IMPROVED PERFORMANCE OF THE SCS-SA MODEL AND DEVELOPMENT OF A FRAMEWORK FOR UNCERTAINTY ESTIMATION FOR DESIGN FLOOD ESTIMATION IN SOUTH AFRICA USING THE SCS-SA MODEL AS A CASE STUDY

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ABSTRACT

Design Flood Estimation (DFE) is required for the design of hydraulic structures and to limit the risk of failure with the consequent potential loss of life and economic losses. The DFE methods currently used in South Africa (SA) need to be revised and updated. The Soil Conservation Service Curve Number (SCS-CN) model is a widely used DFE method for small catchments. The stormflow estimated using the SCS-CN equation is extremely sensitive to the Curve Number (CN) used. However, there is uncertainty surrounding the development and origin of the published CN tables used in practice. The relatively long periods of observed rainfall-runoff (P-Q) data, that are currently available in SA, could be used to assess the performance of CN derivation techniques to derive CNs specific to SA. The general approach of the MSc Eng study was to investigate whether the published CNs could be replicated using observed and simulated data, and to evaluate the performance of the SCS-CN equation when applied with published CNs or with the CNs derived using observed P-Q data from small South African catchments. The results from the study showed that CNs derived with a coefficient of initial abstraction (c) = 0.1 that were applied with the SCS-CN equation performed better than the published CNs that were derived with c = 0.2. In SA, the recommended value of c is 0.1, therefore the definition of the Potential Maximum Retention, S, and the CN has changed from the original version of the SCS-CN model where the recommended value of c is 0.2. The published CNs were derived with c = 0.2 and therefore there is an inconsistency between the c value used to derive the published CN values and the c value recommended for use with the SCS-SA model. The same c has to be used to calculate the CN and stormflow depths using the SCS-CN equation. The results from the study also indicated that design stormflow depths are better estimated when data derived CNs are used with the SCS-CN equation. However, it is also important to improve the conversion of stormflow depths to peak discharge values when using the SCS-SA model. Therefore, one aim of the PhD study is to assess the performance of the SCS-SA model with a national scale dataset containing parameter values that represent the entire country, and to improve the transformation of design volumes into design peak discharge estimates. Hydrological modelling should include uncertainty analysis to allow for risk-informed decision making and design. When using P-Q methods for DFE, generally only the probabilistic nature of rainfall is accounted for, however, if all important input variables are treated probabilistically, the key shortcomings associated with P-Q methods for DFE could be addressed. Although there is a plethora of literature focussed on the principles and techniques that deal with uncertainty, there is a lack of clear rules to implement these techniques, and

estimation of uncertainty is not applied in DFE practice in SA. Hence, a second aim of the PhD is to conduct a thorough review of literature pertaining to quantifying uncertainty when conducting DFE, and to subsequently develop a methodology to determine the uncertainty associated with the widely used DFE methods that are applied in SA.

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1. BACKGROUND TO THE STUDY AND LITERATURE REVIEW

The evaluation of the risk associated with a flood by relating a flood event with an exceedance probability, or Return Period (RP), is the accepted approach to Design Flood Estimation (DFE) in many countries (Smithers, 2012; Kang *et al.*, 2013). These design flood estimates are essential to design hydraulic infrastructure such as bridges, culverts, dams, and other drainage structures (Lamb *et al.*, 2016).

Discharge data from rivers in Africa have shown an increase in the annual maximum peak discharge after 1980 in Western and Southern Africa (Tramblay *et al.*, 2020). Furthermore, various studies have shown that there is a correlation between global climate change and flood risk (Alfieri *et al.*, 2017; Do *et al.*, 2020). Li *et al.* (2016) reported that global climate change has resulted in an increased occurrence of flood disasters in Africa, and economic losses due to floods are larger in developed African countries, such as South Africa. The economic and social problems caused by recent flooding, and the likelihood of increased rainfall variability in the future, highlight that DFE techniques that are used in South Africa are outdated and require review or updating. As a consequence, a National Flood Studies Programme (NFSP) was initiated to update DFE procedures used in South Africa (Smithers, 2016).

The Soil Conservation Service Curve Number (SCS-CN) model is a widely used event-based Rainfall-Runoff (P-Q) model used globally for DFE, and it forms the foundation for various other runoff models (Schulze, 1989; Harbor, 1994; Hawkins *et al.*, 2009; Aichele and Andresen, 2013). The SCS-CN method did not undergo critical review after it was made available for use (Hawkins *et al.*, 2009; Woodward, 2017). Therefore, the published Curve Number (CN) values that were derived using P-Q data from small agricultural catchments in the United States of America (USA) should only serve as a guide and users of the method should determine CN values using local P-Q data to account for any deviations from the published CN values (Hawkins *et al.*, 2009; Stewart *et al.*, 2011; Tedela *et al.*, 2011). It has been recognised that certain aspects about the SCS-CN methodology, such as the accuracy of the published CNs, are inconsistent. Consequently, numerous studies have been undertaken to verify the SCS equation and published CN values (Hjelmfelt, 1991; Ponce and Hawkins, 1996; Hawkins *et al.*, 2009; Maharaj, 2020; Smithers *et al.*, 2021). Despite this, the published CN values derived by the SCS are still widely used internationally, including in South Africa.

Dlamini (2019) applied a Joint Probability Approach (JPA) to the SCS-SA model (Ensemble SCS-SA) to derive flood frequency curves. In the Ensemble SCS-SA model, the input design rainfall and the main input model parameters (excluding the CN) are treated probabilistically. The results obtained by Dlamini (2019) have shown that the standard single event SCS-SA model performed poorly when using published CN values ($CN_{published}$). This was confirmed by the results of the analysis of $CN_{published}$ values by Maharaj (2020) for 11 South African catchments which indicated that the published CNs resulted in poor estimates of design floods when compared with observed stormflow depths. Consequently, CNs derived by Maharaj (2020) using observed and simulated P-Q values, were evaluated to determine whether the derived CNs result in better estimates of observed design stormflow depths. In the pilot study, the CNs calculated with a coefficient of initial abstraction (c) equal to 0.1 and design observed or simulated P-Q depths for the 10-year return period resulted in improved estimates of design observed stormflow depths.

The relationship between the Maximum Potential Soil Water Retention (S) and Initial abstraction (I_a) was derived by the SCS, using observed P-Q records from individual storms on catchments in the USA that were less than four hectares, and the c value was found to be 0.2 by doing a linear regression of I_a on S (Schulze and Arnold, 1979). A value of 0.2 for the coefficient of initial abstraction was deemed too high for small to medium storms and it was suggested that a value of 0.1 be used for design analysis in the SCS-SA model (Schulze *et al.*, 1984; Schulze and Schmidt, 1987). According to Plummer and Woodward (1998), each unique relationship between the I_a and S requires an exclusive set of CNs. Maharaj (2020) also highlighted that the calculated CN is sensitive to the c value and recommended that the same c value used to derive the CNs should also be used to estimate design stormflow depths when using the SCS-CN equation. This is not currently the case in South Africa where a value of c = 0.1 is recommended but used with CNs derived with c = 0.2. The CNs currently used in South Africa were derived and interpolated using observed data and land cover and soils classifications developed for use with catchments in the USA, and Hawkins (1975) stressed the importance of accurate CN estimates because the SCS-CN equation is more sensitive to errors in CNs than errors in rainfall of the same magnitude. With the sensitivity of the simulated hydrological responses to the c value and CNs used, it is therefore vital to use a c-value and CN that best represents the prevailing land cover, soil type and hydrological condition representative of catchments in South Africa (Maharaj, 2020).

Deterministic methods for DFE are routinely used for the design of hydraulic infrastructure (Micovic *et al.*, 2017). However, hydrological modelling should include uncertainty assessments to allow for risk-informed decision making and design (Berbića *et al.*, 2015; Teng *et al.*, 2017). Many different sources of epistemic and natural uncertainties, such as knowledge deficiency or natural variability impact DFE (Boelee *et al.*, 2017; Ball *et al.*, 2019; Boelee *et al.*, 2019). There are various techniques that may be used to quantify the uncertainty associated with the outputs from DFE models (Boelee *et al.*, 2019). Although there is interest in the impact that uncertainty has on DFE, and a plethora of literature has focussed on the principles and techniques that deal with uncertainty, there is a lack of clear guidelines or a methodical approach to implement these techniques (Beven, 2006; Montanari, 2007; Montanari *et al.*, 2009; Ball *et al.*, 2019).

The currently used P-Q DFE techniques such as the design event approaches do not take the probabilistic nature of key input variables, except for P, into account (Rahman *et al.*, 2002). To estimate the likelihood of a flood, the probability of high and extreme values of each variable occurring simultaneously need to be known (Hawkes, 2008). According to Kuczera *et al.* (2006), the design flood approaches that are traditionally used lack the rigour of joint probability analyses. Hawkes (2008) defines joint probability as the likelihood of two or more conditions happening concurrently. Kuczera *et al.* (2006) stated that event and total joint probability methods with a firm joint probability framework need to be used for DFE. Rahman *et al.* (2002) proposed the joint probability and continuous simulation approaches to overcome some of the shortcomings of event-based P-Q DFE models. In addition, Smithers (2012) recommended that a JPA to DFE that derives the flood frequency and accounts for uncertainties related to model inputs should be investigated.

Loveridge and Rahman (2012) investigated the probability distribution of losses, i.e., the difference between rainfall and direct runoff, and the associated impact of the losses on flood estimates. The study found that the use of distributed inputs could lead to more realistic estimates of design floods in comparison to the design event approach. Dlamini (2019) applied a JPA using the SCS-SA model (Ensemble SCS-SA) to derive flood frequency curves. The results obtained by Dlamini (2019) have shown that the standard single event SCS-SA model performed poorly when using published CN values. Dlamini (2019) recommended that: (a) further investigations with the Ensemble SCS-SA model be performed at catchments with varying climatic conditions, (b) the probability distributions of both antecedent moisture conditions and time to peak should be improved, and (c) the sampling variability techniques should be investigated. Dlamini (2019) and Smithers *et al.* (2021) have recommended that the Ensemble SCS-SA approach be further investigated.

2. SUMMARY OF PROGRESS MADE IN MSC ENG STUDY

In the following section, the key findings from the MSc study by Maharaj (2020) are presented.

2.1 Key Findings

The SCS-CN model is simple to use and only requires a CN that can be selected from a published CN table and readily available design rainfall data for T-year RPs (P_T) as an input (Mishra and Singh, 2003; Hawkins *et al.*, 2009). Therefore, the CN used to estimate a stormflow depth is a fundamental aspect of the model. The SCS-CN runoff equation was originally developed to transform a daily rainfall depth to a stormflow depth. The CNs used for the transformation, are generally obtained from published tables, containing CNs derived from observed data from catchments in the USA for selected land cover and soil classes used in the USA, and using c = 0.2 (Hawkins *et al.*, 2009). The published CNs are widely used internationally, however, the accuracy of the CN values that were published by the SCS are unknown (Woodward *et al.*, 2002; Woodward, 2017).

The use of published CNs limits the application of the SCS-SA model on catchments with land cover classes and Hydrological Soil Groups (HSGs) specific to South Africa (SA). In addition, numerous studies have concluded that CNs derived from local data result in better estimates of stormflow (Hawkins *et al.*, 2009; Stewart *et al.*, 2011; Tedela *et al.*, 2011; Maharaj, 2020). In the SCS-SA model, the c value used with the SCS-CN equation is not consistent with the c value used to calculate the published CNs, thus increasing the accuracy and uncertainty related to the estimated stormflow depths. With the increasing occurrence of flood events, evaluating the CNs used with the SCS-SA model is vital to improve the estimates of design stormflow depths from the model.

A review of literature indicated that the relatively long periods of observed and simulated P-Q data, that are currently available, could be used to verify popular CN derivation techniques. A significant effort was spent trying to identify and correct errors associated with the observed P-Q data to be used in the study. However, despite the challenges with sourcing reliable observed data and identifying catchments with relatively homogeneous land cover and soil characteristics, 11 catchments were used in the study. A methodology was developed to assess various CN derivation techniques to best derive published CNs, using either observed or simulated P-Q values.

The ACRU model (Schulze, 1989) was parameterised using the conventional rules (Schulze *et al.*, 1994; Smithers and Schulze, 1995) and the Rowe (2020) rules to simulate runoff depths and subsequently derive CNs. Rowe (2020) defined an additional output called the UQFLOW On the Day (UQFLOW OTD) to correct the discrepancy (in the conventional ACRU model) between the volume of STORMF that is used to estimate the simulated peak discharge and the UQFLOW volume released on a particular day. Therefore, Maharaj (2020) used the simulated UQLOW OTD values to derive CNs. In this document, the simulated UQFLOW OTD are referred to as simulated Q depths for ease of readability. When simulated daily Q depths were used to derive CNs, an "S" was added before the abbreviation, for example, if simulated daily Q values were used to calculate the CN with a c of 0.1, the abbreviation would be S-$CN_{,0.1}$.

A range of goodness-of-fit and performance statistics such as linear regression analyses, the coefficient of determination (R^2), Mean Absolute Relative Error (MARE), mean relative error, Nash-Sutcliffe efficiency coefficient and the root mean square error were identified and used in the evaluation of the derived CNs and simulated Q depths from the SCS-SA model. The performances of published and data derived CNs were evaluated in terms of observed design stormflow depth ($Q_{T,O}$) estimation. The published and derived CNs were assessed to identify the optimum CNs, and the single best CN derivation technique that results in the best estimates of $Q_{T,O}$ was selected.

Based on the results that were obtained, there were differences between the CNs derived with c = 0.2 and the published CNs that were associated with c = 0.2. The CNs derived using observed Annual Maximum P-Q events and c = 0.1 (AMS $CN_{0.1}$) were closest to the published CNs. If observed P-Q data are available, the most suitable method currently identified in this study to replicate the published CNs is the CN derived graphically using the Annual Maximum P-Q series. This is the method that was originally used to graphically derive the CNs (Hawkins *et al.*, 2009) that are published in the National Engineering Handbook (AMS $CN_{NEH,0.1}$). The methods that resulted in CNs similar to the published CNs were applied with Q depths simulated using the ACRU model. The CNs derived using simulated Q values from the conventional ACRU parameterisation ($ACRU_{CON-P}$) were comparable to the CNs derived using observed P-Q data. The simulated annual maximum Q depths from ACRU parameterised using the rules developed by Rowe (2020) ($ACRU_{TR-P}$) resulted in derived CNs that were more similar to the published CNs than the CNs derived using observed P-Q data. This was expected because the $CN_{published}$ values were used to calibrate some of the parameters used with $ACRU_{TR-}$

$_P$. Nevertheless, the mean S-$CN_{AMS,0.1}$ and AMS S-$CN_{NEH,0.1}$ (derived using simulated Q depths from $ACRU_{TR-P}$) resulted in derived CN values that were most similar to the published CNs, with the least error.

The published CNs were then assessed to determine whether the stormflow estimated using the SCS-CN equation ($Q_{T,S}$) applied with published CN values resulted in good estimates of design observed stormflow depths ($Q_{T,O}$). The results of the analysis using published CNs indicated that the published CNs resulted in poor estimates of $Q_{T,O}$. However, the CNs calculated with c = 0.1 and design observed P-Q depths for the 10-year return period ($CN_{10,0.1}$) resulted in improved estimates of $Q_{T,O}$. Similarly, the $CN_{10,0.1}$ derived using Q depths simulated with $ACRU_{TR-P}$ (S-$CN_{10,0.1}$) also resulted in improved estimates of $Q_{T,O}$ compared to the published CNs. The S-$CN_{10,0.1}$ values derived using Q values simulated using $ACRU_{CON-P}$ resulted in poorer estimates of $Q_{T,O}$ in comparison to the $CN_{10,0.1}$ and S-$CN_{10,0.1}$ ($ACRU_{TR-P}$).

The $CN_{10,0.1}$ and S-$CN_{10,0.1}$ ($ACRU_{TR-P}$) resulted in improved estimates of $Q_{T,O}$ compared to the $CN_{published}$ values. However, errors in the observed data could be translated to the CNs derived with observed data. Errors in rainfall data could also have an impact on the accuracy of simulated Q depths that may be used to derive CNs. Furthermore, errors when selecting a $CN_{published}$ value for a catchment could result in errors when estimating $Q_{T,S}$ using $CN_{published}$ values. Therefore, the derived $CN_{10,0.1}$ or S-$CN_{10,0.1}$ for specific Land Use Land Cover (LULC), Stormflow Potential (SP), and HSG combinations need to be evaluated using P_T and $Q_{T,O}$ depths from multiple different catchments with the same SP, LULC and HSG to gain confidence in the $CN_{10,0.1}$ to estimate $Q_{T,S}$. The successful derivation of $CN_{10,0.1}$ values is also dependent upon the availability of an adequate length of P-Q datasets. Therefore, the reliability of $CN_{10,0.1}$ values on catchments with varying record lengths of data should also be investigated. In addition, it may be beneficial to evaluate the use of the average CN computed from all the CN_{RP} values to eliminate the bias with using the $CN_{10,0.1}$, derived from the $Q_{T,S}$ for the 10-year RP, for all RPs.

The study by Smithers *et al.* (2021) investigated how the estimated design stormflow depths from the different CN determination methods can be used as input in the SCS model to determine the design peak discharges. The design peak discharges obtained from translating the design stormflow depths determined from the CNs simulated from $ACRU_{CON-P}$ parameterisation consistently resulted in better estimates of the observed design peak discharges compared to the other CN determination methods. However, the S-$CN_{10,0.1}$

calculated using Q depths from $ACRU_{CON-P}$ generally resulted in an underestimation of observed Q depths (Maharaj, 2020). It is evident that there is a poor translation of good, simulated design volumes (derived using the $CN_{10,0.1}$ and $S\text{-}CN_{10,0.1}$ from $ACRU_{TR-P}$) into good design peak discharges. There is therefore an inconsistency between the $Q_{T,O}$ and design peak discharge outputs from the SCS-SA model that also needs to be addressed. This could also indicate that there may be a flaw in the peak discharge equation that may have to be investigated.

2.2 Concluding Remarks

There are several different approaches to deriving CNs using observed, or simulated, P-Q depths. However, the CN values derived using the different methods may be dissimilar and could lead to different fundamental definitions of the CN in terms of estimating $Q_{T,S}$. Based on the CNs derived using P-Q values from the catchments used in this study, it is apparent that not all CN derivation techniques perform well on all the catchments and the differences between the data derived CNs on different catchments when using different methods is evident. The c value also plays a role in the magnitude of the calculated CN and an inverse relationship between the c and the CN is evident, where the data derived CNs were lower when a c of 0.1 was used compared to when a c of 0.2 was used to derive CNs.

Based on the assumption that $CN_{published}$ values could be used to reliably estimate Q_T, one aim of the study was to determine a method to replicate the $CN_{published}$ values that were selected for each study catchment. If observed P-Q data are available, the most suitable method currently identified to replicate the published CNs is the AMS $CN_{NEH,0.1}$. The CNs derived using $ACRU_{TR-P}$ resulted in CNs closest to the published CNs. Therefore, if observed Q data are not available and to overcome the challenge with the non-homogeneity between the land cover and soils in the catchment and those in the published CN tables, the mean $S\text{-}CN_{AMS,0.1}$ and the AMS $S\text{-}CN_{NEH,0.1}$ (derived using simulated Q depths from $ACRU_{TR-P}$) resulted in derived CN values that were similar to the published CNs. It is important to note that the published CNs were used in the calibration of rules for $ACRU_{TR-P}$. Nevertheless, if the user of the SCS-CN model has confidence in the published CNs, the methods that were identified to replicate the published CNs will be useful to derive CNs on catchments with land cover classes that are not currently available in the published CN tables and remove the subjective interpolation when no observed data are available for a given LULC and HSG combination.

An additional aim of the study was to assess the performance of the $Q_{T,S}$ values calculated using the CNs derived using observed P-Q data or simulated Q depths. The use of the $CN_{published}$ values to estimate $Q_{T,S}$ was also evaluated by comparing the $Q_{T,O}$ and $Q_{T,S}$ depths. The $CN_{published}$ values resulted in poor estimates of Q with high MARE values between the $Q_{T,O}$ and $Q_{T,S}$. When the CN derivation methods were assessed using P_T and $Q_{T,O}$ values from all the catchments, the $CN_{10,0.1}$ resulted in the best estimates of $Q_{T,O}$ with the lowest overall MARE and a high R^2. When using Q depths simulated from $ACRU_{TR-P}$ the overall best performance of the SCS-CN method was also achieved when the S-$CN_{10,0.1}$ values were used to estimate $Q_{T,S}$.

From the results obtained it was evident that the CNs derived using observed or simulated P-Q values performed better than the $CN_{published}$ values. The main recommendations from the study are provided in the next section.

2.3 Recommendations

The following key recommendations were made by Maharaj (2020):

(a) The currently available SCS-SA published CN table should be updated to be compatible with South African land cover classes and HSGs.
(b) The $CN_{10,0.1}$ and S-$CN_{10,0.1}$ should be assessed in different climatic regions of SA to determine if the $CN_{10,0.1}$ consistently results in improved estimates of $Q_{T,O}$.
(c) The validity of the coefficient of initial abstraction used with the SCS-SA model needs to be investigated because of the problems associated with treating the initial abstraction as a function of c and S.
(d) The use of national CN maps aligned with CN tables that result in improved estimates of $Q_{T,O}$, SCS-SA HSGs, SA land cover classes and an updated coefficient of initial abstraction, should be investigated.

3. PROJECT PROPOSAL: PHD STUDY

Based on the results obtained by Maharaj (2020) and the information summarised in Chapters 1 and 2, the project proposal for the PhD is provided in this chapter. The proposed title, research question, aims and objectives for the PhD study are provided below.

3.1 Proposed Title

Improved Performance of the SCS-SA Model and Development of a Framework for Uncertainty Estimation for Design Flood Estimation in South Africa using the SCS-SA Model as a Case Study

3.2 Problem Statement

A study carried out by Pablo *et al.* (2017), examined the validity of the c value, because the value of c leads to uncertainty when using the SCS-CN model. The c value is generally fixed at 0.2, however numerous studies have indicated that the most accurate value of c ranges between 0.05 and 0.2 (Woodward *et al.*, 2003; Hawkins *et al.*, 2009; Pablo *et al.*, 2017). Therefore, the relationship between the c value used and the CN needs to be investigated to identify whether the currently available CN values are acceptable for use with the c values recommended for use with the SCS-SA model. The c value also needs to be evaluated to determine if it should be treated as a catchment land cover dependent variable or as a constant value.

From the results obtained in the study by Smithers *et al.* (2021), it is evident that the use of both published and derived CNs resulted in a large over estimation of design peak discharges when using the standard SCS-SA model and that the stormflow depths are poorly estimated when short duration rainfall is used with the SCS-SA model. This indicates that there may be an issue with the SCS-SA model in terms of converting a runoff volume or depth to a peak discharge. Therefore, the peak discharge equation and the methods used to estimate lag time and the effective storm duration need to be analysed and updated if needed.

Various calls have been made for coherent terminology relating to uncertainty (Montanari, 2007), however, this has been difficult to accomplish (Boelee *et al.*, 2019). Both ensemble and statistical methods that are used to quantify uncertainty have associated theoretical and mathematical problems related to them. Presently, there is minimal knowledge regarding the assumptions that need to be made to quantify uncertainty and the consequences to the assumptions are also unknown (Boelee *et al.*, 2019). There are, however, opportunities to enhance the methods used to quantify uncertainty by improving data assimilation and integrating different ideas to create better methods. The JPA accounts for the probability distributed nature of the key input variables of the model, which contains uncertainties. From the literature that was reviewed, it is evident that the event-based SCS-CN model has limitations and the application of a JPA to event-based models could result in improved design flood estimates. Therefore, the ongoing research contributing to uncertainty estimation is vital to develop guidelines to identify a suitable method for uncertainty quantification, and ultimately a framework for an ensemble joint probability approach and uncertainty estimation for DFE models used in South Africa.

To improve the performance and accuracy of the SCS-CN model, the relationship between the CN and c and the conversion of Q depths to peak discharge needs to be investigated, and guidelines for quantifying uncertainty for event-based DFE methods is required to improve the limitations of these methods.

3.3 Research Questions

(a) Can the performance of the SCS-SA model for design volume estimation be improved by using locally derived and optimised input parameters?
(b) Can the derivation of a national scale dataset containing parameter values representative of the whole country improve the SCS-SA model performance?
(c) Can the estimation of design peak discharge values from design volumes be improved?
(d) How can the uncertainty of the results from the SCS-SA and other event-based DFE methods be derived?

3.4 Aim and Objectives

The aims of the research are to investigate and improve the performance of the SCS-SA model in South Africa, and to develop a framework for uncertainty estimation of DFE models in South Africa using the SCS-SA model as a case study. The broad objectives are as follows:

(a) Assess the performance of the SCS-SA model for design volume estimation using locally derived and optimised input parameters.
(b) Assess the performance of the SCS-SA model using national scale model parameters.
(c) Investigate and improve the transformation of design volumes into improved design peak discharge estimates.

(d) Develop a framework to estimate the uncertainty of the results from the SCS-SA and other event-based DFE methods.

3.5 Proposed Methodology

Observed P-Q data for catchments in different climatic regions in SA will be collated and checked for errors and inconsistencies. The observed data will be used to (a) test different CN derivation methods, (b) assess the relationship between c and the CN, (c) investigate the SCS peak discharge equation, and (d) perform initial uncertainty analysis assessments. The methods that perform well when applied with observed data will then be used with observed P values and simulated Q values to represent situations where no observed data are available. The SCS-SA Continuous Simulation Modelling (CSM) system developed by Smithers *et al.* (2021) will be configured for South Africa at a selected spatial scale (for example the quinary scale) using the default assigned or updated climate (Lynch, 2004; Schulze and Maharaj, 2004), soils (Smithers and Schulze, 1995; Rowe, 2015), and land cover information (Smithers and Schulze, 1995; Rowe, 2020) for SA. The simulation results from the SCS-SA CSM will be used to derive CNs for different RPs. The CN output from the SCS-SA CSM will be calculated for: (a) different Hydrological Response Units (HRUs) in the spatial unit selected, and (b) for each combination of soil and land cover in each HRU in the spatial unit. Option (b) is useful when a CN is required for a particular combination of soil and land cover for a smaller catchment in the selected spatial unit. The CNs derived for different soil and land cover combinations will also be used to generate an updated CN table for SA. The updated CN table will be used with South African national soil (Schulze and Schütte, 2018) and landcover (DEA and GTI, 2019) maps to generate CN maps for SA to investigate the spatial variability of CNs and will serve as a product for practitioners to use. The observed data and simulation results from the SCS-SA CSM will also be used to investigate the coefficient of initial abstraction used in the event-based SCS-SA model. Firstly, the I_a and S values that were originally used to obtain the c = 0.1 value will be investigated. In addition, variations of the SCS-CN equation with different interpretations of the c value will be assessed. Lastly, the variability of the CN will be assessed by selecting I_a values from a probability distribution.

Thereafter, design stormflow volumes and peak discharges will be simulated using the event-based SCS-SA with the conventional and updated input values (locally derived CN and c), and with the SCS-SA CSM. Using observed data, the design stormflow volumes and peak discharges will be evaluated and factors such as the lag time and time distribution of rainfall will be evaluated and refined, if necessary.

Using the data and results from the above steps, probabilistic and non-probabilistic methods for uncertainty quantification will be used to assess the uncertainty associated with the SCS-SA model parameters, uncertainty of the observed data and design values, uncertainty in the model structure and uncertainty of the simulated values.

The accuracy and uncertainty of the key input parameters for DFE models are generally unknown. Therefore, the incorporation of the ensemble approach for parameters like the CN or runoff coefficients would result in the selection of the input parameters from a range of expected values and probability neutrality between the input P and estimated Q would be attained. The results from the uncertainty analysis will be used to further develop the ensemble joint probability SCS-SA approach. The updated ensemble joint probability SCS-SA model will be used to estimate design stormflow depths and peak discharges. The results from the refined ensemble JPA, event-based SCS-SA and SCS-SA CSM models will be compared to design stormflow and peak discharges computed from the observed data to determine the performance of the different approaches. Thereafter, the results will be used to develop guidelines for selecting an appropriate uncertainty assessment method for DFE in SA.

3.6 Proposed Work Plan

The proposed work plan for the research is provided in Appendix A.

3.7 Expected Contributions to New Knowledge

The expected outcomes from the study are as follows:

(a) Updated CN and/or c values linked to land cover and HSGs used in South Africa.
(b) Refined stormflow volume and peak discharge estimation for the SCS-SA models.
(c) Development of a framework for uncertainty assessment for event based DFE methods used in South Africa.

The following papers are expected to be published from the study:

(a) A Review of Available Curve Number Derivation Methods and the Estimation of Curve Numbers on South African Catchments using Different Derivation Methods

(b) Evaluation of the Performance of Published Curve Numbers and Curve Number Values Calculated using Different Approaches to Estimate Design Runoff Depths for South African

(c) Assessing the Performance of the SCS-SA Model using National Scale Model Parameters Derived using South African Rainfall-Runoff Data

(d) Development of a Framework to Estimate the Uncertainty of the Results from Event-based DFE methods: SCS-SA Case Study

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5. APPENDIX A: PROPOSED WORK PLAN

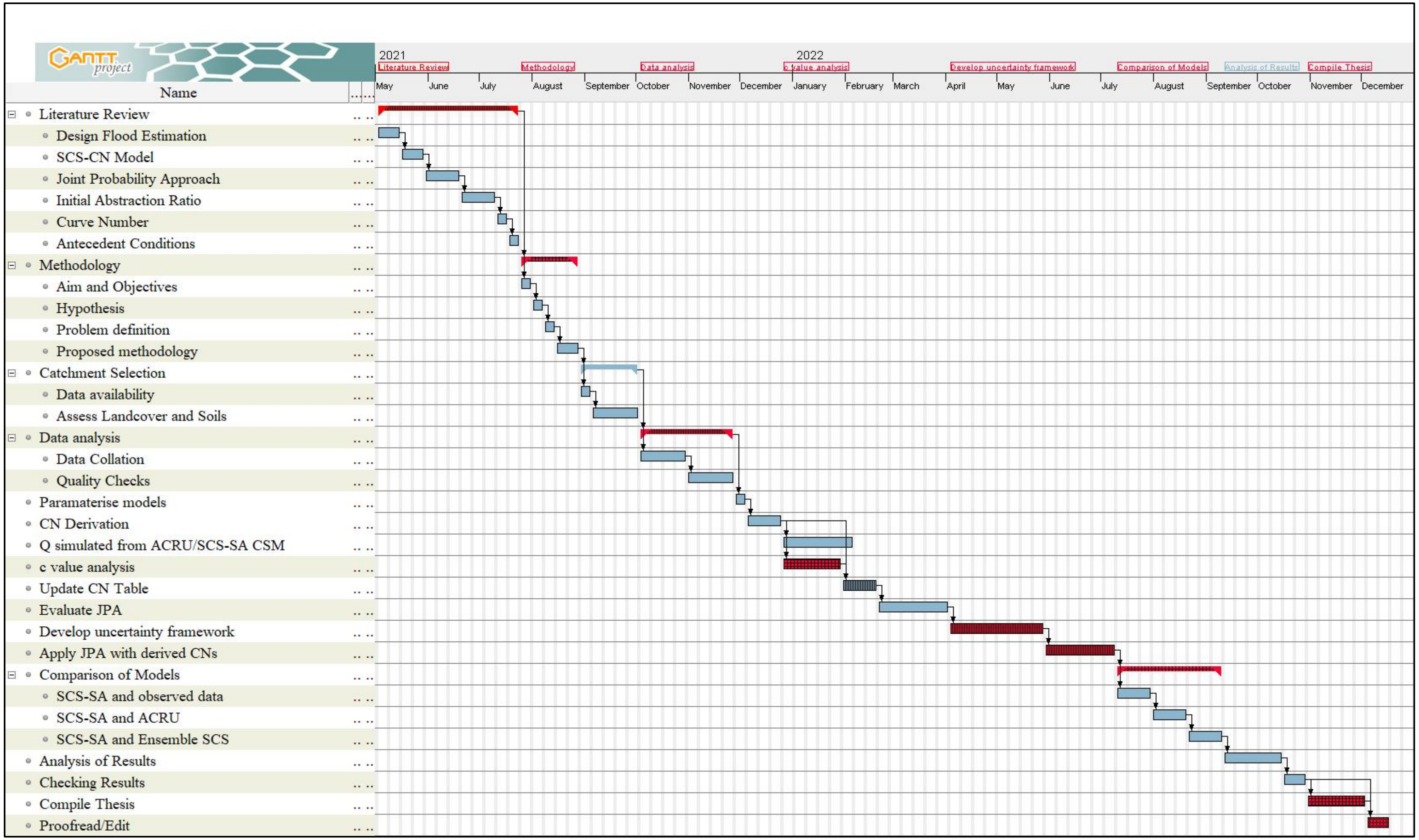

Figure 5.1 Proposed work plan for completion of study