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An empirical method for approximating stream baseflow time series using groundwater table fluctuations

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SUMMARY

Developing reliable methods to estimate stream baseflow has been a subject of interest due to its importance in catchment response and sustainable watershed management. However, to date, in the absence of complex numerical models, baseflow is most commonly estimated using statistically derived empirical approaches that do not directly incorporate physically-meaningful information. On the other hand, Artificial Intelligence (AI) tools such as Genetic Programming (GP) offer unique capabilities to reduce the complexities of hydrological systems without losing relevant physical information. This study presents a simple-to-use empirical equation to estimate baseflow time series using GP so that minimal data is required and physical information is preserved. A groundwater numerical model was first adopted to simulate baseflow for a small semi-urban catchment (0.043 km^2) located in Singapore. GP was then used to derive an empirical equation relating baseflow time series to time series of groundwater table fluctuations, which are relatively easily measured and are physically related to baseflow generation. The equation was then generalized for approximating baseflow in other catchments and validated for a larger vegetation-dominated basin located in the US (24 km^2). Overall, this study used GP to propose a simple-to-use equation to predict baseflow time series based on only three parameters: minimum daily baseflow of the entire period, area of the catchment and groundwater table fluctuations. It serves as an alternative approach for baseflow estimation in un-gauged systems when only groundwater table and soil information is available, and is thus complementary to other methods that require discharge measurements.

1. Introduction

Baseflow is commonly defined as the groundwater contribution to streamflow which can be affected by watershed characteristics of geomorphology, soil, and land use, as well as climate change (Price, 2011). Various studies have pointed out the significance of baseflow estimation for water policy and environmental management as it enhances the understanding of surface-groundwater interactions and related contaminant transport (Gilfedder et al., 2009; Li et al., 2013; Smakhtin, 2001). Therefore, developing reliable methods to estimate baseflow has been a subject of research over the past decades (Gonzales et al., 2009). However, baseflow identification and quantification still remains cumbersome and highly depends on the availability of monitoring networks and the choice of models. Baseflow cannot be identified easily based on direct field measurements (Li et al., 2013). Therefore, indirect methods comprising graphical methods (Linsley et al., 1982), recursive digital filters (RDFs) (Arnold and Allen, 1999; Nathan and McMahon, 1990), rating curve methods (Kliner and Knezek, 1974; Sellinger, 1996), tracer based hydrograph separation techniques (McGlynn and McDonnell, 2003), conceptual models such as IHACRES model (Jakeman and Hornberger, 1993) and numerical models (Partington et al., 2011) are commonly employed to quantify baseflow.

Various graphical baseflow separation methods have been developed by assuming baseflow to be equal to streamflow between distinct and consecutive rainfall events (e.g., Linsley et al., 1982). According to Linsley et al. (1982) this method is not appropriate for long continuous streamflow records. Furthermore, this approach assumes that the baseflow response is significantly slower than the surface runoff. However, as shown in many case studies in mountainous areas, this assumption is not always valid (McDonnell et al., 2001; Uhlenbrook and Hoeg, 2003).

Tracer based hydrograph separation is another widely used baseflow separation method (Barthold et al., 2010; Brown et al.,

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1999; Christophersen and Hooper, 1992; Christophersen et al., 1990; Hooper, 2003; Jones et al., 2006). However, as pointed out by Jones et al. (2006), quantification of pre-event water's contribution to streamflow may lead to huge overestimation due to the importance of dispersivity used in simulating tracer transport.

RDFs are signal processing techniques that remove the high-frequency quick flow signal from a streamflow time series in order to obtain the low-frequency baseflow signal. Numerous RDFs exist for baseflow separation such as one-parameter algorithm (Chapman and Maxwell, 1996), two-parameter algorithm (Chapman, 1999; Eckhardt, 2005) and three-parameter algorithm (Chapman, 1999). As the true values of the baseflow index parameter in these methods are unknown, one cannot conclude which method is best (Eckhardt, 2008). These approaches are often computationally efficient and also overcome the limitations associated with graphical based methods when applied to long continuous streamflow records. Therefore, RDFs are currently the most widely adopted method for baseflow separation. However, these are statistically derived equations that do not directly incorporate physically-meaningful information.

The rating curve method uses the intrinsic relationship between groundwater and stream water levels. According to Kliner and Knezek (1974), baseflow can be estimated by fitting a curve through the available discharge vs. groundwater table time series plot. On the other hand, Sellinger (1996) assumed that the entire stream flow during fair weather periods was composed of baseflow and then proposed to fit a parabolic equation only to the data corresponding to the recession limbs of the hydrograph after the surface runoff is over. However, according to Gonzales et al. (2009), an exponential function was more suitable than a parabolic equation for their study area. The equation also included an intercept term to account for a constant discharge coming from the deeper aquifer. Fitting parameters in this method can be estimated with the least squares method using observed stream flow and groundwater table data which have to be optimized separately for each event.

Application of physically based numerical modeling for baseflow quantification has been recently explored by Partington et al. (2011). In this method, flow solutions obtained from numerical models are processed by a hydraulic mixing-cell method to quantify hydrograph flow components. This method overcomes many of the limitations of other methods mentioned above. However, to date it has only been tested for a hypothetical catchment. Furthermore, such models are complex, requiring significant computational time and large amounts of data which may not always be available.

Artificial Intelligence (AI) tools such as Genetic Algorithms (GA) have been used widely in hydrology (e.g., Anctil et al., 2006; Babovic, 2005; Kim and Kim, 2008; Sedki et al., 2009). Genetic Programming (GP), a specialization of Genetic Algorithms (GA), has been also employed over the past decades to simplify complex hydrological problems such as the development of rainfall-runoff models based on meteorological data (Babovic and Keijzer, 2006), predicting natural channel flood routing (Sivapragasam et al., 2008), estimating saturated hydraulic conductivity (Parasuraman et al., 2007), evapotranspiration (Izadifar and Elshorbagy, 2010) and groundwater levels (Fallah-Mehdipour et al., 2013). As GP has been successful in solving a number of complex hydrological problems, it can potentially be used to estimate baseflow. Compared to numerical hydrological models, GP models require significantly less computation time and input data for calibration. In addition, the simple equations approximated by GP can be implemented in rainfall runoff distributed models for baseflow simulations. Estimating baseflow using discharge data is widely available (e.g., RDFs), however, to date, no equation has been derived using GP for determining baseflow based on physical catchment parameters. Deriving an equation based on easy to measure groundwater table fluctuations enables baseflow predictions in catchments where discharge monitoring is absent. Therefore, the primary objective of this study was to assess whether GP can be adopted to obtain an empirical equation using groundwater table fluctuations. More specifically, this study first derived an empirical equation for approximating baseflow time series using information from a case study, and then generalized the case study specific equation for approximating baseflow in other catchments.

2. Methodology

In this study, Kent Ridge Catchment in Singapore and Beaver River Basin in US were considered as case studies. A numerical model was first adopted to simulate baseflow time series for the Kent Ridge Catchment. Subsequently, an empirical equation was derived using GP to predict the simulated baseflow time series using catchment characteristics and time series of groundwater table elevation in Kent Ridge Catchment. The empirical equation was further modified into a generalized structure for its applicability in other catchments. The generalized baseflow equation was tested in a cross-site, cross-scale application in Beaver River Basin. Finally, its performance was compared to baseflow time series estimates obtained using the RDF method in both study sites.

2.1. Description of the study sites

2.1.1. Kent Ridge Catchment, Singapore

The Kent Ridge Catchment (0.043 km^2), a small semi-urban catchment located inside the Kent Ridge campus of National University of Singapore (NUS), was selected for the current study. The dominating land uses are bushes, grass and paved area and the main soil types are loamy sand, clay loam, sandy loam (Meshgi and Chui, 2014). The mean annual precipitation is 2500 mm and the rainfall pattern varies over the year with two monsoons (mid-November to early March and mid-June to September). There are moderate to heavy rainfall events during the monsoon period, while short shower events interrupted by thunderstorms in the inter-monsoon period.

One discharge measurement station together with a rainfall gauge operated simultaneously from September 2011 to August 2012 and January to June 2013, (Fig. 1). In January 2012, pressure transducers with loggers (i.e., Mini-Divers) recorded groundwater table elevations at 15-min intervals in two boreholes (BH1 and BH2) (Fig. 1). To eliminate the fluctuations in atmospheric pressure from the pressure transducers submerged in the boreholes, another pressure transducer (i.e., a Baro-Diver), suspended in air, was installed at the same location.

2.1.2. Beaver River Basin, US

The second study area was Beaver River Basin (Fig. 2), located in the state of Rhode Island of US. The catchment area is 23 km^2, which is more than 500 times larger than catchment in Singapore. The land-use is also very different compared to the one in Singapore, comprising major parks, forest, non-urban development and water bodies. The mean annual precipitation of this area is about 1350 mm. Daily stream flow and groundwater table data (1990–2013) were downloaded from U.S. Geological Survey (USGS) website.

2.2. Numerical modeling

Baseflow time series needed for the derivation of the empirical equation in Kent Ridge Catchment, using GP, was obtained by the groundwater flow model HYDRUS-3D. HYDRUS-2D/3D package