

**The use of RADAR and Hydrological Models for Flash Flood
Evaluation and Prediction**

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Dissertation Submitted for the degree of Master of Science in Geography at the
University of the Witwatersrand

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FEBRUARY 08, 2016

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Abstract

A flash flood is a flood which occurs within 6 hours from the start of a particular rainfall event. The ability to accurately evaluate and forecast flash floods could help in mitigating their harmful effects by helping communities plan their settlements outside of high risk areas and by providing information for the formulation and implementation of early warning systems. The overall aim of the study is to evaluate the use of RADAR data and hydrological models for flash flood evaluation and prediction. This is done by initialising both a lumped hydrological model (NAM) and a distributed hydrological model (MikeSHE) with both RADAR and raingauge derived precipitation estimates for the Jukskei river catchment located in Gauteng South Africa. The results of the model simulations are compared with each other and with actual streamflow data using various statistical techniques. The hydrometeorological characteristics of flash floods in the study catchment are also evaluated on a case by case basis. A fast response time and short duration are noted as the resounding characteristics of floods in the study catchment. All the model runs failed to correlate with streamflow (with any significant statistical certainty). The models also failed to significantly predict streamflow when using the pair sampled t-test. This highlights the difficulty in using rainfall estimates and hydrological models for discharge prediction. Although it is expected that the more advanced distributed model would fare better when predicting the variables associated with high flow events, it was only marginally better when simulating event timing. The lumped model did, however, fare better when correlating with stream flow, number of high flow events, peak flow, as well as total duration and volume.

Acknowledgments

I would like to thank the following people:

- Roelof Burger for all his insight, help and support during the course of this study, without him it would not have been possible. I would also like to thank Stefan Grab for assisting with supervision.
- Everyone at DHI South Africa for allowing me full use of their models and providing me with their technical expertise. Especially Mehari Fitzgeri, Jason Hallowes, Andrew Pot and Sylvia Nevaro.
- Eugene Poolman for meeting with me and providing me with support.
- My family for putting up with me over the course of the study.

Preface

This dissertation is being submitted in support of the degree of Master of Science at the University of the Witwatersrand in Johannesburg Gauteng. The research described was conducted under the supervision of Roelof Burger and Stefan Graab.

This work is original unless acknowledgments or references have been made to previous work.

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List of Symbols and Abbreviations

A: flow area

CK: Time constant for routing overland flow

CKBIF: Time constant for routing baseflow

CKIF: Time constant for routing interflow flow

CQOF: Overland flow runoff coefficient

FFGS: Flash Flood Guidance System

g: gravity

GANDOLF: Generating Advanced Nowcasts for Deployment in Operational Land-based Flood forecasts: an automated convective rainfall nowcasting and early warning system

GIS: Geographical Information Systems

h: water level

IPCC: Intergovernmental Panel on Climate Change

K: hydraulic conductivity

L_{max} : Maximum water content in root zone storage

M: Manning number

Mike 11: Mike 11 Hydraulic Model

NDMC: National Disaster Management Centre

NWP: Numerical Weather Prediction

NWS: American National Weather Service

Q: discharge

q: lateral flow

QPE: Quantitative Precipitation Estimate

QPF: Quantitative Precipitation Forecast

R: resistance radius

RADAR: Radio Detection and Ranging

SAC-SMA: Sacramento Soil Moisture Accounting Model

SAFFGS: South African Flash Flood Guidance System

SAWS: South African Weather Service

t: time

TG: Root zone threshold value for GW recharge

TIF: Root zone threshold value for interflow

TOF: Root zone threshold value for overland flow

u: flow velocity in x-direction

Umax: Maximum water content in surface storage

v: flow velocity in y-direction

z: ground surface level

α : momentum distribution coefficient

θ : the water content

ψ : pressure head

1: Overview

1.1. Introduction

Flash floods are natural hazards which can cause a significant loss of life and property. Such events are the worst natural disasters in terms of the proportion of fatalities among people affected (Marchi *et al.*, 2010). Flash floods can be infrastructure related, such as dam breaks or glacial lake outbursts, but most commonly are associated with excessive rainfall events (Hapuarachchi, 2011). This study focuses on flash floods, in Gauteng Province South Africa, caused by high rainfall events as they are the common and widespread floods in the region. Flash floods caused by extreme precipitation events are projected to become more frequent and more intense in future, due to both climate and land use change (Bronstert *et al.*, 2002; Modrick and Georgakakos, 2015).

The ability to accurately evaluate and forecast flash floods could assist in mitigating their harmful effects by helping communities plan their settlements outside of high risk areas and by providing information for the formulation and implementation of early warning systems. Any tool which increases the predictability of flash floods could greatly increase our ability to mitigate the risks involved (Unkrich *et al.*, 2010). Henonin *et al* (2010) demonstrates that hydro-informatic tools, whether they be simple or complex, can be beneficial to decision makers dealing with flood risk.

The forecasting of hydraulic events requires an understanding of not only the hydrological processes, but also the meteorological processes that influence water runoff. The field of hydrometeorology attempts to address this by merging the disciplines of hydrology and meteorology. One of the main unresolved issues in this field is hydraulic prediction using remotely sensed meteorological data and is the focus of much hydrometeorological research (Vivoni *et al.*, 2006).

The predictability of flash floods, in particular, is especially difficult as they usually occur in small watersheds [usually less than 500km² (Gaume *et al.*, 2009)] that respond relatively quickly to storm forcing (Vivoni *et al.*, 2006). The ability to forecast flash floods is also hampered by a lack of understanding of both the hydraulic and atmospheric conditions from which they result (Borga *et al.*, 2011).

The use of integrated hydrometeorological approaches might prove to be useful in resolving some of the issues involved in flash flood forecasting (Creutin and Borga, 2003). For example, real time RADAR data as an input for hydrological flood models has been used for flash flood forecasts with promising results (e.g. Unkrich *et al.*, 2010). The use of hydrological modelling as a management tool has in recent years become essential for effective management of water resources. It has, however, only been used to a limited extent in South Africa.

Very few studies have investigated whether newer distributed models outperform older lumped models. The hypothesis that distributed models with their higher resolution data are better at reproducing actual drainage characteristics than lumped models is still, with the exception of Shultz (2007), mainly untested (Smith *et al.*, 2004). A comparison of lumped and distributed modelling has not been performed for flash flooding specifically, and is therefore the main aim of this study. Although some work has been done using distributed hydrological models in South Africa (e.g. Bagan *et al.*, 2009), the use of RADAR data as input into the NAM lumped and the MikeSHE distributed models has not yet been used in a South African context.

The main purpose of this research is to investigate the flash flood evaluation and forecasting potential of lumped as well as distributed hydrological models using RADAR derived rainfall estimates and raingauge data. This study uses the NAM lumped and MikeSHE distributed hydrological models and tests their ability to predict flash flood events in a small semi-arid gauged catchment prone to flash flooding. Lumped models are advantageous due to their low

computing requirements but are disadvantaged in their lack of spatial resolution. While distributed models are advantageous due to their high spatial resolution, they are disadvantaged in their high computing requirements (Shultz, 2007).

1.2. What are Flash Floods?

A flash flood is defined as a flood which occurs within 6 hours from the start of a particular rainfall event (Collier, 2007). If the flood event occurs more than a few hours after the main rainfall event it is then referred to as a flood rather than a flash flood. Most natural hazards occur within specific locations, but flash floods can occur in all parts of the world except for the immediate Polar Regions. If rainfall is possible, there will come a time when rainfall intensity becomes high enough and is sustained for long enough for potential flash flooding to occur (Doswell, 1997). Flash floods are caused by high precipitation rates being sustained for a relatively long period of time and so are mainly associated with stationary, mesoscale convective events (Borga *et al.*, 2008). The minimum intensity and duration of a rainfall event that will cause a flash flood depends entirely on the hydrological conditions associated with that particular event. Therefore, conditions such as topography and soil permeability play a major role in determining the potential for flash flooding (Doswell, 1997).

Topography can influence the potential for flash flooding in various ways. A steep slope gradient is usually associated with flash flooding as it creates a higher potential gravity force for surface runoff. This is due to the higher kinetic energy of the water as a result of gravity, a characteristic which differs greatly from a conventional flood. Conventional flooding generally takes place where there are low slope gradients and the water rises slowly and moves out onto a flood plain (Sene, 2012). This is, however, not a rule and there are cases where flash flooding has occurred over flat areas such as in Venice during 2007 (Rossa *et al.*, 2010). The composition of the topographic relief is also important for flash flooding. Certain areas have

relief patterns that are better at rapidly concentrating water into streams than others, making them more susceptible to flash flooding. The topography of a region can also influence the convective events directly, helping create the meteorological conditions necessary for flash flooding (Marchi *et al.*, 2010). For example, highly mountainous terrain might anchor a convective event causing it to drop more water over a small catchment area, thus increasing the risk of flash flooding (Borga *et al.*, 2011). Soil conditions such as permeability and moisture content must also be considered when evaluating the potential for flash flooding (Norbiato *et al.*, 2008).

Flash floods pose their greatest risk in urban areas. This is due to high population density, surface imperviousness and increased flood wave velocity due to channelisation of stream flow (Looper and Vieux, 2011). Rapid urbanization and aging or inadequate drainage networks further exacerbate this problem. Most drainage networks are designed to manage a particular maximum rainfall and this maximum is often underestimated without accounting for city growth, climate change or flash flooding (Henonin *et al.*, 2010). The past decade has seen growing calls by governments for improved flash flood forecasting in many parts of the world (Hapuarachchi, 2011). In response to this call, the scientific community has developed a range of rainfall observation and modelling techniques. Most of these techniques involve a mixture of precipitation forecasts along with hydrological models.

1.3. Flash Floods and Climate Change

Research undertaken by the Intergovernmental Panel on Climate Change suggests there will be an increased risk associated with extreme weather events as the climate continues to warm (IPCC, 2014). This risk is only beginning to be quantified in terms of flash floods in particular (Modrick and Georgakakos, 2015). Using a distributed hydrological model for a small catchment in Southern California, Modrick and Georgakakos (2015) attempted to understand how flash floods might be affected by climate change. The results suggest that although flash floods look to become less frequent, they are set to become more intense due to an increase in both rainfall intensity and duration, as well as due to higher soil moisture levels (Modrick and Georgakakos, 2015).

1.3.1. Climate change and flash floods in South Africa

Using empirical downscaling of general circulation models, scientists predict that southern Africa will begin to warm as circulation systems which are normally positioned further north, begin moving southward. This may result in fewer mid-latitude depressions making landfall over the Cape region, thus causing drier winters, however, the depressions are expected to be more intense. With added heat in the atmosphere, it is probable that areas which experience wet summers will experience increased rainfall over the summer period (Hewitson and Crane, 2006; Kendon *et al.*, 2014). This increase in intensity of daily rainfall and prolonged rainfall events is correlated with an increased frequency of flooding events (Mason and Joubert, 1997; Arnell & Gosling, 2014).

1.3.2. Flash flood warning systems

Warning systems conceivably play a more important role concerning flash floods, as opposed to other types of floods (Creutin *et al.*, 2009). This is due to flash floods often occurring in sparsely populated areas that have not in their recent past experienced any flooding. In such

areas it is thus seldom feasible to install physical flood barriers or other flood protection measures (Sene, 2012).

As with most other natural hazards, an operating flash flood warning system should include four general steps (Smith and Handmer, 1986). Firstly; real time observations, which investigate conditions that might lead to flash flooding. Secondly; forecasting, which extends the lead time by attempting to predict the occurrence, intensity and path of a rainfall event. Thirdly; warning, which requires preparation, warning decisions, the distribution of the warning, and finally the receipt of the warning and effective response. Finally; action, which entails the implementation of an effective response plan.

1.3.3. Rainfall and Flash Floods

1.3.3.1. *Measuring Precipitation*

The quality of a flash flood forecast relies greatly on the precipitation data which feeds it. It is impossible with today's technology to follow each raindrop from where it leaves the cloud to where it lands on the surface. The quantity and location of rainfall therefore needs to be estimated using available sensors. Unfortunately these methods are fraught with inaccuracies and uncertainties. Raingauges are the obvious starting point in attempting to establish the location and intensity of rainfall (Tao and Barros, 2013). Raingauges can be both automatic and manually operated. Manual raingauges are relatively cheap but require regular checks and maintenance by a qualified individual; this makes them expensive in terms of human resources and also leaves measurements open to human error. Another problem is that if there is excessive rainfall between checks, the gauge might overflow and lead to inaccurate readings. Electronic raingauges overcome these issues by automatically taking rainfall readings. They do, however, come with their own disadvantages; firstly, they are expensive; secondly, they are difficult to install; and thirdly, they require regular calibration and maintenance. In addition to all these issues, the data provided by raingauges are only partially useful in that they give a point value

for a phenomena which is highly variable over space and time (Sene, 2012). This variability might lead to a raingauge overestimating total rainfall if a particularly intense part of a rainfall event moves over the location where the raingauge is situated, and conversely it might underestimate rainfall if a calm sector of the storm moves over the raingauges.

Radio Detection and Ranging (RADAR) is another method by which rainfall can be estimated. A RADAR emits radio waves into the atmosphere; these waves then travel outward and bounce off objects they encounter. These reflected waves are then measured by the receiver. The difference in time between when the wave is emitted and when it is received indicates the location of the object. The strength of the reflected signal can also provide information on the composition of the object. This is called the RADAR reflectivity factor and from this the size and distribution of rain drop size can be estimated. RADAR is thus a good option for estimating both the location and intensity of rainfall (Collier, 1996). The most obvious advantage of RADAR for flash flood applications is that it can provide rainfall estimates over a large area in a distributed rather than point form. It therefore has its benefits in both gauged and ungauged catchments. Unfortunately RADAR rainfall estimates are subject to a myriad of uncertainties. Some of these uncertainties and possible errors may arise from the characteristics of the precipitation itself, such as variations in the vertical reflectivity profiles, as well as hail and the ‘bright band’ phenomena. The ‘bright band’ is described as the zone where ice is melting into liquid water as it falls, which gives it a much higher reflectivity than the rain below it (Terblanche *et al.*, 2001). Another problem is the fact that RADAR values are recorded above the ground surface which may lead to the RADAR overshooting some rainfall closer to the surface. Ground clutter from both natural (mountains etc.) and manmade obstacles (buildings etc.) can also be a problem (Collier, 1996).

Satellites can also help in estimating the extent and intensity of rainfall, as they operate by looking down on storms from above and calculate rainfall using various remote sensing methods. The main drawback of satellite data is the low spatial resolution, which requires it being used in conjunction with RADAR data when estimating the distribution of precipitation over as small area (de Coning and Poolman, 2010). Given their low resolution, satellite derived rainfall estimations are not used in this study.

The use of lightning data for precipitation estimation has also been investigated (Price *et al.*, 2011). However, lighting precipitation estimation will not be considered in this study due to the lack of cloud to cloud lightning measuring devices in South Africa. All ensemble techniques have also been omitted from this study due to their complexity and therefore fall out of the studies scope.

1.3.3.2. Quantitative Precipitation Estimates

Quantitative precipitation estimates (QPE's), as they are referred to by Hapuarachchi (2011), are the main input variables for flood forecasts. QPE's derived from RADAR data alone have proved to be extremely useful in providing spatial distributions of rainfall (Collier, 1996; Krajewski, 2002; Marra & Morin, 2014). Most studies use either C-band or higher frequency S-band RADARs for rainfall estimates, while some use even higher frequency X-band RADAR data (e.g. Anagnostou *et al.*, 2010). In order to correct RADAR biases, techniques have been developed to adjust RADAR data with both raingauge and numerical weather prediction (NWP) data. Raingauge data can also act as a fall back strategy in the absence of RADAR data (Einfalt *et al.*, 2004). Another way of spatially quantifying precipitation rates is by using satellite microwave and infrared data. Ultimately, a blend of RADAR, raingauge, NWP, and satellite data could provide the greatest temporal and spatial accuracy, and therefore further research in this regard, should be useful (Hapuarachchi, 2011).

Once precipitation has been quantified, a method for forecasting the future progression of the storm needs to be established, known as a quantitative precipitation forecast (QPF). This study will not be using these techniques, but they are mentioned here as they may prove useful in further applications of this research. For the purposes of flash flood prediction, the method should be able to accurately predict the path of a storm for only about 0-6 hours into the future. This is therefore referred to as a nowcast rather than a forecast (Sokol, 2006). The traditional method for creating a rainfall nowcast is to use a tracking algorithm to extrapolate RADAR echoes. This method is not very helpful for long lead times due to a rapid decrease in accuracy as the lead time increases. However, extrapolation is effective for lead times between 30 and 60 minutes (Mecklenburg *et al.*, 2000). Extrapolation techniques can be combined with precipitation forecasts from a NWP model to extend the lead time of a nowcast. The NIMROD model does this by using RADAR echo extrapolation for short time periods and then gradually shifts weight to the NWP model as time increases. Then, as the time reaches the 6 hour mark, the NIMROD model is completely reliant on the NWP precipitation forecast (Sokol, 2006). Another nowcasting method is an automated system known as GANDALF. It attempts to simulate storm development by using a conceptual model of the life cycle of storm clouds along with satellite, RADAR and NWP data (Mecklenburg *et al.*, 2000). As with QPE's, the techniques which blend NWP rainfall forecasts along with satellite, RADAR and raingauge data extrapolation (e.g. NIMROD), seem to be the most promising. Systems such as NIMROD have the potential to forecast intense convective events with sufficient accuracy and with up to a 6 hour lead time (Hapuarachchi, 2011). There is always a significant amount of uncertainty regarding QPF's. Much work is being undertaken to both reduce and quantify these uncertainties (Fabry and Seed, 2008). As the QPF's become more accurate, so should the hydrological forecasts they feed (Tao and Barros, 2013).

1.4. Hydrological modelling

There are three fundamental characteristics of hydrological models that often make them more problematic than models in other disciplines. Firstly, the variables used, such as soil or vegetation types, are generally highly heterogeneous and usually unknown or poorly known. Therefore, no matter how fine the resolution, there will always be some uncertainty within the model. It is also very difficult to resolve this uncertainty using statistical methods due to the complexity of the heterogeneity. Secondly, as of yet, there is no unique hydrological equation that can be derived from first principles, and therefore hydrological equations are empirical in nature. Thirdly, hydrological models depend largely on their boundary conditions which are often undefined (Bloschl *et al.*, 2008).

1.4.1. Lumped hydrological models

A lumped hydrological model is a conceptual model that uses mean data values as input. These models are useful when spatial distribution of precipitation data within a particular catchment are limited (Carpenter and Goergakakos, 2006). However, lumped hydrological models are problematic because they use mean precipitation and soil moisture levels for the entire catchment. In essence, they represent a catchment as one lumped unit and consider a small number of variables (Refsgaard, 1997). In reality there is almost always precipitation, soil and vegetation variability within a catchment. In the majority of cases lumped models end up making many assumptions about the drainage basin which leads to possible distortions in the characteristics of the actual catchment (Shultz, 2007). Lumped models are therefore best suited to catchments that are well gauged and have homogeneous conditions. They are also used when there is very little spatial data available, such as in historical flood studies (Ruiz-Bellet *et al.*,

2015). Until recently, lumped models have been the mainstay for operational flow forecasting and are still widely used due to their simplicity as well as their low computational and data requirements (Hapuarachchi, 2011).

Lumped models have been used for flash flood forecasting, specifically with a seemingly good success rate. For example, lumped models conducted in a mountainous region of north eastern Slovenia using the HBV-96 conceptual model, were found to be satisfactory in simulating flash floods (Kobold and Brilly, 2006). According to these authors, lumped models can be used in flash flood early warning systems. The American National Weather Service (NWS) also uses a lumped model called the Sacramento Soil Moisture Accounting Model (SAC-SMA) to produce threshold runoff values for their Flash Flood Guidance System (FFGS) (Ntelekos *et al.*, 2006).

The FFGS was developed by the NWS in its attempt to fulfil its mission of protecting citizens and property from weather related disasters. The ultimate goal is to implement the system on a global scale. The FFGS is a system which assists in determining when and where flood warnings should be issued. The main idea behind the FFGS is to create a threshold runoff figure for each catchment and when that threshold is reached, flood warnings be issued (Georgakakos, 2006). Threshold run-off is the amount of rainfall required over a certain amount of time for possible flash flooding to occur (Carpenter *et al.*, 1999). The SAC-SMA lumped model is used to help determine these threshold values while RADAR is used to provide real time rainfall data for each catchment area (Ntelekos *et al.*, 2006). Accounting for uncertainties of RADAR rainfall estimates is still not fully resolved and is the subject of much research and debate (Villarini *et al.*, 2010; Berne & Krajewski, 2013; Villarini *et al.*, 2014). Reed *et al.* (2007) criticise the use of a lumped model in the FFGS, given that homogenous conditions are assumed throughout a catchment and therefore threshold values for smaller sub-catchments

might be inaccurate. This might lead to false warnings being issued, or no warnings being issued when there is an actual threat. Another issue is that warnings are given for an entire catchment and therefore emergency response is spread out rather than localised (Javelle *et al.*, 2010). It has hence been suggested that a distributed model might be better suited for use in the FFGS due to its ability to take into account heterogeneity within a catchment (Reed *et al.*, 2007).

In 2008, the South African Weather Service (SAWS), in collaboration with the National Disaster Management Centre (NDMC), began work on developing a flash flood early warning system for flash flood prone areas of South Africa. The FFGS developed by the NWS was chosen and was implemented in parts of South Africa toward the end of 2010 and is known as the South African Flash Flood Guidance System (SAFFGS). A lumped model is used to estimate threshold rainfall values for 1633 small catchments in five regions of South Africa. The SAFFGS uses both RADAR and satellite derived rainfall estimates in order to create flash flood warning maps. There is currently much work being done to improve the quality of QPE's that feed the SAFFG (de Coning and Poolman, 2010). By using NWP rainfall forecasts, further work is also being conducted to extend the lead time of forecasts past the current 6 hour maximum (Poolman, 2014).

1.4.2. Distributed hydrological models

Distributed hydrological models are the most recent development in hydrological modelling. Distributed models have been hindered due to the inability of computers to solve the complex mathematical equations required, as well as a lack of data storage capacity. Recently, however, distributed models have been gaining in sophistication and popularity as GIS and computer systems increase in capability (Shultz, 2007). Distributed models are more detailed as they subdivide the catchment up into smaller units, therefore providing a higher resolution than lumped models. They also have the ability to use a variety of spatially varying characteristics

of a catchment, such as land use, soil characteristics, precipitation, temperature and other forcing mechanisms. In short, distributed models are an improvement on lumped models in that they account for the spatial variability within a catchment, rather than lumping these characteristics into catchment averages (Carpenter and Goergakakos, 2006). Distributed hydrological models are thought to give a better representation of reality than lumped models (Shultz, 2007; Blöschl *et al.*, 2008; Tang *et al.*, 2007; Looper and Vieux, 2011).

Distributed hydrological models are most useful in arid and semi-arid zones as these areas have more spatial variability in soil moisture and thus require models with a higher resolution. Arid and semi-arid areas also have less vegetation, which means the soil is the first object on the ground to come into contact with precipitation, and therefore a higher resolution of soil characteristics in these regions is essential. Humid zones have a more even spread of soil types and soil moisture levels across a catchment, making lumped models more acceptable (El-Hames and Richards, 1998).

Distributed hydrological models are supposedly well suited to flash flood forecasting. This is due to flash floods being quite localised and therefore requiring a higher spatial resolution of rainfall estimates than normal floods (Vivoni *et al.*, 2006; Reed *et al.*, 2007; Zoccatelli *et al.*, 2010; Hapuarachchi, 2011). Some of the hydrological models that have been previously used for flash flood evaluation and prediction include TOPMODEL (e.g. Bouilloud *et al.*, 2010; Vincendon *et al.*, 2009), HEC-HMS (Anderson, 2002), FEST (e.g. Vincendon, *et al.* 2009), The Network Model (e.g. Javier *et al.*, 2007), HYDROG (e.g. Salek *et al.*, 2006), CINECAR (Versini, *et al.*, 2010; Naulin *et al.*, 2013), 3D-LSHM (Tao and Barros, 2013), as well as MikeSHE (e.g. Sahoo *et al.*, 2006). Some modellers have opted for creating case specific distributed models for their specific studies (e.g. Gaume *et al.*, 2004).

1.4.3. Neural networks

Neural networks may be incorporated into hydrological models that use statistical methods to generate flow forecasts. They are essentially systems that learn relationships between input and output data sets and then attempt to predict previously unseen data sets with similar characteristics. Neural networks work a bit like a brain and need to be trained with training data sets but once trained are generally fast and easy to use. Neural networks perform well in situations where physical data about the catchment are scarce, as they only need rainfall and discharge data in order to function (Sahoo and Ray, 2005). Neural networks do, however, have limitations, especially concerning flash flooding, although they have recently been used with some success (e.g. Yang *et al.*, 2015). Firstly, they require large amounts of historical data for training purposes, which are often scarce in small catchments prone to flash flooding. Secondly, the derived relationships are site specific and are therefore difficult to apply in a general sense (Hapuarachchi, 2011). Due to these limitations, neural networks are not used in this study.

1.4.4. Sources of error in hydrological models

There are three main sources of error or uncertainty in hydrological models. Firstly those which occur from random or systematic errors in the input data or data used to calibrate the models. Secondly from uncertainties associated with non-optimal parameter values. Thirdly from uncertainties associated with incomplete/biased model structures (Baldassarre and Montanari, 2009).

1.4.4.1. Data Uncertainty

There are a myriad of ways in which errors can occur when measuring precipitation and flow data. They can however be divided into two main categories, those that occur randomly and those that occur systematically. Random errors occur when a random occurrences influence the measurement and are therefore inherently unpredictable. For example if a bird sits above a

raingauge and blocks it, or some debris gets lodged in a flow gauge affecting the measurements for a short period. Random errors are very difficult to correct for due to their uncertain nature. Systematic errors on the other hand occur throughout a dataset and are the result of a specific fault with the gauge or sensor. If for example a tree grows over a raingauge covering a part of it, or a flow gauge is installed incorrectly, the error will persist through the data. This makes systematic errors easier to correct for using bias correction techniques. Uncertainty in input or calibration data is propagated through a hydrological model and can therefore have a significant effect on the simulation outputs (Butts *et al.*, 2004).

1.4.4.2. *Uncertainties associated with non-optimal parameter values*

Hydrological models incorporate multiple parameters which can have a statistical significance, a physical significance, or a combination of the two. It can be quite difficult for a modeller to fully understand the effect that adjustments to each parameter might have on the model outputs. Some parameters might have such a small effect on the model outputs that they can actually be ignored, while small adjustments to certain parameters can have highly significant effect on model outputs. Uncertainty associated with parameter values can therefore vary dramatically depending on the specific parameter in question. Understanding the sensitivity of hydrological models and the parameters associated with them is an important area of study (Benke *et al.*, 2008).

1.4.4.3. *Uncertainties associated with model structure*

Model structure refers to the set of computational approaches used to simulate real world hydrological processes. The possible variations in model structure are vast and can include, but are not limited to:

- process descriptions; such as whether groundwater processes should or should not be included or which wave equation is used to represent channel flow;

- process coupling techniques; such as whether recharge from a river to the surrounding aquifer is included or not;
- representations of spatial variability; such as whether a lumped or distributed approach is used to represent rainfall data;
- process representations on a sub-grid scale; such as different degrees of lumping or if distributed functions are used; and
- interpretations and classifications of spatial data; such as soil type, land use and vegetative cover. (Butts *et al.*, 2004).

The modeller, when selecting the model structure, needs to consider the specific requirements of the project at hand. These decisions are often made on the basis of multiple assumptions and biases by the modeller. Model structure can therefore be the source of much uncertainty in the model outputs. This uncertainty is very difficult to quantify. Butts *et al* (2004) suggests that variations in model structure should be tested, in the context of simulation uncertainty, in order to find the best combination for the specified application.

1.5. Background Flash Flood Forecasting in South Africa and the Modelling Techniques Used

In 1993 the then Department of Water Affairs and Forestry (DWAF) implemented a flood warning and communication system that used antecedent precipitation indices and daily rainfall data. This system eventually fell into disrepair. Subsequently other systems were built using rainfall data, RADAR data as well as numerical weather prediction. These systems were generally ineffective at predicting floods and were not specific to predicting flash floods (du Plessis, 2002).

In recent years South Africa has implemented an early warning system known as the South African Flash Flood Guidance System (SAFFGS). The SAFFGS is based on a system originally designed by K.P Goergakakos at the NRC in Santiago. The purpose of the FFGS is to help guide forecasters as to where flash floods might be likely to occur. It does this by estimating soil moisture levels using real time quantitative precipitation estimates and the Lumped Sacramento Soil Moisture Accounting model (SAC). The system tells the forecaster how much rain is needed in the following 1, 3 or 6 hour period for a particular catchment to experience bank full conditions at its outlet. In other words it provides threshold precipitation values for all catchments within the prescribed area. The forecaster can then use this information along with precipitation forecasts to issue flood warnings if necessary.

The SAFFG system divides the region of South Africa into catchments, the catchment sizes vary greatly depending on the resolution of available rainfall estimates. Due to RADARs higher resolution, catchments are smaller where there is RADAR coverage and larger in areas only covered by lower resolution satellite data. The system runs once an hour using the rainfall data from the previous two days. Each hour the system displays all the catchments and the number of millimetres of rain that need to fall in the following 1, 3 and 6 hour period to cause bank full conditions at their outlets. The forecaster can then look at the NWP and RADAR extrapolation data to decide whether the threshold rainfall values are likely to occur and then subsequently issue warnings. The SAFFG has already shown its worth in being able provide guidance to meteorologists (Poolman, 2012) There are, however, some drawbacks to the system.

The SAFFGS does not provide any discharge information which is useful for predicting the extent of floods. It uses a lumped rather than distributed approach, so does not provide information on the whereabouts of flooding within a catchment. The catchments in South Africa are also often un-gauged, so validation of the model is difficult.

1.6. Research Goals

The overall aim of the study is to evaluate the use of RADAR data and hydrological models for flash flood evaluation and prediction in a semi-arid South African catchment.

In order to achieve this aim, several specific questions are asked:

1. What are the characteristics of flash floods in a semi-arid South African catchment?
2. How do distributed and lumped hydrological models compare in terms of their ability to predict flash floods when initialised with RADAR and raingauge quantitative precipitation estimates?
3. How does the current operational flash flood warning system in South Africa apply in the context of this study?

The chosen study catchment is the Jukskei River catchment in Gauteng, South Africa, and the study covers a fourteen month period between January 2009 and March 2010. This period is chosen as it is the longest period where data exists for all data inputs and therefore includes the most flash flood events possible. A case based approach is used to characterise past flash flood events in the chosen catchment over the study period. Weather RADAR data are used to create distributed quantitative precipitation estimates for the entire study catchment. These data, as with raingauge data from the Johannesburg Zoo raingauge, are used to initialise NAM (a lumped hydrological model) and MikeSHE (a distributed hydrological model). The results of the models are compared with actual streamflow at a gauge within the catchment, as well as a gauge at the catchment outlet.

2. Model Structures and Process Descriptions

The Mike 11 and MikeSHE integrated hydrological modelling tool has been developed to allow multiple modelling structures to be used within the same modelling framework (Butts *et al.*, 2004). This therefore allows different modelling techniques to be used, tested and compared on the same platform and might reduce the possible biases that can arise when different model structures are applied over multiple platforms. The Mike 11 and MikeSHE integrated tool lets the modeller select a myriad of different process descriptions to simulate routing, unsaturated flow, drainage flow and ground water. It also allows the modeller to select different spatial distributions for modelling parameters, such as precipitation and soil characteristics. It is outside the scope of this study to explore all possible model structures available using the Mike 11 and MikeSHE modelling framework. This chapter describes the process descriptions relevant to this study.

2.1. Hydraulic Model- Mike 11

Mike 11 has three choices on how river flow is described. The diffusive wave approach, the kinematic wave approach which assumes a balance between friction and gravity forces and the dynamic wave approach which uses the full momentum equation. It is recommended that the dynamic wave description be used in all cases unless there are problems with computational efficiency in which case the simpler kinematic and diffusive wave approaches might be more suited (DHI, 2009). The dynamic wave approach is therefore used in this study. The dynamic wave approach solves the vertically integrated Saint-Venant equations.

Mike 11 offers two possible descriptions for bed resistance. The Chezy description which uses a coefficient that varies with depth and the Manning description uses a coefficient that is independent of depth (DHI, 2009). The Manning description is used in this study.

The basic flow equations describing one-dimensional river flow combined with the Manning description of bed resistance are described by equations (**Equation 1** and **Equation 2**) below.

Equation 1: Flow Equation 1

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = q$$

Equation 2: Flow Equation 2

$$\frac{\partial Q}{\partial t} + \frac{\partial \alpha \left(\frac{Q^2}{A} \right)}{\partial x} + gA \frac{\partial h}{\partial x} + \frac{gQ|Q|}{M^2 AR^{4/3}} = 0$$

Q: discharge

A: flow area

q: lateral flow

h: water level

g: gravity

M: Manning number

R: resistance radius

α : momentum distribution coefficient

Overland Flow is described by the following equations (**Equation 3** and **Equation 4**)

Equation 3: Overland flow in x direction

$$uh = M \left(-\frac{\partial z}{\partial x} \right)^{1/2} h^{5/3}$$

Equation 4: Overland flow in y direction

$$vh = M \left(-\frac{\partial z}{\partial y} \right)^{1/2} h^{5/3}$$

U: flow velocity in x-direction

V: flow velocity in y-direction

h: water depth

M: Manning Number

Z: ground surface level

2.2. Rainfall Runoff Models

2.2.1. NAM

The rainfall runoff model was developed by the Institute of Hydrodynamics and hydraulic Engineering at the Technical University of Denmark (Nielson and Hansen, 1973). The lumped model is the default rainfall runoff model used in the Mike 11 hydraulic modelling system. The NAM model simulates the rainfall-runoff process by representing four interrelated storages and continually accounting for the water content in each. The storages represent the location of water within different physical elements of a particular catchment, that is; Snow Storage, Surface Storage, Root Zone Storage and Groundwater Storage (**Figure 1**) (DHI, 2009). Water is added to the system by either snow or rain, it is then transferred between the different reservoirs by different hydrological processes, such as overland flow, interflow and baseflow (**Figure 1**).

The snow storage and snow components of the model are not used in this study as snow is extremely rare in the study catchment. The parameters described in **Table 1** are used to

calibrate the model. The parameters are changed according to how well the model outputs agree with observed data in terms of water balance, hydrograph shape, peak flows and low flows. Some trade-offs in how the outputs agree with observed data are often necessary in order to reach the goals of the specific study in question. For example in this study, which looks are flood events, low flows would be of lesser importance to peak flows.

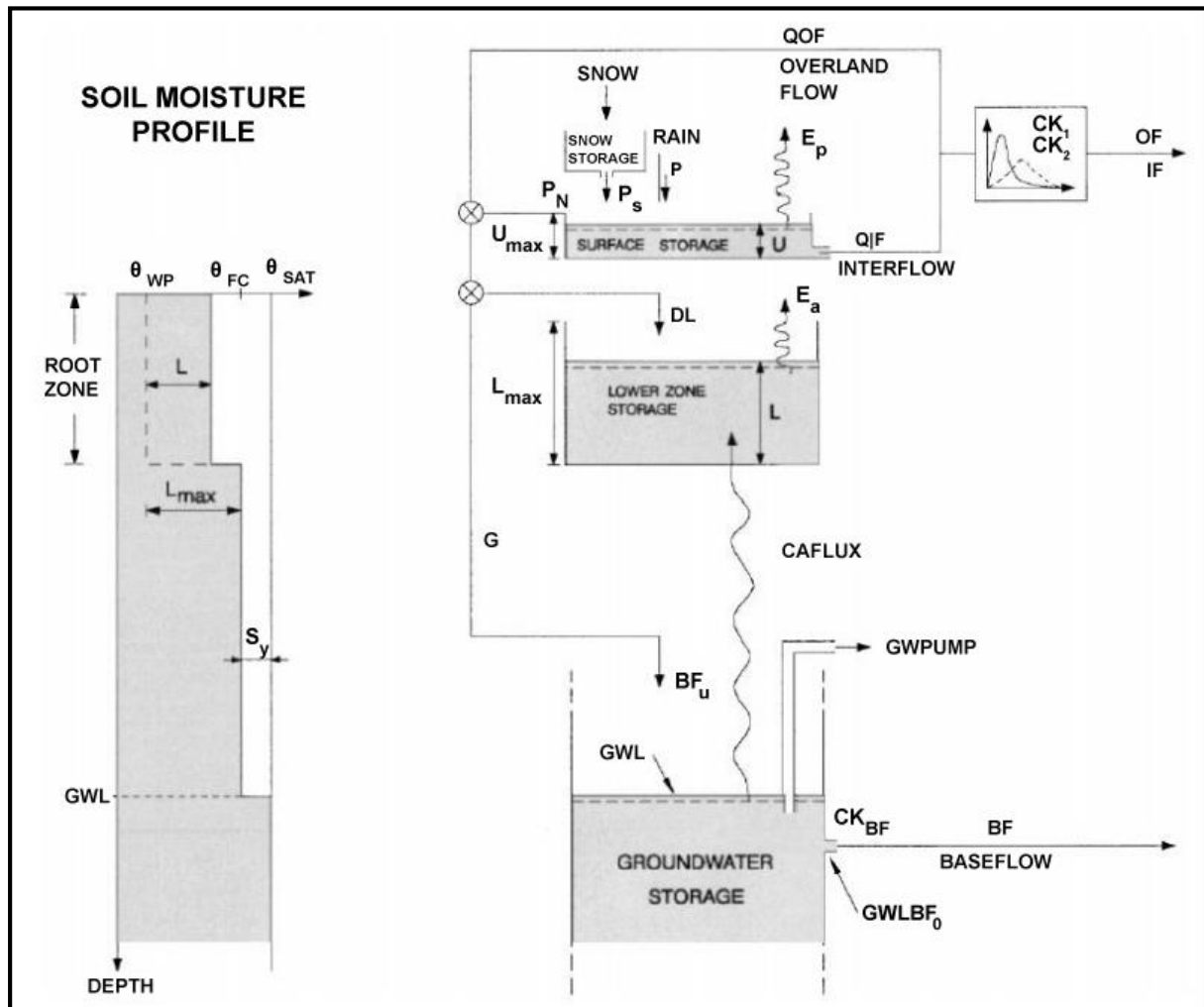


Figure 1: NAM model structure (DHI, 2009)

Table 1: NAM parameter descriptions

Parameter	Description	Lower Limit	Upper Limit
Umax	Maximum water content in surface storage	5	35
CK	Time constant for routing overland flow	500	1000
Lmax	Maximum water content in root zone storage	50	400
TOF	Root zone threshold value for overland flow	0	0.9
CQOF	Overland flow runoff coefficient	0	1
TIF	Root zone threshold value for interflow	0	0.9
CKIF	Time constant for routing interflow flow	200	2000
TG	Root zone threshold value for GW recharge	0	0.9
CK_{BF}	Time constant for routing baseflow	500	5000

2.2.2. MikeSHE

In the 1960's, Freeze and Harlen (1969) began to create a digital hydrological response model to try and simulate the hydrological cycle. There were three purposes to their endeavour. First, to try and synthesise past hydrological events; second, to try and predict future events; and third, to try and evaluate the impacts of artificial changes to the hydrological cycle (Freeze and Harlen, 1969). This model was then extended over the next decade to produce the Systeme Hydrologique Europeen (SHE) hydrological model (Abbott *et al.*, 1986a, 1986b). In the mid 1980's, DHI began further developing and extending the SHE model. Today it is known as MikeSHE (**Figure 2**) and is an advanced and flexible framework for modelling the hydrological cycle (Mc Michael *et al.*, 2005). It includes precipitation interception, infiltration, evapotranspiration, subsurface flow in both saturated and unsaturated zones, surface flow, and channel flow via its integration with Mike 11 (Refsgaard, 1997). MikeSHE allows hydrological processes to be examined at different levels of complexity, depending on both the aims of a particular study and the availability of data (Graham and Butts, 2005). It is this flexibility which makes MikeSHE an attractive model for the purposes of this study. DHI also has a flood model called MikeFLOOD, which is a 2 Dimensional model that simulates flood

inundation. MikeFLOOD is not used in this study as it requires high resolution topographical data to simulate flood inundation, which is not available for the entire study catchment,

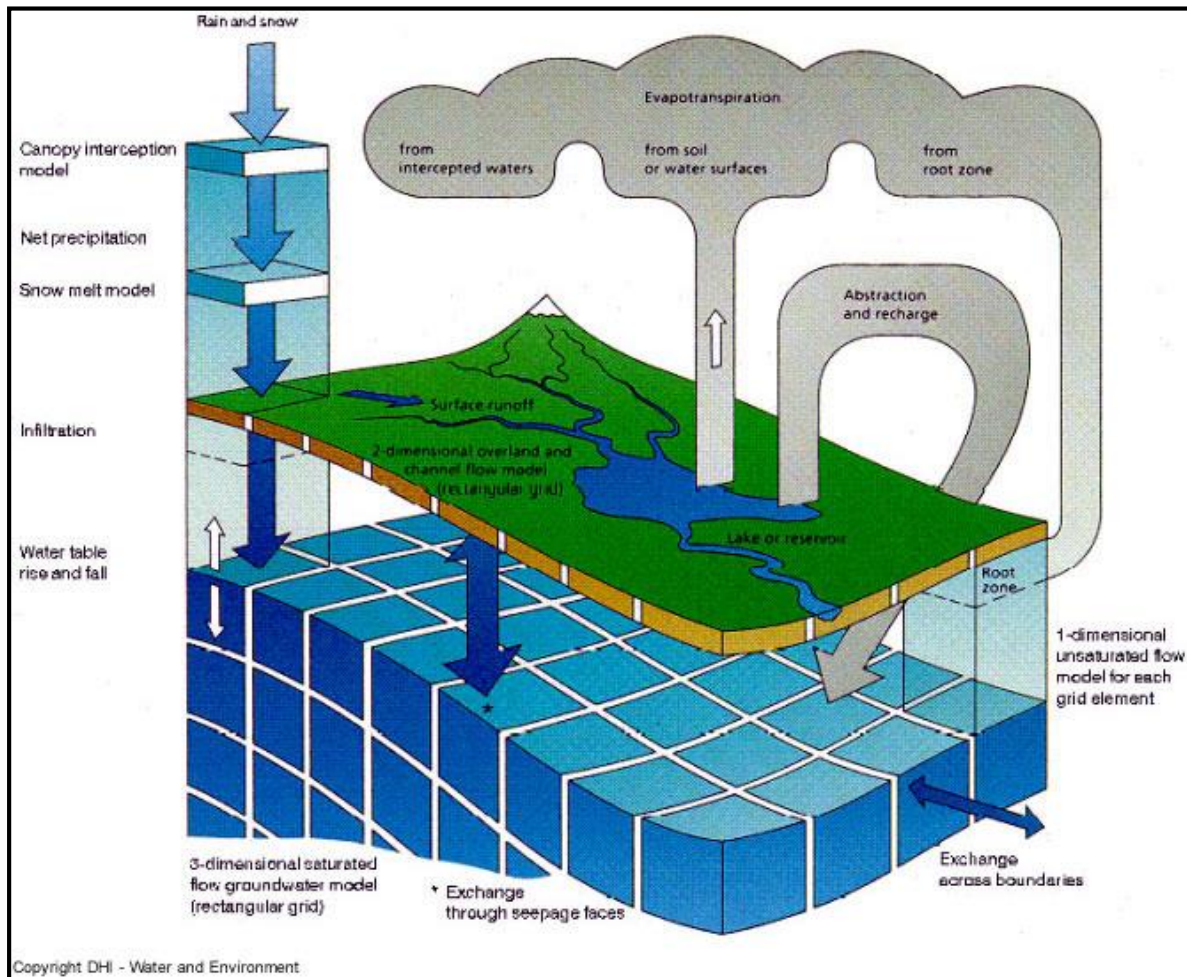


Figure 2: MikeSHE rainfall runoff model (DHI, 2007)

2.2.2.1. Unsaturated Flow

Unsaturated flow refers to the flow of water through soils and due to the heterogeneous nature of soils the flow is itself highly heterogeneous. It is also characterised by cyclic fluctuations in soil moisture. In MikeSHE unsaturated flow is only vertically calculated as horizontal flow in soils is usually insignificant (Graham and Butts, 2005). It is very difficult to measure unsaturated flow on a grid scale, therefore the flow description is essentially conceptual. MikeSHE has three main options for calculating infiltration through the unsaturated zone, namely the full Richards equation, the simplified gravity flow procedure, and a simple two-

layer water balance method (DHI, 2007). The full Richards equation (**Equation 5**) is the most computationally intensive but also the most accurate, for this reason it is used in this study.

Equation 5: Richards equation

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left(K(\theta) \left[\frac{\partial \psi}{\partial z} + 1 \right] \right)$$

K = hydraulic conductivity

ψ = pressure head

z = the elevation above a verticle datum

θ = the water content

t = time

2.2.2.2. Overland Flow

Overland flow occurs whenever ponded water forms on the surface and is then routed downhill as surface runoff. This could be due to rainfall not infiltrating fast enough, groundwater flowing onto the surface or rivers breaking their banks due to a flood. Water flowing over the surface is represented in MikeSHE in three different ways, finite-difference, diffusive wave approximation and slope zone approach using the manning's equation (DHI, 2007). The finite difference method is used in this study and the equations are described below (**Equation 6** and **Equation 7**).

Equation 6: Overland flow in the x direction

$$uh = M \left(K(\theta) \left[-\frac{\partial z}{\partial x} \right] \right)^{1/2} h^{5/3}$$

Equation 7: Overland flow in the y direction

$$vh = M \left(K(\theta) \left[-\frac{\partial z}{\partial y} \right] \right)^{1/2} h^{5/3}$$

u: flow velocity in x-direction

v: flow velocity in y-direction

h: water depth

M: Manning number

z: ground surface level

2.2.2.3. Groundwater Flow

Groundwater sustains streamflow during periods of drought. It is therefore an important component of the hydrological cycle. MikeSHE has two methods for modelling groundwater. There is a detailed approach which uses the finite difference technique by solving the 3D Darcy equation. There is also the simpler linear reservoir method which is more conceptual in nature. The linear reservoir method divides the catchment into a series of shallow reservoirs plus a deep baseflow reservoir (**Figure 3**). Each baseflow reservoir is further divided into two parallel reservoirs. One that handles the slow component of baseflow discharge and storage and one that handles the faster component. Water is routed through the reservoirs as interflow and baseflow and is then laterally directed into the river as inflow from the interflow reservoir. In this study a detailed approach to groundwater is not necessary due to the short timescales associated with flash floods, therefore the simpler linear reservoir method is used.

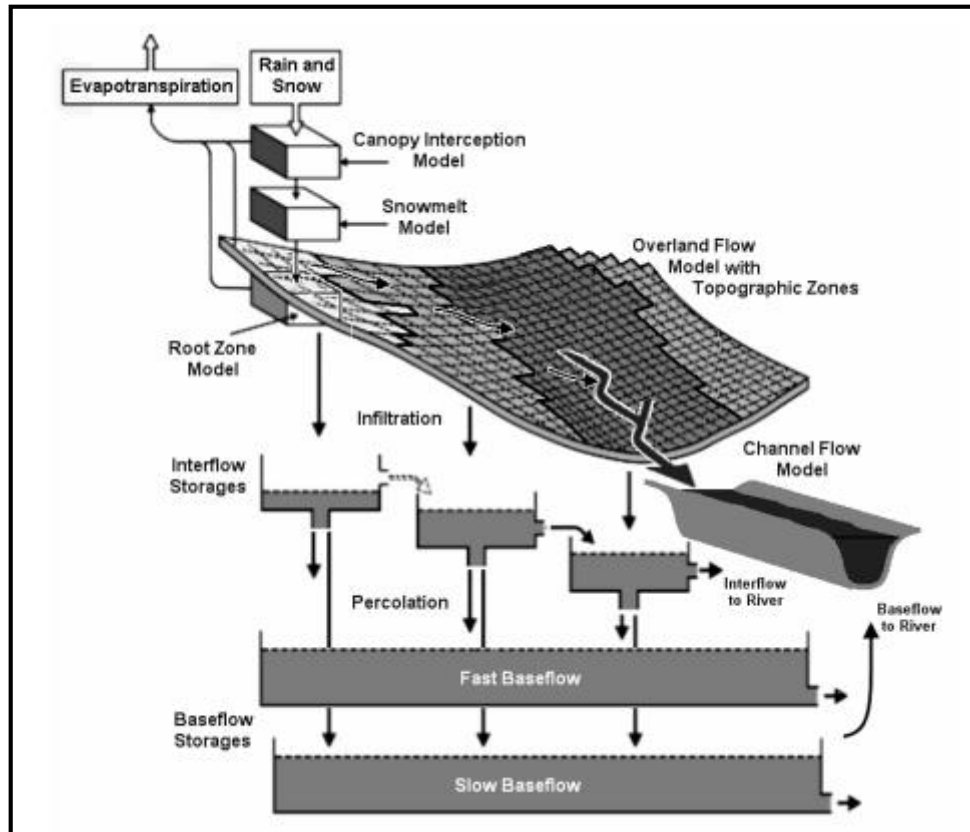


Figure 3: Schematic diagram of the Linear Reservoir Method from Butts et al., 2004

2.3. Summary of Model Structures Used

The model structures used within the Mike 11 and MikeSHE modelling framework are described in **Table 2**.

Table 2: Model structure summary

Simulation Title	Process				Rainfall
	Routing Description	Overland Flow	Unsaturated Flow	Groundwater	
MikeSHE (Raingauge)	Manning	Manning	Richards Equation	Linear Reservoir	Lumped
MikeSHE (RADAR)	Manning	Manning	Richards Equation	Linear Reservoir	Distributed
NAM (Raingauge)	Manning	Manning	Conceptual	Conceptual	Lumped
NAM (RADAR)	Manning	Manning	Conceptual	Conceptual	Lumped

3. Data and Methods

This chapter includes some background on the study area and why it is chosen. It also outlines the data used in the hydrological models as well as the methodologies used. Data analysis methodologies are excluded here as these are outlined in subsequent chapters.

3.1. Study Area

The region selected for this study is the Gauteng Province which is located in the semi-arid north eastern interior of South Africa (**Figure 4**)

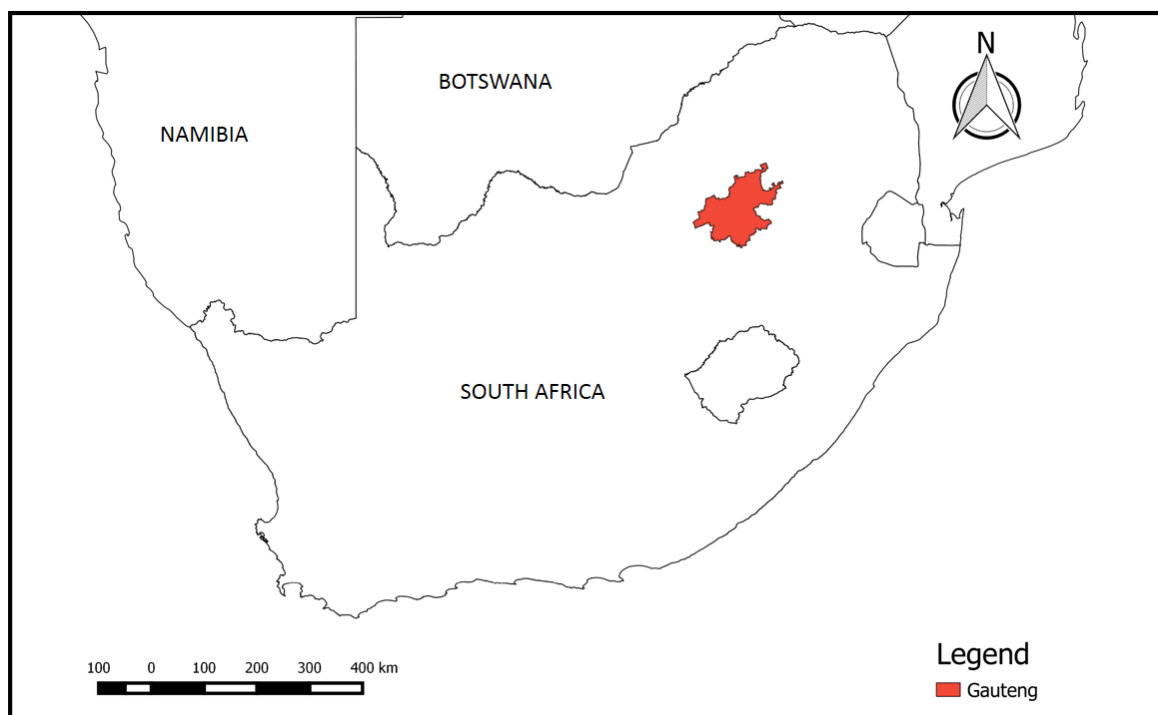


Figure 4: Location of the Gauteng Province within South Africa

3.1.1.1. Background on the Study Area

Gauteng is the economic hub of not only South Africa but Africa as a whole. It is currently experiencing rapid urbanisation with more and more vacant land near rivers being occupied, mainly by informal settlements. Gauteng is situated at an elevation of about 1500m on South Africa's interior plateau and therefore receives most of its rainfall during the summer months. Heavy rainfall events that can cover much of the province and last several days at a time, sometimes result in widespread flooding, damaged infrastructure and loss of life. Gauteng can

also have very intense isolated rainfall events which have the potential to cause flash flooding. These mesoscale events are also often associated with other hazards such as hail or heavy winds. Floods are a major hazard to life and property in Gauteng, due to both the short lead time between the rainfall event and the flood event itself. The large number of informal settlements located along river banks within the flood zone, exacerbates the problem (Dyson, 2009).

3.1.1.2. The Jukskei River Catchment

The quaternary catchment of the Jukskei River within Gauteng was selected for this study. The catchment is situated to the north of Johannesburg central and the southwest of Pretoria. (Figure 5).

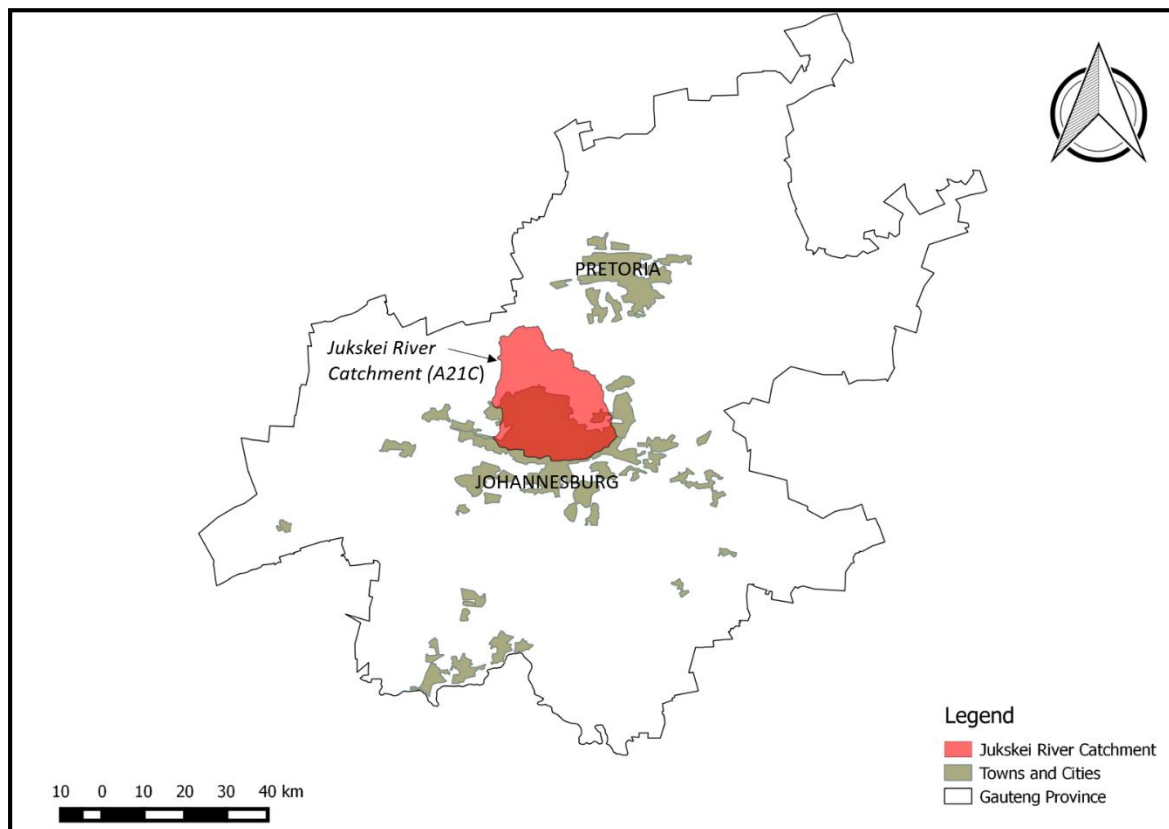


Figure 5: Study catchment location

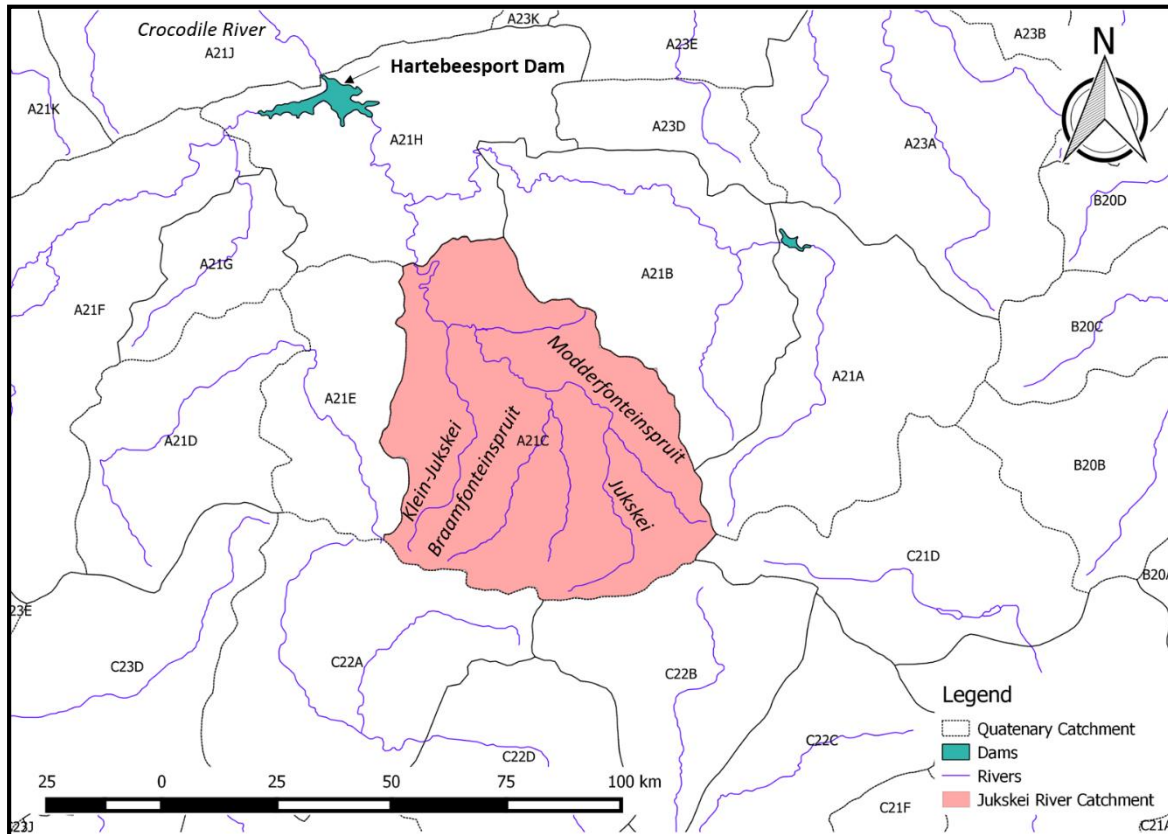


Figure 6: Map Showing the Location of the Study Catchment in the context of surrounding quaternary catchments

The Jukskei Catchment lies on the border of a major South African watershed and covers an area of approximately 761 km² with its rivers passing through the cities of Johannesburg and Midrand. In its upper reaches, the Jukskei River and its tributaries (Klein Jukskei, Braamfonteinspruit, Modderfonteinspruit and Sandspruit) originate from springs located in central Johannesburg. The rivers then flow northwest, through multiple urban areas that make up Johannesburg North, Sandton and Midrand. Multiple informal settlements are located along the banks of the Jukskei and its tributaries, the largest of which is Alexandra. The river ends when it flows into the Crocodile River and then into the Hartbeespoort Dam (**Figure 6**). The Crocodile river continues its path easterly through South Africa and into the Komati river which then continues through Swaziland and Mozambique into the Indian ocean.

The topography of the catchment is moderately complex with elevations ranging between 1,313m-1,745m above sea level (**Figure 7**). The river channels tend to be narrow (mostly between 5m and 20m) with a gentle slope gradient (averaging only 0.38%).

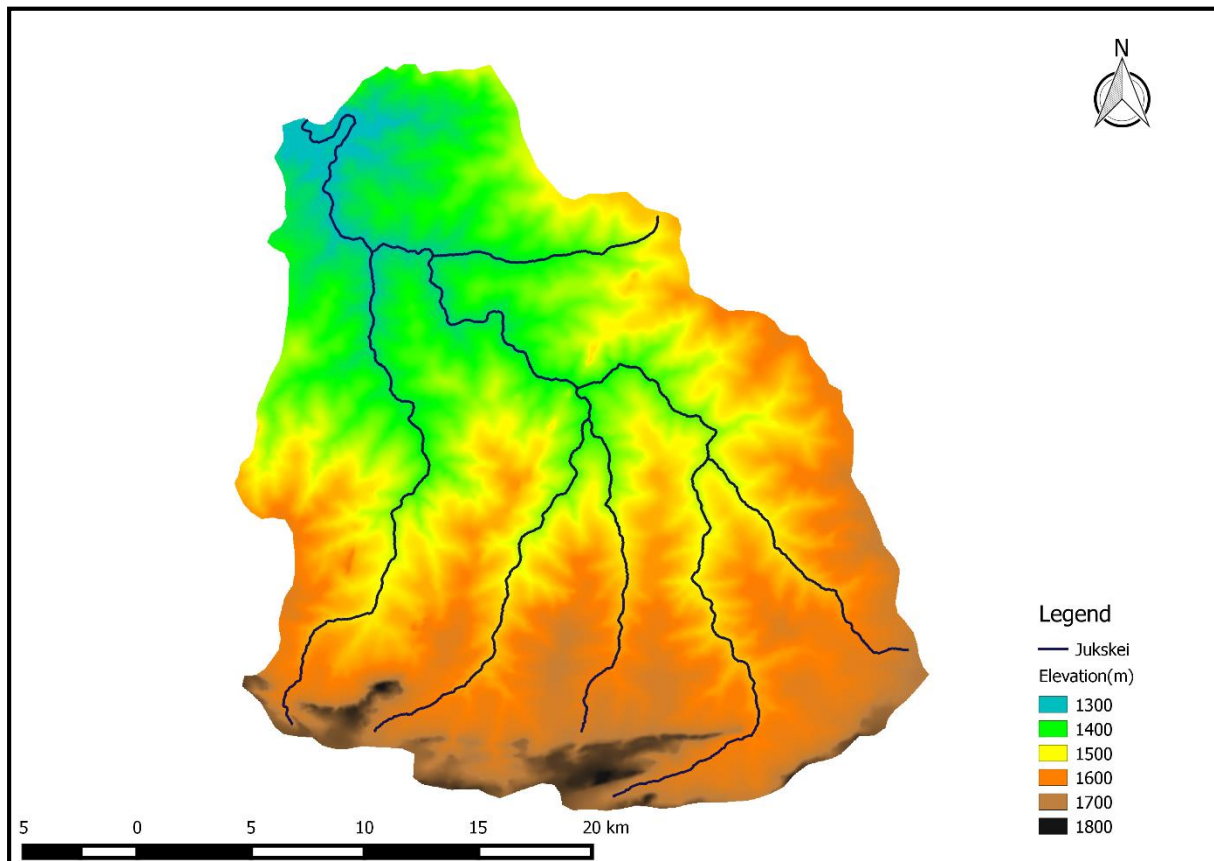


Figure 7: Digital Elevation Model of the Jukskei river catchment (30m resolution)

The Jukskei River catchment was selected for the following reasons:

1. There are two functional river gauges within the catchment namely A2H043 and A2H047 (**Figure 8**). Both these gauges have data available for the study period.
2. There is a functional raingauge in the catchment situated at the Johannesburg Botanical Gardens (**Figure 8**). More gauges do exist in the catchment but there is either no data available for the study period or the data is not available for use in this study.
3. The catchment lies in an area prone to flash flooding (**Figure 12**).
4. The Irene C-Band RADAR is close enough to the catchment to give satisfactory RADAR derived rainfall estimates.

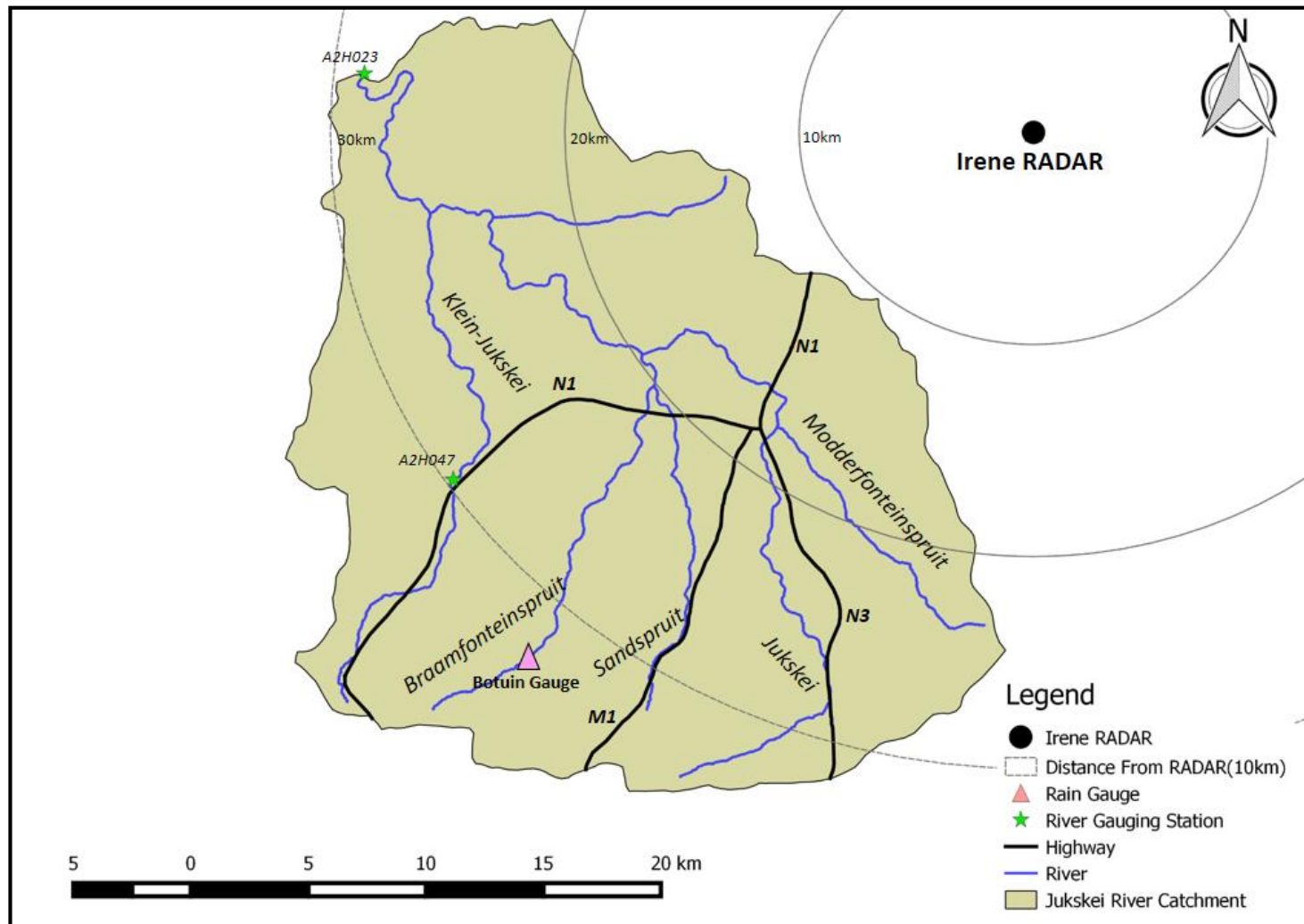


Figure 8: Map depicting the Jukskei river reaches, location of flow and raingauges, location of the RADAR and the main highways

3.2. Data

Various types of data are used to initialise the hydrological models. These are presented:

3.2.1. Digital Elevation Model

The Digital Elevation Model (DEM) used in this study (**Figure 7**) is derived from topographical survey 5m contour maps. Such a resolution was required in order to create satisfactory river cross sections to feed the hydraulic model. The DEM is also added to MikeSHE as a grid file (Appendix A: **Figure 37**).

3.2.2. Soil Characteristics

The soil data used in this study is sources from the South African Atlas of Agrohydrology-Climatology (Schulze, 1997). The atlas divides South Africa into multiple zones with differing hydrological characteristics. According to the atlas, there are 8 soil types in the Jukskei River catchment (**Figure 9**). Their hydrological characteristics are presented in **Table 3**.

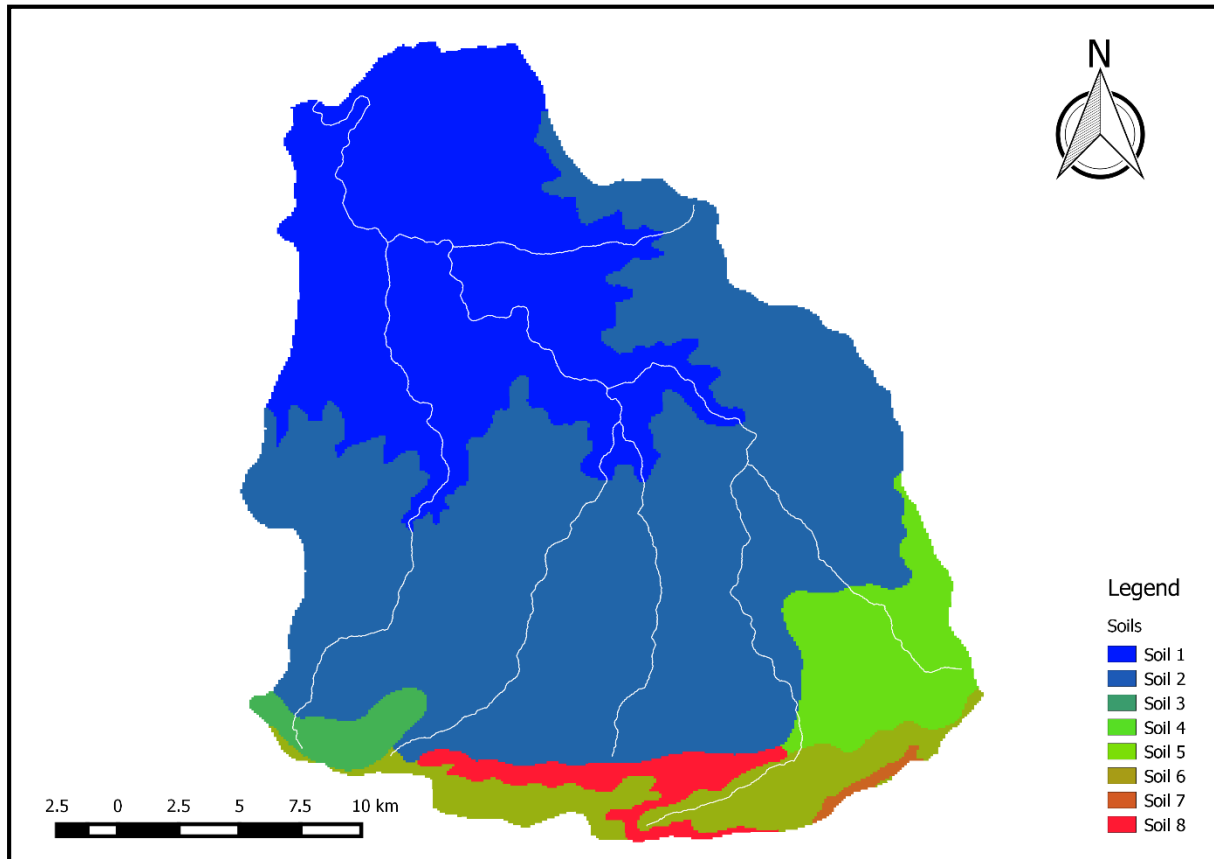


Figure 9: Map of the soil types in the Jukskei river catchment (Shulze, 1997) (see Table 1 for type characteristics)

Table 3: Hydrological characteristics of soil types in the Jukskei river catchment (Schulze, 1997)

Soil ID	Water content at saturation.	Water Content at Field Capacity	Water Content at Wilting Point
Soil 1	43%	23%	15%
Soil 2	36%	20%	11%
Soil 3	46%	20%	11%
Soil 4	44%	20%	11%
Soil 5	45%	26%	12%
Soil 6	45%	26%	12%
Soil 7	44%	22%	14%
Soil 8	44%	22%	14%

3.2.3. River Gauge Data

Quality gauge data for flash flood evaluation are sometimes not available due to gauge failure (Koutroulis and Tsanis, 2010). The first gauge used in this study is located at the outlet of the catchment on the Jukskei river (A2H044) and has a data recovery of 82%. The second gauge is located along the Klein Jukskei river (A2H023), a tributary of the Jukskei river, and has a

data recovery of 73%. The gauges are maintained by the Department of Water Affairs and record an instantaneous discharge every 12 minutes.

3.2.4. Quantitative Precipitation Estimates

Thunderstorm Identification, Tracking, Analysis and Nowcasting (TITAN) software was used to establish rainfall estimates for the study area. TITAN is a storm tracking system that allows the user RADAR to track storms in real time as well as analyse past storm events using various tools (Terblanche et al., 2001). **Figure 10** depicts RADAR reflectivity during one of this studies cases (29 January 20210) as viewed through the TITAN system.

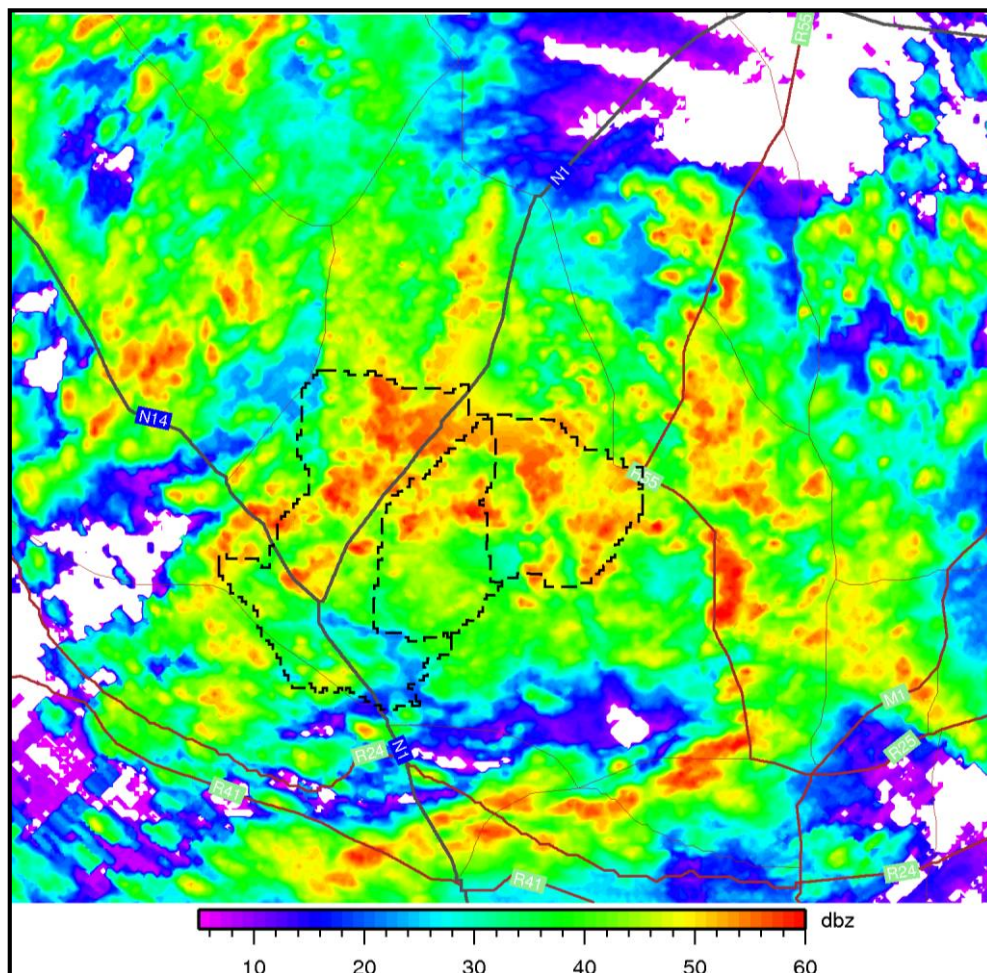


Figure 10: RADAR reflectivity during the 29 January 2010 flood event over the Jukskei river catchment (catchment outlined in black)

The most important consideration when using RADAR data for creating precipitation estimates is the relationship between the RADAR reflectivity factor (z) and precipitation rate

(r). Unfortunately there is no single z-r relationship that can satisfy all meteorological phenomena. As calculating z-r relationships is beyond the scope of this research, the Marshall and Palmer (1948) general stratiform precipitation relationship of $Z = 200R^{1.6}$ is used to estimate rainfall. The resultant data is presented as a grid of 1km by 1km with rainfall values in millimetres for each time step and each block on the grid. An example of this grid once it has been converted to the MikeSHE format can be found in Appendix A (**Figure 36**). Data from the C-band RADAR situated at Irene is used due to the availability of data for the study period. The settings on the C-band RADAR are presented in **Table 4: Settings on the C-band radar situated at Irene during the study period**

Table 4: Settings on the C-band radar situated at Irene during the study period

Date of start	1 Dec 2009
Wavelength (cm)	5.3
Beam Width (°)	1.1
Range (km)	600
Azimuth interval (°)	1
PRF	250
Gate spacing (km)	0.45
Samples per beam	32
Average rotation speed (°/s)	23
Scan Duration(s)	245
Number of elevations	18
Elevation range (°)	0.7–38.8
Elevation sequence	T–B

A new S-band RADAR was installed in 2010 and is more beneficial than the old C-band RADAR due to its lower attenuation problems, as well as its Doppler capabilities (de Coning, 2010).

3.3. Hydrological Modelling Methodology

Four different hydrological model structures are used in order to investigate which method best predicts both continuous discharge as well as abnormal flow events at the outlet of the Jukskei river catchment. A lumped model (NAM) and a distributed model (MikeSHE) are used - each

initialised separately by RADAR and Raingauge data. They are then compared in terms of their ability to predict continuous stream flow as well as their ability to simulate high flow events.

The procedure followed in this study is divided into three parts, the first part involves creating quantitative precipitation estimates for the study period. The second part involves setting up the hydrological and hydraulic models so they are ready to handle the precipitation estimates. The third part involves calibrating the models against actual river gauge data.

3.3.1. Setting up the Hydrological Models

3.3.1.1. Mike 11 Hydraulic Model

Mike 11 is the hydraulic component of the Mike Models. It simulates the route and velocity of the water once it has entered the river channels. It requires a high resolution Digital Elevation Model (DEM) in order to calculate the gradient of the channels, as well as cross sections of the channels in order to route the water correctly.

The DEM is imported into Mike 11, which automatically calculates water flow. The accuracy of these calculations greatly depends on the resolution of the DEM. The use of a 5m resolution DEM is attempted but caused the computer processor to crash when digitizing the reaches. A 30m DEM is then used and turned out to be more than sufficient for digitizing the river reaches. This is confirmed by comparing the digitized reaches with the official river locations supplied by the Department of Water Affairs and Forestry. The Jukskei, Klein Jukskei, Sandspruit, Braamfonteinspruit and Modderfonteinspruit are all digitized. Adding more reaches than this increases the complexity of the model and its run time, without greatly increasing the efficacy of the simulations.

When creating river reaches in Mike 11, the flow of water is directed around the edges of each pixel in the DEM. This can sometimes create an unrealistic model of stream flow due to the right angles created. The impact of this problem also increases as resolution of the DEM grows.

In order to solve this problem, the reaches are smoothed to add a more realistic curve to the right angles. After smoothing, some unrealistic arcs then appeared; these are then adjusted manually using the modeller's discretion. The Mike 11 river network can be found in Appendix B (**Figure 38**).

Mike 11 allows the user to add hydraulic structures to the river network in order to create a more realistic channel model. These include weirs, culverts, bridges, pumps, and dam breaks. It also has the functionality to include user defined structures and insert areas of energy loss. The insertion of structures requires accurate cross sections of the river bed, both before and after the structure. Detailed surveys of the river bed are needed in order to create these cross sections. These surveys would be too costly and time consuming and are unnecessary for the purposes of this research. The most important aspect of this study is to simulate the flow at the discharge point of the entire catchment and to a much lesser extent, simulated flow at specific points within the catchment. The lack of hydraulic structures placed within the Mike 11 model does not have a significant effect on the volume, and this minor effect can be offset by runoff model calibration. The lack of hydraulic structures does, however, greatly impact the accuracy of flow simulations at points within the catchment.

Mike 11 requires cross sections of the river bed along the river network in order to correctly route water through the catchment. Ideally these cross sections should be acquired by means of a detailed river bed profile survey along the river network. As mentioned, this is outside the budget of this study. The lack of highly accurate cross sections does also not have a significant impact on the study's results. An example cross section can be found in Appendix B (**Figure 39**).

The 30m DEM used for delineating the river reaches is too coarse in resolution to be used as cross sections in Mike 11. Therefore, 5m contour lines are converted to a DEM. The river

network was then overlaid onto the 5m DEM and cross sections are automatically created every 1km along the network.

Boundary conditions are then selected. Mike 11 can contain information such as wind, heat balance, base flow and river bed resistance, but for the purposes of this study, base flow is the only boundary variable considered. Base flow is the discharge of a river when there is no water directly from precipitation flowing into the river. The water comes from aquifers, dams or groundwater (Neff et al., 2005). Due to a lack of gauges within the catchment, another method is required to calculate baseflow. This is achieved by dividing the baseflow catchment discharge evenly by the number of branches to obtain a crude approximation of baseflow. The base level is calculated to be 0.35m and the baseflow $0.7\text{m}^3/\text{s}$.

The boundary conditions then needs to be included. The boundary conditions refer to the inflow to a river branch at its starting point. No data are available for the quantity of water flowing into the rivers from their source springs. The value of zero is therefore initially given to all inflow points. With these zero values the model returns errors because the water drops below the river bed and is therefore not channelled. Hence a small amount of inflow needs to be added into the branches at their boundaries in order for the model to run. A value of $0.05\text{m}^3/\text{s}$ is given to all branches except the Jukskei, which is given a value of $0.1\text{m}^3/\text{s}$ given its larger size.

At this point the Mike 11 model is now ready to run. It simulates the channel flow within the catchment assuming no groundwater interaction, precipitation, evaporation or infiltration. A linkage with a rainfall runoff model is therefore required to add these components into the simulation. Mike 11 has the capability to link with both a lumped model (NAM) and a fully distributed model (MikeSHE). The methodology for setting up these models follows.

3.3.1.2. MikeSHE Distributed Rainfall Runoff Model

Firstly, the simulation is specified, this includes the simulation period as well as the time step, with all other parameters here left as default. Then the Mike 11 river network model is coupled with the MikeSHE rainfall runoff model. The simulation specification can be found in Appendix A (**Figure 34**) and the model domain setup can be found in Appendix A (**Figure 35**)

In MikeSHE there are three ways of inputting precipitation data. Firstly, average precipitation for the entire catchment can be added as either a constant or a time varying file. Secondly, station based precipitation data can be added as a station based time series file. Finally, a fully distributed time varying file can be added. In this study both the average precipitation and fully distributed methods are used.

Six months of data are used to calibrate the model to the RADAR rainfall data. The same calibration methods are used for both RADAR and raingauge data. The model is initially run using default values where actual physical data were not available. These parameters are then adjusted from their default values in an attempt to get a satisfactory correlation with the actual discharge. For the purposes of this study, a correlation of 0.75 is chosen. The following parameters are changed from their default values:

- 1.) Net rainfall fraction- the fraction of rainfall that is available for overland flow and infiltration. It is used when evapotranspiration values are not available and are not modelled. Net rainfall fraction is expressed as a number between 0 (no rainfall available for infiltration and overland flow) and 1 (all rainfall available for infiltration and overland flow) (DHI, 2007). A Net Rainfall Fraction of 0.74 is used for the raingauge initialised simulation and a Net Rainfall Fraction of 0.6 is used for the RADAR initialised simulation. The default value is 1. This number is arrived at by trial and error

during calibration and suggests that both the raingauge and the RADAR data significantly over estimate actual rainfall, because it is unlikely that over 20% of rainfall is lost to evapotranspiration.

2.) Manning Number- this is a number between 1 and 100 that specifies the “roughness” of terrain. A low manning number means that the land is non-vegetated and allows for smooth laminar flow while a high number means the land is highly vegetated (DHI 2007). Initially the default manning number of 10 is used, but this causes too much runoff, too quickly, resulting in spiked hydrographs. Multiple numbers are tested and the manning number of 20 settled on due to the more realistic shape of the hydrographs. The manning number is still relatively low, indicating fast overland flow. This is not surprising due to the urban nature of the catchment and therefore impervious surfaces leading to quick runoff.

3.) Interflow (Linear Reservoir Method)- this represents how near surface ground water flows into the channel network; the following parameters can be changed:

- a. Specific Yield- this value dictates the porosity of the reservoir,
- b. Initial Depth- this is the depth of the roof of the reservoir from the ground surface,
- c. Bottom Depth- this is the depth of the bottom of the reservoir from the ground surface,
- d. Interflow time constant- this represents the time it takes for the water to flow between reservoirs,
- e. Percolation time constant- this is the time it takes for the water to reach the base flow reservoir (DHI, 2007).

All of the actual values are unknown due to a lack of data therefore they were used as calibration parameters - the exact values are detailed in These values are presented in **Table 5** and **Table 6** for the average RADAR initialised model and the raingauge initialised model respectively. .

Table 5: Interflow Values for the raingauge initialised model

Value	Specific Yield	Initial Depth (m)	Bottom Depth (m)	Interflow (d)	Threshold Depth (m)	Percolation (d)
Default	0.3	5	5	14	5	14
Calibrated	0.3	5	5	0.13	5	14

Table 6: Interflow Values for the RADAR initialised model

Value	Specific Yield	Initial Depth (m)	Bottom Depth (m)	Interflow (d)	Threshold Depth (m)	Percolation (d)
Default	0.3	5	5	14	5	14
Calibrated	0.3	5	5	0.13	5	14

All interflow values are left at their default values except for the Interflow time constant. The interflow time constant is reduced significantly in both models and suggests that there is very quick movement of water from the interflow reservoirs into the river. This could be due to the presence of storm water drains in the catchment that route water into the rivers quickly.

4.) Baseflow (Linear Reservoir Method)- this represents how water behaves in underground reservoirs a schematic of the linear reservoir method can be found in **Figure 3**, each reservoir is divided into two parts; the following parameters can be changed:

- a. Specific Yield- this value dictates the porosity of the reservoir,

- b. Dead Storage fraction- the fraction of percolation that does not enter the reservoir,
- c. Time constant for baseflow- the time it takes for water to flow through the reservoir,
- d. UZ feedback fraction- the fraction of baseflow available to replenish the nearest interflow reservoir,
- e. Initial depth- the initial depth below the surface of the water in the reservoir,
- f. Threshold depth for baseflow - the depth below ground that base flow stops,
- g. Threshold depth for pumping- the depth below the surface where pumping stops,
- h. Depth of the bottom of the reservoir.

All of the actual values are unknown due to a lack of data, and are therefore used as calibration parameters, however many of the values remain the same as the default values due to the large timeframes associated with baseflow and the short timeframes associated with flash floods. These values are presented in **Table 7** and **Table 8** for the average RADAR initialised model and the raingauge initialised model respectively. .

Table 7: Baseflow Values for the raingauge initialised model

Value	Specific Yield	Time constant for base flow (d)	Dead storage fraction	UZ feedback fraction	Initial depth (m)	Threshold depth for base flow (m)	Threshold depth for pumping (m)	Depth to bottom (m)
Default (Reservoir 1)	0.3	365	0	0.1	20	20	20	20
Calibrated (Reservoir 1)	0.3	1000	0	0.1	15	20	20	20
Default (Reservoir 2)	0.3	3650	0	0.1	50	50	50	50
Calibrated (Reservoir 2)	0.3	3650	0	0.1	30	50	50	50

Table 8: Baseflow Values for the RADAR initialised model

Value	Specific Yield	Time constant for base flow (d)	Dead storage fraction	UZ feedback fraction	Initial depth (m)	Threshold depth for base flow (m)	Threshold depth for pumping (m)	Depth to bottom (m)
Default (Reservoir 1)	0.3	365	0	0.1	20	20	20	20
Calibrated (Reservoir 1)	0.3	3365	0	0.1	10	2	10	10
Default (Reservoir 2)	0.3	3650	0	0.1	50	50	50	50
Calibrated (Reservoir 2)	0.3	33650	0	0.1	20	2	20	20

3.3.1.3. NAM Rainfall Runoff Model

The NAM lumped hydrological model was set up using average rainfall estimates derived from a distributed RADAR rainfall estimate. These are the only data added to the model; the model is then calibrated against actual stream flow data using a six month calibration period. The goal of the calibration is to get the simulations to correlate with observations by over 75%. This proved to be extremely difficult to achieve and a correlation of 60% is settled on. Initially, the model is run using default values wherever actual physical data are not included, these default values are adjusted manually by the modeller in order to achieve the closest correlation with observed stream flow. These values are presented in **Table 9** and **Table 10** for the average RADAR initialised model and the raingauge initialised model respectively. The model is then run for the entire period within which the case studies occurred.

Table 9: NAM Calibration Values (RADAR)

Value	Umax	Lmax	CQOF	CKIF	CK	TOF	TIF	TG	CKBIF
Default	10	100	0.5	1000	10	0	0	50	2000
Calibrated	150	100	0.5	1	20	0.1	0.1	0.1	5026

Table 10: NAM Calibration Values (Raingauge)

Value	Umax	Lmax	CQOF	CKIF	CK	TOF	TIF	TG	CKBIF
Default	10	100	0.5	1000	10	0	0	50	2000
Calibrated	0.1	0.1	0.3	1	1	0.1	0.1	0.1	5026

Umax= Maximum water content in surface storage

CK= Time constant for routing overland flow

Lmax = Maximum water content in root zone storage

TOF= Root zone threshold value for overland flow

CQOF= Overland flow runoff coefficient

TIF= Root zone threshold value for interflow

CKIF= Time constant for routing interflow flow

TG= Root zone threshold value for GW recharge

CKBIF= Time constant for routing baseflow

Maximum water content for surface and root zone storage for the raingauge initialised model are very different to the default values. This indicates a very low water content in both surface and root zone storage, and might be due to the urban nature of the catchment and therefore very little storage in this zone. These values are however much closer to the default values when the RADAR data is used. Therefore it indicates an issue with the raingauge data itself, possibly that the gauge works better when there is higher rainfall and does not pick up the lower rainfall needed to fill these storages.

The time constant for interflow is very different from the default values for both the models, this indicates a very short interflow period and therefore a very fast runoff. This is most likely due to the impervious surfaces and drainages systems associated with an urban catchment. The time constants for routing overland flow as well as the root zone threshold values for overland and interflow are also very small. This is again most likely due to the urban nature of the Catchment.

3.3.2. Flow Diagram of Modelling Methodology

A simplified flow diagram of the modelling methodology is provided in **Figure 11**.

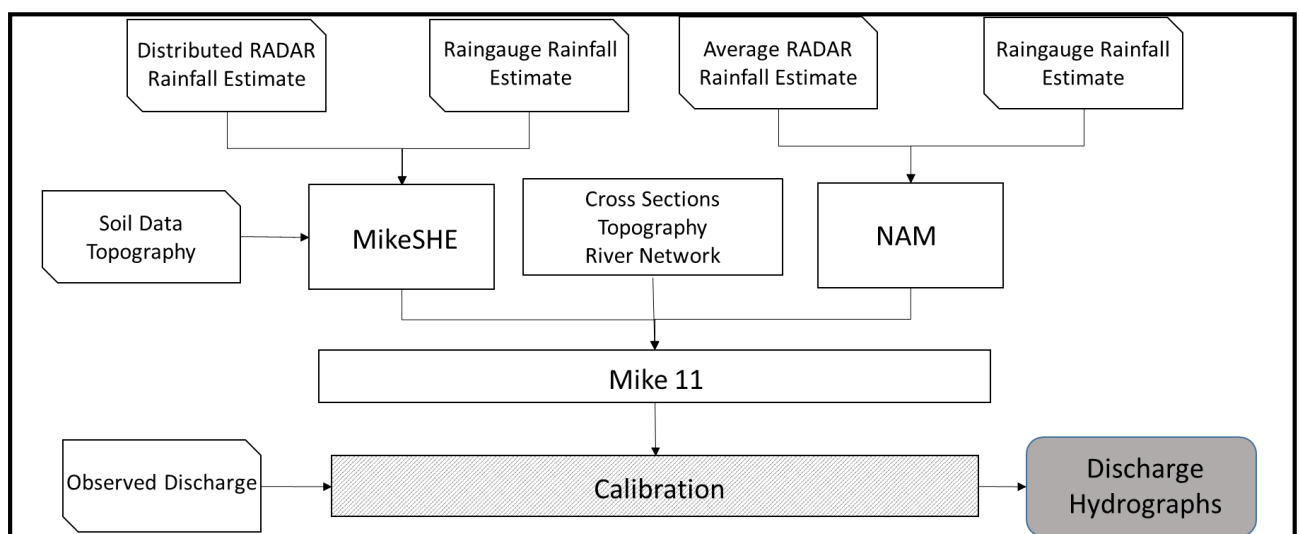


Figure 11: Flow diagram of methodology

4. : Flash Flood Characterisation

The major aim of this chapter is to characterise flash flood events along the Jukskei river for the purpose of providing insight into the predictability of flash floods in the catchment. This is achieved by firstly characterising the hydrological and meteorological conditions which lead to flash floods in the Jukskei river catchment using a case based approach, and secondly by exploring the predictability of flash floods in the Jukskei river catchment with the use of a lumped hydrological model. Although studies characterising flash floods have been previously undertaken (eg. Marchi *et al.*, 2010), none have used a case based approach, and therefore most of the methods used here are specific to this study.

4.1. Recent Flash Floods in the Jukskei Catchment

The catchment is highly prone to flash flooding. **Figure 12** presents all the flash floods in the catchment that are documented in local newspapers. It is safe to assume that they are all flash flood events as they all occur in the upper reaches of the catchment. There were 15 flash floods recorded in the catchment during 5 years [2005-2010](SAWS, 2010). This could be an underestimation as these floods are only those which were released by the press. Note that as they are based on press releases, the locations of the floods in **Figure 12** are not necessarily accurate.

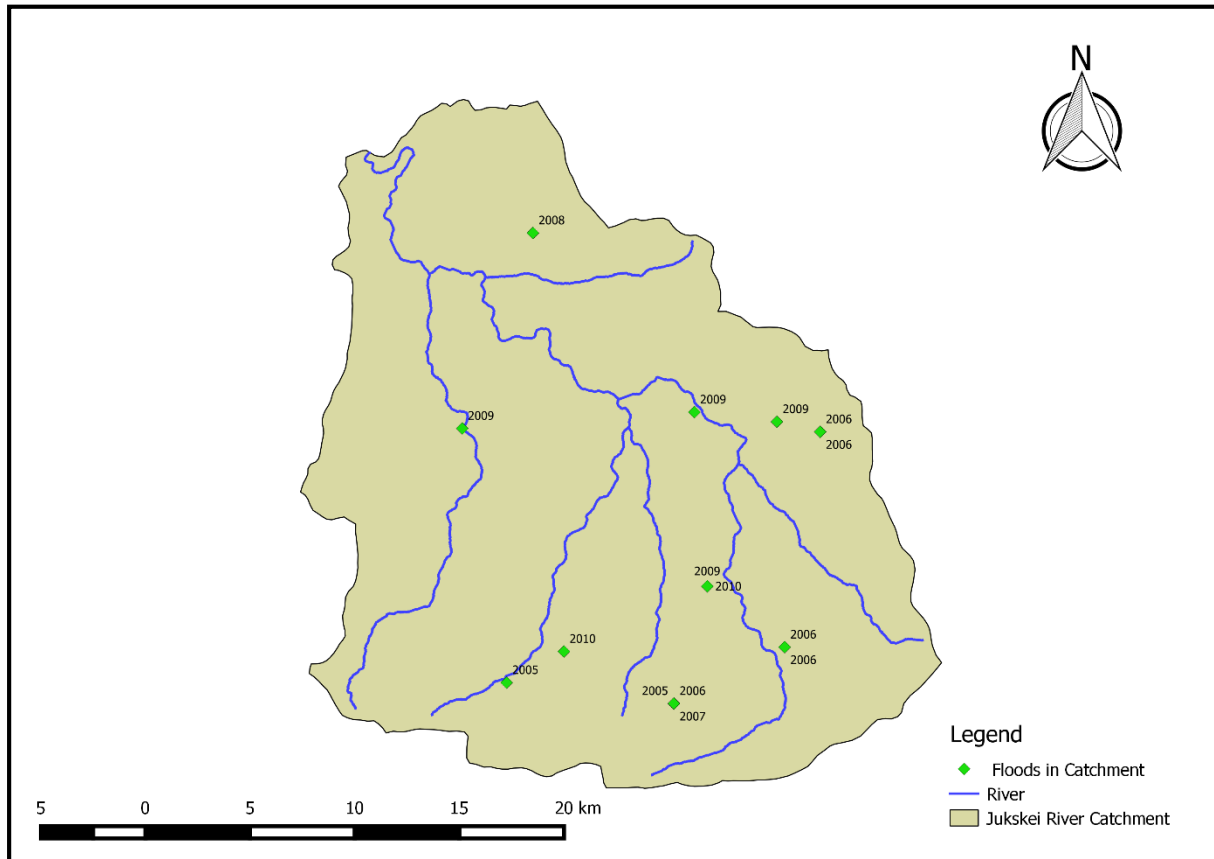


Figure 12: Map of Floods in The Jukskei River Catchment 2005-2010 (SAWS, 2010)

4.2. Case selection

According to SAWS, (2010) six flash flood events occurred during January 2009 and March 2010 in the Jukskei river catchment. It must be noted that the SAWS Caelum data only lists disasters that were reported in the printed media, so flash floods that were not reported or occurred along uninhabited river reaches were not listed. It is therefore most likely that the frequency of flash floods during the study period was much higher than reported in Caelum. These six events are checked against the flash flood characterisation rules set out by Marchi *et al* (2010). When Marchi *et al* (2010) characterises a flash flood a causing storm event, all storms exceeding 34h are excluded. All the rainfall events pertaining to the selected case studies fall well within that limit. Marchi *et al* (2010) also state that the catchment should be less than 1000 km². Given that the Jukskei River Catchment is 761 km², the catchment size is

satisfactory. It was hoped that all six flood events would be used but flow gauge data were only available for four of the events.

4.3. Case Studies

Each case is analysed separately. The duration of a flood event is defined as the time between when the discharge exceeded the threshold of $20\text{m}^3/\text{s}$ and subsequently returned to that threshold. The threshold is selected visually as it is much greater than any possible base flow value, and is therefore assumed to be a flow rate that is indicative of an extreme event within the catchment. In order to define an extreme rainfall event, a similar methodology is used with a threshold rain rate of 0.5 mm/h . The lag times and response times are presented in the results table. The lag time is the time between peak rainfall and peak discharge. The response time is the time from when the discharge begins to rise to the time of peak discharge.

4.3.1. Case 1: 2nd February 2009

This event caused flash flooding in Midrand north of Johannesburg (SAWS, 2010), the characteristics of the event are presented in **Figure 13** and **Table 11**.

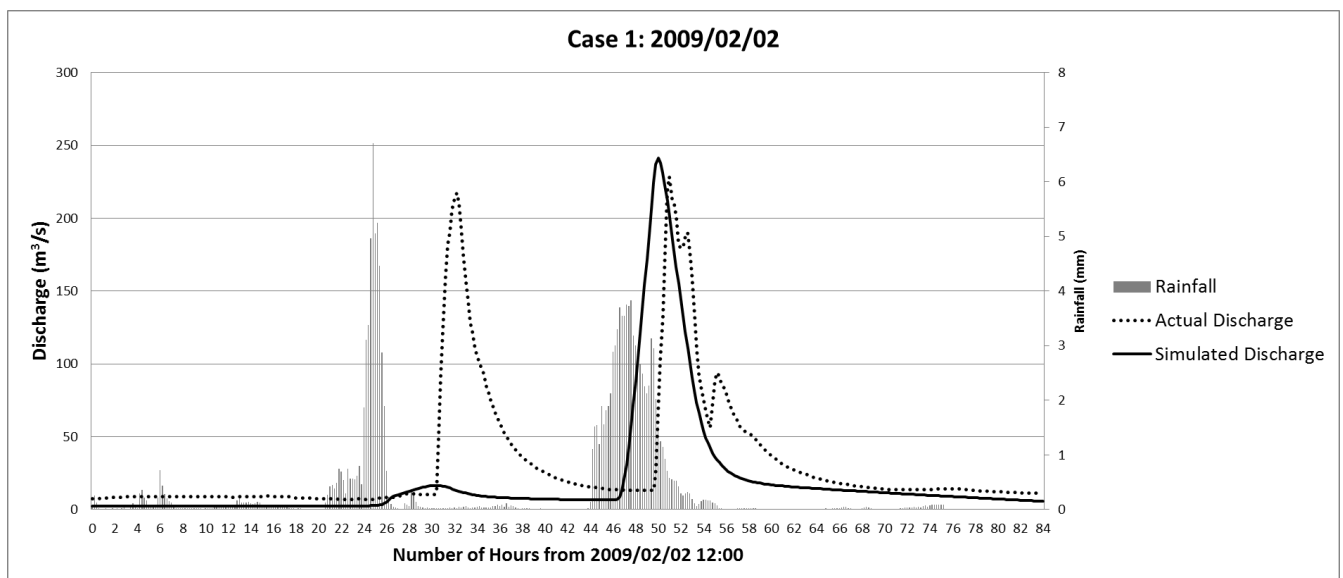


Figure 13: Hyetogram and Hydrograph of a flash flood that occurred on the 2nd of February 2009

Table 11: Hydrometeorological characteristics of a flash flood that occurred on the 2nd of February 2009 in the Jukskei river catchment

	Peak Rainfall (mm/h)	Duration of rainfall event(minutes)	Total rainfall (mm)	Duration of flood(minutes)	Peak discharge(m³/s)	Lag time(minutes)	Response time(minutes)
Case 1: 1st event	33.5	360	49.35	672	217.4	468	108
2nd event	18.5	564	84.64	900	222.2	216	84

Case 1 occurred on the 02/02/2009 and was a binomial event, with each node having an extremely sharp rising limb and therefore very short response times. The first peak with a peak discharge of 217.4 m³/s occurred 468 minutes after the first rainfall peak and 108 minutes after the streamflow began to rise. The peak rainfall rate was 33.5mm/h and a total of 49.35mm of rain fell in 360 minutes. The second peak with a peak discharge of 222.2 m³/s occurred 468 minutes after the second rainfall peak and 84 minutes after the streamflow began to rise. The peak rainfall rate was 18.5 mm/h and a total of 86.6 mm of rain fell in 564 minutes. In this case the hydrological model performed well in simulating the second event but not the first event.

4.3.2. Case 2: 10th February 2009

This was a major event and flooding occurred in multiple regions along the Jukskei including Johannesburg, Alexandra, Molofo South, Meadowlands, Klipspruit, Bramfischerville, and Dobsonville (SAWS, 2010). The events characteristics are presented in **Figure 14** and **Table 12**.

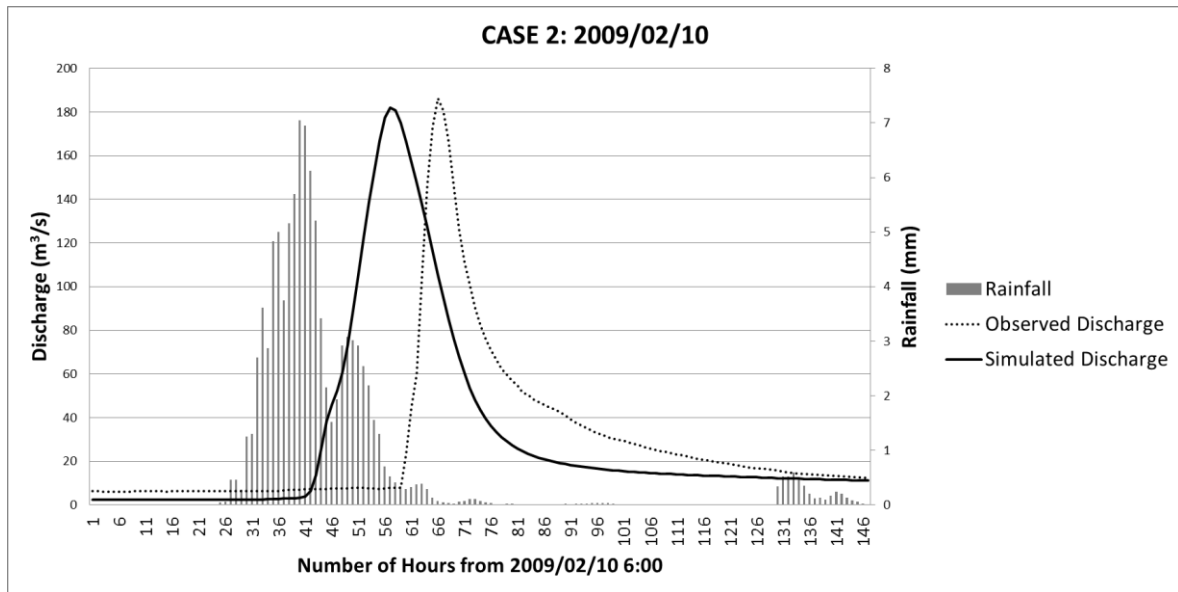


Figure 14: Hyetogram and Hydrograph of a flash flood that occurred on the 10th of February 2009

Table 12: Hydrometeorological characteristics of a flash flood that occurred on the 10th of February 2009 in the Jukskei river Catchment

	Peak Rainfall (mm/h)	Duration of rainfall event(minutes)	Total rainfall (mm)	Duration of flood(minutes)	Peak discharge(m ³ /s)	Lag time(minutes)	Response time(minutes)
Case 2:	35.25	468	95.09	696	180.78	324	84

Peak discharge of 180.78 m³/s occurred 324 minutes after the rainfall peak and 84 minutes after the streamflow began to rise. The peak rainfall rate was 35.25mm/h and a total of 95.09 mm of rain fell in 696 minutes. The hydrological model did well in predicting the peak discharge of the event but it inaccurately estimated the timing of the event.

4.3.3. Case 3: 29th January 2010

This event caused flooding at multiple points along the Jukskei river (SAWS, 2010), the characteristics of this event are presented in **Figure 15** and

Table 13.

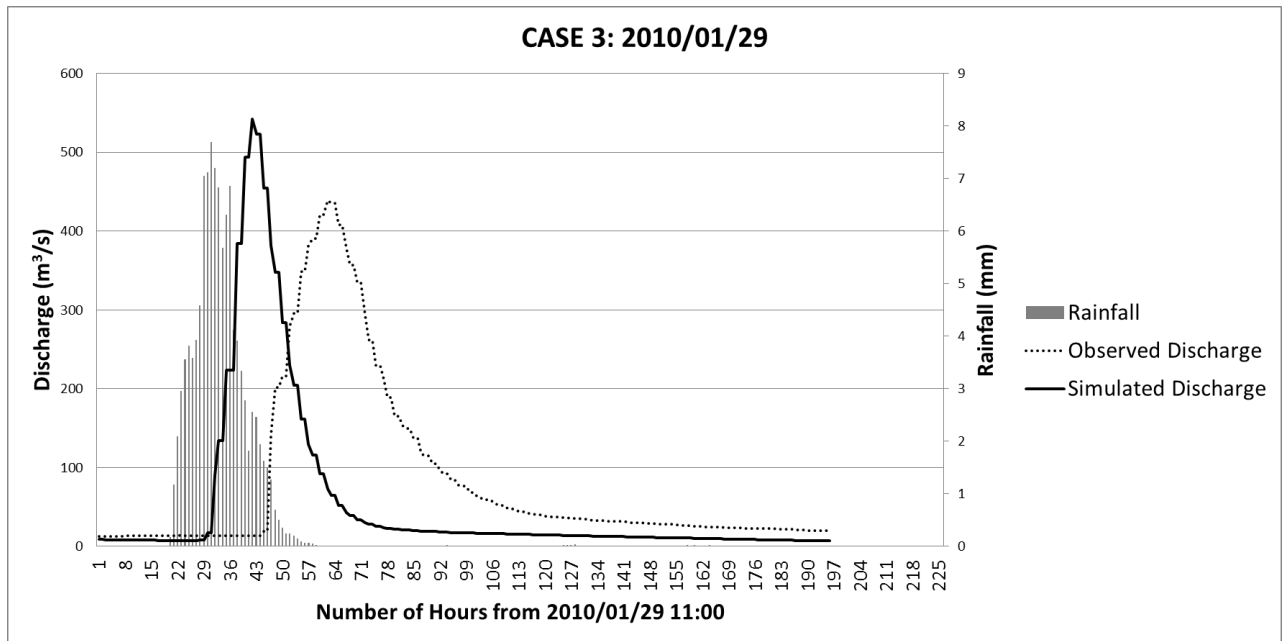


Figure 15: Hyetogram and Hydrograph of a flash flood that occurred on the 29th of January 2010

Table 13: Hydrometeorological characteristics of a flash flood that occurred on the 29th of January 2010 in the Jukskei river Catchment

	Peak Rainfall (mm/h)	Duration of rainfall event(minutes)	Total rainfall (mm)	Duration of flood(minutes)	Peak discharge(m ³ /s)	Lag time(minutes)	Response time(minutes)
Cas e 3:	35.5	420	110.41	1776	421	384	192

Peak discharge of 421 m³/s occurred 384 minutes after the rainfall peak and 192 minutes after the stream flow began to rise. The peak rainfall rate was 35.5mm/h and a total of 110.41mm of rain fell in 420 minutes. The hydrological model over predicted the peak discharge and under predicted the timing as well as the duration.

4.3.4. Case 4: 4th of February 2010

This event caused floods in Alexandra Township (SAWS, 2010), the characteristics of this event are presented in **Figure 16** and **Table 14**.

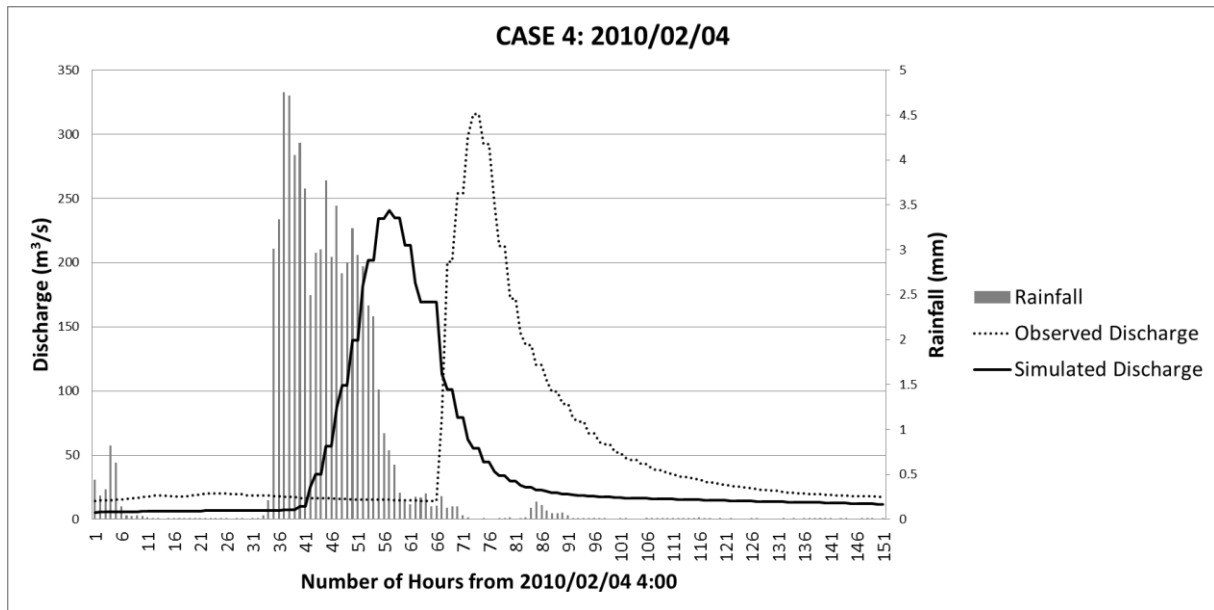


Figure 16: Hyetogram and Hydrograph of a flash flood that occurred on the 4th of February 2010

Table 14: Hydrometeorological characteristics of a flash flood that occurred on the 4th of February 2010 in the Jukskei river Catchment

Peak Rainfall (mm/h)	Duration of rainfall event(minutes)	Total rainfall (mm)	Duration of flood(minutes)	Peak discharge(m ³ /s)	Lag time(minutes)	Response time(minutes)
23.75	444	72.04	768	315	444	84

The peak with a discharge of 315 m³/s occurred 444 minutes after the rainfall peak and 84 minutes after the stream flow began to rise. The peak rainfall rate was 33.5mm/h and a total of 49.35mm of rain fell in 360 minutes. The hydrological model over predicted the peak discharge and as well as the timing and duration of the event.

5. Results

The results are divided into two sections. The first section presents statistical comparisons between the models and the observed data. The second section presents comparisons between simulated high flow events and observed high flow events. The full discharge hydrographs of all the simulations can be found in Appendix C.

5.1. Statistical Comparison

The four model simulations are statistically compared with actual streamflow on three levels; firstly on how well their individual time step values compare with actual values (t-test), secondly on how well their streamflow time series correlates with actual streamflow (Pearsons correlation coefficient), and thirdly on how much their values differ from actual streamflow (average difference). These results are presented in **Table 15**.

Table 15: Statistical comparison between simulated and actual discharge at the catchment outlet

	<i>MIkeSHE Raingauge</i>	<i>MikeSHE RADAR</i>	<i>NAM Raingauge</i>	<i>NAM RADAR</i>
r^2	0.467	0.456	0.26	0.325
<i>Mean Difference(m³/s)</i>	-0.827	-6.271	5.72	4.918

Furthermore the two distributed model runs are compared with each other in their ability to predict streamflow at a point along the Klein Jukskei, a tributary of the Jukskei (**Table 16**). The lumped model does not have this capability and is therefore excluded from the analysis. It is found that the raingauge performed better than the RADAR at this particular point.

Table 16: Statistical comparison between simulated and actual discharge at the Klein Jukskei

	<i>MIkeSHE Raingauge</i>	<i>MikeSHE RADAR</i>
r^2	0.432	0.429
<i>Mean Difference(m³/s)</i>	-0.058	-0.178

A hydrological model simulation is generally deemed successful when its correlation with streamflow exceeds $r^2=0.8$ (**Table 15**). None of the models in this study had a correlation greater than 0.467. Discussions around the reasons for the model failure are discussed in the limitations section.

The t-test which compares each corresponding value of two datasets to see whether they are significantly similar, showed that all of the simulations are significantly different from observed data and therefore the models fail to significantly predict actual discharge. When looking at the average difference between actual streamflow and simulated streamflow, it is clear that both the models initialised with raingauge data performed better than those initialised with RADAR data. This is especially true for the MikeSHE simulation with the average difference being only $0.827\text{m}^3/\text{s}$ from the observed discharge **Table 15**. Although the simulations are not significantly predictive of streamflow on a continuous basis, they might be useful in predicting high flow events. This is explored in the following section.

5.2. Simulating Abnormal Flow Events

Fifteen months of streamflow data are analysed for peaks. A difficulty faced in this study is how to define a high flow event. A baseline threshold of $10\text{m}^3/\text{s}$ is chosen to denote a ‘high flow event’ - this number is assumed as it significantly exceeds any possible baseflow and all events would therefore be a result of high rainfall within the catchment.

The four modelling techniques are compared in terms of their ability to predict high flow events measured at the catchment outlet. In total, 144 high flow events (events that peaks exceeded $10\text{m}^3/\text{s}$) are measured during the study period. NAM (RADAR) predicted the highest number (88 peaks), MikeSHE (RADAR) predicted 71 peaks and the raingauge models predicted the least [NAM (Raingauge) 49 peaks and MikeSHE (Raingauge) 40 peaks] (**Table 17**). All the models generally perform poorly, it is unclear if this is due to a problem with the models

themselves, their calibration or the data itself. The possible sources of uncertainty will be discussed further in the discussion section.

Table 17: Number of observed events predicted by the simulations

	<i>MikeSHE Raingauge</i>	<i>MikeSHE RADAR</i>	<i>NAM Raingauge</i>	<i>NAM RADAR</i>
<i>N=144</i>	40	71	49	88
<i>%</i>	27.7	49.3	34	61.1

The following results represent how the model simulations predicted these events in terms of peak discharge, peak timing, duration and volume. A cumulative distribution curve is used to show to what extent each model simulation differs from the observed data. The nearer the difference between the observed data and the modelled data is to zero for each event, the better the model performed. Therefore a steep rise and flat plateau in the cumulative distribution curve indicates that the model simulation is close to the observed data for the variable in question. A shallow rise in the cumulative distribution curve and a sharp plateau indicates the model performed badly.

5.2.1. Peak Discharge

Peak discharge is the maximum rate of discharge at the catchment outlet for a particular event. In examining the distribution functions for Peak Discharge, NAM (Raingauge) performed the best with 90% of the simulated events Peak Discharge falling within $133\text{m}^3/\text{s}$ of the observed Peak Discharge (**Figure 19**)., MikeSHE (Raingauge) also performed well with 90% of simulated events Peak Discharge falling within $460\text{m}^3/\text{s}$ of the observed Peak Discharge (**Figure 18**).

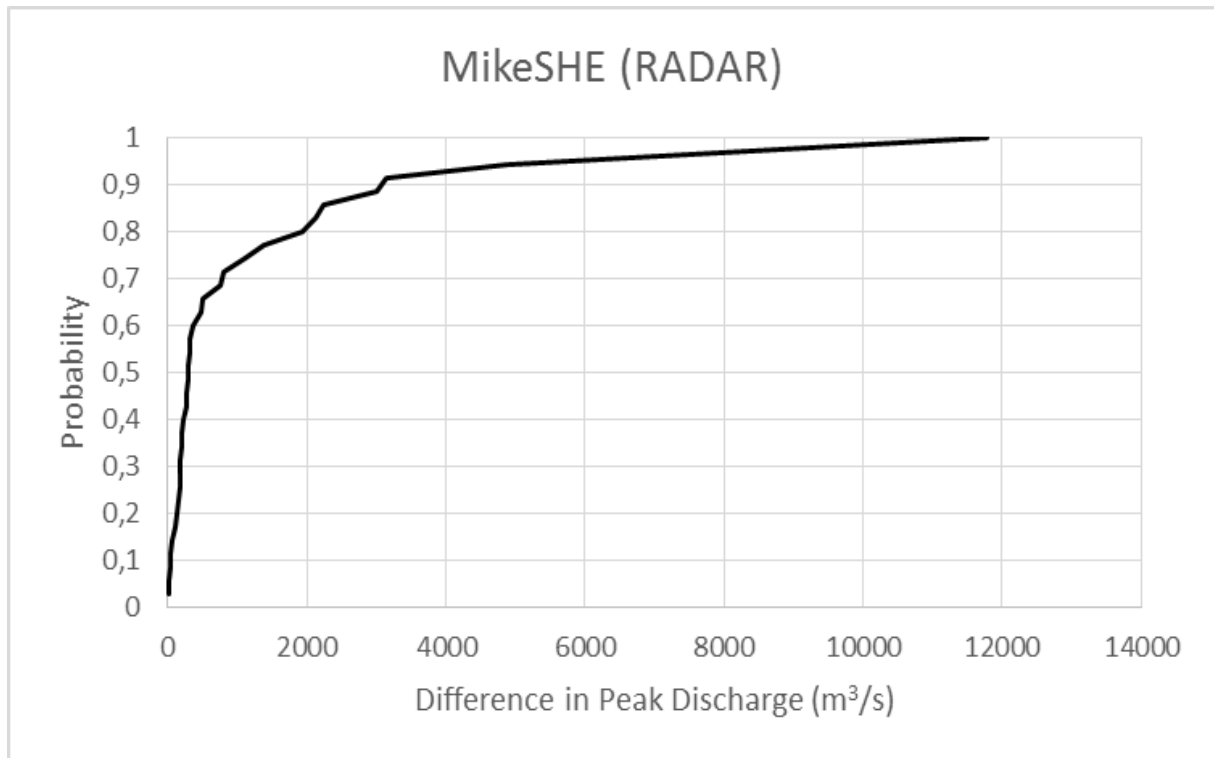


Figure 17: Cumulative Distribution Function of the difference in Peak Discharge between observed events and MikeSHE (RADAR) simulated events

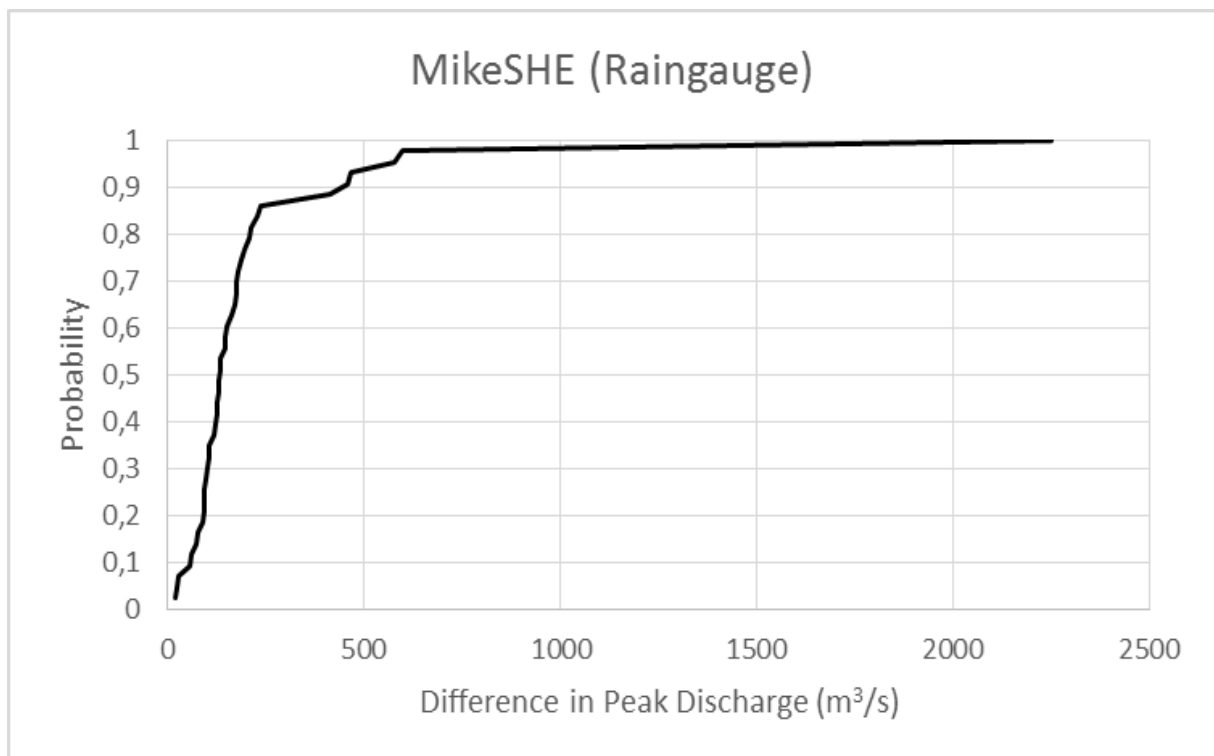


Figure 18: Cumulative Distribution Function of the difference in Peak Discharge between observed events and MikeSHE (Raingauge) simulated events

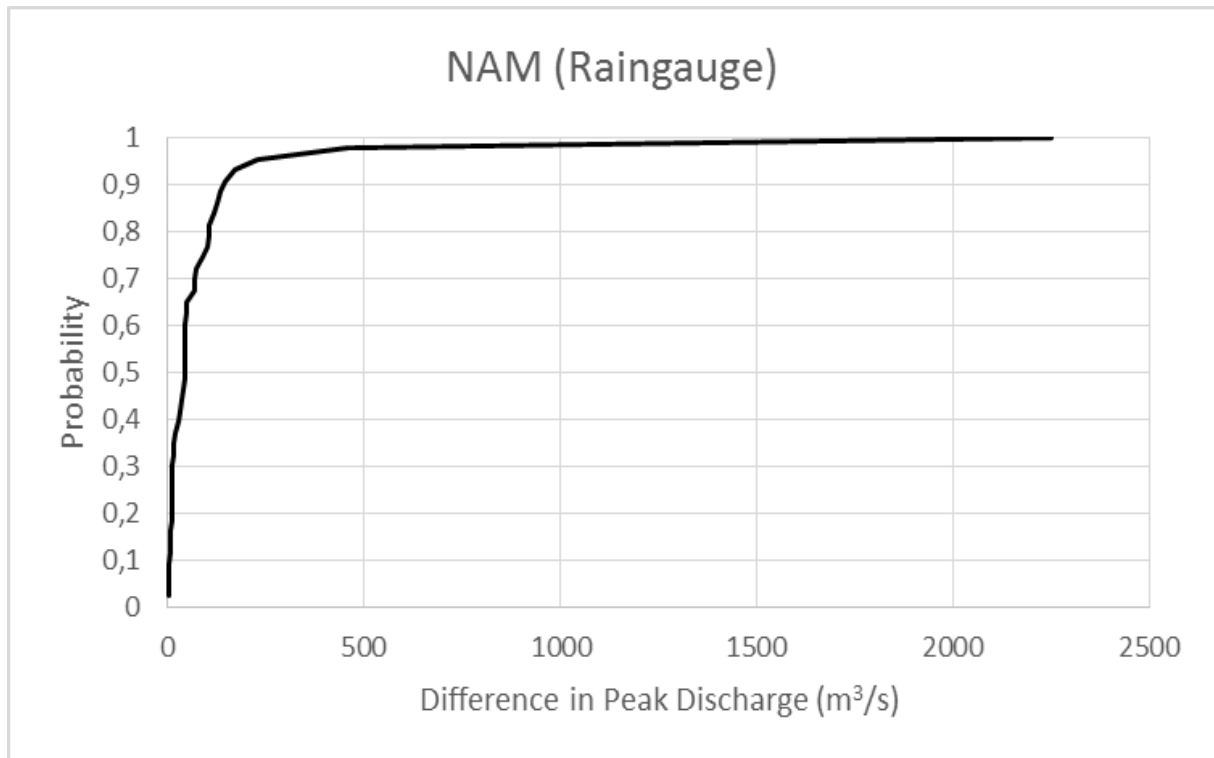


Figure 19: Cumulative Distribution Function of the difference in Peak Discharge between observed events and NAM (Raingauge) simulated events

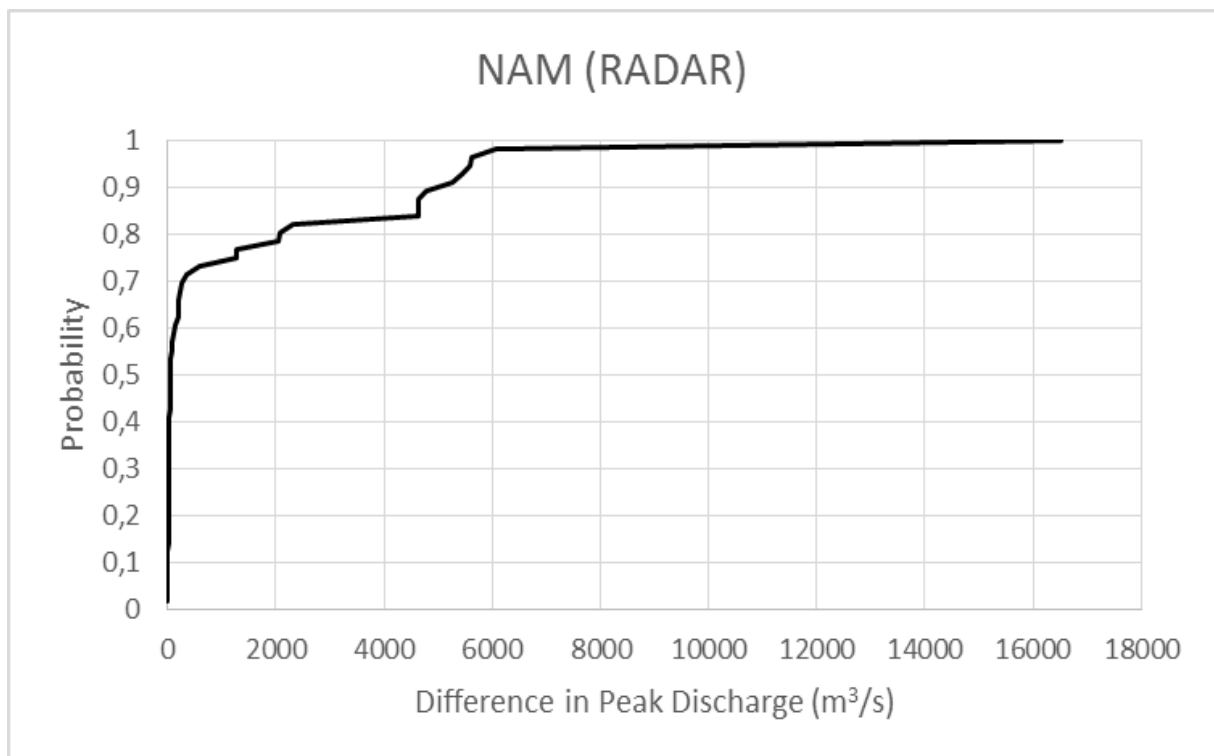


Figure 20: Cumulative Distribution Function of the difference in Peak Discharge between observed events and NAM (RADAR) simulated events

5.2.2. Peak Timing

In examining the distribution functions for peak timing, all models performed similarly in that they failed to predict the timing of events (**Figure 21, Figure 22, Figure 23** and **Figure 24**). However MikeSHE (RADAR) simulation performs the best out of the four simulations with 90% of the event peak timing predictions falling within 80 minutes of the observed values (**Figure 21**).

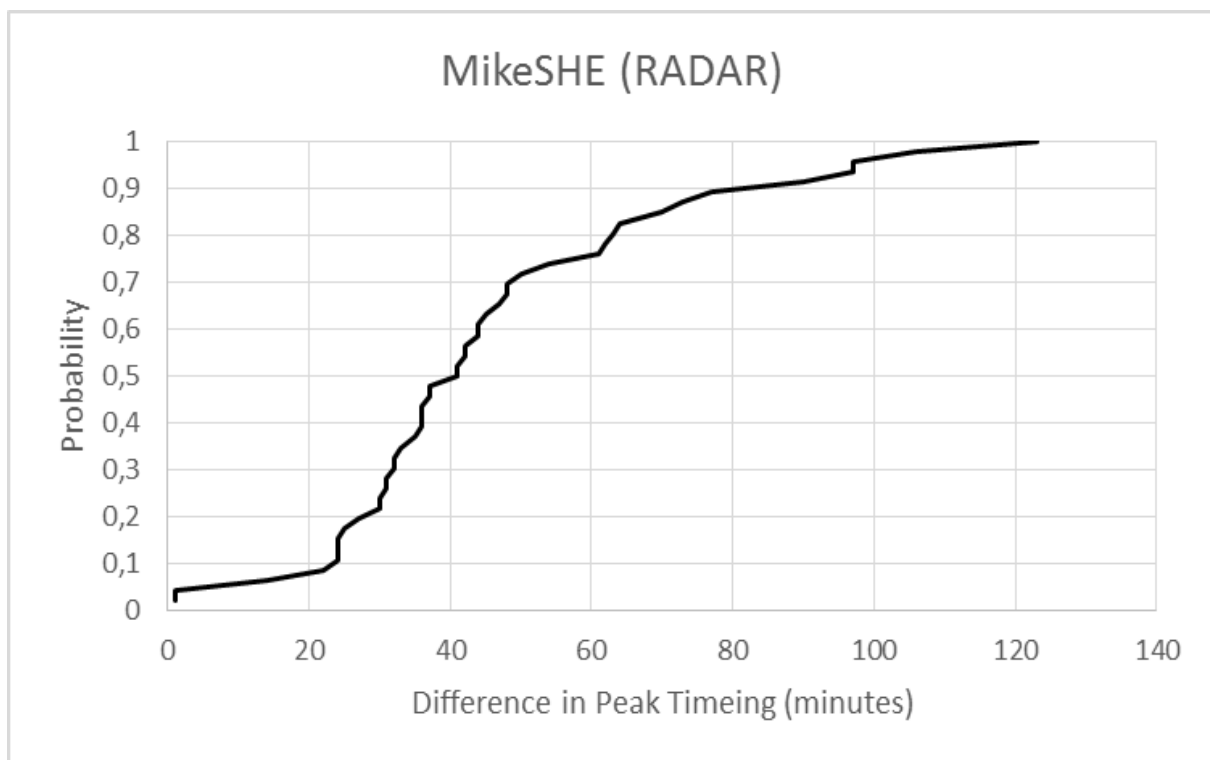


Figure 21: Cumulative Distribution Function of the difference in Peak Timing between observed events and MikeSHE (RADAR) simulated events

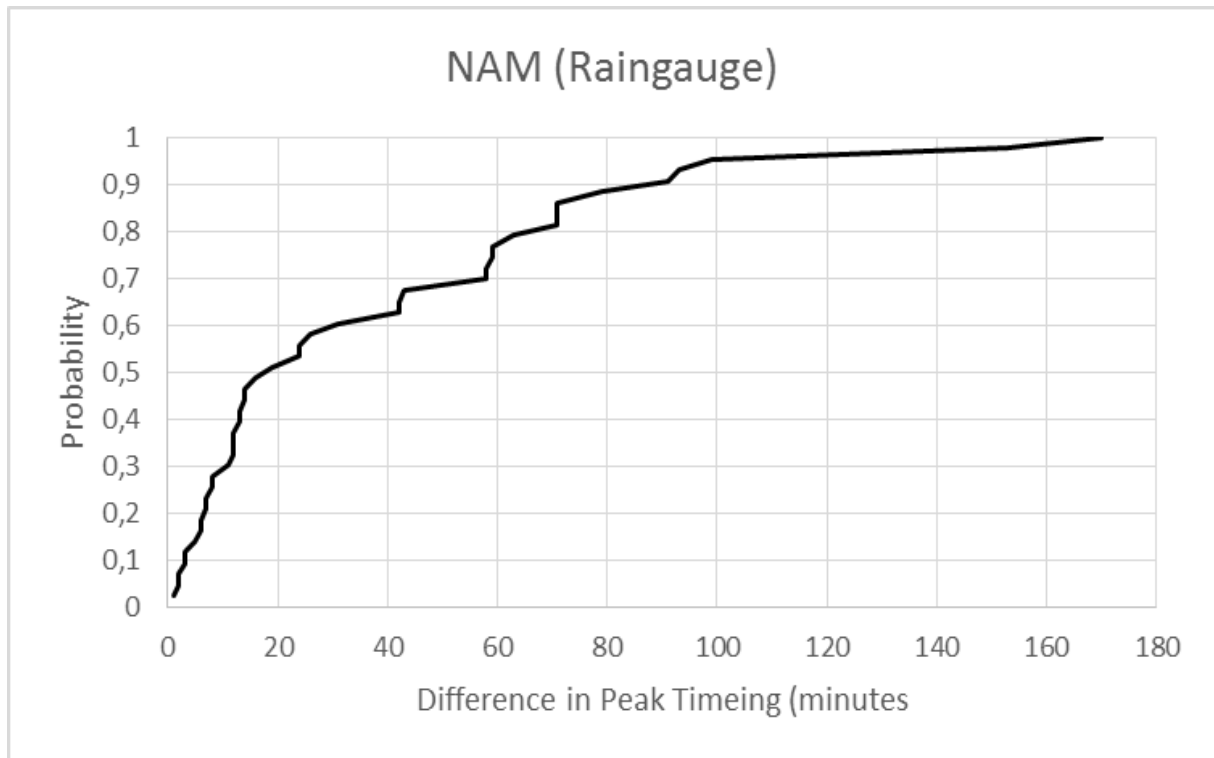


Figure 22: Cumulative Distribution Function of the difference in Peak Timing between observed events and NAM (Raingauge) simulated events

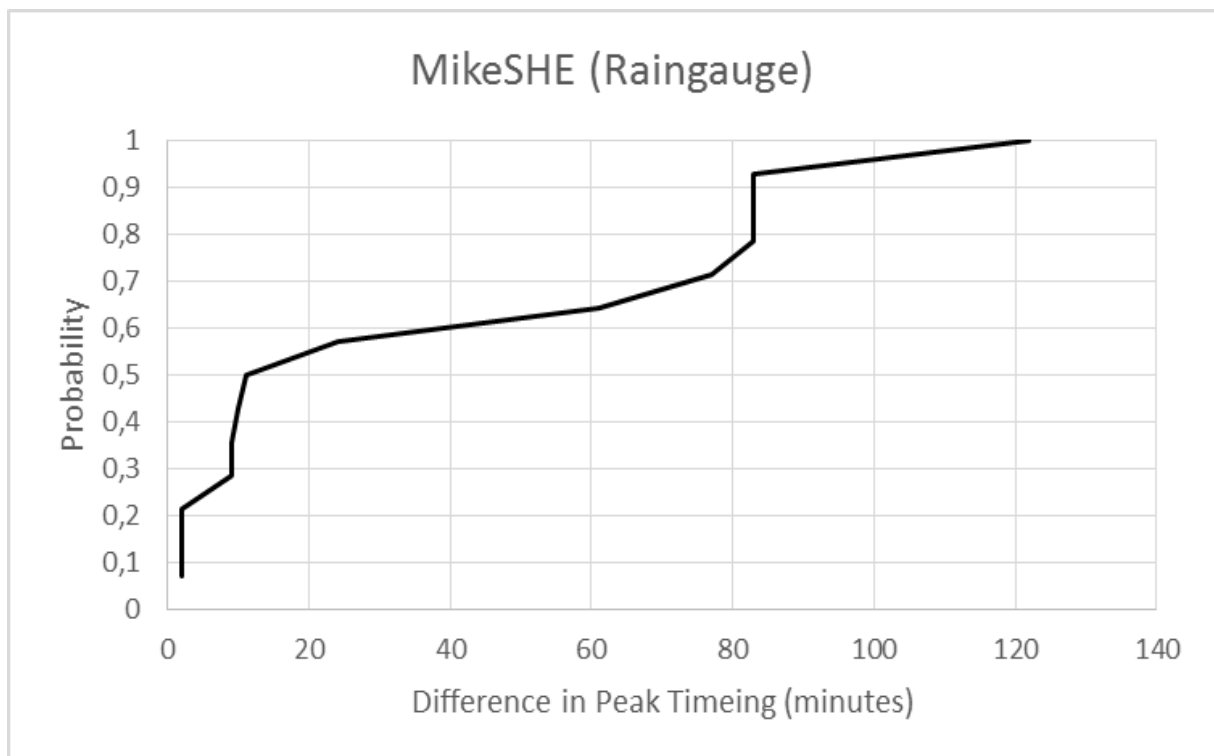


Figure 23: Cumulative Distribution Function of the difference in Peak Timing between observed events and MikeSHE (Raingauge) simulated events

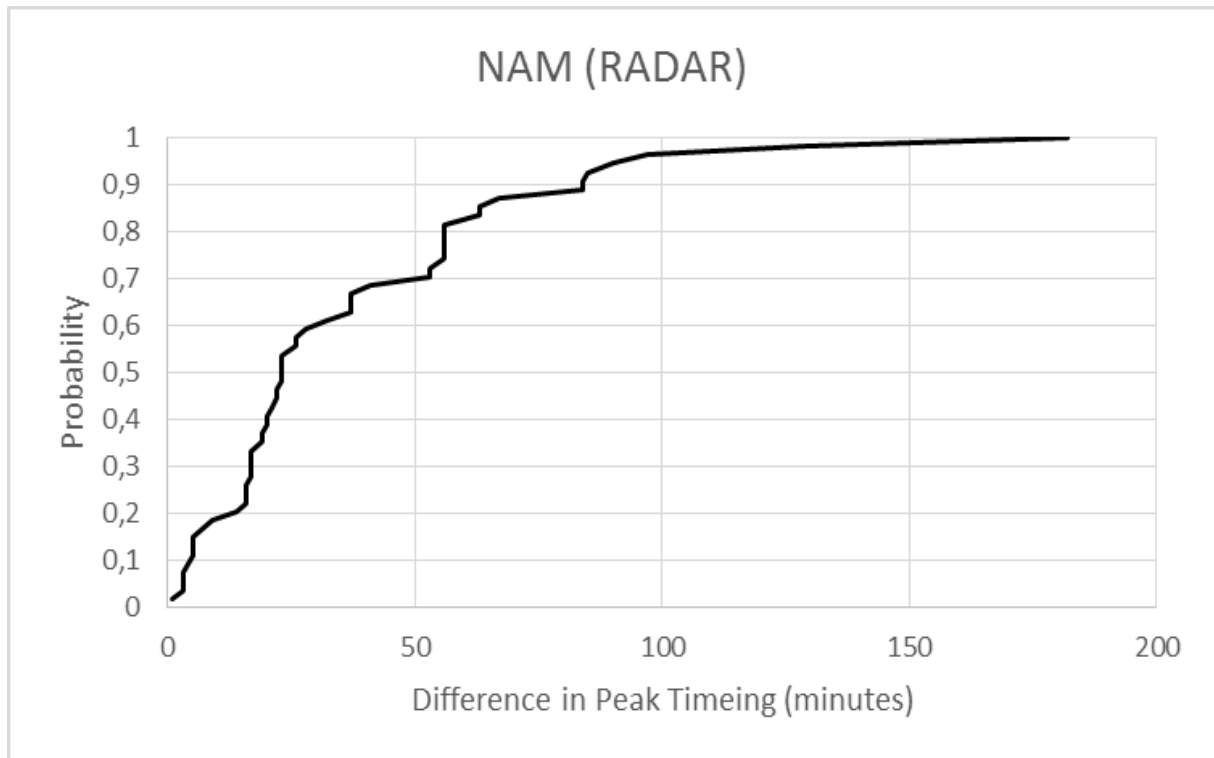


Figure 24: Cumulative Distribution Function of the difference in Peak Timing between observed events and NAM (RADAR) simulated events

5.2.3. Duration

In examining the distribution functions for Duration it is clear that NAM (Raingauge) performed the best in terms of duration prediction with 90% of simulated events falling within 140 minutes of the actual event duration (**Figure 27**). MikeSHE (Raingauge) also performed well with 90% of the simulated events falling within 500 minutes of the actual event duration (**Figure 28**). The other two simulations (**Figure 25** and **Figure 28**) did comparatively badly with most simulated event durations falling within 2000 minutes or more of the actual event durations.

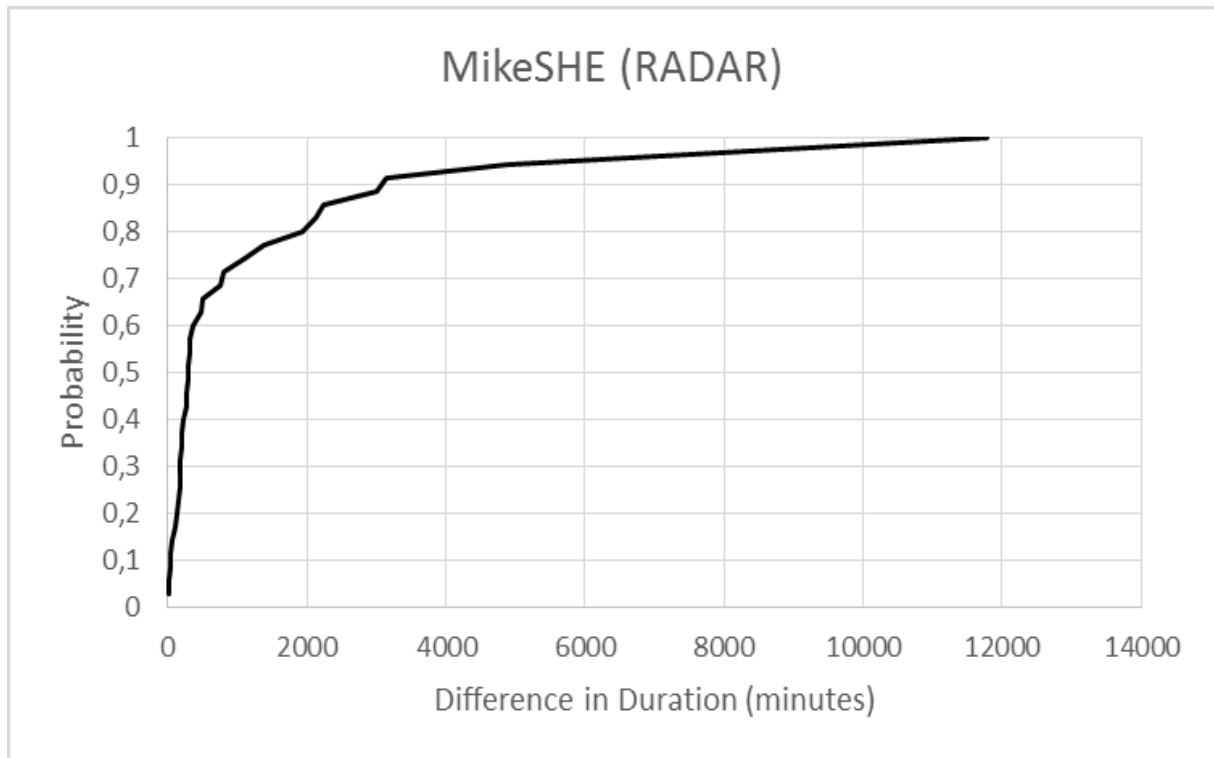


Figure 25: Cumulative Distribution Function of the difference in Duration between observed events and MikeSHE (RADAR) simulated events

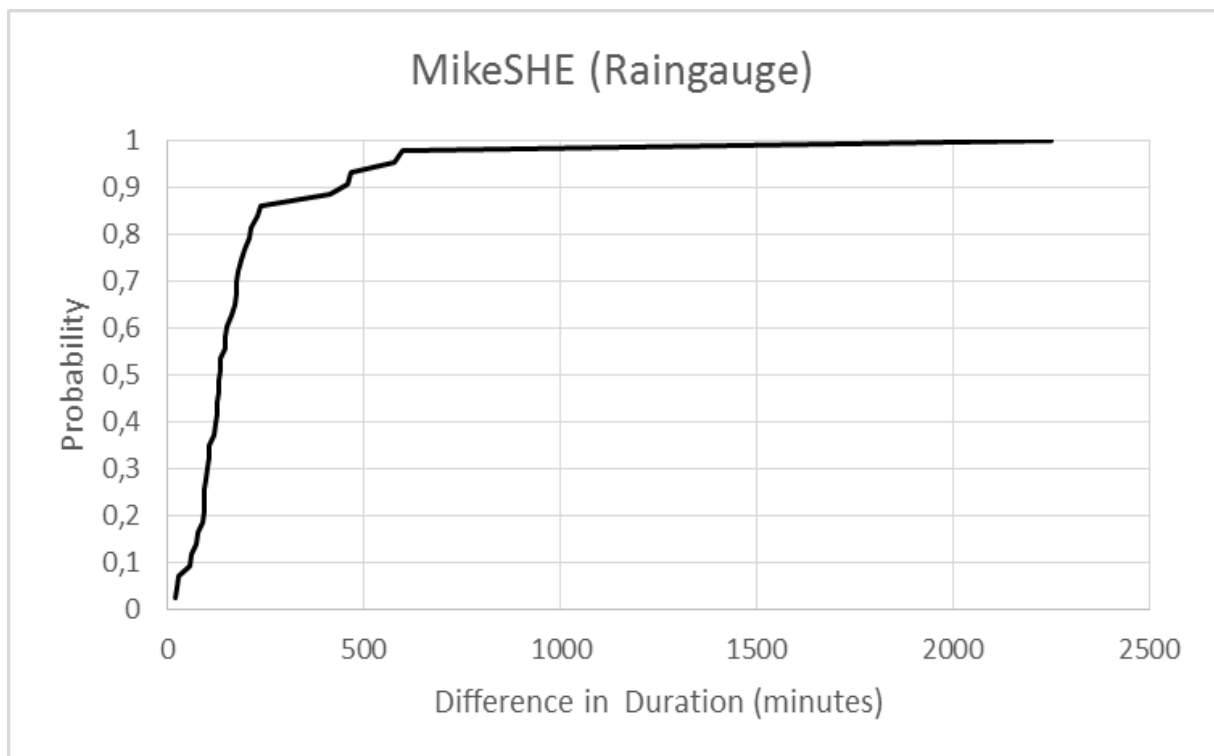


Figure 26: Cumulative Distribution Function of the difference in Duration between observed events and MikeSHE (Raingauge) simulated events

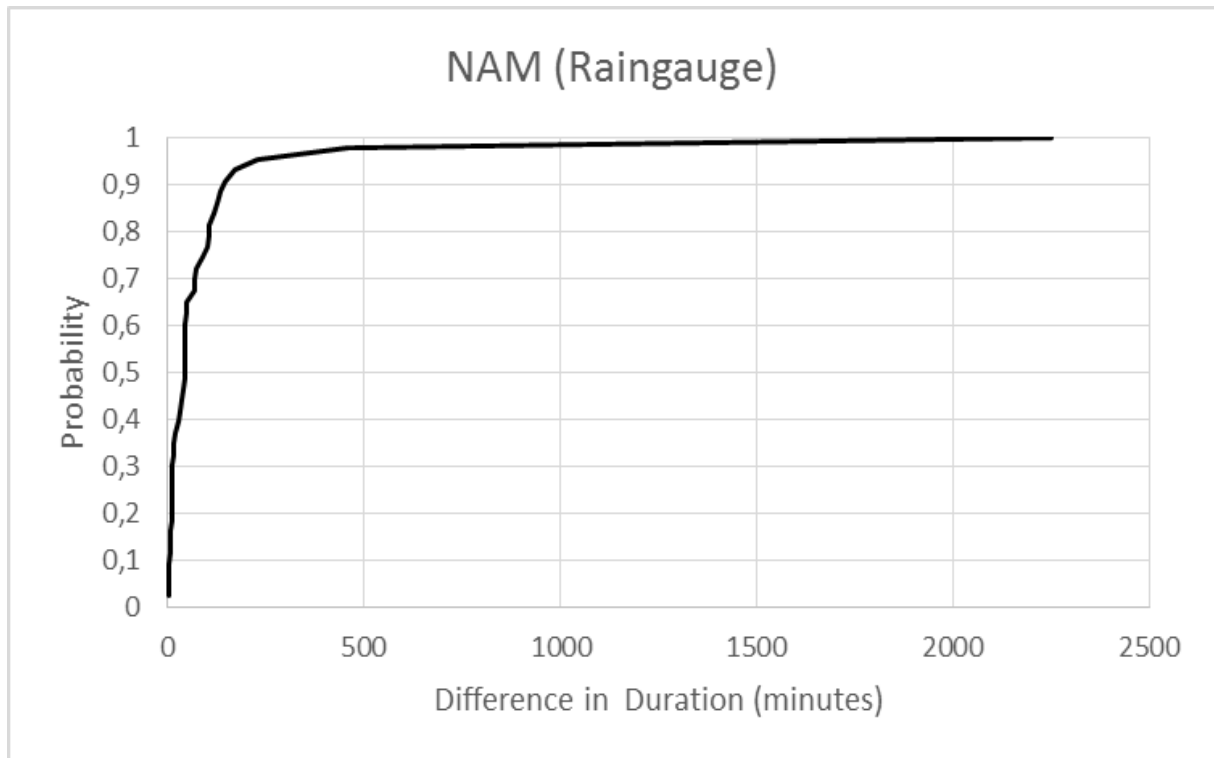


Figure 27: Cumulative Distribution Function of the difference in Duration between observed events and NAM (Raingauge) simulated events

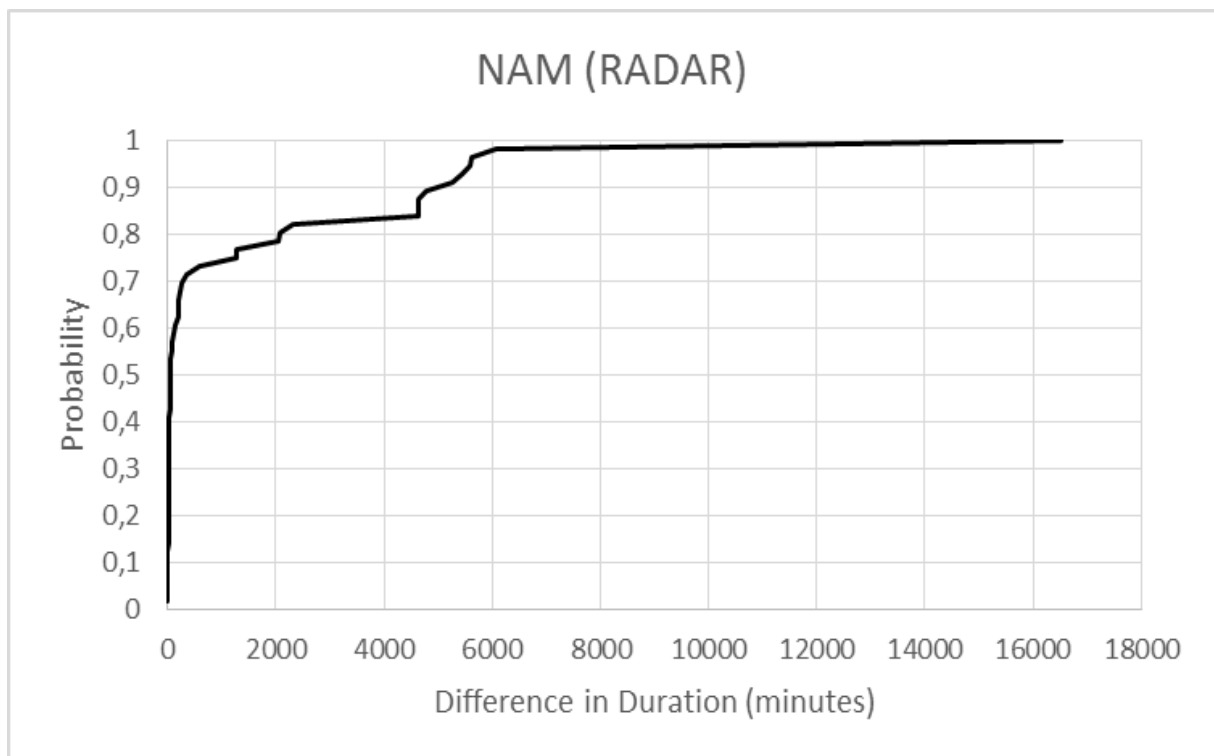


Figure 28: Cumulative Distribution Function of the difference in Duration between observed events and NAM (RADAR) simulated events

5.2.4. Volume

In examining the distribution functions for volume it is clear that NAM (RADAR) performs the best in terms of how close the simulated volume of events are to observed volume with over 90% of the predicted events falling within 10 000 m³ of actual volume (**Figure 32**). MikeSHE (RADAR) performed the worst as the difference between observed and simulated volume ranges greatly (between 0 and 250 000 m³) compared with the other simulations. NAM (Raingauge) (**Figure 31**) and MikeSHE (Raingauge) (**Figure 30**) performed similarly, both failing to significantly predict volume.

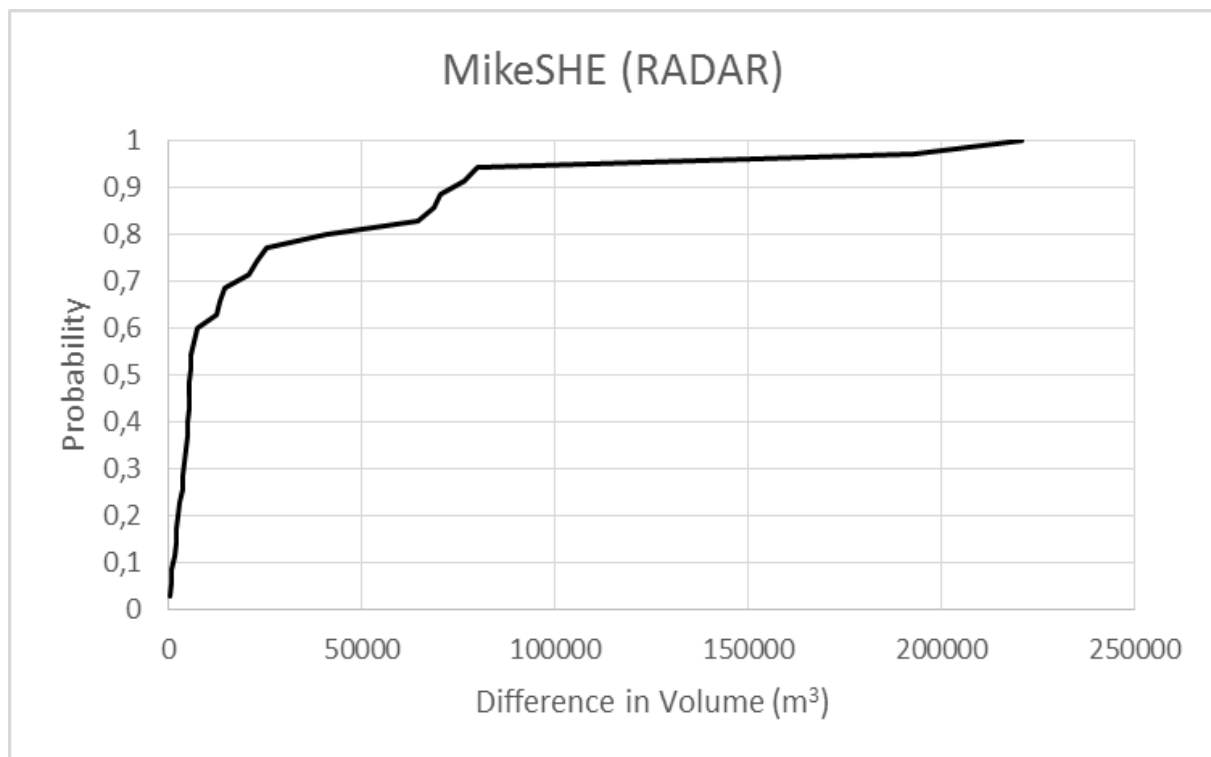


Figure 29: Cumulative Distribution Function of the difference in volume between observed events and MikeSHE (RADAR) simulated events

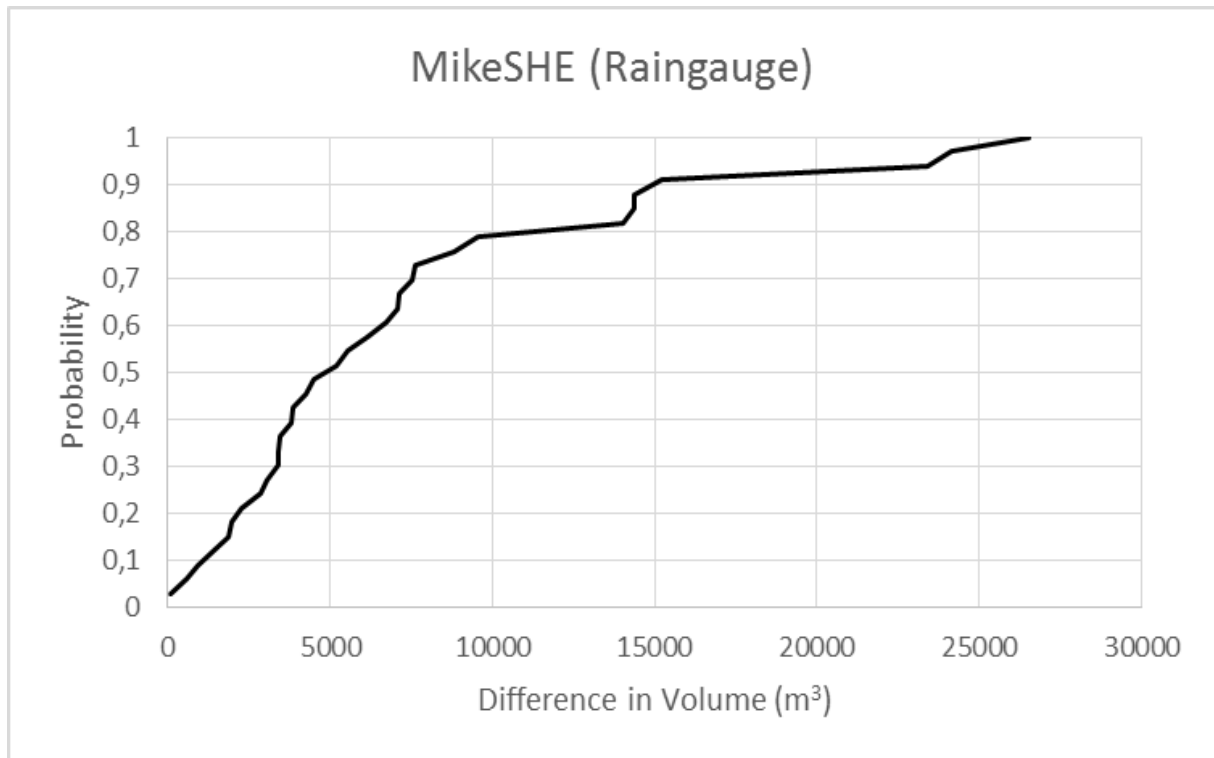


Figure 30: Cumulative Distribution Function of the difference in volume between observed events and MikeSHE (Raingauge) simulated events

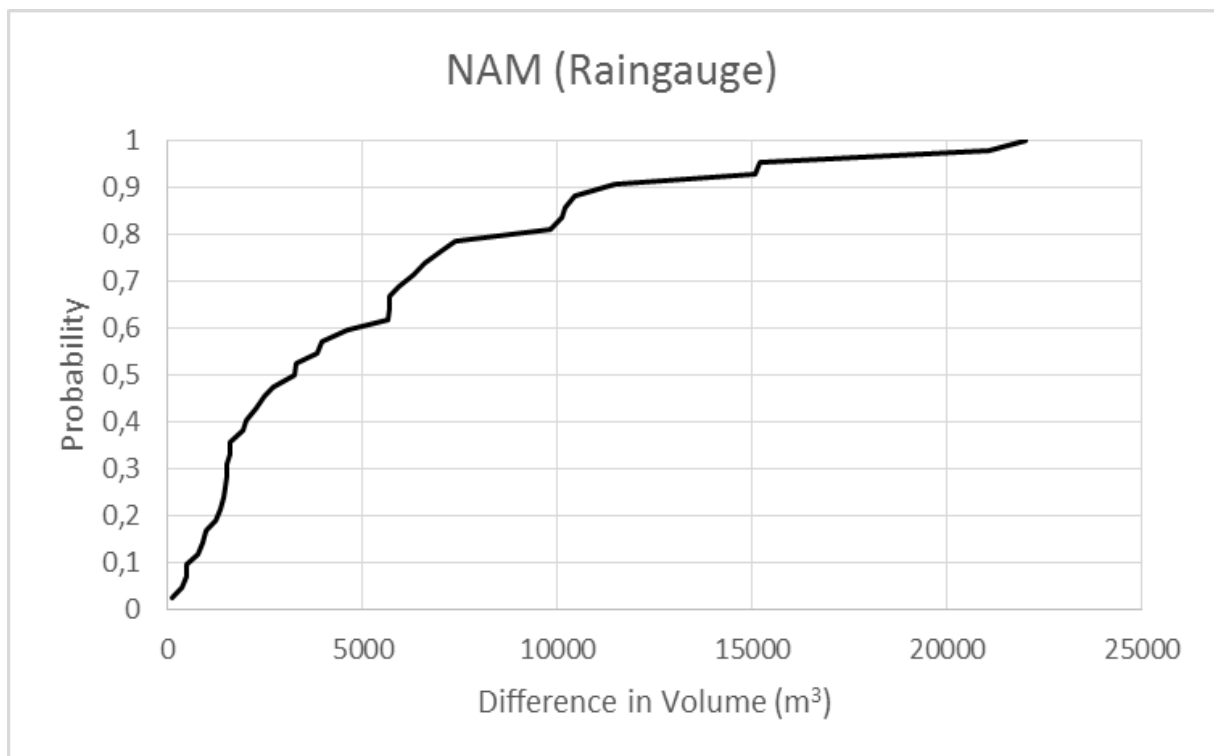


Figure 31: Cumulative Distribution Function of the difference in volume between observed events and NAM (Raingauge) simulated events

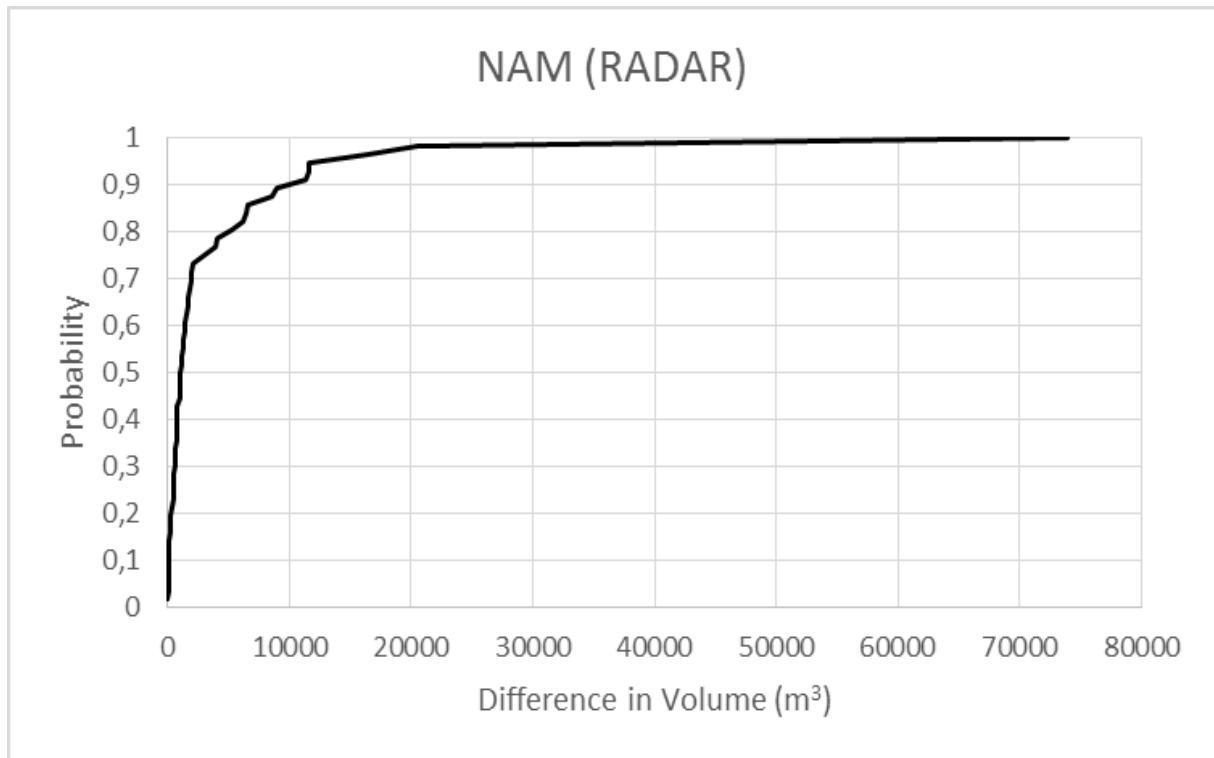


Figure 32: Cumulative Distribution Function of the difference in volume between observed events and NAM (RADAR) simulated events

6. Discussion

All the model simulations failed to simulate flash floods to a level that would be useful for use in a flash flood early warning system. There are multiple possible reasons as to why the models failed. Unfortunately, much difficulty arises in trying to locate the specific sources of uncertainty that lead to the failure of the models. In order to do this, multiple different model structures would need to be tested, similar to the methodology used in (Butts *et al.*, 2004). This would require a large amount of trial and error and therefore a large amount of time and resources. It therefore falls outside the scope of this study. It is however possible to speculate on the sources of error by focusing on the limitations of this specific study and how the simulations might have turned out if these limitations were reduced. This is looked at further in the limitations section.

Although the models failed, it is still useful to compare them in terms of how close the simulations are to observed values in terms of peak discharge, timing, duration and volume. This might shed light on which type of data and which model structures should be focused on in future research into flash flood prediction. A discussion around these comparisons is covered in the following section.

6.1.1. Model Comparisons

6.1.1.1. Peak Discharge

The ability for a model to predict peak correctly discharge is important for effective flash flood prediction in that it gives a good indication of the severity of a flood. Both models that are initialised with raingauge data perform better than models initialised with RADAR data terms of predicting events peak discharge. This suggests that the raingauge data is more representative of actual precipitation than the RADAR derived rainfall estimates when it comes to peak rainfall rates due to the same data being used in two different model structures. This is only suggestive and further testing would be required with the use of multiple model structures.

This does however indicate that possible errors exist in the RADAR data used which will be discussed further in the limitations section. The lumped NAM model performed the better of the two models initialised with raingauge data. This is surprising as it is expected that a more complex model such as MikeSHE would better be able to translate peak rainfall rates to peak discharge than a simple lumped model such as NAM. This suggests some biases in the MikeSHE model structure used, or errors in the parameter values selected. Again this is discussed further in the limitations section.

6.1.1.2. *Timing*

In order to obtain effective early warnings, a model needs to accurately predict the time a flood would likely occur. This would allow warnings issued to give adequate time for responsive action to take place. All the models perform exceptionally badly when it comes to predicting peak timing. This suggests an issue with how quickly the models route water overland and through the river channels. In other words it is suggestive of incorrect parameterisation for the parameters which control the extent of surface roughness, namely the Manning number in MikeSHE and the overland runoff co-efficient in NAM. Issues with parameterisation are a major limitation in this study and are discussed further in the limitations section.

6.1.1.3. *Duration*

Knowing the duration of an event is important for mobilising emergency services as well as issuing warnings. Both models that are initialised with raingauge data perform better than models initialised with RADAR data terms of predicting event duration. This suggests that the raingauge data is more representative of actual event duration than the RADAR derived rainfall estimates when it comes to peak rainfall rates due to the same data being used in two different model structures. This is, as with peak discharge, only suggestive and further testing would be required with the use of multiple model structures.

6.1.1.4. Volume

Knowing the volume of an event is important for predicting the extent of a flash flood. Again, the better performance of raingauge data than RADAR for estimating volume is rather unexpected due to the localised nature of the raingauge data. This is again most likely a result of bias in the RADAR precipitation estimates.

6.1.2. Limitations

A major theme that has emerged from this study is its limitations around model uncertainty. As discussed in section 1.4.4, there are three main sources of error or uncertainty in hydrological models. Firstly, those which occur from random or systematic errors in the input data or data used to calibrate the models. Secondly, from uncertainties associated with non-optimal parameter values. Thirdly, from uncertainties associated with incomplete/biased model structures (Baldassarre and Montanari, 2009). This section looks at how these sources of error might contribute to uncertainties associated with model simulations in this study.

6.1.2.1. Data Limitations

The contribution that hydrological models can make to the understanding of flash floods is limited by the quality of data that feeds them. This is especially true as hydrological models grow in complexity but the data availability remains low. Data scarcity for hydrological applications is a major problem in South Africa (Hughes, 2001). This section looks at the input data used in this study and how possible errors in that data might have impacted the accuracy of the hydrological models.

The Department of Water Affairs does have gauging stations positioned along multiple river reaches in South Africa that measure discharge and water level, but their number is far from adequate for calibration and validation of hydrological models. On top of this, many of the

gauging stations are not functioning due to a lack of maintenance. For example, the study catchment has four gauging stations (A2H023, A2H040, A2H042, A2H043, A2H047) with only two functioning (A2H023, A2H047). The functioning gauges are in different river reaches and are relatively far apart. The ideal scenario is that there is at least two gauges sufficiently close to one another in order to help verify the data. The lack of multiple river gauges means that the data used to calibrate and validate the models in this study are highly reliant on only one gauge measuring catchment discharge. It is therefore difficult to locate both systematic and random errors in the data. This is a major limitation but for the purposes of this study it is assumed that the river flow data is sufficiently representative of actual discharge.

The use of raingauge data for hydrological modelling can be highly problematic (Sene, 2012). This is due to problems associated with data measurement, such as obstructions or lack of maintenance, as well as inaccuracies associated with spatial variability in rainfall. It is therefore ideal to have a large network of raingauges in order to be able to locate systematic and random errors in the data as well as to get an adequate representation of the spatial variability of rainfall within a catchment. For this study, data is only available for one raingauge within the catchment over the study period. The lack of spatially variable estimates are highly problematic in this study in particular as raingauge estimates were used to provide an average precipitation estimate for the entire catchment. The simulations that used raingauge data alone failed to predict flash flood event in terms of timing, peak discharge, total volume and duration. This might be the result of averaging the raingauge data over the entire catchment when the precipitation event is more localised in nature. This emphasises the point made by Sene (2012) that uncertainties associated with raingauge data are often spatial in nature. However, it is difficult to say whether these inaccuracies were a result errors in the raingauge data or with uncertainties in the model setup itself.

As mentioned in section 1.3.3.2, RADAR precipitation data is subject to a myriad of uncertainties. These can range from variations in the rain drop reflectivity profiles and ground clutter to the use of the incorrect z-r factor. The models initialised with RADAR data perform worse in most cases than those initialised with raingauge data. This is suggestive of major errors in the data itself. The most likely obvious error in the data is ground clutter. As is evident in **Figure 33**, there are definite zones of high reflectivity even when there are no storms occurring. The area circled in red is where Johannesburg city is located and therefore suggests that the RADAR is picking up buildings within the city. Locating and correcting for ground clutter is a long and difficult process and falls outside the scope of this study. It is however strongly recommended that it is considered in future studies.

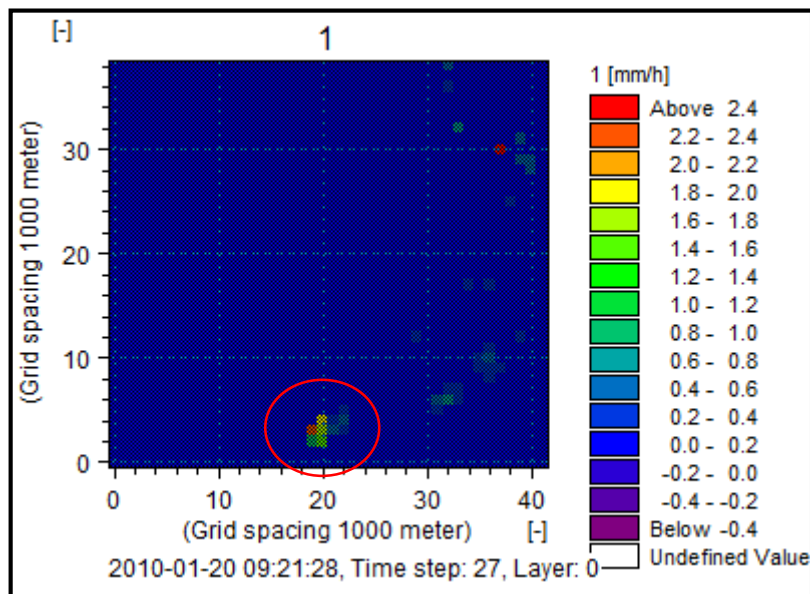


Figure 33: RADAR derived precipitation grid depicting ground clutter during a period of no actual precipitation (ground clutter circled in red).

6.1.2.2. Limitations associated with parameter values

Due to the lack of sufficient input data, both models in this study rely heavily on calibration parameters as a way to get the models to adequately simulate actual discharge. The setting of parameter values to calibrate the models is essentially a trial and error process and is therefore open to much uncertainty. The subjective component of deciding on parameter values often

results in different modellers using different parameter values. It is argued by Beven (2012) that a model simulation that does not significantly agree with the observed data should be viewed with much caution and puts the reliability of the models into question. This is because the model might be over correcting for errors in the input data by over parameterisation. This is highly evident in this study, in particular the NAM model calibration parameters, as it is clear in section 3.3.1.3 that the parameter values are very different from the default parameter values. As mentioned in section 3.3.1.3 this might be due to the urban nature of the catchment, however it is unlikely that the study catchment conditions are so far removed from the default parameters set by the model developers. This suggests over parameterisation of calibration parameters to correct for errors in the input data.

6.1.2.3. Model Structure Limitations

Structural uncertainties are often very difficult to separate from uncertainties associated with parameter and input data uncertainties (Kirchner, 2006). There are two ways in which model structure can be assessed for “correctness”. The first way is to use an expert’s opinion but this is often subject to bias on the part of the expert. The second way is to test the model under multiple circumstances as is done by Butts *et al* (2004). The second method does help but does not eradicate the difficulties in differentiating structural uncertainties from data or parameter uncertainties. The ideal scenario is that multiple model structures are tested in order to try and find the structure most suitable to the application. Only two model structures are used in this study and is therefore a major limitation. Further research would be required to find the most appropriate model structures for flash flood applications in South Africa.

Choice of model structure also relies heavily on data availability. For example in this study, evapotranspiration data was not available therefore the evaporation module is excluded from the MikeSHE setup. This creates room for error as Net Rainfall Fraction is used as a calibration parameter rather than taken from real world data.

7. Conclusions

The conclusions are organized into four sections, the first three attempt to answer their corresponding objective while the fourth suggests angles for further research into modelling flash floods in South Africa.

1. What are the characteristics of flash floods in the study catchment?

From the case studies, it is evident that flash floods in the catchment cannot be characterised by one particular variable, but rather, that multiple factors influence whether a flash flood will occur.

The events response time varied between 84 and 192 minutes, this means there is little time between when a flash flood is detected upstream and the time it reaches the end of the catchment. This makes flash floods in the catchment somewhat dangerous, and little warning can be given to people in the downstream path of the flood. A contributing factor to the fast response time are hard urban surfaces, such as roads and pavements, as they increase runoff and channelization of streamflow (Looper and Vieux, 2011).

The peak rainfall rate for the flood events ranged between 18.5mm/h and 35.5mm/h. The duration of rainfall events ranged between 360 minutes and 564 minutes. This suggests that in order for flash flooding to occur in the catchment, the duration of a rainfall event should exceed a threshold of about 6 hours. Total rainfall per event ranged between 49.35mm and 110.41mm.

The total duration of the case study events ranged between 672 minutes and 1776 minutes. The peak discharge of the events ranged between 180 and 421 m³/s. The lag time between when the RADAR identified peak rainfall and the time the river gauge recorded peak discharge ranged between 216 and 468 minutes.

2. How do distributed and lumped hydrological models initialised with RADAR or raingauge data compare in terms of their ability to predict flash floods?

All the model runs failed to correlate significantly with streamflow. The models also failed to significantly predict streamflow when using the pair sampled t-test. This highlights the difficulty in using rainfall estimates and hydrological models for discharge prediction.

The models fared a little better when predicting high flow events. Of the 144 high flow events measured during the study period, lumped hydrological model initialised with RADAR data predicted the most events, with 88 (61%) of the events, all the other model runs predicted less than 50% of events. Of the events that were simulated, the models initialised with raingauge data are the most accurate when predicting peak discharge. The lumped model initialised with raingauge data is the most accurate when predicting peak timing, duration as well as volume.

Although it is expected that the more advanced distributed model would fare better when predicting the variables associated with the high flow events, it was only marginally better when simulating event timing only. The lumped model fared better when correlating with stream flow, number of high flow events, peaks, as well as total duration and volume.

Another unexpected result was that raingauge derived precipitation estimates fared better in most cases to the RADAR derived estimates. This suggests errors in the RADAR data

The distributed model did allow for measurements to be taken at various points within the study catchment, which is a capability the lumped model does not have. The correlation with flow at the chosen internal gauge was, however, less than 50% for both raingauge and RADAR data.

3. How does the current operational flash flood warning system in South Africa apply in the context of this study?

The results of this study show that a lumped model is preferable in areas where spatial data are patchy or scarce, such as is the case in South Africa. The South African Flash Flood Guidance System currently uses a lumped hydrological model which is shown to be suitable in a South African context. The SAFFGS also uses multiple data sources for precipitation estimation when they are available (satellite, RADAR and raingauge). This is also shown in this study to be the most suitable technique for rainfall estimation due to the multitude of uncertainties associated with remotely sensed data.

The lumped nature of the model used in the SAFFGS makes it impossible to know the discharge and water levels at a specific point within catchment basins. It is suggested that a distributed hydrological model be used in conjunction with the current model in order to better pinpoint the location of flash floods within a catchment. However, it is not practical to run a distributed model in real time due to the high computing requirements. It is therefore suggested that a distributed model such as MikeSHE be run on a catchment specific basis when a basin is showing signs that flooding will occur. This could better help direct future emergency responses.

4. Further research

As discussed in the limitations section, there are a myriad of uncertainties associated with the simulations in this study. It is suggested that further research be conducted with the aim of quantifying the uncertainties arising from errors in data, errors in parameterisation and biases in model structure. This would require the testing of multiple datasets on multiple model structures and in multiple catchments in order to better predict flash floods in South Africa.

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Appendix A: MikeSHE Setup

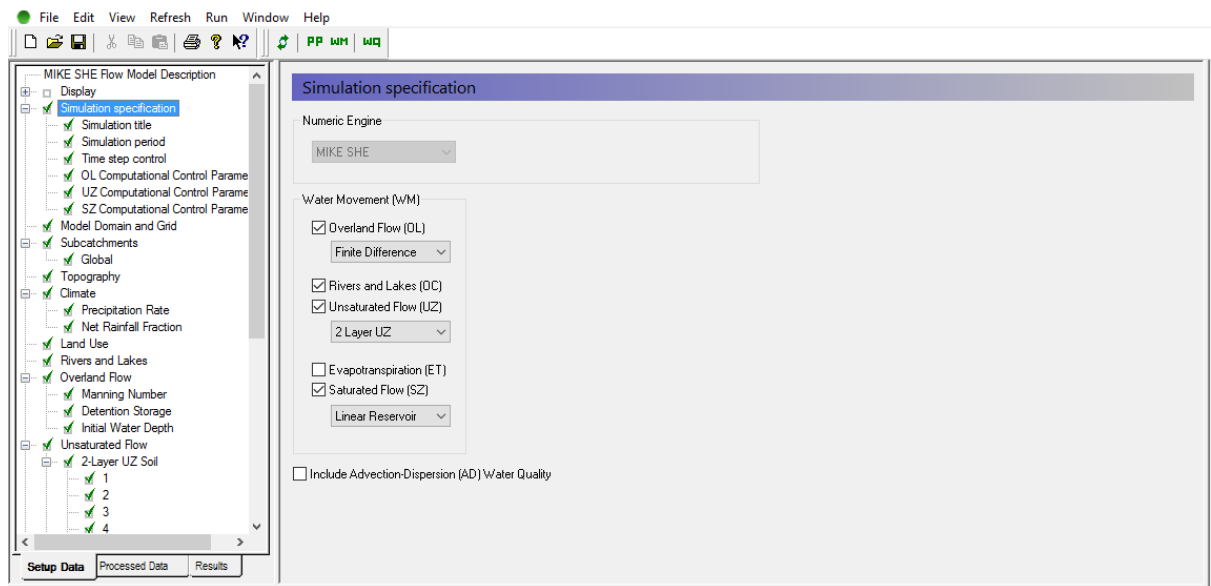


Figure 34: Simulation Specification

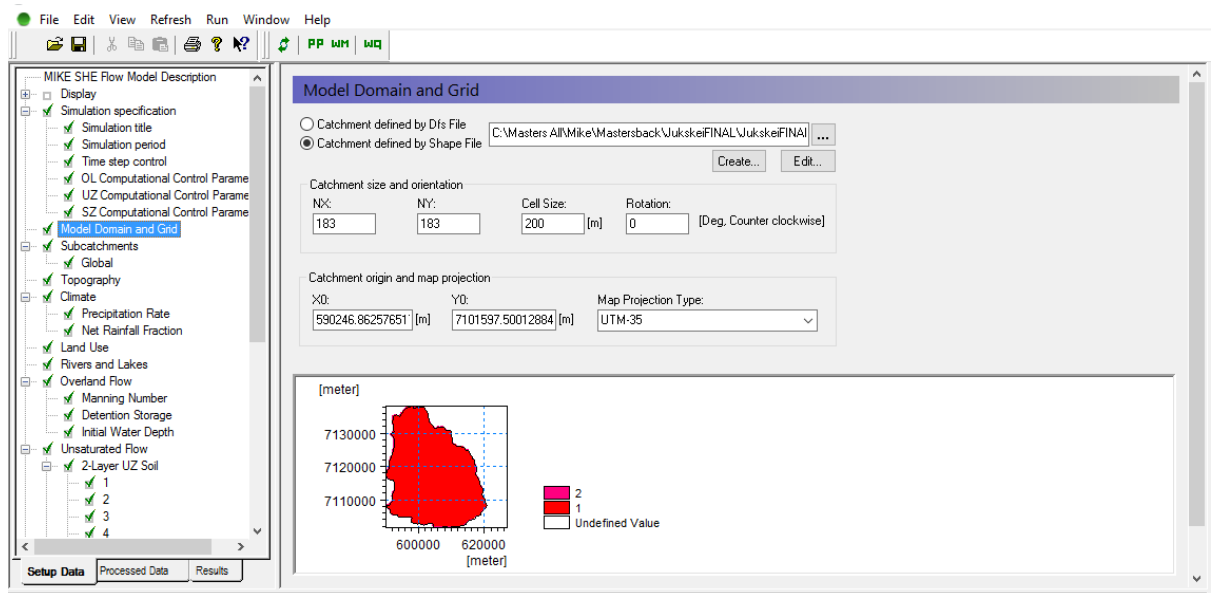


Figure 35: Model Domain and Grid

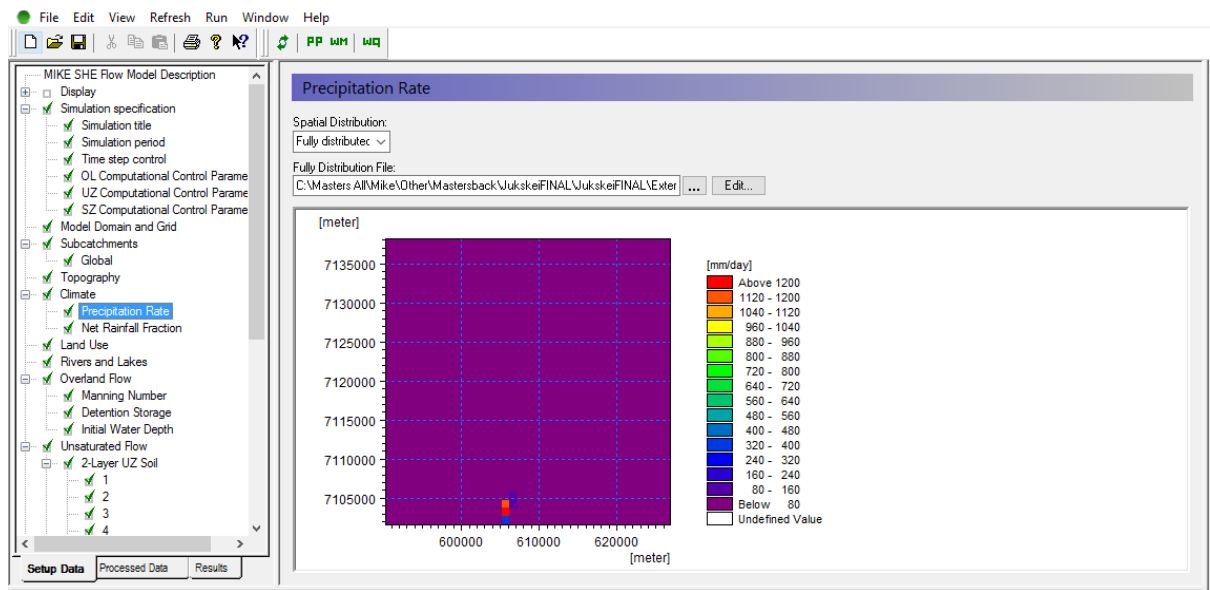


Figure 36: Precipitation Rate

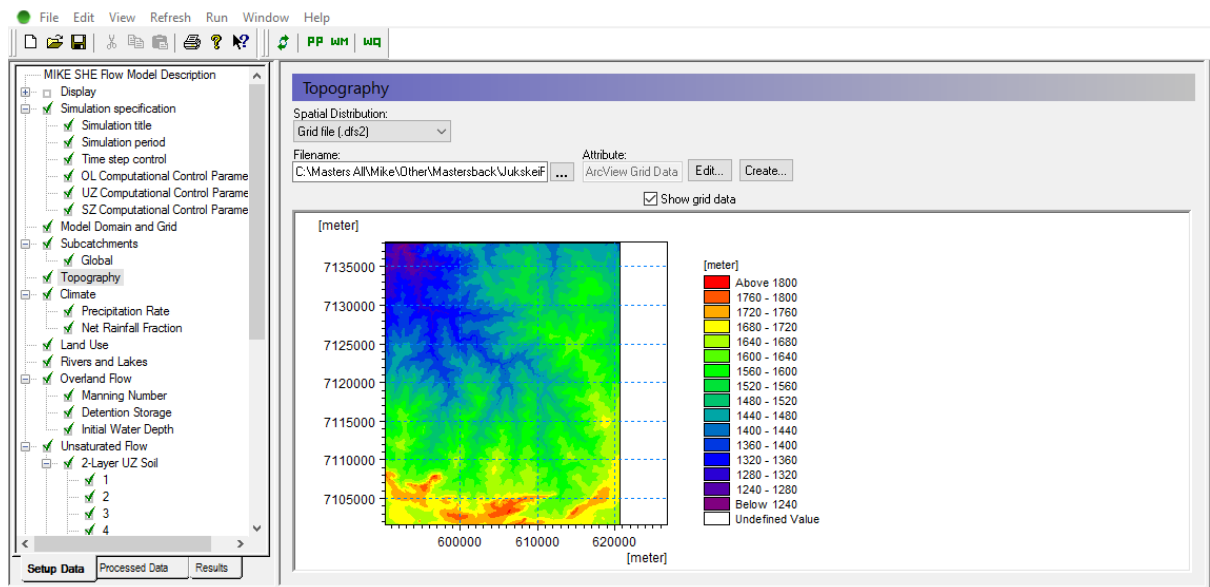


Figure 37: Topography

Appendix B: Mike11 Setup

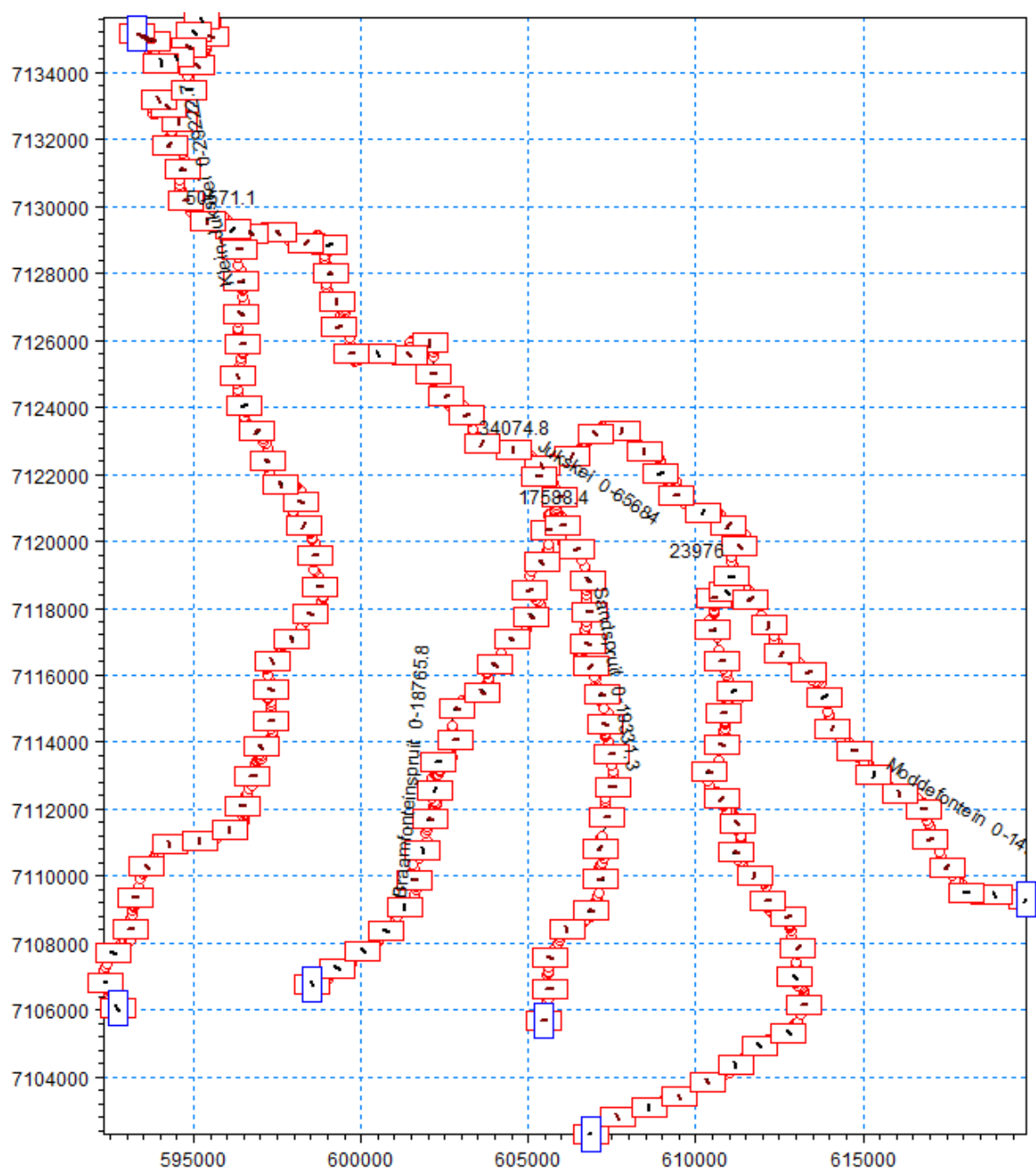


Figure 38: River network with cross sections

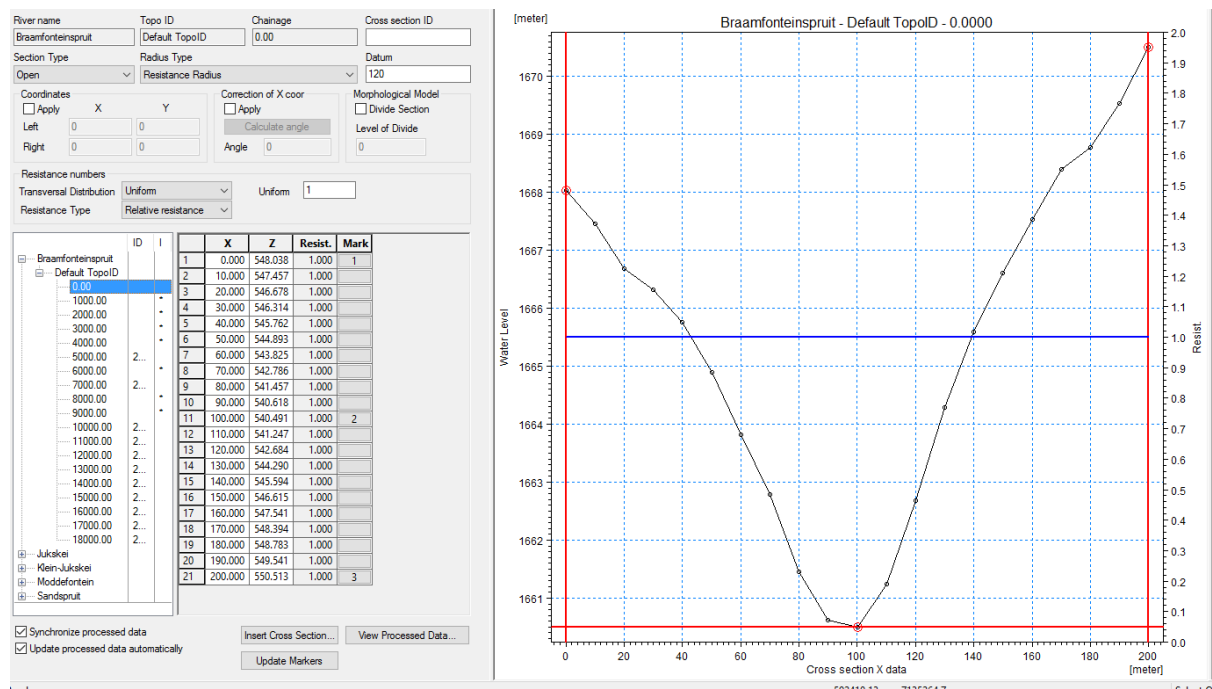


Figure 39: Example of cross section setup

Appendix C: Simulation results

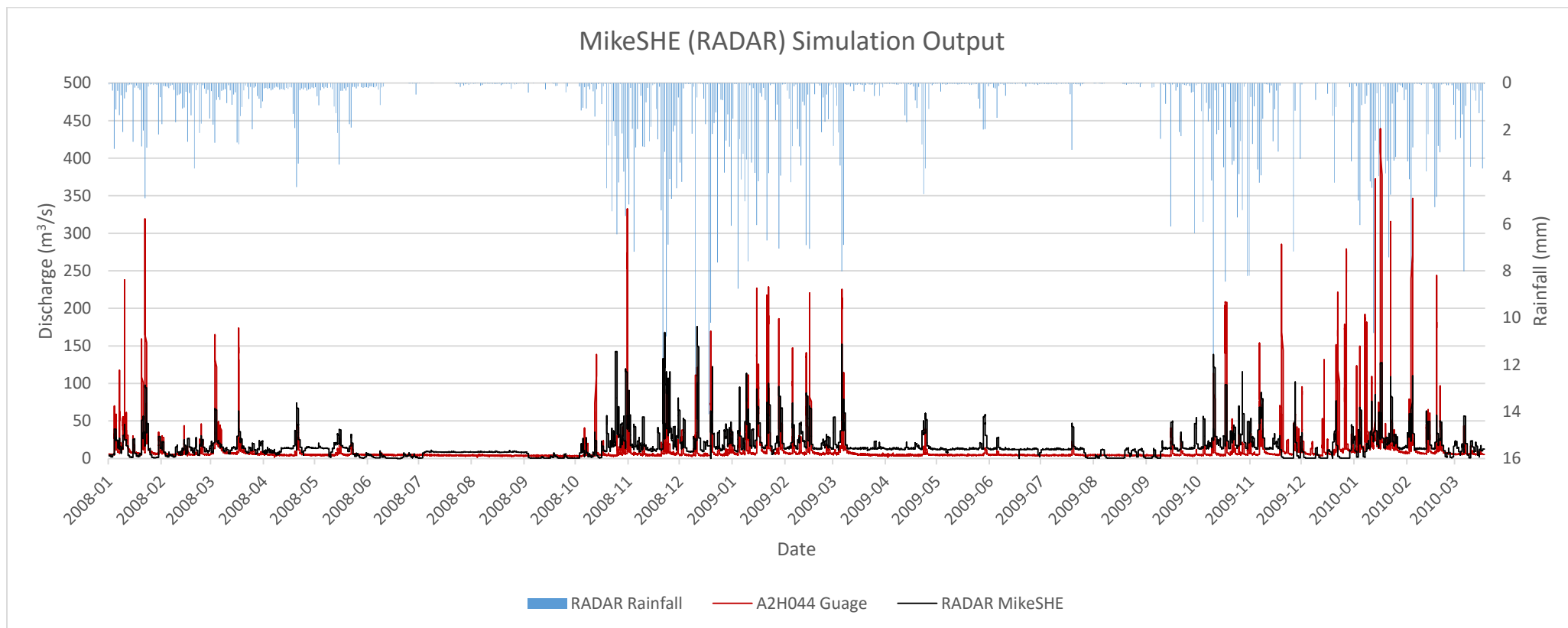


Figure 40: MikeSHE (RADAR) simulation output alongside observed river data and RADAR rainfall estimates for the full study period

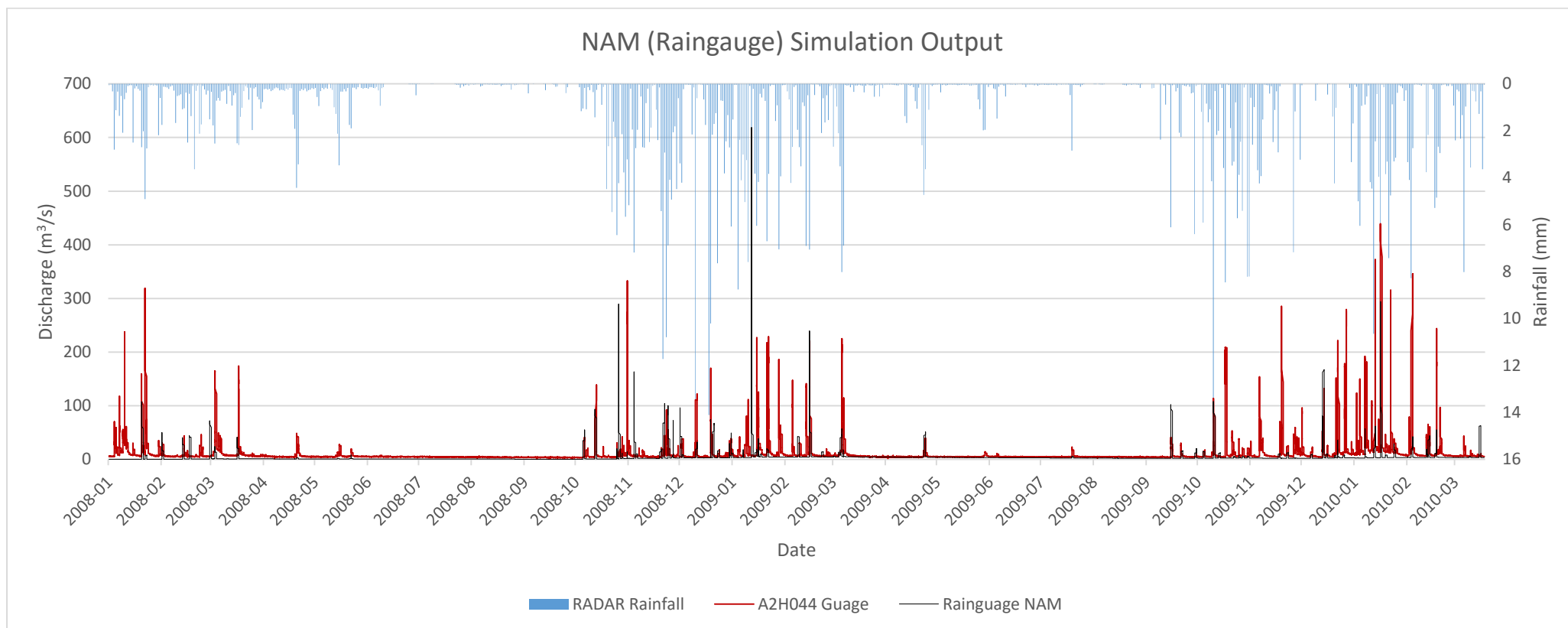


Figure 41: NAM (Raingauge) simulation output alongside observed river data and RADAR rainfall estimates for the full study period

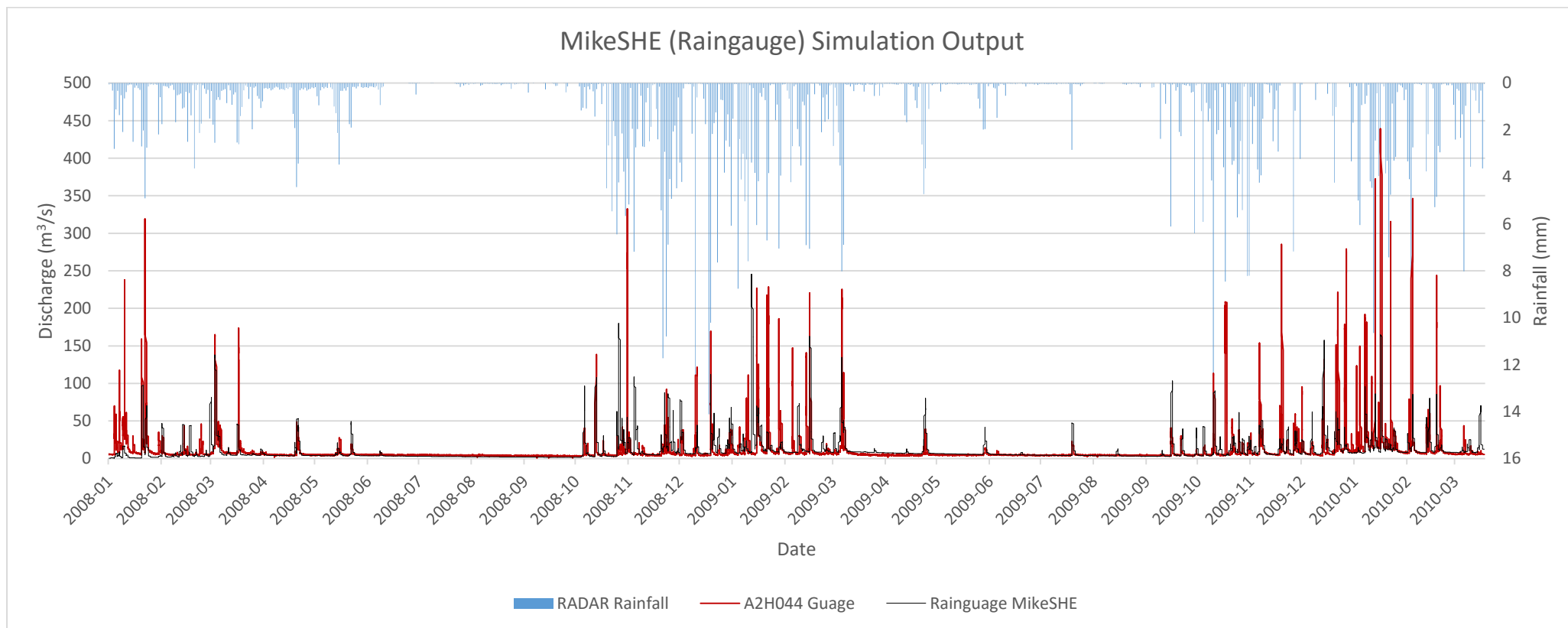


Figure 42: MikeSHE (Raingauge) simulation output alongside observed river data and RADAR rainfall estimates for the full study period

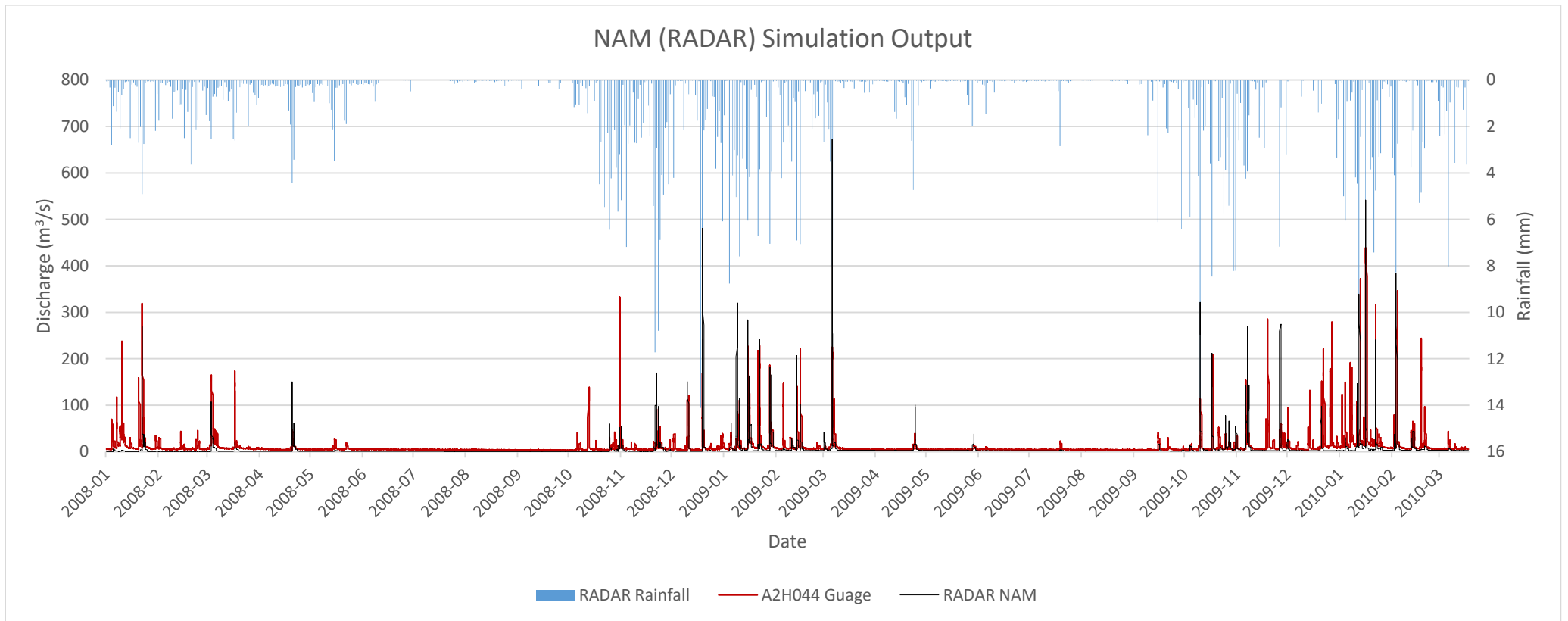


Figure 43: NAM (RADAR) simulation output alongside observed river data and RADAR rainfall estimates for the full study period