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A landscape hydrology approach to inform sustainable water resource management under a changing environment. A case study for the Kaleya River Catchment, Zambia

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ABSTRACT

Study region: Kaleya River Catchment in southern Zambia.
Study focus: The ability of a landscape hydrology approach to detect controls on water availability in a fragmented landscape to inform interventions under a changing environment was investigated. Simple and measurable climatic and landscape pattern attributes were analysed using change detection, trend analysis and backward variable elimination with Partial Least Squares Regression (PLSR) to identify controls on seasonal river flows and how landscape components could be enhanced to augment natural river flows.
New hydrological insights for the region: Landscape pattern showed increasing fragmentation, expansion of irrigated cropland and reservoirs and loss of forestland. Significant increasing trends ($p < 0.05$) were observed for reference evapotranspiration (ET_o), one-day maximum rainfall, coefficient of variation (CV) of rainfall, maximum dry spell length, and start of rains but not annual rainfall. Increased CV of rainfall, rainfall intensity and ET_o were the main climatic stressors on river flows. Increased Percentage of Landscape (PLAND) of irrigated cropland, PLAND of reservoirs, Patch Density (PD) and Largest Patch Index (LPI) of reservoirs were the main landscape pattern stressors. Only the LPI of forestland positively explained seasonal river flows. Water resource interventions in the region must adapt more to changing seasonal rainfall characteristics than to annual rainfall totals. Additionally, regeneration of larger forest patches could improve river flows. The approach can be applied in other regions.

1. Introduction

The landscape is a mosaic of many land use types (land cover composition) with different geometric and spatial arrangements (land cover configuration). Hence the observed hydrological signatures are a result of the linear and non-linear interaction of landscape patterns (landcover composition and configuration) with climatic variables (Ekness and Randhir, 2015; Hughes et al., 2014). Although it can be argued that the inter-relationships between landscape elements such as forest and hydrology are well known, such interactions can be more complex in the rapidly fragmenting landscapes of tropical and subtropical Africa (Guzha et al., 2018; Malmer et al., 2010). Despite a plethora of studies investigating land use impacts on hydrological dynamics, most studies focus on landscape

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composition (proportion of a landcover class in the landscape). Using landscape ecology, it has been shown that processes such as runoff generation, infiltration, evapotranspiration (ET), hydrological connectivity, sediment transport and water quality are also related to landscape configuration at a watershed scale (Shi et al., 2013; Boongaling et al., 2018; Ding et al., 2016). In this regard, landscape metrics (indices of landscape pattern) developed in the field of landscape ecology are increasingly drawing scholarly attention to understand hydrological fluxes in a changing environment (Ekness, 2013; Epting, 2016; Albalawneh et al., 2015; Wang et al., 2020; Yu et al., 2020; Ding et al., 2016).

Combining hydrological modelling with multivariate statistical methods is becoming widely used in attributing land use controls on hydrological change. For example, recently, Partial Least Square Regression (PLSR) was applied to attribute hydrological change to specific changes in land use/landcover composition using river flows and sediment data simulated by hydrological models according to various land use scenarios (Shi et al., 2013; Woldesenbet et al., 2017; Gebremicael et al., 2019). But the underlying drivers of hydrological variability from among climate, landscape composition and configuration controls are rarely investigated simultaneously. Additionally, the studies have mainly used simulated river flows. However, in fragmented, heterogenous and intensively managed meso-scale catchments such as the Kaleya in southern Zambia where dam management operations data does not exist, the actual hydrological signatures and processes are difficult to reproduce due to modelling and calibration uncertainties (Abbaspour et al., 2018;

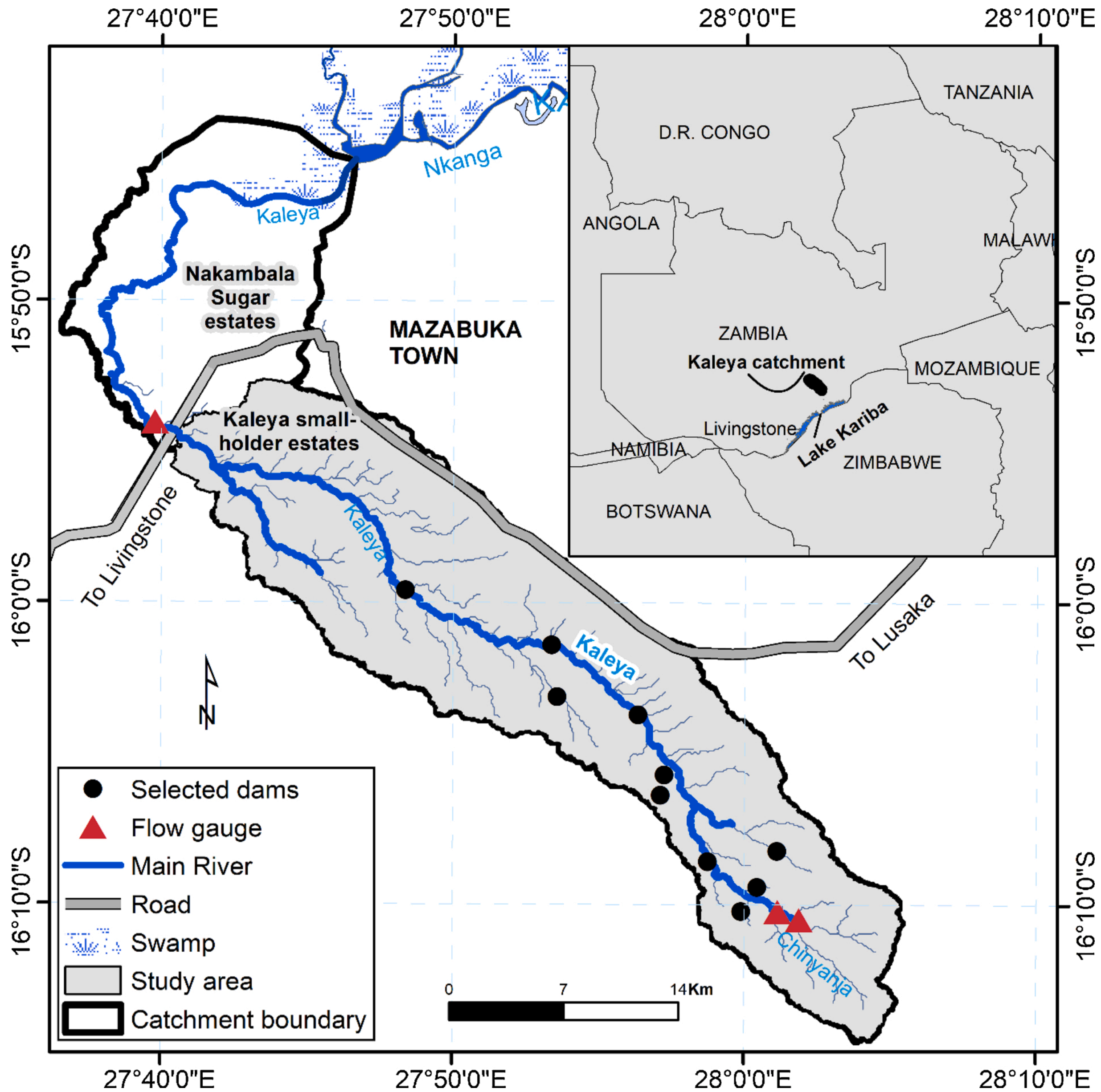

Fig. 1. The Kaleya River Catchment in southern Zambia.

Hughes et al., 2014; Hughes, 2006). Moreover, seasonal climatic characteristics in semi-arid areas like Zambia could be more important in explaining seasonal water availability than annual totals and /or land use composition. Thus, managing water resources under a changing environment requires information on specific climatic changes the water resources must adapt to.

This study addresses these gaps through the lenses of landscape hydrology. The field of landscape hydrology provides an opportunity to integrate landscape ecology and catchment hydrology (Schröder, 2006; Ferguson, 1991). Landscape hydrology deals with landscape components such as climate, land use composition and configuration, including soils, geology and topography and how their interactions affect water movement and storage in the catchment landscape (Ferguson, 1991). One of the most distinguishing features of the landscape hydrology approach is that, it considers the interactions among the landscape components and how they can be modified by human impact to better manage the water resources and the environment in general (Ferguson, 1991). Thus, it can provide a framework for informing water resource management decisions in heterogeneous and increasingly fragmented catchment landscapes under a changing climate.

The Kaleya River Catchment in southern Zambia has undergone extensive landscape transformations since the early 1980s. The catchment hosts Zambia's oldest private-public sugar irrigation scheme (Akayombokwa et al., 2017). Seasonal river flows have reduced drastically in the catchment, leading to conflicts among water users. Studies have attributed deterioration of water resources in Zambia to changes in landcover composition (Sakeyo, 2008; Chisola and Kuraz, 2016; Chomba, 2017; Tena et al., 2019; Muchanga et al., 2019). Climate change and variability are thought to be causing further stress on water resources (GRZ, 2008; Nkhuwa et al., 2013; Ngoma et al., 2017), although this has mostly not been backed up by scientific evidence, as few hydrological studies have been completed (Nkhuwa et al., 2013).

In this regard, we developed and tested a landscape hydrology approach to tease out how the interactions among seasonal climatic, landcover composition and configuration patterns explain the observed hydrological shifts in the Kaleya River Catchment. In particular, the study addressed the following research questions: (1) How have seasonal climatic characteristics and landscape patterns changed in the catchment since 1972? (2) What climatic, land use composition and configuration characteristics are important in explaining changes in seasonal river flows in the catchment? (3) How should landscape components be enhanced in order to augment seasonal river flows? (4) Can a landscape hydrology approach (implemented without hydrological simulation) detect the main interactions among landscape components to inform landscape level water resource management interventions in a heterogeneous and fragmented catchment landscape? Such information can inform improved decision-making and sustainable water resource development under a changing environment.

2. Description of the study area

The Kaleya River Catchment has an area of about 744 km^2 and lies between latitude 15°40′S to 16°20′S and longitude 27°30′ E to 28°10′ E (Fig. 1). The river water originates from the slow flowing springs upstream near the Siamakambo Hills in Chikankata District of the Southern Province and flows in the northwest direction into the Mazabuka District where it drains into the Kafue River. The major tributaries of the Kaleya River include the Chinyanja, Nanswa, Mbolela and Dimba Rivers. The flow in the middle section of the catchment is highly regulated by weirs and small dams (dam height less than 15 m). Of these small dams, the largest has a capacity of about 6.5 Mm^3. The catchment is dominated by savannah woodland with a mixture of *Acacia* trees, mainly *Faidherbia albida* (formerly *Acacia albida*) belonging to the Munga woodlands and the Brachystegia genus of the miombo woodland (Sichingabula et al., 2000).

Agriculture is the major economic activity in the catchment. Riparian-dependent subsistence farmers are present in the upper catchment, many of who were resettled into the area by government before the 1970s. These farmers mainly grow maize (*Zea mays* L.) in the rainy season, and potatoes (*Solanum tuberosum* L.) among other vegetables in the dry season. Commercial farmers occupy about 75 % of the catchment area and are mostly located in the middle part. They mainly grow wheat (*Triticum aestivum* L.), soybeans (*Glycine max* L.), sugarcane (*Saccharum officinarum* L.), lucerne (*Medicago sativa* L.), pasture and seed maize using centre pivots and drip irrigation. Additionally, they keep livestock, mainly for the beef industry. The lower part of the catchment is home to the sugar estates of the Kaleya Small Holders' Company as well as Nakambala Sugar Estates belonging to Zambia Sugar Company. Irrigation water for the two sugar estates is transferred from the Kafue River by the Zambia Sugar Company who also supply water to the Kaleya Small Holders' Company.

3. Materials and methods

3.1. The landscape hydrology approach

We used climatic indices and landscape pattern metrics derived from long-term weather data and satellite images respectively to infer controls on seasonal river flows without need for hydrological modelling. The approach was applied using post classification landscape change detection, trend analysis of hydro-meteorological time series and variable elimination in Partial Least Square Regression (PLSR). The details of how the approach was implemented are discussed in the subsequent sections.

3.2. Data acquisition and pre-processing

Cloud-free Landsat images of the Kaleya River Catchment were downloaded from the website of the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov) for years 1972, 1984, 1989, 1996, 2001 and 2011. The images were pre-processed by applying geometric and radiometric corrections that included noise and haze reduction. Pre-processing also involved resampling the

60 m resolution Landsat MSS image for 1972 to a 30 m resolution using the nearest neighbour resampling method. All the image preprocessing steps were conducted in Erdas Imagine 2014. Historical daily river discharge data from the start of records at the most downstream gauge to 2019 (1975–2019) were provided by the Water Resources Management Authority (WARMA) in Zambia. However, the dataset has gaps between 2011 and 2018, so we restricted our analysis to the 1975–2011 period. Weather data were obtained from the Zambia Meteorological Department (ZMD).

3.3. Data analysis

3.3.1. Hydrological and climate-based metrics

The discharge data was analysed using the Indicators of Hydrological Alteration (IHA) software (The Nature Conservancy, 2009) to derive hydrological metrics that define seasonal water availability (average monthly flows) and the timing of one-day maximum and minimum flows in the catchment for the period 1975–2011. The climate-based metrics involved seasonal characteristics derived from daily rainfall data analysed in R-instant (Parsons et al., 2017). The derived metrics included one-day maximum rainfall, simple rainfall intensity (the ratio of total seasonal rainfall to the number of wet days in the season), onset and cessation dates of rainfall, and the maximum dry spell length (maximum dry period length) in a year and annual rainfall totals.

When deriving the climatic metrics, a rainy day was defined as having more than 0.85 mm of rainfall (Stern et al., 2006). The start (onset) of rainfall was a day after 1 October in each year that gives a total rainfall amount of 20 mm or more over a consecutive period of two days, in addition to the absence of a dry spell of 10 days or more in the next 30 days based on Stern et al. (2006). A dry spell was taken as a period with less than 5 mm of rainfall in five days, adopted from Hachigonta et al. (2008). The date of cessation of rainfall (End of rains) was taken as the last day after 25 February that accumulates a rainfall amount of 10 mm or more, adapted from Hachigonta et al. (2008) and Mupangwa et al. (2011). We also derived Reference Evapotranspiration (ET_o) based on the Hargreaves method (Hargreaves, 1994) in R environment, through the SPEI package (Beguería et al., 2014). The coefficient of variation (CV) was computed as the standard deviation of rainfall divided by the average rainfall.

3.3.2. Digital image processing to derive landscape composition and configuration metrics

The Landsat images were classified using a hybrid of supervised image classification and onscreen digitising in Erdas imagine software to produce landcover maps for the years 1972, 1984, 1989, 1996, 2001 and 2011. The hybrid method involved first classifying the images with maximum likelihood classifier using supervised image classification. This was followed by onscreen digitising to correct any misclassified pixels. The hybrid method has been recommended by other scholars as it reduces misclassifications in heterogeneous landscapes such as Kaleya (Herold et al., 2008; Betru et al., 2019). The generated landcover maps were then subjected to accuracy assessment. Topographic maps, along with Google Earth imagery and field visits in August 2019 were used as sources of ground truth data for accuracy assessment. The landcover maps are based on six classes, namely: Forest, Scrubland, Cropland (rainfed), Cropland (irrigated), Reservoirs, and Built-up area. A description of these landcover classes is given in Table 1.

3.3.3. Generating landscape composition and configuration metrics from landcover maps

Landcover maps for the respective years were analysed using FRAGSTAT 4 software (McGarigal and Marks, 1995) to derive landscape composition and configuration metrics. We evaluated three class level landscape pattern metrics (Table 2) based on their use in literature, and simplicity in interpretation and application (Zhou et al., 2017).

The Largest Patch Index (LPI) indicates patch dominance (McGarigal et al., 2012). The Patch Density (PD) indicates landscape fragmentation. Fragmentation and dominance-based metrics are important indicators of hydrological connectivity and ecosystem functioning (Albalawneh et al., 2015; Schröder, 2006). Hence their changes can lead to significant changes in water and nutrient cycling (Hobbs, 1993). A detailed description of the landscape metrics is given by McGarigal and Marks (1995) and (McGarigal et al., 2012). A summary of all the derived hydrological, climatic and landscape indicators is given in Table 3.

3.3.4. Analysis of trends in hydrometeorological timeseries

3.3.4.1. Mann-Kendall trend test. We conducted the Mann–Kendall trend test (Mann, 1945; Kendall, 1975) on seasonal climatic and hydrological variables in Table 3 to examine the significance of the trends in the study period. To account for serial correlation, we

Table 1
Description of land cover classes.

Landcover	Description
Forest	Land under thick vegetation cover
Scrubland	Grass with scattered trees and bushes, abandoned agricultural lands
Cropland (rainfed)	Land under rainfed agriculture
Cropland (irrigated)	Land under irrigated agriculture
Reservoirs	Land inundated by water arising from impoundments (dams and weirs)
Built-up area	Dense settlement area that can be described as urban

Table 2
Landscape pattern metrics.

Metric	Acronym	Description	Range
Percentage of Landscape	PLAND	Percentage of each landcover class in the landscape	0–100
Patch Density	PD	Number of patches of a landcover class per unit area	> 0
Largest Patch Index	LPI	Percentage of landscape covered by the largest patch of each landcover class	0–100

Table 3
Hydro-climatic and landscape pattern metrics.

Dependent variables	Independent variables		
Hydrological indices	Climate indices	Landscape composition	Landscape configuration
Wet season flows	Start of rains	PLAND of Forest land	*Fragmentation metrics*
Dry season flows	End of rains	PLAND of Rainfed cropland	PD Forest
Date of 1-day minimum flow	Maximum dry spell length	PLAND of Irrigated cropland	PD Rainfed cropland
Date of 1-day maximum flow	Rainfall amount	PLAND of Reservoirs	PD Irrigated cropland
	One-day maximum rainfall	PLAND of Scrubland	PD Reservoirs
	Rainfall intensity	PLAND of Built-up area	PD Scrubland
	CV of intra seasonal rainfall		PD Built-up area
	ET_o		
			Dominance metrics
			LPI Forest
			LPI Rainfed cropland
			LPI Irrigated cropland
			LPI Reservoirs
			LPI Scrubland
			LPI Built-up area

used the Modified Mann Kendall test through the Yue and Wang (2004) variance correction technique in the *modifiedmk* R package (Patakamuri et al., 2017).

The Mann-Kendall test is given by the equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{Sgn}(x_j - x_i) \tag{1}$$

where n is the number of observations, x_j and x_i are the jth and ith observations, respectively, and $j > i$. *Sgn* is the *sign* function between consecutive x values and is defined as:

$$\mathrm{Sgn}(x_j - x_i) = \begin{cases} +1 \ ; & x_j > x_i \\ 0 \ ; & x_j = x_i \\ -1 \ ; & x_j < x_i \end{cases} \tag{2}$$

The variance is defined by:

$$Var(S) = \frac{n\,(n-1)\,(2n+5) - \sum_{j=1}^{n} t_i \ i\,(i-1)(2i + 5)}{18} \tag{3}$$

The modified variance $Var^*(S)$ is:

$$Var^*(S) = Var(S) \cdot \frac{n}{n^*} \tag{4}$$

Where n/n^* is the correction factor.

The test statistic, Z(c) is computed by:

$$Z(c) = \left\{ \begin{array}{ll} \dfrac{S-1}{\sqrt{Var^*(S)}} \ , & S > 0 \\ 0 \ , & S = 0 \\ \dfrac{S+1}{\sqrt{Var^*(S)}} \ , & S < 0 \end{array} \right\} \tag{5}$$

Given a significant level of $\alpha = 0.05$, the null hypothesis of a non-existent trend can be accepted if $-1.96 < Z(c) < 1.96$, for a two-sided test.

3.3.4.2. Theil–Sen's slope estimator. The trend magnitude was evaluated using the Sen's slope estimator (Theil, 1950; Sen, 1968) which is given as:

$$\beta = Median\left(\frac{X_i - X_j}{i - j}\right) \forall j < i \tag{6}$$

Where, (β) is the slope of the trend in the time series and, X_j is the j^{th} observation.

3.4. Partial least squares regression

Studies incorporating landscape composition and configuration metrics to attribute influence on hydrological components have mainly combined hydrological modelling with multiple linear regression (Ekness, 2013; Epting, 2016), Pearson correlation (Chiang et al., 2019), stepwise regression (Amiri et al., 2019; Yu et al., 2020; Wang et al., 2020; Peng et al., 2019) or PLSR (Boongaling et al., 2018; Shi et al., 2013; Gebremicael et al., 2019; Woldesenbet et al., 2017) among other methods. However, previous studies did not incorporate seasonal climatic and landscape composition and configuration metrics simultaneously which could be important in informing water resources management in heterogenous landscapes under a changing environment. The independent and dependent variables for our PLSR models are given in Table 3.

3.4.1. Justification for partial least squares regression (PLSR)

The PLSR was selected for several reasons. Firstly, we had many independent variables (landscape and climate metrics) (Table 3) and most of them are highly correlated. The PLSR is useful when the independent variables are highly correlated and where there are more independent variables than observations (Boongaling et al., 2018; Woldesenbet et al., 2017; Carrascal et al., 2009). Secondly, given the high number of independent variables in our case, variable selection was important to identify only those that are significantly important in explaining seasonal river flows. PLSR is thus also a powerful tool for variable selection. Several methods for variable selection in PLSR are available and are discussed in detail by Mehmood et al. (2012).

Generally, variable selection in PLSR is based on the Variable Importance in Projection (VIP), the loading weights and regression coefficients, but the VIPs are the most used (Mehmood et al., 2012). Variables with VIP > 0.8 are deemed to be significant. Variables with a VIP < 0.8 have no significant influence in the model. The higher the VIP, the more significant the variable is in explaining the dependent variable. The PLSR also gives regression coefficients whose sign indicates a positive or negative influence on the dependent variable. Thus, despite a variable having a small regression coefficient, it can be retained in the model if it has a large VIP (VIP > 0.8). Loading weights greater than a magnitude of 0.3 (irrespective of the sign) are taken to be significant and a variable can be deemed important on this basis. The sign of the loading weight indicates the direction of influence. The higher the loading weight, the larger the influence that a variable has on the respective component.

To obtain the optimum number of components and a balance between the explanatory and the predictive power of the model, cross validation is often used. In this regard, the Root Mean Square Error of Validation (RMSEV) is used. The number of components giving the smallest value of RMSEV are selected as optimal for the model. The quality of the PLSR model is assessed using the goodness of fit (R^2), which indicates the explanatory ability of the model and the cross validated (R^2), which shows the extent to which the model can predict. A good PLSR model is one with $R^2 > 0.5$ and a cross validated (R^2) > 0.097 (Trap et al., 2013).

3.4.2. Implementation of the partial least squares regression (PLSR)

We implemented the PLSR in the 'pls' package (Mevik and Wehrens, 2007) in R software. We developed four separate PLSR models for each of the hydrological variables: wet season flows, dry season flows, date of one-day maximum flow and date of one-day minimum flow. The independent variables (predictors) were all the climate and landcover composition and configuration metrics as outlined in Table 3. The climatic and hydrological variables were averaged within small hydro-meteorological periods, avoiding inclusion of periods and years with data gaps in order to get the most out of the observed data.

The hydro-meteorological periods used were 1975–1979, 1980–1985, 1989–1994, 1995–2000, 2001–2005 and 2006–2011. Due to lack of continuous time series landcover data, the landcover map closest to each of the selected periods was used. The magnitude of landcover change within each hydro-meteorological period was assumed to be negligible. This approach has also been used by other scholars such as Yu et al. (2019). Thus, hydro-meteorological conditions for the periods 1976–1979, 1980–1985, 1989–1994, 1995–2000, 2001–2005, 2006–2011 were assigned to the landcover data for 1972, 1984, 1989, 1996, 2001 and 2011, respectively. We argue that the years and periods left out due to data gaps in hydrological and weather data did not significantly impact the results because what was compared were the hydrological patterns with the corresponding climatic patterns in periods with high quality observed data.

Simulating hydrological data using a hydrological model could overcome some of the challenges in the data gaps. However, hydrological modelling has its own calibration uncertainties in this highly managed heterogenous catchment landscape. Hence the preference was to use observed data to answer all our research questions regarding the individual role of observed seasonal climatic conditions and landscape pattern changes in explaining intra-annual water availability. In the PLSR, all the variables were standardised (scaled and mean-centred). Separate PLSR models were developed for each of the hydrological variables, that is, wet season flows, dry season flows, date of one-day maximum flow and date of one-day minimum flow.

3.4.3. Variable selection

Variable selection was done through backward elimination (Frank, 1987; Pierna et al., 2009) in the 'plsVarSel' R package (Liland et al., 2016; Mehmood et al., 2012). The initial step involved running the PLSR with all the predictors in the model. Predictors with a VIP < 0.8 were iteratively removed from the model. The procedure was repeated until a model with an optimal R^2 and cross validated R^2 was obtained outlined by Mehmood et al. (2012); Shi et al.(2013) and Liland et al. (2016), (Shi et al., 2013). In both the initial and final PLSR models, only the components giving the lowest RMSEV were retained.

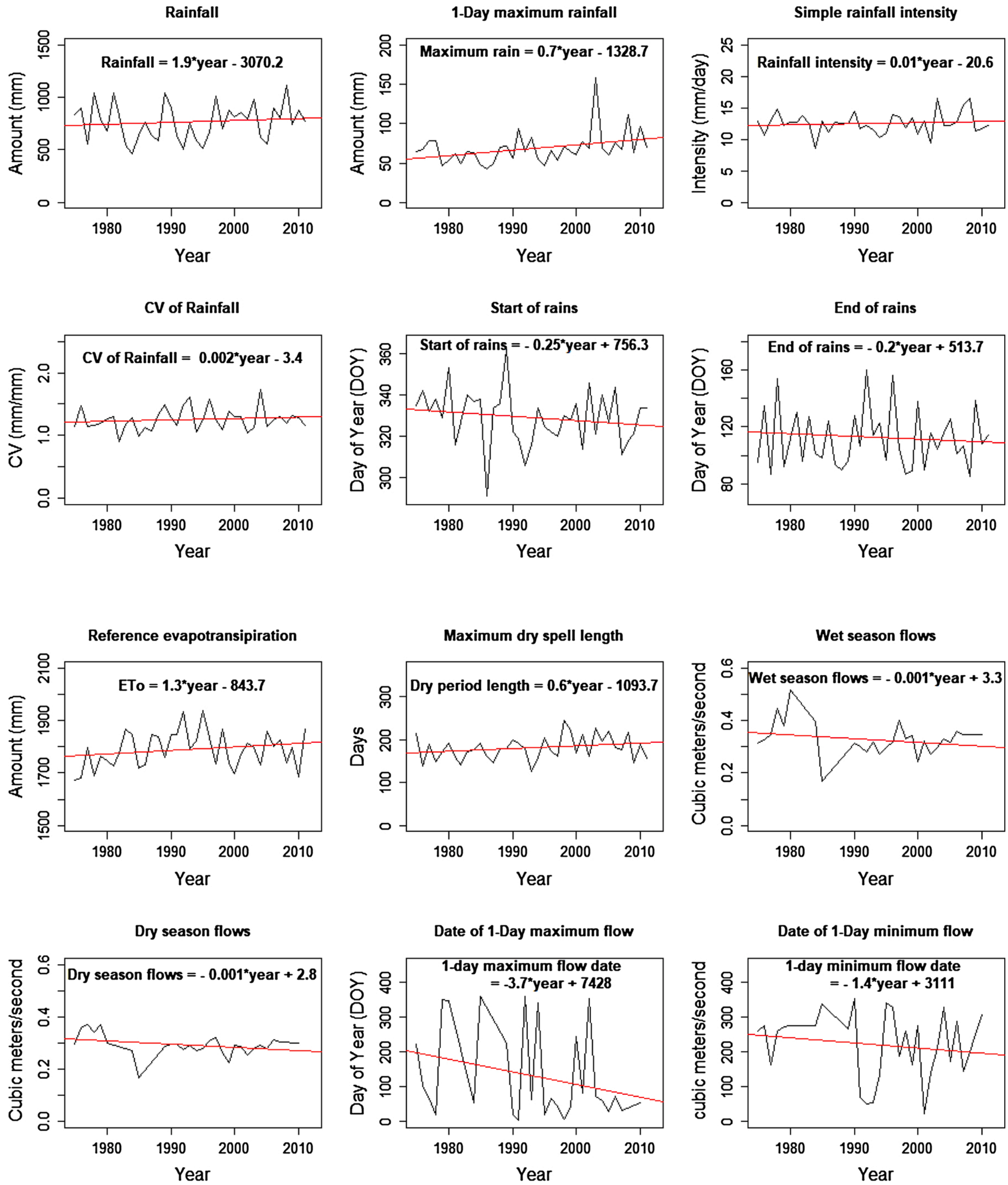

Fig. 2. Hydro-meteorological patterns for Kaleya River Catchment in the study period.

4. Results and discussion

4.1. Hydro-meteorological patterns in the catchment from 1975–2011

Fig. 2 shows patterns in climatic and hydrological time series data. Annual average rainfall exhibited a non-significant increasing trend ($p = 0.218$) over the study period in the catchment. Previous studies in Zambia have found trends in rainfall amounts to be inconclusive with some stations showing non-significant decreasing trends (Mubanga and Umar, 2014; Chisola and Kuraz, 2016). Additionally, our findings reveal significant increasing trends ($P < 0.05$) in one-day maximum rainfall, coefficient of variation of daily rainfall, maximum dry spell length (dry period length), temperature, and reference evapotranspiration (Table 4).

The start of the rains exhibited a significant decreasing trend ($P < 0.00$) implying earlier onset of rains. Although the early onset of rains observed in this study is contrary to the late onset that is generally reported in Zambia (Gannon et al., 2014), it is consistent with Mulenga et al. (2017), who found no evidence of later onset of rains for selected stations in Zambia contrary to the perceptions of farmers. Despite an earlier onset of rainfall, dry spells tend to be more than wet spells once the season has started.

A trend implying earlier ending of the rainy season (end of rains) was observed, but it was not significant ($p = 0.17$). Mulenga et al. (2017) also found that the trends in end of rains were not significant. In our case, this decreasing trend was not significant due to greater year to year variability in cessation dates compared to the onset date. The cessation date of rainfall in southern Zambia is linked with the retreating of the Inter Tropical Convergence Zone (ITCZ) to the north (Hachigonta et al., 2008). Other studies have also observed a tendency towards earlier cessation of the rains even though the significance of the trends was not tested (Hachigonta et al., 2008; Gannon et al., 2014).

Regarding hydrological metrics, the results indicated significant decreasing trends in dry season flows ($p = 0.05$) and in the date in which the one-day maximum flow occurs ($p < 0.10$) (Table 4). The decreasing trend in the timing of one-day maximum flow suggests early occurrence of the maximum flow in the river. On the other hand, non-significant decreasing trends in wet season flows and the date of one-day minimum flow were observed (earlier drying of the river), (Table 4). In general, the results point towards reduction in both wet and dry season river flows. In Chongwe Catchment in Zambia, wet season flows were reported to have increased while dry season flows had declined (Chisola and Kuraz, 2016; Tena et al., 2019). In the following sections, we examine the factors explaining the observed hydrological signatures using PLSR.

4.2. Landscape pattern changes in the catchment

4.2.1. Landcover composition dynamics (Percentage of Landscape (PLAND))

Accuracy assessment conducted on the classified landcover maps showed very good classification assessment statistics. The landcover map for 1972 obtained an overall accuracy of 83 % and a Kappa coefficient of 0.77. The 1984 landcover map obtained an overall accuracy of 94 % and a kappa coefficient of 0.92. The overall accuracy for the 1989 landcover map was 95 % and a kappa coefficient of 0.93. For the 1996 landcover map, the overall accuracy was 96 % and the kappa coefficient was 0.95. The 2001 landcover map obtained an overall accuracy of 94 % and a kappa coefficient of 0.92. Finally, the landcover map for 2011 had a 96 % overall accuracy and a 0.95 kappa coefficient.

Fig. 3 shows landcover composition from 1972 to 2011 in the Kaleya River Catchment. There is a notable reduction in forest cover and an increase in both irrigated and rainfed agricultural land (Fig. 3). It is noted that rainfed agriculture was already a major economic activity by 1972, accounting for 21 % of the landscape (Table 5) and was the third most dominant landcover after forest (44 %) and scrubland (35 %). In 2011, rainfed agriculture increased up to 33 % and irrigated agriculture was at 11 % (Table 5). Thus agriculture (both rainfed and irrigated) accounted for a total of 44 % of the landscape in 2011, while scrubland dominated the landscape at about 48 %.

4.2.1.1. Trends in landcover conversions in the catchment. It is noted from Fig. 3b that irrigated agriculture had a significant presence in

Table 4
Trends in hydro-climatic time series from 1975 - 2011 in the Kaleya River Catchment.

Type	Variable	Years	Zc	Sen's slope	P-value
Climatic	Temperature	36	1.90	0.010	0.057*
	Reference Evapotranspiration	36	2.04	1.412	0.042**
	Rainfall	36	1.23	2.078	0.218
	Start of Rains	36	−3.59	−0.250	0.000*
	End of Rains	36	−1.36	−0.176	0.173
	One-day Maximum rainfall	36	3.74	0.462	0.000**
	Rainfall intensity	36	0.25	0.006	0.801
	CV Daily rainfall	36	2.41	0.002	0.016**
	Maximum Dry Spell Length	36	4.02	0.729	0.000**
Hydrological	Wet season flows	29	−0.57	−0.001	0.572
	Dry season flows	29	−1.94	−0.001	0.05**
	Date of 1-day maximum flow	29	−1.88	−1.500	0.060*
	Date of 1-day minimum flow	29	−0.62	−0.806	0.533

** Significant at $p < 0.05$, * Significant at $p < 0.10$.

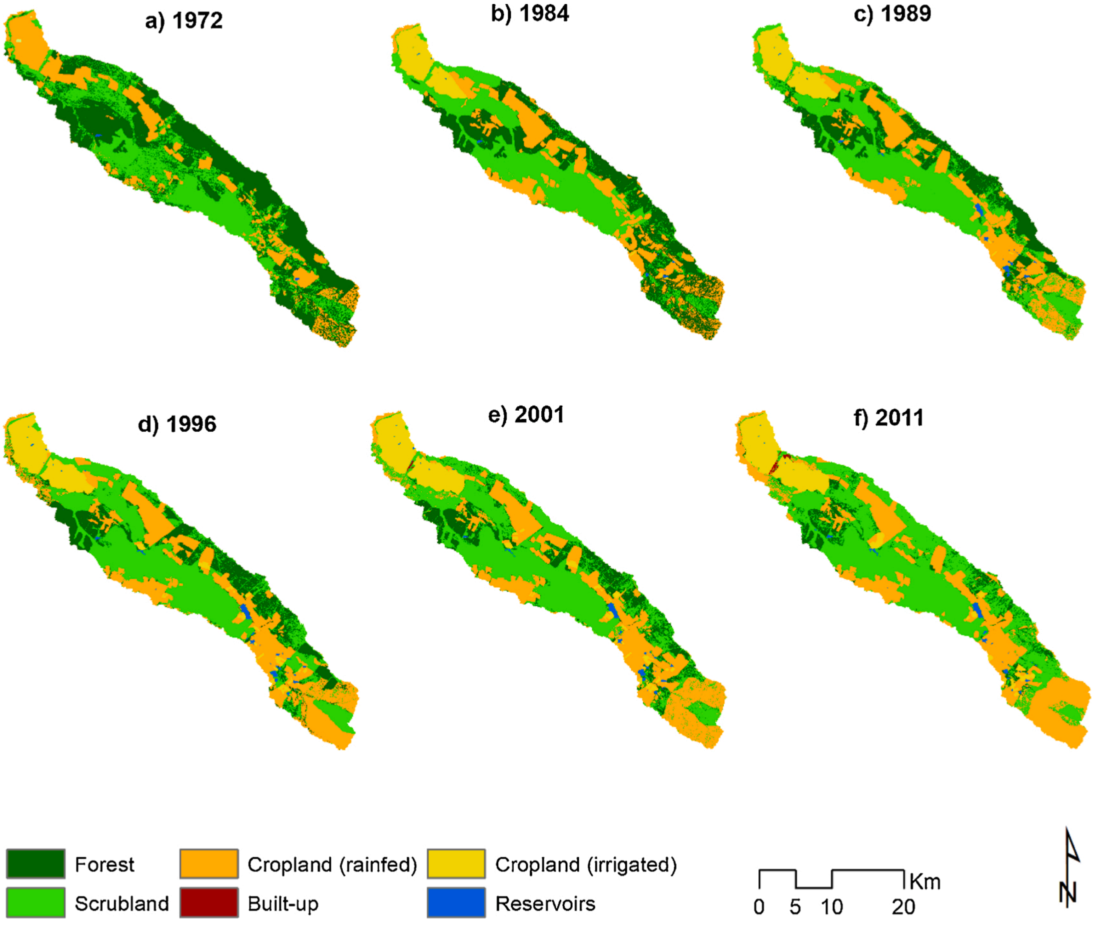

Fig. 3. Landcover maps for Kaleya River Catchment.

the lower catchment by 1984. Results further indicate that most of the rainfed agriculture land was lost to irrigated agriculture especially in the period between 1972 and 1984 (Tables 6 and 7 and Fig. 3). This drastic increase in irrigated land during this period is attributed to the expansion of the Nakambala Sugar Estates in to the Kaleya River Catchment, and the subsequent engagement of communities and commercial farmers through a small-holder out-grower scheme called Kaleya small holders which became operational in the early 1980s (Akayombokwa et al., 2017). This was a form of private-public partnership discussed in the preceding sections aimed at increasing Zambian sugar production for export to the European markets and increasing local agricultural productivity (Akayombokwa et al., 2017).

The results further indicate that since 1984, expansion in irrigated land has mainly occurred from the middle portion of the catchment (Fig. 3c-f). Table 7 shows that between 1972 and 2011, irrigated agriculture gained more land from rainfed agriculture by a

Table 5
Landcover composition (Percentage of Landscape (PLAND)) in the Kaleya River Catchment from 1972 – 2011.

		Land use/Landcover type						Total
Year	Value	Forest	Scrubland	Cropland (rainfed)	Cropland (Irrigated)	Reservoirs	Built-up	
1972	Area (ha)	25488.00	20047.29	12246.37	40.08	46.76	0.00	57868.50
	Percentage (%)	44.04	34.64	21.16	0.07	0.08	0.00	100.00
1984	Area (ha)	17827.89	21103.29	14378.01	4432.81	126.49	0.00	57868.50
	Percentage (%)	30.81	36.47	24.85	7.66	0.22		100.00
1989	Area (ha)	12667.56	24010.76	15899.47	4887.11	403.60	0.00	57868.50
	Percentage (%)	21.89	41.49	27.48	8.45	0.70	0.00	100.00
1996	Area (ha)	10131.68	23805.05	17639.25	5803.95	488.58	0.00	57868.50
	Percentage (%)	17.51	41.14	30.48	10.03	0.84	0.00	100.00
2001	Area (ha)	8201.93	25034.17	17797.03	6377.06	419.01	39.30	57868.50
	Percentage (%)	14.17	43.26	30.75	11.02	0.72	0.07	100.00
2011	Area (ha)	4404.30	27729.97	18905.32	6313.09	385.40	130.41	57868.50
	Percentage (%)	7.61	47.92	32.67	10.91	0.67	0.23	100.00

magnitude of about 8% than from any other landcover class. The tendency to switch from rainfed to irrigated agriculture indicates agricultural intensification in the landscape.

During the 1972–1984 period, the percentage of reservoir area increased from 0.08 % (47 ha) to 0.22 % (126 ha) in the landscape. This relative increase in reservoirs is much smaller compared to the dramatic increase in irrigated land from 40 ha to 4 433 ha in the same period (Table 5). This is because from inception in 1981, the Kaleya small holder irrigation scheme in the lower catchment relies on water transferred from the larger Kafue River using a 14 km canal connecting to a 10 km pipeline (Akayombokwa et al., 2017). The period 1984–1989 recorded the highest gain in the percentage of reservoirs in the landscape (Table 6). This was to support irrigated agriculture that was now expanding from the middle catchment, relying on water abstractions from within the Kaleya River Catchment. The observed lag between reservoirs and irrigated cropland from 1972 to 1984 and a similar pattern in their evolution afterwards is also observable from water permit data from WARMA (Fig. 4).

The net decrease in the percentage of reservoir area in the catchment in the 1996–2011 period (Table 6) is attributed to sedimentation, a problem that has attracted the attention of scholars since the late 1990s (Sichingabula, 1997; Walling et al., 2001; Sichingabula et al., 2018).

The increase in irrigated land and reservoirs could have been a response to the changing climatic patterns. In Table 7 it is further indicated that from 1972 to 2011 forestland has mainly been lost to scrubland and rainfed cropland [Cropland(rainfed)].

4.2.2. Landcover configuration dynamics

4.2.2.1. Patch Density (PD) of landcover classes. Although about 8% of the landscape was still covered by forest in the catchment in 2011, the PD of forest showed that the remaining forest was more fragmented than before (Fig. 5). The PD is an indicator of connectivity of each landcover in the catchment, with higher values indicative of a more fragmented or heterogeneous landcover class or landscape (Yu et al., 2020). Thus, it is possible to have two different periods with the same percentage cover for a landcover class, but the impacts on the flow regime could differ if one is more fragmented. The results show that forest had become more fragmentated, hence less hydrological connectivity in the forested land. The higher PD of reservoirs, rainfed and irrigated agriculture in recent years reflect the increase in the number of reservoirs and crop fields in the landscape. The PD of scrubland does not show major changes during the study period. The general increase in the number of patches for all landcover types relative to the base year (1972) is consistent with the findings of Muleta and Biru (2019) in the Guder watershed in Ethiopia since 1973.

4.2.2.2. Largest Patch Index (LPI) of landcover classes. The Largest Patch Index (LPI) is an indicator of dominance of a landcover class in the landscape. Thus, a landcover class can have a smaller percentage in terms of composition in the landscape but have a large enough patch size to influence eco-hydrological processes. The results indicate that LPI for forest has been reducing, while that of the non-forest landcover classes has been increasing (Fig. 6).

The findings in Fig. 6 provide further evidence of a more fragmented and scattered forest landscape and the increasing dominance and connectivity of scrubland, rainfed and irrigated cropland. Before 1984, there were smaller reservoirs and weirs in the landscape. Since then, bigger reservoirs such as the Kaleya Dam have been constructed, thus explaining the increasing LPI for reservoirs. The LPI value for the built-up area is increasing showing that the built-up area is becoming more compact. Similar trends with respect to decreasing LPI of forests, and increasing LPI of reservoirs and built-up areas were observed by Wang et al. (2020) in the Danjiangkou Reservoir Catchment in China. Hydrologically, the changes in PD and LPI affect the travel times and the timing of extreme river flows such as the date of maximum and minimum flows in the catchment.

Table 6
Landcover change trends from 1972 – 2011 in the Kaleya River Catchment.

Period	Statistic	Forest	Scrubland	Cropland (rainfed)	Built-up	Cropland (irrigated)	Reservoirs
1972–1984	TG (%)	6.61	12.39	13.77	0.00	7.59	0.14
	TL (%)	−19.85	−10.57	−10.09	0.00	0.00	0.00
	NC (%)	−13.24	1.82	3.68	0.00	7.59	0.14
1984–1989	TG (%)	3.49	10.89	7.66	0.00	1.01	0.50
	TL (%)	−12.41	−5.86	−5.03	0.00	−0.22	−0.02
	NC (%)	−8.92	5.02	2.63	0.00	0.79	0.48
1989–1996	TG (%)	4.15	9.38	7.41	0.00	1.75	0.16
	TL (%)	−8.53	−9.74	−4.40	0.00	−0.16	−0.02
	NC (%)	−4.38	−0.36	3.01	0.00	1.58	0.15
1996–2001	TG (%)	3.88	9.40	4.21	0.07	1.14	0.05
	TL (%)	−7.22	−7.28	−3.93	0.00	−0.15	−0.17
	NC (%)	−3.33	2.12	0.27	0.07	0.99	−0.12
2001–2011	TG (%)	2.30	11.47	6.25	0.16	1.04	0.11
	TL (%)	−8.86	−6.81	−4.33	0.00	−1.15	−0.16
	NC (%)	−6.56	4.66	1.92	0.16	−0.11	−0.06
1972–2011	TG (%)	1.51	24.64	21.72	0.23	10.83	0.60
	TL (%)	−37.95	−11.36	−10.21	0.00	0.01	−0.02
	NC (%)	−36.43	13.28	11.51	0.23	10.84	0.59

TG (Total Gain), TL (Total Loss), NC (Net Change)

Table 7
Landcover change matrix comparing 1972 and 2011 landcover.

	LULC	Landcover 2011 Forest (%)	Scrubland (%)	Cropland (rainfed) (%)	Built-up (%)	Cropland (irrigated) (%)	Reservoirs (%)	Total (%)
Landcover 1972	Cropland (irrigated) (%)					0.07		0.07
	Cropland (rainfed) (%)	0.28	1.90	11.02	0.07	7.80	0.09	21.16
	Forest (%)	6.17	22.73	13.23	0.06	1.68	0.18	44.05
	Reservoirs (%)		0.01				0.07	0.08
	Scrubland (%)	1.23	23.14	8.49	0.10	1.34	0.34	34.64
	Total (%)	7.68	47.78	32.74	0.23	10.89	0.68	100.00

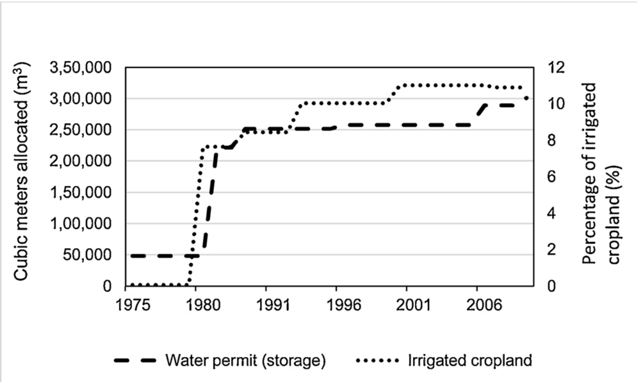

Fig. 4. Water allocations (storage volumes) and the percentage of irrigated cropland in the Kaleya River Catchment.

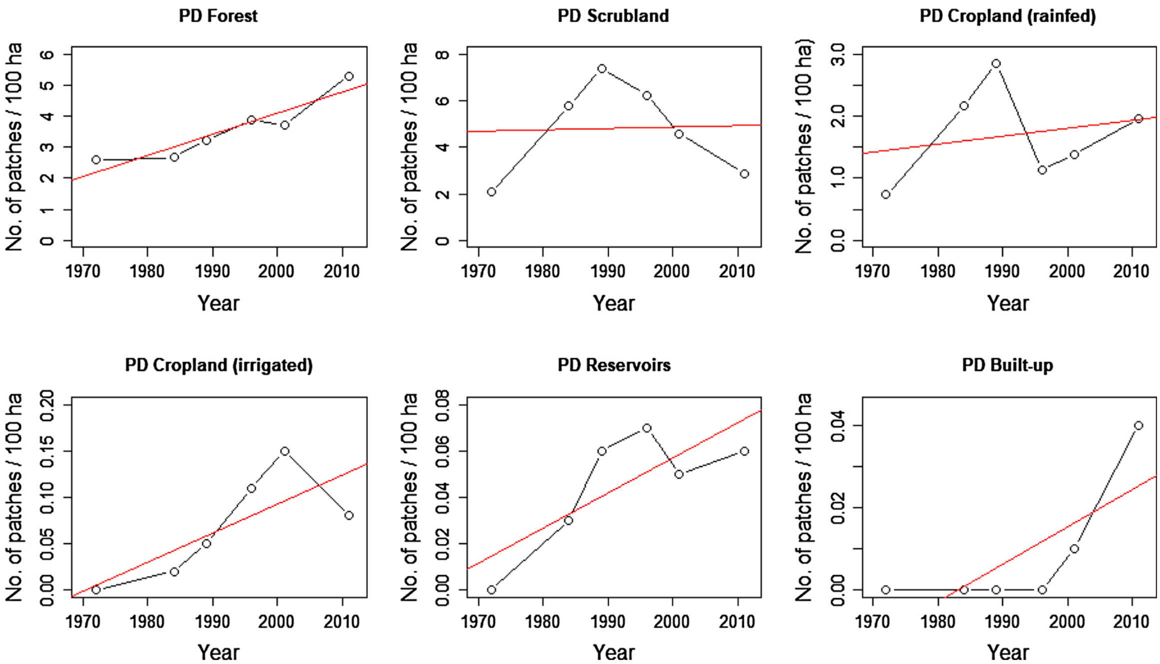

Fig. 5. Patch density for each landcover class from 1972 to 2011 (The straight red line indicates the direction of the trend).

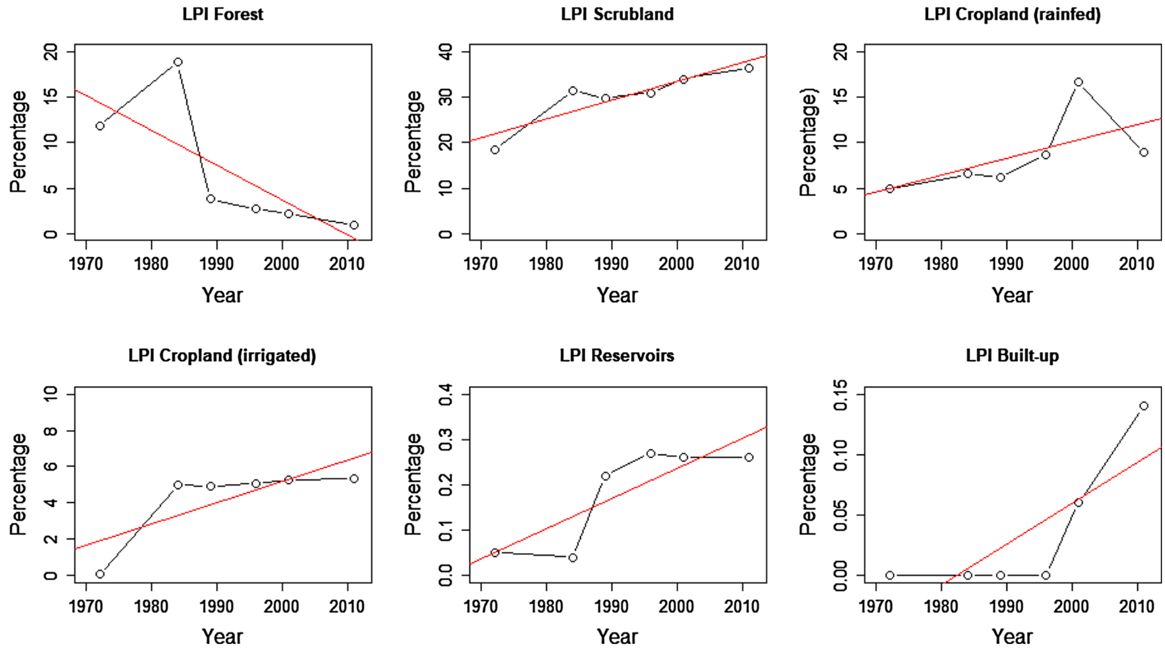

Fig. 6. Largest patch index (LPI) per landcover class from 1972 to 2011 (The straight red line indicates the direction of the trend).

4.3. Attributing river flows to seasonal climatic conditions and landscape dynamics

4.3.1. Wet season flows

The PLSR model for wet season flows had one component explaining 77 % of the variance in the predictors. The R^2 for the model was 0.84 and the cross validated R^2 was 0.64. The major factors explaining the decreasing wet season flows were landscape based, mainly dominated by reservoir metrics (Table 8). These include the percentage of reservoirs (PLAND Reservoirs), along with the largest patch areas of reservoirs (LPI Reservoirs) and patch density of reservoirs (PD Reservoirs) in the landscape. These interacted with climate metrics involving reference evapotranspiration (ET_o) and variability of rainfall events (CV rainfall) to explain decreasing wet season flows.

Higher density of reservoirs (PD reservoirs) increases catchment fragmentation (Chin et al., 2008), and thus reduces landscape connectivity. By impounding the river water, downstream wet season flows are reduced while evaporation losses increase especially in the face of rising temperatures. Increased variability of rainfall events amplifies the effects of reservoirs in reducing downstream wet season flows. Thus, although reservoirs are touted as an adaptation intervention to rainfall variability and or climate change, there effectiveness remains uncertain. Research questions on this subject have revolved around what reservoir capacity, numbers, and density are optimal to build resilience (Chin et al., 2008; Ehsani et al., 2017). This could also be a question for further research in Kaleya Catchment.

Among the important variables explaining wet season flows, only the size of forest patches (LPI Forest) and the onset date of rains (Start of rains) had positive regression coefficients, thus indicating their positive contribution in explaining wet season flows.

Table 8
PLSR for dry and wet season flows.

	Wet season flow			Dry season flow			
	VIP	Coefficients	Component 1	VIP	Coefficients	Component 1	Component 2
CV seasonal Rainfall	0.94	−0.004	−0.27				
ET_o	0.93	−0.004	**−0.33**				
Start of Rains	0.96	0.004	**0.40**				
PLAND Reservoirs	1.09	−0.005	**−0.42**				
PD Reservoirs	1.02	−0.004	**−0.40**				
LPI Forest	1.00	0.004	**0.40**				
LPI Reservoirs	1.04	−0.004	**−0.42**				
Rainfall Intensity				0.95	0.017	0.16	**0.91**
PLAND Crop (irrigated)				0.95	−0.006	**−0.58**	**0.30**
LPI Scrubland				0.98	−0.008	**−0.58**	0.27
LPI Crop (irrigated)				1.11	−0.011	**−0.61**	0.10

CV (Coefficient of variation), ET_o (Reference Evapotranspiration), PLAND (Percentage of Landscape), (PD (Patch Density), LPI (Largest Patch Index). Loading weights in bold are significant (>0.3) on the components.

Generally, larger forest patches reduce direct runoff and soil erosion, but increase groundwater recharge and baseflow (Boongaling et al., 2018; Zong et al., 2020). Promoting larger forest patches in the Kaleya catchment landscape could therefore improve infiltration and baseflow opportunities and reduce direct runoff and sedimentation. This could in turn improve water availability as the upstream catchment is groundwater/baseflow dominated (over 50 % of water is from the spring and subsurface flow in the rainy season. Groundwater/baseflow contribution increases to 100 % in the dry season, based on our ongoing analysis using stable water isotopes in the upper part of the catchment).

4.3.2. Dry season flows

The PLSR model for dry season flows improved with two components, which explained a cumulative total of 98.7 % of the variance in the predictors. The model had an R^2 of 0.89 and a cross validation R^2 of 0.58. Again, the landscape-based metrics dominated the model (Table 8). For dry season flows, the most important (significant) variables were irrigated cropland metrics involving the percentage of irrigated cropland (PLAND Crop (irrigated)) and the large patch areas of the irrigated crop fields (LPI Crop (irrigated)). These along with the extent of the largest scrubland patches (LPI Scrubland) had negative regression coefficients explaining a decrease in dry season flows.

The dominance of scrubland reduces baseflow/ground water contribution to dry season flows due to reduced infiltrated water. On the other hand, larger patches of irrigated cropland (larger LPI Crop (irrigated)) and the increase in the percentage of irrigated cropland in general (PLAND Crop (irrigated)) explained the decline in dry season flows due to water abstraction. These findings are supported by water permit (abstraction) allocation data for the area which shows a very similar pattern (Fig. 4). Thus, allocated water permit data show a strong correlation with PLAND Crop (irrigated) ($r = 0.93$, $p < 0.00$) and LPI Crop (irrigated) ($r = 0.89$, $p < 0.00$), which have been identified by the PLSR as major stressors on dry season flows in the catchment.

4.3.3. Date of one-day maximum flows

The model for date of one-day maximum flows had one component explaining 82.80 % of the variance in the predictors. The R^2 was 0.83 while the cross validation R^2 was 0.44. The results indicate that the tendency towards early date of one-day maximum flow is explained mainly by climatic conditions involving higher rainfall intensities (Rainfall intensity) and the earlier onset of rains (Start of rains) (Table 9). The results further indicate that larger forest patches (larger LPI Forest) are associated with the delay in the timing of one-day maximum flow.

The results are expected as higher rainfall intensities promote quicker concentration of surface runoff on the landscape, which could contribute to early occurrence of maximum river flows. In contrast, increasing the size of forest patches (larger LPI Forest) in the landscape promotes infiltration and slows the movement of surface runoff. Hence the positive effect of larger forest patches (LPI Forest), which explains delay in the date of one-day maximum flows (larger day of the year value for one-day maximum flows) is not surprising. However, the LPI of forest in the catchment has undergone a rapid decline over the years as observed in Fig. 6, and thus it effects in delaying peak flows is predominated by climatic factors. Hence, high rainfall intensities and decreasing dominance of forest patches (LPI Forest) are among the underlying factors explaining reduced infiltration opportunities in the catchment, and thus a tendency towards an earlier date (smaller day of the year value for one-day maximum flows) of maximum flow.

4.3.4. Date of one-day minimum flows

Although the trend in the date of one-day minimum flows was not statically significant, it was important to look at the factors that could explain its variability. The PLSR results for the timing of extreme low flows are given in Table 9. The model had one component explaining 77 % of the variance in the predictors. The R^2 was 0.72 and the cross validated R^2 was 0.40. Seasonal climatic factors involving higher variability of rainfall events (CV seasonal rainfall) and landscape metrics involving the percentage of reservoirs (PLAND Reservoirs) are associated with an early date of minimum flow. Again, the size of forest patches had a positive effect on the date of minimum flow. The results reaffirm that increasing the size of forest patches (larger LPI Forest) could promote baseflow, and thus delay the day of the year on which the minimum flow occurs. Delaying the date on which one-day minimum river flow occurs in the season has positive water availability implications.

4.4. The landscape hydrology approach and Implications for sustainable water resource management

Using the landscape hydrology approach, this study identified the climatic and landscape patterns important for informing water resource interventions in a heterogenous intensively managed semi-arid catchment landscape. The climatic stressors were mainly associated with seasonal rainfall characteristics involving the start of rains, intensity and variability in the season, and ET_o. These together with landscape metrics, particularly reservoir and irrigated agriculture-based expansions, explained much of the observed hydrological variability and declining seasonal water availability in the catchment. Seasonal rainfall characteristics were more important in explaining hydrological patterns than rainfall totals as the former influence landscape hydrological processes of surface runoff generation, infiltration, soil moisture and ET dynamics. Given that most studies in southern African and African region general indicate non-significant increasing or decreasing trends in annual rainfall totals (Kusangaya et al., 2014; Mubanga and Umar, 2014; Taye et al., 2015), this study argues that it is in fact the changing seasonal rainfall distribution that must be of concern for water resources management in the region. An improved understanding of trends in seasonal rainfall characteristics such as its intensity, variability and dry spell lengths could be even more important than annual rainfall trends for building resilience in semi-arid areas.

Our findings indicate that increasing the size of forest patches could offset the negative effect of increasing rainfall intensities and dry spell lengths by helping in flood mitigation through delaying the occurrence of peak river flows and supporting dry season river

Table 9
PLSR for the date of one-day minimum and maximum flows.

	Date of 1-day maximum flow			Date of 1-day minimum flow		
Variable	VIP	Coefficients	Component 1	VIP	Coefficients	Component 1
Rainfall Intensity	0.91	−16.84	**−0.53**			
Start of Rains	1.08	20.08	**0.59**			
LPI Forest	1.01	18.74	**0.61**			
CV seasonal Rainfall				1.23	−17.38	**−0.57**
PLAND Reservoirs				0.87	−12.26	**−0.58**
LPI Forest				0.86	12.26	**0.61**

CV (Coefficient of variation), PLAND (Percentage of Landscape), LPI (Largest Patch Index). Loading weights in bold are significant (>0.3) on the components.

flows by delaying the date of one-day minimum flow. Larger forest patches can promote infiltration and baseflow. We thus recommend increasing the percentage of forest area by promoting larger forest patches widely spread across the catchment to benefit both wet and dry season river flows. This could be achieved through farmer assisted natural regeneration of scrubland and abandoned rainfed agricultural land (Ndeso-Atanga, 2018; Akinnifesi, 2018) as the majority of the catchment landscape is controlled by farmers and the corporate sector. The miombo woodland which is dominant in the catchment has a good coppicing and natural regeneration potential (Luoga et al., 2004; Syampungani, 2009; Handavu et al., 2011).

Zambia's Forest Act No.4 of 2015 (Forest Act, 2015) provides an opportunity for farmers and the corporate sector to own forests and thus diversify their income sources through private forests. Farmers can earn additional revenues from non-timber forest products like mushrooms, honey (bee-keeping) and carbon trading while protecting and enhancing water availability for their agricultural produce. Mfune (2018) proposes the formation of forest cooperatives that can help to increase the volumes of forest produce from individual farmers (forest patches) and enhance the negotiation power so that farmers can get the most out of their forest practices. This diversification could also buffer the farmers against climatic shocks that may affect their agricultural production.

Irrigated agriculture was an important variable explaining reduced water availability, especially during the dry season. This is due to increased abstractions and increasing ET_o (mainly due to increasing temperature) as shown in the results. In this regard, irrigated agriculture in the catchment should move towards more efficient systems and management practices, as well as high value crops farmed on less land.

5. Conclusions

A landscape hydrology approach was successfully applied without hydrological modelling in a highly managed heterogeneous catchment landscape. The approach was able to detect stressors from among the landscape components and inform water resource management interventions at a landscape scale. Significant increasing trends in seasonal climatic characteristics of ET_o, one-day maximum rainfall, CV of daily rainfall, and maximum dry spell length have occurred in the Kaleya River Catchment over 1975–2011 but not in total annual rainfall. In contrast, both the onset and cessation of rains show a trend towards earlier onset and cessation even though the latter was not significant. Both dry and wet season flows show declining trends, but only the former is significant. Based on landscape composition metrics, the study concludes that there has been a dramatic decline in forested land, expansion of irrigated cropland mainly from land previously used for rainfed agriculture and increase in reservoirs and the catchment landscape is more fragmented in recent years.

The major climatic stressors are all associated with increasing ET_o and seasonal rainfall characteristics namely; increasing variability of rainfall, dry spell length and rainfall intensities. In this regard, water resource interventions in the region must adapt more to the changing seasonal climatic characteristics than annual totals. On the landscape side, the major stressors on water availability are the increasing percentage of reservoirs and irrigated cropland, increase in the sizes of reservoirs and irrigated crop fields and increased density of reservoirs. It is recommended that more efficient agricultural water use and farmer-assisted natural regeneration of forest patches towards larger forest patch sizes is needed to enhance landscape hydrological processes that improve seasonal water availability. The approach in this study can be applied to other catchments where no major gaps exist in the timeseries data on climate and hydrology, and where temporal landcover data is available. It could help to support informed decision making when managing water resources under a changing environment.

CRediT authorship contribution statement

Moses N. Chisola: Conceptualization, Methodology, Software, Writing - original draft. **Michael van der Laan:** Supervision, Writing - review & editing. **Keith L. Bristow:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ejrh.2020.100762.

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