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Interpreting characteristic drainage timescale variability across Kilombero Valley, Tanzania

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Abstract:

We explore seasonal variability and spatiotemporal patterns in characteristic drainage timescale (K) estimated from river discharge records across the Kilombero Valley in central Tanzania. K values were determined using streamflow recession analysis with a Brutsaert–Nieber solution to the linearized Boussinesq equation. Estimated K values were variable, comparing between wet and dry seasons for the relatively small catchments draining upland positions. For the larger catchments draining through valley bottoms, K values were typically longer and more consistent across seasons. Variations in K were compared with long-term averaged, Moderate-resolution Imaging Spectroradiometer-derived monthly evapotranspiration. Although the variations in K were potentially related to evapotranspiration, the influence of data quality and analysis procedure could not be discounted. As such, even though recession analysis offers a potential approach to explore aquifer release timescales and thereby gain insight to a region's hydrology to inform water resources management, care must be taken when interpreting spatiotemporal shifts in K in connection with process representation in regions like the Kilombero Valley. © 2014 The Authors. *Hydrological Processes* published by John Wiley & Sons Ltd.

KEY WORDS characteristic drainage timescale; streamflow recession analysis; Kilombero Valley; water resources management

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INTRODUCTION

There is a need to improve water resources management in areas with heavy degradation of water quality and low land productivity (Vörösmarty *et al.*, 2010). Tanzania, for example, has several river basins that if adequately developed from an agricultural perspective could improve food security and reduce poverty. Current agricultural practices, however, utilize few modern techniques (ERB, 2006) and, as such, may limit Tanzania's ability to secure production under potentially increasing vulnerability to the variability associated with rainy seasons (Valimba *et al.*, 2006). Although Tanzania has about 0.9 million hectares of irrigable land, only 15% is currently under irrigation, with 80% of these being traditional irrigation systems (FAO, 2002). As such, development of dry-land irrigated agriculture to extend growing seasons beyond rain-fed periods has the potential to develop Tanzania's economy and provide food security (ERB, 2006). This is particularly true for central Tanzania where much land is estimated to be suitable for irrigated agricultural development (ERB, 2006).

Irrigated agricultural development needs to be carried out in a manner that does not compromise other vital ecosystem services. For example, the Kilombero Valley (Figure 1) of central Tanzania is unique in terms of its ecology and biodiversity. It serves a key role in the Selous–Kilombero seasonal wildlife migrations and contains almost 75% of the world's population of the wetland-dependent puku antelope (*Kobus vardonii*). This uniqueness qualifies the Kilombero Valley floodplain to be included in the Ramsar convention on wetlands (www.ramsar.org), highlighting the need for conservation and wise use of the wetland and its resources. This is particularly true as scenarios to increase irrigated area in the Kilombero Valley floodplain, of which less than 2% is currently irrigated, are considered (ERB, 2006). In addition to balancing the myriad ecosystem services within the wetland, the potential pitfalls associated with expanding irrigation for agricultural intensification are numerous, including problems of environmental degradation (ERB, 2006; Törnqvist *et al.*, 2011), depletion of

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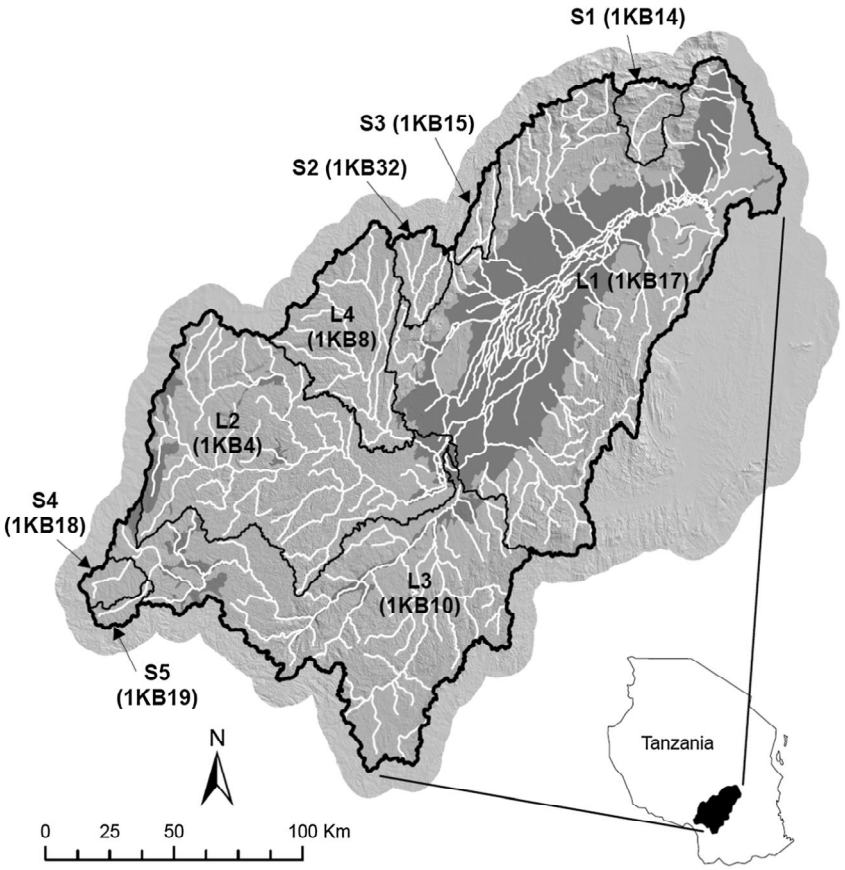


Figure 1. Site map showing Kilombero Valley located in central Tanzania and the nine catchments considered in this study [with L1 (1KB17) draining the entire region]. Streams are indicated as white lines, whereas dark grey shows valley bottoms and alluvial plains and the light grey shows hillslopes and mountains

groundwater resources (Shibuo *et al.*, 2007), and increased incidence of waterborne diseases and malaria (Hetzel *et al.*, 2008). Clearly, the potential impacts of changes in land–water management need to be explored to insure the equitable, efficient, and sustainable use of water resources (Kangalawe and Lyimo, 2010; Jarsjö *et al.*, 2012) in a manner that does not compromise the natural value of the wetland. An adequate and representative modelling framework could potentially aid in the development of such an integrated water resources management policy.

In this regard, data scarcity is a large stumbling block for regions like the Kilombero Valley. The decline of hydro-meteorological observation networks causes regional hydrologic predictions to be highly uncertain (Koutsouris *et al.*, 2010). Data scarcity limits the understanding of coupled water resources–climate systems (Washington *et al.*, 2004) and may also lead to strong errors when interpolations are made across space and time using only a few observation stations or periods (Jung *et al.*, 2012). Instead, approaches that can leverage incomplete or sparse hydrologic data with regard to sampling periods and frequency need to be considered (e.g. Armanios and Fisher, 2013). This is especially true as we develop relevant process-based representations of regions like the Kilombero Valley. Such representations are needed as there may be limited chances for management success in monsoonal Africa when applying approaches originally developed for regions with very different hydroclimatological settings (Steenhuis *et al.*, 2009).

From such a perspective and under the data limitations of the Kilombero Valley, our goal in this study is to explore what can be learned about catchment-scale hydrological processes by adopting a fixed perceptual model and analysis technique (Beven, 2012). In the face of data limitations, recession analysis may be advantageous because it eliminates the time variable of a hydrograph and avoids some of the difficulty of defining the beginning of low-flow responses from continuous-flow observations of alternating wet and dry periods (Brutsaert and Nieber, 1977). This makes applications and theories leveraging baseflow recession attractive in data-limited environments or locations where streamflow observations might not be temporally consistent. For example, solutions to the linearized Boussinesq equation

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(e.g. Brutsaert, 2005; Troch *et al.*, 2013a) could make good candidates for parsimonious conceptualization frameworks (e.g. Carrillo *et al.*, 2011) in such regions because of the common utilization of recession analysis in their implementation. Recession analysis techniques have been used to characterize storage–discharge relationships in applications ranging from groundwater–permafrost interactions (e.g. Lyon *et al.*, 2009a; Lyon and Destouni, 2010) to large-scale aquifer drawdown (Brutsaert, 2008).

In spite of these potential benefits, recession analysis and the often associated Brutsaert–Nieber-style solution to the Boussinesq equation have been criticized because of what can be considered as rather limiting assumptions. Investigations into the impact of vertical aquifer heterogeneity (Rupp and Selker, 2006a) and horizontal catchment heterogeneity (Harman and Sivapalan, 2009) highlight scale dependencies that potentially disconnect theory from real-world applications. For example, El-Kadi and Brutsaert (1985) studied the effects of spatial variability on outflows and found that only under a narrow set of circumstances could a set of effective 'homogeneous equivalent' parameters effectively reproduce the recession behaviour over a range of flows. Further, as such approaches have been largely developed in humid regions (like north-eastern USA), the validity behind applying the same central assumptions to monsoonal and/or arid regions, where evaporative fluxes tend to dominate, is still being explored (e.g. Brutsaert, 2012). Variations in the dominant hydrologic processes across spatial and temporal scales will thus naturally have influence (Carrillo *et al.*, 2011). It is exactly this influence we seek to explore in this current study to gain insights to the hydrology of Kilombero Valley.

In this study, we apply recession analysis across the Kilombero Valley in central Tanzania to explore potential spatiotemporal patterns and seasonal dependence of the characteristic drainage timescale (K). In addition, we attempt to relate patterns of variability in K across catchments and seasons to patterns of evapotranspiration and landscape characteristics. Our motivation is an attempt to leverage baseflow recession analysis in a data-limited setting to improve understanding of aquifer release timescales and how these could inform water resources management. By identifying such patterns and relationships, we hope to facilitate process representation relevant for future hydrologic modelling and water resources management in the Kilombero Valley.

KILOMBERO VALLEY: SITE DESCRIPTION AND DATASETS

The Kilombero Valley (Figure 1) of central Tanzania forms one of the four principal sub-basins of the Rufiji River Basin and covers an area of approximately 35 000 km^2. The Kilombero Valley is situated between 34°33′E and 37°20′E and between 7°39′S and 10°01′S. In the north-western part of the catchment, the Udzungwa Mountains rise up to 2576 m and are comprised of steep slopes and dense forests. Along the south-eastern side, the land rises more gradually, eventually changing to a steep escarpment and the Mahenge Mountains that reach a maximum height of 1516 m (Hughes and Hughes, 1992). Tributaries originating in these mountains form the headwaters of the valley's river system. In the valley's central floodplain, the main river becomes a braided network. The whole valley is thus a complex system with perennial and seasonal river channels, oxbows, swamps, ponds, lakes, grass, and woodland. Kilombero Valley is generally hot and humid in the valley bottom with a mean daily temperature of 24 °C and annual precipitation between 1200 and 1400 mm, whereas the mountainous regions around the basin are considerably cooler and wetter with a mean daily temperature of 17 °C and average annual precipitation ranging from 1500 to 2100 mm (ERB, 2006).

A total of 13 time series of daily streamflow from two different sources were considered. Seven come from the Institute for Resource Assessment (IRA) at the University of Dar es Salaam and constitute raw (i.e. unaltered) data available from stream monitoring stations. The remaining six come from Yawson *et al.* (2005) and have been processed to remove potential inaccuracies and to fill data gaps. Between these two sources, there were four redundant streamflow records such that we have streamflow data for nine unique catchments (Table I). Note that in the naming convention, the catchments have been distinguished as either relatively large (L) or small (S). For the catchments where there are two streamflow records, we use the unfilled and unfiltered data from IRA in this current analysis rather than the processed data from Yawson *et al.* (2005) as the gap-filling techniques from

Table I. Streamflow datasets considered in this study from the Kilombero Valley, Tanzania

Catchment ID	Tanzanian identification code	Period of record	Missing data (%)	Type
L1	1KB17	1957–1981	15	Raw data
L2	1KB4	1955–1982	0	Processed data
L3	1KB10	1960–1987	0	Processed data
L4	1KB8	1956–2007	27	Raw data
S1	1KB14	1958–2002	23	Raw data
S2	1KB32	1984–2011	36	Raw data
S3	1KB15	1960–1989	4	Raw data
S4	1KB18	1976–2010	20	Raw data
S5	1KB19	1961–1978	3	Raw data

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Yawson *et al.* (2005) could potentially influence the results and introduce artefacts to the recession analysis. Comparison of the results obtained using these gap-filled data (Supporting Information) indicates that this influence is likely small as the filled periods typically do not correspond to extensive drought periods and are mainly influencing the highest flows. Still, the quality of the data considered here (as in any attempt to employ a recession analysis technique; Rupp and Selker, 2006b) unavoidably impacts the results. Regardless, there is still potential value in considering the data from Yawson *et al.* (2005) because these data increase the spatial coverage of this study (i.e. they add two additional catchments). Precipitation data from the valley and the surrounding area were available from the IRA at the University of Dar es Salaam and the Rufiji Basin Water Office. The precipitation data were available as daily totals from 34 gauges within the Kilombero Valley catchment. These gauges all experienced periods of missing data and have varying periods of record covering 1957–1990. These data have been averaged spatially and temporally to estimate long-term monthly precipitation totals in this current study.

In addition to hydrologic data, several spatial datasets were considered to characterize the catchments. Catchment drainage areas and corresponding topographic information were derived from a Shuttle Radar Topography Mission digital elevation model with a 90-m raster resolution. Vegetation coverage, soil information, and landform data were obtained from the Food and Agriculture Organization's Africover and GeoNetwork datasets (both available through www.fao.org/geonetwork) and had spatial resolutions ranging from 1 : 100 000 to 1 : 350 000. These catchment characteristics show that there is a clear difference between the smaller, more upland catchments and the larger, valley bottom catchments (Table II). The smaller catchments in upland positions have higher average slopes, shorter stream lengths, proportionately more forested lands, and proportionately more Nitisol soils. Larger catchments draining through more lowland and valley positions have longer stream lengths and proportionately more shrublands and Acrisol soils.

Moderate-resolution Imaging Spectroradiometer (MODIS)-based evapotranspiration was considered for comparison with the recession analysis results. The MODIS evapotranspiration product is based on a Penman–Monteith algorithm, and data from MODIS products (land cover, fraction of photosynthetically active radiation/leaf area index, and albedo) and from the NASA Global Modeling and Assimilation Office reanalysis dataset (Mu *et al.*, 2007, 2011). Monthly data at 1-km resolution were obtained from http://www.ntsg.umt.edu/modis for the period 2000–2013. The data were averaged by catchment boundary such that a single evapotranspiration value was obtained for each catchment and month.

METHODS

Brief review of characteristic drainage timescale estimation

Brutsaert (2008) summarized how under hydraulic groundwater theory, physical considerations suggest that the total groundwater storage in a basin can be approximated as a power function of flow rate at the basin outlet (e.g. Brutsaert and Nieber, 1977; Brutsaert, 2005; Rupp and Selker, 2006a):

$$S = K_n y^m \tag{1}$$

Table II. Catchment characteristics within the Kilombero Valley, Tanzania

		Catchment ID								
		L1	L2	L3	L4	S1	S2	S3	S4	S5
Topographic	Area (km^2)	34230	18048	8577	2531	580	582	337	336	175
	Average slope (%)	7	8	8	9	14	10	16	5	6
	Stream length (km)	5916	2859	1272	440	63	110	69	27	27
	Drainage density (km/km^2)	0.17	0.16	0.15	0.17	0.11	0.19	0.21	0.08	0.15
Vegetation	Forests (%)	24	15	15	18	60	14	38	2	0
	Shrubs (%)	28	43	39	45	17	18	5	7	0
	Herbaceous (%)	30	26	22	34	3	43	57	55	50
Soil	Nitisols (%)	15	3	6	41	98	87	70	99	90
	Lixisols (%)	15	37	24	17	0	10	0	1	10
	Acrisols (%)	46	53	69	24	0	0	0	0	0
	Others[a] (%)	24	6	0	18	2	2	30	0	0
Landform	Valley and alluvial plain (%)	22	8	8	1	0	0	0	0	0
	Hill and mountain (%)	78	92	92	99	100	100	100	100	100

[a] Includes small proportions of Arenosols, Cambisols, Leptosols, and Fluvisols.

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where $y = Q/A$ ($\mathrm{L\,T^{-1}}$) is the specific discharge with Q ($\mathrm{L^3\,T^{-1}}$) as the volumetric flow rate and A ($\mathrm{L^2}$) as the total drainage area, S (L) is the volume of water stored (per unit area) in the upstream aquifers, and K_n (T) and m (–) are constants depending on the physical characteristics of the basin in question. Focusing on the parameter m, we can make arguments built from theory (e.g. the linearized version of the Boussinesq equation) and observation (e.g. Brutsaert, 2008) that m approaches unity as flow rates become small (i.e. late-time drainage). Robust results may be obtained by adopting the value $m = 1$, leading to the convenient simplification of Equation (1) to

$$S = Ky \tag{2}$$

where K (T) defines the characteristic timescale of the catchment drainage process, also commonly referred to as the storage coefficient (Brutsaert, 2008). Of course, there is much debate about the actual value of m and the feasibility of adopting a value $m = 1$ with regard to both theory (Bogaart *et al.*, 2013) and practice (Rupp and Selker, 2006b), but we adopt this value here to provide a consistent and pragmatic method in a data-limited setting.

Although K in Equation (2) is difficult to determine in any truly objective manner, in the absence of precipitation and other dominating hydrological fluxes, it is useful to assume that the water flowing in a river comes mainly from the drainage of groundwater aquifers. As such, when considering the conservation of mass as in Brutsaert (2005), derivatives can be taken on both sides of Equation (2) to yield a relationship (Brutsaert, 2008):

$$y = -K\frac{\mathrm{d}y}{\mathrm{d}t} \tag{3}$$

This relationship presented in Equation (3) is advantageous as it allows us to perform baseflow recession approaches and determine K straightaway.

Although many recession analysis techniques have been proposed (e.g. Hall, 1968; Brutsaert and Nieber, 1977; Nathan and McMahon, 1990; Kirchner, 2009), they typically use a logarithmic representation of low-flow dynamics, allowing K to be determined as the intercept of a straight line. Even though all methods suffer somewhat because of subjectivity and the reliability of data, the procedure put forward by Brutsaert and Nieber (1977) has been widely used over the past several decades (Troch *et al.*, 2013a). Under this procedure, low flows are analysed by considering a lower envelope of a logarithmic plot of $\mathrm{d}y/\mathrm{d}t$ versus y. Flows that are not strictly baseflow, i.e. those occurring during and immediately following precipitation events, are removed.

Application to the Kilombero Valley

Recession analysis as presented by Brutsaert and Nieber (1977) and Brutsaert (2008) was used to determine K according to Equation (3) for the nine catchments within the Kilombero Valley. Log–log plots of $\mathrm{d}y/\mathrm{d}t$ against y based on the available streamflow record were created. Periods of rising hydrographs and periods of 3 days after hydrograph peaks were removed from the recession analysis to avoid the influence of precipitation events. Further, to determine K values for each catchment, we fit a straight line to the lower envelope allowing 15% of the data in the log–log recession plot to fall below the line. We tested a range of values (5–25%) for defining the lower envelope and saw no substantial impact on the relative results. However, there was an influence of this lower-envelope definition on the absolute values for K, and the implications of this were considered. This recession analysis approach was applied to all the available daily streamflow data for each of the nine catchments in the Kilombero Valley. In addition, the recession analysis approach was applied to daily streamflow data grouped by month. Together, this allowed for annual and monthly K values to be estimated from the flow observations for each catchment. Thus, annual K values are based on all the daily streamflow together for all the observation years, and daily streamflow grouped per month gave a K value per month.

As a simple check on mechanisms behind potential spatiotemporal variation in K and to help put the recession responses of these Tanzanian catchments into context, we also explored connections between patterns in K and evapotranspiration [E ($\mathrm{L\,T^{-1}}$)]. This was carried out by calibration of the amount of E needed to account for shifts in y to bring about the observed variations in K values:

$$(y + E) = -K\frac{\mathrm{d}y}{\mathrm{d}t} \tag{4}$$

This is fundamentally the same as the approach of Zecharias and Brutsaert (1998) who used a quasi-steady-state solution to the linearized Boussinesq equation to estimate evapotranspiration from groundwater in 19 watersheds in the Allegheny Mountains. Szilagyi *et al.* (2007) took a similar approach considering deviations between observed recessions and theoretical recessions, assuming no evapotranspiration. Note that we differ from Szilagyi *et al.* (2007) who used as methodological approach in that we are not considering variations in the value of the slope parameter (m) from Equation (1). Rather, calibrated values of E for each sub-catchment are based on an assumption that K has a typical value of 45 ± 15 days, which, considering Brutsaert (2008), should suffice when K is difficult to determine or when mainly order-of-magnitude estimates are required. This of course is a strong assumption taken here because of

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data limitations across these sites and because we intend the analysis to provide a context for our estimated K values in the Kilombero Valley against literature values. Calibrated values of E for each catchment at monthly scales were compared with independent assessments of evapotranspiration from remotely sensed MODIS products.

RESULTS

Hydroclimatic setting

There were clear wet and dry seasons within the Kilombero Valley over the period of record considered (Figure 2). Average monthly total rainfall values ranged from 174 to 233 mm between December and April (the wet season) and were less than 80 mm between May and November (the dry season). This is consistent with previous work in the region (e.g. Valimba *et al.*, 2006). The higher rainfall values in the wet season were accompanied by higher variability, with the last month of the wet season (April) showing the highest standard deviation of monthly rainfall totals.

This wet season with respect to precipitation creates a clear hydrologic response in specific discharge across the catchments within the Kilombero Valley (Figure 2). This response is variable across the catchments. The small and more upland catchments (Table II) exhibit quicker responses with relatively high specific discharges. For example, catchment S4 has a peak in monthly average flow occurring in March, whereas the catchment that drains the valley bottom (L1) peaks in April. The catchment draining the valley bottom also exhibited a more subdued hydrologic response with specific discharge values consistently lower than those seen in the more upland catchments. It should be noted that, as these data come from observations covering different periods of record (Table I), the differences between these catchments may partially be due to changes within the catchments (e.g. irrigation expansion) or climatic forcing (e.g. shifts in precipitation patterns).

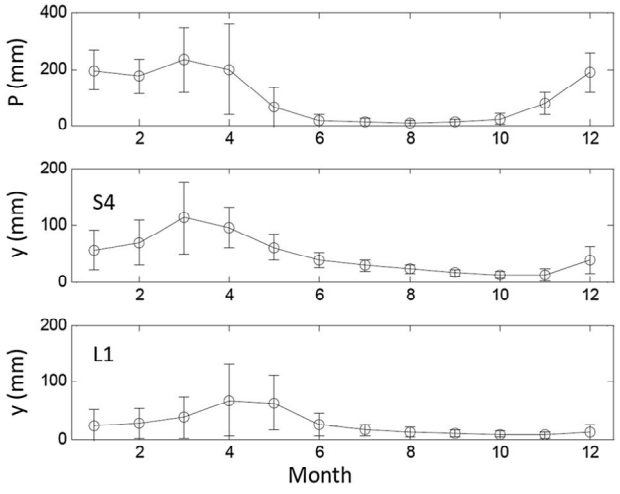


Figure 2. Seasonal variation in the monthly average (bars indicate standard deviations) of the rainfall occurring in the Kilombero Valley region and the representative hydrologic response from an upland catchment (S4) and the catchment for the entire valley (L1) derived from the daily data considered in this study

Estimating characteristic drainage timescales

Annual K values ranged from 61 days for S3 to 435 days for S2 (Figure 3 and Table III). Across all nine catchments, this leads to an average K of 203 days with a standard deviation of 139 days. Owing to the wet and dry season dynamics (Figure 2), further insight may be gained by applying the Brutsaert–Nieber recession analysis to the available daily streamflow data grouped into monthly intervals (Figure 4). There is a strong change associated with the storage–discharge relationship moving from the wet season to the dry season. This change is seen to various degrees across all of the nine catchments within the Kilombero Valley through variations in the K (Table III). The estimated K values for all the smaller, more upland catchments (i.e. S1–S5) showed more variability between wet and dry seasons. Indeed, averaging across the wet season months (here, December–April), the smaller, more upland catchments exhibited an average K of 52 days in the wet season compared with an average K of 199 days in the dry season. In contrast, the larger catchments draining parts of the valley bottom (i.e. L1–L3) exhibited less variability between wet and dry seasons and typically had longer K values. The exception here is the catchment L4 that exhibited variations in monthly estimated K values similar to the smaller catchments.

Relating drainage timescales to physical characteristics

We compared K across the nine catchments (Table III) with the general catchment characteristics (Table II). This is an attempt to explore potential explanations in the spatiotemporal variability of K beyond the first-cut observation that catchment area and position influence K. Because there is a large potential correlation between catchment characteristics (as is often the case when working with fractional areas), we highlight only the clearest relationships.

The first relationship that can be highlighted is the threshold relationship between valley landform in each catchment and wet season averaged characteristic drainage timescale (Figure 5a). Of course, there are few (three out of nine) catchments with more than about 1% valley landform, and these catchments are also the largest in total area (about an order of magnitude larger than those catchments with less than 1% valley landform) and have the longest total stream lengths (again, about an order of

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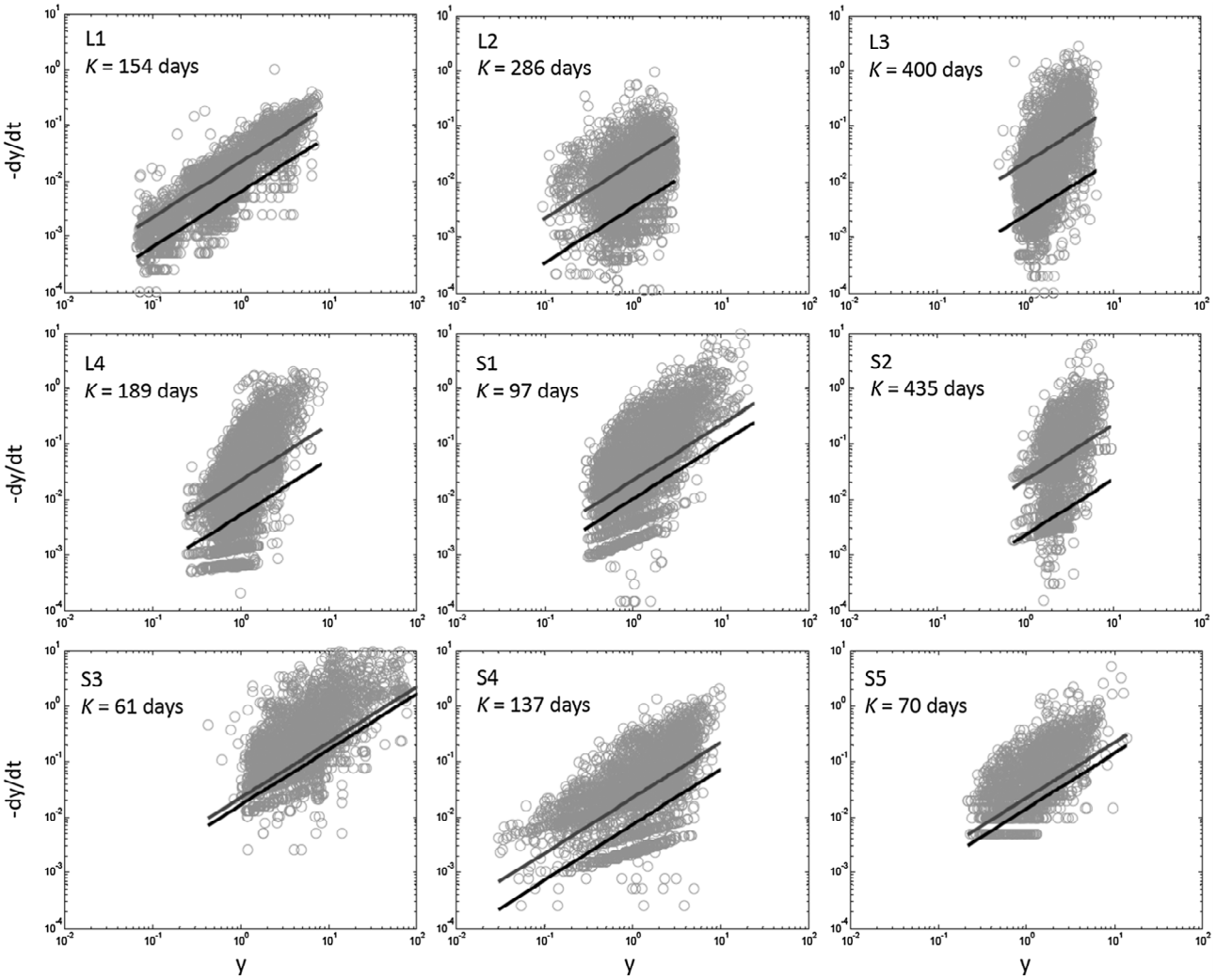


Figure 3. Brutsaert–Nieber-style recession analysis demonstrated using all data available for all the catchments with the estimated K values corresponding to the fit black line (which has a slope of unity). The grey lines show the locations of the Brutsaert–Nieber linear solution to the Boussinesq equation assuming $K = 45$ days for context

magnitude larger than those catchments with less than 1% valley landform). Counter to the wet season, no clear threshold relationship is observed between valley landforms and K in the dry season. Because of the relationships with total area and stream length, we expect that landforms are serving here as proxies for landscape position with subsequent influence on flow pathway distributions. These factors have previously been seen to influence hydrological response (Heidbüchel *et al.*, 2013) and aquifer timescales (e.g. Carrillo *et al.*, 2011) across various hydroclimatic settings.

Exploring such relationships further, we can consider more distributed phenomena such as vegetation cover and soils. Focusing on vegetation, there is some potential connection between, for example, percentage area of shrubland (or the absence of forest cover) and the wet season K values in these catchments (Figure 5b). Again, as the shrubland is mainly found in lower landscape positions (whereas forests are largely in the uplands), there is some correlation with catchment areas and valley landforms. However, there appears to emerge a connection between catchments with lower shrubland coverage (and, thus, larger forest cover) and lower wet season K values. This relationship is not perfect as one catchment (L4) has a rather large shrubland cover (45%) and exhibits a wet season average K value (57 days) that is relatively low compared with catchments with a similar percentage area of shrubland. Considering the subsurface condition by looking at soils within the catchments, there is some relationship (Figure 5c) between soil coverage (in particular, percentage of the catchment area containing Nitisol soils) and wet season K values. As the percentage area containing these typically deep and permeable soils increases, there is a decrease in the wet season K values. Taken altogether, these relationships support the idea that hydrologic responses and landscapes

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Table III. Characteristic drainage timescale (K) determined using all available streamflow data and considering each month separately for the Kilombero Valley. Here, wet season is the average K value from December through April, and dry season is the average K value from May through November

	Catchment ID										
	L1	L2	L3	L4	S1	S2	S3	S4	S5	Average large	Average small
All data	154	286	400	189	97	435	61	137	70	257	160
Jan	182	152	109	55	41	55	56	39	40	124	46
Feb	182	196	175	68	53	83	51	47	41	155	55
Mar	233	244	135	54	34	83	48	50	45	166	52
Apr	238	833	116	33	31	69	38	84	49	305	54
May	88	114	159	81	52	175	63	98	81	110	94
Jun	82	294	313	208	110	625	76	256	89	224	231
Jul	167	313	435	476	208	625	72	345	89	348	268
Aug	179	400	769	588	250	556	71	345	94	484	263
Sep	159	385	769	500	213	556	75	263	65	453	234
Oct	175	286	1000	400	149	476	56	149	57	465	177
Nov	172	263	588	250	115	385	52	41	47	318	128
Dec	172	164	192	74	74	75	43	53	25	151	54
Wet season	201	318	146	57	47	73	47	54	40	180	52
Dry season	146	293	576	358	157	485	66	214	75	343	199

develop in concert (Troch *et al.*, 2013b); however, only limited mechanistic insight is possible here given limitations in data.

Relating drainage timescales to evapotranspiration

Calibrated values of monthly evapotranspiration (E) for each sub-catchment were lower than those obtained from MODIS (Figure 6). This should be expected to some extent because MODIS-derived E represents an energy-balance derived flux, whereas the recession analysis-calibrated values represent E primarily subtracted from the groundwater. Because the period for the average monthly E from MODIS (2000–2013) does not overlap with the periods for the streamflow records that were used for the calibrated values of monthly E in the recession analysis (Table I), it would also not be expected that the different E estimates agree perfectly. As would be expected given the form of Equation (5), greater differences between observed monthly K values (Table III) and an assumed K of 45 days led to higher calibrated values of E. This creates a noticeable difference in wet season E relative to dry season E in the smaller catchments with regard to the apparent relationship between recession-calibrated E and the MODIS-derived E. Further, this difference between the wet season and dry season appears more pronounced (perhaps with the exception of L4) in the smaller upland sub-catchments relative to the large valley bottom catchments.

It should be noted that it is possible to obtain higher E values through Equation (5). First, because Brutsaert (2008) clearly intends that $K = 45 \pm 15$ days is merely a 'working assumption' that we have adopted here for simplicity in a data-limited setting, it is possible to calibrate higher values for E by assuming shorter values of K (see bars in Figure 6). Carrillo *et al.* (2011), for example, found K values as low as 20 days (and as high as 83 days) across the continental USA, indicating possibilities of a wider range of values. Second, the values of K obtained (and subsequent E inferred) could be adjusted through the lower-envelope definition. By reducing the percentage of points in the recession plot that are excluded by a lower enveloping line (e.g. excluding 5% as opposed to 15%, which amounts to shifting the lower lines in Figures 3 and 4 downward), it is possible to obtain higher calibrated values of E (analysis not shown). As such, it is clear that care must be taken with regard to the methodological aspects of recession analysis (Rupp and Selker, 2006a,b). This is particularly the case here as subsequent interpretation is potentially confounded by the recession analysis procedure adopted in combination with data quality and the general applicability of the underlying theory in this arid and monsoonal landscape.

DISCUSSION AND CONCLUDING REMARKS

Spatiotemporal variability in characteristic drainage timescale

There is clear temporal variability of the monthly K values for all the catchments using the recession technique considered here. This potentially indicates a changing relative dominance of various hydrologic processes and storages in both space and time within the Kilombero Valley. This interpretation supports recent work by Shaw and Riha (2012), indicating the utility of

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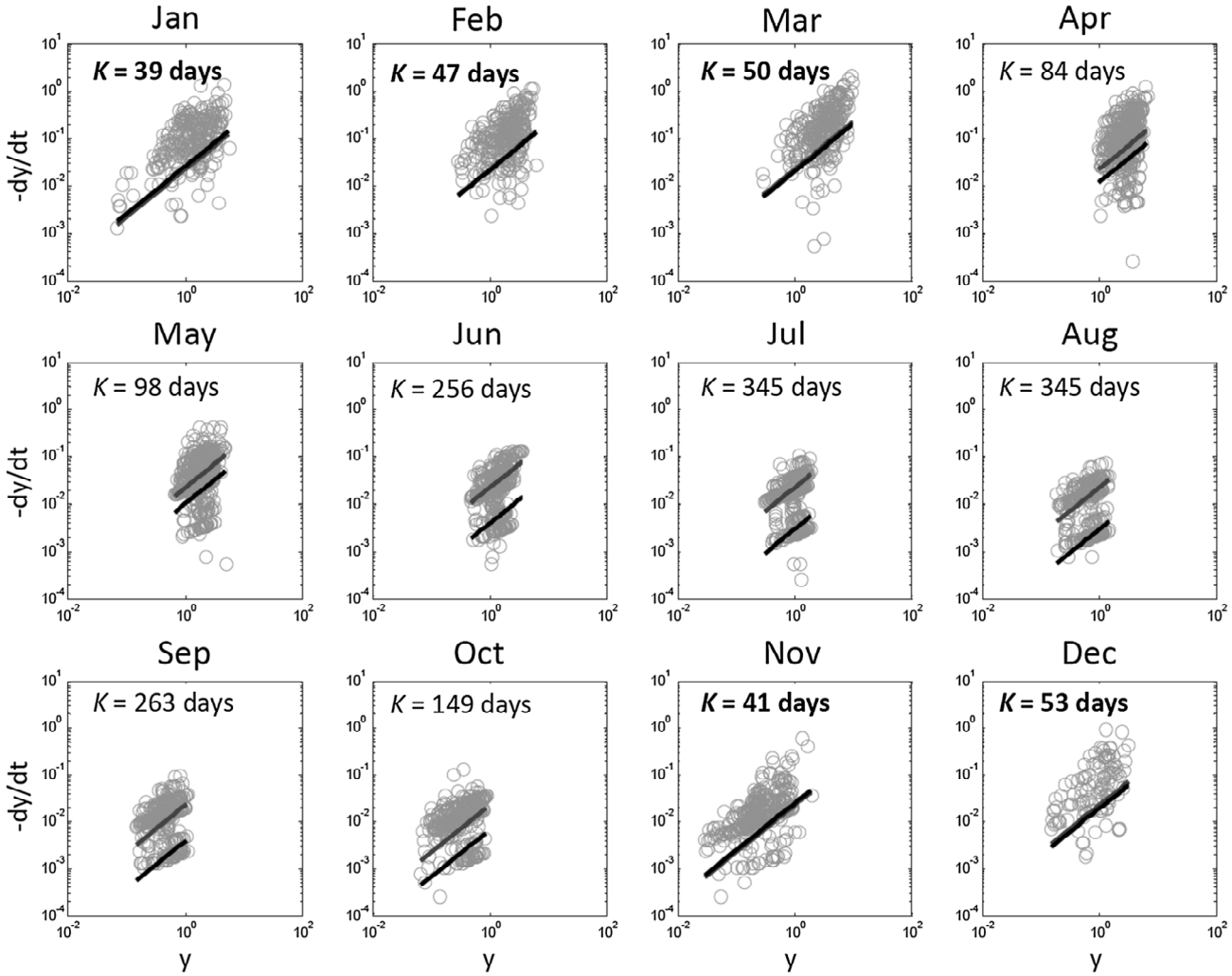


Figure 4. Brutsaert–Nieber-style recession analysis demonstrated for monthly grouping of the data available from the catchment S4 with the estimated K values corresponding to the fit line (which has a slope of unity). The grey lines show the locations of the Brutsaert–Nieber linear solution to the Boussinesq equation assuming $K = 45$ days for context

event-based or seasonal recession analysis as a valuable tool for gaining insights into hydrological processes for watersheds not possible through consideration of only the absolute amounts of water and changes within streams.

From a process point of view for the small upland catchments, the shift in K across seasons implies a shift in the dominant hydrologic mode of these catchments. Primarily, this could be seen as a transition from mainly horizontal-flux systems where saturated flows connect the landscape to the streams under wet conditions to mainly vertical-flux systems where evaporative potentials dominate under drier conditions. This is confirmed through the calibrated values of E obtained using the recession analysis (Figure 6). These are consistently higher during the dry season relative to the wet season in the small catchments. This implies that the assumption that vertical gradients are negligible compared with the horizontal gradient (Equation (3)) is likely less valid in the dry season when evapotranspiration fluxes are larger relative to discharge (Equation 5). Such implications differ from recent findings in the more humid USA by Shaw *et al.* (2013) where evapotranspiration showed limited impact on recession intercepts, whereas subsurface geological heterogeneities were hypothesized to be a main control. This difference could be attributed to the stronger seasonality and higher potential for evapotranspiration across these Tanzanian catchments relative to those considered by Shaw *et al.* (2013). Still, although these small upland catchments function dynamically across the wet and dry seasons, it is difficult, in the strictest sense and given the limiting assumptions of our approach, to separate the explicit roles of evapotranspiration and geology on the basis of these analyses.

Counter to the small upland catchments, the larger catchments of Kilombero Valley exhibited more temporally consistent and longer K values. This can be explained (again) in part through evapotranspiration impacts that

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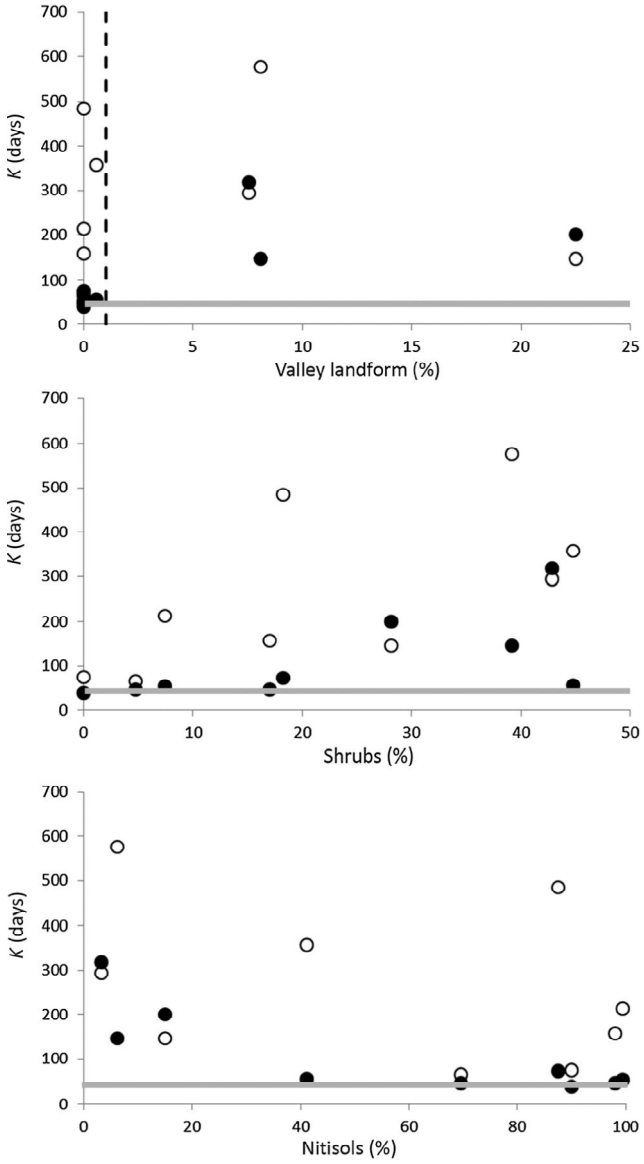


Figure 5. Relationship between landscape characteristics and wet season (filled circles) and dry season (open circles) characteristic drainage timescales across the Kilombero Valley, Tanzania. The vertical dashed line shows a threshold of 1% catchment areas as valley bottom landform and the horizontal grey line shows $K = 45$ days for context

appear more consistently related with MODIS-derived estimates relative to the small catchments (Figure 6). In addition, the presence of wetlands in the larger catchments increases the relative importance of surface waters and riparian zones, as evidenced by the delay in peak discharge between the uplands and the valley (Figure 2). Brutsaert (2005) suggests that in steeper catchments, the hydrological response in the early stages of recession is dominated by the steep hillslopes, but during later stages of recession, when the catchment dries up and saturated area extents decrease, it becomes dominated by riparian areas. Thus, the interplay of two distinct storages (e.g. upland hillslopes and valley wetlands) could also have an impact at the scale of the entire Kilombero Valley. At this scale, catchments are composed of not only well-drained hillslopes in the upland catchments responding to monsoonal variations but also deeper sediments of fluvial origin in the valley bottoms. The effective conductivities (and resultant transmissivities) are thus likely different through the valley bottoms relative to the potentially seasonally dynamic effective hydraulic conductivity of the more upland hillslopes. However, more exploration is needed in this regard to isolate flow pathways in connection to mechanisms.

Impacts of data quality and availability

Clearly, as is often the case, data quality and availability affect this current study. Previous work in this region (e.g. Yawson *et al.*, 2005) has attempted to bypass this influence with respect to hydrological modelling by filtering and processing data. The impact of this filtering can be seen to some extent in this study as a truncation of relatively high flows (Figure 3). However, because the approach considered in this study deals primarily with the differential between daily flows under recession conditions, there is likely minimal impact on the estimated K values (Supporting Information), which are derived from fitting low-flow conditions. Further, the Brutsaert–Nieber-style approach considered allows us to avoid the potential influence of long periods of no data as it needs only short periods of data corresponding to streamflow recessions. This is a clear benefit of the approach for data-limited or data-poor environments (i.e. its ease of use in exploratory settings).

However, this exploratory benefit provided by the method presents a potential double-edged sword. This is seen by considering the different E estimations possible using different ranges of K values (Figure 6). Care must be taken because we are applying a simplified linear theory in what are likely to be dynamic catchment systems. It is not entirely clear to what extent the results are impacted or confounded by (1) limitations in the general theory, (2) the quality of the data, and/or (3) actual shifts in the hydrological processes within the landscape. As such, further work is required to isolate the exact mechanisms behind the spatiotemporal patterns of K values and develop an appropriate modelling framework to encompass them. Clearly, the groundwater gradients change with seasonal monsoon rainfall (Figure 4) for some of the catchments with subsequent impact on the estimated K values. Illumination and quantification of the mechanisms behind these patterns could be achieved through, for example, hydrologic tracer studies (e.g. Lyon *et al.*, 2008, 2009b; Hrachowitz *et al.*, 2011) in the region. This has the potential to allow for separation of flow pathways and identification of contributing source areas through the different stores of

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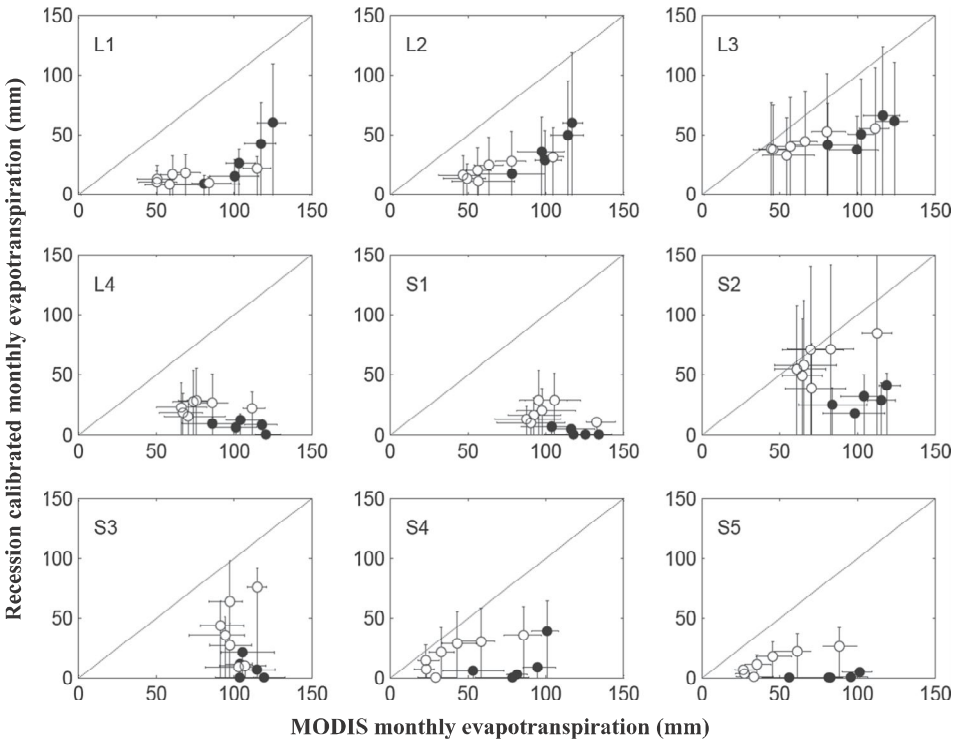


Figure 6. Monthly evapotranspiration (E) calibrated from the recession flow analysis compared with monthly average Moderate-resolution Imaging Spectroradiometer (MODIS)-derived evapotranspiration (with 1 : 1 line shown). Vertical bars show the impact of the range of assuming K from 60 to 30 days, whereas horizontal bars show maximum and minimum MODIS evapotranspiration over the period 2000–2013. Open circles correspond to dry season (May–November), and filled circles correspond to wet season (December–April)

water across the landscape and is the focus of ongoing research. This ability to design and pinpoint subsequent analysis and field investigations, as highlighted by Troch *et al.* (2013a), can be considered a central strength of the experimental approach considered here.

Implications for management and model development

In spite of the aforementioned limitations, the results of this study (and the utility of the exploratory approach adopted) may still have implications on how future hydrologic model development as a tool for water resources management in the Kilombero Valley (and regionally) will proceed. For example, it can be concluded that lumped (in either a spatial or temporal sense) modelling approaches that do not allow for dynamics in spatial patterns of catchment storage to affect the hydrologic response will not be applicable in these catchments. Yawson *et al.* (2005), for example, explored several general modelling approaches in this region ranging from lumped conceptual models (e.g. the soil moisture accounting and routing model of Singh, 1995) to linear transfer approaches (similar to those put forward by Clark, 1945). That study, while highlighting that these simple approaches were more feasible in such a data-limited environment over more complex and parameterized modelling approaches, had limited success in the ability to model daily streamflow across the Kilombero Valley. As the linear approaches considered worked somewhat better for the larger catchments, Yawson *et al.* (2005) attributed the inability to model flow dynamics across the Kilombero Valley to the general ability of such modelling approaches to perform better over large catchments (e.g. Shamseldin and O'Connor, 2001).

From results of this current study, we would argue that there are spatiotemporal variations in dominant hydrologic processes that need to be considered in model development. What should be highlighted here is that this variability does not inherently imply increased complexity. For example, Steenhuis *et al.* (2009) and Collick *et al.* (2009) put forward a simple, semi-distributed hydrology model for highland systems in Ethiopia using a water balance approach that divides a watershed into different regions that become hydrologically active given different amounts of effective cumulative rainfall after the start of the rainy season. This approach differs from other water balance models (such as those of Conway, 1997, or Kim and Kaluarachchi, 2008) that assume the whole watershed behaves in a similar manner. This conceptual difference starts from a basic assumption that models developed for temperate climates might not be suitable for monsoonal climates and/or mountainous regions with distinct wet and dry periods. Collick *et al.* (2009) highlight that the development of such simple (but robust) hydrological

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models can provide relevant tools for watershed management planning and conservation activities (Herweg and Ludi, 1999; Bewket and Sterk, 2002).

This is consistent with Yawson *et al.* (2005) who conclude that simple black-box models with fewer parameters and simplistic mathematical procedures may be more appropriate than complex models with numerous parameters in Kilombero Valley (and other) data-limited regions. We agree with this assessment and its nod to a parsimonious approach to modelling hydrology systems; however, we add the corollary here that for simple models to truly be advantageous, particularly as management tools for exploring scenarios of development, they need to be founded in and consistent with our process-based understanding (Carrillo *et al.*, 2011). To this end, recession analysis offers a potential approach to explore aquifer release timescales and thereby gain insight to a region's hydrology to inform water resources management and model development. Care must be taken, however, when interpreting spatiotemporal shifts in K in connection with process representation because the influence of data quality and analysis procedure, as was evidenced in this study, may be considerable.

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