ASSESSING AND UPDATING TECHNIQUES FOR DISAGGREGATING DAILY RAINFALL FOR DESIGN FLOOD ESTIMATION IN SOUTH AFRICA

Literature Review and Proposal

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PREFACE

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ABSTRACT

Design Flood Estimation (DFE) methods are used to limit the risk of failure and ensure the safe design of hydrological and related infrastructure and for the planning and management of water resources. The temporal distribution of rainfall has a significant impact on the magnitude and timing of flood peak discharges. Rainfall temporal distributions are therefore an important component of DFE approaches. In order to improve DFE methods which are based on event or continuous simulation rainfall-runoff models, it is generally necessary to use sub-daily time step rainfall hyetographs as input, particularly for smaller rural and urban catchments. However, the number of recording raingauges which provide sub-daily timesteps in South Africa is relatively scarce compared to those which provide daily data. Rainfall Temporal Disaggregation (RTD) techniques can be used to produce finer resolution data from coarser resolution data. A number of such approaches to disaggregate daily rainfall into sub-daily hyetographs have been developed and applied in South Africa. However, the approaches available for use are limited in comparison those developed in recent years and utilised internationally. Therefore, there is a need to update the available rainfall temporal disaggregation approaches and regionalize them or test their viability for application in ungauged locations.

This document presents a review of the local and international literature on rainfall temporal disaggregation approaches and their applications in Design Flood Estimation procedures. The literature review forms the foundation for the proposed research, which is aimed at assessing the performance of the various rainfall temporal disaggregation methods and to adopt, or adapt, a suitable approach or approaches for application under South African conditions.

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LIST OF ABBREVIATIONS

ABM	Alternating Block Method
AVM	Average Variability Method
BLRP	Bartlett-Lewis Rectangular Pulse
BLRPG	Bartlett-Lewis Rectangular Pulse Gamma
CUM	Continuous Universal Multifractal
DFE	Design Flood Estimation
IDF	Intensity-Duration-Frequency
IIM	Instantaneous Intensity Method
MBLRPG	Modified Bartlett-Lewis Rectangular Pulse Gamma
MOF	Method of Fragments
NSRP	Neyman-Scott Rectangular Pulse
RBLM	Randomised Bartlett-Lewis Model
RMC	Random Multiplicative Cascade
RTD	Rainfall Temporal Disaggregation
SA	South Africa
SAWS	South African Weather Service
SCS	Soil Conservation Service
USA	United States of America

1. INTRODUCTION

Although a natural part of Earth system processes, flood occurrence has numerous negative impacts on society. These include economic losses due to infrastructure damage, loss of productivity time, injuries and loss of human life (Ward *et al.*, 2016). Therefore, the management of and prediction of floods is important to maintaining the overall well-being of society (Parkes and Demeritt, 2016). Design Flood Estimation (DFE) comprises of the assessment of flood risk through determining the return periods of extreme events which have the potential to impose design hazard (Rowe and Smithers, 2018). The technique is vital to ensuring that the design of hydrological and related infrastructure, planning and management of water resources is carried out with safety in consideration (Rowe and Smithers, 2018).

Rainfall is a driver of hydrological models and therefore its data is a key component in DFE techniques (Smithers and Schulze, 2002). Rainfall data is utilised to determine hyetographs and subsequently hydrographs from which the peak discharge is obtained, against which hydrological structures and management plans are designed (Arnaud *et al.*, 2007; Hassini and Guo, 2017; Rowe and Smithers, 2018). Rainfall is highly variable both temporally and spatially on any given day or for a given event (Koutsoyiannis, 2003). In order to accurately calculate flood peaks in design flood estimation, rainfall data at fine temporal scales are needed (Knoesen and Smithers, 2008).

DFE is generally performed utilising daily rainfall data, due to the relative abundance and longer record lengths as opposed to sub-daily data (Pui *et al.*, 2012). However, such data may not adequately represent the important characteristics of rainfall processes occurring at hourly and sub-hourly scales (Smithers and Schulze, 2000; Pui *et al.*, 2012). The inadequate representation of such processes may be attributed to the non-linear nature of the formulative processes of rainfall events, which may suggest that a number of individual storms could occur within a short time period (Socolofsky *et al.*, 2001). Coarser data resolutions may also inaccurately represent the distribution of rainfall occurring at different times within the overall event period (Huff, 1967; Huff, 1990). Rainfall data at sub-daily levels is necessary for numerous hydrological applications, including *inter-alia* erosion and sediment transport monitoring, water quality modelling, flood risk assessments and the design of hydraulic structures, owing to its advantages over coarser data in representing rainfall characteristics and modelling rainfall-runoff interactions (Engida and Esteves, 2011). However, a major disadvantage in utilising such data is that both internationally and in South Africa (SA), the number of gauges which provide data at sub-daily time steps is far less than those which provide daily-level data (Koutsoyiannis and Onof, 2001; Smithers and Schulze, 2002; Segond *et al.*, 2006; Pui *et al.*, 2012). Data at such timesteps is required for accurately modelling sub-daily processes, infiltration (Smithers and Schulze, 2002). Therefore, in order to obtain adequate data at finer temporal resolutions, Rainfall Temporal Disaggregation (RTD) techniques are often employed (Pui *et al.*, 2012).

RTD methods disaggregate coarser resolution data, such as daily data, to produce data of a finer resolution, such as hourly (Koutsoyiannis, 2003) . The finer resolution data is able to more accurately represent rainfall hyetographs required for design flood estimation (Koutsoyiannis *et al.*, 2003). RTD techniques have been successfully applied under South African conditions to obtain finer resolution rainfall data for DFE applications (Adamson, 1981; Lambourne and Stephenson, 1987; Weddepohl, 1988; Knoesen, 2005; Knoesen and Smithers, 2008). However, such methods may be seen as limited in variety, since a plethora of newer approaches have been developed and successfully applied internationally (Smithers and Schulze, 2002).

The temporal distribution of rainfall intensity within storms influences the magnitude and timing of peak discharges within a catchment, and as a result, the flood-generation potential of the event (Knoesen and Smithers, 2008). In recent years, attention has been drawn to the implications of climate change and altered atmospheric-hydrological patterns on higher flood risks (Burn and Hag Elnur, 2002; Parkes and Demeritt, 2016; Hu *et al.*, 2018). The need for improved understanding of the non-stationarity of rainfall processes advocates for utilization of shorter-duration, finer resolution data and use of more accurate disaggregation techniques for their production. Hence, there is a need to assess the feasibility of new methods for application in SA and subsequently update the toolbox of RTD techniques.

An extensive literature review will be conducted on approaches used for disaggregating rainfall data internationally and locally. Suitable approaches will be identified based on examination of case studies of their application. It is likely that a substantial number of approaches may be identified. Therefore, those which display favourable characteristics, based on simplicity of application, data requirements and performance in regions with similar climates to SA, will be selected for application. Chapter 2 describes the various disaggregation approaches reviewed and leads into the discussion and selection of approaches for investigation in Chapter 3. The proposed research is outlined in Chapter 4.

2. APPROACHES FOR TEMPORAL DISAGGREGATION OF RAINFALL

Some of the various commonly applied techniques for the temporal disaggregation of coarser-level rainfall data into finer resolutions are discussed. These can be broadly classified as either distribution curves or mathematical and computational models, as shown in Figure 2.1.

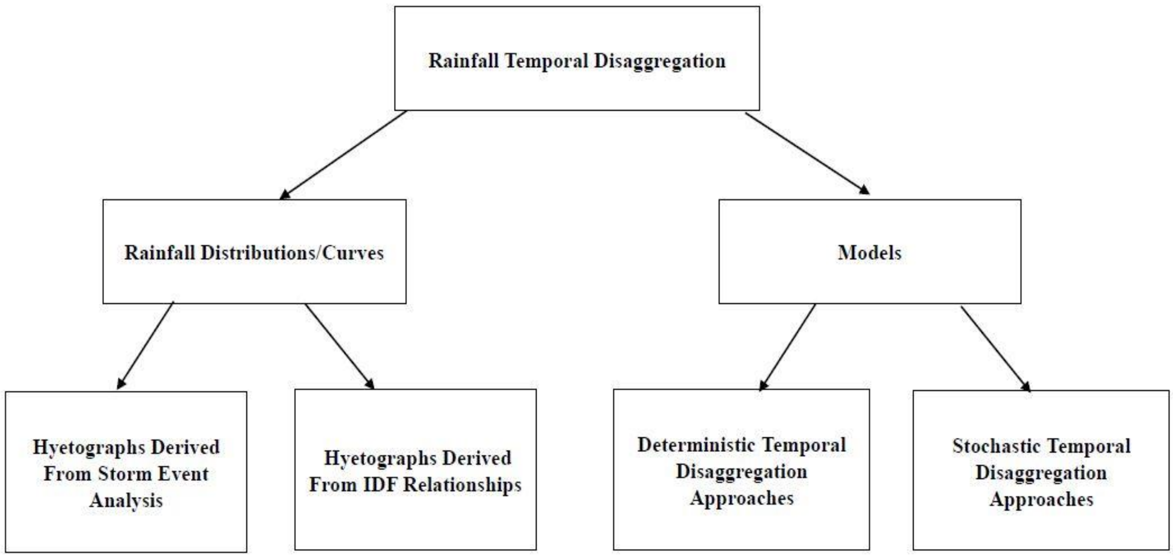

Figure 2.1 Categorisation of rainfall temporal disaggregation approaches (after Knoessen, 2005)

2.1 Rainfall Distribution Curves

A synthetic event or distribution can be developed through statistical and time sequence analysis of rainfall intensity data from nearby gauges for a particular event. Development over a large area may enable the production of a regional synthetic rainfall distribution (Chow *et al.*, 1988; Weddepohl, 1988). Temporal distribution curves have seen extensive application in SA for rainfall-runoff modelling and design applications (Adamson, 1981). Rainfall distributions may be divided into two broad categories; design hyetographs derived from direct analysis of storm events, and hyetographs derived using Intensity-Duration-Frequency (IDF) relationships or curves (Weddepohl, 1988).

2.1.1 Hyetographs derived from storm event analysis

2.1.1.1 Huff curves

Huff (1967) developed time distributions for heavy storms in Illinois, USA, utilizing a 12-year, data record of 49 gauges from the surrounding area. Storms were defined as rainy periods with a gap of 6-hours or more between previous and successive event (Huff, 1967). The distributions were smooth curves, characterizing the average rainfall distribution with time (Figure 2.2). However, they did not show the burst characteristic of observed storms (Huff, 1967;Chow *et al.*, 1988). The time distribution models, known as the 'Huff Curves', employed the mass curve method and were presented as probability distributions, representing inter-storm variability and the general rainfall temporal pattern (Adamson, 1981; Chow *et al.*, 1988; Weddepohl, 1988). Huff (1967) identified a trend in rainfall that showed that a major proportion occurs in a relatively short time frame of the total event duration. This allowed for classification of events in to four major quartile groups depending on the quarter of the storm period in which contained the heaviest rainfall, as shown in Figure 2.2 (Adamson, 1981). The probability distributions allow for determination of the most suitable temporal pattern for a specific application. However, guidelines for construction of the curves in selected area are generally limited (Bonta, 2004).

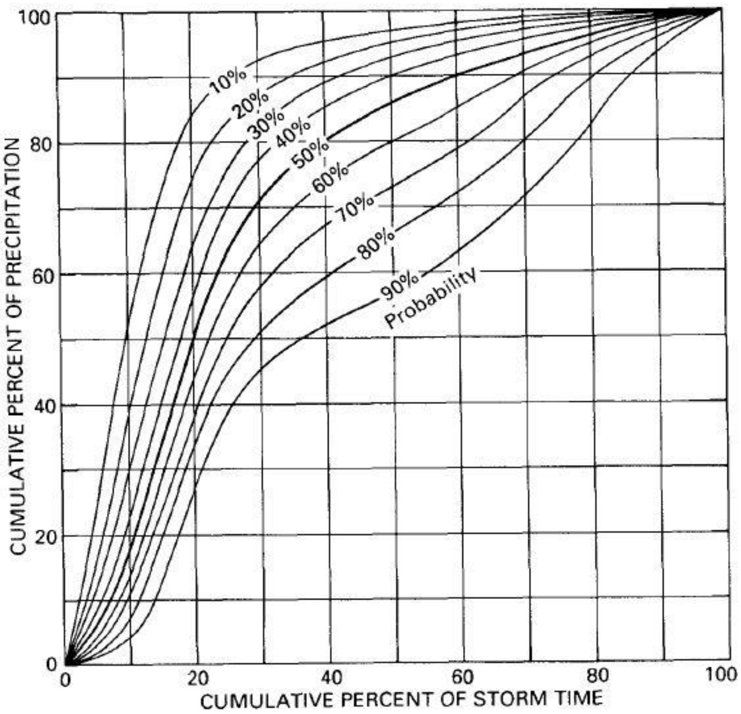

Figure 2.2 Example of Huff curve for time distribution of rainfall in first quartile storms (Huff, 1990)

2.1.1.2 SCS rainfall distributions

The United States Soil Conservation Service (SCS) developed synthetic storm hyetographs for storms of 6-24 hours in duration (Chow *et al.*, 1988). These 24-hour storm duration distribution types are related to the storm type and rainfall produced. Additional distribution types were developed after the original Type I and Type II distributions, to account for regional climatic variation, giving a total of four 24-hour duration storms, as shown in Figure 2.3 (Chow *et al.*, 1988; Knoesen, 2005). The SCS Type II distribution represents high intensity convective storms while less intensive events fall under the Type I distribution (Weddepohl, 1988). Fractional representation of the 24-hour depth values allowed for combination of different return periods into a generalised, single distribution (Weddepohl, 1988).

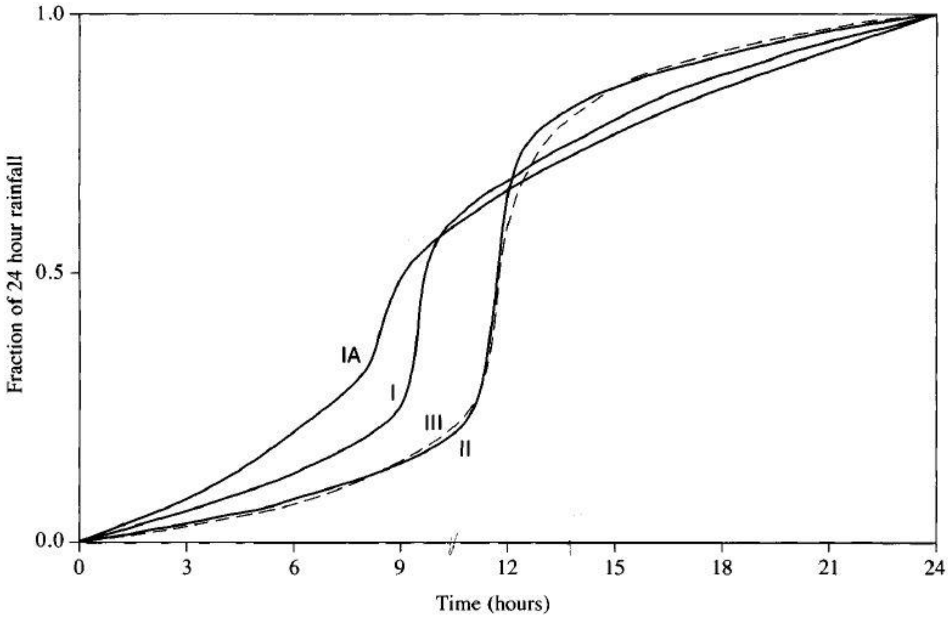

Figure 2.3 SCS 24-hour rainfall hyetographs (Chow *et al.*, 1988)

2.1.1.3 SCS-SA storm temporal distributions

The SCS distributions initially adapted for use in Southern Africa were further developed by addition of additional distribution types to account for higher observed intensities (Weddepohl, 1988). Four revised grouped were adopted and regionalised for use in SA by Schulze (1984), resulting in the SCS-SA Type I, II, III and IV rainfall distributions (Figure 2.4). Similar to the original distributions, frontal rain producing the lowest intensity rainfall is represented by Type I while convective thunderstorms, likely to yield the highest design intensities, are represented by Type IV (Schulze, 1984; Knoesen, 2005). The distributions consist of extreme rainfall depths for each sub-duration centred on the middle of 24-hours, since it is assumed to be unlikely that different duration individual rainfall intensities will correspond to the design intensities (Knoesen, 2005). The SCS-SA regionalised distributions were later further revised by Weddepohl (1988) based on an expanded digitized dataset, enabling countrywide applicability.

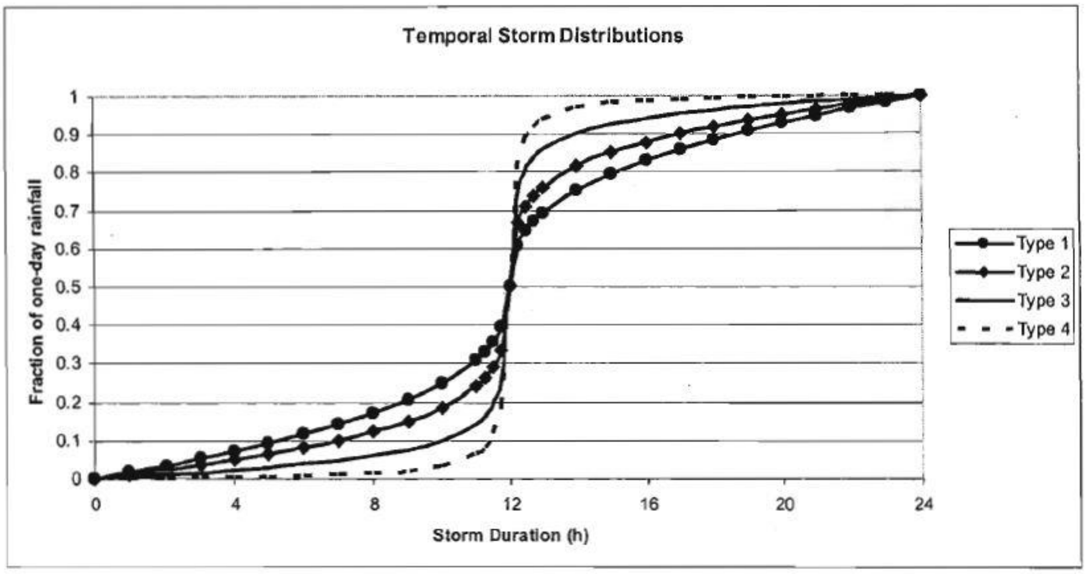

Figure 2.4 Synthetic design rainfall distributions for use in South Africa (Schmidt and Schulze, 1987; cited by Knoessen, 2005)

2.1.1.4 Uniform distribution

The uniform synthetic rainfall distribution is a simple and extensively accepted approach for generating the temporal distribution of rainfall. It assumes a constant rainfall intensity for the complete storm duration (Weddepohl, 1988). This assumption, as well as its simplistic nature render the distribution as an unrealistic representation of rainstorm characteristics, which are generally dynamic and complex (Weddepohl, 1988).

2.1.1.5 Triangular distribution

The triangular distribution rests on the concept that any temporal distribution can be determined once precipitation depth *P*, and duration T_d, are found, which allows for the height and base length of the triangle to be calculated (Chow *et al.*, 1988; Knoesen, 2005). A storm advancement coefficient *r*, which is the ratio of the time before peak t_a to the total storm duration, is used to determine the location of the peak intensity within the distribution, as shown in Figure 2.5 (Chow *et al.*, 1988). This value is computed as the mean of observed values for a series of storms with various durations, weighted according storm event duration. The coefficient also allows for the recession time t_b to be calculated (Knoesen, 2005). It has been shown that triangular hyetographs for heavy storms are nearly identical in shape with factors such as duration and geographic location only having secondary influences (Chow *et al.*, 1988).

The distribution has been shown to accurately represent natural storms in applications, such as those by Lambourne and Stephenson (1987) in SA.

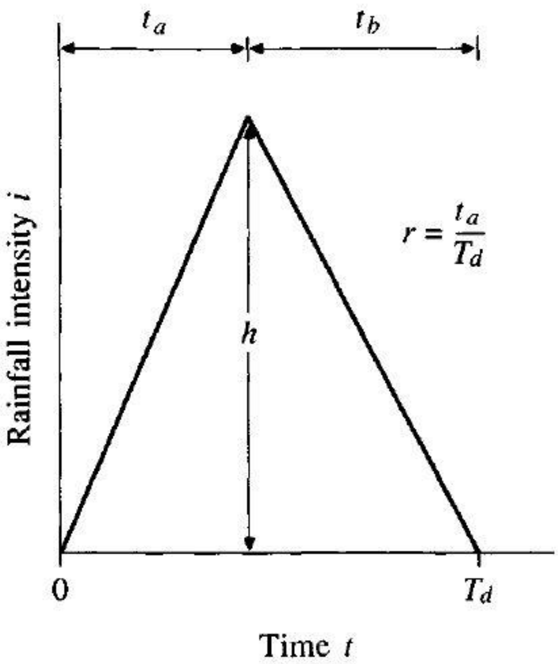

Figure 2.5 General model of the triangular distribution hyetograph (Chow *et al.*, 1988)

2.1.1.6 Average variability method

The Average Variability Method (AVM) was developed for the determination of design rainfall temporal distributions through analysing various duration intense bursts as opposed to complete storms (Knoesen, 2005). A burst rainfall event is identified for a selected duration and zone and each period within the burst is ranked based on the depth. Following this, the rainfall depth is represented as a percentage of the total depth of the rainfall burst (Green *et al.*, 2005; ARR, 2015). This method is repeated for multiple bursts and the average rainfall percentage is determined for each rainfall period, with a weighting towards larger events, as shown in Figure 2.6 (Pilgrim *et al.*, 1969; Bhuiyan *et al.*, 2010). This averaged pattern is taken as the design rainfall burst temporal pattern for the given duration and zone (ARR, 2015). The approach is conceptually simple and has been extensively applied in Australia as a recommended temporal distribution (Green *et al.*, 2005; Knoesen, 2005; Bhuiyan *et al.*, 2010). However, the AVM has been shown to produce unrealistic event temporal patterns, with higher temporal correlations than observed rainfall bursts (ARR, 2015).

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Date	Rain in mm	Rank	Rain in Each Period-points Period				Rank of Each Period's Rainfall Period				% of Rain in Period of Each Rank			
			1	2	3	4	1	2	3	4	1	2	3	4
20.11.32	176	1	32	48	48	48	4	2	2	2	27	27	27	18
20.03.14	168	2	30	44	44	50	4	2.5	2.5	1	30	26	26	18
29.09.43	166	3	48	46	31	41	1	2	4	3	29	28	25	19
26.10.22	157	4	42	65	35	15	2	1	3	4	41	27	22	10
09.03.13	153	5	18	50	45	40	4	1	2	3	33	29	26	12
25.10.19	150	6	40	27	41	42	3	4	2	1	28	27	27	18
20.11.61	140	7	35	35	35	35	2.5	2.5	2.5	2.5	25	25	25	25
19.01.26	139	8	36	48	40	15	3	1	2	4	35	29	26	11
25.09.51	137	9	44	20	37	36	1	4	2	3	32	27	26	15
15.06.49	133	10	42	40	35	16	1	2	3	4	32	30	26	11
			Average				2.55	2.20	2.50	2.75	31	27	26	16
			Standard Deviation				1.25	1.11	0.66	1.13	4.6	1.5	1.4	4.8
			Assigned Rank				3	1	2	4				
			Period				1	2	3	4				
			Final Pattern (% of Total Rainfall)				26	31	27	16				

Figure 2.6 Ranking of storms and periods for the AVM (Pilgrim *et al*., 1969; cited by Bhuiyan *et al*., 2010)

2.1.1.7 Monobe model

The Monobe model was developed by Na and Yoo (2018) for distributing design rainfall depths obtained from analysis of observed rainfall data in Seoul, Korea. The approach was based on an equation of the distribution of cumulative rainfall R_t (mm) up to a specified time *t*, as shown in Equation 2.1.

$$R_t = \frac{R_T}{T}\left(\frac{T}{t}\right)^n t \tag{2.1}$$

The design rainfall depth R_T (mm), and rainfall duration T (h) were the main variables in addition to a constant n of an assumed value of 2/3 (Na and Yoo, 2018). The derived rainfall intensity data for development of the temporal distribution was taken as the difference between the cumulative rainfall depths of the current and previous time periods. Once the peak value was located, the second highest rainfall intensity is positioned alternately around the peak, until all intensities are distributed for the storm duration (Na and Yoo, 2018).

2.1.2 Hyetographs derived from intensity-duration-frequency (IDF) relationships

2.1.2.1 Alternating block method

The Alternating Block Method (ABM) is a simplistic approach for utilising an Intensity-Duration-Frequency (IDF) relationship to construct a design rainfall hyetograph (Chow *et al.*, 1988). The storm duration ($T_d = n\Delta t$) is divided into n equal time increments of duration Δt and for a particular return period, rainfall intensity is derived from the IDF curve for each duration (Δt, $2\Delta t$, $3\Delta t$…) and the corresponding rainfall depth is computed as a product of intensity and duration (Chow *et al.*, 1988; Knoesen, 2005). The rainfall amount to be added for each of the equal time increments Δt is taken as the difference between successive depths, after which they are re-ordered to allow the maximum depth to occur at the centre of the total storm duration T_d (Chow *et al.*, 1988). The remaining incremental depths are then alternately placed in descending order on either side of the maximum depth to form the design hyetograph, as shown in Figure 2.7 (Nguyen *et al.*, 2014). Although simple in design, the ABM has been shown to be effective in representing peak rainfall depths from observed events (Na and Yoo, 2018).

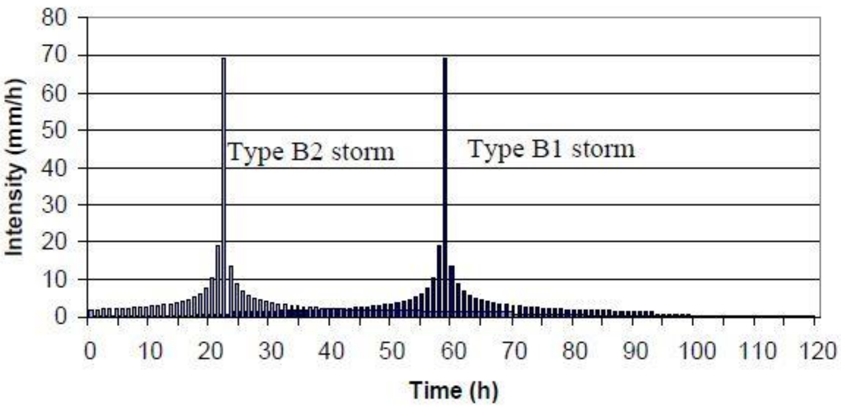

Figure 2.7 Example of design hyetographs derived from the ABM with a 1-hour timestep (Nguyen *et al.*, 2008)

2.1.2.2 Instantaneous intensity method

The Instantaneous Intensity Method (IIM), also known as the Keifer and Chu (1957) method or Chicago design storm is based on the premise that an equation defining an IDF curve or relationship can be used to develop equations for determining temporal variation of intensity in a design hyetograph (Chow *et al.*, 1988). It assumes that rainfall depth for a period of duration (time interval) around the storm peak T_d is equal to the depth given by the IDF curves, which similar to the ABM approach (Chow *et al.*, 1988; Knoesen, 2005). However, intensity is considered to vary for the entire storm duration, allowing for the location of the peak to change but not the magnitude (Chow *et al.*, 1988). The distribution of alternating rainfall intensities i preceding and succeeding, the peak, t_a and t_b, respectively, are assumed to form a hyetograph, as shown in Figure 2.8. The relationship of these points to T_d is given by Equation 2.2. The approaches employs a storm advancement coefficient r, shown in Equation 2.3, in the same manner as the Triangular distribution (Prodanovic and Simonovic, 2004; Na and Yoo, 2018). The total amount of rainfall R within time T_d is given by the area under the curves in Equation 2.4 (Chow *et al.*, 1988).

$$T_d = t_a + t_b \tag{2.2}$$

$$r = \frac{t_a}{T_d} \tag{2.3}$$

$$R = \int_0^{rT_d} f(t_a)dt_a + \int_0^{(1-r)T_d} f(t_b)dt_b \tag{2.4}$$

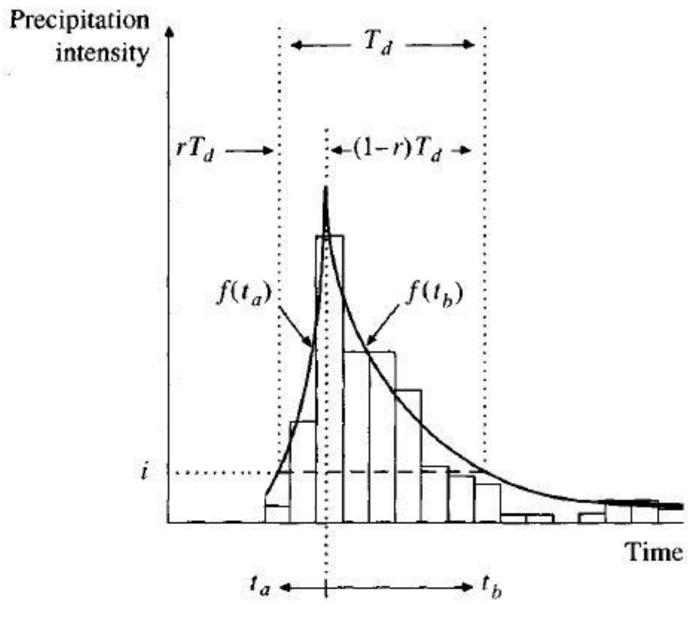

Figure 2.8 Fitting a curve to a hyetograph with the Instantaneous Intensity Method (Chow *et al.*, 1988)

2.2 Models

The second main category of RTD approaches contains mathematical and computational models, which can be either stochastic or deterministic in nature. There are a considerable number of stochastic, deterministic and semi-deterministic models which have been applied for RTD. However, only a few of the more commonly applied examples are discussed in this section.

2.2.1 Stochastic Rainfall Temporal Disaggregation Models

2.2.1.1 Bartlett-Lewis models

Bartlett-Lewis models are Poisson cluster models which generally represent major observable characteristics of rainfall, including rain-cell clustering within storms in continuous time periods, utilizing simple stochastic assumptions and limited physically-related parameters (Segond *et al.*, 2006). They can be calibrated to different climates, are widely applicable and capable of reproducing important rainfall characteristics at various spatial resolutions (Koutsoyiannis and Onof, 2001). Variants of the original approach described by Rodriguez-Iturbe *et al.* (1987), include the Bartlett-Lewis Rectangular Pulse Model (BLRP), Modified BLRP (MBLRP), Randomized Bartlett-Lewis Model (RBLM) and Bartlett-Lewis Rectangular Pulse Gamma (BLRPG) (Rodriguez-Iturbe *et al.*, 1987; Entekhabi *et al.*, 1989; Glasbey *et al.*, 1995; Koutsoyiannis and Onof, 2001; Smithers and Schulze, 2002; Pui *et al.*, 2012). The general concept of the commonly applied BLRP approach assumes that the occurrence of storm cell origins t_i follows a Poisson process with rate λ. Cell origins t_{ij} of each storm i follow a Poisson process with rate β. Cell arrivals of each storm i are exponentially distributed, with parameter y, and terminate after a given time v_i. Cells durations w_{ij} are exponentially distributed with parameter η and a uniform intensity X_{ij} for the specific distribution, as shown in Figure 2.9 (Rodriguez-Iturbe *et al.*, 1987; Smithers, 1998; Koutsoyiannis and Onof, 2001). The BLRP model may be considered one of the most widely utilized available stochastic approaches for RTD internationally. It has been shown to adequately represent important statistical rainfall characteristics at different time scales (Smithers and Schulze, 2000; Koutsoyiannis and Onof, 2001). The cluster design permits flexible representation of complex rainfall processes at various time-scales in a fairly simplified manner (Kossieris *et al.*, 2018).

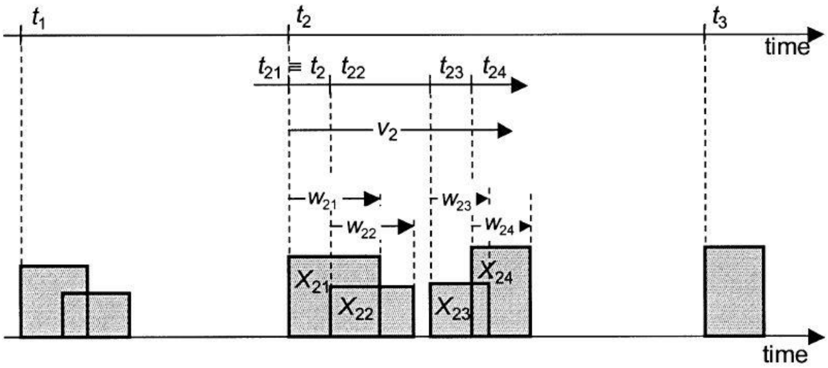

Figure 2.9 Schematic of the BLRP model process (Koutsoyiannis and Onof, 2001)

2.2.1.2 Neyman-Scott models

Neyman-Scott models are similar to Bartlett-Lewis models in that they are Poisson cluster based and have several variants, depending on the rainfall depth of each rain cell distributed over a specific time period (Cowpertwait, 1991). The cell positions are governed by a set of identically-distributed and independent random variables characterizing time intervals between the storm origin and new cell formation (Entekhabi *et al.*, 1989). The commonly utilised Neyman-Scott Rectangular Pulse (NSRP) model characterises rainfall as a series of storms with individual storms consisting of a set of rectangular pulse cells defining events (Hingray *et al.*, 2002; Frost *et al.*, 2004). The superposition of pulses is used to describe the profile of the storm, as shown in Figure 2.10 (Olsson and Burlando, 2002). NSRP displays natural generalisation of spatial point processes, for design applications requiring spatial representation of processes (Cowpertwait, 1991). Model parameters adequately represent seasonal and climatological characteristics of rainfall-generating mechanisms (Olsson and Burlando, 2002). However, it displays inadequate preservation of dry and wet periods of events, which may potentially be associated with a lack of inherent scaling behaviour in the construction of rectangular pulse models (Entekhabi *et al.*, 1989; Olsson and Burlando, 2002).

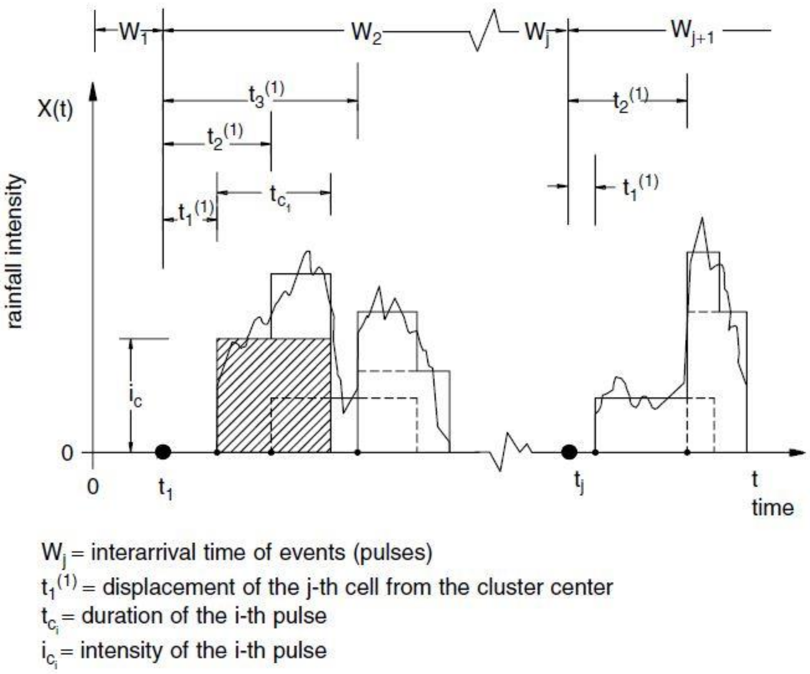

Figure 2.10 Schematic of the NSRP model process (Olsson and Burlando, 2002)

2.2.1.3 Cascade-based approaches

Cascade-based methods include the commonly applied Random Multiplicative Cascade (RMC) approach, the Microcanonical model, the Continuous Universal Multifractal model (CUM) and cascade models with scale-and-intensity-dependent parameters (Serinaldi, 2010; Pui *et al.*, 2012; Müller and Haberlandt, 2018). The underlying cascade process was targeted at reproducing empirically observed scaling behaviour in rainfall processes (Güntner *et al.*, 2001). Cascade-based models multiply values assumed by physical attributes, such as rainfall intensity for a particular time scale and cascade level $k - 1$, by an appropriate set of random weights W to acquire values at a smaller time scale k, which maintain statistical characteristics of the observed original data (Serinaldi, 2010). A key structural element is the branching number b, which regulates the number of subintervals, divided as $i = 1, 2, \ldots, b^k$, generated from the coarser-level data at timescale L_0 to the finer-level time step L_k. The rainfall intensity R for the i^{th} subinterval at a generic cascade level k is determined by Equation 2.5, where λ_k is the scale ratio and $A_{i,k}$ is the corresponding rainfall amount (Serinaldi, 2010).

$$R_{i,k} = R_0 \prod_{j=1}^{k} W_j(i) = A_{i,k}\lambda_k \text{ for } i = 1,2, \ldots, b^k; k > 0 \quad (2.5)$$

The approaches are relatively simplistic and have been extensively applied for generating higher resolution rainfall time series, producing results which adequately matched observed data characteristics (Lisniak *et al.*, 2013; Müller and Haberlandt, 2018). However, the exact nature of the underlying relationship between turbulence and rainfall, is not explicitly clear (Pui *et al.*, 2012). Furthermore, issues of parameter transferability have been noted in semi-arid regions, due to higher inter-annual rainfall variability (Güntner *et al.*, 2001).

2.2.1.4 Method of fragments

The Method of Fragments (MOF) or Analog method is a non-parametric technique which resamples based on a vector of fragments, or analog days, which represent the ratio between sub-daily and daily rainfall at a particular time step. Disaggregated sequences are obtained through multiplication of the available coarser-level values by the designated proportion vector (Li *et al.*, 2018). It does not consider a relationship between continuous and aggregate rainfall (Pui *et al.*, 2012; Carreau *et al.*, 2019). The MOF produces rainfall sequences which display persistence attributes similar to the observed data. This is achieved through maintaining temporal dependence at the daily timescale and employing non-parametric disaggregation logic for creating sub-daily timesteps which also display dependence (Pui *et al.*, 2012). The approach is conceptually simple and has been shown to perform well against other disaggregation approaches such as Poisson cluster models (Carreau *et al.*, 2019). Furthermore, it considers the influence of yearly changes in sub-daily temporal patterns and the magnitude of rainfall (Pui *et al.*, 2012). However, some variations may be considered data-intensive (Li *et al.*, 2018).

2.2.1.5 Regionalized daily rainfall disaggregation model

Knoesen (2005) adapted a daily-to-hourly rainfall disaggregation model developed in Australia by Boughton (2000) for use in SA. The original stochastic approach was based on a dimensional hyetograph, and was initially designed for design flood estimation procedures in combination with daily rainfall generators (Boughton, 2000; Knoesen, 2005). A major component of the model involved consideration of the distribution of the fraction of the daily rainfall total occurring in the hour of maximum rainfall *R*, which indicates the degree of uniformity (Knoesen and Smithers, 2008). These fractions were used to form rainfall clusters, which were organized as random patterns to reproduce possible variations in the daily rainfall distribution (Knoesen and Smithers, 2008). Modification allowed for reproduction of synthetic hourly rainfalls displaying characteristics of the daily observed rainfall data distributions

(Knoesen, 2005; Knoesen and Smithers, 2008). The modified and regionalised model were found to adequately reproduced rainfall statistics at the test stations. However, it was less suited to simulating event characteristics of the phasing properties of rainfall, and at locations with lower fractions of daily rainfall totals occurring in the maximum hour (Knoesen and Smithers, 2008).

2.2.2 Deterministic rainfall temporal disaggregation models

2.2.2.1 The constant model

This highly simple disaggregation approach assumes a constant rainfall intensity for the rain hour (Hingray and Ben Haha, 2005). The disaggregated time steps produced within rain hours are all wet and the model has no parameter. Assessment in producing important rainfall event statistical characteristics found that the Constant model underestimates rainfall variability and extremes (Hingray and Ben Haha, 2005). For 10-minute rainfall, the model gave lower limits of standard deviation, skewness and the peak value for return periods. The model was also found to overestimate 10-minute rainfall autocorrelations and occurrence probability (Hingray and Ben Haha, 2005). Hence it is a simple but relatively poor-performing model for rainfall temporal disaggregation.

2.2.2.2 Ormsbee discrete disaggregation model

Ormsbee (1989) reasoned that historical rainfall data at one-hour time steps were too coarse to adequately represent hydrological response on small catchments. Uniform distributions employed for disaggregation were identified to potentially underestimate peak discharges (Ormsbee, 1989). Hence a discrete disaggregation model, with both a deterministic and stochastic pathway, was developed for improving upon this limitation. The model assumed proportionality between the rainfall distribution within the central hour t of a 3-hour moving sequence and the hourly distribution over the 3-hour sequence, as shown in Figure 2.11. This allowed for disaggregation of hourly rainfall volumes into three 20-minute volumes V_t^1, V_t^2 , V_t^3 (Ormsbee, 1989). The 20-minute rainfall volumes are expressed as fractions of the total volume V_T, as given by Equation 2.6. The central hour volume can be disaggregated into 20-minute rainfall volumes as shown in Equations 2.7, 2.8 and 2.9, and the rainfall intensities are then determined by division of the rainfall volume by the disaggregation time interval (Ormsbee, 1989).

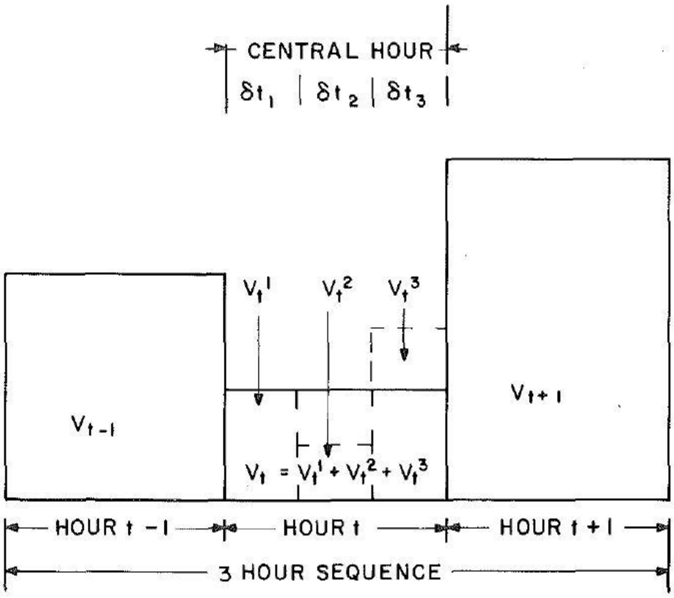

Figure 2.11 Discrete disaggregation model (Ormsbee, 1989)

$$V_T = V_{t-1} + V_t + V_{t+1} \tag{2.6}$$

$$V_t^1 = V_t * \left(\frac{V_{t-1}}{V_T}\right) \tag{2.7}$$

$$V_t^2 = V_t * \left(\frac{V_t}{V_T}\right) \tag{2.8}$$

$$V_t^3 = V_t * \left(\frac{V_{t+1}}{V_T}\right) \tag{2.9}$$

2.2.2.3 Ormsbee continuous disaggregation model

The Continuous Disaggregation Model developed by Ormsbee (1989) was based on a continuous distribution approach, applicable for disaggregating to time intervals of 1-30 minutes. The rainfall volume is deterministically distributed, in a similar approach to the Discrete Disaggregation model, allowing for the distribution in each hour to be explicitly defined according to rainfall sequence types. A rainfall sequence index table is used to define the rainfall sequence type in the first hour of the continuous sequence (Ormsbee, 1989). Following this, the central hour is then disaggregated into T time intervals of δt minutes, among which the total volume of rainfall for the central hour V_t is distributed, as shown in Equation 2.10. The probability associated with each time interval $P(\delta t_i)$ is determined using Equations 2.11a, 2.11b and 2.12, with t^* being the time parameter for different rainfall sequence types. The expanded set of equations can be found in Ormsbee (1989). After complete distribution of the total volume for the hour, the process is repeated for the next hour containing measurable rainfall (Ormsbee, 1989).

$$V_t^i = V_t * P(\delta t_i), \text{ for } i = 1, \dots, T \tag{2.10}$$

$$F(t) = \frac{V_{t-1}t}{V_t^*} - \frac{(V_{t-1} - V_t)t^2}{2V_t^* t^*}, \text{ for } 0 \le t < t^* \tag{2.11a}$$

$$F(t) = \frac{(V_t + V_{t-1})t^*}{2V_t^*} + \frac{V_t(t - t^*)}{V_t^*} - \frac{(V_t - V_{t+1})(t - t^*)^2}{2V_t^*(60 - t^*)}, \text{ for } t^* \le t \le 60 \tag{2.11b}$$

$$P(\delta t_i) = P(t_{i-1} \le \tau \le t_i) = F(t_i) - F(t_{i-1}) \tag{2.12}$$

2.2.2.4 Chaotic approach to rainfall temporal disaggregation

Deterministic chaos is the notion that seemingly irregular behaviour in simple deterministic systems may be a result of the influence of non-linear interdependent variables (Sivakumar *et al.*, 2001). Sivakumar *et al*. (2001) identified that stochastic approaches generally display disconnection between model structure and the underlying physics of rainfall processes. A new framework utilizing the concept of deterministic chaos was proposed to firstly study transformation between rainfall temporal scales, and improve upon the limitations of stochastic approaches (Sivakumar *et al.*, 2001). A simple chaotic disaggregation model was formulated and applied. The approach could be used to take a rainfall series X_i, with values $i = 1, 2, \dots, N$ at temporal resolution T_1, and obtain values for series $(Z_i)_k$, where $k = 1, 2, \dots, p$ at a higher resolution T_2, with $p = (T_1/T_2)$. It is assumed that the values of series X_i are distributed into series $(Z_i)_k$ according to equations 2.13 and 2.14 , with $(W_i)_k$ as the distributions of weights of X_i to $(Z_i)_k$. An additional assumption is that information regarding the historical distribution of weights and time series is available, in order to determine the future distributions of the weights and series values, with $i = n + 1, \dots N$, and N always being equal to the total number of points. The initial step for determining the distribution of weights $(W_{n+1})_k$ involves the reconstruction of the time series for X_i, $i = 1, 2, \dots, n + 1$ for resolution T_1 using Equation 2.15. The second step involves assuming a functional relationship between the vectors Y_j as shown in Equation 2.16, with F_T derived using the local approximation method. Disaggregation of X_{n+1} is performed based on Y_j and its neighbours, which are given by the minimum values of $\|Y_j - Y_j'\|$. The expanded set of equations and variates can be found in Sivakumar *et al.* (2001).

$$(Z_i)_k = (W_i)_k X_i \quad (2.13)$$

$$\sum_{k=1}^{p}(W_i)_k = 1 \quad (2.14)$$

$$Y_j = \left(X_j, X_{j+\tau}, X_{j+2\tau}, \dots, X_{j+(m-1)\tau}\right), \text{ for } j = 1, 2, \dots, (n+1) - (m-1)\tau/\Delta t \quad (2.15)$$

$$Y_{j+T} = F_T(Y_j) \quad (2.16)$$

The model performed reasonably well and seemed more suited to the application than a stochastic framework. However, there was need for further study on the occurrence of chaos in rainfall data (Sivakumar *et al.*, 2001). Other studies which have discussed chaotic approaches have labelled them as controversial, due to the assumptions utilised and limited available literature on applications (Rodriguez-Iturbe *et al.*, 1987; Koutsoyiannis, 2003; Segond *et al.*, 2006).

2.3 Summary of Methods

The applications of the above approaches and the key findings describing their characteristics are summarized in Table 2.1 for comparison of their strengths and weakness.

Table 2.1 Selected case studies for rainfall temporal disaggregation approaches

Category	Approach	Case study	Location	Key findings
Hyetographs derived from storm event analysis	Huff Curves	Huff and Angel (1992)	Nine states in the USA	• Curves developed from a dense raingauge network were applicable over nine states because of similar climate and rainfall.
		Bonta (2004)	USA	• Curves can be developed using point data. • Potential for regionalisation; a single set can be applied over a large area.
	Triangular Distribution	Lambourne and Stephenson (1987)	Vanderbiljpark, South Africa	• Triangular hyetograph was adequate for design applications. • More accurately represents natural storms than Chicago and Uniform distributions.
	AVM	Green *et al.* (2005)	Australia	• An unsmoothed single design pattern AVM temporal distribution for design flood applications should be based on the 10 highest events for a duration • Approach is still applicable for estimating probable maximum floods despite higher intensity distributions being available.

		Bhuiyan *et al.* (2010)	Australia	• AVM for determining design rainfall temporal patterns successfully showed climate change-related changes in regional rainfall temporal patterns since original derivation
	The Monobe Model	Na and Yoo (2018)	Seoul, Korea	• Model overestimates rainfall peaks in comparison to ABM, Huff curves and the IIM • May be useful in design calculations where over-design is intended for safety but requires testing under different climatic conditions.
Hyetographs derived from IDF relationships	ABM	Na and Yoo (2018)	Seoul, Korea	• Approach was the best suited for estimation of annual maximum rainfall events that closely matched observed rainfall data.
	IIM	Marsalek and Watt (1984)	Canada	• Unrealistic temporal distribution due to assumption that that the design storm contains all maximum intensities for the various durations. • Design hyetograph should consider antecedent conditions during computation. • Inadequate for application for development of design storms for Canadian rainfall data.
		Na and Yoo (2018)	Seoul, Korea	• In comparison to the Alternating Block Method, Huff curves and Monobe model, the approach was the most accurate in producing peak values close to observed data.
Stochastic Models	BLRP model	Koutsoyiannis and Onof (2001)	London, UK Arizona, USA	• Model could generate hourly-level data capable of aggregating to observed daily totals. • Approach was applicable in cases were limited hourly data was available for fitting. • Performed well in maintaining statistical properties of the rainfall process, including proportions of dry and wet period, coefficients of variation and skewness of rainfall intensities.

	BLRPG and MBLRP models	Smithers *et al.* (2002)	South Africa	• Historical data statistics were well replicated by both models. • Design rainfall events estimated by BLRPG model were more accurate. • Derivation of BLRPG parameters using only available daily data allows for estimation of short-duration data values down to 1-hour time frames.
	NSRP model	Frost *et al.* (2004)	Multiple Australian cities	• Model adequately reproduced rainfall characteristics of observed pluviograph data records. • Less capable of reproducing wet-spells and dry-spells, possibly due to the range of statistics for which it is calibrated.
	RMC model	Güntner *et al.* (2001)	Brazil UK	• Highly accurate in reproducing rainfall characteristics at an hourly time step, with performance being generally better for semi-arid tropical rainfall. • Extreme values were accurately estimated in Brazil, while overestimated in the UK temperate climate.
	RMC, Microcanonical and Canonical models	Pui *et al.* (2012)	Australia	• For daily-to-hourly disaggregation, canonical approach underestimated extreme rainfall values while microcanonical generally overestimated. • Models performed reasonably well in simulating statistical rainfall properties such as the mean values and dry periods but not as well as MOF
	MOF	Pui *et al.* (2012)	Sydney, Perth, Caims and Hobart in Australia	• For daily-to-hourly disaggregation, MOF performed better than other models such as RMC and RBLM in preserving important rainfall event statistical characteristics as well as estimating extreme values.
		Li *et al.* (2018)	Singapore China	• MOF approaches were capable of reproducing characteristics of site-specific historical rainfall data.

				• Regionalised and multi-site approaches were found to better represent annual extremes and antecedent precipitation values, making them more viable for capturing the variability in the historical rainfall data.
Deterministic models	Constant model	Hingray and Ben Haha (2005)	Lausanne, Switzerland	• Underestimates rainfall variability and extremes. • Overestimates autocorrelations and occurrence probability.
	Ormsbee discrete disaggregation model	Hingray and Ben Haha (2005)	Lausanne, Switzerland	• Underestimates rainfall variability and extremes. • Overestimated autocorrelations at 10-minute timesteps. • Model may be unsuitable when these need to be maintained at high resolution timesteps.
	Ormsbee continuous disaggregation model	Ormsbee (1989)	West Virginia and Kentucky, USA	• Model adequately predicts first three rainfall moments. • Performance is improved with 15-minute data. • Employing synthetic distributions instead of average distributions produced more accurately predicted peak flow frequencies.
	Chaotic approach	Sivakumar *et al.* (2001)	Mississippi, USA	• Model was found to yield reasonable disaggregation results. • Chaotic framework seemed to be more suitable for modelling temporal scale transformation dynamics than a stochastic framework. • Deterministic chaos showed potential for temporal scale transformation applications.

3. DISCUSSION AND CONCLUSIONS

Improving the accuracy of design flood estimates, may require the use of data at finer resolutions than the traditional daily timestep. However, a point of concern is the relatively limited availability of sub-daily rainfall data, in comparison to daily data, both internationally and locally. As a result, rainfall temporal disaggregation approaches have been applied to generate finer resolution data from coarser resolution data. Relative to international research and development, such approaches available for use in SA may be considered limited in terms of the variety which have been applied and adapted in the past. Hence, there is potential for updating approaches used, through review of newer approaches applied internationally and assessing their viability for adoption for disaggregation of available daily rainfall to derive realistic hydrographs.

The RTD approaches identified through review of the literature on the subject, could be broadly classified as either rainfall distribution curves or models. A given disaggregation approach which is applied should ideally formulate a hyetograph which can give a realistic representation of sub-daily rainfall. The applied approach should disaggregate the daily values to the sub-daily level, while maintaining the characteristics of the rainfall process and the increments being able to be summed back up to the daily total.

Rainfall distributions are used in design and modelling applications for determining the distribution of rainfall depths or intensities throughout the duration of a storm. These synthetic distributions may be used to derive hyetographs and determine the location of peak discharges within the storm duration. While the approaches may require substantial historical records in certain cases, some could be adapted for use with observed daily data with short record lengths. Furthermore, approaches such as the Huff curves and AVM have shown potential for regionalisation. Therefore, curves could be developed and possibly regionalised based on general storm patterns for use in disaggregating daily rainfall into sub-daily incremental intensity values.

Stochastic model approaches generally simulate hourly-level data using statistical parameters derived from the observed daily data. An element of randomness is included in sampling procedures. Therefore, despite their proven adequacy for producing sub-daily data capable of aggregation to daily-level, such approaches may not be suitable for production of realistic hyetographs with sub-daily increments. However, since rainfall processes are, by nature, complex, it is unlikely that a model will be able to completely and accurately describe event characteristics. Hence, the use of stochastic models which may produce results similar to observed data, is still justifiable. Furthermore, such approaches are highly applicable to continuous simulation modelling in which the aim is to exhaustively simulate potential outcomes for rainfall event processes. Deterministic model RTD approaches are less commonly applied than stochastic models or distribution approaches, due to their parameters being more physically-related to rainfall processes, which in some cases, are difficult and time-consuming to derive. Therefore, the variety of models identified was comparatively limited. As previously mentioned, the rainfall process is highly complex, dynamic and difficult to accurately represent with limited data. Therefore, an approach which considers deterministic chaos may more accurately represent rainfall physical characteristics than a purely stochastic or deterministic method.

Several commonly applied disaggregation approaches were identified. For the purposes of this research, focus shall be given approaches which are more physically-based, such as distributions and deterministic models. However, the application of stochastic models shall be investigated as well. The case studies reviewed provided general indications of the strengths and weaknesses of each approach and where they may be the most applicable.

Approaches which have been successfully applied in SA include the SCS-SA distributions, Triangular distributions, Huff Curves, BLRP models and an adapted semi-stochastic regionalised disaggregation model. These approaches fell into the categories of rainfall distributions and stochastic models. These models shall therefore be applied in different regions, and their performance compared as part of the study.

The additional approaches which will be assessed are the, AVM, Ormsbee discrete and continuous models, Chaotic approach and MOF. The AVM is extensively applied in Australia, which has a similar climate to SA. The Ormsbee discrete and continuous deterministic disaggregation models, while not extensively applied, are applicable to observed data which suits the needs of the study. The Chaotic approach discussed may be considered semi-deterministic and more accurate than stochastic frameworks in some cases. Internationally, the MOF approach has shown to perform well in disaggregating with adequate reproduction of rainfall trends and could be used if properly developed for local conditions. The above models and their applications internationally have shown promising results and could be adapted for use in SA for production of realistic hyetographs with sub-daily increments. Furthermore, some of the distribution approaches, such as Huff curves and AVM show potential for regionalisation. The performance of models shall be assessed based on preservation of rainfall process characteristics and the accuracy of extreme values calculated in comparison to utilizing observed daily data.

4. PROJECT PROPOSAL

4.1 Problem Statement

RTD approaches which have been successfully applied in South Africa (SA) and are currently available for use are limited in comparison to the numerous approaches available internationally. Changes in atmospheric and rainfall processes due to climate change may result in increased occurrence of extreme events. Hence there is a need to firstly be able to more accurately model these events, and then adequately design hydraulic structures and water resources management approaches to withstand them. This requires improved availability of finer resolution data and an expanded array of RTD approaches to produce them under various conditions. Therefore, a need exists to assess currently available techniques and the viability of additional methods for updating methods which can be used for various applications.

4.2 Aim and Objectives

The overall aim of this research is to assess the performance of various RTD methods and adopt or adapt one or more of these for application under South African conditions. Achieving this aim will require the following objectives to be met:

- Acquiring an understanding of previously used methods as well as recently developed approaches through a literature review of disaggregation approaches
- Assessing the performance of methods in SA
- Adoption, adaptation or development of a rainfall disaggregation method(s) for design flood estimation in SA

4.3 Proposed Methodology

The techniques identified through the literature review will be applied to rainfall data from different regions in SA, obtained from the South African Weather Service (SAWS) and University of KwaZulu-Natal databases. The preliminary stage will involve aggregating short-duration data to the daily level, applying RTD methods and then comparing disaggregated values to the original data. Model performance will be assessed based on preservation of key statistical rainfall characteristics displayed by the observed data. Once the applicability of the approaches has been assessed, the viability for regionalisation shall be determined, which will include the use of inferences from synoptic conditions and climatological drivers for determining the characteristics of events as indicators for selection of the appropriate disaggregation procedure to use in improving the simulation of flood hydrographs and peak discharges.

4.4 Resources Required for Study

The desktop-based study will require a computer capable of performing extensive modelling and data analysis. Access to a relatively continuous and accurate historical rainfall database is another requirement, this will be obtained from the Centre for Water Resources Research at the University of KwaZulu-Natal. The bulk of the data analysis will be performed using Microsoft Excel software as well as scripting languages such as Python and R in the advanced stages.

4.5 Research Schedule

The schedule for the proposed research, shown in Table 4.1, has been designed to ensure that the work is completed timeously.

Table 4.1 Schedule of activities for proposed research timeframe

Activity	2019												2020					
	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J
Literature Review	■	■	■															
Identification of models for initial application, data sorting and extraction				■														
Application of selected approaches, including available South African methods					■	■	■											
Statistical analysis and write-up of preliminary results							■											
Application of further approaches, including newer international methods, possible regionalisation								■	■	■	■							
Statistical analysis of results, verification against observed hyetographs, further testing, write-up												■	■					
Write-up of final results, discussion and conclusions														■				
Submission of draft for revision															■			
Editing, corrections and resubmissions																■	■	
Submission of final thesis for assessment																		■

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