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Effect of catchment characteristics on the relationship between past discharge and the power law recession coefficient

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SUMMARY

This study concerns the relationship between the power law recession coefficient k (in $-dQ/dt = kQ^{\alpha}$, Q being discharge at the basin outlet) and past average discharge Q_N (where N is the temporal distance from the center of the selected time span in the past to the recession peak), which serves as a proxy for past storage state of the basin. The strength of the k–Q_N relationship is characterized by the coefficient of determination $R^2{}_N$, which is expected to indicate the basin's ability to hold water for N days. The main objective of this study is to examine how $R^2{}_N$ value of a basin is related with its physical characteristics. For this purpose, we use streamflow data from 358 basins in the United States and selected 18 physical parameters for each basin. First, we transform the physical parameters into mutually independent principal components. Then we employ multiple linear regression method to construct a model of $R^2{}_N$ in terms of the principal components. Furthermore, we employ step-wise multiple linear regression method to identify the dominant catchment characteristics that influence $R^2{}_N$ and their directions of influence. Our results indicate that $R^2{}_N$ is appreciably related to catchment characteristics. Particularly, it is noteworthy that the coefficient of determination of the relationship between $R^2{}_N$ and the catchment characteristics is 0.643 for $N = 45$. We found that topographical characteristics of a basin are the most dominant factors in controlling the value of $R^2{}_N$. Our results may be suggesting that it is possible to tell about the water holding capacity of a basin by just knowing about a few of its physical characteristics.

1. Introduction

One of the key features of a drainage basin is its ability to store rain water and discharge it later at a much slower late, thereby sustaining many of the biotic and abiotic activities (Botter et al., 2011; Kirchner et al., 2001; McDonnell et al., 1991; Pearce et al., 1986; Sivakumar et al., 2005; Wolock et al., 1989). Individual water particles follow various surface and subsurface flow paths to reach the basin outlet. Interestingly, the travel time distribution of individual water particles in a basin is very different from the streamflow hydrograph or the hydrologic response, owing to the difference between celerity and velocity (Botter et al., 2011, 2010; McDonnell and Beven, 2014). Nevertheless, hydrologic response represents the functional relationship between storage and discharge at basin scale. In fact, all practical hydrological models are based on the mass balance equation involving storage (S) and discharge (Q) (Anderson et al., 1997; Biswal and Nagesh Kumar, 2015; Bonell, 1998; Brutsaert and Nieber, 1977; Hooper, 2001; McGlynn et al., 2003, 2002; Rupp and Selker, 2006; Sidle et al., 2000; Thomas et al., 2013). However, the biggest challenge in implementing the mass balance equation is that it is not practically possible to observe storage due to technological limitations. An alternative avenue is to obtain information indirectly by analyzing streamflow time series. In particular, streamflow observations during recession periods or no-rain periods can give valuable information, since during these periods streamflow is sustained by drainage from subsurface storage systems only (Arnold et al., 1995; Biswal and Marani, 2014, 2010; Biswal and Nagesh Kumar, 2014a, 2014b; Brutsaert and Nieber, 1977; Marani et al., 2001; Mutzner et al., 2013; Palmroth et al., 2010; Rupp and Selker, 2006; Szilagyi et al., 1998; Tallaksen, 1995).

For recession flow analysis, Brutsaert and Nieber (1977) proposed the classical method of expressing dQ/dt as a function of Q itself, where Q is discharge at the basin outlet at time t. dQ/dt vs. Q curves generally display a power law profile as:

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$$-\frac{dQ}{dt} = kQ^{\alpha} \qquad (1)$$

Biswal and Marani (2010) found that although α for a particular basin remains fairly constant, k displays considerable variation across recession events, indicating that dQ/dt–Q relationship (or storage–discharge relationship) is dynamic. Therefore, $-dQ/dt$ vs. Q curves need to be analyzed separately for the available recession events (Biswal and Marani, 2014, 2010; Biswal and Nagesh Kumar, 2014a, 2013; Mutzner et al., 2013; Shaw and Riha, 2012). The logical question, therefore, is: what controls the eventual variability of k? It appears that the coefficient k depends on initial drainable storage in the basin (Biswal and Nagesh Kumar, 2015, 2014a, 2014b). A basin accumulates water during a rainfall event and releases it gradually during the following no-rain or recession periods. Because no-rain periods are usually shorter than the time period a basin requires to drain the stored water, the basin may not drain water completely during a particular recession event. This means that the basin will still have some water left to be drained in the later recession events. Therefore, k of a recession event can be expected to be influenced by the past storage in the basin, represented by the past average discharge (Biswal and Nagesh Kumar, 2014a, 2014b; Shaw et al., 2013). Also, the effect of storage is expected to diminish with time. This means that k will be affected less by storage in the basin, say, 20 days before the recession event than by storage, say, 5 days before the event (Biswal and Nagesh Kumar, 2014a, 2014b). Essentially, the relation between k and past average discharge indicates the basin's ability to store and release water.

The basic objective of this study is to investigate the physical controls over the relationship between the coefficient k and past average discharge considering data from 358 basins situated in the United States. More specifically, we attempt to identify the dominant parameters (Sivakumar, 2004) that govern the power law relationship between k and past average discharge. The main intention is to provide a first order understanding of recession flow processes from catchment characteristics.

2. Data and analysis

2.1. Streamflow data collection and preliminary analysis

Daily average streamflow data were collected for 358 basins from the USGS database (http://waterwatch.usgs.gov/) (Table S1 of the supplementary material provides the basin ids). Satellite images (courtesy of Google Earth) were used to select the basins that are relatively less influenced by human activities. Since we were particularly interested in analyzing streamflows contributed by subsurface storage systems, we did not consider basins that contain relatively large natural or artificial lakes. Any streamflow time series in which discharge was observed to be declining continuously for at least 5 days was considered as a recession curve (Biswal and Marani, 2010; Biswal and Nagesh Kumar, 2014b). $-dQ/dt$ and Q were computed as (Brutsaert and Nieber, 1977):

$$-dQ/dt = (Q_t - Q_{t+\Delta t})/\Delta t, \text{and} \qquad (2a)$$

$$Q = (Q_t + Q_{t+\Delta t})/2 \qquad (2b)$$

The time step Δt is 1 day in this study. Note that for computation of α and k recession peaks were not considered as they are supposed to be influenced by surface flows (Biswal and Nagesh Kumar, 2014a). For each study basin, the available recession curves were collected and the corresponding values of α were computed. The median of the values of α was considered to be the representative α (α_r) for the basin (Biswal and Marani, 2010). Then, for each recession curve of the basin, k was computed by fixing α at its α_r (Biswal and Marani, 2014). Subsequently, we analyzed the power law relationship between k of a recession event and Q_N, expressed in a more general form:

$$k \propto Q_N^{-\delta_N} \qquad (3)$$

where Q_N is the average discharge observed from N'' to N' days before the peak of the recession event, and $N = (N'' + N')/2$ and δ_N is the exponent. The main difference between our analysis and the analysis of Biswal and Nagesh Kumar (2014b) is that while Biswal and Nagesh Kumar (2014b) considered only the case of $N'' = 2$, we considered different values of N'' (Fig. 1). We noted the values of R^2_N (coefficients of regression) for power law relationship between k and Q_N for four combinations of (N'', N'): (2, 10), (10, 30), (30, 60) and (60, 120), as shown in Fig. 2 for USGS gauging station #01586610 (Morgan Run, MD).

2.2. R^2_N and catchment characteristics

To investigate how different catchment characteristics affect R^2_N, we used the hydrologic database of Falcone et al. (2010), which gives various physical properties for the selected basins. The coefficient of determination of the relationship between each of the selected catchment parameter and R^2_N for each N was found out by employing the least square linear regression method. We denote R^2_{NPi} as the coefficient of determination of the relationship between R^2_N and the ith parameter, P_i. In total, 18 catchment characteristics were selected for the rest of the analysis (Table 1) that were statistically significant (see the p-values in the table), although a few parameters not satisfying the criterion were also added since we thought that they are important catchment characteristics.

The catchment parameters were normalized by subtracting the respective mean and dividing it by the standard deviation. Then, the dataset (catchment variables) was transformed into a set of principal components, as we found that many of the selected parameters are not mutually independent (Abdi and Williams, 2010; Brown, 1993). The procedure makes use of orthogonal transformation method to convert a set of mutually-dependent variables into a set of principal components that are independent of one another. PC_i is referred here as the ith principal component.

Multiple linear regression analysis was performed between (R^2_N) (dependent variable) and the first Z principal components (independent variables) for each N. The general relationship is represented as:

$$R^2_N = \beta_0 + \sum_{i=1}^{Z} \beta_i PC_i \qquad (4)$$

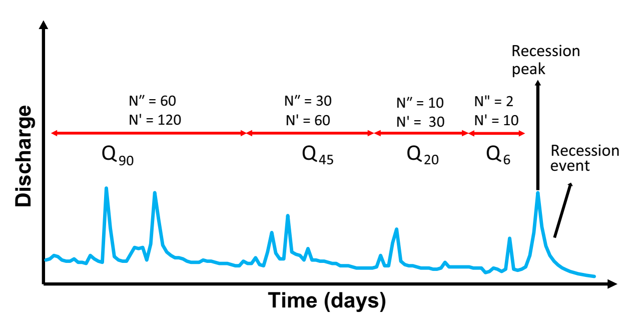

Fig. 1. An illustration of the analysis of streamflow time series data as done in this study. Q_N is the average discharge from N'' to N' days before the recession peak, where $N = (N'' + N')/2$. The relationship between the recession flow parameter k and Q_N is investigated by considering four values of N (N = 6, 20, 45 and 90) as shown in the figure.

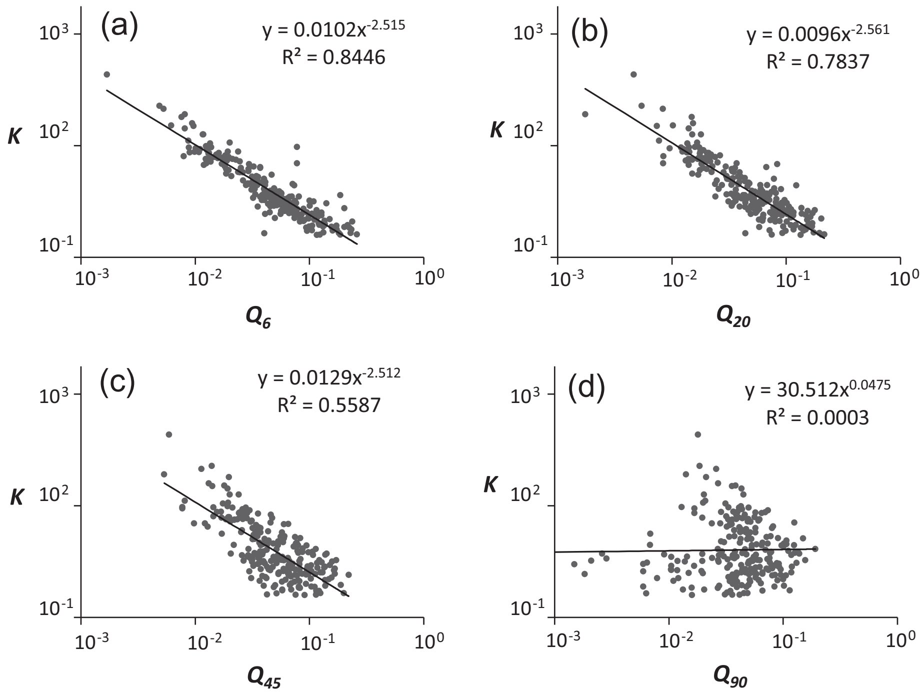

Fig. 2. Scatter plot between the power law recession flow coefficient k and past average discharge Q_N for the basin with USGS id 01586610 for N equal to (a) 6, (b) 20, (c) 45 and (d) 90.

where β_i is a constant and PC_i is the i-th principal component. We measured the strength of Eq. (4) in terms of coefficient of determination (R^2_{NPCZ}). Note that in case of mutually dependent parameters, the first few principal components explain much of the variability. Here we set 92% variability criterion to choose the initial principal components. The other analysis we decided to pursue is to divide the dataset (W_{358}) into two halves according to the R^2_N values, the upper half (U_{179}) having basins with higher R^2_N values and the lower half (L_{179}) having basins with lower R^2_N values. This was done to investigate how R^2_{NPCZ} is influenced by the magnitude of R^2_N. Subsequently, multiple linear regression analysis was repeated using the initial principal components. Then for each dataset, a multiple linear regression model (see Eq. (4)) was formed randomly selecting 70% of the catchments for calibration and the rest 30% was kept for validation. This was done to study the robustness of the regression models.

2.3. Identification of dominant parameters

Our main aim here is to find out the direction of influence of the dominant catchment characteristics, therefore relative values of β_i coefficient of principal components have not been analyzed in this study. Therefore, analysis was carried out to identify the dominant parameters that control the value of R^2_N following stepwise multiple linear regression method. Step-wise multiple linear regression uses an exhaustive method to identify the best model. This approach uses p_{value} (which is read from t distribution table, based on the t_{score} and the degrees of freedom) criterion to judge whether a predictor variable should be entered or removed from the model. A predictor is added to the model if its $p_{value} < 0.05$ and the predictor is removed if its $p_{value} > 0.1$.

The significant principal components (i.e. the components affecting R^2_N appreciably) were selected using student's t test, satisfying the following relationship: $|t_{score}| > t_{cr}$, where t_{cr} is the critical t_{score} value, which was found from the degree of freedom and for the significance level of $\varepsilon = 0.05$. Note that the constant term of the stepwise multiple linear regression was not included in the analysis, as we were mainly concerned about the directions of influences of the catchment characteristics. The relationship between the principal components and the dominant catchment characteristics was explored by investigating the principal component transformation matrix:

$$PC_i = \sum_{j=1}^{j=18} \theta_j P_j \tag{5}$$

A threshold $|\theta_j| > 0.1$ was chosen to filter out important catchment variables affecting each principal component. The threshold was established to keep a maximum of 3–4 important catchment parameters influencing a principal component. By limiting to 3–4 parameters, we intended to identify the dominant catchment parameters. Also it should be noted that more importance was given to the initial principal components in finding out the direction. Then the directions of their influence were noted.

3. Results and discussion

Analysis of the relationship between past discharge and the recession coefficient k seems to suggest that k is indeed influenced by past storage. The R^2_N values obtained in this study (Table S1) suggest that the influence of past storage over k is significant. In particular, R^2_N was observed to be appreciably high for lower values of N (6, 20 and 45) (Fig. 2). It was also observed that R^2_N decreases consistently with N, with the general order being $R^2_6 > R^2_{20} > R^2_{45} > R^2_{90}$ for all but a few basins (for e.g., see Fig. 3). This systematic pattern further confirms the earlier notion that the effect of storage diminishes with time (Biswal and Nagesh Kumar, 2014a, 2014b). Our hypothesis therefore is that if R^2_N value is higher, there is more chance the basin releases significant amount of water after N days during a recession event. In other words, R^2_N represents the water holding capacity of the basin.

Our investigation on how the catchment characteristics are related with R^2_N values yielded some interesting results. Table 2

Table 1
Catchment characteristics that are considered in this study.

Sl. no. (i)	Catchment characteristic	Description
1	AREA_SQ_KM	Area of the Catchment in sq. km
2	PPTMAX_SITE	Site average of maximum monthly precipitation (cm) from 2 km PRISM, derived from 30 years of record (1961–1990)
3	PET	Mean-annual Potential Evapotranspiration (PET)
4	STREAMS_KM_SQ_KM	Stream density, km of streams per watershed sq km
5	TOPWET	Topographic wetness index, ln(a/S);where "ln" is the natural log, "a" is the upslope area per unit contour length and "S" is the slope at that point
6	CONTACT	Subsurface flow contact time index. The subsurface contact time index estimates the number of days that infiltrated water resides in the saturated subsurface zone of the basin before discharging into the stream
7	RUNAVE7100	Estimated watershed annual runoff, mm/year, mean for the period 1971–2000. Estimation method integrated effects of climate, land use, water use, regulation, etc.
8	BAS01_FOREST	Watershed percent "forest", 2001 era
9	PCT_1ST_ORDER	Percent of stream lengths in the watershed which are first-order streams (Strahler order)
10	PERMAVE	Average permeability (in./h)
11	BDAVE	Average value of bulk density (grams per cubic centimeter)
12	OMAVE	Average value of organic matter content (% by weight)
13	WTDEPAVE	Average value of depth to seasonally high water table (feet)
14	ROCKDEPAVE	Average value of total soil thickness examined (in.)
15	CLAYAVE	Average value of clay content (%)
16	SANDAVE	Average value of sand content (%)
17	ELEV_STD_M_BASIN	Standard deviation of elevation (m) across the watershed from 100 m, National Elevation Dataset
18	SLOPE_PCT	Mean watershed slope, percent. Derived from 100 m resolution, National Elevation Dataset, so slope values may differ from those calculated from data of other resolutions

shows R^2_{NPi} values for the individual catchment parameters for each N. Individual R^2_{NPi} values were found to be falling in between 0 and 0.233 (Table 2). In most cases, we observed R^2_{NPi} for $N = 45$ to be generally higher than R^2_{NPi} for any other N (see Table 2). This is indeed interesting given the fact that R^2_N is consistently higher for $N = 6$. It can therefore be assumed that the influence of catchment variables on R^2_N is strong for $N = 45$. Our speculation is that for $N = 45$ subsurface flow processes are simpler, and hence catchment characteristics have a better control over R^2_N. In other words, for $N = 6$ flow processes may be more complex, characterized by thresholds (Zehe and Sivapalan, 2008). We also checked how R^2_N values for $N = 45$ are spatially distributed over the 358 river basins (Fig. 4). The redder points in Fig. 4 indicate higher R^2_{45} values and greener points represent lower R^2_{45} values. It can be observed that the north-western regions are dominated by higher R^2_{45} values, supporting the notion that spatial variation of R^2_N affects the value of R^2_N. It can also be noted that for most of the catchment parameters p-value for the relationship between R^2_N and the catchment parameter is less than 0.05 (see Table 2), which strengthens the notion that R^2_{45} has physical bases.

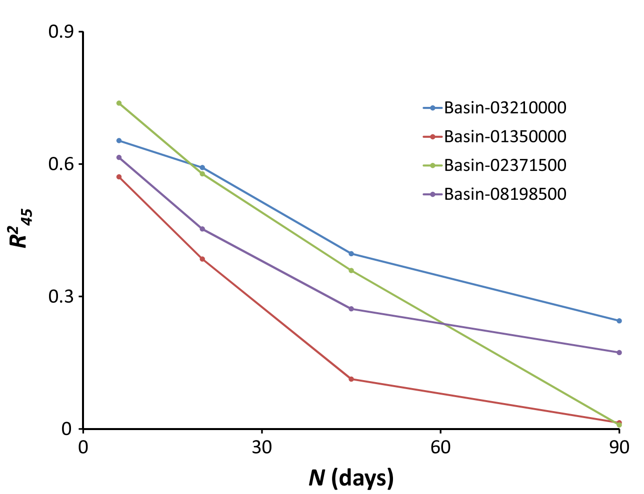

Fig. 3. R^2_N (the correlation coefficient between recession flow parameter k and Q_N) decreases in general with the number of days (N). The graphs show four basins (with their USGS ids) and their R^2_N vs. N plots.

We measured the strength of Eq. (4) in terms of coefficient of determination (R^2_{NPCZ}), which was found to be appreciable considering the W_{358} dataset (Table S1 supplementary material). For example, considering all the principal components (i.e. $Z = 18$), the R^2_{NPCZ} values were found to be 0.243, 0.277, 0.375 and 0.124, respectively, for $N = 6$, 20, 45 and 90. Fig. 5 shows the relationship between R^2_{NPCZ} and Z for $N = 45$ (note that R^2_{NPCZ} for $N = 45$ is more than that of any other N value). Note that the first 7 principal components explain 93.4% of the total variability (see Fig. 5). Therefore, we have considered those 7 principal components in rest of our analysis. It can be observed that with the first 7 principal components only R^2_{NPCZ} value is close to the maximum value for R^2_{NPCZ} (i.e. R^2_{NPCZ} for $Z = 18$), which justifies our assumption that the principal components with Z greater than 7 are dominated by noise. Therefore, for the subsequent analysis only first 7 principal components were considered. An intriguing observation was made while investigating how the value of R^2_{NPCZ} for U_{179} is different from that of L_{179}. The multiple linear regression analysis reveals that R^2_{NPCZ} for the dataset U_{179} is consistently higher than that of the L_{179}. For example, $R^2_{NPCZ} = 0.570$ for U_{179} and 0.252 for L_{179} when $N = 45$, which implies that the catchment parameters are better indicative of a basin's behavior when the basin's R^2_{45} is higher. This may be because some other physical factors that have not been considered in this study dominate in low R^2_{45} basins.

Table 3 shows the results from the multiple linear regression models for all the three datasets (W_{358}, U_{179} and L_{179}) for $N = 45$ (note that for R^2_{NPCZ} is generally highest for $N = 45$) for both calibration and validation datasets. For the W_{358} dataset R^2_{NPC7} values obtained during validation (considering 30% of the basins) are quite close to those obtained during calibration (randomly considering 70% of the basins), except for $N = 90$ where both calibration and validation results seem to suggest no significant relationship. The low value of R^2_{NPC7} for $N = 90$ might be an indication that the influence of basin storage on streamflows becomes negligible after 90 days. Similarly, the results obtained by separately analyzing U_{179} and L_{179} datasets are given in Table 3 (also see Figs. 6 and 7). The general pattern observed for all datasets except L_{179} is: $R^2_{45PC7} > R^2_{20PC7} > R^2_{6PC7} > R^2_{90PC7}$. The lower R^2_{NPC7} values (Tables 3) for $N = 6$ indicate that recent storage being discharged into streams from the subsurface systems is influenced less by catchment characteristics. Note that particularly for $N = 45$, R^2_{NPC7} for calibration and validation for U_{179} are 0.521 and 0.643,

Table 2
Individual correlation coefficient (R^2_{NPi}) and p values between streamflow parameter R^2_N and the catchment characteristics for N = 6, 20, 45, and 90.

Catchment characteristics	R^2_{NPI}				p-value			
	N = 6	N = 20	N = 45	N = 90	N = 6	N = 20	N = 45	N = 90
AREA_SQ_KM	0.005	0.007	0.010	0.000	0.181	0.120	0.057	0.877
PPTMAX_SITE	0.071	0.127	0.233	0.025	0.000	0.000	0.000	0.003
PET	0.028	0.003	0.007	0.017	0.002	0.266	0.108	0.013
STREAMS_KM_SQ_KM	0.012	0.027	0.031	0.002	0.037	0.002	0.001	0.401
TOPWET	0.060	0.049	0.028	0.001	0.000	0.000	0.001	0.638
CONTACT	0.027	0.025	0.012	0.002	0.002	0.003	0.035	0.383
RUNAVE7100	0.068	0.098	0.146	0.016	0.000	0.000	0.000	0.015
PCT_1ST_ORDER	0.067	0.063	0.037	0.000	0.000	0.000	0.000	0.951
BAS01_FOREST	0.027	0.007	0.000	0.003	0.002	0.113	0.689	0.320
PERMAVE	0.001	0.004	0.035	0.008	0.555	0.243	0.000	0.089
BDAVE	0.035	0.049	0.058	0.014	0.000	0.000	0.000	0.026
OMAVE	0.031	0.046	0.064	0.006	0.001	0.000	0.000	0.155
WTDEPAVE	0.017	0.037	0.051	0.010	0.013	0.000	0.000	0.063
ROCKDEPAVE	0.001	0.008	0.012	0.002	0.485	0.098	0.040	0.395
CLAYAVE	0.017	0.001	0.013	0.000	0.015	0.557	0.030	0.885
SILTAVE	0.010	0.018	0.013	0.019	0.056	0.012	0.033	0.009
ELEV_STD_M_BASIN	0.085	0.081	0.055	0.000	0.000	0.000	0.000	0.814
SLOPE_PCT	0.063	0.066	0.052	0.000	0.000	0.000	0.000	0.848

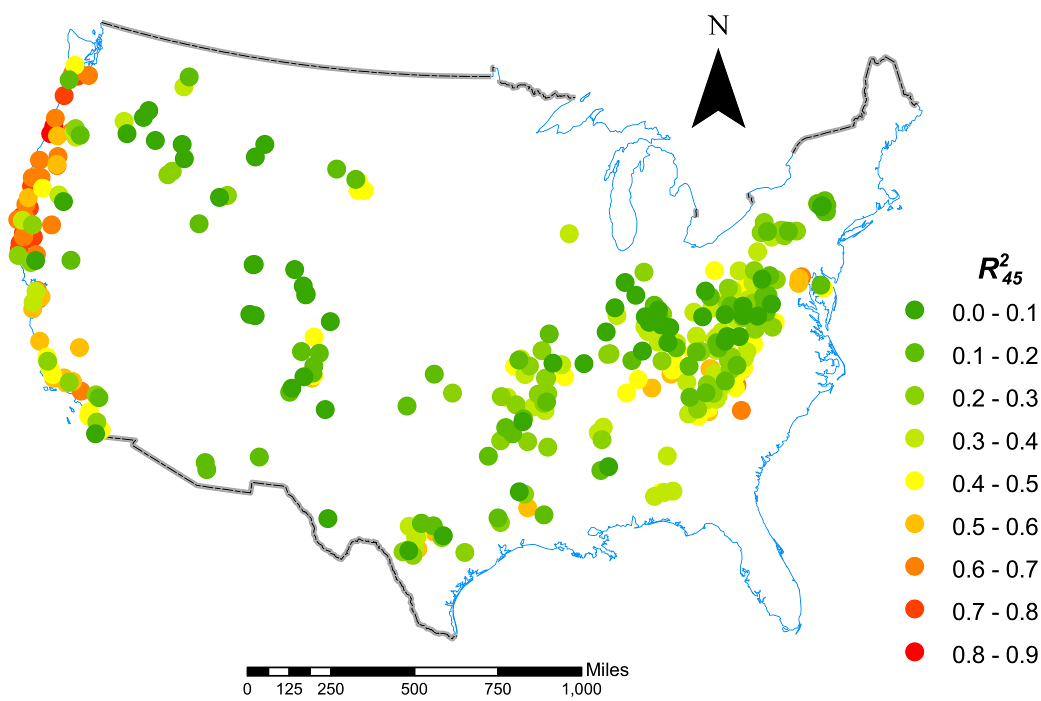

Fig. 4. Spatial distribution of R^2_{45} values of all the study basins. It can be observed that higher R^2_{45} values (redder dots) are concentrated in the north western coast of the US. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

respectively, which is quite significant. This may be indicating that at N = 45 days the selected catchment characteristics have maximum control over a basin's k-past storage relationship.

Now the question arises as to the direction of influence of catchment characteristics on the value of R^2_N. Stepwise multiple linear regression method revealed that the following principal components dominate the relationship between k and average discharge: PC_1, PC_2, PC_3, PC_6 and PC_7 for N = 6, 20, 45 and 90. Table 4 lists the dominant physical parameters (obtained from the principal components) and their direction of influences. The parameters are sorted according to their degree of influence (the highest on the top). It can be noticed that topographical parameters have the strongest influence on R^2_N. Particularly, mean watershed slope (*SLOPE_PCT*) and standard deviation of elevation (*ELEV_STD_M_BASIN*) were found to influence R^2_N in positive direction. Also, *SLOPE_PCT* was found to have better control over R^2_N than standard deviation of elevation (*ELEV_STD_M_BASIN*), although individual coefficient of determination between R^2_N and *ELEV_STD_M_BASIN* is slightly higher than that of *SLOPE_PCT*. *ELEV_STD_M_BASIN* and *SLOPE_PCT* affecting R^2_N positively probably suggest that water holding capacity is more for a mountainous basin. Among soil parameters, permeability (*PERMAVE*) which reflects the ease at which movement of water takes place in the soil mass was found to be the most significant parameter. The consistently positive influence of percentage of organic matter (*OMAVE*) suggests that the organic matter plays a far more dominant role in controlling the value of R^2_N than the other soil properties, such as average value of clay content in percentage (*CLAYAVE*) and average value of sand content in percentage (*SANDAVE*). Among streamflow parameters, estimated watershed annual

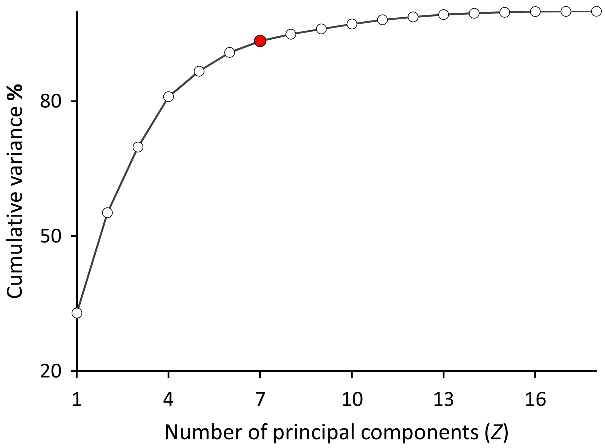

Fig. 5. The plot between cumulative variance explained by the principal components and the number of initial principal components Z for the study basins. It should be noted that the initial 7 principal components are able to explain 93.4% of the total variability.

runoff (*RUNAVE7100*) influences $R^2{}_N$ in positive direction. This indicates that water holding capacity is higher for wet basins, which is again supported by the observation that maximum precipitation (*PPTMAX_SITE*) also influences $R^2{}_N$ positively. Interestingly, subsurface flow contact time index (*CONTACT*) and percentage of clay content (*CLAYAVE*) are negatively affecting $R^2{}_N$. The variable Area (*AREA_SQ_KM*) influences $R^2{}_N$ in both the directions, which can be an indication that it may not have significant effect on $R^2{}_N$. Interestingly, the directions of influences of some of the physical parameters were found to be reversed for the case of R^2_{90}. This finding can be attributed to the fact that R^2_{90} has very little relationship with the catchment variables ($R^2{}_{90PC7} = 0.029$ during validation in case of U_{179}). Also, unlike for other N values, the directions of influence of *CONTACT* and *PERMAVE* for $N = 90$ are positive and negative, respectively. Detail explanations for the roles of different parameters are hard to be made. For example, one would expect *PERMAVE* to influence $R^2{}_N$ negatively as increase in permeability would help in faster draining of water. This might be due to nonlinear interaction among different catchment characteristics.

The analyses performed in this study might have been affected by various errors and uncertainties. It should also be noted that past storage will only have a limited effect on k as total drainable storage at the beginning of the recession event, which supposedly controls the value of k (Biswal and Nagesh Kumar, 2015), will be composed of carried-over past storage as well as storage built up during the associated rainfall event. The main source of errors might be the assumption that the average discharge during a time period represents storage state of the basin during that period, because, as the study itself points out, the storage–discharge relationship can vary across events. Moreover, surface flow mechanism might be different from subsurface flow mechanism (e.g. Biswal and Marani, 2014; Biswal and Nagesh Kumar, 2014a). Therefore, if a significant portion of streamflows during a time period is composed of surface flows, then the average discharge during the period might not very well represent storage state for that time period. Furthermore, although to a lesser extent, parameters α and k might have been associated with errors as well, mainly because discharge during recession periods is quite sensitive to observational and numerical errors. Finally, these analyses are based on the assumption that recession events occur randomly, such that the relationship between k and past average discharge for a recession event is not affected by the seasonal patterns in discharge time series data. This assumption might not have been strictly correct for all the cases. For example, the north-west coast basins witness higher $R^2{}_N$ values, which might be due to the fact that the region has a non-seasonal rainfall pattern.

Nevertheless, the results obtained in this study seem to hold significant theoretical and practical relevance. First of all, our study puts the finding by Biswal and Nagesh Kumar, 2014b in a more formal context by explicitly analyzing the physical bases of the

Table 3
Linear regression $R^2{}_{NPC7}$ summary of the multiple linear regression models of the streamflow parameter ($R^2{}_N$) with 7 initial principal components for the three datasets (W_{358}, L_{179} and U_{179}) during calibration (Cal) and validation (Val).

Streamflow parameter	Dataset W_{358}		Dataset L_{179}		Dataset U_{179}	
	Cal	Val	Cal	Val	Cal	Val
$R^2{}_6$	0.221	0.137	0.289	0.143	0.441	0.395
$R^2{}_{20}$	0.220	0.273	0.295	0.172	0.449	0.475
$R^2{}_{45}$	0.302	0.440	0.339	0.067	0.521	0.643
$R^2{}_{90}$	0.113	0.091	0.243	0.144	0.192	0.029

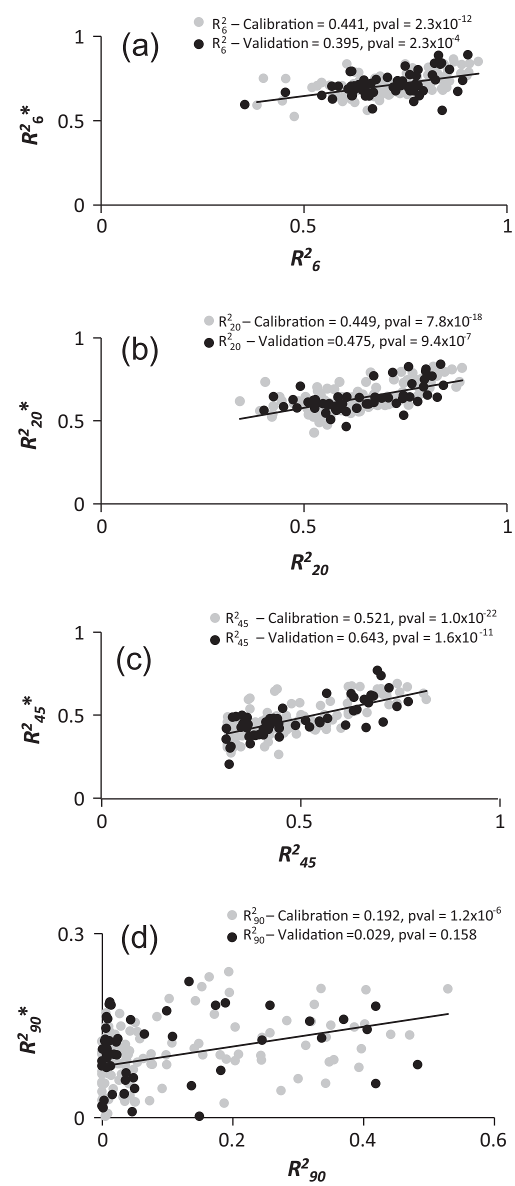

Fig. 6. (a) $R^2_{6^*}$ (predicted) vs. R^2_6 (observed) for U_{179} dataset, (b) $R^2_{20^*}$ (predicted) vs. R^2_{20} (observed) for U_{179} dataset, (c) $R^2_{45^*}$ (predicted) vs. R^2_{45} (observed) for U_{179} dataset, and (d) $R^2_{6^*}$ (predicted) vs. R^2_6 (observed) for U_{179} dataset.

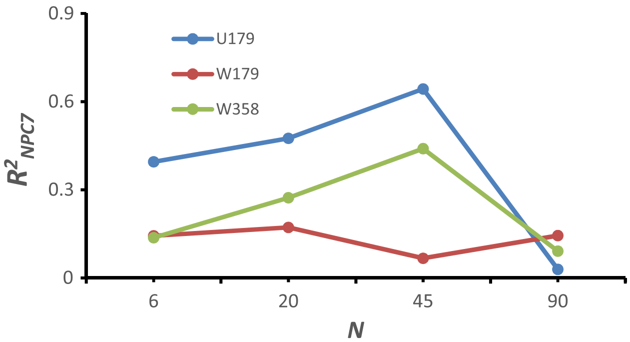

Fig. 7. Plot between R^2_{NPC7} (multiple linear regression R^2 using 7 initial principal components) vs. N for the three datasets (W_{358}, L_{179} and U_{179}).

Table 4
Directions of influence of the dominant catchment characteristics on recession flow parameter R^2_N.

	Positive	Negative
R^2_6	SLOPE_PCT ELEV_STD_M_BASIN PERMAVE RUNAVE7100 PPTMAX_SITE OMAVE AREA_SQ_KM	CLAYAVE AREA_SQ_KM CONTACT
R^2_{20}	SLOPE_PCT ELEV_STD_M_BASIN PERMAVE RUNAVE7100 PPTMAX_SITE OMAVE AREA_SQ_KM	CLAYAVE AREA_SQ_KM CONTACT
R^2_{45}	SLOPE_PCT ELEV_STD_M_BASIN PERMAVE RUNAVE7100 OMAVE PPTMAX_SITE AREA_SQ_KM CONTACT	CLAYAVE AREA_SQ_KM CONTACT
R^2_{90}	CLAYAVE AREA_SQ_KM CONTACT	SLOPE_PCT ELEV_STD_M_BASIN PERMAVE RUNAVE7100 PPTMAX_SITE OMAVE AREA_SQ_KM

relationship between the dynamic parameter k and past average discharge. Using measurable catchment characteristics and by applying multiple regression models, our study indicates that readily available physical parameters can be used to predict R^2_N, the strength of the relationship between past storage and the recession coefficient k, especially when the R^2_N is high. Although R^2_N does not provide any direct information on the storage–discharge relationship, its value seems to indicate the basin's ability to store water. In future, the analytical approach proposed in this study might help in constructing storage–discharge relationship for natural basins utilizing past discharge data for various practical applications water resources planning and management, including prediction of drought flows and baseflow separation. Moreover, the analysis can be improved further by considering other relevant factors (for e.g. subsurface flow path structure) which we have not considered. For example, the effect of seasonal patterns can be eliminated to some extent by introducing numerical corrections (see for e.g., Kobayashi and Yokoo, 2013; Teuling et al., 2010; Yokoo et al., 2014).

4. Conclusions

Our results seem to suggest that, indeed, the relationship between the recession coefficient k and past average discharge, representative of past storage state, has physical origins. That means it is possible to predict R^2_N by just considering the catchment parameters. Particularly, it was found that for the U_{179} dataset the predicted R^2_{45PC7} is 0.643, which is quite appreciable. It was also found out that some of the catchment parameters influence R^2_N in positive direction while others in negative direction. This will help towards reduction in the complexity of models for studying recession flows, and for studying the functioning of river basins. This will also be consistent with the recent efforts in addressing a number of concerns associated with the development of highly complex hydrologic models (e.g. too many parameters, too much data requirement, lack of generalization, etc., for details see Beven, 2012; Jakeman and Hornberger, 1993; Sivakumar, 2008a,b; Hrachowitz et al., 2013), especially within the context of the dominant processes concept (DPC) for simplification and generalization in hydrologic modeling practice (e.g. Grayson and Blöschl, 2001; Sivakumar, 2008b, 2004). The results from the present study have important implications for an easier understanding of a basin's storage–discharge relationship and, therefore, more efficient management of water resources (e.g. prediction of drainage from aquifers just from catchment characteristics). Efforts to further advance the present analysis towards an even better quantification of the relationship between recession flow properties and past storage are continuing by searching for new analytical methods and identifying meaningful physical parameters that were not considered in this study.

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Appendix A. Notations

Q: discharge at the outlet at time t.
α: the exponent of the power law relationship between $-dQ/dt$ and Q.
k: the coefficient of the power law relationship between $-dQ/dt$ and Q.
α_r: is the representative α for a basin.
N: is equal to $(N'' + N')/2$, where N'' and N' are the number of days before the recession event.
Q_N: is the average discharge from the period N'' and N' before the recession event.
R^2_N: the coefficient of determination of the relationship between k and Q_N.
Pi: the ith physical parameter.
R^2_{NPi}: the coefficient of determination of the relationship R^2_N and the ith physical parameter.
PC_i: the ith principal component.
R^2_{NPCZ}: the coefficient of determination for multiple linear regression relationship between equation R^2_N and the first Z principal components.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2015.06.032.

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