Implementation and Evaluation of the Pitman model in seasonal hydrological forecasting mode using the Kraai River catchment in Eastern Cape South Africa as a case study

by

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Dedication

I dedicate this dissertation to myself, my family, and friends who supported me during the time I was doing this research thesis. A special dedication of this thesis, goes to my late Grandmother MaMtolo, “Ulale ngoxolo Tolokazi”

Declarations

"I declare that the dissertation entitled "*Implementation and Evaluation of the Pitman model in seasonal hydrological forecasting mode using the Kraai River in Eastern Cape South Africa as a case study*" is my own work, and it has not been submitted before for any degree or examination in any other university, and all the sources that I have used or quoted have been acknowledged by means of complete references."

Signed by candidate

Signed by Sesethu Fikileni at University of Cape Town on 05 day of February 2020

Abstract

Seasonal hydrologic extremes such as drought and floods have devastating impacts on human and natural systems (e.g. 2015-2017 Western Cape drought). Sentence has been reworded to: Therefore, the need for a reliable seasonal hydrologic forecast is significant and becoming even more urgent under future climate, as the assimilation of seasonal forecast information in decision making. Hence, SHF becomes part of the short and long-term climate change adaptation strategies in a range of contexts such as energy supply, water supply and management, rural-urban, agriculture, infrastructure and disaster preparedness and relief. This work deals with implementation and evaluation of the Pitman/Water Resources Simulation Model 2012 model (WR2012) in seasonal hydrological forecasting mode. The aim of the study is to improve the understanding of seasonal hydrological forecasting by evaluating the performance of a hydrological model (Pitman Model) in the seasonal forecast mode in Kraai River tertiary catchment (D13) as a case study and the objectives are: To determine steps to be undertaken to implement integration of Pitman in WR2012 configuration with climate forecast to generate seasonal hydrological forecast and to evaluate the performance of the model forced by climate model data in the simulation and forecast mode.

Pitman model in the WR2012 version works with a specific rainfall dataset spanning the period of 1920-2009. Operationalizing the seasonal hydrological forecast with Pitman model requires, therefore, updating of the WR2012 rainfall so that it extends to-date. To achieve that, two datasets were evaluated: Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS), which is a satellite-based gridded rainfall dataset, and rain gauge-based dataset from South African Weather Service (SAWS). The analyses revealed that CHIRPS rainfall data had better correlation and lower bias with respect to the WR2012 data when compared with SAWS rainfall data for the overlap period 1981-2009. The CHIRPS data showed no significant difference from the WR2012 in all the three rainfall zones of the Kraai River catchment. Therefore, CHIRPS data were used to extend the WR2012 data and were used as input to set up Pitman model/WR2012 in the seasonal hydrological forecasting mode.

The Pitman/WR2012 model was forced with 10 ensemble seasonal climate forecast from Climate Forecast Systems v.2 which is downscaled using the Principal Components Regression (PCR) approach. The generated seasonal hydrological forecast focused on the summer season, in particular on the Dec-Jan-Feb (DJF) period, which is the rainy season in the catchment. The hydrological forecast showed skills more especially in Dec and Feb (assessed through ROC and RPSS forecast verification methods) with Jan having a poor skill. Importantly, the skill of streamflow forecast was better than that of rainfall forecast, which likely results from the influence of initial conditions of the hydrological model. In conclusion Pitman/WR2012 model can perform realistically when implemented in seasonal hydrological forecasts mode, and it is important that in that model, the model is run with near real time rainfall data in order to achieve good initial conditions. However, the results in terms of forecast skill are specific to the studied catchment and analysed forecast, and skill of forecast in any other catchment has to be investigated separately.

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Chapter 1: General introduction

1.1 Introduction

The hydroclimatological extremes (i.e. droughts, floods) and hydroclimatological variability in general pose many challenges in water resource management. Flooding and drought events are expected to become more commonplace in the changing climate (Kundzewicz *et al*., 2007). In Southern Africa, where runoff coefficients, or the rate of conversion of the mean annual precipitation to mean annual runoff, of less than 9% (FAO, 2003) water is scarce, and water availability is highly variable both spatially and temporally. Sustainable management of water resource systems is becoming increasingly challenging as a result of intensification of anthropogenic disturbances, channel modifications, land cover changes, and future uncertainty in climate change and variability. Water managers need to solve a variety of interrelated water issues, such as balancing the water quality and quantity, drought, flooding, sustaining biodiversity and ecological purposes and supply of water to service the people (Kapangaziwiri *et al.,* 2013). However, regardless of these constraints, water resource developments and optimal utilisation must continue in order to satisfy the economic and social development needs of communities (Mazvimavi, 2003).

One of the prerequisites for optimal resource utilisation is the prediction of possible hydrological state of an area in the future. Hydrological forecasts can inform applications such as navigation, flood and drought mitigation, reservoir management for hydropower generation, water allocation in agriculture, drinking water and informing the decision-making process for water resource management. The potential economic benefits resulting from accurate hydrological forecasts may include prevention of extremes (drought) related crises, but also economic benefits from improved management of water resources during "ordinary" years. Yao and Georgakakos (2001) and Hamlet *et al.,* (2002) have shown how hydropower revenues can be increased through the incorporation of climate information in hydrologic forecasts. Additionally, the use of hydrological forecasts may be an important adaptation to the non-stationary climate in the future (Pagano *et al*., 2001; Steinschneider and Brown, 2012). Seasonal hydrological forecasts may also influence reservoir operating procedures (Whateley, 2012).

In view of the above, there is a need for the improved understanding of the process of implementation of seasonal hydrological forecasts, their capability to skillfully forecast hydroclimatological conditions leading towards optimal water resource management. Forecasting is the technique to provide information about the meteorological conditions that are expected in the future. There are several types of forecasts, such as weather forecasting, climate forecasting and hydrological forecasting.

The seasonal climate forecasting and seasonal hydrological forecasting have to be contrasted with a weather forecast: weather can be considered as a snapshot of continually changing atmospheric conditions (i.e. over 1-5 days ahead of present) (Iseh and Woma, 2013), climate forecasting is better considered as the statistical summary of the weather events occurring in each season (i.e. average conditions over 3-6 months ahead of present lead time) (Troccoli, 2010). Meanwhile, a seasonal hydrological forecasting is an estimation of future states of hydrological phenomena (Ting, 2012). Therefore, the aim of seasonal hydrological forecast (SHF) is to forecast the land surface hydrologic variables (e.g. streamflow, soil moisture) at monthly to seasonal time scales.

Given the potential benefits of using seasonal hydrological forecasting, these forecasts are surprisingly rarely used (Pagano, *et al.*, 2014, Wolski *et al.* 2018). There are a number of reasons for this. Operational hydrological forecasting systems are not perfect and often observations of precipitation, soil moisture content or evaporation, necessary to implement a good quality seasonal hydrological forecast are lacking. These observations (i.e. precipitation or evaporation) have a huge influence on the initial conditions and initial conditions might be a source of skill in seasonal hydrological forecast (Wood and Lettenmaier, 2006). Moreover, Wood *et al.*, (2005), argued that physical processes that control runoff and streamflow production are much more spatially heterogeneous than those that control weather and climate, which makes preparation of forecasts conditional on the ability to adequately represent hydrological processes at relevant spatial scales.

The most important challenge, seems however, to be low skill in climate forecasts which are used to force hydrological models, as the usability of a seasonal hydrological forecast is strongly conditional on the quality of the seasonal climate forecast. Another challenge arises due to the fact that seasonal hydrological forecasting requires collaboration across disciplines - climate science, and hydrology and water resources. These two sets of disciplines involve use of different models, tools, approaches, modelling paradigms, understanding of uncertainty etc. (Wolski *et al*., 2018). Thus, the simple challenge simply arises in formalizing the process of translation of seasonal climate forecasts into suitable form that is required by a hydrological model to run in the hydrological forecasting mode.

The above-mentioned problems make the operational hydrological forecasting challenging. These issues often lead to water managers or decision makers, in general, even if seasonal hydrological forecast is available, acting in a risk-averse manner and to a mismatch between specific operator needs and accessible information, management and political disincentives (Marshall *et al.*, 2010, Millner and Washington, 2011). Therefore, this leads to limited uptake of the seasonal hydrological forecast, both in the water sector and in the agricultural sector.

In the context of South Africa, there are examples of simple forecasts of hydrological responses (Landman, 2001), and research was conducted towards the development of seamless hydrological forecasting system (Lumsden *et al*., 2019). To our knowledge, there are no operational hydrological forecasting systems in place in any of the water management areas. Additionally, in spite of the earlier research, there is limited knowledge on the use of hydrological or land surface models for operational seasonal hydrological forecasting. Therefore, this study is aimed at improving the knowledge and understanding enabling operationalization of seasonal hydrological forecasting in South Africa. This is done using a hydrological model that is a basis for water resources management in South Africa (Pitman model/WRSM 2012). In this study the Kraai River catchment in Eastern Cape was used as a case study because it is one of the catchments in South Africa that has no significant water or land use development, relatively stable long term Mean Annual Precipitation (MAP) with also less wide ranges of MAP. This catchment thus provides a good testbed for seasonal hydrological forecasting where the quality of the forecast and hydrological simulation in general is influenced by very few factors that are unrelated to the forecast itself, such as quality of data on water abstractions and land use changes.

1.2 Research Question

In order to achieve the aim and objectives of this study the following questions were formulated as the basis of this research project:

1. What are the steps to be taken to implement the Pitman model/WR2012 in seasonal hydrological forecasting mode in the Kraai River?
2. What is the performance of seasonal hydrological forecast based on Pitman model and a selected climate forecast in the Kraai River?

1.3 Problem Statement

There is a limited application of hydrological models in operational seasonal hydrological forecasting in South Africa. The Pitman model/WR2012 is used as the principal tool for water management in RSA (at the country scale) and some parts of Southern Africa (Pitman, 1973, Midgley *et al.*, 1994; Hughes, 2004; Hughes *et al.*, 2006; Kapangaziwiri, 2007a, 2010b; Bailey, 2008). However, to our knowledge, there are no implementations of the Pitman model/WR2012 in seasonal forecasting mode in South Africa. When Pitman model is used to evaluate future (i.e. forthcoming season) state of water resources for catchment water management, that is typically done with stochastic rainfall that are based on historical time series (Hughes *et al*., 2011). As a result, there is no information about the actual "expected" future conditions. Furthermore, in South Africa hydrological forecasting appears to be less studied than seasonal agricultural forecast and seasonal climate forecast.

The reasons for the limited application of hydrological models in seasonal hydrological forecasting mode in South Africa are as follows; (a) the fact that seasonal hydrological forecasts are generated within the science and practice domain which emanate from different disciplines (i.e. hydrology and climate science). This has implications in terms or understanding and using the climate forecast by hydrologists and water managers; (b) The low to fairly predictive skill of seasonal climate forecasts which seasonal hydrological forecasts have to rely on to generate the forecasts (Wolski *et al*, 2017).

1.4 Study aim and objectives

1.4.1 Aim

The aim of this study is to improve the understanding of seasonal hydrological forecasting by implementing and evaluating the performance of Pitman Hydrological Model (WR2012 version) in the seasonal forecast mode in Kraai River of Upper Orange catchment management area as a case study.

1.4.2 Objectives

To determine steps to be undertaken to implement integration of Pitman in WR2012 configuration with climate forecast to generate seasonal hydrological forecast.

To implement Pitman/WR2012 model in the seasonal forecast mode.

To evaluate the performance of the model forced by climate model data in the simulation and forecast mode.

1.5 Rationale

Seasonal hydrological forecasting is very important and is linked to a variety of practical applications from socio-economic sectors such as energy management, agricultural management, health planning, and tourism to weather risk and security issues such as disaster forecasts and

prevention, food security or water resource management. The information from seasonal hydrological forecasts can assist in planning, management and mitigation decisions for users from many sectors of the economy. The analysis of projection of both climate and population changes in the 21st century serves as an indicator of a general likelihood of increased water stress in South Africa (Arnell, 2004).

Given the serious state of the current climate condition and increase in water demand and supply in South Africa an improved understanding of the linkages between climate and hydrology is highly beneficial (MacKellar *et al.*, 2013). Therefore, the need for a reliable seasonal hydrologic forecast is significant and becoming even more urgent under future climate, as the assimilation of seasonal forecast information in decision making becomes part of the short and long-term climate change adaptation strategies in a range of contexts such as energy supply, water supply, rural-urban, agriculture, infrastructure and disaster preparedness and relief.

Seasonal hydrological forecasting is an essential component of an early drought forecasting system that can provide advance warning and alleviate drought impacts (Pozzi *et al.*, 2013). For example, operational seasonal hydrological forecasting would have been critical in the past drought in Western Cape (Wolski, 2017). However, such knowledge of seasonal hydrological forecasts in South Africa is minimal which may greatly inform strongly on how to manage the Western Cape dams.

This case study is very important in South Africa from the perspective of wider utilization of seasonal hydrological forecasts. It illustrates how to operationalise seasonal hydrological forecasts for utilisation by the catchment managers. This information from the SHF may assist to have knowledge about the expected condition of water resources and hydrological conditions at the timescale of months to seasonal in the Water Management Agencies across the country.

1.6 Methodological Approach

The study adopts a quantitative desktop approach, where the data is sourced from different entities. The generic focus of the study is on implementation and evaluation of the Pitman/WR2012 model in seasonal hydrological forecasting because the study seeks to determine steps, procedures and processes to be followed for seasonal hydrological forecast using the Pitman model, and to illustrate how the Pitman model performing in seasonal forecasting when forced with climate forecast.

1.7 Research Study Outline

This study is divided into four chapters as follows: Chapter 1: Introduction - This chapter introduces the intended work and the context of the research conducted. Chapter 2: Literature review - This chapter presents a reviewed literature in an analytical and systematic manner to provide what is known and unknown about the study topic in South Africa and beyond. Chapter 3: Research design and methodology. This chapter describes the research design of the study and explains the methods that were used in the study. Chapter 4: Results - This chapter presents the description results obtained on this study. It further discusses the obtained results and their implication to this study. Chapter 5: Conclusion and Recommendations - This is the last chapter of this project which provide conclusion and recommendations of this study based on Chapter 4.

Chapter 2: Literature Review

This chapter presents a review of literature in an analytical and systematic manner to provide what is known about the study topic in South Africa and beyond. This chapter reviews the literature on seasonal forecast, with the main focus on seasonal hydrological forecasting in general, and data collection methods, data analysis methods and the results found in the reviewed studies in particular. The last part of this chapter is the research framework diagram of this proposed study.

2.1 Background on Water Resources in South Africa

South Africa is generally arid to semi-arid region that is water stressed, with an average rainfall of about 450 mm per year, which is well below the world average of about 860 mm per year (DWA, 2004) and only 8% of our land area produces 50% of our surface run-off (WWF, 2013). The rainfall variability also results in extended wet and dry periods across the country. Hydrological variability is driven by climate and weather variability and moderated by catchment properties.

The total surface water available in South Africa on average is about 49 200 million m^3 per year, of which about 4 800 million m^3 per year originates from Lesotho (DWAF, 2008). South Africa is mainly dependent on surface water resources providing just under 11000 m^3 per year. Although groundwater only provides about 10% of this volume, it is extensively utilized, particularly in rural and arid areas and the main users of surface water resources are agricultural irrigation, domestic, industrial, mining and power generation. The economic growth, urbanization and population growth continues to increase the demand for water resources in the country.

2.2 Hydrological Modelling

The main purpose of hydrological modelling with rainfall-runoff models can be defined as the process of simulating hydrological processes at some level of complexity that allows generating streamflow series based on rainfall and other meteorological variables. Once established, a hydrological model can be used, often in scenario-like approach, to design and manage water supply schemes and civil structures (Hughes, 1995, Mwelwa, 2004). Hydrological models are a simplified representation of the real-world system (Sorooshian et al., 2008). Models are simply sets of mathematical equations implemented in a computer system that enables calculating runoff as a function of hydrological inputs, such as rainfall and evaporation, and various parameters used to describe catchment characteristics, such as soil properties, soil moisture content, vegetation cover, evapotranspiration/evaporation and groundwater aquifer characteristics (Fig. 2.1).

In the context of SA, hydrological modelling has a long history and has played a huge role in water resource management through a number of country-scale water resources assessment studies, from WRSM 1990 (Midgley *et al*., 1994), WRSM 2000 (Pitman, *et al*., 1999), WRSM 2005 (Middleton *et al.,* 2008) and the latest which WRSM 2012 (Bailey and Pitman, 2015) (Appendix 1). On the research side, there is a large number of publications on hydrological modelling in SA (e.g. Hughes, 1995, 2004, 2006; Schulze, 1995; van Tol *et al.*, 2015; Kusangaya *et al.*, 2016). However, there is limited knowledge on seasonal hydrological forecasts using hydrological models which this study is exploring at small scale (Tertiary catchment) (e.g Lumsden and Schulze, 2012).

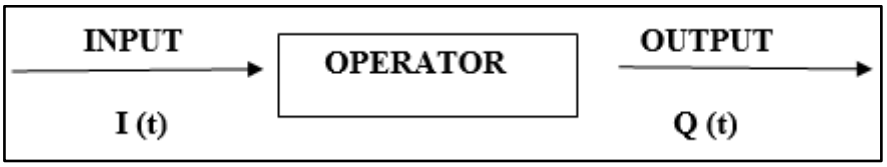

Figure 2.1. Schematic representation of system operation for a hydrological model.

2.2.1 Types of Hydrological Models

There are many different types of hydrological models used to simulate hydrology of a catchment. The choice of a type of a model depends on the nature of research or problem that the modes is to address. Hydrological models are classified based on several criteria (Fig. 2.2):

- spatial representation: lumped, semi-distributed, fully-distributed,
- way of representing hydrological processes: physically-based, empirical and conceptual,
- way of handling variability of inputs/processes/responses: deterministic and stochastic.

Lumped models assume that the entire catchment is taken as one unit where spatial variability is ignored. Hence, its outputs are generated without considering the spatial heterogeneity of hydrological properties and fluxes. Distributed models operate by dividing the whole catchment into small units, normally in square cell network, so that parameters, inputs and outputs can vary spatially (Sorooshian, 2008).

Physically-based models represent hydrological processes, such as infiltration, using equations based on physical description of that process. Conceptual models use simplified equations that capture the nature of relationships, while empirical models are based on statistical relationships between inputs and outputs. Deterministic models are models in which its variables do not vary randomly. Deterministic models normally use non-linear partial differential equations that describe hydrological processes (Jajarmizadeh *et al.*, 2012). Stochastic models have a random component that allows generating stochastic output, which is a way of expressing uncertainty of inputs or parameterization, or model in general. The uncertainty is normally described by statistical properties of the output (i.e. variance or confidence interval).

In the context of SA, there are two hydrological models which are commonly used in SA for water resource management, simulation and research purposes. These models are; Pitman model (Pitman, 1973) and ACRU (Schulze, 1995). Both Pitman and ACRU models are semi-distributed, conceptual, with some processes represented through physical equations, and deterministic. The ACRU model is mostly applied for daily catchment modelling (often in agricultural crop assessment context) with intensive data requirements while Pitman model is used on daily and monthly time step in the context of water resources evaluation. There are also other models such as SWAT, MIKE-SHE that are used in individual catchments for a variety of purposes (e.g. Tetsoane, 2013; Prucha *et al.*, 2016).

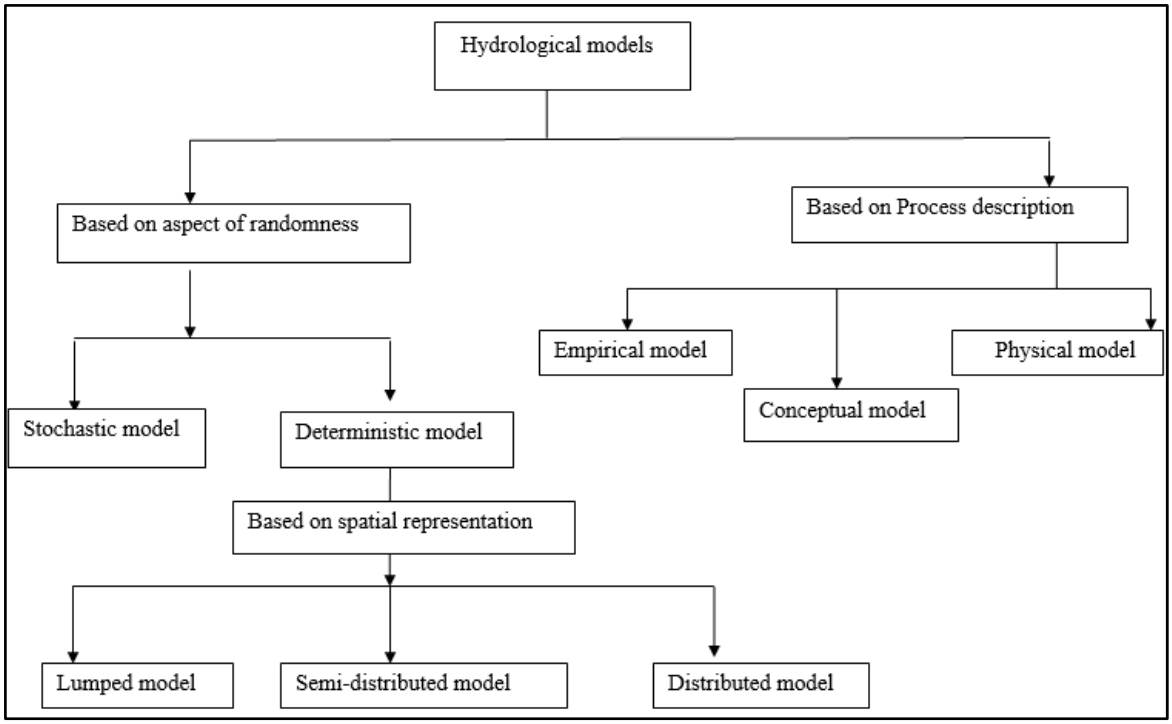

Figure 2.2. General classification of hydrologic model (Adopted from Singh, 2018).

2.2.2 Model Calibration

Performance of hydrological models depends on how well they can capture hydrological processes in a modelled catchment. That depends on model structure (i.e. whether the model can represent relevant hydrological processes, for example baseflow, or wetlands evaporation) and on reasonable values of model parameters. Hydrological model parameters are often difficult or almost impossible to measure and therefore difficult to be known a priori, i.e. before the model is implemented. Parameter values may be guessed by expert knowledge or transferred from a neighbouring or similar hydrological catchment (Brath *et al.*, 2006). Typically, however, parameters are calibrated. Calibration is defined as the process where values of the model parameters are adjusted for the use in a particular location and application. Typically, this process consists of the use of rainfall and streamflow observations and the procedure to identify the model parameters which can give best agreement between observed and simulated stream (Kumarasamy and Belmont, 2018).

2.2.3 Model evaluation

The evaluation of model performance as described by Moriasi *et al.*, (20007) gives guidelines for quantification of accuracy in catchment modelling. Evaluation criteria express closeness of fit between simulated and observed hydrological responses, typically flow at the catchment outlet (Dawson *et al.*, 2005). Evaluation requires both graphical and numerical analyses of differences between simulated and observed data (Hwang *et al.*, 2012). There are many methods used for evaluation but two are commonly used: Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and Percent Bias (PBIAS) (Gupta *et al.*, 1999) known as objective functions.

2.2.4 Sources of uncertainty in hydrological models

Given the usefulness of the hydrological models as tools to be used in water resource management, it is difficult to characterise all the hydrological processes and simulate future responses of a catchment without acknowledging the uncertainty involved in modelling. Therefore, there is a need to understand the sources of uncertainty in hydrological models because this has implications on the model use. Two main sources are input data errors and inadequacies of model structure including model parameterization (Pellicciotti *et al.*, 2012; Her *et al.*, 2019). Furthermore, errors in the runoff measurements can lead to suboptimal model selection and parameterization (Tyralla and Schumann, 2016). These sources of uncertainties are handled in different ways. Errors in input rainfall data can be handled explicitly in some cases, e.g. through performing multiple simulations with errors in input data captured by the error variance of kriging interpolation (Götzinger and Bárdossy, 2008). For model structure error, the most popular used strategy to reduce model structure uncertainty is to use an ensemble of structurally different models and combining their individual results. The combination outperforms single models in cases where the structural diversity within the ensemble approximates the given structural uncertainty sufficiently (Winter and Nychka, 2010).

2.3 Seasonal Climate Forecasting

Forecasting is the process of predicting future conditions. Weather forecasts provide information of atmospheric variables (such as rainfall) expected over the next 3-5 days, often on an hourly or sub-hourly basis. Due to the nature of the climate system, however, it is not possible to predict individual day's conditions in detail beyond that (Iseh and Woma, 2013). Seasonal climate forecasts are forecasts of the expected climate conditions for the next three to six months and more and are typically expressed as monthly or seasonal means of weather variables and not through weather conditions on individual days. As such, seasonal climate forecasts are different than, and occupy an intermediate zone between, weather forecasting and climate projections (Doblas-Reyes *et al.*, 2013).

2.3.1 Source of predictability of seasonal climate forecast

Climate predictability is the extent in which an informative prediction is possible if optimum procedures are used. That is typically considered in the noise-signal framework, with a certain proportion of variance of the predicted variable considered to be a predictable signal related to a certain source of predictability, and the reminder considered to be unpredictable noise. (Doblas-Reyes *et al.*, 2013; NRC, 2010; Kharin and Zwiers, 2003).

Skillful seasonal prediction is related to several sources of predictability, including inertia, external forcing, and patterns of variability (NRC, 2010). However, it is also important to understand that the atmosphere (and the climate system more broadly) is a chaotic system because this has implications on the skill of the seasonal forecast.

Sources of predictability differ between weather and seasonal forecast. The weather forecasts predictability comes from initial atmospheric conditions (i.e. the current state of the atmosphere). The influence of these initial conditions does not last very long because of the chaotic nature of the climate system (i.e. its extreme sensitivity to initial conditions). However, the weather forecast is only for several days ahead when the influence of the initial conditions still manifests. The

same does not apply to seasonal climate forecast, as it spans well beyond the time of persistence of the initial conditions of the atmosphere (Brayshaw, 2018; Krishnamurthy, 2019).

Instead, seasonal forecast relies on persistence of boundary conditions. The common sources of predictability on seasonal and interannual timescales are the slowly varying boundary conditions such as sea surface temperatures (SSTs) soil moisture, sea ice (Li and Ding, 2015). In addition, one of the important sources of predictability is the El Niño-Southern Oscillation (ENSO) phenomenon which is a dominant mode of variability in the tropical Pacific (Li and Ding, 2015; Doblas-Reyes *et al.*, 2013). This is because the large spatial shift in tropical rainfall associated with ENSO leads to large-scale changes in the global circulation and precipitation (Alexander *et al.*, 2002), and because ENSO varies (or persists) at relatively long-time scales (seasons to years), hence ENSO becomes a primary source of predictability in many regions of the world regions. Therefore, the assessment of the skill of ENSO and SSTs predictions is a fundamental requirement for any seasonal forecasting system (Stockdale *et al.*, 2011).

2.3.2 Types of seasonal climate forecast

There are two types of seasonal climate forecasts: statistical and dynamical forecast. The first is the statistical modelling (produce statistical forecast), the simpler of the two, is based on the modelling of historical relationships between the climate anomalies to be predicted and the underlying forcing mechanisms which is typically observed SST (Landman *et al.*, 2011). The shortness and the quality of the climate record often limit accuracy of such forecasts, and non-stationarity of the climate is a further complicating issue (Tippett *et al.*, 2005).

The other approach is the dynamic modelling with a general circulation model (GCM) or Atmosphere-only GCM (AGCM) that simulates processes in the climate system involving solving the numerical equations describing fluid dynamics and thermodynamics processes in the atmosphere. The dynamical models are based on physical laws of nature, but due to computational limitations, they are unable to solve all spatial and temporal scales, which together with the limitations arising due to the chaotic nature of the climate system, leads to uncertainty in forecasts.

2.3.3 Causes of uncertainties in seasonal climate forecast

Uncertainty is a state of incomplete knowledge that can result from lack of information or disagreement about what is known. Uncertainty is an unfortunate yet inevitable part of any forecasting system (DeChant and Moradkhani, 2014). Within the context of seasonal climate forecasting, these uncertainties can be attributed to two main causes: initial condition and model uncertainty.

The initial condition uncertainty is as a result of the chaotic nature of the climate system (not just its complexity) which limits the ability to forecast its state beyond a couple of days in a deterministic way. The initial condition uncertainty is usually regarded as less important than other forms of uncertainty such as model uncertainty (Werndl, 2017). To account for the initial condition uncertainty, seasonal climate forecasts have a probabilistic nature (Klopper and Landman, 2003) and are based on an ensemble of model simulations (Fig. 2.3). Each of the ensemble members expresses a possible state of the climate system that is conditioned (or dependent) on the particular initial condition.

The second type of uncertainty, the model uncertainty arises due to the inability of dynamical models of climate to simulate every single aspect of the climate system with arbitrary detail (Yip

et al., 2011). Climate models have limited spatial and temporal resolution, so that physical processes that are active at smaller scales (e.g. convection, orographic wave drag, cloud physics, mixing, etc.) must be parametrized using semi-empirical relationships (Doblas-Reyes *et al.*, 2009). Different models have different ways of parameterizing processes, which leads to differences between their forecast outputs. Model uncertainty is captured by using a multi-model ensemble. Apart from quantifying model uncertainty, multi-model ensemble forecasts often reduce forecast errors, providing a better forecast (Tebaldi and Knutti, 2007).

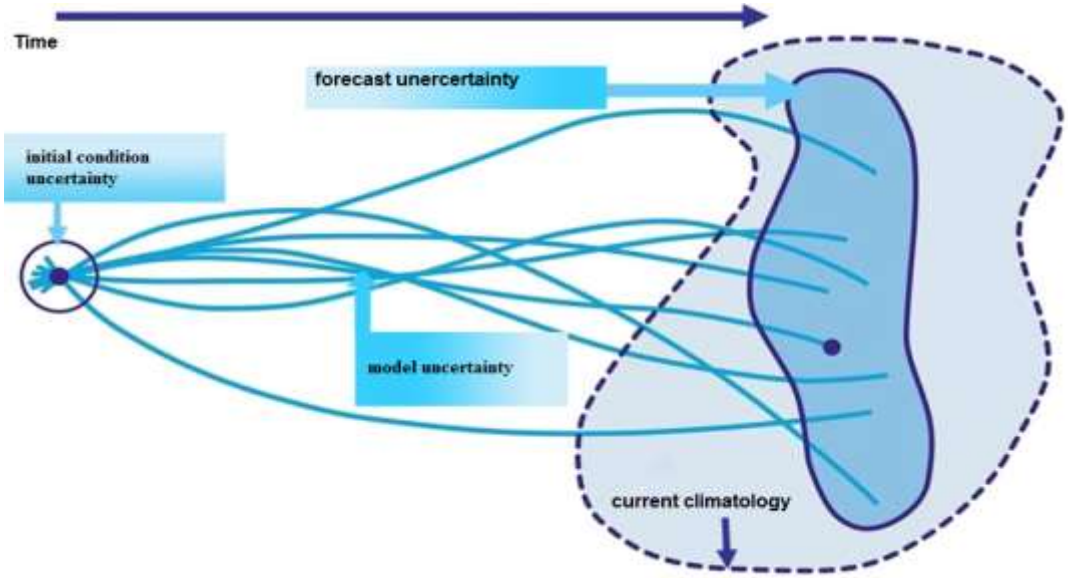

Figure 2.2. Schematic of a probabilistic forecast using initial condition uncertainties (adopted from Slingo and Palmer, 2011).

The blue lines on figure 2.3 shows the trajectories of the individual forecasts that diverge from each other owing to uncertainties in the initial conditions and in the representation of sub-grid scale processes in the model. The dashed, lighter blue envelope represents the range of possible states that the real atmosphere could encompass, and the solid, dark blue envelope represents the range of states sampled by the model predictions (Slingo and Palmer, 2011).

2.3.4 Seasonal Climate Forecasting in South Africa

In terms of application in the country, the seasonal forecasts have evolved from a simple statistical model to forecasts based on the AGCMs and statistical downscaling, fully coupled GCMs and integrated within multi-model (Landman, 2014). South African Weather Services (SAWS) is the country's official meteorological service that currently operates a fully-interactive coupled modelling system, named the SAWS Coupled Model (SCM), the first of its kind in both South Africa and the region (SAWS, 2018). Each month its scientists produce a 3 months rainfall and temperature outlook using a multi-tiered forecast system consisting of a dynamic modelling process, combined with a statistical approach and a consensus discussion (Landman *et al.* 2001; Johnston *et al.* 2004).

Until a few years ago, apart from SAWS, two additional institutions in South Africa generated and produced numerical seasonal climate forecasts which were then made available online at (www.gfcsa.net) every month. These were at the Council for Scientific and Industrial Research

(CSIR) and at the Climate System Analysis Group (CSAG) of University of Cape Town. Due to a number of institutional and human resources reasons, the CSIR initiative has been merged with that of SAWS, the CSAG's forecast has been discontinued in 2016 due to concerns around the poor quality of the forecast and ethical concerns around the consequences of its poor skill for decisions that might be taken based on it in agricultural, water management and other contexts.

In terms of research, there is a large number of published studies that address the issue of implementation and skill of seasonal climate forecast in South Africa. For instance, on the skill of mid-summer rainfall in Southern Africa (Landman *et al.*, 2012; Landman and Bareki, 2012). The skill was assessed over a 22-year retroactive test period (1980/1981 to 2001/2002) by considering multi-model ensembles consisting of downscaled forecasts. Meanwhile, Engelbrecht *et al.*, 2017, on the skill in predicting intraseasonal characteristics of synoptic type occurrence at the seasonal time scale over all year rainfall by utilizing ensemble of simulations performed using GloSea5 coupled ocean–atmosphere model.

The use of seasonal climate forecasts in South Africa is becoming a more established part of climate information. These seasonal climate forecasts have potential uses in the agricultural sector (planning planting dates, irrigation, and crop type) and in water management sector (Klopper *et al*., 2006; Winsemius *et al.*, 2014). For instance, Kgakati and Rautenbach (2014) examined the use of seasonal climate forecast information in the agricultural sector in South Africa, mainly looking at dissemination of early warnings to reduce risks faced by farmers. The study assessed the channels through which the seasonal climate forecast information is disseminated to the end-users. The results showed that improved channels and structures that are reliable and timely seasonal climate forecast information can serve as early warning should be developed. However, the integration of seasonal climate forecast information by smallholder farmers into their farm planning has been poor because of the lack of forecast skill, communication and inability to see the relevance of seasonal climate forecast for specific farming decisions (Chisadza *et al.,* 2020).

Amongst other studies on seasonal climate forecasts in South Africa, is the use of seasonal climate forecasts in the health sector as an early warning system for malaria (Kim *et al*., 2019). The study used well organised malaria surveillance and high-quality climate forecasts to sustain malaria early warning system in conjunction with an effective malaria prediction model. Weather-based malaria prediction model was developed using a weekly time series data including temperature, precipitation and malaria cases from 1998-2015 in Vhembe, Limpopo, South Africa and was applied to seasonal climate forecast. The results showed that the developed weather-based malaria prediction model could be applicable in practice together with skilful seasonal climate forecasts and existing malaria surveillance data.

2.4 Seasonal hydrological forecasting

Hydrological forecasting is often mistaken with hydrological prediction yet these two are not the same. Hydrological forecasting as defined by (Nemec 1986) to be the prior estimate of future states of hydrological phenomena in real-time**.** Meanwhile, the hydrological prediction is defined as a statement regarding the future occurrence of the hydrological phenomena without regard for their actual time of occurrence, for example about the probability distribution of future discharges, return periods of flood (WMO, 1994). Hydrological forecasting comprises additional technical activities (Nemec, 1986) connected with other hydrological and hydrological subjects like data processing, remote sensing, operational use of computer network design etc**.**

Hydrological forecasts are categorised into short-term hydrological forecasts which are generally considered to extend 2 days from issue of the forecast, medium-term forecasts extend from 2 to 10 days, and seasonal forecasts extending for several months (WMO, 2008). The choice of a forecast lead time depends on what the forecast is to be used for (Musy *et al.*, 2014), an example is the short-term hydrologic forecasts that may, for instance, be used to reduce potential flood or drought damage, while longer-term forecasts are used to optimize the management of water resources.

2.4.1 Different ways of generating seasonal hydrological forecasts

Hydrological forecasts can be generated using different techniques, such as dynamical and statistical or hybrid and span different degrees of complexity and information requirements (Grillakis *et al.*, 2018).

Dynamical methods use simulation models to represent hydrological processes, and describe the future using inputs from seasonal climate forecasts, typically in the form of an ensemble of initial condition simulations generated by a numerical weather prediction (NWP) system (Becker *et al.*, 2016, Cloke and Pappenberger, 2009; Cuo *et al*., 2011).

The dynamical models may be implemented in an Ensemble Streamflow Prediction (ESP) approach (Day, 1985; Wood and Lettenmaier, 2006; Yuan *et al.*, 2013; Bazile *et al.*, 2017) which relies on the deterministic hydrological model simulations forced with observed climate inputs up to initialisation time of the forecast.

The statistical approach (Pagano *et al.*, 2009; Moradkhani and Meier, 2010) relies on empirical relationships between seasonal stream flow volumes and large-scale climate variables in catchment observations. The hybrid approach strives to combine the strengths from both statistical and dynamical techniques to produce hydrological forecasts (Sene, 2010; Jiao *et al.*, 2016).

Increasingly, seasonal hydrological forecasts are generated within global climate, or earth system models, reducing the need to link two independent and not always compatible modelling systems. This is possible because as a result of continuous development the land surface models embedded in GCMs attain accuracy in simulating hydrological processes that is compatible with that of fully-fledged hydrological models. The system developed and operated by ECMWF is one of such systems, in which GCM is integrated with a land surface model (Pappenberger *et al.*, 2010).

2.4.2 Hydrological forecasting in South Africa

Currently, seasonal hydrological forecasting activities in SA are limited. There appears to be no operational seasonal forecast where a hydrological model is linked to a seasonal climate forecast, although recently, there have been efforts at SAWS of linking a land surface model with the operational seasonal climate forecast (de Wit *et al.*, 2019).

One of the earlier studies on seasonal hydrological forecasting in South Africa is the work by Landman *et al.*, (2001). The categorical forecasts (above-normal near-normal and below-normal) were issued for Tugela and Vaal rivers. These forecasts were based on a statistical downscaling of GCM fields directly to streamflow at a catchment exit. These forecasts were made for the DJF summer season over an 8-year independent period from 1987/1988 to 1994/1995. This approach

was planned to be later extended to cover the whole South Africa (Landman *et al.,* 2009), where statistical relationship had been based on naturalized streamflow obtained from ACRU hydrological model (Schulze, 1995).

In another initiative, The SAWS initiated implementation of ACRU model linked with a coupled climate model, which was aiming at creating an earth system model like configuration to be used in a seasonal hydrological forecasting context. However, the generated forecasts were last updated in June 2011. These forecasts are available online through South African Risk and Vulnerability Atlas (htt://rava.qsens.net/themes/climate-temperate/seasonal-forecasts/Streamflow.PDF/view).

River flow prediction based on rainfall forecasts from a coupled general circulation model over South Africa was implemented by Olivier *et al.,* (2013). The ACRU model was selected for the purpose of the daily time step. Measured river-flow data was obtained from the Hydrological Information System (HIS) and the Department of Water and Sanitation (DWS). A Multiple Program Multiple Data procedure (Beraki *et al.*, 2013) was applied to provide large scale predictors to be downscaled. A downscaling process was done retroactively by applying the CCA option of Climate Predictability Tool to the CGCM seasonal output and river flow measurements.

In the study conducted by Malherbe *et al.,* (2013) the SINTEX-F coupled model was used to forecast maize yield and streamflow in Limpopo province. SINTEX-F hindcasts of DJF 850 hPa geopotential height fields were statistically downscaled to yields at four agricultural districts and to flows at six river flow gauges using Model Output Statistics (MOS) (Wilks, 2011) approach. Results suggested the potential for a commodity orientated forecast system for application in agriculture in an operational environment. Therefore, the study serves as a baseline study for runoff models using GCM output data towards estimating potential yields and streamflows of a particular catchment.

The recent work was done by Wolski *et al.*, (2017), - used the so-called land surface model (VIC) rather than a traditional hydrological model, targeting relative importance of initial and boundary conditions. The experiments involved running the land surface model multiple times in retrospective forecast mode, with individual simulations differing in both initial and boundary condition in the Ensemble Streamflow Prediction setup described by Wood and Lettenmeier (2006). The results obtained from that study showed that at small spatial scales (~2500km2) there is a very low, almost non-existing sensitivity to initial conditions.

This study stems from the above described landscape of seasonal hydrological forecasting, and, as described in the objectives section, addresses the aspects of the implementation of Pitman model, which is a basis for water resources management in RSA, in the seasonal forecasting mode.

2.4.3 Factors affecting adoption and use of seasonal hydrological forecasts

There are three main issues of concern in SHF from the forecasters, hydrologists, decision-makers and the end-user's perspective:

1) the lack of access to real-time hydrological data (Tao *et al.,* 2016),

2) accuracy (skill) and uncertainty of forecast (Pagano *et al.*, 2014)

3) communication and dissemination of forecast (Yuan *et al*., 2016)

Although real-time hydrological data are a prerequisite to generating good quality seasonal hydrological forecasts, politics and finance are often contributing issues for the lack of data sharing because streamflow and reservoir storage data are considered national assets and are either protected or sold for a fee (Viglione *et al*., 2010; Wolski *et al.*, 2017). There is also not as much incentive for international collaboration in hydrology as there is in other fields (Pagano *et al*., 2014). However, although real-time data remains an issue, some hydrologists have managed to do modeling studies using unprecedented datasets from thousands of catchments in an emerging field called "large-sample hydrology" (Gupta *et al*., 2014).

Skill of seasonal hydrological forecasts is critically important in order for water managers and emergency protection services to adopt forecast in their operations (Pagno *et al.*, 2014). There are quite a few factors that affect the quality of forecast i.e. sources of predictability and theoretical limit of skill of the climate forecast, the practical skill of the climate models at given region, the availability of single model and multi-model ensemble forecast and the process of downscaling GCM forecast to a resolution of a hydrological model. The second has consequences to the use of forecast information. The skill of seasonal hydrological forecasting is typically low at longer lead times (Wanders *et al*., 2016) as it is tied to the skill of the precipitation/temperature forecasts (Hamill, 2017), availability and quality of hydrological monitoring data, also the nature of the hydrological system (i.e. the level of predictability from the initial hydrological conditions (Shukla and Lettenmaier, 2011; Wolski *et al.*, 2018).

Even though the seasonal hydrological forecasts skill is improving, it still remains doubtful to several users whether seasonal forecasts can be trustworthy or skilful enough to enhance decision-making (Rayner *et al*., 2005). There are many issues involved that affect the uptake of SHF such as understanding of the nature of seasonal forecast (probabilistic meanwhile water managers and hydrologist tend to work with deterministic forecast information), communication of the skills and limitations of the forecast. These cannot be resolved without cross-disciplinary dialogue and collaboration (Yuan *et al.*, 2016). This is because hydrological forecasting involves different stakeholders i.e. hydrologist, end-users, water managers, climatologist etc. Therefore, cross-disciplinary dialog could play a better role in resolving the above-mentioned issues (Wolski *et al.*, 2017).

Chapter 3: Research Design, Data and Methodology

This chapter describes the research design, the study area and methods that are used for data collection and data analysis in this study.

3.1 General design of the research project

This study uses a quantitative research approach as it is focusing on seasonal hydrological forecasting in the Kraai River Catchment, which is a part of the Upper Orange River Catchment. This study is a desktop study because secondary data are used which are obtained from different sources like government departments, and research organizations. These data include observed hydrological and climate data, existing hydrological model simulation results and forecast and retrospective forecast data.

This study follows a desktop research approach, where the process of implementation of seasonal hydrological forecast with the Pitman model is first interrogated from the perspective of both practice of that model use, and practice of creation of seasonal climate forecasts. Subsequently, the Pitman model is set up in the seasonal forecasting mode in the Kraai River catchment, and seasonal hydrological forecasts is implemented using retrospective climate forecasts. Finally, the performance of those forecasts is assessed in terms of their ability to predict historical observations. The general methodological approach adopted in this process is illustrated in Fig. 3.1.

The methodological approach is based on three major steps:

1. Description and review of a) the Pitman model, its configuration and implementation from the perspective of data flow and b) typical process of issuing of seasonal climate forecast from the perspective of data flow. That process leads to the identification of critical steps that have to be executed in order to be able to link the seasonal climate forecast with the Pitman model.
2. Setting up of the Pitman model in the seasonal forecasting mode, including analyses and processing of data within the critical steps identified in the first step.
3. Implementation of seasonal hydrological forecast based on retrospective forecasts from a selected forecasting system, and evaluation of results.

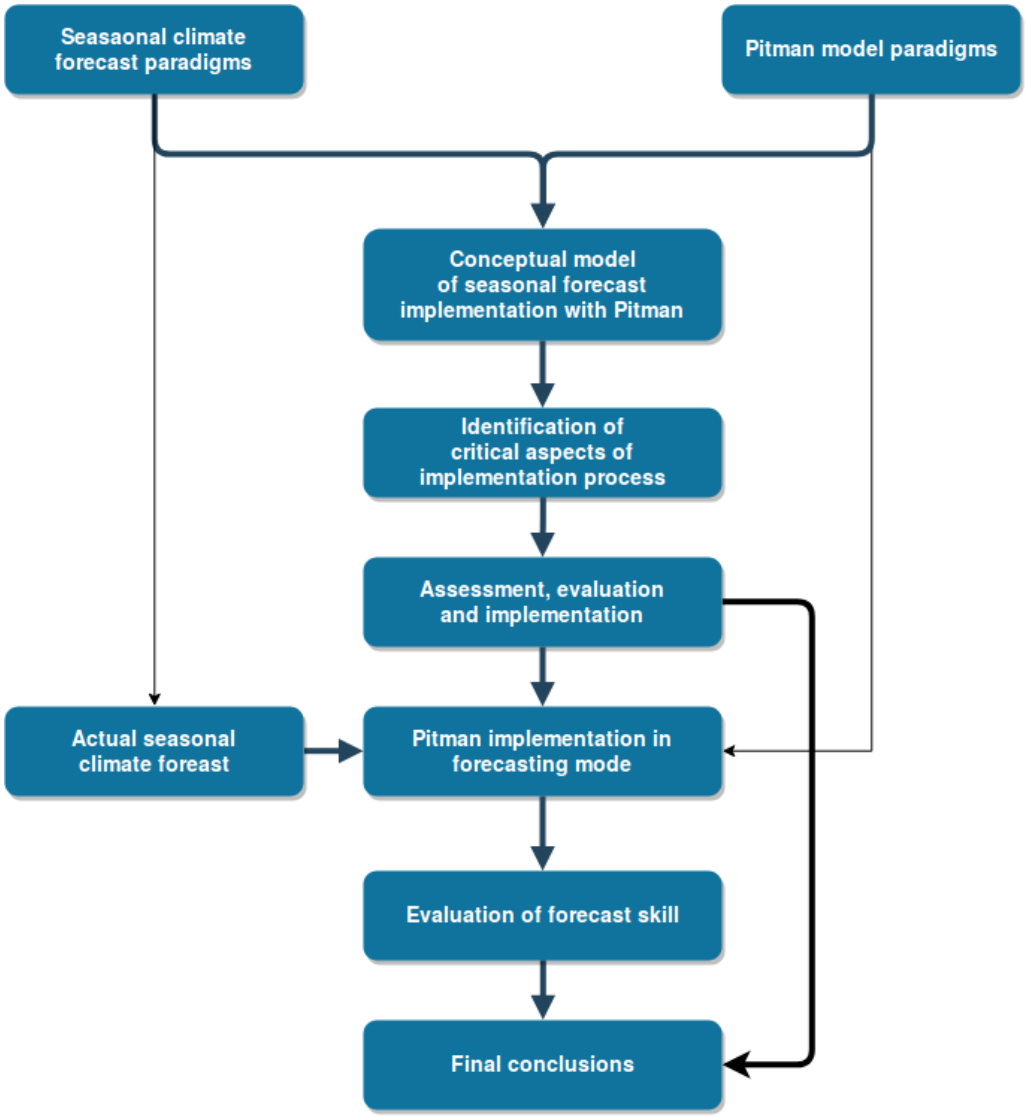

Figure 3.1. Schematic illustrating the general methodological approach of the study

3.2 Data

3.2.1 Seasonal forecast data

This research utilizes seasonal forecasts data generated by Climate Forecasting System v.2, (CFS) (https://www.cpc.ncep.noaa.gov/products/CFSv2/CFSv2_body.html). The CFS system is a medium and long-range numerical weather prediction and climate model which is operated by the National Centres for Environmental Prediction (NCEP) and based on initial conditions of the last 30 days, with 4 runs from each day (Saha *et al.*, 2014). The reforecast spans on the period of Dec 1981 to March 2011, with the period of April 2011 to date covered by archived operational seasonal climate forecasts.

For the purpose of this research, reforecast and operational data for the period of 1982-2016 were downloaded from (http://www.cpc.ncep.noaa.gov). The data included 10 members of forecast ensemble issued in the beginning of December and covering the period of Dec-Jan-Feb of each year.

The downscaling of the forecast was done using PCR approach described in detail in section 3.3.3. That approach utilizes forecast fields of geopotential height at 850mb, that are subject to Principal Component decomposition, and WR2012 data as observational data to develop the regression relationship.

The downloading, processing and downscaling steps described above on this study were not carried out explicitly for this study, but rather, data processed at CSAG in the framework of a WRC project on seasonal hydrological forecasting was used.

3.2.2 WR2012 dataset

The WR2012 rainfall and streamflow data was downloaded from the (waterresourceswr2012.co.za) online website summarizing the Water Resources of South Africa, 2012 Study (WR2012) for water resources of South Africa (Bailey and Pitman, 2015). This data was compiled through a WRC funded project for Water Resources of South Africa. The study was done to have an accessible data inventory for water resources of South Africa, Lesotho and Swaziland and the relevant data on water resource management.

The rainfall data in the WR2012 covers a period from 1920 to 2009 at monthly time step (Allan *et al*., 2015). The WR2012 dataset was developed using data from individual rainfall stations (Figure 3.2). The individual rainfall station's data are in tenths of mm and gaps in record were subject to a gap filling procedure. These individual rainfall stations are then used to set up the rainfall zones-based rainfall time series which are obtained by averaging monthly rainfall from individual stations in the vicinity of the catchment. Rainfall zones either correspond to individual quaternary catchments or cover several neighbouring quaternary catchments. Rainfall figures for a rainfall zone are expressed in percentage of the Mean Annual Precipitation (MAP), with MAP defined separately for each quaternary catchment. The rainfall dataset for this study (Kraai River catchment) is divided into three hydrological zone which in this study are referred to as rainfall-zones. These rainfall-zones are D1N, D1P and D1Q.

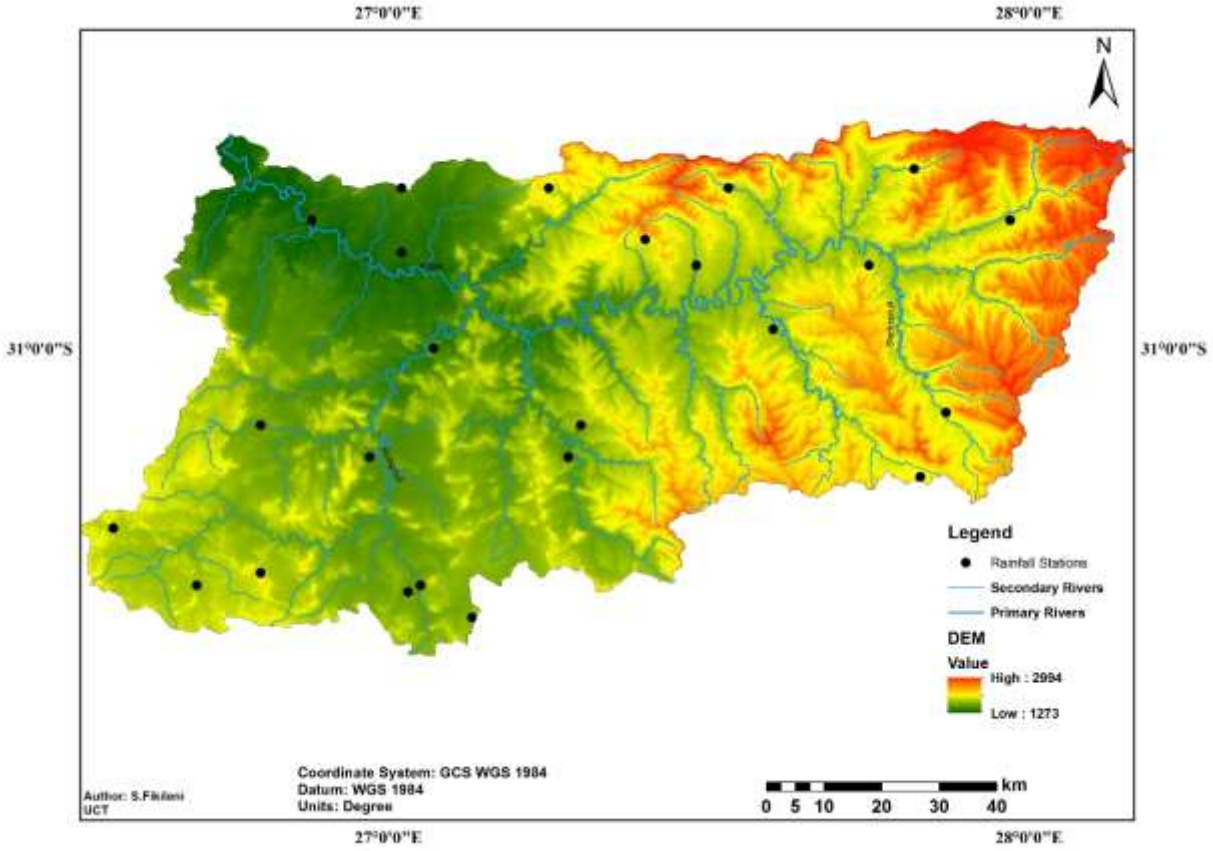

Figure 3.2Rainfall stations used in the WR2012 study in Kraai River Catchment.

3.2.3 Recent rainfall data

One of the obvious factors that affect the implementation of the seasonal hydrological forecast with the Pitman model in the WR2012 configuration is the fact that this model operates with a fixed rainfall dataset that covers the period of 1920-2009. In order to operationalize forecast, there is a need to update and be able to continue updating that rainfall dataset to near-real time.

There are several rainfall measurement techniques that are available for hydrological applications i.e. rain gauges, weather radars, satellites. All these methods have their own spatial and temporal resolution and errors (Behrangi and Wen, 2017; Wong and Chiu, 2008). When using these rainfall datasets as input for hydrological models, their errors and uncertainties propagate through the hydrological system, causing deviations in simulated (e.g. ground and surface) water levels and discharges (Brauer *et al.*, 2016). In the context of this study, there is an obvious need to ensure the compatibility, i.e. minimal biases and errors, between the original WR2012 data and the 2009-current data, as these biases and errors can cause reduction of forecast skill.

The obvious choice for extending and updating the WR2012 rainfall time series is the station data from SAWS. This is because this dataset was the main dataset originally used to create the WR2012 dataset. However, working with this dataset faces several problems:

- it is not time-consistent, i.e. not all the stations report all the time, or data is not available for other reasons
- access to data is not free, and there is no easy procedure to maintain regular updates of data, as data are provided by individual requests

In view of the above, other available datasets were considered, and they are described in detail below.

Conventionally rain gauge records provide the most accurate means to obtain information about the rainfall climate (Maidment *et al.,* 2017). However, the rainfall station data has quality issues, such, missing data, failure of instruments (Hunziker *et al.,* 2017) hence the use of gridded rainfall data has gained momentum over the recent past, including studies on the physical climate system (Stephens and Kummerow, 2007). There are many satellite rainfall data sources around the world. These satellite rainfall data emerged in the late 1960s (Kidd, 2001). The gridded rainfall datasets are used for different purposes and applications, for example research on various fields i.e. model evaluation (Klutse *et al.*, 2016), and creating rainfall map (Roffe *et al*., 2019).

There are several station datasets in South Africa: SAWS, Department of Water and Sanitation (DWS), Agricultural Research Council (ARC), The South African Sugarcane Research Institute (SASRI) and a number of municipalities plus private companies. These are datasets providers that are normally used in SA but for the WR2012 dataset, SAWS rainfall station data was used to compile it. Details of each of the above-listed station datasets are provided in Appendix 2.

Gridded rainfall data normally integrates one or more primary observations which may include station observations, atmospheric re-analyses, and satellite-based observations. The gridded datasets are divided into three categories: **(a)** gridded rainfall data which are station-based rainfall datasets. Examples of such datasets include Climate Research Unit (CRU, Harris *et al.,* 2014), Global Precipitation Climatology Centre (GPCC, Schneider, *et al.,* 2014); **(b)** gridded data derived from satellite observations blended with limited station data. Examples of such rainfall datasets include Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS, Funk *et al.*, 2015), Tropical Applications of Meteorology using SATellite (TAMSAT, Tarnavsky *et al.,* 2014). Tropical Rainfall Measuring Mission (TRMM, Huffman *et al.*, 2010), and Africa Rainfall Estimate Climatology (ARC, Novella & Thiaw, 2013) **(c)** gridded rainfall data which are based on rainfall data derived from climate models, sometimes blended with observations. Example of such a dataset is WATCH-WFDEI, (Weedon, *et al.,* 2014).

Uncertainty in different types of gridded data arises mainly due to the techniques used for the preparation of gridded data, such as interpolation of observed data, remote-sensing data used, or the model used for the generation of reanalysis data (Nashawan *et al.,* 2019).

Importantly, the gridded datasets differ in the update frequency, e.g. CRU is updated once yearly, while TRMM, CHIRPS, TAMSAT and ARC are available with several days delay. Therefore, for seasonal hydrological forecasting on operational environment needs a data is updated frequently.

Details of each of the above-described gridded datasets are provided in Appendix 2.

- The SAWS rainfall dataset was chosen because it is a primary dataset used to develop the WR2012 data. The SAWS have many rainfall stations and provide data sets that are long enough (Plessis and Schloms, 2017) compared to other sources of rainfall station data. The advantage of the SAWS rainfall dataset is that it is updated every month (Korahanis *et al,*

2008). Furthermore, it is more reliable, accurate rainfall data source used in SA and other neighbouring countries based on their respective quality control measures to ensure the accuracy of the data.

- The CHIRPS rainfall data set was chosen based on what is available on the literature from previous studies. For instance, Funk *et al.*, (2015) mentioned that CHIRPS rainfall dataset can support effective hydrologic forecasts compared to other gridded rainfall data and that there is no significant difference between the CHIRPS estimates and observed data at both daily and monthly level Maswanganye, (2018). This means that CHIRPS estimates are more accurate and can be used in less sensitive hydrological practices such as an input for hydrological models (Tou *et al*. 2016). The important criterion in selecting CHIRPS data is that this dataset is updated regularly, with CHIRPS-prelim available with several days delay. This dataset is thus very well positioned to be used in near-real time.

The SAWS rainfall for the Kraai River catchment was requested and was provided by SAWS. The selected 14 rainfall stations falling within the boundaries of the Kraai River catchment are shown in (Fig 3.3).

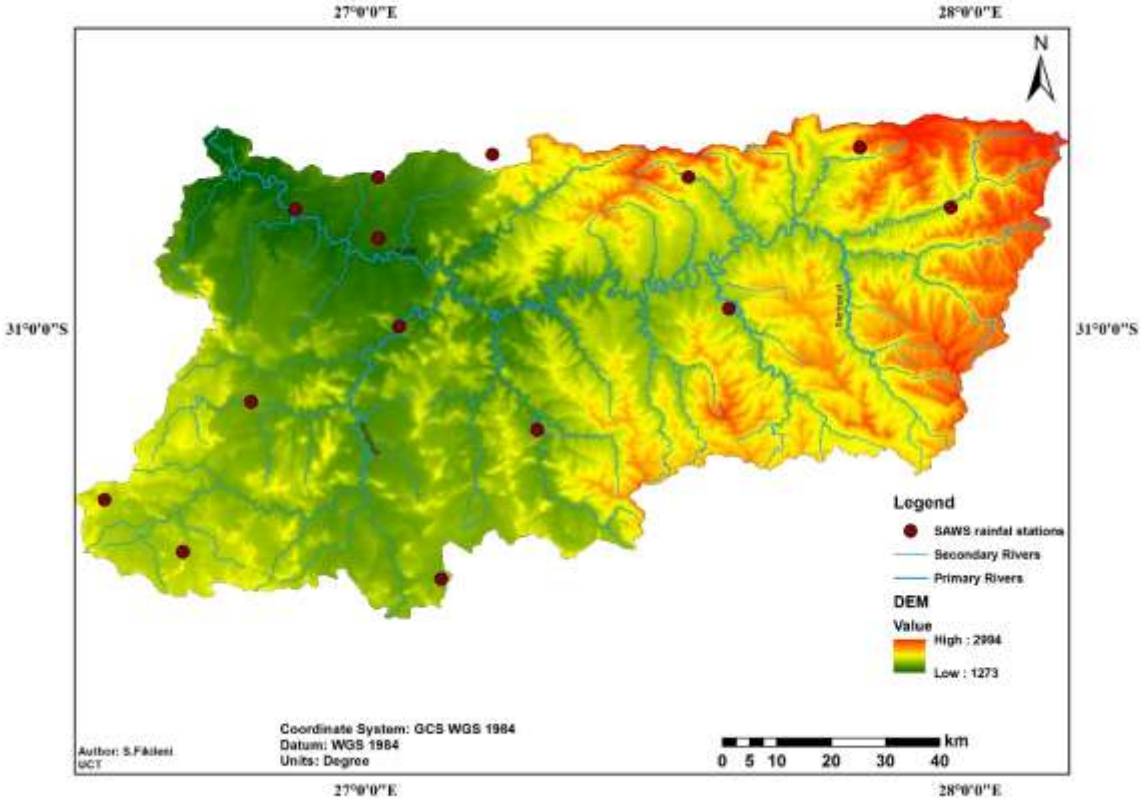

Figure 3.3. DEM map of the selected SAWS rainfall stations locations for Kraai River catchment

The selected rainfall stations were grouped in accordance with the rainfall-zones following the WR2012 format of grouping the rainfall station to create catchment rainfall. The data was again selected from 1981-2016 (Figure 3.5) because this period is where most stations have consistent rainfall records compared to 1920-1980. The total monthly rainfall at individual stations was calculated by summing up the daily rainfall values within each of the calendar months. After the

sum of the daily rainfall was calculated, the monthly means were calculated from those daily sums of the stations.

The CHIRPS rainfall data set was obtained from CSAG data archive. CHIRPS data in that archive were downloaded from the website of the institution generating the data, i.e. Climate Hazards Centre (CHG, https://www.chc.ucsb.edu/data). The raw CHIRPS data are provided by CHG as a daily gridded rainfall with grid resolution of 0.25 degree (approximately 25 km in South Africa). That raw dataset is routinely processed at CSAG to generate monthly rainfall totals, gridded and aggregated for a range of geographical regions. A GIS file (shapefile) with polygons representing the extent of WR2012 rainfall regions was used to derive monthly rainfall totals for the three rainfall zones used in this study. The standard processing script in the CSAG data archive was used for that purpose. For each polygon, that script calculates area-weighted average of values from all grid cells overlapping with that polygon. The data cover the period 1981-2016 (Figure 3.4). The resulting data were then converted into percentages of MAP in each of the rainfall zones, so that data were compatible with format required by the WR2012 data. The percentage conversion was done through dividing the monthly rainfall for each rainfall-zone by the Mean Annual Precipitation (M.A.P) of that rainfall-zone and then multiply by 100.

$$P_{CHIRPS} = CMR \div M.A.P \times 100 \quad (3.1)$$

Where P_{CHIRPS} is the percentage of the CHIRPS,

CMR is the CHIRPS Monthly Rainfall values in a particular rainfall-zone,

M.A.P is the Mean Annual Precipitation of the different rainfall-zones calculated from CHIRPS data over the entire period of 1981-2018.

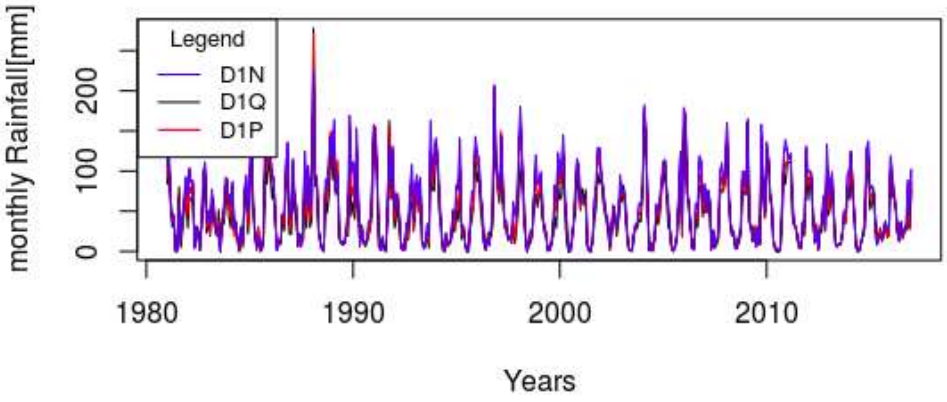

Figure 3.4. CHIRPS rainfall time series of all the rainfall zones of the Kraai River Catchment

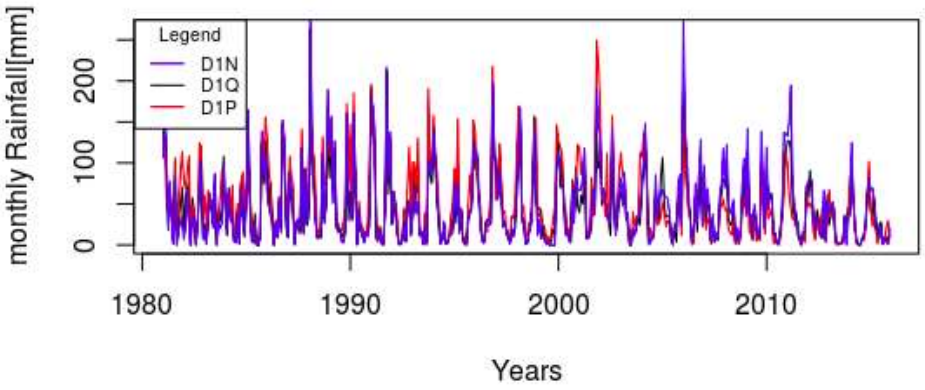

Figure 3.5. SAWS rainfall time series of all the rainfall zones of the Kraai River Catchment.

3.2.4 Observational streamflow data

WR2012 Streamflow data is on a monthly time-scale, and the WR2012 data is a compilation of quality-controlled data measured by Department of Water and Sanitation (DWS) at their river gauge network. The extended streamflow data for D1H011 station was downloaded from the Department of Water and Sanitation online website. The data cover the period 1965-present. This data is processed and verified at DWS.

3.3 Methods

3.3.1 Determination of procedure of implementing Pitman model in the seasonal forecasting mode

This is a qualitative aspect of the research and relies on 3 steps:

a) description and analyses of a typical seasonal climate forecast data
b) description of Pitman model and its implementation in the water resources assessment process
c) based on the above - identification of steps that need to be undertaken in terms of data processing procedures in order to implement Pitman model in seasonal forecasting mode

3.3.2 Updating WR2012 to near-real time

In order to select the best dataset for updating the WR2012 to near-real time, candidate rainfall datasets need to be evaluated from the perspective of bias and error compared to the WR2012 data.

The general framework of evaluation of compatibility of candidate rainfall dataset with the reference dataset, i.e. WR2012 is as follows:

- a period was selected for which both WR2012 and a candidate dataset data are available,
- data from the datasets were plotted and agreement between datasets was evaluated visually,

- bias and error indices (as described below) were calculated based on data for that period, and the calculations were carried out on the entire available data series, and also on a monthly basis.
- A decision on which dataset to adopt was taken based on evaluation of results of that procedure.
- Additionally, the final decision whether or not the recent data needs to be bias corrected or adjusted in any way was taken based on the results of evaluation procedure

In the context of evaluation of similarity between rainfall datasets, two types of error are distinguished - systematic error or bias and non-systematic error, and those are evaluated on the monthly and annual basis. Additionally, analyses of temporal correlation are performed in order to evaluate how well the variability of the reference dataset is captured by the candidate datasets. The evaluation is done using both visual means and numerical indices. A variety of graphs is used - time series graphs, box plots, scatterplots, to capture relevant features of datasets.

Bias is defined by Itkin and Loew (2012) as the difference between two mean true rainfall of different datasets and it can also be called Mean Error (ME). It measures a systematic error of a number of observations found by taking the mean value of the positive and negative error without regard to sign (Gómez, 2007). In this study bias is assessed through ME on a monthly and annual basis and illustrated in visual plots of climatological means and annual total respectively made in the R Statistical programming tool.

$$\text{BIAS}=\underline{R_t}\text{-}\underline{R_s} \tag{3.2}$$

Non-systematic error is defined as the difference between the result of a measurement and the true value of the quantity measured (WMO, 2008). This term is also used for the difference between the result of a measurement and the best approximation of the true value, rather than the true value itself. There are two main methods used to characterise errors in rainfall data that is Mean Absolute Error (*MAE*) and Root Mean Square Error (*RMSE*). The Mean Absolute Error measures the average magnitude of the errors in a set of estimated values, without considering their direction (Gómez, 2007, Mediero *et al.*, 2011).

$$\text{MAE}\ (\theta) = \frac{1}{n} \sum_{k=1}^{n} \left| y_k - y'_k(\theta) \right| \tag{3.3}$$

The Root Mean Square Error is a quadratic scoring rule that measures the average magnitude of error. Normally, the RMSE gives greater weight to large errors than small errors in the average compared with MAE. This means the RMSE is more useful when the errors are undesirable (Murphy 1995; MacLean, 2005).

$$\text{RMSE}\ (\theta) = \sqrt{\frac{1}{n}\sum_{k=1}^{n} \left(y_k - y'_k(\theta) \right)^2} \tag{3.4}$$

Pearson's correlation measures the strength between different variables and their relationships The correlation coefficient can range from the value + 1 to a value - 1, where the value +1 indicates perfect positive relationship between two variables, the value - 1 indicates a perfect negative relationship and the 0 value indicates no relationship between variables (Habib *et al.*, 2001; Adeyemo *et al.*, 2014).

$$r = \frac{\Sigma i(x_i - \underline{x})(y_i - \underline{y})}{\sqrt{\Sigma i(x_i - \underline{x})^2 (\Sigma(y_i - \underline{y})^2}} \quad (3.5)$$

Where r is the pearson correlation coefficient, $x_i$and $\underline{x}$ are variable 1 and its mean while $y_i$and $\underline{y}$ are variable 2 and its mean.

3.3.3 Downscaling of GCM forecasts

In general, there are two main approaches that can be used to downscale the seasonal climate forecasts, namely statistical and dynamical downscaling methods (Manzanas *et al.*, 2018). While downscaling is a key process that is required in order to link climate forecast data with hydrological models in the context of seasonal climate forecast, it was beyond the scope of this research to implement and evaluate customized downscaling approaches.

The method used in this research is one of Model Output Statistics (MOS) approaches - Principal Components Regression (PCR) approach, with one of the key atmospheric variables - geopotential height at 850mb as a predictor, and monthly catchment rainfall as a predictand. The predictor variable is taken as monthly means of retrospective forecast fields covering the period of 1982-2017 over the following domain: -45S-0S 0E-55E, and subject to dimensionality reduction using Principal Component (PC) analysis. This domain and predictor variable are typically used in MOS downscaling of forecasts over South Africa (Landman and Goddard, 2002; Mahlerbe *et al.*, 2014). The Only significant PC components are retained and used as variables in multiple regression. The multiple regression equation is established for each month of forecast and for each lead time up to 3 months ahead of the forecast month (i.e. there will be three equations for forecast issued in November and forecasting November, December and January rainfall, and subsequently three equations for forecast issued in December forecasting December, January and February rainfall, etc.)

The advantage of this method of downscaling is that it generates data that are by design bias-free, and directly compatible with the input to the hydrological model. Lack of bias is achieved because the predictors in the PCR model are actual forecasts rather than observations, and in this way, systematic bias of forecast is removed. The compatibility with the hydrological model is achieved through the fact that the input observational data from hydrological models are actually used as a predictand in the PCR regression model, and so the predicted values do not have to be processed in any way.

It has to be noted that the process of downloading, processing and downscaling of CFSv2 forecast data was not carried out specifically in this project. Instead, downscaled data were used that are generated by a system of routine processing of climate forecast data on the Climate System Analysis Group computing cluster, created within the framework of a Water Research Commission project (Wolski *et al.*, 2017).

3.3.4 Hydrological Model (Pitman Model)

There are several hydrological models which are used for seasonal hydrological forecasting. However, in this study, the Pitman model was used to implement and evaluate its performance in seasonal hydrological forecasting mode in Kraai River catchment. The Pitman model was chosen for this study because of two reasons: (a) the model was never used before in seasonal hydrological

forecasting, (b) the Pitman model is used as a principal tool for water resource management in South Africa and it has enjoyed relatively popular use as a water resource estimation tool in Southern Africa (Kapangaziwiri, 2010).

The Pitman model was developed by V.W. Pitman working in the Hydrological Research Unit at Witwatersrand University. This model is a conceptual model which runs on monthly values. A conceptual hydrological model includes the relevant hydrological processes to determine the relationship between input (meteorological variables) and output (runoff) (Knoben, 2013). Similar to many other conceptual models, the model (Pitman, 1973, Midgley *et al.*, 1994; Hughes, 2004, Kapangaziwiri, 2007a, 2010b) consists of storages linked by functions designed to represent the main hydrological processes prevailing at the basin scale (Fig 3.6). The development of the model was principally aimed at simulating "runoff in a form suitable for water resources appraisal" (Pitman, 1973).

The compulsory data requirements for the rainfall-runoff model include catchment area, a time series of catchment average rainfall, a mean monthly potential evaporation, or an annual value and monthly distributions. The optional requirements include seasonal distributions of irrigation water requirements and other water abstractions, as well as time series of upstream inflow, transfer inflow, and downstream compensation flow requirements. Pitman model and its use in a database management and modelling framework system developed Pitman (1973) modified to a series of Water Resource Management reports and updates from WRSM 1990 (Midgley *et al*.,1994), WRSM 2000 (Pitman, *et al*., 1999), WRSM 2005 (Middleton *et al.*, 2008) and the latest which WRSM 2012 (Bailey and Pitman, 2015).

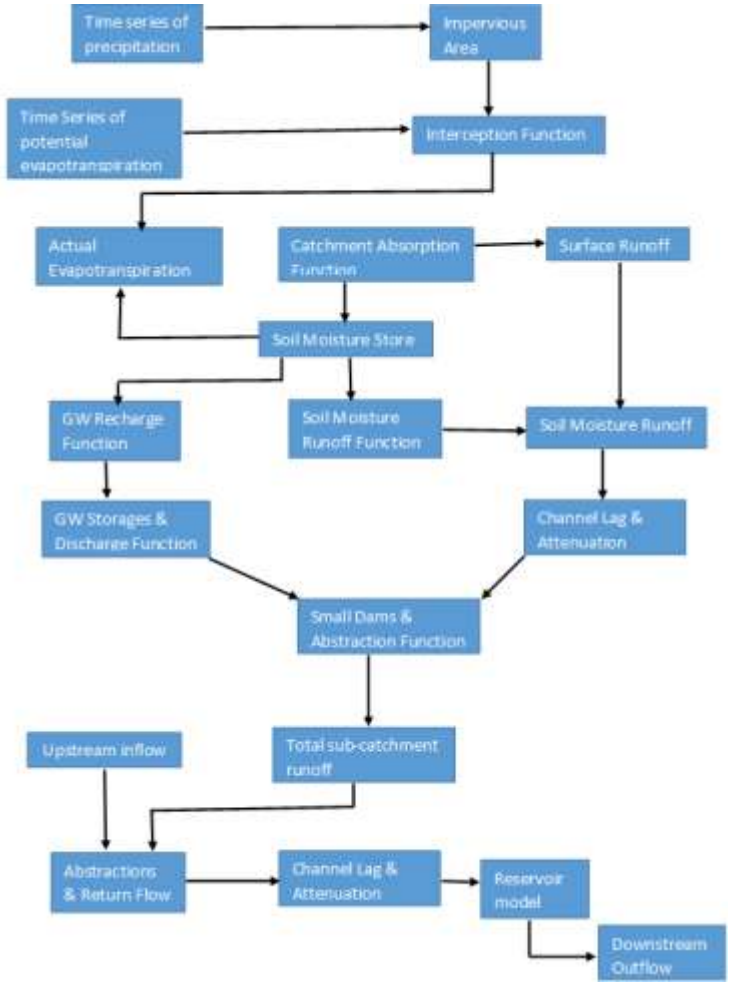

Figure 3.6. Flow diagram of the main component of the Pitman Model (Hughes et al., 2006).

3.3.5 Setup of the Pitman/WR2012 model for Kraai River Catchment

The process of setting up a hydrological model for a catchment requires a number of steps such as conceptualization of the catchment. The following are the generic steps that are required to setup the model:

- Conceptualization of the catchment processes - development of the so called "conceptual model".
- Determination and implementation of model structure that reflects the conceptual model (Figure 3.7),
- Preparation of input and observed responses datasets,
- A-priori determination of model parameters (if possible),
- Calibration of model parameters,
- Model evaluation (sensitivity analyses) and finally
- Application of the model for intended purpose.

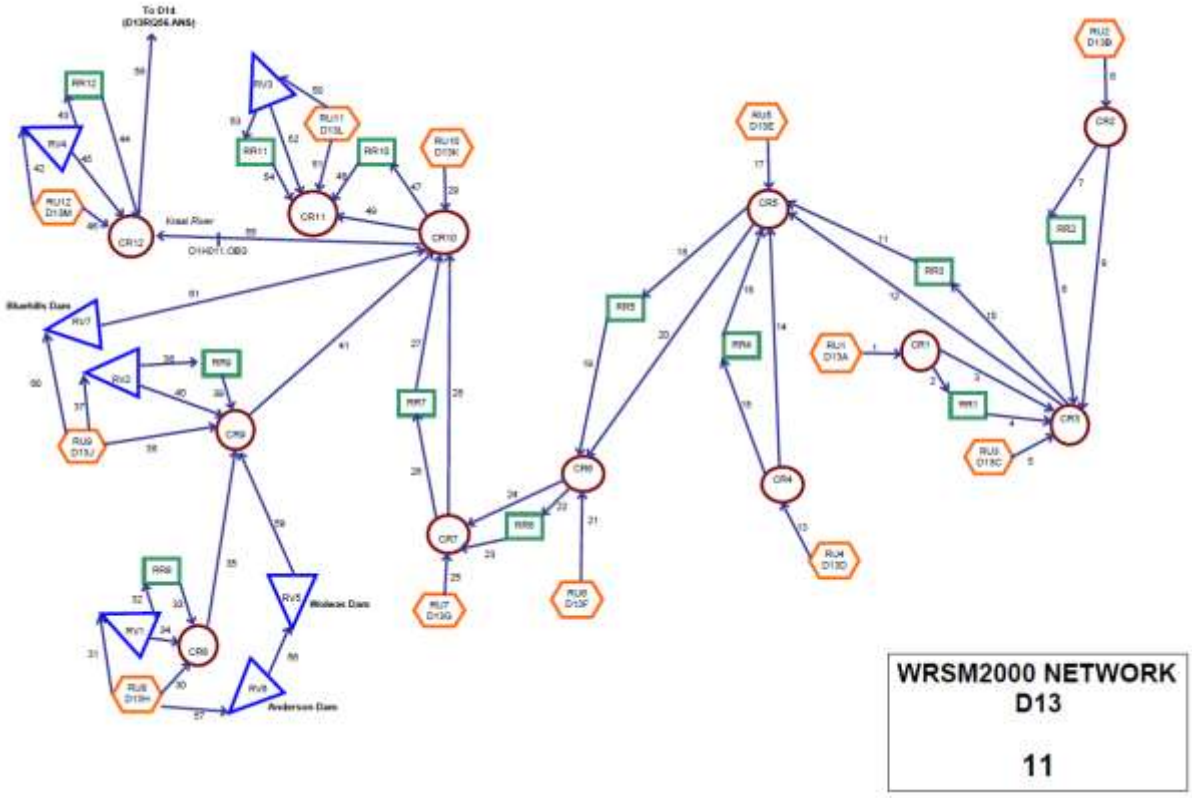

Figure 3.7. The network setup for D13 (Kraai river) tertiary catchment taken from the WRSM 2012 study (Bailey et al., 2015).

3.3.6 Pitman model/WR2012 evaluation

In many hydrological model studies (Moriasi *et al*, 2007), model evaluation is done to compare the model output (simulated) with corresponding measured data (observed). The model performance indices commonly used in model evaluation which are as follows; Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and Percent Bias (PBIAS) (Gupta *et al.*, 1999).

The Nash-Sutcliffe Efficiency (NSE) estimates the relative degree of the modelled residual variance against observed data variance. The values of NSE range between – ∞ and 1. When NSE = 1, it indicates a perfect match between observed and simulated. NSE is calculated as follows:

$$NSE = \left[\frac{\Sigma_{i=1}^{n}(y_i^{obs} - y_i^{sim})^2}{\Sigma_{i=1}^{n}(y_i^{obs} - y^{mean})^2}\right] \quad (3.6)$$

The Percent Bias (PBIAS): PBIAS measures the mean magnitude of which the simulated data is greater or less than the observed data. Lower magnitude values indicate accurate model simulation, with 0.0 being the optimal desired value. Negative values indicate model overestimation bias, positive values indicate a model underestimation bias. PBIAS is calculated as follows

$$PBIAS = \left[\frac{\Sigma_{i=1}^{n}(y_i^{obs} - y_i^{sim}) \times 100}{\Sigma_{i=1}^{n}(y_i^{obs})}\right] \quad (3.7)$$

where: y_i^{obs} is observed discharge,y_i^{sim} is simulated discharge, $y_i^{mean}$is the mean value of observed runoff, *n* is the total number of observations.

Table 3.1. Recommended model performance rating for NSE and PBIAS for streamflow (adopted from Moraisi et al., 2007).

Performance Rating	NSE	PBIAS (%)
Very Good	0.75 ≤ NSE < 1	PBIAS < ± 10
Good	0.65 ≤ NSE < 0.75	± 10 ≤ PBIAS < ± 15
Satisfactory	0.50 ≤ NSE < 0.65	± 15 ≤ PBIAS < ± 25
Unsatisfactory	NSE < 0.5	PBIAS ≥ ± 25

3.3.7 Forecast verification

There are various ways to assess the skill of a forecast depending on the forecaster's interest and the nature of the forecast produced. These methods range from the absolute mean error (MAE, Tan *et al.*, 2006; Gómez, 2007, Mediero *et al.*, 2011), root mean square error (RMSE, Cloke and Pappenberger, 2008; Shukla and Lettenmaier, 2011; Smith *et al.*, 2015), Brier score (BS, Brier, 1950; Bergh and Roulin, 2016), reliability diagrams (also called attributes diagram, Manson, 1982; Manson, 2004), ranked probability score and ranked probability score skill (RPS, RPSS, Wilks, 2005; Tippett, 2008), continuous rank probability score (CRPS, Zamo and Naveau, 2018; Brocker, 2012), receiver operating characteristic (ROC, Mason, 1982; Chang *et al*., 2015) just to mention the few. In this study, the forecast skill assessment is done considering that the implemented forecast is probabilistic in nature. The probabilistic forecasts give a probability of an event occurring with a value between 0-1 or 0 and 100%. In this study two methods were used to assess the skill of the forecasts produced by forcing the Pitman model/WR2012. These methods are; RPSS and ROC score. These methods were chosen because they are commonly used when assessing the skill of probabilistic forecasts. The skill of probability forecast system has; reliability - agreement between forecast probability and mean observed frequency, sharpness - tendency to forecast probabilities near 0 or 1, as opposed to values clustered around the mean, lastly is the resolution - the ability of the forecast to resolve the set of sample events into subsets with characteristically different outcome (WMO, 2018).

Ranked Probability Skill Score (RPSS) is a skill score that is based on the Rank Probability Score (RPS) values.

Rank Probability Score (RPS) measures the sum of squared differences in cumulative probability space for a multi-category probabilistic forecast. This method penalises forecasts more severely when their probabilities are further from the actual outcome. This method uses a range of 0 to 1, with 0 being a perfect score. The equation for calculation of RPS:

$$\text{RPS}=\sum_{k=1}^{k} (Y_k - O_k)^2 = (\boldsymbol{Y} - \boldsymbol{O})^2 \quad (3.8)$$

where; Y_k and O_k denotes the kth component of cumulative forecast and observation vectors Y and O, respectively. $Y_k=\sum_{k=1}^{k} \quad y_i$, with y_i being the probabilistic forecast for the event to happen in category i and $O_k=\sum_{k=1}^{k} \quad O_i$ with O_i=1 if the observation falls into a category $j \neq i$.

The above equation for the RPS is for a given probabilistic forecast-observation pair.

RPSS is then defined as follows:

$$\text{RPSS} = 1 - \frac{RPS_{forecast}}{RPS_{reference}} \tag{3.9}$$

where $RPS_{reference}$ is the RPS of a reference forecast. The most commonly used reference forecasts are persistence and climatology. The RPSS is a favourable skill score in that it considers both shape and overall tendency of the forecast. Where 0 indicates no skill when compared to reference forecast and 1 being a perfect score.

Receiver Operating Characteristic (ROC) method originates from the quality control and signal detection theory where the quality of performance is assessed by relations between the hit and false alarm rates. The ROC curve gives a total description of the skill of the model forecasts at all probability threshold. A model having its ROC curve lying above and to the left of the diagonal line ((0; 0) to (1; 1), Fig: 3.8) is considered to have a good skill, while a model with ROC curve below the diagonal has not skill, i.e. it is worse than a climatological guess. The ROC score evaluates the model forecast by examining the relative performance of hit and false alarm rates across the entire range of probability threshold (Fig: 3.8), integrated measurement of the curve can provide the score that is independent of the threshold probability level chosen to transform probability forecast to binary form.

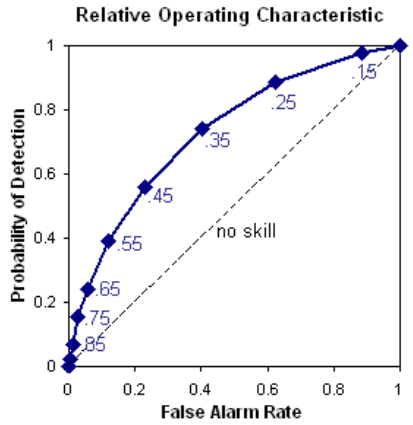

Figure 3.8. A diagram showing the ROC curve (Mason, 1982)

ROC score is defined as the area under the ROC curve. This skill score is equal to 1 for the perfect forecast and 0.5 for no skill (Kharin and Zwiers, 2003). The ROC scores are therefore, given with this equation.

$$S_{ROC} = 2A_{ROC} - 1 \tag{3.10}$$

Where $S_{ROC}$is the ROC score and A_{ROC} the area under the ROC curve.

3.4 Description of the study area

The Kraai River catchment is called D13 Tertiary catchment in terms of Water Management Agencies (WMAs) and it is the part of Upper Orange River Catchment which then forms part of the Orange River Catchment Management Areas which is in the Eastern Cape, SA with an area approximately 9354km^2. This catchment is located 30°51′9″S 27°46′40″E in the northeast and at the southernmost end of the Drakensberg, south of Lesotho, in the magisterial district of Barkly East in Eastern Cape. The Kraai catchment starts at altitudes of up to 3000m on the basaltic rocks of the catchment that forms the boundary between South Africa, Lesotho and the Herschel District (Figure 3.9).

The upper Kraai River catchment (D13A, D13B and D13C) lies between Mosheshis Ford and sources of the streams that drain into the Kraai River at the Ford. The middle (D13F, D13G and D13K) of this river extends from Mosheshis Ford to the confluence of the Kraai and Karringmelkspruit and below that confluence lies the lower Kraai River catchment (D13H, D13J, D13L and D13M). A westerly ridge of the Drakensberg is called Witterberg west of Lundeanis Nek. This ridge forms a continuation of the Upper and the middle Kraai-Orange catchment. In terms of rainfall zones, the catchment is divided into three zones which are as follows: D1N rainfall zone (D13A, D13B and D13C), D1P rainfall zone (D13F, D13G and D13K) and D1Q rainfall zone (D13H, D13J, D13L and D13M) (Fig. 3.9).

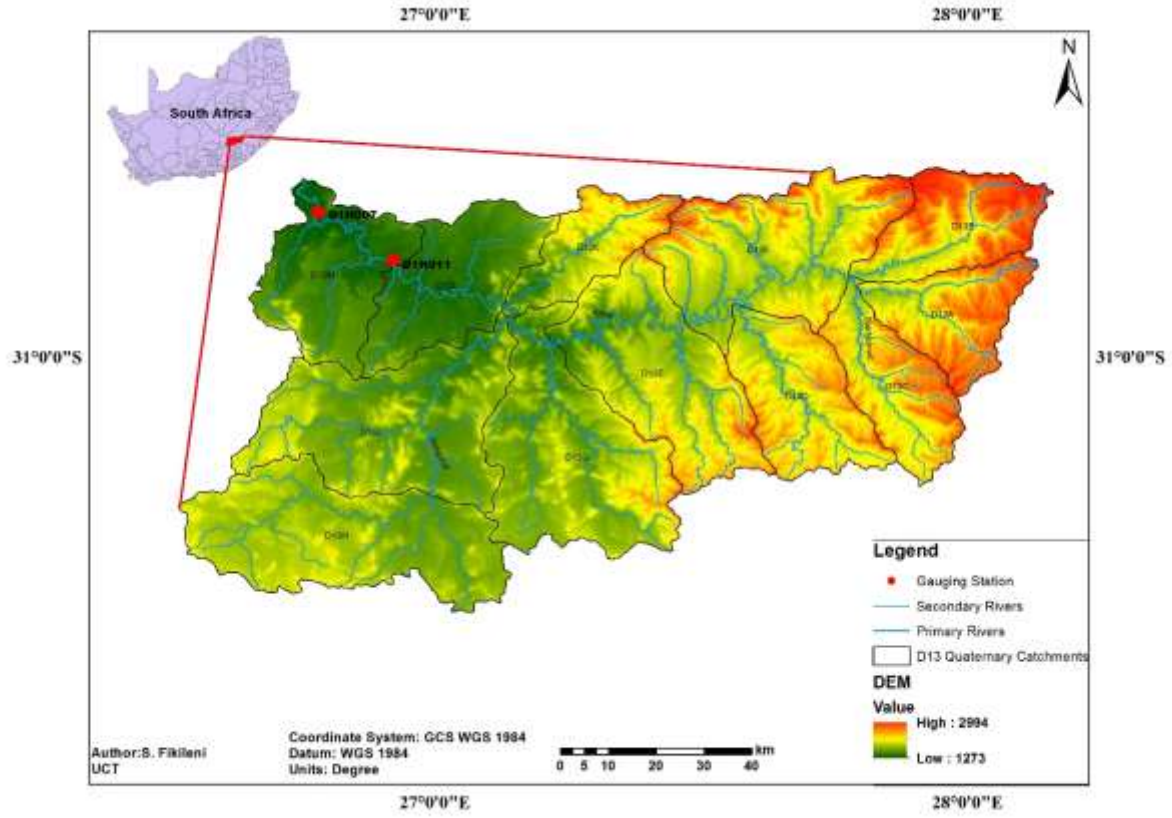

Figure 3.9. Map showing South African primary catchments with enlarged Digital Elevation Map (DEM) of the Kraai River Catchment with major rivers.

3.4.1 Climate of the Kraai River Catchment

The mean annual temperature in the Kraai River catchment ranges between 12°C in the east (mountains) to 18°C in the west (lower-lying areas in the west) with the maximum temperature during summer in January and the minimum in July. Rainfall is predominantly delivered by summer thunderstorms. Annual precipitation rates are variable with the east of the catchment receiving approximately 1000mm/a and the west as little as 200 mm/a (Figure: 3.10). Lesotho's rainfall is the main contribution of surface runoff to the Upper Orange Basin, with an annual rainfall of that region ranging between 600 and 1500 mm/a (DWAF, 2004) and the Kraai River catchment falls within this region of the Upper Orange River catchment.

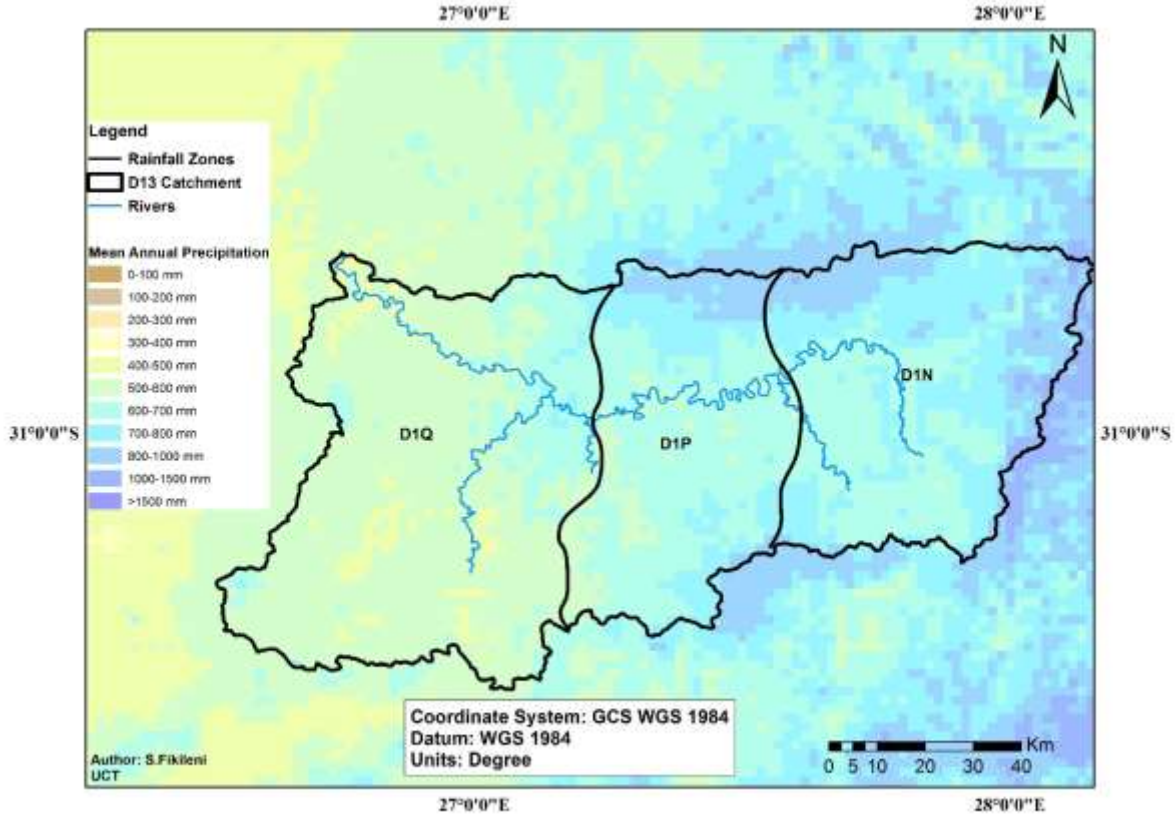

Figure 3.10. This figure shows the Mean Annual Precipitation (MAP) map of the Kraai River catchment for all the rainfall zones of the catchment sources from WR2012.

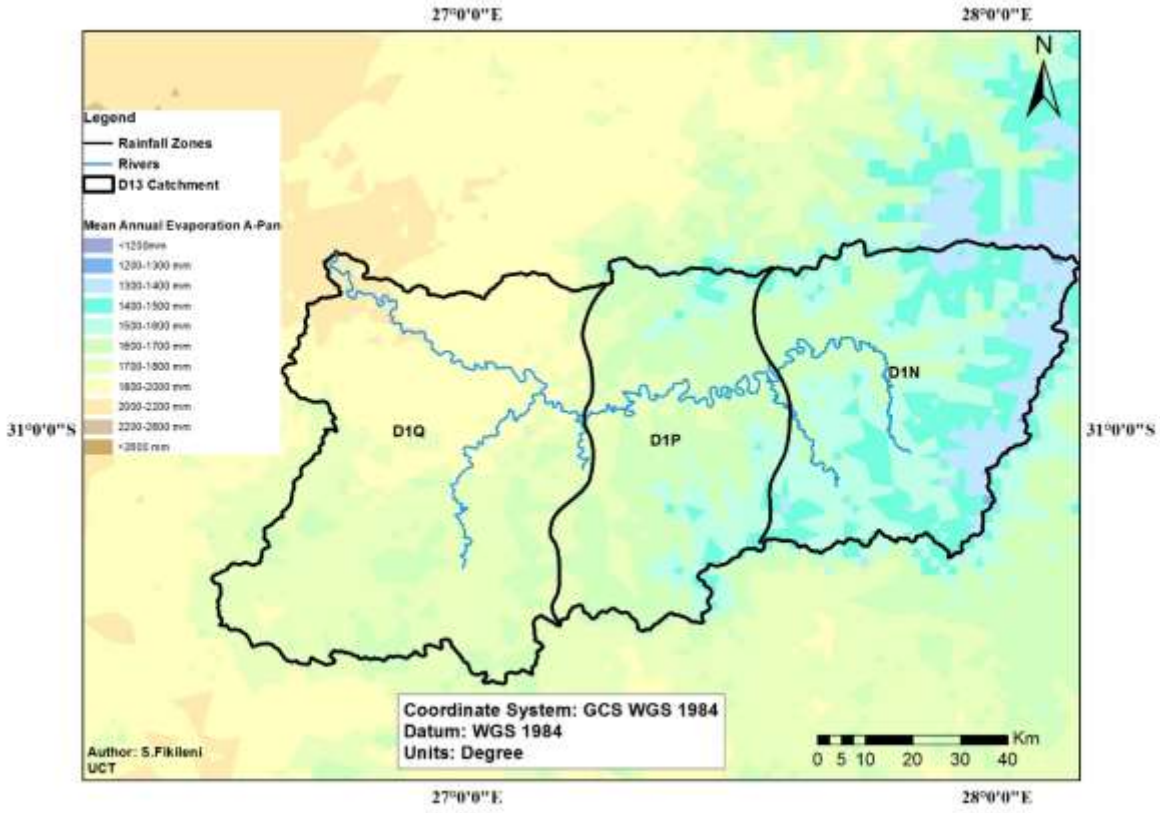

Figure 3.11. This figure shows the Mean Annual Evaporation (A-Pan) map of the Kraai River catchment for all the rainfall zones of the catchment sourced from WR2012.

3.4.2 Hydrology of the Kraai River Catchment

The Kraai River has its origins at the southernmost end of the Dranskenberg, south of Lesotho. The rivers originating from the escarpment are due to the surface run-off from essentially convectional, adiabatic and winter frontal precipitation as well as meltwater from occasional snowfall (Fig 3.9). There are about 6 dams in the Kraai River catchment, with three major dams such as Anderson dam, Wolwas dam and Blue hills dam. In the Upper Orange river region, which the Kraai River falls in and has nearly up to 70% of the total surface run-off (DWAF, 2003), which originates from the Lesotho territory. The surface water resources which occur from within the Kraai River are well developed. However, there are no detailed abstraction figures. In terms of groundwater the region is underlain by hard formations, no large porous aquifers are found in the WMA. Although relatively large quantities of groundwater are abstractable from fracture zones. Higher recharge occurs mostly in the highlands near Lesotho.

3.4.3 Geology of the Kraai River Catchment

The Kraai River Catchment is predominantly underlain by basalt of the Drakensberg formation (Keulder, 1979), across the progressively older strata of the Karoo Sequence (Fig 3.12). The sedimentary rock is found at the convergence between Kraai River and Orange River close to Aliwal North. These sedimentary rocks include; the fine-grained massive sandstone of the Molteno

formation; the interbedded mudstone and fine-grained sandstone of the Beaufort Series (Venter, 2000).

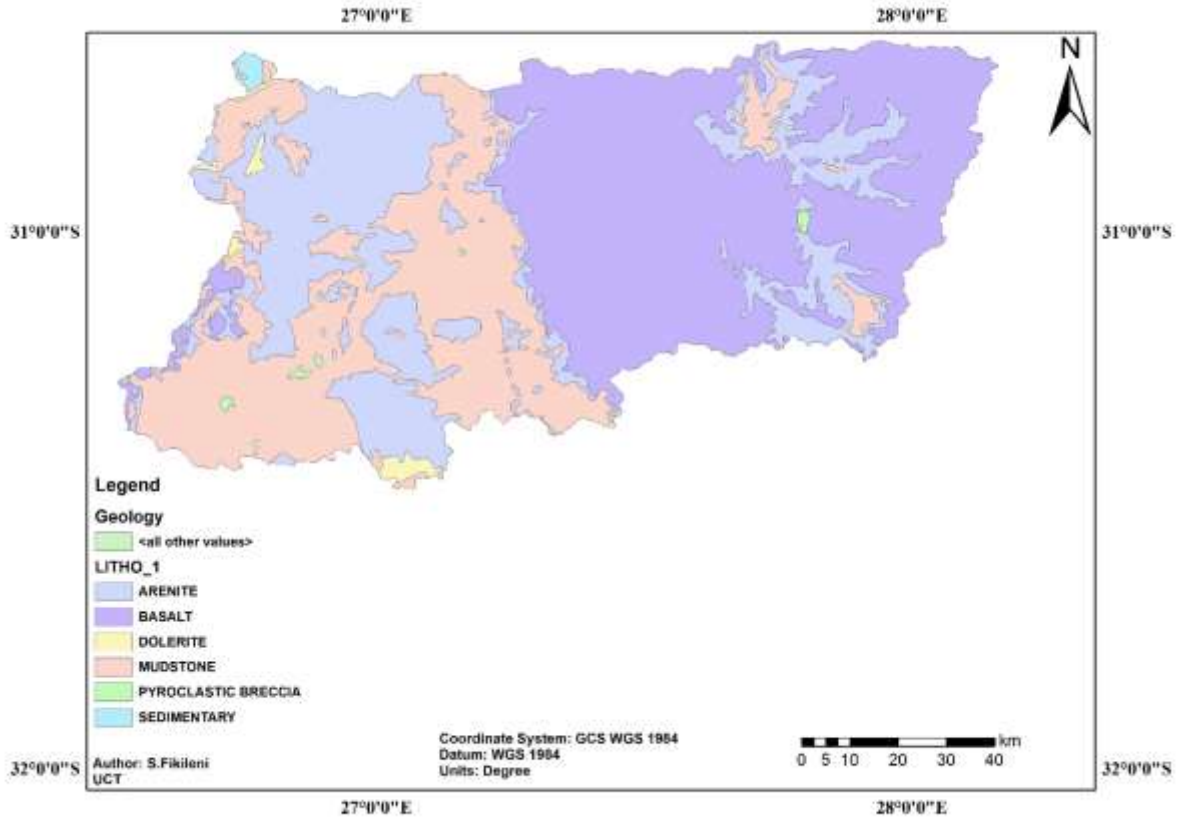

Figure 3.12. Geological map showing the geology of the Kraai River catchment.

3.4.4 Landcover in the Kraai River Catchment

The land-cover in the Kraai River catchment consists of primarily natural areas (vegetation) of little irrigation and dryland cultivation and grazing, small fraction of the area falls under little urban and more of rural settlements. However, the catchment is undeveloped in terms of major towns, commercial irrigation or industrial activities (DWA, 2009). There are small scale irrigation schemes which occur along the banks of the Kraai River and its tributaries. The main agricultural developments are along the lower reaches of the Kraai River. The water for irrigation purposes is abstracted from the Kraai River and any return flows will have an impact on the Kraai River. However, farming is a dominant land-use activity in this catchment although it is not highly commercialised. There are no commercial forests and no serious infestations by alien vegetation occur in the catchment (DWAF, 2003). There are no major dams except farm dams in the catchment although agricultural activities are dominant in the area. Due to their nature and limited extent, the agricultural activities of the Kraai River catchment have little influence on the hydrological processes of the catchment.

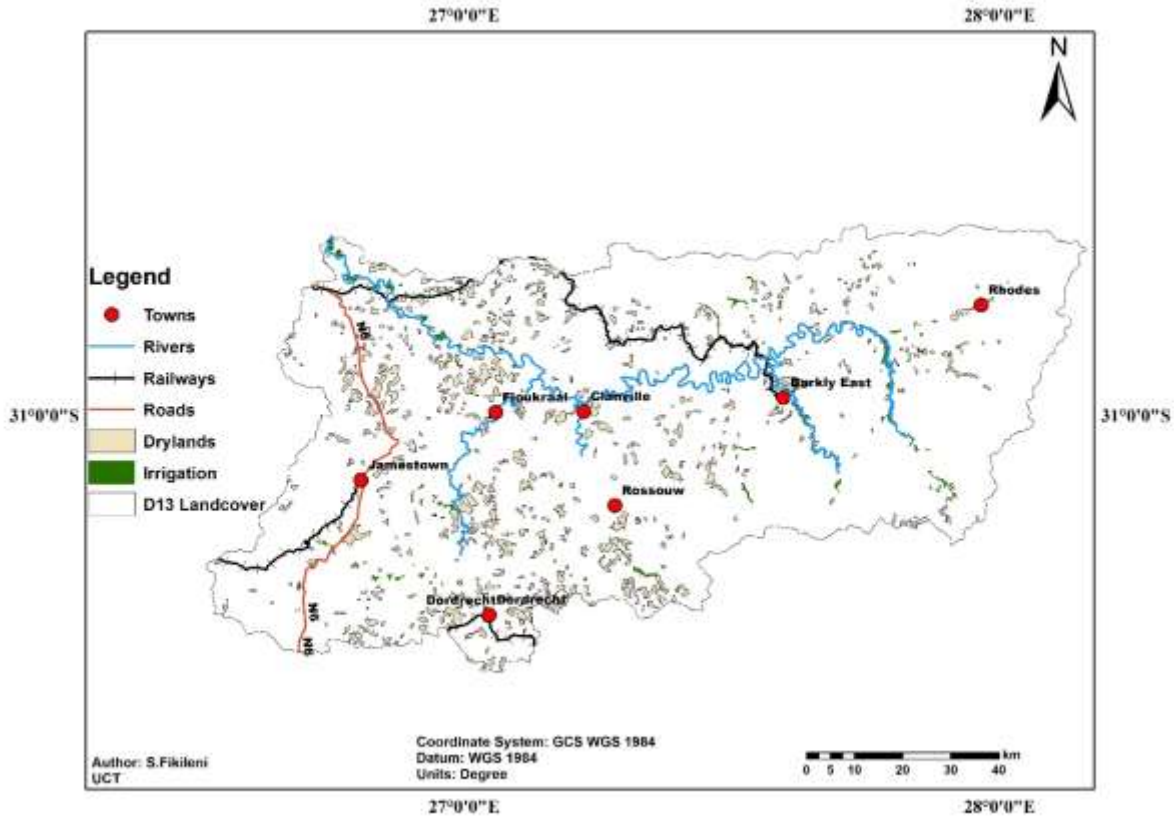

Figure 3.13. Land-cover map showing some of the activities in the Kraai River catchment.

Chapter 4: Results

This chapter outlines and discusses in detail the results obtained during the study. This chapter is divided into four sections. The first part outlines the process and necessary steps of implementation of the Pitman model in the seasonal forecasting mode. The second part of this chapter covers the analyses and data processing performed in order to update the WR2012 rainfall dataset to cover the period 2010 to 2016. The third part of this chapter describes the implementation of the Pitman model in seasonal hydrological forecasting mode with CFSv2 climate forecast data and presents the results of retrospective forecasts. The last section discusses the findings of the study.

4.1 Identification of key aspects of the implementation of seasonal hydrological forecast with the Pitman model

4.1.1 How are numerical seasonal climate forecast simulations organized?

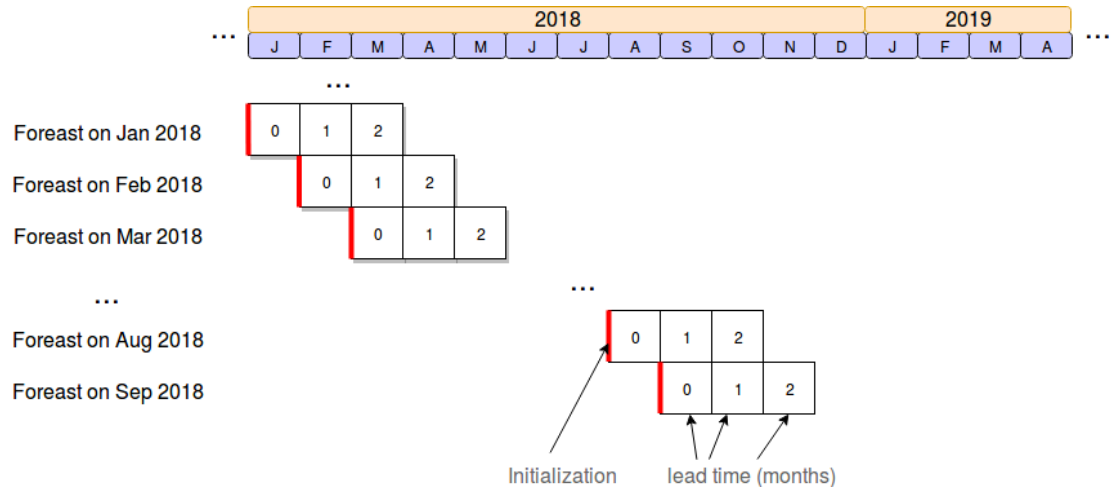

Figure 4.1. Schematic of the typical implementation of seasonal climate forecast.

Seasonal forecasts are issued periodically, mostly at the beginning of the month. These forecasts are initialised, i.e. the initial conditions of the forecast simulations are determined by simulation of GCM's that assimilates historical observations till the time of forecast initialisation (Fig 4.1). Seasonal forecasts are issued as an initial condition ensemble, which could be achieved by using ensembles of simultaneous initial conditions or by staggering forecast initialization with each ensemble member initialised at different timestep of historical simulation. The forecast simulation is run for a period of 3 months up to 9 months.

The lead time for seasonal climate forecast differs from the producer of the seasonal forecast but WMO gave a standardized minimum requirement for Global Producing Centres for Long-Range Forecasts (GPCLRF). All GPCLRF are required that at minimum, the prediction for averages, frequencies over 1-month periods or longer (typically anomalies in 3 month-averaged quantities is a standard format for seasonal forecasts and they are expressed in probabilities. The lead time should be 0-4 months and be issued monthly or quarterly (WMO, 2019). However, because there are deficiencies in coupled models, model data are rarely used as is. They are normally downscaled

using a statistical approach called Model Output Statistics (MOS). There is a need to calibrate the MOS model before the forecast is issued.

The calibration is done using a series of past seasonal hindcasts which are in turn requires ocean initial conditions for a historical period of normally between 15-25 years. These hindcast are also needed for the skill assessment of the seasonal forecast.

4.1.2 How are Pitman model simulations organized?

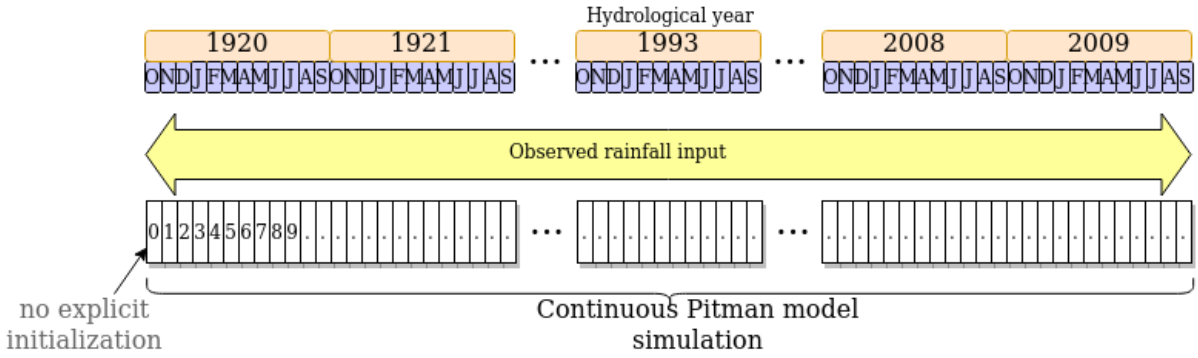

Figure 4.2. Schematic diagram of implementation of the Pitman/WR2012 model.

Pitman model is a continuous simulation rainfall-runoff model. As such it simulates a period of time with prescribed start and end point. Input data has to be available for the entire simulation period. The main input data in Pitman/WR2012 model is rainfall and evaporation data. Only rainfall is provided as a time series. Evaporation is represented as a climatology, i.e. with 12 monthly values. Both are provided at the quaternary catchment level. The evaporation data are Symons-pan evaporation, and not more widely used Class A Pan evaporation. In a typical application for water resources assessment, the Pitman model is implemented in the following way: The model in this setting is run continuously with at least data above 25-90 years of historical data records to produce continuous simulations. The Pitman/WR2012 does not have the option to start from a particular initial condition which means initial conditions are no explicit need as the model is initialized internally. There is therefore no option to re-initialize the model from an initial condition obtained through an earlier continuous model run.

4.1.3 Procedure of running Pitman in seasonal forecasting mode

Two phases of implementation of seasonal hydrological forecasts have to be distinguished. The first is implementation of retrospective forecasts (or re-forecast) for the purpose of evaluation of skill of hydrological forecast. This is done once. The second is the operational forecast, which is an on-going, regular process.

4.1.3.1 Re-forecast for the purpose of assessment of skill

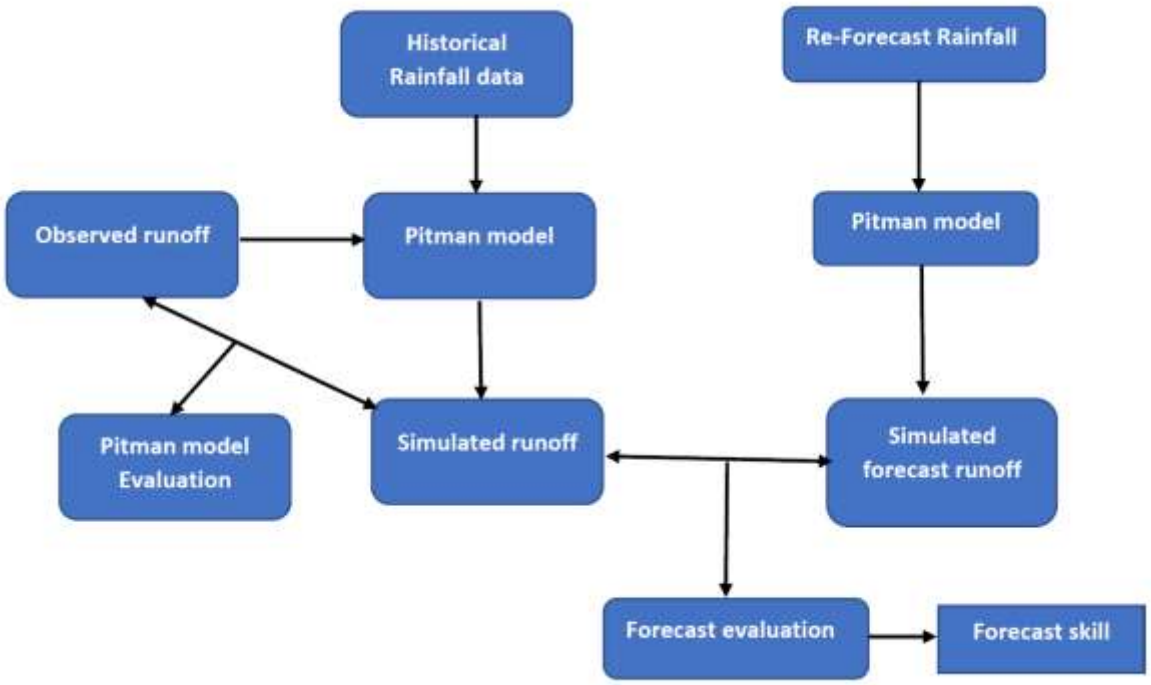

Figure 4.3. Schematic diagram showing the steps for implementation of the Pitman/WR2012 model in retrospective forecast mode for the purpose of evaluation of forecast skill.

For assessment of forecast skill, a number of individual re-forecasts is needed. Forecast skill is specific to a particular time of issuing forecast and a specific lead time, Fig. 4.3 presents a general framework for evaluation of skill of hydrological forecast. Historical rainfall data and re-forecast data are the requirements for this process in order to run the model to produce simulated runoff. The output (simulated runoff) from the model run is then compared with observed runoff i.e. model evaluation which translates to model accuracy. The model is then run with multiple historical rainfall forecasts in order to evaluate the skill of the forecast generated during this process. The skill of the forecast is assessed by comparing the model forecast with simulated streamflow not with observed stream flow because of hydrological model error.

4.1.3.2 Operational forecast

Figure. 4.4 presents a framework of implementation of a single forecast in an operational setting. In such a setting, simply rainfall forecasts (current) from climate forecasts are used to run the model. The model then generates streamflow forecasts. The skill of the forecast is measured by comparing the forecast with observed runoff. The latter process is a basis for interpretation of the forecast.

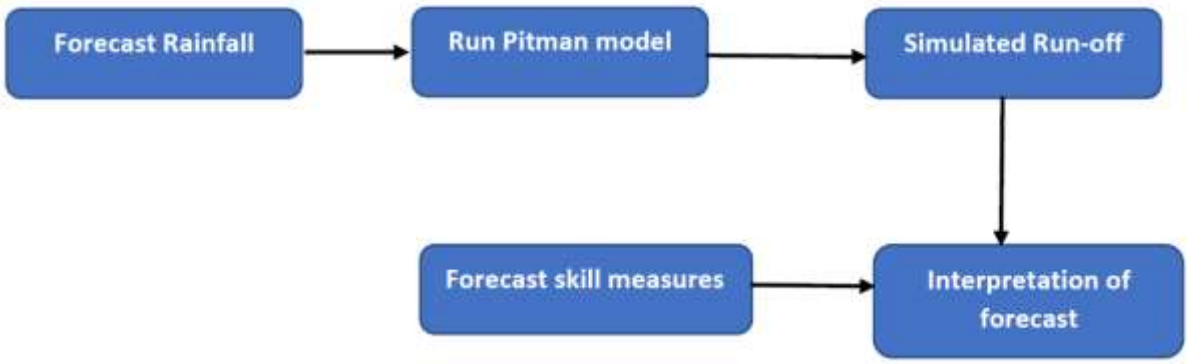

Figure 4.4. Schematic diagram showing the steps for implementation of the Pitman/WR2012 model in the actual operational hydrological forecast.

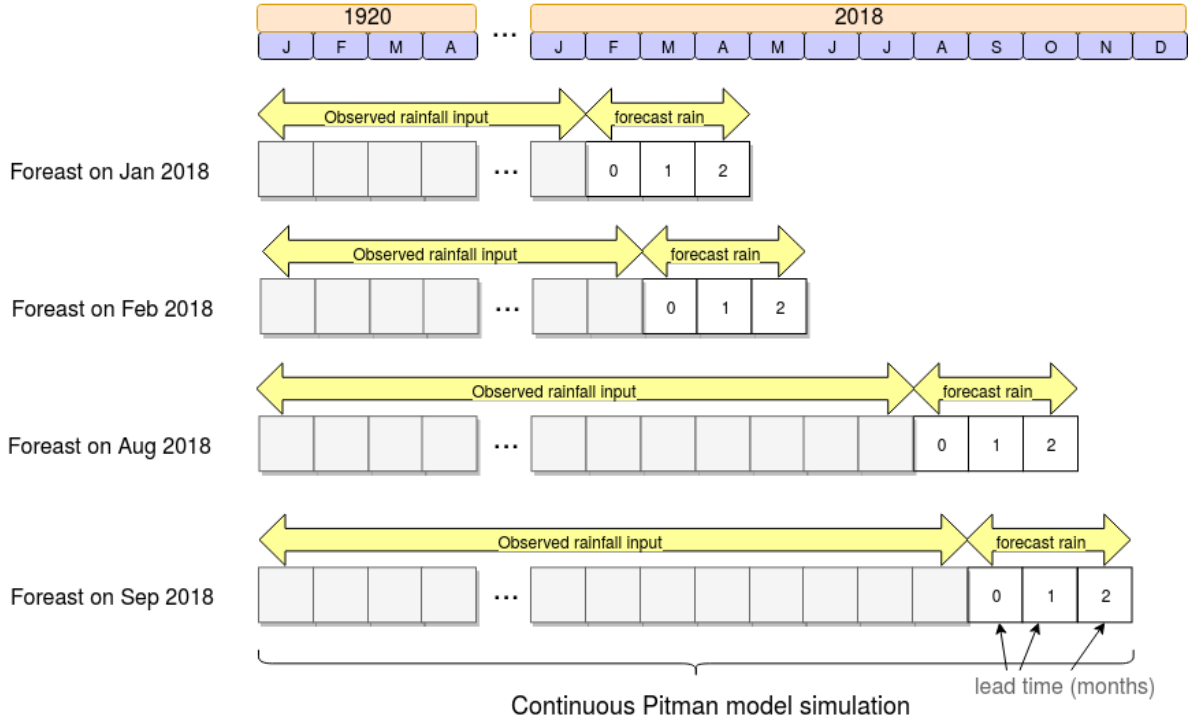

Figure 4.5. Schematic diagram of Pitman/WR2012 model implementation in operational seasonal hydrological forecast.

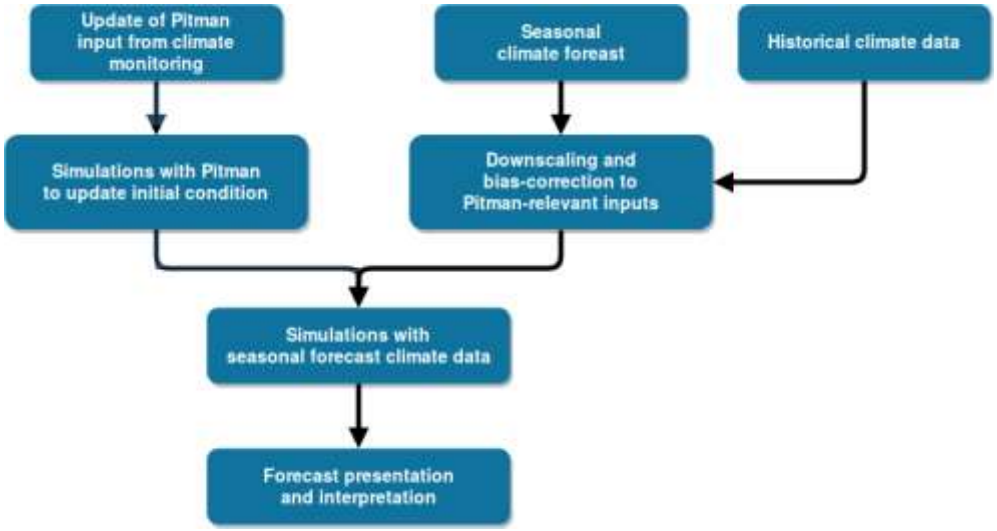

Figure 4.6. Schematic illustrating procedure of implementation of a single forecast with Pitman model.

In view of the information provided in sections 4.1.1 and 4.1.2 the following procedure is proposed for implementation of the Pitman model in the seasonal forecasting mode:

- The seasonal climate forecast data are downscaled and bias correction is done for the forecast data to be compatible in the historical rainfall data..
- historical rainfall data as input in the model needs to be updated to extend to the date of forecast.
- updated historical and forecast rainfall data are to be merged into one time series
- the Pitman model is run with the merged historical-forecast rainfall data to produce simulated streamflow,
- last two steps are repeated for each member of the climate forecast ensemble
- In the forecast evaluation setting, the above steps are repeated for all forecasts that are available, and forecast skill is determined from these simulations,
- In the operational forecast setting, the last step is the presentation and interpretation of the forecast for the end-user, accounting for the forecast skill (Fig. 4.6).

4.2 Updating the WR2012 rainfall dataset to the near-real time

The above section 4.1 of this study gave a conceptual framing of the process of implementation of seasonal hydrological forecast on an operational basis. As argued by Wood and Lettenmaier, 2006), it is critical that the hydrological model used in the forecast is initialized from a condition as close to reality as possible. The WR2012 rainfall data covers only the period of 1920-2009. Therefore, to achieve the objectives of this study, the Pitman model for seasonal forecasting requires extending the WR2012 dataset to cover from 2010 hydrological year to current and be able to do that on an operational basis.

This section illustrates the results of the assessment of biases and errors of the two candidate datasets to achieve that task, identified earlier, namely SAWS station dataset and CHIRPS gridded blended station-satellite dataset, and concludes with the choice of the rainfall dataset.

4.2.1 Comparisons between the CHIRPS and SAWS datasets, and WR2012

The evaluations presented here focus on bias and errors between the reference and candidate datasets. The CHIRPS and SAWS datasets biases and errors with respect to the WR2012 for the overlap period 1981-2009 were evaluated on annual and monthly scale through a number of indices and graphs.

The figures below were plotted, and the indices were derived using the R statistical programming tool.

4.2.1.1 Visual inspection of time series

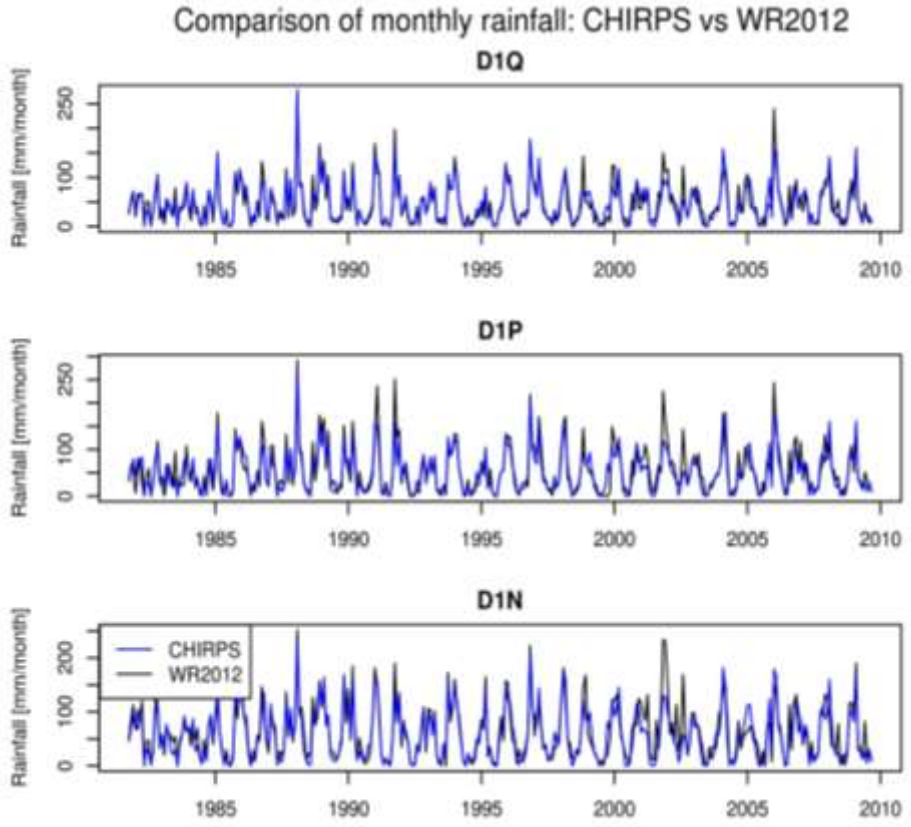

Figure 4.7. Comparison WR2012 and CHIRPS rainfall dataset for all the Kraai River catchment rainfall zones.

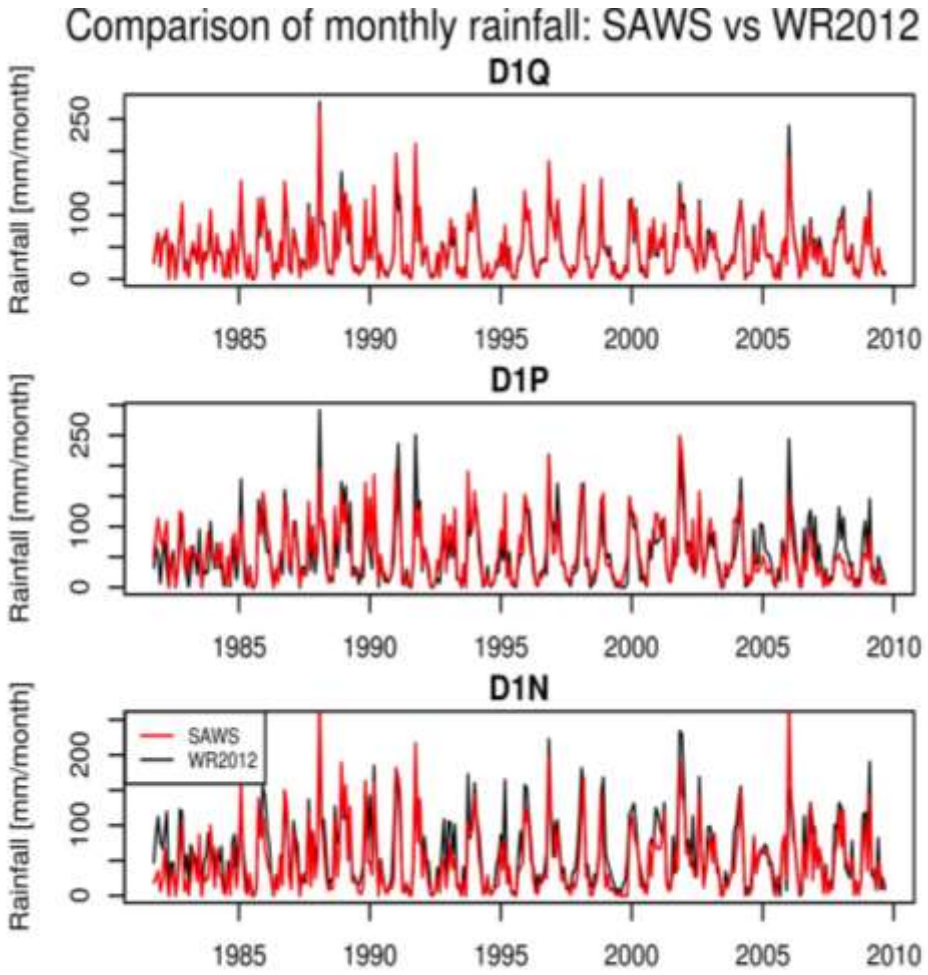

Figure 4.8. Comparison of WR2012 and SAWS rainfall dataset for all the Kraai River catchment rainfall zones.

Figures 4.7 and 4.8 compare WR2012 rainfall time series with SAWS and CHIRPS for the period of overlap, i.e. for 1981-2009. There is a good agreement in the overall pattern between the two datasets and WR2012 i.e. there is a good agreement in monthly variability in individual years, although differences arise in individual months. There is a particularly good agreement of datasets in the D1Q rainfall zone. However, on Fig 4.8. In D1P there is a clear disparity between SAWS and WR2012 during 2007-2010. On the other side the CHIRPS dataset does not show strong visual differences from the WR2012 dataset.

4.2.1.2 Patterns of variability on monthly basis

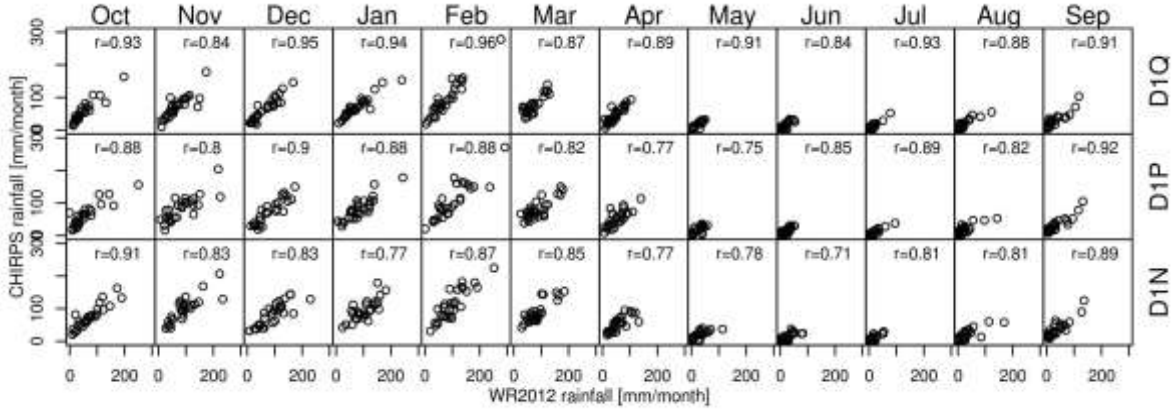

Figure 4.9. Monthly correlation between CHIRPS and WR2012 rainfall datasets in all rainfall-zones of Kraai River catchment.

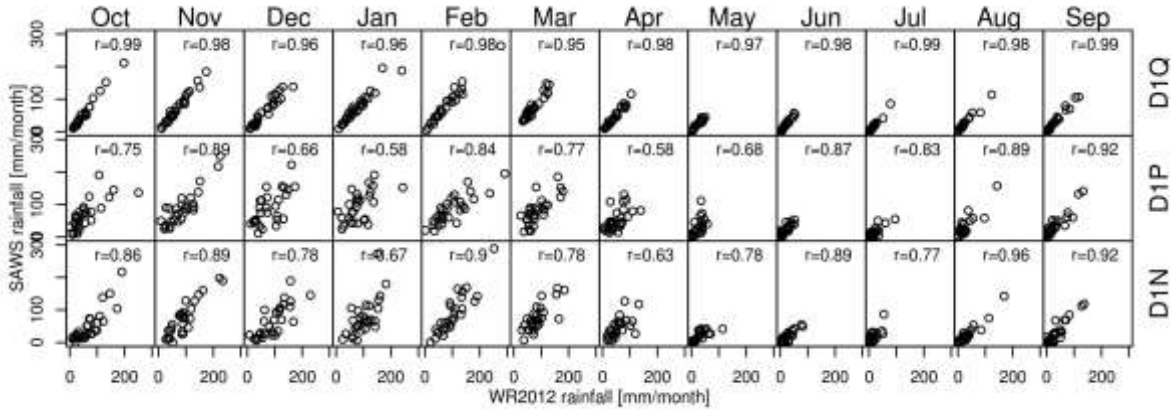

Figure 4.10. Monthly correlation between SAWS and WR2012 rainfall datasets in all rainfall-zones of Kraai River catchment.

Figures 4.9 and 4.10 depict scatterplots of CHIRPS and WR2012, and SAWS and WR2012 on month to month basis, with Pearson's correlation (r) included. This analysis reflects patterns of both datasets when compared with WR2012 dataset and relationship. Both CHIRPS and SAWS show good correspondence and strong correlation in the D1Q rainfall-zone with values of r exceeding 0.95 in SAWS and 0.84 in CHIRPS each month. In D1P and D1N rainfall-zone in the period of October-March (rainy season) SAWS dataset shows weaker correlation with WR2012 than CHIRPS, with r as low as 0.58 for the former and not lower than 0.77 for the latter.

4.2.1.3 Biases and errors on monthly basis

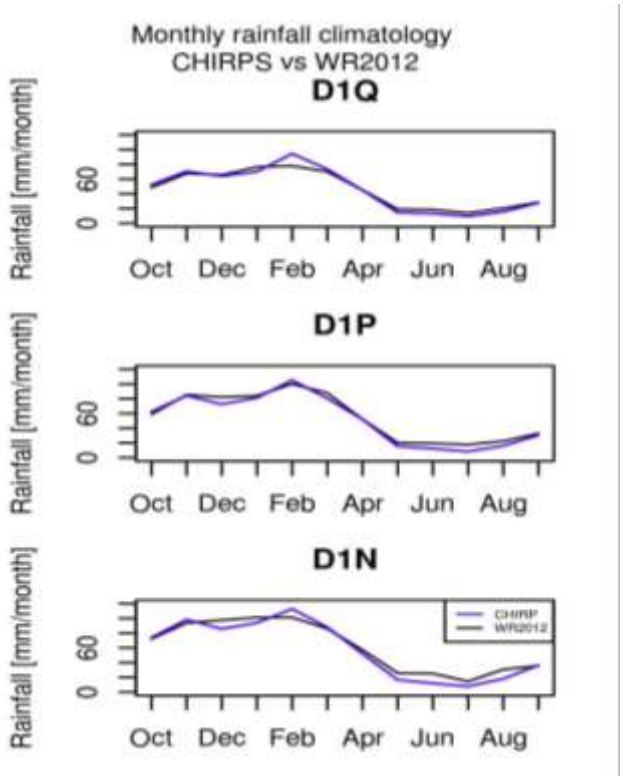

Figure 4.11. WR2012 and CHIRPS mean monthly rainfall for all the rainfall-zones of the Kraai River catchment.

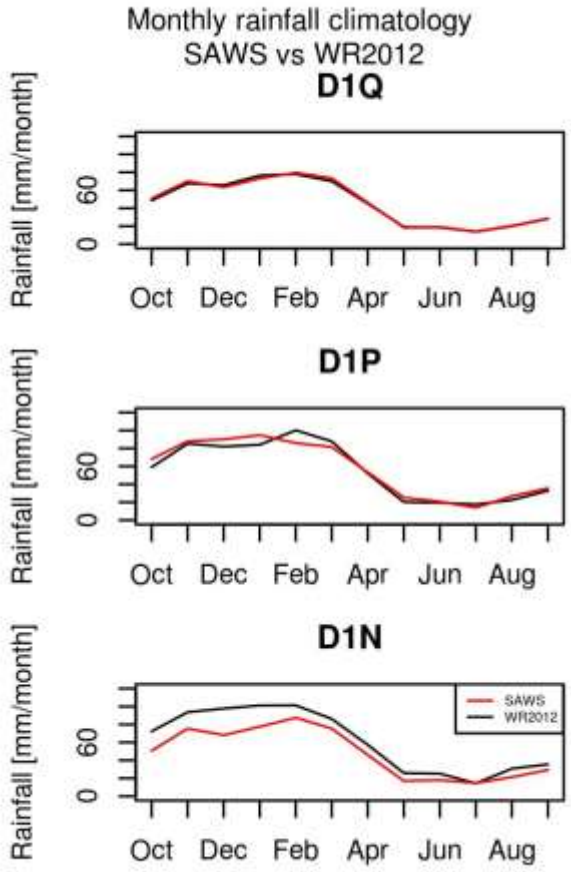

Figure 4.12. WR2012 and SAWS mean monthly rainfall for all the rainfall-zones of the Kraai River catchment.

Figures 4.11 and 4.12 are showing mean monthly, or climatological rainfall of the analysed datasets. This figure captures the bias, or systematic difference between datasets, on a monthly basis. The main reason for doing such analysis was to see if there is a need to bias correct the rainfall data in order for the two datasets to correspond to the WR2012. The CHIRPS dataset does not show substantial bias in any of the rainfall zones. In D1Q rainfall-zone and in D1P SAWS dataset has a similar (small) bias to CHIRPS. In D1N rainfall zone, the SAWS dataset shows a systematic bias where it underestimates the rainfall values compared to the WR2012.

Table 4.1. Comparison of RMSE and MAE on monthly (mm and %) basis for CHIRPS and SAWS against WR2012 datasets in all the Kraai River catchment rainfall-zones.

	D1Q		**D1P**		**D1N**	
	CHIRPS	**SAWS**	**CHIRPS**	**SAWS**	**CHIRPS**	**SAWS**
MMAP	53.70		53.86		54.61	
RMSE (monthly)(mm)	23.22	16.67	23.99	29.51	23.33	26.06
MAE (monthly) (mm)	15.35	10.30	16.88	20.63	16.50	17.88

RMSE in %	42.45	30.47	44.55	54.79	42.73	47.73
MAE in %	28.06	18.82	31.34	38.30	30.22	32.74

The table 4.1 shows RMSE and MAE of both CHIRPS and SAWS datasets against WR2012 dataset as reference data on a monthly basis. The error values in the table confirm results of analyses of figures, i.e. that SAWS data shows higher values of errors than the CHIRPS data in D1P and D1N. However, in D1Q rainfall-zone the SAWS dataset errors are less than those of CHIRPS dataset.

4.2.1.4 Biases and errors on an annual basis

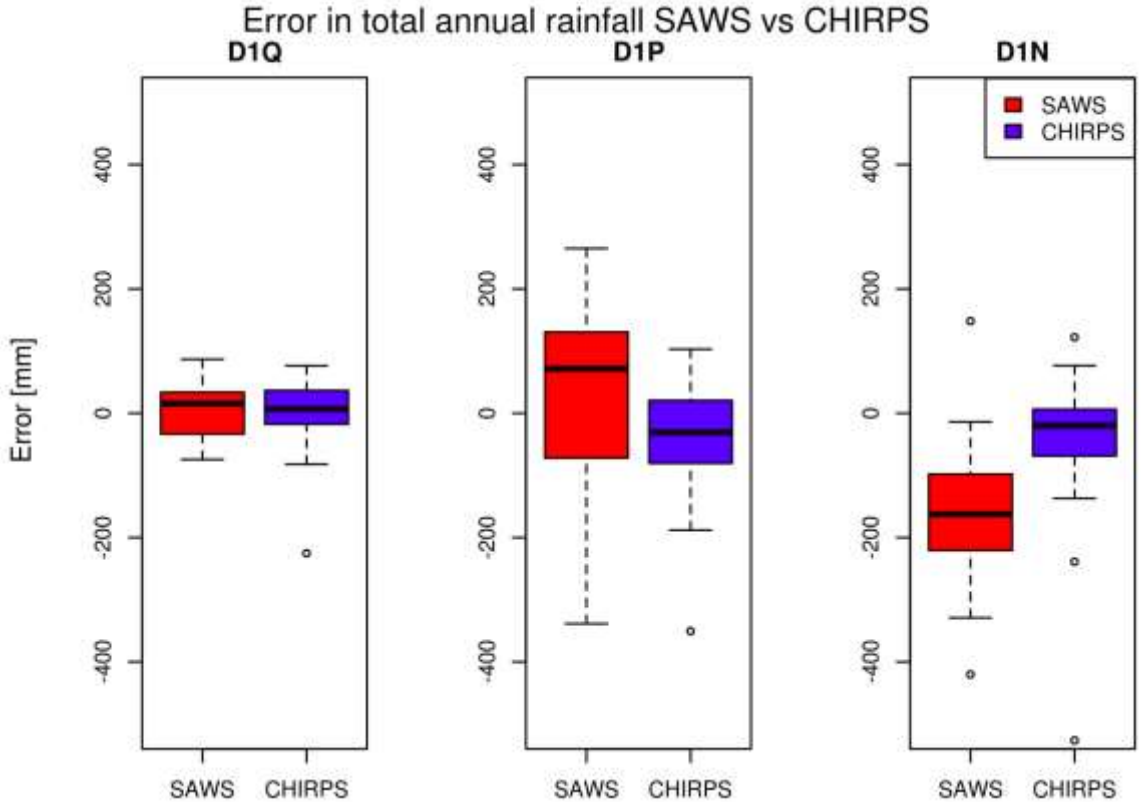

Figure 4.13. Boxplots of errors in total annual rainfall between SAWS and CHIRPS dataset for all the rainfall-zones of Kraai River catchment.

Figure. 4.13 shows boxplots of errors (differences between values in corresponding years) in total annual rainfall for CHIRPS and SAWS datasets. In this figure the median (black bar in the middle of the box) expresses bias and the width of the box and whiskers expresses distribution of errors in individual years. In the D1Q rainfall-zone the biases and errors of both datasets (medians and the box-whiskers) are close to zero. As for D1P and D1N rainfall-zones the SAWS dataset has larger bias and errors compared to the CHIRPS dataset, with the CHIRPS dataset errors and bias in those zones close to zero.

Table 4.2. Comparison of RMSE and MAE on annual (mm and %) basis for CHIRPS and SAWS against WR2012 datasets in all the Kraai River catchment rainfall-zones.

	D1Q		D1P		D1N	
	CHIRPS	**SAWS**	**CHIRPS**	**SAWS**	**CHIRPS**	**SAWS**
MAP (mm)	656.46		646.38		655.32	
RMSE (annual) (mm)	132.52	116.90	91.58	160.90	112.42	128.96
MAE (annual) (mm)	106.25	100.55	66.08	136.84	82.98	100.64
RMSE in %	20.18	17.80	14.16	24.81	17.15	19.67
MAE in %	16.18	15.31	10.22	21.17	12.66	15.35

Table 4.2 shows RMSE and MAE of both CHIRPS and SAWS datasets against WR2012 dataset as reference data on an annual basis. The error values in the table confirm results of analyses of figures, i.e. that SAWS data shows higher values of errors than the CHIRPS data in D1P and D1N. However, in D1Q rainfall-zone the SAWS dataset errors are less than those of CHIRPS dataset.

4.2.1.1 Time evolution of errors

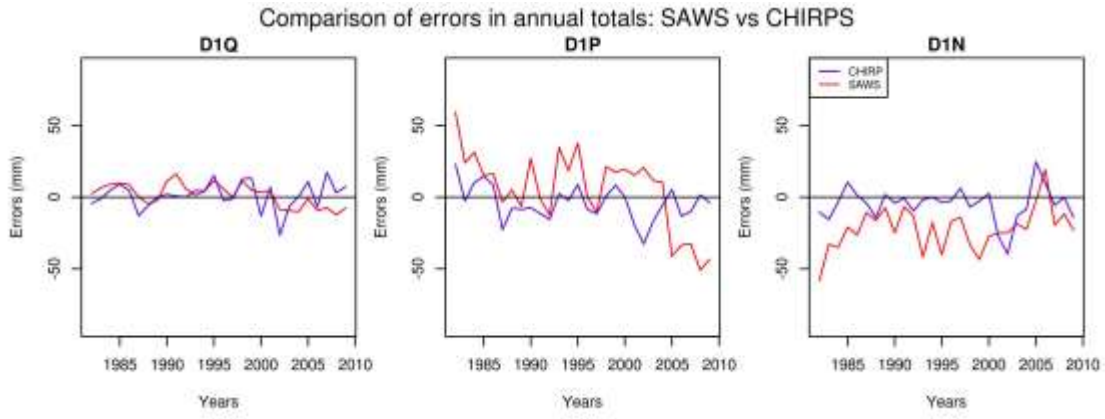

Figure 4.14. This figure shows the errors (mm) in annual totals change in time of CHIRPS and SAWS datasets for all the rainfall-zones of Kraai River catchment.

Figure 4.14 shows time series of errors of CHIRPS and SAWS over the overlap period 1981-2009. This figure was created to evaluate whether or not there are any systematic effects in the annual errors, such as trends or periods with larger/smaller errors. In the D1N rainfall-zone the SAWS data has large errors that are below zero (i.e. this may mean the SAWS dataset is underestimating) most of the years till about year 2003 when the errors above the zero line (which this may mean overestimation) compared to the CHIRPS data. Although there are larger similar errors in CHIRPS

in both D1P and D1N from about year 2000 till year 2003. Furthermore, SAWS errors show temporal trends and patterns over time which is more visible in D1P and D1N, but CHIRPS data has no prominent patterns.

4.2.2 Summary of the evaluation

Based on the above analyses, it was decided that the CHIRPS dataset is considered to be a good dataset to be used for this study. A study of this kind requires an accurate observed and continuous and near-real time rainfall data in order to get reliable operational hydrological forecasts. The SAWS data has errors and biases that may likely be attributed to missing data in some of the stations, not using uniform stations to create the catchment rainfall for the rainfall-zones and because the subset of stations changes depending on the availability of data from individual stations, thus there is a potential that average rainfall has some errors. CHIRPS rainfall dataset does not need bias correction as these biases and errors are minimal compared to the SAWS data. The CHIRPS dataset is readily available and there is no bureaucracy to follow when one needs the data compared to SAWS dataset. Overall, the figures above show that the CHIRPS dataset is more consistent with the WR2012 dataset that was used in the Pitman /WR2012 model. Therefore, CHIRPS dataset is used to merge the WR2012 dataset.

4.2.3 Extended rainfall dataset for Kraai River catchment

The extended WR2012-CHIRPS dataset was obtained by simply merging 1920-2009 WR2012 data with 2010-2016 CHIRPS data as explained in chapter 3. This time series is shown in Figure 4.15.

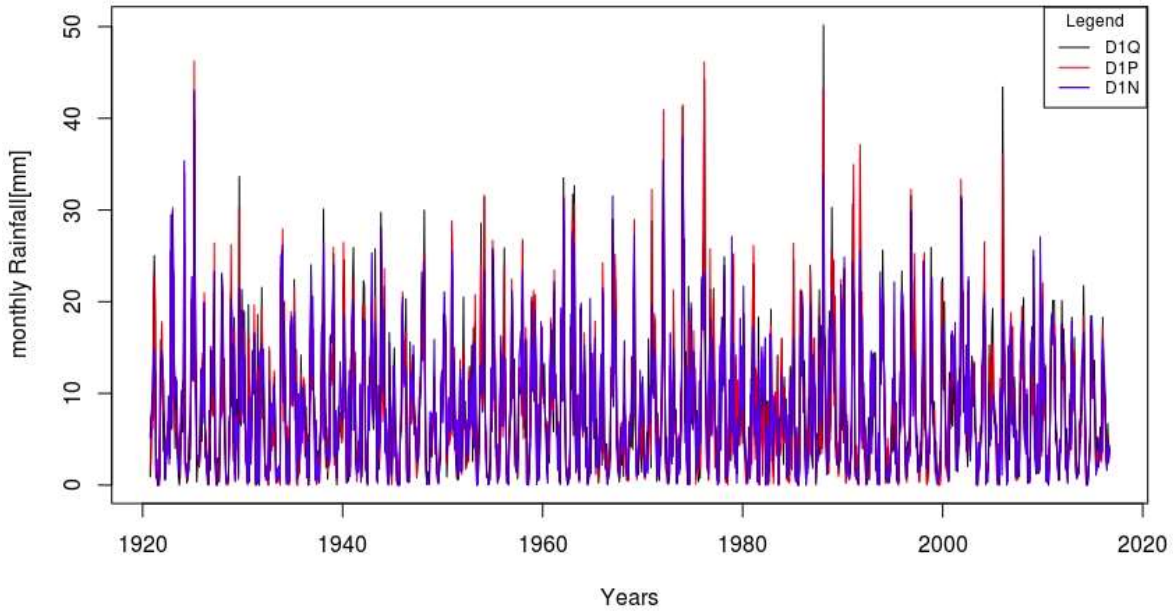

Figure 4.15. Time series of monthly rainfall of WR2012-CHIRPS dataset covering 1920 to 2016for all the three rainfall-zones of the Kraai River catchment.

4.3 Evaluation of Pitman/WR2012 model run with extended rainfall dataset

The evaluation of the Pitman model/WR2012 was carried out for 1965-2016 using the NSE and PBIAS performance indices. This period was selected because the available observed streamflow starts in 1965-present, 2016 is the period where the simulation of streamflow ends for the purpose of this study. The Pitman/WR2012 model was forced with the extended WR2012-CHIRPS rainfall.

Table 4.3. Performance statistics of the Pitman model/WR2012 in the Kraai River catchment for the period 1965-2016.

Rainfall Dataset	Period	MAR (mcm/a)		NSE	PBIAS(%)
		Obs	Sim		
WR2012-CHIRPS	1965-2016	707.29	784.50	0.61	11%
WR2012	1965-2009	702.35	848.86	0.68	16%

The table above (Table 4.3) shows model performance indices calculated for Pitman model/WR2012 output against observations at the streamflow gauge D1H011. The PBIAS value is 11% which falls within the good range (i.e. PBIAS < ± 10%). The NSE value is 0.61 which falls within the very good range (i.e. 0.50 ≤ NSE < 0.65) indicating acceptable levels of performance for streamflow simulation at D1H011 streamflow gauge. For the period covered by WR2012 data, i.e. 1965-2009, the Pitman/WR2012 model for both methods showed acceptable performance levels (Table 4.3) with PBIAS 16% and NSE 0.68. The values ofWR2012-CHIRPS time series almost agree with the WR2012 series with a difference of NSE 0.07 and PBIAS of 5%. Therefore, the new data used to run the model is considerably acceptable.

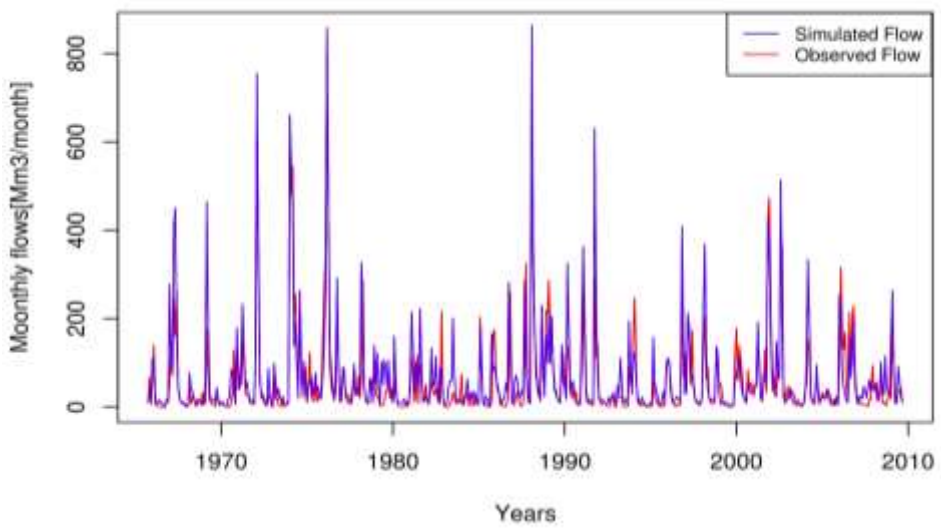

Figure 4.16. Pitman/WR2012 simulated and observed streamflow from 1965-2009 at D1H011 for Kraai River Catchment.

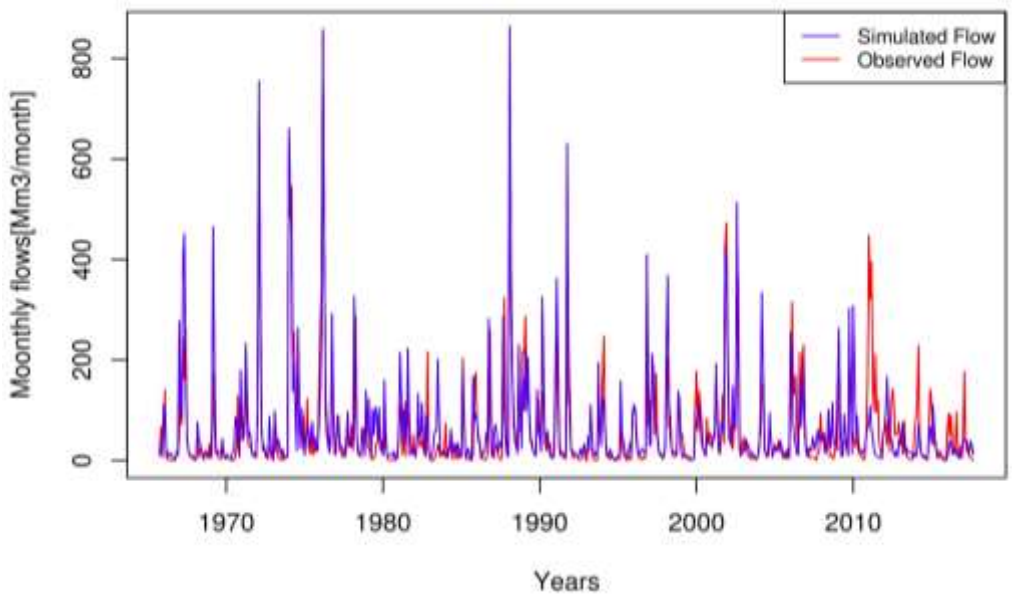

Figure 4.17. Pitman/WR2012 simulated and observed streamflow with WR2012-CHIRPS data from 1965-2016 at D1H011 for Kraai River Catchment.

The above figures show observed and simulated streamflow from the model run from 1920-2009 with WR2012 data (Fig 4.17) and 1920-2016 with WR2012-CHIRPS data. In figure 4.16 the observed streamflow is much higher than simulated streamflow in 2010. This could be as a result of data error from the observed streamflow because the observed discharges in neighbouring catchment do not show the same pattern in 2010.

4.4 Implementation of Pitman model in the Seasonal Hydrological Forecasting mode

Figures 4.3-4.6 are illustrating the steps that were identified during this study in order to implement the Pitman/WR2012 model in both re-forecast and actual operational hydrological forecasting mode.

In practice this was implemented in the following way:

- downscaled rainfall for a given forecast and for a given rainfall zone was substituted for the original rainfall for the forecast period in the Pitman model rainfall file (with WR2012-CHIRPS data) for that zone,
- the model was executed for the entire WR2012-CHIIPR data period, i.e. 1920-2016
- results of runoff simulations for the period of forecast were extracted for further analyses, and data after that period were discarded
- steps 1-3 were repeated for each year and for each ensemble member

Figures 4.18-4.20 show streamflow forecasts during selected years of wet, dry and average years in the 1982-2016 period in order to illustrate how the Pitman/WR20102 hydrological forecast looks during a range of conditions. These forecasts of streamflow at the D1H011 gauge were produced by forcing the Pitman model/WR2012 with 10 Ensemble members of seasonal climate forecasts for the December, January and February (DJF) season. For each of the wet, dry and average years, four years were selected by looking at observed streamflow of the Kraai River catchment (Appendix 3).

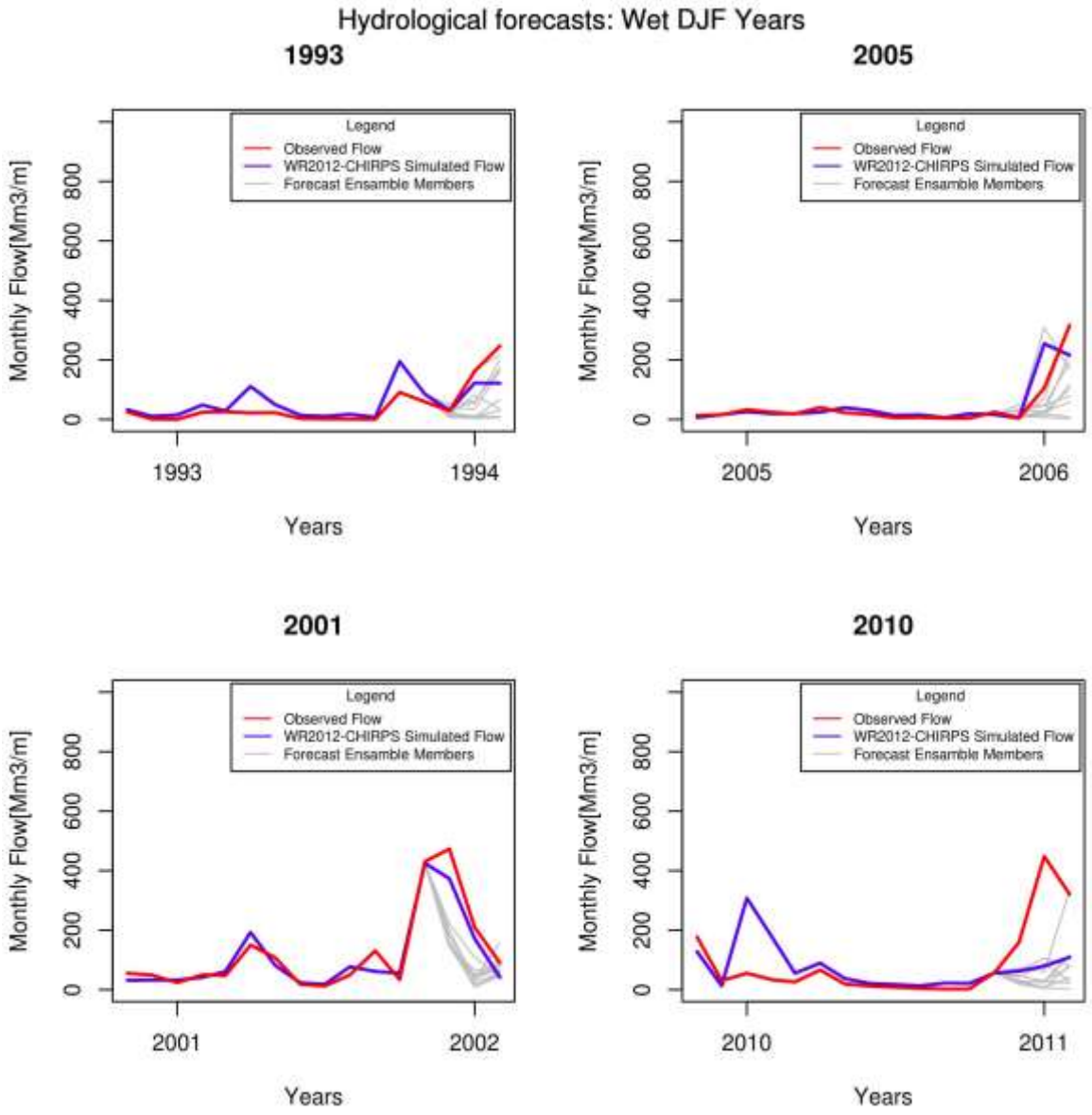

Figure 4.18. Selected wet years for the seasonal hydrological forecast (DJF) from 10 ensemble members using the Pitman model/WR2012.

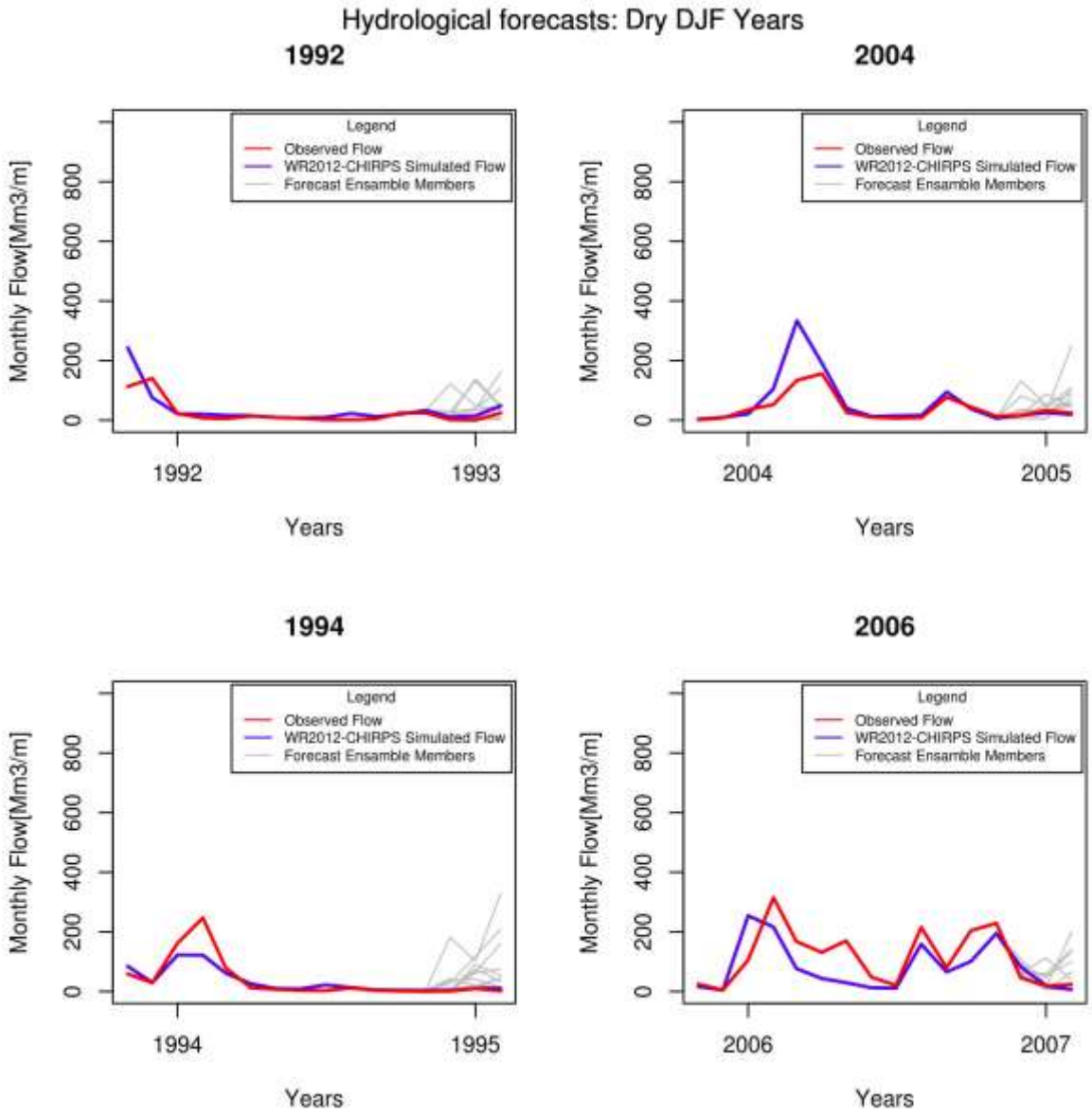

Figure 4.19. Dry years for the seasonal hydrological forecast (DJF) from 10 ensemble members using the Pitman model/WR2012 model.

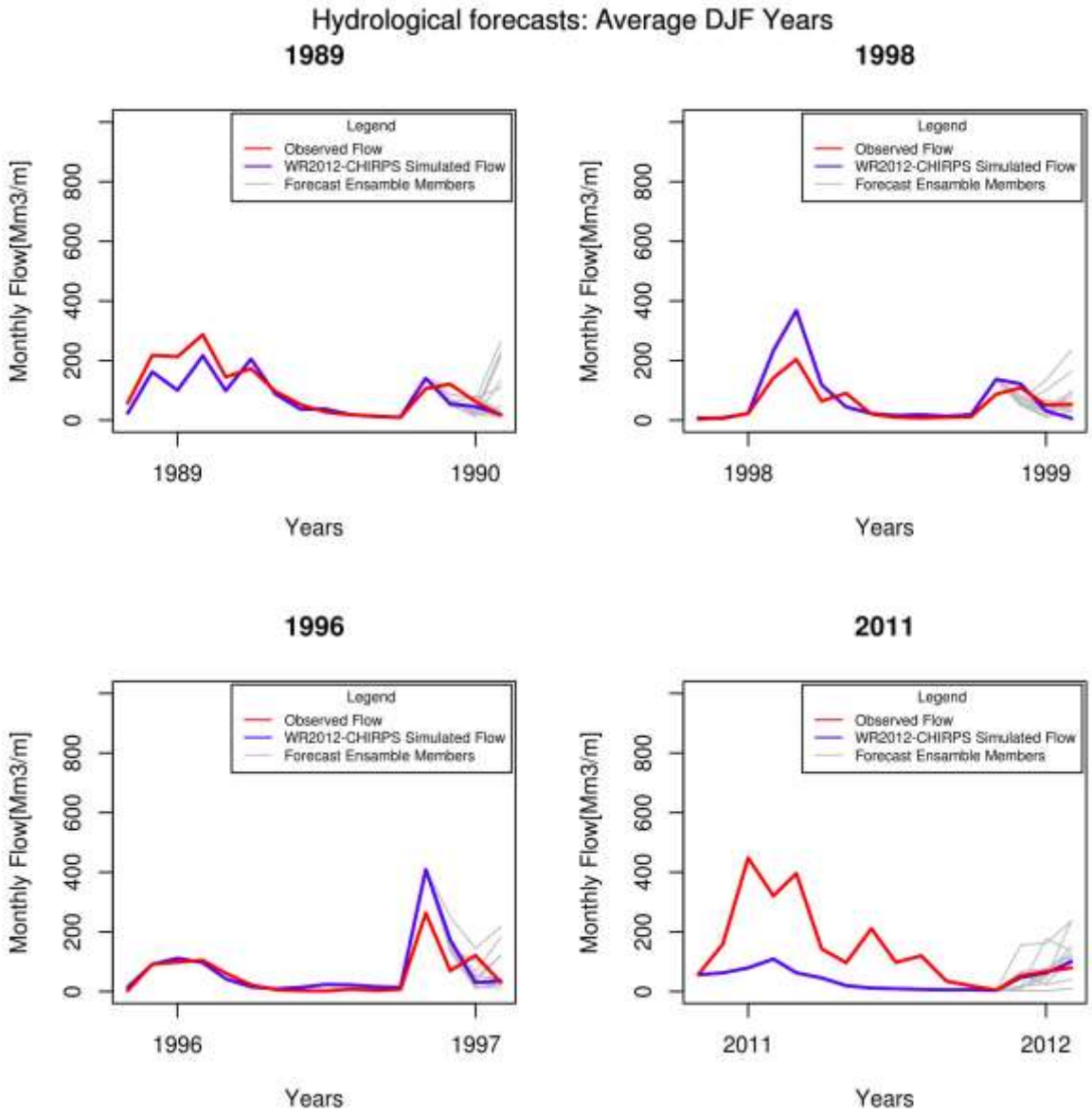

Figure 4.20. Selected average years for the seasonal hydrological forecast (DJF) from 10 ensemble members using the Pitman model/WR2012 model.

During the wet years the most ensemble forecasts are not distributed around the observed and simulated streamflow in all the selected years (Fig 4.18). However, average and dry years the ensemble member forecast are mostly distributed around the observed and simulated streamflow (Fig 4.19-4.20), except in dry year 1994. The differences between selected dry and wet years might indicate differences in forecast climate model skill that is conditional on the strength of regional climate forcing as explained by Landman and Beraki (2012). The exploration of this, is however, beyond the scope of this research.

4.5 The skill assessment of the forecast produced by forcing the Pitman/WR2012 model.

For the purpose of assessment of hydrological forecast skill, a series of historical forecasts, or re-forecasts were implemented. Each re-forecast covered a period of 3 months. Although in an operational setting forecasts could be issued every month, the focus here is on forecasting the core of the rainy season, i.e. the months of December, January and February. The re-forecasts implemented here spanned the period of 1982-2016, i.e. there was a forecast issued starting on each December in that period. Each forecast was based on 10 member ensembles of climate forecast.

Two methods are used to assess the skill of the forecasts These methods are Relative Operating Characteristic (ROC) and Ranked Probability Score (RPS) together with Ranked Probability Score Skill (RPSS) as extracted from RPS, and they are described in detail in chapter 3 of this study. Skill scores were calculated for streamflow forecast, but also for the downscaled rainfall forecast used to force the Pitman model. The value of skills scores were obtained using the verification package of R statistical software.

4.5.1. RPS and RPSS

Table 4.4. Ranked Probability Scores and Ranked Probability Score skill on the probability streamflow forecast for DJF, issued in December (i.e. Summer season).

Forecast months	Ranked probability Score (RPS)	Ranked Probability Score skill (RPSS)
Dec	0.19	0.15
Jan	0.24	-0.05
Feb	0.23	-0.01

Table 4.5 Ranked Probability Scores and Ranked Probability Score skill on the probability rainfall forecast for DJF, issued in December (i.e. Summer season).

Forecast months	Ranked probability Score (RPS)	Ranked Probability Score skill (RPSS)
Dec	0.29	-0.29
Jan	0.25	-0.14
Feb	0.23	-0.3

The tables 4.4 -4.5 above show the results of ranked probability score skill for both streamflow and rainfall forecasts for DJF with ranked probability score. The RPSS showed skill in streamflow forecast in Jan but in Dec and Feb (Table 4.4). There is no skill for the rainfall forecast in any of the months (Table 4.5). The RPSS values higher for streamflow are higher for streamflow than rainfall forecasts.

4.5.2. ROC score and ROC curve

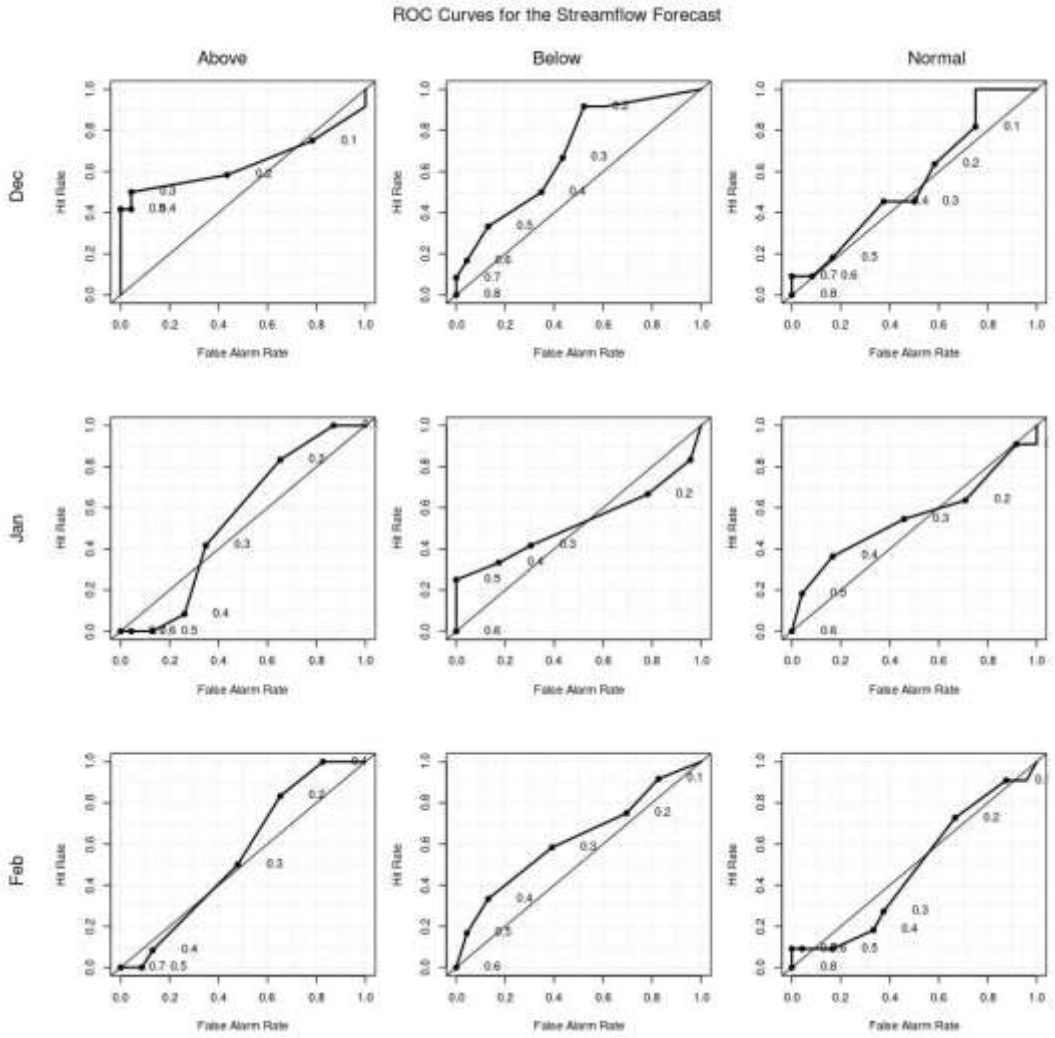

Figure 4.21. ROC score plot for probability seasonal streamflow forecast above, below and normal category for the DJF season.

Figure 4.21 shows ROC curves for all the categories (Above, Below and Normal) of streamflow forecast at D1H011 in the Kraai River catchment for each month of forecast. For the December and Feb month on all the categories the forecasts are mostly above the 1:1 line besides Feb (Normal) which the forecast is below and above the 1:1 line. The month of Jan in all the categories is the forecasts are mostly below the 1:1 line.

Table 4.6. The ROC scores for the probability streamflow forecast months DJF (i.e. Summer season).

Forecast Months	Above	Below	Normal
Dec	0.64	0.69	0.56
Jan	0.55	0.52	0.55
Feb	0.55	0.62	0.48

Table 4.7. The ROC scores for the probability rainfall forecasts for summer (DJF)

Forecast Months	Above	Below	Normal
Dec	0.59	0.59	0.51
Jan	0.43	0.33	0.48
Feb	0.61	0.53	0.48

Table 4.6-4.7 shows ROC skill scores of the forecast of streamflow and rainfall for the summer season (DJF). The tables 4.6-4.7 distinguishes skill for the probabilistic forecast of above, below and normal streamflow for each of the months during the summer season (DJF). Generally, the forecasts are skilful as most of the scores are above the no-skill values of 0.5 for all the months apart from Feb for normal conditions (Table 4.6). The skill is generally higher for above and below normal runoff than for normal runoff. The skill is generally better for Dec and Feb than Jan. There is a similar pattern of skill for the rainfall forecast (Table 4.7) and streamflow forecast. Importantly, the skill of streamflow forecast is considerably better than the skill of rainfall forecast.

4.6 Summary and discussion of results

4.6.1 Framework for implementation of seasonal hydrological forecast

In this study, seasonal climate forecasts 10 ensemble members (i.e. rainfall) from CFS v2 were used as an input to the Pitman model/WR2012 to produce seasonal hydrological forecast for the Kraai River catchment. This approach, i.e. using hydrological model linked to seasonal climate forecast to produce seasonal hydrological forecasts is often used in research and operational setting (Tucci *et al.*, 2003; Ceron *et al.*, 2010; Yuan *et al.*, 2015; Wolski *et al.*, 2018; Liu *et al.*, 2019).

The nature of the Pitman WR2012 model required developing a specific framework for this application. That main aspects of this framework are:

- Historical rainfall data as input to run the model and this data must be updated to near real-time as the WR2012 data ends in 2009.
- Downscaled forecasts are used to force the model to run with seasonal climate forecast ahead of time when the climate forecast was issued.
- The model run generates forecasted streamflow and other hydrological variables that contribute to hydrological forecast.
- In the retrospective forecast setting, the above are repeated for the entire period for which forecast data are available, and individual forecasts are compared to simulated streamflow. This comparison enables calculation of forecast skill measures.

In an operational setting, the forecast is implemented and used, but must be interpreted accounting for the skill of the hydrological forecasts for given initialization and lead time, because, as the results indicate, skill varies strongly between those.

Updating the WR2012 rainfall to near real-time is a critical step of implementing the Pitman/WR2012 model in seasonal hydrological forecasting operational or skill evaluation of the forecasts. For the purpose of this study two candidate rainfall datasets (i.e. SAWS and CHIRPS) were selected based on their availability in SA and the fact that they are available in near-real time. Because these datasets have biases and errors, assessment was done. These datasets were compared with the WR2012 dataset as reference data over the period of 1982-2009 which is an overlap period of the three datasets. The results of the comparison showed that CHIRPS data has lower errors and biases compared to SAWS rainfall more especially at D1P and D1N rainfall-zone (Fig 4.11-4.12; 4.13). Also, SAWS data showed trends and patterns when looking at the evolution of errors (Fig 4.14).

The performance of the Pitman/WR2012 model with a merged WR2012-CHIRPS rainfall was then evaluated. The results showed that from this period the model performed well with the merged dataset, with NSE of 0.61 and PBIAS at 11% which both indicate a very good range of model performance. These values were compared with the PBIAS and NSE values obtained for the period of 1965-2009.

In view of the above, the CHIRPS dataset was chosen to update the WR2012 to near real-time for the purpose of this study. The statement of adequacy of CHIRPS rainfall data as input into hydrological models applies to the study catchment only. It was, in fact, indicated by Funk *et al.*, (2015) that the CHIRPS rainfall data can be used to support effective hydrological forecasts. Again Tou *et al.*, (2016) also used the CHIRPS rainfall data as input into SWAT model and the streamflow results were satisfactory. However, the use of CHIRPS rainfall data as input into a hydrological model must be done with caution, as this data might not be accurate in some regions. For example, Maswanganye (2018) found that the CHIRPS rainfall tends to overestimate rainfall along the west coast of the Western Cape province and underestimate rainfall in the eastern part of the province.

The above summary addresses the objective one of this study and the first question of this study which is the steps to be used in implementing the Pitman/WR2012 model in seasonal hydrological forecasting. Also, it contributes to the objective two of the study which was the actual implementation of the Pitman/WR2012 model in the seasonal forecast mode.

4.6.2 Skill of the hydrological forecast in Kraai River catchment

The Pitman model was implemented in the forecast mode in a re-forecast, or retrospective forecast setting. Forecast covers the 1982-2016 and they are for the summer season (DJF).

The produced seasonal hydrological forecasts were verified using two forecast verification methods for probabilistic categorical forecast, i.e. for the forecast of probabilities of above-normal, below-normal and normal conditions. This was done to assess the skill of the seasonal hydrological forecasts as part of objective 2 of the study. These methods are as follows: RPSS and ROC methods for probabilistic forecast verification.

The skill of the forecast is not consistent across different measures of skill, which is not unexpected, as they measure various aspects of the forecast quality. For example, the ROC method measures the ability of the forecast to discriminate between two alternative outcomes. However, the RPSS method measures the improvement of the multi-category probabilistic forecast relative to a reference forecast. This method takes climatological frequency into account.

In general, however, both the RPSS and the ROC method showed that the seasonal hydrological forecast is generally more skilful than the rainfall forecasts used in this study. The best skill is achieved for December, weaker for January and then skill increases for February. Also, the skill is better for above- and below-normal conditions than for normal conditions.

The finding that the skill of the hydrological forecast is better than that of rainfall forecast is of profound importance. This illustrates that the hydrological forecast, as implemented in the framing improves on the skill of seasonal rainfall forecast. This is in fact surprising because hydrological forecast involves a hydrological model that has an inherent model error, and as a result one would expect reduction of skill of simulations. However, this effect of improvement on skill is likely to be caused by the initial condition of the hydrological model.

The above summary addresses the third objective of this study and the second research question of this study which the evaluation of the performance (skill) of the seasonally hydrological forecast implemented with the Pitman/WR2012 model in the Kraai River catchment.

5 Chapter 5: Conclusion and Recommendations

This chapter provides a conclusion and suggested recommendation based on the finding of the study. This chapter also provides an insight to the original research question based on what has been discovered throughout the study period.

5.1 Conclusion

In view of the potential of use of seasonal hydrological forecasting in water resources management and the fact that such forecasts are scarce in South Africa this study set out to investigate the following:

1. What are the steps to be taken to implement the Pitman model/WR2012 in seasonal hydrological forecasting mode?
2. What is the performance of seasonal hydrological forecast based on Pitman model and a selected climate forecast?

The investigations were based on the example of the Kraai River catchment.

The research questions above were addressed through two sets of objectives. With respect to objective 1, it can be concluded that the identified framework for implementation of the Pitman/WR2012 in seasonal hydrological forecasting mode either operational or retrospective forecast forced with seasonal climate forecasts from climate models can be achieved following the approach developed in this study. The comparison of forecast skill between rainfall forecast and streamflow forecast suggests that updating of the WR2012 data to near-real time is the most important step of this framework. Therefore, in this study it can be concluded that the CHIRPS rainfall data can be used to patch the WR2012 rainfall data in order to run the Pitman/WR2012 model with near real time rainfall. This is because the CHIRPS data showed better results than the SAWS rainfall data when compared with WR2012 data for the overlap period 1982-2009 (Chapter 4). Furthermore, the CHIRPS data is free and readily available for use and that minimises the bureaucracy of obtaining data at SAWS and other sources of rainfall in SA with many missing values. However, the CHIRPS data must be used with caution as input data in hydrological practices such as hydrological modelling and forecasting.

With respect to objective 2, it can be concluded that the Pitman/WR2012 model can perform realistically when implemented in seasonal hydrological forecasts mode through forcing the model with seasonal climate forecast for the Kraai River catchment for different selected states of DJF season i.e. wet, dry and average years of the observed streamflow. This is also supported by the considerable good skill of the streamflow forecast even though it is not perfect.

It has to be mentioned here that this study, but its nature and context, is not an exhaustive, comprehensive study of seasonal hydrological forecasting, and the forecast it is based on is not directly applicable to water resources management of the studied catchment. Rather, this study has to be treated as a “proof-of-concept” of implementation of hydrological forecast using the Pitman/WR2012 model. The main limitations of the study that prevent it from being operationalized are as follows:

- Only one climate forecasting system is used (CFSv2), while it is known that better forecast quality can be obtained from an ensemble of forecasting systems

- Results in terms of forecast skill are specific to the studied catchment and analysed forecast, and skill of forecast in any other catchment has to be investigated separately.

5.2 Recommendations

Seasonal hydrological forecasting in South Africa is still in its early stages, be it for research or operational purposes. There are several issues that can be attributed to the above-mentioned issue as highlighted by Wolski *et al.,* (2018). The lack of station rainfall data and bureaucratic way of obtaining station rainfall in the SA which provide ground truthing is one of the limiting factors for this kind of study as it requires intensive data for hydrological modelling of the catchment. The latter has serious implications on the skill and usefulness of the seasonal hydrological forecasts by different end users. Therefore, data dissemination is very important for this kind of research and its operational purposes. Furthermore, the use of ensemble of seasonal climate forecasts would likely further improve the quality of the seasonal hydrological forecast. This study was focusing on a tertiary catchment with low level of development of water resources, low level of transformation of land cover, and relatively simple hydrology. Seasonal hydrological forecasting testing should be done in bigger catchments with complex hydrological systems, catchments with high abstraction of water from the stream and groundwater abstraction. It is recommended that the forecast should also be produced for other seasons to see if the skill of the forecast will improve from the skill of the summer season (DJF). The forecast implementation framework developed in this study lays foundation for such extended studies. It is also recommended that a new research be done on gap-filling or use of the SAWS areal averaged rainfall data as the SAWS data on this study showed little consistency with WR2012 than CHIRPS dataset.

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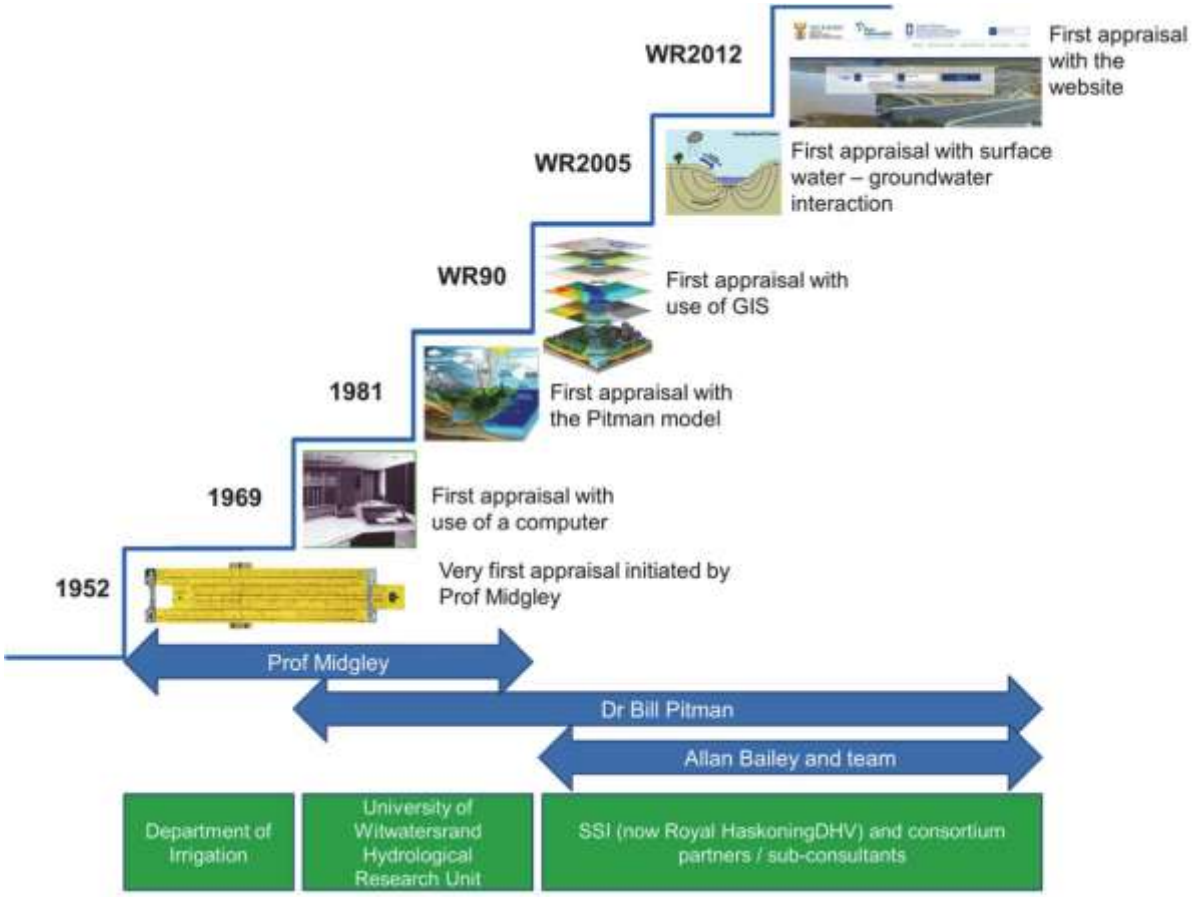
7 Appendices

***Appendix 1**. The history of country wide water resources appraisals for South Africa, Lesotho and Swaziland.*



Appendix 2. Station and gridded rainfall datasets available for RSA

Station datasets

The SAWS is responsible for collection of about 161 rainfall stations with 5 minutes data, 1165 rainfall stations with daily data (SAWS, 2016). The SAWS divide the country into 93 rainfall districts. The SAWS rainfall database is in its natural state because it is only gauge data without any interpolation. It covers exclusively South Africa land and provides monthly precipitation from 1921 to the present in some stations (Korahanis *et al.*, 2008).

The ARC automatic weather station network comprises of 500 operational stations across the country and a small number of mechanical weather stations. The data from ARC is loaded onto a database from which various climate information products can be derived (Umlindi, 2015). Data is available at a fee, unless requested for a research project.

The DWS has about 150 rainfall stations covering the country and data from these stations are available from the DWS website (www...). The start and end year of the station rainfall vary from station to station, and for operational stations data are updated sometimes with several months delay.

Appendix 2 *.Mostly used sources rainfall data per organisation and their estimated number of stations in South Africa.*

Organisations	No. of Station
SAWS	1326
DWS	150
SASRI	161
ARC	500
PVT	±1050

Gridded dataset

The CRU gridded data (New *et al.*, 1999; 2000) is based on rainfall station data integrated under World Meteorological Organization (WMO) and several independent sources, with approximately 4,000 stations globally (Harris *et al.*, 2014). GPCP gridded data is generated by combining microwave-based observations from a low-orbit satellite and the frequent time sampling of the geosynchronous infrared (IR) observations using an enhanced satellite-gauge-model (SGM) technique (Adler *et al.*, 1994).

The CHIRPS rainfall data is generated from station data (Durre *et al.*, 2010), quasi-global geostationary thermal infrared (IR) satellite observations (Janowiak *et al.*, 2001), Tropical Rainfall Measuring Mission (TRMM) (Huffman *et al.*, 2007, 2010) and the NOAA Climate Forecast System, version 2 (CFS) re-analysis (Saha *et al.*, 2010). There are two processes involved to produce CHIRPS: (a) First, the global grids for long-term (1980-2009) average precipitation called CHIRP are estimated for each month based on averaged satellite data (Funk *et al.*, 2015): (b) second process involves implementation of station blending procedure as described by Funk *et al*., (2015) assigning relative weights to both CHIRP and station values. The latter procedure is based on the expected correlation between rainfall at a given target location and rainfall at the locations of neighbouring stations using CHIRP values (Funk *et al.,* 2015).

The ARC version 2 is generated by linearly combining Geostationary Operational Environmental Satellite (GOES) Precipitation Index (GPI) estimates and Passive Microwave Measurement (PMW) rainfall estimates before merging with GTS station records following a method described by Reynolds (1988).The other gridded rainfall datasets are generated by using a combination of two or more of station, satellite and reanalysis data (Novella and Thiaw, 2012; Ayehu *et al.*, 2018).

Lastly, the WFDEI gridded rainfall data is generated by spatially separating CRU and European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim reanalysis dataset to produce number of wet days and rainfall gauge correction respectively, then merged with rainfall totals from either CRU (Mitchell and Jones, 2005) or GPCC (Schneider *et al.*, 2014) to produce WFDEI-CRU and WFDEI-GPCC respectively (Weedon *et al.*, 2014).

***Appendix 3**. Some of the available gridded rainfall datasets for South Africa.*

Organisation	Name & Acronym	Temporal resolution	Spatial resolution(s)	Start and end dates
Climate Research Unit, University of East Anglia	Climate Research Unit v3.24 CRU	Monthly	0.5°	1901 - 2015
Climate Hazards Group (CHG).	Climate Hazards Group InfraRed Precipitation with Station data CHIRPS	Daily	0.05° 0.25°	1981 - present
National Oceanic and Atmospheric Administration (NOAA), Climate Prediction Centre (CPC), NCEP, Famine Early Warning Systems (FEWS)	Africa Rainfall Climatology V2 ARC	Daily	0.1°	1983 - present
Global Precipitation Climatology	Global Precipitation Climatology Project V2.3 GPCP	Monthly	2.5°	1979 - present
NASA and the Japan Aerospace Exploration Agency (JAXA).	Tropical Rainfall Measuring Mission (TRMM).	Daily	0.5º	1997-2015
University of Reading	Tropical Applications of Meteorology using satellite. TAMSAT	Monthly and 10-Daily	0.0375°	1983-01to 2018-12

Appendix 4. *The figure shows the selected conditions of years for seasonal hydrological forecast for DJF season.*