Attribution of the 2015-2016 hydrological drought in KwaZulu-Natal to anthropogenic climate change.

By

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DECLARATION

I, …Makeya Karlie… hereby declare that the work on which this dissertation/thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university.

Signature: Signed by candidate ……………………………….

Date: … 10 January 2020 ……….

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Dedicated to SK, gone but never forgotten.

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LIST OF ACRONYMS

ACE- Attribution of Climate Related Extremes
ACRU- Agricultural Catchments Research Unit Model
AGCM- Atmospheric Global Climate Model
AMS- American Meteorological Society
AOGC EC- Earth 2.3- Climate Model
ArcSWAT- SWAT model with ArcGIS interface
AR5- IPCC Fifth Assessment Report
BAMS- The Bulletin of the American Meteorological Society
CAMS.1-2 degree- Climate Model
CFSR- Climate Forecast System Reanalysis
CMIP5- Coupled Model Intercomparison Project Phase 5
CRU- Climate Research Unit Data
CSAG- Climate Systems Analysis Group
CSV- Comma-separated Values File Format
DEM- Digital Elevation Model
DJF- December, January, February
DWS- Department of Water and Sanitation
ENSO- El Nino Southern Oscillation
FAR-Fractional Attribution Risk
GCMS- General Circulation Models
GHG- Greenhouse Gas
GIS- Geographic Information Systems
GLUE- Generalised Likelihood Uncertainty Estimation
HadAM3p- Global Climate Model
HadAM3p-N96- Climate Model
HadAM3-N144- Atmosphere only climate model
HRU- Hydrological Response Unit
IPCC- The Intergovernmental Panel On Climate Change
IPSS- Ingula Pumped Storage Scheme
km- kilometer
KZN- KwaZulu Natal
LISFLOOD- Hydrological Model
LTAS- Long Term Adaptation Scenarios
m- meter
MAP- Mean Annual Precipitation
MAR- Mean Annual Runoff
MAT- Mean Annual Temperature
MCMC- Markov Chain Monte Carlo
NAS- National Academies of Sciences, Engineering, and Medicine
NCEP- National Centres for Environmental Prediction
NSE- Nash-Sutcliffe efficiency
NWRS- National Water Resource Strategy
OISST- NOAA’S Optimum Interpolation SST
ParaSol- Parameter Solution
PBIAS- Percent Bias
PCR-GLOBWB 2- Hydrological Model

PDF- Probability Density Function
PEA- Probabilistic Event Attribution
PITMAN- Hydrological rainfall/runoff Model
PSO- Particle Swarm Optimization
p_0 - counterfactual climate
p_1- current real world climate
PnonGHG- Counterfactual Climate without Greenhouse Gasses
Preal- Current Day Climate
QGIS- Quantum Geographical Information System
QSWAT- Qantum/ QGIS Soil Water Assessment Tool
R^2- Coefficient of determination
RCM- Regional Climate Model
RR- Risk Ratio
RSA- Republic of South Africa
RSR- Ratio of Mean Square Error
SA- South Africa
SB- Subbasin
SAWS- South African Weather Service
SCS-CN- Soil Conservation Service-Curve Number
SOM- Self Organising Maps
SOMD- Self Organising Maps Downscaling
SPATSIM- Spatial and Time Series Information Modelling Framework
SRTM- Shuttle Radar Topography Mission
SST- Sea Surface Temperature
SSURGO- USA Soil Data
STATSGO2- USA Soil Data
SUFI-2- Sequential Uncertainty Fitting Version 2
SWAT- Soil and Water Assessment Tool
SWATCUP- Calibration and Uncertainty Procedures
SWRRB- Simulator for Water Resources in Rural Basins model
TauDEM- Terrain Analysis using Digital Elevation Model
UCT- University of Cape Town
WATCH- Water and Global Change
weather@home- Climate Model
WFD- WATCH Forcing Data
WFDEI- WATCH Forcing Data and WERA- interim reanalysis
WMA- Water Management Area
WRC- Water Research Council
WR2012- Water Resources of South Africa, 2012 Study
WWA- World Weather Attribution
WWF- World Wildlife Foundation
95PPU- 95% Prediction Uncertainty
$\circ C$- Degrees Celcius

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ABSTRACT

In 2015-2016 Kwa-Zulu Natal (KZN) and other provinces in South Africa suffered from drought conditions. Drought can have negative impacts on the environment, society and the economy. Climate change is predicted to exacerbate extreme events such as droughts that would adversely affect already vulnerable regions such as KZN. The main aim of this study is to implement the attribution procedure, to determine if climate change has contributed to the 2015-2016 hydrological drought in selected KZN catchments. Methodology of the study followed a general framework of implementation of hydrological attribution experiments with climate data obtained from attribution simulations with HadAM3p global climate model. Prior to simulations in attribution mode, QSWAT model was set up for the study area and calibrated using SWAT-CUP and SUFI-2. Calibration results were poor but the model could be applied in the context of this study, under certain constraints. Results of attribution experiments revealed that for all 3 subbasins studied no increase of risk was observed and hence no influence of climate change on the 2015-2016 magnitude of drought for selected catchments was concluded by this study. These results are limited, as they are based on climate attribution experiments with only one climate model, rather than with a multi-model ensemble. Also, QSWAT model, in its implementation with generic climate data is of limited use in attribution (or hydrological) simulations as even after calibration the model performs poorly.

EXTENDED ABSTRACT

In South Africa Kwa-Zulu Natal (KZN) province has suffered a crippling drought throughout the 2015 and 2016 period that has seen dam levels drop to an all-time low, such as Midmar Dam dropping to its lowest since 1983 in the 2015 drought period. Key impacts from the drought in the province included reduced flow in river channels that led to reduced dam levels and subsequent poor water quality that threatened the health and wellbeing of residents. The drought also reduced the production of crops which threatened food security in the province. As the drought affected agriculture a knock-on effect of unemployment in this industry occurred, affecting livelihoods. The drought also gave rise to potential cases of increased mortality rates for livestock and wildlife and increased potential for fire hazards. Economic effects of the drought included a threat to electricity supply as the coal power stations utilize a substantial amount of water, and similarly less water was available for other heavy industries, negatively impacting these industries. With the frequency and magnitude of extreme weather expected to increase because of climate change, in provinces such as Kwa-Zulu Natal vulnerabilities are highlighted due to existing poverty levels, water scarce areas and rain-fed agricultural production. This study aims to determine whether anthropogenic climate change has contributed to the 2015-2016 hydrological drought conditions experienced in KwaZulu-Natal catchments. To see if climate change has contributed to the 2015-2016 drought, a probabilistic event attribution procedure is implemented and QSWAT model is tested as a tool for rapid attribution studies. Attribution experiments are typically designed to estimate if anthropogenic climate change has altered the chance of extreme weather events occurring. The focus here is on attribution of hydrological drought. This is achieved by integrating results of attribution experiments with a global circulation model (HadAM3p), with simulations of hydrological responses using a hydrological model (QSWAT).

The 2015-2016 drought is examined in the study by utilizing the Department of Water and Sanitation (DWS) discharge stations data. The first part of this study focused on setting up the QSWAT hydrological model which included delineation of the catchment, creation of HRUs, editing model inputs and running the model. Data sets used to setup and run the model include WR2012 data, SWAT CRU data, SWAT CFSR and WATCH WFDEI data. Following setup, the best model simulations were used (WATCH WFDEI data) and the model calibration was performed. Calibration was performed using the SWAT- CUP automatic calibration software which utilizes the SUFI-2 algorithm. Following this the attribution experiments were implemented with QSWAT. The attribution procedure involved using the downscaled climate data from climate attribution experiments to obtain simulations of real world conditions (current climate) and under conditions that might have been had anthropogenic greenhouse gas conditions never occurred (counterfactual climate). The approach followed the risk-based methodology described in Stone and Allen (2005). The study used the Risk Ratio (RR) measure where the chance of the event occurring under current real-world climate conditions is p_1 and the chance of the event occurring under the conditions of a counterfactual world in which humans had never emitted greenhouse gases is p_0 where the RR = p_1/p_0 .This study used probabilistic framing as it is suited for events that are defined via the exceedance of a threshold of a hydrological variable, where the observed event is utilized to define the threshold. QSWAT hydrological model was set up with generic global data. The calibration procedure was carried out using SWAT-CUP and although calibration results were poor they were applicable for use in this study under constraints (since the calibrated hydrological model was not performing well, model simulations based on WATCH WFDEI observation data was used to define the drought, avoiding error from the weak performance of the model). Results of the attribution experiments revealed that for all 3 subbasins studied no increase of risk was observed and hence no influence of climate change on the 2015-2016 magnitude of drought for selected catchments was concluded by this study. Limitations of the attribution study implemented here include that results are limited since they are based on climate attribution experiments with only one climate model, rather than with a multi-model ensemble. QSWAT model, implemented with generic climate data is of limited use in attribution (or hydrological) simulations as even after calibration the model performs poorly.

KEYWORDS

Event attribution, anthropogenic climate change, hydrological drought, extreme event, QSWAT, QGIS

1. INTRODUCTION

1.1 Droughts as a global and South African (SA) problem

Drought is generally understood as a period with unusual dry weather with insufficient precipitation. Depending on severity, drought can cause a shortage of water supply and may have devastating effects on ecosystems and organisms. Drought is an extreme physical process initiated slowly with complex impacts that can affect many sectors (Botai et al., 2016). Drought periods vary and span periods from short term (month to several months) to long term periods such as millennia. From the hydrological perspective drought manifests through a shortage of surface or subsurface water. In the period of 1900 to 2013, 642 drought events were recorded globally (Masih et al., 2014). Masih et al. (2014) reported that these drought events affected more than 2 billion people and resulted in 12 million deaths.

South Africa is described as a semi- arid or arid country that has variable climate conditions. According to the WRC (2015) the country's freshwater resources were highly strained and these resources were affected by extreme weather events resulting from climate variability and climate change (WRC, 2015). Drought continues to be a natural hazard of the countries climate (WRC, 2015) and under current climate scenarios for the country it is expected to worsen, so the country needs to prepare for this extreme weather event (DEA, 2013).

1.1.1 Drought in SA and KZN in 2015-2016

In South Africa, rainfall in all nine provinces in the period since 1904 has averaged 608 mm per year. South Africa in 2015 received only an average of 403 mm/year (66% of the annual average). Previously, the lowest rainfall received in a year was in 1945 when South Africa received 437 mm/year (72%) (Africa Check, 2016). In 2015-2016 KZN had below normal cumulative rainfall conditions from Oct-Jun (<500mm/year) and normal cumulative rainfall conditions (<800mm/year) for Jul-Sep, illustrated in ***Figure 1*** below:

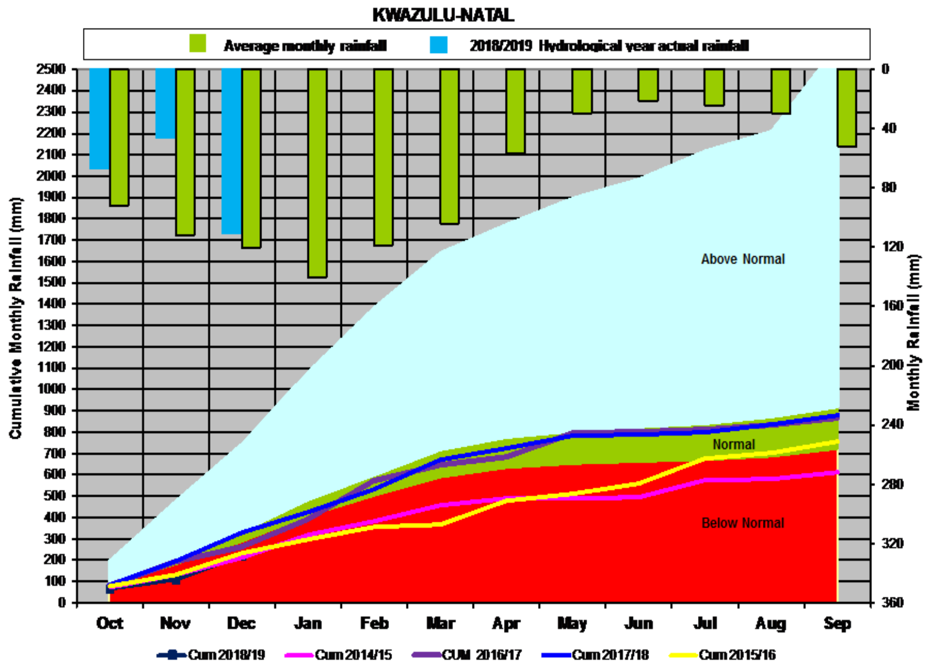


Figure 1: Monthly rainfall and cumulative monthly rainfall (mm/year) for KZN (Source: DWS, 2019)

Figure 2 also illustrates total annual rainfall (WATCH WFDEI data) for a KZN subbasin (11) in the Mvoti to Umzimkulu WMA, 2015-2016 is displayed as below normal rainfall in this 35 year context.

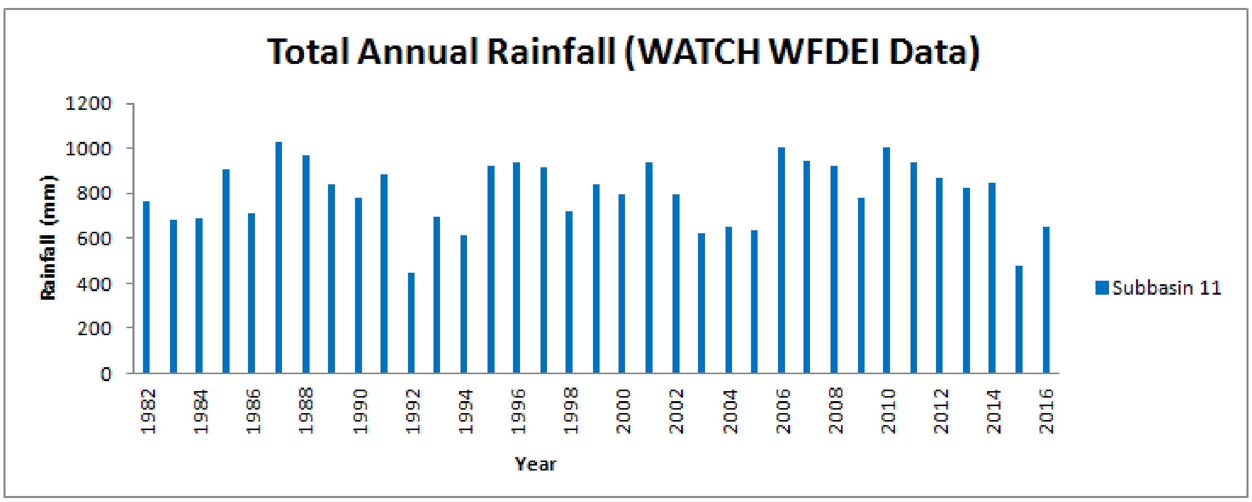


Figure 2: Total annual rainfall (mm/year) for KZN subbasin 11

In other provinces such as the Free State, below normal rainfall conditions (<400mm/year) were recorded throughout the whole 2015-2016 hydrological year (Oct 2015-Sep 2016). Similarly, Mpumalanga experienced below normal rainfall throughout that year (<550 mm/year).

The runoff status overview below (***Figure 3***) also illustrates below normal streamflow conditions where the Department of Water and Sanitation (DWS) utilised verified flow data.

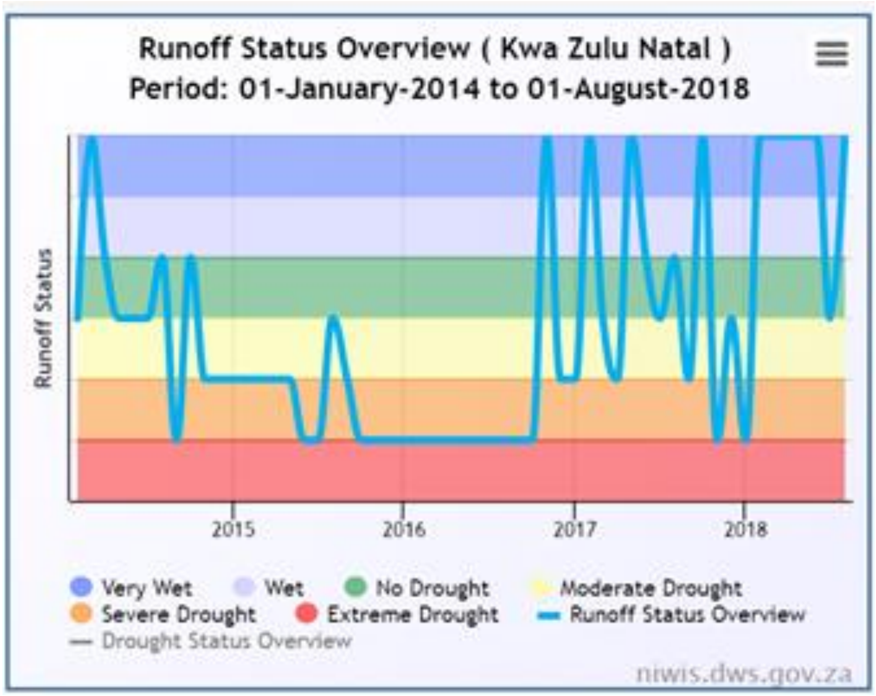


Figure 3: KwaZulu- Natal Runoff Status Overview (Source: http://www.dwa.gov.za/niwis2/DroughtStatusManagement/RunoffStatusOverview)

Effects of the drought in South Africa included impacts on agriculture that could be seen in the Free State, KwaZulu-Natal and the North West such as summer crops like maize that could not be planted in many areas or that plantings were severely damaged by the drought and heat. Products such as soya, sorghum, groundnuts and sunflower crops that were affected had negative impacts for South Africa's food security at the time. For livestock issues such as availability of drinking water caused a problem in many areas in these provinces. This was predicted to result in an increase in food prices for South Africa during the 2015-2016 period. Water resources were affected by the drought as the whole country experienced water shortages at different scales for different parts of the country. KwaZulu-Natal was one of the worst affected regions and this could have been exacerbated by little or no water resource storage facilities (Africa Check, 2016).

1.1.2 Causes of droughts

Climate variability can be defined as "any deviation from the long term expected value that occurs naturally and is non- permanent". Variability can be as a result of internal processes of the climate system or variability of natural or anthropogenic external forces (Schulze, 2011). A driver of climate variability that is important in the South African context is the El Nino Southern Oscillation (ENSO). ENSO phenomenon is a naturally recurring climate phenomenon. ENSO is comprised of El Nino which is relative warming of the eastern Pacific Ocean and cooling of the western Pacific Ocean due to a change in wind patterns. The opposite of this state is known as La Nina. El Nino can be associated with drought conditions (defined as less than long term average rainfall - these also range from mild to severe) in South Africa

(SAWS, n.d.), with dry years often associated with El Niño events in the Pacific, the relationship being particularly robust after the 1970s (Crétat et al., 2010). In other regions such as the southern United States La Nina causes drought conditions (University of Texas at Austin, 2017).

1.1.3 Droughts and climate change

Anthropogenic climate change, natural climate variability and ENSO are critical elements to consider when explaining current weather phenomena (WWF, 2016). Anthropogenic climate change is a leading challenge for humanity today. It is manifested by an increasing trend in annual mean global temperature, detectable already 20 years ago, and robust regional seasonal mean temperature trends emerging 10 years ago (v.Oldenborgh, 2018). According to IPCC AR5 future temperatures for Africa are projected to rise by as much as 4^{o}C by the end of the 21st century (Niang et al., 2014). The warming can lead to extreme events, both droughts and floods (NAS, 2016). Changes in the occurrence of extreme events have already been associated with climate change (Easterling et al., 2016) but drought is affected differently in different regions and different seasons due to anthropogenic climate change (NAS, 2016).

1.1.4 Attributing droughts to climate change

A general understanding exists that climate change affects droughts, and has likely affected the KZN drought. Assessment of the role of climate change in a particular drought has to be done using attribution methodology. However, events of a given magnitude may occur naturally, with given probability and a particular event may be a result of normal climate variability, and not related to climate change at all. Attribution methodology allows for assessment of the change in probability of an event's occurrence under climate change compared to natural conditions. It is worth noting the attribution pertains to the risk of event and not the event itself. Presently, we know that the climate is changing and we know that in the analysed region it is changing towards a drier climate, which we know can potentially have consequences for severity and frequency of droughts. It is therefore likely that it has made the 2015-2016 drought more severe and this is the hypothesis we tested in this study. The study is also significant in understanding the impacts of climate change and climate variability.

There are a number of drought attribution studies addressing recent droughts on African continent (e.g. Bellprat et al. 2015, Otto et al. 2018a, Philip et al. 2018, Lott et al. 2013, Marthews et al. 2015). All these studies focused on climatological drought, and to my knowledge, there are no studies addressing hydrological droughts on African continent.

The American Meteorological Society (AMS) produces special reports (BAMS- Bulletin American Meteorological Society) that determine how human induced climate change has affected the strength and likelihood of individual extreme events. Reports (*Explaining Extreme Events from a Climate Perspective*) are currently available from 2011-2018 (AMS, 2019). The 2015 special edition report presented a selection of studies relating to extreme events such as droughts, heavy rains and storms. A climate change influence was found to affect the strength and likelihood of extreme events in some studies and in some instances not in others. These studies highlighted challenges attribution studies face and included the limited observational record and some models inability to reproduce extreme events well (Herring et al., 2016).

1.2 Formulation of research objectives

1.2.1 Problem statement

Currently we know that climate change has the potential to affect droughts in South Africa and climate change projections by the WRC (2015) emphasises the expected worsening of drought as a natural hazard in South Africa in the future. Presently the country is prone to recurring droughts that have severe negative socio- economic impacts (WRC, 2015). Furthermore, the WRC (2015) reports that the country's climate is also affected by the ENSO phenomenon, with La Nina causing above normal rainfall and El Nino causing below normal rainfall. These factors affect regions of the country differently. This study addresses the question of whether or not there is an influence of climate change on the 2015-2016 drought from a water resources perspective. This means that this study does not look at just the meteorological drought, but focuses on the hydrological and water resources consequences of that drought. Additionally, considering that event attribution studies in Africa face severe data and model limitations, this study evaluates the applicability of QSWAT model with generic climate datasets as a tool for rapid implementation of hydrological attribution.

1.2.2 Aims

Determine if climate change has contributed to the 2015-2016 hydrological drought for catchments in KwaZulu-Natal by implementing the attribution procedure using QSWAT hydrological model.

1.2.3 Objectives

- Investigate the set-up of QSWAT model with generic global datasets for KwaZulu- Natal catchments, to evaluate the hydrological modelling process.
- Implement the attribution procedure for hydrological responses (runoff) using QSWAT model to ascertain if climate change has contributed to the 2015-2016 hydrological drought.
- Assess the sensitivity and limitations of the proposed attribution procedure, including applicability of QSWAT set up with global generic datasets as a tool for rapid implementation of hydrological attribution experiments.
- Accept or reject the stated research hypothesis.

1.2.4 Research Hypothesis

That anthropogenic climate change has contributed to the 2015- 2016 drought conditions experienced in KwaZulu- Natal catchments.

1.2.5 Rationale

In the context of climate change event attribution studies are relevant as they potentially provide a better understanding of the drivers of extreme events such as these studies increasing comprehension of how and why the prevalence and extremity of extreme events has altered over time (Otto et al., 2015). These studies could lead to model improvements which could subsequently lead to improvements in how adequately events are represented (NAS, 2016). Furthermore, these studies are relevant as attribution of current events assists in understanding future risk related to extreme events. The study of these events and the human influence on these events can also provide guidance on whether these events will increase or decrease in the future (Otto et al., 2015).

Since attribution studies can potentially provide information and evidence on climate risk (Easterling et al., 2016) and predictions of the timelines of extreme events (NAS, 2016) this knowledge can be relevant for adaptation activities (Easterling et al., 2016) and informing policy makers and government (Stott et al., 2016). Consequences of extreme events can include loss of life, increases in food and energy tariffs, increases in disaster relief costs, increases in insurance premiums, infrastructure damage, fluctuations in property values, security concerns, negative health effects, damage of transportation networks and negatively altered water demand and supply situations NAS (2016). These studies have the possibility of providing information that is invaluable especially for vulnerable communities (NAS, 2016) such as in KZN. These studies are relevant in terms of attributing responsibility for impacts of extreme events, although not yet through legal means (litigation). Information regarding climate risks could be of use to the insurance industry, to litigators, to policy makers and for disaster risk reduction.

Event attribution is a relatively new science, where very few studies have been done. *Carbon Brief* (www.carbonbrief.org) reports that till 2018 the number of extreme weather events across the globe for which scientists have carried out attribution studies was 257. In the past 20 years the literature up until 2018 included attribution studies of extreme heat (31%), rainfall or flooding (20%) and drought (18%) (Carbon Brief, 2017). NAS (2016) presents the state of attribution science for extreme events (with regards to the event type) (***Figure 4***). Attribution studies on hydrological droughts on African continent are few, and obstacles for their implementation include data limitations and limited availability of hydrological models. This study aims to contribute to the drought niche implementing attribution experiments with a generic hydrological model.

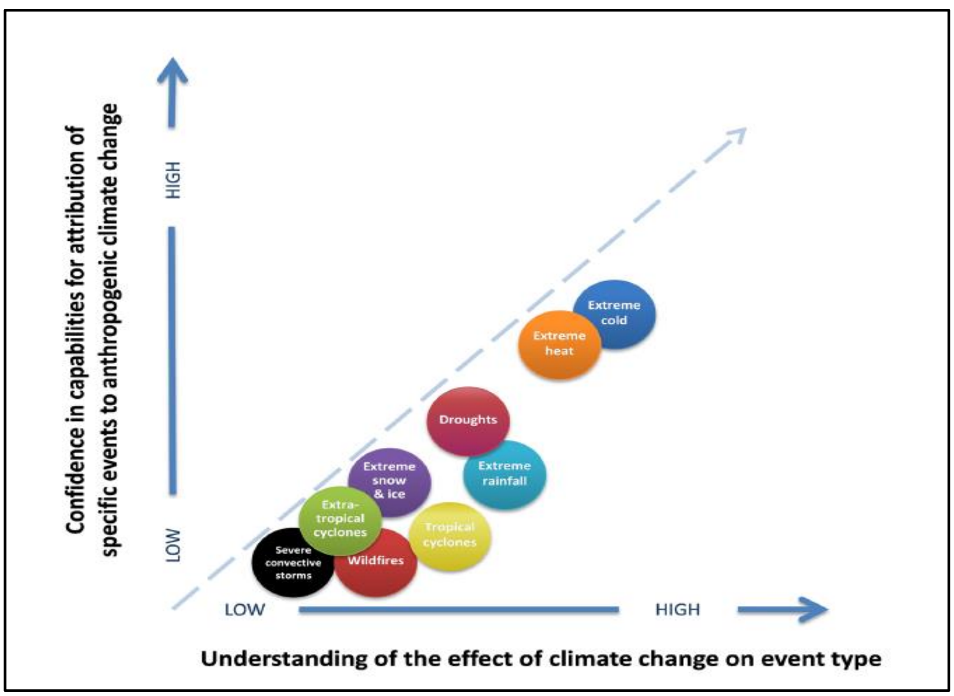


Figure 4: A summary of progress on extreme event attribution science in 2016 (Source: NAS, 2016)

It is reported that in the science of event attribution a lack of geographical coverage for extreme events and in particular for attribution of extreme events exists. A need arises to develop regional capacity to understand attribution science and conduct attribution studies for building on local knowledge (Stott et al., 2016). For the southern hemisphere very few studies exist (***Figure 5***) and for KZN no attribution study was found during a literature search for this study.

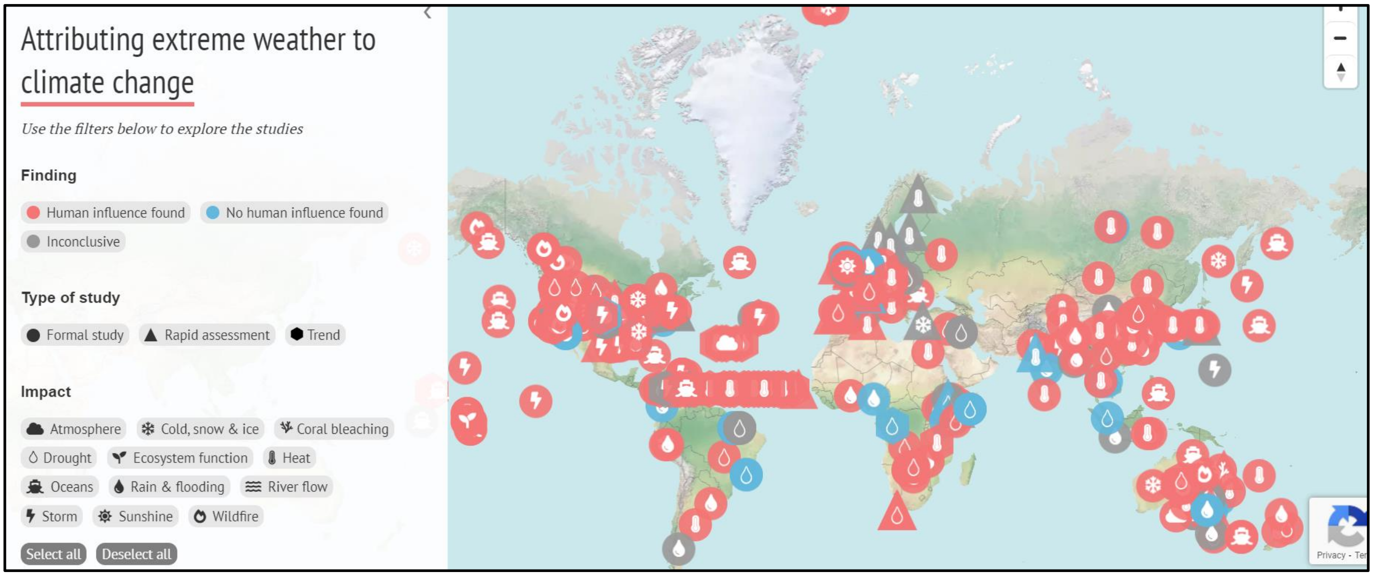


Figure 5: Carbon brief map of attribution studies with map legend (Source: www.carbonbrief.org)

1.2.6 Thesis outline

The proposed thesis outline will be as follows with Chapter 1 consisting of the introduction, formulation of research objectives and rationale of the study. Chapter 2 presents a literature review of the study looking at drought, the SWAT model and climate change attribution. The focus of Chapter 3 will be the study area description. Chapter 4 looks at the methodology utilised in the study including a general framework of implementation of hydrological experiments and attribution experiments. Chapter 5 presents the results and discussion for hydrological modelling and attribution simulations. The study concludes with chapter 6 that includes recommendations for future studies. Chapter 7 provides the references utilized in this study.

2. LITERATURE REVIEW

2.1 Drought

2.1.1 Types and definitions of drought

There are different types of drought that occur and these can include: meteorological drought, hydrological drought, agricultural drought and socio- economic drought (NAS, 2016). Meteorological drought is defined through lower than expected precipitation. Hydrological drought is defined as shortages of surface or subsurface water resources. Agricultural droughts are described as being comprised of aspects of meteorological or hydrological droughts that have an impact on agriculture such as reduced crop yield as a result of low precipitation. Socio- economic drought is explained by the effects experienced on the supply of economic goods (NAS, 2016). ***Figure 6*** illustrates the relationship between the above mentioned droughts.

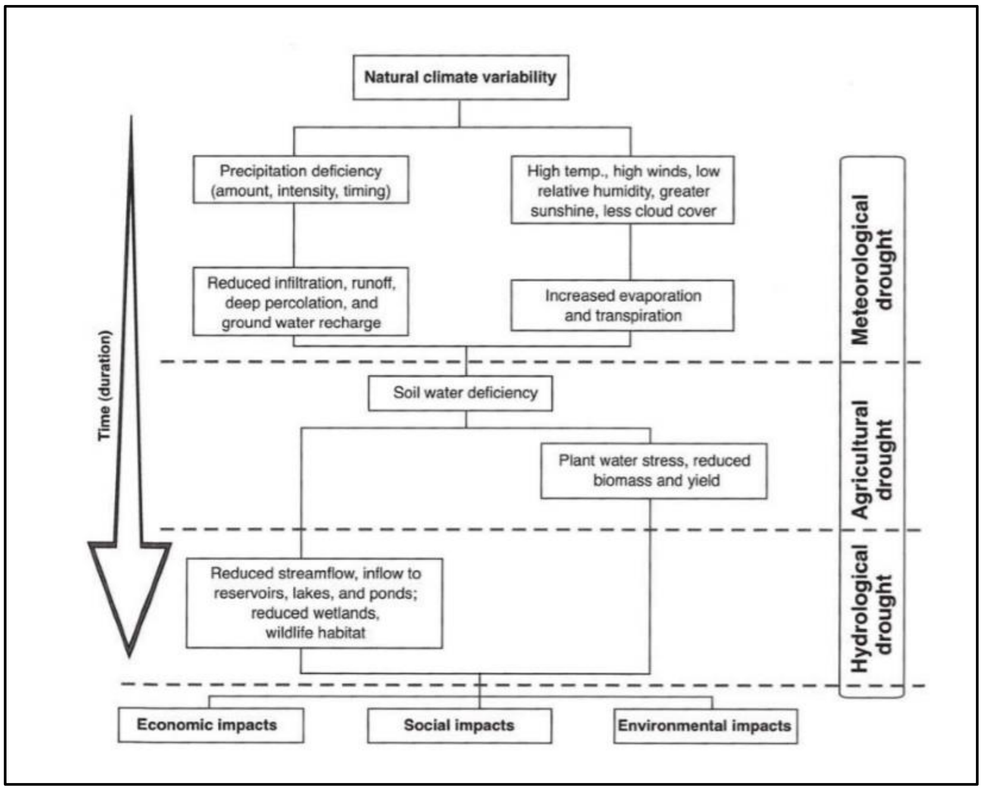


Figure 6: The relationship between different types of drought (Source: Wilhite, 2000)

Droughts are multifaceted. They differ geographically in location and in scale. Droughts can be extensive and cover regions reaching sub-continental scale, but they can also be very local, and have different implications for communities that are in close proximity to each other. Furthermore, drought intensity can also vary strongly, from mild to severe, as expressed by the magnitude of water deficit and its consequences (NAS, 2016).

Drought can span a range of time scales – from monthly to seasonal to annual to multi-annual to decadal, and even to centennial (such as drought in spring and early summer in China on the centennial scale between 1901-2013) (Huo-Po and Jian-Qi, 2015) and millennial (Australian drought 1997-2010) (Kiem et al., 2016).

2.1.2 Climatic drivers of droughts

Droughts are complex extreme events that can be driven by multiple factors including (IPCC, 2013; NAS, 2016):

- Precipitation deficits
- Increase in temperature leading to increased evaporation and thus water deficit
- Soil moisture and evapotranspiration feedbacks
- Increase in wind speed leading to increased evaporation and thus water deficit

In Africa, drought is a part of the natural climate variability spanning "intra- annual, inter- annual, decadal and century" timescales. A number of studies found that the predominant natural factors contributing to inducing drought conditions in the African continent is El-Niño Southern Oscillation (ENSO) and Sea Surface Temperature anomalies (SSTs) (for example for southern African droughts, the southwest Indian Ocean SST anomaly) (Masih et al., 2014). Anthropogenic factors such as climate change, aerosol emissions, land- use practices and land- atmospheric interactions are also drought inducing mechanisms (Masih et al., 2014).

2.1.2.1 El-Niño Southern Oscillation (ENSO)

ENSO is a global climate phenomenon, occurring naturally in the climate system, where El-Niño represents the warm phase of ENSO and La Nina represents the cold phase of ENSO. El-Niño is a pseudo-cyclic event which affects the global climate every 3 to 5 years and lasts approximately 9 to 12 months. ***Figure 7*** illustrates El-Niño conditions and normal conditions (Roux, 2016).

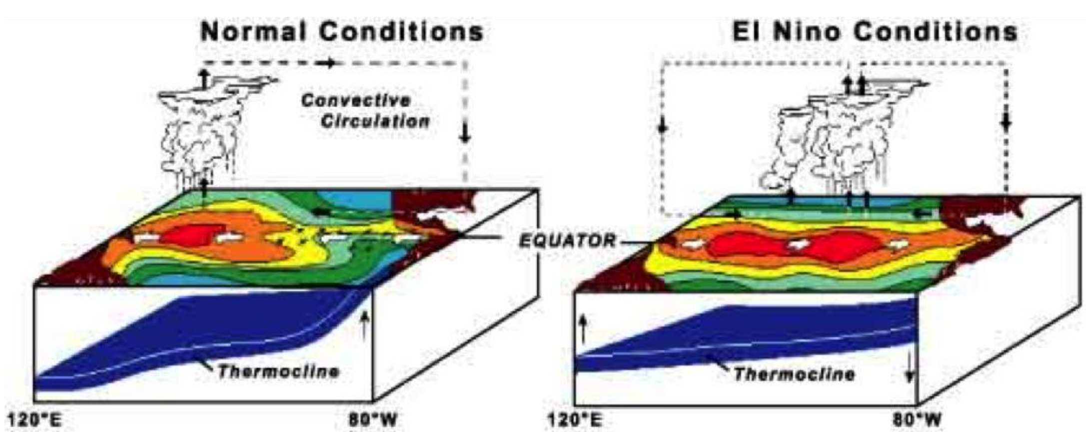


Figure 7: Normal conditions and El-Niño conditions (Source: Roux, 2016)

El-Niño leads to the warming of sea surface temperatures in the equatorial Pacific Ocean which influences atmospheric circulation and hence rainfall and temperatures in certain regions as illustrated in ***Figure 8*** (Grobler, 2016). ENSO is considered to be a main driver of inter-annual rainfall variability, as a global climate mode of variability (Dieppois et al., 2015). It has been observed that for SA below-normal rainfall conditions usually occur during El-Niño years and for La Nina normal or above-normal rainfall conditions occur, this is however not accepted as a rule. South Africa can be divided into numerous rainfall regions where each region has displayed different correlations to ENSO (SAWS, n.d.). Drought conditions in South Africa are not always associated with El-Niño events, although most El-Niño years have been associated with below-normal rainfall (SAWS, n.d.).

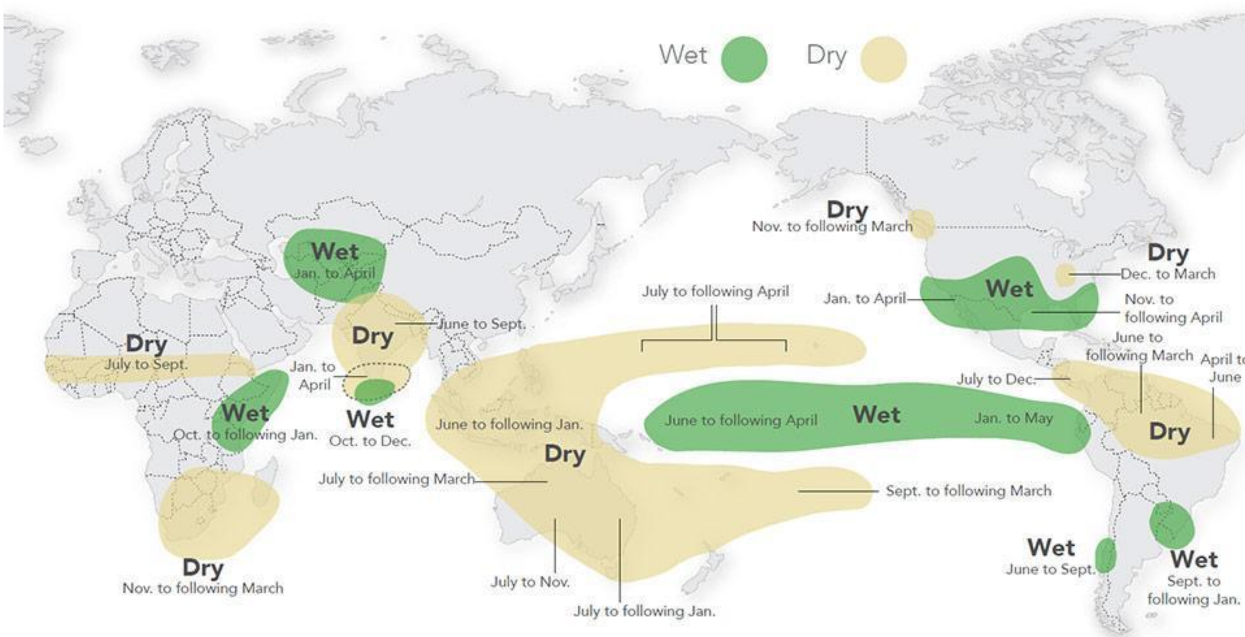


Figure 8: Relationship between ENSO index and rainfall (Source: http://www.fao.org/el-nino/en/)

2.1.2.2 Climate change

In IPCC (2013) it is reported through observations and modelling that changes to the climate system including the warming of the atmosphere and the ocean, sea level rise and changes in the hydrological cycle, are a consequence of anthropogenic increases in greenhouse gas (GHG) concentrations. Anthropogenic climate change is projected to continue during this century and beyond this century (conclusion robust for various future GHG scenarios including scenarios anticipating a reduction in emissions) (Lavell et al., 2012). Stott et al. (2016) gives an account of the basic expectation that climate change will alter the occurrence of some extreme events. The IPCC (2012) projects alteration in the frequency, intensity, spatial extent and duration of climate and weather extremes including drought. Climate is associated with certain probability distributions of weather events. Weather event values far away from the mean such as droughts are by definition less likely to occur. These events are known as extreme events, and extreme events in one region can be normal in another. There is evidence from observations starting in 1950, of change in some extremes (IPCC, 2012). Schulze (2011) reported that while there are projected changes in means of climatic variables over time, in the outer ends of distributions of variables, critical thresholds are exceeded and extremes such as droughts occur, and illustrates how the frequencies in extremes become significant over time when the mean of a variable changes over time (***Figure 9***). Changes observed in climate extremes reflect the influence of anthropogenic climate change as well as natural climate variability. There is medium confidence that droughts will intensify in the 21st century due to reduced precipitation and or increased evapotranspiration (IPCC, 2012). A recent study by Marvel et al. (2019) using reconstructions from tree rings data and multiple observational datasets revealed that anthropogenic activities have probably been affecting worldwide risks of drought as early as the beginning of the twentieth century.

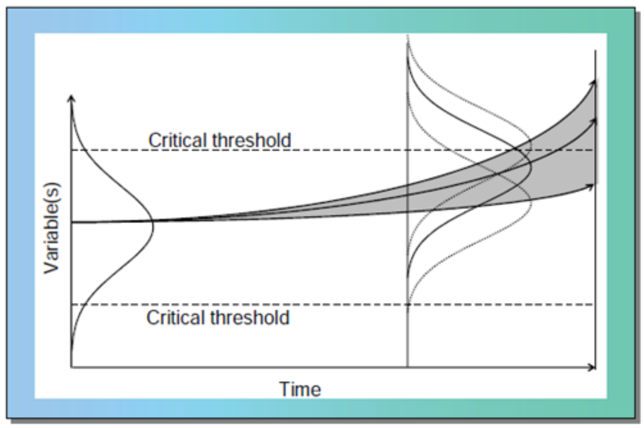


Figure 9: Frequencies of extreme events changing over time (Source: Schulze, 2011)

2.1.3 Drought in South Africa

2.1.3.1 Occurrence

In "A review of droughts on the African continent" droughts during 1970–1988 were found to be intense and widespread compared to those during 1950–1969. Furthermore, the study revealed that droughts from 1900-2013 intensified where they have become more frequent, more severe and their geospatial coverage has increased. The study also highlighted that all regions in Africa have witnessed severe droughts over the last few decades such as the 2010–2011 drought in East Africa, 1999–2002 drought in North Africa, 2001–2003 drought in southern Africa and persistent droughts in Sahel during the 1970s and 1980s. In the 19th century droughts experienced by southern Africa included single and multi-year droughts (Masih et al., 2014).

Davis-Reddy et al. (2017) provides evidence of droughts becoming more intense and widespread throughout South Africa. One of the worst droughts reported was in 1992 where dry conditions were amplified by excessive high temperatures and approximately 70% of crops failed. They further reported that in 2015 South Africa experienced one of the worst droughts since 1930 when the lowest annual rainfall amount on record was recorded with 403mm/year. Temperatures during this period were also recorded as the hottest over the previous 10 years (Davis- Reddy et al., 2017). More recently the Western Cape region in South Africa experienced below average rainfall for the period 2015-2017, that led to the worst water shortages since 1904 (Botai et al. 2017, Wolski 2018, Otto et al., 2018). This water shortage led to an extreme scenario in the City of Cape Town where it was expected the city would run out of water “day zero” (Joubert and Ziervogel, 2019).

2.1.3.2 Impacts of droughts on SA

Droughts affect people, animals, the environment and the economy (Masih et al., 2014). The South African Weather Service (SAWS) expresses impacts from droughts for South Africa, including the effect of dwindling water supplies on staple crops and commercial crops. SAWS highlights that between 1992 and 1993 when the country experienced widespread drought maize had to be imported to the country. This led to a knock on effect as crop failure led to population drift (rural areas to cities), job losses due to farm closures and increased debt in the agricultural sector. Another serious impact is veld fires as a result of drought. The fires destroy areas of grazing when grass is in short supply. The year 1992 saw fires destroy thousands of hectares of grassland. In 1994 similar fires led to the loss of six people’s lives. In 2002 Mpumalanga wildfires destroyed thousands of hectares of pasture, led to the loss of people’s lives and damages of more than R32 million rand in the province (SAWSa, n.d.). The more recent drought (2015-2018) in the Western Cape, South Africa has seen implications for agriculture, water and settlement areas. Key impacts included the effects on the agriculture sector through decreased availability of irrigation water. This led to non- planting of low priority vegetables, damage to perennial crops and production losses. Additionally depleted grazing and fodder led to necessary cattle and sheep herd size reductions (Archer et al., 2019).

The overview of drought, including climatic drivers of drought, climate change and drought and drought in South Africa is reviewed in this context as this study will examine if climate change has contributed to the 2015-2016 hydrological drought in KZN, South Africa.

2.2 Climate change event attribution

Climate change event attribution studies are defined as studies determining how anthropogenic climate change has altered the probability or magnitude of extreme events and include combining statistical analysis with a physical understanding (IPCC, 2013). In event attribution studies different physical variables can be studied such as drought which can be characterised by a below normal precipitation, excessively dry soil, or reduced streamflow, floods or abnormally high rainfall, heat waves, extreme winds etc. (NAS, 2016).

The Intergovernmental Panel on Climate Change (IPCC) (2013) in their Fifth Assessment Report (AR5) reveals that event attribution approaches include observational records and relying on these records to determine these changes in probability or magnitude of events, and model simulations performed to compare the manifestation of events in a world with human caused climate change (factual) to that in a world without (counterfactual) (IPCC, 2013).

2.2.1 Attribution of extreme events

For extreme events, attribution can be applied to those classified as a weather extreme or a climate related extreme (Stott et al., 2016). In one of the first studies, in 2003 a European summer heatwave that led to the death of thousands of people was attributed to climate change (Stott et al., 2004). The analysis of the 2003 European heatwave introduced the Fraction Attributable Risk (FAR) concept and provided a general approach to quantifying the link between anthropogenic climate change and individual extreme climate events. Another early attribution study was that of UK floods in 2000 conducted by Pall et al. (2011), where a multi- step assessment of attributable risk using a physically based model was utilised. Later, Kay et al. (2011a) used the same event analysing the same ensembles, but used a more sophisticated hydrological model (IPCC, 2013). Rahmstorf and Coumou (2011) looked at the 2010 Russian heatwave event and applied an empirical approach to estimate the attributable risk. For the same event Dole et al. (2011) focused on attributable magnitude analysing external factors and their contribution where it was considered the event was natural in origin (IPCC, 2013). In Otto et al. (2012) she links the results of both these studies by relating the attributable risk and attributable magnitude approaches to framing of the attribution question.

The studies listed above are keystone studies of attribution science (Stott et al., 2016). Since 2011, The American Meteorological Society has published a special report that compiles articles on extreme weather events of the past year (NAS, 2016). These publications establish the role of anthropogenic emissions on extreme events from the previous year. The World Weather Attribution (WWA) network (https://www.worldweatherattribution.org/) was established in 2014 to provide near real time analysis of possible links between climate change and extreme events. Similarly, Carbon brief (https://www.carbonbrief.org/data-dashboard-climate-change) has mapped all peer reviewed attribution studies in scientific literature.

2.2.2 Attribution studies in Africa

In Africa, Lott et al. (2013) conducted the first Probabilistic Event Attribution (PEA) focusing on the East African drought, though notoriously difficult to define. Methodology followed in the study is the ACE 2010 method developed at the Met Office Hadley Centre ACE (Attribution of Climate-related Extremes) system for studying extremes around the globe. The study utilizes observed sea surface temperatures (SSTs), sea ice conditions and an atmosphere model. Results from comparison of model distributions to observed rainfall revealed no evidence for human influence on 2010 short rains. Furthermore, the study revealed that human influence was found to increase the probability of long rains as dry as or drier than 2011 (Lott et al., 2013).

Marthews et al. (2015) examined the 2014 drought in the horn of Africa: attribution of meteorological drivers. The main aim of the study is to determine if human-induced climate change has played a role in the meteorology of the 2014 East African long rains season that could have contributed to the drought in the greater horn of Africa. The study utilized probabilistic event attribution (PEA) techniques making use of an ensemble approach. The study concludes that an anthropogenic influence could have contributed to drought conditions during the east African long rains (Marthews et al., 2015).

An event attribution study by Bellprat et al. (2015) looked at dry and wet rainy seasons over South Africa, studying events because of the high socio-economic impact as a result of floods and droughts. The study analysis utilized GCMs from CMIP5 that included all atmospheric forcing and natural forcing to determine if human activities have altered the occurrence of such events. Study results reveal that for dry austral summers (DJF) for South Africa during 2002/2003 the risk was increased due to human influence. The study also looked at the risk of a wet summer occurring during 1999/2000 and found the risk decreased. In conclusion the study highlights the different conclusions that can arise by the different questions when determining the attributable risk of extreme events (Bellprat et al., 2015).

Philip et al. (2018) performed an attribution analysis for the Ethiopian drought of 2015. A multimethod attribution approach was utilized using both models and observations with the aim of assessing the influence of large-scale climate forcing or phenomena on the probability of occurrence of an event of interest. The study highlights that the lack of studies available at the time for the region was due to the impact of short observational records. The study makes use of four different model setups including a coupled model, an atmosphere-only model, large ensemble of an SST forced model and set of coupled global climate models. Results from the study revealed that taking the model spread into account the drought could not be clearly attributed to climate change and the soil moisture dataset utilized shows a non-significant drying trend. In the study, ENSO correlations with rainfall suggest the primary driver of the drought was the strong the 2015 El Niño phenomenon (Philip et al., 2018).

Otto et al. (2018a) investigated the anthropogenic influence on the recent Western Cape drought of 2015-2017. For the Western Cape Province 3 years of below average precipitation led to a prolonged drought. The study determined precipitation deficit as the primary driver behind water availability and utilized a multi-method attribution analysis to determine if climate change has altered the likelihood of this prolonged extreme event. Multi-model ensemble results as well as observed data results illustrated an increase of likelihood that such an event occurred because of anthropogenic climate change. Results also further suggested that for future global warming this trend is likely to continue. The study concludes that according to the modelling results the future increase in drought risk for the Western Cape, South Africa is predominantly precipitation-driven (Otto et al., 2018a).

Other studies on attribution of drought events in Africa include the Rapid analysis of drought in Somalia 2016 (Jan van Oldenborgh et al., 2017) and the Severe drought in Kenya 2016-2017 (Uhe et al., 2017). The studies examined above are of particular relevance in the context of the study area used in this study.

2.2.3 Event attribution methodology

Several methods can be utilized for event attribution and they are based on climate model simulations and observations where user choice will determine the method and data utilized (Hauser et al., 2017). Knutson (2017) highlights four general types of attribution methods applied practically: 1) physical reasoning, 2) statistical analysis of time series, 3) the philosophical argument that there are no longer any purely natural weather events and finally, 4) probabilistic event attribution, or risk-based event attribution, using dedicated model simulations and quantification of climate change role through fraction of attributable risk (FAR) estimation.

Physical reasoning

An example of physical reasoning can be thermodynamic arguments such as suggesting more intense precipitation is expected in an atmosphere which holds more water vapour (O'Gorman and Schneider, 2009). A similar example would be in Trenberth (2011) where an upward shift in mean monthly temperature would lead to a disproportionate increase in the frequency of extreme hot daily temperatures. General physical reasoning can only lead to broad qualitative statements such as "this extreme weather is consistent with" what is known about the human- enhanced greenhouse effect (Hulme, 2014).

Statistical analysis of time series

This method uses statistical analysis of meteorological time series data determining if a particular weather or climate extreme falls outside the range of what the normal or unperturbed climate might have delivered. This method estimates the likelihood of a specified meteorological extreme occurring with no external human forcing (Luterbacher et al., 2004). A different time series approach utilises observational data with model simulations to determine whether trends in extreme weather predicted by climate models have been observed in meteorological statistics (Hulme, 2014).

Philosophical argument

The argument is that since human influences on the climate system as a whole are now clearly established e.g. as through changing atmospheric composition, there can no longer be such a thing as a purely natural weather event. All weather is now thought to be attributable to human influence, at least to some extent (Hulme, 2014).

Probabilistic event attribution

Probabilistic event attribution is a relatively new branch of climate science. In the seminal study, Allen (2003) proposed the event attribution methodology which Stott et al. (2004) utilised to analyse the 2003 European heat wave. The methodology allows for quantifying the change in probability of an extreme event caused by human alteration of the climate system. This is obtained through the use of climate model simulations of a world with anthropogenic forcing and a world without anthropogenic forcing (Stott et al., 2016). This methodological approach is known as "Oxford" methodology.

In this method multiple model- simulations of the climate system, first without the forcing agent/s accused of causing the event and then with external forcing introduced into the model (Hulme, 2014). A model is used to estimate the probability (p) of occurrence of a weather or climate event in two climate states: one state with anthropogenic influence (p_1) (forcing) and the other state without anthropogenic influence (p_0) (forcing) (Stott et al., 2016). Each of those probabilities is determined from the probability distribution function describing the variable underlying the event in model data. The two probabilities are then compared to derive an attribution statement that describes how the chance of occurrence of the event has changed between climate without and with anthropogenic influence (Hulme, 2014).

2.2.4 Attribution of hydrological events vs climate events

Multi- step attribution looks at attributing an observed change in a variable to changes in climate or environmental conditions. Separate assessments attribute the change in climate conditions or environmental conditions to external drivers. This methodology can include synthesis of observed data and model applications. The link between climate and the variable of interest can also utilise a process model, statistical link or downscaling (Hegerl et al., 2010). For regional application it is noted to be difficult to separate the effects of different external forcing's (IPCC, 2013).

Philip et al. (2019) performs an attribution experiment on both precipitation and discharge to determine the role of climate change in the context of flooding for the area. From a meteorological perspective the flood is explored by using precipitation data and from a hydrological perspective, using discharge data. For comparison of attribution results of the two variables return periods and risk ratios are calculated for the August 2017 flood in Bangladesh. Data used includes observational and model data for pre-industrial, present and future conditions. The study uses two event definitions one for precipitation and one for discharge. Models used for precipitation include AOGC EC-Earth 2.3 and weather@home. For discharge the PCR-GLOBWB 2 hydrological model was used and SWAT in the context of investigating climate change impacts on water resources. Furthermore, LISFLOOD and River flow model, hydrological models were also used. The study methodology includes the following steps: firstly, detecting a trend by using a statistical model, for the study trends of extreme high- precipitation and river discharge values are used. Next is the attribution of the detected trend to global warming, natural variability or other factors such as ENSO. The third step is calculating the risk ratio or change in probability for different time intervals. For the study a last step in the analysis was synthesising the results into a single attribution statement. Results for the study reveals that for precipitation two out of three of the observed series illustrated an increased probability for extreme precipitation, the study however notes that in all three observational datasets the trends are not significant due to short records. The change in risk for high precipitation that has occurred since pre- industrial times are uncertain but results indicate that risk will increase significantly for the future with 2°C global warming since pre-industrial times. Change in risk for high discharge reveals an increase in risk since pre-industrial times to present-day conditions. Results reveal an increase in probability of high discharge in a 2°C warmer world (Philip et al., 2019).

A multi-step, physically based probabilistic event attribution framework was presented by Pall et al. (2011). The study used publically volunteered distributed computing that generated several thousand seasonal-forecast-resolution climate model simulations of autumn 2000 weather under realistic conditions and under conditions as they might have been, had greenhouse gas emissions and the resulting warming not occurred. The study used the HadAM3-N144 atmosphere only model with sea surface temperatures (SSTs) and sea ice as bottom boundary conditions. The study used daily river runoff as it was a better measure for flooding than precipitation, in the context of the study. Runoff was synthesised using a simple precipitation-runoff model derived from a coupled land-surface and river-routing scheme with empirically estimated hydrologic parameters for the England and Wales catchments. The study used FAR= 1-(PnonGHG/Preal) where PnonGHG represents counterfactual climate without greenhouse gas emissions and Preal represents current day climate and where distributions of FAR (histograms) show the increase in flood risk under realistic conditions. Results from the framework illustrated that it is very likely that global anthropogenic greenhouse gas emissions substantially increased the risk of flood occurrence in England and Wales in autumn 2000.

Wolski et al. (2014) uses an attribution modelling system to determine if anthropogenic greenhouse gas emissions have contributed to weather and flood risk in the current climate. The system compares real world climate and hydrologic simulations with parallel counterfactual simulations of the climate and hydrological conditions that might have been, had human activities not emitted greenhouse gasses. The study aims to address the question of whether anthropogenic climate change contributed to increasing the risk of high flood events in the Okavango system. The study followed the attribution method developed by Pall et al. (2011). The study performed the analysis on results of a hydrological model (Pitman model) driven by climate variables: rainfall and temperature obtained from climate models (HadAM3P-N96 and CAM5.1-2degree). The method includes running a global atmospheric model (AGCM) in two modes, the “real world” and “non-GHG world”. In the study in order to link the output of the AGCM with the hydrological model, the AGCM data had to be downscaled. The downscaling procedure used was SOM downscaling or SOM-D (based on self-organising maps). Downscaling was performed for only HadAMP3P-N96 data. The study uses the “risk-based” approach, examining how the probability of exceeding a threshold has been altered due to emissions (Stone and Allen, 2005). Assessment of change in risk of high floods due to anthropogenic climate change is based on the method developed by Stone and Allen (2005): FAR= 1-(PnonGHG/Preal). For the study simulations with both ACGMs illustrated reduced probability of occurrence of high floods in the “real world” conditions so FAR results were <0, the study therefore reversed the index definition to express the fraction of decrease in risk that is attributable to GHG- induced climate change so FADR= 1-(Preal/PnonGHG). The study differs from other examples such as Pall et al. (2011) and Kay et al. (2011) in that they have analysed events at time scales whilst this study focused on the events during an entire rainy season occurring once in 4-25 years. This study was limited to 50 ensemble members whilst the other studies used an ensemble of 1000 simulations. Results indicated that the probability of occurrence of high floods during 2009-2011 in the current climate is likely lower than it would have been in a climate without anthropogenic greenhouse gasses. A sensitivity analysis indicated that the reduction in flood risk is attributed to higher temperatures in the current world, with little difference in the rainfall simulated in the two scenarios.

Event attribution methodology and multi- step attribution studies are reviewed in the section above as this study will utilise the risk based methodology to determine if anthropogenic climate change has altered the chance of an extreme weather event (drought) occurring.

2.3 Soil and Water Assessment Tool (SWAT)

2.3.1 SWAT model

The Simulator for Water Resources in Rural Basins model (SWRRB) gave rise to the SWAT model, whose development is still ongoing (Devi et al., 2015). SWAT is a watershed modelling tool that utilises an ArcSWAT interface for it inputs (Dile et al., 2016). ArcSWAT is software is public domain but has to be used in the licensed ArcGIS environment (Dile et al., 2016). SWAT aims to determine the impact of land management practices on watersheds, particularly how these practices affect water, sediment and agricultural chemical yields. SWAT has also been used for investigating pollution problems, water availability and quality and climate change (Dile et al., 2016).

SWAT components include (Neitsch et al., 2011):

- Weather
- Surface runoff

- Return flow
- Percolation
- Evapotranspiration
- Transmission losses
- Pond & reservoir storage
- Crop growth & irrigation
- Groundwater flow
- Reach routing
- Nutrient & pesticide loading
- Water transfer

SWAT, a physically based model requires specific information about weather, soil properties, topography, vegetation and land management practices occurring in the watershed of interest (Neitsch et al., 2011). Dile et al. (2016) reports that SWAT is used in approximately 100 countries with a publication record of 2772 peer-reviewed articles in March 2016, according to the SWAT publication database.

In 2016 an open source GIS interface for SWAT was introduced namely QSWAT (Dile et al., 2016). The QSWAT model was established as a credible tool in relation to the SWAT model (Dile et. al, 2016). Few studies were found at the time of literature search for this study, besides the case study that used Gumera watershed in the Lake Tana basin, Ethiopia. Model results illustrated a successful performance in simulating observed streamflow (Dile et al., 2016). QSWAT uses Python programming open source geographic information system (QGIS) (Dile et al., 2016). Enhancements included in QSWAT not available in ArcSWAT are a merging feature for small basins and visualisation of outputs (Dile et al., 2016). QSWAT is installed as a plugin in QGIS. The conceptual framework is illustrated in ***Figure 10***.

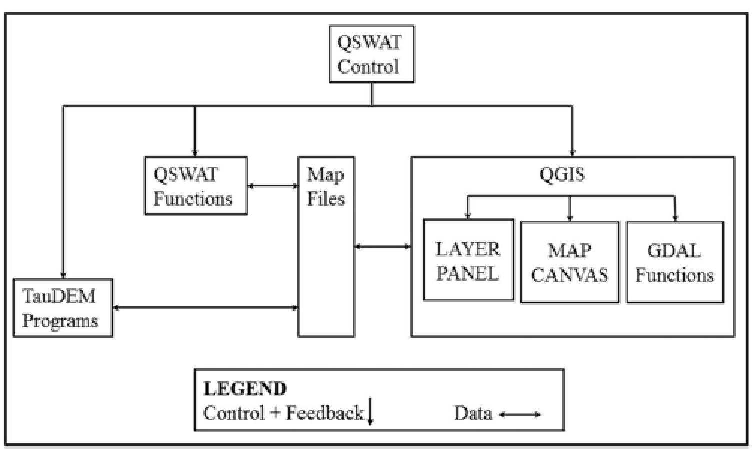


Figure 10: Conceptual framework of QSWAT (Source: Dile et al., 2016)

QSWAT has two main components: the Control containing the code which reacts to user's inputs and Functions that contains the code performing certain tasks such as the merging of sub basins. QSWAT utilises programs such as the Terrain Analysis Using Digital Elevation Models (TauDEM) that performs geoprocessing functions. QSWAT interacts with QGIS itself using the Layers Panel and Map Canvas. From QGIS the Geospatial Data Abstraction Library is also used where interaction with map files, rasters and shapefiles from a computer's file system is made possible (Dile et al., 2016). The main components of QSWAT are watershed delineation, Hydrological Response Units (HRUs), SwatEditor for model inputs and running the SWAT model and lastly visualisation of results (Dile et al., 2016). From the Dile et al. study in 2016, QSWAT was established as a credible tool in relation to the SWAT model.

QSWAT was used in the Luvuvhu River catchment, South Africa to simulate runoff and the study concluded that calibration produced acceptable results. The study however found that the model would be a useful tool for general water resource assessment but not for analysing hydrological extremes (Thavhana et al, 2018). In this study we want to determine if the model could be set up generically for use in KZN catchments and if it could be applied for use in the context of attribution.

2.3.2 SWAT studies in South Africa

In South Africa the SWAT model studies continues to increase and include the following studies: A study by Govender and Everson (2005) aimed to determine if the SWAT model could reasonably simulate hydrological processes in daily time steps for South African catchments. Catchments chosen were in the KwaZulu Natal Drakensberg mountains. The study utilised observed and simulated streamflow to compare a grassland catchment and a pine afforested catchment. For the grass catchment, simulated streamflow was acceptable whilst for the pine afforested catchment streamflow was over simulated. The importance of parametrizing the model as accurately and efficiently as possible was concluded in the study. Furthermore, the study concluded that SWAT could be useful as a tool in assisting management decisions and additionally with respect to water allocation scenarios (Govender and Everson, 2005).

In a study by Ncube and Taigbenu (2008), SWAT model was applied in the Olifants WMA assessing impacts of human-environment interactions on streamflow outputs. The authors performed a sensitivity analysis that identified the driving parameters of hydrology. In the catchment analysis results indicated that modelling at small spatial scales was more representative as different areas in the watershed responded differently to parameter changes. Results from the study displayed a correlation between land cover and the hydrologic response. With increased land cover a streamflow reduction occurred. The study concluded that SWAT was able to represent a South African watershed and provide a streamflow time series (Ncube and Taigbenu, 2008).

Another study simulated transport of water through the Verlorenvlei catchment in the Western Cape where model results compared favourably to measured flow data (Lewarne, 2009).

Andersson et al. (2011) described the potential of increasing water and nutrient availability. The study looked at water harvesting and fertilisation utilising stored human urine (Ecosan). The study was conducted for the Thukela River Basin. The SWAT model simulated impacts on maize yields, river flow regimes, plant transpiration and soil and canopy evaporation. Results for the study displayed maize yields more likely to be small with water harvesting and significant with Ecosan (Andersson et al., 2011).

In 2012 the SWAT model was used to look at impacts of rainwater harvesting on water resources. The study area was the Modder River Basin in the Free State, South Africa. The study area faces droughts that lead to the shortage of water for livestock, agriculture and domestic use. In the catchment, techniques were developed for rainwater harvesting, however the hydrologic impact of this technique by farmers were not well quantified. The model simulated potential hydrological impacts of such practices. Results from the study were expected to assist water resource management in the area by strategic allocations and use of water in the catchment (Welderufael et al., 2012).

The performance of SWAT was evaluated by Tetsoane (2013), by modelling of stream flow in the Modder River Basin. The evaluation included the use of quantitative statistics and graphical techniques. Statistics included Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the mean square error to the standard deviation of measured data (RSR). Results based on calibration indicate that the model performed well and for validation the model performed satisfactory (Tetsoane, 2013). The author concludes that meaningful catchment predictions can be made when the model is calibrated effectively.

Perry (2014) utilised the SWAT model to determine if it could successfully simulate runoff in a mountainous catchment. For the study observed streamflow data was obtained from the DWS. Observed data was calibrated and validated using Sequential Uncertainty Fitting (SUFI-2) the SWAT-CUP programme. The study concluded that the SWAT model could competently simulate streamflow data for the catchment.

SWAT model was utilised for the Olifants Basin in South Africa where the study focused on calibration, validation and uncertainty analysis. The study reveals the models applicability to simulate hydrology of the basin and emphasises that it could be used as a decision support tool by water managers and other relevant stakeholders (Gyamfi et al., 2016).

In 2017 SWAT model was applied in a study looking at Ingula Pumped Storage Scheme (IPSS) catchments, in the KwaZulu-Natal and Free State Provinces of South Africa. The main aim of the study was to determine the suitability of ArcSWAT for modelling mountainous, data-scarce catchments in Southern Africa. The SWAT model was successfully calibrated and validated to simulate the stream flow responses of the IPSS catchments on a monthly time-scale (Ngubane, 2017).

South African SWAT studies are relevant to this study as a version of the SWAT model will be used and the study area is located in South Africa (KZN).

2.4 Literature review summary

The first section of the literature review looks at drought including the different types and definitions of drought. The section then looks at location and scale of drought as well as intensity of drought and the different time scales they span. The next section looks at climatic drivers of drought, discussing causes of droughts. Masih et al. (2014) highlighted that while there was a growing number of studies on various drought related issues in the last decade, and studies covered parts of Africa, knowledge gaps remained such as for middle Africa where low coverage existed. Furthermore meteorological followed by agricultural drought remained the subject of most studies and Masih et al. (2014) highlighted that examination of hydrological droughts remained limited. Many studies investigated natural causes associated with drought in Africa and some also examined anthropogenic factors. ENSO is examined in the literature review as it is regarded as one of the major weather influencing factors in Africa. Climate change as a drought influencing factor is also reviewed in the above literature review and is of particular importance in the context of this study that aims to determine if climate change has contributed to the 2015-2016 drought in KZN. The last section on drought in the literature review looks at drought in South Africa. Occurrence of drought in South Africa is discussed and knowledge gaps identified includes publications on recent drought events experienced such as severe water shortages experienced in Western Cape in 2018 that lead to a projected "day zero". To conclude the section, impacts of droughts on SA are examined. The next section of the literature review looks at climate change event attribution. In this section studies determining how anthropogenic climate change has altered the probability or magnitude of extreme events are reviewed. The section also looks at the definition of event attribution studies and approaches of these studies. Keynote studies in attribution are then listed. The next section is attribution of extreme events that looks at founding literature in the subject matter including introduction of FAR- fraction of attributable risk concept. The attribution studies in Africa section follows, and looks at African based attribution studies. An identified gap in knowledge was publications on more recent drought events, this was however addressed with analysis of the Western Cape 2015-2017 drought being published, and subsequently added to the review section above. The next section of the literature review looks at event attribution methodology available for attribution studies. Methods include physical reasoning, statistical analysis of time series, philosophical argument and probabilistic event attribution. Gaps identified in this literature search revealed not many available studies for all listed methods. Probabilistic event attribution method is the methodology applied in this study. The last section explores attribution of hydrological events vs climate events. The section looks at multi-step attribution studies, relevant as applied in this study. The final section in the literature review examines literature on the SWAT model. The section provides an overview of the SWAT model including development, aim and current uses. An overview of the QSWAT model is presented in the following section including the QSWAT conceptual framework. This section has relevance for this study as it is the model used and tested in this study. Knowledge gaps identified include very few published studies available on the QSWAT model. A potential means to address this gap includes publication of this study being undertaken as QSWAT model will be utilised in this study. The final section of the literature review looks at available SWAT studies in South Africa (South African case studies), this is relevant to this study as the study area chosen for this study is KZN located in South Africa.

3. STUDY AREA

As indicated in section 1.2.3 one of the objectives of this study is to assess the role of climate change in the 2015-2016 hydrological drought in Kwa-Zulu Natal province of South Africa. In fact, as shown in sections 1.1.1 and 2.1.3 the 2015-2016 drought was not limited in extent to that province, but has covered almost the entire summer rainfall region of South Africa and countries to the north of it. This study does not look at the entire area influenced by the drought but rather examines catchments within KZN Mvoti to Umzimkulu Water Management Area, part of the area influenced by the drought, due to the scale of the study and data availability. Section 4.2.3.1 in the methodology chapter elaborates on the selection of catchments.

3.1 Characteristics of Mvoti to Umzimkulu WMA

The total catchment area for Mvoti to Umzimkulu WMA is approximately 27,000 km^2. The town of Zinkwazi is where the WMA area extends from in the north to Port Edward and in the southern region along the KwaZulu-Natal coastline and up until the Drakensberg escarpment. The Mvoti to Umzimkulu WMA makes up one of South Africa's primary catchments (the primary catchment "U") (***Figure 11***) which is divided into ninety quaternary catchments.

Major rivers draining in the WMA includes the Umzimkulu, Mkomazi, uMngeni and Mtamvuna. Smaller river systems and parallel river systems also occur in the WMA and discharges into the Indian Ocean (DWS, 2015).

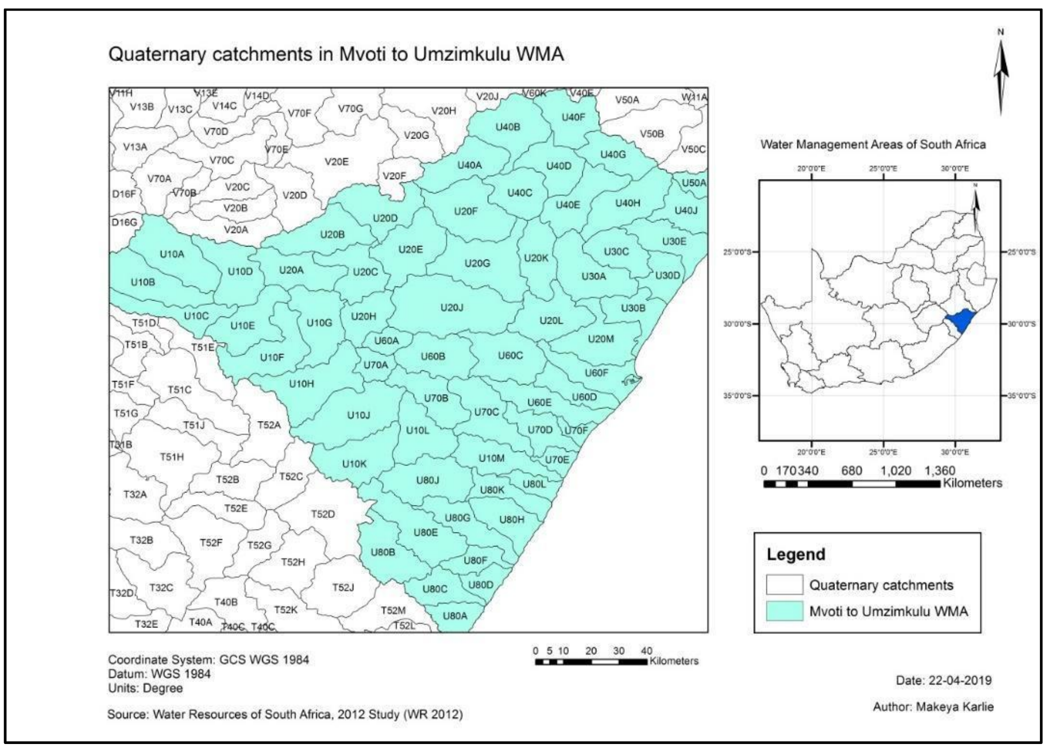


Figure 11: Mvoti to Umzimkulu WMA

3.1.1 General characteristics of the region

The total population reported in 2001 for the WMA was approximately 5.12 million people, one of the most populated WMA's at the time of publication. The WMA incorporates both the Durban and Pietermaritzburg areas which accounted for 2.5 million people alone. The population was also reported as being distributed unevenly (Wilson, 2001). For the WMA rural areas is characterised by subsistence and commercial farming. The areas include cultivation of sugarcane along the coast and commercial forests in areas with higher rainfall. The WMA displays a range of diverse activities (NWRS, 2004).

Geology in the WMA (***Figure 12***) is comprised of Karoo sedimentary rocks that include sandstones, mudstones, basalts, granites, tilites, dolerite intrusions and shale which all influence the topography of the region. Furthermore, these are overlain by the Lebombo Group basalt and rhyolite extrusive rocks and underlain by Natal Group sandstone and basement rocks (Wilson, 2001).

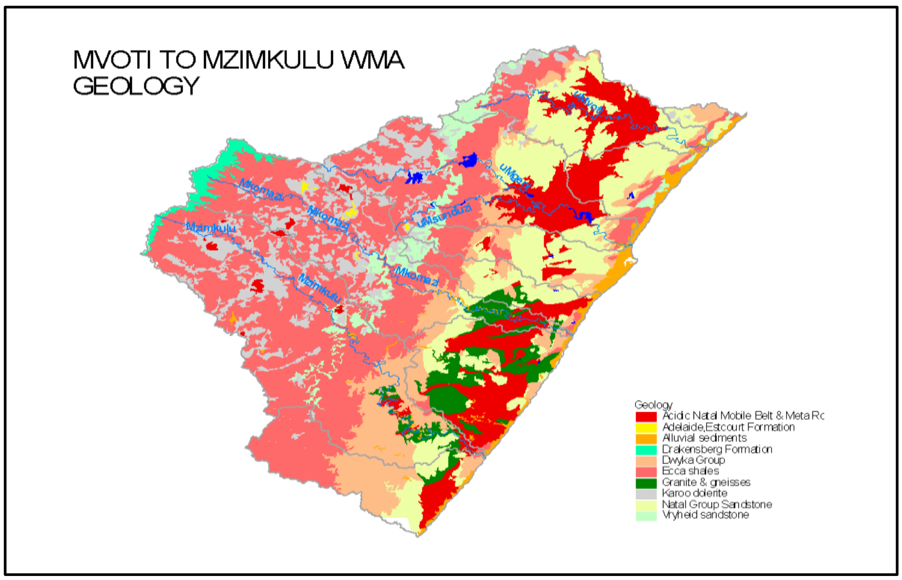


Figure 12: Geology of Mvoti to Umzimkulu WMA (Source: Wilson, 2001)

Land use in the region includes forestry, grasslands, agriculture and allocations to game reserves and parks. One of the largest reserve areas is the Drakensberg Reserve. Agriculture types that occur include sugar cane, bananas, citrus, vegetables, beef and dairy pastures (Wilson, 2001).

Vegetation types in the region include coastal vegetation, forest, drier veld and valleys known and bushveld. Alien vegetation known to be occurring in the WMA varies greatly in percentage and density and includes weed species (Wilson, 2001). These alien plant species have an impact on water resources. DWS (2015) reported thousands of varying wetlands in the WMA.

The WMA spans a range of topographic characteristics with Drakensberg Mountains in the west over 3000m and over a distance of approximately 250 km sea level in the east (Umgeni Water, 2017).

3.1.2 Climate

Various climatic conditions exist across the WMA spanning the Drakensberg Mountain and the Indian Ocean. The area managed by Umgeni Water has been classified into 3 distinct climate zones according to the Köppen classification (***Figure 13***): the alpine-type climate (Cwb) found in and along the Drakensberg Mountains, temperate summer rain climate (Cfb) of the Midlands region and subtropical perennial rainfall zone (Cfa) characterising the areas along the coast (Umgeni Water, 2017).

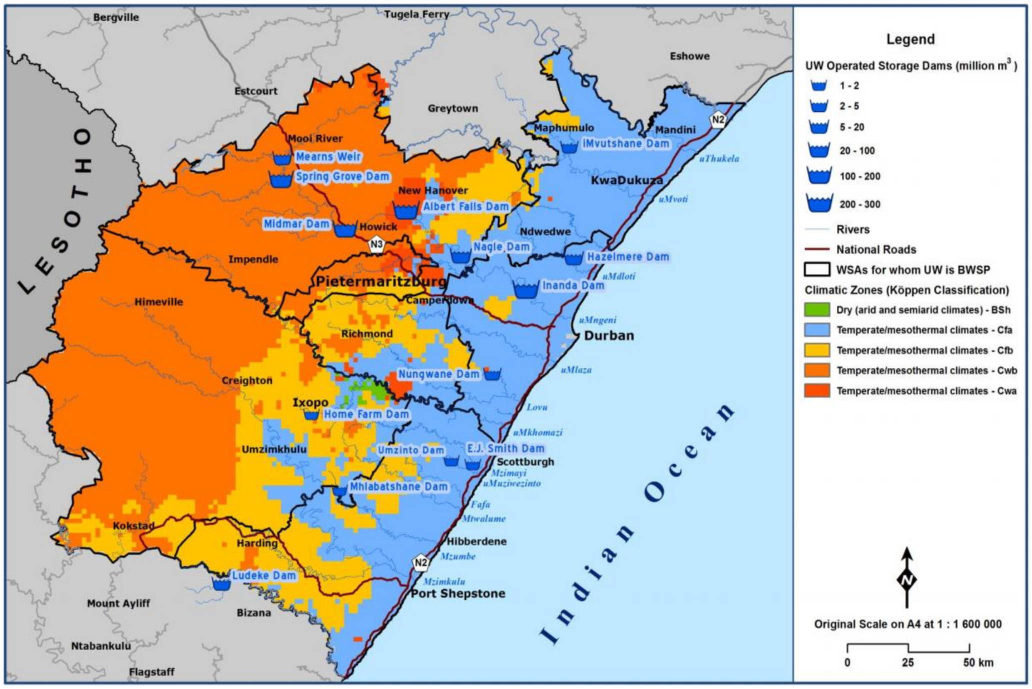


Figure 13: Climatic Zones (Köppen Classification) for KZN (Source: Umgeni Water, 2017).

3.1.2.1 Rainfall

The WMA mean annual precipitation (MAP) ranges between 700 and 1000 mm/year, illustrated in ***Figure 14***. The region is characterized by summer rainfall regime, with most rainfall in summer between October and March. Inland areas display peak rainfall months as December to February and for the coastal area from November to March. During April and September snowfall occurs in the Drakensberg mountain region and this influences the climate in the WMA. Similarly, frost occurs during the same time period over inland areas (Wilson, 2001).

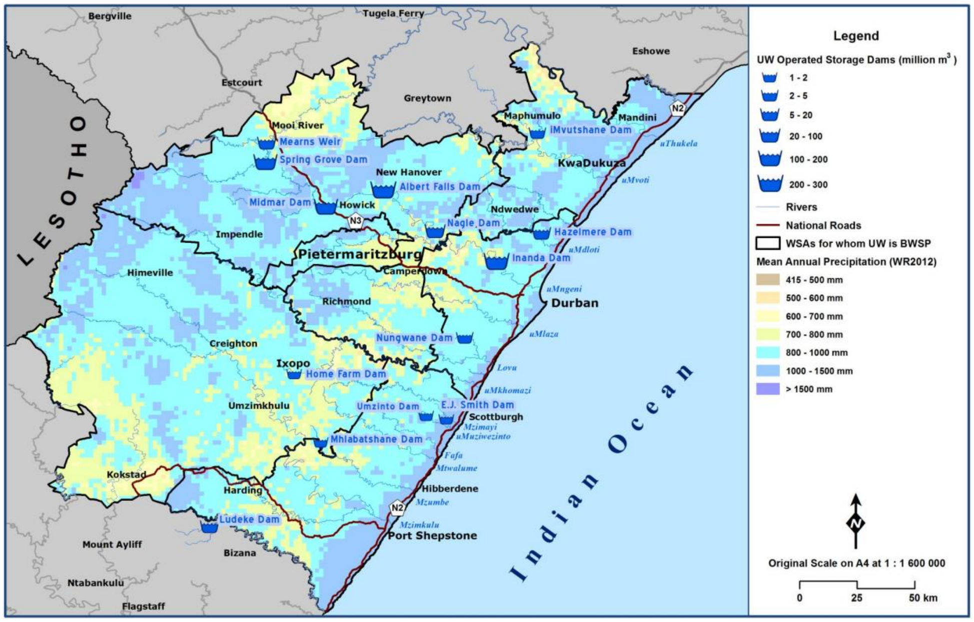


Figure 14: Mean annual precipitation (MAP) for KZN (Source: Umgeni Water 2017).

3.1.2.2 Temperature

Figure 15 illustrates mean annual temperature for the WMA. In the west region of the WMA temperature ranges between 12°C and 14°C and along the coast temperature ranges between 20°C and 22°C. Maximum temperatures are experienced in the summer months of December to February and minimum temperatures in the winter months of June and July. The Drakensberg Mountain experiences snowfall and frost April- September (Umgeni Water, 2017).

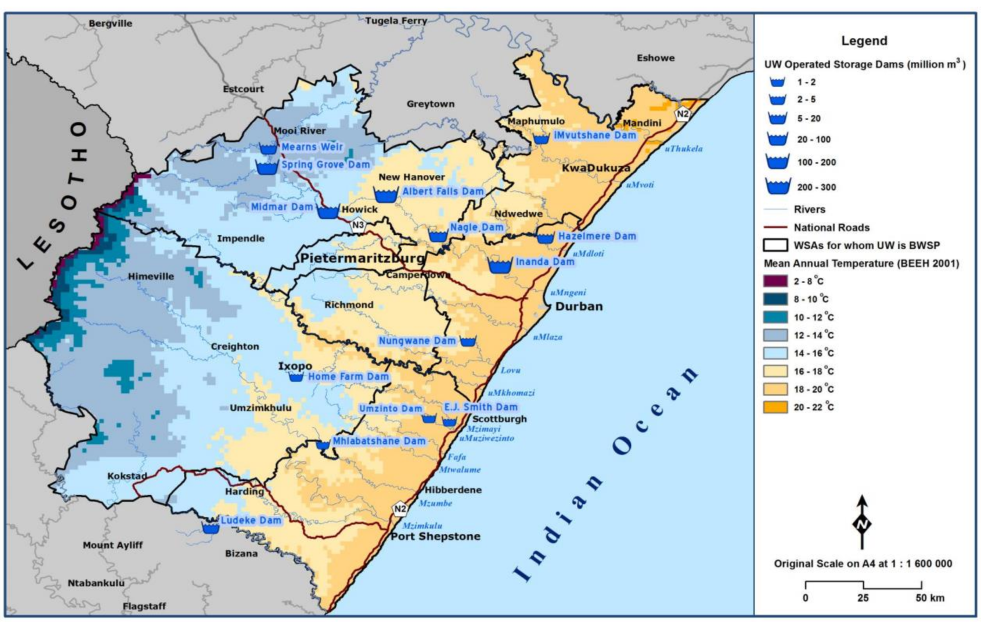


Figure 15: Mean annual temperature (MAT) for KZN (Source: Umgeni Water, 2017).

3.1.2.3 Evaporation

The spatial distribution of evaporation has a similar pattern to rainfall where a relative high humidity is experienced in summer. Potential mean annual gross evaporation ranges from 1 600 mm/year to 1 800 mm+/year in the west to between 1 400 mm/year to 1 600 mm/year in the coastal areas (Umgeni Water, 2017).

3.1.3 Hydrology

3.1.3.1 Runoff

The mean annual runoff (MAR) is illustrated in ***Figure 16***. The spatial distribution of MAR is highly variable from the Drakensberg mountain range towards the coastal areas with more runoff generated from the mountains and the coastal areas and lesser generated in the inland regions (Umgeni Water, 2017).

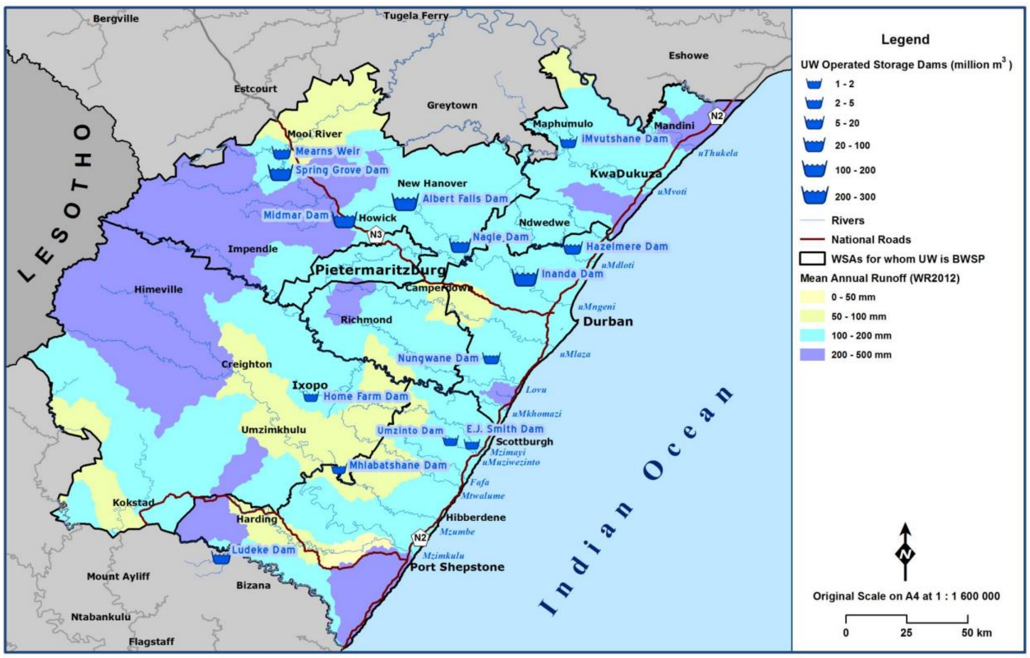


Figure 16: Mean annual runoff (MAR) in mm/year for KZN (Source: Umgeni Water, 2017).

3.1.3.2 Groundwater

Groundwater discharge occurs from springs, seeps and boreholes. Almost no primary aquifers occur in the WMA so groundwater potential is associated with structural features such as faults, joints, fractures and dykes. There is little use of groundwater at a large scale in this WMA.

4. METHODOLOGY AND DATA

This chapter starts with presenting the general framework of implementation of hydrological attribution experiments. This is followed by a description of the general implementation procedure of a hydrological model and description of SWAT as a hydrological model adopted in this study. Subsequently, available data required to implement SWAT model are described, and evaluated from the perspective of use in an attribution study. That includes generic SWAT datasets, other generic global datasets, and various local datasets. Following that, the SWAT configuration adopted for the study is presented. Finally, the chapter presents a setup of attribution experiments including sections on climate attribution experiments, downscaling, and implementation of SWAT in the attribution mode. Lastly the approach to analysis of results of SWAT attribution simulations is presented.

4.1 General framework of implementation of hydrological attribution experiments

Figure 17 illustrates the framework or study design followed for this study. The study was initiated with the formulation of the attribution question. Following this a hydrological event was identified namely the 2015- 2016 drought in KwaZulu-Natal. Identifying a hydrological event led to the initiation of hydrological modelling. Hydrological model development included selection of the study area, setting up the hydrological model (described in the section after this) and calibration of the hydrological model. Hydrological drought attribution simulations were then implemented with the hydrological model. These attribution simulations were based on downscaled data from climate attribution experiments with HadAM3p global climate model available from Climate System Analysis Group (CSAG), University of Cape Town (UCT). Lastly the study focused on interpretation of results obtained from the SWAT attribution simulations.

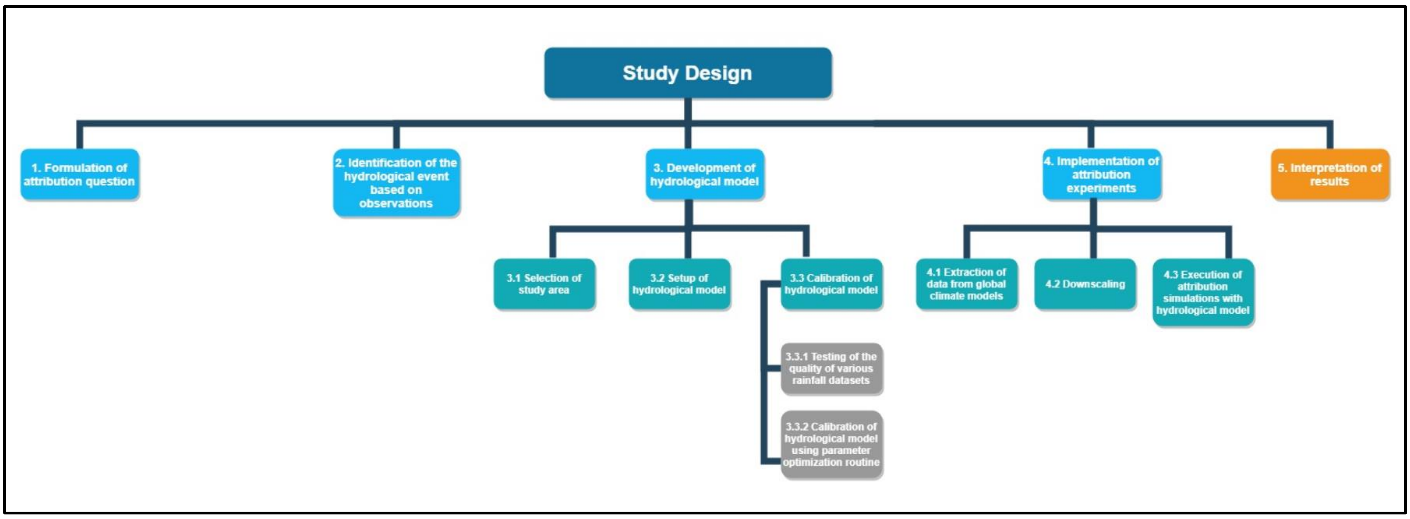


Figure 17: Study design

4.2 Development of hydrological model for attribution simulations

The section below describes the process of setting up and calibration of the hydrological model used in this study.

4.2.1 Motivation for using SWAT/QSWAT as the hydrological modelling software

There are a number of hydrological models that are used in South Africa and that can potentially be applied in the context of attribution – two most notable ones are Pitman-WR2012 (WR2012, 2012), Pitman-SPATSIM (SPATSIM, n.d.) and ACRU (ACRU, n.d.). They are embedded in (or associated with) institutional setting – WRC/DHV, Rhodes University and University of KZN respectively. The models are calibrated and have their own climate and parameter datasets. As a result, they are not very "flexible", so they cannot easily be applied out of context intended by their creators, or with other than their own datasets.

This study utilizes a different hydrological model namely SWAT. SWAT is a generic hydrological model, operating with generic (global) climate datasets. SWAT is an open source software, which is designed to be implementable in essentially any location. As a result, it offers a good alternative to the established hydrological models for implementation of rapid attribution studies, particularly outside of RSA, in other African countries, where hydrological modelling base is not as well developed as that in RSA. SWAT has been applied in RSA and elsewhere on African continent (e.g. Dile et al., 2016; Thavhana et al., 2018; Govender and Everson, 2005; Ncube and Taigbenu, 2008; Lewarne, 2009; Andersson et al., 2011; Welderufael et al., 2012; Tetsoane, 2013; Perry, 2014; Gyamfi et al., 2016 and Ngubane, 2017). SWAT studies in Africa include topics such as hydrology/water balance, calibration/uncertainty, erosion, land management, land use change, climate change, SWAT development, data and water quality. For the Nile basin countries specifically Ethiopia, erosion studies were prevalent. In North Africa many studies looked at the importance of water resources. In southern Africa crop modelling studies were prevalent. In Schuol et al. (2008) the study looks at an Africa continent model using SWAT. In Easton et al. (2010) a modified version of SWAT was used to predict runoff and sediment losses from the Blue Nile Basin (Van Griensven et al., 2011). More recent studies include multi-site calibration and validation of SWAT with satellite-based data for southwestern Nigeria (Odusanya et al., 2019). In South Africa, techniques for calibration and validation of SWAT model in data scarce arid and semi-arid catchments (Northern Cape as study area) were explored by Mengistu et al. (2019).

4.2.2 Description of SWAT hydrological model

The hydrological model utilized for this study was the QSWAT 1.4 model. Software for the QSWAT model is available freely on the SWAT website (http://swat.tamu.edu/software/qswat/).

4.2.2.1 Representation of hydrological processes in SWAT/QSWAT

SWAT can be classified as a semi-distributed, semi-conceptual hydrological model. It represents rainfall-runoff processes, and it has capacity to simulate the impact of land management practices on water, sediment and agricultural chemical yields in complex watersheds with varying soils and land use and management conditions. Spatial heterogeneity of hydrological processes is represented by dividing the watershed into sub basins and then each sub basin is divided into HRUs delineated based on (uniform) soil and land use. The hydrological cycle simulated by SWAT can be divided into 2 phases: land phase and routing phase. The land phase first calculates loadings of water, sediment, nutrients and pesticides for each HRU and for each sub basin loading is calculated by aggregating the loadings of its HRU which is then entered into the main channel of the sub basin. Major hydrological processes of the land phase include evapotranspiration, canopy storage, infiltration, surface runoff and sub-surface runoff. Potential evaporation in the model is calculated by Penman-Monteith, Priestley-Taylor and Hargreaves. Surface runoff is estimated by modified SCS curve number method or Green-Ampt infiltration method. Infiltration into soil is calculated by the water balance equation. Routing equations describe the movement of water, sediment etc. through the main channel to the sub basin outlet. Catchment runoff can be routed through the river system, from sub basins to the basin outlet using either variable storage routing method or Muskingum River routing method.

4.2.2.2 QSWAT general implementation procedure

Figure 18 illustrates the general implementation of QSWAT. The main steps for implementation of SWAT include:

- The process of configuring model units and derivation of model parameters that comprises:

  - Watershed delineation based on DEM, with automatic identification of subbasins, stream network and catchment outlets. Alternatively, any or all of these elements can be defined by the user.
  - Creation of Hydrological Response Units (HRU), which express a combination of classes of soil properties, land use types and terrain slope within each sub-catchment identified in the previous step. These can be based on the generic soil, land use and topography data, included in the SWAT installation, or on user-defined soil, land use and topography maps. HRUs are defined based on a set of pre-defined rules of merging and combining the input maps.

- The process of derivation of model inputs for subbasins. This process can take as input climatic data from scattered stations or from gridded datasets.

- The process of running or execution of the model

- The process of visualisation of results.

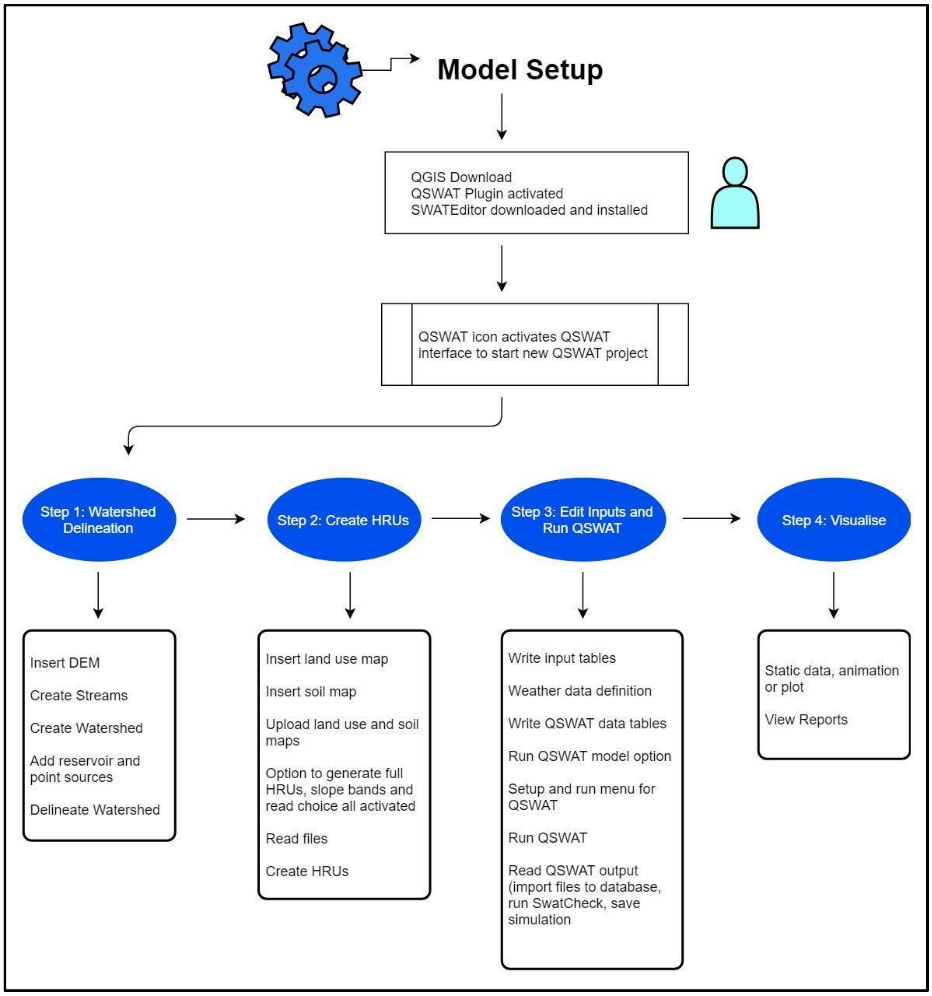


Figure 18: General QSWAT implementation

It should be noted that QSWAT is implemented as a plugin within QGIS. QGIS is an open source desktop GIS application which is available freely. QGIS features include data viewing, editing and analysis capabilities. QGIS is also enhanced with plugins enabling tools for geoprocessing, geocoding and many more (Dile et al., 2016). In QGIS, QSWAT utilises programs including “Terrain Analysis Using Digital Elevation Models (TauDEM)” used for geoprocessing. QSWAT utilises QGIS tools directly by using the “Layers Panel” and “Map Canvas”. QSWAT also makes use of the “Geospatial Data Abstraction Library” in QGIS that allows the SWAT model to use maps, rasters and shape files on the computer.

4.2.2.3 Generic SWAT datasets

SWAT is designed to be implemented in a “generic” catchment by following a particular implementation procedure based on generic datasets that come with the software. That generic implementation can be modified to reflect specific local conditions and datasets. Below, the generic implementation is described.

Spatial data - model parameters

Spatial data required includes a Digital Elevation Model (DEM) used to delineate the watershed. The SWAT website offers a manual detailing how to obtain a DEM. Options include obtaining Shuttle Radar Topography Mission (SRTM) 90m or 30m data. 90 m data is made available from (http://srtm.csi.cgiar.org/) and 30 m data is made available from (http://earthexplorer.usgs.gov/). Furthermore, spatial data the model requires includes land use and soil maps. The SWAT website offers manuals for global soil and land use data. USA soil data is also available namely SSURGO and STATSGO2 at (http://datagateway.nrcs.usda.gov/) and the soil database which is the data required can be found at (http://swat.tamu.edu/software/arcswat/). The SWAT global soil and land use data is available at the WaterBase website (http://www.waterbase.org/download_data.html) for maps.

Temporal data- climate and hydrological inputs

Weather data is required for the hydrological processes in SWAT. Rainfall, temperature, relative humidity, solar radiation and wind speed data can be user-defined or, alternatively, SWAT can be run with data generated by a built-in weather generator. The weather generator can also be used to fill data gaps. Climate and weather data can be obtained from the SWAT website (http://globalweather.tamu.edu/). The data available is the daily Climate Forecast System Reanalysis (CFSR) data developed by The National Centres for Environmental Prediction (NCEP). Climate data is available for the period 1/1/1979 to 7/31/2014 and is available in both "SWAT format" and as "CSV files". The available data is daily rainfall, temperature, wind speed, relative humidity and solar radiation. From the Water Weather Energy Ecosystem Project (https://www.2w2e.com/), global historical climate CRU data is also available for use in SWAT. The CRU data available is from 1979-2005 for precipitation and temperature. Data is available in SWAT format with a points file for precipitation and temperature.

4.2.3 Adopted SWAT configuration

While it is possible to substitute the generic SWAT DEM, soil and land cover datasets with locally-specific ones, the time frame, scope and objectives of this project did not allow for this. The SWAT model was thus implemented with SWAT-provided soil and land cover data, a global DEM data, with locally-specific configuration of subbasins, and with several various climate datasets.

4.2.3.1 Delineation of subbasins for simulation with QSWAT

This study does not look at the entire area influenced by the drought but rather examines selected catchments within KZN Mvoti to Umzimkulu WMA, part of the area influenced by the drought. This was motivated by the limited time frame of the study and data availability.

For delineation of sub-basins SRTM 90m resolution DEM was used (***Figure 19***).

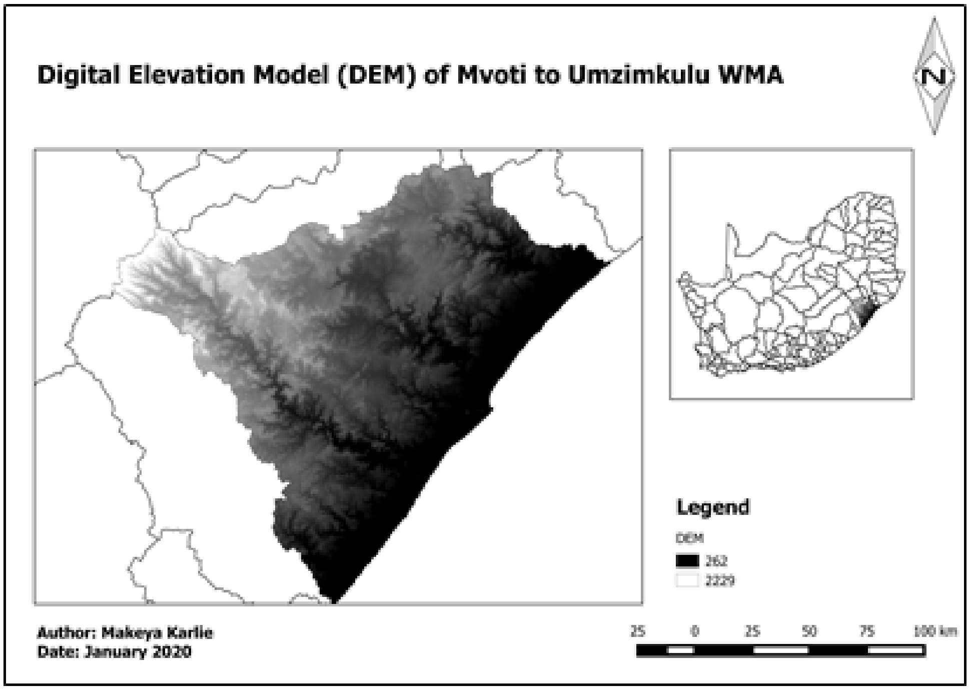


Figure 19: Spatial coverage of the Mvoti to Umzimkulu WMA illustrated by the Digital Elevation Model of the catchment area.

The SWAT delineation routine allows inserting an existing stream network or using an existing watershed. For this study a predefined WR2012 (Bailey and Pitman, 2015) stream network was utilised. The WR2012 study describes the water resources of South Africa (described in section 4.3.3.2 below). Outlets were set to correspond to streamflow gauges with available DWS data.

The DWS database contains records of 58 stations (Source: DWS, 2018) in the analysed WMA (drainage region U according to DWS). Out of these, 8 stations have substantial temporal coverage of data, and three were selected and used to delineate subbasins for further analyses (***Table 1***).

Table 1: Streamflow gauges with significant time period data (Source: DWS, 2018)

Station No	Place	Latitude	Longitude	Data Available
U1H005	Mkomazi River @ Lot 93 1821	-29.74369	29.90494	1960-08-14 to 2018-01-26
U2H007	Lions River (Mpofana River) @ Weltevreden	-29.44258	30.14852	1954-07-16 to 2017-11-14
U2H013	Mgeni River @ Petrus Stroom	-29.51261	30.09441	1960-08-10 to 2017-07-04

Figure 20 illustrates the location of the selected DWS streamflow gauges and the resulting subbasins used in model simulations.

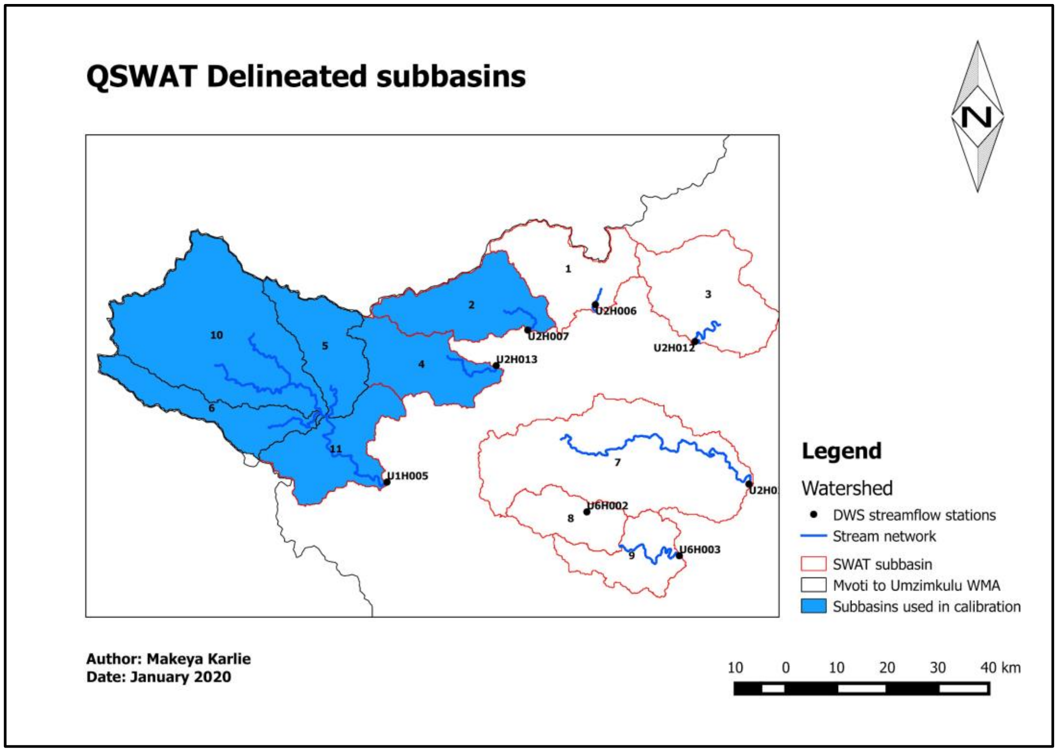


Figure 20: QSWAT delineated subbasins

4.2.3.2 Delineation of Hydrological Response Units

Following the delineation of the watershed the next step in the model is creation of HRUs. The generic SWAT soil map af_soil_2 and the land use map af_land_2 downloaded from WaterBase.org were used (***Figure 21*** and ***Figure 22*** respectively). The database (lookup tables) for these maps (global_soils and global_landuses) are available in the QSWAT project database discussed in section 4.2.2.3.

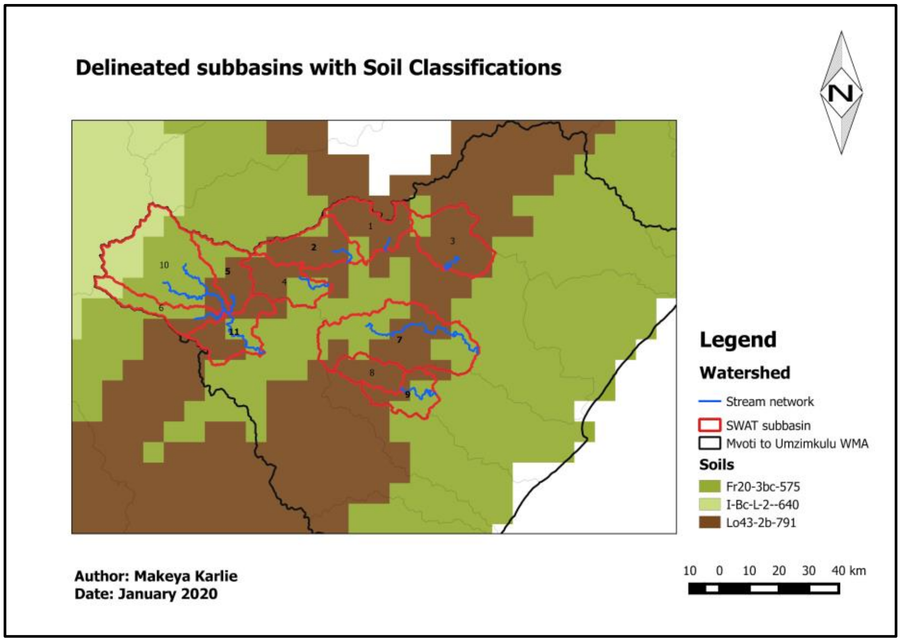


Figure 21: Delineated subbasins with Soil Classification

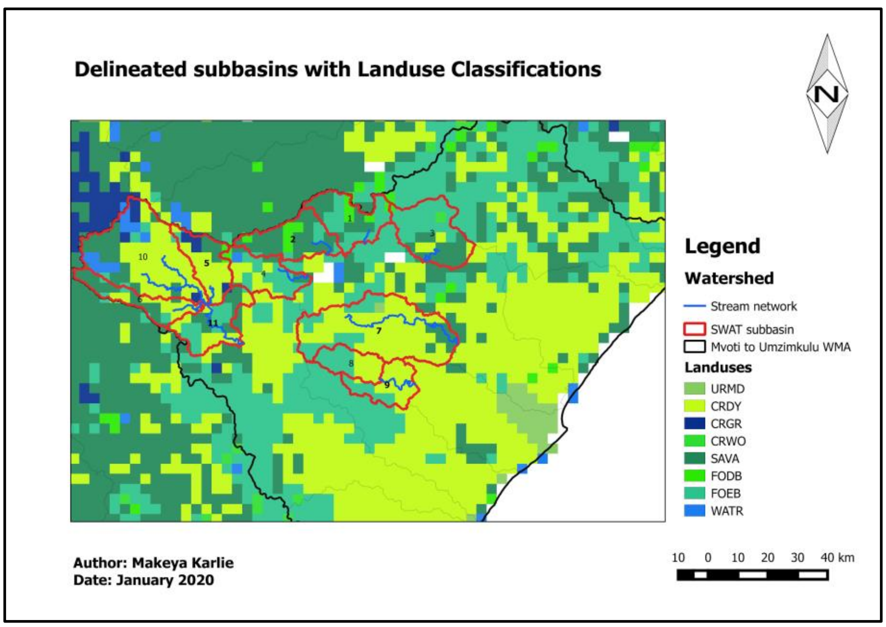


Figure 22: Delineated subbasins with Landuse Classification

The modelled catchment was predominantly classified by the following land use classes: Water (WATR), Urban or built up land (URMD -residential medium density), Forest (FODB- deciduous broadleaf forest and FOEB- evergreen broadleaf forest), Rangeland (SAVA- Savanna) and Agricultural land (CRDY- dryland and cropland pasture; CRGR-mosaic cropland/grassland and CRWO- mosaic cropland/woodland). The soil classification for the catchment included Ferralsols (Fr- rhodic ferralsols), Lithosols and Luvisols (Lo- orthic luvisols).

4.2.3.3 Climate data

In order to be able to conduct attribution simulations for the event of interest, i.e. for the 2015-2016 drought, the SWAT model needed to be run with observed climate data spanning that period. Since the climate data included in SWAT installation, i.e. SWAT CRU and SWAT CFSR (section 4.2.2.3) did not cover that period, another climate dataset had to be used.

WATCH WFDEI climate dataset was selected for the attribution simulations. The two other datasets, SWAT CRU and SWAT CFSR were used in order to compare model performance when driven by different rainfall datasets.

The WATCH project (Water and Global Change) has produced global data sets for utilisation in global and regional studies of climate and water (WATCH, 2018). Data sets include meteorological data utilised by hydrological models, land surface models and model outputs for the 20th and 21st century (WATCH, 2018). WATCH WFDEI meteorological forcing data set is generated by merging WATCH Forcing Data (WFD) and ERA-Interim reanalysis, WFDEI standing for "WATCH Forcing Data Era-Interim". The WFDEI data set utilised in this study has 8 meteorological variables, with daily averages and a 0.5^{o}x 0.5^{o} resolution (Weedon et al., 2014). Data available for utilisation in this study is precipitation, relative humidity, absolute humidity, minimum temperature, maximum temperature, mean temperature, wind speed and shortwave incoming radiation.

4.2.3.4. Hydrological data

Department of Water and Sanitation (DWS) data

DWS has a website with available verified surface water data (http://www.dwa.gov.za/Hydrology/). For the study area all available flow gauges are discussed in section 4.3.3.1 above.

4.2.4 SWAT calibration

Calibration is defined as a procedure where the difference between model simulation and observation are minimized. Current modelling practice requires models that are in use to be transparently described. SWAT-CUP program (automated) is typically used for the calibration of the SWAT model. SWAT- CUP has five different calibration procedures available including Sequential Uncertainty Fitting Version 2 (SUFI-2), Particle Swarm Optimization (PSO), Generalised Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol) and Markov Chain Monte Carlo (MCMC) (Abbaspour et al., 2015). SUFI-2 algorithm was used in this study for model calibration. SUFI-2 allows usage of ten different objective functions and in this study we look at Coefficient of Determination (R^2) and Nash- Sutcliffe efficiency (NSE). In Abbaspour et al. (2015) a calibration protocol is presented, which was utilised as a guide for calibration in this study.

4.2.4.1 SWAT-CUP implementation

The automated calibration procedure included using the built model in QSWAT with the best parameter estimates that were found from available data and literature. The best default model in terms of simulation results was then used to initiate the calibration procedure. A basic data check was performed to ensure all input data required was read from the saved QSWAT simulation. From the QSWAT simulation the TxtInOut file is checked, which should be in the required SWAT-CUP format. A SWAT-CUP project was then set up, navigating to the TxtInOut directory and the SWAT model version architecture is chosen (2012 and 64- bit architecture for this study). SUFI-2 algorithm was then selected along with a project name and location. The next step in SWAT-CUP was running the calibration where adjustments were made to the following files: Par_inf.txt (where parameters were chosen to use in calibration), SUFI2_swEdit.def (start and ending date of simulations are edited according to study data), File.cio (general watershed information according to study model) and Observed_rch.txt (entering observed values from study data). Furthermore, extraction files (.txt and.def files) are edited; these files correspond to output files (output.rch, output.hru and output.sub). Var_file_rch.txt is where names of the files values extracted should be written to (specify subbasin chosen). SUFI_extract_rch.def is where variables are identified for extraction and corresponding subbasin specified. Lastly, files to be edited before the calibration run are objective function files, where Observed.txt contains all observed text files information and information regarding the calculation of objective function. The Var_file_name.txt file contains all variable names included in the objective function. Executing the calibration procedure then required running the .bat files (SUFI2_pre.bat, SUFI2_run.bat and SUFI2_post.bat) in that order. SUFI2_pre.bat file performs pre-processing procedures, SUFI2_run.bat executes SUFI2_execute.exe programme which runs the SWAT_Edit.exe and SWAT.exe files. SUFI2_post.bat runs the post-processing files (objective function calculation, new parameters and 95ppu calculation). Calibration was executed for each subbasin used in the study (4 iterations and 300 simulations in each iteration). Following completed simulations available outputs are the objective function and the 95PPU for all observed variables in the objective function. After each iteration new parameter ranges are suggested by the program for another iteration, which modifies previous ranges focusing on the best parameter set of the current iteration. The last step implemented was the global sensitivity analysis after each iteration performed. In this global sensitivity analysis each parameter has a corresponding t-stat value and p-value. The larger the t-stat value and the smaller the p-value the more sensitive the parameter. The process was continued for each subbasin until satisfactory results were reached in the objective function. ***Figure 23*** is the process of calibration in SWAT-CUP using SUFI-2.

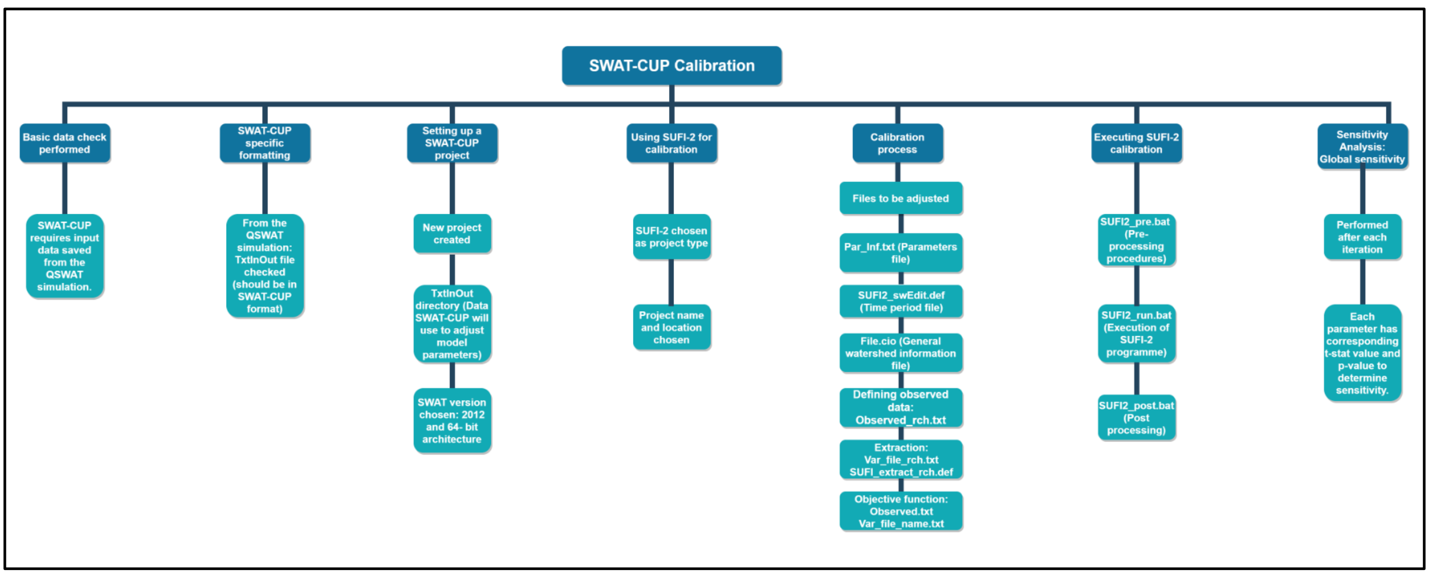


Figure 23: Performing a calibration utilising SUFI- 2

4.2.4.2 Model performance evaluation criteria

The process of model calibration, either manual or automated, involves optimization of an objective function (Abbaspour et al., 2006). An objective function expresses model performance, and in this automated calibration we use the functions: coefficient of determination R^2 and Nash- Sutcliffe (NSE) efficiency.

Coefficient of Determination (R^2)

Coefficient of determination (***Equation 1***) is calculated to describe the proportion of the variance in measured data explained by the model. R^2 ranges from 0 to 1 with higher values indicating less variance error and typically values greater than 0.5 are considered acceptable (Tomy and Sumam, 2016).

$$R^2 = \left[\frac{\sum_{i=1}^{n} (o_i - o_{aver})(P_i - P_{aver})}{[\sum_{i=1}^{n} (o_i - o_{aver})^{2} \sum_{i=1}^{n} (P_i - P_{aver})^2]^{.5}}\right]^2$$

Equation 1: Coefficient of Determination

O is measured values, P is predicted outputs, index i denotes time step.

Nash- Sutcliffe efficiency (NSE)

NSE (***Equation 2***) is a normalized statistic calculated to determine the relative magnitude of the residual variance compared to the measured data variance (Tomy and Sumam, 2016). NSE indicates how the simulated value, from a calibrated model represents observations (Moriasi et al., 2007).

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{mean})^2}\right]$$

Equation 2: Nash- Sutcliffe efficiency

Y_i^{obs} is the ith observation for variable being evaluated, Y_i^{sim} is the ith simulated value of that variable, N total number of observations.

NSE ranges from -∞ to 1, with an NSE of 1 being the perfect reproduction of observed data by model. NSE values between 0 and 1 are viewed as acceptable, and NSE values are typically qualified as follows: Good calibration: NSE >0.75, satisfactory 0.75>NSE>0.36, unsatisfactory NSE<0.36 and <0.0 unacceptable as it indicates the mean observed value is a better predictor than the simulated value.

4.3 Attribution experiments

One of the objectives of this thesis is to examine if anthropogenic climate change (emissions) has altered the probability of an extreme event such as the 2015-2016 hydrological drought in KZN catchments.

The approach to address that objective follows the risk based methodology described in Stone and Allen (2005) and described in the general attribution methodology literature (section 2.2.3) above.

In that, change in probability of the event (hydrological drought) is derived from a comparison of two sets of hydrological simulations. One set represents hydrological responses in the analysed catchment under factual or "current" climate. The other set represents these responses under a "counterfactual" climate that represent pre-industrial conditions, or conditions that would have been had there been no anthropogenic emissions of greenhouse gases. The two "climates" are obtained from dedicated attribution simulations by a global climate model. Each "climate" is represented by an ensemble (a number) of climate model simulations that capture the range of possible climate responses under given radiative or GHG forcing.

In detail, the procedure is implemented in the following steps:

1. Formulation of Attribution question and identification of hydrological event
2. Setting up and implementation of attribution experiments with global climate model
3. Downscaling climate variables from attribution simulations to spatial resolution appropriate to drive SWAT hydrological model
4. Implementation of simulations with SWAT under current and counterfactual forcing
5. Analyses of outputs (simulated runoff) of SWAT simulations

4.3.1 Formulation of attribution question and identification of hydrological event

The attribution question (examining if anthropogenic climate change has altered the probability of the 2015-2016 hydrological drought in selected KZN catchments) was formulated from the study aim and objectives described in sections 1.2.2 and 1.2.3 above. The event identified for this study was the 2015-2016 hydrological drought in the studied catchments, expressed by the anomaly of the October-March runoff from these catchments. Such an event definition approaches the event from impact perspective rather than from the climate process perspective. As illustrated in the introduction, the 2015-2016 drought had a large extent, spanning a large part of South Africa, and the KZN province was strongly affected (***Figure 24***). As such, the event was much larger in spatial extent than the three catchments selected for the analyses here. The interest here is, however, in (hypothetical) impacts of the event on water resources in the studied catchments, and thus limiting the spatial extent of the event to the individual catchments is considered appropriate. The magnitude of the event is defined using runoff simulated with the SWAT model forced with WATCH WFDEI climate data, as explained in section 5.2.1 below.

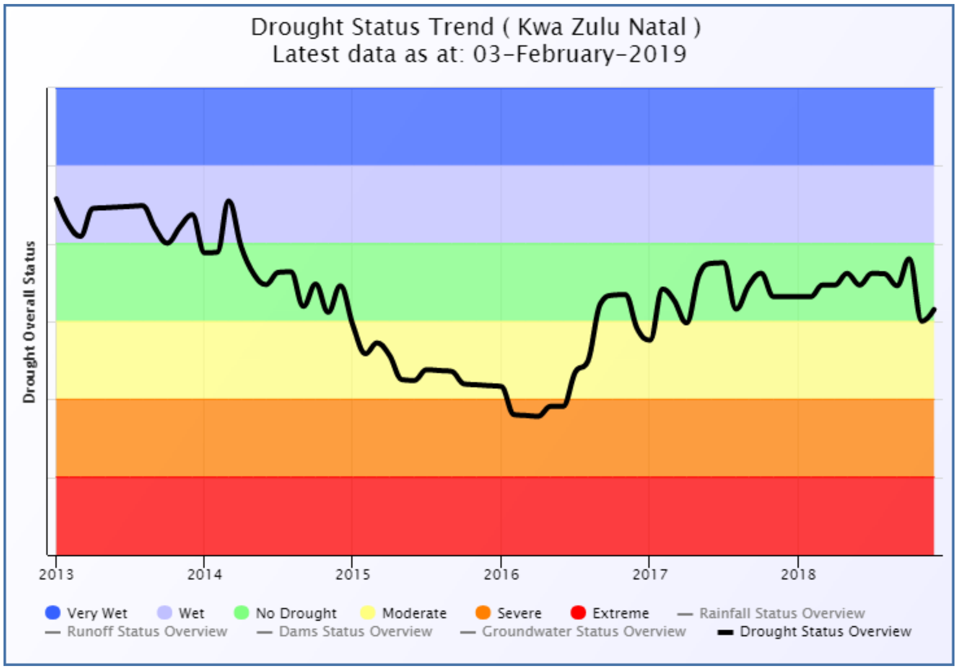


Figure 24: Drought Status Overview for KwaZulu-Natal (Source: http://www.dwa.gov.za/niwis2/DroughtStatusManagement/DroughtStatusOverview)

4.3.2 Climate attribution experiments used in this study

This study utilizes dedicated climate change attribution experiments with HadAM3P global climate model implemented at Climate System Analysis Group. HadAM3P model is a global, atmosphere-only climate model with a 15 min timestep, 19 vertical levels and a horizontal resolution of 1.875° by 1.25° latitude. The model is the same as that used in Weather@Home (www.climateprediction.net) attribution simulations. The attribution simulations performed under C20C+ Detection and Attribution experiment and described in detail in Stone et al. (2019) were used here. Those involved continuous simulations of climate for the 1959-2017 period under "all-histories" and "natural-histories" forcing's. "All-hist" forcing comprised observed sea surface temperatures and sea ice concentrations (NOAA's Optimum Interpolation Sea Surface temperature -OISST, also known as Reynolds' SST), observed carbon dioxide concentrations and observed anthropogenic sulphide aerosols. "Nat-hist" forcing comprised pre-industrial levels of carbon dioxide and aerosols, and observed SST reduced by the so-called attributable anthropogenic warming. A single attributable anthropogenic warming scenario was used that was derived from climate change projections using coupled GCMs contributing to the CMIP5 multi-model ensemble archive. Attribution of the Okavango floods by Wolski et al. (2014) was based on identically formulated and implemented experiment.

4.3.3 Downscaling approach utilized in this study

Since output of the GCM attribution experiments is at relatively low spatial resolution (see section 4.3.2 and 4.3.4) and the GCM output is in general not compatible in nature with high resolution information required to force a catchment hydrological model, GCM data needs to be downscaled. The process of downscaling is a complex one and numerous approaches exist (Trzaska and Schnarr, 2014). Downscaling can be applied spatially or temporally, but two approaches are commonly utilised to bridge the gap of large- scale and local climate change scenarios namely, dynamical and statistical (empirical) downscaling.

Dynamical downscaling includes the use of high-resolution regional climate models (RCMs) utilising lateral boundary conditions from a GCM to obtain smaller scale information. This method is known to be computationally intensive with large data requirements as well as expertise to implement and interpret results. Statistical downscaling methodology includes statistical relationships between local climate variables and large scale climate features and applying the relationship to simulate local climate in the future. The statistical method is thought to be easily implemented and interpreted. Minimal computing resources are required but this method relies heavily on historical climate observations. There is no single best downscaling method; the method chosen will depend on the required spatial and temporal resolution of outputs and climate characteristics of the impacts of interest (Trzaska and Schnarr, 2014).

No dedicated downscaling was performed for this study. Rather, this study utilized output of routine downscaling of HadAM3P simulations carried out at CSAG.

That downscaling uses an empirical-statistical approach known as SOM-D method (Hewitson & Crane, 2006). The method is based on a relationship between rainfall (or other local, at-surface variable) and synoptic circulation classes based on observational data. The circulation classes are obtained by classification of synoptic fields: wind, humidity and temperature at two levels of atmosphere (500 hPa and 700 hPa) using self-organizing maps (SOM). The relationships are then used to determine rainfall under synoptic forcing simulated within the given GCM experiment.

The downscaling was based on WATCH WFDEI data, and only rainfall and air temperature were downscaled.

4.3.4 Implementation of attribution simulations with SWAT

The downscaled climate data from attribution simulations with HadAM3P model comprised a 50-member ensemble of daily data covering the period of Jan 2015-Dec 2016, for each of the current and counterfactual climate. The data were for grid points of the WATCH WFDEI dataset used in development and calibration of the SWAT model in the studied catchments.

A straightforward implementation of the attribution simulations would require merging the downscaled data for each member of the climate simulations ensemble that covers 2015-2016 period with the 1981-2015 WATCH WFDEI data, and running SWAT with such merged data. Since there are 2 sets of simulations with 50 members each, that would involve repeating the process of data merging, running SWAT and saving output 100 times.

However, the period for which climate attribution simulations data are available spans the entire 2015-2016 period, and the period of interest (the drought event) is the summer rainfall period of November 2015-March 2016 and the later period extending till the end of 2016. In such a situation it is possible to merge the individual attribution ensemble members data into one long time series and implement just two long simulations - one for current and one for counterfactual climate. This is possible because with effective initialization of the model in January, the influence of the initial condition on November-March responses will likely be minimal. Thus this approach was implemented in the study.

4.3.5 Analysis of results of SWAT attribution simulations

SWAT attribution simulations as implemented above generate streamflow for the period of Jan 2015- Dec 2016 for each of the 50 members ensemble for the two “climates”. Since the attributed event is defined as the November 2015-March 2016 hydrological drought, the total streamflow during that period was used as a quantitative measure for further assessment.

A measure of change in probability of the event is the fraction of attributable risk (FAR) (***Equation 3***), defined as:

$$FAR = 1 - (\frac{p_0}{p_1})$$

Equation 3: Fraction of attributable risk

Where (p_1) is the probability of the event in the current climate (including climate change) and (p_0) is the probability of the same event in the counterfactual climate (without anthropogenic climate change).

Another measure is the ratio (p_1/p_0) (***Equation 4***) which describes how much more or less likely the event is in the modelled climate with anthropogenic influence compared to the modelled hypothetical climate without anthropogenic influence (Knutson 2017), and is simply called Risk Ratio:

$$RR = \frac{p_1}{p_0}$$

Equation 4: Risk Ratio

In the event attribution experiments, probabilities p_0 and p_1 are associated with the occurrence of a given event in the current and counterfactual climates are derived from the ensemble of model simulations reflecting these climates.

Figure 25 illustrates estimation of the RR on the example of air temperatures. In that figure, a set of air temperatures obtained from model simulations of climate conditions during the analysed event is a distribution of values described by a probability density function (PDF). Two PDFs describe the two simulated climates, real (actual in the nomenclature used in this study) and nonGHG (counterfactual in this study). Probability of occurrence of the analysed event is estimated as the probability of exceedance of that event from the probability distributions as the area of those distributions beyond a threshold corresponding to the value of the event.

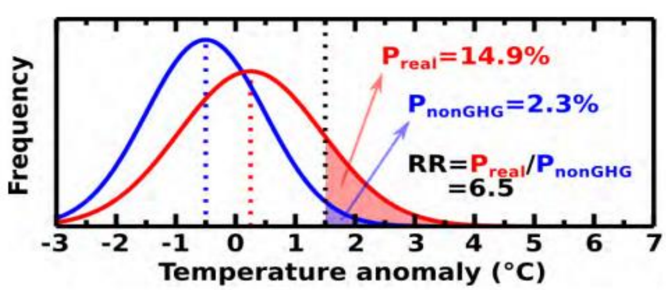


Figure 25: Risk Ratio estimation (Source: Wolski et al., 2014)

In the context of this study the following approach is adopted in order to determine RR and FAR from SWAT simulations in the attribution mode:

- The Nov 2015-March 2016 total runoff is extracted from streamflow time series from each of the 50 model simulation representing each of the two climates (there are two sets of 50 simulations for current climate and counterfactual climate).
- The extracted values (50) form a distribution
- Since there is no prior knowledge on what distribution should be fitted, a test is performed where several candidate distributions are evaluated to see which fits the data best. The best distribution is then fitted to data.
- From this distribution the probability of the event is calculated by calculating cumulative probability from the fitted distribution for the event. Due to errors associated with the hydrological model, the event is defined using the model simulations rather than using actual observations.
- The next step is to calculate uncertainties around RR and FAR values, using a bootstrapping procedure (as per Wolski et al. 2014). A bootstrapping procedure is when a subset of values are randomly selected from the original data, and the subset is used to fit a PDF and calculate the probability of the event, and subsequently the RR and FAR values. The procedure is repeated 1000 times, where a distribution of RR and FAR is obtained. The median and 95% confidence interval of this distribution is then reported. This procedure was, however, not implemented in this study due to time constraints.

5. RESULTS AND DISCUSSION

This chapter presents the results of the study framework illustrated in chapter 4. The chapter illustrates results for the process of implementing the hydrological model QSWAT and includes calibration results. Subsequently, the chapter presents the results of the attribution experiment.

5.1 Hydrological modelling

5.1.1 Hydrological model performance with various meteorological datasets

The initial part of the process of implementation of the SWAT hydrological model was the evaluation of the performance of the uncalibrated model with various rainfall datasets for simulation of hydrological processes and runoff in the study area. In that, the SWAT model was configured with soil, land use and topography data as described in the methodology section and three different sets of simulations were performed, with three rainfall datasets: SWAT CFSR, SWAT CRU and WATCH WFDEI. Runoff and rainfall was simulated and results presented below. The period of simulations range for 35-38 years across all three datasets dependent on the available data. For each dataset simulation the model warm up period was stipulated as 3 years.

The performance evaluation criteria used was the Coefficient of Determination and Nash-Sutcliffe efficiency coefficient. ***Table 2*** presents performance criteria for the 3 datasets for sub-basins 11, 4 and 2. Comparison of simulated and observed runoff time series for each of the 3 datasets, for one subbasin (11) is shown in ***Figure 26***, ***Figure 27*** and ***Figure 28***.

Table 2: Performance of uncalibrated model forced by 3 rainfall datasets

Subbasin	Reference	CFSR		CRU		WFDEI	
		R^2	NSE	R^2	NSE	R^2	NSE
11	U1H005	0.65	-0.75	0.67	0.18	0.54	0.04
4	U2H013	0.70	-3.70	0.62	-1.00	0.61	0.19
2	U2H007	0.65	-7.75	0.60	-2.67	0.67	-0.09

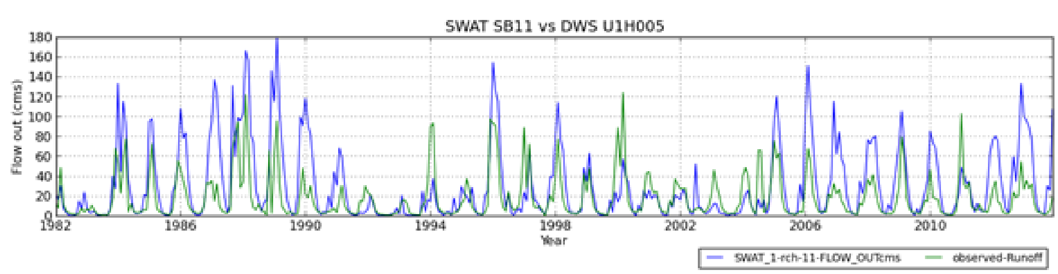


Figure 26: SWAT CFSR runoff for subbasin 11 vs DWS data

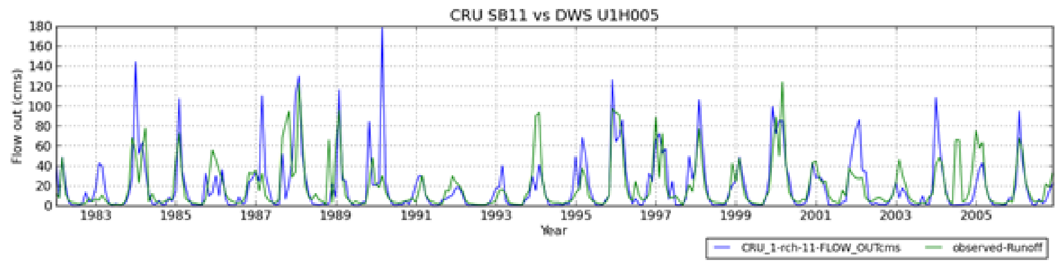


Figure 27: SWAT CRU runoff for subbasin 11 vs DWS data

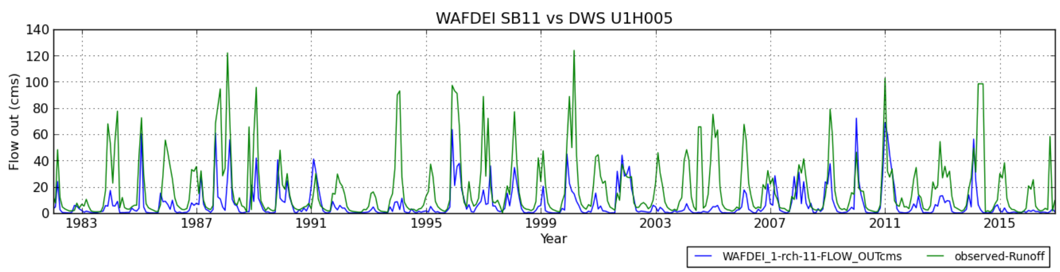


Figure 28: WATCH WFDEI runoff for subbasin 11 vs DWS data

SWAT CFSR data simulations were run for 35 years with a 3 year warm up period. Initial Coefficient of Determination for all runoff simulations was more than 0.6, regarded as acceptable. Nash- Sutcliffe efficiency coefficient results recorded for all the runoff simulations were negative and regarded as unacceptable.

SWAT CRU data simulations and comparisons were run for 37 years with a 3 year warm up period. Coefficient of Determination for all runoff simulations were recorded as more than 0.6 therefore regarded as acceptable. The majority NSE results recorded for runoff simulations were negative and therefore regarded as unacceptable.

WATCH WFDEI data simulations were run for 38 years with a 3 year warm up period. Coefficient of Determination for all runoff simulations were reported as more than 0.5 illustrating a positive correlation for the two datasets. NSE values for Sub basin 11 and Sub basin 4 were more than 0 where they are viewed as acceptable values, whilst subbasin 2 had negative NSE, regarded as unacceptable.

Overall, subbasins 11 and 4 produced better NSE results across all datasets, while subbasin 2 performed poorer with negative NSE values for all datasets. The Coefficient of determination results illustrated a better performance than NSE across all basins and different datasets. Overall, subbasins 11 and 4 produced better results and this could be because of better quality of rainfall observation data for these particular regions.

In view of the above the WATCH WFDEI dataset appears to perform similarly to, and in fact slightly better than the other two generic SWAT datasets. But the performance is relatively poor. It is clear that the SWAT model cannot be applied "off-the shelf" with its generic global datasets to simulate hydrological responses in the analysed sub-basins. There is, therefore, a need to improve the quality of simulations though model calibration.

5.1.2 Model Calibration with adopted rainfall dataset

Calibration was performed with WATCH WFDEI data. Overall from all the data sources WATCH WFDEI runoff simulation produced better results and similarly precipitation data had a better agreement with DWS station data than the other 3 datasets. SWAT-CUP automatic calibration for flow was done with flow related parameters based on the selected WATCH WFDEI simulation. ***Table 3*** presents suggested parameters and suggested parameter ranges.

Table 3: Calibration suggested parameter ranges

Parameter	Description	Suggested Range	Source
ESCO.hru (-)	Soil evaporation compensation factor	0,1	Yan et al. (2018)
CN2.mgt (-)	Initial SCS runoff curve number for moisture condition 2	-0.3,0.3	Yan et al. (2018)
SOL_AWC.sol (-)	Available water capacity for the soil layer (mm H_2O/mm soil)	-0.5,0.5	Yan et al. (2018)
GWQMN.gw (-)	Threshold depth in shallow aquifer (mm) required for return flow to occur)	-0.783,0.238 0,200	Taghvaye Salimi et al. (2016) SWAT calibration techniques (swat.tamu.edu) Mamo and Jain (2013)
GW_REVAP.gw (-)	Groundwater revap coefficient	0.02,0.20	SWAT calibration techniques (swat.tamu.edu) Mamo and Jain (2013)
REVAMPM.gw (+)	Threshold depth of water in shallow aquifer for revap to occur(mm)	0,20	SWAT calibration techniques (swat.tamu.edu) Mamo and Jain (2013)

Calibration was performed for 3 subbasins in the catchment namely subbasin 11, 4 and 2 (***Table 4***), based on the fact that they produced the best simulations before calibration.

Table 4: Calibration fitted values

Subbasin	R^2 before calibration	R^2 after calibration	NSE before calibration	NSE after calibration	Parameters	Fitted Value
11	0.54	0.38	0.04	0.29	1: R__ESCO.bsn	0.620

					2: R__SOL_AWC(..).sol	-0.601
					3: R__CN2.mgt	-0.009
4	0.61	0.46	0.19	0.35	1: R__ESCO.bsn	0.621
					2: R__SOL_AWC(..).sol	-0.392
					3: R__CN2.mgt	-0.0463
					4: R__GWQMN.gw	-551
					5: R__GW_REVAP.gw	0.105
					6: R__REVAPMN.gw	197
2	0.67	0.31	-0.09	0.03	1: R__ESCO.bsn	0.867
					2: R__SOL_AWC(..).sol	-0.398
					3: R__CN2.mgt	-0.054
					4: R__GWQMN.gw	7737
					5: R__GW_REVAP.gw	0.200
					6: R__REVAPMN.gw	293

Figure 29 shows the calibrated WATCH WFDEI discharge for subbasin 11 compared to DWS station U1H005.

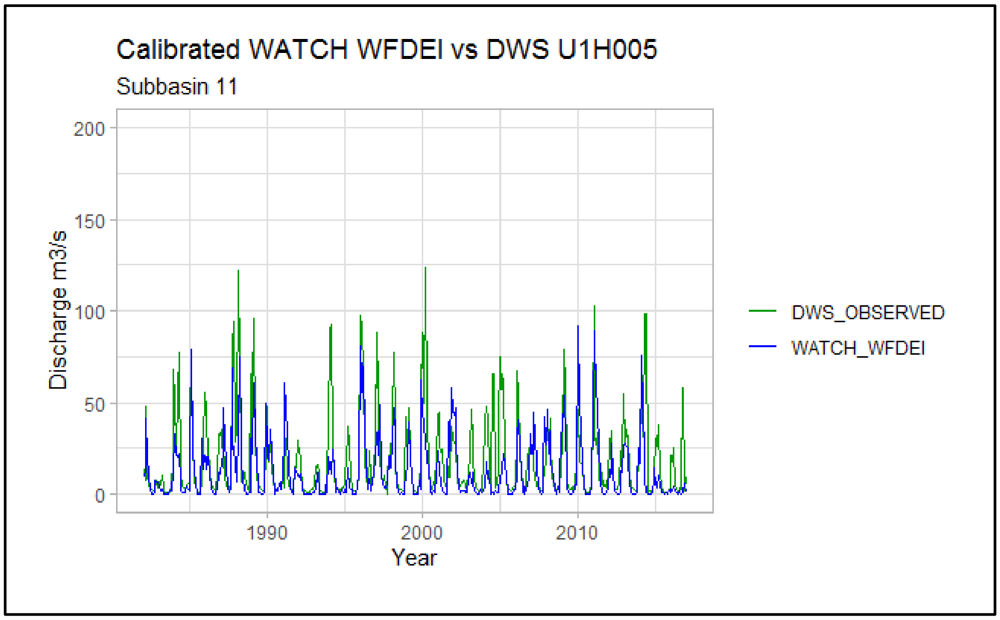


Figure 29: Calibrated WATCH WFDEI runoff for subbasin 11 vs DWS data

5.1.2.1 SWAT-CUP Automatic calibration results

SWAT-CUP automatic calibration entailed running 4 iterations with 300 simulations in each iteration, for each subbasin. SWAT-CUP also presents supporting information such as the 95PPU plot, illustrating the best model estimation and data bracketed by the 95PPU. Dotty Plots are also available to provide an idea of parameter sensitivity after each simulation. SWAT- CUP calibration also includes a maps option utilised to visually inspect the calibrated catchments to aid in analysis of the subbasins.

5.1.3 Hydrological model and calibration summary

The model setup described in chapter 4 was performed successfully as results were obtained with climate data from various data sources. WATCH WFDEI runoff data simulations produced better results and were therefore utilized for calibration. The study utilized automatic calibration, namely SWAT-CUP. Calibration followed the protocol developed by Abbaspour et al. (2015) and further research revealed the best parameters to calibrate each subbasin with and all NSE values were improved using suggested parameter ranges. Calibration outputs included 95PPU plots, dotty plots, parameter sensitivity and visual inspection of subbasins. Calibration was performed successfully as it improved the model performance for the selected WATCH WFDEI climate dataset. Results after calibration for the hydrological model overall were weak but utilized in the context of this study.

The disparities between SWAT simulations and observations are likely due to:

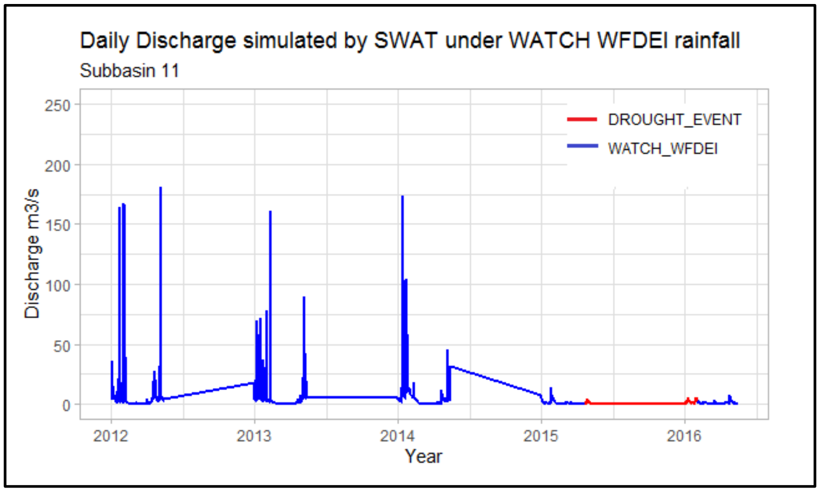
- The quality of the SWAT model parameter files, as in this study parameters based on global datasets are used,
- Due to quality of WATCH WFDEI data, which too, is a global rather than local dataset,
- Possibly due to the SWAT model implemented without any water abstractions or water management operations.

5.2 Attribution experiments

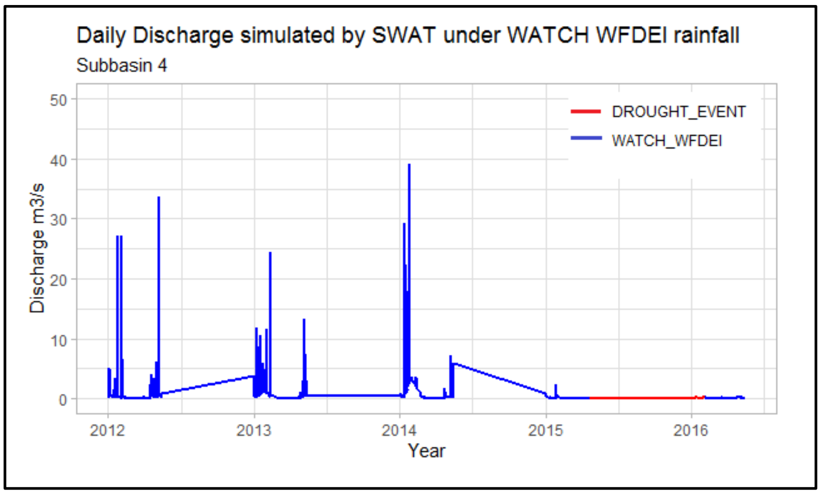
This section presents the findings on the attribution of 2015-2016 hydrological drought in selected KZN subbasins. With the attribution data output from QSWAT the attribution analysis was performed as described in chapter 4.

5.2.1 Event definition

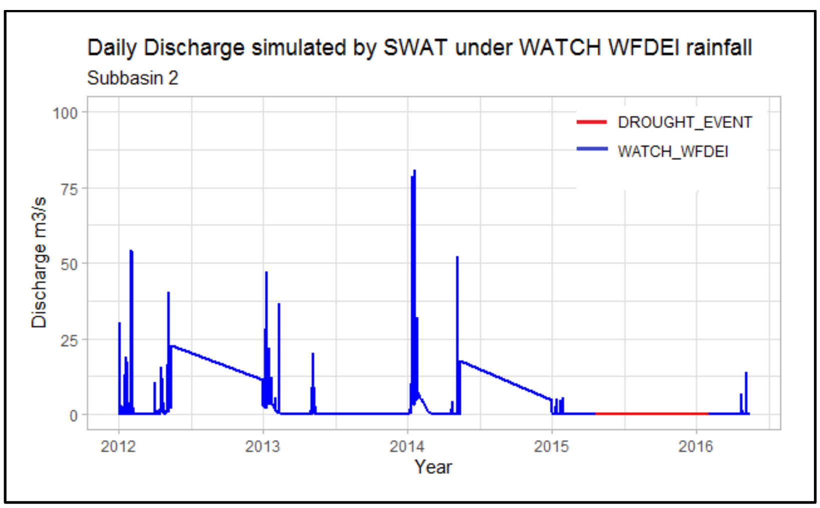
Risk based attribution considers the definition of the extreme event. In this study thus far the event has been loosely termed “2015-2016” drought. To properly define the event, it was firstly considered that the main period when runoff occurs in the study region spans November-March, and thus the event is defined as a total runoff in the period of November 2015-March 2016 in each of the analysed subbasins. Secondly, it was considered that the attribution analysis is to be carried out based on simulations with the SWAT model, which, as shown in section 5.1, does not represent hydrological processes in the catchment perfectly. In view of that, the event magnitude for each subbasin is defined as the total discharge simulated by SWAT under WATCH WFDEI forcing for the period 1 November 2015 to 31 March 2016. The magnitude of the event is thus: 220.67 m3/s in SB11, 12.81 m3/s in SB4 and 3.70 m3/s in SB2. Streamflow during the event is illustrated in ***Figure 30***, and the magnitude of total discharges during the event in relation to long-term discharges during that period are shown in ***Figure 31***.



a)

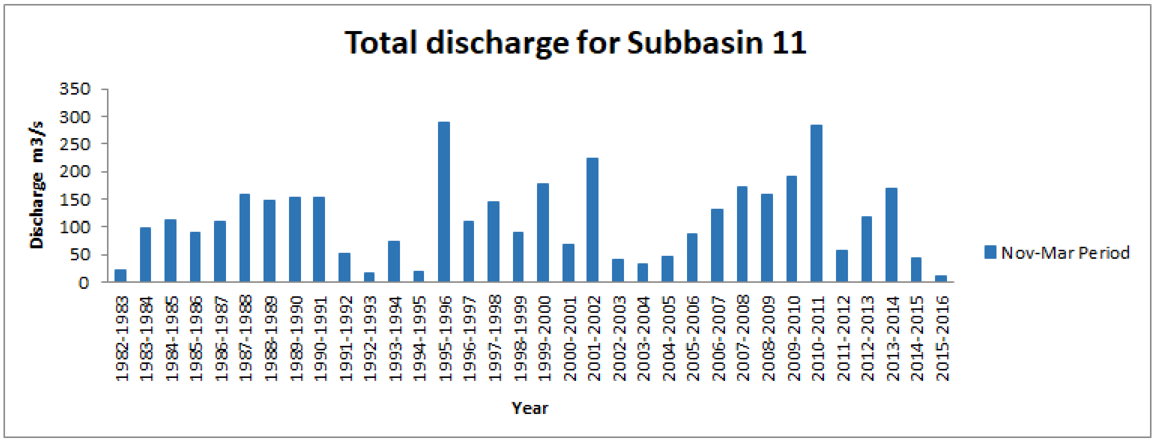


b)

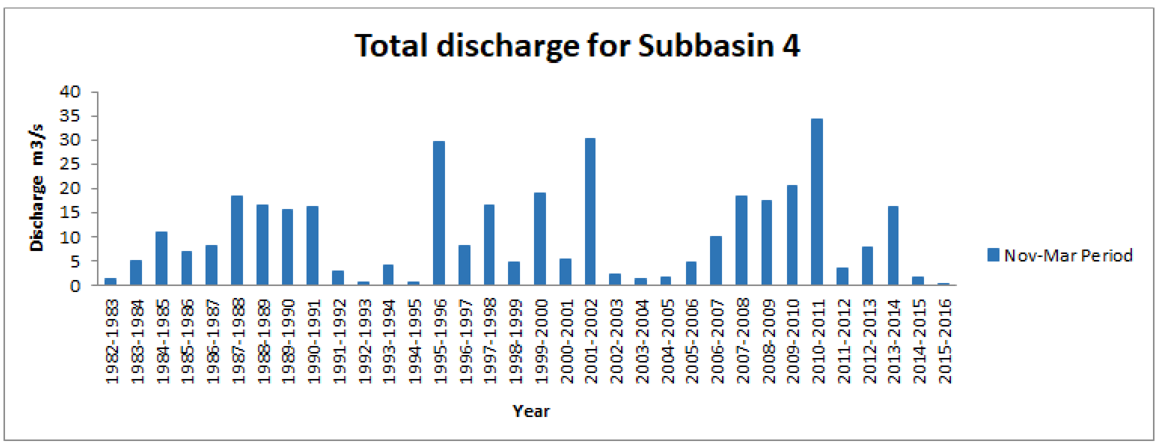


c)

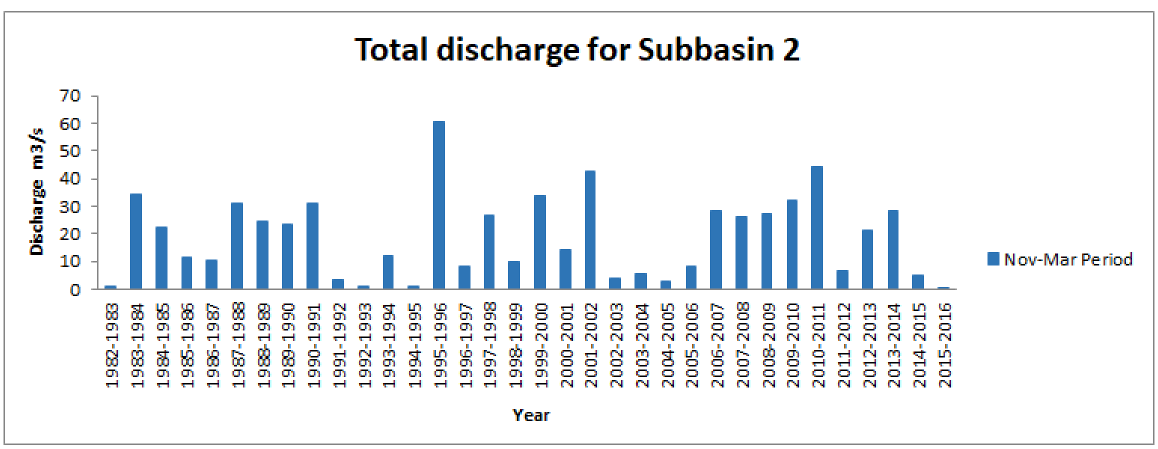
Figure 30: Daily discharges simulated by SWAT under WATCH WFDEI rainfall, with the drought event illustrated for SB 11 (a), SB 4(b) and SB 2(c)



a)



b)



c)

Figure 31: Long term total discharge (1982-2016) for November- March for SB11 (a) SB4 (b) and SB2(c), simulated by calibrated SWAT with WATCH WFDEI rainfall, with the value for 2015-2016 representing the hydrological drought event analysed in this study.

5.2.2 Results of attribution experiments

Figure 32 presents results of simulations of the Nov2015-Mar2016 streamflow for subbasin 11 (as an example), forced by downscaled attribution experiment climate data for current climate, compared with streamflow simulated under WATCH WFDEI forcing in the period 2013-2017. In this figure years prior to the drought event are included to put 2015-2016 conditions in context of other, non-drought years.

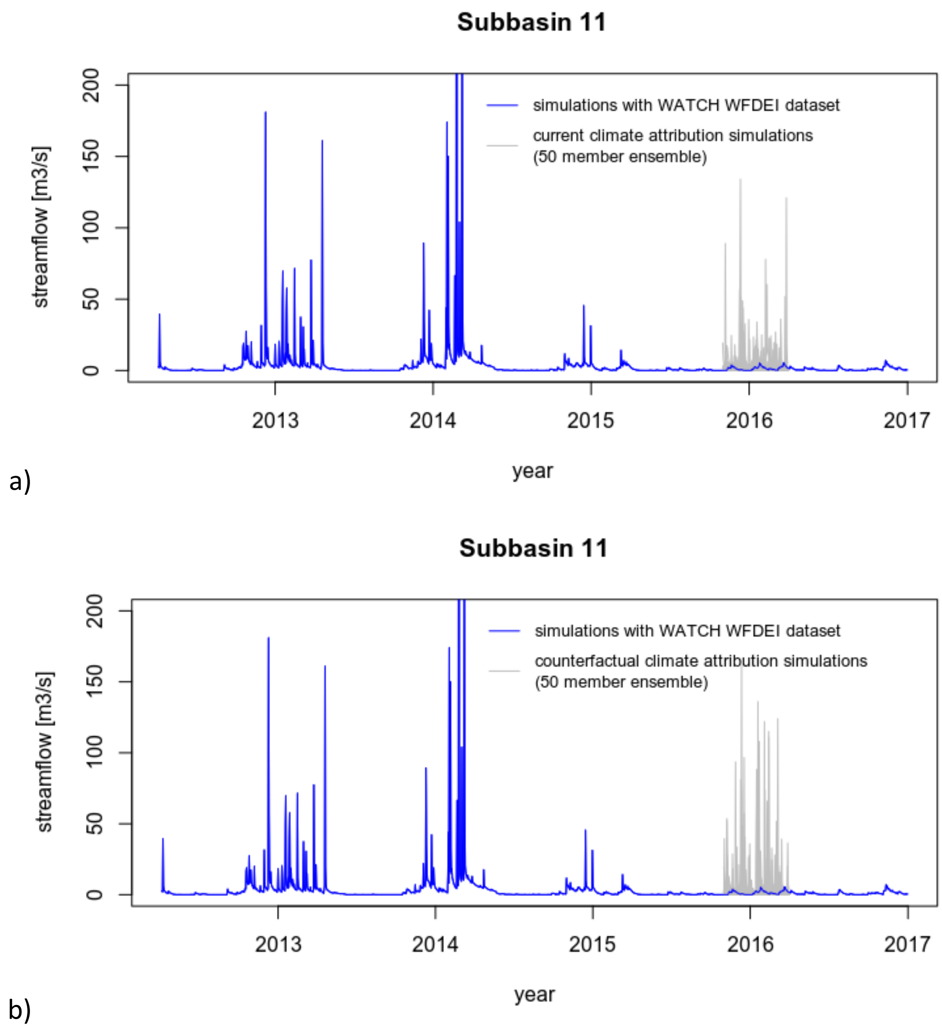


Figure 32: Results of QSWAT Subbasin 11's streamflow simulations (50 member ensemble) for current climate (a), and for counterfactual climate (b) compared with simulations forced by WATCH WFDEI data

The downscaled attribution climate data reveals a peak in streamflow for 2015-2016 period for both current climate and even more pronounced in the counterfactual climate as opposed to the WATCH WFDEI (observed) climate data that shows a decrease in streamflow for the 2015-2016 years, illustrative of drought conditions experienced during this time period.

5.2.3. Attribution statement

The histograms of total Nov2015-Mar2016 streamflow for SB11 obtained from QSWAT simulations forced by climate data from attribution experiments for current and counterfactual climate are illustrated in ***Figure 33***. The histograms are plotted for runoff data that are log-transformed in order to obtain a near-normal distribution.

The inspection of the shape of the distribution in ***Figure 33*** reveals that the histograms looked bell shaped indicating that a normal distribution is appropriate. The assumption of normal distribution of data was examined with the Shapiro- Wilk's test and Kolmogorov-Smirnov (K-S) normality test (***Table 5***).

Table 5: Normality statistics

Subbasin	Data	S-W test (p-value)	K-S test (p-value)
SB11	Counterfactual	0.116	0.111
	Current	0.0007	0.029
SB4	Counterfactual	0.023	< 2.2e-16
	Current	2.859e-05	< 2.2e-16
SB2	Counterfactual	4.894e-07	0.0018
	Current	6.731e-09	3.517e-07

For the SB11, the p-values of the S-W test for counterfactual climate test is > 0.05, implying the distribution of the data is not significantly different from the normal distribution and hence we can assume normality with the standard 95% confidence. For the current climate, p-value is low suggests that the data do not follow normal distribution. The K-S test produces similar results. For the two other basins, SB4 and SB2, both texts reject normality of distribution. The inspection of the histograms and the empirical distribution functions shown in ***Figure 33*** indicate that the deviation from normality is due to irregularity of the histogram rather than due to some systematic effect (such as skewness or thick tail) that could be captured by another distribution such as Gamma. The irregularity of the empirical distribution is likely due to the small sample size (50), and in order to proceed with calculations, the normal distribution is accepted, and the constraint noted.

Figure 34 shows normal distributions fitted to the log-transformed data,

Parameters of the fitted distributions are shown in ***Table 6***.

The fitted distributions for current and counterfactual climates are plotted together in ***Figure 35***, with the value of event (also log-transformed) superimposed.

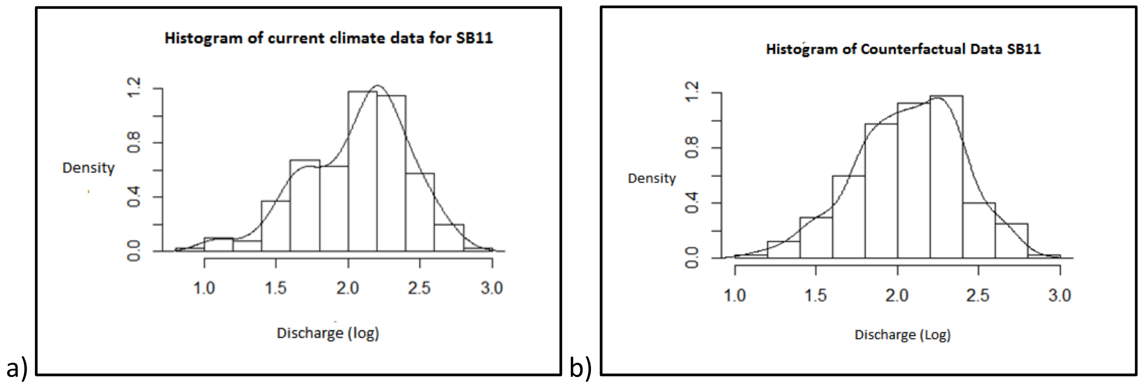


Figure 33: Histogram and empirical density function of simulated streamflow for SB11 for current climate (a) and counterfactual climate (b)

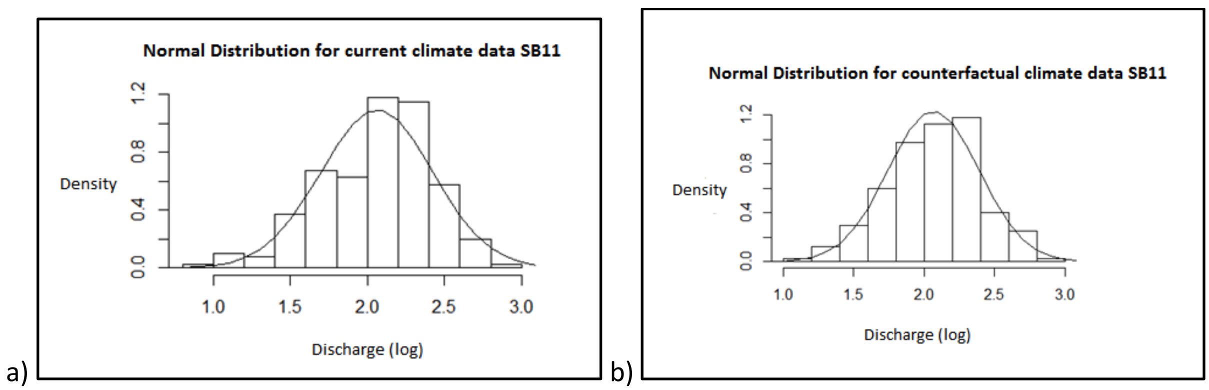


Figure 34: Normal Distributions fitted to simulated streamflows for SB 11 for current climate data (a) and counterfactual climate (b)

Table 6: Parameters of the fitted distributions

Data	Mean	Standard deviation
Current Climate	2.06	0.36
Counterfactual climate	2.06	0.32

The next step was to calculate probabilities associated with the drought event obtained as a sum of SWAT simulated discharges under WATCH WFDEI rainfall for the period of 1 Nov 2015- 31 March 2016. The value of the event was also transformed into a log scale. The WATCH WFDEI total discharge for subbasin 11 is 220.67 m3/s and transformed to log discharge is 2.34. ***Figure 35*** shows the probability density function for counterfactual and current climate together with the drought event for subbasin 11.

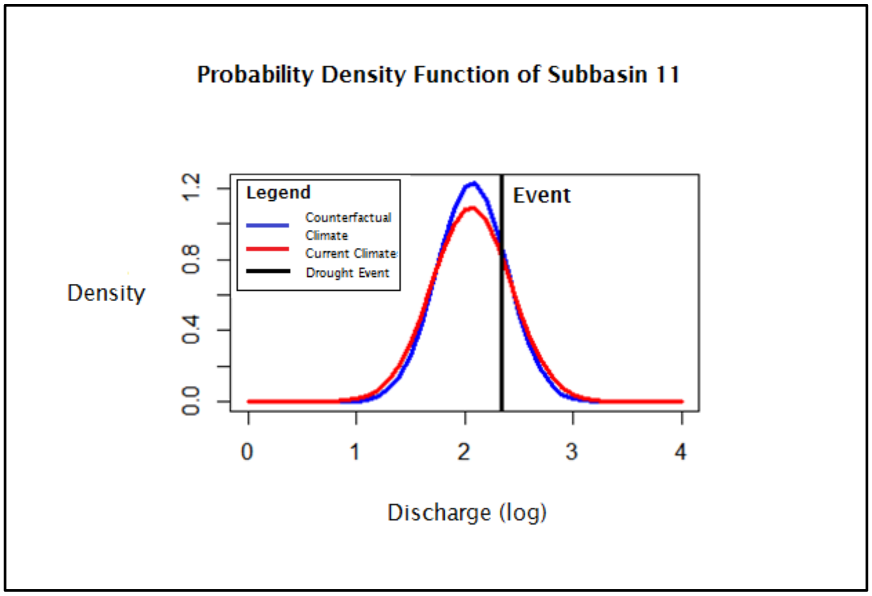


Figure 35: Probability density function for SB 11

From the probability density functions we calculate the probability of the event occurring under the current climate and probability of event under counterfactual climate. For the sub-basin SB11 these are equal to 0.78 and 0.80 respectively. Risk ratio is thus:

$$RR = \frac{0.78}{0.80} = 0.98$$

And fraction of attribute risk FAR is:

$$FAR = 1 - \frac{0.80}{0.78} = -0.03$$

The risk ratio value of <1 indicates that there is a lower risk of the event under the current climate than under the counterfactual climate. As a result, the FAR value is negative, and thus meaningless (similarly to values obtained by Wolski et al. 2014), as FAR by definition expresses only an increase and not decrease in risk. FAR is thus not reported below.

In order to evaluate the uncertainty of the obtained RR, the bootstrapping procedure is normally used (e.g. Wolski et al., 2014). However, the results presented here are based on one data point only, derived directly from probability density functions fitted to all data. This was considered to be appropriate to the level of analyses presented here.

The analysis above is also performed for subbasin 4 and 2 and produces the results illustrated in ***Table 7***.

Table 7: Risk Ratios

Sub basin	Drought Event (SWAT simulated discharge)	p_1 (current climate)	p_0 (counterfactual climate)	Risk Ratio RR
11	220.67	0.78	0.80	0.98
4	12.81	0.62	0.64	0.97
2	3.70	0.72	0.71	1.01

Values higher than 1 show increasing risk, values less than 1 show decrease in risk, and values close to 1 represent no change in risk. An increase in risk means a higher probability of an extreme event (drought) occurring in the subbasin currently compared to that in the past. Results from the table indicate values for all 3 sub-basins very close to 1, and no change in risk can be concluded and that there is no influence of climate change on the magnitude of the drought.

5.2.4 Attribution Summary

The aim of the study was to determine if climate change has contributed to the 2015-2016 hydrological drought for catchements in KwaZulu- Natal and this was done by exploring the implementation of the hydrological model, QSWAT in a context of climate attribution analysis. The attribution analysis looks at assessing an extreme event as it occurs. Risk ratio methodology was utilised, using probability of the current climate and the probability of the counterfactual climate to determine the probability of exceedance using a fitted normal distribution. Since the calibrated hydrological model was not performing well, model simulations based on WATCH WFDEI observation data were used to define the drought event. In this way, error arising from the weak performance of the model was avoided. WATCH WFDEI data is reasonable to use in this context and provides a good representation of the drought. Due to the extreme event being a seasonal drought the event was expressed as a seasonal total streamflow. A normal distribution was fitted to the total seasonal streamflow simulated by the SWAT model under climate forcing from attribution simulations of HadAM3p global climate model. This was done for each subbasin. The analysis included working in the logarithmic space as is common practice when working with discharge. Histograms (normal distribution) and density plots were utilised to obtain the probability density function from which risk ratio was calculated. Normality statistics revealed that for subbasin 11 the counterfactual climate histogram followed a normal distribution whilst current climate histogram did not follow a normal distribution and similarly for subbasin 4 and 2 normality of distribution was rejected for S-W and K-S test. Irregularity of the distributions was likely due to the small sample size (50) and for this study we proceeded with the normal distribution for calculations but the limitation was noted. Risk ratios revealed that for all 3 subbasins there was no increase of risk.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The section below presents conclusions for the study and recommendations for future studies.

6.1.1 Hydrological modelling

Since the link between climate change and extreme weather events has been detected, interest has grown in the attribution of hydrologic events and in particular, as in this study, droughts and their associated impacts. The study examined the 2015-2016 KZN drought event through the actual event reports, and through hydrological modelling with QSWAT. The first objective of this study was realized with the setup of the hydrological model QSWAT with global, generic datasets (global_soils, global_landuse, SWAT CFSR rainfall, SWAT CRU rainfall and WATCH WFDEI climate). The calibration procedure using SWAT- CUP was successful in that it improved on model performance with the selected climate dataset (WATCH WFDEI) although results produced were weak overall. The model was then utilized in this study under certain constraints.

Consideration should be given to the fact that calibration of models at a catchment scale is challenging because of possible uncertainties that can exist. Examples of such uncertainties include effects of wetlands and reservoirs on hydrology and chemical transport, interaction between surface and groundwater, occurrences of landslides and large constructions (roads, dams, tunnels, bridges) that produce large amounts of sediment affecting water quantity and quality. The catchment during the period of study was not free of such activities and hence model uncertainties should be considered. Calibration results of the catchment qualified as unsatisfactory in the study indicating either bad quality of input data or conceptual model errors in the dominant processes in the catchment. Given the complexities of a catchment and the large number of interactive processes taking place simultaneously and consecutively at different times and places within a catchment, and in particular, the not-locally specific, large scale nature of the global datasets used to represent soils, land use and climate, it is good that simulated results comply with measurements to the degree that they do.

The WATCH WFDEI dataset appears to perform similarly to, and in fact slightly better than the other two generic SWAT datasets. But the performance is relatively poor. It is clear that the SWAT model cannot be applied “off-the shelf” with its generic global datasets to simulate hydrological responses in the analysed sub-basins. There is, therefore, a need to improve the quality of simulations though model calibration.

6.1.2 Attribution experiments implementation

To address objective two of the thesis, downscaled climate data for current and counterfactual climate for grid points of the WATCH WFDEI dataset were used in the development and calibration of QSWAT model in KZN catchments. The approach followed in the study was to merge individual attribution ensemble members data into one long time series, implementing just two long simulations (current and counterfactual climate). This was possible because of effective initialization of the model in January and hence influence on the initial conditions on November-March (drought event) responses were likely to be minimal.

6.1.3 Attribution experiments results

A drought, a climate event that evolves in its own way is attributable to a unique set of causes that is not applicable to any other events. This study explores attribution analysis to determine if climate change has resulted in the probability of a drought event, such as the 2015-2016 KZN drought occurring, has increased or decreased in the future. Evaluation has been possible in the study using a moderate modelling resource compared to as an example extreme ensemble of atmosphere ocean climate models used in other attribution studies. Risk ratio methodology utilized in the study includes the use of fitting a normal distribution to data where from a theoretical basis one would expect normal or gamma distributions. Conclusions from the study are that for all three subbasins there is no increase in risk, implying no influence of climate change on the magnitude of the drought. Based on literature explored in chapter 2 these results are slightly unexpected in the context of climate change and it should therefore be noted that results come from a single attribution method with data from a single GCM attribution experiment. Event attribution assessments have relevance for the occurrence of similar types of events in the future. The above addresses objectives three and four of the thesis.

6.2 Recommendations

6.2.1 Hydrological modelling

Recommendations for a hydrologic study includes consideration of the error in measured data (especially driving variables such as rainfall and temperature), the error in measured output variables (river dischargers used for calibration) and the error in conceptual model (inclusion of all the physics in the model that contributes significantly to the data). Further recommendations are that any study can be improved with improvements of the conceptual model (soil, land and climate data) and similarly calibration of the model can then be improved. To improve calibration, other techniques such as manual calibration are also recommended as a technique. Another option to explore is sensitivity of input data where a possible experiment could be modifying rainfall and temperature data by 5% and to then see the differences produced and different errors that propagate. This experiment would ultimately look at the uncertainty associated with input data and the resulting hydrologic response.

Furthermore, to assist in evaluating modelling results it is recommended to first analyse historical rainfall and flow records. Additionally describing these patterns and what they reveal can assist in understanding variability of flows.

6.2.2 Attribution

From this study a recommendation includes looking at other methods to determine risk ratio which can include fitting a gamma distribution and using bootstrapping methodology that would include an associated confidence interval. Furthermore increasing sample size is recommended to improve distributions and normality statistics. Limitations of models and methods have to be considered for any study when looking at hydrologic effects in a changing climate. Consideration includes looking at ENSO and the effect on rainfall in the region, uncertainties inherent in the hydrological model and uncertainties involved in the process of transforming course data outputs from GCMs to hydrological model inputs.

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