS
W1H016(Zululand)	11	1976 -1986	CWRR
X2H026	27	1966 - 1992	DWS
A9H006	15	1965 - 1979	DWS
H4H005	33	1950 - 1981	DWS

Catchment	Record Length (years)	Period of Record	Data Source
C5H022	28	1980 - 2008	DWS
V1H032	20	1974 - 1993	DWS
A9H002	70	1931 - 2000	DWS
G4H005	55	1957 - 2018	DWS
C5H023	30	1983 - 2007	DWS
*CSIR – Council for Scientific and Industrial Research *CWRR - Centre for Water Resources Research *DWS - Department of Water and Sanitation			

4.4.2.1 Distribution of design rainfall

To estimate design rainfall, the Regional L-Moment Algorithm and Scale Invariance Approach was adopted, which estimates rainfall depths for return periods of 2 to 200 years with durations ranging from 5 minutes to 7 days (Smithers and Schulze, 2003).

4.4.2.2 Distribution of time to peak

The catchments used by Gericke (2016) had readily available time to peak data calculated for observed events. For catchments without readily available time to peak data, the time to peak was extracted from the observed data using the Hydro-Extract software (Cullis *et al.*, 2007), which enables the user to extract flood hydrographs from a flow data record. Once the hydrographs were extracted, a flood hydrograph analysis spreadsheet developed by Gericke (2016) was utilised to estimate the time to peak for the individual storm events. This was only done for stations obtained from Rowe (2019) and included in Table 4.3, which is observed data obtained from the CWRR and CSIR.

4.4.2.3 Distribution of antecedent moisture conditions

The Initial curve number was determined from the predominant soil and land cover condition, then adjusted using the Median Condition Method to account for changes in antecedent soil moisture condition (AMC), as described in Equation 4.1 (Schulze *et al.*, 2004):

$$ CN_f = \frac{1100}{\frac{1100}{Cn\text{-}II} - \frac{\Delta S}{25.4}} \tag{4.1} $$

where: CN_f = final curve number (dimensionless),

CN-II = initial curve number (dimensionless), and

ΔS = change in AMC (mm).

The data used to determine the probability distribution for the AMC was obtained from the study by Schmidt *et al.* (1987), who extracted the five largest rainfall events each year for the entire record length, for 712 homogeneous zones in South Africa. The change in soil moisture (ΔS) from average conditions was then simulated using the ACRU model (Schmidt *et al.*, 1987) for a 30-day period prior to the five largest events per year in each homogenous zone and for three soil textures (sand, loam and clay), three soil depths (shallow, intermediate and deep) and three land covers (sparse, intermediate and dense). A frequency analysis was then performed on the results, and the 20th, 50th and 80th percentiles of the change in soil moisture (ΔS) status was estimated for each soil texture, soil depth and land cover combination in each of the 712 zones (Schmidt *et al.*, 1987). In this study, a trend line was fitted to the three percentiles and used to extrapolate to the 10th and 90th percentiles. A probability distribution was then fitted to the five percentile values of ΔS.

4.4.2.4 Distribution of the temporal pattern

Knoesen (2005) developed a semi-stochastic daily rainfall disaggregation model for South Africa that is based on the distribution of the fraction of the daily total rainfall (R), which occurs in the hour of maximum rainfall. Knoesen (2005) extracted the distribution of R at multiple sites across the country and then collated the computed R values into 20 range bins, which can also be referred to as groupings or clusters of the fraction of daily rainfall. For each range bin, all 24 hourly fractions were determined and these 24 hourly fractions are arranged to recreate multiple realisations of the temporal distribution of daily rainfall to account for all permutations when the hour of maximum can occur (Knoesen, 2005). The combination of the 24 arrangements and the 20 range bins resulted in a total of 480 different temporal patterns ranging from uniform to non-uniform (Knoesen, 2005).

## 4.5	Assessment of Distribution Fitting

Once the data to determine the probability distribution for the variable had been collected and processed as described above, a distribution fitting software (EASY-FIT, 2013a) was used to determine which probability distribution best fits the data. Goodness-of-fit tests were then applied by the software to the probability distribution to determine how well the distributions fit the observed data. These tests include the Kolmogorov-Smirnov (K-S) test, Anderson-Darling test (A-D), and the Chi Squared test (C-S) (Stephens, 1974; Kottegoda and Rosso, 1997).

The K-S test is a nonparametric test of continuous probability distributions which tends to be more sensitive towards the center of the distribution than at the tails (Stephens, 1974). The test is based on the absolute maximum difference between the observed cumulative distribution function (cdf) and the expected cumulative distribution function (Kottegoda and Rosso, 1997).

The A-D test is used to test if the generated sample of data came from the population that has a specific distribution (Stephens, 1974), and the test also gives heavier weightings to the tails of a distribution compared to the K-S test (Kottegoda and Rosso, 1997).

The C-S test can be applied to both continuous and discrete probability distributions, but depends on an adequate sample size in order for the approximations to be valid (Stephens, 1974). The C-S is a test of significance based on the weighted sum of squared differences between the observed and theoretical frequencies (Kottegoda and Rosso, 1997).

## 4.6	Ensemble SCS-SA Model Set Up

Once the distributions for design rainfall, time to peak and ΔS were determined as described above, the Ensemble SCS-SA JPA model was set up. The normal procedures and functioning of the SCS-SA model were kept the same and transferred to an excel spreadsheet. Two sheets in the spreadsheet were used to: (i) input the relative sampled distributions, and (ii) store the results of the ensemble events. Since SCS-SA is an event-based model, it had to be refined to enable it to run an ensemble of events. This was achieved by developing Visual Basic for Application (VBA) code to the model structure to include a loop function. The loop function performs the function of transferring the sampled parameters for every loop into the model individually, then transferring the ensemble results to the storage sheet. Once the model

completed simulating all the events, VBA code was applied to sort, organize and perform statistical analyses on the results.

Three test catchments were initially used to rigorously validate and assess the performance of the Ensemble SCS-SA and the standard event based SCS-SA models. These include catchments U2H020 (0.26 km^2), X2H026 (13.82 km^2), and A9H006 (16 km^2). The models were then assessed on more catchments that are located in different climatic regions of the country after the initial validation of the models and verification of their performance.

4.7   Model Evaluation Criteria

To evaluate the performance of the model, simulated design values were compared to design values computed from the observed streamflow data. Graphs and a statistical analysis was used for visual evaluation and analysis. The Nash-Sutcliff Efficiency (NSE), absolute relative difference, and Mean Absolute Relative Error (MARE) were also be used to evaluate the performance of the model.

4.7.1   Nash-Sutcliff Efficiency

The NSE is a commonly applied method to assess the agreement between observed streamflow and modelled streamflow (Vaze *et al.*, 2011). The NSE ranges between the values of -∞ and one, where an NSE value that is less than zero indicates that the model is performing poorly, and an NSE value greater than 0.5 indicates the model is performing reasonably well (Vaze *et al.*, 2011). The NSE is determined using Equation 4.2 (Nash and Sutcliffe, 1970):

$$\text{NSE} \quad = \quad 1 - \left[\frac{\sum_{i=1}^{n}(S_i - Q_i)^2}{\sum_{i=1}^{n}(Q_i - \bar{Q})^2} \right] \qquad (4.2)$$

where: NSE   =   Nash-Sutcliff Efficiency (dimensionless),

Q$_i$ =   observed peak discharge (m^3.s^{-1}),

n   =   number of values

S$_i$ =   simulated peak discharge (m^3.s^{-1}), and

$\bar{Q}$ =   mean peak discharge (m^3.s^{-1}).

4.7.2   Absolute relative difference

The absolute relative difference is a measure of the uncertainty or accuracy of a measurement relative to the true value, with the assumption the true value is correct. The absolute relative difference is determined using Equation 4.3:

$$RE_M \quad = \quad \frac{|Q_o - Q_i|}{Q_i} \times 100 \tag{4.3}$$

where: RE_M =   relative difference of model (%),

   Q_i =   estimate value from the model, and.

   Q_o =   estimate value from observed data.

4.7.3   Mean absolute relative error

The mean absolute relative error is a measure of difference between two continuous variables and is an average of the absolute errors. The mean absolute relative error is determined using Equation 4.4 (Smithers *et al.*, 2015):

$$MARE = \quad \frac{100}{n} \sum_{i=1}^{n} \frac{|Q_i - Q_o|}{Q_o} \tag{4.4}$$

where:

   Q_i =   simulated peak discharge for SCS-SA / mean simulated peak discharge

      for Ensemble SCS-SA $(m^3.s^{-1})$,

   Q_o =   observed peak discharge $(m^3.s^{-1})$, and

   n   =   number of observations.

5. RESULTS: ENSEMBLE AND SINGLE EVENT SCS-SA MODELS USING ONE-DAY DURATION DESIGN RAINFALL INPUT

This chapter expands on the assessment of the fitted probability distributions for the selected variables, which were than sampled from and used as input into the Ensemble SCS-SA model. The chapter contains the verification of design storm volumes and peak discharges simulated using both the Ensemble SCS-SA and single event SCS-SA (Standard) models against design values computed from the observed data. As described in Chapter 4, the Ensemble SCS-SA initially includes fitting a probability distribution to the mean 1-day design rainfall and the 90 % confidence intervals for each return period. The single event SCS-SA (Standard) also entails using the model with 1-day design rainfall. Probability distributions were also derived from readily available data for the other key input variables (Antecedent Moisture Condition, Time to Peak, and Temporal Distribution) and random samples generated from the fitted distributions. Three test catchments with a range of areas were used to validate and to initially assess the performance of the model, and these includes Catchments U2H020 (0.26 km^2), X2H026 (13.82 km^2), and A9H006 (16 km^2).

5.1 Assessment of Fitted Distributions

Once the observed data was obtained, Easy-Fit software (EASY-FIT, 2013b) was utilised to fit the best distribution and to assess the fit using goodness-of-fit tests.

5.1.1 Time to peak

Figure 5.1 is an example of the 3-parameter Lognormal probability distribution fitted to the observed time to peak data from Catchment X2H026. The histogram in blue represents the frequency of the time to peak for given intervals of duration. The orange line represents the probability density function fitted to the frequencies. The three parameter Log-Normal probability distribution fitted the observed time to peak relatively well for Catchment X2H026.
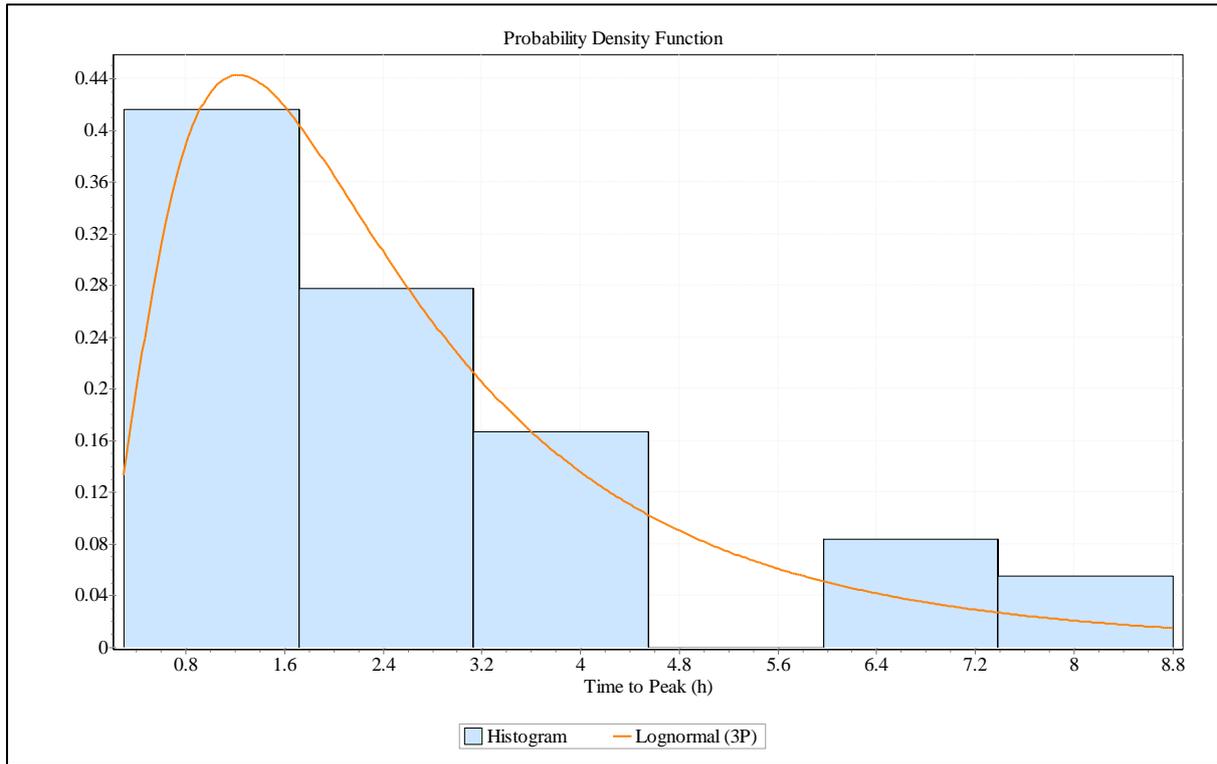
Figure 5.1   Probability distribution of time to peak (h) data from Catchment X2H026

5.1.2   Antecedent soil moisture

The available data for ΔS was limited as only the 20th, 50th, and 80th percentile values were reported by Schmidt and Schulze (1987), and these values were then extrapolated to 10th and 90th percentile values, as indicated in Figure 5.2. This was done in order to increase the data available for distribution fitting. A regression was then fitted to the values, and the resulting equation used to extrapolate to the 10th and 90th percentile values, respectively. A probability distribution was then fitted to the five values of ΔS. Figure 5.3 illustrates a uniform probability distribution fitted to the observed data of the change in soil moisture (ΔS). The distribution indicates that samples will be selected uniformly across the range of the distribution of the change in soil moisture, and this distribution is a result of the limitation in the data record.
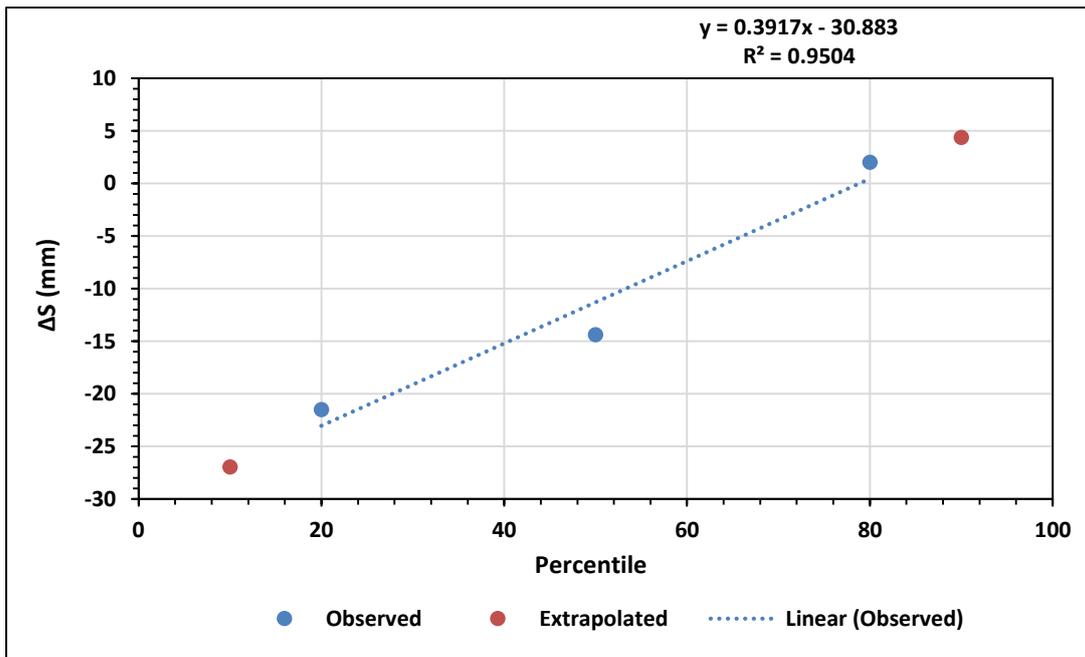
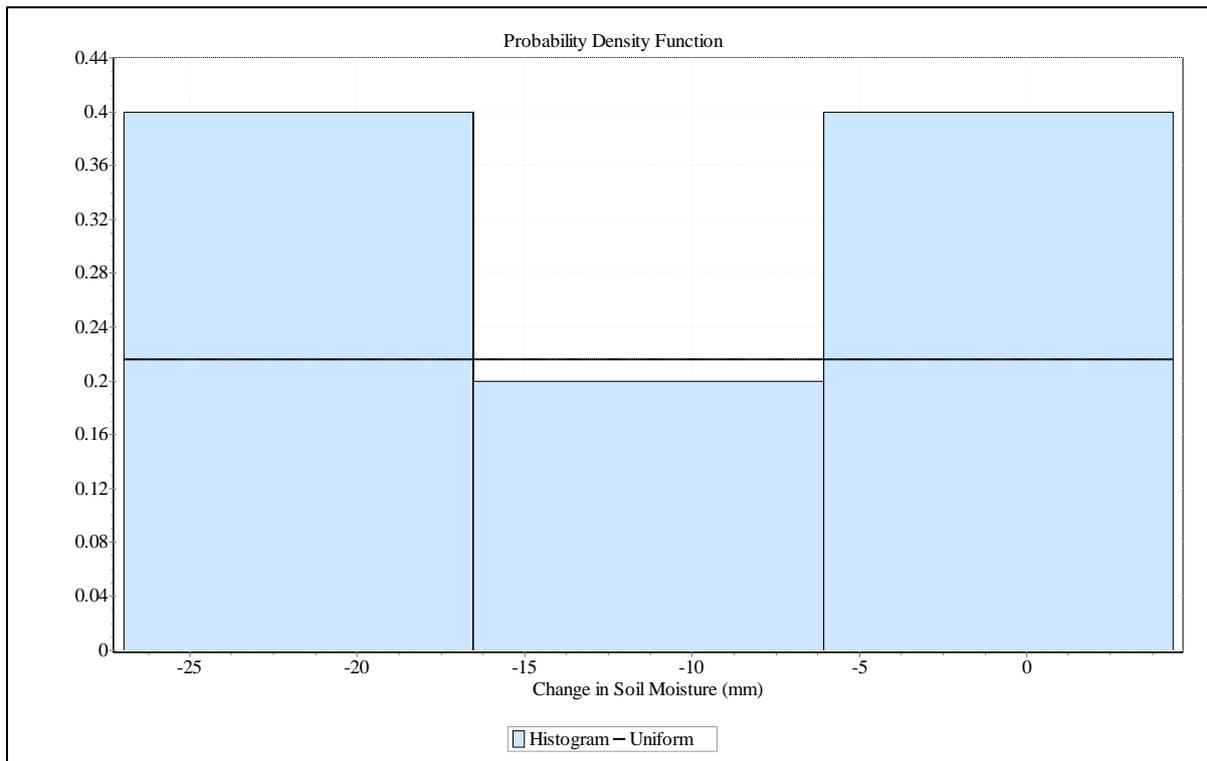Figure 5.2   Regression analysis for ΔS (mm) data for Catchment X2H026

Figure 5.3   Probability distribution of change in soil moisture (mm) data for Catchment X2H026

5.1.3 Temporal Distribution

The data for the temporal distribution was readily available and obtained from Knoesen and Smithers (2008). The temporal distributions were then incorporated into the Ensemble SCS-SA model. Figure 5.4 illustrates a sample of the different 480 different temporal distributions that were incorporated into the Ensemble SCS-SA model.
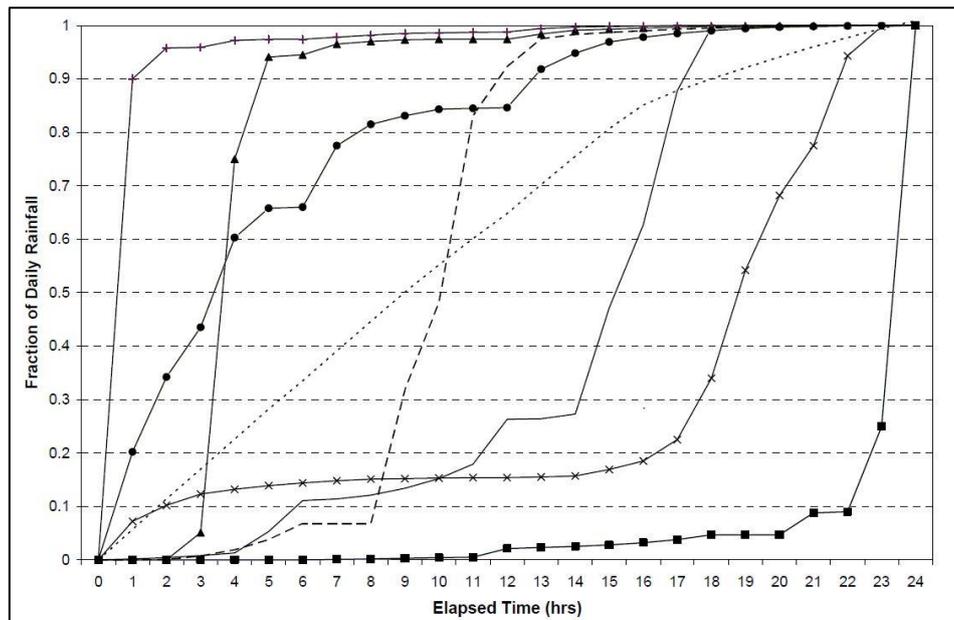

Figure 5.4   Samples of the 480 different temporal distributions (Knoesen, 2005)

5.1.4 One-day design rainfall

The rainfall distribution was determined by interpolating the 30th and 70th percentiles from the 10th, 50th and 90th 1-day design rainfall percentiles (Smithers and Schulze, 2003). This process is illustrated in Figure 5, where a trend line and the resulting equations were used to determine the 30th and 70th percentile for three return periods shown as an example. The estimation of the 30th and 70th percentiles was done to have sufficient data points to fit a probability distribution for each return period to sample from the fitted distribution.
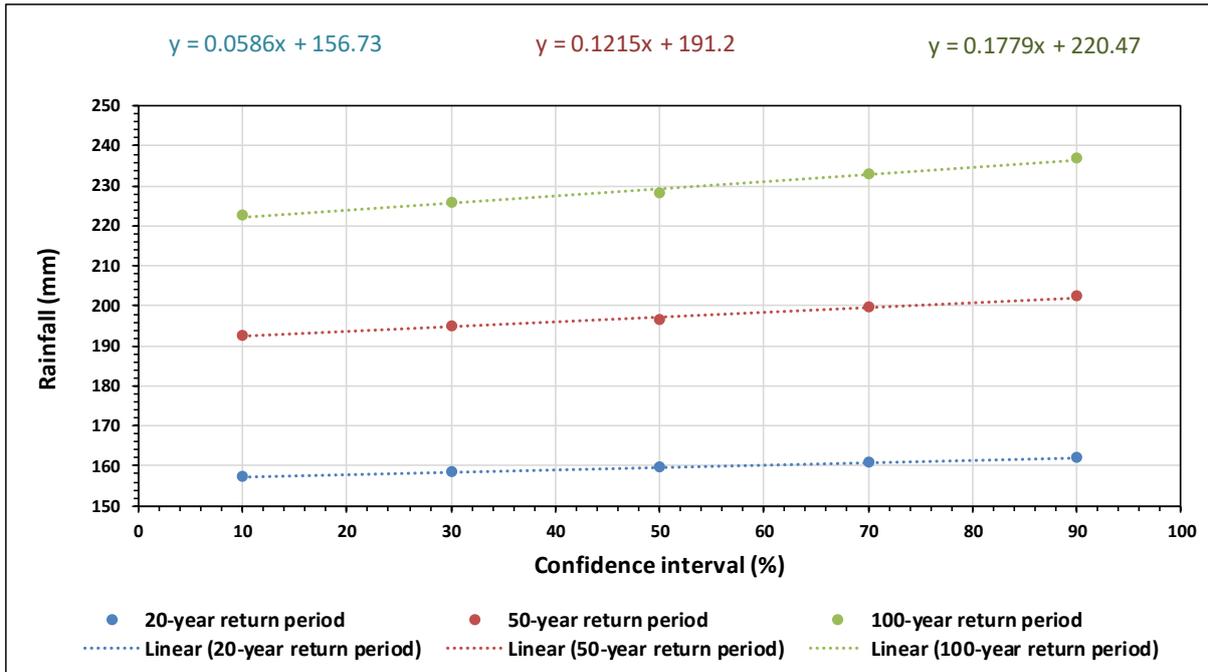
Figure 5.5   One-day design rainfall confidence intervals for different return periods
for Catchment X2H026

5.2   Verification of Runoff Volumes

The observed design runoff volumes were estimated by fitting a GEV distribution to the annual maximum series (AMS) extracted from the observed data, using a FORTRAN distribution fitting tool (Smithers and Schulze, 2000). The design runoff volumes simulated by the models were verified against design values computed from the observed runoff data. From the design runoff volume simulations for the Ensemble SCS-SA, a frequency analysis was performed where the minimum, maximum, 10th, 50th (median) and 90th percentiles were calculated with the 10th and 90th percentiles used as 90% confidence limits. The 50th (median) represents the runoff volume estimates from the Ensemble SCS-SA.

Figure 5.6 to Figure 5.8 are plots of the design volumes estimated using the Ensemble SCS-SA and the single event SCS-SA (Standard) models and includes design volumes computed from the observed data, for the three test catchments. Figure 5.6 illustrates the design runoff volume from Catchment U2H020 which has a catchment area of 0.26 km^2. It can be seen that the single event SCS-SA (Standard) is generally estimating the runoff volumes relatively well compared to the Ensemble SCS-SA approach which is represented by the median estimate for all 100 values simulated. When compared to the observed design runoff estimates, it is evident that

both methods are performing relatively poorly, especially for return periods ≥ 20-year return period.
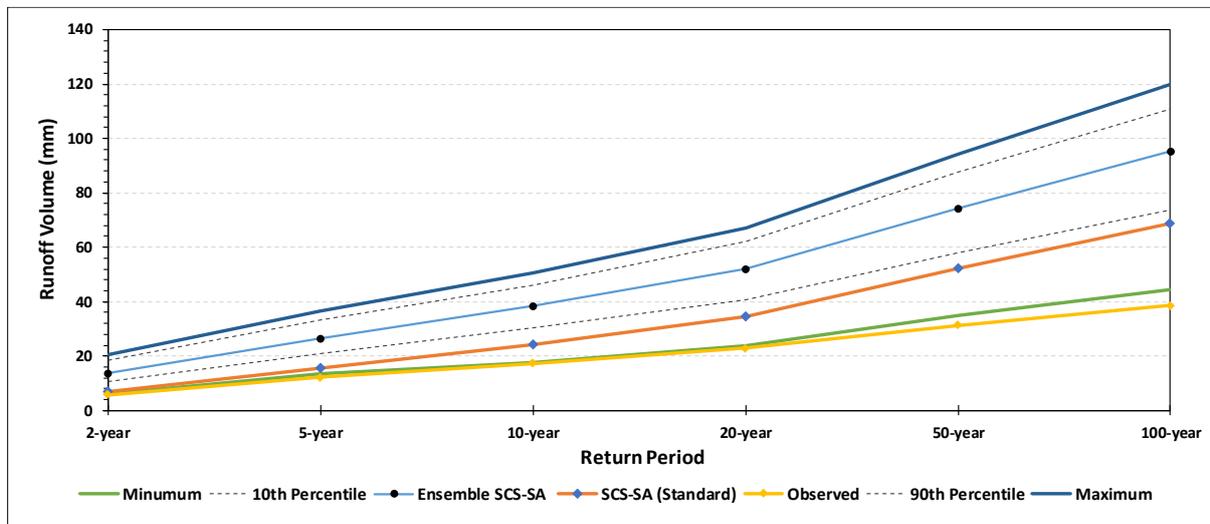

Figure 5.6   Simulated and observed design runoff volumes for Catchment U2H020

Figure 5.7 illustrates the runoff volume from Catchment X2H026 with a catchment area of 13.82 km^2. The Ensemble SCS-SA and the single event SCS-SA (Standard) are performing similarly for all the return periods, and both models simulate the design runoff volume poorly for all return periods.
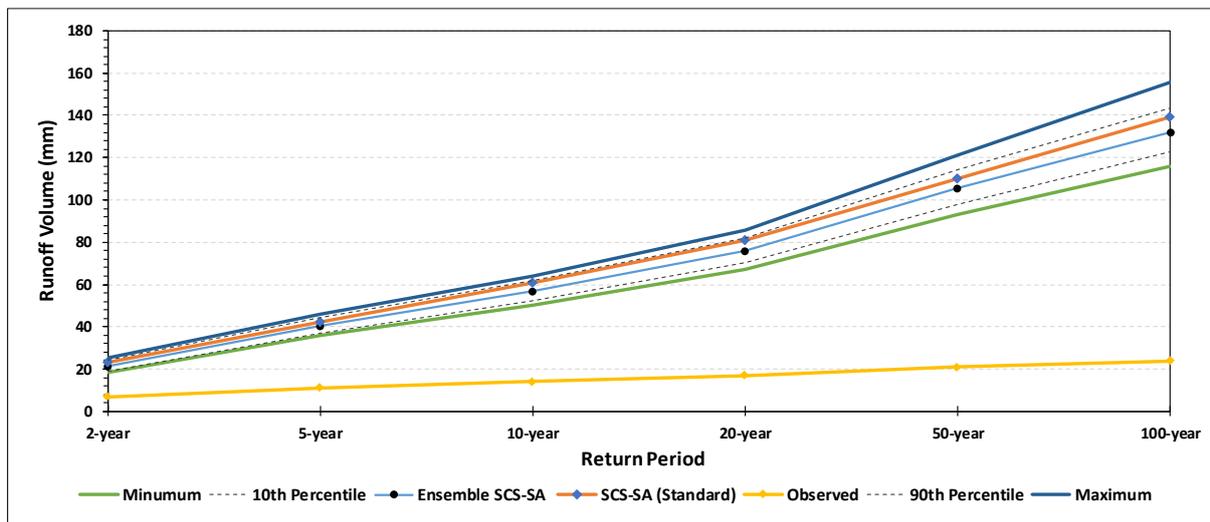

Figure 5.7   Simulted and oberved design runofff volumes for Catchment X2H026

Figure 5.8 illustrates the runoff volume from Catchment A9H006 with a catchment area of 16 km^2. It is evident that both the Ensemble SCS-SA and single event SCS-SA

(Standard) approach are performing similarly, where both methods are performing relatively well for the 2-year and 5-year return periods, and then perform poorly compared to the observed design runoff volume estimates for all other return periods. It is also evident that the performance for both models declines as the return periods increase.
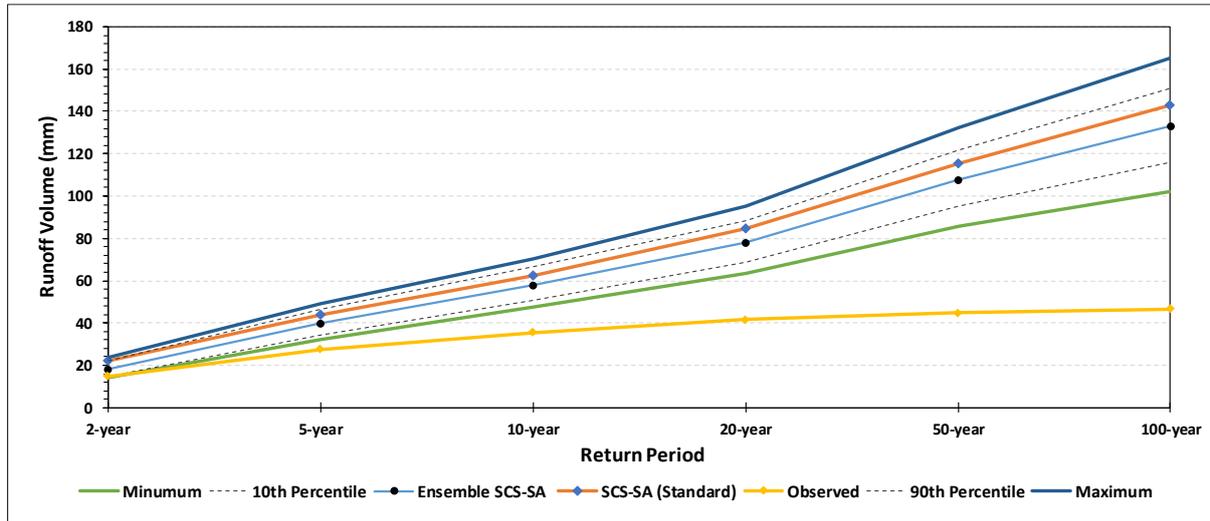

Figure 5.8   Simulted and oberved design runofff volumes for Catchment A9H006

The MARE values computed using Equation 4.6 for all return periods as the difference between the simulated and observed values of the runoff volumes for the test catchments is shown in Figure 5.9. For the ensemble SCS-SA model, the simulated value used in the MARE calculation is the median value. It is evident from Figure 5.9 that the Ensemble SCS-SA model generally has a higher error in estimating the runoff volume compared to the estimates of the single event SCS-SA (Standard), particularly for the smallest Catchment (U2H020).

Figure 5.10 illustrates the Nash Sutcliff Efficiency for the test catchments and it is evident that Catchment X2H026 has the poorest Nash-Sutcliff Efficiency, and both models performed relatively poorly with values less than zero on the other catchments.

It is evident from the above assessments used to indicate the performance of the models, that both the Ensemble SCS-SA and the SCS-SA (Standard) approach are generally simulating the observed design runoff volume relatively poorly.
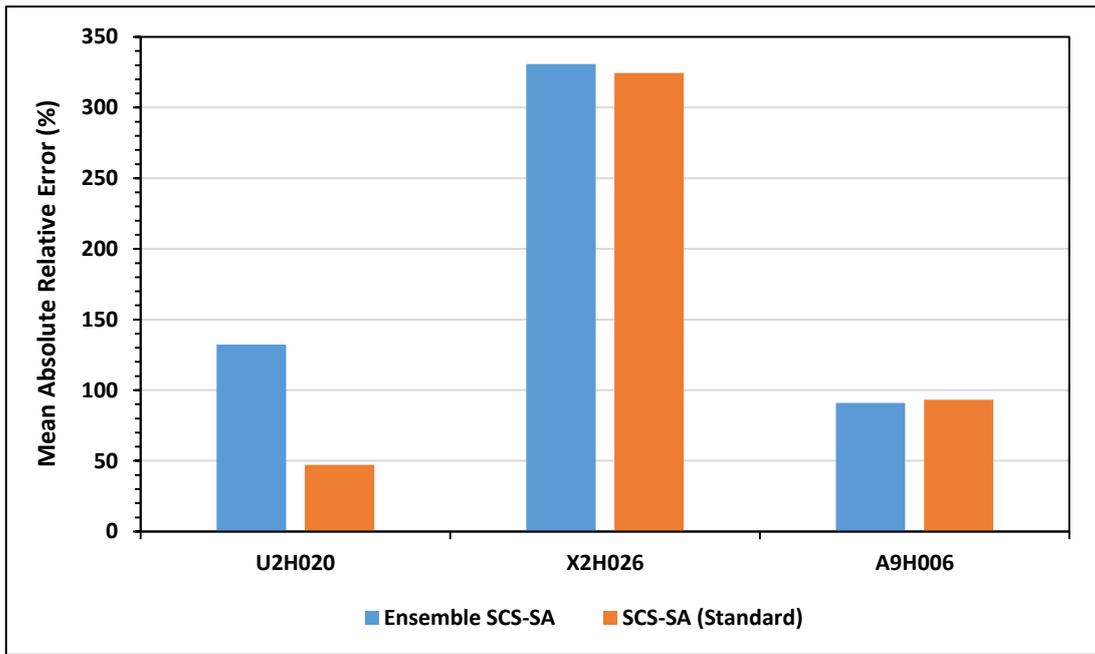
Figure 5.9   Mean absolute relative error of the estimated design runoff volume for the relative test catchments
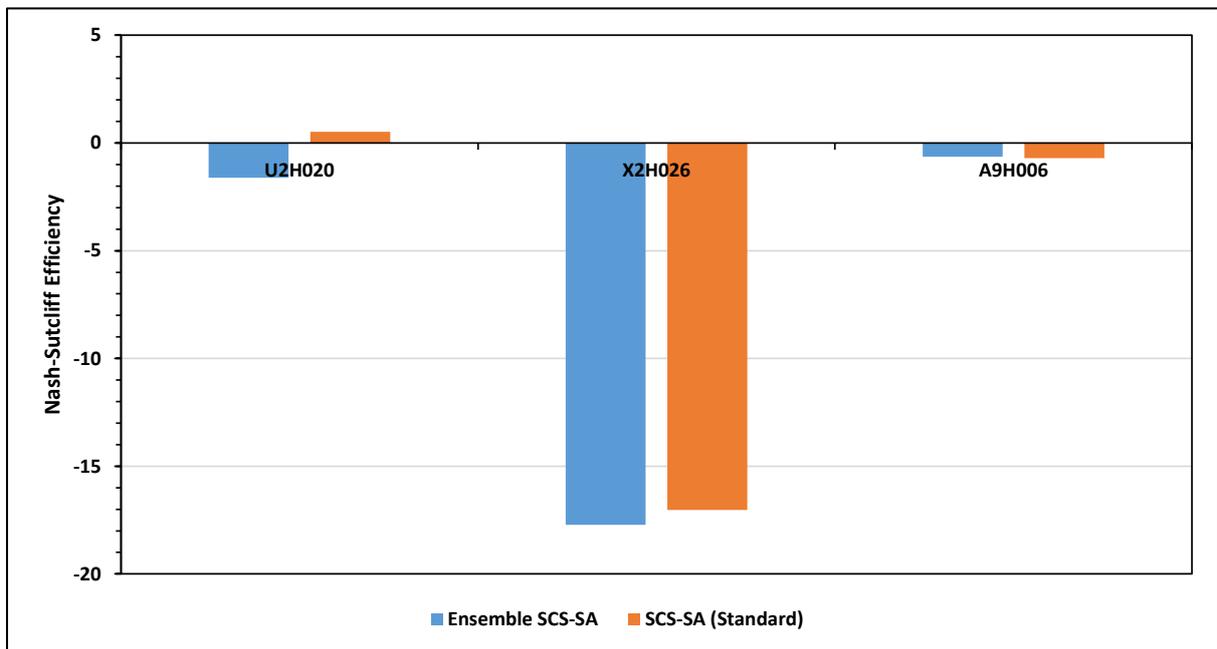

Figure 5.10   Nash-Sutcliff efficiency of the estimated design runoff volume for the relative test cathments

5.3 Verification of Peak Discharges

The observed design peak discharge was estimated by fitting a GEV distribution to the AMS of the observed peak discharge using a FORTRAN distribution fitting tool (Smithers and Schulze, 2000). Figure 5.11 to Figure 5.13 are plots for both the Ensemble SCS-SA and single event SCS-SA (Standard) models, while Figure 5.14 illustrates the MARE for the three test catchments, and Figure 5.15 illustrates the Nash-Sutcliff Efficiency of the three test catchments.

It is evident from Figure 5.11 that both the Ensemble SCS-SA and the single event SCS-SA models are performing relatively poorly at Catchment U2H020, as they consistently over-simulate the observed design peak discharge for all return periods. It can be seen that the models are simulating similarly for the shorter return periods, and for the longer return periods.
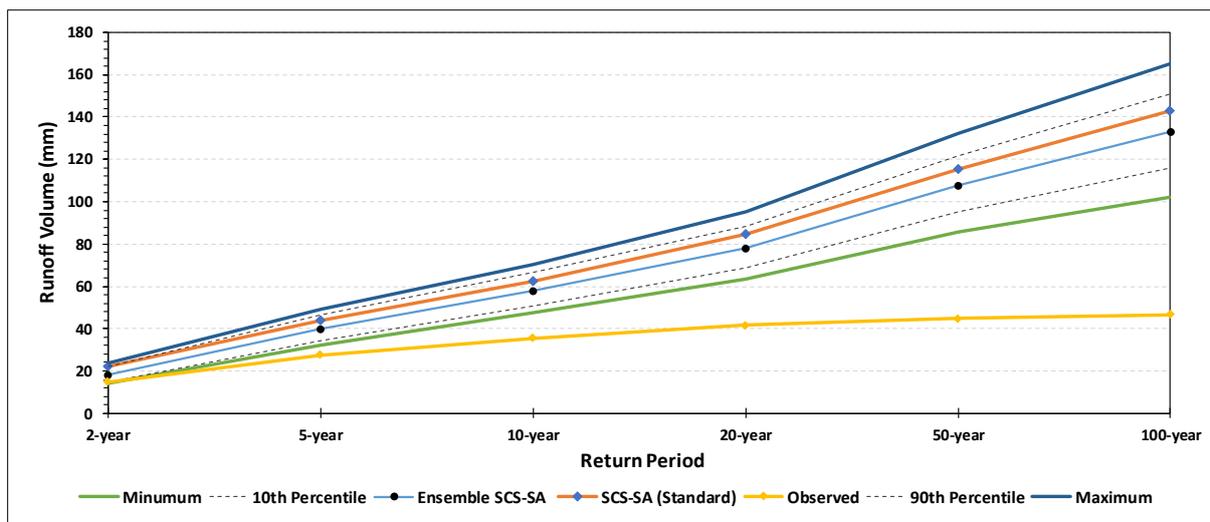
Figure 5.11   Simulated and observed design peak discharges for Catchment U2H020

It can be seen from Figure 5.12 that the Ensemble SCS-SA is performing relatively better than the single event SCS-SA (Standard) model for all return periods at Catchment X2H026. It is also evident that both models are estimating the shorter return periods relatively well, however, as the return periods increase, the performance for both models decreases.
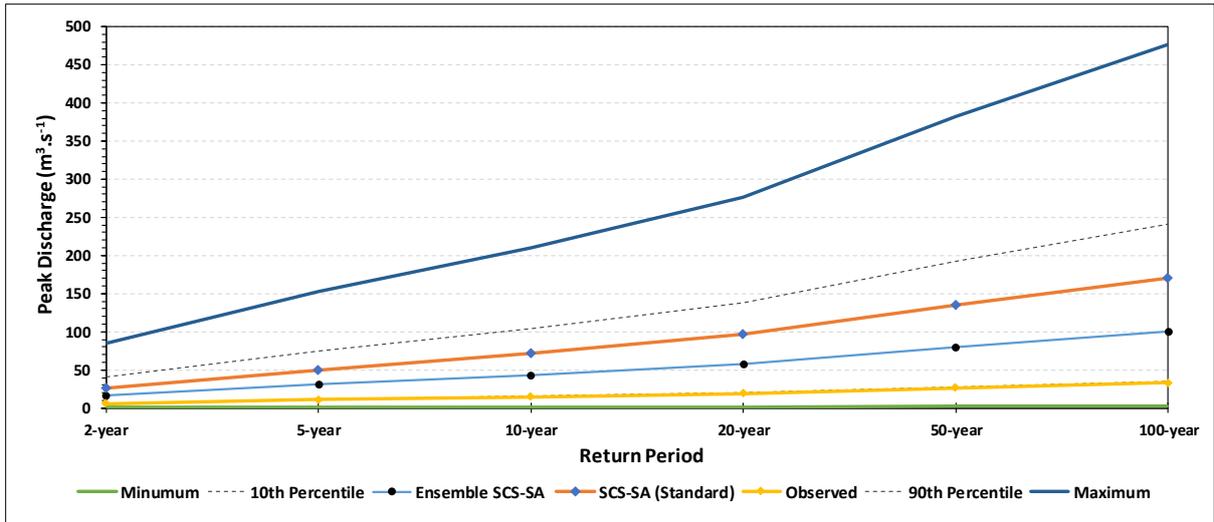
Figure 5.12 Simulated and observed design peak discharges for Catchment X2H026

Similar trends are also noted in Figure 5.13 where the Ensemble SCS-SA model is performing better than the single event SCS-SA (Standard) model compared to the observed design flood estimates. In this study site both models are simulating the shorter return periods relatively well, and the higher return periods relatively poorly. It can also be seen that, as the return periods increases, the performance of the Ensemble SCS-SA model is estimating the observed design peak discharges is increasingly better than the single event SCS-SA (Standard).
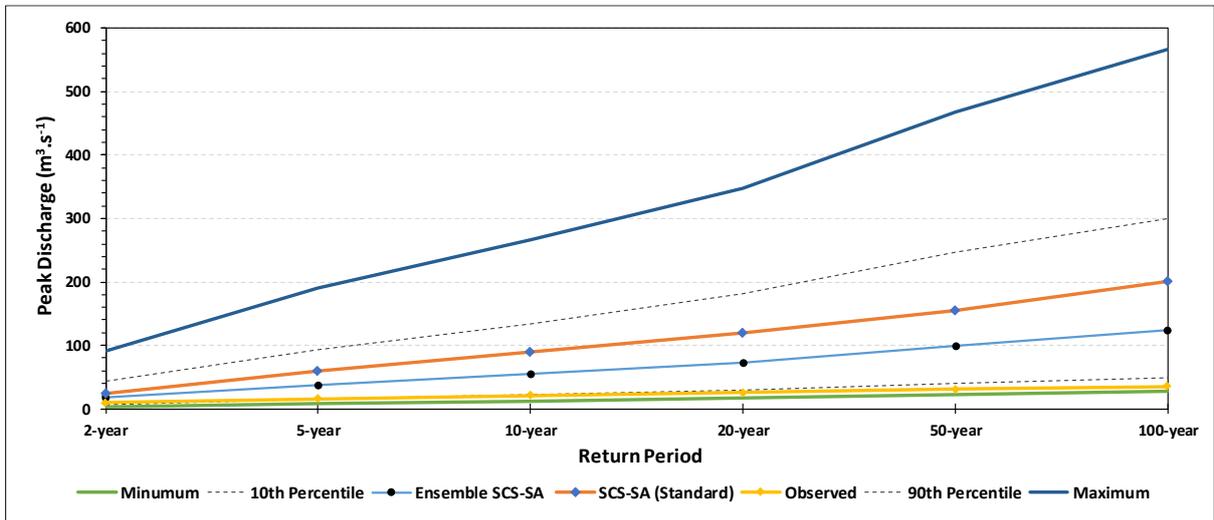

Figure 5.13 Simulated and observed design peak discharges for Catchment A9H006

Figure 5.14 illustrates the MARE for the three test catchments. It is evident that the smallest Catchment (U2H020) has the largest errors in simulating the design peak discharge. However, it can also be seen that the Ensemble SCS-SA has consistently lower MARE values than the

single event SCS-SA model, indicating better performance of the Ensemble SCS-SA in estimating observed design peak discharge compared to the single event SCS-SA (Standard). Overall both methods are still performing relatively poorly, as they still have relatively high MARE values. This is probably a consequence of the poor estimates of the design volumes, although this is not consistent across the catchments.
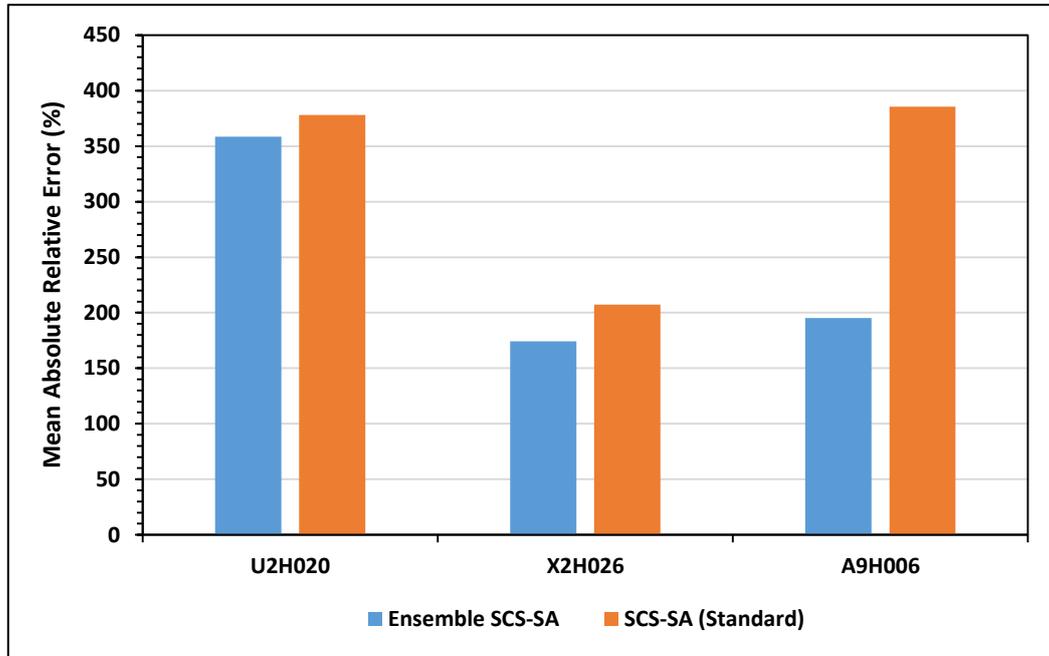
Figure 5.14   Mean absolute relative error of the estimated design peak discharge for the relative test catchments

The Nash-Sutcliff Efficiency illustrated by Figure 5.15 also shows that the Ensemble SCS-SA model is still performing better for all catchments compared to the single event SCS-SA (Standard) model for design peak discharge estimation. However, both models are still performing relatively poorly compared to the observed design peak discharge as the Nash-Sutcliff Efficiency for both models and across all three test catchments is below zero, indicating a poor performance of the models when estimating design peak discharge.
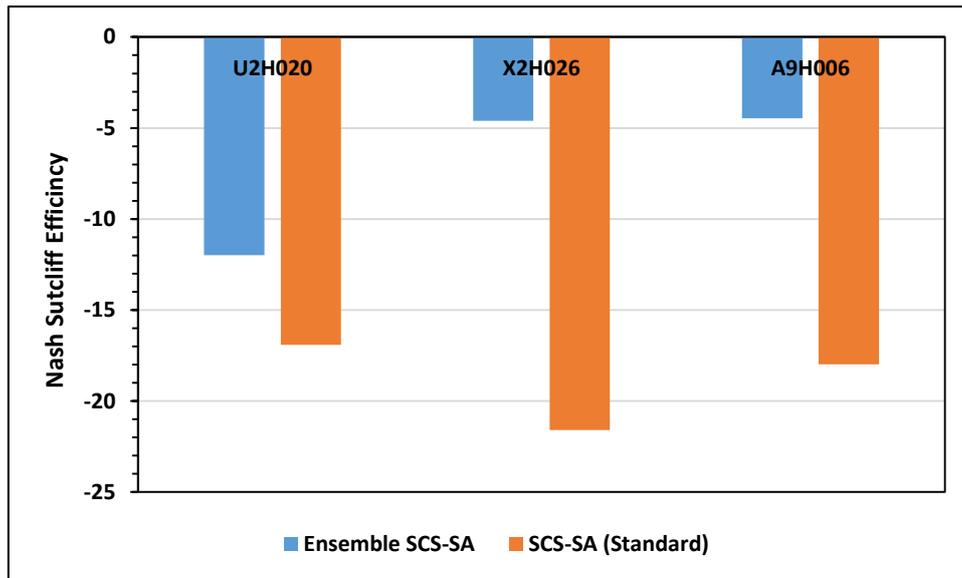
Figure 5.15   Nash-Sutcliff efficiency of the estimated design peak discharge for the
relative test cathments

5.4   Summary

In conclusion it is evident that the both the single event SCS-SA (standard) and Ensemble SCS-SA models are performing relatively poorly in terms of simulating both the observed design runoff volume and the observed design peak discharge. The overestimation of the observed design peak discharges for both models is a consequence of the estimated daily runoff depth. The peak discharge equation is influenced by the change in stormflow depth, thus higher stormflows would result in overestimated design peak discharges.

The results obtained show that Ensemble SCS-SA model framework does work and provides an estimate of the confidence limits for all return periods. Given the poor performance of both models at all three test sites, further investigation is necessary to determine reasons for the poor performance and to assess options to improve the performance of the models.

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6. SENSITIVITY OF PEAK DISCHARGE TO DISTRIBUTIONS OF KEY INPUT VARIABLES

This chapter expands on the further investigation and assessment of the SCS-SA model, and includes the sensitivity of the design peak discharge to the input variables, i.e. time to peak, antecedent moisture conditions, the temporal distribution, and the rainfall depth. This is used to focus the investigation to improve the model's performance.

This was achieved by simulating selected percentile values of the observed data (10th, 20th, 80th, and 90th percentiles) for the time to peak and the antecedent moisture conditions, and comparing the differences to when the simulation is run using the 50th percentile for both the time to peak and antecedent moisture conditions. For the temporal distribution, a distribution was selected between range Bin 10 and Bin 11 as the median for all 20 range bins, then the bin selected was decreased. Similarly, the distributions were selected from the median bin to the upper end of the bin range. The sensitivity to input rainfall was performed by decreasing and increasing the rainfall from the selected 1-day design rainfall estimates by 10%, 20%, and 50%.

6.1 Time to peak and antecedent moisture conditions (ΔS)

The sensitivity of the estimated design peak discharge to the Time to Peak (T_P) converted to a lag time and antecedent moisture conditions, are illustrated jointly due to both variables having observed data with percentile ranges. The results are illustrated by the absolute relative difference shown in Figure 6.1 for Catchment X2H026, which shows the relative difference of each percentile change from the median (50th percentile). It can be seen from Figure 6.1 that the time to peak variable has the largest absolute relative difference for each change in the percentile value from the median value, and the antecedent moisture condition (ΔS) has small relative differences with each change in the input percentile value. This indicates that the estimates of the observed peak discharge from the single event SCS-SA (Standard) are more sensitive to the time to peak variable than the ΔS values. The antecedent moisture condition (ΔS) has a relatively low relative difference regardless of whether the antecedent moisture condition is increased or decreased, showing that the model is least sensitive to this variable.
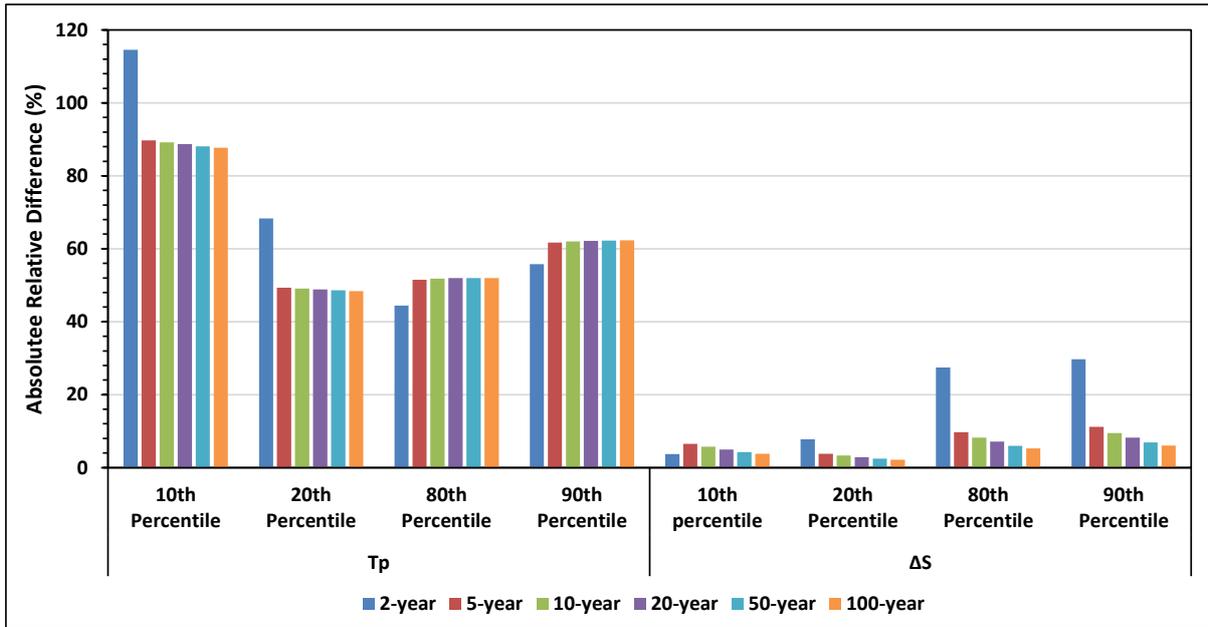
Figure 6.1   Absolute relative difference of the sensitivity analysis for the time to peak
              variable and antecedent moisture conditiond (ΔS) for Catchment X2H026

6.2   Temporal distribution

The sensitivity of the design peak discharge to the temporal pattern is illustrated by Figure 6.2 for Catchment X2H026, where the median temporal pattern was selected as Bin range 10/11 then varied around the median while keeping the other input variables constant at their representative median values.

It can be seen that the temporal pattern has a significant impact on the estimated design peak discharge. The impact is evident as the bin range increases, i.e. more non-uniform and intense rainfall intense distributions, or decreases, i.e. more uniform rainfall distributions. This also shows larger absolute relative difference values observed for the lowest and largest bin ranges, and that both the uniform and non-uniform temporal patterns can have a significant impact on the estimated peak discharge for the same simulated event.
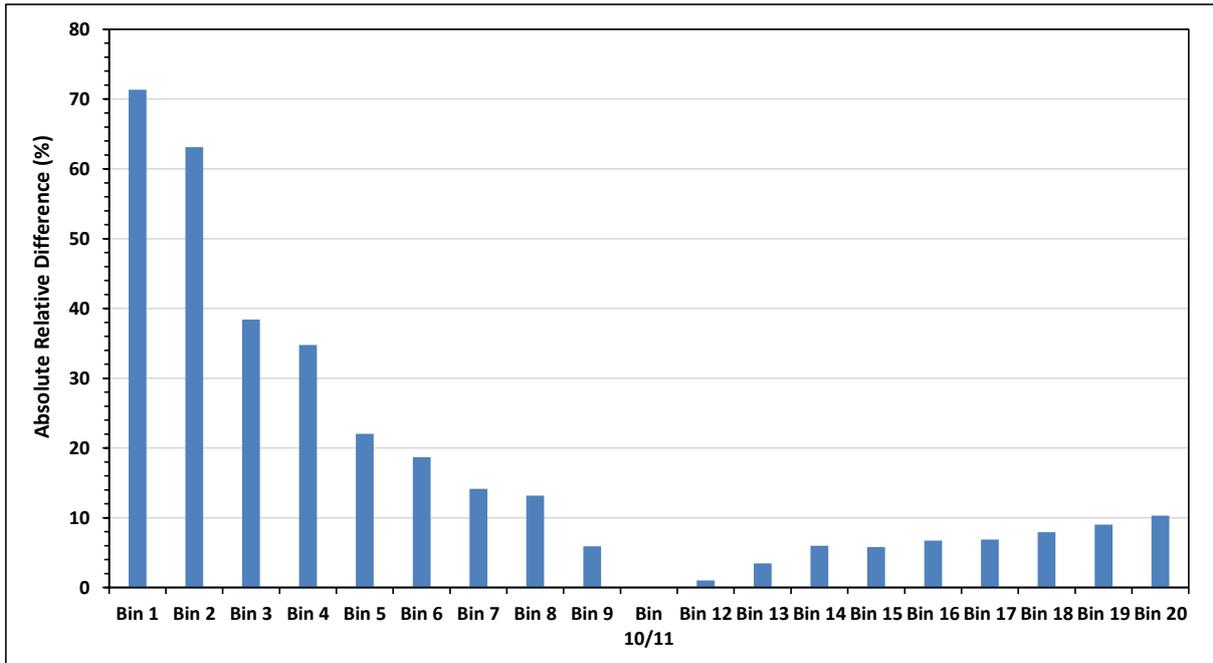
Figure 6.2   Mean absolute relative difference of the sensitivtiy of the peak discharge
to the temporal distribution range bins for Catchment X2H026

6.3   Rainfall

The sensitivity of the design peak discharge to design rainfall depth is illustrated by Figure 6.3 for Catchment X2H026, where the 1-day design rainfall was used as the median estimate. It is evident from Figure 6.3 that when the rainfall is increased it has a significant impact, increasing the design peak discharge as the percent of rainfall increases. Similarly, when the percent of rainfall is decreased there is a significant decrease in the estimated design peak discharge.
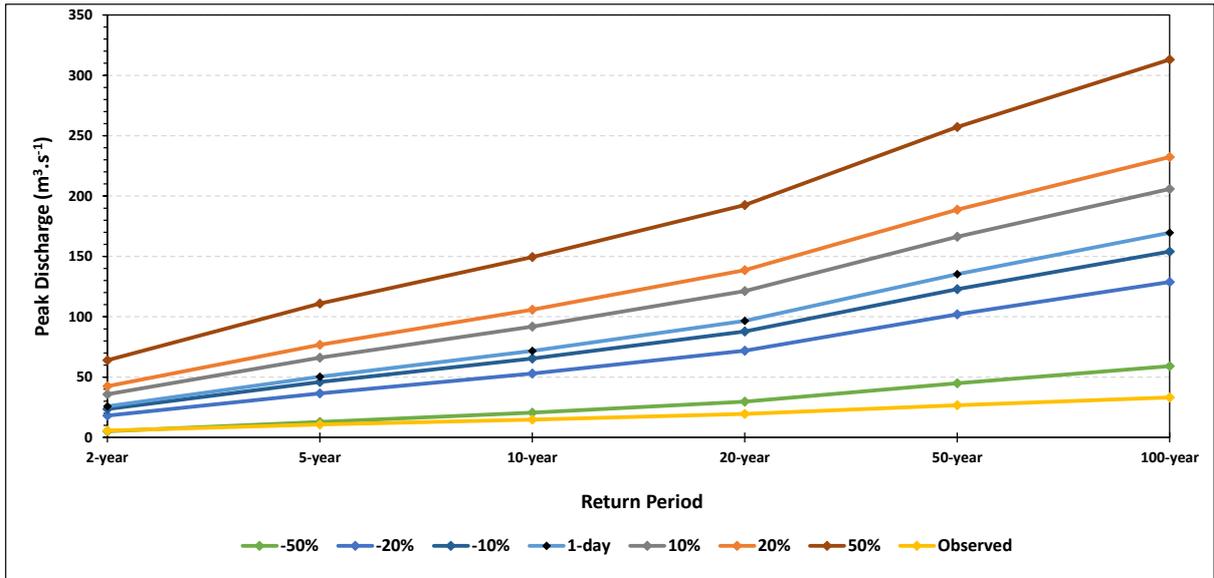
Figure 6.3   Sensitivity analysis of the percent change in precipitation for Catchment X2H026

The absolute relative difference for each return period per percent change in the design rainfall depth at catchment X2H026 is illustrated by Figure 6.4. It can be seen from Figure 6.4 that as the percent rainfall increases from the 1-day design rainfall the relative difference significantly increases for all the return periods, indicating larger errors in estimating the observed design peak discharge. When the percent rainfall decreases from the 1-day design rainfall, the relative difference significantly decreases to a point where it is closer to a relative difference of zero indicating an improvement in the estimated design peak discharge.

Figure 6.4   Relative difference of the percent change in rainfall from the 1-day design rainfall for Catchment X2H026

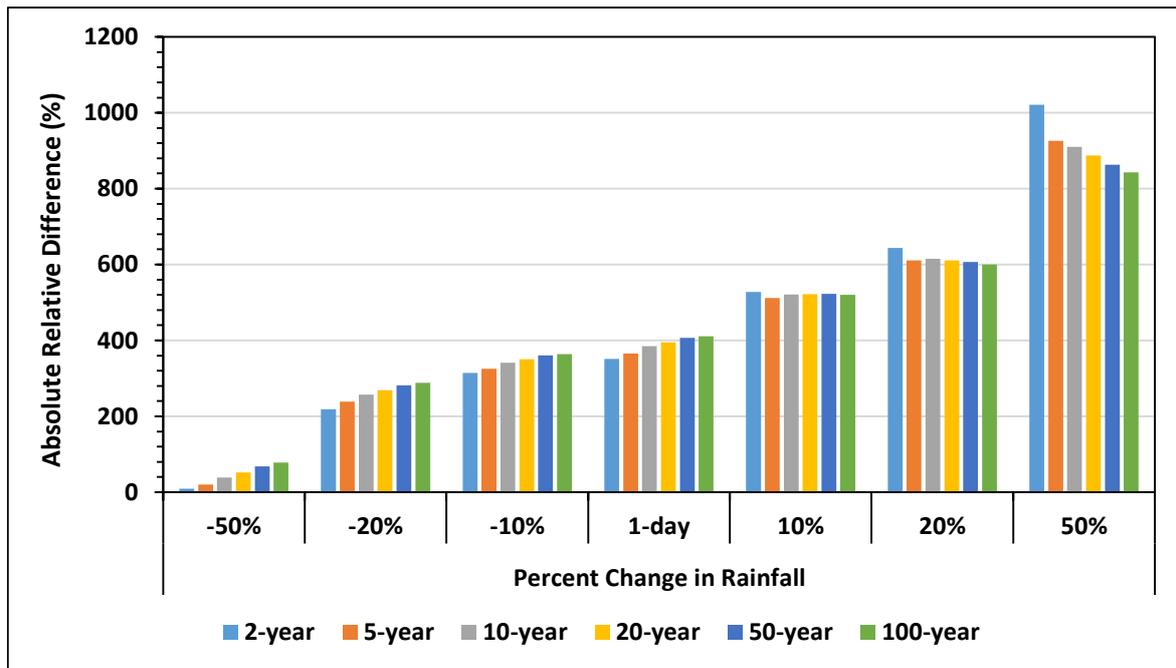An investigation was done at the study sites where autographic rainfall data is available, to determine the rainfall characteristics of the catchment. This is illustrated in Table 6.1 and Table 6.2, for Catchment U2H020 and X2H026, respectively. The events are ranked from highest to lowest. It is evident from both catchments that the rainfall duration and the time for the storm to reach the peak is generally less than one day for both catchments.

Table 6.1   Rainfall analysis for Catchment U2H020

Event	Event Rainfall depth [Autographic station] (mm)	Daily Rainfall Depth [Daily station] (mm)	Rainfall Duration (h)	Time to Peak (h)	Peak Discharge (m^3.s^{-1})
1	68.2	56.6	4	0.4	0.60
2	77.8	64.6	3	0.7	0.20
3	33.3	35.5	3	1.2	0.10
4	41.7	26.0	2	1.9	0.08

Event	Event Rainfall depth [Autographic station] (mm)	Daily Rainfall Depth [Daily station] (mm)	Rainfall Duration (h)	Time to Peak (h)	Peak Discharge (m³.s⁻¹)
5	44.9	71.6	4	2.1	0.05

Table 6.2   Rainfall analysis for Catchment X2H026

Event	Event Rainfall Depth (Autographic station)	Daily Rainfall Depth (Daily station)	Rainfall duration (h)	Time to Peak (h)	Peak Discharge (m³.s⁻¹)
1	81.8	89	8	1.2	20.1
2	23.5	27.1	5	1.4	10.1
3	46	21	8	4.5	7.8
4	41.5	56	6	7.2	6.2
5	45	12.5	5	4.2	5.8
6	37.5	56	9	6.1	4.6

6.4   Summary

The above sensitivity analysis has shown, based on the method used, that the impact changing the time to peak variable and antecedent moisture condition from the 10th to the 90th percentile of the range of observed input values resulted in absolute relative difference values of less than 100%. However, the impact of changing the input by rainfall only 20% resulted in MARE values > 200%. Furthermore, it is evident from the test catchments that rainfall duration as well as the time to peak is less than day. Hence, it is concluded from these results that the estimation of peak discharge is most sensitive to the input design rainfall.

7. RESULTS: ENSEMBLE AND SINGLE EVENT SCS-SA MODELS USING DESIGN RAINFALL DURATION EQUAL TO CATCHMENT RESPONSE TIME

It is widely accepted that when estimating peak discharge from a catchment, the duration of design rainfall input to event rainfall based design flood estimation models is the time of concentration, i.e. the peak discharge at the catchment outlet occurs when the runoff from the furthest point in the catchment reaches the outlet, and it is still raining (Gericke, 2016; Gericke, 2018). As shown above, the estimation of peak discharge is most sensitive to the input design rainfall depth. Hence, the duration of rainfall input to the Ensemble SCS-SA model was conditioned to the catchment response time using a derived relationship between the rainfall depth and rainfall durations. The design rainfall estimated by Smithers and Schulze (2003) was used to derive a depth-duration- frequency curve and an example of this procedure is illustrated in Figure 7.1 for design rainfall at Catchment X2H026.
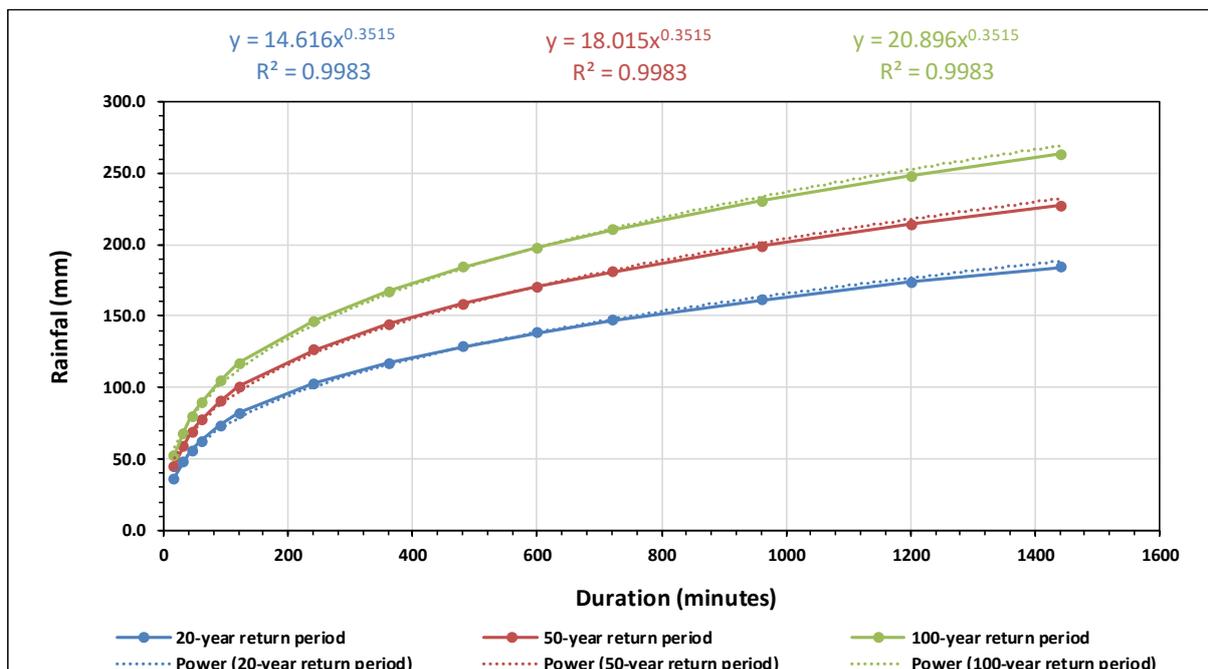
Figure 7.1   Rainfall depth-duration-frequency curve for Catchment X2H026

A trend line was fitted to the relationship between the time to peak and the rainfall depth , the resulting equation used to sample rainfall depth using the time of concentration, estimated as the time to peak (Gericke, 2016) as the input. The input to the single event SCS-SA (Standard) method was also altered with the input 1-day design rainfall depth replaced with the design

rainfall depth for a duration equal to the time of concentration computed from the lag time estimated using the Schmidt-Schulze equation (Schulze *et al.*, 2004). Therefore, in this section the model is referred to as the single event SCS-SA (Short duration) model. Equation 7.1 by Schulze *et al.* (2004) was used to convert the time of concentration to a lag time.

$$L \quad = \quad 0.6 \, T_c \tag{7.1}$$

where: L =   lag time (h), and

      T_c =   time of concentration (h).

7.1   Verification of Runoff Volumes

Figure 7.2 to Figure 7.4 illustrates plots of the Ensemble SCS-SA and the single event SCS-SA (Short duration) runoff volume estimates compared to the observed runoff volume. The same three test catchments were used to assess if there was any improvement in the performance of the models. In Figure 7.2 at Catchment U2H020, it is evident that there was a significant improvement in the performance of the Ensemble SCS-SA model in terms of estimating the observed runoff volume. The Ensemble SCS-SA model is simulating the shorter return periods such as the 2-year and 5-year return periods relatively well, and the other return periods reasonably well. However, it is evident that the Ensemble SCS-SA is consistently under simulating the observed runoff volume for all the return periods, but the performance is much better compared to when the 1-day design rainfall was used (Figure 5.6). The single event SCS-SA (Short duration) performed poorly in estimating the observed runoff volume, as it was biased and consistently underestimating the observed runoff volume, but compared to the 1-day design rainfall, the performance did not improve.
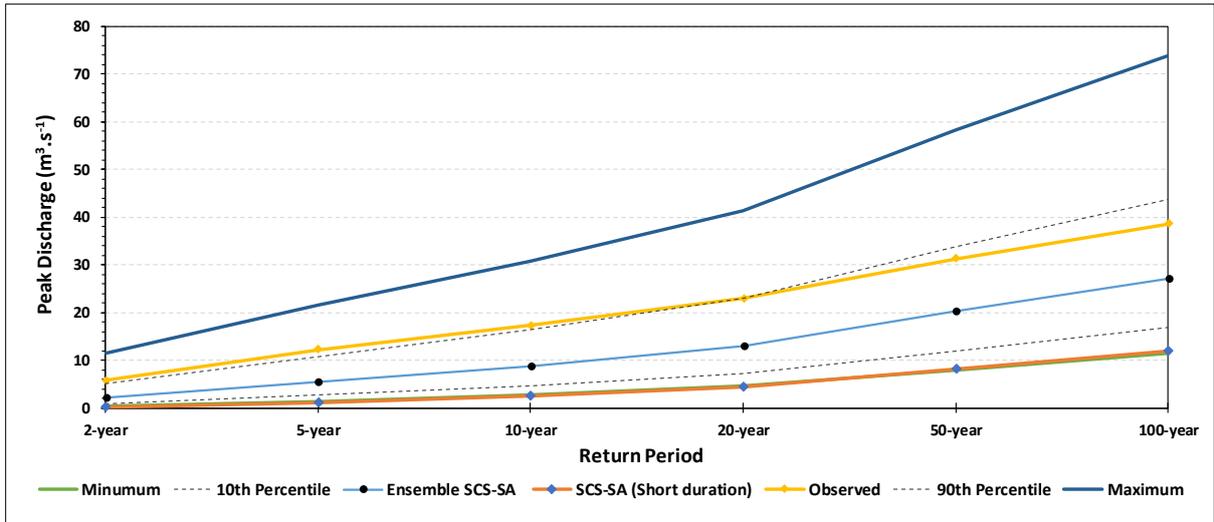
Figure 7.2   Simulated and observed design runoff volumes for Catchment U2H020

It can be seen from Figure 7.3 at Catchment X26026 that the Ensemble SCS-SA is performing relatively well in terms of estimating the observed runoff volume. This is evident in the lower return periods such as the 2-year to 20-year return periods where the model is simulating the observed runoff volumes relatively well, and as the return periods increase the model starts to overestimate the observed runoff estimate. Overall the model seemed to have performed relatively well in simulating the observed runoff estimate for all the return periods, as all observed estimates lie within the 10th and 90th percentiles. Compared to the 1-day design rainfall results (Figure 5.6) the Ensemble SCS-SA and single event SCS-SA (Short duration) design runoff estimates significantly improved.
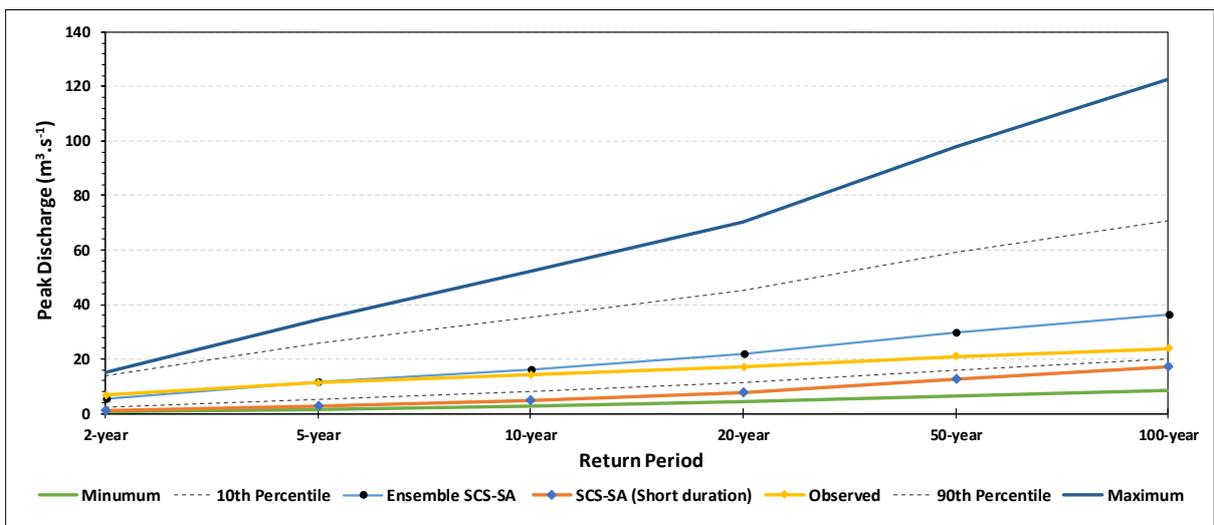

Figure 7.3   Simulated and observed design runoff volumes for Catchment X2H026

Figure 7.4 illustrates that the Ensemble SCS-SA is performing poorly in terms of estimating the observed runoff volume at Catchment A9H006, as it is biased and consistently under estimating the observed runoff volume for the lower return periods such as 2-year return to the 10-year return period, and as the return periods increase the simulations are estimated relatively well. The single event SCS-SA (Short duration) estimates the design runoff volume for the shorter return periods poorly. Overall both models significantly improved in estimating the design runoff volume compared to the 1-day design rainfall results (Figure 5.7).
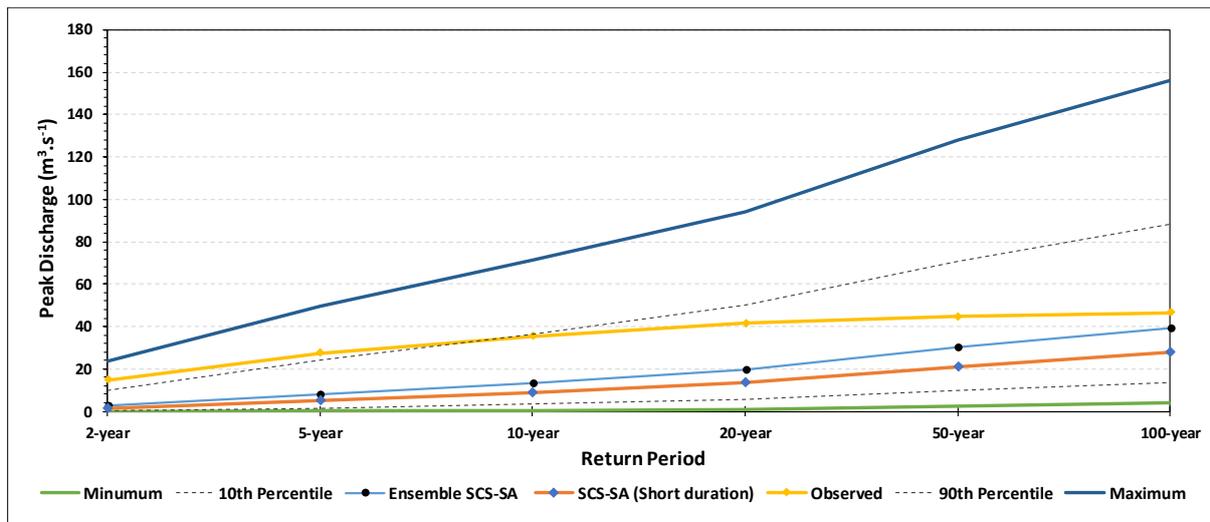

Figure 7.4   Simulated and observed design runoff volumes for Catchment A9H006

The MARE for the runoff volume simulated using the ensemble SCS-SA model for the three test catchments is illustrated by Figure 7.5 for both the 1-day and shorter design rainfall durations used as input. It is evident from the MARE values that the estimation of the observed runoff volumes has generally improved for all the catchments using rainfall duration equal to the catchment response time. For Catchment A9H006 there was a significant decrease in the MARE for design runoff volume. Similarly, there is notable improvement for catchment X2H026.

There was also an improvement in the performance of the single event SCS-SA (Short duration) model as the MARE values also decreased for Catchments X2H026 and A9H006. However, the Ensemble SCS-SA model is still performing better compared to the single event SCS-SA (Short duration) as the Ensemble SCS-SA model generally has lower MARE values in terms of estimating the runoff volume.
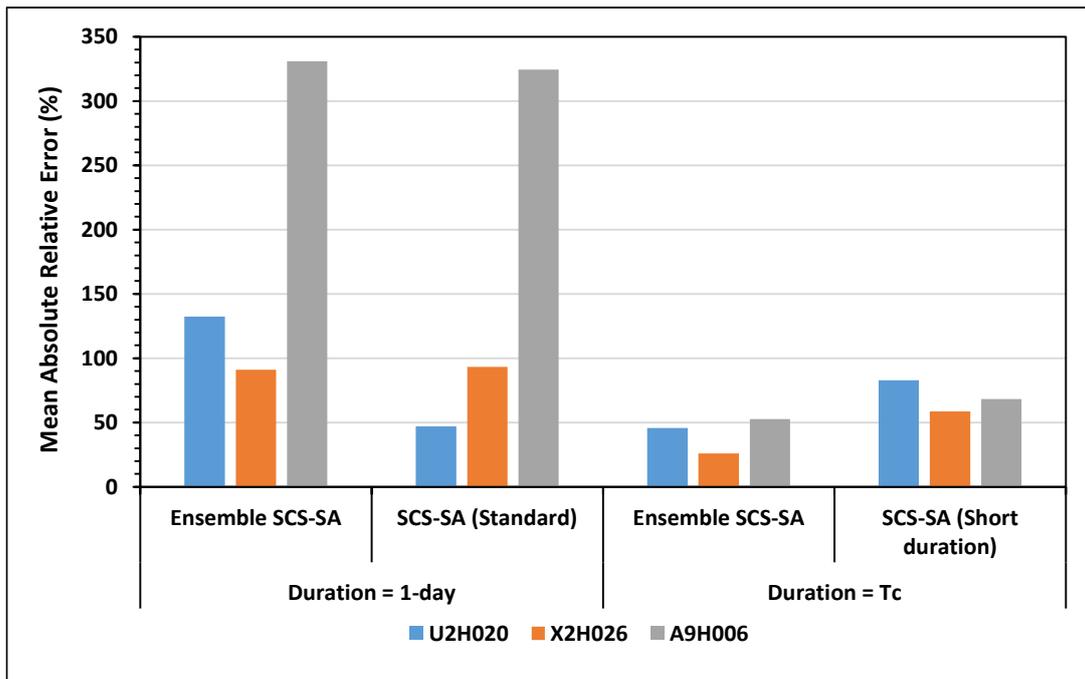
Figure 7.5   Mean absolute relative error of the estimated runoff volume for the three
test catchments

The Nash-Sutcliff Efficiency for the relative test catchments is illustrated by Figure 7.6. It can
be seen that the Ensemble SCS-SA generally has a higher Nash-Sutcliff Efficiency compared
to the event SCS-SA (Short duration) for all the relative test catchments, and the Nash-Sutcliff
Efficiency for the Ensemble SCS-SA is also closer to one for Catchments U2H020 and
X2H026, indicating that the Ensemble SCS-SA estimated the observed runoff volume for these
catchments relatively well and better than the single event SCS-SA (Short duration) model. It
is also noticeable that the Nash-Sutcliff Efficiency has significantly improved after initial runs
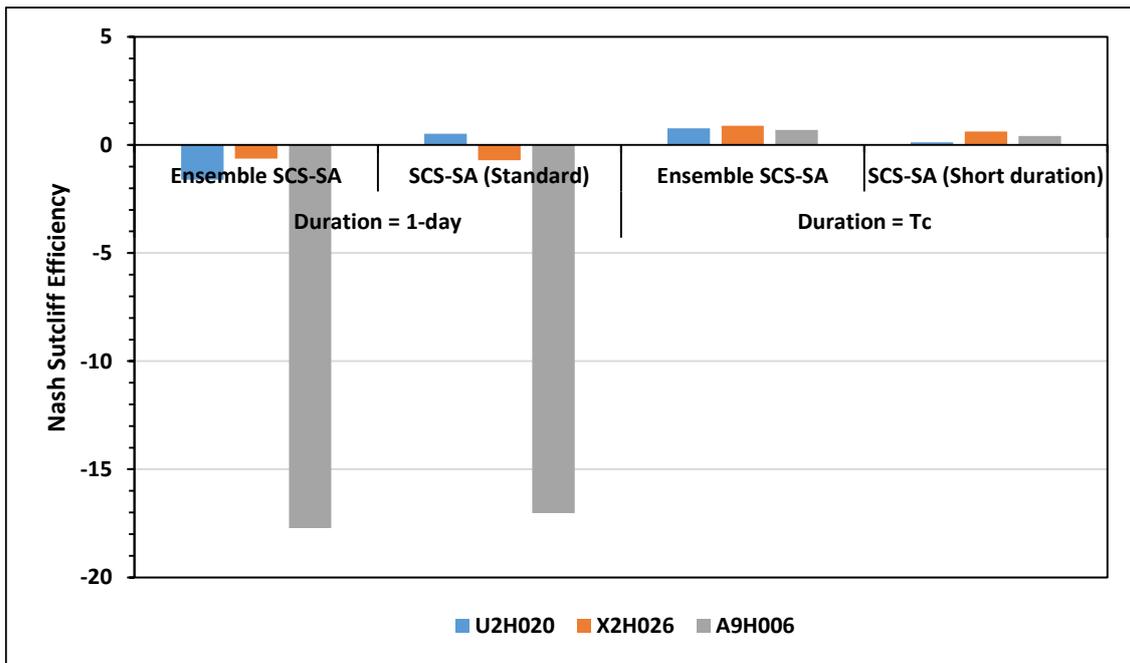and modifications were done to the models.

Figure 7.6   Nash-Sutcliff efficiency of the estimated runoff volume for the relative
test cathments

7.2   Verification of Peak Discharges

7.2.1   Test catchments

Figure 7.7 to Figure 7.9 contains plots of the estimated design peak discharge for the three test catchments compared to the observed design peak discharge. It was assumed that Equation 2.2 was still applicable to estimating the design peak discharge when short duration rainfall is used and that daily temporal distribution (Knoesen, 2005) could be used to disaggregate the short duration rainfall data. In Figure 7.7 at Catchment U2H020, it is evident that the Ensemble SCS-SA is simulating the observed peak discharges relatively well for all the return periods. The single event SCS-SA (short duration) model simulates the observed peak discharges for the lower return periods also relatively well.
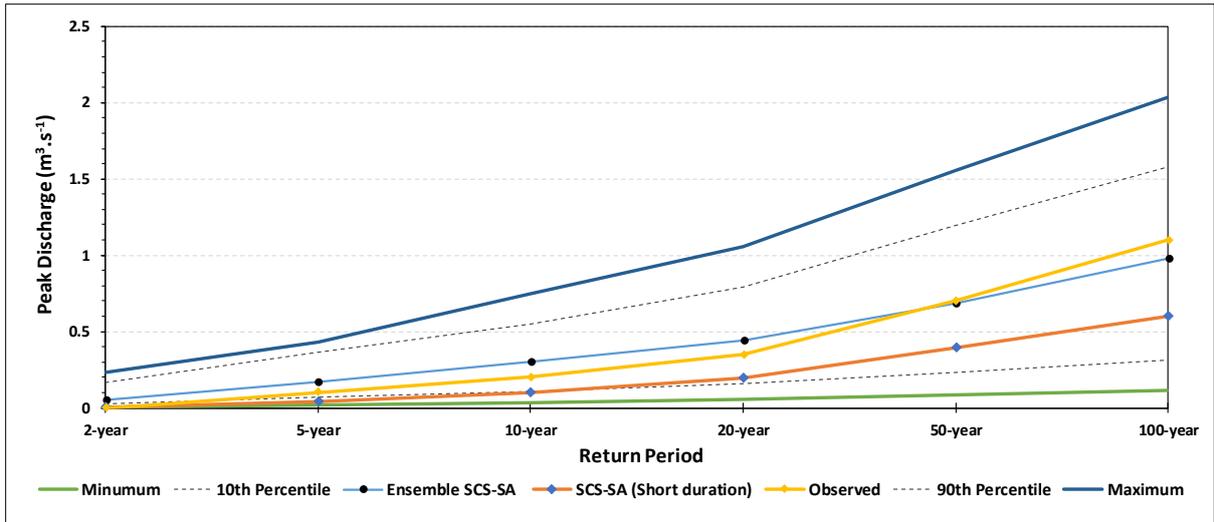
Figure 7.7   Simulated and observed design peak discharges for Catchment U2H020

In Figure 7.8 it is evident that the Ensemble SCS-SA model performed well in terms of estimating the observed peak discharges for all the return periods at Catchment X2H026. All the observed peak discharge estimates were within the 10th and 90th percentile which can give confidence in the simulated peak discharges by the Ensemble SCS-SA model, the median design peak discharges are also relatively close to observed design peak discharge. Thus, the median peak discharge estimates can be the recommended value for use. It is evident that the model has a general trend of slightly under simulating the observed peak discharge for all the return periods. The single event SCS-SA (Short duration) model performed poorly in estimating the observed peak discharge as it consistently under simulated the observed peak discharge for all return periods.
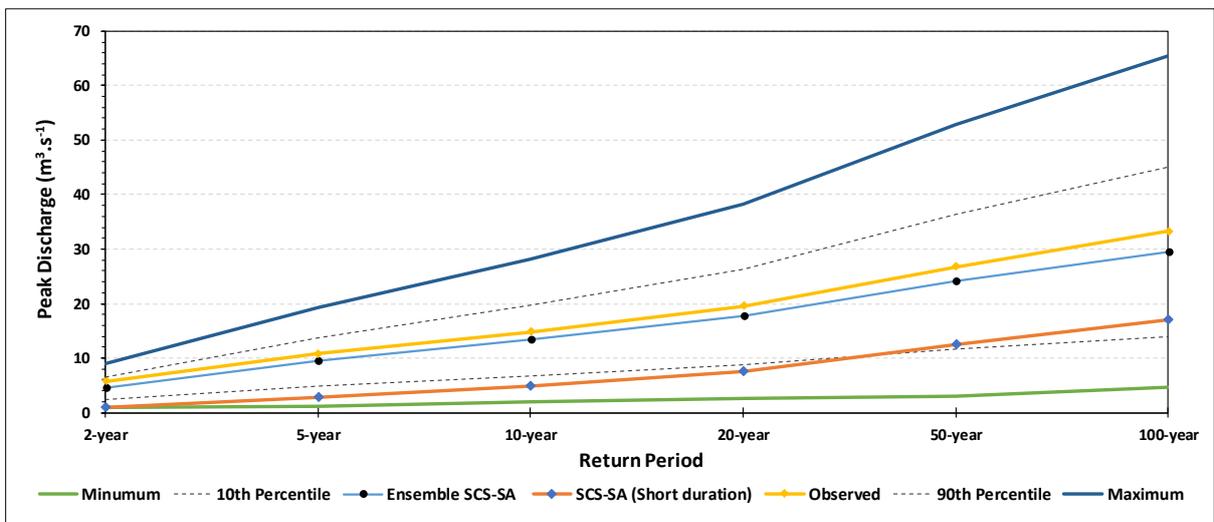

Figure 7.8   Simulated and observed design peak discharges for Catchment X2H026

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It is evident from Figure 7.9 that at Catchment A9H006 the Ensemble SCS-SA is performing relatively well for return periods ≥ 20-year and this is supported by the observed peak discharge estimates which are within the 10th and 90th percentile, thus giving confidence in these peak discharge estimates. It can also be seen for the lower return periods such as the 2-year to the 10-year return period, the Ensemble SCS-SA is performing relatively poorly and under simulating the observed peak discharge. The observed peak discharge estimates for the lower return periods are outside the 10th and 90th percentile estimates, decreasing the confidence in the Ensemble SCS-SA estimates for the lower return periods. The single event SCS (Short duration) performs similarly but is generally under simulating the observed peak discharge for all return periods.
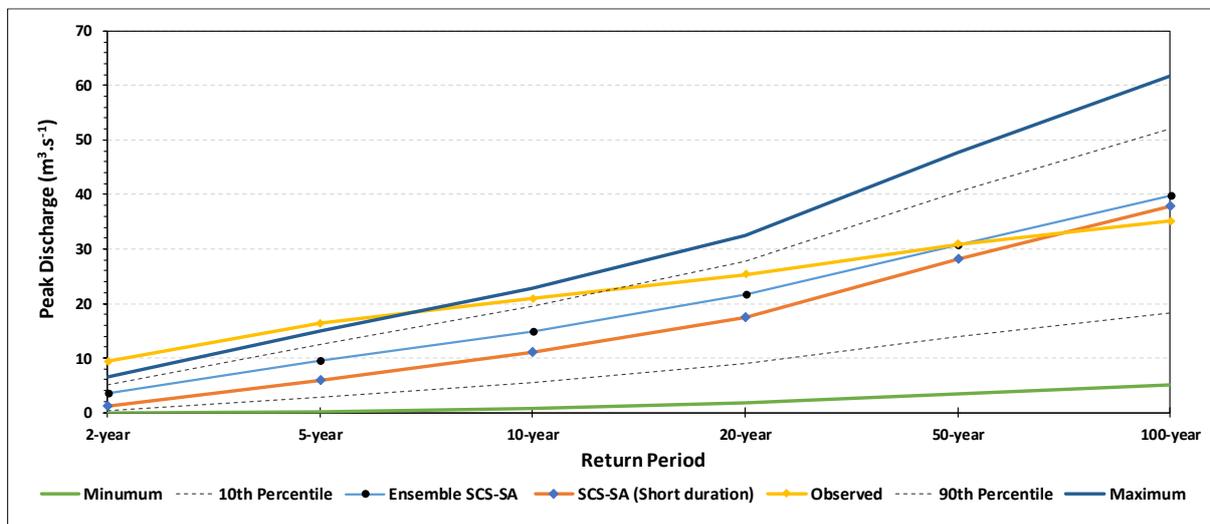
Figure 7.9   Simulated and observed design peak discharges for Catchment A9H006

Figure 7.10 illustrates the MARE for the peak discharge for the three test catchments. It can be seen that for all the catchments, the MARE has significantly decreased for the Ensemble SCS-SA model, showing an improvement in the estimates of the observed peak discharge due to the reduced MARE values. It is also evident that Catchment A9H006 has the lowest MARE value, indicating that Ensemble SCS-SA performed relatively well for this catchment compared to the other test catchments, as the catchment has a lower MARE value indicating less error in estimating the observed design peak discharge.
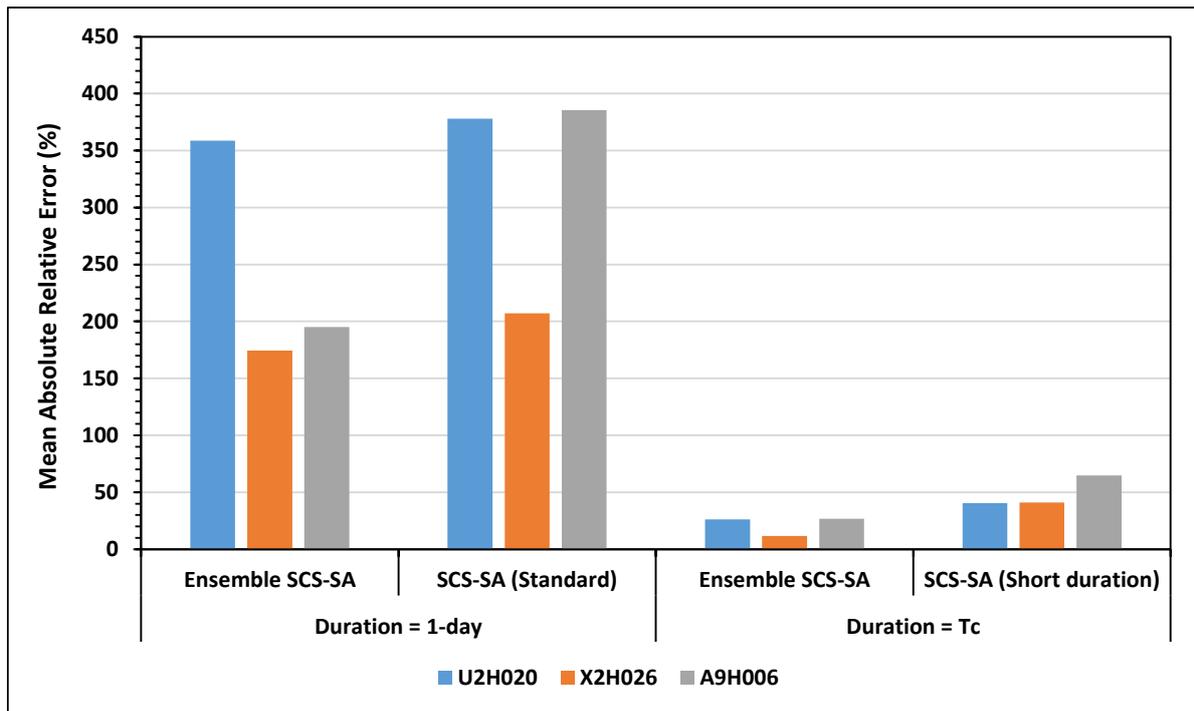
Figure 7.10   Mean absolute relative error of the estimated design peak discharge for the test catchments

The Nash-Sutcliff Efficiency is illustrated by Figure 7.11 for the three test catchments, and it can be seen that the Ensemble SCS-SA has a generally higher Nash-Sutcliff Efficiency which is closer to one for all the test catchments, which provides an overall image that the Ensemble SCS-SA is performing relatively better when estimating the observed peak discharge compared to the single event SCS-SA (Short duration) model. It is also evident that the peak discharge estimates from the Ensemble SCS-SA and single event SCS-SA (short duration) are similar as there is no significant difference in the Nash-Sutcliff Efficiency.
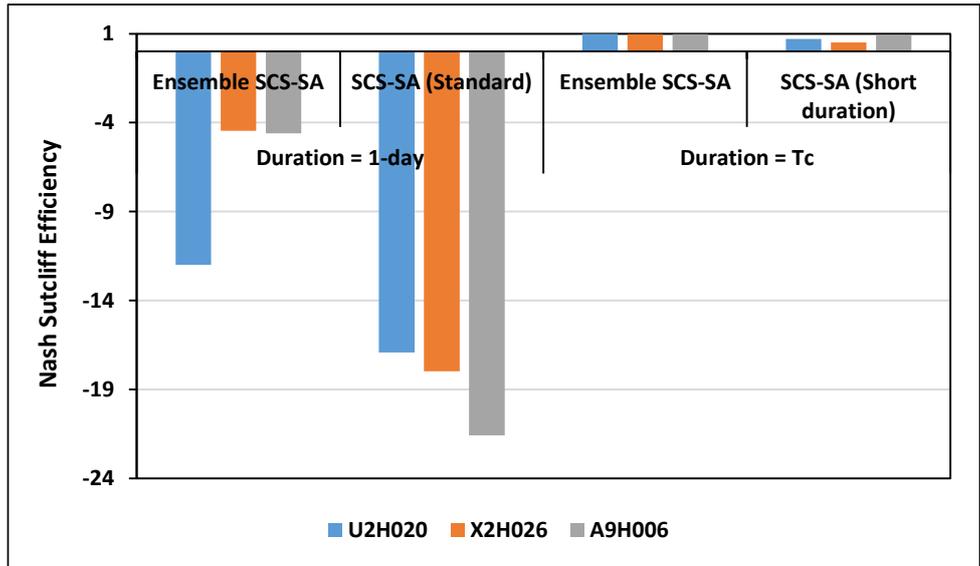
Figure 7.11 Nash-Sutcliff efficiency of the estimated design peak discharge for the test catchments

7.2.2 All catchments

It is evident that use of the design rainfall duration equal to the catchment response time has, in both the Ensemble SCS-SA and single event SCS-SA (Short duration) models, significantly improved the model's performance for both runoff volume and peak discharge estimation. With the improvements and satisfactory model performance, the models were applied to more catchments in order to assess their performance over a wider range of catchments in different climate regions in South Africa. Details of the performance at the various catchments are contained in Appendix A. The MARE as well as Nash Sutcliff Efficiency values for design peak discharges are shown in Figures 7.12 and 7.13, respectively.

Figure 7.12 illustrates the MARE of the peak discharge for all the catchments in the order of the catchment size (0.26 – 185 km^2), similar to the order listed in Appendix A. It can be seen that the Ensemble SCS-SA model generally has lower MARE values than the event SCS-SA (Short duration), and the MARE of the Ensemble SCS-SA model are generally less than 20 % for the majority of the catchments. This indicates that the model generally has lower errors in estimating the observed design peak discharge except for Catchment C5H022 and Catchment VH1032 where the Ensemble SCS-SA model has a larger MARE values compared to the event SCS-SA (Short duration) estimates. The single event SCS-SA (Short duration) generally has an error higher than 30 % for the majority of the catchments, and also performs relatively well on larger catchments.

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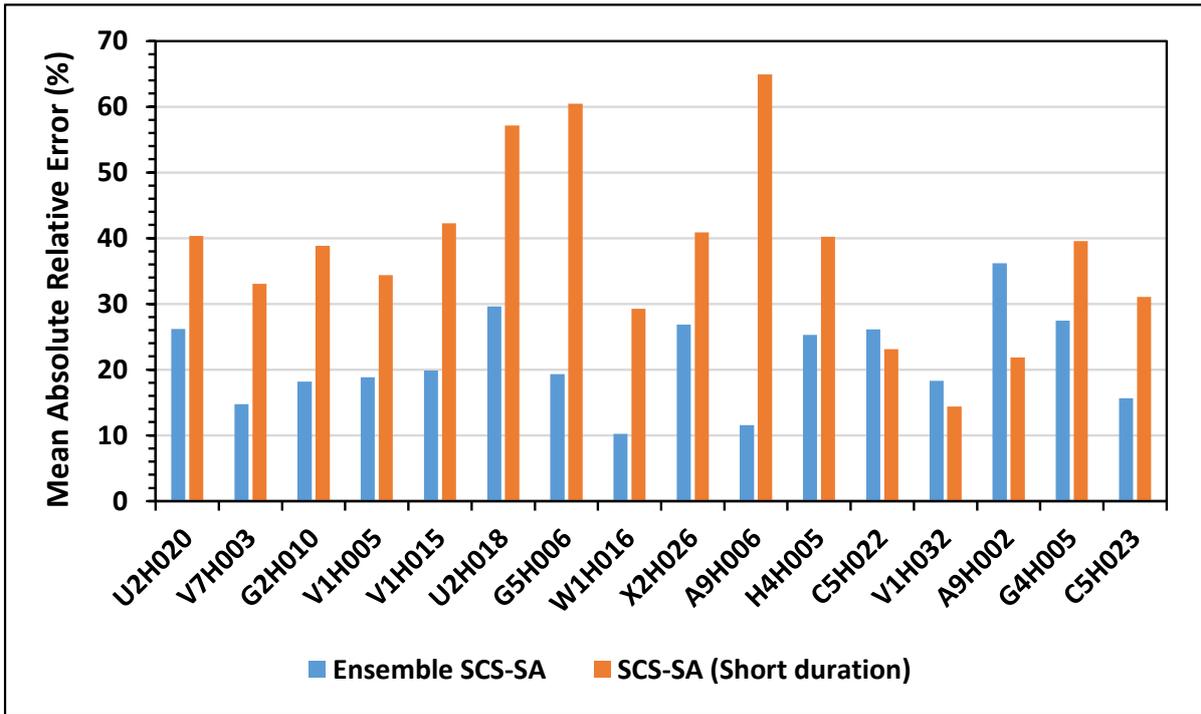
Figure 7.12   Mean absolute relative error of the estimated peak discharge for all the catchments used in the study

The Nash Sutcliff Efficiency is illustrated by Figure 7.13 for all the catchments used in the study, and it is evident that the Ensemble SCS-SA model has a Nash Sutcliff Efficiency very close to one for the majority of the catchments, indicating that the Ensemble SCS-SA is performing relatively well in estimating the observed peak discharge. It is also evident that the single event SCS-SA (Short duration) is also performing relatively well with the majority of the catchments generally having a Nash-Sutcliff Efficiency greater than 0.7. It is also evident from Figure 7.12 and 7.13 that the performance of the models do not appear to decrease with increasing catchment area and this is investigated further in the next section.
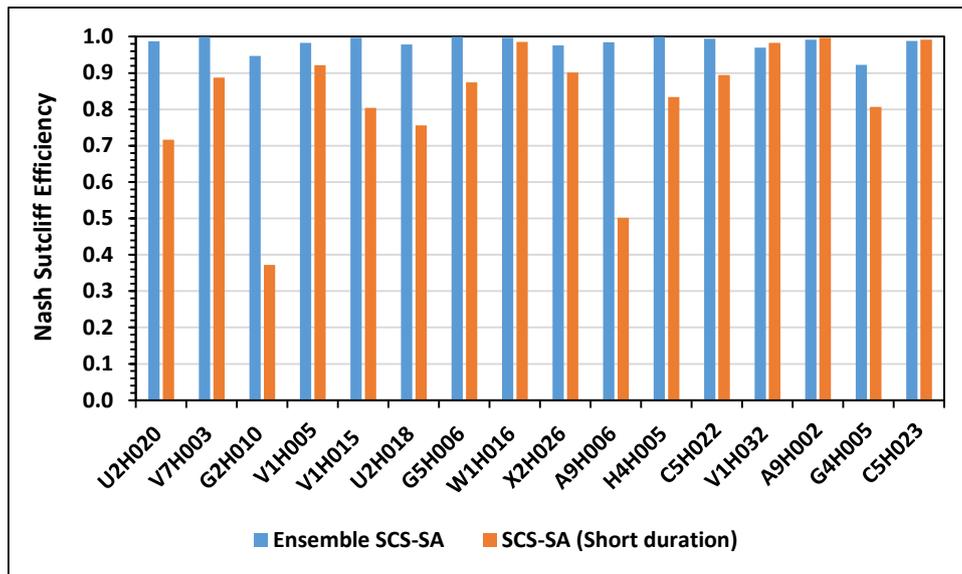
Figure 7.13   Nash-Sutcliff efficiency of the estimated peak discharge for all the catchments used in the study

7.3   Performance of Ensemble and Standard SCS-SA Models on Larger Catchments

The MARE relative to the catchment area was assessed to see if there was any deterioration in the performance of the models with increasing catchment area size. This was done for the same catchments presented above. Figure 7.14 illustrates the relationship between MARE and catchment area, where it is evident that both models seem to be performing relatively well as the catchment area increases and the performance of the models does not deteriorate as recommended maximum catchment area (30 km^2) for the models is exceeded.

Figure 7.14   MARE of peak discharge estimation vs catchment area

Figure 7.15 illustrates the scatter plot for the NSE relative to the catchment area and indicates that the models are still performing relatively well as the catchment area increases. Both models have a high Nash Sutcliff Efficiency that is close to one, indicating a relatively good performance for both models in estimating the observed design peak discharge.

Figure 7.15   Scatter plot of Nash Sutciff Efficiency with increasing catchment area size

8. DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

The aim of this study was to apply and assess the performance an Ensemble Joint Probability Approach to an event based rainfall-runoff model used for design flood estimation in South Africa and the specific objectives included the following:

(i) undertaking a comprehensive review of the literature,
(ii) model selection,
(iii) development of probability distributions for key input variables using readily available data, and
(iv) the development, application and assessment of an ensemble model configuration.

It is evident from literature reviewed that the event based models for design flood estimation have limitations in their application, as their assumptions lead to systematic bias and inconsistencies in design flood estimates. Application of an Ensemble Joint Probability Approach to event based models has the potential to improve event based models, as the method accounts for the probability distributed nature and behaviour of the main flood producing variables, each of which has an associated degree of uncertainty that can affect the shape and magnitude of the estimated design flood hydrograph and design peak discharge.

From the event-based models used for design flood estimation in South Africa, the SCS-SA model was selected because it was easily accessible and there was sufficient operational support for the model. The key input variables of the SCS-SA includes the rainfall, the time to peak, the temporal distribution, and the change in soil moisture. Probability distributions were fitted to readily available observed data of the relative key input variables, using a distribution fitting software as a tool to develop the probability distributions. The software performed relatively well in fitting the probability distributions and generating random samples for variables which had a sufficient record length. The Ensemble SCS-SA model was developed and configured with VBA coding in Microsoft Excel to run an ensemble of events from the generated samples.

The following sections includes the discussion of the initial performance of the single event SCS-SA (Standard) and Ensemble SCS-SA model, how the model was further investigated through a sensitivity analysis of the estimated peak discharge to key input variables, the overall performance of the single and Ensemble SCS-SA models, as well as a summary of the main

findings. Lastly, conclusions are drawn from the study and recommendations for future research are presented.

8.1   Performance of Models using One-day Design Rainfall Input

The results produced from applying the both Ensemble SCS-SA and single event SCS-SA models using the 1-day duration design rainfall as input, as is the norm when using the SCS-SA model, indicated that the models were performing relatively poorly in terms of estimating both the observed design runoff volume and design peak discharge for all the test catchments. Even though the probability distributions for the other key input variables were considered for the Ensemble SCS-SA model, the model still significantly over estimated the observed design runoff volume and design peak discharge for all the return periods. The observed design runoff volume and design peak discharge estimates consistently fell outside of the 10th and 90th percentiles simulated with the Ensemble model, indicating very low confidence in both the estimated design runoff volumes and design peak discharges. The single event SCS-SA (Standard) model also performed similarly to the Ensemble SCS-SA, where the model also performed poorly and over estimated both the observed design runoff volume and design peak discharge. These results are also supported by the MARE values for the test catchments, where the MARE values are generally above 100 % for both the estimated design runoff volume and design peak discharge, indicating that both the Ensemble SCS-SA and single event SCS-SA (Standard) models estimates are relatively poor compared to the observed estimates. The Nash-Sutcliff Efficiency of both the estimated design runoff volume and design peak discharge for the Ensemble SCS-SA and single event SCS-SA (Standard) models was less than zero, indicating a poor performance in the model estimates of the observed design runoff volume and design peak discharge. Given the poor performance of both models at all three test sites, further investigation was undertaken to investigate reasons for the poor performance and to assess options to improve the performance.

8.2   Sensitivity Analysis

The sensitivity analysis performed showed that the SCS-SA model is the most sensitive to the input design rainfall variable as it had the highest relative errors of 300 % when increasing or decreasing the rainfall amount. An analysis of rainfall and runoff data at two test catchments showed that, for the largest observed rainfall events, the rainfall duration and runoff time to peak are generally less than 24 hours at a catchment scale. Thus, a rainfall depth-duration-

frequency relationship was adopted in the model to account for this. The time to peak variable was the second most sensitive variable. The model was least sensitive to the antecedent moisture condition variable as it had the lowest relative difference for the percentile ranges used, indicating that the antecedent moisture conditions do not have a significant impact on the estimated design peak discharges. The model was also reasonably sensitive to the temporal rainfall distribution as it had high relative differences as the temporal pattern became more uniform for the lower bin ranges, and also for the non-uniform temporal pattern for the higher bin ranges. This indicates that the model estimates are impacted by uniform and non-uniform temporal patterns.

8.3   Overall Performance of the Ensemble SCS-SA and Single Event SCS-SA

When the Ensemble SCS-SA model used short duration rainfall, in conjunction with the probability distributions of the other key input variables, the results of the estimated design runoff volume and design peak discharges produced by the Ensemble SCS-SA model and single event SCS-SA (Short duration) improved significantly. In terms of estimating the observed design runoff volume for the test catchments, the Ensemble SCS-SA performed relatively well, where 80 % of the observed runoff volume estimates for the various return periods fitted within the 10th and 90th percentiles, indicating a relatively good confidence in the estimates of the observed design runoff volumes. The single event SCS-SA (Short duration) model performance in estimating the observed design runoff volumes and design peak discharges is generally poorer compared to the Ensemble SCS-SA estimates. However, the single event SCS-SA (Short duration) model estimates of the design runoff volumes and design peak discharges did improve considerably compared to when sampling from the 1-day duration rainfall probability distribution.

When short duration rainfall was adopted, the Ensemble SCS-SA and single event SCS-SA (short duration) models generally simulated the observed design peak discharges relatively well for all the return periods for all catchments. The single event SCS-SA (Short duration) estimates of the observed design peak discharge also considerably improved, however, the model still seems to be performing poorly compared to the Ensemble SCS-SA model estimates. These results are also supported by the MARE values of the estimated design runoff volume and design peak discharges for the relative test catchments. It is evident that the Ensemble SCS-SA and single event SCS-SA (Short duration) has MARE values generally less than 30 % and 50 %, respectively for the estimated design peak discharge. This shows a significant

decrease in the relative error which was generally greater than 100 %, thus indicating that the Ensemble SCS-SA model generally has lower errors in estimating the observed design peak discharges. The single event SCS-SA (Short duration) model estimates generally have a higher error compared to the Ensemble SCS–SA model estimates. The Nash-Sutcliff Efficiency of the estimated design peak discharge was closer to one for all the catchments, indicating a relatively good performance in estimating the design peak discharge from the Ensemble SCS-SA model and single event SCS-SA (Short duration).

8.4   Performance of the Ensemble SCS-SA on Larger Catchments

When the Ensemble SCS-SA and single event SCS-SA models were tested on larger catchments than the recommended range, the model showed promising results as it estimated the observed design peak discharge reasonably well for all the catchments. The MARE of the simulated design peak discharge for the three larger catchments also indicates that the Ensemble SCS-SA and single event SCS-SA generally have a lower error in estimating the observed design peak discharge estimates except for Catchment A9H002, and this can be attributed to the single event SCS-SA (Standard) generally over estimating the lower return periods which results in higher errors. The Nash-Sutcliff Efficiency of the estimated design peak discharge is generally higher for the Ensemble SCS-SA model estimates compared to the single event SCS-SA (Standard) model estimates. The results indicate that both the Ensemble SCS-SA and the single event SCS-SA performed reasonably well on larger catchments, even when the standard 1-day duration design rainfall is used as input. However, assessment at more study sites are required in order to adequately assess the performance of both models on larger catchments.

8.5   Conclusions

This study has demonstrated how a JPA can be applied using ensemble event simulation by adapting the single event SCS-SA model in South Africa. The application of the Ensemble SCS-SA model showed how it can reproduce the observed design flood estimates with reasonable accuracy over a wide range of return periods and for catchments larger than the recommended sizes. The Ensemble SCS-SA model has also shown potential and flexibility to dealing with uncertainty by accounting for the distributed nature of the input variables and taking on values across the full range of their distribution in the modelling process, thus

avoiding the potential bias that can occur when adopting a single set of pre-determined input values.

An unexpected result from this study is the much improved performances of both the single event and ensemble SCS-SA models when the duration of the input design rainfall was changed from 1-day to the catchment response time. This could have potential consequences to the application of the SCS-SA model in practice.

8.6 Recommendations

The following recommendations are made from the results generated in this study:

- Further investigations at more sites are required to confirm that the standard application of the SCS-SA model using 1-day duration design rainfall input should be changed to using input design rainfall with a duration equal to the catchment response time.
- To further assess the performance of the Ensemble SCS-SA on additional catchments representing a broader range of hydrological conditions around different climatic regions of the country.
- Detailed studies to improve the probability distributions for the antecedent moisture conditions and time to peak when used for sampling.
- Thoroughly investigate how to deal with sampling variability in order to prevent the occurrence of unusual, and possibly unrealistic, combinations of randomly sampled input variables.
- Further assess the application and performance of the model on catchments larger than the currently recommended area range of 30 km^2.

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APPENDIX A: PERFORMANCE OF MODELS TO ESTIMATE PEAK DISCHARGE AT ADDITIONAL SITES

Figures A1 to A10 contains plots of the simulated (using short duration design rainfall = Tc) and observed peak discharge for the rest of the catchments used in the study in the order of increasing catchment size. The catchments area and catchment parameters adopted for each catchments are listed in Table 4.2.
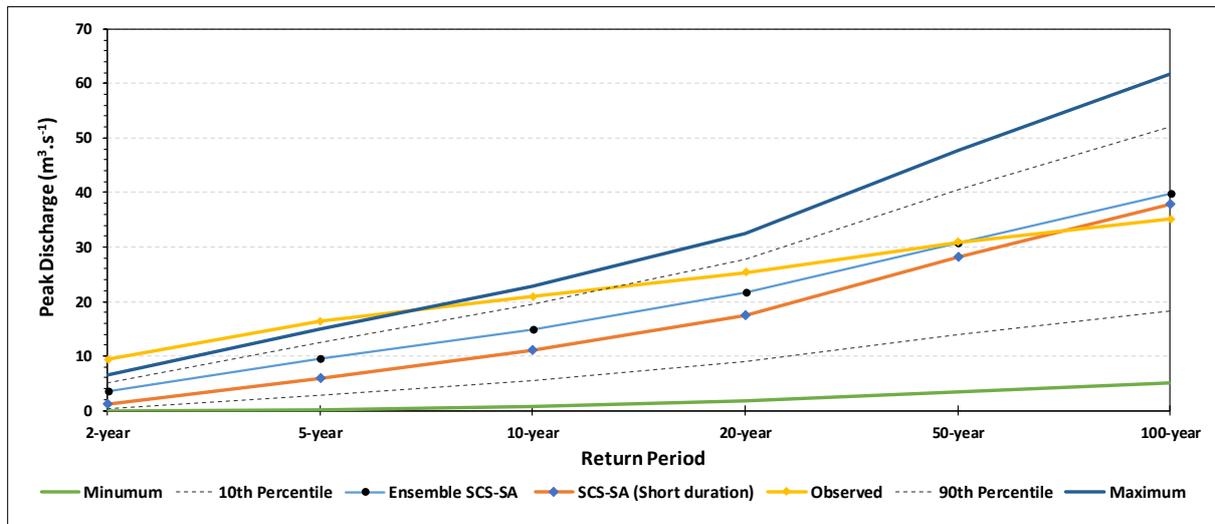

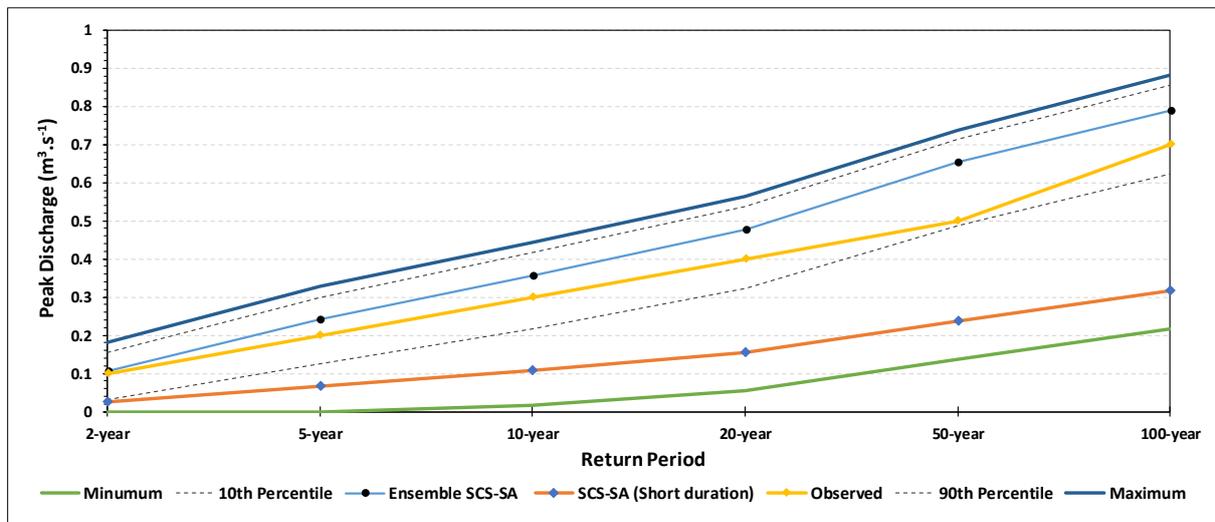Figure A1   Simulated and observed design peak discharges for Catchment V7H003

Figure A2   Simulated and observed design peak discharges for Catchment G2H010
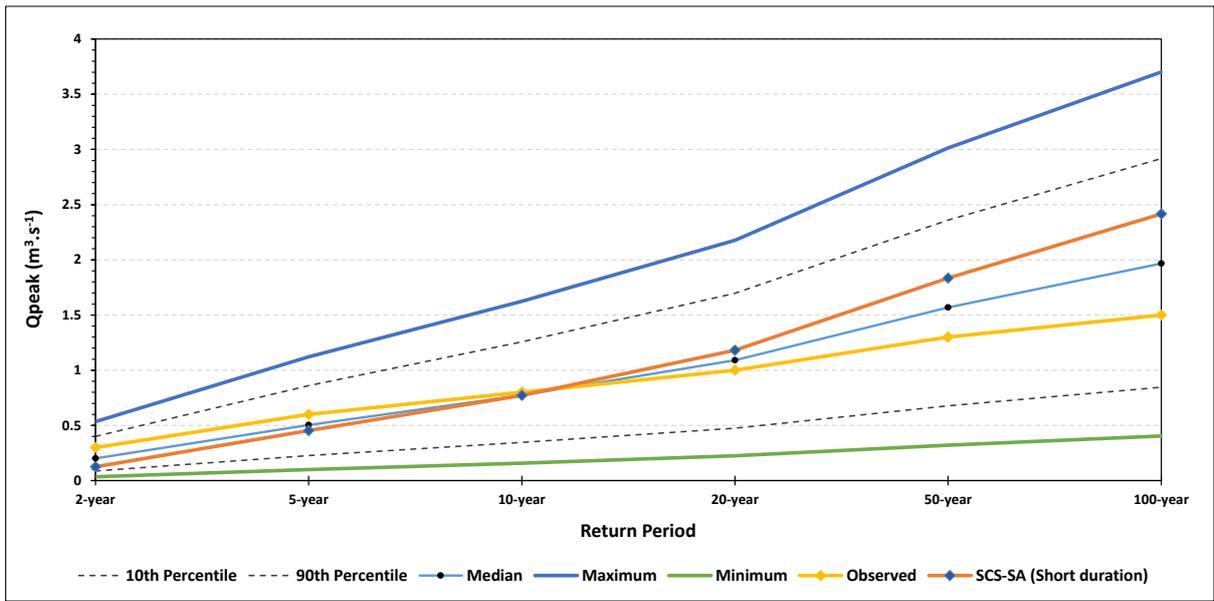
Figure A3   Simulated and observed design peak discharges for Catchment V1H005
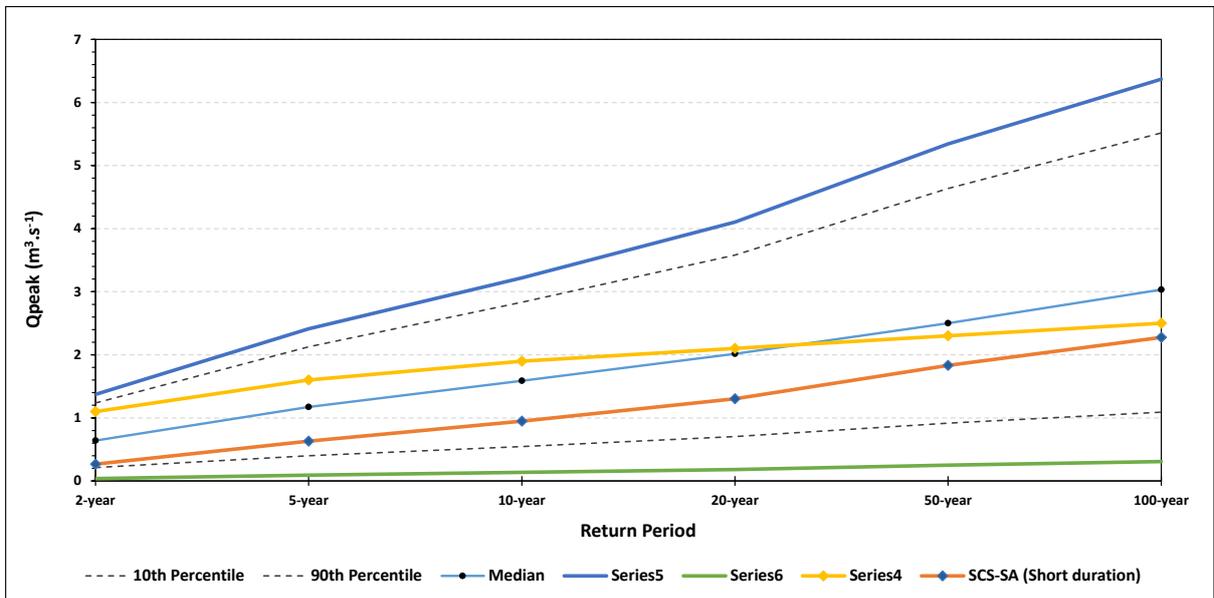
Figure A4   Simulated and observed design peak discharges for Catchment V1H015

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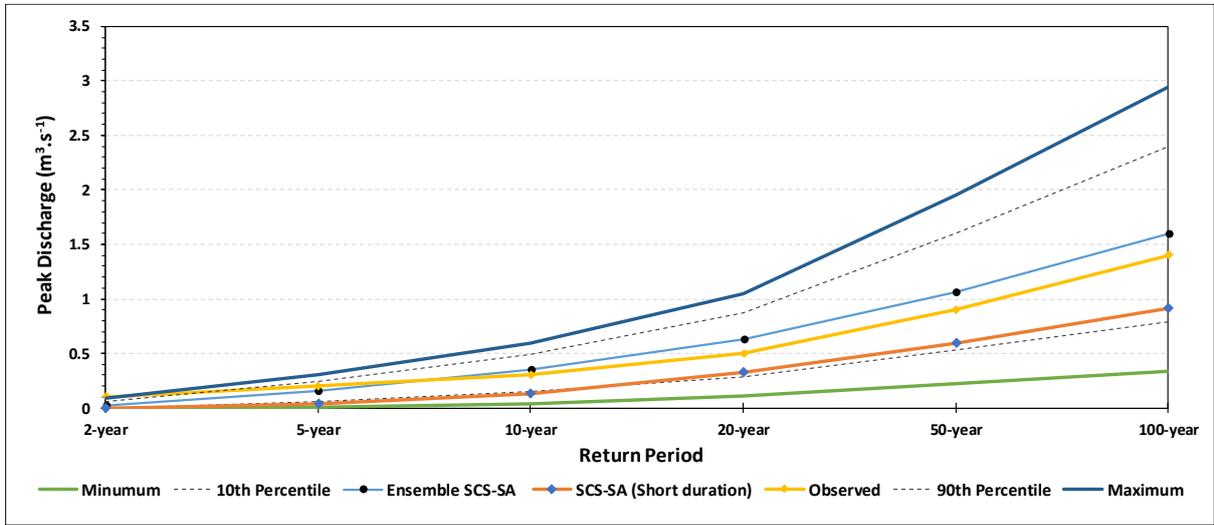
Figure A5   Simulated and observed design peak discharges for Catchment U2H018
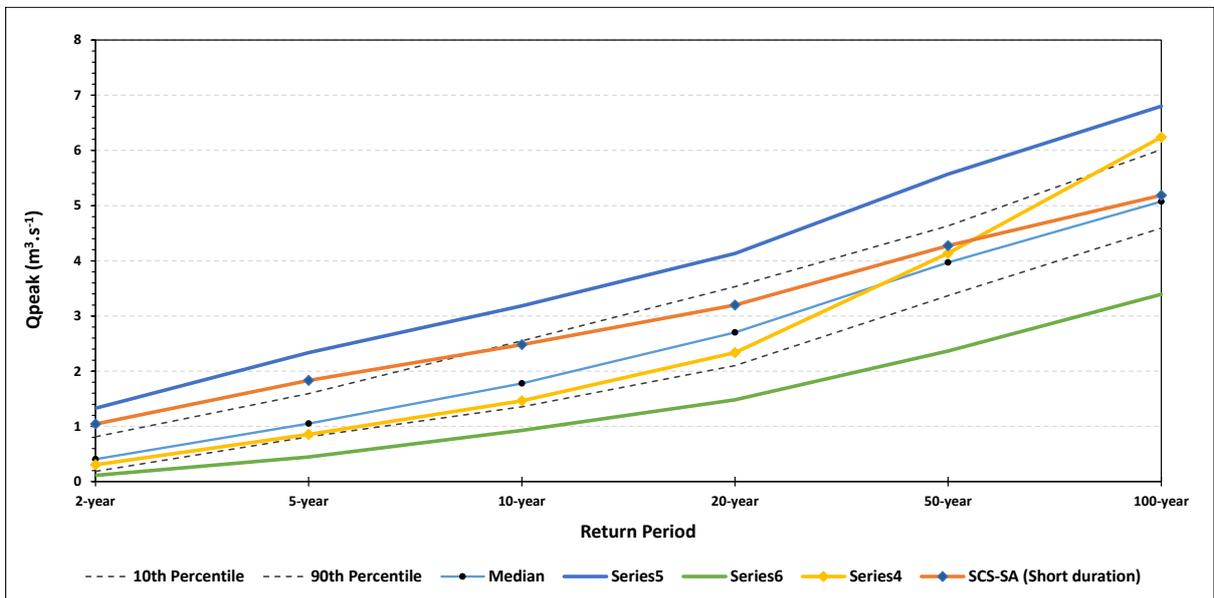
Figure A6   Simulated and observed design peak discharges for Catchment G5H006
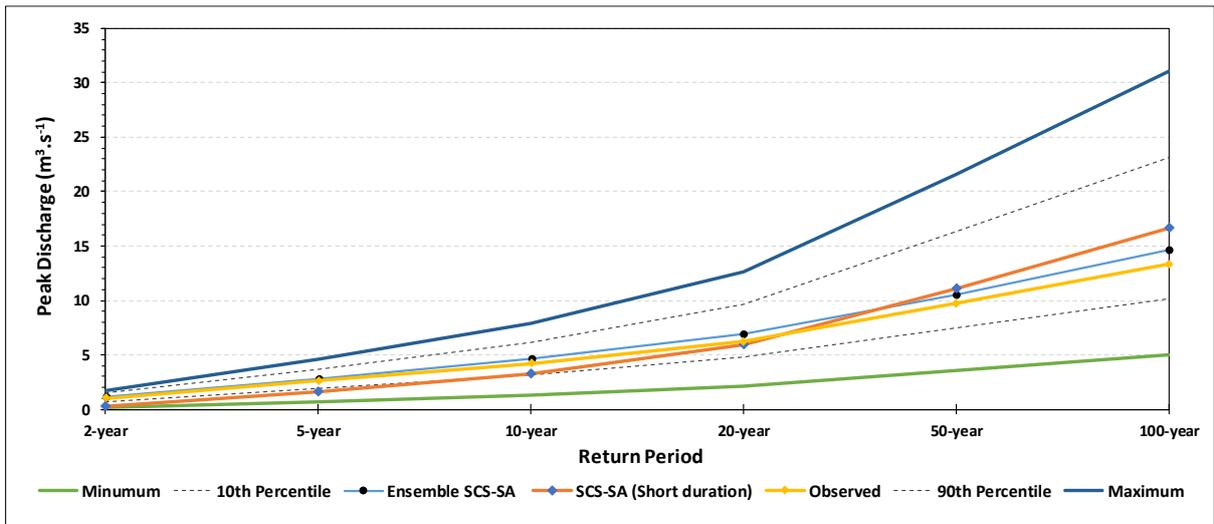
Figure A7   Simulated and observed design peak discharges for Catchment W1H016
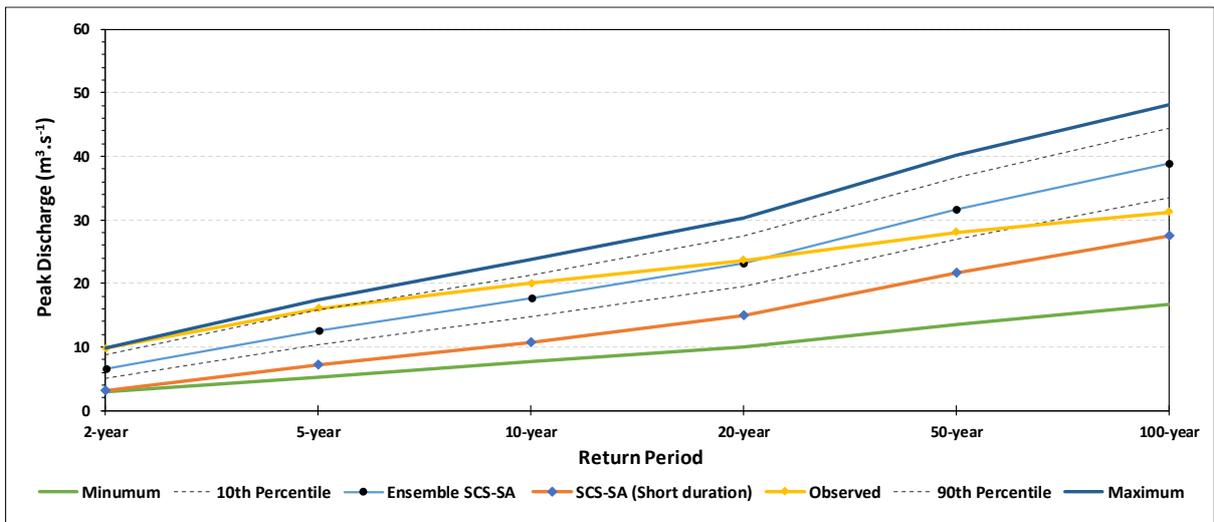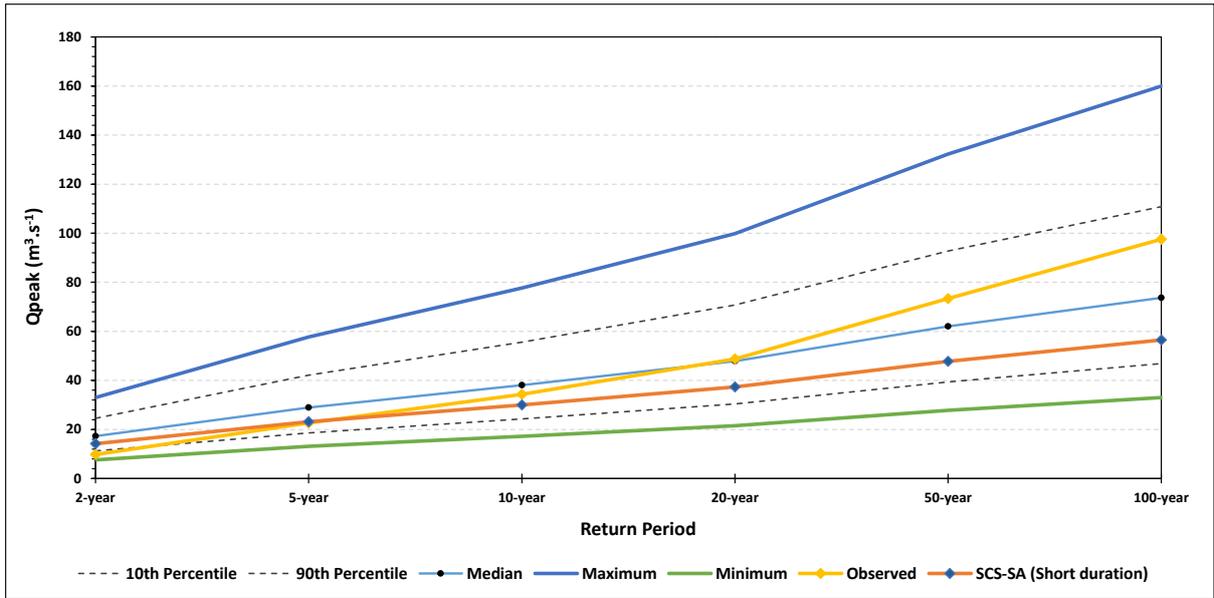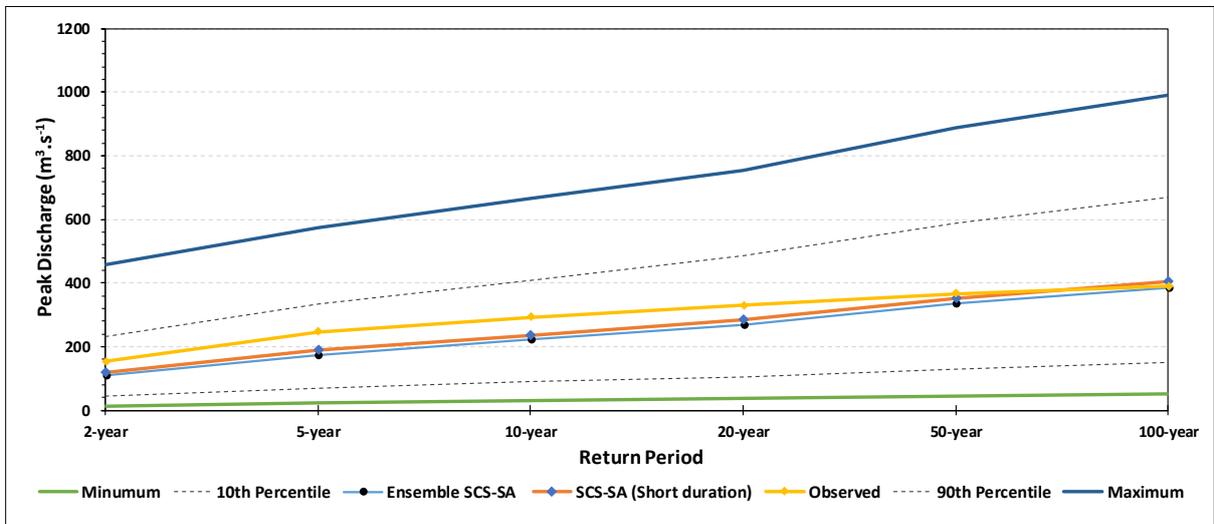

Figure A8   Simulated and observed design peak discharges for Catchment H4H005

Figure A9   Simulated and observed design peak discharges for Catchment C5H022

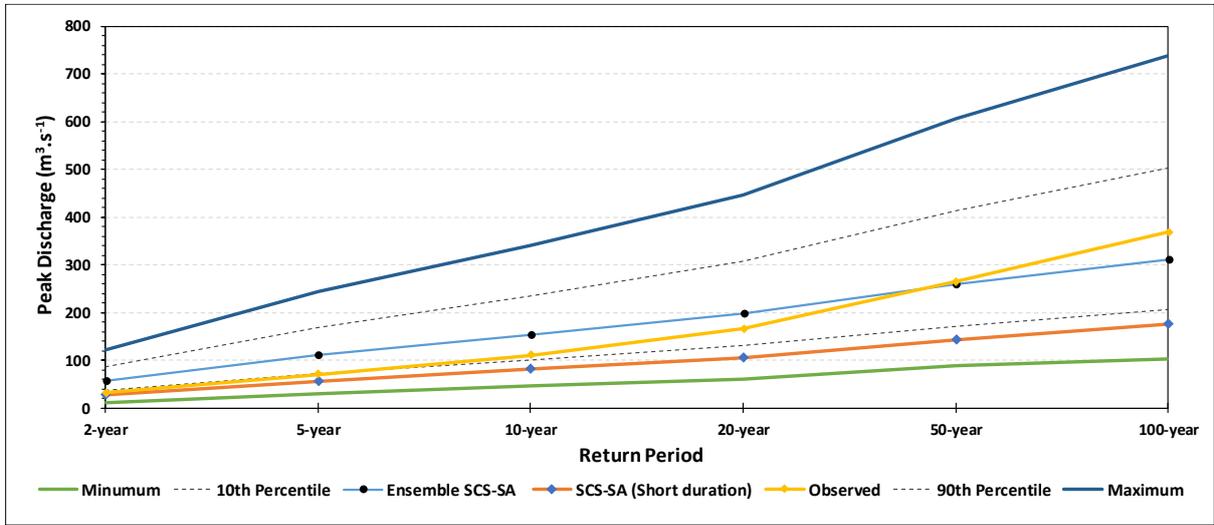Figure A10   Simulated and observed design peak discharges for Catchment V1H032

Figure A11   Simulated and observed design peak discharges for Catchment A9H002
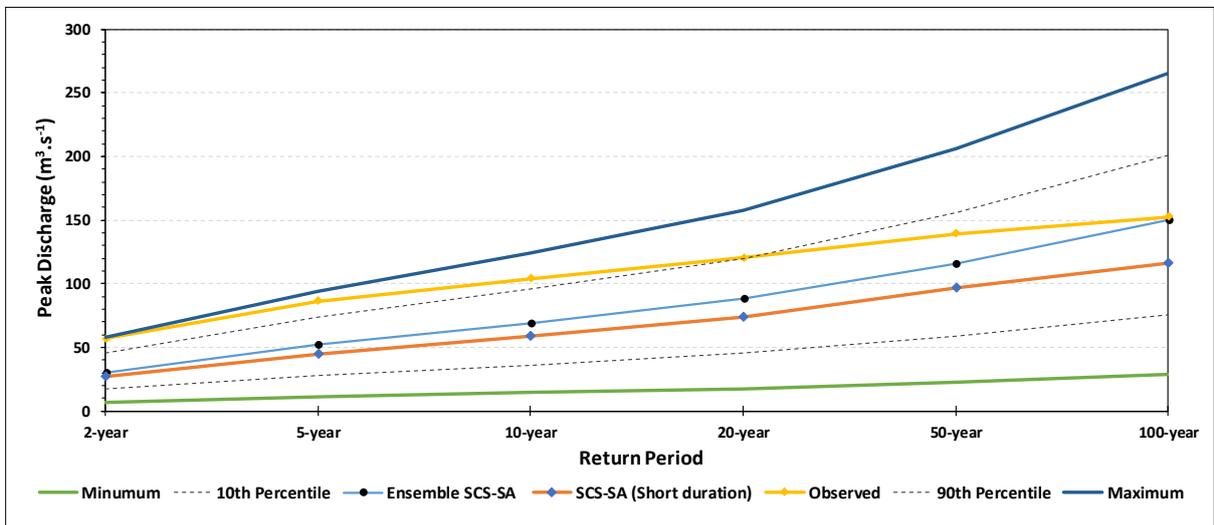

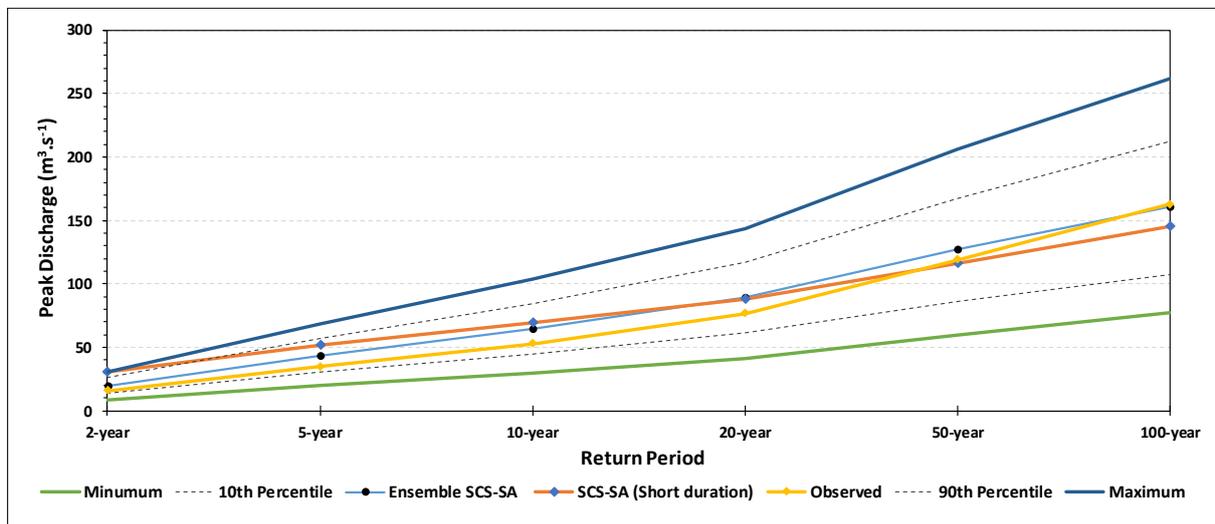Figure A12   Simulated and observed design peak discharges for Catchment C5H023

Figure A13   Simulated and observed design peak discharges for Catchment G4H005