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Generalised Storage-Yield-Reliability Relationships for the Sizing of Rainwater Harvesting Systems in South Africa

RESEARCH REPORT

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ABSTRACT

A challenge that still exists in rainwater harvesting system (RWHS) design is the need for quick and accurate tools with which to determine the appropriate dimensions of the system given specific performance criteria. Very limited work has been done in southern Africa for the development of models or general guidelines to assist in the design and simplified assessment of RWHS across any scale. This study was therefore carried out using multiple daily simulations and regression analysis on a sample of 118 rainfall gauging stations located across South Africa, with the goal of improving the predictive abilities of a recently developed generalized storage-yield-reliability model. This was achieved through a re-evaluation of the relationships between the key variables of interest namely: the supply-demand ratio, yield ratio and storage-demand ratio, rainfall variability characteristics, rainwater losses and variability of demand.

Regression analysis on the data collected under conditions of constant unvaried demand revealed the non-linear power model to fit the relationship between the ratio of supply-demand and yield ratio best, whilst the non-linear exponential model fitted the relationship between the storage-demand ratio and the yield ratio the best. Variability in demand was modelled using a wave function whose amplitude quantified the magnitude of variability and whose lag quantified the time difference between the peak demand and the peak of the 61-day moving average rainfall. Variability in demand was found to affect the number of days of supply from a RWHS and the magnitude of this effect depends on both lag and amplitude. However, the two parameters of amplitude and lag have a limited impact on the optimum tank size. It was also noted that areas with rainfall peaks in December, January and June tend to show high sensitivity to the lag whilst areas with rainfall peaks in March and September appear minimally sensitive to the same. A new parameter relating number of days of supply under variable demand to the number of days of supply under constant demand is proposed and regression against amplitude, lag, supply-demand ratio and reliability is done. Three sets of regression models are proposed and analysed, two of which account for the effects of rainfall variability through incorporation of the coefficient of variation of daily rainfall and the ratio of dry days to rainy days. An adjustment to the supply-demand ratio to account for rainwater losses by first flush is also explored.

Verification of the models incorporating rainfall variability characteristics and those that do not indicates that incorporating rainfall characteristics results in some improvement in the prediction of the number of days of supply and tank size. However if only average annual rainfall (MAP) data is available, a model whose only climatic input is the MAP could still be satisfactorily used to estimate tank size and number of days of supply for a RWHS. The extended model that incorporates rainfall variability characteristics nonetheless offers better predictive performance as it is able to distinguish the effects of two different rainfall intra-annual distributions affecting systems which describe identical supply-demand values. Applying this extended model however requires the availability of daily time series data which may not be as easily available as the MAP. In conclusion, this study recommends the use of the proposed models for the basic preliminary assessment of rainwater harvesting systems in South Africa.

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Author,

Sibusisiwe L Mpofu

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CHAPTER 1 INTRODUCTION

1.1. Background Statement

The rapid expansion of urban areas combined with rapid population growth and the drive for improved standards of living has seen the demand for fresh water and its related services grow almost six-fold in the 20th century. Climate change has also added to the pressures facing the water sector and recent statistics indicate that by 2030 there will be an estimated 40% deficit in the global water supply if the world does not take the time to re-evaluate the way in which it utilises its limited water resources (Guppy & Anderson, 2017).

South Africa is the 30th driest country in the world with a mean annual precipitation of 464mm, well below the world average. The climatic regime of South Africa is varied both spatially and temporally. In recent times, rainwater harvesting (RWH) has been put forward as one of many key interventions in the mitigation of climate change impacts on the nations' water resource systems (Department of Water Affairs, 2013). Global climate models indicate that in future there will be increased variability in precipitation and that a semi-arid region like southern Africa, which is already classified as water scarce, will be placed under further water stress (Kundzewicz et al., 2007).

Principles of integrated water resource management call for the water sector to take an adaptive stance in the face of climatic uncertainty. Despite this, the popularisation of centralised water supply, that draws water to a rapidly growing population from distant parts of the catchment, has meant that technologies such as RWH took a backseat and became the reserve for the rural or peri-urban populations that had no way to access a reticulated water supply (Tam et al., 2010). On the other hand, in pursuing the holistic implementation of principles of integrated water resources management, adaptation calls for the adoption of a range of technologies that address both demand side and supply side challenges even within urbanised centres (Kundzewicz et al., 2007). One such intervention is the use of RWH which has seen an upsurge in popularity amongst urban dwellers in recent times.

Many definitions have been offered in the literature of what RWH entails some of which include:

"... [the] *methods to induce, collect and store runoff from various sources and for various purposes*" (Boers & Ben-Asher, 1982).

"... [The] *collection and storage of rainwater and other activities aimed at harvesting surface and ground water. It also includes prevention of losses through evaporation and seepage and all other hydrological and engineering interventions, aimed at* *conservation and efficient utilisation of the limited water endowment of physiographic units such as a watershed*." (UN-Habitat, 2005)

The definitions whilst broad, speak to a wide range of techniques that can be used for the capture of rainwater with the mind to put it to any number of uses for the purposes of enhancing productivity, all without compromising the environment's integrity. Capture of rainwater could be for a variety of purposes including groundwater recharge, crop irrigation, livestock watering, floodwater management, domestic, commercial or industrial use especially where there is no access or limited access to conventional forms of water supply (Thomas & Martinson, 2007; UN-Habitat, 2005).

1.1.1. Advantages of Rainwater Harvesting

Many benefits to society can be realised by the implementation of rainwater harvesting systems (RWHS). They are a relatively environmentally friendly technology and offer a means to supply water to communities which cannot access groundwater or surface water of acceptable quality or quantity for their daily needs (UN-Habitat, 2005). As a standalone, independent system they can be implemented almost anywhere in the world and the ability to store precipitation means the increased reliability of water availability even after the rains have passed (UN-Habitat, 2005). RWH is also seen as step forward to drought-proofing some of the most vulnerable of communities around the world (UN-Habitat, 2005) and whilst not necessarily cheap, RWHS are relatively simple to implement and the ease of maintenance mean it is a technology easily accessible to all sectors of society (UN-Habitat, 2005).

In the rural space the use of RWHS offers the advantage of allowing access to an improved source of water for both potable and non-potable water needs (Ndiritu et al., 2011; UN-Habitat, 2005). They reduce the time and labour associated with the gathering of water and thus allow household members, in particular women and children, to engage in more productive activities that can grow the economic and food security of the family (Mutekwa & Kusangaya, 2006; Mwenge Kahinda et al., 2007). Within the urban and peri-urban space, harvested rainwater can be used as an additional supply to municipal water in times of drought (Aladenola & Adeboye, 2010; Coombes & Barry, 2008). It is also a possible substitute the supply for the non-potable water needs of a business or family (Aladenola & Adeboye, 2010; Coombes & Kuczera, 2003) and consequently, it presents an opportunity for water savings in terms of water bill reductions (Imteaz et al., 2011). Although urbanisation increases the imperviousness of the catchment RWH offers the additional benefit of capture and attenuation of stormwater (Fewkes & Warm, 2000; Sample & Lui, 2014).

The adoption of RWH at large scales has also been posited to present an opportunity to delay the need for capacity expansion of municipal infrastructure (Fewkes & Warm, 2000) and as a way to reduce greenhouse gas emissions by traditional supply networks (Aladenola & Adeboye, 2010). The diversification of water sources means there is less pressure on groundwater wells and if rainwater is used to recharge these, they are able to recover water levels faster and thus reduce costs associated with pumping (UN-Habitat, 2005).

1.1.2. Limitations to Rainwater Harvesting

In spite of the many advantages that RWHS bring to the community at large, their success is largely dependent on the rainfall regime. If the rainy season is poor or a severe drought occurs, not much utility is to be gained by the presence of a RWHS (Gould & Nissen-Petersen, 1999). The quality of rainwater that may be harvested may also limit the viability of use of harvested rainwater and if not managed properly RWHS could become potential sources for water borne diseases (Mwenge Kahinda et al., 2007).

Another disadvantage that comes with the dependence on harvested rainwater is the limit on the amount of water which can be harvested as this is dictated by the size of catchment utilised and the amount of storage available (Thomas & Martinson, 2007). Added to this, the high initial cost of implementing a RWHS is frequently quoted as one of the leading reasons for the lack of headway in the adoption of the technology in urban areas (e.g. Allen, 2013; Kim et al., 2016). Moreover, a poorly sized RWHS that is not designed with climate or demand variability in mind may result in systems that do not perform as expected (e.g. Ward et al., 2012).

1.2. Research Need

A challenge that still exists with respect to RWHS design is the need for simple, quick and accurate tools with which to determine the appropriate dimensions of the system, given specific performance criteria, even in cases of limited input data. A report to the Department of Water Affairs (van Rooyen & Versfeld, 2010) recognised the lack of technical support in the form of detailed guidelines to support the assessment, design, implementation, operation and maintenance of different types of RWHS found across South Africa as hindering the progress of the nationwide implementation of this technology. Further to this, very limited work has been done in southern Africa for the development of models or general guidelines to assist in the design and simplified assessment of RWHS across any scale.

A recent advancement in this regard is the storage-yield-reliability model for shopping malls in South Africa developed by Ndiritu et al., (2017). This model is a simple assessment tool focussed towards evaluating the RWH potential of a site in terms of the expected number of days of supply per annum and tank size given a supply-to-demand ratio and reliability.

An overview of this study is presented in the section that follows from which the gaps in knowledge, research questions and objectives for this study were identified.

Generalized Storage-Yield-Reliability Relationships for Sizing and Assessing Shopping Centre Rainwater Harvesting Systems in South Africa

Three dimensionless relationships between rainwater supply and demand and (a) tank size (b) yield and (c) reliability were developed in the study by Ndiritu et al., (2017). These relationships were derived using 101 years of historical daily rainfall data, using a total of 19 shopping centres of various sizes located in the South African provinces of Kwazulu Natal, Gauteng, Western Cape and Limpopo.

Rainwater harvesting potential was assessed by the daily simulation of the system for a specified tank size where complete satisfaction of demand was assumed as long as there was sufficient water in storage. Performance of the system was measured based on the ability to fully satisfy non-potable water demands estimated to be 45% of the total average annual water demand. Trial run simulations showed within-year storage behaviour for the majority of RWHS analysed. To incorporate variability in performance within the simulation period, a single simulation run was considered to provide 101 independent annual yields. This allowed for statistical analysis using the Weibull plotting positions formula (Weibull, 1939) and hence realistic reliability assessment and system sizing. In each simulation run, the tank size was increased up till the yield levelled off to its highest value for a given reliability, roof area and rainfall input. Reliability ranges applied to this study were between 85% and 99%.

Yield-storage curves produced for a range of tank sizes showed that above a given tank size at a fixed reliability, the yield of the system will stabilise and as such relationships between the supply and demand ($\boldsymbol{R_{SD}}$), expected number of days of supply per year for a specified reliability ($\boldsymbol{S_{P\text{-}r}}$) and the ratio of optimum tank size to the volume of average annual demand for a specified reliability ($\boldsymbol{R_{TD\text{-}r}}$) could be defined. The non-linear power model was found to provide the best fit relationships between $\boldsymbol{R_{SD}}$ and $\boldsymbol{S_{P\text{-}r}}$ and between $\boldsymbol{S_{P\text{-}r}}$ and $\boldsymbol{R_{TD\text{-}r}}$ at all reliabilities tested. Further analysis was done to determine the relationships between the regression coefficients of these relationships and reliability. It was also noted that RWHS are rarely operated at the hydrological optimum hence an alternative model was sought to account for this in system sizing relationships. Using the slope of the reliability-yield line $\boldsymbol{S_{LR}}$, and the dimensionless ratio $\boldsymbol{S_{P\text{-}r}}$, a relationship was obtained between the yield and reliability in non-optimal space. Values of $\boldsymbol{S_{LR}}$ were determined for 4 ranges of reliabilities (85-90, 85-95, 85-98 and 85-99) and plotted against $\boldsymbol{S_{P\text{-}r}}$ where another power law relationship was obtained.

Model verification using four other rain gauging stations located in other regions of South Africa, indicated the models to perform satisfactorily. However, the authors highlight several limitations to the modelling as follows:

- The results of the study are based on the data collected from a total of 14 rainfall gauging stations which could be viewed as a rather narrow representation of rainfall's spatial and temporal variability within South Africa. A secondary aspect tied to this is that the model does not fully consider the influence of rainfall variability characteristics.

- The generalised model has been developed using a constant unvaried demand and this means the model is not equipped to assess the more realistic operational situation of intra-annual variations in the demand due to human habits or activities which may or may not be influenced by annual variations in climatic parameters such as temperature.

- The current model does not explicitly account for losses due to a first flush – the model appears to assume this parameter can be accounted for through the water collection efficiency coefficient. Whilst this coefficient could be satisfactorily used to account for such losses the main limitation is that it inherently assumes that all water losses are time-invariant across the years of simulation which is not necessarily the case as the amount of rainfall received and lost varies from year to year and indeed from rainfall event to rainfall event.

1.2.1. Research Goal and Objectives

With the aforementioned limitations in mind, a research project was thus proposed whose overarching goal was:

> The improvement of the predictive ability of the generalized storage-yield-reliability model through an evaluation of the relationships between the key variables of interest including rainfall variability characteristics, rainwater losses and variable demands

The research project set out to achieve this goal by pursuing the following questions and specific objectives:

Question 1

What is the influence of increasing the number of rainfall gauging stations on the developed models?

1.1. Assess the influence of using more rainfall gauging stations on system performance and regression relationships
1.2. Analyse the influence incorporating rainfall variability characteristics on the predictive performance of the generalised model

Question 2

What is the influence of using an intra-annually varied demand on the behaviour of a RWHS?

2.1. Evaluate the impact to number of days of supply and tank size when using a variable demand
2.2. Assess the utility of developing generalised storage-yield-reliability relationships that incorporate parameters used to describe variability in demand

Question 3
In what ways does the explicit consideration of the first flush impact on the storage-yield behaviour of a RWHS?

3.1. Assess the effect of the first flush on system performance
3.2. Examine the efficacy of incorporating this parameter as a variable in generalised storage-yield-reliability relationships.

1.2.2. The significance of the proposed study

While various models and methods continue to be formulated for the preliminary sizing and evaluation of RWHS (Campisano et al., 2017), all these models and methods have been developed in other parts of the world based on the climatic characteristics of the area under study which limit their generality. A review of the global literature shows researchers from other parts of the world to frequently highlight the importance of accounting for the influence of rainfall variability characteristics on the behaviour of RWHS and incorporating these into predictive models (e.g. Andrade et al., 2017; Allen & Haarhoff, 2015; Campisano & Modica, 2012; Hanson & Vogel, 2014). This has not truly been done for the southern African context and thus while the current model proposed by Ndiritu et al., (2017) has proven to be realistic in its predictions, further interrogation of the model is required using a larger sample of rainfall gauging stations across South Africa. This is to enhance confidence in the capabilities of the proposed model coupled with an understanding of how different rainfall regimes determine the performance of RWHS.

In addition, the use of high resolution demand data that is reflective of actual consumer patterns can lead to more accurate behavioural modelling of the rainwater tank (Campisano et al., 2017) and thus lead to more realistic storage-yield-reliability relationships. The current available models from the global pool of knowledge have not looked in-depth at the influence of a variable demand on the behaviour of a RWHS nor have they taken the step to incorporate parameters that quantify this variability into generalisations. This study is an opportunity to examine the likely impacts of such types of demand on the yield and storage requirements of a RWHS. In addition, this study seeks to find out if variability of demand could be efficiently incorporated into generalized RWHS models and thereby enhance their capabilities.

It is posited that the explicit inclusion of first flush loss of water would be beneficial to the modelling process as more dependable storage-yield-reliability model could be obtained. The incorporation of first flush losses into generalised modelling could offer a simple method to assess the comparative benefits of improvement in water quality that result from first flush to the losses in flushing out the water.

1.2.3. Scope of Study

The time limitations set on this study mean the study confines its analytical focus to optimally operated RWHS in South Africa.

1.3. Layout of Research Report

The research report is structured as follows:

Chapter 1 presents the introduction to the study alongside the gaps in knowledge and the questions this study seeks to answer.

Chapter 2 analyses various studies on different aspects of rainwater harvesting that have been completed by researchers from around the world in recent times.

Chapter 3 presents the materials and main methods used to complete the work of this study.

Chapters 4 presents and analyses results of data collected to address the first research question regarding the impact of increasing the number of rainfall stations and the influence of rainfall characteristics. A step by step development of regression models are also presented therein.

Chapter 5 presents and analyses results of data collected to address the second research question regarding the impact of variability in demand. A step by step development of regression models that build on those established in Chapter 4 is also presented therein.

Chapter 6 presents and analyses the results of data collected to address the third research question regarding the impact first flush on RWH yields and suggests a method for its incorporation into generalised models.

Chapter 7 pulls the proposed models together and evaluates their performance using an independent data set. In addition, the models are applied to an engineering problem.

Chapter 8 closes out the report with a summary of the main lessons learned from the research work and recommendations for future studies are also made.

CHAPTER 2 LITERATURE REVIEW

A review of the literature is presented in this chapter to better understand and place the proposed work of this study in the broader context of the current body of knowledge.

2.1. Overview of Rainwater Harvesting

2.1.1. A Brief History of Rainwater Harvesting

The origins of RWH, although not precisely known, have been traced back to the early civilisations of the Middle East and Asia (Gould & Nissen-Petersen, 1999). Many a site can be found today in places like Jordan, Iran and Israel showcasing the various techniques that have been in use for over 4000 years to capture water for both domestic and agricultural purposes (see Abdulla & Al-Shareef, 2009; Gould & Nissen-Petersen, 1999). Even the civilisations of North Africa and the Mediterranean practiced RWH, as evidenced by the presence of large subsurface cisterns, some of which are still in use today. The Romans are credited with the construction of the world's largest known rainwater cistern – it can be found in Istanbul with a capacity of 80 000m^3 (Gould & Nissen-Petersen, 1999).

The use of RWH in East, South and South East Asia also dates back many centuries; evidence suggests that rainwater harvesting has been in use in the Gansu Province of China for well over 6000 years and for over 2000 years in Thailand. On the Indian sub-continent RWH has also been practised for well over 4000 years. It also enjoys a rich history in sub-Saharan Africa, where the likes of the San people used ostrich eggshells to gather and store rainwater. A variety of ancient RWH techniques are also still popularly practiced in East Africa (Gould & Nissen-Petersen, 1999). A review on the indigenous practices of water harvesting and conservation in South Africa by Denison & Wotshela (2009) highlights a variety of techniques that have been used by the peoples settled in South Africa from pre-colonial times through to the institution of apartheid to support the agrarian way of life.

2.1.2. Classification of Water Harvesting Systems

RWH is practiced using a variety of techniques, from the use of simple jars and tanks placed under the edges of roofs to more complex engineered systems, designed to capture and store the runoff generated from a variety of surfaces. Helmreich & Horn (2009) identify three major groupings of water harvesting systems namely:

- **In-situ RWH** – also termed infield RWH, rainwater is collected and stored directly or very near to where it falls; this system is typically used in agriculture where water is effectively stored in the soil profile of the cultivated area
- **External RWH** – also known as ex-field RWH, rainwater is collected on a surface at some appreciable distance from the storage point; this technique is

typically utilised in agriculture but could be modified to supply domestic water to a community

- **Domestic RWH** – this is the collection of rainwater off of surfaces such as roofs, courtyards and streets; the water is typically used to satisfy human needs

Domestic-type RWHS will be the focus of this study.

2.1.3. Components of a Roof-Rainwater Harvesting System

The most commonly utilised RWH surface is the roof. Figure 2-1 illustrates a typical roof RWHS whose various components are herein discussed:

Roof Collection Area: This is the surface upon which the rain falls. A suitable roofing surface is usually one that is made up of hard, relatively impervious materials like metal or tile (Thomas & Martinson, 2007). High surface temperatures and UV light exposure on roof surfaces immobilise and kill off most forms of bacteria. Mendez et al., (2011) highlight the fact that although metallic roofs are the most recommended material when it comes to rainwater harvesting, when compared to other materials, they do not necessarily produce water of a better quality.

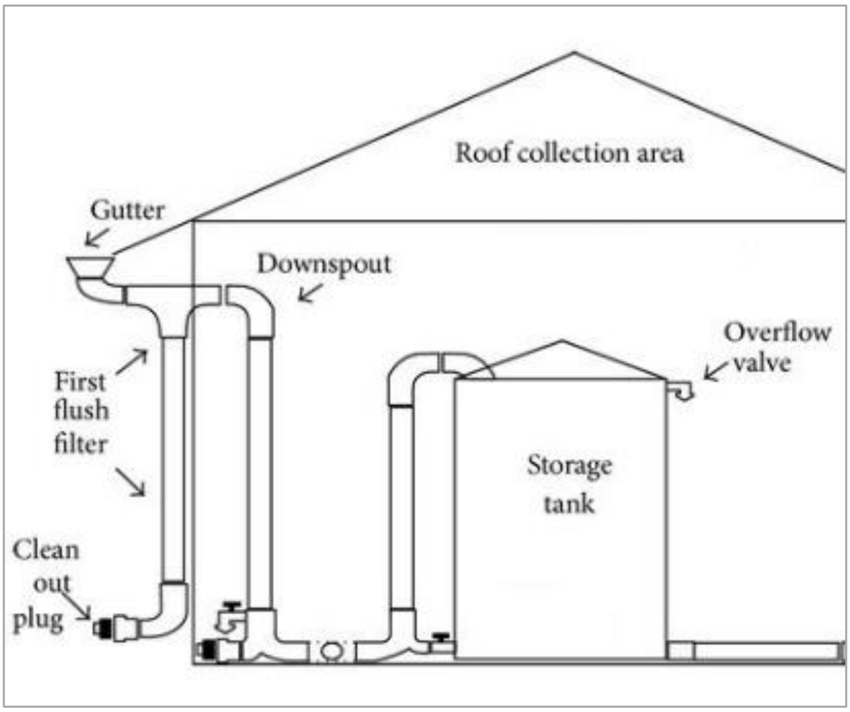


Figure 2-1: Typical Roof RWHS (Image adapted from Rahman S et al., (2014))

Conveyance system: This is a system of gutters connected along the edges of the roof catchment used to capture and channel the runoff collected from the roof to the downspouts which then direct the water to the entrance of the storage tank. Typical guttering materials used include PVC, galvanised steel or asbestos. Debris screens may also be installed over the gutters to prevent large particulate matter from entering the storage tank (UN-Habitat, 2005).

Flush diverter: First flush devices are regarded as the first line of defence in improving the quality of stored harvested water. The device acts as a contaminated water diverter by allowing a pre-determined volume of the first runoff from the roof to drain into a separate chamber or downpipe before allowing cleaner water to flow into the storage tank. The device can be designed to operate and drain automatically or it can be operated and drained manually (Doyle, 2008; Martinson, 2007). Frequent removal of debris and sludge is required to maintain the optimal functionality of the device (Doyle, 2008). Different types of first flush diverters are available on the market some of which are illustrated in Figure 2-2.

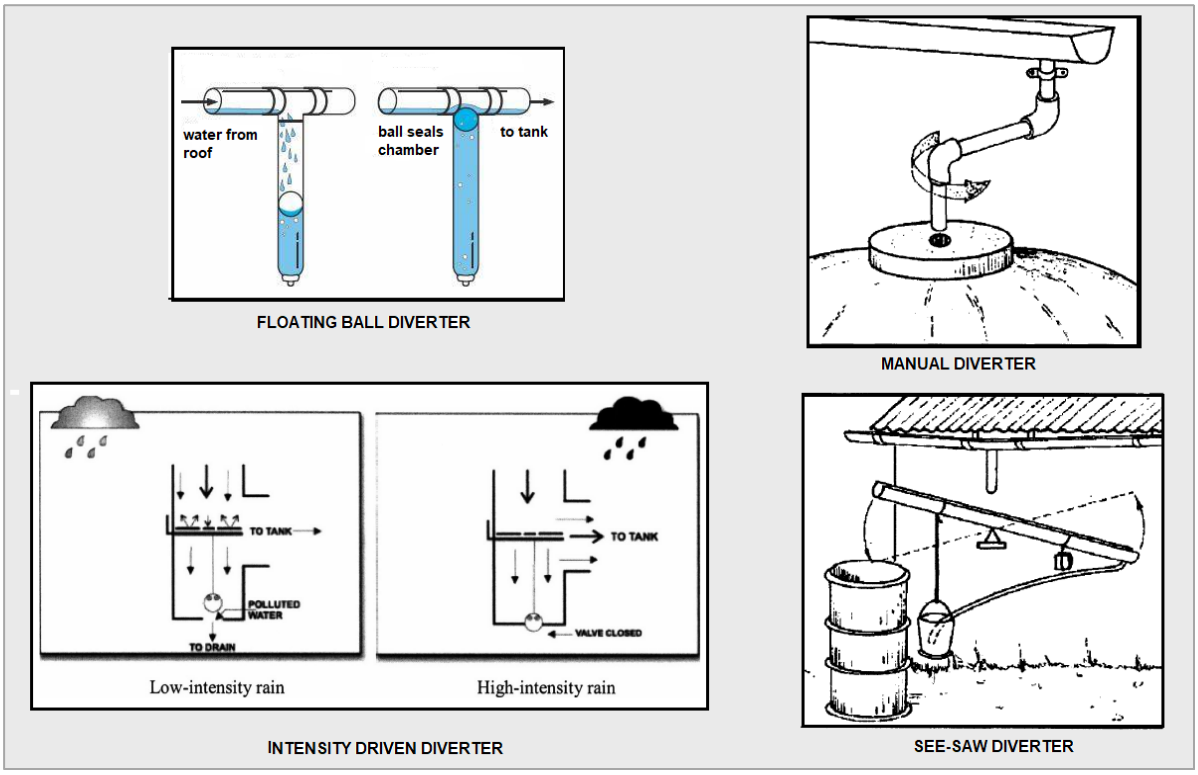


Figure 2-2: Types of First Flush Diverters (Adapted from (Doyle, 2008))

Filter Unit: This is used to remove the finer particulate matter from harvested rainwater. If the rainwater is to be used for potable uses, a sand filter (in conjunction with other treatment options) may be added to the system (UN-Habitat, 2005)

Storage tank: This is a small reservoir used for the safe keeping of collected rainwater for use when there is a demand. Storage tanks come in different shapes and sizes and may be constructed from a variety of materials including metal, plastic, clay and concrete. Depending on spatial constraints and the type of catchment used storage tanks may be located either above ground or underground (UN-Habitat, 2005).

Reticulation to the point of use may also be installed or alternatively a simple tap (or trapdoor for underground tanks) may be installed, to facilitate access to the harvested rainwater.

2.1.4. Perspectives on Rainwater Harvesting

Undeniably, RWHS are set to play an important part in the development of sustainable water supply systems with decision-makers around the world looking to restore the balance of the urban water cycle with the natural water cycle through the visible promotion of decentralised water technologies that are sustainable and environmentally friendly (Chubaka et al., 2018; Ward et al., 2013; Campisano et al., 2017). The re-introduction of RWH to urban areas around the globe has however received mixed reactions.

In the Kingdom of Thailand**,** RWH enjoys much popularity and this is ascribed to the successful implementation of the “Thai Jar Programme” (Saladin, 2016). Its endurance throughout the Kingdom has been as a result of the buy-in and willing participation of all sectors of government and the general public in implementing critical policies in the 80’s targeted at the development of decentralised solutions for rural improvement - although Government has now diminished its role in the roll out of RWH, the market continues to flourish in all parts of the country as the programme paved the way for the establishment of an industry, where much competition continues to keep RWH affordable to most (Saladin, 2016). In northeast Asia, the Republic of Korea has also been working towards sustainable urban water systems with local governing bodies mandating the installation of RWHS in both private and public buildings (Kim & Yoo, 2009). This is despite the highly variable nature of their rainfall. However, Lee et al., (2010) point out that some legislative alignment is still required across the different governing bodies of South Korea, if urban RWH is to maintain its continued success. Star City is one of South Korea’s pioneering multipurpose RWH installations and researchers like Han (2013) continue to promote the development of RWH in the major cities as a way to not only control storm water, but to supplement water supply in the dry season and for other purposes such as firefighting.

Whilst RWHS have been a necessary part of life in rural and peri-urban Australia, the extensive drought experienced by the nation in the years 2000 to 2009, led to the imposition of water restrictions and this resulted in the mandatory uptake of water conservation measures such as RWH by residents and the spread of the practice into the larger cities (Tam et al., 2010). The latest statistics indicate that 34% of Australian households found to be suited to the implementation of RWHS had implemented the system by 2013 (ABS, 2013). The continued adoption of the practice in urban spaces has been motivated by the prospect of real savings in potable water consumption, the great environmental awareness of the citizenry and a national rebate scheme that sponsored part of the installation costs (Chubaka et al., 2018; Coombes & Kuczera, 2003).

In contrast to other parts of the world, RWH has not gained a firm foothold in European nations. In the United Kingdom, although RWH has been practiced in the past, the technology has seen a rather slow resurgence in the 21^{st} century. In spite of this Ward (2007) notes the presence of a number of fully operational RWHS at different scales across the country. Ward et al., (2008) indicated that the RWH industry in the United Kingdom was on course to expand as water demand continued to put pressure on increasingly scarce water resources. However, a later study by Ward et al., (2013) found that whilst receptivity of the technology is high amongst the general population, several barriers such as the cost associated with installation and maintenance, the lack of accessibility to relevant information for prospective users and the lack of institutional support still need to be overcome if there is to be sustained growth in the adoption of RWH. Germany, a global leader in decentralised water technologies, is much further ahead of its other European counterparts with an estimated 75 000 facilities installed per annum (Schuetze, 2013). The successful implementation of RWH in Germany can be largely attributed to the introduction of supportive government policies on water conservation combined with investment grants and unique tariff systems targeted at discouraging the discharge of rainwater to storm sewers (see Schuetze, 2013). However the strict rules on the permitted uses of harvested rainwater and obligatory connection of all buildings to mains water supply has resulted in there not being an immediate incentive to adopt decentralised water technologies nor for RWH to receive support from local authorities in charge of centralised water supply (Partzsch, 2009).

Within the African urban context, very little advancement has been made with respect to the introduction of decentralised water supply strategies. This is in spite of the lack of water security experienced by the most vulnerable of the population as a consequence of rapid growth outpacing the rate at which centralised water supply systems can be developed (WWAP, 2015). The vast majority of RWH interventions and studies continue to be focused on the use of RWH to improve food security in sub-Saharan Africa or as a temporary alternative water source for low demand domestic uses in rural Africa (e.g. Mutekwa & Kusangaya, 2006; Mwenge Kahinda et al., 2007; Pachpute et al., 2009; Muriu-Ng'ang'a et al., 2017). More recently some researchers have begun to look into RWH as a solution to the water supply problems associated with informal settlements and peri-urban populations (e.g. Amos et al., 2016; Enninful, 2013).

Rainwater Harvesting in Urban South Africa

Although South Africa recognises that it is a water scarce nation, RWH is still widely viewed as a temporary water supply measure for those who are as yet to access a municipal water supply (Department of Water Affairs, 2013). As a consequence of this line of thought, the government continues to focus its attention on the provision of RWHS to rural populations in the name of fulfilling a citizen's right to basic water and sanitation and as a means of supporting agriculture, both at domestic and commercial scales (Allen, 2013; Dobrowsky et al., 2014; Mwenge Kahinda & Taigbenu, 2011).

Fisher-Jeffes (2015) highlights that there have been few meaningful studies on RWHS in urban areas but interest in the use of RWH in urban areas seems to be on the rise (e.g. Ndiritu et al., 2018; Viljoen, 2014; Allen, 2013; Enninful, 2013).The uptake of RWH technologies for non-domestic uses has largely been driven by the private sector wanting to achieve the maximum green buildings rating, as per the Green Buildings Council of South Africa (2017) requirements, though this is still done on a purely voluntary basis. Notable projects to date include the Mall of Africa, Menlyn Shopping Centre and the Aurecon Head office in Cape Town (Anon, 2015; Anon, 2016; Aurecon, 2011).

On the domestic front, RWH has not really flourished, with Allen (2013) suggesting that this is due to the high cost and lack of aesthetic appeal of the tanks combined with the limited water savings that can be achieved. On the positive, Fisher-Jeffes (2015) notes that there is substantial potential in South Africa for RWH to reduce the demand on over-stretched municipal water systems notwithstanding any other benefits that might accrue from the adoption of the technology.

2.1.5. The Economics of Rainwater Harvesting

While the rain that falls is a resource considered to be available to all for free, the implementation of a RWHS will have some financial implications, where the costs of investment must be balanced against the expected benefits. The main cost elements of a typical RWHS include (i) the storage tank (ii) installation (iii) operation and maintenance and (iv) a water pump (Tam et al., 2010). Studies of the economics of RWHS have been done around the world using different financial forecasting models and it is noted that the findings of the various studies are highly subjective as different researchers have used different assumptions and metrics in coming up with their data (Kim et al., 2016).

Pay-back analyses carried out by different researchers reveal a wide variation in the time it takes one to recoup an investment in RWH, with Khastagir & Jayasuriya (2011) making the observation that in general the payback period will be a function of the prevailing interest and inflation rates, with a reduction expected if interest rates are high and inflationary rates are low. Payback periods will also be a function of the range of uses that the harvested rainwater is put to – the higher the demand for harvested rainwater, the more financially viable the system can become (Matos et al., 2015). The literature reports payback periods in the range of 15-60 years for most small to medium scale domestic RWHS (Domenech & Sauri, 2011; Farreny et al., 2011; Imteaz et al., 2011; Khastagir & Jayasuriya, 2011; Kim et al., 2016). Economic investigations on commercial buildings reveals the possibility for shorter payback periods in the range of 1.5 years to 12 years (Chilton et al., 1999; Matos et al., 2015).

A whole life cost analysis on domestic RWHS was adopted by Roebuck et al (2011) as they recognised that it is not only the capital cost of the system that matters but as RWHS require some form of regular maintenance, the operational and maintenance costs will form a significant part of the lifetime costs; therefore, they must also be weighed against the potential benefits. Findings from their study, based on values and typical rainwater uses in the United Kingdom, revealed that the whole lifecycle cost of simulated RWHS was always greater than the equivalent mains-only-supply system. The greatest expense was found to be caused by maintenance activities, which reduced the impact of the monetary gains from the substitution of mains water with harvested rainwater. On average the simulation revealed a net loss to individuals investing in RWHS equivalent to the capital cost of the system and thus they conclude that there is still need for third party intervention if RWHS are to become a financially competitive alternative to mains water supply.

Despite the fact that incentives and subsidies can ease the initial investment burden, researchers are quick to point out the fact that the price of access to mains water will still have to substantially rise before RWH can be a truly competitive option regardless of the many benefits (not just monetary) that could be realised in the short term (Farreny et al., 2011; Kim et al., 2016). However, introduction of incentive and rebate schemes like those employed in Australia and Germany (Chubaka et al., 2018; Schuetze, 2013) is essential if the full potential of RWHS is to be realised.

2.1.6. Legal and Institutional Frameworks Supporting Rainwater Harvesting

Part of the successful implementation of rainwater harvesting has been the presence of strong and clear legislative frameworks, with the requisite institutional support, to provide guidance to those wishing to implement RWH. Australia is a leader in this respect, with government developing a regulatory framework in 2004 to support water conservation efforts. The different states and territories took this further by developing local regulations and guidelines whose implementation is overseen and supported by institutions such as the Australian Rainwater Industry Development group and the Master Plumbers and Mechanical Services Association of Australia (MPMSAA, 2008). In the United States of America, the application of legislation and regulation of RWH is varied with individual states left to determine their own stance on the practice (Loper, 2015). The state of Texas has by far the most advanced legislative framework that supports RWH through rebates and tax cuts on the purchase of RWH equipment, including access to institutions such as the Texas Water Development Board and the American Rainwater Catchment Systems Association to guide those seeking to implement RWH (Boulware et al., 2009; TWDB, 2005). The United Kingdom's first comprehensive guideline document for the design and installation of RWHS in the United Kingdom is the British standard, BS 8515:2009+A1:2013—Rainwater Harvesting Systems—Code of Practice (Melville-Shreeve et al., 2016). Before the promulgation of this document those interested in implementing RWHS largely depended on the general guidelines provided by the

Building Research Establishment through the Code for Sustainable Homes (Department for Communities and Local Government, 2008).

Contrasting the global situation to that found in South Africa, Mwenge-Khahinda (2015) points out the continued lack of a clear legislative mandate and stimulatory environment to encourage the adoption of the rainwater harvesting project at a national level. The use of water resources is governed by the National Water Act (Act No. 36 of 1998) which allows for the lawful use of a water resource for any domestic activity. Whilst Schedule 1, part 1(c) of the same Act allows for the storage and use of roof harvested rainwater without a license, a contradiction appears to exist as the Water Services Act (Act No. 108 of 1997) prohibits the sourcing of water outside of the authority of the local water services provider. No mention of the lawful use of harvested rainwater for non-domestic purposes can be found in any national legislation but the water by-laws of the City of Johannesburg (2003) seem to allow for the use of rainwater for domestic, commercial or industrial activity.

2.1.7. Roof Harvested Rainwater Quality

There are many complex pathways that may introduce contaminants into harvested rainwater. The quality of harvested rainwater is largely dependent on the surrounding environment in terms of the levels of development, geographic location, meteorological conditions and on the design aspects of the actual RWHS (DeBusk & Hunt, 2012; Meera & Ahammed, 2006). The following discussion highlights the dominant means by which pollutants are introduced into harvested rainwater.

Wet Deposition

Rainwater is well known for its ability to scour the surrounding atmosphere and clean the air. As a solvent, it is able to scavenge airborne particulate matter including pollutant compounds (Sanchez et al., 2015). The quality of the rainfall incident on a given catchment area will be a function of the environment within which it falls. The presence of inorganic chemical compounds like sulphur and nitrogen oxides, introduced into the atmosphere through industrial activity and automobiles leads to the formation of acid rain (Mphepya et al., 2004; Polkowska et al., 2002; Yaziz et al., 1989) thus reducing the quality of the rain that is harvested.

Atmospheric (Dry) Deposition on Roofs

Dry deposition of pollutants is as a result of the interception and accumulation of particulate matter on the roof surface. The sources of the deposited pollutants are numerous and constitute both chemical and microbial matter generated as a result of the geomorphology, meteorology, industrial, automotive and agricultural activities of an area (Abbasi & Abbasi, S., 2011; Evans et al., 2006). The presence of such potentially harmful substances results in the collection of rainwater that is not up to set national or global standards like those set by the World Health Organisation (Abbasi & Abbasi, 2011).

Microbial Contamination

Microbial contaminants may be introduced into harvested rainwater through the washing out of accumulated decomposed vegetative matter from the roof or in the gutters, the droppings of insects, small reptiles, rodents and birds, dry deposition by wind on roofing surfaces or the falling in of dead insects and other wildlife into the tank (Martinson, 2007). Studies focused on the microbial quality of harvested rainwater indicate that the types and levels of bacterial contamination will be environment specific and will tend to vary throughout a storm and throughout a given rainy season (Evans et al., 2006; Lee, Yang, et al., 2010; Sazakli et al., 2007; Yaziz et al., 1989). Bacterial species of concern to human health that have been identified as present in harvested rainwater include but are not limited to some species of *Salmonella spp., Campylobacter, Escherichia Coli, Enterococci, Aeromonas spp., Vibrio spp., Cryptosporidium, Legionella, Giardia* and *Pseudomonas aeruginosa* (Adeniyi & Olabanji, 2005; Gikas & Tsihrintzis, 2012; Lee et al., 2012; Sazakli et al., 2007; Simmons et al., 2001; Zhu et al., 2004).

The microbial quality of rainwater in South Africa is also of concern. A study by Chidamba & Korsten (2015) exposed the potential presence of pathogenic bacteria such as *Legionella*, *Acinetobacter*, *Pseudomonas, Clostridia, Chromobacterium, Yersinia*, and *Serratia* in roof harvested rainwater in the rural areas of the Eastern Cape. In another study by Dobrowsky et al., (2014) in Kleinmond, levels of *E. Coli* in violation of South African water quality standards were exposed.

Roofing Materials and Gutters

Roofing materials and gutters contribute to the contamination of rainwater through weathering processes and through physical or chemical reaction with rainwater (Adeniyi & Olabanji, 2005). Researchers have found that leaching of metal ions such as zinc, aluminium, lead, iron and copper into the runoff occurs due to the typically acidic nature of the incident rainfall (Despins et al., 2009; Polkowska et al., 2002; Yaziz et al., 1989). The experiments of Mendez et al., (2011) point to significant levels of arsenic and lead from green roofs and tile roofs. Depending on the texture of the roofing material some pollutants may become trapped within the materials' pores and this can significantly alter the observed pollutant loads in harvested water (Adeniyi & Olabanji, 2005; Lee et al., 2012). A water quality parameter which has been found to be directly affected by the type of roofing material is microbial levels, where contaminant concentrations have been found to be greatly reduced, if not eliminated, on metallic roofs when compared to other materials (Lee et al., 2012; Mendez et al., 2011; Yaziz et al., 1989).

Effect of Storage on Harvested Rainwater Quality

Storage tank material interaction with rainwater can result in changes to the physico-chemical and microbiological composition of stored water (Despins et al., 2009; Simmons et al., 2001). Processes of flocculation and sedimentation, in conjunction with the fact that enclosed tanks present an environment unfavourable to growth of most organisms, have been shown to account for the removal of some pathogenic species from harvested rainwater (Martinson, 2007) thus improving the quality of water accessed by the end-user. However, the natural warming of water in some enclosed tanks could create a breeding ground for pathogens such as *Legionella* (Simmons et al., 2008).

The residence time of harvested rainwater also has a role to play in the improvement of the quality of harvested rainwater. If enough time is allowed between the water entering the tank and it being accessed by the end-user, settlement can occur clearing the water of a significant proportion of its suspended solids and heavy metals (Martinson, 2007).

Impacts to Human Health of Harvested Rainwater

A few cases have been reported in the literature of human health being possibly compromised by the use of poorly treated roof harvested rainwater (e.g. Simmons et al., 2008). However, the general consensus seems to be that poor maintenance and management of rainwater harvesting systems is what is most likely to lead to instances where human health could be threatened by harvested rainwater (Lee Yang et al., 2010).

2.2. Developing Generalised Rainwater Harvesting System Models

Although the main physical components of a RWHS are typically the same the world over, elements of the design of RWHS will vary according to the designer's goals be it water savings efficiency, water supply reliability, economic/financial feasibility or rainwater capture efficiency (Hanson & Vogel, 2014). Santos & Taviero-Pinto (2013) identify two classes of design methods: simplified design methods and detailed design methods. Simplified design methods largely depend on the 'rule of thumb' whereas detailed methods will generally involve the behavioural simulation of a RWHS.

The analyses of different researchers into simplified versus detailed design methods (see Santos & Taviera-Pinto, 2013; Ward et al., 2008), has shown that different methods will produce widely different storage volumes, each having a significant impact on the economics of a RWHS. Given that the storage tank is the most expensive component of any RWHS, the findings of such studies and those discussed in the preceding section, mean that accurate optimised design, that also meets performance and economic requirements, is essential to improve the feasibility of RWHS in the long term.

The following sub-sections explore the various approaches to the sizing of RWHS that have been proposed by different researchers, including a discussion on the key design variables that determine the performance of a RWHS, exposing some of the challenges that have arisen in the development of the various design models.

2.2.1. Modelling of Rainwater Harvesting Systems

Various models and methods have been proposed and used by a number of researchers in the evaluation and design of RWHS. However, the heavy dependence of models or methods on local conditions limits the level to which generalisation of the design of RWHS can be done. As such the applicability of generalised models is frequently restricted to the preliminary design stages of a RWH project (e.g. Ndiritu et al., 2017).

In traditional design, methods such as sequent peak or mass curve analysis were used to determine the required capacity of the storage reservoir (e.g. Gould & Nissen-Petersen, 1999). These methods are very simple to apply but they suffer some critical shortcomings: the mass curve method is a graphical technique that can only accommodate a single constant demand which is not realistic in many instances and whilst the sequent peak algorithm overcomes this, neither method can give the designer a measure of the reliability of water supply over the chosen assessment period. Lee et al., (2000) recognised this deficiency and combined sequent peak analysis with frequency analysis to derive an empirical relationship between the storage capacity, collection efficiency coefficient, probability of failure, catchment and cultivated area for RWH cisterns. The immediate limitation to their proposed model was that it was valid for the conditions of their study site.

A second approach to generalised modelling and design of RWHS is the use of analytic or stochastic procedures. Guo & Baetz (2007) developed analytic equations that consider the basic hydrologic operation of a rainwater storage unit and use stochastic analysis to take into consideration different local climatic conditions through the use of probabilistic rainfall models. Whilst the derived equations are straightforward to apply, the use of pre-defined probability distributions in describing rainfall distributions limited the generality of the equations as said probability distributions do not necessarily apply to other sites outside of those considered in the study - this was shown by Basinger et al., (2010) for New York City. Basinger et al., (2010) also developed an alternative RWHS sizing model using a non-parametric stochastic rainfall generator arguing that techniques of non-parametric analysis are able to derive probabilistic rainfall records using local data without the need to know the underlying probability distribution thus making for a more widely applicable model. Other generalised semi-analytic relationships have been proposed by researchers such as Su et al., (2009), Raimondi & Becciu (2014) and Becciu et al., (2018).

A third option is behavioural modelling. This is the simplest and the most popular of the detailed techniques for the analysis and sizing of RWHS. Behavioural modelling involves the continuous simulation of reservoir operations over a given period and utilises the historical rainfall record as its driving input. This is a flexible technique that allows one to capture the influence of the temporal variability of the local rainfall and it also enables the modelling of complex temporally varied water demands; one can also easily integrate stochastically generated rainfall series (e.g. Basinger et al., 2010). The simplicity of the underlying algorithm means the method also lends itself to easy implementation using simple spreadsheets (Mitchell, 2007).

A behavioural model may be built in any number of ways, with Mitchell et al., (2008) highlighting the fact that the choice of method will be influenced by the level of accuracy required and type of storage being assessed i.e. within-year versus over-year storage. They also note that urban RWHS are most likely to exhibit within-year storage behaviour due to the observed low variability in urban runoff and limitations imposed on the system by storage size. Some studies have been done to assess the sensitivity of behavioural model results to a selection of model parameters such as computational time-step, the length of the rainfall time series, starting conditions and the operating rules that govern the sequence in which water is allocated to the demand. Some key findings from these studies are summarised in Table 2-1.

Table 2-1: Parameters Influencing the Accuracy of a Behavioural Model

Parameter	Study	Findings
Computational Time-step	(Fewkes & Butler, 2000)	The most satisfactory modelling results are produced by the use of a daily time-step but smaller stores are better modelled at hourly steps; larger stores can be reasonably modelled at monthly steps
	(Liaw & Tsai, 2004)	Daily time-step produces more accurate results when compared to a 10 day time-step
	(Coombes & Barry, 2007)	A time interval of 6min produces more accurate results when compared to a daily computational step
Operating Rules	(Fewkes & Butler, 2000)	Yield-After-Spillage will produce better results than Yield-Before-Spillage at a daily time step
	(Liaw & Tsai, 2004)	Yield-After-Spillage gives lower reliabilities when compared to Yield-Before-Spillage; Yield-After-Spillage is better suited to the combination of small storages experiencing large demands

Parameter	Study	Findings
	(Mitchell, 2007)	Yield-After-Spillage tends to underestimate system yield and reliability; supply-spill order becomes increasingly important as computational time step increases; Yield-After-Spillage tends to produce more accurate results than Yield-Before-Spillage regardless of time-step; the mean value of these two rules is the recommended value in design in the case where the Storage-Inflow ratio lies above 0.007 and the required accuracy of analysis is set at about ±10%
Length of Rainfall Record	(Mitchell et al., 2008)	The response of behavioural models is sensitive to the length of rainfall records; minimum of a 10 year continuous record is recommended especially if considering seasonal demand patterns
	(Ghisi et al., 2012)	Required length for short term rainfall series is a function of the level of rainwater demand – the higher the demand the longer the rainfall series required; longer rainfall time series are recommended for reliable storage estimations
	(Geraldi & Ghisi, 2017)	Comparison of optimal storage values prescribed by the use of short term rainfall series to a 30 year rainfall series reveal a minimum record length of 10 years is required to produce reliable results
Starting Conditions	(Mitchell, 2007)	For shorter time series it is more preferable to set initial storage to empty

The findings of the studies highlighted in Table 2-1 indicate that whilst this is the most dependable method with which to assess and size a RWHS, there is still the need for a high level of detail in the input data in order to obtain dependable results. The need for sufficiently long records of rainfall data perhaps presents the most critical limitation to the application of behavioural models as more often than not this type of record is not available (Raimondi & Becciu, 2014). However, the findings from the studies of Ghisi et al., (2012) and Geraldi & Ghisi (2017) as highlighted in Table 2-1 do show there is potential to utilise shorter records and still obtain reliable results.

The need for a high speed computing device also limits the usefulness of the behavioural model as a design tool when designers may not have access to computers. However the results obtained therefrom can be used in the development of generalised relationships or models (e.g. Su et al., 2009; Campisano & Modica, 2012; Hanson & Vogel, 2014; Liaw & Chiang, 2014; Ndiritu et al., 2018) in part to alleviate the designer of the burden of having to undertake an expensive exercise to source highly detailed data in order to do preliminary work.

Other computer-based models and socio-economic decision-making tools ranging from simple to detailed integrative models for the assessment and design of RWHS continue to be developed (e.g. Okoye et al., 2015; Sousa et al., 2018).

2.2.2. Design Parameters

Given the increasing interest to develop generalised models that can be applied to a broad spectrum of demands and rainfall profiles, it is important to have some understanding of the influence of key design parameters on the performance of a RWHS.

The literature identifies the following as the critical design variables required to determine the optimal dimensions of a RWHS: MAP and its distribution, use-specific demand and its distribution, rainwater losses as captured through the water collection efficiency coefficient and first flush, required reliability of supply and catchment area. Whilst studies looking into the impacts of each parameter on the performance of RWHS in isolation are few, the work of Ghisi (2010) points to the high interdependency between all these variables in determining the performance and by extension the size of a RWHS.

The following sub-sections review a few studies that have analysed to some extent the effect of some of these key input parameters on the performance of a RWHS.

Rainfall Characteristics

Globally, the distribution of rainfall varies both spatially and temporally. In order to develop a set of general design curves or equations researchers have had to overcome the challenge of capturing the influence of different rainfall patterns in a design equation. The local rainfall patterns have frequently been shown to have a strong influence on the overall performance of a RWHS and as rainfall is the critical hydrological parameter used in modelling, this aspect must be thoroughly understood when it comes to selecting the size of a storage device (Hanson & Vogel, 2014).

A study by Palla et al., (2012) examined the influence of different European climates, as expressed by various rainfall statistical parameters, on the performance of RWHS. The results of the study showed a range of responses where RWHS in regions characterised by high rainfall and low inter-annual variability tended to be more efficient in meeting the demand than those in regions with less frequent rainfall and high inter-annual variability. Mehrabadi et al., (2013) also drew similar conclusions for three climate types found in Iran and the findings of a more recent study by Andrade et al., (2017) highlighted the importance of the temporal variability characteristics of rainfall in determining the performance of a RWHS. Palla et al., (2012) drew strong correlations between the antecedent dry weather period and performance parameters for Italy, whilst Andrade et al., (2017) showed the precipitation concentration degree (a measure of the distribution of total annual rainfall in a 12-month period) to most influence the performance of RWHS in Brazil.

The afore-mentioned studies also support the general observation that analytic/stochastic models developed by researchers frequently hardcode rainfall statistical parameters (e.g. Guo & Baetz, 2007; Lee et al., 2000) in design equations. However there are a few researchers who have developed generalised models via behavioural modelling who have also accounted for the influence of the temporal variation of rainfall. Campisano & Modica (2012) derive regional regressive relationships for Sicily, and incorporate the dimensionless parameter of the ratio of number of dry days to number of rainy days as part of their generalisation. This parameter was selected on the basis of its ability to characterise intra-annual rainfall patterns as it represents the “average dry period in the year per each rainy day” (Campisano & Modica, 2012). They argue that this ratio allows the designer to better relate tank storage capacity to the water demand during the average dry period. Hanson & Vogel (2014) also recognised the influence of rainfall variability characteristics on the behaviour of RWHS and used multivariate regression analysis to develop generalised storage-yield-reliability relationships for the continental United States. Their relationships integrate rainfall variability parameters such as the coefficient of variation, lag-1 correlation of daily rainfall depth, mean and standard deviation of the daily wet-day rainfall series associated with the historical daily rainfall record for different climatic regions. These were also the parameters found to most influence the behaviour of a RWHS.

Testing of the models developed by Hanson & Vogel (2014) revealed that generalisation by regions sharing similar rainfall characteristics tends to predict system behaviour much more accurately than a single model integrating all regions. A similar approach was adopted by Liaw & Chiang (2014) for Northern Taiwan. They observed that in order to optimally design a RWHS one requires detailed local rainfall data which at the best of times is either unavailable or incomplete and went on to argue that grouping regions into areas of climatic similarity (where rainfall is concerned) combined with the use of non-dimensional parameters is able to iron out some of these deficiencies. Using the dimensionless parameters of storage fraction and demand fraction (after Fewkes & Butler, 2000), and production theory the authors developed a set of four system sizing curves which were found to strongly mirror simulated behaviour. While this illustrates that it is possible to generate an accurate generalised model for the sizing of RWHS with input from rainfall limited to the MAP, the observation that they still calibrate their generalised models using climatically homogenous regions once again points to the criticality of incorporating parameters characterising the spatial and temporal distribution of rainfall.

Allen & Harhoff (2015) investigated generalisation of RWHS design using 3 randomly selected cities in South Africa. In their analysis they take a very simplistic view of the operations of a rainwater harvesting system. They define two dimensionless parameters (runoff coefficient and storage coefficient) and use simulation to calibrate regression relationships for each site in turn. Part of the conclusions reached in this study was that the seasonal variability of rainfall has a significant role to play in determining the storage size of a RWHS. The previous work of Allen (2013) analysed the correlation between regression parameters and various rainfall variability statistics and found poor correlation to MAP but promising relationships for average percentage of MAP falling in the driest six months, average number of consecutive dry days per year and longest period of consecutive dry days.

When assessing the findings of the above quoted studies, it becomes apparent that scope and depth of analysis into such factors is still lacking for southern Africa especially where the development of generalised design models is concerned. Whilst the use of the MAP alone could be suitable in predicting storage capacities for RWHS, it is expected that the predictive abilities of a generalised model could be further improved by a more comprehensive characterisation and integration of parameters that best describe South Africa's spatial and temporal distribution of rainfall.

Rainwater Demand and its Variability

The demands on a RWHS are another critical parameter in determining the performance of a RWHS. Just like rainfall, demand can be variable in time, space and in magnitude. In spite of this, a limited number of studies that have reflected on the impacts of different aspects of rainwater demand on the performance of RWHS were found in the literature.

Ghisi et al., (2007) analysed the impact that different constant unvaried rainwater demand levels (low, medium and high) can have on RWH tank sizes in Southeast Brazil. The results of the study indicated that low demands required larger storages when compared to medium and high demand scenarios. Statistical analyses between storage and rainwater demand (as a percentage of potable water demand) also showed strong correlations above 60% inferring that the magnitude of demand will influence the performance of a RWHS. Lopes et al., (2017) approached the issue of a variation in the magnitude of non-potable water demand in a different manner whereby they assessed its influence on tank size as a function of a demand-roof area ratio. They found that for the rainfall region studied, as the demand-area ratio reduces (larger collection areas for a fixed demand) a smaller tank is required to meet the demand; equally so, a larger ratio (larger demand to collection area) also offers its best utility when using a small storage tank as the storage is likely to be empty most of the time. The findings of these studies show that the performance of a RWHS has some sensitivity towards both the magnitude and the demand-supply dynamics that it may be subjected to.

Coombes & Barry (2007) on the other hand, showed through simulation, rainwater yields will vary depending on the demand pattern one chooses to model a RWHS with; they observe that the use of climate-dependent demands that capture to a certain degree the inter-seasonal variability of certain demands are more likely to be more representative of the actual behaviour of a RWHS than the use of constant unvaried average demands. This is echoed in another study by Mitchell et al., (2008), who found that the use of an inter-annually variable demand, as a function of a wet versus dry year rainfall pattern, resulted in some significant changes to the reliability of water supply. In contrast, the more recent study of Silva & Ghisi (2016) analysed the impact of stochastically generated water demand patterns at annual, monthly and weekly scales on the performance of RWHS in urban centres of Brazil. This study found that variations at these levels to have a low impact to water savings but they could potentially significantly impact on the optimal storage sizes.

The afore-mentioned studies highlight the importance of accurately capturing the influence of two critical aspects of water demand as they will impact on the yield and reliability of a RWHS: its temporal distribution and magnitude. It is also these two aspects that are frequently difficult to accurately quantify (Campisano et al., 2017) and these aspects that have frequently been avoided in analyses that develop generalised storage-yield-reliability relationships as the majority of the studies found in the literature have applied constant demands. Given the observations of these studies, not only are the two aspects important in and of themselves, but as their impact is interlinked with the impacts of other key variables of design such as the size of the catchment area and rainfall characteristics (Silva & Ghisi, 2016), improved understanding of the impact of variability of demand on system performance is an especially important aspect for consideration in the development of generalised relationships.

Water Collection Efficiency Coefficient

The rainwater collection efficiency coefficient is defined as the ratio of volume of runoff to volume of rainwater collected (Gould & Nissen-Petersen, 1999). It is used to account for the various rainwater losses that can occur; for example rainwater losses that result from evaporation, the influence of roof shape and slope, leakage of gutters and filter screens and depression storage.

This aspect of RWH is well researched and quantitative measures of this coefficient from various studies are presented in Table 2-2.

Table 2-2: Water Collection Efficiency Coefficients

Reference	Water Collection Efficiency Coefficient	
(Gould & Nissen-Petersen, 1999)	Sheet-metal: Cement tile: Clay tile (machine made): Clay tile (handmade):	0.8 - 0.85 0.62 – 0.69 0.30 – 0.39 0.24 – 0.31
(Fewkes & Warm, 2000)	Pitched roof without filtration (tile/slate): Pitched roof with filtration (tile/slate): Flat roof with impervious membrane: Flat green roof:	0.9 – 1 0.75 – 0.9 0 – 0.5 0 – 0.5

Reference	Water Collection Efficiency Coefficient	
(Liaw & Tsai, 2004)	Inverted V (metal): Flat (cement): Parabolic (metal): Saw-tooth (metal):	0.82 0.81 0.81 0.83
(UN-Habitat, 2005)	Tiles: Corrugated metal sheets:	0.8 - 0.9 0.7 – 0.9
(Woods Ballard et al., 2015)	Pitched roof with profiled metal: Pitched Roof (tile): Flat roof (no gravel): Flat roof (gravel): Intensive green roof: Extensive green roof:	0.96 0.9 0.8 0.6 0.3 0.6

Researchers in their various studies into generalised model forms have at times not accounted for rainwater losses by assuming a value of unity for this parameter (e.g. Campisano & Modica, 2012; Hanson & Vogel, 2014; Liaw & Chiang, 2014). However, a study by Fewkes (1999) compared the performance of an installed RWHS to that predicted using a behavioural model that assumed no losses and concluded that the explicit inclusion of water losses in a RWHS model will lead to more accurate system performance measurements. The results of the study by Liaw & Tsai (2004) and Kim & Yoo (2009) agree with this view - the performance of a RWHS will show some sensitivity to the rainwater collection efficiency coefficient.

The First Flush

The first flush has traditionally been studied in the field of storm water or storm sewer management where researchers recognised the fact that storm water coming off of the urban catchment contained a significant proportion of pollutants that were leading to the rapid deterioration of urban waterways. A study of the literature showed most researchers to be in agreement with the position that some proportion of the total runoff from a catchment will contain the largest mass/concentration of pollutants; however putting a quantitative definition to this qualitative statement is still a major bone of contention amongst those in the field.

In traditional storm water facilities design, researchers frequently refer to the curves of the cumulative fraction of total pollutant mass versus the fraction of total cumulative runoff volume, also known as M (V) curves, to identify the presence of the flushing effect in storm sewers (Bertrand-Krajewski et al., 1998). However because of the highly dispersed, site specific and unique nature of these curves for a single pollutant parameter (and indeed for all pollutant parameters), many a definition have been put forward in order to identify the presence of this phenomenon. For example, Bertrand-Krajewski et al., (1998) and Saget et al., (1996) proposed the use of the 30/80 rule arguing that 80% of the pollutant mass must be carried in the first 30% of the runoff in order for one to claim a flushing effect in storm sewers. However both studies went on to admit that the choice in proportions is quite arbitrary - these proportions happen to fall within the range of values of the regression parameter used to define the deviation of the M (V) curves from the diagonal that indicates the presence of a strong flushing effect. The application of this criteria to measured data by Saget et al., (1996) failed to identify a significant first flush for storm and combined sewers for different sites in France. Sansalone & Buchberger (1997) also used their own criteria of the cumulative mass curve being above the cumulative runoff volume curve as an indication of the presence of a first flush. This definition led to the identification of a first flush for some pollutant indicators and no first flush for others. Deletic (1998) analysed the various definitions of the first flush phenomenon and went on to propose another criterion: the percentage of total event pollution load transported by the first 20% of storm runoff volume. This definition also identifies the first flush for some pollutants and not others in experimental results. In 2010, Bach et al., (2010) also proposed a new methodology seeking to overcome the shortcomings of the traditional approach.

Quantifying the First Flush in Harvested Rainwater

For the case of RWH, it is also usual that a proportion of the total volume of runoff from a given catchment will contain the largest concentration of pollutants (Ntale & Moses, 2003; Polkowska et al., 2002; Yaziz et al., 1989) and this fraction of water ideally should not find its way into storage lest it compromise the quality of water already present. Thus some quantity of the total storm depth is usually recommended to be diverted before entering the storage tank. However, once again there is no consensus as to what quantity of the runoff should constitute the first flush. Martinson (2007) notes that there is still some disagreement as whether to base this quantity on volume, depth or rainfall intensity and Doyle (2008) also notes that the anticipated end-uses of harvested rainwater will influence the amount one may choose to divert. Martinson (2007) further adds to the debate by arguing that for self-draining devices, the actual flushed depth can possibly vary from one rain event to the next as the amount of the first flush removed will depend on the time it takes the device to empty - hence some sort of balance has to be struck in order to ensure the system flushes enough water to meet the required contaminant removal efficiencies with each rainfall event.

There is however agreement that its presence will be the combined result of a number of factors, including the amount of accumulated pollutant matter and dissolved pollutant elements which in turn are a function of other site specific variables (Martinson, 2007; Yaziz et al., 1989). For example, experiments by Yaziz et al., (1989) showed a positive correlation between the length of a dry spell and the pollutant concentration in subsequent first flush samples. Some studies have also found that rainfall intensity plays a role in the observed levels of pollutant in successive first flush samples – the more intense a storm the smaller the first flush volume can be (Yaziz et al., 1989). Martinson (2007) also noted that whilst the pollutant accumulation and wash-off processes for roof catchments and those of overland catchments or storm sewers are fundamentally the same, some key differences include aspects such as time of concentration - roofs have uniform smooth materials and much steeper slopes than overland catchments and the flow is predominantly channel flow rather than sheet flow. Models and formulae for overland storm water management cannot therefore be simply adopted to determine a first flush depth for a roof RWHS. Accordingly, to date many studies have put forward what they believe to be a suitable amount of water to flush. A few of these recommendations are presented in Table 2-3.

Table 2-3: Recommended values for the first flush volume

Reference	First Flush Quantity	Notes
(Yaziz et al., 1989)	0.33mm	Based on observations of changes in microbial contamination of rainwater
(Michaelides, 1987)	0.28mm	Based on the capacity of the foul flush diverter used in experiments which was determined by the typical first flush devices used in Thailand
(Ntale & Moses, 2003)	0.82mm or first 10min of a rainstorm	Based on measurements taken using an actual RWHS in Uganda (recommend the depth be can be reduced as rainy season proceeds)
Texas Water Development Board (2005)	0.4 – 0.8 mm	Volume will depend on the number of antecedent dry days, nature of the roof and contaminants, rainfall intensity etc.
(Martinson & Thomas, 2009)	$ff_d = \frac{r_a}{450000} \frac{t_r}{(1-\eta_r)} + 0.24e^{2.4\eta_r}$ where: $\boldsymbol{ff_d}$ is the first flush diversion in mm, $\boldsymbol{\eta_r}$ is the target contaminant removal efficiency, $\boldsymbol{r_a}$ is the annual rainfall in mm, $\boldsymbol{t_r}$ is the time to reset the diverter in hrs	Empirical sizing equation derived by simulation using data based on several broad global climate types;
American Rainwater Catchment Systems Association (2009)	High contamination – 8mm Medium contamination – 2mm Low contamination – 0.5mm	High contamination – high content of organic debris or airborne pollutants Low contamination – frequent precipitation that keeps the collection surface relatively clean ** no definition is given for medium contamination**
(WHO, 2017)	20 – 25 litres	Initial roof cleaning wash volume that should not go to storage tank

As can be seen in Table 2-3, many different assumptions underlie the recommended values and as such prudent judgement has to be employed in selecting the appropriate depth to use in an analysis. Martinson &Thomas (2009) showed that most values recommended in the literature are in any case possibly far too low to achieve any significant contaminant removal.

Designing for the first flush

Review of the literature revealed very few studies that account for the first flush in the analysis of RWHS (e.g. Doyle, 2008; Khastagir & Jayasuriya, 2010; Notaro et al., 2016). Martinson (2007) has extensively studied the impact of first flush devices on RWHS performance and found that with increasing demand, the more one flushes the less a system is able to satisfy demand. On analysis of the interaction of tank size, first flush depth and demand satisfaction Martinson (2007) also found that whilst increasing the tank size is able to increasingly meet the demand, a much smaller fraction is met as first flush depth increases. Doyle and Shanahan (2012) similarly studied the effect of removing the first flush on domestic RWHS reliability in Rwanda. By simulating a variety of first flush depths they found that accounting for this loss can result in system yield reductions of up to 8%. These two studies highlight that removal of the first flush has the potential to impact on the performance of a RWHS, especially where small tanks are subject to large demands.

Of the studies reviewed that develop some form of generalised storage-yield-reliability relationships, only Khastagir & Jayasuriya (2010) and Notaro et al., (2016) account for first flush losses in their simulations. However, none of these studies has attempted to incorporate the first flush loss as a variable of design into the generalised model. This presents an opportunity for this study to analyse the impacts of this parameter on the behaviour of a RWHS and to determine if it is worthwhile to incorporate this as a design variable into generalised design equations.

Reliability of Water Supply

The complex interactions of the various design variables presented before determine the levels of security with which water can be supplied to meet the demand. The literature reveals two ways in which this level of security has been traditionally measured:

Volumetric Reliability: A measure of the actual supply to demand over the full simulation period

Time-based Reliability: A measure of the fraction of time when demand is fully satisfied

Basinger et al., (2010) compared their model to those developed by other researchers and found that the procedure taken to determine system reliability matters; for example, comparison to the parametric model of Guo & Baetz (2007), which also does not account for the temporal variation in water demand, tended to giver lower system reliabilities whilst simple mass balance methods gave higher reliabilities. Liaw & Tsai (2004) assessed the use of both these definitions on observed system behaviour and concluded that volumetric reliability is the more dependable measure as it is available in all circumstances whereas time-based reliability only registers a value when the full demand is met but not when it is partially met. The use of time-based reliability can thus lead to underestimations of system performance especially for small stores subjected to large demands. Thus while time-based reliability may offer a more conservative measure of system performance, it would appear to have some limitations to its applicability.

The different studies into the development of generalised design methods have utilised different definitions of reliability to measure system performance but most researchers have shown a preference for volumetric reliability (e.g. Allen & Haarhoff, 2015; Liaw & Chiang, 2014) over time-based reliability. This is not the case with Ndiritu et al., (2017) who argue that the above definitions of reliability do not fully account for the intra and inter-annual variability of the rainfall which would have a significant impact on the actual observed reliability of a RWHS. As such, the Weibull plotting positions formulation was adopted by their study as way to incorporate the effects of this variability in the modelling of RWHS.

The Weibull plotting position formula is an empirical formulation that enables the determination of probabilities of exceedance i.e. reliabilities. It is advantageous in that it is independent of any form of probability distribution, simple to apply and lends itself to the realistic characterisation of return periods for extreme values (Cunnane, 1978; Makkonen, 2006; Weibull, 1939). The formulation requires that the data collected from a simulation run be ranked in descending order and thus allow Equation 2-1 to be applied – in the case of Ndiritu et al., (2017) each year of the simulated rainfall series was taken to represent an independent estimate of the yield thus allowing for the ranking procedure to be used to determine the long-term reliability.

$$\boldsymbol{p} = \frac{\boldsymbol{m}}{\boldsymbol{n}+\mathbf{1}} \qquad \textbf{(2-1)}$$

Where: $\boldsymbol{p}$ is the probability of exceedance (reliability) of supply; $\boldsymbol{m}$ is the mth ranked number of days of supply and $\boldsymbol{n}$ is the number of years used in simulation.

While Notaro et al., (2016) develop some general relationships to relate volumetric reliability to the MAP, it is only Ndiritu et al., (2017) who have successfully shown that reliability can be incorporated as a variable into generalised design equations.

2.3. Summary

A review of the literature related to the practice, design and assessment of RWH was carried out and the following points summarise the main findings:

- RWH is slowly regaining popularity within the urban space. However much still remains to be done in terms of encouraging the buy-in of the end user through alignment of legislation to allow for the ease of implementation of RWHS and improvement of the economies of scale to allow for investment in the technology on a large scale.
- Many design and assessment methods continue to be proposed by researchers around the world. These range from probabilistic equations to the use of behavioural models. What has come to light through this literature review is that the key to dependable predictions being made by these models lies in the adequate consideration of the interactions of critical design variables namely: rainfall's quantity and temporal distribution, demand's magnitude and temporal distribution and losses.
- The studies presented have shown that there is a multitude of rainfall characteristics that determine the long-term performance of a RWHS and that these can be incorporated into predictive models. A critical point to note is that the performance assessment models proposed by different researchers tend to implicitly incorporate the effects of rainfall characteristics unique to the locations of their studies, making it difficult for any one model to be proposed for use at a global level. A region-specific model that analyses which rainfall statistics in southern Africa are important in determining RWH performance and can be incorporated into the modelling process is still lacking in the southern African context where RWH represents a critical source of water for some parts of the population.
- There are very few studies that have looked at the impacts of demand variability on the yield and consequent storage requirements for a RWHS. However, from the studies reviewed this is clearly a critical variable to consider in assessing the performance of a RWHS. None of the studies reviewed have considered the incorporation of parameters of variable demand into a generalised model.
- Whilst some disagreement exist in the literature on the 'fit for use' quality of roof harvested rainwater, if adequate material design in conjunction with the diversion of the first-flush and treatment precautions are taken, rainwater can be viewed as being of sufficient quality to meet at least the day to day non-potable demands of society. An interesting gap still to be addressed by scholars is the integration of the water loss by first flush as a way of accounting for water quality concerns in generalised models and how this parameter influences the viability of investing in a RWHS.

This study therefore offers the opportunity to develop a tool/s that design practitioners can easily use to evaluate upfront, the feasibility of using RWH in any part of South Africa.

CHAPTER 3 DATA PREPARATION AND ACQUISITION

Several researchers including Ndiritu et al., (2017), Hanson & Vogel (2014) and Liaw & Chiang (2014) used continuous simulation to generate empirical data from which generalised relationships were derived. As such, for this study simulation was also adopted as the appropriate means by which to obtain the required empirical data in order to assess RWHS behaviour and develop the generalised models. Ndiritu et al., (2017) and Liaw & Chiang (2014) also used a case study approach to develop their generalised relationships. However for this study a more general approach was adopted. This chapter details the materials and main methods used to acquire and analyse the input and performance data.

3.1. Inputs to Simulation Model

The key inputs to the simulation model utilised in this study include:

- Daily rainfall
- Mean daily demand and its temporal distribution
- Catchment Area
- Losses

As with Ndiritu et al., (2017) these inputs were combined into a dimensionless coefficient denoted as the ratio of supply-to-demand (S-D) as shown in Equation 3-1.

$$\boldsymbol{R_{SD}} = \frac{\boldsymbol{\eta A \overline{R}}}{\boldsymbol{\overline{D_t}}} \qquad \textbf{(3-1)}$$

Where: $\boldsymbol{R_{SD}}$ is the ratio of average supply to average demand, $\boldsymbol{\eta}$ is the rainwater collection efficiency coefficient, $\boldsymbol{A}$ is the catchment area, $\boldsymbol{\overline{R}}$ is the average daily rainfall, $\boldsymbol{\overline{D_t}}$ is the average daily demand.

The dimensionless nature of this parameter allowed for an analysis that is able to capture an infinite number of combinations of catchment area and magnitudes of demand without being user specific.

For this study RWHS were considered to exhibit within-year behaviour. This type of behaviour implies that the storage empties at some point during the year, which in turn would require that the supply component be less than the demand component in Equation 3-1. If the average daily demand level and average daily rainfall are taken as known parameters, for a pre-defined $\boldsymbol{R_{SD}}$, a corresponding catchment area can be determined using this equation. It is these catchment, rainfall and demand values that were used as the input to the behavioural model.

In order to more or less attain within-year behaviour, at each rain gauge used in this study a diverse range of supply-to-demand ratios lying between the values of 0.1 and 0.9 were selected.

The following sections give details on the acquisition and preparation of the input data for rainfall, demand and losses.

3.1.1. Daily Rainfall

Objective 1.1 of this study sets out to assess the impact to the predictive ability of generalised storage-yield-reliability relationships when the number of rain gauges used is increased. Tied to this is objective 1.2 that involves assessing whether different rainfall regimes have any type of influence on the behaviour of a RWHS and if so, could an alternative set of models be developed to capture the influence of intra-annual rainfall variability.

Given the high variability of rainfall in South Africa, a large sample of rain gauges needed to be selected in such a manner as to sufficiently represent the different climatic regions of South Africa.

Climate zones of South Africa

The Köppen-Geiger classification is the world's most frequently used climatic referencing system and primarily utilises the temperature and rainfall characteristics of an area to assign a two or three letter code to describe the climate type (Kottek et al., 2006). The characteristics of temperature considered are:

- Mean annual near surface temperature and
- Monthly mean temperatures of the warmest and coldest months

Characteristics of precipitation considered are:

- Accumulated annual precipitation,
- Precipitation of the driest month and,
- The lowest and highest monthly precipitation values for the summer and winter half-years on the hemisphere considered.

This classification system was primarily chosen as it is considered to describe the climate regions of South Africa (and by extension the rainfall regimes) in a simple, accurate and sufficiently detailed manner. A Köppen-Geiger classification map for South Africa was formulated by Shulze (1947) but for this project reference is made to the map produced by the CSIR (2012). This map was produced using a rather short record of 20 years of raw precipitation and temperature data (1985 - 2005) collected from around South Africa and may be found in Appendix 1. Table 3-1 provides a summary of the main climate types found in South Africa and these were used as a guide in the grouping of rainfall gauging stations identified for this study.

Table 3-1: Climate Types of South Africa (Conradie, 2012)

Köppen-Geiger Classification	Description
BSh	Arid, steppe, hot arid
BSk	Arid, steppe, cold arid
BWh	Arid, desert, hot arid
BWk	Arid, desert, cold arid
Cfa	Warm temperate, fully humid, hot summer
Cfb	Warm temperate, fully humid, warm summer
Csa	Warm temperate, summer dry, hot summer
Csb	Warm temperate, summer dry, cool summer
Cwa	Warm temperate, winter dry, hot summer
Cwb	Warm temperate, winter dry, warm summer
Cfc	Warm temperate, fully humid, cool summer

Rain Gauge Data

Long term daily rainfall data for southern Africa is available on a database developed by Lynch (2003). The database is composed of rainfall data records collected from approximately 14,000 rainfall stations scattered across the general southern African region. These daily rainfall data are stored in flat ACSII files but the developers of the database have also developed a complementary suite of programs to enable the extraction of the requisite data and its conversion to other user selected common data formats. The sub-routines of the software allow the user to interrogate the data and to discard infilled data if deemed necessary.

A grid search was employed in order to find rainfall gauging stations and due to time constraints, only a limited number of stations could be used for the analysis. Hence some criteria had to be set up in order to select suitable rainfall data. The criteria applied in the selection of rainfall stations was as follows:

(a) Length of daily rainfall record greater than 50 years
(b) Percentage missing data that is less than 5% and
(c) Reliability of data greater than 50%.

In addition to these criteria care was taken to select the rain gauges in such a manner as to also achieve as equal a distribution of the rain gauge sites across South Africa as possible. Table 3-2 presents a summary of the final set of the 118 rainfall stations chosen and utilised in this study. A detailed description of each individual station is given in Appendix 2. On average 27.7% the rainfall data for the selected stations is patched using the data of neighbouring stations and on average 1.7% of the data is recorded as missing whilst 70.9% is reliably observed data. The majority of records used have built using a combination of observed data and patched using the data of neighbouring stations.

Table 3-2: Summary of Rainfall data used in Analysis

Total Number of Rainfall Stations:		118	
Climate Zone	Number of Rain Gauges	Average Length of record after patching (years)	Average MAP (mm/year)
BSh	19	103	481
BSk	20	122	413
BWh	10	115	201
BWk	12	123	217
Cfa	9	125	910
Cfb	12	121	737
Cfc	6	121	896
Csa	5	150	623
Csb	9	150	624
Cwa	9	103	744
Cwb	7	103	679

Figure 3-1 shows the geographical locations of the 118 rain gauges selected for use in this study. The rain gauges were fairly evenly distributed across the country although some large gaps were created where rain gauges meeting the set criteria could not be found.

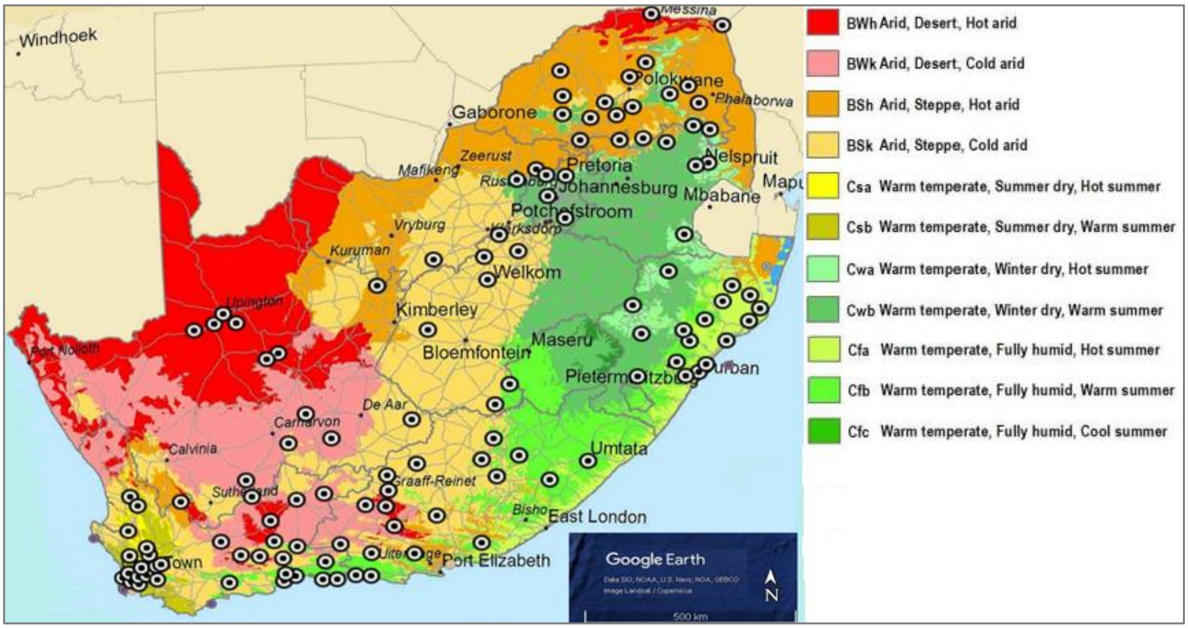


Figure 3-1: Distribution of rain gauges across South Africa (Image created using Google Earth Pro (2018))

3.1.2. Water Demand

Water users may be grouped into categories such as domestic, commercial, industrial, institutional, educational, recreational/sport parks and agricultural users. However, many water demand studies carried out recently in South Africa have mostly concentrated on the domestic water user, with very few studies analysing the water demand characteristics of other categories. As such, to facilitate the use of the simulation model, which requires the average annual daily demand as input, the water demand data of South African urban domestic users was considered and used to create the required supply-demand ratios from Equation 3-1.

The non-availability of actual measured water consumption data also meant that alternative information sources needed to be used to develop the required data for use in the study.

Average annual daily demand for domestic water users
The main source of information which can be used to estimate water consumption levels in the place of actual measurements is the Red Book produced by the CSIR (2003). However several studies in South Africa (e.g. Ilemobade et al., 2009; Jacobs et al., 2004; van Zyl. et al., 2008) have consistently highlighted that it has been some years since these guidelines were updated and as such they potentially do not adequately represent the latest in water usage trends.

Some water consumption statistics at household level are presented by Griffioen & van Zyl (2014). The data was derived from metered consumption data from 739 suburbs in South Africa, ranging in stand size from 50 - 5 000m^2; the water user data was extracted from the municipal treasury database. The statistics are summarised in Table 3-3. The average water consumption was adopted as an estimate of the total water demand that could be expected from formally developed housing areas.

Table 3-3: Average Annual Daily Demand for Domestic Water Users (Griffioen & van Zyl, 2014)

	Average Annual Daily Demand (L/m^2/day)
Average	1.33
Min	0.12
Max	4.42

The studies of van Zyl et al., (2017) and van Zyl et al., (2008) have shown property size to be the most critical driving variable in predicting water demand levels for most categories of water user. The mean stand area for the study by Griffioen & van Zyl (2014) was 970m^2, however Loos & Erasmus (2017) revealed that typical residential stand areas in South Africa are closer to 550m^2. The figure of 550m^2 was subsequently adopted as it was considered to better represent the area of demand of formal housing properties.

Quantitative Distribution of Water Demand
Rainwater can be used to meet both potable and non-potable water needs, however considering water quality issues, it is more likely that in most cases, a RWHS will be designed from the point of view of being a complementary source of water to meet non-potable water needs and not as a means to completely replace the conventional means of water supply (Ndiritu et al., 2018). A study of the literature was carried out to determine the potential uses of rainwater for the various types of water user who could potentially adopt rainwater harvesting to replace some of their water needs.

These were identified as follows: toilet flushing & hand basins, air conditioning cooling towers, irrigation and laundry.

Toilet Flushing & Hand basins: As an indoor demand, this water use is relatively simple to predict and most researchers assume it to be independent of seasonality effects (e.g. Ndiritu et al., 2018) for domestic households. However some variation with respect to the time of year can be expected for users such as educational facilities and shopping malls.

Irrigation: As an outdoor water use, this demand is difficult to predict as it is affected by many factors including the type of vegetation, temperature, rainfall and the type of irrigation system utilised. This water use is typically responsible for the observed seasonal variation of water demand especially for domestic households (du Plessis & Jacobs, 2014).

Air-conditioning Cooling Towers: Air-conditioning units are typically used to moderate the indoor climate of large buildings, especially those in the commercial and institutional sector. The day to day variation of water consumption by air-conditioning units is largely dictated by climatic factors and the water use efficiency associated with installed units. Unpublished data indicates that air conditioning demand could be considered to vary in direct proportion to the temperature (in °C) (Personal Communication Ndiritu, 2018)

Laundry: Rainwater may also be used to do domestic laundry and Khastagir & Jayasuriya (2010) note that the magnitude of water demand is in part a function of the number of people in a household and the frequency of the event.

Various studies were then utilised to determine the fractions of the total demand taken up by the identified water uses. These are presented in Table 3-4.

Table 3-4: Distribution of Water Demand between Different Water Uses

Water user	Non-potable Water Demand as % of Total Demand				Source
	Water use				
	Toilet & Hand basin	Irrigation	Air-conditioning cooling tower	Laundry	
Retail Centres	20	-	30	-	(Saunders, 2012)
Educational Buildings	45	36	11	3	(USEPA, 2017)
Domestic	30	35	-	13	(O'Brien, 2014)

As can be seen from Table 3-4, a large proportion of a user's demand could be non-potable and could therefore be met by the use of rainwater if available. It was noted that different users could utilise different combinations of the above demands with up to 80% of the total demand being met by RWHS. Given this, the fraction of 80% of total average annual demand (as highlighted in Table 3-3) was used as the fixed/known input of average demand **($\overline{\boldsymbol{D_t}}$)** to Equation 3-1 in order to facilitate the derivation the required supply-demand ratios for simulation - it can be appreciated that a different proportioning of the total demand could be used to achieve the same result.

Temporal variation of demand

Objectives 2.1 and 2.2 of this study are to assess the effect of a temporal variation of demand on the behaviour of a RWHS and to investigate whether mathematical relationships can be established between the temporal variation in demand, the yield and storage of a RWHS. As highlighted in section 3.1.2., RWH can be utilised by a broad group users and whilst property size drives the magnitude of the water demand, its distribution within the year will be largely driven by human behaviour. This behaviour is probabilistic in nature and can be influenced by any number of factors including climate, population density, rainwater uses, geographic location and socio-economic status (van Zyl et al., 2008). It can thus be reasonably expected that different water users will have their own distinct water use patterns, each of which could potentially impact on the performance of a RWHS differently.

Studies into the temporal water demand patterns of different users have mostly focussed on its diurnal variation (e.g. Fisher-Jeffes, 2015; O'Brien, 2014) but as this study needed to utilise a daily time-step, the water demand patterns observed by these studies could not be readily adopted and alternative means of deriving water demand patterns at the requisite time-scale had to be sought. According to van Zyl et al., (2017) whilst domestic water requirements are mostly driven by human needs, which may be easily predicted from historical records, water requirements of non-domestic users are quite variable and are driven to a large extent by the type of activity an entity is engaged in. The variations of indoor water uses by the different user groups is also more likely to be a function of the fluidity of occupancy levels which in turn depend on time of week/month/year (Ndiritu et al., 2018). Irrigation and air conditioning demands on the other hand, are more likely to exhibit a strong correlation with the observed variation in seasonal attributes such as temperature and evapotranspiration rates.

With this in mind, an intuitive argument was first used to develop a small and rather general set of possible within-year demand patterns that a RWHS could be subjected to whilst recognising that it may not be possible to exhaust them all. The demand patterns formulated are presented below:

D1 constant daily demand < the typically modelled situation>

D2 demand for summer months is less than the demand for the winter months < as is characteristic of winter irrigation water use>

D3 demand for summer months is higher than the demand for the winter months <as is characteristic of summer irrigation water use>

D4 demand in the summer months is greater than the demand in the winter months <as is characteristic for air conditioning water use>

D5 demand during holiday periods is higher than the rest of the year <as is characteristic of shopping malls>

D6 demand on weekends is greater than demand on week days <as is characteristic of shopping malls>

The above demand scenarios inform that water demands can peak or diminish at different and multiple times within a year, month or week.

The behavioural model is programmed to utilise a ratio of the actual daily demand to average daily demand to create the demand pattern desired. This ratio is determined by the user inputting appropriate monthly, weekly or daily demand distribution factors. In order to analyse the impact of peak-and-trough type demand patterns as described by D2 to D4, a simple mathematical model was derived that could be used as the input to the simulation model.

Alvisi et al., (2007) studied the variation in demand for the Municipality of Castelfranco Emilia in Italy where water use data was collected over some years. Figure 3-2 shows a sample of the observed water consumption data from their study.

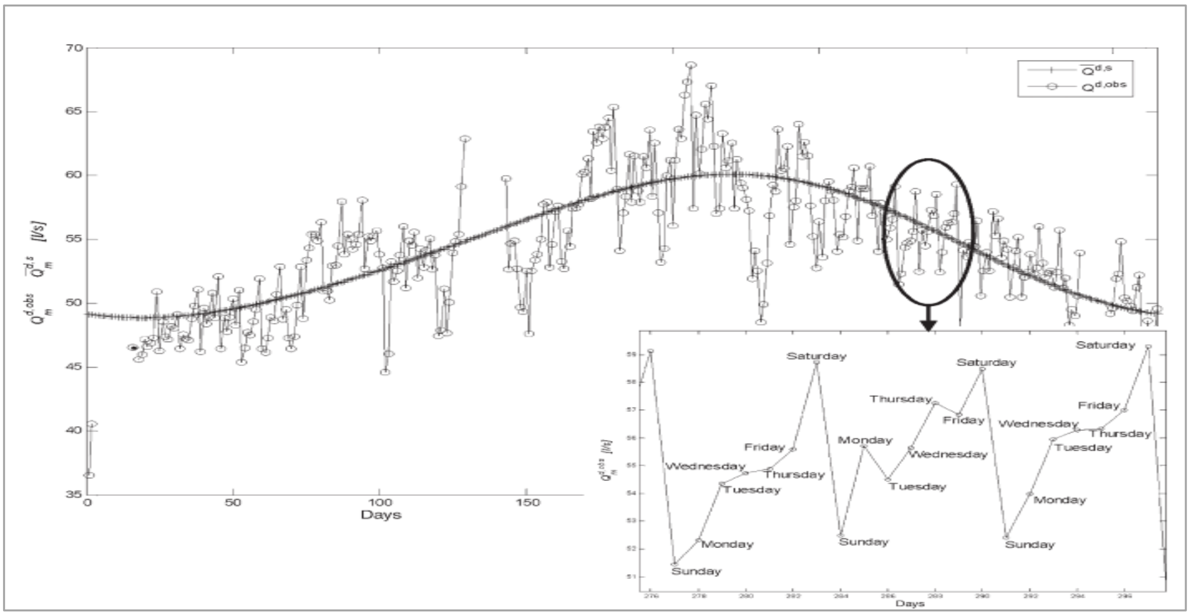


Figure 3-2: Observed daily and seasonal variation of demand for Castelfranco Emilia (from Alvisi et al., (2007))

What was observed is the smooth wave-like variation of the mean daily water demand in tandem with the seasons within a year. The wave-like nature of this variation is also reminiscent of a cosine function. Assuming the demand to be annually cyclical, the general cosine function shown in Equation 3-2 could then be used to formulate a mathematical representation for a similar type of mean variation at a daily scale. Figure 3-3 illustrates one such variation that could be formulated using the parameters ***a, l*** and ***b*** of Equation 3-2.

$$\boldsymbol{y(t) = 1 + a\left[\cos\left(\frac{2\pi}{366}(bt + l)\right)\right]} \tag{3-2}$$

Where: $\boldsymbol{y(t)}$**,** represents the ratio of daily demand to average annual demand as a function of time**,** $\boldsymbol{a}$ represents the amplitude of variation (taking on values between 0 and 1)**,** $\boldsymbol{b}$ represents the number of times the demand peaks within a year**,** $\boldsymbol{t}$ represents the day of the year (taking on values between 1 and 366)**,** $\boldsymbol{l}$ represents the position of the maximum demand (taking on values between 0 and 365).

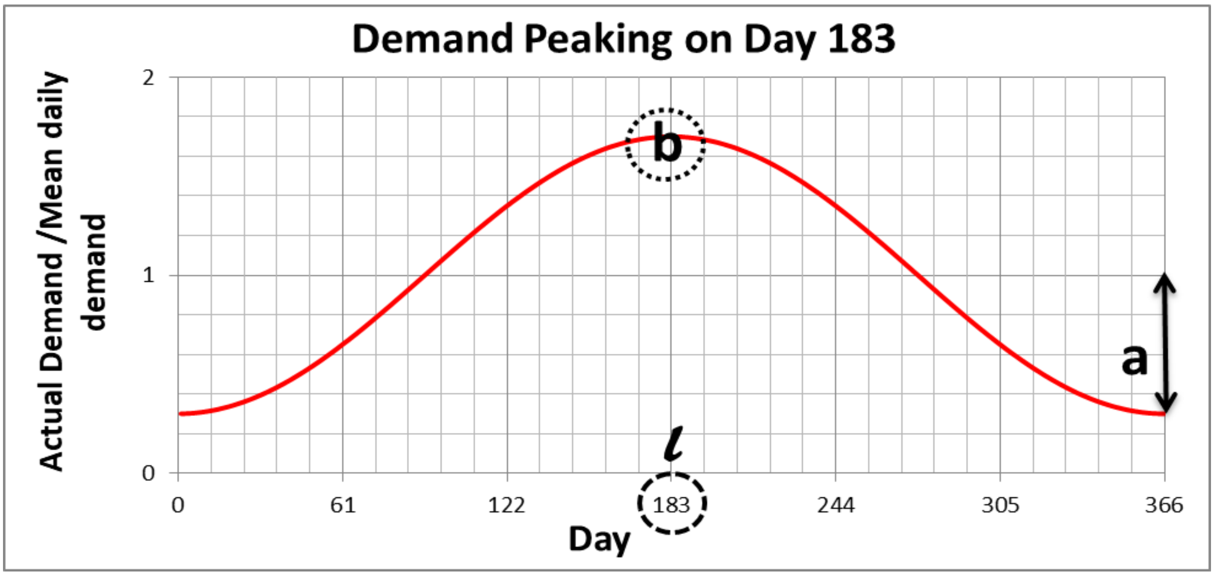


Figure 3-3: An illustration of parameters *a* (amplitude) and *l* (lag) for modelling variability of demand

The parameter $\boldsymbol{l}$ allowed for the modelling of a peak in demand that could occur on different days of the year, with a zero value representing a peak in demand on the last day of the year and a value of 365 representing a peak in demand on the first day of the year. Parameter $\boldsymbol{b}$ allowed the function to model the occurrence of multiple peaks within a single year as illustrated by scenarios D5 and D6, however, only a single peak was applied for this study.

The value of $\boldsymbol{a}$ represents the magnitude of the peak in demand about the mean daily demand, where a value of zero represented a constant unvaried demand pattern and a value of 1 represented the theoretical extreme of the demand variation - beyond this value the cosine function gives negative values of variation which are not realistic as the demand cannot be negative. The amplitude thus essentially serves to quantify how far from the average annual daily demand each day's demand lies. Equation 3-3 provides a general definition of the amplitude

$$\frac{\boldsymbol{Maximum\ Daily\ demand} - \overline{\boldsymbol{D_t}}}{\overline{\boldsymbol{D_t}}} \qquad \textbf{(3-3)}$$

Where: $\overline{\boldsymbol{D_t}}$ represents the mean annual daily demand.

For the simulations, a constant daily demand was adopted as the base case scenario to which all other demand distributions were compared and scaled.

3.1.3. Rainwater Losses

The third input to the simulation model utilised in this project were the various water losses that can be experienced by the system as the water is routed from the catchment through the storage and to the point of demand. For this study these losses were grouped into two categories, namely general losses and first flush losses.

General Losses

General losses encompass water losses to the system that may occur as result of evaporation, leakage of gutters, initial abstraction through depression storage, loss of water in filters etc. For this study, these losses were taken to be accounted for by a water loss coefficient alternatively expressed as the water collection efficiency coefficient.

From Table 2-2 in the Literature Review, the water collection efficiency coefficients for different types of roof catchment materials and orientations range from 0.6 – 1. A median figure of 0.8, which is also recommended by Gould & Nissen-Petersen (1999) and used by Ndiritu et al., (2017), was selected for use in the behavioural model although it must be noted that the ability of Equation 3-1 to accommodate different types or sizes of RWHS also allows for any other collection efficiency to be utilised to achieve the desired result.

First Flush

The third objective of this study was to assess the influence of accounting for first flush losses separately from the general losses on the performance of RWHS. An internet survey of available first flush systems in South Africa revealed that most suppliers recommend a minimum flush of 20L per 100m^2 of catchment depending on the perceived pollutant levels and rainwater end uses (e.g. http://www.gutterguard.co.za/First-Flush-Systems-and-Pricing/; https://www.eco3.co.za/rain_water_harvest_catch.htm;https://www.faithful-to-nature.co.za/gutter-guard-first-flush-diy-kit). This translates to a rainwater depth of 0.2mm. This first flush depth is lower than other recommended values as presented in Table 2-3 of the Literature Review. Thus for this study it was decided to analyse the impact of a range of potential first flush depths with the minimum first flush depth set to value of 0.2mm. Details of other first flush depths considered are given under the relevant section in Chapter 6.

3.2. Simulation Procedure and Methods of Data Analysis

3.2.1. Behavioural Model

The computer program ***RWHSimulator*** was used to gather the research data. The algorithm applied by this program involves the use of a daily time-step simulation of inflows and outflows through a typical RWHS as illustrated in Figure 3-4.

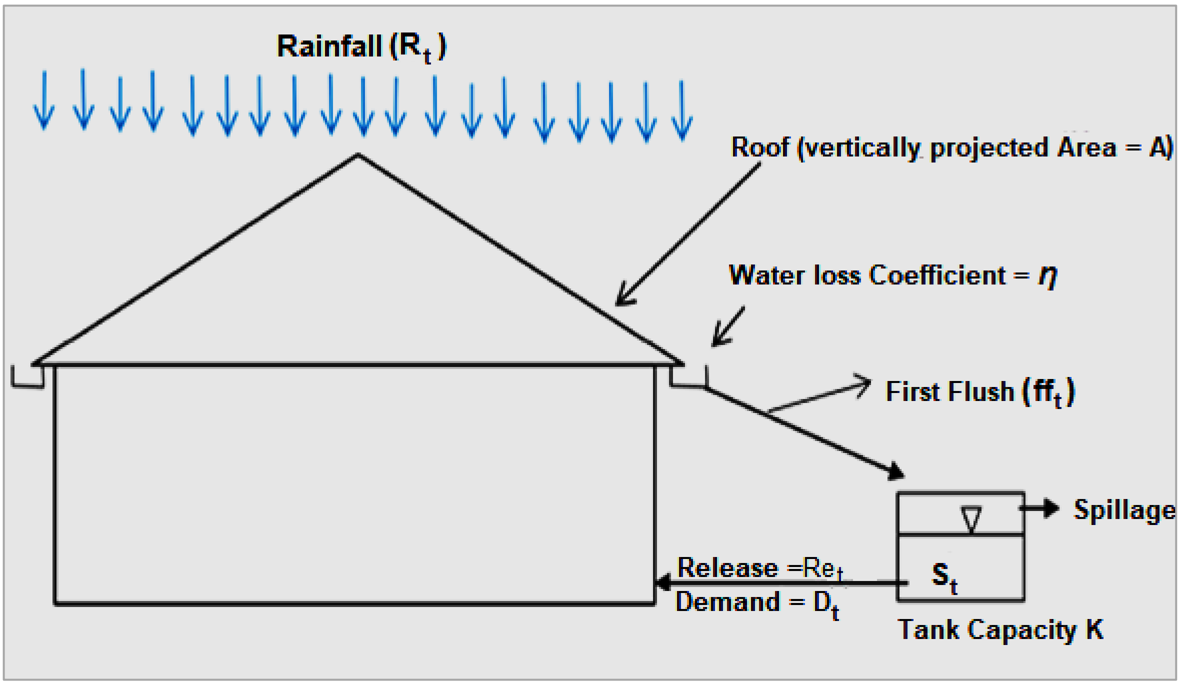


Figure 3-4: Components of a typical Rainwater Harvesting Model (Adapted from Ndiritu et al., (2017))

The computer program utilises the yield after spillage (YAS) operating rule and routes the inflow collected from the catchment (after deduction of losses) through storage and to the demand as described by Equations 3-4 and 3-5.

$$S_{t+1} = min \quad (S_t + \eta A R_t - Re_t) \quad or \quad (K - Re_t) \qquad \textbf{(3-4)}$$

$$Re_t = [D_t \quad if \quad S_t \geq D_t] \quad or \quad [S_t \quad if \; S_t \leq D_t] \qquad \textbf{(3-5)}$$

Where: S_t is the storage in time period t, Re_t is the release to demand in time period t, η is the water loss coefficient, A is the projected roof area, R_t is the rainfall depth in time period t, K is the capacity of the storage tank and D_t is the demand in time period t.

The simulation proceeds by adding the inflow of the current time-step t to the storage calculated at the end of the previous time-step, $t-1$. If the sum exceeds the capacity of the storage K, spillage is calculated and deducted. Water is then allocated to the demand from the remaining fraction of water as follows: if the total in storage after deduction of spillage is greater than the demand D_t then the full demand is deducted from storage; if the total in storage after deduction of spillage is less than the demand then all the water in storage is allocated to meet the demand as far as practicable. The behavioural model also allows for the modelling of a temporally varied demand at monthly, weekly and daily scales. For this study, the demand was temporally varied at a daily scale as described in section 3.1.2.

In addition to this, an alteration to the mass balance equation shown in Equation 3-4 was introduced in order to explicitly include water losses due to the first flush as shown in Equation 3-6.

$$S_{t+1} = min \quad (S_t + \eta A(R_t - ff_t) - Re_t) or \quad (K - Re_t) \qquad \textbf{(3-6)}$$

Where: S_t is the storage in time period t, Re_t is the release to demand in time period t, η is the water loss coefficient, A is the projected roof area, R_t is the rainfall depth in time period t, K is the capacity of the storage tank and ff_t is the depth of water removed as first flush in time period t.

To select the appropriate depth to flush in each time step, the conditional statement expressed by Equation 3-7 was applied in conjunction with the altered mass balance equation.

$$ff_t = \quad [ff_d \quad if\ R_t \geq ff_d] \quad or \quad [R_t \quad if\ R_t \leq ff_d] \qquad \textbf{(3-7)}$$

Where: R_t is the rainfall depth in time period t, ff_d is the design capacity of the first flush diverter and ff_t is the depth of water removed as first flush in time period t.

3.2.2. RWHS Performance Measurement

Performance parameters of interest for this project were the potential yield of a RWHS system and its associated optimal tank size at a given reliability. These parameters were selected as they are generally the favoured metrics by which water resource system performance is measured within South Africa (Basson et al., 1994).

A single simulation run for each of the 118 rain gauges selected for analysis involved the iteration of a set of 20 user defined tank capacities inputted to the behavioural model for a particular setting of supply-to-demand (S-D) ratio, demand pattern and first flush depth. The iterations were done in such a manner as to identify the tank size that maximises the yield. This ideal value was defined as the minimum tank capacity at which the maximum number of days of supply is achieved at the required reliability. These optimal data as shown on Figure 3-5(a), define a Pareto efficiency front. This efficiency front represents that set of feasible solutions for which one cannot improve the performance of one objective without worsening the performance of the other objectives under the set circumstances – for example looking at Figure 3-5(b) in order to increase the yield from a RWHS along the red line (Pareto front) the reliability with which the system operates has to reduce. It is these data on the red-line which were subsequently used to derive generalised storage-yield-reliability relationships.

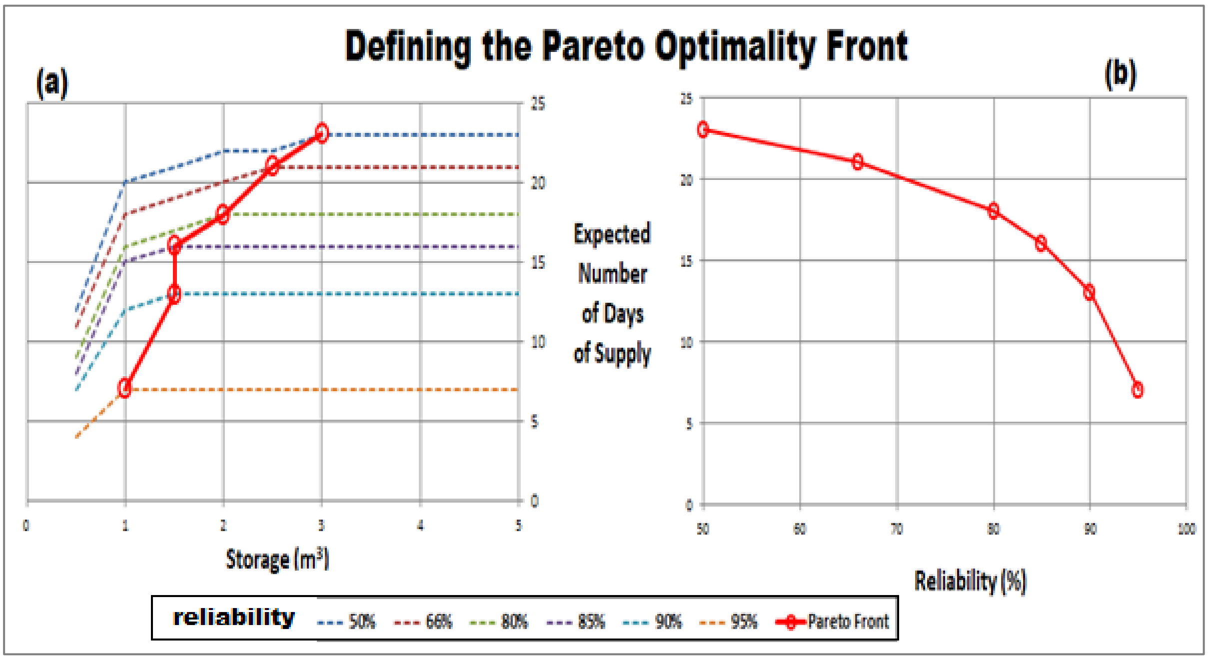


Figure 3-5: Defining the Pareto Optimal Front

As with Ndiritu et al., (2017), it was assumed that each year of the rainfall record used in the simulation produced an independent estimate of the number of days supplied - this was in order to allow for the incorporation of reliability (derived using Weibull's plotting positions formula) into the analysis. Reliabilities considered included: 50%, 66%, 80%, 85%, 90% and 95%. These reliabilities translate to levels of assurance of 1-in-2 years, 2-in-3 years, 4-in-5 years, 17-in-20 years, 9-in-10 years, and 19-in-20 years respectively.

3.2.3. Developing Generalised Relationships for RWHS Operating Under Constant Demand

The data obtained from the simulations was evaluated using regression analysis. The regressions were done in Microsoft Excel with the aim of establishing the best fit mathematical form between the previously identified dimensionless variables of Ndiritu et al., (2017) which are defined in Equations 3-1, 3-8 and 3-9.

$$\boldsymbol{S_{P-r} = \frac{N_r}{365.25}} \tag{3-8}$$

$$\boldsymbol{R_{TD-r} = \frac{K_r}{\overline{D_t} \times 365.25}} \tag{3-9}$$

where: $\overline{\boldsymbol{D_t}}$ is the average daily demand, $\boldsymbol{S_{P-r}}$ is the proportion of the year supplied at reliability $\boldsymbol{r}$, $\boldsymbol{N_r}$ is the expected number of days of full supply, $\boldsymbol{R_{TD-r}}$ is the ratio of storage to average annual demand at reliability $\boldsymbol{r}$ and $\boldsymbol{K_r}$ is the storage required to achieve reliability $\boldsymbol{r}$

Multiple linear regressions were then also employed in order to assess the ability of additional climatic variables to improve the predictive ability of the model. The climatic variables selected are described below. The choice of these characteristics was mainly based on the parameters that Hanson & Vogel (2014) and Campisano & Modica (2012) had applied.

Standard deviation of daily rainfall (*σ*): A measure of the spread of rainfall data from the mean value

Coefficient of Variation (*CV*): A measure of the extent of variability in the rainfall data in relation to the mean expressed as the dimensionless ratio shown in Equation 3-10.

$$\boldsymbol{CV = \frac{\sigma}{\mu}} \tag{3-10}$$

Ratio of Number of dry days (*n_d*) to Number of rain days (*n_r*): A ratio proposed by Campisano & Modica (2012) as a means by which to characterise the intra-annual variation in rainfall patterns. The dimensionless ratio is shown in Equation 3-11.

$$\boldsymbol{\frac{n_d}{n_r}} \tag{3-11}$$

Seasonality Index (*SI*): This index is a simplistic way of characterising the distribution of precipitation throughout a given year. The seasonality index (SI) as defined in Walsh and Lawler (1981) is given in Equation 3-12.

$$\boldsymbol{SI = \frac{1}{R}\sum_{i=0}^{12}\left|r_i - \frac{R}{12}\right|} \qquad \textbf{(3-12)}$$

Where: $\boldsymbol{SI}$ represents the seasonality index (the higher the value the more seasonal the rainfall)**,** $\boldsymbol{R}$ represents the total annual rainfall and $\boldsymbol{r_i}$ represents the monthly rainfall for each month of the year.

For this study the above equation is adapted to daily scale where 12 is replaced with 366; $\boldsymbol{R}$ and $\boldsymbol{r_i}$ represent their daily equivalents.

Mean daily rainfall for the wet-day series (μ_w): A measure of the average annual rainfall of rain days only

Standard deviation of the wet-day series (σ_w): A measure of the spread of rainfall values based on data from rain days only

Coefficient of variation of the wet day series (CV_w): A measure of the extent of variability in rainfall amount based on rainy days only. It is obtained by using an expression similar to that of Equation 3-10.

3.2.4. Simulation Analysis under Variable Demand

In this analysis, 33 out of the sample of 118 rain gauges as indicated in Figure 3-6 were first simulated to ascertain the general behaviour of a RWHS under variable demand.

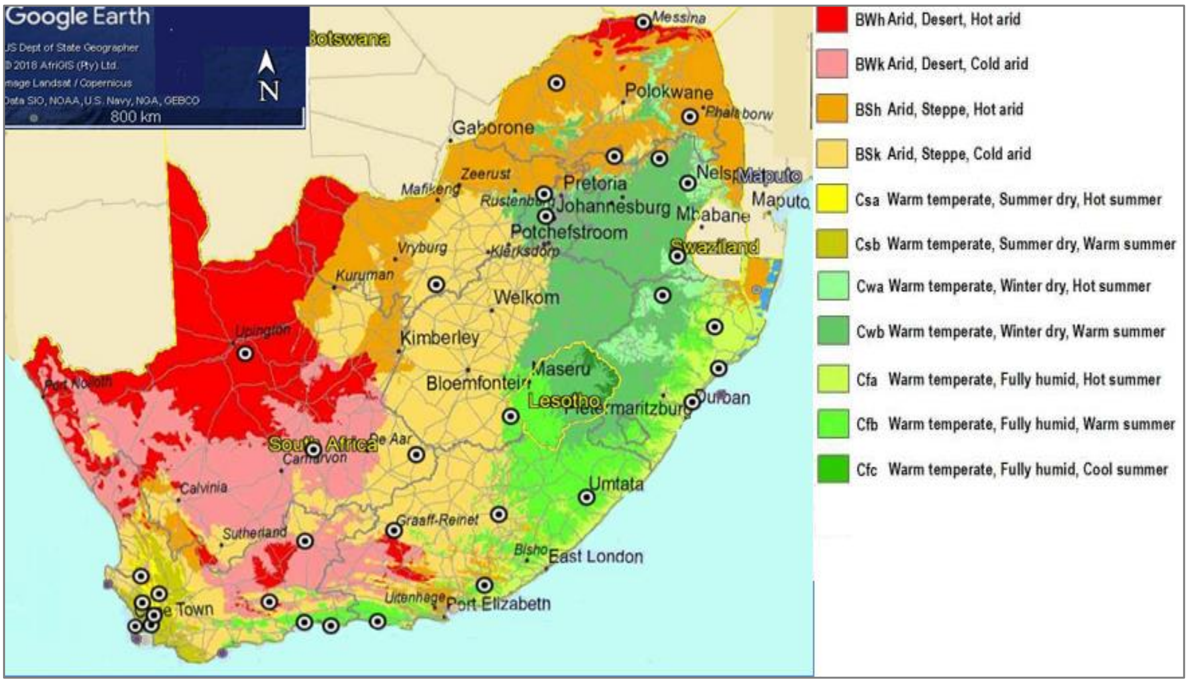


Figure 3-6: Map of rain gauges used in the variable demand analysis (Image created using Google Earth Pro (2018))

The model of variability of demand was formulated in Section 3.1.2 (Equation 3.2) and uses two parameters, namely the location of the demand peak (***l***) and amplitude (**a**) as illustrated in Figure 3-3. The simulations were run for each of the selected rain gauges at pre-set S-D ratios of 0.1, 0.3, 0.5, 0.7 and 0.9. Storage-yield data was collected at reliabilities of 50%, 66%, 80%, 85%, 90% and 95% for all simulations.

The first set of simulations evaluated the impact of using two demand patterns derived from Equation 3-2 and shown on Figure 3-7 that changed the location of the peak in demand but maintained the same amplitude which was set to 0.7.

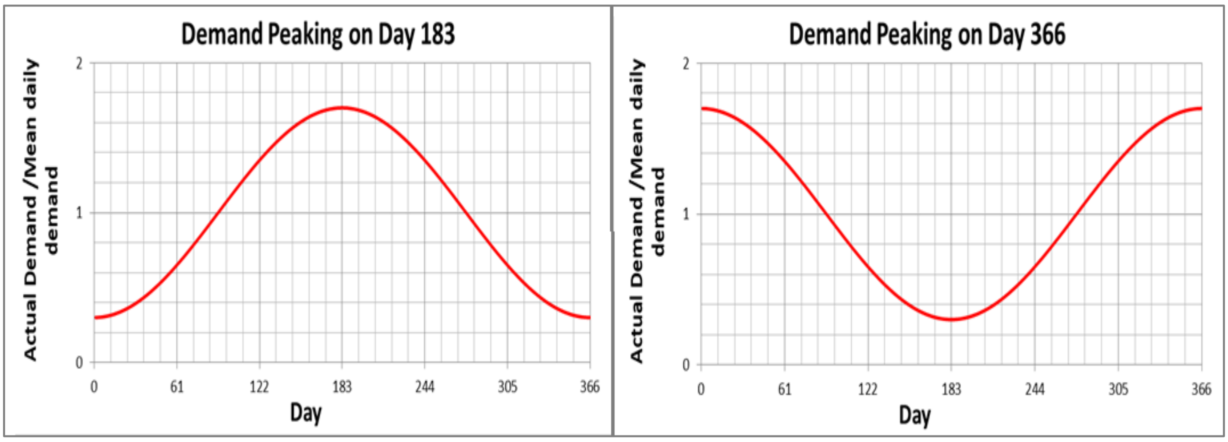


Figure 3-7: Demand Patterns applied to analysis of 33 rain gauges

The location (day) of maximum demand in relation to parameter ***l*** was determined as shown in Equation 3-13.

$$\boldsymbol{Peak\ day = 366 - l} \tag{3-13}$$

The second set of simulations set out to establish if the amplitude of a variable demand exerted any significant influence on the number of days of supply and optimal tank size of a RWHS. With reference to Equation 3-2, the variable ***a*** represents this amplitude. Figure 3-8 illustrates the simulation settings used to obtain a general understanding of behaviour.

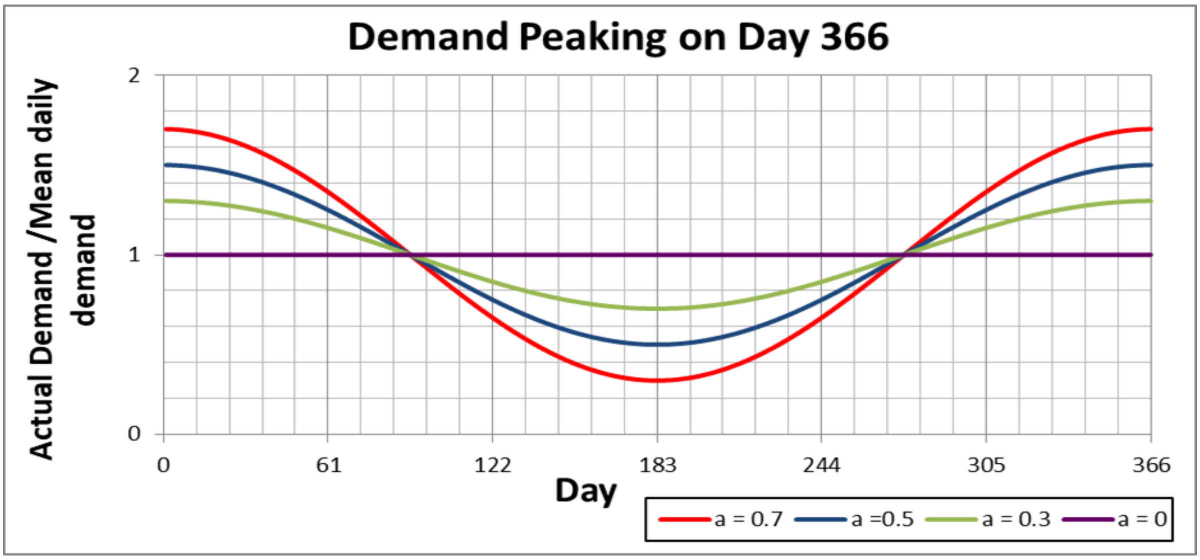


Figure 3-8: Demand amplitudes tested

A set of 11 out of 33 rain gauges were subsequently selected for further analysis to assess whether regression relationships could be established between tank size, the number of days of supply, reliability and the parameters used to quantify variability of demand. A lag (***L***) was defined as the difference in time between the day of occurrence of maximum rainfall and the day of occurrence of the maximum demand as shown in Figure 3-9. Equation 3-14 illustrates how this parameter is determined.

$$\boldsymbol{L = |Day\ of\ peak\ of\ the\ 61\_day\ moving\ average\ rainfall - Day\ of\ peak\ demand|} \tag{3-14}$$

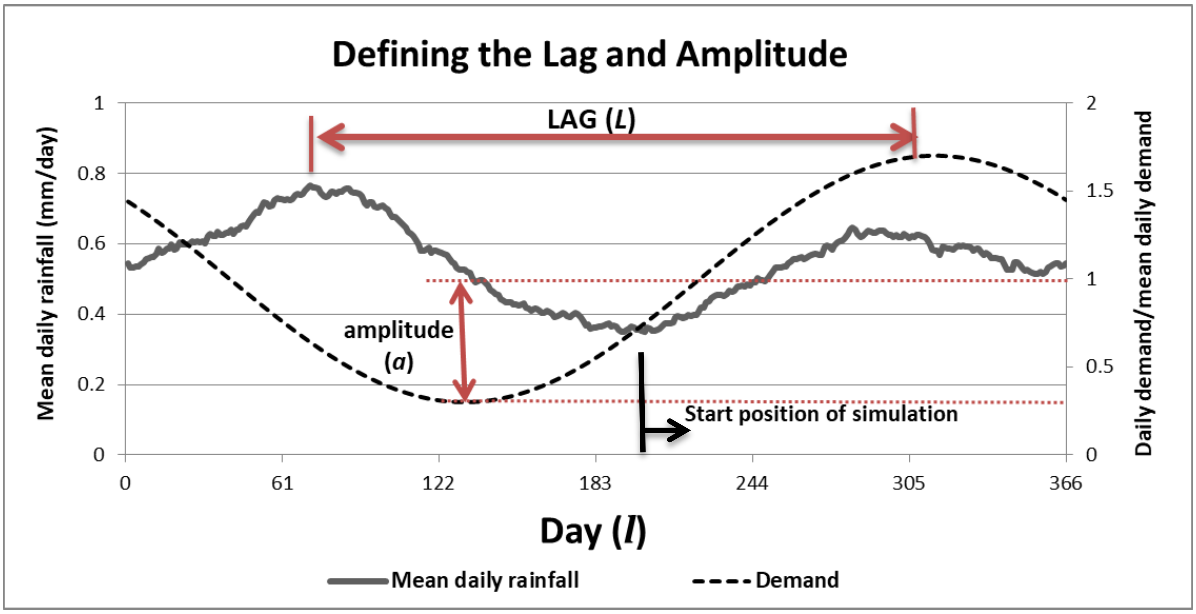


Figure 3-9: Defining the Lag

The start position and direction in which the simulation proceeds was used to determine whether the demand peaks before rainfall of if the rainfall peaks before demand. The day of peak rainfall was computed by locating the maximum of the 61-day moving average of mean daily rainfall values. The lag values were set in such a manner that the two peaks were 0, 0.25, 0.5 and 0.75 of a year apart

Simulations were initially done with amplitude set to a value 0.7, with S-D ratios of 0.1, 0.3, 0.5, 0.7 and 0.9 and data was collected at reliabilities of 50%, 66%, 80%, 85%, 90% and 95%.

3.2.5. Limitations to Simulation

The following limitations were identified during the course of data collection:

The search procedure for the optimal storage value relies heavily on discrete user defined values – due to the manual nature in which the storage is sought combined with the time limitations set for this study meant a bit of subjectivity had to be applied to decide the resolution of the capacity for the tanks sizes which were tested.

CHAPTER 4 THE INFLUENCE OF CLIMATE AND RAINFALL CHARACTERISTICS

Objectives 1.1 and 1.2 of this study were to assess the influence of using more rainfall gauging stations on system performance, regression relationships and to analyse the impact of rainfall variability characteristics. To achieve this, the full set of 118 rain gauges from across South Africa was used in an analysis of a RWHS operating under a constant demand. Simulations were run for each rain gauge at pre-set supply-demand (S-D) ratios of 0.1, 0.3, 0.5, 0.7 and 0.9. These were achieved by varying the catchment areas at fixed demand and daily rainfall values. Storage-yield data was collected at reliabilities of 50%, 66%, 80%, 85%, 90% and 95%.

Impact of extending rainfall record

It was recognised at the beginning of this study that the rainfall records from the database developed by Lynch (2003) are only up to the year 2001. Thus it was considered necessary to obtain a few up-to-date rainfall records for a small sample of the rainfall stations in order to evaluate whether the additional data collected in the last 17 years i.e. years 2000 to 2017, would result in any significant differences in observed system behaviour. The additional rainfall data for the years 2000-2017 for five rainfall stations randomly selected from the 118 gauges was kindly provided by the South African Weather Services.

The analysis was done by adding on the last 17 years of data to the current rainfall records of Lynch (2003) and the simulations run to determine the maximum number of days of supply and optimum tank size at reliabilities of 50%, 66%, 80%, 85%, 90% and 95%. A brief summary of these additional data are presented in Table 4-1. To patch some of the accumulated data it was assumed that for accumulation periods less than 5 days, all the rainfall fell at the end of the period of accumulation and for periods greater than 5 days the data was considered as missing – no other quality checks were performed on the data.

Table 4-1: Summary of Data obtained from SAWS (years 2000 – 2017)

Rainfall Station ID	Climate Zone	Number of years of complete of data	% Missing data	% Data Accumulated over several days
0172163W	BSk	16	0.07	0
0317447A	BWh	16	0.18	0
0339065W	Cfa	11	0.04	0.18
0014063W	Cfc	2	0	1.84
0021823W	Csa	5	1.07	0

The results of the analysis showed that extending the record to include the last 17 years of data has an almost negligible impact on the resulting number of days of days of supply – an average difference of 5% in the results was recorded across all the S-D ratios and reliabilities with the longer record showing a tendency to increase the number of days of supply by no more than on average 3.7 days (range of variation lies between 0 days to about 15 days). There was also limited impact on the optimal tank size with on average a 10% difference measured between the two series. Overall, it would appear that the optimum capacity of storages could be sensitive to the length of the rainfall record utilised. However given the general uncertain nature of inputs such as rainfall, for the purposes of this study, this difference was not viewed as being sufficiently large enough to cause concern and as such the rainfall records from the database were taken as adequate for the study. The full results of this analysis are presented in Appendix 3(a).

4.1. The Influence of Climate on Observed Rainwater Harvesting System Behaviour

As a starting point in addressing objective 1.1 and 1.2, the influence of the different climatic settings on the level of supply and optimal tank size was assessed. Figures 4-1 to 4-6 show the variation in maximum number of days of supply per year at each of the pre-defined S-D ratios for the selected stations in each climate zone for all reliabilities considered. Individual data points on a line graph were chosen as the best way to visually illustrate the changes in the number of days of supply with increasing S-D ratio and across the different climate zones. It also makes for easier comparison of behaviour between each rain gauge and climate zone (horizontal axis).

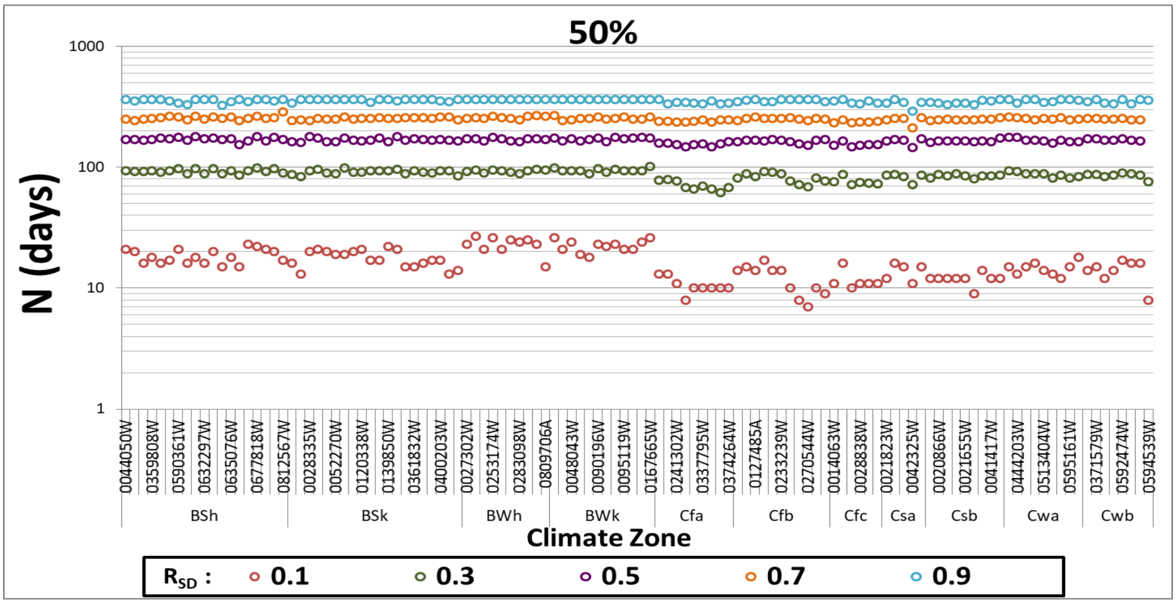


Figure 4-1: Variation in number of days of supply with S-D ratio at 50% reliability

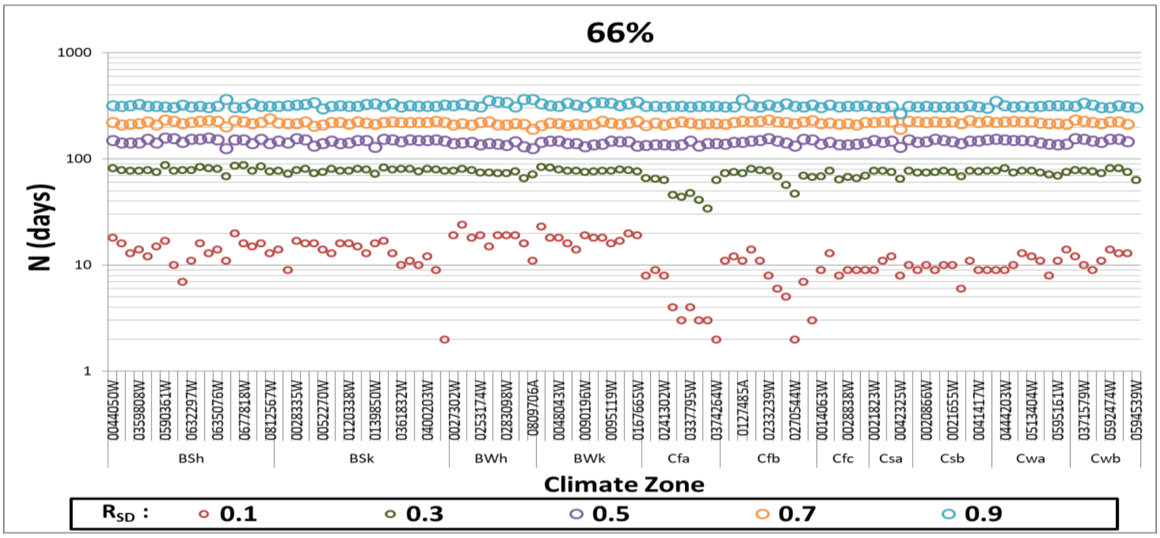


Figure 4-2: Variation in number of days of supply with S-D ratio at 66% reliability

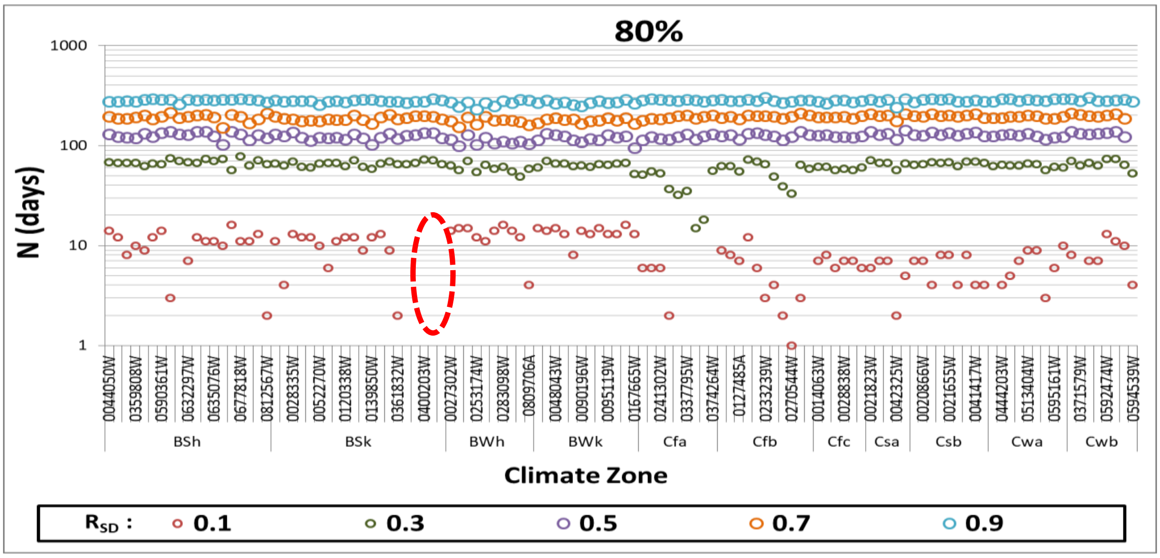


Figure 4-3: Variation in number of days of supply with S-D ratio at 80% reliability

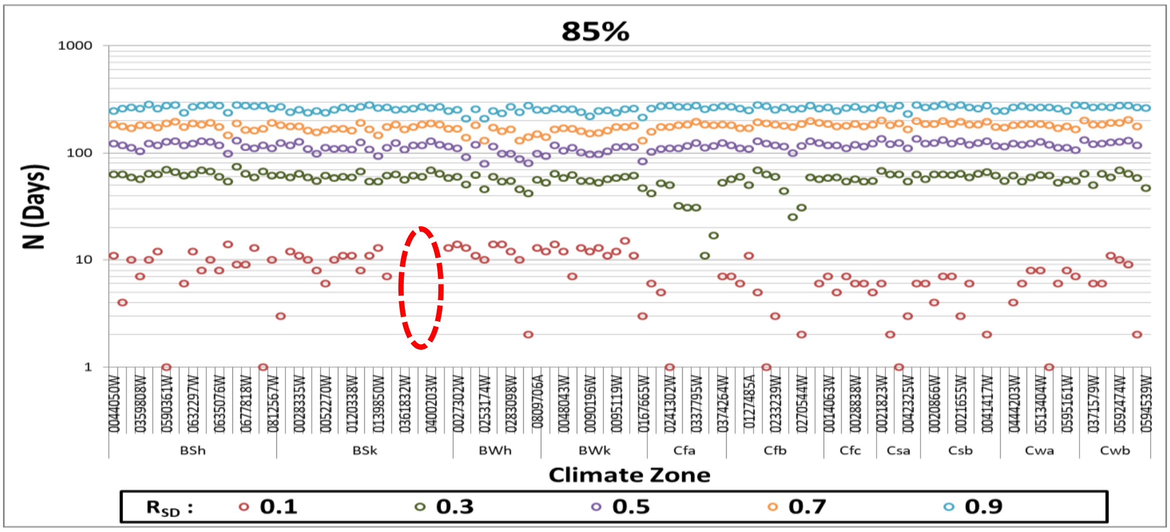


Figure 4-4: Variation in number of days of supply with S-D ratio at 85% reliability

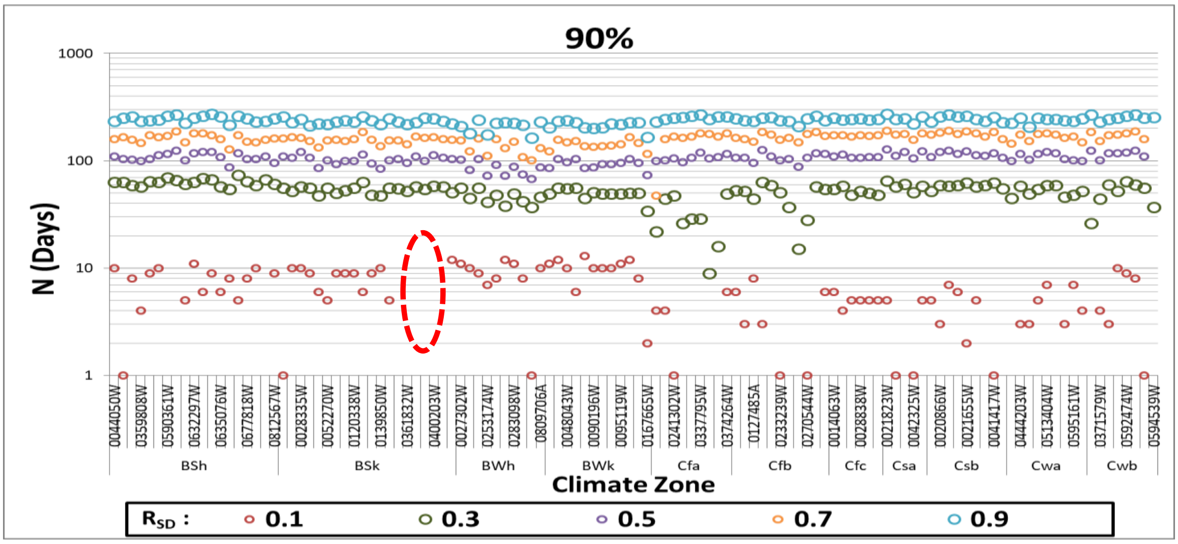


Figure 4-5: Variation in number of days of supply with S-D ratio at 90% reliability

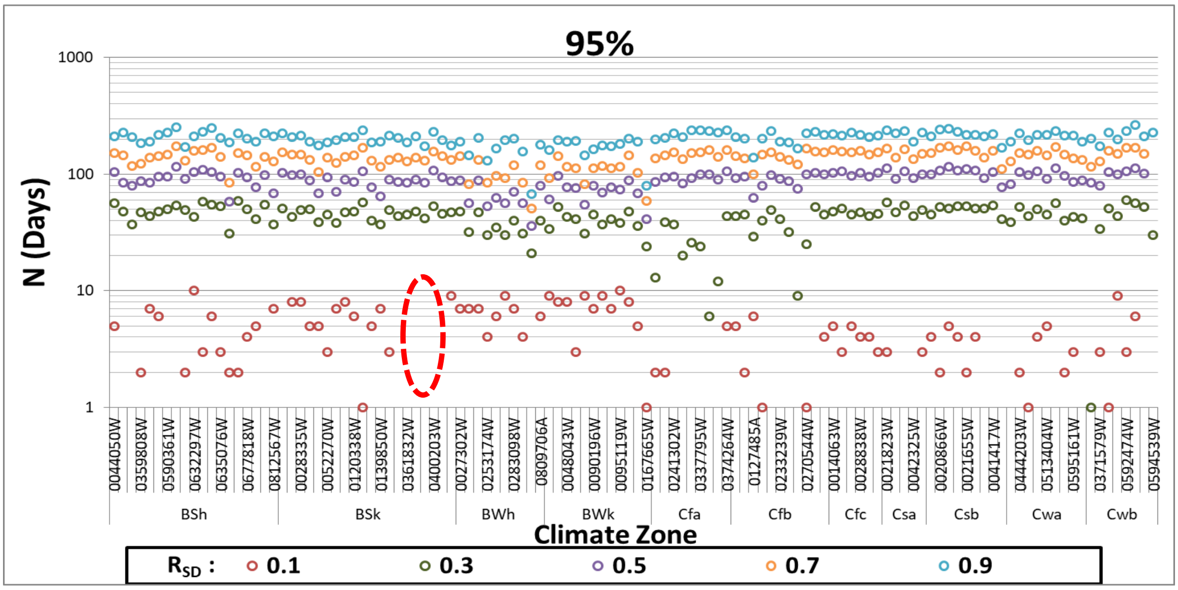


Figure 4-6: Variation in number of days of supply with S-D ratio at 95% reliability

One of the observations in Figures 4-1 to 4-6 is the increasing variation of the number of days of supply within and across the different climatic regions with increasing reliability and decreasing S-D ratio. This variability is thought to be caused by the influence of other rainfall characteristics besides the MAP that are described by the individual rain gauges. It was also observed that as the S-D ratio decreases and reliability increases above 66%, an increasingly greater proportion of the rain gauges record a supply of zero days (as shown by the red circle) at an S-D ratio of 0.1 - this indicates failure of the system to meet the full demand on any day during the simulation period.

Another interesting trend observed from the data is that on average, at low reliabilities dry/desert climate zones (i.e. BSh, BSk, BWh and BWk) tended to supply over a greater number of days than the wetter climate regions. However, at high reliabilities on average, the wetter climate zones supply water over a greater number of days when compared to the dry/desert zones with the exception being at an S-D ratio of 0.1 where the drier climate zones always yielded more days than the wet zones. This observation suggests that whilst any two systems in a wet or dry climate zone may describe an identical supply-demand dynamic, the variations in time of when rainfall is available to be collected (which would be unique to each rainfall gauging station) influences the overall number of days of supply from a RWHS.

Figures 4-7 to 4-12 show the corresponding ideal tank sizes and how they varied across the different climatic regions.

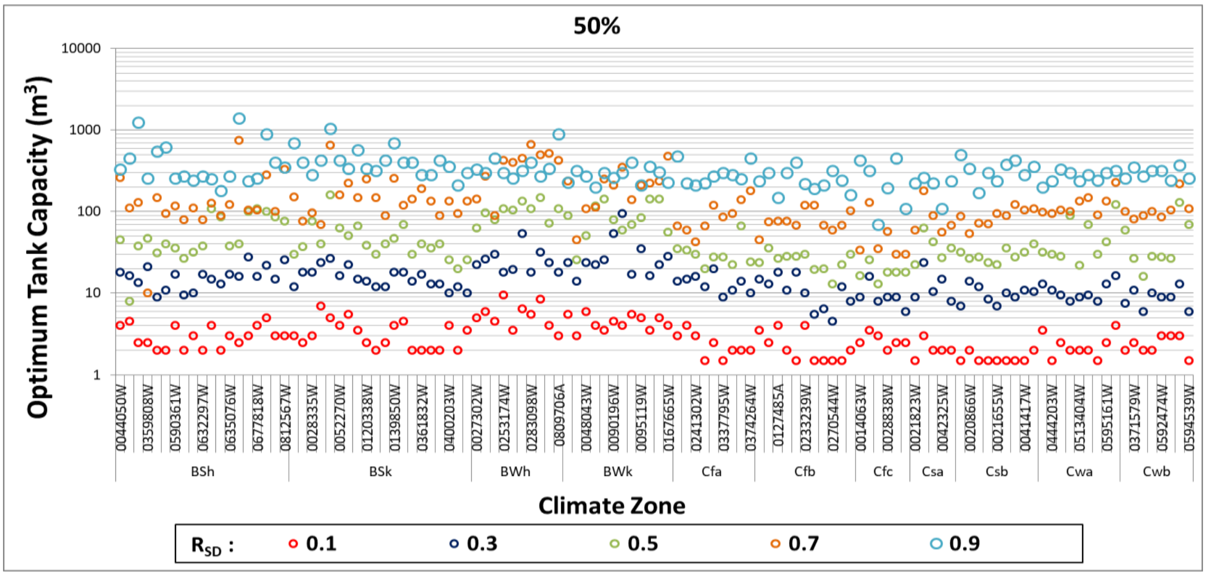


Figure 4-7: Variation of optimum tank size with S-D ratios at 50% reliability

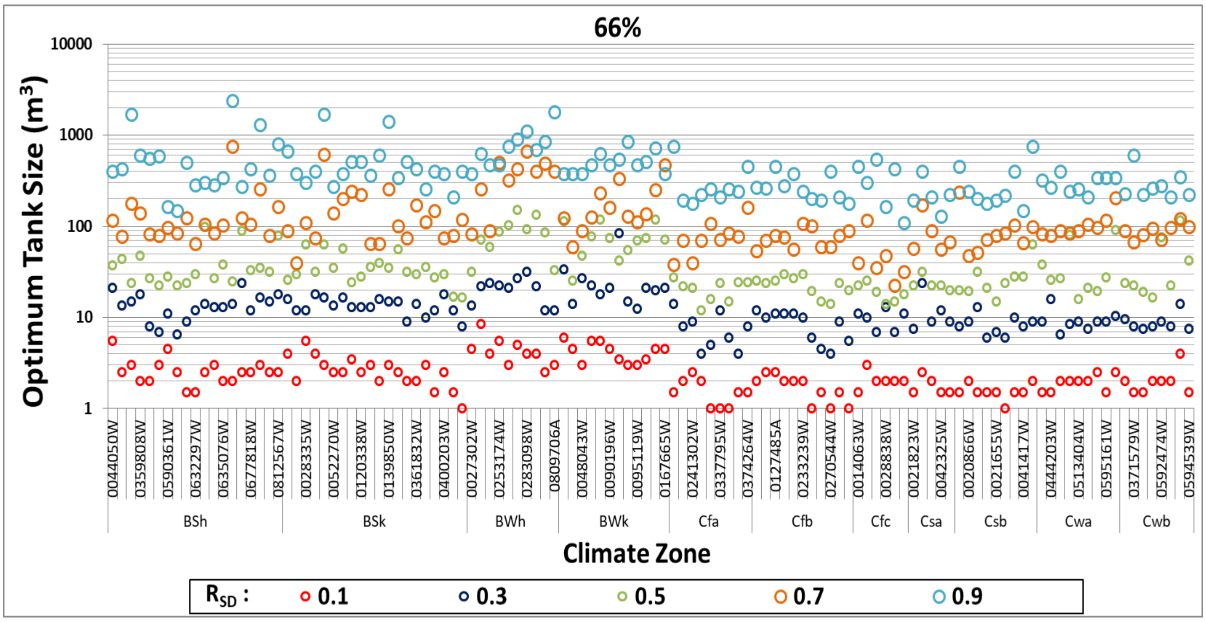


Figure 4-8: Variation of optimum tank size with S-D ratio at 66% reliability

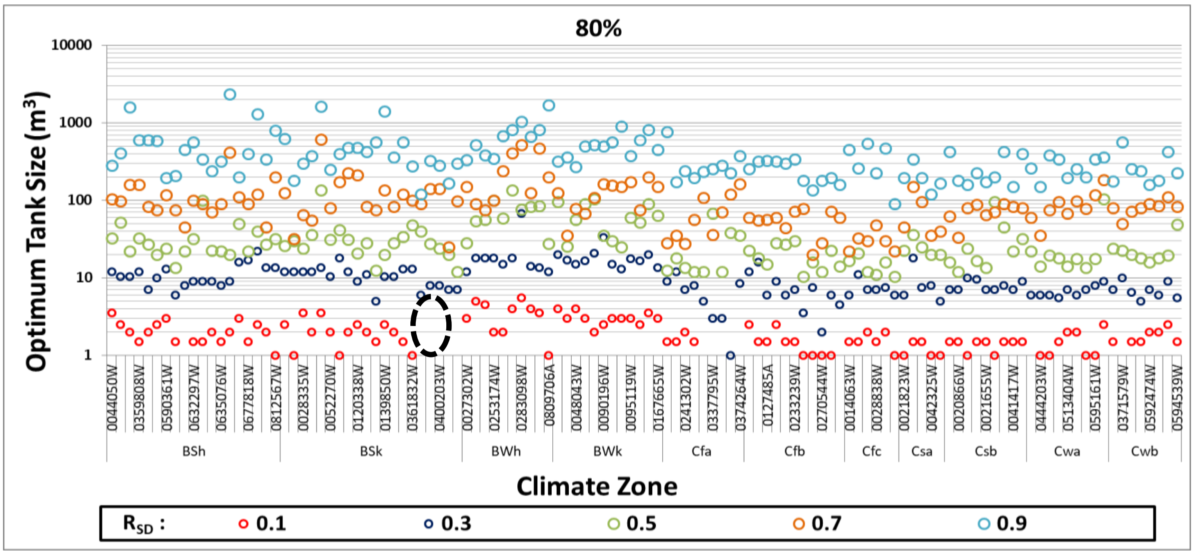


Figure 4-9: Variation of optimum tank size with S-D ratio at 80% reliability

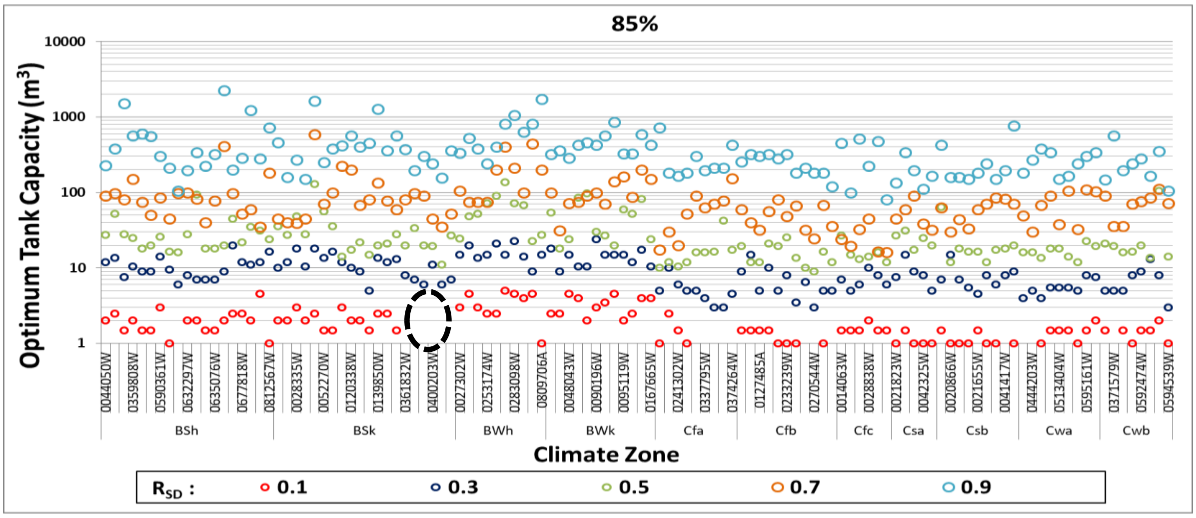


Figure 4-10: Variation of optimum tank size with S-D ratio at 85% reliability

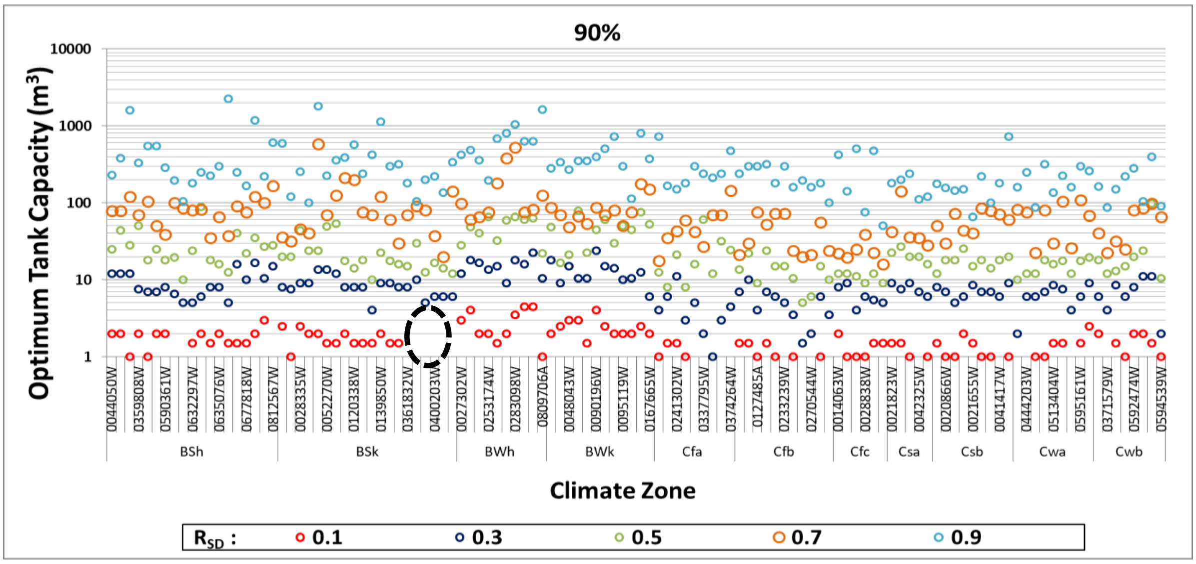


Figure 4-11: Variation of optimum tank size with S-D ratio at 90% reliability

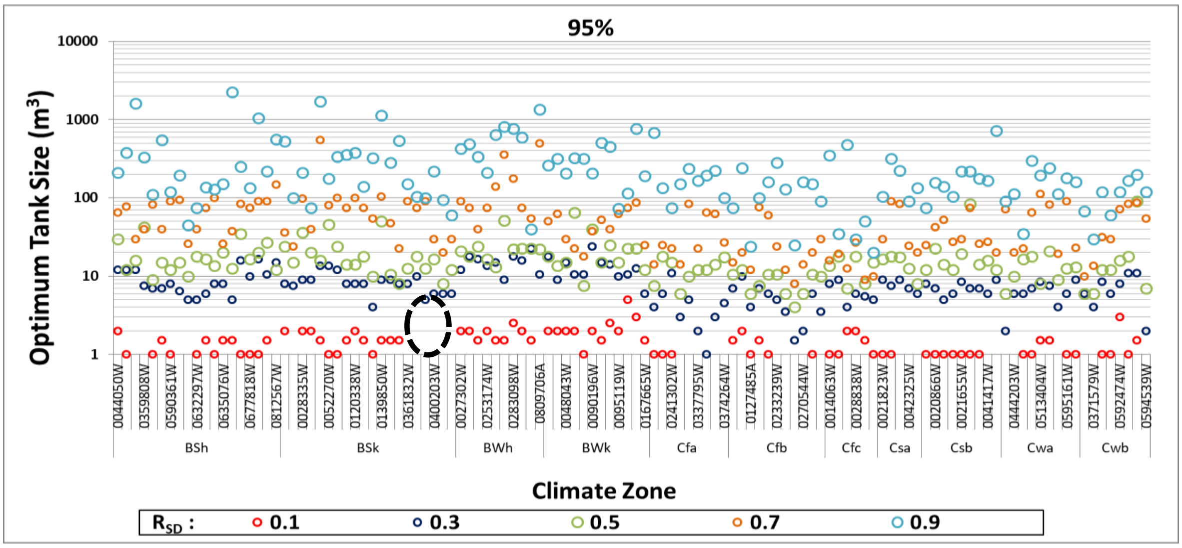


Figure 4-12: Variation of optimum tank size with S-D ratio at 95% reliability

The rain gauges showed a much greater variation in tank size than the number of days of supply with both increasing reliability and S-D ratio. A trend noted in the simulation data was that the drier regions (i.e. BSh, BSk, BWh and BWk) on average require larger tanks than the wetter regions (i.e. Cfa, Cfb, Cfc, Csa, Csb, Cwa and Cwb) to satisfy identical S-D ratios. The higher rainfall variability in the drier climates is considered as the probable cause of the observed larger tank requirements for these regions. The gaps in plotted data (black circle) indicate that in some areas the full demand could not be met on any day during the simulation period and as such a tank size could not be defined.

The S-D ratio of 0.1 represents a small tank undergoing a relatively large demand – thus a more refined analysis such as a sub-daily time-step simulation may be required to obtain a more accurate assessment of the behaviour of the RWHS at this level. However, it can also be appreciated that in practice, given the relatively low number of days of supply produced by such systems, RWH will probably not be considered as practical or feasible.

4.2. Influence of Increasing the Number of Rain Gauges on Regression Relationships

4.2.1. The Relationship between Supply-Demand Ratio, Level of Supply and Reliability

The influence of increasing the number of gauges on regression relationships was assessed by analysing the degree of correlation (R^2 value) between the dimensionless parameters used by Ndiritu et al., (2017). These are presented in Equations 3-1, 3-8 and 3-9. Ndiritu et al., (2017) drew correlations between $\boldsymbol{R_{SD}}$ and $\boldsymbol{S_{P-r}}$ and between $\boldsymbol{S_{P-r}}$ and $\boldsymbol{R_{TD-r}}$ for the reliabilities of 85%, 90%, 95% and 99%.

As such to facilitate some comparisons, plots of the simulated data were made to find the corresponding R^2 values when the number of gauges is increased from 14 to 118. Figures 4-13 to 4-18 show the variation of the yield ratio (Equation 3-8) with the S-D ratio (Equation 3-1). The plots show the data obtained across all the reliabilities considered for this study.

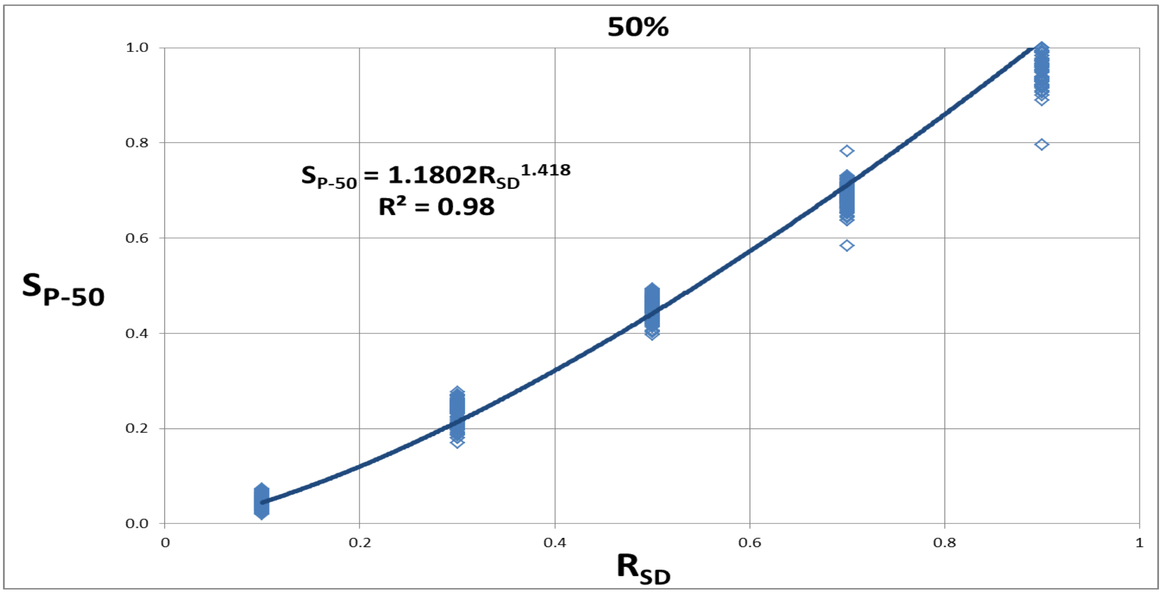


Figure 4-13: Variation of normalised yield with S-D ratio at 50% reliability

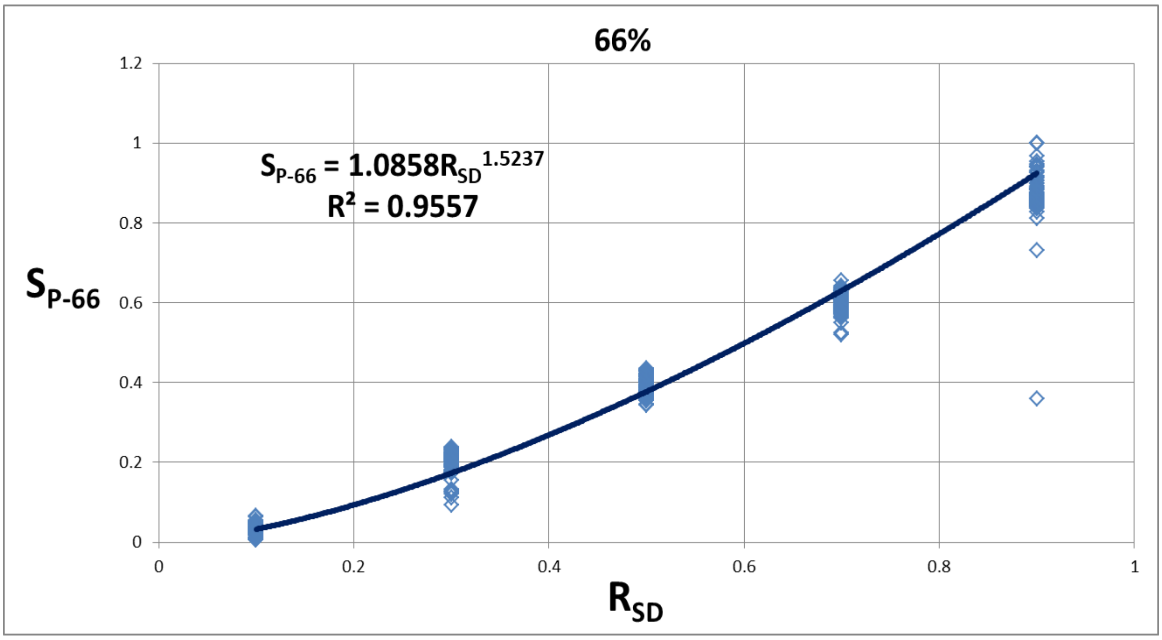


Figure 4-14: Variation of normalised yield with S-D ratio at 66% reliability

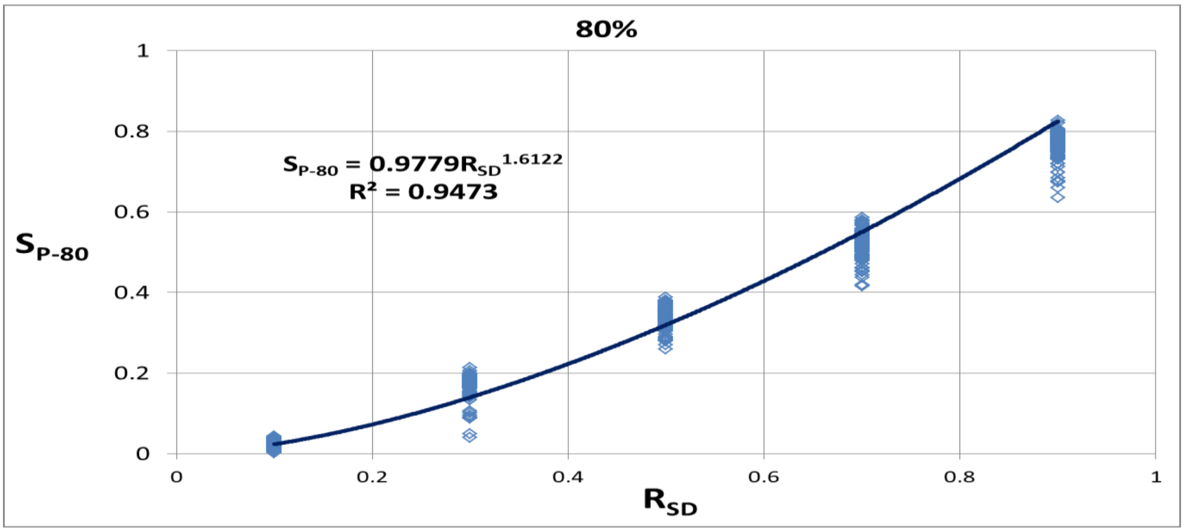


Figure 4-15: Variation of normalised yield with S-D ratio at 80% reliability

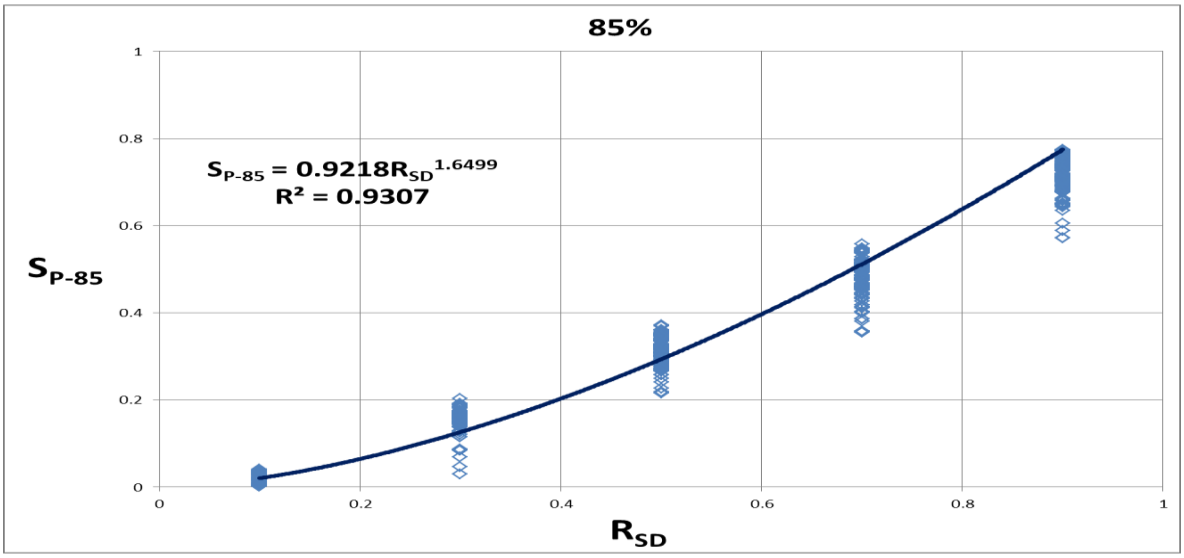


Figure 4-16: Variation of normalised yield with S-D ratio at 85% reliability

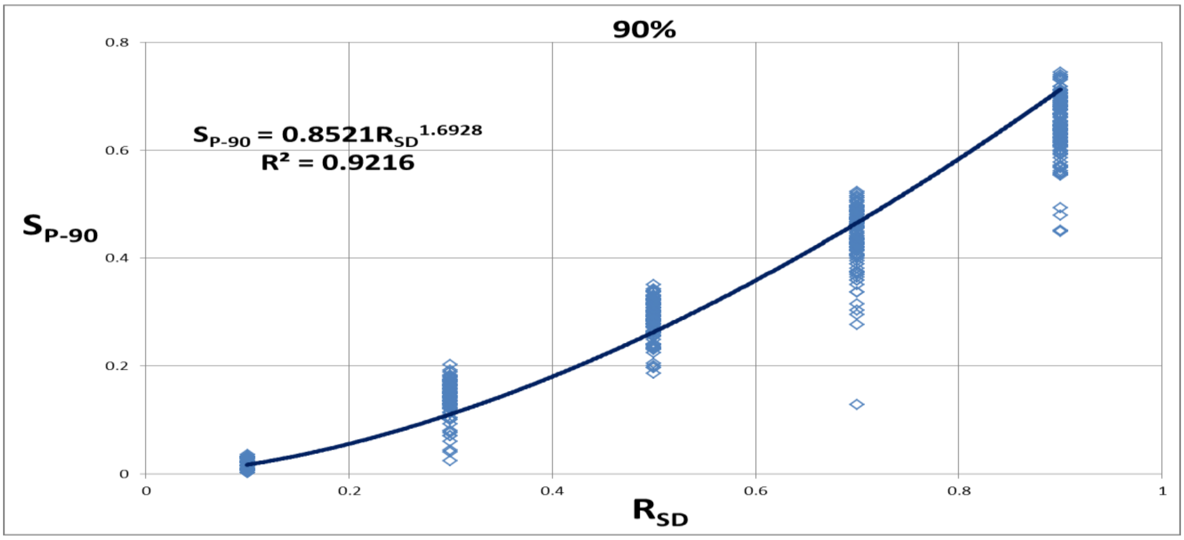


Figure 4-17: Variation of normalised yield with S-D ratio at 90% reliability

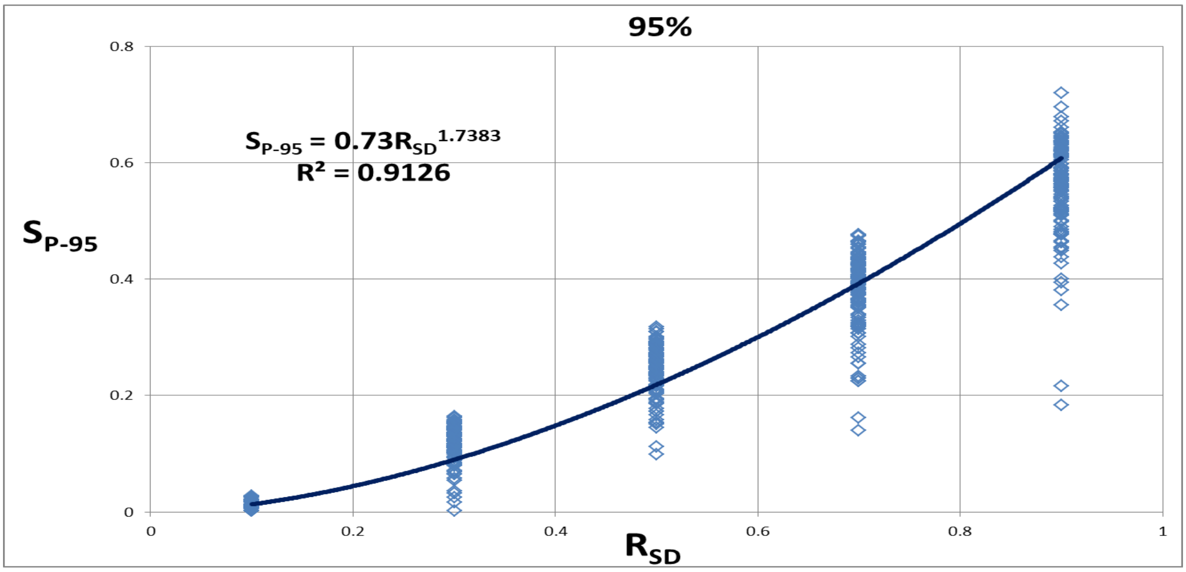


Figure 4-18: Variation of normalised yield with S-D ratio at 95% reliability

At all reliabilities, graphical analysis showed that the power-model best described the relationship between the two variables. It was observed from the plots that there was an increase in the spread of the data points with increasing reliability and S-D ratio and this is thought to be a function of gauge-specific characteristics. A comparison of the R^2 values for the power model (as indicated in the graphs) to those obtained by Ndiritu et al., (2017) is shown in Table 4-2. The same downward trend in goodness of fit is observed in both sets of data. However, increasing the number of gauges reduced the overall goodness-of-fit of a lumped model. This could be attributed to the highly variable nature of rainfall across the country.

Table 4-2: Comparison of R^2 values when number of rain gauges is increased

Reliability (%)	R^2	
	118 gauges	Ndiritu et al., (2017) 14 gauges
50	0.9800	-
66	0.9557	-
80	0.9473	-
85	0.9307	0.9822
90	0.9216	0.9767
95	0.9126	0.9625

To assess if the rainfall regime has any influence on the observed yield, the data for each climate zone was plotted separately and is presented in Figures 4-19 to 4-24 for the full set of reliabilities considered.

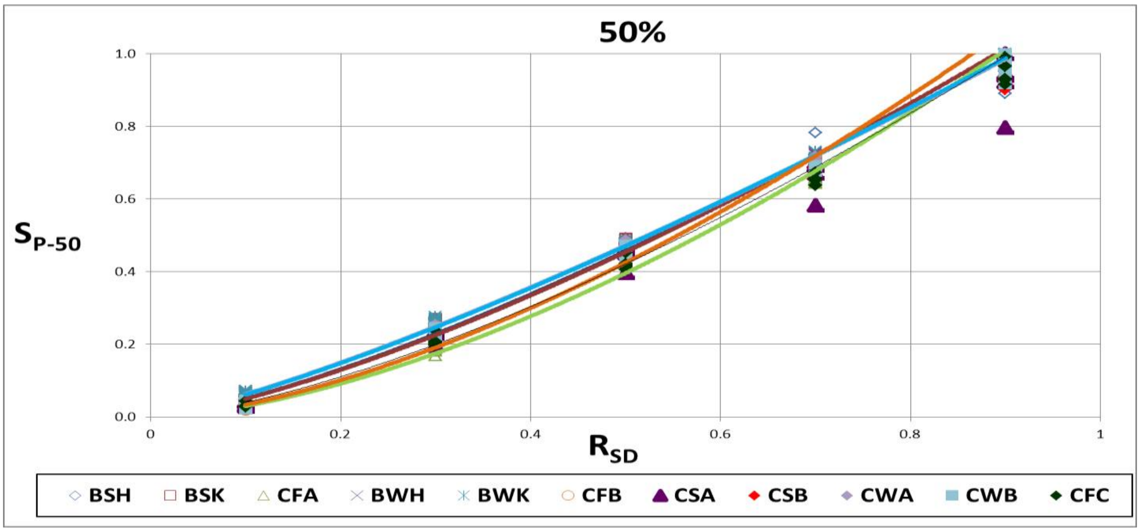


Figure 4-19: Variation of normalised yield with S-D ratio by climate zone at 50% reliability

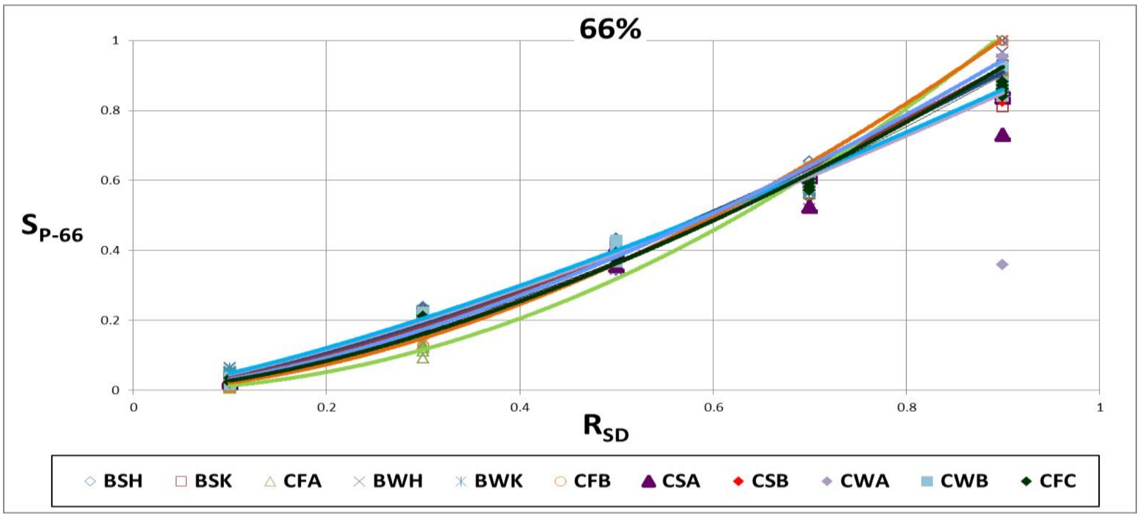


Figure 4-20: Variation of normalised yield with S-D ratio by climate zone at 66% reliability

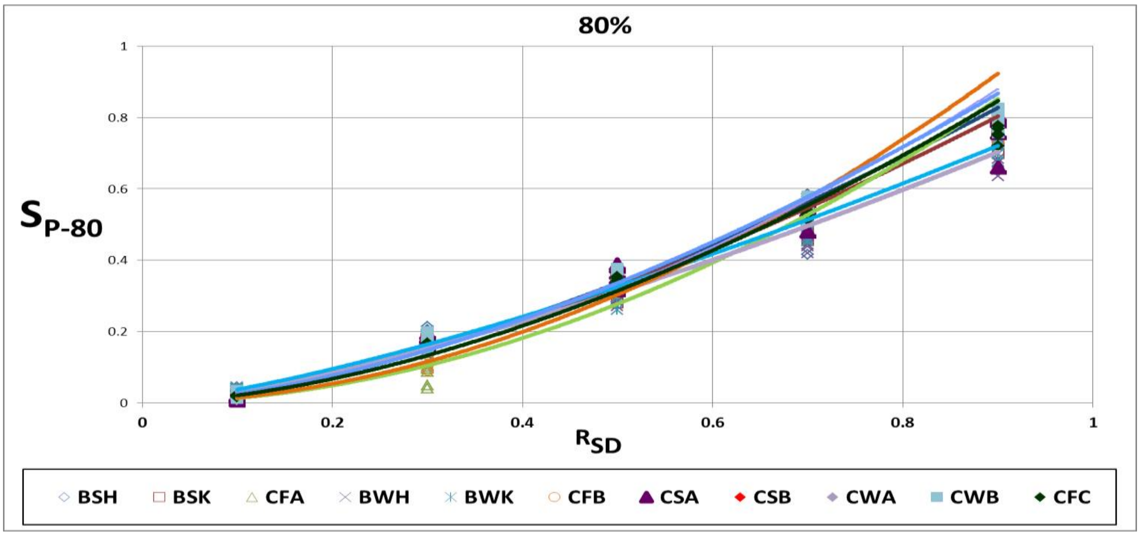


Figure 4-21: Variation of normalised yield with S-D ratio by climate zone at 80% reliability

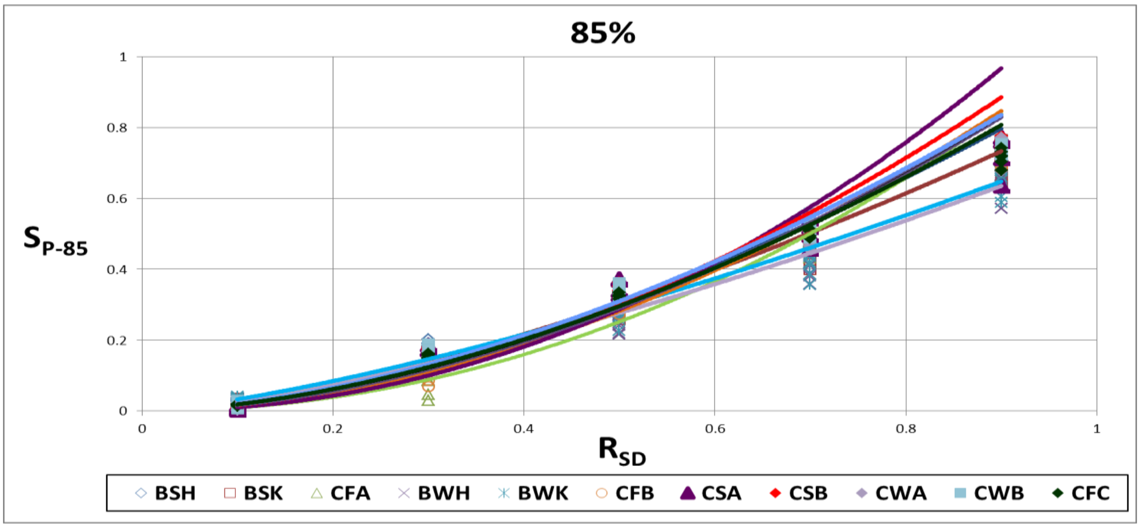


Figure 4-22: Variation of normalised yield with S-D ratio by climate zone at 85% reliability

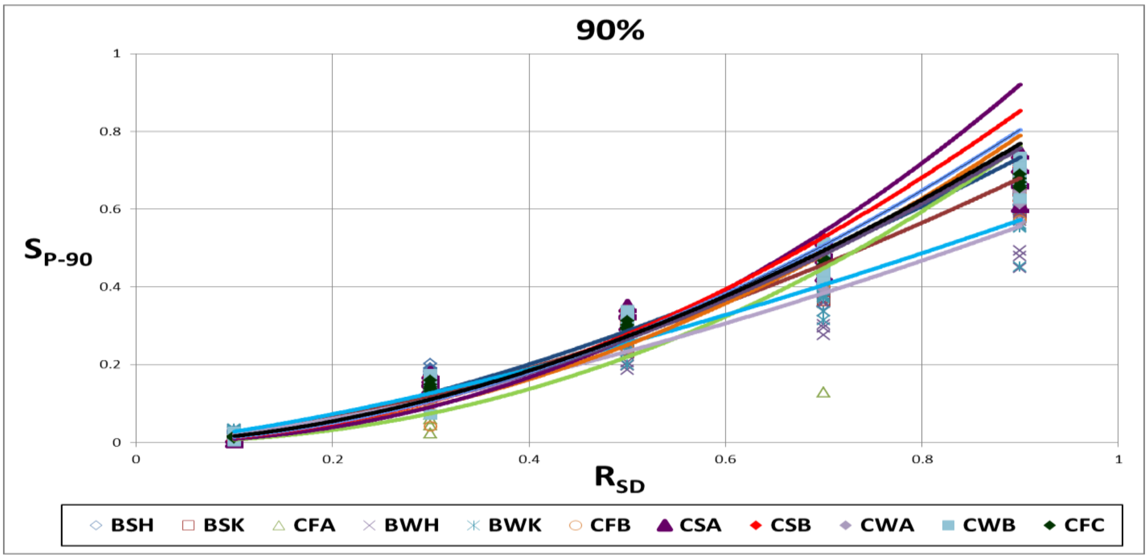


Figure 4-23: Variation of normalised yield with S-D ratio by climate zone at 90% reliability

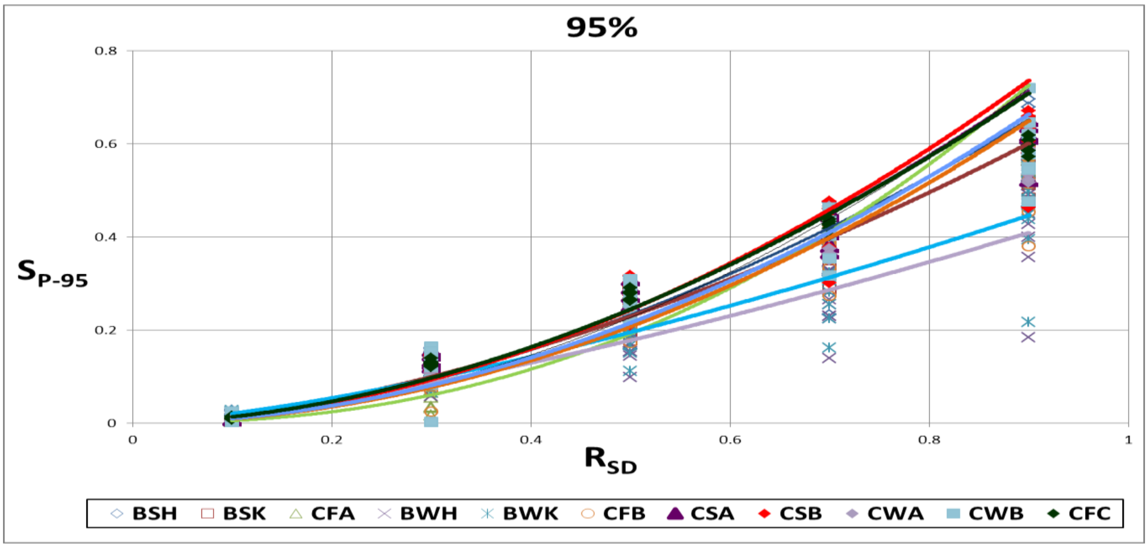


Figure 4-24: Variation of normalised yield with S-D ratio by climate zone at 95% reliability

It was observed from Figures 4-19 to 4-24 that there are no clear distinctive bands of data points distinguishing each climate region, but instead there is quite a substantial amount of intermingling of the data. By observing the movement of the trend-lines it can be seen that for each of the reliabilities, at low S-D ratios the drier climate zones yield more but as the S-D ratio increases the reverse begins to occur –as highlighted before, this may be as a result of the influence of rainfall variability characterising the different climate types. It was also observed that the increasing scatter of the data with increasing reliability at S-D ratios of 0.3 and below could largely be attributed to the lower yield values obtained for wetter climate zones like Cfa and Cfb, whilst at higher S-D ratios the scatter is attributable to the lower yields obtained from the dry/desert climate zone rain gauges BWh and BWk. It is clear from observing the climate-zone specific trend-lines that a model based on the climate-zone specific data may offer a better representation of RWHS behaviour.

Table 4-3 takes a closer look at the climate-specific data, by assessing the R^2 fit of the power model to each climate zone's data. The percentage difference measures the difference in goodness-of-fit between the data presented in Table 4-3 for the 118 gauges and the curves fitted for each climate zone. A negative value indicates a better fit of the power-model to climate region specific data rather than a lumped model that does not distinguish between the different rainfall regimes.

Table 4-3: S-D Ratio vs Normalised Yield R^2 values for different climate zones

Climate Zone	50%		66%		80%		85%		90%		95%	
	R^2	% Diff	R^2	% Diff	R^2	% Diff	R^2	% Diff	R^2	% Diff	R^2	% Diff
BSH	0.9931	-1.34	0.9848	-3.02	0.9536	-0.67	0.9192	1.24	0.9379	-1.77	0.9362	-2.59
BSk	0.9921	-1.23	0.9624	-0.68	0.9580	-0.22	0.9730	-4.54	0.9478	-2.84	0.9467	-3.74
Bwh	0.9940	-1.43	0.9888	-3.44	0.9702	-1.50	0.9406	-1.06	0.9156	0.65	0.9359	-2.55
BWk	0.9962	-1.65	0.9948	-4.07	0.9906	-3.63	0.9859	-5.93	0.9832	-6.68	0.9487	-3.96
Cfa	0.9933	-1.36	0.9933	-3.91	0.9487	0.75	0.9339	-0.34	0.9216	0.00	0.9355	-2.51
Cfb	0.9825	-0.26	0.9499	0.63	0.9350	2.19	0.9329	-0.24	0.9213	0.03	0.9148	-0.24
Cfc	0.9924	-1.27	0.9910	-3.67	0.9900	-3.57	0.9885	-6.21	0.9862	-7.01	0.8557	6.23
Csa	0.9889	-0.91	0.9859	-3.14	0.9544	0.16	0.9323	-0.17	0.9128	0.95	0.9517	-4.28
Csb	0.9898	-1.00	0.9856	-3.11	0.9701	-1.49	0.9598	-3.13	0.9399	-1.99	0.9553	-4.68
Cwa	0.9929	-1.32	0.9743	-1.92	0.9696	-1.43	0.9385	-0.84	0.9630	-4.49	0.9438	-3.42
Cwb	0.9863	-0.64	0.9822	-2.75	0.9743	-1.92	0.9571	-2.84	0.9313	-1.05	0.7980	12.56

The table reveals that the differences in goodness of fit predominately favour the use of a climate specific model. The lowest goodness-of-fit for a climate-based model is obtained for Cwb where the data goes against the trend at a reliability of 95% - a study of the numbers revealed there to be a couple of rain gauge stations that seemed to obtained uncharacteristically low yields at this reliability for the same S-D ratios of 0.1 and 0.3.

While the overall percentage differences appear to be small, further investigation of the utility of pursing a model that incorporates rainfall characteristics was deemed necessary and the results of this analysis are presented in section 4.3.2.

Incorporating reliability into generalised relationships

Ndiritu et al., (2017) successfully showed there to be a link between the coefficients of regression (denoted α and β) and reliability and through these, incorporated reliability into the generalized relationships. With this in mind, a secondary analysis was carried on the coefficients obtained from the regression analysis of the data from the 118 rain gauges to establish if there was any correlation between these values and reliability. The high R^2 values of 0.9994 and 0.9982 when using the power model for coefficient α and an exponential model for coefficient β, as shown in Figure 4-25, illustrates that reliability can be effectively incorporated as a variable in generalised relationships.

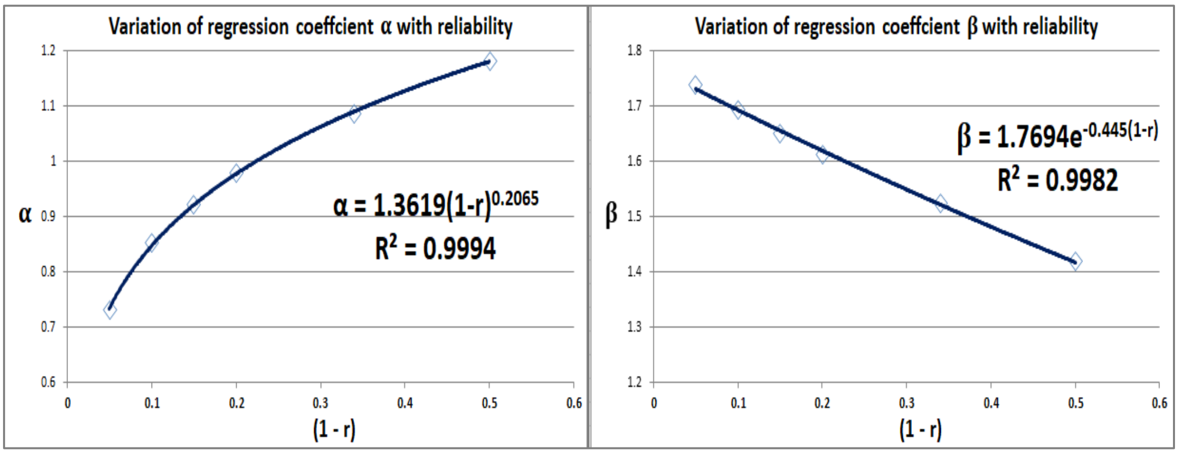


Figure 4-25: Variation of regression coefficients α and β with reliability

4.2.2. The Relationship between Level of Supply, Storage-Demand ratio and Reliability

Figures 4-26 to 4-31 show the variation of the storage-demand ratio (Equation 3-9) with the yield ratio. The plots are for the reliabilities of 50%, 66%, 80%, 85%, 90% and 95%.

Regression on data without distinguishing between the different climate zones revealed an exponential model to best describe the relationship between the variables where high R^2 values were obtained as shown on each of the plots.

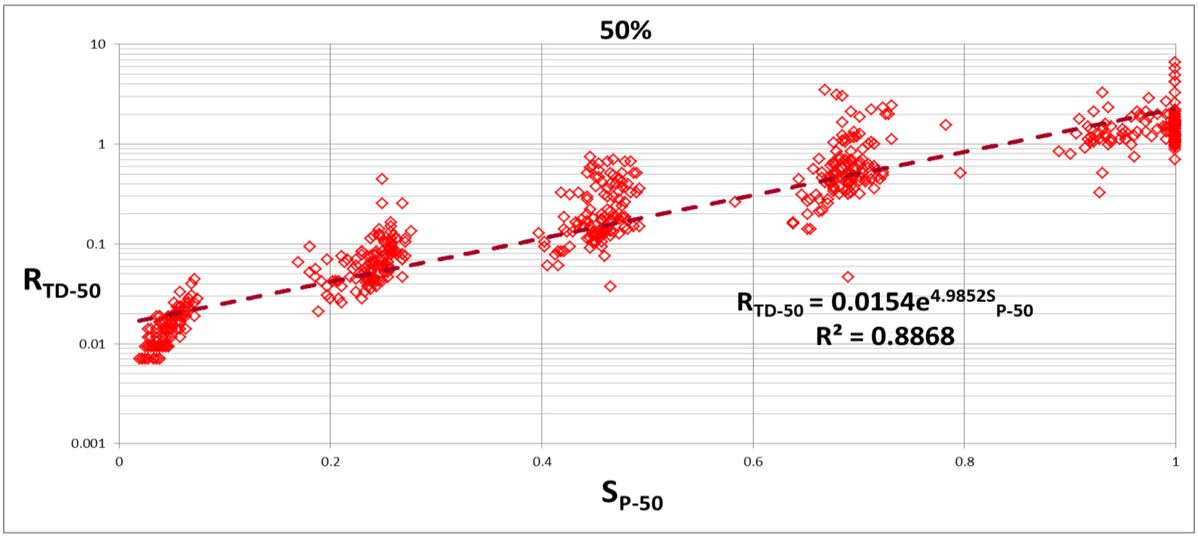


Figure 4-26: Variation of normalised yield vs normalised storage at 50% reliability

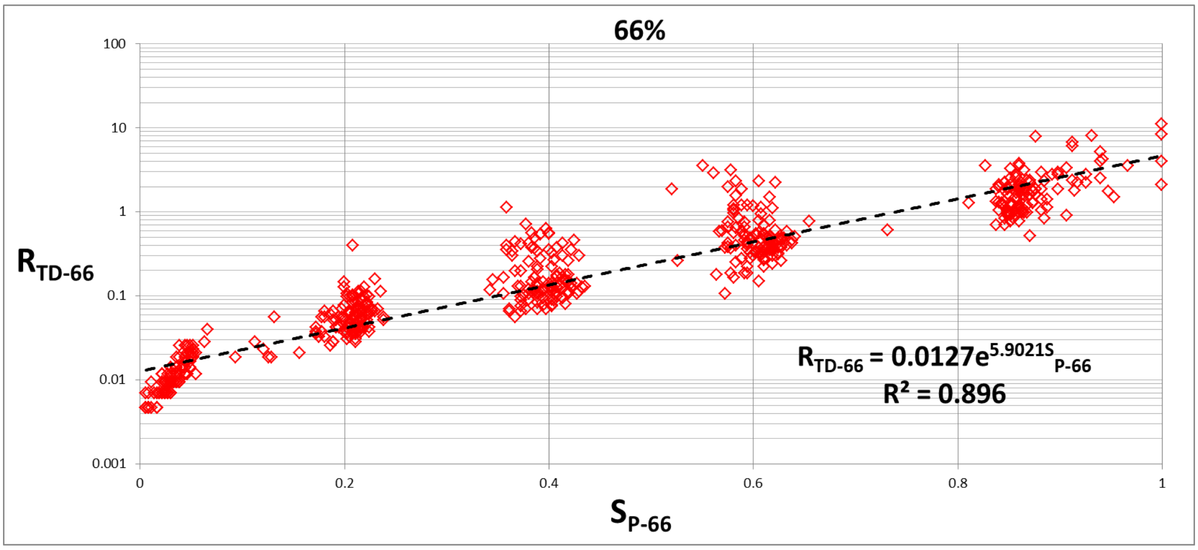


Figure 4-27: Variation of normalised yield vs normalised storage at 66% reliability

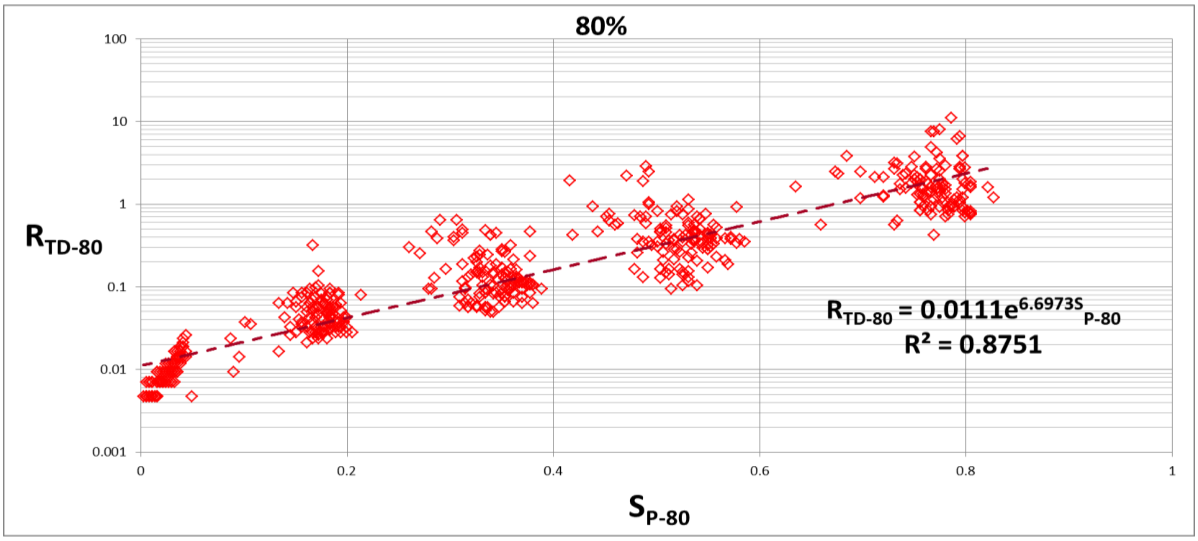


Figure 4-28: Variation of normalised yield vs normalised storage at 80% reliability

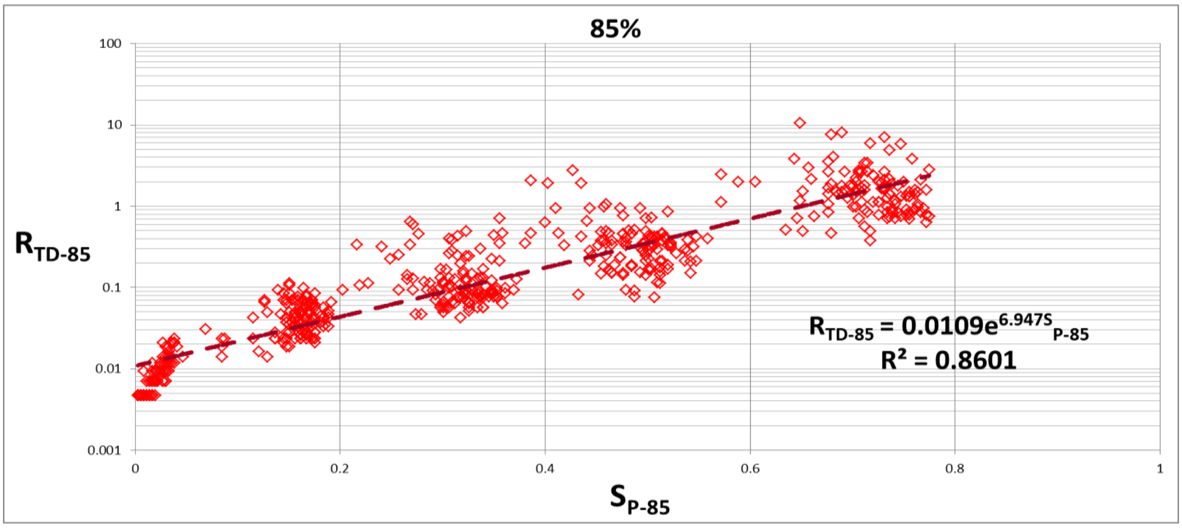


Figure 4-29: Variation of normalised yield vs normalised storage at 85% reliability

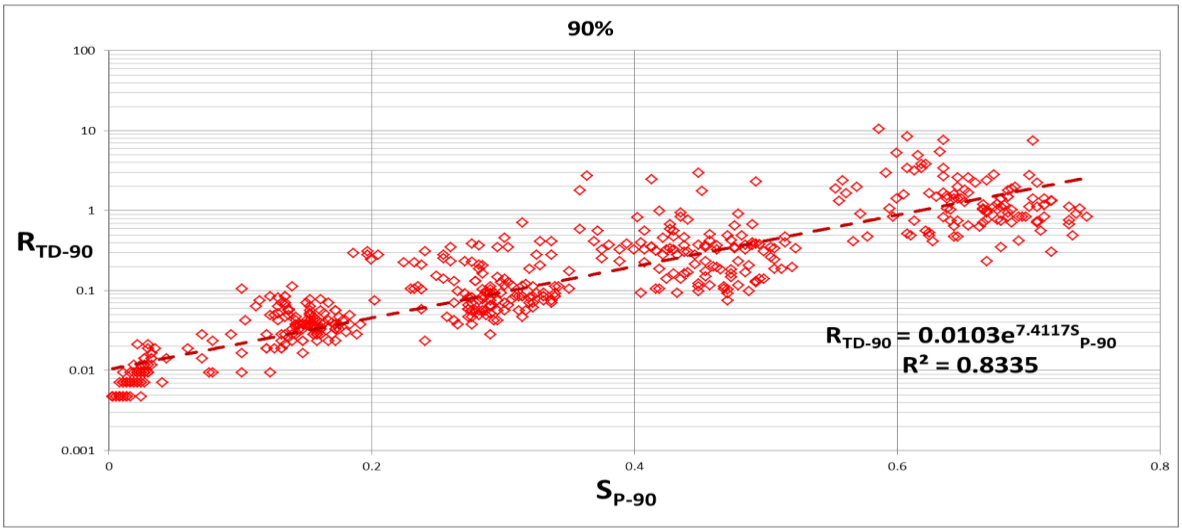


Figure 4-30: Variation of normalised yield vs normalised storage at 90% reliability

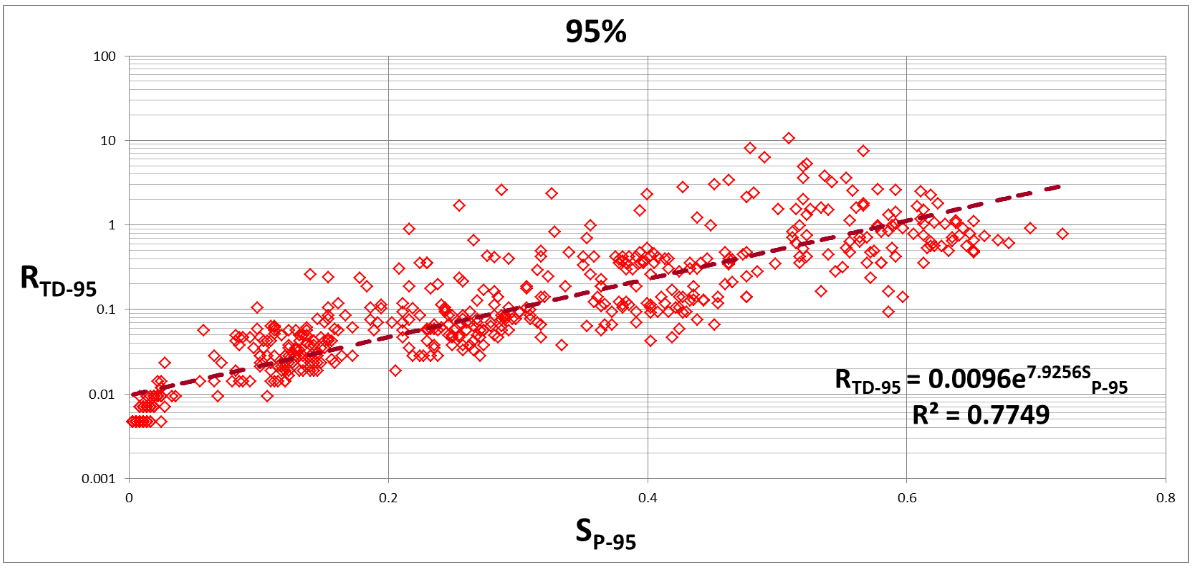


Figure 4-31: Variation of normalised yield vs normalised storage at 95% reliability

A key observation from the plots presented in Figures 4-26 to 4-31 was the increase in scatter of the data with increasing reliability. This increasingly reduces the goodness of fit of the exponential model to the data. The spread in the data was also much more pronounced than that observed for the relationship between the S-D ratio (***R_{SD}***) and Level of Supply (***S_{P-r}***).

Table 4-4 shows a comparison of the goodness-of-fit of the fitted exponential model to the values obtained by Ndiritu et al., (2017) who use a power model to describe simulated data. Whilst the R^2 values of Ndiritu et al., (2017) would indicate that a power-model is a better fit the data, a comparison using the power model for the simulation data of this study reveals the exponential model to actually predict the trend in the data better.

Table 4-4: Comparison of R^2 values when number of rain gauges is increased

Reliability (%)	R^2		
	118 gauges (exponential model)	Ndiritu et al., (2017) 14 gauges	118 gauges (power model)
50	0.8868	-	0.8617
66	0.8960	-	0.8273
80	0.8751	-	0.7947
85	0.8601	0.8931	0.7651
90	0.8335	0.8442	0.7412
95	0.7749	0.8750	0.6982

A closer look was taken by plotting the data by climate zone and the resulting graphs are presented in Figures 4-32 to 4-37.

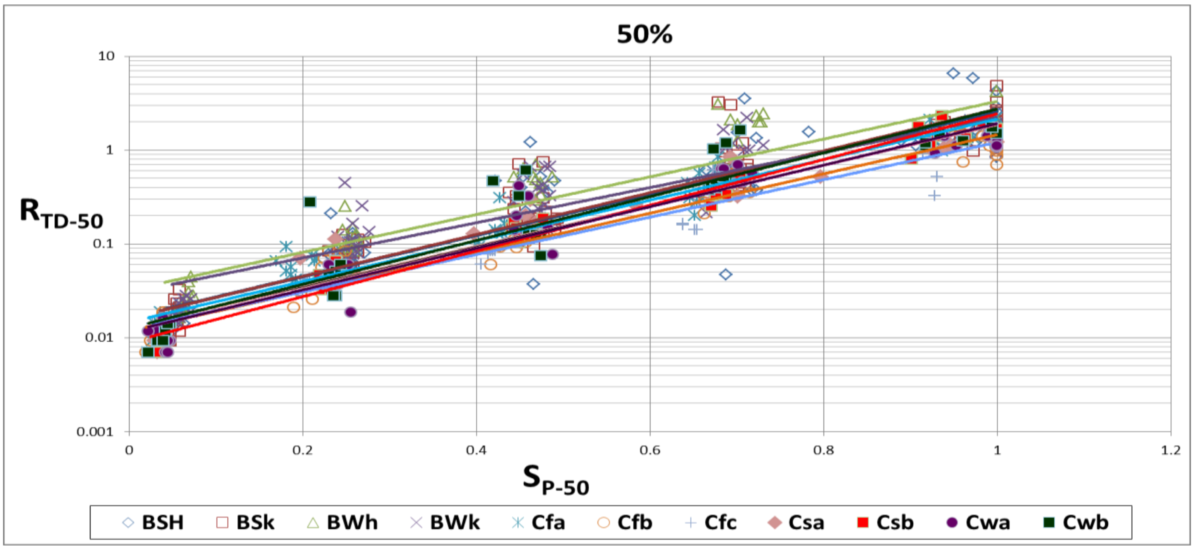


Figure 4-32: Variation by climate zone of normalised yield vs normalised storage at 50% reliability

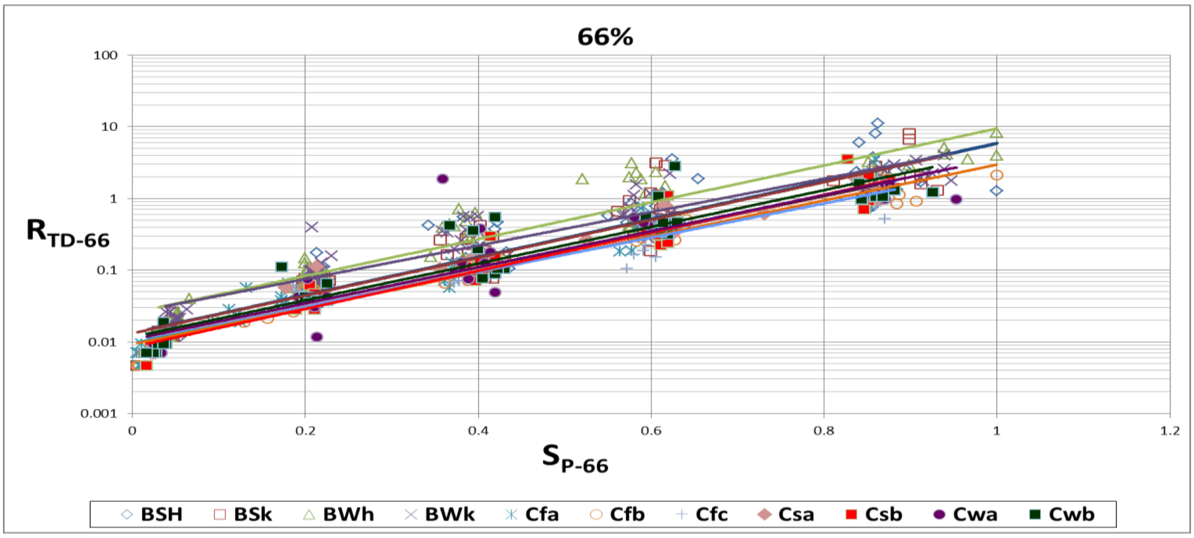


Figure 4-33: Variation by climate zone of normalised yield vs normalised storage at 66% reliability

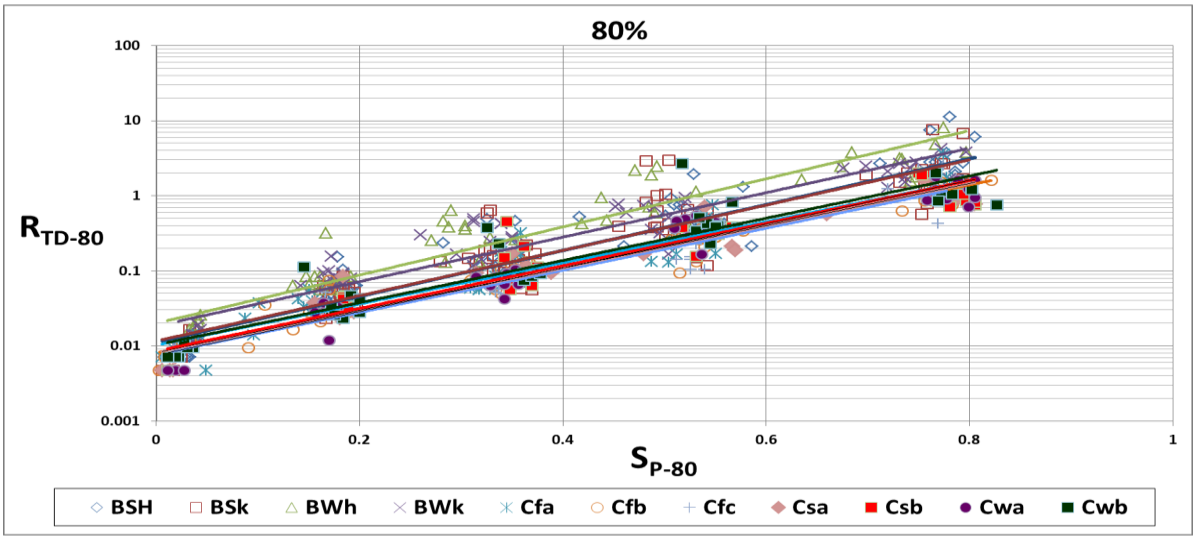


Figure 4-34: Variation by climate zone of normalised yield vs normalised storage at 80% reliability

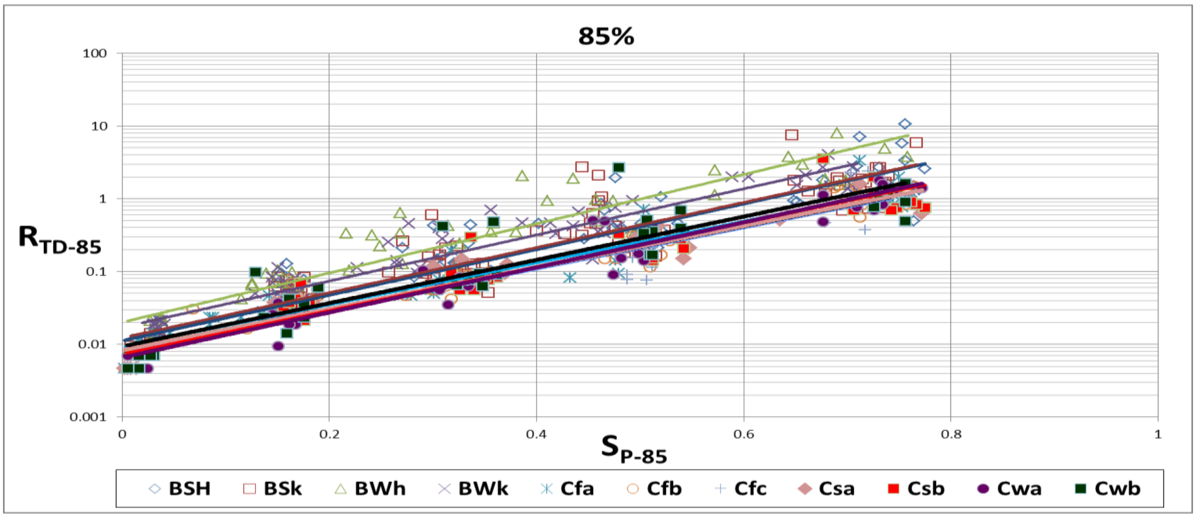


Figure 4-35: Variation by climate zone of normalised yield vs normalised storage at 85% reliability

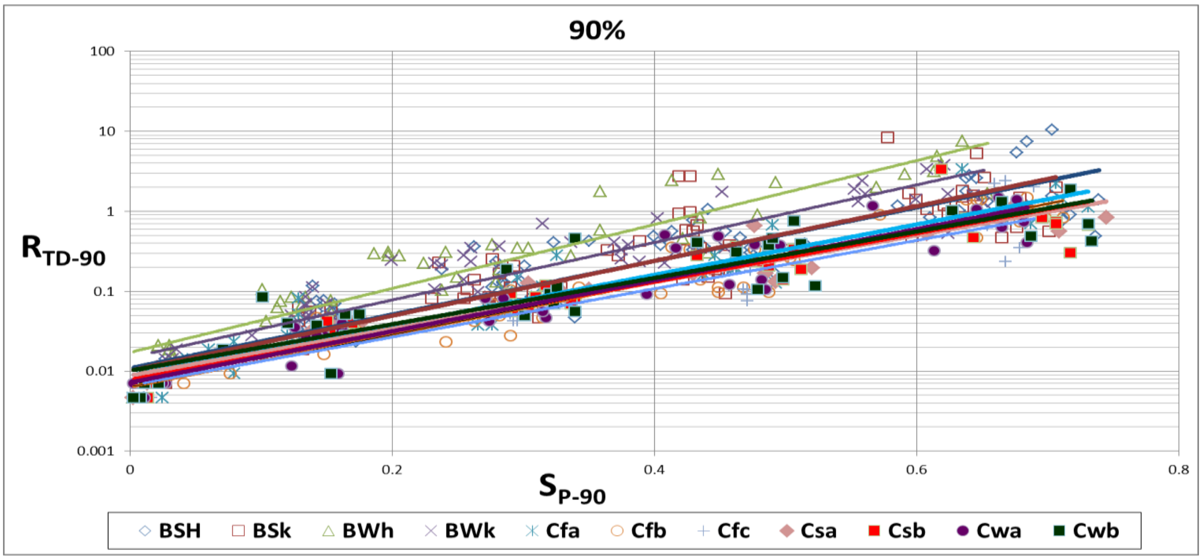


Figure 4-36: Variation by climate zone of normalised yield vs normalised storage at 90% reliability

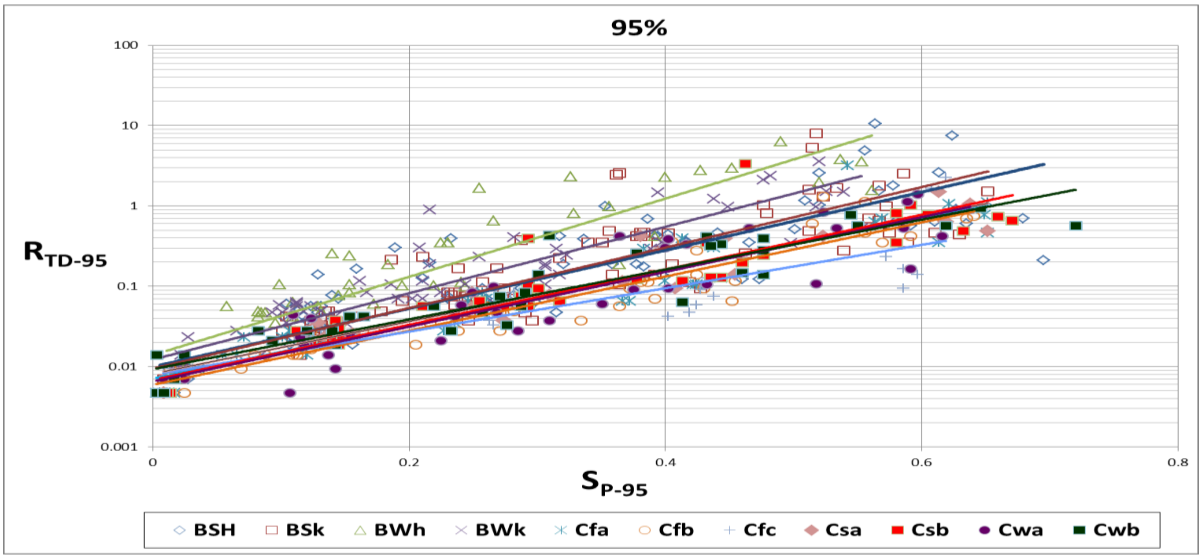


Figure 4-37: Variation by climate zone of normalised yield vs normalised storage at 95% reliability

From Figures 4-32 to 4-37, it was observed that it is the drier climates (i.e. BSh, BSk, BWh and BWK) that introduce the tendency to exponential variation of the data as optimum storage-demand values could go as high as 11.1 for reliabilities above 66% at the S-D ratio of 0.9. When tracking the trend lines, it was observed that there are roughly two zones of storage behaviour – one for the dry/desert climates and one for the wetter climates (Cfa, Cfb, Cfc, Csa, Csb, Cwa and Cwb) with increasing reliability. This shift in the trend lines, especially for the dry/desert zones may be attributed to the increased scattering of the data with increasing reliability and this would appear to support the argument that rainfall characteristics peculiar to the location of the rain gauge have an influence on the optimal storage size.

Table 4-5 compares the fitness's at the individual climate zone curves to that of the lumped model. As with the yield data before, a negative value indicates a better fit of the exponential model to climate specific data rather than a lumped model (R^2 values presented in Table 4-4) that does not distinguish between the climate zones.

Table 4-5: Normalised Yield vs Normalised Storage R^2 values for different climate zones

Climate Zone	50%		66%		80%		85%		90%		95%	
	R^2	% Diff	R^2	% Diff	R^2	% Diff	R^2	% Diff	R^2	% Diff	R^2	% Diff
BSh	0.8591	3.12	0.8978	-0.20	0.9035	-3.25	0.8916	-3.66	0.8732	-4.76	0.7873	-1.60
BSk	0.9106	-2.68	0.9170	-2.34	0.8713	0.43	0.8662	-0.71	0.8489	-1.85	0.8046	-3.83
BWh	0.8436	4.87	0.8873	0.97	0.8838	-0.99	0.8845	-2.84	0.8816	-5.77	0.8522	-9.98
BWk	0.8288	6.54	0.8904	0.63	0.9103	-4.02	0.9123	-6.07	0.8832	-5.96	0.8551	-10.35
Cfa	0.9335	-5.27	0.9454	-5.51	0.9147	-4.53	0.9305	-8.19	0.9125	-9.48	0.9040	-16.66
Cfb	0.9462	-6.70	0.9651	-7.71	0.9510	-8.67	0.9508	-10.55	0.9389	-12.65	0.9184	-18.52
Cfc	0.9297	-4.84	0.9254	-3.28	0.9223	-5.39	0.9004	-4.69	0.8907	-6.86	0.7884	-1.74
Csa	0.9230	-4.08	0.9376	-4.64	0.9198	-5.11	0.9152	-6.41	0.9245	-10.92	0.9045	-16.72
Csb	0.9697	-9.35	0.9456	-5.54	0.9291	-6.17	0.9147	-6.35	0.9145	-9.72	0.8754	-12.97
Cwa	0.9346	-5.39	0.8718	2.70	0.9517	-8.75	0.9442	-9.78	0.9007	-8.06	0.8372	-8.04
Cwb	0.8782	0.97	0.8715	2.73	0.8738	0.15	0.8392	2.43	0.8397	-0.74	0.8664	-11.81

In this case there is a much more appreciable variation in the coefficients of determination. It was observed that at each of the reliabilities assessed, the climate zone specific curve tends to give a much tighter fit relationship than the lumped curve. The exception to this was the data of climate region Cwb where curve fitting by region tended to produce a slightly worse fit than the combined data curve for reliabilities below 85%. This was also observed from the drier climate zones.

The performance of the individual models was considered significantly better than the lumped model. Thus, it was considered necessary to assess whether the incorporation of the rainfall variability characteristics could improve the performance of the lumped model. This analysis and a comparison in performance to a lumped model without considering rainfall characteristics are presented section 4.3.1.

Incorporating reliability into generalised relationships

An additional exercise was carried out to determine whether a relationship exists between the regression coefficients of the storage-demand and yield ratio curves (denoted $\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$) and reliability. Figure 4-38 illustrates that very strong exponential relationships could be established between these two parameters. Thus it was concluded that reliability can also be effectively included as variable in the generalised relationship between storage and yield.

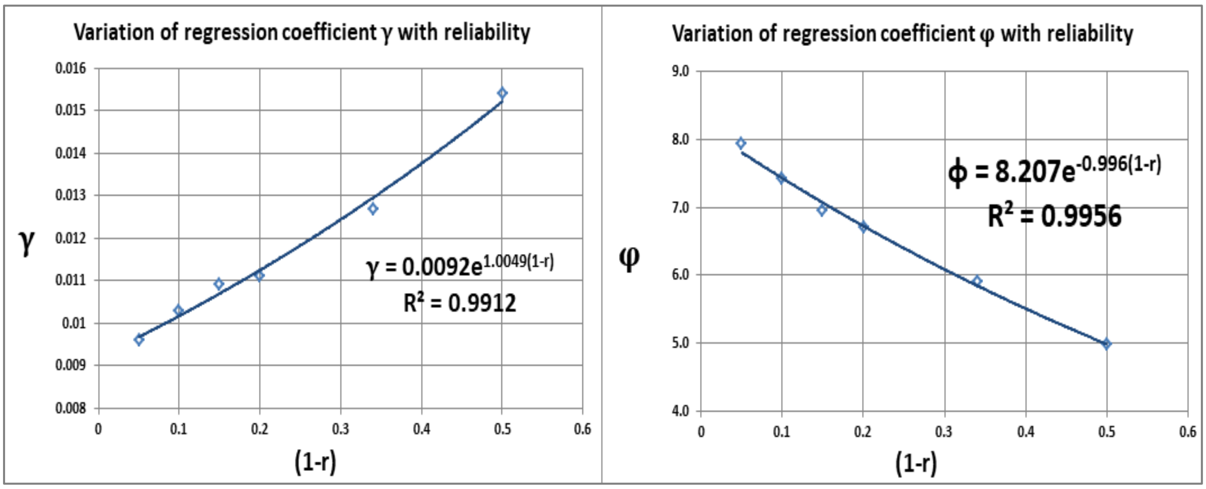


Figure 4-38: Variation of regression coefficients γ and φ with reliability

4.3. Influence of Rainfall Characteristics on Storage-Yield-Reliability Regression Relationships

The observations in the previous section indicate that the characteristics of rainfall have an impact on the observed optimum tank size and number of days of supply. This had also been observed by researchers such as Hanson & Vogel (2014) and Campisano & Modica (2012) who also sought to incorporate these characteristics into generalised relationships. The following sub-sections present the methods, results and analysis of the investigation into the influence of incorporating at least one of the rainfall variability parameters described in section 3.2.3 into generalised relationships.

4.3.1. Influence of Rainfall Characteristics on the Regression Relationship between the Yield ratio(S_{P-r}) and Storage-Demand Ratio (R_{TD-r})

The influence of incorporating the ratio of the number of dry days to the number of rainy days

Two basic rainfall statistics that can be easily extracted from a rainfall time series are the mean number of rain days and mean number of dry days in a year for a particular location/rainfall station. In developing a generalised model for the sizing of RWH tanks for Italy, Campisano et al., (2013) utilise a storage ratio defined in a similar manner to that proposed by Ndiritu et al., (2017) with the major difference being that they included the dimensionless parameter n_d/n_r as a way to account for the influence of the intra-annual differences in rainfall patterns for the different regions of Italy. The ratio n_d/n_r was included in the study of Campisano et al., (2013) as a means by which one could relate the demand to the storage tank capacity and to the average length of the dry period as this was viewed as critical to determining the ideal storage. Using a similar concept for this study, addition of this parameter to the storage-demand ratio of Ndiritu et al., (2017) leads to the modified expression of the storage-demand ratio as shown in Equation 4-1.

$$mR_{TD-r} = \frac{K_r}{\overline{D_t} \times 365.25 \times \frac{n_d}{n_r}} \qquad \textbf{(4-1)}$$

where: mR_{TD-r} represents the modified storage ratio and all other symbols are as defined in equation 3-9.

Using the modified expression of Equation 4-1, plots were obtained at reliabilities of 50%, 66%, 80%, 85%, 90% and 95%. An illustration of the result of this transformation at 50% reliability is shown in Figure 4-39; a similar trend in the data was observed for all other reliabilities.

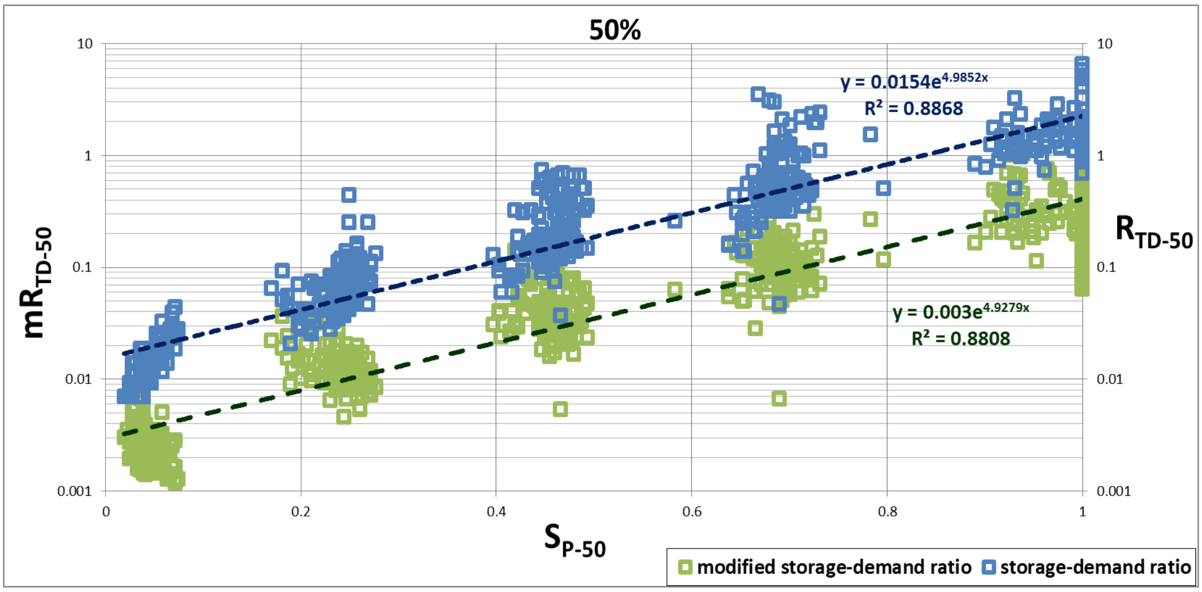


Figure 4-39: Variation of the modified storage ratio and storage ratio with yield ratio at 50% reliability

It was observed from the graphs that the effect of adding the ratio n_d/n_r as part of the storage ratio results in the scaling of the data with no change in the form of relationship between the parameters of storage-demand and yield. Addition of the rainfall characteristic however, results in an overall increase of the goodness-of-fit of the exponential model across all reliabilities (except 50%) as shown in Table 4-6. This improvement in the goodness-of-fit suggested that in addition to the supply-demand dynamic (as captured by the S_{P-r} vs. R_{SD} relationship), the variability of rainfall with respect to the relative length of the dry period influences the optimal storage value in the design of RWHS. This is also as alluded to by Allen (2013) who interrogated the interaction of the length of the dry weather period and observed behaviour of RWHS.

Table 4-6: Comparison of R^2 values for modified storage ratio to original storage ratio

Reliability (%)	R^2		% Difference
	S_{P-r} vs. R_{TD-r}	S_{P-r} vs. mR_{TD-r}	
50	0.8868	0.8808	+0.68
66	0.8960	0.9153	-2.15
80	0.8751	0.9125	-4.27
85	0.8601	0.8999	-4.63
90	0.8335	0.8867	-6.38
95	0.7749	0.8624	-11.3

The overall improvement in R^2 values across all reliabilities came to 4.5% implying that pursuing a modified relationship that accounts for rainfall variability would be valuable in increasing the reliability of predictions made by a lumped model. An alternative formulation through multiple regressions was also pursued whose results follow.

The Influence of rainfall characteristics on regression relationships using ordinary least squares multi-variable regression

The aim of the following analysis was to evaluate the utility of the addition of a single rainfall parameter as an independent variable in improving the goodness-of-fit of the lumped regression model. This was achieved by the use of ordinary least squares multi-variable regression using the regression module on the Microsoft Excel (2010) spreadsheet.

As indicated by the results of section 4.2.2., the best fit form of the generalised relationship between the yield ratio $\boldsymbol{S_{P-r}}$ and the storage demand ratio $\boldsymbol{R_{TD-r}}$ is the exponential curve as described in Equation 4-2.

$$\boldsymbol{R_{TD-r} = \gamma e^{\varphi S_{P-r}}} \tag{4-2}$$

Where: $\boldsymbol{R_{TD-r}}$ and $\boldsymbol{S_{P-r}}$ are as defined before and $\boldsymbol{\varphi}$ and $\boldsymbol{\gamma}$ represent the coefficients of regression.

The proposed addition of a single parameter (after Hanson & Vogel (2014)) results in the formulation of the generalised expression of the multi-variable relationship between the yield ratio S_{P-r} and the storage demand ratio R_{TD-r} as shown in Equation 4-3.

$$R_{TD-r} = \delta e^{bS_{P-r}} \cdot x_1{}^c \quad \textbf{(4-3)}$$

Where: $x_1$represents the rainfall parameter of interest and δ, b and c represent the regression coefficients.

Both forms of the general model shown in Equations 4-2 and 4-3 allow for the use of ordinary least squares regression as the equations may be expressed in linear form. As the aim of the analysis was to identify any improvement in the goodness-of-fit of the current model with the addition of a rainfall parameter, Equation 4-3 was converted to it log-linear equivalent as shown in Equation 4-4 to allow for the regressions to be carried out.

$$\ln(R_{TD-r}) = \ln(\delta) + bS_{P-r} + c\ln x_1 \quad \textbf{(4-4)}$$

A comparison was done amongst each of the parameters presented in section 3.2.3, to assess which of them had the most influence in improving the R^2 value of the generalised relationship. Table 4-7 presents the comparison of the R^2 values of the modified model (denoted multi-variable model) to the original model (denoted uni-variable model) that does not explicitly account for the influence of rainfall characteristics.

As Table 4-7 shows, the ***CV*** of daily rainfall resulted in the largest overall increase in the coefficient of determination providing an improvement of 6.7%. It is closely followed by the n_d/n_r ratio which provides an improvement of 5.8% - a slight improvement than when the ratio is incorporated as shown in Equation 4-1. The rainfall characteristic with the least impact on the R^2 value is CV_w.

Given that ***CV*** quantifies the extent of variability of rainfall from the mean and the n_d/n_r ratio quantifies the relative length of dry periods, it was concluded that these particular distributive characteristics are significant in the determination of the optimum storage capacity and its relation to RWH yield.

Table 4-7: R^2 values obtained using different rainfall characteristic parameters

Reliability (%)	R^2 for multi-variable models							
	CV	$n_{d/}$ n_r	SI	σ (mm)	CV_w	μ_w (mm d^{-1})	σ_w (mm)	Uni-variable model
50	0.9139	0.9087	0.8874	0.8994	0.8881	0.8891	0.8871	0.8868
66	0.9339	0.9295	0.8971	0.9180	0.8965	0.9006	0.8985	0.8960
80	0.9265	0.9199	0.8760	0.9046	0.8759	0.8813	0.8785	0.8751
85	0.9209	0.9128	0.8607	0.8968	0.8608	0.8691	0.8657	0.8601
90	0.9089	0.8975	0.8357	0.8774	0.8345	0.8444	0.8399	0.8335
95	0.8639	0.8547	0.7785	0.8317	0.7749	0.7879	0.7844	0.7749
MEAN	**0.9113**	**0.9039**	**0.8559**	**0.8880**	**0.8551**	**0.8621**	**0.8590**	**0.8544**

To test the statistical validity of adding the variables of ***CV*** and ***n_d/n_r*** into the generalised model, the P-value of the coefficient ***c*** (Equation 4-3) associated with the rainfall parameters was computed at a significance level of 0.05. Table 4-8 presents the results of this determination and shows ***CV*** and ***n_d/n_r*** to be strongly statistically significant as the resulting P-values across all reliabilities lie well below the threshold value of 0.05. In addition to this, analysis of the residual plots associated with this coefficient revealed the requisite random behaviour that assures one the form of the relationship between the dependent and independent variable is indeed log-linear.

Table 4-8: Statistical significance between coefficient c and rainfall characteristics *CV* and n_d/ n_r

Reliability		Parameter	
		CV	***n_d/ n_r***
50%	Coefficient Value	1.205	0.483
	P-value	3.15E-37	8.77E-30
66%	Coefficient Value	1.51	0.631
	P-value	4.18E-60	6.86E-52
80%	Coefficient Value	1.76	0.732
	P-value	2.18E-68	1.34E-57
85%	Coefficient Value	1.88	0.779
	P-value	7.26E-73	1.10E-60
90%	Coefficient Value	2.08	0.851
	P-value	5.25E-76	9.50E-62
95%	Coefficient Value	2.21	0.926
	P-value	9.87E-63	6.94E-55

Assessment of the P-values of the same coefficient for all the other rainfall parameters revealed ***SI***, ***σ***, ***μ_w*** and ***σ_w*** to be statistically significant across all reliabilities. However, the P-values for ***CV_w*** revealed this parameter to be statistically insignificant in agreement with the resulting relatively low improvements (averaging 1.1%) to the coefficient of determination.

Incorporating reliability into generalised relationships

As with the uni-variable generalised models, the regression coefficients of the multi-variable model incorporating the best fit parameter ***CV*** were plotted against reliability to ascertain if relationships could be established. Figures 4-40 to 4-42 illustrate that even for the case of a generalised multi-variable model, very strong regression relationships exist between the coefficients of regression and reliability. In this case, the best fit regression curve across all three coefficients is the exponential model which gave R^2 values of 0.9837, 0.9887, and 0.9950 for coefficients ***δ***, ***b*** and ***c*** respectively.

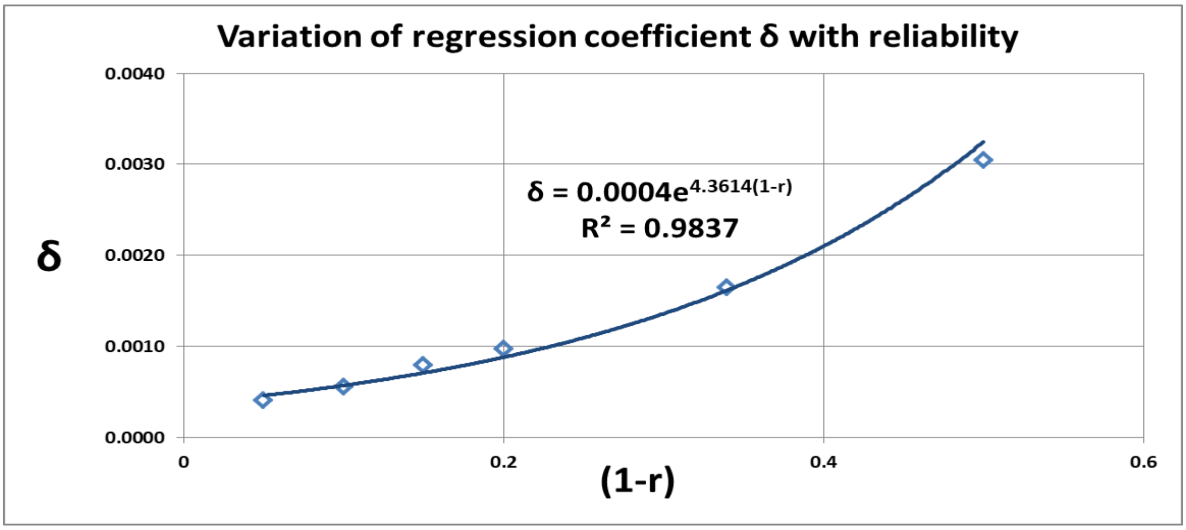


Figure 4-40: Variation of the multi-variable model coefficient a with reliability

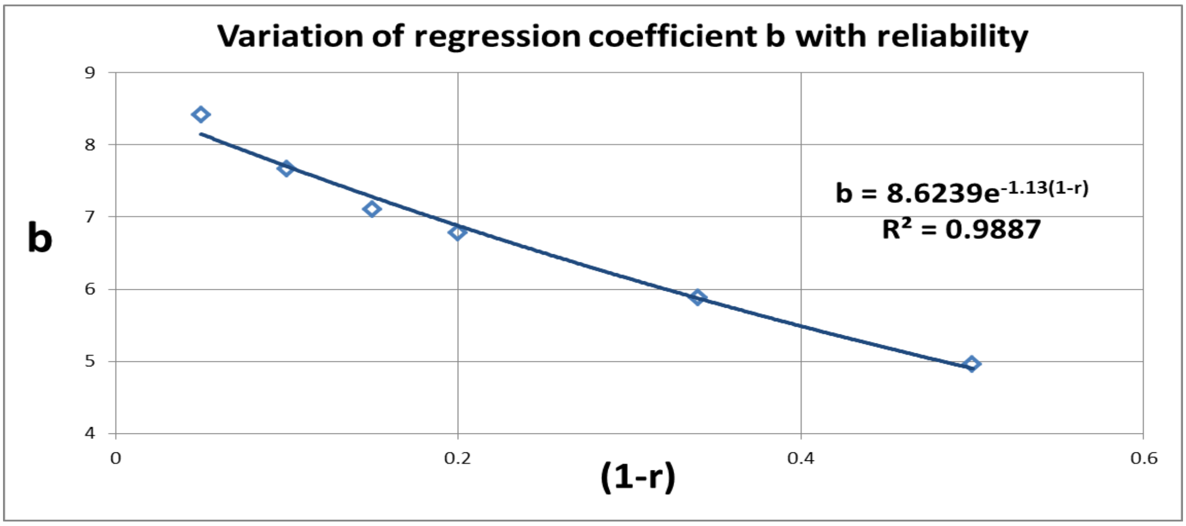


Figure 4-41: Variation of the multi-variable model coefficient b with reliability

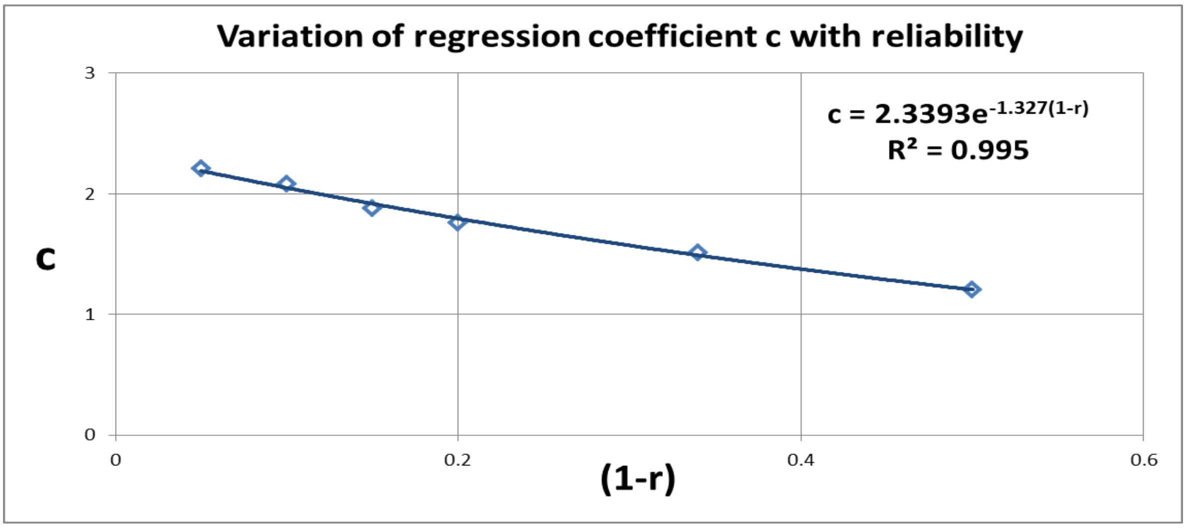


Figure 4-42: Variation of the multi-variable model coefficient c with reliability

4.3.2. Influence of Rainfall Characteristics on the Regression Relationship between the Yield ratio (S_{P-r}) and the Supply-Demand ratio (R_{SD})

As with the analysis of the utility of using a multi-variable regression equation to describe the relationship between the yield ratio (S_{P-r}) and the storage-demand ratio (R_{TD-r}), the aim of the following analysis was to evaluate the efficacy of the addition of a rainfall variability parameter, to improve the goodness-of-fit of the lumped regression model that relates the yield ratio, S_{P-r} to the supply-demand ratio, R_{SD}. The multi-variable generalised relationship in this instance is as described in Equation 4-5.

$$S_{p-r} = dR_{SD}^{e} \cdot x_2^{f} \qquad \textbf{(4-5)}$$

Where: x_2 represents the rainfall parameter and ***d, e*** and ***f*** are the coefficients of regression.

The relationship expressed by Equation 4-5 can also be expressed in its log-linear equivalent as shown in Equation 4-6, thus allowing multiple linear regressions to be carried out.

$$ln(S_{p-r}) = ln(d) + eln(R_{SD}) + fln(x_2) \qquad \textbf{(4-6)}$$

The results of regression against all the rainfall parameters listed in section 3.2.3 resulted in negligible improvements in the coefficient of determination as shown in Table 4-9.

Table 4-9: Percentage change in R^2 when rainfall characteristics are included in the S_{P-r} vs. R_{SD} relationship

Rainfall Characteristic	Percentage change in average R^2 across all reliabilities
CV	0.22%
σ	0.20%
n_d/n_r	0.29%
SI	0.05%
CV_w	0.03%
μ_w:	0.08%
σ_w	0.06%

The rainfall parameter found to improve the coefficient of determination the most was the ratio of dry days to rainy days which gave a percentage improvement of 0.29% with the averaged R^2 value improving from 0.9413 to 0.9440 across all reliabilities. Statistical significance testing at a threshold level of 0.05 revealed varied results for this parameter. It was found to be statistically significant for all reliabilities except 95% as shown in Table 4-10.

Table 4-10: Statistical significance between coefficient f and rainfall characteristic n_d/ n_r

Reliability		Parameter
		n_d/ n_r
50%	Coefficient Value	0.153
	P-value	1.76E-42
66%	Coefficient Value	0.171
	P-value	2.56E-19
80%	Coefficient Value	0.122
	P-value	2.89E-08
85%	Coefficient Value	0.104
	P-value	6.49E-05
90%	Coefficient Value	0.091
	P-value	0.00125
95%	Coefficient Value	**-0.016**
	P-value	**0.6007**

This result implies that it may not be necessary to incorporate the rainfall parameter x_2 into the relationship between the yield ratio and supply-demand ratio. However considering the results of a comparison between the predictions of the uni-variable model (combined storage–yield-reliability model) and simulation as shown in Figures 4-43 and 4-44, the results from the model imply that at equal S-D ratios anywhere in South Africa, a RWHS should produce an identical yield and by extension an identical corresponding storage value which is not the case when looking at the monotonic response of the model versus the varied response of simulation.

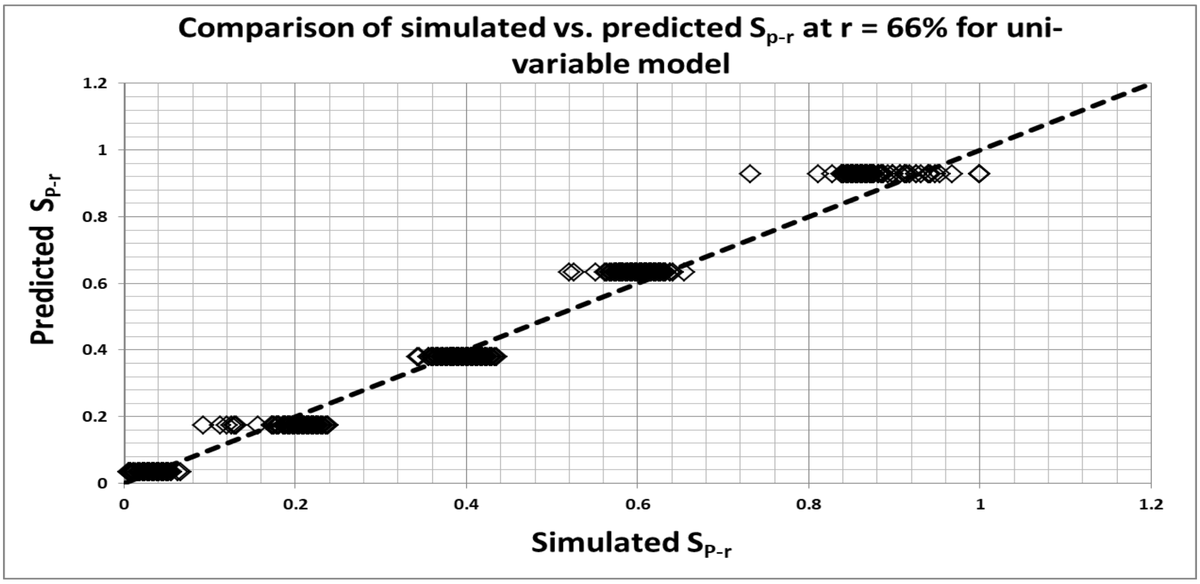


Figure 4-43: Comparison of predicted S_{P-r} and simulated S_{P-r} at 66% reliability using the uni-variable model

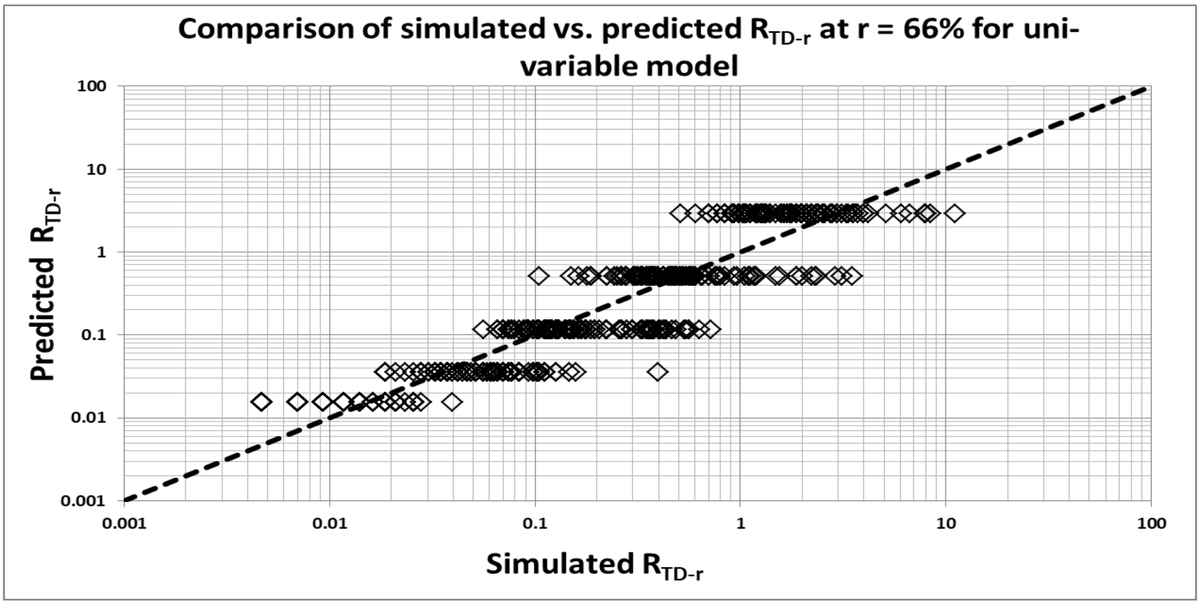


Figure 4-44: Comparison of predicted R_{TD-r} and simulated R_{TD-r} at 66% reliability using the uni-variable model

Thus it was deemed necessary to further investigate and justify the need for the inclusion of rainfall characteristics in a relationship between the yield ratio and the S-D ratio as a way of distinguishing between two RWHS that describe identical S-D ratios but are subject to different rainfall regimes.

Figure 4-45 illustrates for a reliability of 66% across the tested S-D ratios (at its weakest) a logarithmic/exponential relationship exists between the yield ratio and the rainfall characteristic n_d/n_r. Similar trends in the data are observed at all other reliabilities and their data is presented in Appendix 3(b).

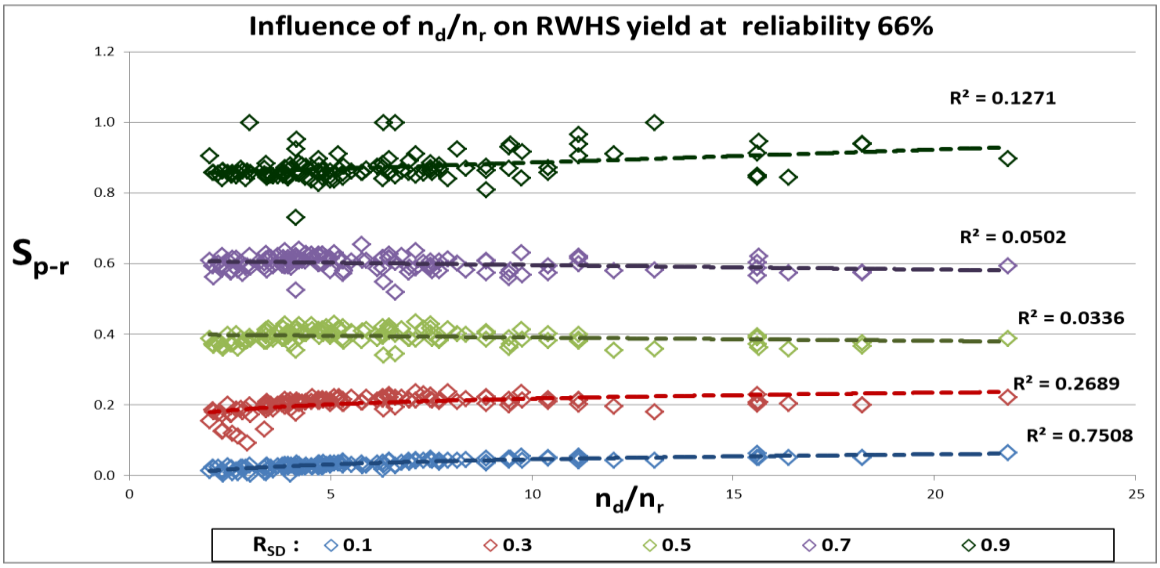


Figure 4-45: Influence of n_d/n_r on S_{P-r} of a RWHS at reliability 66%

What can be said is that while the averaged R^2 value for this relationship is relatively low across all reliabilities and S-D ratios, it is quite clear that rainfall variability exerts some influence on the level of supply from a RWHS and this is especially so for systems described by an S-D ratio of 0.1. Comparison of a multi-variable model incorporating rainfall characteristics to simulation, as illustrated in Figure 4-46, shows a more realistic characterisation RWHS yields when systems operate under different rainfall regimes at identical S-D ratios.

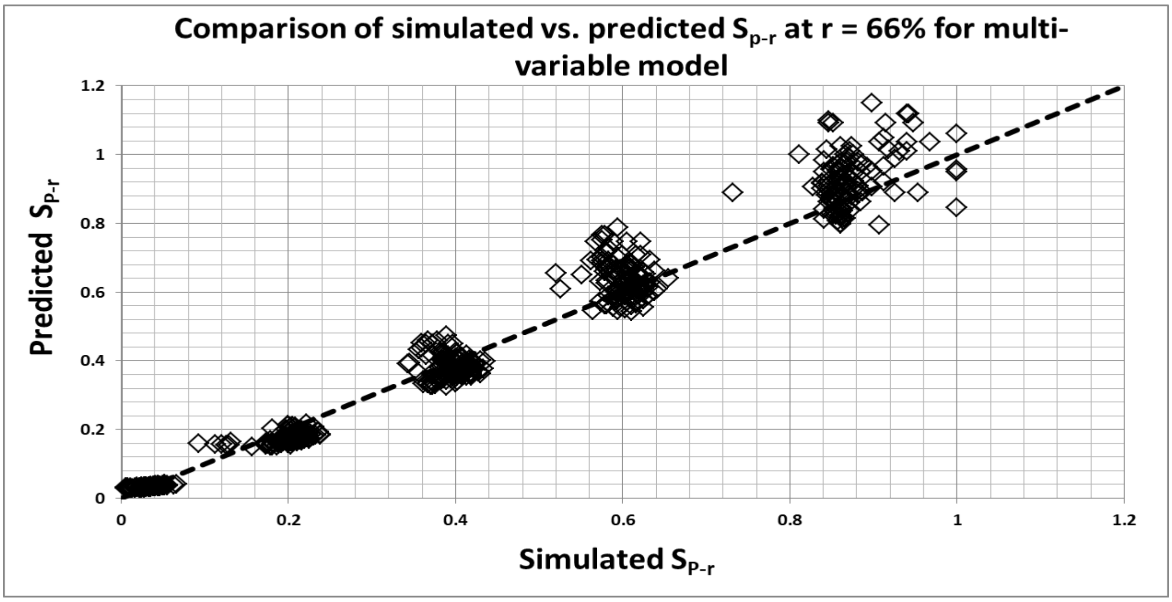


Figure 4-46: Comparison of predicted yield and simulated yield at 66% reliability for multi-variable model

A graphical comparison between the multi-variable storage-demand-yield model and simulation data is presented in Figure 4-47. Once again contrasting Figures 4.44 and 4.47 reveals that the multi-variable model leads to a more realistic characterisation of the behaviour of RWHS defined by identical S-D ratios.

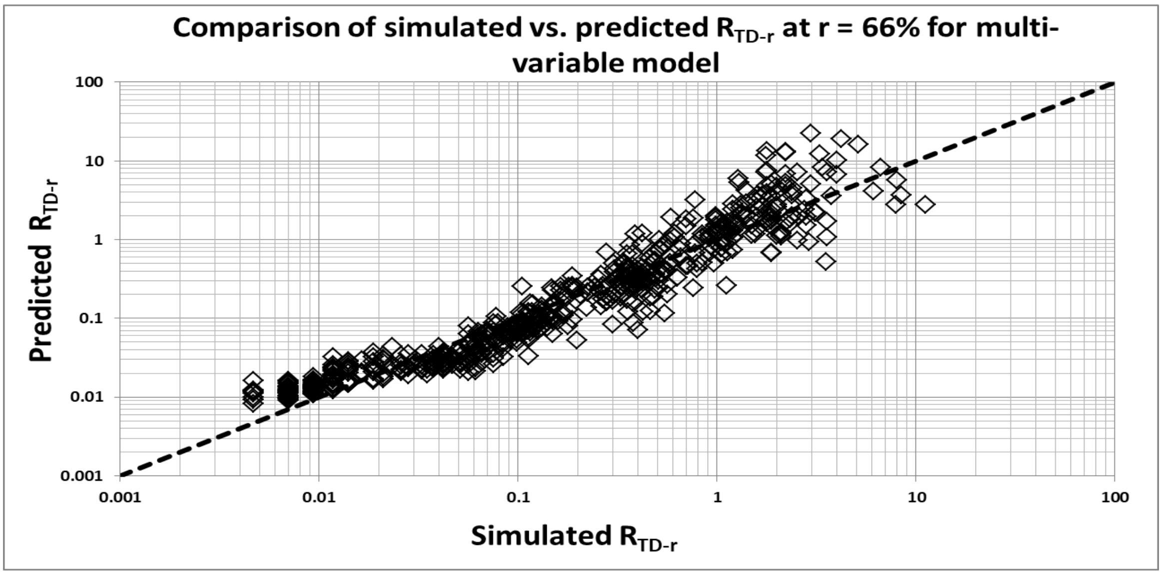


Figure 4-47: Comparison of simulation and multi-variable model R_{TD-r} results at reliability of 66%

Further comparison between the predictions of the uni-variable model and multi-variable model relating yield to supply-demand was done and analysis across all the S-D ratios and reliabilities showed both models to predict near identical yields - a percentage difference of -0.33% was observed between the two models with the multi-variable model predicting higher yield than the uni-variable model. An evaluation of the standard error of regression between the two models and simulated data revealed that the uni-variable model, with a standard error of 0.05 to marginally better describe the simulated data when compared to the multi-variable models whose standard error of regression came to 0.06.

Comparison was also carried out between the predictions of the uni-variable model and multi-variable model relating storage-demand to yield and a substantial difference was observed – a percentage difference of -20% was found across all S-D ratios and reliabilities, indicating that the multi-variable model predict larger storage values than the uni-variable model. Comparison of the standard error of regression between the two models and simulated data revealed that the uni-variable model, with a standard error 0.77 to better describe the simulated data when compared to the multi-variable model whose standard error of regression came to 1.36 with respect to the storage.

Although the standard error test suggests that the multi-variable model is less representative than the univariate model, it certainly has been shown to offer the advantage of accounting for the influence of rainfall variability on the behaviour of a RWHS and to result in a more realistic representation of the simulation data.

Incorporating reliability into the multi-variable generalized relationship

Relationships between regression coefficients of Equation 4-5 and reliability were also investigated and good fits of an exponential model was found for coefficient ***d***, whilst a power-model was found for coefficient ***e*** and a logarithmic model was found for ***f***. Figures 4-48 to 4-50 present the relationships.

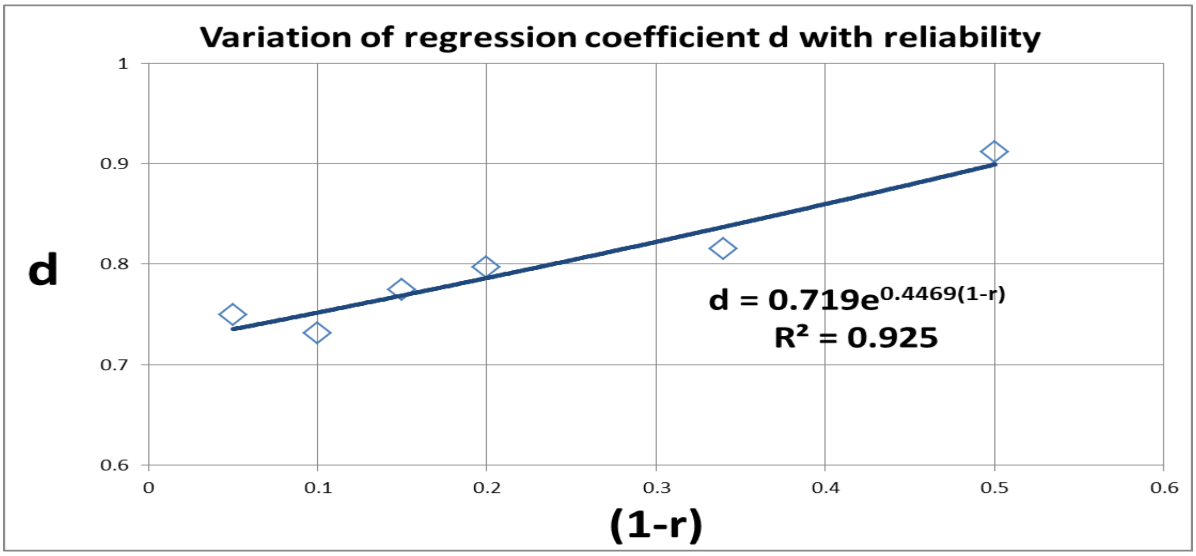


Figure 4-48: Variation of the multi-variable model coefficient d with reliability

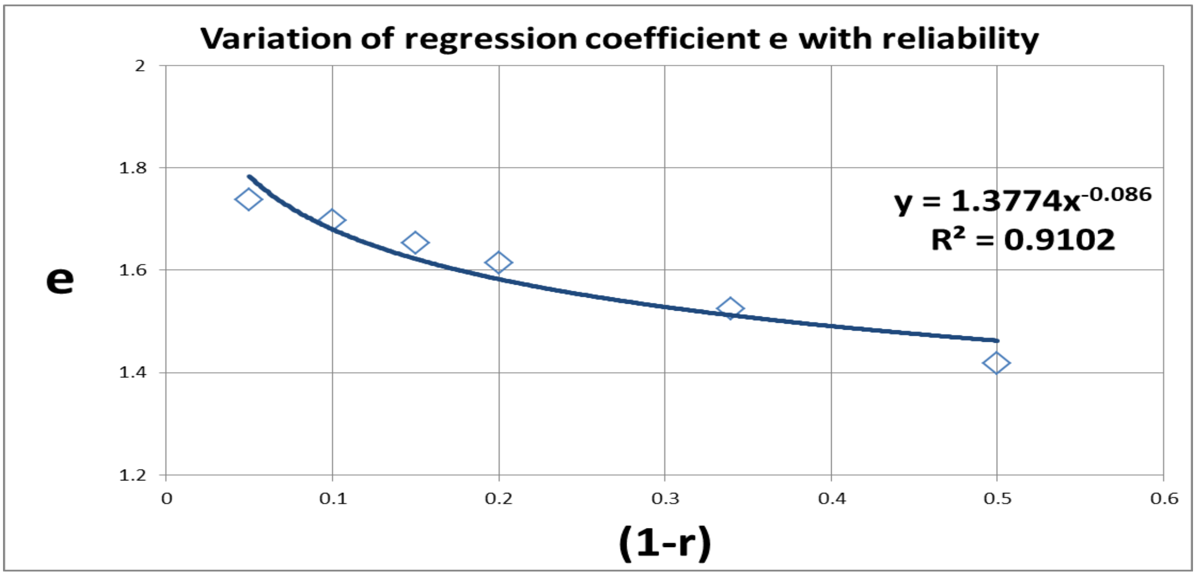


Figure 4-49: Variation of the multi-variable model coefficient f with reliability

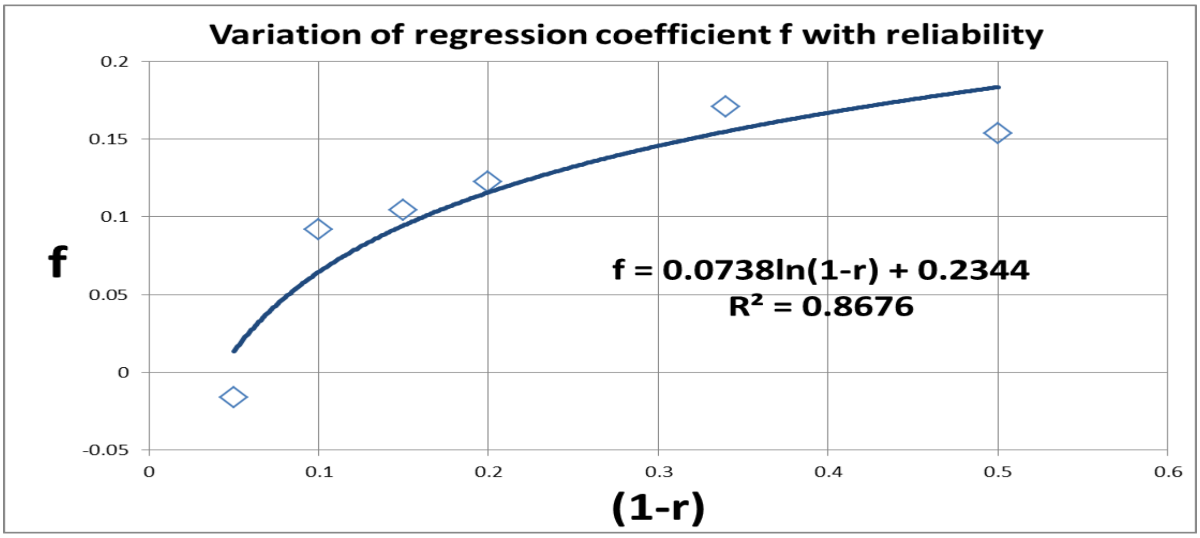


Figure 4-50: Variation of the multi-variable model coefficient f with reliability

4.4. Summary

This chapter has presented the results of the analysis of the relationships between the yield ratio, storage ratio, S-D ratio and reliability when using a larger sample of gauges. In addition to this, the influence of rainfall characteristics on the behaviour of RWHS was investigated, with regression used as the main tool to develop generalised relationships between the key variables of: the yield ratio, the S-D ratio, the storage ratio and the rainfall characteristics of the coefficient of variation of daily rainfall and the ratio of dry days to rain days. From the analysis the following key findings were made:

- Increasing the number of gauges increases variability in the observed behaviour a RWHS.
- The power model best describes the relationship between the supply-demand ratio and the yield ratio, whilst the exponential model best describes the relationship between the storage-demand ratio and yield ratio.
- Incorporation of rainfall variability characteristics improves the fit of the generalized regression models. Greater improvements of the model were observed for the storage-demand-yield model when compared to the yield-supply-demand ratio relationship
- Comparison of the storage-demand-yield model without rainfall variability characteristics to the storage-demand-yield model with rainfall variability characteristics has shown that incorporating rainfall variability characteristics leads to better fitting generalized models. Incorporating these characteristics allows the model to account for the influence of intra-annual rainfall distribution which is unique to the locations of the different rain gauges - the incorporation of rainfall characteristics eliminates the monotonous response of the model that excluded rainfall characteristics (a monotonous response implies identical

behaviour of a RWHS in different parts of South Africa when the same supply-demand ratio is used which is not case from the simulated data)

- Coefficients of regression from the relationship between the yield ratio and supply-demand ratio and the relationship between the storage-demand ratio and yield ratio show very strong correlations with reliability for both the model incorporating rainfall characteristics and the model the model that does not incorporate these characteristics

Based on the results presented in this chapter, the following generalised models, for the case of constant demand, are proposed:

$$\boldsymbol{S_{p-r}} = \frac{\boldsymbol{N_r}}{\mathbf{365.25}} = \boldsymbol{\alpha}(\boldsymbol{R_{SD}})^{\boldsymbol{\beta}}$$

Where: **(4-7)**

$\alpha = 1.362(1-r)^{0.207}$ $\qquad \mathbf{0.5} \le \boldsymbol{r} \le \mathbf{0.95}$

$\beta = 1.769e^{-0.445(1-r)}$

Where: $\boldsymbol{S_{p-r}}$ is the yield ratio, $\boldsymbol{N_r}$ is the expected number of days of rainwater supply per year, $\boldsymbol{R_{SD}}$ is the supply to demand ratio, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are coefficients of regression and $\boldsymbol{r}$ is the reliability.

$$\boldsymbol{R_{TD-r}} = \boldsymbol{\gamma e^{\varphi(S_{p-r})}}$$

Where for $\boldsymbol{amplitude\ of\ demand} = \mathbf{0}$:

$\gamma = 0.009e^{1.005(1-r)}$ $\qquad \mathbf{0.5} \le \boldsymbol{r} \le \mathbf{0.95}$ **(4-8)**

$\varphi = 8.207e^{-0.996(1-r)}$

Where: $\boldsymbol{S_{p-r}}$ is the yield ratio, $\boldsymbol{R_{TD-r}}$ is the storage-demand ratio, $\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$ are coefficients of regression, and $\boldsymbol{r}$ is the reliability.

If rainfall characteristics are included then:

$$S_{p-r} = \frac{N_r}{365.25} = d(R_{SD})^e \cdot \left(\frac{n_d}{n_r}\right)^f$$

Where:

$d = 0.719e^{0.447(1-r)}$ $\quad\quad$ $0.5 \leq r \leq 0.95$ $\quad\quad$ **(4-9)**

$e = 1.38(1-r)^{-0.086}$

$f = 0.074\ln(1-\mathrm{r}) + 0.2344$

Where: S_{p-r} is the yield ratio, N_r is the expected number of days of rainwater supply per year, R_{SD} is the supply to demand ratio, d, e and f are coefficients of regression, n_d is the number of dry days per year, n_r is the number of rainy days per year and r is the reliability.

$$R_{TD-r} = \delta e^{b(S_{p-r})} \cdot CV^c$$

Where:

$\delta = 0.0004e^{4.361(1-r)}$

$b = 8.624e^{-1.13(1-r)}$ $\quad\quad$ $0.5 \leq r \leq 0.95$ $\quad\quad$ **(4-10)**

$c = 2.339e^{-1.327(1-r)}$

Where: $S_{p-r}$is the yield ratio, R_{TD-r} is the storage-demand ratio, δ, b and c are coefficients of regression, CV is the coefficient of variation of daily rainfall, and r is the reliability.

CHAPTER 5 THE IMPACT OF VARIABILITY IN WATER DEMAND

Objectives 2.1 and 2.2 of this study involved assessing the influence of demand variability on a RWHS with the aim to incorporate the parameters that describe this variability into the generalized relationships developed in Chapter 4. This chapter presents the results of analysis of the observed general behaviour of RWHS under variable demands and sets out the methods used and the results of analysis to establish relationships between the level of supply, tank size and the parameters of used to describe demand variability.

5.1. Effect of Varying the Location and Magnitude of the Maximum Demand on Yield and Storage

As per objective 2.1, simulations were performed on a sample of 33 rainfall stations to better understand the potential impacts that variability in demand could have on the behaviour of RWHS.

5.1.1. Effect of varying the location of the maximum demand

The first set of simulations evaluated the impact of using two demand patterns derived from Equation 3-2 and shown on Figure 3-7 that changed the location of the peak in demand but maintained the same amplitude. Figures 5-1 up to 5-5 present the observed effect of varying the location of the peak of demand on the number of days of supply from a RWHS. The vertical axis quantifies the proportion of the number of days of supply that are retained under each of the chosen demand scenarios – this proportion is determined by means of a dimensionless ratio that divides the expected number of days of supply under variable demand ($\boldsymbol{N_{VD}}$) with the number of days of supply under constant demand ($\boldsymbol{N_C}$).

A negative value indicates a reduction in the number of days of supply retained whilst a positive value indicates an increase in number of days of supply retained. The axis value of zero represents the base case of constant demand where there is no change the number of days of supply. If a variable demand case indicates a value of zero then the number of days of supply under variable demand is the same as the number of days of supply under constant demand. Given the number of rainfall stations used, individual points on a line graph mixed with a column graph were viewed as the best way to illustrate the changes in the number of days of supply with changing location of the peak in demand (vertical axis). It also makes for easier comparison of behaviour across each rain gauge and climate zone (horizontal axis). The graphs depict the data for a reliability of 50% across all S-D ratios and climate zones. Similar trends in the data were observed at all other reliabilities and data for these may be found in Appendix 4(a).

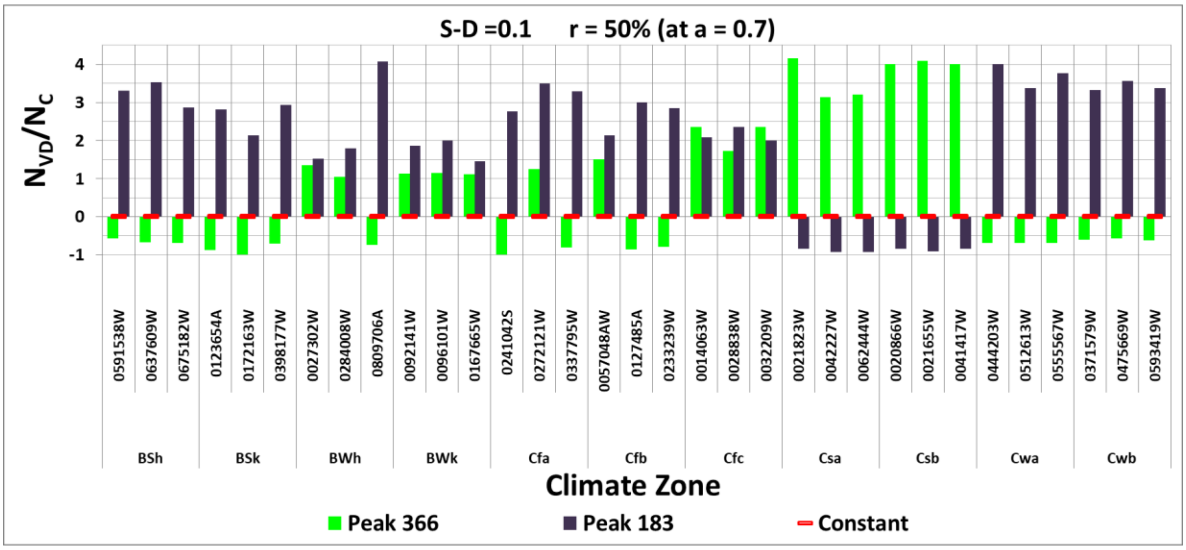


Figure 5-1: Effect of a variable demand at S-D ratio 0.1 and 50% reliability

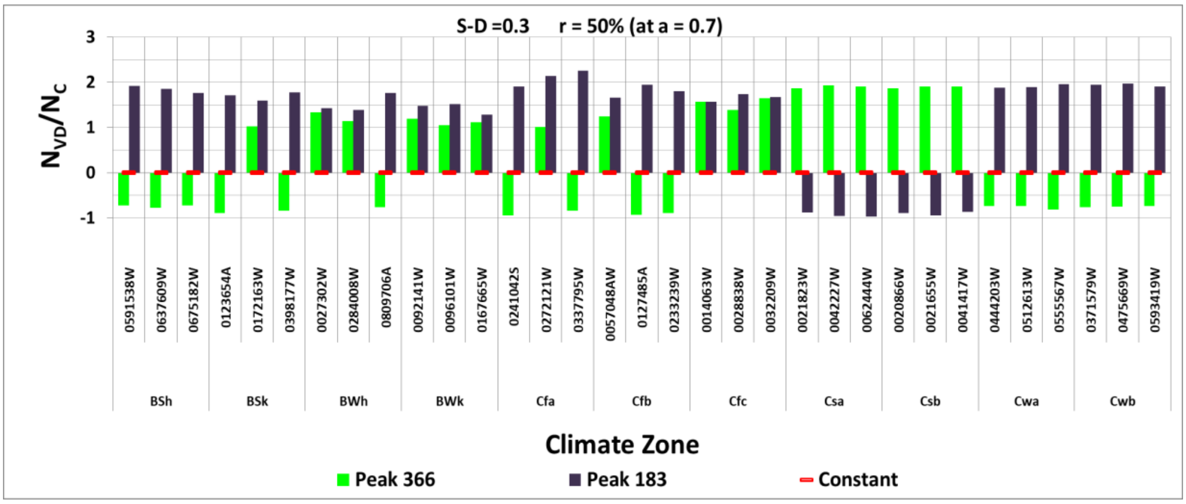


Figure 5-2: Effect of a variable demand at S-D ratio 0.3 and 50% reliability

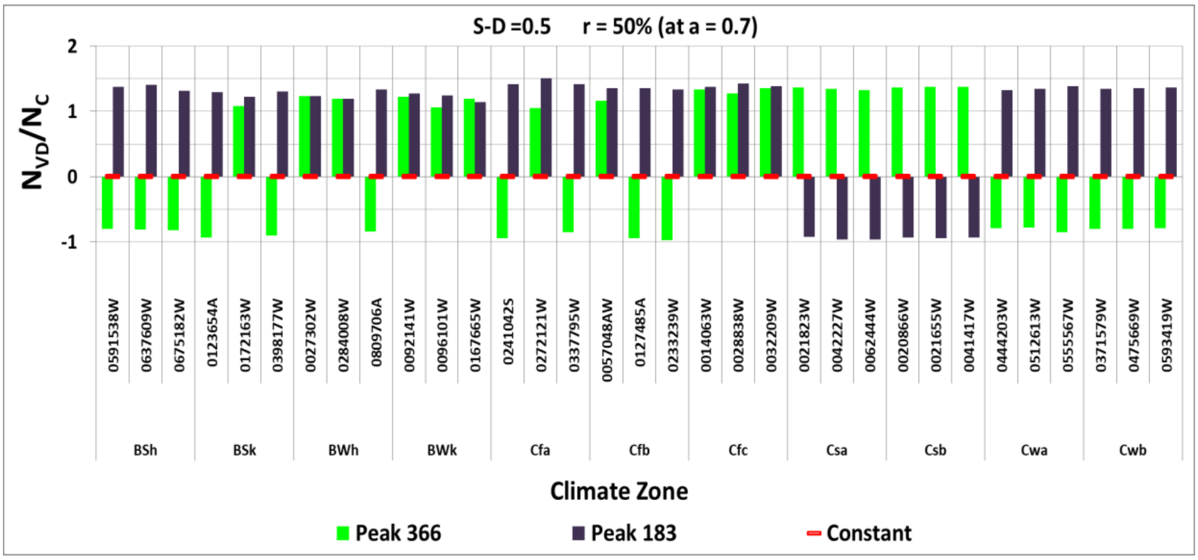


Figure 5-3: Effect of a variable demand at S-D ratio 0.5 and 50% reliability

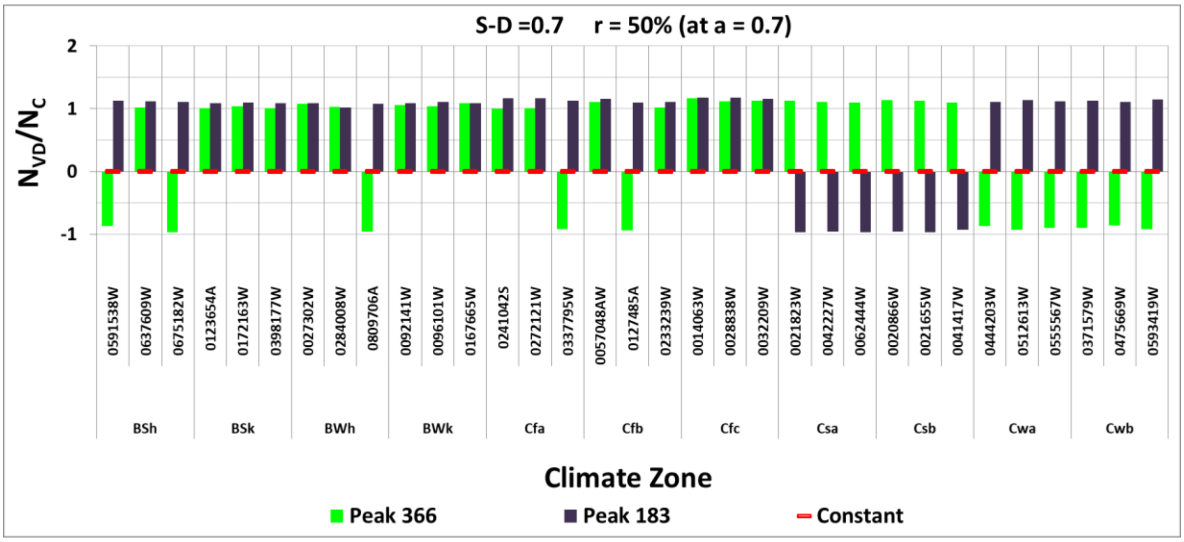


Figure 5-4: Effect of a variable demand at S-D ratio 0.7 and 50% reliability

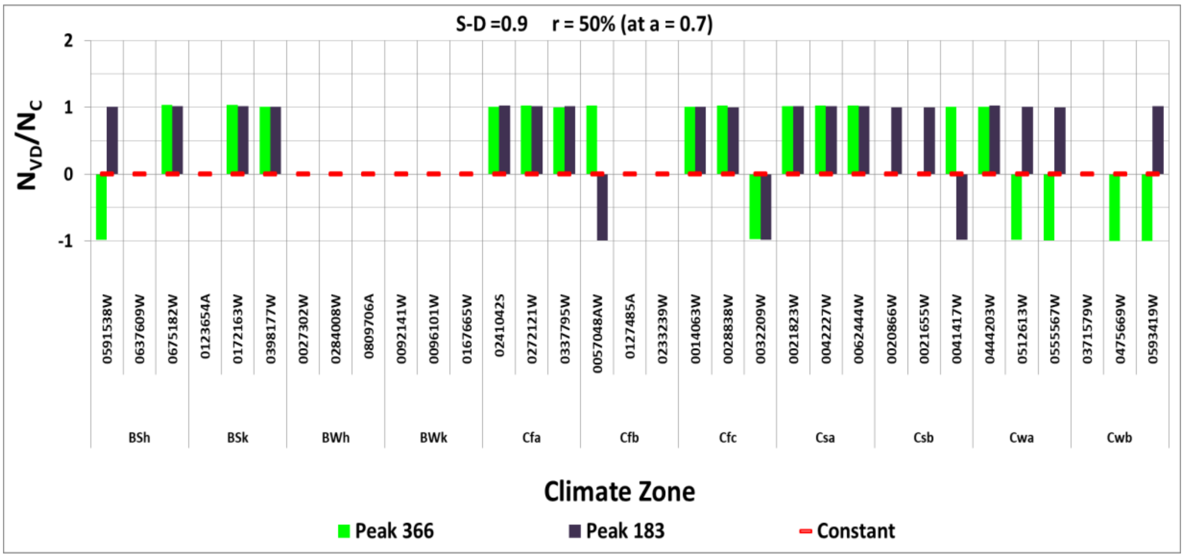


Figure 5-5: Effect of a variable demand at S-D ratio 0.9 and 50% reliability

From Figures 5-1 to 5-5, a reduction in difference of the number of days of supply retained with increasing S-D ratio across the two demand patterns is observed. This trend is also carried across the different reliabilities. At an S-D ratio of 0.9 it was observed that the number of days of supply remains the same under both scenarios for rainfall station located in climate zones BWh, BWk, Cfb BSh, BSk and Cwb. The average observed percentage difference in the number of days of supply retained across the S-D ratios, climate zones and reliability are presented in Table 5-1. In this case a negative value indicates that a variable demand results in a RWHS producing a higher number of days of supply than when it is subject to a constant unvaried demand.

Table 5-1: Observed percentage difference in yield when RWHS is subject to a variable demand

Reliability	Observed % difference									
	S-D Ratio									
	Peak 366					Peak 183				
	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9
50	-52	-15	-6	-2	-1	-145.6	-61	-26	-8	-0.6
66	-61	-11	-7	-3	-1	-177	-70	-32	-13	-1.94
80	-114	-16.9	-7.8	-2.8	-0.1	-246	-82.6	-39.6	-19.1	-4.2
85	-161	-16.3	-7.9	-4.2	-0.1	-420	-86.9	-41.9	-22.5	-6.8
90	-294	-14.1	-7.2	-6.2	-1.1	-331	-88.9	-45.6	-24.8	-9.7
95	-100	-14	-8.7	-5.8	-3.8	-503	-92	-49.8	-30.9	-17.3
Average	**-130**	**-14.6**	**-7.4**	**-4**	**-1.2**	**-304**	**-80.2**	**-39.2**	**-19.7**	**-6.8**

As can be seen, a variable demand will have its highest impact on the number of days supplied at the lowest S-D ratio - the magnitude of this effect also appears to be a function of the relative location of demand peak to rainfall peak. It must also be noted that, given South Africa is dominantly a summer rainfall area, this introduces some bias to the percentage differences especially for Peak 183 data. Referring back to Figures 5-1 to 5-5, it can be also observed across all the S-D ratios that when the maximum demand occurs in the middle of the year (winter peak at day 183), a RWHS tends to produce much higher number of days of supply, in the rainfall regions with mid-summer peaks (Cwa, Cwb, BSh, BSk, Cfa) than when it is subject to a constant unvaried demand. The opposite is also true with a RWHS producing more days of supply in regions with winter rainfall peaks (Csb, Csa) when the demand peaks at the end of year (mid-summer peak). The exceptions to this are zones Cfb, Cfc, BWk and BWh (late-summer / early spring rainfall peaks) which consistently either supply more or the same number of days when subjected to a variable demand. Thus it can be concluded that the level of supply from a RWHS is highly sensitive to the demand regime under which it has to operate.

Figures 5-6 to 5-10 present the effect of the variable demands on the corresponding optimal tank size of a RWHS as S-D ratio increases across the different climate zones at a reliability of 50%. The comparison is done in terms of the ratio of optimal tank size under variable demand ($\boldsymbol{K_{VD}}$) to optimal tank size under a constant demand ($\boldsymbol{K_C}$) – this ratio and the interpretation of the graphs take on the same meaning as that described for the number of days of supply. Once again, similar trends for the ratio were observed at all other reliabilities and the data for these are in Appendix 4(b).

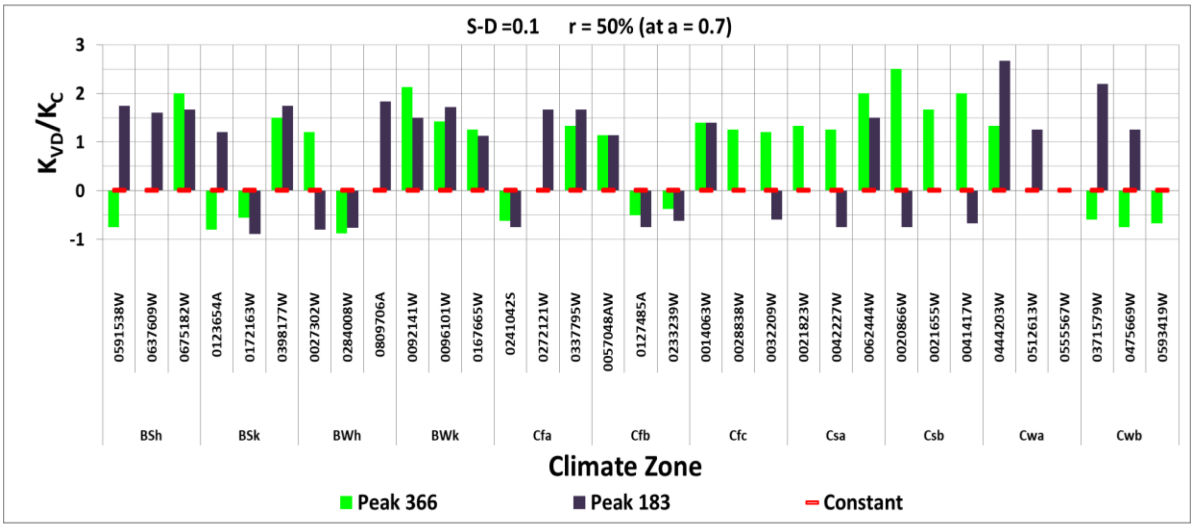


Figure 5-6: Effect of a variable demand on optimum storage at S-D ratio 0.1 and reliability 50%

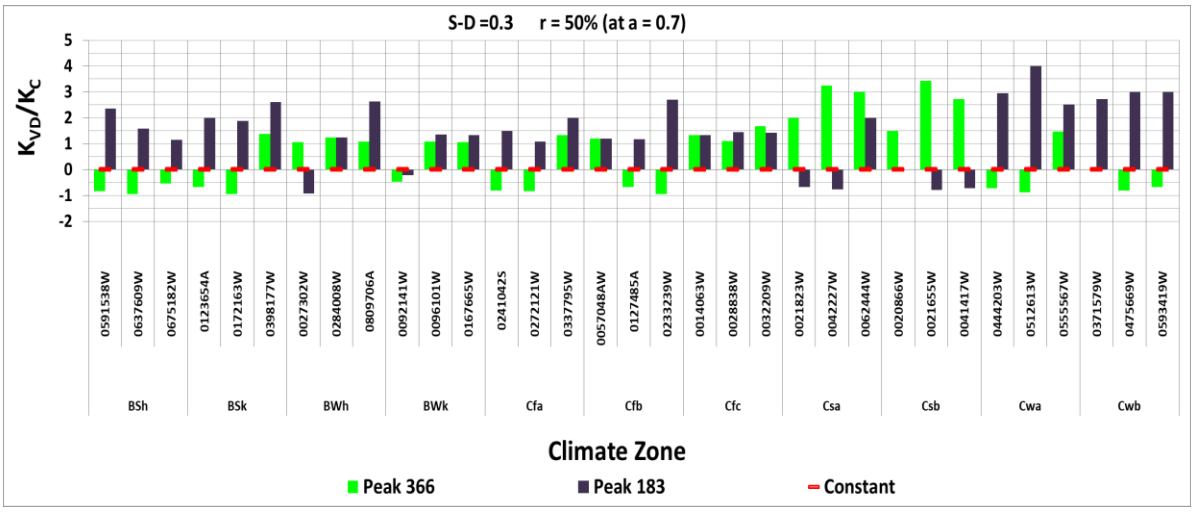


Figure 5-7: Effect of a variable demand on optimum storage at S-D ratio 0.3 and reliability 50%

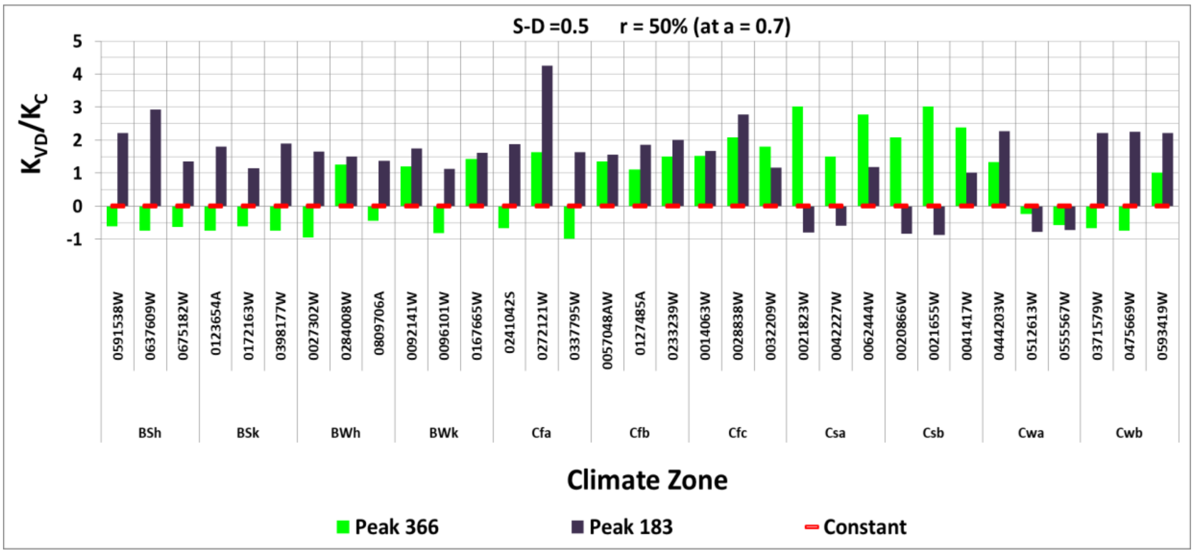


Figure 5-8: Effect of a variable demand on optimum storage at S-D ratio 0.5 and reliability 50%

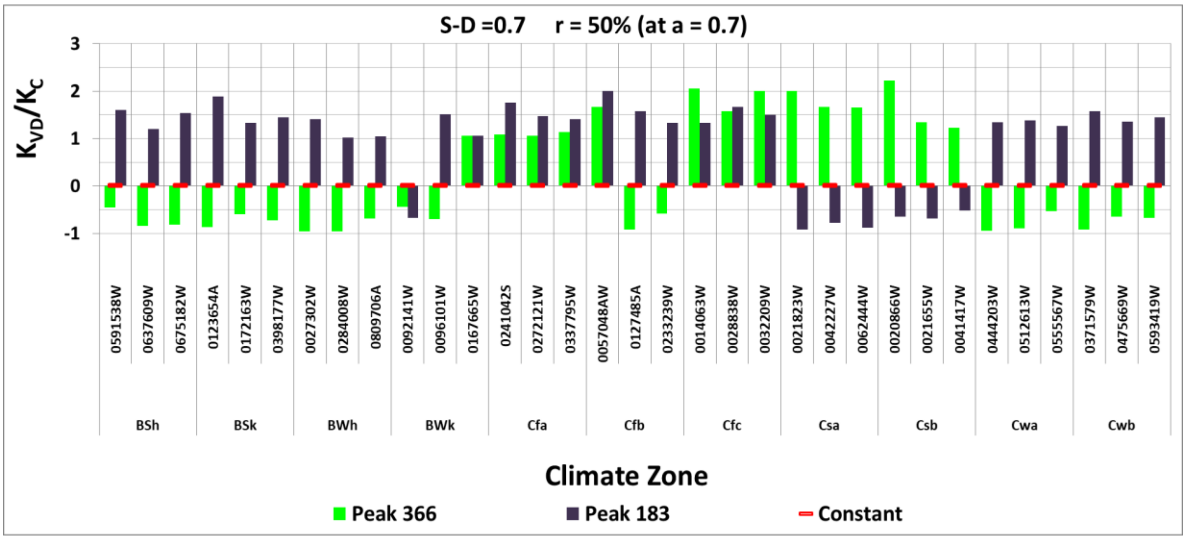


Figure 5-9: Effect of a variable demand on optimum storage at S-D ratio 0.7 and reliability 50%

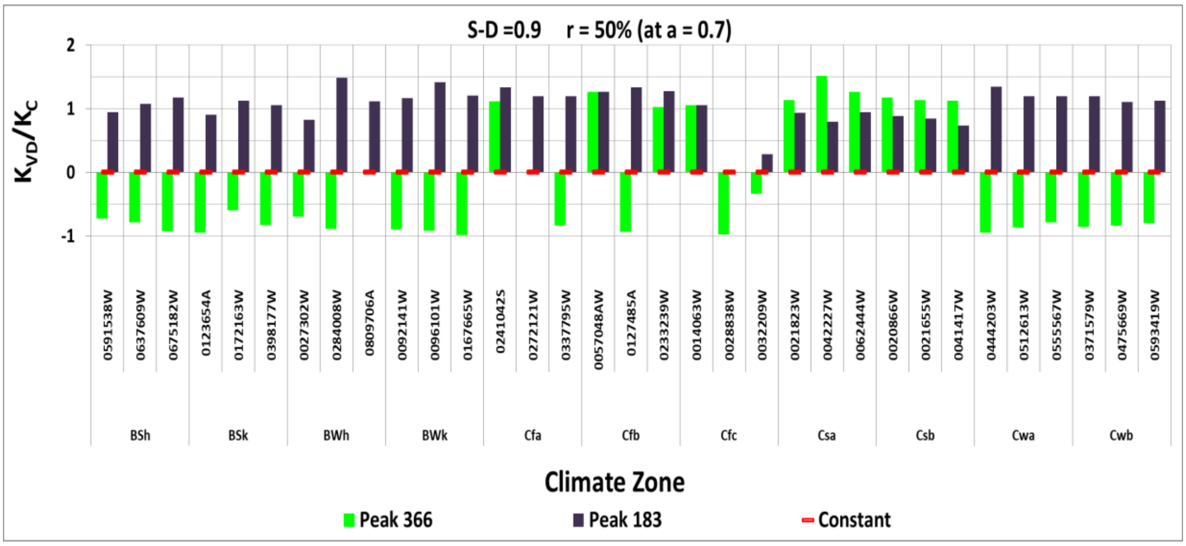


Figure 5-10: Effect of a variable demand on optimum storage at S-D ratio 0.9 and reliability 50%

It was observed from Figures 5-6 to 5-10 that there is tendency to increase the size of the tank when a RWHS is subjected to a variable demand across all climate zones - this trend holds as S-D fraction and reliability increases as indicated in Table 5-2 (a negative value indicates that tank sizes are larger for a variable demand).However the changes in tank size are much less than the observed changes in the number of days of supply at corresponding S-D ratios and reliabilities highlighting the presence of reduced sensitivity of tank size to variability in demand.

Table 5-2: Observed percentage difference in storage when RWHS is subject to a variable demand

Reliability	Observed % difference									
	S-D Ratio									
	Peak 366					Peak 183				
	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9
50	-19	-29	-28	-9	6	-25	-74	-66	-29	-8
66	-19	-33	-34	0	5	-28	-58	-79	-34	-10
80	-17	-46	-34	-11	6.9	-32	-93	-99	-56	-8
85	-4.7	-21.6	-33.4	-5	3.4	-40	-62	-91	-65	-2.2
90	-44	-14.7	-29.9	-13	-21	-18.1	-70	-82.9	-117	-41
95	-24	-17.8	-22	-39	-5.9	-25	-34	-100	-112	-43
Average	**-21**	**-27**	**-30.2**	**-13**	**-0.9**	**-28**	**-65**	**-86**	**-69**	**-19**

5.1.2. Effect of varying the amplitude of the peak in demand on yield and storage

As outlined in section 3.2.4 a second set of simulations set out to establish if the amplitude of a variable demand exerted any significant influence on the number of days of supply and optimal tank size of a RWHS. Figures 5-11 to 5-15 present the results of simulation across the different climate zones with respect to the yield. For brevity, data is presented for the reliability of 50% across all S-D ratios. The comparison is also done in terms the proportion of the number of days of supply retained for the different amplitude values when compared to the constant demand case i.e. $N_{P366\text{-}a}/N_C$. The data of all other reliabilities showed a similar trend to those presented and will be found in Appendix 4(c) where a line graph is chosen as it best illustrates the trends in number of days supplied with changing first flush for each gauge (vertical axis) and makes for easier comparison of behaviour across each rain gauge and climate zone (horizontal axis).

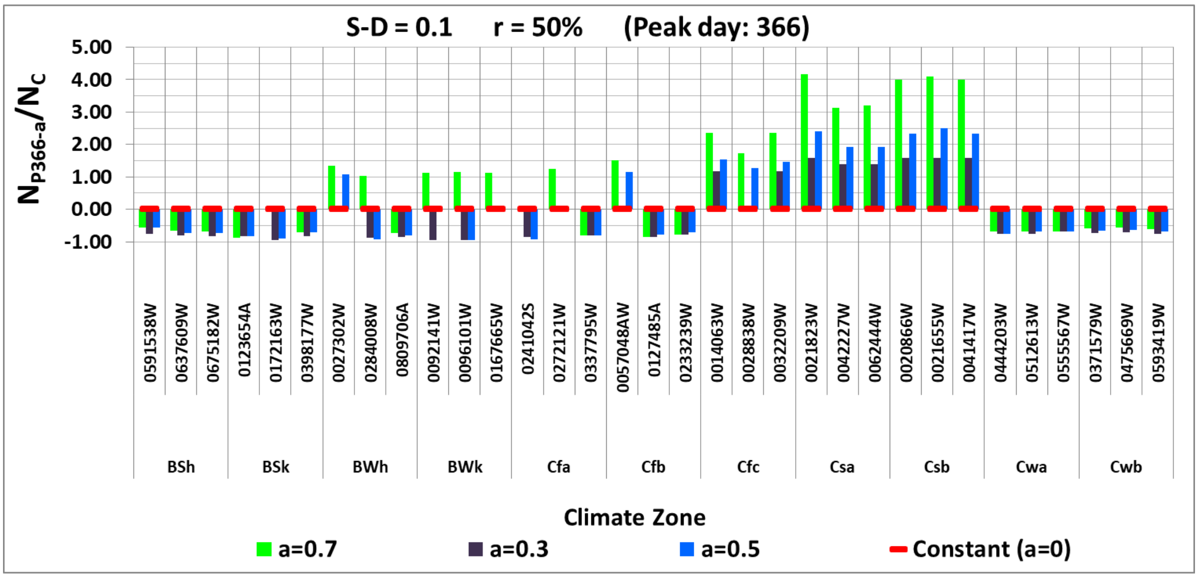


Figure 5-11: Effect of varying the amplitude of demand on yield at S-D ratio 0.1 and 50% reliability

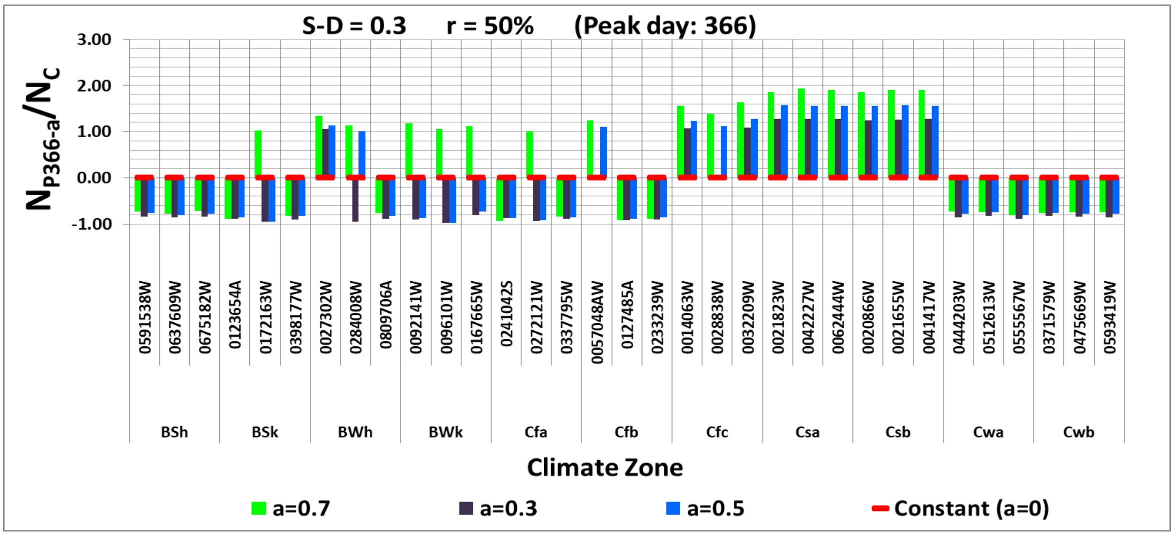


Figure 5-12: Effect of varying the amplitude of demand on yield at S-D ratio 0.3 and 50% reliability

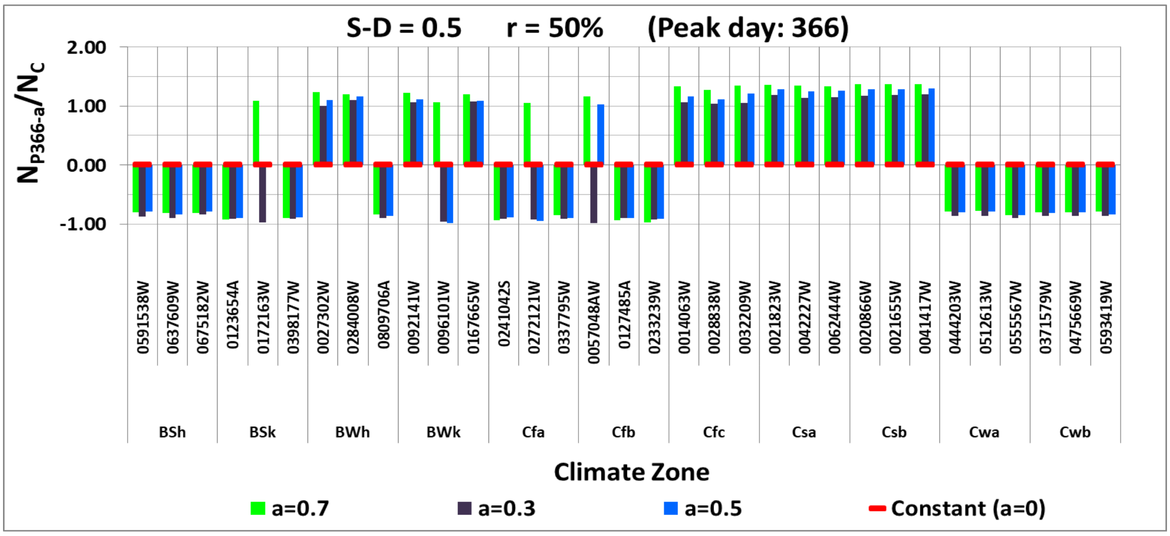


Figure 5-13: Effect of varying the amplitude of demand on yield at S-D ratio 0.5 and 50% reliability

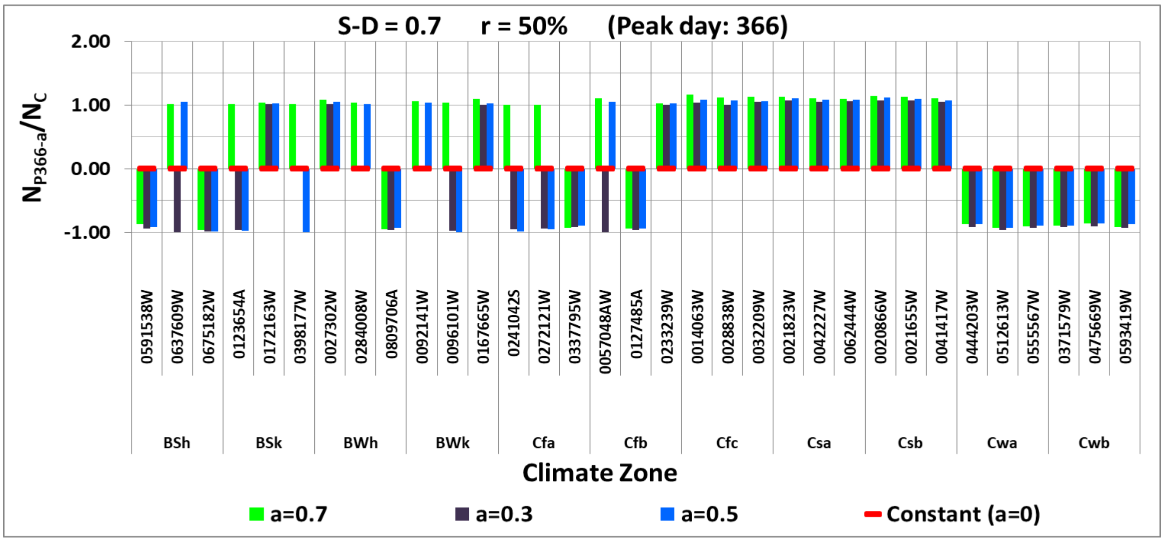


Figure 5-14: Effect of varying the amplitude of demand on yield at S-D ratio 0.7 and 50% reliability

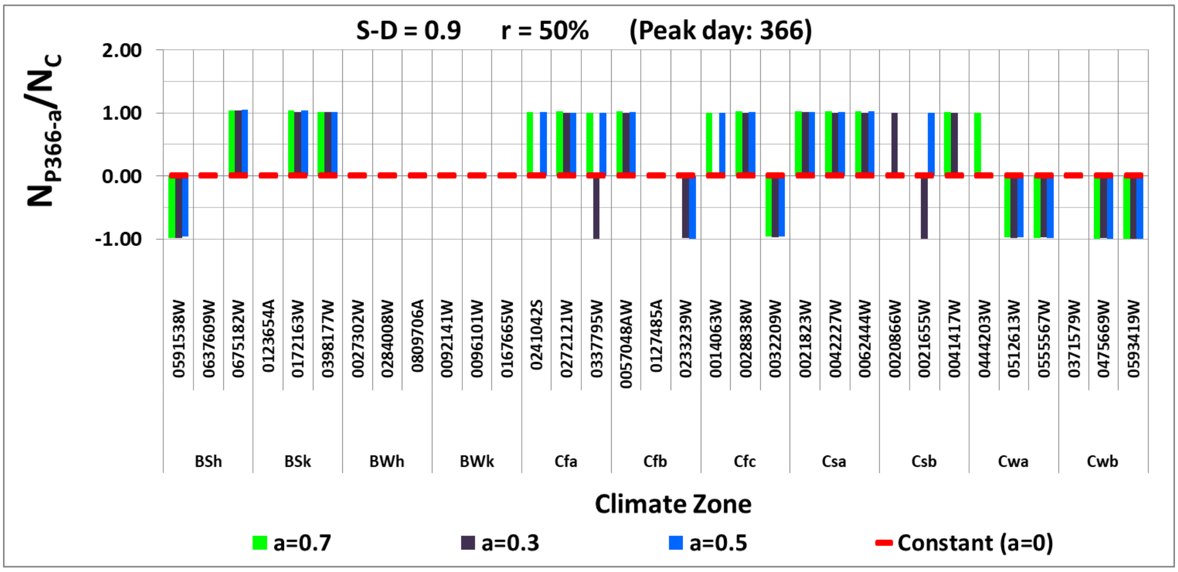


Figure 5-15: Effect of varying the amplitude of demand on yield at S-D ratio 0.9 and 50% reliability

On comparing the plots of the three amplitudes; a=0.3, 0.5 and 0.7, it was observed that there appears to be no real appreciable difference in the number of days of supply retained as the amplitude of variable demand changes for all climate zones with the exception of Cfc, Csa and Csb. The overall trend of decreasing variability of in the number of days of supply with increasing S-D ratio and increasing variability with increasing reliability is maintained. The averaged percentage differences in yield between a=0.3 and a=0.7 came to -8.5% whilst that between a=0.5 and a= 0.7 came to -6.7% and between a=0.5 and a=0.3 came to -1.54% for all climate zones across the S-D ratios and reliabilities excluding Cfc, Csa and Csb. The averaged percentage differences for zones Cfc, Csa and Csb came to -61% for the comparison between a=0.3 and a=0.7, -27.1% between a=0.5 and a=0.7 and came to +14.9% between a=0.5 and a=0.3. These larger difference are thought to be as a result of the geographic location of the rain gauges in a predominately winter/spring rainfall region. As previously observed in Figures 5-1 to 5-5, these zones produce higher yields when the relative difference between the occurrence of the peak of demand and the peak in rainfall is at its highest. From the data presented, it can be concluded that the amplitude of a variable demand can have a significant impact on the yield of a RWHS – the larger the amplitude the greater the proportion of days with low demand therefore the easier it is for a RWHS to satisfy demand and increase the number of days of supply. The degree of this impact will also likely depend on the distance in time between the peak in rainfall and peak in demand.

Figures 5-16 to 5-20 illustrate the corresponding variation in the tank sizes. Comparison is also done by analysing the proportion of original tank size retained at each of the variable demand scenarios ($K_{P366\text{-}a}/K_C$) for all S-D ratios at a reliability of 50%. Similar trends in the data were observed for all other reliabilities and the results for this are given in Appendix 4(d) - a line graph is also used.

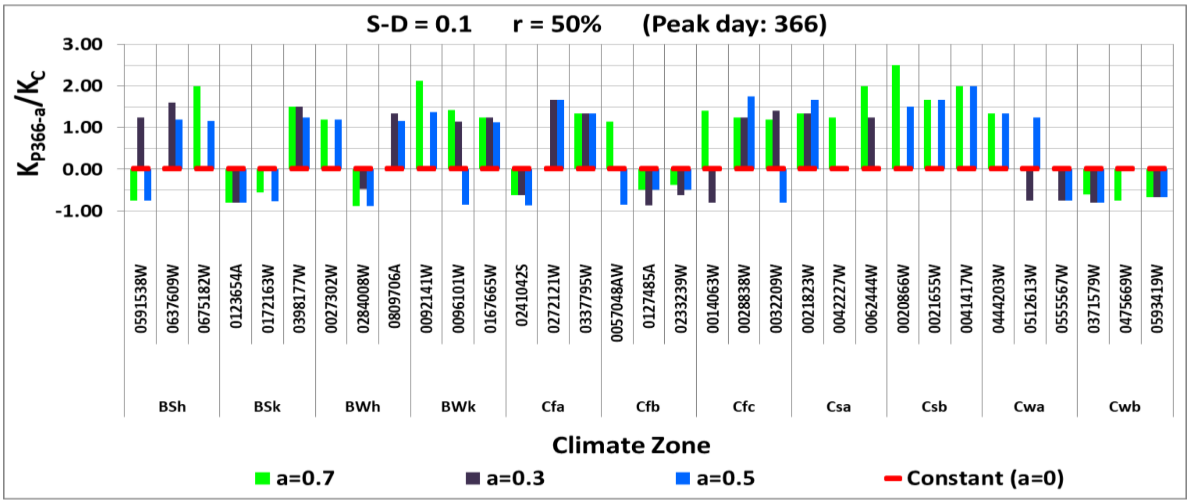


Figure 5-16: Effect of varying the amplitude of demand on optimum storage at S-D ratio 0.1 and 50% reliability

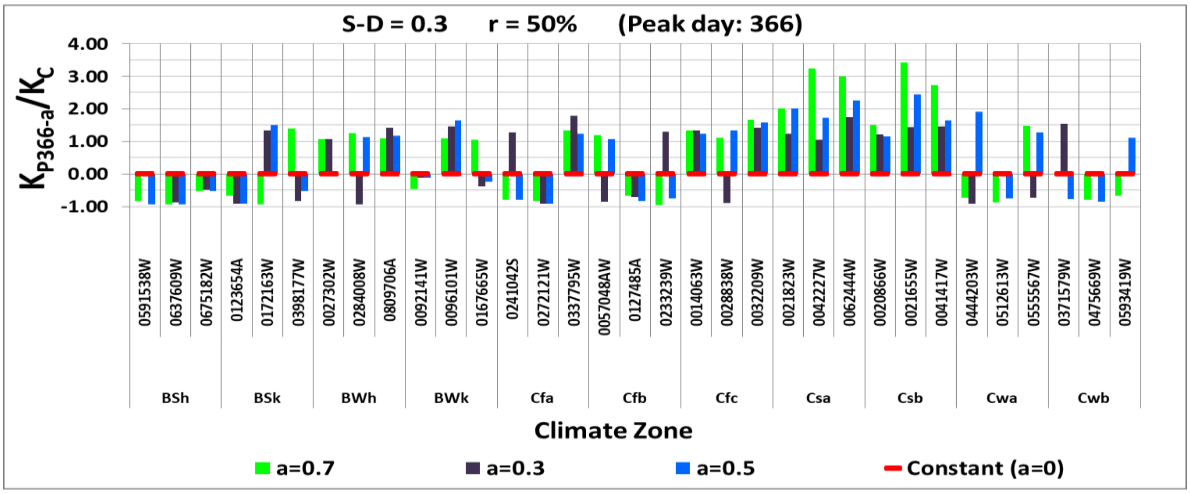


Figure 5-17: Effect of varying the amplitude of demand on optimum storage at S-D ratio 0.3 and 50% reliability

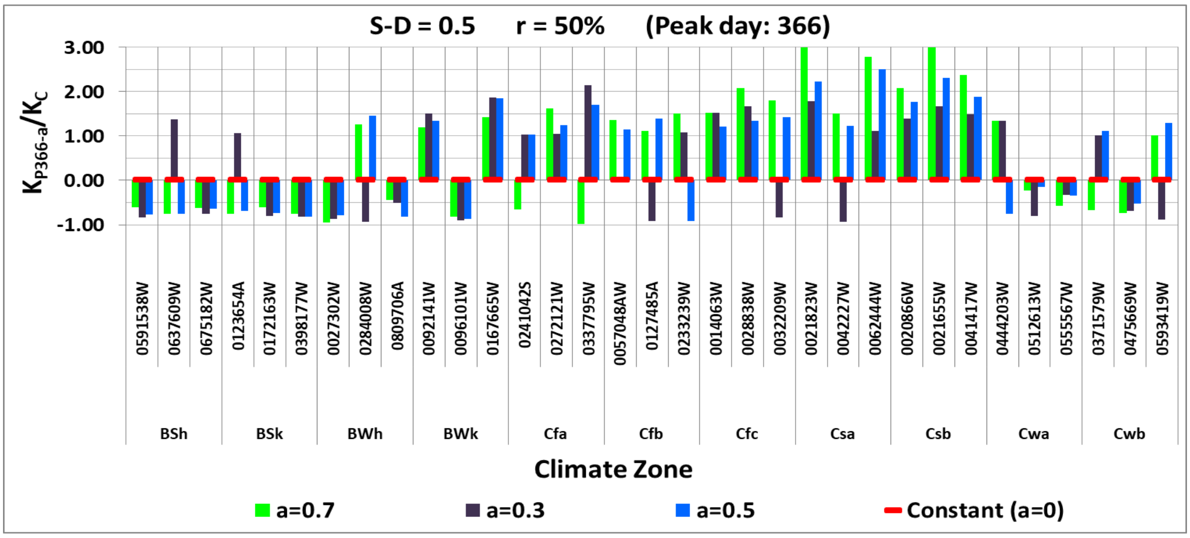


Figure 5-18: Effect of varying the amplitude of demand on optimum storage at S-D ratio 0.5 and 50% reliability

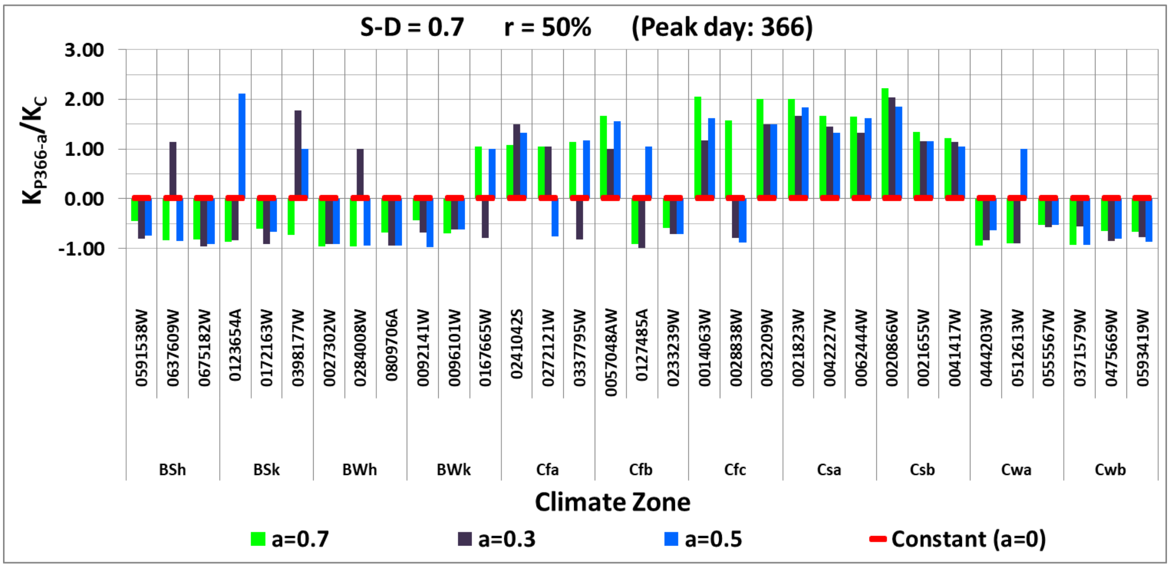


Figure 5-19: Effect of varying the amplitude of demand on optimum storage at S-D ratio 0.7 and 50% reliability

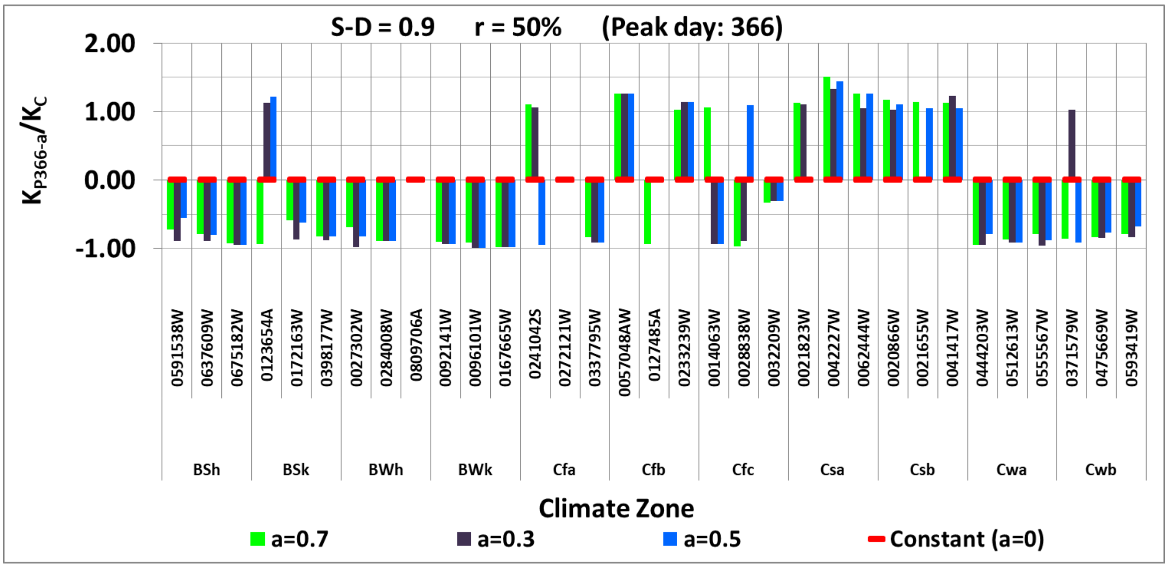


Figure 5-20: Effect of varying the amplitude of demand on optimum storage at S-D ratio 0.9 and 50% reliability

It was observed from Figures 5-16 to 5-20 and Appendix 4(d) that for the three variations in demand (a=0.3, 0.5 and 0.7), the optimal tank size remains quite close in magnitude across all the S-D ratios, with a percentage difference of -3.9% measured between a=0.3 and a= 0.7, a difference of -4.1% between a=0.5 and 0.7 and difference of -10.3% between a=0.5 and a=0.3 taken across all reliabilities and climate zones except Cfc, Csa and Csb. In these climate zones the average percentage difference between a=0.3 and 0.7 comes to -45%, whilst the difference comes to -28% between a=0.5 and a=0.7 and comes to 5.9% between a=0.5 and a=0.3. The changes observed in the tank size as amplitude of demand changes would appear to be driven by the relative distance in time between the peak in demand and the peak in rainfall e.g. rainfall peaks for rain gauges in the Csa and

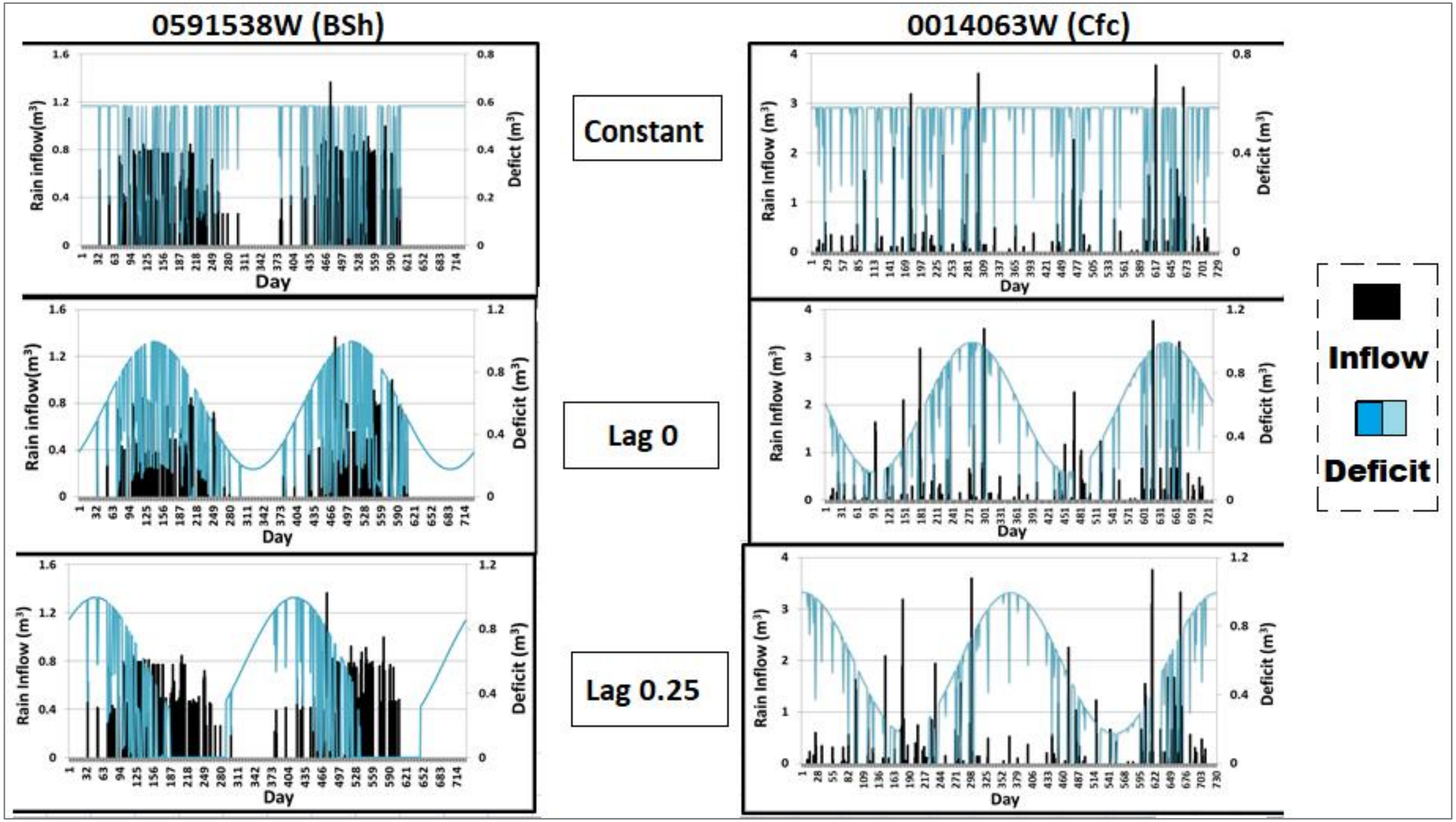
Csb regions in this scenario are lagged by up to half year with respect to the demand peak and show some large variations in the tank size as the amplitude of demand increases whereas rainfall in regions like Cwa and Cwb which are effectively peaking at the same time as the demand, the variation of tank volume is very low as the amplitude of demand changes. Rain gauges with rainfall peaking in between these two extremes (Cfc, Cfb, BWk, BWh) show a bit more variation than gauges with simultaneous demand and rainfall peaks but much less variation than the out of phase scenario.

5.2. Investigating the Influence of Lag and Amplitude on Storage-Yield -Reliability Relationships

As per objective 2.2., the following section describes the methods and results of an analysis to ascertain the types of relationships that could be established between the number of days of supply, tank size, the location of the peak in demand in relation to the location of the peak in rainfall and amplitude of demand. Due to time limitations, a rapid analysis was done with a set of 11 rainfall stations each representing one of the 11 climate zones.

5.2.1. Influence of lag on observed RWHS behaviour

Using the lag as defined by Equation 3-14, simulations were performed on the 11 rainfall records and the impact of this variable on RWHS behaviour analysed. Lag values assessed were set at 0, 0.25, 0.5 and 0.75 of year. Figure 5-21 illustrates the interaction between the supply from rainfall and a RWHS ability to satisfy the requisite demand (measured by the reduction in deficit where a deficit of zero means demand is fully satisfied) for the two clusters of behaviour observed from the simulated data. The data presented were collected at an S-D ratio of 0.3.


0591538W (BSh)
0014063W (Cfc)
Constant
Lag 0
Lag 0.25
Rain inflow(m³)
Rain Inflow (m³)
Deficit (m³)
Day
Inflow
Deficit

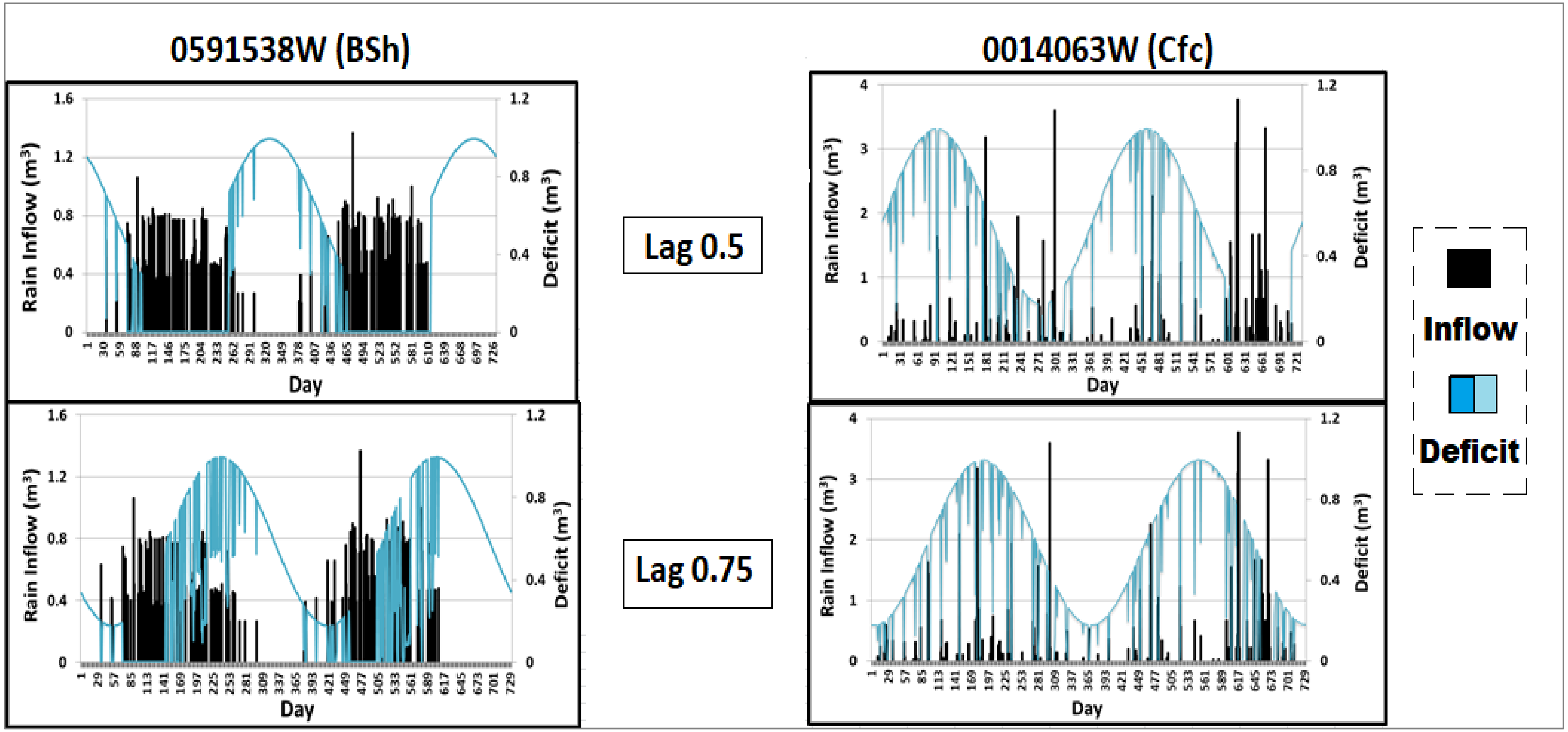


Figure 5-21: Comparison of demand satisfaction under different yield scenarios

It was observed from the simulation that using station 0591538W, changing the location of the peak of a variable demand results in significant changes in the number of days of supply while for station 0014063W, changing the location of the peak of a variable demand results in negligible changes to the same. For the scenario with a lag of 0 (which represents a situation where demand and supply are both increasing in tandem) it was noted that in the more distinctly seasonal areas as exemplified by station 0591538W, RWHS are less able to eliminate the full deficit when compared to less distinctly seasonal areas as exemplified by station 0014063W. The distinctly seasonal zones also appear to eliminate the deficit in similar proportion to the constant demand scenario. Regarding areas which have very short dry seasons like Cfc introducing this type of variability in the demand results in the deficit being met for a greater proportion of the year when compared to the constant demand scenario.

Figure 5-22 contrasts for the case of an S-D ratio of 0.3 at a reliability of 50%, the differences observed in the number of days of supply as the lag increases. This trend holds across all the other reliabilities with a reduction in effect with increasing S-D ratio (re-call trends observed in Figures 5-1 to 5-5). Assessment of the number of days of supply shows there is a reduction in supply when rainfall and demand peak together in distinctly seasonal zones (Cwa, Cwb, Csa, Csb, BSh, BSk), whilst it increases for the less seasonal zones (Cfc, Cfa, Cfb) when compared to the constant demand scenario. The exception to this is BWh and BWk which are somewhat seasonal but show an increase in number of days of supply under variable demand.

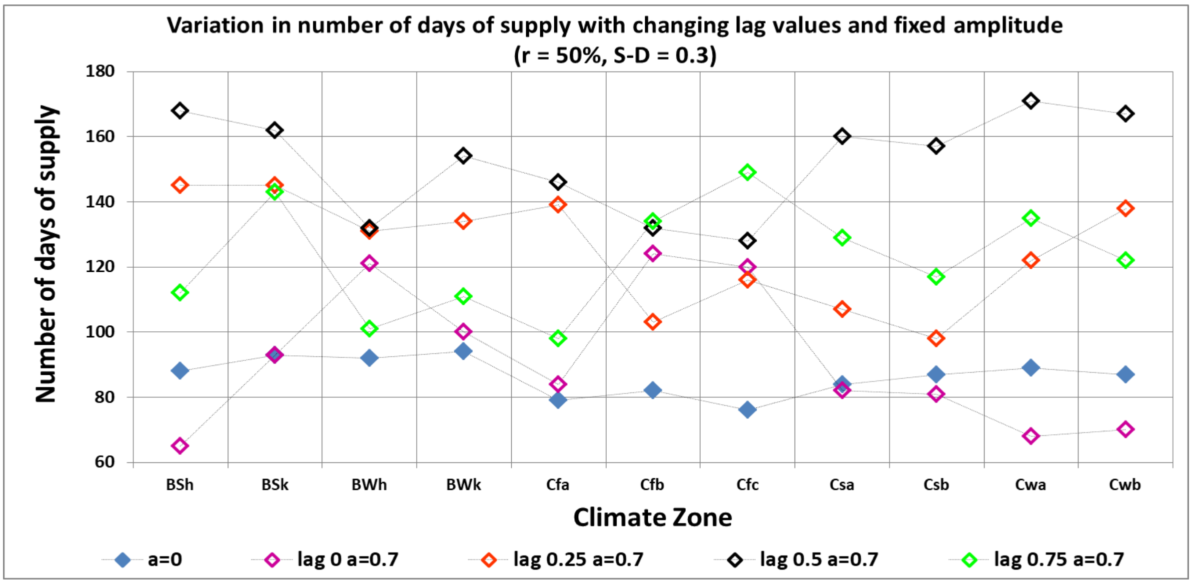


Figure 5-22: Differences in number of days supplied with changing lag at S-D 0.3 and r=50%

Comparison of the number of days of supply when rainfall and demand are lagged by 0.25 and 0.75 of year generally showed a RWHS to yield more days when rainfall peaks after the demand. The out of phase scenario is represented by lag 0.5 and looking back at Figure 5-21, what this meant for gauges in distinctly seasonal areas is that when water is required the most (maximum deficit) the tank is empty and unable to supply whereas when water is required the least the supply to the tank is able to eliminate the deficit for a greater proportion of the time. Analysis of Figure 5-22 reveals this set-up to result in the highest number of days of supply for all the rain gauges as the demand is more frequently satisfied by a system chasing a lower target during peak inflows. With regard to low seasonality areas i.e. Cfb and Cfc, the yields appear less sensitive with small gains recorded when moving from lag 0 to lag 0.5 as shown on Figure 5-22.

Figure 5-23 shows one of the results of an analysis to determine the likely form of a mathematical relationship between the number of days of supply and lag (expressed in its normalised form: $L/365.25$) for a reliability of 50% and S-D ratio of 0.3. Inspection of plots at each S-D ratio across all reliabilities revealed the data to predominantly describe linear relationships between normalised lag values 0 and 0.5 and between normalised lag values 0.5 and 1. There is also an appreciable spread of the data for the lower S-D ratios of 0.1 and 0.3 and this spread is thought to be linked to climate-specific characteristics unique to each of the stations. Attention is drawn to the data for climate zones Cfc and Cfb whose yields, as highlighted on Figure 5-22, do not change appreciably with lag values. A similar sort of behaviour is shown by gauges in climate zones BWh and BWk. These sets of gauges represent areas showing low seasonality and as such it can be concluded that seasonal variability in rainfall may be a factor in determining the level of supply one can expect from a RWHS where variable demands are concerned at the lower S-D ratios. As highlighted in section 5.1.1., as the S-D ratio increases above 0.5 the impact of demand variability decreases.

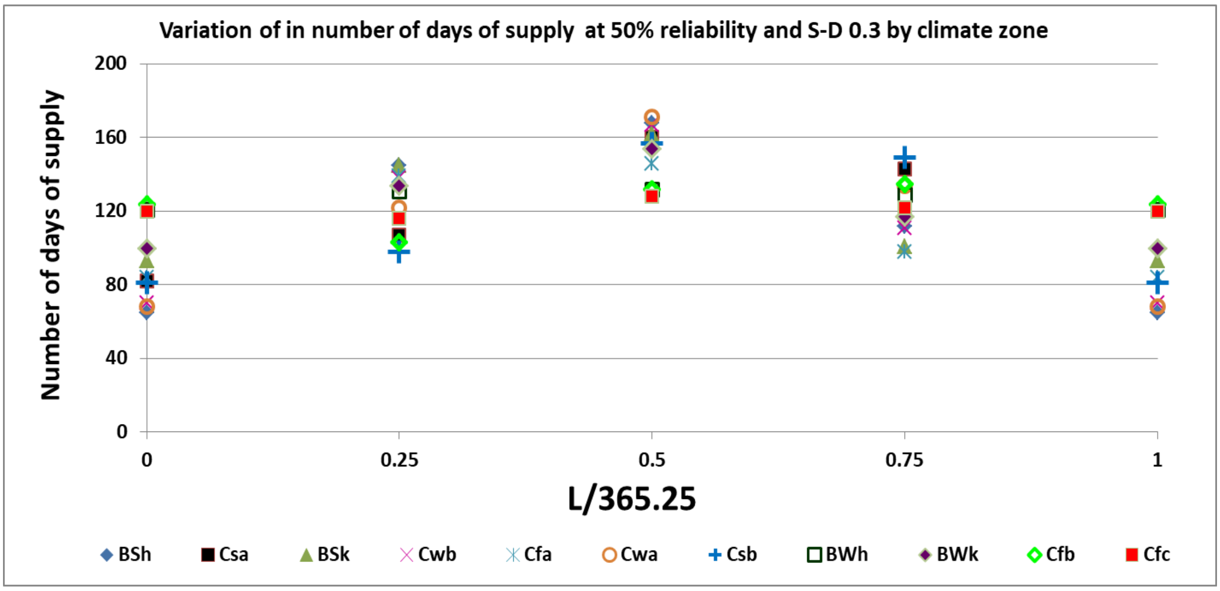


Figure 5-23: Variation of yield with lag at S-D ratio 0.1 and reliability 50% by climate zone

Zooming in on the range of lag values from 0 to 0.5 of a year, another observation made is that there is a reduction in the spread of the data points as the lag increases. This could imply that as lag increases up to 0.5 the influence of rainfall variability decreases with its largest impact felt at a lag of 0.

Analysis of the effect of lag on the tank size is shown in Figure 5-24 for an S-D ratio of 0.3 and a reliability of 50%. It was observed from the data is that there is also an appreciable spread across all the S-D ratios with the data also showing slight curvature with changing lag values and this spread in the data is likely due to the influence of rainfall variability characteristics. By tracking the individual climate zone data, it was however observed that rather weak relationships exist between the two parameters of storage and lag; therefore it may not be necessary to pursue storage-yield relationships that incorporate this dimension.

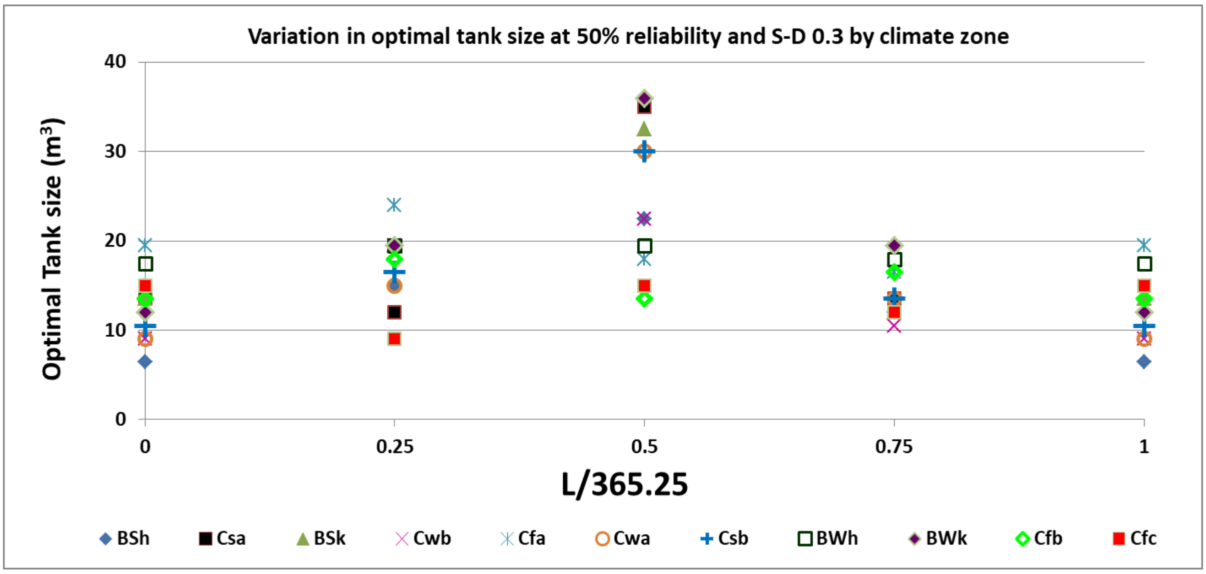


Figure 5-24: Influence of climate characteristics on storage under variable demand

The remainder of this analysis focuses in on the range of lag values from 0 to 0.5 of a year as it is expected that similar results would be obtaining between 0.5 and 1.

5.2.2. Influence of amplitude on the observed behaviour of RWHS

From the discussion of section 5.1.2., it was posited that the amplitude of the variable demand could have a substantial impact on the yield especially when the peak in rainfall and peak in demand is lagged by up to half a year. Thus relationships between amplitude (set to 0, 0.35, 0.5, 0.7 and 1) and the yield at the lag values of 0, 0.25 and 0.5 were investigated for the same 11 rain gauges investigated for the influence of lag.

Figures 5-25 to 5-27 illustrate across the different S-D ratios at a reliability of 50%, that as the lag value increases so too does the influence of amplitude – the spreading of the data at the lower S-D ratios is once again posited as a function of rainfall characteristics peculiar to the location of the rain gauge. All other reliabilities showed a similar trend in their data and this data is presented in Appendix 4(e).

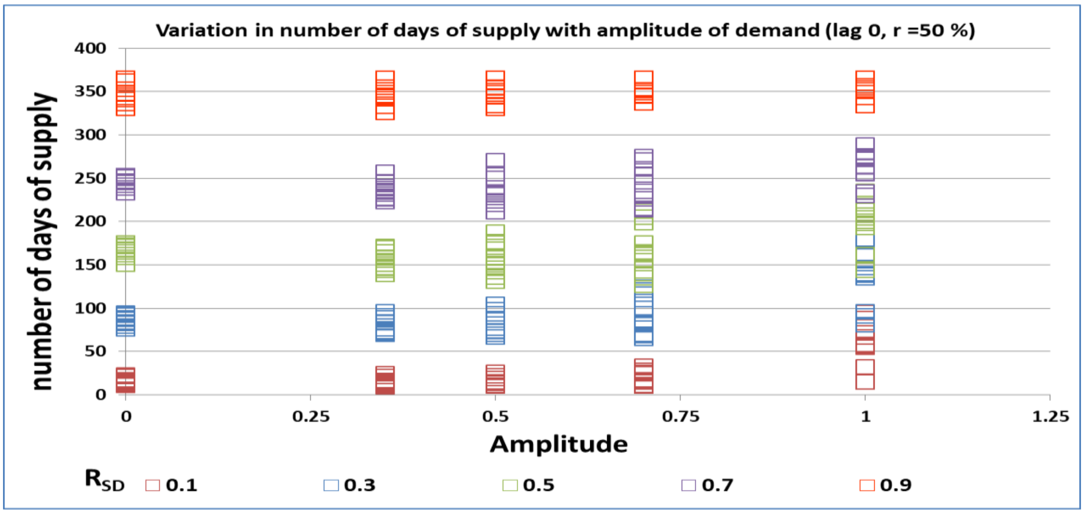


Figure 5-25: Variation of yield with amplitude of demand (lag 0 and reliability 50%)

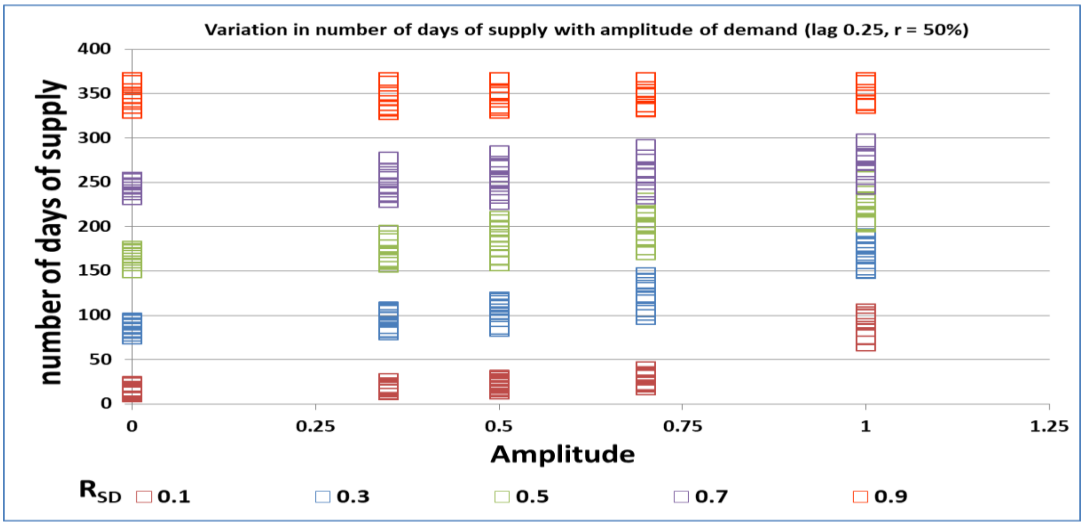


Figure 5-26: Variation of yield with amplitude of demand (lag 0.25 and reliability 50%)

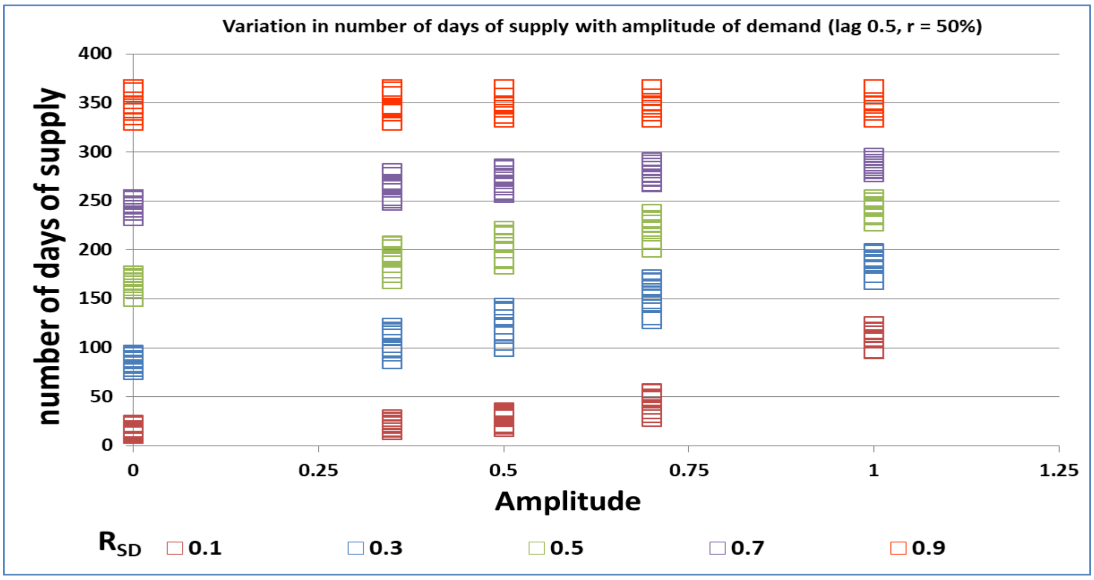


Figure 5-27: Variation of yield with amplitude of demand (lag 0.5 and reliability 50%)

With regard to the corresponding tank sizes, Figures 5-28 to 5-30 show a much weaker correlation between tank size and amplitude. However, just as with the number of days of supply data, the impact of the amplitude on the optimal tank size appears to increase with increasing lag value. Just as with the lag data, the spread of the data at each of the S-D ratios is thought to be a function of the rainfall variability characteristics peculiar to each of the rain gauges. Additional data for other reliabilities is presented in Appendix 4(f).

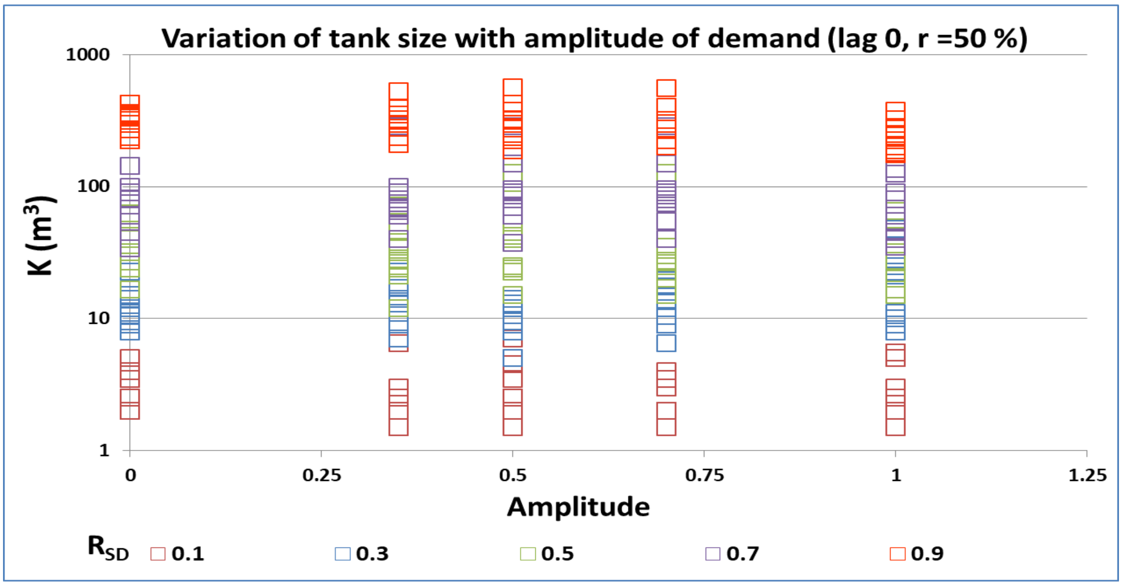


Figure 5-28: Variation of storage with amplitude of demand (lag 0 and reliability 50%)

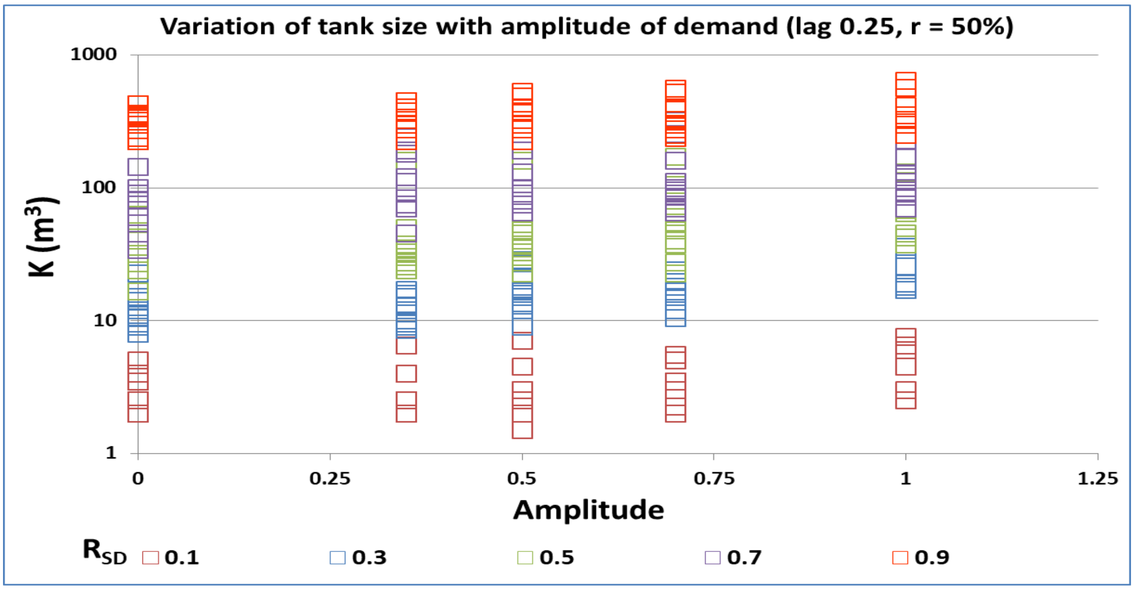


Figure 5-29: Variation of storage with amplitude of demand (lag 0.25 and reliability 50%)

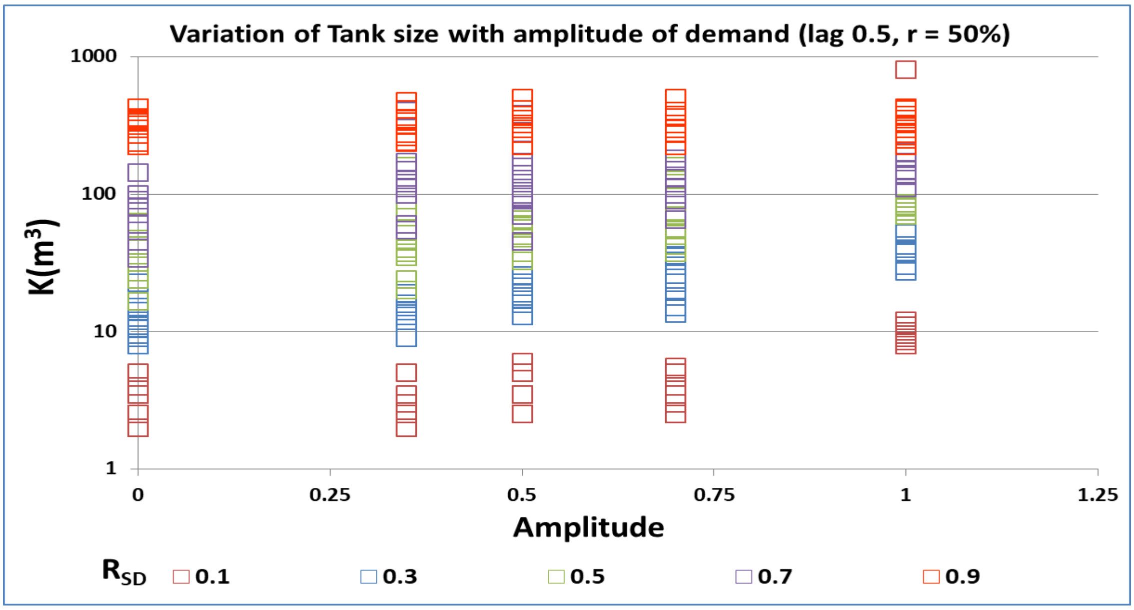


Figure 5-30: Variation of storage with amplitude of demand (lag 0.5 and reliability 50%)

5.2.3. Regression modelling of yield, lag, amplitude, S-D ratio and reliability data

The following analysis builds on the models developed in Chapter 4, whereby the number of days of supply obtained under a variable demand normalised using the number of days of supply obtained under a constant unvaried demand is introduced as a new dimensionless parameter. For the modelling, this parameter is posed as a function of the amplitude and lag of a variable demand, the S-D ratio and the reliability as shown in Equation 5-1.

$$\frac{N_{vd-r}}{N_r} = f(a, L, R_{SD}, r) \qquad \textbf{(5-1)}$$

Where: N_{vd-r} is the number of days of supply under a variable demand with amplitude ***a*** and lag ***L***, at a given reliability ***r*** and S-D ratio R_{SD} and N_r is the corresponding number of days of supply under a constant demand at the same reliability and S-D ratio.

The analysis limited itself to the rising limb of the graph shown in 5-23 i.e. normalised lag values lying between 0 and 0.5 to further investigate the form of the generalised relationship described in Equation 5-1. This links to the observation that the range of influence of the lag on the number of days of supply is at most 0.5 of year. The S-D ratio of 0.1 is excluded from the analysis as this size of system is generally unfeasible given the low number of days of supply one would obtain (typically less than 30 days).

Given the large number of variables influencing the number of days of supply, a piece-wise regression approach was adopted that started by determining a form of the relationship between $\frac{N_{vd-r}}{N_r}$ and the amplitude at fixed S-D ratio, lag and reliability. Figures 5-31 to 5-32 illustrate for an S-D ratio of 0.5 at reliability 50%, the form of relationship that was found to best describe the trend in the data. This relationship holds across all the other S-D ratios, reliabilities and lag values.

It is noted that the way in which $\frac{N_{vd-r}}{N_r}$ has been defined means that by setting the intercept to a value of one (1) for all lag values, at amplitude zero (which represents the constant demand case), the entire equation reduces to 1 thus effectively equating the yield under variable demand ($\boldsymbol{N_{vd-r}}$) to the yield under constant demand ($\boldsymbol{N_r}$).

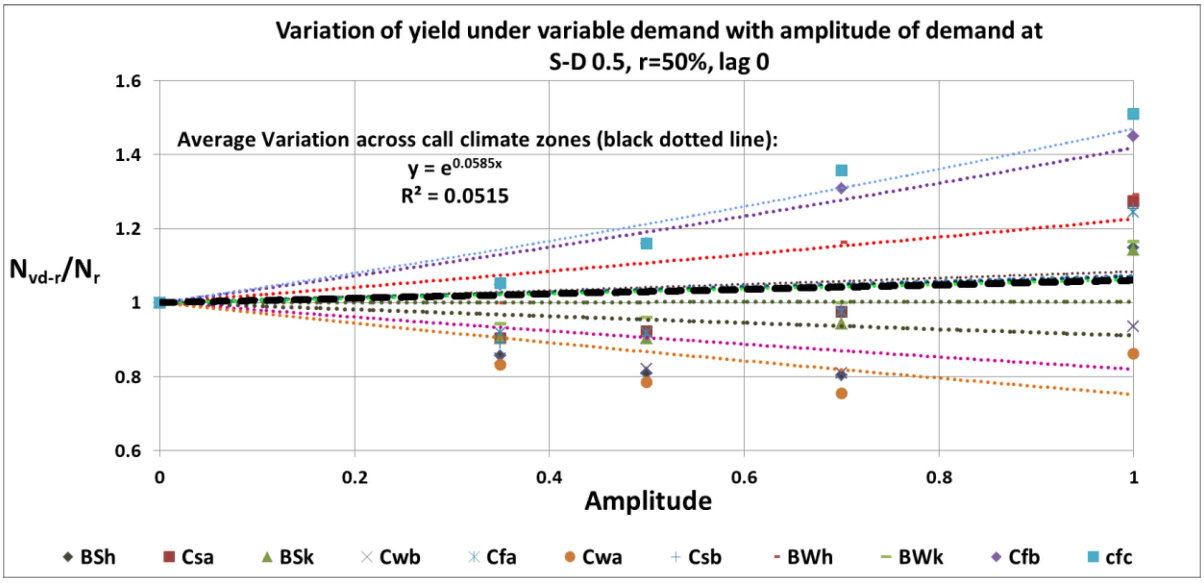


Figure 5-31: Variation of yield under variable demand with amplitude of demand at S-D 0.5, lag 0 and reliability 50%

It was observed from full set of data (all other S-D ratios and reliabilities) that when there is no lag between the peaks of rainfall and demand, all climate zones except Cfb and Cfc tend to describe weak relationships to the amplitude – an average R^2 value of 0.2655 was observed across all the reliabilities. Other behavioural observations at this lag value were that there is an increase in spread of the data points with increasing reliability and decreasing spread with increasing S-D ratio. The spread of data is possibly tied to the influence of rainfall characteristics, where plotting the seasonality index ($\boldsymbol{SI}$) against the regression coefficient for each climate zone [see Appendix (g)] revealed rather strong linear relationships for this lag value. This influence however does not appear to carry across to the other lag values assessed as illustrated by the additional graphs found in Appendix 4(g).

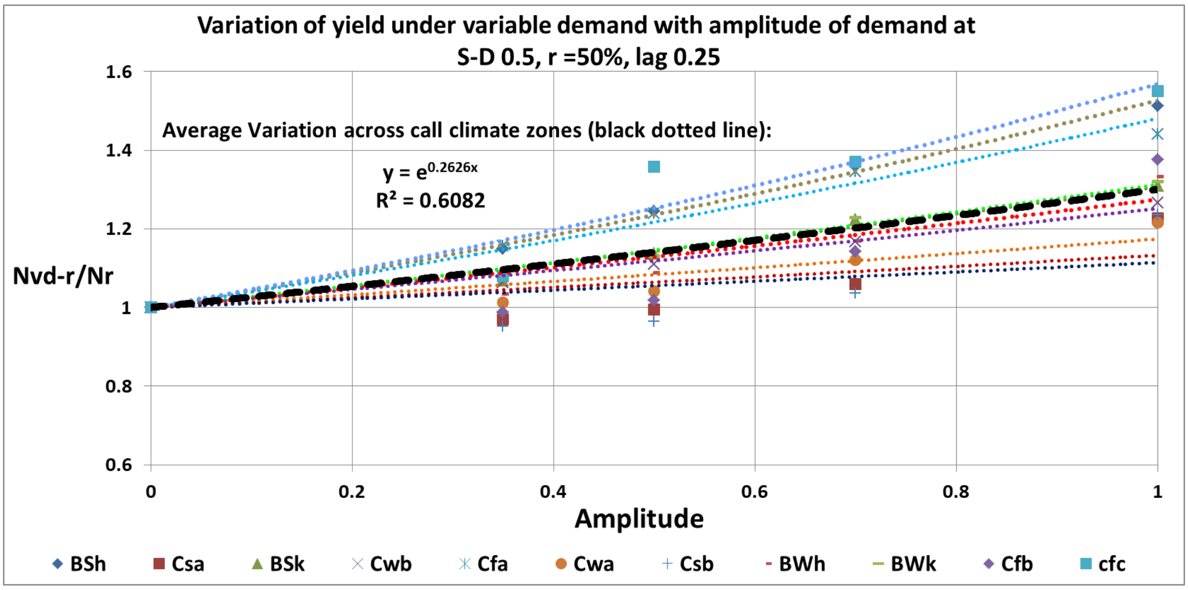


Figure 5-32: Variation of yield under variable demand with amplitude of demand at S-D 0.5, lag 0.25 and reliability 50%

The data for a quarter-of-a-year lag in peaks (Figure 5-32), revealed a much stronger relationship between parameters at individual climate zone level (an averaged R^2 of 0.7278 was found across all reliabilities and climate zones). There is also a reduction in the spread of the data points when compared to Figure 5-31. This implies a diminished influence of rainfall characteristics a highlighted earlier by the graphs found in appendix (g). The reduced spreading of the data thus allows for the simplification of the modelling by using a single lumped curve (black dotted line) to describe the general trend in the data. However, considering the trends in the data at a lag of 0, the high degree of spreading means there is a very poor fit for a single lumped model and this will not truly capture the trends in the data.

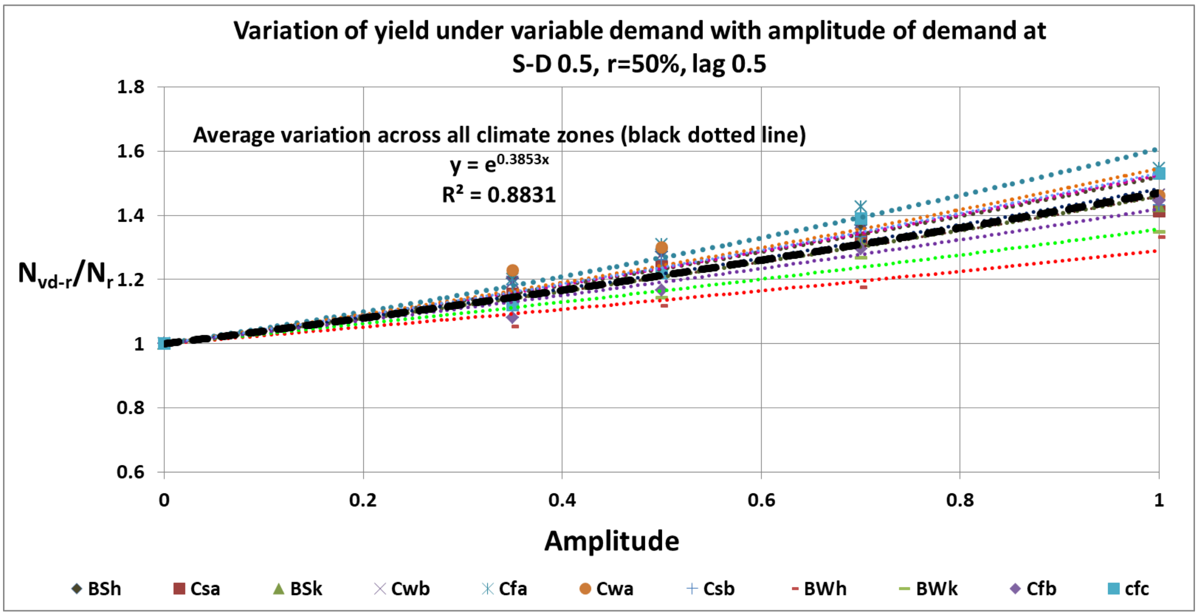


Figure 5-33: Variation of yield under variable demand with amplitude of demand at S-D 0.5, lag 0.5 and reliability 50%

The data for peaks that occur half-a-year apart (as shown in Figure 5-33), revealed that there is even less distinction to be made across the different climate zones and a single curve would be a good estimator of the proportion of the number of days of supply retained under variable demand.

Looking back on all three curves presented in Figures 5-31 to 5-33, reveals that there are different types of influences that the lag, rainfall characteristics and amplitude have on the proportion of days of supply retained. However, at this juncture, the role played by rainfall characteristics was not investigated further. The regression modelling thus only focused on building a rainfall-characteristic free lumped model, with relationships sought between the regression coefficients, lag, S-D ratio and reliability.

To start, relationships were sought between the regression coefficient ($\boldsymbol{\lambda}$) of the $\frac{\boldsymbol{N_{vd-r}}}{\boldsymbol{N_r}}$ versus amplitude curve. Figure 5-34 illustrates that at fixed supply demand ratio across all reliabilities, a strong linear relationship is described between the regression coefficient and the normalised lag. Taking the coefficients of regression from the linear relationships shown in Figure 5-34, relationships were then sought with the S-D ratio. These are illustrated in Figure 5-35 across all reliabilities where a logarithmic relationship was found between slope ($\boldsymbol{A}$) and S-D ratio. A linear relationship was found between intercept ($\mathbf{B}$) and S-D ratio.

The last set of relationships was established between reliability and the coefficients of regression extracted from the relationships shown on Figure 5-35. A logarithmic relationship was found between coefficients $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ with reliability, whilst a linear relationship was found between the coefficient $\boldsymbol{d_1}$ and reliability. A power relationship best described the trend in data between $\boldsymbol{d_2}$ and reliability. These relationships are illustrated in Figure 5-36.

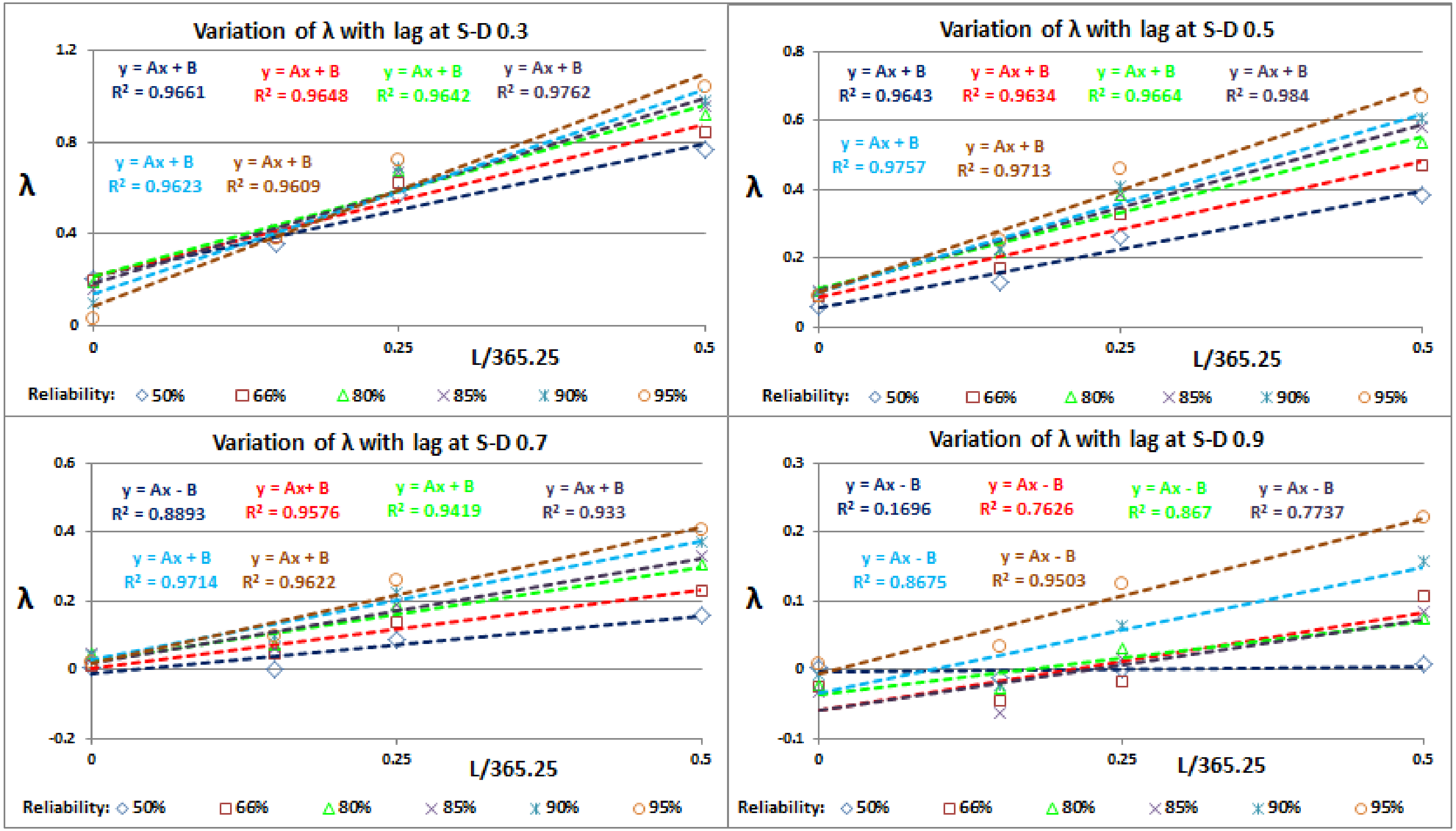


Figure 5-34: Relationships found with regression coefficient λ with normalised lag across different S-D ratios

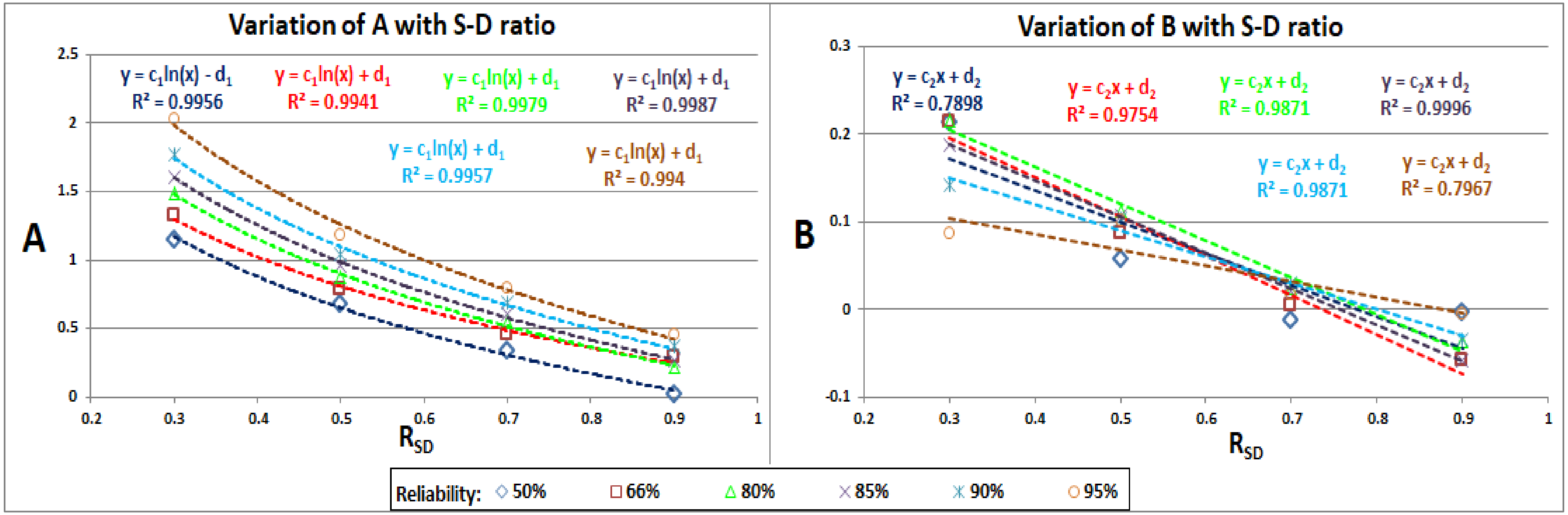


Figure 5-35: Relationships found between regression coefficients A and B with S-D ratio

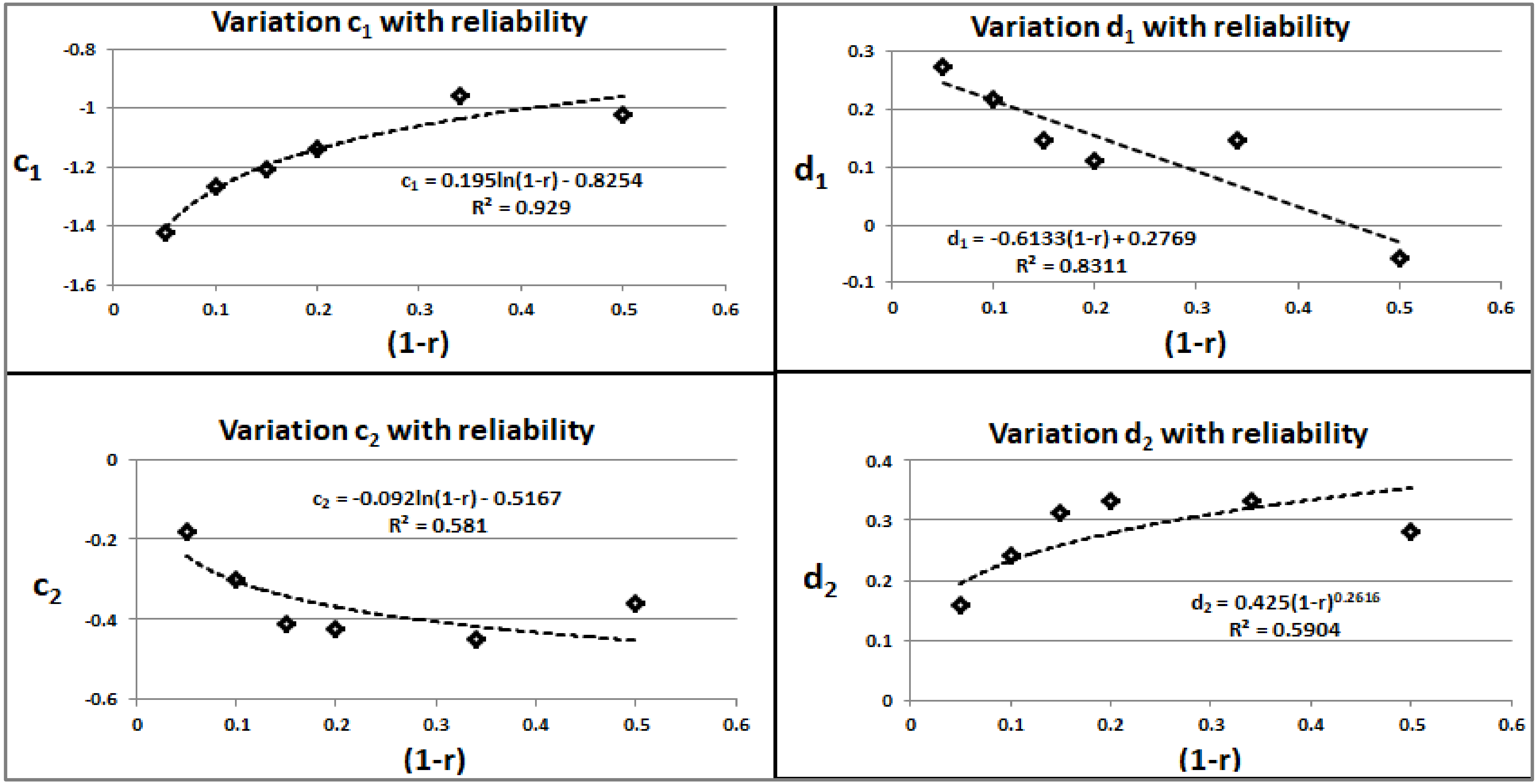


Figure 5-36: Relationships found between regression coefficients c_1, c_2, d_1 and d_2 with reliability

Comparison of the model's predictions of $\frac{N_{vd-r}}{N_r}$ to simulated data is done for normalised lag values of 0, 0.25 and 0.5 across all amplitudes and reliabilities. The results are illustrated in Figures 5-37 to 5-39. What was observed is that the regression model appears to capture behaviour well at a normalised lag of 0.5. Its ability to accurately model the behaviour of a RWHS diminishes as the lag decreases to 0 where it dominantly under-predicts $\frac{N_{vd-r}}{N_r}$. This is especially the case when the amplitude of demand is set to 1 and at the higher S-D ratios (encircled in red).

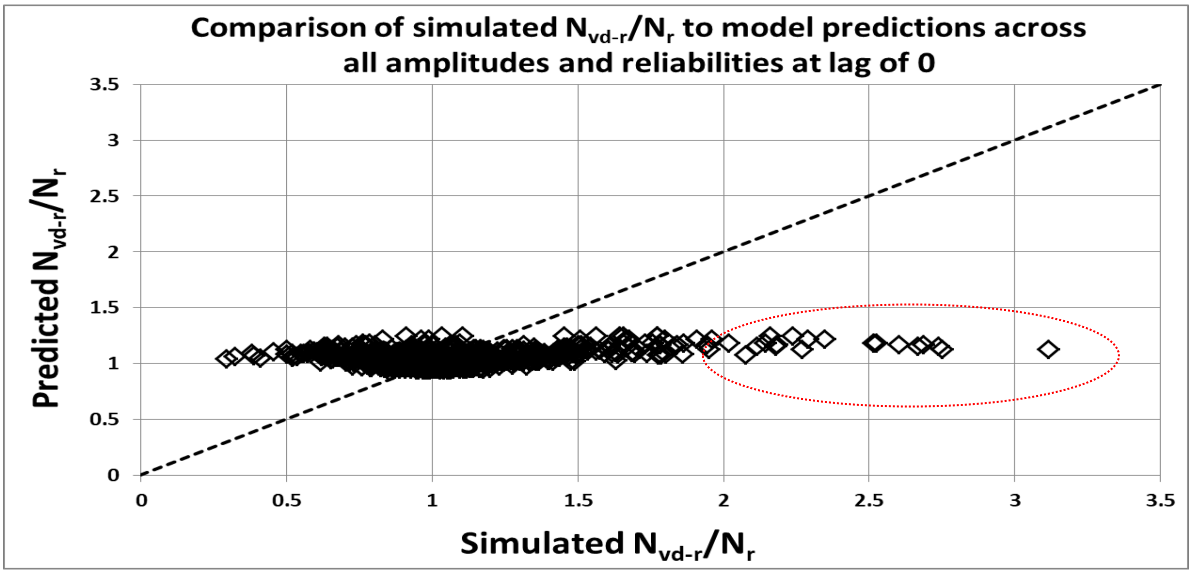


Figure 5-37: Comparison of simulated and predicted $\frac{N_{vd-r}}{N_r}$ across all amplitudes and reliabilities at lag 0

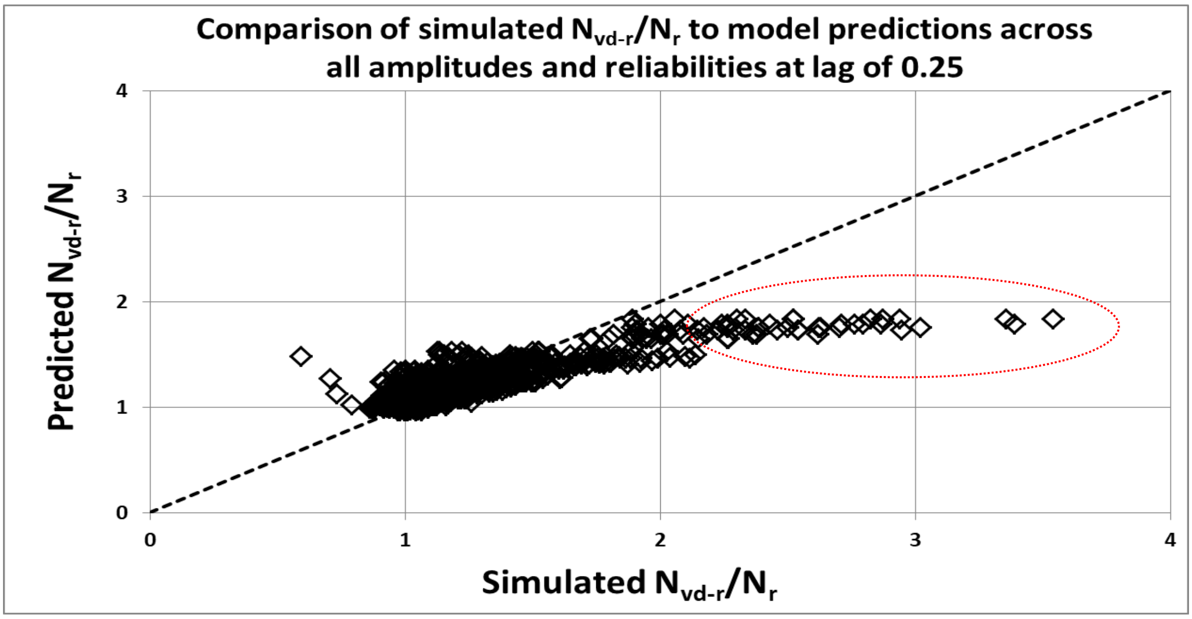


Figure 5-38: Comparison of simulated and predicted $\frac{N_{vd-r}}{N_r}$ across all amplitudes and reliabilities at lag 0.25

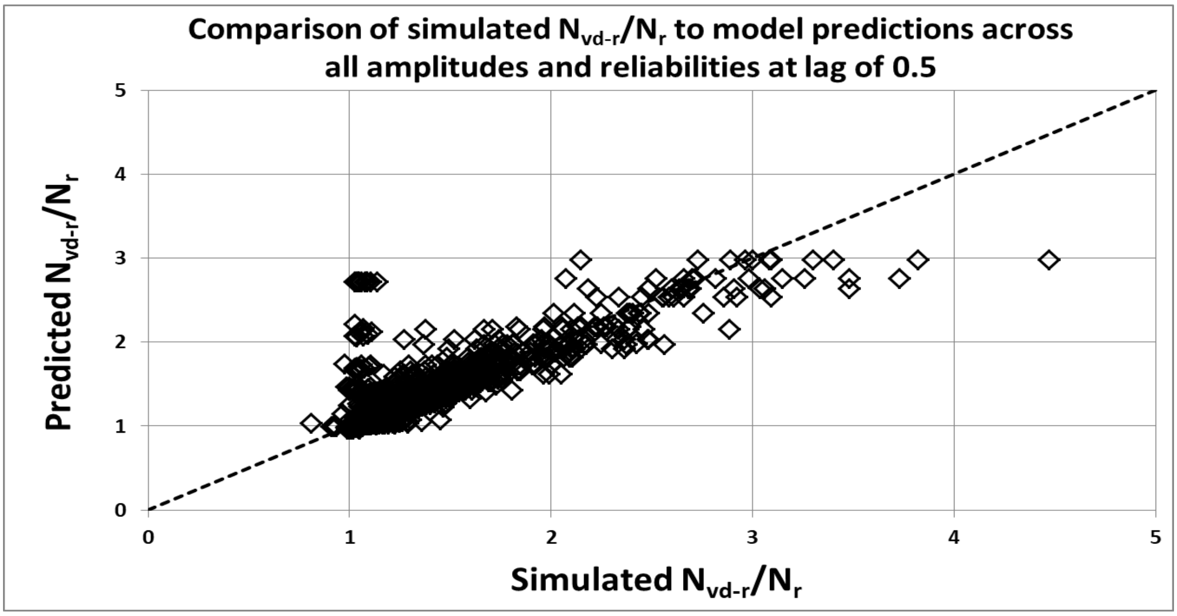


Figure 5-39: Comparison of simulated and predicted $\frac{N_{vd-r}}{N_r}$ across all amplitudes and reliabilities at lag 0.5

For the lower amplitude values it largely over-predicts at the normalised lag of 0. Some of the scattering is also thought to be caused by the model over-predicting values at the lower S-D ratio of 0.3. It was also noted from the lag 0 data that the regression model strongly exhibits monotonous behaviour when compared to the simulated data – this is posited to be tied to the influence of rainfall characteristics whose influence is not too well defined at the other lag values. Thus additional modelling is still required to ascertain the best way to account for this critical variable.

5.2.4. Regression modelling of storage, yield, lag, amplitude and reliability data

Results of regression at each of the amplitude values at fixed lag between the parameters $\frac{N_{vd}}{365.25}$ (where $\boldsymbol{N_{vd}}$ represents either a yield under variable demand or constant demand) and $\boldsymbol{R_{TD-r}}$ (representing storage-demand values for both variable and constant demand scenarios) revealed an identical form of relationship as has been previously shown for constant demand data only (see Equation 4-2). Figures 5-40 to 5-42 illustrate the results of regression for the reliability of 50% across the 3 amplitude values for all S-D ratios and lag values of 0, 0.25 and 0.5.

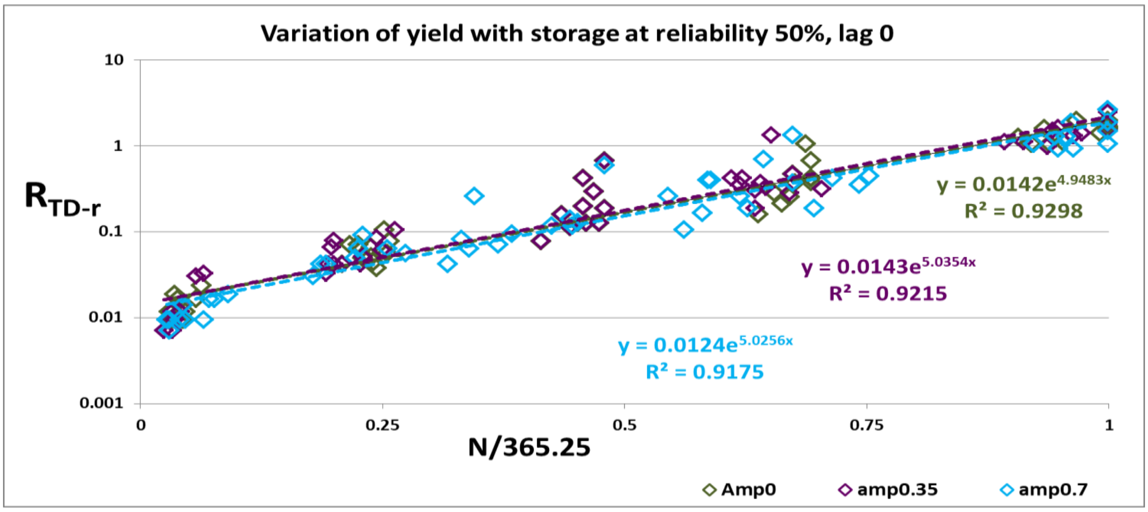


Figure 5-40: Variation of $R_{TD\text{-}r}$ with $\frac{N_{vd}}{365.25}$ at a reliability of 50% and lag 0 split by amplitude

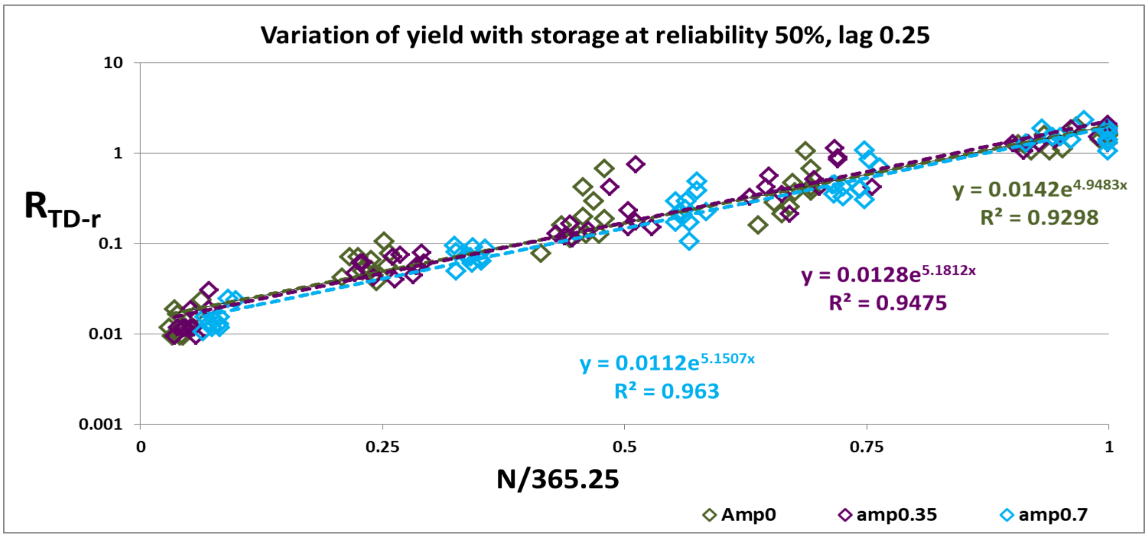


Figure 5-41: Variation of $R_{TD\text{-}r}$ with $\frac{N_{vd}}{365.25}$ at a reliability of 50% and lag 0.25 split by amplitude

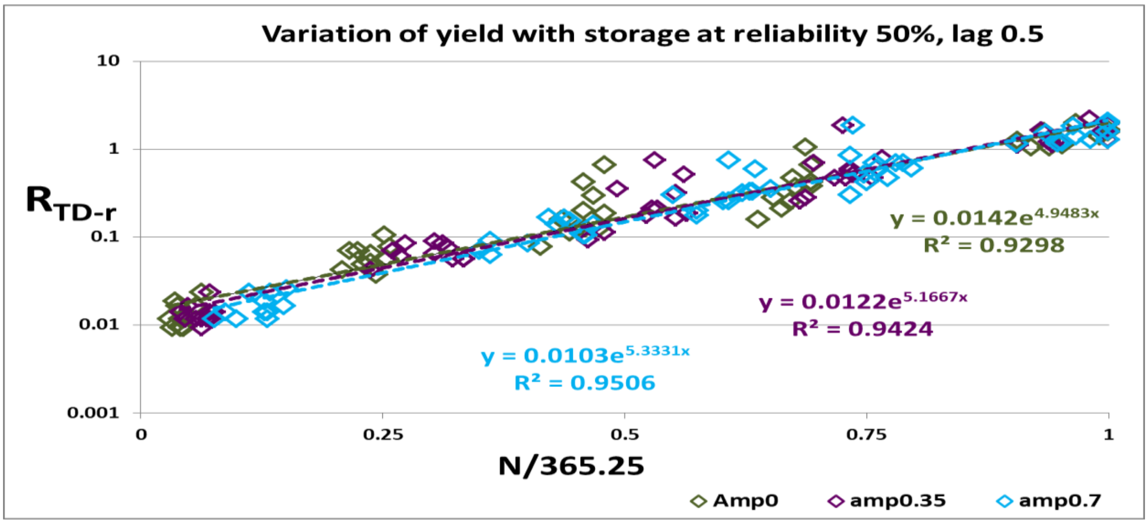


Figure 5-42: Variation of $R_{TD\text{-}r}$ with $\frac{N_{vd}}{365.25}$ at a reliability of 50% and lag 0.5 split by amplitude

It was observed at each lag value that the best fit curves described by each of the amplitudes do not significantly differ from one another. A curious point noted is the apparent lack of a trend in the regression coefficients with increasing amplitude for the lag values of 0 and 0.25 in contrast to the presence of a trend for the lag 0.5 data - this would seem to support observations made before (section 5.1.2) that the degree of the impact of the amplitude on storage is dictated by the lag.

However comparing the slopes of the three curves across the different lag values shows there is negligible difference between the curves with changing amplitude value. The above is contrasted to an alternative set of plots of varying lag at fixed amplitude as exemplified by Figures 5-43 and 5-44 (an amplitude of 0 would be identical to Figures 4-26 to 4-31 as this is the constant demand case). Thus, it could reasonably be argued that amplitude and lag do not significantly affect the relationship between $\boldsymbol{R_{TD-r}}$ and $\frac{N_{vd}}{365.25}$.

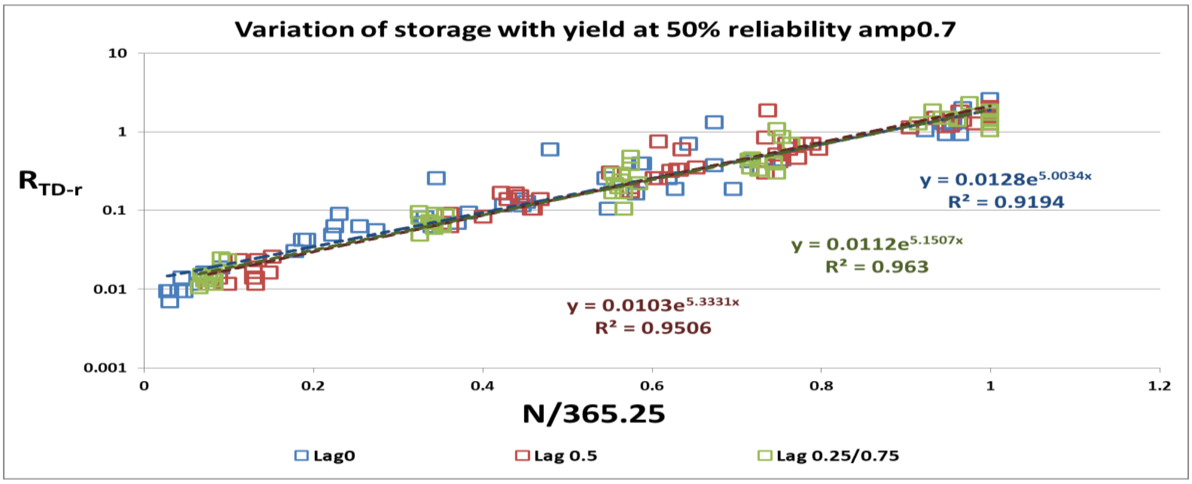


Figure 5-43: Variation of storage-demand ratio with $\frac{N_{vd}}{365.25}$ at a reliability of 50% and amplitude 0.7 split by lag

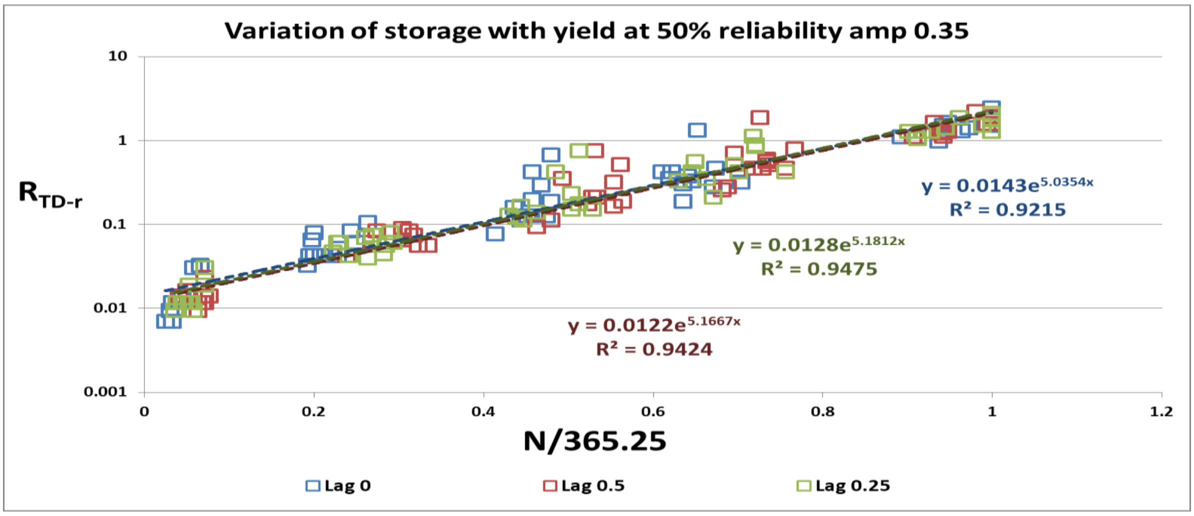


Figure 5-44: Variation of storage-demand ratio with $\frac{N_{vd}}{365.25}$ at a reliability of 50% and amplitude 0.35 split by lag

Having developed a model that incorporates the effects of these parameters through $\frac{N_{vd}}{365.25}$ in section 5.2.3, one could reasonably consider the influence of variability in demand to already be incorporated into $\boldsymbol{R_{TD-r}}$ indirectly. This then allowed for the development of a simpler model mirroring the one developed with the constant demand data using Equation 4-3; the main difference is now found in the way the coefficients of regression relate to reliability.

Using the general form of the relationship given in Equation 4-3, multiple linear regressions were performed on the variable demand data with $\boldsymbol{CV}$ taken as the parameter accounting for the effects of rainfall variability. Examination of the statistical significance of coefficients of $\boldsymbol{CV}$ at a level of 0.05 revealed the parameter to be statistically significant as indicated in Table 5-3. The overall averaged R^2 value for the regression over all reliabilities came to 0.9209.

Table 5-3: Statistical significance between coefficient c_{vd} and rainfall characteristic CV

Reliability		Parameter
		CV
50%	Coefficient Value	0.911
	P-value	1.49E-29
66%	Coefficient Value	1.190
	P-value	3.36E-50
80%	Coefficient Value	1.355
	P-value	2.76E-53
85%	Coefficient Value	1.349
	P-value	1.32E-44
90%	Coefficient Value	1.611
	P-value	4.09E-60
95%	Coefficient Value	1.617
	P-value	1.64E-47

Relationships between the regression parameters $\boldsymbol{a_{vd}}$, $\boldsymbol{b_{vd}}$ and $\boldsymbol{c_{vd}}$ and reliability were also sought and the results are presented in Figures 5-45 to 5-47.

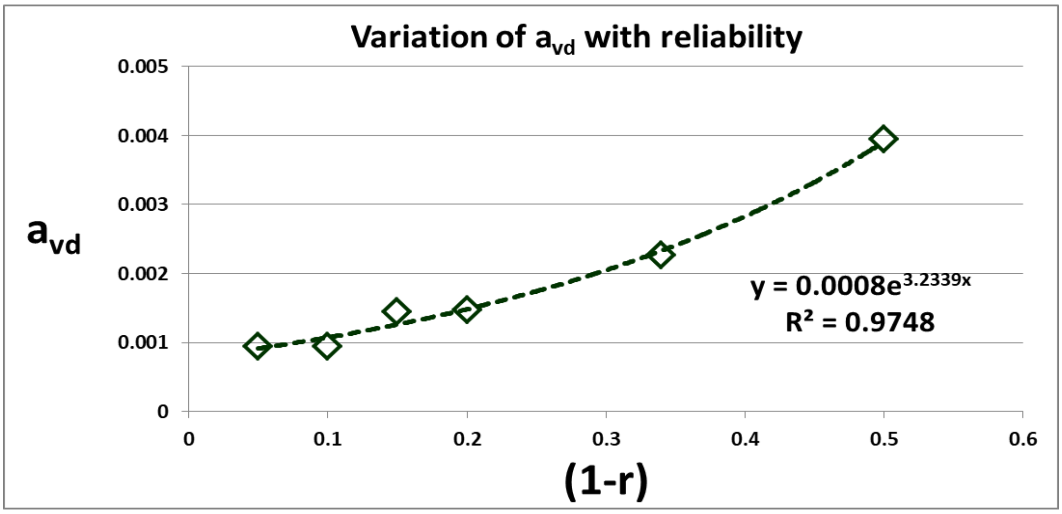


Figure 5-45: Variation of a_{vd} with reliability

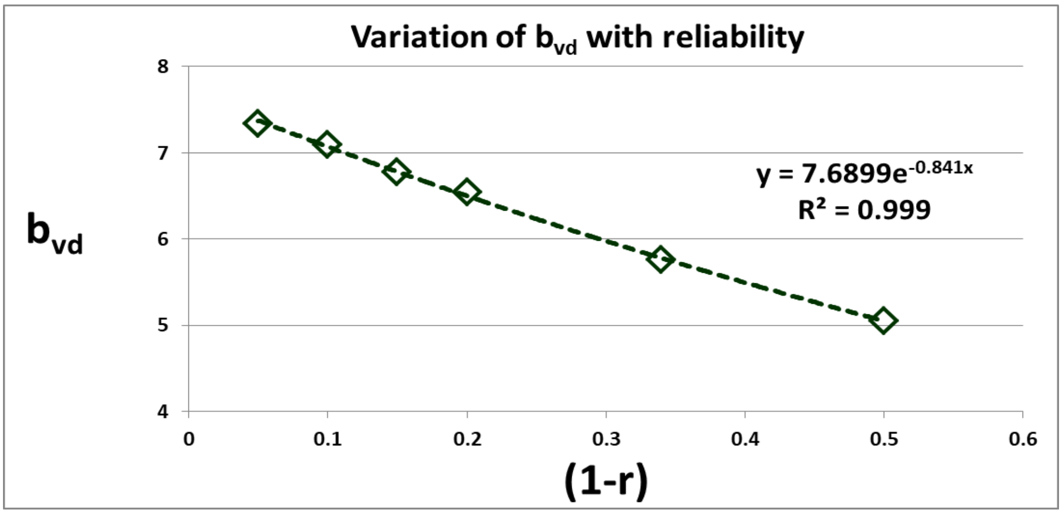


Figure 5-46: Variation of b_{vd} with reliability

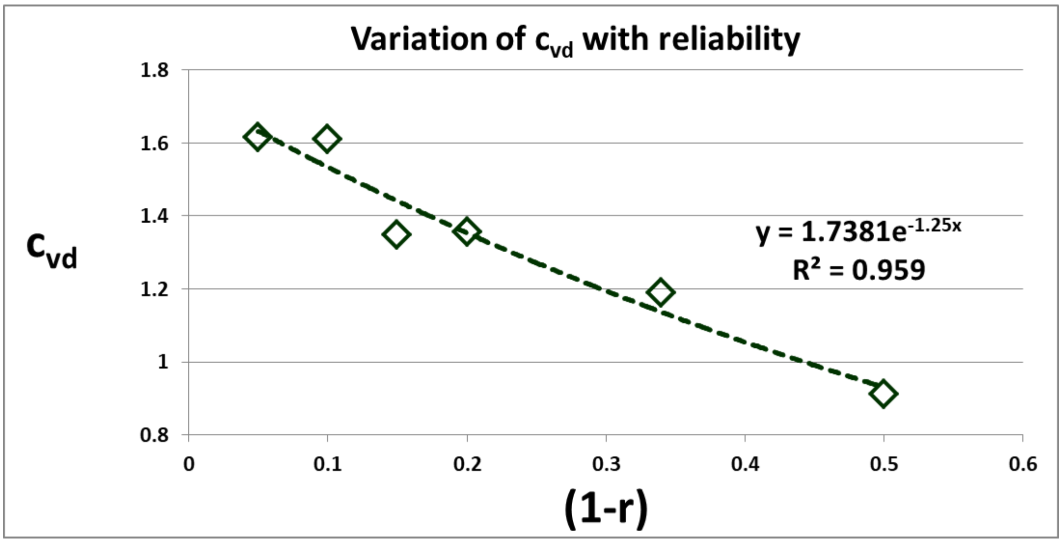


Figure 5-47: Variation of c_{vd} with reliability

Comparison to simulated $\boldsymbol{R_{TD-r}}$ values incorporating the predictions by the yield model developed in section 5.2.3, revealed the model to under-predict the tank size at lag 0. The same can be said for the data when peaks are 0.25 of a year apart – this is tied to the observation that the lumped yield model already under-predicts the changes in number of days of supply with variable demand especially when amplitude of demand is equal to 1. In some instances the model also over-predicts the required tank size due to the over-prediction of the number of days of supply.

Figures 5-48 to 5-50 illustrate the comparisons for normalised lag values of 0, 0.25 and 0.5 across all demand amplitudes and reliabilities.

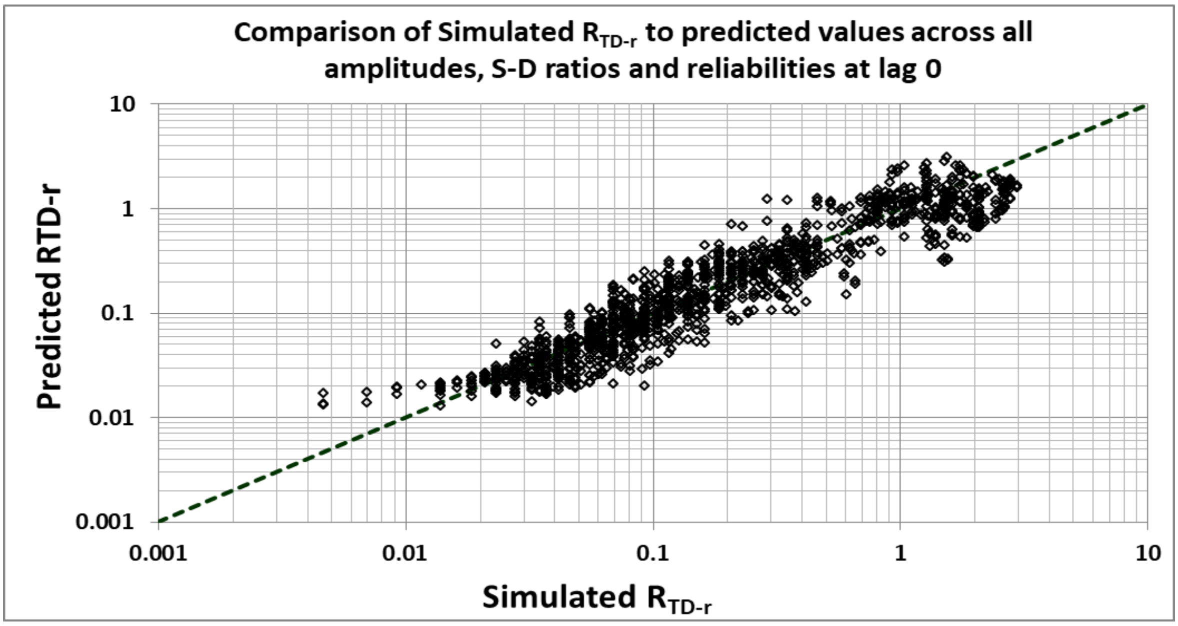


Figure 5-48: Comparison of simulated and predicted R_{TD-r} for lag 0 across all reliabilities and amplitudes

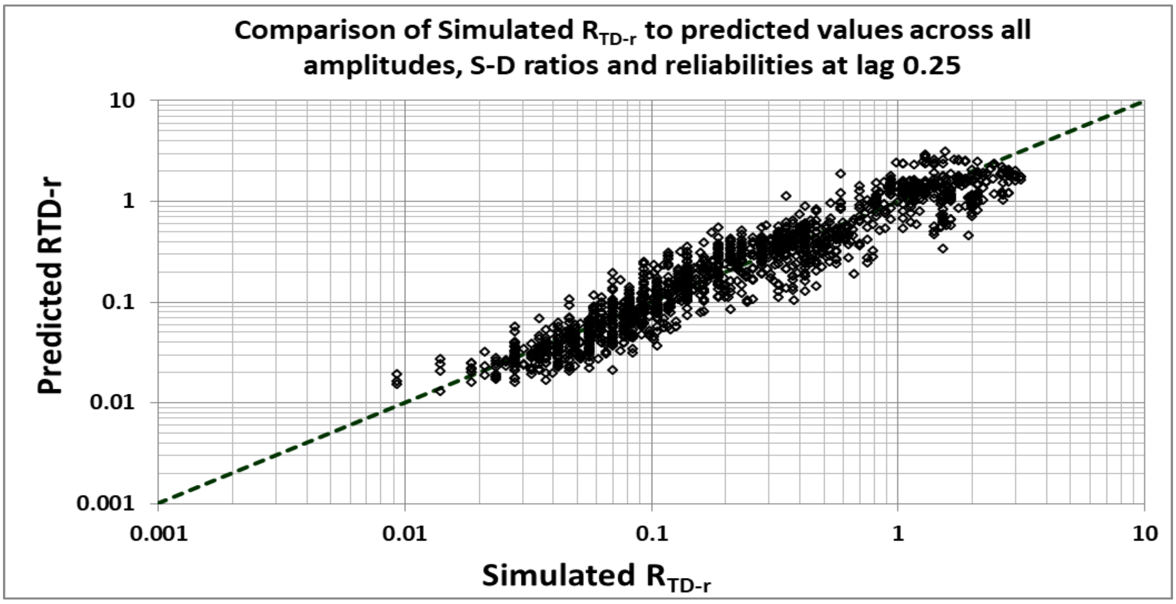


Figure 5-49: Comparison of simulated and predicted R_{TD-r} for lag 0.25 across all reliabilities and amplitudes

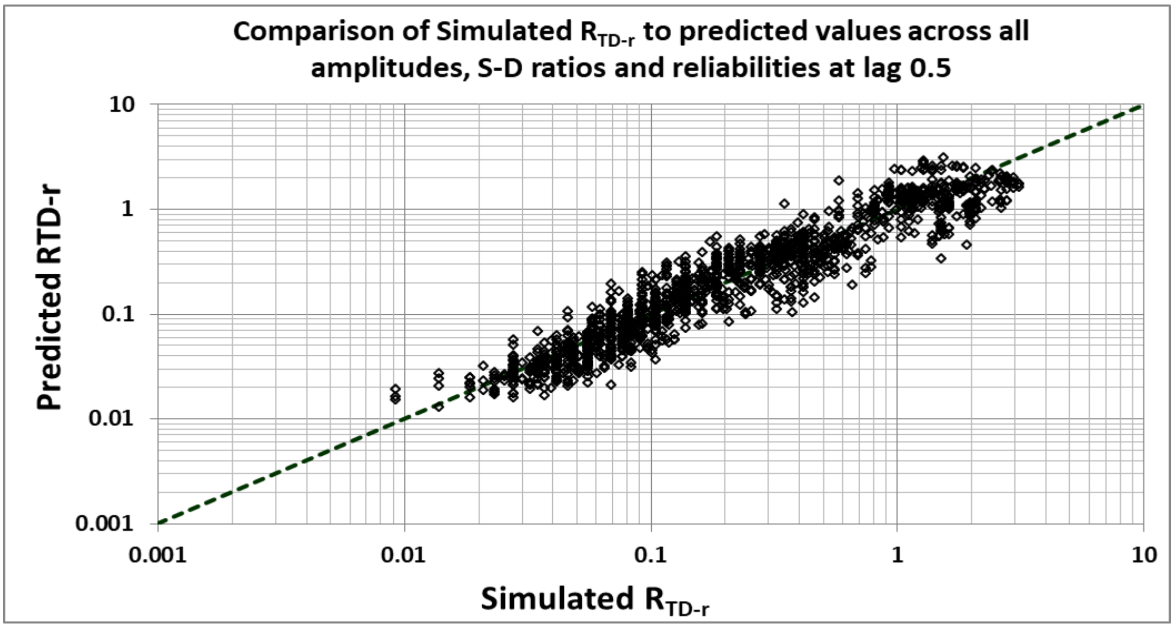


Figure 5-50: Comparison of simulated and predicted R_{TD-r} for lag 0.5 across all reliabilities and amplitudes

A similar development process as presented in section 4.2.2 was applied to a storage-demand-yield model that does not incorporate rainfall characteristics, using the general form shown in Equation 4-2. The relationships derived for each of the regression coefficients $\boldsymbol{\gamma_{vd}}$ and $\boldsymbol{\varphi_{vd}}$ are presented in Figure 5-51.

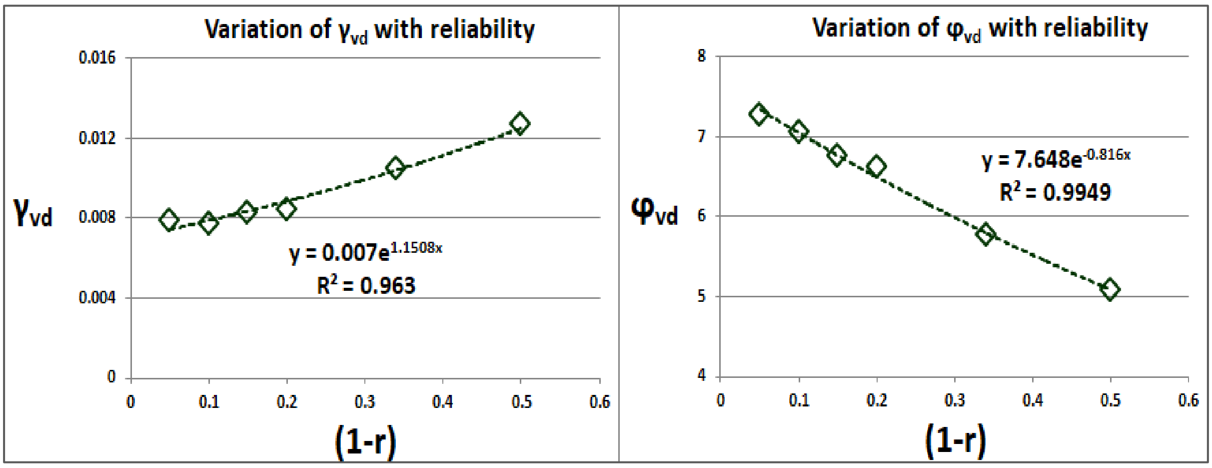


Figure 5-51: Relationship between coefficients of regression γ_{vd} and ϕ_{vd} and reliability

An alternative (and more complex) formulation for the storage-demand-yield models to account for the influences of amplitude and lag is explored in Appendix 4(h) - the results of the regressions were rather mixed with strong linear and exponential relationship established between the lag and reliability respectively.

5.3. Summary

This chapter has explored the results of the impact that variability in demand has on the behaviour of RWHS. Regression was the main tool used to investigate potential generalised relationships that incorporate parameters used to quantify variability in demand. From the results presented the following findings and conclusions are made:

- Variable demands tend to increase the number of days of supply from a RWHS with the relative location of the peak in demand to the peak in rainfall i.e. the lag ($\boldsymbol{L}$) and the range of variability i.e. the amplitude ($\boldsymbol{a}$) influencing the number of days of supply that may be obtained.
- The degree of variation in number of days of supply with lag is influenced by the time of year at which the rainfall peaks i.e. areas with rainfall peaks in January, December and June tend to show large changes in number of days of supply with lag whilst areas with rainfall peaks in March and September appear minimally sensitive to the same. The impact of amplitude appears to be dictated by the lag.
- Variability in demand can prescribe either a larger or a smaller optimal tank size when compared to a constant unvaried demand and this tank size is also dependent on the rainfall characteristics of the gauge under study. The impact of lag and amplitude on the optimal tank size is limited and is largely as a result of the changes observed in the number of days of supply
- Results of the regression modelling revealed an exponential relationship to best describe the changes in number of days of supply with amplitude – this form and the proposed dimensionless parameter $\frac{\boldsymbol{N_{vd-r}}}{\boldsymbol{N_r}}$ conveniently allow the model to accommodate both the constant demand case and the variable demand case. The use of this parameter resulted in some simplifications in the regression of data across climate zones by permitting the use of a single curve to describe the trend in the data. However, it was noted that the effect of rainfall characteristics is not too clearly defined for lag values other than that of zero, although there is clearly an influence that can be observed from the simulated data. Thus additional work is still required to understand the best way to account for this variable in models incorporating variable demand. Strong linear, logarithmic and power relationships were established between regression coefficients and the parameters of lag, S-D ratio and reliability.
- The regression exercise seeking relationships between the storage-demand ratio and the normalised number of days of supply revealed that a similar form of model to that developed under constant demand could be adopted for generalisation – the relationships developed in section 5.2.4 could in theory replace those developed in section 4.2.2., and 4.3.1., as they accommodate both cases of constant and variable demand. The results of regression also revealed strong exponential relationships between the coefficients of regression and reliability.

- Comparison of the predictions made by the regression models to simulated data revealed reasonable performance at lag 0.5. The regression models however tend to under-predict or over-predict the number of days of supply and corresponding tank size at the other lag values assessed depending on the amplitude and S-D ratio. This is especially the case for a lag 0. Thus, additional modelling is required to better understand the behavioural differences observed between lag 0 and other lag values.

Based on the results of analysis presented in this Chapter, the following generalised model is proposed:

$$\frac{\boldsymbol{N_{vd-r}}}{\boldsymbol{N_r}} = \boldsymbol{e}^{\boldsymbol{\lambda}(\boldsymbol{a})}$$

Where for $\boldsymbol{0 < a \leq 1}$, $\boldsymbol{0 \leq \frac{L}{365.25} \leq 0.5}$, $\boldsymbol{0.3 \leq R_{SD} \leq 0.9}$:

$$\lambda = A\left(\frac{L}{365.25}\right) + B \qquad \textbf{(5-2)}$$

$$A = c_1 ln(R_{SD}) + d_1 \qquad B = c_2 R_{SD} + d_2$$

$$\boldsymbol{for\ 0.5 \leq r \leq 0.95}$$

$$c_1 = 0.195\ln(1-r) - 0.825 \qquad d_1 = -0.613(1-r) + 0.277$$

$$c_2 = -0.092\ln(1-r) - 0.517 \qquad d_2 = 0.425(1-r)^{0.262}$$

Where: $\boldsymbol{N_{vd-r}}$ is the expected number of days of supply at reliability $\boldsymbol{r}$**,** $\boldsymbol{N_r}$ is the expected number of days of supply under constant demand at reliability $\boldsymbol{r}$ as given by Equation 4-7 or 4-9**,** $\boldsymbol{a}$ is the amplitude of variable demand computed using Equation 3-3 **,** $\boldsymbol{L}$ is the lag computed using Equation 3-14, $\boldsymbol{R_{SD}}$ is the supply-demand ratio and $\boldsymbol{r}$ is the reliability.

$$\boldsymbol{R_{TD-r} = a_{vd} e^{b_{vd}\left(\frac{N_{vd-r}}{365.25}\right)} \cdot CV^{c_{vd}}}$$

Where for $\boldsymbol{0 < a \leq 1\ and\ 0 \leq \frac{L}{365.25} \leq 0.5}$**:** **(5-3)**

$$a_{vd} = 0.0008e^{3.23(1-r)}$$

$$\boldsymbol{0.5 \leq r \leq 0.95}$$

$b_{vd} = 7.69e^{-0.841(1-r)}$
$c_{vd} = 1.74e^{-1.25(1-r)}$

Where: $\boldsymbol{N_{vd-r}}$ is the expected number of days of supply**,** $\boldsymbol{CV}$ is the coefficient of variation of daily rainfall, $\boldsymbol{R_{TD-r}}$is the storage –demand ratio at reliability $\boldsymbol{r}$**.**

If rainfall characteristics are not included then:

$$\boldsymbol{R_{TD-r} = \gamma_{vd} e^{\varphi_{vd}\left(\frac{N_{vd-r}}{365.25}\right)}}$$

Where for $\boldsymbol{0 < a \leq 0.7 \; and \; 0 \leq L \leq 0.5}$**:**

$a_{vd} = 0.007e^{1.15(1-r)}$ **(5-4)**

$b_{vd} = 7.65e^{-0.82(1-r)}$ $\boldsymbol{0.5 \leq r \leq 0.95}$

Where: symbols are as defined before.

A worked example of application of the models is presented in Chapter 7.

CHAPTER 6 INCORPORATING FIRST FLUSH LOSSES

The third question to be answered by this study, as set out in objectives 3.1 and 3.2 was that of assessing the influence of the first flush on RWHS behaviour and whether it was worthwhile to explicitly integrate this parameter into generalised relationships. As time was constrained this analysis limited itself to the 33 sampled gauges shown in Figure 3-6.

First flush depths considered in this analysis included: 0.2mm, 1.5mm and 3mm. The simulations were run under constant demand and reliabilities considered include 50%, 66%, 80%, 85%, 90% and 95%.

6.1. Influence of the First Flush on RWHS Yield and Storage

The starting point of analysis involved interrogating the effects on the number of days supplied and the tank size when a RWHS is subjected to the aforementioned first flush depths. The sections that follow discuss these impacts.

6.1.1. Impact of the first flush on the expected number of days of supply

Figures 6-1 to 6-5 illustrate for a reliability of 50% the observed differences in the number of days supplied per year when various design first flush depths ff_d are applied

The vertical axis quantifies the expected number of days of supply that are retained under each of the chosen first flush scenarios – this is determined by means of a dimensionless ratio that divides the expected number of days of supply with a first flush (N_{ff}) with the expected number of days of supply without a first flush ($N_{ff=0}$). The ratio was computed across the different S-D ratios and reliabilities. A negative value indicates a reduction in the number of days of supply retained whilst a positive value indicates an increase in number of days of supply retained. The axis value of zero represents the base case of no first flush where there is no change the number of days of supply. If a first flush case indicates a value of zero then the number of days of supply under first flush is the same as the number of days of supply without first flush. Given the number of rainfall stations used, individual points on a line graph mixed with a column graph were viewed as the best way to illustrate the changes in the number of days of supply.

Similar trends to ones shown in Figures 6-1 to 6-5 were observed at all other reliabilities considered for this study and the data are attached in Appendix 5(a) as line graphs - a line graph is chosen as it best illustrates the trends in number of days supplied with changing first flush for each gauge (vertical axis) and makes for easier comparison of behaviour across each rain gauge and climate zone (horizontal axis).

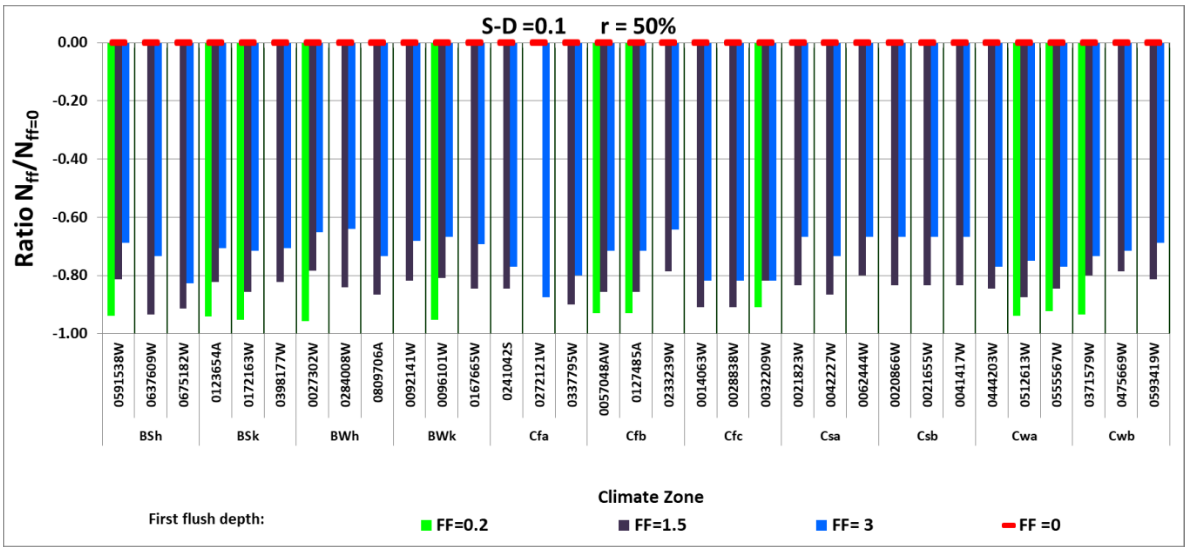


Figure 6-1: Differences in yield when various design first flush depths are applied at S-D =0.1 and r = 50%

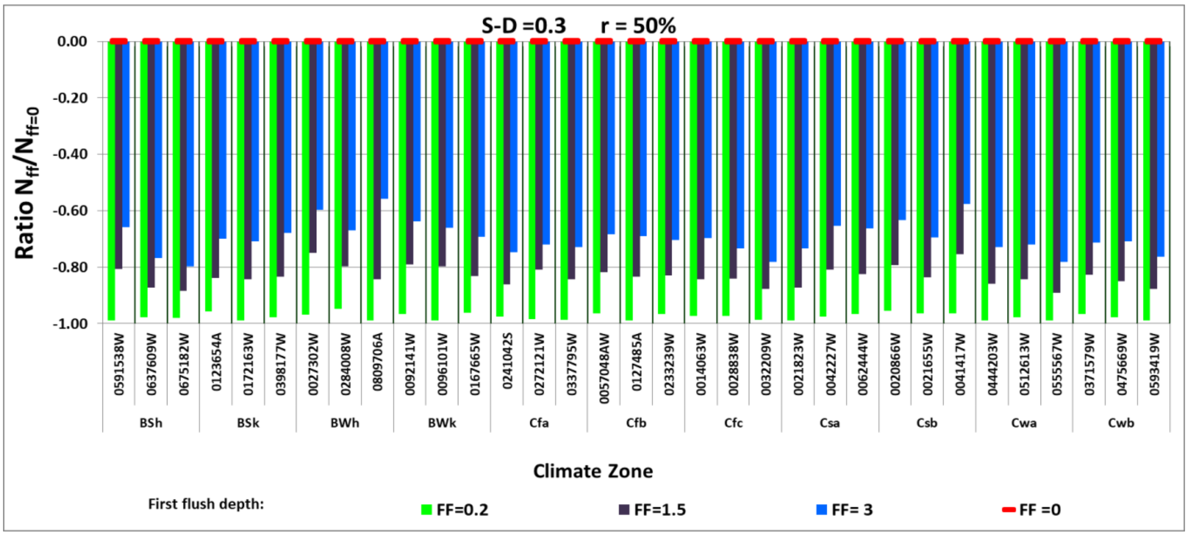


Figure 6-2: Differences in yield when various design first flush depths are applied at S-D =0.3 and r = 50%

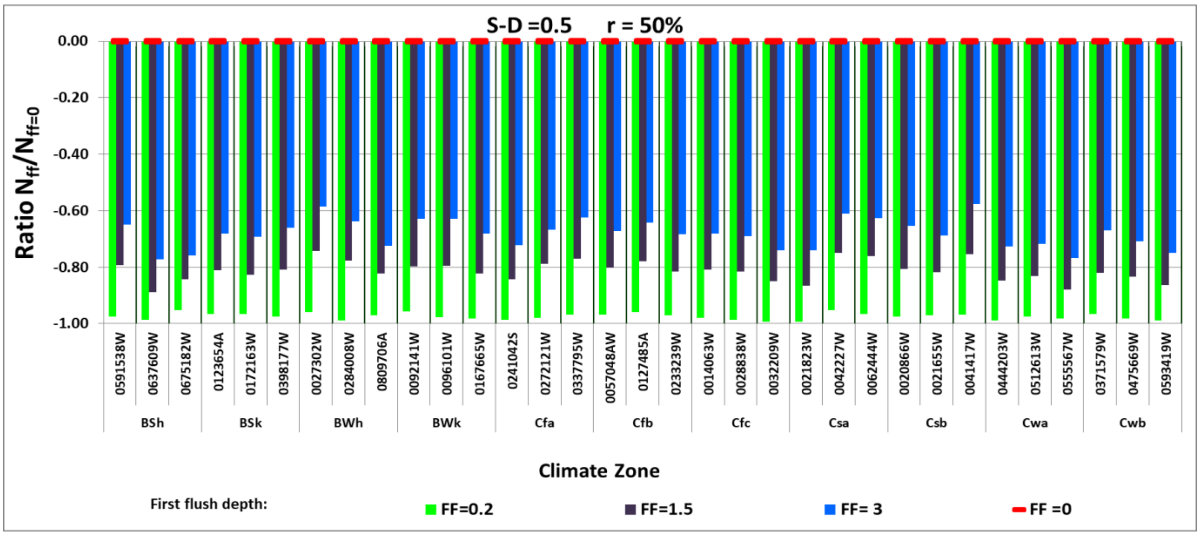


Figure 6-3: Differences in yield when various design first flush depths are applied at S-D =0.5 and r = 50%

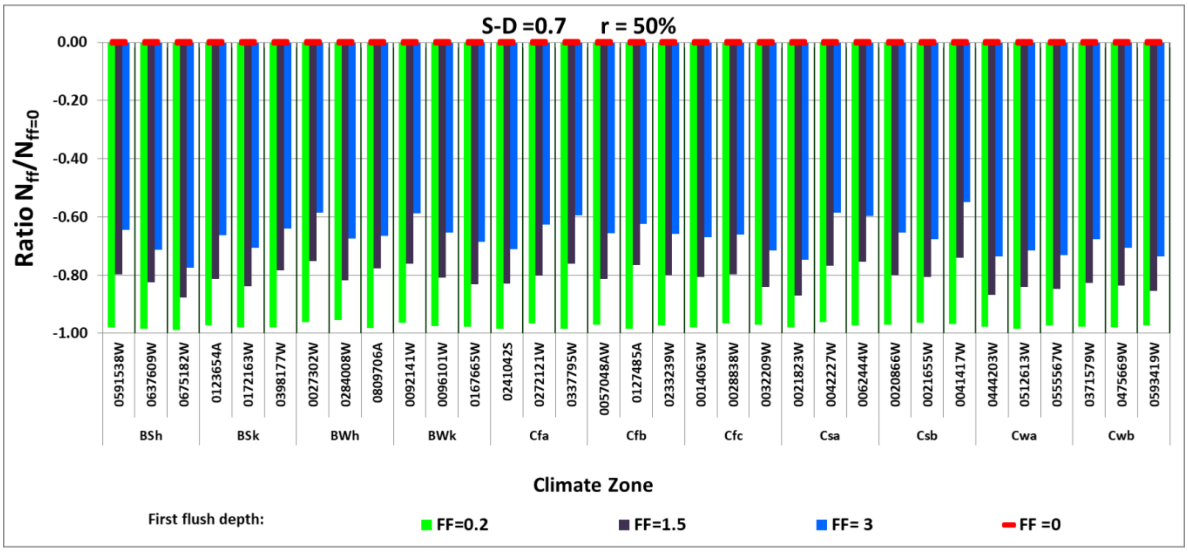


Figure 6-4: Differences in yield when various design first flush depths are applied at S-D =0.7 and r = 50%

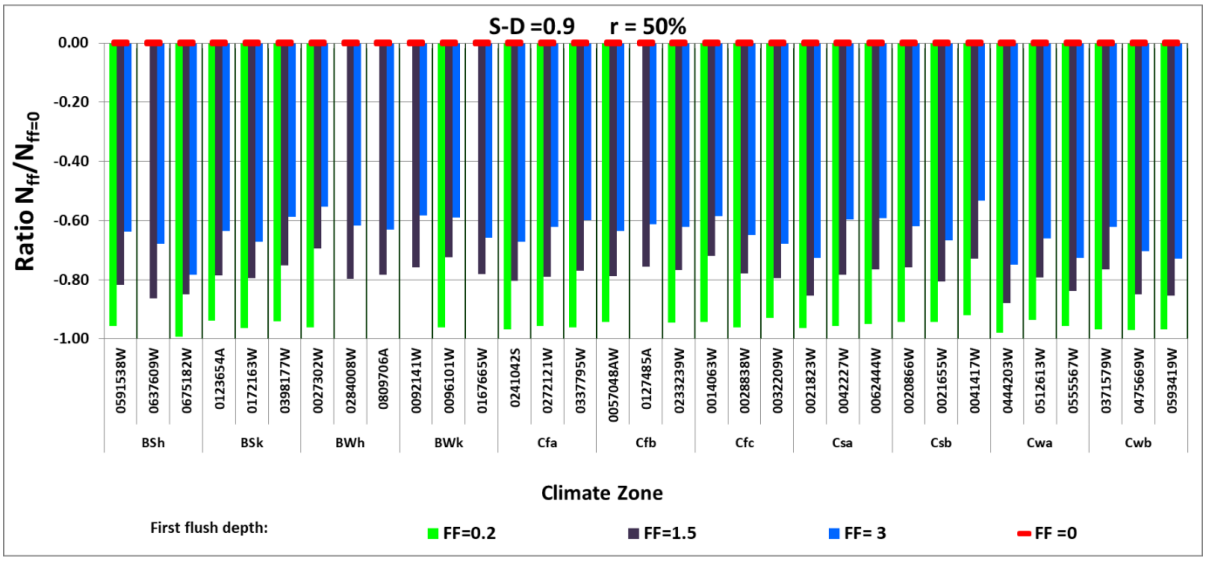


Figure 6-5: Differences in yield when various design first flush depths are applied at S-D =0.9 and r = 50%

It was observed from Figures 6-1 through 6-5 that at each of the S-D ratios considered, the expected number of days of supply decrease with an increase in flushed depth. For each of the applied flush depths, the reduction in expected number of days of supply also increased slightly with increasing S-D ratio. Closer inspection of the graphs reveals that when a first flush depth of 0.2mm (corresponding to the current recommended depth in South Africa (e.g. http://www.gutterguard.co.za/First-Flush-Systems-and-Pricing/)) is applied, the loss in number of days of supply is relatively insignificant with an average percentage reduction of 2.9% measured across all climate zones, S-D ratios and reliabilities. This would indicate that at the currently recommended depth the first flush is not a critical variable in determining the expected number of days of supply from a RWHS.

However, increasing the flushed depth to 1.5mm (the approximate mean daily rainfall for South Africa) or 3mm results in much larger losses in yield - the average reductions in expected number of days of supply come to 23.2% and 40.8% respectively across all S-D ratios and reliabilities respectively. This then implies that should a user of a RWHS choose to flush above the current recommended depth, then the first flush depth could become a significant variable to consider in the sizing of the tank.

6.1.2. Impact of first flush on tank size

Figures 6-6 to 6-10 show the corresponding impact to the optimal tank size when the various first flush depths ff_d are applied to a RWHS, with the comparison done in a similar manner to that highlighted in section 6.1.1 – the ratio of optimal tank size when first flush is applied (K_{ff}) to optimal tank size when no first flush is applied ($K_{ff=0}$) is used. The data presented is for a reliability of 50% across all S-D ratios. The data obtained for all other reliabilities showed similar variations and this data is in Appendix 5(b).

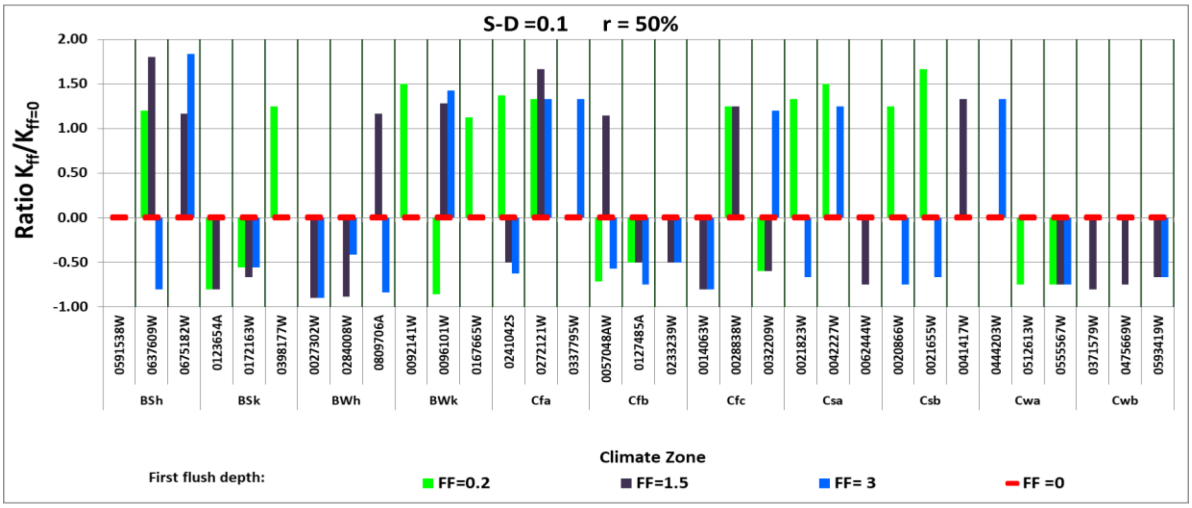


Figure 6-6: Differences in storage when various design first flush depths are applied at S-D =0.1 and r = 50%

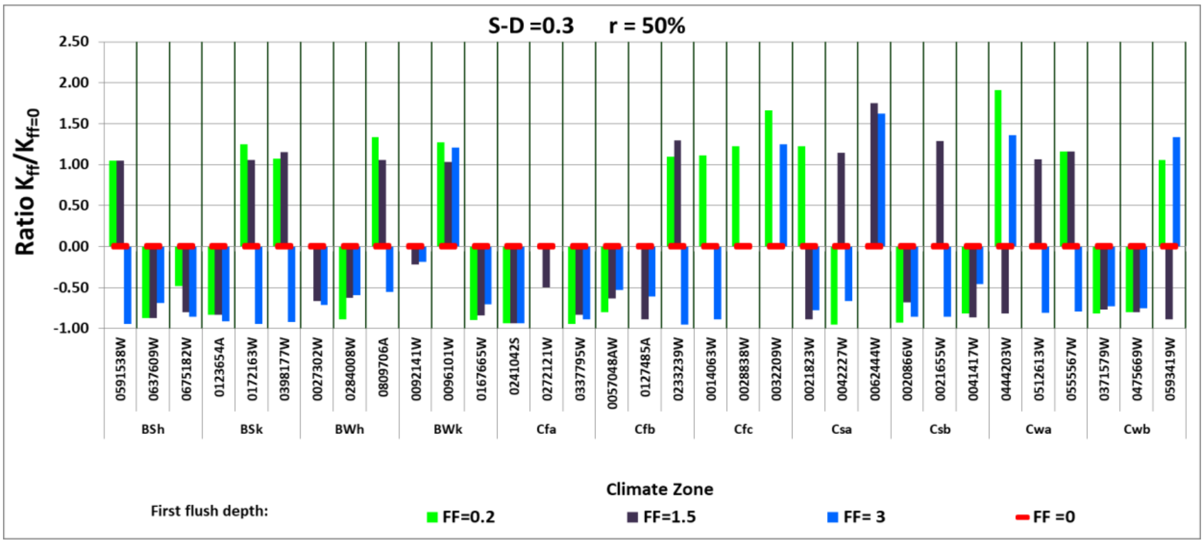


Figure 6-7: Differences in storage when various design first flush depths are applied at S-D =0.3 and r = 50%

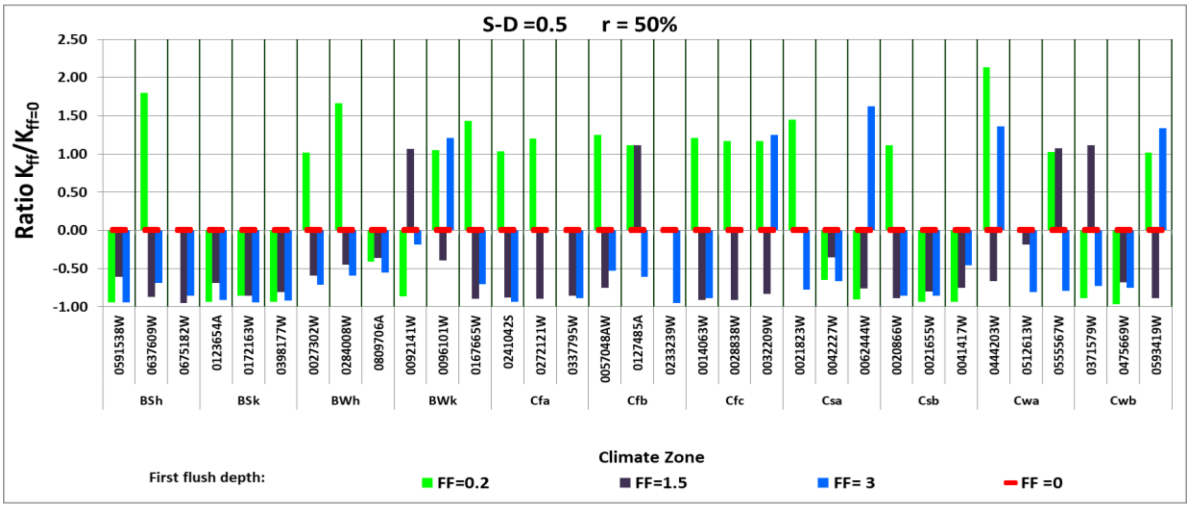


Figure 6-8: Differences in storage when various design first flush depths are applied at S-D =0.5 and r = 50%

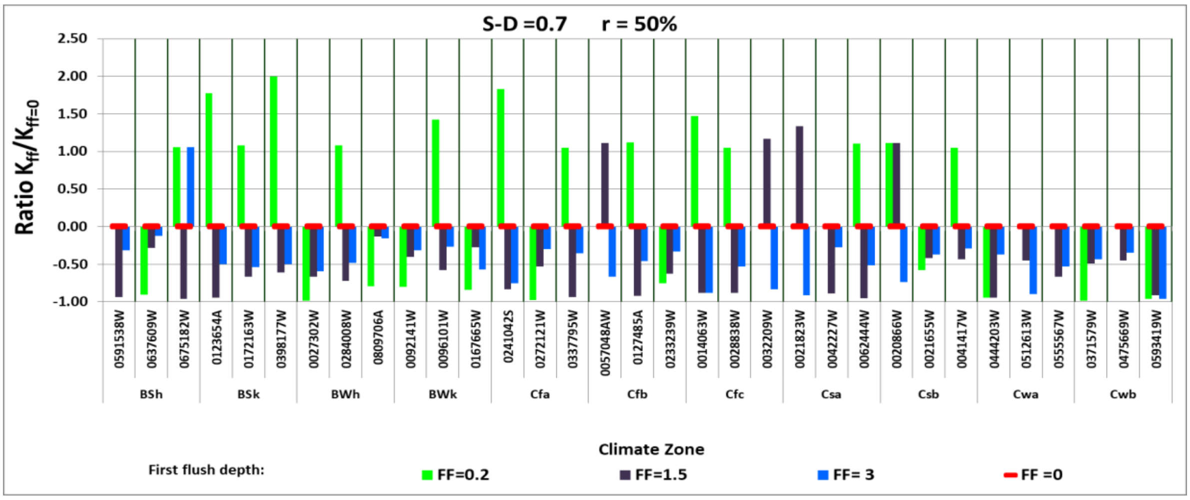


Figure 6-9: Differences in storage when various design first flush depths are applied at S-D =0.7 and r = 50%

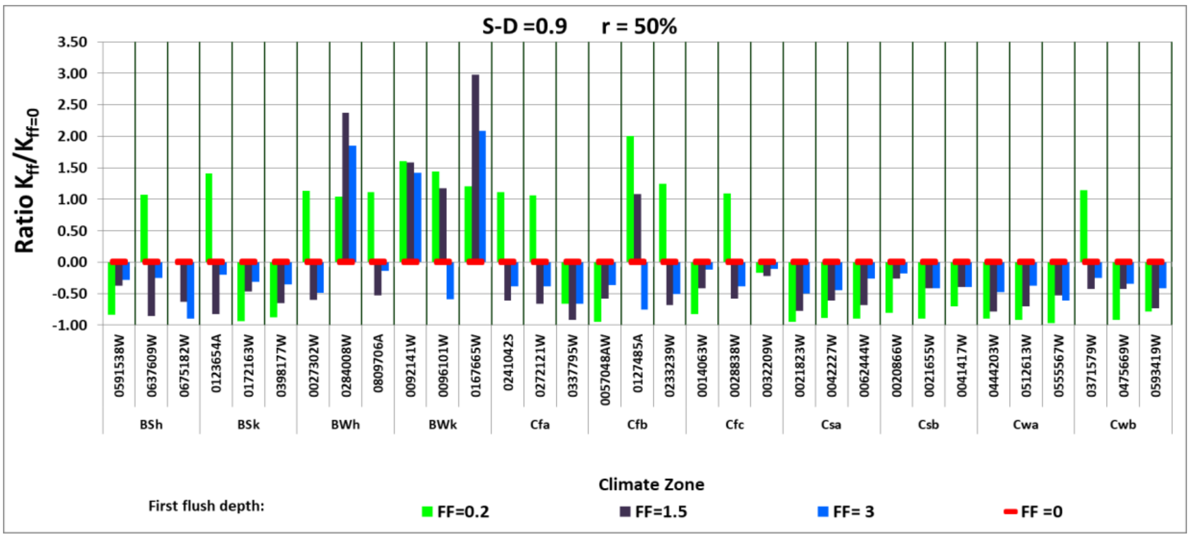


Figure 6-10: Differences in storage when various design first flush depths are applied at S-D =0.9 and r = 50%

It was observed from the fore-going plots that there is no consistent variation of tank size with increasing first flush depth, S-D ratio or climate zone – while the tendency is to lower storage with increasing flushing depth, in some instances storage increases as the corresponding yield decreases.

A measure of the average percentage differences across all climate zones, S-D ratios and reliabilities at each of the first flush depths of 0.2mm, 1.5mm and 3mm revealed tank size differences of -4.4%, +20% and +37% respectively. These differences indicate an overall tendency to increase storage at flushing depth 0.2mm but overall reductions in the required tank size as the flushing depths increase. The discrepancy in the 0.2mm data may indicate that additional modelling work needs to be done to ensure the behavioural model returns a more stable result under the two different scenarios. It is also noted that these figures are of similar magnitude to the differences observed with respect to the number of days of supply – thus a reduction available supply and yield at a given first flush depth in general results in a near-proportional reduction in the required tank size.

6.2. Integrating the First Flush into Generalised Storage-Yield-Reliability Relationships – A Thought Experiment

The first flush depth limits the available supply i.e. causes a reduction in rainfall that can be collected, therefore this inherently alters the given S-D ratio. This is to say for the same roof area, demand and MAP, the system essentially operates at a lower S-D ratio. Information directly accessible to the user with reference to the first flush would be the depth of water they wish to flush, ff_d. While this is the expected flush per rainfall event, as indicated by Equation 3-7, this will not always be the case. However it can be appreciated that assuming a first flush loss equivalent to the full design depth for each rain event would represent the worst case scenario for the potential yield. As the goal of design is to account for such a scenario using this assumption would result in a design that is as conservative as practicable. However, a direct subtraction of this depth from the MAP would be erroneous in that this loss only applies to a rainfall event thus the key parameter to include within the expression of the S-D ratio (Equation 3-1) would be the equivalent 'mean annual daily first flush depth'. This would be a function of the roof area, design first flush depth and the average number of rain days per year experienced in that particular location. Equation 6-1 derives an expression for this parameter in mathematical form:

$$\boldsymbol{FF} = \frac{(\boldsymbol{ff_d}) \times \boldsymbol{n_r}}{\mathbf{365.25}} \tag{6-1}$$

Where: $\boldsymbol{FF}$ represents the mean annual daily first flush depth, $\boldsymbol{ff_d}$ is the desired first flush depth, $\boldsymbol{A}$ is the area of the catchment and $\boldsymbol{n_r}$ is the average number of rain days expected in a year at a particular location.

Substituting Equation 6-1 into Equation 3-1 gives Equation 6-2 as the adjusted S-D ratio.

$$R_{SD}^{adj} = \frac{\eta A(\mu - FF)}{\bar{D}} \tag{6-2}$$

Where: all symbols are as defined before

To assess the utility of using this expression, the constant demand simulation data was used to compare to what would be predicted by the generalised multi-variable model by substituting the above modification. Figures 6-11 to 6-13 present a comparison between the simulated number of days of supply and predicted number of days of supply when the different $\boldsymbol{ff_d}$ values are used at a reliability of 50% - the graphs are based on all 33 rain gauges and depict typical trends across all S-D ratios.

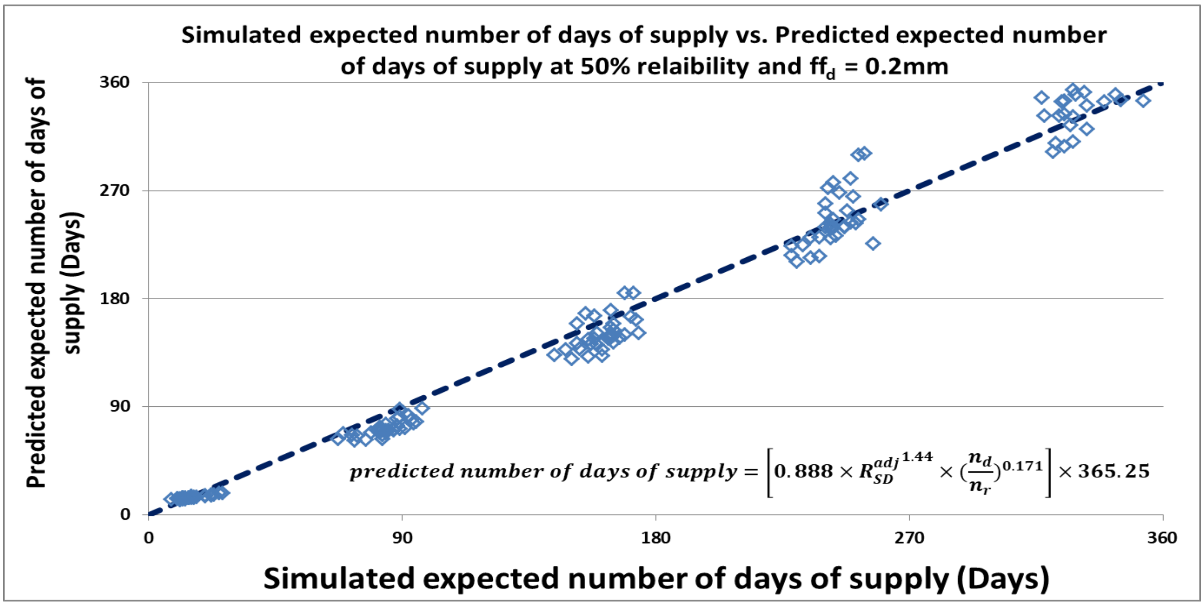


Figure 6-11: Comparison of predicted yield and simulated yield for modified S-D ratio at r =50% an d ff_d = 0.2mm

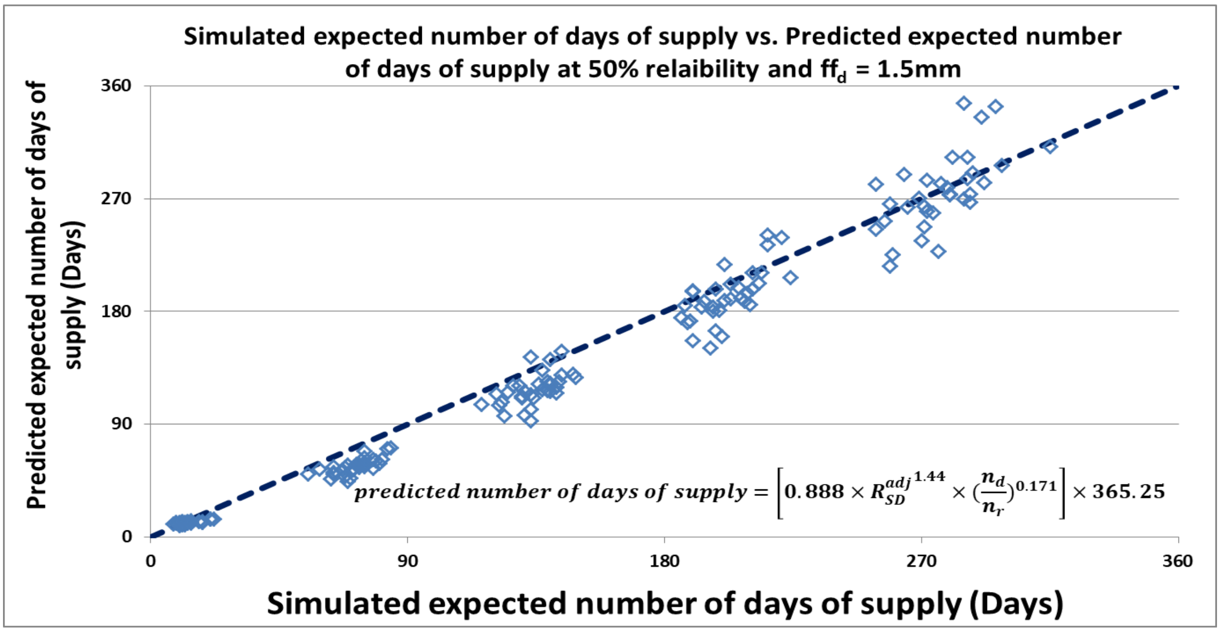


Figure 6-12: Comparison of predicted yield and simulated yield for modified S-D ratio at r =50% an d ff$_d$ = 1.5mm

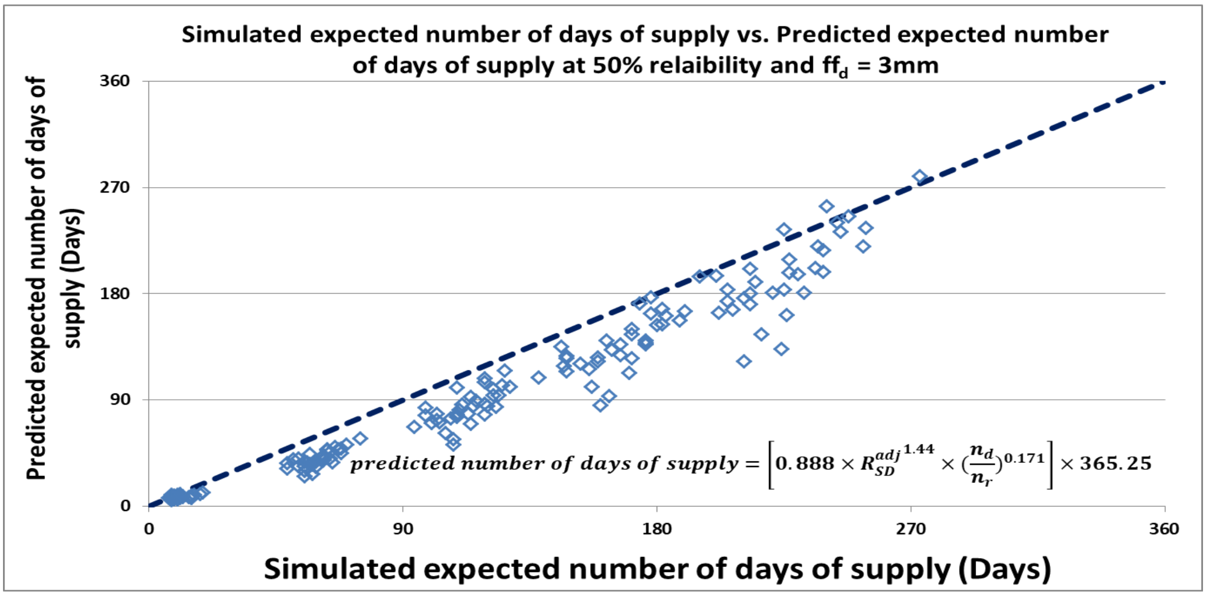


Figure 6-13: Comparison of predicted yield and simulated yield for modified S-D ratio at r =50% an d ff$_d$ = 3mm

Analysis of the foregoing Figures revealed the modification as proposed in Equation 6-2 to perform reasonably well in the prediction of yields when a first flush loss is contemplated – the average percentage differences between simulated and predicted number of days of supply come to -4.9% for a flushed depth of 0.2mm, -5.4% for a flushed depth of 1.5mm and -1.2% for a flushed depth of 3mm across all reliabilities. In this case, the negative value indicates a tendency of the model to overestimate the number of days of supply.

Analysis of the corresponding predicted tank sizes derived from the predicted number of days of supply also revealed a reasonable model fit. Figures 6-14 to 6-16 illustrate the comparison between simulated values and predicted values. What was observed is a tendency to overestimate the tank size at low flushing depths (Figure 6-14) and a tendency to underestimate the same at higher flushing depths (Figure 6-16).

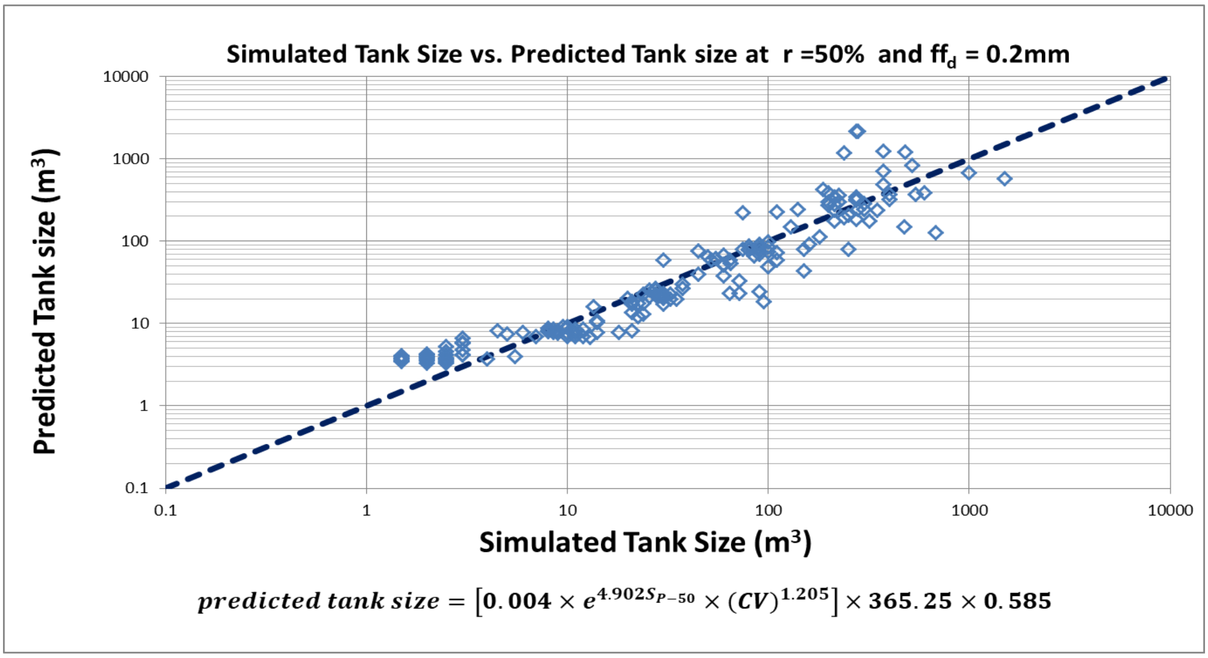


Figure 6-14: Comparison of predicted storage and simulated storage for modified S-D ratio at r =50% and ff$_d$ = 0.2mm

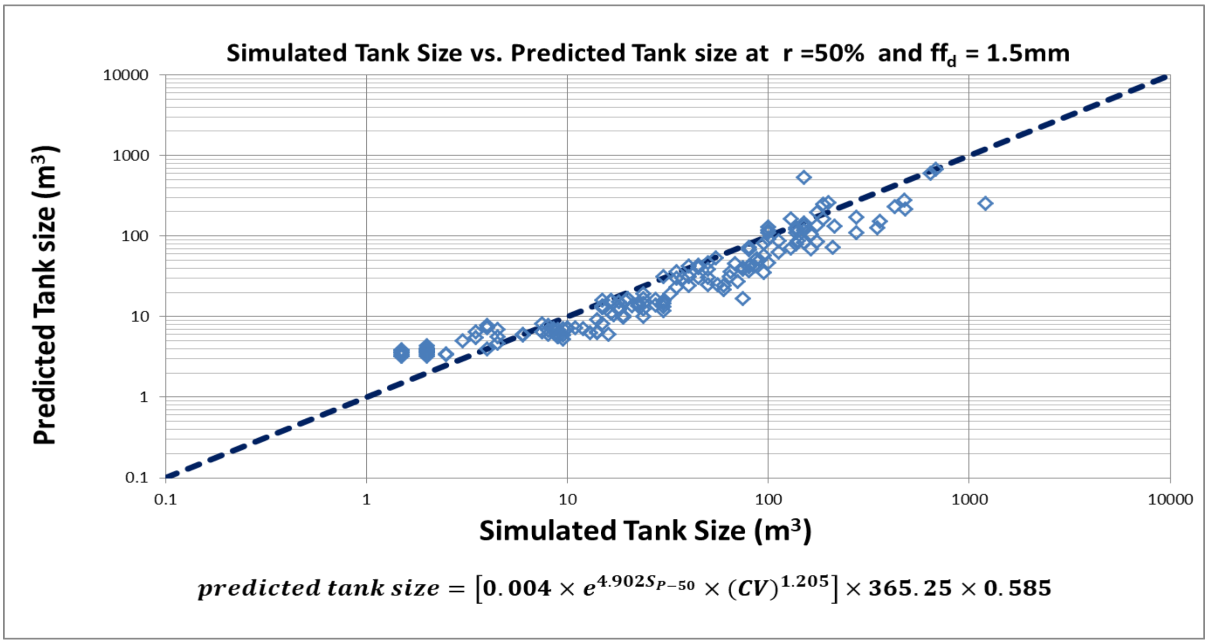


Figure 6-15: Comparison of predicted storage and simulated storage for modified S-D ratio at r =50% and ff$_d$ = 1.5mm

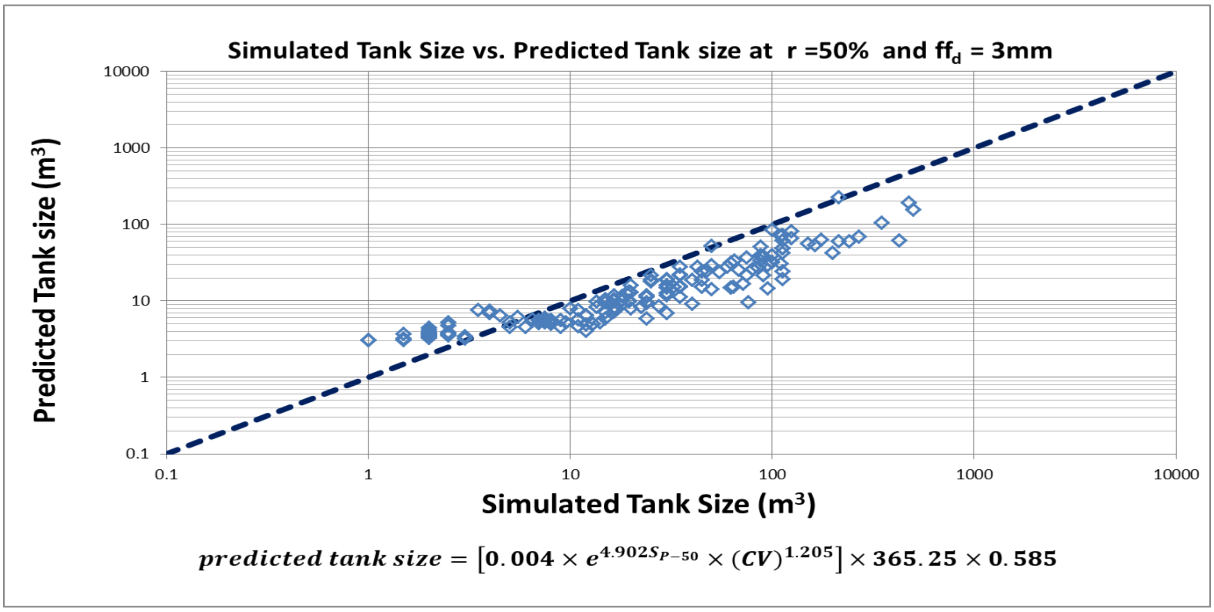


Figure 6-16: Comparison of predicted storage and simulated storage for modified S-D ratio at r =50% and ff_d = 3mm

An assessment of the numbers revealed an average percentage difference of -28.7% when a flushing depth of 0.2mm is applied, +4.4% when a flushing depth of 1.5mm is applied and +19.5% when a flushing depth of 3mm applied across all reliabilities. In this case a negative number would indicate a tendency to over-predict the tank size whilst a positive difference would indicate a tendency to under-predict the simulated tank size. Closer inspection of the numbers for tank volumes revealed a tendency to overestimate the tank size at low S-D ratios and a tendency to underestimate the tank size at high S-D ratios at any of the flushing depths across all reliabilities.

6.3. Summary

This chapter on incorporating first flush losses into generalised storage-yield-reliability models has presented the data collected from simulation. From the results presented the following key findings were made:

- The higher the first flush the greater the reductions in yield with a proportionate reduction in tank sizes
- First flush losses can be integrated into the generalised model through the modified S-D ratio; however the method proposed in this study would still require some refinement as it is based on a highly limited data sample.
- The procedure of incorporating the first flush loss adopted in this study has to some extent been based on a time-averaged view of the loss without necessarily accounting for the fact that the amount lost changes from year to year depending on the total number of rainy days in each year. Hence a more refined analysis is still required in order to capture this aspect

CHAPTER 7 VERIFICATION OF PROPOSED GENERALISED STORAGE-YIELD-RELIABILITY RELATIONSHIPS

7.1. Verification of Models

Verification by assessing derived storage-yield-reliability relationships using an independent data set is important in the development of models as it enhances the confidence with which proposed models can be used. In this study model verification was carried out using two randomly selected rain gauges not utilised in the development of the regression models. Table 7-1 presents the general description of the gauges used whilst Figure 7-1 shows their approximate locations within South Africa.

Table 7-1: Gauge characteristic for rain gauges used in verification

Gauge ID	Years on record	MAP (mm/yr)	Rainfall peak (day)	CV	n_r (days)	n_d (days)
0677834W	96	485	357	4.26	50	315
0477309W	107	681	14	3.38	70	295

CV: coefficient of variation of daily rainfall, n_r: number of rainy days n_d: number of dry days

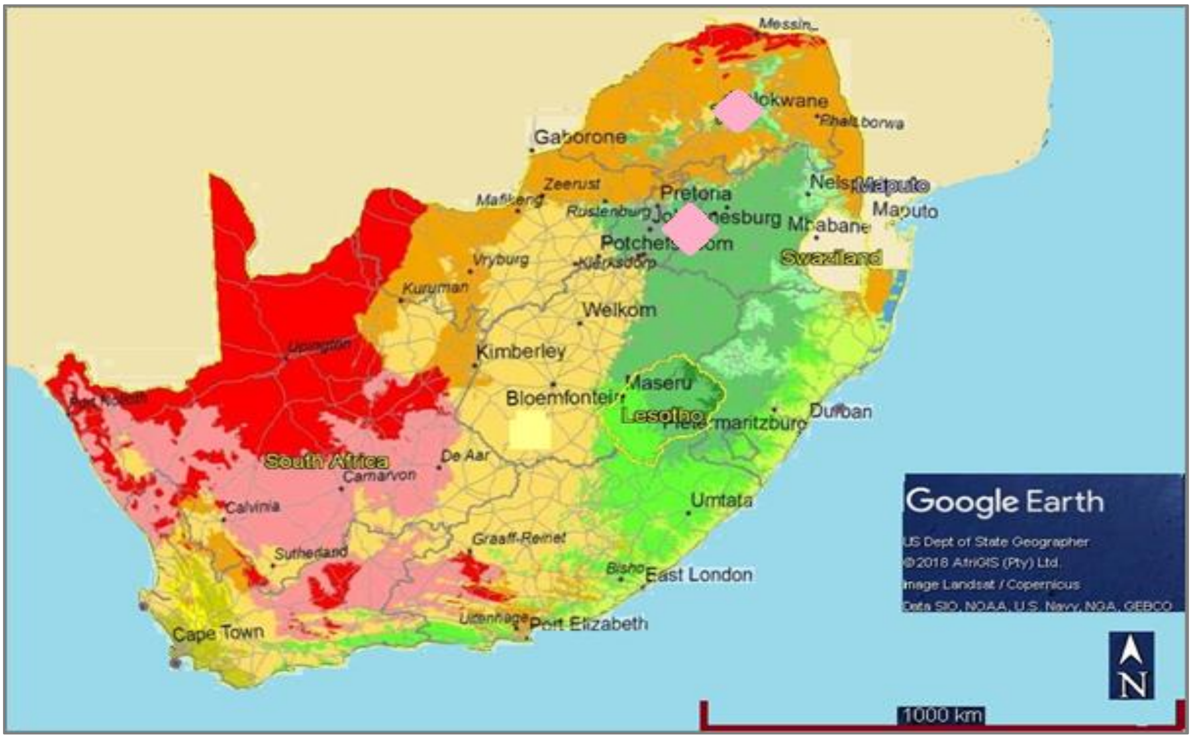


Figure 7-1: Location of rain gauges used in the verification exercise (Image created using Google Earth Pro (2018))

The verification was done on a test case of regional shopping malls. A survey of the shopping centre directory for southern Africa (SACSC, 2015) allowed for the determination of an average floor area typical of a regional shopping centre in South Africa as **69 891m^2**. The annual water demand per square meter for such a shopping centre was assumed to be of a similar magnitude to that of the data presented in Saunders (2012) which comes to approximately **1.347m^3/m^2/year**. Catchment sizes which provided S-D ratios of 0.2, 0.6 and 0.8 as input to the models were determined. The water collection efficiency coefficient was maintained at 0.8.

Three cases were tested as follows:

- Constant unvaried demand without first flush
- Constant unvaried demand with first flush of 1mm
- Variable demand with peak in demand set to the middle of December (peak day 351) and amplitude set to 0.7

The results obtained using the models shown below for an independent set of rain gauges were compared to the results obtained from the simulation of the two gauges.

$$\boldsymbol{S_{p-r} = \frac{N_r}{365.25} = \alpha(R_{SD})^{\beta}}$$

Where: **(4-7)**

$\alpha = 1.362(1-r)^{0.207}$ $\qquad$ $\boldsymbol{0.5 \leq r \leq 0.95}$

$\beta = 1.769e^{-0.445(1-r)}$

Where: $\boldsymbol{S_{p-r}}$ is the yield ratio, $\boldsymbol{N_r}$ is the expected number of days of rainwater supply per year, $\boldsymbol{R_{SD}}$ is the supply to demand ratio, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are coefficients of regression and $\boldsymbol{r}$ is the reliability.

$$\boldsymbol{R_{TD-r} = \gamma e^{\varphi(S_{p-r})}}$$

Where for $\boldsymbol{amplitude\ of\ demand = 0}$: **(4-8)**

$\gamma = 0.009e^{1.005(1-r)}$ $\qquad$ $\boldsymbol{0.5 \leq r \leq 0.95}$

$\varphi = 8.207e^{-0.996(1-r)}$

Where: $\boldsymbol{S_{p-r}}$ is the yield ratio, $\boldsymbol{R_{TD-r}}$ is the storage-demand ratio, $\boldsymbol{\gamma}$ and $\boldsymbol{\varphi}$ are coefficients of regression, and $\boldsymbol{r}$ is the reliability.

If rainfall characteristics are included then:

$$S_{p-r} = \frac{N_r}{365.25} = d(R_{SD})^e \cdot \left(\frac{n_d}{n_r}\right)^f$$

Where:

$d = 0.719e^{0.447(1-r)}$

$e = 1.38(1-r)^{-0.086}$ $\quad 0.5 \le r \le 0.95$ **(4-9)**

$f = 0.074\ln(1-\mathrm{r}) + 0.2344$

Where: S_{p-r} is the yield ratio, N_r is the expected number of days of rainwater supply per year, R_{SD} is the supply to demand ratio, d, e and f are coefficients of regression, n_d is the number of dry days per year, n_r is the number of rainy days per year and r is the reliability.

$$R_{TD-r} = \delta e^{b(S_{p-r})} \cdot CV^c$$

Where:

$\delta = 0.0004e^{4.361(1-r)}$

$b = 8.624e^{-1.13(1-r)}$ $\quad 0.5 \le r \le 0.95$ **(4-10)**

$c = 2.339e^{-1.327(1-r)}$

Where: S_{p-r} is the expected number of days of rainwater supply per year, R_{TD-r} is the storage-demand ratio, δ, b and c are coefficients of regression, CV is the coefficient of variation of daily rainfall, and r is the reliability.

$$\frac{N_{vd-r}}{N_r} = e^{\lambda(a)}$$

Where for $0 < a \le 1$, $\quad 0 \le \frac{L}{365.25} \le 0.5$, $\quad 0.3 \le R_{SD} \le 0.9$: **(5-2)**

$\lambda = A\left(\frac{L}{365.25}\right) + B$

$A = c_1 ln(R_{SD}) + d_1$ $\qquad B = c_2 R_{SD} + d_2$

$$\boldsymbol{for\ 0.5 \le r \le 0.95}$$

$c_1 = 0.195 \ln(1-r) - 0.825 \qquad d_1 = -0.613(1-r) + 0.277$

$c_2 = -0.092 \ln(1-r) - 0.517 \qquad d_2 = 0.425(1-r)^{0.262}$

Where: $\boldsymbol{N_{vd-r}}$ is the expected number of days of supply at reliability $\boldsymbol{r}$**,** $\boldsymbol{N_r}$ is the expected number of days of supply under constant demand at reliability $\boldsymbol{r}$ as given by Equation 4-7 or 4-9**,** $\boldsymbol{a}$ is the amplitude of variable demand computed using Equation 3-3 **,** $\boldsymbol{L}$ is the lag computed using Equation 3-14, $\boldsymbol{R_{SD}}$ is the supply-demand ratio and $\boldsymbol{r}$ is the reliability.

$$\boldsymbol{R_{TD-r} = a_{vd} e^{b_{vd}\left(\frac{N_{vd-r}}{365.25}\right)} \cdot CV^{c_{vd}}}$$

Where for $\boldsymbol{0 < a \le 1\ and\ 0 \le \frac{L}{365.25} \le 0.5}$**:** **(5-3)**

$a_{vd} = 0.0008e^{3.23(1-r)}$
$b_{vd} = 7.69e^{-0.841(1-r)}$ $\qquad \boldsymbol{0.5 \le r \le 0.95}$
$c_{vd} = 1.74e^{-1.25(1-r)}$

Where: $\boldsymbol{N_{vd-r}}$ is the expected number of days of supply**,** $\boldsymbol{CV}$ is the coefficient of variation of daily rainfall, $\boldsymbol{R_{TD-r}}$is the storage –demand ratio at reliability $\boldsymbol{r}$**.**

If rainfall characteristics are not included then:

$$\boldsymbol{R_{TD-r} = \gamma_{vd} e^{\varphi_{vd}\left(\frac{N_{vd-r}}{365.25}\right)}}$$

Where for $\boldsymbol{0 < a \le 0.7\ and\ 0 \le L \le 0.5}$**:** **(5-4)**

$a_{vd} = 0.007e^{1.15(1-r)}$
$b_{vd} = 7.65e^{-0.82(1-r)}$ $\qquad \boldsymbol{0.5 \le r \le 0.95}$

It needs to be recalled that uni-variable refers to the models that do not incorporate rainfall characteristics i.e. Equations 4-7, 4-8 and 5-4 whilst multi-variable refers to the models incorporating rainfall characteristics i.e. Equations 4-9, 4-10 and 5-3. Equation 5-2 incorporates the two forms through $\boldsymbol{N_r}$.

For the first case of a constant demand without first flush, Figures 7-2 to 7-7 illustrate the variation of yield and storage with reliability with increasing S-D ratio.

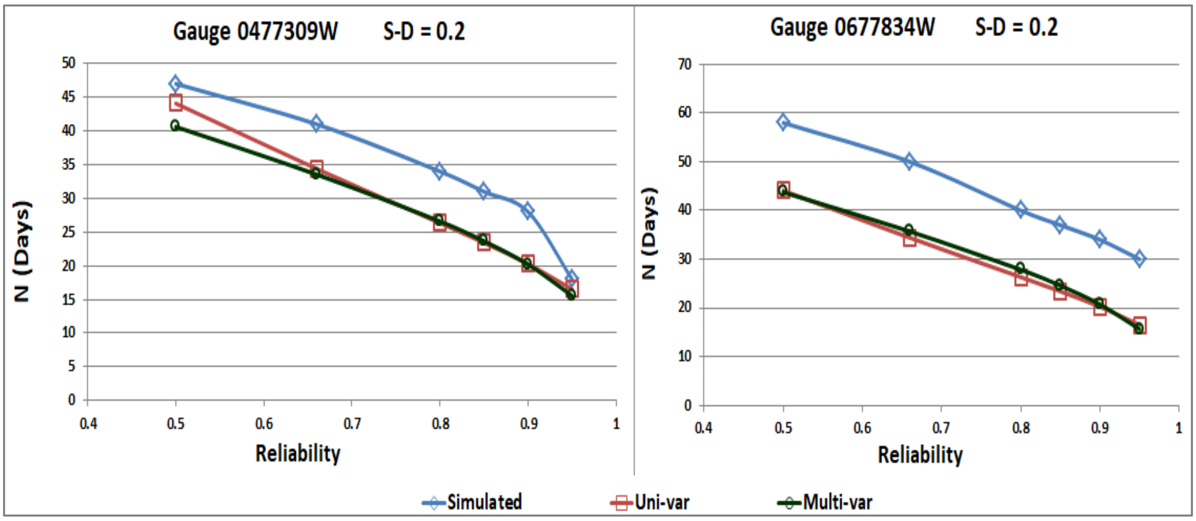


Figure 7-2: Variation of number of days of supply with reliability at S-D of 0.2 under constant demand

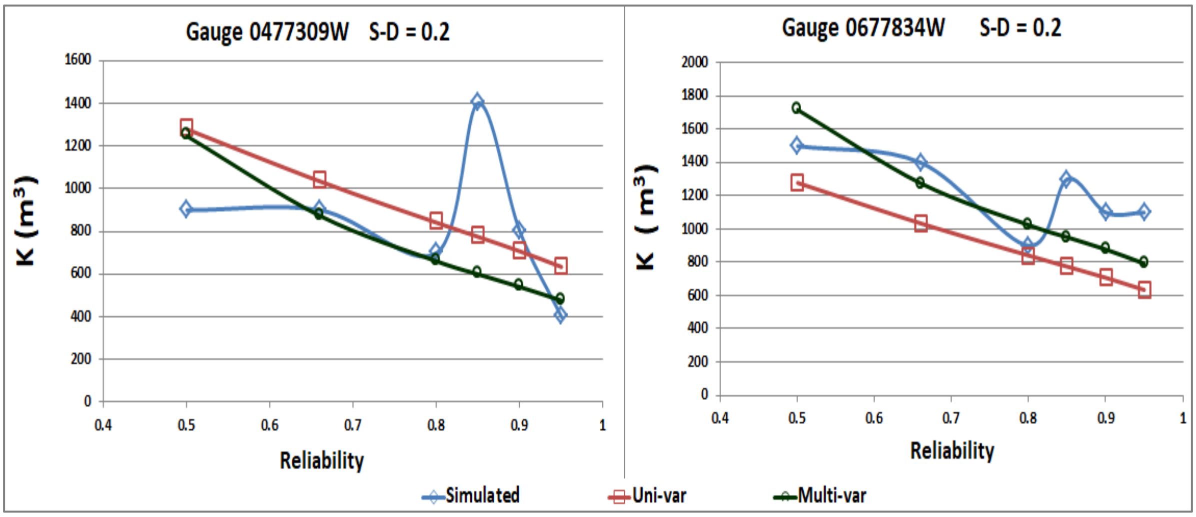


Figure 7-3: Variation of tank size with reliability at S-D of 0.2 under constant demand

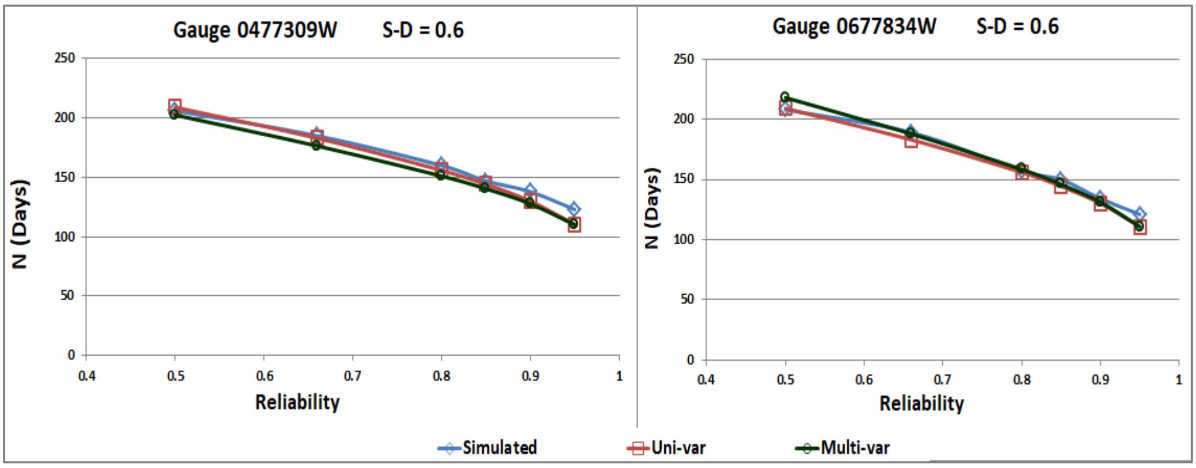


Figure 7-4: Variation of number of days of supply with reliability at S-D ratio 0.6 under constant demand

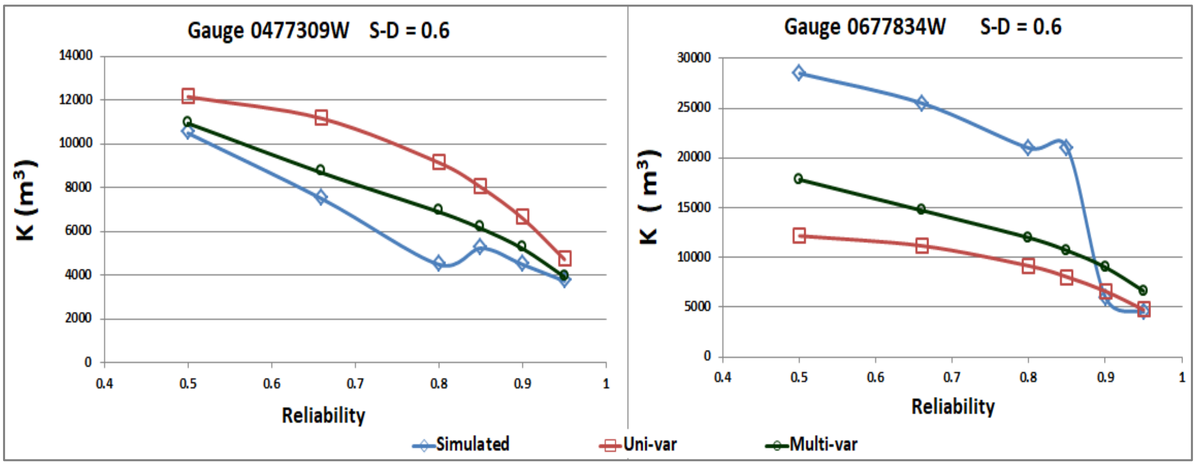


Figure 7-5: Variation of tank size with reliability at S-D ratio 0.6 under constant demand

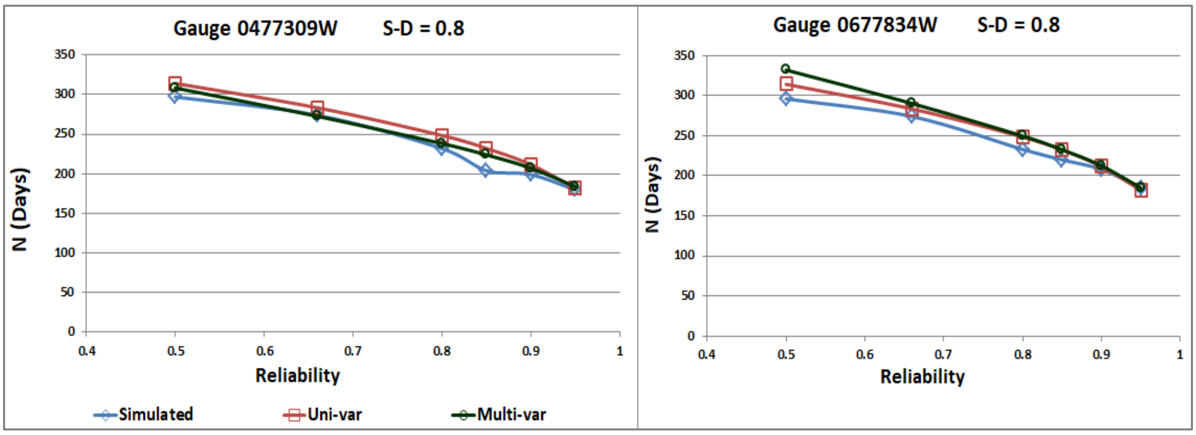


Figure 7-6: Variation of number of days of supply with reliability at S-D ratio 0.8 under constant demand

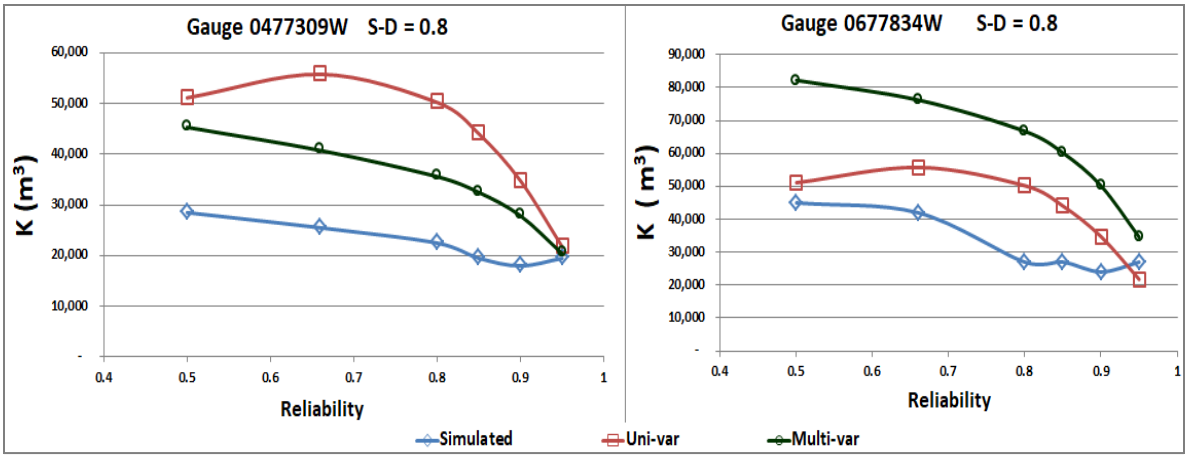


Figure 7-7: Variation of tank size with reliability at S-D ratio 0.8 under constant demand

From the plots presented before, it is observed that the performance of the models tends to improve with increasing S-D ratio with regard to predicting the number of days of supply. However, at the higher S-D ratios (above 0.8) both models tend to over-predict these values. Comparison between the regression models themselves reveals that they predict near identical number of days of supply and the multi-variable model under-predicts the number of days of supply more than the uni-variable model at the lowest S-D ratio. Analysing the prediction of tank size by the regression models also revealed relatively good performance at the lowest S-D ratio; however, the graphs do show the models inclination to over-predict the tank size at high S-D ratios. The multi-variable model out-performs the uni-variable model where tank sizing is concerned.

While the regression models capture the general trend in the simulation results very well, the optimum tank sizes from simulation exhibit highly variable behaviour (as was also found by Ndiritu et al., (2017)).This is considered to be an indication of the inadequacy of using a single rainfall time series to obtain storage-yield-reliability relationships. Stochastic rainfall sequences may be used to resolve the problem but this is beyond the scope of the current study.

The results of the second case where a RWHS operates under a constant demand and with a design first flush depth of 1mm are illustrated in Figures 7-8 to 7-13 in order of increasing S-D ratio.

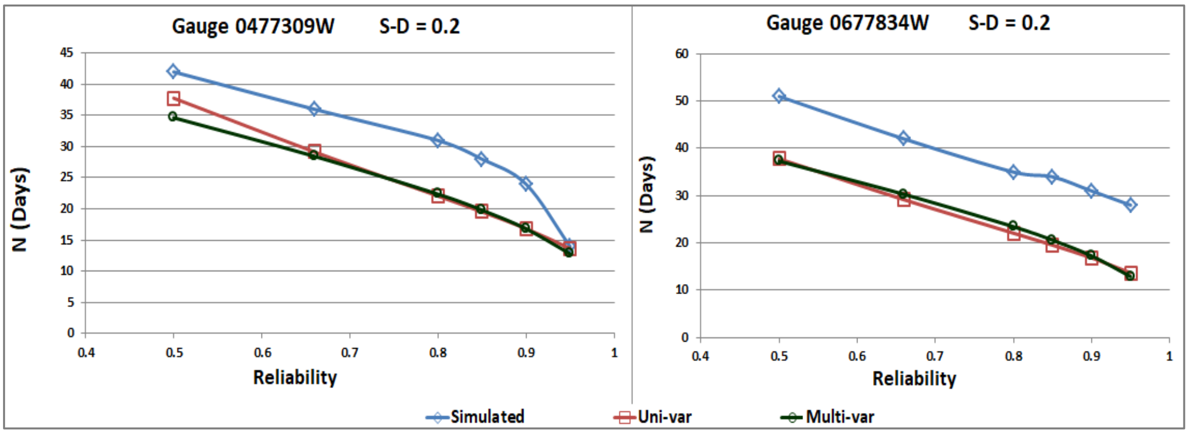


Figure 7-8: Variation of number of days of supply with reliability at S-D ratio 0.2 under constant demand and FF = 1mm

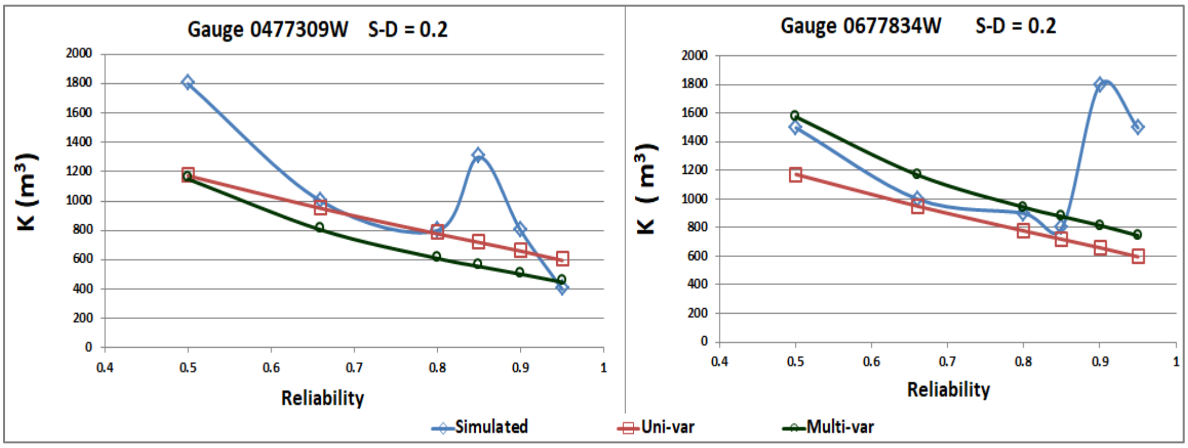


Figure 7-9: Variation of tank size with reliability at S-D ratio 0.2 under constant demand and FF = 1mm

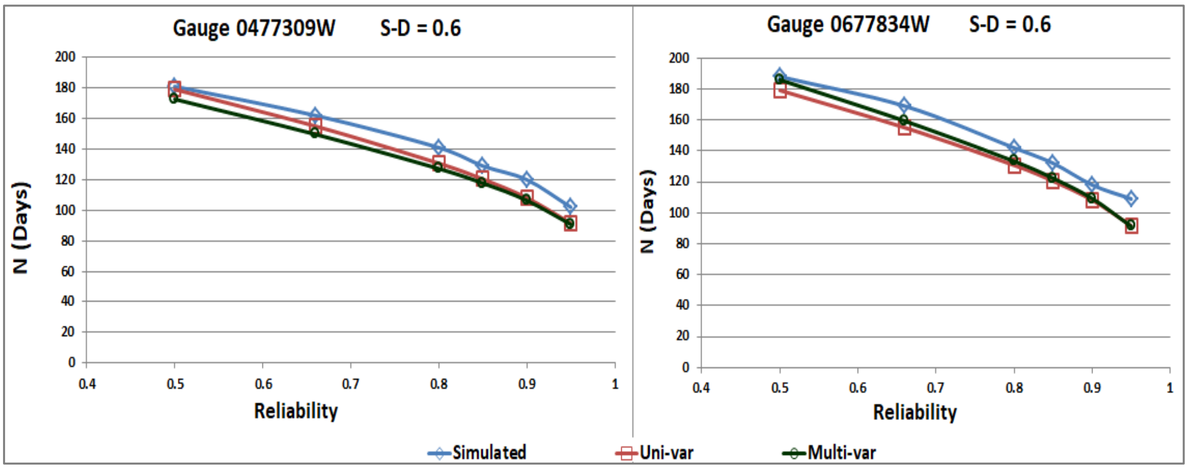


Figure 7-10: Variation of number of days of supply with reliability at S-D ratio 0.6 under constant demand and FF = 1mm

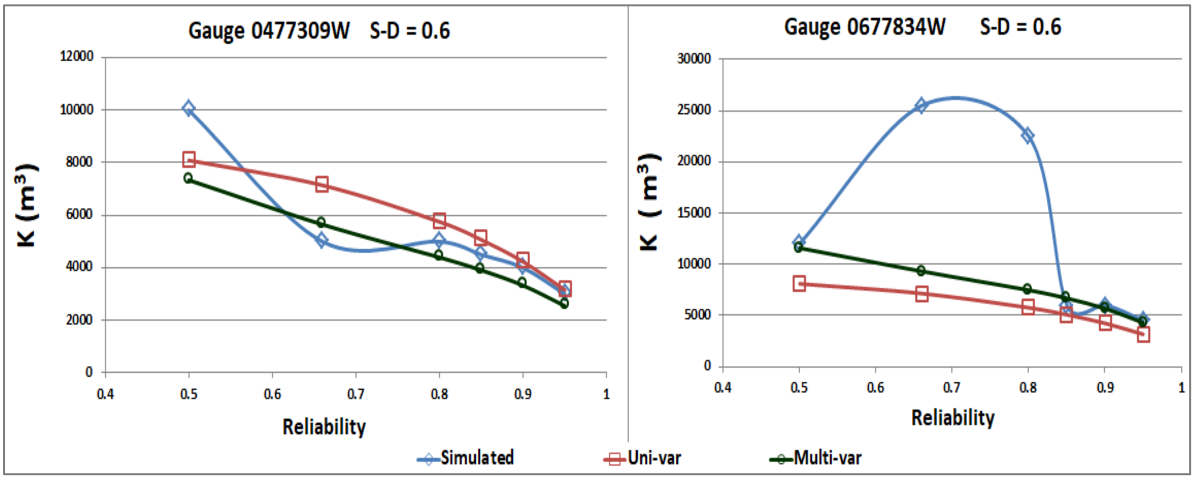


Figure 7-11: Variation of tank size with reliability at S-D ratio 0.6 under constant demand and FF = 1mm

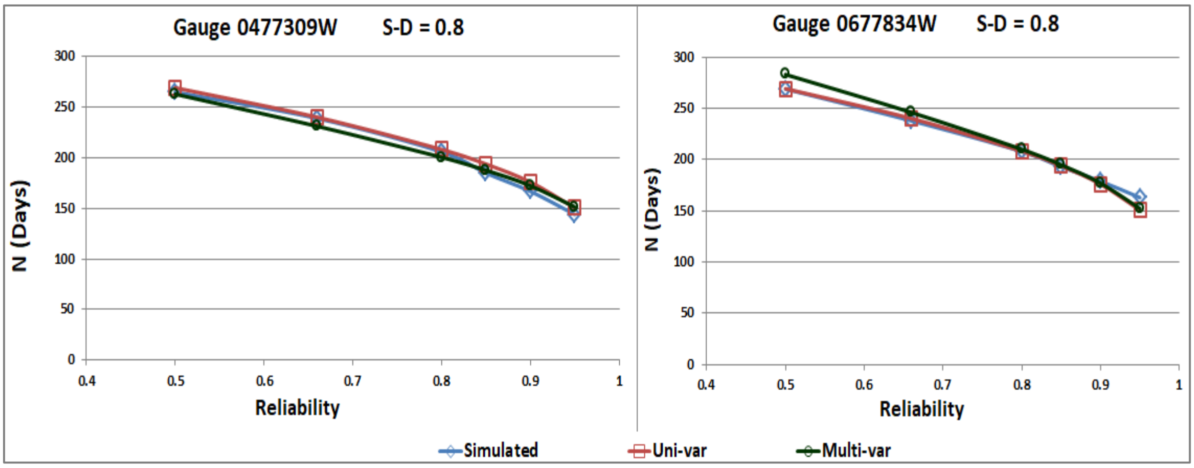


Figure 7-12: Variation of number of days of supply with reliability at S-D ratio 0.8 under constant demand and FF = 1mm

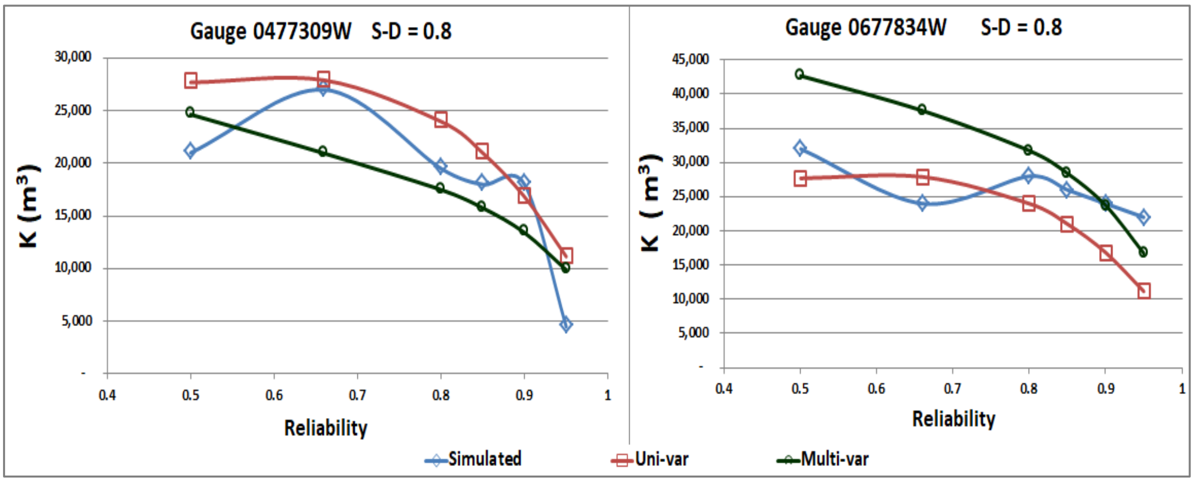


Figure 7-13: Variation of tank size with reliability at S-D ratio 0.8 under constant demand and FF = 1mm

It was observed from Figures 7-8 to 7-13 that the yield regression models performed satisfactorily across the S-D ratios although they tend to under-estimate the number of days of supply. With respect to the tanks size, the models also performed relatively well and mirrored the observed trend in the simulated data well; however, as previously noted, the instability of simulated values persists even in this data set.

The third scenario tested in the verification exercise was a RWHS operating under a variable demand with first flush set to zero. Figures 7-14 to 7-19 illustrate the number of days of supply and corresponding tank size results from the analysis.

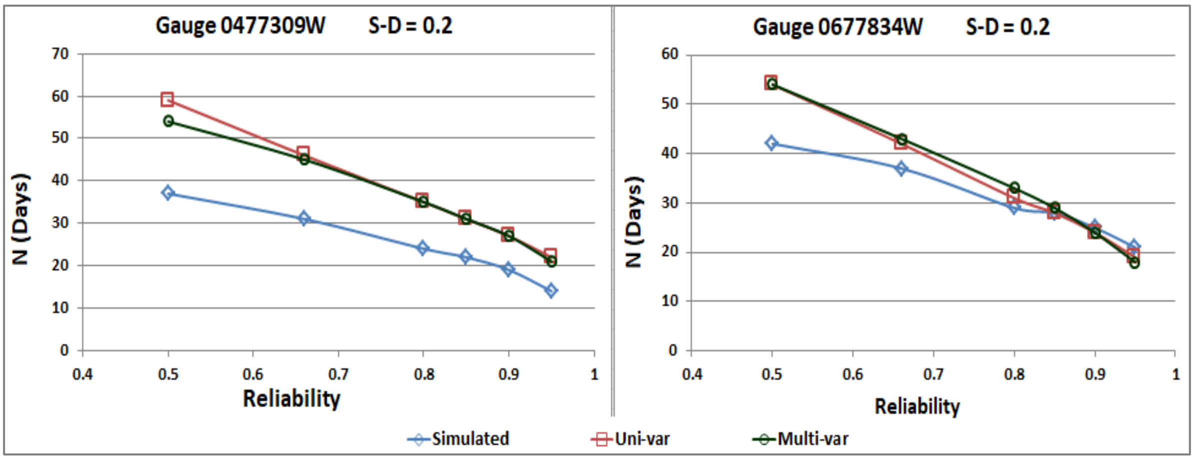


Figure 7-14: Variation of number of days of supply with reliability at S-D ratio 0.2 under variable demand

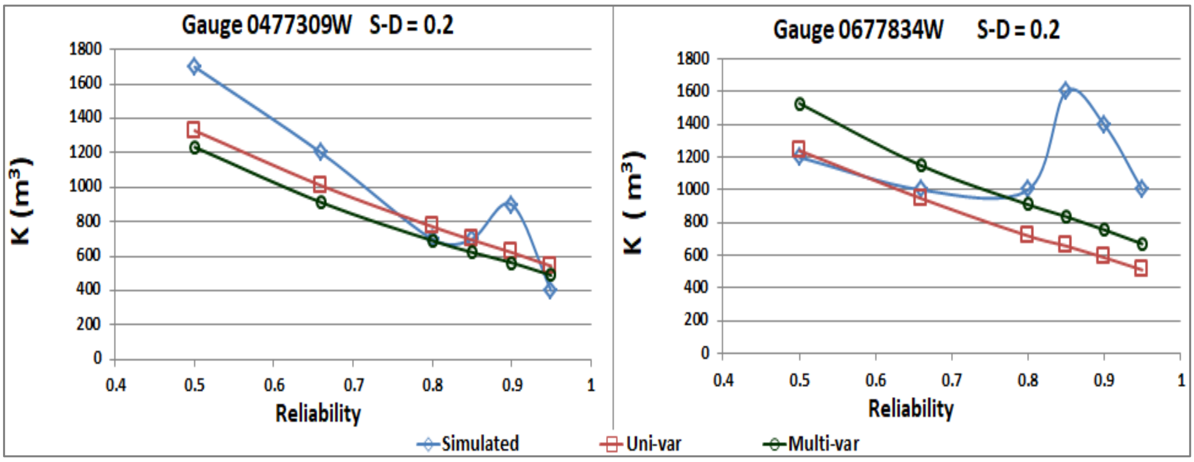


Figure 7-15: Variation of tank size with reliability at S-D ratio 0.2 under variable demand

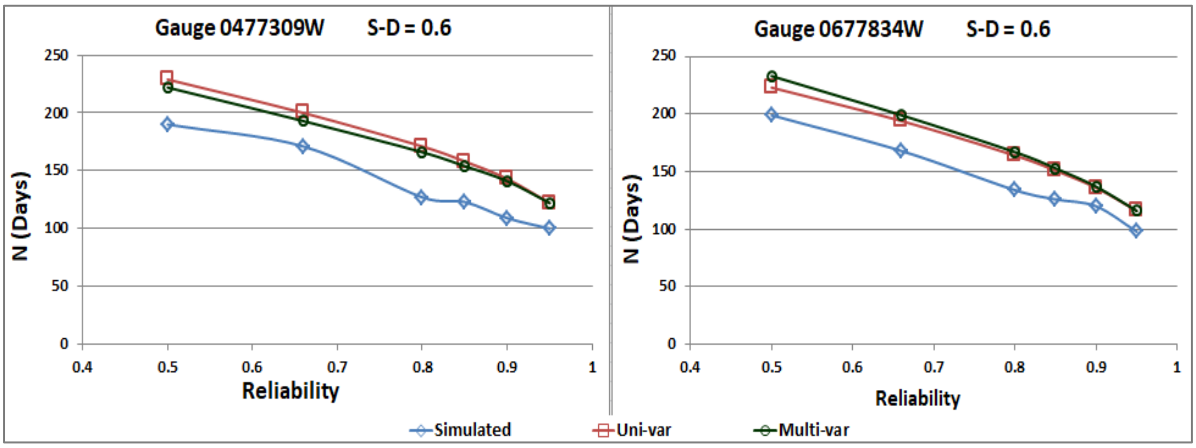


Figure 7-16: Variation of number of days of supply with reliability at S-D ratio 0.6 under variable demand

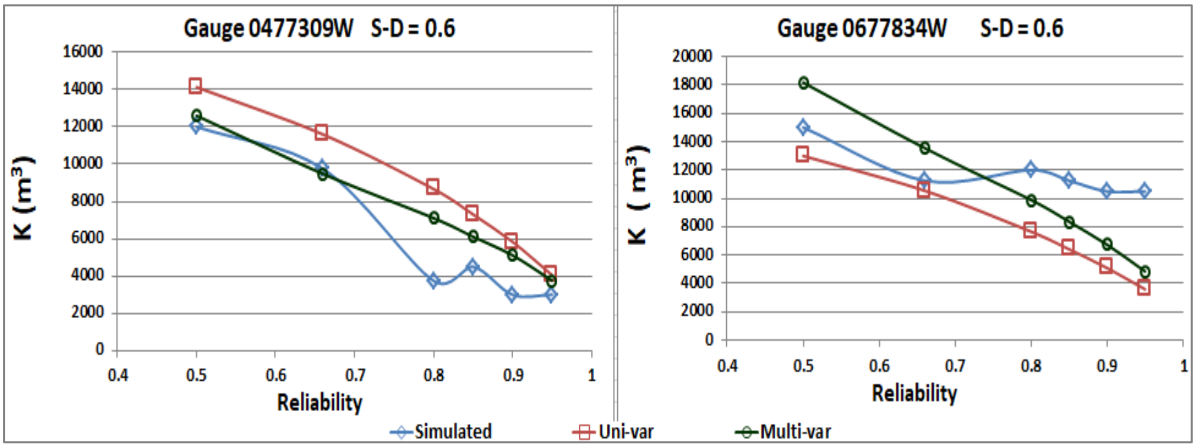


Figure 7-17: Variation of tank size with reliability at S-D ratio 0.6 under variable demand

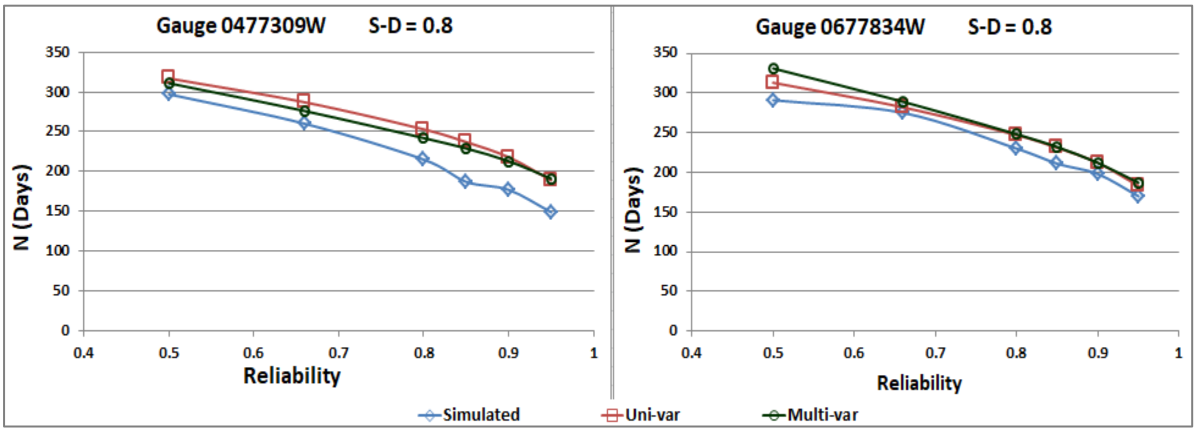


Figure 7-18: Variation of number of days of supply with reliability at S-D ratio 0.8 under variable demand

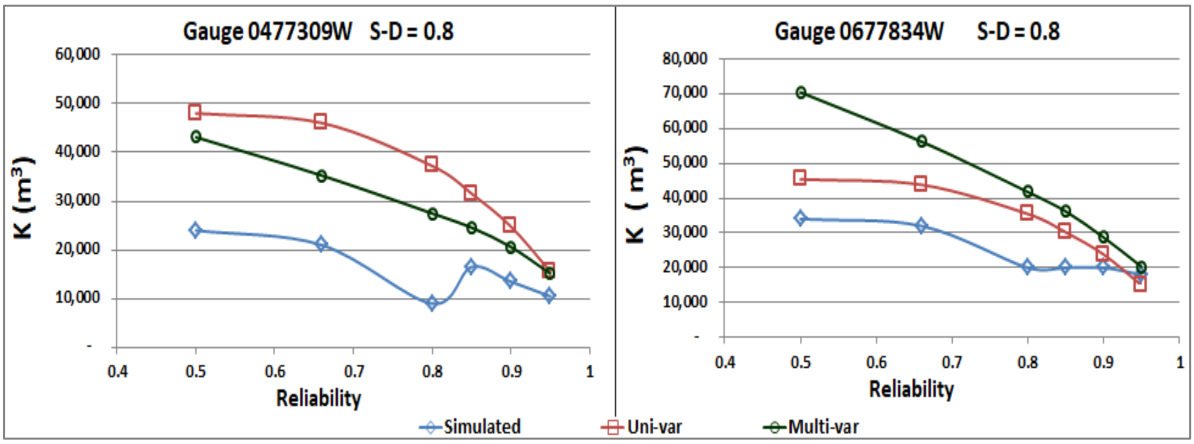


Figure 7-19: Variation of tank size with reliability at S-D ratio 0.8 under variable demand

With respect to the number of days of supply it was seen that for both gauges that the two types of model over-predict the simulated results across the S-D ratios and reliabilities. The corresponding tank sizes revealed a more mixed result with the models in some instances over-predicting and in other instances under predicting the optimum tank size. Overall, the uni-variable model performs better than the multi-variable model.

7.2. Worked Example of Model Application

An example of the practical application for the models is presented as follows:

A potential user wishes to understand the options available should they choose to invest in a domestic RWHS in a part of South Africa which on average receives 650mm of rainfall per annum and whose rainfall season typically peaks in the middle of January (peak day 15). An average of 70 rain days per annum is observed alongside a coefficient of variation in daily rainfall of 3.5. The RWHS will operate under variable demand with the peak in demand expected to occur in the middle of the year (peak day of 180). The maximum daily demand from the system is estimated to be $0.5m^3$/day with the annual average demand expected to be

$0.3m^3$/day; the user wishes the system to operate with a reliability of 80% ($\boldsymbol{r}$ = 0.8). The catchment area available to the user is a $120m^2$ pitched tile roof with a water collection efficiency of 0.9. No first flush devices will be employed.

From Equation 3-1:

$$R_{SD} = \frac{\eta A\bar{R}}{\overline{D_t}}$$

Where: $\boldsymbol{\eta}$ = 0.9, $\boldsymbol{A}$ =120, $\bar{\boldsymbol{R}} = \frac{650}{365.25\times1000}$ and $\overline{\boldsymbol{D_t}} =$ 0.3

$$\Longrightarrow \qquad \boldsymbol{R_{SD}} = \mathbf{0.64}$$

From Equation 4-9:

$$\frac{n_d}{n_r} = \frac{(366-70)}{70} = 4.23$$

$$d = 0.719exp^{[0.447(1-0.8)]} \qquad \Rightarrow \qquad d = 0.786$$

$$e = 1.38(1-0.8)^{-0.086} \qquad \Rightarrow \qquad e = 1.58$$

$$f = 0.074\ln(1-0.8) + 0.23 \qquad \Rightarrow \qquad f = 0.11$$

$$N_r = \left[d \times R_{SD}^{e} \times (\tfrac{n_d}{n_r})^f\right] \times 365.25$$

$$\Longrightarrow \qquad \boldsymbol{N_r = 166.5\ days\ per\ annum}$$

From Equation 5-2:

$$\frac{Lag}{365.25} = \left|\frac{15-180}{365.25}\right| \qquad \Longrightarrow \qquad \frac{L}{365.25} = 0.45$$

$$a = \frac{0.5-0.3}{0.3} \qquad \Longrightarrow \qquad a = 0.67$$

$$c_1 = 0.195\ln(1-0.8) - 0.83 \qquad \Longrightarrow \qquad c_1 = -1.14$$

$$c_2 = -0.092\ln(1-0.8) - 0.52 \qquad \Longrightarrow \qquad c_2 = -0.372$$

$$d_1 = -0.613(1-0.8) + 0.28 \qquad \Longrightarrow \qquad d_1 = 0.157$$

$$d_2 = 0.42(1-0.8)^{0.262} \qquad \Longrightarrow \qquad d_2 = \ 0.275$$

$$A = c_1\ln(R_{SD)} + d_1 \qquad \Longrightarrow \qquad A = 0.666$$

$$B = c_2(R_{SD}) + d_2 \qquad \Longrightarrow \qquad B = 0.0369$$

$\lambda = A\left(\frac{L}{365.25}\right) + B \qquad \Longrightarrow \qquad \lambda = 0.337$

$N_{vd-r} = (1 \times exp^{\lambda a}) \times N_r$

$$\Longrightarrow \qquad \boldsymbol{N_{vd-r} = 208\ days\ per\ annum}$$

This translates to the proposed RWHS being able to supply just under 7-months' worth of water per year against the imposed demands

From Equation 5-3:

$a_{vd} = 0.0008exp^{3.23(1-0.8)} \qquad \Longrightarrow \qquad a_{vd} = 0.00153$

$b_{vd} = 7.69exp^{-0.841(1-0.8)} \qquad \Longrightarrow \qquad b_{vd} = 6.499$

$c_{vd} = 1.74exp^{-1.25(1-0.8)} \qquad \Longrightarrow \qquad c_{vd} = 1.355$

$S_{p-r} = \frac{N_{vd-r}}{365.25} \qquad \Longrightarrow \qquad S_{P-r} = 0.569$

$R_{TD-r} = a_{vd} \times exp^{(b_{vd} \times S_{P-r})} \times CV^{C_{vd}} \qquad \Longrightarrow \qquad R_{TD-r} = 0.337$

From Equation 3-9:

$K = R_{TD-r} \times \overline{D}_t \times 365.25$

$$\Longrightarrow \qquad \boldsymbol{minimum\ tank\ size\ required} \qquad \boldsymbol{K = 36.9m^3}$$

Given that commercially available tanks sizes come in multiples of 0.5m^3 *(see* https://www.jojo.co.za/product-category/vertical-water-storage-tanks/)*, the user would need to invest in a minimum of 37m*^{3} *translating to 2 no. x 20m*^{3} *tanks provided the ground space is available. If the user finds that there is space for at most 5m*^{3} *the number of days of supply available falls to 95 days or just over 3-months' worth of water supply under the same demand and reliability scenario.*

Given that rainwater is likely to be used as supplementary source of water, if system reliability is reduced to 50% the user can expect to have rainwater supply over an average of 258 days per year under the same demand scenario but using a 50m^3 *tank; if relying on a 40m*^{3} *tank the number of days of supply reduce to 241 days and if relying on a 5m*^{3} *it further reduces to 91 days.*

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

The rapid growth of the global population and economic activity has made the global water resource base come under increasing pressure to satisfy growing and more varied demands. The rate of this increase has also outpaced the rate at which centralised water supply technologies can be implemented. This continued disjuncture between supply and demand has lead water resource managers and users to search for alternative means of utilising the available water resources. One such strategy that has received much renewed interest by stakeholders is the use of rainwater harvesting (RWH). It is viewed as one means to augment water supplies thereby curbing the level of demand on over-stretched centralised water supply systems. In spite of this, limitations still exist with regard to the efficacy of utilising RWH systems (RWHS) and these continue to hamper their widespread acceptance and implementation.

A big limitation to the investment in RWHS on a large scale appears to be the financial/economic cost of installing and maintaining the system at individual household level and this has led many researchers to study ways and means by which to make this technology more accessible to the end user. One branch of research has looked at design and assessment aspects of RWHS with a focus on the optimal sizing of a RWHS to ensure that it performs as required whilst minimising the initial cost of the system which is largely driven by the storage tank. However an examination of the literature showed only a limited effort in developing models or general design guidelines for southern Africa. A recent advancement is by Ndiritu et al., (2017) who developed generalised dimensionless relationships that relate i) the number of days of supply to the ratio of supply to demand; and ii) tank size to number of days of supply for systems operated at reliabilities of 85% up to 98%. Although the model was verified and found capable of producing dependable results, it was based on the simulated data from 14 rainfall gauging stations and assumed that the RWHS would operate under fixed constant demand. Further interrogation of the literature revealed that different types of model continue to be formulated by various researchers around the world; however, RWHS assessment models cannot truly be generic since observed performance is implicitly tied to the rainfall characteristics of the area under study. While some isolated investigations into the impacts of rainfall characteristics on the behaviour of RWHS have been done for South Africa, none of these studies have taken the step to incorporate these characteristics into a generalised model for the region. In addition, there has been limited study into the effects of variability in demand and first flush losses on the generalised modelling process. In light of these shortcomings, this study aimed to improve on the model proposed by Ndiritu et al., (2017) by:

i) Assessing the influence of using more rainfall gauging stations on system performance and regression relationships;
ii) Analysing the influence incorporating rainfall variability characteristics on the predictive performance of the generalised model
iii) Evaluating the impact to yield and storage of using a variable demand
iv) Assess the utility of developing generalised storage-yield-reliability relationships that can incorporate parameters used to describe variability in demand
v) Assess the effect of the first flush on system performance
vi) Examine the efficacy of incorporating this parameter as a variable in generalised storage-yield-reliability relationships.

To achieve the objectives of the study as highlighted above, 118 individual rainfall records captured in different parts of South Africa were selected and used in analysis. This set of rain gauges were further split into eleven zones that exhibit similarity in rainfall characteristics using the Köppen-Geiger classification system. Multiple simulations were carried out for each rain gauge using a daily time-step behavioural model, from which the maximum number of days of supply and the corresponding optimal tank size were obtained for a set of pre-defined ratios of average supply to average demand (S-D ratios) and reliabilities. Variability of demand was modelled using a wave function defined by two parameters: amplitude to quantify the range of variation of demand from the mean, and the lag to quantify the difference in time between the occurrence of the peak demand and the peak of the 61-day moving average rainfall. For this case, a smaller sample of 11 rain gauges was used.

Regarding objectives i) and ii), the key findings that can be drawn from results of this study include:

- Increasing the number of rain gauges used to develop the generalised model exposed the presence of variability in the behaviour of RWHS that is dependent on the characteristics of the rainfall where the rain gauge is located. On evaluation of the form of the model between the supply-demand ratio and yield ratio under constant demand, the power model proposed by Ndiritu et al., (2017) provided a suitable fit to the expanded data set whilst the form of relationship between the storage-demand ratio and the yield ratio was shown to be better described by an exponential curve when compared to the power model proposed by Ndiritu et al., (2017).
- Regression results suggest that models developed for zones exhibiting similar rainfall variability characteristics are more dependable than a lumped model that does not make this distinction. However, a comparison of the predictions made by the lumped regression model to regression models developed by grouping rain gauging stations into sets exhibiting similar rainfall characteristics revealed minor differences to simulated data – in some cases localised models were the better option but overall, the lumped model performed just as well. Incorporation

of the coefficient of variation of daily rainfall into the lumped model relating the storage–demand ratio to the yield ratio through multiple linear regressions resulted in some improvements to the coefficient of determination. In contrast, incorporating the ratio of dry days to rainy days brought very little improvement to the coefficient of determination of the regression model relating the yield ratio to the supply-demand ratio. However the inclusion of a characteristic of rainfall was shown to be justified through the observation that the single-value prediction of a model without rainfall characteristics does not realistically emulate the variability shown through simulation.

The key finding drawn from this analysis is that, although a simpler model that uses the mean annual precipitation (MAP) as its only hydrological input appears to predict simulation data better, a model that accounts for rainfall's intra-annual and inter-annual variability offers greater advantage of being able to distinguish the behavioural nuances of two systems that describe identical supply-demand ratios but whose rainfall regimes exhibit vastly different distributive characteristics. The critical downside to this is that this extended model incorporating rainfall characteristics requires additional data that may not be easily accessible to the modeller, limiting it use in practice. A re-evaluation of the relationships between the yield ratio and rainfall characteristics is required for the case of a RWHS operating under constant demand. In addition to this, the analysis could look into extending the assessments at climate zone level through more balanced sampling of rain gauges across the different climate zones coupled with the re-evaluation of the multi-variable model to analyse the impact of incorporating other rainfall variability characteristics such as the antecedent dry weather period and precipitation concentration index on model performance

Regarding objectives iii) and iv), the main findings drawn from results of this study include:

- The number of days of supply from a RWHS operating under a variable demand are significantly influenced by both the separation in time of the peaks of rainfall and demand (i.e. the lag) and the amplitude of the demand; this value is also to some extent also affected by the order of peaking i.e. whether demand peaks before rainfall or whether rainfall peaks before demand. The degree of impact of variability in demand is also dependent on the degree of seasonality in the rainfall with areas with distinctly seasonal rainfall tending to be a lot more sensitive to variations in the demand than areas that exhibit low seasonality in rainfall. The corresponding optimum tank size is not as directly impacted by these two parameters. In the case of large shifts in the number of days of supply additional work could be done to analyse whether the same shifts occur if the volumetric yields are considered instead of the number of days of supply
- Regression relationships could be established between the number of days of supply under variable demand (normalised by the number of days of supply

under constant demand), the amplitude, the normalised lag, the supply-demand ratio and reliability. Normalising the number of days of supply under variable demand with the number of days of supply under constant demand allowed the incorporation of demand variability into the generalized model. However, a critical observation from the regressions was what appears to be a diminished influence of rainfall characteristics for the lag values tested with the exception being for a lag of 0. While this allowed for the development of a simpler model, this has meant that the current model will not always replicate the behaviour of a RWHS especially when the lag between peaks is zero. With regard to relationships between the tank size, number of days of supply, reliability, lag and amplitude, the modelling process revealed that the parameters of variable demand i.e. amplitude and lag, may not need to be directly integrated into a new model. Instead it is possible to use an identical form of model to that developed under the constant demand scenarios to relate the storage-demand ratio to the yield ratio, the coefficient of variation of daily rainfall and reliability – the differences arise in coefficient values for each different case. The analysis of variability of demand has led to the formulation of a yield model that incorporates the parameters of variable demand to determine the yield ratio.

The generalised model that accounts for the effects of variations in demand enables a more realistic assessment of RWHS design and operation. However, the development of this component of the modelling has been developed for a limited range of lag values (0 to 0.5 of a year) using a relatively small sample of 11 rainfall stations. Given the broad range of rainfall regimes within the country, it is imperative that additional rainfall gauging stations be applied to verify and possibly improve the proposed relationships. In addition, more clarity is required on how rainfall characteristics are influencing the RWHS behaviour as variability of demand changes. Future work should also look to developing models for the range of lag values lying between 0.5 and 1.

This study developed the model based on a smooth continuously varying demand. Thus future work could also look at quantifying the effects of other types of demand variation such as multiple peaks in demand. Further studies could also use actual measured water consumption and stochastically derived data in place of trigonometric distribution used in this study.

Regarding objectives v) and vi), the main findings drawn from results of this study include:

- Rainwater losses due to the first flush can have significant impacts to the number of days of supply that can be obtained from a RWHS. These losses can be incorporated explicitly into the model by simply adjusting the rainfall supply using an equivalent "mean annual daily first flush" derived from the desired/design flush depth and expected number of rainy days per year. This adjustment to the rainfall supply resulted in the regression models tends to overestimate the number of days of supply and tank size at the current recommended flushing depth of 0.2mm for South Africa but as flushed depth increases, the model appears to perform satisfactorily

The key finding from analysis is that it is possible to explicitly integrate first flush into generalised models. The incorporation of first flush losses in this manner offers a simple method to assess the comparative benefits of improvement in water quality that result from first flush to the losses in flushing out the water.

Additional recommendations for future studies include:

- Results from simulation revealed some instability in the optimal storage values that maximise the yield with increasing reliability, thus additional work is still required to prevent these instabilities and improve the performance of the modelling. It may prove worthwhile to apply large ensembles of stochastically derived rainfall data to improve the determination of optimal storages. In addition to this, there is scope for the incorporation of additional criteria like cost of the system to refine the choice of optimal values of tank size.
- Assessment of the impact to the generalized model if the computational time step is reduced from daily to sub-daily especially for RWHS with a small storage and a high demand i.e. situations represented by supply-demand fractions below 0.2.
- The assessment of the behaviour of RWHS when multiple tank units are utilised coupled with the development of predictive relationships for such situations. In addition, generalisations could also be done to accommodate the case of non-optimal operation of RWHS in concert with the establishment of confidence intervals for multi-variable relationships.

REFERENCES

Abbasi, T. & Abbasi, S.A. (2011) Sources of Pollution in Rooftop Rainwater Harvesting Systems and their Control. *Critical Reviews in Environmental Science and Technology*, 41 (23), pp.2097–2167.

Abdulla, F.A. & Al-Shareef, A.W. (2009) Roof Rainwater Harvesting Systems for Household Water Supply in Jordan. *Desalination*, 243, pp.195–207.

ABS (2013) Environmental Issues: Water use and Conservation [Internet]. Available from: <http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/4602.0.55.003main+features4Mar%202013> [Accessed 5 February 2018].

Adeniyi, I.F. & Olabanji, I.O. (2005) The Physico-Chemical and Bacteriological Quality of Rainwater Collected Over Different Roofing Materials in Ile-Ife, Southwestern Nigeria. *Chemistry and Ecology*, 21 (3), pp.149–166.

Aladenola, O.O. & Adeboye, O.B. (2010) Assessing the Potential for Rainwater Harvesting. *Water Resources Management*, 24, pp.2129–2137.

Allen, J. (2013) Tank Sizing from Rainfall Records for Rainwater Harvesting Under Constant Demand. M.Ing. (Civil Engineering Science. Johannesburg, South Africa, University of Johannesburg. Available from: <https://ujcontent.uj.ac.za/vital/access/manager/Repository/uj:7459?f0=sm_subject%3A%22Water-supply%22> [Accessed 8 February 2018].

Allen, J. & Haarhoff, J. (2015) A Proposal for the Probabilistic Sizing of Rainwater Tanks for Constant Demand. *Journal of the South African Institution of Civil Engineering*, 57 (2), pp.22–27.

Alvisi, S., Franchini, M. & Marinelli, A. (2007) A Short-Term Pattern-Based Water Demand Forecasting Model. *Journal of Hydroinformatics*, 09 (1), pp.39–50.

Amos, C.C., Rahman, A. & Gathenya, J.M. (2016) Economic Analysis and Feasibility of Rainwater Harvesting Systems in Urban and Peri-Urban Environments: A Review of the Global Situation with a Special Focus on Australia and Kenya. *Water*, 8 (4).

Andrade, L.R., Maia, A.G. & Lucio, P.S. (2017) Relevance of Hydrological Variables in Water-Saving Efficiency of Domestic Rainwater Tanks: Multivariate Statistical Analysis. *Journal of Hydrology*, pp.163–171.

Anon (2016) Greener Retail at Menlyn Park Shopping Centre [Internet]. Available from: <http://www.earthworksmagazine.co.za/greener-retail-at-menlyn-park-shopping-centre/> [Accessed 2 February 2018].

Anon (2015) Mall of Africa an enticing retail Proposition at 90% let [Internet]. Available from: <http://www.atterbury.co.za/mall-of-africa-an-enticing-retail-proposition-at-90-let/> [Accessed 2 February 2018].

Aurecon (2011) Aurecon's office building achieves first 5 Star Green Star SA Rating in South Africa [Internet]. Available from: <https://www.aurecongroup.com/en/about/latest-news/2011/jul/aurecons-office-building-achieves-first-5-star-green-star-sa-rating-in-south-africa.aspx> [Accessed 8 February 2018].

Bach, P.M., McCarthy, D.T. & Deletic, A. (2010) Redefining the Stormwater First Flush Phenomenon. *Water Research*, 44, pp.2487–2498.

Basinger, M., Montalto, F. & Lall, U. (2010) A Rainwater Harvesting System Reliability Model based on Non-parametric Stochastic Rainfall Generator. *Journal of Hydrology*, 392, pp.105–118.

Basson, M.S., Allen, R.B., Pegram, G.G.S. & van Rooyen, J.A. (1994) *Probabilistic Management of Water Resource and Hydropower systems*. USA, Water Resources Publications.

Becciu, G., Raimondi, A. & Dresti, C. (2018) Semi-probabilistic Design of Rainwater Tanks: A Case Study in Northern Italy. *Urban Water Journal*, 15 (3), pp.192–199.

Bertrand-Krajewski, J., Chebbo, G. & Saget, A. (1998) Distribution of Pollutant Mass vs Volume in Stormwater Discharges and the First Flush Phenomenon. *Water Resources*, 32 (8), pp.2341–2356.

Boers, T.M. & Ben-Asher, J. (1982) A Review of Rainwater Harvesting. *Agricultural Water Managment*, 5, pp.145–158.

Boulware, E.W., Pope, T., Lye, D., Kniffen, B.A., Wheeler, J., Morris, W., Jennings, R., Shultz, J., Winters, W.E., Daily, C. & Kight, J. (2009) Rainwater Catchment Design and Installation Standards.

Campisano, A., Butler, D., Ward, S., Burns, M.J., Friedler, E., DeBusk, K., Fisher-Jeffes, L., Ghisi, E., Rahman, A., Furumai, H. & Han, M. (2017) Urban Rainwater Harvesting Systems: Research, Implementation and Future Perspectives. *Water Research*, 115, pp.195–209.

Campisano, A., Gnecco, I., Modica, C. & Palla, A. (2013) Designing Domestic Rainwater Harvesting Systems under Different Climatic Regimes in Italy. *Water Science &Technology*, 67 (11), pp.2511–2518.

Campisano, A. & Modica, C. (2012) Optimal Sizing of Storage Tanks for Domestic Rainwater Harvesting in Sicily. *Resources, Conservation and Recycling*, 63, pp.9–16.

Chidamba, L. & Korsten, L. (2015) Pyrosequencing Analysis of Roof-Harvested Rainwater and River Water used for domestic Purposes in Luthengele Village in the Eastern Cape Province of South Africa. *Environmental Monitoring and Assessment*, 18 (2), p.4237.

Chilton, J.C., Maidment, G.G., Marriott, D., Francis, A. & Tobias, G. (1999) Case Study of a Rainwater Recovery System in a Commercial Building with a Large Roof. *Urban Water*, 1, pp.345–354.

Chubaka, C.E., Whiley, H., Edwards, J.W. & Ross, K. (2018) A review of Roof Harvested Rainwater in Australia. *Journal of Environmental and Public Health*, 2018, pp.1–14.

City of Johannesburg (2003) *Water Services By-Laws*. Available from: <https://openbylaws.org.za/za-jhb/act/by-law/2004/water-services/#section-50> [Accessed 5 February 2018].

Conradie, D.C.U. (2012) South Africa's Climate Zones: Today, Tomorrow. In: Sandton, South Africa, CSIR.

Coombes, P.J. & Barry, M.E. (2007) The Effect of Selection of Time-Steps and Average Assumptions on the Continuous Simulation of Rainwater Harvesting Strategies. *Water Science &Technology*, 55 (4), pp.125–133.

Coombes, P.J. & Barry, M.E. (2008) The Relative Efficiency of Water Supply Catchments and Rainwater Tanks in Cities Subject to Variable Climate and Potential for Climate Change. *Australasian Journal of Water Resources*, 12 (2), pp.85–100.

Coombes, P.J. & Kuczera, G. (2003) Analysis of the Performance of Rainwater Tanks in Australian Capital Cities. In: *28th International Hydrology and Water Resources Symposium*. Wollongong NSW, The Institution of Engineers Australia. Available from: <https://www.researchgate.net/publication/242131373_Analysis_of_the_Performance_of_Rainwater_Tanks_in_Australian_Capital_Cities>.

Cunnane, C. (1978) Unbiased Plotting Positions- A Review. *Journal of Hydrology*, 37, pp.205–222.

DeBusk, K. & Hunt, W.F. (2012) *Rainwater Harvesting: A Comprehensive Review of Literature*. USA, North Carolina Water Resources Research Institute.

Deletic, A. (1998) The First Flush Load of Urban Surface Runoff. *Water Resources*, 32 (8), pp.2462–2470.

Denison, J. & Wotshela, L. (2009) *Indigenous Water Harvesting and Conservation Practices: Historical Context, Cases and Implications*. RSA, Water Research Commission.

Department for Communities and Local Government (2008) The Code for Sustainable Homes: Setting the standard in sustainability for new homes. Available from: <http://webarchive.nationalarchives.gov.uk/20120919233342/http://www.communities.gov.uk/documents/planningandbuilding/pdf/codesustainhomesstandard.pdf> [Accessed 5 February 2018].

Department of Water Affairs (2013) National Water Resource Strategy. Available from: <http://www.dwa.gov.za/documents/Other/Strategic%20Plan/NWRS2-Final-email-version.pdf> [Accessed 3 August 2017].

Despins, C., Farahbakhsh, K. & Leidl, C. (2009) Assessment of Rainwater Quality from Rainwater Harvesting Systems in Ontario, Canada. *Journal of Water Supply: Research and Technology -AQUA*, 58 (2), pp.117–134.

Dobrowsky, P.H., Mannel, D., De Kwaadsteniet, M., Prozesky, H., Cloete, T.E. & Khan, W. (2014) Quality assessment and primary uses of harvested rainwater in Kleinmond, South Africa. *Water SA*, 40 (3), pp.401–406.

Domenech, L. & Sauri, D. (2011) A comparative appraisal of the use of rainwater harvesting in single and multi-family buildings of the Metropolitan Area of Barcelona (Spain); social experience, drinking water savings and economic costs. *Journal of Cleaner Production*, 19, pp.598–608.

Doyle, K.C. (2008) Sizing the First Flush and its Effects on the Storage-Reliability-Yield Behaviour of Rainwater Harvesting in Rwanda. Master of Science in Civil and

Environmental Engineering. USA, Massachusetts Institute of Technology. Available from: <https://dspace.mit.edu/handle/1721.1/44289#files-area> [Accessed 24 October 2017].

Doyle, K.C. & Shanahan, P. (2012) Effect of first flush on Storage-Reliability-Yield of Rainwater Harvesting. *Journal of Water,Sanitation and Hygiene for Development*, 2 (1), pp.1–9.

duPlessis, J.L. & Jacobs, H.E. (2014) Model for Estimating Domestic Outdoor Water Demand of Properties in Residential Estates. In: *Procedia Engineering*. pp.967–974.

Enninful, J.P. (2013) Rainwater Harvesting: A Sustainable Practice for Low- Income Housing in South Africa. Master of the Built Environment in Housing. Johannesburg, South Africa, University of the Witwatersrand. Available from: <http://wiredspace.wits.ac.za/jspui/bitstream/10539/13642/2/JP%20ENNINFUL%20RR.pdf> [Accessed 17 January 2018].

Evans, C.A., Coombes, P.J. & Dunstan, R.H. (2006) Wind, Rain, and Bacteria: The Effect of Weather on the Microbial composition of Roof-Harvested Rainwater. *Water Research*, 40, pp.37–44.

Farreny, R., Gabarell, X. & Rieradevall, J. (2011) Cost- efficiency of Rainwater Harvesting Strategies in dense Mediterranean Neighbourhoods. *Resources, Conservation and Recycling*, 55, pp.686–694.

Fewkes, A. (1999) The Use of Rainwater for WC Flushing: The Field testing of a Collection System. *Building and Environment*, 34, pp.765–772.

Fewkes, A. & Butler, D. (2000) Simulating the Performance of Rainwater Collection and Reuse Systems using Behavioural Models. *Building Services Engineering Research and Technology*, 21 (2), pp.99–106.

Fewkes, A. & Warm, P. (2000) Method of Modelling the Performance of Rainwater Collection Systems in the United Kingdom. *Building Services Engineering Research and Technology*, 21 (4), pp.257–265.

Fisher-Jeffes, L. (2015) The Viability of Rainwater and Stormwater Harvesting in the Residential Areas of the Liesbeek River Catchment, Cape Town. Doctor of Philosophy (PhD). Cape Town, South Africa, University of Cape Town. Available from: <https://open.uct.ac.za/handle/11427/16523> [Accessed 6 September 2017].

GBCSA (2017) Green Star SA Rating System [Internet]. Available from: <https://www.gbcsa.org.za/green-star-sa-rating-system/> [Accessed 17 October 2017].

Geraldi, M.S. & Ghisi, E. (2017) Influence of the Length of Rainfall Time Series on Rainwater Harvesting Systems: A Case Study in Berlin. *Resources, Conservation and Recycling*, 125, pp.169–180.

Ghisi, E. (2010) Parameters Influencing the Sizing of Rainwater Tanks for use in Houses. *Water Resources Management*, 24, pp.2381–2403.

Ghisi, E., Bressan, D.L. & Martini, M. (2007) Rainwater Tank Capacity and Potential for Potable Water Savings by Using Rainwater in the Residential Sector of Southeastern Brazil. *Building and Environment*, 42, pp.1654–1666.

Ghisi, E., Cardoso, K.A. & Rupp, R.F. (2012) Short-term versus Lon-term Rainfall Time Series in the Assessment of Potable Water Savings by using Rainwater in Houses. *Journal of Environmental Management*, 100, pp.109–119.

Gikas, G.D. & Tsihrintzis, V.A. (2012) Assessment of Water Quality of First-Flush Roof Runoff and Harvested Rainwater. *Journal of Hydrology*, 466–467, pp.115–126.

Gould, J. & Nissen-Petersen, E. (1999) *Rainwater Catchment Systems for Domestic Supply: Design, Construction and Implementation*. Warwickshire, UK, Intermediate Technology Publications Ltd.

Griffioen, M.L. & vanZyl, J.E. (2014) Proposed Guideline for Modelling Water Demand by Suburb. *Journal of the South African Institution of Civil Engineering*, 56 (1), pp.63–68.

Guo, Y. & Baetz, B.W. (2007) Sizing of Rainwater Storage Units for Green Building Applications. *Journal of Hydrologic Engineering*, 12 (2), pp.197–205.

Guppy, L. & Anderson, K. (2017) *Water Crisis Report*. Hamilton, Canada., United Nations University Institute for Water, Environment and Health. Available from: <http://inweh.unu.edu> [Accessed 6 February 2018].

Han, M.Y. (2013) Progress of Multipurpose and Proactive Rainwater Management in Korea. *Environmental Engineering Research*, 18 (2), pp.65–69.

Hanson, L.S. & Vogel, R.M. (2014) Generalized Storage-Reliability-Yield Relationships for Rainwater Harvesting Systems. *Environmental Research Letters*, 9.

Helmreich, B. & Horn, H. (2009) Opportunities in rainwater harvesting. *Desalination*, 248, pp.118–124.

Imteaz, M.A., Shanableh, A., Rahman, A. & Ahsan, A. (2011) Optimisation of Rainwater Tank Design from Large Roofs: A Case Study in Melbourne, Australia. *Resources, Conservation and Recycling*, 55, pp.1022–1029.

Khastagir, A. & Jayasuriya, N. (2011) Investment Evaluation of Rainwater Tanks. *Water Resources Management*, 25, pp.3769–3784.

Khastagir, A. & Jayasuriya, N. (2010) Optimal Sizing of Rainwater Tanks for Domestic Water Conservation. *Journal of Hydrology*, 381, pp.181–188.

Kim, H.W., Li, M., Kim, H. & Lee, H.. K. (2016) Cost-Benefit Analysis and Equitable Cost Allocation for a Residential Rainwater Harvesting System in the City of Austin, Texas. *International Journal of Water Resources Development*, 32 (5), pp.749–764.

Kim, K. & Yoo, C. (2009) Hydrological Modelling and Evaluation of Rainwater Harvesting Facilities: Case Study on several Rainwater Harvesting Facilities in Korea. *Journal of Hydrologic Engineering*, 14 (6), pp.545–561.

Kottek, M., Grieser, J., Beck, C., Rudolf, B. & Rubel, F. (2006) World Map of the Koppen-Geiger Climate Classification Updated. *Meteorologische Zeitschrift*, 15 (3), pp.259–263.

Kundzewicz, Z.W., Mata, L.J., Arnell, N.W., Doll, P., Kabat, P., Jimenez, B., Miller, K.A., Oki, T., Sen, Z. & Shiklomanov, I.A. (2007) Freshwater Resources and their Management. In: *Climate Change 2007: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK, Cambridge University Press, pp.173–210. Available from: <https://www.ipcc.ch/pdf/assessment-report/ar4/wg2/ar4-wg2-chapter3.pdf> [Accessed 6 September 2017].

Lee, J., Bak, G. & Han, M. (2012) Quality of Roof-Harvested Rainwater - Comparison of different Roofing Materials. *Environmental Pollution*, 162, pp.422–429.

Lee, J., Han, M. & Kim, H. (2010) Review on Codes and Application of Urban Rainwater Harvesting Utilization: Focused on Case Study in South Korea. *International Journal of Urban Sciences*, 14 (3), pp.307–319.

Lee, J., Yang, J., Han, M. & Choi, J. (2010) Comparison of the Microbiological and Chemical Characterization of Harvested Rainwater and Reservoir Water as Alternative Water Resources. *Science of the Total Environment*, 408, pp.896–905.

Lee, K.T., Lee, C., Yang, M. & Yu, C. (2000) Probabilistic Design of Storage Capacity for Rainwater Cistern Systems. *Journal of Agricultural Engineering Resources*, 77 (3), pp.343–348.

Liaw, C. & Chiang, Y. (2014) Dimensionless analysis for Designing Domestic Rainwater Harvesting Systems at the Regional Level in Northern Taiwan. *Water*, 6, pp.3913–3933.

Liaw, C. & Tsai, Y. (2004) Optimum Storage Volume of Rooftop Rainwater Harvesting Systems for Domestic Use. *Journal of the American Water Resources Association*, 40 (4), pp.901–912.

Loos, J. & Erasmus, L. (2017) Property Barometer-Longterm Building Trends Update. Available from: <http://c.ymcdn.com/sites/www.saiv.org.za/resource/collection/B70457DF-B11F-442D-94B2-8B1BF7C28C2F/FNB_Property_Barometer_Long_Term_Building_Characteristics_Update__Aug_2017.pdf> [Accessed 4 May 2018].

Loper, S. (2015) *Rainwater Harvesting State Regulations and Technical Resources*. Washington, USA, United States Department of Energy. Available from: <https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-24347.pdf> [Accessed 5 February 2018].

Lopes, V.A.R., Marques, G.F., Dornelles, F. & Medellin-Azuara, J. (2017) Performance of Rainwater Harvesting Systems of Non-Potable Water Demand and Roof Area Typologies using a Stochastic Approach. *Journal of Cleaner Production*, 148, pp.304–313.

Lynch, S. (2003) *The Development of a Raster Database of Annual, Monthly, and Daily Rainfall for Southern Africa*. Pretoria, South Africa, Water Research Commission.

Makkonen, L. (2006) Plotting Positions in Extreme Value Analysis. *Journal of Applied Meteorology and Climatology*, 45, pp.334–340.

Martinson, D.B. (2007) Improving the Viability of Roofwater Harvesting in Low-Income Countries. PhD. University of Warwick. Available from: <https://warwick.ac.uk/fac/sci/eng/research/grouplist/structural/dtu/pubs/reviewed/rwh/dbm_thesis/dbm_thesis.pdf> [Accessed 30 October 2017].

Martinson, D.B. & Thomas, T. (2009) Quantifying the First-Flush Phenomenon: Effects of First-Flush on Water Yield and Quality. In: Kuala Lumpur, Singapore.

Matos, C., Bentes, I., Santos, C., Imteaz, M.A. & Pereira, S. (2015) Economic analysis of a Rainwater Harvesting System in a Commercial Building. *Water Resources Management*, 29, pp.3971–3986.

Meera, V. & Ahammed, M. (2006) Water Quality of Rooftop Rainwater Harvesting Systems: A Review. *Journal of Water Supply: Research and Technology -AQUA*, pp.1–13.

Mehrabadi, M.H.R., Saghafian, B. & Fashi, F.H. (2013) Assessment of Residential Rainwater Harvesting Efficiency for Meeting Non-potable Water Demands in Three Climate Conditions. *Resources, Conservation and Recycling*, 73, pp.86–93.

Melville-Shreeve, P., Ward, S. & Butler, D. (2016) Rainwater Harvesting Typologies for UK Houses: A Multi Criteria Analysis of System Configurations. *Water*, 8.

Mendez, C., Klenzendorf, J.B., Afshar, B.R., Simmons, M., T., Barret, M.E., Kinney, K.A. & Kirisits, M.J. (2011) The Effect of Roofing Material on the Quality of Harvested Rainwater. *Water Research*, 45, pp.2049–2059.

Michaelides, G. (1987) Laboratory Experiments on Efficiency of Foul Flush Diversion Systems.

Mitchell, V.G. (2007) How Important is the Selection of Computational Analysis Method to the Accuracy of Rainwater Tank Behaviour Modelling. *Hydrological Processes*, 21, pp.2850–2861.

Mitchell, V.G., McCarthy, D.T., Deletic, A. & Fletcher, T.D. (2008) Urban Stormwater Harvesting - Sensitivity of Storage Behaviour Model. *Environmental Modelling & Software*, 23, pp.782–793.

Moodley, S. (2015) Rainwater Harvesting Can Boost Water Security, but Stimulatory Legal Framework Required. *Engineering News*. Available from: <http://www.engineeringnews.co.za/article/rainwater-harvesting-can-boost-water-security-but-stimulatory-legal-framework-required-2015-04-10> [Accessed 5 February 2018].

Mphepya, J.N., Pienaar, J.J., Galy-Lacaux, C., Held, G. & Turner, C.R. (2004) Precipitation Chemistry in Semi-Arid Areas of Southern Africa: A Case Study of a Rural and an Industrial Site. *Journal of Atmospheric Chemistry*, 47, pp.1–24.

MPMSAA (2008) *Rainwater Tank Design and Installation Handbook*. Australia, Master Plumbers & Mechanical Services Association of Australia. Available from: <https://qbis.com.au/wp-content/uploads/2015/08/Rainwater-Hand-book.pdf> [Accessed 5 February 2018].

Muriu-Ng'ang'a, F.W., Mucheru-Muna, M., Waswa, F. & Mairura, F.S. (2017) Socio-Economic Factors Influencing Utilisation of Rainwater Harvesting and Saving Technologies in Tharaka South, Eastern Kenya. *Agricultural Water Managment*, 194, pp.150–159.

Mutekwa, V. & Kusangaya, S. (2006) Contribution of Rainwater Harvesting technologies to Rural Livelihoods in Zimbabwe: The Case of Ngundu ward in Chivi District. *Water SA*, 32 (3), pp.437–444.

Mwenge Kahinda, J. & Taigbenu, A.E. (2011) Rainwater Harvesting in South Africa: Challenges and Opportunities. *Physics and Chemistry of the Earth*, 36, pp.968–976.

Mwenge Kahinda, J., Taigbenu, A.E. & Boroto, R.J. (2007) Domestic Rainwater Harvesting to Improve Water Supply in Rural South Africa. *Physics and Chemistry of the Earth*, 32, pp.1050–1057.

Ndiritu, J.G. (2018) Personal Communication.

Ndiritu, J.G., Ilemobade, A.A. & Kagoda, P. (2018) Guidelines for Rainwater Harvesting System Design and Assessment for the City of Johannesburg, South Africa. *Proc. IAHS*, 95, pp.1–6.

Ndiritu, J.G., Moodley, Y. & Guliwe, M. (2017) Generalized Storage-Yield-Reliability Relationships for Analyzing Shopping centre Rainwater Harvesting Systems. *Water*, 9, p.771.

Ndiritu, J.G., Odiyo, J.O., Ntuli, C. & Mwaka, B. (2011) Yield-reliability analysis for Rural Domestic Water Supply from Combined Rainwater Harvesting and Run-of- River Abstraction. *Hydrological Sciences Journal*, 56 (2), pp.238–248.

Notaro, V., Liuzzo, L. & Freni, G. (2016) Reliability Analysis of Rainwater Harvesting Systems in Southern Italy. *Procedia Engineering*, 162, pp.373–380.

Ntale, H.K. & Moses, N. (2003) Improving the Quality of Harvested Rainwater by using First Flush Interceptors/Retainers. In: Texcoco, Mexico.

O'Brien, O. (2014) Domestic Water Demand for Consumers with Rainwater Harvesting Systems. Master of Science. Stellenbosch, South Africa, Stellenbosch University. Available from: <http://scholar.sun.ac.za/handle/10019.1/86514> [Accessed 5 February 2018].

Okoye, C.O., Solyali, O. & Akintug, B. (2015) Optimal Sizing of Storage Tanks in Domestic Harvesting Systems: A Linear Programming Approach. *Resources, Conservation and Recycling*, 104, pp.131–140.

Pachpute, J.S., Tumbo, S.D., Sally, H. & Mul, M.L. (2009) Sustainability of Rainwater Harvesting Systems in Rural Catchment of Sub-Saharan Africa. *Water Resources Management*, 23, pp.2815–2839.

Palla, A., Gnecco, I., Lanza, L.G. & La Barbera, P. (2012) Performance Analysis of Domestic Rainwater Harvesting Systems Under Various European Climate Zones. *Resources, Conservation and Recycling*, 62, pp.71–80.

Partzsch, L. (2009) Smart Regulation for Water Innovation - The Case of Decentralised Rainwater Technology. *Journal of Cleaner Production*, 17 (11), pp.985–991.

Polkowska, Z., Goreki, T. & Namiesnik, J. (2002) Quality of Roof Runoff waters from an Urban Region (Gdansk, Poland). *Chemosphere*, 49, pp.1275–1283.

Rahman, S., Khan, M.T.R., Akib, S., bin Che, D.N., Biswas, S.K. & Shirazi, S.M. (2014) Sustainability of Rainwater Harvesting Systems in Terms of Water Quality: A Case Study. *The Scientific World Journal*, 2014, pp.1–10.

Raimondi, A. & Becciu, G. (2014) Probabilistic Modelling of Rainwater Tanks. *Procedia Engineering*, 89, pp.1493–1499.

Republic of South Africa (1998) *National Water Act*. Available from: <http://www.dwa.gov.za/Documents/Legislature/nw_act/NWA.pdf>.

Republic of South Africa (1997) *Water Services Act*. Available from: <http://www.dwaf.gov.za/Documents/Legislature/a108-97.pdf> [Accessed 5 February 2018].

Roebuck, R.M., Oltean-Dumbrava, C. & Tait, S. (2011) Whole Life cost Performance of Domestic Rainwater Harvesting Systems in the United Kingdom. *Water and Environment Journal*, 25, pp.355–365.

SACSC (2015) Southern African Shopping Centre Directory.

Saget, A., Chebbo, G. & Bertrand-Krajewski, J. (1996) The First Flush in Sewer Systems. *Water Science &Technology*, 33 (9), pp.101–108.

Saladin, M. (2016) Rainwater Harvesting in Thailand: Learning from the World Champions. Available from: <http://www.rural-water-supply.net/_ressources/documents/default/1-759-55-1464085609.pdf> [Accessed 30 January 2018].

Sample, D.J. & Lui, J. (2014) Optimising Rainwater Harvesting Systems for the Dual Purposes of water supply and runoff Capture. *Journal of Cleaner Production*, 75, pp.174–194.

Sanchez, A.S., Cohim, E. & Kalid, R.A. (2015) A review on the Physico-Chemical and Microbiological Contamination of Roof-Harvested Rainwater in Urban Areas. *Sustainability of Water Quality and Ecology*, 6, pp.119–137.

Sansalone, J.J. & Buchberger, S.G. (1997) Partitioning and First Flush of Metals in Urban Roadway Storm Sewer. *Journal of Environmental Engineering*, 123 (2), pp.134–143.

Santos, C. & Taviera-Pinto, F. (2013) Analysis of Different Criteria to Size Rainwater Storage Tanks Using Detailed Methods. *Resources, Conservation and Recycling*, 71, pp.1–6.

Saunders, A. (2012) *Shopping Centre Water Efficiency Report*. Perth, Australia, HFM Asset Management:

Sazakli, E., Alexopoulos, A. & Leotsinidis, M. (2007) Rainwater Harvesting, Quality Assessment and Utilization in Kefalonia Island, Greece. *Water Research*, 41, pp.2039–2047.

Schuetze, T. (2013) Rainwater Harvesting and Management - Policy and Regulations in Germany. *Water Science &Technology*, 13 (2), pp.376–385.

Schulze, R., E. & Maharaj, M. (2007) A-Pan Equivalent Reference Potential Evaporation. In: *South African Atlas of Climatology and Agrohydrology*. Pretoria, Water Research Commission. Available from: <http://sarva2.dirisa.org/resources/documents/beeh/Section%2013.2%20A-pan%20Eq%20Ref%20Pot%20Evap.pdf>.

Shulze, B.R. (1947) The Climates of South Africa According to the Classifications of Koppen and Thornthwaite. *South African Geographical Journal*, 29 (1), pp.32–42.

Silva, A.S. & Ghisi, E. (2016) Uncertainity Analysis of Daily Potable Water Demand on the Performance Evaluation of Rainwater Harvesting Systems in Residential Buildings. *Journal of Environmental Management*, 180, pp.82–93.

Simmons, G., Hope, V., Lewis, G., Whitmore, J. & Gao, W. (2001) Contamination of Potable Roof-Collected Rainwater in Auckland, New Zealand. *Water Resources*, 35 (6), pp.1518–1524.

Simmons, G., Jury, S., Thornley, C., Harte, D., Mohiuddin, J. & Taylor, M. (2008) A Legionnaire's Disease Outbreak: A Water Blaster and Roof-Collected Rainwater Systems. *Water Research*, 42, pp.1449–1458.

Sousa, V., Matos Silva, C. & Meireles, I.C. (2018) Technical-Financial Evaluation of Rainwater Harvesting Systems in Commercial Buildings - Case Studies from Sonae Sierra in Portugal and Brazil. *Environmental Science and Pollution Research*, 25, pp.19283–19297.

Su, M., Lin, C., Chang, L. & Lin, M. (2009) A Probabilistic Approach to Rainwater Harvesting Systems Design and Evaluation. *Resources, Conservation and Recycling*, 53 (7), pp.393–399.

Tam, V.W.Y., Tam, L. & Zeng, S.X. (2010) Cost Effectiveness and Trade-off on the use of Rainwater Tank: An Empirical Study in Australian Residential decision-making. *Resources, Conservation and Recycling*, 54, pp.178–186.

Thomas, T.H. & Martinson, D.B. (2007) *Roofwater Harvesting: A Handbook for Practioners*. Delft, The Netherlands, IRC International Water and Sanitation Centre. Available from: <https://www.ircwash.org/sites/default/files/Thomas-2007-Roofwater.pdf> [Accessed 27 October 2017].

TWDB (2005) The Texas Manual on Rainwater Harvesting. Available from: <http://www.twdb.texas.gov/publications/brochures/conservation/doc/RainwaterHarvestingManual_3rdedition.pdf> [Accessed 27 October 2017].

UN-Habitat (2005) *Blue Drop Series on Rainwater Harvesting and Utilization - Book 3: Project Managers and Implementation Agencies*. Kenya, UN-Habitat. Available from: <https://unhabitat.org/books/blue-drop-series-on-rainwater-harvesting-and-utilisation-book-3project-managers-and-implemetation-agency/> [Accessed 21 November 2017].

USEPA (2017) WaterSense: Types of Facilities [Internet]. Available from: <https://www.epa.gov/watersense/types-facilities> [Accessed 19 March 2018].

vanRooyen, J.A. & Versfeld, D.B. (2010) *Integrated Water Resource Planning for South Africa: A Situation Analysis*. Republic of South Africa, Department of Water Affairs.

vanZyl, H.J., Ilemobade, A.A. & vanZyl, J.E. (2008) An Improved Area-Based Guideline for Domestic Water Demand Estimation in South Africa. *Water SA*, 34 (3).

vanZyl, H.J., Ilemobade, A.A., vanZyl, J.E. & LeGat, Y. (2017) Statistical Characterisation and Estimation of Non-Domestic Water Demand. *Urban Water Journal*, 14 (7), pp.720–726.

Viljoen, N.S. (2014) The Feasibility of Rainwater and Stormwater Harvesting Within a Winter Rainfall Climate Context: A Commercial Building Focus. Master of Science in Environmental Engineering. Pretoria, South Africa, UNIVERSITY OF SOUTH AFRICA.

Walsh, R.P.D. & Lawler, D.M. (1981) Rainfall Seasonality: Description, Spatial Patterns and Change Through Time. *Weather*, 36, pp.201–208.

Ward, S. (2007) Rainwater Harvesting in the UK - current Practice and future Trends [Internet]. Available from: <http://www.harvesth2o.com/rainwater_harvesting_UK.shtml> [Accessed 1 February 2018].

Ward, S., Barr, S., Memon, F.A. & Butler, D. (2013) Rainwater Harvesting in the UK: Exploring Water user Perceptions. *Urban Water Journal*, 10 (2), pp.112–126.

Ward, S., Memon, F.A. & Butler, D. (2012) Performance of a Large Building Rainwater Harvesting System. *Water Research*, 46, pp.5127–5134.

Ward, S., Memon, F.A. & Butler, D. (2008) Rainwater Harvesting: Model-Based Design Evaluation. In: Edinburgh, Scotland, UK. Available from: <https://web.sbe.hw.ac.uk/staffprofiles/bdgsa/11th_International_Conference_on_Urban_Drainage_CD/ICUD08/pdfs/577.pdf> [Accessed 5 September 2017].

Weibull, W. (1939) *A statistical theory of strength of materials*. Stockholm, Generalstabens litografiska anstalts förlag,.

WHO (2017) Water Safety Plans. In: *Guidelines for drinking-water quality, 4th edition, incorporating the 1st addendum*. Geneva, World Health Organisation. Available from: <http://www.who.int/water_sanitation_health/publications/gdwq4-with-add1-chap4.pdf?ua=1> [Accessed 8 March 2018].

WoodsBallard, B., Wilson, S., Udale-Clarke, H., Scott, T., Ashley, R. & Kellagher, R. (2015) The SuDS Manual. Available from: <https://www.ciria.org/Resources/Free_publications/SuDS_manual_C753.aspx> [Accessed 8 March 2018].

WWAP (2015) *The United Nations World Water Development Report 2015: Water for a Sustainable World*. Paris, UNESCO.

Yaziz, M.I., Gunting, H., Sapari, N. & Ghazali, A.W. (1989) Variation in Rainwater Quality from Roof Catchments. *Water Research*, 23 (6), pp.761–765.

Zhu, K., Zhang, L., Hart, W., Lui, M. & Chen, H. (2004) Quality Issues in Harvested Rainwater in Arid and Semi-Arid Loess Plateau of Northern China. *Journal of Arid Environments*, 57, pp.487–505.

Web links

First Flush Devices: http://www.gutterguard.co.za/First-Flush-Systems-and-Pricing/

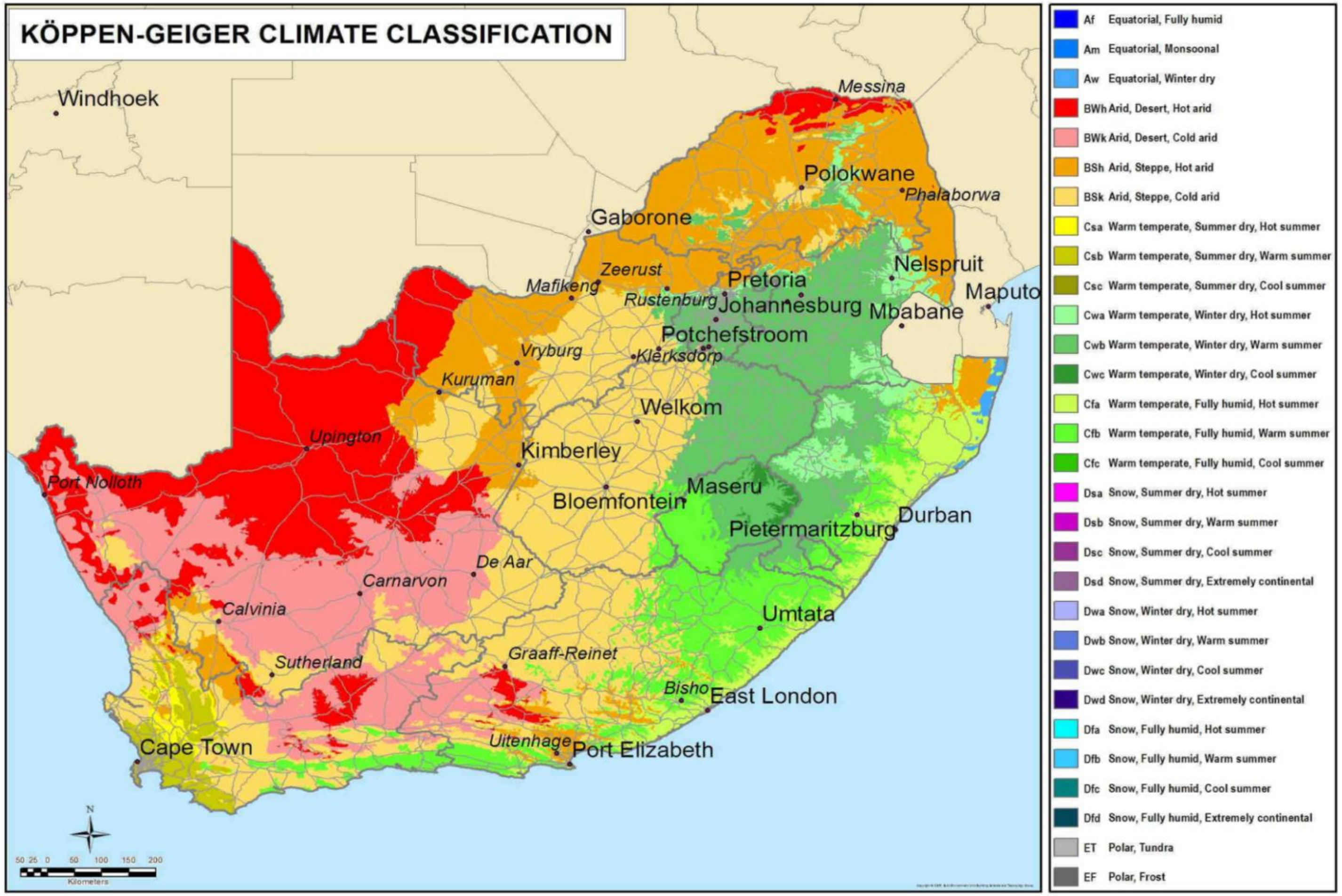
First flush design: https://www.eco3.co.za/rain_water_harvest_catch.htm

First Flush Devices: https://www.faithful-to-nature.co.za/gutter-guard-first-flush-diy-kit

Vertical Jojo tanks: https://www.jojo.co.za/product-category/vertical-water-storage-tanks/

APPENDIX

APPENDIX 1 Köppen-Geiger Map



APPENDIX 2 Rainfall Gauging Stations

Koppen-Geiger Classification	Description	Rainfall station Name	Rainfall Station ID	Location		Years on Record		Observed MAP (mm)	Years on Record	% Observed data	% Missing data	% Patched Data	σ	CV	ADR_w	σ_w	CV_w	Av. n_d (days/yr)	Av. n_r (days/yr)
				Longitude	Latitude	Start	End												
BSh	Arid, Steppe, hot arid	Touwsrivier (SAR)	0044050W	20° 02'	33° 20'	1850	2001	225	122	62.4	4.7	32.9	2.967	4.8	6.092	7.34	1.2	328	37
		Jansenville	0074296W	24° 40'	32° 56'	1874	2001	266	121	62.1	4.3	33.6	3.88	5.3	5.747	7.8	1.4	319	46
		Clanwilliam (POL)	0084701W	18° 54'	32° 11'	1850	2001	230	150	83.1	0.1	16.8	2.464	3.9	4.518	5.1	1.1	314	51
		Boetsap (POL)	0359808W	24° 27'	27° 58'	1878	2000	421	122	78.5	0	21.5	4.826	4.2	9.251	10.6	1.1	320	46
		Geluk (POL)	0512246W	27° 39'	25° 36'	1893	2000	623	106	66.5	0	33.5	6.039	3.5	9.934	11.4	1.2	303	62
		Illawarra	0590028W	28° 31'	24° 59'	1903	2000	573	96	92.2	0.7	7.1	6.06	3.9	9.937	12.2	1.2	307	58
		Naboomspruit (POL)	0590361W	28° 43'	24° 31'	1903	2000	593	96	93.6	0.6	5.8	6.639	4	13.47	14.1	1	320	45
		Marble Hall (POL)	0591538W	29° 18'	24° 58'	1903	2000	506	96	59.2	0.6	40.2	4.878	3.5	7.638	9.12	1.2	299	66
		Dorset	0632274W	28° 10'	24° 04'	1903	2000	544	96	65	0.6	34.4	5.762	3.9	10.94	11.8	1.1	315	50
		Boekenhoutskloof	0632297W	28° 10'	24° 27'	1903	2000	591	96	62.7	0	37.3	5.93	3.7	10.17	11.6	1.1	307	58
		Potgietersrus (POL)	0633881AW	29° 01'	24° 11'	1903	2000	606	96	85.7	0.6	13.7	6.563	3.9	12.49	13.7	1.1	316	49
		Uitzich	0634417W	29° 14'	24° 27'	1903	2000	568	96	67.8	0.6	31.6	5.636	3.6	9.348	10.9	1.2	305	60
		Chunniespoort (POL)	0635076W	29° 33'	24° 16'	1903	2000	501	96	54.9	0.6	44.6	5.445	4	10.68	11.4	1.1	318	47
		Inyoko	0637609W	30° 52'	24° 08'	1903	2000	573	96	66.9	0.7	32.4	6.094	3.9	11.67	12.6	1.1	316	50
		Villa Nora (POL)	0675182W	28° 07'	23° 32'	1903	2000	431	96	91.2	0.6	8.2	5.943	5	12.83	15.3	1.2	331	34
		Thornloe	0677818W	29° 29'	23° 38'	1903	2000	396	96	65.4	0.6	34	4.698	4.4	9.536	10.7	1.1	324	41
		Black Hills	0680225W	30° 39'	23° 47'	1903	2000	585	96	64.4	0.8	34.6	7.291	4.8	12.87	16.9	1.3	320	45
		Banderlierkop (POL)	0722529W	29° 48'	23° 19'	1903	2000	436	96	84	0.8	15.2	5.139	4.3	9.83	11.6	1.2	321	44
		Pafuri	0812567W	31° 19'	22° 27'	1903	2000	466	94	70.3	0.4	29.2	6.256	4.8	8.778	14.1	1.6	311	54
BSk	Arid, Steppe, Cold Arid	Heidelberg Cape (POL)	0009815W	20° 57'	34° 05'	1874	2001	425	124	77.8	3	19.2	4.545	3.9	6.806	9.07	1.3	303	63
		Sandhoogte (PUR)	0012303W	22° 11'	34° 04'	1874	2001	470	122	54.6	3	42.4	4.537	3.5	6.253	8.32	1.3	290	75
		Oudtshoorn (MUN)	0028335W	22° 12'	33° 35'	1874	2001	243	123	95.1	3.2	1.8	3.118	4.7	5.596	7.35	1.3	322	43
		Uniondale (MUN)	0030219W	23° 08'	33° 40'	1874	2001	324	121	76.5	4.4	19.2	4.058	4.6	6.569	9.22	1.4	316	49
		Adolphskraal	0034121W	25° 05'	33° 31'	1874	2001	283	122	59	3.2	37.9	3.862	5	8.065	9.79	1.2	330	35
		Koeifontein	0052270W	24° 09'	33° 30'	1874	2001	232	121	52.5	4.2	43.3	3.173	5	6.361	7.99	1.3	328	37
		Gannaskraal	0115595W	22° 50'	31° 55'	1874	2001	247	123	51.9	3.1	45	3.148	4.7	6.586	7.6	1.2	328	37
		Nieu-Bethesda (POL)	0119082W	24° 33'	31° 52'	1874	2000	355	127	88.7	0.2	11.2	4.325	4.4	8.426	9.92	1.2	323	42
		Tafelburg Hall	0120338W	25° 11'	31° 38'	1874	2001	350	128	83.8	0	16.2	4.043	4.2	8.236	8.96	1.1	323	43
		Sterkstrom	0123063W	26° 33'	31° 33'	1874	2001	479	123	89	3.5	7.5	5.001	3.8	9.756	10.1	1	316	49
		Queenstown	0123654A	26° 52'	31° 54'	1874	2001	495	121	82.1	3.9	13.9	4.927	3.6	7.814	9.38	1.2	301	64
		Prinshof	0139850W	22° 22'	31° 10'	1874	2001	270	121	51.4	3.3	45.3	4.093	5.6	9.592	11.5	1.2	337	28
		Colesburg (MUN)	0172163W	25° 06'	30° 43'	1874	2001	390	123	95.3	3.1	1.6	4.509	4.2	8.976	10	1.1	322	43
		Rouxville (POL)	0203595W	26° 50'	30° 25'	1874	2001	565	124	72.8	3.1	24.2	5.335	3.5	9.52	10	1.1	306	59
		Kalkpoort	0361832W	25° 28'	27° 53'	1878	2000	473	122	56.8	0	43.2	4.891	3.8	9.865	9.88	1	317	48
		Odendaalsrus	0364322W	26° 41'	27° 52'	1878	2000	495	122	74.8	0	25.2	4.985	3.7	9.295	9.81	1.1	312	53
		Zevenfontein	0398177W	25° 36'	27° 27'	1878	2000	459	122	72.3	0	27.7	4.771	3.8	8.59	9.6	1.1	312	54
		Bothaville (MUN)	0400203W	26° 37'	27° 24'	1878	2000	533	122	72.3	0	27.7	5.264	3.6	9.488	10.2	1.1	309	56
		Heilbron (MUN)	0402827W	27° 18'	27° 17'	1878	2000	622	122	66.5	0	33.5	5.69	3.3	9.827	10.3	1.1	302	63
		Bushy Band	0436747W	26° 55'	26° 57'	1878	2000	549	122	63	0	37	5.916	3.9	7.464	8.69	1.2	292	73

Koppen-Geiger Classification	Description	Rainfall station Name	Rainfall Station ID	Location		Years on Record		Observed MAP (mm)	Years on Record	% Observed data	% Missing data	% Patched Data	σ	CV	ADR_w	σ_w	CV_w	Av. n_d (days/yr)	Av. n_r (days/yr)
				Longitude	Latitude	Start	End												
BWh	Arid, desert, hot arid	Caliztdorp (POL)	0027302W	21° 41'	33° 32'	1874	2001	202	124	95.5	3	1.5	3.1	5.5	6.3	8.4	1.3	333	32
		Leeu Gamka (SAR)	0068857W	21° 59'	32° 47'	1874	2001	119	122	81.5	3.3	15.2	2.4	7.3	7.4	8.8	1.2	349	16
		Kendrew Estates	0073871W	24° 30'	32° 10'	1874	2001	313	124	84.2	3.1	12.7	3.8	4.8	8.1	9.4	1.2	330	35
		Marydale	0253174W	22° 07'	29° 25'	1878	2001	176	120	66.7	1.3	31.9	3.1	6.3	8.0	9.7	1.2	343	22
		Koegasburg	0253648W	22° 22'	29° 18'	1878	2001	201	120	55.6	1.3	43.1	2.9	5.3	6.7	8.0	1.2	335	30
		Kakamas SKL	0282166W	20° 37'	28° 46'	1878	2001	122	104	51.3	4.4	44.3	2.5	7.4	6.5	9.1	1.4	346	19
		Geelkop	0283098W	21° 03'	28° 39'	1878	2001	140	116	56.3	1.7	42	2.6	6.7	7.3	8.7	1.2	346	19
		Thornlea	0284008W	21° 31'	28° 39'	1878	2001	185	117	80	1	18.4	3.1	6.1	8.4	9.6	1.1	343	22
		Upington AGR	0317447A	21° 15'	28° 27'	1878	2001	166	112	69.3	1.9	28.8	2.7	6.1	6.3	8.3	1.3	339	26
		Messina AGR RES	0809706A	29° 54'	22° 16'	1903	2000	383	94	57	0.3	48.7	4.8	4.6	8.0	11.0	1.4	317	48
BWk	Arid, desert, cold arid	Laingsburg	0045611W	20° 51'	33° 12'	1874	2001	126	122	74.2	3.4	22.4	2.232	6.5	5.738	7.23	1.3	343	22
		Ladismith	0046479W	21° 26'	33° 30'	1874	2001	314	124	95.4	3	1.6	3.824	4.4	7.252	8.75	1.2	322	43
		Prince Albert	0048043W	22° 02'	33° 13'	1874	2001	171	124	84.6	3	12.4	2.637	5.7	5.282	7.3	1.4	333	32
		Klaarstroom (POL)	0049050W	22° 32'	33° 20'	1874	2001	187	124	69.8	3	27.2	2.817	5.5	5.698	7.68	1.3	332	34
		Willowmore (MUN)	0050887W	23° 29'	33° 18'	1874	2001	242	123	68.8	3	28.2	3.451	5.2	5.696	8.62	1.5	323	42
		Tafelberg	0090196W	21° 37'	32° 16'	1874	2001	164	120	62.9	4	33	2.81	6.3	7.804	8.93	1.1	344	21
		Beaufort Wes (MUN)	0092141W	22° 35'	32° 21'	1874	2001	230	122	76.4	3	20.5	3.657	5.8	6.686	10	1.5	331	35
		Bakensrug	0093314W	23° 11'	32° 14'	1874	2001	228	123	86.4	3.1	10.5	3.159	5.1	7.578	8.29	1.1	335	30
		Aberdeen (MUN)	0095119W	24° 04'	32° 29'	1874	2001	282	124	79.6	3.1	17.3	3.772	4.9	7.117	9.26	1.3	326	40
		Roodebloem	0096101W	24° 34'	32° 11'	1874	2001	289	127	88.8	0	11.2	3.657	4.6	7.401	8.72	1.2	326	39
		Fraserburg (POW)	0113025W	21° 31'	31° 55'	1874	2001	170	122	66.2	3.3	30.5	2.682	5.8	5.62	7.67	1.4	335	30
		Vosburg	0167665W	22° 53'	30° 34'	1874	2001	205	121	75.7	3.5	20.8	3.313	5.9	9.429	10.1	1.1	344	22
Cfa	Warm temperate, fully humid, hot summer	Intake	0240564W	30° 46'	29° 47'	1871	2000	895	125	51.8	2.7	45.5	8.908	3.6	7.676	14.3	1.9	247	118
		Experiment STN	0241042S	31° 02'	29° 42'	1871	2001	919	126	56.2	1.9	41.8	8.694	3.5	8.009	14	1.8	251	114
		Frasers	0241302W	31° 11'	29° 32'	1871	2001	964	125	53.6	2.7	43.7	8.758	3.3	9.315	14.4	1.5	261	104
		Gingindlovu	0272121W	31° 35'	29° 02'	1871	2001	1010	125	60.1	2.7	31.2	8.633	3.1	9.135	13.7	1.5	255	111
		Fairview	0305037W	32° 02'	28° 37'	1871	2000	965	125	60.5	2.7	36.8	8.59	3.2	9.433	14.1	1.5	263	103
		Mahlabathini (MAG)	0337795W	31° 28'	28° 14'	1871	2000	780	125	64.6	1.9	33.4	6.932	3.3	9.308	12	1.3	282	84
		Hluhlulwe game reserve	0339065W	32° 02'	28° 05'	1871	2000	911	125	52.9	1.9	45.2	8.027	3.2	9.28	13.2	1.4	266	99
		Dukuduku (BOS)	0339441W	32° 15'	28° 21'	1871	2000	840	125	51.5	1.9	46.6	8.013	3.5	8.983	13.8	1.5	272	93
		Nongoma	0374264W	31° 39'	27° 54'	1871	2000	905	125	54.5	1.9	43.6	7.646	3.1	9.978	12.6	1.3	274	91
Cfb	Warm temperate, fully humid, warm summer	Grahamstown (MUN)	0057048AW	33° 18'	26° 32'	1877	2001	690	122	96.9	1.1	2.3	6.681	3.5	8.377	12	1.4	283	83
		Somerset east	0076133W	25° 35'	32° 43'	1874	2001	601	122	91.3	4.2	4.2	5.976	3.6	8.562	11.2	1.3	295	70
		Umtata	0127485A	31° 35'	28° 47'	1888	2000	582	109	54.3	0.8	44.9	5.313	3.3	6.341	9.07	1.4	274	92
		Jamestown (POL)	0148517W	26° 48'	31° 07'	1874	2001	531	123	93.8	3.1	3.1	5.295	3.6	10.59	10.3	1	315	50
		Indwe (MUN)	0149598W	27° 20'	31° 28'	1874	2001	576	123	69.5	3.3	27.1	5.328	3.4	9.136	9.75	1.1	302	63
		Ladysdale	0233239W	27° 08'	30° 00'	1874	2001	627	124	59.7	3.1	37.3	5.411	3.2	8.959	9.4	1	295	70
		Bulwer (MUN)	0238468W	29° 46'	24° 49'	1882	2000	943	114	64.9	1.1	33.9	6.881	2.7	9.302	10.5	1.1	265	100
		Windy Hill No. 2	0270119W	30° 34'	29° 30'	1871	2000	908	125	51.5	1.9	46.6	6.738	2.7	7.515	9.91	1.3	243	122
		Boscombe	0270544W	30° 49'	29° 04'	1871	2000	965	125	54	1.8	44.2	6.743	2.5	8.858	9.83	1.1	256	110
		Nadi	0302320W	30° 41'	28° 51'	1871	2000	662	125	50.2	1.8	47.9	5.545	3.1	8.063	9.3	1.2	283	82
		Nkandla (POL) Nkandla	0303127W	31° 07'	28° 37'	1871	2001	879	125	57.2	2.7	40.1	6.887	2.8	10.66	11	1	282	83

Koppen-Geiger Classification	Description	Rainfall station Name	Rainfall Station ID	Location		Years on Record		Observed MAP (mm)	Years on Record	% Observed data	% Missing data	% Patched Data	σ	CV	ADR_w	$σ_w$	CV_w	Av. n_d (days/yr)	Av. n_r (days/yr)
				Longitude	Latitude	Start	End												
Cfc	Warm temperate, fully humid, cool summer	Witelbos (BOS)	0032209W	24° 07'	33° 55'	1874	2001	1123	119	84.1	3.4	12.5	6.622	3.3	7.825	11.2	1.4	271	94
		George	0028838W	22° 27'	33° 58'	1874	2001	858	122	83.8	4	12.1	6.482	3.7	10.14	12.5	1.2	302	64
		Plettenberg bay (POL)	0014633W	23° 22'	34° 03'	1874	2001	644	122	81.5	3.3	15.2	8.124	3.1	9.313	13.1	1.4	262	103
		Lottering (BOS)	0031507W	23° 47'	33° 58'	1874	2001	1058	122	81.4	3.1	15.5	7.498	3.2	7.245	11.7	1.6	246	119
		Knysna	0014063W	23° 03'	34° 03'	1874	2001	737	122	76.7	3.4	19.9	9.423	3.2	11.08	15.7	1.4	269	96
		Jonkersberg (BOS)	0028415W	22° 14'	33° 55'	1874	2001	956	123	63.5	3	33.5	9.377	3	11.63	15.2	1.3	268	97
Csa	Warm temperate, summer dry, hot summer	Paarl (MUN)	0021823W	18° 58'	33° 43'	1850	2001	883	152	71.4	0	28.6	7.013	2.9	11.81	11.4	1	291	74
		Rawsonville	0022521W	19° 19'	33° 41'	1850	2001	614	150	61.8	0.9	37.3	6.26	3.7	10.01	12.2	1.2	304	61
		Tulbagh	0042227W	19° 09'	33° 17'	1850	2001	479	150	80.7	0.1	19.2	4.537	3.5	7.866	8.49	1.1	304	61
		Kluitjeskraal	0042325W	19° 11'	33° 26'	1850	2001	661	150	60.1	0.9	38.9	5.705	2.8	9.297	9.87	1.1	294	71
		Piketberg (MUN)	0062444W	18° 46'	32° 55'	1850	2001	478	152	79.1	0	20.9	4.201	3.2	7.491	7.39	1	301	64
Csb	Warm temperate, summer dry, cool summer	Bizweni	0005605A	18° 51'	34° 05'	1850	2001	628	149	61.5	1	37.5	5.244	3.1	7.772	8.8	1.1	285	81
		Royal Observatory	0020866W	18° 29'	33° 56'	1850	2001	622	150	94.2	0.9	4.8	5.151	3	6.127	8.31	1.4	246	101
		Durbanville	0021260W	18° 39'	33° 50'	1850	2001	610	150	58.3	0.9	40.7	4.769	2.9	8.071	7.62	0.9	290	76
		Eersteriver	0021330W	18° 41'	34° 01'	1850	2001	513	150	55.3	0.9	43	4.291	3	6.229	7.17	1.2	283	83
		Stellenbosch	0021655W	18° 52'	33° 56'	1850	2001	705	150	69.3	0.9	29.7	5.674	2.9	8.503	9.27	1.1	282	83
		La Motte	0022113W	19° 04'	33° 53'	1850	2001	786	150	51.6	0.9	47.5	6.618	3.1	9.835	11.2	1.1	285	80
		Villiersdorp	0022539W	19° 18'	34° 00'	1850	2001	580	151	50.8	0	49.2	5.575	3.5	8.598	10.4	1.2	298	68
		Malmesbury (MUN)	0041417W	18° 44'	33° 27'	1850	2001	469	150	79.3	0	20.6	3.972	3.1	6.862	6.79	1	297	68
		Algeria	0085112W	19° 03'	32° 23'	1850	2001	706	150	60.5	0.1	39.4	6.331	3.3	10.96	11.3	1	301	64
Cwa	Warm temperate, winter dry, hot summer	Moorside	0334174W	29°37'	28° 24'	1882	2000	785	115	71.1	0.2	28.7	6.927	3.2	11.08	12.2	1.1	295	71
		Idalia	0444203W	30° 38'	26° 53'	1882	2000	785	115	62.4	0.2	37.2	6.824	3.2	11.83	12	1	300	66
		Oliphantspoort	0511469W	27° 16'	25° 49'	1893	2000	631	106	72.9	0	27.1	5.825	3.4	8.072	10.4	1.3	287	78
		Haartebespoort Dam (IRR)	0512613W	27° 51'	25° 43'	1893	2000	643	106	72.2	0.1	27.7	6.083	3.5	9.008	11.2	1.2	295	71
		Pretoria-Bryntirion-1	0513404W	28° 14'	25° 44'	1893	2000	710	106	85.2	0	14.8	6.838	3.5	9.577	12.5	1.3	291	74
		Alkmaar	0555567W	30° 50'	25° 27'	1903	2000	832	96	94.6	0.6	4.8	7.716	3.4	10.84	13.8	1.3	289	76
		The Knoll	0556143W	31° 05'	25° 23'	1903	2000	784	96	52.7	0.6	46.7	7.174	3.4	9.273	12.5	1.4	281	84
		Champagne (NAF)	0595161W	31°06'	24° 41'	1903	2000	811	96	69.5	0.7	29.8	8.626	3.9	11.09	16.6	1.5	293	73
		Thabina	0679508W	30° 17'	23° 58'	1903	2000	716	96	76.8	0.8	22.4	8.031	4.1	12.4	16.7	1.3	308	58
Cwb	Warm temperate, winter dry, warm summer	Heavitree	0300567A	29° 49'	28° 57'	1882	2000	710	106	72.1	5	23	6.158	3.2	9.301	10.7	1.2	290	75
		Utrecht (MUN)	0371579W	30° 20'	27° 39'	1882	2000	690	115	67.6	0.2	32.2	6.164	3.3	9.739	10.9	1.1	294	71
		Schikfontein	0439396W	28° 14'	26° 36'	1882	2000	700	107	65.9	7.4	26.7	6.043	3.2	10.09	10.5	1	296	69
		Roodepoort (MUN)	0475669W	27° 53'	26° 09'	1893	2000	714	106	82.4	0	17.6	6.614	3.4	9.665	11.9	1.2	291	74
		Nebo	0592474W	29° 46'	24° 55'	1903	2000	618	96	88.4	0.6	11	6.62	3.9	12.31	12.2	1	315	50
		Martenshoop (POL)	0593419W	30° 14'	24° 59'	1903	2000	683	96	90.4	0.6	9	6.5	3.5	11.65	12.2	1	307	59
		Elandsfontein	0594457W	30° 46'	24° 37'	1903	2000	638	96	80	0.7	19.3	6.994	4	10.4	14.2	1.4	304	61
		Mac Mac (BOS)	0594539W	30° 49'	24° 59'	1903	2000	1464	96	74.6	0.7	24.7	11.15	2.8	13.2	17	1.3	255	111

APPENDIX 3 Rainfall Characteristics

(a) The effect of increasing the length of the rainfall time series on observed rainwater harvesting system behaviour

Figures A-1 to A-6 plot a comparison of the maximum yield values obtained when using the rainfall record ending in 2001(**$N_{end2001}$**) against the maximum yield values obtained when using the rainfall record ending in 2017 (**$N_{end2017}$**) for the five rainfall stations across all S-D ratios. The inclined straight line represents the situation where both records produce identical simulation results.

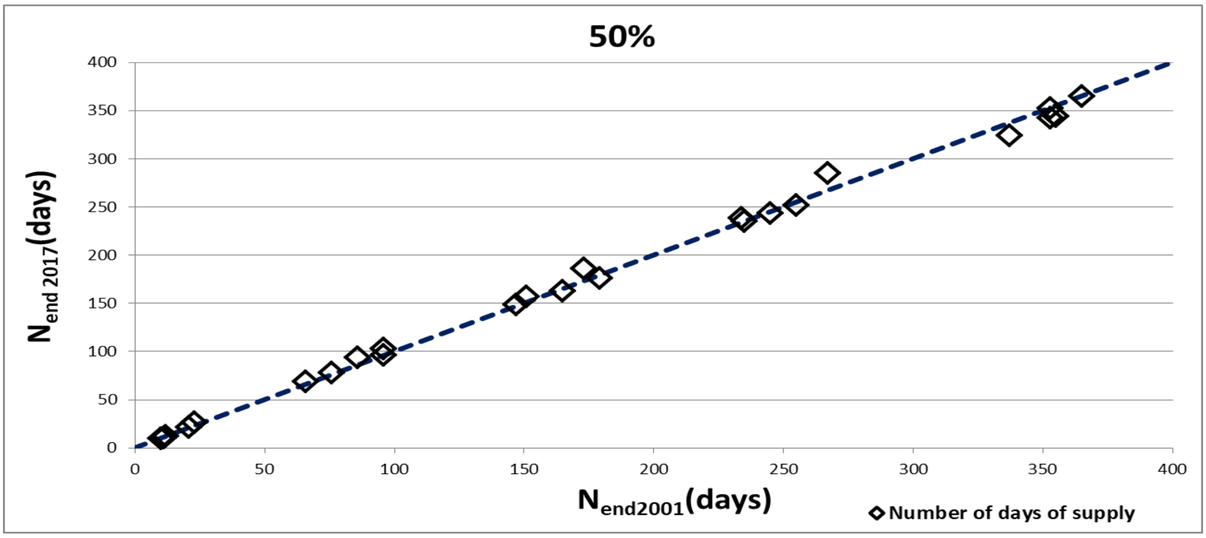


Figure A-1: Comparison of maximum yield values at 50% reliability

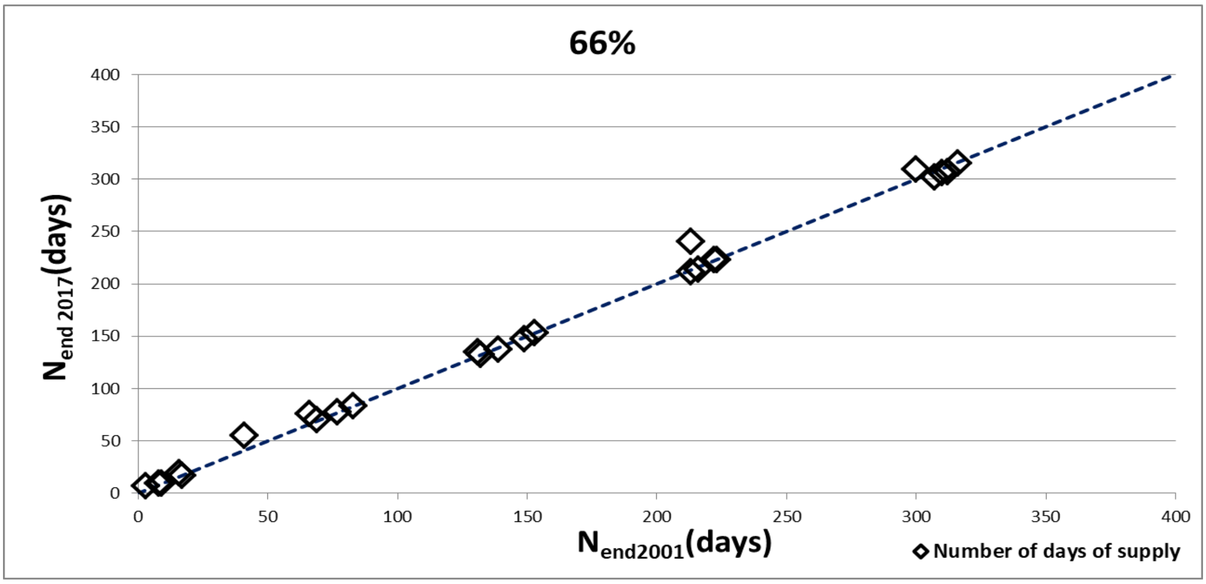


Figure A-2: Comparison of maximum yield values at 66% reliability

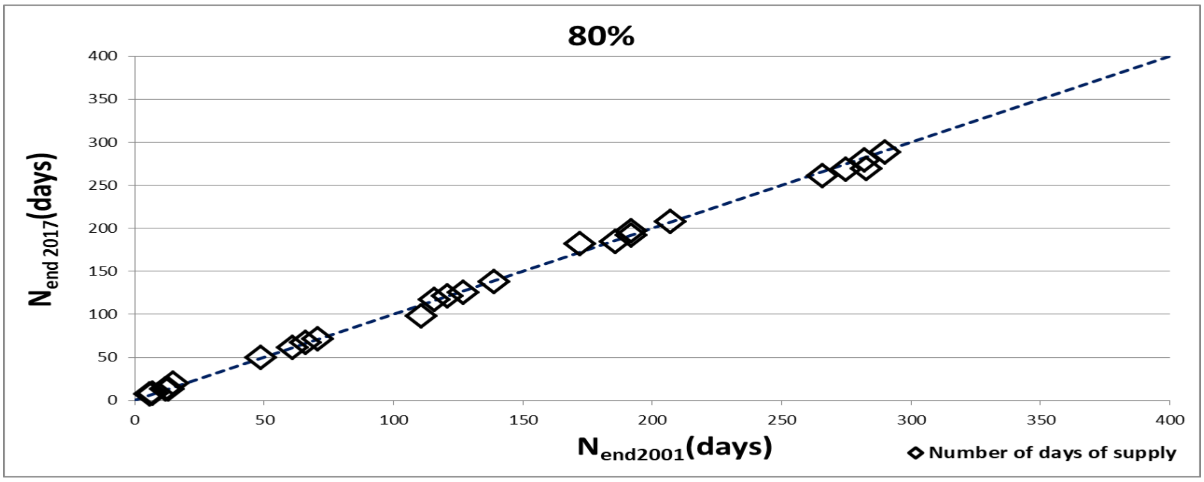


Figure A-3: Comparison of maximum yield values at 80% reliability

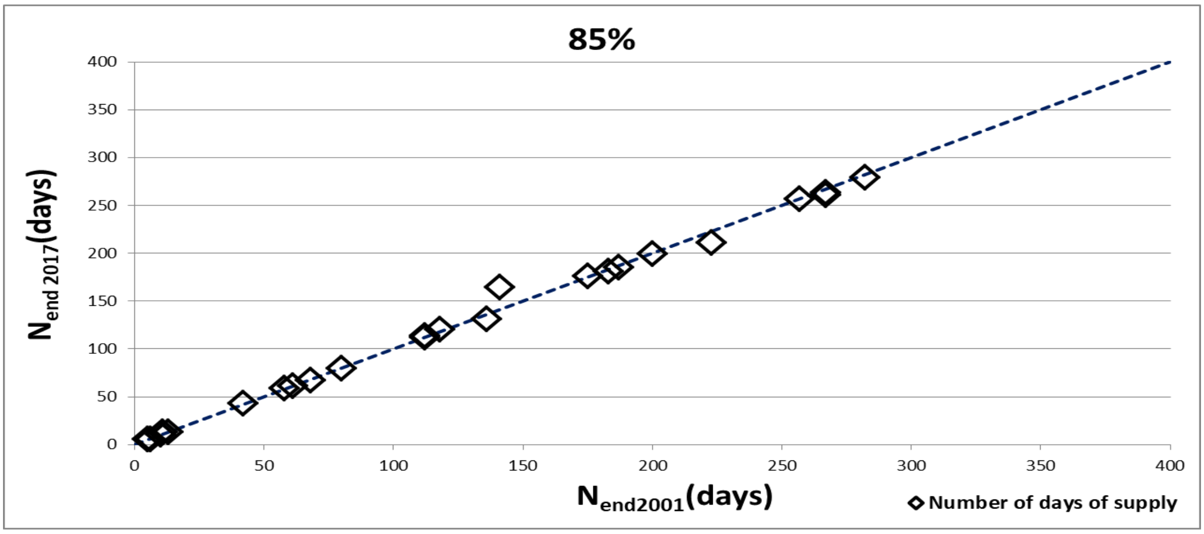


Figure A-4: Comparison of maximum yield values at 85% reliability

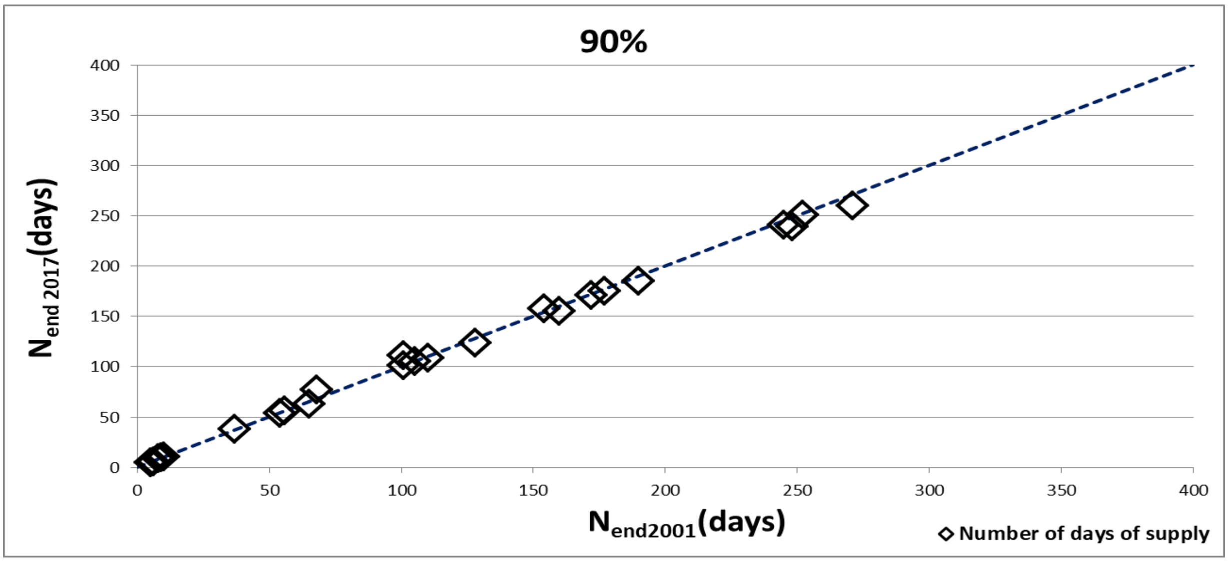


Figure A-5: Comparison of maximum yield values at 90% reliability

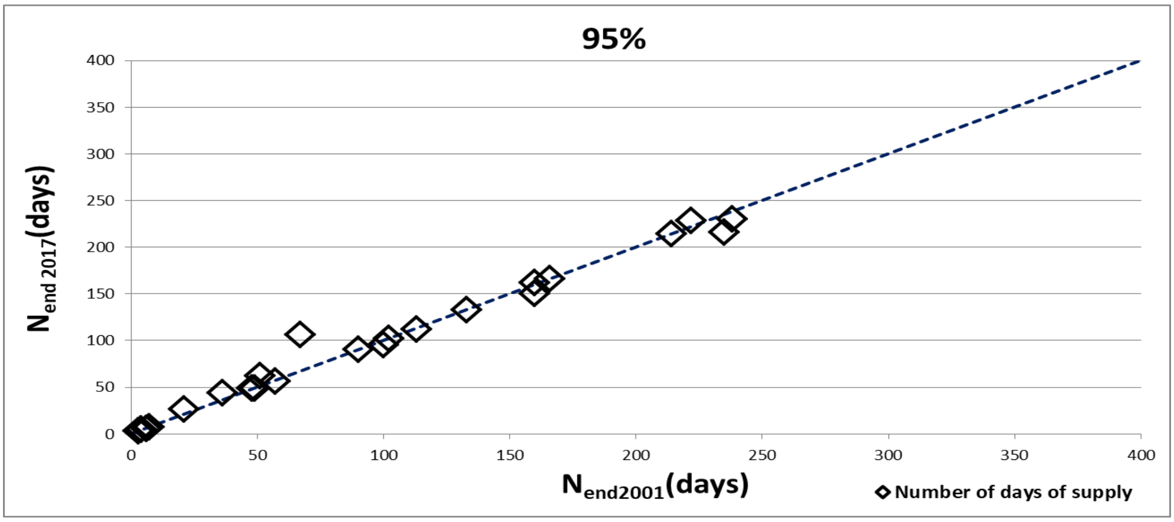


Figure A-6: Comparison of maximum yield values at 95% reliability

The Figures show that extending the record to include the last 17 years of data has an almost negligible impact on the resulting maximum yield. Thus it was concluded that an analysis based on the data obtained using the rainfall records from the database could be considered as a reliable representation of the expected behaviour of RWHS in South Africa.

Figures A-7 to A-12 shows a similar comparison for the corresponding optimum storage values.

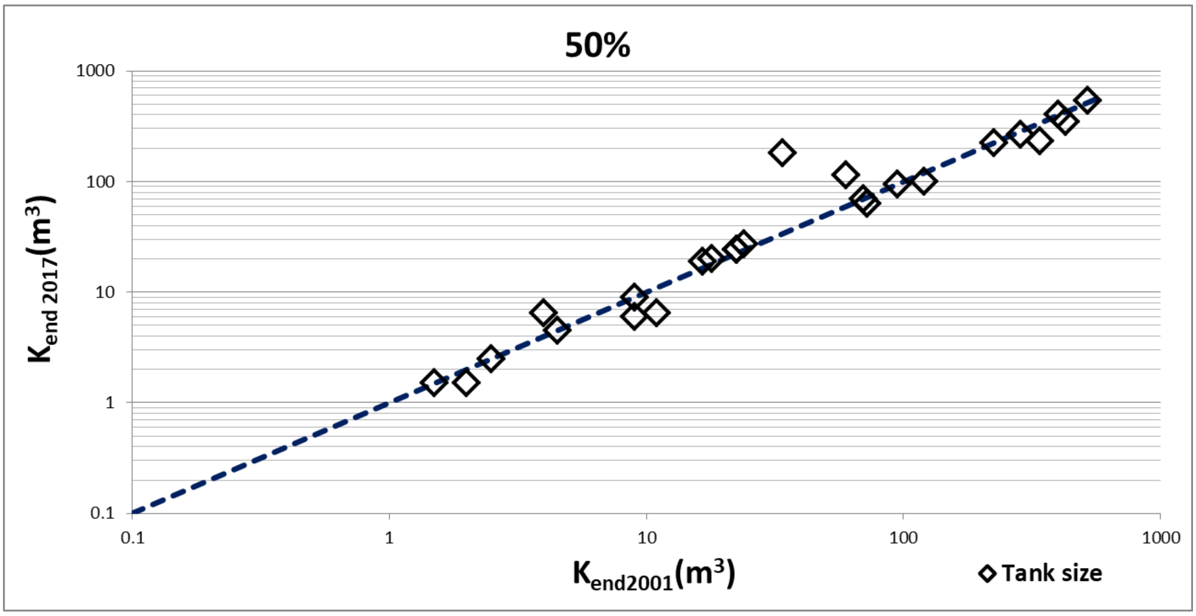


Figure A-7: Comparison of optimum storage values at 50% reliability

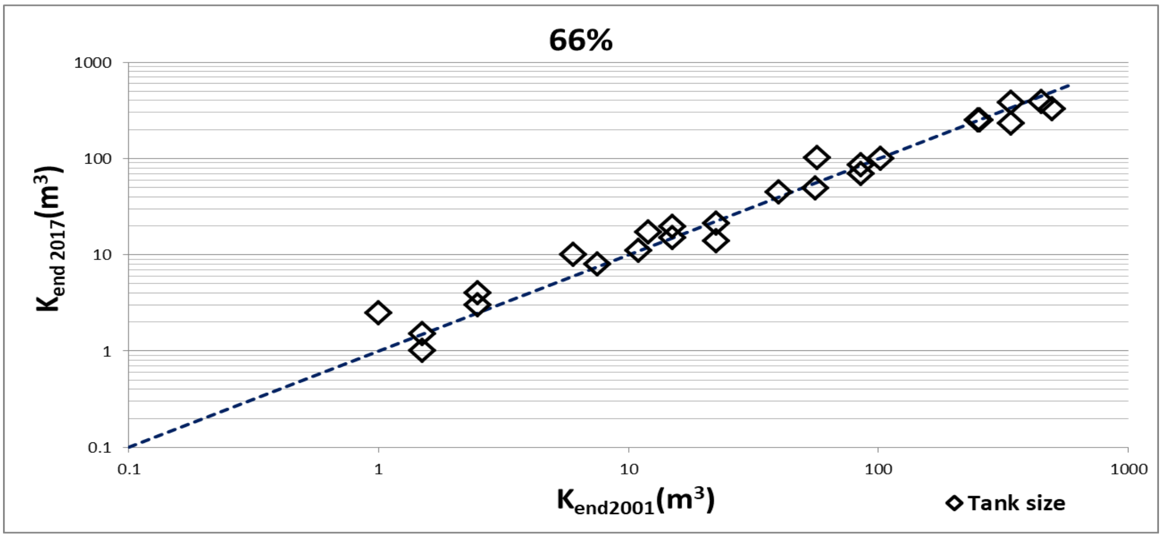


Figure A-8: Comparison of optimum storage values at 66% reliability

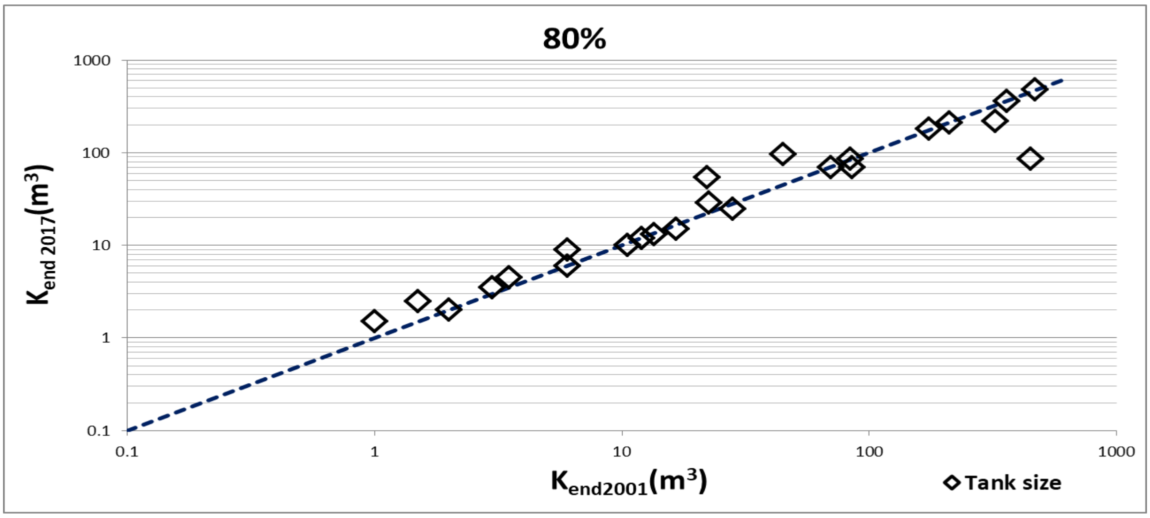


Figure A-9: Comparison of optimum storage values at 80% reliability

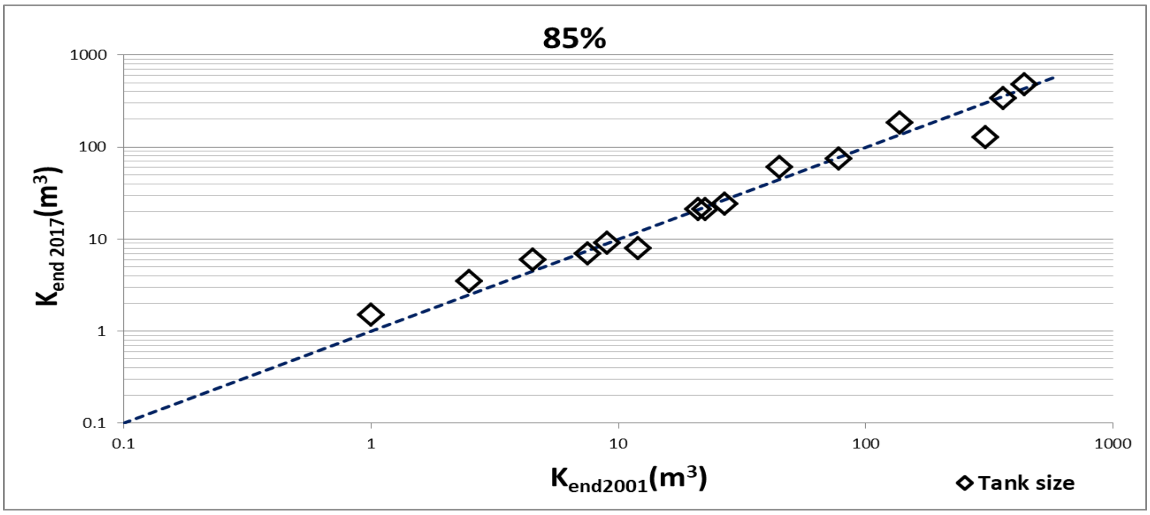


Figure A-10: Comparison of optimum storage values at 85% reliability

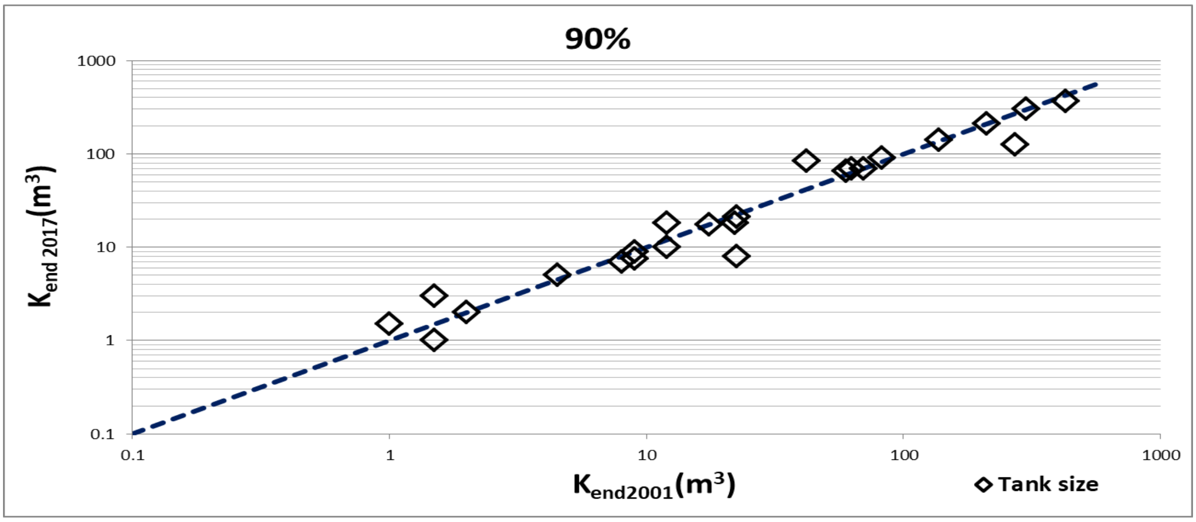


Figure A-11: Comparison of optimum storage values at 90% reliability

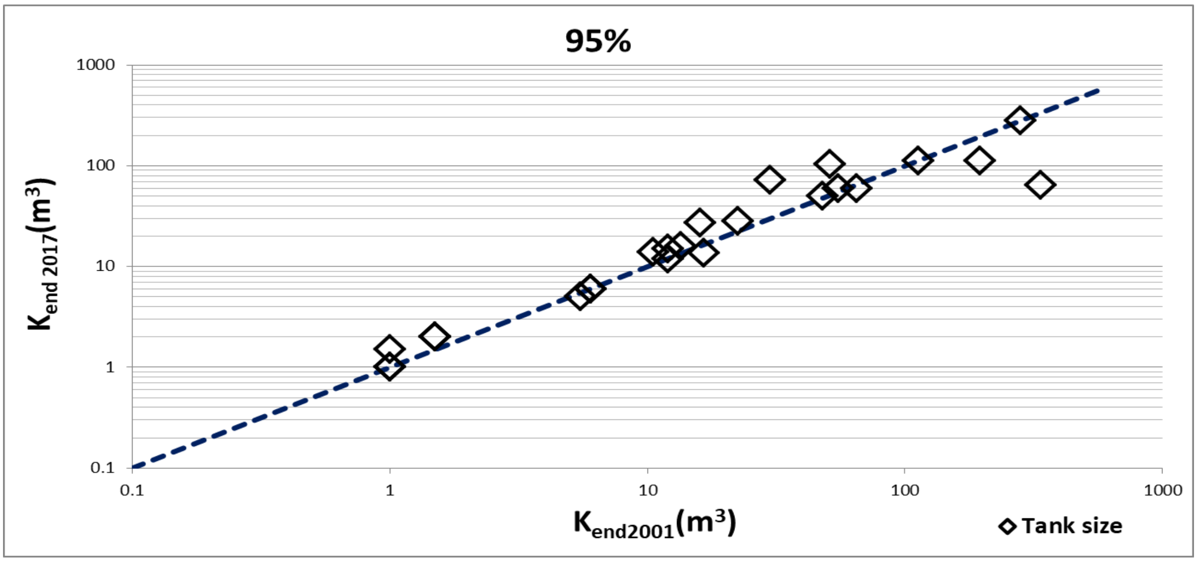
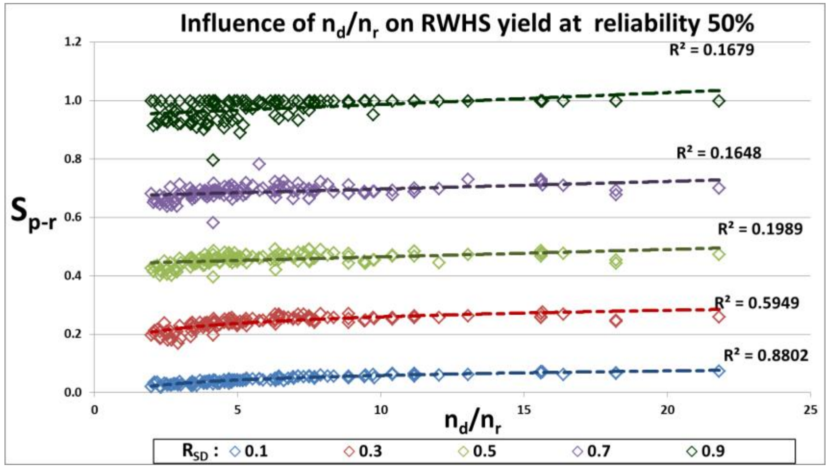


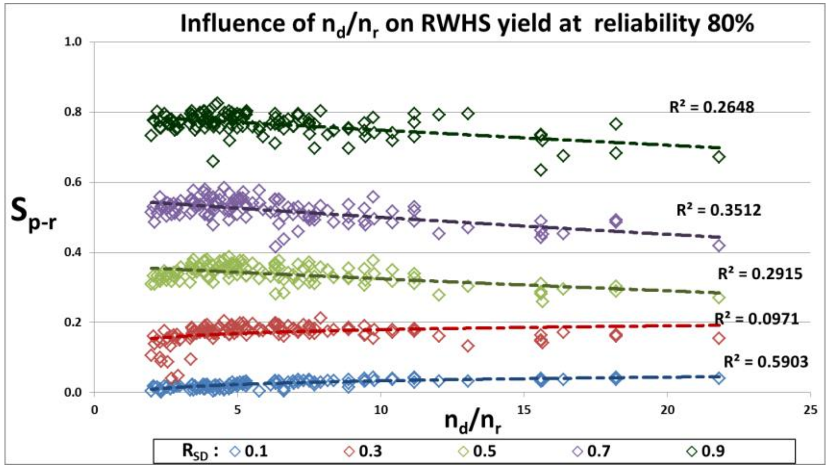
Figure A-12: Comparison of optimum storage values at 95% reliability

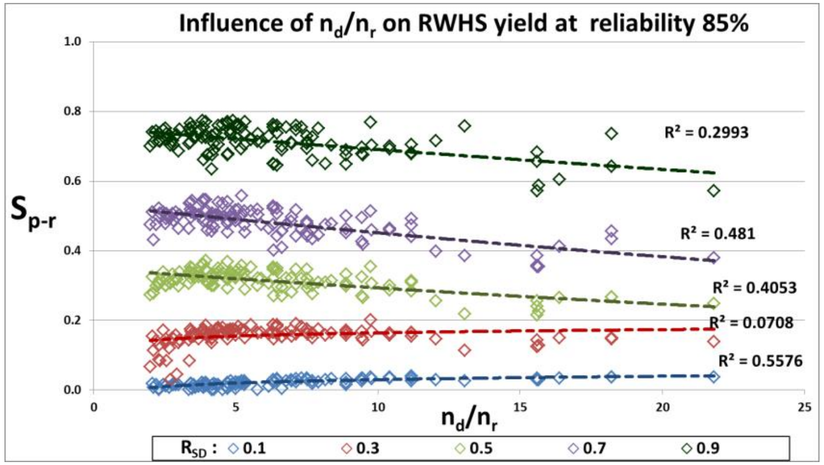
When compared to the data for yield, the data for storage values showed more variability when the record was extended. The general trend observed was that the extended rainfall record on average prescribed larger storages with an approximate percentage difference of 10% measured across all reliabilities and rain gauges.

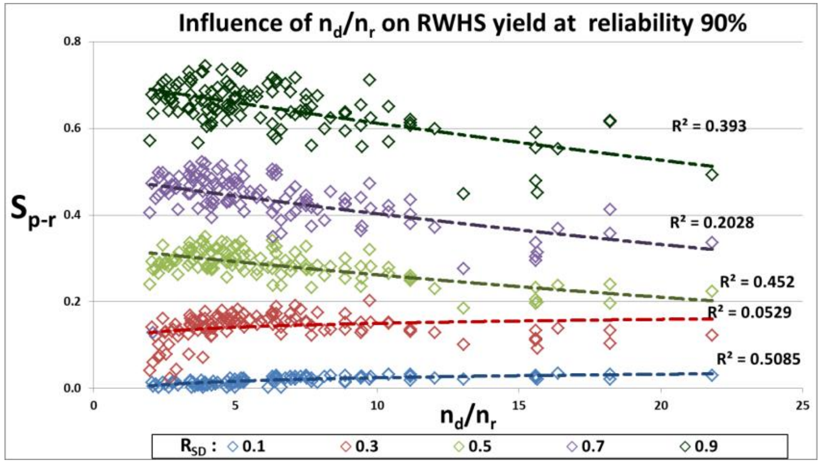
Overall, it would appear that the optimum capacity of storages is to some extent sensitive to the length of the rainfall record utilised as this could introduce significant shifts in the intra-annual distributive characteristics of the rainfall. However given the general uncertain nature of inputs such as rainfall, for the purposes of this study, this difference was not viewed as being sufficiently large enough to cause concern and as such the rainfall records from the database were taken as adequate for the study.

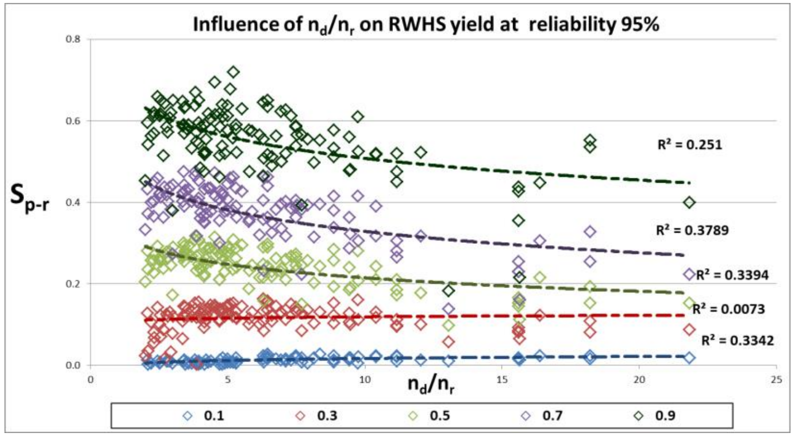
(b) Influence of n_d/n_r on yield ratio





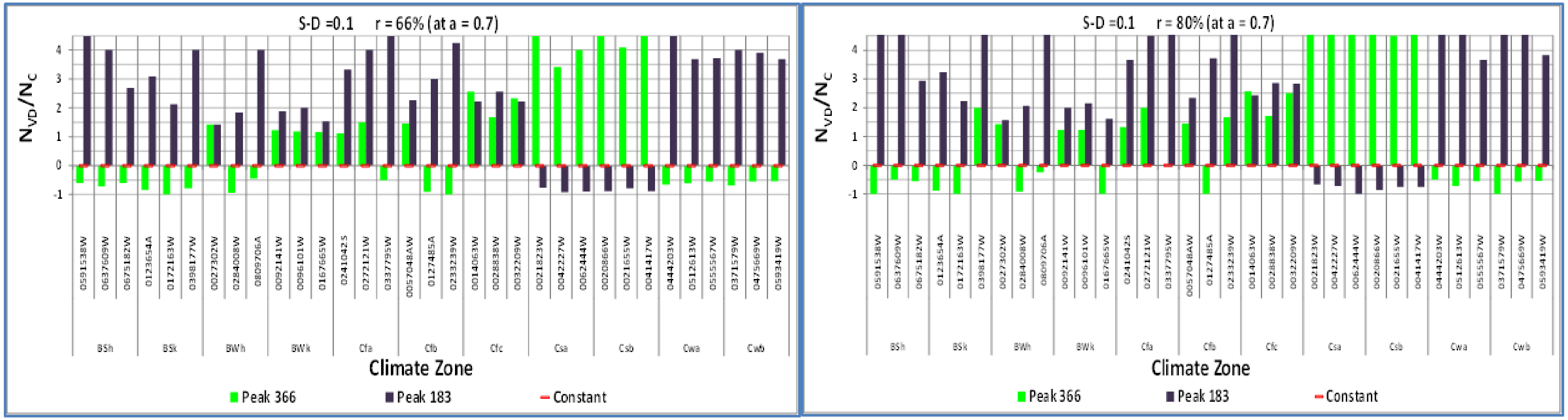


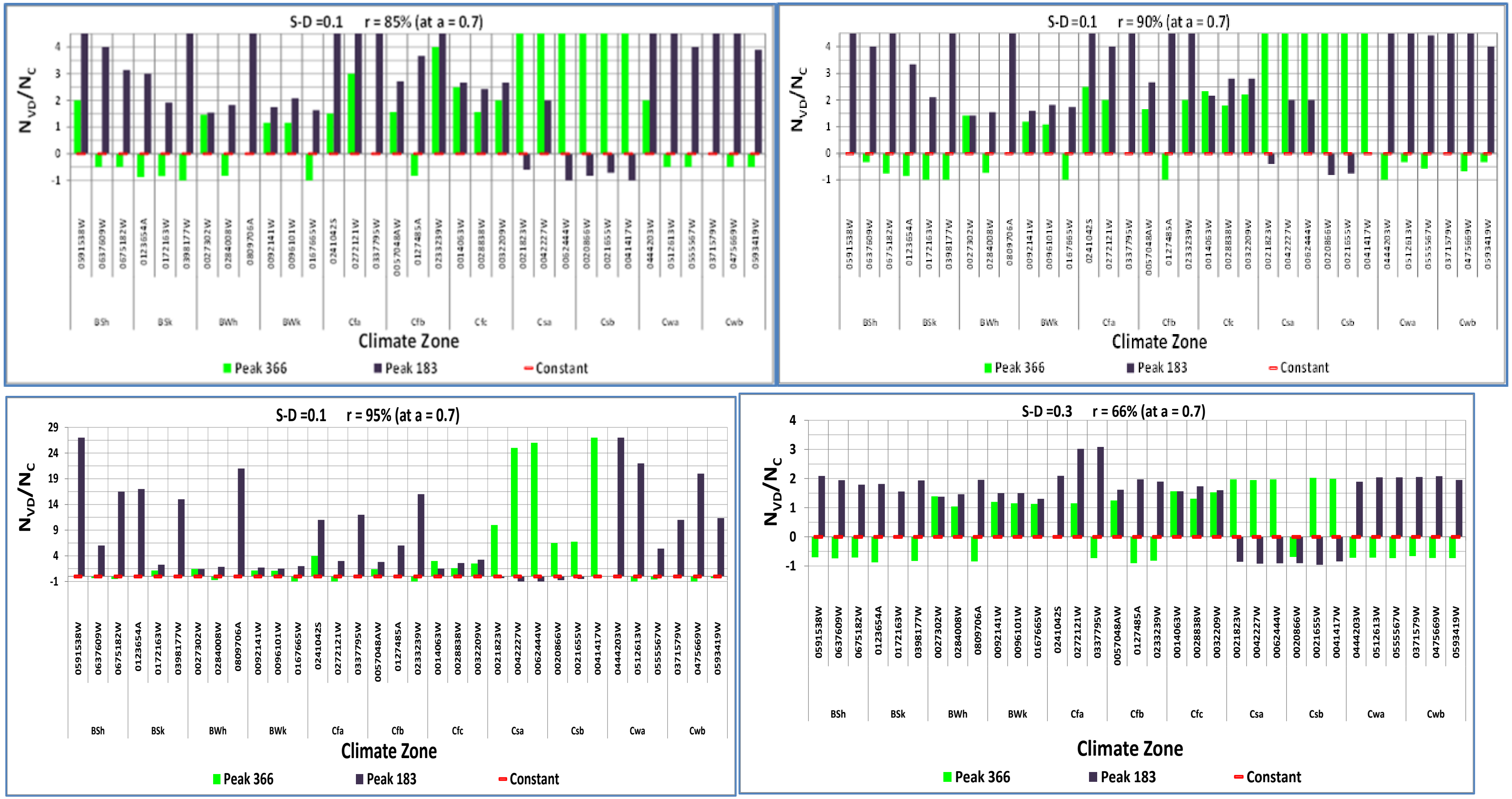


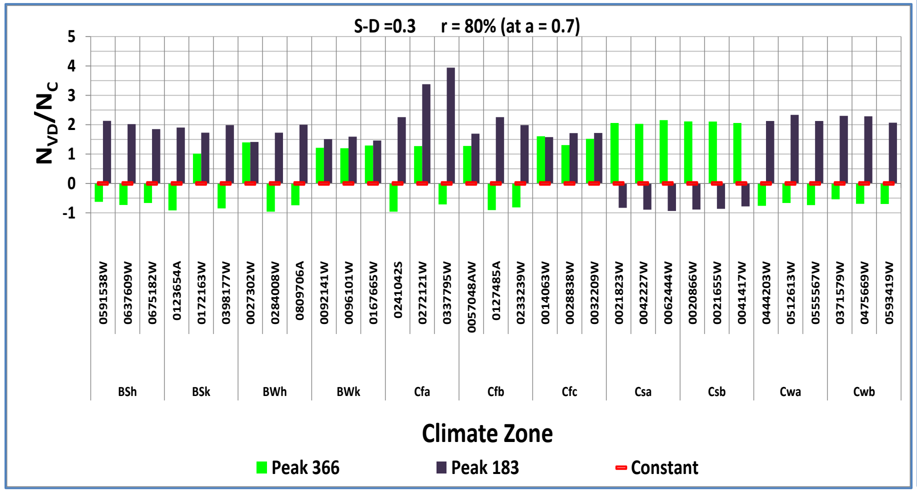


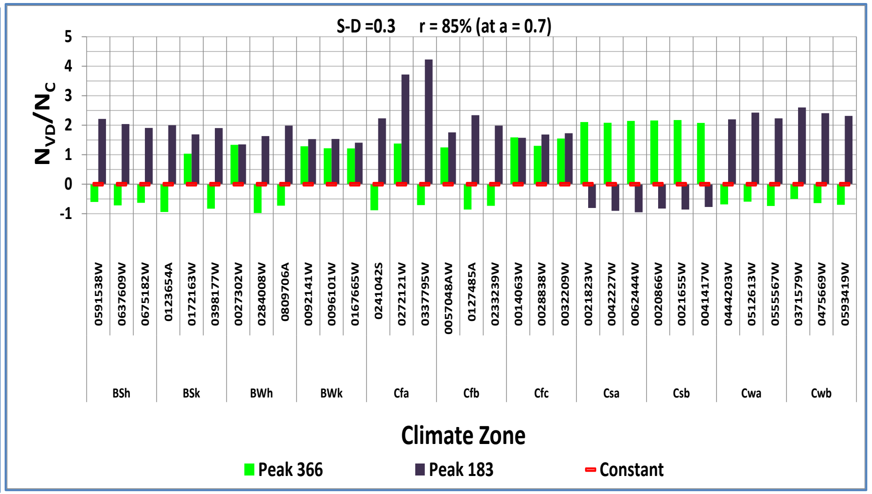
APPENDIX 4 Variable Demand (Additional Simulation Data)

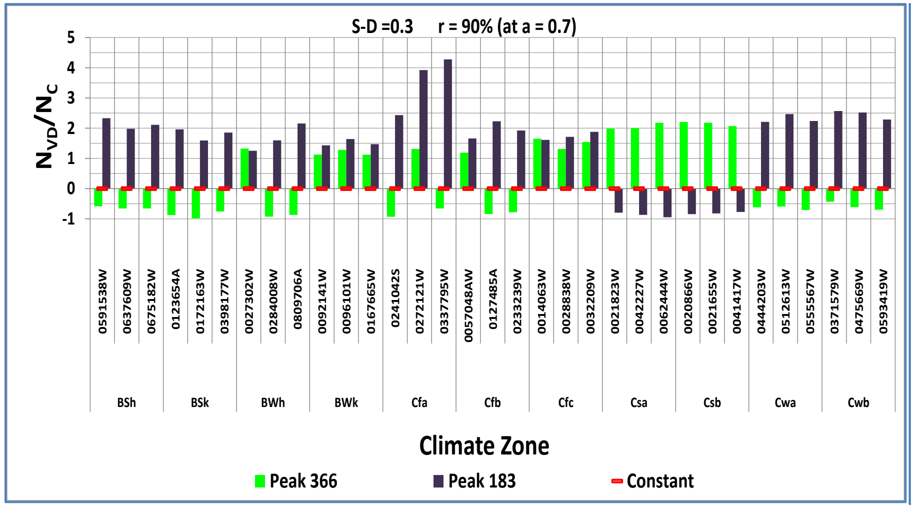
(a) Variation of yield with location of peak demand fixed amplitude

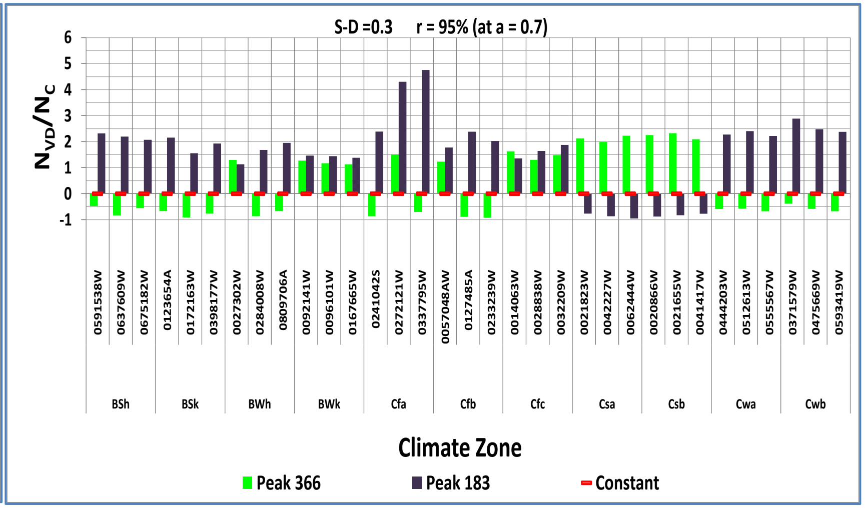


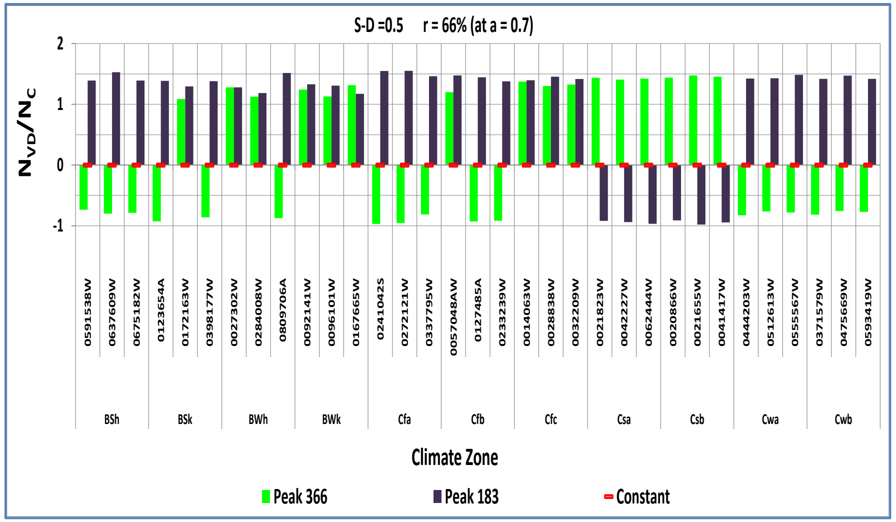

S-D =0.1 r = 85% (at a = 0.7)
S-D =0.1 r = 90% (at a = 0.7)
S-D =0.1 r = 95% (at a = 0.7)
S-D =0.3 r = 66% (at a = 0.7)
N_VD/N_C
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Peak 366
Peak 183
Constant

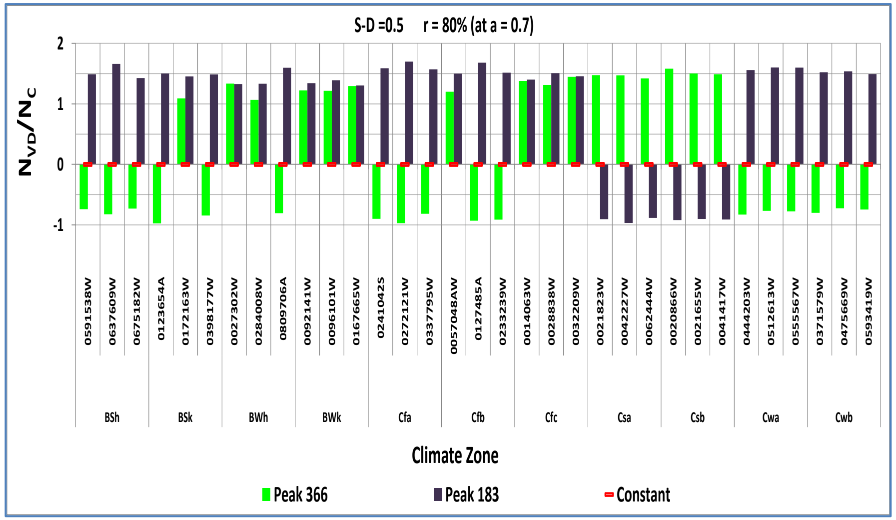

S-D =0.3 r = 80% (at a = 0.7)
N_{VD}/N_C
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Peak 366
Peak 183
Constant

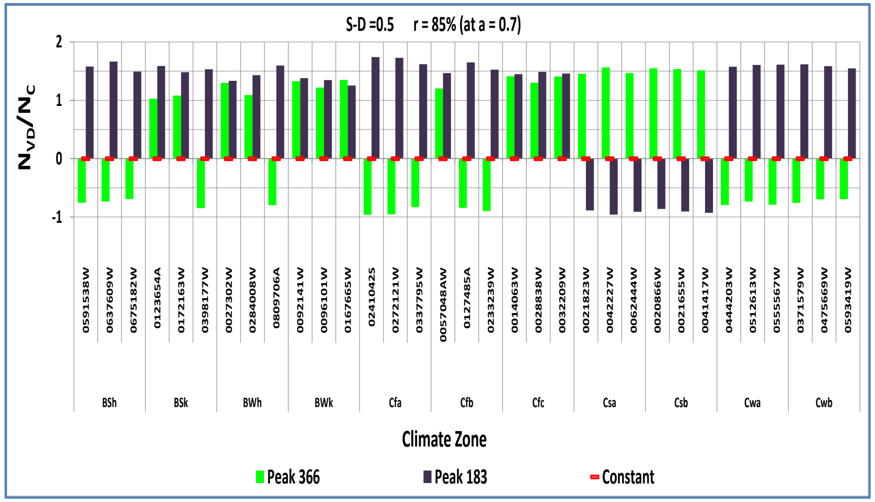

S-D =0.3 r = 85% (at a = 0.7)
N_{VD}/N_C
Climate Zone
Peak 366
Peak 183
Constant

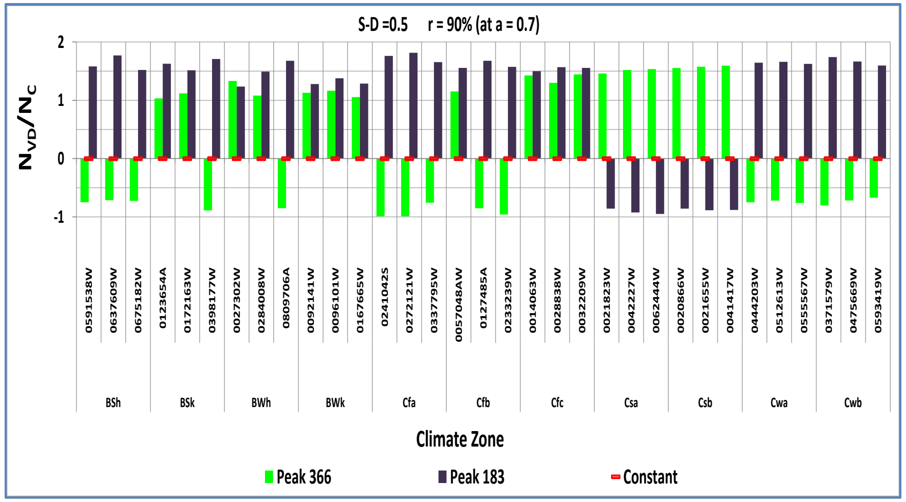

S-D =0.3 r = 90% (at a = 0.7)
N_{VD}/N_C
Climate Zone
Peak 366
Peak 183
Constant

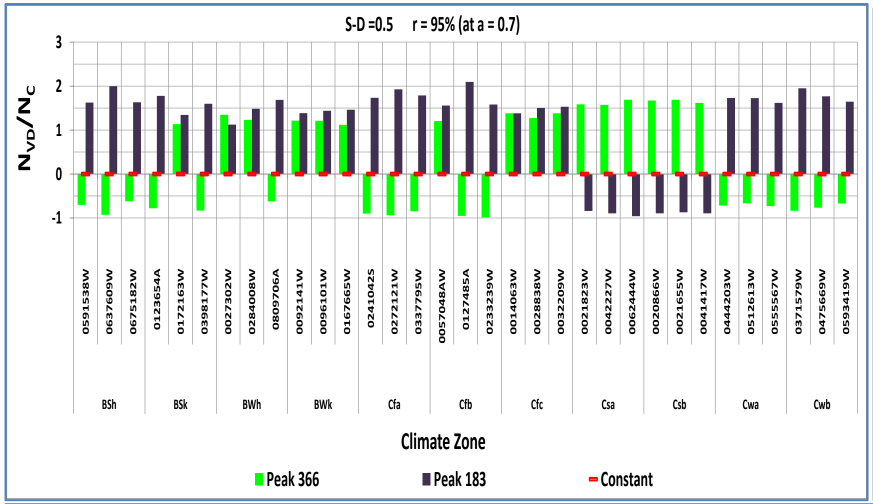

S-D =0.3 r = 95% (at a = 0.7)
N_{VD}/N_C
Climate Zone
Peak 366
Peak 183
Constant

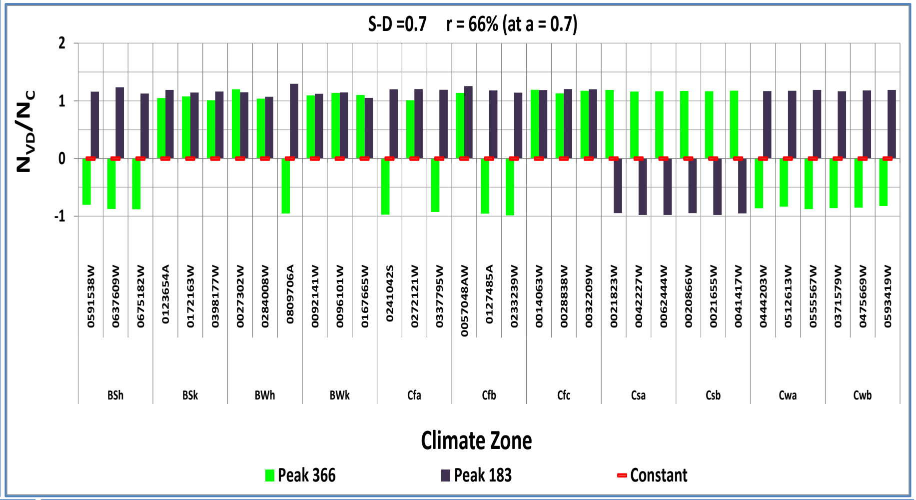

S-D =0.5 r = 66% (at a = 0.7)
NVD/NC
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

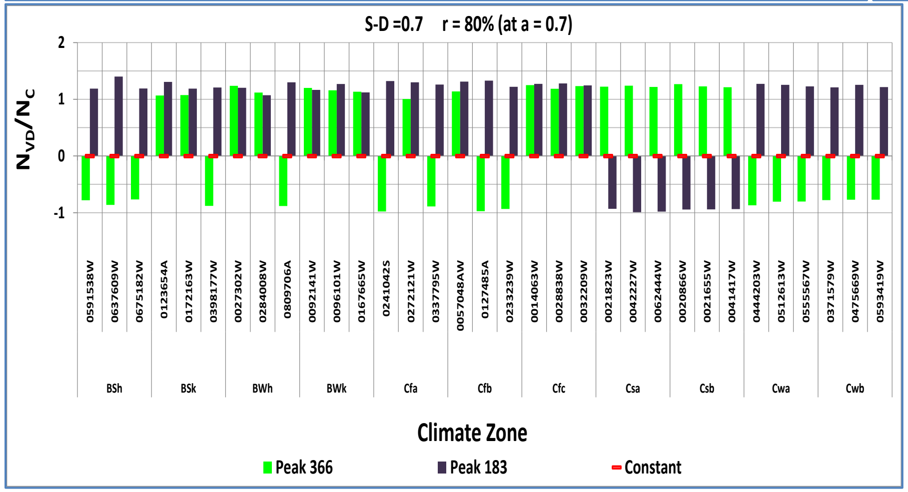

S-D =0.5 r = 80% (at a = 0.7)
NVD/NC
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

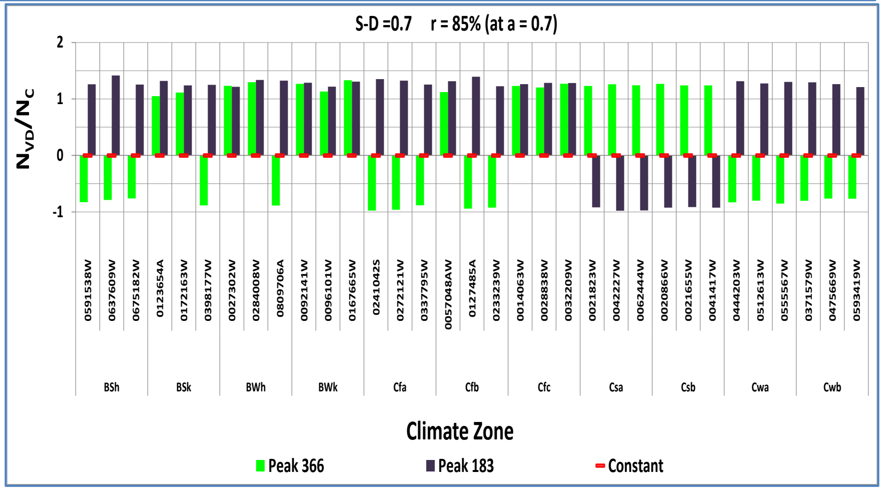

S-D =0.5 r = 85% (at a = 0.7)
NVD/NC
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

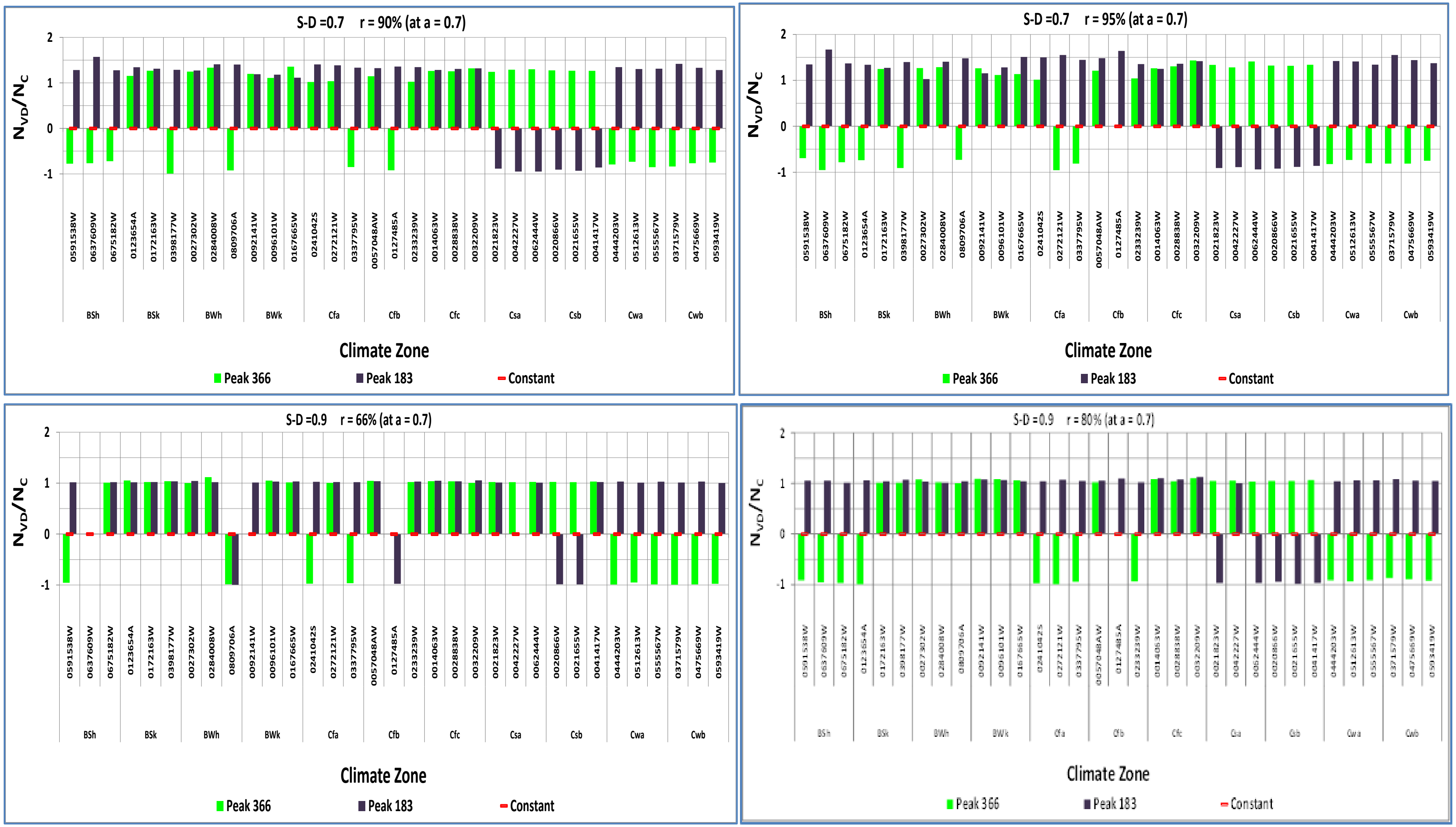

S-D =0.5 r = 90% (at a = 0.7)
NVD/NC
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

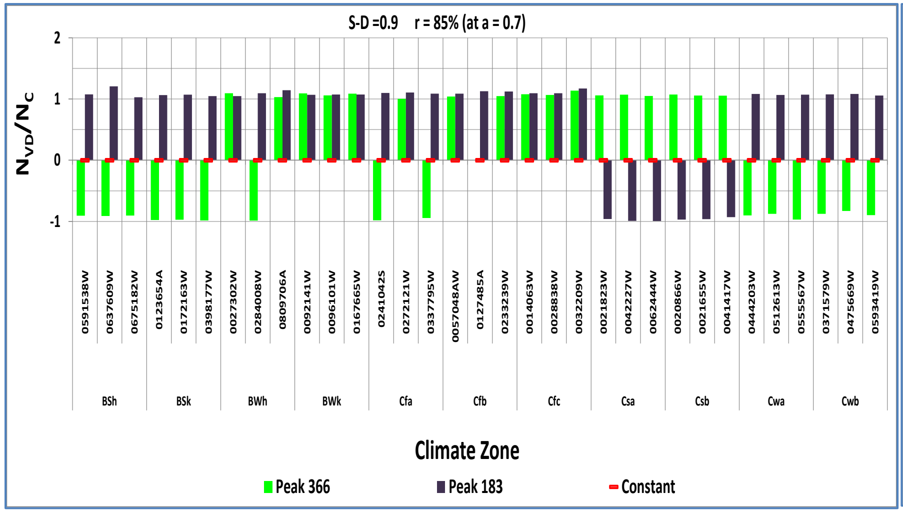

S-D =0.5 r = 95% (at a = 0.7)
Climate Zone
Peak 366
Peak 183
Constant

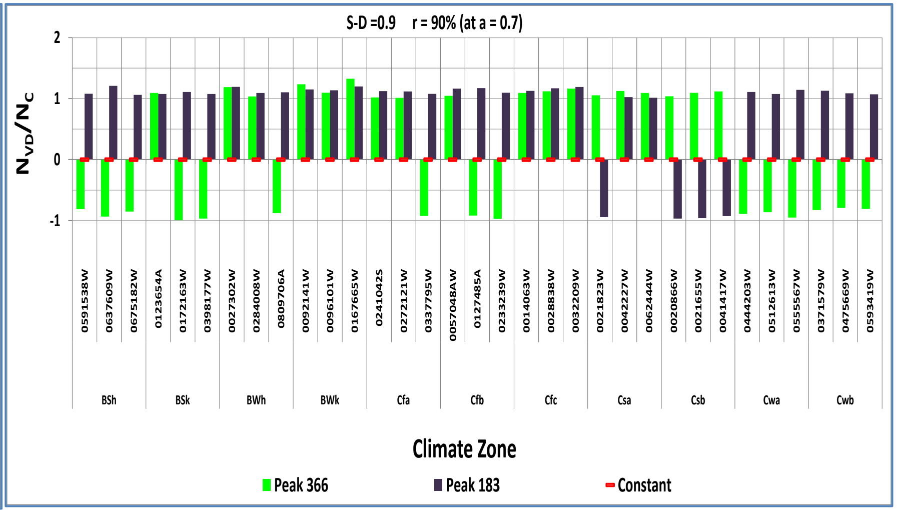

S-D =0.7 r = 66% (at a = 0.7)
Climate Zone
Peak 366
Peak 183
Constant

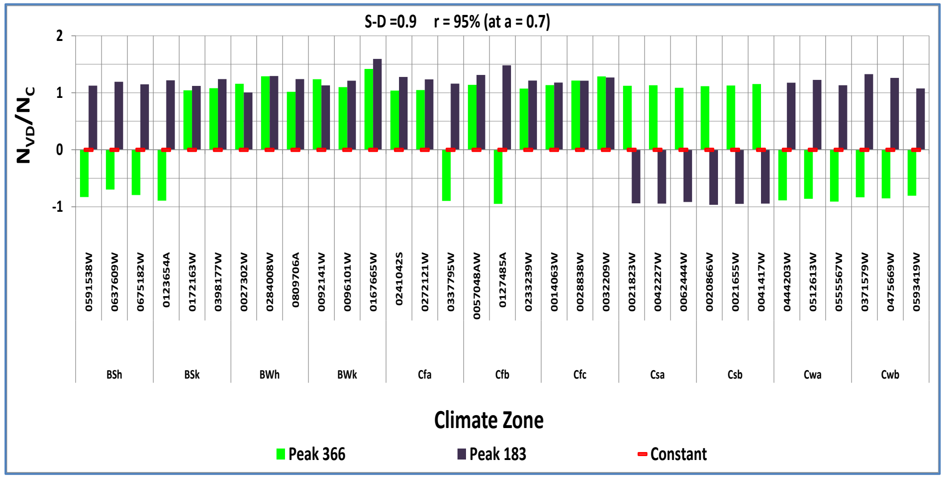

S-D =0.7 r = 80% (at a = 0.7)
Climate Zone
Peak 366
Peak 183
Constant


S-D =0.7 r = 85% (at a = 0.7)
Climate Zone
Peak 366
Peak 183
Constant

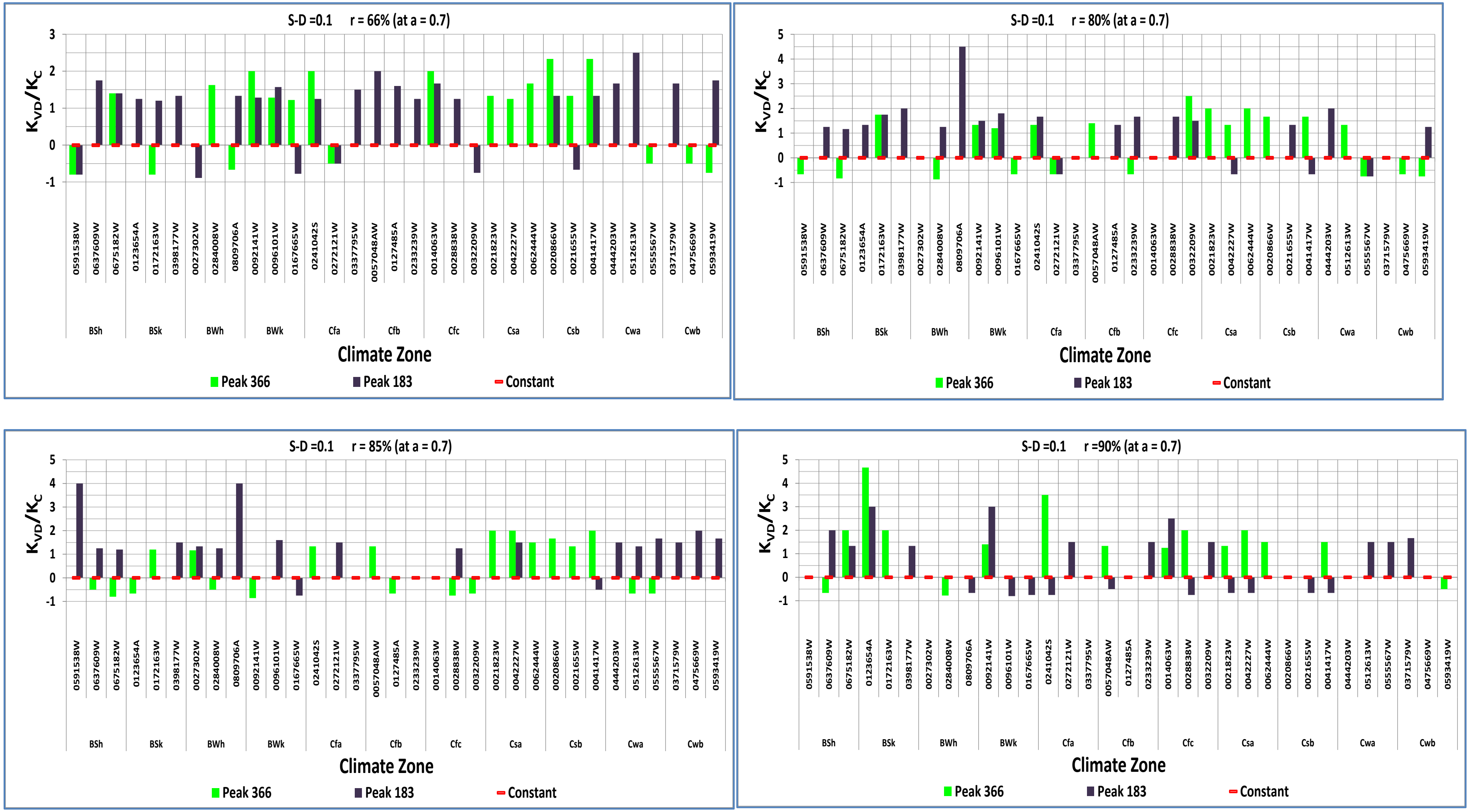

S-D =0.7 r = 90% (at a = 0.7)
N_{VD}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant
S-D =0.7 r = 95% (at a = 0.7)
N_{VD}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant
S-D =0.9 r = 66% (at a = 0.7)
N_{VD}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant
S-D =0.9 r = 80% (at a = 0.7)
N_{VD}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

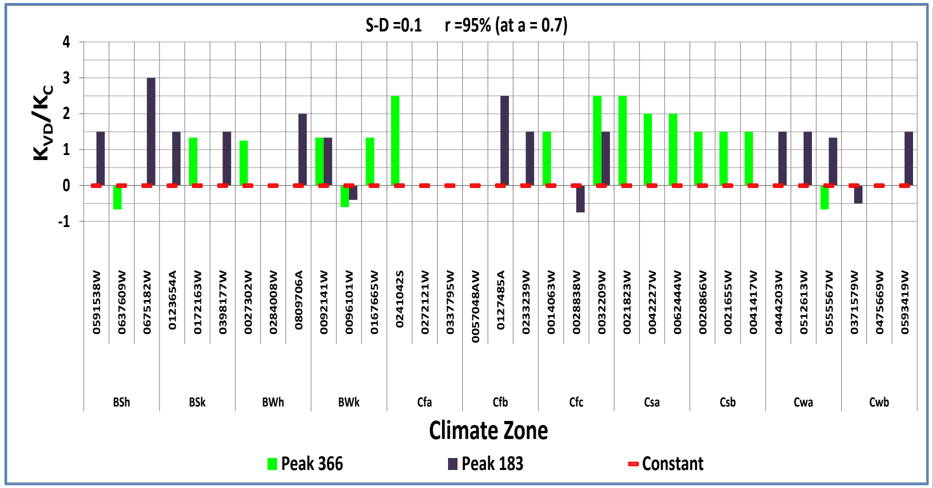

S-D =0.9 r = 85% (at a = 0.7)
N_{VD}/N_C
Climate Zone
Peak 366
Peak 183
Constant

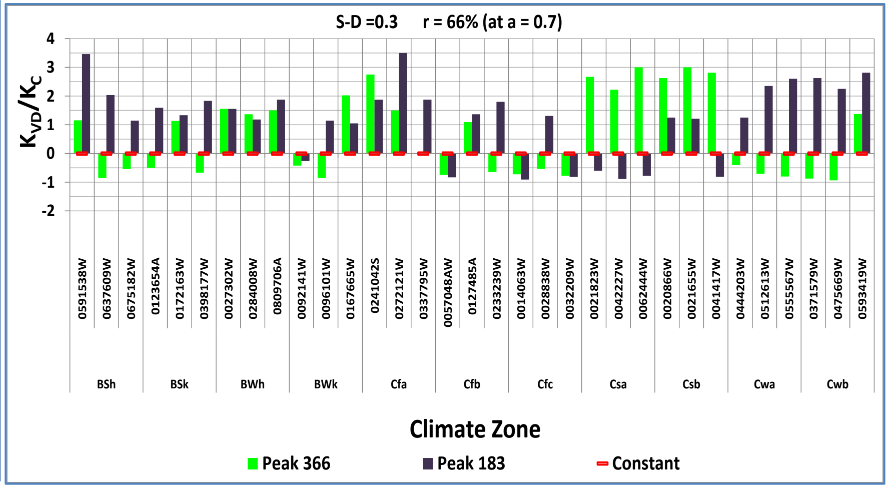

S-D =0.9 r = 90% (at a = 0.7)
N_{VD}/N_C
Climate Zone
Peak 366
Peak 183
Constant

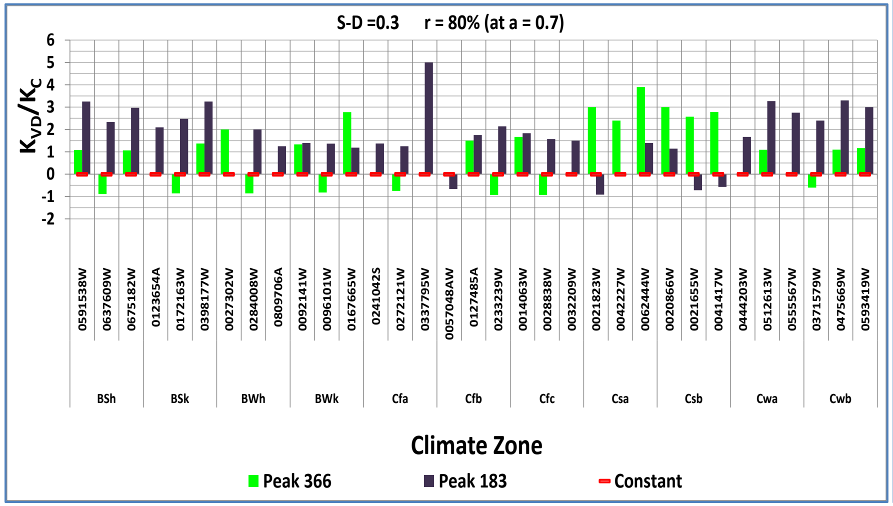

S-D =0.9 r = 95% (at a = 0.7)
N_{VD}/N_C
Climate Zone
Peak 366
Peak 183
Constant

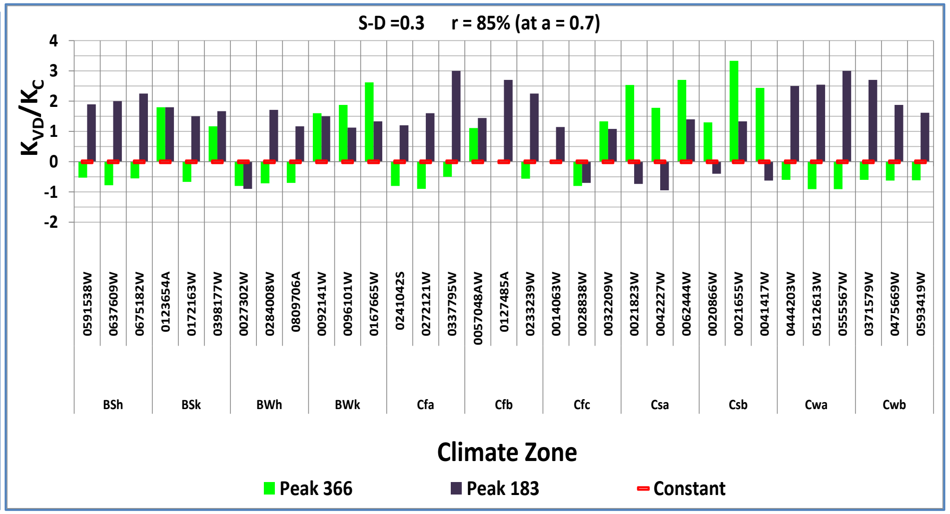
(b) Variation of storage with location of peak demand at fixed amplitude

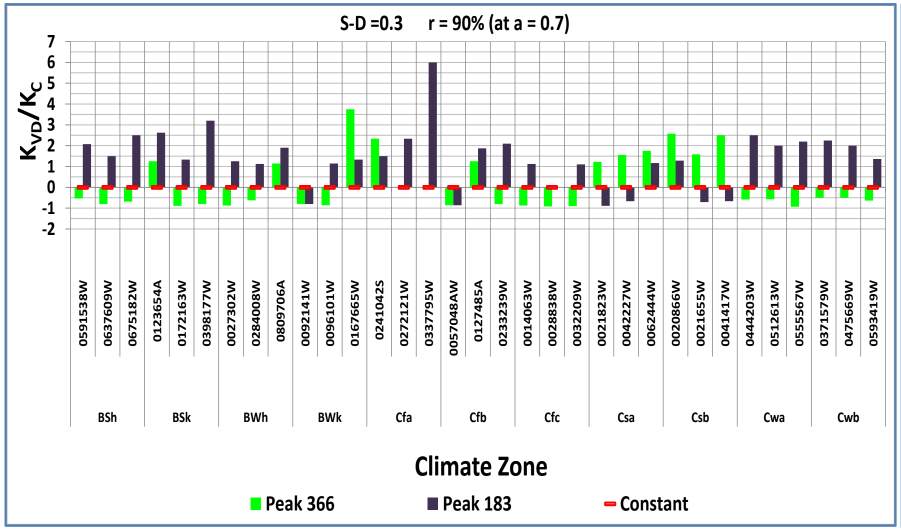



S-D =0.1 r =95% (at a = 0.7)
K_{VD}/K_C
4
3
2
1
0
-1
0591538W
0637609W
0675182W
0123654A
0172163W
0398177W
0027302W
0284008W
0809706A
0092141W
0096101W
0167665W
0241042S
0272121W
0337795W
0057048AW
0127485A
0233239W
0014063W
0028838W
0032209W
0021823W
0042227W
0062444W
0020866W
0021655W
0041417W
0444203W
0512613W
0555567W
0371579W
0475669W
0593419W
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Climate Zone
Peak 366
Peak 183
Constant

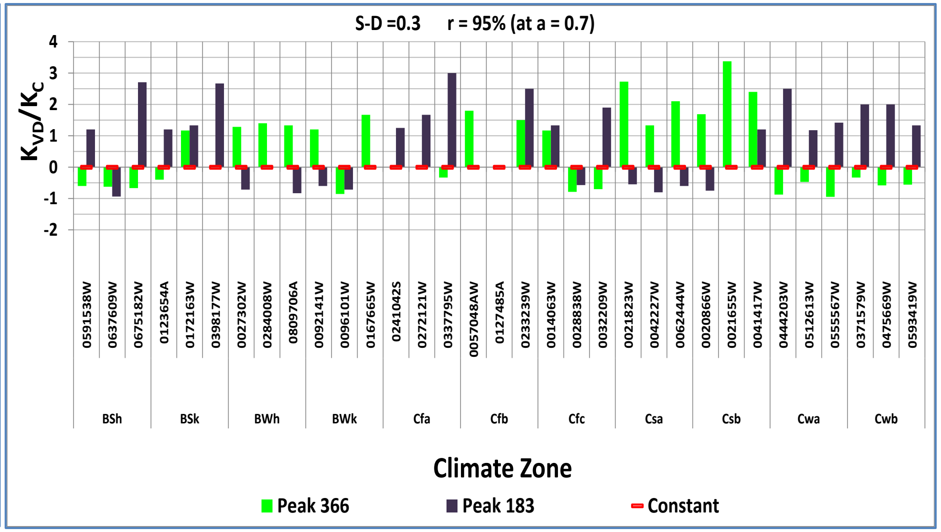

S-D =0.3 r = 66% (at a = 0.7)
K_{VD}/K_C
4
3
2
1
0
-1
-2
0591538W
0637609W
0675182W
0123654A
0172163W
0398177W
0027302W
0284008W
0809706A
0092141W
0096101W
0167665W
0241042S
0272121W
0337795W
0057048AW
0127485A
0233239W
0014063W
0028838W
0032209W
0021823W
0042227W
0062444W
0020866W
0021655W
0041417W
0444203W
0512613W
0555567W
0371579W
0475669W
0593419W
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Climate Zone
Peak 366
Peak 183
Constant


S-D =0.3 r = 80% (at a = 0.7)
K_{VD}/K_C
6
5
4
3
2
1
0
-1
-2
0591538W
0637609W
0675182W
0123654A
0172163W
0398177W
0027302W
0284008W
0809706A
0092141W
0096101W
0167665W
0241042S
0272121W
0337795W
0057048AW
0127485A
0233239W
0014063W
0028838W
0032209W
0021823W
0042227W
0062444W
0020866W
0021655W
0041417W
0444203W
0512613W
0555567W
0371579W
0475669W
0593419W
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Climate Zone
Peak 366
Peak 183
Constant

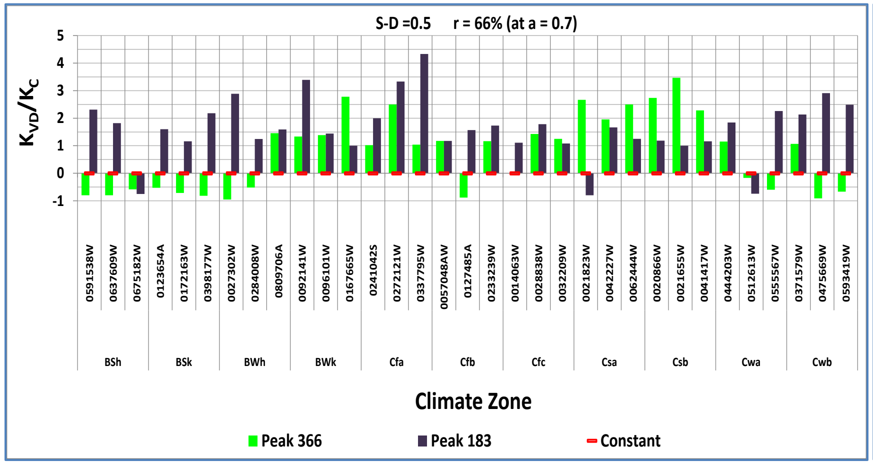

S-D =0.3 r = 85% (at a = 0.7)
K_{VD}/K_C
4
3
2
1
0
-1
-2
0591538W
0637609W
0675182W
0123654A
0172163W
0398177W
0027302W
0284008W
0809706A
0092141W
0096101W
0167665W
0241042S
0272121W
0337795W
0057048AW
0127485A
0233239W
0014063W
0028838W
0032209W
0021823W
0042227W
0062444W
0020866W
0021655W
0041417W
0444203W
0512613W
0555567W
0371579W
0475669W
0593419W
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Climate Zone
Peak 366
Peak 183
Constant



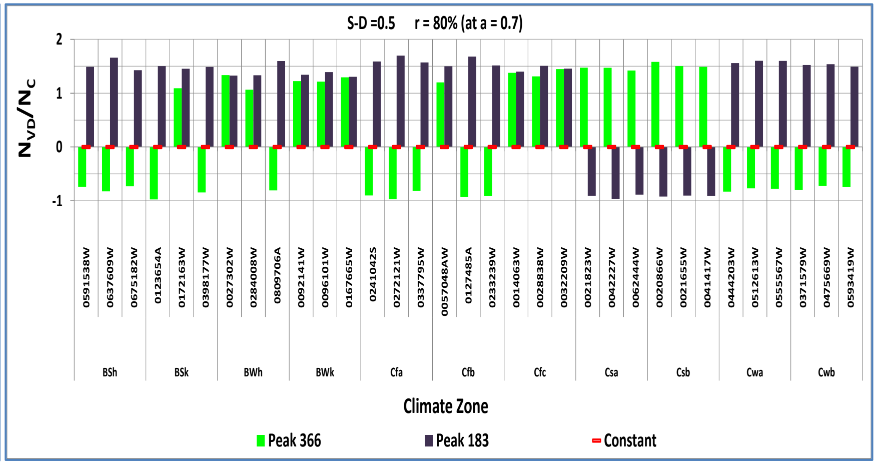
S-D =0.3 r = 90% (at a = 0.7)
K_{VD}/K_C
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant



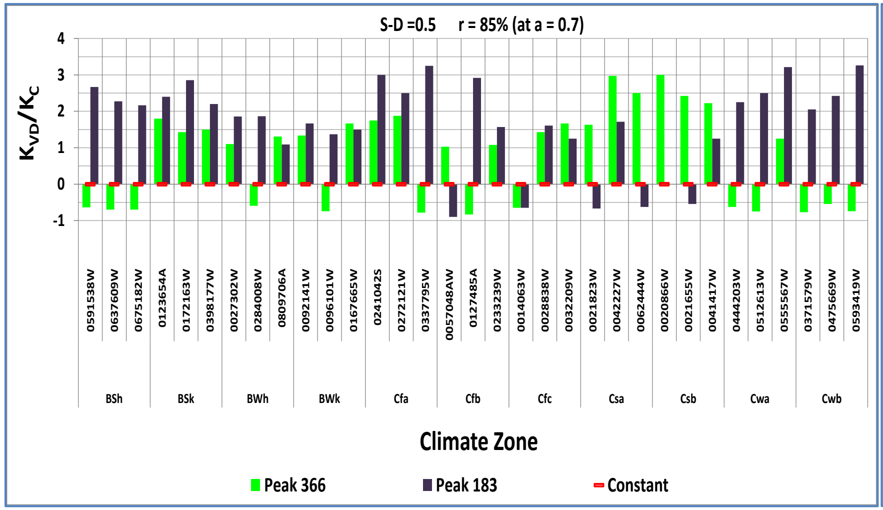
S-D =0.3 r = 95% (at a = 0.7)
K_{VD}/K_C
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

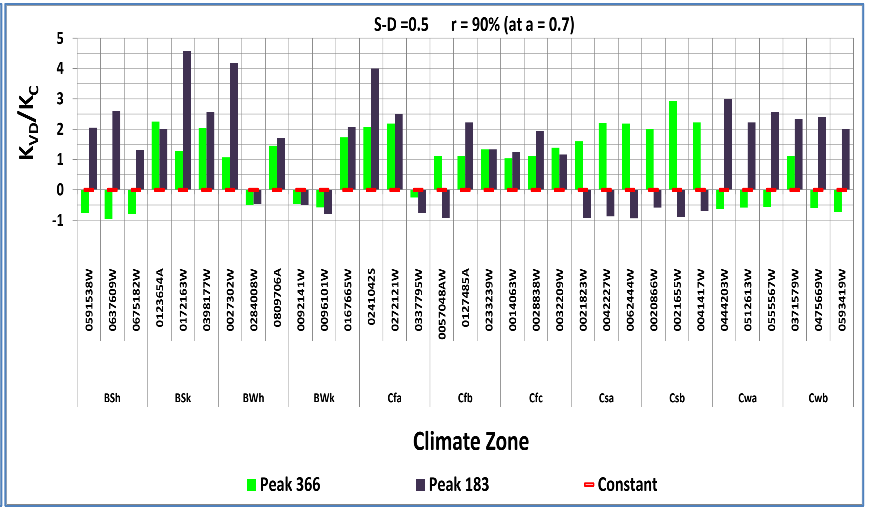


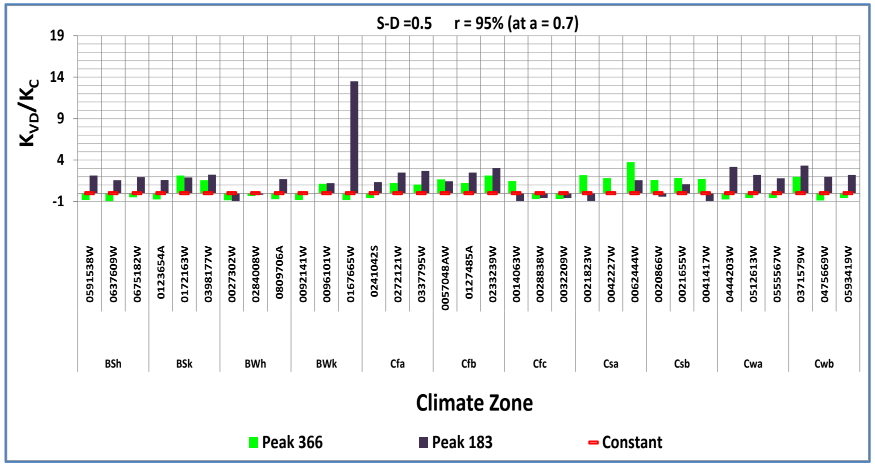
S-D =0.5 r = 66% (at a = 0.7)
K_{VD}/K_C
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

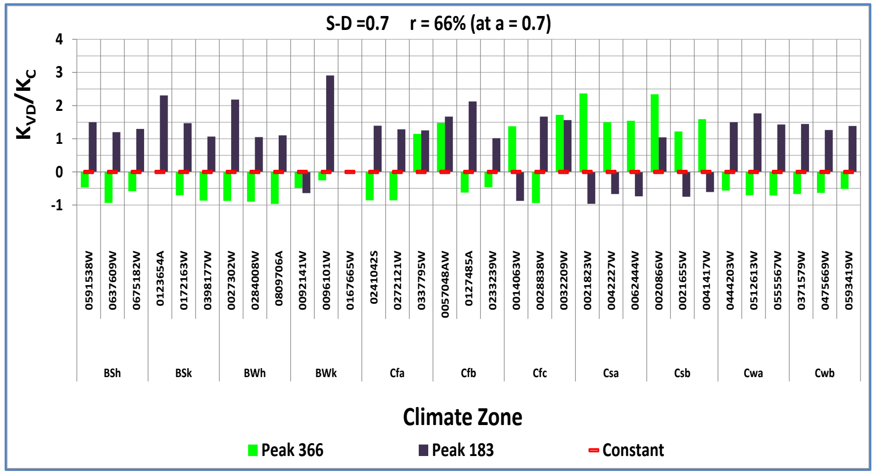


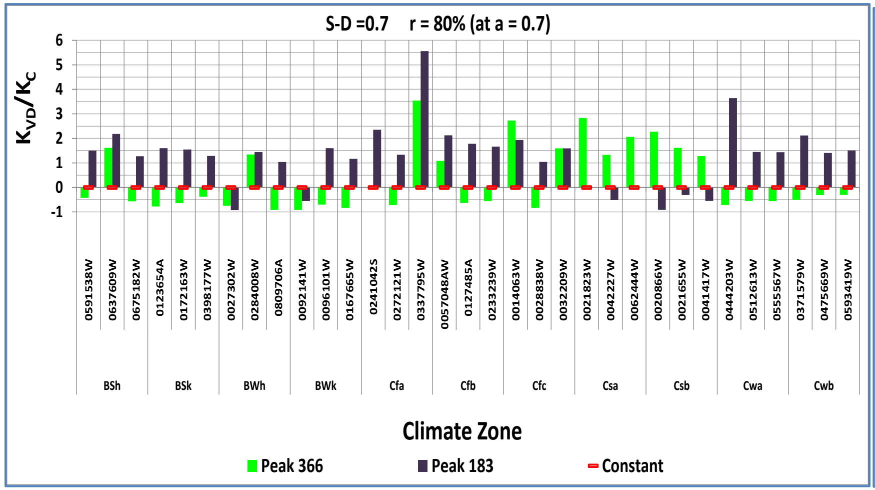
S-D =0.5 r = 80% (at a = 0.7)
N_{VD}/N_C
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

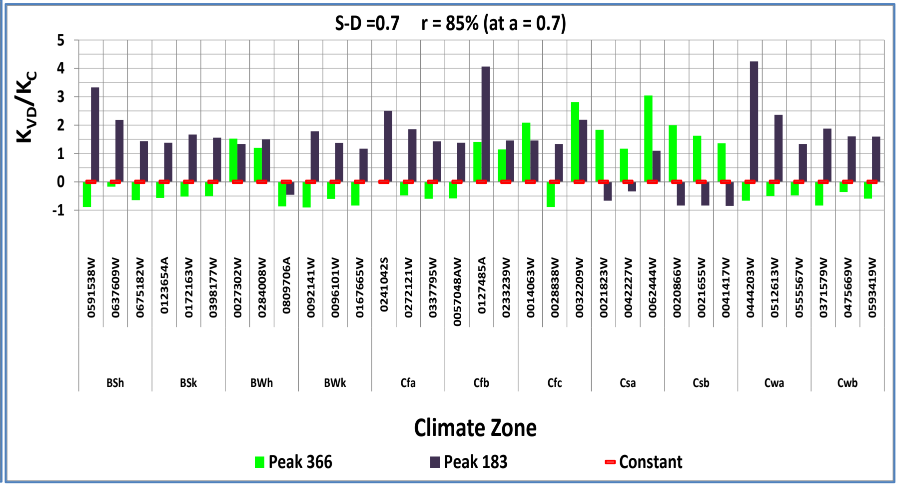

S-D =0.5 r = 85% (at a = 0.7)
K_{VD}/K_C
4
3
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

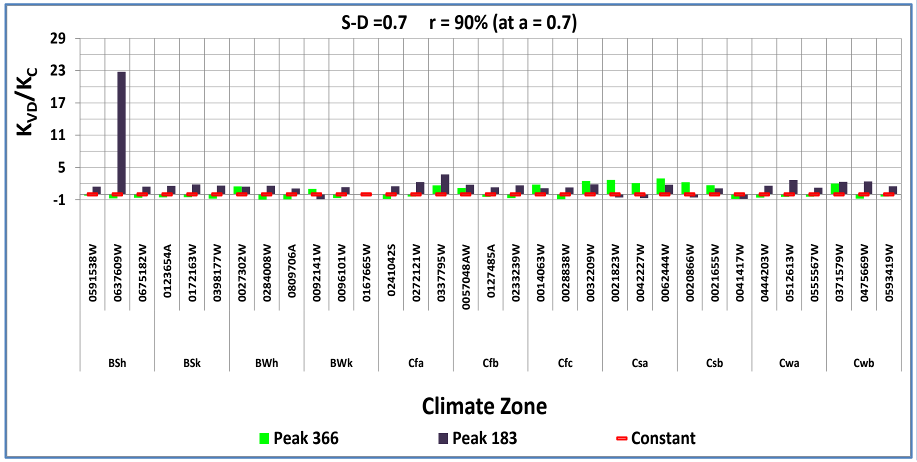

S-D =0.5 r = 90% (at a = 0.7)
K_{VD}/K_C
5
4
3
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

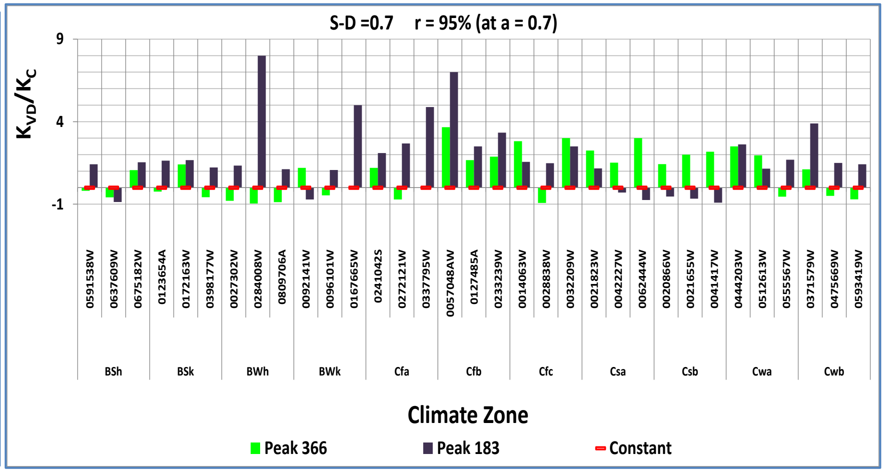

S-D =0.5 r = 95% (at a = 0.7)
K_{VD}/K_C
19
14
9
4
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant

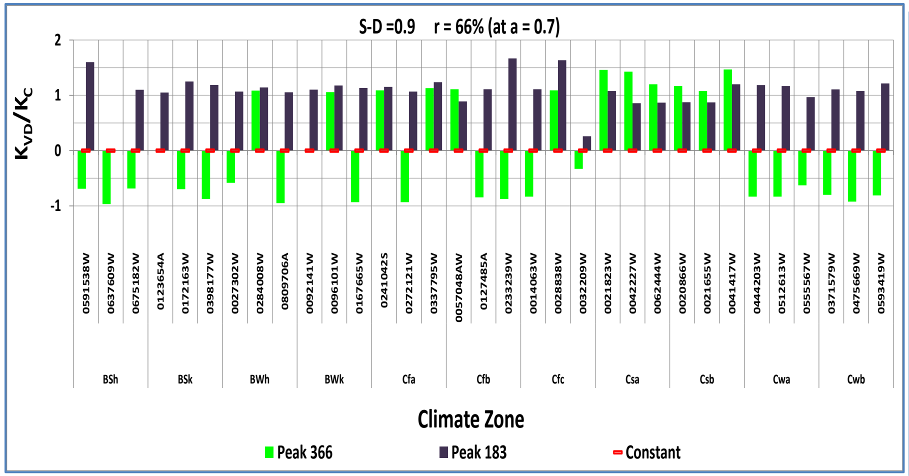

S-D =0.7 r = 66% (at a = 0.7)
K_{VD}/K_C
4
3
2
1
0
-1
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Peak 366
Peak 183
Constant


S-D =0.7 r = 80% (at a = 0.7)
K_{VD}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Peak 366
Peak 183
Constant

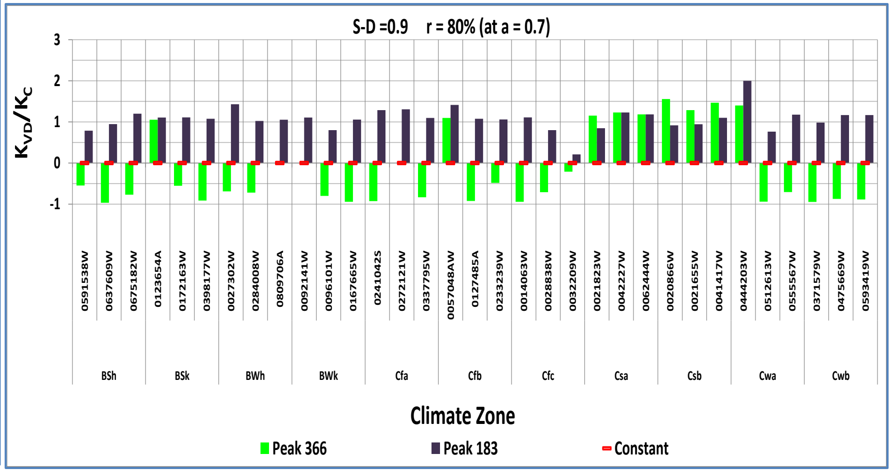

S-D =0.7 r = 85% (at a = 0.7)
K_{VD}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Peak 366
Peak 183
Constant


S-D =0.7 r = 90% (at a = 0.7)
K_{VD}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Peak 366
Peak 183
Constant

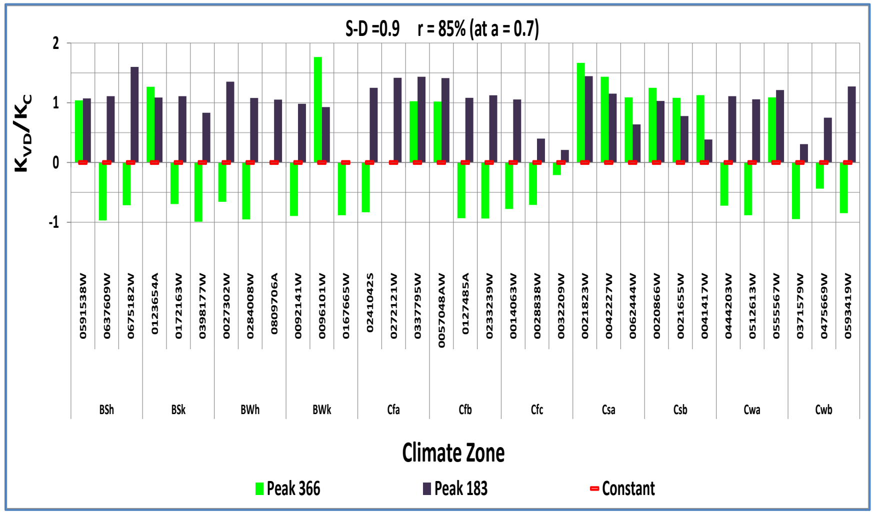

S-D =0.7 r = 95% (at a = 0.7)
K_{VD}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Peak 366
Peak 183
Constant



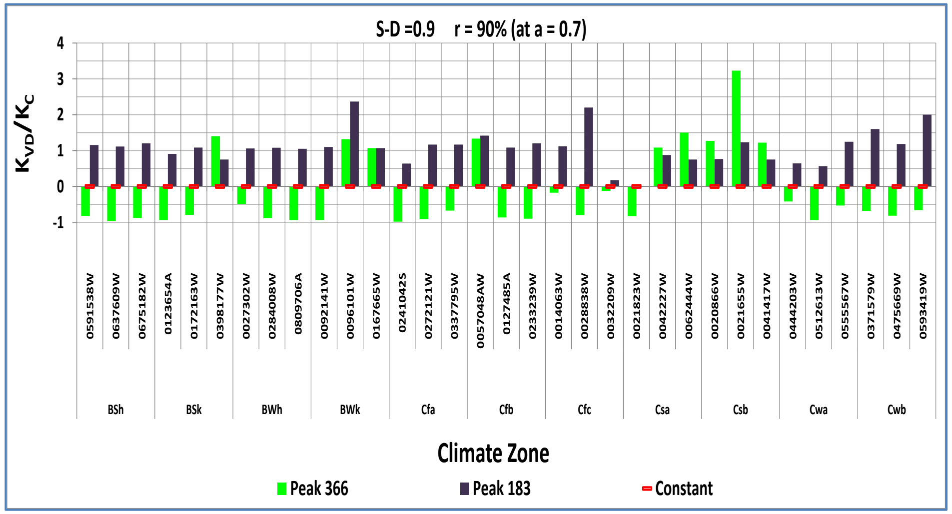
S-D =0.9 r = 66% (at a = 0.7)
K_{VD}/K_C
Climate Zone
Peak 366
Peak 183
Constant



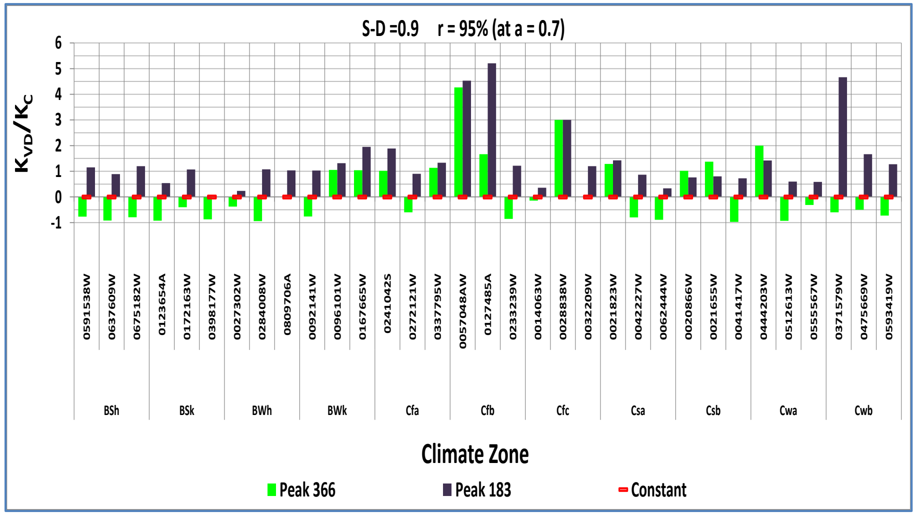
S-D =0.9 r = 80% (at a = 0.7)
K_{VD}/K_C
Climate Zone
Peak 366
Peak 183
Constant



S-D =0.9 r = 85% (at a = 0.7)
K_{VD}/K_C
Climate Zone
Peak 366
Peak 183
Constant

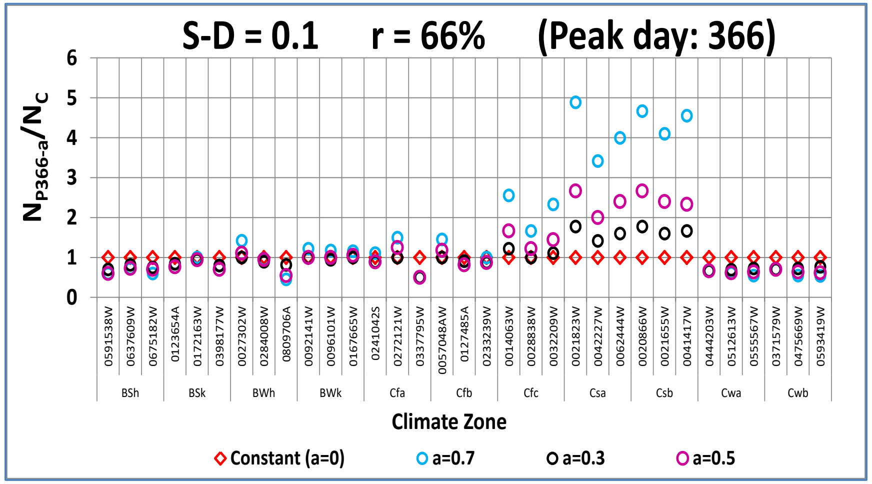


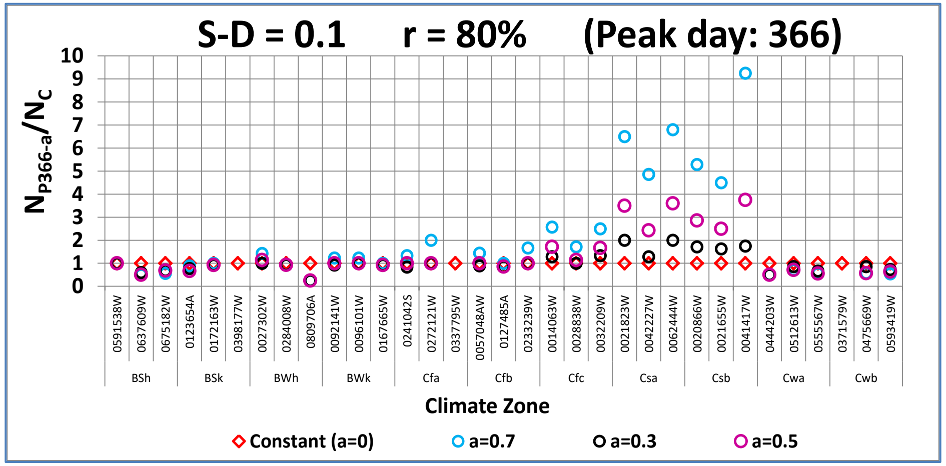
S-D =0.9 r = 90% (at a = 0.7)
K_{VD}/K_C
Climate Zone
Peak 366
Peak 183
Constant

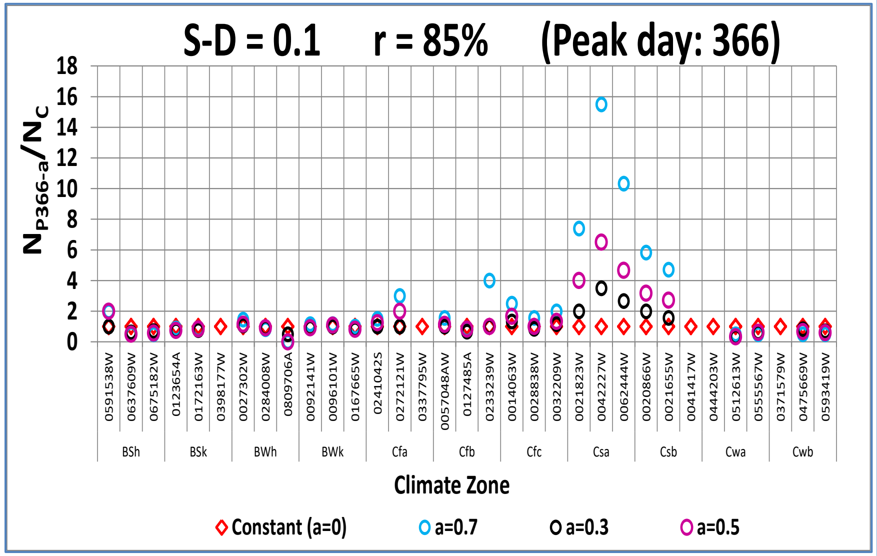


(c) Proportion of the expected number of days of supply retained with variation of amplitude at fixed peak location

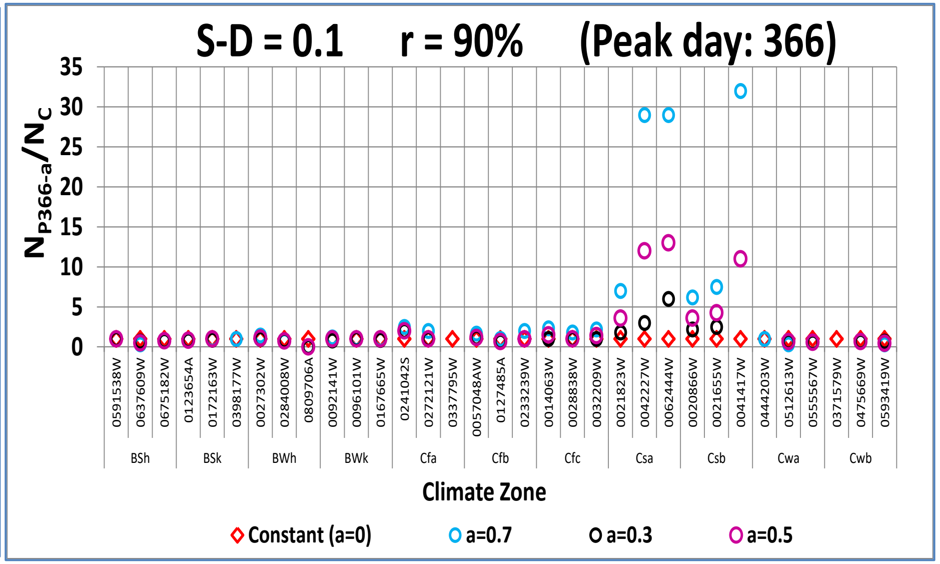
(Variations are read against an axis value 1 representing the constant demand case where there is no change in number of days of supply)



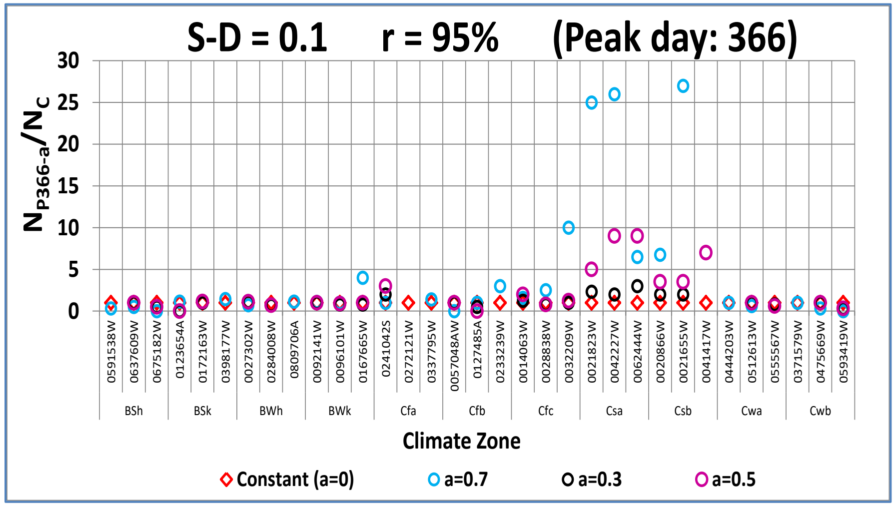




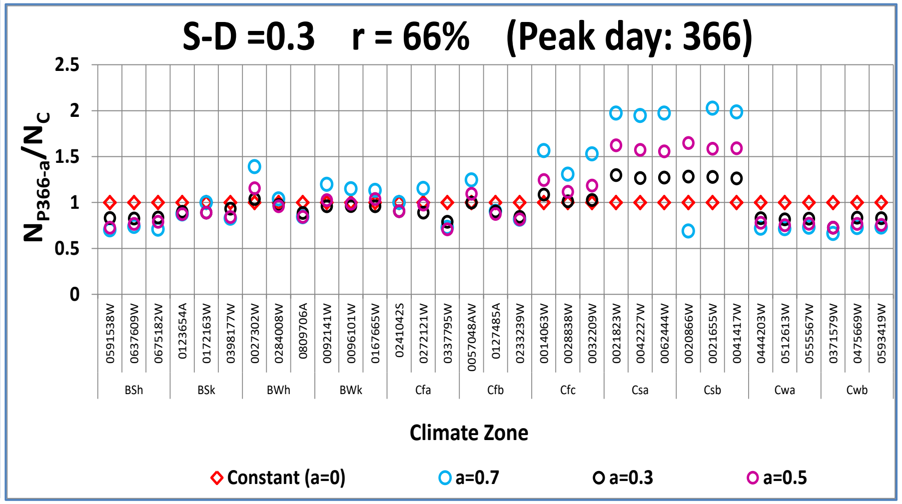
S-D = 0.1 r = 85% (Peak day: 366)
N_{P366-a}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5



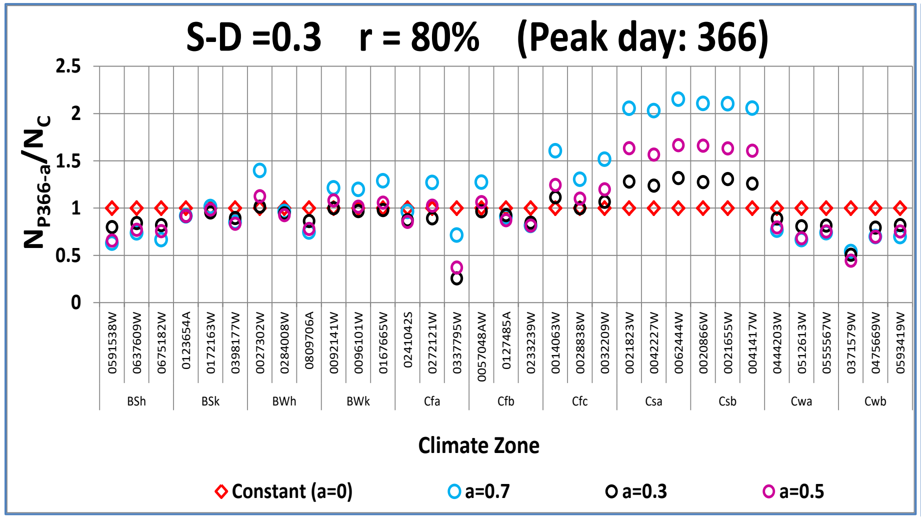
S-D = 0.1 r = 90% (Peak day: 366)
N_{P366-a}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

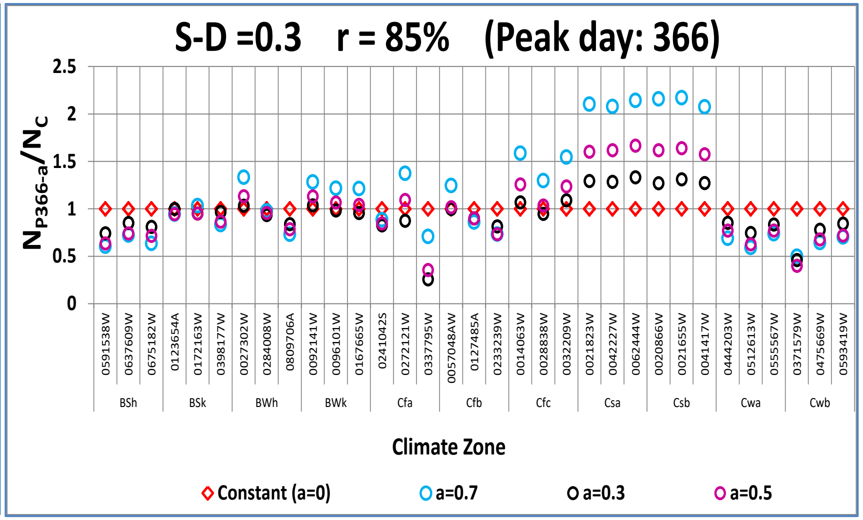


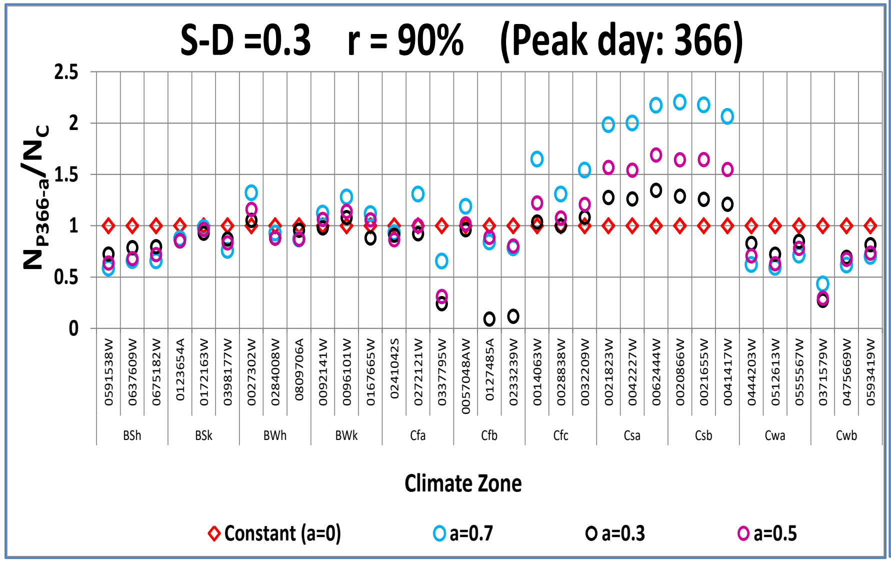
S-D = 0.1 r = 95% (Peak day: 366)
N_{P366-a}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

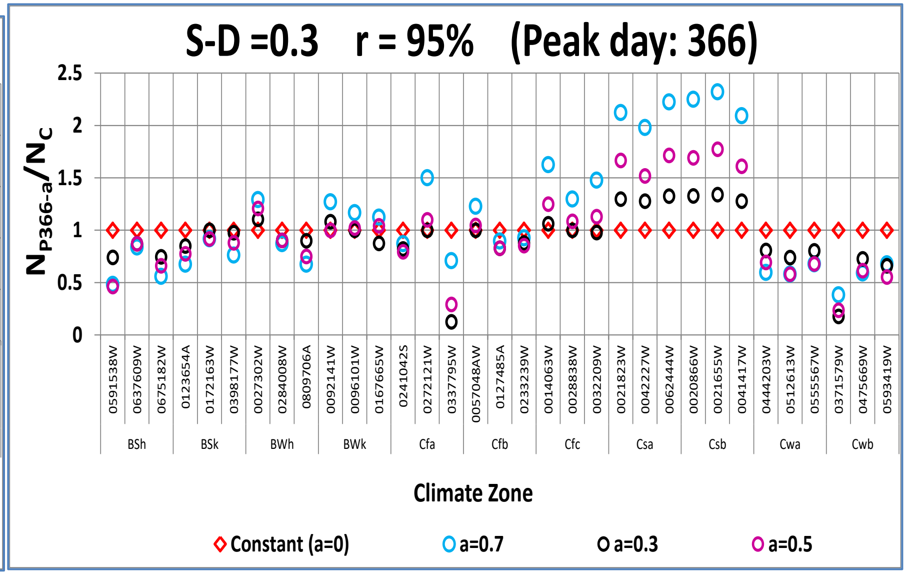


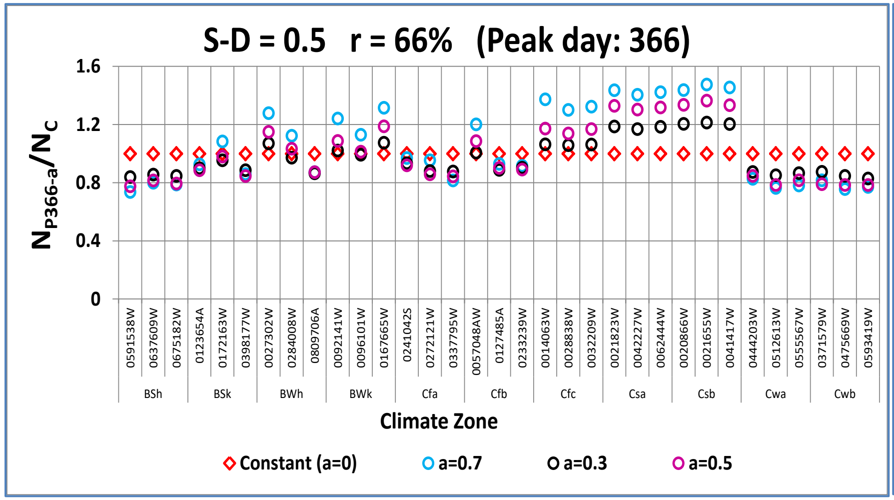
S-D =0.3 r = 66% (Peak day: 366)
N_{P366-a}/N_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

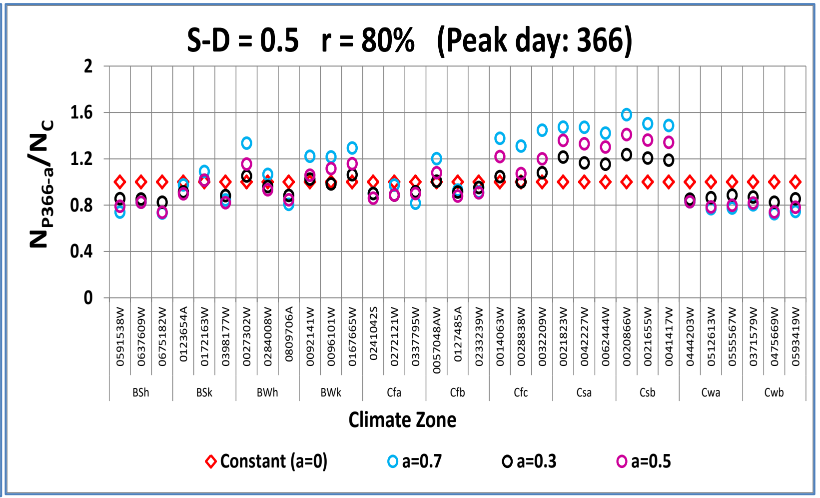

S-D =0.3 r = 80% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

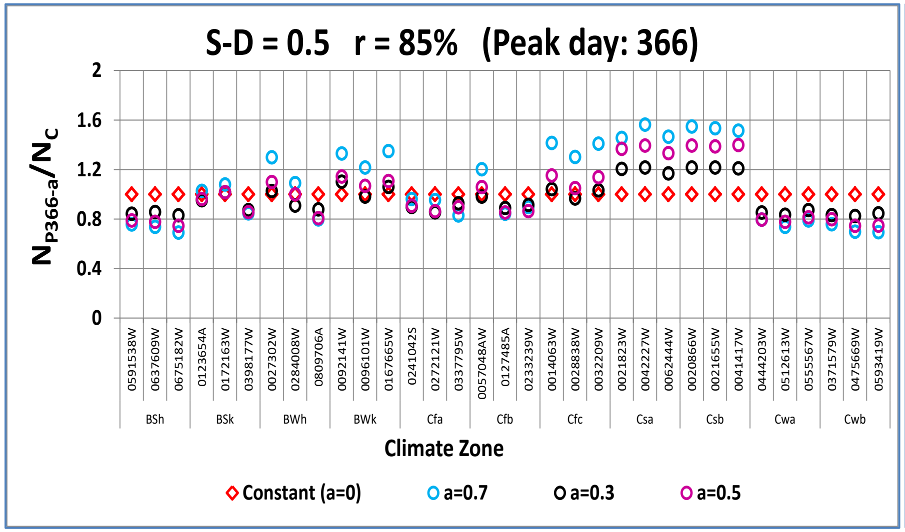

S-D =0.3 r = 85% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

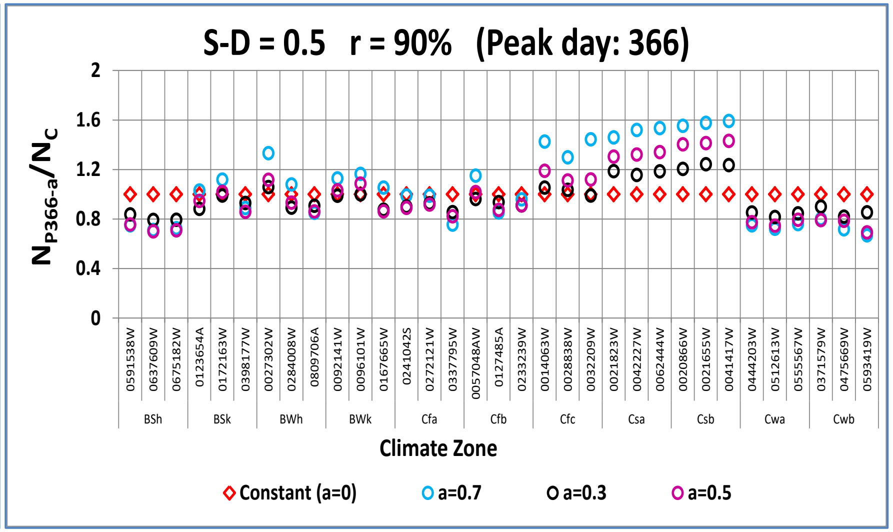

S-D =0.3 r = 90% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

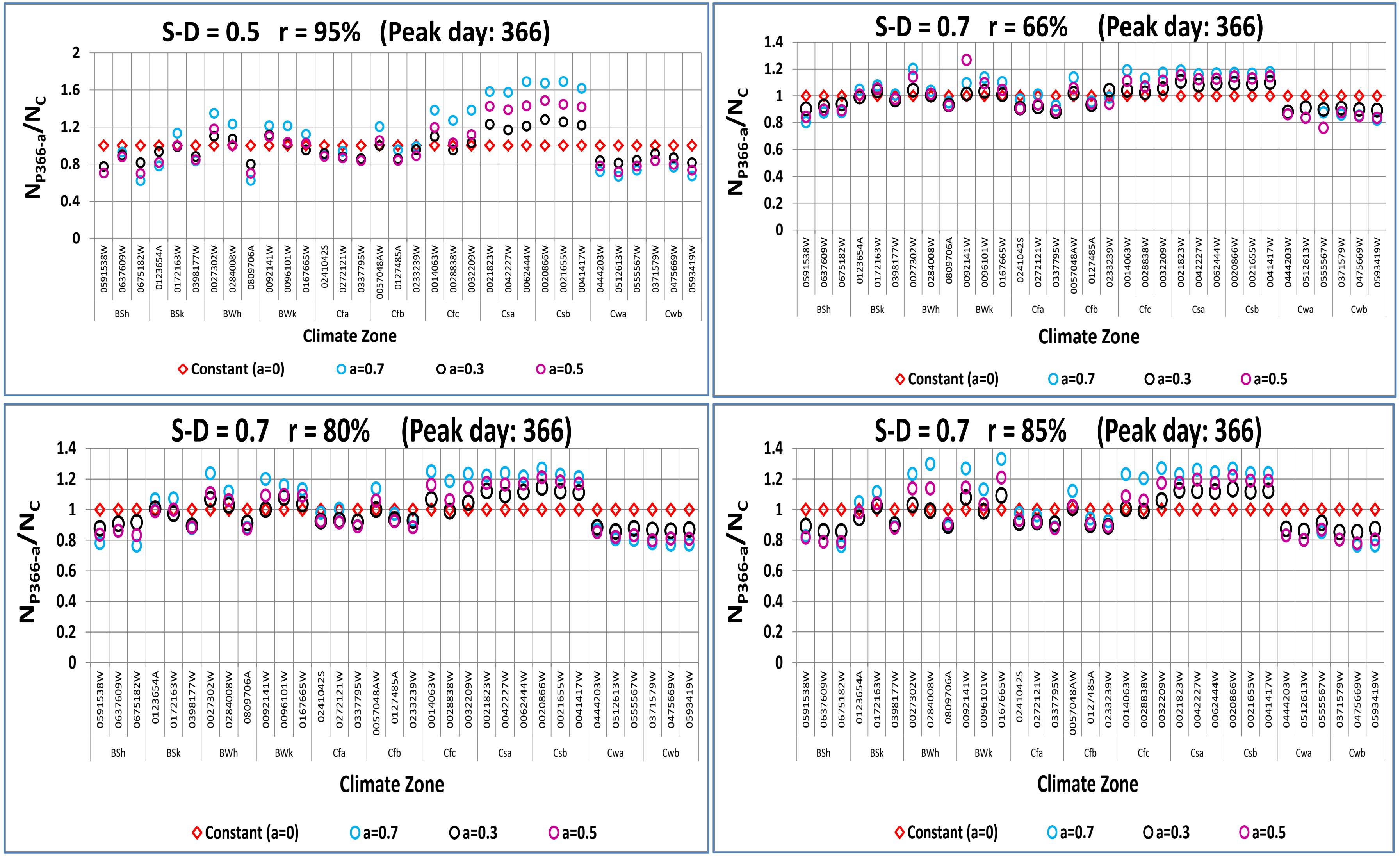

S-D =0.3 r = 95% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5


S-D = 0.5 r = 66% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

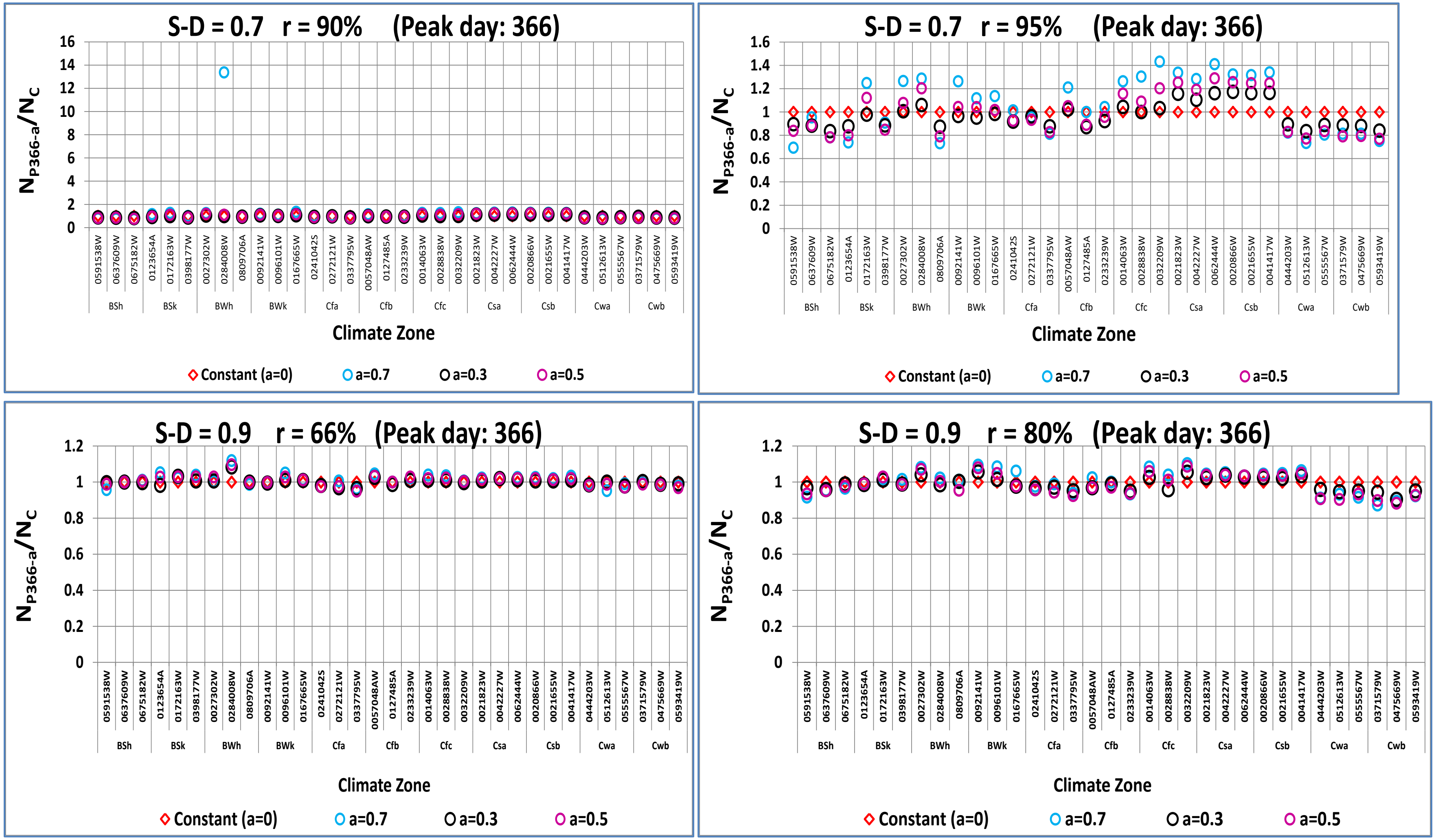

S-D = 0.5 r = 80% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5


S-D = 0.5 r = 85% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

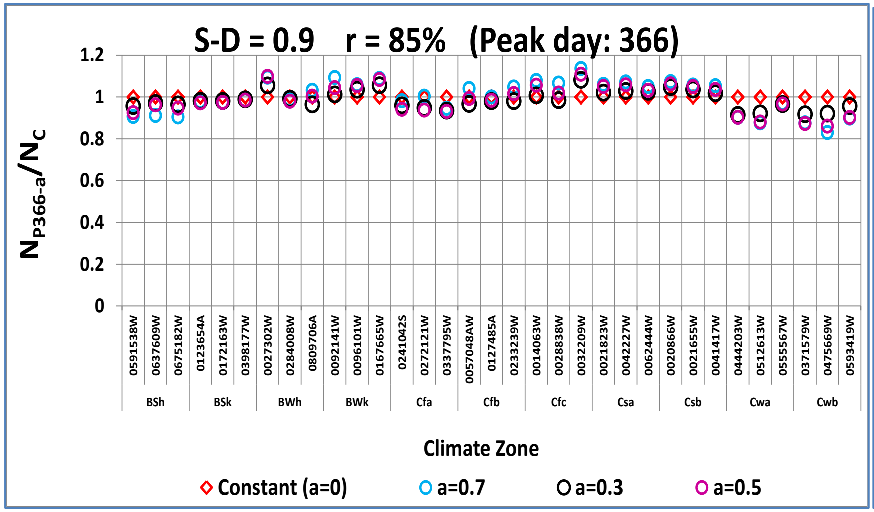

S-D = 0.5 r = 90% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

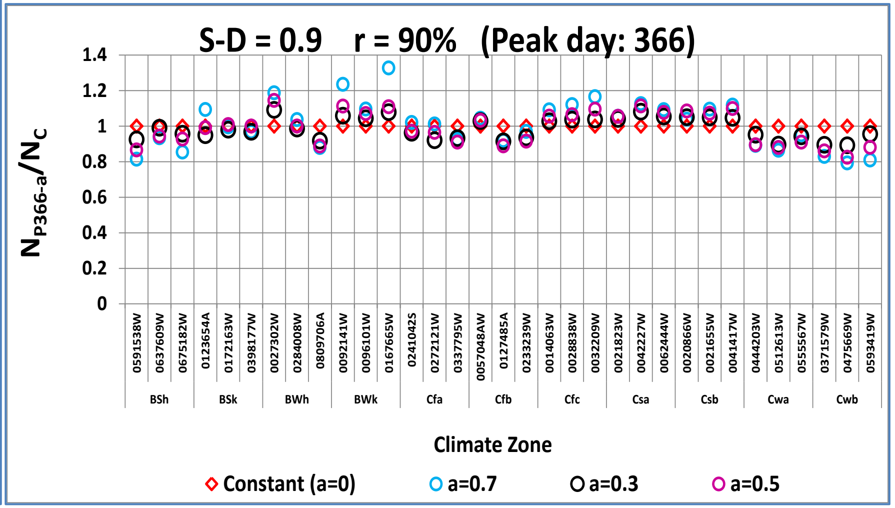


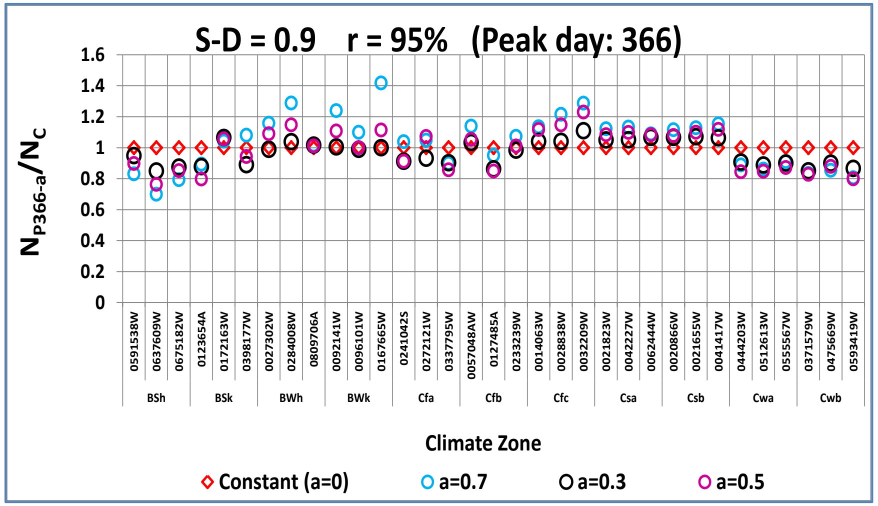
S-D = 0.5 r = 95% (Peak day: 366)
S-D = 0.7 r = 66% (Peak day: 366)
S-D = 0.7 r = 80% (Peak day: 366)
S-D = 0.7 r = 85% (Peak day: 366)
N P366-a/N C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5



S-D = 0.7 r = 90% (Peak day: 366)
S-D = 0.7 r = 95% (Peak day: 366)
S-D = 0.9 r = 66% (Peak day: 366)
S-D = 0.9 r = 80% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
0591538W
0637609W
0675182W
0123654A
0172163W
0398177W
0027302W
0284008W
0809706A
0092141W
0096101W
0167665W
0241042S
0272121W
0337795W
0057048AW
0127485A
0233239W
0014063W
0028838W
0032209W
0021823W
0042227W
0062444W
0020866W
0021655W
0041417W
0444203W
0512613W
0555567W
0371579W
0475669W
0593419W
Constant (a=0)
a=0.7
a=0.3
a=0.5

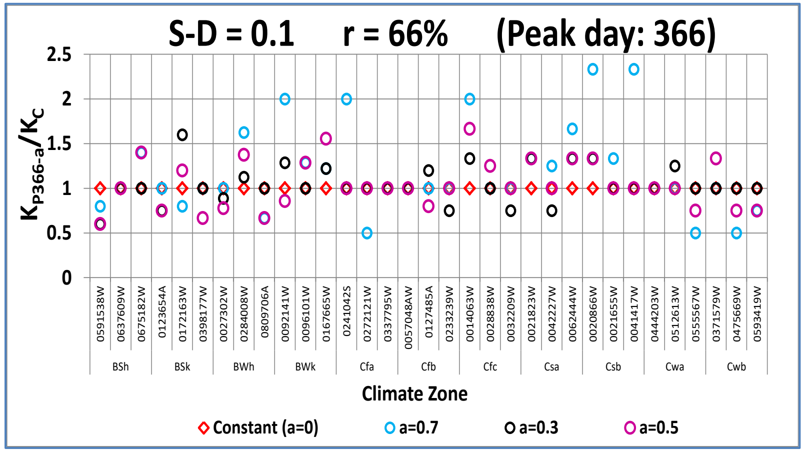

S-D = 0.9 r = 85% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5

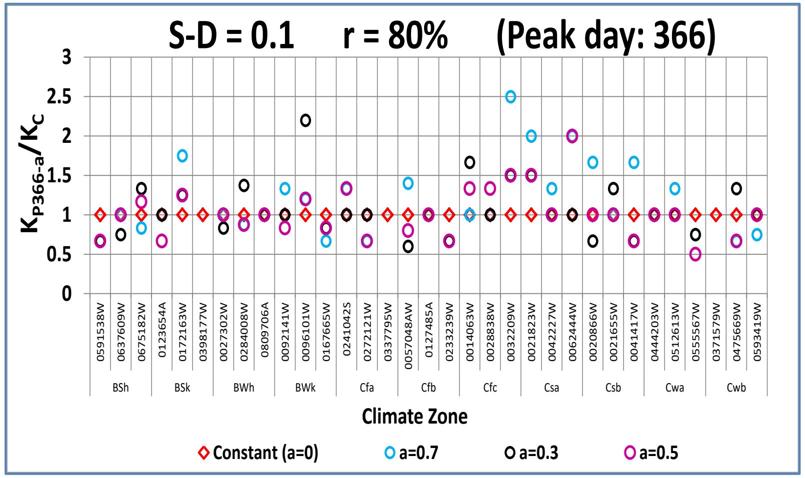

S-D = 0.9 r = 90% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5

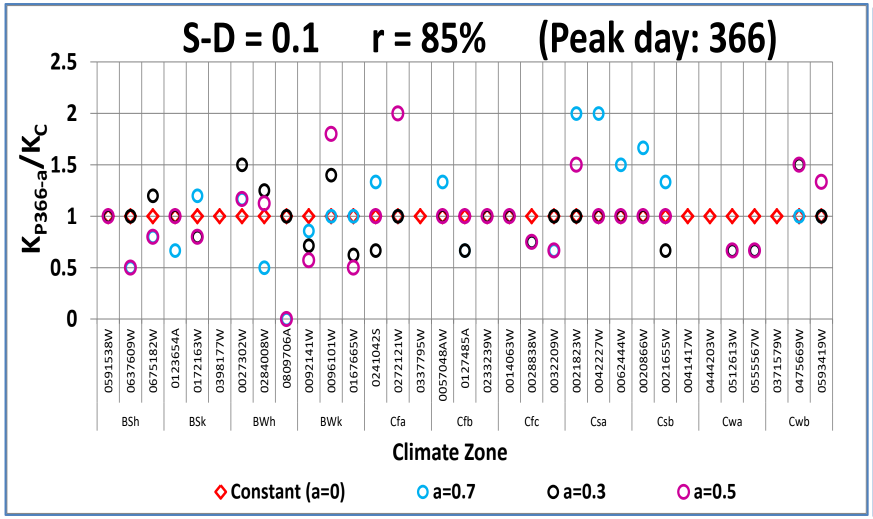

S-D = 0.9 r = 95% (Peak day: 366)
N_{P366-a}/N_C
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5

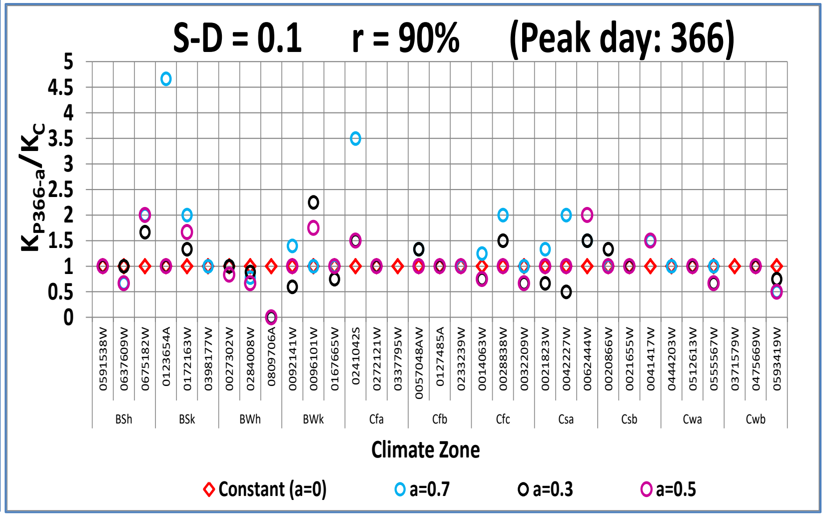
(d)Volume of tank size retained with changing amplitude at fixed peak location

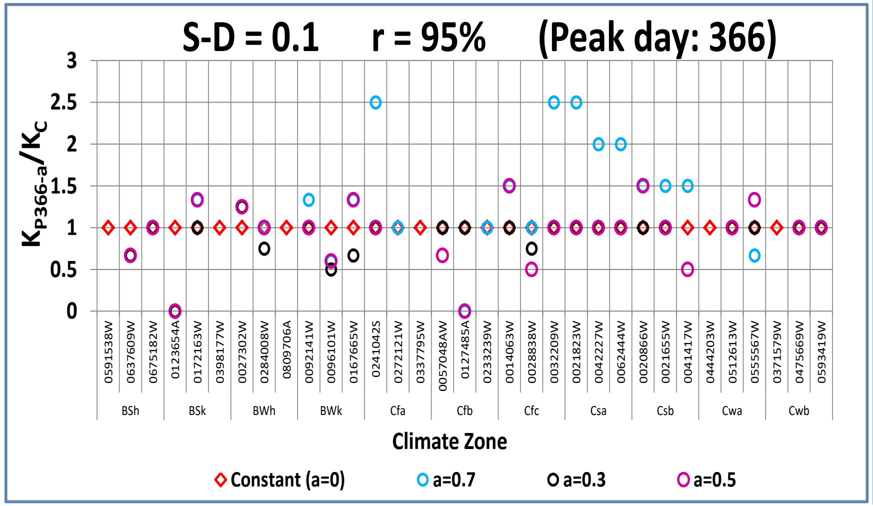
(Variations are read against an axis value 1 representing the constant demand case where there is no change in number of days of supply)

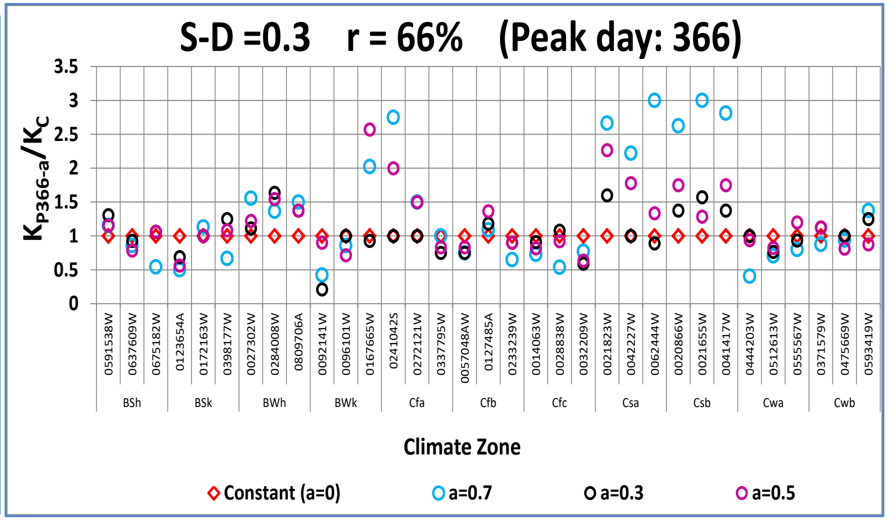


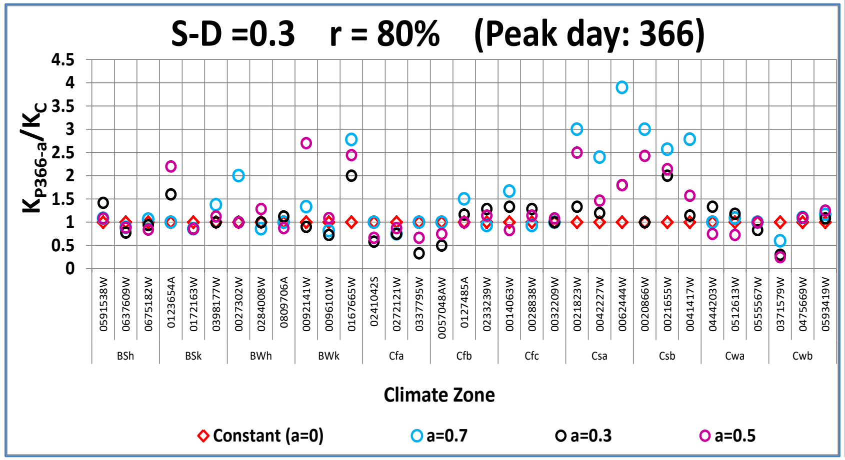


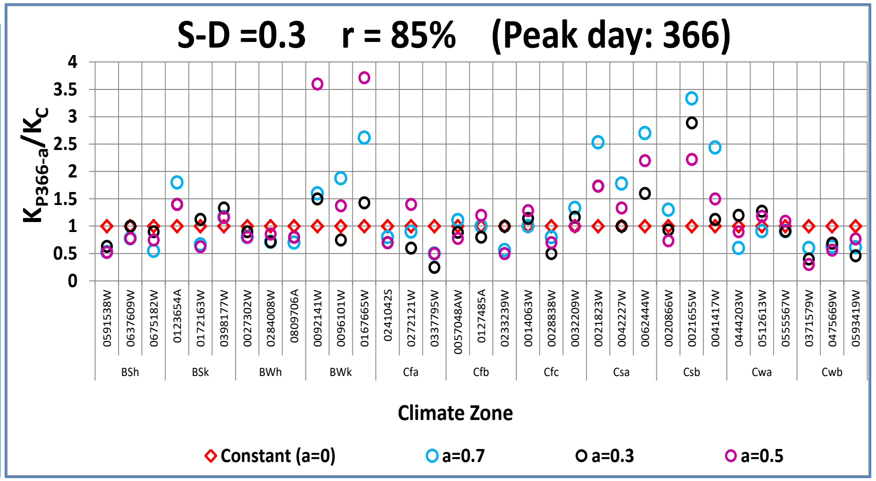


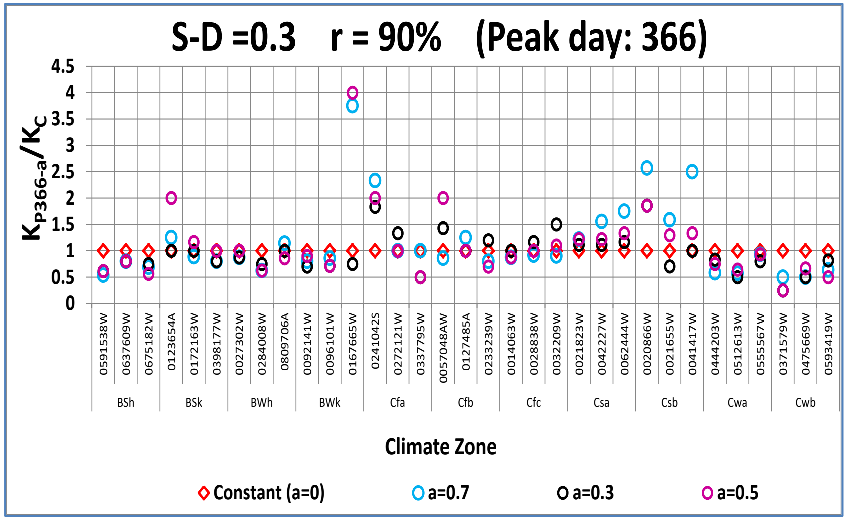



S-D = 0.1 r = 95% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5

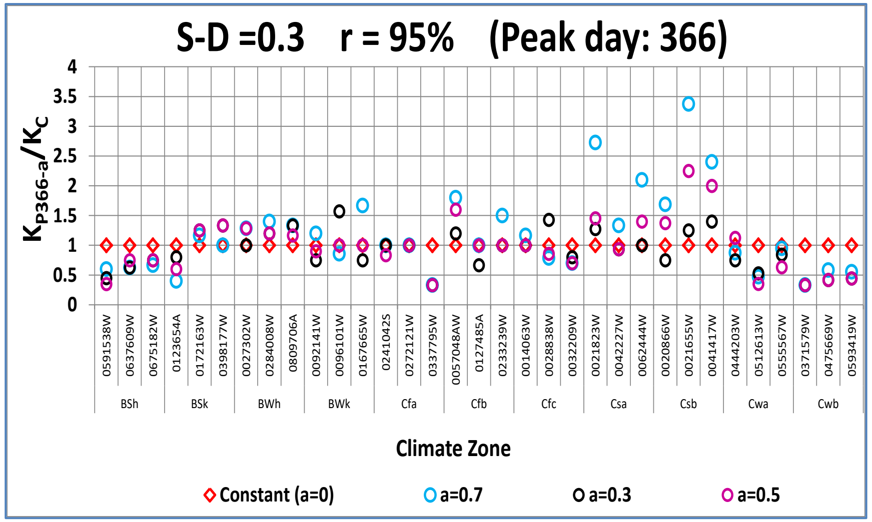

S-D =0.3 r = 66% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5


S-D =0.3 r = 80% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5

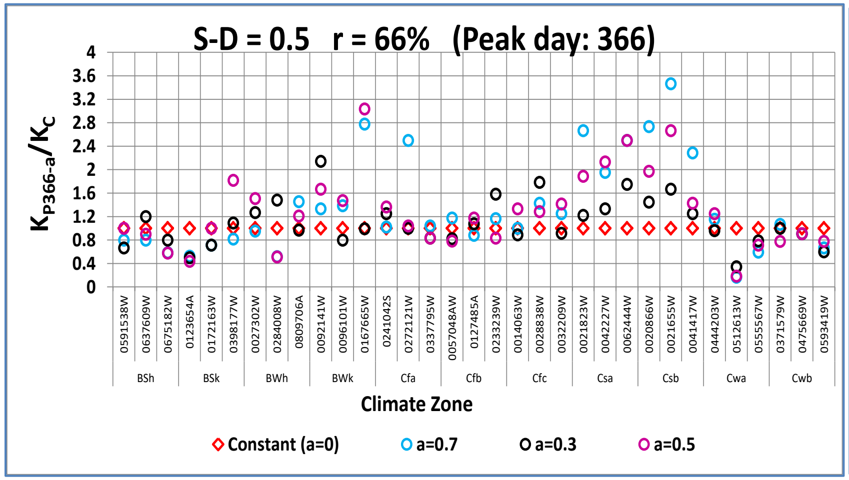

S-D =0.3 r = 85% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5



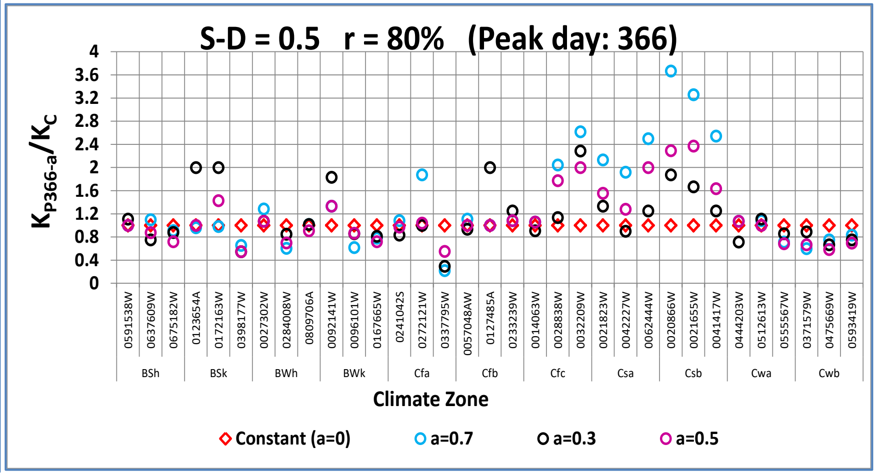
S-D =0.3 r = 90% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5



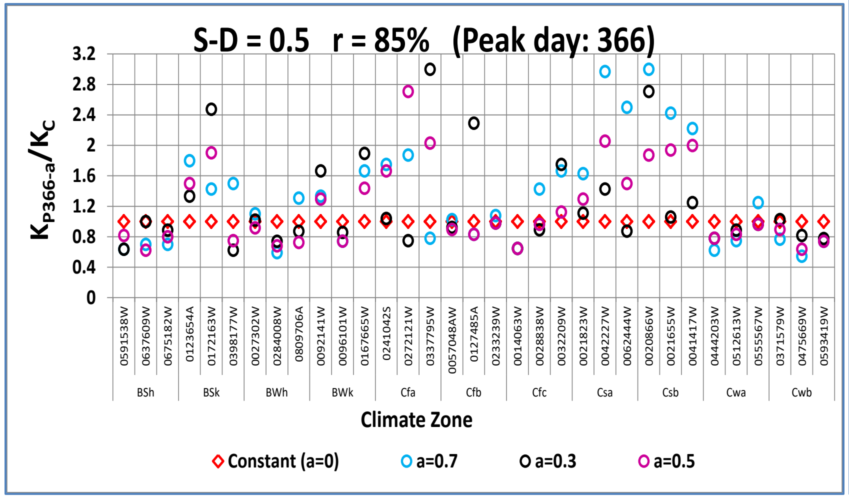
S-D =0.3 r = 95% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5

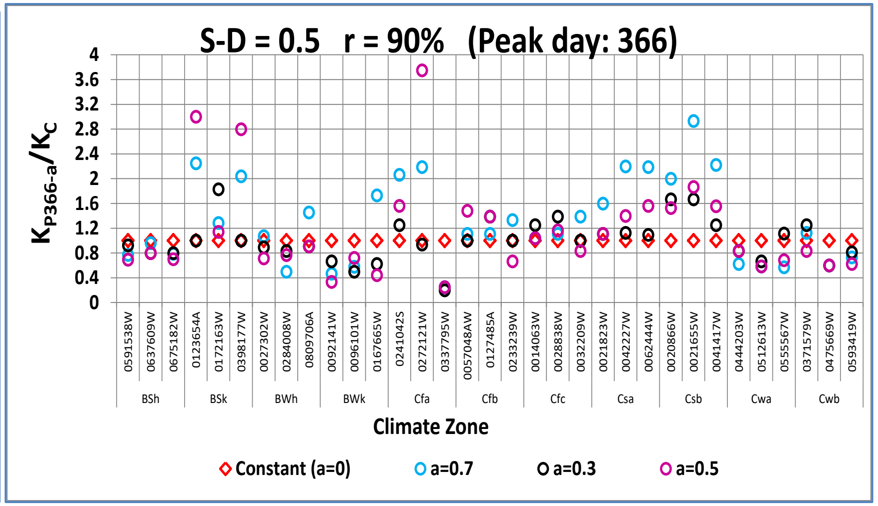


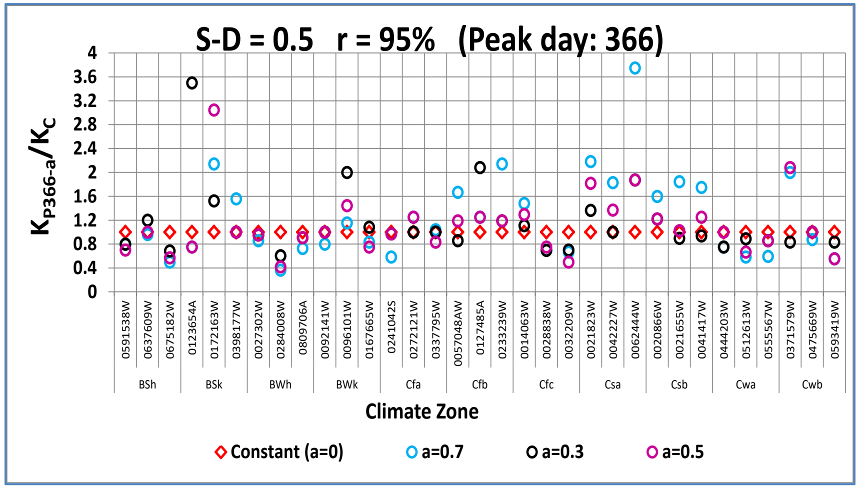
S-D = 0.5 r = 66% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5

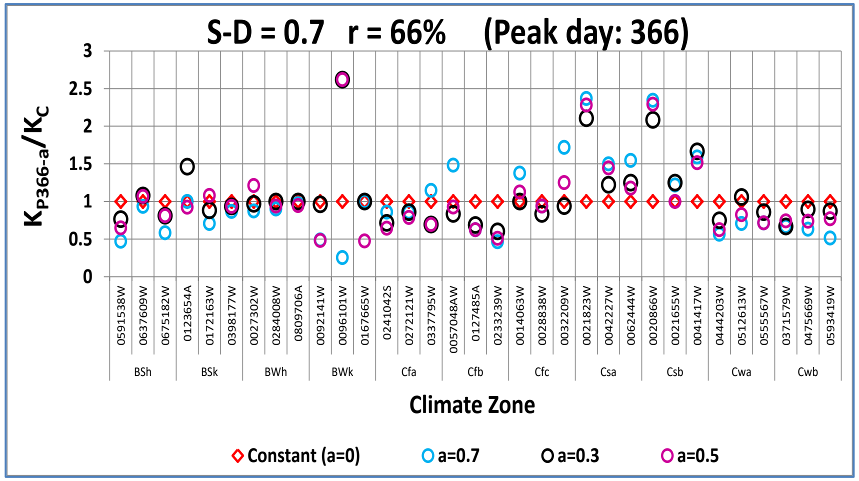


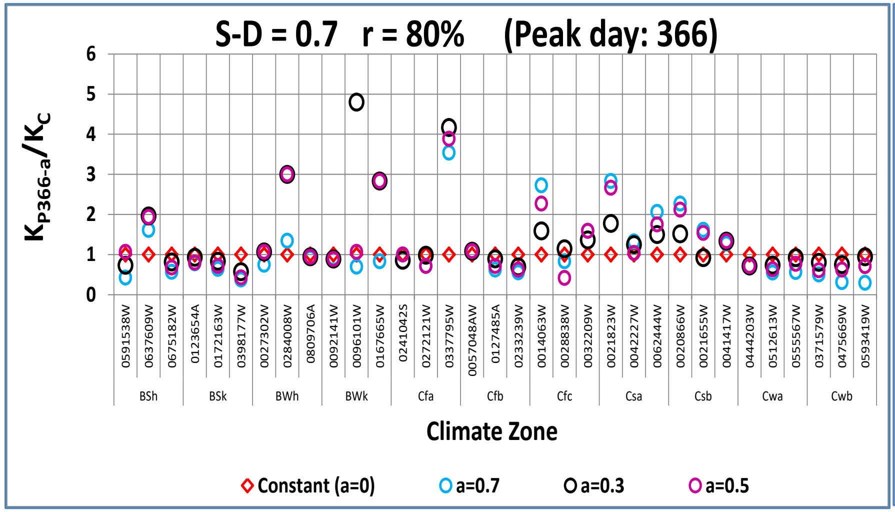
S-D = 0.5 r = 80% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0) a=0.7 a=0.3 a=0.5


S-D = 0.5 r = 85% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5


S-D = 0.5 r = 90% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5


S-D = 0.5 r = 95% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5


S-D = 0.7 r = 66% (Peak day: 366)
K_{P366-a}/K_C
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Constant (a=0)
a=0.7
a=0.3
a=0.5


S-D = 0.7 r = 80% (Peak day: 366)
K_{P366-a}/K_C
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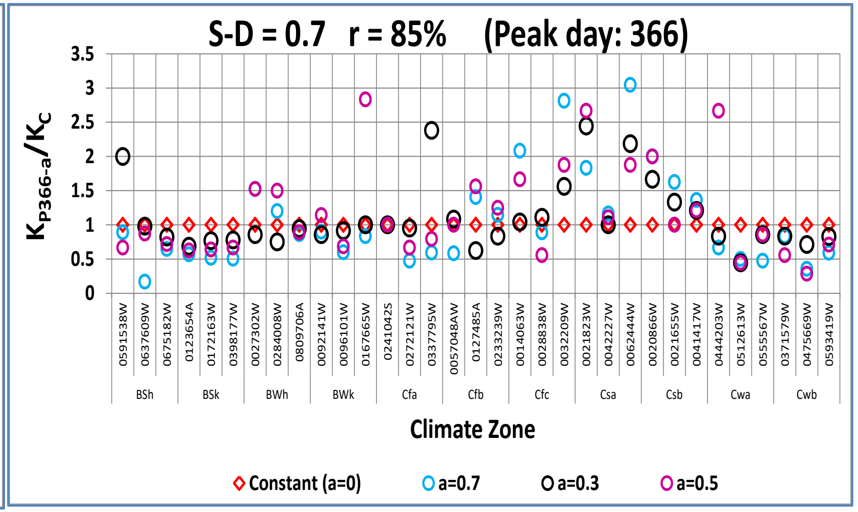
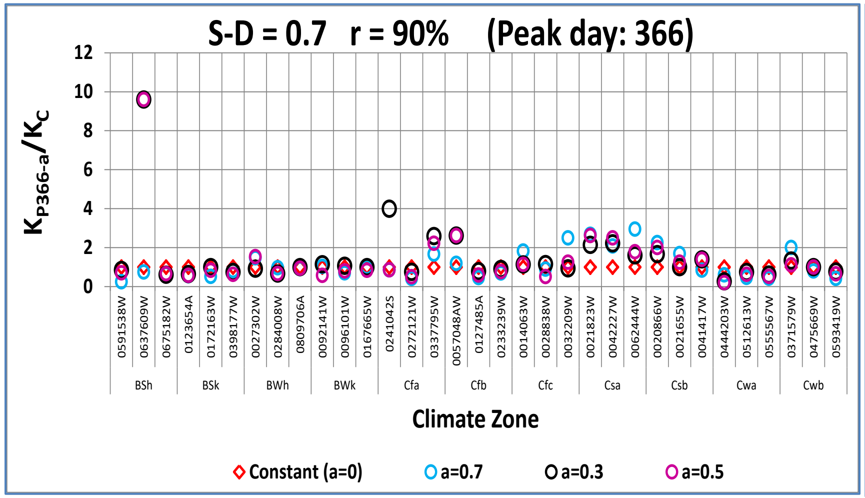
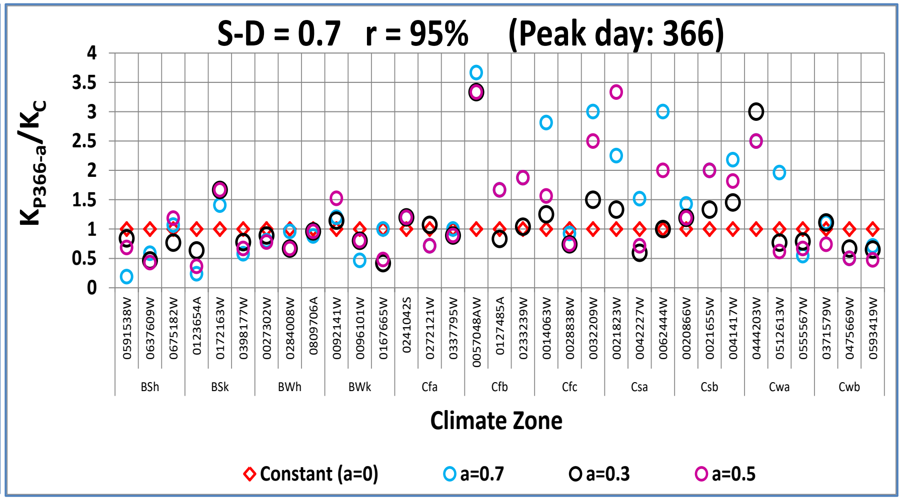
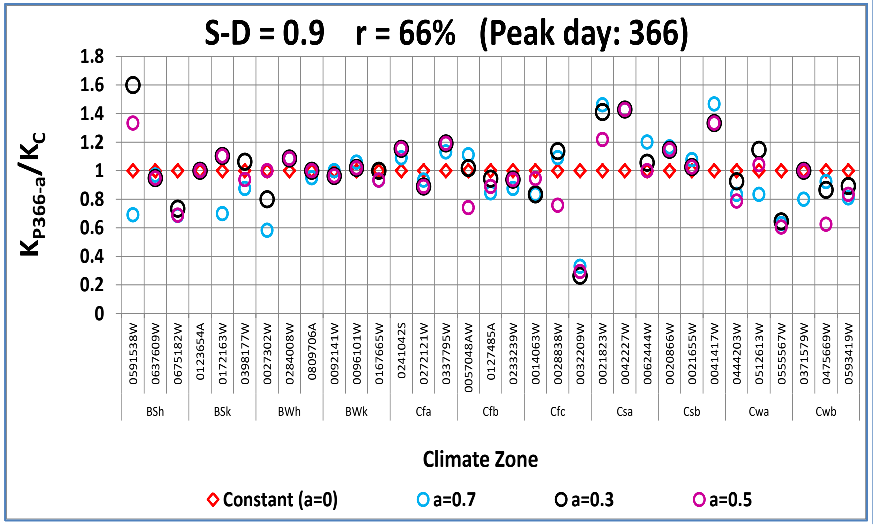
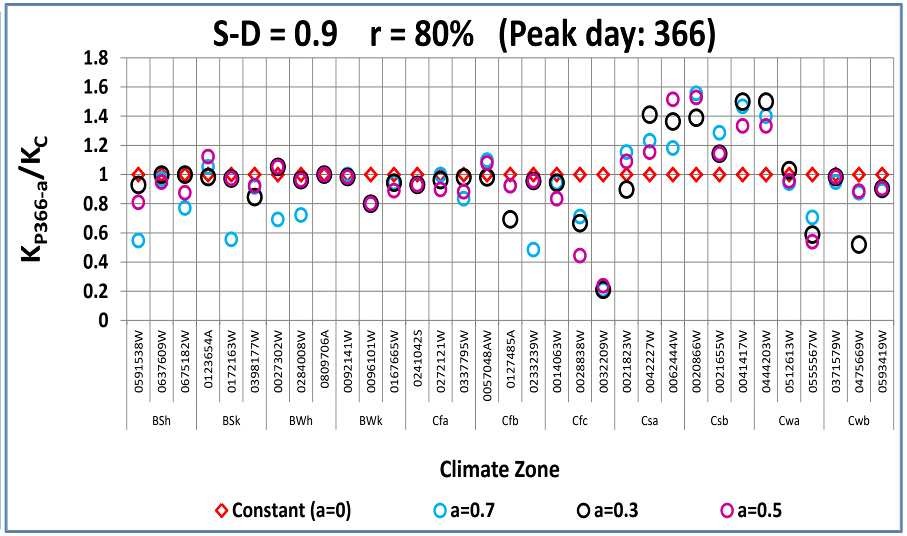
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

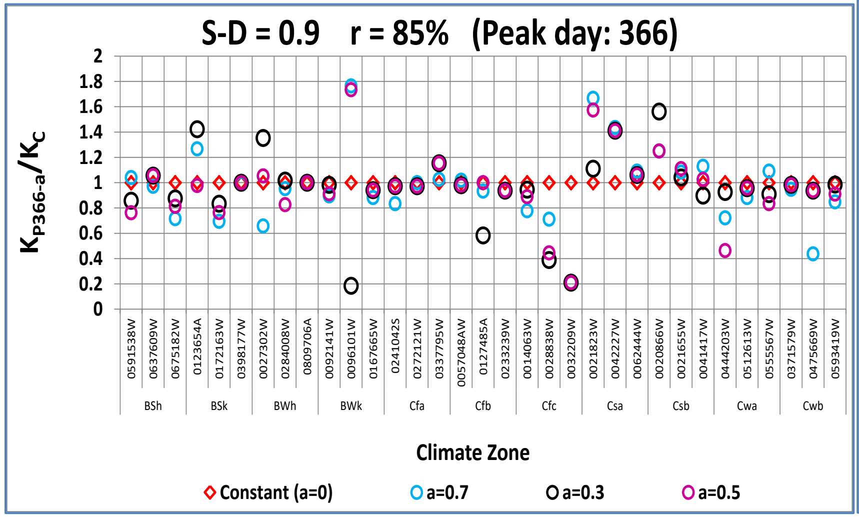

S-D = 0.7 r = 85% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

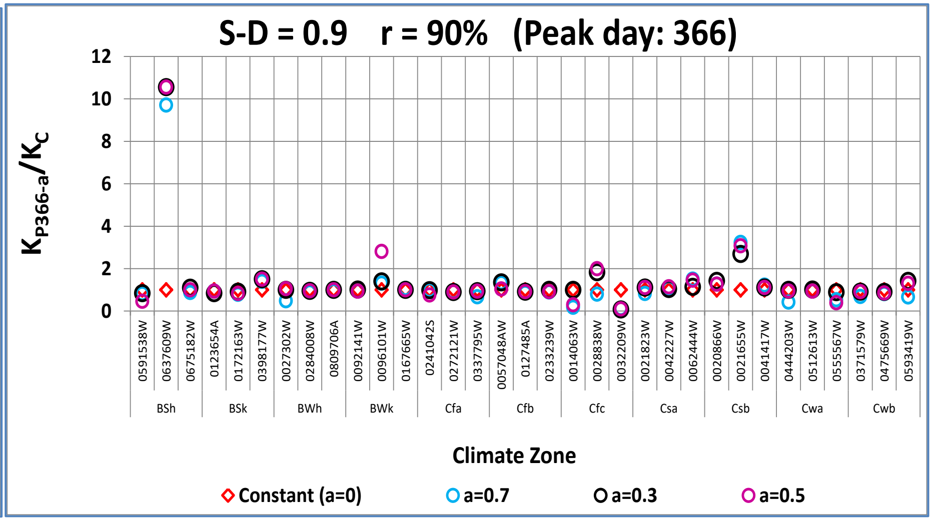

S-D = 0.7 r = 90% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5

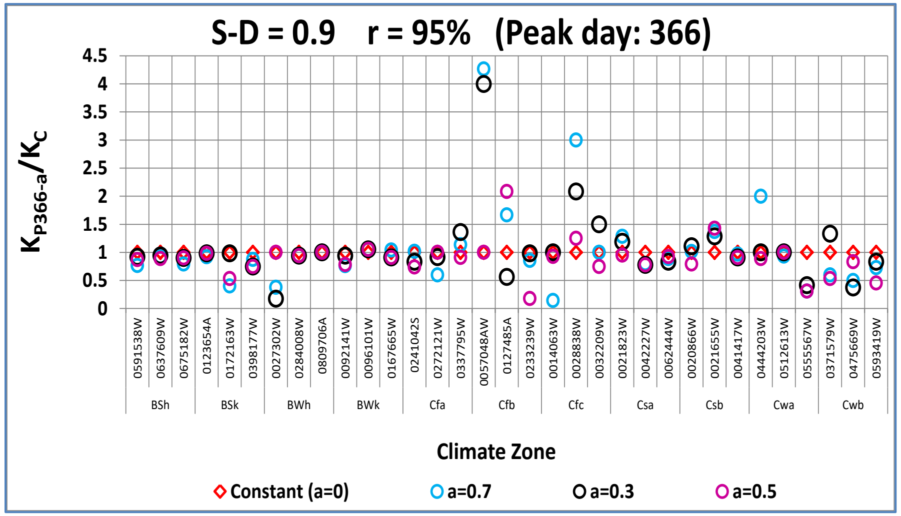

S-D = 0.7 r = 95% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0)
a=0.7
a=0.3
a=0.5


S-D = 0.9 r = 66% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

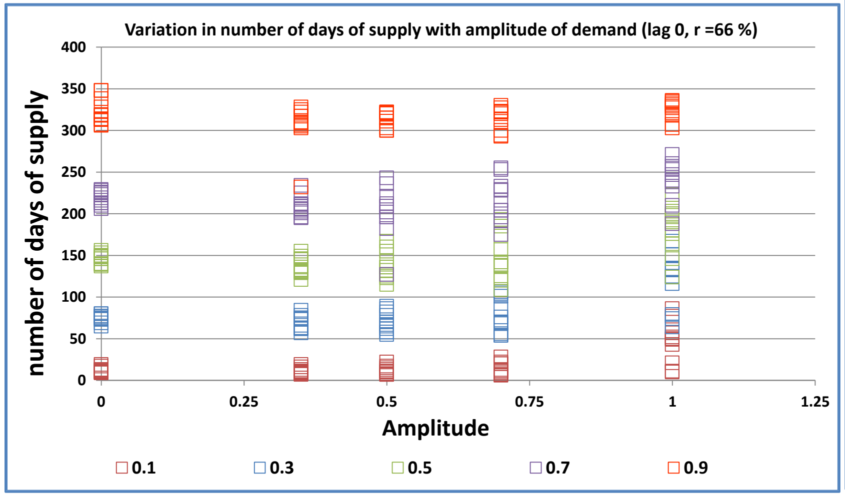

S-D = 0.9 r = 80% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

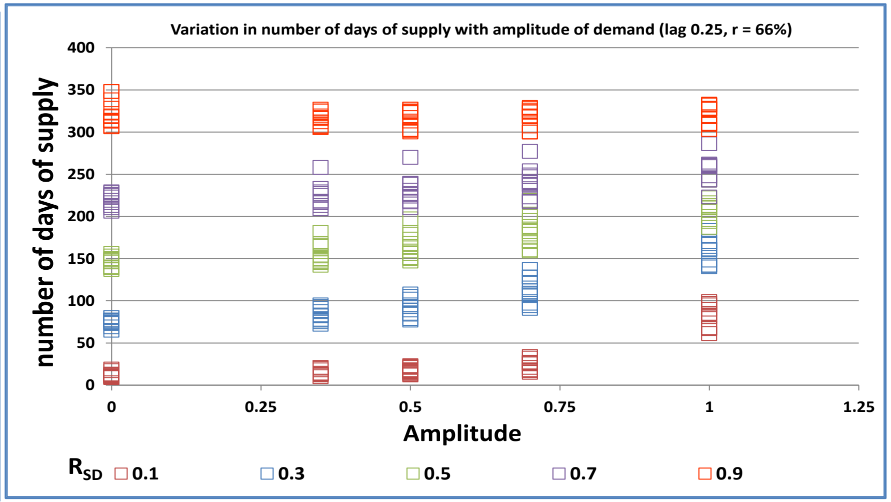

S-D = 0.9 r = 85% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

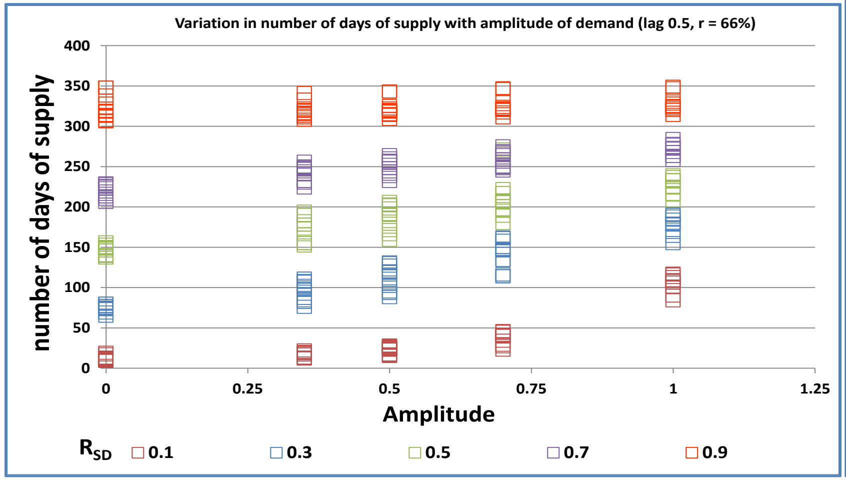

S-D = 0.9 r = 90% (Peak day: 366)
K_{P366-a}/K_C
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
Constant (a=0) a=0.7 a=0.3 a=0.5

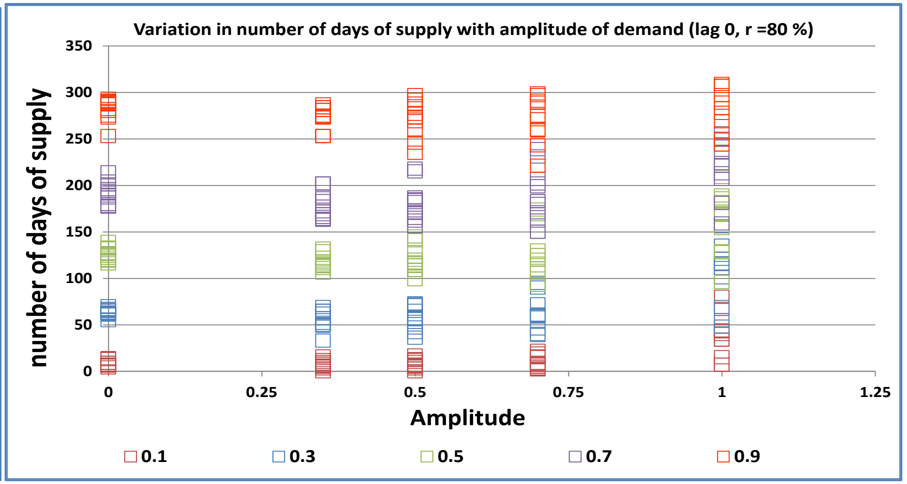


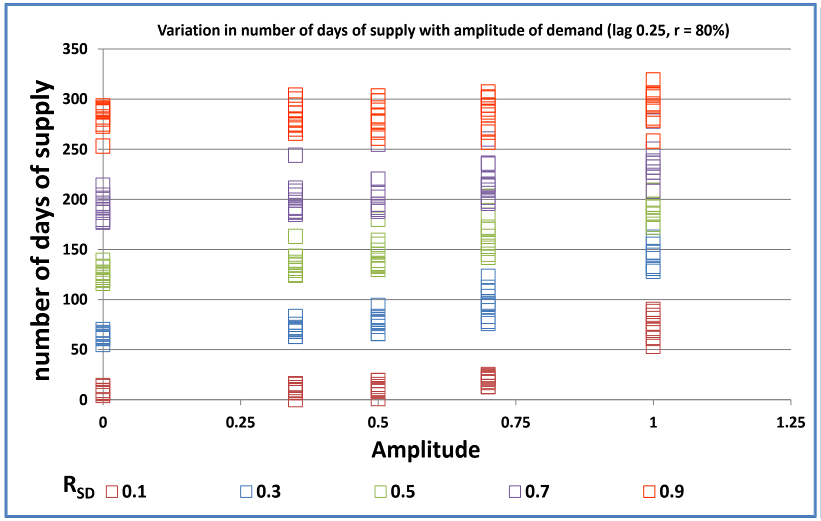
(e) Relationship between yield, S-D, lag and amplitude

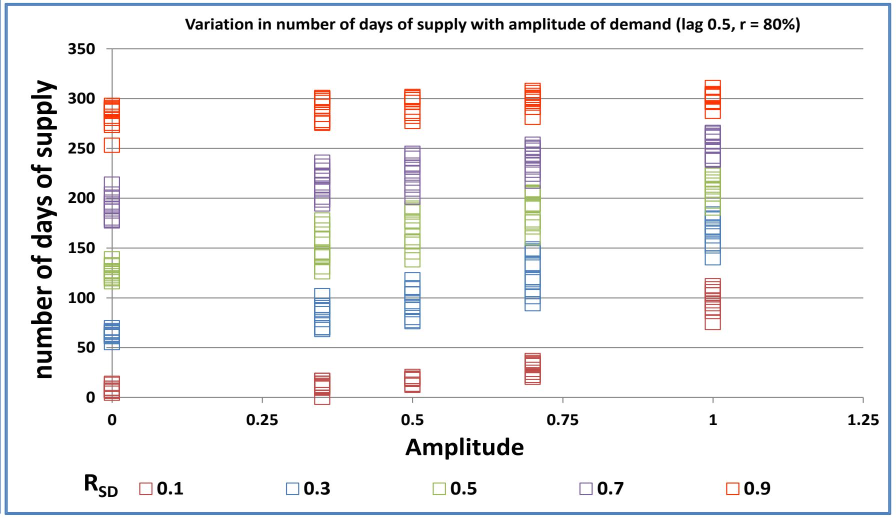


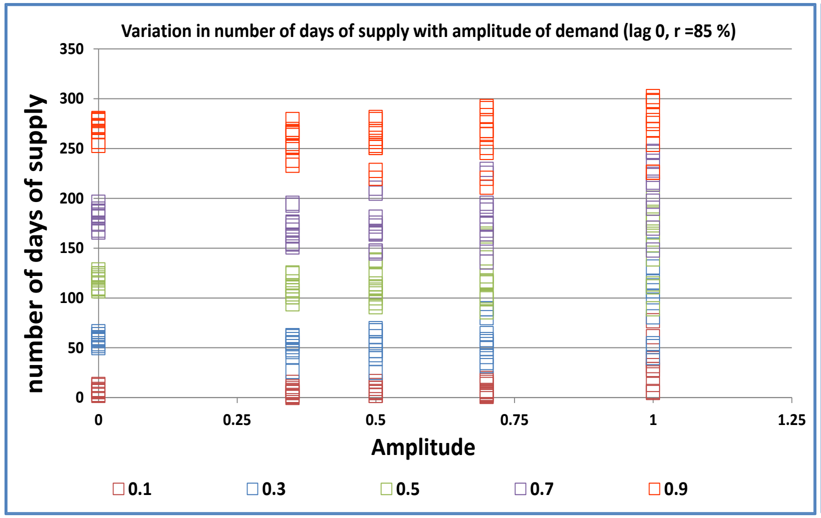


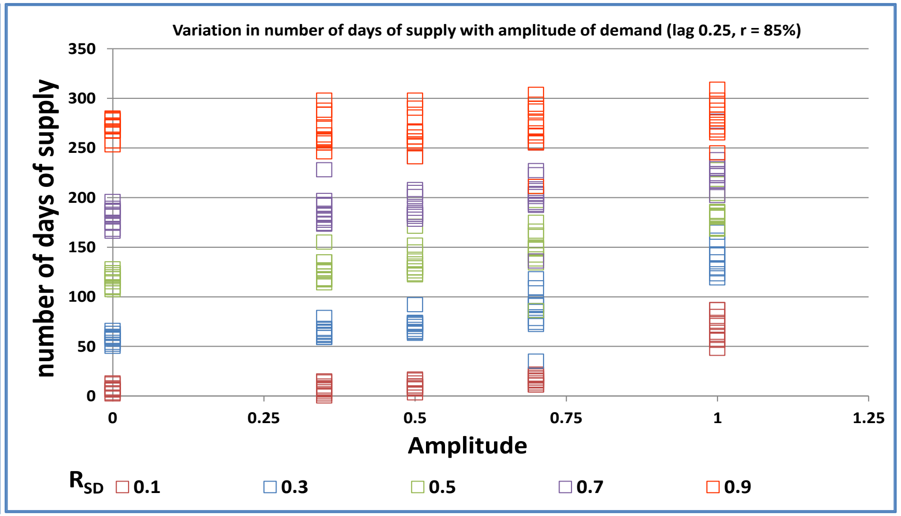

Variation in number of days of supply with amplitude of demand (lag 0.5, r = 66%)
number of days of supply
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9

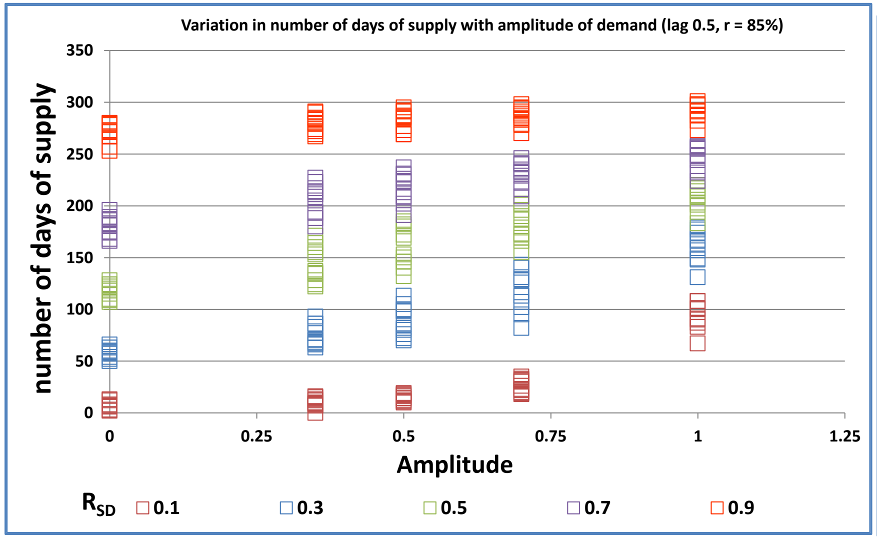

Variation in number of days of supply with amplitude of demand (lag 0, r =80 %)
number of days of supply
Amplitude
0.1 0.3 0.5 0.7 0.9

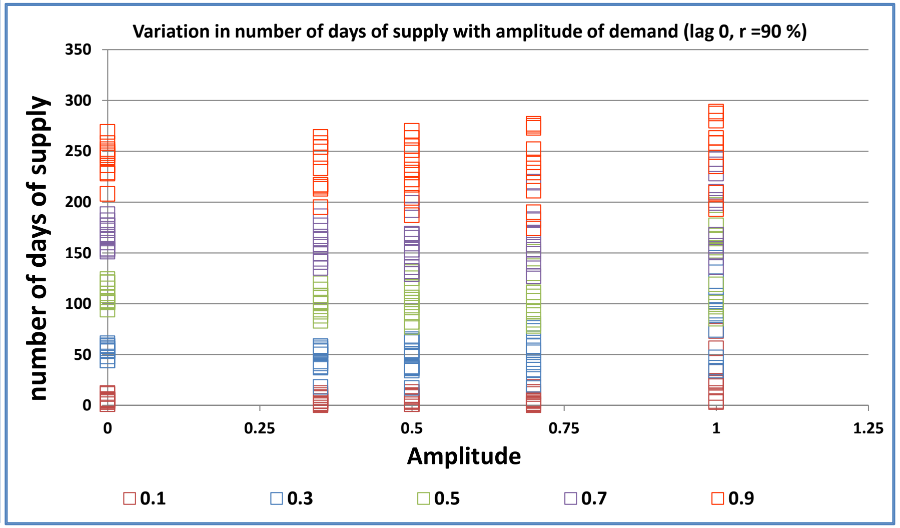

Variation in number of days of supply with amplitude of demand (lag 0.25, r = 80%)
number of days of supply
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9

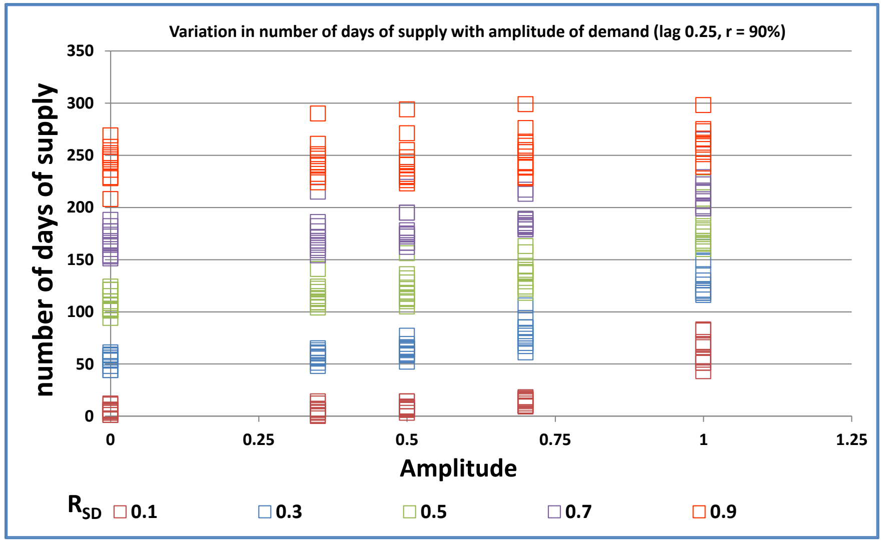

Variation in number of days of supply with amplitude of demand (lag 0.5, r = 80%)
number of days of supply
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9

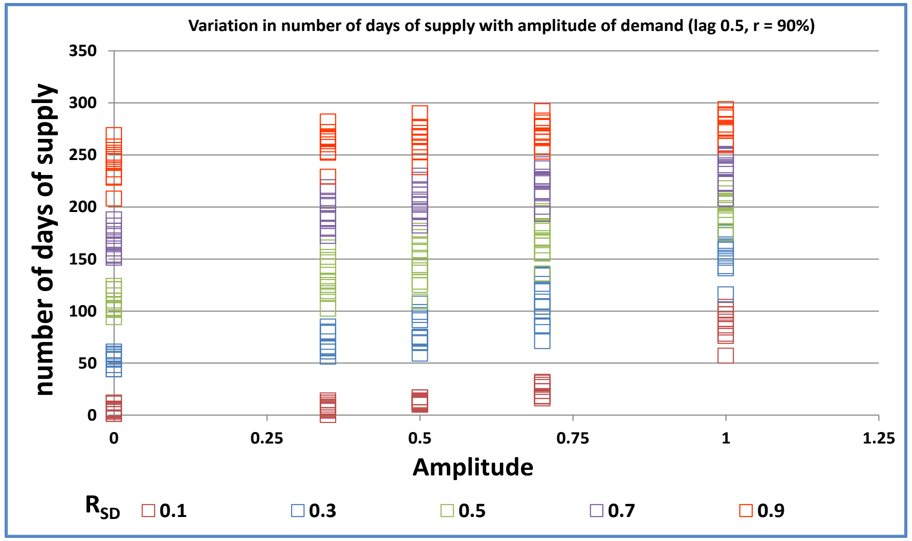

Variation in number of days of supply with amplitude of demand (lag 0, r =85 %)
number of days of supply
Amplitude
0.1
0.3
0.5
0.7
0.9

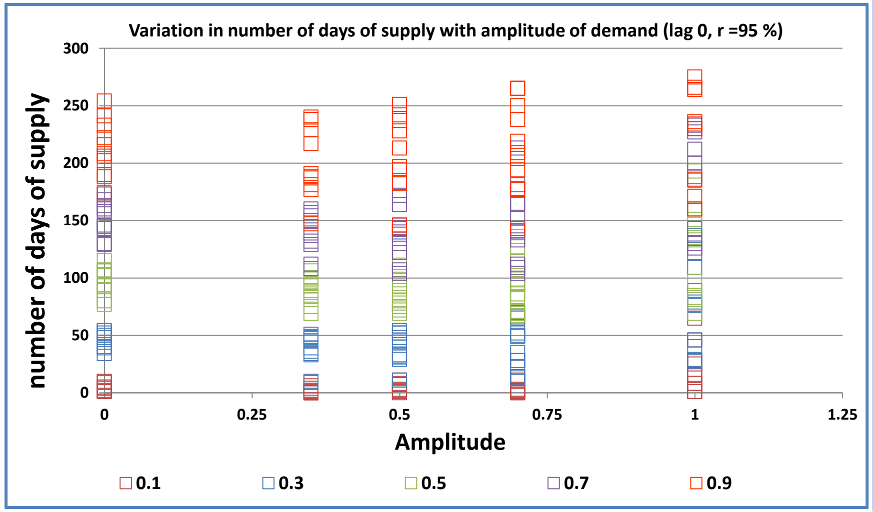

Variation in number of days of supply with amplitude of demand (lag 0.25, r = 85%)
number of days of supply
Amplitude
R_{SD}
0.1
0.3
0.5
0.7
0.9

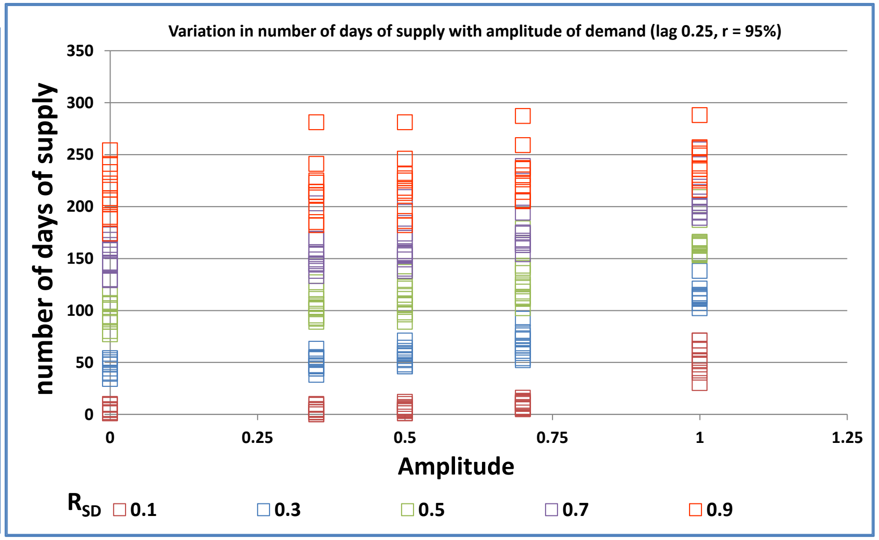

Variation in number of days of supply with amplitude of demand (lag 0.5, r = 85%)
number of days of supply
Amplitude
R_{SD}
0.1
0.3
0.5
0.7
0.9

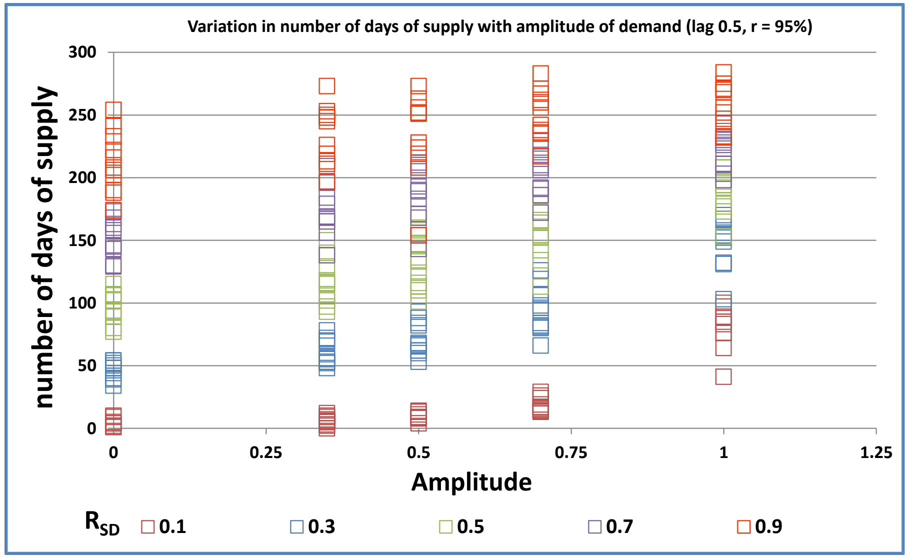

Variation in number of days of supply with amplitude of demand (lag 0, r =90 %)
number of days of supply
Amplitude
0.1
0.3
0.5
0.7
0.9


Variation in number of days of supply with amplitude of demand (lag 0.25, r = 90%)
number of days of supply
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9

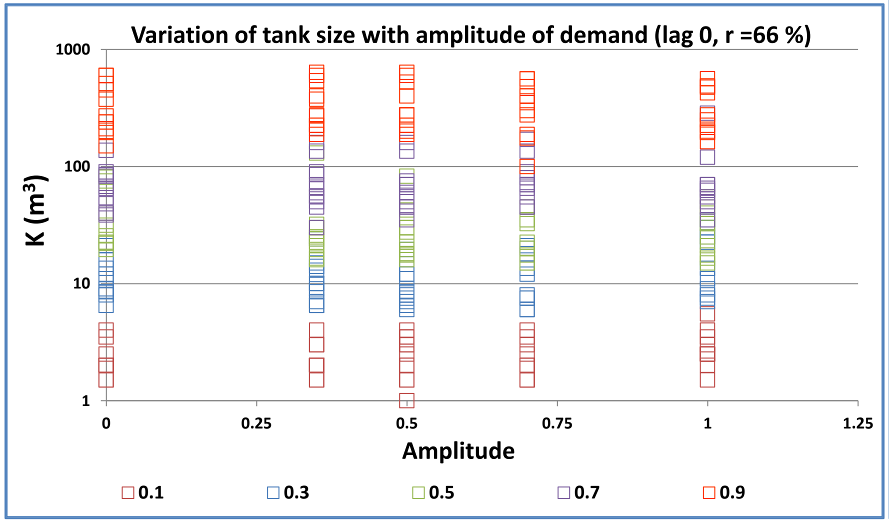

Variation in number of days of supply with amplitude of demand (lag 0.5, r = 90%)
number of days of supply
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9

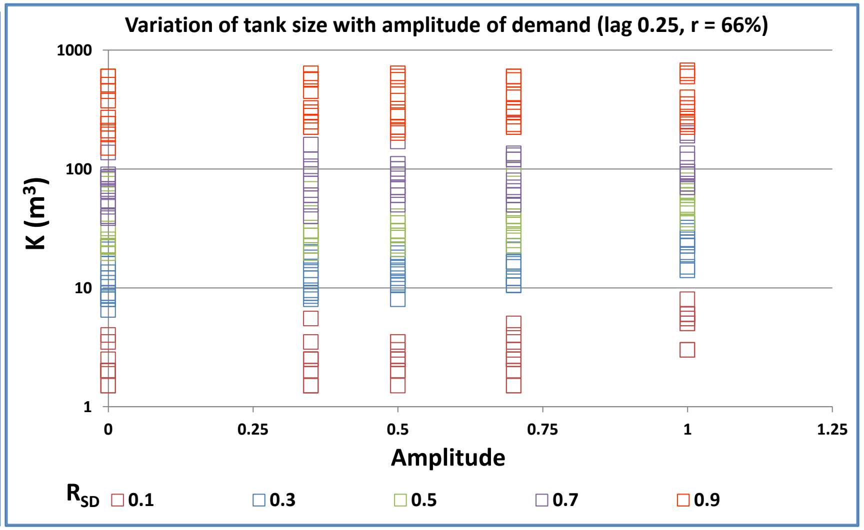

Variation in number of days of supply with amplitude of demand (lag 0, r =95 %)
number of days of supply
Amplitude
0.1 0.3 0.5 0.7 0.9

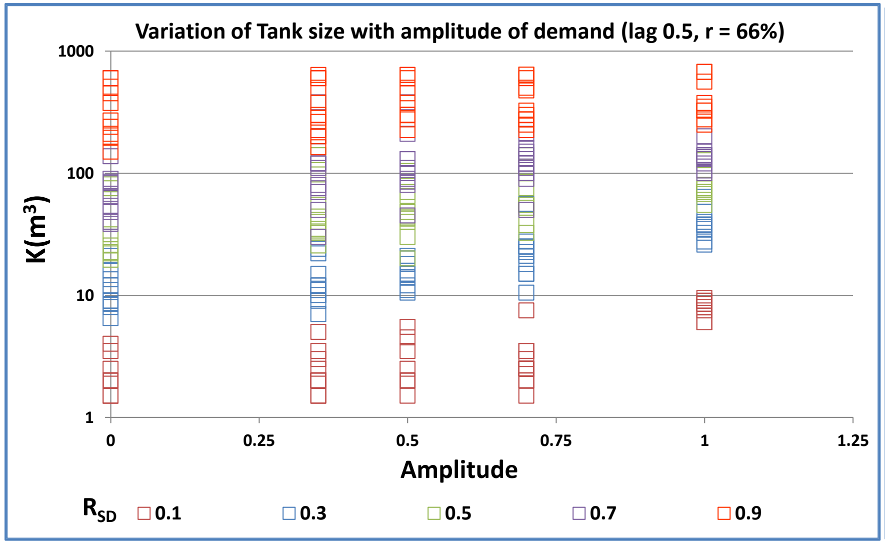

Variation in number of days of supply with amplitude of demand (lag 0.25, r = 95%)
number of days of supply
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9



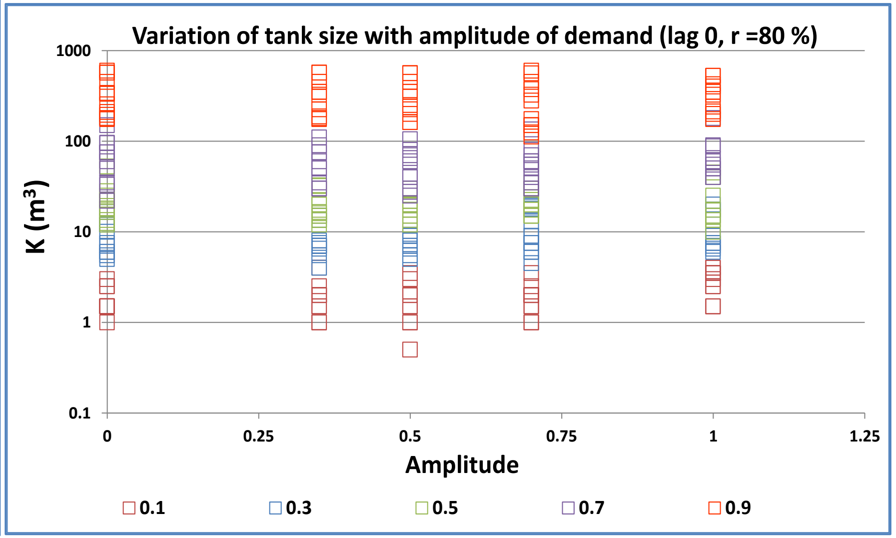
(f) Relationship between storage, yield, lag and amplitude



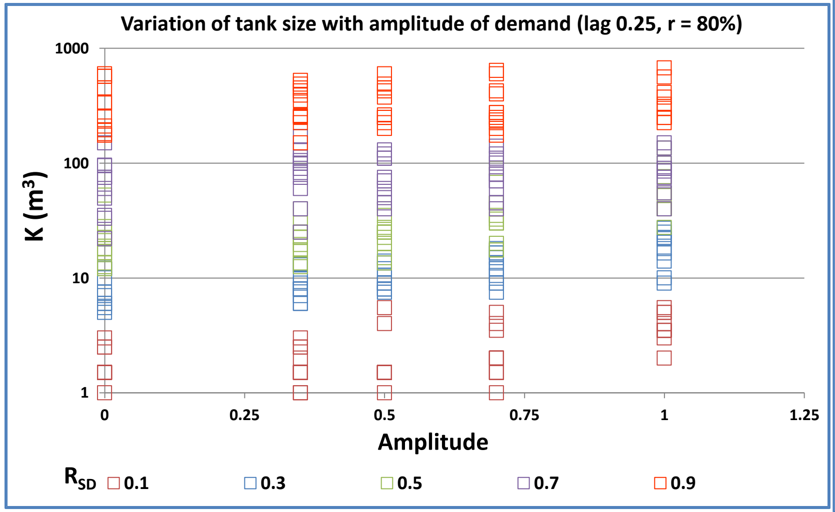




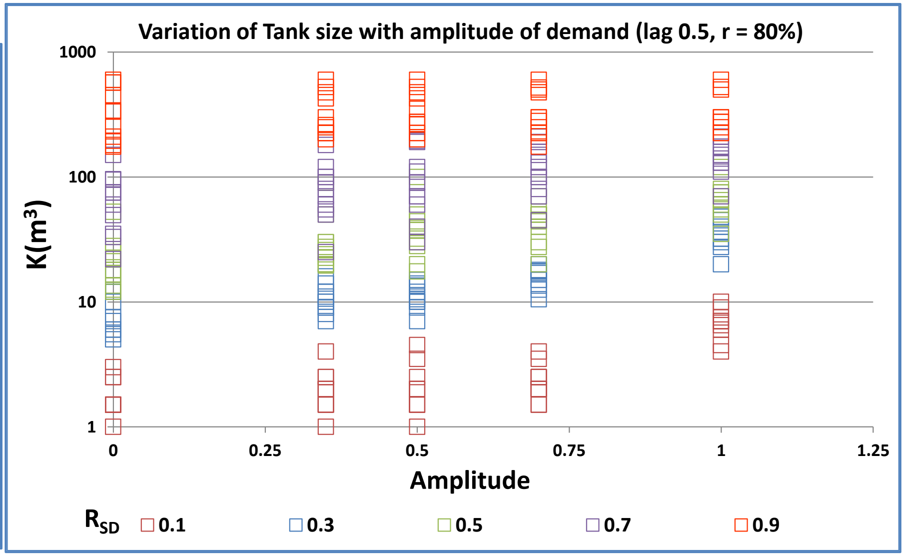
Variation of Tank size with amplitude of demand (lag 0.5, r = 66%)
1000
100
10
1
K(m3)
0
0.25
0.5
0.75
1
1.25
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9



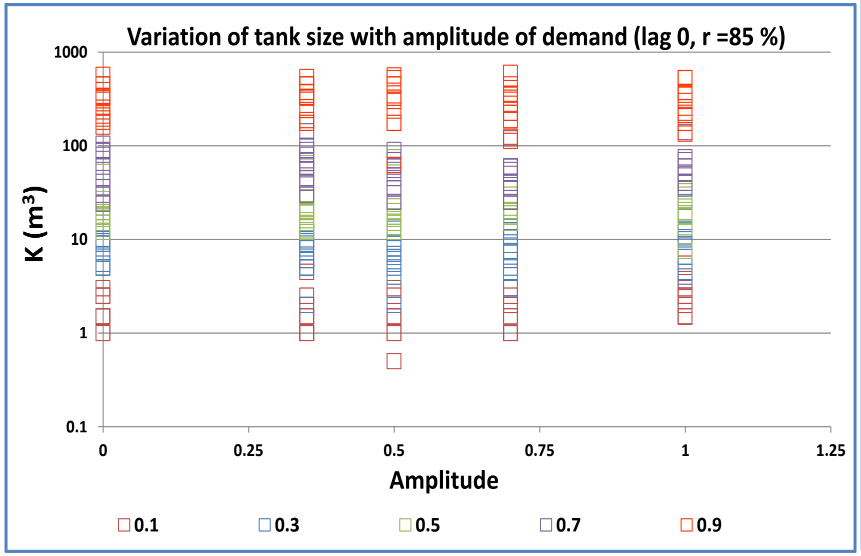
Variation of tank size with amplitude of demand (lag 0, r =80 %)
1000
100
10
1
0.1
K (m3)
0
0.25
0.5
0.75
1
1.25
Amplitude
0.1 0.3 0.5 0.7 0.9

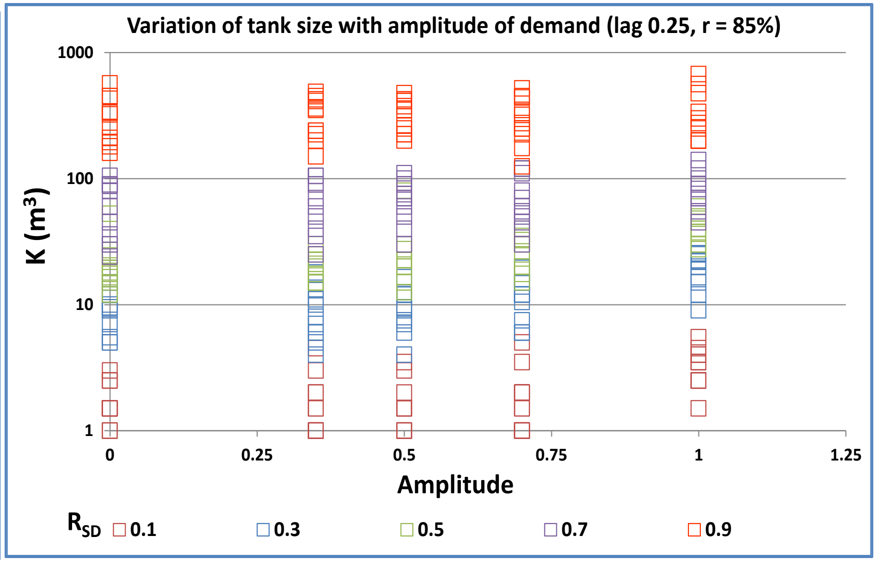


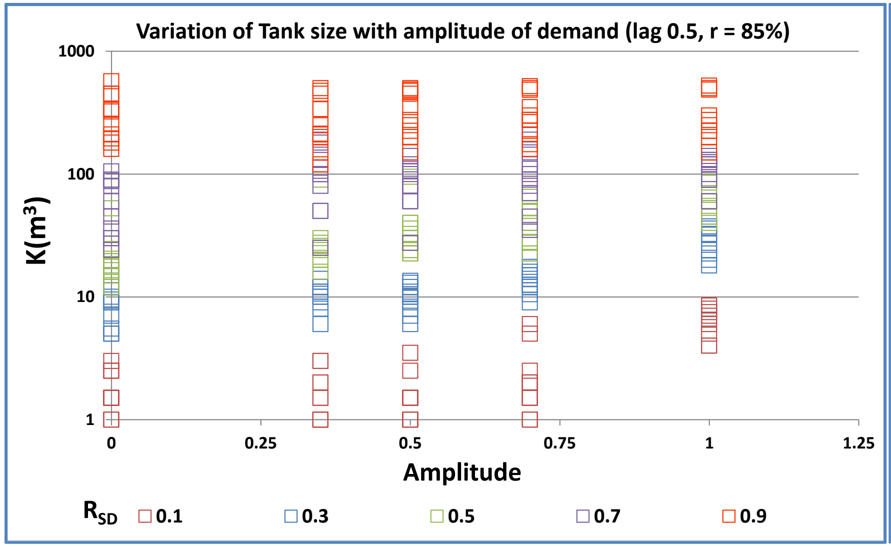
Variation of tank size with amplitude of demand (lag 0.25, r = 80%)
1000
100
10
1
K (m3)
0
0.25
0.5
0.75
1
1.25
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9

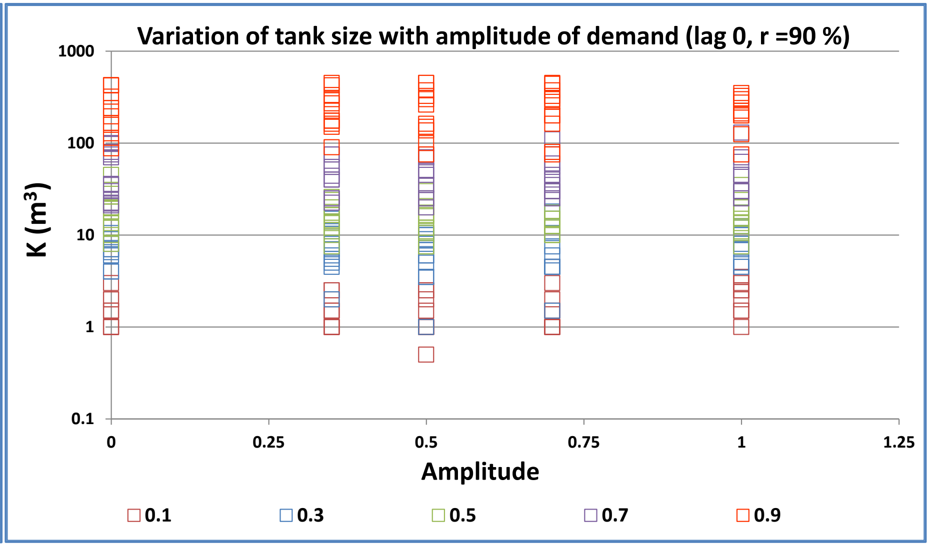


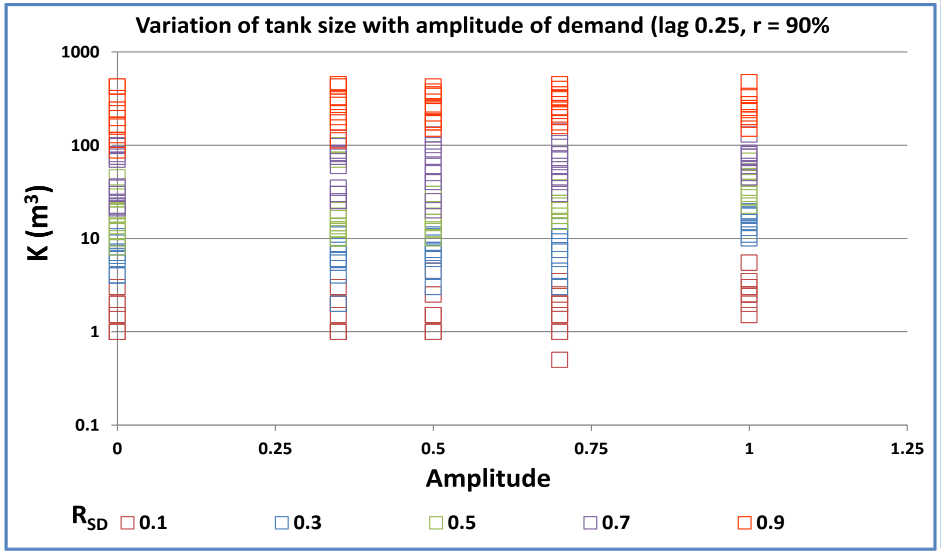
Variation of Tank size with amplitude of demand (lag 0.5, r = 80%)
1000
100
10
1
K(m3)
0
0.25
0.5
0.75
1
1.25
Amplitude
RSD 0.1 0.3 0.5 0.7 0.9


Variation of tank size with amplitude of demand (lag 0, r =85 %)
K (m³)
1000
100
10
1
0.1
0
0.25
0.5
0.75
1
1.25
Amplitude
0.1
0.3
0.5
0.7
0.9

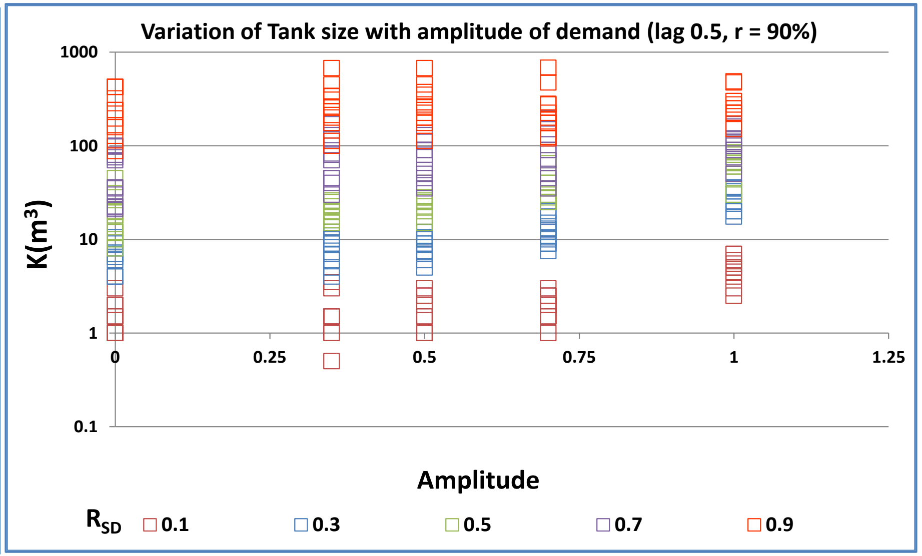

Variation of tank size with amplitude of demand (lag 0.25, r = 85%)
K (m³)
1000
100
10
1
0
0.25
0.5
0.75
1
1.25
Amplitude
RSD
0.1
0.3
0.5
0.7
0.9


Variation of Tank size with amplitude of demand (lag 0.5, r = 85%)
K(m³)
1000
100
10
1
0
0.25
0.5
0.75
1
1.25
Amplitude
RSD
0.1
0.3
0.5
0.7
0.9

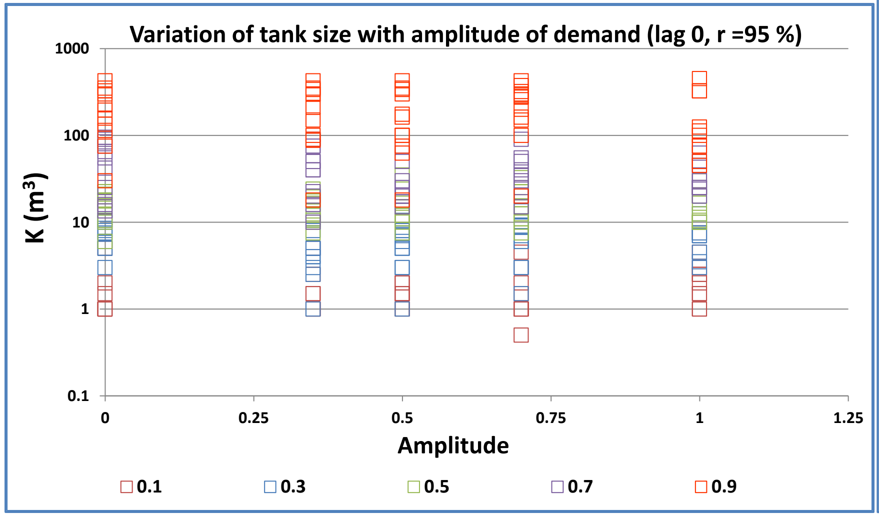

Variation of tank size with amplitude of demand (lag 0, r =90 %)
K (m³)
1000
100
10
1
0.1
0
0.25
0.5
0.75
1
1.25
Amplitude
0.1
0.3
0.5
0.7
0.9



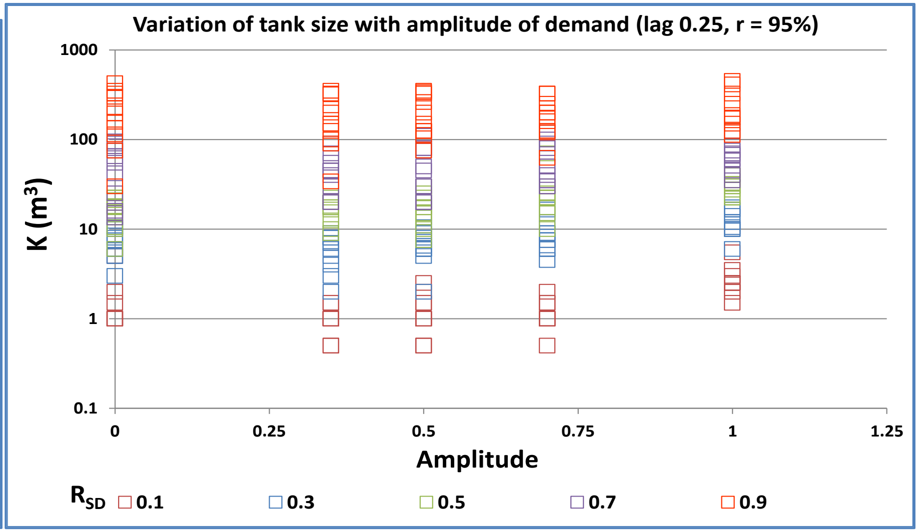
Variation of tank size with amplitude of demand (lag 0.25, r = 90%
1000
100
10
1
0.1
K (m³)
0
0.25
0.5
0.75
1
1.25
Amplitude
R_SD 0.1 0.3 0.5 0.7 0.9



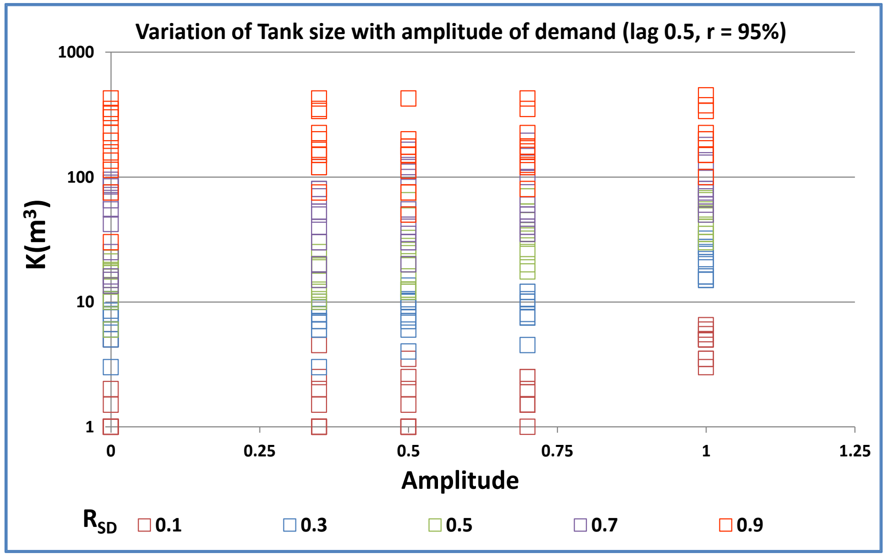
Variation of Tank size with amplitude of demand (lag 0.5, r = 90%)
1000
100
10
1
0.1
K(m³)
0
0.25
0.5
0.75
1
1.25
Amplitude
R_SD 0.1 0.3 0.5 0.7 0.9



Variation of tank size with amplitude of demand (lag 0, r =95 %)
1000
100
10
1
0.1
K (m³)
0
0.25
0.5
0.75
1
1.25
Amplitude
0.1 0.3 0.5 0.7 0.9

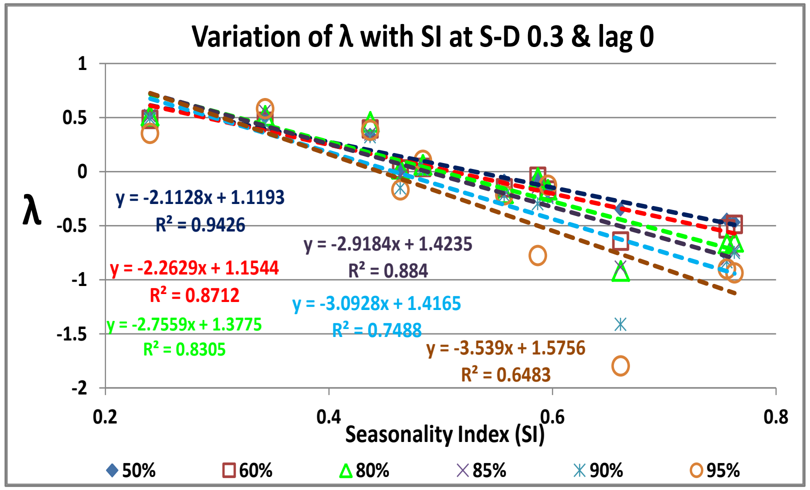


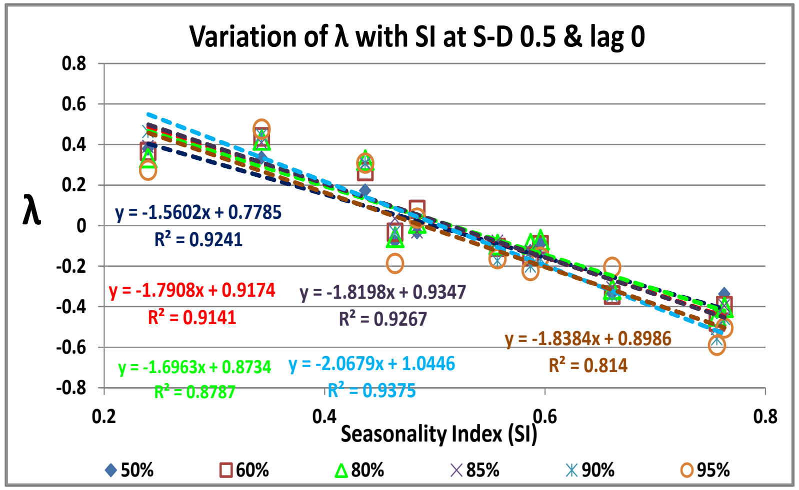
Variation of tank size with amplitude of demand (lag 0.25, r = 95%)
1000
100
10
1
0.1
K (m³)
0
0.25
0.5
0.75
1
1.25
Amplitude
R_SD 0.1 0.3 0.5 0.7 0.9

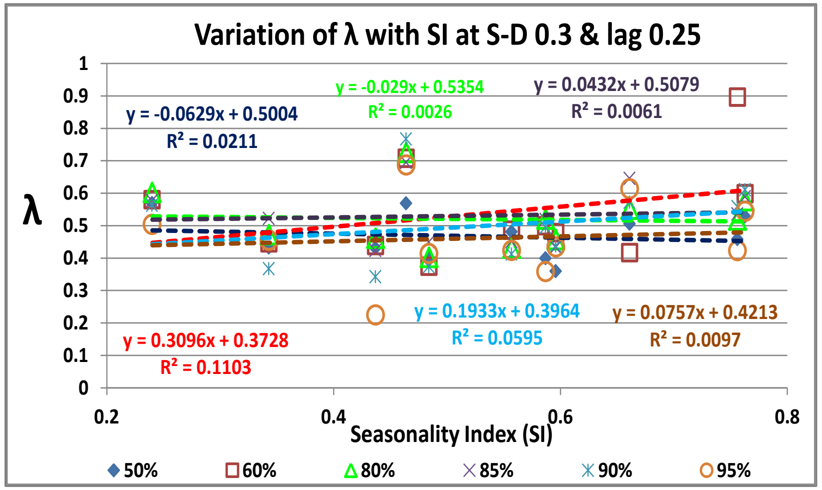


(g) Regression parameter relationships for yield, supply-demand, lag, amplitude, reliability

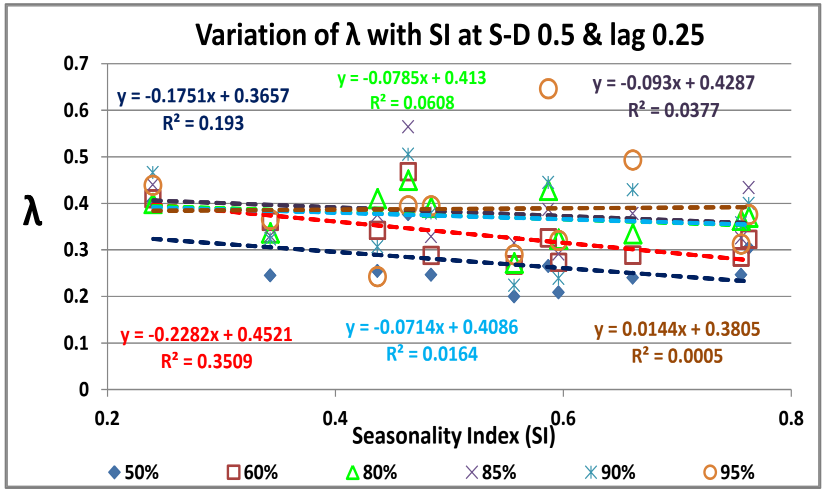
1. Variation of λ(regression parameter) with Seasonality



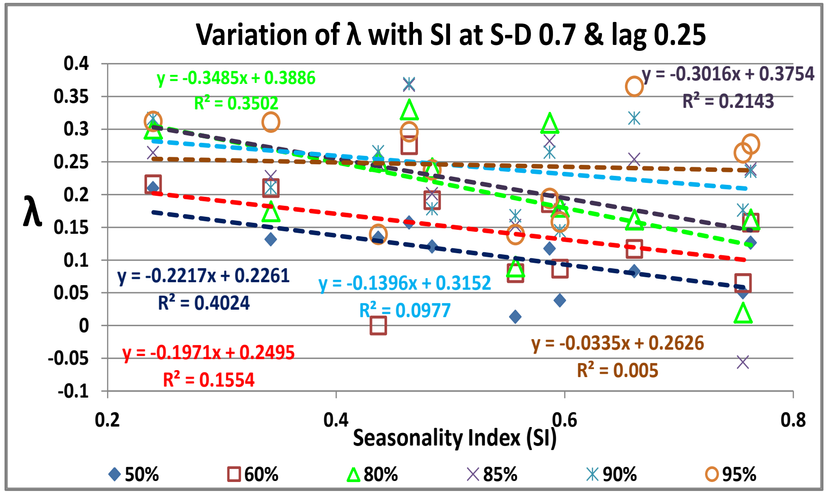




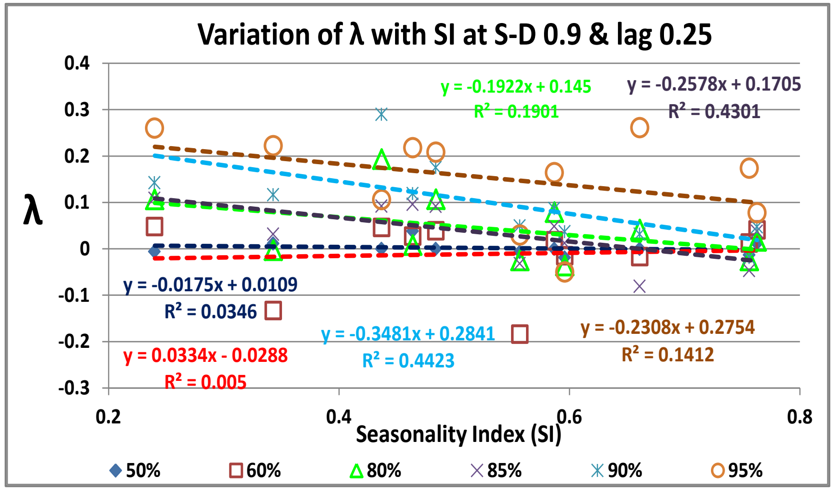
Variation of λ with SI at S-D 0.3 & lag 0.25
y = -0.0629x + 0.5004
R² = 0.0211
y = -0.029x + 0.5354
R² = 0.0026
y = 0.0432x + 0.5079
R² = 0.0061
y = 0.3096x + 0.3728
R² = 0.1103
y = 0.1933x + 0.3964
R² = 0.0595
y = 0.0757x + 0.4213
R² = 0.0097
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%



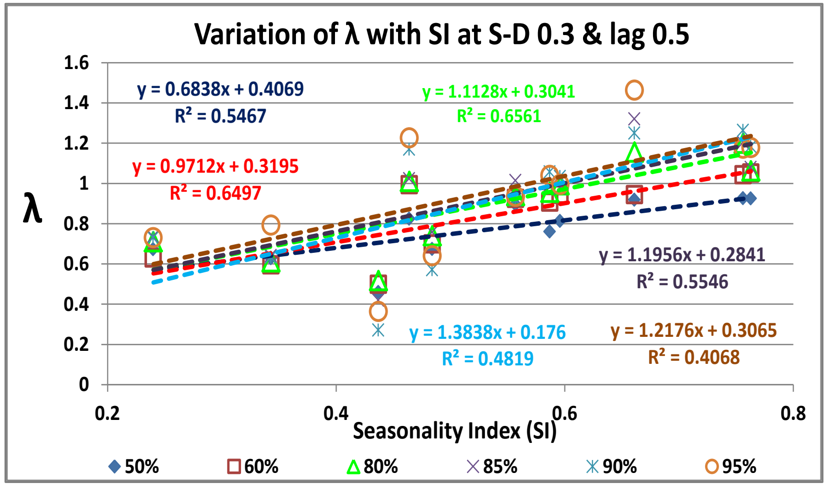
Variation of λ with SI at S-D 0.5 & lag 0.25
y = -0.1751x + 0.3657
R² = 0.193
y = -0.0785x + 0.413
R² = 0.0608
y = -0.093x + 0.4287
R² = 0.0377
y = -0.2282x + 0.4521
R² = 0.3509
y = -0.0714x + 0.4086
R² = 0.0164
y = 0.0144x + 0.3805
R² = 0.0005
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%

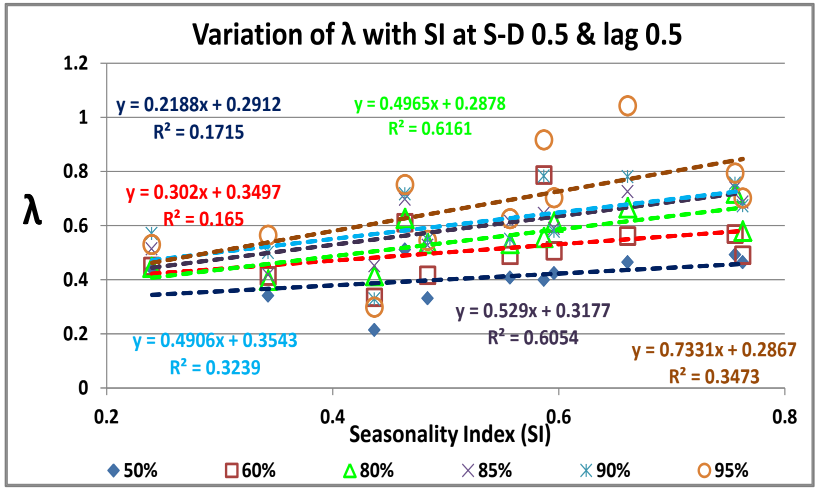


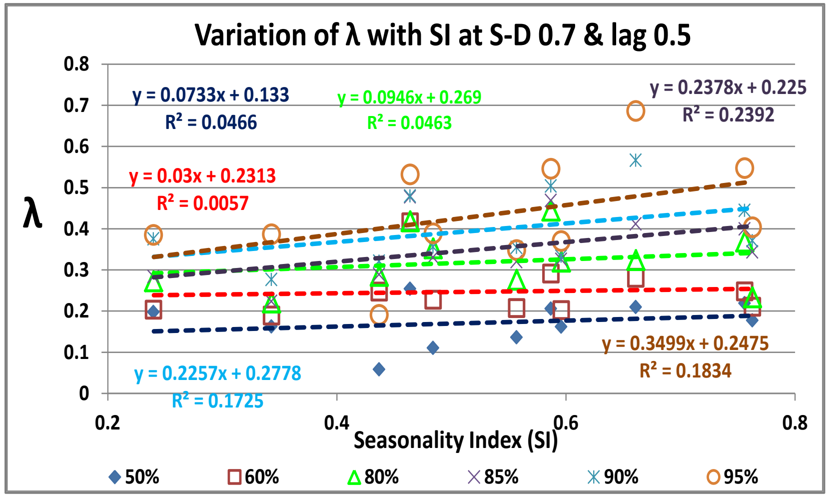
Variation of λ with SI at S-D 0.7 & lag 0.25
y = -0.3485x + 0.3886
R² = 0.3502
y = -0.3016x + 0.3754
R² = 0.2143
y = -0.2217x + 0.2261
R² = 0.4024
y = -0.1396x + 0.3152
R² = 0.0977
y = -0.1971x + 0.2495
R² = 0.1554
y = -0.0335x + 0.2626
R² = 0.005
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%

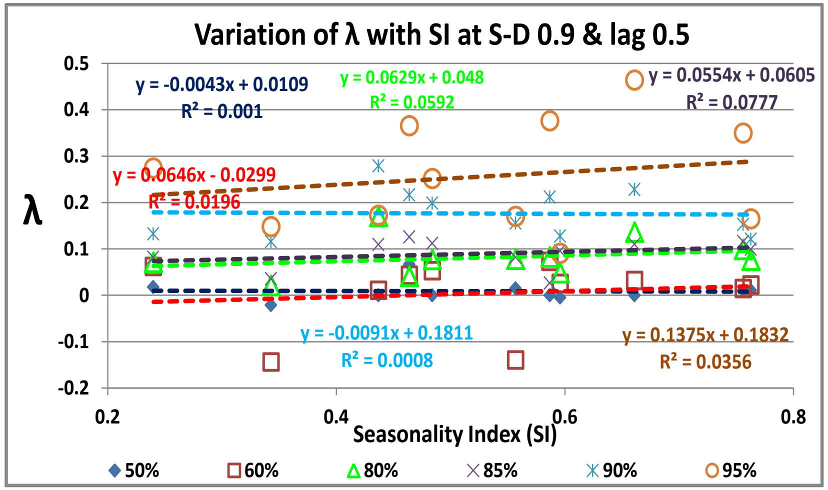


Variation of λ with SI at S-D 0.9 & lag 0.25
y = -0.1922x + 0.145
R² = 0.1901
y = -0.2578x + 0.1705
R² = 0.4301
y = -0.0175x + 0.0109
R² = 0.0346
y = -0.3481x + 0.2841
R² = 0.4423
y = -0.2308x + 0.2754
R² = 0.1412
y = 0.0334x - 0.0288
R² = 0.005
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%


Variation of λ with SI at S-D 0.3 & lag 0.5
y = 0.6838x + 0.4069
R² = 0.5467
y = 1.1128x + 0.3041
R² = 0.6561
y = 0.9712x + 0.3195
R² = 0.6497
y = 1.1956x + 0.2841
R² = 0.5546
y = 1.3838x + 0.176
R² = 0.4819
y = 1.2176x + 0.3065
R² = 0.4068
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%

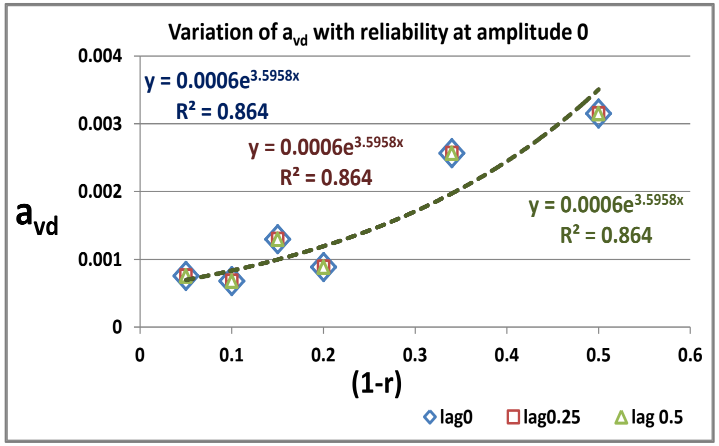

Variation of λ with SI at S-D 0.5 & lag 0.5
y = 0.2188x + 0.2912
R² = 0.1715
y = 0.4965x + 0.2878
R² = 0.6161
y = 0.302x + 0.3497
R² = 0.165
y = 0.529x + 0.3177
R² = 0.6054
y = 0.4906x + 0.3543
R² = 0.3239
y = 0.7331x + 0.2867
R² = 0.3473
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%

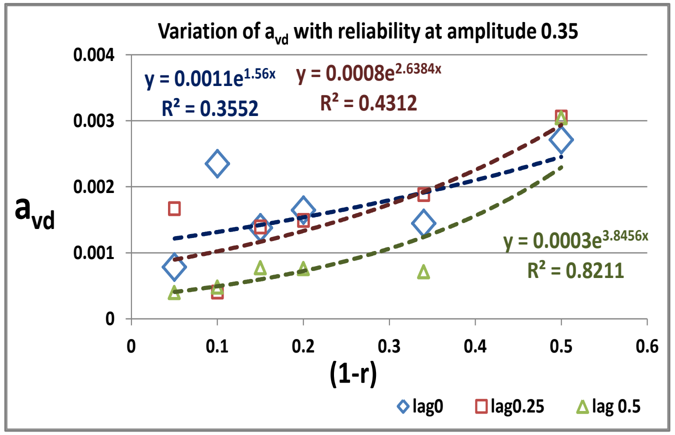

Variation of λ with SI at S-D 0.7 & lag 0.5
y = 0.0733x + 0.133
R² = 0.0466
y = 0.0946x + 0.269
R² = 0.0463
y = 0.2378x + 0.225
R² = 0.2392
y = 0.03x + 0.2313
R² = 0.0057
y = 0.3499x + 0.2475
R² = 0.1834
y = 0.2257x + 0.2778
R² = 0.1725
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%

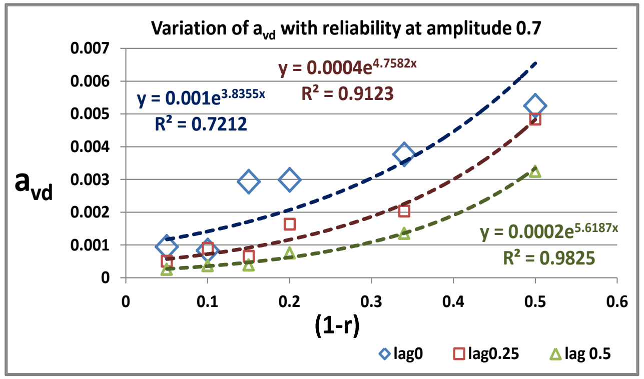

Variation of λ with SI at S-D 0.9 & lag 0.5
y = -0.0043x + 0.0109
R² = 0.001
y = 0.0629x + 0.048
R² = 0.0592
y = 0.0554x + 0.0605
R² = 0.0777
y = 0.0646x - 0.0299
R² = 0.0196
y = -0.0091x + 0.1811
R² = 0.0008
y = 0.1375x + 0.1832
R² = 0.0356
λ
Seasonality Index (SI)
50% 60% 80% 85% 90% 95%

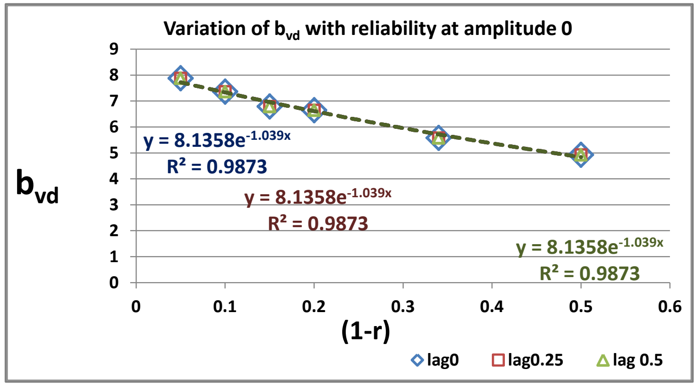
(h) Alternative Formulation for storage-demand-yield model incorporating amplitude and lag

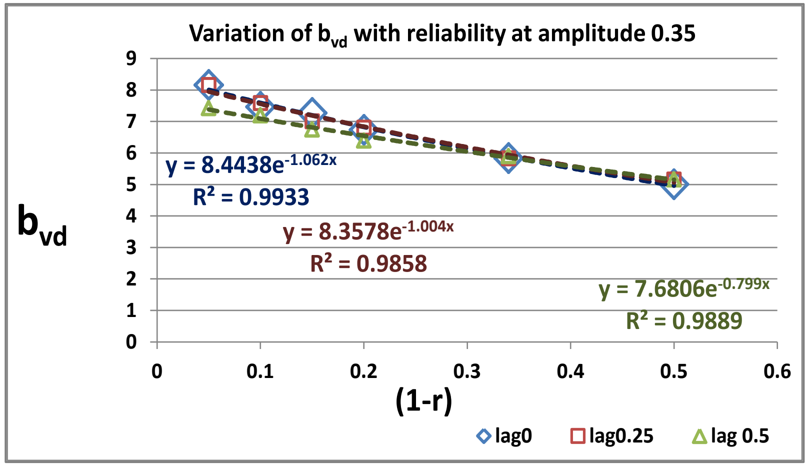
Relationships were first sought between reliability and coefficients of regression obtained from multiple linear regressions using general form $R_{TD-r} = a_{vd} \cdot e^{b_{vd}\left(\frac{N}{365.25}\right)} \cdot CV^{c_{vd}}$ at fixed amplitude and lag values. The following Figures illustrate the best fit relationships found for all lag values - the curves generally described moderate fits with parameter $\boldsymbol{a_{vd}}$ for amplitudes greater than zero, very good fits with parameter $\boldsymbol{b_{vd}}$ and rather poor fits for parameter $\boldsymbol{c_{vd}}$ for amplitudes greater than 0, with the exception being the data for lag 0.5 where strong relationships were found all round.



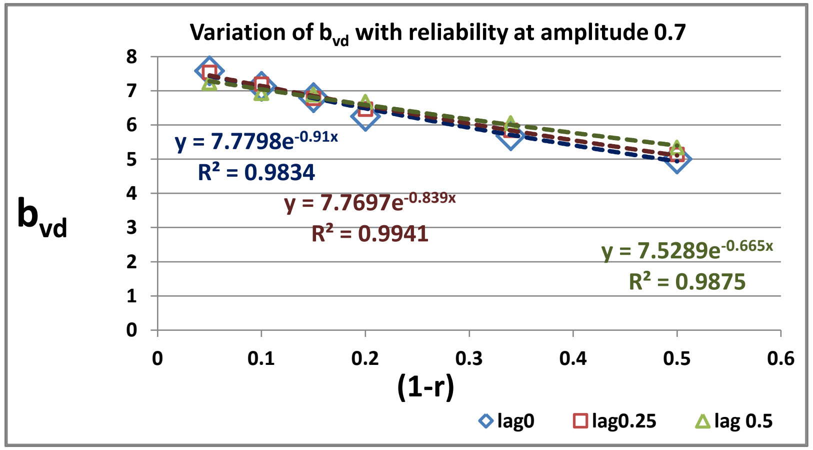




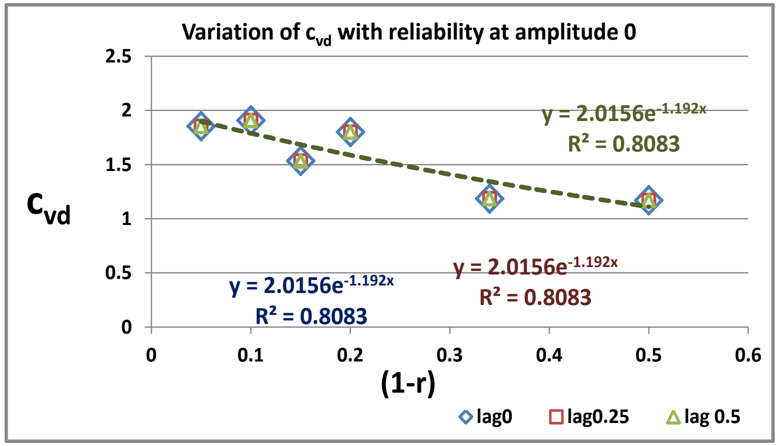




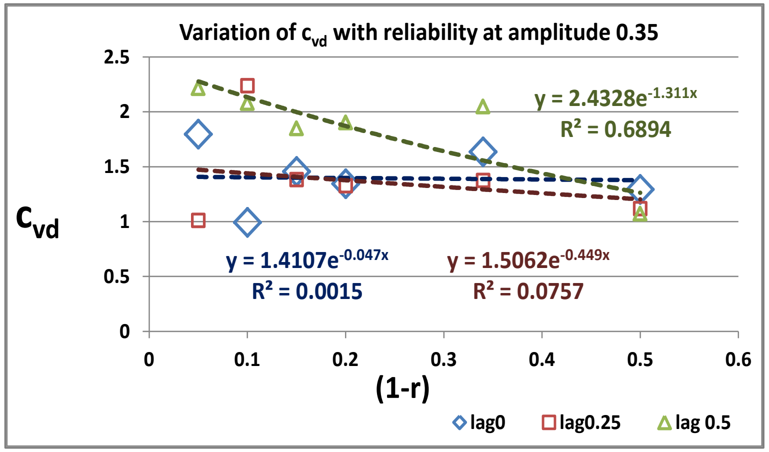
Variation of b_vd with reliability at amplitude 0.35
b_vd
(1-r)
y = 8.4438e^-1.062x
R² = 0.9933
y = 8.3578e^-1.004x
R² = 0.9858
y = 7.6806e^-0.799x
R² = 0.9889
lag0
lag0.25
lag 0.5



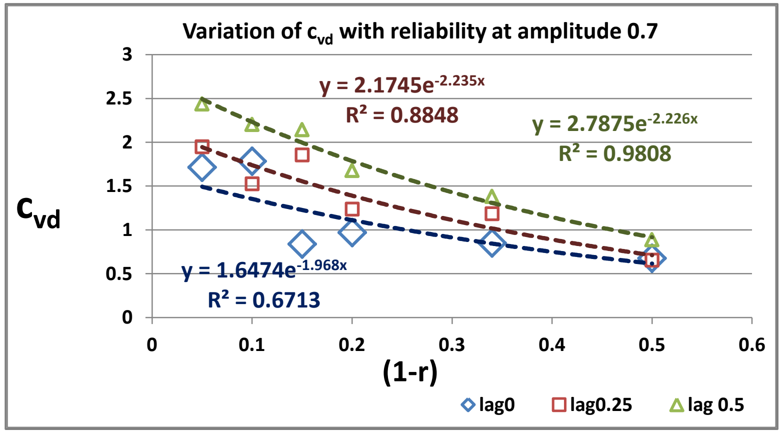
Variation of b_vd with reliability at amplitude 0.7
b_vd
(1-r)
y = 7.7798e^-0.91x
R² = 0.9834
y = 7.7697e^-0.839x
R² = 0.9941
y = 7.5289e^-0.665x
R² = 0.9875
lag0
lag0.25
lag 0.5



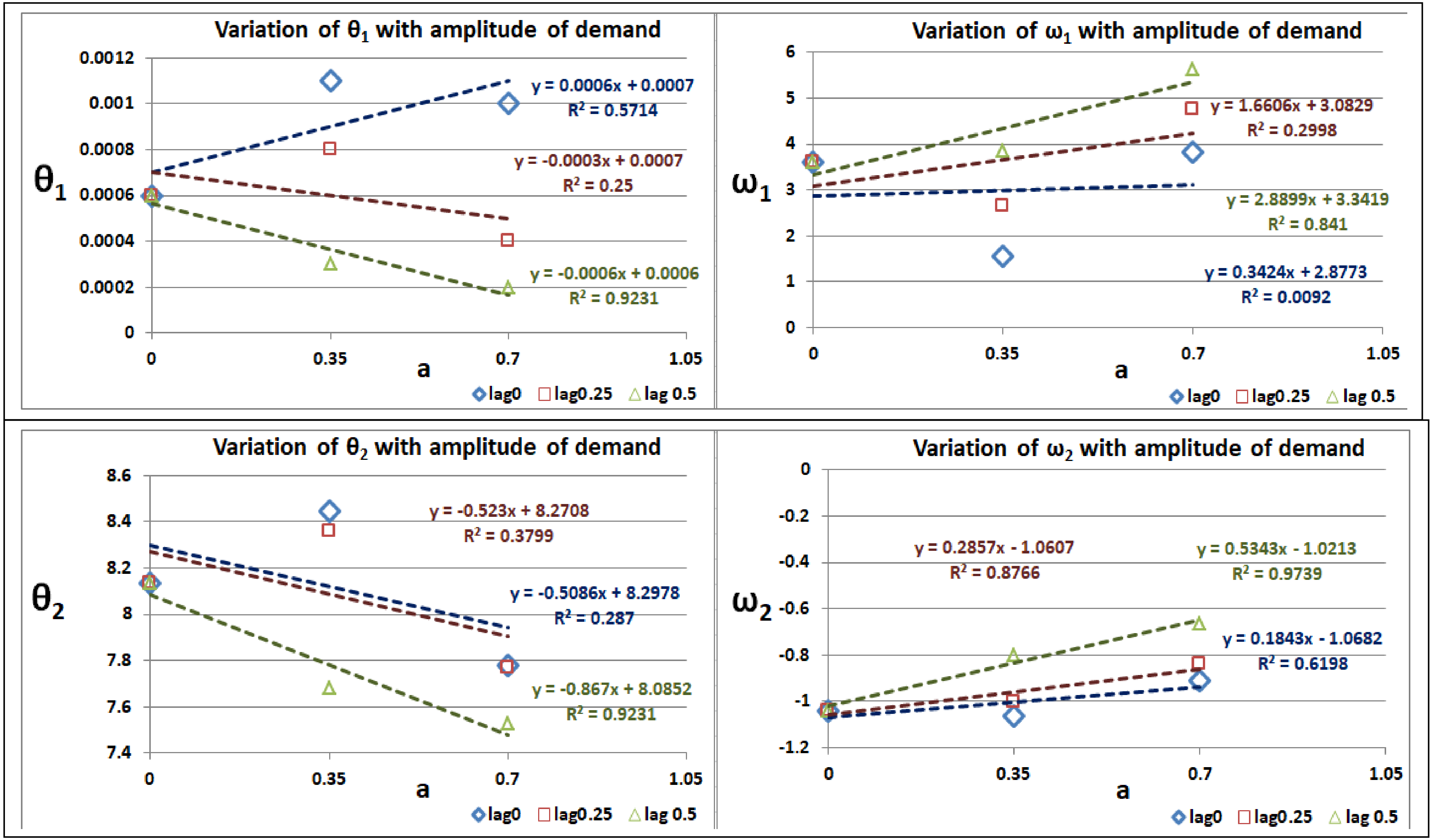
Variation of c_vd with reliability at amplitude 0
c_vd
(1-r)
y = 2.0156e^-1.192x
R² = 0.8083
y = 2.0156e^-1.192x
R² = 0.8083
y = 2.0156e^-1.192x
R² = 0.8083
lag0
lag0.25
lag 0.5

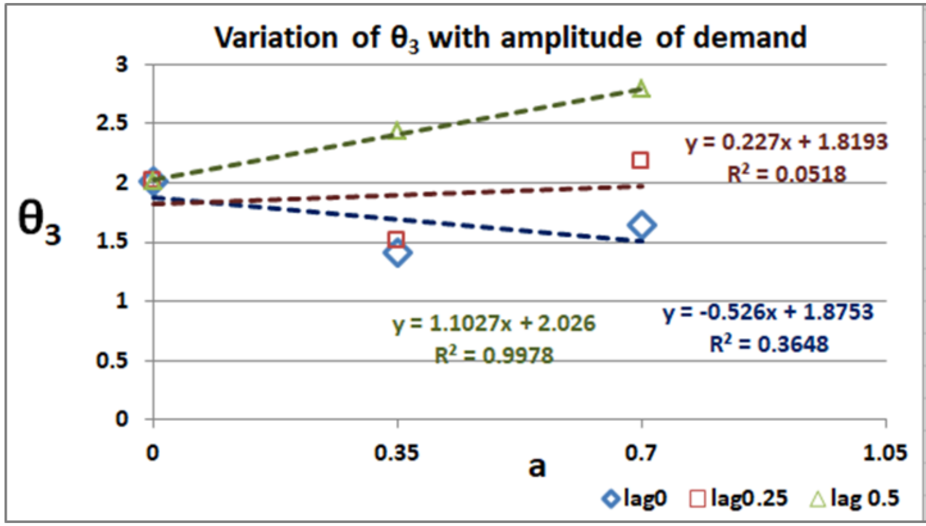


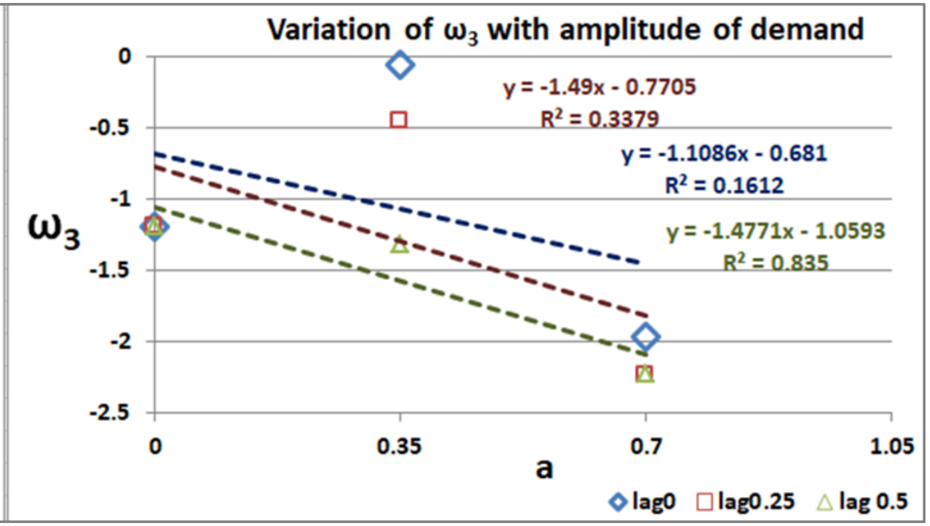
Variation of c_vd with reliability at amplitude 0.35
c_vd
(1-r)
y = 2.4328e^-1.311x
R² = 0.6894
y = 1.4107e^-0.047x
R² = 0.0015
y = 1.5062e^-0.449x
R² = 0.0757
lag0
lag0.25
lag 0.5



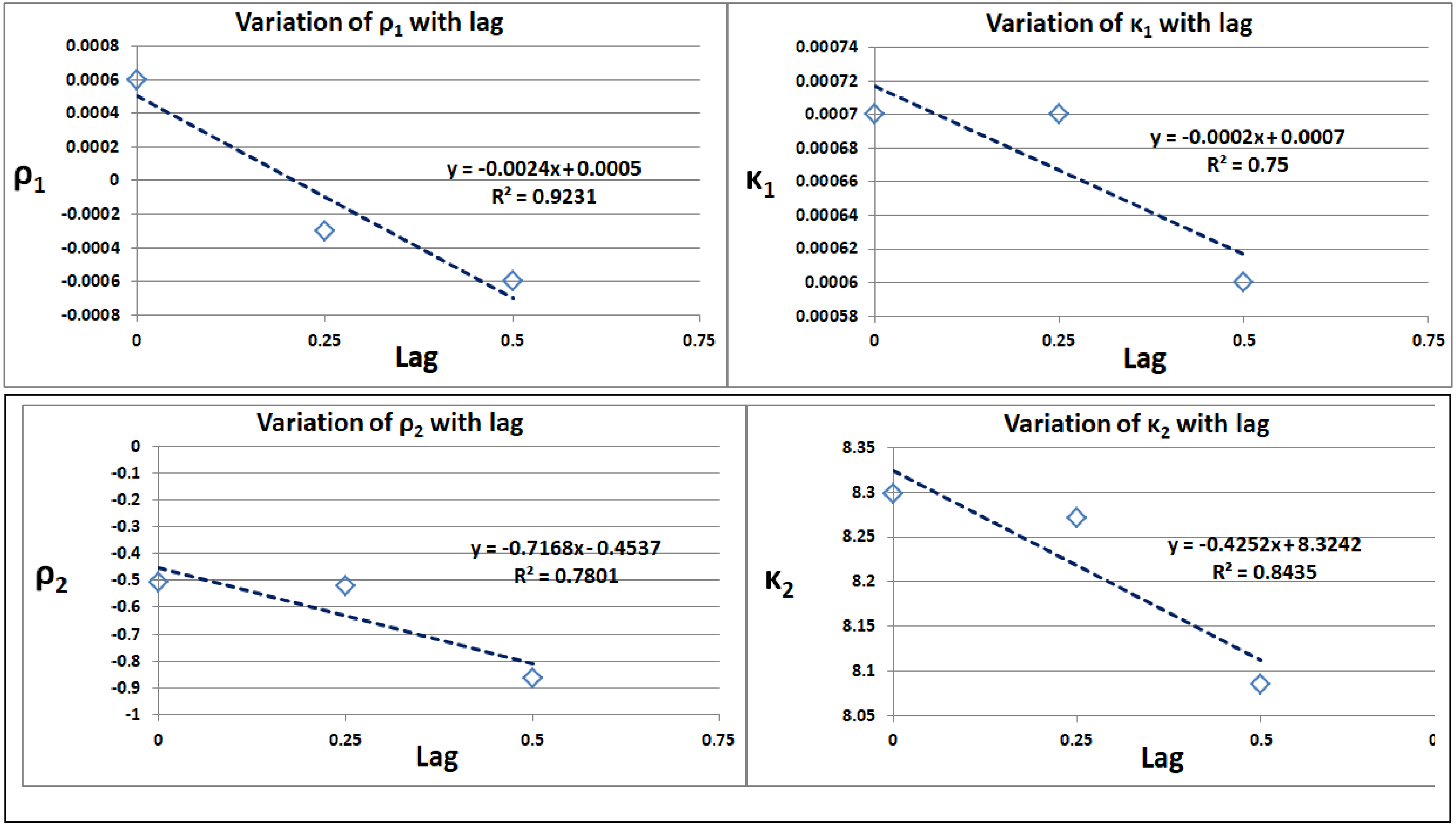
Using the general forms $a_{vd} = \theta_1 e^{\omega_1(1-r)}, b_{vd} = \theta_2 e^{\omega_2(1-r)} and\ a_{vd} = \theta_3 e^{\omega_3(1-r)}$, the amplitude values were in turn related to each of the regression coefficients $\boldsymbol{\theta_1}$ to $\boldsymbol{\theta_3}$ and $\boldsymbol{\omega_1}$ to $\boldsymbol{\omega_3}$ of the foregoing exponential relationships – the form of relationships found is


Variation of θ1 with amplitude of demand
θ1
0.0012
0.001
0.0008
0.0006
0.0004
0.0002
0
0
0.35
0.7
1.05
a
y = 0.0006x + 0.0007
R² = 0.5714
y = -0.0003x + 0.0007
R² = 0.25
y = -0.0006x + 0.0006
R² = 0.9231
lag0
lag0.25
lag 0.5
Variation of ω1 with amplitude of demand
ω1
6
5
4
3
2
1
0
0
0.35
0.7
1.05
a
y = 1.6606x + 3.0829
R² = 0.2998
y = 2.8899x + 3.3419
R² = 0.841
y = 0.3424x + 2.8773
R² = 0.0092
lag0
lag0.25
lag 0.5
Variation of θ2 with amplitude of demand
θ2
8.6
8.4
8.2
8
7.8
7.6
7.4
0
0.35
0.7
1.05
a
y = -0.523x + 8.2708
R² = 0.3799
y = -0.5086x + 8.2978
R² = 0.287
y = -0.867x + 8.0852
R² = 0.9231
lag0
lag0.25
lag 0.5
Variation of ω2 with amplitude of demand
ω2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
0
0.35
0.7
1.05
a
y = 0.2857x - 1.0607
R² = 0.8766
y = 0.5343x - 1.0213
R² = 0.9739
y = 0.1843x - 1.0682
R² = 0.6198
lag0
lag0.25
lag 0.5

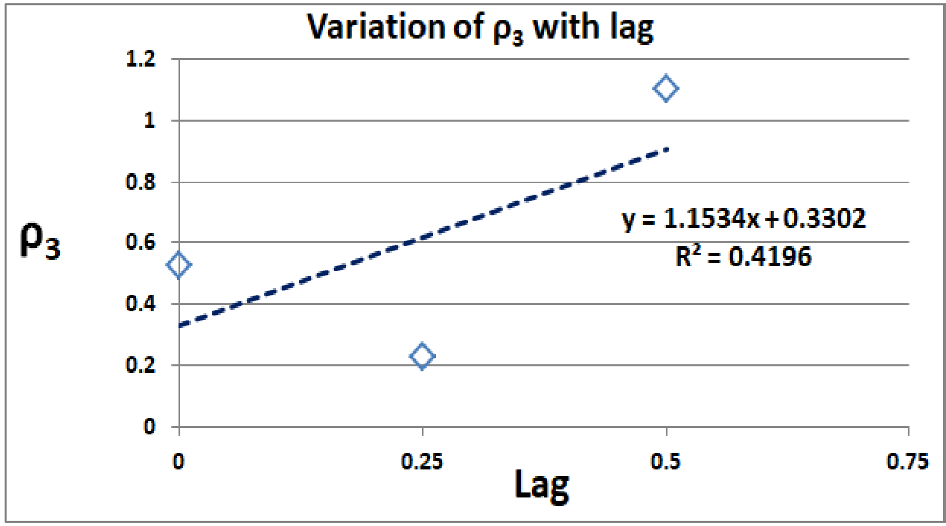


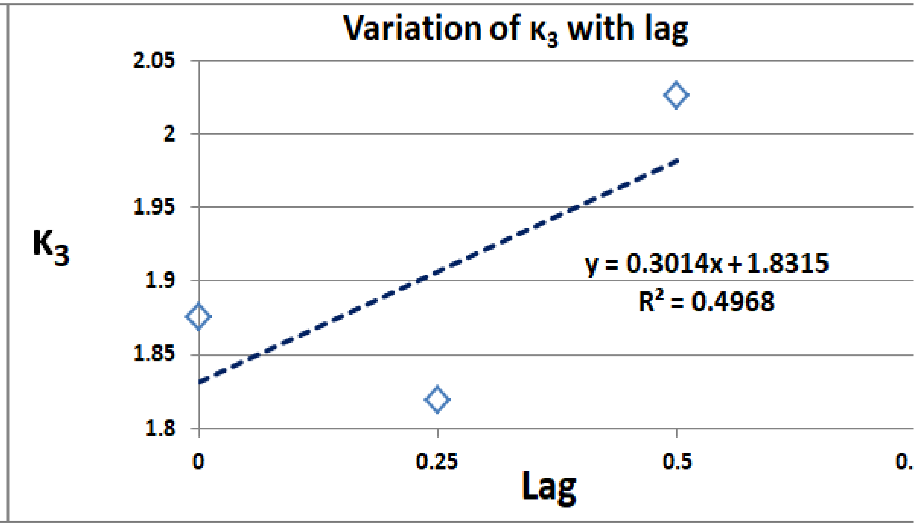


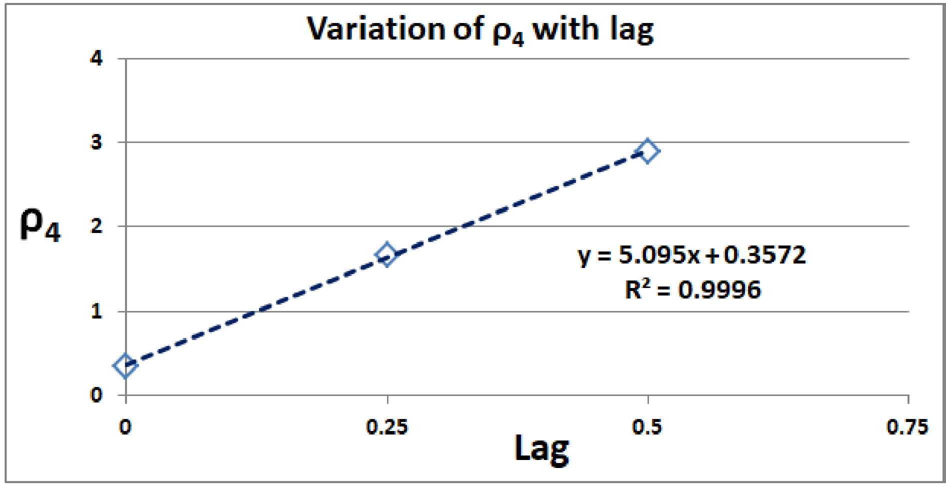
As can be seen, for this particular set of parameters rather poor linear relationships could be established. It would appear that the data take on a parabolic relationship, however additional data points would be required to confirm this and time has not allowed for this study to obtain this additional data. The data for a lag 0.5 on the other hand indicated strong linear relationships for all the parameters. For the purposes of completing the model a linear relationship was assumed for all the lag values. Thus, the final set of relationships, using the general forms: $\theta_1 = \rho_1(a) + \kappa_1$, $\theta_2 = \rho_2(a) + \kappa_2$, $\theta_3 = \rho_3(a) + \kappa_3$, $\omega_1 = \rho_4(a) + \kappa_4$, $\omega_2 = \rho_5(a) + \kappa_5$ and $\omega_3 = \rho_6(a) + \kappa_6$ was sought between the coefficients $\boldsymbol{\rho_1}$ to $\boldsymbol{\rho_6}$ and $\boldsymbol{\kappa_1}$ to $\boldsymbol{\kappa_6}$ and the lag. The best fit curves are presented in the following figures:

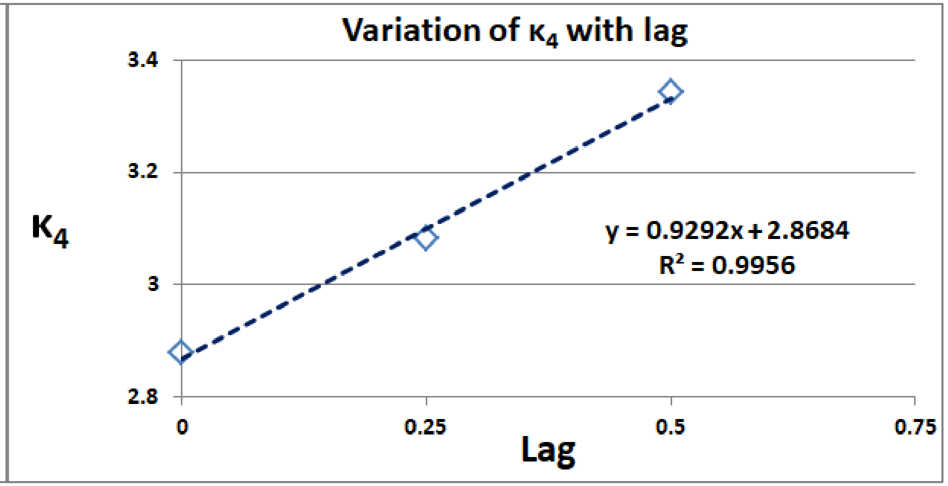


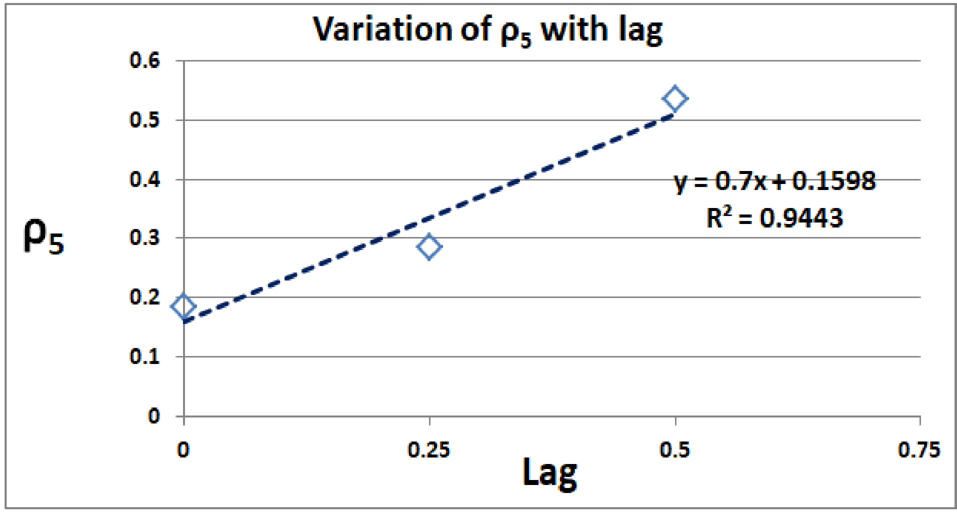
Variation of ρ1 with lag
ρ1
Lag
y = -0.0024x+0.0005
R² = 0.9231
Variation of κ1 with lag
κ1
Lag
y = -0.0002x+0.0007
R² = 0.75
Variation of ρ2 with lag
ρ2
Lag
y = -0.7168x-0.4537
R² = 0.7801
Variation of κ2 with lag
κ2
Lag
y = -0.4252x+8.3242
R² = 0.8435

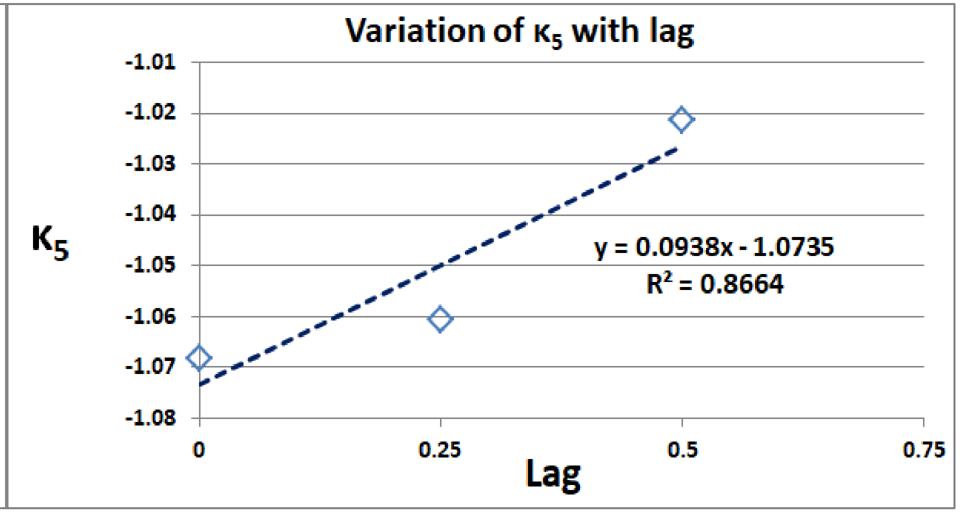

Variation of ρ3 with lag
ρ3
1.2
1
0.8
0.6
0.4
0.2
0
0
0.25
0.5
0.75
Lag
y = 1.1534x + 0.3302
R² = 0.4196

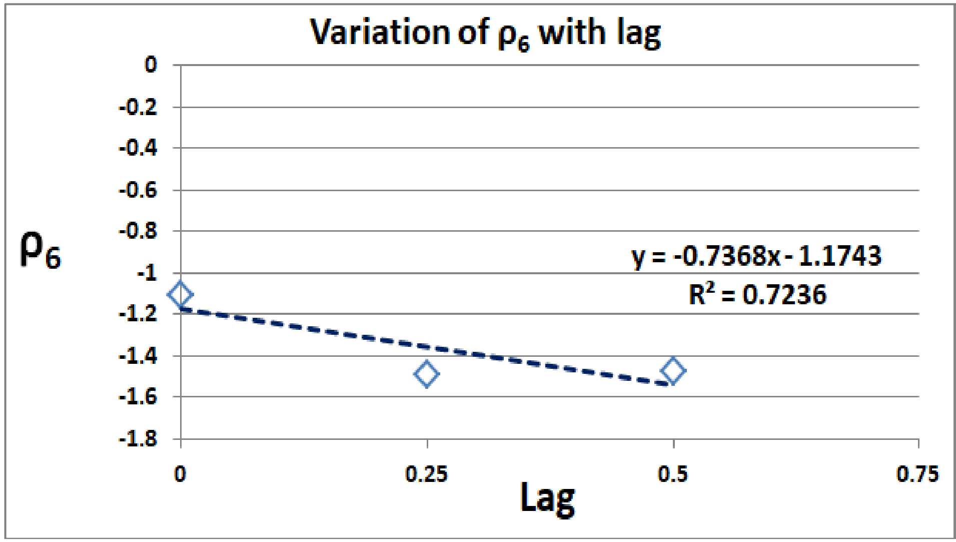

Variation of κ3 with lag
κ3
2.05
2
1.95
1.9
1.85
1.8
0
0.25
0.5
0.
Lag
y = 0.3014x + 1.8315
R² = 0.4968

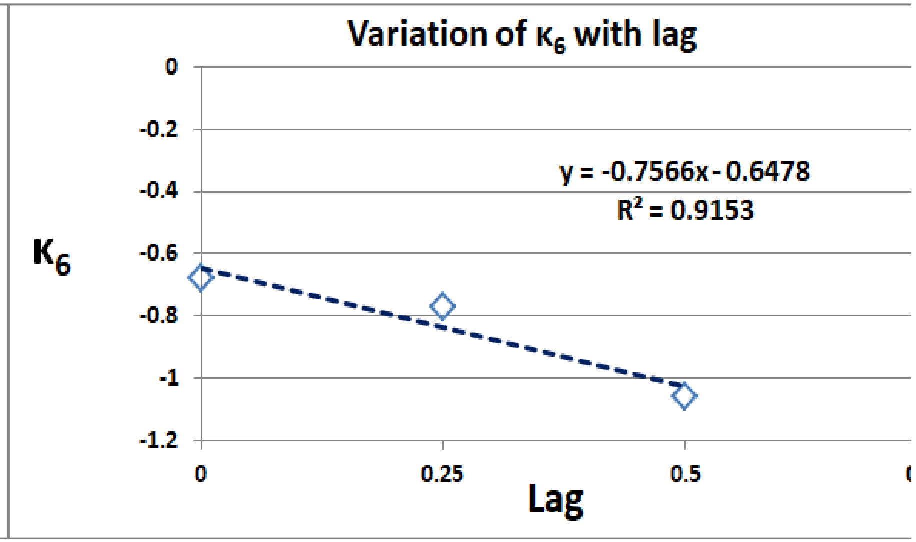

Variation of ρ4 with lag
ρ4
4
3
2
1
0
0
0.25
0.5
0.75
Lag
y = 5.095x + 0.3572
R² = 0.9996


Variation of κ4 with lag
κ4
3.4
3.2
3
2.8
0
0.25
0.5
0.75
Lag
y = 0.9292x + 2.8684
R² = 0.9956


Variation of ρ5 with lag
ρ5
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.25
0.5
0.75
Lag
y = 0.7x + 0.1598
R² = 0.9443


Variation of κ5 with lag
κ5
-1.01
-1.02
-1.03
-1.04
-1.05
-1.06
-1.07
-1.08
0
0.25
0.5
0.75
Lag
y = 0.0938x - 1.0735
R² = 0.8664


Variation of ρ6 with lag
ρ6
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
-1.8
0
0.25
0.5
0.75
Lag
y = -0.7368x - 1.1743
R² = 0.7236


Variation of κ6 with lag
κ6
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
0
0.25
0.5
Lag
y = -0.7566x - 0.6478
R² = 0.9153

The final modelled equation becomes:

$$\boldsymbol{R_{TD-r} = a_{vd} e^{b\left(\frac{N}{365.25}\right)} \cdot CV^c}$$

Where for $0 < \boldsymbol{a} \leq \mathbf{0.7}$:

$a_{vd} = \theta_1 e^{\omega_1(1-r)}$

$b_{vd} = \theta_2 e^{\omega_2(1-r)}$ $\qquad \mathbf{0.} \leq \boldsymbol{r} \leq \mathbf{0.95}$

$c_{vd} = \theta_3 e^{\omega_3(1-r)}$

$\theta_1 = \rho_1(a) + \kappa_1 \qquad \omega_1 = \rho_4(a) + \kappa_4$

$\theta_2 = \rho_2(a) + \kappa_2 \qquad \omega_2 = \rho_5(a) + \kappa_5$

$\theta_3 = \rho_3(a) + \kappa_3 \qquad \omega_3 = \rho_6(a) + \kappa_6$

$\rho_1 = -0.002(l) + 0.001 \qquad \kappa_1 = -0.0002(l) + 0.001$

$\rho_2 = -0.717(l) - 0.454 \qquad \kappa_2 = -0.425(l) + 8.32$ **(A-1)**

$\rho_3 = 1.15(l) + 0.332 \qquad \kappa_3 = 0.301(l) + 1.83$

$\rho_4 = 5.09(l) + 0.357 \qquad \kappa_4 = -0.929(l) + 0.287$

$\rho_5 = 0.7(l) + 0.159 \qquad \kappa_5 = 0.894(l) - 1.07$

$\rho_6 = -0.737(l) - 1.17 \qquad \kappa_6 = -0.757(l) - 0.648$

$\mathbf{0} \leq \boldsymbol{l} \leq \mathbf{0.5}$

Where for a$=$ 0:

$\delta = 0.0004 e^{4.361(1-r)}$

$b = 8.624 e^{-1.13(1-r)}$ $\qquad \mathbf{0.5} \leq \boldsymbol{r} \leq \mathbf{0.95}$

$c = 2.339 e^{-1.327(1-r)}$

If rainfall characteristics are not considered the model simplifies to:

$$\boldsymbol{R_{TD-r} = \gamma e^{\varphi\left(\frac{N}{365.25}\right)}}$$

Where for $\boldsymbol{a} = \mathbf{0}$:

$\gamma = 0.009 e^{1.005(1-r)}$ $\qquad \mathbf{0.5} \leq \boldsymbol{r} \leq \mathbf{0.95}$

$\varphi = 8.207 e^{-0.996(1-r)}$

(A-2)

Where for $\mathbf{0} < \boldsymbol{a} \leq \mathbf{0.7}$

$\gamma = \theta_1(1-r) + \omega_1$

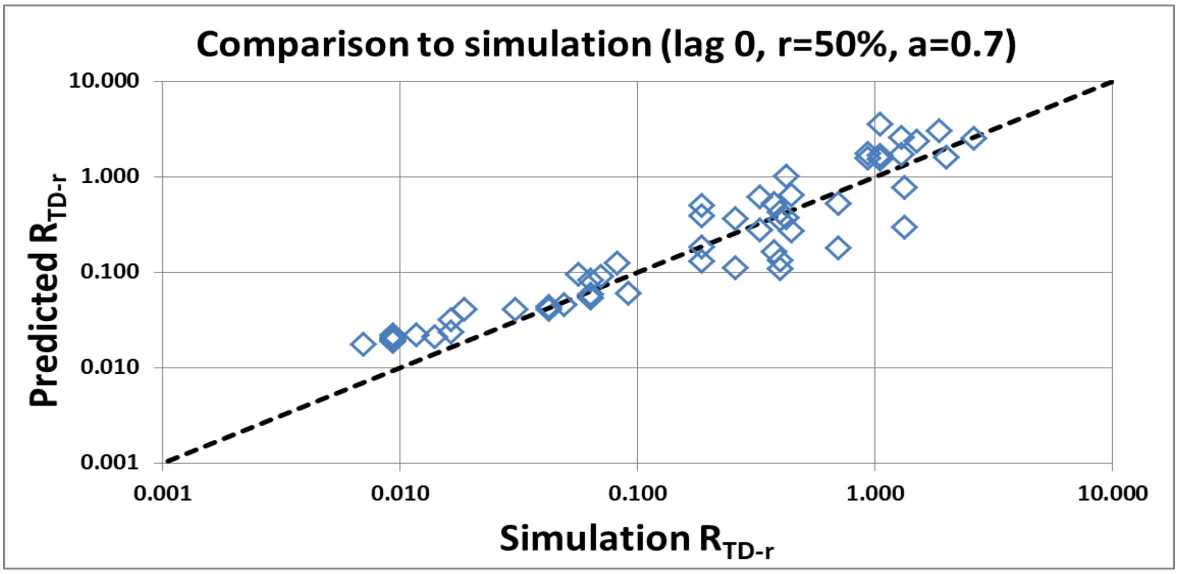
$\varphi = \theta_2 e^{\omega_2(1-r)}$

$\theta_1 = \rho_1(a) + \kappa_1 \qquad \omega_1 = \rho_2(a) + \kappa_2$

$\theta_2 = \rho_3(a) + \kappa_3 \qquad \omega_2 = \rho_4(a) + \kappa_4$

$$\rho_1 = -0.002(l) - 0.004 \qquad \kappa_1 = -0.002(l) + 0.014$$
$$\rho_2 = -0.007(l) + 0.00002 \qquad \kappa_2 = 0.0006(l) + 0.0072$$
$$\rho_3 = -1.36(l) - 0.246 \qquad \kappa_3 = -0.439(l) + 8.21$$
$$\rho_4 = 0.854(l) + 0.109 \qquad \kappa_4 = 0.097(l) - 1.04$$

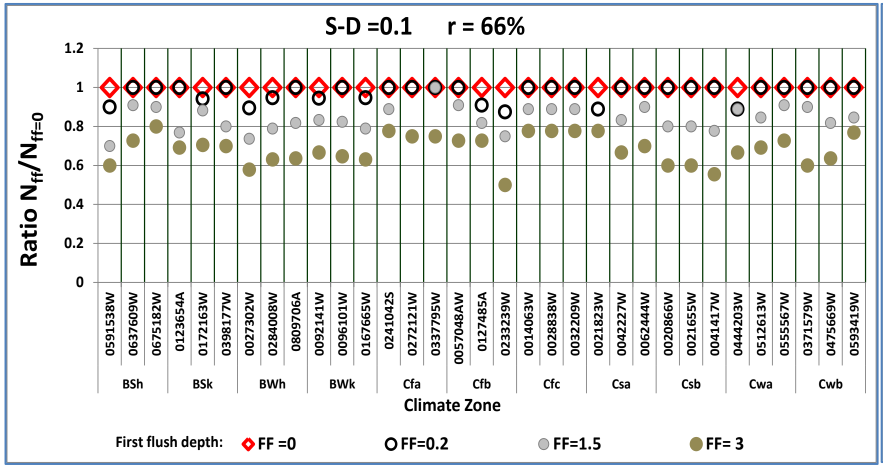
Brief comparion of this model to simulated data reveals good perfromance – although it may not be as good as the simpler formulation of section 5.2.4.

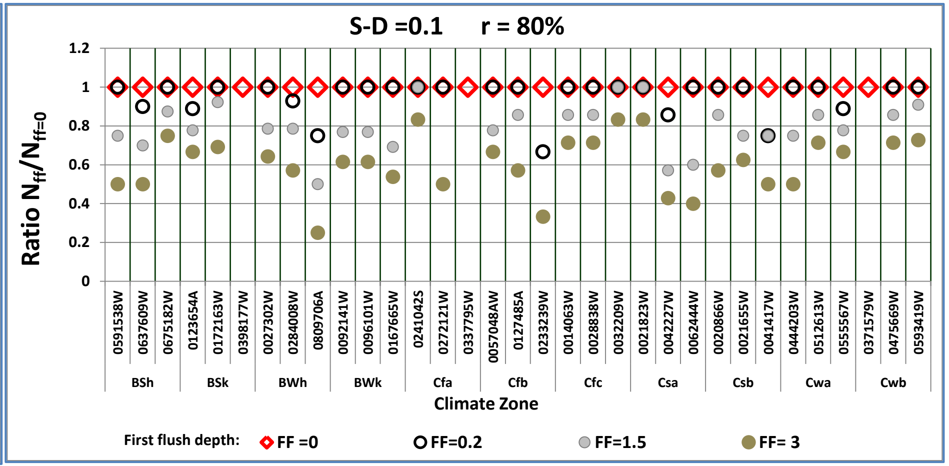


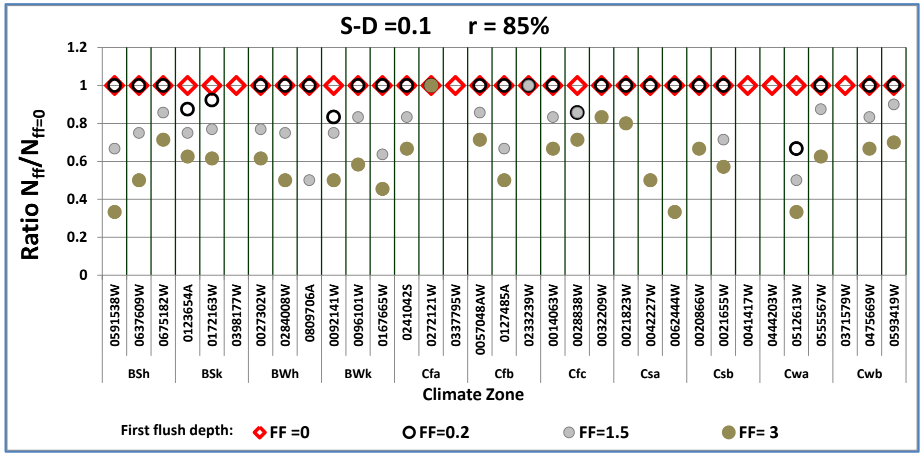
APPENDIX 5 First Flush Additional Data

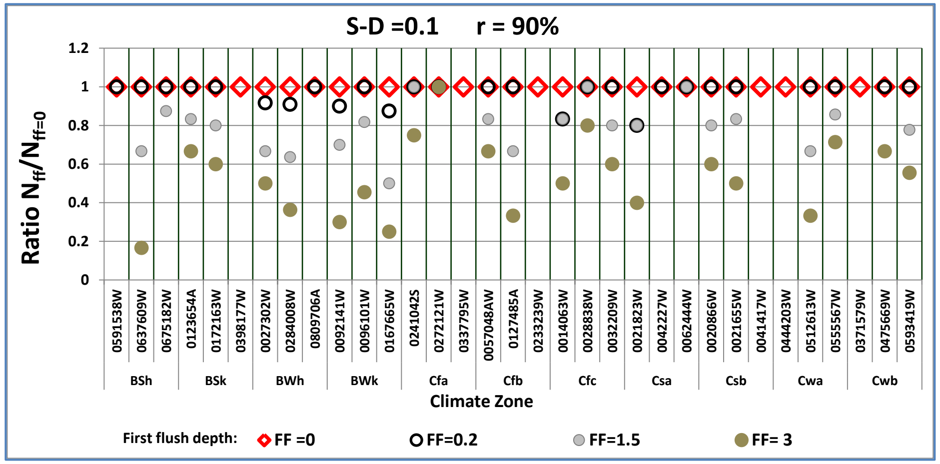
(a) Effect on Yield

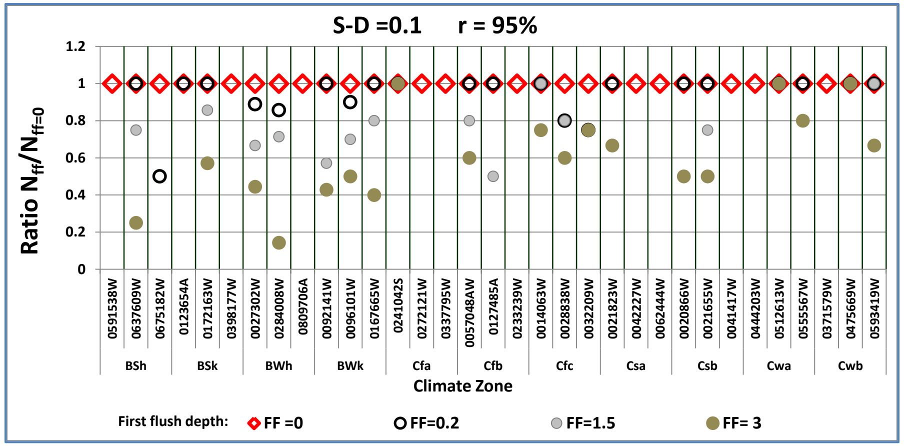
(Variations are read against an axis value 1 representing the constant demand case where there is no change in number of days of supply)

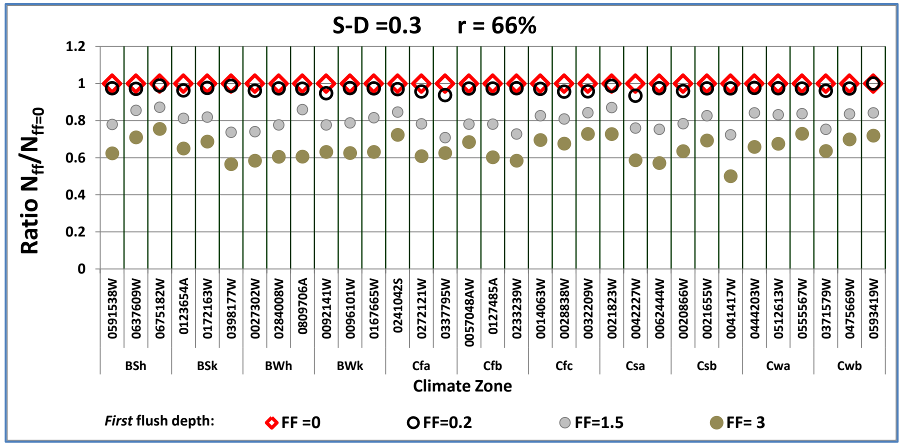


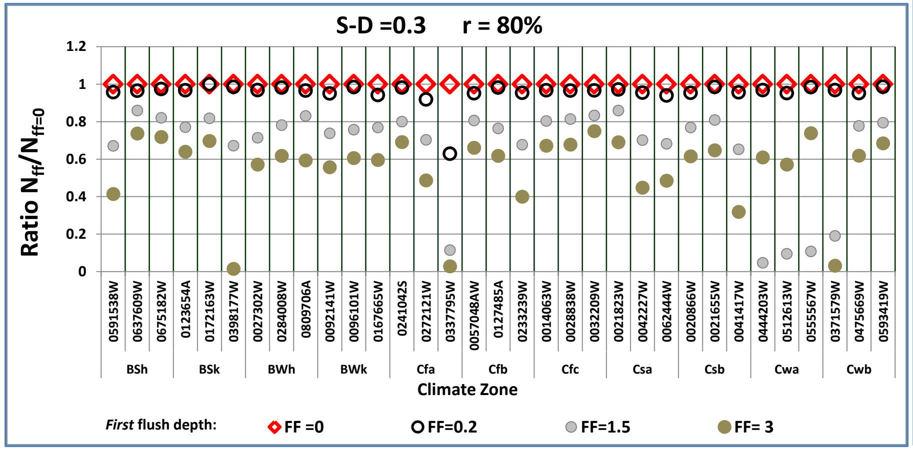


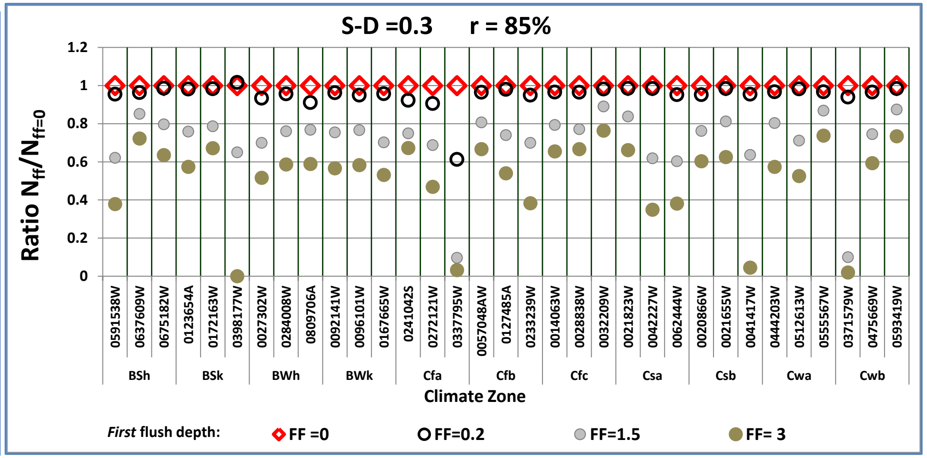


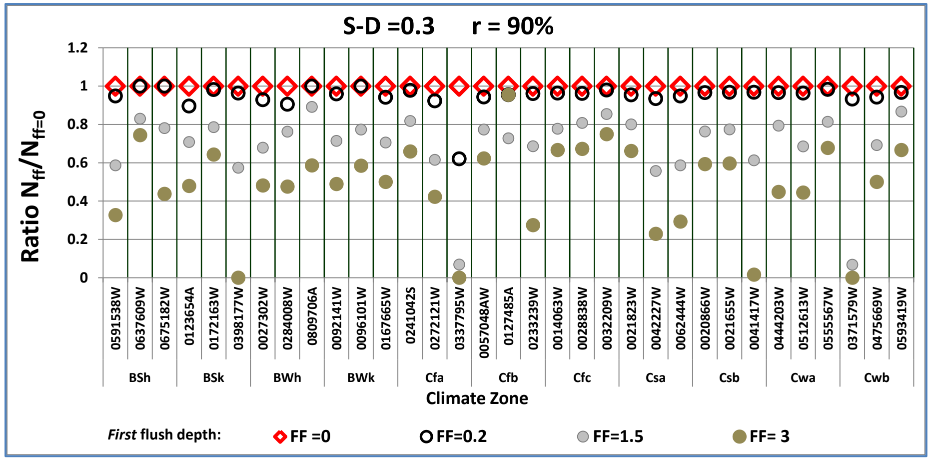



S-D =0.1 r = 95%
Ratio N_ff/N_ff=0
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

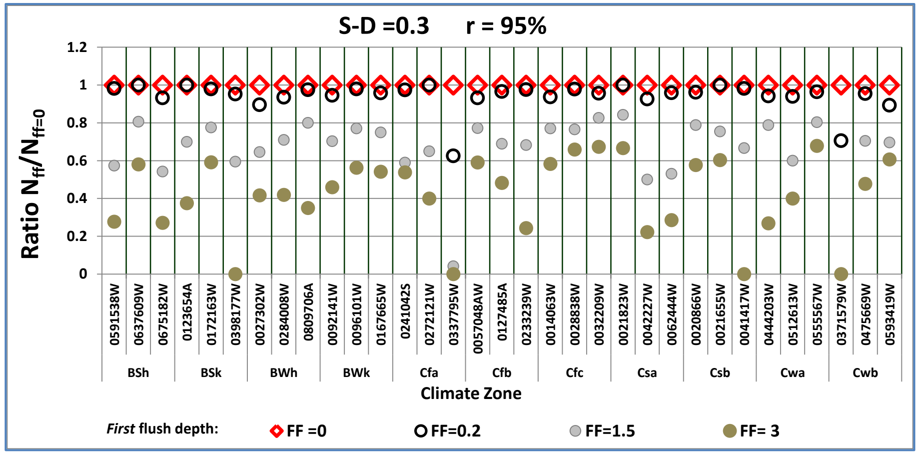

S-D =0.3 r = 66%
Ratio N_ff/N_ff=0
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.3 r = 80%
Ratio N_ff/N_ff=0
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

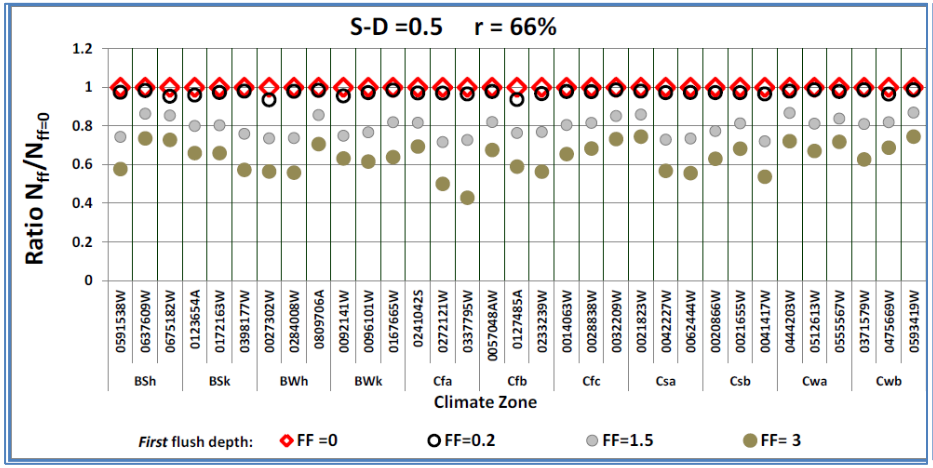

S-D =0.3 r = 85%
Ratio N_ff/N_ff=0
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3



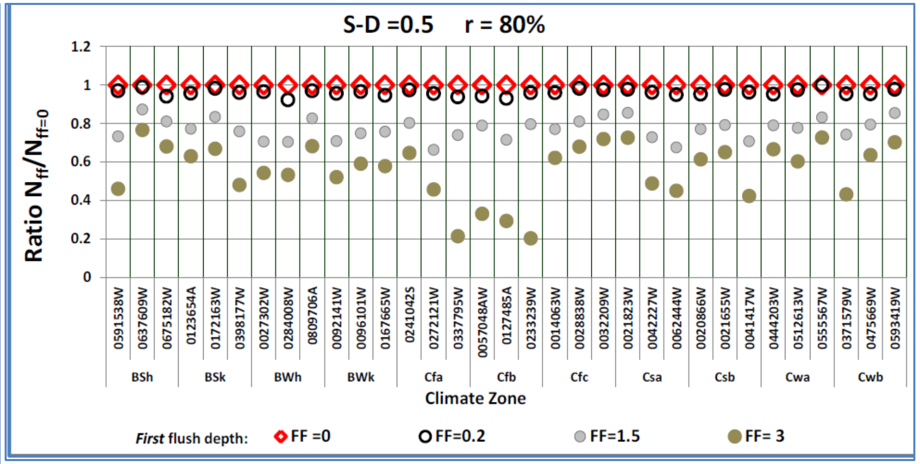
S-D =0.3 r = 90%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3



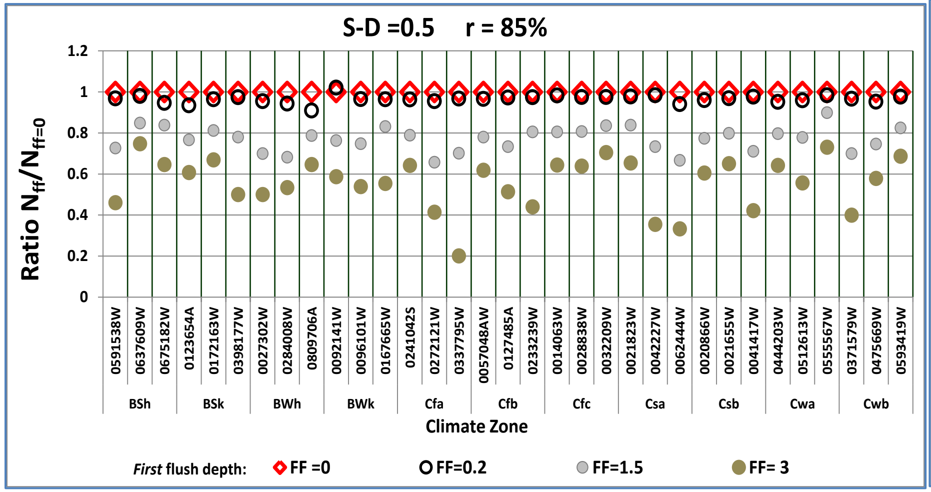
S-D =0.3 r = 95%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

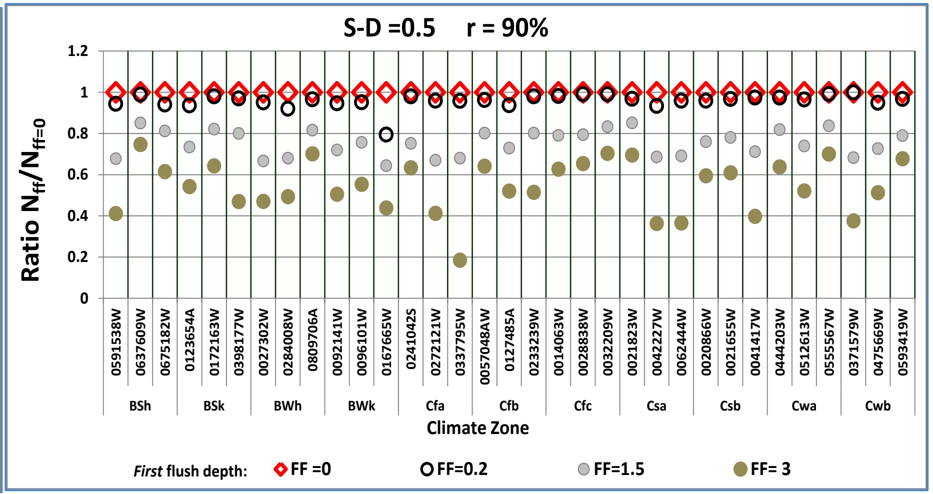


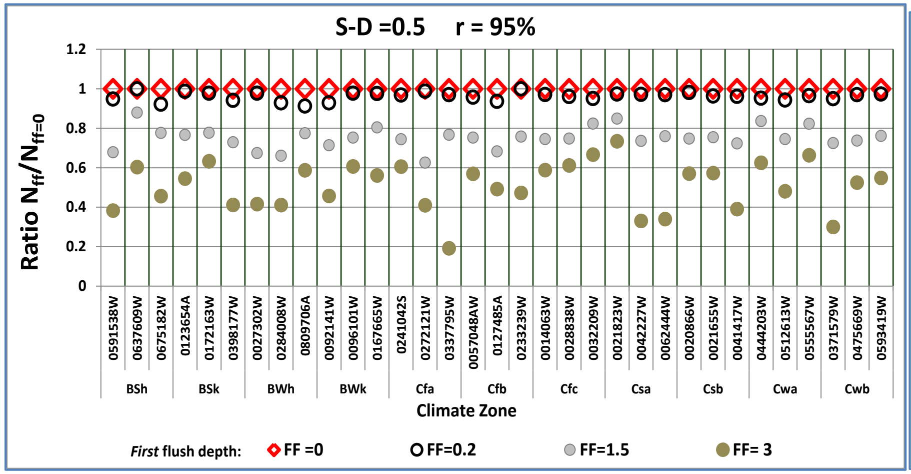
S-D =0.5 r = 66%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

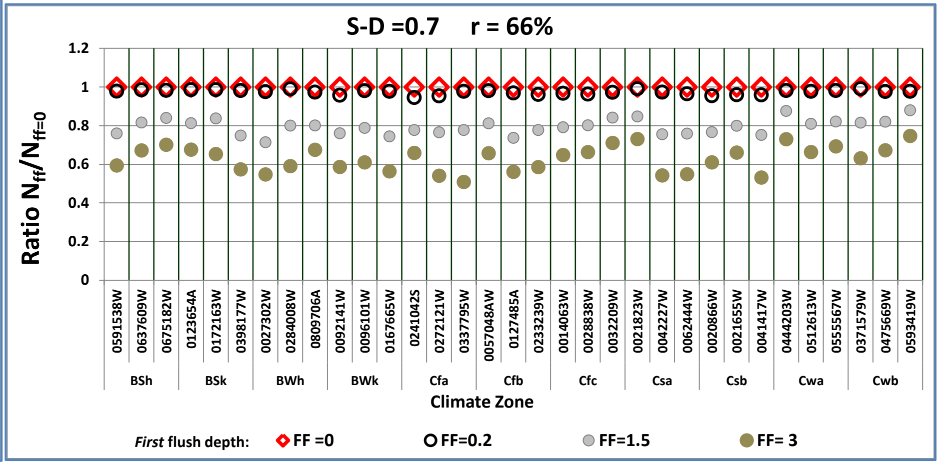


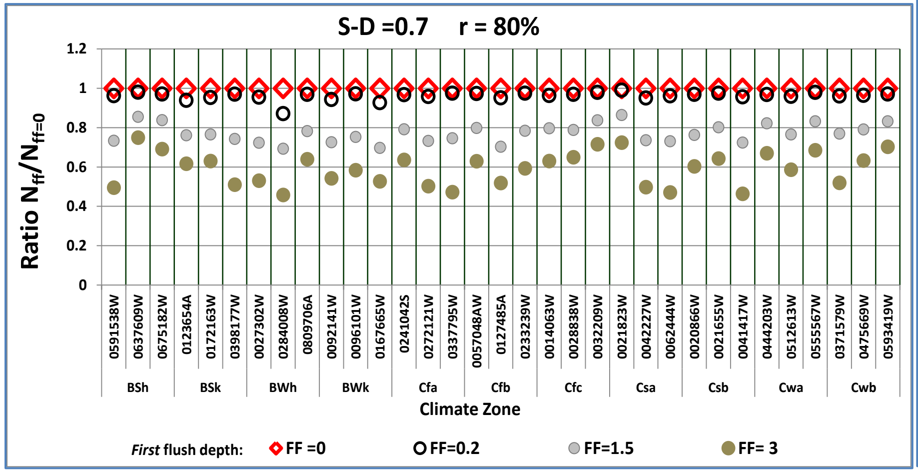
S-D =0.5 r = 80%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

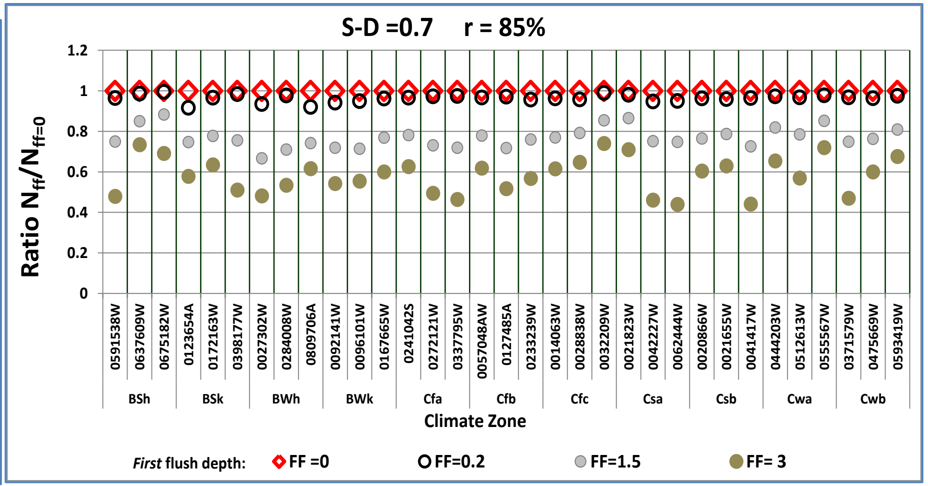

S-D =0.5 r = 85%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

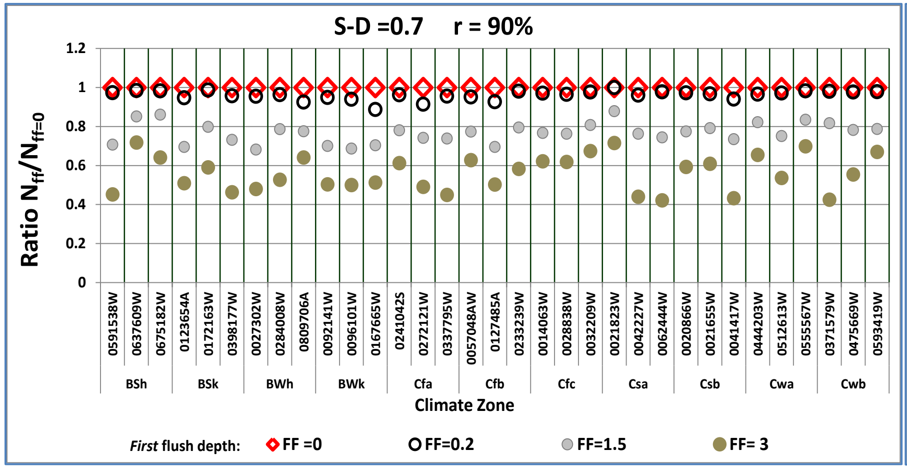

S-D =0.5 r = 90%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

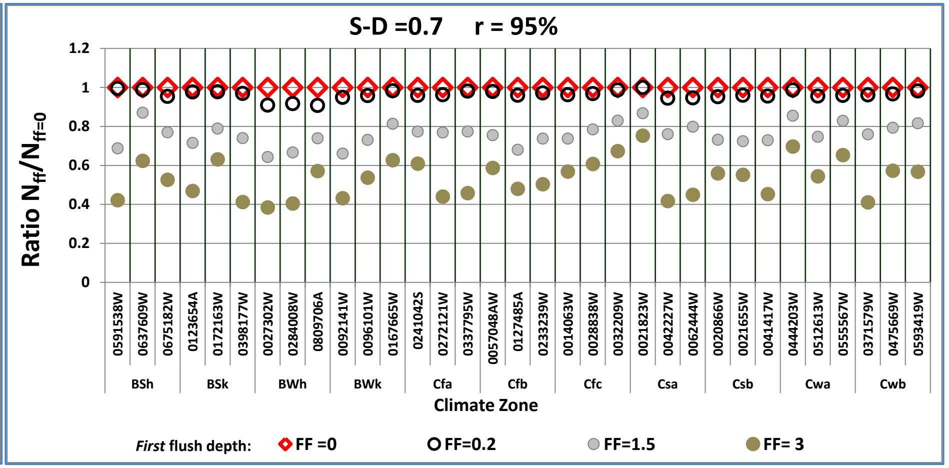

S-D =0.5 r = 95%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

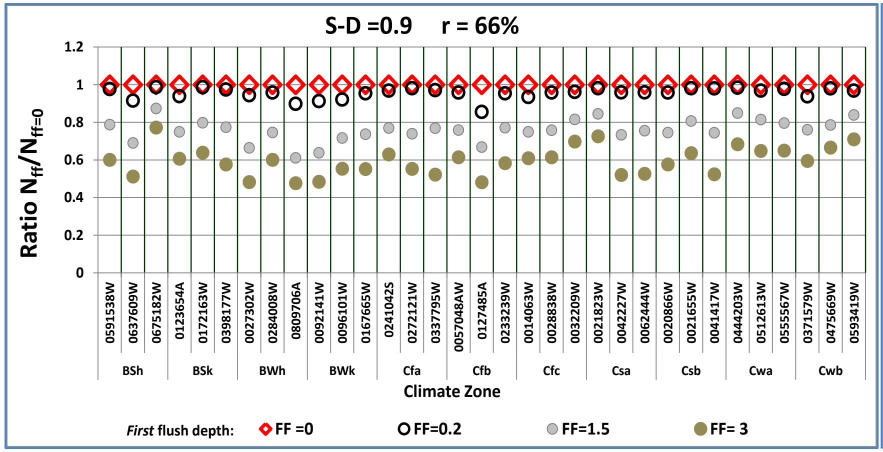

S-D =0.7 r = 66%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

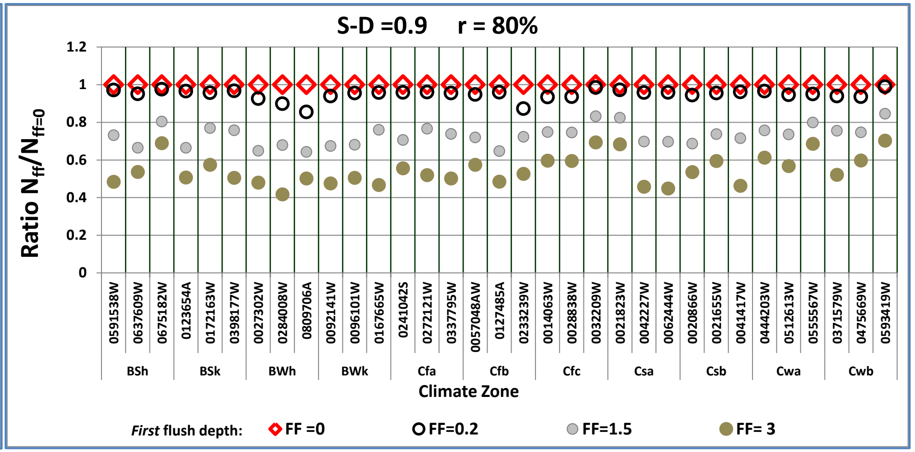

S-D =0.7 r = 80%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

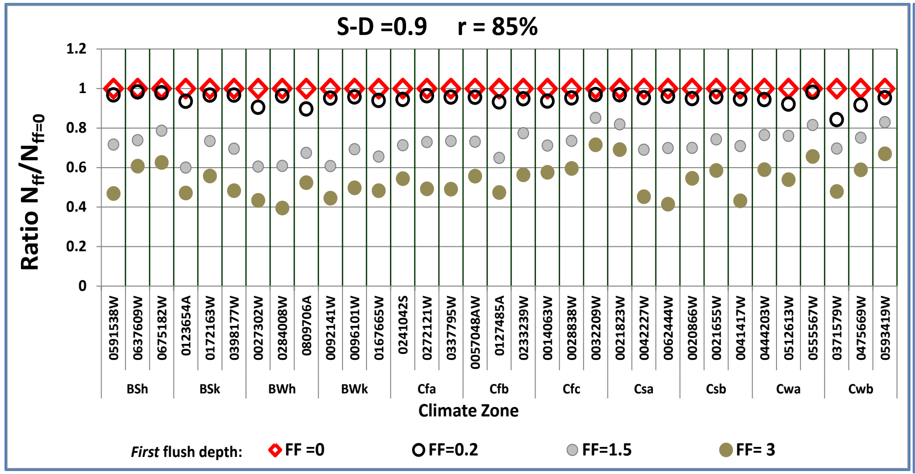

S-D =0.7 r = 85%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

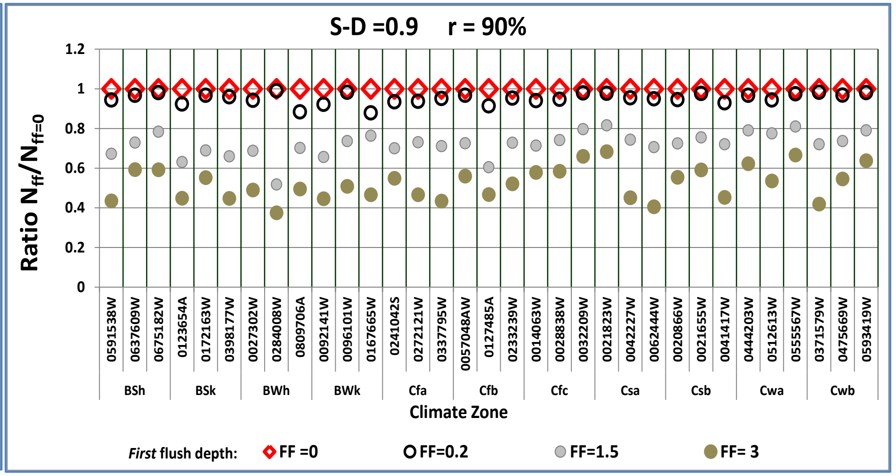

S-D =0.7 r = 90%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

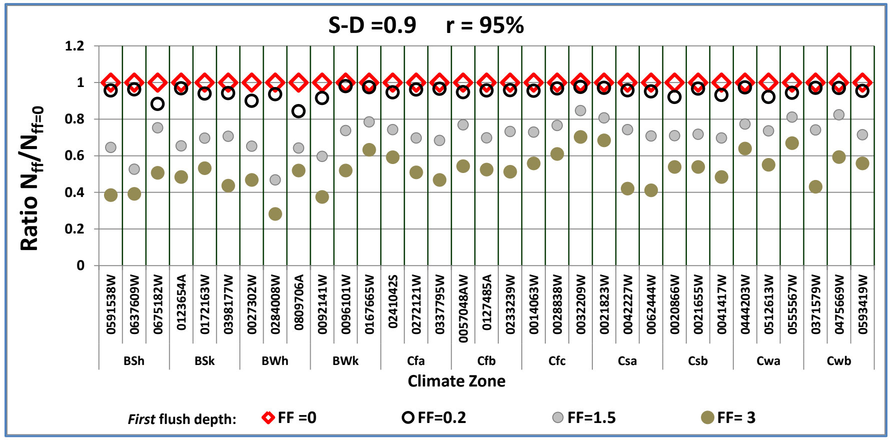

S-D =0.7 r = 95%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.9 r = 66%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.9 r = 80%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

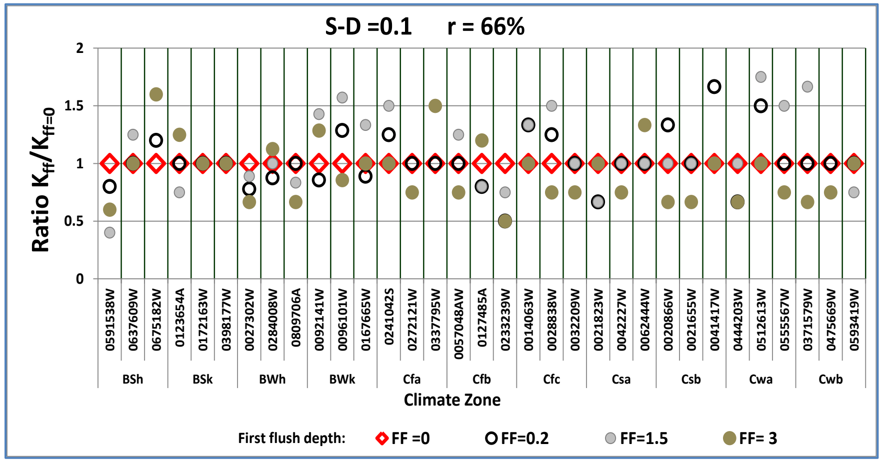

S-D =0.9 r = 85%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

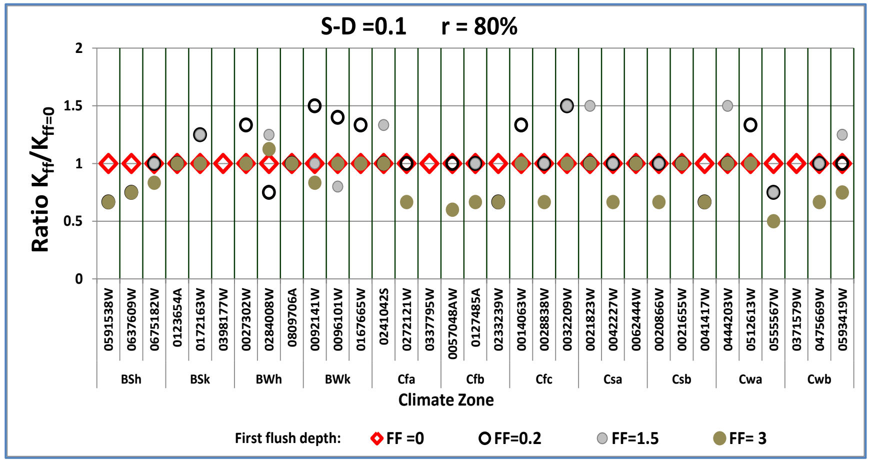

S-D =0.9 r = 90%
Ratio $N_{ff}/N_{ff=0}$
Climate Zone
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

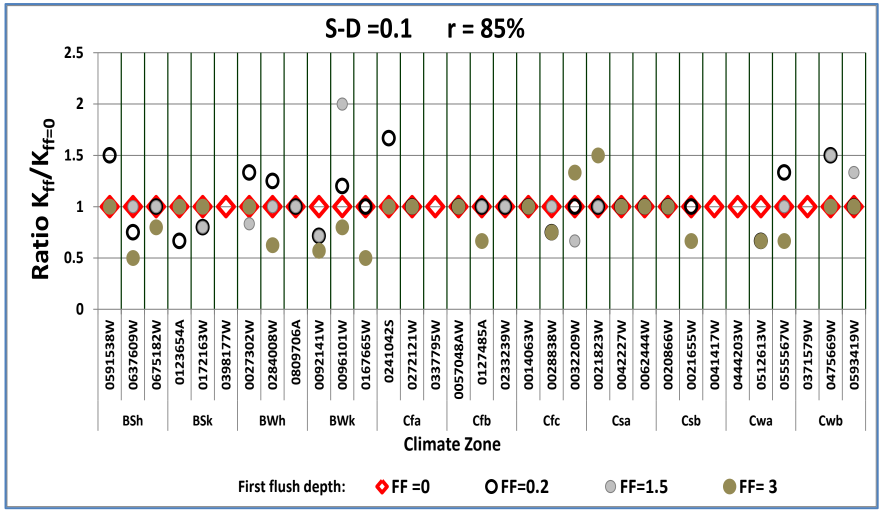


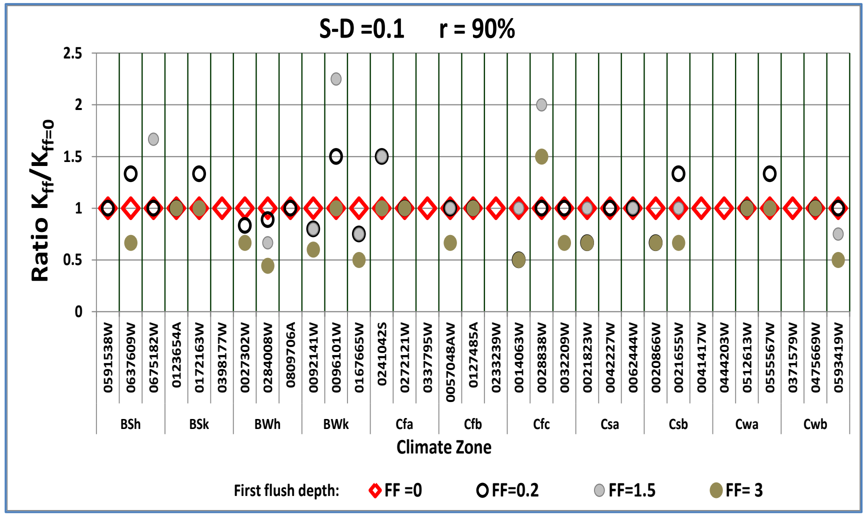
(b)Effect on Storage

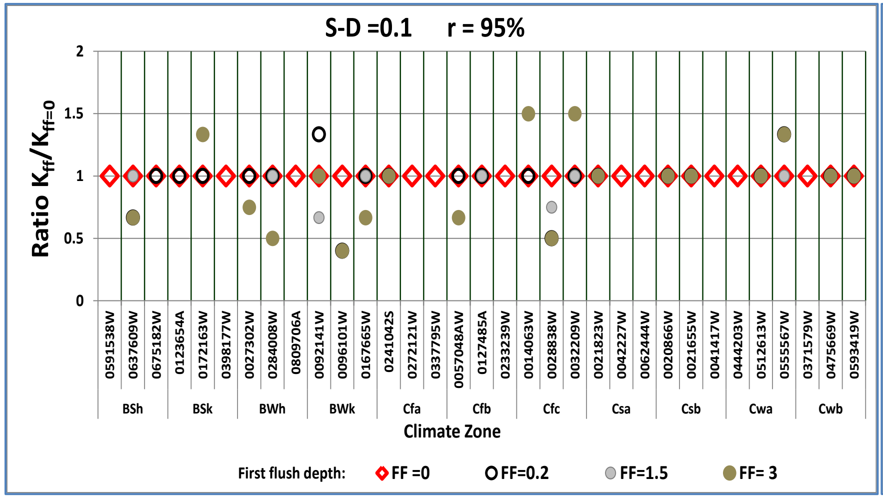
(Variations are read against an axis value 1 representing the constant demand case where there is no change in number of days of supply)

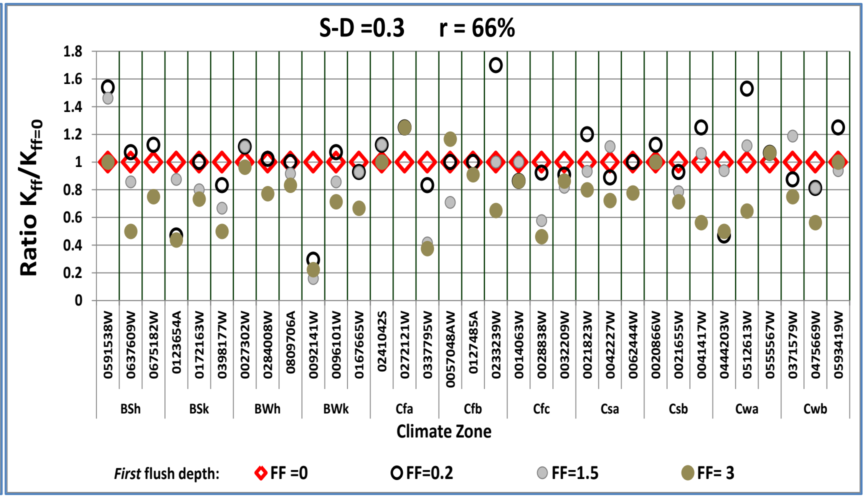


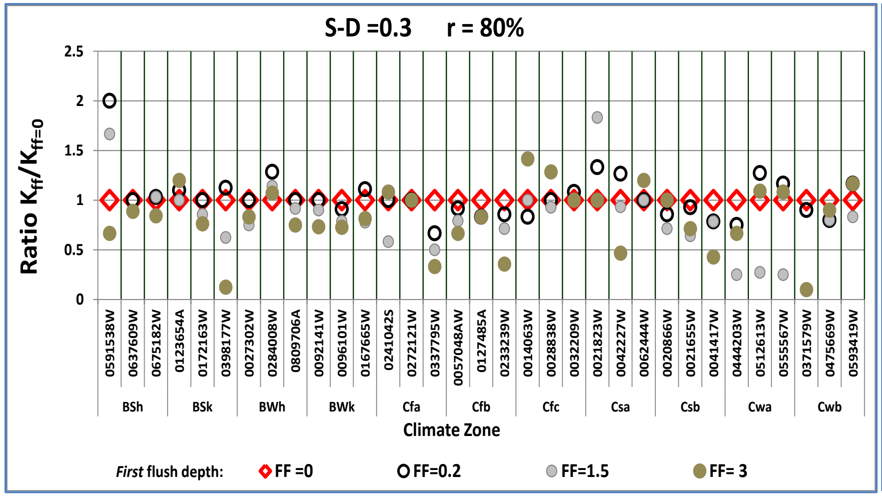



S-D =0.1 r = 85%
Ratio $K_{ff}/K_{ff=0}$
2.5
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0044203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

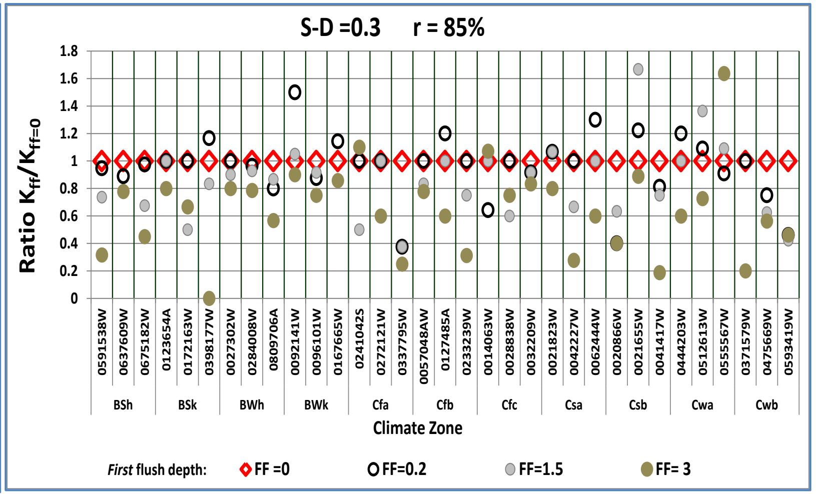

S-D =0.1 r = 90%
Ratio $K_{ff}/K_{ff=0}$
2.5
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0044203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.1 r = 95%
Ratio $K_{ff}/K_{ff=0}$
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0044203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

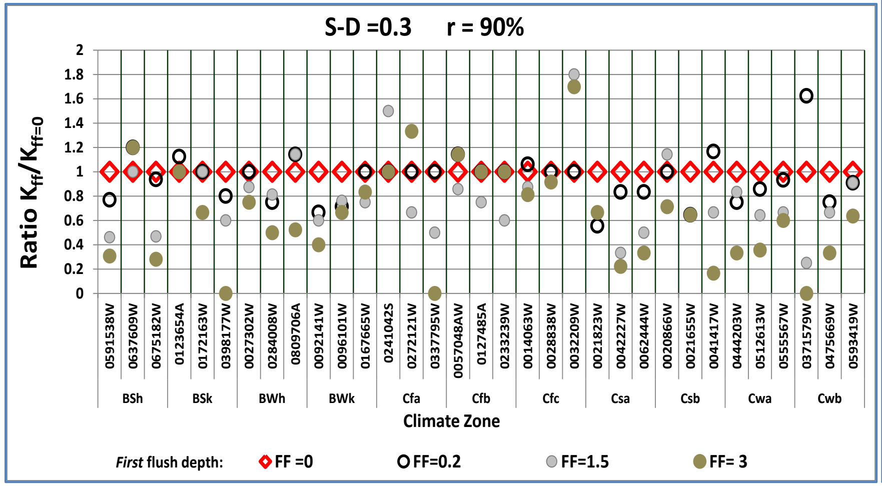

S-D =0.3 r = 66%
Ratio $K_{ff}/K_{ff=0}$
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0044203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3



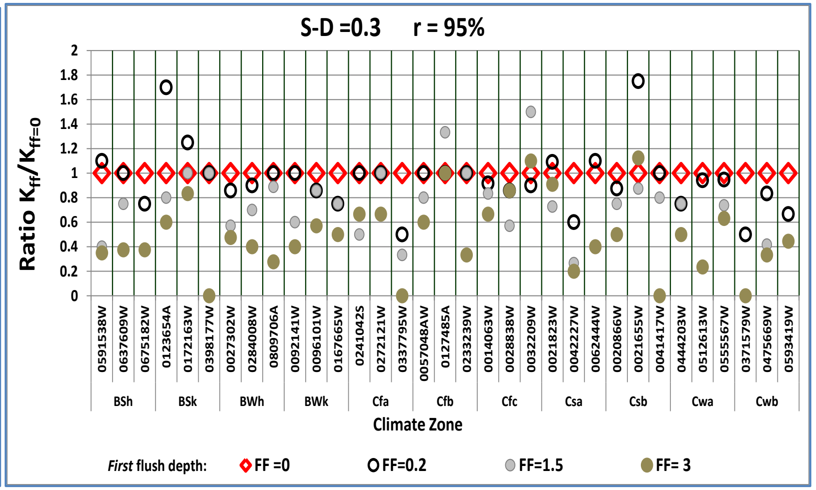
S-D =0.3 r = 80%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3



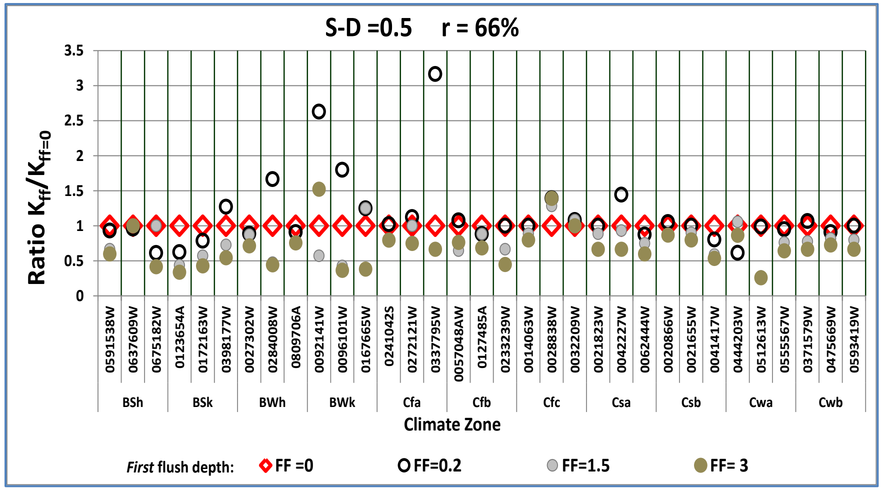
S-D =0.3 r = 85%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3

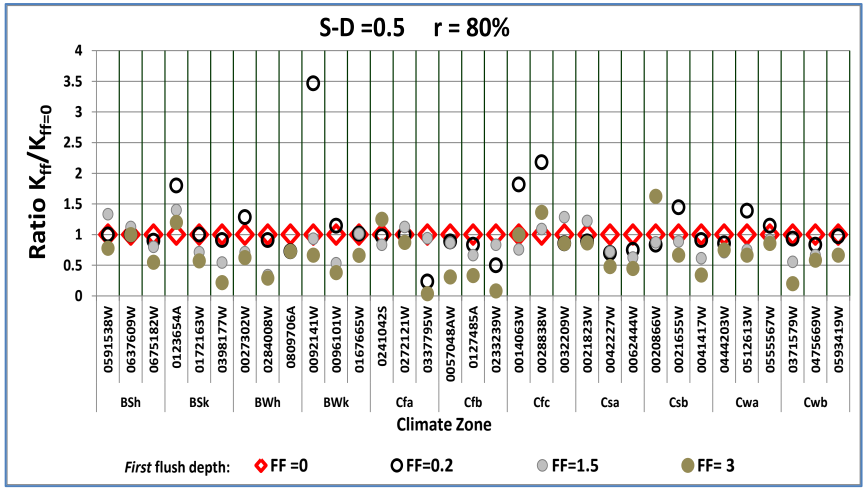


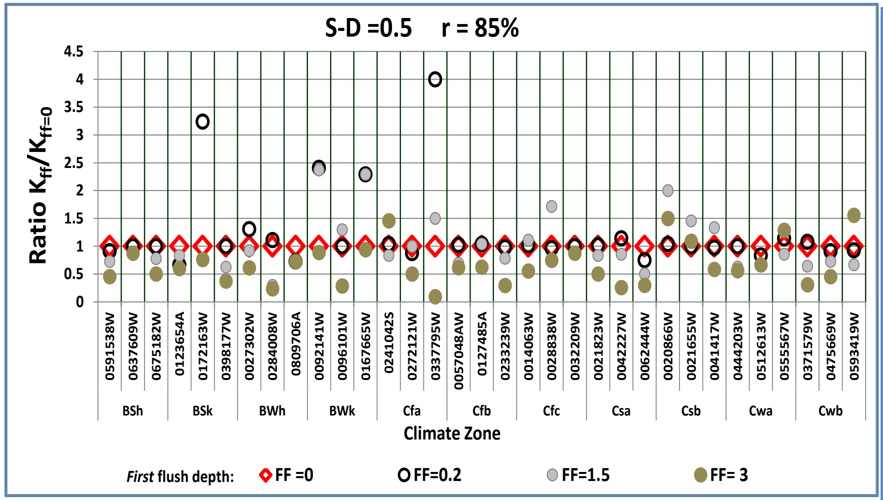
S-D =0.3 r = 90%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3

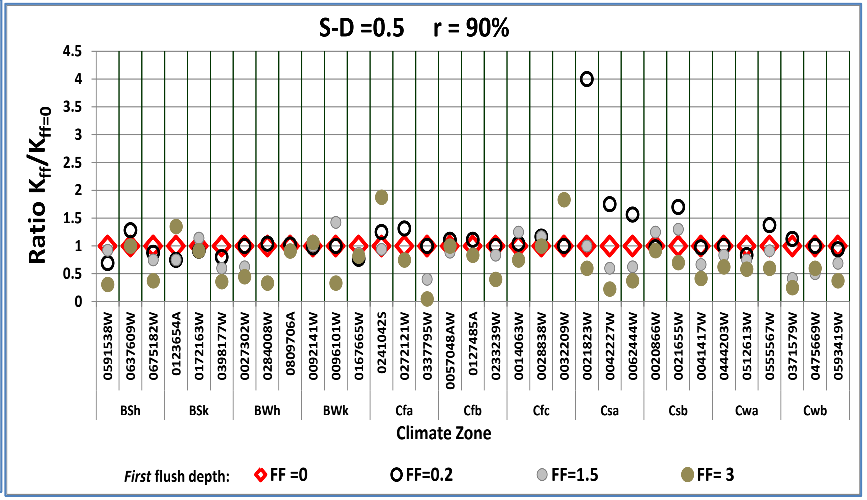


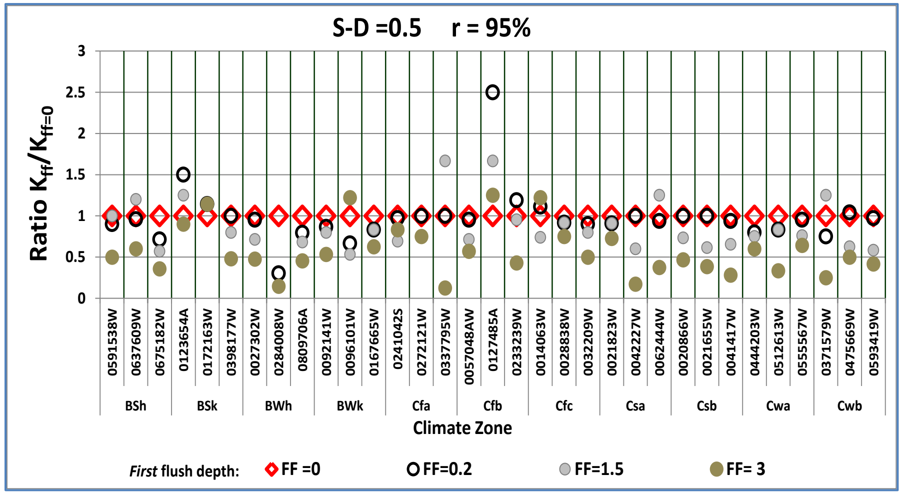
S-D =0.3 r = 95%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3

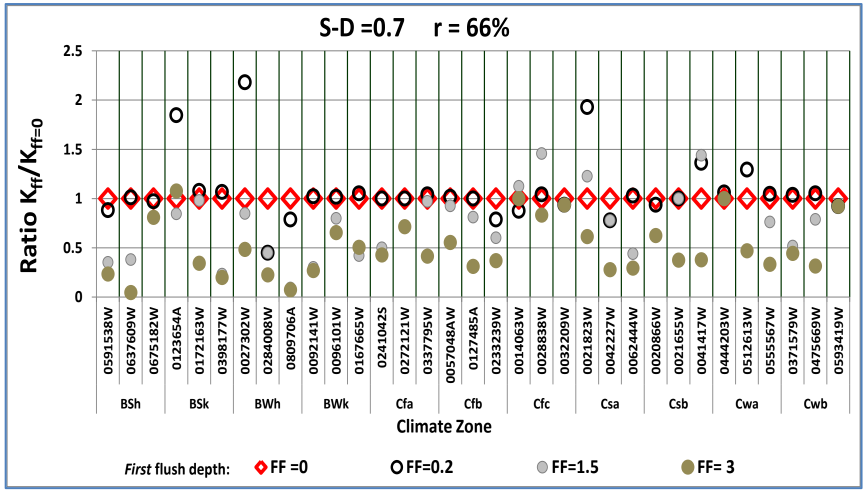

S-D =0.5 r = 66%
Ratio $K_{ff}/K_{ff=0}$
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

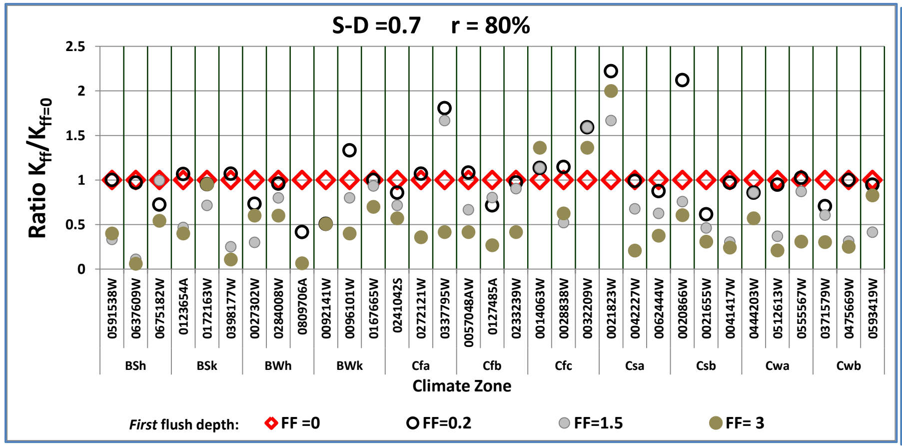

S-D =0.5 r = 80%
Ratio $K_{ff}/K_{ff=0}$
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

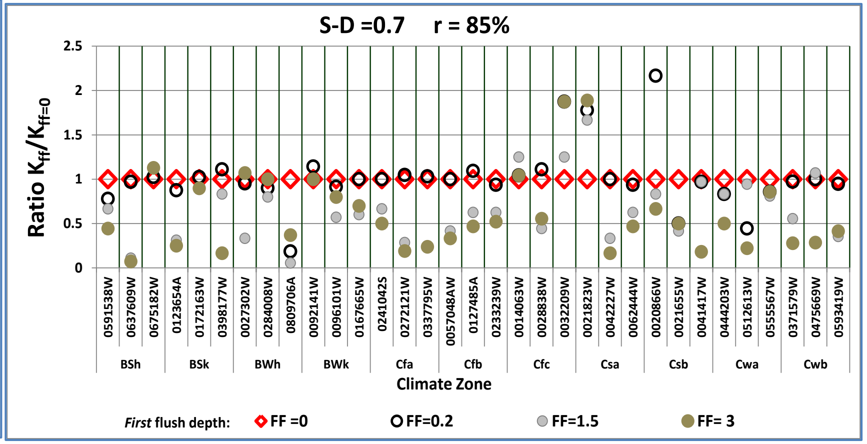

S-D =0.5 r = 85%
Ratio $K_{ff}/K_{ff=0}$
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

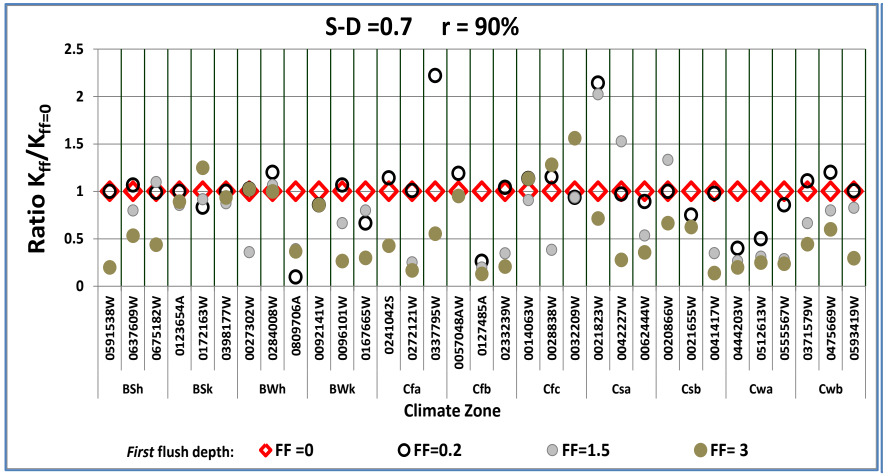

S-D =0.5 r = 90%
Ratio $K_{ff}/K_{ff=0}$
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

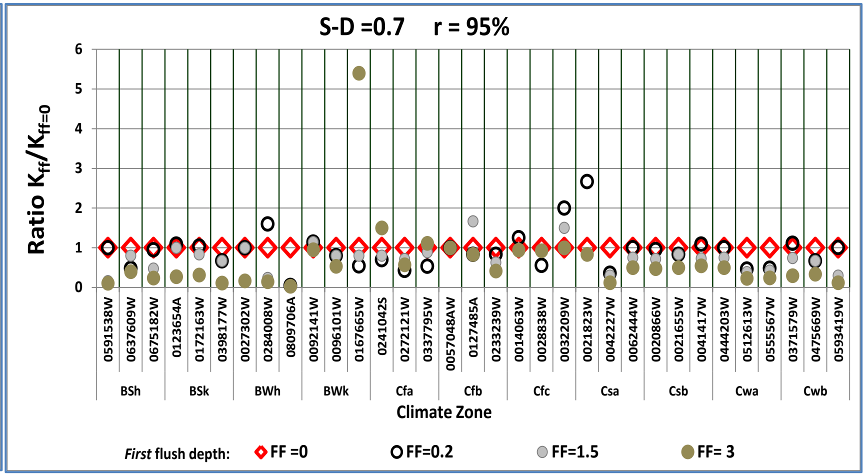

S-D =0.5 r = 95%
Ratio $K_{ff}/K_{ff=0}$
3
2.5
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

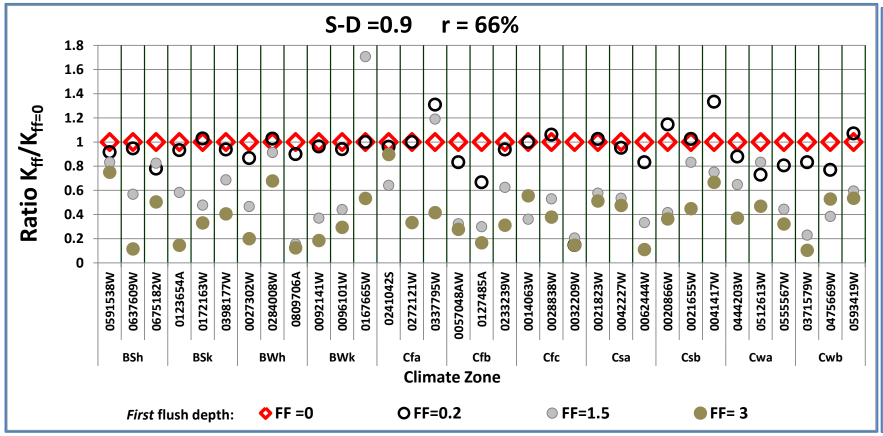

S-D =0.7 r = 66%
Ratio $K_{ff}/K_{ff=0}$
2.5
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

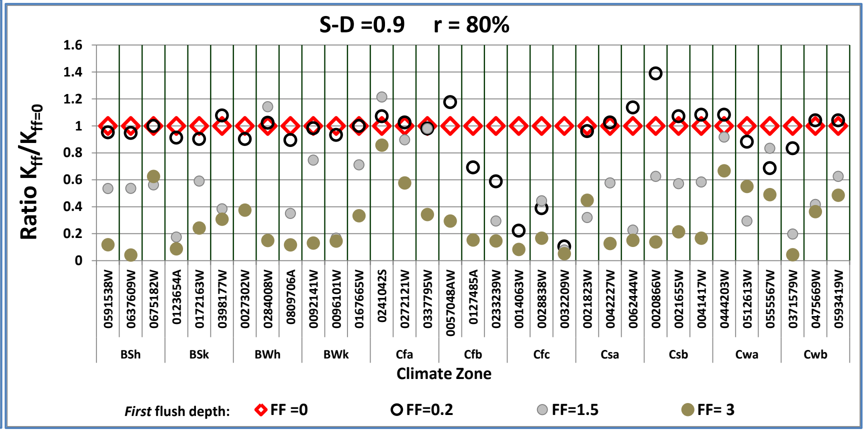

S-D =0.7 r = 80%
Ratio $K_{ff}/K_{ff=0}$
2.5
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

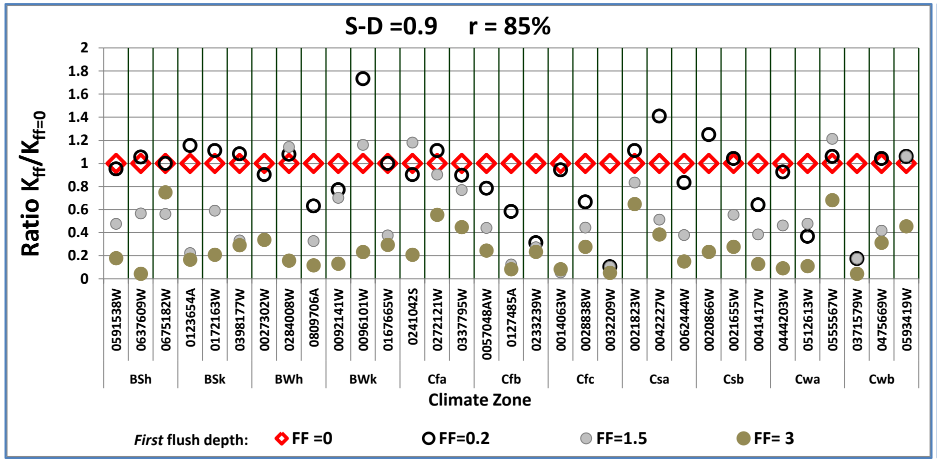

S-D =0.7 r = 85%
Ratio $K_{ff}/K_{ff=0}$
2.5
2
1.5
1
0.5
0
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

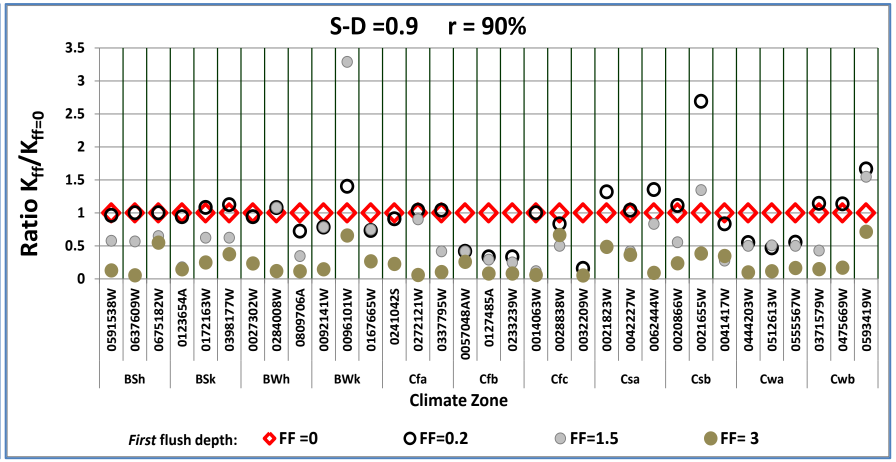

S-D =0.7 r = 90%
Ratio $K_{ff}/K_{ff=0}$
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3

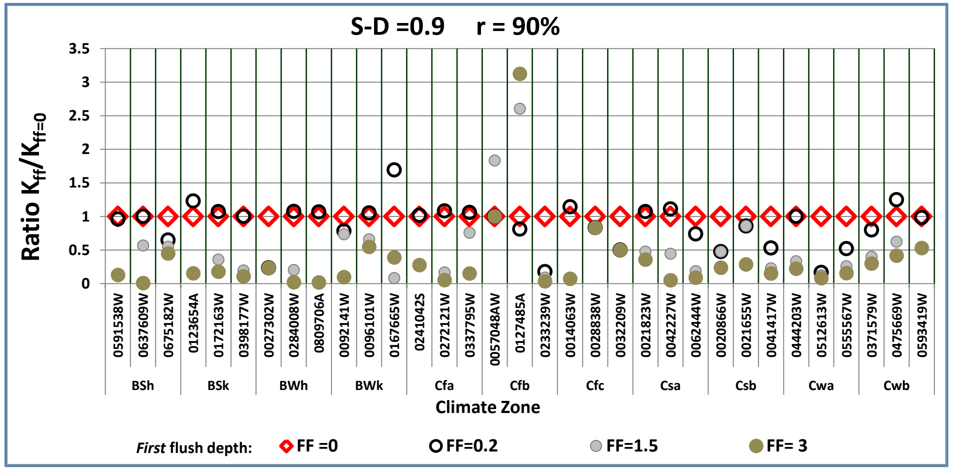

S-D =0.7 r = 95%
Ratio $K_{ff}/K_{ff=0}$
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.9 r = 66%
Ratio $K_{ff}/K_{ff=0}$
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.9 r = 80%
Ratio $K_{ff}/K_{ff=0}$
0591538W 0637609W 0675182W 0123654A 0172163W 0398177W 0027302W 0284008W 0809706A 0092141W 0096101W 0167665W 0241042S 0272121W 0337795W 0057048AW 0127485A 0233239W 0014063W 0028838W 0032209W 0021823W 0042227W 0062444W 0020866W 0021655W 0041417W 0444203W 0512613W 0555567W 0371579W 0475669W 0593419W
BSh BSk BWh BWk Cfa Cfb Cfc Csa Csb Cwa Cwb
Climate Zone
First flush depth: FF =0 FF=0.2 FF=1.5 FF= 3


S-D =0.9 r = 85%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3


S-D =0.9 r = 90%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3


S-D =0.9 r = 90%
Ratio $K_{ff}/K_{ff=0}$
Climate Zone
BSh
BSk
BWh
BWk
Cfa
Cfb
Cfc
Csa
Csb
Cwa
Cwb
First flush depth:
FF =0
FF=0.2
FF=1.5
FF= 3

APPENDIX 6 Sample of Simulation Input and Output Files

(a) Input File

U43

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	124	45351																		
2	1291	0.8	0																	
3	20																			
4	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800	1900	2000
5	1	0.001064	0	550																
6	0049050W-InputData.txt																			
7	0049050W-AppliedContinuousRainfall.txt																			
8	0049050W-Human-Simulation.txt						Do not leave spaces in file names													
9	0049050W-Human-DaysOfSupply.txt																			
10	0049050W-Human-ReliabilityOfSupply.txt																			
11	0049050W-Human-VolumetricReliability.txt																			
12	0049050W-Human-ReliabilityOfVol.Reliability.txt																			
13	JoburgVariationOfHVACDemand.txt																			
14	Variation of human monthly demand																			
15	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec								
16	1	1	1	1	1	1	1	1	1	1	1	1								
17	Variation of human daily demand																			
18	Weekda	Weekend																		
19	1	1																		
20	Monthly irrigation demand (mm/month)																			
21	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total							
22	96	83	66	61	53	44	53	61	66	83	96	110	872							
23	Area of irrigation (m2)																			
24	0																			
25	Frequency of irrigation (1 for once per week or 2 for twice a week - no more options available)																			
26	1																			
27	Number of days to determine antecedent rainfall [30 is suggestec The day of the year with the least antedent rainfall is when simulation starts																			
28	30																			
29	First flush (mm)																			
30	0																			
31																				

	V	W	X	AB	AE
1	Number of years	number of days			
2	Roof Area (m2)	Efficiency of rain collectior	Initial storage state of tank (ratio 0 to 1)		
3	Number of tanks in computation				
4	Size of the tanks (m3)				
5	Number of units (set to 1)		Demand per unit area	HVAC demand per unit area	Area of demand(m2)
6	Full name of text file containing input data				
7	Full name of text file containing the applied data from years with continuous rainfall only				
8	Full name of text file where simulation data will be placed (output)				
9	Full name of text file where days of fsupply each year and their ranking will be placed (output)				
10	Full name of text file where data on supply days for set reliabilities will be placed (output)				

(b) Output files

Ranked Days of supply

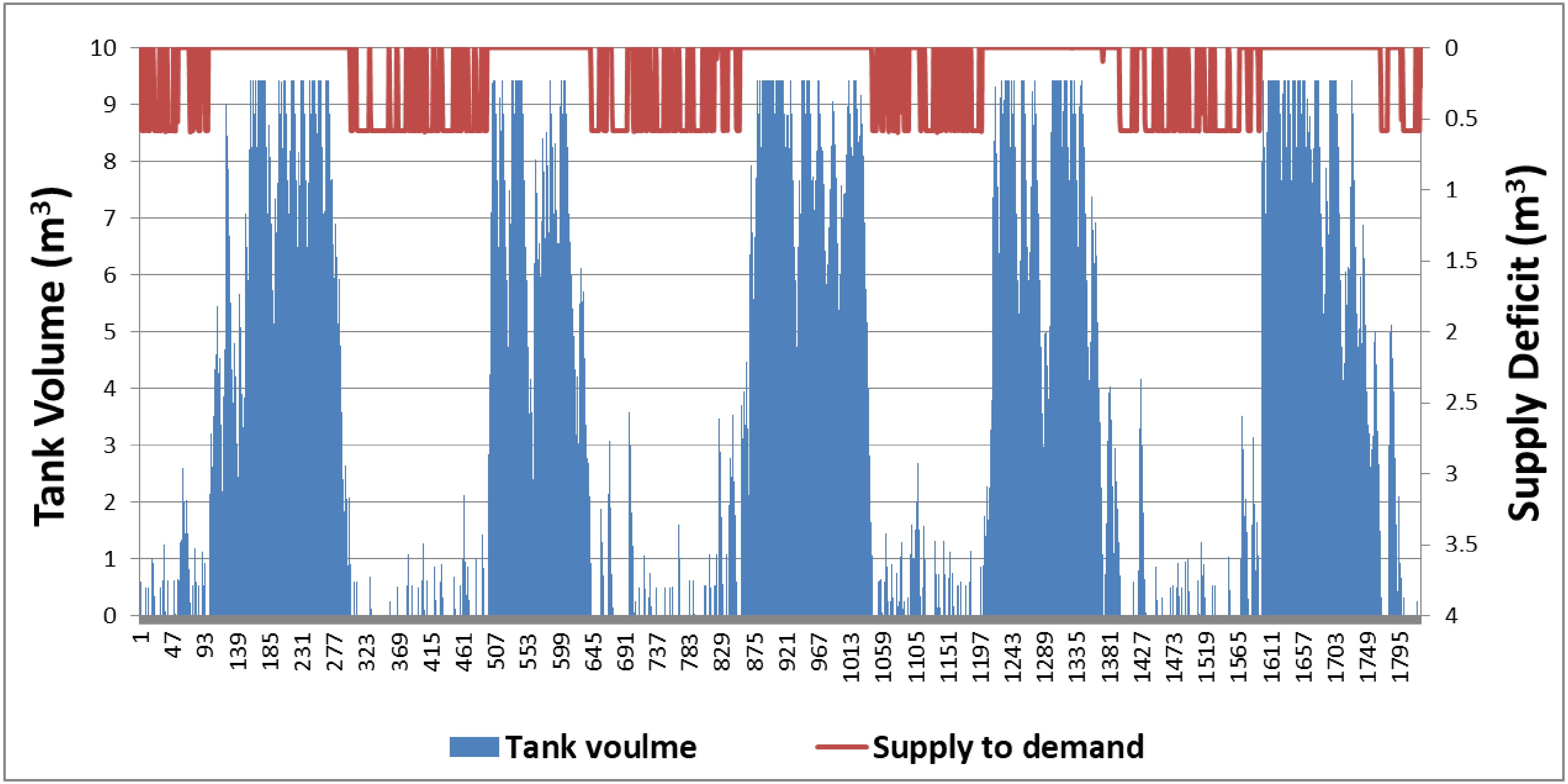
TankVolume(m3)	Rank	DaysOfSupply	RankedDaysOfSupply		TankVolume(m3)	Rank	DaysOfSupply	RankedDaysOfSupply
100	1	228	366		200	1	228	366
100	2	243	366		200	2	243	366
100	3	266	366		200	3	266	366
100	4	192	366		200	4	192	366
100	5	251	366		200	5	251	366
100	6	365	366		200	6	365	366
100	7	366	366		200	7	366	366
100	8	365	366		200	8	365	366
100	9	365	366		200	9	365	366
100	10	365	366		200	10	365	366
100	11	366	366		200	11	366	366
100	12	365	366		200	12	365	366
100	13	365	365		200	13	365	366
100	14	365	365		200	14	365	366
100	15	366	365		200	15	366	365
100	16	365	365		200	16	365	365
100	17	365	365		200	17	365	365
100	18	365	365		200	18	365	365
100	19	366	365		200	19	366	365
100	20	365	365		200	20	365	365
100	21	232	365		200	21	365	365
100	22	234	365		200	22	277	365
100	23	271	365		200	23	271	365
100	24	202	365		200	24	202	365

Storage-yield-reliability

TankVolumes(m3)		100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800	1900	2000
	Reliability(%)	Number of days of supply																			
	0.82	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	1.64	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	2.46	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	3.28	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	4.1	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	4.92	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	5.74	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	6.56	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	7.38	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	8.2	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	9.02	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	9.84	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	10.66	365	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	11.48	365	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	12.3	365	365	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	13.11	365	365	365	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	13.93	365	365	365	365	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366	366
	14.75	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	15.57	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	16.39	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	17.21	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	18.03	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	18.85	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	19.67	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	20.49	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	21.31	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365
	22.13	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365	365

* The red box identifies the optimal storage to achieve the maximum yield at the selected reliability of 13.1%

Simulation output for a 10m[3] tank over 5 years of rainfall data



APPENDIX 7 Conference paper

Conference Name: International Conference on Enhanced Hydrological Understanding for a Better Society

Date: 25-27 October 2018

Location: Harare, Zimbabwe

Generalised Storage-Yield-Reliability Relationships for the Assessment of Rainwater Harvesting Systems in South Africa

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Abstract. In order to develop a set of general hydrologic design and assessment methods for rainwater harvesting systems, the influence of different rainfall regimes needs to be captured in an efficient manner. This study aims at developing relationships that accomplish this by applying multiple daily simulations of potential rainwater harvesting sites across South Africa. Regression analysis is utilised to determine the form of the relationships between three dimensionless parameters; supply-demand, storage-demand and yield ratio. Reliability, defined as the probability of exceedance of yield, is also incorporated into the generalised relationships by regression. In addition, the influence of incorporating intra-annual rainfall variability quantified by the coefficient of variation of daily rainfall and the ratio of dry days to rain days is investigated by use of a multi-variable regression model that relates the dimensionless ratios to the rainfall characteristics. A power model fit between supply-demand and yield ratio gave an average R^2 value of 0.9413 and this improved to 0.9440 by including the ratio of dry days to rain days. An exponential model fitted the relationship between storage-demand and yield ratios best and the R^2 value averaged 0.8554. Incorporating the coefficient of variation of daily rainfall improved the average R^2 value of the exponential models to 0.9113. The simpler model that uses the mean rainfall as the only climatic input is considered to perform well given the high R^2 values. Nevertheless, incorporating rainfall variability using the coefficient of variation and the ratio of dry to rain days improves the modelling and therefore needs to be incorporated into the modelling. However, since it may be easier to obtain average rainfall than the coefficient of variation of daily rainfall and the ratio of dry to rain days, the simpler model plays a valuable complementary role to the more detailed one.

Key words: Rainwater harvesting, Reliability, Storage, Yield, Intra-annual rainfall variability

1 Introduction

In order to develop a set of general hydrologic design and assessment methods for rainwater harvesting systems (RWHS), the influence of different rainfall regimes needs to be captured in an efficient manner. Very limited work has been done in South Africa for the development of such models or general guidelines to assist in the design and assessment of RWHS across any scale. A recent advancement in this regard is presented by Ndiritu et al., (2017) who developed storage-yield-reliability relationships by regression analysis of the simulation data of RWHS for shopping malls in South Africa. A limitation highlighted in this study is that the regression models are based on a limited sample of 14 rainfall stations. The study also did not consider the impact that rainfall variability characteristics could have on the modelling. Researchers from different parts of the world have frequently highlighted the influence of different rainfall regimes in predictive models (Allen & Haarhoff, 2015; Campisano & Modica, 2012; Hanson & Vogel, 2014), thus the aim of the following study is to develop a set of regression relationships that capture the influence of different rainfall regimes on the behaviour of RWHS in South Africa.

2 Materials and Methods

Multiple daily simulations of potential rainwater harvesting sites across the different climate zones found in South Africa was done using the long-term (on average 124 years in length) daily rainfall data from a total of 118 rainfall gauging stations, roughly split into 11 climate zones using the Köppen-Geiger classification system (Kottek et al., 2006) and whose locations are as indicated in Fig. 1. The simulation models the behaviour of a RWHS according to Eq. (1) and (2).

$$S_{t+1} = \min \begin{matrix} S_t + \eta A R_t - R_{et} \\ K - R_{et}, \end{matrix} \quad (1)$$

$$R_{et} = \begin{matrix} D_t & if\ S_t \geq D_t \\ S_t & if\ S_t \leq D_t, \end{matrix} \quad (2)$$

where S_t is the storage in time period *t*, R_{et} is the release to demand in time period *t*, *η* is the water collection efficiency, *A* is the projected roof area, R_t is the rainfall depth in time period *t*, *K* is the capacity of the storage tank and D_t is the demand in time period *t*. The daily water demand was assumed to be constant throughout the simulation period and is based on the mean daily demand data presented in Griffioen and van Zyl (2014). As harvested water is most likely to be used for non-potable water needs, this fraction of water demand was estimated to account for 80% of the total daily demand (O'Brien, 2014). To allow for generalisation of the results to situations of low, moderate and high demand, a wide range of supply-demand ratios was formulated by varying the size of the catchment area relative to the fixed value of demand. A water collection efficiency coefficient of 0.8 was selected based on the findings of various studies (Gould & Nissen-Petersen, 1999; Liaw & Tsai, 2004).

The simulations were run for a range of tank sizes using different supply-demand ratios from which the hydrologically optimum combinations of storage and yield for pre-selected reliabilities of 50%, 66%, 80%, 85%, 90% and 95% were extracted. These reliabilities translate to levels of assurance of 1-in-2 years, 2-in-3 years, 4-in-5 years, 5.7-in-6.7 years, 9-in-10 years and 19-in-20 years respectively and were selected on the basis that it is more likely that a RWHS will be treated as complementary source of water rather than the main supply (Ndiritu et al., 2018). This negates the need to design for higher reliabilities associated with mains water supply systems. The levels of assurance in this study are defined in such a way that each year of the simulation period produces an independent estimate of the yield and using the Weibull's plotting positions formula (Weibull, 1939) each annual value is ranked and assigned a probability of exceedance. To calculate the annual yield the time-based definition of reliability, which only considers the days when the full demand is met, is adopted. This gives a lower estimate of the overall yield that one can expect from a RWHS (Liaw & Tsai, 2004). The hydrological optimum is defined as the minimum tank capacity that maximises the yield and reliability (Ndiritu et al., 2017). It is these 'optimal' data that are used as the basis for the development of the regression relationships between the dimensionless variables supply-demand, yield and storage-demand ratio defined as shown in Eqns. (3), (4) and (5) respectively; these had previously been applied by Ndiritu et al. (2017) and use the average rainfall as the only hydrologic input.

$$R_{SD} = \frac{\eta A \bar{R}}{\overline{D_t}}, \qquad (3)$$

$$S_{P-r} = \frac{N_r}{365.25}, \qquad (4)$$

$$\mathrm{R_{TD-r}} = \frac{\mathrm{K_r}}{\overline{\mathrm{D_t}} \times 365.25}, \qquad (5)$$

where R_{SD} is the ratio of average supply to average demand, η is the rainwater collection efficiency coefficient, A is the vertically projected catchment area, $\bar{R}$ is the average daily rainfall, $\overline{D_t}$ is the average daily demand, S_{P-r} is the proportion of the year supplied at reliability r, N_r is the expected number of days of full supply, R_{TD-r} is the ratio of storage to average annual demand at reliability r and K_r is the storage required to achieve reliability r.

3 Development of Generalised Relationships

3.1 Influence of different rainfall regimes on optimum yield and storage

As a starting point, the influence of the different rainfall regimes, as defined by the different climate zones, on the maximum yield (i.e. maximum number of days of supply) and optimal tank size was assessed. Fig. 2 shows the data obtained with respect to the yield at a reliability of 80% for R_{SD} values of 0.1, 0.3, 0.5, 0.7 and 0.9 utilised in simulation. It is observed that at R_{SD} values above 0.5 there is very little variation in the maximum yield across different rainfall regimes; however this is more pronounced at R_{SD} values of 0.1 and 0.3 with some areas failing to meet the full demand on any day throughout the simulation period. Fig. 3 shows the corresponding optimum storage values and there is a much more appreciable variation across different rainfall regimes and R_{SD} ratios. This suggests that, in addition to the average rainfall (MAP) there may be other rainfall characteristics influencing the behaviour of a RWHS, particularly in determining the optimal storage values.

3.2 Regression relationships between dimensionless variables

Simple linear regression analysis was employed using the three dimensionless parameters in Eqs. (3), (4) and (5), to ascertain if mathematical relationships could be established between the three and reliability. Curve fitting revealed a power model, as described by Eq. (6), to best describe the relationship between S_{P-r} and R_{SD} with the R^2 value averaging 0.9413 across all reliabilities considered.

$$S_{P-r} = \alpha R_{SD}^{\beta}\ , \qquad (6)$$

where α and β represent the coefficients of regression. Fig. 4 presents one of the relationships between S_{P-r} and R_{SD} at a reliability of 80%. Performing the regressions at climate zone level in turn revealed marginally better fits of the same model with the R^2 values ranging from 0.9962 to 0.7980, averaging to 0.9584. Fig. 5 presents one of the relationships between S_{P-r} and R_{TD-r} for a reliability of 80%. Curve fitting between these two variables indicated an exponential model, as described by Eq. (7), to best describe the trend in the data with the R^2 value averaging 0.8544 across all reliabilities.

$$R_{TD-r} = \gamma e^{\varphi S_{P-r}}\ , \qquad (7)$$

where γ and φ are the coefficients of regression. Further to this, regressions done on the data at climate zone level showed an improved fit of the model with R^2 values ranging from 0.9697 to 0.7873 and averaging to 0.8969. The foregoing results would thus suggest that the incorporation of rainfall characteristics unique to each climate zone/rain gauge to be an important consideration especially if a single equation is to be used to model the general behaviour of a RWHS. A comparison between R_{TD-r} and S_{P-r} values predicted by Eqs. (6) and (7) and simulated data showed the regression models to be inclined to over-predict the values especially at high R_{SD} values. A comparison of predictions made by regression curves obtained from the climate zone data to Eqs. (6) and (7) revealed marginal differences in S_{P-r} and R_{TD-r} values, with local data curves having a minor predictive advantage in some of the climate zones when compared to simulated data. Overall, the data from both sets of relationships seem to support the development of models at national scale, as described by Eqs. (6) and (7).

3.2.1 Influence of rainfall characteristics on regression relationships

Given the slight predictive edge of climate zone specific models, the next phase of the analysis sought to investigate the influence of including the common rainfall parameters used to quantify variability of rainfall on predicted optimum storage and yield. Parameters considered included the standard deviation of daily rainfall, the coefficient of variation of daily rainfall, the ratio of dry days to rain days and the seasonality index. Also considered were the coefficient of variation, standard deviation and mean associated with a rainfall series censored for days of no rainfall. Incorporation of these parameters was done using multiple linear regressions (after the analysis presented in Hanson and Vogel (2014)) with the aim of assessing whether a parameter's inclusion could improve the R^2 value of the model. Eqs. (8) and (9) show the general form of the multi-variable models considered.

$$S_{p-r} = dR_{SD}^{e} \cdot x_4^{f}\ , \qquad (8)$$

$$R_{td-r} = ae^{bS_{P-r}} \cdot {x_2}^{c}\ , \qquad (9)$$

where x_2 and x_4 represents the rainfall parameter of interest, and a, b, c, *d*, *e* and *f* represent the coefficients of regression. Of the seven parameters analysed the coefficient of variation of daily rainfall and the ratio of dry days to rainy days resulted in the most improvement of the R^2 values for the S_{P-r} vs. R_{TD-r} and the S_{P-r} vs. R_{SD} relationships respectively. The average of the R^2 values of the relationship between S_{P-r} , $R_{TD-r}$and the coefficient of variation across all reliabilities came to 0.9113 and came to 0.9440 for the relationship between, the ratio of dry days to rainy days, S_{P-r} and R_{SD}. Comparison to the curves of the uni-variate models would suggest that rainfall variability has a minor role to play and is thus a parameter not required in the generalised model. However it was observed that the multi-variable model is better able to capture some of the scatter observed in the simulated data. For example, when considering that Eq. (6) uses an R_{SD}which can be described anywhere in the country, it is observed from the simulation data, especially at low R_{SD}(see Fig. 2), that the same R_{SD} applied to different rainfall areas does not necessarily result in identical S_{P-r} or R_{TD-r} as would be predicted by Eqs. (6) and (7); incorporating rainfall variability as done in Eqs. (8) and (9) thus becomes a valuable way in which to account for this.

3.2.2 Relationships between coefficients of regression and reliability

Ndiritu et al., (2017) established relationships between the regression coefficients of the S_{P-r} vs. R_{TD-r} curves and the S_{P-r} vs. R_{SD} curves and reliability. As such a similar analysis was pursued in this study and it was found that very strong regression relationships could be described. The exponential model was found to best fit the data of the regression coefficients γ and φ, giving R^2 values of 0.9912 and 0.9956 respectively. For regression coefficients α and β, the power-model best described the data, giving R^2 values of 0.9994 and 0.9161 respectively.

Relationships between the regression coefficients of the multi-variable models and reliability were also investigated and with respect to$a$,b and$c$, R^2 values of 0.9837, 0.9887 and 0.9950 were obtained when using an exponential model. For regression coefficients *d*, *e* and *f*, R^2 values of 0.9124, 0.9602 and 0.8727 were obtained for the best-fit power model. However, the data for a reliability of 95% were excluded as they appeared to present as possible outlier data with respect to coefficient *f*.

3.3. Proposed storage-yield-reliability relationships for RWHS in South Africa

The following uni-variate models are thus proposed for use in the assessment of RWHS in South Africa:

$$\begin{aligned} S_{P-r} &= \alpha R_{SD}{}^{\beta} \\ \alpha &= 1.362(1-r)^{0.207} \qquad 0.5 \le r \le 0.95, \\ \beta &= 1.377(1-r)^{-0.086} \end{aligned}$$

(10)

$$\begin{aligned} R_{TD-r} &= \gamma e^{\varphi S_{p-r}} \\ \gamma &= 0.009 e^{1.005(1-r)} \qquad 0.5 \le r \le 0.95, \\ \varphi &= 8.207 e^{-0.996(1-r)} \end{aligned}$$

(11)

In addition to the uni-variate models, multi-variable relationships as described by Eq. (12) and (13) are proposed as an alternative for use in the assessment of RWHS in South Africa:

$$\begin{aligned} R_{TD-r} &= a e^{b S_{p-r}} \cdot CV^{c} \\ a &= 0.0004 e^{4.361(1-r)} \qquad 0.5 \le r \le 0.95, \text{ (12)} \\ b &= 8.624 e^{-1.13(1-r)} \\ c &= 2.339 e^{-1.327(1-r)} \end{aligned}$$

$$S_{P-r} = dR_{SD}{}^{e} \cdot \left(\frac{n_d}{n_r}\right)^{f}$$
$$d = 0.966(1-r)^{0.121} \qquad 0.5 \le r \le 0.9, \quad (13)$$
$$e = 1.336(1-r)^{-0.110}$$
$$f = 0.222(1-r)^{0.377}$$

Where CV is the coefficient of variation and n_d is the number of dry days in a year and n_r is the number of rain days in a year.

As an example of how Eq. (10 - 13) could be used in the assessment of a RWHS, a user may wish to ascertain the yield and size of catchment for a RWHS if they were to install a 5m^3 tank subject to a constant average annual daily demand of 0.5m^3/day. The RWHS is required to operate at a reliability of 85% and is located in a place whose MAP and CV are 550mm and 3.9 respectively and which on average experiences 50 rainy days per year - By re-arranging Eq. (12) the level of supply comes to 48 days per year. This yield is then used as input to Eq. (13) which is re-arranged to give an estimate of the required R_{SD} from which a suitable size catchment of 138m^2 is obtained. Applying the uni-variable models to the same example gives an expected level of supply of 50 days per year and corresponding catchment size of 128m^2. If the same system were to be implemented in area with the same MAP but a CV of 4.8 the univariate model predicts the same yield and catchment area whereas the multi-variable model now predicts a tank size of 7.6m^3 to achieve the same 50 day yield using a128m^2 catchment. Comparison of the solutions highlights that if only average rainfall data is available, the uni-variate model, whose only climatic input is the MAP could be used to estimate storages and yields for RWHS; however, the multi-variable model offers the advantage of being able to distinguish the effects of two different rainfall regimes which describe similar MAP.

4 Conclusions and Recommendations

This study has considered the impact that different rainfall regimes may have on the observed behaviour of a RWHS; from the results of analysis, it appears that the explicit inclusion of the intra-annual variability characteristics of rainfall to the generalised model has a minor role to play in improving its predictive ability. However, the incorporation of rainfall characteristics as shown by the example could go some way in allowing the model to distinguish between rainfall regimes that share the same MAP. The models tend over-predict S_{P-r} and R_{TD-r} , but the integration of statistical reliability into the generalised models (Eqs. 10-13) offers flexibility for both multi-variable and uni-variable models. The two models are considered applicable for preliminary design and assessment of RWHS in South Africa.

References

Allen, J. and Haarhoff, J.: A Proposal for the Probabilistic Sizing of Rainwater Tanks for Constant Demand, J. South Afr. Inst. Civ. Eng., 57(2), 22–27, doi:10.17159/2309-8775/2015/v57n2a3, 2015.

Campisano, A. and Modica, C.: Optimal Sizing of Storage Tanks for Domestic Rainwater Harvesting in Sicily, Resour. Conserv. Recycl., 63, 9–16, doi:10.1016/j.resconrec.2012.03.007, 2012.

Gould, J. and Nissen-Petersen, E.: Rainwater Catchment Systems for Domestic Supply: Design, Construction and Implementation, Intermediate Technology Publications Ltd, Warwickshire, UK., 1999.

Griffioen, M. L. and vanZyl, J. E.: Proposed Guideline for Modelling Water Demand by Suburb, J. South Afr. Inst. Civ. Eng., 56(1), 63–68, 2014.

Hanson, L. . and Vogel, R. M.: Generalized Storage-Reliability-Yield Relationships for Rainwater Harvesting Systems, Environ. Res. Lett., 9, doi:10.1088/1748-9326/9/7/075007, 2014.

Kottek, M., Grieser, J., Beck, C., Rudolf, B. and Rubel, F.: World Map of the Koppen-Geiger Climate Classification Updated, Meteorol. Z., 15(3), 259–263, doi:10.1127/0941-2948/2006/0130, 2006.

Liaw, C. and Tsai, Y.: Optimum Storage Volume of Rooftop Rainwater Harvesting Systems for Domestic Use, J. Am. Water Resour. Assoc., 40(4), 901–912, 2004.

Ndiritu, J. ., Moodley, Y. and Guliwe, M.: Generalized Storage-Yield-Reliability Relationships for Analyzing Shopping centre Rainwater Harvesting Systems, Water, 9, 771, doi:10.3390/w9100771, 2017.

Ndiritu, J. ., Ilemobade, A. A. and Kagoda, P.: Guidelines for Rainwater Harvesting System Design and Assessment for the City of Johannesburg, South Africa, Proc IAHS, 95, 1–6, doi:10.5194/piahs-379-409-2018, 2018.

O'Brien, O.: Domestic Water Demand for Consumers with Rainwater Harvesting Systems, Master of Science, Stellenbosch University, Stellenbosch, South Africa. [online] Available from: http://scholar.sun.ac.za/handle/10019.1/86514 (Accessed 5 February 2018), 2014.

Weibull, W.: A statistical theory of strength of materials, Generalstabens litografiska anstalts förlag, Stockholm., 1939.

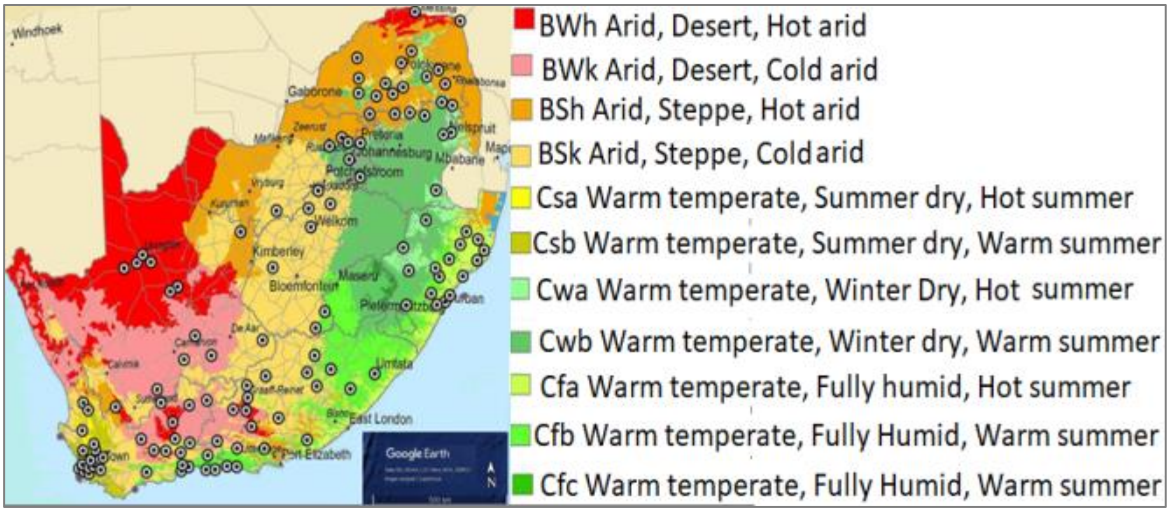

Figure 1: Location of rainfall gauging stations used in analysis

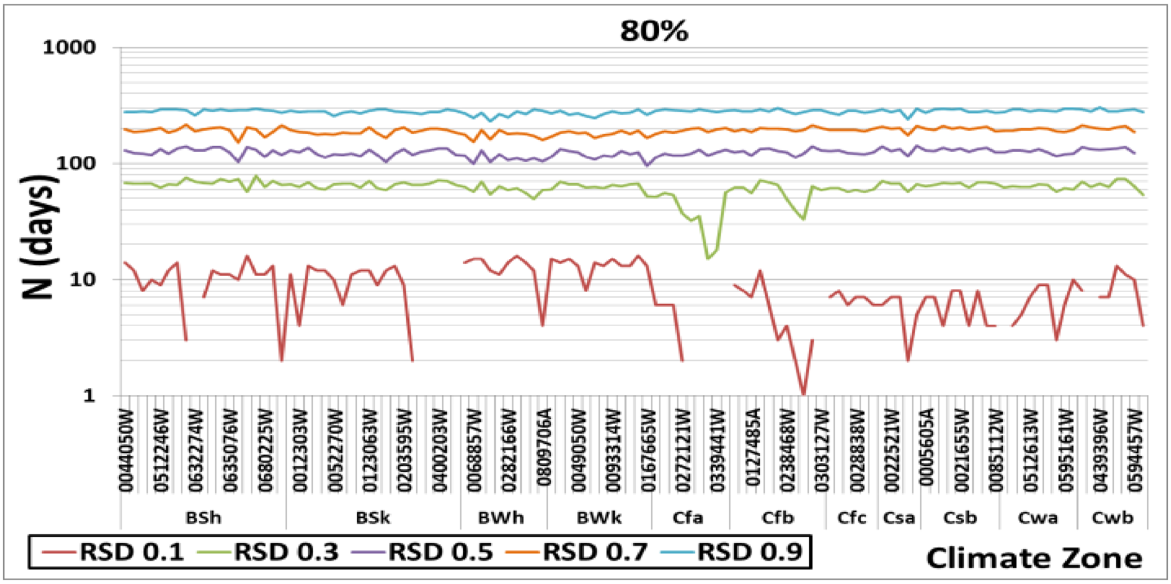

Figure 2: Variation of maximum number of days supplied with S-D ratio and climate zone

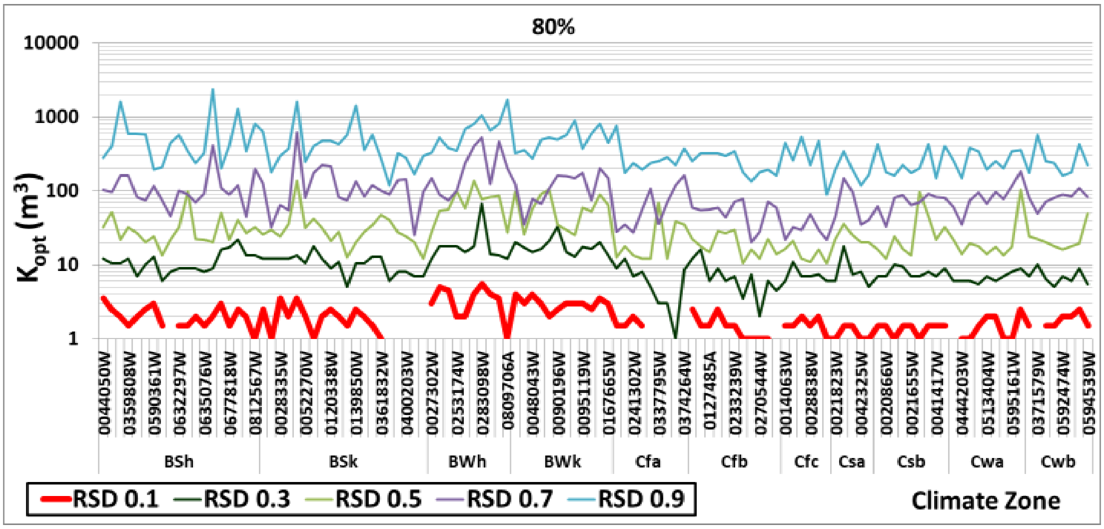

Figure 3: Variation of optimal storage with S-D ratio and climate zone

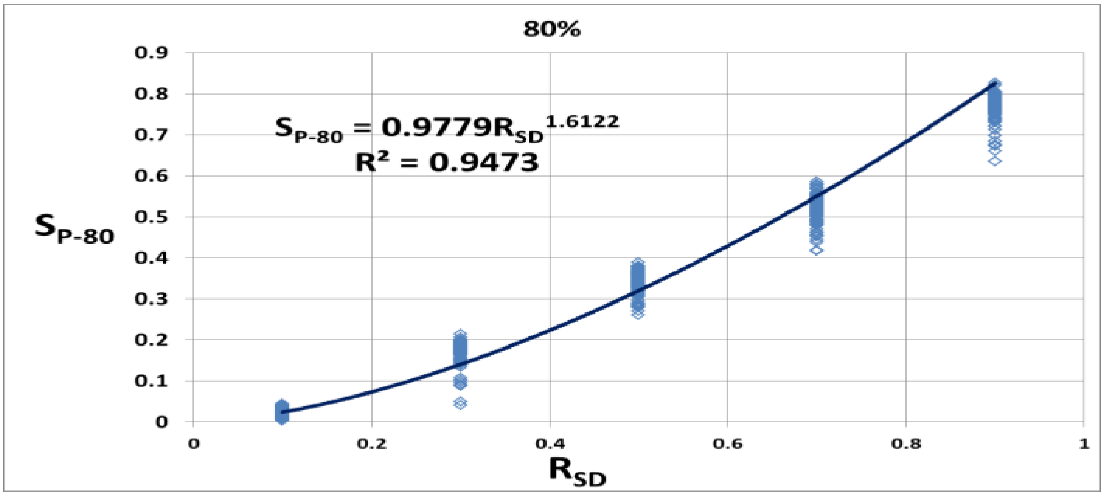

Figure 4: Relationship between yield ratio and S-D ratio at 80% reliability

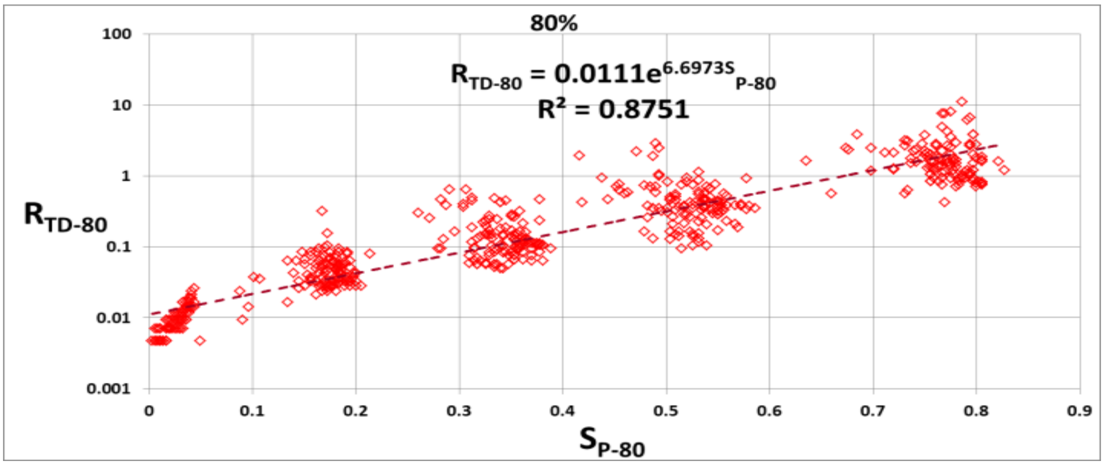

Figure 5: Relationship between storage-demand ratio and yield ratio at 80% reliability