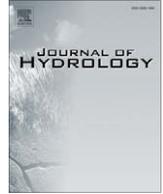




Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Development of representative indicators of hydrologic alteration

Yongxuan Gao^a, Richard M. Vogel^{a,*}, Charles N. Kroll^b, N. LeRoy Poff^c, Julian D. Olden^d^a Department of Civil and Environmental Engineering, Tufts University, Medford, MA 02155, United States^b Department of Environmental Resources and Forest Engineering, SUNY College of Environmental Science and Forestry, Syracuse, NY 13210, United States^c Department of Biology and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO 80523, United States^d School of Aquatic and Fishery Sciences, University of Washington, P.O. Box 355020, Seattle, WA 98195, United States

ARTICLE INFO

Article history:

Received 31 October 2008

Received in revised form 9 May 2009

Accepted 1 June 2009

This manuscript was handled by
K. Georgakakos, Editor-in-Chief, with the
assistance of Taha Ouarda, Associate Editor

Keywords:

Hydroecology

Ecohydrology

Instream flow

Ecodeficit

Principal component analysis

Flow duration curve

SUMMARY

In an ideal world, a few overall indicators of hydrologic alteration would adequately describe the degree of hydrologic alteration caused by various forms of river regulation. Currently over 170 hydrologic indicators have been developed to describe different components of flow regimes, including the widely used Indicators of Hydrologic Alteration (IHA) that characterize the impact of river regulation on flow regimes in environmental flow studies. Many of these IHA indicators are intercorrelated, resulting in considerable information redundancy, which could lead to ineffective environmental flow management decisions. The objective of this research is to develop a small set of independent and representative hydrologic indicators that can best characterize hydrologic alteration caused by reservoirs and other forms of river regulation. Two sets of pre- and post-dam streamflow records are used: (1) based on artificial simulations of a wide range of reservoir release rules and (2) streamflow records for 189 gaging stations throughout the United States. Principal component analysis was used to address the intercorrelation among the IHA parameters. Results revealed that the recently introduced metrics termed ecodeficit and ecosurplus can provide a good overall representation of the degree of alteration of a streamflow time series. Across both datasets, 32 individual IHA statistics and several potential generalized indices, three indices based on the ecodeficit and ecosurplus explained the most variability associated with the ensemble of 32 IHA statistics.

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Introduction

Rivers provide numerous goods and services for humankind, including a source of water for domestic, industrial and agricultural purposes, a means of power generation and waste disposal, routes for navigation, and sites for recreation and spiritual activities (Ripl, 2003). At the same time, flow variability is well recognized by ecologists as being the primary driver of riverine ecosystem function and structure (Poff et al., 1997). Ironically, the great utility of rivers has also resulted in their demise through their extensive exploitation throughout the world, a process greatly facilitated by the construction of thousands of dams globally (Nilsson et al., 2005; Poff et al., 2007). Although human manipulation of river flows provides many societal benefits, it also degrades and eliminates valuable ecosystem services and threatens freshwater biodiversity by altering natural flow regimes (Bunn and Arthington, 2002; Magilligan and Nislow, 2005). There is now widespread understanding that the environment is a legitimate

user of the river and that environmental flows, or the provision of water within rivers to conserve freshwater biodiversity while meeting the water demand of human society, are needed for most riverine systems (Brown and King, 2003). However, there is little consensus as to which hydrologic indicators should be used to summarize instream flow properties analogous to the use of the widely accepted metrics in the field of water supply engineering, such as mean annual water supply yield and reliability of a reservoir.

To evaluate the ecological effect of reservoir operations and other forms of river regulation, and to design optimal reservoir release rules, indicators are needed to evaluate the overall ecological health of the river and the degree of hydrologic alteration caused by a particular operating policy. To date, over 170 hydrologic metrics have been published to summarize various aspects of the flow regime, although there has been little consideration of the correlation among indicators or the statistical redundancy involved (see Olden and Poff, 2003). Consequently, researchers are now confronted with the task of having to choose among a large number of competing hydrologic indicators. One commonly used suite of metrics for characterizing the impact of regulation on flow regimes are the Indicators of Hydrologic Alteration (IHA) developed by Richter et al. (1996) of The Nature Conservancy.

* Corresponding author. Tel.: +1 617 627 4260; fax: +1 617 627 3994.

E-mail addresses: xuan.gao@tufts.edu (Y. Gao), richard.vogel@tufts.edu (R.M. Vogel), cnkroll@esf.edu (C.N. Kroll), poff@lamar.colostate.edu (N. LeRoy Poff), olden@u.washington.edu (J.D. Olden).

The IHA contains 33 hydrologic parameters that characterize the intra- and inter-annual variation in flows, according to the following five characteristics of flow regimes: magnitude of monthly streamflows, magnitude and duration of annual extreme flows, timing of annual extreme flows, frequency and duration of high and low pulses, rate and frequency of flow changes (Mathews and Richter, 2007). Similar to most other proposed indicators, many IHA parameters are intercorrelated (Olden and Poff, 2003), promoting a level of numerical redundancy and potentially complicating environmental flow assessments (Arthington et al. 2006).

Developing a small number of statistics that capture key components of ecologically relevant flow variation will: (1) contribute to a general approach for characterizing flow alteration, (2) minimize statistical redundancy and computational effort in future analyses, and (3) facilitate our ability to obtain Pareto-optimal solutions for environmental flow schemes (see Shiau and Wu, 2006, 2007; Suen and Eheart, 2006). Pareto-optimal solutions for environmental flow schemes involve a determination of the tradeoffs between human water supply and ecological flow objectives. While there are a wide range of possible water supply objectives, ranging from such concepts as vulnerability, resilience and reliability, to water quality, security and cost, many studies simply focus on a single objective such as reliability. By comparison, there is no accepted single or even small set of environmental or instream flow objectives. Thus one of the biggest current challenges associated with balancing human and ecological flow needs involves a determination of a small set of representative indicators which reflect alteration to ecological flow regimes. This is the subject of our paper.

Previous studies have sought to explore redundancy among hydrologic metrics. For example, Olden and Poff (2003) used principal component analysis (PCA) to evaluate patterns of statistical variation among 171 published hydrologic indicators and concluded that the 33 IHAs capture the majority of the variation, and thus can be used to represent the major aspects of the flow regime. Similarly, Yang et al. (2008) identified a small subset of hydrologic indicators that were the most representative of ecological flow regimes. They evaluated three approaches (genetic programming, principal component analysis and autecology matrix) resulting the selection of six IHA parameters (Date of minimum, Rise Rate, Number of reversals, 3-day maximum, 7-day minimum and May flow) as the most ecologically relevant hydrologic indicators (ERHIs).

The primary goal of our study is to determine, among a large suite of indicators of hydrologic alteration, the combination of statistics that best provide an overall measure of hydrologic alteration. For this purpose, we consider the suite of IHA statistics, as well as a few generalized indicators of the ecological flow regimes termed the Dundee Hydrological Regime Alteration Method (DHRAM) (Black et al., 2005) and the recently introduced indices termed ecosurplus and ecodeficit (Vogel et al., 2007).

Methodology

Data

The IHA is a suite of statistics developed by The US Nature Conservancy (<http://www.nature.org/>) to assess the degree of hydrologic alteration caused by human activities. It consists of 67 parameters, which are subdivided into two groups—33 IHA parameters and 34 EFC (Environmental Flow Component) parameters. These hydrologic parameters were developed based on their ecological relevance and their ability to reflect human-induced changes in flow regimes across a broad range of influences including dam operations, water diversions, ground-water pumping, and landscape modification (Mathews and Richter, 2007). The IHA

parameters, listed in Table 1, are the subject of this study (see IHA User's Manual (The Nature Conservancy, 2006) for definition of the parameters). A common approach to assessing hydrologic alteration involves a comparison of flow regimes between present-day (impacted) and past (unimpacted) time periods. Following Richter et al. (1996), we considered the percentage change in the median values of the IHA parameters between unregulated (pre-dam) and regulated (post-dam) flow regimes for two sets of streamflow data, a simulated set and an empirical set. The parameter “number of zero-flow days” was excluded from the analysis, because there was no zero-flow day for most of the gages during the unregulated periods in our study; thus the percentage of change could not be computed because the denominator was zero.

The simulated data series was the same series introduced by Vogel et al. (2007) for the purpose of evaluating a wide range of reservoir release policies corresponding to a wide range of hypothetical reservoir systems all simulated for a single river. The unregulated streamflow data in the simulated data set come from the USGS gage 01333000 (Green River at Williamstown, MA; drainage area = 110 km²), and the regulated streamflow, for the simulated data set, are generated from the water management software, Water Evaluation And Planning System (WEAP), developed by the Stockholm Environment Institute (Yates et al., 2005). Streamflow regulation in this case refers to 12 release rules operating on eight imaginary reservoirs with storage ratios (ratio of storage capacity S to mean annual inflow μ) in the range of 0.01–3 (see Vogel et al., 2007 for further details). Hence, the number of observations of the simulated streamflow series is $12 \times 8 = 96$. Since this dataset is only based on a single river gage, we felt it was important to expand our experiment by using another dataset, described below, which employs actual streamflow data subject to a variety of flow alteration schemes from many rivers and dams.

A second data set, termed the empirical data set, is a set of streamflow data from 189 USGS streamflow gages in third-through seventh-order rivers distributed across the continental US. Flow gages were located 0.1–74 km downstream of dams (mean = 17 km). The following criteria were used to ensure that the record of each gage reflected the influence of a single dam: (1) no pre-existing upstream mainstem dam, (2) at least 15 years of daily streamflow data both before and after the dam completion date, (3) no more than two tributary inputs between the upstream dam and the gage, and (4) no dams on tributaries with an estimated drainage area larger than the mainstem river of the candidate dam (see Poff et al., 2007 for more details). Fig. 1 shows the locations of the 189 dams. No information is available regarding the type of reservoir release rules employed by these dams.

Multicollinearity of IHA statistics

Figs. 2 and 3 illustrate boxplots of the correlation coefficients between each IHA statistic and the remaining 31 IHA statistics

Table 1
Thirty-three indicators of hydrologic alteration.

October flow	September flow	Number of zero-flow days ^a
November flow	1-day minimum	Base flow index
December flow	3-day minimum	Date of minimum
January flow	7-day minimum	Date of maximum
February flow	30-day minimum	Low pulse count
March flow	90-day minimum	Low pulse duration
April flow	1-day maximum	High pulse count
May flow	3-day maximum	High pulse duration
June flow	7-day maximum	Rise rate
July flow	30-day maximum	Fall rate
August flow	90-day maximum	Number of reversals

^a This parameter is excluded from the study.

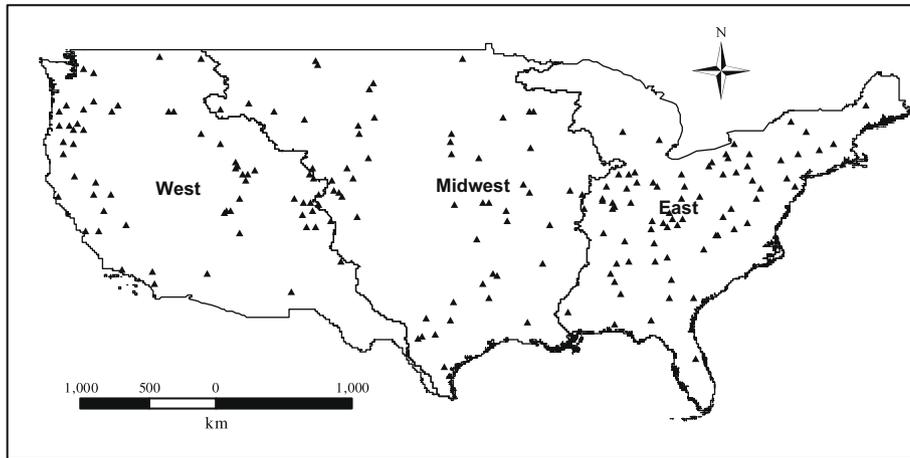


Fig. 1. Location of the 189 dams of the empirical data set.

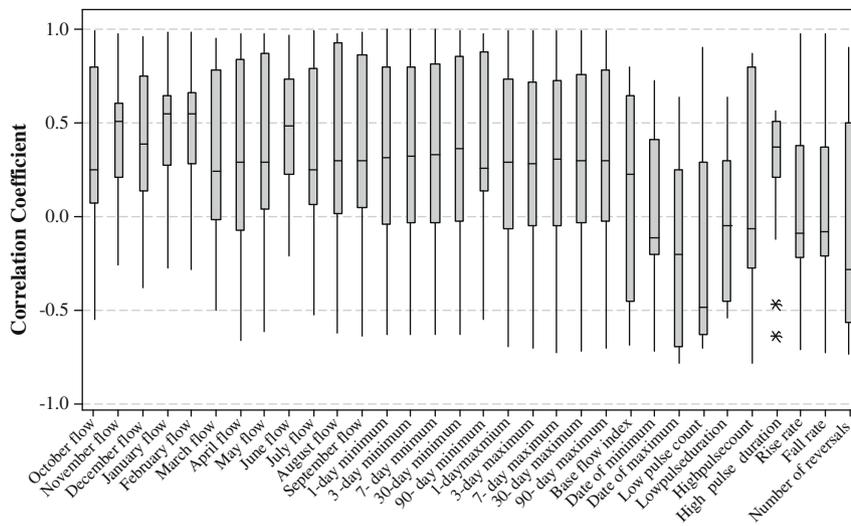


Fig. 2. Correlation coefficients among the IHA statistics for the simulated data set.

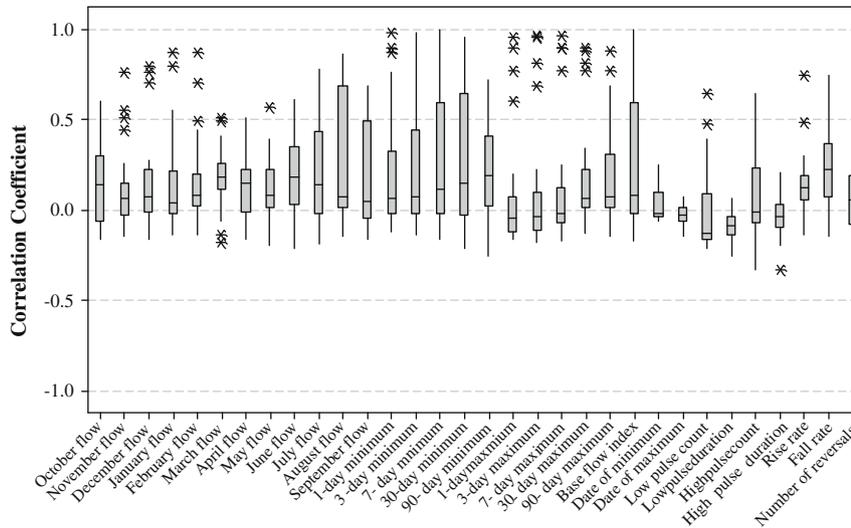


Fig. 3. Correlation coefficients among the IHA statistics for the empirical data set.

for the simulated and empirical data sets, respectively. As shown in the figures, some of the IHA statistics are highly correlated. The absolute values of the correlation coefficients among the IHA statistics in the simulated data set range from 0.002 to 1.00, with a mean of 0.45 with many larger than 0.95. The absolute values of the correlation coefficients in the empirical data set range from 0.0 to 0.993, with a mean of 0.194. The correlations among statistics are not as strong in the empirical data set, but still there are several correlation coefficients that are higher than 0.95.

Figs. 2 and 3 document that the IHA statistics are highly inter-correlated. Hence a principal component analysis (PCA) was conducted in Section 3 to reduce the dimensionality of the IHA data set while retaining as much of the variation inherent in the original data set as possible. This analysis enabled us to examine patterns of intercorrelation among the IHA statistics, thus providing an approach to select a subset of statistically non-redundant IHA parameters.

Generalized indices: eco-flow statistics and DHRAM

Several researchers have developed generalized indices to evaluate the overall impact of streamflow regulation on flow regimes. Vogel et al. (2007) introduced the nondimensional metrics of ecodeficit and ecosurplus, which are based on a flow duration curve (FDC). Importantly the ecodeficit and ecosurplus can be computed over any time period of interest (month, season, or year) and reflect the overall loss or gain, respectively, in streamflow due to flow regulation during that period (Vogel et al., 2007). The ecosurplus and ecodeficit can be computed using either a period of record FDC or a median annual FDC which is used here (see Vogel and Fennessey, 1994, for further details). A median annual FDC reflects the variability of daily streamflow during a typical or median year. The bold curve in Fig. 4 is the median annual FDC for a stream that is not subject to regulation and the dotted curve represents the median annual FDC for the same stream subject to regulation. The area below the unregulated FDC and above the regulated FDC represents the amount of water now unavailable to river due to flow alteration caused by the withdrawal. Ecodeficit is then defined as the ratio of this area over the total area under the unregulated median annual FDC. This ratio represents the fraction of streamflow no longer available to the river during that period. Conversely, ecosurplus is the area above the unregulated FDC

and below the regulated FDC divided by the total area under the unregulated median FDC. Thus, ecodeficit and ecosurplus are dimensionless measures which represent the deficit or surplus of streamflow resulting from flow alteration, as a fraction of the mean streamflow in a typical or median year. It is also important to mention that the ecodeficit and ecosurplus can be computed using direct ecological measures such as habitat suitability measures. See Vogel and Fennessey (1995) for a discussion of how habitat suitability indices can be used in combination with FDC's.

In this study, we divide the year into three seasons: spring (March–June), winter (November–February) and summer (July–October), and computed both the annual and seasonal ecodeficits and ecosurpluses. We also introduce a new overall index of hydrologic alteration termed total seasonal ecochange, which is the sum of all the seasonal ecodeficits and ecosurpluses within a year. The prefix “eco” is added to the word deficit and surplus, because that any change in the natural flow regime can impair ecological integrity, depending on the magnitude, timing, duration, and frequency of those deviations (Poff et al., 1997). Hence, we hypothesize that both ecosurplus and ecodeficits are important metrics of ecosystem health. Even though FDCs do not account for the timing of streamflows, the use of seasonal ecodeficit and ecosurplus can capture some timing impacts (Vogel et al., 2007). We term this new class of nine metrics the eco-flow statistics.

Another generalized index of hydrologic alteration is the Dundee Hydrological Regime Alteration Method (DHRAM) developed by Black et al. (2005) to assess the severity and extent of human alteration to hydrologic regimes. DHRAM yields a score (from 0 to 30) based on the overall percentage of change in the 33 IHA parameters before and after streamflow regulation. The higher the score, the greater the impact the system has on the flow regime and higher the risk of damage to the ecosystem. The score enables one to determine the DHRAM class between Class 1 (Un-impacted condition) and Class 5 (severely impacted condition) (Black et al., 2005). The raw DHRAM scores, not the final class designation, were used in the present study.

IHA subset selection using PCA

The power of PCA lies in finding a subset of the matrix of original variables X to represent as much as possible of the overall internal variation of X . When p , the number of variables observed, is

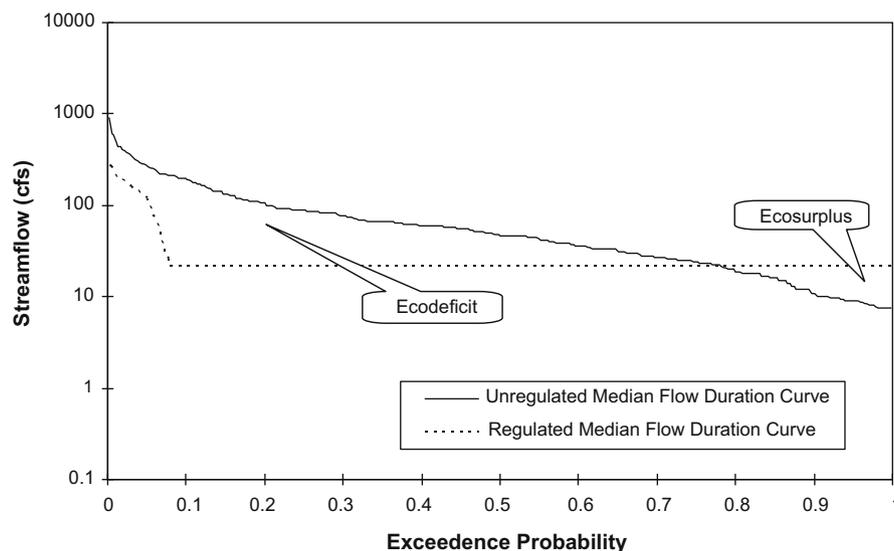


Fig. 4. Corresponding areas of ecodeficit and ecosurplus between regulated and unregulated flow duration curves of a stream.

large as is the case here for the IHA statistics, it is often the case that a subset of m variables, with $m \ll p$, contains virtually all the information available in all p variables (Jolliffe, 2002). Fig. 5 shows the percentage of variation explained by the PCs in each data set. To explain the same amount of overall variation in the data sets, more PCs were needed in the empirical data set than in the simulated data. This was expected because the empirical data set represented a much richer variation in both streamflow regimes and reservoir regulation, as data came from 189 different river basins. Several statistical methods are available to determine the number of PCs to be retained without losing the ability to explain a significant amount of the original variation. The Kaiser-Guttman criterion, which retains PCs with $\lambda > 1.0$ (Jackson, 1993), is used in this study. Therefore, the first 4 PCs, which explained 91.6% of the variation, were retained for the simulated data set. The first 8 PCs, which explained 77.7% of the variation, were retained for the empirical data set.

Next, a single variable (i.e. one IHA statistic) was selected to represent each of the retained PCs. The variable that has the highest loading (in absolute value) on a PC is selected to represent that PC (Dunteman, 1989). Table 2 summarizes the loadings of the four PCs retained for the simulated data set and Table 3 summarizes the loadings of the eight PCs retained for the empirical data set. The resulting representative IHA parameters for the simulated data are May flow, 30-day minimum, Date of maximum and Rise rate. They represent particular facets of the flow regime that are relatively independent of one another, because they are derived from different PCs (Olden and Poff, 2003). The resulting eight representative parameters for the empirical data are November flow, February flow, March flow, June flow, 30-day minimum, 7-day maximum, High pulse duration and Rise rate.

A close examination of Tables 2 and 3 reveals that the IHA statistics that have similar values of loadings form clusters, which are highlighted using gray shading in the tables. Such a clustering effect is more prominent in PCs that explain a greater degree of variation. The clusters indicate which group of IHA statistics dominate, or relate to, a particular PC and, therefore, can be used to interpret the PC axis. For example, in the simulated data set, PC1 was related to both monthly flow statistics and high flow magnitude statistics, PC2 was related to base flow magnitude and monthly flow, and PC3 was related to high flow magnitude and rate of change of the flow. PC 4 showed mixed loadings with no particular dominance or clustering of IHA statistics observed.

In the empirical data set, PC1 can be interpreted as being dominated by base flow magnitude and monthly flow; PC2 can be interpreted as being dominated by high flow magnitude; PC3 can be interpreted as monthly flow, rate of change and frequency; PC4 can be interpreted as monthly flow and rate of change; PC5 can be interpreted by monthly flow and frequency; and PC6 can be interpreted by timing of extreme events. Both PC7 and PC8 show mixed loadings and no dominance or clustering by any group of IHA statistics.

In the above analyses, the selection of dominant IHA statistics using λ s and loadings is arbitrary. For example, if we had decided to retain only 60% of the variation of the original data, we would have retained fewer PCs. To avoid the arbitrary nature of the above analysis and its associated uncertainty, another approach was to develop a comprehensive or overall index that can represent all of the 32 IHA parameters. Additional analyses were performed to evaluate if any of the generalized indices such as the eco-flow statistics or DHRAM was an effective overall index and to confirm if the above selected subsets of IHA statistics were truly representative indicators of hydrologic alteration.

Analysis 1 – multiple linear regression: generalized index vs. the 32 IHA statistics

This analysis evaluated whether the generalized indices, eco-deficit, ecosurplus or DHRAM, were correlated to the 32 IHA statistics and if they could be considered as an effective overall measure to represent the entire set of IHA statistics. A separate multiple linear regression (MLR) was performed for each of the 10 generalized indices using the 32 IHA parameters as the predictor (explanatory) variables for each data set. The names of the 10 generalized indices and the results from this analysis are given in Table 4.

For the simulated data set, almost all of the generalized indices (except winter and spring ecosurplus) had adjusted coefficient of determination (R^2 -adj) values in excess of 0.99. In contrast, for the empirical data set, only three generalized indices had R^2 -adj values that exceeded 0.8: total seasonal ecochange (0.807), summer ecosurplus (0.929) and winter ecosurplus (0.919). Across both datasets, the three generalized indices, total seasonal ecochange, summer ecosurplus and winter ecosurplus, explained the most variability in the 32 IHA statistics. Furthermore, those three eco-flow statistics explained much more of the variability in IHA statistics than the DHRAM index for the empirical data set.

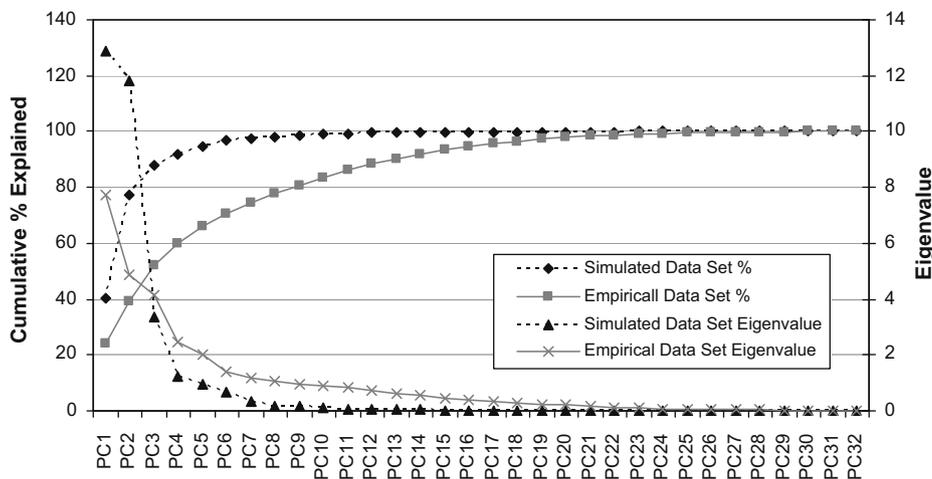


Fig. 5. Eigenvalue and cumulative % of variation explained by the PCs.

Table 2
Loadings for the first four PCs of the simulated data set.

Parameter	PC1	PC2	PC3	PC4
October flow	-0.337	0.858	-0.267	0.144
November flow	-0.832	0.295	-0.296	-0.269
December flow	-0.907	0.089	-0.183	-0.328
January flow	-0.868	0.320	-0.272	-0.230
February flow	-0.879	0.290	-0.218	-0.268
March flow	-0.914	-0.104	-0.122	-0.274
April flow	-0.924	-0.208	0.231	0.000
May flow	-0.967	-0.093	0.137	-0.049
June flow	-0.791	0.460	-0.352	-0.137
July flow	-0.361	0.847	-0.287	0.129
August flow	-0.246	0.940	-0.127	0.167
September flow	-0.281	0.918	-0.157	0.110
1-day minimum	-0.112	0.944	0.088	0.195
3-day minimum	-0.119	0.946	0.081	0.194
7-day minimum	-0.128	0.949	0.067	0.196
30-day minimum	-0.151	0.956	0.019	0.199
90-day minimum	-0.388	0.894	-0.151	0.097
1-day maximum	-0.870	-0.210	0.394	0.056
3-day maximum	-0.868	-0.193	0.412	0.085
7-day maximum	-0.877	-0.199	0.391	0.102
30-day maximum	-0.897	-0.182	0.357	0.072
90-day maximum	-0.918	-0.166	0.320	0.061
Base flow index	0.274	0.863	-0.164	0.010
Date of minimum	0.264	0.510	0.612	-0.071
Date of maximum	0.634	0.479	-0.107	-0.493
Low pulse count	-0.270	-0.801	-0.251	0.283
Low pulse duration	0.402	0.450	-0.195	-0.316
High pulse count	-0.853	-0.438	0.001	-0.015
High pulse duration	-0.284	0.582	0.548	-0.027
Rise rate	0.278	0.448	0.728	-0.217
Fall rate	0.272	0.454	0.721	-0.231
Number of reversals	-0.562	-0.699	-0.350	0.164
Axis interpretation	Winter to spring monthly flow, high flow	Base flow, summer monthly flow	High flow, rate of change	Mix

Note: The value in bold italics for each PC is the highest loading corresponding to that PC.

Analysis 2 – Pearson's r and Kendall's Tau between a generalized index and an individual PC

The goal of analysis 2 was to evaluate whether the various generalized indices could be used to represent the variability in the 32 IHA statistics explained by each PC. Each generalized index was plotted against the scores of each PC. Fig. 6 is an example of such plots. In Fig. 6, we observe a relationship between the annual ecodeficit and the first two PCs for both data sets. In general, the relationships among the generalized indices and the PCs are nonlinear, hence we investigated their correlation using the nonparametric correlation coefficient, Kendall's Tau, as well as the traditional linear measure of correlation, Pearson's r . Fig. 7a–d shows the absolute value of the two correlation coefficients. Values of the two correlation coefficients and their p values are reported in Appendix A.

In the simulated data set, the highest Pearson's r and highest Kendall's Tau values always corresponded to either PC1 or PC2 and were always in excess of 0.5. The absolute value of the highest Pearson's r ranged from 0.545 (spring ecosurplus vs. PC1) to 0.987 (annual ecodeficit vs. PC1). The absolute values of the highest Kendall's Tau ranged from 0.563 (DHRAM score vs. PC1 and summer ecodeficit vs. PC2) to 0.938 (annual ecodeficit vs. PC1).

In the empirical data set, the highest Pearson's r values and highest Kendall's Tau values always occurred with the first 3 PCs, except Pearson's r for summer ecodeficit, which was with PC6. The absolute values of the highest Pearson's r ranged from 0.241 (summer ecodeficit vs. PC6) to 0.751 (winter ecosurplus vs. PC3). The absolute values of the highest Kendall's Tau ranged from 0.273 (summer ecodeficit vs. PC1) to 0.631 (annual ecodeficit vs. PC2).

Analysis 3 – PCA on different subsets of the empirical data set

Since the reservoirs associated with both data sets have a wide range of different storage ratios, we investigated if the magnitude of the storage ratio, $s = S/\mu$, would have an impact on our analyses. To investigate the effect of s on the results, the 189 dams were divided into three subsets: (1) $s < 0.1$ ($n = 139$), (2) $s < 0.01$ ($n = 102$), (3) $s > 0.01$ ($n = 87$). Here the storage ratio can be interpreted as the average number of years of watershed runoff that the reservoir can hold so that values of $s = 0.01$ and 0.1 represent 3.6 and 36 days of storage, respectively. We grouped the dams into categories according to their storage ratio because Vogel et al. (1999) show that S/μ plays a key role in the behavior of water supply reservoirs and Vogel et al. (2007) document that reservoirs with larger storage ratios tend to have a greater impact on the overall ecological flow regime. Results of the PCA and the MLR between each of the generalized index and the 32 IHA statistics for the subsets are shown in Fig. 8 and Tables 5 and 6. The results of these analyses on subsets of the databases were not different from the results obtained earlier using the entire empirical data set.

Discussion

PCA subset selection

The PCA resulted in the selection of four IHA statistics from the simulated data set, eight from the empirical data set, and eight from each subset of the empirical data set. Results of the analyses on different subsets of the empirical data set were not significantly different from the original empirical data set.

Table 3
Loadings for the first 8 PCs of the empirical data set.

Parameter	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
October flow	-0.499	-0.168	0.082	0.411	-0.029	-0.290	0.425	0.017
November flow	-0.247	-0.044	0.470	0.625	-0.190	-0.235	0.102	0.163
December flow	-0.217	-0.004	0.658	0.595	-0.091	0.049	-0.047	0.010
January flow	-0.164	-0.030	0.754	0.476	-0.007	0.143	0.015	-0.090
February flow	-0.184	0.079	0.771	0.331	-0.099	0.265	-0.043	-0.032
March flow	-0.317	0.308	0.476	-0.213	-0.173	0.434	-0.220	-0.113
April flow	-0.269	0.479	0.122	-0.259	-0.401	0.239	-0.179	0.054
May flow	-0.198	0.442	0.051	-0.196	-0.526	-0.050	-0.113	0.201
June flow	-0.475	0.376	-0.032	-0.221	-0.572	-0.185	0.088	-0.001
July flow	-0.732	0.056	-0.131	-0.181	-0.304	-0.249	0.010	-0.112
August flow	-0.884	-0.075	-0.185	-0.090	0.085	-0.068	-0.086	-0.107
September flow	-0.715	-0.158	-0.168	0.146	0.244	-0.099	0.211	-0.164
1-day minimum	-0.785	-0.007	-0.269	0.099	0.326	0.327	-0.108	-0.040
3-day minimum	-0.863	-0.019	-0.252	0.078	0.267	0.256	-0.087	-0.014
7-day minimum	-0.940	-0.033	-0.206	0.014	0.124	0.101	-0.061	0.025
30-day minimum	-0.949	-0.043	-0.154	0.061	-0.006	-0.032	0.009	0.083
90-day minimum	-0.739	-0.017	0.096	-0.025	-0.133	-0.226	-0.072	0.190
1-day maximum	0.135	0.851	0.000	0.091	0.327	-0.098	-0.036	0.102
3-day maximum	0.125	0.896	-0.015	0.089	0.313	-0.111	-0.015	0.078
7-day maximum	0.046	0.919	-0.020	0.091	0.295	-0.135	0.026	-0.002
30-day maximum	-0.095	0.916	0.020	0.086	0.149	-0.101	0.041	-0.160
90-day maximum	-0.102	0.869	0.050	0.028	-0.015	0.031	0.074	-0.232
Base flow index	-0.932	-0.076	-0.229	0.024	0.136	0.128	-0.069	0.032
Date of minimum	-0.011	0.011	0.282	-0.201	0.007	0.396	0.300	0.000
Date of maximum	0.019	-0.112	-0.085	0.116	0.093	-0.390	-0.224	-0.327
Low pulse count	0.101	-0.254	0.542	-0.364	0.360	-0.094	-0.060	-0.341
Low pulse duration	0.202	0.029	-0.246	0.003	0.093	0.219	0.442	0.095
High pulse count	-0.110	-0.133	0.706	-0.387	0.341	-0.012	0.035	-0.029
High pulse duration	0.023	0.098	-0.248	0.076	-0.412	0.126	0.324	-0.700
Rise rate	-0.274	0.068	0.435	-0.481	0.102	-0.066	0.466	0.186
Fall rate	-0.493	0.026	0.493	-0.527	0.090	-0.182	0.220	0.038
Number of reversals	-0.170	-0.202	0.536	-0.226	0.045	-0.331	-0.312	-0.152
Axis interpretation	Base flow, summer monthly flow	High flow	Winter monthly flow, rate of change, frequency	Fall to winter monthly flow, rate of change	Spring to summer monthly flow, frequency	Timing of extreme events	Mix	Mix

Note: The value in bold italics for each PC is the highest loading corresponding to that PC.

Table 4
Adjusted coefficient of determination (R^2 -adj) of the multivariate linear regression between a generalized index and the 32 IHA parameters for both data sets.

Generalized index	Simulated data set ($n = 96$)	Empirical data set ($n = 189$)
Annual ecodeficit	0.998	0.603
Annual ecosurplus	0.989	0.663
Winter ecodeficit	0.990	0.453
Winter ecosurplus	0.898	0.919
Spring ecodeficit	0.995	0.699
Spring ecosurplus	0.783	0.559
Summer ecodeficit	0.998	0.296
Summer ecosurplus	0.993	0.929
Total seasonal ecochange	0.995	0.807
DHRAM score	0.988	0.540

Hence, we conclude that storage ratio does not play a significant role in determining which IHA statistics are most representative of ecological flow regimes.

The six ERHIs selected by Yang et al. (2008) are date of minimum, rise rate, number of reversals, 3-day maximum, 7-day minimum and May flow. Table 5 lists those IHA statistics that were selected in our analyses for both data sets. The four groups of IHA statistics selected are not exactly the same, but a closer examination reveals that most of them contain three common elements: at least one monthly flow statistic, two extreme event statistics representing both high and low extremes, and one statistic associated with frequency of the low pulse and high pulse. These three elements can also be seen in Yang et al.'s (2008) selection of the six ERHIs, although our subset selection is not

the same as theirs. Similar patterns can also be found by examining the loadings of the PCs in Tables 2 and 3. There appears to be clusters of IHA statistics that dominate each PC and each of those clusters match with one of the three elements identified above. Each of these elements corresponds to a certain type of ecological influence, and one of the five flow regime characteristics identified by Richter et al. (1996).

Interpretation of the principal components and selection of the most representative subset of indicators requires statistically sound criteria, and should be combined with physical and biological knowledge of the streamflow regimes of interest (Olden and Poff, 2003). In order to justify the selection of a particular subset of IHA statistics from PCA, the ecological relevance of those parameters needs to be demonstrated.

Effectiveness of the eco-flow statistics as overall metrics of hydrologic alteration

In analysis 1, multivariate linear regression was performed to investigate relationships between each of the 10 generalized indices and the 32 IHA statistics. Our results in Table 4 indicated a strong relationship between all 10 generalized indices and the 32 IHA statistics in the simulated data set. The values of R^2 -adj derived from the empirical data set (see Tables 4 and 6) are not as high as those derived from simulated data set though a few eco-flow statistics in the empirical data set had R^2 -adj values that were higher than 0.8 (winter ecosurplus, summer ecosurplus and total seasonal ecochange). Across both datasets, the three generalized indices, total seasonal ecochange, summer ecosurplus and winter

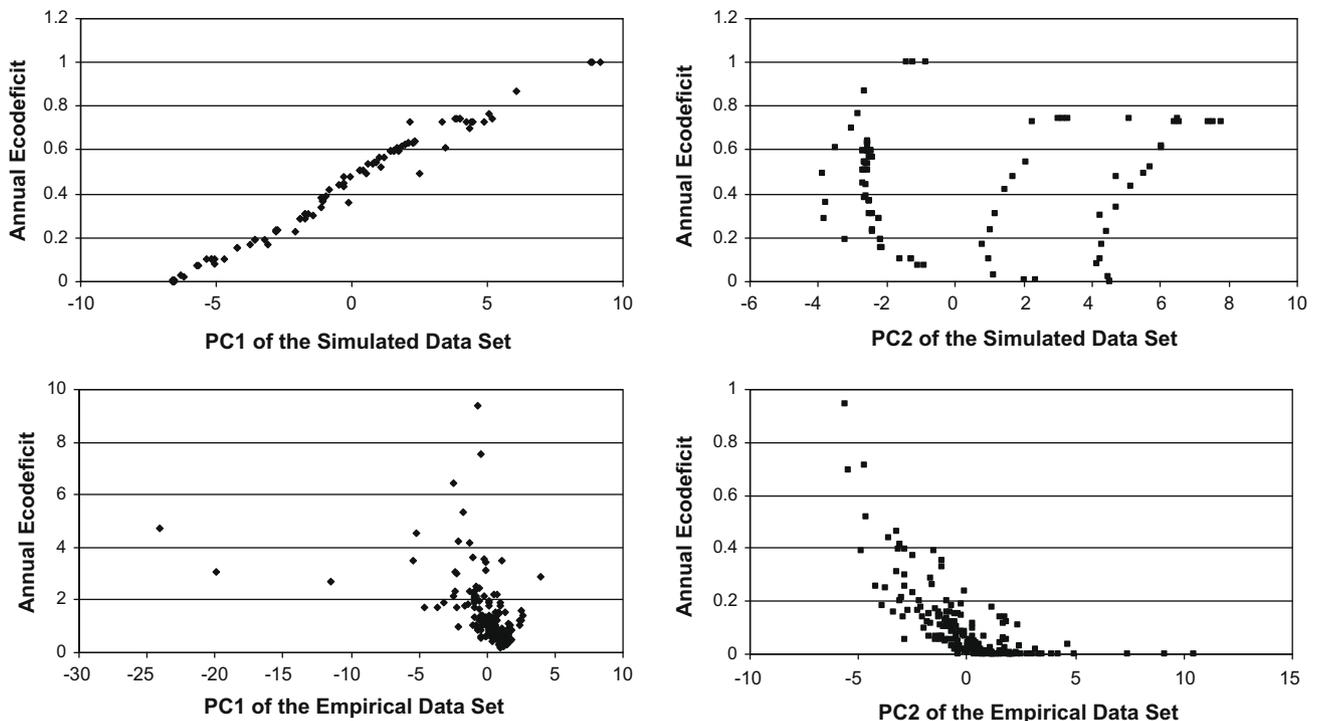


Fig. 6. Scatter plot of annual ecodeficit vs. the first two PCs (the top two plots are for the simulated data set and the bottom two plots are for the empirical data set).

ecosurplus, explained the most variability in the 32 IHA statistics. Furthermore, those three eco-flow statistics explained much more of the variability in IHA statistics, than the DHRAM index for the empirical data set.

In analysis 2, correlation coefficients (Pearson's r and Kendall's Tau) were computed between each generalized index and the individual PCs. The results indicate a strong correlation between each generalized index and one of the first two PCs in the simulated data set, and between a generalized index and one of the first three PCs in the empirical data set.

In terms of correlations with the IHA statistics, DHRAM performs similarly to the eco-flow statistics for the simulated data set (Tables 4 and 6, and Fig. 7a and b), because it has similar values of R^2 -adj, Kendall's Tau and Pearson's r values to the eco-flow statistics. However, in the empirical data set, DHRAM has generally lower values of R^2 -adj, Kendall's Tau and Pearson's r (Tables 4 and 6, and Fig. 7c and d) than the eco-flow statistics. Therefore, the eco-flow statistics appear to be a better generalized index than DHRAM.

Conclusions

There is an increasing need to account for natural differences in flow variability among rivers and to understand the importance of such differences for the protection of freshwater biodiversity and maintenance of goods and services that rivers provide (Arthington et al., 2006). One should not ignore natural system complexity in favor of simple and static environmental flow "rules" to manage our water resources. On the other hand, there is a need to develop a reduced suite of indices to replace the commonly used 33 IHA parameters and to provide an accurate overall determination of the impact of hydrologic alteration. The use of a single or just a few indices of hydrologic alteration can minimize statistical redundancy and lead to significant reductions in the complexity associated with the formulation and development of optimal reservoir operation policies and other river regulation schemes. There

should be a balance between statistical simplicity and natural system complexity to enable the design of logical and environmentally sustainable reservoir release rules and river regulation guidelines.

This study has sought to evaluate the ability of a set of generalized indices of hydrologic alteration to describe the variations in stream discharge resulting from reservoir operating release rules. In general, we found that the eco-flow statistics termed the ecodeficit and the ecosurplus can provide good overall measures of hydrologic alteration. The annual ecodeficit appears to be the best generalized index among all the indices in the simulated data set. On the other hand, winter ecosurplus and summer ecosurplus appear to perform best in the empirical data set. In addition, total seasonal ecochange appears to a good generalized index in both data sets since it accounts for all the seasonal deficits and surpluses and because it accounts for seasonal changes, thus taking timing of the flow into consideration. The total seasonal ecochange resulted in high values of R^2 -adj values with the 32 IHA parameters in both data sets and all subsets of the empirical data set; and resulted in a high correlation with PC1 even when the Pearson's r and Kendall's Tau values of the seasonal ecodeficit and ecosurplus were low, as indicated (Fig. 7a–d).

We expected the results for the simulated data set and the empirical data set to differ, because the simulated data set only considers a wide range of reservoir release rules for a wide range of hypothetical reservoir systems on a single river, whereas the empirical data set considers a wide range of reservoir release rules for a wide range of actual reservoir systems on 189 rivers that occur across a wide spectrum hydroclimatic regions. The empirical data set may also contain variations in streamflow that are not caused by the reservoirs release rules. Nevertheless, the ecodeficit and ecosurplus indices as well as the total seasonal ecochange statistic still appear to be good generalized indices of hydrologic alteration. Furthermore, the eco-flow statistics are computed in a manner that is independent of other IHA statistics, hence they are statistical aggregates of other indicators and their application may eliminate some of the statistical redundancy and

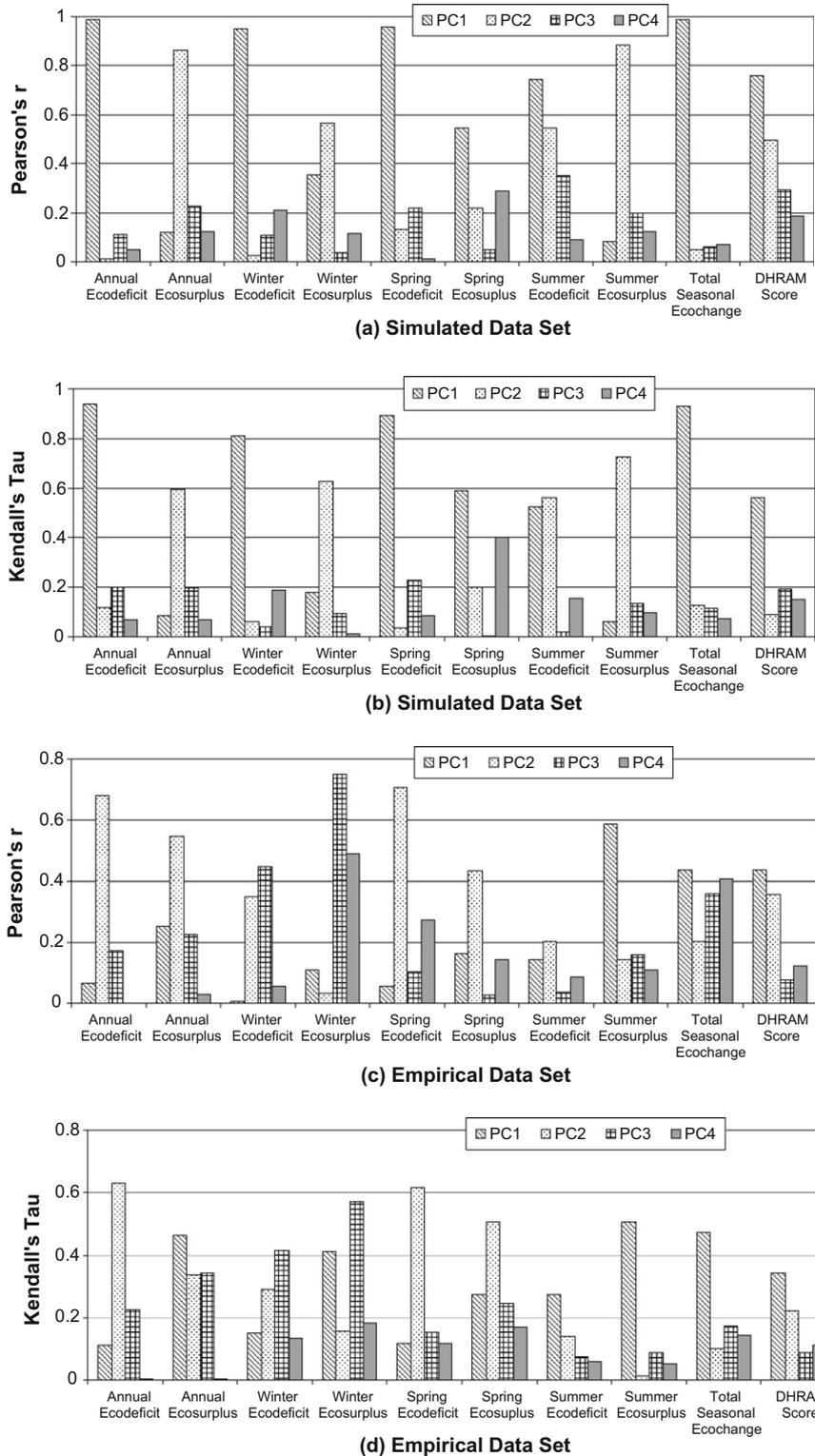


Fig. 7. Absolute values of Pearson's r and Kendall's Tau between the generalized index and the first 4 PCs of the simulated data set (a and b) and the empirical data set (c and d).

intercorrelation issues that plague other more commonly used statistics. Although nine eco-flow statistics are introduced here, it is our intention to advance only a few such statistics to avoid intercorrelation.

Our results are specific to the two data sets employed. Future work should be conducted to extend our analyses using other data

sets where reservoir operating rules are better understood and controlled, other types of river regulation schemes, as well as other methods for selecting ERHI's including the bootstrap approach introduced by Yu et al. (1998) and the genetic programming and autecology matrix approaches introduced by Yang et al. (2008). In addition, future research should evaluate other recently

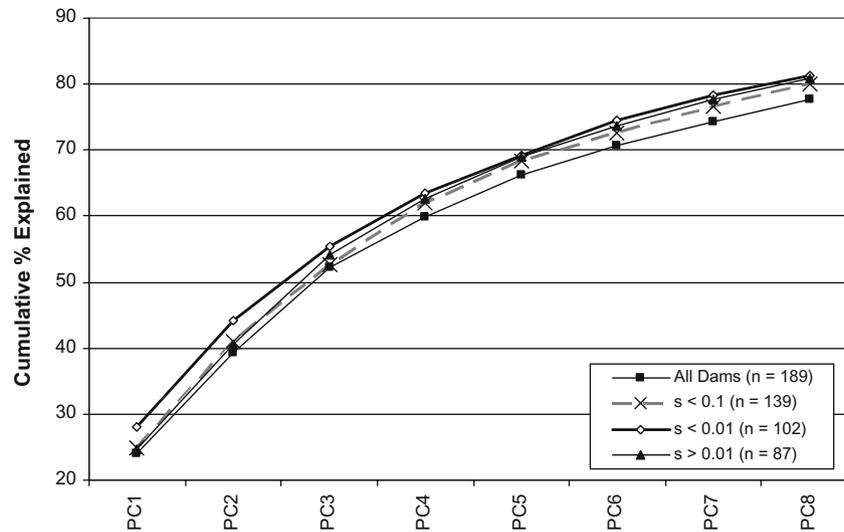


Fig. 8. Cumulative percentage of variation explained by different subsets of the empirical data set.

Table 5

Summary of PCA subset selection for the simulated data set and different subsets of the empirical data sets.

Simulated data set (n = 96)		Real data real			
		All dams (n = 189)	s < 0.1 (n = 139)	s < 0.01 (n = 102)	s > 0.01 (n = 87)
PC1	May flow	30-day minimum	30-day minimum	30-day minimum	7-day minimum
PC2	30-day minimum	7-day maximum	30-day maximum	30-day maximum	7-day maximum
PC3	Rise rate	February flow	December flow	Fall rate	February flow
PC4	Date of maximum	November flow	Fall rate	May flow	November flow
PC5		June flow	March flow	February flow	June flow
PC6		March flow	Date of maximum	High pulse duration	Date of minimum
PC7		Rise rate	Date of minimum	December flow	October flow
PC8		High pulse duration	Rise rate	April flow	Date of maximum

Table 6

Adjusted coefficient of determination (R^2 -adj) of the multivariate linear regression for different subsets of the empirical data sets.

Generalized Index	All Dams (n = 189)	s < 0.1 (n = 139)	s < 0.01 (n = 102)	s > 0.01 (n = 87)
Annual ecodeficit	0.603	0.578	0.654	0.626
Annual ecosurplus	0.663	0.738	0.825	0.554
Winter ecodeficit	0.453	0.375	0.522	0.460
Winter ecosurplus	0.919	0.940	0.883	0.938
Spring ecodeficit	0.699	0.652	0.552	0.716
Spring ecosurplus	0.559	0.756	0.821	0.487
Summer ecodeficit	0.296	0.445	0.385	0.304
Summer ecosurplus	0.929	0.857	0.912	0.928
Total seasonal ecochange	0.807	0.770	0.797	0.818
DHRAM score	0.540	0.331	0.521	0.633

introduced generalized indices of hydrologic alteration, such the index D_o introduced in Eq. (4) of Shiao and Wu (2007) and Eqs. (1) and (2) of Shiao and Wu (2006) and the indices recommended by Monk et al. (2007). Importantly, future research should also address systematic approaches for integrating indicators of hydrologic alteration into studies which seek to integrate the tradeoffs among various hydrologic and ecologic factors into planning studies (Loucks 2006).

Generally, small values of the ecodeficit/ecosurplus correspond to low values of hydrologic alteration. However, unlike DHRAM scores, which enable water resources managers to determine the level of risks that a particular reservoir regulation scheme has on a river, the ecodeficit/ecosurplus does not yet include the level of risks. Future research should: (1) investigate the hydrologic and ecological significance of the values of ecodeficit/ecosurplus

needed to fully address the ecologically-based environmental flow requirement; and (2) establish a system to classify what level of ecodeficit/ecosurplus is acceptable and unacceptable for a particular reservoir operation in a river.

Acknowledgements

The first author received an EGU Young Scientist Outstanding Poster Presentation award for her poster presentation of this research at the European Geosciences Union General Assembly 2008 in Vienna, Austria – Hydrological Sciences Division. This research was supported in part by a grant from the US Environmental Protection Agency’s (EPA) Science to Achieve Results (STAR) program. Although the research described in this manuscript has been partially funded by the US EPA (NCER Grant

X3832386), it has not been subjected to any EPA review and therefore does not necessarily reflect the views of the Agency, and no official endorsement should be inferred. The authors are also grateful to Colin Apse and Mark Smith of the Nature Conservancy, and Jack Sieber and Brian Joyce of the Stockholm

Environment Institute for their input on an early version of this manuscript; Stacey Archfield of the US Geological Survey for her assistance with the simulated data set; and Antarpreet Singh Jutla and Jim Limbrunner of Tufts University their assistance in coding Matlab and VBA.

Appendix A. Values of Pearson's r and Kendall's Tau in experiment 2

(a) Pearson's r and the corresponding p value between the generalized indices and the first 4 PCs of the simulated data set.

Generalized index	PC1		PC2		PC3		PC4	
	r	p	r	p	r	p	r	p
Annual ecodeficit	0.987	0.000	-0.013	0.900	-0.110	0.288	0.051	0.621
Annual ecosurplus	-0.121	0.241	0.863	0.000	0.228	0.026	0.124	0.227
Winter ecodeficit	0.949	0.000	-0.023	0.822	0.108	0.297	0.212	0.038
Winter ecosurplus	-0.356	0.000	0.565	0.000	0.037	0.721	-0.117	0.255
Spring ecodeficit	0.958	0.000	0.133	0.197	-0.219	0.032	0.013	0.900
Spring ecosurplus	-0.545	0.000	0.219	0.032	-0.049	0.637	-0.290	0.004
Summer ecodeficit	0.745	0.000	-0.546	0.000	0.353	0.000	0.090	0.386
Summer ecosurplus	-0.083	0.422	0.883	0.000	0.200	0.051	0.125	0.226
Total seasonal ecochange	0.988	0.000	-0.051	0.621	0.063	0.541	0.071	0.489
DHRAM score	0.759	0.000	0.497	0.000	0.292	0.004	-0.188	0.067

(b) Kendall's Tau and the corresponding p value between the generalized indices and the first 4 PCs of the simulated data set.

Generalized index	PC1		PC2		PC3		PC4	
	T	P	τ	p	τ	p	τ	p
Annual ecodeficit	0.938	0.000	-0.120	0.086	-0.202	0.004	0.070	0.314
Annual ecosurplus	-0.086	0.288	0.596	0.000	0.196	0.015	0.071	0.383
Winter ecodeficit	0.812	0.000	-0.061	0.385	-0.042	0.547	0.190	0.007
Winter ecosurplus	-0.182	0.022	0.628	0.000	0.095	0.231	-0.013	0.874
Spring ecodeficit	0.892	0.000	-0.037	0.599	-0.230	0.001	0.087	0.212
Spring ecosurplus	-0.591	0.000	0.203	0.012	0.002	0.982	-0.403	0.000
Summer ecodeficit	0.525	0.000	-0.563	0.000	0.022	0.761	0.154	0.029
Summer ecosurplus	-0.063	0.434	0.727	0.000	0.134	0.096	0.099	0.221
Total seasonal ecochange	0.929	0.000	-0.128	0.066	-0.115	0.098	0.075	0.282
DHRAM score	0.563	0.000	0.092	0.201	0.193	0.007	0.153	0.033

(c) Pearson's r and the corresponding p value between the generalized indices and the first 8 PCs of the empirical data set.

Generalized index	PC1		PC2		PC3		PC4		PC5		PC6		PC7		PC8	
	r	p	r	P	r	p	r	p	p	r	r	p	r	p	r	p
Annual ecodeficit	0.068	0.353	-0.679	0.000	-0.172	0.018	0.001	0.986	-0.078	0.283	0.072	0.327	-0.075	0.302	0.009	0.900
Annual ecosurplus	-0.254	0.000	0.548	0.000	0.226	0.002	-0.028	0.698	-0.194	0.007	-0.072	0.322	0.167	0.021	-0.271	0.000
Winter ecodeficit	-0.006	0.935	-0.350	0.000	-0.448	0.000	-0.058	0.428	0.020	0.786	-0.025	0.734	0.079	0.283	-0.215	0.003
Winter ecosurplus	-0.109	0.136	-0.032	0.663	0.751	0.000	0.491	0.000	0.039	0.592	0.111	0.129	-0.029	0.688	-0.111	0.127
Spring ecodeficit	0.056	0.442	-0.706	0.000	0.103	0.159	0.273	0.000	0.093	0.202	-0.019	0.793	-0.018	0.805	-0.087	0.236
Spring ecosurplus	-0.163	0.025	0.432	0.000	0.027	0.711	-0.143	0.049	-0.381	0.000	0.073	0.318	0.043	0.553	-0.327	0.000
Summer ecodeficit	0.142	0.051	-0.202	0.005	0.037	0.613	0.086	0.238	-0.113	0.121	0.241	0.001	-0.181	0.013	0.054	0.462
Summer ecosurplus	-0.586	0.000	-0.143	0.050	-0.161	0.027	0.109	0.135	0.106	0.147	-0.295	0.000	0.224	0.002	-0.199	0.006
Total seasonal ecochange	-0.437	0.000	-0.203	0.005	0.360	0.000	0.406	0.000	0.024	0.744	-0.075	0.306	0.115	0.114	-0.295	0.000
DHRAM score	-0.438	0.000	-0.358	0.000	0.076	0.299	0.124	0.089	0.011	0.880	-0.152	0.036	0.173	0.017	-0.181	0.013

(d) Kendall's Tau and the corresponding *p* value between the generalized indices and the first 8 PCs of the empirical data set.

Generalized index	PC1		PC2		PC3		PC4		PC5		PC6		PC7		PC8	
	τ	<i>p</i>														
Annual ecodeficit	0.111	0.023	-0.631	0.000	-0.224	0.000	-0.002	0.973	-0.080	0.102	0.106	0.031	-0.190	0.000	0.012	0.810
Annual ecosurplus	-0.465	0.000	0.336	0.000	0.344	0.000	0.004	0.939	-0.188	0.000	-0.130	0.008	0.205	0.000	-0.062	0.203
Winter ecodeficit	0.150	0.003	-0.290	0.000	-0.415	0.000	-0.135	0.008	0.046	0.363	-0.098	0.051	-0.099	0.051	-0.058	0.253
Winter ecosurplus	-0.411	0.000	0.156	0.001	0.572	0.000	0.182	0.000	-0.165	0.001	-0.008	0.874	0.107	0.029	0.026	0.605
Spring ecodeficit	0.116	0.018	-0.616	0.000	-0.152	0.002	0.116	0.018	0.062	0.206	0.009	0.854	-0.119	0.015	-0.037	0.450
Spring ecosurplus	-0.274	0.000	0.508	0.000	0.244	0.000	-0.168	0.001	-0.252	0.000	0.021	0.676	0.072	0.143	0.031	0.530
Summer ecodeficit	0.273	0.000	-0.141	0.006	-0.074	0.148	-0.060	0.243	0.004	0.942	0.270	0.000	-0.232	0.000	-0.070	0.171
Summer ecosurplus	-0.508	0.000	0.014	0.775	0.087	0.077	0.051	0.296	-0.132	0.007	-0.340	0.000	0.218	0.000	0.016	0.740
Total seasonal ecochange	-0.473	0.000	-0.100	0.041	0.171	0.000	0.145	0.003	-0.170	0.001	-0.191	0.000	0.097	0.049	0.005	0.915
DHRAM Score	-0.343	0.000	-0.222	0.000	0.088	0.085	0.112	0.028	-0.050	0.321	-0.176	0.001	0.088	0.082	0.026	0.602

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