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Baseflow separation based on a meteorology-corrected nonlinear reservoir algorithm in a typical rainy agricultural watershed

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SUMMARY

A baseflow separation model called meteorology-corrected nonlinear reservoir algorithm (MNRA) was developed by combining nonlinear reservoir algorithm with a meteorological regression model, in which the effects of meteorological factors on daily baseflow recession were fully expressed. Using MNRA and the monitored data of daily streamflow and meteorological factors (including precipitation, evaporation, wind speed, water vapor pressure and relative humidity) from 2003 to 2012, we determined the daily, monthly, and yearly variations in baseflow from ChangLe River watershed, a typical rainy agricultural watershed in eastern China. Results showed that the estimated annual baseflow of the ChangLe River watershed varied from 18.8 cm (2004) to 61.9 cm (2012) with an average of 35.7 cm, and the baseflow index (the ratio of baseflow to streamflow) varied from 0.58 (2007) to 0.74 (2003) with an average of 0.65. Comparative analysis of different methods showed that the meteorological regression statistical model was a better alternative to the Fourier fitted curve for daily recession parameter estimation. Thus, the reliability and accuracy of the baseflow separation was obviously improved by MNRA, i.e., the Nash–Sutcliffe efficiency increased from 0.90 to 0.98. Compared with the Kalinin's and Eckhardt's recursive digital filter methods, the MNRA approach could usually be more sensitive for baseflow response to precipitation and obtained a higher goodness-of-fit for streamflow recession, especially in the area with high-level shallow groundwater and frequent rain.

1. Introduction

Baseflow is commonly defined as the water that sustains flow in a river during low-flow periods, and it is an important component of streamflow during high-flow conditions, which originates from groundwater and other delayed shallow subsurface flow into the stream (Hall, 1968; Smakhtin, 2001; Cherkauer and Ansari, 2005; Santhi et al., 2008). Determining the baseflow component and understanding the interaction between surface water and groundwater play a crucial role in water resources and water quality management (Eckhardt, 2008; Ahiablame et al., 2013), in the control of river algal blooms and salinity (Santhi et al., 2008), and in calibrating and validating hydrological models (Cao et al., 2006; Vázquez et al., 2008; Ferket et al., 2010). However, no direct approach exists for continuously measuring the baseflow (Lin et al., 2007) and the variability of its recession under different conditions (Datta et al., 2011) because it is usually affected by diverse climatological, morphological, and geological factors, with considerable variations in time and space (Singh, 1968). Although growing numbers of field-indirect determination methods (temperature, artificial, and natural tracer concentrations, stream-bed seepage meter, and others) have been used to quantify the baseflow in a relatively short period (Cook et al., 2003, 2008; Becker et al., 2004; Meredith and Kuzara, 2012), baseflow separation remains "one of the most desperate analysis techniques in use in hydrology" because such methods are labor-intensive and are difficult to apply continuously for long periods (Huyck et al., 2005; Longobardi and Villani, 2008).

Consequently, some alternative methods are developed for baseflow estimation, such as the hydrograph method and digital filtering approaches. For the hydrograph method, the main defect of such a type of baseflow separation is either physically not well-founded or might be subjective to varying degrees (Tallaksen, 1995). The digital filtering approaches for baseflow separation are generally not physically based to a certain degree as well, but they are easier, faster, and more objective to apply to long time series of discharge than graphical methods. For instance, smoothed minima approaches (low-pass filters) based on the "time

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of the cessation of runoff" (Pettyjohn and Henning, 1979) are developed to estimate baseflow in the long term, which is used in the models of the Hydrograph Separation Program (Sloto and Crouse, 1996; Brandes et al., 2005; Eckhardt, 2008), the BFI (Wahl and Wahl, 1988; Piggott et al., 2005), and the recursive digital filter algorithm (Lyne and Hollick, 1979; Nathan and McMahon, 1990; Arnold and Allen, 1999; Chapman, 1999; Eckhardt, 2005). However, one obvious flaw of the smoothed minima approaches is that the characteristic points of a hydrograph are connected with straight lines, thereby immediately giving the impression of an unrealistic baseflow progression (Eckhardt, 2008). Although the recursive digital filters, by contrast, provide an extensively smooth time series of baseflow that seems to be more plausible according to hydrology, they still make the physics behind baseflow estimation particularly during rising periods of streamflow because of the calibration on which they heavily rely (Furey and Gupta, 2001).

To overcome the subjective elements in earlier simpler filters and to alleviate some of their simplified assumptions, physically based mathematical filters for continuous baseflow separation are developed based on a linear reservoir expression together with the Boussinesq-derived (Huyck et al., 2005) or hill slope mass-balance equations (Furey and Gupta, 2001, 2003) for the confined aquifer watershed condition. Nevertheless, the algorithm of a single linear reservoir can be satisfactorily fitted to shorter recessions only (Chapman, 1999; Wittenberg, 1999). In most cases, the shallow groundwater aquifers of rivers are predominantly unconfined; thus, the recession curves for such watersheds can be effectively modeled by using the nonlinear groundwater storage–outflow model (Eq. (2)) rather than the linear one (Wittenberg, 1999). The nonlinear reservoir algorithm based on the assumption of nonlinear storage–discharge relationships has also been developed and applied to baseflow separation recently. Compared with some traditional low-pass filters, the consideration of the seasonal variation in recession parameters (commonly described using the Fourier function, e.g., Aksoy and Wittenberg, 2011; Datta et al., 2011) in nonlinear reservoir algorithm is an obvious improvement in baseflow separation.

However, estimating the recession parameters used for baseflow separation based on nonlinear reservoir algorithm is still confined to several typical recessions (Wittenberg, 1999) or on a monthly basis (Aksoy and Wittenberg, 2011) without sufficiently considering the effects of meteorological factors on baseflow recession, thereby leading to uncertainty in baseflow estimation during non-recession periods. Thus, the main objective of the present study is to construct a statistical regression model based on certain meteorological factors for daily recession parameter estimation in both recession and non recession periods to reduce the uncertainty in the baseflow estimation by nonlinear reservoir algorithm. The Kalinin's method (Chen et al., 2008) and the recursive digital filter of Eckhardt (2005) are also used to compare and evaluate the performance of the nonlinear reservoir algorithm baseflow estimation based on daily recession parameter.

2. Material and methods

2.1. Study area

The ChangLe River watershed (120°35′E–120°49′E and 29°27′N–29°35′N) is located in the Ningshao Plain of eastern Zhejiang Province, southeast China (Fig. 1). As one of the main tributaries of the Cao-E River, the ChangLe River system ultimately flows into the Qiantang Estuary and East China Sea; it flows to approximately 70.5 km with 0.36% of gradient sandy-gravel riverbed and 40–70 m width, draining a total area of 864 km^2. The altitude of ChangLe River watershed is ranged from 15.4 to 1094.4 m, with an average of 259.3 m. The study area represents a typical agricultural watershed in southeast China, with an evident subtropical monsoon climate (Chen et al., 2009). The annual and monthly average meteorological data in the ChangLe River watershed from the year of 2003 to 2012 were given in Table 1 and Supplementary Fig. S1, respectively. The long-term average annual precipitation is 1228 mm, with 45.2–68.7% of rainfall usually occurring from May to September in 2003–2012 for the catchment recorded at the weather station in Shengzhou City. Approximately 74.9% (920 mm) of average annual precipitation is returned to the atmosphere through evaporation. There has not been any snow during the period of 2003–2012 in the ChangLe River watershed. The average annual runoff is 55.08 cm, with monthly variations ranging from 2.43 to 9.79 cm. The primary land-use categories are woodland and farmland (including paddy fields, uplands, and garden plots), with an average of ∼48.6% and ∼41.9% of total watershed area, respectively.

2.2. Data collection

The continuous daily stream discharges at the monitoring site (Yazhi, Fig. 1) from 2003 to 2012 were supplied by the Zhejiang Provincial Government Hydrology Office. The corresponding daily meteorological data for the study area were obtained from the Shengzhou Weather Bureau and the China Meteorological Data Center.

2.3. Recession analysis and parameter calibration

The concrete process of recession analysis and parameters ("a" and "b") calibration of nonlinear reservoir algorithm is shown in Fig. 2. The recession representative curves extracted from the daily streamflow data should satisfy both of the following criteria to minimize the uncertainty caused by recession analysis as much as possible. Once the selection of representative recession curves completed, parameter "a" and "b" can be calibrated using an iterative least-squares method.

(i) According to the empirical equation ($N = 0.83A^{0.2}$, where N is the time, in days after a peak value of baseflow discharge, and A is the drainage area in km^2) (Linsley et al., 1949; Halford and Mayer, 2000), the point along the falling limb of a flood hydrograph event was determined. For this study, N was calculated as 4 days; therefore, each of the streamflow data y_k and y_{k+1} would be considered, which were part of a recession period of at least five days, i.e., it must be $y_{k-3} > y_{k-2} > y_{k-1} > y_k > y_{k+1} > y_{k+2}$ (Eckhardt, 2008). The minimum length of the extracted flow data is 5 days (Aksoy and Wittenberg, 2011).

(ii) The extracted flow sequence for recession analysis in step (i) was further verified by the method of nonlinear reservoir algorithm fitting. The corresponding coefficient of variation (CV) (defined in Eq. (1), Aksoy and Wittenberg (2011)) between the observed records (Q) and the fitted values (Q_{calc}) was calculated. If the CV for fitting a flow recession was less than 0.1, then these data could represent a "real" baseflow recession, which will be used for the subsequent parameter estimation.

$$\mathrm{CV} = \sqrt{\frac{n^2}{n-1}\,\frac{\sum_{i=1}^{n}(Q(i) - Q_{calc}(i))^2}{\left(\sum_{i=1}^{n}(Q(i))\right)^2}} \qquad (1)$$