Constrained ordination techniques aim to identify the underlying structure in a date set by considering the relationships between response and explanatory variables. In the case of RDA, x_i is a linear combination of explanatory variables, z_{ij}, where j = 1, 2,…, n_p is the number of explanatory variables. z_i refers to the standardized catchment characteristics. For example, if p = 2, x_i is given by:

$$x_i = c_1 z_{i1} + c_2 z_{i2} \quad (5.2)$$

Where, c_1 and c_2 are the weights, also called the canonical coefficients, to measure explanatory variables z_{i1} and z_{i2} to derive x, the theoretical explanatory variable (ter Braak & Šmilauer, 2018). Substituting for x_i in Eq 5.1 gives the RDA model

$$y_{ik} = a_k + b_k c_1 z_{i1} + b_k c_2 z_{i2} \quad (5.3)$$

RDA aims to estimate the unknowns in this model, a_k and b_k of the response variables and c_1 and c_2, the weights from the explanatory variables (ter Braak & Šmilauer, 2018).

CANOCO has the ability to statistically test the significance of the constrained ordination model, using Monte-Carlo permutation tests. CANOCO uses the false discovery rate, Holms correction or Bonferroni correction. The Bonferroni correction method multiples each p value by the number of performed tests, which has often been identified as being too conservative and leads to large loss of power (Roback & Askins, 2005; Gordon *et al.*, 2007). The Holms correction is an improvement of the Bonferroni correction, in which once the first hypothesis has been rejected, the second hypothesis is treated as a completely new test. In Holms correction the tests are first sorted on the basis of their p values from smallest to largest. If the first hypothesis is rejected, we no longer deal with q but rather q-1, where q refers to the number of tests. The false discovery rate (FDR) is a popular approach for controlling Type 1 error, which is defined as the expected proportion of incorrectly rejected H_0 among all rejections. The FDR allows the occurrence of Type 1 error under a reasonable proportion by taking the number of rejections into consideration. The false discovery rate was therefore used in the study, due to the fact that the Bonferroni and Holms corrections tend to be too conservative (ter Braak & Šmilauer, 2018). The permutation tests were used in the study to identify the catchment characteristics that are significant at a 5 % level in explaining the variance of flow characteristics.

Table 5.1 presents the catchment characteristics selected for redundancy analysis that are likely to influence the flow characteristics presented in the same table. The flow characteristics were standardized by converting the initial flow data, given as m^3/sec to mm/year. CV of annual flow, IC, CVB and BFI are given as a ratio and the number of zero flow days are represented as days.

Table 5.1: Flow and catchment characteristics selected for redundancy analysis

Symbol	Flow Characteristics	Catchment Characteristics
Q	Mean annual runoff	Mean annual rainfall (MAP)
CV	Coefficient of variation of annual flows	Mean annual evaporation (ET)
q_{90}	Dimensionless daily flow with a 90 % exceedence	River length (RL) Drainage density (Dd)
q_{75}	Dimensionless daily flow with a 75 % exceedence	Slope (S_{ave}, S_{20}, S_{50}, S_{90}) Elevation (E_{min}, E_{max}, E_{range})
q_{25}	Dimensionless daily flow with a 25 % exceedence	Proportion of each catchment under different lithologies (GL)
q_{10}	Dimensionless daily flow with a 10 % exceedence	Proportion of each catchment under different land cover types
IC	Concavity Index	(LC)
CVB	Hydrological Index	Proportion of each catchment
3-day min	3-day minimum of daily discharge	under different soil textures (Ss)
3-day max	3-day maximum of daily discharge	
ZFD	Number of zero flow days	
BFI	Baseflow Index	

5.3 Results

5.3.1 Relationships between catchment characteristics

Figure 5.1 shows which catchment characteristics vary in a similar manner among the selected catchments in the study. Mean annual rainfall and slope tends to vary in a similar manner from one catchment to another, which suggests that catchments that have high rainfall tend to occur within catchments with steep slopes. The relationship between rainfall and slope is expected since steep slopes occur in areas with high elevation which also receive high rainfall (Jencso & McGlynn, 2011; Parajka *et al.*, 2013; David & Davidova, 2014; Hallema *et al.*, 2016). The variation of land cover types (thicket and plantations) and geology (Cape Granite and Table Mountain) with rainfall and slope suggests that these land cover types typically occur within catchments with high rainfall, steep slope and low evaporation (Figure 5.1).

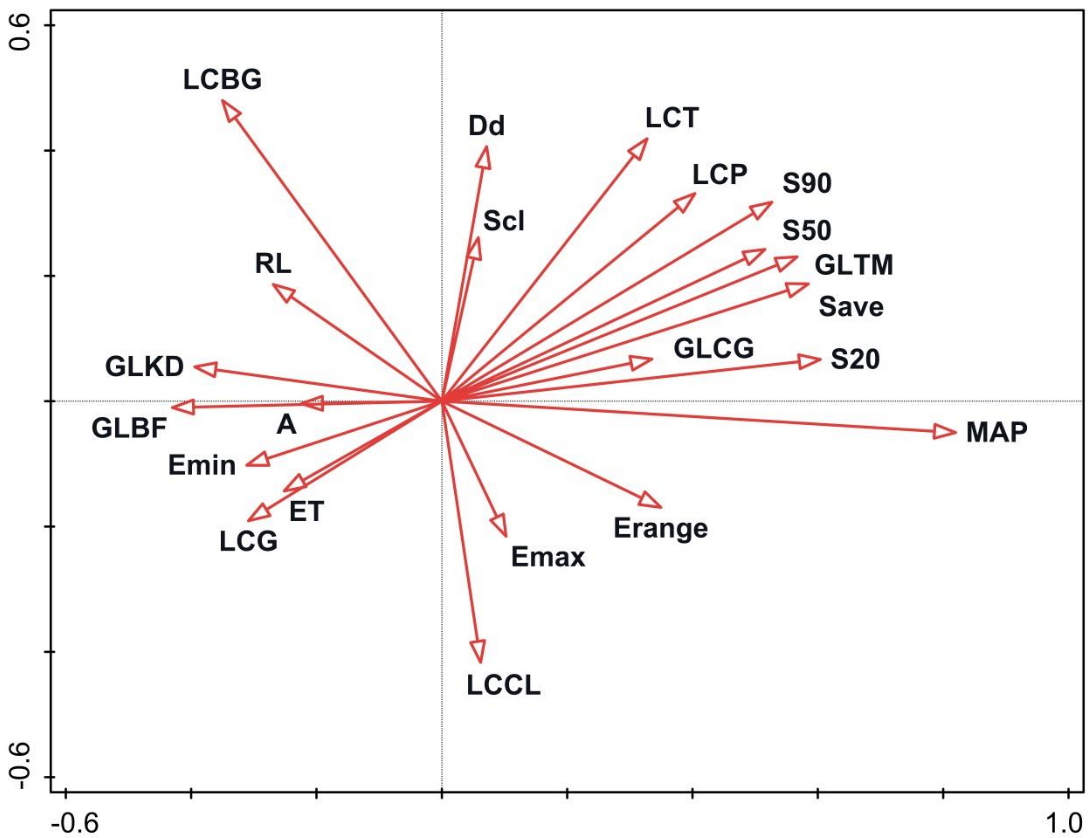


Figure 5.1: Variation of catchment characteristics among selected catchments

Figure 5.1 shows that evaporation varies in an opposite manner to rainfall. This reveals that as rainfall increases among catchments evaporation rates reduce. River length (RL), area (*A*) and minimum elevation (E_{min}) show a similar variation with evaporation among catchments, which indicates that catchments with high evaporation rates tend to have increased river lengths, large catchment areas and low elevation. Large catchment areas tend to occur in low-lying areas with high temperatures, and therefore high evaporation values.

Bare ground (LC_{BG}), grasslands (LC_{G}), Karoo dolerite (GL_{KD}) and Beaufort (GL_{BF}) tend to vary in a similar manner with evaporation. This relationship indicates that catchments characterized by land cover types (LC_{BG} and LC_{G}) and geology (GL_{KD} and GL_{BF}) typically occur within catchments characterised by low rainfall and flat slopes, and consequently high evaporation rates.

5.3.2 Relationship between flow characteristics

Figure 5.2 shows which flow characteristics vary in a similar manner among the selected catchments. Mean annual runoff tends to vary in a similar manner with q_{10}, q_{25}, q_{75}, q_{90}, BFI, IC, 3-day min and 3-day max (Figure 5.2). The relationship between mean annual runoff and these flow characteristics suggests that catchments that have high runoff will also have large values of these flow characteristics.

The number of zero flow days varies in an opposite way to mean annual runoff and BFI (Figure 5.2). This suggests that catchments characterised by high runoff and BFI tend to have a low number of zero flow days. This relationship is expected as an increase in runoff and BFI reduces the number of zero flow days. Catchments that are characterized by high BFI therefore have low number of zero flow days. A large baseflow means flow throughout the year and therefore a reduction in the number of zero flow days.

CV of annual flows and CVB tend to vary in an opposite way to runoff, BFI and IC among the catchments. Mean annual runoff and BFI are inversely related to the coefficient of variation of annual flows. Catchments characterised by high BFI and runoff have a low CV of annual flows. The CVB represents the ratio of CV of annual flows to BFI. Catchments that are characterised by low CVB values therefore exhibit low inter-annual variability and large groundwater storages with higher baseflow contribution.

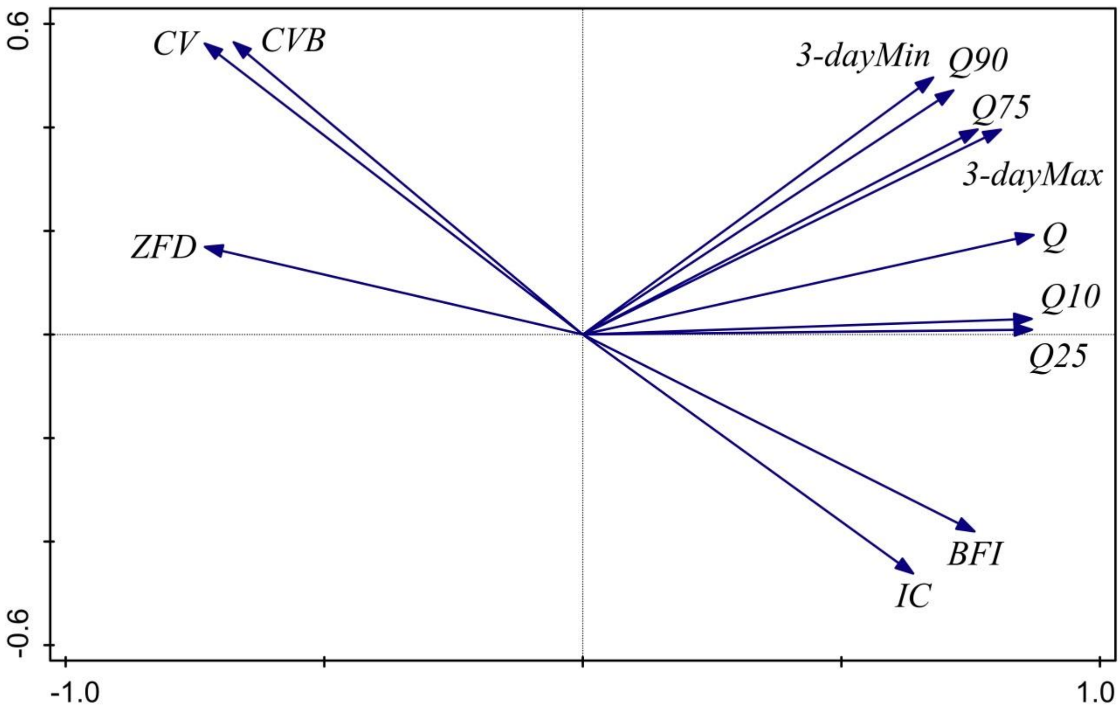


Figure 5.2: Variation of flow characteristics among selected catchments

The concavity index (IC) and BFI tend to vary in a similar manner among the catchments (Figure 5.2). The concavity index measures the contrast between high and low flow conditions, thus representing the shape of the flow duration curve (Bloschl *et al.,* 2013). Catchments IC values close to 1 do not have a large difference between low and high flows. Catchments that are dominated by contrasting climates and poor groundwater storage typically have values close to 0, resulting in severe flow conditions from low-flow to quickflow due to rainfall events (Bloschl *et al.,* 2013). The variation of BFI and IC is therefore expected, as catchments characterised by higher BFI tend to exhibit lower contrast between high and low-flow conditions and a flatter flow duration curve. Figure 5.2 illustrates that IC and BFI are inversely related to CV and CVB, which is expected as catchments characterised by higher IC and BFI show lower CV and CVB values.

5.3.3 Relationship between flow and catchment characteristics

Figure 5.3 shows the relationship between catchment characteristics with the ordination axes of flow characteristics. This identifies catchment characteristics that account for the variance of flow characteristics represented by each ordination axis. Figure 5.3 shows that MAP, slope, GL_{TM}, GL_{CG}, LC_P and LC_T varies in a similar way with flow characteristics in the first axis amongst catchments. Slope and elevation have been found in previous studies to significantly influence mean annual runoff, through governing the movement of water to the catchment outlet (Mazvimavi, 2003; Masoudian, 2009; Jencso & McGlynn, 2011; Mirus & Loague, 2013).

GL_{TM} varies in a similar manner with flow characteristics in the first axis. This suggests that the occurrence of GL_{TM} among catchments tends to be associated with high runoff, flow percentiles, and BFI. Catchment geology has a substantial influence on the subsurface storage and drainage network (Jencso & McGlynn, 2011; Rumsey *et al.*, 2015; Ries *et al.,* 2017). GL_{TM} consists of faults and fractures which promote the direct recharge of rainfall into the subsurface storage. Previous studies have shown baseflow contribution to be high within the Table Mountain Group (Sun, 2005 and Le Maitre & Colvin, 2008). The results of the ordination show that GL_{TM} is typically found within catchments of high rainfall and steep slopes, which therefore results in high rates of recharge. As a result, the baseflow contribution within these regions would be high, which is evident as BFI shows a moderate correlation with GL_{TM} (Figure 5.3). However, the relationship between the Table Mountain Group and flow characteristics in the first axis may merely be as a result that these rock types are associated with mountainous areas receiving high rainfall. GL_{KD} tends to vary in an opposite way with BFI (Figure 5.3). Although previous studies have identified Karoo dolerite as having a high potential for groundwater storage (Molaba, 2017), the relationship was not identified in the study as Karoo dolerite typically underlies regions with low rainfall and flat slopes. This relationship is expected as Sun (2005) pointed out that low recharge rates coincide with low rainfall and high evaporation rates.

The variation of thicket, plantations and forest with flow characteristics in the first axis, such as runoff, is a result of these land cover types being mostly found in catchments of high rainfall and steep slopes, and subsequently high runoff. For example, plantations have been found to decrease mean annual runoff due to higher interception, infiltration and transpiration rates (Farley & Jobbágy, 2005; Zhao *et al.,* 2015). The occurrence of plantations reduces net rainfall reaching the surface due to interception by tree canopy, which increases ET due to transpiration from vegetation. Plantations also generally have deep roots and infiltration is generally high under areas characterised by plantations. However, the degree to which plantations influence runoff is dependent on the characteristics of plants. For example, some trees may be characterised by dense tree canopy or shallow root systems which affects interception and infiltration of rainfall differently. Farley and Jobbágy (2005) and Zhao *et* al (2015) found that afforestation substantially influences catchment hydrology, through the reduction of runoff. The relationship between flow characteristics in the first axis and plantations is thus more related to the climatic and physiographic characteristics of areas covered by plantations. Plantations are typically found within the mountainous regions of the study area, with higher elevation, slope and MAP, which consequently increases runoff.

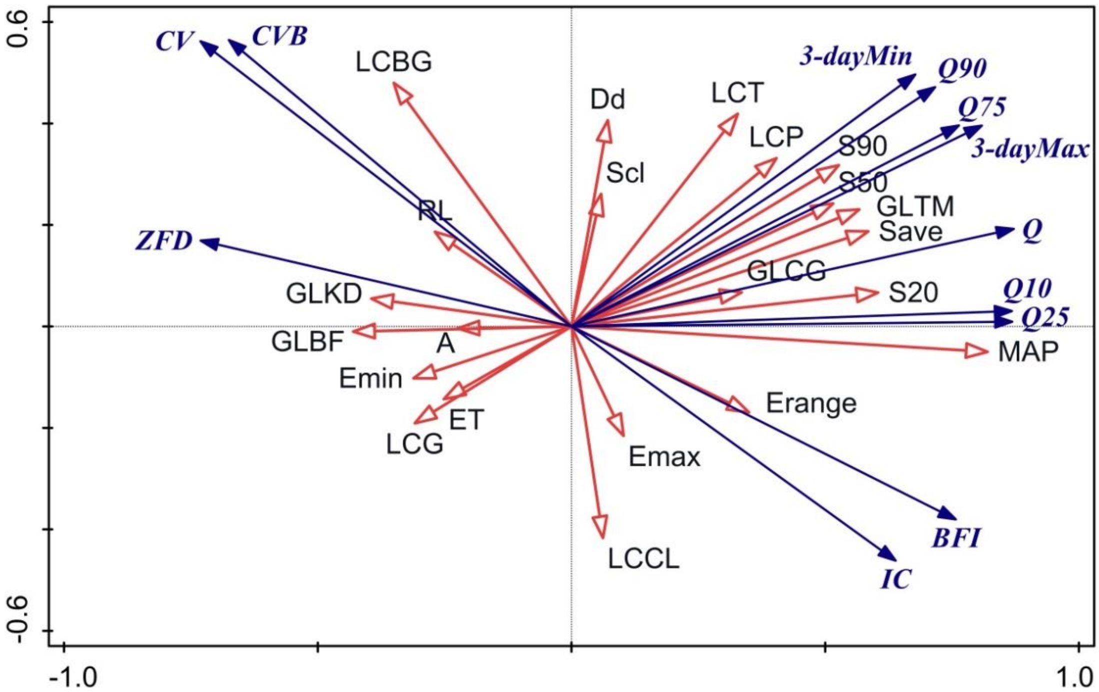


Figure 5.3: Relationship between flow and catchment characteristics among selected catchments

The occurrence of bare ground and grasslands, which are typically underlain by Karoo Dolerite and Beaufort Group (Figure 5.3), tends to vary in an opposite way with flow characteristics in the first axis among catchments. This relationship indicates that catchments covered by these land cover types are characterised by low MAP, flat slopes, high evaporation rates, and consequently low mean annual runoff. Previous studies have shown grasslands to influence mean annual runoff (Mazvimavi, 2003; Chikodzi, 2013; Duan *et al.*, 2017). Grasslands have been identified in previous studies as generating runoff in the channel, due to higher infiltration rates and contribution to the river channel (Chikodzi, 2013). However, Mazvimavi (2003) and Duan *et al* (2017) identified that mean annual runoff decreases with the proportion of the catchment covered by grasslands, due to the presence of wetlands which increases the rate of ET. This relationship is further explained with the number of zero flow days (ZFD) varying in a similar manner with land cover types of bare ground and grasslands. LC_G shows a negative correlation with flow characteristics in the first axis, including runoff, flow percentiles and BFI.

ZFD varies in a similar manner with ET, RL and *A* among catchments (Figure 5.3). The results suggest that an increase in evaporation, river length and area consequently increases the number of zero flow days among catchments. The reason for this phenomenon could be due to longer travel time of flow to the main channel, resulting in high infiltration and evaporation rates (Love *et al.,* 2011; Chikodzi, 2013; Huang *et al.*, 2017). Ries *et al* (2017) pointed out that runoff coefficients were observed to decrease with increasing river length due to increased infiltration rates. Ries *et al* (2017) also pointed out that increasing catchment area is often associated with decreasing runoff among catchments, as smaller catchments are generally found within mountainous areas with high runoff rates per unit area. Catchments with large areas are typically found within areas of gentle slopes, low rainfall and high evaporation in the study area (Figure 5.3), which subsequently result in longer travel times due to low flow velocities. Catchments characterised with small areas are typically found in mountainous areas, promoting runoff with high flow velocity, which reduces the rate of infiltration and travel time to the main channel. Love *et* al (2011) and Chikodzi (2013) showed similar results to this study where actual runoff was shown to decrease with increasing catchment area. Table 5.2 presents the total proportion of variance of the flow characteristics explained by the derived ordination axes of catchment characteristics.

Table 5.2: Proportion of variance of flow characteristics explained by catchment characteristics in the derived ordination axes

	Axis 1	Axis 2	Axis 3	Axis 4
Eigenvalues	58.20	15.40	5.80	2.30
Explained variation (cumulative)	58.20	73.55	79.32	81.65
Pseudo-canonical correlation	0.97	0.89	0.91	0.81
Explained fitted variation (cumulative)	67.84	85.73	92.46	95.17

The first axis explains 58.2 % of the variance of flow characteristics, 15.4 % by the second axis, 5.8 % by the third axis and 2.3 % by the fourth axis. The total variance explained is represented by the explained variation (Table 5.2) with the total variance of flow characteristics explained by 81.65 %. The pseudo-canonical correlation in Table 5.2 describes the linear correlation between the case scores of the axis derived from flow and the corresponding case scores derived from the catchment characteristics (ter Braak & Šmilauer, 2018). The first flow characteristics axis has a high correlation coefficient of 0.97 with the first axis of catchment characteristics. A high correlation coefficient indicates a strong linear relationship with the derived catchment characteristics. However, this does not necessarily mean that the catchment characteristics in the derived axis explain the variance of the flow characteristics. It may merely mean that the catchment characteristics and flow characteristics are closely correlated and vary in a similar way. The "explained fitted variation (cumulative)" in Table 5.2 shows the contribution of each catchment characteristics axis compared to the total variance of flow characteristics explained by all the catchment characteristics axes, with the first axis of catchment characteristics explaining 67.84 % of the variance of flow characteristics (ter Braak & Šmilauer, 2018).

Monte Carlo permutation test was used to determine those catchment characteristics that are significant at a 5 % level explaining the variance of flow characteristics. Table 5.3 presents the catchment characteristics that were found to be significant at a 5 % level in explaining the variance of flow characteristics and identifies the amount of variance explained for each catchment characteristic. Mean annual rainfall and slope equalled or exceeded 90 % of the time (S_{90}) were the only catchment characteristics that were found to significantly explain the variance of flow characteristics. The results reveal that the cumulative percentage explained by MAP and S_{90} is 57 %.

Table 5.3: Proportion of variance of flow characteristics explained by catchment characteristics

Catchment Characteristics	Percentage Explained (%)	Cumulative Percentage (%)
MAP (mm)	46	46
S_{90} (degrees)	11	57

5.4 Discussion and conclusion

Redundancy analysis has shown that MAP and S_{90} are the only catchment characteristics that are significant in explaining the variance of flow characteristics in this study. The importance of rainfall in explaining the variance of flow characteristics has been shown in several studies and has been identified as the main climatic forcing of the hydrological catchment response (Mazvimavi, 2003; Mazvimavi *et al.*, 2005; Chikodzi, 2013; Blöschl *et al.*, 2013; Drogue & Khediri, 2016).

Slope is an important characteristic of a catchment as it explains the rate of movement of water by kinetic energy to the catchment outlet (Mazvimavi, 2003; Masoudian, 2009; Mirus & Loague, 2013; David & Davidova, 2014). The slope influences the catchment response time to rainfall events, which has a substantial effect on the concentration and travel times of flow (Masoudian, 2009; Gericke & du Plessis, 2012; David & Davidova, 2014; Huang *et al.*, 2017). David and Davidova (2014) showed that high slope led to fast concentrations and consequently to high volumes of peak discharge. Mu *et al* (2015) and Malan (2016) identified that soil depth decreases with increasing slope, which would consequently reduce rates of infiltration and enhance the generation of runoff.

The results of redundancy analysis show that 18 % of the variation of flow characteristics cannot be accounted for by the catchment characteristics used in the study. The unexplained variation of 18 % may be due to random hydrological behaviour which cannot be distinguished, or due to the limitation of the data sources used in the study. The use of more hydrologically-meaningful data for geological and soil data sets, such as depth to the water table, permeability and porosity may increase the variance explained for the flow characteristics used in the study. Such data, in developing countries especially, are not readily available and the data provided is often a generalised coverage of various geological characteristics (Mazvimavi, 2003; Hughes, 2006). Hughes (2006) expressed that in many developing countries; the derivation of geological characteristics is based on coarse geological maps with low resolution that have not been generated using hydrologically meaningful source data. This limitation may urge the development of more hydrologically meaningful data in developing countries, which would be more suitable for hydrological studies.

Catchment characteristics that have been identified in this chapter as significant in explaining the variance of flow characteristics can be used as a basis to group catchments into hydrologically homogenous groups. MAP and S_{90} were found to significantly explain the variance of flow characteristics. Although other catchment characteristics are important, such as the Table Mountain Group and ET, they are not significant at explaining the variance of flow characteristics. The results of ordination were also used as the basis for cluster analysis for grouping catchments into hydrologically similar groups based on similarities of catchment characteristics in Chapter 7.

CHAPTER 6: PREDICTION OF FLOW CHARACTERISTICS

6.1 Introduction

The aim of this chapter is to explore the model performance of predicting flow characteristics through the use of univariate statistical methods and artificial neural networks. The development of regression models and neural networks provides the opportunity to predict flow characteristics in ungauged catchments and determines which approach is more suitable for predicting selected flow characteristics of non-perennial rivers.

6.2 Methodology

The study used multiple linear regression (MLR) and artificial neural networks (ANN) to predict flow characteristics from catchment attributes (Mazvimavi, 2003; Riad *et al.,* 2004; Mazvimavi *et al.,* 2005; Aichouri *et al.,* 2015).

6.2.1 Multiple linear regression

Multiple linear regressions is an extension of simple linear regression, in which multiple explanatory variables are used to establish the relation between the response and explanatory variables, which can be expressed as (Patel *et al.,* 2016):

$$Y = \alpha + \beta_i X_i + \beta_{i+1} X_{i+1} + \ldots\ldots\ldots.. + \beta_P X_P + e \qquad (6.1)$$

where; Y = dependent variable, α = constant or intercept, β_i = slope (beta coefficient), X_i = independent variables, i = 1, 2, 3,…, p, and p = number of independent variables.

Multiple regression methods are only applicable if there is a linear relationship between flow and catchment characteristics, and the variables approximate a normal distribution (Mazvimavi, 2003). The study used forward selection to produce regression models of flow characteristics, which was based on data from 36 gauging stations. The forward selection approach starts with no independent variables in the model. At the first step, the independent variable that shows the highest coefficient of determination is selected in the model. At each step, the independent variable that increases the coefficient of determination of the model is selected. The process is terminated once the remaining independent variables are not significant. Once a variable has been selected in the model, the variable cannot be removed. The selection of independent variables for the prediction of flow characteristics was based on previous studies, which identified influential catchment characteristics governing hydrological response.

Numerous techniques have been developed to predict flow duration curves (FDCs) in ungauged catchments. The use of exponential (Eq 6.2), logarithmic (Eq 6.3), and power models (Eq 6.4) tend to be popular for predicting FDCs in ungauged catchments (Mazvimavi, 2003; Mazvimavi *et al*, 2005; Sauquet & Catalogne, 2011). The advantage of these approaches is the reduction of computational effort for regionalisation of FDCs in ungauged catchments.

$$q_p(i) = \beta(i) \exp(-\alpha\, p) \tag{6.2}$$

$$q_p(i) = \beta(i) + \alpha(i) \ln(p) \tag{6.3}$$

$$q_p(i) = \beta(i)\, p^{\alpha(i)} \tag{6.4}$$

where q_p is dimensionless daily flows, p is the percentage exceedence and α and β are coefficients.

6.2.2 Artificial neural networks

ANN's have been widely used due to the ability to model both linear and non-linear relationships (Riad *et al.*, 2004; Aichori *et al.*, 2015). Generally there are four steps that are required for developing an ANN (Londhe & Charhate, 2010). Firstly, the data needs to be transformed or scaled. Large variation in input data can slow down or prevent the training of the network, thus data is scaled using linear, logarithmic or normal transformation. The second step is the network architecture definition, where the number of layers is set (Londhe & Charhate, 2010). The ANN consists of three layers (Figure 6.1), the input, hidden and output layer, with each layer comprising of a series of nodes that are interconnected (Londhe & Charhate, 2010; Elsafi, 2014; Aichouri *et al.*, 2015). Figure 6.1 illustrates the network architecture of a simple multi-layer perceptron neural network.

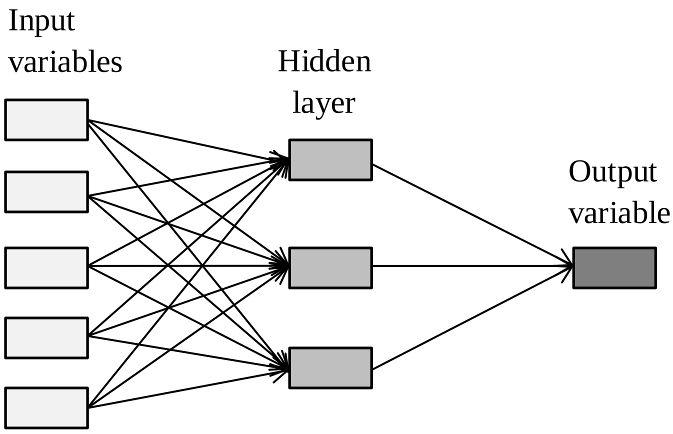


Figure 6.1: Simple illustration of a multi-layer perceptron with 5 input variables, 3 units in the hidden layer and 1 output variable

The number of nodes that is required in the input and hidden layer depends on the complexity of the problem being studied. For example, if the number of nodes used in the hidden layer is too small, the network may be insufficient to characterise the process correctly. On the other hand, if the number of nodes is too high, the training of the ANN may take too long and the network may sometimes over-fit the data. The next step involves the training of the ANN, through determining the weights of the ANN, which forms the connection between the neurons. The ANN is trained with a set of input and known output data (Londhe & Charhate, 2010; Elsafi, 2014). At the beginning, the weights of the neurons may be assigned randomly or based on experience. The learning algorithm of the ANN changes the weights of the neurons accordingly, so that the difference between the ANN output and the actual value is small. Once the difference between the ANN output and the actual value is within a specified range, the ANN can be considered as trained.

The last process is the validation of the performance of the ANN. Training of the ANN was based on using a sub-sample of catchments. The validation of the ANN is based on using a sub-sample that was not used during training to evaluate the performance of the ANN. The validation process determines whether the ANN needs to be re-trained or if the network can be applied for the intended use (Riad *et al.*, 2004; Londhe & Charhate, 2010; Aichouri *et al.*, 2015). The model performance for predicting flow characteristics can be determined by a range of statistical criteria, including root mean square error (RMSE), coefficient of correlation (r), and coefficient of determination (R^2).

6.2.3 Model performance evaluation

The model performance of both multiple regression and neural networks were evaluated using the coefficient of determination (R^2), root mean square error (RMSE) and the standard deviation ratio (RSR). The coefficient of determination (Eq 6.2), which ranges between 0 and 1, describes the proportion of variance in the observed data, which is explained by the model, with higher values indicating a better model performance (Golmohammadi *et al.,* 2014). Previous studies have identified that the model performance of R^2 greater than 0.50 can be considered as being acceptable (Golmohammadi *et al.,* 2014). The RMSE (Eq 6.3) indicates a perfect match between the observed and predicted data when the value is 0, with increasing RMSE increasing the error in prediction. Singh *et al* (2004) identified that when the RMSE is less than half the value of the observed standard deviation of the population, the model can be considered low and indicating a good model performance for prediction. The RSR (Eq 6.4) is calculated based on the ratio of the RMSE and standard deviation of the observed data, where the lower the value the more reliable the performance of the model (Golmohammadi *et al.,* 2014). The equations for R^2, RMSE and RSR are presented below (Golmohammadi *et al.,* 2014):

$$R^2 = \left[\frac{\sum_{i=1}^{n} + (O_i - O)(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - O)^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}\right] \quad (6.5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \ (P_i - O_i)^2}{n}} \quad (6.6)$$

$$RSR = \frac{\sum_{i=0}^{n} \ (O_i - P_i)^2}{\sqrt{\sum_{i=0}^{n} \ (O_i - \bar{O})^2}} \quad (6.7)$$

6.3 Correlation between flow and catchment characteristics

Table 6.1 presents the correlation between flow and catchment characteristics. Catchment characteristics are only presented if they show a significant correlation coefficient at 5 % confidence level with flow characteristics.

Table 6.1: Correlation between flow and catchment characteristics

	Q	CV	Q90	Q75	Q25	Q10	IC	3-day min	3-day max	ZFD	BFI
MAP	**0.73**	**-0.59**	**0.54**	**0.59**	**0.74**	**0.75**	**0.61**	**0.49**	**0.63**	**-0.69**	**0.55**
ET	-0.27	0.03	-0.21	-0.21	-0.21	-0.22	-0.14	-0.21	**-0.36**	0.23	-0.03
Dd	0.03	0.25	0.32	0.24	-0.06	-0.07	-0.17	**0.39**	0.17	-0.11	0.13
Emin	**-0.34**	0.08	-0.21	-0.24	-0.32	-0.31	-0.13	-0.19	**-0.36**	0.18	-0.27
Erange	0.30	**-0.33**	0.12	0.19	**0.38**	**0.38**	**0.34**	0.10	0.17	**-0.33**	**0.34**
Save	**0.45**	-0.30	**0.57**	**0.63**	**0.37**	**0.35**	0.22	**0.59**	**0.50**	**-0.44**	**0.56**
S20	**0.51**	**-0.37**	**0.47**	**0.54**	**0.49**	**0.48**	0.32	**0.46**	**0.49**	**-0.47**	**0.53**
S50	**0.38**	-0.22	**0.57**	**0.61**	0.26	0.25	0.13	**0.61**	**0.48**	**-0.38**	**0.51**
S90	**0.39**	-0.21	**0.63**	**0.67**	0.28	0.24	0.09	**0.67**	**0.50**	**-0.36**	**0.50**
LCS	-0.13	0.16	-0.18	-0.16	-0.07	-0.07	-0.08	-0.18	-0.20	0.21	0.07
LCG	**-0.35**	0.04	-0.26	-0.30	**-0.35**	**-0.34**	-0.02	-0.25	**-0.33**	0.02	**-0.41**
LCBG	-0.17	**0.56**	-0.08	-0.08	-0.16	-0.18	-0.34	-0.08	-0.16	**0.43**	**-0.35**
LCCL	0.05	-0.30	-0.20	-0.17	0.11	0.13	0.21	-0.24	-0.04	0.01	0.17
LCT	**0.34**	0.03	**0.47**	**0.38**	0.18	0.23	-0.03	**0.49**	**0.47**	-0.29	0.06
LCP	**0.36**	-0.12	**0.45**	**0.56**	**0.35**	0.25	0.03	**0.47**	**0.44**	-0.21	0.28
GLBF	**-0.41**	0.24	-0.26	-0.32	**-0.42**	**-0.42**	-0.23	-0.25	**-0.37**	0.19	**-0.50**
GLBV	-0.10	0.13	-0.21	-0.17	-0.06	-0.05	-0.05	-0.20	-0.14	0.19	0.03
GLKD	**-0.34**	0.24	-0.23	-0.28	**-0.36**	**-0.36**	-0.31	-0.22	-0.30	0.25	**-0.46**
GLTM	**0.47**	-0.25	**0.56**	**0.60**	**0.40**	**0.39**	0.15	**0.59**	**0.51**	**-0.38**	**0.56**
GLCG	**0.40**	-0.21	0.21	0.21	**0.37**	**0.40**	0.21	0.15	**0.37**	-0.21	0.07

Note: Bold values indicate correlation coefficients that are significant at the 5 % level

6.4 Mean annual runoff

Table 6.1 shows a strong correlation between mean annual runoff (Q) and mean annual rainfall (MAP) (r = 0.73), which indicates an increase in runoff with increasing rainfall. ET shows a negative correlation with Q (r = -0.27).

Mean annual runoff shows a moderate correlation with S_{ave}, S_{20}, S_{50}, and S_{90} (Table 6.1), which is expected as Chapter 5 identified that high runoff tends to occur within catchments of steep slopes and high rainfall. Soil depth has also been found to decrease with increasing elevation, which consequently reduces infiltration in headwater regions and promotes runoff (Mu *et al.,* 2015; Malan, 2016). The correlation between runoff and slope decreases with decreasing slope (Table 6.1). S_{20} shows a correlation of 0.51, whereas S_{90} shows a correlation of 0.39 with runoff.

Q shows a moderate correlation with GL_{TM} (r = 0.47) (Table 6.1). A moderate correlation between runoff and the Table Mountain Group is expected as Chapter 5 identified that catchments underlain by the Table Mountain Group are typically found within parts of the study area characterised by high rainfall and steep slopes, and consequently high runoff. GL_{KD} shows a negative correlation with Q (r = -0.34) (Table 6.1), which is a result of the lithology being found within parts of the study area characterised by low rainfall and slope, and consequently low runoff. Plantations (LC_P) also show a moderate correlation with runoff (Table 6.1). Chapter 5 identified that plantations are typically found within mountainous parts of the study area, with high elevation, steep slopes and high rainfall, and consequently high runoff. Grasslands (LC_G) show a negative correlation with runoff (Table 6.1). Grasslands are typically found within parts of the study area characterised by low elevation, high evaporation and low rainfall, which was identified in Chapter 5.

The predictive equation for estimating mean annual runoff based on catchment attributes using step-wise regression and the model performance is presented in Figure 6.2. The observed results show a good model performance based on the R^2 (0.73), % RMSE (60) and RSR (0.51). The results suggest that mean annual runoff can be predicted with a good model accuracy and low predictive error based on guidelines of previous studies (Moriasi *et al*, 2007).

Neural networks were used to compare the model performance for predicting mean annual runoff with multiple regression. Table 6.2 presents the neural networks that were selected for predicting mean annual runoff. The neural networks were selected on the basis of the R^2, % RMSE and RSR of the model. Table 6.2 also presents the characteristics of the neural networks, including the type of neural network, and the number of input and hidden layers used to predict the output variable. Neural networks have the ability to model non-linear relationships between flow and catchment characteristics, and the inclusion of S_{20}, S_{90} and GL_{TM} in the neural networks (Table 6.2) suggests that these catchment characteristics are non-linearly related to Q, which cannot be identified using multiple linear regression.

Table 6.2: Neural networks used for predicting mean annual runoff from catchment characteristics

Type of network	Number of units in the hidden layer	Catchment characteristics	R^2	% RMSE	RSR
MLP 7-9-1	9	S_{20}, S_{90}, MAP, GL_{TM}, ET, LC_G, BFI	0.72	66.16	0.56
Linear 6-1	None	MAP, LC_G, S_{20}, GL_{TM}, S_{90}, ET	0.64	70.22	0.60

Notes:

1. MLP 7-9-1: multi-layer perceptron with 7 input variables, 9 units in the hidden, and 1 output unit
2. Linear 6-1: Linear model with 6 input variables and 1 output unit

MLR and MLP 7-9-1 demonstrate a good model performance for predicting mean annual runoff (Figure 6.2). These models have a low RMSE and RSR, which suggest a low predictive error for predicting mean annual runoff.

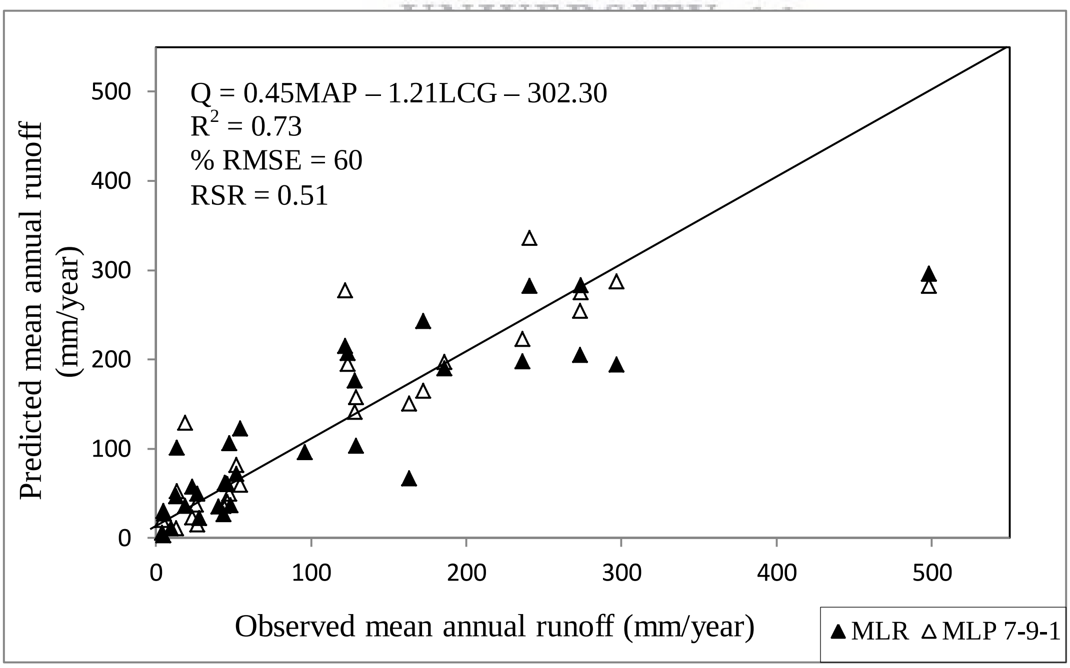


Figure 6. 2: Comparison between the performance of multiple regression and an MLP 7-9-1 artificial neural network in predicting mean annual runoff

The use of multiple regression and MLP 7-9-1 are suitable for predicting mean annual runoff of non-perennial rivers based on their model performance. Although multiple regression is recommended as the method is simpler and has a lower predictive error compared to the MLP 7-9-1. The use of multiple regression was also shown to be suitable for predicting runoff in previous studies (Mazvimavi, 2003; Mazvimavi *et al*, 2005; Lacombe *et al*, 2014). The model for predicting mean annual runoff using multiple regression can be recommended for future studies.

6.5 Flow duration curve

An exponential model (Eq. 6.2) was found to be suitable for modelling the relationship between dimensionless daily flows and the exceedence probability of non-perennial rivers. The α coefficient in Eq. 6.2 can be related to BFI, with the following equation being derived:

$$a = 32.96\,\exp -6.07\,(BFI) \qquad R^2 = 0.73 \qquad (6.8)$$

The coefficient, β, is not related to any catchment attribute used in the study. The exponential model equation for predicting FDCs in ungauged basins therefore becomes:

$$q_p = \beta\,\exp\{-[32.96\,\exp(-6.07BFI)p]\} \qquad (6.9)$$

The prediction of flow percentiles using an exponential model shows a good model performance based on the R^2 ranging between 0.99 to 0.61 and RSR ranging between 0.66 to 0.1 (Figure 6.3). Predicting high flow percentiles, such as q_{10} to q_{60}, shows a high model performance where the RSR value is less than 0.5 (Moriasi *et al*, 2007). Although the prediction of low flow percentiles, such as q_{90} and q_{80}, shows a poor performance in comparison to high flow prediction (Figure 6.3), the accuracy of predicting low flow percentiles can be considered acceptable as R^2 is greater 0.6 and RSR is less than 0.66 (Moriasi *et al*, 2007). This trend is expected as the accuracy for predicting flow percentiles has been shown to decrease from high to low flow percentiles (Hope & Bart, 2012).

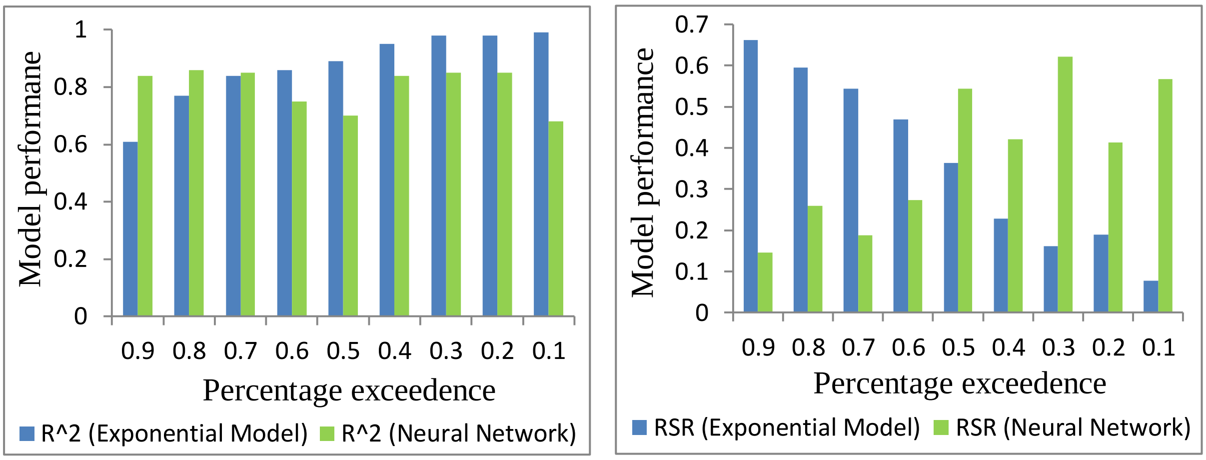


Figure 6. 3: Comparison of the model performance for predicting flow percentiles using an exponential model and neural networks based on the RSR and R^2

The possibility of using neural networks to predict flow percentiles from catchment attributes was explored. The most suitable prediction of flow percentiles was made by a multi-layer perceptron with input variables including MAP, S_{20}, S_{50}, S_{90}, ET, Dd and BFI. Prediction of flow percentiles using neural networks show opposing trends compared to the exponential model, where low flow percentiles, q_{70} to q_{90}, are predicted with higher model accuracy compared to high flow percentiles, such as q_{10} (Figure 6.3). This suggest that neural networks have a greater ability to predict low flows, q_{90}, q_{80} and q_{70}, from catchment attributes than flood events, q_{10}. Although the prediction of high flows has a considerable lower predictive accuracy compared to low flows, these models can be regarded as acceptable, as the R^2 and RSR value is within a specific range of acceptance.

Figure 6.4 compares the flow duration curve derived using observed flows with those predicted using a neural network and exponential model. For the catchments presented, the prediction of the flow duration curve using the exponential model has a lower predictive error in comparison to the use of neural networks (Figure 6.4). The results show that the prediction of high flow percentiles, q_{10} and q_{20}, using neural networks has a higher RMSE in comparison to the exponential model.

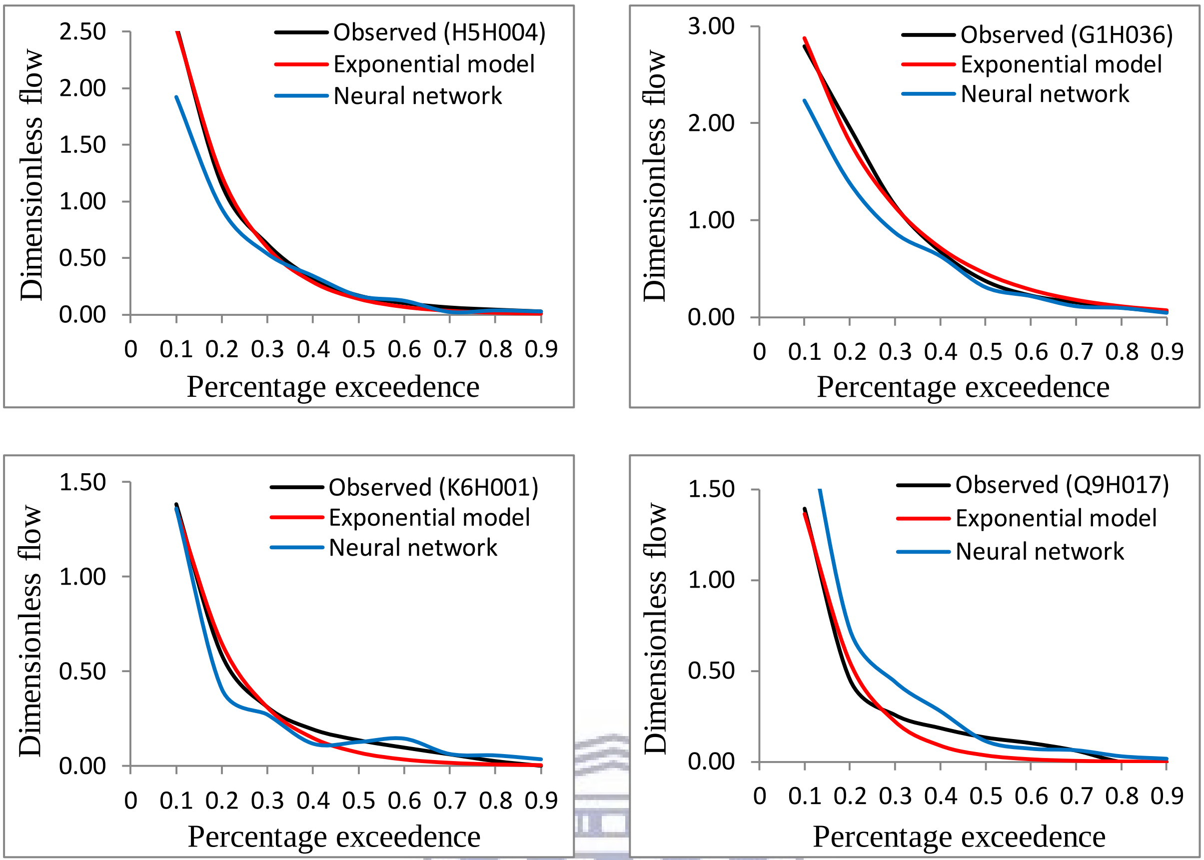


Figure 6.4: Comparison of observed flow duration curves with those predicted using an exponential model and neural network for catchments H5H004, G1H036, K6H001 and Q9H017

The results suggest that the prediction of flow duration curves of non-perennial rivers in ungauged catchments reveal a good model performance using an exponential model. The prediction of flow duration curves in ungauged catchments may be improved by increasing the sample size of catchments used in the study, which may improve in deriving the β coefficient. The study used 36 gauged non-perennial rivers which may not have been sufficient to derive the β coefficient using catchment attributes. In the case of this study, the β coefficient was shown to have no relationship with catchment attributes. An alternative approach could be recommended by estimating the β coefficient as a cluster average through clustering catchments into homogenous groups. We could assume that catchments belonging to the same cluster have similar β coefficients.

6.6 Baseflow Index

The use of multiple regression for predicting BFI shows a good model performance based on R^2, RSR and RMSE (Figure 6.5). This model can be considered satisfactory as the R^2 and RSR is within a specific range (Moriasi *et al*, 2007). Mazvimavi *et al* (2005) predicted BFI with a higher coefficient of determination ($R^2 = 0.75$) compared to model performance of this study ($R^2 = 0.58$). This may be due to the fact that the correlation between BFI with mean annual rainfall and slope were not found to be as significant in this study (Table 6.1). This study observed a correlation coefficient of (r = 0.55) between BFI and rainfall and (r = 0.51) between BFI and S_{50}, whereas Mazvimvi *et al* (2005) observed a correlation coefficient of (r = 0.60) between BFI and rainfall and (r = 0.74) between BFI and S_{50}. Rainfall tends to be high in mountainous areas; however, there are parts of the study area that are characterised by arid and semi-arid conditions with high elevation, steep slopes and low rainfall. This would therefore decrease the correlation between rainfall and slope with BFI. Previous studies have shown a strong correlation between BFI with rainfall and slope (Mazvimavi, 2003; Rumsey *et al*, 2015), which observed an increase in BFI with increasing rainfall and slope.

The neural networks that were recognised as most promising for predicting BFI based on the statistical performance indices used in the study are presented in Table 6.3. The results indicate that the use of neural networks shows a poor model performance as the R^2 value is less than 0.5 and the RSR value is in the range that is considered as an unsatisfactory model (Moriasi *et al*, 2007).

Table 6.3: Neural networks used for predicting baseflow index (BFI) based on catchment characteristics

Type of Network	Number of units in the hidden layer	Catchment characteristics	R^2	% RMSE	RSR
Linear 3-1	None	MAP, LC_G, GL_{TM}	0.42	31.04	0.75
MLP 5-4-1	4	MAP, GL_{TM}, LC_G, S_{50}, LC_P	0.40	37.37	0.91

Notes:

1. Linear 3-1: Linear model with 3 input variables and 1 output unit

2. MLP 5-4-1: multi-layer perceptron with 5 input variables, 4 units in the hidden, and 1 output unit

The use of a Linear 3-1 neural network has a higher predictive error for predicting BFI compared to the use multiple regression (Figure 6.5). Multiple regression is therefore more suitable for predicting baseflow index of non-perennial rivers compared to neural networks due to higher model performance.

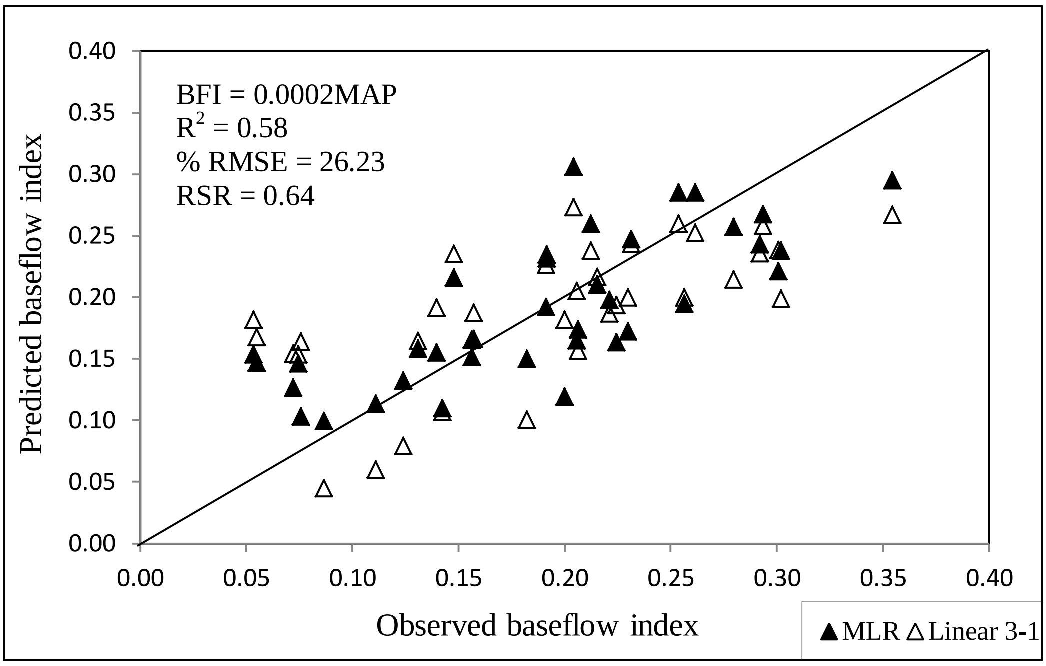


Figure 6.5: Comparison between the performance of multiple regression and a Linear 3-1 neural network for predicting baseflow index

The quantification of hydrogeological characteristics in terms of the depth to the water table, permeability, and porosity may improve the prediction performance of BFI. The proportion of catchments underlain by different lithology types may not have been sensitive in describing the variation of BFI in the study, which was shown to have to have a satisfactory model performance. Such catchment attributes are important in controlling the water storage and groundwater flow routing in the catchment, which are essential in explaining low flows (Abebe & Foerch, 2006; Cervi *et al*, 2017). Studies have suggested that characterising the fracture behaviour and geometry of geological units within the catchment may improve the prediction of low flows (Cervi *et al*, 2017).

6.7 Number of zero flow days

The prediction of the number of zero flow days using multiple regression shows a satisfactory model performance based on the R^2 and RSR value (Figure 6.6). Table 6.4 presents the neural networks that were found to be most suitable for predicting number of zero flow days. The results show that the MLP 5-6-1 neural network can be considered as a satisfactory performance for predicting the number of zero flow days, based on the R^2 and RSR.

Table 6. 3: Neural networks used for predicting number of zero flow days (ZFD) from catchment attributes

Type of Network	Number of units in the hidden layer	Catchment attributes	R^2	% RMSE	RSR
MLP 5-6-1	6	BFI, MAP, E_{min}, ET, Dd	0.58	72.70	0.67
MLP 5-7-1	7	MAP, BFI, E_{min}, Dd, ET	0.56	71.59	0.66

Notes:

1. MLP 5-6-1: multi-layer perceptron with 5 input variables, 6 units in the hidden layer, and 1 output unit
2. MLP 5-7-1: multi-layer perceptron with 5 input variables, 7 units in the hidden layer, and 1 output unit

MLR and MLP 5-6-1 underestimates catchments with high number of zero flow days, as well as over-estimating for catchments with low number of zero flow days (Figure 6.6). Although there are several catchments where the number of zero flow days is under and over-estimated, these models can be considered as satisfactory in terms of the model performance.

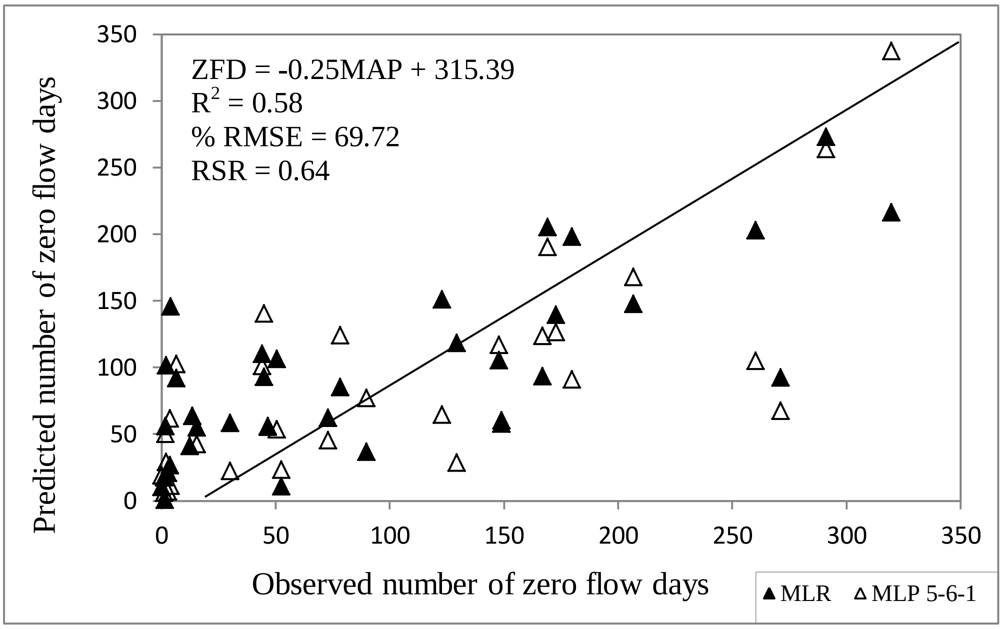


Figure 6. 6: Comparison between the performance of multiple regression and a MLP 5-6-1 artificial neural network for predicting number of zero flow days

The use of multiple regression would be considered as more suitable for prediction of the number of zero flow days of non-perennial rivers, as the approach has a higher model performance based on the coefficient of determination, RMSE and RSR compared to the use of neural networks.

6.8 3-day minima and 3-day maxima of daily flows

Table 6.4 presents the model performance for predicting 3-day min and 3-day max using multiple regression. The results indicate the prediction of 3-day min shows a higher model performance compared to predicting 3-day max. The prediction of 3-day min shows a moderate R^2; however, the results indicate a high % RMSE.

Table 6.4: Predictive equations for predicting 3-day minima and maxima of daily means of discharge

Dependent variable	Predictive equation	R^2	% RSME	RSR	
3-day min	$1.46S_{90} + 0.02MAP - 0.41S_{20} - 0.10S_S$	0.65	137.90	0.58	(6.10)
3-day max	$5.27MAP + 20.86GL_{TM}$	0.58	0.31	0.64	(6.11)

Table 6.5 presents the results for predicting 3-day min and 3-day max using neural networks, which only provides the best performing neural network. The model performance for predicting 3-day min and 3-day max shows similar trends to multiple regression (Table 6.4), where the prediction of 3-day min shows a higher model performance, as well as a higher margin of error for prediction based on the % RMSE compared to predicting 3-day max.

Table 6.5: Predicting 3-day minima and maxima of daily means of discharge using neural networks

Dependent variable		R^2	% RMSE	RSR
3-day min	MLP 4-8-1	0.80	113.90	0.48
3-day max	MLP 4-8-1	0.48	80.42	0.73

The results suggest that the use of neural networks seems to be more suitable for the prediction of 3-day min due to a higher coefficient of determination. The results suggest that the margin of error for predicting 3-day min is high based on the % RMSE. Multiple regression is more suitable for the prediction of 3-day max than the use of neural networks due to higher model performance based on the coefficient of determination and lower % RMSE.

6.9 Discussion and conclusion

In this chapter, two data driven modelling techniques, namely multiple linear regression (MLR) and artificial neural networks (ANNs) were used for the prediction of flow characteristics of non-perennial rivers. The aim of the chapter was to identify which approach would be more suitable for predicting selected flow characteristics of non-perennial rivers. Overall MLR seems to be more suitable for predicting flow characteristics of non-perennial rivers compared to the use of neural networks. The chapter found that the prediction of mean annual runoff, BFI, number of zero flow days and 3-day max show a good model performance using multiple regression and these equations can be recommended for future studies. Mazvimavi (2003), Mazvimavi *et al* (2005) and Lacombe *et al* (2014) showed that multiple regression models perform well for predicting discharge of flow, which was also shown in this study.

An exponential model was found to be a promising approach for predicting the flow duration curve of non-perennial rivers with a lower predictive error than neural networks. The prediction of high flow percentiles, q_{10} and q_{20}, was shown to have a higher model performance compared to low flow percentiles, such as q_{80} and q_{90}. The use of neural networks seems to be a feasible approach for predicting low flow percentiles, which was shown to outperform the exponential model. The results urge future studies to increase the sample size of catchments used which may improve the derivation of the β coefficient of the exponential model equation.

The chapter also highlighted the importance of using artificial neural networks for predicting selected flow characteristics, such as 3-day min and low flow percentiles, q_{90} and q_{80}. Riad *et al* (2004) and Aichouri *et al* (2015) showed that artificial neural networks perform better than the traditional regression model in predicting flow. The results of these studies showed that neural networks are capable of modelling complex non-linear rainfall-runoff relationships in arid and semi-arid regions, where the relationship between rainfall and runoff is typically irregular. The chapter revealed that the prediction of 3-day min using neural networks shows a higher model performance compared to multiple regression. This suggests that some catchment characteristics have a non-linear relationship with these flow characteristics and cannot be suitable identified using multiple regression. In instances where the model performance of prediction using ANNs are similar or marginally better compared to multiple regression, multiple regression should be considered as more suitable, as the approach is simpler. Previous studies have identified that the network architecture of the neural network can have a substantial influence on the model performance, as well as issues surrounding over-parameterization, which reduces the predictive powers of the model. Although the results show that multiple regression and neural networks have the capability of predicting selected flow characteristics of non-perennial rivers based on the coefficient of determination, some flow characteristics show a high margin of error for prediction based on the RMSE, such as 3-day min, which needs to be taken into consideration when predicting these flow characteristics in ungauged catchments.

The results of the study urge the use of hydrogeological characteristics such as depth to the water table, permeability and porosity which is important catchment attributes controlling the water storage and groundwater flow routing in the catchment. This may improve the prediction of low flow percentiles, number of zero flow days and BFI. The results of the study recommend future studies to increase the number of catchments used, which may improve the accuracy of prediction. This would increase the variability of flow characteristics and catchment attribute which may allow to the relationship between flow indices and catchment attributes to be more discernible.

CHAPTER 7: IDENTIFICATION OF CATCHMENTS WITH SIMILAR HYDROLOGICAL PROCESSES

7.1 Introduction

Chapter 6 developed predictive equations for predicting flow characteristics in ungauged catchments. This chapter explores whether or not the prediction of flow characteristics is improved by clustering catchments into homogenous groups. A homogenous group refers to grouping of catchments that have a similar hydrological response. The primary objective of clustering catchments into homogenous groups is to assess the membership of ungauged catchments, thus predicting hydrological responses of such catchments.

7.2 Methodology

Cluster analysis is the process of grouping similar catchments according to one or more chosen hydrological signatures, where catchments belonging to the same group are similar (Sawicz *et al.*, 2011; Olden *et al.*, 2015; Elesbon *et al.*, 2015; Begou *et al.*, 2015; Singh *et al.*, 2016; Rahmat *et al.*, 2017). The aim of cluster analysis in the context of the study is to delineate hydrologically homogenous groups, which would allow the transfer of information between gauged and ungauged catchments (Toth, 2013; Singh *et al.*, 2016). Flow characteristics of ungauged catchments can be estimated based on the cluster to which the catchment belongs to, whereby average flow characteristics can be given. The assumption is that catchments within the same group have similar hydrological responses and information can be transferred between them.

Cluster analysis methods are broadly classified into hierarchical and partitioning clustering methods (Ahmad *et al.*, 2013; Zhou *et al.*, 2017; Li *et al.*, 2018). Hierarchical clustering algorithm is the most widely used algorithm (Demirel & Kahya, 2007; Rahmat *et al.*, 2017), whereas k-mean clustering is the one of the most commonly used partitioning clustering method (Li *et al.*, 2018). The Euclidean distance is commonly used as the distance metric in hydrological studies (Blöschl *et al.*, 2013; Latt *et al.*, 2015; Rahmat *et al.*, 2017).

The main issue with cluster analysis in the context of hydrological studies is the availability of different clustering algorithms and distance metrics (Olden *et al.*, 2015). Unfortunately, different clustering algorithms and distance metrics used on the same dataset produce different results (Ahuja, 2012; Olden *et al.*, 2015; Begou *et al.*, 2015). The selection of clustering methods is therefore subjective, and for this particular reason there is no generally agreed clustering method in hydrological studies (Sawicz *et al.*, 2011, Singh *et al.*, 2016).

Cluster analysis was used in the study to group catchments in hydrological homogenous groups. The study used agglomerative hierarchical clustering algorithms and euclidean distance to define homogenous classes between the flow characteristics, as this algorithm and distance metric is widely used in hydrological studies (Demirel & Kahya, 2007; Blöschl *et al.*, 2013; Latt *et al.*, 2015). The use of agglomerative clustering has become more common due to the less time complexity and computational stability (Zhou *et al.*, 2017). The Euclidean distance commonly gives the similarity between two catchments and a distance can be represented by the difference between analytical values from the catchments (Rahmat *et al.*, 2017). Agglomerative clustering is displayed as a dendrogram and starts with n clusters, each of which contains a single object in the data (Yan, 2005; Ahmad *et al.*, 2013; Singh *et al.*, 2016). In the second step, the catchments that are most similar are fused and create a new cluster (Yan, 2005; Ahmad *et al.*, 2013). Eventually, the final result of agglomerative clustering shows all the subgroups fused into one group, where the vertical axis on the dendrogram shows the level of similarity to increase with increasing the number of clusters (Yan, 2005; Li *et al.*, 2018; Ahmad *et al.*, 2013; Singh *et al.*, 2016).

7.2.1 Selection of catchment descriptors for the derivation of clusters

Fraiman *et al* (2008) pointed out that the determination of which variables are important in cluster analysis can be a difficult task. The inclusion of insignificant and redundant variables introduces ‘noise’ in cluster analysis and the results of the clusters may not reveal the classification objectives, such as classifying catchments into hydrologically homogenous groups (Fraiman *et al.*, 2008; Marlini & Zani, 2013). Redundancy analysis in Chapter 5 identified catchment characteristics that significantly explain the variance of flow characteristics, which included MAP and $S_{90.}$ These catchment characteristics are standardized to ensure that the analysis is independent of measurement units used for the above mentioned catchment characteristics, which can be expressed as (Mazvimavi, 2003):

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \quad (7.1)$$

Where; i= 1,…n_c catchments, j= 1,…n_c explanatory variables, z_{ij} = standardized variable j at catchment i, x_{ij} = value of variable j at catchment i, $\bar{x}_j$ = mean of variable across all catchments, and S_j= standard deviation for variable j over all catchments.

7.2.2 Determination of the number of clusters and validation

The final step of cluster analysis is to determine a suitable estimate for the number of clusters, which has a deterministic effect on the results obtained (Yan, 2005). One of the main difficulties with using this approach is that the correct number of clusters is often unknown (Yan, 2005; Kodinariya & Makwana, 2013; Zhou *et al.*, 2017).

Cluster validation is an approach of assessing the validity of the classifications that have been obtained in the clustering algorithm (Yan, 2005; Yu *et al.*, 2014). Cluster validation provides a mean of checking the quality of the cluster results and the optimum number of clusters from the clustering algorithm (Yu *et al.*, 2014). Higher cluster validity reflects a higher agreement between the clustering results and the members associated with clusters (Yan, 2005). The validation of clustering algorithms can be done by simple visual inspection. For example, if a catchment with high mean annual runoff and high rainfall is grouped within a cluster associated with high rates of evaporation and low mean annual runoff. The groupings of these two catchments are therefore not hydrologically sensible. An alternative approach to validate the results obtained in the clustering algorithm is the use of Andrew's curve.

Andrews curve or plot provides a graphical observation of the homogenous groups (Rahmat *et al.*, 2017). The use of Andrews curve can be used to determine the homogeneity of catchments within clusters and catchments that show distinct differences based on the curves can be placed into another group. One of the limitations with Andrews curve is that they are not able to preserve the order (Rahmat *et al.*, 2017). For example, the curve will be completely different if the variables used in the clustering algorithm are altered (Rahmat *et al.*, 2017). The Andrews curves are produced as (Mazvimavi, 2003):

$$f(v) = \frac{z_{i1}}{\sqrt{2}} + z_{i2}\sin(v) + z_{i3}\cos(v) + z_{i4}\sin(v) + z_{i5}\cos(v) \qquad (7.2)$$

Where; z_{i1}, z_{i2}, z_{i3} are the standardized catchment characteristics. The shape of the curves are affected by the order in which the catchment characteristics are presented. Studies have identified that it is important to represent the most important catchment characteristic explaining the variance of flow characteristics as z_{i1}. The reason for the ordering of variables is that the variables at the beginning have low frequency cycles and are readily discerned; whilst variables at the end show higher frequency cycles and may not being easily discerned (Mazvimavi, 2003; Gharibnezhad *et al.*, 2011). The results of redundancy analysis identified which catchment characteristics are significant in explaining the variance of flow characteristics. The following order of catchment characteristics was used to generate Andrews curve, MAP (z_{i1}), S_{90} (z_{i2}) and GL_{TM} (z_{i3}). Andrews curve identifies whether or not catchments have been grouped correctly based on the shape of the curves and if catchments have been placed in the wrong cluster, the catchment is removed from the cluster (Rahmat *et al.*, 2017).

Mazvimavi (2003) pointed out that it is important in the context of hydrological regionalisation studies to group catchments that explain the variability of flow characteristics. An important validation technique is to compare the clustering results from those derived from catchment characteristics and those derived from flow characteristics. An agreement between clusters derived from both catchment and flow characteristics validates the delineation of homogenous groups. The Rand Index (R_g) can be used to determine the level of agreement between clusters derived from catchment and flow characteristics. R_g is the ratio of the total number of pairs of catchments that are grouped in both clustering algorithms and those which occur in different groups, to the total number of possible combinations. The R_g can be expressed as (Mazvimavi, 2003):

$$R_g = \left[T_g - \frac{U_g}{2} - \frac{V_g}{2} + \binom{n}{2}\right] / \frac{n}{2} \qquad (7.3)$$

$$T_g = \sum_{i=1}^{g}\sum_{j=1}^{g} mij^2 - n \qquad (7.4)$$

$$U_g = \sum_{i=1}^{g} mj.^2 - n \qquad (7.5)$$

$$V_g = \sum_{i=1}^{g} m.j^2 - n \qquad (7.6)$$

Where g is the number of clusters, m_{ij} is the number of catchments in common between the ith cluster (catchment characteristics) and jth cluster (flow characteristics), which forms a matrix M. The matrix calculates $m_{.j}$ which is the marginal column total of M and $m_{j.}$ which is the marginal row total of M. The R_g index ranges between 0 and 1, where values closer to 1 show a strong agreement between clusters derived from catchment and flow characteristics.

7.3 Results and Discussion

7.3.1 Classification of clusters using catchment characteristics

Table 7.1 shows the membership of catchments for 2 to 10 cluster. There are no significant changes in the composition of clusters when the number of clusters increases from 4 to 6. Catchments that are affected by an increase in clusters from 4 to 6 include; E2H007, J3H017, H3H005, J2H005 and H4H015 which form a new cluster when the number of clusters is 5 and K3H001, K5H002 and K3H004 form a new cluster when the number of clusters is 6. An increase in the number of clusters from 6 to 10 results in minor subdivisions.

7.3.2 Classification of clusters using flow characteristics

Table 7.2 shows the membership of catchments for 2 to 10 clusters, which was derived from catchment characteristics. Increasing the number of clusters from 3 to 5 shows no significant change in the composition of members, with H4H015, K3H001 and K3H004 forming a new cluster. K3H004 is an outlier and forms an individual cluster when the number of clusters is 3. Cluster 1 has a major subdivision of cluster membership when the number of clusters increases from 6 to 7 clusters

Table 7.1: Cluster membership for 2 to 10 clusters based on cluster analysis of catchment characteristics

	10	9	8	7	6	5	4	3	2
D3H015	1	1	1	1	1	1	1	1	1
D5H011	1	1	1	1	1	1	1	1	1
G5H008	1	1	1	1	1	1	1	1	1
J1H018	1	1	1	1	1	1	1	1	1
E3H001	1	1	1	1	1	1	1	1	1
J1H017	1	1	1	1	1	1	1	1	1
E2H007	2	2	2	2	2	2	1	1	1
J3H017	2	2	2	2	2	2	1	1	1
H3H005	3	2	2	2	2	2	1	1	1
J2H005	3	2	2	2	2	2	1	1	1
H4H016	3	2	2	2	2	2	1	1	1
G1H031	4	3	3	3	3	3	2	2	1
K3H003	4	3	3	3	3	3	2	2	1
G1H041	4	3	3	3	3	3	2	2	1
G1H036	4	3	3	3	3	3	2	2	1
G4H014	5	4	4	3	3	3	2	2	1
H1H006	5	4	4	3	3	3	2	2	1
H5H004	5	4	4	3	3	3	2	2	1
G2H012	6	5	5	4	4	4	3	2	1
S3H006	6	5	5	4	4	4	3	2	1
R2H009	6	5	5	4	4	4	3	2	1
H8H001	6	5	5	4	4	4	3	2	1
J3H018	7	6	6	5	4	4	3	2	1
Q6H003	7	6	6	5	4	4	3	2	1
P4H001	7	6	6	5	4	4	3	2	1
S3H012	7	6	6	5	4	4	3	2	1
R3H001	7	6	6	5	4	4	3	2	1
R3H003	7	6	6	5	4	4	3	2	1
Q9H002	7	6	6	5	4	4	3	2	1
Q9H017	7	6	6	5	4	4	3	2	1
H4H015	8	7	7	6	5	5	4	3	2
J3H016	9	8	7	6	5	5	4	3	2
K6H001	9	8	7	6	5	5	4	3	2
K3H001	10	9	8	7	6	5	4	3	2
K5H002	10	9	8	7	6	5	4	3	2
K3H004	10	9	8	7	6	5	4	3	2

Table 7.2: Cluster membership for 2 to 10 clusters based on cluster analysis of flow characteristics

	10	9	8	7	6	5	4	3	2
D3H015	1	1	1	1	1	1	1	1	1
S3H006	1	1	1	1	1	1	1	1	1
D5H011	1	1	1	1	1	1	1	1	1
E3H001	1	1	1	1	1	1	1	1	1
G5H008	1	1	1	1	1	1	1	1	1
J1H018	1	1	1	1	1	1	1	1	1
Q6H003	1	1	1	1	1	1	1	1	1
Q9H017	1	1	1	1	1	1	1	1	1
S3H012	1	1	1	1	1	1	1	1	1
G2H012	2	2	2	2	1	1	1	1	1
H3H005	2	2	2	2	1	1	1	1	1
J1H017	2	2	2	2	1	1	1	1	1
J3H017	2	2	2	2	1	1	1	1	1
J2H005	2	2	2	2	1	1	1	1	1
J3H018	2	2	2	2	1	1	1	1	1
Q9H002	2	2	2	2	1	1	1	1	1
E2H007	3	3	3	3	2	2	2	2	1
G1H031	3	3	3	3	2	2	2	2	1
G4H014	3	3	3	3	2	2	2	2	1
K6H001	3	3	3	3	2	2	2	2	1
P4H001	3	3	3	3	2	2	2	2	1
R3H003	3	3	3	3	2	2	2	2	1
G1H036	4	4	4	4	3	2	2	2	1
H4H016	4	4	4	4	3	2	2	2	1
H5H004	4	4	4	4	3	2	2	2	1
J3H016	5	5	4	4	3	2	2	2	1
R2H009	5	5	4	4	3	2	2	2	1
R3H001	5	5	4	4	3	2	2	2	1
G1H041	6	6	5	5	4	3	3	3	2
K5H002	6	6	5	5	4	3	3	3	2
H8H001	6	6	5	5	4	3	3	3	2
H1H006	7	7	6	5	4	3	3	3	2
K3H003	7	7	6	5	4	3	3	3	2
H4H015	8	8	7	6	5	4	3	3	2
K3H001	9	8	7	6	5	4	3	3	2
K3H004	10	9	8	7	6	5	4	3	2

7.3.3 Number of clusters

Figure 7.1 presents the results of the Rg statistic which determines the level of agreement between cluster memberships derived from catchment characteristics and flow characteristics.

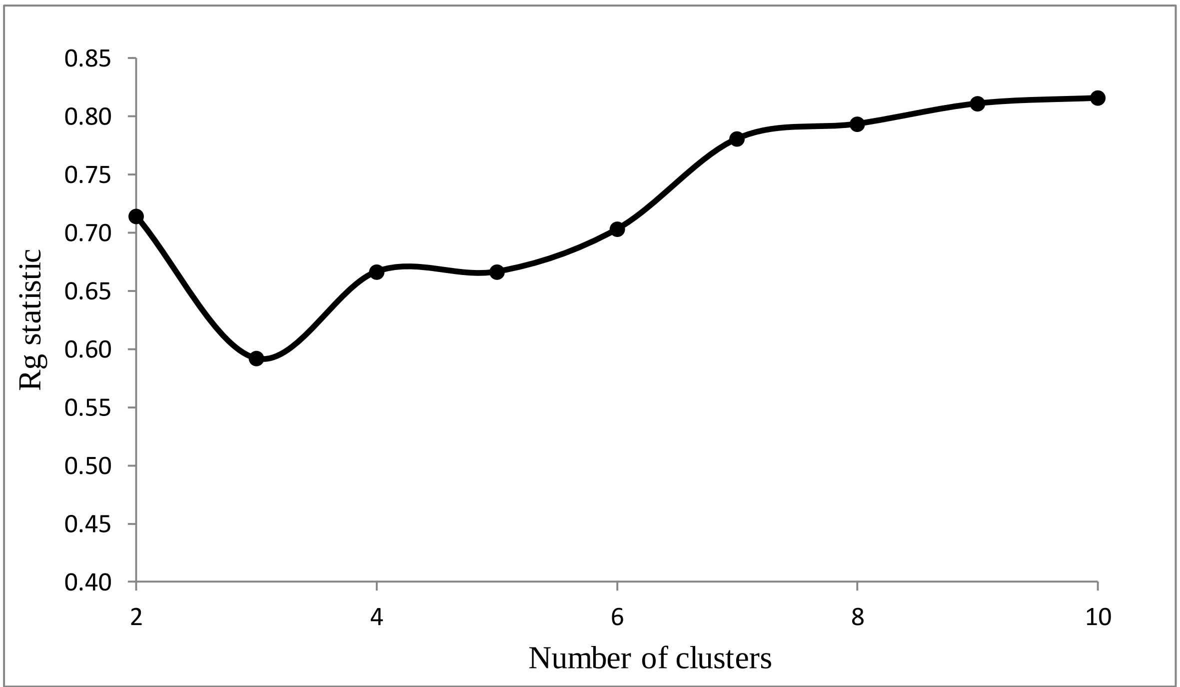


Figure 7.1: Variation of R_g statistics with increases in the number of clusters

Figure 7.1 shows that increasing the number of clusters from 2 to 3 causes Rg statistic to decrease from 0.71 to 0.59. An increase in the number of clusters from 4 to 6 causes Rg to increase from 0.67 to 0.70. An increase in the number of clusters from 6 to 7 causes Rg statistic to increase from 0.70 to 0.78. No significant change in the Rg statistic occurs when the number of clusters increases from 7 to 10. R_g statistic suggests that the number of clusters should be 7. An alternative approach that was used to select the number of clusters was the analysis of the flow duration curve of the clusters. For each cluster, the average flow duration curve was plotted based on q_{10}, q_{25}, q_{75}, and q_{90} (Figure 7.2). This identifies whether or not there are distinct hydrological responses between different clusters and whether or not they are hydrologically different. The analysis was undertaken for 4 to 7 clusters based on the results of the Rg statistic, which would identify the optimum number of clusters for the study.

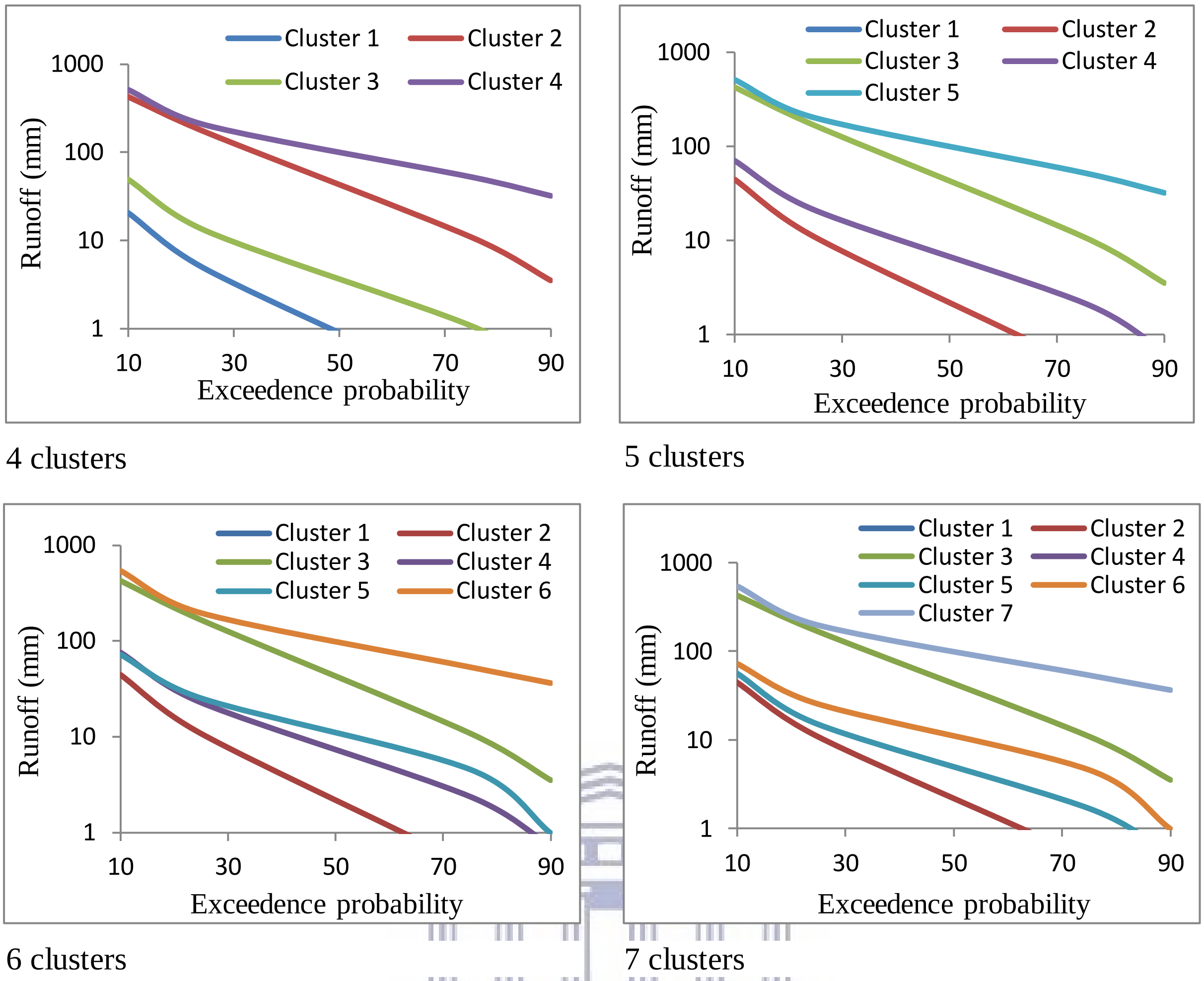
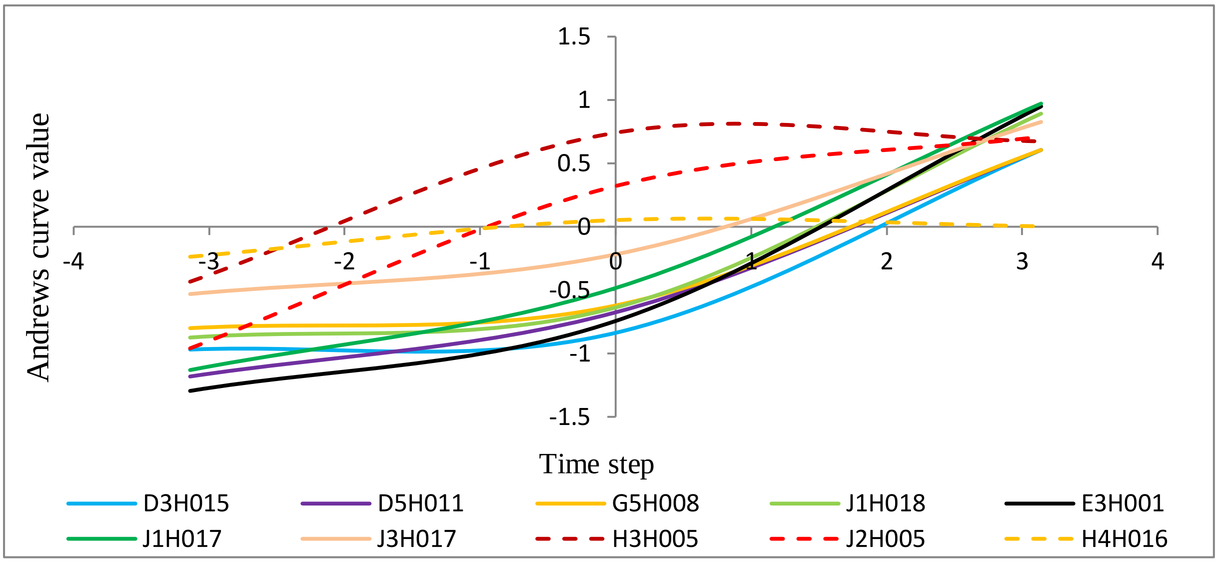
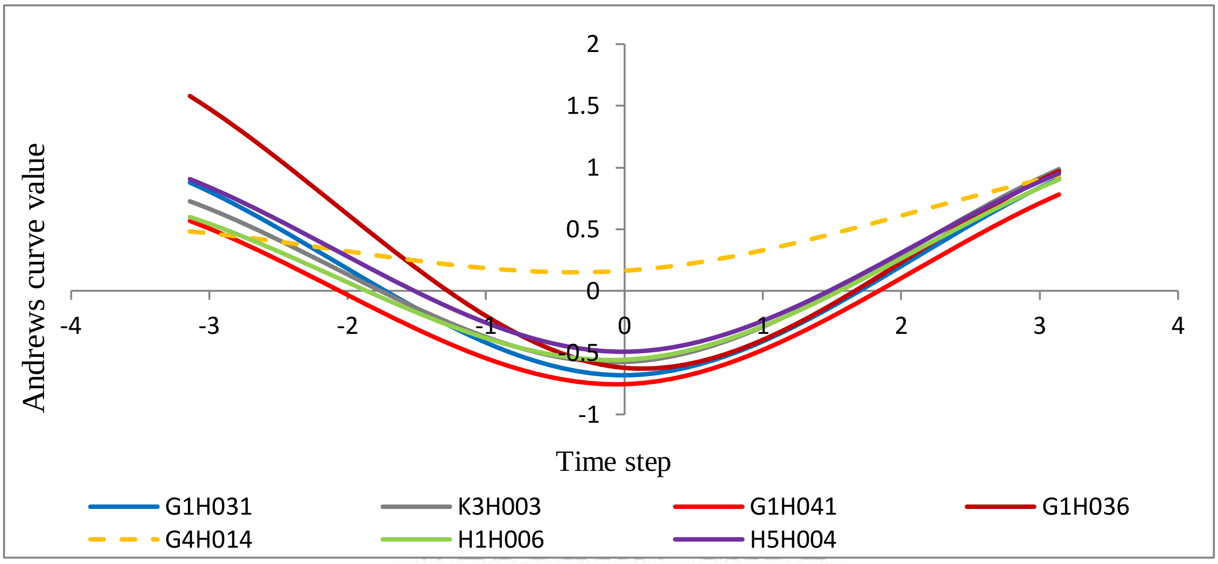


Figure 7.2: Comparison of the average flow duration curve for cluster membership when the number of clusters is 4, 5, 6 and 7

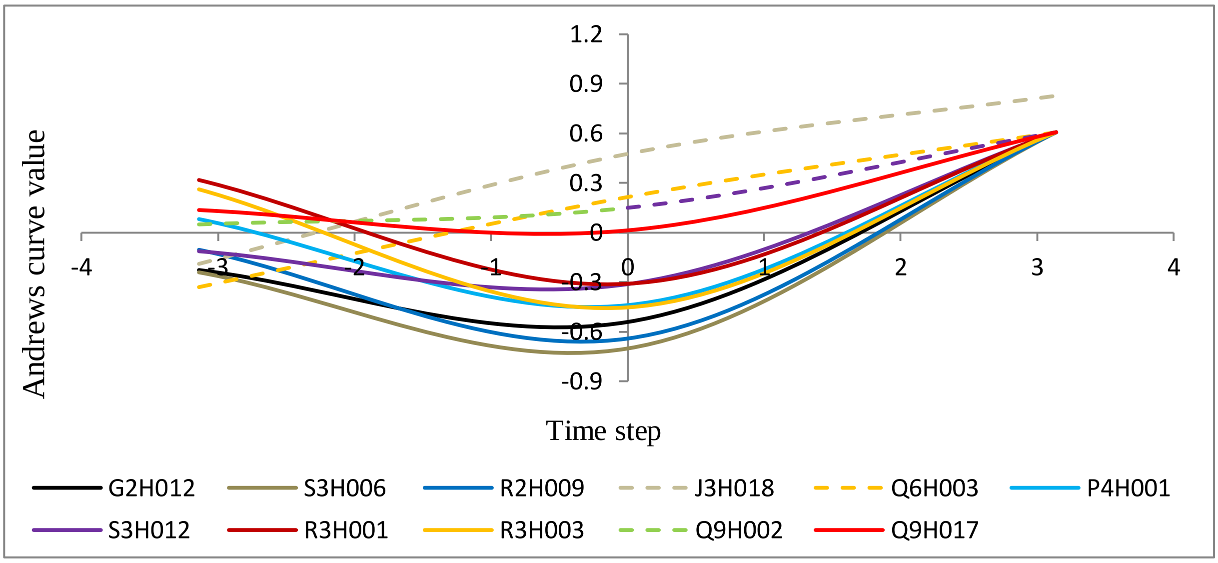
Figure 7.2 illustrates that when the number of clusters is 4, cluster 2 and 4 seem similar in terms of q_{10} and q_{25}. However cluster 2 represents a steeper flow duration curve compared to cluster 1 and thus is hydrologically different. Similar trends are found between cluster 1 and 3, however cluster 3 is representative of higher discharge. When the number of clusters increases from 5 to 7 there does not seem to be noticeable differences between the flow duration curves amongst the clusters and therefore the hydrological responses within clusters are no longer unique. The results suggest that the number of clusters should be 4, which is representative of hydrologically similar clusters. Andrew's curves were plotted for these clusters, which are presented in Figure 7.3.



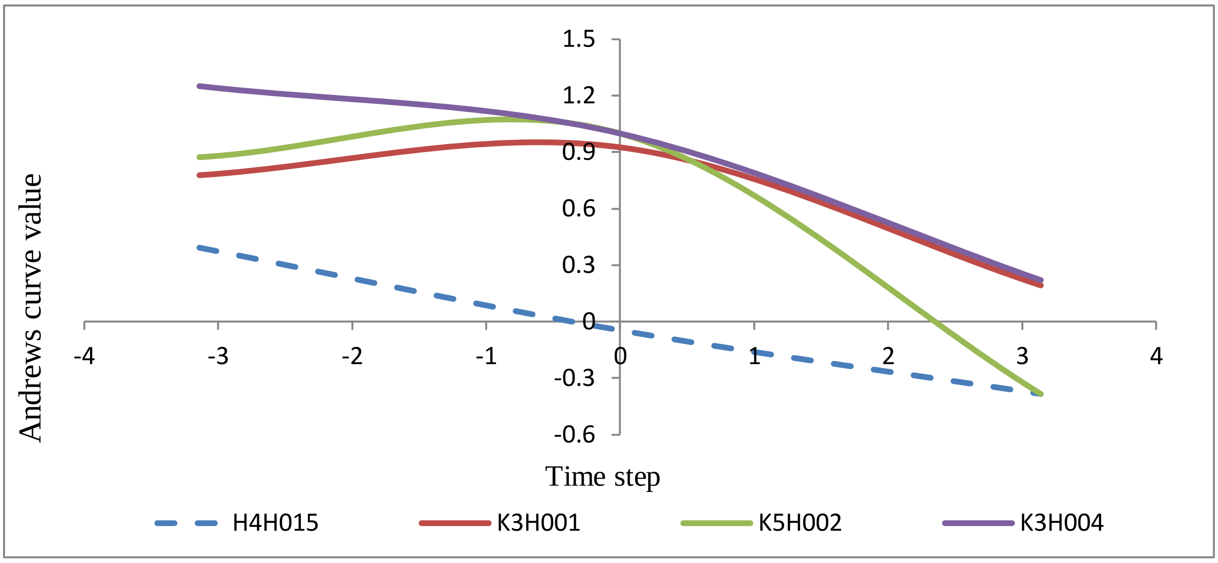
Cluster 1



Cluster 2



Cluster 3



Cluster 4

Figure 7.3: Andrew's curves for the clusters based on the catchment characteristics that significantly explain the variance of flow characteristics

H3H005, J2H005 and H4H016 show differing curves in cluster 1 compared to the rest of the members. These catchments have higher S_{90} compared to the cluster average of 3.43º. These catchments were therefore removed from the cluster.

G4H014 has a curve that differs from the rest of the members of cluster 2. G4H014 has similar catchment characteristics in terms of rainfall and geology in comparison to the rest of the group, however, G4H014 has a very high S_{90} of 5.43º in comparison to the cluster mean of 2.63º. G4H014 was therefore removed from the cluster.

J3H018, Q6H003 and Q9H002 show curves that differ to the other members of cluster 3. These catchments are characterised higher S_{90} in comparison to cluster mean of 3.80º. These catchments were therefore removed from the cluster.

H4H015 shows a curve that differs from the other members in cluster 4. H4H015 has a very high S_{90} of 17.32º in comparison to the cluster mean of 12.93º. H4H015 also has low mean annual rainfall in comparison to the other members of the clusters. H4H015 was therefore removed from the cluster.

7.3.4 Catchment characteristics of clusters

Figure 7.4 presents the spatial distribution of cluster memberships within the study area. Cluster 1 shows the largest diversity in terms of geographic coverage within the study area. Catchments belonging to cluster 2 and 4 are found within the same geographic area. Cluster 3 is found predominantly within the south-eastern regions of the study area.

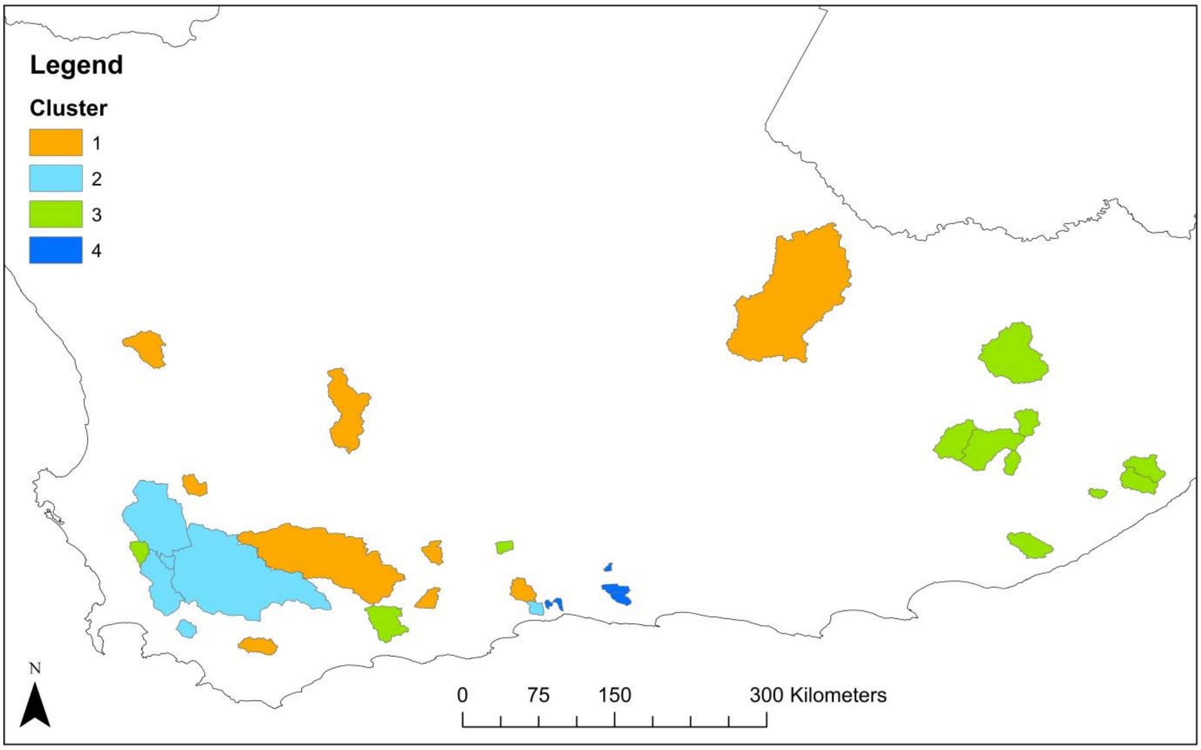


Figure 7.4: Cluster membership of the selected catchments in the study area

Table 7.3 presents the average catchment characteristics for the derived clusters. Cluster 1 shows the lowest mean annual rainfall and highest mean annual evaporation and is therefore characterised as the most arid. Cluster 4 shows the highest mean annual rainfall and lowest evaporation. Rainfall increases from cluster 1, 3 to 4 and there are no overlapping clusters. Although clusters 2 and 4 display similar mean annual rainfall, the hydrological response between the clusters is expected to be different as cluster 4 is characterised by steeper slopes, as well as being underlain by higher proportion of the Table Mountain Group. Cluster 1, 2 and 3 show similar S_{90}, with cluster 4 showing the highest average of 11.47º. Cluster 3 has no proportion of the catchment underlain by the Table Mountain Group, cluster 1 and 2 have moderate proportions and cluster 4 has a high proportion of the catchment underlain by the Table Mountain Group.

Table 7.3: Mean values for catchment characteristics of the derived clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
MAP (mm)	333	841	603	866
ET (mm)	1688	1575	1513	1509
S_{90} (degrees)	2.17	2.16	3.01	11.47
GL_{TM} (%)	16.11	27.52	0	86.08
LC_T (%)	1.74	13.11	22.34	45.03

In terms of land cover, cluster 4 shows the highest proportion of thicket, with cluster 1 showing small proportions. Figure 7.5 provides a graphical representation of the range of catchment characteristics between the derived clusters and the variation amongst them.

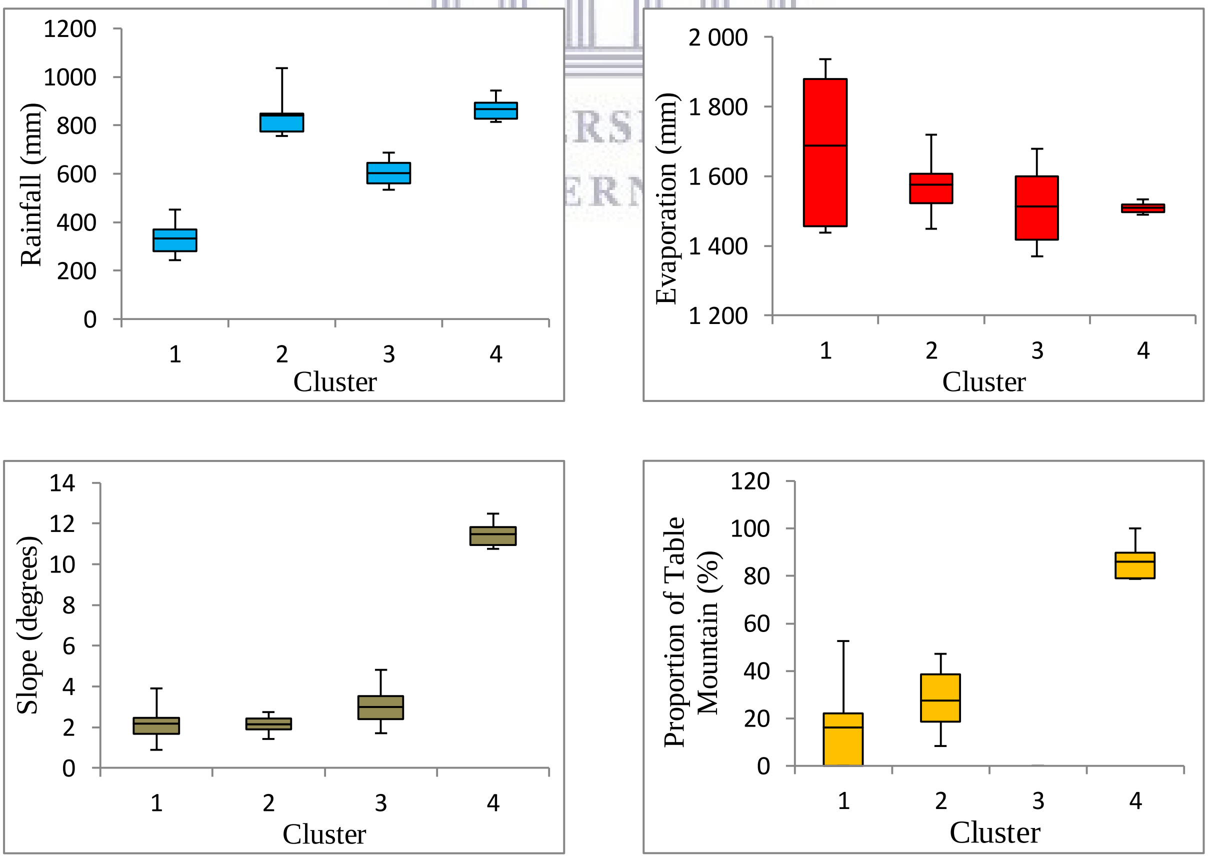


Figure 7.5: Range of variation of catchment characteristics for the derived clusters

7.3.5 Flow characteristics of clusters

Table 7.4 presents the average values of flow characteristics of the clusters derived from catchment characteristics. This identifies whether or not the grouping of catchments can be considered as hydrologically homogenous. Cluster 1 shows the lowest mean annual runoff, which is expected as Table 7.3 identified cluster 1 as being the most arid. Cluster 4 shows the highest mean annual runoff, as well as the highest flow percentiles of q_{10}, q_{25}, q_{75}, q_{90}. Cluster 2 and 4 show the highest BFI and as a result these clusters have the lowest number of zero flow days. Cluster 1 and 3 show lowest BFI and mean annual runoff and as a result have the highest number of days of zero flow. This identifies that catchments belonging to cluster 1 and 3 would have prolonged periods of no flow.

Table 7.4: Average values of flow characteristics for the derived clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Q (mm)	9.52	198.73	32.61	319.21
CV (%)	624	258	465	309
CVB	82.47	12.71	39.30	12.17
q_{90}	0	3.12	0.01	36.40
q_{75}	0	10.29	0.13	53.41
q_{25}	1.60	173.26	9.59	196.02
q_{10}	8.77	446.79	45.74	541.10
IC	0.04	0.19	0.10	0.13
3-day min (mm)	0	1.22	0.20	27.38
3-day max (mm)	477.39	3454.14	1260.82	7525.15
ZFD (days)	228	27	96	1
BFI	0.11	0.23	0.14	0.27

The concavity index (IC) is a measure of the contrast between high and low flow events, which represents the shape of the flow duration curve. Catchments having an IC value close to 1 are represented by large aquifers with moderate daily variations of flow. Clusters 2 and 4 are characterised by the highest IC value, which is expected as these clusters also have high

BFI. These clusters also exhibit the lowest CV of annual flows and CVB values, which is expected as a result of stable flow conditions and higher baseflow contribution. Cluster 1 and 3 can therefore be characterised as the most variable in terms of the flow regime. Cluster 1 has the lowest IC of 0.04, which means catchments belonging to the cluster are represented by steeper flow duration curves, where poor groundwater storage does not moderate the daily variation of flow. Figure 7.6 presents the variation of flow characteristics within the derived clusters.

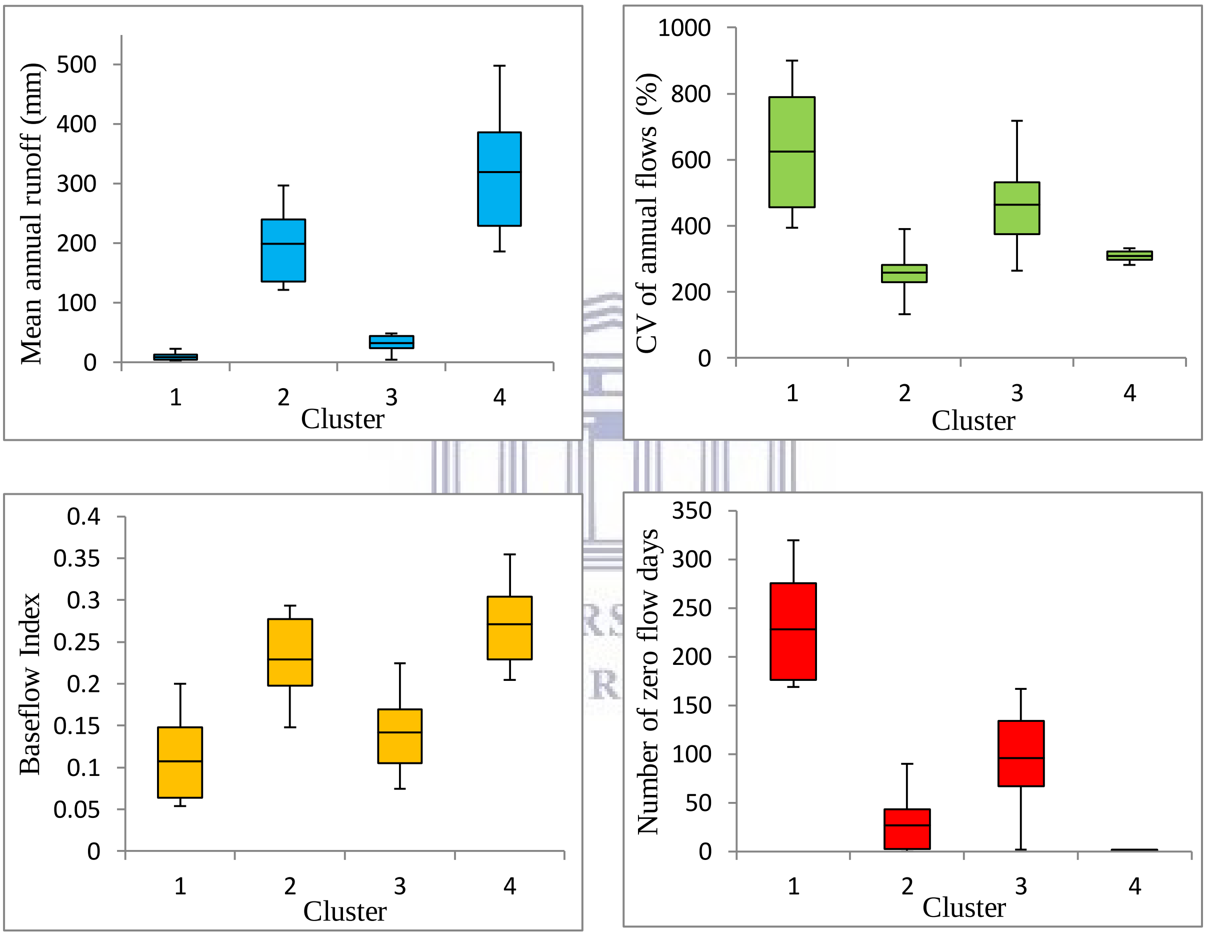


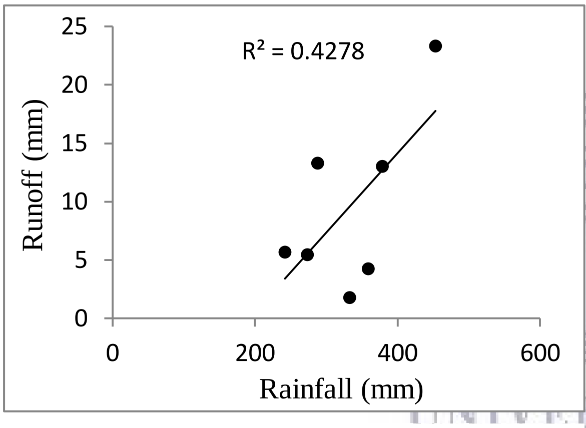
Figure 7.6: Range of variation of flow characteristics for the derived clusters

7.3.6 Prediction of flow characteristics based on clusters

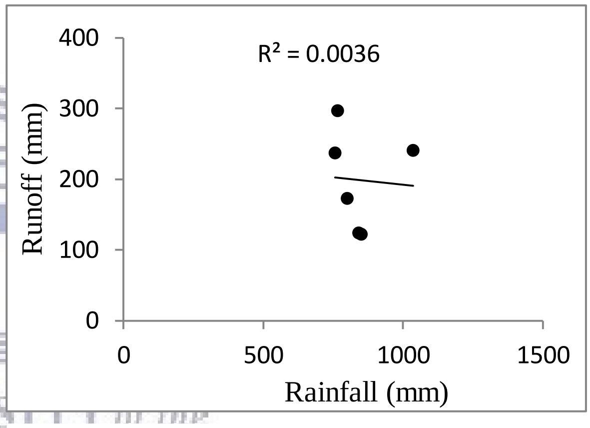
Chapter 6 identified catchment characteristics that can be used to predict flow characteristics in ungauged catchments. The regional regression models and predictive equations developed were based on data of all 36 catchments. One of the assumptions of regionalisation is that the grouping of catchments into hydrologically homogenous groups can improve the prediction of flow characteristics in ungauged catchments.

7.3.6.1 Prediction of mean annual runoff

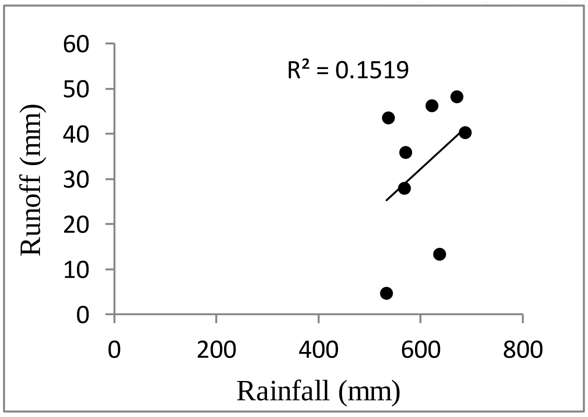
Chapter 6 identified that MAP and the proportion of catchment under grasslands are important for predicting mean annual runoff. Chapter 6 also identified a strong correlation between mean annual runoff and rainfall (r = 0.73). Figure 7.7 presents the relationship between runoff and rainfall for the derived clusters.



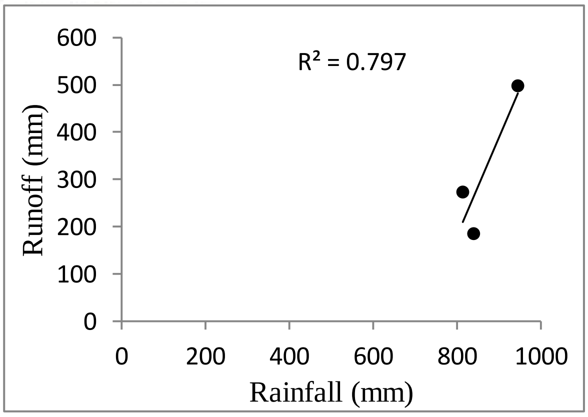
Cluster 1



Cluster 2



Cluster 3

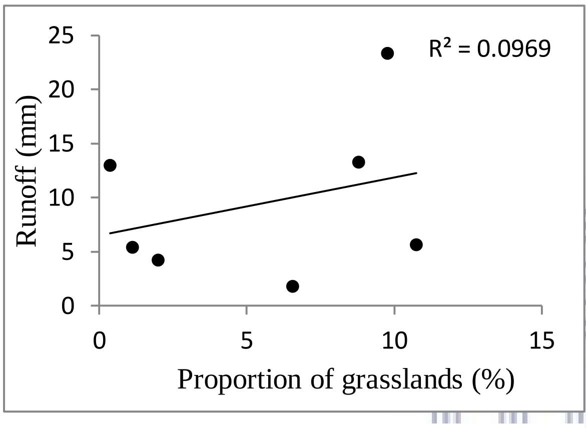


Cluster 4

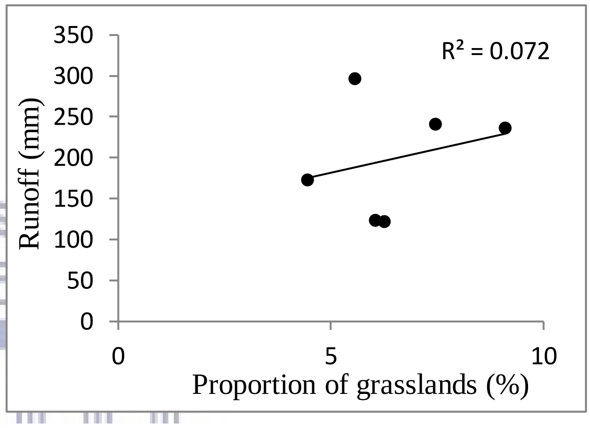
Figure 7.7: Relationship between mean annual runoff and mean annual rainfall for the derived clusters

Figure 7.7 shows that only cluster 4 have a significant correlation between rainfall and runoff, whilst cluster 1 shows a moderate correlation between rainfall and runoff. Clusters 2 and 3 display poor relationships between rainfall and runoff. Therefore the grouping of catchments into hydrologically homogenous groups has not improved the prediction of mean annual runoff.

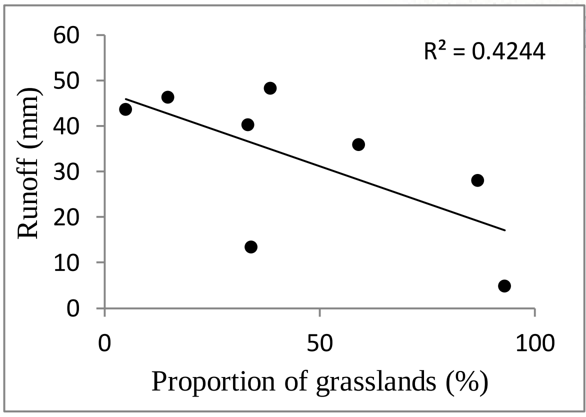
The proportion of grasslands were also found to be important for predicting mean annual runoff. Figure 7.8 illustrates the relationship between mean annual runoff and the proportion of the catchment covered by grasslands.



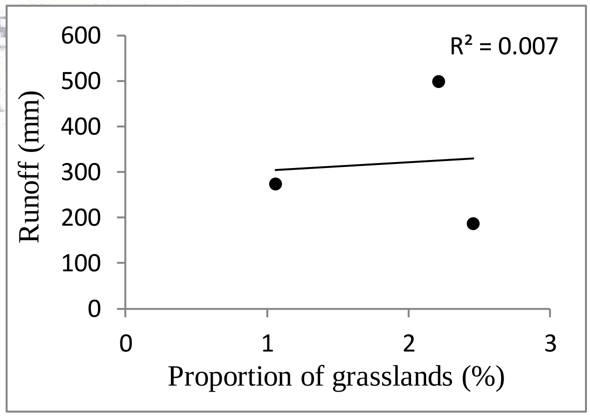
Cluster 1



Cluster 2



Cluster 3



Cluster 4

Figure 7.8: Relationship between mean annual runoff and proportion of grasslands for the derived clusters

Chapter 6 identified a moderate negative correlation between mean annual runoff and the proportion of the catchment covered by grasslands (r = -0.35). Only cluster 3 shows or significant correlation between mean annual runoff and proportion of grasslands. The grouping of catchments has not improved the prediction of mean annual runoff, as there is no significant relationship between mean annual runoff and proportion of grasslands (Figure 7.8)

7.3.6.2 Prediction of baseflow index (BFI)

Chapter 6 identified that mean annual rainfall is important for predicting BFI. Rainfall was shown to have a moderate correlation with BFI (r = 0.55). The relationship between rainfall and BFI for the derived clusters is presented below:

Cluster 1: r = 0.58

Cluster 2: r = 0.42

Cluster 3: r = 0.16

Cluster 4: r = 0.61

When rainfall was correlated with BFI based on all catchments without clustering, the correlation coefficient was 0.55. Therefore clustering has not improved the prediction of BFI, except for cluster 1 and 4 which show a higher correlation coefficient.

7.3.6.3 Prediction of the number of zero flow days

Chapter 6 identified that the prediction of the number of zero flow days can be predicted using rainfall. Rainfall was identified to have a strong negative correlation with number of zero flow days (r = – 0.69). The relationship between rainfall and number of zero flow days is presented below:

Cluster 1: r = -0.61

Cluster 2: r = -0.64

Cluster 3: r = -0.32

Cluster 4: r = 0.57

The grouping of catchments into clusters has not improved the prediction of the number of zero flow days. The correlation between rainfall and the number of zero flow days is lower within the derived clusters compared to the results in Chapter 6.

7.4 Conclusion

This chapter has demonstrated the importance of using redundancy analysis as the basis for grouping catchments into clusters that share similar hydrological response. The use of R_g statistic and analysis of the flow duration curve was used to determine the optimum number of clusters. Andrew's curves were then used to validate the clusters and ensure that there are no outliers present within the derived clusters.

The chapter identified that the clusters have unique flow characteristics and therefore can be regarded as having hydrologically similar response. The most distinguishable difference between clusters in terms of catchment characteristics are mean annual rainfall, slope and proportion underlain by Table Mountain Group. Rainfall is similar between two clusters; however, these clusters are differentiated by differences in slope and proportion underlain by the Table Mountain Group. Land cover types of thicket do not significantly vary between clusters.

One of the aims of the chapter was to establish whether or not the prediction of flow characteristics could be improved by grouping catchments into hydrologically homogenous groups. The chapter has shown that the prediction of flow characteristics was not improved. The grouping of catchments into hydrologically homogenous groups has narrowed the range of variability of the physiographic characteristics and the relationship between flow and catchment characteristics are no longer discernible. Although the predictive equations for estimating flow characteristics has not been improved, the average values of the derived clusters can be used to predict flow characteristics in ungauged catchments. Identifying the Andrews curve of catchment characteristics between ungauged catchments and clusters can provide a means to place an ungauged catchment within a cluster. This would provide the opportunity to the transfer of information from gauged to ungauged catchments based on determining the cluster to which the ungauged catchment belongs to and then an average value of flow characteristics can be predicted for the ungauged catchment.

A major issue in hydrology is that there is no commonly agreed method for cluster analysis and the optimum number of clusters is often unknown. This limitation causes doubt within the results of cluster analysis by means of whether or not the correct number of clusters was selected and if the groups share similar hydrological response. It is therefore important to develop a clustering algorithm and distance metric that would enhance the reliability of obtained results and reduce the current subjectivity present within cluster analysis.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

The aim of the study was to characterise the flow regime of non-perennial rivers in an ecologically meaningful way and to determine factors that account for the spatial variations of ecologically relevant river flow indices. A case study was adopted for 36 river gauging stations in the Western, Eastern and Northern Cape Provinces of South Africa. The flow characteristics in the study included mean annual runoff, coefficient of variation of annual flows, q_{10}, q_{25}, q_{75}, q_{90}, baseflow index, concavity index, hydrological index, number of zero flow days, 3-day minima and 3-day maxima of daily means of discharge. These flow characteristics were selected on the recommendations of previous studies with the attempt to characterise the flow regime in an ecologically meaningful way that can be used to efficiently manage non-perennial rivers. Assessing the spatial variation of these flow characteristics was based the relationship between flow and catchment characteristics. The selection of catchment characteristics were based on the recommendations of previous studies on the characteristics that influence hydrological response which included rainfall, evaporation, slope and elevation, land cover, geology, soil, drainage density, river length and catchment area.

8.2 Factors accounting for the spatial variation of selected ecologically relevant flow characteristics

Redundancy analysis provided the opportunity to identify catchment characteristics that significantly explain the variance of flow characteristics at a 5 % confidence level. Mean annual rainfall and the slope exceeded or equally 90 % of the time (S_{90}) were the only catchment characteristics that were identified as significantly explaining the variance of flow characteristics. The total variance of flow characteristics explained by MAP and S_{90} accounted for 57 %, with MAP accounting for 46 % of variance. The results of the chapter identified catchment characteristics that account for the spatial variation of flow characteristics, which was used to predict these flow characteristics in Chapter 6 using multiple regression and artificial neural networks. The results were also used as a basis for grouping catchments that share similar hydrological responses and to determine whether or not the grouping of catchments improves the prediction of flow characteristics.

8.3 Prediction of flow characteristics using multiple regression and artificial neural networks

The study used multiple regression and artificial neural networks to determine which approach would be more suitable for the prediction of selected flow characteristics of non-perennial rivers. The model performance of both multiple regression and neural networks was based on R^2, % RMSE and RSR. Overall, multiple regression shows a higher model performance and accuracy for predicting flow characteristics in the study compared to neural networks. The prediction of mean annual runoff, BFI, number of zero flow days and 3-day max show a good model performance using multiple regression. Generally the results show good performance for predicting flow characteristics based on the coefficient of determination, however, the prediction of some flow characteristics illustrates a higher degree of error based on the % RMSE. An exponential model was shown to be feasible for predicting the flow duration curves of non-perennial rivers which was shown to have a lower predictive error than artificial neural networks. The prediction of flow duration curves in ungauged catchments may be improved by increasing the sample size of catchments used in the study. The study used 36 gauged non-perennial rivers which were insufficient to derive the β coefficient of the exponential model equation using catchment attributes. In the case of this study, the β coefficient was shown to have no relationship with catchment attributes. The use of artificial neural networks shows a higher model performance for predicting 3-day min, which suggests that some catchment characteristics have non-linear relationships with flow characteristics which cannot be discerned using multiple regression. In cases where the model performance is similar between neural networks and multiple regression, the use of multiple regression is recommended as the approach is simpler.

8.4 Identification of catchments with similar hydrological responses

The results of ordination in Chapter 5 provided a set of catchment characteristics that were used to classify catchments into homogenous groups, which was mean annual rainfall and S_{90}. The rand index (R_g) was used to determine the number of clusters in the study, which identifies the level of agreement between clusters derived based on catchment characteristics and those derived by flow characteristics. Previous studies have elaborated on the limitation of determining the optimum number of clusters and the approach is often subjective. The study assessed the flow duration curves of the derived clusters to assist in determining the optimum number of clusters. The approach identified whether or not the clusters could be regarded as sharing similar hydrological response and hydrologically different between clusters. Andrews curves were then used to validate the membership of clusters and removed outliers of the cluster that showed differing curves.

8.5 Prediction of flow characteristics based on hydrologically similar catchments

One of the assumptions of regionalisation is that the grouping of catchments into hydrologically homogenous groups can improve the prediction of flow characteristics in ungauged catchments. The prediction of flow characteristics based on clusters provided the opportunity to determine whether or not the grouping of catchments improved the model performance of the predictive equation. However, the grouping of catchments into homogenous group did not improve the prediction of flow characteristics. The grouping of catchments into homogenous groups resulted in narrow ranges of physiographic attributes and the relationship between flow and catchment characteristics were no longer discernible. The prediction of flow characteristics may be improved with increasing the number of memberships within each cluster and increasing the variability of catchment characteristics. Although the predictive equations were not improved, flow characteristics can be estimated in ungauged catchments by placing the ungauged catchment in a cluster that share similar catchment characteristics. The transfer of information from gauged to ungauged catchments can be based on determining the cluster to which the ungauged catchment belongs to and then an average value of flow characteristics of the cluster can be assigned to the ungauged catchment.

8.6 Recommendations

The study identified that there is limited knowledge regarding the functioning and operation of non-perennial rivers. In the context of perennial rivers, a range of environmental flow assessments have been developed ranging from simple hydrological methods, to complex holistic approaches. Non-perennial rivers differ with regards to their flow regime compared to perennial rivers and it is therefore important to design approaches for the determination of environmental flow that are explicit for these river systems. Studies need to identify an adequate set of flow indices that can be used efficiently to characterise the flow regime of non-perennial rivers in an ecologically meaningful way. Studies have also pointed out the issue of inherent redundancy that exists among hydrological indices. An approach should be carried out to efficiently characterise the flow regime, limiting redundant indices and adequately representing the flow regime in an ecologically meaningful way.

One of the main issues with reference to assessing the spatial variation of flow characteristics was the use of high resolution geological data and hydrologically meaningless data. In the context of hydrology, hydrologically meaningful data such as water depth, porosity and permeability are important for understanding the relationship between subsurface storage and river flow. The use of more hydrologically meaningful data may improve the understanding of these rivers systems. Studies have argued that this is a major concern in developing countries where such data is not readily available.

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